NFL

October 5, 2020

1 Goal

Build one or more regression models to determine the scores for each team using the other columns as features

Predict the scores, predict the outcome of the game

Do feature engineering. Build a few regression models.

Citing Sources Along with the sources I sprinkled in, I used these sources below throughout the text to better attack this problem.

https://towardsdatascience.com/how-to-improve-sports-betting-odds-step-by-step-guide-in-python-94626b852f45

[1]:
```
import numpy as np
import pandas as pd
```

[2]:
```
data = pd.read_csv('~/Documents/EECS/EECS_731/HW/EECS731_4/data/nfl_games.csv')
```

I added the difference in score to see if that could introduce a relationship.

[3]:
```
data['score_diff'] = (data['score1'] - data['score2'])
```

[4]:
```
data['team1_win'] = np.where(data['score_diff'] > 0, 1, 0)
data['team2_win'] = np.where(data['score_diff'] < 0, 1, 0)
```

[5]:
```
#data['date'] = pd.to_datetime(data['date'], format='%Y-%m-%d')
data['elo_diff'] = (data['elo1'] - data['elo2'])
```

[6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16274 entries, 0 to 16273
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   date        16274 non-null  object
 1   season      16274 non-null  int64
 2   neutral     16274 non-null  int64
```

```
 3   playoff     16274 non-null  int64
 4   team1       16274 non-null  object
 5   team2       16274 non-null  object
 6   elo1        16274 non-null  float64
 7   elo2        16274 non-null  float64
 8   elo_prob1   16274 non-null  float64
 9   score1      16274 non-null  int64
 10  score2      16274 non-null  int64
 11  result1     16274 non-null  float64
 12  score_diff  16274 non-null  int64
 13  team1_win   16274 non-null  int64
 14  team2_win   16274 non-null  int64
 15  elo_diff    16274 non-null  float64
dtypes: float64(5), int64(8), object(3)
memory usage: 2.0+ MB
```

[7]:
```python
data = data.dropna()
```

[8]:
```python
data.describe()
```

[8]:
```
             season       neutral       playoff          elo1          elo2  \
count  16274.000000  16274.000000  16274.000000  16274.000000  16274.000000
mean    1982.437569      0.005223      0.034779   1502.458394   1498.918375
std       25.448049      0.072084      0.183226    105.015371    104.541271
min     1920.000000      0.000000      0.000000   1119.595000   1156.551000
25%     1967.000000      0.000000      0.000000   1429.242750   1425.864750
50%     1987.000000      0.000000      0.000000   1504.015000   1500.185000
75%     2003.000000      0.000000      0.000000   1578.071500   1575.753000
max     2018.000000      1.000000      1.000000   1839.663000   1849.484000

          elo_prob1        score1        score2       result1    score_diff  \
count  16274.000000  16274.000000  16274.000000  16274.000000  16274.000000
mean       0.584829     21.544058     18.578161      0.580681      2.965897
std        0.175302     11.289422     10.794566      0.488551     15.469792
min        0.070953      0.000000      0.000000      0.000000    -73.000000
25%        0.461231     14.000000     10.000000      0.000000     -7.000000
50%        0.596354     21.000000     17.000000      1.000000      3.000000
75%        0.719930     28.000000     26.000000      1.000000     13.000000
max        0.970516     72.000000     73.000000      1.000000     66.000000

          team1_win     team2_win      elo_diff
count  16274.000000  16274.000000  16274.000000
mean       0.571034      0.409672      3.540020
std        0.494944      0.491788    141.791884
min        0.000000      0.000000   -511.826000
25%        0.000000      0.000000    -91.493250
50%        1.000000      0.000000      3.203000
```

```
75%        1.000000      1.000000      99.353500
max        1.000000      1.000000     541.969000
```

There are 16,274 entries. The first season starting in 1920. I agree that some teams that were good in 1920 might still be good today, but I think I will only take into account the last 15 years. So I will drop any game before the 2005 season.

[9]:
```
data = data[data['season'] >= 2005]
```

[10]:
```
data.head(5)
```

[10]:
```
             date  season  neutral  playoff team1 team2      elo1      elo2  \
12536  2005-09-08    2005        0        0    NE   OAK  1712.670  1403.871
12537  2005-09-11    2005        0        0   CAR    NO  1530.111  1506.978
12538  2005-09-11    2005        0        0    KC   NYJ  1533.474  1547.067
12539  2005-09-11    2005        0        0   JAX   SEA  1485.276  1480.542
12540  2005-09-11    2005        0        0   WSH   CHI  1459.026  1410.741

       elo_prob1  score1  score2  result1  score_diff  team1_win  team2_win  \
12536   0.895833      30      20      1.0          10          1          0
12537   0.624181      20      23      0.0          -3          0          1
12538   0.573445      27       7      1.0          20          1          0
12539   0.599029      26      14      1.0          12          1          0
12540   0.657488       9       7      1.0           2          1          0

       elo_diff
12536   308.799
12537    23.133
12538   -13.593
12539     4.734
12540    48.285
```

[11]:
```
data.team1.unique()
```

[11]:
```
array(['NE', 'CAR', 'KC', 'JAX', 'WSH', 'SF', 'CLE', 'BUF', 'LAC', 'MIN',
       'MIA', 'DET', 'PIT', 'BAL', 'NYG', 'ATL', 'CIN', 'TB', 'TEN',
       'OAK', 'CHI', 'NYJ', 'DEN', 'HOU', 'GB', 'IND', 'ARI', 'SEA',
       'PHI', 'DAL', 'LAR', 'NO'], dtype=object)
```

By dropping games before 2005, I now have a better idea of what teams are currently active.

2 Faceting

I decided to try faceting to better understand the data.

Tips for faceting I found at https://www.kaggle.com/residentmario/faceting-with-seaborn

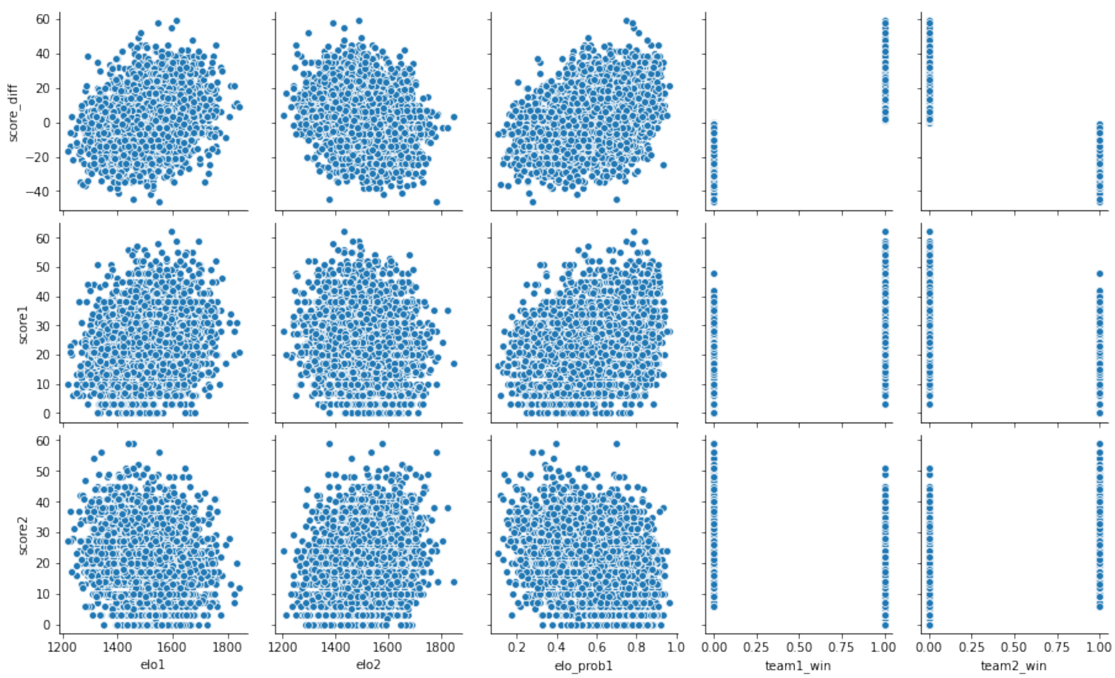
I was interested in comparing scores and the teams that played.

[12]:
```
import seaborn as sns
```

[13]:
```
# data2010 = data[data['season'].isin(['2010'])]
```

[14]:
```
sns.pairplot(data,
             x_vars = ['elo1', 'elo2', 'elo_prob1', 'team1_win', 'team2_win'],
             y_vars = ['score_diff', 'score1', 'score2'])
             #hue = "team1")
```

[14]: <seaborn.axisgrid.PairGrid at 0x11ed350d0>



It looks like there may be a linear correlation with score1 and elo1 and score2 and elo2. Although that seems intuitive.

I didn't see any great correlations to use. So, I moved onto a heat map. The closer to 1 or -1 the value is on the map, the stronger the corelation. There isn't a great correlation between anything except maybe elo_prob1 and result_1. That seems like the highest non-trival value.

[15]:
```
data_corr = data.corr()
data_corr
```

[15]:

	season	neutral	playoff	elo1	elo2 \
season	1.000000e+00	0.028296	-5.931427e-19	0.007367	0.005822
neutral	2.829635e-02	1.000000	1.499114e-01	0.041492	0.036028
playoff	-5.931427e-19	0.149911	1.000000e+00	0.264268	0.241292
elo1	7.366663e-03	0.041492	2.642684e-01	1.000000	0.074469

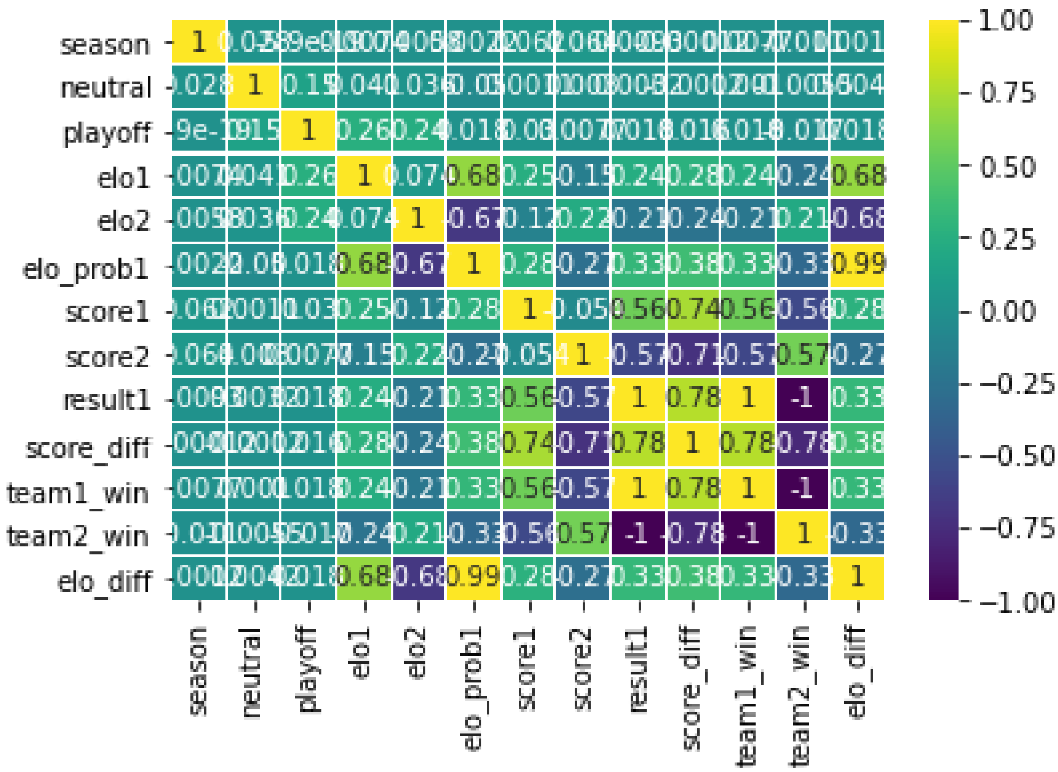
```
elo2        5.821616e-03  0.036028  2.412920e-01  0.074469  1.000000
elo_prob1   2.189256e-03 -0.049735  1.789909e-02  0.675980 -0.673994
score1      6.174932e-02  0.001141  3.029494e-02  0.250805 -0.124768
score2      6.417428e-02  0.002981  7.697921e-03 -0.153109  0.219881
result1     9.271437e-03  0.003245  1.784226e-02  0.237555 -0.209652
score_diff -1.188288e-04 -0.001217  1.603222e-02  0.279407 -0.236212
team1_win   7.715245e-03  0.000999  1.826544e-02  0.237385 -0.209955
team2_win  -1.080838e-02 -0.005485 -1.737979e-02 -0.237205  0.208890
elo_diff    1.163446e-03  0.004179  1.795476e-02  0.682533 -0.677998

            elo_prob1    score1    score2   result1  score_diff  team1_win  \
season       0.002189  0.061749  0.064174  0.009271   -0.000119   0.007715
neutral     -0.049735  0.001141  0.002981  0.003245   -0.001217   0.000999
playoff      0.017899  0.030295  0.007698  0.017842    0.016032   0.018265
elo1         0.675980  0.250805 -0.153109  0.237555    0.279407   0.237385
elo2        -0.673994 -0.124768  0.219881 -0.209652   -0.236212  -0.209955
elo_prob1    1.000000  0.275833 -0.271637  0.327205    0.377132   0.327480
score1       0.275833  1.000000 -0.053653  0.557326    0.737383   0.556660
score2      -0.271637 -0.053653  1.000000 -0.571707   -0.714065  -0.571322
result1      0.327205  0.557326 -0.571707  1.000000    0.777466   0.998908
score_diff   0.377132  0.737383 -0.714065  0.777466    1.000000   0.776739
team1_win    0.327480  0.556660 -0.571322  0.998908    0.776739   1.000000
team2_win   -0.326215 -0.556774  0.570843 -0.998907   -0.776495  -0.995632
elo_diff     0.992235  0.276312 -0.274007  0.328756    0.379071   0.328853

            team2_win  elo_diff
season      -0.010808  0.001163
neutral     -0.005485  0.004179
playoff     -0.017380  0.017955
elo1        -0.237205  0.682533
elo2         0.208890 -0.677998
elo_prob1   -0.326215  0.992235
score1      -0.556774  0.276312
score2       0.570843 -0.274007
result1     -0.998907  0.328756
score_diff  -0.776495  0.379071
team1_win   -0.995632  0.328853
team2_win    1.000000 -0.327940
elo_diff    -0.327940  1.000000
```

[16]:
```python
sns.heatmap(data_corr, vmin=-1, vmax=1, cmap="viridis", annot=True, linewidth=0.
↪1)
```

[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11af6b940>
```



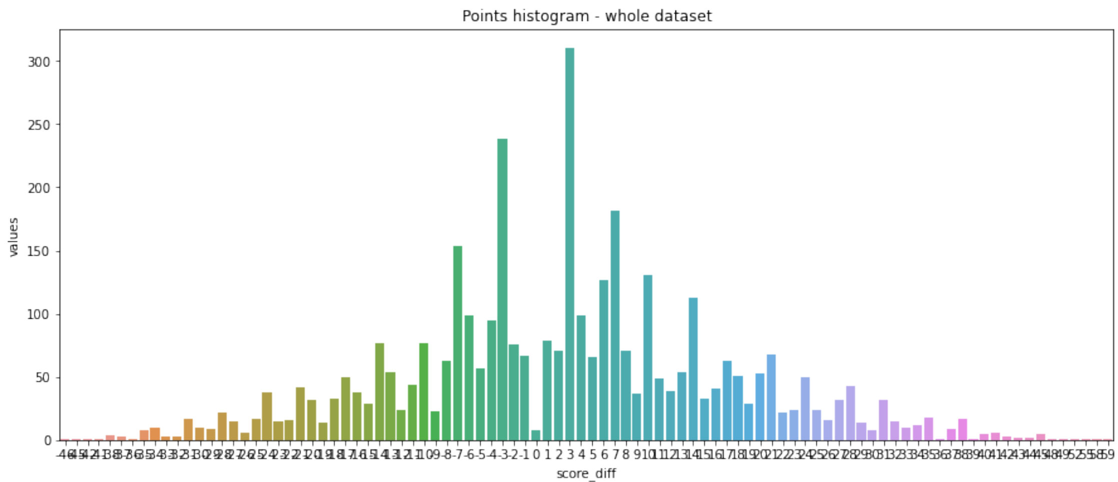
[17]:
```
import matplotlib.pyplot as plt

def pastel_plot(data, x, y):
    plt.figure(figsize = (15,6))
    plt.title('Points histogram - whole dataset')
    sns.set_color_codes("pastel")
    sns.barplot(x = x, y=y, data=df)
    locs, labels = plt.xticks()
    plt.show()
```

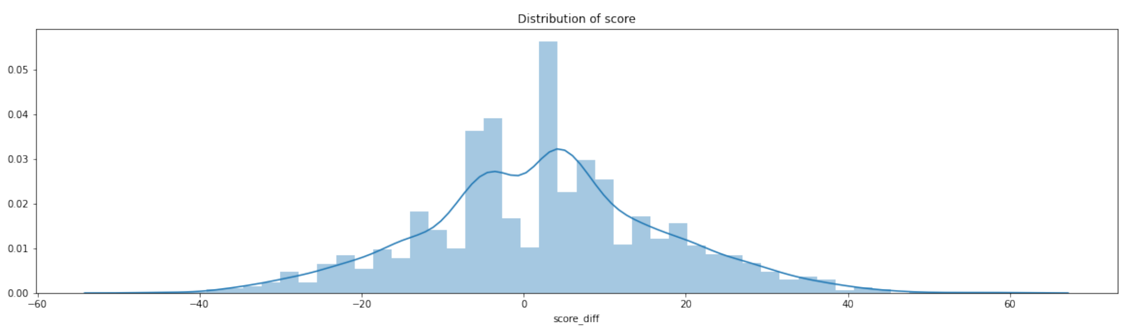
I thought maybe a histogram would help to look at the distrbution of the values for the difference in score. This revealed there were no crazy outliers.

[18]:
```
temp = data['score_diff'].value_counts()
df = pd.DataFrame({'score_diff': temp.index,
                   'values': temp.values
                  })

pastel_plot(df,'score_diff', 'values')
```



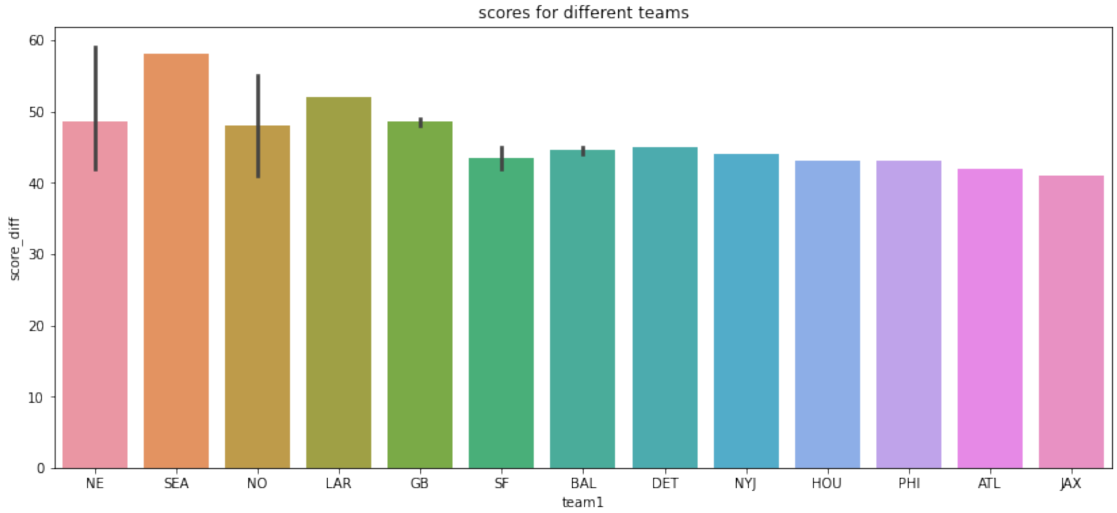

```
[19]: plt.figure(figsize=(20,5))
      plt.title("Distribution of score")
      ax = sns.distplot(data["score_diff"])
```




```
[20]: data=data.sort_values('score_diff', ascending=False)
```

The following bar graphs releaved the best teams in the team1 category and the worst teams in the team2 catagory.

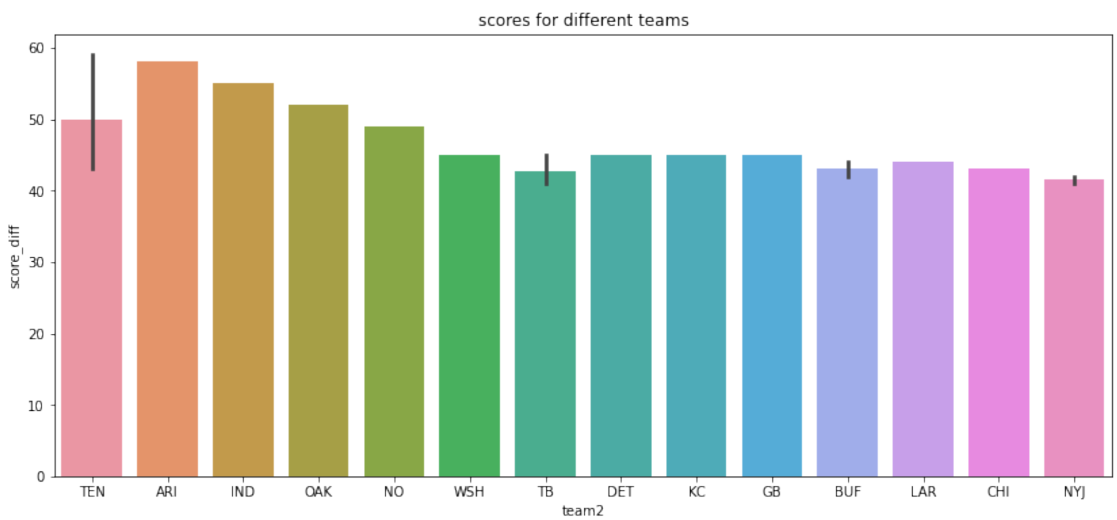
```
[21]: plt.figure(figsize = (14,6))
      plt.title('scores for different teams')
      sns.barplot(x = 'team1', y="score_diff", data=data.head(20))
      locs, labels = plt.xticks()
      plt.show()
```



NE has the greatest score difference. This means they win by the most amount of points. Still, I needed to figure out some way to interact the two teams.

Also, below TEN looses by the most amount of points.

[22]:
```
plt.figure(figsize = (14,6))
plt.title('scores for different teams')
sns.barplot(x = 'team2', y="score_diff", data=data.head(20))
locs, labels = plt.xticks()
plt.show()
```



3 Feature Engineering

Before I could continue, I needed some way to get an interaction between the two teams. I started by making a one hot encoding of team1 and team2. I then combined the encodings. To maintain a sense of who won and who lost, I made the team2 values negative, ie -1, and the team1 values positive. Then, if the score difference was negative, team2 won and if the score difference was positive, team1 won.

[23]:
```python
from random import shuffle
data = data.sample(frac = 1)
```

[24]:
```python
team1_oh = pd.get_dummies(data['team1'], dtype=np.int64)
team2_oh = pd.get_dummies(data['team2'], dtype=np.int64)
```

[25]:
```python
team1_oh.head(5)
```

[25]:
```
       ARI  ATL  BAL  BUF  CAR  CHI  CIN  CLE  DAL  DEN  …  NYG  NYJ  OAK  \
12954    0    0    1    0    0    0    0    0    0    0  …    0    0    0
13206    0    0    1    0    0    0    0    0    0    0  …    0    0    0
15459    0    0    0    0    0    0    0    0    0    1  …    0    0    0
14659    0    0    0    0    0    0    0    0    0    0  …    0    0    0
16075    0    0    0    0    0    0    1    0    0    0  …    0    0    0

       PHI  PIT  SEA  SF  TB  TEN  WSH
12954    0    0    0   0   0    0    0
13206    0    0    0   0   0    0    0
15459    0    0    0   0   0    0    0
14659    0    0    0   0   0    1    0
16075    0    0    0   0   0    0    0

[5 rows x 32 columns]
```

Now, I need to fit the teams together.

[26]:
```python
teams_oh = team1_oh.sub(team2_oh)
teams_oh['score_diff'] = data['score_diff']
teams_oh['elo_diff'] = data['elo_diff']
teams_oh['date'] = data['date']
teams_oh.head(5)
```

[26]:
```
       ARI  ATL  BAL  BUF  CAR  CHI  CIN  CLE  DAL  DEN  …  PHI  PIT  SEA  \
12954    0   -1    1    0    0    0    0    0    0    0  …    0    0    0
13206    0    0    1    0    0    0   -1    0    0    0  …    0    0    0
15459    0    0    0    0    0    0    0    0    0    1  …    0    0    0
14659    0    0    0    0    0    0    0    0    0    0  …    0    0    0
16075    0    0    0    0    0    0    1    0    0    0  …    0    0    0

       SF  TB  TEN  WSH  score_diff    elo_diff        date
```

```
12954   0   0   0   0         14  114.856000  2006-11-19
13206   0   0   0   0        -14   78.454000  2007-11-11
15459   0   0   0   0          7  228.311337  2016-01-03
14659   0   0   1   0         18  137.787000  2012-12-30
16075   0   0   0   0         10   26.205895  2018-10-07

[5 rows x 35 columns]
```

If the row has a 1, it was team1 and if the row has a -1, then it was team2.

If the score is positive, then team1 won, and if the score was negative then team2 won.

Encoding this way ensures I can know which team won and which team lost.

Later in the project, I realized I needed to predict the scores of each team, not their difference. So I made the data table `scores` to be able to predict the score of the teams.

[27]:
```
scores = data[['score1', 'score2']]
scores.head()
```

[27]:

	score1	score2
12954	24	10
13206	7	21
15459	27	20
14659	38	20
16075	27	17

4 Regression

Regression is useful to determine the relationship between independent valiables (features) and dependent variables (target values).

In this problem, I tasked to predict the scores based on features. That is, the score is a function of the teams playing, and the elo predictions.

4.1 Linear Regression

I used https://www.geeksforgeeks.org/linear-regression-python-implementation/ for help in implementing linear regression.

This was my first attempt at regression. I tried to fit the data to predict the score difference. The coefficients of the regression were the rating of each time. If the team was a good, then they had a high positive rating. If the team was loosing, then the had a high negative rating.

From the faceting before, TEN should have a low negative rating and NE should have a high positive rating. This is true below.

[28]:
```
from sklearn import datasets, linear_model, metrics
from sklearn.linear_model import Ridge, LinearRegression
import matplotlib.pyplot as plt
```

[29]:
```
data_train = teams_oh
data_train = data_train.dropna(axis='columns')
data_train.head(5)
```

[29]:
```
       ARI  ATL  BAL  BUF  CAR  CHI  CIN  CLE  DAL  DEN  …  PHI  PIT  SEA  \
12954    0   -1    1    0    0    0    0    0    0    0  …    0    0    0
13206    0    0    1    0    0    0   -1    0    0    0  …    0    0    0
15459    0    0    0    0    0    0    0    0    0    1  …    0    0    0
14659    0    0    0    0    0    0    0    0    0    0  …    0    0    0
16075    0    0    0    0    0    0    1    0    0    0  …    0    0    0

       SF  TB  TEN  WSH  score_diff    elo_diff        date
12954   0   0    0    0          14  114.856000  2006-11-19
13206   0   0    0    0         -14   78.454000  2007-11-11
15459   0   0    0    0           7  228.311337  2016-01-03
14659   0   0    1    0          18  137.787000  2012-12-30
16075   0   0    0    0          10   26.205895  2018-10-07

[5 rows x 35 columns]
```

[30]:
```
# defining feature matrix(X) and response vector(y)
X = data_train.drop(['score_diff'], axis=1)
X = data_train.drop(['date'], axis=1)
#X = np.array(data.elo1).reshape(-1, 1)
y = data_train['score_diff']
```

[31]:
```
# splitting X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=1)
```

[32]:
```
lr = Ridge(alpha=0.001)
lr.fit(X_train, y_train)
```

[32]:
```
Ridge(alpha=0.001)
```

[33]:
```
df_ratings = pd.DataFrame(data={'team': X.columns, 'rating': lr.coef_})
df_ratings
```

[33]:
```
          team        rating
0          ARI -2.532983e-09
1          ATL  1.041983e-09
2          BAL  4.207294e-09
3          BUF -2.992732e-09
4          CAR  4.624595e-10
5          CHI  2.845380e-09
6          CIN -1.355059e-09
```

```
7           CLE -2.302405e-09
8           DAL  2.169938e-09
9           DEN -9.807869e-10
10          DET -1.777190e-09
11           GB  3.438865e-09
12          HOU -8.266760e-10
13          IND  3.359043e-10
14          JAX -2.593188e-09
15           KC  6.747566e-10
16          LAC  4.960689e-09
17          LAR -2.454958e-09
18          MIA -2.852748e-09
19          MIN  1.227153e-10
20           NE  6.434558e-09
21           NO  3.456554e-09
22          NYG  1.861281e-09
23          NYJ -2.200696e-09
24          OAK -5.696832e-09
25          PHI  2.540132e-09
26          PIT  3.378906e-09
27          SEA  2.902558e-09
28           SF -1.823715e-09
29           TB -2.249039e-09
30          TEN -2.815024e-09
31          WSH -1.712477e-09
32   score_diff  1.000000e+00
33     elo_diff  5.629231e-11
```

[34]:
```
print('Score: \n', lr.score(X_test, y_test))
```

```
Score:
 1.0
```

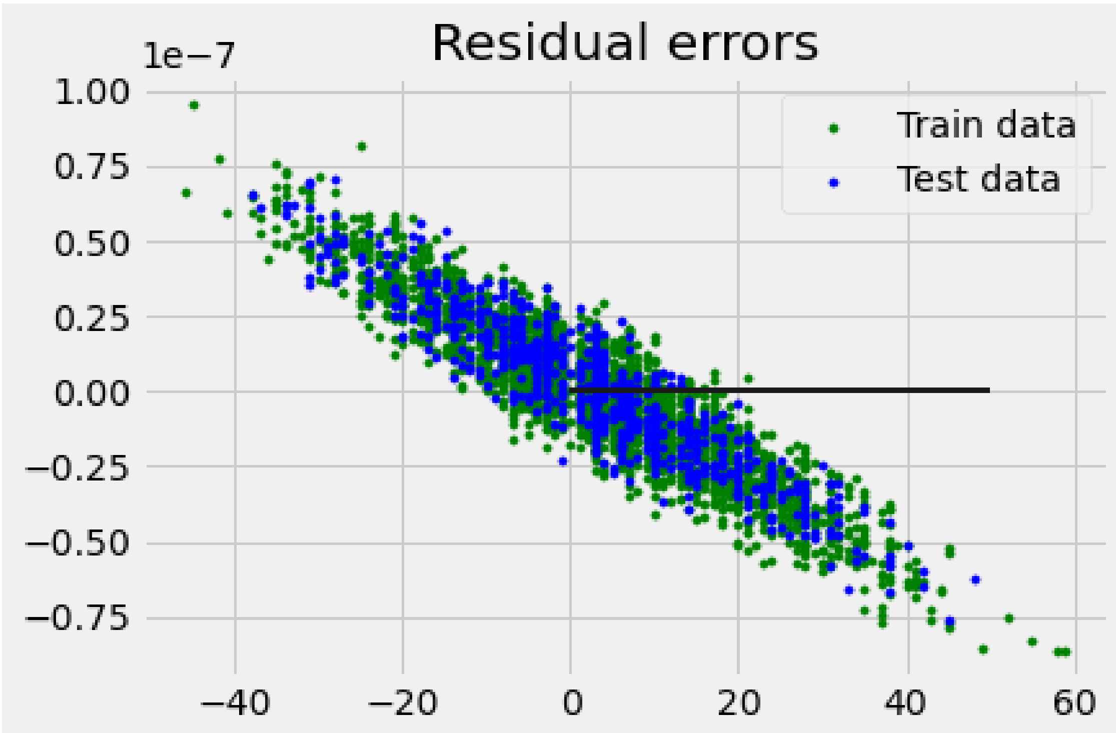
As found here: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

The score is the R^2 coefficent for this fit. A model is "good" when the R^2 value is close to 1. A score of exactly 1 means the model is overfit. It's not a good representation of the data.

The graph below showing the residual errors also proves this is not a good model.

[35]:
```
plt.style.use('fivethirtyeight')
plt.scatter(lr.predict(X_train), lr.predict(X_train) - y_train, color =␣
 ↪"green", s = 10, label = 'Train data')
plt.scatter(lr.predict(X_test), lr.predict(X_test) - y_test,
            color = "blue", s = 10, label = 'Test data')
## plotting line for zero residual error
plt.hlines(y = 0, xmin = 0, xmax = 50, linewidth = 2)
## plotting legend
plt.legend(loc = 'upper right')
```

```
## plot title
plt.title("Residual errors")
## function to show plot
plt.show()
```



It is overfit.

4.2 Random Forest

I tried again with Random Forest Regression. This time, instead of predicting the score difference, I predicted the scores of each team using the `scores` data set.

Here is where I got tips to do it https://towardsdatascience.com/random-forest-and-its-implementation-71824ced454f

[36]:
```
#X = teams_oh.drop(['score_diff'], axis=1)
X = teams_oh.drop(['date'], axis=1)
y = scores
```

[37]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=1)
```

[38]:
```
X_train
```

[38]:

```
        ARI  ATL  BAL  BUF  CAR  CHI  CIN  CLE  DAL  DEN  …  OAK  PHI  PIT  \
15729     0    0    0    0    0    0    0    0    0    0  …   -1    0    0
15712     0    0    0    0    0    0    0    0    1    0  …    0    0    0
14405     0    0    0    0    0    0    0    0   -1    0  …    0    0    0
13614     0    0    0    0    1    0    0    0    0    0  …    0   -1    0
15517     0    0    0    0    0    0    0    0    0    0  …    0    0    0
…     …   …   …   …   …   …   …   …   …   …   …   …   …   …   …
15683     0    0    0    0    0    0    1    0    0    0  …    0    0   -1
13768     0    0    0    0    0    0    0    0    0    0  …    0    0    0
13201     0    0    0    0    0    0    0    0    0    0  …    0    0    0
15510     0    0    0    0    0    0    0    0    0    0  …    0    0    0
13524     0    0    0    0    0    0    0    0    0    0  …    0    0    0

        SEA  SF  TB  TEN  WSH  score_diff    elo_diff
15729     0   0   0    0    0          13  -90.945651
15712     0   0   0    0    0          21   84.793225
14405     0   0   0    0    0          -7  125.441000
13614     0   0   0    0    0         -28  -74.013000
15517     0   0   0    0    0          21   66.198425
…     …  ..  ..  …   …          …           …
15683     0   0   0    0    0          -4  -86.545743
13768     0   0   0    0    0          29  247.249000
13201     0   0   0    0    0           2 -153.999000
15510     0   0   0    0   -1          -2   40.148062
13524     0   0   1    0    0           3   48.438000

[2990 rows x 34 columns]
```

Number of estimators is equal to the number of trees.

[39]:

```
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators = 10, random_state = 0)
regressor.fit(X, y)
```

[39]:

```
RandomForestRegressor(n_estimators=10, random_state=0)
```

[40]:

```
pred = regressor.predict(X_test)
```

[41]:

```
print(metrics.r2_score(y_test, pred))
```

```
0.9058527703721649
```

This model has an R^2 value closer to 1. The value is 0.82. I am getting closer!

[42]:

```
from sklearn.ensemble import RandomForestRegressor
regressor1 = RandomForestRegressor(n_estimators = 100, random_state = 0)
regressor1.fit(X, y)
pred1 = regressor1.predict(X_test)
```

```
print(metrics.r2_score(y_test, pred1))
```

0.928080229287205

It seems that more trees provide a better value for R^2.

[43]:
```
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators = 500, random_state = 0)
regressor.fit(X, y)
pred = regressor.predict(X_test)
print(metrics.r2_score(y_test, pred))
```

0.9310127291918824

I needed to do cross-validation to test if the model was a good fit.

I learned how to do cross validation here: https://jamesrledoux.com/code/k_fold_cross_validation

[44]:
```
from sklearn.model_selection import cross_validate
cv = cross_validate(regressor1, X_test, y_test, cv=5)
print(cv['test_score'])
print(cv['test_score'].mean())
```

```
[0.52270444 0.39376462 0.41070127 0.32560158 0.42161389]
0.414877160534797
```

So, I see that this is not a good model at all. Ideally, you would want teh values close to 0.99 to get an accurate fit of the data. Nevertheless, I proceeded with this choice to predict scores.

5 Predicting Scores

Now that I have the test data, I used the model to predict the scores between some teams.

I first turned the data into a dataframe.

[45]:
```
pred_scores = pd.DataFrame({'predscore_1': pred1[:, 0], 'predscore_2': pred1[:,␣
↪1]})
pred_scores
```

[45]:

	predscore_1	predscore_2
0	18.19	29.28
1	22.61	16.59
2	27.27	14.05
3	23.84	29.78
4	40.96	9.16
..	…	…
743	28.53	10.32
744	24.86	10.90
745	30.57	27.59
746	21.56	29.39

```
747        53.91         5.98

[748 rows x 2 columns]
```

[46]:
```
X_test['team1']=''
X_test['team2']=''
```

```
<ipython-input-46-aace447a7dd7>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_test['team1']=''
<ipython-input-46-aace447a7dd7>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_test['team2']=''
```

I readded which team is which.

[47]:
```
for col_name in X_test.columns:
    #X_test.loc[X_test[col_name]==1,'team1']= X_test['team1']+' '+col_name
    X_test.loc[X_test[col_name]==1,'team1']= col_name
    X_test.loc[X_test[col_name]==-1,'team2']= col_name

X_test = X_test.reset_index()
X_test = X_test.drop(columns='index')
X_test
```

```
/Users/annarosefritz/opt/anaconda3/lib/python3.8/site-
packages/pandas/core/indexing.py:966: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self.obj[item] = s
```

[47]:

	ARI	ATL	BAL	BUF	CAR	CHI	CIN	CLE	DAL	DEN	…	PIT	SEA	SF	TB	\
0	1	0	0	0	0	0	0	0	-1	0	…	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	…	0	0	0	0	
2	0	0	0	0	-1	0	0	0	0	0	…	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	…	1	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	…	0	0	0	0	

```
..   …   …   …   …   …   …   …   …   …   …   …   …   …  ..  ..
743   0   0   1   0   0   0   0  -1   0   0  …   0   0   0   0
744   0   0   0   0   0   0   0   0   0   0  …   0   1   0   0
745   0   0   0   0   0   0   0   0   0   0  …   0  -1   0   0
746   0   0   0   0   0   0  -1   0   0   0  …   0   0   0   0
747   0   0   0   0   0   0   0   0   0   0  …   0   0   0   0

     TEN  WSH  score_diff    elo_diff  team1  team2
0      0    0         -11  -31.646891    ARI    DAL
1      1    0           6   68.641000    TEN    JAX
2      0    0          13  -65.287000    NYG    CAR
3      0    0          -6  -49.732000    PIT     GB
4      0    0          32   63.115000    MIN    DET
..   …    …          …          …     …      …
743    0    0          18    9.831000    BAL    CLE
744    0    0          14  -76.314334    SEA    PHI
745    0    0           3 -200.607000    LAR    SEA
746    1    0          -8 -108.414000    TEN    CIN
747   -1    0          48  237.609000     GB    TEN

[748 rows x 36 columns]
```

[48]:
```python
df_pred_scores = X_test[['team1','team2']]
df_pred_scores = pd.merge(df_pred_scores, pred_scores, on=df_pred_scores.index)
df_pred_scores['home_away'] = list(zip(df_pred_scores['team1'], df_pred_scores['team2']))
df_pred_scores
```

[48]:
```
     key_0 team1 team2  predscore_1  predscore_2   home_away
0        0   ARI   DAL        18.19        29.28  (ARI, DAL)
1        1   TEN   JAX        22.61        16.59  (TEN, JAX)
2        2   NYG   CAR        27.27        14.05  (NYG, CAR)
3        3   PIT    GB        23.84        29.78   (PIT, GB)
4        4   MIN   DET        40.96         9.16  (MIN, DET)
..     …   …   …          …          …         …
743    743   BAL   CLE        28.53        10.32  (BAL, CLE)
744    744   SEA   PHI        24.86        10.90  (SEA, PHI)
745    745   LAR   SEA        30.57        27.59  (LAR, SEA)
746    746   TEN   CIN        21.56        29.39  (TEN, CIN)
747    747    GB   TEN        53.91         5.98   (GB, TEN)

[748 rows x 6 columns]
```

[49]:
```python
def predict (team1_in, team2_in):

    df = df_pred_scores[(df_pred_scores['team1'] == team1_in) & (df_pred_scores['team2'] == team2_in)]
```

```
    print(team1_in, "score is predicted to be:", df[['predscore_1']])
    print(team2_in, "score is predicted to be:", df[['predscore_2']])
```

[50]:
```
predict('PIT', 'KC')
```

```
PIT score is predicted to be:      predscore_1
351        40.83
KC score is predicted to be:      predscore_2
351        11.84
```

Here it gives you the predicted score of the game.