Sales transactions

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```
sales = read.csv("SalesJan2009.csv")
sales$Price <- as.numeric(sales$Price)
```

For this assignment we found dataset of the sales carried out in January 2009. The data is about 3 main products, where and who bought them and how much it costs. In the dataset you can find the following data: transaction date, the product that was purchased, the price of the product, the payment type, the name of the person who bought the product, The city state and country where the purchase was made, the latitude and the longitude of the place where the purchase was made. Payment type: Amex=1 Diners=2 Mastercard=3 Visa=4

```
summary(sales)
```

```
##      Product    Transaction_date   ProductNum        Price
##  Product1:847   Min.   : 1.00    Min.   :1.000   Min.   :  250
##  Product2:136   1st Qu.: 7.00    1st Qu.:1.000   1st Qu.: 1200
##  Product3: 15   Median :14.00    Median :1.000   Median : 1200
##                 Mean   :14.94    Mean   :1.166   Mean   : 1634
##                 3rd Qu.:22.75    3rd Qu.:1.000   3rd Qu.: 1200
##                 Max.   :31.00    Max.   :3.000   Max.   :13000
##
##   Payment_Type      Latitude        Longitude             Name
##  Min.   :1.000   Min.   :-41.47   Min.   :-159.485   Sarah    : 11
##  1st Qu.:3.000   1st Qu.: 35.82   1st Qu.: -87.992   Elizabeth:  9
##  Median :4.000   Median : 42.32   Median : -73.731   Lisa     :  9
##  Mean   :3.213   Mean   : 39.02   Mean   : -41.338   Nicole   :  8
##  3rd Qu.:4.000   3rd Qu.: 51.05   3rd Qu.:   4.917   Kim      :  7
##  Max.   :4.000   Max.   : 64.84   Max.   : 174.767   Jessica  :  6
##                                                      (Other)  :948
##                             City          State             Country
##  London                       : 19   England: 86   United States :463
##  Calgary                      : 11   CA     : 66   United Kingdom:100
##  Den Haag                     :  9   NY     : 41   Canada        : 76
##  New York                     :  9   TX     : 37   Ireland       : 49
##  Vancouver                    :  8   VA     : 30   Australia     : 38
##  Houston                      :  7   FL     : 29   Switzerland   : 36
##  (Other)                      :935   (Other):709   (Other)       :236
```

Here you can see a sample of the data

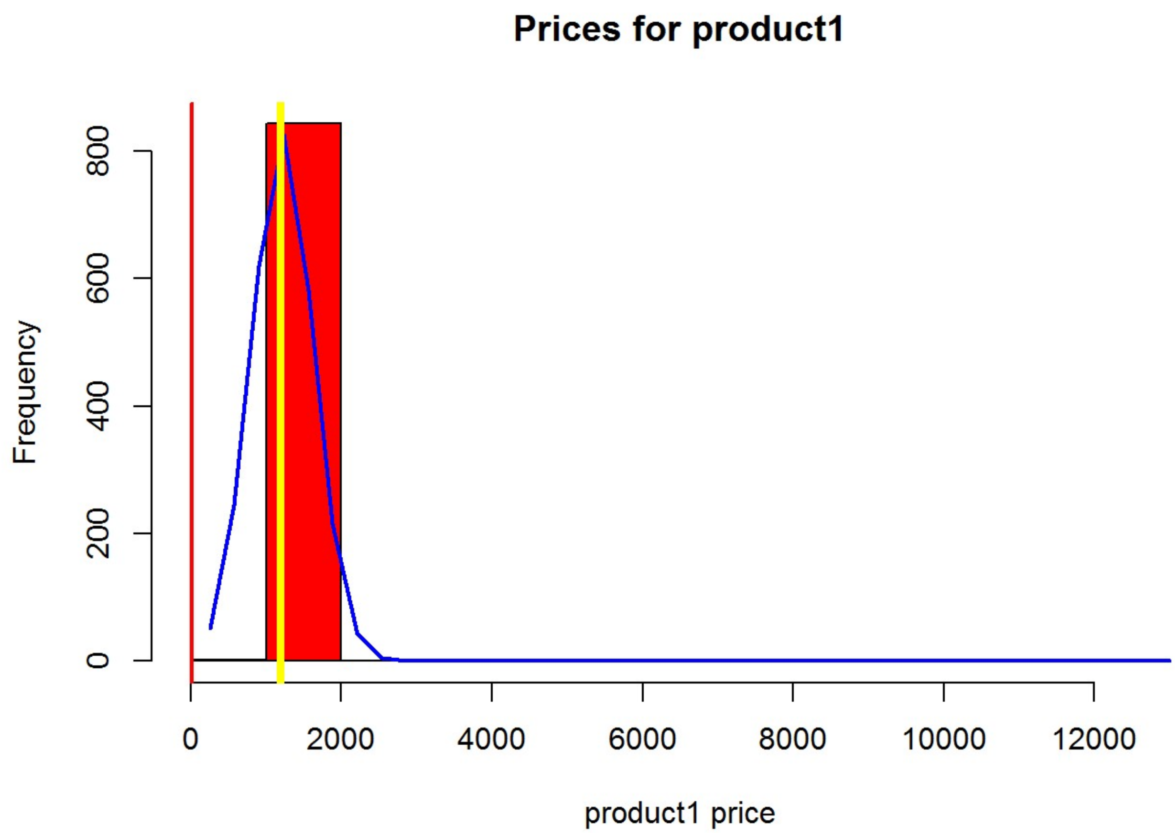
```
head(sales)
```

```
##    Product Transaction_date ProductNum Price Payment_Type  Latitude
## 1 Product1                1          1  1200            3  51.50000
## 2 Product1                2          1  1200            4  39.19500
## 3 Product1                2          1  1200            3  46.18806
## 4 Product1                3          1  1200            4 -36.13333
## 5 Product1                4          1  1200            4  39.79000
## 6 Product1                4          1  1200            3  40.69361
##     Longitude             Name                           City    State
## 1   -1.116667          carolina                     Basildon  England
## 2  -94.681940            Betina Parkville                           MO
## 3 -123.830000 Federica e Andrea Astoria                             OR
## 4  144.750000             Gouya                         Echuca Victoria
## 5  -75.238060          LAURENCE Mickleton                           NJ
## 6  -89.588890             Fleur Peoria                              IL
##          Country
## 1 United Kingdom
## 2  United States
## 3  United States
## 4      Australia
## 5  United States
## 6  United States
```

The data analysis

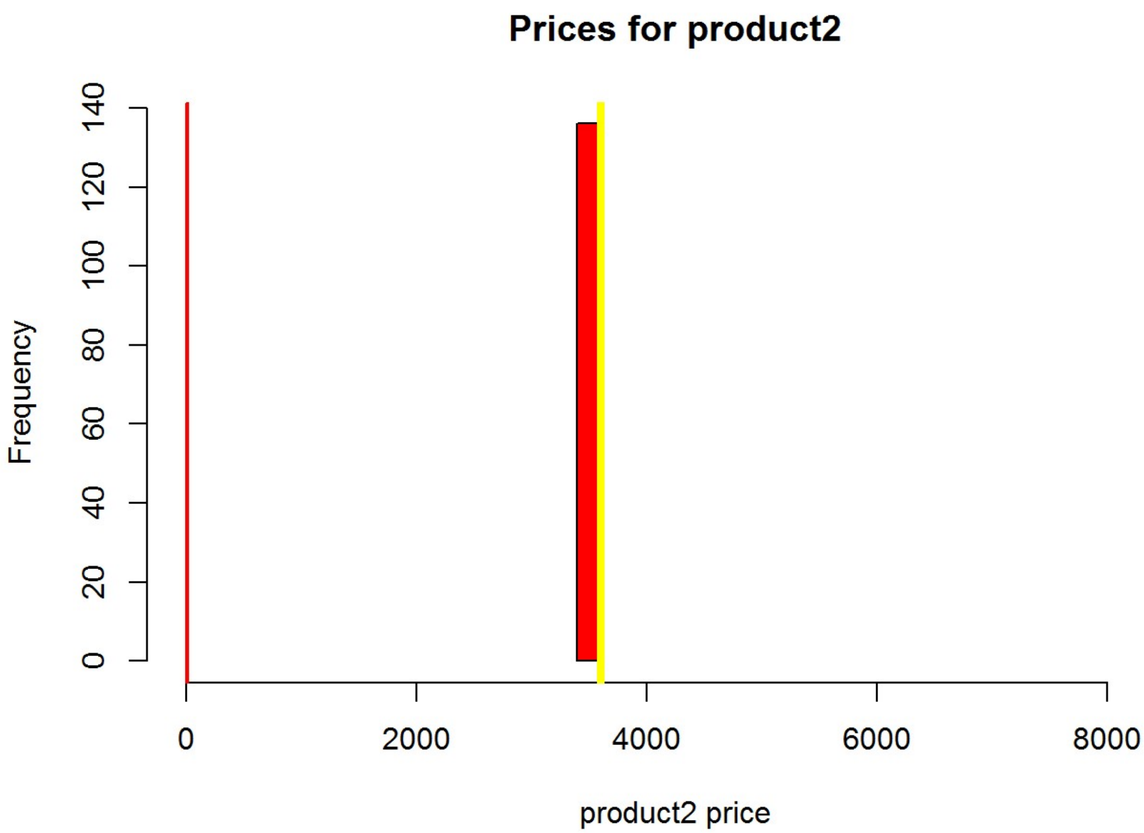
Frequency of each product price

```
p1<-subset(sales,Product=="Product1")$Price
h<-hist(p1, breaks=10, col="red", xlab="product1 price",main="Prices for produc
t1")
xfit<-seq(min(p1),max(p1),length=40)
yfit<-dnorm(xfit,mean=mean(p1),sd=sd(p1))
yfit <- yfit*diff(h$mids[1:2])*length(p1)
lines(xfit, yfit, col="blue", lwd=2)
abline(v=12,lwd=2,col="red")
abline(v=median(p1),lwd=4,col="yellow")
```



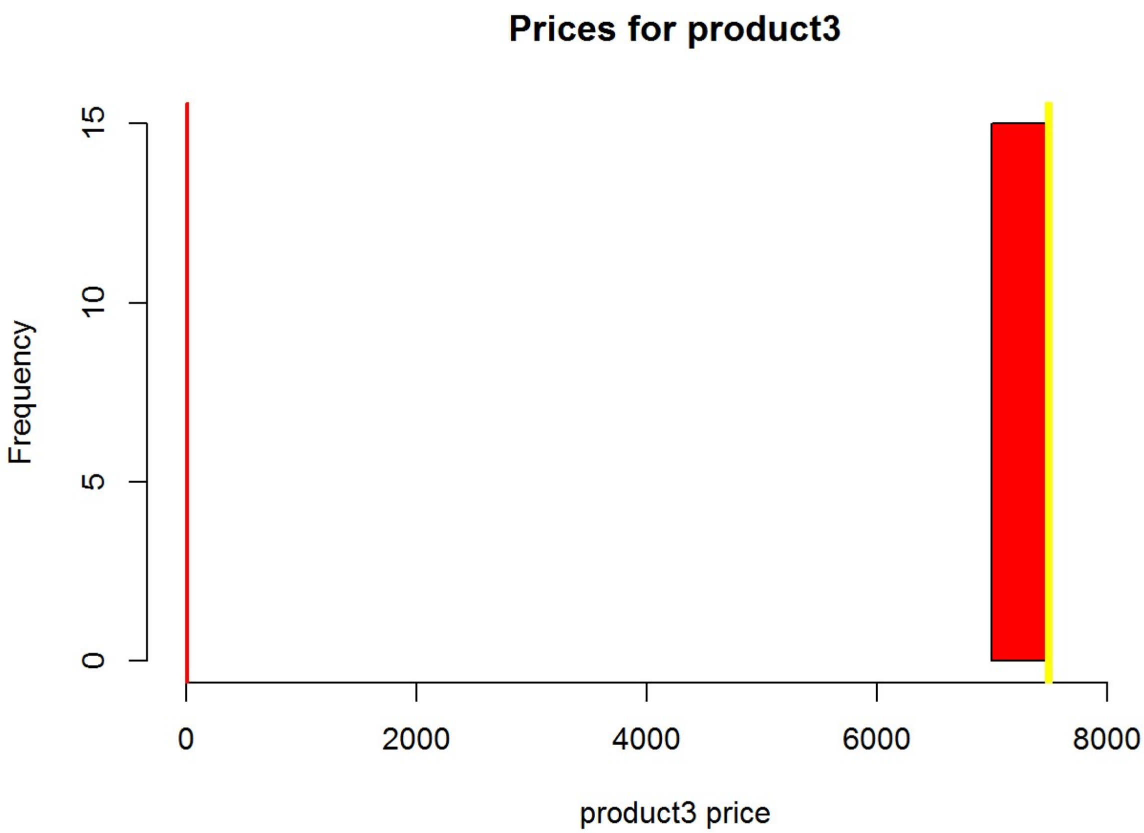
As we can see, for product1, we have variety of prices.

```
p2<-subset(sales,Product=="Product2")$Price
h<-hist(p2, breaks=10, col="red", xlab="product2 price",main="Prices for produc
t2", xlim = c(0,8500))
xfit<-seq(min(p2),max(p2),length=40)
yfit<-dnorm(xfit,mean=mean(p2),sd=sd(p2))
yfit <- yfit*diff(h$mids[1:2])*length(p2)
lines(xfit, yfit, col="blue", lwd=2)
abline(v=12,lwd=2,col="red")
abline(v=median(p2),lwd=4,col="yellow")
```



As we can see, for product2, we have only on price

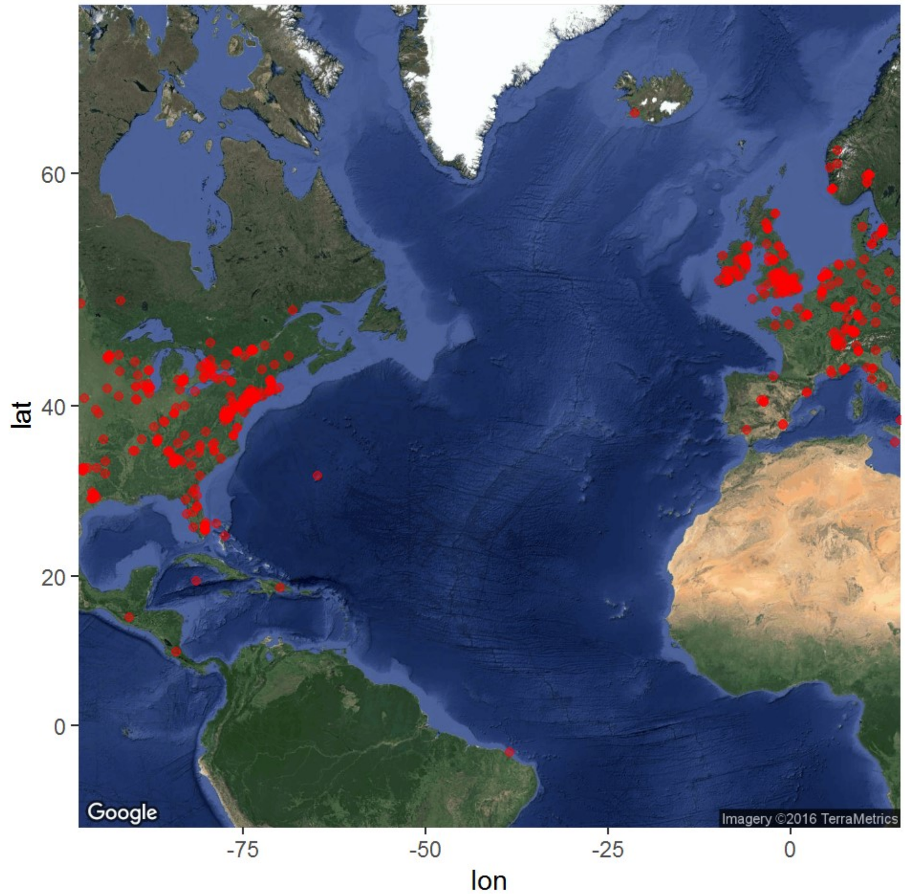
```
p3<-subset(sales,Product=="Product3")$Price
h<-hist(p3, breaks=10, col="red", xlab="product3 price",main="Prices for produc
t3", xlim = c(0,8500))
xfit<-seq(min(p3),max(p3),length=40)
yfit<-dnorm(xfit,mean=mean(p3),sd=sd(p3))
yfit <- yfit*diff(h$mids[1:2])*length(p3)
lines(xfit, yfit, col="blue", lwd=2)
abline(v=12,lwd=2,col="red")
abline(v=median(p3),lwd=4,col="yellow")
```



As we can see, for product3, we have only on price

We want to explore more the prices for product1.

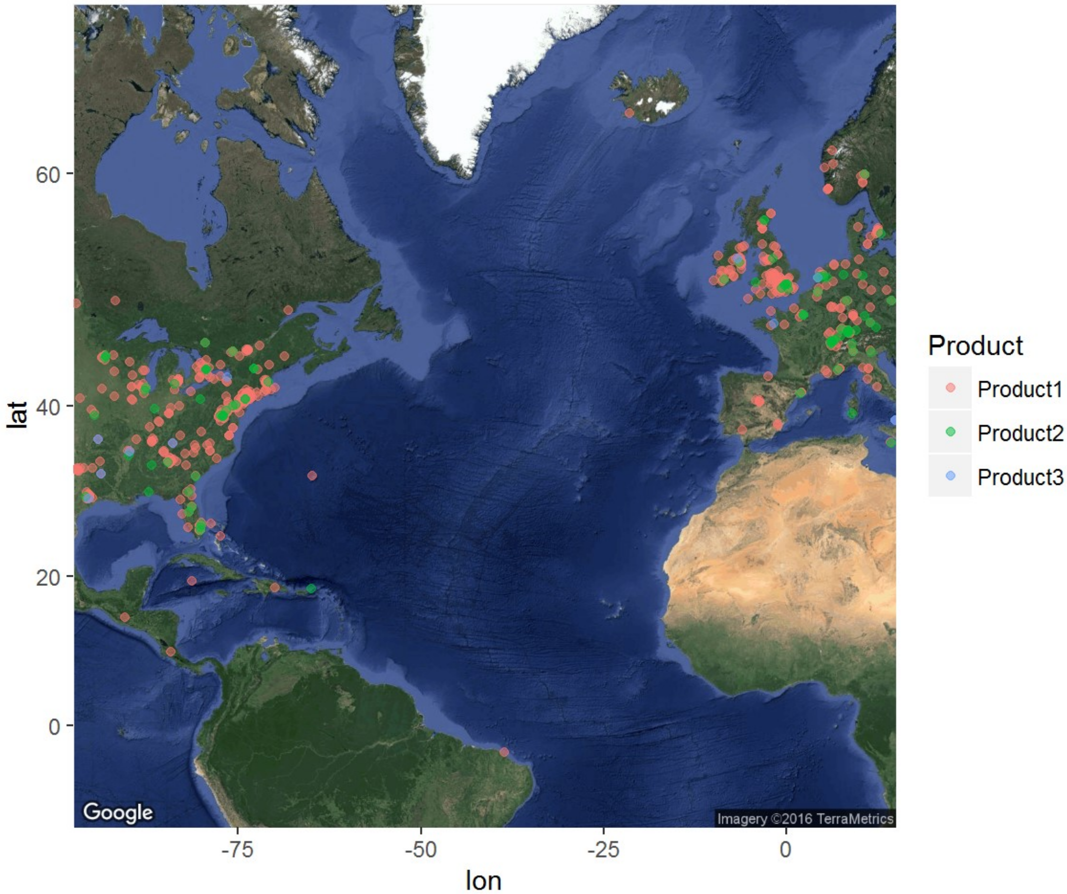
```
library(ggmap)
map <- get_map(location = c(lon = mean(sales$Longitude), lat = mean(sales$Latit
ude)), zoom = 3,maptype = "satellite", scale = 2)

map1<-subset(sales,Product=="Product1")
ggmap(map) + geom_point(data = map1, aes(x = Longitude, y = Latitude, Size=Pric
e , alpha = 0.5),colour="Red", fill="Red", alpha = 0.5)+ scale_size(range=c(3,2
0))
```



We can see in the map the way that the prices distribut across the world But every location as more than one price. so we can assume that the diffrent prices is not per place

Frequency of each product

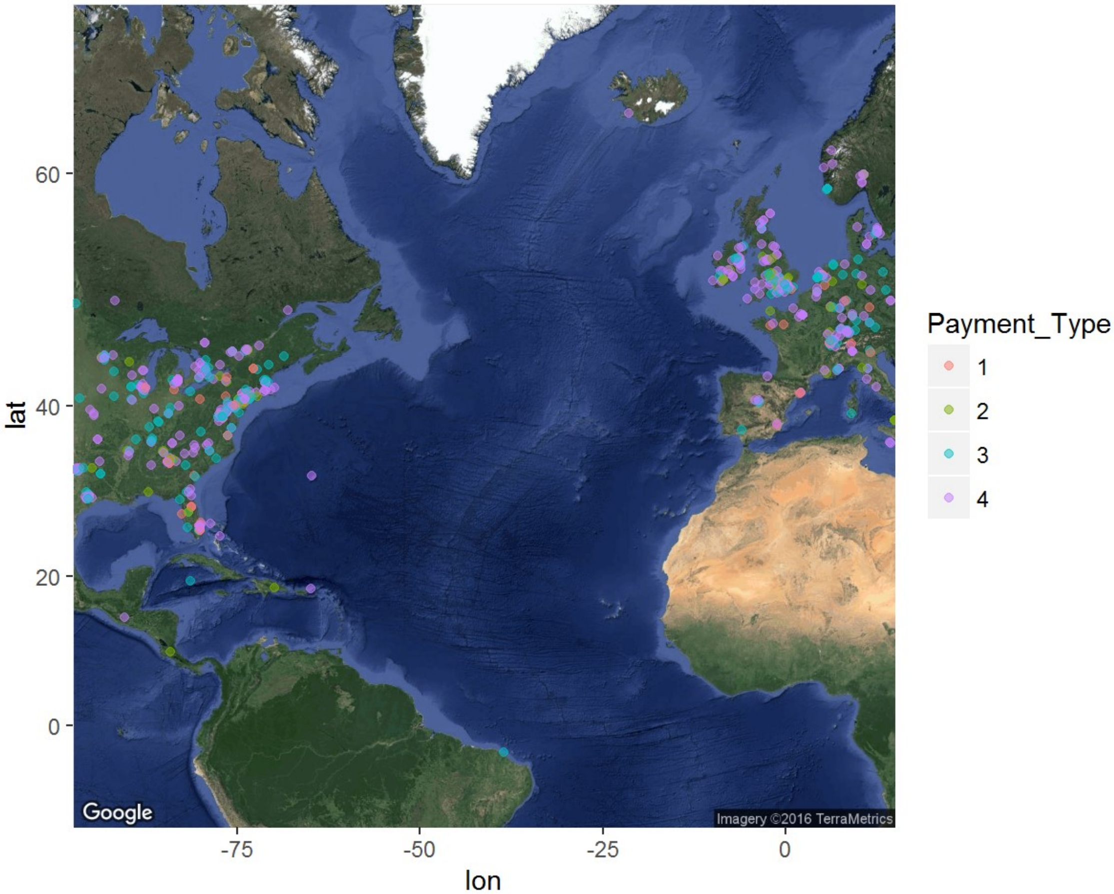
```
library(ggmap)
map <- get_map(location = c(lon = mean(sales$Longitude), lat = mean(sales$Latit
ude)), zoom = 3,maptype = "satellite", scale = 2)

ggmap(map) + geom_point(data = sales, aes(x = Longitude, y = Latitude, color=Pr
oduct , alpha = 0.5),size=1.5,alpha = 0.5)+ scale_size(range=c(3,20))
```



We can see that each product appear in more than one location and each location as more than one product.

Frequency of each payment type

```
library(ggmap)
sales$Payment_Type<-as.factor(sales$Payment_Type)
map <- get_map(location = c(lon = mean(sales$Longitude), lat = mean(sales$Latit
ude)), zoom = 3,maptype = "satellite", scale = 2)
ggmap(map) + geom_point(data = sales, aes(x = Longitude, y = Latitude, color=Pa
yment_Type , alpha = 0.5),size=1.5,alpha = 0.5)+ scale_size(range=c(3,20))
```




```
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```

We can see that eash location uses more than one payment type. But more people uses payment type 3 and 4(Mastercard and Visa).

Explore importance between attribute

By price:

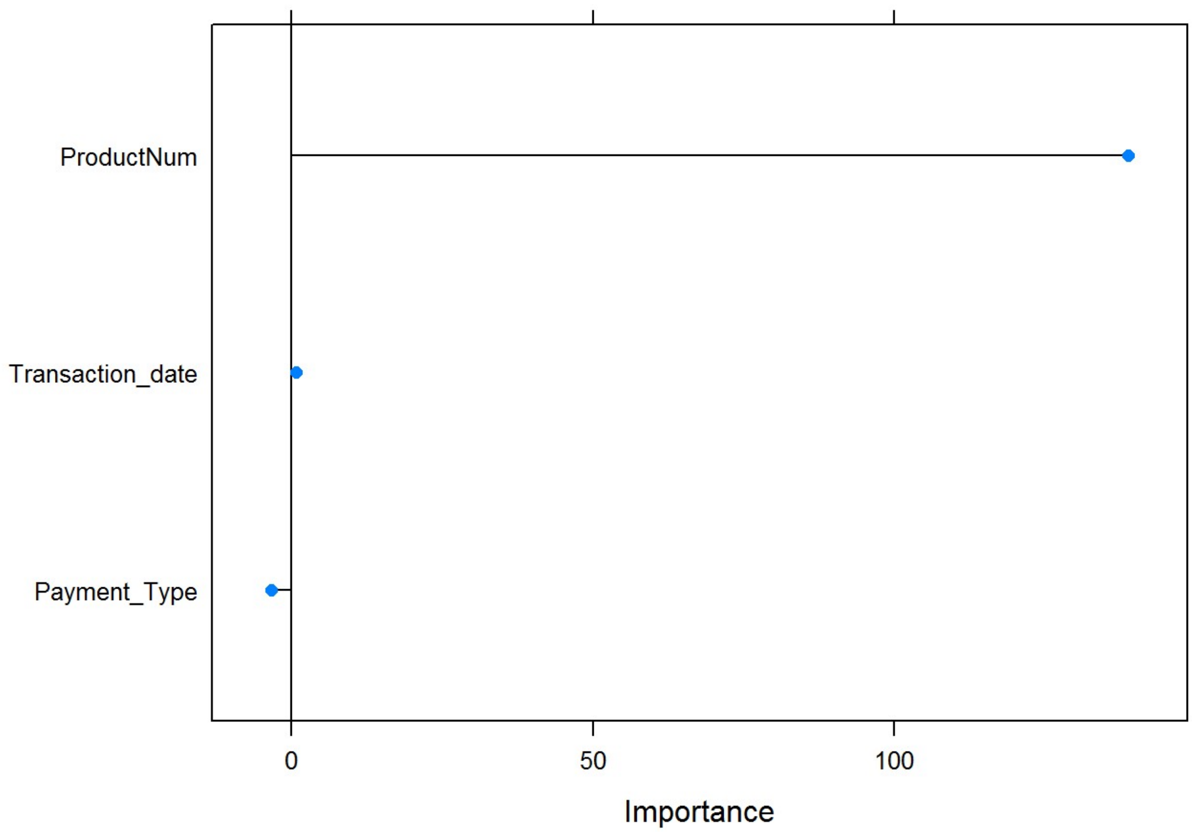
```
library(mlbench)
library(caret)
sales$Payment_type <- as.numeric(sales$Payment_Type)
data<-sales[2:5]
set.seed(7)
control<- trainControl(method = "repeatedcv",number = 10, repeats = 3)
model<-train(Price~.,data=data, method="rf" ,importance = TRUE)
```

```
## note: only 2 unique complexity parameters in default grid. Truncating the gr
id to 2 .
```

```
importance<-varImp(model,scale=FALSE)
print(importance)
```

```
## rf variable importance
##
##                   Overall
## ProductNum       138.7481
## Transaction_date   0.7408
## Payment_Type      -3.3036
```

```
plot(importance)
```



It shows that the product is the most important attribute. payment type attribute is the least important.

By product:

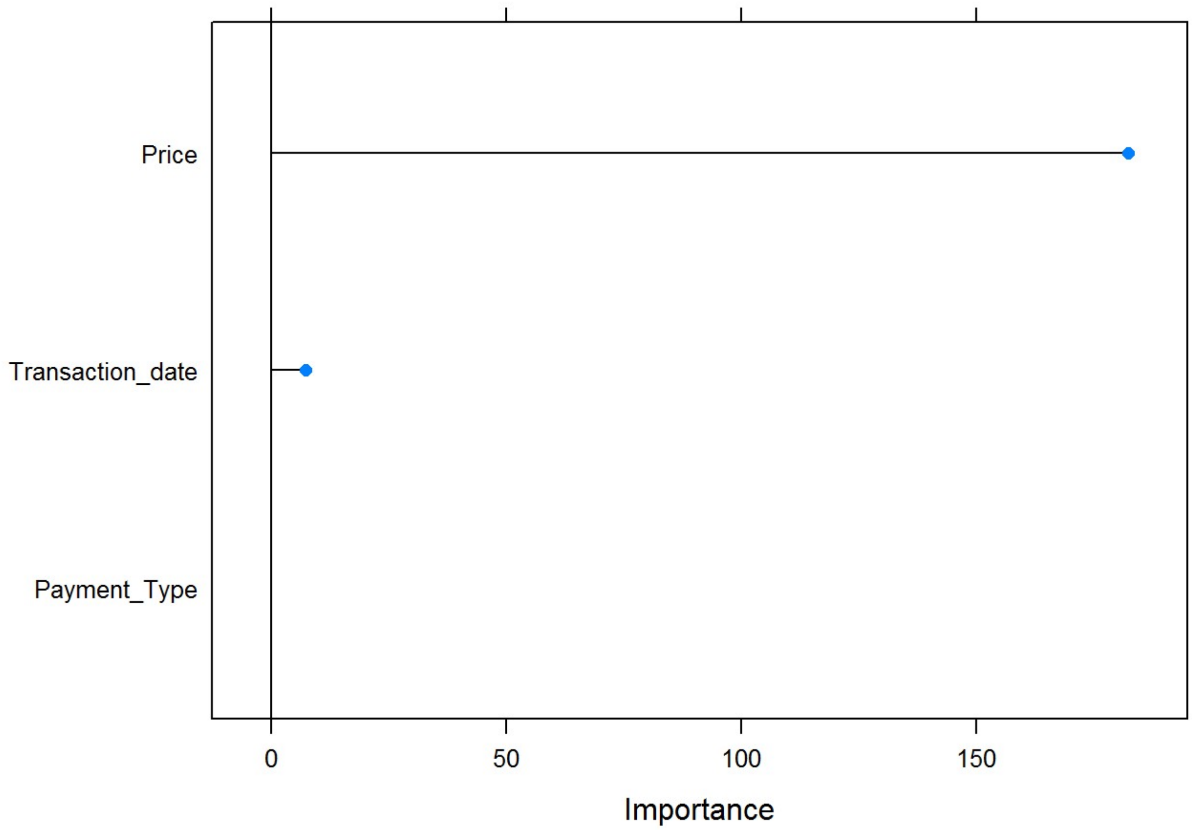
```
library(mlbench)
library(caret)
sales$Payment_type <- as.numeric(sales$Payment_Type)
data<-sales[2:5]
set.seed(7)
control<- trainControl(method = "repeatedcv",number = 10, repeats = 3)
model<-train(ProductNum~.,data=data, method="rf" ,importance = TRUE)
```

```
## note: only 2 unique complexity parameters in default grid. Truncating the gr
id to 2 .
```

```
importance<-varImp(model,scale=FALSE)
print(importance)
```

```
## rf variable importance
##
##                  Overall
## Price            182.197
## Transaction_date   7.311
## Payment_Type       0.000
```

```
plot(importance)
```



It shows that the price is the most important attribute. payment type attribute is the least important.

Explore correlation between attribute

```
set.seed(7)
correlationMatrix<-cor(sales[,2:5])
print(correlationMatrix)
```

```
##                  Transaction_date  ProductNum        Price Payment_Type
## Transaction_date       1.00000000  0.02305024  0.036803494  0.048271160
## ProductNum             0.02305024  1.00000000  0.936085156 -0.018053681
## Price                  0.03680349  0.93608516  1.000000000 -0.008848857
## Payment_Type           0.04827116 -0.01805368 -0.008848857  1.000000000
```

```
highlyCorrelated<- findCorrelation(correlationMatrix, cutoff = 0.5)
```

It shows that product and price are highly correlated

Summary, Conclusions:

In this research we saw that for some products everyone will pay the same price but there is some products that the payment is different between each person.

We couldn’t find that for each location has a diffrent price

The price of the product and the date that we bought the product are important when we look at the prduct.

Product and price is the highly correlated.

Recommendations:

I think that credit card companies can use this data to target locations who don’t use in their credit card. visa can make a campain in those locations to get more cusomers.

If we want to sell a specific product, and we want to get higher payment, We can find out where people buy similar products and what is the price that they are willing to pay for it.