Data Reduction

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Contents

Data reduction is a technique that we can use when the number of the data is too large and using full data requires a costly and time-consuming computational method. There are two techniques to reduce the data:

1) Dimension Data Reduction
2) Numerosity Data Reduction

Dimensional

Removing Attributes

```r
library(ISLR)
```

```
## Warning: package 'ISLR' was built under R version 4.4.2
```

```r
data(package='ISLR')
data("Hitters")
?Hitters
```

```
## starting httpd help server ... done
```

```r
hitters2 = na.omit(Hitters)
model.f = lm(Salary~., data=hitters2)
summary(model.f)
```

```
##
## Call:
## lm(formula = Salary ~ ., data = hitters2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -907.62 -178.35  -31.11  139.09 1877.04
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  163.10359   90.77854   1.797 0.073622 .
## AtBat         -1.97987    0.63398  -3.123 0.002008 **
## Hits           7.50077    2.37753   3.155 0.001808 **
## HmRun          4.33088    6.20145   0.698 0.485616
## Runs          -2.37621    2.98076  -0.797 0.426122
## RBI           -1.04496    2.60088  -0.402 0.688204
## Walks          6.23129    1.82850   3.408 0.000766 ***
## Years         -3.48905   12.41219  -0.281 0.778874
## CAtBat        -0.17134    0.13524  -1.267 0.206380
## CHits          0.13399    0.67455   0.199 0.842713
## CHmRun        -0.17286    1.61724  -0.107 0.914967
## CRuns          1.45430    0.75046   1.938 0.053795 .
## CRBI           0.80771    0.69262   1.166 0.244691
## CWalks        -0.81157    0.32808  -2.474 0.014057 *
## LeagueN       62.59942   79.26140   0.790 0.430424
## DivisionW   -116.84925   40.36695  -2.895 0.004141 **
## PutOuts        0.28189    0.07744   3.640 0.000333 ***
## Assists        0.37107    0.22120   1.678 0.094723 .
## Errors        -3.36076    4.39163  -0.765 0.444857
## NewLeagueN   -24.76233   79.00263  -0.313 0.754218
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 315.6 on 243 degrees of freedom
## Multiple R-squared:  0.5461, Adjusted R-squared:  0.5106
## F-statistic: 15.39 on 19 and 243 DF,  p-value: < 2.2e-16
```

As we can see from the above summary for linear model of salary with other variables, only certain variables can be considered significant as indicate by at least one '*' at the right of the column. This indicates that the variables are at least significance at alpha =0.05

```r
hitters3 = cbind(hitters2$AtBat, hitters2$Hits, hitters2$Walks, hitters2$CWalks,
                 hitters2$Division, hitters2$PutOuts)
head(hitters3)
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6]
## [1,]  315   81   39  375    2  632
## [2,]  479  130   76  263    2  880
## [3,]  496  141   37  354    1  200
## [4,]  321   87   30   33    1  805
## [5,]  594  169   35  194    2  282
## [6,]  185   37   21   24    1   76
```

Primary Component Analysis (PCA)

```r
reading = read.csv('READING120n.csv')
head(reading)
```

```
##   GEN rhyme Begsnd ABC LS Spelling COW
## 1   M    10     10   6  7        4   7
## 2   F    10     10  22 19        9  15
## 3   M     9     10  23 15        5   6
## 4   F     5     10  10  3        2   3
## 5   F     2     10   4  0        0   2
## 6   M     5      6  22  8       17   6
```

Remove non-numeric column.

```r
reading2 = reading[,-1]
head(reading2)
```

```
##   rhyme Begsnd ABC LS Spelling COW
## 1    10     10   6  7        4   7
## 2    10     10  22 19        9  15
## 3     9     10  23 15        5   6
## 4     5     10  10  3        2   3
## 5     2     10   4  0        0   2
## 6     5      6  22  8       17   6
```

```r
library(psych)
```

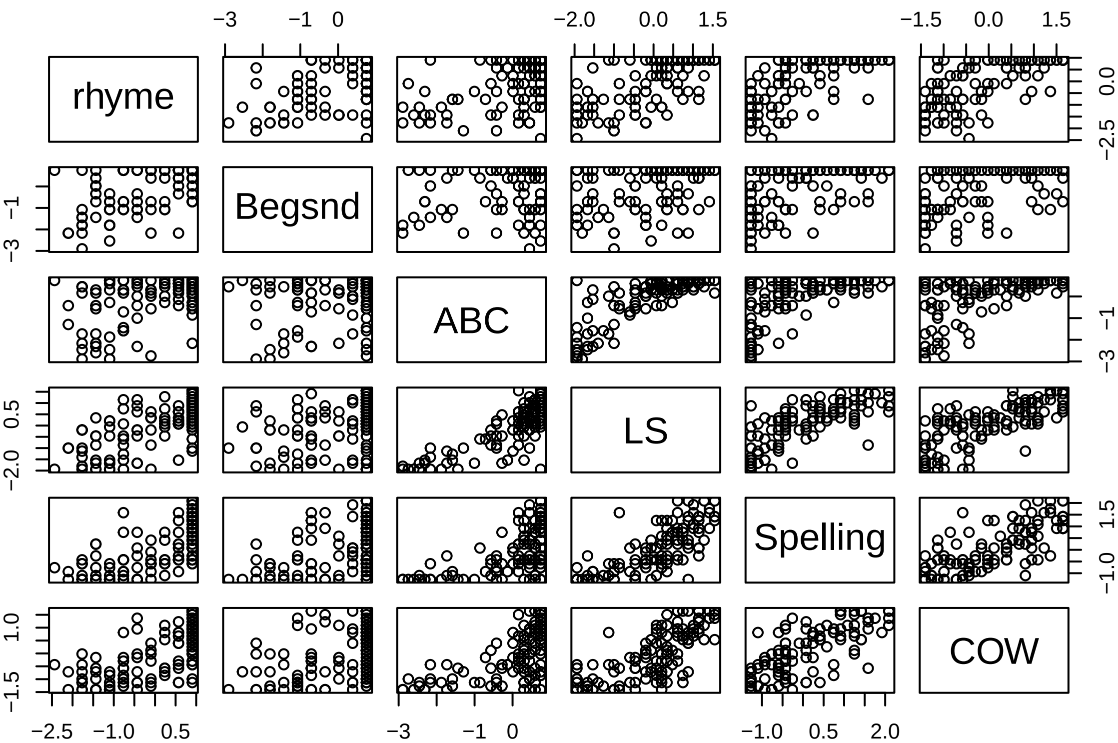
```
## Warning: package 'psych' was built under R version 4.4.2
```

```r
describe(reading2)
```

```
##          vars   n  mean   sd median trimmed  mad min max range  skew kurtosis
## rhyme       1 120  7.29 2.99      9    7.65 1.48   0  10    10 -0.65    -1.02
## Begsnd      2 120  7.94 2.74     10    8.41 0.00   0  10    10 -1.03    -0.23
## ABC         3 120 20.92 6.89     24   22.36 2.97   1  26    25 -1.54     1.19
```

```
## LS          4 120 14.46 7.45     16    14.92 7.41    0   26     26 -0.53    -0.77
## Spelling    5 120  7.55 5.96      6     7.18 7.41    0   20     20  0.39    -1.03
## COW         6 120 10.15 7.21     10     9.96 9.64    0   22     22  0.13    -1.33
##             se
## rhyme     0.27
## Begsnd    0.25
## ABC       0.63
## LS        0.68
## Spelling 0.54
## COW       0.66
```

```r
z = scale(reading2)
pairs(~., data=z)
```



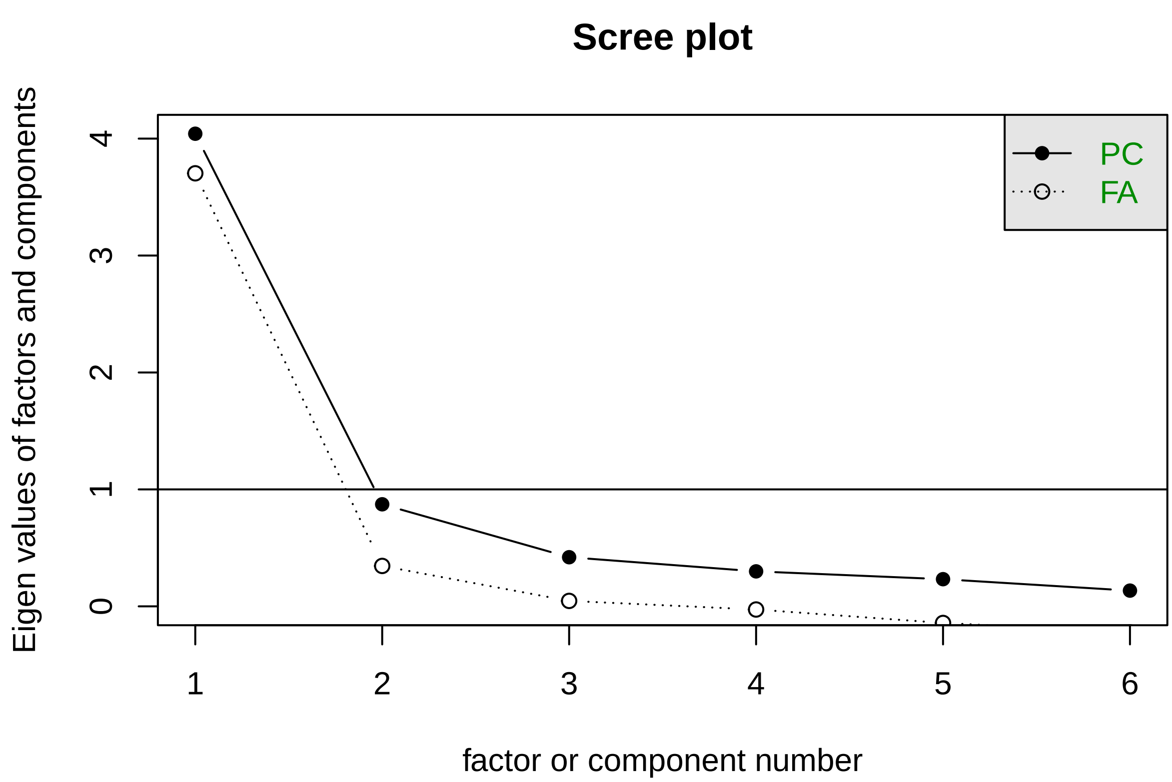

```r
cor_z = cor(z)
cor_z
```

```
##              rhyme    Begsnd       ABC        LS  Spelling       COW
## rhyme    1.0000000 0.6161831 0.4994385 0.6769710 0.6682135 0.6929980
## Begsnd   0.6161831 1.0000000 0.2850706 0.3467132 0.4688980 0.4694738
## ABC      0.4994385 0.2850706 1.0000000 0.7955943 0.5888044 0.5981786
## LS       0.6769710 0.3467132 0.7955943 1.0000000 0.7579600 0.7492896
## Spelling 0.6682135 0.4688980 0.5888044 0.7579600 1.0000000 0.7668598
## COW      0.6929980 0.4694738 0.5981786 0.7492896 0.7668598 1.0000000
```

```r
eigen(cor_z)
```

```
## eigen() decomposition
## $values
## [1] 4.0417265 0.8725973 0.4200022 0.2990629 0.2322152 0.1343960
##
## $vectors
##            [,1]        [,2]        [,3]        [,4]        [,5]        [,6]
## [1,] -0.4202540  0.29934149 -0.09269853  0.80020266 -0.12282334  0.26415587
## [2,] -0.3068973  0.75974276  0.43140561 -0.33291224  0.02990871 -0.17541132
## [3,] -0.3849778 -0.46782622  0.65714698 -0.08464742  0.06601473  0.43539111
## [4,] -0.4458305 -0.33461651  0.06528679  0.14407269 -0.13081189 -0.80444760
## [5,] -0.4358068 -0.03894126 -0.43902727 -0.43785381 -0.60459527  0.24199105
## [6,] -0.4385206 -0.02897612 -0.42005561 -0.17090073  0.77266730  0.06474189
```

```r
scree(cor_z)
```




```r
eigen(cor_z)$vectors
```

```
##            [,1]        [,2]        [,3]        [,4]        [,5]        [,6]
## [1,] -0.4202540  0.29934149 -0.09269853  0.80020266 -0.12282334  0.26415587
## [2,] -0.3068973  0.75974276  0.43140561 -0.33291224  0.02990871 -0.17541132
## [3,] -0.3849778 -0.46782622  0.65714698 -0.08464742  0.06601473  0.43539111
## [4,] -0.4458305 -0.33461651  0.06528679  0.14407269 -0.13081189 -0.80444760
```

```
## [5,] -0.4358068 -0.03894126 -0.43902727 -0.43785381 -0.60459527  0.24199105
## [6,] -0.4385206 -0.02897612 -0.42005561 -0.17090073  0.77266730  0.06474189
```

```
y = z %*% eigen(cor_z)$vectors
colnames(y) = c('PCA1', 'PCA2', 'PCA3', 'PCA4', 'PCA5', 'PCA6')
prop.var = eigen(cor_z)$values / length(eigen(cor_z)$values)
cumsum(prop.var)
```

```
## [1] 0.6736211 0.8190540 0.8890543 0.9388981 0.9776007 1.0000000
```

Factor Analysis

```
# = factanal(cor_z, factors=2, rotation='varimax')
```

Numerosity

Parametric Model

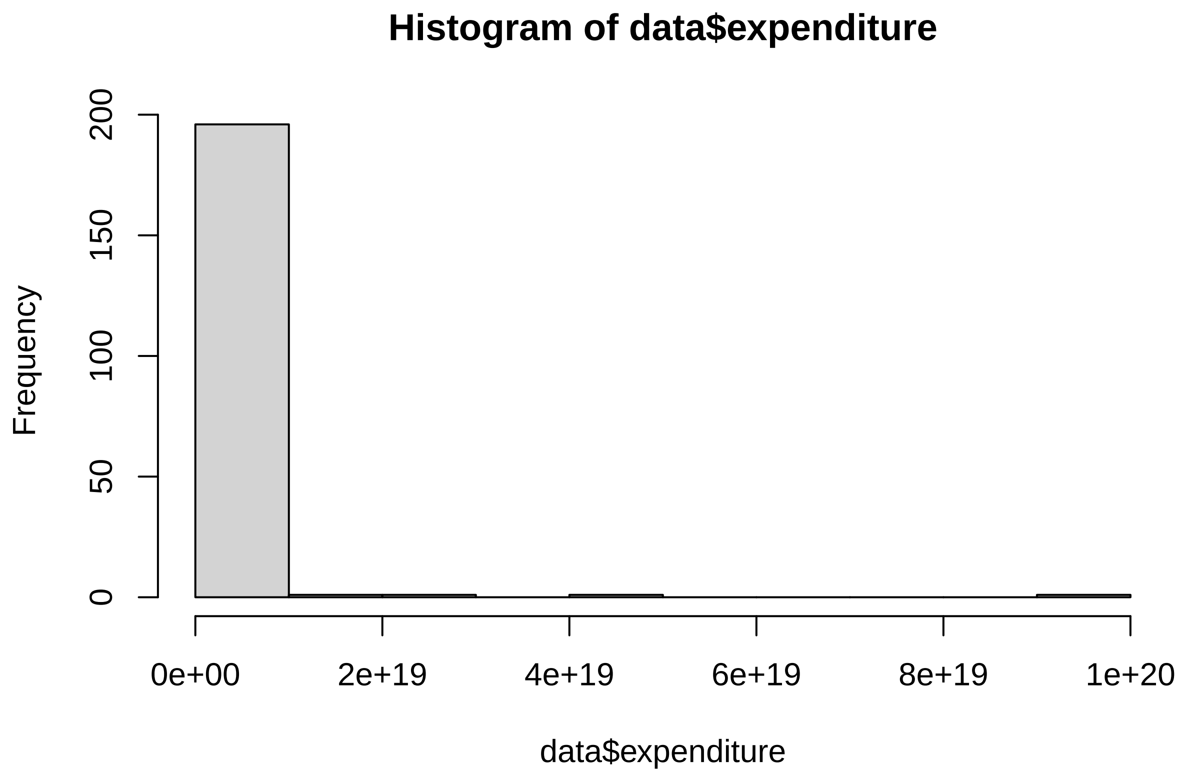
Regression Model

```
data = read.csv('data.csv', sep=';')
head(data)
```

```
##     income education_level work_experience  expenditure
## 1 45435.43               3       13.568200 2.743065e+10
## 2 36910.20               1        6.407732 4.532608e+08
## 3 16836.11               1        7.943813 2.658155e+04
## 4 47458.35               5       20.478526 8.593200e+11
## 5 17016.09               2       15.450881 4.224400e+04
## 6 46910.73               1        4.273132 2.991605e+10
```

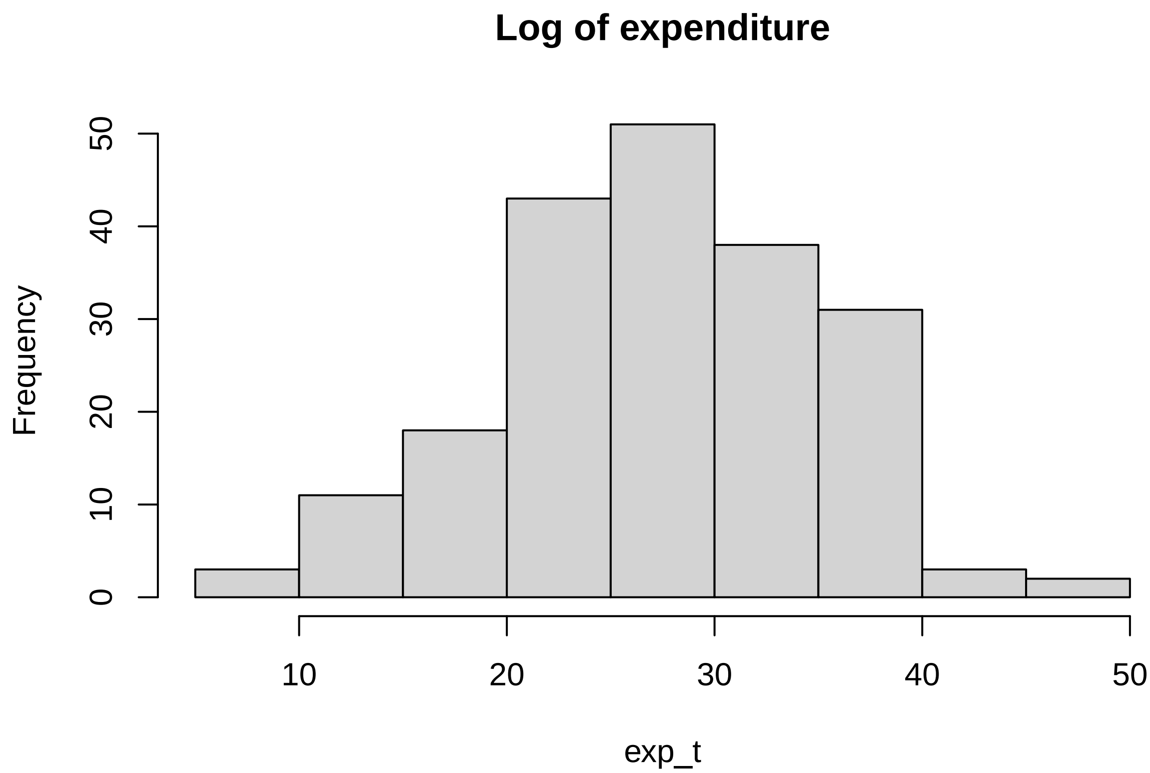
In this model, we're trying to predict the expenditure using 3 predictor variable which is the income, education level, and work experience. We assume the **Y is nearly normally distributed**

```
hist(data$expenditure)
```



Since the response variable is not normal, we need to transform the data to be normal. For this example, we use log to transform the data

```
exp_t = log(data$expenditure)
hist(exp_t, main='Log of expenditure')
```




```r
str(data)
```

```
## 'data.frame':    200 obs. of  4 variables:
##  $ income         : num  45435 36910 16836 47458 17016 ...
##  $ education_level: int  3 1 1 5 2 1 2 3 1 5 ...
##  $ work_experience: num  13.57 6.41 7.94 20.48 15.45 ...
##  $ expenditure    : num  2.74e+10 4.53e+08 2.66e+04 8.59e+11 4.22e+04 ...
```

Next, we notice that the education level is supposed to be a categorical variable instead of numerical variable. Thus, we need to change the data type first

```r
data$education_level = as.factor(data$education_level)
str(data)
```

```
## 'data.frame':    200 obs. of  4 variables:
##  $ income         : num  45435 36910 16836 47458 17016 ...
##  $ education_level: Factor w/ 5 levels "1","2","3","4",..: 3 1 1 5 2 1 2 3 1 5 ...
##  $ work_experience: num  13.57 6.41 7.94 20.48 15.45 ...
##  $ expenditure    : num  2.74e+10 4.53e+08 2.66e+04 8.59e+11 4.22e+04 ...
```

Now, we can start to fit the data into linear regression model.

```r
data_lm = lm(log(expenditure)~income+education_level+work_experience, data=data)
summary(data_lm)
```

```
##
## Call:
## lm(formula = log(expenditure) ~ income + education_level + work_experience,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.05108 -0.35025 -0.00016  0.31069  1.21984
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      9.621e-01  1.544e-01   6.233 2.82e-09 ***
## income           4.987e-04  2.316e-06 215.315  < 2e-16 ***
## education_level2 1.873e-01  1.080e-01   1.734 0.084517 .
## education_level3 3.292e-01  1.055e-01   3.120 0.002087 **
## education_level4 4.297e-01  1.186e-01   3.623 0.000373 ***
## education_level5 8.723e-01  1.111e-01   7.852 2.76e-13 ***
## work_experience  8.311e-02  7.239e-03  11.479  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5001 on 193 degrees of freedom
## Multiple R-squared:  0.9959, Adjusted R-squared:  0.9958
## F-statistic:  7782 on 6 and 193 DF,  p-value: < 2.2e-16
```

$R^2 > 0.99$ shows that this model is suitable for represent the original data. Save information related to this model

1. Parameter coefficient:
2.

$$log(expenditure) = 0.09621 + 0.0005(income) + 0.1872(education_level) + 0.3292(education_level3$$

Log-linear Model

Probability Distribution

Non-Parametric Model

Histogram

Resampling

Clustering

Types of sampling

Simple