

# ITEC 621 Exercise 2 - Foundations

## Descriptive and Predictive Analytics

J. Alberto Espinosa

January 15, 2023

### Table of Contents

General Instructions.....	1
1. Descriptive Analytics.....	1
2. Basic Predictive Modeling.....	4

### General Instructions

In this exercise you will do quick descriptive and predictive analytics to evaluate if the Salaries data set (with professor salaries) supports the **gender pay gap hypothesis**.

First, download the R Markdown template for this exercise

**Ex2\_Foundations\_YourLastName.Rmd** and save it with your own last name **exactly**.

Then open it in R Studio and complete all the exercises and answer the questions below in the template.

**Knitting and Formatting:** no or improper knitting and formatting is worth up to **3 points** in this exercise. Once all your R code is working properly, **knit** your R Markdown file into a Word document and upload it into Canvas. If for some reason you can't knit a Word file, you can knit an HTML or PDF file. But please ensure that all your text narratives are fully visible (if I can't see the text I can't grade it). Also, please ensure that your **Table of Contents** is properly formatted.

**Note about where to write interpretations:** Please write your interpretations in the text area of R Markdown and **DO NOT** use the # or ## tags. These cause your text to appear as headings or sub-headings and show up in the table of contents. I use the # tag, but inside the R code chunks. I write my solutions inside the R code chunk rather than in the text area, so that I can suppress the solution. But you don't need to do this, so write all your narratives in the text areas.

### 1. Descriptive Analytics

#### 1.1 Examine the data

**Is there a gender pay gap?** Let's analyze this important question using professor salaries.

Load the library **{car}**, which contains the **Salaries** data set. Then, list the first few records with `head(Salaries)`. The display the `summary()` for this dataset, which will show frequencies.

```
##      rank discipline yrs.since.phd yrs.service sex salary
## 1     Prof         B           19           18 Male 139750
## 2     Prof         B           20           16 Male 173200
## 3 AsstProf         B            4            3 Male  79750
## 4     Prof         B           45           39 Male 115000
## 5     Prof         B           40           41 Male 141500
## 6 AssocProf        B            6            6 Male  97000

##      rank      discipline yrs.since.phd      yrs.service      sex
## AsstProf : 67  A:181      Min.      : 1.00      Min.      : 0.00  Female: 39
## AssocProf: 64  B:216      1st Qu.:12.00      1st Qu.: 7.00   Male   :358
## Prof      :266      Median :21.00      Median :16.00
##                                     Mean  :22.31      Mean   :17.61
##                                     3rd Qu.:32.00      3rd Qu.:27.00
##                                     Max.   :56.00      Max.   :60.00
##      salary
## Min.      : 57800
## 1st Qu.: 91000
## Median :107300
## Mean   :113706
## 3rd Qu.:134185
## Max.    :231545
```

Then, load the library **{psych}** which contains the `describe()` function and use this function to list the descriptive statistics for the data set. Then display the mean salary grouped by gender using the `aggregate()` function (feed grouping formula first, followed by the dataset **Salaries** and then the aggregate function to apply, i.e., mean).

```
##      vars  n      mean      sd median  trimmed      mad  min
## rank*      1 397      2.50      0.77      3      2.62      0.00      1
## discipline* 2 397      1.54      0.50      2      1.55      0.00      1
## yrs.since.phd 3 397     22.31     12.89     21     21.83     14.83      1
## yrs.service  4 397     17.61     13.01     16     16.51     14.83      0
## sex*         5 397      1.90      0.30      2      2.00      0.00      1
## salary       6 397 113706.46 30289.04 107300 111401.61 29355.48 57800
##      max range skew kurtosis      se
## rank*      3      2 -1.12     -0.38      0.04
## discipline* 2      1 -0.18     -1.97      0.03
## yrs.since.phd 56     55  0.30     -0.81      0.65
## yrs.service  60     60  0.65     -0.34      0.65
## sex*         2      1 -2.69      5.25      0.01
## salary      231545 173745  0.71      0.18 1520.16

##      sex  salary
## 1 Female 101002.4
## 2  Male 115090.4
```

## 1.2 Correlation, Boxplots and ANOVA

The means by gender above suggest that there may be a gender pay gap at this institution. Let's analyze this visually and statistically. Load the library **GGally** and run the **ggpairs()** function on the **salary**, **sex** and **yrs.since.phd** variables (only) in the **Salaries** data set to display some basic descriptive statistics and correlation, visually. Please note that the **Salary** data set is **capitalized**, whereas the variable **salary** is not. Please also label your variables appropriately (see graph below).

Tips: `ggpairs()` requires a **data frame**. So you need to use the `data.frame()` function to bind the necessary column vectors into a data frame (e.g., `ggpairs(data.frame("Salary" = Salaries$salary, etc.))`). Notice the difference in the quality of the graphics and how categorical variables are labeled. Also, add the attribute `upper = list(combo='box')` in the `ggpairs()` function to get labels for the boxplot.



Finally, conduct an ANOVA test to evaluate if there is a significant difference between mean salaries for male and female faculty. Feed `Salaries$salary ~ Salaries$sex` into the `aov()` function. Embed the `aov()` function inside the `summary()` function to see the statistical test results.

```
##           Df    Sum Sq   Mean Sq F value    Pr(>F)
## Salaries$sex      1 6.980e+09 6.980e+09   7.738 0.00567 **
## Residuals    395 3.563e+11 9.021e+08
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## 1.3 Preliminary Interpretation

Based on the output above, does it appear to be a gender pay gap? Why or why not. In your answer, please refer to as much of the data above to support your answer.

## 2. Basic Predictive Modeling

### 2.1 Salary Gender Gap: Simple OLS Regression

Suppose that you hypothesized that there is a salary gender pay gap.

**\*\* Technical Note:\*\*** it is more effective to set the null hypothesis to the contrary of what you want to prove, so that you can reject it if not supported.

Fit a linear model function `lm()` to test this hypothesis by predicting salary using only **sex** as a predictor. Store the results in an object called `lm.fit.1`, then inspect the results using the `summary()` function.

```
##
## Call:
## lm(formula = salary ~ sex, data = Salaries)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -57290 -23502  -6828   19710 116455
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   101002      4809   21.001  < 2e-16 ***
## sexMale        14088       5065    2.782  0.00567 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 30030 on 395 degrees of freedom
## Multiple R-squared:  0.01921,    Adjusted R-squared:  0.01673
## F-statistic: 7.738 on 1 and 395 DF,  p-value: 0.005667
```

Do these results support the salary gender gap hypothesis? Briefly explain why.

### 2.2 Multivariate OLS Regression

Now fit a 2-predictor linear model (quantitative + dummy variable) with **yrs.since.phd** and **sex** as predictors, and save it in an object named `lm.fit.2`. Then inspect the results using the `summary()` function.

```
##
## Call:
## lm(formula = salary ~ sex + yrs.since.phd, data = Salaries)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -84167 -19735 -2551 15427 102033
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  85181.8     4748.3  17.939  <2e-16 ***
## sexMale      7923.6     4684.1   1.692   0.0915 .
## yrs.since.phd  958.1      108.3   8.845  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27470 on 394 degrees of freedom
## Multiple R-squared:  0.1817, Adjusted R-squared:  0.1775
## F-statistic: 43.74 on 2 and 394 DF, p-value: < 2.2e-16
```

Do these results support the salary gender gap hypothesis? Briefly explain why.

### 2.3 Comparing Models with ANOVA F-Test

Run an ANOVA test using the `anova()` function to compare **lm.fit.1** to **lm.fit.2**.

```
## Analysis of Variance Table
##
## Model 1: salary ~ sex
## Model 2: salary ~ sex + yrs.since.phd
##   Res.Df      RSS Df Sum of Sq    F    Pr(>F)
## 1     395 3.5632e+11
## 2     394 2.9729e+11  1 5.9031e+10 78.234 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

### 2.4 Interpretation

Provide your brief conclusions (in **6 lines** or so) about whether you think there is a gender pay gap based on this analysis (you will expand this analysis much further in HW2). First, based on the Anova test above, which `lm()` model is better and why? Then, compare the best predictive model of the two against the descriptive analytics results you obtained in 1.2 above. If the null hypothesis is that there is no gender pay gap, is this hypothesis supported? Why or why not?