Coaches

July 23, 2020

1 Intro

Scenario: We were tasked with coming up with the salary of the next Syracuse Football coach. To do so, we were given a list of Schools and their Coache's salary. While this could be enough information to do a simple analysis, we will find more online resources to add information to our prediction. This includes finding the stadium sizes, the school's record, and the graduation rate.

2 Imports

```
In [ ]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        import statsmodels.api as sm  # statistical models (including regression)
        import statsmodels.formula.api as smf   # R-like model specification
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas
  import pandas.util.testing as tm
```

3 Path

```
In [ ]: pwd
```

```
Out[ ]: '/content'
```

```
In [ ]: path = '' # Do not need a path for Colab
```

4 Read Data

The file Coaches9.csv was provided for us. There is a limited amount of information in this file. The prediction column is 'TotalPay' while the other columns are not very helpful since they cant be used to predict the salary since they are part of the salary. On the other hand, the Conference column will be helpful to classify and visualize the data.

```
In [ ]: df = pd.read_csv(path + 'Coaches9.csv')
```

In [ ]: df.head()

```
Out[ ]:                     School Conference  ... AssistantPay        Buyout
        0                Air Force   Mt. West  ...           $0            --
        1                    Akron        MAC  ...           $0      $688,500
        2                  Alabama        SEC  ...           $0   $33,600,000
        3  Alabama at Birmingham      C-USA  ...           $0    $3,847,500
        4        Appalachian State   Sun Belt  ...           $0    $2,160,417

        [5 rows x 9 columns]
```

5 Convert Money to Float

In [ ]: df.describe()

```
Out[ ]:                School Conference           Coach  ... BonusPaid AssistantPay Buyout
        count             129        129             129  ...       129          129    129
        unique            129         11             129  ...        51            1    102
        top      Old Dominion      C-USA  Charlie Strong  ...        --           $0     --
        freq                1         14               1  ...        41          129     22

        [4 rows x 9 columns]
```

```
In [ ]: from re import sub
        from decimal import Decimal
        moneyCols = ['SchoolPay', 'TotalPay', 'Bonus', 'BonusPaid', 'AssistantPay', 'Buyout']
        for col in moneyCols:
            df[col] = [float(Decimal(sub(r'[^\d.]', '', val))) if val != '--' else np.nan for v
```

In [ ]: df[moneyCols].head()

```
Out[ ]:    SchoolPay   TotalPay      Bonus  BonusPaid  AssistantPay      Buyout
        0   885000.0   885000.0   247000.0        NaN           0.0         NaN
        1   411000.0   412500.0   225000.0    50000.0           0.0    688500.0
        2  8307000.0  8307000.0  1100000.0   500000.0           0.0  33600000.0
        3   900000.0   900000.0   950000.0   165471.0           0.0   3847500.0
        4   712500.0   712500.0   295000.0   145000.0           0.0   2160417.0
```

In [ ]: df[moneyCols].describe()

```
Out[ ]:           SchoolPay      TotalPay  ...  AssistantPay        Buyout
        count  1.250000e+02  1.250000e+02  ...         129.0  1.070000e+02
        mean   2.410301e+06  2.417061e+06  ...           0.0  8.119107e+06
        std    1.881377e+06  1.885752e+06  ...           0.0  1.046135e+07
        min    3.900000e+05  3.900000e+05  ...           0.0  0.000000e+00
        25%    8.015040e+05  8.058500e+05  ...           0.0  1.200000e+06
        50%    1.831580e+06  1.900008e+06  ...           0.0  4.000000e+06
        75%    3.605000e+06  3.617500e+06  ...           0.0  1.106500e+07
        max    8.307000e+06  8.307000e+06  ...           0.0  6.812500e+07

        [8 rows x 6 columns]
```

5.1 Drop Unimportant Columns and Rows

```
In [ ]: df = df.drop(['AssistantPay'], axis=1) # Always empty
```

```
In [ ]: moneyCols = ['SchoolPay', 'TotalPay', 'Bonus', 'BonusPaid', 'Buyout']
        df.loc[(df[moneyCols].isnull()).all(axis=1)] # Find Rows with all empty values
```

```
Out[ ]:                 School Conference          Coach  ...  Bonus  BonusPaid  Buyout
        12              Baylor     Big 12     Matt Rhule  ...    NaN        NaN     NaN
        16       Brigham Young       Ind.  Kalani Sitake  ...    NaN        NaN     NaN
        91                Rice      C-USA Mike Bloomgren  ...    NaN        NaN     NaN
        99  Southern Methodist        AAC    Sonny Dykes  ...    NaN        NaN     NaN

        [4 rows x 8 columns]
```

```
In [ ]: df = df.loc[~(df[moneyCols].isnull()).all(axis=1)].reset_index(drop=True) # Drop empty
```

```
In [ ]: df.head()
```

```
Out[ ]:                   School Conference  ... BonusPaid      Buyout
        0              Air Force   Mt. West  ...       NaN         NaN
        1                  Akron        MAC  ...   50000.0    688500.0
        2                Alabama        SEC  ...  500000.0  33600000.0
        3  Alabama at Birmingham      C-USA  ...  165471.0   3847500.0
        4      Appalachian State   Sun Belt  ...  145000.0   2160417.0

        [5 rows x 8 columns]
```

6 Merge Other Datasets

6.0.1 Mapping Other School Data to Coaches csv

The simName.csv file contains a mapping file for the school names to match the graduation rate to the school name.

```
In [ ]: simnames = pd.read_csv(path + 'simName.csv')
```

```
In [ ]: simnames.head()
```

```
Out[ ]:               SchoolName                              FullName
        0              Air Force      United States Air Force Academy
        1                  Akron      University of Akron Main Campus
        2                Alabama            The University of Alabama
        3  Alabama at Birmingham University of Alabama at Birmingham
        4      Appalachian State         Appalachian State University
```

```
In [ ]: df = df.merge(simnames, left_on='School', right_on='SchoolName', how='left')
```

```
In [ ]: df.head()
```

```
Out[ ]:                  School  ...                              FullName
        0             Air Force  ...       United States Air Force Academy
        1                 Akron  ...       University of Akron Main Campus
        2               Alabama  ...             The University of Alabama
        3  Alabama at Birmingham  ...  University of Alabama at Birmingham
        4      Appalachian State  ...          Appalachian State University

        [5 rows x 10 columns]
```

6.1 Merge GSR and FEDRATE

The file was gotten from 'https://www.icpsr.umich.edu/icpsrweb/NCAA/studies/30022/datadocumentation'. It contains the GSR and FED information for a couple of years, but we will only be using the 2006 data for simplicity.

```
In [ ]: odf = pd.read_csv(path + 'OtherSchoolData.csv')
```

6.1.1 Get Relevant Columns Only

```
In [ ]: # We need to find the most relevant columns. In order to do so, we take the latest yea
        goodCols = ['DATATAB_SCHOOL_INFO', 'SCL_UNITID', 'SCL_NAME', 'SCL_DIVISION',
               'SCL_SUBDIVISION', 'SCL_CONFERENCE', 'DIV1_FB_CONFERENCE',
               'SCL_HBCU', 'SCL_PRIVATE', 'DATATAB_4YR_OVERALL_FED_SA',
               'FED_N_SA', 'FED_RATE_SA', 'DATATAB_4YR_OVERALL_GSR_SA',
               'GSR_N_SA', 'GSR_SA', 'DATATAB_4YR_GENDER_FED_SA', 'FED_N_MALE_SA',
               'FED_RATE_MALE_SA', 'FED_N_FEMALE_SA', 'FED_RATE_FEMALE_SA',
               'DATATAB_4YR_GENDER_GSR_SA', 'GSR_N_MALE_SA', 'GSR_MALE_SA',
               'GSR_N_FEMALE_SA', 'GSR_FEMALE_SA', 'DATATAB_4YR_RACE_FED_SA',
               'FED_RATE_AA_SA', 'FED_RATE_OTHER_SA', 'FED_RATE_WH_SA',
               'DATATAB_4YR_RACE_GSR_SA', 'GSR_AA_SA', 'GSR_OTHER_SA',
               'GSR_WH_SA', 'DATATAB_4YR_GENDERRACE_FED_SA',
               'FED_RATE_MALE_AA_SA', 'FED_RATE_MALE_OTHER_SA',
               'FED_RATE_MALE_WH_SA', 'FED_RATE_FEMALE_AA_SA',
               'FED_RATE_FEMALE_OTHER_SA', 'FED_RATE_FEMALE_WH_SA',
               'DATATAB_4YR_GENDERRACE_GSR_SA', 'GSR_MALE_AA_SA',
               'GSR_MALE_OTHER_SA', 'GSR_MALE_WH_SA', 'GSR_FEMALE_AA_SA',
               'GSR_FEMALE_OTHER_SA', 'GSR_FEMALE_WH_SA',
               'DATATAB_SINGLEYR_OVERALL_FED_SA']

        for col in odf.columns.values:
            if (col in goodCols):
                continue
            elif '2006' in col:
                goodCols.append(col)
        odf = odf[goodCols]
```

```
In [ ]: print(len(odf.columns.values))
```

```
59
```

6.1.2 Merge Files Together

```
In [ ]: df = df.merge(odf, how='left', left_on='FullName', right_on='SCL_NAME')
```

```
In [ ]: # Make Sure all Rows were merged correctly
        df.loc[(df[goodCols].isnull()).all(axis=1)]
```

```
Out[ ]: Empty DataFrame
        Columns: [School, Conference, Coach, SchoolPay, TotalPay, Bonus, BonusPaid, Buyout, Scl
        Index: []
```

```
In [ ]: df.columns
```

```
Out[ ]: Index(['School', 'Conference', 'Coach', 'SchoolPay', 'TotalPay', 'Bonus',
               'BonusPaid', 'Buyout', 'SchoolName', 'FullName', 'DATATAB_SCHOOL_INFO',
               'SCL_UNITID', 'SCL_NAME', 'SCL_DIVISION', 'SCL_SUBDIVISION',
               'SCL_CONFERENCE', 'DIV1_FB_CONFERENCE', 'SCL_HBCU', 'SCL_PRIVATE',
               'DATATAB_4YR_OVERALL_FED_SA', 'FED_N_SA', 'FED_RATE_SA',
               'DATATAB_4YR_OVERALL_GSR_SA', 'GSR_N_SA', 'GSR_SA',
               'DATATAB_4YR_GENDER_FED_SA', 'FED_N_MALE_SA', 'FED_RATE_MALE_SA',
               'FED_N_FEMALE_SA', 'FED_RATE_FEMALE_SA', 'DATATAB_4YR_GENDER_GSR_SA',
               'GSR_N_MALE_SA', 'GSR_MALE_SA', 'GSR_N_FEMALE_SA', 'GSR_FEMALE_SA',
               'DATATAB_4YR_RACE_FED_SA', 'FED_RATE_AA_SA', 'FED_RATE_OTHER_SA',
               'FED_RATE_WH_SA', 'DATATAB_4YR_RACE_GSR_SA', 'GSR_AA_SA',
               'GSR_OTHER_SA', 'GSR_WH_SA', 'DATATAB_4YR_GENDERRACE_FED_SA',
               'FED_RATE_MALE_AA_SA', 'FED_RATE_MALE_OTHER_SA', 'FED_RATE_MALE_WH_SA',
               'FED_RATE_FEMALE_AA_SA', 'FED_RATE_FEMALE_OTHER_SA',
               'FED_RATE_FEMALE_WH_SA', 'DATATAB_4YR_GENDERRACE_GSR_SA',
               'GSR_MALE_AA_SA', 'GSR_MALE_OTHER_SA', 'GSR_MALE_WH_SA',
               'GSR_FEMALE_AA_SA', 'GSR_FEMALE_OTHER_SA', 'GSR_FEMALE_WH_SA',
               'DATATAB_SINGLEYR_OVERALL_FED_SA', 'FED_N_2006_SA', 'FED_RATE_2006_SA',
               'GSR_N_2006_SA', 'GSR_2006_SA', 'FED_RATE_MALE_2006_SA',
               'FED_RATE_FEMALE_2006_SA', 'GSR_MALE_2006_SA', 'GSR_FEMALE_2006_SA',
               'FED_RATE_2006_SB', 'FED_RATE_MALE_2006_SB', 'FED_RATE_FEMALE_2006_SB'],
              dtype='object')
```

```
In [ ]: # Should Only Keep Columns from 2006 (According to Lab Description)
        goodCols = ['School', 'Conference', 'Coach', 'SchoolPay', 'TotalPay', 'Bonus',
               'BonusPaid', 'Buyout', 'FullName', 'SCL_HBCU', 'SCL_PRIVATE',
               'FED_N_2006_SA', 'FED_RATE_2006_SA',
               'GSR_N_2006_SA', 'GSR_2006_SA', 'FED_RATE_MALE_2006_SA',
               'FED_RATE_FEMALE_2006_SA', 'GSR_MALE_2006_SA', 'GSR_FEMALE_2006_SA',
               'FED_RATE_2006_SB', 'FED_RATE_MALE_2006_SB', 'FED_RATE_FEMALE_2006_SB']
        df = df[goodCols]
```

```
In [ ]: df.head()
```

```
Out[ ]:                     School  ... FED_RATE_FEMALE_2006_SB
        0                Air Force  ...                      77
```

```
1                   Akron  ...                      45
2                 Alabama  ...                      69
3  Alabama at Birmingham   ...                      49
4       Appalachian State  ...                      71

[5 rows x 22 columns]
```

6.2 Merge Stadium Size Dataset

The stadium size dataset was gotten from a github repository: 'https://github.com/gboeing/data-visualization/blob/master/ncaa-football-stadiums/data/stadiums-geocoded.csv'. It contains the geolocation as well as the date of remodeling for each stadium.

```
In [ ]: dd = pd.read_csv(path + 'stadiums.csv')

In [ ]: df = df.merge(dd, left_on=['School'],right_on=['team'], how='left')

In [ ]: df.loc[df['capacity'].isnull()]['School']

Out[ ]: 3    Alabama at Birmingham
        Name: School, dtype: object

In [ ]: df.head()

Out[ ]:                   School Conference  ...   latitude   longitude
        0             Air Force   Mt. West  ...  38.996907 -104.843688
        1                 Akron        MAC  ...  41.072570  -81.508384
        2               Alabama        SEC  ...  33.207490  -87.550392
        3  Alabama at Birmingham      C-USA  ...        NaN         NaN
        4       Appalachian State   Sun Belt  ...  36.211515  -81.685506

        [5 rows x 34 columns]

In [ ]: dd.columns

Out[ ]: Index(['Unnamed: 0', 'stadium', 'city', 'state', 'team', 'conference',
               'capacity', 'built', 'expanded', 'div', 'latitude', 'longitude'],
              dtype='object')
```

6.3 Merge School Record

The final sets of columns we are going to use includes the Schools' football record. This information was gotten from the sportref website. The file also contains the number of Offensive Points, Defensive Points, Games won, Games lost, and Ranking.

```
In [ ]: de = pd.read_csv(path + 'sportsref_download.csv')

In [ ]: df = df.merge(de, how='left', on='School')

In [ ]: de.columns

Out[ ]: Index(['Rk', 'School', 'W', 'L', 'Pct', 'Off Pts', 'Def Pts'], dtype='object')
```

6.4 Get Rid of Empty Rows

```
In [ ]: df.columns.values
```

```
Out[ ]: array(['School', 'Conference', 'Coach', 'SchoolPay', 'TotalPay', 'Bonus',
               'BonusPaid', 'Buyout', 'FullName', 'SCL_HBCU', 'SCL_PRIVATE',
               'FED_N_2006_SA', 'FED_RATE_2006_SA', 'GSR_N_2006_SA',
               'GSR_2006_SA', 'FED_RATE_MALE_2006_SA', 'FED_RATE_FEMALE_2006_SA',
               'GSR_MALE_2006_SA', 'GSR_FEMALE_2006_SA', 'FED_RATE_2006_SB',
               'FED_RATE_MALE_2006_SB', 'FED_RATE_FEMALE_2006_SB', 'Unnamed: 0',
               'stadium', 'city', 'state', 'team', 'conference', 'capacity',
               'built', 'expanded', 'div', 'latitude', 'longitude', 'Rk', 'W',
               'L', 'Pct', 'Off Pts', 'Def Pts'], dtype=object)
```

```
In [ ]: newCols = ['School', 'Conference', 'Coach', 'SchoolPay', 'TotalPay', 'Bonus',
               'BonusPaid', 'Buyout', 'FullName', 'SCL_HBCU', 'SCL_PRIVATE',
               'FED_N_2006_SA', 'FED_RATE_2006_SA', 'GSR_N_2006_SA', 'GSR_2006_SA',
               'FED_RATE_MALE_2006_SA', 'FED_RATE_FEMALE_2006_SA', 'GSR_MALE_2006_SA',
               'GSR_FEMALE_2006_SA', 'FED_RATE_2006_SB', 'FED_RATE_MALE_2006_SB',
               'FED_RATE_FEMALE_2006_SB', 'Rk', 'W', 'L', 'Pct', 'Off Pts',
               'Def Pts', 'stadium', 'city', 'state', 'capacity', 'latitude', 'longitude']
```

```
In [ ]: df = df[newCols]
```

```
In [ ]: df = df.loc[~(df['W'].isnull())].reset_index(drop=True) # Find Rows with all empty val
```

```
In [ ]: df = df.loc[~(df['stadium'].isnull())].reset_index(drop=True)
```

```
In [ ]: len(df)
```

```
Out[ ]: 122
```

We are left with 122 rows after getting rid of Teams that did not have corresponding information in the datafiles that we got from the internet.

7 Create Relevant Columns

```
In [ ]: df.columns
```

```
Out[ ]: Index(['School', 'Conference', 'Coach', 'SchoolPay', 'TotalPay', 'Bonus',
               'BonusPaid', 'Buyout', 'FullName', 'SCL_HBCU', 'SCL_PRIVATE',
               'FED_N_2006_SA', 'FED_RATE_2006_SA', 'GSR_N_2006_SA', 'GSR_2006_SA',
               'FED_RATE_MALE_2006_SA', 'FED_RATE_FEMALE_2006_SA', 'GSR_MALE_2006_SA',
               'GSR_FEMALE_2006_SA', 'FED_RATE_2006_SB', 'FED_RATE_MALE_2006_SB',
               'FED_RATE_FEMALE_2006_SB', 'Rk', 'W', 'L', 'Pct', 'Off Pts', 'Def Pts',
               'stadium', 'city', 'state', 'capacity', 'latitude', 'longitude'],
              dtype='object')
```

```
In [ ]: df['Rk'].values
```

Out[ ]:
```
array([ 84.,  76., 115., 121., 106., 103., 120., 127.,  69., 116.,  79.,
        83.,   4.,  75.,  72.,  96.,  16.,  77.,  54.,  15.,   1., 125.,
       105.,  87.,  20.,  13.,  19.,  82., 107.,  51.,  55.,   5.,  93.,
       108., 122., 123.,  14.,  90.,  25.,  47.,  40.,  46.,  32.,  36.,
        29.,  73., 110.,  65.,  58., 128.,   2., 114.,  52.,  42.,  67.,
        21.,   8.,  71.,  39.,  41.,  56.,  44., 118., 111.,  22.,  48.,
        91.,  94.,  88.,  66.,  12.,   7.,  61.,  80.,  50.,  70.,  74.,
        37.,  27.,  30.,  57.,  95.,  98.,  38.,  11.,  49.,  43.,  89.,
        92., 130., 112.,  18., 102.,  60., 100.,   6., 109.,  31., 117.,
        33., 129.,  35.,  64.,  62.,  81., 124.,  24.,  26., 104., 101.,
        85., 113.,   9.,  10.,   3.,  97.,  99.,  34.,  53.,  78.,  45.,
        86.])
```

In [ ]:
```
df['GSR_SA'] = df['GSR_2006_SA'] # We mostly case about student athletes. SB might not
df['FGR_SA'] = df['FED_RATE_2006_SA'] # We mostly case about student athletes. SB migh
df['WinPerc'] = df['Pct']*100 # Convert to percentage
df['HistBlack'] = [0 if x == 2 else x for x in df['SCL_HBCU'].values]
df['PublicOrPrivate'] = df['SCL_PRIVATE']
df['TotalPoints'] = df['Off Pts'] + df['Def Pts'] # Total Number of Points
df['Top25'] = [1 if x <= 25 else 0 for x in df['Rk'].astype(int).values] # This column
```

7.1 Drop Unecessary Columns

In [ ]:
```
df = df.drop(['SCL_HBCU', 'SCL_PRIVATE', 'FED_N_2006_SA', 'FED_RATE_2006_SA', 'GSR_N_20
       'FED_RATE_MALE_2006_SA', 'FED_RATE_FEMALE_2006_SA', 'GSR_MALE_2006_SA',
       'GSR_FEMALE_2006_SA', 'FED_RATE_2006_SB', 'FED_RATE_MALE_2006_SB',
       'FED_RATE_FEMALE_2006_SB', 'stadium', 'city', 'state', 'latitude', 'longitude',
       'BonusPaid', 'Buyout', 'Pct'], axis=1)
```

8 Analyze

Set Y Parameter

In [ ]:
```
# Define Y Parameter (The variable we are trying to predict)
yParm = 'TotalPay'
yPamrmL = ['TotalPay']
```

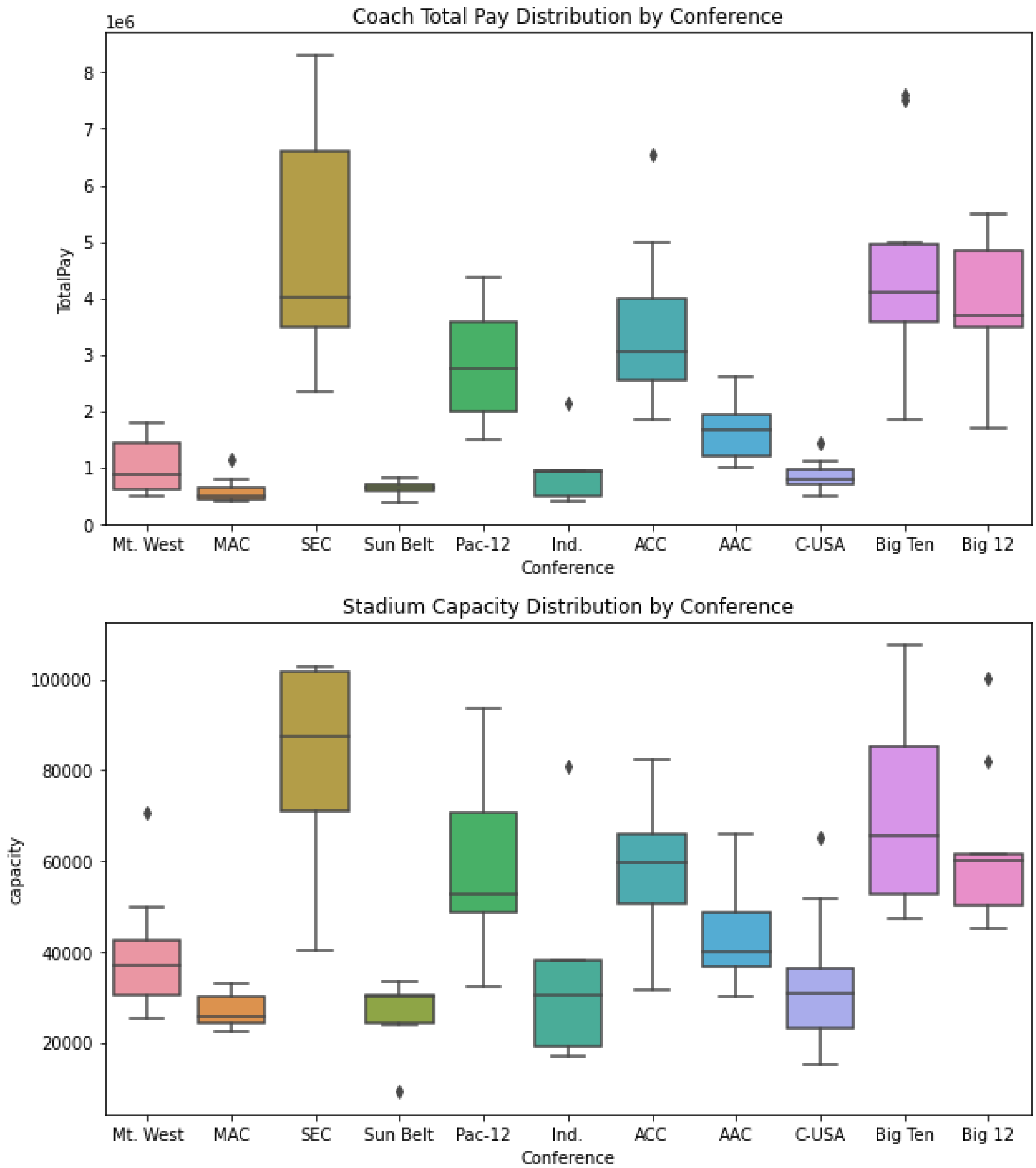
8.1 Check Big Schools vs Small School Pay

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['School', 'Conference', 'Coach', 'TotalPay', 'FullName', 'Rk', 'W', 'L',
       'Off Pts', 'Def Pts', 'capacity', 'GSR_SA', 'FGR_SA', 'WinPerc',
       'HistBlack', 'PublicOrPrivate', 'TotalPoints', 'Top25'],
      dtype='object')
```

In [ ]:
```
plt.figure(figsize=(10,12))
plt.subplot(2,1,1)
sns.boxplot(x='Conference', y=yParm, data=df)
```

```
plt.title('Coach Total Pay Distribution by Conference')

plt.subplot(2,1,2)
sns.boxplot(x='Conference', y='capacity', data=df)
plt.title('Stadium Capacity Distribution by Conference')
plt.show()
```

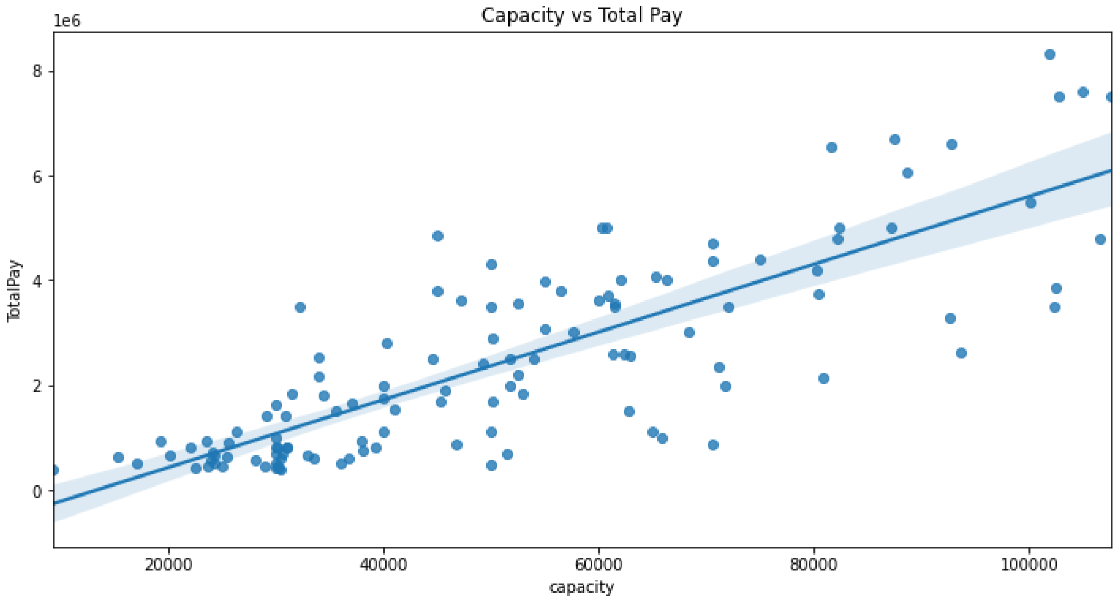


Syracuse Belongs in the ACC, but if we look closely, there are only a few of conferences where their schools Total Paid to their coaches resembles the ACC's total distribution. Now, even if the Small Pay Conferences are not comparable to the AAC, we will still include them since they might have other information that might benefit the prediction. Another observation is that the stadium capacity seems to closely resemble the total pay, so it will be a strong factor to use in our model.

8.1.1 Plot Capacity against Total Pay

In [ ]:
```
plt.figure(figsize=(12,6))
sns.regplot(x='capacity', y=yParm, data=df)
plt.title('Capacity vs Total Pay')
```

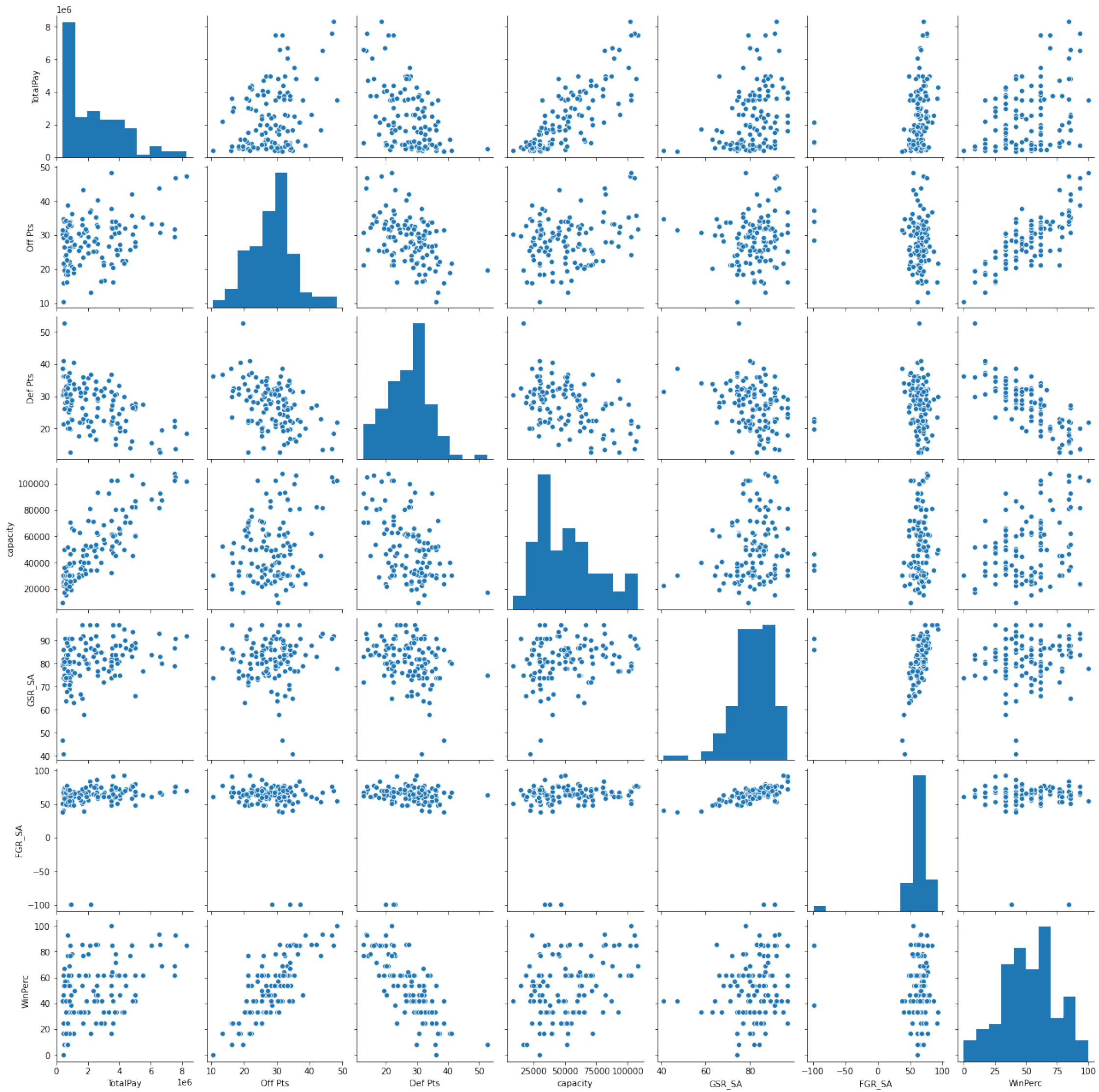
Out[ ]:
```
Text(0.5, 1.0, 'Capacity vs Total Pay')
```



8.2 Check for Correlations

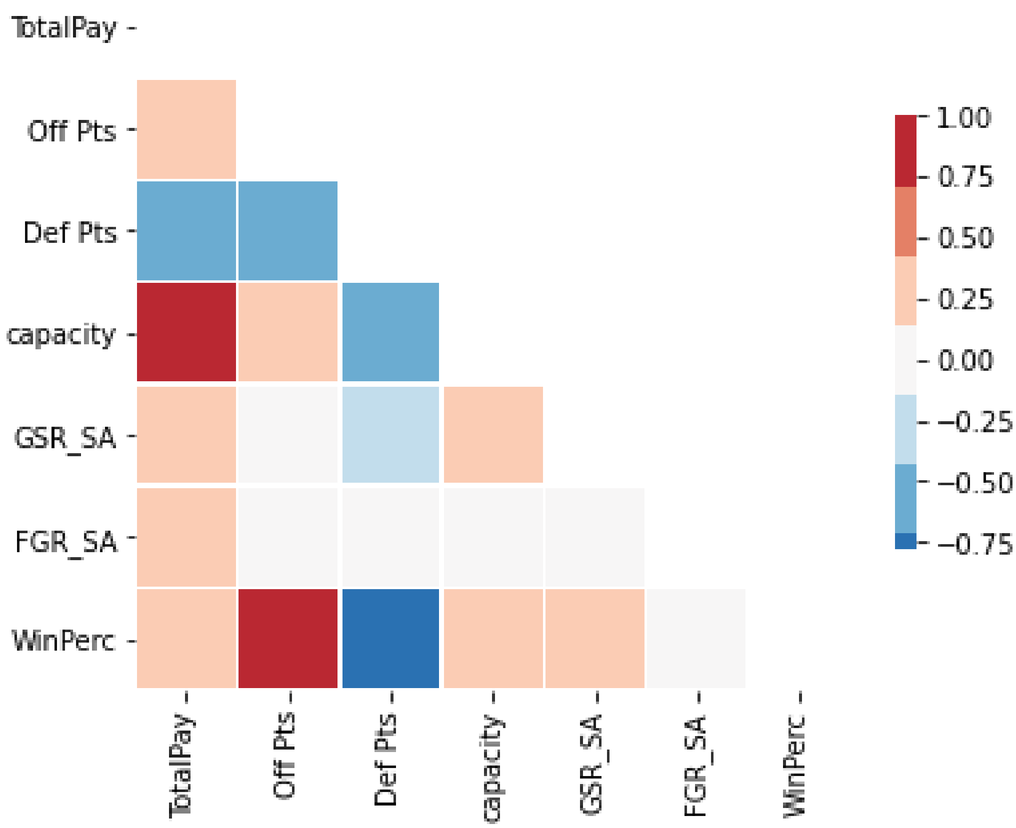
In [ ]:
```
plt.figure(figsize=(12,12))
numCols = ['TotalPay', 'Off Pts', 'Def Pts', 'capacity', 'GSR_SA', 'FGR_SA', 'WinPerc']
sns.pairplot(df[numCols])
plt.show()
```

```
<Figure size 864x864 with 0 Axes>
```




```
In [ ]: plt.figure(figsize=(6,6))
        numCols = ['TotalPay', 'Off Pts', 'Def Pts', 'capacity', 'GSR_SA', 'FGR_SA', 'WinPerc']

        corr = df[numCols].corr()

        # Generate a mask for the upper triangle
        mask = np.zeros_like(corr, dtype=np.bool)
        mask[np.triu_indices_from(mask)] = True

        # Set up the matplotlib figure
        #f, ax = plt.subplots(figsize=(11, 9))

        # Generate a custom diverging colormap
```

```
cmap = sns.color_palette("RdBu_r", 7)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.show()
```



Offensive Points has a strong positive correlation with Winning Percentage. Also, the Winning Percentage has a semi-strong positive correlation with Total Pay. On the other hand, FGR_SA (Federal Graduation Rate) seems to have no interesting distribution which can mean that there is no value of using it in the model. I will be excluding it from now on.

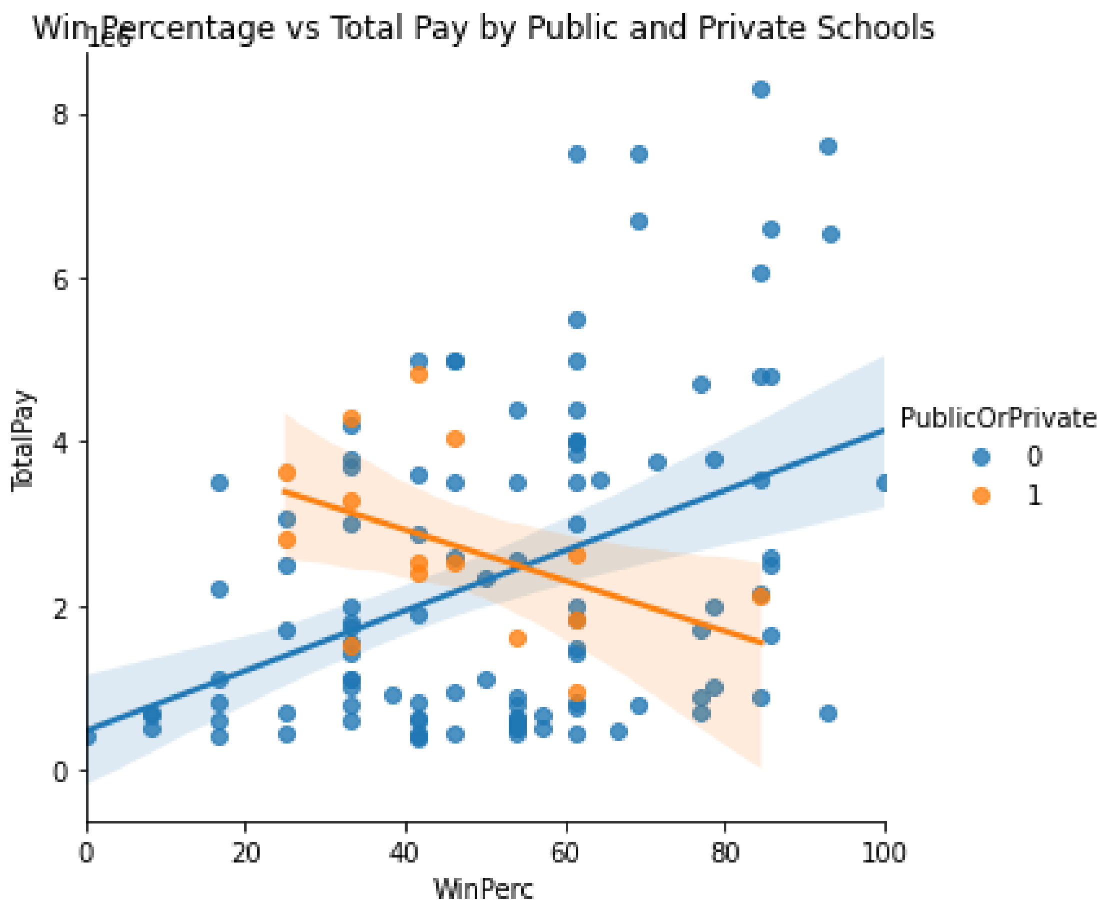
```
In [ ]: df = df.drop(['FGR_SA'], axis=1) # Exclude Federal Graduation Rate for Student Athlete
```

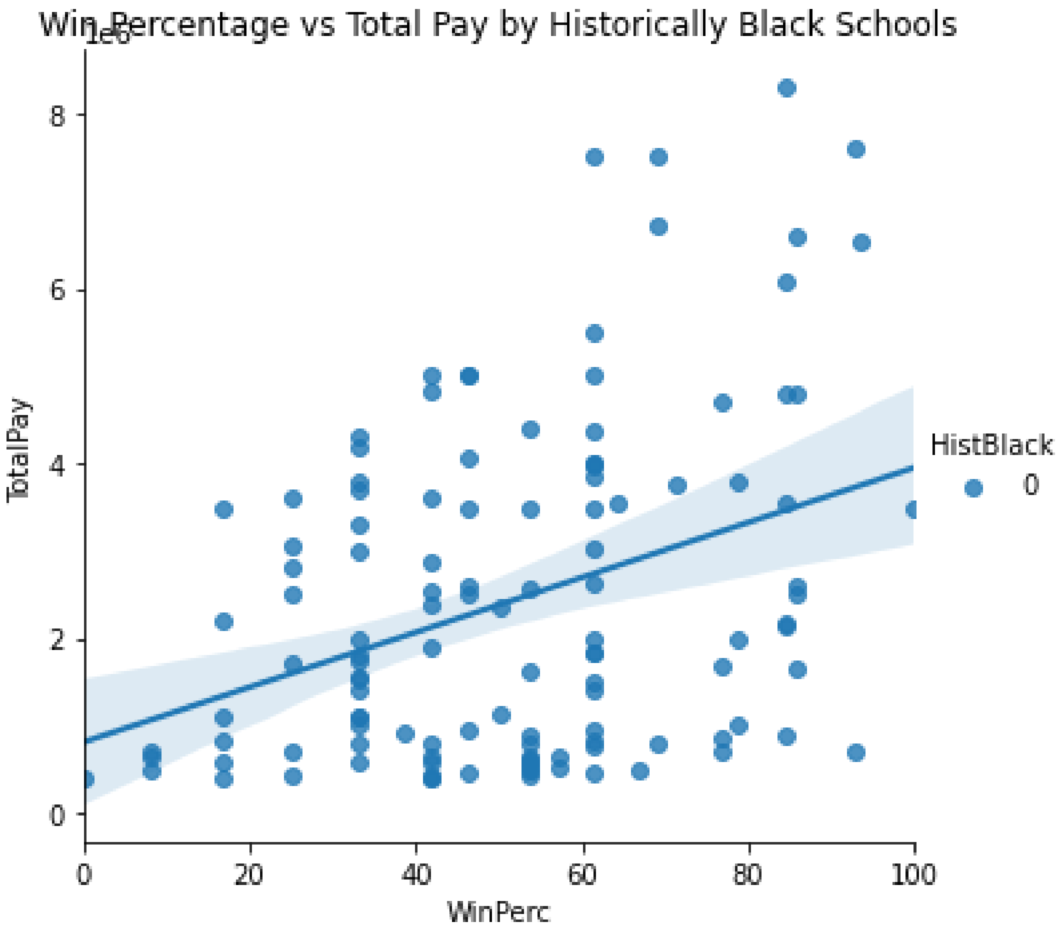
8.2.1 Check for Differences in Total Pay with Private vs Public Schools, Black vs Non-Black, and Top25 vs Not Top25

```
In [ ]: fig = plt.figure(figsize=(18,6))
        # plt.subplot(3,1,1)
        sns.lmplot(x='WinPerc', hue='PublicOrPrivate', y=yParm, data=df)
        fig.show()
```

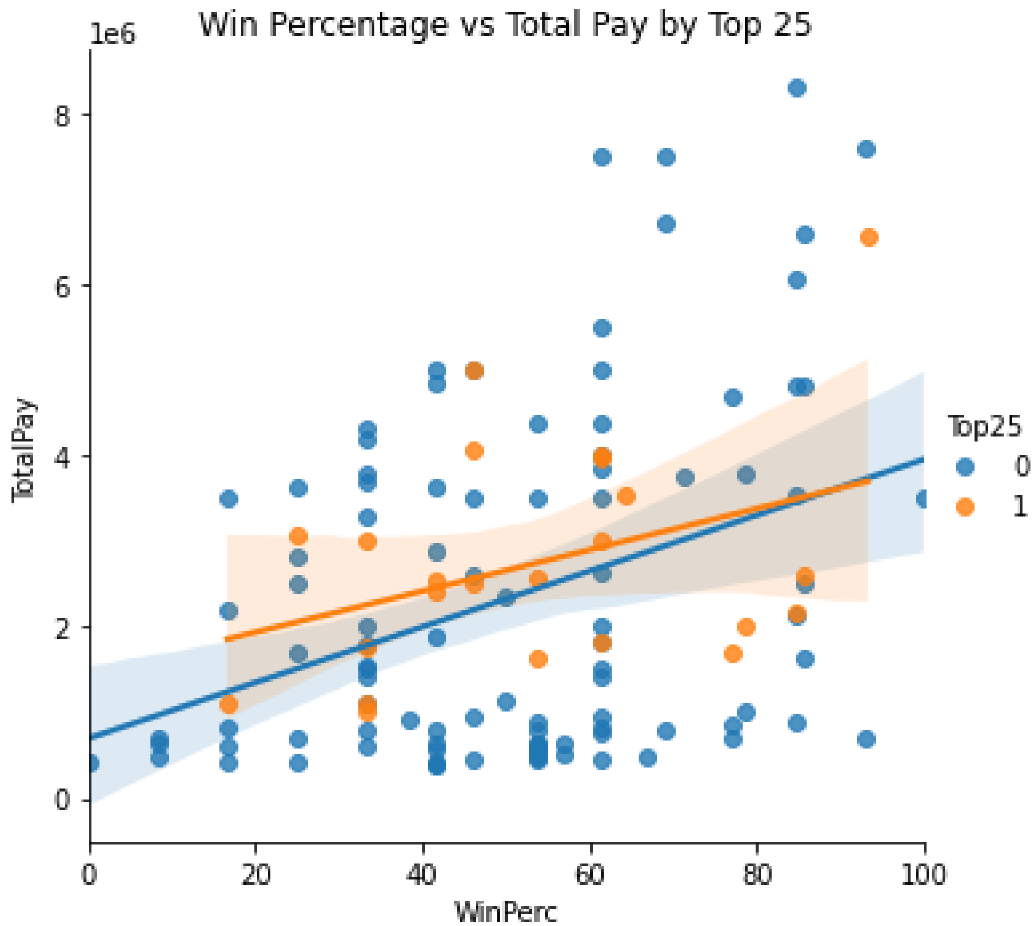
```python
plt.title('Win Percentage vs Total Pay by Public and Private Schools')
fig.show()
# plt.subplot(3,1,2)
sns.lmplot(x='WinPerc', hue='HistBlack', y=yParm, data=df)
plt.title('Win Percentage vs Total Pay by Historically Black Schools')
fig.show()
# plt.subplot(3,1,3)
sns.lmplot(x='WinPerc', hue='Top25', y=yParm, data=df)
plt.title('Win Percentage vs Total Pay by Top 25')
fig.show()
```

```
<Figure size 1296x432 with 0 Axes>
```





Win Percentage vs Total Pay by Historically Black Schools
1e6
TotalPay
WinPerc
HistBlack
0



No definitive pattern in the above graph except that the higher the win percentage at a Public School, the higher the pay is for the coach. On the other hand, there is only Non-Historically black schools in the dataset, so we will drop the column from the analysis. No clear patter in Top25 schools either. We will keep the information for now, but will monitor the importance of the column in the model.

```
In [ ]: df = df.drop(['HistBlack'], axis=1)
```

9 Create Models

```
In [ ]: df.head()
```

```
Out[ ]:              School Conference  ... TotalPoints  Top25
        0         Air Force   Mt. West  ...        53.9      0
        1             Akron        MAC  ...        46.8      0
        2           Alabama        SEC  ...        65.8      0
        3  Appalachian State   Sun Belt  ...        58.8      0
        4           Arizona     Pac-12  ...        62.7      0
```

```
[5 rows x 16 columns]
```

10 Need to Convert Categorical Columns to Binary Columns by Values

```
In [ ]: conferencesL = df['Conference'].unique()
        for conf in conferencesL:
            print(conf)
            df[conf] = [1 if conf == x else 0 for x in df['Conference'].values]
```

```
Mt. West
MAC
SEC
Sun Belt
Pac-12
Ind.
ACC
AAC
C-USA
Big Ten
Big 12
```

10.1 Separate Into Train and Test Set

The Train and Test set need to be representative of the dataset, so I will be picking one team from each conference for the testing set in order to keep it constant. I will also exclude Syrcause from the training set to make sure I dont train on the value we are trying to predict.

```
In [ ]: # Take out Syracuse from dataset. Leave out for testing
        syr = df.loc[df['School'] == 'Syracuse'].reset_index(drop=True)
        df = df.loc[df['School'] != 'Syracuse'].reset_index(drop=True)
```

```
In [ ]: # Pick a Random Value from each Conference
        size = 1         # sample size
        replace = True   # with replacement
        fn = lambda obj: obj.loc[np.random.choice(obj.index, size, replace),:]
        test = df.groupby('Conference', as_index=False).apply(fn).reset_index(drop=True)
        train = df.loc[~(df['School'].isin(test['School'].values))].reset_index(drop=True)
```

```
In [ ]: print('df len: ', len(df))
        print('df train: ', len(train))
        print('df test: ', len(test))
```

```
df len:  121
df train:  110
df test:  11
```

10.2 Picking X Parameters for Model

10.2.1 We can now select the X Parameters

Ranking, W and L are not relevant since we have the Win Percentage which is a better computational parameter. We can also drop the Conference column since we convereted it into binary columns for each conference used.

```
In [ ]: df.columns

Out[ ]: Index(['School', 'Conference', 'Coach', 'TotalPay', 'FullName', 'Rk', 'W', 'L',
               'Off Pts', 'Def Pts', 'capacity', 'GSR_SA', 'WinPerc',
               'PublicOrPrivate', 'TotalPoints', 'Top25', 'Mt. West', 'MAC', 'SEC',
               'Sun Belt', 'Pac-12', 'Ind.', 'ACC', 'AAC', 'C-USA', 'Big Ten',
               'Big 12'],
              dtype='object')
```

```
In [ ]: xParm = ['TotalPoints', 'Top25', 'capacity', 'GSR_SA', 'WinPerc', 'W', 'L',
               'PublicOrPrivate', 'SEC', 'Pac-12', 'ACC', 'AAC', 'Mt. West', 'MAC', 'SEC',
               'Sun Belt', 'Pac-12', 'Ind.', 'ACC', 'AAC', 'C-USA', 'Big Ten',
               'Big 12']

        # We also create the list of parameters used in the OLS Model
        xParmStr = 'Q("'+xParm[0]+'")'
        for x in xParm[1:]:
            xParmStr += ' + ' + 'Q("'+x+'")'
```

```
In [ ]: xParmStr

Out[ ]: 'Q("TotalPoints") + Q("Top25") + Q("capacity") + Q("GSR_SA") + Q("WinPerc") + Q("W") +
```

10.3 Create Models

10.3.1 OLS Model

```
In [ ]: # specify a simple model with bobblehead entered last
        my_model = str(yParm +  ' ~ ' + xParmStr)

        # fit the model to the training set
        train_model_fit = smf.ols(my_model, data = train).fit()
        # summary of model fit to the training set
        print(train_model_fit.summary())
        # training set predictions from the model fit to the training set
        train['TotalPayPred_OLS'] = train_model_fit.fittedvalues
        # Get test values
        test['TotalPayPred_OLS'] = train_model_fit.predict(test)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               TotalPay   R-squared:                       0.837
```

```
Model:                            OLS   Adj. R-squared:                  0.805
Method:                 Least Squares   F-statistic:                     26.00
Date:                Thu, 23 Jul 2020   Prob (F-statistic):           3.25e-28
Time:                        18:02:26   Log-Likelihood:                -1647.5
No. Observations:                 110   AIC:                             3333.
Df Residuals:                      91   BIC:                             3384.
Df Model:                          18
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept              1.111e+07   5.46e+06      2.035      0.045    2.67e+05    2.19e+07
Q("TotalPoints")       1.678e+04   1.26e+04      1.329      0.187   -8306.114    4.19e+04
Q("Top25")            -8.693e+04   9.38e+05     -0.093      0.926   -1.95e+06    1.78e+06
Q("capacity")            36.1871      5.950      6.082      0.000      24.369      48.005
Q("GSR_SA")            1.842e+04   1.07e+04      1.726      0.088   -2779.135    3.96e+04
Q("WinPerc")          -1.757e+05   7.77e+04     -2.261      0.026    -3.3e+05   -2.13e+04
Q("W")                 3.573e+05   2.86e+05      1.249      0.215   -2.11e+05    9.25e+05
Q("L")                -1.219e+06   4.69e+05     -2.598      0.011   -2.15e+06   -2.87e+05
Q("PublicOrPrivate")   2.993e+05   2.99e+05      1.002      0.319   -2.94e+05    8.93e+05
Q("SEC")               2.425e+06   6.04e+05      4.013      0.000    1.22e+06    3.62e+06
Q("Pac-12")            9.148e+05   5.75e+05      1.592      0.115   -2.27e+05    2.06e+06
Q("ACC")               1.752e+06    9.9e+05      1.771      0.080   -2.13e+05    3.72e+06
Q("AAC")               3.527e+05   8.73e+05      0.404      0.687   -1.38e+06    2.09e+06
Q("Mt. West")          1.263e+05    5.6e+05      0.226      0.822   -9.85e+05    1.24e+06
Q("MAC")               4.198e+05   6.24e+05      0.672      0.503   -8.21e+05    1.66e+06
Q("Sun Belt")          2.585e+05   5.78e+05      0.447      0.656   -8.89e+05    1.41e+06
Q("Ind.")              5.174e+05   7.01e+05      0.738      0.462   -8.75e+05    1.91e+06
Q("C-USA")             3.347e+05   5.91e+05      0.566      0.573   -8.39e+05    1.51e+06
Q("Big Ten")           1.885e+06   5.88e+05      3.205      0.002    7.17e+05    3.05e+06
Q("Big 12")             2.12e+06   6.22e+05      3.409      0.001    8.85e+05    3.36e+06
==============================================================================
Omnibus:                        0.763   Durbin-Watson:                   1.963
Prob(Omnibus):                  0.683   Jarque-Bera (JB):                0.367
Skew:                           0.087   Prob(JB):                        0.832
Kurtosis:                       3.223   Cond. No.                     9.66e+20
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.72e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

10.4 Decision Tree

In [ ]:
```python
# Define the classifier
from sklearn.tree import DecisionTreeRegressor
```

```
from sklearn.model_selection import GridSearchCV
```

10.4.1 Train Model

```
In [ ]: parameters = {'max_depth':[5,10,15,20], 'max_features':[5,10,15,20, 30], 'max_leaf_node
```

```
In [ ]: dt = GridSearchCV(DecisionTreeRegressor(), parameters, n_jobs=5, cv=5, verbose=10)
```

```
In [ ]: dt = dt.fit(train[xParm].values, train[yParm].values)
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits


[Parallel(n_jobs=5)]: Using backend LokyBackend with 5 concurrent workers.
[Parallel(n_jobs=5)]: Done   3 tasks      | elapsed:    2.3s
[Parallel(n_jobs=5)]: Done   8 tasks      | elapsed:    2.4s
[Parallel(n_jobs=5)]: Done  15 tasks      | elapsed:    2.5s
[Parallel(n_jobs=5)]: Done  22 tasks      | elapsed:    2.5s
[Parallel(n_jobs=5)]: Batch computation too fast (0.1962s.) Setting batch_size=2.
[Parallel(n_jobs=5)]: Done  31 tasks      | elapsed:    2.6s
[Parallel(n_jobs=5)]: Batch computation too fast (0.0412s.) Setting batch_size=4.
[Parallel(n_jobs=5)]: Done  45 tasks      | elapsed:    2.6s
[Parallel(n_jobs=5)]: Batch computation too fast (0.0388s.) Setting batch_size=8.
[Parallel(n_jobs=5)]: Done  79 tasks      | elapsed:    2.7s
[Parallel(n_jobs=5)]: Batch computation too fast (0.0735s.) Setting batch_size=16.
[Parallel(n_jobs=5)]: Done 151 tasks      | elapsed:    2.8s
[Parallel(n_jobs=5)]: Batch computation too fast (0.1453s.) Setting batch_size=32.
[Parallel(n_jobs=5)]: Done 215 tasks      | elapsed:    3.0s
[Parallel(n_jobs=5)]: Done 273 tasks      | elapsed:    3.0s
[Parallel(n_jobs=5)]: Done 288 tasks      | elapsed:    3.1s
[Parallel(n_jobs=5)]: Done 300 out of 300 | elapsed:    3.1s finished
```

10.4.2 Get the best DT Model out of the Grid Search

```
In [ ]: dt_model = dt.best_estimator_
        print (dt.best_score_, dt.best_params_)
```

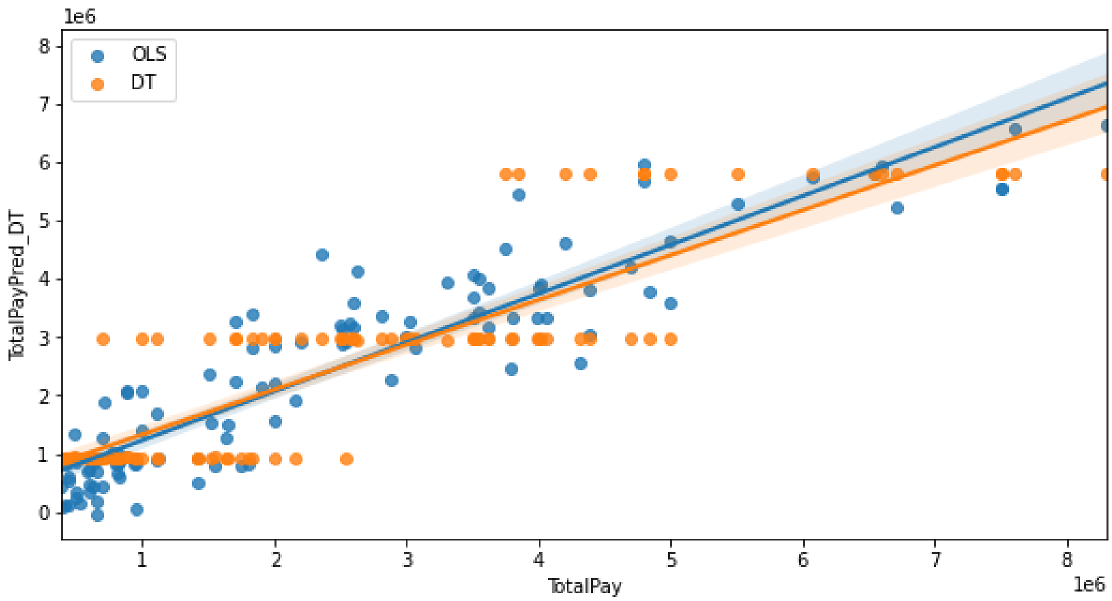
```
0.550612230764821 {'max_depth': 5, 'max_features': 15, 'max_leaf_nodes': 5}
```

```
In [ ]: train['TotalPayPred_DT'] = dt_model.predict(train[xParm].values)
        test['TotalPayPred_DT'] = dt_model.predict(test[xParm].values)
```

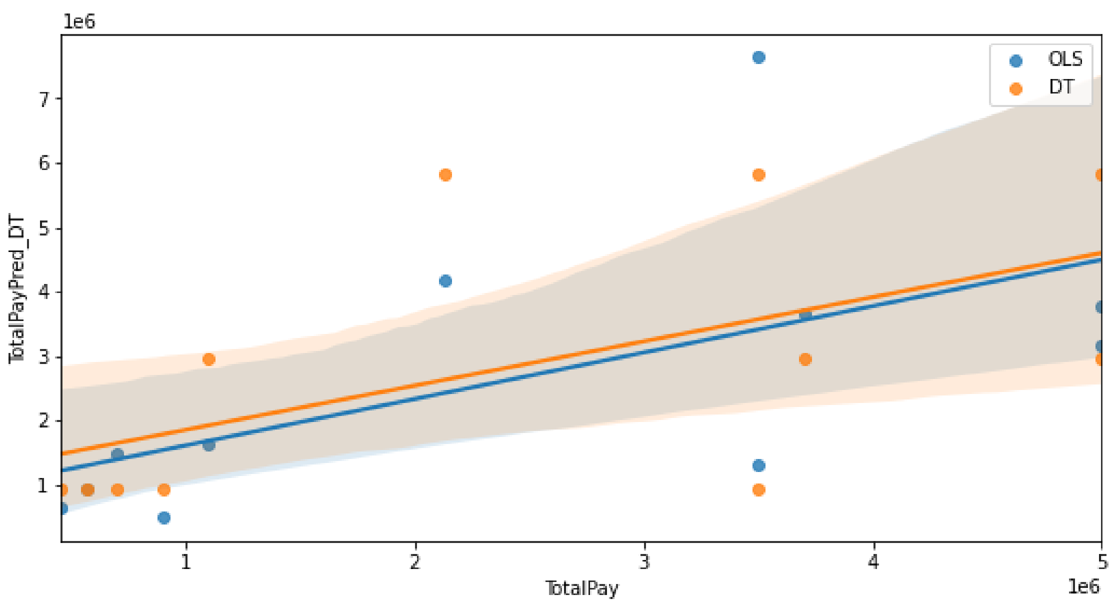
10.5 Compare Models

```
In [ ]: ## Training Set
        fig,ax = plt.subplots(figsize=(10,5))
        sns.regplot(x=yParm, y='TotalPayPred_OLS', data=train, ax=ax, label='OLS')
```

```
sns.regplot(x=yParm, y='TotalPayPred_DT', data=train, ax=ax, label='DT')
ax.legend()
fig.show()
```

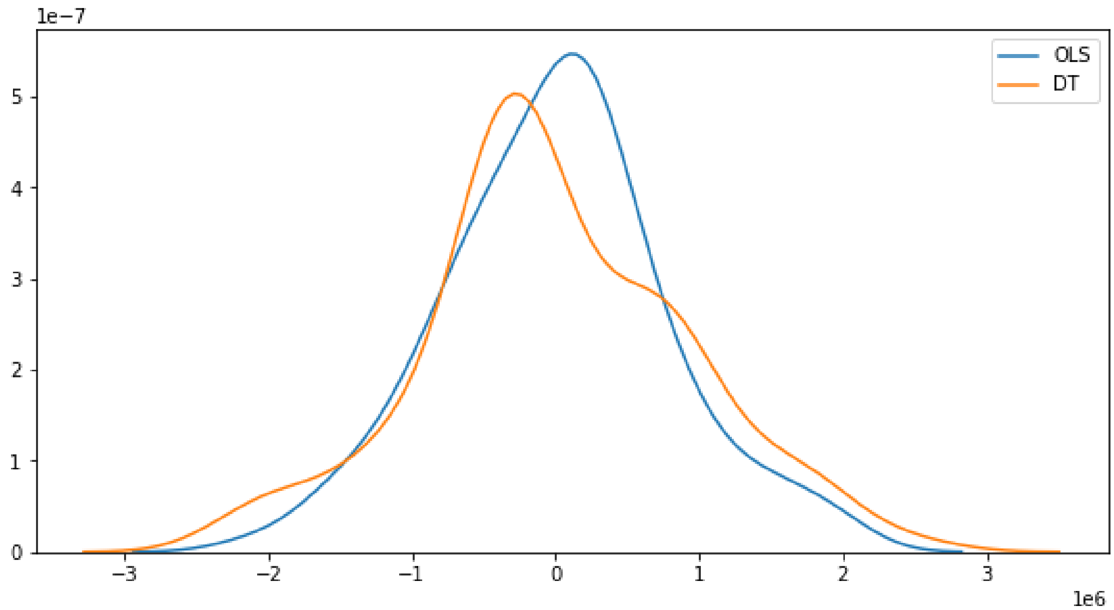



```
In [ ]: ## Test Set
        fig,ax = plt.subplots(figsize=(10,5))
        sns.regplot(x=yParm, y='TotalPayPred_OLS', data=test, ax=ax, label='OLS')
        sns.regplot(x=yParm, y='TotalPayPred_DT', data=test, ax=ax, label='DT')
        ax.legend()
        fig.show()
```

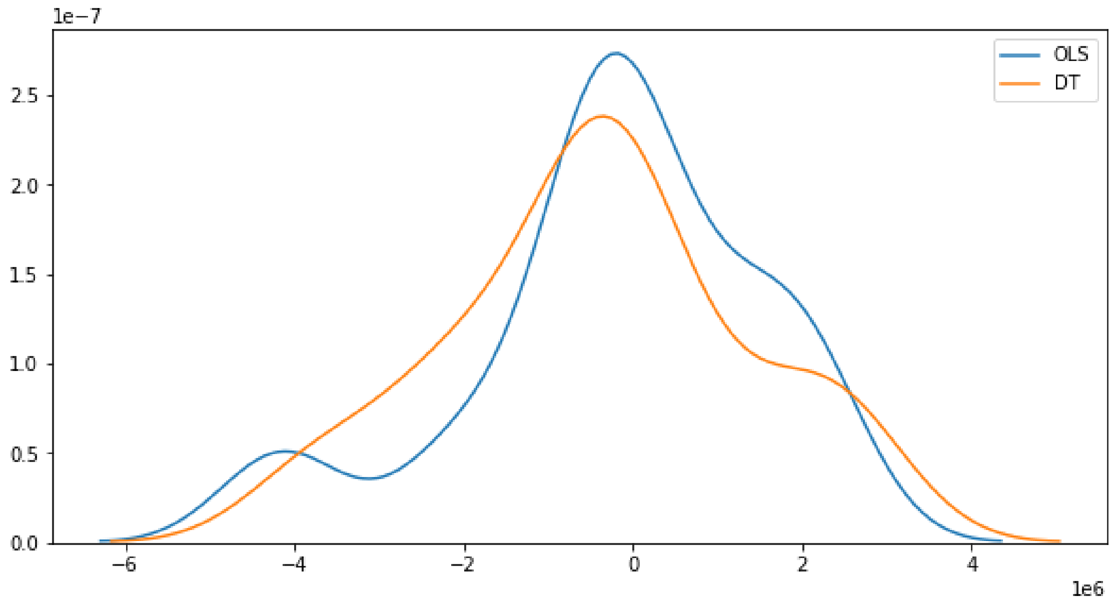


Visually speaking, the OLS model is showing better results in the Test set. Now we will quantify the accuracy of the models using the Mean Square Difference.

```
In [ ]: ## Train Set
        train['DiffPred_OLS'] = train['TotalPay'] - train['TotalPayPred_OLS']
        train['DiffPred_DT'] = train['TotalPay'] - train['TotalPayPred_DT']

        fig,ax = plt.subplots(figsize=(10,5))
        sns.kdeplot(train['DiffPred_OLS'].values,ax=ax, label='OLS')
        sns.kdeplot(train['DiffPred_DT'].values, ax=ax, label='DT')
        ax.legend()
        fig.show()
```




```
In [ ]: ## Test Set
        test['DiffPred_OLS'] = test['TotalPay'] - test['TotalPayPred_OLS']
        test['DiffPred_DT'] = test['TotalPay'] - test['TotalPayPred_DT']

        fig,ax = plt.subplots(figsize=(10,5))
        sns.kdeplot(test['DiffPred_OLS'].values,ax=ax, label='OLS')
        sns.kdeplot(test['DiffPred_DT'].values, ax=ax, label='DT')
        ax.legend()
        fig.show()
```




```
In [ ]: print('Absolute Mean Difference Train OLS:', abs(train['DiffPred_OLS']).mean())
        print('Absolute Mean Difference Train DT:', abs(train['DiffPred_DT']).mean())
        print('Absolute Mean Difference Test OLS:', abs(test['DiffPred_OLS']).mean())
        print('Absolute Mean Difference Test DT:', abs(test['DiffPred_DT']).mean())
```

```
Absolute Mean Difference Train OLS: 598523.4658410905
Absolute Mean Difference Train DT: 719152.2417134499
Absolute Mean Difference Test OLS: 1249012.5184749502
Absolute Mean Difference Test DT: 1375446.1882902058
```

10.6 Conclusion on Model Decision

While the Decision Tree model has better results in the training dataset, the OLS model has much better results in the Test set. The OLS test absolute mean difference is 425638 while the DT test absolute mean difference is 885423 which is much larger. This could be an overfitting problem with the Decision Tree model. Therefore, we will move on with the OLS model as the Champion Model.

11 Answer the Questions

11.1 What is the predicted Pay for Syracuse Coach?

```
In [ ]: syr['TotalPayPred'] = train_model_fit.predict(syr)
```

```
In [ ]: syr
```

```
Out[ ]:      School Conference        Coach  ...  Big Ten Big 12  TotalPayPred
        0  Syracuse        ACC  Dino Babers  ...        0      0  3.356648e+06

        [1 rows x 28 columns]
```

```
In [ ]: 3.356648e+06 - 2401206.0
```

```
Out[ ]: 955442.0
```

The prediction says that the Syracuse coach shoudl be making $ 3,356,648 which is almost a million more than he is. It is understandable since ACC coaches make a lot of money, but last year's record was terrible for this coach.

11.2 What is the predicted pay for Syracuse Coach if we were in the Big East?

Trick question, since Big East schools went to AAC

```
In [ ]: # Change ACC to Big East or AAC
        syr['ACC'] = [0]
        syr['AAC'] = [1]
        syr.head()
```

```
Out[ ]:      School Conference        Coach  ...  Big Ten Big 12  TotalPayPred
        0  Syracuse        ACC  Dino Babers  ...        0      0  3.356648e+06

        [1 rows x 28 columns]
```

```
In [ ]: # test set predictions from the model fit to the training set
        syr['TotalPayPred'] = train_model_fit.predict(syr)
```

```
In [ ]: syr[['School', 'TotalPay', 'TotalPayPred']]
```

```
Out[ ]:      School   TotalPay  TotalPayPred
        0  Syracuse  2401206.0  1.957271e+06
```

```
In [ ]: 3.356648e+06 - 1.957271e+06
```

```
Out[ ]: 1399377.0
```

The pay for the coach would go down by $1,399,377.0

11.3 What is the predicted pay for Syracuse Coach if we were in the Big Ten?

```
In [ ]: # Change ACC to Big Ten
        syr['AAC'] = [0]
        syr['Big Ten'] = [1]
        syr.head()
```

```
Out[ ]:      School Conference        Coach  ...  Big Ten Big 12  TotalPayPred
        0  Syracuse        ACC  Dino Babers  ...        1      0  1.957271e+06

        [1 rows x 28 columns]
```

```
In [ ]: # test set predictions from the model fit to the training set
        syr['TotalPayPred'] = train_model_fit.predict(syr)
```

```
In [ ]: syr[['School', 'TotalPay', 'TotalPayPred']]
```

```
Out[ ]:      School   TotalPay  TotalPayPred
        0  Syracuse  2401206.0  3.489457e+06
```

```
In [ ]: 3.356648e+06 - 3.489457e+06
```

```
Out[ ]: -132809.0
```

If Syracuse went from the ACC to the Big Ten, the coach would get paid $123,809.0 more.

11.4 What effect does Graduation Rate have on Coaches Pay?

```
In [ ]: # To Check for this, we set all other variables to the a constant amount and test out
        testdf = pd.DataFrame()
        for gsr in [0,10,20, 30, 40,50,60, 70,80, 90, 100]:
          syr['GSR_SA'] = gsr
          testdf = pd.concat([testdf, syr])

        print(testdf['GSR_SA'])
```

```
0      0
0     10
0     20
0     30
0     40
0     50
0     60
0     70
0     80
0     90
0    100
Name: GSR_SA, dtype: int64
```

```
In [ ]: # Plug into model to see how the values change
        testdf['TotalPayPred'] = train_model_fit.predict(testdf)
```

```
In [ ]: # Look at how the GSR increases the predicted pay.
        print(testdf[['GSR_SA', 'TotalPayPred']])
```

```
   GSR_SA  TotalPayPred
0       0  1.905155e+06
0      10  2.089376e+06
0      20  2.273598e+06
0      30  2.457819e+06
```

```
0      40  2.642040e+06
0      50  2.826261e+06
0      60  3.010482e+06
0      70  3.194703e+06
0      80  3.378924e+06
0      90  3.563145e+06
0     100  3.747366e+06
```

```
In [ ]: print(testdf['TotalPayPred'].diff())
```

```
0              NaN
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
0    184221.108892
Name: TotalPayPred, dtype: float64
```

According to the model output, the model goes up by $184,221 for every 10 percente increase in Graduation Rate.

11.5 How good is our model?

```
In [ ]: print(train_model_fit.summary())
```

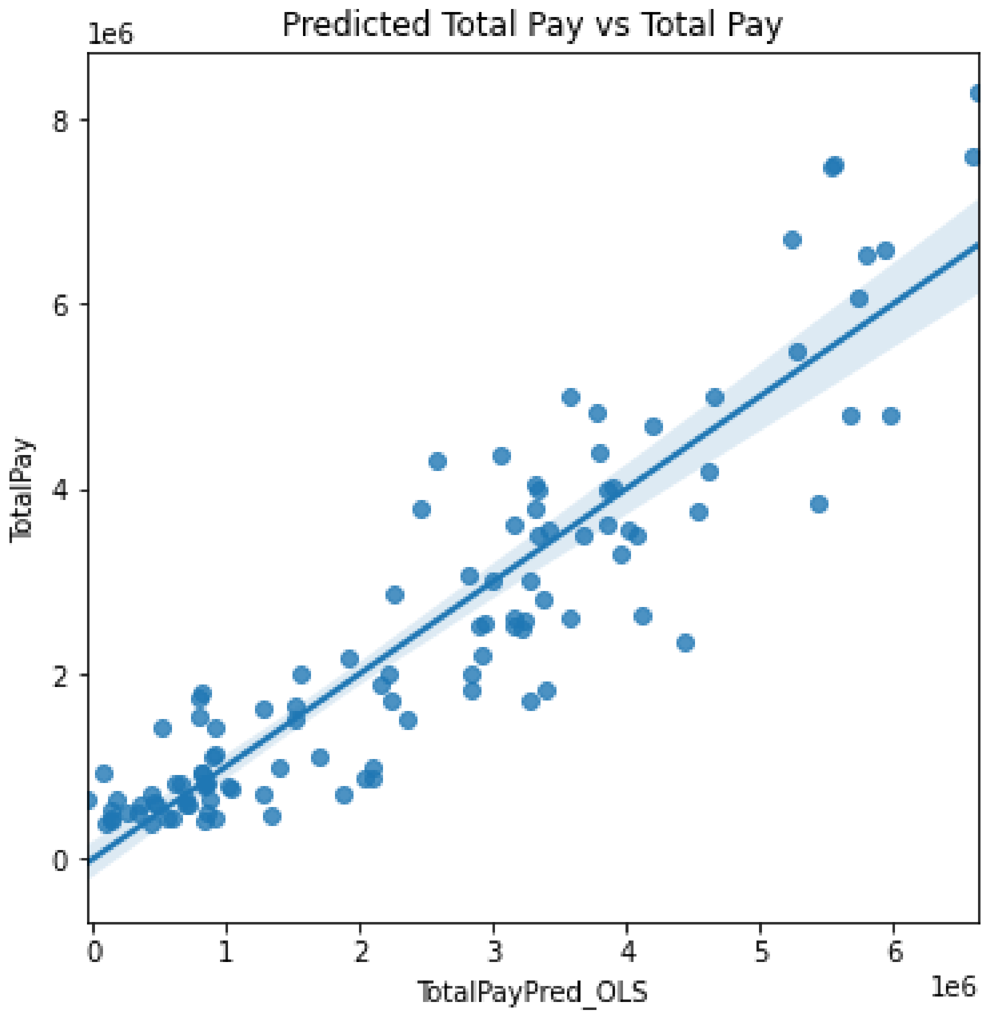
```
                            OLS Regression Results
==============================================================================
Dep. Variable:               TotalPay   R-squared:                       0.837
Model:                            OLS   Adj. R-squared:                  0.805
Method:                 Least Squares   F-statistic:                     26.00
Date:                Thu, 23 Jul 2020   Prob (F-statistic):           3.25e-28
Time:                        18:07:56   Log-Likelihood:                -1647.5
No. Observations:                 110   AIC:                             3333.
Df Residuals:                      91   BIC:                             3384.
Df Model:                          18
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept             1.111e+07   5.46e+06      2.035      0.045    2.67e+05    2.19e+07
Q("TotalPoints")      1.678e+04   1.26e+04      1.329      0.187   -8306.114    4.19e+04
Q("Top25")           -8.693e+04   9.38e+05     -0.093      0.926   -1.95e+06    1.78e+06
```

```
Q("capacity")           36.1871      5.950      6.082      0.000      24.369      48.005
Q("GSR_SA")           1.842e+04   1.07e+04      1.726      0.088   -2779.135    3.96e+04
Q("WinPerc")         -1.757e+05   7.77e+04     -2.261      0.026    -3.3e+05   -2.13e+04
Q("W")                3.573e+05   2.86e+05      1.249      0.215   -2.11e+05    9.25e+05
Q("L")               -1.219e+06   4.69e+05     -2.598      0.011   -2.15e+06   -2.87e+05
Q("PublicOrPrivate")  2.993e+05   2.99e+05      1.002      0.319   -2.94e+05    8.93e+05
Q("SEC")              2.425e+06   6.04e+05      4.013      0.000    1.22e+06    3.62e+06
Q("Pac-12")           9.148e+05   5.75e+05      1.592      0.115   -2.27e+05    2.06e+06
Q("ACC")              1.752e+06    9.9e+05      1.771      0.080   -2.13e+05    3.72e+06
Q("AAC")              3.527e+05   8.73e+05      0.404      0.687   -1.38e+06    2.09e+06
Q("Mt. West")         1.263e+05    5.6e+05      0.226      0.822   -9.85e+05    1.24e+06
Q("MAC")              4.198e+05   6.24e+05      0.672      0.503   -8.21e+05    1.66e+06
Q("Sun Belt")         2.585e+05   5.78e+05      0.447      0.656   -8.89e+05    1.41e+06
Q("Ind.")             5.174e+05   7.01e+05      0.738      0.462   -8.75e+05    1.91e+06
Q("C-USA")            3.347e+05   5.91e+05      0.566      0.573   -8.39e+05    1.51e+06
Q("Big Ten")          1.885e+06   5.88e+05      3.205      0.002    7.17e+05    3.05e+06
Q("Big 12")            2.12e+06   6.22e+05      3.409      0.001    8.85e+05    3.36e+06
==============================================================================
Omnibus:                        0.763   Durbin-Watson:                   1.963
Prob(Omnibus):                  0.683   Jarque-Bera (JB):                0.367
Skew:                           0.087   Prob(JB):                        0.832
Kurtosis:                       3.223   Cond. No.                     9.66e+20
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.72e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

The Adjusted R^2 value is equal to .805 which is a pretty strong correlation, and we are getting some interpretable results. The actual R^2 is about .837 which means that .837 of the Total Pay variation is explaning by the x paramters in the model. Only three variables have P-values that don't go from positive to negative. This includes the variables: Big Ten, Big 12 and the Stadium Capacity. The P-value for the stadium capacity seems to be the most important out of the whole set of parameters since it has the smallest p-value. As show below, we can see that there is a big correlation between the predicted and actual total pay.

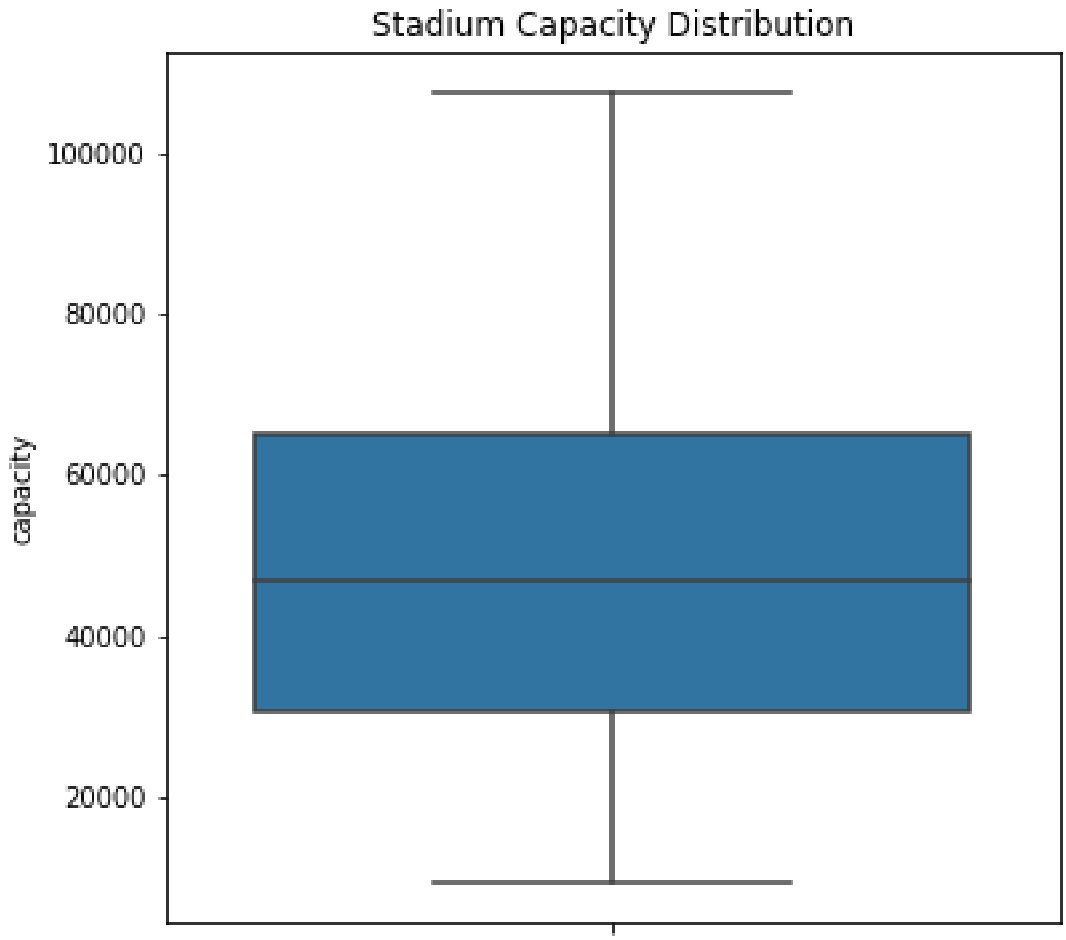
In [ ]:
```
plt.figure(figsize=(6,6))
sns.regplot(x='TotalPayPred_OLS', y=yParm, data=train)
plt.title('Predicted Total Pay vs Total Pay')
```

Out[ ]:
```
Text(0.5, 1.0, 'Predicted Total Pay vs Total Pay')
```



11.6 What is the single biggest impact on salary size?

```
In [ ]: plt.figure(figsize=(6,6))
        sns.boxplot(y='capacity', data=train)
        plt.title('Stadium Capacity Distribution')

Out[ ]: Text(0.5, 1.0, 'Stadium Capacity Distribution')
```



The most important variable for the total pay of a coach is the stadium size. For every 1 extra fan, the coach gets an increase of 36.1871 dollars. To put this into perspective, the stadium capacity distribution ranges from about 30,000 fans to 110,000 fans. Therefore, if we increase the capacity by 10,000, the total pay increase by $360,000.

12 Conclusion

The OLS model seems to be the best model so far. With a .83 R-squared value, the model is a strong prediction of the actual Total Pay. All in all, the Syracuse Coach is currently underpaid even if he had a terrible season.