HW11

106022113

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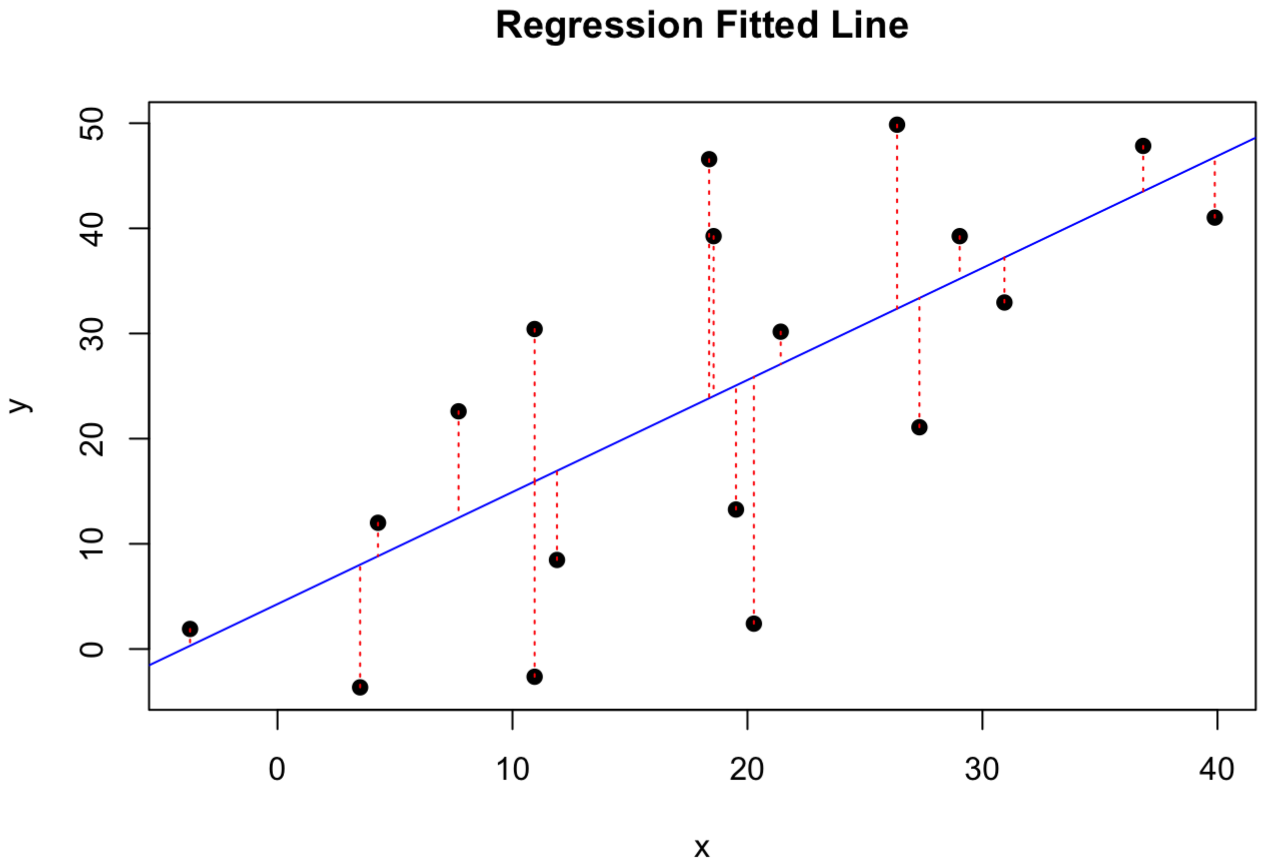
Question 1 : Answer Questions by simulating the four scenarios below

a. What regression is doing to compute model fit

```
pts <- data.frame(x = c(-3.719323,3.516220,10.942172,4.277856,11.894217,20.272214,  7.705219, 1
9.510578,10.942172,27.317348,21.414669,18.558533,30.935120,29.031030,18.368124,39.884344,26.365
303,36.837800) ,y =c(1.905846,-3.646499, -2.636982, 12.001020, 8.467709,2.410605, 22.600952, 1
3.262916,30.424711,21.086676,30.172332, 39.257988,32.948504,39.257988,46.576988,41.024643,49.85
7920,47.838885))
regr <- lm(y ~ x, data=pts)
summary(regr)
```

```
##
## Call:
## lm(formula = y ~ x, data = pts)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -23.460 -10.867   2.341   8.669  22.735
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    4.270      5.969   0.715  0.48462
## x              1.065      0.273   3.903  0.00126 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.39 on 16 degrees of freedom
## Multiple R-squared:  0.4878, Adjusted R-squared:  0.4558
## F-statistic: 15.24 on 1 and 16 DF,  p-value: 0.001264
```

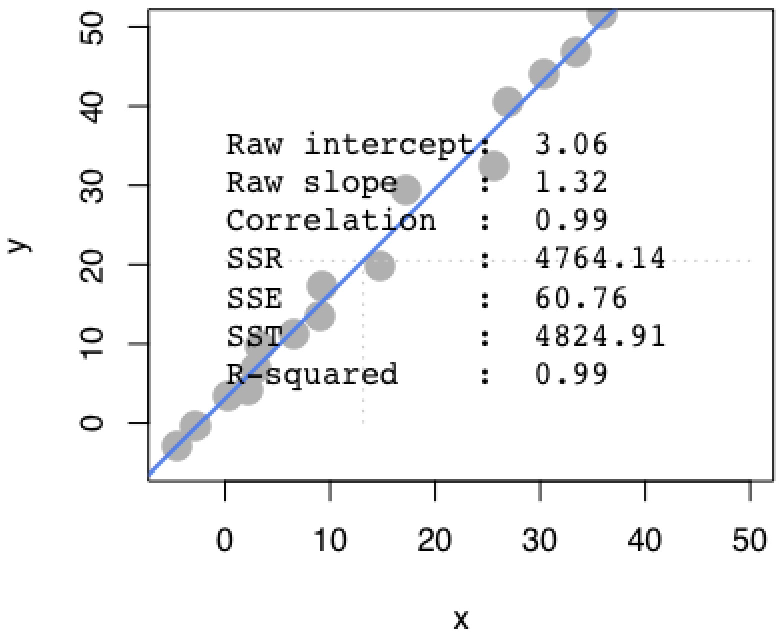
```
y_hat <- regr$fitted.values
plot(pts,main = "Regression Fitted Line",pch = 19)
abline(regr, col = 'blue')
segments(pts$x, pts$y, pts$x, y_hat, col="red", lty="dotted")
```




```
regression_fit <- function(pts){
  regr <- lm(y~x,  data = pts)
  y_hat <- regr$fitted.values
  SSE <- sum((pts$y-y_hat)^2)
  SSR <- sum((mean(pts$y)-y_hat)^2)
  SST <- sum((pts$y-mean(pts$y))^2)
  Rsq <- SSR/SST
  return(data.frame(SSE = SSE, SSR = SSR, SST= SST, Rsq = Rsq))
}
regression_fit(pts)
```

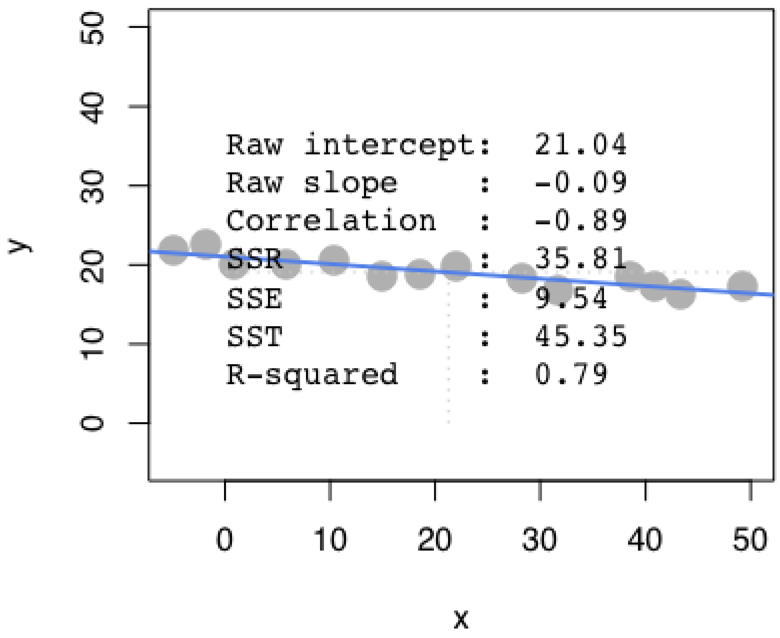
```
##         SSE      SSR      SST       Rsq
## 1 2868.667 2731.911 5600.578 0.4877909
```

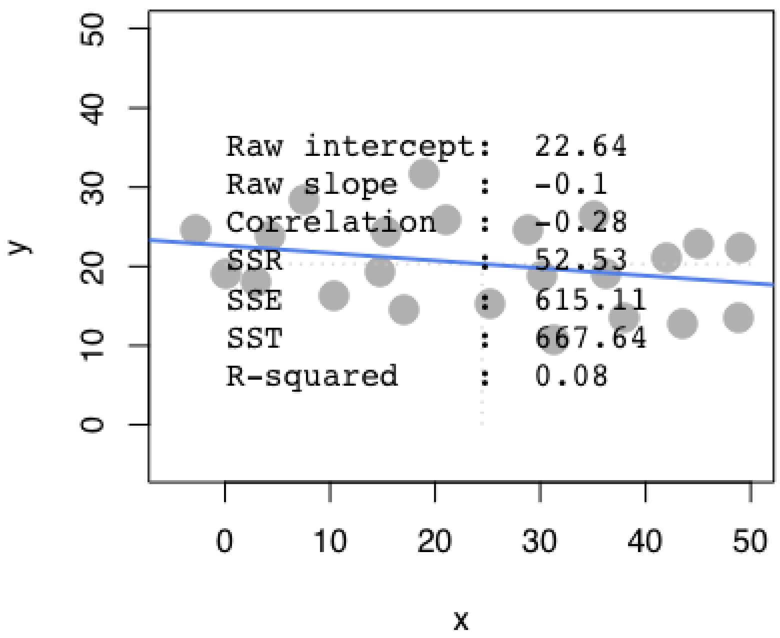
b. Compare Scenario 1, 2 which to expect to have stronger R square



ANSWER: Since scenario 1 is obviously more closer to a fitted line because it's more dense, which also indicates it obtains a more stronger linear characteristic. Hence, we should expect Scenario 1 obtain higher R sqaure than Scenario 2

c. Compare Scenario 3, 4 for larger R sqaure





ANSWER: Since scenario 3 is more denser and obtain more linear characteristic, it will have higher r square compared to the more widespread distribution of scenario 4.

d. Comparing scenarios 1 and 2, which do we expect has bigger/smaller SSE, SSR, and SST?

ANSWER: SST and SSE of scenario 1 will be smaller than scenario 2, while SSR(depends on slope) for scenario 2 will be smaller than scenario 1. Because scenario 1 has a better fit than scenario 2.

e. Comparing scenarios 3 and 4, which do we expect has bigger/smaller SSE, SSR, and SST?

ANSWER: SST and SSE of scenario 3 will be smaller than scenario 4, while SSR(depends on slope) for scenario 4 will be smaller than scenario 3. Because scenario 3 has a better fit than scenario 2.

Question 2.

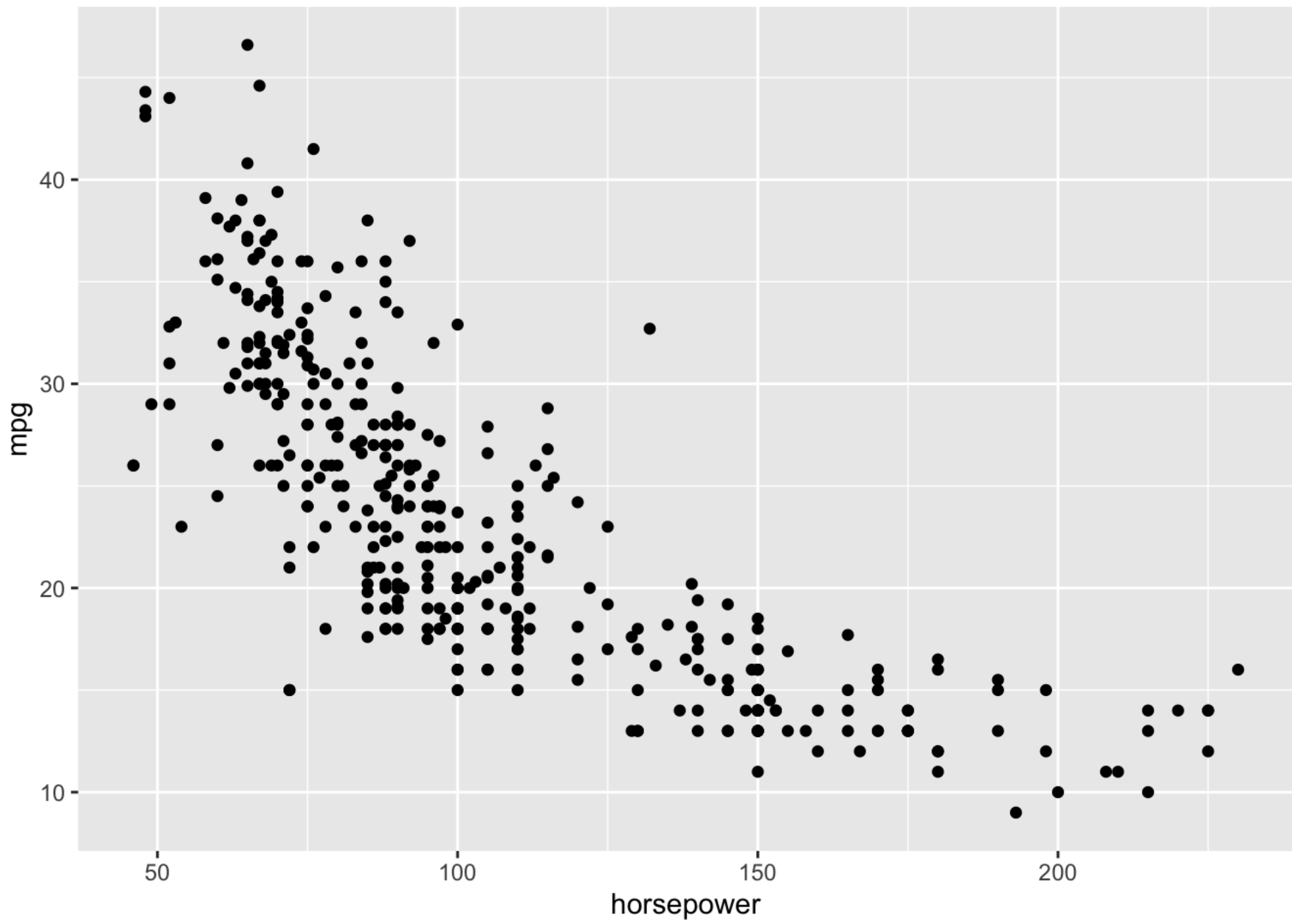
```
auto <- read.table("auto-data.txt", header=FALSE, na.strings = "?")
names(auto) <- c("mpg", "cylinders", "displacement", "horsepower", "weight",
                 "acceleration", "model_year", "origin", "car_name")
```

a. Explore Data

i. Visualize

```
library(ggplot2)
ggplot(auto, aes(x=horsepower, y=mpg)) + geom_point()
```

```
## Warning: Removed 6 rows containing missing values (geom_point).
```



This is a plot indicating that with bigger horsepower, the cars cannot achieve good fuel efficiency. Hence, there is a negative correlation here between horsepower and mpg.

ii. Correlation table

```
cor_table <- cor(auto[,1:8], use = "pairwise.complete.obs")
cor_table
```

```
##                     mpg  cylinders displacement horsepower     weight
## mpg           1.0000000 -0.7753963   -0.8042028 -0.7784268 -0.8317409
## cylinders    -0.7753963  1.0000000    0.9507214  0.8429834  0.8960168
## displacement -0.8042028  0.9507214    1.0000000  0.8972570  0.9328241
## horsepower   -0.7784268  0.8429834    0.8972570  1.0000000  0.8645377
## weight       -0.8317409  0.8960168    0.9328241  0.8645377  1.0000000
## acceleration  0.4202889 -0.5054195   -0.5436841 -0.6891955 -0.4174573
## model_year    0.5792671 -0.3487458   -0.3701642 -0.4163615 -0.3065643
## origin        0.5634504 -0.5625433   -0.6094094 -0.4551715 -0.5810239
##              acceleration model_year     origin
## mpg             0.4202889  0.5792671  0.5634504
## cylinders      -0.5054195 -0.3487458 -0.5625433
## displacement   -0.5436841 -0.3701642 -0.6094094
## horsepower     -0.6891955 -0.4163615 -0.4551715
## weight         -0.4174573 -0.3065643 -0.5810239
## acceleration    1.0000000  0.2881370  0.2058730
## model_year      0.2881370  1.0000000  0.1806622
## origin          0.2058730  0.1806622  1.0000000
```

iii. Which variables seems to related to mpg

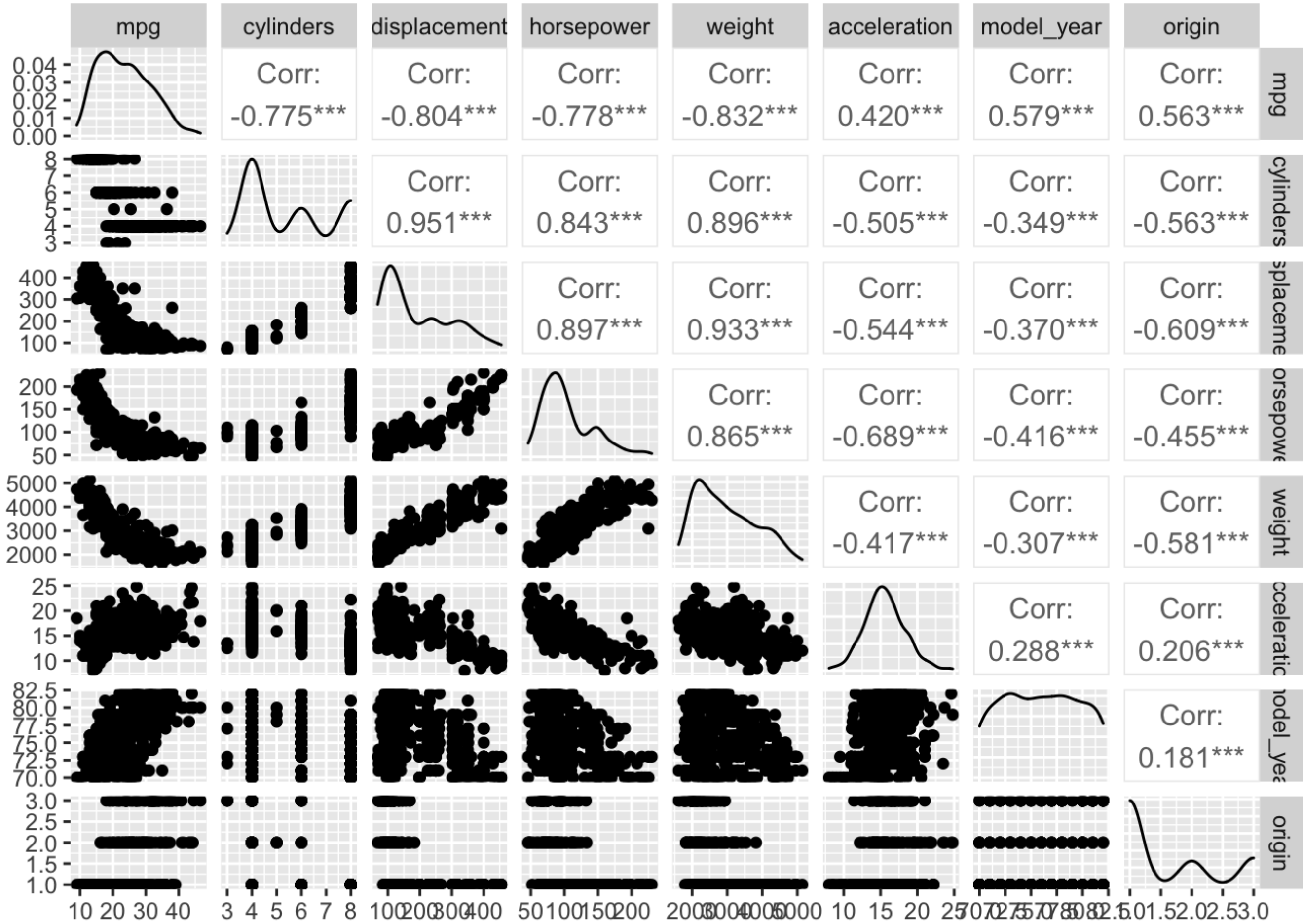
ANSWER: According to the table above, seems like *cylinders, displacement, horsepower,weight,model_year* are negetively correlated to mpg. The other factors doesn't have a very strong positive correlation to mpg.

iv. Which relations might not be linear?

```
library(GGally)
```

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

```
ggpairs(auto[1:8])
```



From the plot above, relationships between *model_year, origin, cylinders* doesn't seem to show linear characteristics.

v. Are there any pairs of independent variables that are highly correlated

```
library(reshape2)
diag(cor_table) <- 0
cor_melt <- melt(cor_table)
new_cor <- cor_melt[abs(cor_melt$value)>0.7,]
new_cor[!duplicated(new_cor[1:2]),]
```

```
##            Var1         Var2      value
## 2     cylinders          mpg -0.7753963
## 3  displacement          mpg -0.8042028
## 4    horsepower          mpg -0.7784268
## 5        weight          mpg -0.8317409
## 9           mpg    cylinders -0.7753963
## 11 displacement    cylinders  0.9507214
## 12   horsepower    cylinders  0.8429834
## 13       weight    cylinders  0.8960168
## 17          mpg displacement -0.8042028
## 18    cylinders displacement  0.9507214
## 20   horsepower displacement  0.8972570
## 21       weight displacement  0.9328241
## 25          mpg   horsepower -0.7784268
## 26    cylinders   horsepower  0.8429834
## 27 displacement   horsepower  0.8972570
## 29       weight   horsepower  0.8645377
## 33          mpg       weight -0.8317409
## 34    cylinders       weight  0.8960168
## 35 displacement       weight  0.9328241
## 36   horsepower       weight  0.8645377
```

` ### b. Create a linear regression model where mpg is dependent upon all other suitable variables

```
regr <- lm(mpg ~ cylinders+displacement+horsepower+weight+acceleration+model_year+factor(origi
n)
           ,data = auto)
summary(regr)
```

```
##
## Call:
## lm(formula = mpg ~ cylinders + displacement + horsepower + weight +
##     acceleration + model_year + factor(origin), data = auto)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.0095 -2.0785 -0.0982  1.9856 13.3608
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -1.795e+01  4.677e+00  -3.839 0.000145 ***
## cylinders       -4.897e-01  3.212e-01  -1.524 0.128215
## displacement     2.398e-02  7.653e-03   3.133 0.001863 **
## horsepower      -1.818e-02  1.371e-02  -1.326 0.185488
## weight          -6.710e-03  6.551e-04 -10.243  < 2e-16 ***
## acceleration     7.910e-02  9.822e-02   0.805 0.421101
## model_year       7.770e-01  5.178e-02  15.005  < 2e-16 ***
## factor(origin)2  2.630e+00  5.664e-01   4.643 4.72e-06 ***
## factor(origin)3  2.853e+00  5.527e-01   5.162 3.93e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.307 on 383 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.8242, Adjusted R-squared:  0.8205
## F-statistic: 224.5 on 8 and 383 DF,  p-value: < 2.2e-16
```

i. which factors have significant on mpg at 1% significance?

ANSWER: By the summary upon, the *intercept, displacement, weight, model_year, and origin have significant on mpg at 1% significance.

ii. Is it possible to determine which independent variables are most effective at increasing mpg?

ANSWER: Not possible, since the variables aren't standardized, the scales for the factors are different. Hence we can not merely observe the coefficients and give out answers for this question.

###. c. Create standardized regression results

```
sd_data <- cbind(scale(auto[1:7]),auto$origin)
colnames(sd_data) <- colnames(auto[1:8])
sd_df <- as.data.frame(sd_data)
new_regr <- lm(mpg~ cylinders+displacement+horsepower+weight+acceleration+model_year+factor(ori
gin),data = sd_df)
summary(new_regr)
```

```
##
## Call:
## lm(formula = mpg ~ cylinders + displacement + horsepower + weight +
##     acceleration + model_year + factor(origin), data = sd_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.15270 -0.26593 -0.01257  0.25404  1.70942
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -0.13323    0.03174  -4.198 3.35e-05 ***
## cylinders       -0.10658    0.06991  -1.524  0.12821
## displacement     0.31989    0.10210   3.133  0.00186 **
## horsepower      -0.08955    0.06751  -1.326  0.18549
## weight          -0.72705    0.07098 -10.243  < 2e-16 ***
## acceleration     0.02791    0.03465   0.805  0.42110
## model_year       0.36760    0.02450  15.005  < 2e-16 ***
## factor(origin)2  0.33649    0.07247   4.643 4.72e-06 ***
## factor(origin)3  0.36505    0.07072   5.162 3.93e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.423 on 383 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.8242, Adjusted R-squared:  0.8205
## F-statistic: 224.5 on 8 and 383 DF,  p-value: < 2.2e-16
```

i. Are these figures easier to interpret?

Yes, it will be easier to interpret since we can see that weight is most effective at increasing mpg. Which is quite reasonable.

ii. Regress mpg over each nonsignificant independent variable. Which one will become significant over mpg?

```
fit1 <- lm(mpg~cylinders,data = sd_df)
fit2 <- lm(mpg~displacement,data = sd_df)
fit3 <- lm(mpg~horsepower,data = sd_df)
fit4 <- lm(mpg~weight,data = sd_df)
fit5 <- lm(mpg~acceleration,data = sd_df)
fit6 <- lm(mpg~model_year,data = sd_df)
fit7 <- lm(mpg~origin,data = sd_df)
signifi<- function(fit){
  return (signif(summary(fit)$coef[2,4],2))
}
paste('cylinders:',signifi(fit1))
```

```
## [1] "cylinders: 4.5e-81"
```

```
paste('displacement:',signifi(fit2))
```

```
## [1] "displacement: 1.7e-91"
```

```
paste('horsepower:',signifi(fit3))
```

```
## [1] "horsepower: 7e-81"
```

```
paste('weight:',signifi(fit4))
```

```
## [1] "weight: 3e-103"
```

```
paste('accerleration:',signifi(fit5))
```

```
## [1] "accerleration: 1.8e-18"
```

```
paste('mdoel_year:',signifi(fit6))
```

```
## [1] "mdoel_year: 4.8e-37"
```

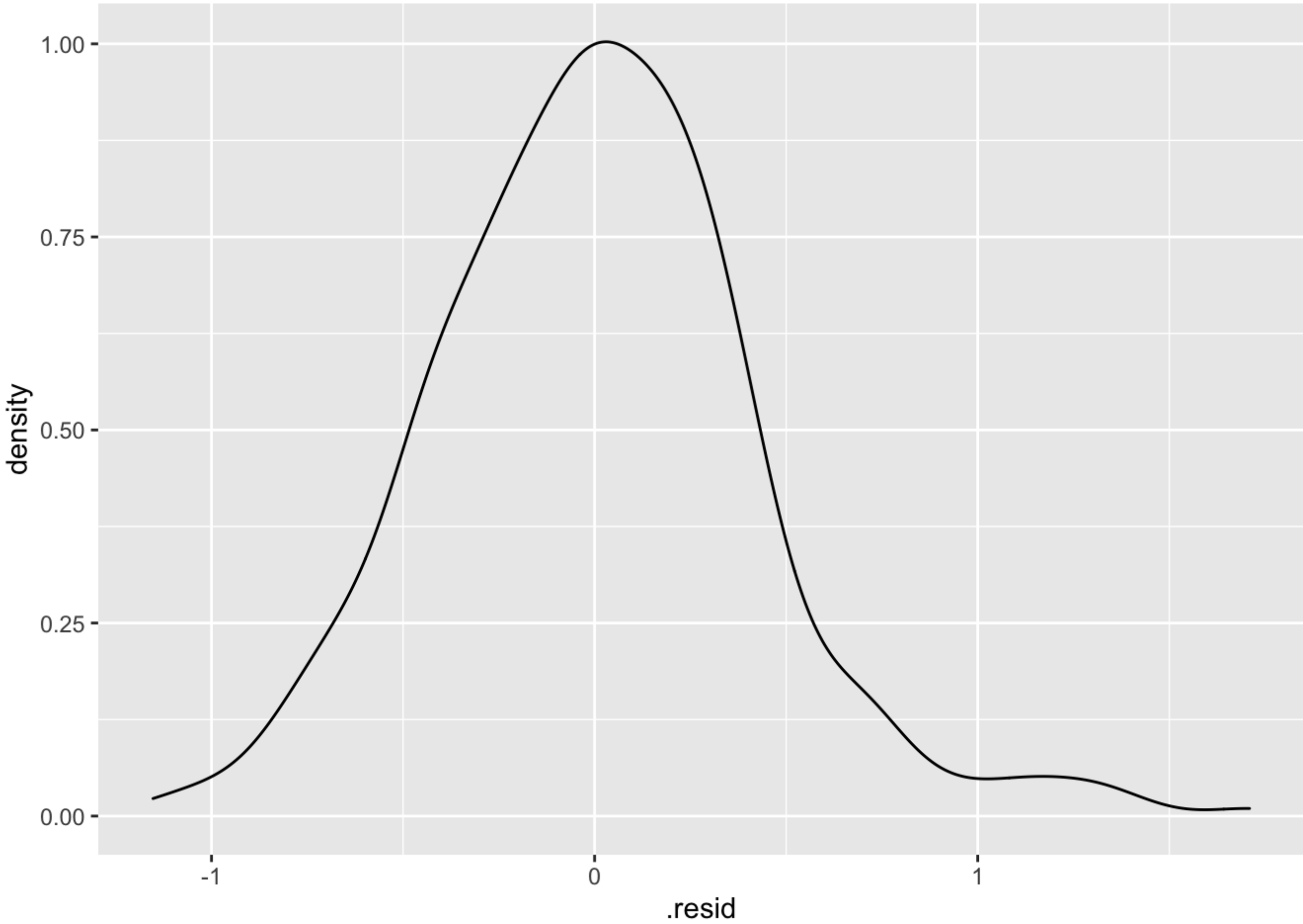
```
paste('origin:',signifi(fit7))
```

```
## [1] "origin: 1e-34"
```

ANSWER: After fitted with every independent variable, they are all significant since the p-values are very low.

iii. Plot the density of the residuals, are they normally distributed and centered around zero?

```
library(ggplot2)
regr_plt <- fortify(new_regr)
ggplot(new_regr,aes(.resid))+ geom_density()
```



ANSWER:

It’s near a normal distribution with mean near 0. Can be verified by QQ plot.