Jeff Levesque

Professor Fox

IST 718

Lab #1

**Introduction**

Coaching salaries are often topics of interest within many educational institutions. The privilege of education is generally an attempt to foster intellectual growth, to better prepare students for the eventual workplace. Thus, one may wonder whether the purpose of athletics at these educational institutions is to build character, and interpersonal problem-solving skill. Then, should a coaches’ salary should be contingent on graduation success rate, along with season performance? However, in some cases, if the ability of a team to generate income is the major factor, should stadium attendance, and team performance be major factors on the coaches’ salary? Before attempting to tackle such questions, understanding the driving mechanisms is a fundamental first step.

In this study both linear regression, and ordinary least squares will be used to predict a recommended salary for the Syracuse football team. Therefore, several data sources will need to be aggregated to allow a normalized comparison between various NCAA Division I coaches. Then, out of the chosen factors, a determination will be made, indicating which were factors were significant for the given model.

**Analysis**

Data Preparation:

Four csv datasets were used, three were manually created using various sources:

* coaches: supplied list of division 1 football coaches
* season\_2017[[1]](#footnote-1)
* ncaa football stadiums[[2]](#footnote-2)
* graduation rates[[3]](#footnote-3)

Typical conversion techniques were implemented, including conversion to lowercased, replacing non-numeric characters to empty spaces, along with coercing numeric values from string. However, since multiple datasets were loaded to their own dataframes, each eventually needed to be joined. Therefore, standardization required column names to be consistently coded:

stadium['school'] = stadium['school'].replace(['ucf'], 'central florida')

stadium['school'] = stadium['school'].replace(['usf'], 'south florida')

stadium['school'] = stadium['school'].replace(['utsa'], 'texas-san antonio')

Techniques such as these, allowed the stadium dataframe to join with the coaches dataframe, then with the grad\_rate, and season\_2017 dataframes. Once all three dataframe were joined, a single merged\_df was used for successive analysis.

However, since requirements for this study involved the 2006 student athlete cohort, stadiums expanded after 2006 were removed. Otherwise, the parameters for the graduation rates would not be relevant.

Finally, the train was created using 2/3 of the original merged\_df dataset, while the remaining 1/3 was reserved for testing. This allowed the sklearn LinearRegression, as well as the scipy ols (ordinary least squares) to be implemented for model fitting. Originally, several independent variables were used for training:

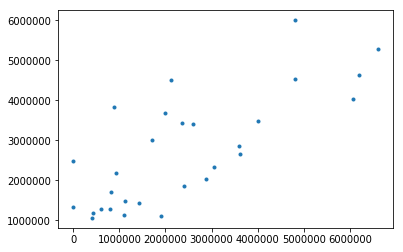
* capacity: football stadium capacity
* gsr: graduation success rate
* fgr: federal graduation rate
* win: total 2017 season wins for a given team
* loss: total 2017 season losses for a given team
* pct: ratio of win / loss

However, the independent variables were reduced to the following:

* capacity: football stadium capacity
* gsr: graduation success rate
* pct: ratio of win / loss

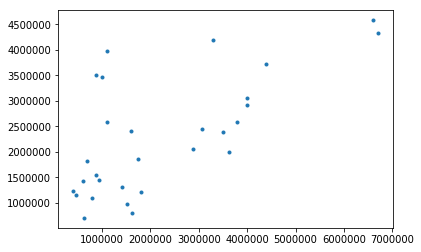
**Results**

The determined LinearRegression fit generated an r-squared of 0.512:



This indicates the model is not good at accounting variance of coaches’ salary with the selected independent variables. Using the associated model, the predicted salary for a Syracuse football coach is estimated at $1,863,383.60.

Next, the ols model was computed using the same factors:



This method generated better insight, by providing measures indicating which components of the model were significant:

OLS Regression Results

==================================================w============================

Dep. Variable: schoolpay R-squared: 0.814

Model: OLS Adj. R-squared: 0.804

Method: Least Squares F-statistic: 78.90

Date: Sun, 28 Oct 2018 Prob (F-statistic): 9.84e-20

Time: 01:00:55 Log-Likelihood: -876.87

No. Observations: 57 AIC: 1760.

Df Residuals: 54 BIC: 1766.

Df Model: 3

Covariance Type: nonrobust

==============================================================================

coef std err t P>|t| [0.025 0.975]

------------------------------------------------------------------------------

capacity 53.6009 7.966 6.729 0.000 37.630 69.572

gsr -1.436e+04 6615.861 -2.171 0.034 -2.76e+04 -1098.499

pct 9.094e+05 6.66e+05 1.365 0.178 -4.26e+05 2.24e+06

==============================================================================

Omnibus: 0.365 Durbin-Watson: 2.424

Prob(Omnibus): 0.833 Jarque-Bera (JB): 0.050

Skew: 0.048 Prob(JB): 0.976

Kurtosis: 3.109 Cond. No. 2.26e+05

==============================================================================

Specifically, the stadium capacity, along with gsr for a given team are significant. The pct wins was not significant for the overall model, while the above 9.84e-20 Prob (F-Statistic) indicates a significant regression model. Most importantly, the ols model generated an r-squared of 0.814. This indicates a significantly better result than the LinearRegression. Furthermore, the 2.424 for the Durbin-Watson indicates limited autocorrelation exists between the selected factors. Therefore, the selected factors to train were not redundant. The computed prediction of what a Syracuse football coach was found to be $1,837,076.

Since the ols method proved to generate better results, this implementation was used for the hypothetical scenario if Syracuse was in the Big 10. The dataset used was significantly reduced, by filtering on the Big 10 conference:

train\_big10, test\_big\_10 = train\_test\_split(merged\_df[merged\_df['conference'] == 'big ten'], test\_size=0.33)

The corresponding model generated a nonsignificant probability F-Statistic, with an overall salary prediction of $3,437,561. Additionally, the corresponding factors were all nonsignificant:

OLS Regression Results

==============================================================================

Dep. Variable: schoolpay R-squared: 0.992

Model: OLS Adj. R-squared: 0.969

Method: Least Squares F-statistic: 42.15

Date: Sun, 28 Oct 2018 Prob (F-statistic): 0.113

Time: 01:41:52 Log-Likelihood: -56.963

No. Observations: 4 AIC: 119.9

Df Residuals: 1 BIC: 118.1

Df Model: 3

Covariance Type: nonrobust

==============================================================================

coef std err t P>|t| [0.025 0.975]

------------------------------------------------------------------------------

capacity 21.0401 21.313 0.987 0.504 -249.763 291.843

gsr 2.861e+04 5.64e+04 0.508 0.701 -6.88e+05 7.45e+05

pct 5.94e+05 6.84e+06 0.087 0.945 -8.63e+07 8.75e+07

==============================================================================

Omnibus: nan Durbin-Watson: 1.994

Prob(Omnibus): nan Jarque-Bera (JB): 0.607

Skew: -0.004 Prob(JB): 0.738

Kurtosis: 1.092 Cond. No. 1.38e+06

==============================================================================

Instead of filtering the dataset on the Big 10 conference, it may have been more appropriate to factor the column into integer values, then retain the column during train. The latter implementation had too few coaches to accurately model the given scenario. Furthermore, since the original coach dataset does not contain any Big East coaches, a similar hypothetical question of a Syracuse coach being in the Big East cannot be estimated.

To better improve the overall modeling, rows with missing coaching salaries (normalized to $0), could have been forced to the test set. Rather in this study, the test and train set were randomly distributed.

**Conclusions**

Choosing an appropriate regression model is often an important task when attempting to make a prediction. As indicated in this study, the linear regression model using sklearn LinearRegression generates an r-squared significantly worse than the ordinary least squares available through the statsmodel package. Both techniques though having different results, internally implement the ordinary least squares model. Therefore, given more time, it would be interesting to determine which parameters could be adjusted using the sklearn, and whether model performance could be improved. Additionally, both techniques suggest that a Syracuse football coach should make roughly $1.8M. More generally, the predicted coaches’ salary is significantly lower than the current $2.4M.

When trying to understand the discrepancy between the two salaries, its difficult to argue that the team record was not accounted for, since in 2017, the football team had a 4-8 record. Additionally, the graduation success rate as 77 for 2006 was about average relative to other teams used for the analysis. However, when reviewing the overall model holistically, it does not seem like a reasonable approach. Specifically, using the 2006 graduate success rate, while using the 2017 (last years) season record seem disjoint. Having this level of difference, would have a large impact on the overall model. Instead, having the two factors both represent 2006, or 2017 would be more appropriate when generating the corresponding model.

Lastly, more data for the coaches’ dataset would have improved the overall model. Specifically, no coaching information was provided for the Big East conference in the original coaches’ dataset. Therefore, attempting to answer any related question would not have been possible without additional data aggregation.

1. Google search: ncaa 2017 football [↑](#footnote-ref-1)
2. <https://github.com/gboeing/data-visualization/blob/master/ncaa-football-stadiums/data/stadiums-geocoded.csv> [↑](#footnote-ref-2)
3. <http://www.ncaa.org/about/resources/research/graduation-rates> [↑](#footnote-ref-3)