### **FUNDAMENTALS OF DATA SCIENCE**

# **HOMEWORK – 1**

## NAME – GOUTHAM SELVAKUMAR

<u>ID</u> - 2092286

#### PROBLEM - 1

### **INSTALLING PACKAGES:**

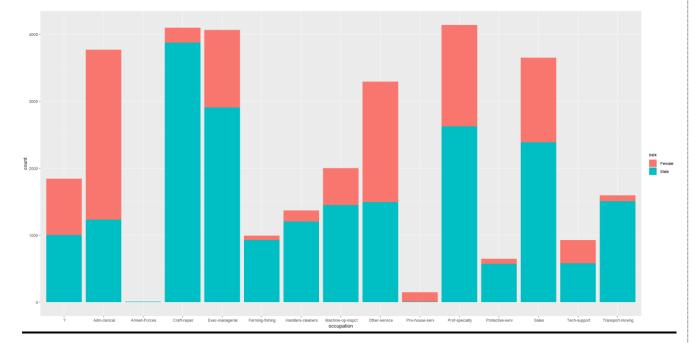
```
> # PROBLEM 1library(tidyverse)
> library(psych)
Warning message:
package 'psych' was built under R version 4.0.5
> library(matrixStats)
Warning message:
package 'matrixStats' was built under R version 4.0.5
> library(GGally)
Loading required package: ggplot2
Attaching package: 'ggplot2'
The following objects are masked from 'package:psych':
        %+%, alpha
Registered S3 method overwritten by 'GGally':
    method from
        +.gg ggplot2
Warning messages:
l: package 'GGally' was built under R version 4.0.5
2: package 'ggplot2' was built under R version 4.0.5
```

<u>a.</u> First, we look at the summary statistics for all the variables. Based on those metrics, including the quartiles, compare two variables. What can you tell about their shape from these summaries?

Based on this summary, I decided to compare sex to occupation. Based on this summary alone, since the two chosen variables are categoricals, we cannot tell what the relationship is between them.

<u>b.</u> Use a visualization to get a fine-grain comparison (you don't have to use QQ plots, though) of the distributions of those two variables. Why did you choose the type of visualization that you chose? How do your part (a) assumptions compare to what you can see visually?

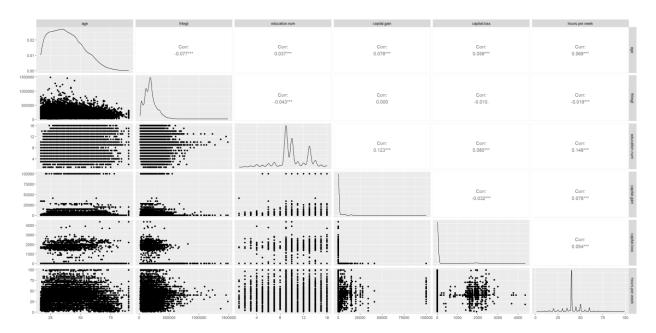
```
# Using ggplot for visualizing
df <- as.data.frame(adult)
p <- ggplot(adult, aes(x=occupation, fill=sex))
p + geom_bar(position="stack")</pre>
```



- I chose a Bar Chart to display the number of females and males in each occupation and color-coded it.
- While the initial summary did not provide an accurate description of the data due to the non-numeric nature of the input, the Bar Chart allowed us to visualize it better.
- Per the bar chart above, you can see a clear distribution of how many females and
  males are represented in each occupation. For example, while not many in this dataset
  are Priv-house-serv, the females in this dataset dominate this occupation. On the other
  hand, many males and females are working in the craft-repair field, however, males
  clearly dominate this field.

**c.** Now create a scatterplot matrix of the numerical variables. What does this view show you that would be difficult to see looking at distributions?



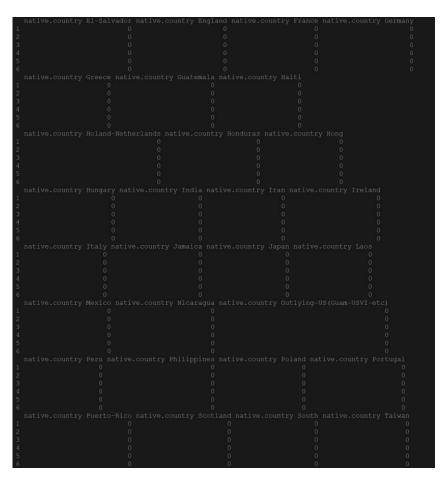


- There are a few things to point out on this Scatter Plot Matrix: 1. The number of adults in this dataset decreases with age, as in the data may be biased towards ages of 17-70, with data points decreasing dramatically after age 75. This could be due to several factors including mortality and employment rates at higher age groups.
- The Pearson-Correlation coefficient is near 0 for most correlations, however, there is a positive correlation between education-num and age. Therefore, this suggests that there is a positive correlation between the years of education and the age of the person.
- <u>d.</u> These data are a selection of US adults. It might not be a very balanced sample, though. Take a look at some categorical variables and see if any have a lot more of one category than others. There are many ways to do this, including histograms and following tidyererse group by with count. I recommend you try a few for practice.

I chose to view data using group-by to view information on race and education. The white race dominates this dataset, and most within this dataset have a bachelor's degree.

<u>e.</u> Now we'll consider a relationship between two categorical variables. Create a cross tabulation and then a corresponding visualization and explain a relationship between some of the values of the categoricals.

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```
> # Make a table to look at workclass vs sex summary
> table(adult$workclass, adult$sex)

Female Male
? 839 997
Federal-gov 315 645
Local-gov 835 1258
Never-worked 2 5
Private 7752 14944
Self-emp-inc 135 981
Self-emp-not-inc 399 2142
State-gov 489 809
Without-pay 5 9
```

```
# Use new data frame to look at more specific data points
table(dummies$'occupationTransport-moving', dummies$educationBachelors)
```

Based on the cross-tabulation above: 25,671 in this survey said they did not work in transport/moving and do not have a bachelors 5293 do not work in transport/moving but have a bachelors 1535 work in transport/moving but do not have a bachelors 62 work in transport/moving and have a bachelors.

## PROBLEM – 2

a. Join the two tables together so that you have one table with each state's population for years 2010- 2019. If you are unsure about what variable to use as the key for the join, consider what variable the two original tables have in common. (Show a head of the resulting table.)

b. Clean this data up a bit (show a head of the data after): a. Remove the duplicate state ID column if your process created one.

c. Deal with missing values in the data by replacing them with the average of the surrounding years. For example, if you had a missing value for Georgia in 2016, you would replace it with the average of Georgia's 2015 and 2017 numbers. This may require some manual effort.

```
# For 2015
x<-population_new$`2014`[13] + population_new$`2016`[13]
population_new$`2015`<- population_new$`2015` %>% replace_na(mean(x/2, na.rm = TRUE))
# For 2013
x<-population_new$`2012`[36] + population_new$`2014`[36]
population_new$`2013` <- population_new$`2013` %>% replace_na(mean(x/2, na.rm = TRUE))
# For 2011
x<-population_new$`2012`[3] - (population_new$`2013`[3]-population_new$`2012`[3])
population_new$`2011` <- population_new$`2011` %>% replace_na(mean(x, na.rm = TRUE))
# For 2017
x<-population_new$`2016`[27] + population_new$`2018`[27]
population_new$`2017` <- population_new$`2017` %>% replace_na(mean(x, na.rm = TRUE))
# For 2019
x<-population_new$`2018`[50] + (population_new$`2018`[50]-population_new$`2017`[50])
population_new$`2019` <- population_new$`2019` %>% replace_na(mean(x, na.rm = TRUE))
head(population_new)
```

```
State Name 2011 2012 2013 2014 2015 2016

Alabama 1 4799069 4785437 4830081 4815588 4852347 4841799

Alaska 2 722128 713910 737068 730443 737498 736283

Arizona 4 6181580 6407172 6632764 6554978 6829676 6730413

Arkansas 5 2940667 2921964 2959400 2952164 2978048 2967392

California 6 37638369 37319502 38260787 37948800 38918045 38596972

Colorado 8 5121108 5047349 5269035 5192647 5450623 5350101

2017 2018 2019

4874486 4863525 4903185

7044008 6941072 7278717

3001345 2989918 3017804

5 39358497 39167117 39512223

6 5611885 5539215 5758736
```

d. We can use some tidy verse aggregation to learn about the population.

a. Get the maximum population for a single year for each state. Note that because you are using an aggregation function (max) across a row, you will need the row wise () command in your tidy verse pipe. If you do not, the max value will not be individual to the row. Of course there are alternative ways.

b. Now get the total population across all years for each state. This should be possible with a very minor change to the code from (d). Why is that?

```
> # sum of each row

> rowSums(adultscopy[,-1])

[1] 38766448 5867903 54418800 23788035 309081943 43219591 28666873

[8] 7491595 5314929 160798760 81161158 11271424 13208766 102632724

[15] 52823515 24878233 23179021 35337634 37076161 10652283 47614541

[22] 54075351 79459825 43762667 23874611 48520223 9232758 15074693

[29] 22874562 10688112 70872376 16703236 156579533 80042773 5860832

[36] NA 31034277 32089334 102199631 27882848 8447466 38960588

[43] 6815688 52619925 217446671 23793929 5000599 66543219 57155211

[50] 14696738 42067510 4632963
```

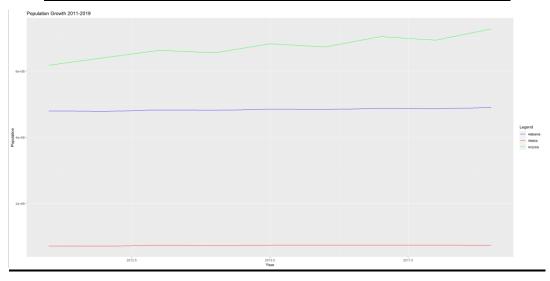
e. Finally, get the total US population for one single year. Keep in mind that this can be done with a single line of code even without the tidy verse, so keep it simple.

```
> sum(adultscopy$`2011`)
[1] 314944543
```

#### PROBLEM – 3

Continuing with the data from Problem 2, let's create a graph of population over time for a few states (choose at least three yourself). This will require another data transformation, a reshaping. In order to create a line graph, we will need a variable that represents the year, so that it can be mapped to the x axis. Use a transformation to turn all those year columns into one column that holds the year, reducing the 10 year columns down to 2 columns (year and population). Once the data are in the right shape, it will be no harder than any line graph: put the population on the y axis and color by the state. One important point: make sure you have named the columns to have only the year number (i.e.,

without popestimate). That can be done manually or by reading up on string (text) parsing (see the stringr library for a super useful tool). Even after doing that, you have a string version of the year. R is seeing the 'word' spelled two-zero-one-five instead of the number two thousand fifteen. It needs to be a number to work on a time axis. There are many ways to fix this. You can look into type\_convert or do more string parsing (e.g., stringr). The simplest way is to apply the transformation right as you do the graphing. You can replace the year variable in the ggplot command with as.integer (year).



# PROBLEM – 4

- a. Describe two ways in which data can be dirty, and for each one, provide a potential solution.
  - Data can contain typographical errors, there could be duplicates too.
     Missing values could be deleted or replaced/corrected by inferring data from known variables, such as using means and percentage to fill gaps.
  - Data may have come from different sources/servers/storage mechanisms
    where the data was handled differently. A potential solution for this would
    be to add the factors missing in other data (or) simply only relying on
    same-source data from comparable devices/systems. Otherwise, ignore this
    data if we have the privilege of doing so.
  - Sensor failures; I personally encounter this often and we created failure
    messages/warnings that trigger a data point in a spreadsheet, which we
    check every day and use to replace the sensors accordingly. Once a server

fails, the server filters out all data that sensor and completely ignores it. We get an abundant amount of data so ignoring data is not an issue.

- b. Explain which data mining functionality you would use to help with each of these data questions.
  - a. Suppose we have data where each row is a customer and we have columns that describe their purchases. What are five groups of customers who buy similar things?

Cluster Analysis – grouping customers based on their similar characteristics.

b. For the same data: can I predict if a customer will buy milk based on what else they bought?

Classification and Prediction – Using a historical data to predict future outcomes.

c. Suppose we have data listing items in individual purchases. What are different sets of products that are often purchased together?

Association Rule Mining – Events that occur together.

- c. Explain if each of the following is a data mining task
  - a. Organizing the customers of a company according to education level.

Not data mining, database query task

b. Computing the total sales of a company.

Not data mining, simple mathematical calculation

c. Sorting a student database according to identification numbers.

Not data mining, database query task

d. Predicting the outcomes of tossing a (fair) pair of dice.

Not data mining, it's a probability calculation

e. Predicting the future stock price of a company using historical records.

Data mining, using historical data to predict future outcome.