Winner WinnerChickie Dinner?

DSI26 Capstone: Winner Prediction for Fortnite

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About the project







Overview

Electronic sports (or esports) is a form of competition utilizing video game. Esports differs from regular video gaming in that it is competitive (human-vs-human) and, like traditional sports, usually has an interesting spectator element.

Genres of Esports

- Multiplayer Online Battle Arena (MOBA)
- First-Person Shooter (FPS)
- Battle Royale
- Real-Time Strategy (RTS)
- Fighting
- Collectible Card Games (CCG)
- Sports & Racing





1 billion °

Global Revenue for Esports in 2020

495 million *****

Global Audience for Esports in 2020

125 million

Prize money awarded in tournaments in 2020



"Our world-class events and digital infrastructure have also made Singapore an attractive location for the industry to hold gaming and e-sports events here. The government will continue to support companies as they push boundaries through experimenting with new and immersive content formats and business models, as well as level up the quality of our local talent to become leading creators of world-class content."

—Singapore Tourism

Board and Enterprise

Singapore





Top 3 Games Awarding Prize Money



According to Esports Earnings.

Problem Statement

 Predicting the winner of a match using historical player data











Genre

Battle Royale - Fortnite



Solo Matches, where the winner competes with up to 99 other players

Model

Classification-based model to predict winner







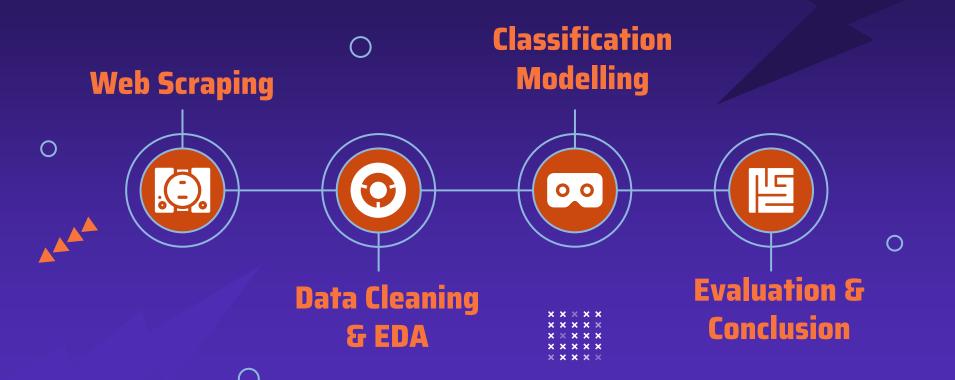








Workflow







First set of data to be gathered from Fortnite Tracker, Match Statistics, using:

- Requests library
- Selenium Webdriver









^OWeb Scraping

Second set of data to be gathered from Fortnite Tracker, Player Statistics, using:

Fortnite Tracker API



Data: Datasets



Match Statistics O

Critical information:

- Eliminations
- Points
- Time Alive
- Placement

Misc info such as:

- Team ID
- **Event ID**
- Geo Identities, etc.



Player Statistics



- Kills per game / per minute
- Win ratio
- Score per match per minute
- Average Time Played
- Kills to deaths ratio



Cumulative Statistics:

- Matches
- Kills
- Wins
- Score
- Minutes Played
- Top Rankings, etc.







Data: Player Statistics - Match Modes



Solo

Solo Player



Trios

A Maximum of a Team of 3



Lifetime

Cumulative Statistics of All Modes



Duos

A Maximum of a Team of 2



Squads

A Maximum of a Team of 4

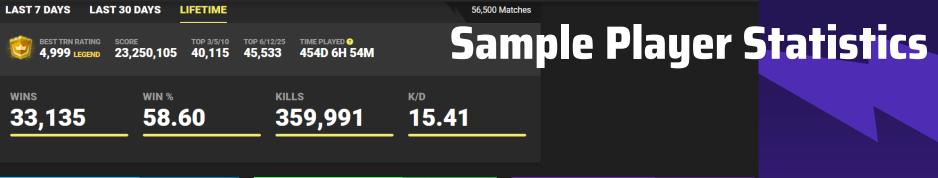




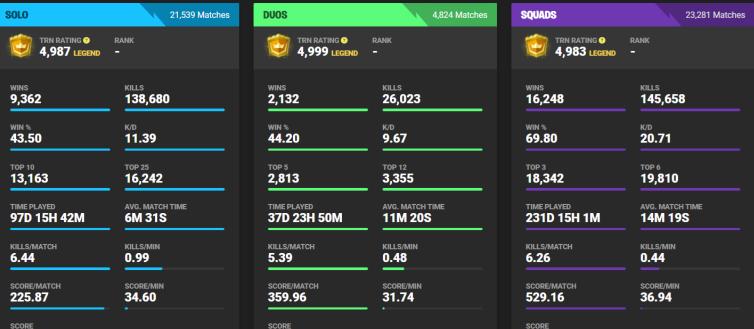


Limited Time Modes with Special Rules, not counted in Lifetime





12,319,410



1,736,445

4,864,983



Data Cleaning



Match Statistics

 Missing data: Dropping said rows as the data is faulty



Dropping
 Miscellaneous Columns such as IDs, Insert Time and End Time that is non-float

Player Statistics

- Missing data: Dropping Ratings columns and dropping rows with mostly empty values
- Dropping Zero value columns



Feature Engineering







Player Statistics

Lifetime Statistics

- Feature columns
 available in the
 individual sections but
 not provided (Mostly
 the ratio statistics)
- Making the Top statistics more interpretable (Top 3/5/10 & Top 6/12/25)





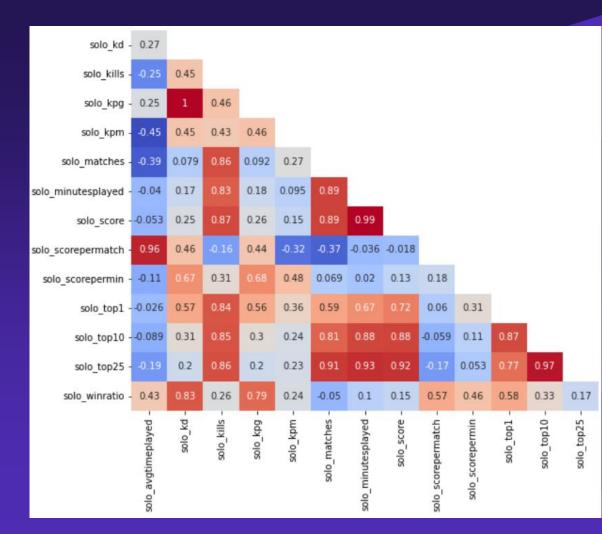
Winner Count in Data



Correlation

Solo Statistics

- Unsurprisingly, all of the columns are heavily correlated with one another
- The correlation for match modes are also similar.



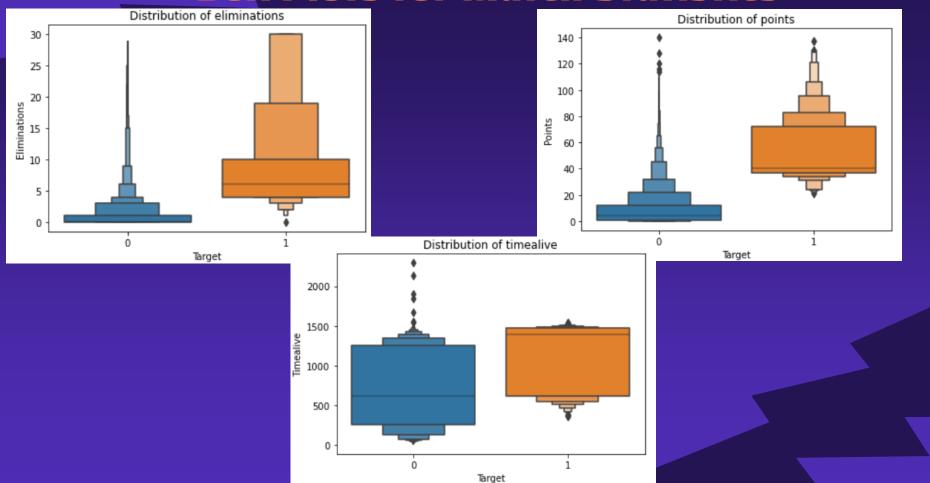
Correlation

Correlation to the Winner

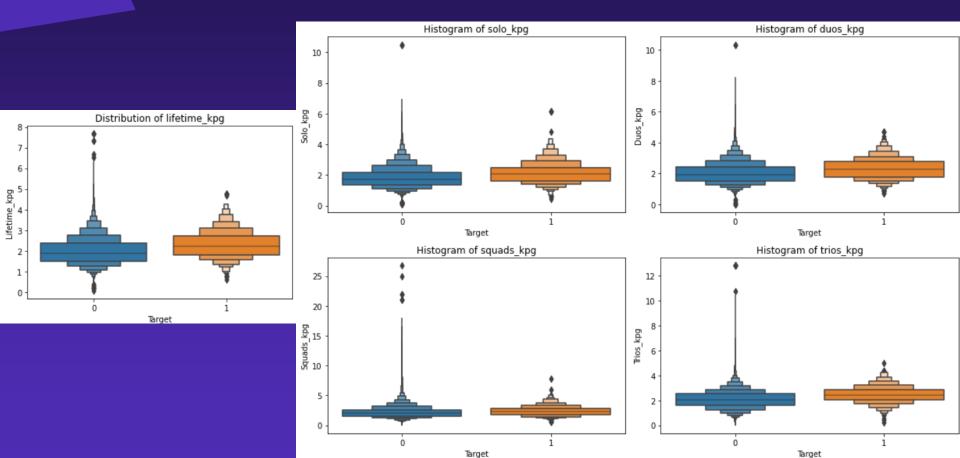
- The 3 match statistics 'eliminations', 'points' and 'timealive' are more correlated compared to the player statistics.
- Very low correlations for the player statistics
 => Model not being very effective

target -	1
eliminations -	0.36
points -	0.36
timealive -	0.11
trios kpg -	0.065
trios kd -	0.063
trios scorepermatch -	0.059
trios winratio -	0.057
lifetime_kpg -	0.057
lifetime kd -	0.056
solo kd -	0.056
solo kpg -	0.056
trios_avgtimeplayed -	0.053
duos_kpg -	0.053
duos kd -	0.052
solo winratio -	0.051
trios kpm -	0.048
trios top1 -	0.048
trios kills -	0.046
solo top1 -	0.046
lifetime kills -	0.045
solo kills -	0.045
lifetime wins -	0.045
lifetime winratio -	0.044
duos winratio -	0.044
trios_top3 -	0.044
trios top6 -	0.039
solo scorepermin -	0.039
lifetime score -	0.039
duos top1 -	0.038
duos_kills -	0.038
trios score -	0.038
lifetime top3/5/10 -	0.037
solo score -	0.036
trios minutesplayed -	0.036
lifetime minutesplayed -	0.035
lifetime kpm -	0.034
solo top10 -	0.034
lifetime_scorepermin -	0.033
lifetime top6/12/25 -	0.032
	target

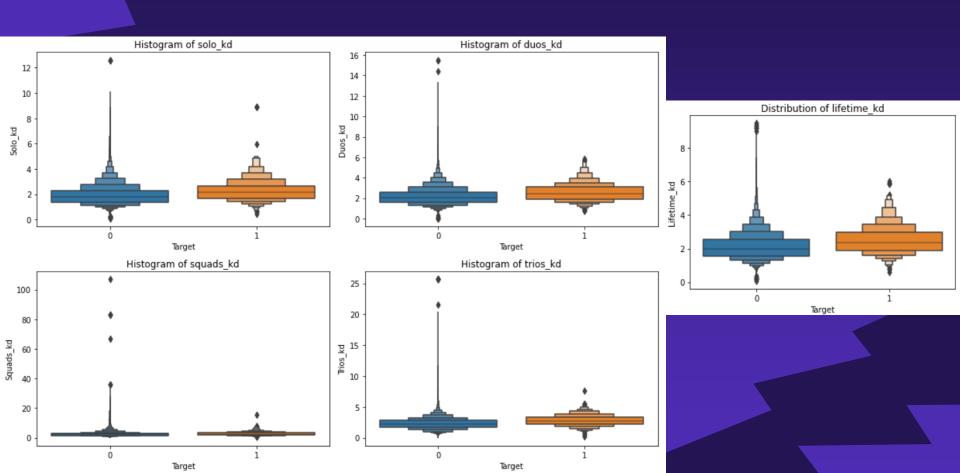
Box Plots for Match Statistics



Box Plots for Player Statistics



Box Plots for Player Statistics





Model Framework



Basic Classifiers

- Logistics Regression
- K Neighbors Classifier



Tree-based Classifier

Random Forest Classifier





• Light GBM Classifier



Neural Network

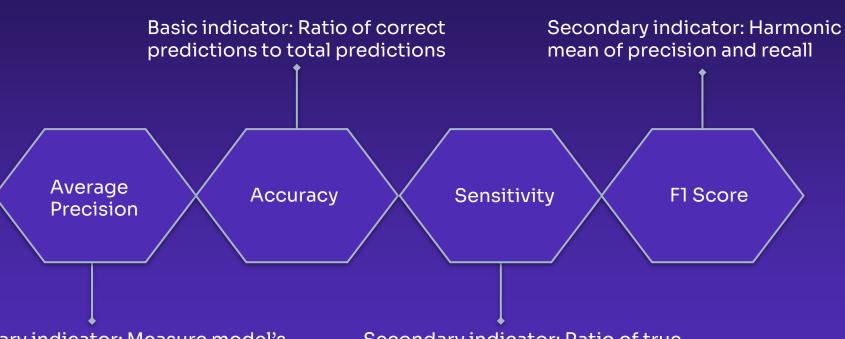
Keras Classifier

Modelling

- Various parameters are used to tune the above models through the use of Grid Search CV.
- The results are as follows:

model	GridSearch_score	train_score	test_score	accuracy	recall	precision	roc_auc_score	f1score	average_precision
Dummy	0.0144	0.0144	0.0144	0.9856	0.0000	0.0000	0.5000	0.0000	0.0144
LogReg	0.0327	0.0347	0.0246	0.6611	0.5839	0.0247	0.6230	0.0473	0.0204
KNN	0.1520	0.2769	0.1559	0.6201	0.6510	0.0244	0.6353	0.0471	0.0209
RandomForest	0.1945	0.3222	0.1861	0.8310	0.4899	0.0419	0.6629	0.0771	0.0279
Light GBM	0.2177	0.4424	0.2230	0.9275	0.4497	0.0913	0.6921	0.1518	0.0490
Neural Network	0.1543	0.2896	0.2005	0.7551	0.5906	0.0344	0.6741	0.0650	0.0262

Scoring Metrics

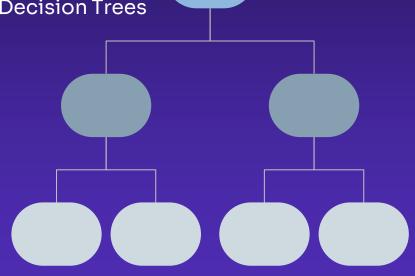


Primary indicator: Measure model's ability to identify the positive class while minimizing false positives

Secondary indicator: Ratio of true positives over true positives plus false negatives

Final Model

- The best model is the Light GBM Classifier.
- The parameters are as follows:
 - Boosting Type: Gradient Boosting Decision Trees
 - Scale Pos Weight: 99
 - Max Bin: 200
 - N Estimators: 200
 - Learning Rate: 0.01
 - o Max Depth: 25
 - o Num Leaves: 255
 - Min Child Samples: 200
 - o Colsample by Tree: 0.9
 - Subsample: 0.9
 - Subsample Freq: 2





Evaluationo





Confusion Matrix

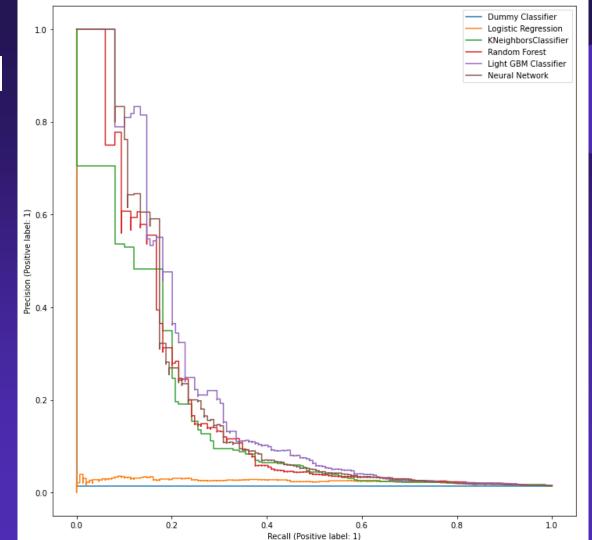
Predicted **Predicted** Non-Winners Winners **Actual Non-**9,519 667 Winners ****** Actual Winners** 82

Precision-Recall Curve

Average Precision:

0.0490,

Compared to Baseline of 0.0144



Other Scoring Metrics



Accuracy:



Compared to Baseline of 0.9856



Sensitivity:

0.4497,

Compared to Baseline of O



F1 Score:

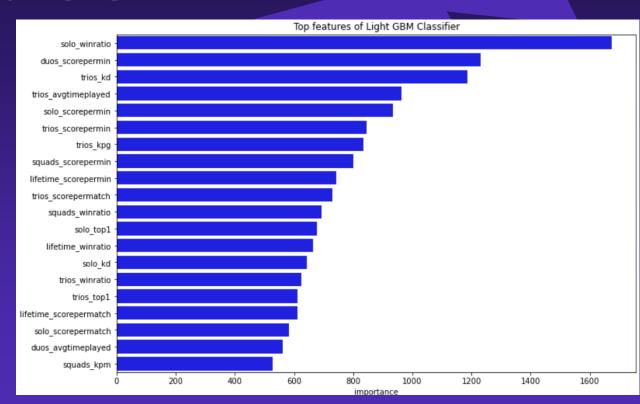
0.1518

Compared to Baseline of O

Recommendations

Features to use to judge:

- Solo Win Ratio
- Score per min (for various match modes)
- Win Ratio (for various match modes)
- Ratio Statistics related to Trios match mode





Conclusion

Improvements to current model:

- More match and player statistics data => Limited scale due to limitations of web scraping
- Other forms of player statistics not directly related to game-based =>
 Not readily available and may be irrelevant

Using match statistics to model:

Model using match statistics like `eliminations` and `time alive` =>
 Instead of predicting the winner, identify factors to increase chances
 of winning.

Future Applications to other games

Thanks!

Do you have any questions?

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