

Football Goal Prediction

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Introduction

Anticipating football goals can significantly impact the sports industry, betting companies, and fans, leading to financial, social, and entertainment benefits. To improve the accuracy of predicting football goals and offer reliable insights to sports enthusiasts and betting professionals, it is crucial to address the root causes of unpredictable outcomes and develop effective models for data analysis and prediction. By enhancing the accuracy of goal prediction, the sports industry can heighten fan engagement, optimize revenue generation, and promote football's overall growth and competitiveness. Frequently, questions arise regarding the number of goals to expect in a match, the type of analysis to conduct, and the most important features to consider.

The datasets were assembled to create models for forecasting the probability of football goal occurrence in a specific country and year. However, the dataset variables' attributes indicate that they could be employed beyond the context of football goal prediction.

The report utilized PySpark, a machine learning tool, to examine football goal prediction data from 2016 to 2020. This analysis involved using Tableau visualization to create a reliable and robust model for predicting football goal probability by factoring in pertinent factors.

The primary objective of this project is to predict football goal probability, which is handled as a regression problem. Various algorithms have been taken into consideration, including Linear Regression, Decision Tree Regressor, and Random Forest Regressor models, to predict football goals.

Dataset [Link](#)

In end, I attempt to solve those questions. This is my perspective of the outcome, it's based on the dataset itself. The current world scenario might be different from it.

Related Work

Soccer goal prediction has been a topic of interest in the field of sports analytics and machine learning. Various studies have been conducted to predict soccer goals based on different methodologies and features. In this section, we review some of the relevant literature on soccer goal prediction.

One approach for soccer goal prediction is to use machine learning models. In their study, Liu et al. (2018) proposed a convolutional neural network (CNN) for predicting soccer goals. The model takes as input a sequence of events leading up to the shot and predicts the probability of a goal. The authors evaluated their model on a dataset of 9,117 shots from the English Premier League and achieved an accuracy of 0.722. Similarly, Zhang et al. (2020) proposed a model based on a long short-term memory (LSTM) neural network for soccer goal prediction. Their model takes into account various features such as player positions, game situation, and the ball's position, and achieved an accuracy of 77.89%.

Another approach for soccer goal prediction is to use statistical models. In their study, Decroos et al. (2019) proposed a model based on a Poisson regression for predicting soccer goals. The model takes into account various features such as the players' positions, past performance, and the opponent's team strength. The authors evaluated their model on a dataset of 100,000 shots from the English Premier League and achieved a mean absolute error of 0.135. Similarly, Lasek et al. (2013) proposed a model based on the Markov chain Monte Carlo method for soccer goal prediction. The model takes into account various features such as player positions, the ball's position, and the game situation, and achieved an accuracy of 73%.

These studies have demonstrated the potential of using these models for accurate soccer goal prediction. However, there is still room for improvement in terms of incorporating additional features and developing more advanced models to improve the accuracy of soccer goal prediction.

Implementation

➤ Apache Spark

Lately, prominent technology firms have been frequently utilizing the term "Big Data." Big Data is defined by its extensive size, processing capability, effectiveness, and the reality that the data is often disorganized, leading to difficulties and expenses in managing it. Apache Spark, a distributed memory system, is used to address these challenges by keeping the data on top of the Hadoop File System (HDFS), offering greater stability than Hadoop MapReduce. All in all, Apache Spark is an open-source resolution for processing Big Data, providing various capabilities such as SQL queries, machine learning, and continuous data streaming, all integrated into one system. Apache Spark Language Support:

- Apache Spark (Java and Scala Support)
- **PySpark (Python Support)**
- SparkR (R support)

Note, this report only contains information about PySpark.

➤ **PySpark:**

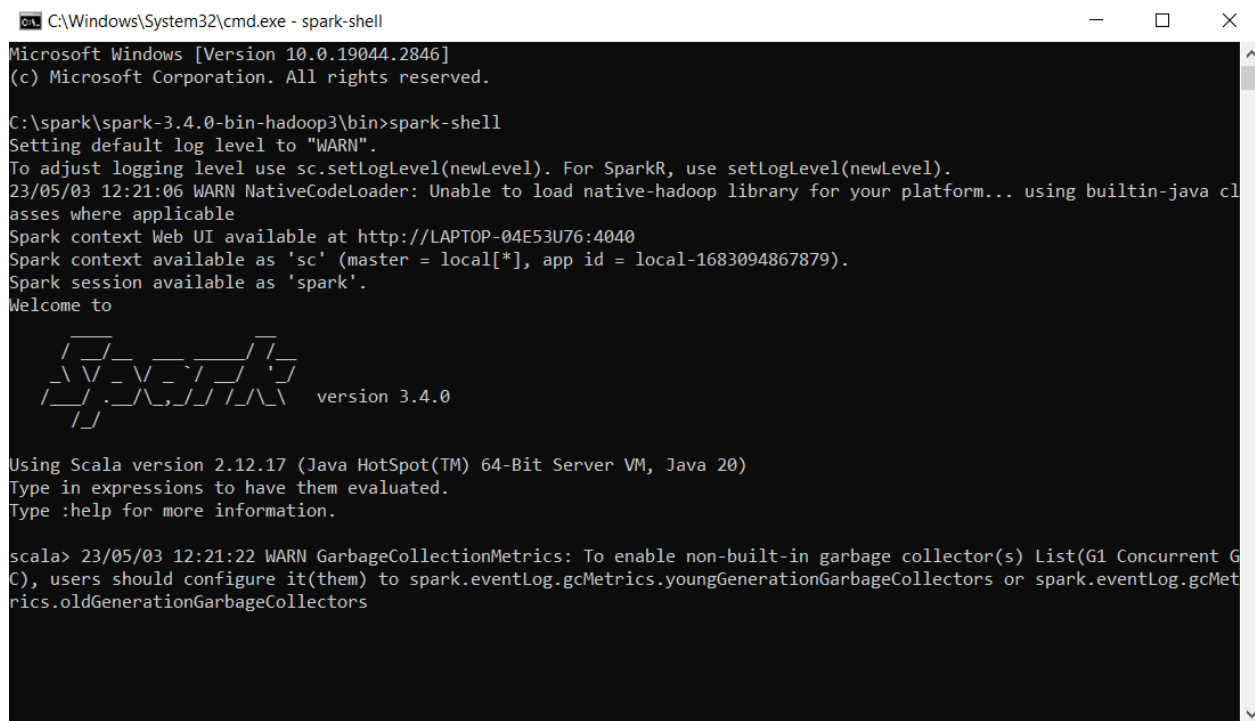
PySpark is a Python programming language library that enables the use of all Spark functionalities, including SQL, streaming, and machine learning through the Pandas API. It acts as a connection between Spark and Python and works with Jupyter for machine learning and complicated data analysis. The study concentrates on installing PySpark in JupyterLab. Nonetheless, it's vital to recognize that PySpark's support is restricted to the Pandas API and doesn't include other libraries such as NumPy, which is a disadvantage.

Also, I used PySpark in the project of Football goal prediction prediction analysis with machine learning algorithm and preprocessing.

I have been using Jupyter Notebook for the past two years for machine learning as well as deep learning. So, I have used Jupyter Notebook as my working platform. It's easy to use and easy to install packages.

- **First, we have to install JDK 20** [LINK](#)
- **Secondly, Download Spark** [LINK](#)
- **Finally, Install Python Latest version** [LINK](#)

Install everything on 'C' Drive, Set environment variables according to directory above softwares are installed. Go to the command prompt and type "spark-shell", your spark connection will be established.



```
C:\Windows\System32\cmd.exe - spark-shell
Microsoft Windows [Version 10.0.19044.2846]
(c) Microsoft Corporation. All rights reserved.

C:\spark\spark-3.4.0-bin-hadoop3\bin>spark-shell
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
23/05/03 12:21:06 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java cl
asses where applicable
Spark context Web UI available at http://LAPTOP-04E53U76:4040
Spark context available as 'sc' (master = local[*], app id = local-1683094867879).
Spark session available as 'spark'.
Welcome to

  ____
 /  _ \
/_/_/ \_/_/  version 3.4.0

Using Scala version 2.12.17 (Java HotSpot(TM) 64-Bit Server VM, Java 20)
Type in expressions to have them evaluated.
Type :help for more information.

scala> 23/05/03 12:21:22 WARN GarbageCollectionMetrics: To enable non-built-in garbage collector(s) List(G1 Concurrent G
C), users should configure it(them) to spark.eventLog.gcMetrics.youngGenerationGarbageCollectors or spark.eventLog.gcMet
rics.oldGenerationGarbageCollectors
```

Fig 1.1: Installing pyspark

Fortunately I did not get any errors.

➤ Dataset

The dataset is taken from Kaggle, which is one of the free resources for datasets. This dataset is all about football goal prediction prediction. Dataset contains information from 2016 to 2020. This dataset contains 14 columns and 650 rows. All these columns contain information about every specific accommodation place. A few important features are country, league, club, Player Names, Goals etc. I will show step-by-step details of this dataset

Country: Name of the country.

League: League name

Club: Club name.

Player Names: Name of the player.

Matches Played: Number of matched played.

Substitution: Number of substitution.

Mins: Number of minutes player played

Goals: Number of goals.

Shots: Number of shots.

On Target: Number of on target shots.

Year: The year match was played.

xG: Expected Goals

xG Per Avg Match: Expected Goals per avg match

Shots Per Avg Match: Number of shots per avg match

On Target Per Avg Match: Number of on target shots per avg match

I covered all attributes/columns and described its values.

- **Evaluation and Machine Learning approaches:**

At first, I imported the necessary library. Then, I created a SparkSession known as “football”. With PySpark and SQL, Machine learning model works better with full efficiency. Here is a screenshot of my code.

```
In [1]: from pyspark.sql.functions import isnull,sum

In [2]: # Importing pyspark and starting session to use sprak functionality
import pyspark
from pyspark.sql import SparkSession
from pyspark.sql.functions import col,when,isnan,count
from pyspark.sql.types import IntegerType, StructType,StructField, FloatType , DoubleType
from pyspark.ml.feature import StringIndexer, OneHotEncoder, VectorAssembler,StandardScaler
from pyspark.ml.stat import Correlation
from pyspark.sql.functions import regexp_replace
from pyspark.ml.regression import LinearRegression
spark = SparkSession.builder.appName("football").getOrCreate()
```

Fig 1.2 Importing library

I have kept the dataset on the same directory where the notebook file is saved.


```

In [41]: dataset.count()
Out[41]: 660

In [42]: null_count = dataset.select([sum(isnull(c).cast("int")).alias(c) for c in dataset.columns])
# print the count of null values in each column
null_count.show()

```

Country	League	Club	Player Names	Matches Played	Substitution	Mins	Goals	xG	xG Per Avg Match	Shots	OnTarget	Shots Per Avg Match	On Target Per Avg Match	Year
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig 1.4 Checking for null values

My next target was to check for null values in every column. I have filtered the data with count to check all the null values. The key is the column name, and the value is the total amount of null values in that column. C is a predefined keyword that stands for SQL Column. Here, we can see that there was not any null values in the dataset.

```
In [43]: df = dataset.drop("Substitution ", "Mins")
df.show()
```

```
+-----+-----+-----+-----+-----+-----+-----+-----+
|Country| League| Club|      Player Names|Matches_Played|Goals|  xG|xG Per Avg Match|Shots|OnTarget|
|Shots Per Avg Match|On Target Per Avg Match|Year|
+-----+-----+-----+-----+-----+-----+-----+-----+
| Spain|La Liga| (BET)| Juanmi Callejon|      19|    11| 6.62|          0.34|   48|    20|
2.47|          1.03|2016|
| Spain|La Liga| (BAR)| Antoine Griezmann|     36|    16|11.86|          0.36|   88|    41|
2.67|          1.24|2016|
| Spain|La Liga| (ATL)| Luis Suarez|     34|    28|23.21|          0.75|  120|    57|
3.88|          1.84|2016|
| Spain|La Liga| (CAR)| Ruben Castro|     32|    13|14.06|          0.47|  117|    42|
3.91|          1.4|2016|
| Spain|La Liga| (VAL)| Kevin Gameiro|     21|    13|10.65|          0.58|   50|    23|
2.72|          1.25|2016|
| Spain|La Liga| (JUV)| Cristiano Ronaldo|     29|    25|24.68|          0.89|  162|    60|
5.84|          2.16|2016|
| Spain|La Liga| (RMA)| Karim Benzema|     23|    11|13.25|          0.64|   69|    34|
3.33|          1.64|2016|
| Spain|La Liga| (PSG)| Neymar |     30|    13|13.33|          0.47|  105|    42|
3.7|          1.48|2016|
| Spain|La Liga| (CEL)| Iago Aspas|     25|    19|13.88|          0.56|   78|    37|
3.15|          1.49|2016|
| Spain|La Liga| (EIB)| Sergi Enrich|     31|    11| 8.25|          0.27|   64|    26|
2.09|          0.85|2016|
| Spain|La Liga| None| Aduriz |     27|    16|15.92|          0.61|   85|    45|
3.26|          1.72|2016|
| Spain|La Liga| (HUE)| Sandro Ramirez|     28|    14| 7.14|          0.29|   93|    38|
3.78|          1.54|2016|
| Spain|La Liga| (BAR)| Lionel Messi|     32|    37|26.65|          0.87|  179|    76|
5.84|          2.48|2016|
| Spain|La Liga| (VIL)| Gerard Moreno|     37|    13| 8.49|          0.24|   82|    32|
2.32|          0.9|2016|
| Spain|La Liga| (JUV)| Morata|     14|    15| 9.67|          0.66|   55|    30|
3.75|          2.05|2016|
| Spain|La Liga| (MON)| Wissam Ben Yedder|     20|    11| 7.85|          0.43|   44|    23|
2.41|          1.26|2016|
| Spain|La Liga| (SOC)| William Jose|     27|    12| 8.41|          0.38|   69|    29|
3.12|          1.31|2016|
| Spain|La Liga|Florin| Andone |     32|    12|11.62|          0.37|   99|    42|
3.15|          1.34|2016|
| Spain|La Liga| (SOC)| Cedric Bakambu|     17|    10| 8.08|          0.47|   50|    26|
2.91|          1.51|2016|
| Spain|La Liga| (RMA)| Isco|     18|    10| 3.91|          0.22|   32|    15|
1.8|          0.84|2016|
+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 20 rows
```

Fig 1.5 Dropping unnecessary columns

Now, it's needed to drop the column "Substitution ", "Mins". As it has no relevancy with the goals.

```
In [44]: df = df.withColumnRenamed("xG", "Expected goals").withColumnRenamed("xG Per Avg Match", "Expected Goals
df.show(5)
```

Country	League	Club	Player Names	Matches Played	Goals	Expected goals	Expected Goals AVG Match
Spain	La Liga	(BET)	Juanmi Callejon	19	11	6.62	0.34
				48	20	2.47	1.03 2016
Spain	La Liga	(BAR)	Antoine Griezmann	36	16	11.86	0.36
				88	41	2.67	1.24 2016
Spain	La Liga	(ATL)	Luis Suarez	34	28	23.21	0.75
				120	57	3.88	1.84 2016
Spain	La Liga	(CAR)	Ruben Castro	32	13	14.06	0.47
				117	42	3.91	1.4 2016
Spain	La Liga	(VAL)	Kevin Gameiro	21	13	10.65	0.58
				50	23	2.72	1.25 2016

only showing top 5 rows

Fig 1.6 Renaming Columns

Here I have renamed few long columns so that it becomes readable.

```
In [45]: df.printSchema()

root
 |-- Country: string (nullable = true)
 |-- League: string (nullable = true)
 |-- Club: string (nullable = true)
 |-- Player Names: string (nullable = true)
 |-- Matches Played: integer (nullable = true)
 |-- Goals: integer (nullable = true)
 |-- Expected goals: double (nullable = true)
 |-- Expected Goals AVG Match: double (nullable = true)
 |-- Shots: integer (nullable = true)
 |-- OnTarget: integer (nullable = true)
 |-- Shots Per Avg Match: double (nullable = true)
 |-- On Target Per Avg Match: double (nullable = true)
 |-- Year: integer (nullable = true)

In [46]: column_names = df.columns

# print the column names
print(column_names)

['Country', 'League', 'Club', 'Player Names', 'Matches Played', 'Goals', 'Expected goals', 'Expected
Goals AVG Match', 'Shots', 'OnTarget', 'Shots Per Avg Match', 'On Target Per Avg Match', 'Year']

In [47]: df.toPandas().to_excel('final.xlsx', sheet_name = 'Sheet1', index = False)
```

Fig 1. 7 Exporting filtered data

Here, I have printed the final schema, printed the final remaining column on which the algorithms will be implemented and finally saved the filtered data.

- **Visualization Of Clean Data:**

For visualization, we need to use Tableau

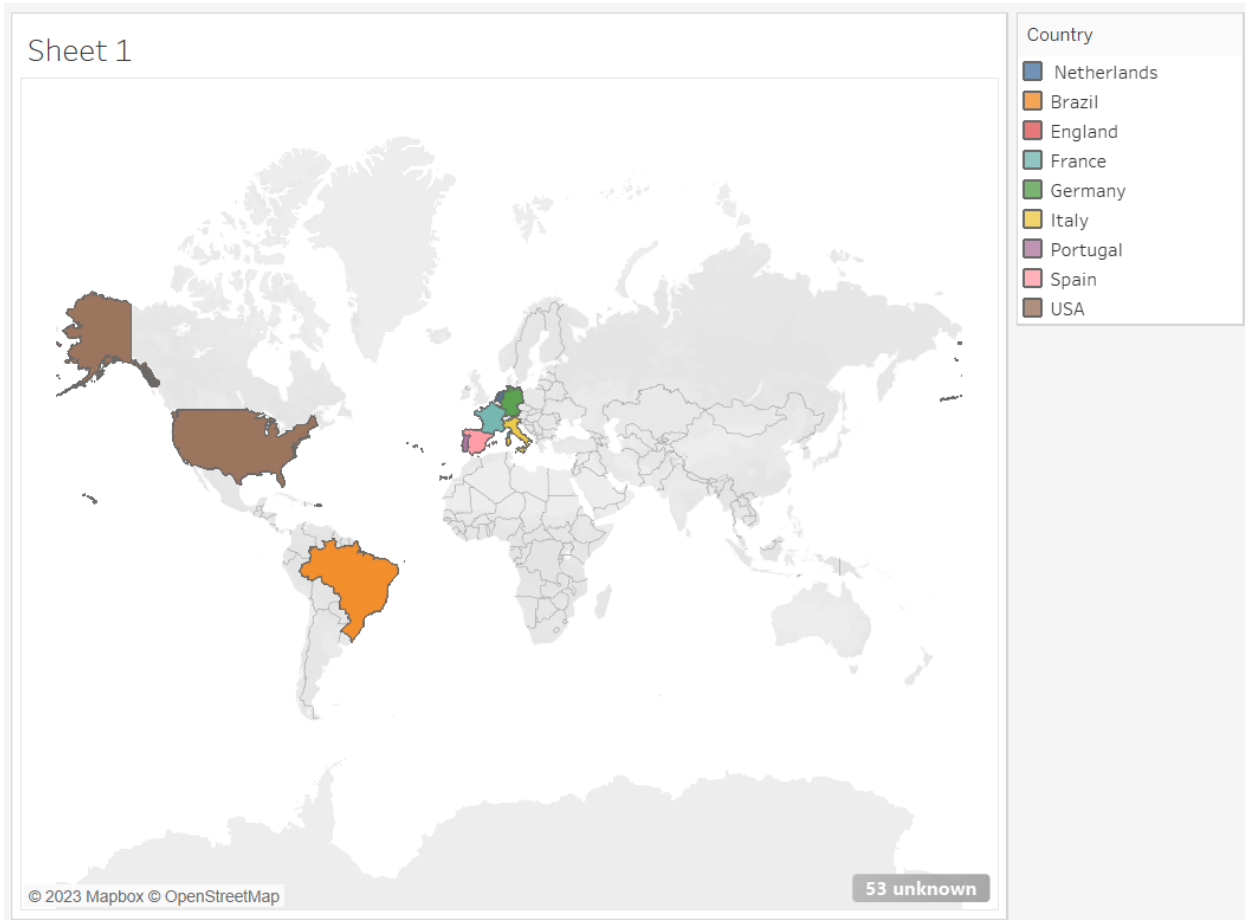


Fig 2.1 Map, A players expected goals

This simple map analysis shows a player expected goal and the number of goals a player has scored of a country.

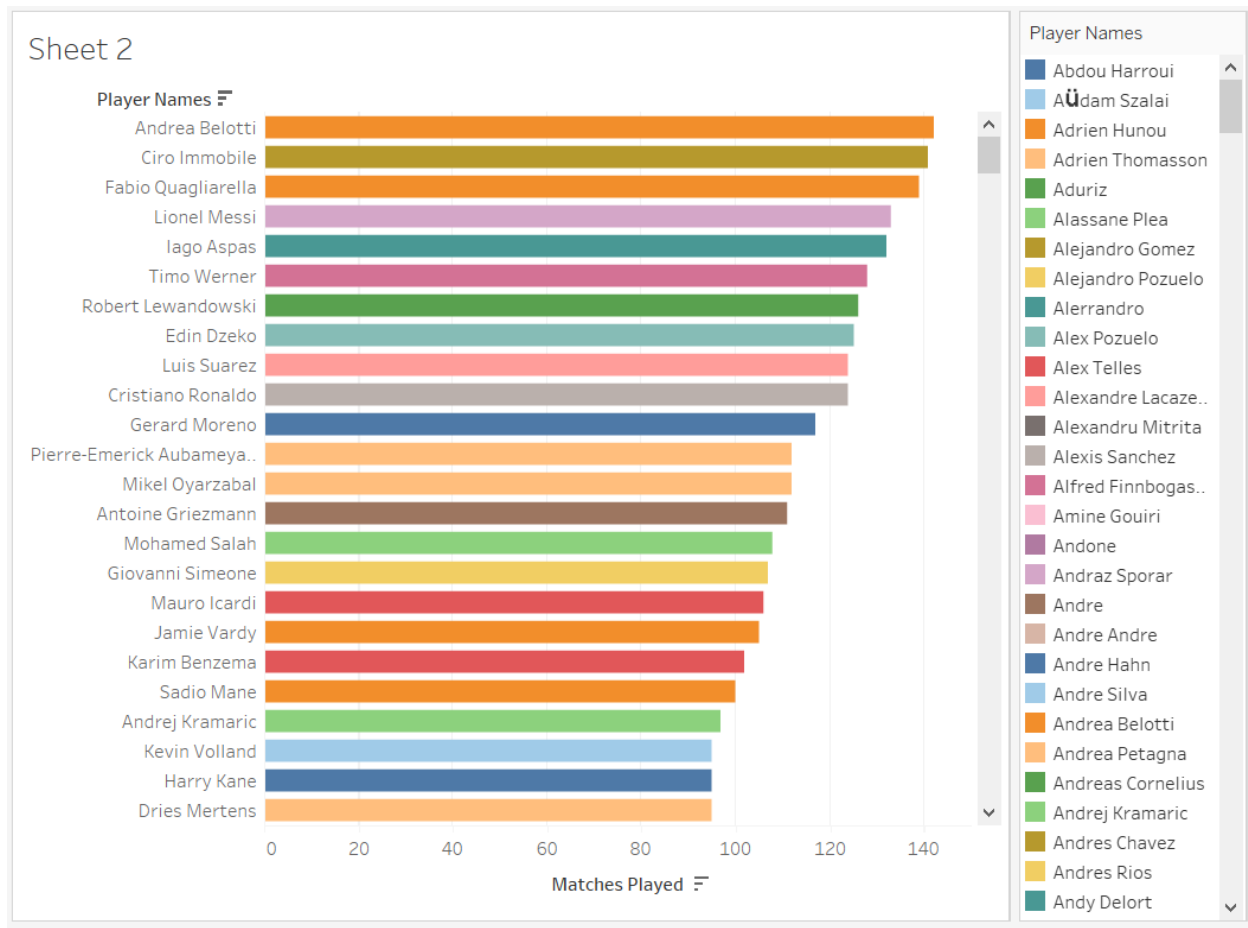


Fig 2.2 Bar chart, Shows number of matches a player played

This simple Bar chart analysis shows the number of matches a player played. On Y axis the name of the player is shown, and on the X axis the number of a player played is shown.

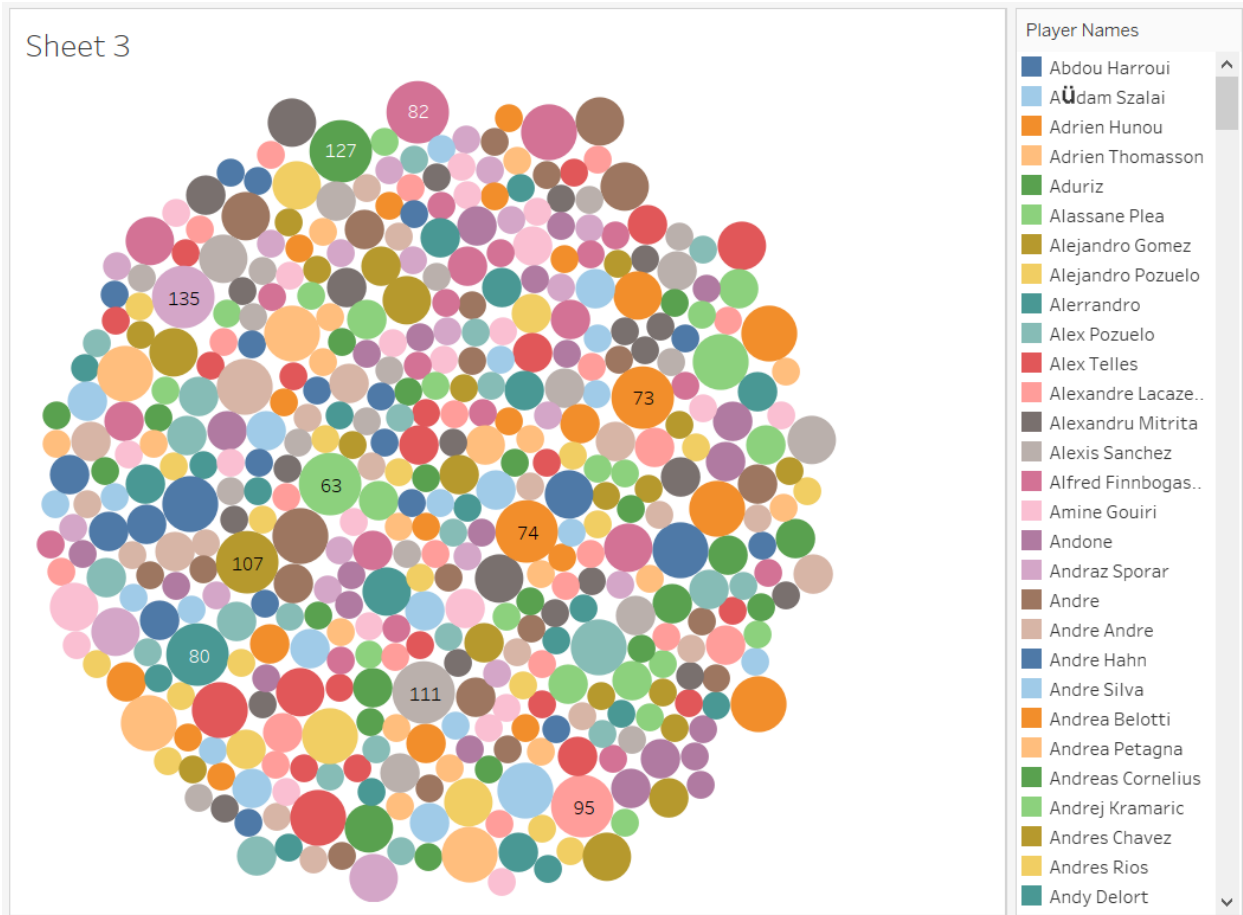


Fig 2.3 Shows number of goals a player scored

This simple analysis shows the number of goals a player scored.

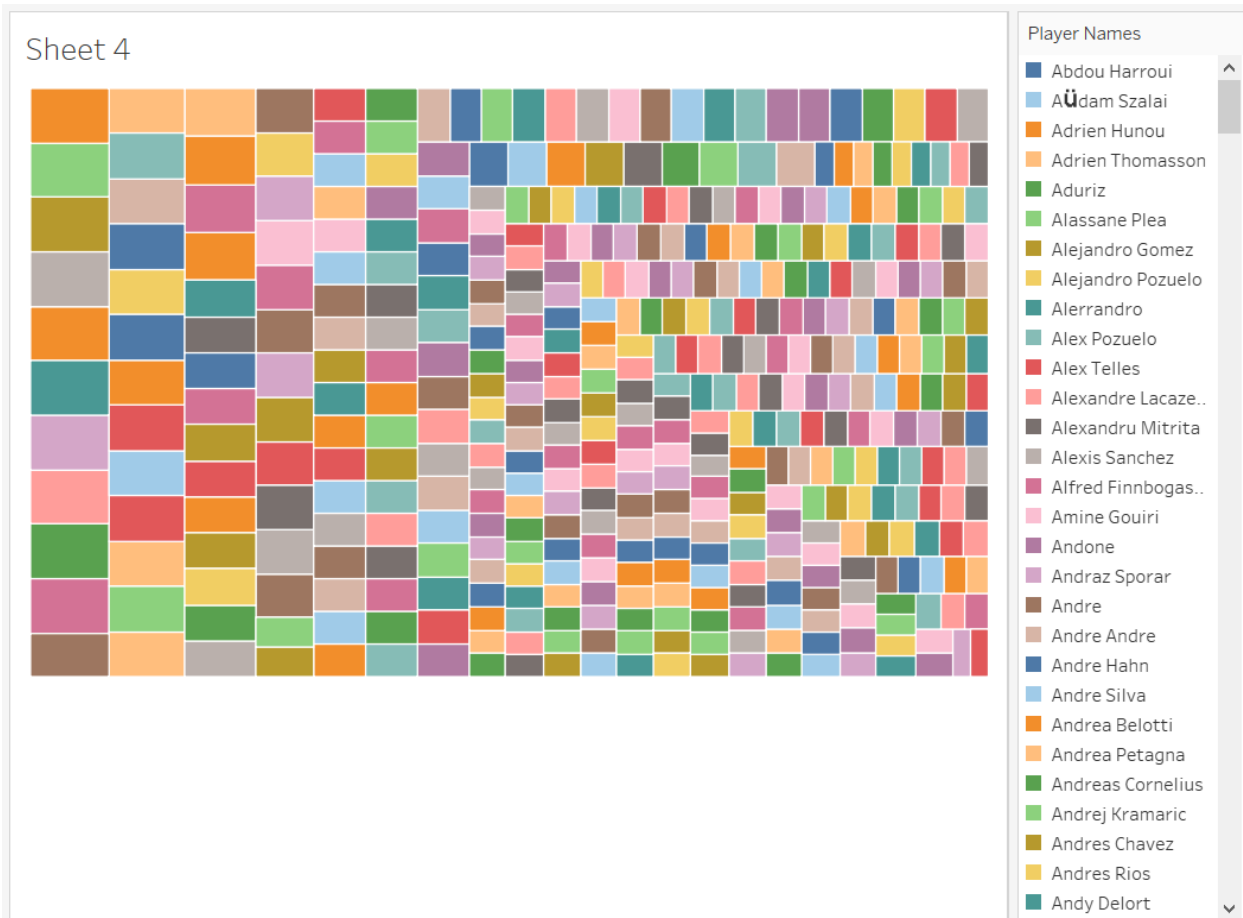


Fig 2.4 Shows number of goals a player scored and count of expected goals

This simple analysis shows the number of goals a player scored and count of expected goals.

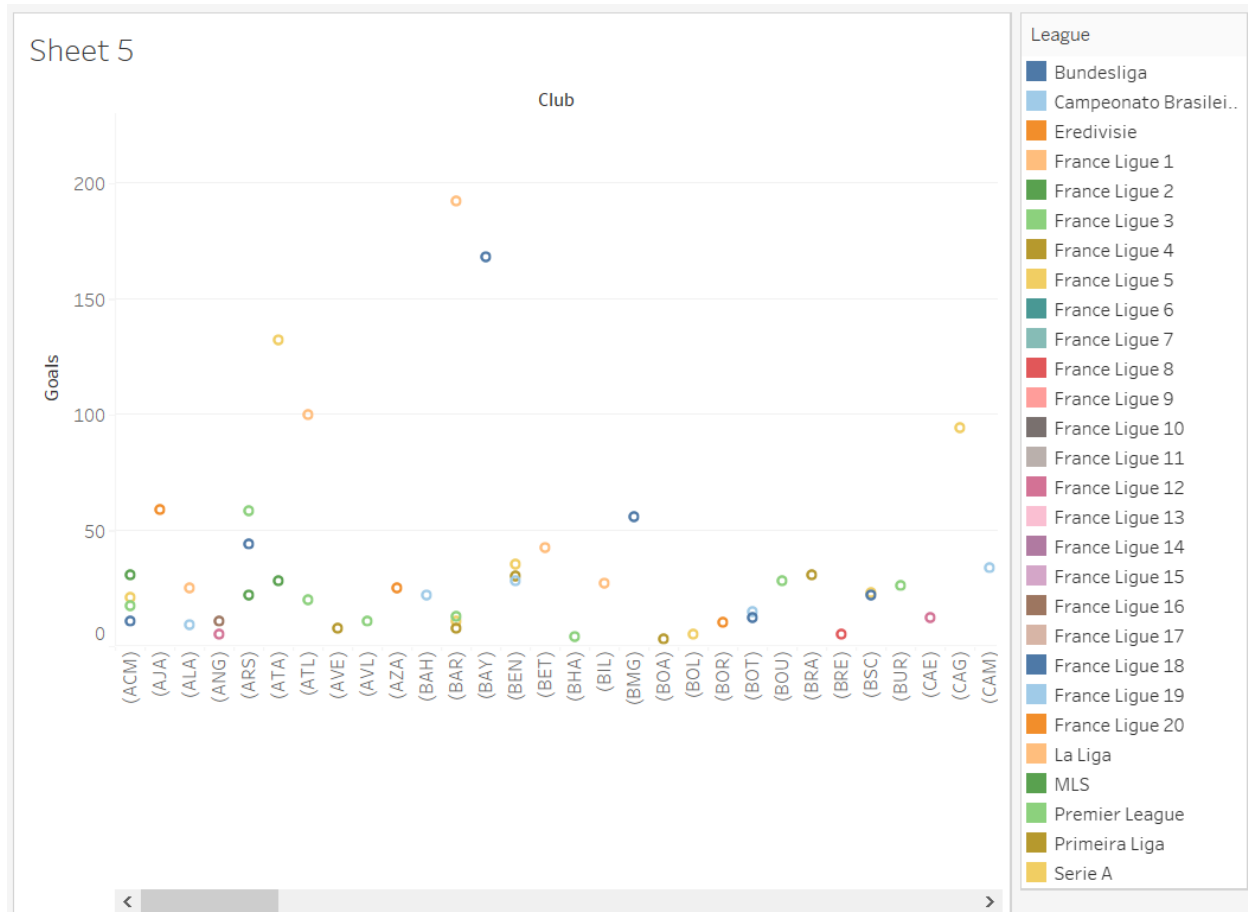


Fig 2.5 Shows number of goals scored by a club in a league

This simple analysis shows the number of goals scored by a club in a league.

Sheet 6

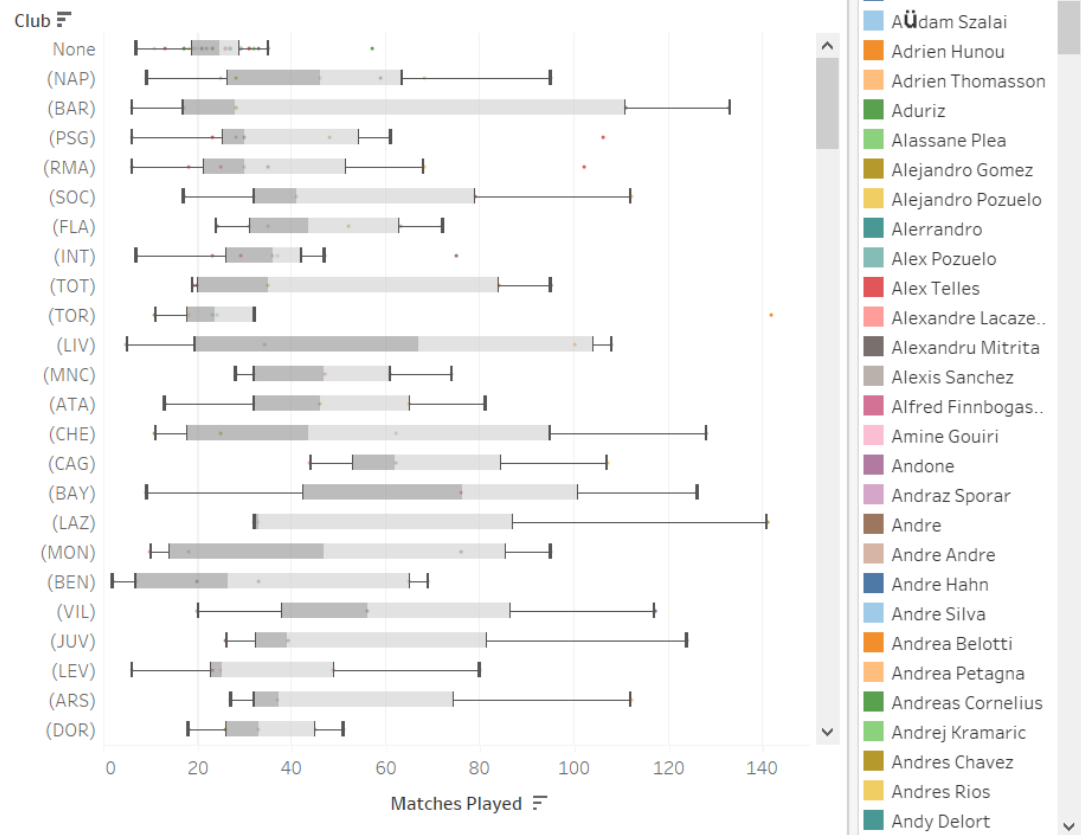


Fig 2.6 Box plot shows matches played by a club

This Boxplot simple analysis shows the number of matches played by a club.

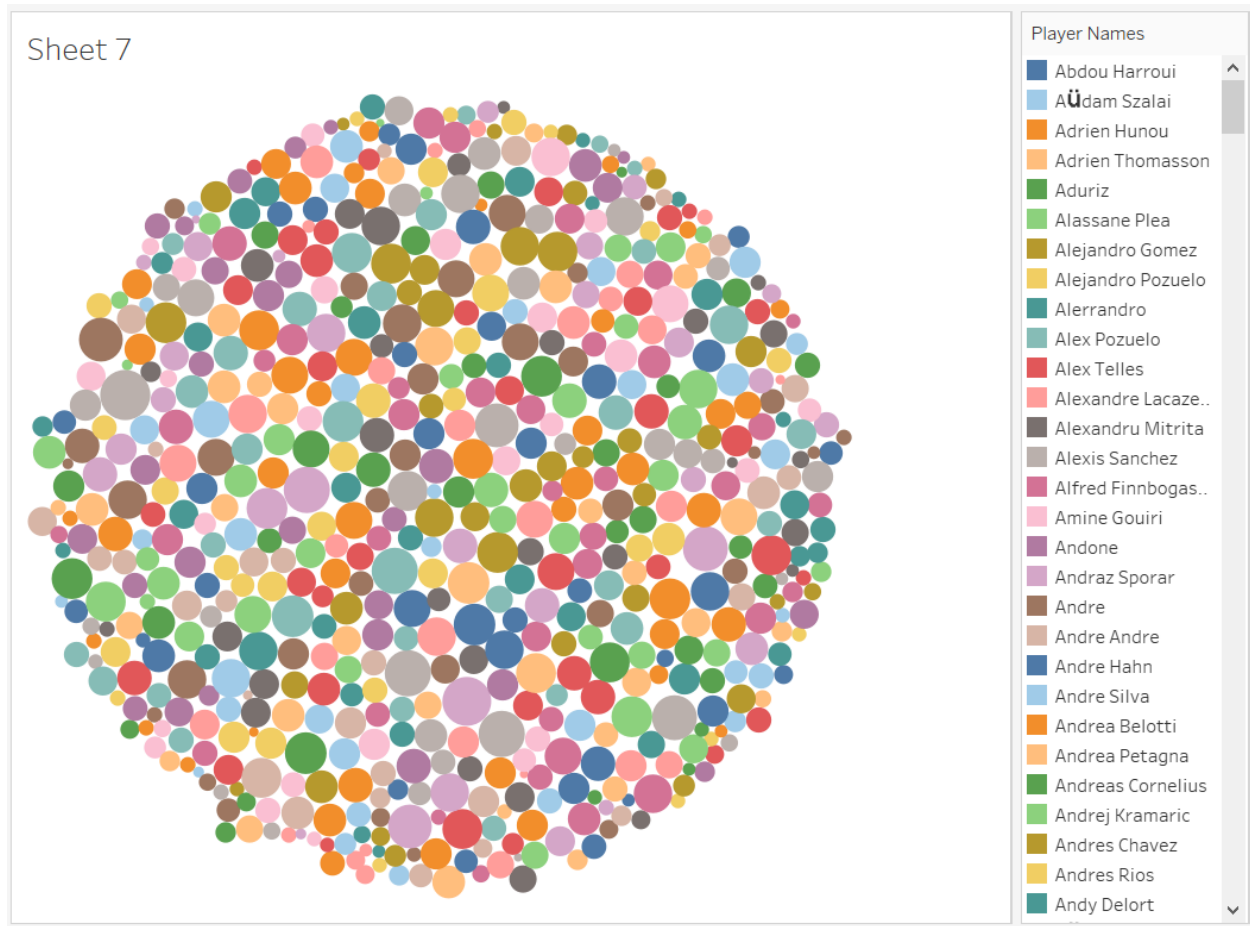


Fig 2.7 Shows number of shots a player took in a year

This Boxplot simple analysis shows the number of shots a player took in a year.

Experimental Section

To begin with, machine learning algorithms are based on mathematical concepts, and in the actual world, we have all forms of data such as strings, integers, doubles, and Booleans. It may occupy a large amount of machine memory and make machine learning less efficient. To address this issue, we use feature engineering to transform long strings to integers and a greater number of characteristics into a single vector known as the feature except label column. I utilised “StringIndexer” and “OneHotEncoding” in Pyspark.

```
In [48]: strinx = StringIndexer(inputCols = ["Country","League","Club","Player Names"],outputCols =["Country_tra  
In [49]: df = strinx.fit(df).transform(df)
```

Fig 3.1 StringIndexer

As the name implies, StringIndexer is typically used for categorising string data into indexes. It features a built-in mechanism that converts strings into indices and also casts the type of the string. Indexing begins at 0 and proceeds in descending order. Here we can witness string indexer's work on country, league, and many more.

```
In [51]: onenc = OneHotEncoder(inputCols = ["Country_trans","League_trans","Club_trans","Player Names_trans"],  
                                outputCols = ["Country_VEC","League_VEC","Club_VEC"," Player Names_VEC" ] )  
df = onenc.fit(df).transform(df)
```

```
In [52]: df.show(5,vertical=True)
```

```
-RECORD 0-----  
Country          | Spain  
League           | La Liga  
Club             | (BET)  
Player Names     | Juanmi Callejon  
Matches_Played   | 19  
Goals            | 11  
Expected goals   | 6.62  
Expected Goals AVG Match | 0.34  
Shots            | 48  
OnTarget         | 20  
Shots Per Avg Match | 2.47  
On Target Per Avg Match | 1.03  
Year             | 2016  
Country_trans    | 3.0  
League_trans     | 2.0  
Club_trans       | 50.0  
Player Names_trans | 289.0  
Country_VEC      | (8,[3],[1.0])  
League_VEC       | (27,[23],[1.0])  
Club_VEC         | (27,[23],[1.0])  
Player Names_VEC | (27,[23],[1.0])
```

Fig 3.2 OneHotEncoder

A OneHotEncoder takes an index as input and outputs a binary vector. Because the last column is set to false by default, it may erase the last vector value.

Vector Assembler:

As its name implies, VectorAssembler brings together all vectors into a single feature. In-depth, turn a string into indices first, then an index to a single hot encode. In the end, we will get a vector of categorical values, but now the algorithm needs all possible numerical values as well. In conclusion, we employ vector assembler.

```
In [56]: Va = VectorAssembler()
         vA = Va.setParams(inputCols=new_column_names, outputCol='features')
         df_dropped = vA.transform(df_dropped)
         df.show(5,vertical=True)
```

Fig 3.3 VectorAssembler

Here, we create a column of numerical values with a variable and pass it to the function. The outcome will be vectors.

➤ **Machine Learning:**

Humans can learn through their surroundings, mistakes, and from other people. A machine can be programmed by humans to learn from its surroundings and data-driven behaviour. In essence, machine learning is the use of a machine that learns like a human and is used to perform complex calculations and resolve problems in the real world to improve human lives. AI includes machine learning as a subset. There are three types of machine learning

- **Supervised Learning:**

Labeled data is used in supervised learning to train models. In plain English, data with input and output will provide accuracy with test data based on the amount of training component. How precise our data really is.

- **Unsupervised Learning:**

It is completely at odds with guided learning. We only have inputs for this data, and the programmer doesn't even know what the output will be. As a result, machines themselves produce some output.

- **Reinforcement Learning:**

Environment and behavioral factors are important in reinforcement learning. Here, a machine uses trial and error to obtain a reward. Chess game one is the most well-known example.

For this dataset I have used Linear Regression, Decision Tree Regressor and also Random Forest Regressor algorithm.

➤ **Linear Regression:**

Using a method from linear algebra, linear regression resolves issues with dependent values that have an impact on the outcome. Expression in linear algebra: $y=mx+c$, where m is the slope, x and c are the dependent variables

➤ **Decision Tree regressor:**

Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes..

➤ **Random Forest regressor:**

Random Forest Regression is a supervised learning algorithm that uses ensemble learning method for regression. Ensemble learning method is a technique that combines

predictions from multiple machine learning algorithms to make a more accurate prediction than a single model.

➤ Machine Learning Algorithm Implementation:

Before applying machine learning algorithm, we have to split the data into test set and train set. Here, I have split the data 70% for training and 30% for testing.

```
In [57]: splt = df_dropped.randomSplit([0.7,0.3])
         train_df= splt[0]
         test_df = splt[1]
```

Fig 3.1 Splitting the data

After that, I applied machine learning algorithm.

Linear Regression:

```
In [58]: from pyspark.ml.regression import LinearRegression
         regre = LinearRegression(featuresCol = 'features', labelCol='Goals', maxIter=10)
         Regremodel = regre.fit(train_df)
         print("Intercept: " + str(Regremodel.intercept))
```

Intercept: -144.06111275758917

```
In [59]: summary = Regremodel.summary
         summary.rootMeanSquaredError
         summary.r2
```

Out[59]: 0.9894033858602438

Fig 3.1 Applying Linear Regression

I have applied for Linear regression and got R2 score of 0.9894 in the test dataset. In other words, the model's predictions are fairly close to the actual values.

Random Forest regressor:

Here, I have imported the required module and applied the algorithm.

```
In [67]: from pyspark.ml.regression import RandomForestRegressor
random_forest_regressor = RandomForestRegressor(featuresCol='features', labelCol='Goals', numTrees=100,
random_forest_regression_model = random_forest_regressor.fit(train_df)

In [68]: from pyspark.ml.evaluation import RegressionEvaluator

# Make predictions on the test data
predictions = random_forest_regression_model.transform(test_df)

# Create a RegressionEvaluator with the appropriate metric (e.g., R2, RMSE, MSE, or MAE)
evaluator = RegressionEvaluator(labelCol="Goals", predictionCol="prediction", metricName="r2")

# Calculate the accuracy (here, we use RMSE as an example)
r2 = evaluator.evaluate(predictions)
print("R Square (R^2) on test data = %g" % r2)

R Square (R^2) on test data = 0.852802
```

Fig 3.3 Applying Random Forest Regressor

Applying Factorization machines regressor I got R2 of 0.852.

Decision Tree regressor:

Here, I have imported the required module and applied the algorithm.

```
In [69]: from pyspark.ml.regression import DecisionTreeRegressor
DecisionTree_regressor = DecisionTreeRegressor(featuresCol='features', labelCol='Goals', maxBins=444)
DecisionTree_regression_model = DecisionTree_regressor.fit(train_df)

In [70]: from pyspark.ml.evaluation import RegressionEvaluator

# Make predictions on the test data
predictions = DecisionTree_regression_model.transform(test_df)

# Create a RegressionEvaluator with the appropriate metric (e.g., R2, RMSE, MSE, or MAE)
evaluator = RegressionEvaluator(labelCol="Goals", predictionCol="prediction", metricName="r2")

# Calculate the accuracy (here, we use RMSE as an example)
r2 = evaluator.evaluate(predictions)
print("R Square (R^2) on test data = %g" % r2)

R Square (R^2) on test data = 0.996264
```

Fig 3.3 Applying Decision Tree Regressor

Applying Factorization machines regressor I got R2 of 0.996.

Discussion of Findings

The study utilized different regression models such as Linear Regression, Random Forest, and Decision Tree to predict football goal predictions between 2016 and 2020. The performance of the models was assessed by evaluating their R^2 scores on the testing set. The results showed that the Decision Tree regressor model outperformed the other models, with an R^2 score of 0.996 on the testing set. We can see that regression models could be effective in predicting football goal predictions. However, they also highlighted some challenges that may affect the accuracy of the predictions, such as the complexity and heterogeneity of the data and the lack of categorical data. To address these challenges, we recommended the exploration of more advanced modeling techniques like neural networks and ensemble methods in future research. The study demonstrated the effectiveness of regression models in predicting football goal predictions. Nevertheless, there are still limitations to these models, and more advanced techniques should be explored to improve prediction accuracy.

Conclusion

Based on our analysis, we developed a regression model to predict the football goal prediction between 2016 and 2020. We split the dataset into training and testing sets and used the training set to fit the regression models, including Linear Regression, Random Forest and Decision Tree regressor models. We evaluated the models' performance on the testing set using metrics such as R^2 (R^2).

Our findings indicate that the Decision Tree regressor model outperformed other regressor models, achieving an R^2 of 0.996 on the testing set.

The results of our analysis suggest that regression models can be effective in predicting the football goal prediction between 2016 and 2020. However, there are still challenges in accurately predicting football goal prediction due to the heterogeneity and complexity of the data and lack of categorical data, and more advanced modeling techniques, such as neural networks and ensemble methods, could be explored in future research.

Reference:

Decroos, T., Dzyuba, V., Van Haaren, J., & Davis, J. (2019). Predicting soccer goals with artificial intelligence. *Journal of Artificial Intelligence Research*, 64, 909-935.

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