# EDA and Descriptive Statistics using RStudio

Course Taught at SUAD

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# What we quest to achieve through the sessions

- Data Pre-processing
- Playing around Email dataset
- Exploratory Data Analysis

*Data Pre-processing*

## DATA PREPROCESSING

1. Missing value replenishment
2. Transformation or normalization
3. Random Sampling

## Missing Value Handling

Example: Suppose a telecom company wants to analyze the performance of its circles based on the following parameters

1. Current Month’s Usage
2. Last 3 Month’s Usage
3. Average Recharge
4. Projected Growth

The data set is given in next slide. (Missing_Values_Telecom Data)

# Missing Value Handling

Example: Circle wise Data

| SL No. | Current Month's Usage | Last 3 Month's Usage | Average Recharge | Projected Growth | Circle |
|---|---|---|---|---|---|
| 1 | 5.1 | 3.5 | 99.4 | 99.2 | A |
| 2 | 4.9 | 3 | 98.6 | 99.2 | A |
| 3 | | 3.2 | | 99.2 | A |
| 4 | 4.6 | 3.1 | 98.5 | 9..2 | A |
| 5 | 5 | | 98.4 | 99.2 | A |
| 6 | 5.4 | 3.9 | 98.3 | 99.4 | A |
| 7 | 7 | 3.2 | 95.3 | 98.4. | B |
| 8 | 6.4 | 3.2 | 95.5 | 98.5 | B |
| 9 | 6.9 | 3.1 | 95.1 | 98.5 | B |
| 10 | | 2.3 | 96 | 98.3 | B |
| 11 | 6.5 | 2.8 | 95.4 | 98.5 | B |
| 12 | 5.7 | | 95.5 | 98.3 | B |
| 13 | 6.3 | 3.3 | | 98.6 | B |
| 14 | 6.7 | 3.3 | 94.3 | 97.5 | C |
| 15 | 6.7 | 3 | 94.8 | 97.3 | C |
| 16 | 6.3 | 2.5 | 95 | 98.9 | C |
| 17 | | 3 | 94.8 | 98 | C |
| 18 | 6.2 | 3.4 | 94.6 | 97.3 | C |
| 19 | 5.9 | 3 | 94.9 | 98.8 | C |

## Missing Value Handling

Example: Read data and variables to R

```
> mydata = Missing_Values_Telecom
> cmusage = mydata[,2]
> l3musage = mydata[,3]
> avrecharge = mydata[,4]
```

# Missing Value Handling

## Option 1: Discard all records with missing values

```
>newdata = na.omit(mydata)

>write.csv(newdata,"E:/SUAD/newdata.csv")
```

| SL.No. | Current.Month.s.Usage | Last.3.Month.s.Usage | Average.Recharge | Projected.Growth | Circle |
|---|---|---|---|---|---|
| 1 | 5.1 | 3.5 | 99.4 | 99.2 | A |
| 2 | 4.9 | 3 | 98.6 | 99.2 | A |
| 4 | 4.6 | 3.1 | 98.5 | 9..2 | A |
| 6 | 5.4 | 3.9 | 98.3 | 99.4 | A |
| 7 | 7 | 3.2 | 95.3 | 98.4. | B |
| 8 | 6.4 | 3.2 | 95.5 | 98.5 | B |
| 9 | 6.9 | 3.1 | 95.1 | 98.5 | B |
| 11 | 6.5 | 2.8 | 95.4 | 98.5 | B |
| 14 | 6.7 | 3.3 | 94.3 | 97.5 | C |
| 15 | 6.7 | 3 | 94.8 | 97.3 | C |
| 16 | 6.3 | 2.5 | 95 | 98.9 | C |
| 18 | 6.2 | 3.4 | 94.6 | 97.3 | C |
| 19 | 5.9 | 3 | 94.9 | 98.8 | C |

# Missing Value Handling

Option 2: Replace the missing values with variable mean, median, etc

## Replacing the missing values with mean

Compute the means excluding the missing values

```
>cmusage_mean = mean(cmusage, na.rm = TRUE)
>l3musage_mean = mean(l3musage, na.rm = TRUE)
> avrecharge_mean = mean(avrecharge, na.rm = TRUE)
```

Replace the missing values with mean

```
> cmusage[is.na(cmusage)]=cmusage_mean
> l3musage[is.na(l3musage)]= l3musage_mean
>avrecharge[is.na(avrecharge)]=avrecharge_mean
```

## Missing Value Handling

Option 2: Replace the missing values with variable  mean, median, etc

Replacing the missing values with mean

Replace the missing values with mean

```
> cmusage[is.na(cmusage)]=cmusage_mean
> l3musage[is.na(l3musage)]= l3musage_mean
>avrecharge[is.na(avrecharge)]=avrecharge_mean
```

Making the new file

```
> mynewdata = cbind(cmusage, l3musage, avrecharge, mydata[,5],mydata[,6])
> write.csv(mynewdata, "E:/SUAD/mynewdata.csv")
```

## Missing Value Handling

Option 2: Replace the missing values with variable mean, median, etc

Replacing the missing values with men

| SL No | cmusage | l3musage | avrecharge | Proj Growth | Circle |
|---|---|---|---|---|---|
| 1 | 5.1 | 3.5 | 99.4 | 11 | 1 |
| 2 | 4.9 | 3 | 98.6 | 11 | 1 |
| 3 | 5.975 | 3.2 | 96.14117647 | 11 | 1 |
| 4 | 4.6 | 3.1 | 98.5 | 1 | 1 |
| 5 | 5 | 3.105882353 | 98.4 | 11 | 1 |
| 6 | 5.4 | 3.9 | 98.3 | 12 | 1 |
| 7 | 7 | 3.2 | 95.3 | 6 | 2 |
| 8 | 6.4 | 3.2 | 95.5 | 7 | 2 |
| 9 | 6.9 | 3.1 | 95.1 | 7 | 2 |
| 10 | 5.975 | 2.3 | 96 | 5 | 2 |
| 11 | 6.5 | 2.8 | 95.4 | 7 | 2 |
| 12 | 5.7 | 3.105882353 | 95.5 | 5 | 2 |
| 13 | 6.3 | 3.3 | 96.14117647 | 8 | 2 |
| 14 | 6.7 | 3.3 | 94.3 | 3 | 3 |
| 15 | 6.7 | 3 | 94.8 | 2 | 3 |
| 16 | 6.3 | 2.5 | 95 | 10 | 3 |
| 17 | 5.975 | 3 | 94.8 | 4 | 3 |
| 18 | 6.2 | 3.4 | 94.6 | 2 | 3 |
| 19 | 5.9 | 3 | 94.9 | 9 | 3 |

## TRANSFORMATION / NORMALIZATION

z transform:

Transformed data = (Data – Mean) / SD

Exercise : Normalize the variables in the Supply_Chain.csv ?

Read the files

```
>mydata  = Supply_Chain
> mydata = mydata[,2:7]
```

Normalize or standardize the variable

```
>mystddata = scale(mydata)
```

## RANDOM SAMPLING

Example: Take a sample of size 60 (10%) randomly from the data given in the file bank data.csv and save it as a new csv file?

Read the files

```
>mydata  = bank data
> mysample = mydata[sample(1:nrow(mydata), 60, replace = FALSE),]
>write.csv(mysample,"E:/SUAD/mysample.csv")
```

Example: Split randomly the data given in the file bank data.csv into sets namely training (75%) and test (25%) ?

Read the files

```
>mydata  = bank data
>sample = sample(2, nrow(mydata), replace = TRUE, prob = c(0.75, 0.25))
> sample1 = mydata[sample ==1, ]
> sample2 = mydata[sample ==2,]
```

PLAY WITH YOUR DATA

## WHAT WE WILL LEARN IN THIS?

- Tools for data exploration and transformation
- Intuitive to write and easy to read
- Super-fast on data frames

## INSTALLATION OF PACKAGES

We will use the ‘dplyr’ package in R. Since it is a part of ‘tidyverse’ package installing ‘dplyr’ separately is not mandatory.

```
library(tidyverse)
```

## LOAD AN EXAMPLE DATASET

```
suppressMessages(library(dplyr))

install.packages("hflights")

library(hflights)
data(hflights)          # hflights is flights departing from two Houston airports in 2011
```

## EXPLORE THE DATA

head(hflights)

```
     Year Month DayofMonth DayOfWeek DepTime ArrTime UniqueCarrier FlightNum TailNum ActualElapsedTime
5424 2011     1          1         6    1400    1500            AA       428  N576AA                60
5425 2011     1          2         7    1401    1501            AA       428  N557AA                60
5426 2011     1          3         1    1352    1502            AA       428  N541AA                70
5427 2011     1          4         2    1403    1513            AA       428  N403AA                70
5428 2011     1          5         3    1405    1507            AA       428  N492AA                62
5429 2011     1          6         4    1359    1503            AA       428  N262AA                64
     AirTime ArrDelay DepDelay Origin Dest Distance TaxiIn TaxiOut Cancelled CancellationCode Diverted
5424      40      -10        0    IAH  DFW      224      7      13         0                         0
5425      45       -9        1    IAH  DFW      224      6       9         0                         0
5426      48       -8       -8    IAH  DFW      224      5      17         0                         0
5427      39        3        3    IAH  DFW      224      9      22         0                         0
5428      44       -3        5    IAH  DFW      224      9       9         0                         0
5429      45       -7       -1    IAH  DFW      224      6      13         0                         0
```

*as_tibble* creates a "local data frame", which is just a wrapper for a data frame that prints nicely.

```
# convert to local data frame
flights <- as_tibble(hflights)
```

# EXPLORE THE DATA

```
flights
```

```
## A tibble: 227,496 x 21
##    Year Month DayofMonth DayOfWeek DepTime ArrTime UniqueCarrier FlightNum TailNum
##   <int> <int> <int>          <int>   <int>   <int> <chr>             <int> <chr>
## 1  2011     1     1              6    1400    1500 AA                  428 N576AA
## 2  2011     1     2              7    1401    1501 AA                  428 N557AA
## 3  2011     1     3              1    1352    1502 AA                  428 N541AA
## 4  2011     1     4              2    1403    1513 AA                  428 N403AA
## 5  2011     1     5              3    1405    1507 AA                  428 N492AA
## 6  2011     1     6              4    1359    1503 AA                  428 N262AA
## 7  2011     1     7              5    1359    1509 AA                  428 N493AA
## 8  2011     1     8              6    1355    1454 AA                  428 N477AA
## 9  2011     1     9              7    1443    1554 AA                  428 N476AA
## 10 2011     1    10              1    1443    1553 AA                  428 N504AA
## ... with 227,486 more rows, and 12 more variables: ActualElapsedTime <int>,
##   AirTime <int>, ArrDelay <int>, DepDelay <int>, Origin <chr>, Dest <chr>,
##   Distance <int>, TaxiIn <int>, TaxiOut <int>, Cancelled <int>,
##   CancellationCode <chr>, Diverted <int>
```

This prints the data nicely with 10 rows and as many columns that fits the screen.

## EXPLORE THE DATA

**# Revert to the original data frame to view all the columns**

head(data.frame(flights))

```
  Year Month DayofMonth DayOfWeek DepTime ArrTime UniqueCarrier FlightNum TailNum
1 2011     1          1         6    1400    1500            AA       428  N576AA
2 2011     1          2         7    1401    1501            AA       428  N557AA
3 2011     1          3         1    1352    1502            AA       428  N541AA
4 2011     1          4         2    1403    1513            AA       428  N403AA
5 2011     1          5         3    1405    1507            AA       428  N492AA
6 2011     1          6         4    1359    1503            AA       428  N262AA
  ActualElapsedTime AirTime ArrDelay DepDelay Origin Dest Distance TaxiIn TaxiOut
1                60      40      -10        0    IAH  DFW      224      7      13
2                60      45       -9        1    IAH  DFW      224      6       9
3                70      48       -8       -8    IAH  DFW      224      5      17
4                70      39        3        3    IAH  DFW      224      9      22
5                62      44       -3        5    IAH  DFW      224      9       9
6                64      45       -7       -1    IAH  DFW      224      6      13
  Cancelled CancellationCode Diverted
1         0                         0
2         0                         0
3         0                         0
4         0                         0
5         0                         0
6         0                         0
```

## EXPLORE THE DATA

Functions in dplyr:

- Pick observations by their values: *filter()*
- Reorder the rows: *arrange()*.
- Pick variables by their names: *select()*.
- Create new variables with functions of existing variables: *mutate()*
- Collapse many values down to a single summary: *summarise()*
- These can all be used in conjunction with *group_by()* which changes the scope of each function from operating on the entire dataset to operating on it group-by-group.

These six functions provide the verbs for a language of data manipulation.

## EXPLORE THE DATA

***filter***: Keep rows matching criteria

- Base R approach to filtering forces you to repeat the data frame's name
- dplyr approach is simpler to write and read
- Command structure (for all dplyr verbs):
  - first argument is a data frame
  - return value is a data frame
  - nothing is modified in place

**Qn:** Extract details of flights operating on January 01.

```
# base R approach to view all flights on January 1
flights[flights$Month==1 & flights$DayofMonth==1, ]

# try the filter function of dplyr for the same question
# dplyr approach
# note: you can use comma or ampersand to represent AND condition
filter(flights, Month==1, DayofMonth==1)
```

## EXPLORE THE DATA

Qn: Extract details of flights operated by American Airlines or United Airlines.

```
# use pipe for OR condition
filter(flights, UniqueCarrier=="AA" | UniqueCarrier=="UA")

# you can also use %in% operator
filter(flights, UniqueCarrier %in% c("AA", "UA"))
# Check the two answers
```

## EXPLORE THE DATA

***select***: Pick columns by name
Qn: Show flight details with Dep/Arr times along with flight numbers only.

```
# Show flight details with Dep/Arr times alongwith flight numbers only.
# base R approach to select DepTime, ArrTime, and FlightNum columns
flights[, c("DepTime", "ArrTime", "FlightNum")]

# dplyr approach
select(flights, DepTime, ArrTime, FlightNum)
# Check the two answers

# Use colon to select multiple contiguous columns, and use contains to match columns by name
select(flights, Year:DayofMonth, contains("Taxi"), contains("Delay"))

# starts_with, ends_with, and matches (for regular expressions) can also be used to match columns by name
select(flights, Year:DayofMonth, starts_with("Taxi"), ends_with("Delay"))
# Check the two answers
```

## EXPLORE THE DATA

### "Chaining" or "Pipelining“

Usual way to perform multiple operations in one line is by nestingCan write commands in a natural order by using the %>% infix operator (pipes, which can be pronounced as "then")

```
# Show unique carrier details for flights having departure delays of more than 1 hour.
# nesting method
filter(select(flights, UniqueCarrier, DepDelay), DepDelay > 60)

# chaining method
flights %>% select(UniqueCarrier, DepDelay) %>% filter(DepDelay > 60)
```

- Chaining increases readability significantly when there are many commands
- Operator is automatically imported from the magrittr package
- Can be used to replace nesting in R commands outside of dplyr

```
# create two vectors and calculate Euclidian distance between them
x1 <- 1:5; x2 <- 2:6
sqrt(sum((x1-x2)^2))

# chaining method
(x1-x2)^2 %>% sum() %>% sqrt()
## [1] 2.236068
```

## EXPLORE THE DATA

***arrange***: Reorder rows

Qn: Extract flight carrier details and show departure delays only sorted by delay lengths.

```
# base R approach
flights[order(flights$DepDelay), c("UniqueCarrier", "DepDelay")]

# dplyr approach
flights %>% select(UniqueCarrier, DepDelay) %>% arrange(DepDelay)
# arrange(desc(DepDelay)) for descending order
```

## EXPLORE THE DATA

***mutate***: Add new variables

Qn. Find mean speed of flights.

```
# base R approach
flights$Speed <- flights$Distance / flights$AirTime*60
flights[, c("Distance", "AirTime", "Speed")]

# dplyr approach (prints the new variable but does not store it)
flights %>%
  select(Distance, AirTime) %>%
  mutate(Speed = Distance/AirTime*60)

# storing the speed variable
flights <- flights %>% mutate(Speed = Distance/AirTime*60)
flights
```

## EXPLORE THE DATA

***summarise***: Reduce variables to values

- Primarily useful with data that has been grouped by one or more variables
- group_by creates the groups that will be operated on
- summarise uses the provided aggregation function to summarise each group

Qn. Find average delay to each destination.

```
# dplyr approach: create a table grouped by Dest, and then summarise each group by taking the mean of ArrDelay
flights %>% group_by(Dest) %>% summarise(avg_delay = mean(ArrDelay, na.rm=TRUE))
```

## EXPLORE THE DATA

***group_by*** function

Qn. For each day of the year, count the total number of flights and sort in descending order.

```
flights %>% group_by(Month, DayofMonth) %>% summarise(flight_count = n()) %>%
  arrange(desc(flight_count))
```

```
## `summarise()` has grouped output by 'Month'. You can override using the
## `.groups` argument.
```

***n_distinct*** (vector): counts the number of unique items in the vector

Qn. For each destination, count the total number of flights and the number of distinct planes that flew there.

```
flights %>% group_by(Dest) %>%  summarise(flight_count = n(), plane_count =
n_distinct(TailNum))
```

## EXPLORE THE DATA

### *Window Functions*

- Aggregation function (like mean ) takes \$n\$ inputs and returns 1 value
- Window function takes n inputs and returns n values
- Includes ranking and ordering functions (like min_rank), offset functions (lead and lag), and cumulative aggregates (like cummean ).

Qn. For each carrier, calculate which two days of the year they had their longest departure delays.

**# Note: smallest (not largest) value is ranked as 1, so you have to use `desc` to rank by largest value**

```
flights %>%   group_by(UniqueCarrier) %>%  select(Month, DayofMonth, DepDelay) %>%
  filter(min_rank(desc(DepDelay)) <= 2) %>%   arrange(UniqueCarrier, desc(DepDelay))
```

**# rewrite more simply with the `top_n` function**

```
flights %>%  group_by(UniqueCarrier) %>%  select(Month, DayofMonth, DepDelay) %>%
  top_n(2) %>%  arrange(UniqueCarrier, desc(DepDelay))
```

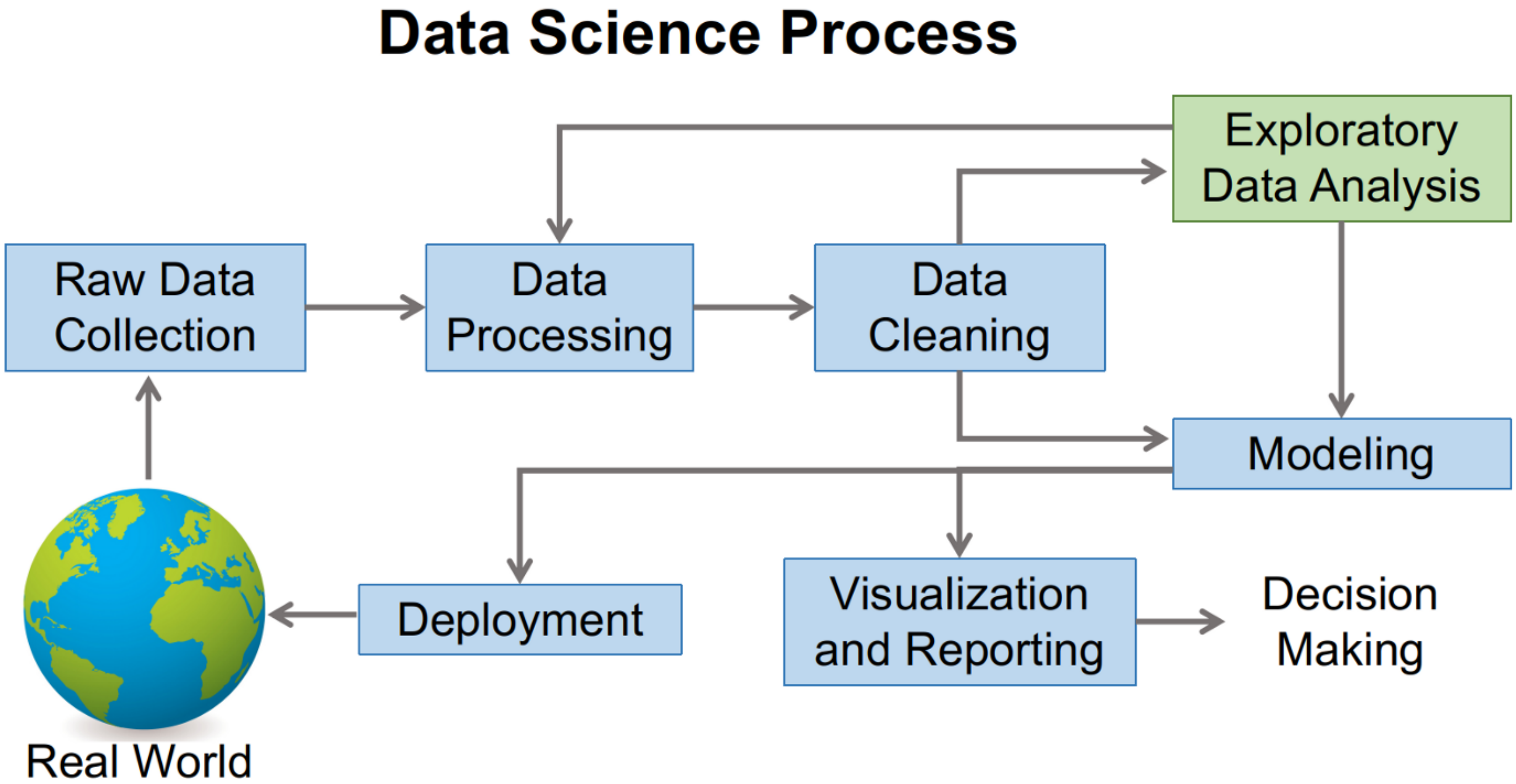
## EXPLORE THE DATA

### Useful Convenience Functions

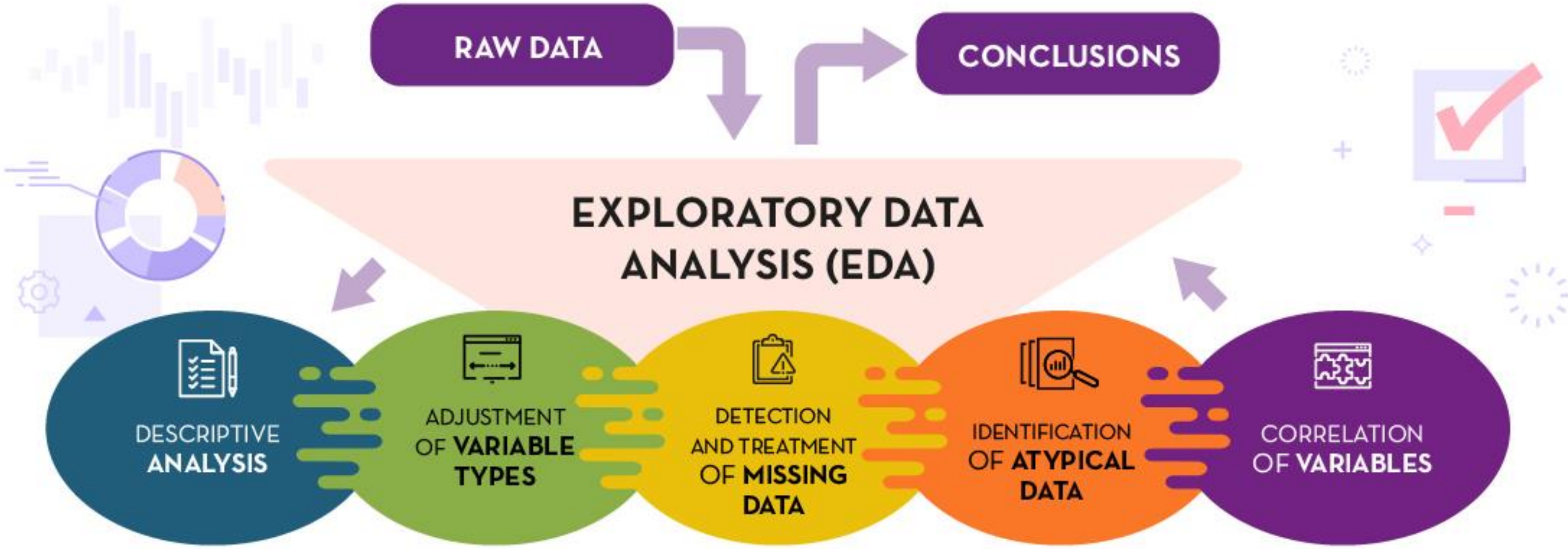
```
# randomly sample a fixed number of rows, without replacement
flights %>% sample_n(5)

# randomly sample a fraction of rows, with replacement
flights %>% sample_frac(0.25, replace=TRUE)

# base R approach to view the structure of an object
str(flights)

# dplyr approach: better formatting, and adapts to your screen width
glimpse(flights)
```

# EXPLORATORY DATA ANALYSIS (EDA)

# WHAT IS EDA IN DATA SCIENCE?



# WHAT IS EDA?



RAW DATA
CONCLUSIONS
EXPLORATORY DATA ANALYSIS (EDA)
DESCRIPTIVE ANALYSIS
ADJUSTMENT OF VARIABLE TYPES
DETECTION AND TREATMENT OF MISSING DATA
IDENTIFICATION OF ATYPICAL DATA
CORRELATION OF VARIABLES

## WHAT IS EDA?

- Exploratory Data Analysis, or EDA in short, use visualization and transformation to explore data in a systematic way. It is an iterative cycle where one
  - Generates questions about the data.
  - Search for answers by visualizing, transforming, and modelling the data.
  - Use what we learn to refine our questions and/or generate new questions.

- EDA is not a formal process with a strict set of rules. During the initial phases of EDA one should feel free to investigate every idea that occurs.

- Some of these ideas will pan out, and some will be dead ends. As our exploration continues, we will home in on a few particularly productive areas that you'll eventually write up and communicate to others.

- EDA is an important part of any data analysis, even if the questions are handed to you on a platter, because you always need to investigate the quality of your data.

- Data cleaning is just one application of EDA: we ask questions about whether our data meets our expectations or not.

- To do data cleaning, we'll need to deploy all the tools of EDA: visualisation, transformation, and modelling.

## EDA Case Study

Let’s begin with the ***email*** dataset


- These data represent incoming emails for the first three months of 2012 for an email account.
- The data frame has 3921 observations on 21 variables.
- Some of the variables are:

  - ***spam***: Indicator for whether the email was spam.
  - ***to multiple***: Indicator for whether the email was addressed to more than one recipient.
  - ***from***: Whether the message was listed as from anyone (this is usually set by default for regular outgoing email).
  - ***dollar***: The number of times a dollar sign or the word "dollar" appeared in the email.
  - ***winner*** : Indicates whether "winner" appeared in the email.
  - ***inherit***: The number of times "inherit" (or an extension, such as "inheritance") appeared in the email.
  - ***num_char***: The number of characters in the email, in thousands.
  - ***urgent_subj*** : Whether the word "urgent" was in the email subject.

# EDA Case Study

**Loading the dataset**

```
library(tidyverse)
library(openintro) #for loading our case study dataset
data(email)
email
```

Can you tell the format of the dataset?

# EDA Case Study

**Possible Questions for EDA:**

- How is the length of an email related to an email being a spam one?
- Experience tells us that presence of excessive exclamation marks in an email makes it more likely to be a spam. Explore that relationship for this dataset.
- How is the number of images attached with the email relate to spam emails?
- Returning to the length of an email, how do non-spam emails characterize wrt the number of recipients?

**EDA**

- Data Analysis is not always about providing answers to the specific questions asked.
- More than often, asking the right questions are more than important.
- Many industries/institutions generate huge volume of data, but have no clue what to do with them.

# EDA Case Study

## Measuring variability

- Variation is the tendency of the values of a variable to change from measurement to measurement.
- You can see variation easily in real life; if you measure any continuous variable twice, you will get two different results. This is true even if you measure quantities that are constant, like the speed of light.
- Each of your measurements will include a small amount of error that varies from measurement to measurement.
- Categorical variables can also vary if you measure across different subjects (e.g. the eye colors of different people), or different times (e.g. fluctuation [up/down] of a stock over different time periods).
- Every variable has its own pattern of variation, which can reveal interesting information.
- The best way to understand that pattern is to visualize the distribution of the variable's values.

## EDA Case Study

**Exploring number of characters in spam vs non-spam emails**

- Let us first explore how the number of characters vary from spam to non-spam emails.
- In this quest, we can first look into summaries of central tendencies and variability for the ***num_char*** variable grouped by the ***spam*** status.
- A good way to visualize and compare the location and spread is to create side-by-side boxplots.
- Note that spam is of numeric type. We have to change it to factor type.
- We also rename 0s as "Not_spam" and 1s as "Spam".

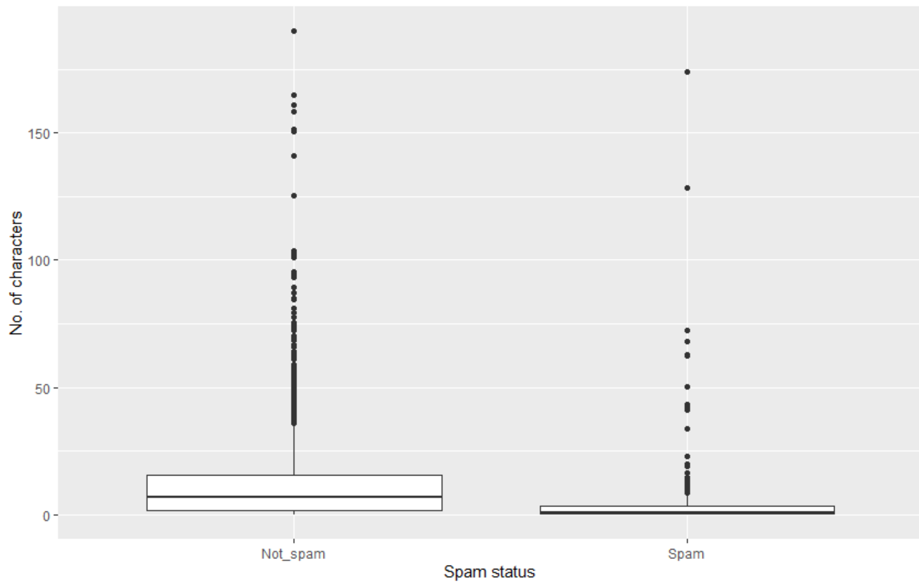
```
# Exploring number of characters in spam vs non-spam emails
email <- email %>%
  mutate(spam = as.factor(spam)) %>%
  mutate(spam = recode(spam, "0" = "Not_spam", "1" = "Spam"))

email
```

What change do you notice?

# EDA Case Study

```
# Compute summary statistics
email %>%
  group_by(spam) %>% summarize(median(num_char), IQR(num_char))

# A tibble: 2 × 3
##    spam      `median(num_char)` `IQR(num_char)`
##    <fct>          <dbl>                <dbl>
## 1 Not_spam        6.83                 13.6
## 2   Spam          1.05                 2.82
```

```
# Visualize
email %>%
  ggplot(aes(x = spam, y = num_char)) +
  geom_boxplot() +
  labs(x = "Spam status",
       y = "No. of characters")
```

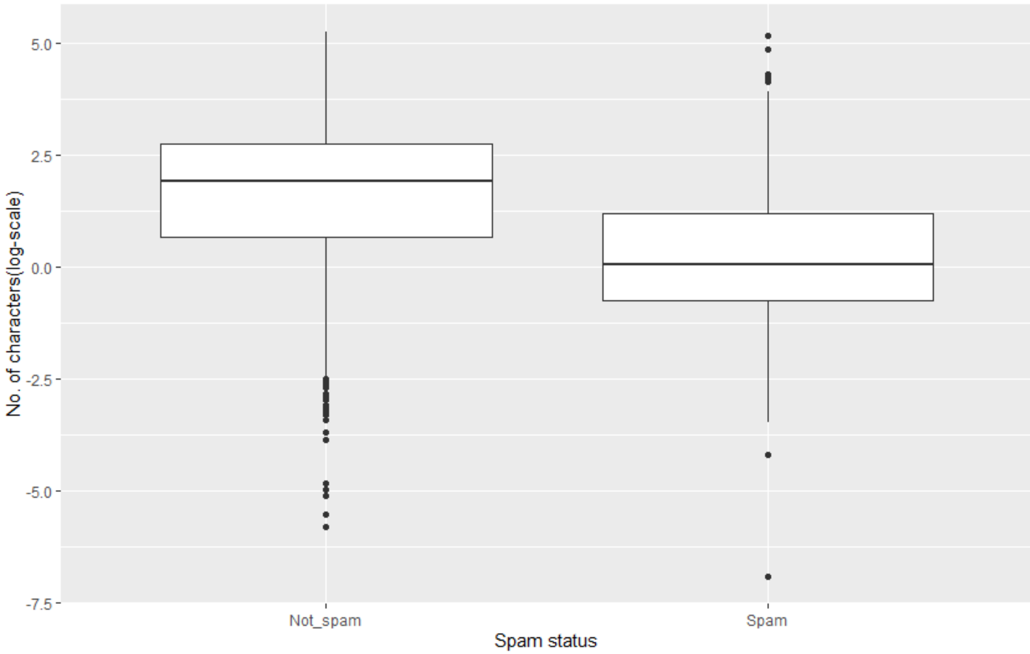



What can you infer from the plot?
Any suggestions on how to improve the plot?

# EDA Case Study

## # It might be a good idea to change the scale of the y-axis.

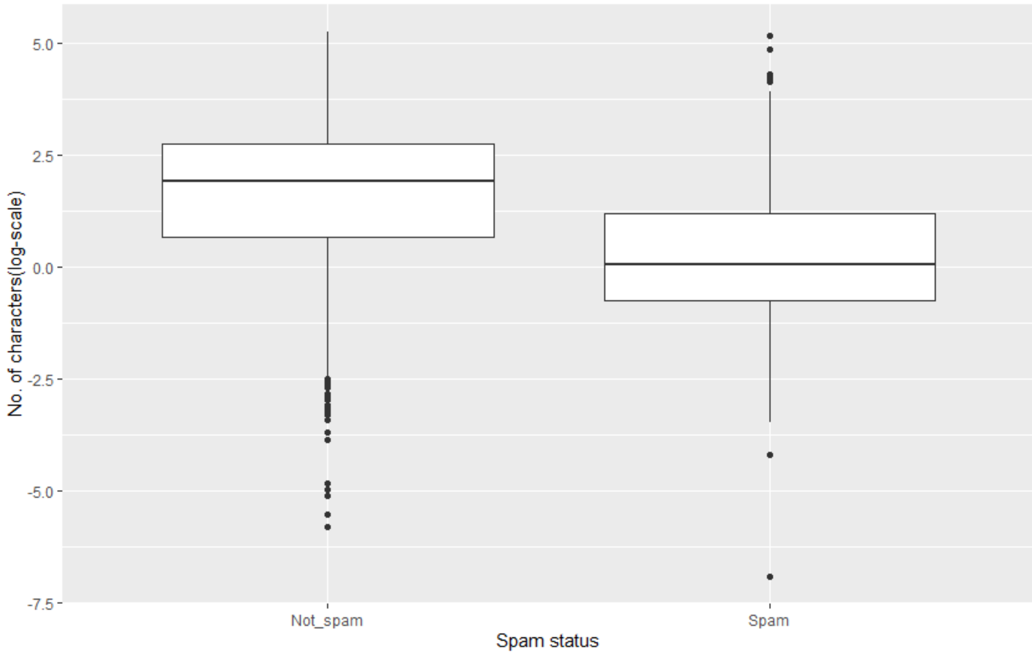
```
email %>%
  mutate(log_num_char = log(num_char)) %>%
  ggplot(aes(x = spam, y = log_num_char)) +
  geom_boxplot()+
  labs(x = "Spam status", y = "No. of characters(log-scale)")
```



# EDA Case Study

**# It might be a good idea to change the scale of the y-axis.**

```
email %>%
  mutate(log_num_char = log(num_char)) %>%
  ggplot(aes(x = spam, y = log_num_char)) +
  geom_boxplot()+
  labs(x = "Spam status", y = "No. of characters(log-scale)")
```



## EDA Case Study

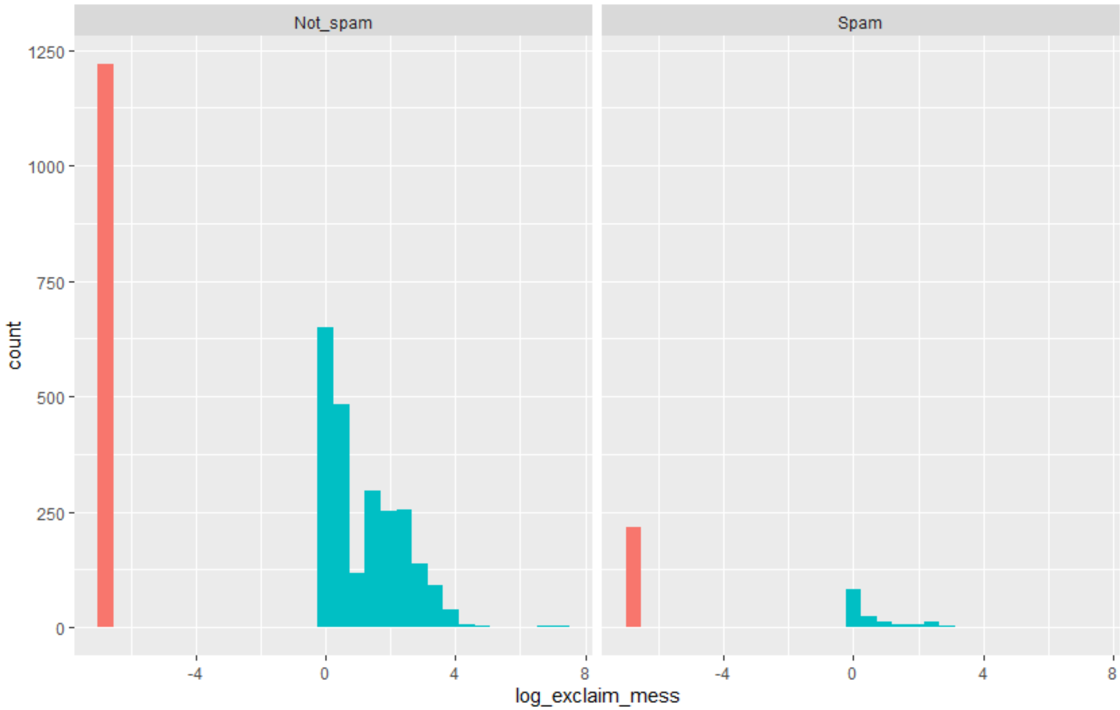
### exclaim_mess vs spam

- We now explore another variable ***exclaim_mess***, the number of exclamation marks in the emails.
- We deploy summary statistics and visualizations to explore the differences.
- Note that many of the emails do not have any exclamation mark, hence log-transformation of the scale will return $-Inf$, corresponding to log(0).
- A way-around is to add a small quantity, say 0.001 to the values to prevent returning $-Inf$ $(-\infty)$.

```
email %>%
  group_by(spam) %>%
  summarise(MED = median(exclaim_mess),
            IQR = IQR(exclaim_mess), SD = sd(exclaim_mess))

## A tibble: 2 × 4
##   spam      MED   IQR    SD
##   <fct>    <dbl> <dbl> <dbl>
## 1 Not_spam    1     5   47.6
## 2 Spam        0     1   79.9
```

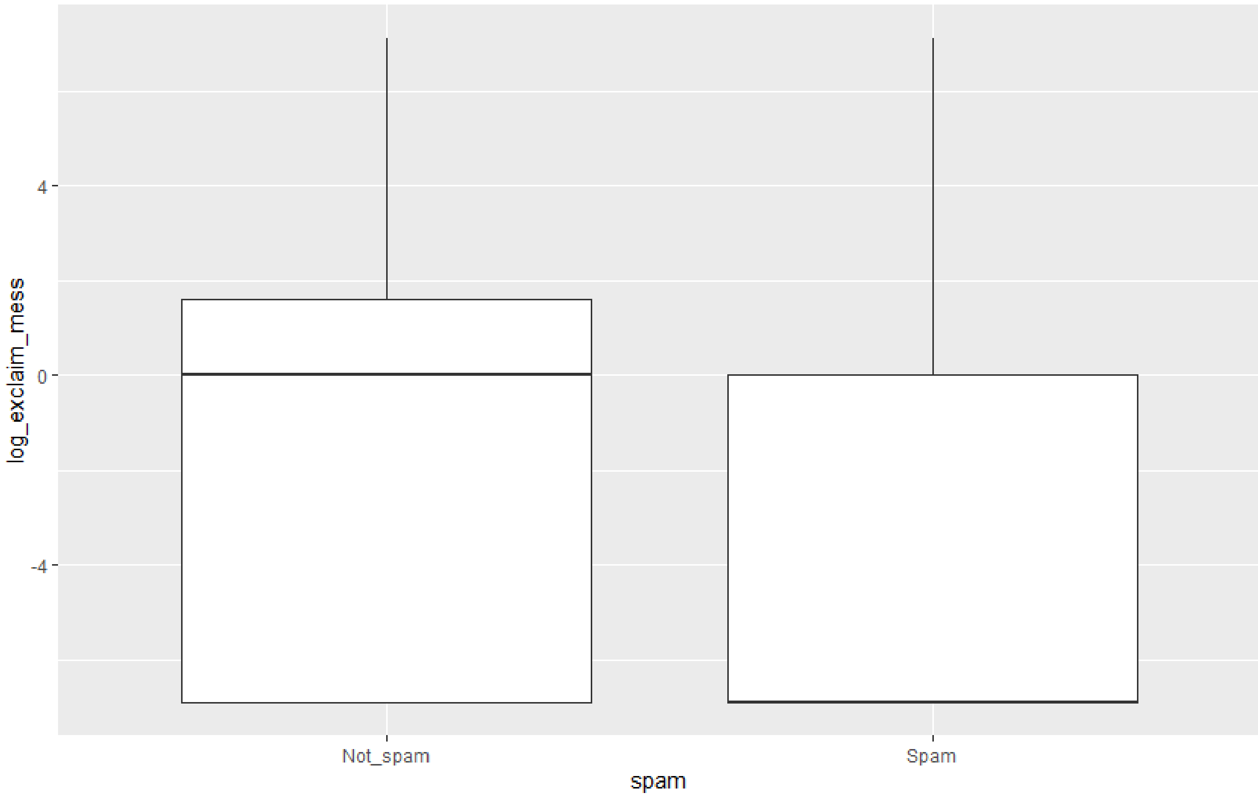
# EDA Case Study

```
# Visualize
email %>%
  mutate(log_exclaim_mess = log(exclaim_mess + 0.001)) %>%
  mutate(custom_fill = as.factor(exclaim_mess > 0)) %>%
  ggplot(aes(x = log_exclaim_mess, fill = custom_fill)) +
  geom_histogram() + theme(legend.position = "none") + facet_wrap(~ spam)
```



# EDA Case Study

```
# Visualize: Box-plots
email %>%
  mutate(log_exclaim_mess = log(exclaim_mess + 0.001)) %>%
  ggplot(aes(x = spam, y = log_exclaim_mess)) +
  geom_boxplot()
```



## EDA Case Study

### Tackling inflated Zeroes

- We can see that both the non-spam and spam groups have the maximum counts for zeroes (no exclamation marks). This 'inflation' of zeroes affects the summary of data.

- Zero Inflation is common in many data applications.

- Suppose you are monitoring the sales of a new chocolate recently launched in the market.

- Data is collected from every customer entering a store, and number of the new chocolate bought by that customer is stored in a variable.

- A zero might not mean that a customer is choosing an alternate product; it may also mean that the customer is not interested in buying chocolates.

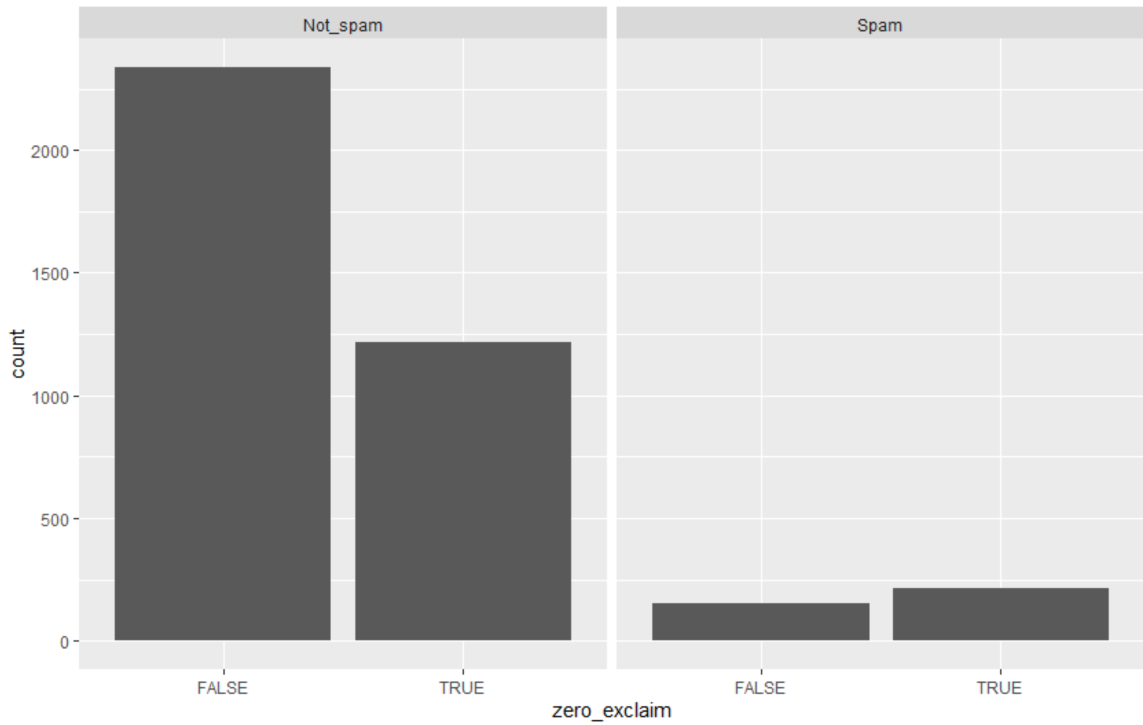
- One strategy is to categorize the variable into levels; for example, we can have two groups, one with zero exclamation marks, and the other with positive number of exclamation marks.

- Next, we can summarize and visualize the data for the two groups separately.

## EDA Case Study

### # Tackling inflated Zeroes

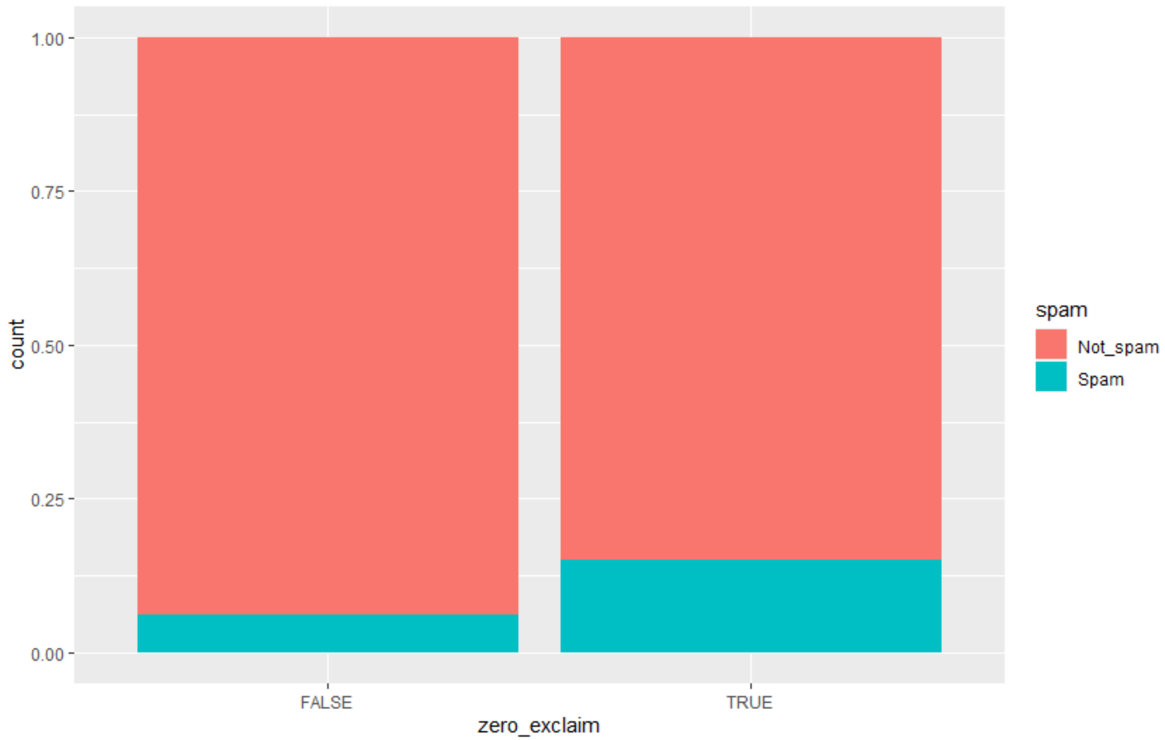
```
email %>%
mutate(zero_exclaim = (exclaim_mess == 0)) %>%
ggplot(aes(x = zero_exclaim)) +
geom_bar() +
facet_wrap(~spam)
```



# EDA Case Study

## # Tackling inflated Zeroes

```
email %>%
mutate(zero_exclaim = (exclaim_mess == 0)) %>%
ggplot(aes(x = zero_exclaim, fill = spam)) +
geom_bar(position = "fill")
```



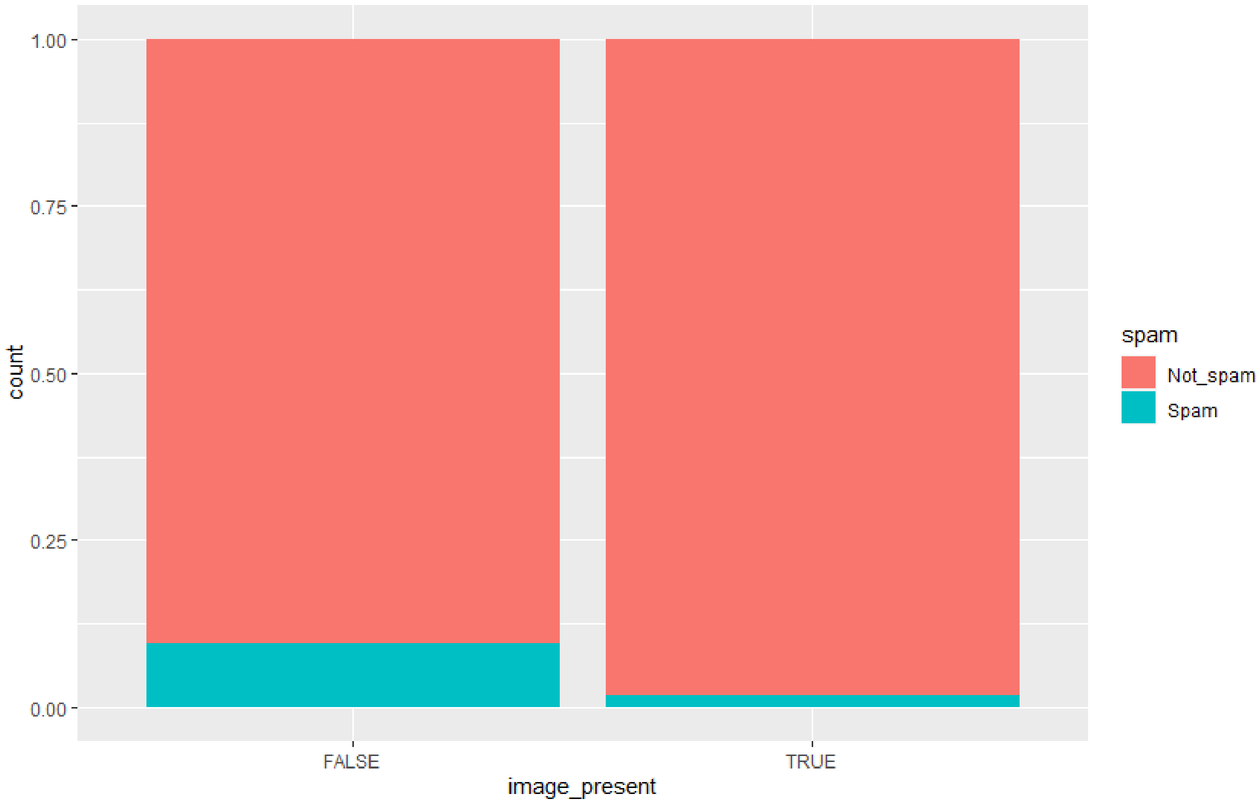
# EDA Case Study

```
# Tackling inflated zeroes: example with the image variable
email %>%
  count(image)

## A tibble: 8 × 2
##   image     n
##   <dbl> <int>
## 1     0  3811
## 2     1    76
## 3     2    17
## 4     3    11
## 5     4     2
## 6     5     2
## 7     9     1
## 8    20     1
```

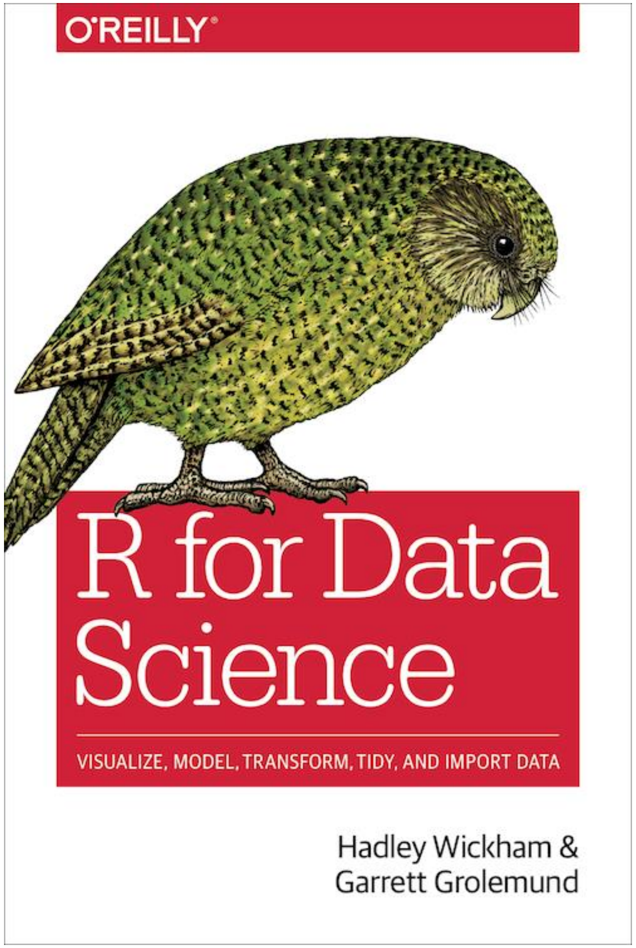
- There are 3811 images with no images attached.
- This poses a zero inflation problem.

# EDA Case Study

```
email %>%
  mutate(image_present = (image > 0)) %>%
  ggplot(aes(x = image_present, fill = spam)) +
  geom_bar(position = "fill")
```



# Reference

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