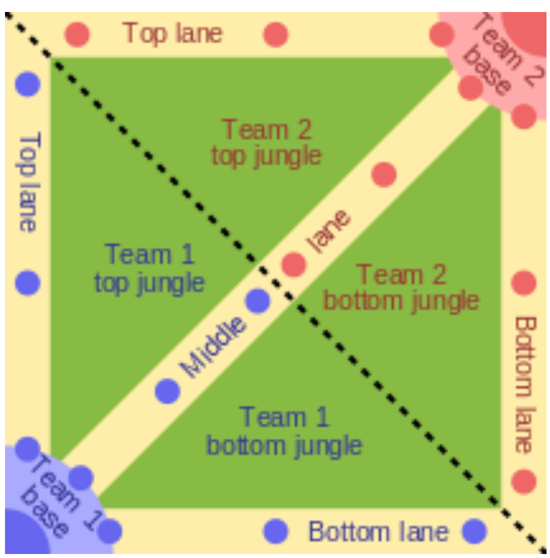
Final Project Proposal

Chen Chen—Cohort 19

Dota 2's Winning Strategy Picker

Defense of the Ancients 2 (DotA 2) is a popular multiplayer online battle arena (MOBA) game. The game started out as a modded version of Blizzard's crazy popular real time strategy game Warcraft 3, known as Dota. As its popularity grew, many game developers decided to jump in to the MOBA fray with their own creations, most notably League of Legends (LoL) by Riot Games in 2009 and DotA 2 by Valve in 2011. Since then, MOBA games has enjoyed soaring popularity, with an official International game being held for each game every year and many other big matches across 5 continents. It is then, without a doubt, that players care deeply about winning in MOBA games. I will be focusing on providing a winning strategy picker for DotA 2, which starts with a simple game outcome prediction.

Following the standard MOBA tradition, DotA 2 pits two groups of five players against each other, with one team named the 'Radiant' and the other 'Dire'. In the graph, bottom left will be the Radiant and the top right the Dire. The game objective is to destroy the Ancient, which is a giant structure with lots of hit points, in enemy team's base. Creeps spawn in both teams' lanes from the base and marches toward the enemy base. They will automatically fight each other, attack enemy towers and structures (denoted by small red dots on the picture).



Two opposing teams pick five heroes each (one per player) for battling. Every hero fulfills different roles, which can be split into 4 major categories: carry, support, jungler and pusher.

Carrys can literally carry the late game when they accumulate a strong gold/item advantage. Supports have strong presence in the early game in order to create growth space for carrys. Junglers mainly roam the jungle killing neutral creeps (non-Radiant/Dire) to attain gold advantage. Pushers are good at killing enemy creeps and by extension advancing ally creeps. It should come as no surprise, then, that hero selection factors a lot into winning a game. This will be the prime suspect of my investigation. A paper done by two Stanford students used only hero selection (1 for selected, 0 otherwise) as their feature vectors and achieved decent prediction accuracy (70%) using a logistic regression model. That being said, these two researchers used only the top 8% of the DotA 2 player base for their sample size. They argued that strategies used by pro players should be plenty for recommending good strategies. However, in lower skill rating brackets, hero type composition in each team should be a more prominent factor in determining match outcome. It is based on this lack of coverage over players with varying skills that I want to expand their findings.

First, although DotA 2 works on a game by game basis, their skills are still progressing. It is therefore better to provide advice to players based on skills just one level above their own skill levels. Advice like that will be more constructive and achievable. My first expansion will focus on clustering different players by their skill ratings according to their play style, which can be inferred from their hero picks, diversity of hero picks, number of games played, game time and win/loss rates. My motivation for developing an independent skill rating is due to the fact that DotA 2's MMR rating can be abused. Players can get extremely high MMR by playing a few heroes over and over again. That in no way means that they are skilled overall. It is my job to penalize them for playing so few heroes in my skill rating calculation. Game data should offer a more objective picture. In the case where my clustering algorithm fails, I will fall back to the MMR rating and normalize MMRs with some feature engineering. From that point, I will attempt to get the top 50-60% player base, make 4-5 bins of skill ratings and model predictions on every bin. It would be pointless to include all bins in a single model, since that would simply make my model assign higher win rate to those with higher skill ratings. It basically defeats my purpose of providing different advice for players with different levels of skills.

Second, evenly matched hero lineup could use some extra help from other features recorded in a game to increase my prediction accuracy. In the extremely pro player bracket, it is not uncommon to have evenly matched lineups because those players know exactly what constitutes a good team. Beyond the golden triangle of carry-support-jungle, they also know how to counter-pick enemy heroes. Since the selection of heroes is not simultaneous, players will engage in a sort of tit-for-tat strategy that could easily lead to a rather balanced team composition. In this case, a model based purely on hero selection will likely assign a 50% chance of winning to both teams. It is then other components of a game that help determine the outcome. I will mainly look at the numbers/results of team fights, player net worth and player kills in the first 15-20 minutes of a game to help increase the accuracy of my model. I believe that these extra stats will not rock previously correct predictions too much, because a team of good heroes is bound to put more pressure on the enemy team in the early/mid-game stage.

The two proposed extensions do interact with each other. In fact, I believe their interaction will only become stronger as I move further away from the top 8% bracket used by the referenced study. My tools will include all of Python and its sub-libraries such as numpy, pandas and scikit-learn. I will most likely enlist the help of Amazon's EC2 cloud, as the data file is relatively large. In that spirit, Hadoop and Spark will be quite handy to have as well. So to recap:

My project will encompass the following:

1. Work on the 50,000 ranked matches dataset from Kaggle, and later expand into a larger dataset offered by yasp.co on Academic Torrents
2. Feature Engineering on the recorded game dataset through aggregation/normalization to make it more informative
3. Make player brackets bins according to a more representative skill rating metric, which I will devise myself.
4. Run different classification model on every single bin to account for the differences in player skills, which can extend to how they think about strategies
5. Recommend best hero compositions/strategies for players in bracket i based on the max predicted win rates of the model in bracket i+1