Final Project: Are data science skills predictive of salary?

CUNY MSDA DATA 606

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May 18, 2017

Part 1 - Introduction:

Nowadays with the increase in data collection and processing; companies, governments and agencies have a need to extract and produce educated decisions based on factual data. Extracting that kind of information and knowledge from large, heterogeneous, and noisy data sets requires not only powerful computing resources, but the programming abstractions to use them effectively.

In that context, data scientist need to have the skills in order to overcome the challenges that implies to work diverse structures in a given data science project.

By looking at this relationship (data processing / data scientist), we know that it creates a third component with a numerical variable named salary.

With that in mind, I will explore and try to answer a very important research question:

Are data science skills predictive of salary?

Hypothesis

From our exploration question, we can define our hypothesis as follows:

H_0 : Data Science skills are not predictive of salary; that is, the mean for all Skill Values are the same.

H_1 : Data Science skills are predictive of salary; that is, at least one mean for all Skill Values is different.

Part 2 - Data:

Data Source

The data that I will be working with, is collected by `Paysa` and is available online here: http://paysa.com

Figure 1:

For this project, the data was extracted by copying and pasting a job search of *"Data Science"* on March 16, 2017 into a text file, then cleaned and uploaded into a table in a local MySQL server.

This data is collected by Paysa as part of the integrated job posting website and this data is submitted by employers daily.

Raw Data

The below table display all job listings compiled from Paysa.

```
## QApplication: invalid style override passed, ignoring it.
## TypeError: Attempting to change the setter of an unconfigurable property.
## TypeError: Attempting to change the setter of an unconfigurable property.
```

Cases

Each case represents a job posting in the United States. There are 390 observations in the given data set.

Explanatory variable

The explanatory variable is `Data Science skills` and is categorical.

Response variable

The response variable is `Base Salary` and is numerical.

Curated Data

From the above table I will focus on the `Base Salary` and combination of `Skills` as follows:

```
## QApplication: invalid style override passed, ignoring it.
## TypeError: Attempting to change the setter of an unconfigurable property.
## TypeError: Attempting to change the setter of an unconfigurable property.
```

Skill value per job listing

Since each case list multiple skills combined for a single base salary. For this study purposes, I will assign a "Skill Value" salary per skill listed on each listing; that is, by taking the base salary and dividing it by the number of skills listed for that study case.

For example: In the first case, there is a base salary of $253000 with 6 skills listed (Distributed Systems, Big Data, Algorithms, Data Science, Strategy, Databases). By taking $253000 and dividing it by 6, we obtain an average of $42167. That is, each skill value will be taken as $42167 in the first case study. Similar process will be applied for the rest of the cases.

The below table shows the number of skills per job listing and also shows the "average" base salary for each skill in that listing.

```
## QApplication: invalid style override passed, ignoring it.
## TypeError: Attempting to change the setter of an unconfigurable property.
## TypeError: Attempting to change the setter of an unconfigurable property.
```

Part 3 - Exploratory data analysis:

From the above table, we have defined a series of `Skill Value` for each skill listed on each job posting.

From the raw data, we have a total of 2220 skills listed in the 390 job postings.

```
## QApplication: invalid style override passed, ignoring it.
## TypeError: Attempting to change the setter of an unconfigurable property.
## TypeError: Attempting to change the setter of an unconfigurable property.
```

Summary

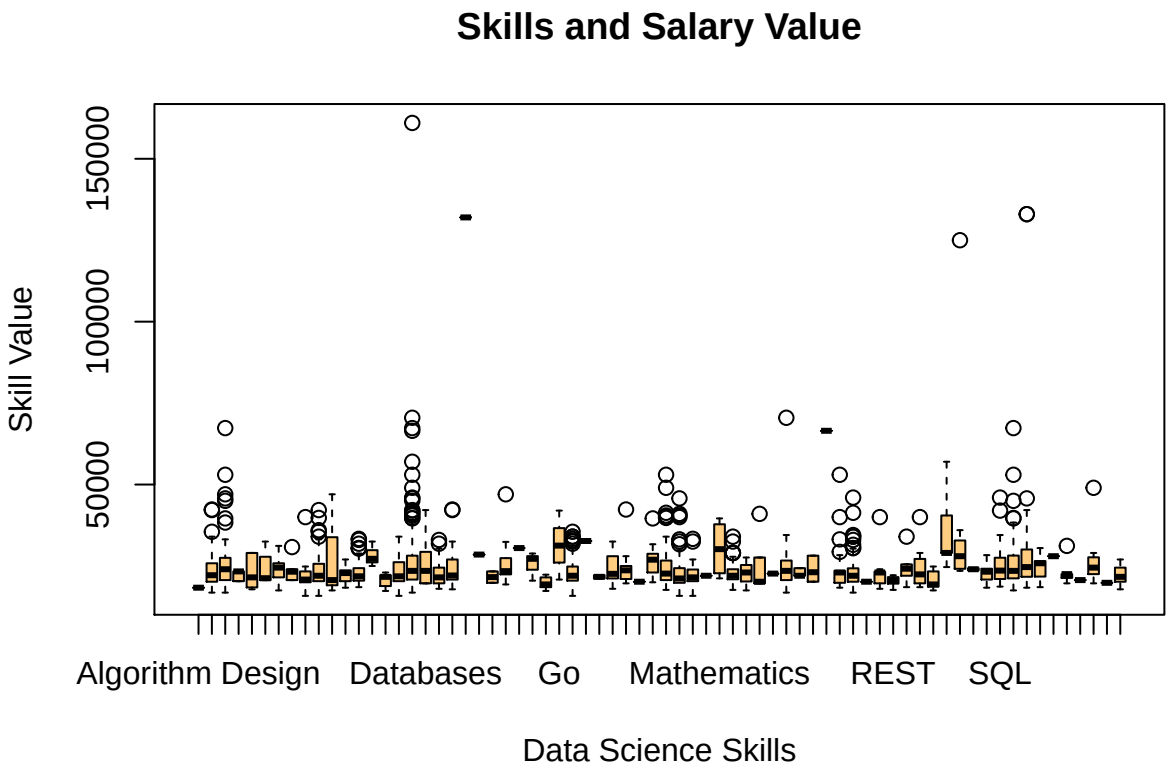
Below is a summary of the individual skills data.

```
##     Skills           Skill Value
##  Length:2220        Min.   : 15833
##  Class :character   1st Qu.: 20500
##  Mode  :character   Median : 22500
##                     Mean   : 24255
##                     3rd Qu.: 26617
##                     Max.   :161000
```

From the above summary table, we can quickly identify that the minimum skill value is set at $15833 and the maximum is at $161000 with a median skill value of $22500 per skill.

Count, Mean and Standard deviation

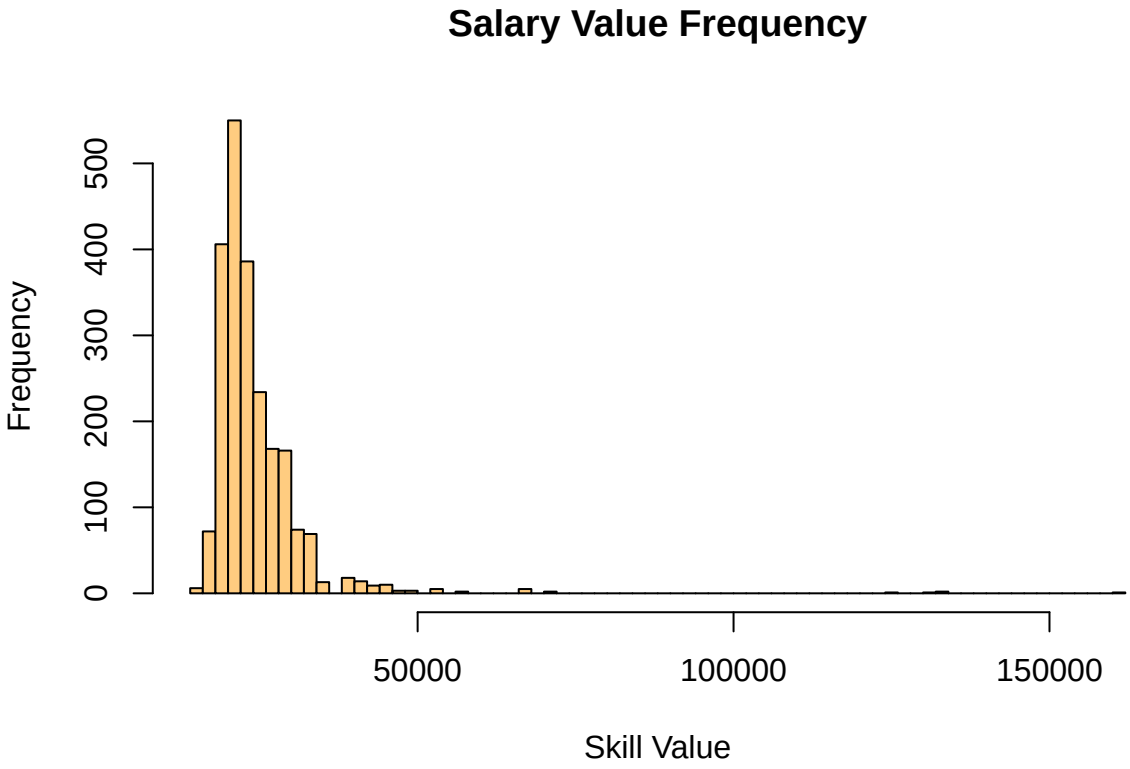
```
## QApplication: invalid style override passed, ignoring it.
## TypeError: Attempting to change the setter of an unconfigurable property.
## TypeError: Attempting to change the setter of an unconfigurable property.
```



From the above plot, as an initial inspection of the data, it suggests that there are differences in between the medians but is not clear at this point.

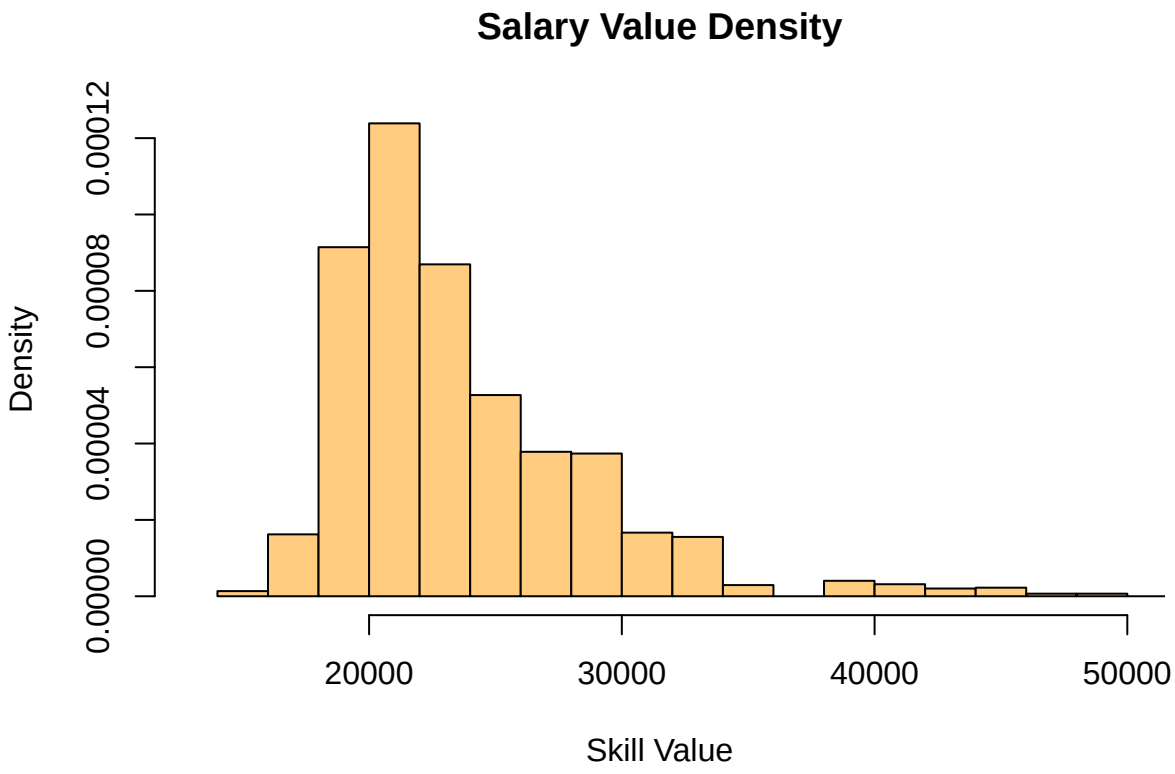
Outliers

From the above set of box plots we can quickly identify that there are some outliers in the remaining data set, while the different medians seems to vary depending on the skill; this could be taking as an indication that the skills could be predictive of salary as established in our introduction.



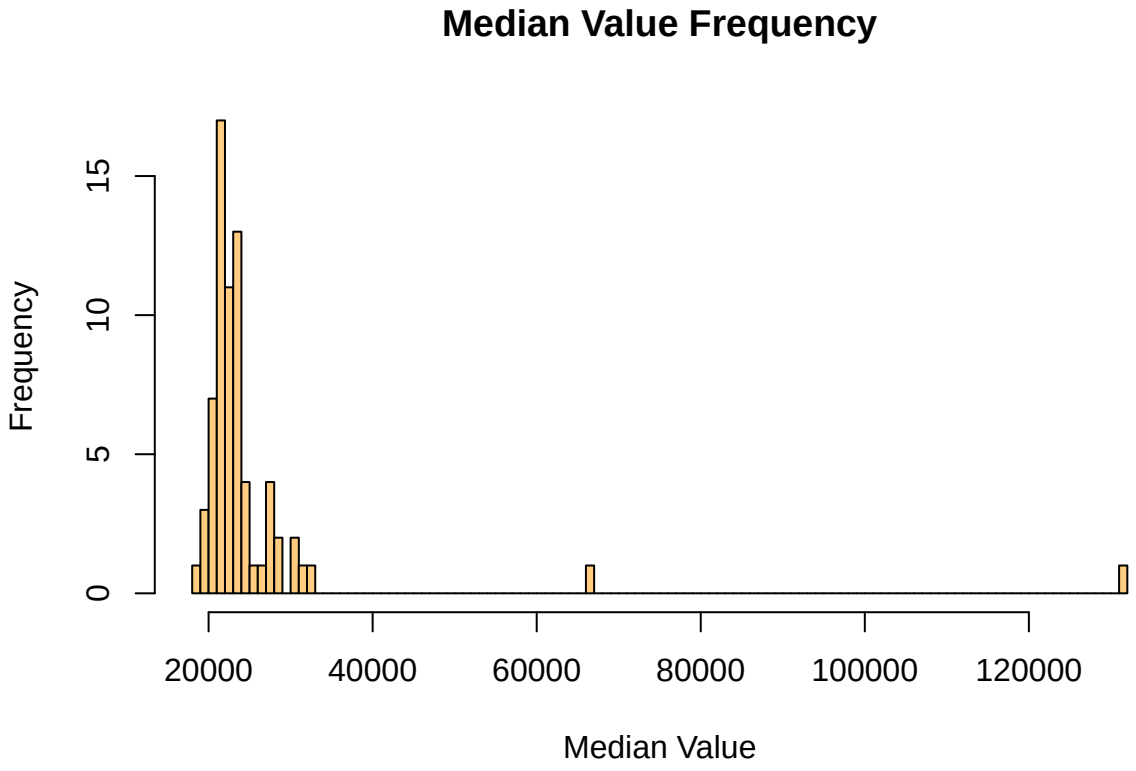
From the above histogram we can visualize some sort of normality and skewness to the right, also we can confirm the outliers as well.

For visualization purposes, I will include a new density histogram with a limited domain as follows:



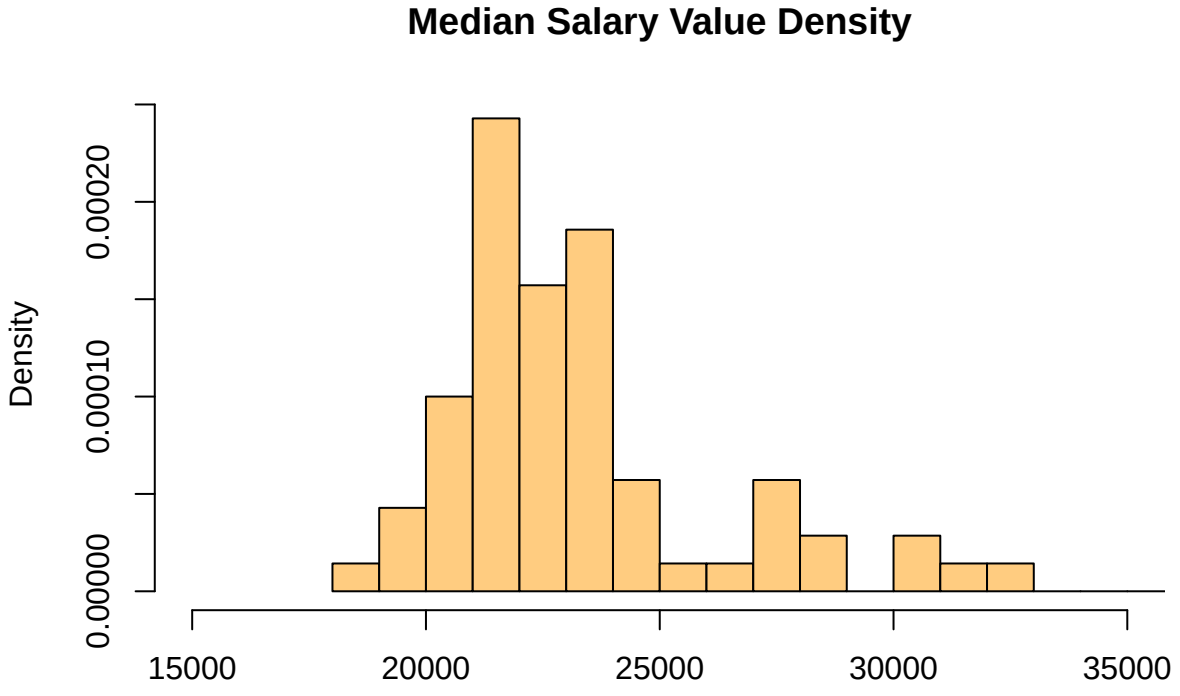
Medians

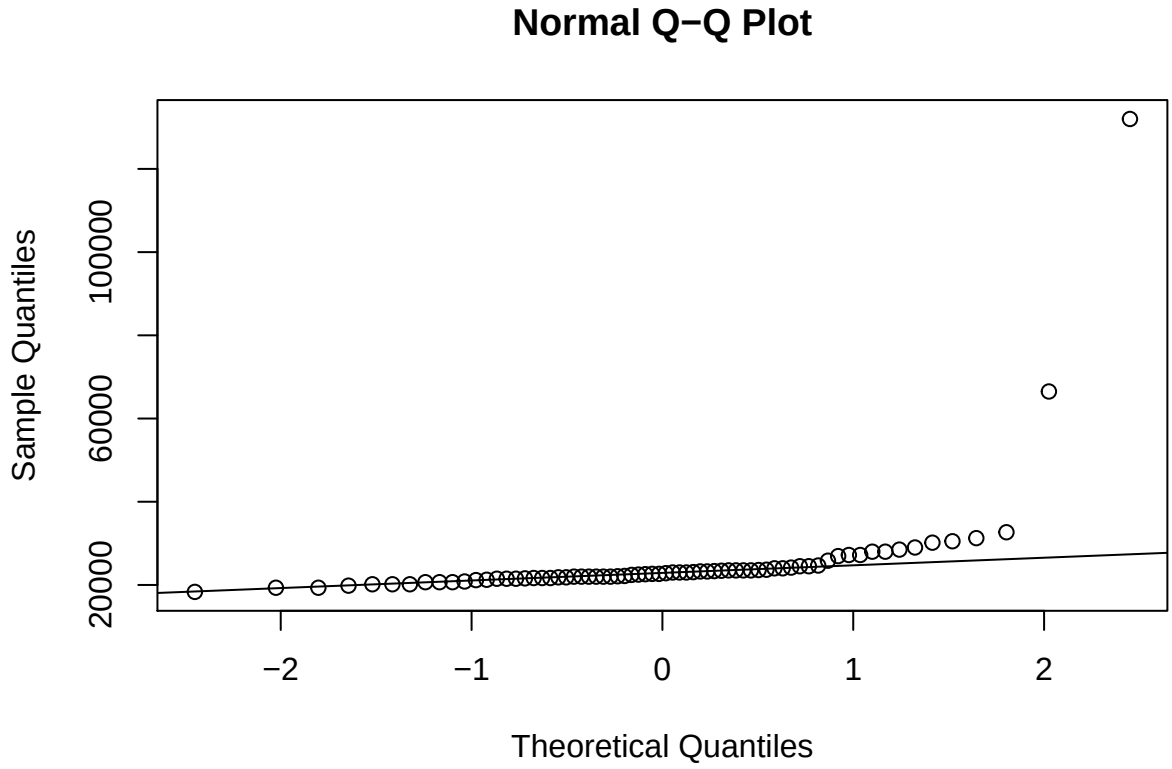
From the calculated medians, we can have the following histograms:



From the above histogram we can still visualize some sort of normality and skewness to the right, also we can confirm the presence of outliers, performing leverage.

For visualization purposes, I will include a new density histogram with a limited domain as follows:





Based on out Q-Q Plot, we can visualize how our medians data follow the qqline most of the trajectory then

due to leverage a couple of points fall away from it.

Part 4 - Inference:

Satisfying conditions for inference:

Conditions:

- The sample size is greater than 30.
- The data sets follow a uni modal normal distribution.
- The samples are random.

Hence, the conditions for inference seems to be satisfied.

ANOVA

Summary

```
##
## Call:
## lm(formula = `Skill Value` ~ Skills, data = my.skills.data_long)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -17991  -3594  -1297   1854 134444
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        18333       7298   2.512  0.01208 *
## SkillsAlgorithms                    5128       7318   0.701  0.48357
## SkillsAnalytics                     7499       7341   1.021  0.30715
## SkillsAndroid                       3800       7995   0.475  0.63463
## SkillsApache Spark                  4750       7741   0.614  0.53952
## SkillsArchitecture                  5695       7883   0.722  0.47013
## SkillsArchitectures                 5387       7462   0.722  0.47048
## SkillsAutomation                    5439       7883   0.690  0.49028
## SkillsAWS                           3873       7510   0.516  0.60613
## SkillsBig Data                      4928       7319   0.673  0.50085
## SkillsBusiness Intelligence        10056       8428   1.193  0.23291
## SkillsC                             3977       7802   0.510  0.61034
## SkillsC++                           4721       7350   0.642  0.52072
## SkillsCassandra                     9900       8428   1.175  0.24022
## SkillsComputer Vision               2334       7655   0.305  0.76051
## SkillsData Mining                   4729       7329   0.645  0.51881
## SkillsData Science                  8223       7316   1.124  0.26113
## SkillsDatabases                     7521       7741   0.972  0.33136
## SkillsDeep Learning                 4380       7498   0.584  0.55920
## SkillsDistributed Systems           6723       7498   0.897  0.37007
## SkillsEMPTY                       113667      10322  11.013  < 2e-16 ***
## SkillsEngineering Management       10167      10322   0.985  0.32473
## SkillsEnterprise Software           3250       8939   0.364  0.71620
```

```
## SkillsETL                              7509       7523   0.998  0.31836
## SkillsFirewalls                       12167      10322   1.179  0.23861
## SkillsFunctional Programming           7178       8428   0.852  0.39446
## SkillsGame Development                 1467       7995   0.183  0.85445
## SkillsGo                              13028       8428   1.546  0.12228
## SkillsHadoop                           4650       7318   0.635  0.52522
## SkillsHTTP                            14334      10322   1.389  0.16506
## SkillsImage Processing                 3334       8939   0.373  0.70920
## SkillsInformation Retrieval            5858       7498   0.781  0.43478
## SkillsJava                             6439       7574   0.850  0.39534
## SkillsLAMP                             1834       8939   0.205  0.83746
## SkillsLeadership                       8739       7655   1.142  0.25374
## SkillsMachine Learning                 5584       7312   0.764  0.44514
## SkillsManagement                       5165       7358   0.702  0.48278
## SkillsMapReduce                        4027       7415   0.543  0.58712
## SkillsMathematical Modeling            3667      10322   0.355  0.72242
## SkillsMathematics                     11950       8160   1.464  0.14320
## SkillsMatlab                           4940       7389   0.669  0.50383
## SkillsMySQL                            4367       8428   0.518  0.60439
## SkillsNatural Language Processing      6378       7883   0.809  0.41855
## SkillsNetwork Architecture             4334      10322   0.420  0.67460
## SkillsOptimization                     5755       7336   0.785  0.43278
## SkillsOS X                             4600       7995   0.575  0.56510
## SkillsPHP                              5473       7883   0.694  0.48761
## SkillsProduct Design                  48167      10322   4.667 3.25e-06 ***
## SkillsProduct Management               5758       7408   0.777  0.43712
## SkillsPython                           4771       7328   0.651  0.51510
## SkillsRecommender Systems              1834       8939   0.205  0.83746
## SkillsRelational Databases             4223       7538   0.560  0.57541
## SkillsREST                             2122       7623   0.278  0.78079
## SkillsRuby                             5462       7574   0.721  0.47091
## SkillsScala                            5207       7394   0.704  0.48140
## SkillsScalability                      2205       7574   0.291  0.77094
## SkillsScripting                       17700       7995   2.214  0.02694 *
## SkillsSearch                          23158       7802   2.968  0.00303 **
## SkillsSignal Processing                5667       8939   0.634  0.52616
## SkillsSoftware Design                  4400       7655   0.575  0.56545
## SkillsSQL                              6801       7363   0.924  0.35581
## SkillsStatistics                       8266       7367   1.122  0.26195
## SkillsStrategy                        16047       7432   2.159  0.03096 *
## SkillsTechnical Leadership             6123       7488   0.818  0.41362
## SkillsTest Driven Development          9667      10322   0.937  0.34908
## SkillsTime Series Analysis             4667       7802   0.598  0.54979
## SkillsTomcat                           2334       8939   0.261  0.79403
## SkillsUser Experience                  7855       7555   1.040  0.29856
## SkillsWeb Services                     1500      10322   0.145  0.88447
## SkillsWindows                          3941       7555   0.522  0.60199
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7298 on 2150 degrees of freedom
## Multiple R-squared:  0.1714, Adjusted R-squared:  0.1448
## F-statistic: 6.444 on 69 and 2150 DF,  p-value: < 2.2e-16
```

From the above results, the model output indicates some evidence of a difference in the average value for the skills.

Results

```
## Analysis of Variance Table
##
## Response: Skill Value
##             Df     Sum Sq   Mean Sq F value    Pr(>F)
## Skills      69 2.3685e+10 343255703   6.444 < 2.2e-16 ***
## Residuals 2150 1.1453e+11  53267887
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Based on the above table confirms that there are differences between the skills which were highlighted in the model summary.

Part 5 - Conclusion:

From our initial question: Are data science skills predictive of salary? we can conclude as follows:

By observing the above plots, linear modeling, and statistical analysis; we can observe how data science skills and income did appear to be correlated.

The validity of the data was indicated by summary statistics in which our hypothesis H_0 gets discarded and our alternative hypothesis H_1 is accepted. The above conclusion is statistically accepted since our analysis of variance returned an extremely low p-value (2.2e-16) which is less than 0.05. This can be enforced by comparing our results with the normality and qqplots for the medians as well.

References:

- OpenIntro Statistics, Third Edition. Diez, D. et all. 2015

Links

In order to open, right click and select **"Open Link in New Tab"**.

dvillalobos.github.io

GitHub | Linkedin