Major Leagues

1. INDUSTRY ¶

Sports industry is assigned.

2. DATA SETS

2.1. SOURCE: The dataset is from Github (https://github.com) in this link (https://github.com/fivethirtyeight/data/tree/master/soccer-spi).

DESCRIPTION: The datasets contains data related to soccer league, team, spi, probability, projected score and scores. The following attributes from the datasets will be used for analysis.

Attribute	Datatype
team	object
spi	float64
prob	float64
proj_score	float64
score	float64

3. IDEAS

3.1. To predict a team's score irrespective of the opposite team.

3.2. To predict a team's score when it is playing with certain team.

4. LOADING THE DATASETS

Load the libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Import the csv files of dataset

In [2]:
```
soccer_data=pd.read_csv("/Users/madhumithrasubramaniankarthikesh/Downloads/spi_matches_latest.csv")
soccer_data.head()
```

Out[2]:

	season	date	league_id	league	team1	team2	spi1	spi2	prob1	prob2	...
0	2019	2019-03-01	1979	Chinese Super League	Shandong Luneng	Guizhou Renhe	48.22	37.83	0.5755	0.1740	...
1	2019	2019-03-01	1979	Chinese Super League	Guangzhou Evergrande	Tianjin Quanujian	65.59	39.99	0.7832	0.0673	...
2	2019	2019-03-01	1979	Chinese Super League	Shanghai Greenland	Shanghai SIPG	39.81	60.08	0.2387	0.5203	...
3	2019	2019-03-01	1979	Chinese Super League	Wuhan Zall	Beijing Guoan	32.25	54.82	0.2276	0.5226	...
4	2019	2019-03-01	1979	Chinese Super League	Chongqing Lifan	Guangzhou RF	38.24	40.45	0.4403	0.2932	...

5 rows × 23 columns

5. DATA PREPARATION

5.1 DATA CLEANING AND FEATURE ENGINEERING

Shape of all the data

In [3]:
```
print("Shape of soccer: "+str(soccer_data.shape))
```

```
Shape of soccer: (10930, 23)
```

Make into a new dataset with scores for all team in each matches

In [4]:
```
team1_data=pd.DataFrame(soccer_data[['season','date','league_id','team
1','spi1','prob1','proj_score1','importance1','score1','xg1','nsxg1','
adj_score1']])
team1_data.rename(columns={"team1": "team", "spi1": "spi","prob1": "pr
ob", "proj_score1": "proj_score","score1": "score", "xg1": "xg"}, inpl
ace=True)
team1_data.rename(columns={"importance1": "importance","nsxg1": "nsxg"
, "adj_score1": "adj_score"}, inplace=True)
team1_data.head()
```

Out[4]:

	season	date	league_id	team	spi	prob	proj_score	importance	score	xg	r
0	2019	2019-03-01	1979	Shandong Luneng	48.22	0.5755	1.75	45.9	1.0	1.39	
1	2019	2019-03-01	1979	Guangzhou Evergrande	65.59	0.7832	2.58	77.1	3.0	0.49	
2	2019	2019-03-01	1979	Shanghai Greenland	39.81	0.2387	1.22	25.6	0.0	0.57	
3	2019	2019-03-01	1979	Wuhan Zall	32.25	0.2276	1.10	35.8	0.0	1.12	
4	2019	2019-03-01	1979	Chongqing Lifan	38.24	0.4403	1.57	26.2	2.0	2.77	

In [5]:
```
team2_data=pd.DataFrame(soccer_data[['season','date','league_id','team
2','spi2','prob2','proj_score2','importance2','score2','xg2','nsxg2','
adj_score2']])
team2_data.rename(columns={"team2": "team", "spi2": "spi","prob2": "pr
ob", "proj_score2": "proj_score","score2": "score", "xg2": "xg","impor
tance2": "importance", "nsxg2": "nsxg", "adj_score2": "adj_score"}, in
place=True)
team2_data.head()
```

Out[5]:

	season	date	league_id	team	spi	prob	proj_score	importance	score	xg	r
0	2019	2019-03-01	1979	Guizhou Renhe	37.83	0.1740	0.84	22.1	0.0	0.26	
1	2019	2019-03-01	1979	Tianjin Quanujian	39.99	0.0673	0.62	28.8	0.0	0.45	
2	2019	2019-03-01	1979	Shanghai SIPG	60.08	0.5203	1.89	63.4	4.0	2.76	
3	2019	2019-03-01	1979	Beijing Guoan	54.82	0.5226	1.79	58.9	1.0	0.97	
4	2019	2019-03-01	1979	Guangzhou RF	40.45	0.2932	1.24	21.3	2.0	3.17	

In [6]:
```
soccer_data = pd.concat([team1_data, team2_data], axis=0)
soccer_data.head()
```

Out[6]:

	season	date	league_id	team	spi	prob	proj_score	importance	score	xg	r
0	2019	2019-03-01	1979	Shandong Luneng	48.22	0.5755	1.75	45.9	1.0	1.39	
1	2019	2019-03-01	1979	Guangzhou Evergrande	65.59	0.7832	2.58	77.1	3.0	0.49	
2	2019	2019-03-01	1979	Shanghai Greenland	39.81	0.2387	1.22	25.6	0.0	0.57	
3	2019	2019-03-01	1979	Wuhan Zall	32.25	0.2276	1.10	35.8	0.0	1.12	
4	2019	2019-03-01	1979	Chongqing Lifan	38.24	0.4403	1.57	26.2	2.0	2.77	

In [7]:
```
soccer_data.shape
```

Out[7]:
```
(21860, 12)
```

Drop the NaN rows

In [8]:
```
del soccer_data["xg"]
del soccer_data["nsxg"]
del soccer_data["adj_score"]
del soccer_data["season"]
del soccer_data["date"]
del soccer_data["league_id"]
del soccer_data["importance"]
soccer_data=soccer_data.dropna()
soccer_data.head()
```

Out[8]:

	team	spi	prob	proj_score	score
0	Shandong Luneng	48.22	0.5755	1.75	1.0
1	Guangzhou Evergrande	65.59	0.7832	2.58	3.0
2	Shanghai Greenland	39.81	0.2387	1.22	0.0
3	Wuhan Zall	32.25	0.2276	1.10	0.0
4	Chongqing Lifan	38.24	0.4403	1.57	2.0

Shape of all the data

In [9]:
```
print("Soccer: "+str(soccer_data.shape))
```

```
Soccer: (7186, 5)
```

Attributes and datatypes of the dataset

In [10]:
```
for column in soccer_data.columns:
    print(column, " is ", soccer_data[column].dtype.name)
```

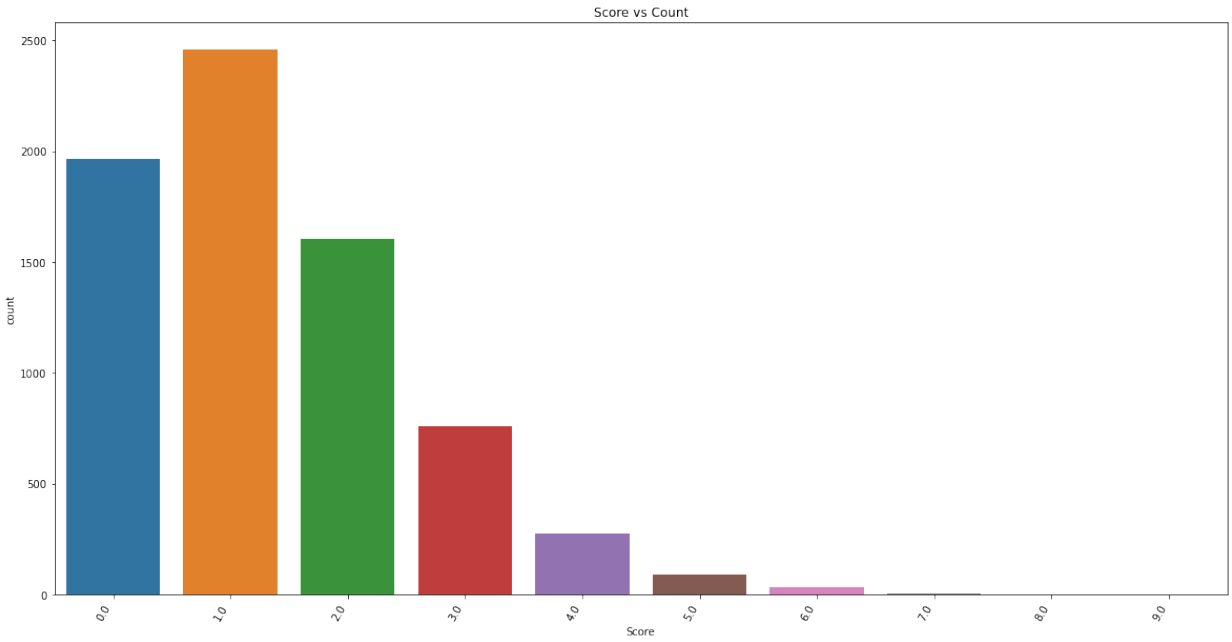
```
team  is  object
spi  is  float64
prob  is  float64
proj_score  is  float64
score  is  float64
```

5.2 VISUALIZATION

Barplot for score

In [11]:
```
plt.figure(figsize=(20,10))
g = sns.countplot(x=soccer_data['score'], data=soccer_data)
g.set_xticklabels(g.get_xticklabels(), rotation=60, ha="right");
g.set_title('Score vs Count');
g.set_xlabel('Score')
```

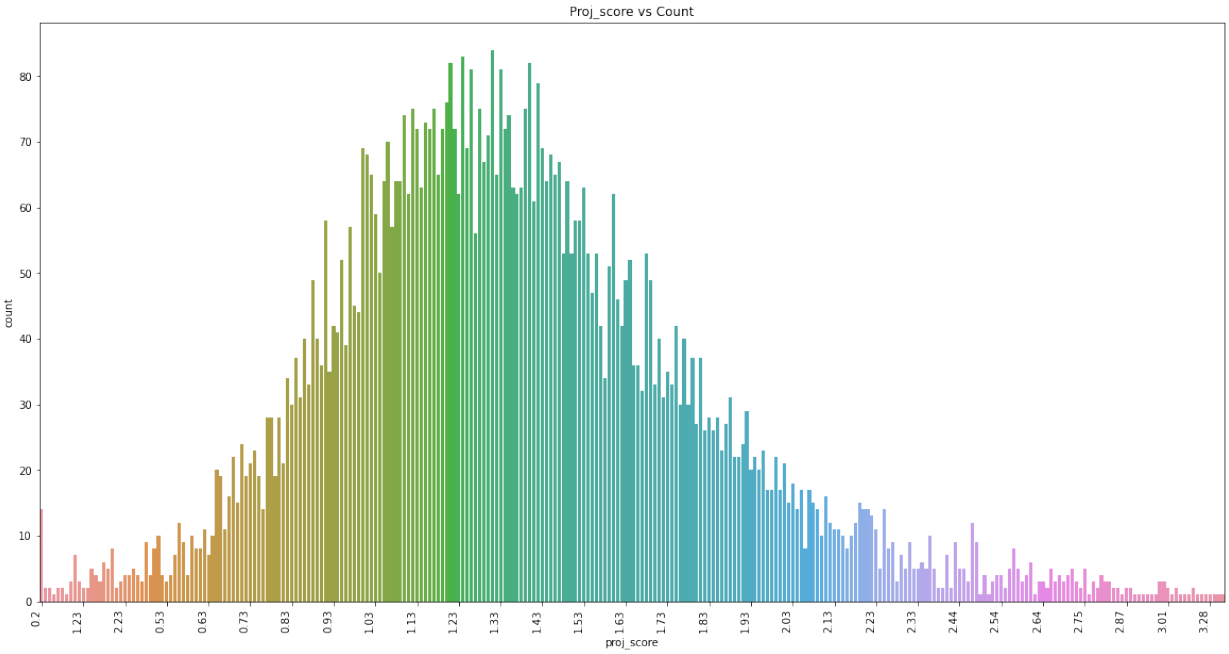
Out[11]:
```
Text(0.5, 0, 'Score')
```



The number of times teams have got a score of 1 is greater than any other score.

Countplot for projected score

In [27]:
```
plt.figure(figsize=(20,10))
g = sns.countplot(x=soccer_data['proj_score'], data=soccer_data)
g.set_xticklabels(g.get_xticklabels()[::10], rotation=90, ha="right",
fontsize=10);
new_ticks=g.get_xticklabels()
plt.xticks(range(0, len(new_ticks), 10), new_ticks[::10])
g.set_title('Proj_score vs Count');
```



The projected score also lies within 1 and 1.5 for the same data which is in agreement with the actual score of 1.

5.3 Regression

Train, test and validation dataset for predicting scores of the teams

In [13]:
```
from numpy import mean
from numpy import std
from pandas import read_csv
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
train_ratio = 0.8
validation_ratio = 0.1
test_ratio = 0.1
cols=['team','spi','prob','proj_score']

#replace 0 as 5
col=soccer_data['score'].replace(0, 5)

# define one hot encoding for the categorical independent variables
encoder = OneHotEncoder(sparse=False)
# transform data
x = encoder.fit_transform(soccer_data[cols])

# define label encoding for the dependent variable
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(col)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=1
- train_ratio)

# test = 10% of the initial data set
# validation = 10% of the initial data set
x_val, x_test, y_val, y_test = train_test_split(x_test, y_test, test_s
ize=test_ratio/(test_ratio + validation_ratio))
```

5.3.1 Linear Regression

Training and Testing: Linear regression for predicting the scores of the team

In [14]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
clf = LinearRegression().fit(x_train, y_train)
y_pred=clf.predict(x_test)
# The coefficients
print("Test Coefficients:",clf.coef_)
# The mean squared error
print("Test Mean squared error: ",mean_squared_error(y_test, y_pred))
# The coefficient of determination: 1 is perfect prediction
print("Test Coefficient of determination: ",r2_score(y_test, y_pred))
# print the coefficients
list(zip(cols, clf.coef_))
```

```
Test Coefficients: [ 0.7111271   0.06660344 -0.45442077 ... -0.35614
945  0.
  1.23768951]
Test Mean squared error:  6.87927735547539
Test Coefficient of determination:  -1.6014428823427225
```

Out[14]:
```
[('team', 0.7111270964839373),
 ('spi', 0.06660343651810852),
 ('prob', -0.4544207709540689),
 ('proj_score', 0.21738030414425213)]
```

Validation: Linear regression for predicting the scores of the team

In [15]:
```
y_pred = clf.predict(x_val)

# The coefficients
print("Coefficients: "+ str(clf.coef_))
# The mean squared error
print("Mean squared error: "+ str(mean_squared_error(y_val, y_pred)))
# The coefficient of determination: 1 is perfect prediction
print("Coefficient of determination: "+str(r2_score(y_val, y_pred)))
```

```
Coefficients: [ 0.7111271   0.06660344 -0.45442077 ... -0.35614945
0.
  1.23768951]
Mean squared error: 6.836565968761102
Coefficient of determination: -1.3542407317350187
```

5.3.2 Random Forest

Training: Random forest classifier for predicting the scores of the team

In [16]:
```
# Import the model we are using
from sklearn.ensemble import RandomForestRegressor
# Instantiate model with 10 decision trees
rf = RandomForestRegressor(n_estimators = 10)
# Train the model on training data
rf.fit(x_train, y_train);
```

Testing: Random forest classifier for predicting the scores of the team

In [20]:
```
# Use the forest's predict method on the test data
y_pred = rf.predict(x_test)

from scipy.stats import pearsonr
# find the correlation between real answer and prediction
correlation = pearsonr(y_pred, y_test)
print('Correlation: ',correlation)

from sklearn.metrics import mean_absolute_error
print('Validation Accuracy: ',rf.score(x_test, y_test))
print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, y
_pred)))
import warnings
warnings.filterwarnings('ignore')
accuracy= (~np.isnan(100*((mean_absolute_error(y_test, y_pred))/y_test
)))
accuracy=round (100 - np.mean(accuracy),2)
print('Accuracy for Random Forest:',accuracy)


# The coefficient of determination: 1 is perfect prediction
print("Coefficient of determination: "+str(r2_score(y_test, y_pred)))
```

```
Correlation:  (0.09999825271236096, 0.007287033022755875)
Validation Accuracy:  -0.2796886813707702
Mean Absolute Error: 1.4315716272600834
Mean Squared Error: 3.3840194714881777
Root Mean Squared Error: 1.8395704584190782
Accuracy for Random Forest: 99.0
Coefficient of determination: -0.2796886813707702
```

Validation: Random forest classifier for predicting the scores of the team

In [28]:
```
# Use the forest's predict method on the test data
y_pred = rf.predict(x_val)

print('Validation Accuracy: ',rf.score(x_val, y_val))
print('Mean Absolute Error:', mean_absolute_error(y_val, y_pred))
print('Mean Squared Error:', mean_squared_error(y_val, y_pred))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_val, y_
pred)))

accuracy= (~np.isnan(100*((mean_absolute_error(y_val, y_pred))/y_val))
)
accuracy=round (100 - np.mean(accuracy),2)
print('Accuracy for Random Forest:',accuracy)

# The coefficient of determination: 1 is perfect prediction
print("Coefficient of determination: "+str(r2_score(y_val, y_pred)))
```

```
Validation Accuracy:  -0.4403113796627016
Mean Absolute Error: 1.6479833101529904
Mean Squared Error: 4.182573018080667
Root Mean Squared Error: 2.0451339853615136
Accuracy for Random Forest: 99.0
Coefficient of determination: -0.4403113796627016
```

The random forest regression works better when compared to the linear regression. This can be seen from the accuracy of random forest. The mean squared error value is higher for linear regression when compared to the random forest.