# CUNY DATA 621 - Business Analytics and Data Mining

Mental Health Survey - Data Prep and Basic EDA

*Group 1, 2018*

```
if (!require('countrycode')) (install.packages('countrycode'))
if (!require('dplyr')) (install.packages('dplyr'))
if (!require('psych')) (install.packages('psych'))
if (!require('DataExplorer')) (install.packages('DataExplorer'))
if (!require('lubridate')) (install.packages('lubridate'))

df <- read.csv("../Data/survey_RAW.csv")
```

## Data Source

https://www.kaggle.com/osmi/mental-health-in-tech-survey

### Basic Statistics

The data is 307.5 Kb in size. There are 1,259 rows and 27 columns (features). Of all 27 columns, 26 are discrete, 1 are continuous, and 0 are all missing. There are 1,892 missing values out of 33,993 data points.

## DATA PREPARATION

### Comments

This field is fascinating and ripe for text analysis. We'll leave it in for now, but it would need to be further prepared for any regression to be done.

```
sample <- df[!(is.na(df$comments)), ]
head(sample$comments)
```

```
## [1] I'm not on my company's health insurance which could be part of the reason I answered Don't know
## [2] I have chronic low-level neurological issues that have mental health side effects. One of my sup
## [3] My company does provide healthcare but not to me as I'm on a fixed-term contract. The mental hea
## [4] Relatively new job. Ask again later
## [5] Sometimes I think  about using drugs for my mental health issues. If i use drugs I feel better
## [6] I selected my current employer based on its policies about self care and the quality of their ov
## 160 Levels:   ... you rock for doing this!
```

### Date

It's likely that the timestamp field will be omitted entirely from analysis, but should someone wish to use it, we'll convert it to the appropriate type.

```
df$Timestamp <- ymd_hms(df$Timestamp)
```

### Age

Our Age variable has some clear and impossible outliers. There are multiple values $< 18$ (even some negative numbers) and some values $> 200$ years old. Instead of replacing these, for now, let's set to NA and impute later.

```
df$Age[df$Age > 73 | df$Age < 18 ] <- NA
```

### Gender

Gender is more complex in this dataset. Let's start by doing some rough matching and cleaning.

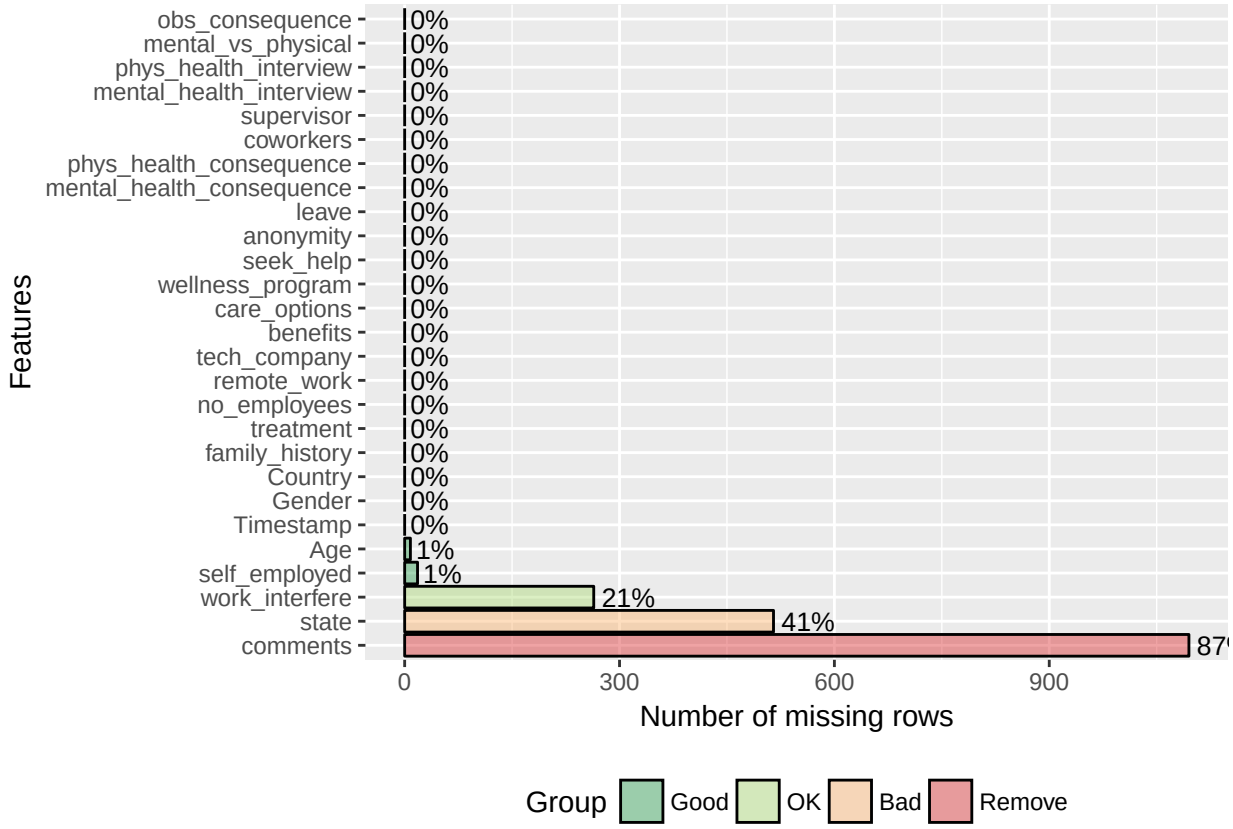
```
df$Gender <- tolower(df$Gender)
df$Gender <- trimws(df$Gender)

### start with the obvious
cis_female_syn <- c("femail", "f", "woman", "femail", "female (cis)",
                    "cis female", "cis-female/femme", "femake",
                    "female")
df$Gender[df$Gender %in% cis_female_syn] <- "female_cis"

cis_male_syn <- c("m", "man", "male (cis)", "male", "mal", "mail",
                  "maile", "cis man", "cis male", "msle", "malr",
                  "make")
df$Gender[df$Gender %in% cis_male_syn] <- "male_cis"

trans_female_syn <- c("trans woman", "trans-female", "female (trans)")
df$Gender[df$Gender %in% trans_female_syn] <- "female_trans"

genderqueer_syn <- c("non-binary", "enby", "queer", "queer/she/they",
                     "fluid", "androgyne", "agender", "neuter")
df$Gender[df$Gender %in% genderqueer_syn] <- "genderqueer"

fluid_syn <- c("male leaning androgynous", "male-ish",
                   "ostensibly male, unsure what that really means",
                   "something kinda male?", "guy (-ish) ^_^")
df$Gender[df$Gender %in% fluid_syn] <- "fluid"

unknown <- c("a little about you", "all", "p", "nah")
df$Gender[df$Gender %in% unknown] <- "unknown"

### Let's update some call out issues.   Obvs 967 reported "female"
# in the Gender field, but noted being a trans woman in the comments.
df$Gender[967] <- "female_trans"

df$Gender <- as.factor(df$Gender)
table(df$Gender)
```

```
##
##   female_cis female_trans        fluid  genderqueer     male_cis
##          246            5            5            9          990
##      unknown
##            4
```

## Missing

### Plot and Review Missing

```
plot_missing(df)
```




### State

Most of our missing values are for US States. While it's fine for this to be missing if it's a non-US country, let's make sure that's all that's happening.

```
#Number of observations that aren't United States
nrow(df[df$Country != "United States",])
```

```
## [1] 508
```

```
#Number of missing states
sum(is.na(df$state))
```

```
## [1] 515
```

```
nrow(df[df$Country == "United States" & is.na(df$state),])
```

```
## [1] 11
```

```
# there are 11 missing states.
df$state <- as.character(df$state)
df$state[df$Country == "United States" & is.na(df$state)] <- "Unknown"
```

```
# Still some missing:   non-US countries w/ states?!
sub <- df[df$Country != "United States" & !is.na(df$state),]

knitr::kable(sub[, c("state", "Country")])
```

| | state | Country |
|---|---|---|
| 320 | NY | Latvia |
| 489 | MD | Israel |
| 990 | IL | Bahamas, The |
| 1180 | UT | Bulgaria |

```
# Ok, that's weird.   Let's NA those
df$state[df$Country != "United States" & !is.na(df$state)] <- NA

df$state <- as.factor(df$state)
rm(sub)
```

### Feature Creation: Continent

Since country and state are proving to be non-uniform, let's use the great country code package to create a "continent" feature that may be useful for regression.

```
df$continent <- as.factor(countrycode(sourcevar = df[, "Country"],
                                      origin = "country.name",
                                      destination = "continent"))
table(df$continent)
```

```
##
##   Africa Americas     Asia   Europe  Oceania
##        8      837       24      361       29
```

### Work Interfere | Self Employed | Age

```
summary(df[, c("work_interfere", "self_employed", "Age")])
```

```
##    work_interfere self_employed      Age
##  Never    :213    No  :1095     Min.   :18.00
##  Often    :144    Yes : 146     1st Qu.:27.00
##  Rarely   :173    NA's:  18     Median :31.00
##  Sometimes:465                  Mean   :32.08
##  NA's     :264                  3rd Qu.:36.00
##                                 Max.   :72.00
##                                 NA's   :8
```

The work_interfere variable is a response to the question: "If you have a mental health condition, do you feel that it interferes with your work?" I would suggest two possibile interpretations:

1) "I do not have a mental health condition"
2) "I don't want to respond about how my work is affected"

Since the treatment variable is pretty evenly split (No=622/Yes=637) on whether they've sought treatment for a mental health condition, it may not always be option 1. Since we have no way of knowing which condition is likely, let's simply add a 5th category for "No Response"

```
df$work_interfere <- as.character(df$work_interfere)
df$work_interfere[is.na(df$work_interfere)] <- "No Response"
df$work_interfere <- as.factor(df$work_interfere)
```

For the remaining two fields, since we will only lose 26 observations, let's simply remove those observations.

```
df <- df[!is.na(df$self_employed),]
df <- df[!is.na(df$Age),]
```

# EDA

With this, our data is roughly ready for review. We still have NAs in State and Comments, but if used, both would need to be handled carefully in other ways (eg - State, but subsetting to only US data, Comments to craft some NLP features). The Timestamp variable may also be easily dropped.

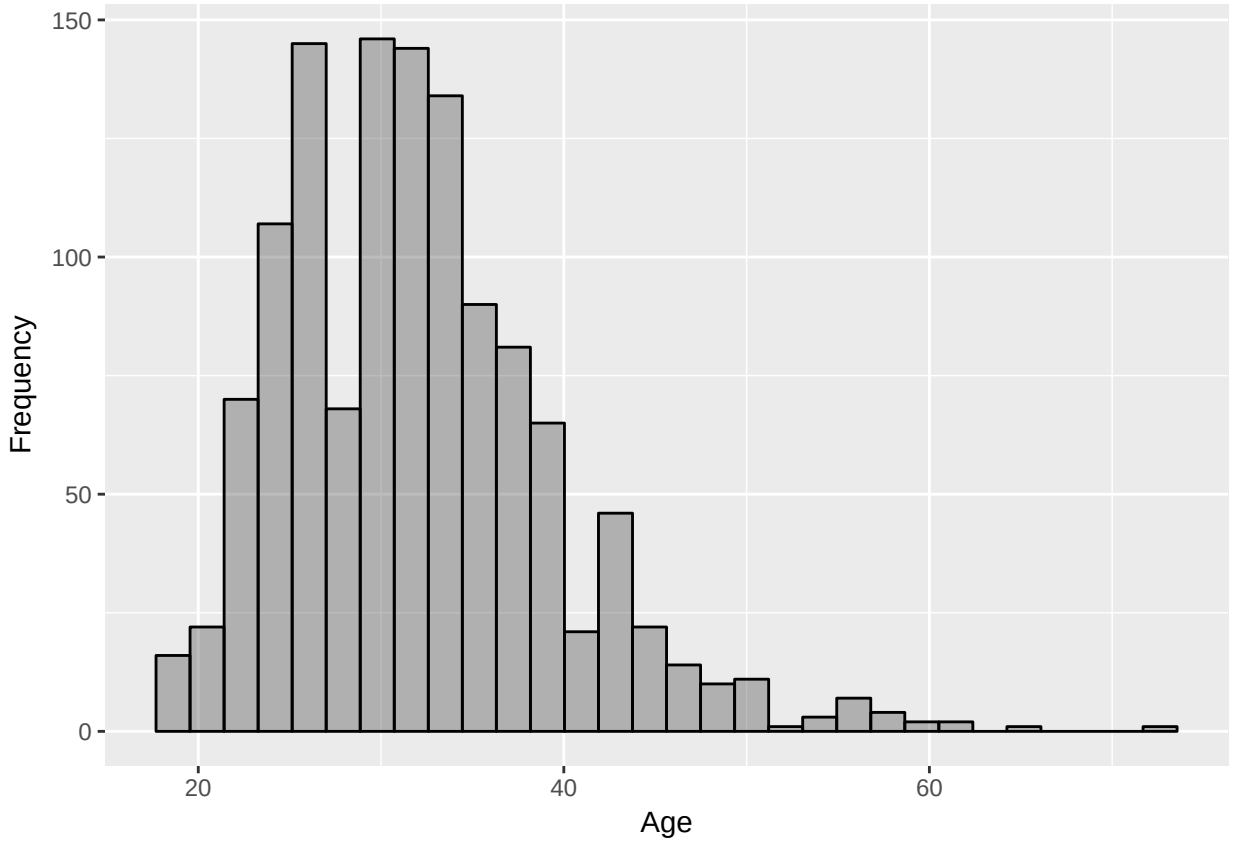
## Data Summary

```
summary <- describe(df[,c(2:26, 28)])[,c(2:5,8,9,11,12)]
knitr::kable(summary)
```

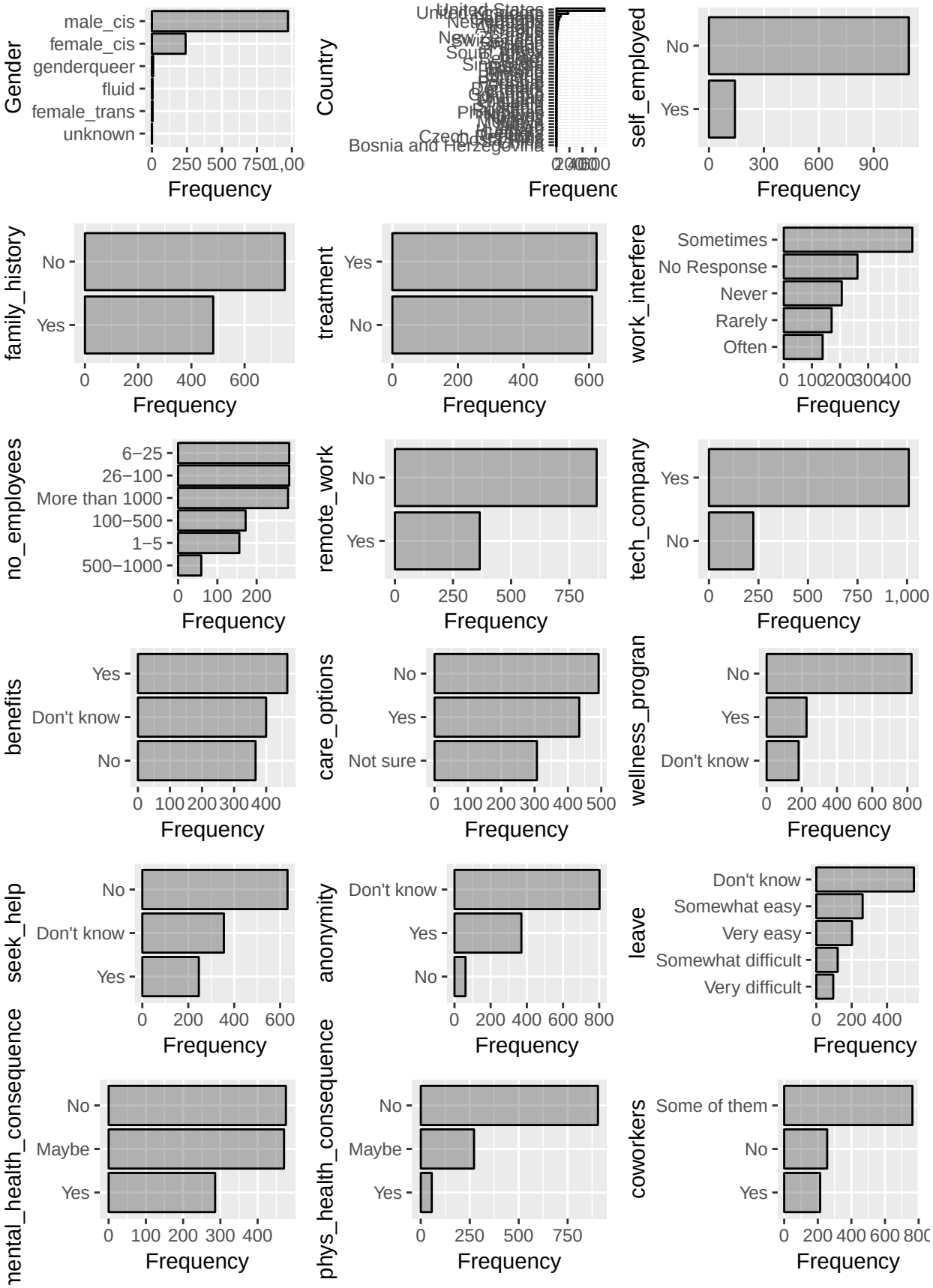
| | n | mean | sd | median | min | max | skew | kurtosis |
|---|---|---|---|---|---|---|---|---|
| Age | 1233 | 32.061638 | 7.3053372 | 31 | 18 | 72 | 1.0190819 | 1.8785954 |
| Gender* | 1233 | 4.191403 | 1.5926039 | 5 | 1 | 6 | -1.4807195 | 0.2212752 |
| Country* | 1233 | 38.831306 | 13.2436861 | 46 | 1 | 47 | -1.6255591 | 1.0946610 |
| state* | 735 | 23.068027 | 14.6803637 | 27 | 1 | 46 | -0.1375923 | -1.4753130 |
| self_employed* | 1233 | 1.115166 | 0.3193520 | 1 | 1 | 2 | 2.4081366 | 3.8022074 |
| family_history* | 1233 | 1.390916 | 0.4881537 | 1 | 1 | 2 | 0.4465604 | -1.8020433 |
| treatment* | 1233 | 1.505272 | 0.5001751 | 2 | 1 | 2 | -0.0210623 | -2.0011774 |
| work_interfere* | 1233 | 3.332522 | 1.5467986 | 4 | 1 | 5 | -0.2344497 | -1.5134693 |
| no_employees* | 1233 | 3.795620 | 1.7391819 | 4 | 1 | 6 | -0.1622824 | -1.3478810 |
| remote_work* | 1233 | 1.296026 | 0.4566878 | 1 | 1 | 2 | 0.8925512 | -1.2043271 |
| tech_company* | 1233 | 1.818329 | 0.3857294 | 2 | 1 | 2 | -1.6491931 | 0.7204242 |
| benefits* | 1233 | 2.053528 | 0.8366926 | 2 | 1 | 3 | -0.1006465 | -1.5656502 |
| care_options* | 1233 | 1.952960 | 0.8656840 | 2 | 1 | 3 | 0.0905348 | -1.6607894 |
| wellness_program* | 1233 | 2.036496 | 0.5750195 | 2 | 1 | 3 | 0.0014455 | 0.0095658 |
| seek_help* | 1233 | 1.911598 | 0.6928228 | 2 | 1 | 3 | 0.1187330 | -0.9217245 |
| anonymity* | 1233 | 1.649635 | 0.9101887 | 1 | 1 | 3 | 0.7462613 | -1.3762742 |
| leave* | 1233 | 2.412003 | 1.5093600 | 2 | 1 | 5 | 0.5605637 | -1.1402516 |
| mental_health_consequence* | 1233 | 1.849959 | 0.7693618 | 2 | 1 | 3 | 0.2625304 | -1.2723555 |
| phys_health_consequence* | 1233 | 1.824817 | 0.4853040 | 2 | 1 | 3 | -0.4035896 | 0.4148329 |
| coworkers* | 1233 | 1.965937 | 0.6167108 | 2 | 1 | 3 | 0.0205104 | -0.3785987 |
| supervisor* | 1233 | 2.094079 | 0.8427916 | 2 | 1 | 3 | -0.1788474 | -1.5707405 |
| mental_health_interview* | 1233 | 1.867802 | 0.4201226 | 2 | 1 | 3 | -0.8083882 | 1.6011142 |
| phys_health_interview* | 1233 | 1.715329 | 0.7224824 | 2 | 1 | 3 | 0.4874161 | -0.9749955 |
| mental_vs_physical* | 1233 | 1.813463 | 0.8350560 | 2 | 1 | 3 | 0.3604057 | -1.4751512 |
| obs_consequence* | 1233 | 1.145174 | 0.3524195 | 1 | 1 | 2 | 2.0120218 | 2.0498962 |
| continent* | 1233 | 2.663422 | 0.9775567 | 2 | 1 | 5 | 0.8271968 | -1.0322071 |

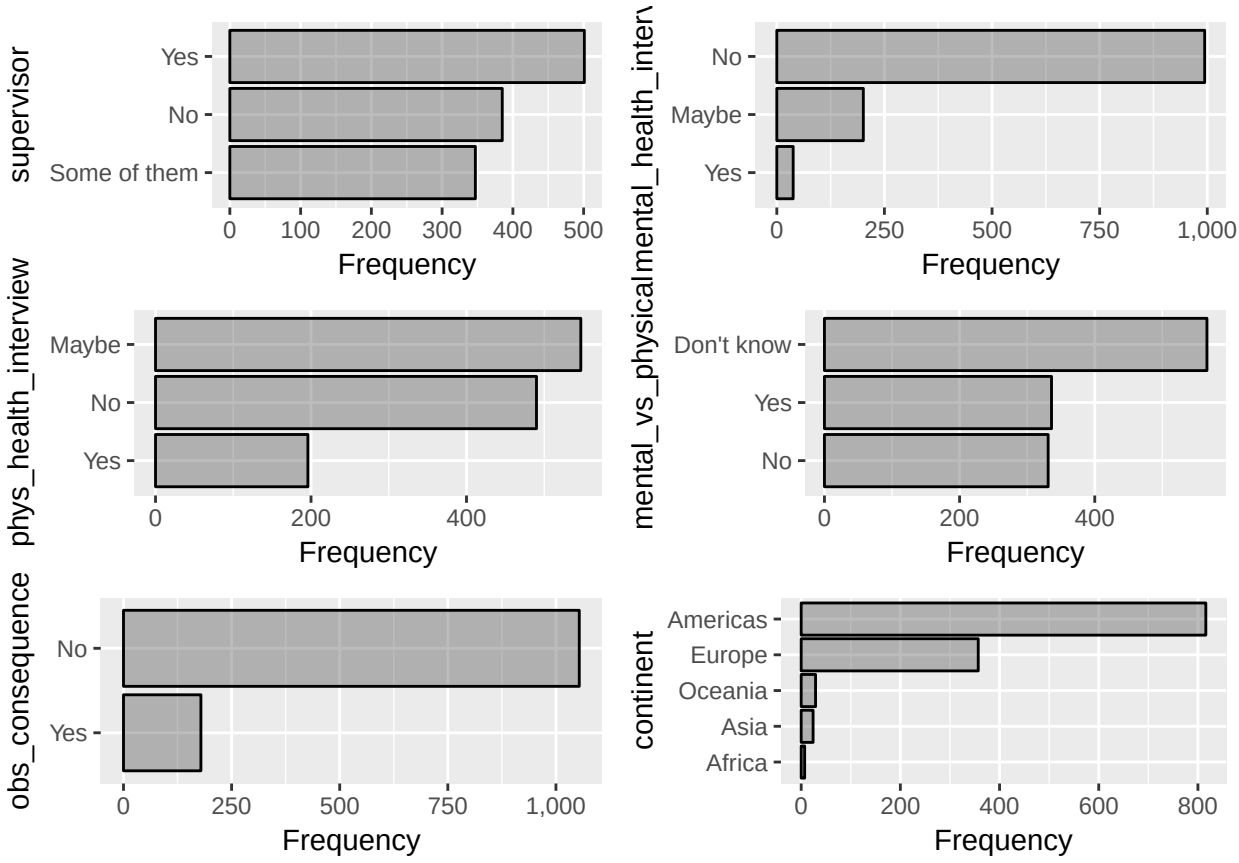
### Histogram of Variables

```
clean <- df
clean$Timestamp <- NULL
clean$comments <- NULL
clean$state <- NULL

out <- split_columns(clean)

plot_histogram(out$continuous)
```



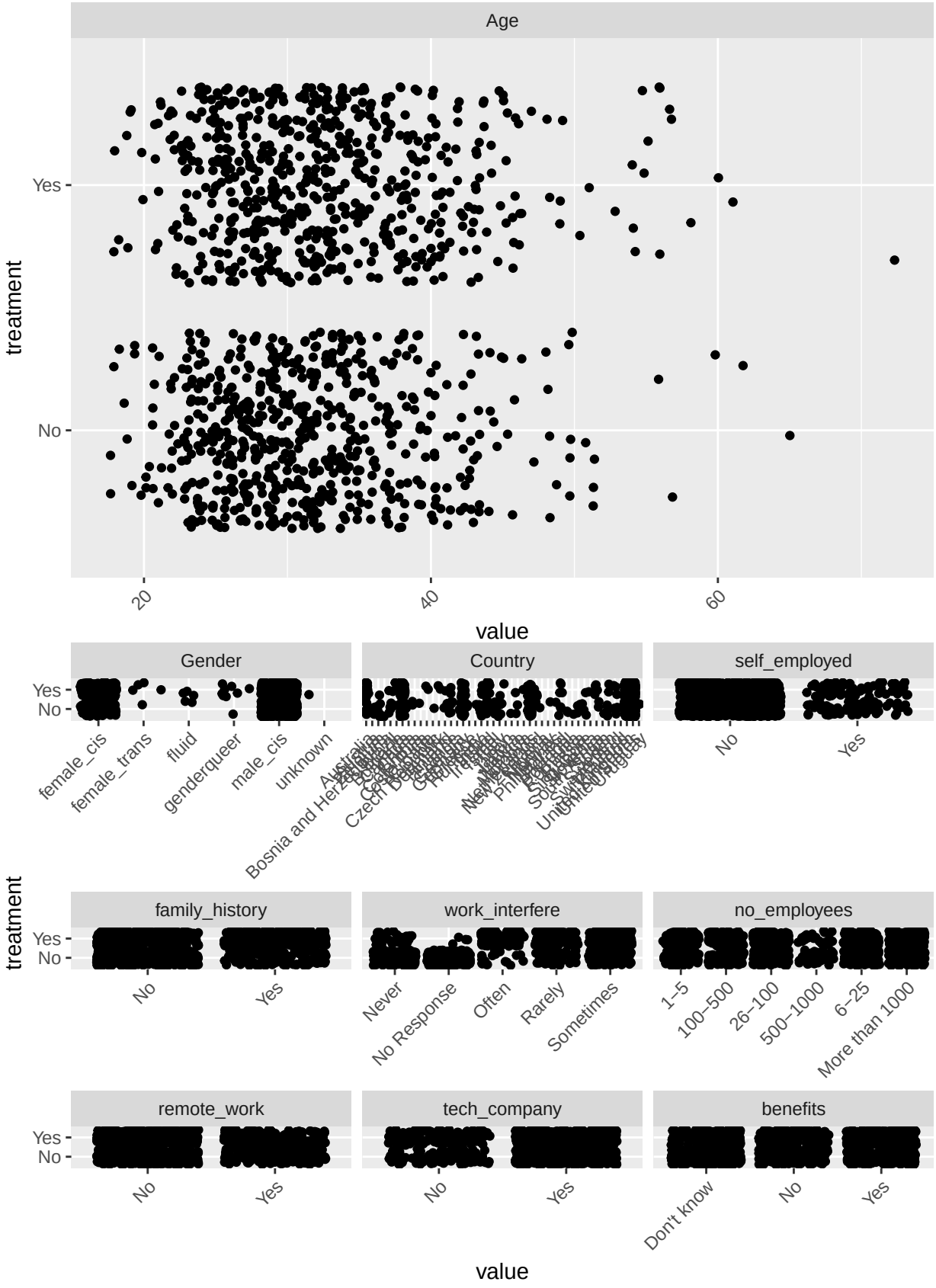

```
plot_bar(out$discrete)
```

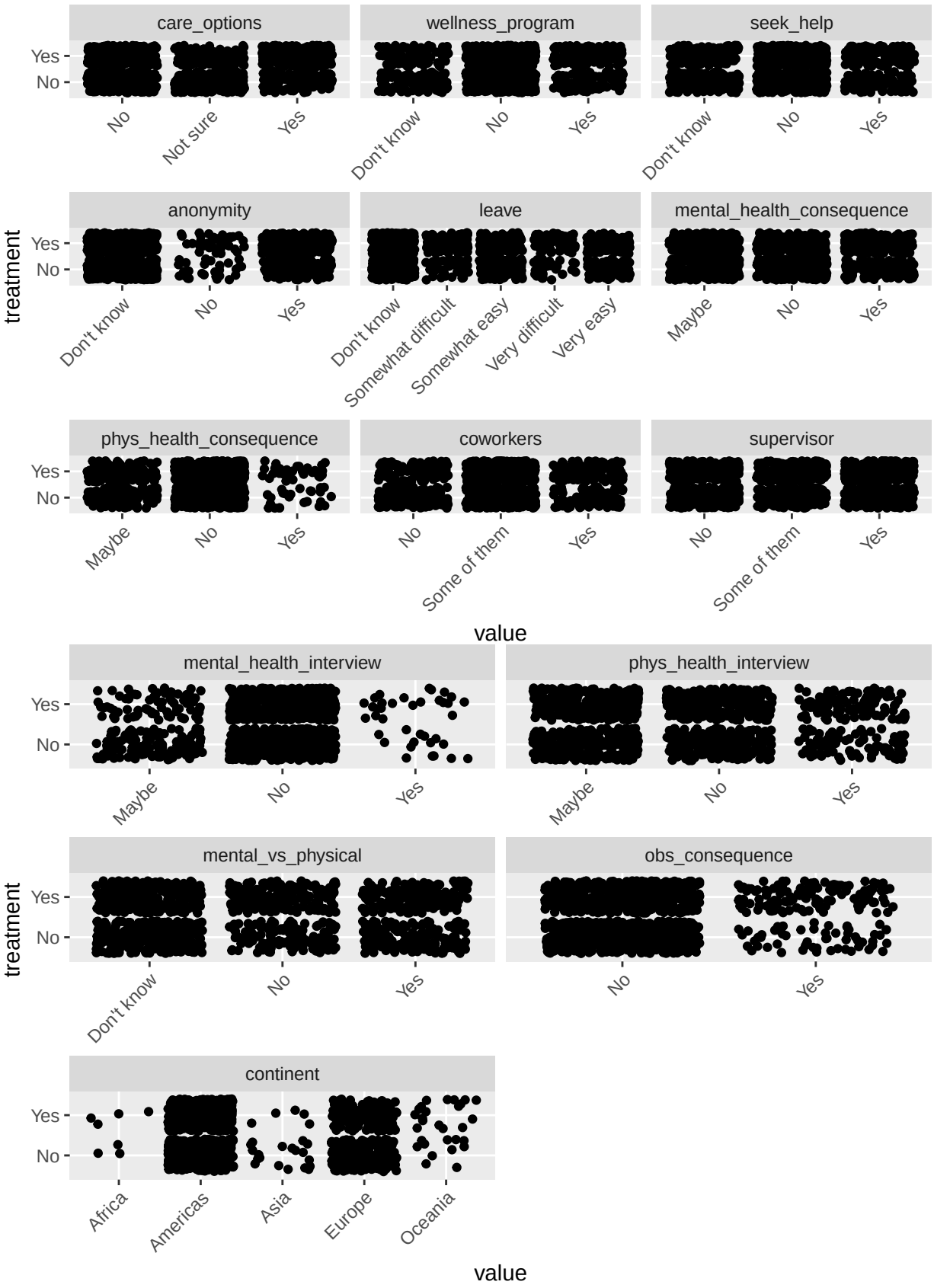

Gender
male_cis
female_cis
genderqueer
fluid
female_trans
unknown
0 250 500 750 1,00
Frequency
Country
Bosnia and Herzegovina
Frequenc
self_employed
No
Yes
0 300 600 900
Frequency
family_history
No
Yes
0 200 400 600
Frequency
treatment
Yes
No
0 200 400 600
Frequency
work_interfere
Sometimes
No Response
Never
Rarely
Often
0 100 200 300 400
Frequency
no_employees
6−25
26−100
More than 1000
100−500
1−5
500−1000
0 100 200
Frequency
remote_work
No
Yes
0 250 500 750
Frequency
tech_company
Yes
No
0 250 500 750 1,000
Frequency
benefits
Yes
Don't know
No
0 100 200 300 400
Frequency
care_options
No
Yes
Not sure
0 100 200 300 400 500
Frequency
wellness_progran
No
Yes
Don't know
0 200 400 600 800
Frequency
seek_help
No
Don't know
Yes
0 200 400 600
Frequency
anonymity
Don't know
Yes
No
0 200 400 600 800
Frequency
leave
Don't know
Somewhat easy
Very easy
Somewhat difficult
Very difficult
0 200 400
Frequency
mental_health_consequence
No
Maybe
Yes
0 100 200 300 400
Frequency
phys_health_consequence
No
Maybe
Yes
0 250 500 750
Frequency
coworkers
Some of them
No
Yes
0 200 400 600 800
Frequency




**Relationship of Predictors to Target: "treatment"**

```
plot_scatterplot(clean, "treatment", position = "jitter")
```


Age
treatment
Yes
No
20
40
60
value
Gender
Country
self_employed
female_cis
female_trans
fluid
genderqueer
male_cis
unknown
No
Yes
family_history
work_interfere
no_employees
Never
No Response
Often
Rarely
Sometimes
1–5
100–500
26–100
500–1000
6–25
More than 1000
remote_work
tech_company
benefits
Don't know


care_options
wellness_program
seek_help
anonymity
leave
mental_health_consequence
phys_health_consequence
coworkers
supervisor
mental_health_interview
phys_health_interview
mental_vs_physical
obs_consequence
continent
treatment
Yes
No
No
Not sure
Yes
Don't know
No
Yes
Don't know
No
Yes
Don't know
No
Yes
Don't know
Somewhat difficult
Somewhat easy
Very difficult
Very easy
Maybe
No
Yes
Maybe
No
Yes
No
Some of them
Yes
No
Some of them
Yes
Maybe
No
Yes
Maybe
No
Yes
Don't know
No
Yes
No
Yes
Africa
Americas
Asia
Europe
Oceania
value
value

## Cleanup and Save

```
saveRDS(df, "../Data/MentalHealthCLEAN.rds")
```