

# PCA

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## UNDERSTANDING PRINCIPAL COMPONENT ANALYSIS (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
```

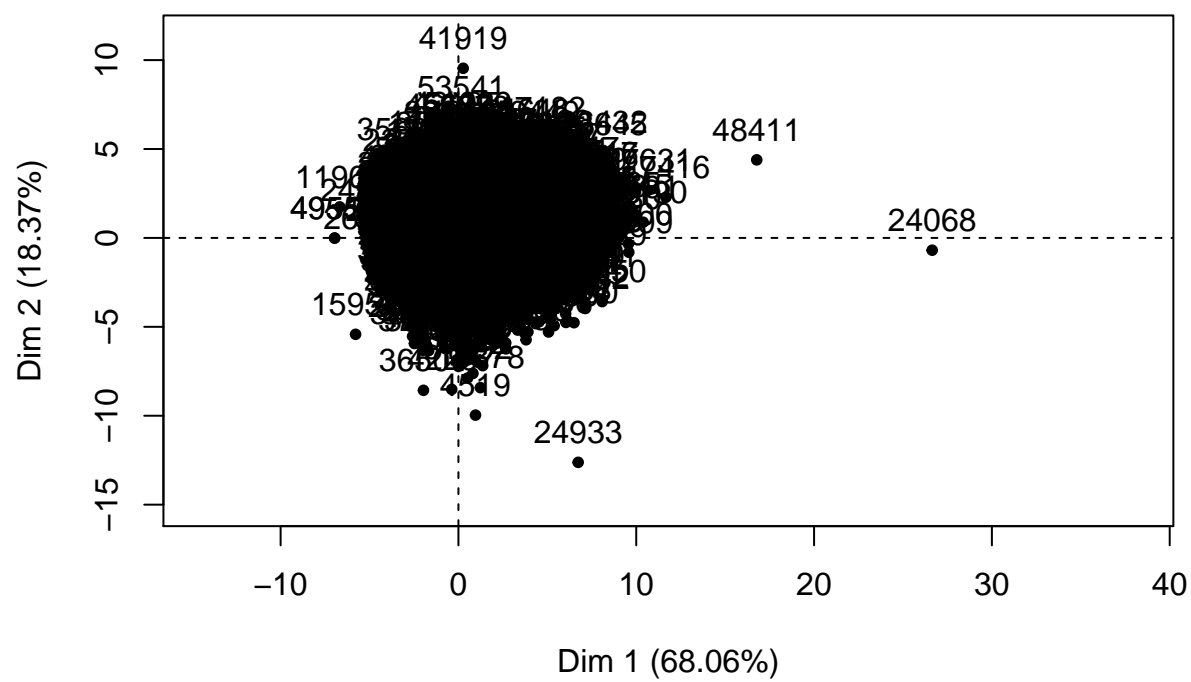
```
data_for_pca <- select(data, -X, -cut, -color, -clarity)
```

Installing the factominer package for PCA

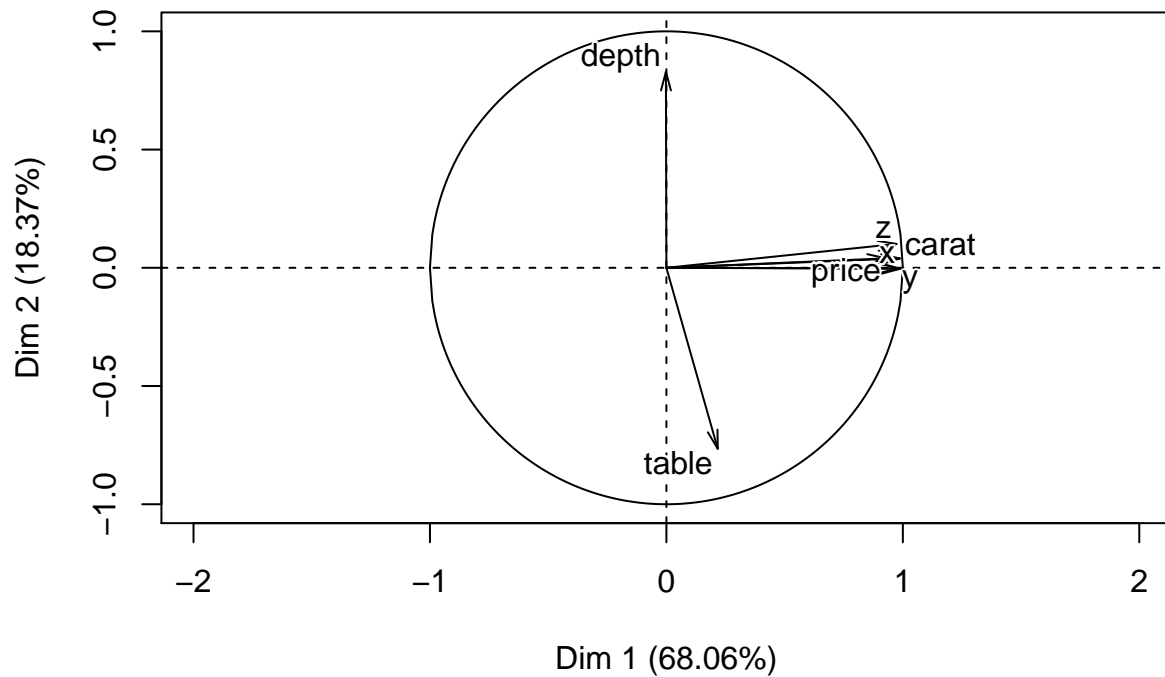
```
library(FactoMineR)
```

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

### Individuals factor map (PCA)



## Variables 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