Data Analysis on Whether Underperforming Coaches are More Likely to be Fired in College Basketball¶

By Aaron Cronin, Thomas Hurtubise, and Tony Rosler

Executive Summary of Each Section

Section 1: Introduces research question, does single-season underperformance mean a coach is more likely to be fired?
Section 2: Establishes the benchmark performance level for each school using 20 years of win-loss data.
Section 3: Evaluates coach firings and use performance data to run regressions to reveal the relationship between performance and firing.
Section 4: Explores whether the chosen benchmark may be flawed using machine learning techniques.
Section 5: Concludes on the findings and provide future research avenues.

Section 1: Introduction

Turnover at the head of college athletics teams is an interesting phenomenon. These highly paid positions have their job performance televised and scrutinized by sports analysts and commentators who pontificate on whether any given season may be a coach's last. As a result, this report is motivated to explore one of the most salient indicators of performance, the win-loss record for a coach over the course of a season, to determine how this factor indicates whether a coach will be fired after that season. One's intuition may predict that the performance of a college basketball team would obviously portend to a coach's firing, but the empirical findings may murky that clear heuristical picture.

Section 2: Setting Performance Benchmarks and other School Level Analysis

To evaluate whether a coach underperformed in a given season, one must first determine the benchmark for performance. Across college basketball as a whole, the mean performance for all teams is an even number of wins and losses, or .500 on a scale where zero is all losses and 1 is all wins. This expected value arises because college basketball is a zero-sum game; for every team that wins, another must lose. However, using .500 as the benchmark for a coaches' performance is fallacious. Each team is apt to have different standards for its coach because not all schools perform at an equal level. Some teams that win far more than they lose, and vice versa for other teams.

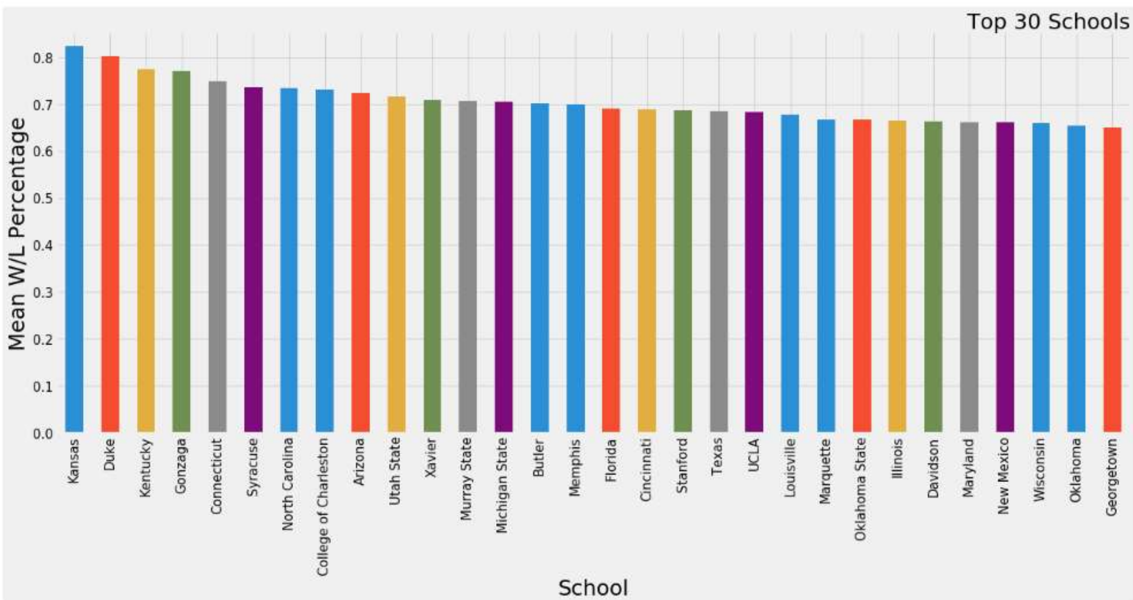
In an effort to quantify this performance differential by school, we pulled 20 years of data from https://www.sports-reference.com/cbb/ which reports college basketball figures statistics. We selected the 1993-1994 season up until the 2012-2013 season. We chose this range because we wanted to make sure that the performance benchmarks we created would be align with how teams have performed over a medium timespan. Too few years may lack validity, as certain teams may have performed notably well or poorly, skewing the data. Conversely, too many years would lead to the inclusion of data that is too old to factor into institutional decision making because of changes to the sport and the level of competition. Twenty years strikes a fair middle ground. Additionally, we stopped at the 2012-2013 season, so we could have five years of coaching performance data starting with the 2013-2014 season that are not auto-correlated with the data used to create the performance benchmarks. Finally, in the initialized DataFrames, the data from a given year is notated using the first year for the season unless stated otherwise, meaning the 1993-94 season is given by 1993.

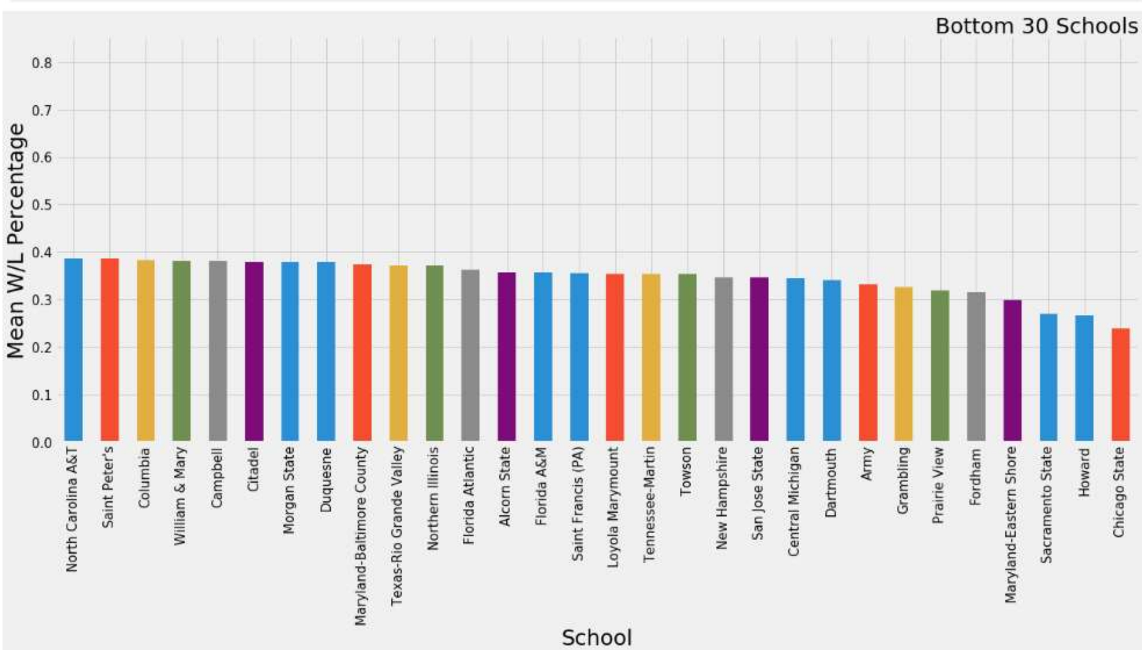
To explore each team's performance, we created a dictionary that contained the 20 separate DataFrames for each year of data. The dictionary stores the name of the DataFrames as the keys, and the actual DataFrames as the values, allowing us to iterate over the keys by making them into a callable list. Subsequently, we created an if-else statement nested within a for loop that could quickly select the columns from each DataFrame with the parameter of interest, namely the win-loss percentage for each school, and merge them on school to a new DataFrame containing 20 years of win-loss records by school. The DataFrames for each year are identical in shape and column headings, so we could use the same index numbers to slice all of the DataFrames as we merged them. We chose to use inner when running this merge to eliminate all the schools that do not have all 20 years of data. Schools that were eliminated fall into one of two categories: either they have stopped competing in college basketball and thus will not have coaching data in the range in which we are interested, or they are newer teams whose coaching may be more or less volatile than average. By limiting our data set to established teams, we can mitigate the potential for confounding from the potential volatility from the newer teams altering our statistical models. Even with this selection process, we still have nearly 300 Schools to consider in the full DataFrame.

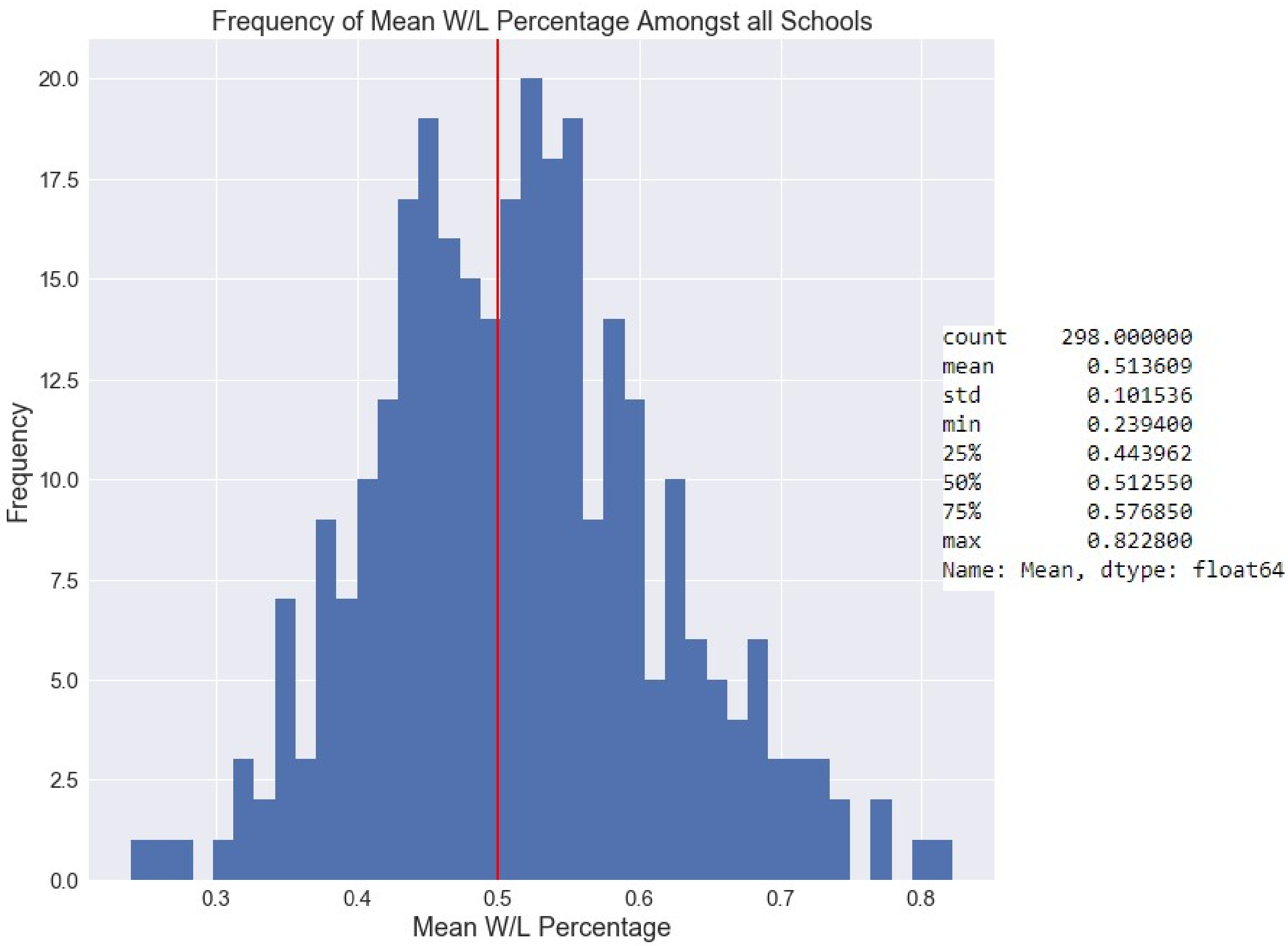
	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
School																				
Air Force	0.308	0.286	0.179	0.269	0.385	0.385	0.286	0.276	0.321	0.429	0.759	0.600	0.774	0.743	0.533	0.323	0.323	0.500	0.448	0.563
Akron	0.308	0.308	0.115	0.308	0.630	0.667	0.607	0.429	0.323	0.500	0.464	0.655	0.697	0.788	0.686	0.639	0.686	0.639	0.647	0.788
Alabama-Birmingham	0.733	0.467	0.533	0.563	0.636	0.625	0.500	0.548	0.433	0.618	0.688	0.667	0.774	0.484	0.676	0.647	0.735	0.710	0.484	0.485
Alabama State	0.655	0.423	0.333	0.276	0.393	0.407	0.464	0.710	0.594	0.483	0.516	0.500	0.400	0.333	0.645	0.688	0.516	0.486	0.387	0.313
Alabama	0.667	0.697	0.594	0.548	0.484	0.531	0.448	0.694	0.771	0.586	0.606	0.750	0.581	0.625	0.515	0.563	0.531	0.676	0.636	0.639

After performing some column renaming to make the data more easily readable, we calculated the average win-loss percentage for all the teams to verify our initial assumption about the performance differential between the teams. From here, we have made a series of graphs to explore the statistical features of the different performance levels for various college basketball teams.

School	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	...	2004	2005	2006	2007	2008	2009	2010	2011	2012	Mean
Kansas	0.771	0.806	0.853	0.944	0.897	0.697	0.706	0.788	0.892	0.789	...	0.767	0.758	0.868	0.925	0.771	0.917	0.921	0.821	0.838	0.82280
Duke	0.824	0.419	0.581	0.727	0.889	0.949	0.853	0.897	0.886	0.788	...	0.818	0.889	0.667	0.824	0.811	0.875	0.865	0.794	0.833	0.80135
Kentucky	0.794	0.848	0.944	0.875	0.897	0.757	0.697	0.706	0.688	0.889	...	0.824	0.629	0.647	0.581	0.611	0.921	0.763	0.950	0.636	0.77505
Gonzaga	0.733	0.700	0.700	0.556	0.706	0.800	0.743	0.788	0.879	0.727	...	0.839	0.879	0.676	0.758	0.824	0.794	0.714	0.788	0.914	0.77105
Connecticut	0.853	0.848	0.914	0.545	0.865	0.944	0.714	0.625	0.794	0.697	...	0.742	0.882	0.548	0.727	0.861	0.529	0.780	0.588	0.667	0.74845







The graphs of the top and bottom 30 teams reveal there are teams that compete at a very high level and those that compete at a very low level, confirming our original assumption. All of the top 30 schools' average performance exceeds .600, and Kansas and Duke both exceed .800, meaning they have won 80% of their games from 1993-2013. Conversely, none of the bottom 30 schools exceed .400, and Chicago State won less than 25% of its games over the same 20 years. The histogram of win-loss averages illustrates the full spectrum of school performance levels and shows that an average performance level is distributed roughly normally around .500, which makes sense given the zero-sum nature of college basketball. Interestingly, the histogram reveals two distinct peaks on either side of .500, meaning more teams do somewhat better or worse than average than those that actually match the average. Additionally, the mean of the win-loss averages is slightly above .500. Ultimately, this anomaly means that the teams eliminated in the merging process lost games at a slightly higher rate than those included in the model. This finding heuristically makes sense when considering that the merging process eliminated teams that stopped competing or new teams that may still be adjusting to the level of competition in Division 1 college basketball.¶

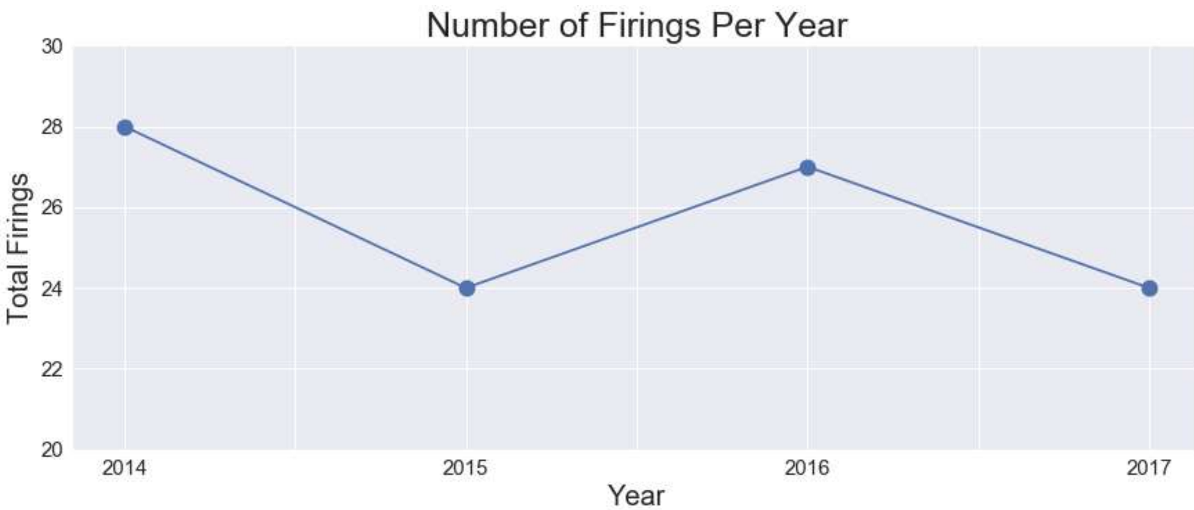
Given that the data supports our assumptions about the differential performance levels of the college basketball teams, we feel comfortable using the average win-loss percentage across 20 years for each school as the benchmark of performance against which coaches are measured when Universities make firing decisions.

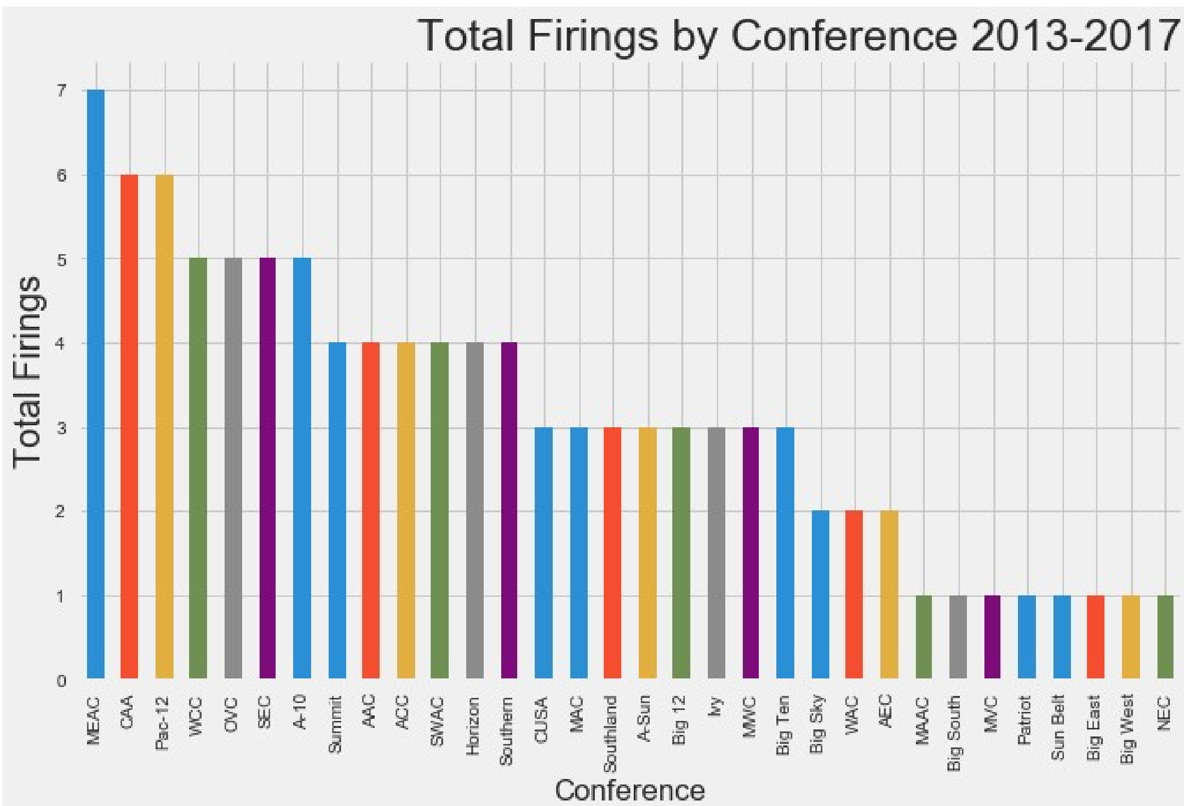
Section 3: Analyzing Coach Firing Using Underperformance Relative to Historical Benchmarks¶

Using the same website as before, we created five DataFrames with coaching data and merged them to make a master DataFrame. At this point, we realized that although we would be able to delineate between coaches who were present one year and gone the next, that would not reveal whether or not their departure was because they were fired. Coaches also resign to pursue better coaching positions, often predicated on good performance in their current coaching job, or retire, neither of which is congruent with our model. Therefore, we decided to get a list of all the coaches who were fired as given by http://collegesportsinfo.com and use the export function to pull the master coach DataFrame and manually add columns that show whether or not a coach was fired and when. In the notation for when a coach was fired, 2014 refers to being fired after the 2013-2014 season, and so on up until 2017. We did not include 2018 firings to potentially test and see whether or not our regressions could create a threshold of single season underperformance that we could apply to the 2017-18 season to assess its validity in predicting actual fired coaches. Once the variables of if and when a coach was fired had been added, we imported the new DataFrame to run further analysis.

Now that the data includes who was fired and when, we decided to create some plots to explore some interesting features of just the fired coaches, such as how many firings happened per year and which conferences fired the most coaches.

	Unnamed: 0	Coach	School_x	Conference_x	W_2013	L_2013	W-L%_2013	AP_Pre_2013	AP_Post_2013	NCAA_Tournament_2013	...	FIRED?	WHEN
3	3	Anthony Grant	Alabama	SEC	13.0	19.0	0.406	NaN	NaN	NaN	...	Y	2015.0
8	8	Luther Riley	Alcorn State	SWAC	12.0	19.0	0.387	NaN	NaN	NaN	...	Y	2015.0
10	10	Jason Capel	Appalachian State	Southern	9.0	21.0	0.300	NaN	NaN	NaN	...	Y	2014.0
12	12	Herb Sendek	Arizona State	Pac-12	21.0	12.0	0.636	NaN	NaN	Lost Second Round	...	Y	2015.0
14	14	Steve Shields	Little Rock	Sun Belt	15.0	17.0	0.469	NaN	NaN	NaN	...	Y	2015.0





First, looking at the number of firings per year, we noticed that they are remarkably stable, oscillating between 24 and 28 across all four years. Next, using groupby, we took the coach level data and aggregated up to the conference level to create a plot of the conferences that fire the most coaches. This graph was meant to give some insight as to whether major or minor conferences are more likely to fire coaches. Yet, the graph shows that both are among the highest frequency firers, with large conferences like the Pac-12 and SEC and small conferences like the MEAC and CAA all firing 5 or more coaches in 4 years, which is interesting in its own right.

Having examined these basic features of just the fired coaches, we moved to explore all the coaches at schools where we generated performance benchmarks to see if there is a strong correlation between a coach underperforming in one season and their being fired. To determine the actual degree of underperformance, we subtracted the average win-loss percentage for each school over 20 years from the corresponding coach's win-loss percentage in each season, giving us nearly 300 coaches performance for each of the 5 years of coaching data. Once we had generated this coach performance data, we created a new DataFrame that only contained performance data. In the performance DataFrame we established binary variables that capture whether or not a coach underperformed in each season by creating code with a lambda function that filled columns with a 1 if a coach's performance value was negative for that season. Finally, we established another set of binary columns to capture if and when each coach was fired to enable us to run regressions, where a 1 in the column Fired2014 means they were fired after the 2013-2014 season and so on. With these manipulations we can finally assess whether there is a relationship between a coach underperforming in a season and whether they were fired after that season.

	Coach	School_x	Conference_x	FIRED?	WHEN	Performance_2013	Performance_2014	Performance_2015	Performance_2016	Performance_2017
0	Joe Golding	Abilene Christian	Southland	N	NaN	NaN	NaN	NaN	NaN	NaN
1	Dave Pilipovich	Air Force	MWC	N	NaN	-0.0345	0.0175	0.0035	-0.0705	-0.04750
2	Keith Dambrot	Akron	MAC	N	NaN	0.0738	0.0558	0.1988	0.2058	0.12170
3	Anthony Grant	Alabama	SEC	Y	2015.0	-0.2011	-0.0451	NaN	NaN	-0.12765
4	Willie Hayes	Alabama A&M	SWAC	N	NaN	NaN	NaN	NaN	NaN	NaN

Under_Performance_2013	Under_Performance_2014	Under_Performance_2015	Under_Performance_2016	Under_Performance_2017	Never_fired	Fired2015	Fired2014	Fired2017	Fired2016
NaN	NaN	NaN	NaN	NaN	1	0	0	0	0
1.0	0.0	0.0	1.0	1.0	1	0	0	0	0
0.0	0.0	0.0	0.0	0.0	1	0	0	0	0
1.0	1.0	NaN	NaN	1.0	0	1	0	0	0
NaN	NaN	NaN	NaN	NaN	1	0	0	0	0

This first set of regressions explores the relationship between whether a coach underperforms and whether they were fired using the binary underperformance and firing variables. As a result, these regressions have some unique properties, and do not take into account the degree to which any given coach underperformed.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Fired2014   R-squared:                       0.057
Model:                             OLS   Adj. R-squared:                  0.053
Method:                  Least Squares   F-statistic:                     17.75
Date:                 Fri, 21 Dec 2018   Prob (F-statistic):           3.36e-05
Time:                         01:05:16   Log-Likelihood:                -37.155
No. Observations:                  298   AIC:                             78.31
Df Residuals:                      296   BIC:                             85.70
Df Model:                            1
Covariance Type:             nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
Intercept                  0.0201      0.023      0.894      0.372      -0.024       0.064
Under_Performance_2013     0.1342      0.032      4.213      0.000       0.072       0.197
==============================================================================
Omnibus:                      173.663   Durbin-Watson:                   2.085
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              749.329
Skew:                           2.651   Prob(JB):                    1.93e-163
Kurtosis:                       8.679   Cond. No.                         2.62
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Fired2015   R-squared:                       0.027
Model:                             OLS   Adj. R-squared:                  0.024
Method:                  Least Squares   F-statistic:                     8.148
Date:                 Fri, 21 Dec 2018   Prob (F-statistic):            0.00462
Time:                         01:05:16   Log-Likelihood:                -6.3731
No. Observations:                  297   AIC:                             16.75
Df Residuals:                      295   BIC:                             24.13
Df Model:                            1
Covariance Type:             nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
Intercept                  0.0267      0.020      1.317      0.189      -0.013       0.067
Under_Performance_2014     0.0822      0.029      2.854      0.005       0.026       0.139
==============================================================================
Omnibus:                      221.565   Durbin-Watson:                   2.132
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1622.923
Skew:                           3.307   Prob(JB):                         0.00
Kurtosis:                      12.349   Cond. No.                         2.61
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fired2016   R-squared:                       0.027
Model:                            OLS   Adj. R-squared:                  0.023
Method:                 Least Squares   F-statistic:                     8.217
Date:                Fri, 21 Dec 2018   Prob (F-statistic):            0.00444
Time:                        01:05:16   Log-Likelihood:                -35.491
No. Observations:                 301   AIC:                             74.98
Df Residuals:                     299   BIC:                             82.40
Df Model:                           1
Covariance Type:            nonrobust
============================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
Intercept                  0.0390      0.022      1.770      0.078      -0.004       0.082
Under_Performance_2015     0.0903      0.031      2.867      0.004       0.028       0.152
==============================================================================
Omnibus:                      193.005   Durbin-Watson:                   2.096
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              987.122
Skew:                           2.895   Prob(JB):                    4.46e-215
Kurtosis:                       9.722   Cond. No.                         2.59
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

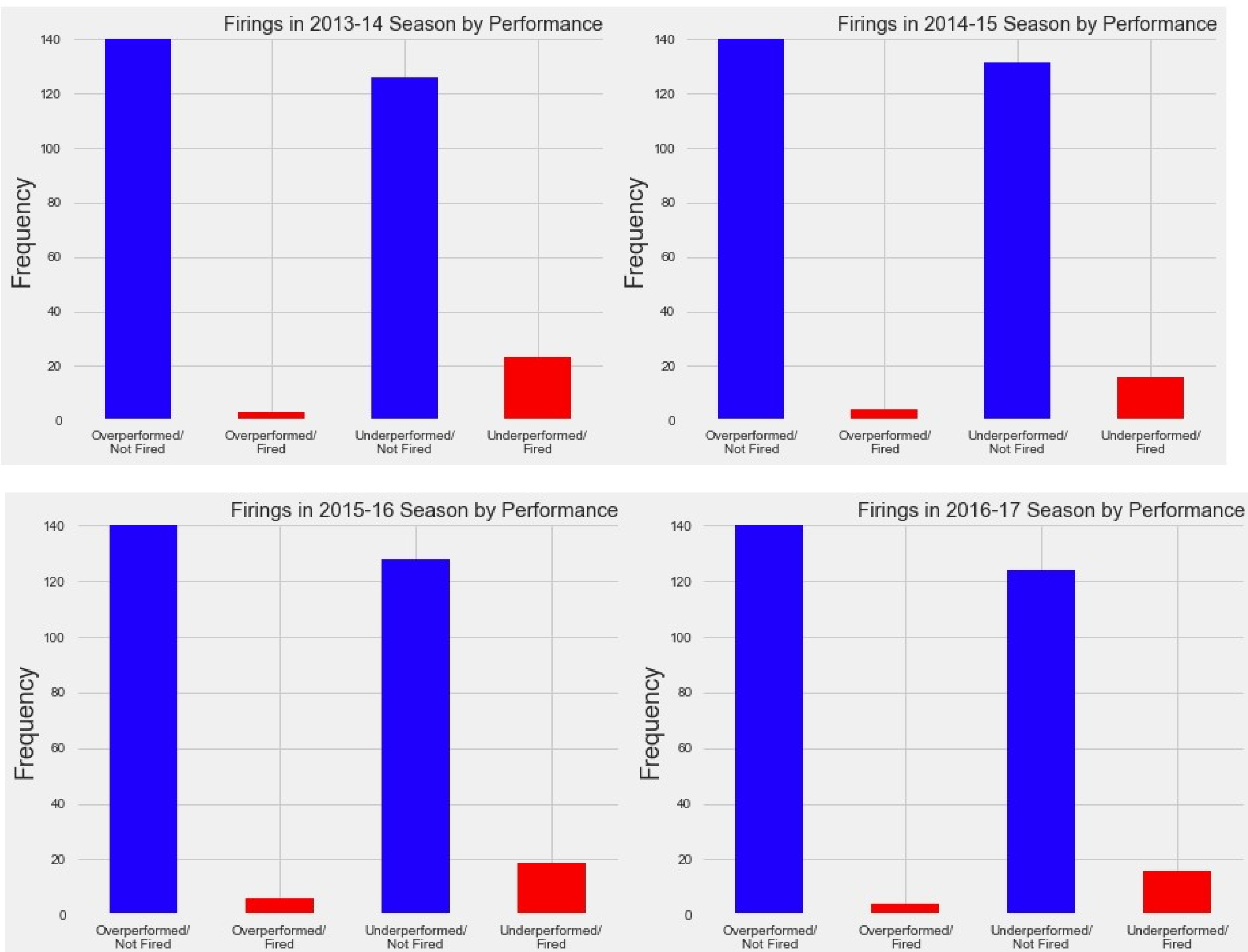
```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fired2017   R-squared:                       0.032
Model:                            OLS   Adj. R-squared:                  0.028
Method:                 Least Squares   F-statistic:                     9.720
Date:                Fri, 21 Dec 2018   Prob (F-statistic):            0.00200
Time:                        01:05:16   Log-Likelihood:                -4.7438
No. Observations:                 299   AIC:                             13.49
Df Residuals:                     297   BIC:                             20.89
Df Model:                           1
Covariance Type:            nonrobust
============================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
Intercept                  0.0252      0.020      1.286      0.199      -0.013       0.064
Under_Performance_2016     0.0891      0.029      3.118      0.002       0.033       0.145
==============================================================================
Omnibus:                      222.288   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1628.344
Skew:                           3.294   Prob(JB):                         0.00
Kurtosis:                      12.343   Cond. No.                         2.55
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Using the four years of firing data against the binary underperformance variable for each commensurate season, the regressions revealed very low R-squared values across the board, ranging from .027 to .057. This figure means that only ~3%-6% of the variance in fired coaches can be explained by whether or not coaches underperformed. As a result, the greatest correlation, found in the 2013-2014 season, is only r = .239, which is fairly weak. Despite this small relationship, the F-statistics were 8.217 or greater, demonstrating that each regression has a less than 1% likelihood of being due to random chance, meaning these relationships are still statistically significant. The coefficients on the underperformance variable within the regressions also have statistically significant t-statistics.

The conditional expectation function in these regressions also reveals the underwhelming nature of the result. The expected value for the dependent variable whether or not a coach was fired, given as E[Fired] is conditional on whether or not a coach underperformed. If they did not underperform, E[Fired] is equivalent to the coefficient for the intercept, which shows a 2-4% chance of a coach being fired if they overperformed depending on the year. If the coach did underperform E[Fired] is equivalent to the intercept coefficient plus the underperformance coefficient, which corresponds to only an 11-15% chance of firing for underperforming coaches.

Overall, these results were underwhelming as we were hoping this underperformance indicator would demonstrate a stronger correlation between coaches that underperform and those who are fired. To explore why this result occurred, we chose to look again at the total number of coaches who were fired in a given year and compare that to whether they overperformed or underperformed the benchmark, as too many overperformers being fired may hinder the result of the regression.



These four bar plots confirm a general expectation: fired coaches are more likely to be underperforming coaches. The Underperformed/Fired is larger than Overperformed/Fired in every graph. However, these graphs more clearly depict that far more coaches that underperform are not fired than those that are. This finding means that the regressions failed to show a stronger correlation because there simply are not that many coaches being fired in a given year. Additionally, the 2013-14 season showing the strongest correlation supports this assertion because it was the year with the most firings total.¶

Yet, we felt the degree of performance may still be a significant factor, as the coaches who slightly underperform may keep their jobs, but those who significantly underperform ought to be more likely to be fired. We examined this premise with the following regressions.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fired2014   R-squared:                       0.092
Model:                            OLS   Adj. R-squared:                  0.089
Method:                 Least Squares   F-statistic:                     29.88
Date:                Fri, 21 Dec 2018   Prob (F-statistic):           9.78e-08
Time:                        01:05:17   Log-Likelihood:                -31.503
No. Observations:                 298   AIC:                             67.01
Df Residuals:                     296   BIC:                             74.40
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept          0.0889      0.016      5.686      0.000       0.058       0.120
Performance_2013  -0.5843      0.107     -5.466      0.000      -0.795      -0.374
==============================================================================
Omnibus:                      164.203   Durbin-Watson:                   2.080
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              660.448
Skew:                           2.508   Prob(JB):                    3.85e-144
Kurtosis:                       8.294   Cond. No.                         6.84
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fired2015   R-squared:                       0.034
Model:                            OLS   Adj. R-squared:                  0.031
Method:                 Least Squares   F-statistic:                     10.37
Date:                Fri, 21 Dec 2018   Prob (F-statistic):            0.00143
Time:                        01:05:17   Log-Likelihood:                -5.2895
No. Observations:                 297   AIC:                             14.58
Df Residuals:                     295   BIC:                             21.97
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept            0.0675      0.014      4.705      0.000       0.039       0.096
Performance_2014    -0.2937      0.091     -3.220      0.001      -0.473      -0.114
==============================================================================
Omnibus:                      219.083   Durbin-Watson:                   2.101
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1571.742
Skew:                           3.267   Prob(JB):                         0.00
Kurtosis:                      12.183   Cond. No.                         6.36
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fired2016   R-squared:                       0.046
Model:                            OLS   Adj. R-squared:                  0.043
Method:                 Least Squares   F-statistic:                     14.44
Date:                Fri, 21 Dec 2018   Prob (F-statistic):           0.000176
Time:                        01:05:17   Log-Likelihood:                -32.475
No. Observations:                 301   AIC:                             68.95
Df Residuals:                     299   BIC:                             76.36
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept            0.0840      0.016      5.390      0.000       0.053       0.115
Performance_2015    -0.3682      0.097     -3.800      0.000      -0.559      -0.177
==============================================================================
Omnibus:                      187.567   Durbin-Watson:                   2.116
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              920.896
Skew:                           2.811   Prob(JB):                    1.07e-200
Kurtosis:                       9.467   Cond. No.                         6.22
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

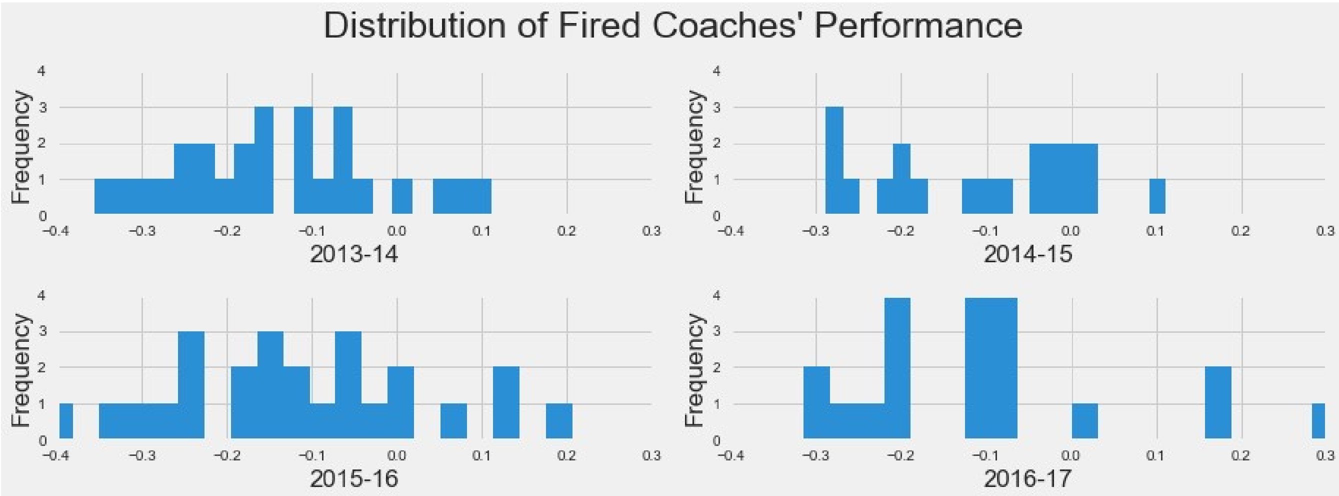
```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fired2017   R-squared:                       0.029
Model:                            OLS   Adj. R-squared:                  0.026
Method:                 Least Squares   F-statistic:                     8.943
Date:                Fri, 21 Dec 2018   Prob (F-statistic):            0.00302
Time:                        01:05:17   Log-Likelihood:                -5.1228
No. Observations:                 299   AIC:                             14.25
Df Residuals:                     297   BIC:                             21.65
Df Model:                           1
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept            0.0665      0.014      4.656      0.000       0.038       0.095
Performance_2016    -0.2715      0.091     -2.991      0.003      -0.450      -0.093
==============================================================================
Omnibus:                      223.773   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1663.103
Skew:                           3.317   Prob(JB):                         0.00
Kurtosis:                      12.459   Cond. No.                         6.36
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The results of regressing degree of performance against firing did not prove to be much better than the previous regressions. Some R-squared values increased as they now range from .029 to .092, but curiously the R-squared value for the 2016-2017 season fell. Ultimately the highest correlation at r = .3033 is still in the 2013-14 season, which has the highest number of firings. The F-statistics range from 8.943 to 29.88, showing that despite the fact that the degree of performance still predicts very little variance in firings, the result is statistically significant. Likewise, the coefficients also have statistically significant t-values across the board.

With this data set we hoped to use the conditional expectation function to determine an exact threshold for underperformance beyond which point a coach would be more likely to be fired. To determine this threshold for each regression, one could set y-hat equal to .5 and manipulate the CEF to get x, the performance level, alone on one side of the equation. Thus, (.5-intercept_coefficient)/performance_coefficient should reveal that threshold. However, in practice, all but one of the thresholds are less than -1, which is impossible. The value -1 is the absolute limit for performance and would represent a team that won every game for the 20-year period we assessed to set the benchmark and then lost every game in one of the season we assessed in the coach DataFrames. The only possible threshold is 2013-2014 at -0.7036, however no coach came anywhere near this value, meaning it has no predictive validity.¶

Again, we found the lack of a stronger result fairly surprising and decided to examine the degree of underperformance among the fired coaches in each year using histograms to see if our prediction that the worst performing coaches were the ones that were fired was actually true.

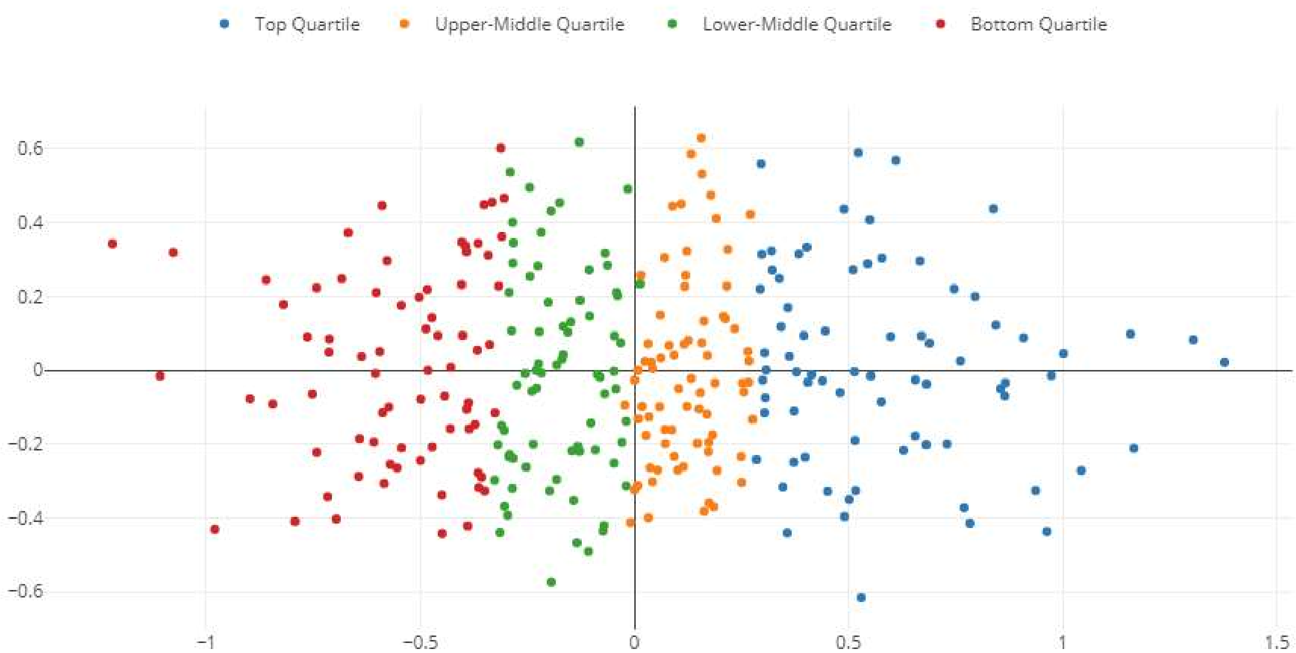


These histograms demonstrate that fired coaches come from all levels of performance, and even include some overperformers as the bar plots also showed. This result revealed why regressing on degree of performance did not provide much more validity than just a coach underperforming. Additionally, the 2016-2017 season had the highest positive outlier, with a fired coach who significantly overperformed, which may demonstrate why the 2016-2017 regression on degree of performance against firing was the weakest.

Without any clear threshold for underperformance that makes a coach more likely to be fired, we have no way to predict which coaches would be fired from the 2017-2018 season. Instead, we turned to the benchmark itself, the average win-loss percentages for all the schools. Perhaps simplifying 20 years of data into a single metric is not a valid benchmark, and therefore threw off our calculations and regressions. As a result, we decided to explore ways to reintroduce information lost in the process of distilling the variables to see if they retained similar stratification.

Section 4: Using Machine Learning Techniques to Assess Performance Clusters in 2 Dimensions

Using PCA from Scikit Learn, we can decompose our twenty years of win-loss percentages into a set number of dimensions and assess how much information each level reveals. The explained variance ratio attribute demonstrates how much information about the original data is given by each component when a DataFrame is limited to fewer dimensions. Using the win-loss data by school, simplifying the data to one dimension, like taking the mean win-loss percentage across 20 years, gives only 33% of the information contained in all 20 years. Having two dimensions means the two values provide over 44% of the information. Although this is still not the entire picture of each school’s performance, we can create labels using the original one-dimensional stratification by sorting schools into 4 quartiles based on their mean win-loss percentage, and graphically see if those quartiles make distinct clusters when the performance data is decomposed into two dimensions to assess the veracity of the benchmark we chose.



NOTE: If an error appears when looking at this block of code or the plot does not appear, check to make sure you have plotly installed and reopen it or follow this link to see the same interactive plot on the plotly website https://plot.ly/~tcr278/0¶

The scatterplot demonstrates that the quartiles established by the mean still show up in very clear clusters when the scatterplot assess the school's performance in two dimensions. These clusters show that although the benchmark we chose does eliminate information about the performance of the schools, it still seems to tell a lot about their relative standing amongst other college basketball teams. Ultimately, this suggests that the benchmark was also not the cause for the limited findings from the regression, meaning the most likely culprit was the low n for firings.

Section 5: Conclusion and Future Research Opportunities

The data as analyzed ultimately suggests that a coach who underperforms in any given season is only slightly more likely to be fired, and degree of underperformance does not significantly compound that probability. As a result, one must conclude that other factors contribute to firing decisions in college basketball, and others may loom larger than a coach's performance. For example, whether or not a coach underperforms in multiple successive years may predict firing. Firing may also hinge upon a coach's ability to win against rivals or do well in post-season tournaments. Furthermore, firing decisions may depend on harder to measure factors like a coach's successfulness as a recruiter, or their temperament and rapport with the student athletes. Additionally, scandals may cause coaches at varying levels of performance to be fired, and it would be interesting to somehow quantify how bad a scandal needs to be in order for a coach to be fired. All in all, despite the underwhelming result, our research does quantify the extent to which single-season underperformance relates to firing college basketball coaches and gives clear opportunities to further explore this phenomenon.

Section 6: Data Sources and Coding Resources Used

Data Sources:

https://www.sports-reference.com/cbb/seasons/1994-school-stats.html
https://www.sports-reference.com/cbb/seasons/1995-school-stats.html
https://www.sports-reference.com/cbb/seasons/1996-school-stats.html
https://www.sports-reference.com/cbb/seasons/1997-school-stats.html
https://www.sports-reference.com/cbb/seasons/1998-school-stats.html
https://www.sports-reference.com/cbb/seasons/1999-school-stats.html
https://www.sports-reference.com/cbb/seasons/2000-school-stats.html
https://www.sports-reference.com/cbb/seasons/2001-school-stats.html
https://www.sports-reference.com/cbb/seasons/2002-school-stats.html
https://www.sports-reference.com/cbb/seasons/2003-school-stats.html
https://www.sports-reference.com/cbb/seasons/2004-school-stats.html
https://www.sports-reference.com/cbb/seasons/2005-school-stats.html
https://www.sports-reference.com/cbb/seasons/2006-school-stats.html
https://www.sports-reference.com/cbb/seasons/2007-school-stats.html
https://www.sports-reference.com/cbb/seasons/2008-school-stats.html
https://www.sports-reference.com/cbb/seasons/2009-school-stats.html
https://www.sports-reference.com/cbb/seasons/2010-school-stats.html
https://www.sports-reference.com/cbb/seasons/2011-school-stats.html
https://www.sports-reference.com/cbb/seasons/2012-school-stats.html
https://www.sports-reference.com/cbb/seasons/2013-school-stats.html
https://www.sports-reference.com/cbb/seasons/2014-coaches.html
https://www.sports-reference.com/cbb/seasons/2015-coaches.html
https://www.sports-reference.com/cbb/seasons/2016-coaches.html
https://www.sports-reference.com/cbb/seasons/2017-coaches.html
https://www.sports-reference.com/cbb/seasons/2018-coaches.html
http://collegesportsinfo.com/2014/01/31/2014-college-basketball-coach-changes/
http://collegesportsinfo.com/2015/03/05/2015-college-basketball-coaching-changes/
http://collegesportsinfo.com/2016/01/17/2016-college-basketball-coaching-changes/
http://collegesportsinfo.com/2017/08/08/2017-college-basketball-coach-changes/

Coding Resources:

https://nyudatabootcamp.gitbook.io/thebook/
Data Bootcamp Lectures - Fall 2018
Stackoverflow for miscellaneous help
https://plot.ly/python/line-and-scatter/

Github with Complete Code and Set of Files Used for the Project¶

https://github.com/aaroncronin/CroninHurtubiseRosler_DataBootcampProject