Price and Performance in Central Processing Units

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Introduction

```
# Load library
library(tidyverse)
## -- Attaching packages -------
## 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()
# 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
# 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")</pre>
## 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

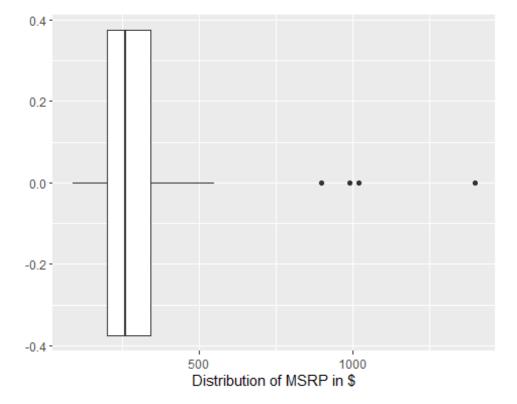
Processor - Name, categorical variable that displays the associated chip

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
##
                                             sd
    rowname
                      vars
                               n
                                   mean
                                                  min
                                                        max range
                                                                        se
##
    <chr>>
                     <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <</pre>
                                                                    <dbl>
## 1 MSRP
                         1
                                   313.
                                         234.
                                                   88 1399 1311
                              61
                                                                    30.0
## 2 Year
                         2
                              61 2016.
                                           2.71
                                                 2010 2020
                                                               10
                                                                     0.346
                              61 11611. 9255.
                                                 1792 64205 62413 1185.
## 3 Benchmark_Result
                         3
```

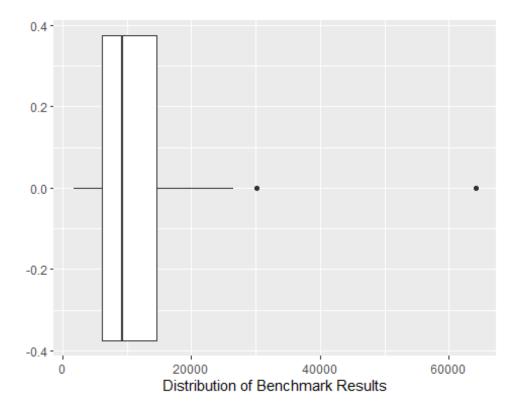
Variable Regression Analysis

```
# 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 $")
```



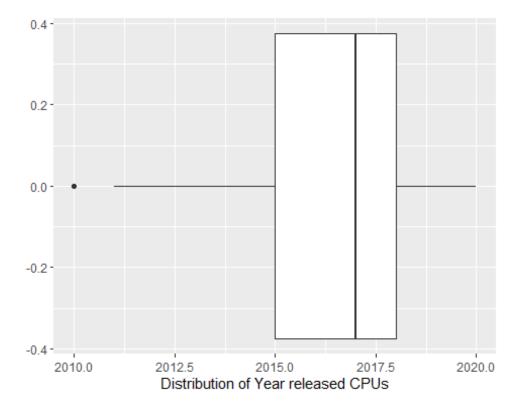
This box plot shows a distribution of the MSRP across the 60 CPUs in the data.

```
# 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")
```



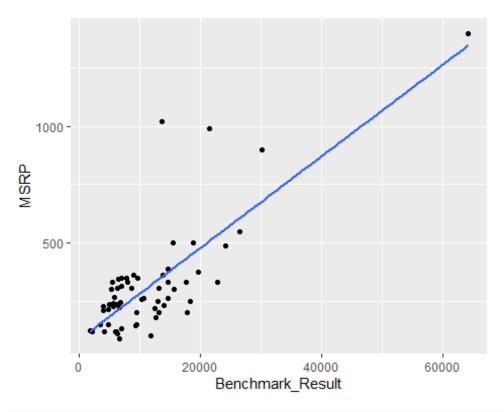
This box plot shows a distribution of the Benchmark Results for all the CPUs. The higher the score, the better performance the CPU has.

```
# 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'
```

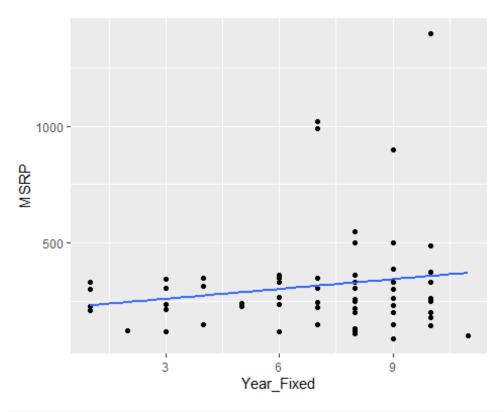


```
# Summary statistics : Correlation coefficient
# Calculates the correlation coefficient for Air Permeability
cor(cpudata$MSRP,cpudata$Benchmark_Result)

## [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'
```

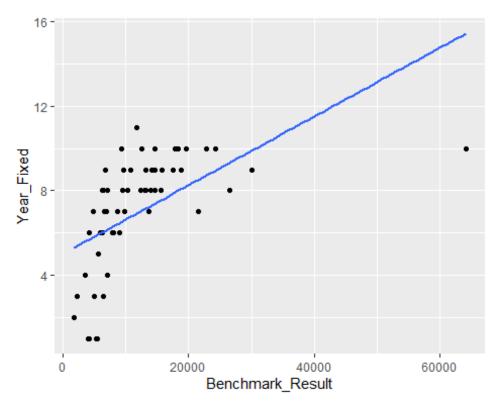


```
# Summary statistics : Correlation coefficient
# Calculates the correlation coefficient for Air Permeability
cor(cpudata$MSRP,cpudata$Year_Fixed)

## [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)

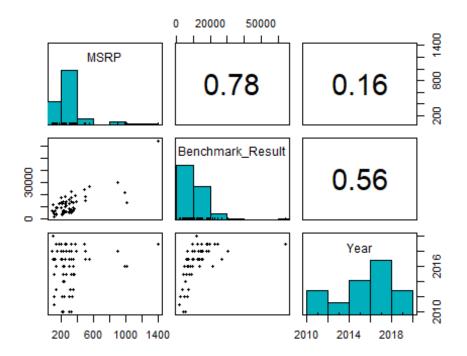
## `geom_smooth()` using formula 'y ~ x'
```



```
# 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)</pre>
# 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)
                                           5.615 5.82e-07 ***
                    253.73198
                                45.18730
## 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

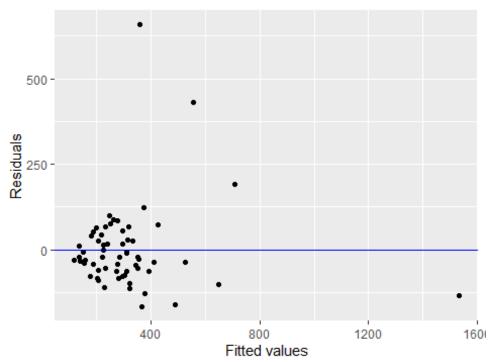
# Display the correlation coefficient
coefficients(reg)

## (Intercept) Benchmark_Result Year_Fixed
## 253.73197738 0.02517316 -33.74488399</pre>
```

Assumptions Check

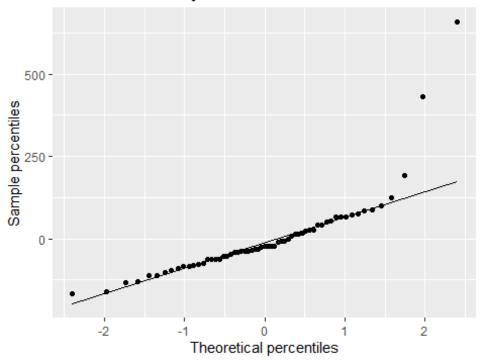
```
# Residuals versus Fitted values
cpudata$resids <- residuals(reg)
cpudata$predicted <- predict(reg)
ggplot(cpudata, aes(x=predicted, y=resids)) + geom_point() +
geom_hline(yintercept=0, color = "blue") +
labs(title = "Residuals versus Fitted values", x = "Fitted values", y
= "Residuals")</pre>
```

Residuals versus Fitted values



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

Normal Probability Plot

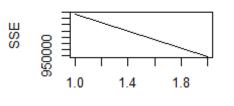


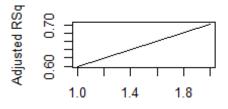
```
# Check the interaction effect of all variables
vif(reg)
## Benchmark_Result Year_Fixed
## 1.445602 1.445602
```

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

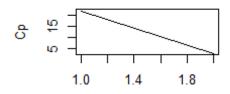
```
# Find the best model for each number of predictors (with 3 predictors
maximum)
models <- regsubsets(MSRP ~ Benchmark_Result + Year_Fixed, cpudata, nvmax =
3)
models.sum <- summary(models)
# Create four plots within a 2x2 frame to compare the different criteria
par(mfrow = c(2,2))
# SSE
plot(models.sum$rss,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

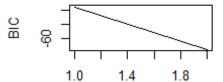




Number of predictors

Number of predictors





Number of predictors

Number of predictors

```
# 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,</pre>
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)
                                           -1.675
                    -1.248e+02
                                7.450e+01
                                                     0.0996 .
## Year Fixed
                     7.194e+00
                                             0.618
                                 1.164e+01
                                                     0.5390
                                 1.164e-02
                     9.490e-02
                                             8.152 4.34e-11 ***
## Benchmark_Result
## bench2
                     9.386e-08
                                8.796e-08
                                             1.067
                                                     0.2905
                    -7.826e-03 1.424e-03 -5.497 9.85e-07 ***
## bench.year
```

```
## ---
## 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

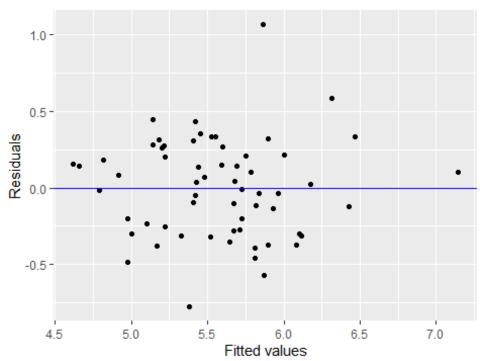
## Benchmark_Result Year_Fixed
## 1 ( 1 ) "*" " ""
## 2 ( 1 ) "*" "*"
```

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
                  10
                      Median
                                    30
                                            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 ***
                                       0.12480 -6.662 1.08e-08 ***
## log1p(Year_Fixed)
                           -0.83145
## ---
## Signif. codes: 0 '***' 0.001 '**' 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$resids2 <- residuals(lm log.model)</pre>
cpudata$predicted2 <- predict(lm log.model)</pre>
ggplot(cpudata, aes(x=predicted2, y=resids2)) + geom point() +
geom hline(yintercept=0, color = "blue") +
```

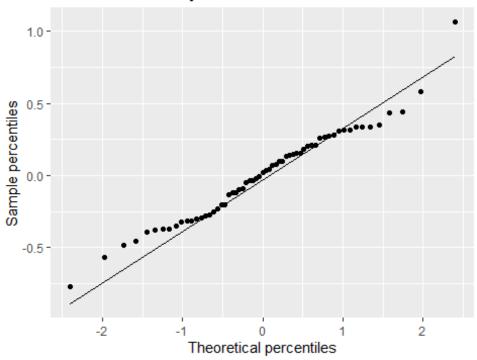
```
labs(title ="Residuals versus Fitted values", x = "Fitted values", y
="Residuals")
```

Residuals versus Fitted values



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

Normal Probability Plot



```
# 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