Price and Performance in Central Processing Units

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11/19/2020

Introduction

```r
# Load library
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------------------------
----------------------------------------------------- tidyverse 1.3.0 --
```

```
## v ggplot2 3.3.2     v purrr   0.3.4
## v tibble  3.0.3     v dplyr   1.0.2
## v tidyr   1.1.1     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
```

```
## Warning: package 'ggplot2' was built under R version 4.0.3
```

```
## -- Conflicts ------------------------------------------------------------
----------------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
# install.packages(readr)
library(readr)

# install.packages(car) on a separate R script
library(car)
```

```
## Warning: package 'car' was built under R version 4.0.3
```

```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 4.0.3
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
## The following object is masked from 'package:purrr':
##
##     some
```

```r
# install.packages(psych) on a separate R script
library(psych)
```

```
##
## Attaching package: 'psych'

## The following object is masked from 'package:car':
##
##     logit

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha

# install.packages('readr'leaps')
library(leaps)

# Import data
cpudata <- read_csv("researchproject_data.csv")

## Parsed with column specification:
## cols(
##   MSRP = col_double(),
##   Year = col_double(),
##   Year_Fixed = col_double(),
##   Benchmark_Result = col_double(),
##   Brand = col_character(),
##   Processor = col_character(),
##   Chipset = col_character()
## )
```

Variables Analysis

MSRP - Currency, numerical variable that displays the original price a chip was marketed for

Year - Date, numerical variable that is the original year of release for the chip

Benchmark_Result - Rating, numerical variable that calculates the performance of a chip

Brand - Name, categorical variable that displays the branding of a chip

Processor - Name, categorical variable that displays the associated chip

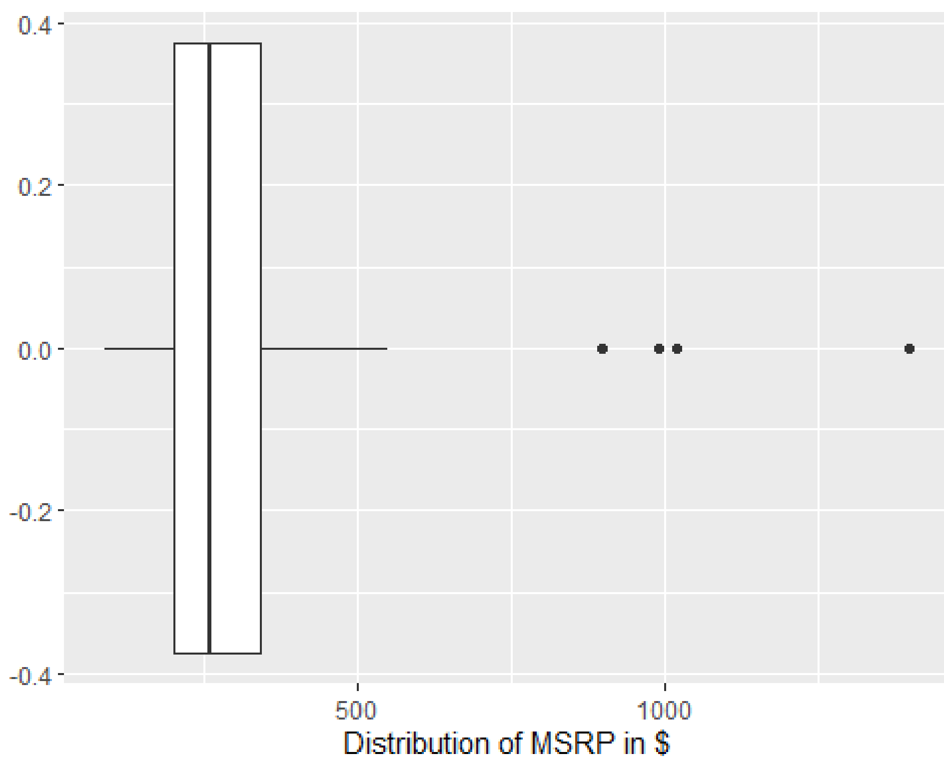
Chipset - Name, categorical variable that displays the chipset the processor was built on

```
# Univariate Stats
summary.extended <- cpudata %>%
  select(MSRP,Year,Benchmark_Result) %>%
  psych::describe(fast = TRUE) %>%
  as_tibble(rownames="rowname") %>%
  print(summary.extended)

## # A tibble: 3 x 9
##   rowname           vars     n    mean      sd    min    max range       se
```

```
##   <chr>            <int> <dbl>  <dbl>   <dbl> <dbl> <dbl> <dbl>    <dbl>
## 1 MSRP                 1    61   313.   234.      88  1399  1311   30.0
## 2 Year                 2    61  2016.     2.71  2010  2020    10    0.346
## 3 Benchmark_Result     3    61 11611. 9255.     1792 64205 62413 1185.
```

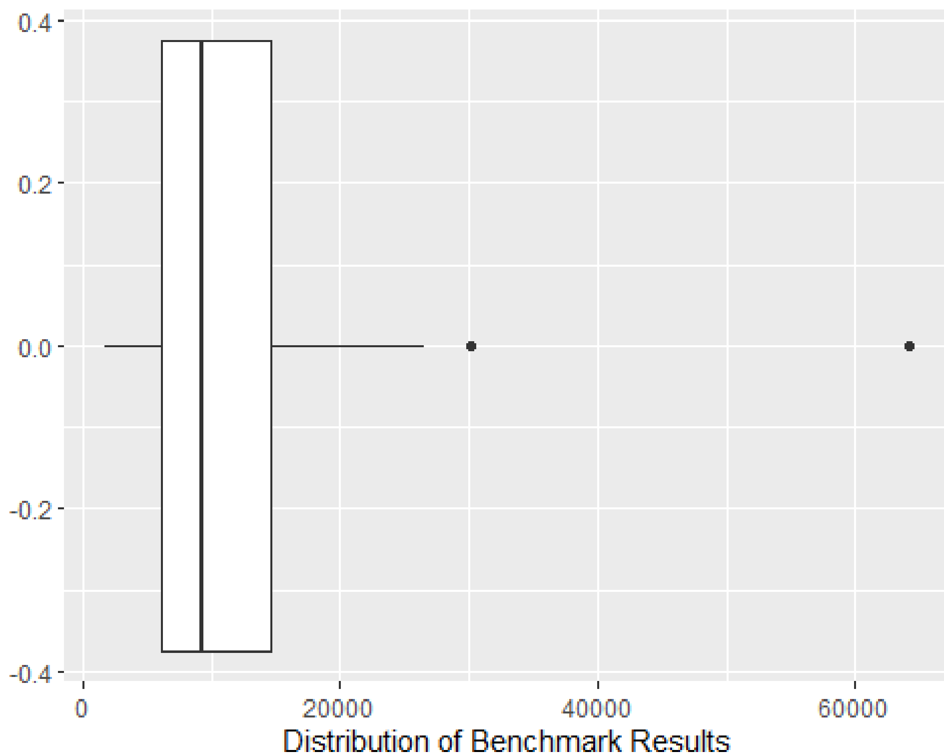
Variable Regression Analysis

```
# Visualize the predictor variable
# Creates the box plot for MSRP
ggplot(cpudata, aes(y=MSRP)) +
  geom_boxplot() + coord_flip() +
  labs(y = "Distribution of MSRP in $")
```



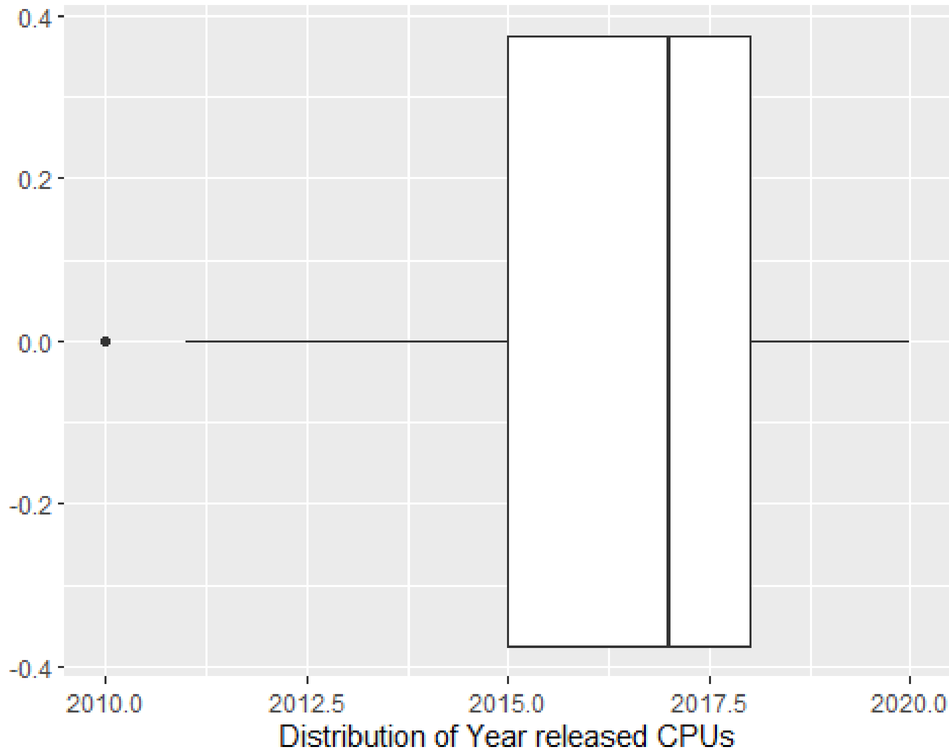
This box plot shows a distribution of the MSRP across the 60 CPUs in the data.

```
# Visualize the predictor variable
# Creates the box plot for Benchmark_Results
ggplot(cpudata, aes(y=Benchmark_Result)) + geom_boxplot() + coord_flip() +
  labs(y = "Distribution of Benchmark Results")
```



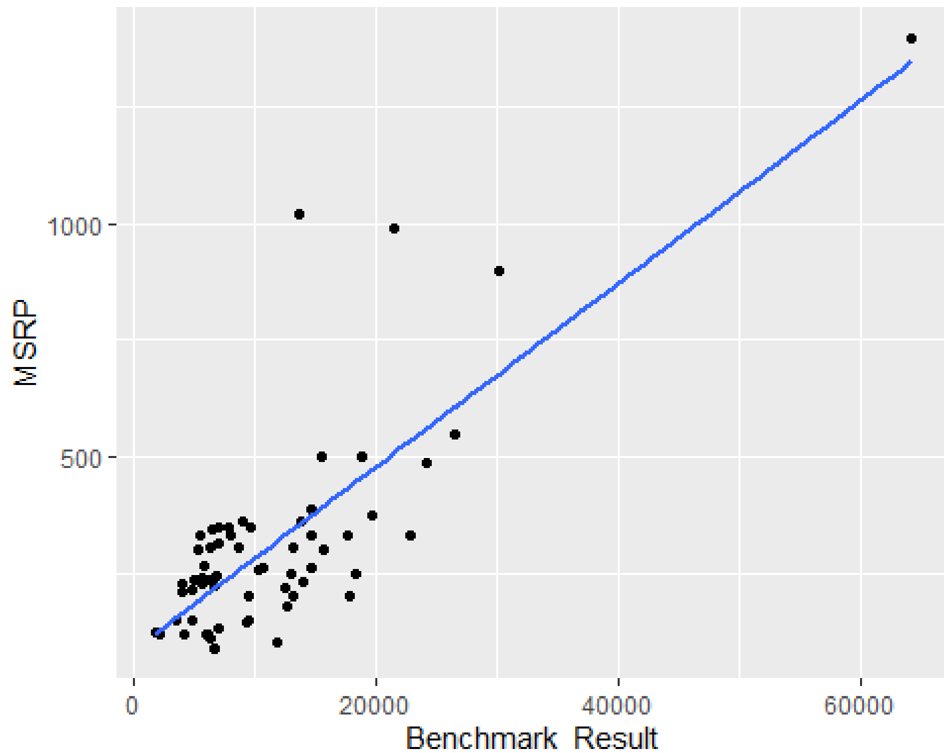
This box plot shows a distribution of the Benchmark Results for all the CPUs. The higher the score, the better performance the CPU has.

```
# Visualize the predictor variable
# Creates the box plot for Year
ggplot(cpudata, aes(y=Year)) + geom_boxplot() + coord_flip() +
  labs(y = "Distribution of Year released CPUs")
```

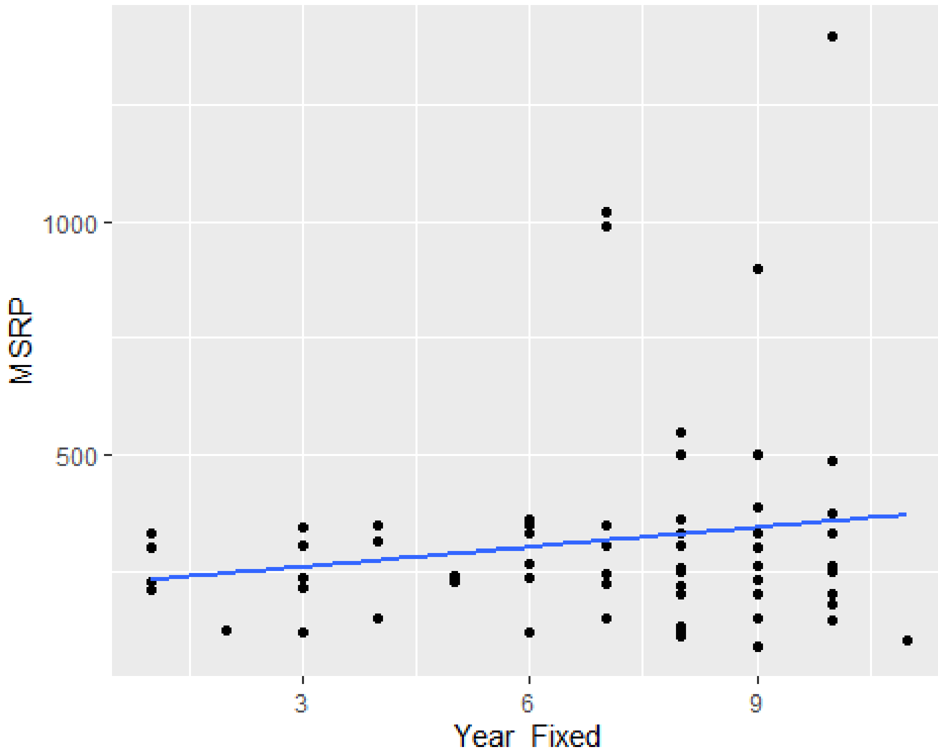


This box plot shows a distribution of the years released for all the CPUs.

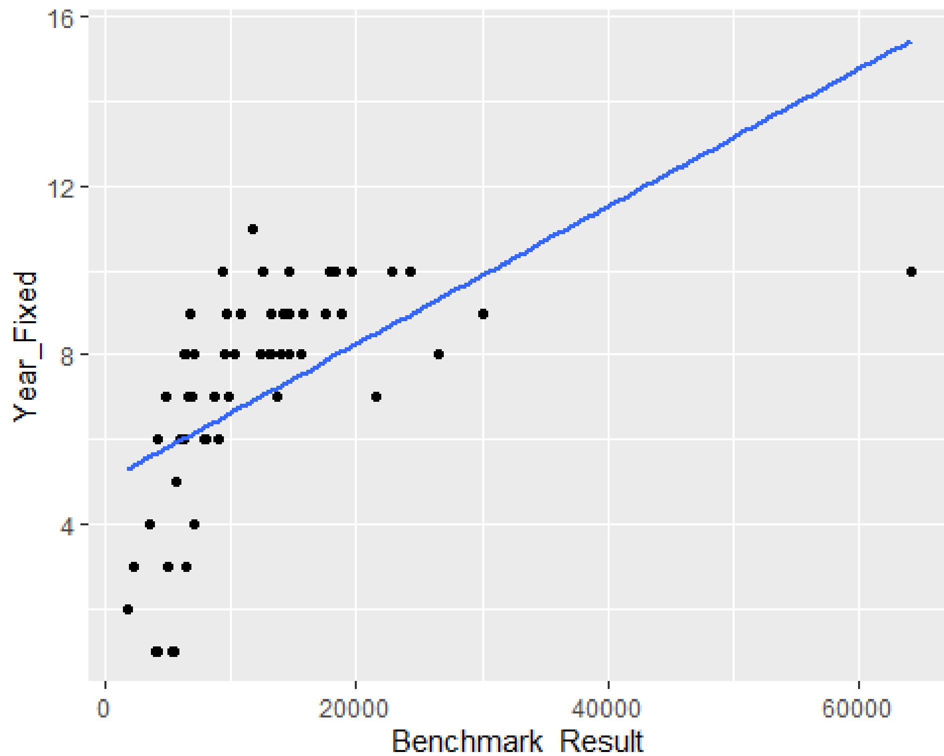
```
# Visualize the data with the regression line
# Creates the scatterplot for MSRP
ggplot(cpudata, aes(x=Benchmark_Result, y=MSRP)) +
  geom_point() +
  geom_smooth(method='lm', se = FALSE)

## `geom_smooth()` using formula 'y ~ x'
```



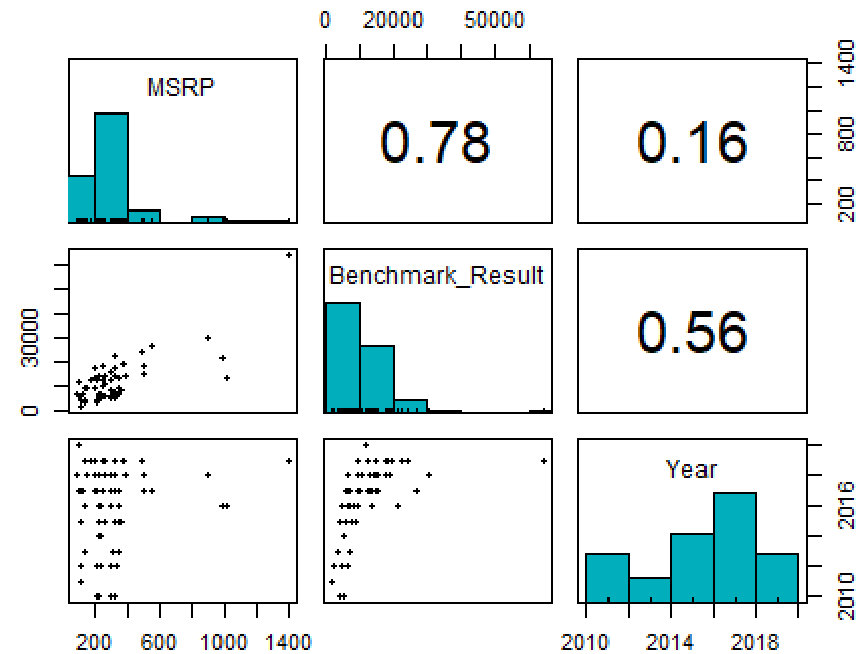

```r
# Summary statistics : Correlation coefficient
# Calculates the correlation coefficient for Air Permeability
cor(cpudata$MSRP,cpudata$Benchmark_Result)

## [1] 0.7791367

# Visualize the data with the regression line
# Creates the scatterplot for Year
ggplot(cpudata, aes(x=Year_Fixed, y=MSRP)) +
  geom_point() +
  geom_smooth(method='lm', se = FALSE)

## `geom_smooth()` using formula 'y ~ x'
```




```
# Summary statistics : Correlation coefficient
# Calculates the correlation coefficient for Air Permeability
cor(cpudata$MSRP,cpudata$Year_Fixed)

## [1] 0.1625529

# Visualize the data with the regression line
# Creates the scatterplot for Predictors
ggplot(cpudata, aes(x=Benchmark_Result, y=Year_Fixed)) +
  geom_point() +
  geom_smooth(method='lm', se = FALSE)

## `geom_smooth()` using formula 'y ~ x'
```




```r
# Summary statistics : Correlation coefficient
# Calculates the correlation coefficient for Air Permeability
cor(cpudata$Year_Fixed,cpudata$Benchmark_Result)

## [1] 0.5551998

# A fancy scatterplot matrix
pairs.panels(cpudata[c("MSRP","Benchmark_Result","Year")],
method = "pearson", # correlation method
hist.col = "#00AFBB", # color of histogram
smooth = FALSE, density = FALSE, ellipses = FALSE)
```



Graphs indicate the correlation coefficients among all three variables and provide various plots that indicate point distributions (via histograms and scatterplots).

Model Building Strategy

```
# Fit the regression model with 1 predictor, Benchmark Results
reg <- lm(MSRP ~ Benchmark_Result + Year_Fixed, cpudata)

# Display the summary table for the regression model
summary(reg)

##
## Call:
## lm(formula = MSRP ~ Benchmark_Result + Year_Fixed, data = cpudata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -166.93  -63.79  -23.16   40.69  658.42
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      253.73198   45.18730   5.615 5.82e-07 ***
## Benchmark_Result   0.02517    0.00214  11.763  < 2e-16 ***
## Year_Fixed       -33.74488    7.31845  -4.611 2.25e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

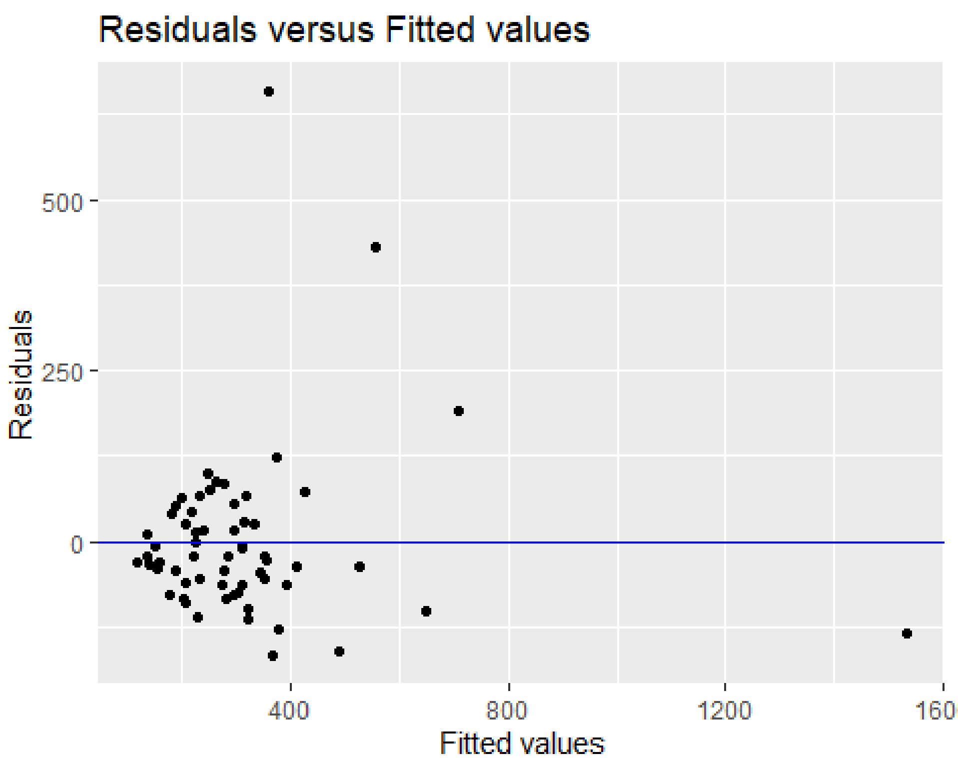
```
## Residual standard error: 127.6 on 58 degrees of freedom
## Multiple R-squared:  0.7125, Adjusted R-squared:  0.7025
## F-statistic: 71.85 on 2 and 58 DF,  p-value: < 2.2e-16
```

```r
# Display the correlation coefficient
coefficients(reg)
```

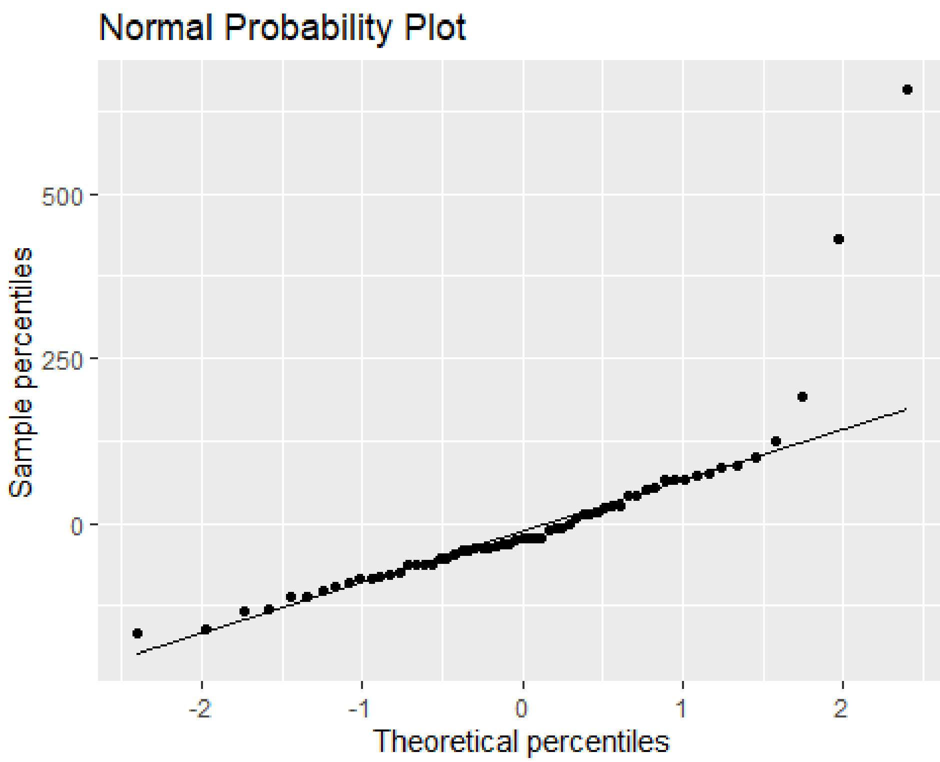
```
##      (Intercept) Benchmark_Result       Year_Fixed
##     253.73197738       0.02517316     -33.74488399
```

Assumptions Check

```r
# Residuals versus Fitted values
cpudata$resids <- residuals(reg)
cpudata$predicted <- predict(reg)
ggplot(cpudata, aes(x=predicted, y=resids)) + geom_point() +
geom_hline(yintercept=0, color = "blue") +
labs(title ="Residuals versus Fitted values", x = "Fitted values", y
="Residuals")
```




```r
# Normal probability plot
ggplot(cpudata, aes(sample = resids)) + stat_qq() + stat_qq_line() +
labs(title ="Normal Probability Plot", x = "Theoretical percentiles", y =
"Sample percentiles")
```

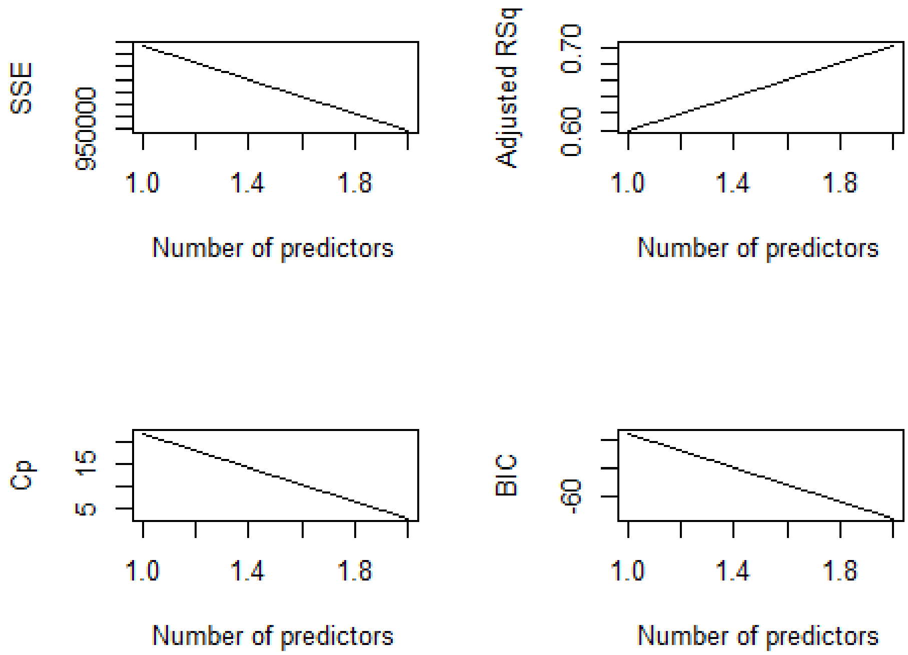



```
# Check the interaction effect of all variables
vif(reg)

## Benchmark_Result       Year_Fixed
##         1.445602         1.445602
```

Will have to ejected some outliers in order to make the assumptions checks pass. Too many outliers that could lead to incorrect assumptions.

Deciding on the Best Model

```
# Find the best model for each number of predictors (with 3 predictors
maximum)
models <- regsubsets(MSRP ~ Benchmark_Result + Year_Fixed, cpudata, nvmax =
3)
models.sum <- summary(models)
# Create four plots within a 2x2 frame to compare the different criteria
par(mfrow = c(2,2))
# SSE
plot(models.sum$rss, xlab = "Number of predictors", ylab = "SSE", type = "l")
# R2
plot(models.sum$adjr2, xlab = "Number of predictors", ylab = "Adjusted RSq",
type = "l")
# Mallow's Cp
plot(models.sum$cp, xlab = "Number of predictors", ylab = "Cp", type = "l")
# BIC
plot(models.sum$bic, xlab = "Number of predictors", ylab = "BIC", type = "l")
```




```
# Calculate the squared predictor variables to include in the model and the
interaction term:
cpudata <- cpudata %>%
mutate(bench2 = Benchmark_Result^2,
bench.year = Benchmark_Result*Year_Fixed)
# Fit the polynomial regression model
reg2 <- lm(MSRP ~ Year_Fixed + Benchmark_Result + bench2 + bench.year,
cpudata)
# Display the summary table for the regression model
summary(reg2)

##
## Call:
## lm(formula = MSRP ~ Year_Fixed + Benchmark_Result + bench2 +
##     bench.year, data = cpudata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -305.43  -43.84   -6.61   32.58  529.29
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -1.248e+02  7.450e+01  -1.675   0.0996 .
## Year_Fixed        7.194e+00  1.164e+01   0.618   0.5390
## Benchmark_Result  9.490e-02  1.164e-02   8.152 4.34e-11 ***
## bench2            9.386e-08  8.796e-08   1.067   0.2905
## bench.year       -7.826e-03  1.424e-03  -5.497 9.85e-07 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 100.9 on 56 degrees of freedom
## Multiple R-squared:  0.8263, Adjusted R-squared:  0.8139
## F-statistic: 66.59 on 4 and 56 DF,  p-value: < 2.2e-16
```

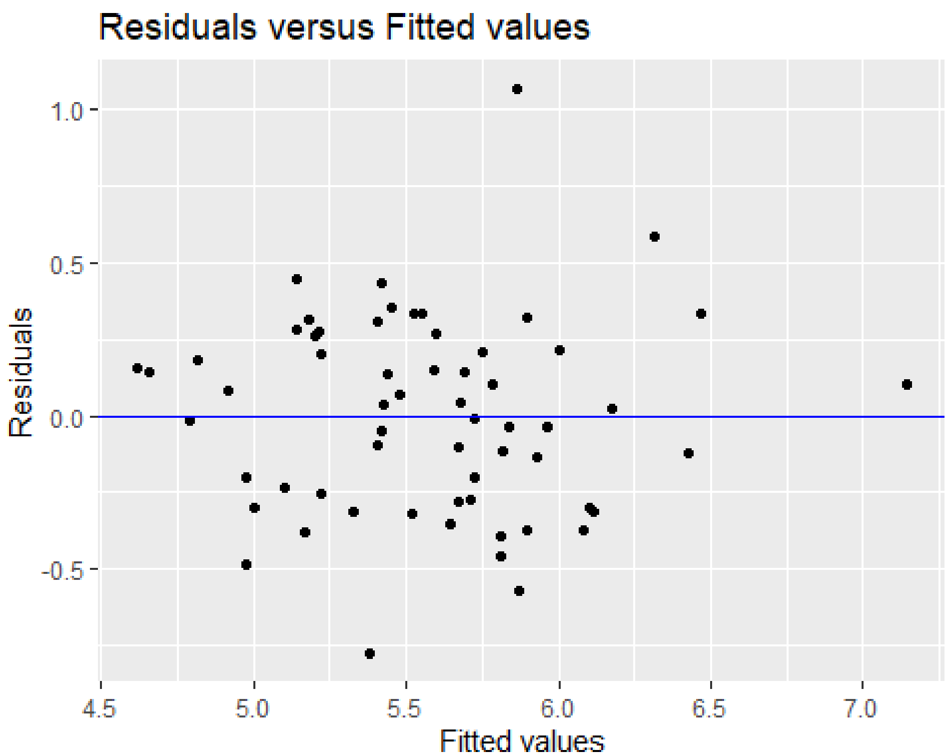
Choose the best model.

```
# Display the best model (selected predictors are indicated by *) for each
number of predictors
models.sum$outmat

##          Benchmark_Result Year_Fixed
## 1  ( 1 ) "*"              " "
## 2  ( 1 ) "*"              "*"
```

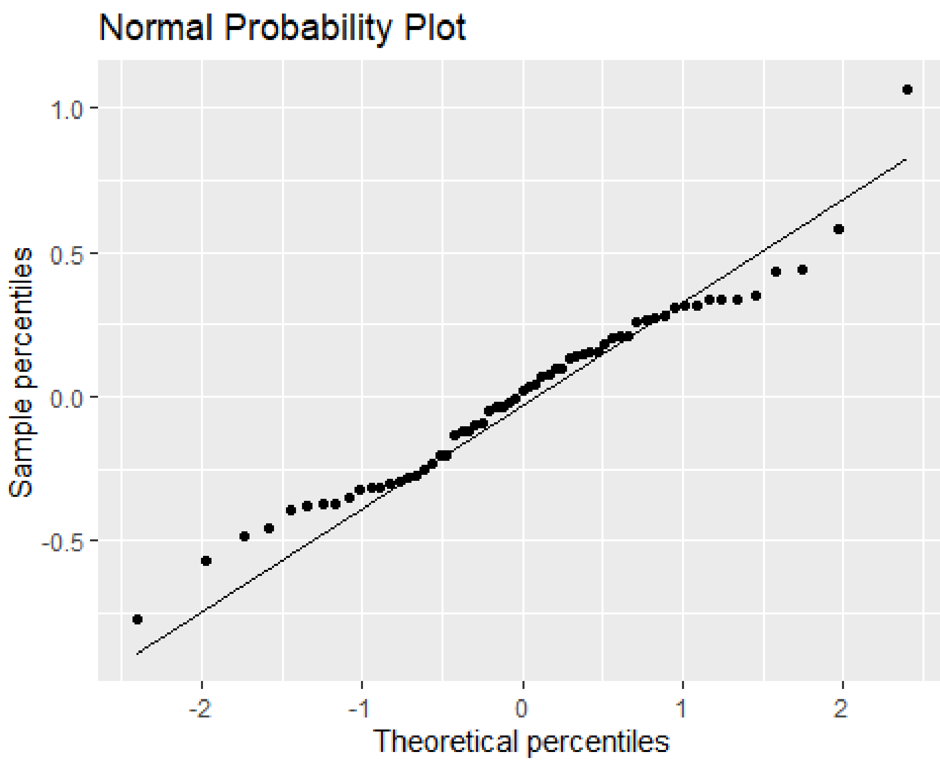
Creating the final model

```
# Printing the final model with the best number of predictor variables
lm_log.model = lm(log1p(MSRP) ~ log1p(Benchmark_Result) + log1p(Year_Fixed),
data = cpudata)
summary(lm_log.model)

##
## Call:
## lm(formula = log1p(MSRP) ~ log1p(Benchmark_Result) + log1p(Year_Fixed),
##     data = cpudata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.77414 -0.27192  0.02001  0.21139  1.06391
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -1.89780    0.67994  -2.791   0.0071 **
## log1p(Benchmark_Result)  0.99690    0.09037  11.032 7.20e-16 ***
## log1p(Year_Fixed)       -0.83145    0.12480  -6.662 1.08e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.326 on 58 degrees of freedom
## Multiple R-squared:  0.6806, Adjusted R-squared:  0.6696
## F-statistic: 61.79 on 2 and 58 DF,  p-value: 4.225e-15

# Residuals versus Fitted values
cpudata$resids2 <- residuals(lm_log.model)
cpudata$predicted2 <- predict(lm_log.model)
ggplot(cpudata, aes(x=predicted2, y=resids2)) + geom_point() +
geom_hline(yintercept=0, color = "blue") +
```

```
labs(title ="Residuals versus Fitted values", x = "Fitted values", y
="Residuals")
```




```
# Normal probability plot
ggplot(cpudata, aes(sample = resids2)) + stat_qq() + stat_qq_line() +
labs(title ="Normal Probability Plot", x = "Theoretical percentiles", y =
"Sample percentiles")
```




```
# Check the interaction effect of all variables
vif(lm_log.model)

## log1p(Benchmark_Result)       log1p(Year_Fixed)
##                 1.928061                1.928061
```

The equation for the final model is without outliers removed in logit form:

MSRP = -1.897 + 0.997log1p(Benchmark_Result) - 0.832log1p(Year_Fixed)

The coefficient of determination is 0.681