Factors of Head Coach Salaries of Collegiate Sports Teams

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Introduction

While it seems to be common knowledge that many of the highest paid US public employees are college sports teams head coaches (Michaels 2018), less is known about the salaries of college-level sports head coaches in general. Is head coaching a lucrative career for all or only a select few? What knowledge can we gain about head coaches in private schools or across other divisions and classifications?

In this project, we examined institution-level data from the Equity in Athletics Survey, academic year 2017-2018, from the U.S. Department of Education Office of Postsecondary Education (2018). In this analysis we investigated potential predictors for salaries of sports team head coaches at four-year colleges and universities in the United States. This project focused on differences of salaries between head coaches of male teams and female teams; salary diversity between division classifications; and the effects of the number of student participants (i.e. athletes) on head coach salaries. Classifications were defined by the Equity in Athletics Survey according to the athletic association (such as NAIA, NCAA, etc) and divisions or subdivisions where applicable (e.g. NCAA Division I-FBS, NCAA Division I-FCS, NCAA Division I without football).

The full data set listed completed surveys for 2079 institutions. Excluded were the 578 two-year colleges, the 120 four-year schools with co-ed teams, and 18 institutions with missing values for head coach salaries. Our working data set had 1363 four-year institutions without co-ed sports teams. Data was available from the Office of Postsecondary Education from academic year 2002-03 up to 2017-18, but this study focused on the most recent available data.

Hypotheses

Overall, we examined whether school classification and/or gender of the teams affect head coach salaries. To do this, we first tested the equality of variances of head coach salaries for male teams versus female teams: H_0: $\sigma^2_{men} = \sigma^2_{women}$; H_1: $\sigma^2_{men} \neq \sigma^2_{women}$. As noted in the Results section below, we concluded that this data does not meet the assumption of equal variances for parametric testing of means, so we went on to test the equality of the medians: H_0: $M_{male} = M_{female}$; H_1: $M_{male} \neq M_{female}$. Next, we checked for interaction effects between classification and gender of team: H_0: there is not an interaction between classification and gender; H_1: there is an interaction between classification and gender. We also assessed the homogeneity of variances between the classifications: H_0: $\sigma^2_{DivI} = \sigma^2_{DivI-FBS} = \sigma^2_{DivI-FCS} = ... = \sigma^2_{n=18}$; H_1: at least one is different. Based on the results of this test, we then moved forward with testing for a difference in the median salaries of head coaches between the various classifications: H_0: $M_{DivI} = M_{DivI-FBS} = M_{DivI-FCS} = ... = M_{n=18}$; H_1: at least one is different. We also investigated whether the number of participants institution-wide predicts head coach salaries: H_0: $\beta = 0$; H_1: $\beta \neq 0$. Finally, we tested the appropriateness of a linear regression model: H_0: a linear regression model is appropriate; H_1: a linear regression model is not appropriate.

Methods

Data was analyzed using R version 3.6.1 (2019-07-05) (R Core Team 2019). The data was described using counts (percentage) for categorical variables and mean (standard deviation) for continuous variables.

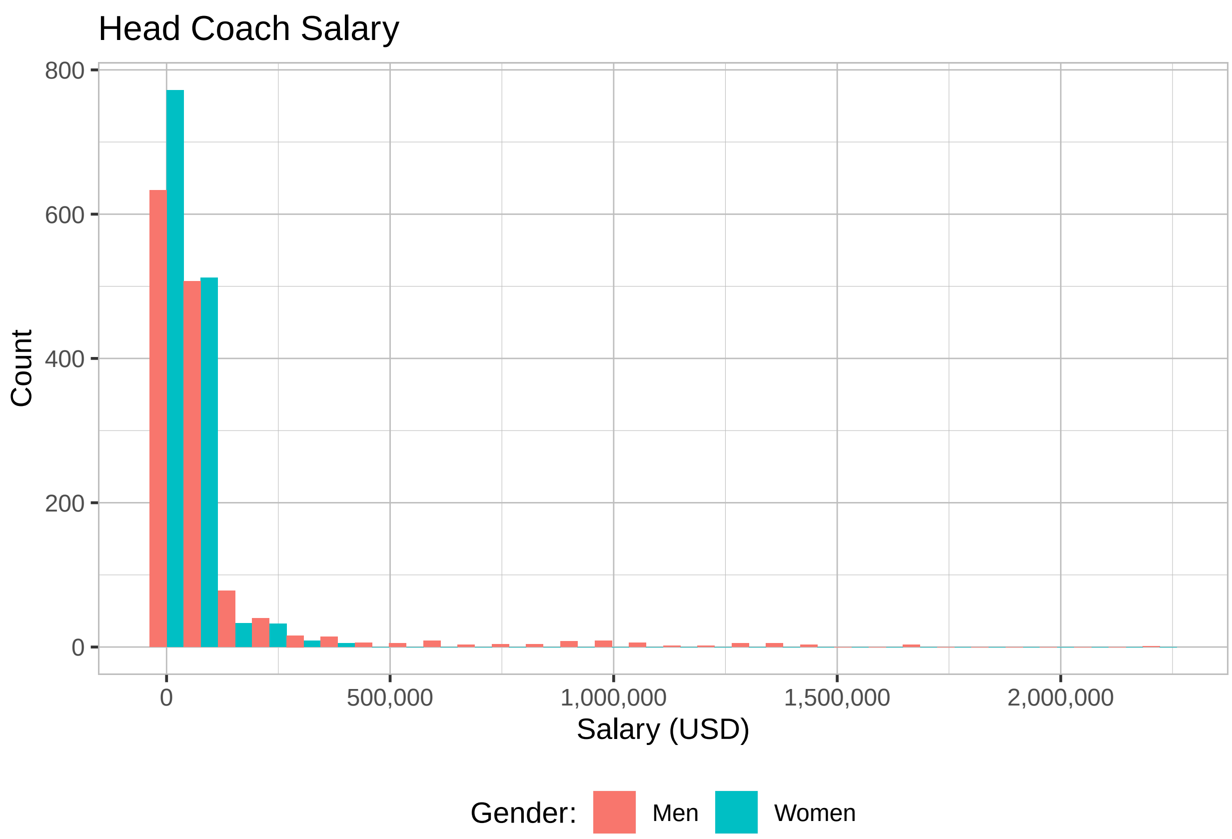
To assess the homogeneity of variances for salaries of head coaches of male teams versus female teams, we employed the testing procedure utilizing the F-distribution. Because the results of this test suggest there is not equal variances, we next examined the salary medians using the Wilcoxon Rank Sum Test. To analyze the interactions of gender and classification, a two-way ANOVA was completed. A Brown-Forsythe-Levene Test for homogeneity of variances was conducted on the variances of the classifications. After an examination of the residuals, a Kruskal-Wallis was used to test if there are differences between the classifications, and the posthoc Kruskal-Wallis procedure was used for pairwise comparisons.

Results

Description of Data

Variable	Mean	SD
Head Coach–Men's Salary	107,801.45	230,718.91
Head Coach–Women's Salary	48,110.37	51,009.74
Head Coach–All Salary	77,955.91	169,698.1
Participation–Men	218.26	123.14
Participation–Women	169.02	94.32
Participation–Total	387.28	207.9

Classification	Count	Percentage	Salary Mean	Salary SD
Independent	4	0.3%	7,406.25	2,969.149
NAIA Division I	90	6.6%	30,560.88	11,576.56
NAIA Division II	102	7.5%	25,299.23	10,985.52
NCAA Division I without football	95	7.0%	115,310.71	91,262.84
NCAA Division I-FBS	117	8.6%	431,159.52	421,253.92
NCAA Division I-FCS	114	8.4%	100,266.23	62,701.30
NCAA Division II with football	160	11.7%	47,834.02	18,145.77
NCAA Division II without football	138	10.1%	41,016.35	20,359.58
NCAA Division III with football	223	16.4%	34,898.80	13,059.53
NCAA Division III without football	162	11.9%	24,589.05	14,933.11
NCCAA Division I	9	0.7%	20,168.89	12,021.08
NCCAA Division II	25	1.8%	12,522.12	10,128.83
NJCAA Division I	35	2.6%	35,547.23	20,867.87
NJCAA Division II	9	0.7%	15,033.67	8,274.244
NJCAA Division III	4	0.3%	16,895.75	10,753.45
NWAC	9	0.7%	6,894.611	1,444.328
Other	33	2.4%	17,607.74	31,676.31
USCAA	34	2.5%	11,719.66	12,993.22



Analysis Results

```
gender.variance.test <- institution_data %$% var.test(HDCOACH_SALARY_MEN, HDCOACH_SALARY_WOMEN, alterna

gender.var.p.val <- p.value.string(gender.variance.test$p.value)
```

The test for equality of variances between salaries of head coaches of men's versus women's teams resulted in a test statistic of $F_0 = 20.46$ ($p < 0.0001$) and critical value of $F_{\alpha/2, df_{\text{men}}, df_{\text{women}}} = 1.081$, using $\alpha = 0.05$. There was sufficient evidence to suggest a difference between the variances of the two groups.

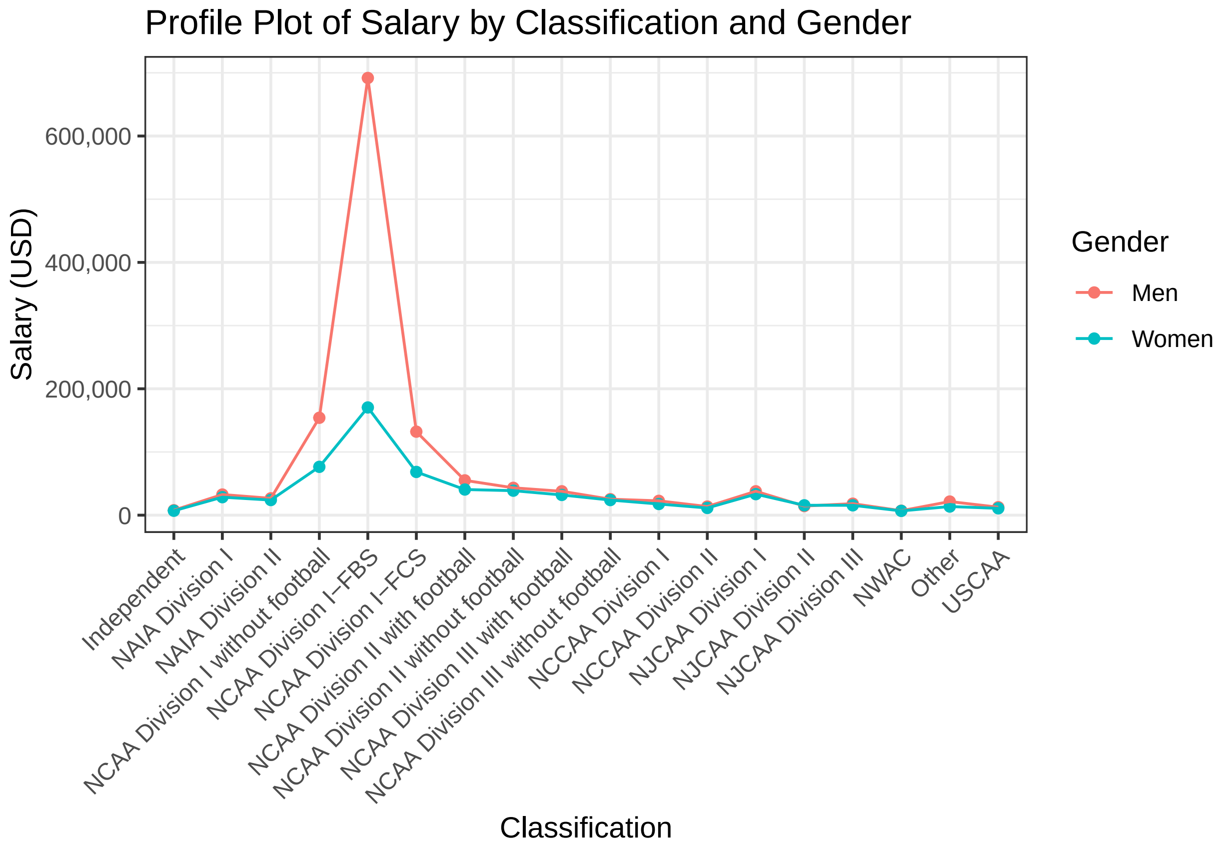
```
gender.wilcoxon.test <- wilcox.test(institution_data$HDCOACH_SALARY_MEN, institution_data$HDCOACH_SALAR

gender.wilcoxon.p.val <- p.value.string(gender.wilcoxon.test$p.value)
```

Testing to see if salaries of head coaches of men's teams tend to be greater than those of head coaches of women's teams resulted in a test statistic of $T_0 = 1.064179 \times 10^6$ ($p < 0.0001$). There was sufficient evidence to suggest that salaries for head coaches of men's teams are greater than the salaries for head coaches of women's teams.

```
classification.gender.interaction.results <- gender.separated_data %$% aov(Salary ~ Classification * Ge
interaction.summary <- classification.gender.interaction.results %>% summary()
```

An ANOVA model with gender and classification models resulted in a test statistic for interactions of $F_0 = 79.5$ ($p < 0.0001$). There was sufficient evidence to suggest that there are interaction effects between gender and classification.



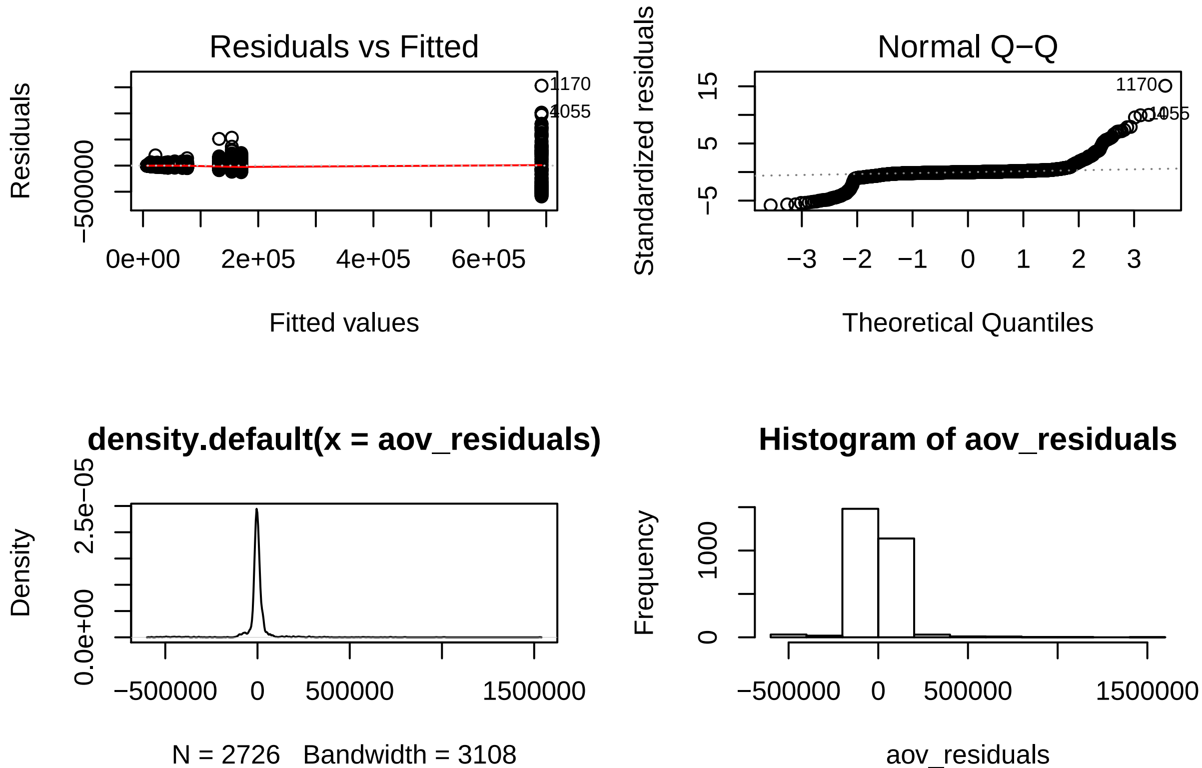
While this profile plot shows interaction effects, upon visual inspection, it seems to be limited to the three NCAA Division I classifications: NCAA Division I without football, NCAA Division I-FBS, and NCAA Division I-FCS. In those three cases, head coaches for men's teams have higher salaries, especially in the case of NCAA Division I-FBS.

To check the assumptions of the ANOVA model, we examined the variance across classifications to see if the variance was constant and the normality of the residuals.

```
gender.separated_data %$% leveneTest(Salary ~ Classification, center = median) -> classification.varian
```

The Brown-Forsythe-Levene Test for Homogeneity of Variances resulted in a test statistic of $F_0 = 77.03$ ($p < 0.0001$), so there is sufficient evidence to suggest that at least one of the classifications' salaries have a variance different from the others.

Upon a visual examination of the residuals and the q-q plot, it is also clear that the normality assumptions of the residuals was not satisfied.




```
classification.kw.test <- gender.separated_data %$% kruskal.test(Salary ~ Classification) %>% tidy()
```

The Kruskal-Wallis test on the salaries grouped by classifications resulted in a test statistic $H = 1752.51$ ($p < 0.0001$), so there is sufficient evidence to suggest that at least one classification is different from the others. Thus, the posthoc procedure for the Kruskal-Wallis test was completed to find pairwise differences between the classifications.

```
classification.kw.posthoc <- gender.separated_data %$% kruskalmc(Salary ~ Classification)
```

From the 153 possible pairwise comparisons, 91 resulted in significant difference. Complete results are not included, but of particular interest is the NCAA Division I: NCAA Division I-FBS had a significant difference from all of the 17 other classifications, NCAA Division I-FCS had a significant different from 16 other classifications, NCAA Division I without football the only exception, and similarly, with NCAA Division I without football, the only non-significant difference was with NCAA Division I-FCS.

```
total.salary <- (institution_data$HDCOACH_SALARY_MEN + institution_data$HDCOACH_SALARY_WOMEN)
total.participants <- (institution_data$IL_PARTIC_MEN + institution_data$IL_PARTIC_WOMEN)

participants.regression <- tibble(total.salary, total.participants)

participants.regression_model <- lm(total.salary ~ total.participants, data=participants.regression)
participants.regression_coef <- coefficients(participants.regression_model)
participants.regression_summary <- summary(participants.regression_model)
participants.regression_t <- as_tibble(participants.regression_summary[[4]])
```

The resulting regression model is

$$\hat{y} = -3.772481 \times 10^4 + 499.99x$$

The test for significance of a regression line using the number of student participants resulted in a test statistic of $t_0 = 14.94$ ($p < 0.0001$).There was There is sufficient evidence to suggest that the regression line is significant.

```
participants.regression_lack <- pureErrorAnova(participants.regression_model)
```

The lack of fit ANOVA table is as follows:

Table 1: Analysis of Variance Table

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
total.participants	1	1.472e+13	1.472e+13	240.1	6.358e-47
Residuals	1361	8.97e+13	6.591e+10	NA	NA
Lack of fit	645	4.583e+13	7.105e+10	1.159	0.02682
Pure Error	716	4.387e+13	6.128e+10	NA	NA

Testing whether or not a linear regression model is appropriate resulted in test statistic $F_0 = 1.16$ ($p = 0.0268$. There is sufficient evidence to suggest that a linear regression model is not appropriate.

Conclusion

We sought to understand the factors of head coach salaries at the collegiate level, and while the highest salaries are commonly reported, not all head coaches have those headline-worth salaries.

Examining the interaction effects between classification and gender, revealed that the NCAA Division I had the most differences between male and female head coaches. Furthermore, it appears that the NCAA Division I, with its different subdivisions (FBS, FCS, without football) were each different from all of the remaining classifications. This makes sense as there are different funding allowances between these subdivisions, but only between football teams. A future study might investigate the head coach salaries of collegiate football head coaches separately from the other sports or compare head coaches across classification and sport. Perhaps the sport of football is where the greatest gender disparity of salary exists.

Our data set contained only the averages of head coach salaries of a given institution, so we were unable to capture any variance within an institution. Of particular interest would be variation between head coaches by type of sports, within and across institutions. Additionally, this study only used the surveys from one year and future studies should investigate the salaries over multiple years.

This was an initial study of salaries of head coaches of collegiate sports teams. While there is more work to be done, we believe we have paved the way in identifying important factors of their salaries, and we hope others will continue the investigation.

Session Info

```r
sessionInfo()
```

```
## R version 3.6.1 (2019-07-05)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS High Sierra 10.13.6
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] alr3_2.0.8       haven_2.1.1      magrittr_1.5     kableExtra_1.1.0
##  [5] knitr_1.24       broom_0.5.2      forcats_0.4.0    stringr_1.4.0
##  [9] dplyr_0.8.3      purrr_0.3.2      readr_1.3.1      tidyr_0.8.3
## [13] tibble_2.1.3     ggplot2_3.2.1    tidyverse_1.2.1  scales_1.0.0
## [17] pander_0.6.3     car_3.0-3        carData_3.0-2    pgirmess_1.6.9
##
## loaded via a namespace (and not attached):
##  [1] nlme_3.1-140       sf_0.8-0           lubridate_1.7.4
##  [4] webshot_0.5.1      gmodels_2.18.1     httr_1.4.1
##  [7] tools_3.6.1        backports_1.1.4    rgdal_1.4-6
## [10] R6_2.4.0           KernSmooth_2.23-15 spData_0.3.2
## [13] rgeos_0.5-2        DBI_1.0.0          lazyeval_0.2.2
## [16] colorspace_1.4-1   withr_2.1.2        sp_1.3-1
## [19] tidyselect_0.2.5   splancs_2.01-40    curl_4.0
## [22] compiler_3.6.1     cli_1.1.0          rvest_0.3.4
## [25] expm_0.999-4       xml2_1.2.2         labeling_0.3
## [28] classInt_0.4-2     digest_0.6.20      foreign_0.8-71
## [31] rmarkdown_1.15     rio_0.5.16         pkgconfig_2.0.2
## [34] htmltools_0.4.0    rlang_0.4.0        readxl_1.3.1
## [37] rstudioapi_0.10    generics_0.0.2     jsonlite_1.6
## [40] gtools_3.8.1       spdep_1.1-3        zip_2.0.4
## [43] Matrix_1.2-17      Rcpp_1.0.2         munsell_0.5.0
## [46] abind_1.4-5        stringi_1.4.3      yaml_2.2.0
## [49] MASS_7.3-51.4      grid_3.6.1         maptools_0.9-8
## [52] gdata_2.18.0       crayon_1.3.4       deldir_0.1-23
## [55] lattice_0.20-38    splines_3.6.1      hms_0.5.1
## [58] zeallot_0.1.0      pillar_1.4.2       boot_1.3-22
## [61] LearnBayes_2.15.1  glue_1.3.1         evaluate_0.14
## [64] data.table_1.12.2  modelr_0.1.5       vctrs_0.2.0
## [67] cellranger_1.1.0   gtable_0.3.0       assertthat_0.2.1
## [70] xfun_0.9           openxlsx_4.1.0.1   e1071_1.7-2
## [73] coda_0.19-3        viridisLite_0.3.0  class_7.3-15
## [76] units_0.6-5
```

References

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