EPL: Data Analysis and Prediction using Machine Learning

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Certificate of Originality

The work embodied in this report entitled “EPL: Data Analysis and Predictions using Machine Learning” has been carried out by *Nishant Joywardhan (11824)*, and *Satyam Sinha (11834)*, for the paper **“*III.7 Summer Internship: Projects drawn from the world around us*”.** This internship has been carried out under the supervision of *Prof. Shobha Bagai*, Cluster Innovation Centre, University of Delhi. We declare that the work and language included in this project report is free from any kind of plagiarism.

Nishant Joywardhan **Satyam Sinha**

Acknowledgement

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Abstract

EPL: Data Analysis and Predictions using Machine Learning

by

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Cluster Innovation Centre, 2019

Machine Learning is basically an application of Artificial Intelligence (AI) that provides a computer system, the ability to automatically learn and improve from its experience, without any human intervention or explicit coding. Machine Learning is being used these days in many walks of our daily life such as: Facebook face recognition, Motion Sensing in Video Games, VR headsets, Text to speech and vice versa, Space Technology, Recommendations on Amazon, etc.

This particular project is intended towards connecting Machine Learning with a real life sport, which is played by almost 250 million players in over 200 countries, namely Football.

We first use our knowledge in doing an extensive analysis of a dataset of English Premier League which is then followed by an attempt to make a prediction of the football matches of EPL on another small, but extensive dataset. This is done by applying some famous algorithms of machine learning to the dataset, such as the Logistic Regression and Support Vector Machine (SVM). Finally we see our limitations and the scope of improvement.

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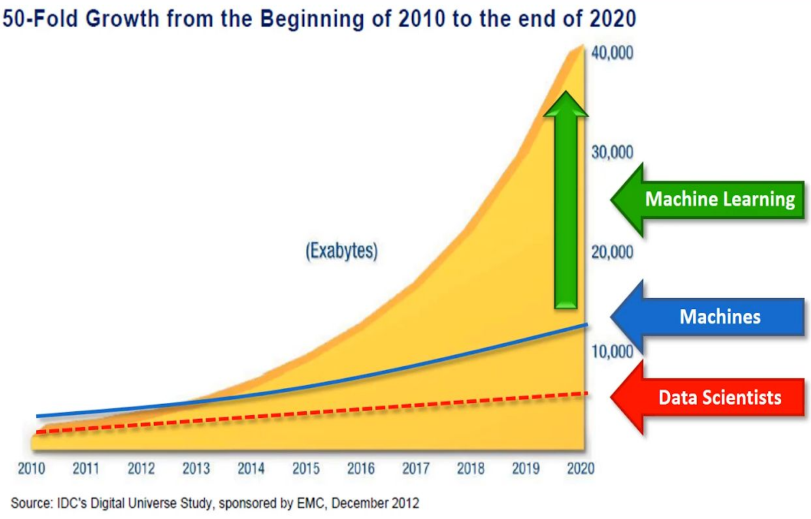
Chapter 1

Introduction to Machine Learning

In this modern world, we are surrounded by 'Data'. It is literally everywhere around us and we as humans, constantly undergo "Data Exhaust", which is the generation of Data as a byproduct of the online actions and choices of the users. The byproducts contain various files generated by web browsers and their plug-ins such as cookies, log files, flash cookies, etc.

All this is leading to an exponential growth of data.

Upto 2005, we had around 130 exabytes of data which is expected to rise upto 40,000 exabytes of data by the year 2020. This is a massive growth, and this enormous amount of data becomes very difficult to be handled by human beings. Thus comes the need of machines and precisely, Machine Learning. This fact can be demonstrated by the following diagram:-



Source: IDC's Digital Universe Study, sponsored by EMC, December 2012

Data Preprocessing

Before applying any Machine Learning algorithm to a dataset, we need to prepare the dataset. This process is called Data Preprocessing, and it is the prerequisite of applying machine learning models.

One of the most basic steps is to import the libraries and the dependencies that we will need for our code to successfully execute.

A library is basically a tool that helps a job get done by returning the desired output. In machine learning, we use three most common python libraries:-

- **Numpy (np) -** NumPy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays. It basically contains mathematical tools.
- **Matplotlib.pyplot (plt) -**Matplotlib is an amazing visualization library in Python for 2D plots of arrays. Matplotlib is a multi-platform data visualization library built on NumPy arrays and designed to work with the broader SciPy stack. It is used to plot charts and graphs with its intuitive tools.
- **Pandas (pd) -** it is the most popular python library that is used for data analysis. It provides highly optimized performance with back-end source code is purely written in *C* or Python. It is used to import datasets and manage them.

Before importing any dataset, we set a working directory, which the folder that contains the dataset. After setting the working directory, we get all set for importing libraries and carrying out our work.

For the available data, we create a matrix of features and the dependent variable or the variable that needs to be predicted.One real life problem which we face is some missing data in our dataset and we need to find a solution for the ML models to run correctly on them. The simple solution is, we replace the missing data with the **mean** of all the available data. For achieving this, we use a very famous library of python, the **Sklearn** library and import the class **Imputer** from its sublibrary **preprocessing**.

After completing all the above steps, the data is ready for further processing!

Other steps involved in Data Preprocessing

- ***Dealing with Categorical Data-*** In our dataset, we might have some data points which are texts and not numbers. However, to apply Machine Learning models to the data, it has to be converted into numbers. That is how the categorical data is dealt with. This step also involves a concept known as Dummy encoding, which is used when any text to number conversion makes no sense.

- ***Splitting the dataset into Training set and Test set-*** \This is one very important step. The concept is, we apply ML model to our training set and it understands the correlation between the independent and the dependent variables. Now to check if the model can adapt to any new situation or not, we apply it on the test set and do the checking part.
    - Training set→ The data on which the machine learns
    - Test set→ The data on which we check if the machine learnt correct

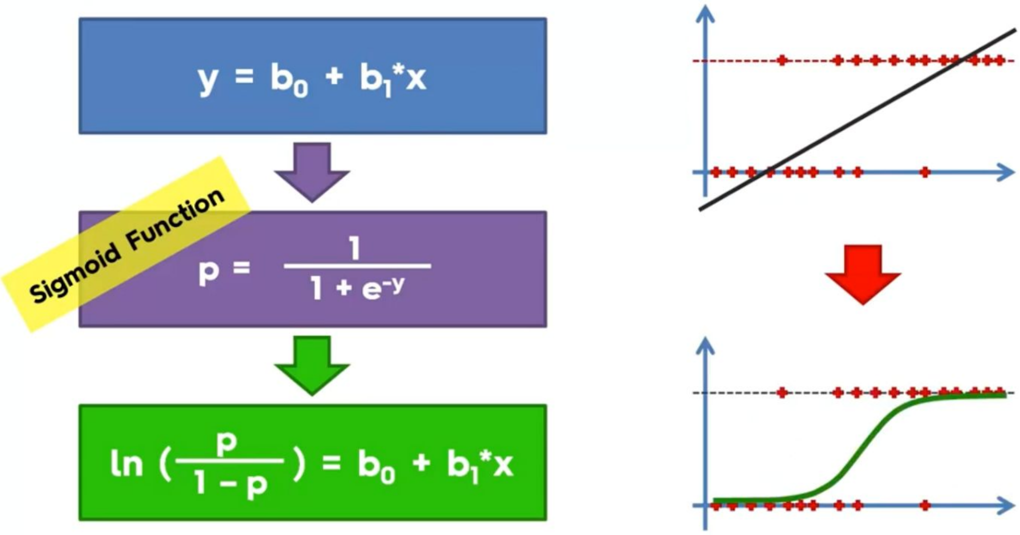
- ***Feature Scaling-*** One very basic requirement of ML is to have data on a common scale. This is because in many ML models, we apply the Euclidean distance to predict some results and we don't want that distance to be dominated by just one entry of input data, because of it being in a different scale.Thus, the process of feature scaling is applied and we obtain all the dataset in a common scale.

After completing all the above mentioned steps, we have our data preprocessed and ready to be used further in our code!

Logistic Regression

Logistic Regression is basically a classification technique that is used to predict a category, unlike the normal regression methods where we predict a continuous number or variable. Logistic Regression is applied by taking a linear regression model and then modifying it according to our needs.

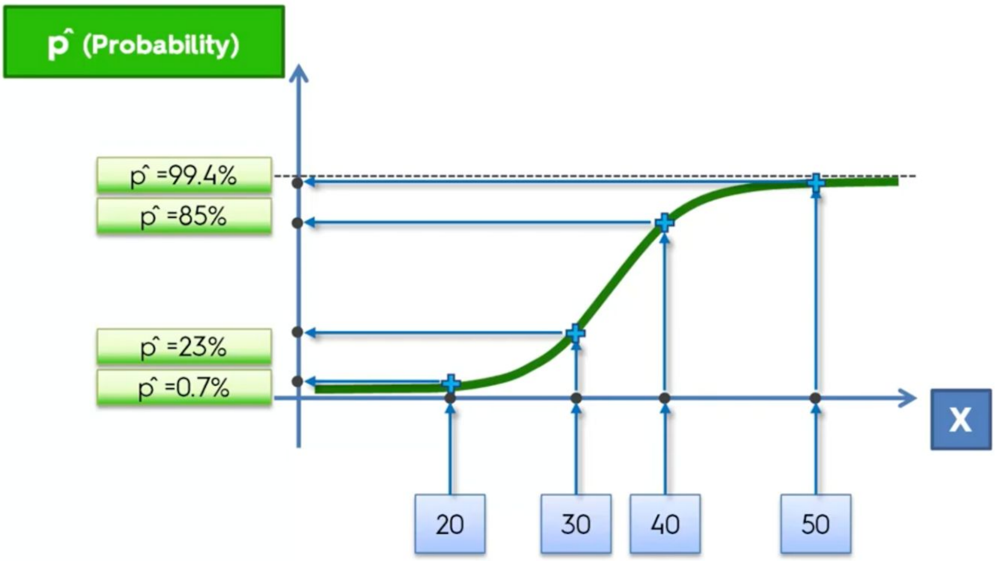
This modification can be demonstrated by the following pictorial representation:-


$y = b_0 + b_1 {}^* x$
Sigmoid Function
$p = \frac{1}{1 + e^{-y}}$
$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1 {}^* x$

We see that with the application of the sigmoid function, we change the linear regression model to our logistic regression model and similarly, the straight line best fit changes to a curved best fit and suits the type of data distribution for which it is deployed.

The final formula obtained is termed as the Logistic Regression Formula, and it can be further used for predicting the probabilities in different situations, as per the need.

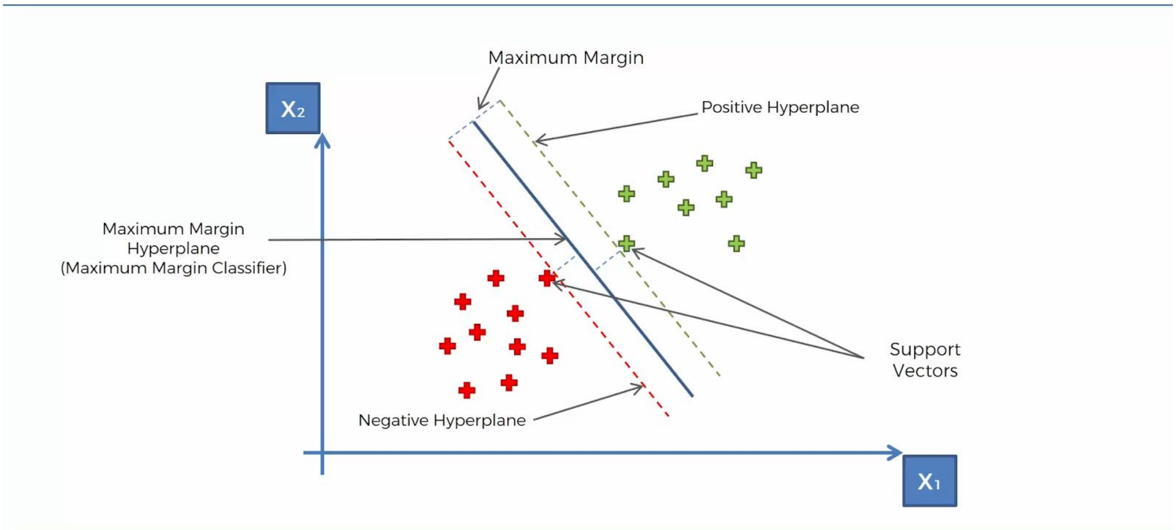
This can be demonstrated in the following pictorial representation:-



In simple terms, this model helps us to find a correlation between the X and Y variables which was not possible earlier. Once the probabilities are determined, we can use it further for other determinations and result analysis.

Support Vector Machine (SVM)

Support Vector Machines try to find a classifier which maximizes the margin between positive and negative data points. This technique basically can be demonstrated by the following pictorial representation:



In case we have two categories of data and we need to draw a decision boundary line to determine into which category should we place a new data point, that's where we make use of the Support Vector Machines.

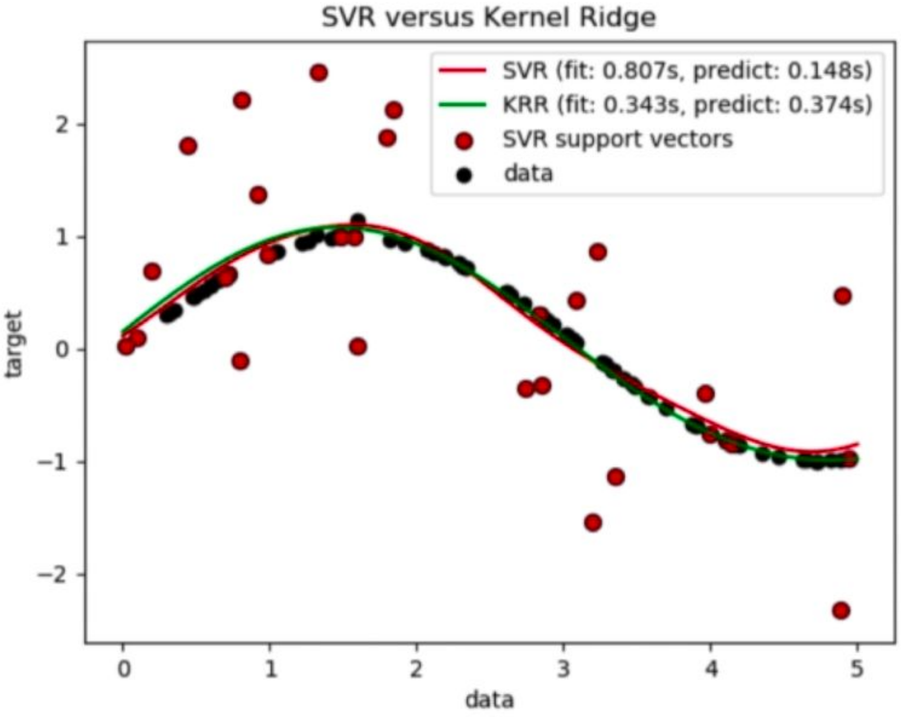
The line marked as the 'Maximum Margin' is equidistant from the two support vectors. The length of the margin has to basically be maximum for the line to be the justified result of Support Vector Machine.

The support vectors are the data points that are supporting the whole algorithm. Once the points through which support vectors pass are identified, then the other points can be removed as well and still the algorithm will behave the same as they don't contribute to the result.

The decision boundary line is termed as the Maximum Margin Hyperplane or Maximum Margin Classifier.

Support Vector Machines generally do the classification on the basis of the EXTREME or the BOUNDARY case and uses it to provide its results. This in itself is a very unique thing. These boundary case data points are the support vectors, used for further classification.
This new approach makes SVM really effective and special.

Support Vector Regression (SVR) is a type of SVM that can support both Linear and Non-Linear Regression. In higher dimensional space, SVR performs Linear Regression.
It can be represented by the following diagram:-



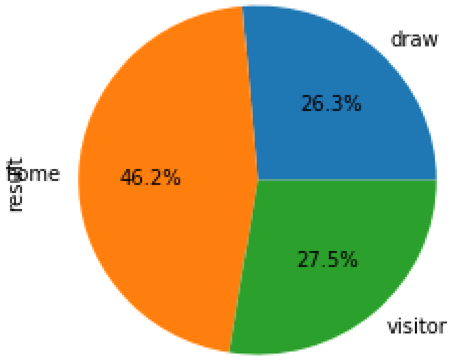
Chapter - 2

Analysis of EPL dataset

The dataset that we have picked out for this analysis is basically a confined data which has columns like Home team, the away team, the half time results for both teams, the season to which the match belongs, and finally the FTR or the full time result.

The major aim of this analysis is to visualize all the above-mentioned data points in a better manner with the help of graphs, pie charts, dot plot, and a heat map.

The first step involves recording who won the game, the home team, the away team or was it a draw between them. This result is visualized in the form of a pie chart:-



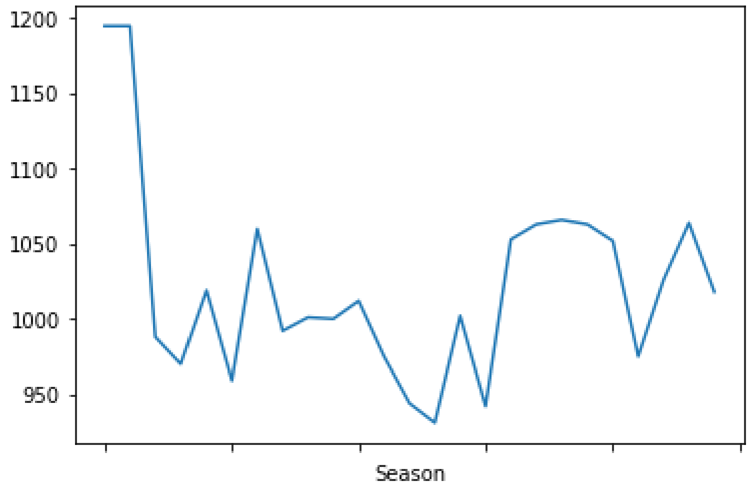
We can clearly see that the home team has a massive 46.2% chance of winning the game. We can reason this in the following manner:-

- Football is a team sport. A cheering crowd helps the morale of the players. That's why we have many times seen a less powerful home team defeat a stronger away team.
- Familiarity with the pitch and the weather conditions helps. Just like any other sport, the physical conditions matter a lot in football and a good understanding of it is always beneficial.

- No travel involved, which implies no fatigue. The away team needs to travel to the home team's city and the stadium and however small the trip might be, it always causes some fatigue which is reflected in the performance of the players on the pitch.

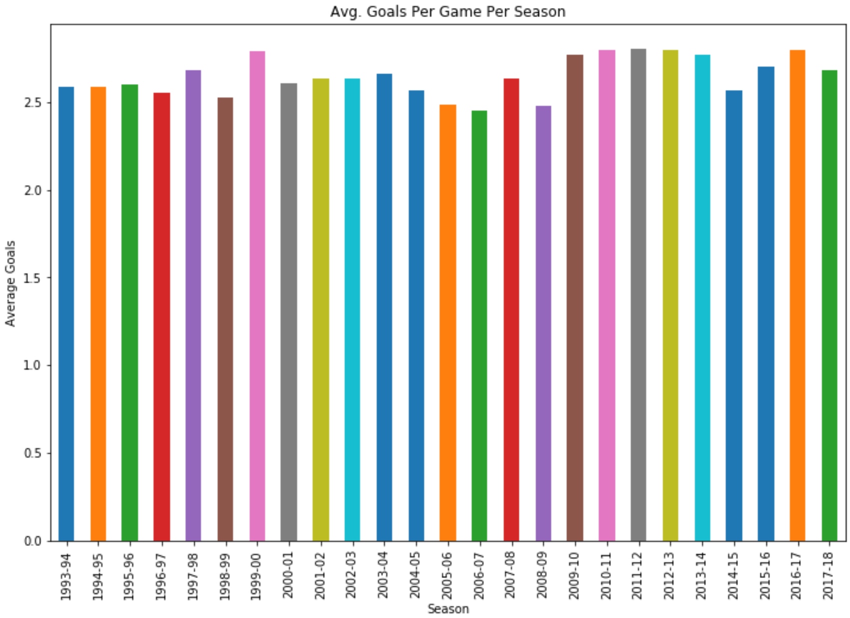
After this, we analyze various different stats of the dataset, and try to visualize each of them with the help of graphs.

- Total goals per season over time:-



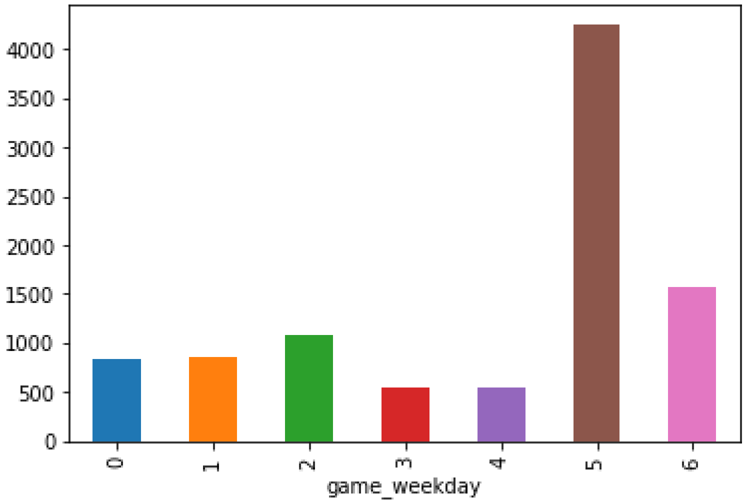
We can see that the total number of goals per season has gone down due in part with the fact that the number of games per season has decreased since the earlier stages of the game. For eg- initially there used to be 45+ matches in the entire league, but now its just limited to 36.

- Number of goals per game per season:-



We see that the average goal per season per game is generally between 2 and 3, which is fair enough as each game generally does see at least 2-3 goals being scored in totality.

- Number of goals scored on a day of the month, per season :-

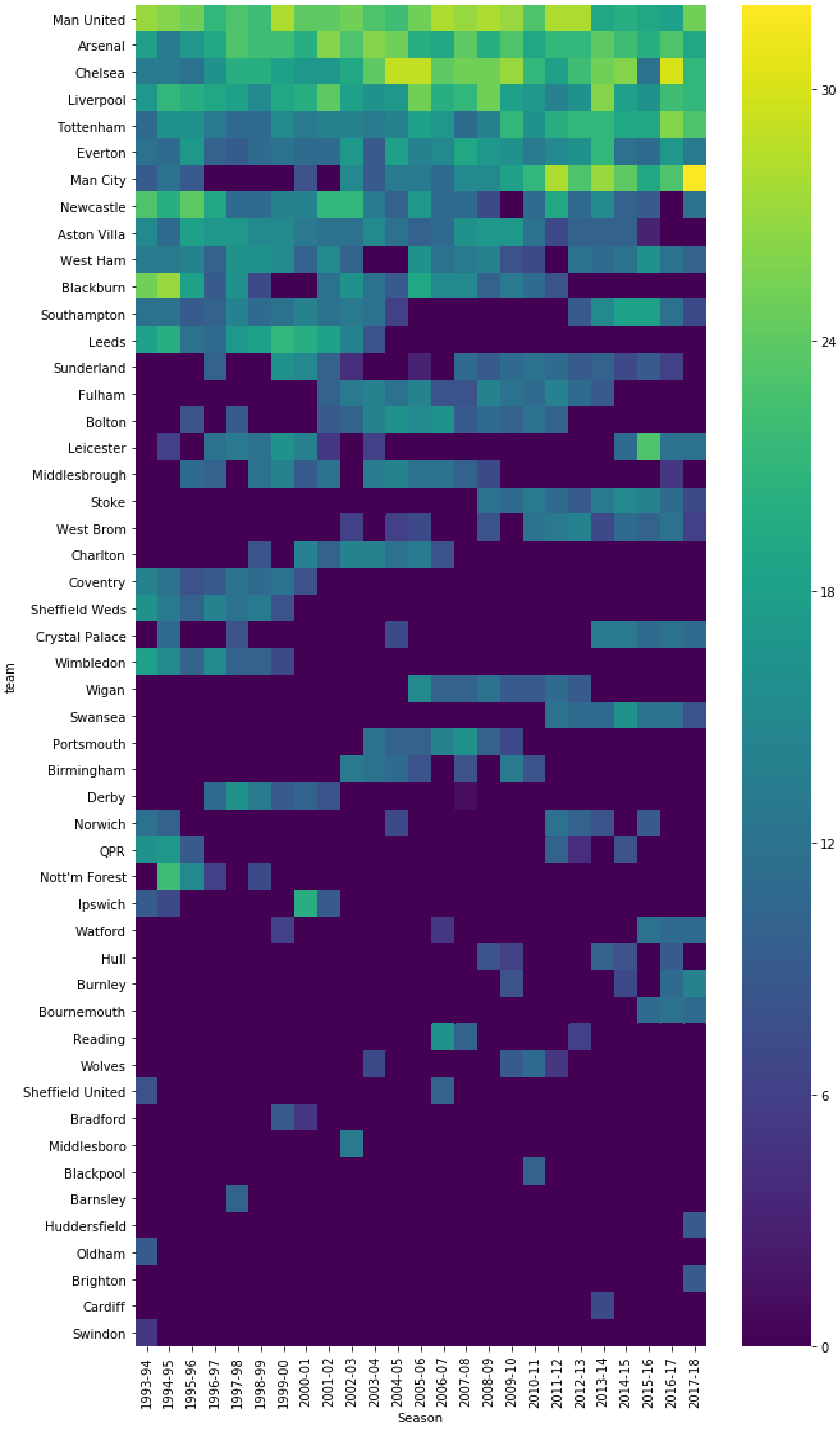


The above graph is again justified as Saturday is the day of the week on which the maximum number of matches are played and hence, the maximum number of goals are scored.

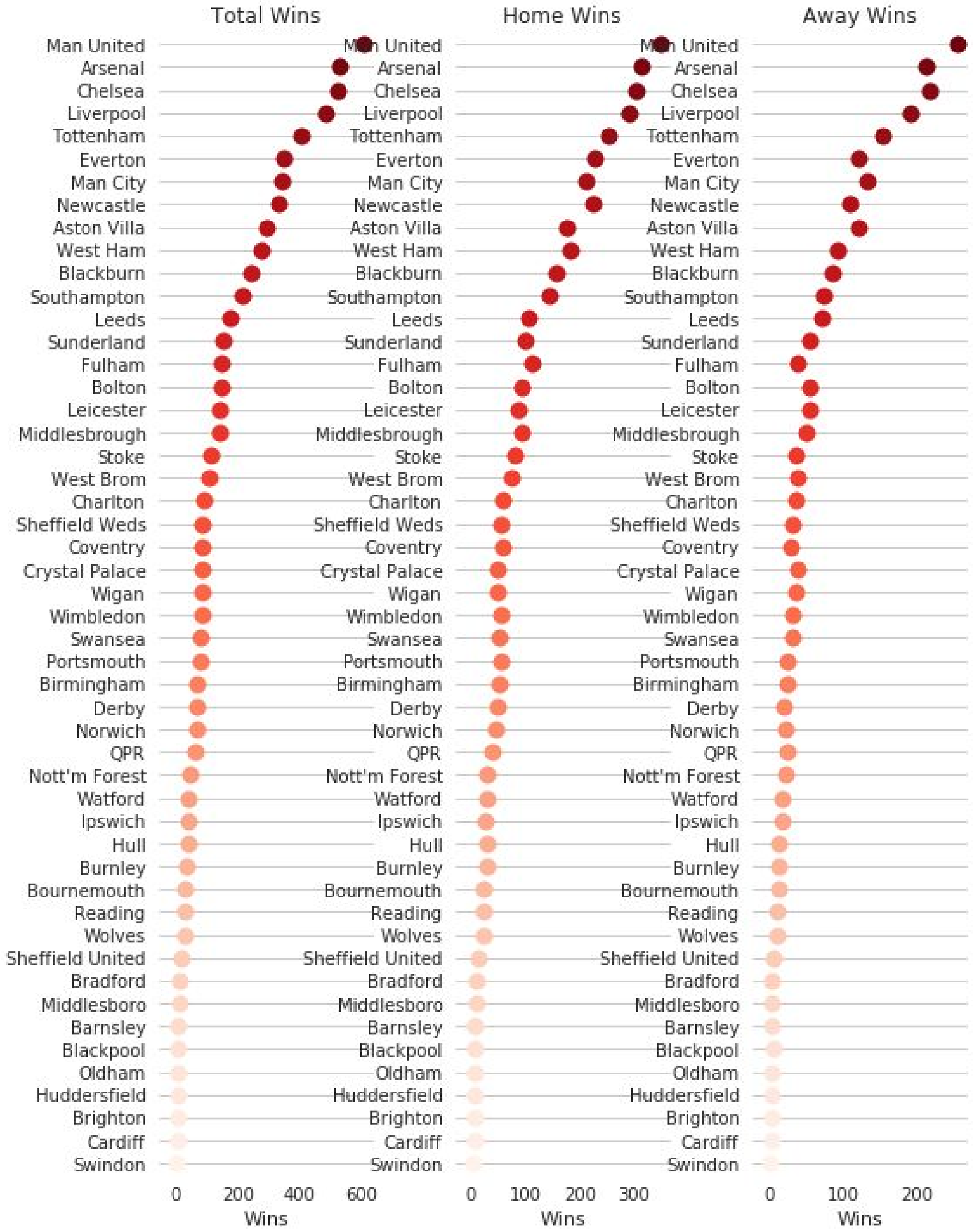
- After visualizing these basic stats, we look at the home and away wins per team and we chart them. This gives us an idea as to how each team has performed on a common scale.
- We then come to one of the major parts of this analysis, where we plot the heat map of teams for their win over time. Also, the heat map generated is very accurate, as we can see, some very rare discrete points on it which represent the rare victories of teams in any particular season.

  For eg- Leicester City miraculously won the English Premier League in the 2015-16 season, and this is very well shown on the heat map by a rare green spot.

  Similarly, other such incidents has also been taken care of, to make the heat map, an accurate plot.


Man United
Arsenal
Chelsea
Liverpool
Tottenham
Everton
Man City
Newcastle
Aston Villa
West Ham
Blackburn
Southampton
Leeds
Sunderland
Fulham
Bolton
Leicester
Middlesbrough
Stoke
West Brom
Charlton
Coventry
Sheffield Weds
Crystal Palace
Wimbledon
Wigan
Swansea
Portsmouth
Birmingham
Derby
Norwich
QPR
Nott'm Forest
Ipswich
Watford
Hull
Burnley
Bournemouth
Reading
Wolves
Sheffield United
Bradford
Middlesboro
Blackpool
Barnsley
Huddersfield
Oldham
Brighton
Cardiff
Swindon
team
1993-94
1994-95
1995-96
1996-97
1997-98
1998-99
1999-00
2000-01
2001-02
2002-03
2003-04
2004-05
2005-06
2006-07
2007-08
2008-09
2009-10
2010-11
2011-12
2012-13
2013-14
2014-15
2015-16
2016-17
2017-18
Season
30
24
18
12
6
0

- The final step in this analysis is to make a dot plot of wins of teams in home and away conditions. The result obtained is:-



The above dot plot is again an accurate one, showing the overall standings of the teams with respect to their victories in home and away games. It tells us a lot about the teams and in itself, can be used to make future analysis and predictions.

One fun fact which can be mentioned at this point is, the previous results and fixtures between two teams is always a determining criteria for what the outcome of future matches is going to be. For example, a match between Chelsea and FC Barcelona in the knockout round of the UEFA Champions League of 2008-09 edition saw Chelsea being knocked out by Barcelona by a 90th min stunner by the club legend Andres Iniesta. That season saw FC Barcelona go on to win the prestigious trophy for the third time in their career.

3 years later, the two teams met again in the knockout round of the same competition. However, no one had forgotten the last meeting between the two clubs. The emotions of the fans and the cheering crowd was really high throughout the two legs and it ultimately saw Chelsea have their hands on revenge, by knocking Barcelona out of the competition and ultimately go on to win that year's UCL trophy.

This above example makes us realize the importance of analyzing the previous match data between the teams to reach an optimum level of future match predictions involving the same teams.

Chapter - 3

Attempt to make match predictions

This section saw us making an attempt to make predictions on another ‘extensive’ dataset of the English Premier League. To make this possible, we took help of two famous algorithms of Machine Learning, namely Logistic Regression and Support Vector Machine (SVM).

This process is done in four simple steps:-

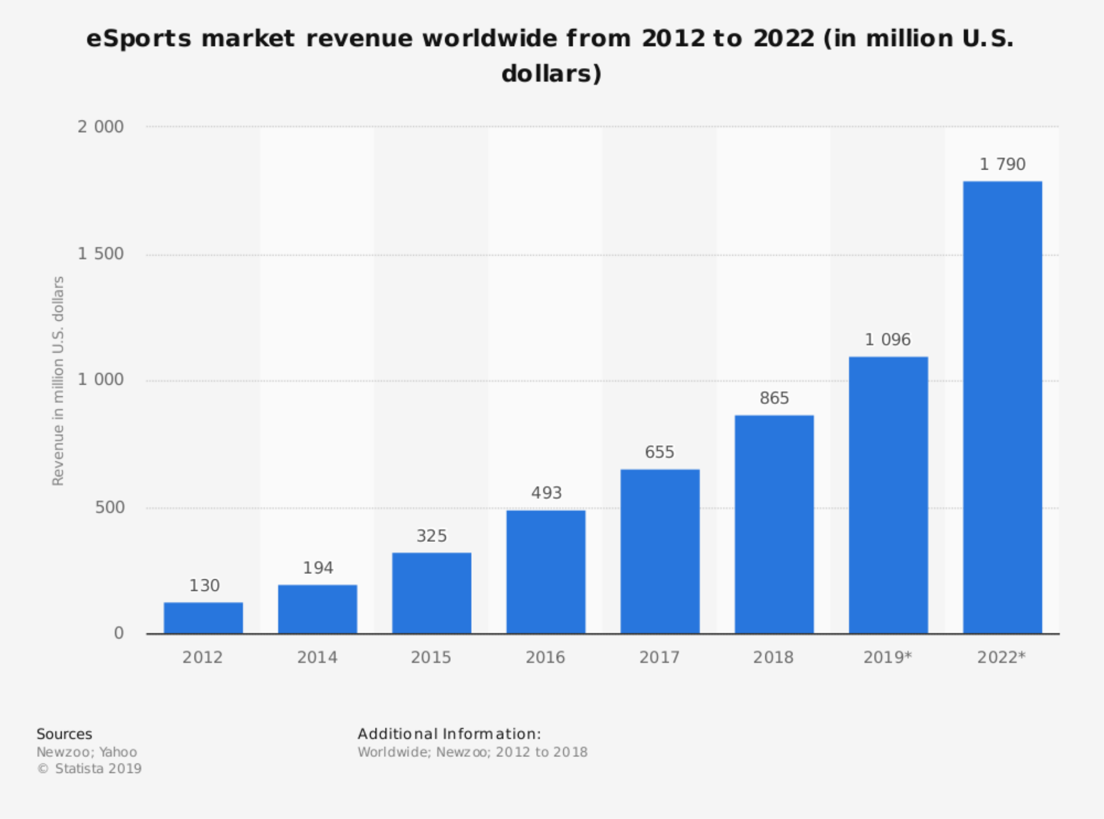
- Cleaning the dataset, which implies taking only those features from the dataset, which will actually impact the outcomes of the matches and which are predictable in themselves, such as who is going to start the game, the lineup, the weather condition that day, etc.
- Splitting the dataset into training and test set with almost 12 features in the feature matrix and one dependent variable to be predicted, namely the FTR (Full Time Result).
- Training the two different classifiers on the dataset, namely LR and SVM.
- Using the better classifier to predict who is going to win the game, given a home and an away team.

So we again follow the steps. We prepare our dataset and we split it into training and test set. Then after going through all the other steps of applying a machine learning algorithm, we see that both SVM and LR give nearly equal and good prediction with an accuracy of about 72% in both the cases.

Hence in this manner, we can use our ML models to predict many results by taking a detailed and extensive dataset.
However, this result still has a lot of scope of improvement and can give much better results.

Real life application

Presently, sports betting is a market of around 500 billion dollars and this market is ever increasing. Many different techniques are used to accomplish the task of predicting which team is going to win a match. There is a whole industry around it. There are pre match analysis, in game analysis by commentators, and there are entire channels like ESPN dedicated for this work. The below graph shows the ever increasing numbers in the sports market:-



In 2014, Bing owned by Microsoft made predictions of the knockout stages of the FIFA World Cup with an accuracy of 100%, that is it could correctly predict the outcome of every single knockout game of the tournament. This is a massive achievement by any prediction model and it would have led to huge turnovers in the sports market.

Thus, we can apply machine learning to this happening market around us, and maybe make some money out of it!

Conclusion

The objectives of this project have been well achieved by our earnest efforts.

To tackle the problem efficiently and in a professional manner, first, we brushed up our skills with respect to Python, Machine Learning and different platforms like Spyder and Jupyter Notebook.

After extensive working and some sincere inputs, our achievements through this project have been at par with the objectives. However, just like everything has a scope of improvement, so is the case with our project.

The data points used by us in making the prediction is limited and thus leading to not enough accuracy in our model. This can be improved by adding some more data points before making the prediction such as, Sentiments from Twitter (hashtags trending on twitter and what people are talking about teams as a whole can provide us with some really effective data points), more features from other data sources such as how much others have bet and on which team, or player specific health and fitness stats, etc. Addition of these mentioned features can very well help us in enhancing our accuracy of predictions.

We would surely like to extend this project further and incorporate these missing features and technicalities.

As already mentioned, sports betting is a HUGE market, and if we can target it with the concepts of a tool as powerful as Machine Learning, then we can surely make significant progress in it, and the complexity of the situations and hence the dataset, can help us learn and grow a lot as individuals on a personal level and as a CSE student on a professional level.

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Appendix

Snippets of data analysis code:

#1

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv("EPL_set.csv")
len(df)
df.head(5)
```

#2

```
df['result'] = 'draw'
df.loc[df['FTHG'] > df['FTAG'], 'result'] = 'home'
df.loc[df['FTAG'] > df['FTHG'], 'result'] = 'visitor'
df.groupby('result')['result'].count()
```

#3

```
df.groupby('result')['result'].count().plot(kind='pie',
autopct='%1.1f%%', figsize=(4,4))
```

#4

```
df.groupby('result')['result'].count().plot(kind='pie',
autopct='%1.1f%%', figsize=(4,4))
```

#5

```
df.groupby('result')['result'].count().plot(kind='pie',
autopct='%1.1f%%', figsize=(4,4))
```

#6

```
# show average goals per game per season
ab = df.groupby('Season')['total_goals'].mean().plot(kind="bar",
title="Avg. Goals Per Game Per Season", figsize=(12, 8))
ab.set_xlabel("Season")
ab.set_ylabel("Average Goals")
```

#7

```
# determine number of games per month and day
df['game_date'] = pd.to_datetime(df['Date'])
df['game_month'] = df['game_date'].dt.month
df['game_weekday'] = df['game_date'].dt.weekday
# by month
df.groupby([df['game_date'].dt.month])["Div"].count().plot(kind='bar')
```

#8

```
# by week day - most games are on saturday
df.groupby('game_weekday')['Div'].count().plot(kind='bar')
# where 0 = monday and so forth
```

#9

```
# Goals per month
sns.boxplot(x='game_month', y='total_goals', data=df)
```

#10

```
# Goals per gameday
sns.boxplot(x='game_weekday', y='total_goals', data=df)
```

#11

```
# Goals per gameday
sns.boxplot(x='game_weekday', y='total_goals', data=df)
# How many home and visitor wins added as new columns
```

```
df = df.merge(pd.get_dummies(df['result']), left_index=True,
right_index=True)
df['home_wins_this_season'] =
df.groupby(['Season','HomeTeam'])['home'].transform('sum')
df['visitor_wins_this_season'] =
df.groupby(['Season','AwayTeam'])['visitor'].transform('sum')
```

#12

```
# Which teams win the most home games on average
(
    df.groupby(['HomeTeam'])['home_wins_this_season']
    .agg(['count','mean'])
    .sort_values(ascending=False, by='mean')
    .round(1)
    .head(10)
)
```

#13

```
# Which teams win the most away games on average
(
    df.groupby(['AwayTeam'])['visitor_wins_this_season']
    .agg(['count','mean'])
    .sort_values(ascending=False, by='mean')
    .round(1)
    .head(10)
)
```

#14

```
# tally up the results
visitor_results = (df
                   .groupby(['Season', 'AwayTeam'])['visitor']
                   .sum()
                   .reset_index()
                   .rename(columns={'AwayTeam': 'team',
                                    'visitor': 'visitor_wins'}))

home_results = (df
                 .groupby(['Season', 'HomeTeam'])['home']
                 .sum()
                 .reset_index()
                 .rename(columns={'HomeTeam': 'team',
                                  'home': 'home_wins'}))

wins_per_season = visitor_results.merge(home_results,
on=['Season', 'team'])

Wins_per_season['total_wins'] = wins_per_season['visitor_wins'] +
wins_per_season['home_wins']
wins_per_season.head(5)
```

#15

```
# Make a heatmap of wins over time
total_wins_sorted_desc = (wins_per_season
                          .groupby(['team'])['total_wins']
                          .sum()
                          .sort_values(ascending=False)
                          .reset_index()['team'])

wins_per_season_pivot = (wins_per_season
                         .pivot_table(index='team',
                                      columns='Season',
                                      values='total_wins')
                         .fillna(0)
                         .reindex(total_wins_sorted_desc))

plt.figure(figsize=(10, 20))
sns.heatmap(wins_per_season_pivot, cmap='viridis')
```

#16

```
# showing dot plot of wins per team per home/away
sns.set(style="whitegrid")
wps =
wins_per_season.groupby(['team'])['total_wins','home_wins','visito
r_wins'].sum().reset_index()
g = sns.PairGrid(wps.sort_values("total_wins", ascending=False),
                 x_vars=wps.columns[1:], y_vars=["team"],
                 size=10, aspect=.25)

# Draw a dot plot using the stripplot function
g.map(sns.stripplot, size=10, orient="h",
      palette="Reds_r", edgecolor="gray")

# Use the same x axis limits on all columns and add better labels
g.set(xlabel="Wins", ylabel="")

# Add titles for the columns
titles = ["Total Wins", "Home Wins", "Away Wins"]

for ax, title in zip(g.axes.flat, titles):

    # Set a different title for each axes
    ax.set(title=title)

    # Make the grid horizontal instead of vertical
    ax.xaxis.grid(False)
    ax.yaxis.grid(True)

sns.despine(left=True, bottom=True)
```

Snippet of the ML models implementation code:

```
# Initialize the two models
clf_A = LogisticRegression(random_state = 42)
clf_B = SVC(random_state = 912, kernel='rbf')
#Boosting refers to this general problem of producing a very
accurate prediction rule
#by combining rough and moderately inaccurate rules-of-thumb
train_predict(clf_A, X_train, y_train, X_test, y_test)
print ''
train_predict(clf_B, X_train, y_train, X_test, y_test)
print ''
```

Output:

```
Training a LogisticRegression using a training set size of 5550. . .
Trained model in 0.2450 seconds
Made predictions in 0.0380 seconds.
0.621561035256 0.665405405405
F1 score and accuracy score for training set: 0.6216 , 0.6654.
Made predictions in 0.0000 seconds.
F1 score and accuracy score for test set: 0.6957 , 0.7200.
```

```
Training a SVC using a training set size of 5550. . .
Trained model in 2.5040 seconds
Made predictions in 1.2430 seconds.
0.620453572957 0.68036036036
F1 score and accuracy score for training set: 0.6205 , 0.6804.
Made predictions in 0.0250 seconds.
F1 score and accuracy score for test set: 0.6818 , 0.7200.
```