Predicting eSports Outcome:
Teamfight Tactics

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Introduction

Teamfight Tactics is a popular competitive video game, developed by Riot games, of the *Auto-Chess* genre. The game has millions of daily players worldwide, a vibrant competitive scene and recently hit a peak of 10 million daily players worldwide in March of 2021. The game consists of 8 players who share a common pool of characters, called ***champions***, from which they will randomly draw their teams from. There are different means of customizing a player's team from positioning, item distribution, team composition and more. They will then battle each other and each loss lowers a player's health and the last player with positive health wins. Player's are then placed in the reverse order of when their health reaches zero. Players who consistently achieve higher placement in matches ascend in rank while players who consistently fall into the lower placement will decrease in rank. Part of the game's strategy is determining the best champions to select, the best items to use, the best team composition and the interactions between all three.

For this project, I focus on the contributions of champions, items and the team composition to a player's placement in a match. More specifically, I want to predict the viability of a team composition in achieving high placement in ranked Teamfight Tactics matches. These predictions would give insight in determining strategies on selecting champions and building team compositions that would increase chances of high placement in matches and consequently allow a player to ascend in ranking.

Data

The data was obtained via the Riot Games API in obtaining 100,000 match information from the top 10,000 players in North America (which is approximately 1% of all NA players). The information consists of the final state of each team composition before the player lost or won. For consistency, I used only matches that were a part of patch 11.18 since each patch makes adjustments to aspects of the game which can drastically change strategies between patches. This resulted in approximately 18,0000 matches and produced approximately 144,000 team compositions. The data set used is derived from these 144,000 team composition

Feature Engineering

To simplify the team composition, I focused on the ***team synergy traits***. Each champion has synergy attributes and pairing champions with the same synergy attributes gives beneficial effects to strengthen the team. There are a total of 22 true synergy traits (I omitted synergy traits that did not require more than 1 champion) and each become a feature with one of the following values: grey, bronze, silver, gold, chromatic. These will undergo ordinal encoding since there is a clear ranking among the values.

For champions selected, I focused on the idea of the ***carry champion***. These champions are the focal point of the team composition. If the team composition was a spear then the spear point would be the carry champion and the shaft would be the synergies and the other champions. Determining the carry champion depends on the intent of the player which is not obvious from the data extracted but from a player's perspective the carry champions are the ones a player would put items on since items can drastically make a champion stronger. Since each game has approximately 10-11 complete items, we sort the champions list of each composition by items, tier and cost and select the first 3 in the sorted list to be the carry champions. These will undergo one-hot encoding since they are categorical variables with no relations to each other. The ***Tier*** of each carry champion is the "level" of the champion in question, this can increase during the game by combining lower level champions together. Higher tier champions are more expensive in game and are more powerful.

Vertical synergy determines if the team composition is vertical, in other words, the majority of the team is meant to obtain a specific synergy. Typically teams with 6 champions contributing to the same synergy are considered to have vertical synergy. ***Synergy contest*** determines if the synergy of said team is being contested by another player. ***Carry contest*** determines if the carry champions of said team are being contested by another player. ***Value*** is the total gold cost of the team composition. ***Difference from max***, computes the difference between max team value in the match compared to the player. ***Last round*** is the round where a player's health reaches zero and the ***difference from max round*** is the difference from the winner.

Placement is the player's placement in match but I included a rougher estimate of placement in Top 4, since I am simplifying the raw data to be more useful and understandable and, as a consequence, some of the lost information (as well as some teactical information not in the data) contributes to the placement. Since the goal of the player is to ascend in rank, Top 4 is a reasonable predictor variable since in ranking points placing 8th loses about 40 points and placing 4th gains 10 points. So if we use compositions predicted by the models to be in the top 4 then we should expect no worse than staying at the same rank in the long term.

Models and Techniques

K-Nearest Neighbors - It is natural to assume that similar team compositions should perform similarly. Even with a slight change in some aspects of the team composition like a carry hero the performance of the team should not vary too wildly in terms of placing top 4

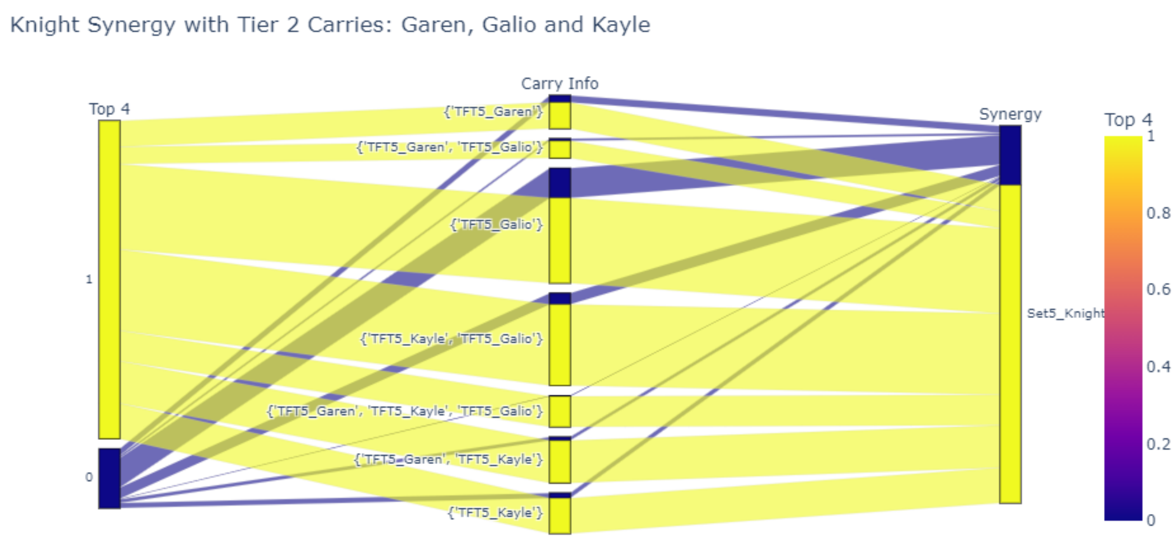
Random Forest - As a lot of the data is categorical it is reasonable to use random forest since decision trees can perform well on categorical data.

Neural Networks - The use of neural networks have found some use in traditional sports and there has been research into the possibility of transferring these ideas into the situation of eSports. Determining the boundaries of Top 4 of this majority categorical data set is suitable for Neural Network. Also as a matter of prediction, neural networks may be better in the cases where we do not have enough data of specific team composition in our data set.

Results & Discussion

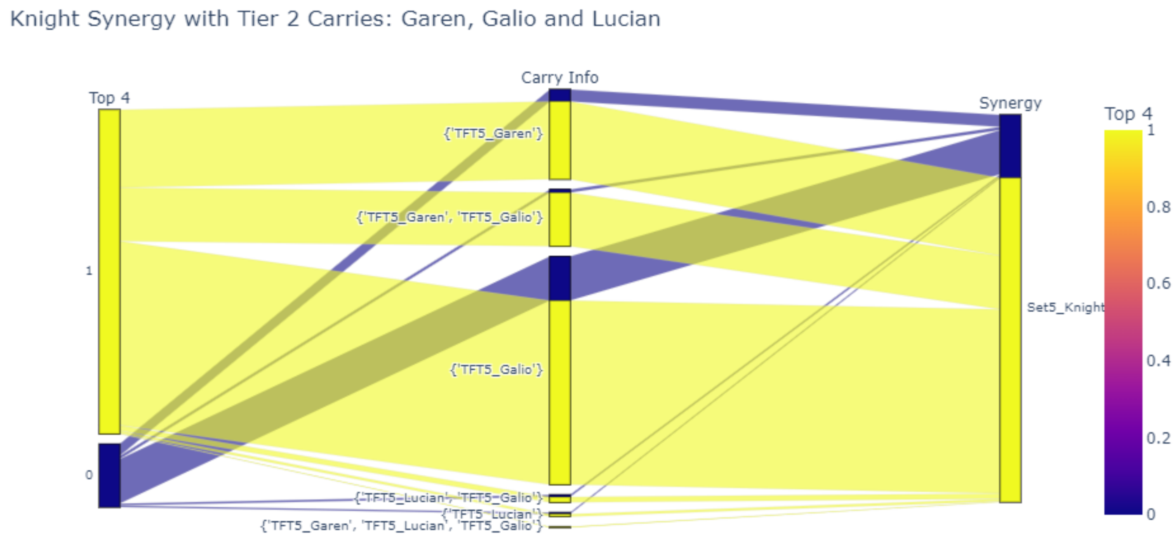
The performance of each model in average cross validation of the area under the ROC curve and accuracy is around the same with .85-.9 ROC and .75-.81 in accuracy but the Neural Network performed the best in both cases achieving .9 in area under ROC and .81 accuracy.

The analysis of the data reveals common team compositions which are frequently used and are considered optimal teams or the strongest teams by players under the constraint of champion carry or team synergy. For example, consider the “Knight” synergy where the most common champion carries are Galio, Garen and Kayle.



In the above plot, we are assuming that all three carry champions are tier 2. We see that Kayle, Garen and Galio are all commonly used carries within the Knight synergy to achieve a high rate of top 4 placement. But what about other possible carry champions other than Kayle? It is quite often that due to other players in the game competing for the same champion that a player may need to use alternate strategies in the event that Kayle is unavailable. This is not only prudent but wise.

Now we consider the same "Knight" synergy but instead consider Garen, Galio and Lucian. Lucian is a very viable carry in the "Sentinel" synergy but from the analysis of the data rarely used in "Knight" synergy.



Consequently, we do not have much data to work with or to derive some inference from other than the small slivers in the above plot.

This is where the Top 4 placement predictor model is useful. We can determine the viability of a composition in placing top 4 by using the performance of carry champions in other compositions. While Lucian is not a common carry for Knights synergy we can come up with team compositions to determine if Lucian is a viable carry with the knight synergy through the neural network model. In fact, we can consider that for other typical carry champions like: Akshan, Teemo, Heimerdinger, Karma, Lucian, Draven. This can be seen in the Mock Data series of notebooks. Where I create some mock data with the above carries and run it through the model to determine the top 4 placing conditions of each team composition.

Strategies/Decisions

We focus on two different synergies: *Dawnbringer* and *Knight*. The main reason for this choice is due to the fact that they both achieve top 4 above 50% of the time and furthermore, from a playing perspective, acquiring the champions for such synergies is relatively easier. This analysis can be done with other synergies by creating the mock data compositions, where the one making it has some intimate knowledge of the game. Running it through the Neural Network model to compute placement and probabilities and then having a player who understands the champions and compositions interpret the data.

The Knight synergy, with *Garen* and *Galio* as carry champions, reveals that obtaining Tier 2 carries is the most important top 4 placing condition but there is some leeway when it comes to 5-cost champion carries (like *Akshan*, *Teemo*, *Heimerdinger*) in possibly winning with a Tier 1 carry hero. Alternatively, with 4-cost champion carries like Lucian, Draven, Karma then Tier 2 is an absolute requirement in increasing likelihood in placing top 4. As a means to increase chances placing high, a player should consider replacing the Tier 2 4-cost champions above with a Tier 1 5-cost champion above as a means to build towards a stronger composition.

The Dawnbringer synergy is more flexible with only a *Garen* carry champion requirement but analyzing the carries between *Karma*, *Teemo* and *Heimerdinger* in the model shows that while *Karma* is a natural carry for the *Dawnbringer* synergy since *Karma* has the *Dawnbringer* attribute, *Teemo* is the stronger carry hero that would increase likelihood of placing top 4. Thus replacing *Karma* with *Teemo* as a carry champion in the *Dawnbringer* synergy strengthens the composition more.

Implementation of this and other strategies derived from the above analysis have proven to be fruitful. This can be seen in my rankings in Teamfight Tactics which can be seen in the following link: https://lolchess.gg/profile/na/elchaire/s5.5
I started implementing these strategies in patch 11.20 which is different from 11.18 in that the carry champions of the Forgotten synergy were adjusted and so strategies derived for Dawnbringer and Knight synergies would be still viable. I began playing these strategies from Oct 13th to Oct 20th and within that time frame I rose in rank from Gold I to Platnium II. This means that I went from approximately top 20% of ranked players in North America to top 9% of ranked players in North America.

Conclusion

In this project, I began with raw data that was too detailed and difficult to manage and engineered features which were more interpretable and understandable for players of the game. From this I trained the Neural Network on the data to predict probabilities of top 4 placement and achieved an accuracy score of 81% and an AUC ROC score of .9. This is sufficient to use as a predictor since based on how points are distributed in placement a player playing team composition predicted as a top 4 finish by the model should not drop in ranking on average. From the strategies developed using the neural network model prediction, I was able to advance in North American ranking from being top 20% to top 9% in North America, which in total has about 1 million players.

A natural follow up project would be the inclusion of items into the discussion of predicting placement. Items were used mostly as a means to determine the carry hero but the type of items do matter and some items synergize better with certain champions than others. This would be a necessary step to improve the model even further. Other possible future work would depend on the state of the game as every 6 months the developers fundamentally changes the game to keep player's interest but the core gameplay is the same so the core aspects of these approaches will still work.