#### Assignment 2 ETC1010 5510

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```
library(naniar)
library(broom)
library(ggmap)
library(knitr)
library(lubridate)
library(timeDate)
library(tsibble)
library(here)
library(readr)
library(tidyverse)
library(kableExtra)
library(ggResidpanel)
library(gridExtra)
```

```
tree_data0 <- read_csv("Data/Assignment_data.csv")</pre>
```

#### Part I

Question 1: Rename the variables Date Planted and Year Planted to Dateplanted and Yearplanted using the rename() function. Make sure Dateplanted is defined as a date variable. Then extract from the variable Dateplanted the year and store it in a new variable called Year. Display the first 6 rows of the data frame. (5pts)

Table 1: Tree Data: All Variables



Question 2: Have you noticed any differences between the variables Year and Yearplanted? Why is that? Demonstrate your claims using R code. Fix the problem if there is one (Hint: Use ifelse inside a mutate function to fix the problem and store the data in tree\_data\_clean). After this question, please use the data in tree\_data\_clean to proceed. (3pts)

The corresponding values in the variables Year and Yearplanted are different. The newly created variable Year contains the year 2000 in all observations but one (1977). Correct value for the year of tree plantation is present in Yearplanted.

This difference is because the original variable,  $Date\ Planted$  in tree\_data0 has the  $Date\ Planted$  as "2/1/00" where the dmy() interprets the year "00" as 2000 and hence for both 1900 and 2000. The year 1977 is mapped correctly owing to the fact that 2077 has not yet arrived. These claims can be seen below.

```
tree_data %>%
  select(`CoM ID`, Yearplanted, Dateplanted, Year) %>%
  filter(`CoM ID` %in% c("1028440", "1058665", "1060068")) %>%
  kable(caption = "Mismatching Years") %>%
  kable_styling(latex_options = c("hold_position"))
```

Table 2: Mismatching Years

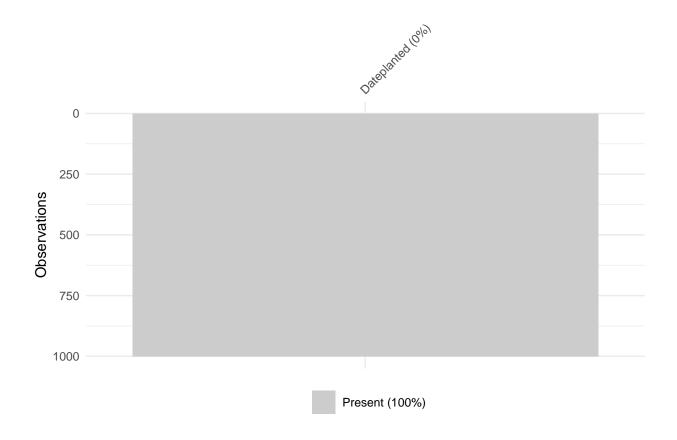
CoM ID	Yearplanted	Dateplanted	Year
1028440	1900	2000-01-02	2000
1058665	2000	2000-05-29	2000
1060068	1977	1977-07-07	1977

Question 3: Investigate graphically the missing values in the variable *Dateplanted* for the last 1000 rows of the data set. What do you observe? (max 30 words) (2pts)

We don't see any missing values in "Dateplanted".

```
tree_data_singlevariable <- tree_data_clean %>%
  select(Dateplanted) %>%
  tail(1000)

vis_miss(tree_data_singlevariable)
```



## Question 4: What is the proportion of missing values in each variable in the tree data set? Display the results in descending order of the proportion. (2pts)

The missingness in the variables of the tree data set is listed below in decsending order of proportion.

```
miss_var_summary(tree_data_clean) %>%
  mutate(pct_miss = round(pct_miss/100,3)) %>%
  rename(prop_miss = pct_miss) %>%
  kable(caption = "Proportion of missing values in each variable") %>%
  kable_styling(latex_options = "hold_position")
```

Table 3: Proportion of missing values in each variable

variable	n_miss	prop_miss
Precinct	6828	1.000
Diameter Breast Height	1454	0.213
Age Description	1454	0.213
Useful Life Expectency	1454	0.213
Useful Life Expectency Value	1454	0.213
Dateplanted	2	0.000
Common Name	1	0.000
Located in	1	0.000
CoM ID	0	0.000
Scientific Name	0	0.000
Genus	0	0.000
Family	0	0.000
Yearplanted	0	0.000
UploadDate	0	0.000
CoordinateLocation	0	0.000
Latitude	0	0.000
Longitude	0	0.000
Easting	0	0.000
Northing	0	0.000
Year	0	0.000

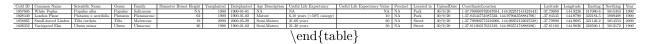
Question 5: How many observations have a missing value in the variable *Dateplanted*? Identify the rows and display the information in those rows. Remove all the rows in the data set of which the variable *Dateplanted* has a missing value recorded and store the data in *tree\_data\_clean1*. Display the first 4 rows of *tree\_data\_clean1*. Use R inline code to complete the sentense below. (6pts)

There are 2 observations with missing values in Dateplanted variable.

```
tree_data_clean %>%
  filter(is.na(Dateplanted)) %>%
  kable(caption = "Observations with missing Dateplanted") %>%
  kable_styling(latex_options = c("hold_position", "scale_down"))
```

Table 4: Observations with missing Dateplanted

```
tree_data_clean1 <- tree_data_clean %>%
  filter(!is.na(Dateplanted))
  head(tree_data_clean1, 4) %>%
kable(caption = "tree_data_clean1") %>%
  kable_styling(latex_options = c("scale_down", "hold_position"))
```



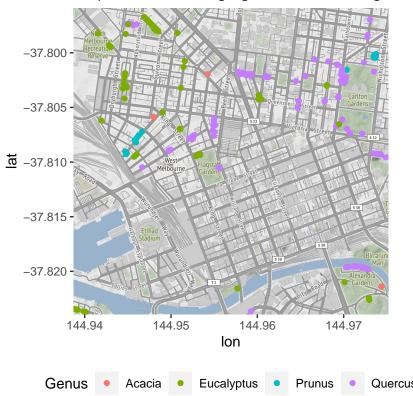
The number of rows in the cleaned data set are 6826 and the number of columns are 20

### Question 6: Create a map with the tree locations in the data set. (2pts)



Question 7: Create another map and draw trees in the *Genus* groups of Eucalyptus, Macadamia, Prunus, Acacia, and Quercus. Use the "Dark2" color palette and display the legend at the bottom of the plot. (8pts)

#### Map of trees belonging to the selected genus group



Question 8: Filter the data tree\_data\_clean1 so that only the variables Year, Located in, and Common Name are displayed. Arrange the data set by Year in descending order and display the first 4 lines. Call this new data set tree\_data\_clean\_filter. Then answer the following question using inline R code: When (Year), where (Located in) and what tree (Common Name) was the first tree planted in Melbourne according to this data set? (8pts)

```
tree_data_clean_filter <- tree_data_clean1 %>%
select(Year,`Located in`,`Common Name`) %>%
    arrange(-Year)

head(tree_data_clean_filter,4) %>%
    kable(caption = "Selected Variables of Tree Data") %>%
    kable_styling(latex_options = "hold_position")
```

Table 5: Selected Variables of Tree Data

Year	Located in	Common Name
2000	Street	Small-leaved Linden
2000	Street	Spotted Gum
2000	Street	Drooping sheoak
2000	Park	Kanooka

The first tree was planted in 1900 at a Street and the tree name is London Plane

Question 9: How many trees were planted in parks and how many in streets? Tabulate the results (only for locations in parks and streets) using the function kable() from the kableExtra R package. (3pts)

```
tree_data_clean1 %>%
  filter(`Located in` %in% c("Park","Street")) %>%
  group_by(`Located in`) %>%
  summarise(Count = n()) %>%
  kable(caption = "Tree Count by Location") %>%
  kable_styling(latex_options = "hold_position")
```

Table 6: Tree Count by Location

Located in	Count
Park	2737
Street	4088

Question 10: How many trees are there in each of the Family groups in the data set  $tree\_data\_clean1$  (display the first 5 lines of the results in descending order)? (2pt)

```
tree_data_clean1 %>%
  group_by(Family) %>%
  summarise(`Number of trees` = n()) %>%
  arrange(-`Number of trees`) %>%
  head(5) %>%
  kable(caption = "Tree Count by Family") %>%
  kable_styling(latex_options = "hold_position")
```

Table 7: Tree Count by Family

Family	Number of trees
Myrtaceae	2102
Platanaceae	1512
Ulmaceae	1125
Fabaceae	327
Fagaceae	254

Question 11: Create a markdown table displaying the number of trees planted in each year (use variable Yearplanted) with common names Ironbark, Olive, Plum, Oak, and Elm (Hint: Use kable() from the gridExtra R package). What is the oldest most abundant tree in this group? (8pts)

**Elm** is the oldest most abundant tree in this group.

```
tree_data_clean1 %>%
  filter(`Common Name`
    %in% c("Ironbark", "Olive", "Plum", "Oak", "Elm")) %>%
  group_by(Yearplanted, `Common Name`) %>%
    summarise(`number of trees` = n()) %>%
    arrange(Yearplanted, desc(`number of trees`)) %>%
    knitr::kable(caption="Summary of trees in each year",booktabs = TRUE) %>%
  kable_styling(bootstrap_options = c("striped", "hover"), latex_options = "hold_position")
```

Table 8: Summary of trees in each year

Yearplanted	Common Name	number of trees
1900	Elm	179
1900	Ironbark	29
1900	Olive	17
1900	Oak	4
2000	Ironbark	23
2000	$\operatorname{Elm}$	18
2000	Oak	9

Question 12: Select the trees with diameters (Diameter Breast Height) greater than 40 cm and smaller 100 cm and comment on where the trees are located (streets or parks). (max 25 words) (3pts)

We see that, for the diameters 41 to 56, there are more trees planted on the streets than in parks. Larger trees are prevalent more in parks and their number reduces with diameter.

Question 13: Plot the trees within the diameter range that you have selected in Question 12, which are located in parks and streets on a map using 2 different colours to differentiate their locations (streets or parks). (6pts)

#### Spatial Visualization of Large Trees



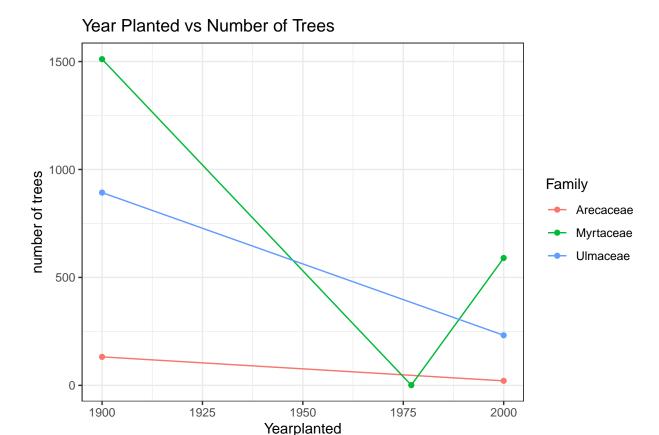
Question 14: Create a time series plot (using geom\_line) that displays the total number of trees planted per year in the data set  $tree\_data\_clean1$  that belong to the Families: Myrtaceae, Arecaceae, and Ulmaceae. What do you observe from the plot?

(6pts)

We see that the number of trees that were planted decreases from 1900 to 2000. More trees belonging to Myrtaceae were planted with one tree uniquely planted in 1977.

```
Fig_data <- tree_data_clean1 %>%
  filter(`Family` %in% c("Myrtaceae", "Arecaceae", "Ulmaceae")) %>%
  group_by(`Yearplanted`, `Family`) %>%
  summarise(`number of trees` = n()) %>%
  arrange(desc(`number of trees`))

Fig_data %>%
  ggplot() +
  geom_line(mapping = aes(x = `Yearplanted`, y = `number of trees`, colour = `Family`)) +
  geom_point(mapping = aes(x = `Yearplanted`, y = `number of trees`, colour = `Family`))+
  theme(legend.position = "bottom") +
  theme_bw() +
  labs(title = "Year Planted vs Number of Trees")
```



Part 2: Simulation Exercise

Question 15: Create a data frame called *simulation\_data* that contains 2 variables with names *response* and *covariate*. Generate the variables according to the following model:

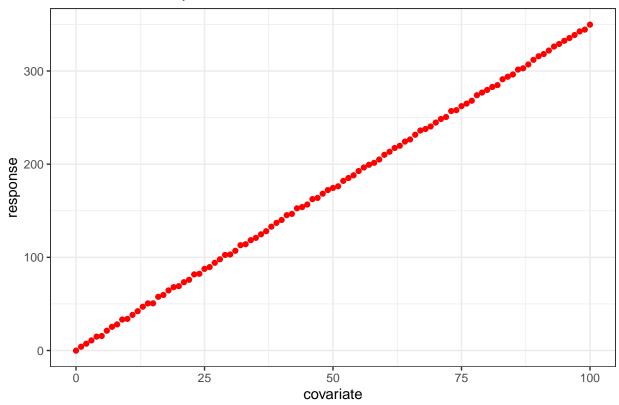
 $response = 3.5 \times covariate + epsilon$  where covariate is a variable that takes values 0, 1, 2, ..., 100 and  $\epsilon$  is generated according to a Normal distribution (Hint: Use the function rnorm() to generate epsilon.)

(3pts)

## Question 16: Display graphically the relationship between the variables response and covariate (1pt) using a point plot. Which kind of relationship do you observe? (2pts)

We observe a linear relationship where the response variable increases with the covariate.

#### Covariate vs Response



Question 17: Fit a linear model between the variables *response* and *covariate* that you generate in Question 15 and display the model summary. (2pts)

```
simulation_data_lm <- lm(response~covariate, data=simulation_data)
summary(simulation_data_lm)</pre>
```

```
##
## Call:
## lm(formula = response ~ covariate, data = simulation_data)
## Residuals:
##
       Min
                  1Q
                      Median
                                    3Q
                                            Max
   -2.07431 -0.71466 0.05844 0.64196
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.135896
                          0.199948
                                      0.68
                                              0.498
              3.493775
                          0.003455 1011.35
                                             <2e-16 ***
  covariate
##
## Signif. codes:
                   0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.012 on 99 degrees of freedom
## Multiple R-squared: 0.9999, Adjusted R-squared: 0.9999
## F-statistic: 1.023e+06 on 1 and 99 DF, p-value: < 2.2e-16
```

Question 18: What are the values for the intercept and the slope in the estimated model in Question 17 (Hint: Use the function coef())? How do these values compare with the values in the simulation model? (max 50 words) (2pts)

```
#coef(summary(simulation_data_lm))
slope_intercept <- tidy(summary(simulation_data_lm)) %>%
select(term, estimate)
```

The generated model has a slope of 3.49 and an intercept of 0.14

The simulation data was generated from the equation,  $response = 3.5 \times covariate + epsilon$  where epsilon is an error factor. The generated linear model is of the form  $response = 3.4937754 \times covariate + 0.1358957$ . The value  $3.49 \sim 3.5$  is the slope of the linear equation and the intercept of the model is 0.14. The fitted model differs from the simulation data in epsilon, which is centered around zero. The intercept of the model is close to zero.

```
#coef(summary(simulation_data_lm))
slope_intercept %>%
  kable(caption = "Slope and Intercept")%>%
  kable_styling(latex_options = "hold_position")
```

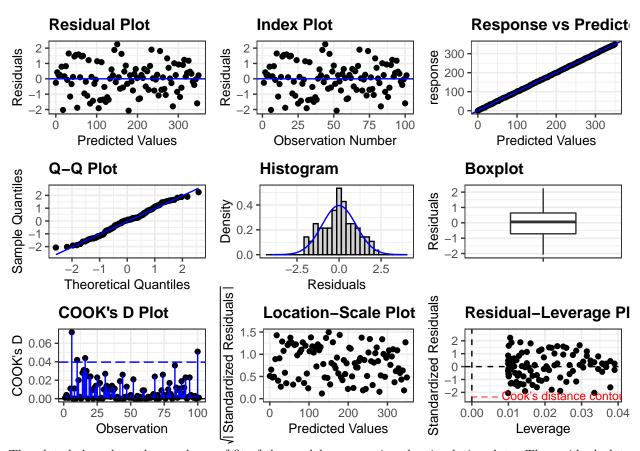
Table 9: Slope and Intercept

term	estimate	
(Intercept)	0.1358957	
covariate	3.4937754	

# Question 19: Create a figure to display the diagnostic plots of the linear model that you fit in Question 17. Comment on the diagnostic plots (max 50 words). Is this a good/bad model and why? (max 30 words) (4pts)

- The Residual plot is a scatter plot of predicted values vs residuals. Residual is the difference between actual values and the predicted values. For a good model, the residuals ~ 0. The residual plot for a model having randomly dispersed points suggests that the model is good.
- the Response vs Predicted plot is a scatter plot. A good model will have points aligned such that predicted values ~ response.
- The plots in the second row show the distribution of the residuals. A good model has a normal distribution of residuals centered around 0.

resid\_panel(simulation\_data\_lm, plots = "all")



The plots below show the goodness of fit of the model representing the simulation data. The residual plot has points scattered indefinitely, the response vs predicted plot is a straight line(slope = 1, response  $\sim$  predicted), showing that it is a well fitted model. The residuals lie within (-1,1) with a median of 0 suggesting goodness of the model.

## Question 20: Report R2, Radjusted, AIC, and BIC. Is this a good/bad model? Please explain your answer. (max 30 words) (2pts)

The model generated for the simulation data is a good model.

```
glance(simulation_data_lm) %>%
  select(r.squared, adj.r.squared, AIC, BIC) %>%
  kable(caption = "Measures of Goodness of Fit")%>%
  kable_styling(latex_options = "hold_position")
```

Table 10: Measures of Goodness of Fit

r.squared	adj.r.squared	AIC	BIC
0.9999032	0.9999022	293.0547	300.9001

The generated model has an R2 and Radjusted of 0.9999, and hence is a good model. The model with lowest AIC and BIC is a good model. For this model, the AIC and BIC are comparable and have low values.