
Predicting League of Legends Results Based on Character Selection

Luke Slyder and Sam Lowenstein



FNATIC

[2-3]

COACH: DYLAN FALCO

EU - NA

PATCH 7.13

PICK PHASE 2

:21

CLOUD9

[2-3]

COACH: BDK "REAPERED" HAN-GYU



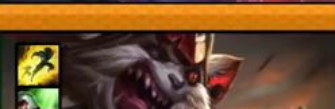
FNC.s04Z



FNC Broxah



FNC Caps



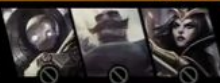
FNC Rekkles



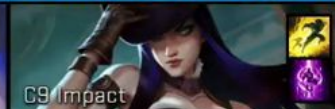
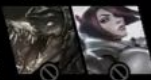
FNC Jesiz

BANS

PHASE 1



PHASE 2



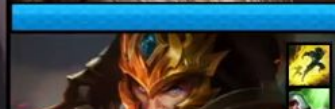
C9 Impact



C9 Contractz



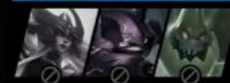
C9 Jensen



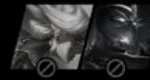
C9 Sneaky

PICKING
C9 Smoothie

BANS



PHASE 1



PHASE 2



Motivations and Questions

Competitive 5 vs. 5 matches where 10 Players select 10 independent characters from a pool of over 100.

Look at Data of Character Selection in League of Legends.

How well can we predict the winning team from just Character Selection?

Dataset: League of Legends Ranked Games¹

Data from over 50,000 matches.

Label: Match winner (1 or 2).

Features include champion selections of each individual player.

Champion ID's: Integers ranging from 1 to 518.

1. <https://www.kaggle.com/datasnaek/league-of-legends>

Dataset: League of Legends Ranked Games¹

Data from over 50,000 matches.

Label: Match winner (1 or 2).

Features include champion selections of each individual player.

Champion ID's: Integers ranging from 1 to 518.

Preprocessing: Restructure the data, make each champion a feature with a value of 0 (not picked), 1 (picked by team 1), or 2 (picked by team 2).

1. <https://www.kaggle.com/datasnaek/league-of-legends>

Naive Bayes

Naive Bayes Assumption:

$$p(y = k | c) \propto p(y = k) * p(c_1 | y = k) * p(c_2 | y = k) * \dots * p(c_{518} | y = k)^1$$

Naive Bayes

Naive Bayes Assumption:

$$p(y = k | c) \propto p(y = k) * p(c_1 | y = k) * p(c_2 | y = k) * \dots * p(c_{518} | y = k)^1$$

Prediction Accuracy: 54.22%

	Team 1 (Predicted)	Team 2 (Predicted)
Team 1	2883	2332
Team 2	2382	2701

Naive Bayes

Naive Bayes Assumption:

$$p(y = k | c) \propto p(y = k) * p(c_1 | y = k) * p(c_2 | y = k) * \dots * p(c_{518} | y = k)^1$$

Prediction Accuracy: 54.22%

Effectively assigns a **score** to each champion.

	Team 1 (Predicted)	Team 2 (Predicted)
Team 1	2883	2332
Team 2	2382	2701

Modified Decision Tree

Capture Character matchups: What happens if Character Zed is picked against Character Yi?

Create a Tree with Depth 2.

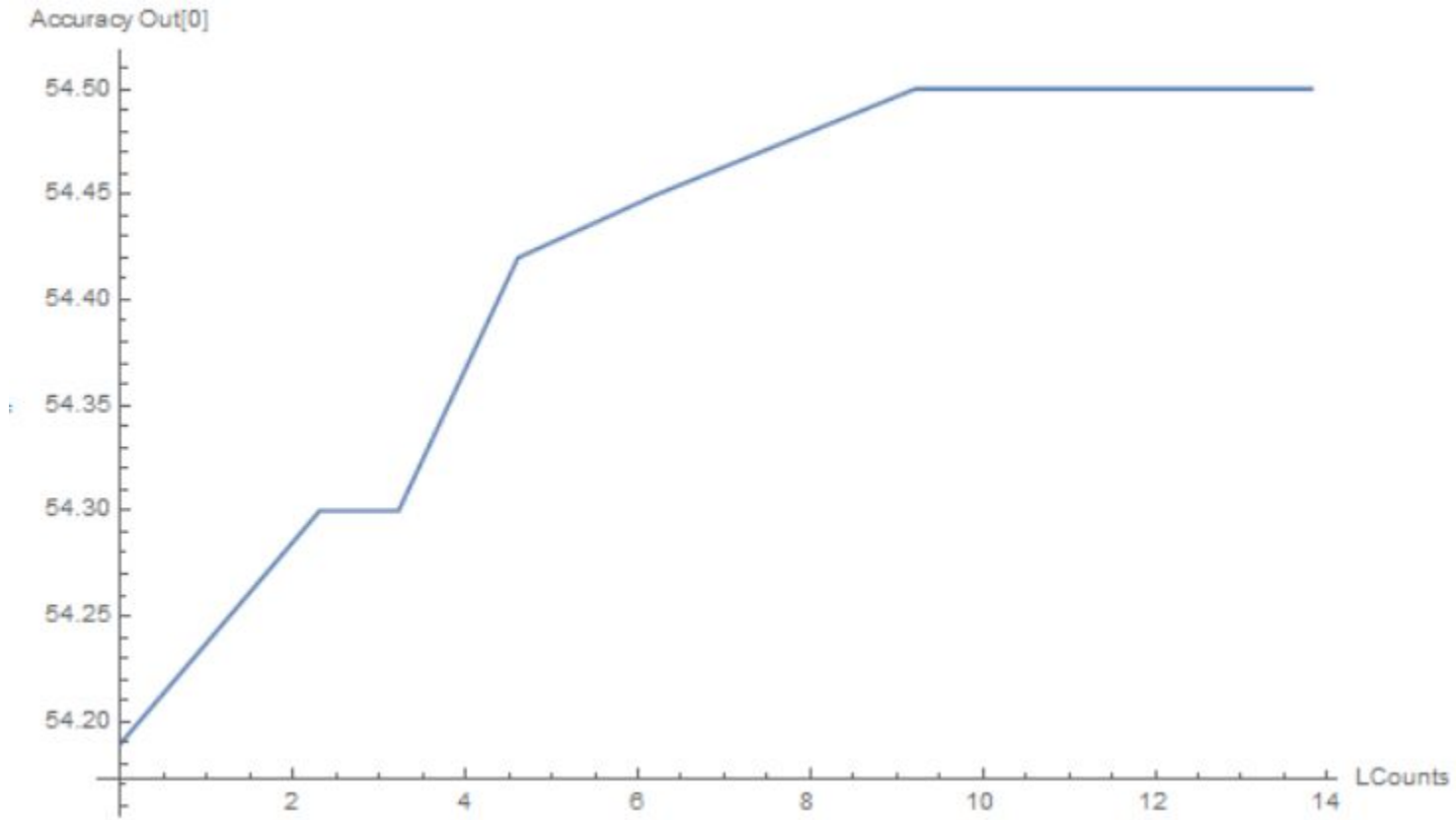
A Branch for Every Champion at Every Node.

Every Leaf counts $X = \text{Laplace} + \text{Number of Wins of Team A}$; $Y = \text{Laplace} + \text{Wins Team B}$,

Gives $(X)/(X+Y)$ as Win% of Team A for given Character Matchup

Prediction: if Average Win% of all 25 Character Matchups is $>50\%$, Predict Team A Victory.

Accuracy vs. Log(Laplace Counts)



Conclusions

Correlation vs. causation.

Conclusions

Correlation vs. causation.

Predictions are more accurate when we can look at **interactions** between champions.

Conclusions

Correlation vs. causation.

Predictions are more accurate when we can look at **interactions** between champions.

Future Work: A model that can examine interactions between champions on the **same team**.

Use data that is sensitive to **player roles** and **summoner spells**.

100 THIEVES

[9-5]

:58

WEEK 8

PATCH 8.15

:58

ECHO FOX

[9-5]

COACH: PROLLY

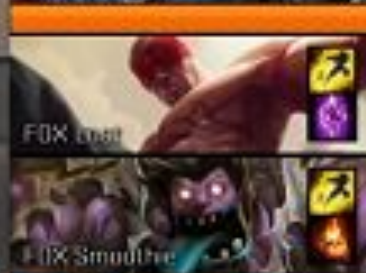
COACHES: THINKCARD & JIM



BANS



2018 NA LCS SUMMER



BANS

PHASE 1

PHASE 2



PICK RATE

4%

BAN RATE

6%

WIN RATE

33%



PHASE 1

PHASE 2