DOTA2 MATCH RESULT PREDICTION BASED ON HERO LINEUPS

NEW YORK UNIVERSITY

TEAM 509: ZHAOYIN ZHU AND SHUANG ZHOU

DOTA 2

INTRODUCTION

Dota 2 is a free-to-play multiplayer online battle arena (MOBA) video game developed and published by Valve Corporation. Dota 2 is played in matches between two five-player teams, represented by the name "dire" and "radiant", each of which occupies a stronghold in a corner of the playing field.

A team wins by destroying the other side's "Ancient" building, located within the opposing stronghold. Each player controls one of 113 playable "Hero" characters that feature unique powers and styles of play. During a match, the player collects gold, items, and experience points for their Hero, while combating Heroes of the opposite team.

MOTIVATION

ESports are getting growing attention and popularity. In 2015, the fifth TI tounament (TI5) in Seattle had the largest prize pool in eSports history, with a total of \$10.9 million. Therefore, it is very worthwhile to research the strategies and tactics within the game to have a better chance against competitions,yet this is a very new ground awaiting discovery.

Each match in Dota starts with the players picking their heroes. This stage of a match is much more important than it seems, and very often a bad lineup will pretty much rule the team out. A lot of strategies can be applied during the banning and picking. To name a few, a team may want to ban the heroes that worked really well for the opposing team before, or they want to counter a specific hero in the opposing lineup by picking one that can contain it with a later pick, or they want to achieve a 1+1 > 2 effect by designing their lineup in a way that heroes supplement each other.

OBJECTIVES

With the purpose of proposing a programmatic strategy to pick out a lineup that puts a team in the driver seat before the match even begins, two capstones have been established:

- Predict the outcome of a match given only the lineups under the assumption that both sides perform around the same level.
- In order to obtain a high winning rate, recommend a sequence of picks in response to another sequence of picks to simulate the actual hero selection stage.

RESULTS

After some trials, the number of appearances in the dataset has random effect on performance, that is, no obvious relation between the threshold we set and the accuracy we obtain is observed. The best cut-off point for Pearson correlation coefficients is 0.011. Furthermore, model-based penalized methods do not increase accuracy significantly.

The best performers among various models after feature selection is displayed in the following table,

Model	Training	Validation
Random Forest	0.9967	0.6285
SVM	0.8403	0.6720
Logistic Regression	0.7861	0.6800

Other trials are Decision Trees, KNN classifier and adaBoost. However, these models prove to be ill-suited for this dataset so we have omitted them in the table.

METHODS

The outcome of this data is binary and defined as:

$$Y = \begin{cases} 1, \text{if radiant wins} \\ 0, \text{otherwise} \end{cases}$$

In order to achieve desirable prediction accuracy, 3 types of features are included as potential predictors:

Single heroes:

$$D_i = \begin{cases} 1, \text{if dire has hero with id i} \\ 0, \text{otherwise} \end{cases}$$

$$R_i = \begin{cases} 1, \text{if radiant has hero with id i} \\ 0, \text{otherwise} \end{cases}$$

Joint combinations of two heroes on the same side

$$D_iD_j = \begin{cases} 1, \text{if dire has both hero i and hero j} \\ 0, \text{otherwise} \end{cases}$$

$$R_iR_j = \begin{cases} 1, \text{if radiant has both hero i and hero j} \\ 0, \text{otherwise} \end{cases}$$

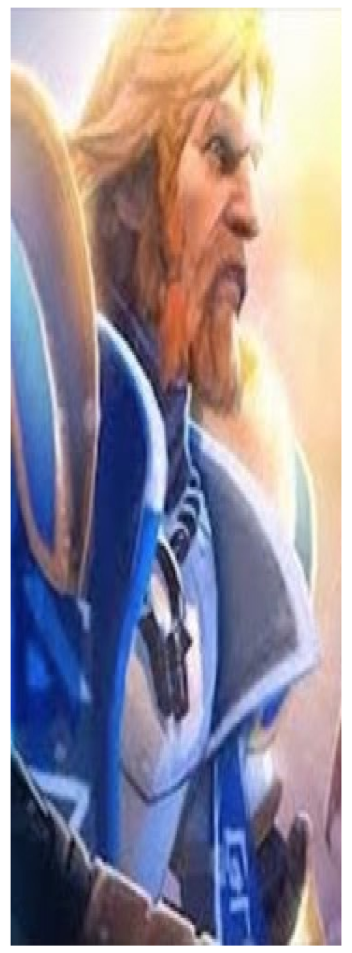
Joint combinations of two heroes on the opposite side:

$$D_iR_j = \begin{cases} 1, \text{if dire has hero i, radiant has hero j} \\ 0, \text{otherwise} \end{cases}$$

The number of features in this case is slight larger than the number of instances, thus for parametric models such as Logistic Regression to work, model-free feature selection is required. This can be done based on the appearance frequency of each feature and Pearson product-moment correlation coefficients between each feature and the binary outcome.

In modeling the data, both nonparametric methods (KNN, random forest) and parametric methods (SVM, logistic regression) can be used. In parametric models, penalized methods like LASSO and SCAD can be used as well. In order to evaluate the performance of different methods, the dataset will be randomly split into training set ($n_{training} = 10000$) and testing set ($n_{test=2000}$).

RECOMMENDATION EIGINE



```
-----------------------------------------lineup-----------------------------------------
                  dire: ['Omniknight', 'Lifestealer', 'Lich']
            radiant: ['Arc Warden', 'Skeleton King', 'Juggernaut']
----------------------------------------------------------------------------------------
-----------------------------------winning probability----------------------------------
                              dire: 0.5961
                            radiant: 0.4039
----------------------------------------------------------------------------------------
What is your pick for Dire: Razor
Recommendation engine picks Enigma for Radiant
-----------------------------------------lineup-----------------------------------------
               dire: ['Omniknight', 'Lifestealer', 'Lich', 'Razor']
        radiant: ['Arc Warden', 'Skeleton King', 'Juggernaut', 'Enigma']
----------------------------------------------------------------------------------------
-----------------------------------winning probability----------------------------------
                              dire: 0.2576
                            radiant: 0.7424
----------------------------------------------------------------------------------------
What is your pick for Dire: Nature's Prophet
Recommendation engine picks Spectre for Radiant
-----------------------------------------lineup-----------------------------------------
        dire: ['Omniknight', 'Lifestealer', 'Lich', 'Razor', "Nature's Prophet"]
    radiant: ['Arc Warden', 'Skeleton King', 'Juggernaut', 'Enigma', 'Spectre']
----------------------------------------------------------------------------------------
-----------------------------------winning probability----------------------------------
                              dire: 0.0592
                            radiant: 0.9408
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FUTURE RESEARCH

A new patch will be released every few months that dramatically changes the balance of the game and thousands of games have been played everyday. We believe that a sliding window of new match history data could help maintain data relevancy.

REFERENCES

[1] James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). New York: springer.

[2] Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1). Springer, Berlin: Springer series in statistics.