

Predicting Seasonal Rank Changes in League of Legends

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- LOL(League of Legends) is an online multiplayer game where 10 players are matched up in 2 teams of 5 to choose game characters and fight against each other.
- Each player's level is represented by their Rank (25 in total)
- I wanted to use the supervised learning techniques that I learned in CS229 to predict a player's rank at the end of the season. Just because we all want to know how high we can get!





<u>What is the Training Data?</u>

- Riot (The developer of LOL) provides a rich API allowing us to query its internal gaming statistics of a given player.
- I used the Stats API which returns a JSON object per player : {"totalPhysicalDamageDealt": 6562106, "totalTurretsKilled": 124, "curRank": 25, "totalSessionsPlayed": 236, "totalAssists": 2935, "totalDamageDealt": 11818577, "mostChampionKillsPerSession": 16, }

Selecting Features

- Transformed each JSON object into a python dictionary
- Manipulate the dictionary to represent meaningful information (ex. Death -> 1/Death, Kills -> Kills/Death). Total 57 Features!
- I used SVM with RBF Kernel for one of the learners, so did not add experimental cross terms. (only added those with human-level meaning)



Riot Games Server Collect Data using LoL API

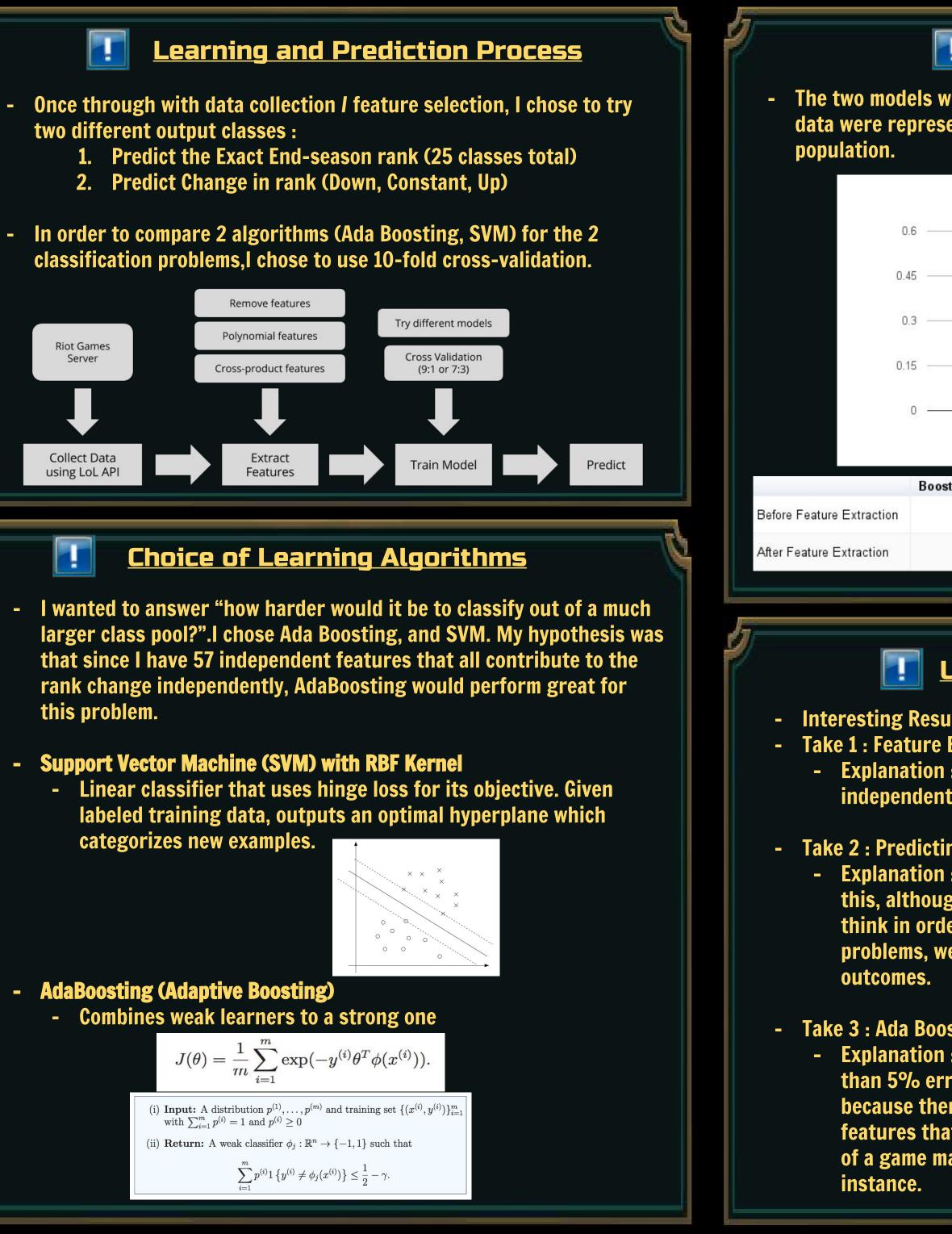
this problem.

Github Repository

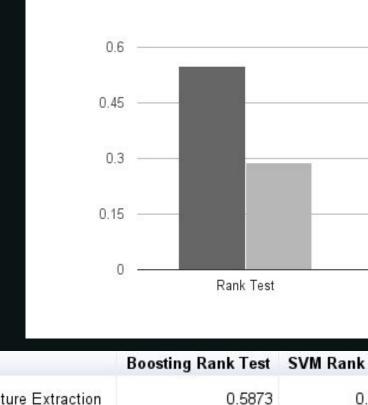
https://github.com/sjang92/LOLRankPredictor

Reference

Riot API: https://developer.riotgames.com/api/methods MMR: https://na.op.gg/, https://na.whatismymmr.com Scikit-learn: http://scikit-learn.org SVM: http://cs229.stanford.edu/extra-notes/cs229-notes3.pdf Boosting: http://cs229.stanford.edu/extra-notes/boosting.pdf NOTE: Overlaps with my CS221 Project



The two models were trained with 600 LOL player season data. The data were representative of the rank distribution of the LOL



0.5484

- Interesting Results!
- Take 1 : Feature Extraction didn't make a lot of difference (1 ~ 3%)
- **Explanation : My hypothesis is that since the features are**
- Take 2 : Predicting out of 25 classes is extremely hard think in order for boosting to work well with multi-class problems, we need a lot of dataset to cover many types of
- Take 3 : Ada Boosting worked much better than SVM (Up Down)
 - of a game may only be affected by one of the features, for



Prediction Results

	Updown Task	■ Boosting SVM
k Test	Boosting Updown Task	SVM Updown Task
0.3037	0.0661	0.1473
0.2874	0.0381	0.1202

<u>Understanding the Results</u>

independent, adding their cross-terms don't have much effect

- Explanation : Both SVM and Boosting performed very poorly on this, although SVM still performed much better than Boosting. I

- Explanation : boosting algorithm performed very well with less than 5% error rate, compared to the SVM model. I think this is because there might not be an inherent relationship between the features that makes a player go up or down in rank. An outcome