01_Measuring_Differences_Means

June 24, 2019

Part 1: 01_Measuring_Differences_Means

```
In [1]: library( tidyverse )
```

```
Registered S3 methods overwritten by 'ggplot2':
  method         from
  [.quosures     rlang
  c.quosures     rlang
  print.quosures rlang
Registered S3 method overwritten by 'rvest':
  method            from
  read_xml.response xml2
 Attaching packages  tidyverse 1.2.1
 ggplot2 3.1.1      purrr   0.3.2
 tibble  2.1.1      dplyr   0.8.1
 tidyr   0.8.3      stringr 1.4.0
 readr   1.3.1      forcats 0.4.0
 Conflicts  tidyverse_conflicts()
 dplyr::filter() masks stats::filter()
 dplyr::lag()    masks stats::lag()
```

```
In [2]: library( broom )
```

```
In [3]: options(repr.plot.width=4, repr.plot.height=3)
```

1 Intercepts

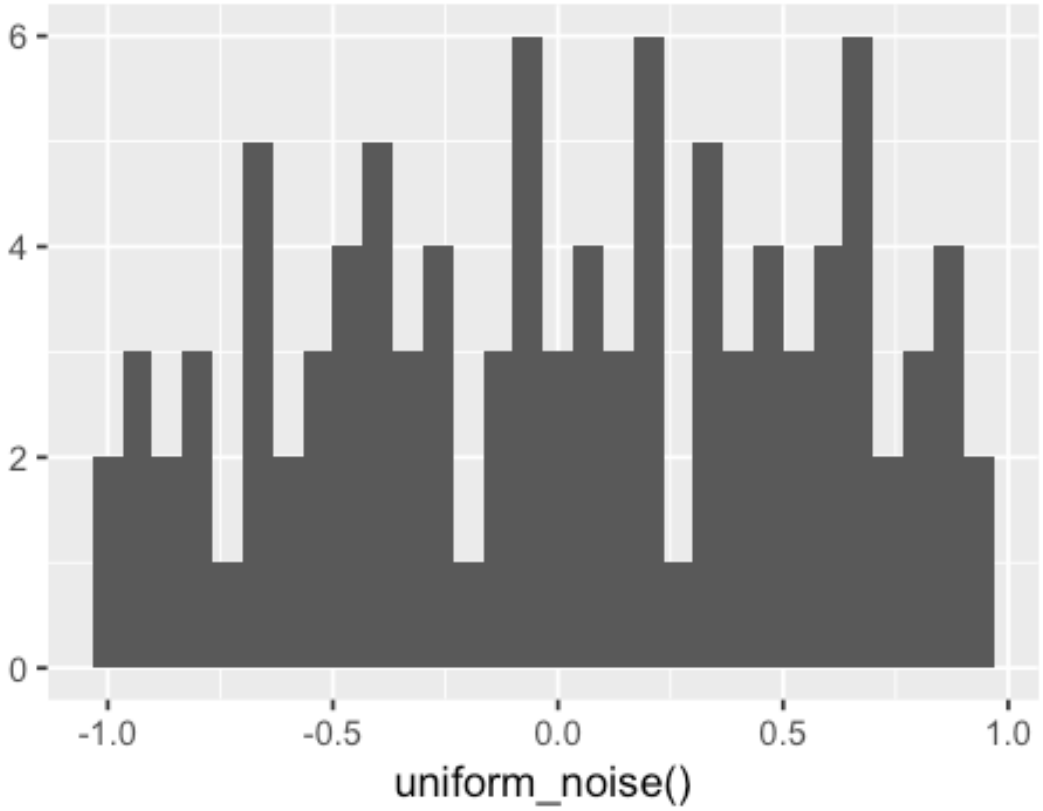
```
In [4]: uniform_noise <- function() {
            runif( n=100, min=-1, max=1 )
        }
```

1.1 Helper function 1: Uniform Noise

- Gives 100 values between -1 and 1 spread evenly.

```
In [5]: qplot( uniform_noise() )
```

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

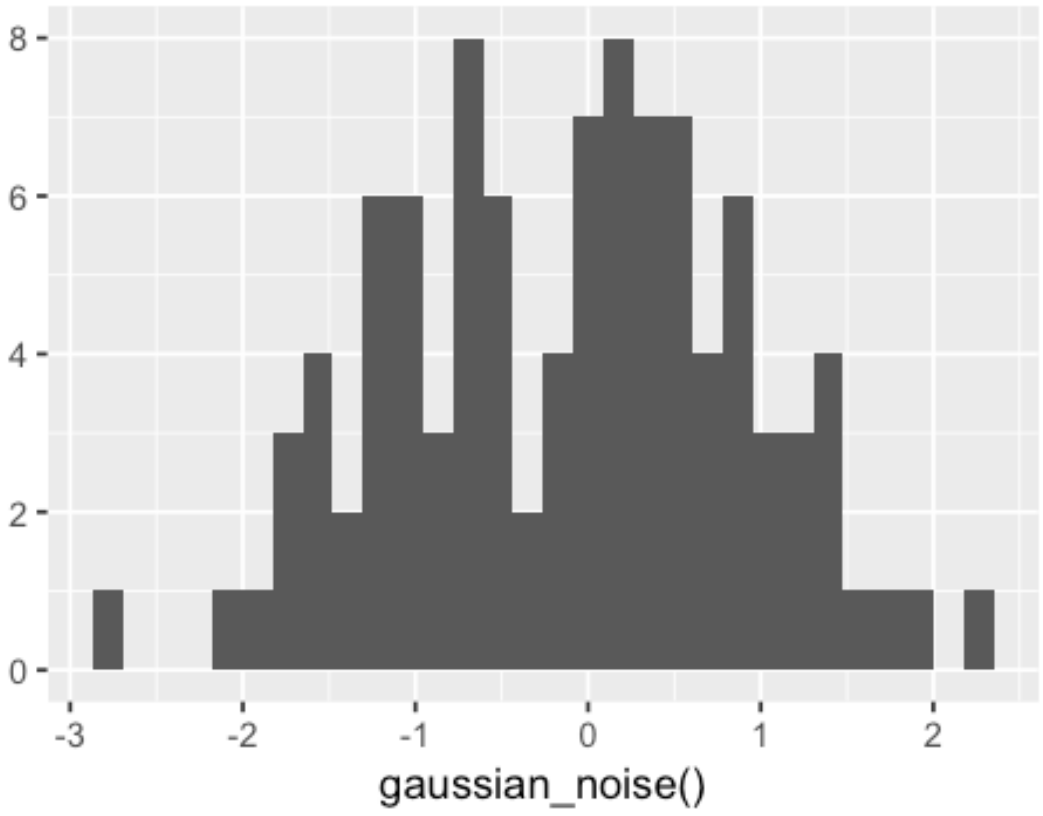


1.2 Helper funciton 2: Gaussian Noise

- Gives 100 values on a bell curve with mean=0 and standard deviation = 1

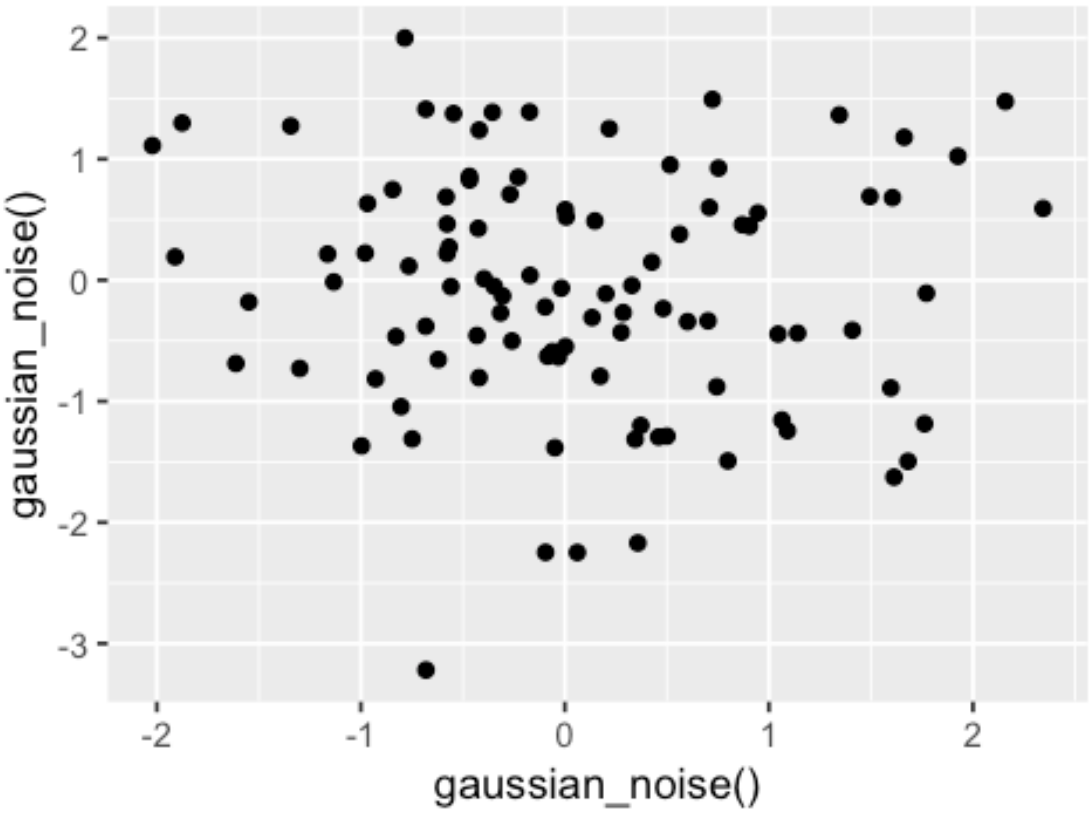
```
In [6]: gaussian_noise <- function() {
            rnorm( n=100 )
        }

In [7]: qplot( gaussian_noise() )
```

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



1.2.1 E.g. Target practice

```
In [8]: qplot( x=gaussian_noise(), y=gaussian_noise() )
```



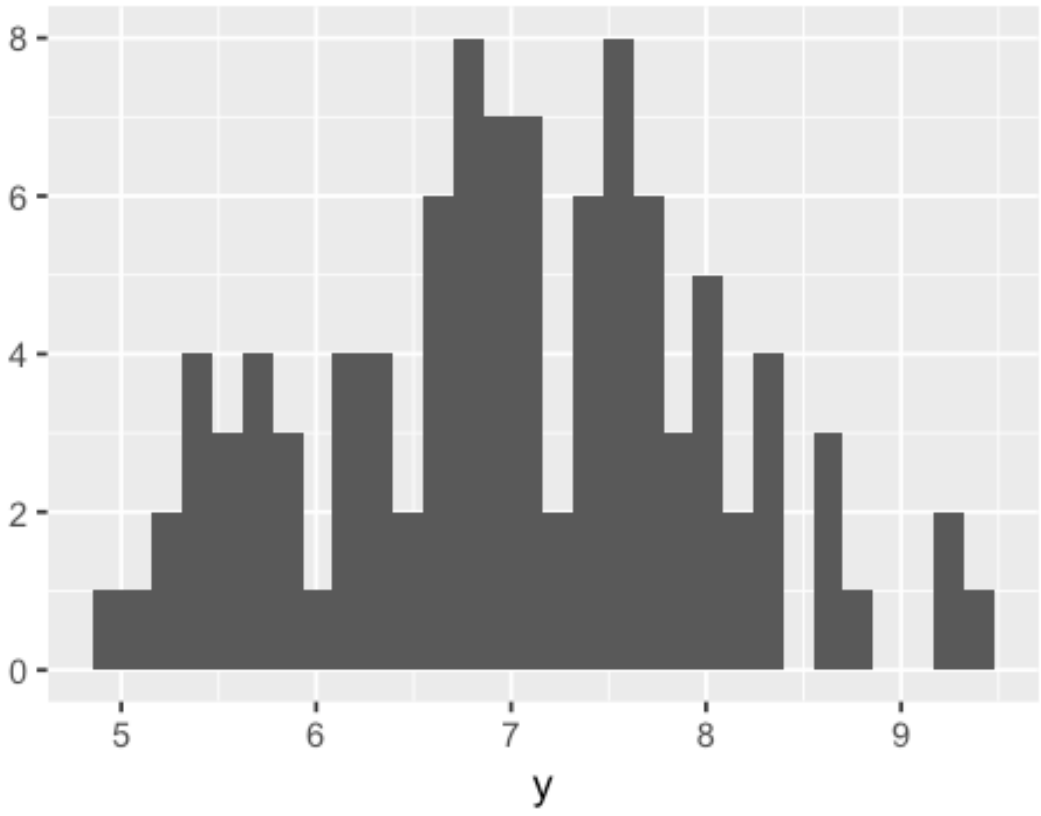
2 Descriptive statistics

- The mean: a very simple statistical model:
- $Y = \beta_0 + \epsilon$ (no mx here)

```
In [9]: y <- 7 + gaussian_noise()
```

```
In [10]: qplot( y )
```

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




```
In [11]: mean( y )
```

7.01673024904236

```
In [12]: library( skimr )
```

```
Attaching package: skimr

The following object is masked from package:stats:

    filter
```

```
In [13]: skim_to_wide( y )
```

A tibble: 1 Œ 13

type <chr>	variable <chr>	missing <chr>	complete <chr>	n <chr>	mean <chr>	sd <chr>	p0 <chr>	p25 <chr>	p50 <chr>
numeric	x	0	100	100	7.02	1	4.95	6.32	7.02

2.1 The lm() function in R wears many hats

```
In [14]: model0 <- lm( y ~ 1 )
```

```
In [15]: summary( model0 )
```

```
Call:
lm(formula = y ~ 1)

Residuals:
     Min       1Q   Median       3Q      Max
-2.06591 -0.69209 -0.00125  0.62155  2.40156

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.01673    0.09986   70.26   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.9986 on 99 degrees of freedom
```

```
In [16]: glance( model0 )
```

A tibble: 1 Œ 11

r.squared <dbl>	adj.r.squared <dbl>	sigma <dbl>	statistic <dbl>	p.value <dbl>	df <int>	logLik <dbl>	AIC <dbl>	B <dbl>
0	0	0.9986491	NA	NA	1	-141.2562	286.5123	29

```
In [17]: tidy( model0 )
```

A tibble: 1 Œ 5

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
(Intercept)	7.01673	0.09986491	70.26222	2.747195e-86

2.2 Compart output of lm function to t-test

```
In [18]: t.test( y )
```

```
One Sample t-test

data:  y
t = 70.262, df = 99, p-value < 2.2e-16
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 6.818577 7.214884
sample estimates:
mean of x
```

```
7.01673
```

```
In [19]: glance( t.test( y ) )
```

A tibble: 1 Œ 8

estimate <dbl>	statistic <dbl>	p.value <dbl>	parameter <dbl>	conf.low <dbl>	conf.high <dbl>	method <chr>
7.01673	70.26222	2.747195e-86	99	6.818577	7.214884	One Sample t-test

```
In [20]: model2 <- lm( y ~ x - 1, blob )
```

```
    Error in is.data.frame(data): object 'blob' not found
Traceback:


    1. lm(y ~ x - 1, blob)

    2. eval(mf, parent.frame())

    3. eval(mf, parent.frame())

    4. stats::model.frame(formula = y ~ x - 1, data = blob, drop.unused.levels = TRUE)

    5. model.frame.default(formula = y ~ x - 1, data = blob, drop.unused.levels = TRUE)

    6. is.data.frame(data)
```

```
In [21]: summary( model2 )
```

```
    Error in summary(model2): object 'model2' not found
Traceback:


    1. summary(model2)
```

```
In [22]: anova( model1, model2 )
```

```
    Error in anova(model1, model2): object 'model1' not found
Traceback:


    1. anova(model1, model2)
```

3 Step response using lm() and aov()

- Let's generate some fake data
- There are two classes here, can think of them as treatment and control

```
In [23]: fake_data_A <- data.frame( X1=uniform_noise(), Y=gaussian_noise(), Class=rep(0,100) )
         fake_data_B <- data.frame( X1=uniform_noise(), Y=gaussian_noise()+1, Class=rep(1,100)
         fake_data_all <- rbind( fake_data_A, fake_data_B )
         fake_data_all$Class <- as.factor( fake_data_all$Class )
```

```
In [24]: skim_to_wide( fake_data_all )
```

A tibble: 3 Œ 16

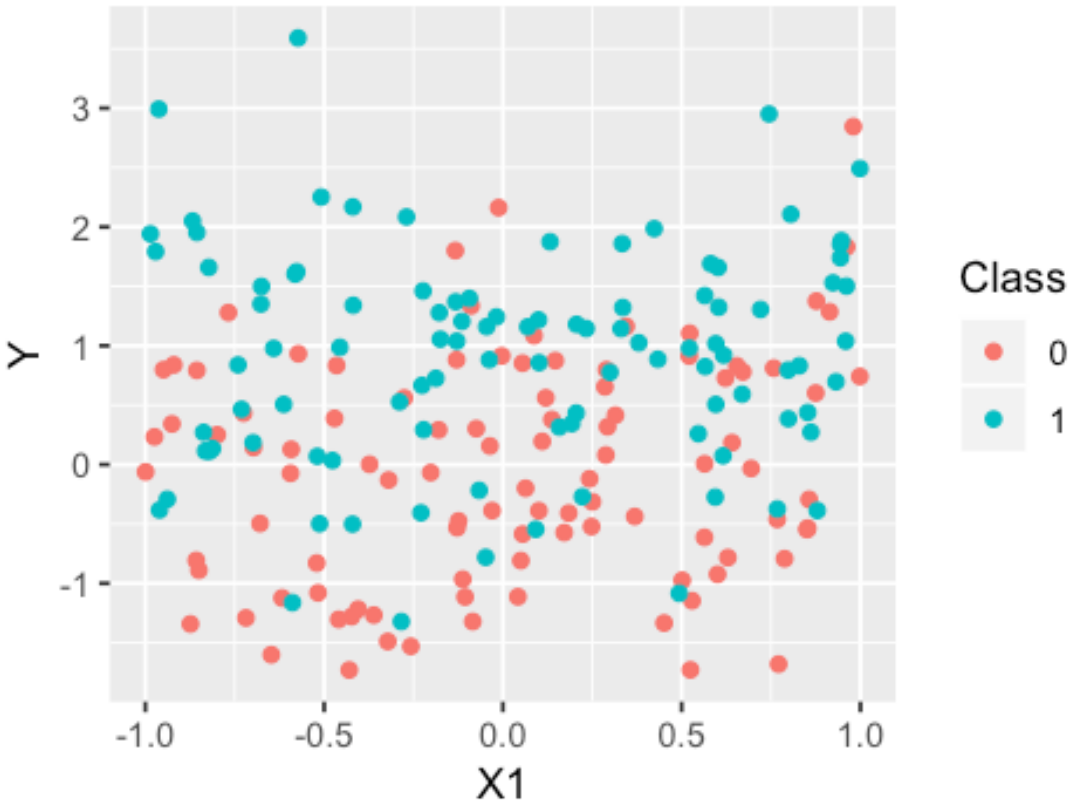
type	variable	missing	complete	n	n_unique	top_counts	order
<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>	<chr>
factor	Class	0	200	200	2	0: 100, 1: 100, NA: 0	FALS
numeric	X1	0	200	200	NA	NA	NA
numeric	Y	0	200	200	NA	NA	NA

```
In [25]: sample_n( fake_data_all, 5)
```

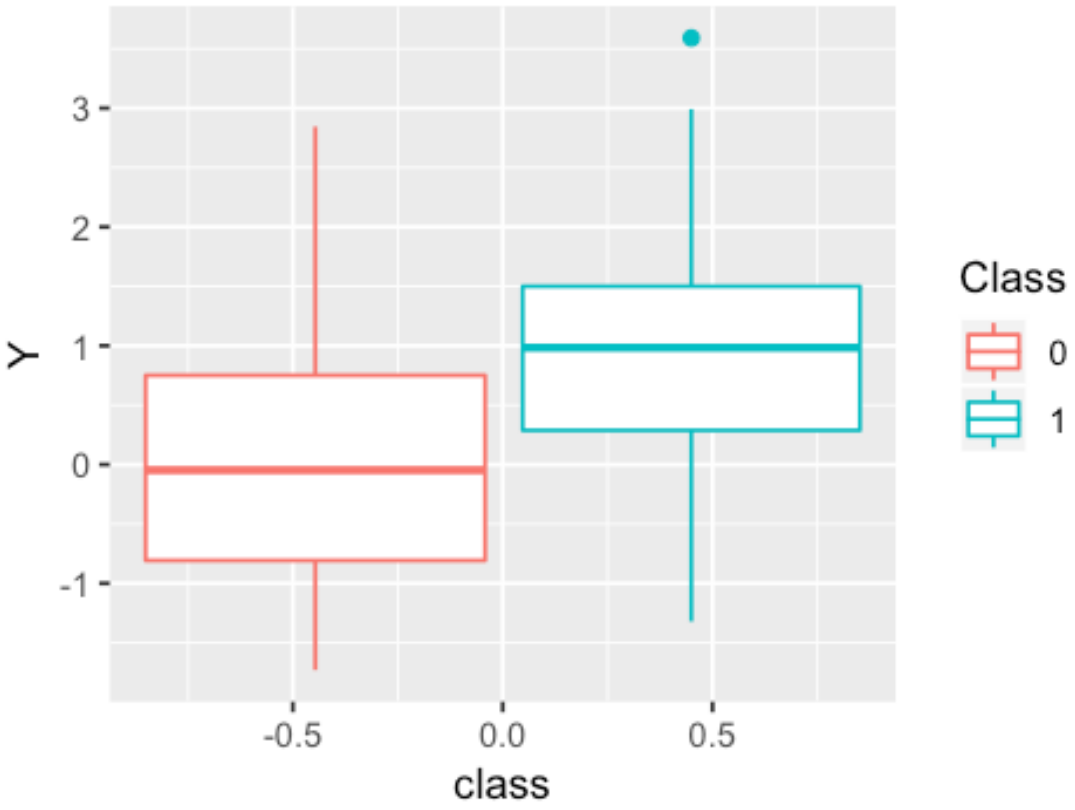
A df[,3]: 5 Œ 3

X1	Y	Class
<dbl>	<dbl>	<fct>
-0.2840288	-1.3214585	1
0.9608457	1.5019410	1
-0.8502784	-0.8891987	0
0.4932882	-1.0839165	1
-0.6976124	0.1432540	0

```
In [26]: ggplot( fake_data_all, aes( x=X1, y=Y, color=Class) ) + geom_point()
```




```
In [27]: ggplot( fake_data_all, aes( x=X1, y=Y, color=Class ) ) +
             geom_boxplot() +
             labs( x='class' )
```



3.1 Adding a non-predictive predictor variable to model

- The Null model is "Y ~ 1" ... a test for the intercept.

```
In [28]: model0 <- lm( Y ~ 1, fake_data_all )

In [29]: summary( model0 )


Call:
lm(formula = Y ~ 1, data = fake_data_all)

Residuals:
     Min       1Q   Median       3Q      Max
-2.16189 -0.81951  0.01935  0.72664  3.15775

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.4327     0.0742   5.831  2.2e-08 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
```

```
Residual standard error: 1.049 on 199 degrees of freedom
```

```
In [30]: model1 <- lm( Y ~ X1, fake_data_all )
```

```
In [31]: summary( model1 )
```

```
Call:
lm(formula = Y ~ X1, data = fake_data_all)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2585 -0.8199  0.0431  0.6768  3.2749

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.42766    0.07403   5.777 2.91e-08 ***
X1           0.19568    0.12760   1.534    0.127
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 1.046 on 198 degrees of freedom
Multiple R-squared:  0.01174,Adjusted R-squared:  0.006748
F-statistic: 2.352 on 1 and 198 DF,  p-value: 0.1267
```

3.2 Add in an informative predictor variable to model

- Here the output variable Y is just the Class identity with some noise, so the variable Class is as informative a predictor as you're going to get

```
In [32]: model2 <- lm( Y ~ Class, fake_data_all )
```

```
In [33]: summary( model2 )
```

```
Call:
lm(formula = Y ~ Class, data = fake_data_all)

Residuals:
     Min       1Q   Median       3Q      Max
-2.23175 -0.66937  0.04916  0.69460  2.88989

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept) -0.04492    0.09362  -0.480    0.632
Class1       0.95521    0.13239   7.215 1.12e-11 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.9362 on 198 degrees of freedom
Multiple R-squared:  0.2082,Adjusted R-squared:  0.2042
F-statistic: 52.05 on 1 and 198 DF,  p-value: 1.123e-11
```

3.3 Compare lm() output with t-test output

```
In [34]: confint( model2 )
```

A matrix: 2 Œ 2 of type dbl[,2]

	2.5 %	97.5 %
(Intercept)	-0.2295333	0.1396942
Class1	0.6941260	1.2162926

```
In [35]: t.test( Y ~ Class, fake_data_all )
```

```
Welch Two Sample t-test

data:  Y by Class
t = -7.2149, df = 197.75, p-value = 1.127e-11
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.2162946 -0.6941239
sample estimates:
mean in group 0 mean in group 1
    -0.04491955      0.91028973
```

4 Comparing models using the deviance (anova) table

- In R, the deviance table is generated using the anova() function

```
In [36]: anova( model0, model1, model2 )
```

A df[,6]: 3 Œ 6

Res.Df <dbl>	RSS <dbl>	Df <dbl>	Sum of Sq <dbl>	F <dbl>	Pr(>F) <dbl>
199	219.1501	NA	NA	NA	NA
198	216.5775	1	2.57266	2.351984	0.12672
198	173.5289	0	43.04858	NA	NA

5 Add a "weak" predictor variable X2 for outcome variable Y

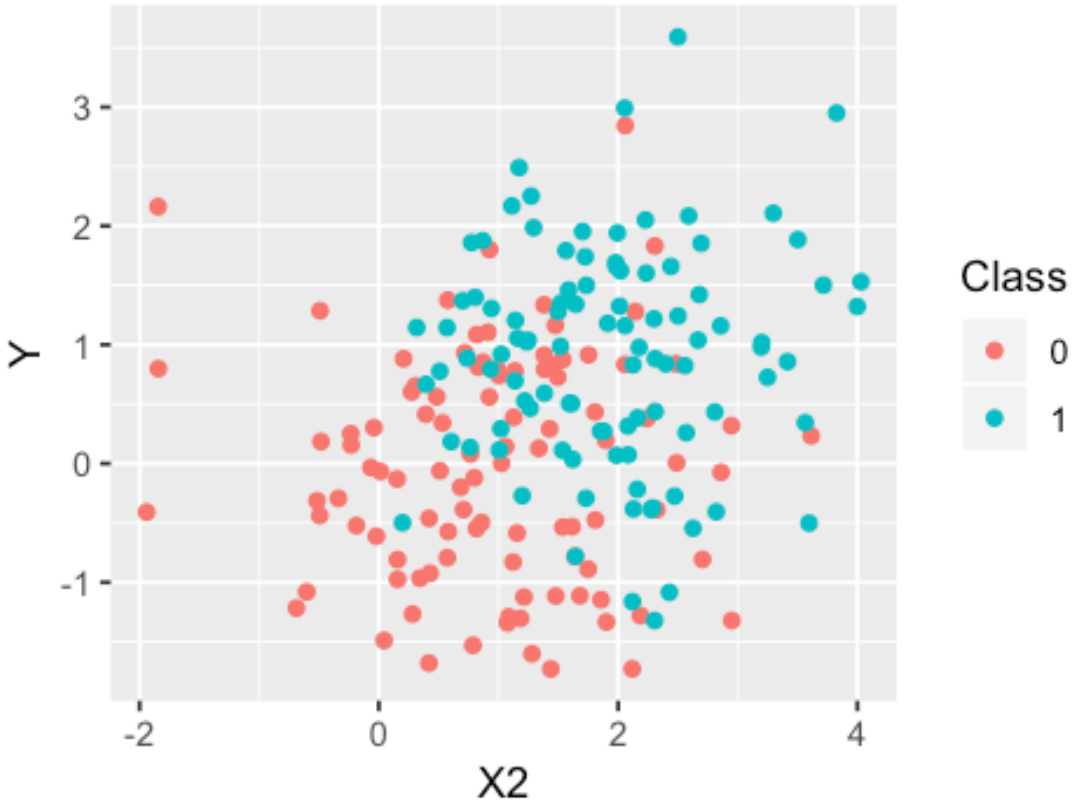
```
In [37]: fake_data_all <- fake_data_all %>%
             mutate( X2 = as.numeric( Class ) + rnorm( n=200 ) )
```

```
In [38]: fake_data_all %>% sample_n( 5 )
```

A df[,4]: 5 Œ 4

X1 <dbl>	Y <dbl>	Class <fct>	X2 <dbl>
0.6943467	-0.0328858	0	-0.06715464
-0.6175377	-1.1233190	0	1.21337614
-0.9744521	0.2328312	0	3.61412451
0.6407990	0.1843036	0	-0.48372036
0.1927531	0.3443875	1	3.56415403

```
In [39]: fake_data_all %>%
             ggplot( aes( x=X2, y=Y, color=Class ) ) +
             geom_point()
```



5.1 Refit the Null model

```
In [40]: model0 <- lm( Y ~ 1, fake_data_all )
```

```
In [41]: summary( model0 )
```

```
Call:
lm(formula = Y ~ 1, data = fake_data_all)

Residuals:
     Min       1Q   Median       3Q      Max
-2.16189 -0.81951  0.01935  0.72664  3.15775

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.4327     0.0742   5.831  2.2e-08 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 1.049 on 199 degrees of freedom
```

5.1.1 How would you interpret the results of this model?

```
In [42]: model1 <- lm( Y ~ X2, fake_data_all )

In [43]: summary( model1 )
```

```
Call:
lm(formula = Y ~ X2, data = fake_data_all)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3100 -0.7381  0.1026  0.6662  2.9241

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.11340    0.12199   0.930  0.35375
X2           0.22121    0.06799   3.254  0.00134 **
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 1.025 on 198 degrees of freedom
Multiple R-squared:  0.05075,Adjusted R-squared:  0.04596
F-statistic: 10.59 on 1 and 198 DF,  p-value: 0.001339
```

```
In [44]: model2 <- lm( Y ~ X1 + X2, fake_data_all )
```

```
In [45]: summary( model2 )
```

```
Call:
lm(formula = Y ~ X1 + X2, data = fake_data_all)

Residuals:
     Min       1Q   Median       3Q      Max
-2.39665 -0.71473  0.08804  0.63468  3.03567

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.11460    0.12167   0.942   0.3474
X1           0.17920    0.12483   1.436   0.1527
X2           0.21719    0.06786   3.200   0.0016 **
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 1.022 on 197 degrees of freedom
Multiple R-squared:  0.06058,Adjusted R-squared:  0.05104
F-statistic: 6.352 on 2 and 197 DF,  p-value: 0.002121
```

```
In [46]: anova( model0, model1, model2)
```

A df[,6]: 3 Œ 6

Res.Df <dbl>	RSS <dbl>	Df <dbl>	Sum of Sq <dbl>	F <dbl>	Pr(>F) <dbl>
199	219.1501	NA	NA	NA	NA
198	208.0273	1	11.122801	10.643388	0.001302017
197	205.8735	1	2.153797	2.060964	0.152700389

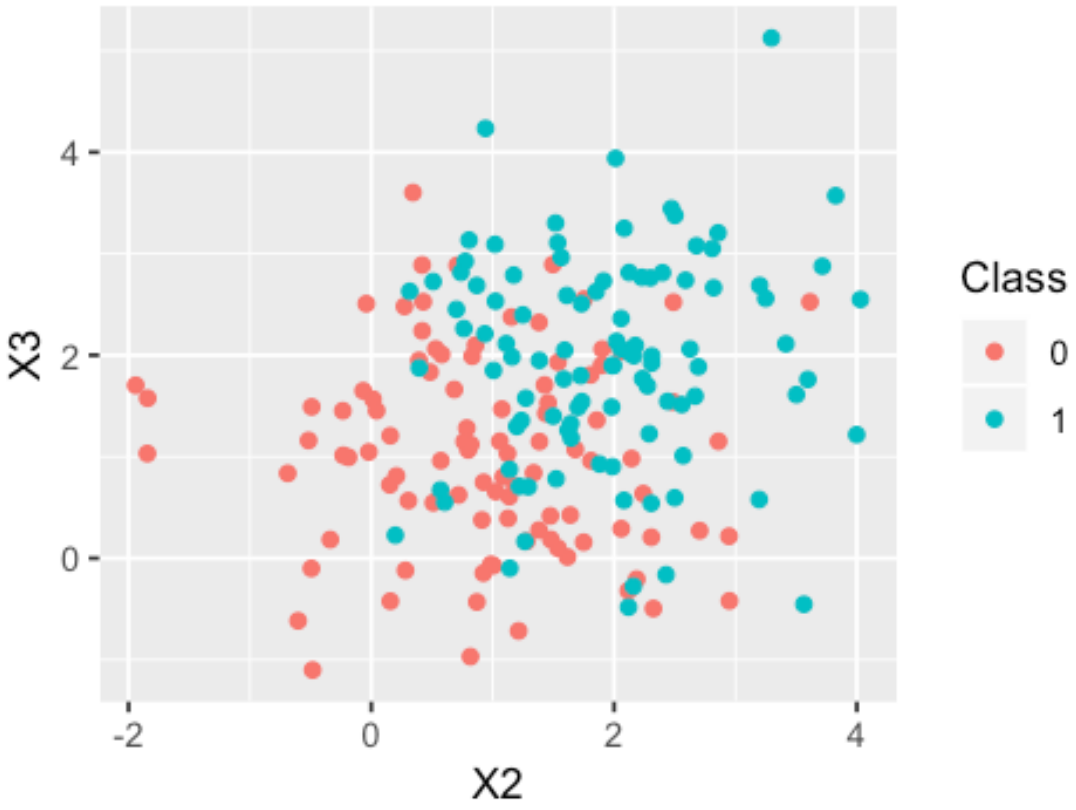
6 Multiple regression - more than one predictor variable

- Add another predictor variable - the class identity plus noise

```
In [47]: fake_data_all <- fake_data_all %>%
             mutate( X3 = as.numeric( Class ) + rnorm( n=200 ) ) %>%
             select( Class, Y, X1, X2, X3 ) # reorder
```

```
In [48]: options(repr.plot.width=4, repr.plot.height=3)
```

```
In [49]: fake_data_all %>%
             ggplot( aes( x=X2, y=X3, color=Class ) ) +
             geom_point()
```



7 Exploratory data analysis: using a scatterpot

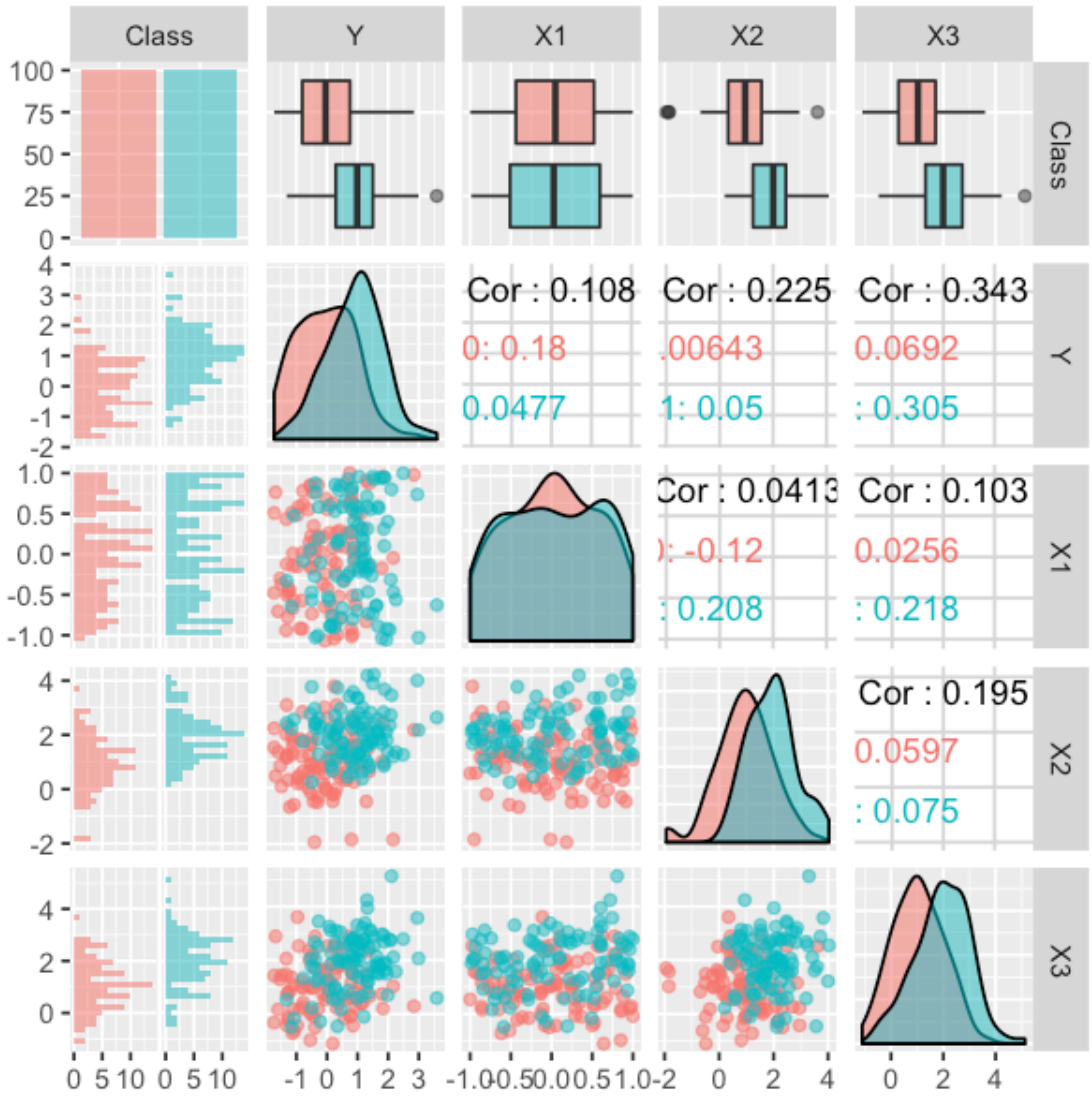
```
In [50]: library( GGally )
```

```
Registered S3 method overwritten by 'GGally':
  method from
  +.gg   ggplot2

Attaching package: GGally

The following object is masked from package:dplyr:

    nasa
```

```
In [51]: options(repr.plot.width=5, repr.plot.height=5)
```

```
In [52]: ggpairs( fake_data_all, aes( color=Class, alpha=0.1) )
```

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




```
In [53]: model0 <- lm( Y ~ 1, fake_data_all )

In [54]: model1 <- lm( Y ~ X2, fake_data_all )

In [55]: model3 <- lm( Y ~ X2 + X3, fake_data_all )

In [56]: summary( model3 )
```

```
Call:
lm(formula = Y ~ X2 + X3, data = fake_data_all)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3558 -0.6427  0.0159  0.6735  3.2543

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.24336    0.13950  -1.745   0.0826 .
X2           0.16160    0.06602   2.448   0.0152 *
X3           0.29480    0.06381   4.620 6.93e-06 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.9761 on 197 degrees of freedom
Multiple R-squared:  0.1435,Adjusted R-squared:  0.1348
F-statistic: 16.51 on 2 and 197 DF,  p-value: 2.355e-07
```