# Using Big Data and Machine Learning to Uncover How Players Choose Mixed Strategies<sup>\*</sup>

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#### Abstract

How do humans behave in a situation where (i) one needs to make one's own behavior unpredictable and (ii) one needs to predict an opponent's behavior? Such a situation can be formulated as a game with a mixed strategy equilibrium. If humans are put in such a situation, it should be obvious that, rather than calculating and following the mixed equilibrium strategy, they use their intuition, hunches, and some heuristics to achieve the above-mentioned goals (i) and (ii). Exactly what kind of mechanisms are employed has not been fully understood. By using a unique big experimental data set we have collected about a game with a mixed strategy equilibrium, which has about 75,000 observations, we compare conventional behavioral economics models and some leading machine learning models to uncover how human behavior is determined in such a situation. Our use of big data enabled us to obtain a reliable comparison of the predictive powers of those models, and we found that machine learning models, most notably a version of the deep learning model LSTM, substantially outperform the leading behavioral model (EWA). Finally, we try to improve the EWA model by incorporating the insights gained from the machine learning models.

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### 1 Introduction

The central research question of this article concerns how humans behave in a situation where (i) one needs to make one's own action unpredictable and (ii) at the same time one needs to predict which action an opponent will take. Examples abound and include tax auditing, terrorist attacks vs. airport security guards (Tambe, 2011), tennis serves (Walker and Wooders, 2001), and penalty kicks in soccer games (Palacios-Huerta, 2003; Chiappori, Levitt and Groseclose, 2002).

Such a situation can be formalized as a game with a mixed strategy equilibrium. A mixed strategy equilibrium is an ideal state where players' random actions constitute the mutual best reply. Previous research (e.g., the aforementioned papers as well as O'Neill, 1987; Camerer, 2011) has revealed that the concept of a mixed strategy equilibrium describes human behavior in field and lab data to some reasonable extent, while it has also been shown that humans do not exactly follow a mixed strategy equilibrium (e.g., Brown and Rosenthal, 1990). The latter point makes good sense; we would like the reader to reflect for a moment on how one might choose the directions of tennis serves or actions in the Rock-Paper-Scissors game. It is rather clear that one uses intuition, hunches, and some kind of limited reasoning to make one's action unpredictable and at the same time to predict the opponent's action. Exactly what kind of cognitive processes are employed has not yet been fully uncovered. The purpose of our research is to address this issue by using machine learning models and big data.

We use a unique data set that one of the authors has collected about a two-player game that has a non-trivial mixed strategy equilibrium. It is a card game invented by O'Neill (1987), where each player has four cards, K, 1, 2, 3, and chooses one of those cards at the same time as the opponent. The winner is determined by a rather complicated set of rules, and as a result, unlike the Rock-Paper-Scissors game, the equilibrium probability distribution over the four cards is not uniform. The data set was collected in a Coursera online course on game theory, and covers more than 5,000 participants, with the number of observations for each player's role being roughly 75,000. To the best of our knowledge, this is one of the largest data sets for a single treatment in economic laboratory experiments.

To uncover how players behave in a game with a mixed strategy equilibrium, we employ some of the leading machine learning models as well as the conventional behavioral economics models. Machine learning refers to a class of models in artificial intelligence used to detect various empirical regularities in big data. It received much public attention when a deep learning model gave a sensational performance in a leading image recognition contest, the ImageNet Large Scale Visual Recognition Challenge (Russakovsky et al., 2015). The task was to recognize the object (such as a tiger) in an image (such as a picture of a tiger). Figure 1 provides the error rates of the winners of the competition over time. Previously, the best error rate was somewhere above 20%, with gradual improvements being made each year, but the introduction of a deep learning model in 2012 resulted in a sudden drop of around 10 percentage points. In the contest, the contestants "trained" their models (i.e., performed parameter fitting) on a big data set of about 1.2 million images, and the actual competitive image recognition was performed on a separate "test" data set.



Figure 1. The graph is created based on data on Russakovsky et al. (2015) and ImageNet https://www.image-net.org/. Note that for 2012 and 2013, we selected the minimum classification error rates by a team not using outside training data. Also, note that the human's error rate is based on test data in 2012 to 2014.

Figure 2 illustrates the motivation of our research: If machine learning is capable of recognizing some patterns in an image, such as the overall shape of the object and its local pattern of black stripes, to conclude that the object in the image is a tiger, it might also recognize patterns in the past history of play in the card game to predict how players choose their current actions. We have a unique big data set that enables us to explore that possibility.

Our main findings are summarized as follows. First, machine learning models substantially improved upon the conventional behavioral models. The best one is based on deep learning, and the leading behavioral model (EWA) achieves only 30.9% of the error rate reduction of the best machine learning model relative to a naïve benchmark of i.i.d. mixture model. Second, our big data set enables us to conduct a reliable non-parametric estimation of players' behavior provided that players' behavior is determined by the history of outcomes in the past two periods. There are 256 two-period histories, and for each one, we have on average 250 and at least 66 observations. The performance of this model is much worse than the best one, and therefore we have obtained strong evidence that players have a longer memory than two periods. Lastly, we tried to obtain insights into the nature of players' behavior from the machine learning models we employed. This is because machine learning models are often "black boxes" in that the meaning of the fitted parameters is not immediately clear. The



Figure 2. The motivation of our research. The image of the tiger is adapted from https://commons.wikimedia.org/wiki/File:2012\_Suedchinesischer\_Tiger.JPG (J. Patrick Fischer, 2011).

best machine learning models in our study successfully replicate how players choose mixed strategies, but what mechanisms they capture remains a crucial, important open research question. This is in line with the recent trend in artificial intelligence research to open the black box and to gain insights or to provide accountability about what is being done inside the machine, something that is called XAI (explainable artificial intelligence) (c.f. Adadi and Berrada, 2018, for the survey). By examining the machine learning models, we incorporated additional mechanisms into the conventional behavioral model (EWA), and the modified model captures 62.1% of the error rate reduction as opposed to the 30.9% captured by EWA.

Finally, our paper suggests the following research program, which can be phrased as *Capture and Decode*, and it proceeds in three steps.

- 1. Collect Big Data: Collect a data set that is large enough to clearly distinguish the relative performance of models. Our analysis in the final section suggests that the number of observations in the order of tens of thousands would be a reasonable target.
- 2. Capture: Use machine learning models to see if there are systematic regularities of data that have previously not been discovered. The regularities are "captured" by a machine learning model, and they are encoded in the fitted parameters of the model. The term "encoded" reflects the fact that the meaning of the parameters of machine learning models is often not immediately clear.
- 3. Decode: "Open" the black box of the machine learning model to identify and understand how the regularities are generated. This is in line with the XAI research mentioned

above. The model and fitted parameters that captured the regularities are to be disclosed in the public domain so that researchers can collaborate on this task.

A previous contribution, Peysakhovich and Naecker (2017), also suggests and follows this procedure for experimental data on decision making under uncertainty and ambiguity.

We have success in the capture stage, but work remains to be done on the decoding stage. How to fully uncover the nature of the regularities captured by our machine learning models remains a challenging open question.

### 1.1 Related Literature

There are a large number of literature on laboratory experiments of games with a unique mixed strategy equilibrium (c.f. Chapter 3 in Camerer, 2011). O'Neill (1987) is one of the most influential works in the literature. He proposed a new experimental design, which we explain in Section 2, to overcome some difficulties of testing the minimax strategy in the previous literature. His finding is that although deviations from the minimax strategy are observed on an individual level, the overall distributions of play and winning rates are very close to the predicted ones from the minimax strategy. In contrast, Brown and Rosenthal (1990) reexamined O'Neill's result and showed that there is less evidence of a minimax strategy than indicates. In particular, they pointed out that people's behavior depends on their own and opponents' behavior, implying that people do not follow an independently mixed Nash strategy under different situations (for example, with a focus on learning in Mookherjee and Sopher, 1997). One of the authors of this paper examines the replicability of O'Neill's results in Kandori (2018). Overall, the literature indicates a modest deviation from a mixed strategy equilibrium.

Our paper is also related to the literature on learning in games that asks how an equilibrium arises in a game. Leading models include reinforcement learning (e.g., Roth and Erev, 1995; Erev and Roth, 1998) and belief learning such as the fictitious play (Brown, 1949). Camerer and Ho (1999) propose an influential generalized model incorporating both reinforcement learning and belief learning, called the experience-weighted attraction (EWA) model. We use the EWA model as a benchmark of economic theories, and thus we explain it in detail in Section 4.3.

Finally, our paper is positioned in the literature on machine learning and economics. In recent years, an increasing number of economics studies have been conducted using machine learning approaches (c.f. Athey and Imbens, 2019; Mullainathan and Spiess, 2017). Behavioral economics and experimental economics are no exception. As Camerer (2019) discusses, behavioral economics and artificial intelligence may interact in future research, and these fields are trying to incorporate the machine learning approach into their analysis. In the literature, our paper is most closely related to Peysakhovich and Naecker (2017) and Fudenberg

et al. (2021). Peysakhovich and Naecker (2017) show that machine learning tools can improve the out-of-sample prediction power over economic models in the domain of ambiguity. Fudenberg et al. (2021) show that machine learning models outperform the out-of-sample predictive power of economic models such as the Level-K model in the initial play of matrix games. What both papers and ours have in common is that they try to improve the economic theory, focusing on the out-of-sample prediction performance and using a measure to quantify the performance. Peysakhovich and Naecker (2017) use regularized regression (including LASSO, explained in Section 5.3), as a benchmark, and compare the out-of-sample mean squared error from regularized regression with that from economic models. Through the comparison, they consider how much out-of-sample variance is explainable. Fudenberg et al. (2021) use the notion of completeness, proposed by Fudenberg et al. (2021), to evaluate how much out-of-sample prediction errors are explained by economic theories. Completeness is defined as the fraction of out-of-sample reducible prediction errors that the model could reduce, where the reducible prediction errors are the difference between prediction errors from the best model minus those from a naive benchmark. We use a version of that concept in our performance comparison of our models.

# 2 O'Neill's Game

In this paper, we consider *O'Neill's game*, introduced by O'Neill (1987). Our game is a normal form game with two players, a red (R) player and a black (B) player. Each player  $i \in I \equiv \{R, B\}$  chooses one of four cards,  $a_i \in C \equiv \{1, 2, 3, K\}$  (Ace, Two, Three, and King) as their action. The payoff matrix is shown in Table 1. In words, the red player wins if and only if

- 1. both players choose K, or
- 2. both players choose numbers (1, 2, or 3), and those two numbers are different,

and the black player wins if and only if

- 1. exactly one player chooses K, or
- 2. both players choose the same number.

This game was designed to be the simplest possible one with a non-trivial mixed strategy equilibrium. More precisely, O'Neill (1987) shows that the game is the unique normal form game that satisfies the following conditions.

- 1. There are binary payoffs for each player.
- 2. Neither player has two identical strategies.
- 3. Neither player has a dominant strategy.
- 4. The game is not completely symmetrical in strategies.

		Black player					
		1	2	3	Κ		
Red player	1	0, 1	1, 0	1, 0	0, 1		
	2	1, 0	0, 1	1, 0	0, 1		
	3	1, 0	1, 0	0, 1	0, 1		
	Κ	0, 1	0, 1	0, 1	1, 0		

Table 1. The payoff matrix of the stage game.

5. Any other game satisfying the conditions above has at least as many strategies for each player.

This is the game played by our subjects, and the labeling of pure strategies described above is slightly different from the one originally used in O'Neil's experiment<sup>\*1</sup>. The game has the unique mixed strategy Nash equilibrium: both players play K with a probability of 0.4 and play 1, 2, and 3 with a probability of 0.2, respectively. In the equilibrium, red players win with a probability of 0.4, and black players win with a probability of 0.6. Hence, unlike the Rock-Paper-Scissors game, the mixed strategy is not trivial. The complexity or non-triviality of the mixed strategy allows us to test and understand how people choose a mixed strategy.

### 3 Data

### 3.1 Data Collection

We collected our data in a Coursera online course offered by one of the authors (M. Kandori), "Welcome to Game Theory"<sup>\*2</sup>. The course started in February 2015 and is still available. In the first week, students are asked to play this game with someone else for 30 periods and submit the results on the course web page before taking lectures on Nash equilibrium and mixed strategy equilibrium. The rules of the game are explained in one of the lectures, and the students are told, "This is a perfect example of a strategic situation because what is best for you depends on what the other player is going to do, and each player is trying to do his or her best against the opponent. By experiencing this game, you can personally see the nature of strategic thinking." The written instruction says the following: "We encourage everyone to give it a shot, ... Please note that no grade will be given to this activity. Your participation into this activity should be on a completely voluntary basis, and your answers will have no bearing on your course grades."

Hence, our data set is different from the usual lab data in the following respects. First,

<sup>\*1</sup> In O'Neil's experiment, the card that played the role of K in the above description of the game was Joker.

<sup>\*2</sup> https://www.coursera.org/learn/game-theory-introduction

experiments were unsupervised. We asked the students to find a partner, to play the game, to record the results, and to report back. Second, we do not know the identity of the students' partners, who we expect to be their friends or family members. Third, no financial rewards were given to the subjects. We expect that these features do not pose a serious problem for the following reasons. First, we asked the students to play this game with a deck of cards, and we are naturally motivated to win when we play a card game, even if no monetary payment is made. Second, we made it clear that participation is completely voluntary and has nothing to do with the course grade, and participation is costly in terms of time and effort. This fact is likely to discourage attempts to submit fake data, as the cost of doing this exceeds the benefit. A person who submits fake data incurs the time and effort of reading and understanding the instructions, cooking up data for 30 rounds, and uploading the file, even though no reward is given. Our view is that only those who are curious about experiencing a strategic situation are likely to have participated in the experiments and that they will have done this for the fun of playing the game.

Our data set here contains 2781 pairs (5562 participants) of play in total, submitted from February 2015 to April 2021. It contains 192 pairs of data in which a player's action was missing in at least one period. We eliminated these pairs and used the remaining 2589 pairs (5178 participants) of data.

### 3.2 Uniqueness of Our "Big" Data

The uniqueness of our data set lies in the number of participants, and especially the number of observations. As indicated in Section 3.1, we collected data from 2589 pairs (5178 participants). Each pair played the stage game for 30 rounds. Hence, the total numbers of observations for the red player and the black player are  $77670=2589 \times 30$ , respectively<sup>\*3</sup>. To our best knowledge, the number of observations in our data set is one of the largest for a single treatment.

To substantiate our claim about how big our data set is, we have checked how many participants and observations other papers obtained. Nunnari, Congiu and Emiliano (2022) create a list of all experimental papers with a lab component published in Top 5 journals<sup>\*4</sup> between 2010 and 2019. Using this list, Fréchette, Sarnoff and Yariv (2022) discuss the trend in the literature on experimental economics. They point out that the number of online experiments has increased, resulting in an increase in the number of participants. As Figure 3 indicates, the median number of participants in lab experiments is still less than 1000, but the median number of participants in online experiments can be as large as 10,000. Thus, in terms of the number of participants, our data is not uniquely large.

<sup>&</sup>lt;sup>\*3</sup> In Section 3.3, we eliminate 12 pairs of data. Therefore, the number of observations for each player's role becomes  $77310 = 2577 \times 30$ .

<sup>\*4</sup> American Economic Reviews, Econometrics, Quarterly Journal of Economics, Journal of Political Economy, and Review of Economic Studies.



Figure 3. Adapted from Figure 5 in Fréchette, Sarnoff and Yariv (2022). "Experimental Economics: Past and Future." Annual Review of Economics (forthcoming).

Since in Figure 3, papers published in 2018 have the largest median number of participants, we took a closer look at those papers. We found that those papers have smaller numbers of observations than ours. De Quidt, Haushofer and Roth (2018) and DellaVigna and Pope (2018) are the top two papers from 2018 in terms of the number of participants (18,866 and 10,069, respectively). Both papers used Amazon Mechanical Turk (MTurk). In De Quidt, Haushofer and Roth (2018), there are 11 experimental tasks and each task has at most 5750 observations. In DellaVigna and Pope (2018), there are 18 treatments and each treatment has about 550 observations. In summary, those papers with a huge number of participants have fewer observations in a single treatment than our paper.

### 3.3 Data Cleaning

Since our data were collected by the participants themselves in an uncontrolled environment, there are concerns about data credibility in some cases, in the sense of whether the submitted data are based on actual play. For example, if the black player in a pair plays  $a_B = 2$  for 30 periods and the red player plays  $a_R = 1$  for 30 periods, this results in a complete win for the black player. We exclude a fairly small number of such "outliers" through the following procedure. First, we list the pairs

• whose win rate for the red or black player is the top 1%, or

• in which either player repeats the same card more than 15 times.

We obtained 53 pairs through this process. We then manually checked them and finally eliminated 12 pairs of obviously suspicious data. In the end, we conducted our analysis using the remaining 2577 pairs (5154 participants) of data.

### 3.4 Descriptive Statistics

In this section, we briefly describe some features of our data based on summary statistics. Hereafter, we use the cleaned data for all analyses: 2577 pairs  $\times 30$  periods.

First, we observe that the choice probabilities of the actual subjects are very close to the Nash equilibrium in the aggregate level. Table 2 shows the empirical distribution of action profiles. The numbers in parentheses represent the theoretical distribution of profiles under the Nash equilibrium. One can see that the actual distribution and the NE distribution are very close, except that there is an "Ace bias" for both players. The original result in O'Neill (1987) exhibits similar patterns as shown in Table 3, and our data largely replicate what O'Neill found.

Table 4 is the win rate distribution for both players. Here, the average win rate (0.419 for red, 0.581 for black) is also very close to that in the Nash equilibrium (0.4 for red, 0.6 for black). However, the standard deviation (std) is a little larger than in the case where the same number of pairs play the mixed Nash equilibrium independently for 30 periods.

Rod / Block	1	1 $2$		K	Marginal
neu / Diack	L		J	К	Distribution
1	.059	.051	.048	.081	.238
1	(.040)	(.040)	(.040)	(.080)	(.200)
0	.051	.047	.043	.073	.214
2	(.040)	(.040)	(.040)	(.080)	(.200)
0	.045	.041	.044	.070	.199
3	(.040)	(.040)	(.040)	(.080)	(.200)
V	.080	.064	.064	.140	.348
ĸ	(.080)	(.080)	(.080)	(.016)	(.400)
Marginal	.235	.202	.198	.364	
Distribution	(.200)	(.200)	(.040)	(.200)	

Table 2.	Distribution	of the a	action	profiles of	f the subjec	cts. The	numbers in	a parentheses	are
the distr	ibution of act	tion pro	files in	the Nasl	ı equilibriu	m.			

Figure 4 represents the pairwise K ratio distribution between 30 periods of each pair. Here, we see that the points are gathered around the mixed NE or the average point.

However, the time series of the choices of the subjects cast doubts on the hypothesis that the subjects play the mixed Nash equilibrium independently every period. The two graphs

Red / Black	1 2		3	ĸ	Marginal
	_ <b>_</b>	4	J	К	Distribution
1	.044	.043	.043	.091	.221
L	(.040)	(.040)	(.040)	(.080)	(.200)
0	.046	.038	.038	.092	.215
4	(.040)	(.040)	(.040)	(.080)	(.200)
	.049	.032	.037	.085	.203
3	(.040)	(.040)	(.040)	(.080)	(.200)
V	.086	.065	.051	.158	.362
<b>N</b>	(.080)	(.080)	(.080)	(.016)	(.400)
Marginal	.226	.179	.169	.426	
Distribution	(.200)	(.200)	(.040)	(.200)	

Table 3. Distribution of action profiles in O'Neill (1987) (shown in Brown and Rosenthal (1990)). The numbers in parentheses are the distribution of action profiles in the Nash equilibrium.

	count	mean	$\operatorname{std}$	min	5%	25%	50%	75%	95%	max
Red	2577	0.419	0.091	0.100	0.267	0.367	0.433	0.467	0.567	0.767
Black	2577	0.581	0.091	0.233	0.433	0.533	0.567	0.633	0.733	0.900

Table 4. Win rate distribution of all pairs of subjects.

in the upper half of Figure 5 illustrate the trajectories of the average choice frequencies of all red and black players in each period. The two graphs in the lower half show the same trajectories in the simulations where the same number of agents play the Nash equilibrium independently. We observe that there are larger variations in the actual data. It is rather clear that players are not following the mixed strategy equilibrium i.i.d over time, as Brown and Rosenthal (1990) statistically showed for the original data by O'Neil. What mechanisms guide the subjects' behavior? This is the question that we address in this paper.

### 4 Econometric Models

We adopt two types of models to emulate actual human behavior: traditional economic models and machine learning models. The economic models include reinforcement learning (RL), belief learning (BL, also known as fictitious play), and the EWA model.

In this section, we explain the economic models that we adopted. We also discuss the estimated parameters using all the sample data. The final performance comparison with the test data will be discussed in Section 7.

Before discussing the models, we first introduce some notation for convenience. In every period  $t \in T \equiv \{1, 2, ..., 30\}$ , each player  $i \in I$  chooses one of four cards,  $a_i^t \in C \equiv \{1, 2, 3, K\}$ . We write the set of action profiles in each stage game as  $A \equiv C^2$ . We denote the set of k-length



Figure 4. Pairwise K ratio distribution. We plot the ratio of K of the red and black players for each pair. The size of the markers represents the number of pairs at that point (a larger marker implies that there are more pairs). The red marker indicates the ratio in the NE ((0.4, 0.4)) and the yellow marker represents the average ratio of all subjects ((0.348, 0.364)).

histories of action profiles by  $A^k \equiv \prod_{\tau=1}^k A$ . We also denote the set of full histories beyond period t by  $H^t \equiv A^{t-1}$ , and write its elements as  $h^t \equiv ((a_{\rm R}^1, a_{\rm B}^1), (a_{\rm R}^2, a_{\rm B}^2), \dots, (a_{\rm R}^{t-1}, a_{\rm B}^{t-1}))$ . For notational convenience, we define the initial dummy history  $h^0 \equiv \emptyset$  and let  $H^1 \equiv \{\emptyset\}$ .

We denote by s = 1, 2, ..., S the sample index (the ID number of pairs) that is used to estimate (train) each model. For the parameter estimation, we use all the data we have (S = 2577). When training a model, on the other hand, we use a random subset of the entire data we randomly picked up.

#### 4.1 Multinomial logit

We first introduce a logistic regression model. Using the dummy variables of the history of action profiles, the probability that a subject in the role of player  $i \in I$  chooses action  $a \in C$  at period t is given by

$$P(a_i^t = a \mid h^t) = \frac{\exp\left\{\beta_{i,a}^{\mathrm{T}} x_i(h^t)\right\}}{\sum_{c \in C} \exp\left\{\beta_{i,c}^{\mathrm{T}} x_i(h^t)\right\}}$$
(1)



Figure 5. Transition of the choice probabilities among all pairs. The two graphs in the upper half show the period transition of the actual choice probabilities (red player: left, black player: right). The two graphs in the lower half show the transition of the simulated choice probabilities when the agents play the NE (red player: left, black player: right).

where  $x_i(h^t) \in \{0,1\}^m$  is a *m*-dimensional vector of dummy variables that depends on the history  $h^t \in H^t$ . For example, if a model includes the dummies of the history of action profiles in the last two periods, the choice probability is

$$P(a_i^t = a \mid h^t) \propto \exp\left\{\sum_{\boldsymbol{c} \in A^2} \beta_a^{\boldsymbol{c}} \cdot \mathbf{1}\left\{((a_{\mathbf{R}}^{t-1}, a_{\mathbf{B}}^{t-1}), (a_{\mathbf{R}}^{t-2}, a_{\mathbf{B}}^{t-2})) = \boldsymbol{c}\right\}\right\}$$

Note that the coefficient of each dummy variable varies depending on the player type  $i \in I$ and the card  $a \in C$ . Ignoring those variation, the number of coefficients to estimate is  $4 \times 2 \times m = 8m$ .

We start by estimating the following three classes of simple "baseline" models (for red and black players) that include different dummy variables. The number m in the parenthesis indicates the dimension of dummy variables used in a model.

1. Constant only (m = 1)

- 2. History of action profiles in the previous one and two periods (m = 16 and 256)
- 3. History of "king or number" profiles in the previous one, two, three, and four periods (m = 4, 16, 64, 256, and 1028)

Here a "king or number" profile (we call it a *K-profile* henceforth) is a summarized action profile in a round that takes one of four values (king, king), (king, number), (number, king), (number, number).

The above models have at most m = 1028 variables, and estimating similar models with longer histories of m > 1028 variables is infeasible for the following reason. There is, for example, no three-period history of action profiles in the data that takes  $((a_{\rm R}^{t-1}, a_{\rm B}^{t-1}), (a_{\rm R}^{t-2}, a_{\rm B}^{t-2}), (a_{\rm R}^{t-3}, a_{\rm B}^{t-3})) = ((1, 2), (2, 2), (2, 2))$ . The three-period sample histories lack seven data points out of 4096 patterns, the four-period sample histories lack 30473 data points out of 65536 patterns, and the six-period histories of K-profiles lack 88 data points out of 4096 patterns.

We estimated the coefficients using conditional maximum likelihood estimation. Note that when a model includes dummies of  $\underline{t}$ -period histories, a maximum of  $30 - \underline{t}$  periods of each pair's data can be used for estimation. The log-likelihood function is given by

$$LL_{i}(\beta_{i}) = \sum_{s=1,...,S} \sum_{t=\underline{t},...,30} \sum_{a\in C} \beta_{i,a}^{T} x_{i}(h_{s}^{t}) - \ln\left(\sum_{c\in C} \exp\left\{\beta_{i,c}^{T} x_{i}(h_{s}^{t})\right\}\right)$$

for each player  $i = \mathbb{R}, \mathbb{B}$ , where  $\beta_i \equiv (\beta_{i,c})_{c \in C}$  are the coefficient vectors of the model.

In specifications 1, 2, and 3, by construction, only one element in a dummy variable vector  $x_i(h^t)$  takes the value 1 at any given time. Let  $H^{(k)}$  be the subset of histories for which the k-th element of a dummy variable vector  $x_i^{(k)}(h)$  takes the value 1. The maximum likelihood estimator of the coefficients of the dummy variable  $\beta_i^{(k)} = \left(\beta_{i,1}^{(k)}, \beta_{i,2}^{(k)}, \beta_{i,3}^{(k)}, \beta_{i,K}^{(k)}\right)$  has the property that the estimated choice probability after the histories  $H^{(k)}$  matches the empirical

frequencies of the actions after  $H^{(k)}$  \*5. That is, for any  $h \in H^{(k)}$ ,

$$P(a_i = a \mid h) = \frac{e^{\beta_{i,a}^{(k)}}}{e^{\beta_{i,1}^{(k)}} + e^{\beta_{i,2}^{(k)}} + e^{\beta_{i,3}^{(k)}} + e^{\beta_{i,K}^{(k)}}}$$
(2)

= (The empirical frequency of card a after histories in  $H^{(k)}$ ).

Note that, the four coefficients in (2) are not identified, because if we replace  $\beta_{i,a}^{(k)}$  with  $\beta_{i,a}^{(k)} + b$  for some constant b, the righ-hand side of (2) remains unchanged. Because of that, when we estimate coefficients, we normalise the coefficients card K to 0. The validity of that procedure can be more directly seen in equation (4) in the next subsection.

# 4.2 The Challenge of Model Selection and Non-Parametric Estimation Using Our Big Data Set

Our goal is to find the model that best describes the subjects' behavior. Note that any model that provides a full-support probability prediction of the current action of a player given the history of play can be written as equation (1) for the following reason. Since probabilities of actions (cards) add up to 1, the ratios of probabilities (odds), such as  $P(a_i^t = a \mid h^t)/P(a_i^t = K \mid h^t), a = 1, 2, 3$  uniquely determine the probabilities of actions. Hence, any full-support model can be written as

$$\frac{P(a_i^t = a \mid h^t)}{P(a_i^t = K \mid h^t)} = g_a(h^t),$$
(3)

$$\prod_{k} \left( \prod_{a} p^{(k)}(a)^{n^{(k)}(a)} \right)$$

where  $n^{(k)}(a)$  is the number of occurrences of action a in the data after histories in  $H^{(k)}$ . Therefore, the log likelihood function is equal to

$$\sum_{k} N^{(k)} \left( \sum_{a} \frac{n^{(k)}(a)}{N^{(k)}} \log p(a) \right),$$

where  $N^{(k)}$  is the number of occurrences of histories in  $H^{(k)}$  in the data. Choosing  $\beta_i^{(k)}$  to maximize the log likelihood is equivalent to

$$\max_{p^{(k)}} \sum_{a} \frac{n^{(k)}(a)}{N^{(k)}} \log p^{(k)}(a) \quad \text{s.t.} \quad \sum_{a} p^{(k)}(a) = 1$$

for each k because there always exists  $\beta_i^{(k)}$  that satisfies (2) for any  $p^{(k)}$ . The lagrangean is  $\mathcal{L} = \sum_a \frac{n^{(k)}(a)}{N^{(k)}} \log p^{(k)}(a) - \lambda^{(k)} \left(\sum_a p^{(k)}(a) - 1\right)$ , and the first order condition is

$$\frac{\partial \mathcal{L}}{\partial p(a)} = 0 \implies \frac{n^{(k)}(a)}{N^{(k)}} / p^{(k)}(a) = \lambda^{(k)}.$$

The constraint is satisfied with  $\lambda^{(k)} = 1$ , and therefore  $p^{(k)}(a) = n^{(k)}(a)/N^{(k)}$ , the empirical frequency of card a after the histories in  $H^{(k)}$ .

<sup>\*5</sup> To see why, first denote the left-hand side of equation (2) by  $p^{(k)}(a)$  for a = 1, 2, 3, K. The likelihood function for the model (1) is equal to

while equation (1) boils down to

$$\frac{P(a_i^t = a \mid h^t)}{P(a_i^t = K \mid h^t)} = \exp\left\{ (\beta_{i,a} - \beta_{i,K})^{\mathrm{T}} x_i(h^t) \right\}.$$
(4)

If we let  $x_i(h^t)$  be the vector of indicator functions for histories  $(\cdots, \mathbf{1}_{\hat{h}^t}, \cdots)$ , where  $\hat{h}^t$  runs over all possible histories, and denote the element of vector  $\beta_{i,a}$  that corresponds to the coefficient of  $\mathbf{1}_{\hat{h}^t}$  by  $\beta_{i,a,\hat{h}^t}$ , then the left-hand side of (4) is simply equal to  $\exp\left\{\beta_{i,a,h^t} - \beta_{i,K,h^t}\right\}$ . Therefore, by setting  $\beta_{i,a,h^t} - \beta_{i,K,h^t} = \log g_a(h^t)$ , any full-support model is represented by (1).

Given that (1) encompasses all models, our quest for the best one boils down to (i) the selection of variables  $x_i(h^t)$  and (ii) possible parametrization of the coefficient vector  $\beta_{i,a}$  by a smaller number of parameters, all within the ambient model (1).

If we have enough data in the sense that we have enough data points for each history  $h^t$ , we can perform non-parametric estimation, by using indicator functions of all histories  $x_i =$  $(\cdots, \mathbf{1}_{\hat{h}^t}, \cdots)$ . This is infeasible because the number of complete histories is astronomical. Non-parametric estimation is feasible, however, if we postulate that subjects have limited memory. For example, if we postulate that current action only depends on the history of outcomes (action profiles) in the past two periods, the number of two-period histories is  $(4 \times 4)^2 = 256$ , and our data set with 74733 observations provides at least 66 observations of actions after each two-period history. The following figure shows the distribution of the number of observations (occurrences) of two-period histories.

# Number of Occurrences of 2-Period Histories 1400 counts ((3,3),(3,3)): 66 counts 1200 ((K,K),(K,K)): 1437 counts 1000 Count 800 600 400 200 0

2-period history of profiles (ascending order)

Figure 6. The number of occurrences of each two-period history  $((a_{\rm R}^t, a_{\rm B}^t), (a_{\rm R}^{t-1}, a_{\rm B}^{t-1}))$  out of 74733 two-period histories in the data. The average count is 291.9. The most frequently observed history is ((K, K), (K, K)), which occurs 1437 times in the data. The history of least frequent observation is ((3,3),(3,3)), which still appears 66 times in the data.

Therefore, one of the models in the previous subsection, the logit model with two-period history dummies, would provide a reliable non-parametric estimation of the subjects' behavior provided that they have two-period memories.

Non-parametric models may not be the best choice for the following well-known reasons. If, for example, if the true data generation process is given by equation (1) with a small number of variables on the right-hand side, such as  $x_i = (\mathbf{1}_H^0, \mathbf{1}_H^1)$  for some subsets of histories  $H^0$  and  $H^1$ , estimating this specification of the model is better (provides a smaller prediction error) than estimating a non-parametric model. How should we decide which variables to include in model (1)? This is a classical statistical problem of model selection, and the statistics theory recommends that we use information criteria such as AIC and BIC. According to those methods, we must estimate each possible specification of the model and calculate a number called the AIC or BIC value, and then select the model with the minimum such value. This guarantees the optimal selection of the model in the appropriate sense as the number of data points goes to infinity.

The challenge of model selection we face is that the statistically optimal procedure is computationally infeasible. Even when we confine our attention to the selection of dummy variables of subsets of two-period history of play, the number of non-empty subsets is equal to  $2^{256} - 1$  and the number of feasible combinations of those dummy variables is even larger. It is clearly impossible to compute and compare such a large number of AIC or BIC values. The machine learning models we introduce in Section 5 can be viewed as a practical way of selecting a good model (or as having been shown to select good models in real-life applications) when statistically optimal model selection is infeasible.

#### 4.3 Experience-Weighted Attraction (EWA) model

Next we study economic learning models commonly used in the literature. Although various kinds of models have been invented, many of (not all of) them are categorized into two groups: reinforcement learning (RL) and belief learning (BL). Reinforcement learning is based on the idea that, if an agent chose an action and the outcome was good, that action is "reinforced" in the sense that the agent is more willing to choose it. This can be formulated as a model in which an agent has (unobserved) attraction (propensity) to an action, which embodies how many payoffs it gains in the past. Belief learning, also known as fictious play, is a model in which an agent forms a belief on the choice probability of the opponent's action based on the weighted average of the past actions taken by the other player and plays the best response to the belief.

Camerer and Ho (1999) developed the experience-weighted attraction (EWA) learning model that is a hybridization of the reinforcement learning model and the belief learning model. In their original EWA model, each player  $i \in I$  chooses action  $a \in C$  at period t with probability

$$P_i(a_i^t = a \mid h^t) = \frac{\exp\{\lambda A_i^a(t-1)\}}{\sum_{c \in C} \exp\{\lambda A_i^c(t-1)\}\}},$$
(5)

where

$$N_i(t) = \rho N_i(t-1) + 1$$
, and (6)

$$A_i^a(t) = \frac{\phi N_i(t-1)A_i^a(t-1) + \left[\delta + (1-\delta)1\left\{a_i^t = j\right\}\right]\pi_i(j, a_{-i}^t)}{N_i(t)}.$$
(7)

Here  $A_i^j(t)$  is player *i*'s attraction to action *a* at period *t*. The agent chooses actions according to the logit of these attractions as expressed in (5).

We have 14 parameters to estimate in total: for each player  $i \in I$ ,  $\lambda_i$ ,  $\rho_i$ ,  $\phi_i$ ,  $\delta_i$ ,  $(A_i^1(0), A_i^2(0), A_i^3(0))$ , and  $N_i(0)$ ; we normalize  $A_i^K(0) = 0$ . Here  $\lambda$  expresses how accurately the choice probability reflects the attractions.  $\lambda \to +\infty$  means that the agent plays the action which has highest attraction with probability one, while  $\lambda = 0$  implies the agent plays all actions with equal probability irrespective of the attractions.  $\rho, \phi$  are the discount factors, and  $\delta$  represents the ratio between RL and BL. Thus naturally we assume  $\lambda \in [0, \infty)$ ,  $\rho, \phi \in [0, 1]$ , and  $\delta \in [0, 1]$ .

When  $\delta = \rho = 0$  and N(0) = 1, the model (5)-(7) reduces to a reinforcement learning models since the agent updates their attractions only if they actually take action j,

$$A_i^j(t) = \phi A_i^j(t-1) + 1 \{a_i(t) = j\} \pi_i(j, a_{-i}(t)).$$

On the other hand when  $\delta = 1$ ,  $\rho = \phi$  and N(0) = 1, the model becomes belief learning models:

$$N(t) = \frac{1 - \rho^t}{1 - \rho}, \text{ and}$$
$$A_i^j(t) = \frac{\rho N(t - 1) A_i^j(t - 1) + \pi_i(j, a_{-i}(t))}{N(t)}.$$

Note that i's belief that the other player plays  $c \in C$  is the weighted empirical frequency

$$\mu_i^c(t+1) = \frac{\sum_{\tau=1}^t \rho^{\tau-1} \cdot 1\{a_{-i}(\tau) = c\}}{\sum_{\tau=1}^t \rho^{\tau-1}},$$

and so  $A_i^j(t)$  is the expected payoff (w.r.t.  $\mu_i$ ) when player *i* plays action *j*.

#### 4.3.1 Estimates of the parameters

We estimate the parameters using all the sample by the maximum liklihood estimation. The estimated parameters and standard errors are in Table 5.

# 5 Machine Learning Models

In this subsection, we provide a brief overview of machine learning in comparison to the conventional econometric models. Machine learning refers to a class of models that make

Models		Logit	
	EWA	RL	BL
Discount factors			
$\phi_{ m R}$	1.014	1.034	2.235
	(0.006)	(0.005)	(0.123)
$\phi_{ m B}$	1.059	1.025	3.000
	(0.009)	(0.003)	(0.309)
$ ho_{ m R}$	0.870	0.000	$=\phi_{\mathrm{R}}$
	(0.081)		<u>.</u>
$ ho_{ m B}$	1.003	0.000	$= \phi_{\mathrm{B}}$
	(0.016)		
Mixing parameters			
$\delta_{ m R}$	0.450	0.000	1.000
	(0.030)		
$\delta_{ m B}$	0.000	0.000	1.000
	(0.027)		
Accuracy parameters			
$\lambda_{ m R}$	0.480	0.084	0.370
	(0.255)	(0.004)	(0.024)
$\lambda_{ m B}$	0.894	0.094	0.277
	(0.113)	(0.003)	(0.030)
Initial values		. ,	× /
$A_{\rm B}^{1}(0)$	-0.835	-6.413	-1.737
	(0.472)	(0.692)	(0.160)
$A_{\rm R}^2(0)$	-1.110	-8.520	-2.278
	(0.627)	(0.772)	(0.207)
$A_{\rm B}^{3}(0)$	-1.270	-8.366	-2.626
	(0.715)	(0.758)	(0.232)
$A_{\rm B}^{1}(0)$	-0.665	-2.285	
	(0.107)	(0.571)	(0.324)
$A_{\rm B}^2(0)$	-0.893	-5.863	-3.056
	(0.142)	(0.636)	(0.432)
$A_{ m B}^{3}(0)$	-0.932	-8.836	-3.172
	(0.145)	(0.714)	(0.450)
$N_{ m R}(0)$	5.258	1.000	1.000
	(2.748)		
$N_{ m B}(0)$	5.162	1.000	1.000
	(0.740)		
No. of Pairs	2577	2577	2577
No. of Observations	77310	77310	77310
Log Likelihood	-208940 8	-209391 3	-209637.0
LB Statistic	2000-10.0	901 0***	1464 4***
$A_{\rm R}^{1}(0)$ $A_{\rm B}^{1}(0)$ $A_{\rm B}^{2}(0)$ $A_{\rm B}^{3}(0)$ $N_{\rm R}(0)$ No. of Pairs No. of Observations Log Likelihood LR Statistic	$\begin{array}{r} -1.270 \\ (0.715) \\ -0.665 \\ (0.107) \\ -0.893 \\ (0.142) \\ -0.932 \\ (0.145) \\ 5.258 \\ (2.748) \\ 5.162 \\ (0.740) \\ \hline \\ 2577 \\ 77310 \\ -208940.8 \\ \end{array}$	$\begin{array}{r} -8.366\\ (0.758)\\ -2.285\\ (0.571)\\ -5.863\\ (0.636)\\ -8.836\\ (0.714)\\ \underline{1.000}\\ \\ \underline{1.000}\\ \\ \underline{2577}\\ 77310\\ -209391.3\\ 901.0^{***} \end{array}$	$\begin{array}{r} -2.626 \\ (0.232) \\ (0.324) \\ -3.056 \\ (0.432) \\ -3.172 \\ (0.450) \\ \underline{1.000} \\ \underline{1.000} \\ \\ \underline{1.000} \\ \\ \underline{2577} \\ 77310 \\ -209637.0 \\ \underline{1464.4^{***}} \end{array}$

Table 5. Estimation Results of EWA-variant Models

Notes: Estimates of the parameters of the EWA variant models using maximum likelihood estimation. Standard errors are in parentheses. Underlined values are determined by the model restrictions and are not to be estimated. The LR Statistic is the likelihood ratio test statistic when we compare the EWA and the RL and the BL. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

predictions or decisions based on observable data. For our purposes, we focus on machine learning models to make a prediction:

$$y = f(x|\beta),$$

where x is the input data, y is the predicted outcome, and  $\beta$  is the vector of parameters. This looks exactly the same as the conventional econometric models, but there are some notable differences.

First, machine learning offers new functional forms that have not been employed in conventional econometrics. Leading examples include deep learning, decision trees, and LASSO, which we will explain and utilize in later sections.

Second, the main objectives of machine learning and econometrics are different. Machine learning is all about selecting the best model to make a prediction (Figure 7, Panel (a)). The dataset at hand is partitioned into "training data" and "test data", and the values of parameters of models are determined to achieve goodness of fit within the training data. Then a prediction contest is conducted using the test data to select the model that makes the best prediction. The main concern is how to make the best prediction, and the calculated parameter values are oftentimes not paid much attention. This reflects the fact that some leading machine learning models are "black boxes" and the meaning of parameters is not immediately clear. (We will come back to this issue in Section 6).

In contrast, the main concern of econometrics is parameter estimation (Figure 7, Panel (b)). Here, the model is given a priori (such as linear regression or logit), and assuming that the true data generating mechanism is within the model, the parameter values are estimated to infer the true values. The magnitude, sign, and statistical significance of the estimated parameter values are the main concerns of the researchers so as to understand how data is generated.

Third, machine learning is data-driven while econometrics is driven by theory. The ultimate goal in machine learning is to make good predictions in real-life data sets. Models of machine learning are not derived by finding the optimal one in a certain class of functional forms for a certain class of tasks, but instead by constantly running prediction contests on real-life data to select and improve the proposed models. As a result, why certain models perform well for certain tasks is often not well understood. In contrast, econometrics methods are derived from the statistical theory of optimal estimation.

In this paper, we adopt the machine learning paradigm of conducting a prediction contest to compare conventional behavioral economic models and machine learning models in our unique "big" data set derived from our mixed strategy experiment. We split our data into training data and test data as illustrated in Panel (a) of Figure 7 to see which models fare well. When we find that machine learning models make good predictions, we try to "open" the black boxes to gain insights into what factors are important in explaining the subjects' behavior in our experiment. This is in line with the recent trend in machine learning known



Figure 7. Difference between econometric models and machine learning models. The left panel (Panel (a)) describes machine learning models, and the right panel (Panel (b)) describes econometric models.

as XAI (explainable artificial intelligence). Before moving on to the description of the models, we explain in the next subsection how data sets are split in the machine learning approach.

In the present paper, we adopt the machine learning paradigm of conducting a prediction contest to compare conventional behavioral economic models and machine learning models in our unique "big" data of our mixed strategy experiment. We will split our data into the training data and the test data as in Panel (a) of Figure 7 to see which models fare well. When we find that machine learning models make good predictions, we try to "open" the black boxes to gain insights into what factors are important to explain the subject's behavior in our experiment. This is in line with the recent trend in machine learning named XAI (explainable artificial intelligence). Before moving on to the description of the models, we explain in the next subsection how data sets are split in the machine learning approach.

#### 5.1 Cross Validation

If we split the data set at hand as in Panel (a) of Figure 7, we can conduct a prediction contest only once. In the machine learning approach, however, prediction contests are conducted multiple times on the given data set. This is called Cross-Validation (CV), and it works as follows. First, the whole data set is split into K subsets of an equal size, with the typical value of K being 5. Call them  $D_1, \ldots, D_5$ . Second, the first subset  $D_1$ , which accounts for 20% of the whole data set, is set aside as the test data and parameter fitting is conducted on the remaining training 80% of data,  $D_2 \cup \cdots \cup D_5$  which is the training data. Next,  $D_2$  is set aside as the test data, and so on. In general, we set aside  $D_k$  as the test data and conduct parameter fitting on the training data  $\bigcup_{h\neq k} D_h$  and this process is conducted for  $k = 1, \ldots, 5$ . In this way, even though we have a single set of data, we can conduct prediction contests five times. We use CV to compare machine learning models and conventional behavioral economics models, and also to determine the basic functional form (via what are called hyperparameters) of a given machine learning model. The latter will be explained when we describe the machine learning models that we consider.

### 5.2 Decision Trees

One of the most commonly used machine learning models is the **decision tree**. The decision tree model partitions the space of "features" of data recursively according to a tree structure, and it returns predictions, one for each subset of features finally obtained by the tree (Figure 8). Figure 8 shows a tree with depth 2. The depth of the tree is defined to be the maximum length of paths from the root to the terminal nodes of the tree.



Figure 8. An example of a decision tree.

In this paper, we predict the choice probability of each action using a regression tree, a decision tree method to return a real value or a real-valued vector as a prediction. We use a set of 893 features that are binary variables based on the history of the past three periods. We do not have enough data points to go beyond three-period histories, as we discussed in Section 4.1.

The decision tree automatically classifies past histories of play according to the similarity of current action choice. We need, however, to provide the set of features of past history of play that the decision tree utilizes to perform its classification. We chose to use the set of 893 features of history of play (action profile) in the past three periods  $F = \{f_1, \ldots, f_{893}\}$ , where each feature  $f_n$  is a property of three-period history whose occurrences can be answered by Yes or No. An example feature f is whether the focal player won in the last period or not. Note that a future f corresponds to a subset of 3-period histories where f is true. By choosing our feature set F, we are effectively looking at subsets of three-period histories that have clear meaning (in some informal, intuitive senses). Features such as "the numbers of the cards chosen in the past three periods add up to 8" is a priori excluded in our feature set, although it may possibly play a role in the focal player's choice and this fact could possibly be detected by other machine learning models. An input data of the decision tree is a pair (x, y) of feature vector  $x = (x_1, \ldots, x_{893})$  and outcome label y, where  $x_i$  is equal to 1 if the history associated with the data has the feature  $f_i$  and otherwise 0, and y = (y(1), y(2), y(3), y(K)) is the degenerated probability vector of the current action of the focal player. For example, if the focal player chooses K in the current period, we have y = (0, 0, 0, 1).

Each node m of a decision tree is associated with a subset of data Q(m), and two outgoing branches Yes and No. The node m uses a feature f(m) to classify Q(m), and let Q(m, Y)be the subset of Q(m) that has the feature f(m), and let Q(m, N) is the subset where the feature does not hold. The successor node of m after the Yes (No) is associated with Q(m, Y)(Q(m, N) respectively).

The decision tree model chooses the feature f(m) to minimize the variation of current choice of action in Q(m, Y) and Q(m, N). In particular, f(m) minimizes the mean squared error

$$\sum_{(x,y)\in Q(m,Y)} (y-\overline{y}(Y))^2 + \sum_{(x,y)\in Q(m,N)} (y-\overline{y}(N))^2,$$

where  $\overline{y}(k)$  is the average of y in the set Q(m,k), k = Y, N. The decision tree branches in this way until the prespecified depth is reached<sup>\*6</sup>. The subsets associated with the final nodes of the tree partition the whole data set, and the prediction of choice probability in each subset is given by the average of the choice vector y, which is equal to the vector of empirical frequencies of cards in the subset.

Now, how is the maximum depth of the tree determined? The depth is called a hyperparameter, which determines the overall structure of the model, and it has to be chosen before the parameter fitting (training) of the model is performed. The choice of hyperparameter is made using the "nested" cross-validation method, and it works as follows. In cross-validation, we split the data into five subsets of an equal size  $D_1, ..., D_5$  and let  $D_i$  be the test data and  $\bigcup_{h\neq i} D_h$  be the training data for  $i \in \{1, \ldots, 5\}$ . Next, each training data subset  $\bigcup_{h\neq i} D_h$  is again partitioned into subsets of an equal size  $d_1^i, \ldots, d_5^i$ . And then, for each depth k = 1, 2, ..., 12, we fit the decision tree model with training data  $\bigcup_{h \neq j} d_h^i$  and derive the prediction performance using the test data  $d_i^i$  for each  $j \in \{1, \ldots, 5\}$ . The prediction performance is measured by the mean squared error, calculated as the mean squared difference between the predicted value and the action actually chosen in the test data. Finally, we select the maximum depth of the tree that achieves the best average prediction based on five test data subsets  $d_1^i, \ldots, d_5^i$ . In this way, we can select the maximum depths of the tree for training data  $\bigcup_{h\neq i} D_h$  for each  $i \in \{1, \ldots, 5\}$ . This is the cross-validation process for selecting the hyperparameter, and the other machine learning methods in this paper also select their hyperparameter in this way.

<sup>&</sup>lt;sup>\*6</sup> If we cannot further classify the past three-period history before reaching the prespecified depth, branching from the node *m* is suppressed. For example, when node *m* is reached after "f = (K, K)is played in t-1, Yes", "f' = (1, 2) was played in t-2, Yes", and "f'' = (K, 1) was played in t-3", that uniquely pins down the past three-period history and there is no room for further classification.

The above decision tree model can be regarded as a procedure to select the right-hand side variables in the multinomial logit model (1) to be estimated by maximum likelihood. Let us illustrate this fact by the example of a decision tree in Figure 8. Let  $D_{K(-1)}, D_{W(-1)}$ , and  $D_{1(-1)}$  be the dummy variables (indicator functions) of "the focal player chose K in the last period", "the focal player won in the last period", and "the focal player chose 1 in the last period." The decision tree in Figure 8 is equivalent to the maximum likelihood estimation of multinomial logit model 1 where the right-hand side variables are

$$x_i = \begin{pmatrix} D_{K(-1)} \times D_{W(-1)} \\ D_{K(-1)} \times (1 - D_{W(-1)}) \\ (1 - D_{K(-1)}) \times D_{W(-1)} \\ (1 - D_{K(-1)}) \times (1 - D_{W(-1)}) \end{pmatrix}.$$

Maximum likelihood estimation of the coefficients of  $D_{K(-1)} \times D_{1(-1)}$ , one for each card, makes the estimated choice probability when  $D_{K(-1)} \times D_{1(-1)} = 1$  equal to the empirical frequencies of actions in the subset of data where  $D_{K(-1)} \times D_{1(-1)} = 1$ , as we explained in Section 4.1. In summary, the above-mentioned version of a decision tree provides a procedure to select the right-hand side variables of the multinomial logit model, where the variables take the form of the product of history dummies and (1-history dummy)'s.

#### 5.2.1 What we can learn from the decision tree model

We fit the trees using all of the samples. The chosen maximum depths of the trees for the red players are all 5 except in one tree, and those for the black players are all 4. The decision trees are depicted in the Appendix A.

Figures 9 and 10 summarize the feature importance and how many of the five trees used each variable for branching for the red players' and black players' trees. The importance of feature f, denoted by I(f) is defined as follows. First, for any subset of data Q, consider predicting the probabilities of current action by means of the empirical frequencies in the subset Q. The resulting mean squared error is  $MSE(Q) = \sum_{(x,y)\in Q} (y-\overline{y})^2$ , where y is the degenerated probability vector of actual choice and  $\overline{y}$  is the vector of average frequencies of current action in the subset Q. Second, define the future importance by

$$I(f) = \frac{\sum_{m \in M(f)} \Delta MSE_m}{\sum_m \Delta MSE_m},$$

where M(f) is the set of nodes associated with future f and

$$\Delta MSE_m = MSE(Q(m)) - MSE(Q(m,Y)) - MSE(Q(m,N))$$

is the mean square error reduction at node m. Intuitively, the feature importance of f indicates how much the use of feature f improves the prediction of the model. Looking at Figures 9 and 10, we can see that for both players, the choice probability is affected when the player did not take the action in the past two periods. In particular, the decision tree shows that actions not taken in the past two periods are more likely to be taken in the current period.



Figure 9. Feature importance and the number of occurrences (duplicates within a single tree do not count) in five trees for the red players. Note that we plot the importance of the features that appear at least twice.

### 5.3 LASSO

Another machine learning model that is commonly used in the literature is LASSO, which enables us to perform an automatic selection of variables. We include m = 1731 variables (for each card  $c \in C$ ) as covariates of the multinomial logit model and add an L1-penalty term into the log-likelihood. That is, the LASSO estimator  $\hat{\beta}$  is the solution to the following penalized log-likelihood maximization problem

$$\max_{\beta} LL(x \mid \beta) - \lambda ||\beta||_1,$$



Figure 10. Feature importance and the number of occurrences (duplicates within a single tree do not count) in five trees for the black players. Note that we plot the importance of the features that appear at least twice.

where LL is the log-likelihood function

$$LL_i(x \mid \beta) \equiv \sum_{s=1}^{S} \sum_{t=1}^{30} \sum_{a \in C} \beta_{i,a}^{\mathrm{T}} x_i(h_s^t) - \ln\left(\sum_{c \in C} \exp\left\{\beta_{i,c}^{\mathrm{T}} x_i(h_s^t)\right\}\right)$$

for each i = R, B. Here  $x_i(\cdot) \in \mathbb{R}^m$  is the candidate covariates computed by the histories. Since we cannot include all dummies of more than three-period histories of action profiles, we focus on the reduced histories such as histories of K-profiles and histories of win-lose patterns, and how many times the red or black player plays K consecutively.

Most of them are dummy variables generated from the last four periods of the histories indicating, for example, the focal player's/the opponent's actions, action profiles in the last four periods, history of action profiles in the last two periods, and which player won in the last four periods. We also include dummy variables generated from more than four periods of history such as how many times the player/the opponent played K consecutively. We normalize nondummy variables to a mean of 0 and standard deviation of 1. All of the variables we used are briefly explained in Table 6 and fully listed in Table 13 in Appendix.

 $\lambda$  (> 0) is a hyperparameter that determines how much the model penalizes the nonzero coefficients. As  $\lambda$  increases, the estimated model tends to have fewer nonzero coefficients. We determined this  $\lambda$  by cross-validating the training data. Specifically, we repeat the following

process for various  $\lambda$ :

- 1. Randomly split the data into two parts, a larger one containing 4/5 and a smaller one containing 1/5 of the data pairs.
- 2. Estimate the LASSO model with the larger subset of data
- 3. Test the performance of the model with the smaller subset of data.

We choose the best  $\lambda$  that minimizes the KL divergence between the estimated mixed actions and the actual actions.

0	R played 1 (or 2, 3, K) consec-		
Constant	utively in the last three periods		
Period specific constant	B played 1 (or 2 3 K) consec		
R's action in t-1, t-2, t-3, t-4	b played 1 (of 2, 3, K) consec-		
B's action in t-1, t-2, t-3, t-4	utively in the last three periods		
Action profile in $t_{-1}$ $t_{-2}$	R did not play 1 (or $2, 3,$		
	K) in the last three periods		
R's action was a number	B did not play 1 (or 2, 3,		
or K in t-1, t-2, t-3, t-4	K) in the last three periods		
B's action was a number	P played K (or numbers) in t 1		
or K in t-1, t-2, t-3, t-4	R played R (of humbers) in t-1,,		
Action profile (number	$\begin{array}{c c} \text{t-n consecutively } (n=4, 5,, 29) \\ \hline \text{B played K (or numbers) in t-1,,} \\ \text{t-n consecutively } (n=4, 5,, 29) \end{array}$		
(m K) in t 1 t 2 t 2 t 4			
History of R's actions in	R won or lost in t-		
the last $2, 3, 4$ periods	1 t-2 t-3 t-4 periods		
History of B's actions in			
the last $2, 3, 4$ periods	History of winners in		
History of action pro-	the last 2, 3, 4 periods		
	History of actions (number or K)		
nies in the last 2 periods	and winners in t-1, t-2, t-3, t-4		
History of action profiles (number	History of action profiles (number or		
or K) in the last 2, 3, 4 periods			
	$\mathbf{n}$ and winners in t-1, t-2, t-3, t-4		

Table 6. The list of variables included in LASSO. Here t is the current period, that is, the LASSO model predicts the action in period t using the variables listed above.

#### 5.3.1 Estimates of the parameters

We estimate the parameters using the entire data. The chosen LASSO hyperparameter is  $\lambda^* = 0.0439$ , and we get 317 nonzero variables in total (the sum of the coefficients of the four cards). The estimates of all the parameters are rather complicated, so we show the full estimation table in Appendix B, and here we instead show the nonzero variables that are

Player	Coefficient	No. of Selected Variables (average of 5 CVs)	No. of Commonly Selected Vari- ables in all 5 CVs
Red	$\beta_{\mathrm{R},1}$	68	12
Red	$\beta_{ m R,2}$	65	21
Red	$\beta_{ m R,3}$	68	18
Red	$\beta_{\mathrm{R},K}$	113	44
Black	$\beta_{\mathrm{B},1}$	84	31
Black	$\beta_{\mathrm{B},2}$	79	31
Black	$\beta_{\mathrm{B},3}$	71	22
Black	$\beta_{\mathrm{B},K}$	112	44

Table 7. Number of Selected Coefficients by LASSO

commonly observed in the five cross-validations for performance testing.

#### 5.3.2 What we can learn from LASSO

Table 8. Parameters that LASSO does not eliminate in all five train-test splits (Red Player, Card 1)

	$\beta_{ m R,1}$	
		<b>a</b>
	Point Estimate	Count
Constant	-0.084	53586
R played 1 at t-1	-0.132	12781
R played 2 at t-2	0.068	12772
R consecutively played 1 in the last 2 periods	0.097	2378
R played 1 at t-1 and 2 at t-2 $$	-0.046	3011
R did not play 1 in the last 2 periods	0.275	30411
R consecutively played 1 in the last 3 periods	0.618	574
R did not play 1 in the last 3 periods	0.071	22266
B did not play 1 in the last 3 periods	0.081	22533
R consecutively played 1 and lost in the last 2 periods	0.139	771
Period Constant $(t=6)$	0.065	2061
Period Constant $(t=27)$	-0.035	2061

*Notes:* The Count column specifies the number of histories in which each dummy variable should be equal to 1.

The cross-validation process chooses different  $\lambda$  parameters and, as a result, nonzero parameters among different training samples. To gain some insight from LASSO, we examined the commonly selected variables in the five cross-validations for performance testing.

Among m = 1731 variables, the average number of selected variables is 314 for the Red players and 346 for Black players in total. On the other hand, the number of commonly selected variables is 95 for the Red players and 128 for the Black players. Details of the numbers are shown in Table 7.

	$\beta_{\mathrm{R},K}$	
	Point Estimate	Count
Constant	0 505	52596
Constant B played K at t 2	0.595	0000 10278
B played K at t-2 B played numbers at t 2	0.014	24208
B played humbers at t-2 B played K at t-3	-0.011	18621
R played K at t-3	0.007	24065
R played humbers at t-3 P played K at t-2	-0.000	34900 10447
B played K at t-3	0.000	19447
D played numbers at t-5 P played 2 at t 4	-0.032	04109 11204
R played Z at t-4	-0.021	11594
R played K at 0-4 P played numbers at t 4	0.029	24901
R played humbers at t-4	-0.024	04091 10512
D played K at t-4 P played numbers at t 4	0.119	19010
b played numbers at t-4 Action profile at t 2 is $(1, 2)$	-0.027	34073 9577
Action prome at t-2 is $(1, 3)$ K profile at t-2 is $(N, K)$	0.042	2077
K profile at t-2 is $(N, K)$	0.000	11090
K profile at t-2 is $(K, K)$	-0.000	23003
K profile at t-3 is $(K, K)$	0.002	7000
Three period K history is $((N, K), (K, N), (N, K))$	-0.150	23021
Three-period K history is $((N, K), (K, N), (N, K))$ Three period K history is $((N, N), (K, N), (N, K))$	0.064	1170
K profile at t 4 is $(K, K)$	-0.144	1179 7515
K profile at t-4 is $(K, K)$	0.021 0.121	7010
R prome at t-4 is $(N, N)$ P played K at t-1 and t-2	-0.131	22095 6160
R played K at t-1 and t-2 P played K at t-1 and numbers at t-2	0.109	12468
R played K at t-1 and numbers at t-2 R played numbers at t-1 and K at t-2	-0.044	12400 12450
R played numbers at t-1 and K at t-2 R played numbers at t-1 and t-2	-0.044	12409
R played numbers at t-1 and t-2 R played K at t-1 and numbers at t-2	0.007	22490 19649
P consecutively played K in the last 3 periods	-0.099	12042
R consecutively played K in the last 3 periods	0.231	2202
B consecutively played R in the last 3 periods	0.108	2092
R consecutively played numbers in the last 5 periods	0.113	14039 8608
R consecutively played numbers in the last 4 periods	-0.008	0090 0093
R consecutively played numbers in the last 7 periods	-0.090	$\frac{2223}{1525}$
R consecutively played numbers in the last 0 periods	-0.115	1020
B consecutively played numbers in the last 10 periods	-0.115	8404
B consecutively played numbers in the last 4 periods	-0.066	3476
B consecutively played numbers in the last 8 periods	-0.000	1650
B won by 3 at t 1	-0.200	1600
R won by K at t 1 and won by a number at t 2	-0.138	4009
R won by a number at t 2 $\mathbf{R}$ won by a number at t 2	-0.138	10206
B won by a number at t-2 $R$ won by a number at t-1 and lost by K at t-2	-0.020	$\frac{19200}{9473}$
K profile at $t_2$ is $(N N)$ and R won	-0.030 -0.017	2475 8061
Period constant $(t-6)$		2061
Period constant $(t-23)$	-0.072	2001 2061
Poriod constant $(t=20)$	0.000	2001 2061
	0.197	2001

Table 9. Parameters that LASSO does not eliminate in all five train-test splits (Red Player, Card K)

Notes: The Count column specifies the number of histories in which each dummy variable should be equal to 1.

#### 5.4 Deep Neural Network (DNN)



Figure 11. An illustration of a DNN model.

Deep Neural Networks (DNNs) are the most successful machine learning model and have many applications such as image recognition, natural language processing, drug discovery, and self-driving cars. For the estimation of behavioral models, Mullainathan and Spiess (2017) show that their DNN model outperforms a reinforcement learning and a fictitious play model in the prediction performance of 2x2 repeated game experiments data.

We created a five-layer neural network that includes one input layer, one output layer, and three hidden layers. To allow us to do the time series prediction, we use the four-period history of action profiles and the payoffs as input and then estimated the choice probabilities of this period. That is, each input is a vector of  $(16 + 1) \times 4 = 68$  dummies across four periods<sup>\*7</sup>, and each output is a four-dimensional probability vector. We chose the number of cells in the three hidden layers from  $\{10, 20, 30, 40, 50, 60\}$  by cross-validation. Each cell in the hidden and output layers is "densely connected" in the sense that it is connected to all cells in the previous layer.

DNN recursively determies the value of each cell in the following way. Let j be a cell in the hidden or output layer and let i = 1, ..., I be the cells in the previous layer. The branch from i to j is associated with parameter (or "weight")  $w_{ij}$ , and given the values  $x_i$  of previous cells i = 1, ..., I, the "input" to cell j is determined as  $\sum_i w_{ij} x_i$  and the value of j, denoted  $x_j$ , is

<sup>\*7</sup> For each period, we used 16-dimensional dummy variables of action profiles and 1-dimensional payoff of Red player as input data.

determined by "activation function" f as  $x_j = f(\sum_i w_{ij}x_i)$ . We adopt the ReLU activation function  $f(x) = \max\{0, x\}$  for all cells except for the ones in the output layer. The cells in the output layer use the softmax activation (multinomial logit) function. The parameters  $w_{ij}$  are selected to provide the best fit of the choice probabilities of the DNN to the actual choice frequencies in the training data in terms of Kullback-Leibler divergence.

We used the Keras TensorFlow implementation of a standard DNN. To avoid overfitting, we used early stopping and dropouts when training the model. We trained our model with the Adam optimizer on Google Colaboratory.

### 5.5 Long-Short Term Memory (LSTM)



Figure 12. An illustration of an RNN model.

Another commonly used neural network model for sequential data is the recurrent neural network (RNN). Unlike a DNN, an RNN has a closed circuit that can maintain states inside its network (Figure 12). Long-Short Term Memory (LSTM) is a specific type of RNN architecture developed by Hochreiter and Schmidhuber (1997), which solves the drawback of simple RNNs only being able to sustain states only for several periods. It is widely used in applications such as Google and Facebook machine translation systems, Google's voice recognition application, and autocorrect on iOS.

We use the Keras TensorFlow implementation of LSTM, which is a standard network introduced in Gers, Schmidhuber and Cummins (2000). Our LSTM model is illustrated in Figure 13. This model includes two state variable vectors, short memory  $s_t$  and long memory  $\ell_t$ , both of which are numerical vectors of dimension L. Here L is a hyperparameter of the model and is determined by the cross-validation procedure.

In each period t, a repeating module (specified by a rounded rectangle in Figure 13) takes as input a dummy vector of an action profile and the red player's payoff in period t-1, along with short memory  $s_t$  and long memory  $\ell_t$ . Then it updates both memories as  $s_{t+1}$  and  $\ell_{t+1}$ , and then outputs the choice probability at time t,  $p_t$ .



Figure 13. An unfolded illustration of the structure of our LSTM architecture, which is based on Gers, Schmidhuber and Cummins (2000). A repeating module at time t (specified by a rounded rectangle) takes two state vectors (a long memory and a short memory) and a new data vector as inputs, and outputs new state variables (a new long memory and short memory) and estimated choice probabilities at time t. A detailed explanation of a module is given in Figure 14.

The detailed structure of a module is illustrated in Figure 14. It consists of three different sections; a **forget gate**, an **input gate**, and an **output gate**. The forget gate is a filter that determines how much it transmits the previous long memory based on the short memory and the new input vector. Formally, a three-layer network (consisting of an input layer, one hidden layer, and an output layer) takes as input  $(s_t, x_t)$  and outputs a single scalar in [0, 1] with a softmax activation function. That is,

$$f_{\sigma}(W_{\text{forgetf}} \cdot (s_t, x_t)^{\mathrm{T}})$$

where  $W_{\text{forgetf}}$  is a 1 × (L + 17) weight matrix and  $f_{\sigma}(v) = \frac{e^{v}}{1+e^{v}}$ . Then the previous long memory is multiplied by this value. If the value of the filter is 1, it fully transfers the long memory. If the value is 0, it completely discards the long memory of the past.

Next, the input gate processes the short memory and the new input vector to update the long memory. A three-layer network takes as input  $(s_t, x_t)$  and outputs an *L*-dimensional new memory with activation function  $\tan(v)$ . Then another three-layer network generates a filter that takes as input  $(s_t, x_t)$  and outputs a scalar in [0, 1] with a softmax activation function;

$$f_{\sigma}(W_{\text{inputf}} \cdot (s_t, x_t)^{\mathrm{T}}) \times f_{\text{tan}}(W_{\text{input}} \cdot (s_t, x_t)^{\mathrm{T}})$$

where  $W_{\text{input}}, W_{\text{inputf}}$  are  $L \times (L + 17), 1 \times (L + 17)$  weight matrices, and  $f_{\text{tan}}(v) = (\tan v^{(1)}, \ldots, \tan v^{(L)})$ . The updated long memory  $\ell_{t+1}$  is

$$\ell_{t+1} = f_{\sigma}(W_{\text{forgetf}} \cdot (s_t, x_t)^{\mathrm{T}}) \times \ell_t + f_{\sigma}(W_{\text{inputf}} \cdot (s_t, x_t)^{\mathrm{T}}) \times f_{\text{tan}}(W_{\text{input}} \cdot (s_t, x_t)^{\mathrm{T}}).$$



Figure 14. The detailed structure of our LSTM. A module of each period t consists of three different sections; a forget gate, an input gate, and an output gate. The forget gate is a filter that determines how the module transmits the previous long memory based on the short memory and the new input vector. The input gate processes the short memory and the new input vector to update the long memory. Finally the output gate generates the short memory from the updated long memory and outputs the choice probabilities of this period.

Finally, the output gate generates the short memory from the updated long memory and outputs the choice probabilities for this period. Here, we also use a three-layer network with a softmax activation function as a filter. The new short memory is generated as

$$s_{t+1} = f_{\sigma}(W_{\text{outputf}} \cdot (s_t, x_t)^{\mathrm{T}}) \times f_{\text{tan}}(\ell_{t+1}),$$

where  $W_{\text{outputf}}$  is a  $1 \times (L + 17)$  weight matrix, and then the attractors are

$$(A_i^1(t), A_i^2(t), A_i^3(t), A_i^K(t)) = f_{\sigma}(W_{\text{output}} \cdot s_{t+1}),$$

where  $W_{\text{output}}$  is a  $1 \times (L+17)$  weight matrix. The softmax function is applied element-wise.

The final choice probabilities are as follows.

$$P(a_i^t = a \mid h^t) = \frac{A_i^a(t)}{\sum_{c \in C} A_i^c(t)}$$

To avoid overfitting, we use early stopping and dropouts when training the model As a result of cross-validation, we adopt L = 10 to 40 from the candidates  $\{5, 10, 15, \ldots, 50\}$ . We trained our model using the Adam optimizer on Google Colaboratory. On average, it takes 3.4 minutes to train one model in each train-test split.

# 6 Modified Economic Models

### 6.1 Modified EWA

Our next task is to incorporate what is captured by the machine learning models into the leading behavioral economic model EWA. The deep learning models of DNN and LSTM, however, are "black boxes". This is because the parameters of those models are the weights attached to the branches in their network structure, so the meaning of those parameters is not immediately clear. Therefore, we focus on the lessons we learn from the more "explainable" machine learning models (the decision tree model and LASSO), and we add a term to the attractions of the original EWA as in (8).

$$P_i^j(t) \propto \exp\left\{\lambda A_i^j(t-1) + \underbrace{\gamma_i^j \mathbb{1}\left\{a_i(t-1) = j\right\}}_{(A)}\right\}$$
(8)

The additional term (A) reflects the fact that agents tend to avoid the number cards that they chose in the previous period.

We estimate  $(\gamma_i^j)$  in three different specifications. Modified EWA (1) is the formulation under the assumption that all gammas are the same:  $\gamma_i^j = \gamma_i$  for all  $j \in C$ . Modified EWA (2) allows the gammas to differ between the numbers and K, but uses the same gamma for each of the numbers. Modified EWA (3) adopts the fully flexible form of gamma.

#### 6.1.1 Estimates of the parameters

We estimate the parameters using all the sample data using the maximum likelihood estimation. The estimated parameters and standard errors are shown in Table 10. We show the estimates of the new parameters  $\gamma_j$  only because the other parameters are not very different from those of the original EWA model.

Table 10 shows that all the estimates of the gammas are negative, which implies that an average player avoids their previous action more or less. We also note that the avoidance tendency is very different between the number cards and the king. It is reflected in the fact that the difference between the log-likelihood of Modified (1) and those of Modified (2) and (3) is relatively large, compared to the small difference between those of (2) and (3).

Models		Lo	ogit	
	EWA	Modified $(1)$	Modified $(2)$	Modified (3)
Avoid previous actions				
$\gamma^1_{ m R}$	<u>0.000</u>	-0.296	-0.408	-0.402
		(0.007)	(0.011)	(0.020)
$\gamma_{ m R}^2$	<u>0.000</u>	$=\gamma_{ m R}^1$	$=\gamma_{ m R}^1$	-0.414
				(0.022)
$\gamma_{ m R}^3$	<u>0.000</u>	$=\gamma_{ m R}^1$	$=\gamma_{ m R}^1$	-0.407
				(0.024)
$\gamma^K_{ m R}$	<u>0.000</u>	$=\gamma_{ m R}^1$	-0.120	-0.121
			(0.016)	(0.016)
$\gamma_{ m B}^1$	<u>0.000</u>	-0.294	-0.427	-0.449
		(0.004)	(0.011)	(0.021)
$\gamma_{ m B}^2$	<u>0.000</u>	$=\gamma_{ m B}^1$	$=\gamma_{ m B}^1$	-0.412
				(0.023)
$\gamma_{ m B}^3$	<u>0.000</u>	$=\gamma_{ m B}^1$	$=\gamma_{ m B}^1$	-0.415
				(0.023)
$\gamma_{ m B}^K$	<u>0.000</u>	$=\gamma_{ m B}^1$	-0.099	-0.100
			(0.016)	(0.016)
No. of Pairs	2577	2577	2577	2577
No. of Observations	77310	77310	77310	77310
Log Likelihood	-208940.8	-207885.1	-207713.5	-207712.6
LR Statistic		$2111.4^{***}$	2454.6***	2456.4***

Table 10. Estimation Results of Modified EWA Models

Notes: Estimates of the parameters of the modified EWA models using maximum likelihood estimation. Standard errors are in parentheses. We show only the estimates of the new parameters  $\gamma_j$  in the table because the other estimates are not very different from the original EWA model. Underlined values are determined by the model restrictions and are not to be estimated. The LR Statistic is the likelihood ratio test statistic when we compare the original EWA and the modified EWAs. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

# 7 Performance Comparison

Our models predict the probability that the subject will choose each action. In the terminology of machine learning, our prediction comparison is categorized as supervised learning, and each model f is a function that assigns to each set of features X a vector of probabilities  $\hat{P} = (\hat{P}(1), \hat{P}(2), \hat{P}(3), \hat{P}(K))$ , where each  $\hat{P}(c) \ge 0$  is a predicted probability of choosing the action  $c \in C$  and  $\sum_{c \in C} \hat{P}(c) = 1$ .

### 7.1 Performance Measures

We evaluate how well the models predict using loss functions. The value of a loss function represents the accuracy of the prediction, and the smaller the loss is, the better the prediction is. We adopt four measures in total: L1 norm, L2 norm, KL divergence, and our own novel **strategic error rate**. Given a set  $\{(X_n, P_n)\}_{n=1}^N$  of N sets of features and degenerate probability distributions that indicate which action was actually selected \*8, we calculate the loss L of a model f using

$$L = \sum_{n=1}^{N} l(P_n, f(X_n)),$$
(9)

where l is a loss function. Each loss function is defined by

$$L1 = \sum_{c \in C} |\hat{P}(c) - P(c)|,$$
(10)

L2 = 
$$\sqrt{\sum_{c \in C} (\hat{P}(c) - P(c))^2},$$
 (11)

KL divergence = 
$$\sum_{c \in C} P(c) \cdot \log\left(\frac{P(c)}{\hat{P}(c)}\right)$$
, and (12)

Strategic Error Rate = 
$$1 - \pi_j(\operatorname{BR}_j((\hat{P}(c))_{c \in C}), (P(c))_{c \in C}))$$
 (13)

Here, the strategic error rate is our novel performance measure that is defined as the hypothetical loss probability when the opponent of the focal player chooses the best response to the estimated choice probabilities of the focal player. Let us illustrate the meaning of this measure. In the mixed strategy equilibrium, the black player's lose rate is 0.4, and if model X of the red player has strategic error rate is 0.38, it means that, when the black player utilizes this model to predict the red player's behavior in any given single period and takes the best reply, on average (across all single periods in the sample) she can reduce the lose rate by 0.02 relative to the mixed strategy equilibrium lose rate. We stress that the strategic error rate concern the usefulness of the estimated model in any given *single* period. In principle, if the back player in the previous story takes the best reply to the estimated model of red

<sup>\*8</sup> P(c) = 1 if c is chosen, and P(c) = 0 otherwise.
player in one period, it has two effects: (i) the lose rate in the current period changes and (ii) the future behavior of the red player changes, which affects the future lose rates of the black player. Our notion of strategic error rate only measures the former effect.

## 7.2 Results

			Red	Player		
	L1	L2	KL	SER	#Params	$\mathbf{RC}$
Baselines						
MLE const	1.473	0.855	1.361	0.348	4	0.000
MLE 1 profile	1.467	0.853	1.355	0.347	64	0.245
MLE 2 profile	1.460	0.852	1.355	0.344	1024	0.218
MLE 1 K-profile	1.472	0.855	1.360	0.348	16	0.010
MLE 2 K-profile	1.470	0.853	1.359	0.346	64	0.083
MLE 3 K-profile	1.466	0.852	1.357	0.337	256	0.141
MLE 4 K-profile	1.462	0.851	1.359	0.336	1024	0.063
EWA-variants						
RL	1.470	0.854	1.359	0.345	5	0.088
BL	1.473	0.854	1.359	0.348	5	0.056
EWA	1.465	0.851	1.354	0.333	8	0.309
Modified EWA $(1)$	1.457	0.848	1.346	0.326	9	0.577
Modified EWA $(2)$	1.456	0.848	1.345	0.324	10	0.621
Modified EWA $(3)$	1.456	0.848	1.345	0.324	12	0.621
Tree Algorithms						
Decision Tree	1.461	0.851	1.351	0.337		0.384
LASSO						
LASSO	1.455	0.847	1.343	0.324	317	0.707
Deep Learning Models						
DNN	1.465	0.851	1.349	0.335	7984	0.449
LSTM	1.446	0.843	1.335	0.310	6220	1.000
Human				0.419		

Table 11. Prediction Peformance Comparison (Red Player)

*Notes:* Average prediction performance scores measured by the test data. We first randomly split the data into five disjoint groups. Then for each group, we train a model using the data of the remaining four groups, and test the performance with it. Hyperparameters of each model are optimized by the cross-validation within the training data. We take the averages of these five train-test splits as the performance scores above. Here L1, L2, KL, SER, and XR are the abbreviations for L1 loss, L2 loss, KL-divergence, strategic error rate, and explainability rate.

			Black	k Player	•	
	L1	L2	KL	SER	#Params	$\mathbf{RC}$
Baselines						
MLE const	1.465	0.852	1.354	0.564	4	0.000
MLE 1 profile	1.458	0.849	1.347	0.540	16	0.309
MLE 2 profile	1.451	0.847	1.346	0.537	1024	0.327
MLE 1 K-profile	1.464	0.851	1.353	0.563	16	0.056
MLE 2 K-profile	1.462	0.850	1.351	0.562	64	0.113
MLE 3 K-profile	1.460	0.849	1.351	0.558	256	0.128
MLE 4 K-profile	1.457	0.849	1.355	0.561	1024	-0.034
EWA-variants						
RL	1.465	0.851	1.354	0.559	5	-0.455
BL	1.465	0.851	1.354	0.559	5	0.017
EWA	1.460	0.849	1.349	0.558	8	0.206
Modified EWA $(1)$	1.453	0.846	1.343	0.529	9	0.473
Modified EWA $(2)$	1.453	0.846	1.342	0.526	10	0.514
Modified EWA $(3)$	1.453	0.846	1.342	0.526	12	0.514
Tree Algorithms						
Decision Tree	1.455	0.848	1.344	0.542		0.395
LASSO						
LASSO	1.448	0.845	1.337	0.526	348	0.705
Deep Learning Models						
DNN	1.456	0.848	1.343	0.533	7984	0.454
LSTM	1.439	0.840	1.330	0.508	7372	1.000
Human				0.581		

Table 12. Prediction Peformance Comparison (Black Player)

*Notes:* Average prediction performance scores measured by the test data. We first randomly split the data into five disjoint groups. Then for each group, we train a model using the data of the remaining four groups, and test the performance with it. Hyperparameters of each model are optimized by the cross-validation within the training data. We take the averages of these five train-test splits as the performance scores above. Here L1, L2, KL, SER, and XR are the abbreviations for L1 loss, L2 loss, KL-divergence, strategic error rate, and explainability rate.



Figure 15. Comparison of KL-divergence of the representative models in each CV train-test split. We can observe that the LSTM outperforms the other models in every CV split.

Performance comparison results are shown in Table 11 and Table 12. Here L1, L2, KL, SER, and RC are the abbreviations for an L1 loss, an L2 loss, a KL-divergence, a strategic error rate, and a relative completeness. Each performance score is the average of the five train-test splits.

Second, we see that the LSTM model exhibits outstanding performance on all performance measures. Therefore, when we compute the relative completeness (RC) as

$$(\text{RC of a model}) = \frac{(\text{KL divergence of the model}) - (\text{KL divergence of MLE const})}{(\text{KL divergence of LSTM}) - (\text{KL divergence of MLE const})}$$

This is a version of the completeness measure introduced by Fudenberg et al. (2021). If, in the above definition of RC, we replace LSTM, the best model we have obtained, with the best one among all specifications of the model equation (1), we obtain the completeness measure. We observe that the original EWA model, which is often used in the literature, achieves only 30.9% (20.6%) performance for the red (black) players relative to the state-of-the-art LSTM model. This result suggests that the EWA model loses some important aspects of actual human behavior in this game.

Also note that the non-parametric model that depends on two-period histories of action profiles (MLE 2-profile) fares much worse (CR is 21.8% for Red player) than MLE and machine learning models. Given that we have a large data set for non-parametric estimation, this is a reliable indication that subjects have longer memory than two periods.

Finally, we find that LASSO performs relatively well, with performance being 70.7% (70.5%) of the LSTM performance for the red (black) players. Since one serious drawback



Figure 16. Resolution: performance comparison of the five representative algorithms when the sample size is smaller. Sample size indicates the number of total periods we use in each setting. For example, we use the data of 500 pairs  $\times$  26 periods for the upper right panel. We can use at most 26 periods data for each pair because LASSO uses a four-period history of action profiles as its explanatory variable.

of the deep learning based models is the difficulty of interpretation, a good starting point is to explore the explanatory variables remaining in the LASSO model to gain some insights for creating a better economic model of agents' behavior. By adding some components to the original EWA model, we succeeded in improving the performance from 30.9% to 62.1% for red players (from 20.6% to 51.4% for black players). However, there is a 8% to 19% difference between the modified EWA and the LASSO models, so we still have room for model improvements.

One of the most important points we would like to stress is the reliability of our performance comparison of various models (Figures 15 and 16). The relative performance of the models is stable across the cross validation as is shown by Figure 15. We also conducted our performance comparison for artificially reduced data sets (Figure 16). Figure 16 basically shows that as we increase the size of the data set, we can get higher resolution in our performance comparison. When we use all of the data with sample size equal to 67,002, the relative performance of models is clearly distinguishable in the sense that (i) there are wide margins in the error rates of different models and (i) the ranking of the model is stable (unchanged) across the five rounds of corss validation, except for one minor rank reversal. If we reduce the sampe size to 26,000, the margins in the error rates of the top three models are much narrower and the ranking of those models differ across the cross validation. Most importantly, the notable dominance of LSTM is no longer clear. If we further reduce the sample size to 13,000, the performance of the top three models becomes indistinguishable. Finally, if the sample size is 2,600 with 100 pairs, which is comparable to the sample sizes of many in-person laboratory experiments, the performance of all models is quite similar, and the rank order of the models is quite different from that with the full sample. Note that the ranking of the traditional ehavioral model (EWA) is quite high under this small sample size, and the speriority of the machine learning models is not at all visible. Figure 16 thus shows that we have succeeded in identifying the relative performance of various models thanks to the unique big data set we collected.



Figure 17. The relative rate of prediction error reduction from the naïve benchmark model (Relative Completeness) for the Red player: Blue fonts refer to machine learning models.

Our results are summarized in Figure 17, which shows the relative rate of prediction error from the naive benchmark of i.i.d. mixture model (MLE const), or more precisely the Relative Completeness. Machine learning models outperform the conventional behavioral model (EWA), and most notably a version of deep learning model of LSTM fares substantially better. This figure also illustrates the "capture and decode" research program explained in the Introduction. The shaded area represents the regularities or mechanisms of the subjects' behavior that have not been captured by the conventional behavioral model. By opening the "black boxes" of machine learning models, we decoded a part of those regularities, which is represented by the modified EWA model. However, a substantial fraction of the captured regularities are yet to be decoded or explained, and this poses a challenging future research agenda.

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# Appendix A. Decision Tree

In this section, we show the decision trees for the red players and the black players in each cross-validation (CV-i)  $(i = 1, \dots 5)$ .



Figure 18. The decision tree for red players (CV-1)



Figure 19. The decision tree for red players (CV-2)



Figure 20. The decision tree for red players (CV-3)



Figure 21. The decision tree for red players (CV-4)



Figure 22. The decision tree for red players (CV-5)



Figure 23. The decision tree for black players (CV-1)











Figure 26. The decision tree for black players (CV-4)



Figure 27. The decision tree for black players (CV-5)

# Appendix B. LASSO

In this section, we list all the 1731 variables we include in the LASSO model and show the maximum likelihood estimates of the coefficients (when we use all the sample data). We only show the table for the red player in Table 13 due to the redundancy. Each line corresponds to one variable. For example, take the line with "history of my actions and winners" in the variable type column, R in the player column, t - 1, t - 2 in the period column, 3, 2 in the card column, and R, B in the winner column. This indicates the coefficients of the dummy variable that the red player played 3 and won in the previous period, and played 2 and lost two periods ago. If an estimate of a coefficient is blank, it means that the variable is eliminated during model selection. If an estimate is 0.000, this implies that the variable is not removed during model selection but that the absolute estimated value is less than 0.0005.

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\rm R,2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
const					-0.084	-0.214	-0.296	0.595
my action	R	t-1	1		-0.132			
my action	R	t-1	2			-0.072	0.005	
my action	R	t-1	3		0.000	0.000	-0.123	0.000
my action	R	t-1	Κ					
my action	R	t-1	Ν		0.000	0.000	0.000	0.000
opponent action	В	t-1	1		0.000	0.000	-0.025	0.000
opponent action	В	t-1	2					
opponent action	В	t-1	3					
opponent action	В	t-1	Κ					
opponent action	В	t-1	Ν		0.000	0.000	0.000	0.000
my action	R	t-2	1		0.068			
my action	R	t-2	2		0.000	0.100	0.000	0.000
my action	R	t-2	3		-0.054		0.046	
my action	R	t-2	Κ					
my action	R	t-2	Ν		0.000	0.000	0.000	0.000
opponent action	В	t-2	1					
opponent action	В	t-2	2		0.030			
opponent action	В	t-2	3				0.000	
opponent action	В	t-2	Κ		0.000	0.000	0.000	0.014
opponent action	В	t-2	Ν					-0.011

Table 13. Full coefficients table of LASSO (Red player)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
my action	R	t-3	1				-0.009	
my action	R	t-3	2					
my action	R	t-3	3				0.022	-0.006
my action	R	t-3	Κ		0.000	0.000	0.000	0.007
my action	R	t-3	Ν					-0.006
opponent action	В	t-3	1					
opponent action	В	t-3	2					
opponent action	В	t-3	3		0.000	0.000	0.000	0.000
opponent action	В	t-3	Κ					0.060
opponent action	В	t-3	Ν		0.000	0.000	0.000	-0.032
my action	R	t-4	1					
my action	R	t-4	2		0.004	0.000	0.000	-0.021
my action	R	t-4	3				0.010	
my action	R	t-4	Κ					0.029
my action	R	t-4	Ν		0.000	0.000	0.000	-0.024
opponent action	В	t-4	1		-0.016			
opponent action	В	t-4	2		0.000	0.000	0.000	-0.059
opponent action	В	t-4	3		0.011			
opponent action	В	t-4	Κ					0.119
opponent action	В	t-4	Ν		0.000	0.000	0.000	-0.027
action profile		t-1	(1,1)					-0.012
action profile		t-1	(1,2)					
action profile		t-1	(1,3)					0.024
action profile		t-1	(1.K)					
action profile		t-1	(2,1)			-0.051		
action profile		t-1	(2,2)					
action profile		t-1	(2,3)					
action profile		t-1	(2.K)					
action profile		t-1	(3,1)		0.000	0.000	0.000	0.000
action profile		t-1	(3.2)					
action profile		t-1	(3.3)					
action profile		t-1	(3, K)		0.002			
action profile		t-1	(K.1)		-0.063	0.049	-0.001	0.005
action profile		t-1	(K.2)			-0.036	0.000	
action profile		t-1	(K.3)			0.000		-0.062
action profile		t-1	(K.K)				-0.005	2.002
action profile		t-2	(1.1)				0.000	
Promo			(+,+)			> Conti	inuo to tho	novt pago

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
action profile		t-2	(1,2)					
action profile		t-2	(1,3)			-0.073		0.042
action profile		t-2	(1,K)					
action profile		t-2	(2,1)					
action profile		t-2	(2,2)					
action profile		t-2	(2,3)					
action profile		t-2	(2,K)		-0.081	0.000	0.000	0.000
action profile		t-2	(3,1)					
action profile		t-2	(3,2)					
action profile		t-2	(3,3)					
action profile		t-2	(3,K)		0.000		0.096	
action profile		t-2	(K,1)					
action profile		t-2	(K,2)				0.019	
action profile		t-2	(K,3)					
action profile		t-2	(K,K)					
history of action profiles		t-1,t-2	(1,1),(1,1)					
history of action profiles		t-1,t-2	(1,1),(1,2)					
history of action profiles		t-1,t-2	(1,1),(1,3)					
history of action profiles		t-1,t-2	(1,1),(1,K)					
history of action profiles		t-1,t-2	(1,1),(2,1)					
history of action profiles		t-1,t-2	(1,1),(2,2)					
history of action profiles		t-1,t-2	(1,1),(2,3)					
history of action profiles		t-1,t-2	(1,1),(2,K)					
history of action profiles		t-1,t-2	(1,1),(3,1)					
history of action profiles		t-1,t-2	(1,1),(3,2)					
history of action profiles		t-1,t-2	(1,1),(3,3)					
history of action profiles		t-1,t-2	(1,1),(3,K)					
history of action profiles		t-1,t-2	(1,1),(K,1)					
history of action profiles		t-1,t-2	(1,1),(K,2)					
history of action profiles		t-1,t-2	(1,1), (K,3)					
history of action profiles		t-1,t-2	(1,1),(K,K)					
history of action profiles		t-1,t-2	(1,2),(1,1)					
history of action profiles		t-1,t-2	(1,2),(1,2)					
history of action profiles		t-1,t-2	(1,2),(1,3)					
history of action profiles		t-1,t-2	(1,2),(1,K)					
history of action profiles		t-1,t-2	(1,2),(2,1)					
history of action profiles		t-1,t-2	(1,2),(2,2)					
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Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\rm R,2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of action profiles		t-1,t-2	(1,2),(2,3)					
history of action profiles		t-1,t-2	(1,2),(2,K)					
history of action profiles		t-1,t-2	(1,2),(3,1)					
history of action profiles		t-1,t-2	(1,2),(3,2)					
history of action profiles		t-1,t-2	(1,2),(3,3)					
history of action profiles		t-1,t-2	(1,2),(3,K)					
history of action profiles		t-1,t-2	(1,2),(K,1)					
history of action profiles		t-1,t-2	(1,2),(K,2)					
history of action profiles		t-1,t-2	(1,2),(K,3)					
history of action profiles		t-1,t-2	(1,2),(K,K)					-0.022
history of action profiles		t-1,t-2	(1,3),(1,1)					
history of action profiles		t-1,t-2	(1,3),(1,2)					
history of action profiles		t-1,t-2	(1,3),(1,3)					
history of action profiles		t-1,t-2	(1,3),(1,K)					
history of action profiles		t-1,t-2	(1,3),(2,1)					
history of action profiles		t-1,t-2	(1,3),(2,2)					
history of action profiles		t-1,t-2	(1,3),(2,3)					
history of action profiles		t-1,t-2	(1,3),(2,K)					
history of action profiles		t-1,t-2	(1,3),(3,1)					
history of action profiles		t-1,t-2	(1,3),(3,2)					
history of action profiles		t-1,t-2	(1,3),(3,3)					
history of action profiles		t-1,t-2	(1,3),(3,K)					
history of action profiles		t-1,t-2	(1,3),(K,1)					
history of action profiles		t-1,t-2	(1,3), (K,2)					
history of action profiles		t-1,t-2	(1,3), (K,3)					
history of action profiles		t-1,t-2	(1,3), (K,K)					
history of action profiles		t-1,t-2	(1,K),(1,1)					
history of action profiles		t-1,t-2	(1,K),(1,2)					
history of action profiles		t-1,t-2	(1,K),(1,3)					
history of action profiles		t-1,t-2	(1,K),(1,K)					
history of action profiles		t-1,t-2	(1,K),(2,1)					
history of action profiles		t-1,t-2	(1,K),(2,2)					
history of action profiles		t-1,t-2	(1,K),(2,3)					
history of action profiles		t-1,t-2	(1,K),(2,K)					
history of action profiles		t-1,t-2	(1,K),(3,1)					
history of action profiles		t-1,t-2	(1,K),(3,2)					
history of action profiles		t-1,t-2	(1,K),(3,3)					
						» Co	ntique to t	he nevt nage

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of action profiles	t	-1, t-2	(1,K),(3,K)					
history of action profiles	t	-1, t-2	(1,K),(K,1)					
history of action profiles	t	-1, t-2	(1,K),(K,2)					
history of action profiles	t	-1, t-2	(1,K),(K,3)					
history of action profiles	t	-1,t-2	(1,K),(K,K)					
history of action profiles	t	-1,t-2	(2,1),(1,1)					
history of action profiles	t	-1,t-2	(2,1),(1,2)					
history of action profiles	t	-1,t-2	(2,1),(1,3)					
history of action profiles	t	-1,t-2	(2,1),(1,K)					
history of action profiles	t	-1, t-2	(2,1),(2,1)					
history of action profiles	t	-1,t-2	(2,1),(2,2)					
history of action profiles	t	-1,t-2	(2,1),(2,3)					
history of action profiles	t	-1,t-2	(2,1),(2,K)					
history of action profiles	t	-1,t-2	(2,1),(3,1)					
history of action profiles	t	-1,t-2	(2,1),(3,2)					
history of action profiles	t	-1,t-2	(2,1),(3,3)					
history of action profiles	t	-1,t-2	(2,1),(3,K)					
history of action profiles	t	-1,t-2	(2,1),(K,1)					
history of action profiles	t	-1,t-2	(2,1),(K,2)					
history of action profiles	t	-1,t-2	(2,1),(K,3)					
history of action profiles	t	-1,t-2	(2,1),(K,K)					
history of action profiles	t	-1,t-2	(2,2),(1,1)					
history of action profiles	t	-1,t-2	(2,2),(1,2)					
history of action profiles	t	-1,t-2	(2,2),(1,3)					
history of action profiles	t	-1,t-2	(2,2),(1,K)					
history of action profiles	t	-1,t-2	(2,2),(2,1)					
history of action profiles	t	-1,t-2	(2,2),(2,2)					
history of action profiles	t	-1,t-2	(2,2),(2,3)					
history of action profiles	t	-1,t-2	(2,2),(2,K)					
history of action profiles	t	-1,t-2	(2,2),(3,1)					
history of action profiles	t	-1,t-2	(2,2),(3,2)					
history of action profiles	t	-1,t-2	(2,2),(3,3)					
history of action profiles	t	-1,t-2	(2,2),(3,K)					
history of action profiles	t	-1,t-2	(2,2),(K,1)					
history of action profiles	t	-1,t-2	(2,2),(K,2)					
history of action profiles	t	-1,t-2	(2,2),(K,3)					
history of action profiles	t	-1,t-2	(2,2),(K,K)					
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Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of action profiles		t-1,t-2	(2,3),(1,1)					
history of action profiles		t-1,t-2	(2,3),(1,2)					
history of action profiles		t-1,t-2	(2,3),(1,3)					
history of action profiles		t-1,t-2	(2,3),(1,K)					
history of action profiles		t-1,t-2	(2,3),(2,1)					
history of action profiles		t-1,t-2	(2,3),(2,2)					
history of action profiles		t-1,t-2	(2,3),(2,3)					
history of action profiles		t-1,t-2	(2,3),(2,K)					
history of action profiles		t-1,t-2	(2,3),(3,1)					
history of action profiles		t-1,t-2	(2,3),(3,2)					
history of action profiles		t-1,t-2	(2,3),(3,3)					
history of action profiles		t-1,t-2	(2,3),(3,K)					
history of action profiles		t-1,t-2	(2,3),(K,1)					
history of action profiles		t-1,t-2	(2,3),(K,2)					
history of action profiles		t-1,t-2	(2,3), (K,3)					
history of action profiles		t-1,t-2	(2,3),(K,K)					
history of action profiles		t-1,t-2	(2,K),(1,1)					
history of action profiles		t-1,t-2	(2,K),(1,2)					
history of action profiles		t-1,t-2	(2,K),(1,3)					
history of action profiles		t-1,t-2	(2,K),(1,K)					
history of action profiles		t-1,t-2	(2,K),(2,1)					
history of action profiles		t-1,t-2	(2,K),(2,2)					
history of action profiles		t-1,t-2	(2,K),(2,3)					
history of action profiles		t-1,t-2	(2,K),(2,K)					
history of action profiles		t-1,t-2	(2,K),(3,1)					
history of action profiles		t-1,t-2	(2,K),(3,2)					
history of action profiles		t-1,t-2	(2,K),(3,3)					
history of action profiles		t-1,t-2	(2,K),(3,K)					
history of action profiles		t-1,t-2	(2,K),(K,1)					
history of action profiles		t-1,t-2	(2,K),(K,2)					
history of action profiles		t-1,t-2	(2,K),(K,3)					
history of action profiles		t-1,t-2	(2,K),(K,K)					
history of action profiles		t-1,t-2	(3,1),(1,1)					
history of action profiles		t-1,t-2	(3,1),(1,2)					
history of action profiles		t-1,t-2	(3,1),(1,3)					
history of action profiles		t-1,t-2	(3,1),(1,K)					
history of action profiles		t-1,t-2	(3,1),(2,1)					
<b>^</b>						» Co	ntinuo to t	he next page

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\rm R,1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of action profiles	t-1,t-2	(3,1),(2,2)					
history of action profiles	t-1,t-2	(3,1),(2,3)					
history of action profiles	t-1,t-2	(3,1),(2,K)		0.000	0.000	0.000	0.000
history of action profiles	t-1,t-2	(3,1),(3,1)					
history of action profiles	t-1,t-2	(3,1),(3,2)					
history of action profiles	t-1,t-2	(3,1),(3,3)					
history of action profiles	t-1,t-2	(3,1),(3,K)					
history of action profiles	t-1,t-2	(3,1),(K,1)					
history of action profiles	t-1,t-2	(3,1),(K,2)					
history of action profiles	t-1,t-2	(3,1),(K,3)					
history of action profiles	t-1,t-2	(3,1),(K,K)					
history of action profiles	t-1,t-2	(3,2),(1,1)					
history of action profiles	t-1,t-2	(3,2),(1,2)					
history of action profiles	t-1,t-2	(3,2),(1,3)					
history of action profiles	t-1,t-2	(3,2),(1,K)					
history of action profiles	t-1,t-2	(3,2),(2,1)					
history of action profiles	t-1,t-2	(3,2),(2,2)					
history of action profiles	t-1,t-2	(3,2),(2,3)					
history of action profiles	t-1,t-2	(3,2),(2,K)					
history of action profiles	t-1,t-2	(3,2),(3,1)					
history of action profiles	t-1,t-2	(3,2),(3,2)					
history of action profiles	t-1,t-2	(3,2),(3,3)					
history of action profiles	t-1,t-2	(3,2),(3,K)					
history of action profiles	t-1,t-2	(3,2),(K,1)					
history of action profiles	t-1,t-2	(3,2),(K,2)					
history of action profiles	t-1,t-2	(3,2),(K,3)					
history of action profiles	t-1,t-2	(3,2),(K,K)					
history of action profiles	t-1,t-2	(3,3),(1,1)					
history of action profiles	t-1,t-2	(3,3),(1,2)					
history of action profiles	t-1,t-2	(3,3),(1,3)					
history of action profiles	t-1,t-2	(3,3),(1,K)					
history of action profiles	t-1,t-2	(3,3),(2,1)					
history of action profiles	t-1,t-2	(3,3),(2,2)					
history of action profiles	t-1,t-2	(3,3),(2,3)					
history of action profiles	t-1,t-2	(3,3),(2,K)					
history of action profiles	t-1,t-2	(3,3),(3,1)					
history of action profiles	t-1,t-2	(3,3),(3,2)					
	,				> Cont	inuo to the	novt page

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
		1 / 0	(2,2) $(2,2)$					
history of action profiles	t.	-1,t-2	(3,3),(3,3)					
history of action profiles	t.	-1,t-2	(3,3),(3,K)					
history of action profiles	t.	-1,t-2	(3,3),(K,1)					
history of action profiles	t.	-1,t-2	(3,3),(K,2)					
history of action profiles	t.	-1,t-2	(3,3),(K,3)					
history of action profiles	t·	-1,t-2	(3,3),(K,K)					
history of action profiles	t·	-1,t-2	(3,K),(1,1)					
history of action profiles	t·	-1,t-2	(3,K),(1,2)					
history of action profiles	t·	-1,t-2	(3,K),(1,3)					
history of action profiles	t·	-1,t-2	(3,K),(1,K)					
history of action profiles	t·	-1, t-2	(3,K),(2,1)					
history of action profiles	t·	-1, t-2	(3,K),(2,2)					
history of action profiles	t·	-1, t-2	(3,K),(2,3)					
history of action profiles	t·	-1,t-2	(3,K),(2,K)					
history of action profiles	t·	-1,t-2	(3,K),(3,1)					
history of action profiles	t·	-1,t-2	(3,K),(3,2)					
history of action profiles	t·	-1, t-2	(3,K),(3,3)					
history of action profiles	t·	-1, t-2	(3,K),(3,K)					
history of action profiles	t·	-1,t-2	(3,K),(K,1)					
history of action profiles	t·	-1,t-2	(3,K),(K,2)					
history of action profiles	t·	-1,t-2	(3,K),(K,3)					
history of action profiles	t·	-1,t-2	(3,K),(K,K)					
history of action profiles	t·	-1,t-2	(K,1),(1,1)					
history of action profiles	t·	-1,t-2	(K,1),(1,2)					
history of action profiles	t·	-1,t-2	(K,1),(1,3)					
history of action profiles	t·	-1,t-2	(K,1),(1,K)					
history of action profiles	t·	-1,t-2	(K,1),(2,1)					
history of action profiles	t·	-1,t-2	(K,1),(2,2)					
history of action profiles	t·	-1,t-2	(K,1),(2,3)					
history of action profiles	t·	-1,t-2	(K,1),(2,K)					
history of action profiles	t·	-1.t-2	(K,1),(3,1)					
history of action profiles	t·	-1.t-2	(K,1),(3,2)					
history of action profiles	t·	-1,t-2	(K,1),(3,3)					
history of action profiles	t·	-1,t-2	(K,1),(3.K)					
history of action profiles	t·	-1.t-2	(K.1).(K.1)					
history of action profiles	t.	-1.t-2	(K.1).(K.2)					
history of action profiles	t.	-1.t-2	(K.1).(K.3)					
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Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of action profiles	t	-1,t-2	(K,1),(K,K)					
history of action profiles	t	-1,t-2	(K,2),(1,1)					
history of action profiles	t	-1,t-2	(K,2),(1,2)					
history of action profiles	t	-1,t-2	(K,2),(1,3)					
history of action profiles	t	-1,t-2	(K,2),(1,K)					
history of action profiles	t	-1,t-2	(K,2),(2,1)					
history of action profiles	t	-1,t-2	(K,2),(2,2)					
history of action profiles	t	-1,t-2	(K,2),(2,3)					
history of action profiles	t	-1,t-2	(K,2),(2,K)					
history of action profiles	t	-1,t-2	(K,2),(3,1)					
history of action profiles	t	-1,t-2	(K,2),(3,2)					
history of action profiles	t	-1,t-2	(K,2),(3,3)					
history of action profiles	t	-1,t-2	(K,2),(3,K)					
history of action profiles	t	-1,t-2	(K,2),(K,1)					
history of action profiles	t	-1,t-2	(K,2),(K,2)					
history of action profiles	t	-1,t-2	(K,2),(K,3)					
history of action profiles	t	-1,t-2	(K,2),(K,K)					
history of action profiles	t	-1,t-2	(K,3),(1,1)					
history of action profiles	t	-1,t-2	(K,3),(1,2)					
history of action profiles	t	-1,t-2	(K,3),(1,3)					
history of action profiles	t	-1,t-2	(K,3),(1,K)					
history of action profiles	t	-1,t-2	(K,3),(2,1)					
history of action profiles	t	-1,t-2	(K,3),(2,2)					
history of action profiles	t	-1,t-2	(K,3),(2,3)					
history of action profiles	t	-1,t-2	(K,3),(2,K)					
history of action profiles	t	-1,t-2	(K,3),(3,1)					
history of action profiles	t	-1,t-2	(K,3),(3,2)					
history of action profiles	t	-1,t-2	(K,3),(3,3)					
history of action profiles	t	-1,t-2	(K,3),(3,K)					
history of action profiles	t	-1,t-2	(K,3),(K,1)					
history of action profiles	t	-1,t-2	(K,3),(K,2)					
history of action profiles	t	-1,t-2	(K,3),(K,3)					
history of action profiles	t	-1,t-2	(K,3),(K,K)					
history of action profiles	t	-1,t-2	(K,K),(1,1)					
history of action profiles	t	-1,t-2	(K,K),(1,2)					
history of action profiles	t	-1,t-2	(K,K),(1,3)					
history of action profiles	t	-1,t-2	(K,K),(1,K)					
<b>*</b>						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
history of action profiles		t-1,t-2	(K,K),(2,1)					
history of action profiles		t-1,t-2	(K,K),(2,2)					
history of action profiles		t-1,t-2	(K,K),(2,3)					
history of action profiles		t-1,t-2	(K,K),(2,K)					
history of action profiles		t-1,t-2	(K,K),(3,1)					
history of action profiles		t-1,t-2	(K,K),(3,2)					
history of action profiles		t-1,t-2	(K,K),(3,3)					
history of action profiles		t-1,t-2	(K,K),(3,K)					
history of action profiles		t-1,t-2	(K,K),(K,1)					
history of action profiles		t-1,t-2	(K,K),(K,2)					
history of action profiles		t-1,t-2	(K,K),(K,3)					
history of action profiles		t-1,t-2	(K,K),(K,K)					0.075
K-profile		t-1	(K,N)					
K-profile		t-1	(N,K)				0.014	
K-profile		t-1	(N,N)		0.000	0.000	0.000	0.000
K-profile		t-2	(K,N)					
K-profile		t-2	(N,K)		0.000	0.000	0.000	0.006
K-profile		t-2	(N,N)			0.044		-0.006
history of K-profiles		t-1,t-2	(K,K),(K,N)					
history of K-profiles		t-1,t-2	(K,K),(N,K)					
history of K-profiles		t-1,t-2	(K,K),(N,N)					-0.022
history of K-profiles		t-1,t-2	(K,N),(K,K)					
history of K-profiles		t-1,t-2	(K,N),(K,N)					
history of K-profiles		t-1,t-2	(K,N),(N,K)					
history of K-profiles		t-1,t-2	(K,N),(N,N)					
history of K-profiles		t-1,t-2	(N,K),(K,K)					
history of K-profiles		t-1,t-2	(N,K),(K,N)					
history of K-profiles		t-1,t-2	(N,K),(N,K)					
history of K-profiles		t-1,t-2	(N,K),(N,N)					
history of K-profiles		t-1,t-2	(N,N),(K,K)					-0.020
history of K-profiles		t-1,t-2	(N,N),(K,N)					
history of K-profiles		t-1,t-2	(N,N),(N,K)		-0.017	0.000	0.000	0.000
history of K-profiles		t-1,t-2	(N,N),(N,N)		0.050		-0.008	
K-profile		t-3	(K,K)			-0.034		0.002
K-profile		t-3	(K,N)		0.000	0.000	0.000	0.000
K-profile		t-3	(N,K)					
K-profile		t-3	(N,N)					-0.130
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Table $13$ .	Full	coefficients	table	of	LASSO	(Red	player,	cont.	)
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Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-3	(K,K),(K,K),					
history of K-profiles	t-1 to t-3	(K,K) (K,K),(K,K), (K,N)					
history of K-profiles	t-1 to t-3	(K,K),(K,K), (N,K)					
history of K-profiles	t-1 to t-3	(K,K),(K,K), (N,N)				0.005	
history of K-profiles	t-1 to t-3	(K,K),(K,N), (K,K)					
history of K-profiles	t-1 to t-3	(K,K),(K,N), (K,N)					
history of K-profiles	t-1 to t-3	(K,K),(K,N), (N,K)					
history of K-profiles	t-1 to t-3	(K,K),(K,N), (N,N)					
history of K-profiles	t-1 to t-3	(K,K),(N,K), (K,K)					
history of K-profiles	t-1 to t-3	(K,K),(N,K), (K,N)					
history of K-profiles	t-1 to t-3	(K,K),(N,K), (N,K)					
history of K-profiles	t-1 to t-3	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K}),$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$				0.000	
history of K-profiles	t-1 to t-3	(K,K),(N,N), (K,K) (K,K) $(N,N)$				0.060	
history of K profiles	t-1 to t-3	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N})$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
history of K profiles	t-1 to t-3	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K})$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
history of K profiles	t - 1 to t - 3	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K profiles	t - 1 to t - 3	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{K})$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K-profiles	t-1 to t ?	$(\mathbf{K},\mathbf{N})$ $(\mathbf{K},\mathbf{N})$ $(\mathbf{K},\mathbf{N})$					
history of K-profiles	t-1 to t-3	(N,K) (N,K) (K N) (K K)					
history of K-profiles	t-1 to t-3	(N,N) (N,N) (K,N) (K,N)					
	u−u 00 u−9	(K,K)			» Ca	ntinus to t	

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R,2}}$	$\beta_{\mathrm{R,3}}$	$\beta_{\mathrm{R},K}$
history of K profiles	+ 1 + 2 + 2	$(\mathbf{V} \mathbf{N}) (\mathbf{V} \mathbf{N})$					
instory of K-promes	t-1 to t-5	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{K},\mathbf{N})$					
history of K-profiles	t-1 to t-3	(K,N),(K,N),					
<b>5 1</b>		(N,K)					
history of K-profiles	t-1 to t-3	(K,N),(K,N),				-0.004	
		(N,N)					
history of K-profiles	t-1 to t-3	(K,N),(N,K),					
		(K,K)					
history of K-profiles	t-1 to t-3	(K,N),(N,K),					
history of K profiles	+1++2	(K,N)					
history of K-promes	t-1 to t-3	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K}),$					
history of K-profiles	t-1 to t-3	(K,N).(N,K).					-0.030
T T		(N,N)					
history of K-profiles	t-1 to t-3	(K,N),(N,N),					
		(K,K)					
history of K-profiles	t-1 to t-3	(K,N),(N,N),				0.004	
		(K,N)					
history of K-profiles	t-1 to t-3	(K,N),(N,N),					
	1 1 4 - 4 9	(N,K)					
history of K-profiles	t-1 to t-3	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$					
history of K-profiles	t-1 to t-3	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K})$ $(\mathbf{K},\mathbf{K})$					
instory of it promes		(K.K)					
history of K-profiles	t-1 to t-3	(N,K),(K,K),					
		(K,N)					
history of K-profiles	t-1 to t-3	(N,K),(K,K),					
		(N,K)					
history of K-profiles	t-1 to t-3	(N,K),(K,K),					
		(N,N)					
history of K-profiles	t-1 to $t-3$	(N,K),(K,N),					
history of K profiles	+1++2	(K,K) (N,K) $(K,N)$					
history of K-promes	t-1 to t-3	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{K},\mathbf{N})$					
history of K-profiles	t-1 to t-3	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K})$ $(\mathbf{K},\mathbf{N})$			-0.072		0.084
instory of it promos		(N,K)			0.012		0.001
history of K-profiles	t-1 to t-3	(N,K),(K,N),					
		(N,N)					
history of K-profiles	t-1 to t-3	(N,K),(N,K),					
		(K,K)					
history of K-profiles	t-1 to t-3	(N,K),(N,K),					
		(K,N)				• , , 1	
					$\gg Cont$	nue to the	next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-3	(N,K),(N,K),					
		(N,K)					
history of K-profiles	t-1 to t-3	(N,K),(N,K),					
		(N,N)					
history of K-profiles	t-1 to t-3	(N,K),(N,N),					
history of K profiles	t 1 to t 3	$(\mathbf{K},\mathbf{K})$ $(\mathbf{N},\mathbf{K})$ $(\mathbf{N},\mathbf{N})$					
instory of R-promes	1-1 10 1-5	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K}),$					
history of K-profiles	t-1 to t-3	(N,K).(N,N).					
F		(N,K)					
history of K-profiles	t-1 to t-3	(N,K),(N,N),					
		(N,N)					
history of K-profiles	t-1 to t-3	(N,N),(K,K),					
		(K,K)					
history of K-profiles	t-1 to t-3	(N,N),(K,K),					
		(K,N)					
history of K-profiles	t-1 to t-3	(N,N),(K,K),					
history of K and Char	4 1 4 - 4 9	(N,K)					
history of K-promes	t-1 to t-5	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K}),$					
history of K-profiles	t-1 to t-3	(N,N) (K N)					
motory of it promot		(K.K)					
history of K-profiles	t-1 to t-3	(N,N),(K,N),				-0.034	
<b>0 1</b>		(K,N)					
history of K-profiles	t-1 to t-3	(N,N),(K,N),					-0.144
		(N,K)					
history of K-profiles	t-1 to t-3	(N,N),(K,N),				0.006	
		(N,N)					
history of K-profiles	t-1 to t-3	(N,N),(N,K),					0.087
		(K,K)		0.000	0.000		0.050
history of K-profiles	t-1 to t-3	(N,N),(N,K),		0.000	0.000	0.000	-0.076
history of K profiles	t 1 to t 3	$(\mathbf{K},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K})$					
instory of it-promes	t-1 to t-5	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{R}),$					
history of K-profiles	t-1 to t-3	(N,N).(N,K).					0.000
		(N,N)					0.000
history of K-profiles	t-1 to t-3	(N,N),(N,N),					
		(K,K)					
history of K-profiles	t-1 to t-3	(N,N),(N,N),					
		(K,N)					
history of K-profiles	t-1 to t-3	(N,N),(N,N),					
		(N,K)			× C ·	····· / /1	

Table 13. Full coefficients table of LASSO (Red player, cont.)

history of K-profiles t-1 to t-3 (N,N),(N,N),	
(N,N)	
K-profile $t-4$ (K,K) $-0.035$ 0	0.021
K-profile $t-4$ (K,N)	
K-profile $t-4$ (N,K) $-0.005$	1.1.9.1
K-profile $t-4$ (N,N) $0.008$ $0.000$ $-0$	0.131
$ \begin{array}{c} \text{nistory of K-profiles} \\ (K,K), (K,K), \\ (K,K), $	
(K,K),(K,K)	
(K,K),(K,K	
history of K-profiles $t_1$ to $t_4$ (K K) (K K)	
(K,K),(K,K	
history of K-profiles $t-1$ to $t-4$ (K K) (K K)	
(K,K),(K,K	
history of K-profiles $t-1$ to $t-4$ (K K) (K K)	
$(\mathbf{K},\mathbf{N}).(\mathbf{K},\mathbf{K})$	
history of K-profiles $t-1$ to $t-4$ (K.K).(K.K).	
(x,y),(x,y	
history of K-profiles t-1 to t-4 (K,K),(K,K),	
(K,N),(N,K)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(K,N),(N,N)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,K),(K,K)	
history of K-profiles t-1 to t-4 (K,K),(K,K),	
(N,K),(K,N)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,K),(N,K)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,K),(N,N)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,N),(K,K)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,N),(K,N)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,N),(N,K)	
history of K-profiles $t-1$ to $t-4$ $(K,K),(K,K),$	
(N,N),(N,N)	
nistory of K-profiles $t-1$ to $t-4$ $(K,K),(K,N),$	
(K,K),(K,K)	
$\begin{array}{ccc} \text{Instory of K-promes} & \text{t-1 to t-4} & (K,K), (K,N), \\ & (K,K), (K,N) \end{array}$	
$(\mathbf{A},\mathbf{A}),(\mathbf{A},\mathbf{N})$	ກລອອ

### Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(K,N),(K,N)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(K,N),(N,K)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(K,N),(N,N)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(N,K),(K,K)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
		(N,K),(K,N)					
history of K-profiles	t-1 to t-4	(K,K),(K,N),					
	. 1	(N,K),(N,K)					
history of K-profiles	t-1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N}),$					
history of V mofles	4 1 4 4 4 4	(N,K),(N,N)					
history of K-profiles	t-1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N}),$					
history of K profiles	+ 1 + 0 + 1	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$ $(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N})$					
instory of R-promes	t-1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K-profiles	t-1 to t-4	(K,K),(K,N)					
instory of Reproducts	1-1 00 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$					
history of K-profiles	t-1 to t-4	(K,K),(K,N)					
metory of it promos		(N,N).(N,N)					
history of K-profiles	t-1 to t-4	(K.K).(N.K).					
J I I I I I I I I I I I I I I I I I I I		(K,K),(K,K)					
history of K-profiles	t-1 to t-4	(K,K),(N,K),					
		(K,K),(K,N)					
history of K-profiles	t-1 to t-4	(K,K),(N,K),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(K,K),(N,K),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(K,K),(N,K),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(K,K),(N,K),					
		$(\mathrm{K,N}),(\mathrm{K,N})$					
history of K-profiles	t-1 to t-4	(K,K),(N,K),					
		(K,N),(N,K)					
					$\gg Co$	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	l Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(K,N),(N,N)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,K),(K,K)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,K),(K,N)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,K),(N,K)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,K),(N,N)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,N),(K,K)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,N),(K,N)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,N),(N,K)					
history of K-profiles	t-1 to t-	4 (K,K),(N,K),					
		(N,N),(N,N)					
history of K-profiles	t-1 to t-	4 (K,K),(N,N),					
		(K,K),(K,K)					
history of K-profiles	t-1 to t-	4 (K,K),(N,N),					
		(K,K),(K,N)					
history of K-profiles	t-1 to t-	4 (K,K),(N,N),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-	$4  (\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-	$4  (K,K),(N,N), \\ (K,N),(K,K)  (K,K)$					
1		(K,N),(K,K)					
history of K-profiles	t-1 to t-	$4  (K,K),(N,N), \\ (K,N),(K,N)  (K,N)$					
		(K,N),(K,N)					
history of K-profiles	t-1 to t-	$4  (K,K),(N,N), \\ (K,N),(N,K)$					
1		(K,N),(N,K)					
history of K-profiles	t-1 to t-	$4  (K,K),(N,N), \\ (K,N),(N,N) $					
1		(K,N),(N,N)					
history of K-profiles	t-1 to t-	4  (K,K),(N,N),					
1		(N,K),(K,K)					
history of K-profiles	t-1 to t-	4  (K,K),(N,N),					
		(N,K),(K,N)					
nistory of K-profiles	t-1 to t-	4  (K,K),(N,N),					
		(N,K),(N,K)					0.054
mistory of K-profiles	t-1 to t-	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N}),$					-0.054
		(N,K),(N,N)			>> C		1 <i></i>
					<i>≫</i> Co	numue to t	ne next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
history of K-profiles		t-1 to t-4	(K,K),(N,N),					
			(N,N),(K,K)					
history of K-profiles		t-1 to t-4	(K,K),(N,N),					
			(N,N),(K,N)					
history of K-profiles		t-1 to $t-4$	(K,K),(N,N),					
			(N,N),(N,K)					
history of K-profiles		t-1 to t-4	(K,K),(N,N),				-0.007	
			(N,N),(N,N)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
			(K,K),(K,K)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
		. 1	(K,K),(K,N)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
history of V mobles		+ 1 + - + 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$					
history of K-promes		t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
history of K profiles		t 1 to t 1	$(\mathbf{K},\mathbf{K}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N})$					
instory of R-promes		1-1 10 1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K profiles		t 1 to t 4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
instory of R-promes		1-1 10 1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K-profiles		t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
motory of it promes		010004	(K, N), (N, K), (K, N), (K, N), (K, N), (K, N), (K, K), (K,					
history of K-profiles		t-1 to t-4	(K,N),(K,K)					
metory of it promos		0 1 00 0 1	(K,N),(N,N)					
history of K-profiles		t-1 to t-4	(K.N).(K.K).					
F			(N.K).(K.K)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
5 I			(N,K),(K,N)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
			(N,K),(N,K)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
			(N,K),(N,N)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
			(N,N),(K,K)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
			(N,N),(K,N)					
history of K-profiles		t-1 to t-4	(K,N),(K,K),					
			(N,N),(N,K)					
history of K-profiles		t-1 to t-4 $$	(K,N),(K,K),	), )				
			(N,N),(N,N)					
history of K-profiles		t-1 to t-4	(K,N),(K,N),					
			(K,K),(K,K)					
						$\gg Cor$	ntinue to the	e next page.

#### Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,K),(K,N)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,N),(K,N)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,N),(N,K)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(K,N),(N,N)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(N,K),(K,K)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
		(N,K),(K,N)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
	. 1	(N,K),(N,K)					
history of K-profiles	t-1 to t-4	(K,N),(K,N),					
history of K profiles	+ 1 +	(IN,K),(IN,IN)					
history of K-promes	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K profiles	t 1 to t 4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
instory of R-promes	1-1 00 0-4	$(\mathbf{R},\mathbf{N}),(\mathbf{R},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K-profiles	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
instory of it promos		(N,N),(N,K)					
history of K-profiles	t-1 to t-4	(K.N).(K.N).					
		(N,N),(N,N)					
history of K-profiles	t-1 to t-4	(K.N).(N.K).					
J I I I I I I I I I I I I I I I I I I I		(K,K),(K,K)					
history of K-profiles	t-1 to t-4	(K,N),(N,K),					
v x		(K,K),(K,N)					
history of K-profiles	t-1 to t-4	(K,N),(N,K),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(K,N),(N,K),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(K,N),(N,K),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(K,N),(N,K),					
		(K,N),(K,N)					
					$\gg Co$	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Per	iod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to	t-4	(K,N),(N,K),					
			(K,N),(N,K)					
history of K-profiles	t-1 to	t-4	(K,N),(N,K),					
			(K,N),(N,N)					
history of K-profiles	t-1 to	t-4	(K,N),(N,K),					
			(N,K),(K,K)					
history of K-profiles	t-1 to	t-4	(K,N),(N,K),					
			(N,K),(K,N)					
history of K-profiles	t-1 tc	t-4	(K,N),(N,K),					
			(N,K),(N,K)					
history of K-profiles	t-1 to	t-4	(K,N),(N,K),					
			(N,K),(N,N)					
history of K-profiles	t-1 tc	t-4	(K,N),(N,K),					
			(N,N),(K,K)					
history of K-profiles	t-1 tc	t-4	(K,N),(N,K),					
			(N,N),(K,N)					
history of K-profiles	t-1 tc	t-4	(K,N),(N,K),					
			(N,N),(N,K)					
history of K-profiles	t-1 to	t-4	(K,N),(N,K),					0.000
			(N,N),(N,N)					
history of K-profiles	t-1 tc	t-4	(K,N),(N,N),					
			(K,K),(K,K)					
history of K-profiles	t-1 to	t-4	(K,N),(N,N),					
	. 1		(K,K),(K,N)					
history of K-profiles	t-1 to	τ-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$					
history of V profiles	4140	± 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$					
history of K-promes	t-1 tC	1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
history of K profiles	+ 1 + 0	+ 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
history of R-promes	t-1 tC	1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K profiles	+ 1 + 0	+ 1	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K-promes	t-1 tC	1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K profiles	+ 1 + c	+ 1	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
instory of R-promes	0-1 UC	1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$					
history of K profiles	t 1 to	+ 1	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$					
instory of it-promes	0-1 00	U-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$					
history of K profiles	t 1 to	+ 1	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$					
motory of it-promes	0-1 UC	U=-±	(N K) (K K)					
history of K-profiles	t_1 to	t_4	(K N) (N N)					
motory of is-promes	0-1 UC	U±	(N K) (K N)					
history of K-profiles	t_1 to	t_4	(K N) (N N)					
motory of it promos	0-1 00	υI	(N K) (N K)					
			(*****)			≫ Co	ntinue to th	ne next page.

Table 13.	Full	coefficients	table	of LA	SSO	(Red	player,	cont.)	)
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Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-4	(K,N),(N,N),					
· ·		(N,K),(N,N)					
history of K-profiles	t-1 to t-4	(K,N),(N,N),					
		(N,N),(K,K)					
history of K-profiles	t-1 to t-4	(K,N),(N,N),		0.046			
		(N,N),(K,N)					
history of K-profiles	t-1 to t-4	(K,N),(N,N),					
		(N,N),(N,K)					
history of K-profiles	t-1 to t-4	(K,N),(N,N),					
		(N,N),(N,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(K,K),(K,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(K,K),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(K,N),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
history of IZ such films	. 1	(K,N),(N,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
history of K profiles	+1 to $+1$	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
instory of K-promes	t-1 to t-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
history of K profiles	t 1 to t 4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
instory of R-promes	1-1 00 0-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N})$					
history of K-profiles	t-1 to t-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
mistory of Repromes	1-1-00-1-1	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$					
history of K-profiles	t-1 to t-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
motory of it promos		(N,K).(N,N)					
history of K-profiles	t-1 to t-4	(N.K).(K.K).					
F		(N.N).(K.K)					
history of K-profiles	t-1 to t-4	(N,K).(K,K).					
U 1 1	, -	(N,N),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
ř –		(N,N),(N,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,K),					
		(N,N),(N,N)					
					≫ Con	tinue to tl	ne next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,K),(K,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,K),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,N),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,N),(N,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(K,N),(N,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
		(N,K),(K,K)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
	. 1	(N,K),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(K,N),					
history of K profiles	+ 1 + + <i>1</i>	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N})$					
history of K-promes	t-1 to t-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
history of K profiles	t 1 to t 4	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
instory of R-promes	1-1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$					
history of K-profiles	t-1 to t-4	(N, K), (K, N)					
instory of it promos		(N,N).(K,N)					
history of K-profiles	t-1 to t-4	(N.K).(K.N).					
		(N,N),(N,K)					
history of K-profiles	t-1 to t-4	(N.K),(K.N),					
<i>v</i> 1		(N,N),(N,N)					
history of K-profiles	t-1 to t-4	(N,K),(N,K),					
· -		(K,K),(K,K)					
history of K-profiles	t-1 to t-4	(N,K),(N,K),					
		(K,K),(K,N)					
history of K-profiles	t-1 to t-4	(N,K),(N,K),					
		(K,K),(N,K)					
history of K-profiles	t-1 to t-4	(N,K),(N,K),					
		(K,K),(N,N)					
history of K-profiles	t-1 to t-4	(N,K),(N,K),					
		(K,N),(K,K)					
					$\gg Co$	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(K,N),(K,N)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(K,N),(N,K)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(K,N),(N,N)	
history of K-profiles t-1 to t-4 (N,K),(N,K),	
(N,K),(K,K)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,K),(K,N)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,K),(N,K)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,K),(N,N)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,N),(K,K)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,N),(K,N)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,N),(N,K)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,K),$	
(N,N),(N,N)	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,N),$	
$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,N),$	
$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N})$	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,N),$	
$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$	
$ \begin{array}{c} \text{Instory of K-profiles} \\ \text{U-1 to t-4} \\ \text{(IV,K),(IV,N),} \\ \text{(IV,K),(IV,N),} \end{array} $	
$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	
history of K-profiles $t-1$ to $t-4$ $(N,K),(N,N),$	
$(\mathbf{K},\mathbf{N}), (\mathbf{K},\mathbf{K})$	
$ \begin{array}{c} \text{Instory of K-profiles} \\ \text{UN} \\ (U \\ N \\ (U \\ (U$	
$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$	
(V, N) (N, K), (V, N) (N, K), (V, N) (N, K), (V, N) (N, K), (V, N) (N, K)	
$(\mathbf{N}, \mathbf{N}), (\mathbf{N}, \mathbf{N})$	
$(\mathbf{V} \mathbf{N}) (\mathbf{N} \mathbf{N})$	
$(\mathbf{I}_{\mathbf{Y}}, \mathbf{V}), (\mathbf{I}_{\mathbf{Y}}, \mathbf{V})$	
$(\mathbf{N} \mathbf{K}) (\mathbf{K} \mathbf{K})$	
history of K-profiles $t_1$ to $t_4$ (N K) (N N)	
$(\mathbf{N} \mathbf{K}) / (\mathbf{K} \mathbf{N})$	
$\sum_{(11,12),(12,11)}$ $\otimes$ Continue to the next part	re

Table 13. Full coefficients table of LASSO (Red player, cont.)
history of K-profiles         t-1 to t-4 $(N,K), (N,N), (N,K), ($	Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
history of K-profiles t-1 to t-4 (N,K), (N,N), (N,K), (N,K) history of K-profiles t-1 to t-4 (N,K), (N,N), (N,K), (N,N), history of K-profiles t-1 to t-4 (N,K), (N,N), history of K-profiles t-1 to t-4 (N,N), (K,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,K), (N,N) history of K-profiles t-1 to t-4 (N,N), (K,K), (N,K), (K,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,N), (K,K), history									
$(N,K), (N,K) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), \\ (N,K), (N,N), \\ (N,K), (N,N), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), \\ (N,N), (K,N), \\ (N,N), (N,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,K), (N,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K), \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (K,N), (N,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,K), (N,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,K), (N,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,K), (N,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,K), (N,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), \\ (N,$	history of K-profiles		t-1 to t-4	(N,K),(N,N),					
history of K-profiles         t-1 to t-4 $(N,K), (N,N)$ history of K-profiles         t-1 to t-4 $(N,N), (K,K)$ history of K-pro				(N,K),(N,K)					
$(N,K), (N,N) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (K,N) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (N,N), (N,N) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (K,K), (K,K$	history of K-profiles		t-1 to t-4	(N,K),(N,N),					
history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, K), (N, N)$ ,         history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (N, N)$ history of K-profiles       t-1 to t-4 $(N, N), (N, N)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K, K)$ history of K-profiles       t-1 to t-4 $(N, N), (K,$				(N,K),(N,N)					
$(N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (K,N) \\ (N,N), (K,N) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,$	history of K-profiles		t-1 to t-4	(N,K),(N,N),					
history of K-profiles       t1 to t-4       (N,K), (N,N),         history of K-profiles       t-1 to t-4       (N,K), (N,N),         history of K-profiles       t-1 to t-4       (N,N), (N,N),         history of K-profiles       t-1 to t-4       (N,N), (N,N),         history of K-profiles       t-1 to t-4       (N,N), (K,K),         history of K-prof				(N,N),(K,K)					
$(N,N), (K,N) \\ history of K-profiles t-1 to t-4 (N,K), (N,N), (N,K) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (N,N), (N,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), (K,$	history of K-profiles		t-1 to t-4	(N,K),(N,N),					
history of K-profiles       t-1 to t-4       (N,K), (N,N), (N,K)       0.176         history of K-profiles       t-1 to t-4       (N,K), (N,N), (N,N)       0.176         history of K-profiles       t-1 to t-4       (N,N), (K,K), (K,K)       0.176         history of K-profiles       t-1 to t-4       (N,N), (K,K), (K,K)       0.176         history of K-profiles       t-1 to t-4       (N,N), (K,K), (K,K)       0.176         history of K-profiles       t-1 to t-4       (N,N), (K,K), (K,K)       0.176         history of K-profiles       t-1 to t-4       (N,N), (K,K), (K,				(N,N),(K,N)					
(N,N), (N,K) (K,K),	history of K-profiles		t-1 to $t-4$	(N,K),(N,N),					
history of K-profiles       t-1 to t-4 $(N, N), (N, N)$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.176         history of K-profiles       t-1 to t-4 $(N, N), (K, K),$ 0.16, (N, N), (				(N,N),(N,K)					
$(N,N), (K,N) \\ history of K-profiles t-1 to t-4 (N,N), (K,K), ($	history of K-profiles		t-1 to $t-4$	(N,K),(N,N),					0.176
history of K-profiles       t-1 to t-4 $(N,N), (K,K),$				(N,N),(N,N)					
(K, K), (K, K) history of K-profiles t-1 to t-4 (N, N), (K, K), (K, K), (K, N) history of K-profiles t-1 to t-4 (N, N), (K, K), (K, K), (N, N) history of K-profiles t-1 to t-4 (N, N), (K, K), history of K-profiles t-1 to t-4 (N, N	history of K-profiles		t-1 to $t-4$	(N,N),(K,K),					
history of K-profiles       t-1 to t-4 $(N,N), (K,K), (K,N)$ history of K-profiles       t-1 to t-4 $(N,N), (K,K), (K,K), (K,K), (K,K), (K,K), (K,K), (K,N), (K,K), (K,K$				(K,K),(K,K)					
(K,K),(K,N) history of K-profiles t-1 to t-4 (N,N),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (K,K),(N,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(K,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(N,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(N,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(N,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,N),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(N,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,N),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profiles       t-1 to t-4 $(N,N), (K,K), (K,N), (K,K), (K,K$				(K,K),(K,N)					
(K,K),(N,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,K),(N,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(N,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(N,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,N),(N,N) history of K-profiles t-1 to t-4 (N,N),(K,K), (K,K),(K,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(N,K) history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (N,K),(K,K), history of K-profiles t-1 to t-4 (N,N),(K,K), (N,N),(K,K), history of K-profiles t-1 to t-4 (N,N)	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profiles t-1 to t-4 (N,N), (K,K), (K,K), (N,N) history of K-profiles t-1 to t-4 (N,N), (K,K), (K,N), (K,K) history of K-profiles t-1 to t-4 (N,N), (K,K), (K,N), (K,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (K,N), (N,K) history of K-profiles t-1 to t-4 (N,N), (K,K), (N,K), (K,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,K), (N,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,K), (N,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,K), (N,N), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,N), (K,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,N), (K,K), (N,N), (K,K), history of K-profiles t-1 to t-4 (N,N), (K,K), (N,N), (K,K				(K,K),(N,K)					
$(K,K),(N,N) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (K,N),(K,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (K,N),(K,N) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (K,N),(N,N) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (K,N),(N,N) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(K,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(K,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(K,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(K,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(N,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(N,K) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,K),(N,N) \\ history of K-profiles t-1 to t-4 (N,N),(K,K), \\ (N,N),(K,K) \\ (N,N),(K,K$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(K,N),(K,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(K,N),(K,K),$ $(K,N),(K,K),$ $(K,N),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(K,N),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(K,N),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K),$ $(N,K),(K,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K),$ $(N,K),(K,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K),$ $(N,K),(N,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$				(K,K),(N,N)					
$(K,N),(K,K)$ history of K-profiles $t-1 \text{ to } t-4  (N,N),(K,K), \\(K,N),(K,K), \\(K,N),(K,K), \\(K,N),(N,K)$ history of K-profiles $t-1 \text{ to } t-4  (N,N),(K,K), \\(K,N),(N,N)$ history of K-profiles $t-1 \text{ to } t-4  (N,N),(K,K), \\(N,K),(K,K) \\(N,K),(K,K) \\(N,K),(K,K) \\(N,K),(K,K) \\(N,K),(K,K) \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(N,K) \\(N,K),(N,K) \\(N,K),(N,K) \\(N,K),(N,K) \\(N,K),(N,K) \\(N,K),(N,K) \\(N,K),(N,K) \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K), \\(N,K),(K,K) \\(N,K),(K,K), \\(N,K),(K,K) \\(K,K), \\(K,K),(K,K) \\(K,K), \\(K,K),(K,K) \\(K,K), \\(K,K),(K,K) \\(K,K),(K,$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (K,N),(K,N) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (K,N),(N,N) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (N,K),(K,K) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (N,K),(K,N) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (N,K),(N,K) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (N,K),(N,K) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (N,K),(N,K) history of K-profiles t-1 to t-4 $(N,N),(K,K),$ (N,N),(K,K), history of K-profiles t-1 to t-4 $(N,N),(K,K),$ history of K-profiles t-1 to t-4 $(N,N),(K,K),$ history of K-profiles t-1 to t-4 $(N,K),(K),(K),(K),(K),(K),(K),(K),(K),(K),$				(K,N),(K,K)					
(K,N),(K,N) history of K-profiles $t-1  to  t-4$ $(N,N),(K,K),$ $(K,N),(N,K)$ history of K-profiles $t-1  to  t-4$ $(N,N),(K,K),$ $(K,N),(N,N)$ history of K-profiles $t-1  to  t-4$ $(N,N),(K,K),$ $(N,K),(K,K),$ $(N,K),(K,K),$ $(N,K),(N,K)$ history of K-profiles $t-1  to  t-4$ $(N,N),(K,K),$ $($	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(K,N),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(K,N),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K),$ $(N,K),(K,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K),$				(K,N),(K,N)					
$(K,N),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(K,N),(N,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,K),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,K),(K,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,K),(N,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,K),(N,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,N),(K,K), \\(N,N),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,N),(K,K), \\(N,N),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,N),(K,K), \\(K,N),(K,K), \\(K,N),(K,K),(K,K),(K,K), \\(K,N),(K,K), \\(K,N$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profilest-1 to t-4 $(N,N),(R,K),$ $(K,N),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profileshistory of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K)$				(K,N),(N,K)					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,K)$ $(N,K),(K,K)$ $(N,K),(K,K)$ $(N,K),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4history of K-profilest-1 to t-4 $(N,N),(K,K),$ <br< td=""><td></td><td></td><td></td><td>(K,N),(N,N)</td><td></td><td></td><td></td><td></td><td></td></br<>				(K,N),(N,N)					
$(N,K),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,K),(K,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,K),(N,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,N),(K,K), \\(N,N),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,N),(K,K), \\(N,N),(K,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K), \\(N,N),(K,K), \\(K,K), \\(K,K$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K)$				(N,K),(K,K)					
$(N,K),(K,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,K),(N,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,N),(K,K),$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,N),(K,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,N),(K,K),$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ history of K-profileshistory of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K)$				(N,K),(K,N)					
$(N,K),(N,K)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,K),(N,N)$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,N),(K,K),$ history of K-profiles $t-1 \text{ to } t-4 \qquad (N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
Instory of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,K),(N,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K)$			. 1	(N,K),(N,K)					
history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K)$	history of K-profiles		t-1 to t-4	(N,N),(K,K),					
Instory of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,N)$ history of K-profilest-1 to t-4 $(N,N),(K,K),$ $(N,N),(K,K),$ $(N,N),(N,K)$			. 1	(N,K),(N,N)					
history of K-profiles t-1 to t-4 $(N,N),(K,K)$ , history of K-profiles t-1 to t-4 $(N,N),(K,K)$ , (N,N),(K,N) (N,N),(K,K), (N,N),(N,K)	mstory of K-profiles		ι-1 το t-4	(IN,IN),(K,K), (N,N),(IZ,IZ)					
$ \begin{array}{c} \text{Instory of K-profiles} \\ \text{history of K-profiles} \\ \hline \\ \\ \\ \hline \\ \hline \\ \hline \\ \\ \hline \\ \\ \hline \\ \hline \\ \hline \\ \\ \hline \\ \hline \\ \\ \hline \\ $	histom of K reafles		+ 1 + - + 4	(IN,IN),(K,K) (N,N),(Z,Z)					
history of K-profiles t-1 to t-4 $(N,N),(K,N)$ (N,N),(K,K), (N,N),(N,K)	mstory of K-profiles		ι-1 ιΟ τ-4	(1N,1N),(K,K), (N,N),(IZ,N)					
(N,N),(N,K) $(N,N),(N,K)$ $(N,N),(N,K)$	histom of K reafles		+ 1 + - + 4	(1N,1N), (K,1N) (N,N), (Z,Z)					
$\sum_{(1N,1N),(1N,N)}$	instory of K-profiles		ι-1 ιΟ τ-4	(1N,1N),(K,K), (N,N),(N,K)					
SS I ADDIDUG TO THE NAME				(11,11),(11,11)			» Ca	ntinuc to t	he next nere

Table 13	. Full	coefficients	table	of ]	LASSO	(Red	player,	cont.)	)
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Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1	l to t-4	(N,N),(K,K),					
			(N,N),(N,N)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,K),(K,K)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,K),(K,N)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,K),(N,K)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,K),(N,N)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,N),(K,K)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,N),(K,N)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,N),(N,K)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(K,N),(N,N)					
history of K-profiles	t-1	l to t-4	(N,N),(K,N),					
			(N,K),(K,K)					
history of K-profiles	t-J	l to t-4	(N,N),(K,N),					
			(N,K),(K,N)					
history of K-profiles	t-J	l to t-4	(N,N),(K,N),					
			(N,K),(N,K)					0.007
history of K-profiles	t-1	l to t-4	(N,N),(K,N), (N,K),(N,N)					-0.007
history of V profiles	. 1	1 + ~ + 1	$(N, \mathbf{K}), (N, N)$					
history of K-promes	U-1	1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K profiles	+ 1	tot 1	(N,N),(K,K)					
instory of K-promes	U-1	1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K profiles	+ 1	tot 1	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K-promes	U-1	1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$					
history of K profiles	+ 1	tot 1	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
instory of R-promes	-1	1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$					
history of K profiles	+ 1	tot 1	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$					
instory of R-promes		1 10 1-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K}),$					
history of K profiles	+ 1	tot 1	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$					
motory of it-promes	-1	1 10 1-4	(K K) (K N)					
history of K-profiles	+ 1	to t-4	$(\mathbf{N} \mathbf{N}) (\mathbf{N} \mathbf{K})$					
motory of it-promes	-1	100-4	(K K) (N K)					
history of K-profiles	+ 1	to t-4	$(\mathbf{N} \mathbf{N}) (\mathbf{N} \mathbf{K})$					
moory of it-promes	-1	100-4	(K K) (N N)					
			(**,**),(**,**)			>> Cor	ntinue to the	e next page

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(K,N),(K,K)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(K,N),(K,N)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(K,N),(N,K)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),		0.000	0.000	0.000	0.000
		(K,N),(N,N)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,K),(K,K)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,K),(K,N)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,K),(N,K)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,K),(N,N)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,N),(K,K)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
1		(N,N),(K,N)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,N),(N,K)					
history of K-profiles	t-1 to t-4	(N,N),(N,K),					
		(N,N),(N,N)					
history of K-profiles	t-1 to t-4	(N,N),(N,N),					
history of Kanadha	. 1	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
history of K-promes	t-1 to t-4	(IN,IN),(IN,IN), (V,V),(V,N)					
history of V speciles	4 1 4 0 4 1	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N})$					0.097
history of K-promes	t-1 to t-4	(IN,IN),(IN,IN), (V,V),(N,V)					-0.027
history of V speciles	4 1 4 0 4 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$					0.060
history of K-promes	t-1 to t-4	(IN,IN),(IN,IN), (K,K),(N,N)					0.000
history of K profiles	+ 1 + 0 + 4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
instory of K-promes	t-1 to t-4	$(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$					
history of K profiles	$t 1 t_0 t 4$	$(\mathbf{R},\mathbf{N}),(\mathbf{R},\mathbf{R})$					
instory of R-promes	1-1 10 1-4	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$					
history of K profiles	t 1 to t 4	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$					
moory of it-promes	1-1 10 1-4	$(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N}),$ (K N) (N K)					
history of K-profiles	$t_{-1}$ to t 4	$(\mathbf{N} \mathbf{N})$ $(\mathbf{N} \mathbf{N})$					
moory of it-promes	0-1 00 0-4	(1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,					
history of K-profiles	$t_{-1}$ to t 4	$(\mathbf{N} \mathbf{N})$ (N N)					
motory of it promes	0-1 00 0 <del>-1</del>	(N,K) (K K)					
		(			≫ Cont	inue to the	e next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\rm R,2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of K profiles		+ 1 + 2 + 1	(NINI) (NINI)					
mistory of K-promes		t-1 to t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N})$					
history of K-profiles		t-1 to t-1	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N})$					
instory of R-promes		1-1 10 1-4	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K}),$					
history of K-profiles		t-1 to t-4	(N, N), (N, N)					0.076
motory of it promes		010004	(N, K), (N, N), (N, N)					0.010
history of K-profiles		t-1 to t-4	(N,N),(N,N),(N,N),					0.018
motory of 11 promot		010001	(N,N).(K,K)					0.010
history of K-profiles		t-1 to t-4	(N,N).(N,N).					
F			(N,N).(K,N)					
history of K-profiles		t-1 to t-4	(N,N).(N,N).					-0.025
F			(N,N).(N,K)					0.020
history of K-profiles		t-1 to t-4	(N,N).(N,N).					
F			(N,N).(N,N)					
history of my actions	R	t-1.t-2	1.1		0.097			
history of my actions	R	t-1.t-2	1.2		-0.046		0.015	
history of my actions	R	t-1.t-2	1.3					0.024
history of my actions	R	t-1.t-2	1.K			0.049		-0.002
history of my actions	R	t-1,t-2	2,1					
history of my actions	R	t-1,t-2	2,2			0.159		
history of my actions	R	t-1,t-2	2,3					
history of my actions	R	t-1,t-2	2,K					
history of my actions	R	t-1,t-2	3,1			0.005	-0.010	
history of my actions	R	t-1,t-2	3,2		0.000	0.000	0.000	0.009
history of my actions	R	t-1,t-2	3,3				0.133	
history of my actions	R	t-1,t-2	3,K					
history of my actions	R	t-1,t-2	K,1					
history of my actions	R	t-1,t-2	K,2					
history of my actions	R	t-1,t-2	K,3					-0.003
history of my actions	R	t-1,t-2	K,K					0.109
history of opponent actions	В	t-1,t-2	1,1			0.033		
history of opponent actions	В	t-1,t-2	1,2		0.010			
history of opponent actions	В	t-1,t-2	1,3					0.001
history of opponent actions	В	t-1,t-2	$1,\mathrm{K}$		0.000	0.000	0.000	0.000
history of opponent actions	В	t-1,t-2	$^{2,1}$					
history of opponent actions	В	t-1,t-2	$^{2,2}$					0.000
history of opponent actions	В	t-1,t-2	2,3					
history of opponent actions	В	t-1,t-2	$_{2,\mathrm{K}}$			-0.024		
history of opponent actions	В	t-1,t-2	3,1			-0.019		0.041
						$\gg Cont$	inue to the	next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
history of opponent actions	В	t-1,t-2	$^{3,2}$					
history of opponent actions	В	t-1,t-2	$3,\!3$					
history of opponent actions	В	t-1,t-2	$_{3,\mathrm{K}}$			0.007		
history of opponent actions	В	t-1,t-2	K,1					
history of opponent actions	В	t-1,t-2	K,2					
history of opponent actions	В	t-1,t-2	K,3					
history of opponent actions	В	t-1,t-2	K,K					
history of my actions	R	t-1,t-2	K,N					-0.044
history of my actions	R	t-1,t-2	N,K					-0.044
history of my actions	R	t-1,t-2	N,N		0.000	0.000	0.000	0.007
history of opponent actions	В	t-1,t-2	K,N					-0.099
history of opponent actions	В	t-1,t-2	N,K		0.000	0.000	0.000	0.000
history of opponent actions	В	t-1,t-2	N,N					
I did not play a card in the last periods	R	t-1,t-2	1		0.275	0.000	0.000	0.000
the opponent did not play a card in the last periods	В	t-1,t-2	1					
I did not play a card in the last	R	t-1,t-2	2			0.311		-0.006
the opponent did not play a	В	t-1,t-2	2		0.000	0.000	0.000	0.000
card in the last periods I did not play a card in the last	R	t-1,t-2	3				0.230	
periods the opponent did not play a	В	t-1,t-2	3		0.000	0.000	0.059	0.000
card in the last periods								
I played a card consecutively in the last three periods	R	t-1 to t-3	1		0.618			
the opponent played a card consecutively in the last three periods	В	t-1 to t-3	1					
I played a card consecutively in the last three periods	R	t-1 to t-3	2			0.003		
the opponent played a card consecutively in the last three periods	В	t-1 to t-3	2					
I played a card consecutively in the last three periods	R	t-1 to t-3	3				0.160	
the opponent played a card consecutively in the last three periods	В	t-1 to t-3	3					
						≫ Conti	nue to the	next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
I played a card consecutively	R	t-1 to t-3	К					0.231
in the last three periods	10	0 1 00 0 0						0.201
the opponent played a card	В	t-1 to t-3	Κ				-0.022	0.168
consecutively in the last three								
periods	Ð		1		0.071	0.004	0.004	0.005
I did not play a card in the last	R	t-1 to t-3	1		0.071	-0.034	-0.004	0.005
the opponent did not play a	в	t-1 to t-3	1		0.081		-0.014	
card in the last periods	D	0 0 0-0	1		0.001		0.014	
I did not play a card in the last	R	t-1 to t-3	2			0.089		
periods								
the opponent did not play a	В	t-1 to t-3	2		-0.021	0.018	-0.022	0.022
card in the last periods								
I did not play a card in the last	R	t-1 to t-3	3		-0.020		0.119	
periods	_		_					
the opponent did not play a	В	t-1 to t-3	3			-0.026	0.008	
card in the last periods	р	+ 1 + 2 + 9	V		0 022			0.119
n did not play a card in the last	ĸ	t-1 to t-5	ĸ		-0.055			0.115
the opponent did not play a	В	t-1 to t-3	К					
card in the last periods	2	010000						
I played K or N in t-1,,t-n	R	t-1 to t-4	К					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t- $5$	Κ					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-6	Κ					
consecutively	D	. 1	τ.					
I played K or N in t-1,,t-n	К	t-1 to t-7	ĸ					
L played K or N in t-1 t-n	в	t-1 to t-8	K					
consecutively	10	1-1 10 1-0	11					
I played K or N in t-1,,t-n	R	t-1 to t-9	К					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-10	Κ					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-11	Κ					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-12	K					
consecutively	р	+ 1 + - + 1	N					0.059
consecutively	11	υ-1 UU U-4	τN					0.000
I played K or N in t-1t-n	R	t-1 to t-5	Ν			0.025		
consecutively	-	··· · ·						

## Table 13. Full coefficients table of LASSO (Red player, cont.)

 $\gg$  Continue to the next page.

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
I played K or N in t-1,,t-n	R	t-1 to t-6	Ν					-0.021
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-7	Ν				0.000	-0.096
consecutively								
I played K or N in t-1,,t-n consecutively	R	t-1 to t-8	Ν				0.087	-0.118
I played K or N in t-1,,t-n consecutively	R	t-1 to t-9	Ν					
I played K or N in t-1,,t-n	R	t-1 to t-10	Ν					-0.115
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-11	Ν					-0.231
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-12	Ν		0.049			
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-13	Ν					-0.117
consecutively	-							
I played K or N in t-1,,t-n	R	t-1 to t-14	Ν					
consecutively	D	+ 1 + 0 + 15	N					
consecutively	п	1-1 10 1-15	1					
I played K or N in t-1t-n	R.	t-1 to t-16	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-17	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-18	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-19	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-20	Ν					
consecutively	D	. 1 01	NT					
I played K or N in t-1,,t-n	R	t-1 to t-21	IN					
L played K or N in t 1 t p	в	t 1 to t 22	N					
consecutively	10	0-1 00 0-22	1					
I played K or N in t-1t-n	R	t-1 to t-23	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-24	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-25	Ν					
consecutively								
I played K or N in t-1,,t-n	R	t-1 to t-26	Ν					
consecutively								

Table 13. Full coefficients table of LASSO (Red player, cont.)

 $\gg$  Continue to the next page.

Variable type	Player	Period		Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
I played K or N in t-1,,t-n	R	t-1 to t-27	Ν						
consecutively									
I played K or N in t-1,,t-n	R	t-1 to t-28	Ν						
consecutively									
I played K or N in t-1,,t-n consecutively	R	t-1 to t-29	Ν						
the opponent played K or N in $t_{-1}$ to consecutively	В		Κ						
the opponent played K or N in	в		K						
t-1t-n consecutively	Ъ								
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively									
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively									
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively									
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively									
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively	_								
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively	Ð								
the opponent played K or N in	В		K						
t-1,,t-n consecutively	ъ		TZ						
the opponent played K or N in	В		ĸ						
the opponent played K or N in	В		ĸ						
t-1 t-n consecutively	Б		п						
the opponent played K or N in	в		K						
t-1t-n consecutively	Ъ								
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively									
the opponent played K or N in	В		Κ						
t-1,,t-n consecutively									
the opponent played K or N in	В		Ν						0.034
t-1,,t-n consecutively									
the opponent played K or N in	В		Ν			0.015	-0.062	0.002	-0.005
t-1,,t-n consecutively									
the opponent played K or N in	В		Ν						-0.066
t-1,,t-n consecutively									
the opponent played K or N in	В		Ν						
t-1,,t-n consecutively									

Table 13. Full coefficients table of LASSO (Red player, cont.)

 $\gg$  Continue to the next page.

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
the opponent played K or N in	В	Ν						-0.260
t-1t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν			0.012			
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						-0.054
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively								
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively	D	N						
the opponent played K or N in	В	IN						
t-1,,t-n consecutively	р	N						
the opponent played K or N in	В	IN						
the appropriate placed K on N in	D	N						
the opponent played K of N in	D	IN						
the opponent played K or N in	В	N						
the opponent played K of N in	Б	11						
the opponent played K or N in	в	N						
t-1 t-n consecutively	D	11						
the opponent played K or N in	В	N						
t-1t-n consecutively	D	1						
the opponent played K or N in	В	Ν						
t-1,,t-n consecutively	-	11						

## Table 13. Full coefficients table of LASSO (Red player, cont.)

 $\gg$  Continue to the next page.

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
the opponent played K or N in	В		Ν					
t-1,,t-n consecutively								
I won or lost		t-1		В				
I won or lost		t-1		R	0.000	0.000	0.000	0.000
I won or lost		t-2		В	0.000	0.000	0.000	0.000
I won or lost		t-2		R				
I won or lost		t-3		В	0.000	0.000	0.000	0.000
I won or lost		t-3		R	0.000			
I won or lost		t-4		В	0.000	0.000	0.000	0.000
I won or lost		t-4		R				
history of winners		t-1,t-2		$^{\mathrm{B,B}}$				
history of winners		t-1,t-2		$^{\mathrm{B,R}}$				
history of winners		t-1,t-2		$_{\rm R,B}$	0.000	0.000	0.000	0.000
history of winners		t-1,t-2		$^{\rm R,R}$				
history of winners		t-1 to t- $3$		$_{\rm B,B,B}$	-0.004			0.020
history of winners		t-1 to t- $3$		$_{\rm B,B,R}$		-0.001		
history of winners		t-1 to t- $3$		$_{\rm B,R,B}$				-0.011
history of winners		t-1 to t- $3$		$_{\rm B,R,R}$				
history of winners		t-1 to t- $3$		$_{ m R,B,B}$	0.000	0.000	0.000	0.000
history of winners		t-1 to t- $3$		$_{ m R,B,R}$			-0.082	
history of winners		t-1 to t- $3$		$_{\rm R,R,B}$				
history of winners		t-1 to t- $3$		$_{\rm R,R,R}$				0.046
history of winners		t-1 to t-4		$_{\mathrm{B,B,B,B}}$			-0.008	
history of winners		t-1 to t-4		$_{\mathrm{B,B,B,R}}$	-0.001			
history of winners		t-1 to t-4		$_{\mathrm{B,B,R,B}}$		-0.029		
history of winners		t-1 to t-4		$_{\mathrm{B,B,R,R}}$				
history of winners		t-1 to t-4		$_{\mathrm{B,R,B,B}}$			0.001	
history of winners		t-1 to t-4		$_{\mathrm{B,R,B,R}}$		0.000		
history of winners		t-1 to t-4		$_{\rm B,R,R,B}$				
history of winners		t-1 to t-4		$_{\mathrm{B,R,R,R}}$				
history of winners		t-1 to t-4		R,B,B,B	0.000	0.000	0.000	0.000
history of winners		t-1 to t-4		$_{ m R,B,B,R}$				
history of winners		t-1 to t-4		R,B,R,B				
history of winners		t-1 to t-4		R,B,R,R	0.003		-0.010	
history of winners		t-1 to t-4		R,R,B,B	-0.020	0.019		
history of winners		t-1 to t-4		R,R,B,R	0.035			
history of winners		t-1 to t-4		R,R,R,B				
history of winners		t-1 to t-4		R,R,R,R	-0.006			0.036
						>> Cont	inue to the	next nage

## Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
my action and winner	R	t-1	1	В				
my action and winner	R	t-1	1	R				
my action and winner	R	t-1	2	В				
my action and winner	R	t-1	2	R		-0.028	0.058	
my action and winner	R	t-1	3	В				
my action and winner	R	t-1	3	R	0.000	0.000	-0.005	0.076
my action and winner	R	t-2	1	В				-0.019
my action and winner	R	t-2	1	R				
my action and winner	R	t-2	2	В	0.000	0.000	0.000	0.013
my action and winner	R	t-2	2	R		0.001		
my action and winner	R	t-2	3	В				
my action and winner	R	t-2	3	R				
my action and winner	R	t-3	1	В				
my action and winner	R	t-3	1	R	0.041			
my action and winner	R	t-3	2	В				
my action and winner	R	t-3	2	R				
my action and winner	R	t-3	3	В				
my action and winner	R	t-3	3	R				
my action and winner	R	t-4	1	В	-0.013			
my action and winner	R	t-4	1	R			-0.009	
my action and winner	R	t-4	2	В	0.000	0.000	0.000	0.000
my action and winner	R	t-4	2	R				-0.024
my action and winner	R	t-4	3	В				
my action and winner	R	t-4	3	R	-0.026		0.012	
hisotry of my actions and win-	R	t-1,t-2	1,1	$_{\rm B,B}$	0.139			
ners								
hisotry of my actions and win-	R	t-1,t-2	1,1	$_{\rm B,R}$				
ners								
hisotry of my actions and win-	R	t-1,t-2	1,1	$_{\rm R,B}$				
ners								
hisotry of my actions and win-	R	t-1,t-2	1,1	R,R				
ners								
hisotry of my actions and win-	R	t-1,t-2	1,2	$_{\rm B,B}$		-0.019	0.060	
ners								
hisotry of my actions and win-	R	t-1,t-2	$^{1,2}$	$^{\mathrm{B,R}}$				
ners				-				
hisotry of my actions and win-	R	t-1,t-2	1,2	$_{\mathrm{R,B}}$				
ners			·	-				
						>> Cont	inue to the	next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R,2}}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of my actions and win-	R	t-1.t-2	1.2	R.R.				
ners		,	_;_					
hisotry of my actions and win- ners	R	t-1,t-2	1,3	B,B				
hisotry of my actions and win-	R	t-1,t-2	1,3	B,R				
hisotry of my actions and win-	R	t-1,t-2	1,3	R,B				
ners	D	. 1 . 0	1.0	DD				
nisotry of my actions and win- ners	ĸ	t-1,t-2	1,3	к,к				
hisotry of my actions and win- ners	R	t-1,t-2	1,K	B,B				
hisotry of my actions and win-	R	t-1,t-2	1,K	B,R				
hisotry of my actions and win-	R	t-1,t-2	1,K	R,B				
ners hisotry of my actions and win-	R	t-1,t-2	1,K	R,R				
ners	_							
hisotry of my actions and win- ners	R	t-1,t-2	2,1	B,B				
hisotry of my actions and win- ners	R	t-1,t-2	2,1	B,R				
hisotry of my actions and win-	R	t-1,t-2	2,1	R,B	0.017			
hisotry of my actions and win-	R	t-1,t-2	$^{2,1}$	R,R				
ners hisotry of my actions and win-	R	t-1,t-2	2,2	B,B			-0.022	
ners								
hisotry of my actions and win- ners	R	t-1,t-2	2,2	B,R				
hisotry of my actions and win- ners	R	t-1,t-2	2,2	R,B				
hisotry of my actions and win-	R	t-1,t-2	2,2	R,R				
hisotry of my actions and win-	R	t-1,t-2	2,3	B,B				
ners	_							
hisotry of my actions and win- ners	R	t-1,t-2	2,3	B,R				
hisotry of my actions and win- ners	R	t-1,t-2	2,3	R,B				
hisotry of my actions and win-	R	t-1,t-2	2,3	R,R				
11012						>> Cont	inue to the n	ext page.

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hightry of my actions and win	D	+ 1 + 9	9 K	ВВ				
ners	10	0-1,0-2	2,11	Б,Б				
hisotry of my actions and win-	R	t-1,t-2	$^{2,\mathrm{K}}$	$^{\mathrm{B,R}}$				
ners	Ð	. 1 . 0	0 <i>V</i>	D D				
hisotry of my actions and win- ners	R	t-1,t-2	2,K	R,B				
hisotry of my actions and win-	R	t-1,t-2	2,K	R,R				
hisotry of my actions and win-	R	t-1,t-2	3,1	B,B				
hisotry of my actions and win-	R	t-1,t-2	$^{3,1}$	B,R				
hisotry of my actions and win-	R	t-1,t-2	$^{3,1}$	R,B				
hisotry of my actions and win-	R	t-1,t-2	$^{3,1}$	R,R				
hisotry of my actions and win-	R	t-1,t-2	3,2	В,В				
ners hisotry of my actions and win-	R	t-1,t-2	3,2	B,R				
ners hisotry of my actions and win-	R	t-1,t-2	3,2	R,B	0.000	0.000	0.000	0.000
ners hisotry of my actions and win-	R	t-1,t-2	3,2	R,R				
ners hisotry of my actions and win-	R	t-1,t-2	3,3	B,B			0.017	
ners hisotry of my actions and win-	R	t-1,t-2	3,3	B,R				
ners hisotry of my actions and win-	R	t-1,t-2	3,3	R,B				
ners hisotry of my actions and win-	R	t-1,t-2	3,3	R,R				
ners hisotry of my actions and win-	R	t-1,t-2	3,K	B,B				
ners hisotry of my actions and win-	R	t-1,t-2	3,K	B,R				
hisotry of my actions and win-	R	t-1,t-2	3,K	R,B				
hisotry of my actions and win-	R	t-1,t-2	3,K	R,R				
ners hisotry of my actions and win-	R	t-1,t-2	K,1	B,B			0.072	
ners							1	

Lable 13. Full coefficients table of LASSO (Red player, cor	able	. Full coefficient	s table of	LASSO	(Red p	player,	cont.	)
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 $\gg$  Continue to the next page.

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of my actions and win-	R	t-1,t-2	K,1	$^{\mathrm{B,R}}$				
ners hisotry of my actions and win-	В	t-1 t-2	K 1	ΒB				
ners	10	• 1,• 1	,-	10,22				
hisotry of my actions and win-	R	t-1,t-2	K,1	$^{ m R,R}$				
ners								
hisotry of my actions and win-	R	t-1,t-2	K,2	B,B				
ners	р	4149	ИO	DD				
ners	ĸ	t-1,t-2	K,2	D,R				
hisotry of my actions and win-	R	t-1.t-2	K.2	R.B				
ners		,	;-					
hisotry of my actions and win-	R	t-1,t-2	K,2	R,R				
ners								
hisotry of my actions and win-	R	t-1,t-2	K,3	B,B		0.022		
ners								
hisotry of my actions and win-	R	t-1,t-2	K,3	$_{\mathrm{B,R}}$				
ners	р	4149	V 9	DD				
ners	ĸ	t-1,t-2	к,з	п,р				
hisotry of my actions and win-	R	t-1.t-2	K.3	R.R.				
ners		,	;-					
my action and winner	R	t-1	Ν	В				
my action and winner	R	t-1	Ν	R	0.000	0.000	0.000	0.000
my action and winner	R	t-1	Ν	В	0.000	0.000	0.000	0.000
my action and winner	R	t-1	Ν	R				
my action and winner	R	t-1	Ν	В				
my action and winner	R	t-1	Ν	R	0.017			
my action and winner	R	t-1	Ν	В	0.000	0.000	0.001	0.000
my action and winner	R	t-1	Ν	R				
hisotry of my actions and win- ners	R	t-1,t-2	K,N	B,B	-0.009			
hisotry of my actions and win-	R	t-1,t-2	K,N	B,R				
ners	_							
hisotry of my actions and win-	R	t-1,t-2	K,N	R,B				
hisotry of my actions and win-	в	t-1 t-2	ΚN	R R				-0.138
ners	10	0 1,0 2		10,10				0.100
hisotry of my actions and win-	R	t-1,t-2	N,K	B,B				
ners		,	,	,				
hisotry of my actions and win-	R	t-1,t-2	N,K	$^{\mathrm{B,R}}$				-0.011
ners								
						$\gg \overline{\text{Contin}}$	ue to the	next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of my actions and win-	R	t-1,t-2	N,K	$_{ m R,B}$				
ners								
hisotry of my actions and win-	R	t-1,t-2	N,K	$^{ m R,R}$				
ners								
hisotry of my actions and win- ners	R	t-1,t-2	N,N	$_{\mathrm{B,B}}$				
hisotry of my actions and win-	R	t-1,t-2	N,N	B,R				
hisotry of my actions and win	в	+ 1 + 9	NN	ВВ	0.000	0.000	0.000	0.000
ners	п	0-1,0-2	11,11	п,в	0.000	0.000	0.000	0.000
hisotry of my actions and win-	в	t-1 t-2	ΝΝ	R R			-0.030	
ners	10	0 1,0 2	1,1,1	10,10			0.000	
opponent action and winner	В	t-1	1	В		0.008		
opponent action and winner	В	t-1	1	R	0.000	0.000	0.000	0.000
opponent action and winner	В	t-1	2	В				
opponent action and winner	В	t-1	2	R	-0.002			
opponent action and winner	В	t-1	3	В				-0.019
opponent action and winner	В	t-1	3	R				
opponent action and winner	В	t-2	1	В				
opponent action and winner	В	t-2	1	R	-0.031			
opponent action and winner	В	t-2	2	В				
opponent action and winner	В	t-2	2	R				-0.012
opponent action and winner	В	t-2	3	В		0.027		-0.004
opponent action and winner	В	t-2	3	R				
opponent action and winner	В	t-3	1	В				
opponent action and winner	В	t-3	1	R				
opponent action and winner	В	t-3	2	В	-0.021			
opponent action and winner	В	t-3	2	R				
opponent action and winner	В	t-3	3	В	0.000	0.000	0.000	-0.005
opponent action and winner	В	t-3	3	R	0.000		-0.056	
opponent action and winner	В	t-4	1	В				
opponent action and winner	В	t-4	1	R				
opponent action and winner	В	t-4	2	В	0.000	-0.067	0.000	0.000
opponent action and winner	В	t-4	2	R				0.000
opponent action and winner	В	t-4	3	В		0.010	-0.021	
opponent action and winner	В	t-4	3	R		-0.022		
hisotry of opponent actions	В	t-1,t-2	$^{1,1}$	$^{\mathrm{B,B}}$				
and winners	_							
hisotry of opponent actions	В	t-1,t-2	1,1	$^{\mathrm{B,R}}$				
and winners						N Cart	inuo to the	nort

Table 13. I	Full coefficients	table of LASSO	(Red player	, cont.)
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Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of opponent actions	в	+ 1 + 9	11	ВВ				
and winners	Б	0-1,0-2	1,1	п,D				
hisotry of opponent actions	В	t-1,t-2	1,1	R,R				
and winners								
hisotry of opponent actions	В	t-1,t-2	$^{1,2}$	$^{\mathrm{B,B}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	$^{1,2}$	$^{\mathrm{B,R}}$				
and winners	_							
hisotry of opponent actions	В	t-1,t-2	1,2	R,B				
and winners	Ð	. 1 . 0	1.0	D D				
hisotry of opponent actions	В	t-1,t-2	1,2	R,R				
and winners	D	4140	1.9	סס				
and winners	D	t-1,t-2	1,5	ь,ь				
hisotry of opponent actions	в	+_1 +_9	13	BB				
and winners	D	0-1,0-2	1,5	D,It				
hisotry of opponent actions	В	t-1.t-2	1.3	R.B				
and winners		,	_,.	,				
hisotry of opponent actions	В	t-1,t-2	1,3	R,R				
and winners								
hisotry of opponent actions	В	t-1,t-2	$1,\mathrm{K}$	$^{\mathrm{B,B}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	$1,\mathrm{K}$	$^{\mathrm{B,R}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	$1,\mathrm{K}$	$_{\rm R,B}$	0.006	0.000	0.000	0.000
and winners								
hisotry of opponent actions	В	t-1,t-2	1,K	R,R				
and winners	D	+ 1 + 9	9.1	DD				
and winners	D	t-1,t-2	2,1	ь,ь				
hisotry of opponent actions	в	+_1 +_9	9.1	BB				
and winners	D	0-1,0-2	2,1	D,It				
hisotry of opponent actions	В	t-1.t-2	2.1	R.B				
and winners		,	_,_	,				
hisotry of opponent actions	В	t-1,t-2	2,1	R,R				
and winners								
hisotry of opponent actions	В	t-1,t-2	2,2	B,B				
and winners								
hisotry of opponent actions	В	t-1,t-2	$^{2,2}$	$^{\mathrm{B,R}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	$^{2,2}$	$_{\rm R,B}$				
and winners								
						$\gg$ Conti	nue to the n	ext page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of opponent actions	В	t-1,t-2	2,2	R,R				
hisotry of opponent actions	В	t-1,t-2	2,3	$^{\mathrm{B,B}}$			-0.004	
and winners								
hisotry of opponent actions	В	t-1,t-2	2,3	$^{\mathrm{B,R}}$				
hisotry of opponent actions	в	t-1.t-2	2.3	R.B				
and winners	_	,	_,~					
hisotry of opponent actions	В	t-1,t-2	2,3	$^{\rm R,R}$				
and winners	D	. 1 . 0	0.17	DD				
and winners	В	t-1,t-2	2,K	в,в				
hisotry of opponent actions	В	t-1,t-2	2,K	$_{\mathrm{B,R}}$				
and winners		,	,	,				
hisotry of opponent actions	В	t-1,t-2	$_{2,\mathrm{K}}$	$^{ m R,B}$				0.015
and winners	р	+ 1 + 9	9 K	DD				
and winners	Б	0-1,0-2	2,11	10,10				
hisotry of opponent actions	В	t-1,t-2	3,1	$^{\mathrm{B,B}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	3,1	$^{\mathrm{B,R}}$				
hisotry of opponent actions	в	t-1 t-2	3.1	ВВ				
and winners	2	• 1,• 1	0,1	10,22				
hisotry of opponent actions	В	t-1,t-2	$^{3,1}$	$^{\rm R,R}$				
and winners	Ð			D D				
hisotry of opponent actions	В	t-1,t-2	3,2	в,в	0.009			
hisotry of opponent actions	В	t-1,t-2	3,2	$_{\mathrm{B,R}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	3,2	$^{\rm R,B}$				
and winners	D	+ 1 + 9	2.9	DЪ				
and winners	Б	1-1,1-2	3,2	n,n				
hisotry of opponent actions	В	t-1,t-2	3,3	$^{\mathrm{B,B}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	3,3	$_{\mathrm{B,R}}$				
and winners	в	+_1 +_9	3 3	ВВ				
and winners	D	J 1,0 4	5,5	10,12				
hisotry of opponent actions	В	t-1,t-2	3,3	$^{\rm R,R}$				
and winners						~		
						$\gg$ Cont	inue to the n	ext page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of opponent actions	В	t-1,t-2	3,K	$^{\mathrm{B,B}}$		0.001		
and winners	р	4149	9 V	ם ח				
and winners	В	t-1,t-2	3,K	B,R				
hisotry of opponent actions	В	t-1.t-2	3.K	R.B				
and winners			- )	-)				
hisotry of opponent actions	В	t-1,t-2	$_{3,\mathrm{K}}$	R,R				
and winners								
hisotry of opponent actions	В	t-1,t-2	K,1	$^{\mathrm{B,B}}$				
and winners	Ð	. 1 . 0	TZ 4	DD				
hisotry of opponent actions	В	t-1,t-2	К,1	$^{\mathrm{B,R}}$				
hisotry of oppopent actions	в	+_1 +_9	K 1	ВВ				
and winners	Ъ	0-1,0-2	11,1	н,Б				
hisotry of opponent actions	В	t-1,t-2	K,1	R,R			0.036	
and winners		,	,	,				
hisotry of opponent actions	В	t-1,t-2	K,2	B,B				
and winners								
hisotry of opponent actions	В	t-1,t-2	K,2	$^{\mathrm{B,R}}$				
and winners	Ð	. 1 . 0	14.0	DD				
hisotry of opponent actions	В	t-1,t-2	K,2	к,в				
hisotry of opponent actions	в	t_1 t_9	КЭ	BB				
and winners	Б	0 1,0 2	11,2	10,10				
hisotry of opponent actions	В	t-1,t-2	K,3	B,B				
and winners		,	,					
hisotry of opponent actions	В	t-1,t-2	K,3	$^{\mathrm{B,R}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	К,3	$_{\mathrm{R,B}}$				
and winners	Ð	. 1 . 0	17.0	DD				
hisotry of opponent actions	В	t-1,t-2	К,3	R,R				
opponent action and winner	в	t_1	Ν	в	0.024			
opponent action and winner	B	t-1	N	B	0.024			-0.020
opponent action and winner	В	t-1	N	В	-0.005	0.000	0.003	0.000
opponent action and winner	В	t-1	N	В	0.000	0.000	0.000	0.000
hisotry of opponent actions	В	t-1,t-2	K,N	B,B		-0.030		
and winners								
hisotry of opponent actions	В	t-1,t-2	K,N	$^{\mathrm{B,R}}$				
and winners								
hisotry of opponent actions	В	t-1,t-2	$_{ m K,N}$	$^{ m R,B}$		0.013		
and winners						> Contini	e to the r	lext nage

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	,	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of opponent	actions	В	t-1,t-2	$^{ m N,K}$	$^{\mathrm{B,B}}$				
hisotry of opponent	actions	В	t-1,t-2	N,K	$^{\mathrm{B,R}}$	0.047			-0.036
and winners									
hisotry of opponent	actions	В	t-1,t-2	$^{ m N,K}$	R,B	0.000	0.000	0.000	0.028
hisotry of opponent	actions	В	t-1,t-2	N,N	B,B				
and winners									
hisotry of opponent	actions	В	t-1,t-2	N,N	$^{\mathrm{B,R}}$		-0.037		
and winners hisotry of opponent	actions	В	t-1.t-2	N.N	R.B				
and winners	detions	2	· 1,• <b>-</b>	1,11,	10,22				
hisotry of actions (N o	or K) and		t-1	(N,N)	В				0.000
hisotry of actions (N c	or K) and		t-2	(N.N)	В				-0.017
winners	<i>iii)</i> and		° <b>-</b>	(1,,1,)	Ð				01011
hisotry of K-profiles a	and win-		t-1,t-2	$(\mathrm{K},\mathrm{K}),(\mathrm{N},\mathrm{N})$	$^{\rm R,B}$				
ners hisotry of K profiles	and win		+ 1 + 9	(K N) (N N)	BB		0.010		
ners	and win-		0-1,0-2	(11,11),(11,11)	ы,ы		0.010		
hisotry of K-profiles a	and win-		t-1,t-2	(N,K),(N,N)	$^{\mathrm{B,B}}$				
ners	1.		. 1 . 0	(NT NT) (12 12)	DD				0.000
nisotry of K-profiles a	and win-		t-1,t-2	(N,N),(K,K)	B,R				-0.022
hisotry of K-profiles a	and win-		t-1,t-2	(N,N),(K,N)	$^{\mathrm{B,B}}$				
ners									
hisotry of K-profiles a	and win-		t-1,t-2	(N,N),(N,K)	$^{\mathrm{B,B}}$		0.041		
hisotry of K-profiles :	and win-		t-1,t-2	(N.N).(N.N)	B,B	0.039			
ners			,		,				
hisotry of K-profiles a	and win-		t-1,t-2	(N,N),(N,N)	$^{\mathrm{B,R}}$				
ners hisotry of K-profiles	and win-		+_1 +_9	(N N) (N N)	RB				_0.012
ners	and win-		0-1,0-2	(1,1,1,1,1,1,1,1)	н, Б				0.012
hisotry of actions (N c	or K) and		t-3	(N,N)	В			0.005	
winners			. 1	(17 17) (17 17)	DDD				
hisotry of K-profiles a	and win-		t-1 to t-3	(K,K),(K,K), (N N)	R,R,B				
hisotry of K-profiles	and win-		t-1 to t-3	(K,K),(K,K),	R.R.R				-0.005
ners			-	(N,N)	, ,				
hisotry of K-profiles a	and win-		t-1 to t- $3$	(K,K),(K,N),	$_{\rm R,B,B}$				
ners				(N,N)			> Contin	up to the	novt perc

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(K,N),	$_{\rm R,B,R}$				
ners hisotry of K-profiles and win-		t-1 to t-3	(IN, IN) (K.K).(N.K).	R.B.B				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t- $3$	(K,K),(N,K),	$_{\rm R,B,R}$				
ners		4 1 4 - 4 9	(N,N)	חחח				
nisotry of K-promes and win-		t-1 to t-5	$(\mathbf{K},\mathbf{K}),(\mathbf{M},\mathbf{N}),$ $(\mathbf{K},\mathbf{K})$	п,р,п				
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(N,N),	$_{ m R,B,B}$				
ners			(K,N)					
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(N,N),	$_{\rm R,B,B}$				
ners hisotry of K-profiles and win-		t-1 to t-3	(N,K) (KK) (NN)	RBB				
ners		010000	(N,N)	10,22,22				
hisotry of K-profiles and win-		t-1 to t- $3$	(K,K),(N,N),	$_{\rm R,B,R}$				
ners		. 1	(N,N)	DDD				
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(N,N), (K,K)	R,R,R				
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(N,N),	R,R,B				
ners			(K,N)					
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(N,N),	$_{\rm R,R,B}$				-0.010
ners bisetry of K profiles and win		t = 1 to $t = 3$	(N,K) (K,K) $(N,N)$	BBB				
ners		t-1 to t-5	(N,N)	10,10,10				
hisotry of K-profiles and win-		t-1 to t-3	(K,K),(N,N),	$_{\rm R,R,R}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(K,K),	$_{\rm B,R,B}$				
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(K,K),	B,R,R				
ners			(N,N)	, ,				
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(K,N),	$_{\rm B,B,B}$				
ners hisotry of K profiles and win		$\pm 1 \pm 0 \pm 3$	(N,N)	BBD				
ners		t-1 to t-3	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$	$^{\mathrm{D},\mathrm{D},\mathrm{II}}$				
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,K),	$_{\rm B,B,B}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,K),	$_{\mathrm{B,B,R}}$				
hisotry of K-profiles and win-		t-1 to t-3	$(\mathbf{N},\mathbf{N})$ $(\mathbf{K},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ .	B.B.R				
ners			(K,K)	_ ,_ ,_ v				
hisotry of K-profiles and win-		t-1 to t- $3$	(K,N),(N,N),	$^{\mathrm{B,B,B}}$				
ners			(K,N)			N Ca		

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\rm R,1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,N),	$_{\rm B,B,B}$				
ners			(N,K)					
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,N),	B,B,B				
hisotry of K-profiles and win-		t-1 to t-3	$(\mathbf{N}, \mathbf{N})$ $(\mathbf{K}, \mathbf{N})$ $(\mathbf{N}, \mathbf{N})$	BBB				
ners		010000	(N,N)	D,D,I(				
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,N),	$_{\mathrm{B,R,R}}$				
ners			(K,K)					
hisotry of K-profiles and win-		t-1 to t- $3$	(K,N),(N,N),	$_{\rm B,R,B}$				
ners			(K,N)					
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,N),	$_{\mathrm{B,R,B}}$				
ners		t 1 to t 3	(N,K) (K,N) $(N,N)$	BBB				
ners		1-1 10 1-5	(N,N)	р,п,р				
hisotry of K-profiles and win-		t-1 to t-3	(K,N),(N,N),	$_{\rm B,R,R}$				
ners			(N,N)	, ,				
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(K,K),	$_{\rm B,R,B}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(K,K),	$_{\mathrm{B,R,R}}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(K,N),	B,B,B				
ners		t 1 to t 3	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K})$ $(\mathbf{K},\mathbf{N})$	BBB				
ners		t-1 to t-3	$(\mathbf{N},\mathbf{N}),(\mathbf{R},\mathbf{N}),$	$^{\mathrm{D},\mathrm{D},\mathrm{II}}$				
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,K),	B,B,B				
ners			(N,N)	, ,				
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,K),	$_{\mathrm{B,B,R}}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	$_{\mathrm{B,B,R}}$				
ners			(K,K)					
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	B,B,B				
hisotry of K-profiles and win-		t-1 to t-3	$(\mathbf{K}, \mathbf{N})$ $(\mathbf{N}, \mathbf{K})$ $(\mathbf{N}, \mathbf{N})$	BBB				
ners		0-1 00 0-5	(N,K),(N,N),(N,N),(N,K)	р,р,р				
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	B,B,B				
ners			(N,N)	, ,				
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	$^{\mathrm{B,B,R}}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	$_{\mathrm{B,R,R}}$				
ners		414.49	(K,K)	ם ם ם				
nisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N), (K,N)	в,к,в				
1101.0			(11,11)			> Cor	ntinuo to th	o novt page

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\rm R,1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	$_{\rm B,R,B}$				-0.021
ners		. 1	(N,K)	חחח				
hisotry of K-profiles and win-		t-1 to t-3	(N,K),(N,N),	B,R,B				
hisotry of K-profiles and win-		t-1 to t-3	(N, K). $(N, N)$ .	B.R.R				
ners			(N,N)	) - ) -				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	$_{\rm B,R,R}$				
ners			(K,K)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	$_{\mathrm{B,R,B}}$				
ners		+1+0+9	(K,N)	DDD				
ners		t-1 to t-5	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K}),$	b,n,b				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	B,R,B				
ners			(N,N)	, ,				
hisotry of K-profiles and win-		t-1 to t- $3$	(N,N),(K,K),	$_{\rm B,R,R}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,N),	$_{\mathrm{B,B,R}}$				
ners		$\pm 1 \pm 2$	(K,K) (N N) (K N)	BBB				
ners		t-1 to t-5	(K.N)	р,р,р				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,N),	$_{\rm B,B,B}$				
ners			(N,K)					
hisotry of K-profiles and win-		t-1 to t- $3$	(N,N),(K,N),	$_{\rm B,B,B}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,N),	$_{\rm B,B,R}$				
hisotry of K-profiles and win-		t-1 to t-3	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K})$	BBB				
ners		010000	(K,K)	2,2,10				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,K),	$_{\rm B,B,B}$				
ners			(K,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,K),	$_{\rm B,B,B}$				
ners		. 1	(N,K)	חחח				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,K), (N,N)	в,в,в				
hisotry of K-profiles and win-		t-1 to t-3	(N,N). $(N,K)$ .	B.B.R				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	$^{\mathrm{B,B,R}}$				
ners			(K,K)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	$_{\mathrm{B,B,B}}$				
ners		+1+0+9	(K,N)	BBD				
ners		t-1 to t-9	(1N,1N),(1N,1N), (N.K)	<b>D</b> , <b>D</b> , <b>D</b>				
			(-1,11)			> Cor	ntinuo to th	o novt paga

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	$_{\rm B,B,B}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	$^{\mathrm{B,B,R}}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	$_{ m B,R,R}$				
ners		. 1	(K,K)	DDD				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	$_{\rm B,R,B}$				
histry of K profiles and win		+ 1 + 2 + 9	$(\mathbf{K}, \mathbf{N})$ $(\mathbf{N}, \mathbf{N})$ $(\mathbf{N}, \mathbf{N})$	DDD				
nisotry of K-promes and win-		t-1 to t-5	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	Б,ћ,Б				
hisotry of K-profiles and win-		t-1 to t-3	(N, N) $(N, N)$	BBB				
ners		11010	(N,N)	D,10,D				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,N),	B.R.R				
ners			(N,N)	, ,				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	R,R,R				
ners			(K,K)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	$_{\rm R,R,B}$				
ners			(K,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	$_{\rm R,R,B}$				
ners			(N,K)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	R,R,B				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,K),	R,R,R				
ners		. 1 9	(N,N)	חחח				
nisotry of K-profiles and win-		t-1 to t-3	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{K},\mathbf{K})$	к,в,к				
hisotry of K profiles and win		$\pm 1 \pm 0 \pm 3$	$(\mathbf{K},\mathbf{K})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{K},\mathbf{N})$	RBB				
ners		1-1 10 1-5	(K N)	п,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-		t-1 to t-3	(N,N).(K,N).	R.B.B				
ners			(N,K)	-) )				
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,N),	R,B,B				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(K,N),	$_{\rm R,B,R}$				
ners			(N,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,K),	$_{\rm R,B,R}$				
ners			(K,K)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,K),	$_{\rm R,B,B}$	0.000	0.000	0.000	0.000
ners			(K,N)					
hisotry of K-profiles and win-		t-1 to t-3	(N,N),(N,K),	R,B,B				
ners		414049	(N,K)	ם ם ם				
nisotry of K-profiles and win-		t-1 to t-3	(1N,1N),(1N,K), (N N)	п, р, в				
1101.0			(11,11)			> Cont	inuo to tho	novt page

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t·	-1 to t-3	(N,N),(N,K),	$_{\rm R,B,R}$				
ners			(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-3	(N,N),(N,N),	R,B,R				
ners		1	(K,K)					
hisotry of K-profiles and win-	t·	-1 to t-3	(N,N),(N,N),	R,B,B				
ners		1	(K,N)					
hisotry of K-profiles and win-	t·	-1 to t-3	(N,N),(N,N),	R,B,B				
ners		14.49	$(\mathbf{N},\mathbf{K})$	DDD				
hisotry of K-profiles and win-	t·	-1 to t-3	(IN,IN),(IN,IN),	R,B,B				
history of K profiles and win	1	1 4 . 4 9	(IN,IN) (N,IN) $(N,IN)$	ססס				
hisotry of K-promes and win-	ſ.	-1 to t-5	(1N,1N),(1N,1N), (N, N)	п, ,, п				
histry of K profiles and win	+	$1 \pm 0 \pm 3$	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$	DDD				
nisotry of R-promes and will-	6-	-1 to t-5	$(\mathbf{I}\mathbf{V},\mathbf{I}\mathbf{V}),(\mathbf{I}\mathbf{V},\mathbf{I}\mathbf{V}),$ $(\mathbf{K},\mathbf{K})$	11,11,11				
hisotry of K profiles and win	+	$1 \pm 0 \pm 3$	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$	BBB				
ners	0.	-1 10 1-5	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N}),$	п.,п.,Б				
hisotry of K-profiles and win-	t.	-1 to t-3	$(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$	BBB				
ners	0	1 10 1 0	$(\mathbf{N},\mathbf{K})$	10,10,10				
hisotry of K-profiles and win-	t	-1 to t-3	(N,N).(N,N).	B.B.B				
ners	-		(N.N)	_ = = = = = = =				
hisotry of K-profiles and win-	t·	-1 to t-3	(N,N),(N,N),	R,R,R				
ners			(N,N)	, ,				
hisotry of actions (N or K) and	t·	-4	(N,N)	В	0.000	0.000	0.000	0.000
winners								
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	R,R,R,B				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	R,R,R,R				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	$_{\rm R,R,B,B}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	$_{\mathrm{R,R,B,R}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	$_{\rm R,R,B,B}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	$_{\mathrm{R,R,B,R}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	$_{\mathrm{R,R,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	R,R,B,B				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t·	-1 to t-4	(K,K),(K,K),	R,R,B,B				
ners			(N,N),(N,K)					
						$\gg Cont$	inue to the	next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player I	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	R,R,B,B				
ners			(N,N),(N,N)	, , ,				
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	R,R,B,R				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	R,R,R,R				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	$_{\rm R,R,R,B}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	$_{\rm R,R,R,B}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	$_{\rm R,R,R,B}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K),	$_{\mathrm{R,R,R,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	$_{\mathrm{R,B,R,B}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R,B,R,R				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R,B,B,B				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R,B,B,R				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R,B,B,B				
ners	. 1		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R,B,B,R				
history of V profiles and win	<u>ل</u> 1	to t 1	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	חחחח				
nisotry of K-promes and win-	t-1	to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$	$\mathbf{n},\mathbf{D},\mathbf{D},\mathbf{n}$				
histry of K profiles and win	+ 1	to t 1	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$ $(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N})$	DBBB				
nisotry of K-promes and win-	t-1	to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	п,в,в,в				
histry of K profiles and win	+ 1	to t 1	$(\mathbf{I},\mathbf{N}),(\mathbf{K},\mathbf{N})$	DBBB				
nisotry of K-promes and win-	U-1	10 1-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$	п, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,				
hisotry of K-profiles and win-	+_1	to t-1	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$	BBBB				
ners	0-1	10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	п,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-	t-1	to t-4	(K,K) (K N)	RBBR				
ners	0 1	00 0 1	(N.N).(N.N)	10,22,22,10				
hisotry of K-profiles and win-	t-1	to t-4	(K.K).(K.N).	R.B.R.R				
ners			(N.N).(K.K)	_ = = ;_ = = = = = = = =				
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R.B.R.B				
ners			(N,N),(K,N)	, , ,				
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,N),	R,B,R,B				
ners			(N,N),(N,K)					
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Peri	od Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to	t-4 (K,K),(K,N	I), R,B,R,B				
ners		(N,N),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 (K,K),(K,N	N), R,B,R,R				
ners		(N,N),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 (K,K),(N,K	K), R,B,R,B				
ners		(K,K),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,R,R				
ners		(K,K),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,B,B				
ners		(K,N),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,B,R				
ners		(K,N),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	X), R,B,B,B				
ners		(N,K),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,B,R				
ners		(N,K),(N,N	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,B,R				
ners		(N,N),(K,K	() N				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,B,B				
ners		(N,N),(K,N					
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	K), R,B,B,B				
ners		(N,N),(N,K)	) A) DDDD				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,K)$	$\mathbf{X}$ ), R,B,B,B				
histry of K profiles and win	t 1 to	(IN,IN),(IN,IN)	) 7) סססס				
nisotry of K-promes and win-	t-1 to	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	$(\mathbf{X}), \mathbf{n}, \mathbf{D}, \mathbf{D}, \mathbf{n}$				
hisotry of K profiles and win	t 1 to	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$	) BBBB				
ners	1-1 10	(N N) (K K)	$(\mathbf{X}), \mathbf{I}(\mathbf{D},\mathbf{I}(\mathbf{U},\mathbf{I}(\mathbf{U})))$				
hisotry of K-profiles and win-	t-1 to	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$	C) BBBB				
ners	1-1 00	(N,N) (K N	$(\mathbf{r}), \mathbf{r}, \mathbf{D}, \mathbf{r}, \mathbf{D}$				
hisotry of K-profiles and win-	t-1 to	(II,II),(II,II)	C) BBBB				
ners	0 1 00	(N,N).(N,K)	(), 10,D,10,D				
hisotry of K-profiles and win-	t-1 to	(I,I,I),(I,I)	C). R.B.R.B				
ners	0 1 00	(N.N).(N.N)	I), 10,2,10,2 I)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K.K).(N.K)$	K). R.B.R.R				
ners		(N,N),(N,N	I)				
hisotry of K-profiles and win-	t-1 to	t-4 $(K,K),(N,N)$	), R,B,R,R				
ners		(K,K),(K,F	X)				
hisotry of K-profiles and win-	t-1 to	t-4 (K,K),(N,N	), R,B,R,B				
ners		(K,K),(K,N	J)				
hisotry of K-profiles and win-	t-1 to	t-4 (K,K),(N,N	I), R,B,R,B				
ners		(K,K),(N,K)	K)				
					≫ Co	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	R,B,R,B				
ners			(K,K),(N,N)	, , , ,				
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	R,B,R,R				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{ m R,B,B,R}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,B,B}}$				
ners			(K,N),(K,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,B,B}}$				
ners			(K,N),(N,K)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,B,B}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,R}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,R}}$				
ners			(N,K),(K,K)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,B,B}}$				
ners			(N,K),(K,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	$_{\mathrm{R,B,B,B}}$				
ners			(N,K),(N,K)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	R,B,B,B				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	R,B,B,R				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K),(N,N),	R,B,B,R				
ners		1	(N,N),(K,K)					
hisotry of K-profiles and win-	t-	-1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$	к,в,в,в				
history of V profiles and win	1	1 + + + 1	(IN,IN),(K,IN) (K,K),(N,IN)	סססס				
hisotry of K-promes and win-	ι-	-1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$	п, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,				
histry of K profiles and win	+	$1 \pm 0 \pm 4$	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	рррр				
nisotry of K-promes and win-	L-	-1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	п,в,в,в				
hisotry of K profiles and win	+	1  to  t 4	$(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N})$ $(\mathbf{K}\mathbf{K}),(\mathbf{N}\mathbf{N})$	BBBB				
ners	6-	-1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	п,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-	t.	1 to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	Ū	1 00 0 4	(N,N),(K,K),(K,K)	10,10,10,10				
hisotry of K-profiles and win-	t.	-1 to t-4	(K K) (N N)	RBBB				
ners	U		(N,N).(K,N)	10,2,10,2				
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K).(N,N)	R.B.R.B				
ners	0	• -	(N,N).(N,K)					
hisotry of K-profiles and win-	t-	-1 to t-4	(K,K).(N.N).	R,B,R.B				
ners	0		(N,N).(N,N)	-, ,,				
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player F	eriod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,B,R,R				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,R,R				
ners			(K,K),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	$_{\rm R,R,R,B}$				
ners			(K,K),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	$_{\rm R,R,R,B}$				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	$_{\rm R,R,R,B}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	$_{\rm R,R,R,R}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	$_{\mathrm{R,R,B,R}}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	$_{\mathrm{R,R,B,B}}$				
ners			(K,N),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,B				
ners			(K,N),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,B				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,R				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,R				
ners			(N,K),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,B				
ners	4.1		(N,K),(K,N)	חחחח				
hisotry of K-promes and win-	l-1	to t-4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$	п,п,d,d				
histry of K profiles and win	+ 1	to t 1	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$	DDBB				
nisotry of K-promes and win-	U-1	10 1-4	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	$\mathbf{n},\mathbf{n},\mathbf{D},\mathbf{D}$				
histry of K profiles and win	+ 1	to t 1	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	DDBD				
nisotry of K-promes and win-	U-1	10 1-4	$(\mathbf{I},\mathbf{K}),(\mathbf{I},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	п,п,D,п				
hisotry of K-profiles and win-	t_1	to t-1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	0-1	10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	10,10,10,10				
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(K,K)	RRBB				
ners	0 1	00 0 1	(N.N).(K.N)	10,10,22,22				
hisotry of K-profiles and win-	t-1	to t-4	(K.K).(N.N).	R.R.B.B				
ners			(N.N).(N.K)					
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,B				
ners			(N,N),(N,N)	, , ,				
hisotry of K-profiles and win-	t-1	to t-4	(K,K),(N,N),	R,R,B,R				
ners			(N,N),(N,N)					
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t	-1 to t-4	(K,K),(N,N),	R,R,R,R				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,K),(N,N),	R,R,R,B				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,K),(N,N),	$_{\rm R,R,R,B}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,K),(N,N),	$_{\rm R,R,R,B}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,K),(N,N),	$_{\rm R,R,R,R}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,R,R}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	B,R,B,B				
ners		1	(N,N),(K,N)					
hisotry of K-profiles and win-	t	-1 to t-4	(K,N),(K,K),	$_{\rm B,R,B,B}$				
ners		1	(N,N),(N,K)	חחחח				
hisotry of K-promes and win-	Ŀ	-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	, к, d, d				
histry of K profiles and win	+	$1 \pm 0 \pm 4$	$(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N})$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$	סססס				
nisotry of K-promes and win-	U	-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	D,n,D,n				
hisotry of K profiles and win	+	1  to  t 4	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$ $(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K})$	BBBB				
ners	6	-1 10 1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$	D,10,10,10				
hisotry of K-profiles and win-	t	-1 to t-4	(K, N), (K, K)	BBBB				
ners	0	1 00 0 1	(N,N),(K,N),(K,N)	D,10,10,D				
hisotry of K-profiles and win-	t	-1 to t-4	(K N) (K K)	BBBB				
ners	U		(N.N).(N.K)	2,10,10,12				
hisotry of K-profiles and win-	t	-1 to t-4	(K.N).(K.K)	B.R.R.B				
ners	0	• -	(N,N).(N,N)	_ ,_ <i>,,,,,,,,</i> ,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-	t	-1 to t-4	(K,N).(K,K).	B,R,R.R				
ners	· · · ·		(N,N).(N,N)	, -,,				
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\rm B,B,R,B}$				
ners		(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,R,R}}$				
ners		(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners		(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners		(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,R}}$				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,R,R}}$				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,R,B}}$				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,R,B}}$				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	B,B,R,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(K,N),	$_{\mathrm{B,B,R,R}}$				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,K),	$_{\rm B,B,R,B}$				
ners		$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	DDDD				
nisotry of K-profiles and win-	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K}),$	в,в,к,к				
ners	. 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$					
hisotry of K-promes and win-	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K}),$	D,D,D,D				
history of V profiles and min	+ 1 + o + 1	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	חחחח				
nisotry of K-promes and Win-	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K}),$	<b>D,D,D,R</b>				
hisotry of K profiles and win	t 1 to t 4	$(\mathbf{I}\mathbf{X},\mathbf{I}\mathbf{N}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N})$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$	BBBB				
ners	t-1 tO t-4	$(\mathbf{I}\mathbf{X},\mathbf{I}\mathbf{Y}),(\mathbf{I}\mathbf{Y},\mathbf{I}\mathbf{X}),$ $(\mathbf{N}\mathbf{K})$ $(\mathbf{N}\mathbf{N})$	<b>D</b> , <b>D</b> , <b>D</b> , <b>D</b>				
1015		(1,11),(1,11)			>> Co	ntinue to t	the next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	l Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,B,R				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,B,R				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,B,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,B,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,B,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,B,R				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,R,R				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,R,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (K,N),(N,K)	, B,B,R,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	4 $(K,N),(N,K)$	, B,B,R,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	$4 \qquad (K,N),(N,K)$	, B,B,R,R				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 $(K,N),(N,N)$	, B,B,R,R				
ners		(K,K),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	4  (K,N),(N,N)	, B,B,R,B				
ners		(K,K),(K,N)	חחחח				
hisotry of K-profiles and win-	t-1 to t-	4  (K,N), (N,N), (V,N) = (V,V), (N,N), (N	, в,в,к,в				
history of V profiles and win	41404	(K,K),(N,K)	מחמת				
hisotry of K-promes and win-	t-1 to t-	$4  (\mathbf{K}, \mathbf{N}), (\mathbf{N}, \mathbf{N}), (\mathbf{K}, \mathbf{N}), (\mathbf{N}, N$	, д,д,ң,д				
histry of K profiles and win	+ 1 + - +	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	סססס				
moore and win-	t-1 to t-	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),(N$	, D,D,N,N				
hisotry of K profiles and win	t 1 to t	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	t-1 to t-	(K,N),(K,K)	, D,D,D,It				
hisotry of K-profiles and win-	t-1 to t-	4  (K,N), (N,N)	BBBB				
ners	01000	(K,N)(K,N)	, D,D,D,D				
hisotry of K-profiles and win-	t-1 to t-	4 (K N) (N N)	BBBB				
ners		(K.N).(N.K)	, <i>2,2,2,2,2</i>				
hisotry of K-profiles and win-	t-1 to t-	4 (K.N).(N.N)	. B.B.B.B				
ners		(K,N).(N,N)	, _,_,_,_,				
hisotry of K-profiles and win-	t-1 to t-	4 (K,N).(N,N)	, B,B.B.R				
ners		(K,N),(N,N)	, , , , , , , , , , , , , , , , , , , ,				
					» Co	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Per	iod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,B,R}}$				
ners		()	N,K),(K,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners		1)	N,K),(K,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners		1)	N,K),(N,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners		1)	N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,R}}$				
ners		1)	N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,B,R}}$				
ners		1)	N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	(N,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners		1)	N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	(N,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners		1)	N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	(N,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners		1)	N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,B,B,R}}$				
ners		1)	N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (l	(N,N)	$_{\mathrm{B,B,R,R}}$				
ners		1)	N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	(N,N)	B,B,R,B				
ners		1)	N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (I	(N,N),(N,N),	$^{\mathrm{B,B,R,B}}$				
ners	. 1	1) 1 (1	(N,N),(N,K)					
hisotry of K-promes and win-	t-1 tC	(I) 4-1 (I	(1,1),(1,1),	<b>D</b> , <b>D</b> , <b>R</b> , <b>D</b>				
histry of K profiles and win	+ 1 + 4	(1 + 1 (1	(N, N), (N, N)	BBBB				
nisotry of K-promes and win-	t-1 tt	1) 4-1 (1 (1)	(1,1,1),(1,1,1),	D,D,N,N				
histry of K profiles and win	+ 1 + 4	(1 + 1 (1	(N, N), (N, N)	BDDD				
nisotry of K-promes and win-	t-1 tt	(I) 4-1 (I	$(\mathbf{X}, \mathbf{N}), (\mathbf{N}, \mathbf{N}), (\mathbf{X}, \mathbf{N}), (\mathbf{X}, \mathbf{N})$	D,11,11,11				
hisotry of K-profiles and win-	t_1 to	(1 (1	$(\mathbf{N}, \mathbf{N}), (\mathbf{N}, \mathbf{N})$	BBBB				
ners	0-1 00	I) I-1 (1	(K, K), (K, N), (K, N)	D,10,10,D				
hisotry of K-profiles and win-	t-1 to	t-4 (I	$(\mathbf{N}, \mathbf{N})$	BBBB				
ners	0 2 00	(]	(N,K)	2,10,10,2				
hisotry of K-profiles and win-	t-1 to	t-4 (1	K.N).(N.N).	B.R.R.B				
ners		(]	(K,K),(N,N)	, -,,				
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	B,R,R,R				
ners		(1	K,K),(N,N)	, , ,				
hisotry of K-profiles and win-	t-1 to	t-4 (I	K,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners		(I	K,N),(K,K)					
						≫ Coi	ntinue to the	e next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(K,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(K,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\rm B,R,B,B}$				
ners		(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners		(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners		(N,K),(K,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(N,K),(K,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(N,K),(N,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,R,R}}$				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners	. 1	(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-4	(K,N),(N,N),	$_{\rm B,R,R,B}$				
ners	. 1	(N,N),(N,K)					
nisotry of K-profiles and win-	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	в,к,к,в				
history of V profiles and min	+ 1 + + 4	(IN,IN),(IN,IN)	סססס				
hisotry of K-promes and win-	t-1 to t-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	<b>D</b> , <b>R</b> , <b>R</b> , <b>R</b>				
history of K profiles and	+ 1 + ~ + 1	(1N,1N),(1N,1N) (N,K),(1Z,K)	ססקק				
nisotry of K-promes and WIN-	t-1 to t-4	$(\mathbf{I}\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	D,R,R,D				
hisotry of K-profiles and win	+ 1 +o + 1	$(\mathbf{I}\mathbf{X},\mathbf{I}\mathbf{X}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N})$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$	BBBB				
ners	t-1 tO t-4	$(\mathbf{I},\mathbf{I},\mathbf{I}),(\mathbf{I},\mathbf{I},\mathbf{I}),$ $(\mathbf{K},\mathbf{K})$ (N N)	D,11,11,11				
		(**,**),(**,**)			≫ Coi	ntinue to	the next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Per	·iod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,B,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,R,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to	o t-4	(N,K),(K,K),	$_{\mathrm{B,R,R,B}}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,K),	$_{\mathrm{B,R,R,B}}$				
ners	. 1 .		(N,N),(N,K)	DDDD				
hisotry of K-profiles and win-	t-1 to	) t-4	(N,K),(K,K),	$_{\rm B,R,R,B}$				
ners	. 1		(N,N),(N,N)					
hisotry of K-promes and win-	t-1 tC	0 1-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	D,R,R,R				
histry of K profiles and win	+ 1 + 2	+ 1	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	BBBB				
nisotry of K-promes and win-	t-1 tt	0 1-4	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	b,b,n,b				
histry of K profiles and win	+ 1 + 2	+ 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBDD				
nisotry of K-promes and win-	t-1 tt	0 1-4	$(\mathbf{I},\mathbf{K}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	$D,D,\Pi,\Pi$				
hisotry of K-profiles and win-	t_1 to	×+_∕	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	0-1 00	, 1-4	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	Ъ,Ъ,Ъ,Ъ				
hisotry of K-profiles and win-	t-1 to	. t-4	(N, K), (K, N)	BBBB				
ners	0 2 00		(K.N).(N.N)	2,2,2,2,10				
hisotry of K-profiles and win-	t-1 to	o t-4	(N.K).(K.N).	B.B.B.B				
ners		-	(N,K),(N,N)	, ,-,-				
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,N).	B,B,B,R				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	• t-4	(N,K),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,N),(K,K)					
			/			≫ Coi	ntinue to the	e next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Perio	d Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,B,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,B,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,B,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,B,R				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,R,R				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,R,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(K,N)	, B,B,R,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	4 $(N,K),(K,N)$	, B,B,R,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4  (N,K),(K,N)	, B,B,R,R				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4  (N,K),(N,K)	, В,В,R,В				
ners		(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 $(N,K),(N,K)$	, B,B,R,R				
ners		(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 $(N,K),(N,K)$	, в,в,в,в				
histry of K profiles and win	+ 1 + 2 +	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	סססס				
nisotry of K-promes and win-	t-1 to t-	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$	, Б,Б,Б,К				
hisotry of K profiles and win	t 1 to t	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$	BBBB				
ners	t-1 to t-	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$	, в,в,в,в				
hisotry of K-profiles and win-	t-1 to t-	$4 \qquad (NK), (NK)$	BBBB				
ners	01000	(N, K), (N, N)	, D,D,D,It				
hisotry of K-profiles and win-	t-1 to t-	4 (NK) (NK)	BBBB				
ners	01000	(N,N),(K,K)	, ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-	t-1 to t-	4 (N.K).(N.K)	. B.B.B.B				
ners	01000	(N,N).(K,N)	, 2,2,2,2,2				
hisotry of K-profiles and win-	t-1 to t-	4 (N.K).(N.K)	. B.B.B.B				
ners		(N,N),(N,K)	, , , , ,				
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(N,K)	, B,B,B,B				
ners		(N,N),(N,N)	, , , ,				
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(N,K)	, B,B,B,R				
ners		(N,N),(N,N)	. , ,				
hisotry of K-profiles and win-	t-1 to t-	4 (N,K),(N,K)	, B,B,R,R				
ners		(N,N),(K,K)					
		· · · ·			≫ Co	ntinue to t	the next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Pe	riod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,K),	$_{\rm B,B,R,B}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,K),	$_{\rm B,B,R,B}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,K),	$_{\mathrm{B,B,R,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,K),	$_{\mathrm{B,B,R,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,R}}$				
ners			(K,K),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(K,K),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,R}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B},\mathrm{B},\mathrm{B},\mathrm{R}}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	B,B,B,B				
ners	. 1 .		(K,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	в,в,в,в				
history of V profiles and min	1 I I	~ + 1	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$	סססס				
nisotry of K-promes and win-	υ-1 υ	0 1-4	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	Б,Б,Б,Б				
hisotry of K profiles and win	+ 1 +	o † 1	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	0-1 0	0 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	D,D,D,It				
hisotry of K-profiles and win-	t_1 t	o t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	0-1 0	0 1-1	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K}),$	D,D,D,It				
hisotry of K-profiles and win-	t-1 t	o t-4	(N K) (N N)	BBBB				
ners	010	001	(N,K),(K,N)	2,2,2,2				
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	B.B.B.B				
ners	010	001	(N.K).(N.K)	2,2,2,2,2				
hisotry of K-profiles and win-	t-1 t	o t-4	(N.K).(N.N).	B.B.B.B				
ners			(N,K),(N,N)	, , ,				
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	B,B,B,R				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\rm B,B,B,B}$				
ners			(N,N),(K,N)					
			· · ·			≫ Coi	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)
Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,B,R,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,R}}$				
ners			(K,K),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	B,R,R,R				
ners			(K,K),(N,N)	DDDD				
hisotry of K-profiles and win-	t-1	to t-4	(N,K),(N,N),	$_{\rm B,R,B,R}$				
ners	. 1	4 - 4 - 4	(K,N),(K,K)	DDDD				
nisotry of K-profiles and win-	T-1	to t-4	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{V},\mathbf{N}),(\mathbf{V},\mathbf{N})$	в,к,в,в				
history of V profiles and win	L 1	4 - 4 1	$(\mathbf{K},\mathbf{N}),(\mathbf{K},\mathbf{N})$	סססס				
hisotry of K-promes and win-	U-1	. to t-4	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$	ь,п,ь,ь				
history of K profiles and win	+ 1	$to \pm 4$	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	рррр				
nisotry of R-promes and will-	U-1	10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	Б,П,Б,Б				
hisotry of K profiles and win	+ 1	to t 1	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	-1	10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	D,10,D,10				
hisotry of K-profiles and win-	t_1	to t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	-1		(N,K) (K K)	1,10,10,10				
hisotry of K-profiles and win-	t_1	to t-4	(N,K) (N N)	B.R.B B				
ners	-1		(N.K).(K.N)	2,10,2,2				
hisotry of K-profiles and win-	t-1	to t-4	(N,K).(N,N)	B.R.B.B				
ners			(N,K).(N,K)	_,_,_,_,_				
						» Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Pe	eriod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,K),(N,N),	$_{\mathrm{B,R,R,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,K),	$_{\mathrm{B,R,R,R}}$				
ners	. 1 .		(K,K),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,K),	$_{\rm B,R,R,B}$				
ners	. 1 .	- + 4	(K,K),(K,N)	חחח				
hisotry of K-promes and win-	ι-1 ι	0 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$	<b>D,R</b> , <b>R</b> , <b>D</b>				
histry of K profiles and win	+ 1 +	o + 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$	рррр				
moore and win-	υ-1 ι	01-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	$^{\mathrm{D,n,n,D}}$				
hisotry of K profiles and win	+ 1 +	o † 1	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$ $(\mathbf{N},\mathbf{N})$ $(\mathbf{K},\mathbf{K})$	BBBB				
ners	U-1 (	0 1-4	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K}),$ $(\mathbf{K},\mathbf{K})$ (N N)	D,10,10,10				
hisotry of K-profiles and win-	t_1 t	o t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	BBBB				
ners	010	004	(K, N), (K, K),	2,10,22,10				
hisotry of K-profiles and win-	t-1 t	o t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$	BBBB				
ners	010	1	(K.N).(K.N)	2,20,20,20				
hisotry of K-profiles and win-	t-1 t	o t-4	(N.N).(K.K)	B.R.B.B				
ners			(K,N).(N,K)	_,_,_,_,_				
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N).(K.K).	B,R.B.B				
ners		. =	(K,N),(N,N)	, -,,				
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Perie	od Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(K,F	K), B,R,B,R				
ners		(K,N),(N,N	1)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(K,F	K), B,R,B,R				
ners		(N,K),(K,F)	K)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(K,F	K), B,R,B,B				
ners		(N,K),(K,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(K,F	K), B,R,B,B				
ners		(N,K),(N,K)	K)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,k)$	K), B,R,B,B				
ners		(N,K),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,k)$	K), B,R,B,R				
ners		(N,K),(N,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,k)$	K), B,R,B,R				
ners		(N,N),(K,k)	K)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,K)$	K), B,R,B,B				
ners		(N,N),(K,N)	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,k)$	K), B,R,B,B				
ners		(N,N),(N,K)	()				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,F)$	K), B,R,B,B				
ners		(N,N),(N,N	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,k)$	K), B,R,B,R				
ners		(N,N),(N,N	1)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,K)$	K), B,R,R,R				
ners		(N,N),(K,K)	() () DDDD				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,F)$	(X), B, R, R, B				
ners	. 1	(N,N),(K,N)	N) Z) DDDD				
hisotry of K-promes and win-	t-1 to	(N,N),(K,R)	(X), D, K, K, D				
histry of K profiles and win	t 1 to	(IN,IN),(IN,IN)	X) BDDB				
nisotry of K-promes and win-	t-1 to	(N,N), (K, K)	$(\mathbf{X}), \mathbf{D}, \mathbf{n}, \mathbf{n}, \mathbf{D}$				
histry of K profiles and win	t 1 to	(1,1),(1,1)	Y) BDDD				
nisotry of K-promes and win-	1-1 10	(N N) (N N)	$(\mathbf{X}), \mathbf{D}, \mathbf{R}, \mathbf{R}, \mathbf{R}$				
hisotry of K-profiles and win-	t-1 to	(1,1),(1,1)	J) BBBB				
ners	1-1 10	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$	(), D, D, D, H, H				
hisotry of K-profiles and win-	t-1 to	(II,II),(II,I)	I) BBBB				
ners	0 1 00	(K.K).(K.N	J)				
hisotry of K-profiles and win-	t-1 to	(1, 2, 2), (1, 2)	I). B.B.R.B				
ners		(K,K),(N.F	() ()				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(K,N)$	), B,B,R,B				
ners		(K,K),(N,N	1)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(K,N	), B,B,R,R				
ners		(K,K),(N,N	1)				
					≫ Co	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Pe	eriod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners			(K,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners			(K,N),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,K),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners			(N,K),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners			(N,K),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,B}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 f	o t-4	(N,N),(K,N),	B,B,B,B				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N),	$_{\mathrm{B},\mathrm{B},\mathrm{B},\mathrm{B}}$				
ners	. 1 .		(N,N),(N,K)					
hisotry of K-promes and win-	l-1 (	0 1-4	(IN,IN),(IX,IN), (N,IN),(N,IN)	$^{D,D,D,D}$				
histry of K profiles and win	+ 1 +	$a \pm 4$	(IN,IN),(IN,IN) (N,N),(K,N)	BBBB				
nisotry of K-promes and win-	U-1 U	0 1-4	(IN,IN),(IX,IN), (N,N),(N,N)	<b>Б,Б,Б,</b> К				
histry of K profiles and win	+ 1 +	$a \pm 4$	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	BBDD				
nisotry of K-promes and win-	U-1 (	0 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$	D,D,R,R				
hisotry of K-profiles and win-	+_1 +	o t-1	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	BBBB				
ners	U-1 (	0 -4	(N,N),(K,N),(K,N)	D,D,It,D				
hisotry of K-profiles and win-	t-1 f	o t-4	(N,N) (K N)	BBBB				
ners	01		(N.N).(N.K)	2,2,2,10,2				
hisotry of K-profiles and win-	t-1 t	o t-4	(N.N).(K.N).	B.B.R.B				
ners			(N,N),(N,N)	, ,,				
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(K,N).	B,B,R,R				
ners			(N,N),(N,N)	, , , , ,				
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,K),	$_{\mathrm{B,B,R,R}}$				
ners			(K,K),(K,K)					
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Per	iod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 tc	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,R,B}}$				
ners		(K	(K,N)					
hisotry of K-profiles and win-	t-1 tc	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,R,B}}$				
ners		(K	,K),(N,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,R,B}}$				
ners		(K	.,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,R,R}}$				
ners		(K	.,K),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,R}}$				
ners		(K	(K,K),(K,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,B}}$				
ners		(К	I,N),(K,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,B}}$				
ners		(K	.,N),(N,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,B}}$				
ners		(K	(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,R}}$				
ners		(K	I,N),(N,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,R}}$				
ners		(N	,K),(K,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B,B,B,B}}$				
ners		(N	,K),(K,N)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	,N),(N,K),	$_{\mathrm{B},\mathrm{B},\mathrm{B},\mathrm{B}}$				
ners		(N	,K),(N,K)					
hisotry of K-profiles and win-	t-1 to	t-4 (N	(N),(N,K),	B,B,B,B				
ners		(IN	$(\mathbf{N},\mathbf{N})$	DDDD				
hisotry of K-profiles and win-	t-1 to	t-4 (N	(N),(N,K),	$^{\mathrm{B},\mathrm{B},\mathrm{B},\mathrm{R}}$				
history of V profiles and win	4140	(IN	$(\mathbf{N}), (\mathbf{N}, \mathbf{N})$	סססס				
hisotry of K-promes and win-	t-1 tC	(N) (N) (N)	$(\mathbf{N}),(\mathbf{N},\mathbf{K}),$	$^{D,D,D,K}$				
histry of K profiles and win	t 1 to	(IN	$(\mathbf{N}), (\mathbf{K}, \mathbf{K})$	рррр				
nisotry of K-promes and win-	t-1 tC	(N	$(\mathbf{N}), (\mathbf{N}, \mathbf{K}),$	<b>Б,Б,Б,Б</b>				
hisotry of K profiles and win	t 1 to	(IN	$(\mathbf{N}), (\mathbf{N}, \mathbf{N})$	BBBB				
ners	t-1 te	(N	$(\mathbf{N}, (\mathbf{N}, \mathbf{K}), (\mathbf{N}, \mathbf{K}))$	<b>D</b> , <b>D</b> , <b>D</b> , <b>D</b>				
hisotry of K-profiles and win-	t-1 to	(IN	(N, K)	BBBB				
ners	0100	(N	(N, (N, N))	D,D,D,D				
hisotry of K-profiles and win-	t-1 to	t-4 (N	(N, (N, K))	BBBB				
ners	0 1 00	(N	.N).(N.N)	2,2,2,10				
hisotry of K-profiles and win-	t-1 to	t-4 (N	.N).(N.K).	B.B.R.R				
ners	0 2 00	(N	.N).(K.K)	_,_,_,_,_				
hisotry of K-profiles and win-	t-1 to	t-4 (N	N),(N.K).	B,B,R.B				
ners		(N	(N),(K,N)	, ,,				
		\\				≫ Cor	ntinue to the	e next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Peri	od Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(N,	K), B,B,R,B				
ners		(N,N),(N,	K)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(N,	K), B,B,R,B				
ners		(N,N),(N,	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,T)$	K), B,B,R,R				
ners		(N,N),(N,N)	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,R,R				
ners		(K,K),(K,	K)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,R,B				
ners		(K,K),(K,	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,T)$	N), B,B,R,B				
ners		(K,K),(N,	K)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,R,B				
ners		(K,K),(N,	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,R,R				
ners		(K,K),(N,	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,N)$	N), B,B,B,R				
ners		(K,N),(K,	K)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,B,B				
ners		(K,N),(K,	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,B,B				
ners		(K,N),(N,	K)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N,N),(N,$	N), B,B,B,B				
ners	. 1	(K,N),(N,	N) DDDD				
hisotry of K-promes and win-	t-1 to	(IV,IV),(IV,	N), D, D, D, R				
histry of K profiles and win	+ 1 + 0	$(\mathbf{K},\mathbf{N}),(\mathbf{N},$	N) DDDD				
nisotry of K-promes and win-	1-1 10	(N, K), (N, K)	$\mathbf{K}$ ), $\mathbf{D}, \mathbf{D}, \mathbf{D}, \mathbf{D}, \mathbf{R}$				
hisotry of K profiles and win	t 1 to	$(\mathbf{N},\mathbf{N}),(\mathbf{R},$	N) BBBB				
ners	1-1 10	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$	N), $D, D, D, D, D$				
hisotry of K-profiles and win-	t-1 to	(IV,IV),(IV, IV)	N) BBBB				
ners	1-1 10	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	$\mathbf{K}$ ), $\mathbf{D}$ , $\mathbf{D}$				
hisotry of K-profiles and win-	t-1 to	(1, R), (1, R)	N) BBBB				
ners	0100	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$	N), $D, D, D, D, D$				
hisotry of K-profiles and win-	t-1 to	(1,1),(1,1)	N). B.B.B.R.				
ners	0 1 00	(N.K).(N.	N)				
hisotry of K-profiles and win-	t-1 to	t-4 $(N.N).(N.)$	N). B.B.B.R.				
ners		(N.N).(K.	K)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(N,	N), B,B,B,B				
ners		(N,N),(K,	N)				
hisotry of K-profiles and win-	t-1 to	t-4 (N,N),(N,	N), B,B,B,B				
ners		(N,N),(N,	K)				
					≫ Co	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,B,B,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,B,B,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,B,R,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\rm B,B,R,B}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,B,R,B}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,B,R,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,R,R,R}}$				
ners			(K,K),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(K,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,R,R,B}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,R,R,R}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\mathrm{B,R,B,R}}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-1	to t-4	(N,N),(N,N),	$_{\rm B,R,B,B}$				
ners	. 1	4 - 4 - 4	(K,N),(K,N)	חחחח				
nisotry of K-profiles and win-	T-1	to t-4	(IN,IN),(IN,IN), (IX,IN),(IN,IN),	в,к,в,в				
history of V profiles and win	L 1	4 - 4 1	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{K})$	סססס				
hisotry of K-promes and win-	U-1	. to t-4	(IN,IN),(IN,IN), (K,N),(N,N)	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
history of K profiles and win	+ 1	$to \pm 1$	$(\mathbf{I},\mathbf{I}\mathbf{N}),(\mathbf{I}\mathbf{N},\mathbf{I}\mathbf{N})$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	рррр				
nisotry of R-promes and will-	U-1	10 1-4	(IN,IN),(IN,IN), (K N) (N N)	D,11,D,11				
hisotry of K profiles and win	+ 1	to t 1	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$	BBBB				
ners	-1	10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$	D,10,D,10				
hisotry of K-profiles and win-	t_1	to t-4	(N, N), (N, N)	BBBB				
ners	-1		(N,K) (K N)	D,10,D,D				
hisotry of K-profiles and win-	t_1	to t-4	(N,N) (N N)	B.R.B B				
ners	-1		(N.K).(N.K)	2,10,2,2				
hisotry of K-profiles and win-	t-1	to t-4	(N,N).(N,N)	B.R.B.B				
ners			(N,K).(N,N)	_,10,2,2				
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Perio	d Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,B,R				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,B,R				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,B,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,B,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,B,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,B,R				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,R,R				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,R,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,R,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,R,B				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(N,N)	, B,R,R,R				
ners		(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	-4 (N,N),(K,K)	, R,R,R,R				
ners		(K,K),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	-4  (N,N), (K,K)	, R,R,R,B				
ners	. 1	(K,K),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	-4  (N,N),(K,K)	, к,к,к,в				
history of V profiles and win	41404	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{K})$	סססס				
hisotry of K-promes and win-	t-1 to t-	$(\mathbf{I},\mathbf{N}),(\mathbf{K},\mathbf{K})$	, п,п,п,д				
histry of K profiles and win	+ 1 + - +	$(\mathbf{K},\mathbf{K}),(\mathbf{N},\mathbf{N})$	סססס				
nisotry of K-promes and win-	t-1 to t-	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$	, n,n,n,n				
hisotry of K profiles and win	t 1 to t	$(\mathbf{I},\mathbf{I}),(\mathbf{I},\mathbf{I})$	BBBB				
ners	t-1 to t	(K N), (K K)	, 10,10,10,10				
hisotry of K-profiles and win-	t-1 to t	$(\mathbf{K}, \mathbf{N}), (\mathbf{K}, \mathbf{K})$	BBBB				
ners	01000	(K N) (K N)	, 10,10,10,10				
hisotry of K-profiles and win-	t-1 to t	(II,IV),(II,IV)	BBBB				
ners	01000	(K.N).(N.K)	,,,,,,,,,,,				
hisotry of K-profiles and win-	t-1 to t	(N.N).(K.K)	. R.R.B.B				
ners		(K.N).(N.N)	,,,,,				
hisotry of K-profiles and win-	t-1 to t	(1.0.1, 1.0.1,	, R.R.B.R				
ners		(K,N),(N,N)	, -, -, -, - 0				
					≫ Coi	ntinue to t	the next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Perio	d Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\rm R,2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,R				
ners		(N,K),(K,K	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,B				
ners		(N,K),(K,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,B				
ners		(N,K),(N,K)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,B				
ners		(N,K),(N,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,R				
ners		(N,K),(N,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,R				
ners		(N,N),(K,K)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,B				
ners		(N,N),(K,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,B				
ners		(N,N),(N,K)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,B				
ners		(N,N),(N,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,B,R				
ners		(N,N),(N,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,R,R				
ners		(N,N),(K,K)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,R,B				
ners		(N,N),(K,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N,N),(K,K)	), R,R,R,B				
ners		(N,N),(N,K)	)				
hisotry of K-profiles and win-	t-1 to t	-4  (N,N), (K,K)	), $\mathbf{R}, \mathbf{R}, \mathbf{R}, \mathbf{B}$				
ners	. 1	(N,N),(N,N)	)				
hisotry of K-profiles and win-	t-1 to t	-4  (N,N), (K,K)	), $\mathbf{R}, \mathbf{R}, \mathbf{R}, \mathbf{R}$				
history of V profiles and win	4 1 4 a 4	(IN,IN),(IN,IN)	) \				
hisotry of K-promes and win-	t-1 to t	$(\mathbf{I}\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	), $\mathbf{n}, \mathbf{D}, \mathbf{n}, \mathbf{n}$				
histry of K profiles and win	t 1 to t	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$					
nisotry of R-promes and will-	t-1 to t	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N})$	), $\mathbf{n}, \mathbf{D}, \mathbf{n}, \mathbf{D}$				
hisotry of K profiles and win	t 1 to t	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{N})$	) BBBB				
ners	U-1 10 U	$(\mathbf{K},\mathbf{K}),(\mathbf{K},\mathbf{K})$	), 10,0,10,0				
hisotry of K-profiles and win-	t-1 to t	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	) BBBB				
ners		(K K) (N N)	), 10,0,10,0				
hisotry of K-profiles and win-	t-1 to t	(N N) (K N)	). R.BBB				
ners	0 1 00 0	(K.K).(N N)	)				
hisotry of K-profiles and win-	t-1 to t	-4 (N.N).(K.N)	, R.B.B.R				
ners		(K.N).(K.K)	)				
		× , ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,,	/		» Co	ntinue to t	the next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Perio	d Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,B				
ners		(K,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,B				
ners		(K,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,B				
ners		(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,R				
ners		(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,R				
ners		(N,K),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,B				
ners		(N,K),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,B				
ners		(N,K),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(K,N)	, R,B,B,B				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 $(N,N),(K,N)$	, R,B,B,R				
ners		(N,K),(N,N)					
hisotry of K-profiles and win-	t-1 to t-	4 $(N,N),(K,N)$	, R,B,B,R				
ners		(N,N),(K,K)					
hisotry of K-profiles and win-	t-1 to t-	4  (N,N),(K,N)	, R,B,B,B				
ners		(N,N),(K,N)					
hisotry of K-profiles and win-	t-1 to t-	$4  (N,N),(K,N) \\ (N,N),(K,N)  (N,N)  (N,N$	, R,B,B,B				
ners		(N,N),(N,K)					
hisotry of K-profiles and win-	t-1 to t-	$4  (N,N),(K,N) \\ (N,N),(N,N)$	, к,в,в,в				
ners	. 1	(IN,IN),(IN,IN)	חחחח				
hisotry of K-promes and win-	t-1 to t-	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	, п,d,d,п				
histry of K profiles and win	t 1 to t	(IN,IN),(IN,IN) (N,N),(K,N)	DBDD				
nisotry of K-promes and win-	t-1 to t-	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	, п, <b>D</b> ,п,п				
histry of K profiles and win	t 1 to t	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{K})$	DBDB				
nisotry of K-promes and win-	t-1 to t-	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	, 11,D,11,D				
hisotry of K-profiles and win-	t-1 to t	$(\mathbf{I},\mathbf{N}),(\mathbf{I},\mathbf{N})$	BBBB				
ners	0-1 00 0-	(N,N)(N,K)	, 10,10,10,10				
hisotry of K-profiles and win-	t-1 to t-	4 (N N) (K N)	RBBB				
ners	01000	(N,N).(N,N)	, 10,2,10,2				
hisotry of K-profiles and win-	t-1 to t-	4 (N.N).(K.N)	. R.B.R.R				
ners		(N,N),(N.N)	, -, -, -, -•, -•				
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(N.K)	, R,B.R.R				
ners		(K,K),(K,K)	. , , , -				
hisotry of K-profiles and win-	t-1 to t-	4 (N,N),(N,K)	, R,B,R,B				
ners		(K,K),(K,N)					
					≫ Co	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	R,B,R,B				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\rm R,B,R,B}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,R,R}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,B,R}}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,B,B}}$				
ners			(K,N),(K,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,B,B}}$				
ners			(K,N),(N,K)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,B,B}}$	0.000	0.000	0.000	0.000
ners			(K,N),(N,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,R}}$				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,R}}$				
ners			(N,K),(K,K)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	$_{\mathrm{R,B,B,B}}$				
ners			(N,K),(K,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	R,B,B,B				
ners			(N,K),(N,K)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	R,B,B,B				
ners			(N,K),(N,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K),	R,B,B,R				
ners		. 1	(N,K),(N,N)					
nisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,K), (N,N),(K,K)	к,в,в,к				
histry of K profiles and win		+1 to $+1$	(N,N),(K,K) (N,N),(N,K)	рррр				
moory of K-promes and win-		1-1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	п, в, в, в				
histry of K profiles and win		t 1 to t 1	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{N})$	DBBB				
nisotry of K-promes and win-		1-1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$	п, ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K profiles and win		$\pm 1 \pm 0 \pm 4$	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{K})$	BBBB				
ners		1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{R}),$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	п,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-		t-1 to t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	BBBB				
ners		010004	(N,N),(N,N),(N,N)	10,12,12,10				
hisotry of K-profiles and win-		t-1 to t-4	(N,N) (N K)	BBBB				
ners			(N,N).(K,K)	10,12,10,10				
hisotry of K-profiles and win-		t-1 to t-4	(N,N).(N,K).	B.B.B.B				
ners			(N,N).(K,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N).(N.K).	R,B,R.B				
ners			(N,N),(N,K)	, , -,				
						>> Cont	inue to the	e next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Pe	eriod	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,K),	R,B,R,B				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,K),	R,B,R,R				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{ m R,B,R,R}$				
ners			(K,K),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{\mathrm{R,B,R,B}}$				
ners			(K,K),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{\mathrm{R,B,R,B}}$				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{\mathrm{R,B,R,B}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{\mathrm{R,B,R,R}}$				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{\mathrm{R,B,B,R}}$				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	$_{\mathrm{R,B,B,B}}$				
ners			(K,N),(K,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	R,B,B,B				
ners			(K,N),(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	R,B,B,B				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 f	o t-4	(N,N),(N,N),	R,B,B,R				
ners			(K,N),(N,N)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N),	R,B,B,R				
ners	. 1 .		(N,K),(K,K)					
hisotry of K-promes and win-	l-1 (	0 1-4	(IN,IN),(IN,IN), (N,K),(K,N)	п, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,				
histry of K profiles and win	+ 1 +	ot 1	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N})$	DBBB				
nisotry of K-promes and win-	U-1 U	0 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$	п, в, в, в				
histry of K profiles and win	+ 1 +	ot 1	$(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{K})$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	DBBB				
nisotry of K-promes and win-	U-1 (	0 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{N},\mathbf{N})$	п, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,, ,				
hisotry of K-profiles and win-	+_1 +	o t-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	RBBB				
ners	U-1 (	0 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$	п.,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				
hisotry of K-profiles and win-	+_1 +	o t-4	(N,N) $(N,N)$	RBBB				
ners	010	011	(N,N) (K K)	10,00,00,10				
hisotry of K-profiles and win-	t-1 f	o t-4	(N,N),(N,N	R.B.B.B				
ners	01		(N.N).(K.N)	10,2,2,2,2				
hisotry of K-profiles and win-	t-1 t	o t-4	(N.N).(N.N).	R.B.B.B				
ners			(N,N).(N,K)					
hisotry of K-profiles and win-	t-1 t	o t-4	(N,N),(N,N).	R,B,B,B				
ners			(N,N),(N,N)	, , , ,				
						≫ Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	R,B,B,R				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	R,B,R,R				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{ m R,B,R,B}$				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{\mathrm{R,B,R,B}}$				
ners			(N,N),(N,K)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{\rm R,B,R,B}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{\mathrm{R,B,R,R}}$				
ners			(N,N),(N,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{\mathrm{R,R,R,R}}$				
ners			(K,K),(K,K)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{\mathrm{R,R,R,B}}$				
ners			(K,K),(K,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	$_{\mathrm{R,R,R,B}}$				
ners			(K,K),(N,K)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	R,R,R,B				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	R,R,R,R				
ners			(K,K),(N,N)					
hisotry of K-profiles and win-	t-1	l to t-4	(N,N),(N,N),	R,R,B,R				
ners			(K,N),(K,K)					
hisotry of K-profiles and win-	t-I	l to t-4	(N,N),(N,N),	R,R,B,B				
ners			(K,N),(K,N)					
hisotry of K-profiles and win-	t-J	l to t-4	(N,N),(N,N),	R,R,B,B				
ners			(K,N),(N,K)					
nisotry of K-profiles and win-	t-J	l to t-4	(IN,IN),(IN,IN), (IZ,NI),(IN,IN)	к,к,в,в				
ners			$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$					
nisotry of K-profiles and win-	t-1	l to t-4	(IN,IN),(IN,IN), (IZ,N),(IN,IN)	к,к,в,к				
histry of K profiles and win	+ 1	$1 \pm \alpha \pm 4$	$(\mathbf{K},\mathbf{N}),(\mathbf{N},\mathbf{N})$	рррр				
nisotry of K-promes and win-	U-1	1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$	n,n,D,n				
histry of K profiles and win	+ 1	$1 \pm 0 \pm 1$	$(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{K})$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	DDBB				
nisotry of R-promes and win-	0-1	1 10 1-4	$(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N}),$ $(\mathbf{N},\mathbf{K}),(\mathbf{K},\mathbf{N})$	п,п,Б,Б				
hisotry of K-profiles and win-	<b>t</b> _1	to t-1	$(\mathbf{N},\mathbf{N}),(\mathbf{R},\mathbf{N})$	RRBR				
ners	U-1	100-1	(N K) (N K)	10,10,10,10				
hisotry of K-profiles and win-	<b>+</b> _1	to t-4	(N N) (N N)	BBBB				
ners	0-1		(N,K) (N N)	10,10,10,10				
hisotry of K-profiles and win-	t1	to t-4	(N,N) $(N,N)$	R.R.B.R				
ners	0 1		(N,K).(N,N)					
			( ) ))()			» Cor	ntinue to t	he next page.

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player	Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R},2}$	$\beta_{ m R,3}$	$\beta_{\mathrm{R},K}$
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,N),	$_{\mathrm{R,R,B,R}}$				
ners			(N,N),(K,K)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,N),	R,R,B,B				
ners			(N,N),(K,N)					
hisotry of K-profiles and win-		t-1 to t-4	(N,N),(N,N),	R,R,B,B				
ners		. 1	(N,N),(N,K)					
hisotry of K-profiles and win-		t-1 to t-4	(IN,IN),(IN,IN),	R,R,B,B				
history of K profiles and min		+ 1 + + + 1	(IN,IN),(IN,IN) (N,IN),(N,IN)	חחחח				
hisotry of K-promes and win-		t-1 to t-4	(IN,IN),(IN,IN), (N,N),(N,N)	п,п,д,п				
history of K profiles and win		+ 1 + 0 + 1	(IN,IN),(IN,IN) (N,IN),(N,IN)	סססס				
nisotry of K-promes and win-		1-1 10 1-4	(IN,IN),(IN,IN), (N,N),(K,K)	11,11,11,11				
hisotry of K profiles and win		$\pm 1$ to $\pm 4$	$(\mathbf{N},\mathbf{N}),(\mathbf{K},\mathbf{K})$ $(\mathbf{N},\mathbf{N}),(\mathbf{N},\mathbf{N})$	BBBB				
nisotry of R-promes and win-		1-1 10 1-4	(IV,IV),(IV,IV), (N N) (K N)	п,п,п,				
hisotry of K-profiles and win-		t-1 to t-1	$(\mathbf{N},\mathbf{N}),(\mathbf{R},\mathbf{N})$	BBBB				
ners		1-1 10 1-4	(N,N),(N,K),(N,K)	10,10,10,10				
hisotry of K-profiles and win-		t-1 to t-4	(N,N) (N N)	BBBB				
ners		010001	(N,N),(N,N)	10,10,10,10				
hisotry of K-profiles and win-		t-1 to t-4	(N.N).(N.N).	R.R.R.R				
ners			(N.N).(N.N)	_ = = = = = = = = = = = = = = =				
period constant		5						-0.016
period constant		6			0.065			-0.072
period constant		7						
period constant		8				-0.003	0.025	
period constant		9						
period constant		10						
period constant		11				0.011	-0.042	
period constant		12				0.025		
period constant		13						0.001
period constant		14						
period constant		15						
period constant		16						
period constant		17						0.042
period constant		18				-0.036	0.003	
period constant		19			0.000	0.000	0.000	0.000
period constant		20				-0.007		
period constant		21						
period constant		22			0.019			
period constant		23						0.058
period constant		24			-0.024		0.061	
$\gg$ Continue to the next page.								

Table 13. Full coefficients table of LASSO (Red player, cont.)

Variable type	Player Period	Card	Winner	$\beta_{\mathrm{R},1}$	$\beta_{\mathrm{R,2}}$	$\beta_{\mathrm{R},3}$	$\beta_{\mathrm{R},K}$
period constant	25						
period constant	26			0.001	-0.013		
period constant	27			-0.035	0.028		
period constant	28						
period constant	29						
period constant	30						0.197

Table 13. Full coefficients table of LASSO (Red player, cont.)