Principal Component Analysis

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UNDERSTANDING PCA (work reproduced from this webpage:https://goo.gl/Wgeieb)

Reading data

```
data = read.csv('diamonds.csv')
```

Viewing all the variable names in the dataset

```
colnames(data)
```

```
##  [1] "X"       "carat"   "cut"     "color"   "clarity" "depth"   "table"  
##  [8] "price"   "x"       "y"       "z"
```

Taking only the numeric variables so we could use it in our analysis

```
library(dplyr)
```

```
## 
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
## 
##     filter, lag

## The following objects are masked from 'package:base':
## 
##     intersect, setdiff, setequal, union
```

```
data_for_pca <- select(data, -X, -cut, -color, -clarity)
```

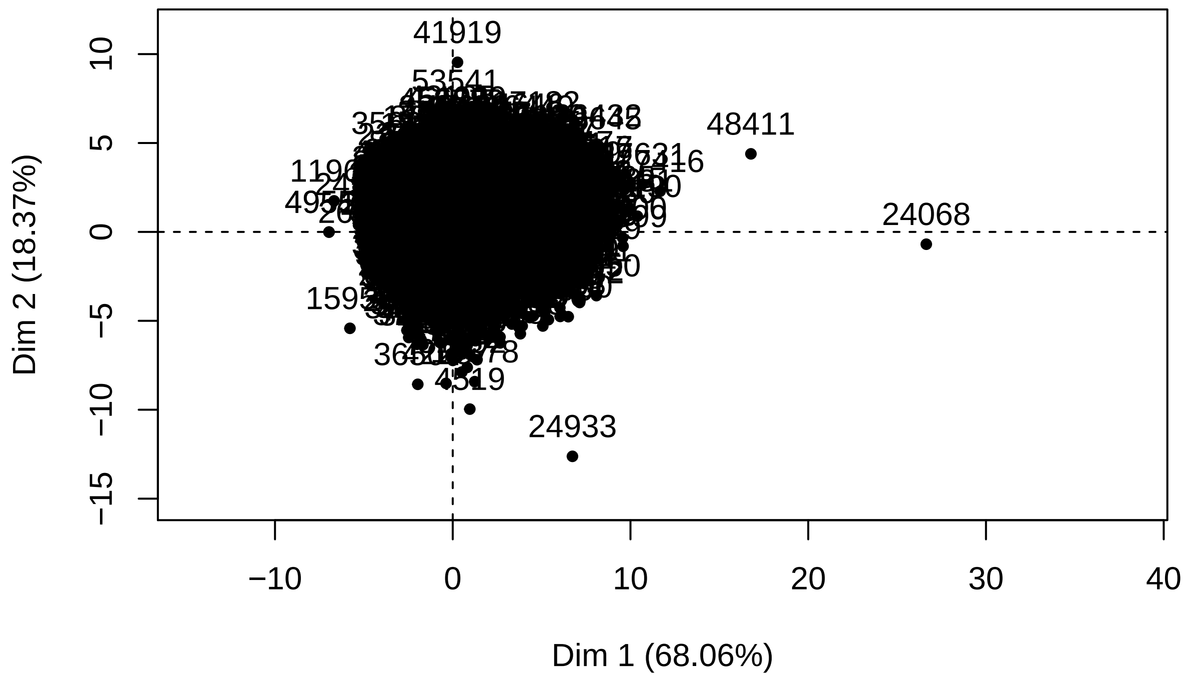
Principal components

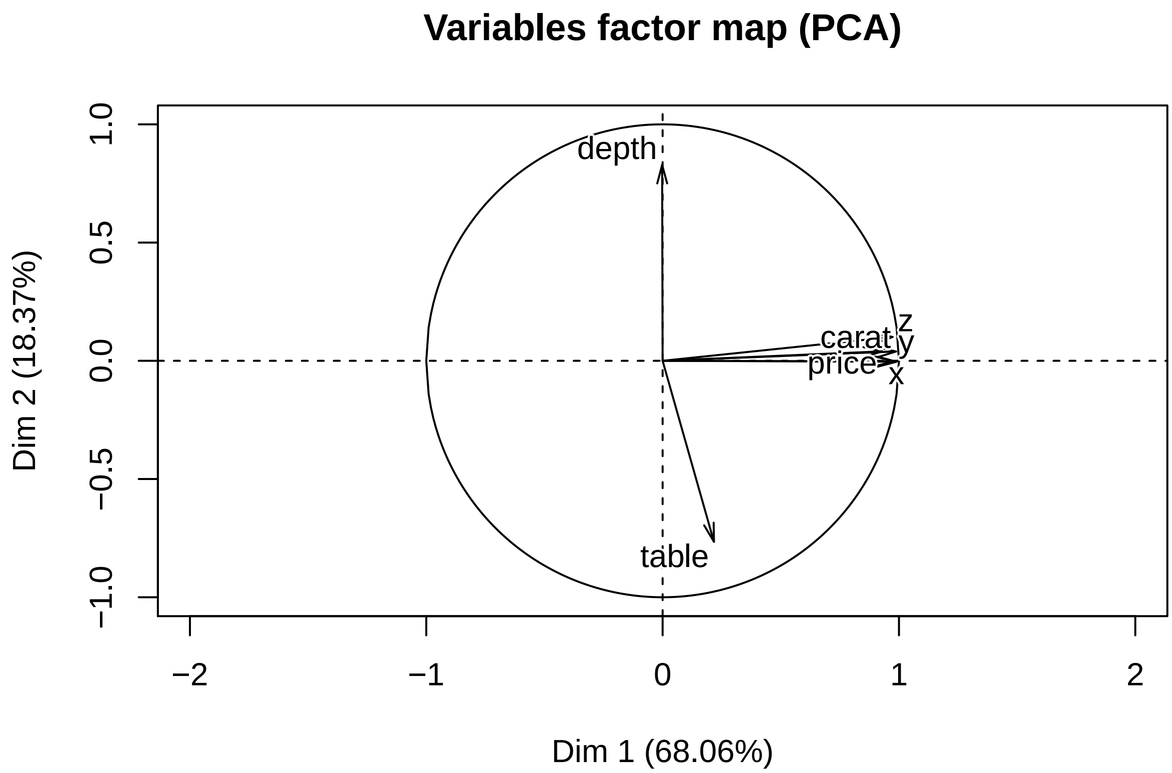
Installing the factominer package for PCA

```
library(FactoMineR)
```

```
pca = PCA(data_for_pca)
```

Individuals factor map (PCA)





Here,the variables, 'price', 'carat', 'x', 'y', and 'z' form a composite variable called the Principal component 1 or Dim 1 which explains 68.06% of the variance in the data. Variable 'depth' explains 18.37% of the variance in the data along the second dimension. The variable 'table' is in the third dimension.

```
pca$eig
```

```
##        eigenvalue percentage of variance cumulative percentage of variance
## comp 1 4.76391480             68.0559258                          68.05593
## comp 2 1.28586808             18.3695440                          86.42547
## comp 3 0.69081126              9.8687323                          96.29420
## comp 4 0.17375333              2.4821905                          98.77639
## comp 5 0.04030722              0.5758174                          99.35221
## comp 6 0.03294659              0.4706656                          99.82288
## comp 7 0.01239871              0.1771245                         100.00000
```

Eigen values

In the table above, eigen values indicate how much variance each component explains. For example if we divide the eigen value 4.763 of the first principal component by the total of the eigen values of all the components then we will get a percentage of variance of 68.055. Likewise, the same for all other components also.

Eigen Vectors

Eigen vectors are the vector locations of these principal components. MAtrix multiplication of our original dataset with eigen vector number 1 will generate data for principal component 1. Each of these components are projected in a different direction in the 3-D space.

Variance in each variable

Now, let's see how much variance of each variable is explained by each principal component.

```
Correlation_Matrix = as.data.frame(round(cor(data_for_pca,pca$ind$coord)^2*100,0))
Correlation_Matrix[with(Correlation_Matrix, order(-Correlation_Matrix[,1])),]
```

```
##       Dim.1 Dim.2 Dim.3 Dim.4 Dim.5
## carat    98     0     0     0     0
## x        98     0     0     1     0
## y        95     0     0     2     2
## z        95     1     0     2     1
## price    86     0     1    13     0
## table     5    59    37     0     0
## depth     0    69    31     0     0
```

This correlation matric tells us that 98% of the information in carat and X variables are loaded in the first dimension, 95% of the information from y and z variables are loaded in the first dimension. Information from the variables table and depth is spread between dimension 2 and 3. Information of the variable price is spread between 1st and 4th principal components.

If we discard the 5th principal component we will only loose 3% of the information from only 2 variables. Therefore it is safe is discard this dimension and only keep the 4 remaining dimensions.