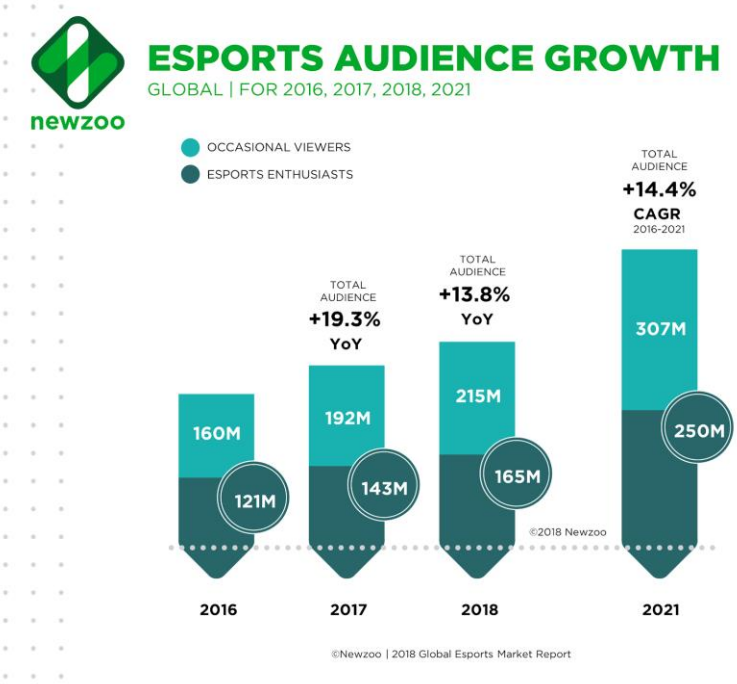
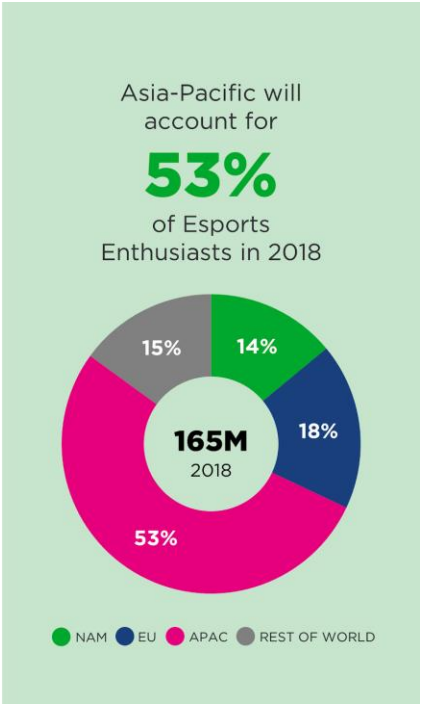
Capstone Project #1: BF4 Player Analysis and Machine Learning modeling

Part 1 Data Collection, Wrangling and EDA

Introduction and Objective

Esports has grown in the past decade or so into a million dollar industry with the development of competitive gaming and faster internet. It is projected that in 2020, esports will exceed $1 billion in revenue generated.





Just as any sports competition, players and coaches are taking note of how data can be used to monitor the performance and status of a player. Stats are collected to see how effective players are in different aspects of the game. On the other side, game designers are collecting data from their games so that they can analyze the competitiveness and balanceness of their games. A good example is Overwatch, a competitive online shooter created by Activision Blizzard, since it's launch in 2016 has been issued more than 100 patches in the course of 3 years so that the game is better balanced.

We gathered BF4 data and analyzed it using statistical analysis and data visualization. The reason BattleField 4 was chosen was mainly it's a popular first person shooter game that has a large player base and a variety of weapons along with different vehicles which allows variability

in playstyle. There has also been rumors amongst players that certain play styles are overpowered, we will use data to verify whether this is true.

In summary, the objective of the capstone is to use BF4 as an example to explore what kinds of analysis is suitable for analyzing online competitive games.

Dataset Acquisition

The player data collected for BF4 was acquired via web scraping and API calls. While there were no obvious API limitations, the data collection still took a considerable amount of time due to the size of the entire data set exceeding 30GB, coupled with unstable internet connections and server response errors.

The approach to acquiring and storing the data is as follows:

- All player rankings are stored on the webpage of the site, using beautifulsoup, a python html parser, we are able to go through player rankings page by page and acquire their ranking information
- API data can be called using the player id obtained from the web scrape mentioned above and used to pull in individual player data and have it stored somewhere

(Player Ranking) Dataset #1: We chose the console platform XOne and found the pages containing player name and ranking, I had my code go through each page individually and use beautifulsoup to parse the data. Each page contained 50 player entries, and there were a total of 600 pages. We were able to collect rankings for about 35,000+ players.

- Estimated time required: 20 minutes
- Actual time: 45 minutes

(Performance Data) Dataset #2: Before collecting this data, we did 5 api calls and came back with about 4MB of data, meaning 1 call would generate 1 player information which would be about 1MB; This meant that our data would be about 35GB in size. Since the data is so big, we decided to store the collected data in a google cloud bucket as google provides great services in regards to processing big data. In the end, we had each individual player data stored in google cloud services as a pickle file with the entire dataset having a total size of 38GB.

- Estimated time required: 72 hours (3 days)
- Actual time: 130 hours (5+ days)

Data Wrangling

The data we collected are individual player files. In order to convert this data to a workable dataframe, we have to first choose which columns we'd like in our dataframe. After reviewing the data, we found that some crucial features existed under subcategories. For instance, if you were to convert "vehicleCategory" into a dataframe, you'd find a table where a number of stats such as "kpm", "spm", "name", "destroys", "kills", "score" etc. expressed as the x-axis, and the names of the type of weapons such as "assault rifle", "LMG", "sidearm" expressed as y-axis.

Weapon categories

Name	Score	Time	↓Kills	Headshots	HK %	Kpm	Shots	Hits	Accuracy %
ASSAULT RIFLE	121,219	23:38:47	757	153	20.21%	0.53	44,371	5,132	11.57%
LMG	83,523	12:50:44	545	85	15.60%	0.71	34,097	2,996	8.79%
SIDEARM	89,303	10:42:08	431	101	23.43%	0.67	12,008	2,191	18.25%
SNIPER RIFLE	45,422	10:06:38	303	90	29.70%	0.50	2,703	601	22.23%
CARBINE	47,768	08:58:52	299	48	16.05%	0.55	15,671	1,973	12.59%
PDW	30,325	06:44:28	239	38	15.90%	0.59	13,359	1,572	11.77%
GADGET	-	05:40:22	129	0	0.00%	0.38	12,063	2,988	24.77%
SHOTGUN	13,191	01:39:53	65	5	7.69%	0.65	631	486	77.02%
KNIFE	-	00:00:00	56	0	0.00%	0.00	0	0	0.00%
GRENADE	8,459	00:19:37	55	0	0.00%	2.80	1,108	261	23.56%
DMR	1,774	00:30:48	17	5	29.41%	0.55	424	63	14.86%
BATTLE PICKUP	-	00:31:36	4	0	0.00%	0.13	145	18	12.41%

The problem with data expressed in a table like this is that it only represents one player, and in order to analyze multiple players, we need to have the data flattened out where all the stats are expressed in one row. For instance, a players "LMG" and "PDW" stats would be expressed in one row as "LMG_Kills", "LMG_headshots", "PDW_Kills", "PDW_headshots".

As we convert the individual player pkl files into dataframe, we wrote a function to conduct this transformation, the function would turn a 12 row * 9 column table to a 1 row * 108 column table. Since we are interested in players' vehicle and weapon usage, we only applied this on this function on the vehicle and weapon categories and ignored the other sub categorical data.

At the same time, in order to save space, we converted all NA values into the numerical value "999.99" so that all our data could be expressed using numbers. Eventually being able to convert our data into a pandas dataframe with the properties below:

Int64Index: 37759 entries Columns: 395 entries dtypes: int64(394), object(1)

To continue on, we can reindex this dataframe and drop any unneeded columns. Then we describe this data and see if there are any unusual information. There are certain columns that contains data where the min and max are the same. Usually this kind of data doesn't really contribute to analysis so we use loop to find all of them and have them dropped from the dataframe. Then we look for duplicate datasets. We found one entry that was collected twice using the value_count function, which auto-sorts counts by highest to lowest. We can remove the duplicate data set. We also notice that the 75% and 25% of the data for bestStreak is somehow the same, we plot bestStreak out to see what's going on and find that only a small

percentage of players are able to make high bestStreak numbers whereas the majority of players only gain 0 to 5 bestStreak numbers, thus we delete this column and other columns similar to it where the 75% and 25% data are the same. Since in the previous processing step, we used 999.99 to replace all NA values, we can try to find which columns contain this value to check for missing values.

Int64Index: 37839 entries Columns: 270 entries dtypes: int64(269), object(1)

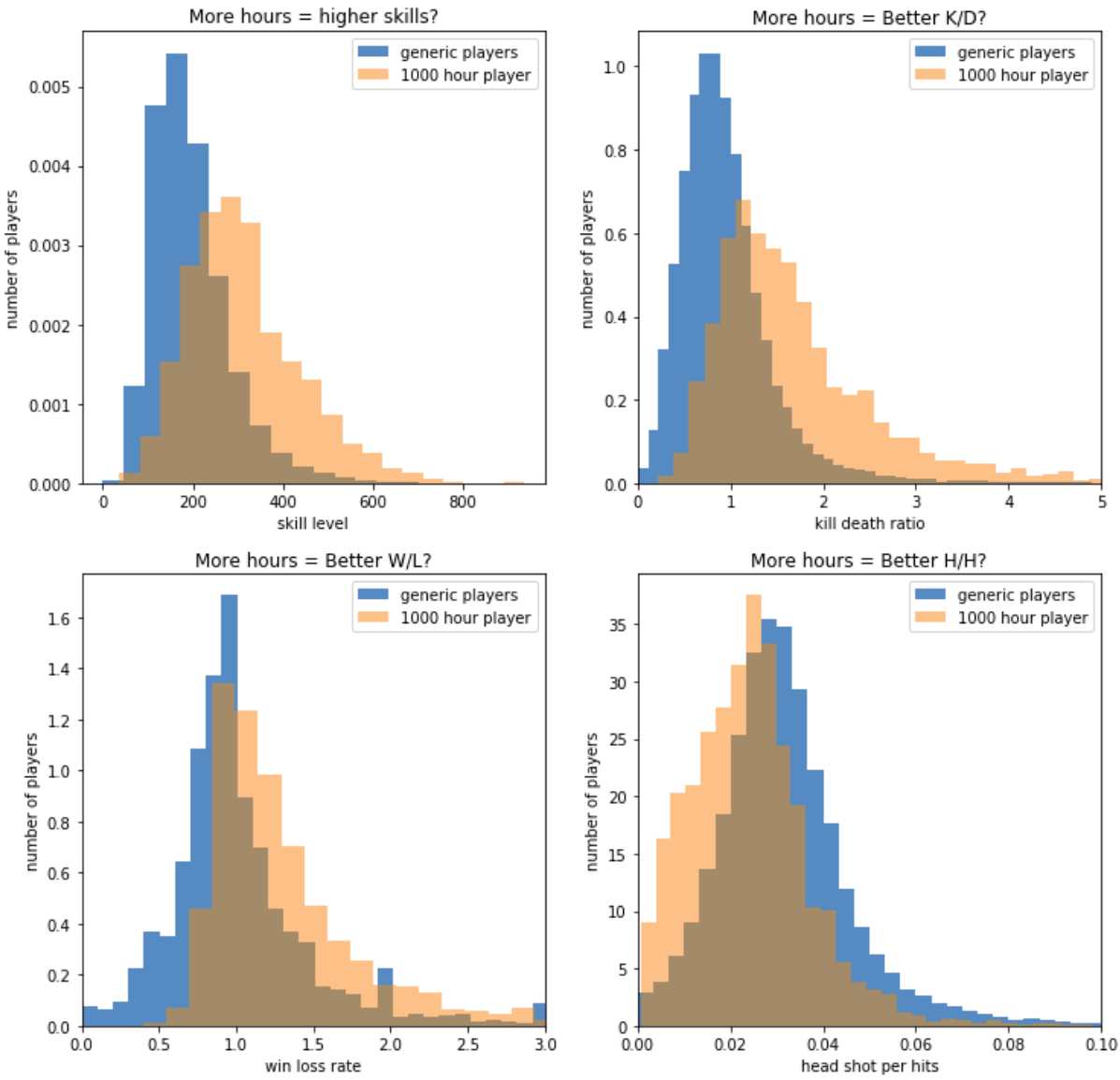
Since no value is returned, we can conclude that our dataframe doesn't contain any missing values. Video game data usually have a high level of completeness and missing data doesn't occur if the game's data collection process is well designed. Lastly, we merge this dataframe with our web scraped data to obtain our final data frame. We can now use this data frame for statistical and machine learning analysis.

Exploratory Data Analysis

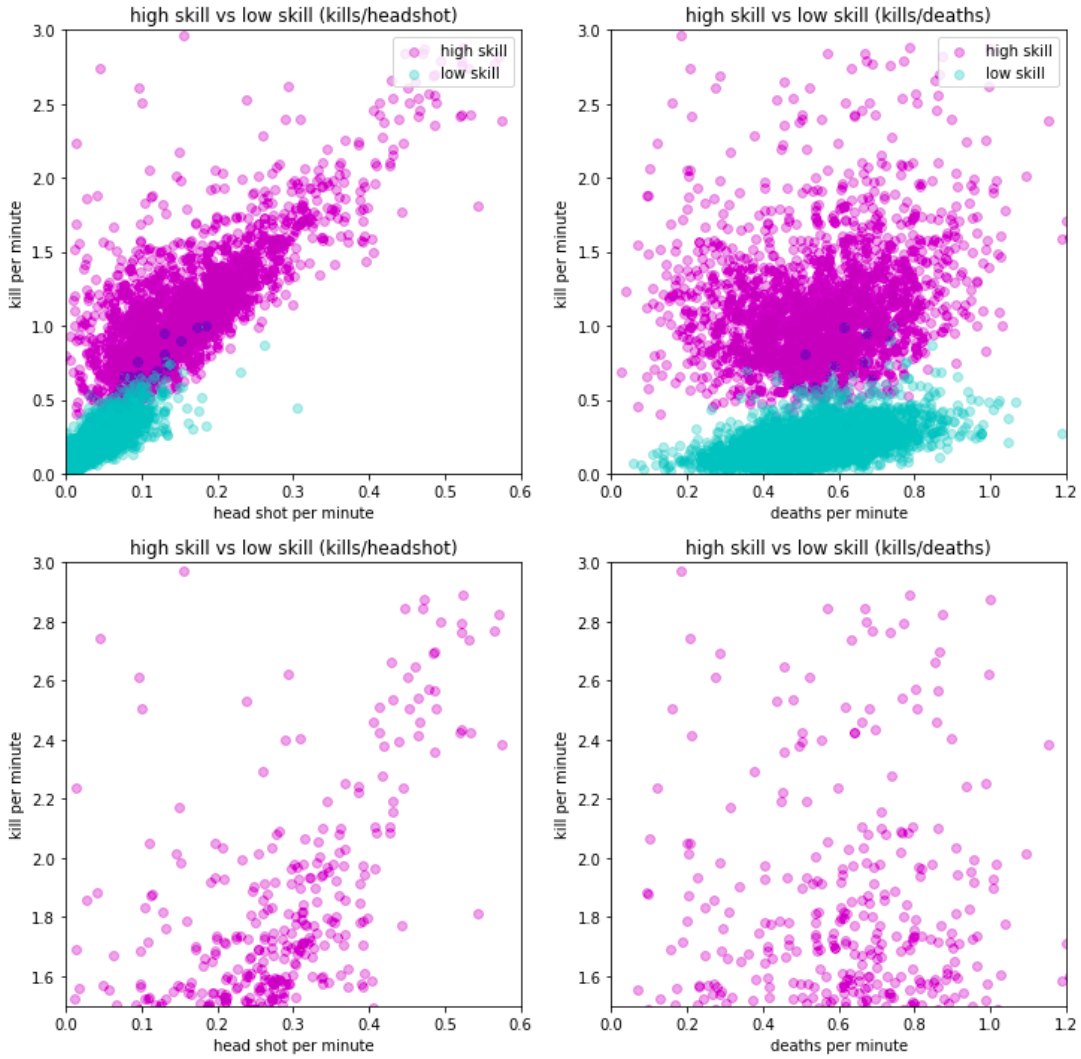
Generic player performance stats (Analysis #1)

In the beginning of the analysis, we mostly focused on overall player performance. The player_ids were removed, leaving only int64 formatted numbers. By looking at the skill level and player frequency, we found that the majority of our players had a skill level below 237 and most players had less than 1000 hours of play time. This meant that our data is heavily skewed left when it comes to hours.

Top players are in general very dedicated to their game. So in order to better understand this data, we split the players into two groups based on the 1000 hour play time, and used histograms to see if 1000 hour players did better than generic player who has less than 1000 hours of play time.



The results showed that contributing to more hours within the game did lead to better wins, higher skills and better Kill/Death ratios. However, one thing that stood out was headshots. In typical first person shooters, headshots are considered the most effective way of eliminating the enemy as it correlates with high damage. Yet in this scenario, players who have long playtime seems to be actively avoiding making headshots and going for body-shots instead.

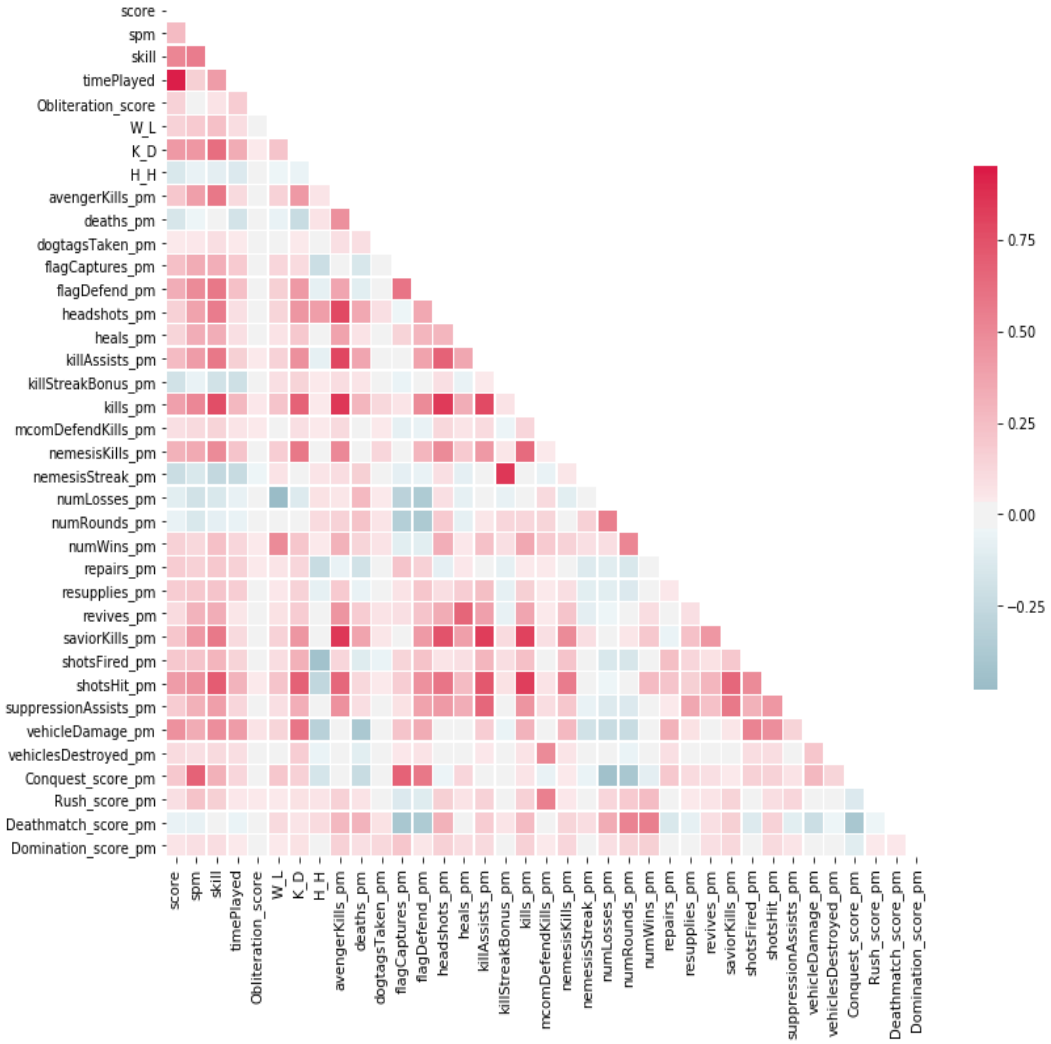


Even highly skilled players seem to only make a little more effort in getting more headshots. This may help us infer that headshots are not an effective way to make more gains within the BF4 game. A few other conclusions drawn from comparing groups and also introducing a correlation matrix:

1. Deaths per minute are nearly the same regardless of skill level;

2. The win-rate for every group is nearly the same since the server does a relatively good job at auto-match making

3. High level players are more likely to target and destroy vehicles which is more likely to contribute to higher win-rates



Gun usage stats (Analysis #2)

Within the gun usage data, we focused on the mean accuracy and standard deviation for all weapon categories. We found that Shotguns have the highest average accuracy, but a high std, which means, this weapon takes a lot of effort to master; LMG is the worst weapon in terms of accuracy; The best and most stable weapon seems to be SNIPER RIFLE, with low standard deviation and a relatively high accuracy.

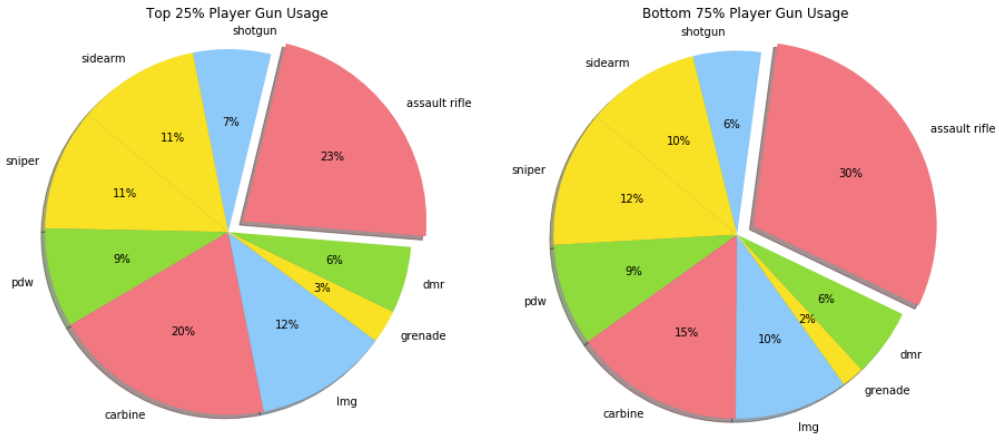
	mean	std	min	25%	50%	75%	max
GADGET_extra.accuracy	23.64	9.88	7.00	16.00	23.00	31.00	46.00
SNIPER RIFLE_extra.accuracy	24.79	5.44	14.00	21.00	25.00	29.00	35.00
PDW_extra.accuracy	11.91	2.97	6.00	10.00	12.00	14.00	17.00
CARBINE_extra.accuracy	12.83	2.88	7.00	11.00	13.00	15.00	18.00
BATTLE PICKUP_extra.accuracy	28.14	8.46	13.00	22.00	28.00	34.00	48.00
LMG_extra.accuracy	9.06	2.50	5.00	7.00	9.00	11.00	14.00
GRENADE_extra.accuracy	24.78	10.54	9.00	16.00	23.00	32.00	51.00
DMR_extra.accuracy	17.55	3.88	10.00	15.00	18.00	20.00	25.00
ASSAULT RIFLE_extra.accuracy	12.32	2.69	7.00	10.00	12.00	14.00	17.00
SHOTGUN_extra.accuracy	63.91	13.89	38.00	53.00	63.00	75.00	93.00
SIDEARM_extra.accuracy	17.90	4.42	9.00	15.00	18.00	21.00	26.00

Since the mean and std of carbines were only slightly better than assault rifles, we compared the two groups using a student t-test. The null hypothesis for our t-test was H0: There is no statistically significant difference between the carbine and assault rifle accuracy.

The t-test resulted in the results below which meant the null hypothesis was rejected and that carbines were indeed better than assault rifles when it came to accuracy.

Ttest_indResult(statistic=-21.71692396390152, pvalue=3.8026573725064386e-104)

Another data group we looked at was weapon usage amongst the top 25% and bottom 75% of players. We used score as a way to look at usage frequency since score highly correlates with weapon usage time.



The null hypothesis was that there isn't a significant difference between top 25% of players and bottom 75% in terms of gun preference. We used the chi-square to compare the two groups and

the results showed that the null hypothesis couldn't be rejected and there was no evidence that the two groups had significant differences.

Power_divergenceResult(statistic=4.55, pvalue=0.804410169231813)

EDA Conclusions

Player patterns are governed by the features of the game. Most players can't or don't make consistent headshots. To increase win-rate, players have to destroy vehicles. Assault rifles and carbines are popular guns due to its range and damage. Shotguns are pretty powerful, but difficult to use. Grenades are pretty effective doing spread damage, which helps ramp up points. The best and most stable weapon seems to be the sniper rifle, which has accuracy amongst players of all skills.

Part 2 Machine Learning, Model Fitting, Hyperparameter Tuning

Introduction and Objective

SPM is a major success indicator within the BF4 game. The general consensus is, since the game is structured around objectives, scores are not generated solely on high Kill/Death Ratios. In the image below, we can see that this player has a moderate K/D of 3.08 and KPM of 0.88, but a high SPM score, which is an indication of him/her being able to understand how to play objectives and support teammates.

The purpose of building our machine learning models are to be able to predict SPM using the various features we've collected and to further explore the relations between features and SPM. The idea is that developers can use what I've built to monitor and adjust in-game mechanics if they want to encourage players to vary their play styles; or they can reconsider whether or not they should adjust the scoring system to better reflect player performance. In other fields, this machine learning method can be applied in sports like baseball, football, basketball as well as various esports games such as Fortnite and Overwatch.

Overview

We are going to start with a somewhat clean dataset in our machine learning model building. The data is good for model fitting with the exception of extreme spm values which will be fixed before we conduct our machine learning.

The steps to cleaning and modeling the data is as follows:

- Load the dataset, sort players by SPM and eliminate the top/bottom 1% of players based on that.
- Build a test linear model using Kills as the independent variable and check the results.
- Remove redundant features that might interfere with the modeling.
- Split the data into training data(75%) and testing data(25%).
- Use Random Forest, SVM, Lasso Regression, Ridge Regression on the training dataset, obtain their RSME, MAE and adjusted R-square.
- Hyperparameter tune the models and evaluate the models again.
- Observe feature importance and coefficient to better understand the models.

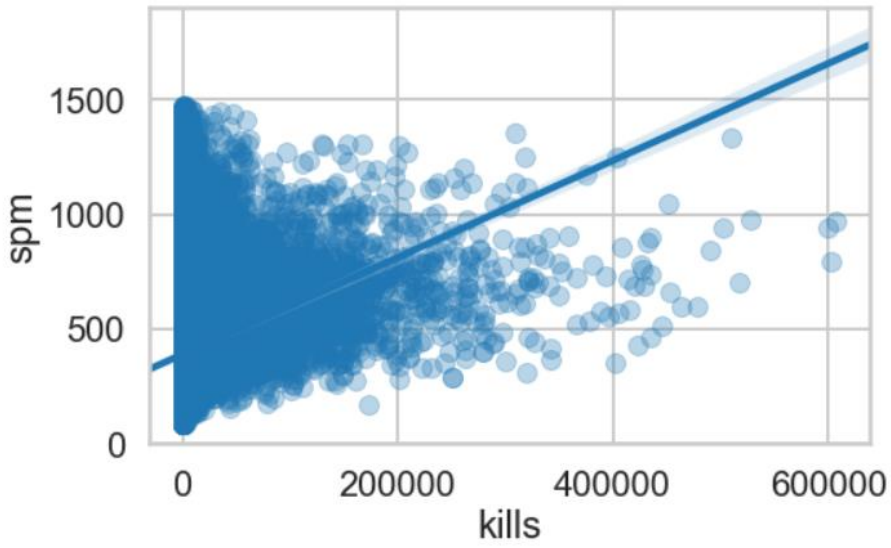
The information of the dataset and the feature size along with dataset sizes are included below, since cleanup was done along the way, the dataset for modeling is a bit smaller than the originally loaded dataset.

- File Size: 34 Megabytes
- Starting Features: 260 columns
- *Actual Features: 246 columns
- Starting Entries: 37081 rows
- *Training data: 27810 rows
- *Testing data: 9271 rows

Single Variable Test

Dependent Variable: SPM Feature: Kills Entries: 37081 R-Square: 7.7%

The first thing that was done was to test whether or not SPM could be explained by one feature. Although BF4 stresses on objectives and co-op, it is still by nature a first person shooting game. Hence Kills might be an important feature to explaining SPM. The idea is that players who have high kills, usually take a lot of time practicing and playing the game. At the beginning of the test, we did a correlation test, showing that kills positively correlates with SPM. We then proceed with modeling kills and spm with a linear regression model.



The eventual result that was obtained was very interesting. As it turns out, Kills alone is not able to explain why a player is able to obtain a high SPM. The R-square for this model is only 7.7% which is very low, which could mean that SPM should be predicted using a combination of features instead of just one feature.

Machine Learning (Random Forest, SVM, Lasso & Ridge)

After testing our data with a single variable, we move on to machine learning models. In our scenario, we used 4 different machine learning methods on our training data and measure their adjusted R-square and Error rates with our testing data. The table below includes a summary of the data based on each method.

Table - Default Models

Original	Random Forest	Support Vector Machine	Lasso Regression	Ridge Regression
RMSE	108.73	222.05	124.07	111.82
MAE	75.67	152.48	80.06	72.69
R^2 adj.	0.799	0.165	0.739	0.788

In the table, we can see the error measurements use RMSE and MAE which signify Root Mean Squared Error and Mean Average Error. Ideally, with a model, the lower the MAE, the less errors between predicted values and original values occur. RMSE on the other hand signifies extreme values, if the MAE is the same among all models, a high RMSE means there are more outliers within the predicted values. R-square is a typical statistical measure that is used to measure goodness-of-fit, however, considering we have 200+ features within our model, it'd be best to use adjusted R-square instead, since it compensates for the addition of variables and only increases if the new predictor enhances the model.

The table shows that the best performing model to predict SPM is random forest, it has a relatively low MAE and RMSE, with an adjusted R-square that is close nearly 80%. The two other models that perform relatively well are the ridge and lasso regression, in which the ridge is the better performing of the two with an adjusted R-square of 78.8%. A main reason that L2 is better than L1, is due to L1 Lasso focusing on the more important features for predictions and L2 being more forgiving for the less important features when doing predictions.

Hyperparameter tuning

Moving onwards, the next step is to find the optimal hyperparameters for each model using gridsearchcv. Using the get_params() function, we are able to obtain the parameters for each model and assign values for tuning. After finding the best value for tuning the model, we rerun the model again and test their accuracy using test data. If the model sees improvements in accuracy, we move to calculate the adj. R-square of the model.

Random Forest Average Error: 51.4744 degrees. Accuracy = 86.32%. Improvement of 10.81%	SVM Average Error: 131.2202 degrees. Accuracy = 66.05%. Improvement of 12.2%
Lasso Average Error: 402.6419 degrees. Accuracy = 48.18%. Improvement of -37.06%	Ridge Average Error: 199.8905 degrees. Accuracy = 67.61%. Improvement of -13.74%

We can see based on the information, only the random forest and SVM models see improvements in accuracy. The reason tuning didn't help with Lasso and Ridge was because both tuning models overfitted the training data, thus lowered its accuracy when we used the same model to fit the testing data. Hence, it's best to keep the Lasso and Ridge models as is for now.

Hyper Adj.	Random Forest	Support Vector Machine	Lasso Regression	Ridge Regression
RMSE	81.35	200.89	N/A	N/A
MAE	51.43	131.22	N/A	N/A
R^2 adj.	0.887	0.316	N/A	N/A

As can be seen in the model above, we see significant improvements in both SVM and Random Forest, but since Random Forest yields the best adj. R-square, which is 87.7%, for predictions, it's best to use the Random Forest model.

Understanding Feature Importance and Coefficients

1. **Random Forest Feature Importance (left):** From our random forest model, we can extract information regarding its feature importance, based on the chart on the left, we can see that the usage of assault kits to earn points seem to be the most important in predicting overall spm. The problem with this table is that there is no way of knowing whether the feature positively or negatively affects the overall score.

2. **Ridge Regression Feature Importance (right):** The ridge regression offers more clarity by offering us the option to look at coefficient, we can see that features like weaponKpm, seems to be a key contributor to spm calculations. Based on our understanding of the previous EDA done, we can see that Assault Rifle and Grenade are both top picks when it comes to score earnings, which shows that players pick are using these weapons frequently for good reason.

	Features	Importance
29	kits.assault.spm	0.678236
58	scores.award	0.068048
36	kits.engineer.spm	0.067571
44	kits.support.spm	0.016708
164	ASSAULT RIFLE_stat.score	0.014352
28	kits.assault.score	0.013097
218	Main Battle Tanks_extra.spm	0.011637
183	SIDEARM_extra.spm	0.008457
17	extra.weaTimeP	0.008365
70	timePlayed	0.008048

	Features	coefficient
16	extra.weaKpm	25.032769
6	extra.kdr	20.248546
20	extra.wlr	13.073811
17	extra.weaTimeP	5.344921
3	extra.accuracy	3.885223
12	extra.vehTimeP	3.668227
9	extra.sfpm	1.113352
160	ASSAULT RIFLE_extra.spm	0.805036
136	GRENADE_extra.accuracy	0.545930
122	BATTLE PICKUP_stat.kills	0.525416