

VIETNAM NATIONAL UNIVERSITY HO CHI MINH CITY
HO CHI MINH CITY UNIVERSITY OF TECHNOLOGY
FACULTY OF APPLIED SCIENCE



PROBABILITY AND STATISTICS (MT2013)

Project topic:

**IDENTIFICATION AND ANALYSIS OF FACTORS
AFFECTING GPU'S PRICES &
EVALUATION OF PRICES OF UNKNOWN GPUS**

Group 03 - Class CC08 - Semester 232

Advisor: Dr. Nguyen Tien Dung

Students: Nguyen Chi Thuan - 2252787
Le Huu Tri - 2252841
Le Hoai Thien An - 2252006
Nguyen Trinh Tien Dat - 2252147
Nguyen Tuan Phong - 2252612

HO CHI MINH CITY, April 2024

MEMBER LIST & DUTY TABLE

No.	Full name	Student ID	Tasks	Contribution
1	Nguyen Chi Thuan	2252787	Summerize & edit files Compose section 8 & 9	100%
2	Le Huu Tri	2252841	Compose section 1 & 2	100%
3	Nguyen Tuan Phong	2252612	Compose section 4, 6 & 7	100%
4	Le Hoai Thien An	2252006	Compose section 5	100%
5	Nguyen Trinh Tien Dat	2252147	Compose R-Code & section 3	100%

TABLE OF CONTENTS

1 THEORETICAL FOUNDATION	3
1.1. Regression Model	3
1.1.1. Linear Regression Model	3
1.1.2. Ordinary least squares	3
2 DATA INTRODUCTION	5
2.1. Dataset description	5
2.2. Variables description	5
3 DATA PRE-PROCEEDING	6
3.1. Data reading (Importing and naming data)	6
3.2. Data cleaning	7
4 DESCRIPTIVE STATISTICS	14
4.1. GPU prices in the market through a histogram table	14
4.2. Scatter plots for the relationship between factors influencing GPU prices	14
5 INFERENCE STATISTICS	17
5.1. Introduction	17
5.2. Processing the data	18
5.3. Splitting the dataset	19
5.4. The initial model	19
5.5. The improved model	20
5.6. Conducting the formula	19
5.7. Testing the formula	21
5.8. Predicting	22
5.9. Conclusion	23
6 DISCUSSION AND EXPANSION	23
7 CONCLUSION	24
8 DATA & CODE SOURCE	24
8.1. Data source	24
8.2. Code source	24
REFERENCES	25

1 THEORETICAL FOUNDATION

1.1. Regression Model

1.1.1. Linear Regression Model

Multiple linear regression (MLR), also known as multiple regression, is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of multiple linear regression is to model the linear relationship between the explanatory (independent) variables and response (dependent) variables. The formula of multiple linear regression: $y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \epsilon$

where:

- y_i is the dependent variable.
- x_{ip} is the explanatory variable.
- β_0 is the y-intercept (constant term).
- β_p is the slope coefficient for each explanatory variable.
- ϵ is the model's error term (also known as the residuals).

When using linear regression, several assumptions are typically made.

- Assumption 1: **Linearity**, the relationship between the dependent variable and the independent variable is linear.

- Assumption 2: **Independence**, the observations are independent of each other

$$\text{Cov}(\epsilon_i, \epsilon_j) = 0, i \neq j$$

where $\text{Cov}(\epsilon_i, \epsilon_j)$ is the covariance between the errors for observations i and j .

- Assumption 3: **Homoscedasticity**, the variance of the errors is constant across all levels of the independent variable(s)

$$\text{Var}(\epsilon_i) = \sigma^2, \forall i$$

where $\text{Var}(\epsilon_i)$ is the variance of the error for observations i and σ^2 is a constant.

- Assumption 4: **Normality**, the errors are normally distributed

$$\epsilon \sim N(0, \sigma^2)$$

where ϵ is the error term and $N(0, \sigma^2)$ denotes a normal distribution with mean 0 and variance σ^2 .

1.1.2. Ordinary least squares

In statistics, **ordinary least squares (OLS)** is a type of linear least squares method for choosing the unknown parameters in a linear regression model (with fixed level-one effects of a linear function of a set of explanatory variables) by the principle of least squares: minimizing the sum of the squares of the differences between the observed dependent variable (values of the variable being observed) in the input dataset and the output of the (linear) function of the independent variable.

Simple linear regression considers a single regressor variable or predictor variable x and a dependent or response variable Y .

The expected value of Y at each level of x is a random variable.

$$E(Y|x) = \beta_0 + \beta_1 x$$

where the intercept β_0 and the slope β_1 are unknown regression coefficients. We assume that each observation, Y , can be described by the model.

$$Y = \beta_0 + \beta_1 x + \epsilon$$

The fitted or estimated regression line is therefore

$$\hat{Y}_i = \beta_0 + \beta_1 x_i$$

Note that each pair of observations satisfies the relationship

$$Y_i = \beta_0 + \beta_1 x_i + e_i, \quad i = 1, \dots, n$$

where $e_i = Y_i - \hat{Y}_i$ is called the residual, which describes the error in the fit of the model to the i -th observation y_i .

The least-squares estimates of the intercept and slope in the simple linear regression model are

$$\beta_1 = \frac{S_{xy}}{S_{xx}}$$

$$\text{and } \beta_0 = \bar{y} - \beta_1 \bar{x},$$

where

$$S_{xx} = \sum_{i=1}^n (x_i - \bar{x})^2$$

$$S_{xy} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$S_{yy} = \sum_{i=1}^n (y_i - \bar{y})^2$$

The sum of squares of the residuals

$$SSE = \sum (y_i - \hat{y}_i)^2.$$

The total sum of squares of the response variable

$$SST = \sum (y_i - \bar{y})^2.$$

The sum of squares for regression

$$SSR = \sum (\hat{y}_i - \bar{y})^2.$$

Fundamental identity

$$SST = SSE + SSR$$

$$\text{Coefficient of determination} \\ r^2 = 1 - \frac{SSE}{SST}.$$

2 DATA INTRODUCTION

2.1. Dataset description

A **graphics processing unit (GPU)** is a specialized electronic circuit initially designed to accelerate computer graphics and image processing (either on a video card or embedded on motherboards, mobile phones, personal computers, workstations, and game consoles). After their initial design, GPUs were found to be useful for non-graphic calculations involving embarrassingly parallel problems due to their parallel structure. Other non-graphical uses include the training of neural networks and cryptocurrency mining.

The dataset is retrieved from Computer Parts (CPUs and GPUs) Dataset (Kaggle) by author Ilissek. In this project, we will analyze a dataset containing detailed technical specifications, release dates, and launch prices of over 3000 Graphics Processing Units (GPUs).

The input data is stored in a CSV file: gpus.csv for GPUs. The data table includes columns representing necessary information of the data, and some of the features will include: Boost_Clock, Core_Speed, Memory, Memory_Bandwidth, Memory_Bus, Memory_Speed, Release_Price and many others. Then, we have made a decision about creating a new dataset consisting of the required data.

2.2. Variables description

Variable	Data type	Unit	Description
Boost_Clock	Continuous	MHz	The processing speed of the graphics card after boost clock.
Core_Speed	Continuous	MHz	The processing speed of the graphics card.
Memory	Continuous	MB	The memory of the graphics card.
Memory_Bandwidth	Continuous	GB/sec	The speed at which a processor can read from or write to semiconductor memory. Memory bandwidth is typically expressed in bytes per second, although this may vary for systems with

			data sizes that are not multiples of the 8-bit bytes commonly used.
Memory_Bus	Continuous	Bit	A type of computer bus, typically in the form of a set of wires or conductors connecting electrical components, allowing the transmission of data and addresses from the main memory to the central processing unit (CPU) or memory controller.
Memory_Speed	Continuous	MHz	The memory speed of the GPU is measured in MHz, simply understood as the speed at which the GPU can access data stored in RAM.
Texture_Rate	Continuous	GTexel/s	The number of pixels the GPU can generate per second.
Release_Price	Continuous	\$	The selling price of the GPU.

3 DATA PRE-PROCEEDING

3.1. Data reading (Importing and naming data)

The first line of this piece of code is importing file name "gpus.csv" into data frame (noted as **data** in R). Then we choose the appropriate data that we want to analyze:

```
data<-read.csv("gpus.csv")
data <- data[, c("Boost_Clock","Core_Speed","Memory","Memory_Bandwidth",
                "Memory_Bus","Memory_Speed","Release_Price","Texture_Rate")]
names(data)<-c("boost_clock", "core_speed",
              "mem", "mem_bandwidth", "mem_bus", "mem_speed", "release_price", "texture_rate")
```

The original labels are very long and descriptive, we might not want that such level of details during coding. Therefore, the labels are suppressed into small, compact abbreviations.

	boost_clock	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
1		738 MHz	1024 MB	64GB/sec	256 Bit	1000 MHz		47 GTexel/s
2		-	512 MB	106GB/sec	512 Bit	828 MHz		12 GTexel/s
3		-	512 MB	51.2GB/sec	256 Bit	800 MHz		10 GTexel/s
4		-	256 MB	36.8GB/sec	128 Bit	1150 MHz		7 GTexel/s
5		-	256 MB	22.4GB/sec	128 Bit	700 MHz		6 GTexel/s
6		-	256 MB	35.2GB/sec	128 Bit	1100 MHz		6 GTexel/s
7		870 MHz	2048 MB	134.4GB/sec	256 Bit	1050 MHz		35 GTexel/s
8		-	256 MB	51.2GB/sec	256 Bit	800 MHz		7 GTexel/s
9		-	2048 MB	160GB/sec	256 Bit	1250 MHz		62 GTexel/s
10		-	64 MB	2.9GB/sec	64 Bit	366 MHz		
11		-	128 MB	5.2GB/sec	128 Bit	325 MHz		2 GTexel/s
12		650 MHz	6144 MB	177.6GB/sec	384 Bit	925 MHz		36 GTexel/s
13		705 MHz	5120 MB	168GB/sec	320 Bit	1050 MHz		
14		706 MHz	12288 MB	288.4GB/sec	384 Bit	1502 MHz		169 GTexel/s
15		-	64 MB	5.8GB/sec	128 Bit	360 MHz		
16	1100 MHz	1050 MHz	3072 MB	57.6GB/sec	128 Bit	900 MHz		62 GTexel/s
17		-	8192 MB	320GB/sec	512 Bit	1250 MHz		
18		732 MHz	6144 MB	249.6GB/sec	384 Bit	1300 MHz		
19	1000 MHz	300 MHz		34.1GB/sec	128 Bit	1067 MHz		8 GTexel/s

Figure 1: The initial data frame

```

> summary(data)
boost_clock      core_speed      mem      mem_bandwidth      mem_bus      mem_speed
Length:3406     Length:3406     Length:3406     Length:3406     Length:3406     Length:3406
Class :character Class :character Class :character Class :character Class :character Class :character
Mode  :character Mode  :character Mode  :character Mode  :character Mode  :character Mode  :character
release_price    texture_rate
Length:3406     Length:3406
Class :character Class :character
Mode  :character Mode  :character

```

Figure 2: Summarize data before cleaning

3.2. Data cleaning

After choosing the appropriate attributes, we now have the subset of the original raw dataset. However, since the values vary in types (such as string and numeric-string), we might want transform them into reproducible types, so that the analysis later on is easier, homogeneous and accurate.

Note that this cleaning process does not remove the NA values, unless necessary. The reason is that, in one instance, there might be important values that should not be eliminated. Under different scopes of study, we can not treat instances with NA as an invalid datum for all scopes. In later sections, when we focus on a specific pattern of the data, only by then that the data will have a tailored NA cleaning, and we will not, by chance, loose any important instance.

a) Boost_Clock, Core_Speed, Memory, Memory_Bandwidth, Memory_Bus, Memory_Speed, Texture_Rate


```

data[, "boost_clock"] <- as.numeric(gsub("( MHz)", "", data[, "boost_clock"]))
#data <- data[!is.na(data$boost_clock), ]

data[, "core_speed"] <- as.numeric(gsub("( MHz)", "", data[, "core_speed"]))
#data <- data[!is.na(data$core_speed), ]

data[, "mem"] <- as.numeric(gsub("( MB)", "", data[, "mem"]))
#data <- data[!is.na(data$mem), ]

data[, "mem_bandwidth"] <- as.numeric(gsub("(GB/sec)", "", data[, "mem_bandwidth"]))
#data <- data[!is.na(data$mem_bandwidth), ]

data[, "mem_bus"] <- as.numeric(gsub("( Bit)", "", data[, "mem_bus"]))
#data <- data[!is.na(data$mem_bus), ]

data[, "mem_speed"] <- as.numeric(gsub("( MHz)", "", data[, "mem_speed"]))
#data <- data[!is.na(data$mem_speed), ]

data[, "texture_rate"] <- as.numeric(gsub("( GTexel/s)", "", data[, "texture_rate"]))
#data <- data[!is.na(data$texture_rate), ]

```

Our goal is to cut out the “ MHz” in Boost_Clock column, since every entry is recorded in mega-hertz. Notice that the pattern are regular expressions, and would be used intensively during this cleaning process.

We do the same for the remain data.

b) Release_Price

```

data[, "release_price"] <- gsub("(^\\$(\\d)+.(\\d)+ - )", "", data[, "release_price"])
data$release_price <- ifelse(data$release_price == "N/A", NA, data$release_price)
data$release_price <- as.numeric(gsub('\\$', '', data$release_price))

```

We want to cut out unnecessary characters and only keep the price. After that, we eliminate \$ symbol from the string, as well as cast the string to numeric type.

	boost_clock	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
1	NA	738	1024	64.0	256	1000	NA	47
2	NA	NA	512	106.0	512	828	NA	12
3	NA	NA	512	51.2	256	800	NA	10
4	NA	NA	256	36.8	128	1150	NA	7
5	NA	NA	256	22.4	128	700	NA	6
6	NA	NA	256	35.2	128	1100	NA	6
7	NA	870	2048	134.4	256	1050	NA	35
8	NA	NA	256	51.2	256	800	NA	7
9	NA	NA	2048	160.0	256	1250	NA	62
10	NA	NA	64	2.9	64	366	NA	NA
11	NA	NA	128	5.2	128	325	NA	2
12	NA	650	6144	177.6	384	925	NA	36
13	NA	705	5120	168.0	320	1050	NA	NA
14	NA	706	12288	288.4	384	1502	NA	169
15	NA	NA	64	5.8	128	360	NA	NA
16	1100	1050	3072	57.6	128	900	NA	62
17	NA	NA	8192	320.0	512	1250	NA	NA
18	NA	732	6144	249.6	384	1300	NA	NA
19	1000	300	NA	34.1	128	1067	NA	8
20	NA	NA	256	23.4	256	730	NA	3
21	NA	575	6144	144.0	384	750	NA	NA
22	NA	575	6144	144.0	384	750	NA	NA

Figure 3: Data after cleaning

```
> summary(data)
```

boost_clock	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price
Min. : 400	Min. : 100.0	Min. : 16	Min. : 1.0	Min. : 32.0	Min. : 100	Min. : 23.0
1st Qu.:1050	1st Qu.: 790.0	1st Qu.: 1024	1st Qu.: 28.8	1st Qu.: 128.0	1st Qu.: 800	1st Qu.: 159.8
Median :1176	Median : 980.0	Median : 2048	Median : 105.8	Median : 128.0	Median :1150	Median : 240.0
Mean :1206	Mean : 946.9	Mean : 2873	Mean : 137.4	Mean : 205.4	Mean :1176	Mean : 371.6
3rd Qu.:1317	3rd Qu.:1090.0	3rd Qu.: 4096	3rd Qu.: 194.5	3rd Qu.: 256.0	3rd Qu.:1502	3rd Qu.: 421.5
Max. :1936	Max. :1784.0	Max. :32000	Max. :1280.0	Max. :8192.0	Max. :2127	Max. :14999.0
NA's :1960	NA's :936	NA's :420	NA's :125	NA's :62	NA's :105	NA's :2850

texture_rate
Min. : 0.00
1st Qu.: 22.00
Median : 60.00
Mean : 90.27
3rd Qu.:135.00
Max. :717.00
NA's :544

Figure 4: Summarize data after cleaning

It can be seen that there are 1960 over 3406 NA's in boost_clock (more than 50%) so we decide to remove that variable in order not to affect out analysis. For other variable, we decide to used the mean value of the known value to replace the NA value:

```
data <- data[, -which(names(data) == "boost_clock")] #delete boost_clock col
data$core_speed[is.na(data$core_speed)] <- mean(data$core_speed, trim = 0, na.rm = TRUE) #change NA to mean value
data$mem[is.na(data$mem)] <- mean(data$mem, trim = 0, na.rm = TRUE)
data$mem_bandwidth[is.na(data$mem_bandwidth)] <- mean(data$mem_bandwidth, trim = 0, na.rm = TRUE)
data$mem_bus[is.na(data$mem_bus)] <- mean(data$mem_bus, trim = 0, na.rm = TRUE)
data$mem_speed[is.na(data$mem_speed)] <- mean(data$mem_speed, trim = 0, na.rm = TRUE)
data$texture_rate[is.na(data$texture_rate)] <- mean(data$texture_rate, trim = 0, na.rm = TRUE)
```

Figure 5: Data after checking missing value

After that, we split out data into 2 frames base on the release_price. We choose the row which the price is known for the first data frame (noted **data**) and the other data frame includes NA price (noted **data_NA**).

	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
1	738.0000	1024.000	64.0000	256.0000	1000.000	NA	47.00000
2	946.8939	512.000	106.0000	512.0000	828.000	NA	12.00000
3	946.8939	512.000	51.2000	256.0000	800.000	NA	10.00000
4	946.8939	256.000	36.8000	128.0000	1150.000	NA	7.00000
5	946.8939	256.000	22.4000	128.0000	700.000	NA	6.00000
6	946.8939	256.000	35.2000	128.0000	1100.000	NA	6.00000
7	870.0000	2048.000	134.4000	256.0000	1050.000	NA	35.00000
8	946.8939	256.000	51.2000	256.0000	800.000	NA	7.00000
9	946.8939	2048.000	160.0000	256.0000	1250.000	NA	62.00000
10	946.8939	64.000	2.9000	64.0000	366.000	NA	90.27463
11	946.8939	128.000	5.2000	128.0000	325.000	NA	2.00000
12	650.0000	6144.000	177.6000	384.0000	925.000	NA	36.00000
13	705.0000	5120.000	168.0000	320.0000	1050.000	NA	90.27463
14	706.0000	12288.000	288.4000	384.0000	1502.000	NA	169.00000
15	946.8939	64.000	5.8000	128.0000	360.000	NA	90.27463
16	1050.0000	3072.000	57.6000	128.0000	900.000	NA	62.00000
17	946.8939	8192.000	320.0000	512.0000	1250.000	NA	90.27463
18	732.0000	6144.000	249.6000	384.0000	1300.000	NA	90.27463

```
data_NA <- data[is.na(data$release_price), ]
View(data_NA)

data <- data[!is.na(data$release_price), ]
```

	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
43	946.8939	2872.769	480.0000	384.0000	1250	1199.00	343
46	946.8939	12288.000	547.2000	96.0000	1425	1199.00	354
48	705.0000	12288.000	672.0000	384.0000	1750	2999.00	420
50	705.0000	12288.000	672.0000	384.0000	1750	2999.00	420
52	1140.0000	12288.000	336.6000	384.0000	1753	1099.00	240
53	1127.0000	24576.000	673.2000	384.0000	1753	2059.00	467
55	1000.0000	24576.000	673.2000	384.0000	1753	1998.00	418
56	1000.0000	12288.000	336.6000	384.0000	1753	999.00	209
57	1127.0000	12288.000	336.6000	384.0000	1753	1029.99	233
60	1000.0000	12288.000	384.0000	3072.0000	500	999.00	320
62	1000.0000	16384.000	512.0000	4096.0000	500	1299.00	320
66	889.0000	6144.000	336.0000	384.0000	1750	999.00	235
69	837.0000	6144.000	288.4000	384.0000	1502	999.00	196
171	960.0000	1024.000	134.4000	256.0000	1050	249.00	38
173	850.0000	1024.000	124.8000	256.0000	975	249.00	34
184	575.0000	512.000	57.6000	256.0000	900	130.00	18
187	750.0000	512.000	51.2000	128.0000	800	109.00	24
203	750.0000	512.000	25.6000	128.0000	800	67.00	24
934	946.8939	8192.000	256.0000	512.0000	500	499.00	384
935	946.8939	8192.000	256.0000	512.0000	500	599.00	410

Showing 1 to 20 of 556 entries. 7 total columns

	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
1	738.0000	1024.000	64.0000	256.0000	1000.000	NA	47.00000
2	946.8939	512.000	106.0000	512.0000	828.0000	NA	12.00000
3	946.8939	512.000	51.2000	256.0000	800.000	NA	10.00000
4	946.8939	256.000	36.8000	128.0000	1150.000	NA	7.00000
5	946.8939	256.000	22.4000	128.0000	700.000	NA	6.00000
6	946.8939	256.000	35.2000	128.0000	1100.000	NA	6.00000
7	870.0000	2048.000	134.4000	256.0000	1050.000	NA	35.00000
8	946.8939	256.000	51.2000	256.0000	800.000	NA	7.00000
9	946.8939	2048.000	160.0000	256.0000	1250.000	NA	62.00000
10	946.8939	64.000	2.9000	64.0000	366.000	NA	90.27463
11	946.8939	128.000	5.2000	128.0000	325.000	NA	2.00000
12	650.0000	6144.000	177.6000	384.0000	925.000	NA	36.00000
13	705.0000	5120.000	168.0000	320.0000	1050.000	NA	90.27463
14	706.0000	12288.000	288.4000	384.0000	1502.000	NA	169.00000
15	946.8939	64.000	5.8000	128.0000	360.000	NA	90.27463
16	1050.0000	3072.000	57.6000	128.0000	900.000	NA	62.00000
17	946.8939	8192.000	320.0000	512.0000	1250.000	NA	90.27463
18	732.0000	6144.000	249.6000	384.0000	1300.000	NA	90.27463
19	300.0000	2872.769	34.1000	128.0000	1067.000	NA	8.00000
20	946.8939	256.000	23.4000	256.0000	730.000	NA	3.00000

Showing 1 to 20 of 2850 entries. 7 total columns

Figure 6: Data frame (556 entries) and data_NA frame (2850 entries)

```
#data summary by xtabs
xtabs(~core_speed,data=data)
xtabs(~mem,data=data)
xtabs(~mem_bandwidth,data=data)
xtabs(~mem_bus,data=data)
xtabs(~mem_speed,data=data)
xtabs(~texture_rate,data=data)
xtabs(~release_price,data=data)
```

```
> summary(data)
  core_speed      mem  mem_bandwidth  mem_bus  mem_speed  release_price  texture_rate
Min.   : 550.0   Min.   : 512   Min.   : 12.8   Min.   : 64   Min.   : 500   Min.   : 23.0   Min.   : 5.0
1st Qu.: 946.9   1st Qu.: 2048   1st Qu.: 112.1   1st Qu.: 128   1st Qu.: 1375   1st Qu.: 159.8   1st Qu.: 68.0
Median :1024.5   Median : 4096   Median : 192.3   Median : 256   Median :1750   Median : 240.0   Median :128.0
Mean   :1080.0   Mean   : 4777   Mean   : 217.3   Mean   : 292   Mean   :1574   Mean   : 371.6   Mean   :141.9
3rd Qu.:1175.0   3rd Qu.: 8192   3rd Qu.: 256.0   3rd Qu.: 256   3rd Qu.:1753   3rd Qu.: 421.5   3rd Qu.:193.2
Max.   :1784.0   Max.   :32000   Max.   :1024.0   Max.   :8192   Max.   :2127   Max.   :14999.0   Max.   :555.0
```

Figure 7: Data summary after that

```
> xtabs(~core_speed,data=data)
```

core_speed	550	574	575	576	600	602	607
	1	1	1	3	4	1	2
	625	633	648	650	675	700	701
	3	1	2	3	3	2	1
	705	720	725	730	732	738	750
	2	2	2	3	1	2	3
	772	778	783	797	800	810	822
	1	1	1	2	7	7	1
	827	837	850	855	860	863	870
	1	1	6	1	2	3	1
	875	876	880	889	900	902	910
	1	1	2	1	5	4	1
	915	918	925	926	928	946.893927125506	947
	5	1	6	17	1	79	1
	950	960	965	967	970	975	980
	4	1	1	1	5	1	8
	985	990	993	1000	1006	1010	1018
	4	2	2	36	1	2	1
	1020	1024	1025	1030	1032	1033	1040
	3	3	2	2	2	1	1
	1046	1050	1051	1058	1060	1076	1088
	2	13	1	1	2	1	1
	1090	1100	1102	1106	1120	1121	1126
	12	4	4	1	42	1	5
	1127	1140	1143	1150	1152	1165	1175
	6	5	1	1	1	3	29
	1178	1180	1190	1200	1203	1208	1216

Figure 7.1: Summary of core speed

```
> xtabs(~mem,data=data)
```

mem	512	768	896	1024	1280	1536	1792
	11	1	3	45	3	3	1
	2048	2872.76892163429	3072	4096	6144	8192	11264
	117	8	32	142	43	119	8
	12288	16384	24576	32000			
	10	7	2	1			

Figure 7.2: Summary of memory

```
> xtabs(~mem_bandwidth,data=data)
```

mem_bandwidth	12.8	14.4	16	25.6	28.5	28.8	29
	1	4	1	3	1	6	1
	38.4	40	40.1	41.6	51.2	54.4	57.6
	2	2	1	2	3	1	5
	57.7	64	70.4	72	73.6	80	86.4
	1	1	3	7	3	3	3
	89.9	96	98.4	102.7	104	105.8	108.8
	1	5	1	1	4	8	1
	111.9	112	112.1	112.2	112.3	115.2	124.8
	2	52	24	11	1	3	2
	127	128	128.1	128.3	128.6	130.6	133.9
	1	2	1	3	1	1	1
	134.4	137.350807680585	140.8	141.7	144.2	152	153.6
	3	6	1	1	4	1	4
	159	163.4	176	177.4	179.2	182.4	185.6
	1	1	8	1	11	8	3
	188.8	192	192.2	192.3	192.4	194.6	196.8
	1	4	37	6	1	2	2
	197	208	211.2	211.6	223.8	224	224.3
	2	1	12	1	1	35	1
	224.4	230.4	240	256	256.3	259.5	262.7
	25	1	4	58	18	1	1
	264	272	272.3	281.6	288	288.4	320
	1	2	3	1	3	4	4
	320.3	323.3	336	336.6	340.6	340.8	352
	13	1	2	18	1	1	1
	354.8	358.4	384	390.4	448.8	480	484.4

Figure 7.3: Summary of memory bandwidth

```
> xtabs(~mem_bus,data=data)
```

mem_bus	64	88	96	128	176	192	205.356459330144
	10	5	1	186	1	53	5
	256	320	352	384	448	512	3072
	209	2	2	46	4	23	1
	4096	8192					
	7	1					

Figure 7.4: Summary of memory bus

```
> xtabs(~mem_speed,data=data)
```

mem_speed	500	650	702	750	800	802	837	850	891	900	902	905	924	950	975	999	1000	1001	1002	1005	1020	1025	1050	1100
	14	2	1	1	9	1	1	2	1	18	1	1	2	1	2	3	3	3	4	1	1	3	3	5
	1107	1125	1134	1150	1200	1242	1250	1251	1252	1263	1350	1375	1376	1400	1425	1426	1450	1475	1500	1502	1525	1625	1650	1653
	1	7	1	3	4	1	15	14	1	1	3	10	6	13	9	2	3	1	24	15	2	5	12	9
	1702	1750	1752	1753	1755	1774	1775	1800	2000	2002	2027	2052	2125	2127										
	1	95	25	63	1	1	1	2	57	54	3	3	2	3										

Figure 7.5: Summary of memory speed

```
> xtabs(~texture_rate,data=data)
```

texture_rate	5	6	11	13	14	15	16	17	18	19	20	21	24	25	26	27	29	32	34	35	36	37	38	40	41	42	43	44	45	47
	2	1	1	5	3	2	3	3	2	4	2	1	2	5	2	1	3	2	6	1	1	1	4	1	1	1	2	2	2	2
	48	49	50	51	52	53	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	77	78	80
	5	2	2	2	4	2	1	1	2	10	8	1	3	3	1	2	4	2	12	9	3	4	2	3	1	1	3	3	3	4
	82	83	84	86	87	89	90	91	92	94	96	99	101	103	104	105	108	109	110	111	112	113	114	118	121	123	124	125	126	127
	20	10	10	2	2	1	1	1	1	1	1	1	1	1	1	3	1	1	1	10	1	2	2	1	3	1	12	3	4	2
	128	129	130	132	133	134	135	137	139	140	141	142	143	145	148	151	152	154	155	156	157	159	160	161	162	163	164	169	170	172
	6	1	1	3	1	3	1	8	2	2	2	4	4	1	3	1	1	2	1	7	1	4	3	4	2	2	3	1	2	1
	173	175	176	178	179	182	184	185	186	188	189	191	192	193	194	195	196	197	199	200	201	202	203	205	206	207	208	209	211	213
	2	1	1	3	1	24	2	6	3	3	7	1	2	8	3	2	2	8	4	2	3	12	2	3	2	3	1	6	1	2
	214	216	217	220	223	224	225	227	228	230	233	235	240	245	249	256	261	269	277	283	284	294	296	298	310	311	320	327	328	333
	1	4	1	3	1	2	3	2	1	1	1	1	1	1	1	3	1	2	10	1	1	1	2	1	1	1	4	1	1	1
	337	343	346	354	358	365	370	377	379	384	396	410	418	420	467	512	538	555												
	1	1	1	7	1	1	1	2	2	2	1	1	1	2	1	1	1	1	1											

Figure 7.6: Summary of texture rate

```
> xtabs(~release_price,data=data)
```

release_price	23	49	55	59	67	69	79	80	89	99	99.99	109	109.99	110	114
	1	1	1	3	1	6	4	1	7	9	1	9	6	1	1
	115	119	119.99	120	127	129	129.99	130	132	135	139	139.99	140	145	149
	1	1	5	18	1	2	7	10	1	3	1	2	5	1	12
	149.99	150	154	159	160	165	169	170	174	179	180	184	185	199	199.99
	2	9	2	4	6	1	5	1	2	7	1	1	10	22	3
	200	203	206	209	209.99	210	214	215	218	219	219.99	220	221	224	229
	28	1	1	3	3	3	1	1	1	2	2	8	2	1	9
	229.99	230	235	235.02	239	239.99	240	243.44	245	249	249.99	250	255	259.99	260
	3	2	1	1	4	1	11	1	3	10	6	15	1	2	2
	265	269	269.99	270	278	279	279.99	289	289.99	292	298	299	299.99	300	300.64
	1	2	1	3	1	5	1	1	4	1	3	9	3	1	1
	318	319.49	320	329	329.99	330	339	339.99	349	349.99	358	359	359.99	369	369.99
	2	1	2	7	4	1	1	1	6	3	1	1	1	2	1
	370	379	380	398	399	400	419	429	430	438	439	449	449.99	450	458
	1	4	1	3	6	1	3	2	1	2	1	7	1	4	1
	480	485	499	500	549	549.99	559	560	569.99	579.99	585	590	599	609	619
	1	2	6	1	3	4	1	1	3	3	2	2	4	1	1
	649	649.99	658	659.98	669	679	690	699	699.99	719	749	779	799	799.99	829
	14	1	2	1	3	3	1	17	3	1	2	1	1	2	1
	858	988	999	999.99	1029.99	1099	1099.98	1158	1159.98	1199	1249	1298	1299	1499	1998
	1	1	8	1	1	1	1	1	1	4	1	2	2	2	1
	2059	2999	14999												
	1	2	1												

Figure 7.7: Summary of release price

4 DESCRIPTIVE STATISTICS

4.1. GPU prices in the market through a histogram table

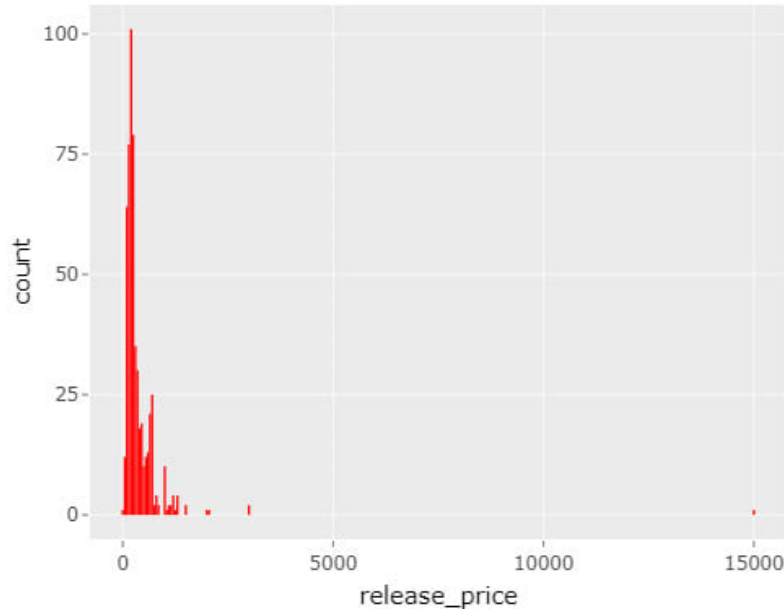


Figure 8: Histogram table for GPU release price

Remark: From this histogram chart, we can see there is only one GPU that approximately has the cost about 15,000\$. Other than that, most of the release price is about 0\$ to 1000\$, and the mode is in the range from 40\$ to 100\$.

4.2. Scatter plots for the relationship between factors influencing GPU prices

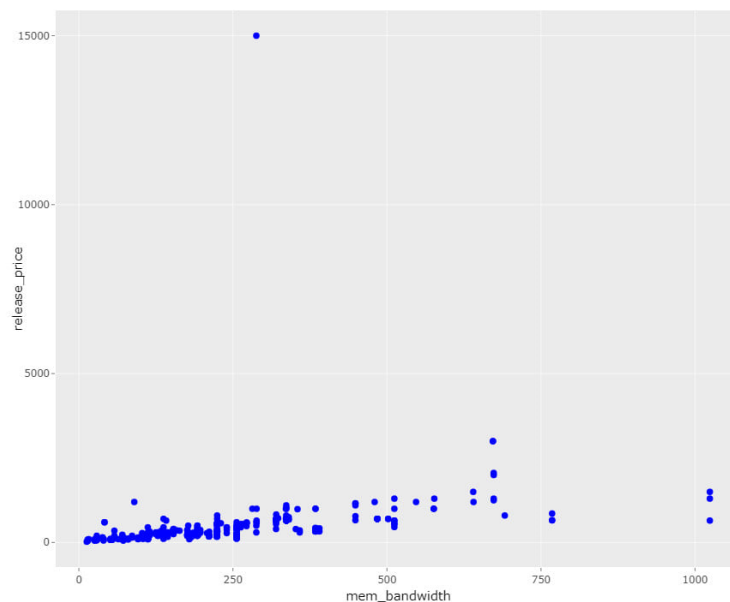


Figure 9: Scatter plot for relationship between memory bandwidth and release price

Remark: As the memory bandwidth is in the range from 0 to 1200 bytes/sec, mostly memory bandwidth in the market will have the value from 10 bytes/sec to 300 bytes/sec, and the value is in the range from 10\$ to 1000\$. Moreover, this graph can use linear regression to predict the cost if we are given the value of memory bandwidth.

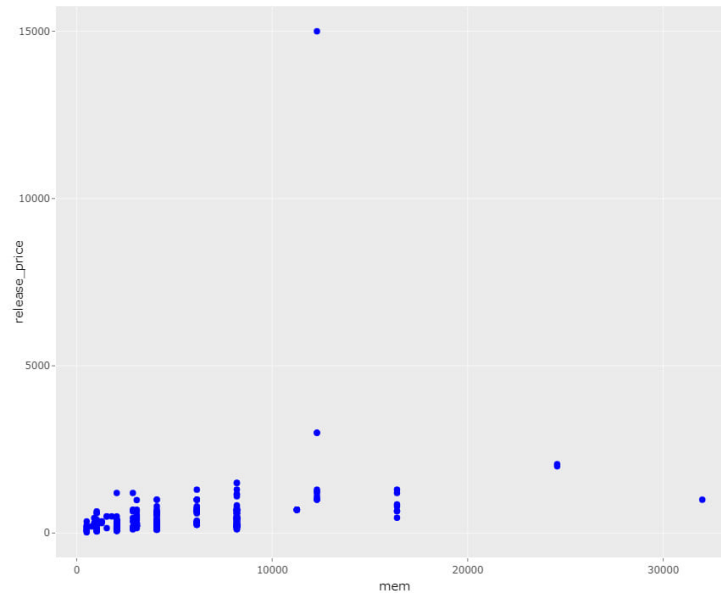


Figure 10: Scatter plot for relationship between memory and release price

Remark: From the scatter plot above, we can see that in the market there are only available some specific sizes of memory. Moreover, most of the price of GPUs is in the range from 10\$ to 1000\$, too.

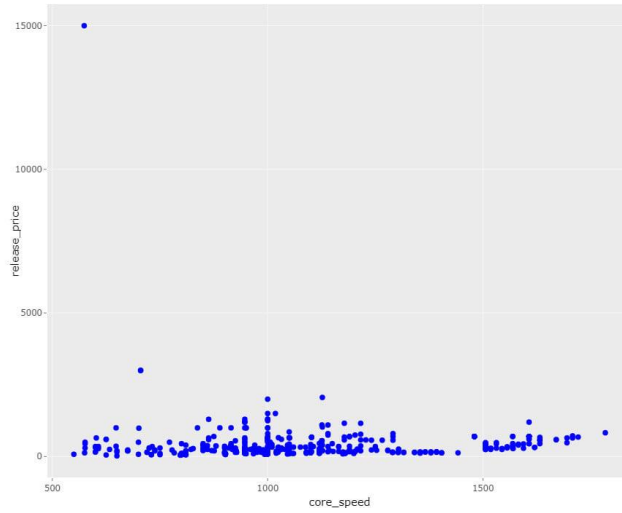


Figure 11: Scatter plot for relationship between core speed and release price

Remark: We can see that the relationship between core speed and release price is unable to be clearly demonstrated, as the dots are randomly distributed.

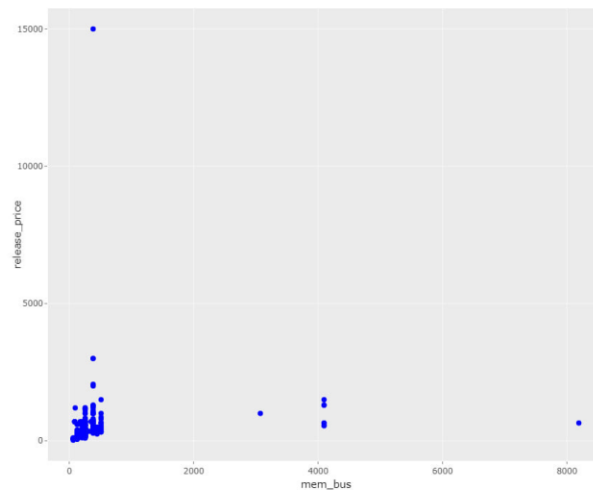


Figure 12: Scatter plot for relationship between memory bus and release price

Remark: Same with memory, memory bus is available in the market with only some specific sizes. From the table above, the size of memory bus is from 16 Bit to 512 Bit or 4096 Bit; and the cost mostly would be lower than 1000\$.

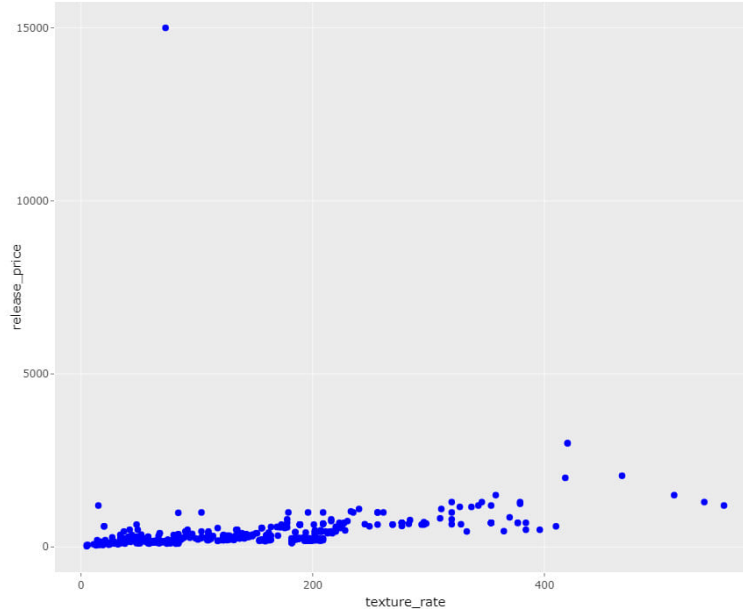


Figure 13: Scatter plot for relationship between texture rate and release price

Remark: As the texture rate is in the range from 0 to 600 GTexel/sec, mostly texture rate in the market will have the value from 10 GTexel/sec to 400 GTexel/sec. Moreover, this graph can use linear regression to predict the cost if we are given the value of texture rate.

5 INFERENCE STATISTICS

5.1. Introduction

Our task is to build a model for the factors influencing the variable Release_Price, where the variable we are interested in ("Release_Price") is the dependent variable and the remaining variables are considered independent variables.

$$\text{Release_Price} = \mathbf{b}_0 + \mathbf{b}_1 \times \text{Core_Speed} + \mathbf{b}_2 \times \text{Memory} + \mathbf{b}_3 \times \text{Memory_Bandwidth} \\ + \mathbf{b}_4 \times \text{Memory_Bus} + \mathbf{b}_5 \times \text{Memory_Speed} + \mathbf{b}_6 \times \text{Texture_Rate} + \boldsymbol{\epsilon}$$

Before constructing the model, we begin by splitting the dataset into 2 new datasets according to the variable Release_Price, as following:

The first set which contains 556 observations with known Release_Price is used to find the formula of the variable of interest Release_Price based on related factors.

The second which contains the 2850 other observations with known Release_Price is used to predict the Release_Price.

5.2. Processing the data

After splitting the dataset, our task is to build a suitable model to describe the factors affecting our targeted variable `Release_Price`.

We statistically analyze values with the quantity of values, as following:

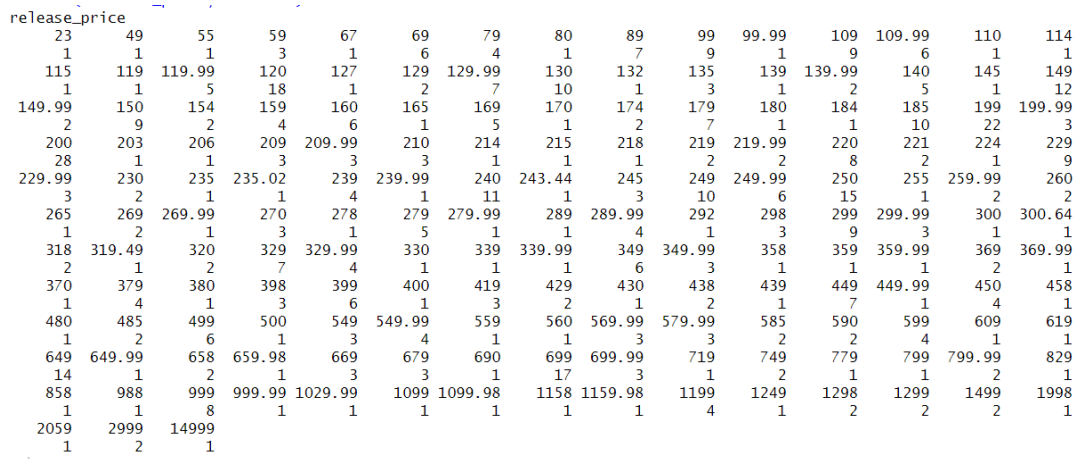


Figure 14

After that, we proceed to filter out outlier values by using STD method. (*R-Code below*)

```
mean_data <- mean(data$release_price)
std_data <- sd(data$release_price)
limit = 3*std_data
lower = mean_data - limit
upper = mean_data + limit
data = data[data$release_price < upper & data$release_price > lower, ]
View(data)
```

Then we only have the dataset of 553 observations (2999 and 14999 are been eliminated)

	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
43	946.8939	2872.769	480.0000	384.0000	1250	1199.00	343
46	946.8939	12288.000	547.2000	96.0000	1425	1199.00	354
52	1140.0000	12288.000	336.6000	384.0000	1753	1099.00	240
53	1127.0000	24576.000	673.2000	384.0000	1753	2059.00	467
55	1000.0000	24576.000	673.2000	384.0000	1753	1998.00	418
56	1000.0000	12288.000	336.6000	384.0000	1753	999.00	209
57	1127.0000	12288.000	336.6000	384.0000	1753	1029.99	233
60	1000.0000	12288.000	384.0000	3072.0000	500	999.00	320
62	1000.0000	16384.000	512.0000	4096.0000	500	1299.00	320
66	889.0000	6144.000	336.0000	384.0000	1750	999.00	235
69	837.0000	6144.000	288.4000	384.0000	1502	999.00	196
171	960.0000	1024.000	134.4000	256.0000	1050	249.00	38
173	850.0000	1024.000	124.8000	256.0000	975	249.00	34
184	575.0000	512.000	57.6000	256.0000	900	130.00	18

Figure 15

5.3. Splitting the dataset

Before constructing the model, we begin by splitting the first dataset containing a total of 553 observation values into two new datasets as follows:

- Set A (Training set) contains 70% of the data, corresponding to 387 observation values.
- Set B (Test set) contains 30% of the data, corresponding to 166 observation values.

Set A is used to find the formula, while set B is used to test that formula.

5.4. The initial model

There are 6 factors affecting our targeted variable Release_Price, including Core_Speed, Memory, Memory_Bandwidth, Memory_Bus, Memory_Speed, Texture_Rate. (*R-Code below*)

```
Call:
lm(formula = release_price ~ core_speed + mem + mem_bandwidth +
    mem_bus + mem_speed + texture_rate, data = train)

Residuals:
    Min       1Q   Median       3Q      Max
-476.23  -97.52   -3.77   52.03  911.21

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  287.506651   48.531148   5.924 7.04e-09 ***
core_speed    0.050274    0.044528   1.129 0.25959
mem           0.010543    0.004056   2.599 0.00971 **
mem_bandwidth 1.392975    0.166490   8.367 1.14e-15 ***
mem_bus      -0.112577    0.019889  -5.660 2.98e-08 ***
mem_speed    -0.245761    0.026959  -9.116 < 2e-16 ***
texture_rate  0.480190    0.227044   2.115 0.03508 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 160.7 on 380 degrees of freedom
Multiple R-squared:  0.6853,    Adjusted R-squared:  0.6803
F-statistic: 137.9 on 6 and 380 DF,  p-value: < 2.2e-16
```

Figure 16

At a glance, we see that the $\Pr(>|t|)$ value of variable Core_Speed is too large, which means the impact of Core_Speed on Release_Price is not significant (*Figure below shows it*). Hence, we decide to eliminate that variable.

```
> summary(reg)$coefficient
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  287.50665126 48.53114768  5.924168 7.036754e-09
core_speed    0.05027433  0.04452775  1.129056 2.595864e-01
mem           0.01054307  0.00405631  2.599178 9.708659e-03
mem_bandwidth 1.39297486  0.16649036  8.366700 1.143006e-15
mem_bus       -0.11257671  0.01988938 -5.660142 2.983931e-08
mem_speed     -0.24576054  0.02695940 -9.115950 4.574299e-18
texture_rate  0.48018967  0.22704370  2.114966 3.508329e-02
> |
```

Figure 17

5.5. The improved model

After removing the variable Core_Speed, we have the new model:

```
Call:
lm(formula = release_price ~ mem + mem_bandwidth + mem_bus +
    mem_speed + texture_rate, data = train)

Residuals:
    Min       1Q   Median       3Q      Max
-473.31  -98.54    0.04   51.52   921.34

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  319.263653  39.563498   8.070 9.30e-15 ***
mem           0.011067   0.004031   2.745  0.00633 **
mem_bandwidth 1.330157   0.156975   8.474 5.26e-16 ***
mem_bus       -0.108309   0.019534  -5.545 5.51e-08 ***
mem_speed     -0.234933   0.025205  -9.321 < 2e-16 ***
texture_rate  0.586546   0.206655   2.838  0.00478 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 160.7 on 381 degrees of freedom
Multiple R-squared:  0.6842,    Adjusted R-squared:  0.6801
F-statistic: 165.1 on 5 and 381 DF,  p-value: < 2.2e-16
```

Figure 18

According to the fact that p-value is not really noticeable (2.2×10^{-16}) and the insignificant difference between the adjusted R-squared of the improved model and the initial model, we can conclude that the data is accurate and this improved model is suitable one.

5.6. Conducting the formula

According to the improved model above, we form a linear regression model, in which the independent variables affect the dependent variable Release_Price. The equation for this model:

$$\text{Release_Price} = 319.263653 + 0.011067 \times \text{Memory} + 1.330157 \times \text{Memory_Bandwidth} - 0.108309 \times \text{Memory_Bus} - 0.234933 \times \text{Memory_Speed} + 0.586546 \times \text{Texture_Rate}$$

The R-code below shows how we predict the unknown value.

```
install.packages("Metrics")
library(Metrics)
data_1 = data.frame(train)
y = data_1$release_price
x = predict(reg)
plot(x,y,xlim = c(0,1500),ylim = c(0,1500),xlab = 'Predicted value',ylab =
      'Actual value',main = 'Relationship between predicted and actual value')

View(test)
actual <- test$release_price
predictions <- predict(reg, newdata = test)
actual <- test$release_price
rmse <- sqrt(mean((predictions - actual)^2))
rmse

data_range <- range(test)
data_range

data_range <- range(test$release_price)
data_range
```

Figure 19

5.7. Testing the formula

In the previous session, we have conducted an equation illustrating the dependence of Release_Price on other factors:

$$\text{Release_Price} = 319.263653 + 0.011067 \times \text{Memory} + 1.330157 \times \text{Memory_Bandwidth} - 0.108309 \times \text{Memory_Bus} - 0.234933 \times \text{Memory_Speed} + 0.586546 \times \text{Texture_Rate}$$

In this session, to test the aforementioned equation, we apply the equation to the set B (test set) and compare the predicted values (using equation) to the actual values (given data). Figure 20 is used to describe that comparison.

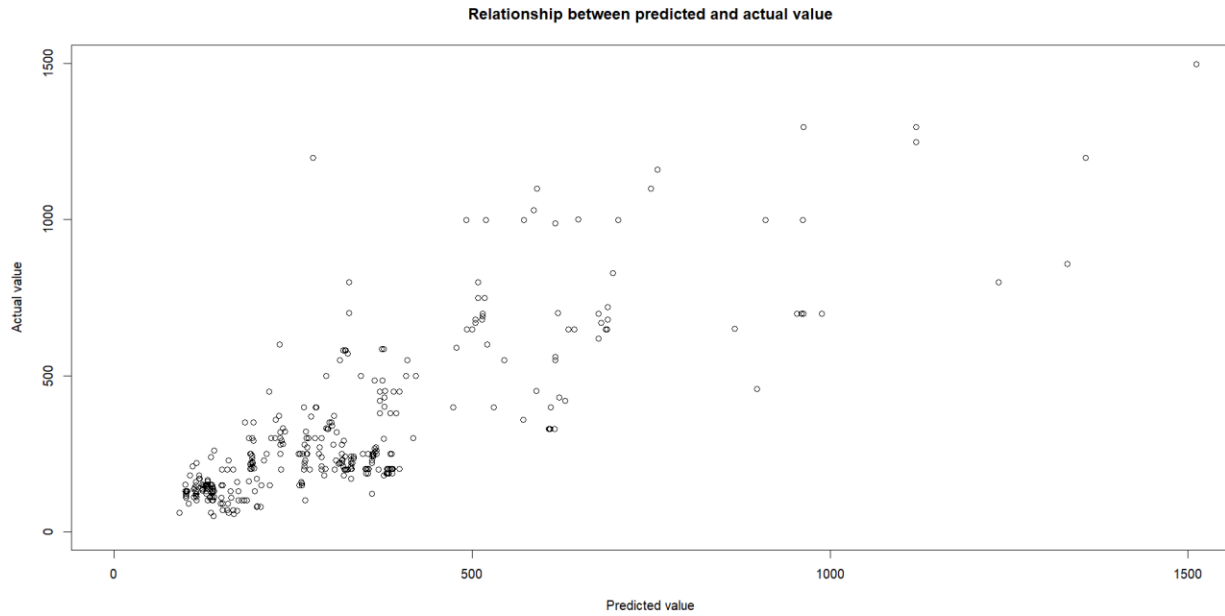


Figure 20

Remark: The horizontal ordinates represent predicted values, while the vertical ordinates represent the actual values. We can observe that these points are on or near the line $y=x$, that means the predicted values (using conducted formula) approximately equal to the actual values. In conclusion, the we can use the formula to predict the unknown Release_Price of second dataset.

5.8. Predicting

The given chart below shows the prediction for unknown Release_Price values:

	core_speed	mem	mem_bandwidth	mem_bus	mem_speed	release_price	texture_rate
1	738.0000	1024.000	64.0000	256.0000	1000.000	180.6339	47.00000
2	946.8939	512.000	106.0000	512.0000	828.000	222.9864	12.00000
3	946.8939	512.000	51.2000	256.0000	800.000	183.2260	10.00000
4	946.8939	256.000	36.8000	128.0000	1150.000	91.1159	7.00000
5	946.8939	256.000	22.4000	128.0000	700.000	177.0949	6.00000
6	946.8939	256.000	35.2000	128.0000	1100.000	100.1478	6.00000
7	870.0000	2048.000	134.4000	256.0000	1050.000	266.8243	35.00000
8	946.8939	256.000	51.2000	256.0000	800.000	178.6332	7.00000
9	946.8939	2048.000	160.0000	256.0000	1250.000	269.7265	62.00000
10	946.8939	64.000	2.9000	64.0000	366.000	283.8624	90.27463
11	946.8939	128.000	5.2000	128.0000	325.000	238.5534	2.00000
12	650.0000	6144.000	177.6000	384.0000	925.000	385.7072	36.00000
13	705.0000	5120.000	168.0000	320.0000	1050.000	371.0048	90.27463
14	706.0000	12288.000	288.4000	384.0000	1502.000	543.5385	169.00000
15	946.8939	64.000	5.8000	128.0000	360.000	282.1976	90.27463
16	1050.0000	3072.000	57.6000	128.0000	900.000	240.9411	62.00000
17	946.8939	8192.000	320.0000	512.0000	1250.000	539.4045	90.27463
18	732.0000	6144.000	249.6000	384.0000	1300.000	425.2132	90.27463

Figure 21

5.9. Conclusion

After employing multiple linear regression method, the team identified significant factors influencing the retail price of the product, and we have derived a model equation to predict GPU prices based solely on measuring 6 indices (Core_Speed, Memory, Memory_Speed, Memory_Bandwidth, Memory_Bus, Texture_Rate). This model will assist both buyers and sellers in assessing the suitability of the retail cost for this product. Therefore, the model has somewhat attracted potential customers to the product and simultaneously supported the manufacturer in pricing the product.

Overall, the retail price of GPUs after using the model is relatively consistent with the original prices.

Furthermore, it is easy to observe that if the values of variables "Memory", "Memory_Bandwidth", "Memory_Bus" and "Texture_Rate" increase, the value of "Release_Price" will also increase. This implies that the retail prices of GPUs are directly proportional to the mentioned variables, while the remaining variables will be inversely proportional to the GPU retail price.

6 DISCUSSION AND EXPANSION

ADVANTAGE:

- Multiple linear regression allows us to analyze the effects of multiple independent variables on a dependent variable. This helps us to determine the relative importance of each independent variable in predicting the dependent variable
- By using 6 key factors impacting the dependent variable “Release_Price”, we were able to predict selling price of GPUs

LIMITATIONS:

- It is necessary to have 6 required variables for the model to work optimally
- To make the model work efficiently, it is necessary to remove outliers, which are observation values significantly different from other observation values in the dataset, as they may influence relationship between predictor variable and dependent variable and lead to inaccurate predictions

7 CONCLUSION

Our team identified significant factors influencing the selling price of the product, and we obtained a model equation to predict GPU prices by measuring 6 variables by using multiple linear regression method. The model helped potential customers consider this product and simultaneously supported the manufacturer in pricing the product.

Overall, the retail price of GPUs after using the model is relatively appropriate compared to the original price. Additionally, if the values of the variables "Memory," "Memory_Bandwidth," and "Texture_Rate" increase, the value of "Release_Price" will also increase. This means that the selling price of GPUs will be directly proportional to those variables, while the remaining variables will be inversely proportional to the GPU's selling price.

8 DATA & CODE SOURCE

8.1. Data source

<https://www.kaggle.com/datasets/iliassekkaf/computerparts?resource=download>

8.2. Code source

[https://drive.google.com/drive/folders/1oDNnHuHQRdTt1pWjedP4onzRmtp9Dr8?usp=share link](https://drive.google.com/drive/folders/1oDNnHuHQRdTt1pWjedP4onzRmtp9Dr8?usp=share_link)

REFERENCES

1. Card màn hình (VGA) và các thông số quan trọng thường gặp, truy cập từ <https://gearvn.com/pages/card-man-hinh-va-cac-thong-so-quan-trong-thuong-gap>
2. Douglas C.Montgomery & George C.Runger, *APPLIED STATISTICS AND PROBABILITY FOR ENGINEERS 6TH EDITION*.
3. *GRAPHICS PROCESSING UNIT*, truy cập từ https://en.wikipedia.org/wiki/Graphics_processing_unit
4. Ilissek, *COMPUTERS PARTS(CPUs and GPUs)*, truy cập từ <https://www.kaggle.com/datasets/iliassekkaf/computerparts/data>
5. Nguyễn Tiên Dũng (eds.), Nguyễn Đình Huy, *Xác suất – Thống kê & Phân tích số liệu*, 2019.
6. *ORDINARY LEAST SQUARES*, truy cập từ https://en.wikipedia.org/wiki/Ordinary_least_squares

