IST-718 Homework/Lab-1 (Week3)

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Introduction

This case study provides an opportunity to demonstrate the ability to combine datasets and produce meaningful analysis learned through the first three-weeks of the course.

Specifically, we are looking to answer the following questions:

- What would his salary be if we were still in the Big East? What if we went to the Big Ten?
- What schools did we drop from our data, and why?
- What effect does graduation rate have on the projected salary?

Bill Clark \$900,000

Scott Satterfield \$712,500

How good is our model?

C-USA

Sun Belt

Pac-12

What is the single biggest impact on salary size?

Dataset

The dataset initially related to Coaches data (an excerpt is seen below) was loaded into a data-frame **df_coaches**. This would be the master data-frame:

```
1 import pandas as pd
   # Read the coaches data using pandas
 5 df_coaches = pd.read_csv('Coaches9.csv', sep = ',')
    print ('Shape of data: \n', df_coaches shape)
 7 df_coaches.head(50)
Shape of data:
 (129, 9)
               School Conference
                                           Coach SchoolPay
                                                            TotalPay
                                                                       Bonus BonusPaid AssistantPay
 0
              Air Force
                         Mt. West
                                      Troy Calhoun
                                                    885000
                                                              885000
                                                                       247000
                            MAC
                                      Terry Bowden $411,000
                                                            $412,500
                                                                      $225,000
                                                                                $50,000
                                                                                                $0
                                                                                                      $688,500
 1
                 Akron
 2
               Alabama
                            SEC
                                       Nick Saban $8,307,000 $8,307,000 $1,100,000
                                                                               $500,000
                                                                                                $0 $33,600,000
```

\$900,000

\$712,500

Kevin Sumlin \$1,600,000 \$2,000,000 \$2,025,000

\$950,000

\$295,000

\$165,471

\$145,000

\$0 \$3,847,500

\$2,160,417 \$0 \$10,000,000

\$0

NOTE:

3 Alabama at Birmingham

Appalachian State

Arizona

Two additional datasets related to Graduation success Rate (GSR)/Federal Graduation Rate (FGR) and Stadium capacities were merged into the master data-frame.

First, data related to GSR/FGR was retrieved from https://web3.ncaa.org/aprsearch/gsrsearch and loaded into a data-frame df_gsr_fgr:

```
1 # Read data of Graduation success Rate (GSR) and Federal Graduation Rate (FGR)
 2 # Definitions:
      |- FGR - Indicates the percentage of freshmen who entered and received athletics aid during a given
         academic year who graduated within six years
     |- GSR - The GSR adds to the first-time freshmen, those students who entered midyear as well as
         student-athletes who transferred into an institution and received athletics aid.
names=['Cohort Year',
'GSR', 'FGR'])
10
11 df_gsr_fgr.head()
  Cohort Year
                         School
                                         Conference
                                                     Sport State GSR FGR
0
       2007 Abilene Christian University
                                   Southland Conference Football
                                                                51 48.0
       2007
                                Mid-American Conference Football
                 University of Akron
                                                           OH
                                                                60 55.0
2
             Alabama A&M University Southwestern Athletic Conf. Football
       2007
                                                                39 50.0
             Alabama State University Southwestern Athletic Conf. Football
                                                           AL
                                                                64 47.0
               University of Alabama Southeastern Conference Football
```

Finally, data related to stadium sizing was retrieved from source https://www.collegegridirons.com/comparisons-by-capacity/ and loaded into data-frame df_stadiums:

```
# Get stadium-size from mapping to school/college from college-stadiums.csv
# Data-source:
# |- https://www.collegegridirons.com/comparisons-by-capacity/

df_stadiums = pd.read_csv('college-stadiums.csv', sep='\t')
df_stadiums.head()
```

| | Stadium | College | Conference | Capacity | Opened |
|---|------------------|------------|------------|----------|--------|
| 0 | Michigan Stadium | Michigan | Big Ten | 107,601 | 1927 |
| 1 | Beaver Stadium | Penn State | Big Ten | 106,572 | 1960 |
| 2 | Ohio Stadium | Ohio State | Big Ten | 104,944 | 1922 |
| 3 | Kyle Field | Texas A&M | SEC | 102,733 | 1904 |
| 4 | Neyland Stadium | Tennessee | SEC | 102,521 | 1921 |

Data cleaning/munging

Data was cleaned and munged in steps.

STEP-1:

On data-frame df_gsr_fgr missing values were replaced with statistical mean for the respective GSR/FGR data. This may not always be the best approach and could potentially skew data. Also, we convert the datatypes for the GSR and FGR columns to type int:

```
# Clean/munge data related to gsr/fgr
from numpy import mean
print('--- Working on dataframe: df_gsr_fgr --- \n')

# Replace all NaN/missing values with mean for respective columns
column_mean = lambda column: mean(df_gsr_fgr.loc[:, column])
values = {'GSR': column_mean('GSR'), 'FGR': column_mean('FGR')}
df_gsr_fgr = df_gsr_fgr.fillna(values)

# Verify no NaN values
print('Missing data in dataset:', df_gsr_fgr.isna().any().any())

# Check datatypes on GSR/FGR columns in specific
print('Data-types: \n', df_gsr_fgr.dtypes)

# Modify the FGR data astype to int64 as well
df_gsr_fgr['FGR'] = df_gsr_fgr['FGR'].astype(int)

print('Data-types after conversion: \n', df_gsr_fgr.dtypes)

Working on dataframe: df_gsr_fgr ---

Working on dataframe: df_gsr_fgr ---
```

Missing data in dataset: False Data-types: Cohort Year int64 School object Conference object Sport object object State GSR **FGR** float64 dtype: object Data-types after conversion: Cohort Year int64 School object Conference object Sport obiect State object int64 GSR FGR int64 dtype: object

1) Data-frame **df_coaches** were munged for the 'Capacity' column replacing characters to make them numbers for data-analysis:

```
for school in df_coaches['School']:
    try:
        capacity = int(df_stadiums[(df_stadiums['College'] == school)]['Capacity'].values[0].replace(',',''))
except IndexError:
        no_data += 1
        capacity = 0
pop_value('Capacity', school, capacity)
```

Data from the two data-frames were then merged into the master data-frame **df_coaches** before preparing the data for visualization and modelling:

- replace missing values/zeros with mean/avg where applicable
- check data types & modify appropriately using astype()
- remove '\$' symbol using Python regex and convert currency columns *SchoolPay, TotalPay, Bonus, BonusPaid, AssistantPay, Buyout* to float.

A sample of the merged data-frame and columns is seen below:

| | School | Conference | Coach | SchoolPay | TotalPay | Bonus | BonusPaid | AssistantPay | Buyout | GSR | FGR | State | Capacity |
|----------|--------------------------|------------|-----------------|-----------|-----------|-----------|-----------|--------------|------------|-----|-----|-------|----------|
| 9 | Army | Ind. | Jeff Monken | 932521.0 | 932521.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | USA | 38000.0 |
| oll outp | ut; double click to hide | Mt. West | Jeff Tedford | 1550000.0 | 1550000.0 | 2765000.0 | 1240000.0 | 0.0 | 5440000.0 | 0 | 0 | USA | 41031.0 |
| 38 | Georgia State | Sun Belt | Shawn Elliott | 569000.0 | 569000.0 | 220000.0 | 60000.0 | 0.0 | 1500000.0 | 0 | 0 | USA | 23000.0 |
| 39 | Georgia Tech | ACC | Paul Johnson | 3060018.0 | 3060018.0 | 1330000.0 | 225000.0 | 0.0 | 4000000.0 | 0 | 0 | USA | 55000.0 |
| 52 | Louisiana-Lafayette | Sun Belt | Billy Napier | 850000.0 | 850000.0 | 435000.0 | 0.0 | 0.0 | 2671875.0 | 0 | 0 | USA | 31000.0 |
| 53 | Louisiana-Monroe | Sun Belt | Matt Viator | 390000.0 | 390000.0 | 50000.0 | 0.0 | 0.0 | 175000.0 | 0 | 0 | USA | 30427.0 |
| 55 | LSU | SEC | Ed Orgeron | 3500000.0 | 3500000.0 | 1575000.0 | 100000.0 | 0.0 | 5291667.0 | 0 | 0 | USA | 100500.0 |
| 69 | Navy | AAC | Ken Niumatalolo | 2163000.0 | 2163000.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | USA | 34000.0 |
| 88 | Penn State | Big Ten | James Franklin | 4800000.0 | 4800000.0 | 1000000.0 | 300000.0 | 0.0 | 18375000.0 | 0 | 0 | USA | 106572.0 |
| 95 | South Alabama | Sun Belt | Steve Campbell | 600000.0 | 600000.0 | 295000.0 | 0.0 | 0.0 | 918333.0 | 0 | 0 | USA | 40646.0 |

Data types on all columns within data-frame **df_coaches**:

| School | object |
|--------------|---------|
| Conference | object |
| Coach | object |
| SchoolPay | float64 |
| TotalPay | float64 |
| Bonus | float64 |
| BonusPaid | float64 |
| AssistantPay | float64 |
| Buyout | float64 |
| GSR | int64 |
| FGR | int64 |
| State | object |
| Capacity | float64 |
| | |

Removal of data-records

During the process of data-retrieval there were instances where few records had to be removed. For instance:

- when retrieving data related to GSR/FGR certain schools from the Coaches dataset could not be matched or found. This resulted in *EIGHTEEN* records being removed or dropped
- similarly, FIFTEEN schools could not be matched or found in stadium capacity data. These were removed too.

NOTE:

The original data-frame was preserved, and all the trimming was saved to df_coaches_trim

After all, the size of Coaches data is shown below — comprising up to SEVENTEEN fewer records: df_coaches shape: (129, 13) VS df_coaches_trim shape: (112, 13) Missing values in df coaches dataframe: False

Exploratory Data Analysis

Since the problem we are trying to solve is related to predicting the Salary of coaches some of the exploratory data analysis or descriptive statistics and visualization are centered around the column TotalPay from the dataset.

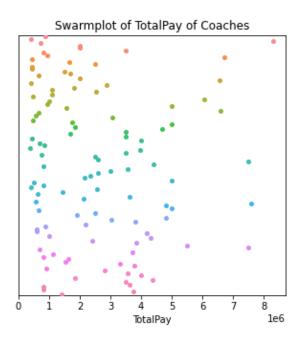
Seen below are the min, max, mean and median values related to *TotalPay* (in USD) paid to Coaches and another column that seemed to have a strong correlation to it, *Capacity* of stadiums:

```
# Exploratory data analysis
df_coaches_trim.describe()

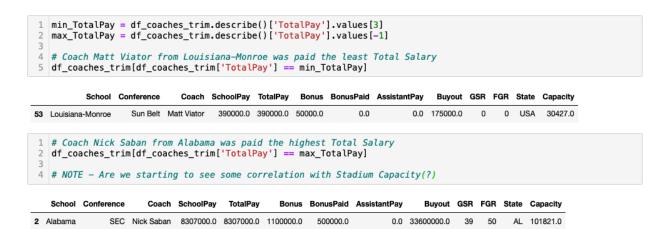
# Of interest are the following:
# - TotalPay (USD) Min, Max, Mean and Median - 390,000, 8,307,000, 2,503,266 & 2,000,000 respectively
# - Capacity of stadiums Min, Max, Mean and Median - 15000, 107601, 51944, 50000 respectively
```

| | SchoolPay | TotalPay | Bonus | BonusPaid | AssistantPay | Buyout | GSR | FGR | Capacity |
|-------|--------------|--------------|--------------|--------------|--------------|--------------|------------|------------|---------------|
| count | 1.120000e+02 | 1.120000e+02 | 1.120000e+02 | 1.120000e+02 | 112.0 | 1.120000e+02 | 112.000000 | 112.000000 | 112.000000 |
| mean | 2.503266e+06 | 2.510810e+06 | 7.872615e+05 | 1.129687e+05 | 0.0 | 7.574159e+06 | 61.892857 | 51.482143 | 51944.803571 |
| std | 1.904339e+06 | 1.908795e+06 | 6.743276e+05 | 2.204314e+05 | 0.0 | 1.046263e+07 | 24.310068 | 20.661573 | 23597.660017 |
| min | 3.900000e+05 | 3.900000e+05 | 0.000000e+00 | 0.000000e+00 | 0.0 | 0.000000e+00 | 0.000000 | 0.000000 | 15000.000000 |
| 25% | 8.244225e+05 | 8.246850e+05 | 2.837500e+05 | 0.000000e+00 | 0.0 | 8.936140e+05 | 57.000000 | 47.000000 | 30564.000000 |
| 50% | 2.000000e+06 | 2.000000e+06 | 7.100000e+05 | 3.712500e+04 | 0.0 | 3.092813e+06 | 68.000000 | 56.000000 | 50000.000000 |
| 75% | 3.640825e+06 | 3.640825e+06 | 1.106250e+06 | 1.062500e+05 | 0.0 | 1.032344e+07 | 74.500000 | 64.000000 | 64403.500000 |
| max | 8.307000e+06 | 8.307000e+06 | 3.100000e+06 | 1.350000e+06 | 0.0 | 6.812500e+07 | 99.000000 | 93.000000 | 107601.000000 |

This distribution and variance can also be seen in a swarm-plot. This particularly indicates the larger set of salaries distributed <4mi USD and just one data-point >8mi USD:



The min and max *TotalPay* values were used to retrieve data of Coaches who were paid the least and most salaries:



Results

Model-1

The first model will attempt to predict the salary of Coaches (here *TotalPay*) using Linear Regression/commonly known Ordinary Least squares method with variables (GSR, FGR, Capacity) from the dataset.

A summary of the model-fit and results as follows:

```
# Split the data into training and test set
np.random.seed(1000)
df_coaches_trim['runiform'] = uniform.rvs(loc = 0, scale = 1, size = len(df_coaches_trim))
df_coaches_trim_train = df_coaches_trim[df_coaches_trim['runiform'] >= 0.33]
df_coaches_trim_test = df_coaches_trim[df_coaches_trim['runiform'] < 0.33]
print('df_coaches dataframe train data (size): \n', df_coaches_trim_train.shape)
print('df_coaches dataframe test data (size): \n', df_coaches_trim_test.shape)

# Let's run a linear regression model using the ordinary least squares method (OLS)
ols_model = str('TotalPay ~ GSR + FGR + Capacity')

# Fit the model on train data
train_model_fit = smf.ols(ols_model, data = df_coaches_trim_train).fit()</pre>
```

| OLS Regression Results | | | | | | | | | | |
|------------------------|------------|---------------|----------|---------|-----------------------|-----------|-----------|--|--|--|
| Dep. Varia | ble: | Tota | | | uared: | | 0.756 | | | |
| Model: | | | 0LS | Adj. | R-squared: | | 0.746 | | | |
| Method: | | Least Squa | ares | F-sta | atistic: | | 73.28 | | | |
| Date: | | Sat, 30 Jan 2 | 2021 | Prob | (F-statisti | .c): | 1.08e-21 | | | |
| Time: | | 21:23 | 3:13 | Log-l | _ikelihood: | | -1140.7 | | | |
| No. Observ | ations: | | 75 | AIC: | | | 2289. | | | |
| Df Residua | ls: | | 71 | BIC: | | | 2299. | | | |
| Df Model: | | | 3 | | | | | | | |
| Covariance | : Type: | non rol | bust | | | | | | | |
| | coe | f std err | | t | P> t | [0.025 | 0.975] | | | |
| Intercept | -2.041e+0 | 5 5.33e+05 | -3. | 829 | 0.000 | -3.1e+06 | -9.78e+05 | | | |
| GSR | -8909.0952 | 1.77e+04 | -0. | 504 | 0.616 | -4.42e+04 | 2.64e+04 | | | |
| FGR | 2.686e+04 | 2.11e+04 | 1. | 276 | 0.206 | -1.51e+04 | 6.88e+04 | | | |
| Capacity | 72.247 | 4.936 | 14. | 637 | 0.000 | 62.405 | 82.090 | | | |
| Omnibus: | | 8 | .344 | Durb: | ======= in-Watson: | | 1.988 | | | |
| Prob(Omnib | us): | 0 | 10.369 | | | | | | | |
| Skew: | | -0 | : | 0.00560 | | | | | | |
| Kurtosis: | | 4 | .549 | Cond | No. | | 2.71e+05 | | | |
| | | | | | | | | | | |

Interpreting the results:

The equation of linear regression can be written as:

TotalPay = 72.2476 * Capacity + 2.686e+04 * FGR - 8909.0952 * GSR - 2.041e+06

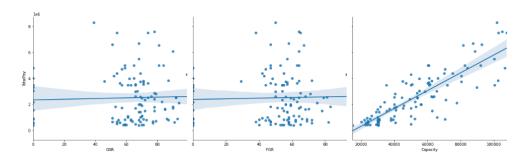
- R-square value

R-square = 0.756 is an indication of a good fit and is reflective of how close the data is to line of best-fit/regression.

- P-value

- o P-value for GSR/FGR >0.05 and may therefore not be statistically significant in this dataset.
- o Stadium Capacity with P-value = 0 is statistically significant.

Further, a plot of the line of least squares for each of the variables was made:



Based on the linear regression model/Model-1, the prediction of Coach Dino Babers' salary is approximated to **2,460,942USD** about 2.5% more than his current pay.

```
# Based on the linear regression model we predict Coach Dino Babers' salary at 2,460,942 USD

df_coaches_trim_test[df_coaches_trim_test['School'] == 'Syracuse']
```

| | School | Conference | Coach | SchoolPay | TotalPay | Bonus | BonusPaid | AssistantPay | Buyout | GSR | FGR | State | Capacity | runiform | Salary(Predict) |
|-----|----------|------------|----------------|-----------|-----------|-------|-----------|--------------|--------|-----|-----|-------|----------|----------|-----------------|
| 102 | Syracuse | ACC | Dino Babers | 2401206.0 | 2401206.0 | 0.0 | 0.0 | 0.0 | 0.0 | 78 | 61 | NY | 49250.0 | 0.236943 | 2.460942e+06 |

Model-2

This model will make a similar prediction as the first, by including an additional response variable *Conference*. Since this variable is categorical and non-numeric the values in the dataset will be mapped and converted to numeric data using a key-value map or Python dictionary:

```
{'Mt. West': 0, 'MAC': 1, 'SEC': 2, 'Sun Belt': 3, 'Pac-12': 4, 'Ind.': 5, 'ACC': 6, 'AAC': 7, 'C-USA': 8, 'Big Ten': 9, 'Big 12': 10}
```

A summary of the model-fit and results as follows:

```
# Let's run a linear regression model using the ordinary least squares method (OLS)

ols_model_enc = str('TotalPay ~ GSR + FGR + Capacity + Conference_num')

# Fit the model on train data
train_model_fit_enc = smf.ols(ols_model_enc, data = df_coaches_trim_train_enc).fit()

print(train_model_fit_enc.summary())
```

| OLS Regression Results | | | | | | | | | | |
|---|---|---|--|---|--|--|--|--|--|--|
| Dep. Variable: Model: Method: Date: Time: No. Observatio Df Residuals: Df Model: Covariance Typ | Sat, 3 | TotalPay OLS ast Squares 30 Jan 2021 22:11:22 75 70 4 nonrobust | R-squared: Adj. R-squ F-statisti Prob (F-st Log-Likeli AIC: BIC: | ared: .c: atistic): | 0.776 0.764 60.75 4.84e-22 -1137.4 2285. 2296. | | | | | |
| ========== | coef | std err | t | P> t | [0.025 | 0.975] | | | | |
| Intercept GSR FGR Capacity Conference_num | -2.191e+06 -1.745e+04 3.498e+04 69.0914 8.721e+04 | 5.17e+05 1.74e+04 2.05e+04 4.919 3.44e+04 | -4.236 -1.004 1.702 14.047 2.532 | 0.000 0.319 0.093 0.000 0.014 | -3.22e+06 -5.21e+04 -6004.994 59.281 1.85e+04 | -1.16e+06 1.72e+04 7.6e+04 78.902 1.56e+05 | | | | |
| Omnibus: Prob(Omnibus): Skew: Kurtosis: | | 2.448 0.294 -0.109 3.757 | Durbin-Wat Jarque-Ber Prob(JB): Cond. No. | | 2.073 1.940 0.379 2.73e+05 | | | | | |

Interpreting the results:

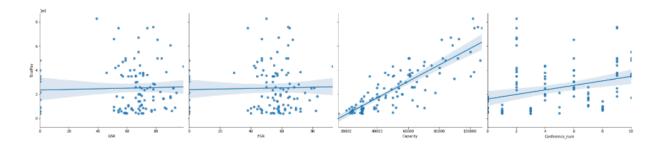
- R-square value

A marginally better R-square = 0.776

P-value

o P-value conference_num < 0.05 indicates being statistically significant.

Pair plots of the line of least squares updated with Conference:



Based on the linear regression model/Model-2, the prediction of Coach Dino Babers' salary is approximated to **2,769,900USD** if Syracuse was in Big-Ten conference.



NOTE:

Conference num is changed to 9 which maps to the 'Big Ten' conference per the dictionary.

Conclusions

The conclusions are mostly presented by answering the questions we originally sought out to answer and covered to some depth throughout this document.

Questions:

- What would his salary be if we were still in the Big East? What if we went to the Big Ten? The dataset across all the data-frames did not comprise any data from Big East.

However, taking column *Conference* into consideration when training the model, prediction has it that Coach Dino Babers' salary could be \sim 15% higher and approximately be **2,769, 900USD**.

- What schools did we drop from our data, and why?
 As stated earlier in the Data cleaning/munging section, had to drop 17-rows or schools owing to the following:
 - o when retrieving data related to GSR/FGR certain schools from the Coaches dataset could not be matched or found. This resulted in *EIGHTEEN* records being removed or dropped
 - o similarly, *FIFTEEN* schools could not be matched or found in stadium capacity data. These were removed too.

- What effect does graduation rate have on the projected salary?
 Graduation rate or GSR does not seem to have a significant role. This is manifested by high P-values and the line of least square plots in the Results section.
- How good is our model?

 One of the measures of a good linear regression model is an R-square value tending towards 1.0 and we have both models yield >0.75. making a moderately good model.
- What is the single biggest impact on salary size?

 Capacity of stadiums has the largest impact on the Salary of coaches. This is corroborated with low P-values and low variance when plotted on the line of least squares.

Speaking in more general terms, bigger stadiums or more seating capacity would certainly put more revenue into the sport as it promotes bolstering the local economy (sale of merchandise, food/beverages, car-parking etc.) and this likely drives the stakes up for sustaining good Team performances, better Coaches and therefore higher Coach salaries.