Analyze Mental health disorder in Tech Companies using R

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Introduction :

In the document we are going to analyze, How does employees mental health affects employees performance and overall company productivity in tech companies.

Mental health affects your emotional, psychological and social well-being.Mental health is a key factor to determine the productivity of the employee as well as the total performance of the company. If someone is not mentally fit, he can't produce the expected output what he is capable of and it also impacts his co-workers performance and impacts the work environment.

This sort of analysis helps the employer to identify and support an individual who may be experiencing a mental health or substance use concern or crisis and connect them with the appropriate employee resources.This sort of analysis helps to increase mental health awareness in employee and co-workers. As a whole this sort of analysis helps employer to increase productivity and make sure they are providing a healthy work environment and takes care of it's employees mental health. This allows employer to recognize the signs of someone who maybe struggling and teaches them the skills to know when to reach out and what resources are available.Organizations that incorporate mental health awareness help to create a healthy and productive work environment that reduces the stigma associated with mental illness, increases the organizations mental health literacy and teaches the skills to safely and responsibly respond to a co-workers mental health concern.

This topic is relevant to data science as we can analyze and identify the factors/variables that impacts the mental health and justify the relations between variables which is closely related to determine the mental health of employees.We can create a model and feed data into it to identify the employees mental health in the company and provide directions to them to overcome the situation.

Research questions :

1. no_employees and tech_company are statistically significant predictors of mental health condition?
2. Does family_history have any relation with mentalhealth?
3. How does the frequency of mental health illness differ by workpace type (i.e., tech vs. non-tech) and size?
4. How easy is it for you to take medical leave for a mental health condition?
5. Is there any relationship between the responders location and the occurrence of mental illness?
6. Would you bring up a mental health issue with a potential employer in an interview?
7. Is the number of employees in the work place a factor of causing mental illness?
8. Which variable has a correlated relationship with the occurrence of mental illness?
9. Would you be willing to discuss a mental health issue with your coworkers?
10. Does the care_options in tech companies varies based on country?

Approach :

- First step for any analysis in data science is to view the data in the dataset and understand the structure of the imported data.
- Understand each attributes in the dataset.
- Data cleansing will be the next step and Null/NA data handling in the source dataset to make it ready for analysis.
- Outlier Analysis and Treatment.Aggregation functions are very useful for understanding the data and present its summarized picture.
- Identify the dependent and independent variable from the dataset.
- perform plotting using the diffrent library functions.
- Compare and contrast predictive models using simple linear, multiple linear, and polynomial regression methods.
- Evaluate a model for overfitting and underfitting conditions and tune its performance using regularization and grid search.
- Create training and test dataset from source data to perform accuracy testing of the model.

Approach to address the problem :

- Prepare data for analysis by handling missing values, formatting and normalizing data, binning, and turning categorical values into numeric values.
- Examine data using descriptive statistics, data grouping, analysis of variance (ANOVA), and correlation statistics.
- Compare and contrast predictive models using simple linear, multiple linear, and polynomial regression methods.
- Evaluate a model for overfitting and underfitting conditions and tune its performance using regularization and grid search.

Datasets and Source of Data :

1. 3 datasets will be analyzed as a pert of this analysis which sourced from one dataset and splitted based on country.
    - survey_USA
    - survey_UK
    - survey_Others
2. Data sourced from : KAGGLE.

This dataset is from a 2014 survey that measures attitudes towards mental health and frequency of mental health disorders in the tech workplace.

no_employees column have date for some of the rows which is data impurities and needs to be cleaned.

```
setwd("C:/Users/14024/Desktop/dsc520-fork-chitro")

## Load the `2014 data' to
survey_USA <- read.csv("Final project/survey_USA.csv")

## Load the `2016 data' to
survey_UK <- read.csv("Final project/survey_UK.csv")

## Load the `Others data' to
survey_others <- read.csv("Final project/survey_others.csv")
```

Understanding dataset columns:

- Timestamp :
- Age : Age of the employee.
- Gender : Male or Female employee.
- Country : Employee working in which country.
- state: If you live in the United States, which state or territory do you live in?
- self_employed: Are you self-employed?
- family_history: Do you have a family history of mental illness?
- treatment: Have you sought treatment for a mental health condition?
- work_interfere: If you have a mental health condition, do you feel that it interferes with your work?
- no_employees: How many employees does your company or organization have?
- remote_work: Do you work remotely (outside of an office) at least 50% of the time?
- tech_company: Is your employer primarily a tech company/organization?
- benefits: Does your employer provide mental health benefits?
- care_options: Do you know the options for mental health care your employer provides?
- wellness_program: Has your employer ever discussed mental health as part of an employee wellness program?
- seek_help: Does your employer provide resources to learn more about mental health issues and how to seek help?
- anonymity: Is your anonymity protected if you choose to take advantage of mental health or substance abuse * treatment resources?
- leave: How easy is it for you to take medical leave for a mental health condition?
- mentalhealthconsequence: Do you think that discussing a mental health issue with your employer would have * negative consequences?
- physhealthconsequence: Do you think that discussing a physical health issue with your employer would have * negative consequences?
- coworkers: Would you be willing to discuss a mental health issue with your coworkers?
- physhealthinterview: Would you bring up a physical health issue with a potential employer in an interview?
- mentalvsphysical: Do you feel that your employer takes mental health as seriously as physical health?
- obs_consequence: Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?
- comments: Any additional notes or comments

Required Packages :

```r
library("ggplot2")# plot
library("plyr")# data cleanning
library("dplyr")# data cleanning
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:plyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following objects are masked from 'package:stats':
##
##     filter, lag
## The following objects are masked from ’package:base’:
##
##     intersect, setdiff, setequal, union
```

```
library("magrittr")
library("foreign")
library("coefplot")
library("caTools")
library("rlang")
```

```
##
## Attaching package: ’rlang’
```

```
## The following object is masked from ’package:magrittr’:
##
##     set_names
```

```
library("lazyeval")
```

```
##
## Attaching package: ’lazyeval’
```

```
## The following objects are masked from ’package:rlang’:
##
##     as_name, call_modify, call_standardise, expr_label, expr_text,
##     f_env, f_env<-, f_label, f_lhs, f_lhs<-, f_rhs, f_rhs<-, f_text,
##     is_atomic, is_call, is_formula, is_lang, is_pairlist, missing_arg
```

```
library("gridExtra")
```

```
##
## Attaching package: ’gridExtra’
```

```
## The following object is masked from ’package:dplyr’:
##
##     combine
```

```
library("tidyr")
```

```
##
## Attaching package: ’tidyr’
```

```
## The following object is masked from ’package:magrittr’:
##
##     extract
```

```
library("readr")
library("purrr")
```

```
##
## Attaching package: 'purrr'

## The following objects are masked from 'package:lazyeval':
##
##     is_atomic, is_formula

## The following objects are masked from 'package:rlang':
##
##     %@%, flatten, flatten_chr, flatten_dbl, flatten_int, flatten_lgl,
##     flatten_raw, invoke, splice

## The following object is masked from 'package:magrittr':
##
##     set_names

## The following object is masked from 'package:plyr':
##
##     compact
```

```r
library("tibble")
library("stringr")
library("forcats")
library("rworldmap")
```

```
## Loading required package: sp

## ### Welcome to rworldmap ###

## For a short introduction type :   vignette('rworldmap')
```

```r
##library('maps')# world map
##library("corrplot")# corrplot
##library("fiftystater")# us map
```

Plots :

- histogram
- boxplot
- Points plot
- bar plot
- line plot
- Points and line plot

Questions for future steps :

- Need to join all 3 datasets to analyze/answer questions across diffrent countries.
- What level of data munjing required to develop a model.
- What should be the split percentage of test and training data for the accuracy testing of the model.

Import and clean data :

- Downloaded the data from kaggle and kept in local machine. Split the 2014 into 3 different dataset based on the country value.
- Use read.csv function to read and import the data into diffent variables.
- Check whcih all columns have ‘NA’ and count of such rows in each dataset.
- As this data entered in the survey by employee and some of the columns data are not consistent which will be useful for analysis, make themconsistent.
- Remove missing values Sometimes, people tend to not put a value while filling their survey. Since there is an abundance of data instances, it is not too much of a worry to drop them from our model.
- Detect anomalies (outliers) in numeric attributes, in this dataset age is only numeric variable.Some of the columns data is invalid which need to filter out before making the dataset final.

```
setwd("C:/Users/14024/Desktop/dsc520-fork-chitro")

## Load the `USA data' to
survey_USA <- read.csv("Final project/survey_USA.csv")
#head(survey_2014)
## Load the `UK data' to
survey_UK <- read.csv("Final project/survey_UK.csv")
#head(survey_UK)
## Load the `Others data' to
survey_Others <- read.csv("Final project/survey_Others.csv")
#head(survey_Others)

## Display internal structure of survey_USA and Columns contains 'NA' value
str(survey_USA)
```

```
## ’data.frame’:    751 obs. of  27 variables:
##  $ Timestamp                : chr  "8/27/2014 11:29" "8/27/2014 11:29" "8/27/2014 11:30" "8/27/2014
##  $ Age                      : int  37 44 31 33 35 42 31 42 36 29 ...
##  $ Gender                   : chr  "Female" "M" "Male" "Male" ...
##  $ Country                  : chr  "United States" "United States" "United States" "United States" .
##  $ state                    : chr  "IL" "IN" "TX" "TN" ...
##  $ self_employed            : chr  NA NA NA NA ...
##  $ family_history           : chr  "No" "No" "No" "Yes" ...
##  $ treatment                : chr  "Yes" "No" "No" "No" ...
##  $ work_interfere           : chr  "Often" "Rarely" "Never" "Sometimes" ...
##  $ no_employees             : chr  "25-Jun" "More than 1000" "100-500" "25-Jun" ...
##  $ remote_work              : chr  "No" "No" "Yes" "No" ...
##  $ tech_company             : chr  "Yes" "No" "Yes" "Yes" ...
##  $ benefits                 : chr  "Yes" "Don’t know" "Yes" "Yes" ...
##  $ care_options             : chr  "Not sure" "No" "No" "Not sure" ...
##  $ wellness_program         : chr  "No" "Don’t know" "Don’t know" "No" ...
##  $ seek_help                : chr  "Yes" "Don’t know" "Don’t know" "Don’t know" ...
##  $ anonymity                : chr  "Yes" "Don’t know" "Don’t know" "Don’t know" ...
##  $ leave                    : chr  "Somewhat easy" "Don’t know" "Don’t know" "Don’t know" ...
##  $ mental_health_consequence: chr  "No" "Maybe" "No" "No" ...
##  $ phys_health_consequence  : chr  "No" "No" "No" "No" ...
##  $ coworkers                : chr  "Some of them" "No" "Some of them" "Yes" ...
##  $ supervisor               : chr  "Yes" "No" "Yes" "Yes" ...
##  $ mental_health_interview  : chr  "No" "No" "Yes" "No" ...
##  $ phys_health_interview    : chr  "Maybe" "No" "Yes" "Maybe" ...
##  $ mental_vs_physical       : chr  "Yes" "Don’t know" "Don’t know" "Don’t know" ...
##  $ obs_consequence          : chr  "No" "No" "No" "No" ...
##  $ comments                 : chr  NA NA NA NA ...
```

```r
sapply(survey_USA, function(x) sum(is.na(x)))
```

```
##                 Timestamp                       Age                    Gender
##                         0                         0                         0
##                   Country                     state             self_employed
##                         0                        11                        11
##            family_history                 treatment            work_interfere
##                         0                         0                       144
##              no_employees               remote_work              tech_company
##                         0                         0                         0
##                  benefits              care_options          wellness_program
##                         0                         0                         0
##                 seek_help                 anonymity                     leave
##                         0                         0                         0
## mental_health_consequence   phys_health_consequence                 coworkers
##                         0                         0                         0
##                supervisor   mental_health_interview     phys_health_interview
##                         0                         0                         0
##        mental_vs_physical           obs_consequence                  comments
##                         0                         0                       647
```

```r
## Display internal structure of survey_UK and Columns contains 'NA' value
str(survey_UK)
```

```
## ’data.frame’:    185 obs. of  27 variables:
##  $ Timestamp                : chr  "8/27/2014 11:29" "8/27/2014 11:34" "8/27/2014 11:38" "8/27/2014
##  $ Age                      : int  31 23 37 32 30 24 28 27 38 19 ...
##  $ Gender                   : chr  "Male" "Male" "Male" "Male" ...
##  $ Country                  : chr  "United Kingdom" "United Kingdom" "United Kingdom" "United Kingdo
##  $ state                    : logi  NA NA NA NA NA NA ...
##  $ self_employed            : chr  NA NA "No" "No" ...
##  $ family_history           : chr  "Yes" "No" "No" "No" ...
##  $ treatment                : chr  "Yes" "Yes" "No" "No" ...
##  $ work_interfere           : chr  "Often" "Sometimes" "Sometimes" "Never" ...
##  $ no_employees             : chr  "26-100" "26-100" "25-Jun" "25-Jun" ...
##  $ remote_work              : chr  "No" "Yes" "No" "Yes" ...
##  $ tech_company             : chr  "Yes" "Yes" "Yes" "Yes" ...
##  $ benefits                 : chr  "No" "Don’t know" "No" "No" ...
##  $ care_options             : chr  "Yes" "No" "No" "No" ...
##  $ wellness_program         : chr  "No" "Don’t know" "No" "No" ...
##  $ seek_help                : chr  "No" "Don’t know" "No" "No" ...
##  $ anonymity                : chr  "No" "Don’t know" "Don’t know" "Don’t know" ...
##  $ leave                    : chr  "Somewhat difficult" "Very easy" "Very difficult" "Don’t know" ..
##  $ mental_health_consequence: chr  "Yes" "Maybe" "Yes" "Yes" ...
##  $ phys_health_consequence  : chr  "Yes" "No" "Maybe" "Yes" ...
##  $ coworkers                : chr  "Some of them" "Some of them" "Some of them" "Some of them" ...
##  $ supervisor               : chr  "No" "No" "No" "Some of them" ...
##  $ mental_health_interview  : chr  "Maybe" "Maybe" "No" "No" ...
##  $ phys_health_interview    : chr  "Maybe" "Maybe" "Maybe" "Maybe" ...
##  $ mental_vs_physical       : chr  "No" "No" "No" "No" ...
##  $ obs_consequence          : chr  "Yes" "No" "No" "No" ...
##  $ comments                 : chr  NA "My company does provide healthcare but not to me as I’m on a 
```

```
sapply(survey_UK, function(x) sum(is.na(x)))
```

```
##                 Timestamp                       Age                    Gender 
##                         0                         0                         0 
##                   Country                     state             self_employed 
##                         0                       185                         2 
##            family_history                 treatment            work_interfere 
##                         0                         0                        44 
##              no_employees               remote_work              tech_company 
##                         0                         0                         0 
##                  benefits              care_options          wellness_program 
##                         0                         0                         0 
##                 seek_help                 anonymity                     leave 
##                         0                         0                         0 
## mental_health_consequence   phys_health_consequence                 coworkers 
##                         0                         0                         0 
##                supervisor   mental_health_interview     phys_health_interview 
##                         0                         0                         0 
##        mental_vs_physical           obs_consequence                  comments 
##                         0                         0                       163 
```

```
## Display internal structure of survey_Others and Columns contains 'NA' value
str(survey_Others)
```

```
## ’data.frame’:    323 obs. of  27 variables:
##  $ Timestamp                : chr  "8/27/2014 11:29" "8/27/2014 11:32" "8/27/2014 11:32" "8/27/2014 
##  $ Age                      : num  32 39 23 29 27 36 29 38 27 18 ...
##  $ Gender                   : chr  "Male" "M" "Male" "male" ...
##  $ Country                  : chr  "Canada" "Canada" "Canada" "Bulgaria" ...
##  $ state                    : chr  NA NA NA NA ...
##  $ self_employed            : chr  NA NA NA NA ...
##  $ family_history           : chr  "No" "No" "No" "No" ...
##  $ treatment                : chr  "No" "No" "No" "No" ...
##  $ work_interfere           : chr  "Rarely" "Never" "Never" "Never" ...
##  $ no_employees             : chr  "25-Jun" "5-Jan" "26-100" "100-500" ...
##  $ remote_work              : chr  "No" "Yes" "No" "Yes" ...
##  $ tech_company             : chr  "Yes" "Yes" "Yes" "Yes" ...
##  $ benefits                 : chr  "No" "No" "Don’t know" "Don’t know" ...
##  $ care_options             : chr  "No" "Yes" "No" "Not sure" ...
##  $ wellness_program         : chr  "No" "No" "Don’t know" "No" ...
##  $ seek_help                : chr  "No" "No" "Don’t know" "No" ...
##  $ anonymity                : chr  "Don’t know" "Yes" "Don’t know" "Don’t know" ...
##  $ leave                    : chr  "Somewhat difficult" "Don’t know" "Don’t know" "Don’t know" ...
##  $ mental_health_consequence: chr  "No" "No" "No" "No" ...
##  $ phys_health_consequence  : chr  "No" "No" "No" "No" ...
##  $ coworkers                : chr  "Yes" "No" "Yes" "Yes" ...
##  $ supervisor               : chr  "Yes" "No" "Yes" "Yes" ...
##  $ mental_health_interview  : chr  "Yes" "No" "Maybe" "Yes" ...
##  $ phys_health_interview    : chr  "Yes" "No" "Maybe" "Yes" ...
##  $ mental_vs_physical       : chr  "No" "No" "Yes" "Don't know" ...
##  $ obs_consequence          : chr  "No" "No" "No" "No" ...
##  $ comments                 : chr  NA NA NA NA ...
```

```
sapply(survey_Others, function(x) sum(is.na(x)))
```

```
##                 Timestamp                       Age                    Gender 
##                         0                         0                         0 
##                   Country                     state             self_employed 
##                         0                       319                         5 
##            family_history                 treatment            work_interfere 
##                         0                         0                        76 
##              no_employees               remote_work              tech_company 
##                         0                         0                         0 
##                  benefits              care_options          wellness_program 
##                         0                         0                         0 
##                 seek_help                 anonymity                     leave 
##                         0                         0                         0 
## mental_health_consequence   phys_health_consequence                 coworkers 
##                         0                         0                         0 
##                supervisor   mental_health_interview     phys_health_interview 
##                         0                         0                         0 
##        mental_vs_physical           obs_consequence                  comments 
##                         0                         0                       285
```

```
## checking the unique values in the Gender column in each dataset
unique(survey_USA$Gender)
```

```
##  [1] "Female"           "M"                "Male"             "female"          
##  [5] "male"             "Male-ish"         "maile"            "Trans-female"    
##  [9] "Cis Female"       "F"                "Cis Male"         "m"               
## [13] "f"                "Male (CIS)"       "queer/she/they"   "non-binary"      
## [17] "Femake"           "woman"            "Make"             "Nah"             
## [21] "Genderqueer"      "Female "          "Woman"            "cis-female/femme"
## [25] "Male "            "Trans woman"      "Man"              "msle"            
## [29] "Female (trans)"   "Female (cis)"     "Mail"             "cis male"        
## [33] "p"                "femail"
```

```
unique(survey_UK$Gender)
```

```
##  [1] "Male"
##  [2] "male"
##  [3] "M"
##  [4] "Woman"
##  [5] "Female"
##  [6] "Enby"
##  [7] "Androgyne"
##  [8] "female"
##  [9] "Agender"
## [10] "f"
## [11] "m"
## [12] "Neuter"
## [13] "F"
## [14] "Male "
## [15] "Cis Man"
## [16] "ostensibly male, unsure what that really means"
```

```
unique(survey_Others$Gender)
```

```
##  [1] "Male"                     "M"
##  [3] "male"                     "m"
##  [5] "Female"                   "something kinda male?"
##  [7] "F"                        "female"
##  [9] "f"                        "Mal"
## [11] "All"                      "fluid"
## [13] "Guy (-ish) ^_^"           "male leaning androgynous"
## [15] "Man"                      "queer"
## [17] "A little about you"       "Malr"
## [19] "Male "
```

```
## converting the column values to lowercase
survey_USA$Gender <- tolower(survey_USA$Gender)
survey_UK$Gender <- tolower(survey_UK$Gender)
survey_Others$Gender <- tolower(survey_Others$Gender)

## defining lists on the basis of unique values present in the dataset
male <- c('male-ish', 'cis male', 'male (cis)', 'make', 'mail',
          'ostensibly male, unsure what that really means', 'm', 'maile',
          'male ', 'msle', 'mal', 'man', 'malr', 'cis man', 'male')
female <- c('female', 'female ', 'female (cis)', 'woman', 'cis female',
            'cis-female/femme', 'femail', 'f', 'femake')
others <- c('p', 'nah', 'all', 'a little about you', 'genderqueer',
            'non-binary', 'trans woman', 'androgyne', 'neuter', 'trans-female',
            'agender', 'female (trans)', 'something kinda male?', 'enby', 'guy (-ish) ^_^',
            'queer', 'queer/she/they', 'male leaning androgynous', 'fluid', 'genderqueer',
            'non-binary', 'trans woman', 'androgyne', 'neuter', 'trans-female',
            'agender', 'female (trans)', 'something kinda male?', 'enby',
            'guy (-ish) ^_^', 'queer', 'queer/she/they', 'male leaning androgynous', 'fluid')


## replace the values in the data set so that the categories are consistent
survey_USA <- survey_USA %>%
  mutate(Gender = replace(Gender, which(Gender %in% male), 'Male'),
                          Gender = replace(Gender, which(Gender %in% female), 'Female'),
                          Gender = replace(Gender, which(Gender %in% others), 'Others'))
survey_UK <- survey_UK %>%
  mutate(Gender = replace(Gender, which(Gender %in% male), 'Male'),
                          Gender = replace(Gender, which(Gender %in% female), 'Female'),
                          Gender = replace(Gender, which(Gender %in% others), 'Others'))
survey_Others <- survey_Others %>%
  mutate(Gender = replace(Gender, which(Gender %in% male), 'Male'),
                         Gender = replace(Gender, which(Gender %in% female), 'Female'),
                         Gender = replace(Gender, which(Gender %in% others), 'Others'))
## checking if all values are covered and category is consistent
unique(survey_USA$Gender)
```

```
## [1] "Female" "Male"   "Others"
```

```
unique(survey_UK$Gender)
```

```
## [1] "Male"   "Female" "Others"
```

```
unique(survey_Others$Gender)
```

```
## [1] "Male"   "Female" "Others"
```

```
## checking the summary of the Age column
summary(survey_USA$Age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##  -29.00   27.50   32.00   33.33   37.50  329.00 
```

```
summary(survey_UK$Age)
```

```
##     Min.   1st Qu.    Median      Mean   3rd Qu.      Max. 
## -1726.00     26.00     31.00     21.44     34.00     55.00 
```

```
summary(survey_Others$Age)
```

```
##      Min.    1st Qu.     Median       Mean    3rd Qu.       Max. 
## 8.000e+00 2.600e+01 2.900e+01 3.096e+08 3.400e+01 1.000e+11 
```

```
## age have some negative and more than 100 values which needs to be cleaned as age -ve is
## invalid and more than can be considered as invalid
## keeping rows with age between 18 and 100

survey_USA_df <- survey_USA %>% filter(Age >= 18 & Age < 100)
survey_UK_df <- survey_UK %>% filter(Age >= 18 & Age < 100)
survey_Others_df <- survey_Others %>% filter(Age >= 18 & Age < 100)

survey_USA_final_df <- survey_USA_df %>% select(-c(Timestamp,comments))
survey_UK_final_df <- survey_UK_df %>% select(-c(Timestamp,comments))
survey_Others_final_df <- survey_Others_df %>% select(-c(Timestamp,comments))
```

What does the final data set look like :

```
survey_data <- rbind(survey_USA_final_df, survey_UK_final_df, survey_Others_final_df)
survey_data %>% dim
```

```
## [1] 1251   25
```

```
summary(survey_data)
```

```
##       Age           Gender            Country             state          
##  Min.   :18.00   Length:1251        Length:1251        Length:1251       
##  1st Qu.:27.00   Class :character   Class :character   Class :character  
##  Median :31.00   Mode  :character   Mode  :character   Mode  :character  
##  Mean   :32.08                                                           
##  3rd Qu.:36.00                                                           
##  Max.   :72.00                                                           
##  self_employed      family_history      treatment         work_interfere    
##  Length:1251        Length:1251        Length:1251        Length:1251       
##  Class :character   Class :character   Class :character   Class :character  
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character  
##                                                                             
##                                                                             
##                                                                             
##  no_employees       remote_work        tech_company         benefits        
##  Length:1251        Length:1251        Length:1251        Length:1251       
##  Class :character   Class :character   Class :character   Class :character  
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character  
##                                                                             
##                                                                             
##                                                                             
##  care_options       wellness_program    seek_help          anonymity        
##  Length:1251        Length:1251        Length:1251        Length:1251       
##  Class :character   Class :character   Class :character   Class :character  
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character  
##                                                                             
##                                                                             
##                                                                             
##     leave           mental_health_consequence phys_health_consequence
##  Length:1251        Length:1251               Length:1251            
##  Class :character   Class :character          Class :character       
##  Mode  :character   Mode  :character          Mode  :character       
##                                                                      
##                                                                      
##                                                                      
##   coworkers          supervisor        mental_health_interview
##  Length:1251        Length:1251        Length:1251            
##  Class :character   Class :character   Class :character       
##  Mode  :character   Mode  :character   Mode  :character       
##                                                               
##                                                               
##                                                               
##  phys_health_interview mental_vs_physical obs_consequence   
##  Length:1251           Length:1251        Length:1251       
##  Class :character      Class :character   Class :character  
##  Mode  :character      Mode  :character   Mode  :character  
##                                                             
##                                                             
##                                                             
```

```
summarise(survey_data, min_age = min(Age))
```

```
##   min_age
## 1      18
```

```
summarise(survey_data, max_age = max(Age))
```

```
##   max_age
## 1      72
```

```
summarise(survey_data, med = median(Age))
```

```
##   med
## 1  31
```

```
state_freq <- as.data.frame(table(survey_data$state))
colnames(state_freq) <- c("state","freq")
as_tibble(state_freq)
```

```
## # A tibble: 45 x 2
##    state  freq
##    <fct> <int>
##  1 AL        7
##  2 AZ        7
##  3 CA      138
##  4 CO        9
##  5 CT        4
##  6 DC        4
##  7 FL       15
##  8 GA       12
##  9 IA        4
## 10 ID        1
## # ... with 35 more rows
```

What information is not self-evident :

- This data is entered by employee during survey, so some of the columns such as family_history, mentalhealthconsequence and physhealthconsequence might not be self evident as some of the employees might think they might have some -ve consequnces for providing this info in survey.

Questions for future steps :

- Binary Vairables are treatment, family_history and Tech_company in the dataset and No_emloyes is categorical variable. Need to use this for linear and logistic model design.
- Based on which column we should group the data from each dataset which will provide relevant answer to the research questions.
- Identify the variables from dataset which have linear relationship between them.
- Identify the variables which will have binomial output and can be used fro logistic regression.

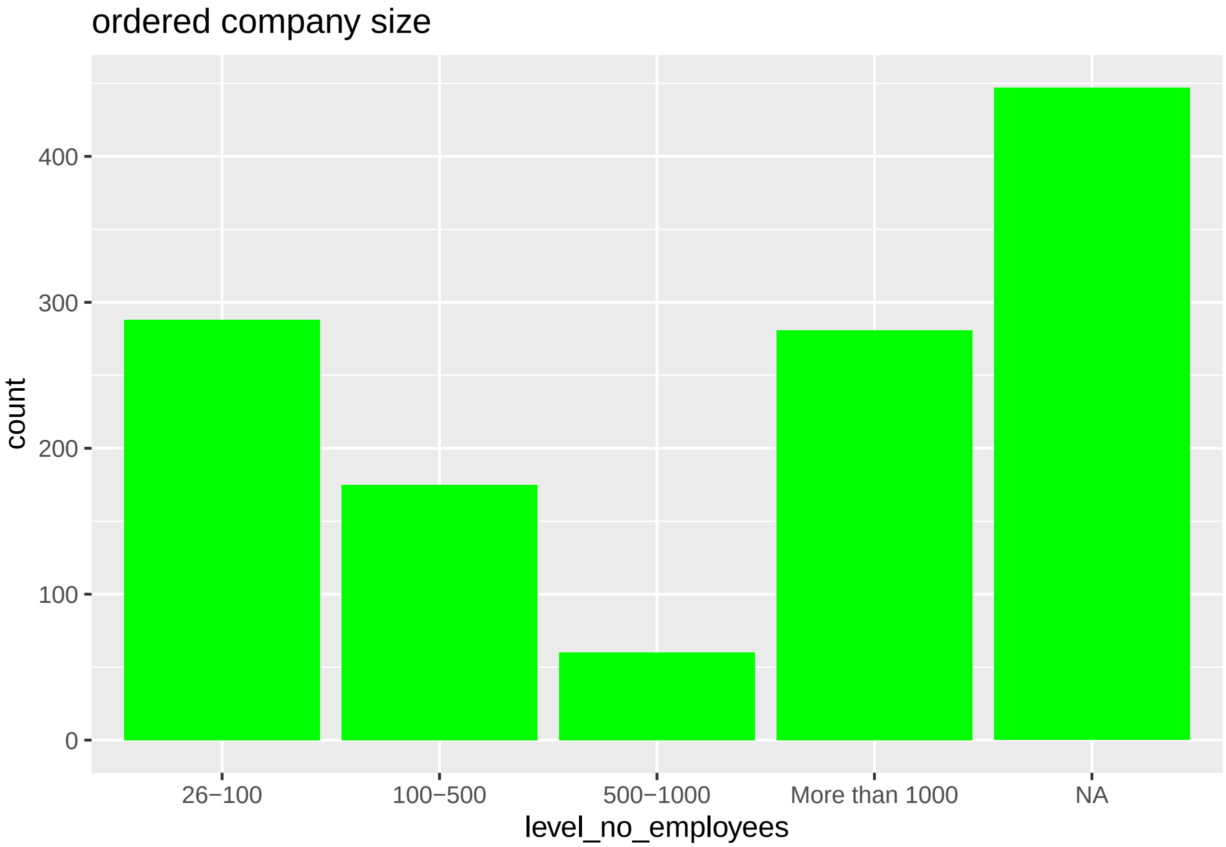
Different ways to look at data and slicing and dicing of data with visualization :

- Visualize based of no_employees in company
- Visualize based on gender
- Visualize based on age

```
## view the specific number of company in each size range
survey_data$no_employees %>% table
```

```
## .
##        100-500         25-Jun         26-100          5-Jan       500-1000
##            175            289            288            158             60
## More than 1000
##            281
```

```
## ordered no_employees level
  level_no_employees <- factor(survey_data$no_employees, levels =
                c("1-5","6-25","26-100","100-500","500-1000","More than 1000"))
## view the company distribution based on company size
survey_data %>% ggplot(aes(x=level_no_employees))+
  geom_bar(fill = "green") + ggtitle("ordered company size")
```



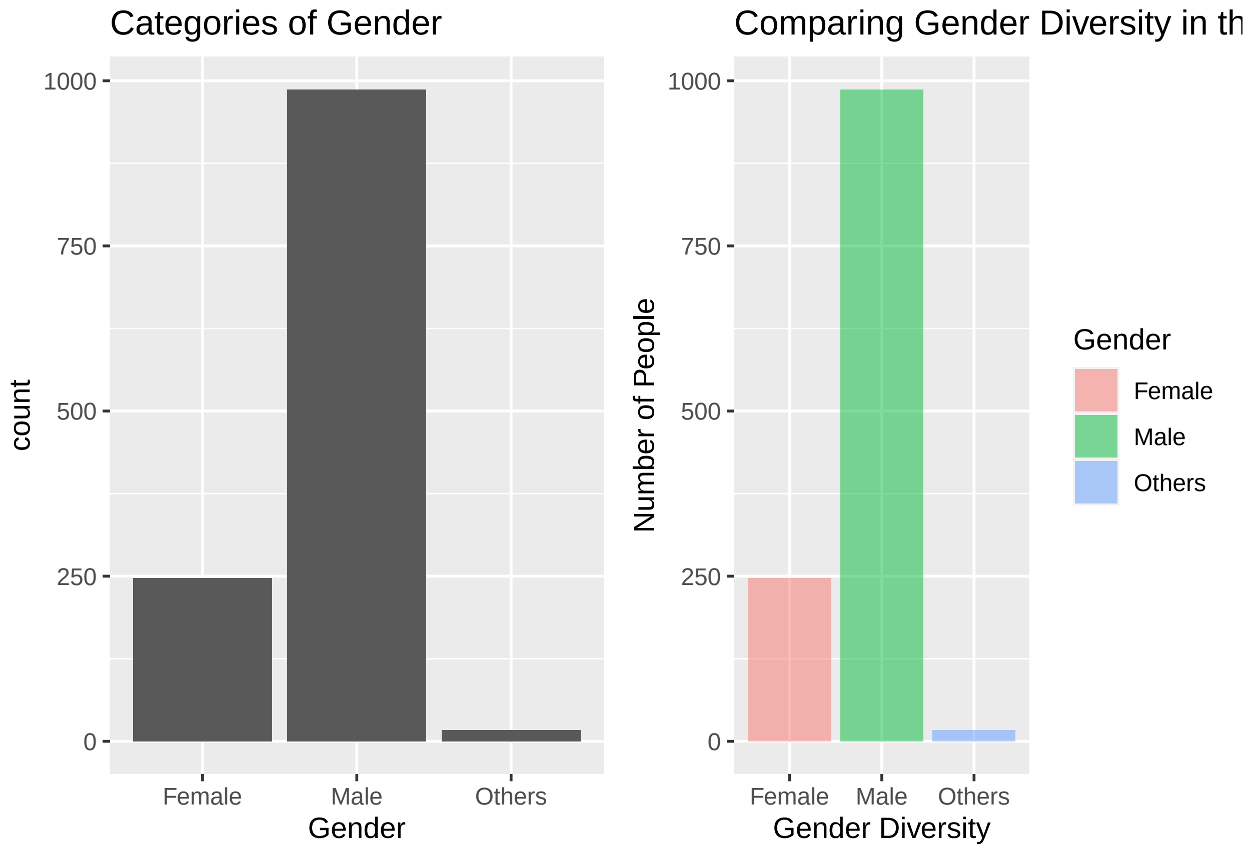
```
gender_diversity <- survey_data %>%
  group_by(Gender) %>%
  dplyr::summarize(count = n())
gender_diversity
```

```
## # A tibble: 3 x 2
##   Gender count
##   <chr>  <int>
## 1 Female   247
## 2 Male     987
## 3 Others    17
```

```
## Visualize the number of subjects in each gender type
G1 <- survey_data %>% ggplot(aes(x=Gender)) +
  geom_bar() + ggtitle("Categories of Gender")

G2 <- ggplot(gender_diversity, aes(x = Gender, y = count, fill = Gender)) +
  geom_bar(stat = "identity", alpha = 0.5) +
  xlab("Gender Diversity") +
  ylab("Number of People") +
  ggtitle("Comparing Gender Diversity in the 2014 Mental Health in Tech Survey")

grid.arrange(G1, G2, nrow = 1)
```



```
#Age distribution
g1 <- survey_data %>% ggplot(aes(x=Age)) +
```

```r
  geom_histogram() + ggtitle("Distribution of Age")

# Histogram of Age
g2 <- ggplot(survey_data,aes(x=Age))+geom_histogram(aes(y=..density..), fill="green")+geom_density(col=
                       title="Distribution of Transformed Age")
# Age categorization#
survey_data$Age<-cut(survey_data$Age, breaks = c(0, 16, 34, 60, 75),
                      labels = c('Fresh', 'Junior', 'Senior', 'Super'))

# Verify Age group
survey_data$Age %>% table
```

```
## .
##  Fresh Junior Senior  Super
##      0    863    384      4
```

```r
# Group by Age Group and count each group
age_group <- survey_data %>%
  group_by(Age) %>%
  dplyr::summarize(count = n())
age_group
```

```
## # A tibble: 3 x 2
##   Age    count
##   <fct>  <int>
## 1 Junior   863
## 2 Senior   384
## 3 Super      4
```

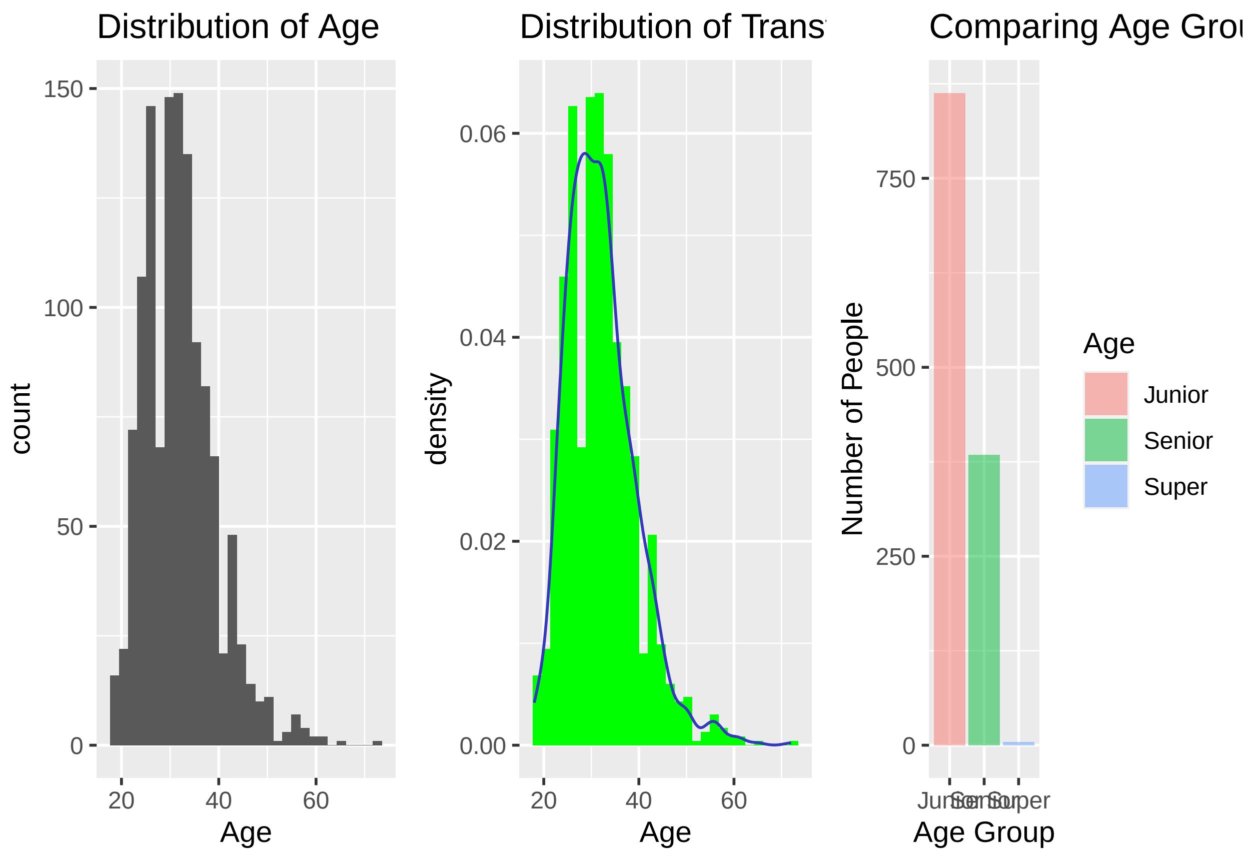
```r
g3 <- ggplot(age_group, aes(x = Age, y = count, fill = Age)) +
  geom_bar(stat = "identity", alpha = 0.5) +
  xlab("Age Group") +
  ylab("Number of People") +
  ggtitle("Comparing Age Group in the 2014 Mental Health in Tech Survey")

grid.arrange(g1, g2, g3, nrow = 1)
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
## i Please use `after_stat(density)` instead.

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



## summarize your data to answer key questions

```
# First, re-value the variables of interest
survey_data$no_employees <- as.factor(revalue(survey_data$no_employees,
                       c("1-5"="1", "6-25"="2", "26-100"="3", "100-500"="4",
                         "500-1000"="5", "More than 1000"="6")))
```

```
## The following `from` values were not present in `x`: 1-5, 6-25
```

```
survey_data$treatment <- as.numeric(revalue(survey_data$treatment,
                                            c("No"="0", "Yes"="1")))
# Get a collection of tables for the responses

questions_only <- survey_data[,5:24]

response_tables <-
  lapply(questions_only, function(Response) as.data.frame(table(Response)))

# Add names of questions for each for plotting purposes
plot_tables <-
  lapply(seq_along(response_tables),
         function(x) mutate(response_tables[[x]], name = names(response_tables)[x]))

all_questions <- bind_rows(plot_tables)
all_questions
```

```
##                Response Freq                                   name
## 1                  No 1091             self_employed
## 2                 Yes  142             self_employed
## 3                  No  762            family_history
## 4                 Yes  489            family_history
## 5                   0  619                 treatment
## 6                   1  632                 treatment
## 7               Never  212            work_interfere
## 8               Often  140            work_interfere
## 9              Rarely  173            work_interfere
## 10          Sometimes  464            work_interfere
## 11             25-Jun  289              no_employees
## 12                  3  288              no_employees
## 13                  4  175              no_employees
## 14                  5   60              no_employees
## 15              5-Jan  158              no_employees
## 16                  6  281              no_employees
## 17                 No  880               remote_work
## 18                Yes  371               remote_work
## 19                 No  226              tech_company
## 20                Yes 1025              tech_company
## 21         Don’t know  407                  benefits
## 22                 No  371                  benefits
## 23                Yes  473                  benefits
## 24                 No  499              care_options
## 25           Not sure  313              care_options
## 26                Yes  439              care_options
## 27         Don’t know  187          wellness_program
## 28                 No  837          wellness_program
## 29                Yes  227          wellness_program
## 30         Don’t know  363                 seek_help
## 31                 No  641                 seek_help
## 32                Yes  247                 seek_help
## 33         Don’t know  815                 anonymity
## 34                 No   64                 anonymity
## 35                Yes  372                 anonymity
## 36         Don’t know  561                     leave
## 37 Somewhat difficult  125                     leave
## 38      Somewhat easy  265                     leave
## 39     Very difficult   97                     leave
## 40          Very easy  203                     leave
## 41              Maybe  476 mental_health_consequence
## 42                 No  487 mental_health_consequence
## 43                Yes  288 mental_health_consequence
## 44              Maybe  273   phys_health_consequence
## 45                 No  920   phys_health_consequence
## 46                Yes   58   phys_health_consequence
## 47                 No  258                 coworkers
## 48       Some of them  771                 coworkers
## 49                Yes  222                 coworkers
## 50                 No  390                supervisor
## 51       Some of them  349                supervisor
## 52                Yes  512                supervisor
## 53              Maybe  207   mental_health_interview
## 54                 No 1003   mental_health_interview
## 55                Yes   41   mental_health_interview
## 56              Maybe  555     phys_health_interview
## 57                 No  496     phys_health_interview
## 58                Yes  200     phys_health_interview
## 59         Don’t know  574        mental_vs_physical
## 60                 No  338        mental_vs_physical
## 61                Yes  339        mental_vs_physical
```

```
# Group by family_history and count each group

fh_count <- survey_data %>%
  group_by(family_history) %>%
  dplyr::summarize(count = n(), proportion = n()/nrow(survey_data))
fh_count
```

```
## # A tibble: 2 x 3
##   family_history count proportion
##   <chr>          <int>      <dbl>
## 1 No               762      0.609
## 2 Yes              489      0.391
```

```
# Group by treatment and Gender and count each group

treat_count <- survey_data %>%
  group_by(treatment, Gender) %>%
  dplyr::summarize(count = n(), proportion = n()/nrow(survey_data))
```

```
## ‘summarise()‘ has grouped output by ’treatment’. You can override using the
## ‘.groups‘ argument.
```

```
treat_count
```

```
## # A tibble: 6 x 4
## # Groups:   treatment [2]
##   treatment Gender count proportion
##       <dbl> <chr>  <int>      <dbl>
## 1         0 Female    77    0.0616
## 2         0 Male     538    0.430
## 3         0 Others     4    0.00320
## 4         1 Female   170    0.136
## 5         1 Male     449    0.359
## 6         1 Others    13    0.0104
```

```
# care_options available based on country

care_count <- survey_data %>% filter(care_options == "Yes") %>%
  group_by(Country) %>%
  dplyr::summarize(count = n(), proportion = n()/nrow(survey_data))
care_count
```

```
## # A tibble: 30 x 3
##    Country        count proportion
##    <chr>          <int>      <dbl>
##  1 Australia          9   0.00719
##  2 Austria            1   0.000799
##  3 Belgium            1   0.000799
##  4 Brazil             2   0.00160
##  5 Canada            28   0.0224
##  6 China              1   0.000799
##  7 Colombia           1   0.000799
##  8 Costa Rica         1   0.000799
##  9 Croatia            1   0.000799
## 10 Czech Republic     1   0.000799
## # ... with 20 more rows
```

```
# Group by work_interfere response and count each group

survey_data$work_interfere <- factor(survey_data$work_interfere, ordered = TRUE,
                  levels = c('NA', 'Never', 'Rarely', 'Sometimes', 'Often'))

wi_count <- survey_data %>%
  group_by(work_interfere) %>%
  dplyr::summarize(count = n(), proportion = n()/nrow(survey_data)) %>%
  arrange(work_interfere)
wi_count
```

```
## # A tibble: 5 x 3
##   work_interfere count proportion
##   <ord>          <int>      <dbl>
## 1 Never            212      0.169
## 2 Rarely           173      0.138
## 3 Sometimes        464      0.371
## 4 Often            140      0.112
## 5 <NA>             262      0.209
```

```
# Group by Country and count each group
country_count <- survey_data %>%
  group_by(Country) %>%
  dplyr::summarize(count = n())
country_count
```

```
## # A tibble: 46 x 2
##    Country                count
##    <chr>                  <int>
##  1 Australia                 21
##  2 Austria                    3
##  3 Belgium                    6
##  4 Bosnia and Herzegovina     1
##  5 Brazil                     6
##  6 Bulgaria                   4
##  7 Canada                    72
##  8 China                      1
##  9 Colombia                   2
## 10 Costa Rica                 1
## # ... with 36 more rows
```

```
mental_health_interview <- survey_data %>%
  group_by(mental_health_interview) %>%
  summarise(n = n()) %>%
  mutate( percentage = signif(100 * ( n /sum(n)),2))
mental_health_interview
```

```
## # A tibble: 3 x 3
##   mental_health_interview     n percentage
##   <chr>                   <int>      <dbl>
## 1 Maybe                     207       17  
## 2 No                       1003       80  
## 3 Yes                        41        3.3
```

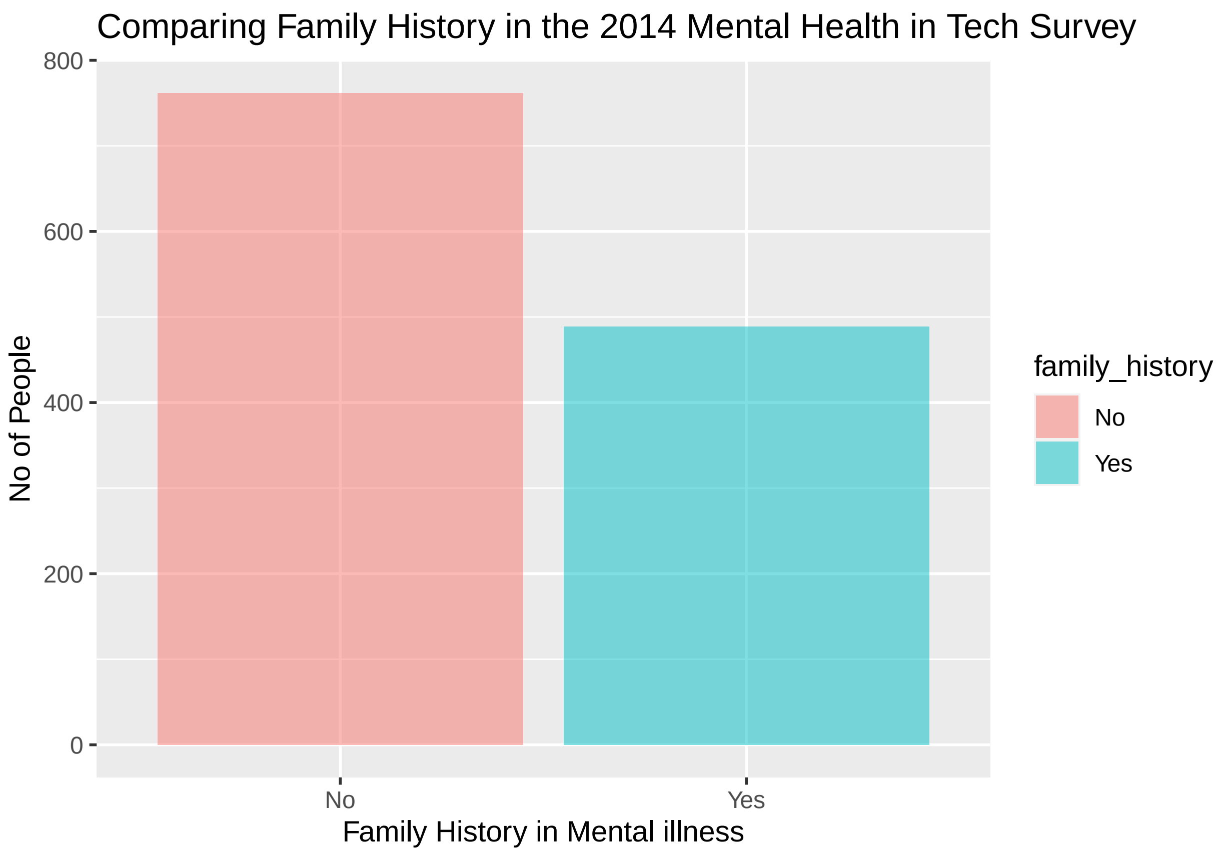
```
coworkers <- survey_data %>%
  group_by(coworkers) %>%
  summarise(n = n()) %>%
  mutate( percentage = signif(100 * ( n /sum(n)),2))
coworkers
```

```
## # A tibble: 3 x 3
##   coworkers        n percentage
##   <chr>        <int>      <dbl>
## 1 No             258         21
## 2 Some of them   771         62
## 3 Yes            222         18
```

Ploting to illustrate the finding of key questions :

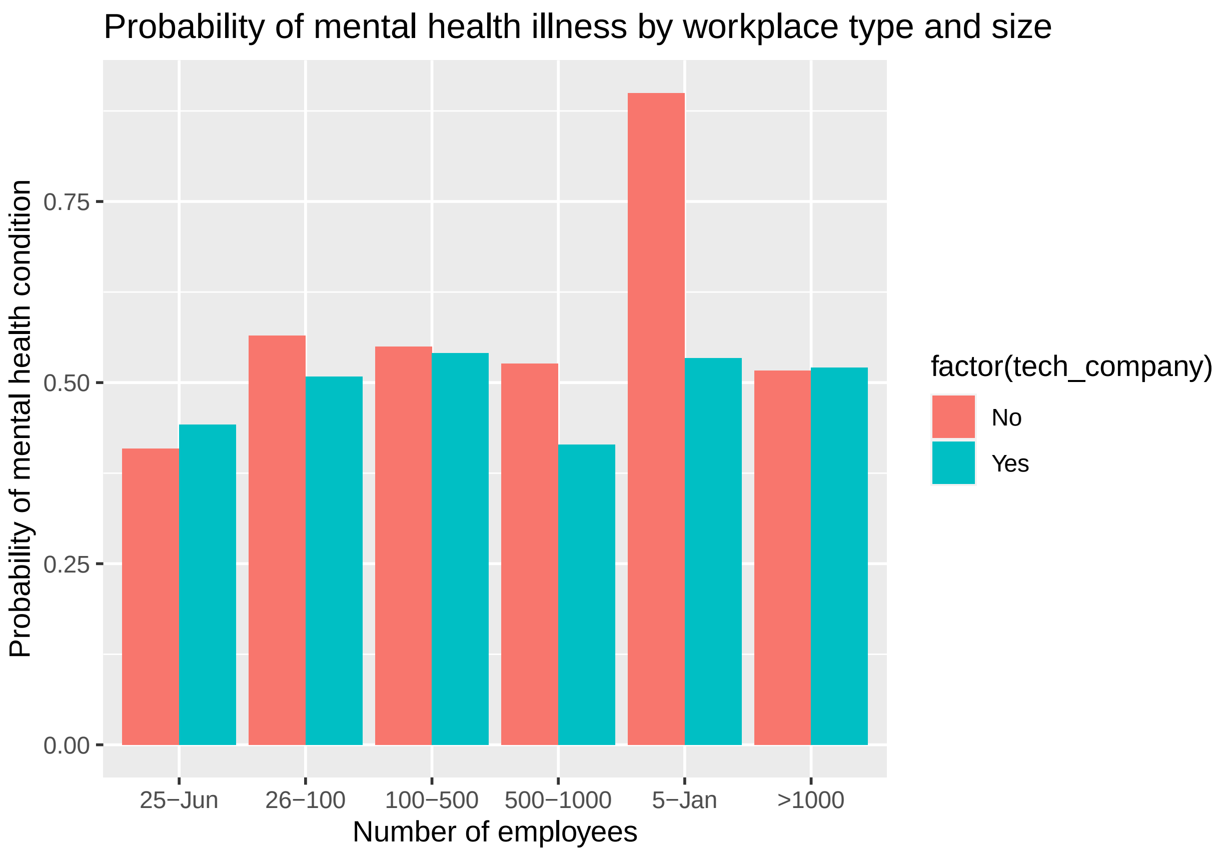
```
# Does family_history have any relation with mentalhealth

ggplot(fh_count, aes(x = family_history, y = count, fill = family_history)) +
  geom_bar(stat = "identity", alpha = 0.5) +
  xlab("Family History in Mental illness") +
  ylab("No of People") +
  ggtitle("Comparing Family History in the 2014 Mental Health in Tech Survey")
```

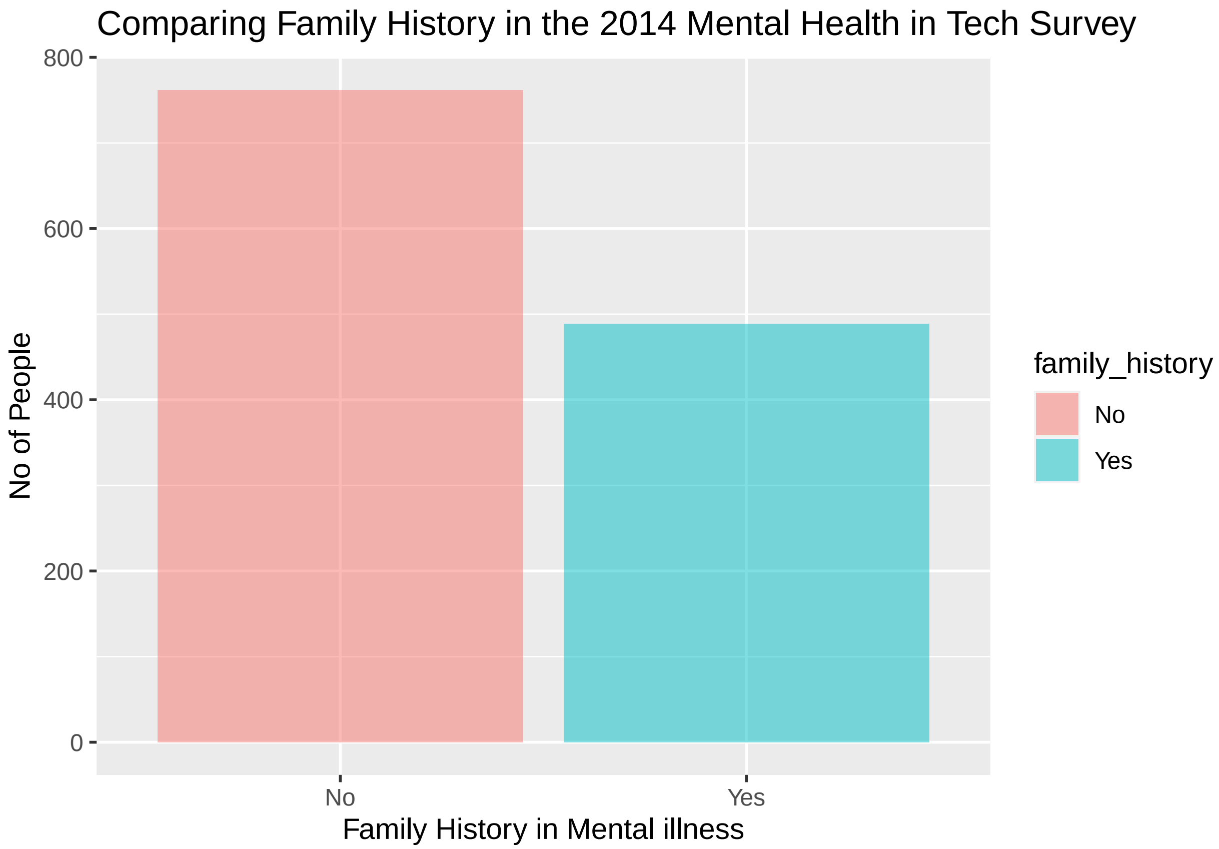


```
# Use a bar graph to graph `treatment` (treated mental health condition)
# over `no_employees` (number of employees) and `tech_company` (company type)
ggplot(survey_data,aes(x=no_employees,y=treatment, fill=factor(tech_company)),
       color=factor(vs)) +
  stat_summary(fun.y=mean,position=position_dodge(),geom="bar") +
  labs(x = "Number of employees", y = "Probability of mental health condition",
       title = "Probability of mental health illness by workplace type and size") +
  scale_x_discrete(labels=c("1" = "1-5", "2" = "6-25", "3" = "26-100", "4"="100-500",
                              "5"="500-1000", "6"=">1000"))
```

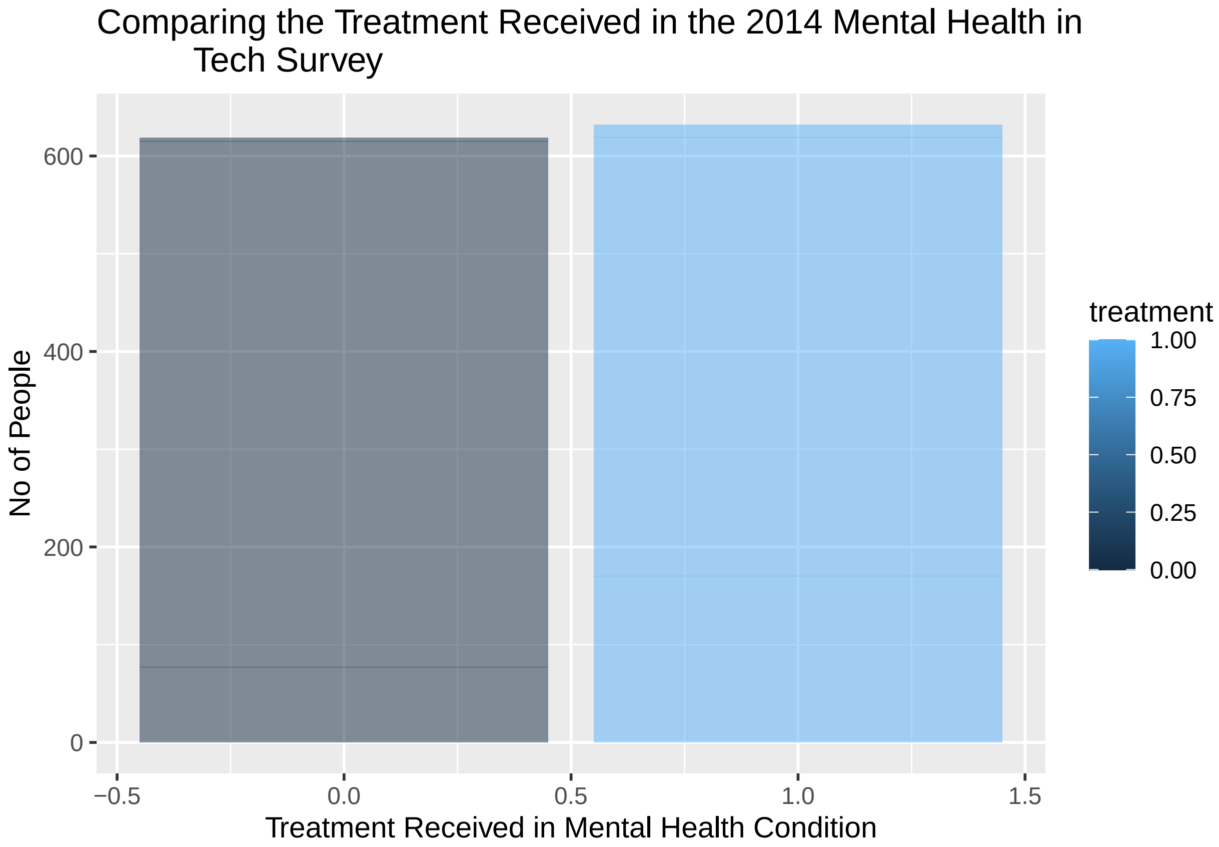
```
## Warning: The ‘fun.y‘ argument of ‘stat_summary()‘ is deprecated as of ggplot2 3.3.0.
## i Please use the ‘fun‘ argument instead.
```



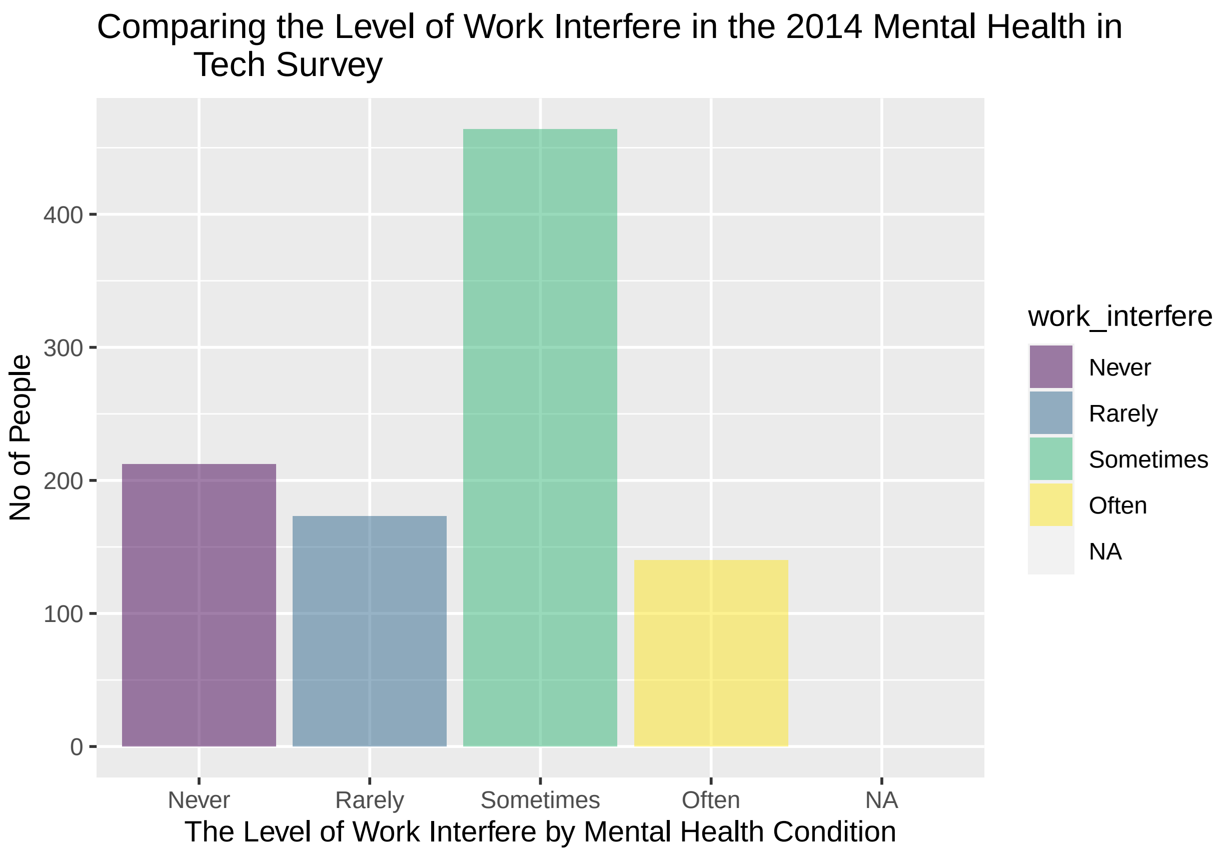
```
ggplot(fh_count, aes(x = family_history, y = count, fill = family_history)) +
  geom_bar(stat = "identity", alpha = 0.5) +
  xlab("Family History in Mental illness") +
  ylab("No of People") +
  ggtitle("Comparing Family History in the 2014 Mental Health in Tech Survey")
```



```
# Visualize the number of subjects
ggplot(treat_count, aes(x = treatment, y = count, fill = treatment)) +
  geom_bar(stat = "identity", alpha = 0.5) +
  xlab("Treatment Received in Mental Health Condition") +
  ylab("No of People") +
  ggtitle("Comparing the Treatment Received in the 2014 Mental Health in
          Tech Survey")
```

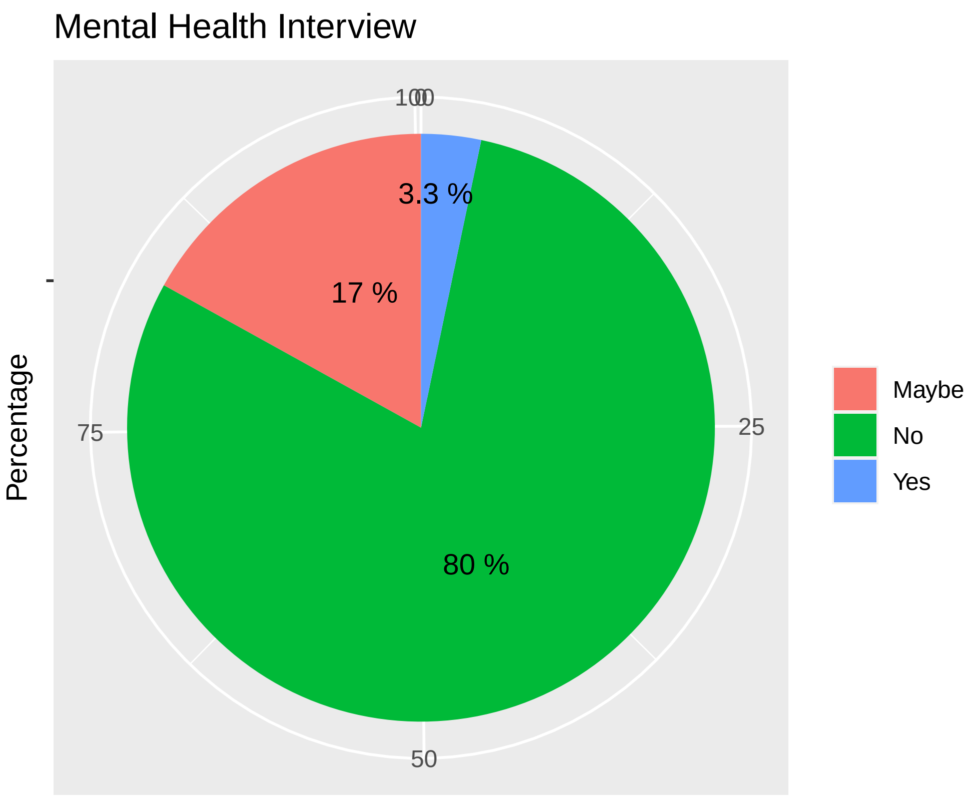


```r
# Visualize the number of subjects
ggplot(wi_count, aes(x = work_interfere, y = count, fill = work_interfere)) +
  geom_bar(stat = "identity", alpha = 0.5) +
  xlab("The Level of Work Interfere by Mental Health Condition") +
  ylab("No of People") +
  ggtitle("Comparing the Level of Work Interfere in the 2014 Mental Health in
          Tech Survey")
```

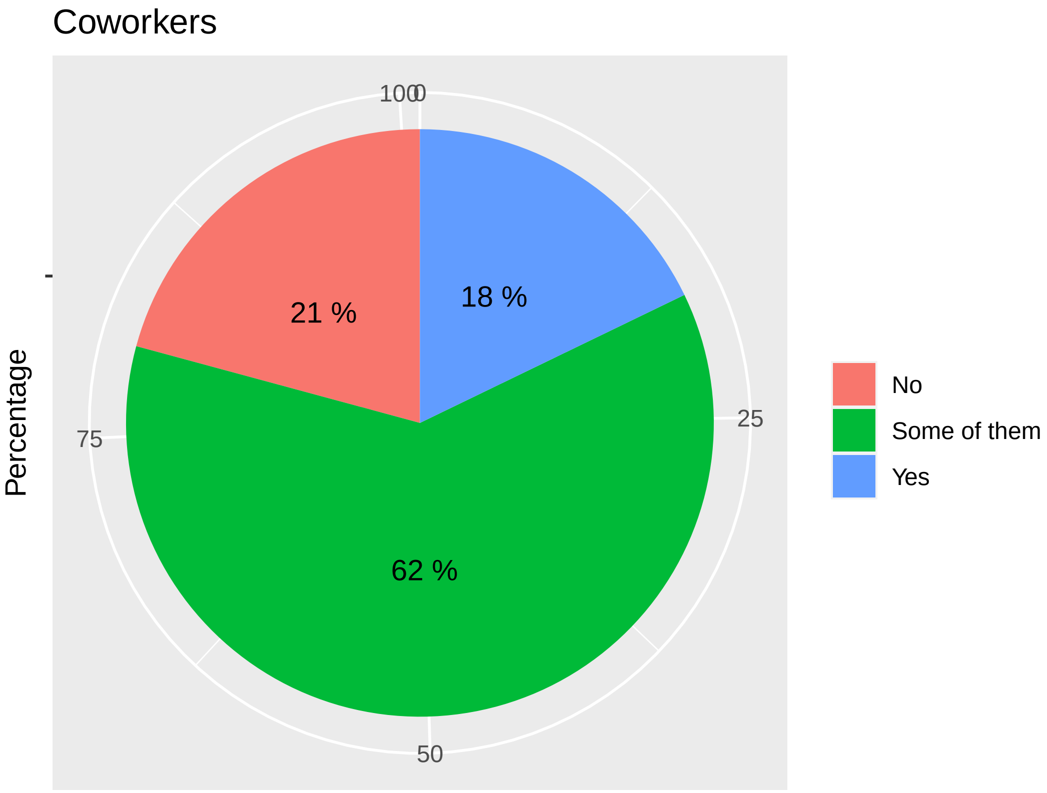


Comparing the Level of Work Interfere in the 2014 Mental Health in Tech Survey

```
ggplot(data = mental_health_interview) +
  geom_bar(mapping  =  aes(x = "", y = percentage, fill = mental_health_interview),
           stat = "identity", width = 1) +
  geom_text ( aes(x = c(1,1,1.3), y = c(94,44,1),label = paste(percentage,"%")),
              size = 4) +
  ggtitle("Mental Health Interview") +
  labs(x = "Percentage",y = "") +
  guides(fill = guide_legend(title = NULL)) +
  coord_polar("y")
```



```
ggplot(data = coworkers) +
  geom_bar(mapping  =  aes(x = "", y = percentage, fill = coworkers),
           stat = "identity", width = 1) +
  geom_text ( aes(x = c(1,1,1), y = c(89.5,50,8.5),label = paste(percentage,"%")),
              size = 4) +
  ggtitle("Coworkers") +
  labs(x = "Percentage",y = "") +
  guides(fill = guide_legend(title = NULL)) +
  coord_polar("y")
```



```
## Few key questions are answered based on the plotting done above and for rest
## of the questions we need to figure out the correlation between those variables
## and have to design linear model or logistic regression model.

## Next step we will plan to build a model (Generalized Liner model) and split
## the input data into train and test data and test the model. Will calculate
## the accuracy of the model based on the input data.
```

Final Step :

The problem statement addressed :

With the rapid development of tech companies, tech industry must exist a little bit or massive pressure on tech employees. At the same time, increasingly tech companies start to focus on employees' mental health issues as they want to make sure that the productivity of the resource and company doenst get impacted due to mental health of the employee. As a part of this project we have considered 3 data sets of 3 differt countries (US, UK and others) and each of them consits 27 variables relating to interview questions of mental health care. The main aim of this analysis is to focus on the mental halth of employee in tech company, but as the dataset contains data about other companies a comparative study can be done between tech company and other company.

The goal is to answer the question: In the tech industry, Who needed to seek mental health care? Based on attributes: such as treatment, gender, age group, family background with mental illness, I want to know which of the employees working in the tech industry has the highest frequency distribution for seeking mental health care.

How the problem statement addressed :

To address the problem statement we have cleaned up the data and filtered out outliers from the dataset and combined all 3 data sets into 1 to perform the analysis accross the globe data. Identified the target variable as “treatment” and Treatment, Age, Gender, Family_History, no_employees and tech company are the key variables for this analysis.

treatment, family_history, no_employees, and tech_company variables, the pattern and type are so clean that they do not need to inspect and transform. As the answer of this variables either “Yes” or “No”, those ar binary variables.

```
# Select variables
df <- survey_data %>% select(treatment, Age, Gender, family_history, no_employees,
                             tech_company)

# Whether employees have sought mental health care?
df$treatment %>% table
```

```
## .
##   0   1
## 619 632
```

```
# Whether employees seeking mental health consultation is affected by family history.
df$family_history %>% table
```

```
## .
##  No Yes
## 762 489
```

```
# Initial plan was to filter out the non-tech company data as we were planing to work
# only on techcompany data, but for now we are just identifying data split between tech
# and non tech company.

df$tech_company %>% table
```

```
## .
##   No  Yes
##  226 1025
```

```
# Identified the categorical variables from the dataset to answer some questions.

# The number of employees in a tech company can help me to answer some questions:
#  Does the size of the company affect the mental health of employees? If the
#  number of employees is large, does it mean that the competition is stronger
#  than small companies and employees are more likely to have mental health problems?

# view the specific number of company in each size range
df$no_employees %>% table
```

```
## .
## 25-Jun      3      4      5  5-Jan      6
##    289    288    175     60    158    281
```

```
# Interpretation of categorical variable

# This variable is categorical; there are six groups.
# Each group represents the number range of employees in a company or organization.
# Based on the summary, there is no missing value under this variable.

# Gender is another categorical variable. We categorised them into 3 categories
# in the earlier section.

df_gender <- survey_data %>%
mutate(Gender = replace(Gender, which(Gender %in% male), 'Male'),
Gender = replace(Gender, which(Gender %in% female), 'Female'),
Gender = replace(Gender, which(Gender %in% others), 'Others'))

# Verify the result
df_gender$Gender %>% table
```

```
## .
## Female   Male Others
##    247    987     17
```

```
# Create the relative frequency table of gender
table(df_gender$Gender)/length(df_gender$Gender)
```

```
##
##     Female       Male     Others
## 0.19744205 0.78896882 0.01358913
```

```
# Identify the continuous variable from the dataset.

# Age can be used to answer many of the questions from this data and in the eralier
# phse we have filtered out the outliers from the data.
```

Logistic Regression Modeling

As the topic focuses on the tech field, we have already filtered Tech companies at the last assignment. Will use logistic regression to predict the treatment of employees who are working in the tech field, so the dataset we used only includes tech companies with relevant information. Based on the tech field data summary, We can know that 49.9% of employees have sought mental health treatment, which means almost half of them meting mental issues before.

```
# Filter a dataset only focusing on tech_company
Tech <- survey_data %>% select(treatment, Age, Gender, family_history,
            no_employees, tech_company) %>% filter(tech_company == "Yes")
summary(Tech)
```

```
##    treatment          Age         Gender          family_history
##  Min.   :0.0000   Fresh :  0   Length:1025        Length:1025
##  1st Qu.:0.0000   Junior:728   Class :character   Class :character
##  Median :0.0000   Senior:295   Mode  :character   Mode  :character
##  Mean   :0.4976   Super :   2
##  3rd Qu.:1.0000
##  Max.   :1.0000
##  no_employees tech_company
##  25-Jun:267   Length:1025
##  3     :242   Class :character
##  4     :135   Mode  :character
##  5     : 41
##  5-Jan :148
##  6     :192
```

```
# For my logistic model, I pay attention to four predictors I have selected,
# which are primary elements relating to the mental health treatment.

# Fit logistic model to full data
lm <- glm( treatment ~ Age + Gender + no_employees + family_history, data =
             Tech, family = "binomial" )
summary(lm)
```

```
##
## Call:
## glm(formula = treatment ~ Age + Gender + no_employees + family_history,
##     family = "binomial", data = Tech)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1135  -0.8818  -0.6592   0.9023   1.8074
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -0.07911    0.21633  -0.366   0.7146
## AgeSenior            0.29481    0.15415   1.912   0.0558 .
## AgeSuper             0.82038    1.42227   0.577   0.5641
## GenderMale          -0.90089    0.18686  -4.821 1.43e-06 ***
## GenderOthers        -0.05297    0.67007  -0.079   0.9370
## no_employees3        0.23607    0.19503   1.210   0.2261
## no_employees4        0.10132    0.23454   0.432   0.6657
## no_employees5       -0.43602    0.38453  -1.134   0.2568
## no_employees5-Jan    0.20382    0.22683   0.899   0.3689
## no_employees6        0.11543    0.21031   0.549   0.5831
## family_historyYes    1.66843    0.14590  11.435  < 2e-16 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1420.9  on 1024  degrees of freedom
## Residual deviance: 1229.8  on 1014  degrees of freedom
## AIC: 1251.8
##
## Number of Fisher Scoring iterations: 4
```

```
# observations from summary output :

# According to the summary of the model, we can see that only two critical
# elements which can affect the treatment that I expected. Those are gender
# and famly_hisotry since those p-values are smaller than 0.05.

# The model has converted the predictor "Gender" into "Gendermale" and "Genderqueer":
# this means that the baseline is the "female" level picking from the model
# automatically and then a dummy variable is defined for "male" to evaluate
# the effect of being male relative to female. Obviously, the number of
# females who have sought mental health treatment is higher than males.

# The model has converted the predictor "family_history" into "family_historyYes":
# this means that the baseline is "Without family history" Level that the model
# picked automatically and then defined a dummy variable for "family_historyYes"
# to evaluate the effect of family_history.

# Lets look at the raw logistic regression coefficients from the model
# Raw logistic regression coefficients
  lm %>% coefficients %>% round(3)
```

```
##       (Intercept)         AgeSenior          AgeSuper        GenderMale
##            -0.079             0.295             0.820            -0.901
##      GenderOthers     no_employees3     no_employees4     no_employees5
##            -0.053             0.236             0.101            -0.436
## no_employees5-Jan     no_employees6 family_historyYes
##             0.204             0.115             1.668
```

```
# look at the odds ratios by exponentiating the log-odds
  lm %>% coefficients %>% exp %>% round(3)
```

```
##       (Intercept)         AgeSenior          AgeSuper        GenderMale
##             0.924             1.343             2.271             0.406
##      GenderOthers     no_employees3     no_employees4     no_employees5
##             0.948             1.266             1.107             0.647
## no_employees5-Jan     no_employees6 family_historyYes
##             1.226             1.122             5.304
```

```
# Interpretation of the outcome :

# There are two main effects gendermale and family_history,reporting
# by percent decreasing or increasing in the odds of treatment.

# Age, GenderQueer, no_employees : Not significant.

# Family_historyYes : Employees with family mental health history are 5.319
# times more likely to receive mental health treatment than employees without
# family history. This result shocked me that the effect of family history is
# such serious.
```

Evaluating predictive performance :

To evaluate predective performance, need to split the dataset into test and train dataset. Train dataset to train the model and test is to test the accuracy of the model. Split the train and test data into 80:20 ratio.

```r
# Randomly select train/test split indices with 80% training size
n <- nrow(Tech)
train_ind <- sample(seq_len(n), size = floor(0.8*n))

# Split training/testing sets
Tech_train <- Tech[train_ind, ]
Tech_test <- Tech[-train_ind, ]

# Define function for feature enginerring pipeline
transformations <- function(Tech) {
   # Gender
   # Create the list of three categories
Male <- c("Male ","Cis Man", "Malr", "Male", "male", "M", "m", "Male-ish",
          "maile", "Mal", "Male (CIS)", "Cis Male", "Make", "Male", "Man",
          "msle", "Mail", "cis male")
Female <- c("Female ","femail","Female (cis)","female","Female","F","Woman","f",
            "Femake","woman","Female",
            "cis-female/femme", "Cis Female", "Trans-female", "Female (trans)",
            "Trans woman")

Queer <-c ("ostensibly male, unsure what that really means",
           "p","A little about you","queer","Neuter","something kinda male?","non-binary",
        "Nah","All","Enby","fluid","Genderqueer","Androgyne","Agender"
           ,"Guy (-ish) ^_^","male leaning androgynous", "queer/she/they")

# Categorize genders
Tech$Gender <- sapply(
  as.vector(Tech$Gender),
  function(x) if(x %in% Male) "Male" else x )

Tech$Gender <- sapply(
  as.vector(Tech$Gender),
  function(x) if(x %in% Female) "Female" else x )

Tech$Gender <- sapply(
  as.vector(Tech$Gender),
  function(x) if(x %in% Queer) "Queer" else x )

# Age
# Replacing negative values and outliers with median
Tech$Age <- as.numeric(Tech$Age)
Tech$Age[which(Tech$Age<0)]<- median(Tech$Age)
Tech$Age[which(Tech$Age>100)]<- median(Tech$Age)

# Summary Age
summary(Tech$Age)

# Age categorization#
Tech$Age1 <- cut(Tech$Age, breaks = c(0, 16, 34, 60, 75), labels =
                   c('Fresh', 'Junior', 'Senior', 'Super'))

# Verify Age group
Tech$Age1 %>% table

# Return the transformed dataframe
return(Tech)
}
# Apply feature engineering to each subset
Tech_train <- Tech_train %>% transformations
Tech_test <- Tech_test %>% transformations

# Checking train data
Tech_train %>% head(2)
```

```
##     treatment Age Gender family_history no_employees tech_company  Age1
## 140         1   2   Male             No            4          Yes Fresh
## 753         0   2   Male             No        5-Jan          Yes Fresh
```

```
# checking test data
Tech_test %>% head(2)
```

```
##   treatment Age Gender family_history no_employees tech_company  Age1
## 1         1   3 Female             No       25-Jun          Yes Fresh
## 7         0   3   Male            Yes            5          Yes Fresh
```

```
#use the training set to re-train the logistical regression model and
#use the trained models to make predictions on the train and test sets.

# Train model
lm_train <- glm(treatment ~ Age + Gender + family_history + no_employees,
                data = Tech_train, family = "binomial")

# Predict on training set
Tech_train$predict_probs <- predict(lm_train, Tech_train, type = "response")
Tech_train$predict <- ifelse(Tech_train$predict_probs < 0.5, "No", "Yes")

# Predict on test set
Tech_test$predict_probs <- predict(lm_train, Tech_test, type = "response")
Tech_test$predict <- ifelse(Tech_test$predict_probs < 0.5, "No", "Yes")

# Confusion matrix - training data
cm_train <- table(Tech_train$treatment, Tech_train$predict, dnn = c("real", "predict"))
cm_train
```

```
##     predict
## real  No Yes
##    0 303 101
##    1 141 275
```

```
accuracy <- (cm_train[[1,1]] + cm_train[[2,2]] ) / sum(cm_train)
accuracy <- accuracy * 100
print(paste(round(accuracy), "%"))
```

```
## [1] "70 %"
```

```
Precision <- cm_train[[2,2]] / sum(cm_train[[2,1]] + cm_train[[2,2]] )
Precision <- Precision * 100
print(paste(round(Precision), "%"))
```

```
## [1] "66 %"
```

```
Recall <- cm_train[[2,2]] / sum(cm_train[[1,2]] + cm_train[[2,2]] )
Recall <- Recall * 100
print(paste(round(Recall), "%"))
```

```
## [1] "73 %"
```

```
# Confusion matrix ~ testing data
cm_test <- table(Tech_test$treatment, Tech_test$predict, dnn = c("real", "predict"))
cm_test
```

```
##     predict
## real No Yes
##    0 80  31
##    1 35  59
```

```
accuracy <- (cm_test[[1,1]] + cm_test[[2,2]] ) / sum(cm_test)
accuracy <- accuracy * 100
print(paste(round(accuracy), "%"))
```

```
## [1] "68 %"
```

```
Precision <- cm_test[[2,2]] / sum(cm_test[[2,1]] + cm_test[[2,2]] )
Precision <- Precision * 100
print(paste(round(Precision), "%"))
```

```
## [1] "63 %"
```

```
Recall <- cm_test[[2,2]] / sum(cm_test[[1,2]] + cm_test[[2,2]] )
Recall <- Recall * 100
print(paste(round(Recall), "%"))
```

```
## [1] "66 %"
```

Analysis Outcome :

1. “Comparing Family History in the 2014 Mental Health in Tech Survey” plot confirms 61% of employees don’t have family history of metal illness among the employee participated in the survey.
2. In tech_company workplace type and size don’t have much impact on mental health.
3. Number of people count is same in case of treatment received in Mental Health Condition from employer.
4. As per the analysis most of the employees thinks sometimes work interfere mental health condition of the employee.
5. Majority of the employee(80%) don’t appear for mental health interview.
6. 62% of employees shares mental health with coworkers.

Implications :

1. This analysis shows that 61% employees seeking mental health condition don’t have any family history of mental illness, so employees shuld not think that they might not be having mental health issue as they don’t have a family history. If any sort of mental illness they feel, they should go for treatment or discuss with supervisor oe co-worker.

2. Intial thought after reviewing the data set was the larger the number of employees in the tech company, the more fierce the competition, so it means that the number of people seeking psychological stress relief will increase. But data show that the number of people seeking mental health treatment has little to do with the size of the company.

3. Having remote work at least 50% of the time versus less than 50% of the time showed no significant difference in mental illness work interference levels.

4. Female employees’ mental health in technology industry should be paid more attention although the input dataset have majority of male data and % of female data analyzed is not significant to draw a fianl conclusion.

5. People feel that their employers somewhat easily sanction leave for mental health issues.The reason maybe that the employer does not want to take any risk of overloading the patient with work.

6. People feel that sharing about their mental or physical health with employers would help them a bit but they are reluctant to share the same with their coworkers.They would prefer to share with only some of the coworkers.

Limitations:

1. Majority of males in our data set compared to females and other categories.
2. Majority data from USA and Canada, so can’t draw any conclusion on this topic across the globe based on this data.
3. This Survey data was for 2014, if this data received for multiple years then we could have analyzed how the trends looks like year over year.
4. All employees might not be aware of company provided wellness_program and they might have responded without knowing that.
5. As this is some sort of personal mental health related data received during survey, authenticity of the data might be a question but this might be the best source for this sort of data.

Concluding Remarks :

1. Mental health of employee is a major factor in any sort of Industry and specifically in Tech as in Tech Industry the employee have to do major thinking during any sort of development, testing or support

work. Your productivity can't be accurate if your mental health is 100%. One of the employees mental health can affect the entire teams and eventually impact a grater audience in the company and that impacts company's productivity. As the analysis shows it's doesn't matter how big the company is, but in current situation to give your 100% output you have to have mentally fine.

2. This case study is majorly based on cases in the US and Canada data. so cant draw any concrete conclusion that it's true all across the globe but if this analysis can be done on more data definitely the outcome will be more or less similar which we have identified here.

3. It is impossible to draw a specific conclusion from the scale of the company because it depends on the company's work culture, competitiveness between employee, other benefits, type of work etc.

4. Cases show that more than 50% of people surveyed in countries like US,Australia and Canada undergo treatment for mental illness and as it's applicable for 1st world country definitely we can conclude it might be similar or worse in 2nd and 3rd world countries.

5. People who are not more prone to work at home are usually bored and filled with anxiety leading to degradation in mental health. THis analysis was done based on 2014 data and after pandemic more remote work or work from home has been introduced, so definitely the company's should more foucs on the employees mental health and bring some plans to keep employees mental health better.

6. People who are in the early 30's usually undergo treatment but there are extreme cases like 8 years and 72 years people receiving the same treatment. Th is concludes that people are more competitive in that age and bringing more challenges to reach their goal at that age and eventually affecting mental health without.

7. It is interesting to find that people face mental trauma regardless of whether they are self employed or not. Self employed people should have more mental health challenges but that is not the outcome of this analysis.

8. The surveyed people agree that their mental health somewhat affects their productivity at work.

9. To conclude this no one is alone in this World,so share your issues which might lead to mental illness with co-workers/family members and take necessary treatment on time to make you more productive and achieve your goal.