Outcome Prediction of DOTA2 Using Machine Learning Methods

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ABSTRACT

With the wide spreading of network and capital inflows, Electronic Sport (ES) is developing rapidly in recent years and has become a competitive sport that cannot be ignored. Compared with traditional sports, the data of this industry is large in size and has the characteristics of easy-accessing and normalization. Based on these, data mining and machine learning methods can be applied to improve players' skills and help players make strategies. In this paper, a new approach predicting the outcome of an electronic sport DOTA2 was proposed. In earlier studies, the heroes' draft of a team was represented by unit vectors or its evolution, so the complex interactions among heroes were not captured. In our approach, the outcome prediction was performed in two steps. In the first step, Heroes in DOTA2 were quantified from 17 aspects in a more accurate way. In the second step, we proposed a new method to represent a heroes' draft. A priority table of 113 heroes was created based on the prior knowledge to support this method. The evaluation indexes of several machine learning methods on this task have been compared and analyzed in this paper. Experimental results demonstrate that our method was more effective and accurate than previous methods.

CCS Concepts

• Computing methodologies→ Machine learning

Keywords

DOTA2; Machine Learning; Electronic Sports.

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1. INTRODUCTION

DOTA2 is a worldwide popular Multiplayer Online Battle Arena(MOBA) game. In each game ten players are divided into two teams (Radiant and Dire) average. Each player picks and controls a game character (usually called hero) from a pool of 113 heroes. The team that destroys the enemy's base first will win. In order to achieve this goal, players need to accumulate gold and experience to purchase items and upgrade skills by killing enemy soldiers, heroes and destroying enemy's defense towers.

In a DOTA2 match, 10 different heroes are picked from the heroes' pool (113 heroes, September 2017) by two teams, in other words, there are

$$\frac{C_{113}^{5} * C_{108}^{5}}{2} = 4.69 \times 10^{17}$$

different heroes' draft to be selected. Different heroes have their own skills and roles in the team. There are five roles in DOTA2: Carry, Solo, Offlane, Support and Hard-Support. Complex interactions are among the heroes for their restraints and improvement to each other.

In major championships, both audiences and players are greatly interested in outcome prediction once the heroes' draft has been determined in a match. An accurate prediction method can establish tournament's authority and improve the enjoyment of the audiences. For players, it can also help build their advantages during the BP (ban & pick) phase. In TI7 (The International DOTA2 Championships 2017), an artificial intelligence nonprofit organization called OpenAI proposed a DOTA2 bot. It challenged 'Dendi', which was one of the best human players, to a 1v1 match. The result was that 'Dendi' has been completely defeated (see Figure 1).

OpenAI said the bot learned the game from scratch by self-play, and does not use imitation learning or tree search. That is a step towards building AI systems which accomplish well-defined goals in messy, complicated situations involving real humans. Their next goal is to get the bot ready for the infinitely more complex 5v5 matches, it might have something ready in TI8.

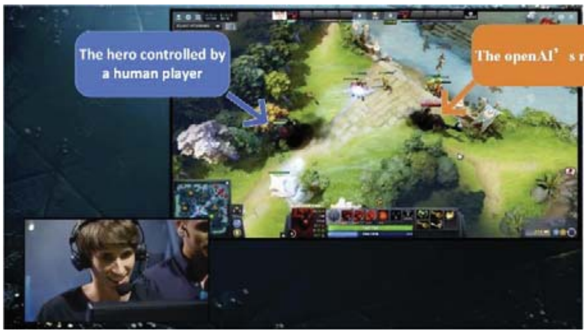

Figure 1. OpenAI's bot dispatches DOTA2's top players live at TI7.

For any team that attempt to win a match needs to analysis the hero drafts of both sides to find the strengths and weaknesses and develop strategies. This work is usually completed by one or more players in a human team. So how to BP heroes and evaluate strengths and weaknesses of the heroes' draft have become an important issue for a robot team. Predicting the outcome of a match from its hero draft is a significant step for the target.

Despite the effect of hero choosing, the Match Making Rating (MMR) of players is the main factor affecting the match result, and it makes the result hard to be predicted. Expert's prediction has been used in most cases nowadays. Different from traditional sports, the data of electronic sports are easily collected. Therefore, machine learning methods can be well used with these large amounts of data. In the paper, a new approach to predict the outcome of a match was developed. In our approach, outcome prediction was performed in two steps. In the first step, Heroes in DOTA2 were quantified from 17 aspects in a more accurate way. In the second step, we proposed a new method to represent heroes' draft. A priority table of 113 heroes was created based on the prior knowledge to support this method. The evaluation indexes of several machine learning methods on this task have been compared and analyzed in this paper. Experimental results demonstrate that our method was more effective and accurate than previous methods.

2. RELATED WORKS

DOTA2 got attention from researchers only recently, the main research directions are 1) outcome prediction from team draft [1][2][3][4][5]. 2) real time prediction [6][7]. 3) BP system [4] 4) AI heroes.

Johansson and Wikstrom have made a real-time prediction in their paper [6] they attempted to create a model using machine learning that can predict the winning team of a DOTA2 game given partial data collected as the game progressed, a couple of different classifiers were tested, out of these Random Forest was chosen to be studied more in depth. Wijaya and Baskara analyzed the interface design of DOTA2 using SAW method for the beginner players by using one of the design principles, ease of use [8] Drachen and Yancey presented three data-driven measures of spatiotemporal behavior in DOTA2: 1) Zone changes; 2) Distribution of team members and: 3) Time series clustering via a fuzzy approach. They presented a method for obtaining accurate positional data from DOTA2. They investigated how behavior varies across these measures as a function of the skill level of teams, using four tiers from novice to professional players [9]

Among the above research directions, the winning probability prediction from team draft is the most popular topic in applications of machine learning to DOTA2. Conley & Perry were the first to demonstrate the importance of information from the draft stage of the game with Logistic Regression and k-Nearest Neighbors (kNN) [2] Wang tries to use naive Bayes model to solve this problem [5]. However, they all represented the heroes' draft by a vector with only value of 0 or 1, it is very clear that the interaction among heroes within and between teams were hard to capture with such a simplistic approach.

Agarwala and Pearce tried to take that into account including the interactions among heroes into the logistic regression model [1]. To define a role of each hero and model their interactions, they used PCA analysis of the heroes' statistics (kills, deaths, gold per minute etc.). However, they got a worse result than without considering the interactions. Although too few features they extracted lead to the PCA-based models could not match predictive accuracy of logistic regression, the composition of teams they suggested looked more balanced and reasonable from the game's point of view. Another approach to that problem of modeling heroes' interactions was proposed by Kuangyan Song [3]. They took 6,000 matches and manually added 50 combinations of two heroes to the features set and used forward stepwise regression for feature selection. With 10-fold CV for Logistic Regression on 3,000 matches. They concluded that only addition of particular heroes improves the model while the others might cause the prediction to go wrong.

The main defects of current methods of outcome prediction from drafts are: 1) the more representative interactions were not captured. 2) 0-1 vectors remain too much useless information that could slow the training speed. 3) 0-1 vectors have significant limitations for it cannot carry more heroes' features. The following sections will describe how we solve those problems.

3. DATA SETS

To get enough real match data, we used the valve's (The company that developed DOTA2) API. The API allows participants to get detailed information about a match by its number. The information includes the account id of players, heroes used, tower damage and hero damage, gold of players, duration, score on both sides, etc.

DOTA2 matches players by their own rank, and the players with similar rank will be matched together. After every ranked match, the MMR of each player in the winning team increases while for the defeated team, the MMR decreases accordingly. This mechanism ensures the two-opposing team are approximately at the same level. In other words, it weakens the effect of players' skills on the match result. However, it is undeniable that the player strength is still an important factor affecting the results of the game. To explore the impact of this factor on the outcome of the game, we split the dataset into two part.

Data set I:

Considering players with low MMR are less able to play full ability of a hero, low-level matches were not used in the training. What we need is the match data of players with high MMR. To get enough high-level match data, an effective method has been implemented. We set "IG.V.Paparazi", the player with highest rank in China (As of September 2017), as a seed. Search for his last 200 matches, list the players who play with him in these matches, then search for their last 200 matches. So that we obtained at most 360200 high-level matches. After filtering out the duplicate data, we collected 125255 different real match data.

Data set II:

To further eliminate the effect of player strength on game results and make the data more representative, we finally selected 38629 match data, all winning teams in the reserved matches have at least twice as much scores as their opponents.

These data sets have the following advantages:1) real and reliable. 2) high-level matches can faithfully reflect the interactions among heroes. 3) Further filtering makes the interactions more obvious.

Our experiments were all completed on those data sets or their subset.

4. FEATURES EXTRACTION FOR HEROES

Heroes have a variety of abilities, such as output damage, heal teammates, control enemies, etc. We divided these abilities into two categories:1) explicit abilities and 2) hidden abilities. An effective feature extraction method requires correctly describe both of the two kinds of abilities. For explicit abilities, it is uncomplicated to describe it by statistical analyzing the heroes' data, such as GPM, XPM, last hits. But this simple method does not work for hidden abilities. Previous researchers have adopted different methods to extract the features of each hero, however the aspects of extraction are not comprehensively considered. To solve this problem, we developed a new approach which is suitable for DOTA2 as well as other MOBA games. We consider that each hero has three levels of inherent features: a) Attributes. b) Statistics. c) Probability. Therefore, we quantify a hero from three levels and 17 aspects, that is, each hero can be mapped into a vector of length 17. The details are shown in Figure 2:

Figure 2. The heroes' features

These features are explained as follows:

1. **Hero damage**: the damage to enemy heroes, including magic damage and physical damage. This feature demonstrates a hero's ability to output damage.

2. **Tower damage**: the damage to enemy structures which can be physical damage only. This feature describes a hero's ability to output physical damage and the ability to attack structures.

3. **Hero healing**: the healing for teammates.

4. **Assists**: the times of helping friendly heroes kill enemies. This feature describes the melee ability of a hero.

5. **Deaths**: death frequency of the heroes during the match. This feature describes the viability of the heroes.

6. **GPM**: average increment of gold per minute during a match. Gold can be used to purchase items, the hero with more gold accordingly has better items.

7. **Last hits**: the number of units killed by a hero, including towers, heroes and soldiers. The last hits are mainly from killing enemy soldiers. This feature describes a hero's pushing ability.

8. **Gold difference**: we statistical analyzed the gold gain speed of each hero in the winning and failing matches separately, and calculate the differences to describe a hero's handing stress ability while under inferior position.

9. **Duration of winning match**: different heroes have their own strong period during a match in DOTA2. As shown in Figure3, we plotted the curves of duration of winning match of 3 different heroes: Lina, Spectre and Lycanthrope. From this figure, you can see Lycanthrope will be stronger in the early period, but Spectre's strong period is later, and Lina's is between them. To extract the feature of heroes' strong period, we statistical analyzed the duration of their winning matches.

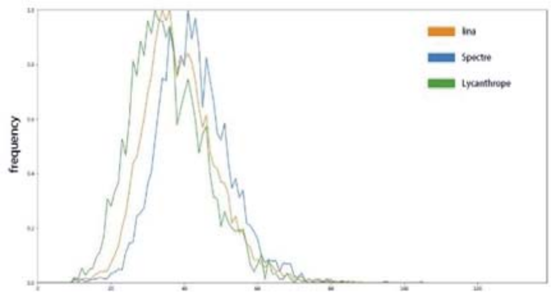

Figure 3. Different heroes have different strong periods

10. **Initial attribute**: each hero has three attributes: intelligence, strength, agility. Different attributes bring different amounts of mana point, health point, and defense.

11. **Attribute gain**: the attributes will increase with the heroes' upgrade. Different heroes have different increased step length; different attributes have different increased step length for one hero as well.

12. **Winning probability Ⅰ**: this feature was statistical analyzed from the high-level match data of past two months according to the following formula:

$$P^i{}_{\mathrm{I}} = \frac{cont^i{}_w}{cont^i}$$

Where $cont^i$ stand for the number of matches that hero i has been picked, $cont^i{}_w$ stand for the number of matches that hero i has won.

13. **Winning probability Ⅱ:** We developed a method to quantify the objective synergy and counter between individual heroes through statistical analysis. For any two heroes i and j, we call $P_c(i|j)$ the counter coefficient of j against i.

$$P_c(i|j) = \frac{cont_j^i{}_w}{cont_j^i} - P^i{}_{\mathrm{I}}$$

where $cont_j^i$ is the number of matches that hero i and hero j were picked as opponents, $cont_j^i{}_w$ is the number of matches that i defeats j.

We call $P_s(i,j)$ the synergistic coefficient between j and i.

$$P_s(i,j) = \frac{cont_{i,j}{}_w}{cont_{i,j}} - P^i{}_{\mathrm{I}}$$

Where $cont_{i,j}$ is the number of matches that hero i and hero j were picked as teammates, $cont_{i,j}{}_w$ is the number of matches that i and j won the game.

Then calculate the Winning probability Ⅱ of a hero by the following formula:

$$P^i{}_{\mathrm{II}} = \sum_{j \in teammates} P_s(i,j) + \sum_{k \in opponents} P_c(i|k)$$

It should be noted that, the winning probability Ⅱ is not the same in different draft for a hero. The counter and synergistic coefficients between every two heroes were visualized as Figure 4 and Figure 5.

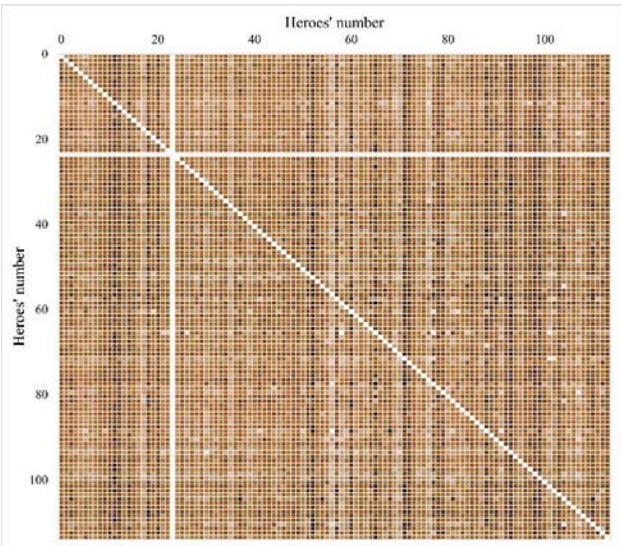

Figure 4. Counter coefficients, each unit stand for the counter degree between corresponding heroes. The darker the color is, the stronger the relationship is.

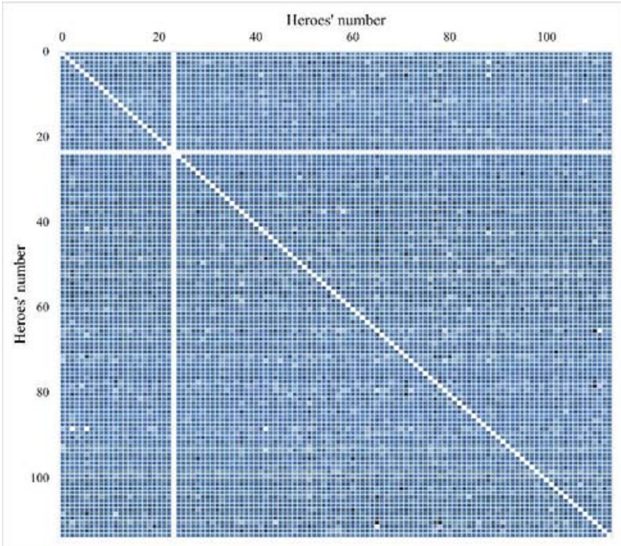

Figure 5. Synergistic coefficients, each unit stand for the synergistic degree between corresponding heroes. The darker the color is, the stronger the relationship is.

14. **Predictive value of Naïve Bayes model:** after repeated Wang's experiment, we produced the idea that treat the results predicted by the Naïve Bayes model as a feature incorporate into the feature vector. There are two reasons for its feasibility:1) the predictive value of the Naïve Bayes model is continuous and 2) relatively reliable.

The Naïve Bayes classifier greatly simplify learning by assuming that features are independent given class. Wang's outcome prediction classifier also based on this hypothesis. He used a vector of length 115 to represent a heroes' draft with only value of 0, 1, and -1 in the vector. The first attribute represents the result of the game with the value of 1 or -1. 1 means victory for the team Radiant and -1 represents victory for the team Dire. Attribute 2 to the 115 represent the selection of heroes with the value of 1, 0 and -1. If the hero is selected by Radiant, the value will be 1, and -1 for team Dire. In addition, 0 means the hero has not been selected by any team.

According to the Bayes' theorem, the wining probability of a given heroes' draft $x(C, a_1, a_2, \ldots, a_{114})$ is:

$$P\big(c_i\big|(a_1, a_2, \ldots, a_{114})\big) = P(c_i) \times \frac{P((a_1, a_2, \ldots, a_{114})|c_i)}{P(a_1, a_2, \ldots, a_{114})}$$

Where c_i stand for Radiant win or Dire win. Then simplifies the above equation with the conditional independence hypothesis into the following form:

$$P\big(c_i\big|(a_4, a_5, \ldots, a_{116})\big) = P(c_i) \times \prod_{j=1}^{n} P(a_j|c_i)$$

The priori probability can be obtained by statistical analyzing a large amount of match data:

$$P\big(a_j\big|c_i\big) = \frac{count(a_j)}{count(c_i)}$$

$$P\big(c_i\big) = \frac{count(c_i)}{count}$$

Finally, the relative winning probability is:

$$P(Radiant\ win) = \frac{P\big(1\big|(a_1, \ldots, a_{114})\big)}{P\big(1\big|(a_1, \ldots, a_{114})\big) + P\big(-1\big|(a_1, \ldots, a_{114})\big)}$$

$$P(Dire\ win) = \frac{P\big(-1\big|(a_1, \dots, a_{114})\big)}{P\big(1\big|(a_1, \dots, a_{114})\big) + P\big(-1\big|(a_1, \dots, a_{114})\big)}$$

Then draw a conclusion by comparing the value of $P(Radiant)$ and $P(Dire)$.

His experiment shows that it is a relatively efficient classifier. However, the accuracy of Naive Bayes classifier needs to be improved. The reason is that Naive Bayes makes the conditional independence hypothesis for conditional probability distribution, that is:

$$P(X = x|Y = c_k) = P(X^{(l)} = x^{(1)}, \dots, X^{(n)} = x^{(n)}|Y = c_k)$$
$$= \prod_{j=1}^{n} P\big(X^j = x^j\big|Y = c_k\big)$$

In other words, Naïve Bayes model assumes that every pick of heroes is independent and distributed. This is clearly untenable. In fact, to make the heroes' draft more reasonable, players are purposeful when choosing a hero. For instance, if two players have picked a Carry hero and a Solo hero, other teammates will no more pick a Carry hero. Although outcome prediction only based on Naïve Bayes Model is not accurate enough, it still worth to reference.

Through the above feature extraction method, for each hero, we obtain 17 features, these features were normalized according to the following formula:

$$f_i = \frac{f_i - f_{min}}{f_{max} - f_{min}}$$

5. A NEW APPROACH TO REPRESENT THE HEROES' DRAFT

The outcome prediction of DOTA2 can be described as a two-classification problem with only two different results: Radiant win or Radiant lose. If the heroes' drafts are represented by continuous vectors correctly, the prediction problem can be solved by using machine learning methods with a large amount of match data.

In the previous studies, heroes' drafts were represented by 0-1 vectors. The vectors are shown as follows:

$$x_i = \begin{cases} 1 & if\ hero\ i\ is\ picked\ by\ Ridant \\ 0 & if\ hero\ i\ is\ not\ picked \end{cases}$$

$$x_{i+114} = \begin{cases} 1 & if\ hero\ i\ is\ picked\ by\ Dire \\ 0 & if\ hero\ i\ is\ not\ picked \end{cases}$$

or

$$x_i = \begin{cases} 1 & if\ hero\ i\ is\ picked\ by\ Ridant \\ -1 & if\ hero\ i\ is\ picked\ by\ Dire \\ 0 & otherwise \end{cases}$$

Where i stand for the hero's number (No.24 has no corresponding hero), x stand for eigenvector of the draft. It is noteworthy that the results of these two methods are equal for machine learning algorithms. Besides, this method is more like a description of heroes' co-occurrence due to the lack of consideration of the interaction among heroes. As mentioned above, there are 4.69×10^{17} different drafts to be selected. It is difficult and inaccurate to use a model trained on tens of thousands of data to predict so many possibilities. Only by developing a different approach can we solve this problem.

To extract the features that can capture the interaction among heroes within and between teams, we developed a new approach: 113 heroes are quantified from 17 different aspects, such as: average hero damage, average tower damage, average gold per minute (gpm), average experience per minute (xpm). For example, assuming each hero has n features. i th hero's features are represented as

$$F_i = < f_0^i, f_1^i, \dots, f_n^i >$$

When the team draft has been selected, the sequence of heroes' number is determined. Suppose Radiant pick $< 23{,}45{,}89{,}113{,}0 >$; Dire pick $< 99{,}24{,}58{,}11{,}8 >$. Re-ordering the heroes' number in the following order:

$$< \mathrm{Carry, Solo, Offlaner, Support, Hard - Support} >$$

A priority table was designed manually according to the prior knowledge to automate the re-ordering procedures.

In this case, the rearranged draft is Radiant:$< 0, 113, 45, 89, 23 >$; Dire:$< 8, 58, 24, 99, 11 >$. By Concatenating them, we obtain a eigenvector of length $10 * n$,:

$$< F_0, F_{113}, F_{45}, F_{89}, F_{23}, F_8, F_{58}, F_{24}, F_{99}, F_{11} >$$

This process is illustrated in Figure 6:

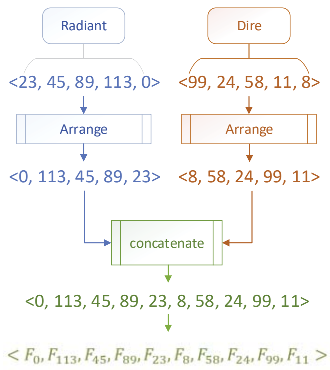

Figure 6. The method of representing the heroes' draft

The feature vectors represented by this approach have the following advantages:1) continuous. 2) the implication of each component of the vector is unchanged. We expect to explore the interaction among heroes through this extraction method.

6. EXPERIMENT AND ANALYSIS

This section presents the results of performance of several machine learning methods on the dataset under study. The experiments were completed with Scikit-learn [10] on Python with an AMD Ryzen 5 1400(3.20GHz) processor. In order to verify the effectiveness of the proposed method in this paper, many experiments, in which feature vectors were obtained by different methods, have been implemented and the experimental results have been analyzed.

The two feature extraction methods are 1) the classical method: represent a draft with 0-1 vector. 2) the method proposed in this paper. Three kinds of classifiers have been used to predict the outcomes of matches. The experiments were completed on the data set I, which contains 125255 samples, including 58061 positive samples and 67194 negative samples. Before the experiments, 18789 samples have been selected as the test data set randomly, the remaining data were the training data set, so the test set and the training set were the same for all the experiments. The results are shown in the Table 1 and Table 2:

Table 1. The results of the classical feature extraction method

classifier	classification	precision	recall	f1-score	support
Logistic Regression	-1	0.58666	0.7221	0.64737	10144
	1	0.55275	0.40301	0.46615	8645
	total	0.57106	0.57528	0.56399	18789
Random Forests	-1	0.58623	0.73423	0.65193	10144
	1	0.55687	0.3919	0.46004	8645
	total	0.57272	0.57672	0.56364	18789
SVM	-1	0.58972	0.72052	0.64859	10144
	1	0.55668	0.4118	0.4734	8645
	total	0.57452	0.57848	0.56799	18789

Table 2. The results of the feature extraction method proposed in this paper

classifier	classification	precision	recall	f1-score	support
Logistic Regression	-1	0.65436	0.70584	0.67912	10144
	1	0.61973	0.56252	0.58974	8645
	total	0.63842	0.63990	0.63800	18789
Random Forests	-1	0.63139	0.73925	0.68108	10144
	1	0.61733	0.49358	0.54856	8645
	total	0.62492	0.62622	0.62011	18789
SVM	-1	0.65446	0.72240	0.68675	10144
	1	0.62908	0.55246	0.58829	8645
	total	0.64278	0.64421	0.64145	18789

The classification evaluation indexes showed that using new method makes the classification accuracy have been significantly improved. This is a result of extracting more accurate features. As mentioned above, 17 features were extracted for each hero. With the increase of the number of features, the prediction accuracy also increases. We draw a fold line chart (see Figure 7) to show the relationship between the number of features and the accuracy (using Logistic Regression). From the chart we can see an obvious promotion after considering the winning probability II.

Furthermore, we have completed the same experiments on data set II. As we mentioned above, data set II only contains the match data that the winning teams have at least twice as much scores as their opponents in those matches. There are stronger constraints between two sides, because usually only the great advantage of drafts can lead to such one-sided situations. Thus, these data further reduce effect of the players' skills on the game, and using these data to test can better reflect the real ability of the model. The results are shown in Table 3:

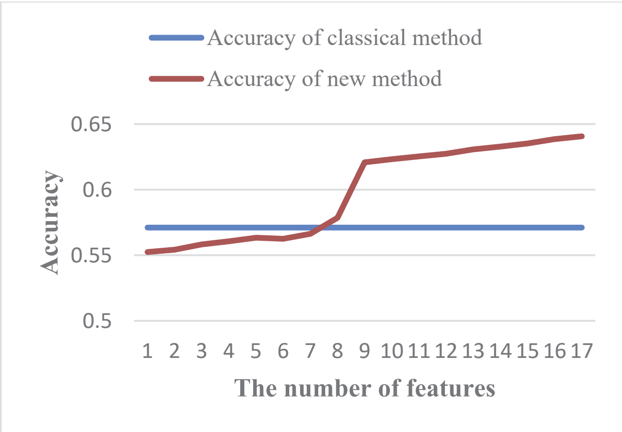

Figure 7. There is a positive correlation between the number of features and the accuracy

Table 3. Results on data set II

classifier	classification	precision	recall	f1-score	support
Logistic Regression	-1	0.72972	0.77826	0.75321	3202
	1	0.70168	0.64404	0.67163	2593
	total	0.71717	0.71821	0.71671	5795
	-1	0.71603	0.76702	0.74065	3202

Forests	1	0.68457	0.62437	0.65309	2593
	total	0.70195	0.70319	0.70147	5795
SVM	-1	0.72831	0.79700	0.76111	3202
	1	0.71628	0.63286	0.67199	2593
	total	0.72293	0.72355	0.72123	5795

From above Table 3, we can see after further reducing the effect of the players' skills, the evaluation indexes have been significantly improved. These experiments have proved the effectiveness of the feature extraction method proposed in this paper, and reflected the influence degree of players' skills on the games.

7. CONCLUSION

Predicting the results of DOTA2 matches form heroes' drafts is a valuable and interesting problem. As researchers pay more attention to the interaction among heroes, feature extraction of heroes becomes more critical. This work is still in the early stage, but both previous researches and the method proposed in this paper are significant attempts. The contribution of this article is to extract the heroes' features faithfully in more details. Heroes' features have been divided into 3 levels and 17 aspects to describe heroes' explicit abilities and hidden abilities in a better way. Besides, a new approach to represent the heroes' draft has been introduced in this paper. We re-order the heroes' sequence according to a priority table to make the implication of each component in the feature vector fixed. This method can carry more features and reduce the useless information. Although the results of this paper were far better than classical method, we still found that the extraction of heroes' features was not comprehensive. This is because the data published by Valve lacks important information such as control time, deceleration time etc. Moreover, the previous authors used different data sets in their researches, so this factor weakens the reference value of their experimental results. Therefore, we call on Valve here to publish the standard data sets, add more match details and update it in time to promote the development of machine learning in DOTA2 and even ES.

8. ACKNOWLEDGMENTS

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