Weekly Summary Template

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```r
library(tidyverse)
```

```
-- Attaching packages --------------------------------------- tidyverse 1.3.2 --
v ggplot2 3.4.0     v purrr   1.0.1
v tibble  3.1.8     v dplyr   1.1.0
v tidyr   1.3.0     v stringr 1.5.0
v readr   2.1.3     v forcats 1.0.0
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
```

```r
library(ISLR2)
library(cowplot)
library(kableExtra)
```

```
Attaching package: 'kableExtra'

The following object is masked from 'package:dplyr':

    group_rows
```

Tuesday, February 7th

> **!** TIL
>
> Include a *very brief* summary of what you learnt in this class here.
> Today, I learnt the following concepts in class:
>
> 1. What the interpretation of β_0 and β_1 is (regression coefficients)
> 2. Categorical covariates
> 3. How to reorder factors

Interpretation of $ _0 and β_1 (regression coefficients)

- The regression model is…

$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$

- β_0 and β_1 are the regression coefficients with β_0 being the intercept and β_1 being the slope

```r
library(ggplot2)
attach(mtcars)
```

```
The following object is masked from package:ggplot2:

    mpg
```

```r
x <- mtcars$hp
y <- mtcars$mpg

model <- lm(y ~ x)
summary(model)
```

```
Call:
lm(formula = y ~ x)

Residuals:
    Min      1Q  Median      3Q     Max
-5.7121 -2.1122 -0.8854  1.5819  8.2360
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 30.09886    1.63392  18.421  < 2e-16 ***
x           -0.06823    0.01012  -6.742 1.79e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.863 on 30 degrees of freedom
Multiple R-squared:  0.6024,    Adjusted R-squared:  0.5892
F-statistic: 45.46 on 1 and 30 DF,  p-value: 1.788e-07
```

Based on the summary model…

- The intercept means that a car with 'hp=0' would have 'mpg=30.09' ## Thursday, February 9th
- From this, if we have some co-variate x_0, then the expected value for $y(x_0)$ is given by:

$$y(x_0) = \beta_0 + \beta_1 x_0$$

- Using this we can find the expected value for $x_0 + 1$, which is…

$y(x_0 + 1) = \beta_0 + \beta_1 \times (x_0 + 1) = \beta_0 + \beta_1 \; x_0 + \beta_1 = y(x_0) + \beta_1$

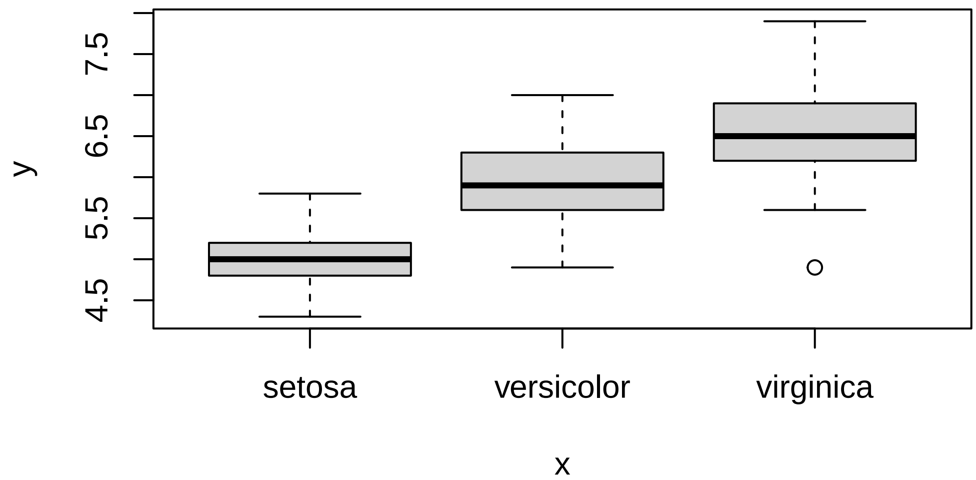
- This implies that $\beta_1 = y(x_0 + 1) - y(x_0)$

Categorical covariates

In class, we looked at categorical covariates in the iris dataset, and created a boxplot and a summary of the model for the categorical covariates

```
x <- iris$Species
y <- iris$Sepal.Length

# boxplot(Sepal.Length ~ Species, df)
boxplot(y ~ x)
```




```r
cat_model <- lm(Sepal.Length ~ Species, iris)
cat_model
```

```
Call:
lm(formula = Sepal.Length ~ Species, data = iris)

Coefficients:
      (Intercept)  Speciesversicolor   Speciesvirginica
            5.006              0.930              1.582
```

Even if x is categorical, we can still write down the regression model as follows:

$$y_i = \beta_0 + \beta_1 x_i$$

where $x_i \in \{setosa,\ versicolor,\ virginica\}$. This means that we end up with, three different models with each one having a different intercept.

1. $y_i = \beta_0 + \beta_1(x_i ==' setosa')$
2. $y_i = \beta_0 + \beta_1(x_i ==' versicolor')$
3. $y_i = \beta_0 + \beta_1(x_i ==' virginica')$

- The interpretation of the intercept (β_0) is the expected y value when x belongs to the base category

- The slope (β_1) with the name 'Species.versicolor' represents the following:
- '(Intercept)' $= y(x = \texttt{setosa})$
- 'Species.versicolor' $= y(x = \texttt{versicolor}) - y(x = \texttt{setosa})$
- 'Species.virginica' $= y(x = \texttt{virginica}) - y(x = \texttt{setosa})$

Reordering factors

Lets say that we didn't want 'setosa' to be the baseline level, and instead, we wanted 'virginica' to be the baseline level. How would we do this?

First we reorder/relevel the categorical covariate

```
# before
iris$Species
```

```
  [1] setosa     setosa     setosa     setosa     setosa     setosa    
  [7] setosa     setosa     setosa     setosa     setosa     setosa    
 [13] setosa     setosa     setosa     setosa     setosa     setosa    
 [19] setosa     setosa     setosa     setosa     setosa     setosa    
 [25] setosa     setosa     setosa     setosa     setosa     setosa    
 [31] setosa     setosa     setosa     setosa     setosa     setosa    
 [37] setosa     setosa     setosa     setosa     setosa     setosa    
 [43] setosa     setosa     setosa     setosa     setosa     setosa    
 [49] setosa     setosa     versicolor versicolor versicolor versicolor
 [55] versicolor versicolor versicolor versicolor versicolor versicolor
 [61] versicolor versicolor versicolor versicolor versicolor versicolor
 [67] versicolor versicolor versicolor versicolor versicolor versicolor
 [73] versicolor versicolor versicolor versicolor versicolor versicolor
 [79] versicolor versicolor versicolor versicolor versicolor versicolor
 [85] versicolor versicolor versicolor versicolor versicolor versicolor
 [91] versicolor versicolor versicolor versicolor versicolor versicolor
 [97] versicolor versicolor versicolor versicolor virginica  virginica 
[103] virginica  virginica  virginica  virginica  virginica  virginica 
[109] virginica  virginica  virginica  virginica  virginica  virginica 
[115] virginica  virginica  virginica  virginica  virginica  virginica 
[121] virginica  virginica  virginica  virginica  virginica  virginica 
[127] virginica  virginica  virginica  virginica  virginica  virginica 
[133] virginica  virginica  virginica  virginica  virginica  virginica 
[139] virginica  virginica  virginica  virginica  virginica  virginica 
[145] virginica  virginica  virginica  virginica  virginica  virginica 
Levels: setosa versicolor virginica
```

```r
iris$Species <- relevel(iris$Species, "virginica")

# after
iris$Species
```

```
  [1] setosa     setosa     setosa     setosa     setosa     setosa
  [7] setosa     setosa     setosa     setosa     setosa     setosa
 [13] setosa     setosa     setosa     setosa     setosa     setosa
 [19] setosa     setosa     setosa     setosa     setosa     setosa
 [25] setosa     setosa     setosa     setosa     setosa     setosa
 [31] setosa     setosa     setosa     setosa     setosa     setosa
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 [79] versicolor versicolor versicolor versicolor versicolor versicolor
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[109] virginica  virginica  virginica  virginica  virginica  virginica
[115] virginica  virginica  virginica  virginica  virginica  virginica
[121] virginica  virginica  virginica  virginica  virginica  virginica
[127] virginica  virginica  virginica  virginica  virginica  virginica
[133] virginica  virginica  virginica  virginica  virginica  virginica
[139] virginica  virginica  virginica  virginica  virginica  virginica
[145] virginica  virginica  virginica  virginica  virginica  virginica
Levels: virginica setosa versicolor
```

Once we do the re-leveling, we can now run the regression model:

```r
new_cat_model <- lm(Sepal.Length ~ Species, iris)
new_cat_model
```

```
Call:
lm(formula = Sepal.Length ~ Species, data = iris)
```

```
Coefficients:
      (Intercept)      Speciessetosa  Speciesversicolor
            6.588             -1.582             -0.652
```

Tuesday, February 9th

> **!** TIL
>
> Include a *very brief* summary of what you learnt in this class here.
> Today, I learnt the following concepts in class:
>
> 1. How to make a plot for a model that incorporates more than 1 quantitative covariate
> 2. The impact of noise and β values on R^2
> 3. Multiple regression with categorical covariates

```r
library(tibble)
library(ISLR2)
attach(Credit)

df <- Credit %>%
  tibble()
colnames(df) <- tolower(colnames(df))
df
```

```
# A tibble: 400 x 11
   income limit rating cards   age educat~1 own   student married region balance
    <dbl> <dbl>  <dbl> <dbl> <dbl>    <dbl> <fct> <fct>   <fct>   <fct>    <dbl>
 1   14.9  3606    283     2    34       11 No    No      Yes     South      333
 2  106.   6645    483     3    82       15 Yes   Yes     Yes     West       903
 3  105.   7075    514     4    71       11 No    No      No      West       580
 4  149.   9504    681     3    36       11 Yes   No      No      West       964
 5   55.9  4897    357     2    68       16 No    No      Yes     South      331
 6   80.2  8047    569     4    77       10 No    No      No      South     1151
 7   21.0  3388    259     2    37       12 Yes   No      No      East       203
 8   71.4  7114    512     2    87        9 No    No      No      West       872
 9   15.1  3300    266     5    66       13 Yes   No      No      South      279
10   71.1  6819    491     3    41       19 Yes   Yes     Yes     East      1350
# ... with 390 more rows, and abbreviated variable name 1: education
```

Plotting a model with more than 1 quantitative covariate

We will look at the following 3 columns: 'income, rating, limit'.

```
df3 <- df %>%
  select('income', 'rating', 'limit')
df3
```

```
# A tibble: 400 x 3
   income rating limit
    <dbl>  <dbl> <dbl>
 1   14.9    283  3606
 2  106.     483  6645
 3  105.     514  7075
 4  149.     681  9504
 5   55.9    357  4897
 6   80.2    569  8047
 7   21.0    259  3388
 8   71.4    512  7114
 9   15.1    266  3300
10   71.1    491  6819
# ... with 390 more rows
```

If we want to see how the credit limit is related to income and credit rating, we can visualize the following plot

```
library(plotly)
```

```
Attaching package: 'plotly'

The following object is masked from 'package:ggplot2':

    last_plot

The following object is masked from 'package:stats':

    filter

The following object is masked from 'package:graphics':

    layout
```

```r
fig <- plot_ly(df3, x=~income, y=~rating, z=~limit)
fig %>% add_markers()
```

This models a linear relationship, which in 3-dimensions is a plane (a hyperplane)

- Was shown in class what the hyperplane looked like but weren't given the code, so couldn't include that in the summary

The regression model is as follows:

```r
model <- lm(limit ~ income + rating, df3)
model
```

```
Call:
lm(formula = limit ~ income + rating, data = df3)

Coefficients:
(Intercept)       income       rating
  -532.4711       0.5573      14.7711
```

- Have 3 different coefficients
- 2nd/3rd numbers are the slopes associated with the income and rating

What is the interpretation for the coefficients?

1. β_0 is the expected value of y when $income = 0$ and $rating = 0$ (the credit limit with 0 income and 0 rating is -532) –> this is an extrapolation
2. β_1 is saying that if *rating* is held constant and *income* changes by 1 unit, then the corresponding change in the 'limit' is 0.5573.
3. β_2 is saying that if *income* is held constant and *rating* changes by 1 unit, then the corresponding change in the 'limit' is 14.7711.

What about the significance?

```r
summary(model)
```

```
Call:
lm(formula = limit ~ income + rating, data = df3)

Residuals:
    Min      1Q  Median      3Q     Max
-420.97 -121.77   14.97  126.72  485.48
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -532.47115   24.17283 -22.028   <2e-16 ***
income         0.55727    0.42349   1.316    0.189    
rating        14.77115    0.09647 153.124   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 182.3 on 397 degrees of freedom
Multiple R-squared:  0.9938,	Adjusted R-squared:  0.9938 
F-statistic: 3.18e+04 on 2 and 397 DF,  p-value: < 2.2e-16
```

The p-value for 'rating' is very significant, while its not significant for 'income'

- Multi-colinearity issue with the 3D model

    1. Not idealisitic that if we hold rating constant and income increases, by one unit then limit increase by 0.5573. –> You can't change income by 1 without impacting rating

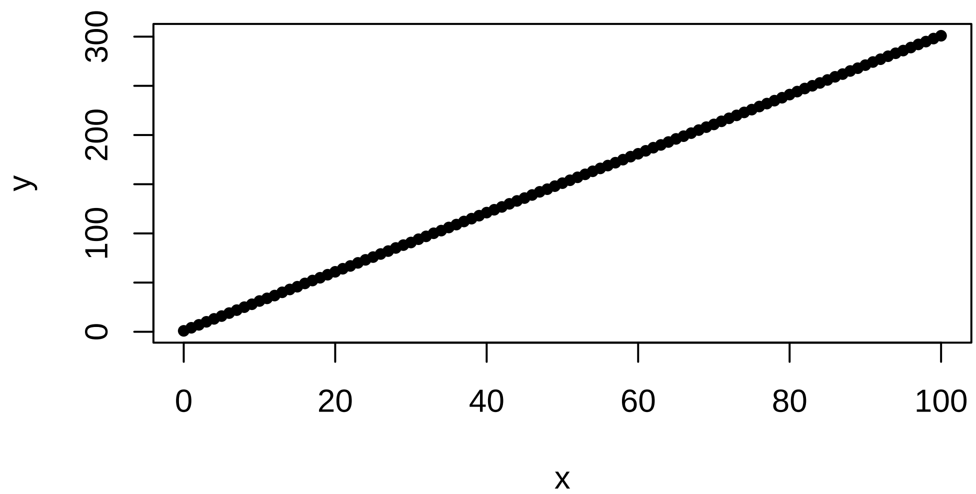
The impact of noise and β values on R^2

This first code chunk shows the model with very little noise and the output model summary to demonstrate the very high R^2 and p-value that occurs with very low noise

```r
x <- seq(0,100,1)
b0 <- 1.0
b1 <- 3.0
y <- b0 + b1 * x + rnorm(100) * 0.1
```

```
Warning in b0 + b1 * x + rnorm(100) * 0.1: longer object length is not a
multiple of shorter object length
```

```r
plot(x, y, pch = 20)
```




```r
model <- lm(y ~ x)
summary(model)
```

```
Call:
lm(formula = y ~ x)

Residuals:
      Min        1Q    Median        3Q       Max
-0.259432 -0.066147 -0.005918  0.065873  0.264160

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.0141490  0.0203853   49.75   <2e-16 ***
x           2.9999584  0.0003522 8517.65   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1032 on 99 degrees of freedom
Multiple R-squared:      1, Adjusted R-squared:      1
F-statistic: 7.255e+07 on 1 and 99 DF,  p-value: < 2.2e-16
```

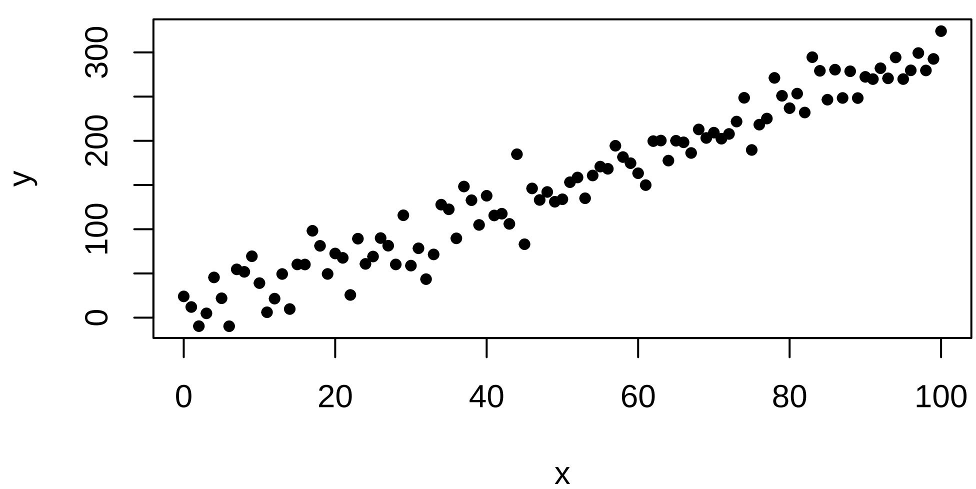
This next code chunk shows what happens with a much greater noise value. The intercept

p-value is much high than the previous model and the R^2 value decreases as well.

```r
x <- seq(0,100,1)
b0 <- 1.0
b1 <- 3.0
y <- b0 + b1 * x + rnorm(100) * 20
```

```
Warning in b0 + b1 * x + rnorm(100) * 20: longer object length is not a
multiple of shorter object length
```

```r
plot(x, y, pch = 20)
```




```r
model <- lm(y ~ x)
summary(model)
```

```
Call:
lm(formula = y ~ x)

Residuals:
```

```
    Min      1Q  Median      3Q     Max 
-54.056 -13.653  -1.043  12.971  51.625 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.78546    4.16550   0.669    0.505    
x            2.96371    0.07197  41.180   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 21.09 on 99 degrees of freedom
Multiple R-squared:  0.9448,	Adjusted R-squared:  0.9443 
F-statistic:  1696 on 1 and 99 DF,  p-value: < 2.2e-16
```

To summarize:

- Lower noise increases the R^2 value
- If you make β_0, β_1, and noise values super small, then p-value will be super high and lead to a low R^2 value
- Can have high p-value with low R^2 value, but CANT have low p-value with high R^2 value

Multiple regression with categorical covariates

To demonstrate how to incorporate both categorical and quantitative covariates into a regression model, we will use the rating and marital status from the Credit dataset to try and predict the limit.

To create the models, you need to run 2 separate models using income, rating, and marital status to predict limit. 1. once for when student is yes 1. once for when student is no

- By adding the categorical variable, you are adding an additional intercept term

```
model <- lm(limit ~ rating + married, df)
summary(model)
```

```
Call:
lm(formula = limit ~ rating + married, data = df)

Residuals:
    Min      1Q  Median      3Q     Max 
```

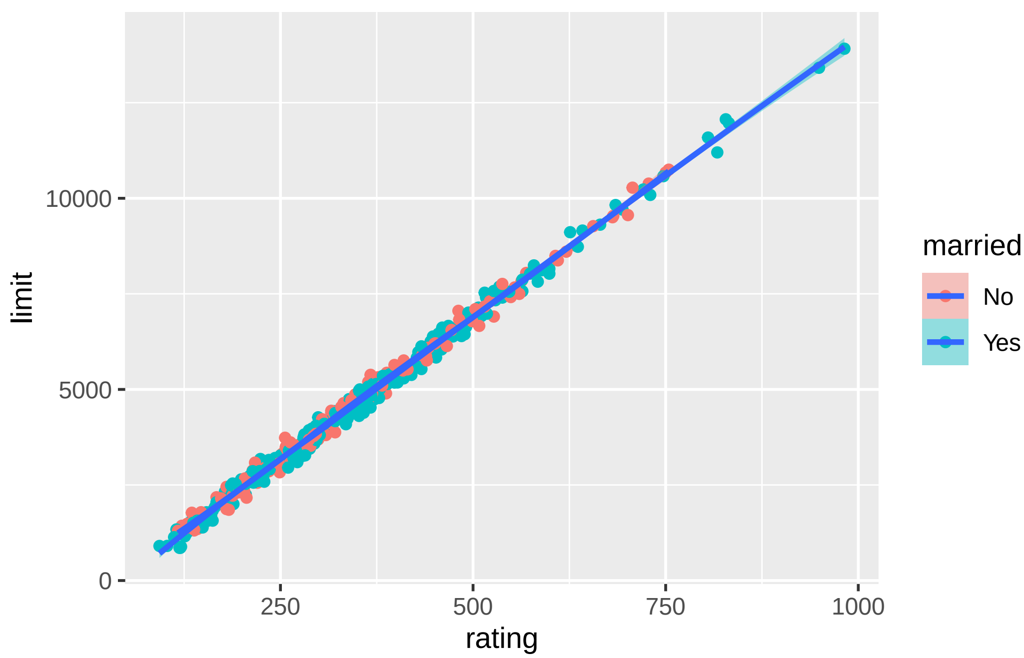
```
-404.83 -126.56   20.86  131.80  456.19

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -528.088     25.204 -20.952   <2e-16 ***
rating        14.875      0.059 252.123   <2e-16 ***
marriedYes   -25.972     18.714  -1.388    0.166
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 182.2 on 397 degrees of freedom
Multiple R-squared:  0.9938,    Adjusted R-squared:  0.9938
F-statistic: 3.181e+04 on 2 and 397 DF,  p-value: < 2.2e-16
```

```r
ggplot(df) +
  geom_point(aes(x=rating, y=limit, color=married)) +
  geom_smooth(aes(x=rating, y=limit, fill=married))
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



The model above does have 2 different lines, they are just so close together, that you can't really see it, which implies that they have the same regression line. From the model summary, you can see that the p-value for marital status is very high, which indicates that it is not a good predictor of someones credit limit.