Top 4 Rank Prediction & Analysis

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Overview

1. Why I chose this topic

2. How I’m going to approach this topic

3. Analysis

4. What are the limits and future work

Why I chose this topic?

I’m a huge soccer and Chelsea FC fan, and I was wondering about what are the crucial factors that teams must have to win the league. Is it number passes, pass accuracy, shot on target, and so on.

What factors should a team to focus on?

It will be interesting to know what factors are actually affecting matches and use that insight to improve team’s performances.

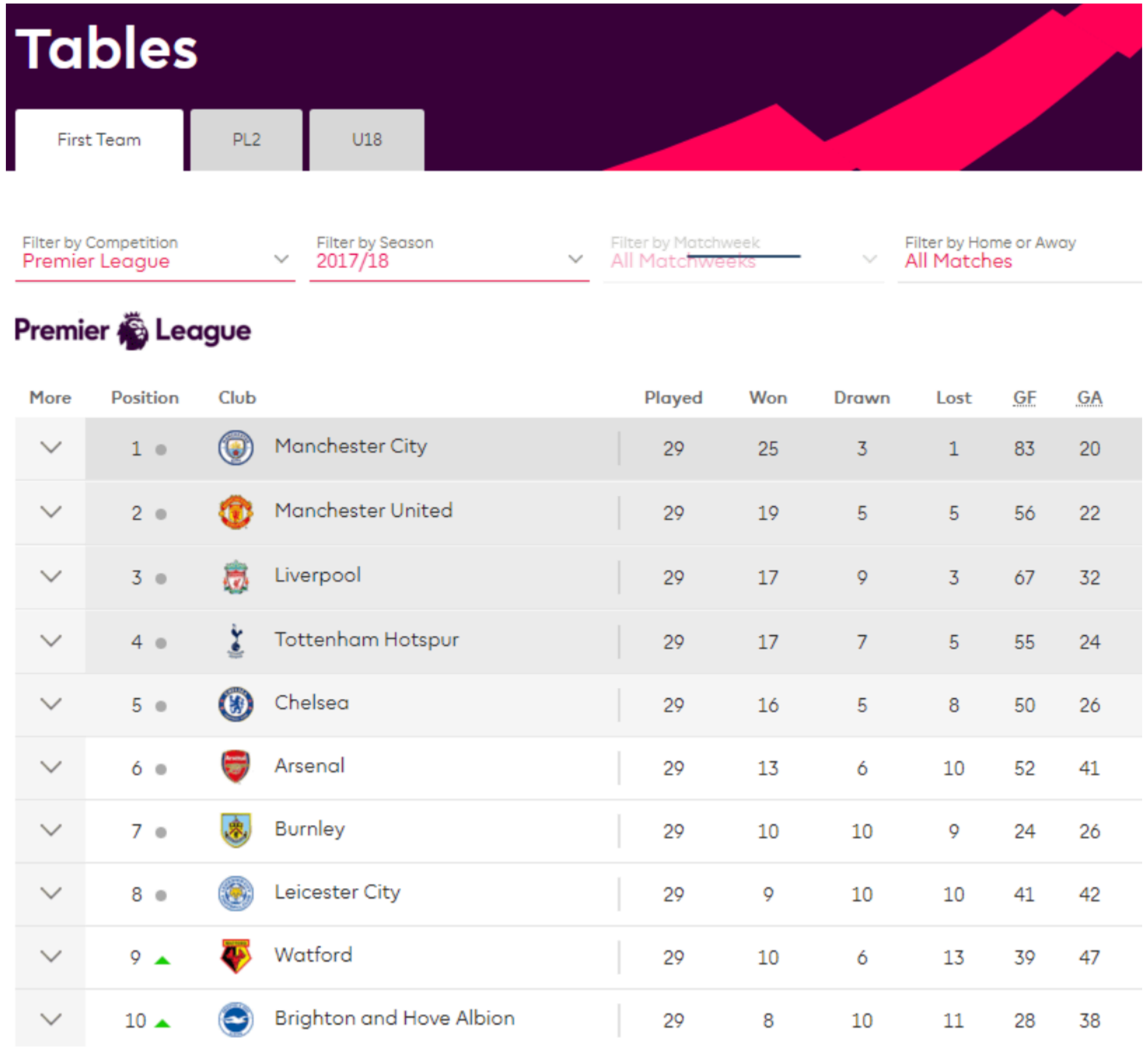
In addition, I’m curious if I can predict the top 4 teams and rank according to how teams do until December which is a half mark in season.

Approach

1. Getting data from the official EPL website
    a. Web scraping
2. Exploring dataset
    a. Data Wrangling
    b. EDA
    c. Selecting features
    d. Normalization
3. Test ML models
4. Predict the Top 4 rank
5. Conclusion/ Limitation

Getting data from official website by web scraping

General table data 2010 to 2017



Tables

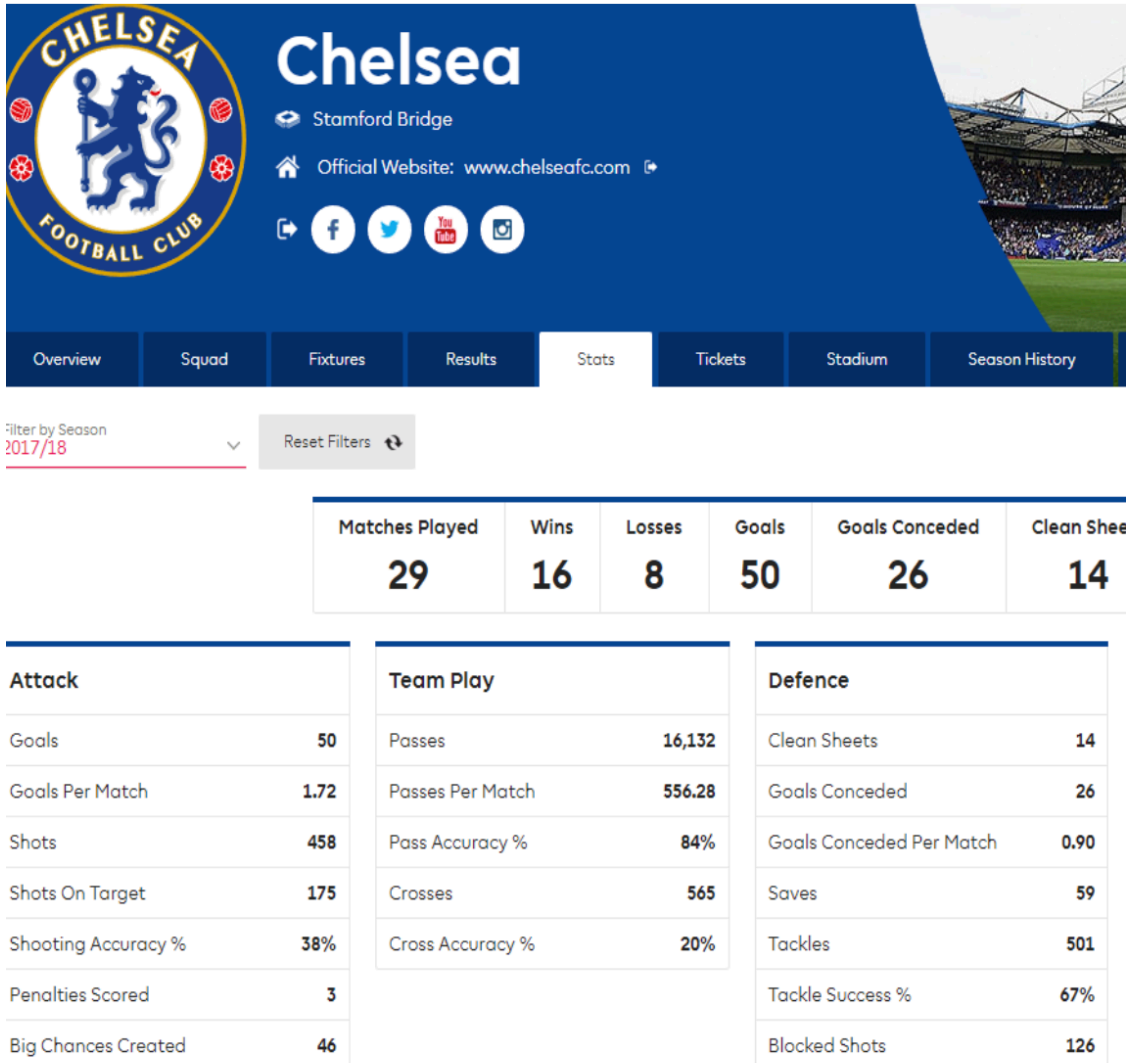
First Team | PL2 | U18

Filter by Competition: Premier League
Filter by Season: 2017/18
Filter by Matchweek: All Matchweeks
Filter by Home or Away: All Matches

Premier League

More	Position	Club	Played	Won	Drawn	Lost	GF	GA
	1	Manchester City	29	25	3	1	83	20
	2	Manchester United	29	19	5	5	56	22
	3	Liverpool	29	17	9	3	67	32
	4	Tottenham Hotspur	29	17	7	5	55	24
	5	Chelsea	29	16	5	8	50	26
	6	Arsenal	29	13	6	10	52	41
	7	Burnley	29	10	10	9	24	26
	8	Leicester City	29	9	10	10	41	42
	9	Watford	29	10	6	13	39	47
	10	Brighton and Hove Albion	29	8	10	11	28	38

Club's statistics data



Chelsea

Stamford Bridge

Official Website: www.chelseafc.com

Overview | Squad | Fixtures | Results | Stats | Tickets | Stadium | Season History

Filter by Season: 2017/18
Reset Filters

Matches Played	Wins	Losses	Goals	Goals Conceded	Clean Shee
29	16	8	50	26	14

Attack	
Goals	50
Goals Per Match	1.72
Shots	458
Shots On Target	175
Shooting Accuracy %	38%
Penalties Scored	3
Big Chances Created	46

Team Play	
Passes	16,132
Passes Per Match	556.28
Pass Accuracy %	84%
Crosses	565
Cross Accuracy %	20%

Defence	
Clean Sheets	14
Goals Conceded	26
Goals Conceded Per Match	0.90
Saves	59
Tackles	501
Tackle Success %	67%
Blocked Shots	126

Example of table data

General table data 2010 to 2017

	club_name	drawn	goal	goal_against	lost	points	position	won
0	Manchester City	3	83	20	1	78	1	25
1	Manchester United	5	58	23	5	65	2	20
2	Liverpool	9	68	34	4	60	3	17
3	Tottenham Hotspur	7	55	24	5	58	4	17
4	Chelsea	5	52	27	8	56	5	17
5	Arsenal	6	52	41	10	45	6	13
6	Burnley	10	27	26	9	43	7	11
7	Leicester City	10	45	43	10	40	8	10
8	Everton	7	35	49	13	37	9	10
9	Watford	6	39	47	13	36	10	10
10	Brighton and Hove Albion	10	28	40	12	34	11	8
11	Bournemouth	9	34	44	12	33	12	8
12	Newcastle United	8	30	40	14	32	13	8
13	Swansea City	7	25	42	15	31	14	8

Example of club's statistics data

```
chelsea
```

	aerial_battles	big_chance_created	clearance	club_name	cross	cross_accuracy	goal_conceded_per_match	goal_per_match	interceptions	pass_accuracy	pass_per_game	shooting_acc
0	2,682	48	839	Chelsea	688	19%	0.87	2.24	510	84%	529.61	
1	3,075	66	1,027	Chelsea	682	22%	0.84	1.92	376	83%	533.37	
2	3,055	50	1,141	Chelsea	809	25%	0.71	1.87	380	83%	480.68	
3	2,469	56	981	Chelsea	863	20%	1.03	1.97	504	83%	484.87	
4	2,551	86	762	Chelsea	995	25%	0.87	1.82	616	84%	506.21	

Reference on club’s statistics data

Soccer Jargons

Aerial Battle: The number of winning the balls in the air.
Big Chance Created: The number of chances that are directly related to score.
Clearance: The number of clearances in the defensive situations.
Cross: The number of crosses that are executed.
Cross Accuracy: The accuracy of cross that delivers the ball to the own team.
Goal Conceded Per Match: Average conceding goals per match.
Goal Per Match: Average scoring goals per match.
Interception: The number of intercepts.
Pass Accuracy: The accuracy of pass that delivers the ball to the own team.
Pass Per Game: The number of passes that are executed.
Shooting Accuracy: The accuracy of shooting that shots on goal.
Shot On Target: The number of shootings on goal.
Tackle Success: The accuracy of takle that successfully steals the ball from opponents.

Exploring dataset - Data Wrangling

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 160 entries, 0 to 159
Data columns (total 8 columns):
club_name       160 non-null object
drawn           160 non-null int64
goal            160 non-null int64
goal_against    160 non-null int64
lost            160 non-null int64
points          160 non-null int64
position        160 non-null int64
won             160 non-null int64
dtypes: int64(7), object(1)
memory usage: 10.1+ KB
```

Table's data types

- 'goal' and 'goal_against' need to be converted to integer data type
- 'position' need to be converted to categorical data type

- Since the purpose of this analysis is which factors should a team to focus on to getting into top 4 on the table, 'win', 'drawn', 'lost', and 'point' will not be included in this analysis.

Exploring dataset - Data Wrangling

	aerial_battles	big_chance_created	clearance	club_name	cross	cross_accuracy	goal_conceded_per_match	goal_per_match
0	2,682	48	839	Chelsea	688	19%	0.87	2.24
1	3,075	66	1,027	Chelsea	682	22%	0.84	1.92
2	3,055	50	1,141	Chelsea	809	25%	0.71	1.87
3	2,469	56	981	Chelsea	863	20%	1.03	1.97
4	2,551	86	762	Chelsea	995	25%	0.87	1.82

interceptions	pass_accuracy	pass_per_game	shooting_accuracy	shot_on_target	tackle_success
510	84%	529.61	35%	204	71%
376	83%	533.37	37%	210	81%
380	83%	480.68	33%	229	77%
504	83%	484.87	34%	212	76%
616	84%	506.21	33%	244	74%

- Unnecessary comma and percentage sign need to be removed before convert the data type to integer

Exploring dataset - Data Wrangling

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 14 columns):
aerial_battles             5 non-null object
big_chance_created         5 non-null int64
clearance                  5 non-null object
club_name                  5 non-null object
cross                      5 non-null int64
cross_accuracy             5 non-null object
goal_conceded_per_match    5 non-null float64
goal_per_match             5 non-null float64
interceptions              5 non-null int64
pass_accuracy              5 non-null object
pass_per_game              5 non-null float64
shooting_accuracy          5 non-null object
shot_on_target             5 non-null int64
tackle_success             5 non-null object
dtypes: float64(3), int64(4), object(7)
memory usage: 640.0+ bytes
```

Club’s statistics data types

- Every features need to be converted to integer

Exploring dataset - Data Wrangling

- The values need to be in average to compare in ‘per match’ unit.

Example of outputs

club_name	goal_per_match	goal_conceded_per_match	shooting_accuracy	shot_on_target	pass_accuracy	pass_per_game	cross	cross_accuracy	interceptions	aerial_battles	big_chance_created	clearance	tackle_success
Chelsea	2.24	0.87	0.35	5.368421	0.84	529.61	18.105263	0.19	13.421053	70.578947	1.263158	22.078947	0.71
Chelsea	1.92	0.84	0.37	5.526316	0.83	533.37	17.947368	0.22	9.894737	80.921053	1.736842	27.026316	0.81
Chelsea	1.87	0.71	0.33	6.026316	0.83	480.68	21.289474	0.25	10.000000	80.394737	1.315789	30.026316	0.77
Chelsea	1.97	1.03	0.34	5.578947	0.83	484.87	22.710526	0.20	13.263158	64.973684	1.473684	25.815789	0.76
Chelsea	1.82	0.87	0.33	6.421053	0.84	506.21	26.184211	0.25	16.210526	67.131579	2.263158	20.052632	0.74

Exploring dataset - Data Wrangling

- Combine 'table' data frame with 'club statistics' data frame for further analysis.

Example of outputs

club_name	goal_per_match	goal_conceded_per_match	shooting_accuracy	shot_on_target	pass_accuracy	pass_per_game	cross	cross_accuracy	interceptions	...	big_chance_created	clearance	tackle_success	drawn	goal
Chelsea	2.24	0.87	0.35	5.368421	0.84	529.61	18.105263	0.19	13.421053	...	1.263158	22.078947	0.71	3	85
Chelsea	1.92	0.84	0.37	5.526316	0.83	533.37	17.947368	0.22	9.894737	...	1.736842	27.026316	0.81	9	73
Chelsea	1.87	0.71	0.33	6.026316	0.83	480.68	21.289474	0.25	10.000000	...	1.315789	30.026316	0.77	7	71
Chelsea	1.97	1.03	0.34	5.578947	0.83	484.87	22.710526	0.20	13.263158	...	1.473684	25.815789	0.76	9	75
Chelsea	1.82	0.87	0.33	6.421053	0.84	506.21	26.184211	0.25	16.210526	...	2.263158	20.052632	0.74	8	69

Continues

goal_against	lost	points	position	won
33	5	93	1	30
32	3	87	1	26
27	6	82	3	25
39	7	75	3	22
33	9	71	2	21

Exploring dataset - Data Wrangling

According to ‘table’ data,
here are the list of teams and the years who were on Top 4 in past 8 years

Manchester City: 2017, 2016, 2015, 2014, 2013, 2012, 2011, 2010
Manchester United: 2017, 2014, 2012, 2011, 2010
Arsenal: 2015, 2014, 2013, 2012, 2011, 2010
Chelsea: 2016, 2014, 2013, 2012, 2010
Liverpool: 2017, 2016, 2013
Tottenham Hotspur: 2017, 2016, 2015, 2011
Leicester City: 2015

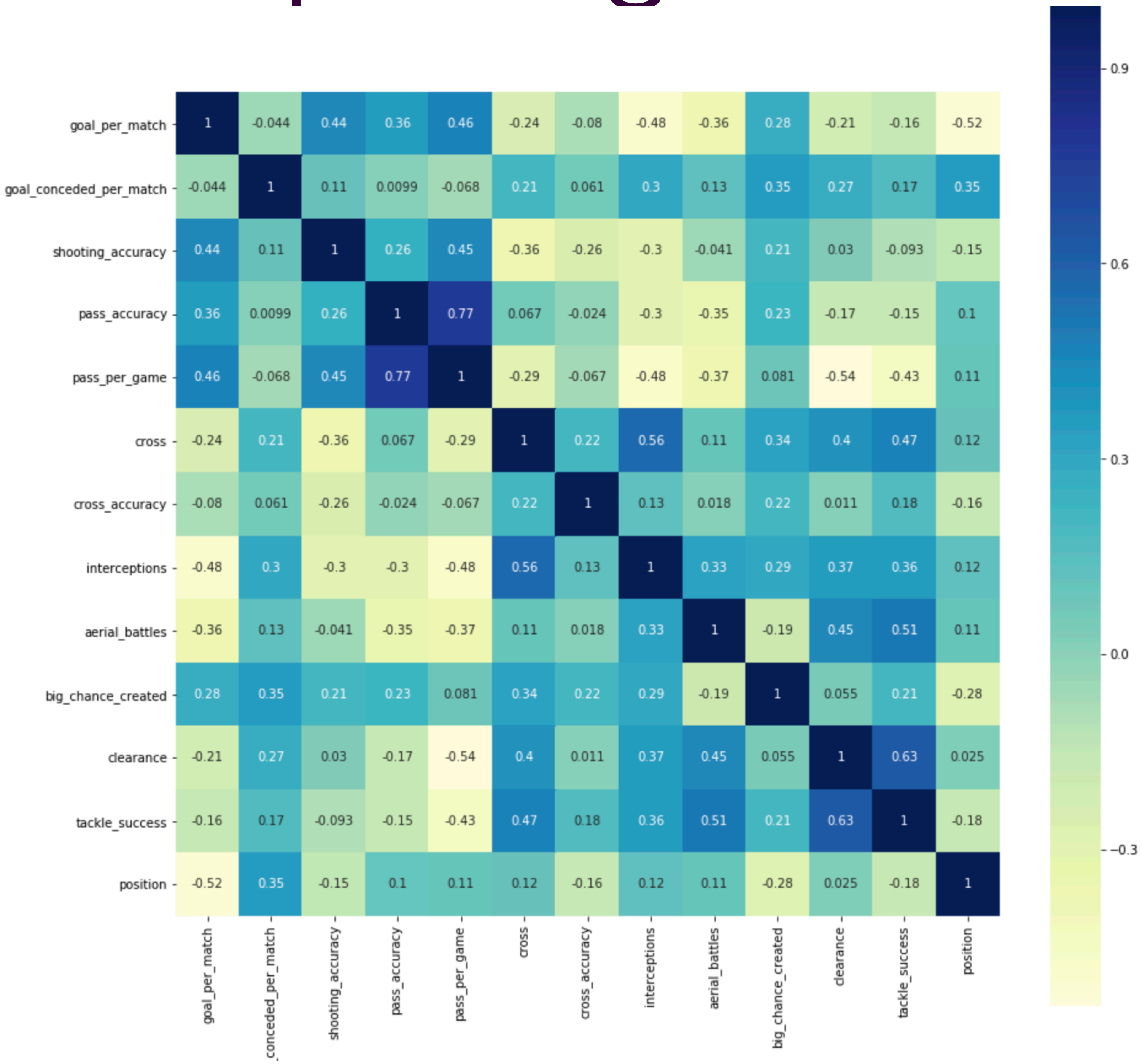
These clubs’ data will be used for further analysis since my interest is in predicting Top 4

Exploring dataset - Data Wrangling

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 13 columns):
goal_per_match              32 non-null float64
goal_conceded_per_match     32 non-null float64
shooting_accuracy           32 non-null float64
pass_accuracy               32 non-null float64
pass_per_game               32 non-null float64
cross                       32 non-null float64
cross_accuracy              32 non-null float64
interceptions               32 non-null float64
aerial_battles              32 non-null float64
big_chance_created          32 non-null float64
clearance                   32 non-null float64
tackle_success              32 non-null float64
position                    32 non-null object
dtypes: float64(12), object(1)
memory usage: 3.3+ KB
```

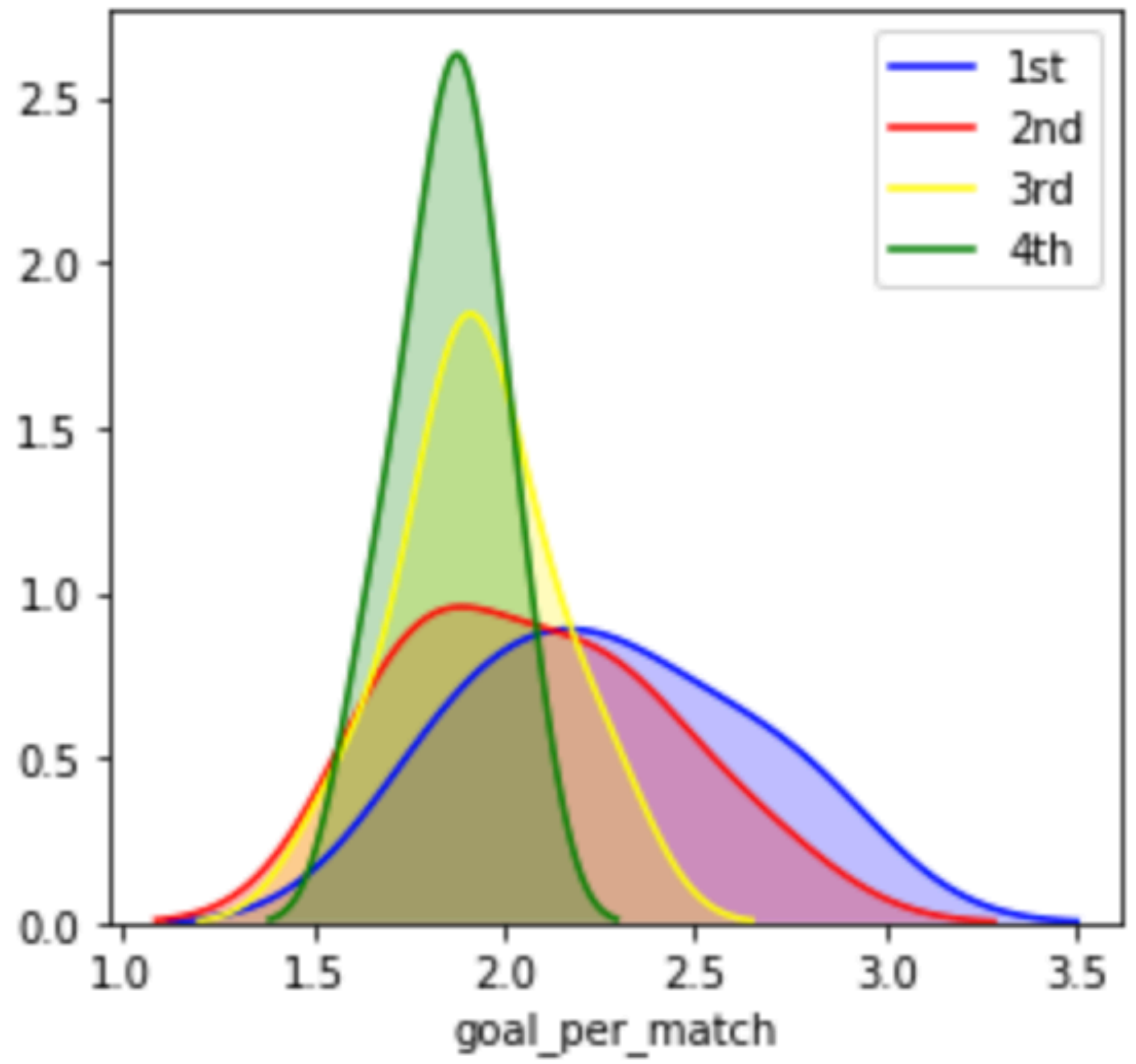
- Combining the data that need in this analysis, result in getting 32 rows of dataset which is very low volume of data. Therefore, overfitting is most likely to occur when performing machine learning models.

Exploring dataset - EDA

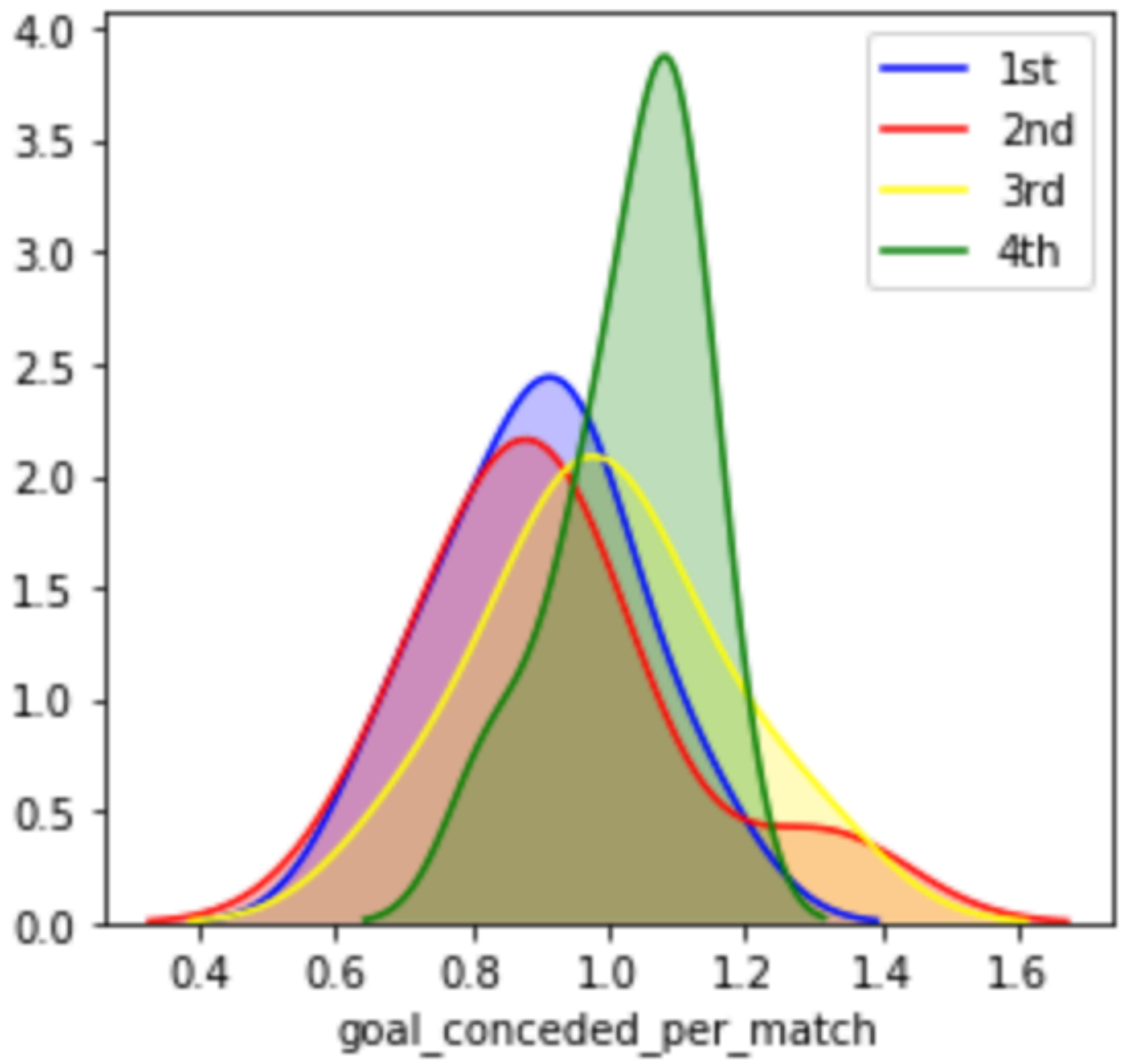


- Insight from heatmap: it looks like '**goal_per_match**', '**goal_per_conceded_per_match**', and '**big_chance_created**' has a correlation with position.

Exploring dataset - EDA

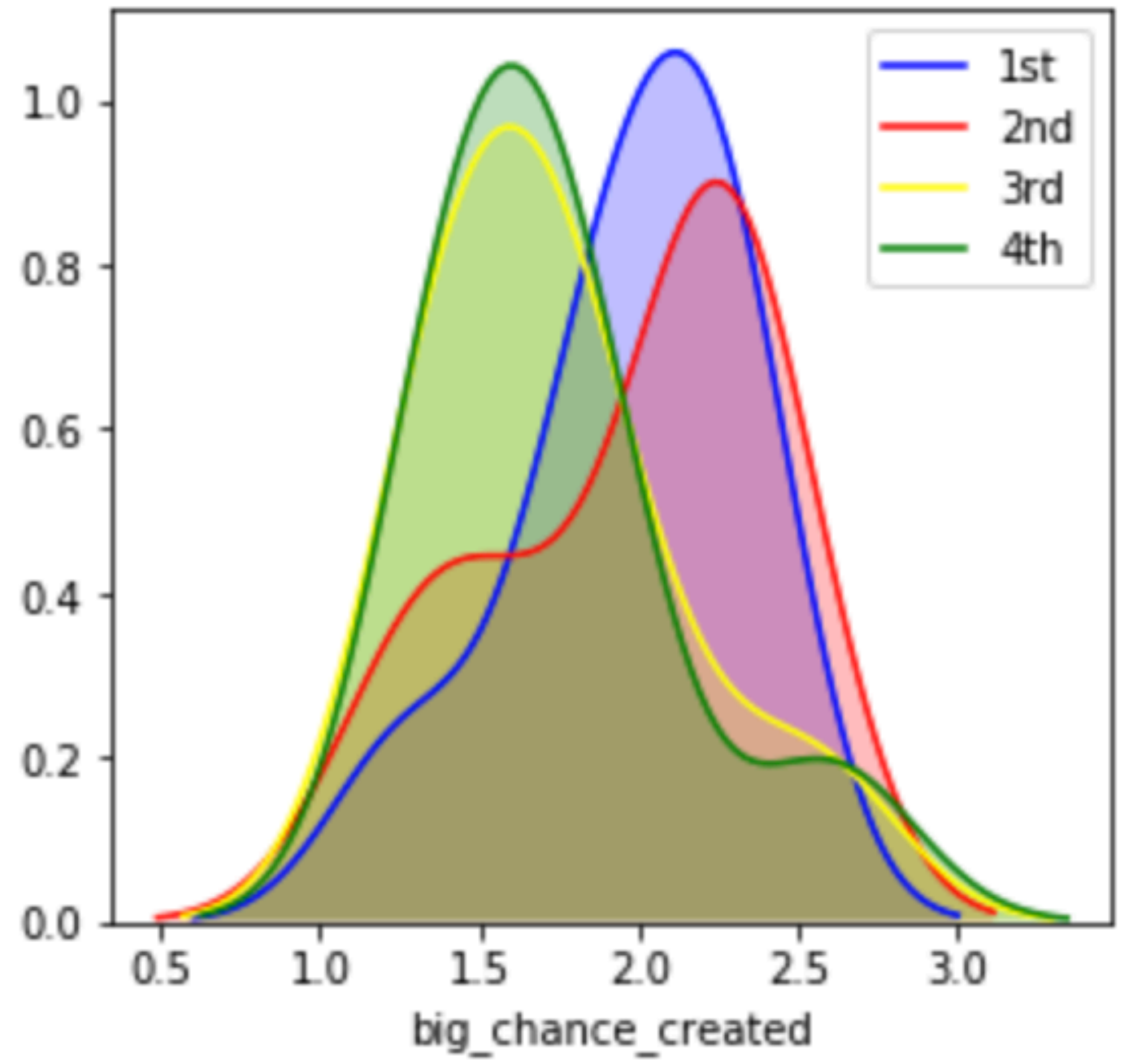


- Goal per match: 1st and 2nd has dispersive range of goal per match, but 3rd and 4th has a lot of goals between 1.5 to 2.5.

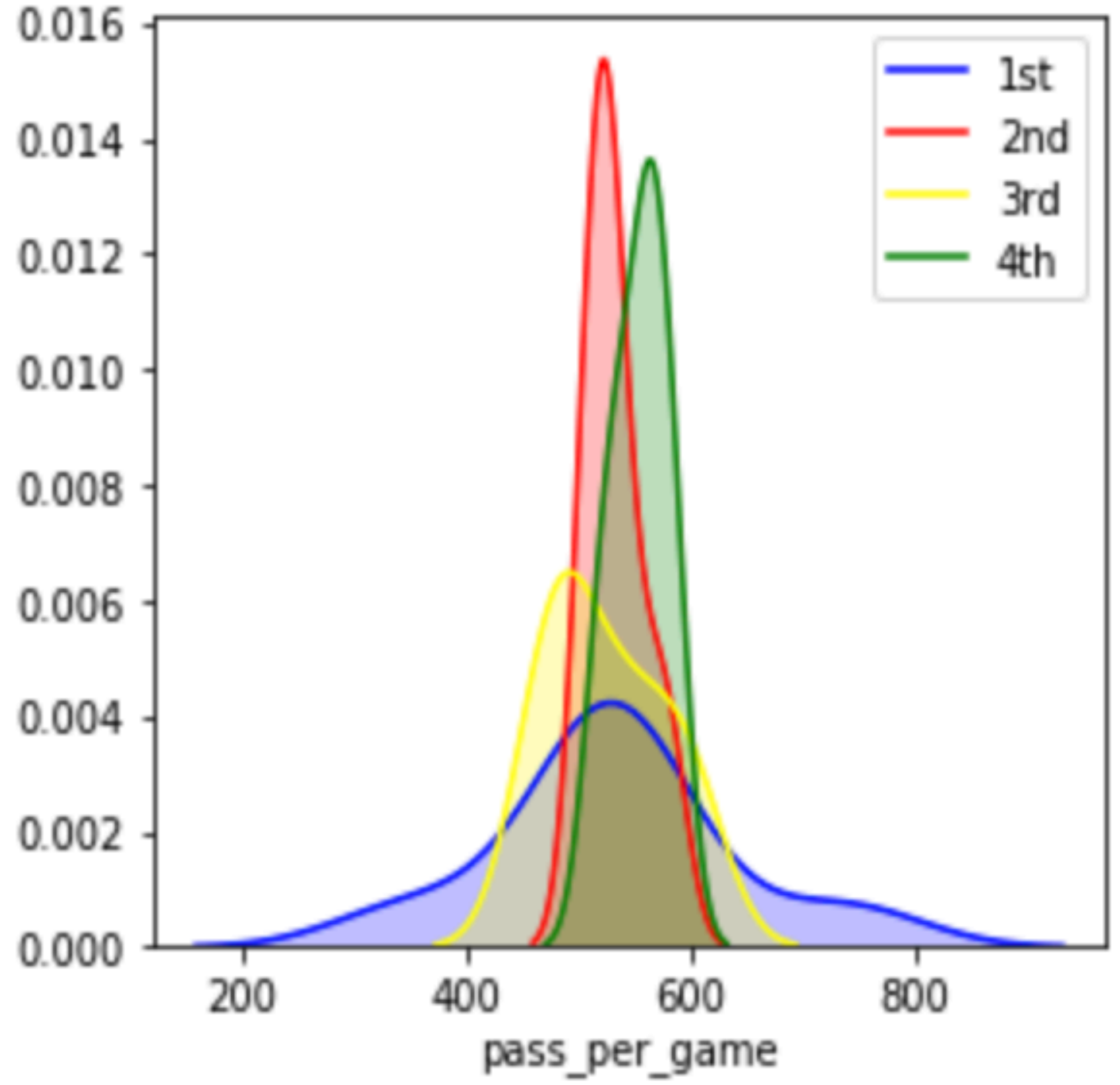


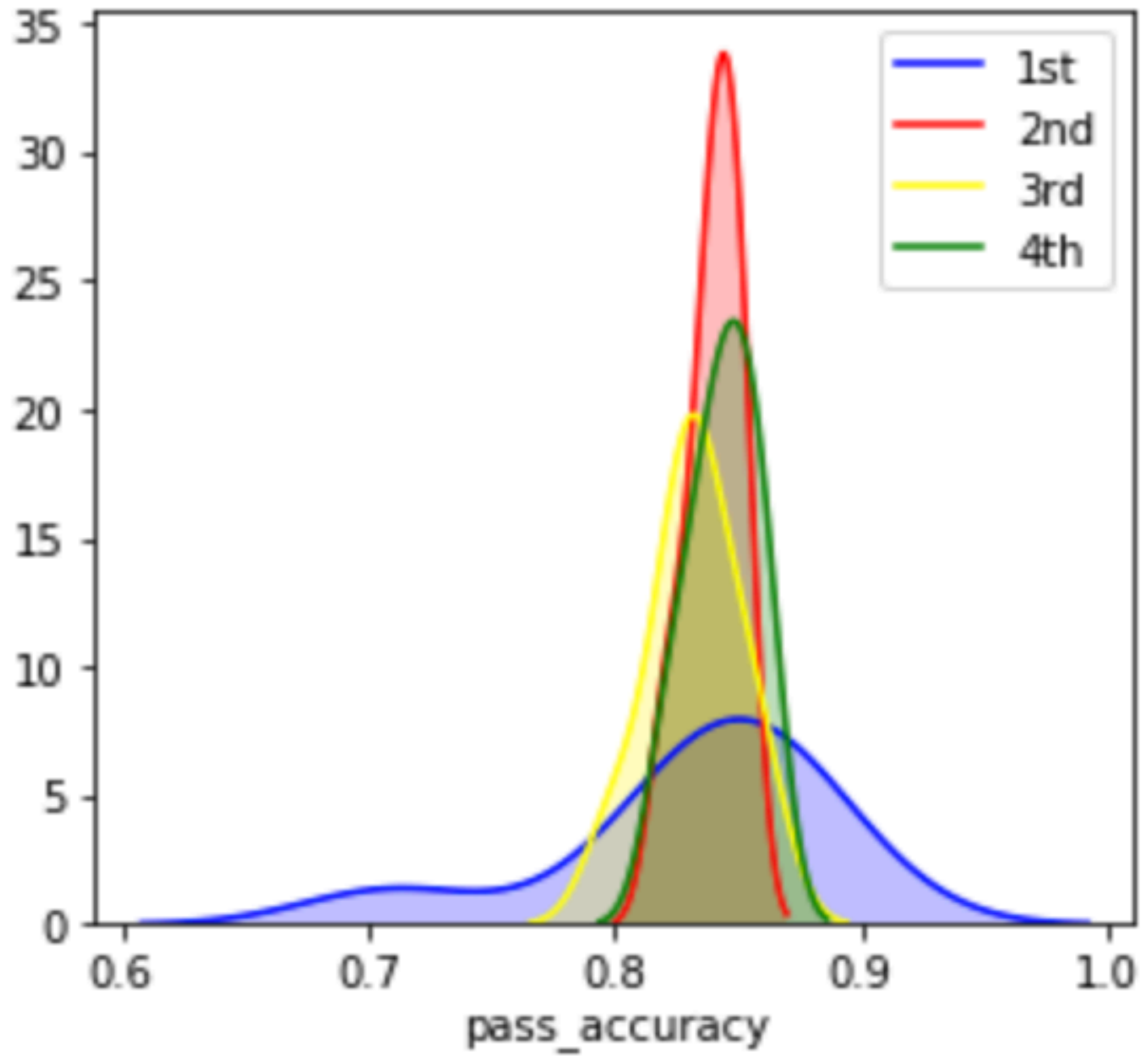
- Goal conceded per match: 4th teams has much more goal conceded than other ranks

Exploring dataset - EDA



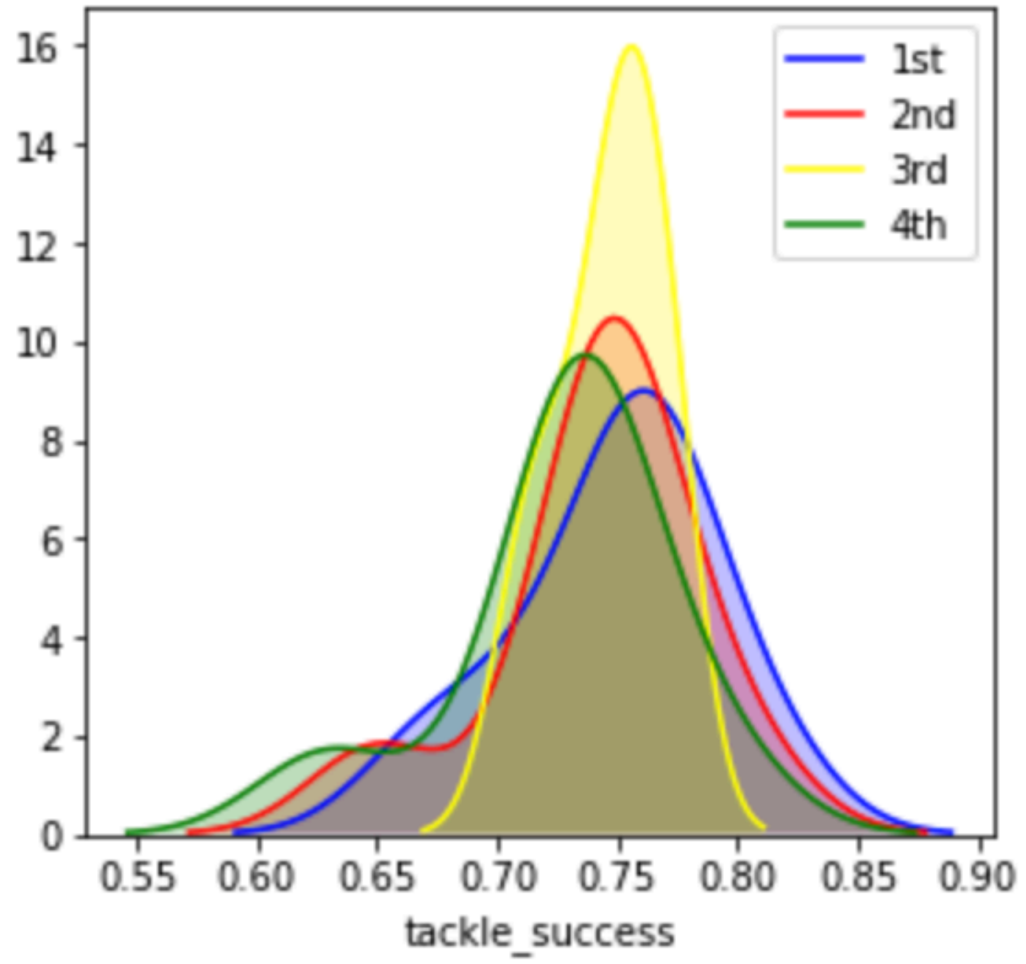
- Big chance created: There is clear signal that more big chance created is better for team's rank.

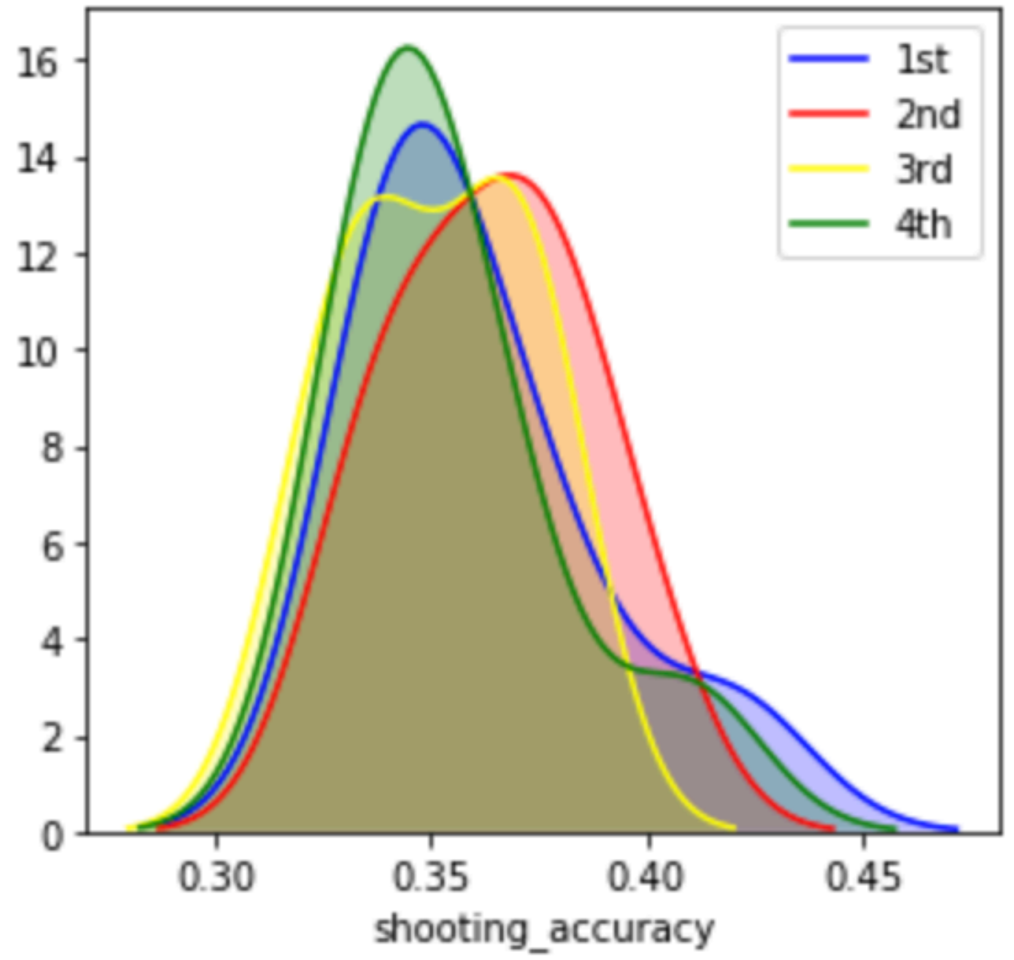


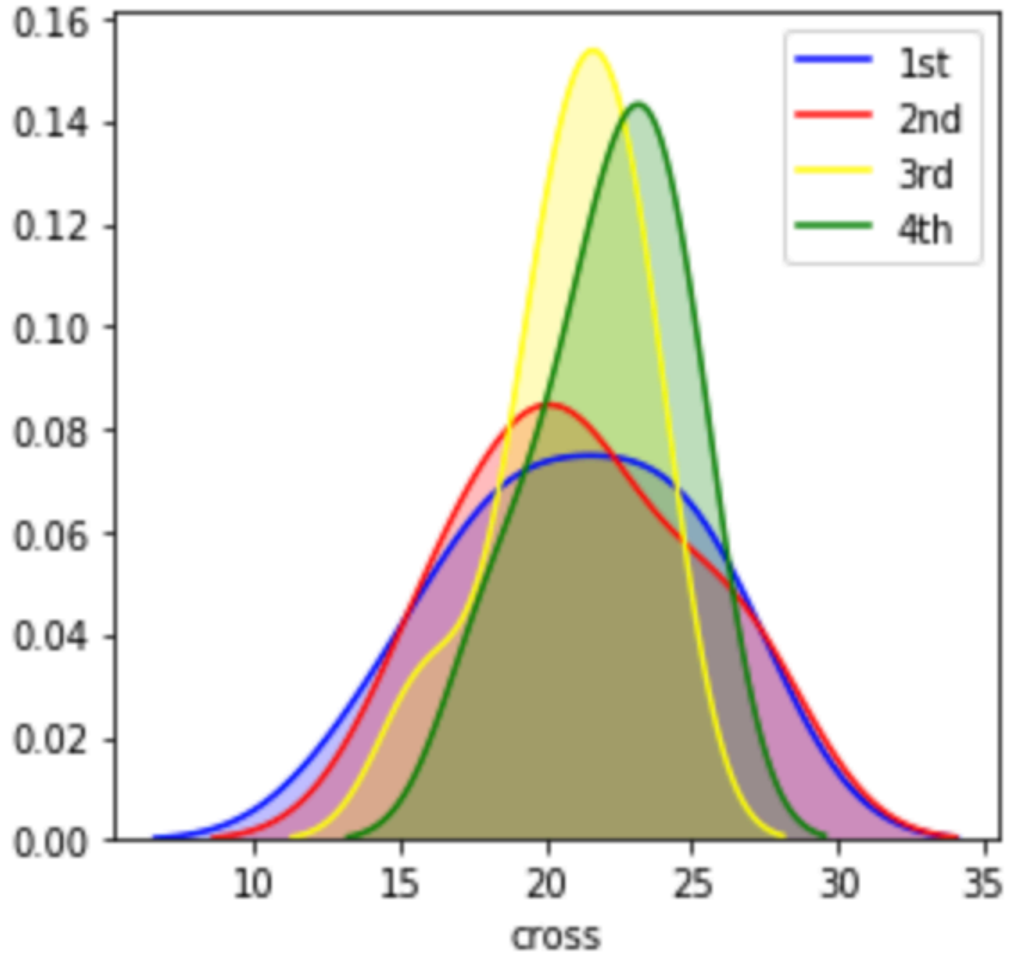


- Pass per game and Pass accuracy: 1st teams usually have dispersive range of the features than other ranks

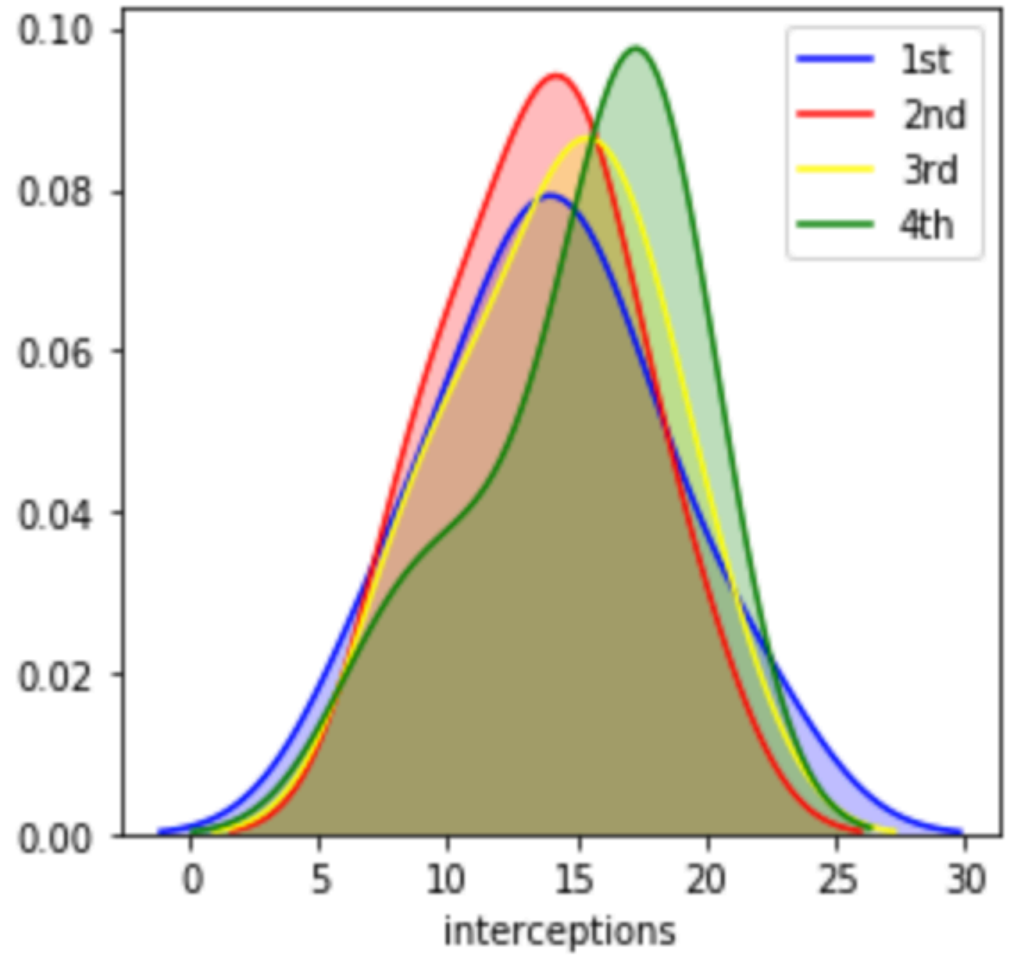
Exploring dataset - EDA

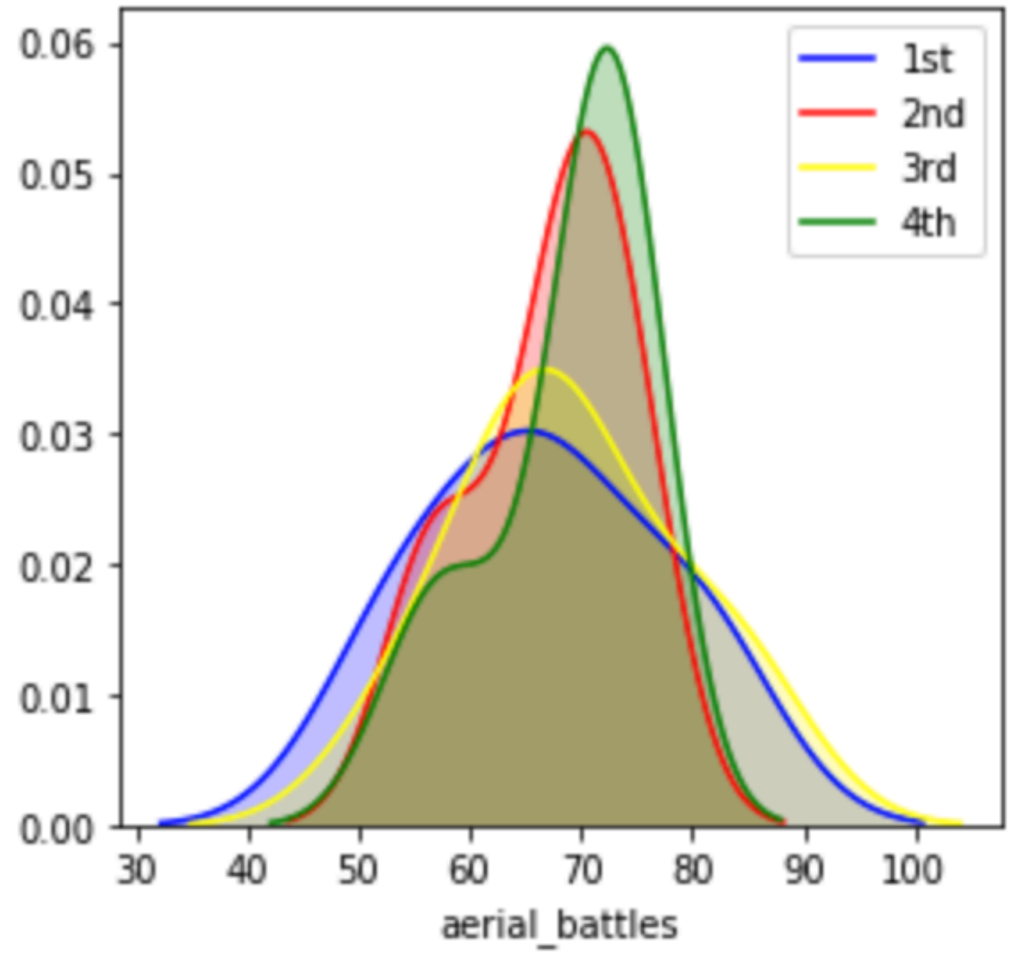


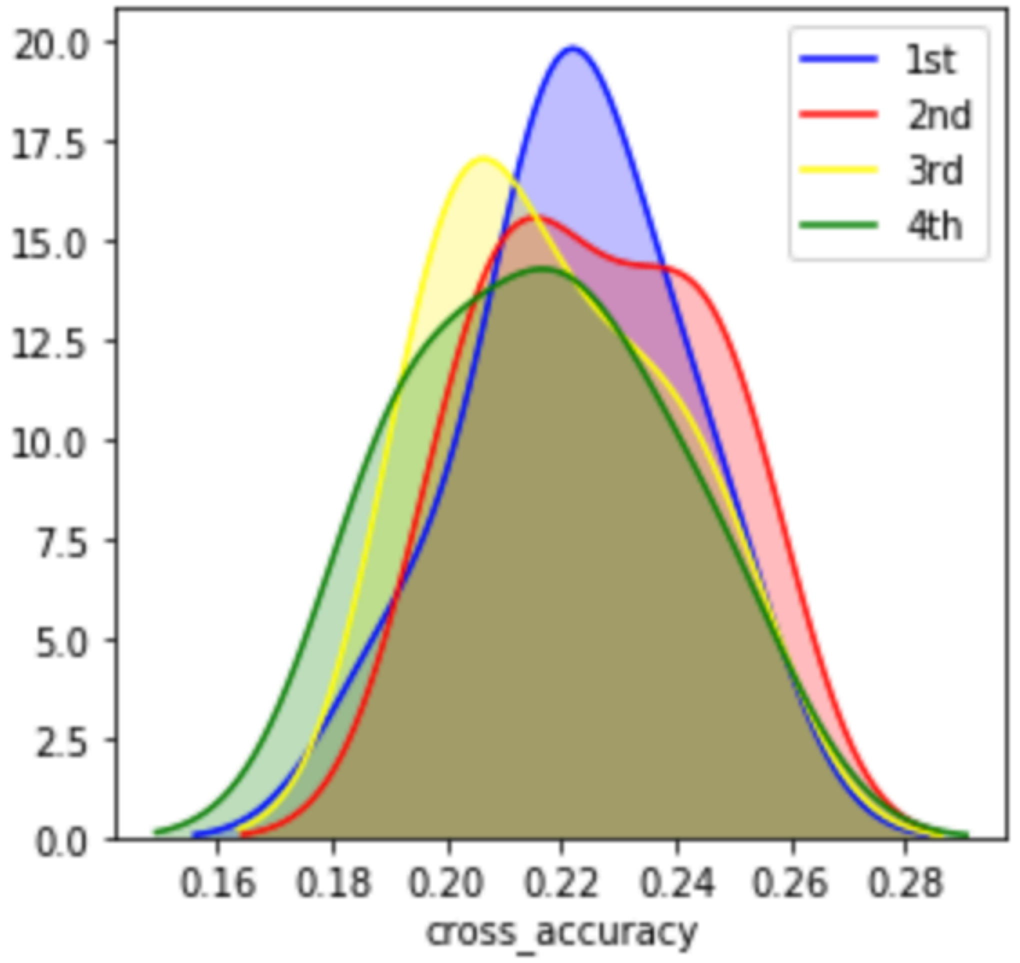


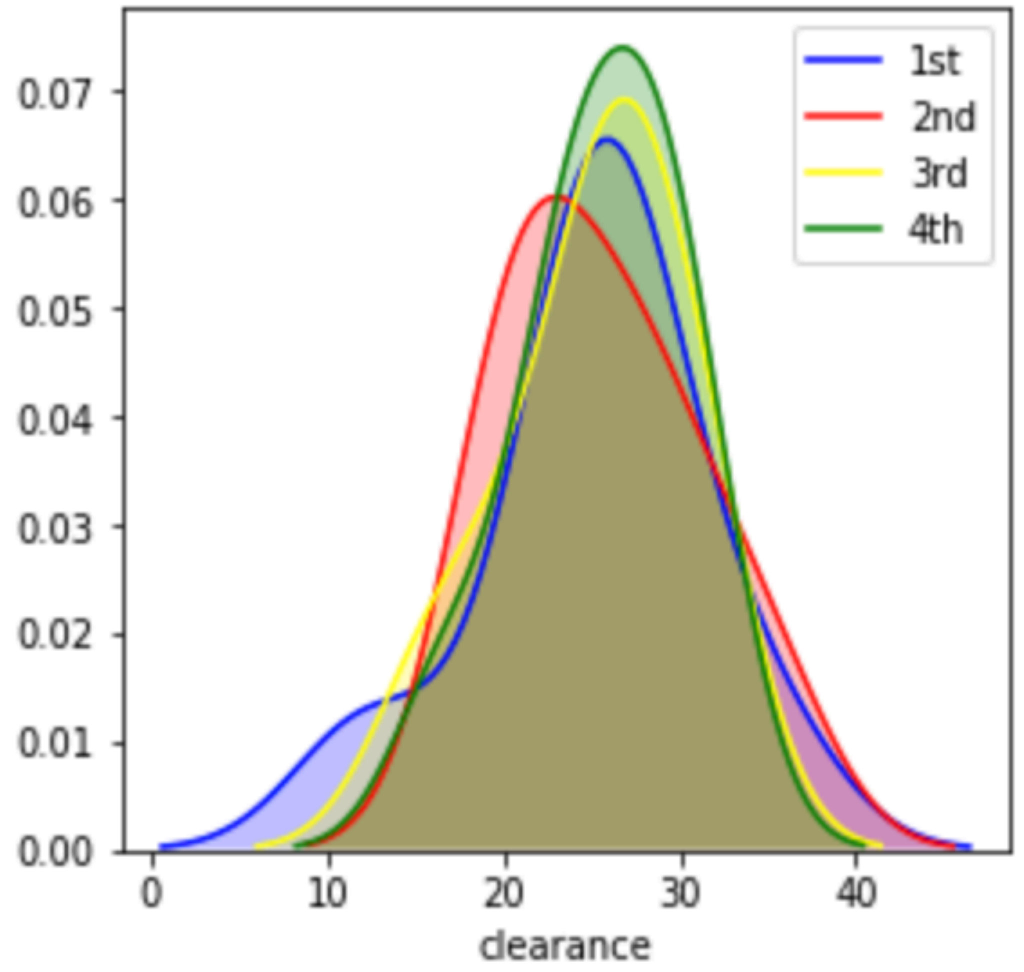


- I do not see much information on these plots.









Exploring dataset - Selecting features

- Let's see if my visual analysis is relevantly correct by using backward elimination and feature selection model from scikit-learn(KBest)

Feature selection based on Logistics Regression model

```
[ True  True False  True False False False False False  True False  True]
 [1 1 4 1 8 2 5 3 7 1 6 1]
 Index(['goal_per_match', 'goal_conceded_per_match', 'shooting_accuracy',
       'pass_accuracy', 'pass_per_game', 'cross', 'cross_accuracy',
       'interceptions', 'aerial_battles', 'big_chance_created', 'clearance',
       'tackle_success'],
      dtype='object')
```

Top 5 features: goal_per_match, goal_conceded_per_match, pass_accuracy, big_chance_created, tackle_success

Exploring dataset - Selecting features

Feature selection based on Xgboost model

```
[ True  True False  True  True False False False False  True False False]
 [1 1 6 1 1 7 4 8 5 1 3 2]
 Index(['goal_per_match', 'goal_conceded_per_match', 'shooting_accuracy',
       'pass_accuracy', 'pass_per_game', 'cross', 'cross_accuracy',
       'interceptions', 'aerial_battles', 'big_chance_created', 'clearance',
       'tackle_success'],
      dtype='object')
```

Top 5 features: goal_per_match, goal_conceded_per_match, pass_accuracy, pass_per_game, big_chance_created

Exploring dataset - Selecting features

Feature selection based on Random Forest model

```
[ True  True False False  True False False False  True  True False False]
 [1 1 8 6 1 4 2 7 1 1 5 3]
 Index(['goal_per_match', 'goal_conceded_per_match', 'shooting_accuracy',
       'pass_accuracy', 'pass_per_game', 'cross', 'cross_accuracy',
       'interceptions', 'aerial_battles', 'big_chance_created', 'clearance',
       'tackle_success'],
      dtype='object')
```

Top 5 features: goal_per_match, goal_conceded_per_match, pass_per_game, aerial_battle, big_chance_created

Exploring dataset - Selecting features

Feature selection based on SVM and KNN

- SVM and KNN does not provie logic to rank the feature; therefore, we cannot implement this method. For SVM and KNN, feature will be selected according to EDA

Top 5 features: goal_per_match, goal_conceded_per_match, pass_accuracy pass_per_game, big_chance_created

Test ML models

- Testing few models to see which model works the best on this problem

    - However, according to analysis from previous, the dataset is too small; therefore, overfitting will likely to occur on every models

1. Multinomial Logistic Regression
2. Support Vector Machine
3. XG boost
4. Knn
5. Random Forest

Test ML models

Training data output

```
Logistic Regression:  0.42857142857142855
 SVM:  0.42857142857142855
 Xgboost:  1.0
 KNN:  0.47619047619047616
 Random Forest:  1.0
```

Test data output

```
Logistic Regression:  0.18181818181818182
 SVM:  0.2727272727272727
 Xgboost:  0.36363636363636365
 KNN:  0.45454545454545453
 Random Forest:  0.18181818181818182
```

- The outputs clearly show that models are overfitting except KNN. KNN is also highly likely to overfit the data, but it might just got lucky or it may work on this analysis.

Predict the Top 4 rank

- Getting a half of 2018 data by the same web scraping method and conduct the same technique to clean the data to perform a prediction.
- Perform predictions with fitted models in a previous step.

Prediction Outcome

	club_name	position	logist	svm	xgboost	knn	random_forest
0	Manchester City	0	2	2	2	2	2
1	Manchester United	1	2	2	3	2	3
2	Liverpool	3	2	2	3	2	3
3	Tottenham Hotspur	2	1	2	1	2	1
4	Chelsea	4	2	2	3	2	3
7	Leicester City	8	2	2	2	2	2

- Based on the results, it is clear that every model is overfitting and giving a poor prediction (so KNN got lucky on training and test data set to validate overfitting).

Conclusion/ Limitation

- Analysis
  There are clearly some differences in features among rank 1 to 4.
  Higher rank teams tent to have:
  - Higher goal_per_match and less goal_conceded_per_match, which means a team that strongly focus on attacking or defensing tactics is less chance to get into higher rank on the table.
  - Higher big_chance_created, pass_accuracy and pass_per_game. This could mean that higher rank teams generally good at passing and execute more passes throughout a game, and this mean it could lead a team to have more chance to score goals.

- Conclusion
  As the analysis above, there are features that favor higher rank teams. According the analysis, training on passing tactics and skills will help a team the most out of all features. Therefore, if a team wants to achieve higher rank on the table, working on passing tactics and skills are recommended.
  On the other hand, predicting the Top 4 rank is not applicable with the low volume dataset. Every machine learning models are overfitting and giving a poor outcome.

Conclusion/ Limitation

- Limitation
  - The volume of dataset was too low to fit machine learning models.
  - There was not enough resource to get the data like the ones I web scraped.
  - Mentality is a huge part of sports, but it is hard to quantify it and could not find any resource to combine with the dataset.

- For future analysis
  - Find a way to replace or get more data to have a large volume of dataset.
  - Apply Bayesian Inference on this analysis. Since it was hard to predict the actual ranks, Bayesian Inference calculates how much a team more likely to be a certain rank.