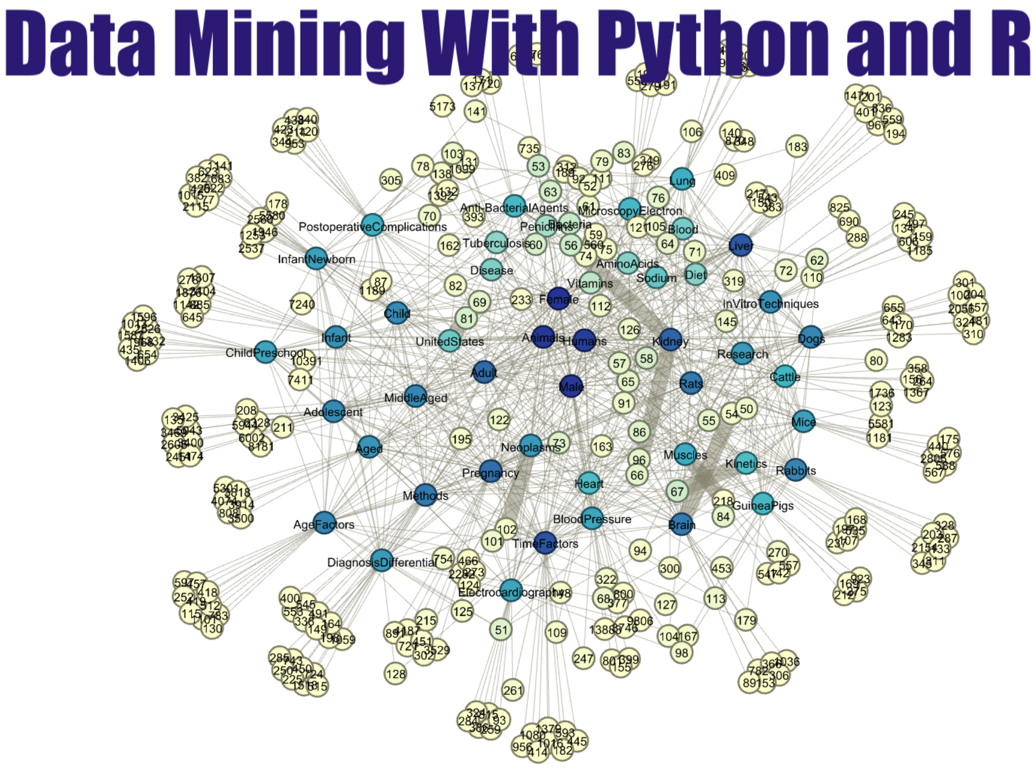


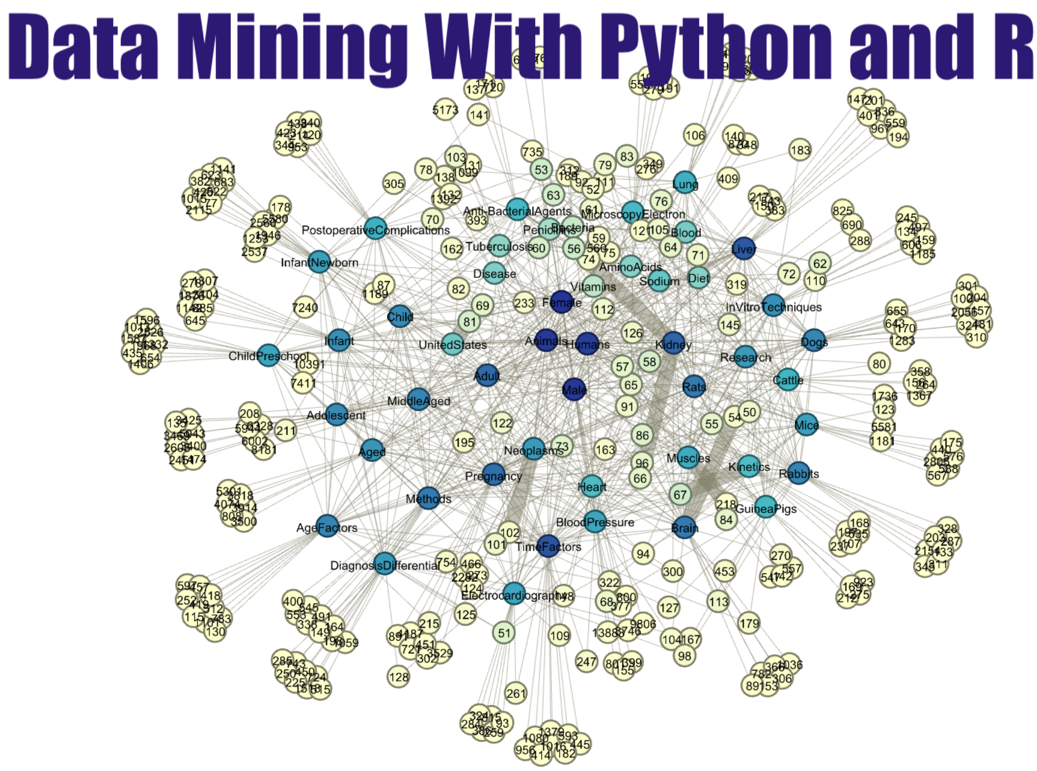
Data Mining With Python and R Tutorials

Release v1.01

Wenqiang Feng

February 15, 2019

CONTENTS



Welcome to my Data Mining With Python and R tutorials! In these tutorials, you will learn a wide array of concepts about Python and R programing in Data Mining. The PDF version can be downloaded from HERE.

CHAPTER

ONE

PREFACE

1.1 About this tutorial

This document is a summary of my Data Mining Methds & Application (STAT 577) course in University of Tennessee at Knoxville. **You may download and distribute it. Please be aware, however, that the note contains typos as well as inaccurate or incorrect description.** At here, I would like to thank Dr. Haileab Hilafu for providing some of his R code and homework solutions. I also would like to thank Bo Gao, Le Yin, Chen Wen, Jian Sun and Huan Chen for the valuable disscussion and thank the generous anonymous authors for providing the detailed solutions and source code on the Internet. Without those help, those tutorials would not have been possible to be made. In those tutorials, I try to use the detailed demo code to show how to use each functions in R and Python to do data mining. If you find your work wasn't cited in this note, please feel free to let me know.

Although I am by no means an data mining programming expert, I decided that it would be useful for me to share what I learned about data mining programming in the form of easy tutorials with detailed example. I hope those tutorials will be a valuable tool for your studies.

The tutorials assume that the reader has a preliminary knowledge of programing and unix. And this document is generated automatically by using sphinx.

1.2 Motivation for this tutorial

Data mining is a relatively new, while the technology is not. Here are the sevaral main motivation for this tutorial:

1. It is no exaggeration to say that data mining has thunderstorms impacted on our real lives. I have great interest in data mining and am eager to learn those technologies.
2. Fortunely, I had a chance to register Dr. Haileab Hilafu's Data Mining Methds & Application class. Dr.Haileab Hilafu and his class inspired me to do a better job.
3. However, I still found that learning data mining programing was a difficult process. I have to Google it and identify which one is true. It was hard to find detailed examples which I can easily learned the full process in one file.
4. Good sources are expensive for a graduate student.

1.3 Feedback and suggestions

Your comments and suggestions are highly appreciated. I am more than happy to receive corrections, suggestions or feedbacks through email (Wenqiang Feng: wfeng1@vols.utk.edu) for improvements.

CHAPTER

TWO

PYTHON OR R FOR DATA ANALYSIS?

Note: Sharpening the knife longer can make it easier to hack the firewood – old Chinese proverb

There is an old Chinese proverb that Says 'sharpening the knife longer can make it easier to hack the firewood'. In other words, take extra time to get it right in the preparation phase and then the work will be easier. So it is worth to take several minites to think about which programming language is better for you.

When you google it, you will get many useful results. Here are some valueable information from Quora:

2.1 Ponder over questions

- Six questions to ponder over from Vipin Tyagi at Quora
    1. Is your problem is purely data analysis based or mixed one involving mathematics, machine-learning, artificial intelligence based?
    2. What are the commonly used tools in your field?
    3. What is the programming expertise of your human resources?
    4. What level of visualization you require in your presentations?
    5. Are you academic, research-oriented or commercial professional?
    6. Do you have access to number of data analytic softwares for doing your assignment?

2.2 Comparison List

- comparative list from Yassine Alouini at Quora

	R	Python
advantages	• great for prototyping • great for statistical analysis • nice IDE	• great for scripting and automating your different data mining pipelines • integrates easily in a production workflow • can be used across different parts of your software engineering team • **scikit-learn** library is awesome for machine-learning tasks. • **Ipython** is also a powerful tool for exploratory analysis and presentations
disadvantages	• syntax could be obscure • libraries documentation isn't always user friendly • harder to integrate to a production workflow.	• It isn't as thorough for statistical analysis as R • learning curve is steeper than R, since you can do much more with Python

2.3 My Opinions

In my opinion, **R** and **Python** are both choice. Since they are open-source softwares (open-source is always good in my eyes) and are free to download. If you are a beginer without any programming experience and only want to do some data analysis, I would definitely suggest to use **R**. Otherwise, I would suggest to use both.

CHAPTER

THREE

GETTING STARTED

Note: Good tools are prerequisite to the successful execution of a job – old Chinese proverb

Let's keep sharpening our tools. A good programming platform can save you lots of troubles and time. Herein I will only present how to install my favorite programming platform for R and Python and only show the easiest way which I know to install them on Linux system. If you want to install on the other operator system, you can Google it. In this section, you may learn how to install R, Python and the corresponding programming platform and package.

3.1 Installing programming language

- **Installing R**

  Go to Ubuntu Software Center and follow the following steps:

  1. Open Ubuntu Software Center
  2. Search for r-base
  3. And click Install

  Or Open your terminal and using the following command:

  ```
  sudo apt-get update
  sudo apt-get install r-base
  ```

- **Insralling Python**

  Go to Ubuntu Software Center and follow the following steps:

  1. Open Ubuntu Software Center
  2. Search for python
  3. And click Install

  Or Open your terminal and using the following command:

```
sudo apt-get install build-essential checkinstall
sudo apt-get install libreadline-gplv2-dev libncursesw5-dev libssl-
↪dev
             libsqlite3-dev tk-dev libgdbm-dev libc6-dev libbz2-dev
sudo apt-get install python
sudo easy_install pip
sudo pip install ipython
```

3.2 Installing programming platform

My favorite programming platform for R is definitely **RStudio** IDE and for Python is **Eclipse+Pydev**.

- **Installing RStudio**

  Go to Ubuntu Software Center and follow the following steps:

  1. Open Ubuntu Software Center
  2. Search for RStudio
  3. And click Install

- **Installing Eclipse + Pydev**

  - Installing Eclipse

    Go to Ubuntu Software Center and follow the following steps:

    1. Open Ubuntu Software Center
    2. Search for Eclipse
    3. And click Install

  - Installing Pydev

    1. Open Eclipse
    2. Go to Eclipse Marketplace
    3. Search for Pydev
    4. And click Pydev- Python IDE for Eclipse

    Here is the video tutorial for installing Pydev for Eclipse on Youtube: Pydev on Youtube

3.3 Installing package

- **Installing package for R**

  Install package for R in RStudio os super easy, I will use tree package as a example:

```
install.packages("tree")
```

The following are the top 20 R machine learning and data science packages from Bhavya Geethika, you may want to install all of them.

- **e1071** Functions for latent class analysis, short time Fourier transform, fuzzy clustering, support vector machines, shortest path computation, bagged clustering, naive Bayes classifier etc (142479 downloads)
- **rpart** Recursive Partitioning and Regression Trees. (135390)
- **igraph** A collection of network analysis tools. (122930)
- **nnet** Feed-forward Neural Networks and Multinomial Log-Linear Models. (108298)
- **randomForest** Breiman and Cutler's random forests for classification and regression. (105375)
- **caret** package (short for Classification And REgression Training) is a set of functions that attempt to streamline the process for creating predictive models. (87151)
- **kernlab** Kernel-based Machine Learning Lab. (62064)
- **glmnet** Lasso and elastic-net regularized generalized linear models. (56948)
- **ROCR** Visualizing the performance of scoring classifiers. (51323)
- **gbm** Generalized Boosted Regression Models. (44760)
- **party** A Laboratory for Recursive Partitioning. (43290)
- **arules** Mining Association Rules and Frequent Itemsets. (39654)
- **tree** Classification and regression trees. (27882)
- **klaR** Classification and visualization. (27828)
- **RWeka** R/Weka interface. (26973)
- **ipred** Improved Predictors. (22358)
- **lars** Least Angle Regression, Lasso and Forward Stagewise. (19691)
- **earth** Multivariate Adaptive Regression Spline Models. (15901)
- **CORElearn** Classification, regression, feature evaluation and ordinal evaluation. (13856)
- **mboost** Model-Based Boosting. (13078)

- **Installing package for Python**

  Install package or modules for Python in Linux can also be quite easy. Here I will only present installation by using pip.

  - **Installing pip**

    ```
    sudo easy_install pip
    ```

  - **Installing numpy**

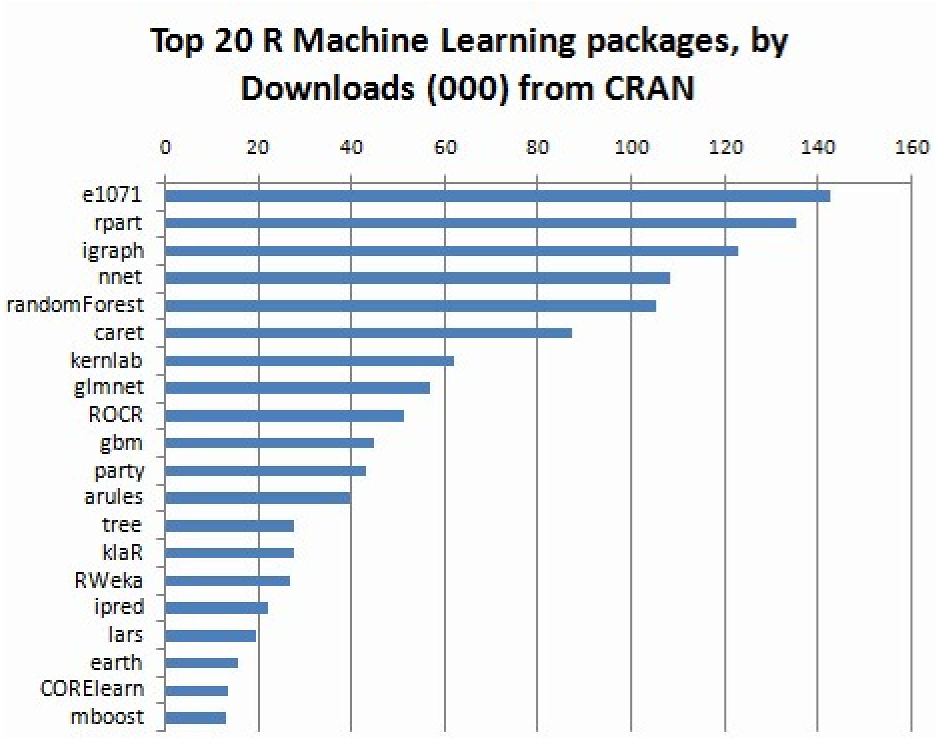


Fig. 1: Top 20 R Machine Learning and Data Science packages. From http://www.kdnuggets.com/2015/06/top-20-r-machine-learning-packages.html

```
pip install numpy
```

- **Installing pandas**

```
pip install pandas
```

- **Installing scikits-learn**

```
pip install -U scikit-learn
```

The following are the best Python modules for data mining from kdnuggets, you may also want to install all of them.

1. Basics

- **numpy** - numerical library, http://numpy.scipy.org/
- **scipy** - Advanced math, signal processing, optimization, statistics, http://www.scipy.org/
- **matplotlib**, python plotting - Matplotlib, http://matplotlib.org

2. Machine Learning and Data Mining

- **MDP**, a collection of supervised and unsupervised learning algorithms, http://pypi.python.org/pypi/MDP/2.4

- **mlpy**, Machine Learning Python, http://mlpy.sourceforge.net
- **NetworkX**, for graph analysis, http://networkx.lanl.gov/
- **Orange**, Data Mining Fruitful & Fun, http://biolab.si
- **pandas**, Python Data Analysis Library, http://pandas.pydata.org
- **pybrain**, http://pybrain.org
- **scikits-learn** - Classic machine learning algorithms - Provide simple an efficient solutions to learning problems, http://scikit-learn.org/stable/

3. Natural Language

- **NLTK**, Natural Language Toolkit, http://nltk.org

4. For web scraping

- **Scrapy**, An open source web scraping framework for Python, http://scrapy.org
- **urllib/urllib2**

Herein I would like to add one more important package **Theano** for deep learning and **textmining** for text mining:

  - **Theano**, deep learning, http://deeplearning.net/tutorial/
  - **textmining**, text mining, https://pypi.python.org/pypi/textmining/1.0

CHAPTER

FOUR

DATA ANALYSIS PROCEDURES

Note: Know yourself and know your enemy, and you will never be defeated – idiom, from Sunzi's Art of War

4.1 Procedures

Data mining is a complex process that aims to discover patterns in large data sets starting from a collection of exsting data. In my opinion, data minig contains four main steps:

1. **Collecting data**: This is a complex step, I will assume we have already gotten the datasets.
2. **Pre-processing**: In this step, we need to try to understand your data, denoise, do dimentation reduction and select proper predictors etc.
3. **Feeding data mining**: In this step, we need to use your data to feed your model.
4. **Post-processing** : In this step, we need to interpret and evaluate your model.

In this section, we will try to know our enemy – datasets. We will learn how to load data, how to understand data with statistics method and how to underdtand data with visualization. Next, we will start with Loading Datasets for the Pre-processing.

4.2 Datasets in this Tutorial

The datasets for this tutorial are available to download: Heart, Energy Efficienency. Those data are from my course matrials, the copyrights blongs to the origial authors.

4.3 Loading Datasets

There are two main data formats ".*csv" and* ".xlsx". We will show how to load those two types of data in **R** and **Python**, respectively.

1. **Loading datasets in R**

- Loading $*.csv$ format data

```
# set the path or enverionment
setwd("/home/feng/R-language/sat577/HW#4/data")

# read data set
rawdata = read.csv("spam.csv")
```

- Loading $*.xlsx$ format data

```
# set the path or enverionment
setwd("~/Dropbox/R-language/sat577/")

#install.packages("readxl") # CRAN version
library(readxl)

# read data set
energy_eff=read_excel("energy_efficiency.xlsx")
```

2. **Loading datasets in Python**

- Loading $*.csv$ format data

```
import pandas as pd

# set data path
path ='~/Dropbox/MachineLearningAlgorithms/python_code/data/
↪Heart.csv'

# read data set
rawdata = pd.read_csv(path)
```

- Loading $*.xlsx$ format data

```
import pandas as pd

# set data path
path = ('/home/feng/Dropbox/MachineLearningAlgorithms/python_
↪code/data/'
'energy_efficiency.xlsx')

# read data set from first sheet
rawdata= pd.read_excel(path,sheetname=0)
```

4.4 Understand Data With Statistics methods

After we get the data in hand, then we can try to understand them. I will use "Heart.csv" dataset as a example to demonstrate how to use those statistics methods.

1. **Summary of the data**

It is always good to have a glance over the summary of the data. Since from the summary you will know some statistics features of your data, and you will also know whether you data contains missing data or not.

- Summary of the data in **R**

```
summary(rawdata)
```

Then you will get

```
> summary(rawdata)
      Age             Sex              ChestPain         ␣
↪RestBP
    Min.   :29.00   Min.   :0.0000   asymptomatic:144   Min.
↪   : 94.0
    1st Qu.:48.00   1st Qu.:0.0000   nonanginal  : 86   1st␣
↪Qu.:120.0
    Median :56.00   Median :1.0000   nontypical  : 50  ␣
↪Median :130.0
    Mean   :54.44   Mean   :0.6799   typical     : 23  ␣
↪Mean   :131.7
    3rd Qu.:61.00   3rd Qu.:1.0000                      3rd␣
↪Qu.:140.0
    Max.   :77.00   Max.   :1.0000                      Max.
↪   :200.0

      Chol             Fbs              RestECG           MaxHR
    Min.   :126.0   Min.   :0.0000   Min.   :0.0000   Min.  ␣
↪ : 71.0
    1st Qu.:211.0   1st Qu.:0.0000   1st Qu.:0.0000   1st␣
↪Qu.:133.5
    Median :241.0   Median :0.0000   Median :1.0000  ␣
↪Median :153.0
    Mean   :246.7   Mean   :0.1485   Mean   :0.9901   Mean  ␣
↪ :149.6
    3rd Qu.:275.0   3rd Qu.:0.0000   3rd Qu.:2.0000   3rd␣
↪Qu.:166.0
    Max.   :564.0   Max.   :1.0000   Max.   :2.0000   Max.  ␣
↪ :202.0

     ExAng            Oldpeak         Slope             Ca
    Min.   :0.0000   Min.   :0.00   Min.   :1.000   Min.   ␣
↪:0.0000
    1st Qu.:0.0000   1st Qu.:0.00   1st Qu.:1.000   1st Qu.
↪:0.0000
    Median :0.0000   Median :0.80   Median :2.000   Median␣
↪:0.0000
    Mean   :0.3267   Mean   :1.04   Mean   :1.601   Mean   ␣
↪:0.6722
    3rd Qu.:1.0000   3rd Qu.:1.60   3rd Qu.:2.000   3rd Qu.
↪:1.0000
    Max.   :1.0000   Max.   :6.20   Max.   :3.000   Max.   ␣
↪:3.0000
```

(continues on next page)

(continued from previous page)

```
                                                      NA's   :4
     Thal       AHD
 fixed     : 18   No :164
 normal    :166   Yes:139
 reversable:117
 NA's      :  2
```

- Summary of the data in **Python**

```
print "data summary"
print rawdata.describe()
```

Then you will get

```
             Age         Sex      RestBP        Chol        ␣
↪ Fbs      RestECG  \
count  303.000000  303.000000  303.000000  303.000000  303.
↪000000  303.000000
mean    54.438944    0.679868  131.689769  246.693069    0.
↪148515    0.990099
std      9.038662    0.467299   17.599748   51.776918    0.
↪356198    0.994971
min     29.000000    0.000000   94.000000  126.000000    0.
↪000000    0.000000
25%     48.000000    0.000000  120.000000  211.000000    0.
↪000000    0.000000
50%     56.000000    1.000000  130.000000  241.000000    0.
↪000000    1.000000
75%     61.000000    1.000000  140.000000  275.000000    0.
↪000000    2.000000
max     77.000000    1.000000  200.000000  564.000000    1.
↪000000    2.000000

        MaxHR       ExAng     Oldpeak       Slope          Ca
count  303.000000  303.000000  303.000000  303.000000  299.
↪000000
mean   149.607261    0.326733    1.039604    1.600660    0.
↪672241
std     22.875003    0.469794    1.161075    0.616226    0.
↪937438
min     71.000000    0.000000    0.000000    1.000000    0.
↪000000
25%    133.500000    0.000000    0.000000    1.000000    0.
↪000000
50%    153.000000    0.000000    0.800000    2.000000    0.
↪000000
75%    166.000000    1.000000    1.600000    2.000000    1.
↪000000
max    202.000000    1.000000    6.200000    3.000000    3.
↪000000
```

2. **The size of the data**

Sometimes we also need to know the size or dimension of our data. Such as when you need to extract the response from the dataset, you need the number of column, or when you try to split your data into train and test data set, you need know the number of row.

- Checking size in **R**

```
dim(rawdata)
```

Or you can use the following code

```
nrow=nrow(rawdata)
ncol=ncol(rawdata)

c(nrow, ncol)
```

Then you will get

```
> dim(rawdata)
[1] 303  14
```

- Checking size in **Python**

```
nrow, ncol = rawdata.shape
print nrow, ncol
```

or you can use the follwing code

```
nrow=rawdata.shape[0] #gives number of row count
ncol=rawdata.shape[1] #gives number of col count
print nrow, ncol
```

Then you will get

```
Raw data size
303 14
```

3. **Data format of the predictors**

Data format is also very important, since some functions or methods can not be applied to the qualitative data, you need to remove those predictors or transform them into quantitative data.

- Checking data format in **R**

```
# install the package
install.packages("mlbench")
library(mlbench)

sapply(rawdata, class)
```

Then you will get

```
   > sapply(rawdata, class)
     Age        Sex ChestPain     RestBP        Chol         Fbs  
↪RestECG
```

(continues on next page)

(continued from previous page)

```
"integer" "integer"  "factor" "integer" "integer" "integer"
↪"integer"
MaxHR      ExAng    Oldpeak     Slope         Ca        Thal      ␣
↪ AHD
"integer" "integer" "numeric" "integer" "integer"  "factor"
↪"factor"
```

- Checking data format in **Pyhton**

```
print rawdata.dtypes
```

Then you will get

```
Data Format:
Age               int64
Sex               int64
ChestPain        object
RestBP            int64
Chol              int64
Fbs               int64
RestECG           int64
MaxHR             int64
ExAng             int64
Oldpeak         float64
Slope             int64
Ca              float64
Thal             object
AHD              object
dtype: object
```

4. **The column names**

- Checking column names of the data in **R**

```
colnames(rawdata)
attach(rawdata)  # enable you can directly use name as␣
↪predictors
```

Then you will get

```
   > colnames(rawdata)
[1]  "Age"        "Sex"        "ChestPain" "RestBP"     "Chol"
[6]  "Fbs"        "RestECG"    "MaxHR"      "ExAng"      "Oldpeak"
[11]  "Slope"      "Ca"         "Thal"       "AHD"
```

- Checking column names of the data in **Python**

```
colNames = rawdata.columns.tolist()

print "Column names:"
print colNames
```

Then you will get

```
    Column names:
['Age', 'Sex', 'ChestPain', 'RestBP', 'Chol', 'Fbs', 'RestECG
↪', 'MaxHR',
 'ExAng', 'Oldpeak', 'Slope', 'Ca', 'Thal', 'AHD']
```

5. **The first or last parts of the data**

- Checking first parts of the data in **R**

```
head(rawdata)
```

Then you will get

```
> head(rawdata)
   Age Sex    ChestPain RestBP Chol Fbs RestECG MaxHR ExAng␣
↪Oldpeak
 1  63   1      typical    145  233   1       2   150     0 ␣
↪   2.3
 2  67   1 asymptomatic    160  286   0       2   108     1 ␣
↪   1.5
 3  67   1 asymptomatic    120  229   0       2   129     1 ␣
↪   2.6
 4  37   1   nonanginal    130  250   0       0   187     0 ␣
↪   3.5
 5  41   0   nontypical    130  204   0       2   172     0 ␣
↪   1.4
 6  56   1   nontypical    120  236   0       0   178     0 ␣
↪   0.8
    Slope Ca       Thal AHD
 1      3  0      fixed  No
 2      2  3     normal Yes
 3      2  2 reversable Yes
 4      3  0     normal  No
 5      1  0     normal  No
 6      1  0     normal  No
```

- Checking first parts of the data in **Python**

```
print "\n Sample data:"
print(rawdata.head(6))
```

Then you will get

```
 Sample data:
    Age  Sex     ChestPain  RestBP  Chol  Fbs  RestECG ␣
↪MaxHR  ExAng  Oldpeak  \
0   63    1       typical     145   233    1        2    150␣
↪      0       2.3
1   67    1  asymptomatic     160   286    0        2    108␣
↪      1       1.5
2   67    1  asymptomatic     120   229    0        2    129␣
↪      1       2.6
```

(continues on next page)

(continued from previous page)

```
3   37    1     nonanginal     130   250    0         0    187␣
↪      0       3.5
4   41    0     nontypical     130   204    0         2    172␣
↪      0       1.4
5   56    1     nontypical     120   236    0         0    178␣
↪      0       0.8

   Slope   Ca         Thal   AHD
0      3    0        fixed    No
1      2    3       normal   Yes
2      2    2   reversable   Yes
3      3    0       normal    No
4      1    0       normal    No
5      1    0       normal    No
```

You can use the samilar way to check the last part of the data, for simplicity, i will skip it.

6. Correlation Matrix

   - Computing correlation matrix in **R**

```
# get numerical data and remove NAN
numdata=na.omit(rawdata[,c(1:2,4:12)])

# computing correlation matrix
cor(numdata)
```

Then you will get

```
    > cor(numdata)
                 Age          Sex       RestBP          Chol           ␣
↪   Fbs
Age       1.00000000 -0.09181347  0.29069633  0.203376601  0.
↪128675921
Sex      -0.09181347  1.00000000 -0.06552127 -0.195907357  0.
↪045861783
RestBP    0.29069633 -0.06552127  1.00000000  0.132284171  0.
↪177623291
Chol      0.20337660 -0.19590736  0.13228417  1.000000000  0.
↪006664176
Fbs       0.12867592  0.04586178  0.17762329  0.006664176  1.
↪000000000
RestECG   0.14974915  0.02643577  0.14870922  0.164957542  0.
↪058425836
MaxHR    -0.39234176 -0.05206445 -0.04805281  0.002179081 -0.
↪003386615
ExAng     0.09510850  0.14903849  0.06588463  0.056387955  0.
↪011636935
Oldpeak   0.19737552  0.11023676  0.19161540  0.040430535  0.
↪009092935
Slope     0.15895990  0.03933739  0.12110773 -0.009008239  0.
↪053776677
```

(continues on next page)

(continued from previous page)

```
Ca         0.36260453  0.09318476  0.09877326  0.119000487  0.
↪145477522
           RestECG        MaxHR        ExAng       Oldpeak     ␣
↪   Slope
Age        0.14974915 -0.392341763  0.09510850  0.197375523  0.
↪158959901
Sex        0.02643577 -0.052064447  0.14903849  0.110236756  0.
↪039337394
RestBP     0.14870922 -0.048052805  0.06588463  0.191615405  0.
↪121107727
Chol       0.16495754  0.002179081  0.05638795  0.040430535 -0.
↪009008239
Fbs        0.05842584 -0.003386615  0.01163693  0.009092935  0.
↪053776677
RestECG    1.00000000 -0.077798148  0.07408360  0.110275054  0.
↪128907169
MaxHR     -0.07779815  1.000000000 -0.37635897 -0.341262236 -0.
↪381348495
ExAng      0.07408360 -0.376358975  1.00000000  0.289573103  0.
↪254302081
Oldpeak    0.11027505 -0.341262236  0.28957310  1.000000000  0.
↪579775260
Slope      0.12890717 -0.381348495  0.25430208  0.579775260  1.
↪000000000
Ca         0.12834265 -0.264246253  0.14556960  0.295832115  0.
↪110119188
            Ca
Age        0.36260453
Sex        0.09318476
RestBP     0.09877326
Chol       0.11900049
Fbs        0.14547752
RestECG    0.12834265
MaxHR     -0.26424625
ExAng      0.14556960
Oldpeak    0.29583211
Slope      0.11011919
Ca         1.00000000
```

- Computing correlation matrix in **Python**

```
print "\n correlation Matrix"
print rawdata.corr()
```

Then you will get

```
     correlation Matrix
           Age        Sex     RestBP       Chol        Fbs    ␣
↪RestECG      MaxHR  \
Age        1.000000 -0.097542  0.284946  0.208950  0.118530  0.
↪148868 -0.393806
```

(continues on next page)

(continued from previous page)

```
Sex      -0.097542  1.000000 -0.064456 -0.199915  0.047862  0.
↪021647 -0.048663
RestBP    0.284946 -0.064456  1.000000  0.130120  0.175340  0.
↪146560 -0.045351
Chol      0.208950 -0.199915  0.130120  1.000000  0.009841  0.
↪171043 -0.003432
Fbs       0.118530  0.047862  0.175340  0.009841  1.000000  0.
↪069564 -0.007854
RestECG   0.148868  0.021647  0.146560  0.171043  0.069564  1.
↪000000 -0.083389
MaxHR    -0.393806 -0.048663 -0.045351 -0.003432 -0.007854 -0.
↪083389  1.000000
ExAng     0.091661  0.146201  0.064762  0.061310  0.025665  0.
↪084867 -0.378103
Oldpeak   0.203805  0.102173  0.189171  0.046564  0.005747  0.
↪114133 -0.343085
Slope     0.161770  0.037533  0.117382 -0.004062  0.059894  0.
↪133946 -0.385601
Ca        0.362605  0.093185  0.098773  0.119000  0.145478  0.
↪128343 -0.264246

            ExAng   Oldpeak     Slope        Ca
Age       0.091661  0.203805  0.161770  0.362605
Sex       0.146201  0.102173  0.037533  0.093185
RestBP    0.064762  0.189171  0.117382  0.098773
Chol      0.061310  0.046564 -0.004062  0.119000
Fbs       0.025665  0.005747  0.059894  0.145478
RestECG   0.084867  0.114133  0.133946  0.128343
MaxHR    -0.378103 -0.343085 -0.385601 -0.264246
ExAng     1.000000  0.288223  0.257748  0.145570
Oldpeak   0.288223  1.000000  0.577537  0.295832
Slope     0.257748  0.577537  1.000000  0.110119
Ca        0.145570  0.295832  0.110119  1.000000
```

7. covariance Matrix

   - Computing covariance matrix in **R**

```
# get numerical data and remove NAN
numdata=na.omit(rawdata[,c(1:2,4:12)])

# computing covariance matrix
cov(numdata)
```

Then you will get

```
 > cov(numdata)
               Age           Sex       RestBP          Chol
↪       Fbs
 Age       81.3775448 -0.388397567  46.4305852   95.2454603
↪0.411909946
Sex       -0.3883976  0.219905277  -0.5440170   -4.7693542  0.
↪007631703
```

(continues on next page)

(continued from previous page)

```
RestBP   46.4305852 -0.544016969 313.4906736  121.5937353 ␣
↪1.116001885
Chol     95.2454603 -4.769354223 121.5937353 2695.1442616 ␣
↪0.122769410
Fbs       0.4119099  0.007631703   1.1160019    0.1227694 ␣
↪0.125923099
RestECG   1.3440551  0.012334179   2.6196943    8.5204709 ␣
↪0.020628044
MaxHR   -81.2442706 -0.560447577 -19.5302126    2.5968104 -
↪0.027586362
ExAng     0.4034028  0.032861215   0.5484838    1.3764001 ␣
↪0.001941595
Oldpeak   2.0721791  0.060162510   3.9484299    2.4427678 ␣
↪0.003755247
Slope     0.8855132  0.011391439   1.3241566   -0.2887926 ␣
↪0.011784247
Ca        3.0663958  0.040964288   1.6394357    5.7913852 ␣
↪0.048393975
           RestECG        MaxHR        ExAng      Oldpeak       ␣
↪Slope
Age      1.34405513 -81.24427061  0.403402842  2.072179076 ␣
↪0.88551323
Sex      0.01233418  -0.56044758  0.032861215  0.060162510 ␣
↪0.01139144
RestBP   2.61969428 -19.53021257  0.548483760  3.948429889 ␣
↪1.32415658
Chol     8.52047092   2.59681040  1.376400081  2.442767839 -
↪0.28879262
Fbs      0.02062804  -0.02758636  0.001941595  0.003755247 ␣
↪0.01178425
RestECG  0.98992166  -1.77682880  0.034656910  0.127690736 ␣
↪0.07920136
MaxHR   -1.77682880 526.92866602 -4.062052479 -9.116871675 -
↪5.40571480
ExAng    0.03465691  -4.06205248  0.221072479  0.158455478 ␣
↪0.07383673
Oldpeak  0.12769074  -9.11687168  0.158455478  1.354451303 ␣
↪0.41667415
Slope    0.07920136  -5.40571480  0.073836726  0.416674149 ␣
↪0.38133824
Ca       0.11970551  -5.68626967  0.064162421  0.322752576 ␣
↪0.06374717
                 Ca
Age      3.06639582
Sex      0.04096429
RestBP   1.63943570
Chol     5.79138515
Fbs      0.04839398
RestECG  0.11970551
MaxHR   -5.68626967
ExAng    0.06416242
Oldpeak  0.32275258
```

(continues on next page)

(continued from previous page)

```
Slope     0.06374717
Ca        0.87879060
```

- Computing covariance matrix in **Python**

```
print "\n covariance Matrix"
print rawdata.corr()
```

Then you will get

```
covariance Matrix
             Age        Sex       RestBP          Chol        Fbs␣
↪   RestECG   \
Age      81.697419 -0.411995   45.328678    97.787489   0.
↪381614   1.338797
Sex      -0.411995  0.218368   -0.530107    -4.836994   0.
↪007967   0.010065
RestBP   45.328678 -0.530107  309.751120   118.573339   1.
↪099207   2.566455
Chol     97.787489 -4.836994  118.573339  2680.849190   0.
↪181496   8.811521
Fbs       0.381614  0.007967    1.099207     0.181496   0.
↪126877   0.024654
RestECG   1.338797  0.010065    2.566455     8.811521   0.
↪024654   0.989968
MaxHR   -81.423065 -0.520184  -18.258005    -4.064651  -0.
↪063996  -1.897941
ExAng     0.389220  0.032096    0.535473     1.491345   0.
↪004295   0.039670
Oldpeak   2.138850  0.055436    3.865638     2.799282   0.
↪002377   0.131850
Slope     0.901034  0.010808    1.273053    -0.129598   0.
↪013147   0.082126
Ca        3.066396  0.040964    1.639436     5.791385   0.
↪048394   0.119706

             MaxHR      ExAng    Oldpeak      Slope         Ca
Age      -81.423065  0.389220  2.138850  0.901034  3.066396
Sex       -0.520184  0.032096  0.055436  0.010808  0.040964
RestBP   -18.258005  0.535473  3.865638  1.273053  1.639436
Chol      -4.064651  1.491345  2.799282 -0.129598  5.791385
Fbs       -0.063996  0.004295  0.002377  0.013147  0.048394
RestECG   -1.897941  0.039670  0.131850  0.082126  0.119706
MaxHR    523.265775 -4.063307 -9.112209 -5.435501 -5.686270
ExAng     -4.063307  0.220707  0.157216  0.074618  0.064162
Oldpeak   -9.112209  0.157216  1.348095  0.413219  0.322753
Slope     -5.435501  0.074618  0.413219  0.379735  0.063747
Ca        -5.686270  0.064162  0.322753  0.063747  0.878791
```

4.5 Understand Data With Visualization

A picture is worth a thousand words. You will see the powerful impact of the figures in this section.

1. Summary plot of data in figure

   - Summary plot in **R**

     ```
     # plot of the summary
     plot(rawdata)
     ```

     Then you will get Figure *Summary plot of the data with R.*

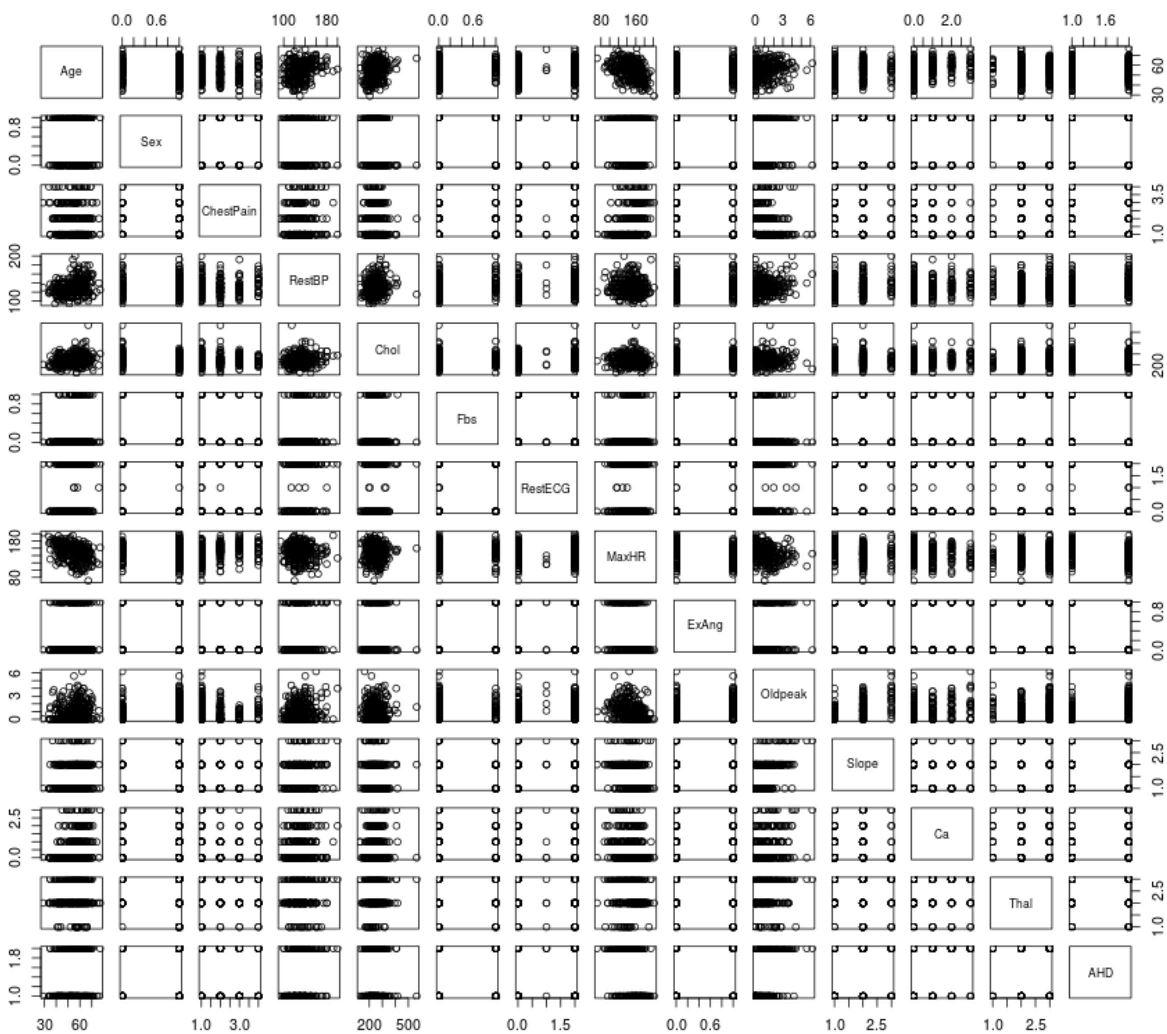


Fig. 1: Summary plot of the data with R.

   - Summary plot in **Python**

```
# plot of the summary
plot(rawdata)
```

Then you will get Figure *Summary plot of the data with Python.*

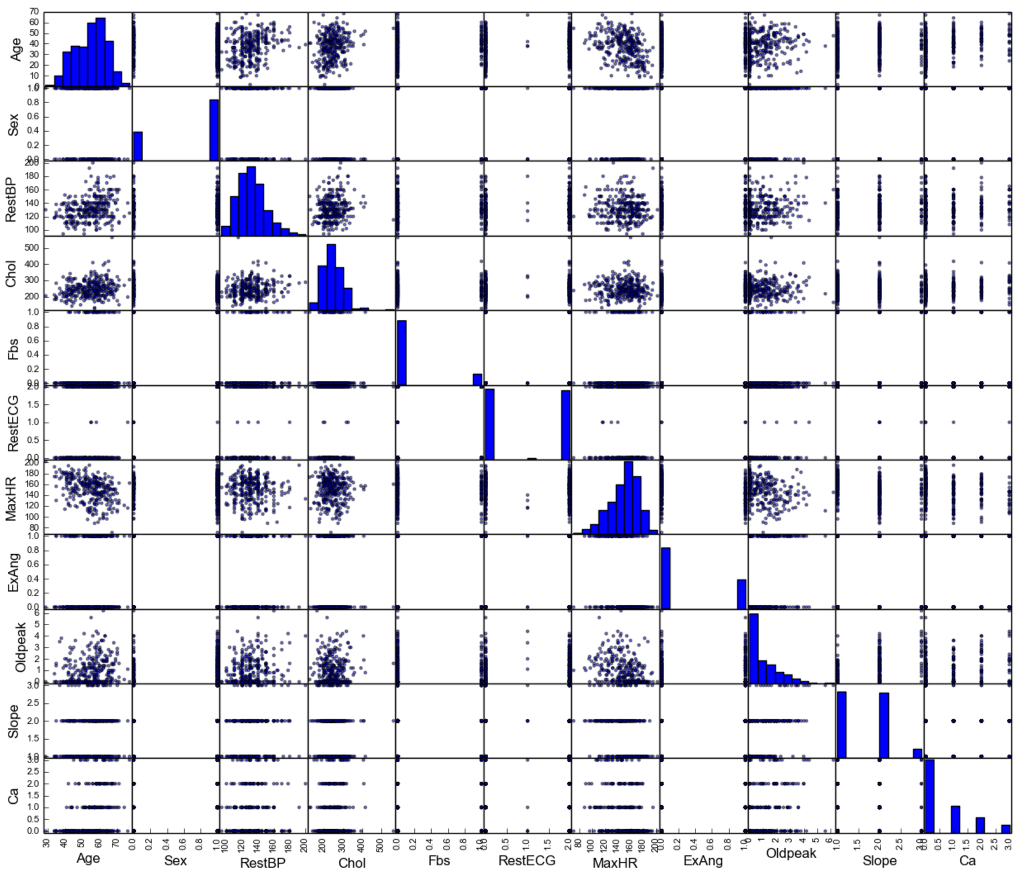


Fig. 2: Summary plot of the data with Python.

2. Histogram of the quantitative predictors

- Histogram in **R**

```
# Histogram with normal curve plot
dev.off()
Nvars=ncol(numdata)
name=colnames(numdata)
par(mfrow =c (4,3))
for (i in 1:Nvars)
{
  x<- numdata[,i]
```

(continues on next page)

(continued from previous page)

```
  h<-hist(x, breaks=10, freq=TRUE, col="blue", xlab=name[i], main=" ",
            font.lab=1)
  axis(1, tck=1, col.ticks="light gray")
  axis(1, tck=-0.015, col.ticks="black")
  axis(2, tck=1, col.ticks="light gray", lwd.ticks="1")
  axis(2, tck=-0.015)
  xfit<-seq(min(x),max(x),length=40)
  yfit<-dnorm(xfit,mean=mean(x),sd=sd(x))
  yfit <- yfit*diff(h$mids[1:2])*length(x)
  lines(xfit, yfit, col="blue", lwd=2)
}
```

Then you will get Figure *Histogram with normal curve plot in R.*

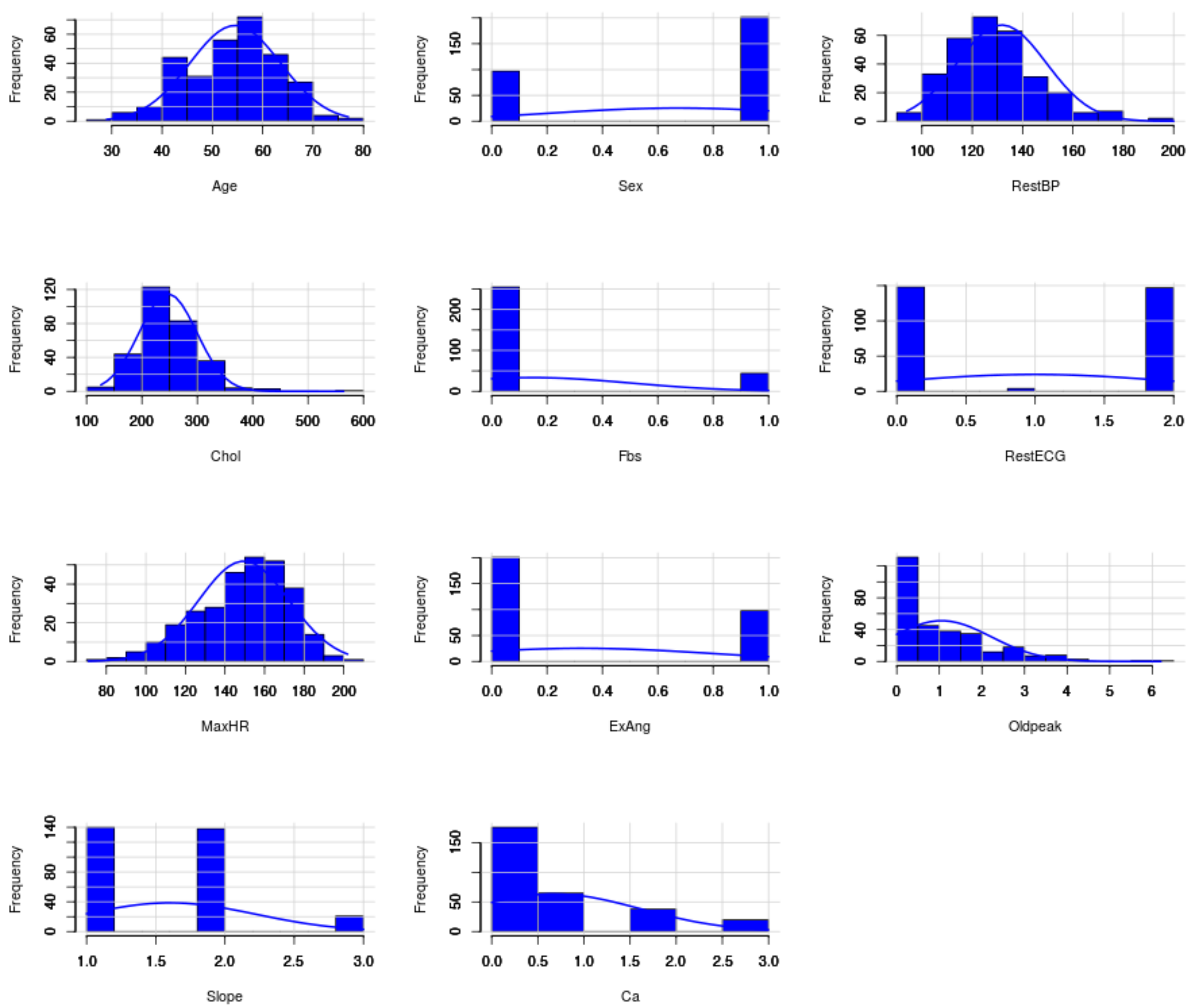


Fig. 3: Histogram with normal curve plot in R.

- Histogram in in **Python**

```
# Histogram
rawdata.hist()
plt.show()
```

Then you will get Figure *Histogram in Python.*

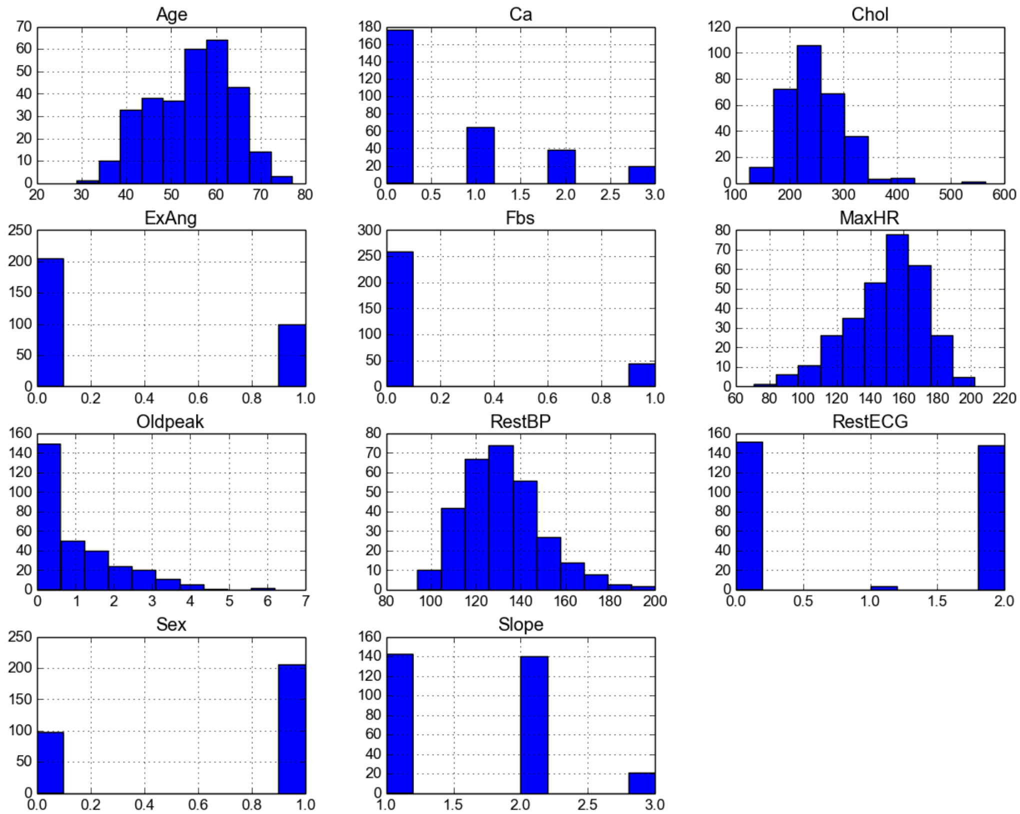


Fig. 4: Histogram in Python.

3. Boxplot of the quantitative predictors

- Boxplot in **R**

```
dev.off()
name=colnames(numdata)
    Nvars=ncol(numdata)
    # boxplot
    par(mfrow =c (4,3))
    for (i in 1:Nvars)
    {
     #boxplot(numdata[,i]~numdata[,Nvars],data=data,
↪main=name[i])
```

(continues on next page)

(continued from previous page)

```
    boxplot(numdata[,i],data=numdata,main=name[i])
   }
```

Then you will get Figure *Boxplots in R*.

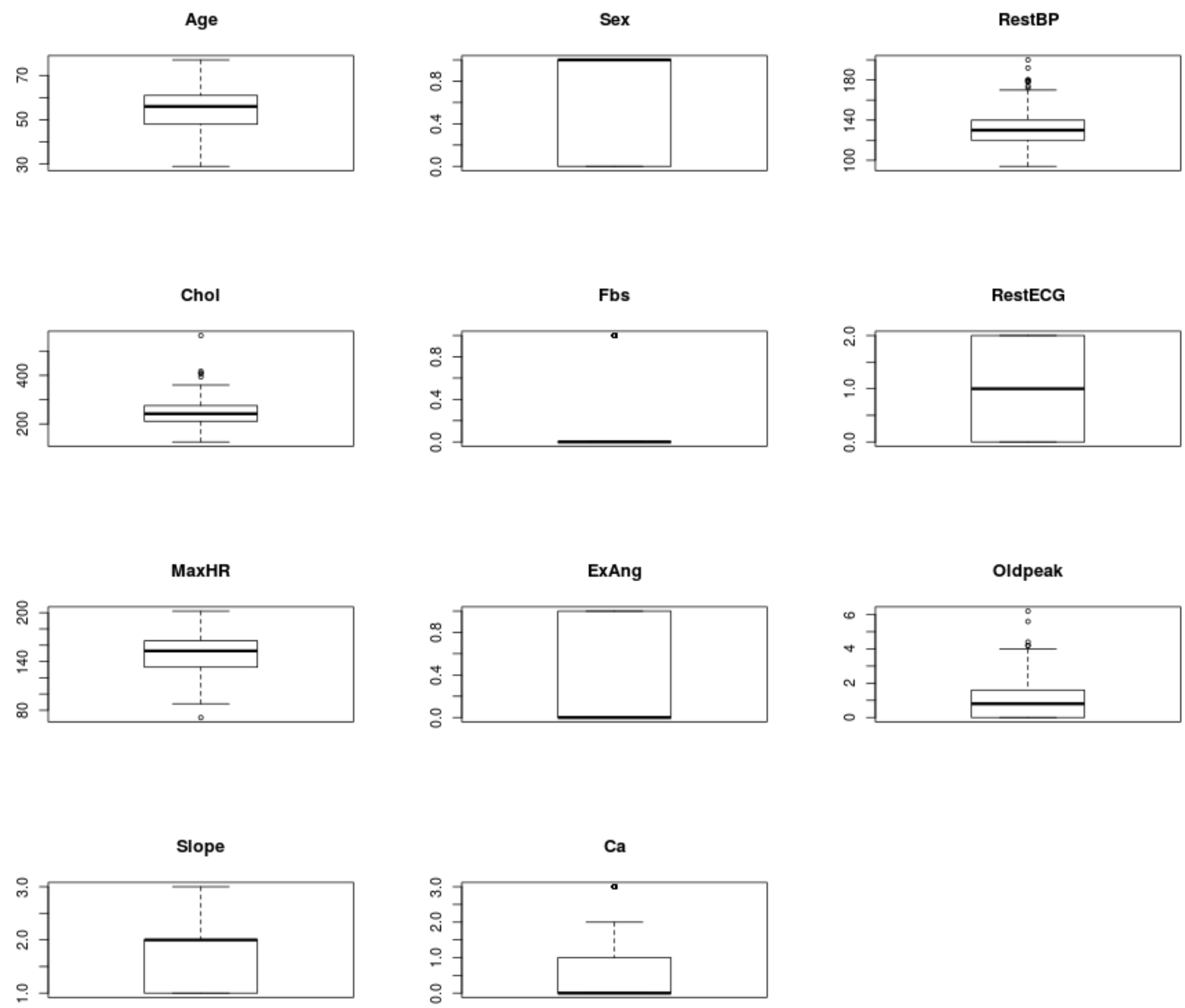


Fig. 5: Boxplots in R.

- Boxplot in **Python**

```
# boxplot
pd.DataFrame.boxplot(rawdata)
plt.show()
```

Then you will get Figure *Histogram in Python*.

4. Correlation Matrix plot of the quantitative predictors

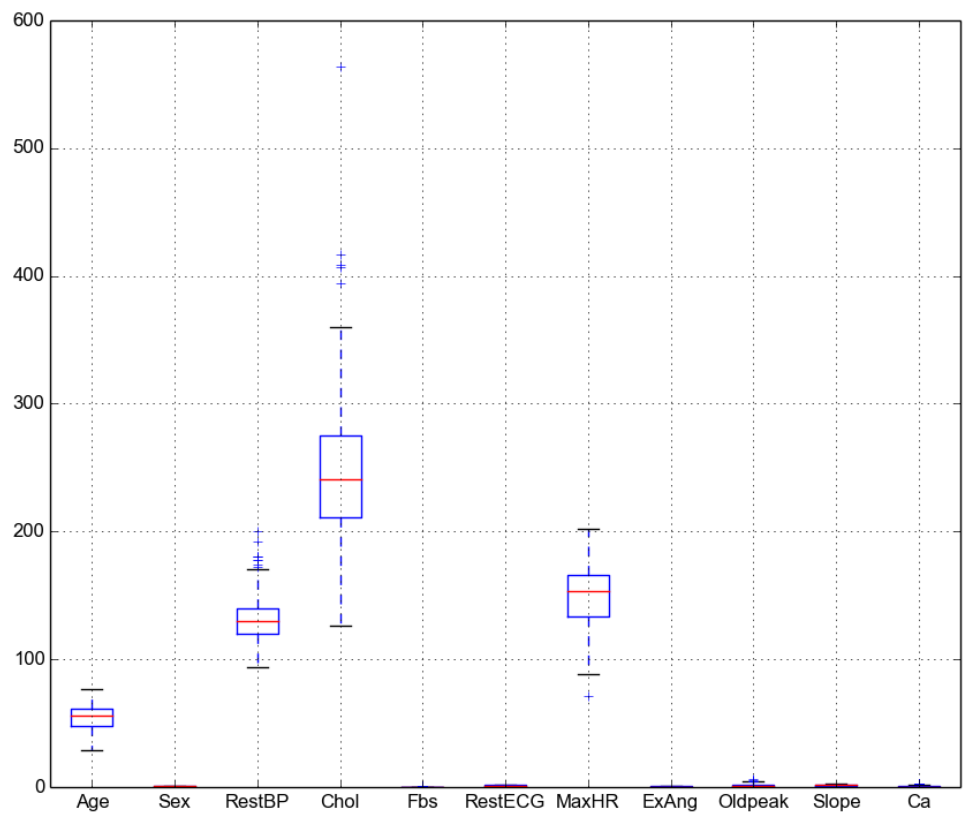


Fig. 6: Histogram in Python.

- Correlation Matrix plot in **R**

```
dev.off()
# laod cocorrelation Matrix plot lib
library(corrplot)
M <- cor(numdata)
#par(mfrow =c (1,2))
#corrplot(M, method = "square")
corrplot.mixed(M)
```

Then you will get Figure *Correlation Matrix plot in R.*

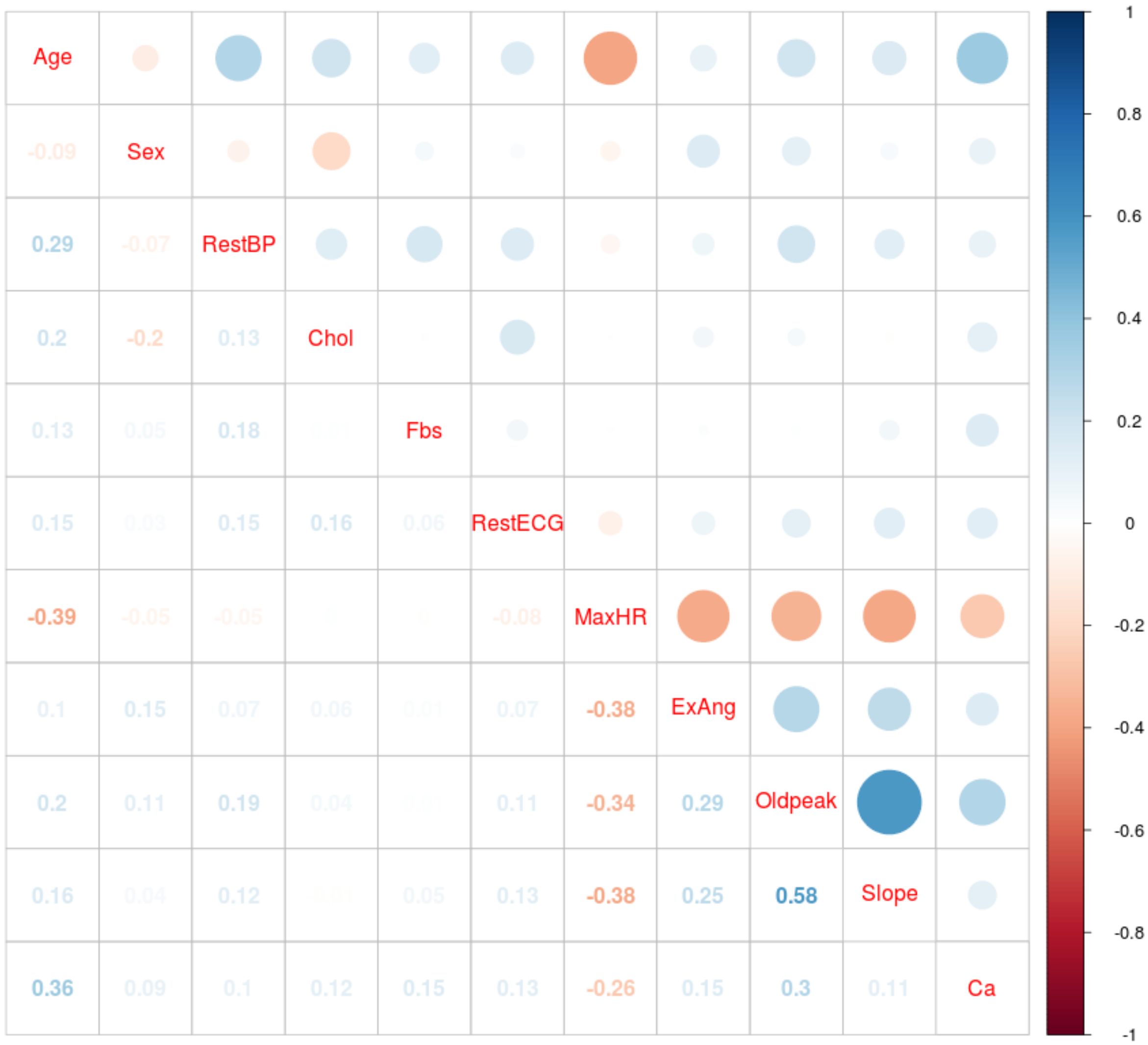


Fig. 7: Correlation Matrix plot in R.

- Correlation Matrix plot in **Python**

```
# cocorrelation Matrix plot
pd.DataFrame.corr(rawdata)
plt.show()
```

Then you will get get Figure *Correlation Matrix plot in Python.*

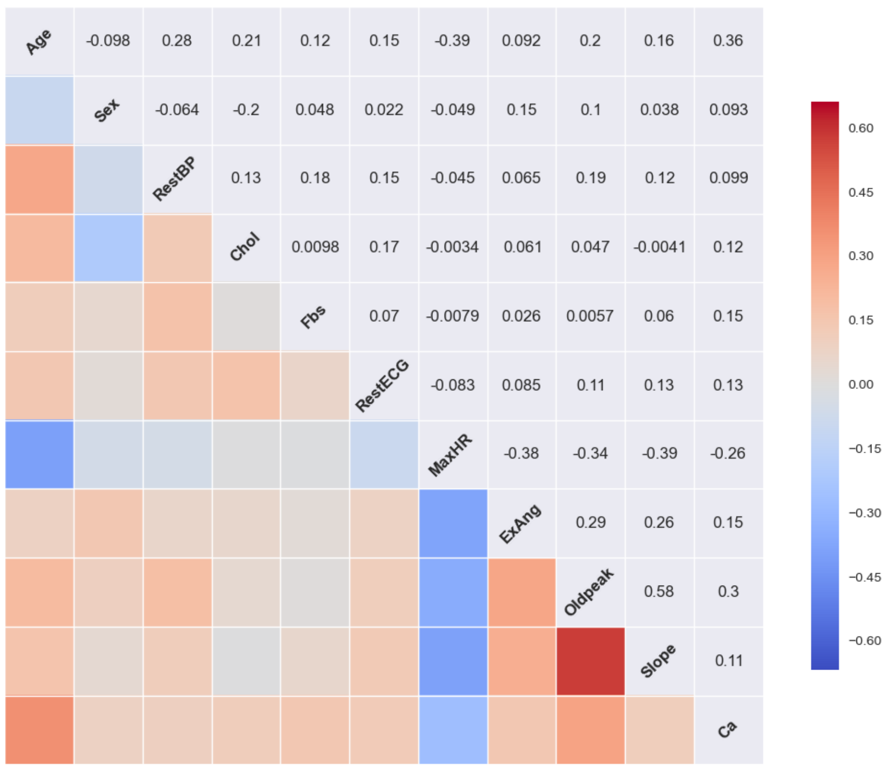


Fig. 8: Correlation Matrix plot in Python.

4.6 Source Code for This Section

The code for this section is available for download for R, for Python,

- R Source code

```
rm(list = ls())
# set the enverionment
path ='~/Dropbox/MachineLearningAlgorithms/python_code/data/
↪Heart.csv'
rawdata = read.csv(path)
```

(continues on next page)

(continued from previous page)

```
# summary of the data
summary(rawdata)
# plot of the summary
plot(rawdata)

dim(rawdata)
head(rawdata)
tail(rawdata)

colnames(rawdata)
attach(rawdata)

# get numerical data and remove NAN
numdata=na.omit(rawdata[,c(1:2,4:12)])

cor(numdata)
cov(numdata)

dev.off()
# laod cocorrelation Matrix plot lib
library(corrplot)
M <- cor(numdata)
#par(mfrow =c (1,2))
#corrplot(M, method = "square")
corrplot.mixed(M)


nrow=nrow(rawdata)
ncol=ncol(rawdata)
c(nrow, ncol)



Nvars=ncol(numdata)
# checking data format
typeof(rawdata)
install.packages("mlbench")
library(mlbench)
sapply(rawdata, class)

dev.off()
name=colnames(numdata)
Nvars=ncol(numdata)
# boxplot
par(mfrow =c (4,3))
for (i in 1:Nvars)
{
  #boxplot(numdata[,i]~numdata[,Nvars],data=data,main=name[i])
  boxplot(numdata[,i],data=numdata,main=name[i])
}
```

(continues on next page)

(continued from previous page)

```
# Histogram with normal curve plot
dev.off()
Nvars=ncol(numdata)
name=colnames(numdata)
par(mfrow =c (3,5))
for (i in 1:Nvars)
{
  x<- numdata[,i]
  h<-hist(x, breaks=10, freq=TRUE, col="blue", xlab=name[i],main=
↪" ",
            font.lab=1)
  axis(1, tck=1, col.ticks="light gray")
  axis(1, tck=-0.015, col.ticks="black")
  axis(2, tck=1, col.ticks="light gray", lwd.ticks="1")
  axis(2, tck=-0.015)
  xfit<-seq(min(x),max(x),length=40)
  yfit<-dnorm(xfit,mean=mean(x),sd=sd(x))
  yfit <- yfit*diff(h$mids[1:2])*length(x)
  lines(xfit, yfit, col="blue", lwd=2)
}


library(reshape2)
library(ggplot2)
d <- melt(diamonds[,-c(2:4)])
ggplot(d,aes(x = value)) +
  facet_wrap(~variable,scales = "free_x") +
  geom_histogram()
```

- Python Source code

```
'''
Created on Apr 25, 2016
test code
@author: Wenqiang Feng
'''
import pandas as pd
#import numpy as np
import matplotlib.pyplot as plt
from pandas.tools.plotting import scatter_matrix
from docutils.parsers.rst.directives import path

if __name__ == '__main__':
    path ='~/Dropbox/MachineLearningAlgorithms/python_code/data/
↪Heart.csv'
    rawdata = pd.read_csv(path)

    print "data summary"
    print rawdata.describe()

    # summary plot of the data
    scatter_matrix(rawdata,figsize=[15,15])
```

(continues on next page)

(continued from previous page)

```
plt.show()

# Histogram
rawdata.hist()
plt.show()

# boxplot
pd.DataFrame.boxplot(rawdata)
plt.show()


print "Raw data size"
nrow, ncol = rawdata.shape
print nrow, ncol

path = ('/home/feng/Dropbox/MachineLearningAlgorithms/python_
↪code/data/'
'energy_efficiency.xlsx')
path

rawdataEnergy= pd.read_excel(path,sheetname=0)

nrow=rawdata.shape[0] #gives number of row count
ncol=rawdata.shape[1] #gives number of col count
print nrow, ncol
col_names = rawdata.columns.tolist()
print "Column names:"
print col_names
print "Data Format:"
print rawdata.dtypes

print "\nSample data:"
print(rawdata.head(6))


print "\n correlation Matrix"
print rawdata.corr()

# cocorrelation Matrix plot
pd.DataFrame.corr(rawdata)
plt.show()

print "\n covariance Matrix"
print rawdata.cov()

print rawdata[['Age','Ca']].corr()
pd.DataFrame.corr(rawdata)
plt.show()



# define colors list, to be used to plot survived either red␣
↪(=0) or green (=1)
```

(continues on next page)

(continued from previous page)

```
    colors=['red','green']

    # make a scatter plot

#    rawdata.info()

    from scipy import stats
    import seaborn as sns # just a conventional alias, don't␣
↪know why
    sns.corrplot(rawdata) # compute and plot the pair-wise␣
↪correlations
    # save to file, remove the big white borders
    #plt.savefig('attribute_correlations.png', tight_layout=True)
    plt.show()


    attr = rawdata['Age']
    sns.distplot(attr)
    plt.show()

    sns.distplot(attr, kde=False, fit=stats.gamma);
    plt.show()

    # Two subplots, the axes array is 1-d
    plt.figure(1)
    plt.title('Histogram of Age')
    plt.subplot(211) # 21,1 means first one of 2 rows, 1 col
    sns.distplot(attr)

    plt.subplot(212) #  21,2 means second one of 2 rows, 1 col
    sns.distplot(attr, kde=False, fit=stats.gamma);

    plt.show()
```

CHAPTER

FIVE

PRE-PROCESSING PROCEDURES

Note: **Well begun is half done** – old Chinese proverb

In my opinion, preprocessing is crucial for the data mining algorithms. If you get a good pre-processing, you will definitely get a beeter result. In this section, we will learn how to do a proper pre-processing in **R** and **Python**.

5.1 Rough Pre-processing

- **dealing with missing data**

  Usually, we have two popular way to deal with the missing data: replacing by 0 or replacing by mean value.

  - dealing with missing data in **R**
  - dealing with missing data in **Python**

5.2 Source Code for This Section

The code for this section is available for download for R, for Python,

- R Source code

```
rm(list = ls())
# set the enverionment
path ='~/Dropbox/MachineLearningAlgorithms/python_code/data/
↪Heart.csv'
rawdata = read.csv(path)

# summary of the data
summary(rawdata)
# plot of the summary
plot(rawdata)
```

(continues on next page)

(continued from previous page)

```
dim(rawdata)
head(rawdata)
tail(rawdata)

colnames(rawdata)
attach(rawdata)

# get numerical data and remove NAN
numdata=na.omit(rawdata[,c(1:2,4:12)])

cor(numdata)
cov(numdata)

dev.off()
# laod cocorrelation Matrix plot lib
library(corrplot)
M <- cor(numdata)
#par(mfrow =c (1,2))
#corrplot(M, method = "square")
corrplot.mixed(M)


nrow=nrow(rawdata)
ncol=ncol(rawdata)
c(nrow, ncol)



Nvars=ncol(numdata)
# checking data format
typeof(rawdata)
install.packages("mlbench")
library(mlbench)
sapply(rawdata, class)

dev.off()
name=colnames(numdata)
Nvars=ncol(numdata)
# boxplot
par(mfrow =c (4,3))
for (i in 1:Nvars)
{
  #boxplot(numdata[,i]~numdata[,Nvars],data=data,main=name[i])
  boxplot(numdata[,i],data=numdata,main=name[i])
}

# Histogram with normal curve plot
dev.off()
Nvars=ncol(numdata)
name=colnames(numdata)
par(mfrow =c (3,5))
for (i in 1:Nvars)
```

(continues on next page)

(continued from previous page)

```
{
  x<- numdata[,i]
  h<-hist(x, breaks=10, freq=TRUE, col="blue", xlab=name[i],main=
↪" ",
             font.lab=1)
  axis(1, tck=1, col.ticks="light gray")
  axis(1, tck=-0.015, col.ticks="black")
  axis(2, tck=1, col.ticks="light gray", lwd.ticks="1")
  axis(2, tck=-0.015)
  xfit<-seq(min(x),max(x),length=40)
  yfit<-dnorm(xfit,mean=mean(x),sd=sd(x))
  yfit <- yfit*diff(h$mids[1:2])*length(x)
  lines(xfit, yfit, col="blue", lwd=2)
}


library(reshape2)
library(ggplot2)
d <- melt(diamonds[,-c(2:4)])
ggplot(d,aes(x = value)) +
  facet_wrap(~variable,scales = "free_x") +
  geom_histogram()
```

- Python Source code

```
'''
Created on Apr 25, 2016
test code
@author: Wenqiang Feng
'''
import pandas as pd
#import numpy as np
import matplotlib.pyplot as plt
from pandas.tools.plotting import scatter_matrix
from docutils.parsers.rst.directives import path

if __name__ == '__main__':
    path ='~/Dropbox/MachineLearningAlgorithms/python_code/data/
↪Heart.csv'
    rawdata = pd.read_csv(path)

    print "data summary"
    print rawdata.describe()

    # summary plot of the data
    scatter_matrix(rawdata,figsize=[15,15])
    plt.show()

    # Histogram
    rawdata.hist()
    plt.show()
```

(continues on next page)

(continued from previous page)

```
    # boxplot
    pd.DataFrame.boxplot(rawdata)
    plt.show()


    print "Raw data size"
    nrow, ncol = rawdata.shape
    print nrow, ncol

    path = ('/home/feng/Dropbox/MachineLearningAlgorithms/python_
↪code/data/'
    'energy_efficiency.xlsx')
    path

    rawdataEnergy= pd.read_excel(path,sheetname=0)

    nrow=rawdata.shape[0] #gives number of row count
    ncol=rawdata.shape[1] #gives number of col count
    print nrow, ncol
    col_names = rawdata.columns.tolist()
    print "Column names:"
    print col_names
    print "Data Format:"
    print rawdata.dtypes

    print "\nSample data:"
    print(rawdata.head(6))


    print "\n correlation Matrix"
    print rawdata.corr()

    # cocorrelation Matrix plot
    pd.DataFrame.corr(rawdata)
    plt.show()

    print "\n covariance Matrix"
    print rawdata.cov()

    print rawdata[['Age','Ca']].corr()
    pd.DataFrame.corr(rawdata)
    plt.show()



    # define colors list, to be used to plot survived either red␣
↪(=0) or green (=1)
    colors=['red','green']

    # make a scatter plot

#     rawdata.info()
```

(continues on next page)

(continued from previous page)

```
    from scipy import stats
    import seaborn as sns # just a conventional alias, don't␣
↪know why
    sns.corrplot(rawdata) # compute and plot the pair-wise␣
↪correlations
    # save to file, remove the big white borders
    #plt.savefig('attribute_correlations.png', tight_layout=True)
    plt.show()


    attr = rawdata['Age']
    sns.distplot(attr)
    plt.show()

    sns.distplot(attr, kde=False, fit=stats.gamma);
    plt.show()

    # Two subplots, the axes array is 1-d
    plt.figure(1)
    plt.title('Histogram of Age')
    plt.subplot(211) # 21,1 means first one of 2 rows, 1 col
    sns.distplot(attr)

    plt.subplot(212) #  21,2 means second one of 2 rows, 1 col
    sns.distplot(attr, kde=False, fit=stats.gamma);

    plt.show()
```

CHAPTER

SIX

SUMMARY OF DATA MINING ALGORITHMS

Note: Know yourself and know your enemy, and you will never be defeated– idiom, from Sunzi's Art of War

Although the tutorials presented here is not plan to focuse on the theoretical frameworks of Data Mining, it is still worth to understand how they are works and know what's the assumption of those algorithm. This is an important steps to know ourselves.

6.1 Diagram of Data Mining Algorithms

An awesome Tour of Machine Learning Algorithms was published online by Jason Brownlee in 2013, it still is a good category diagram.

6.2 Categories of Data Mining Algorithms

0. Dimensionality Reduction Algorithms

- Principal Component Analysis (PCA)
- Nonnegative Matrix Factorization (NMF)
- Independent Component Analysis (ICA)
- Linear Discriminant Analysis (LDA)

1. Regression Algorithms

- Ordinary Least Squares Regression (OLSR)
- Linear Regression
- Logistic Regression

2. Regularization Algorithms

- Ridge Regression

Fig. 1: **Figure** : Machine Learning Algorithms diagram from Jason Brownlee .

- Least Absolute Shrinkage and Selection Operator (LASSO)
- Elastic Net
- Least-Angle Regression (LARS)

3. Decision Tree Algorithms

- Classification and Regression Tree (CART)
- Conditional Decision Trees

5. Bayesian Algorithms

- Naive Bayes

6. Clustering Algorithms

- k-Means
- k-Medians
- Expectation Maximisation (EM)
- Hierarchical Clustering

8. Artificial Neural Network Algorithms

- Perceptron
- Back-Propagation
- Hopfield Network
- Radial Basis Function Network (RBFN)

9. Deep Learning Algorithms

- Deep Boltzmann Machine (DBM)
- Deep Belief Networks (DBN)

11. Ensemble Algorithms

- Boosting
- Bootstrapped Aggregation (Bagging)
- AdaBoost
- Gradient Boosting Machines (GBM)
- Gradient Boosted Regression Trees (GBRT)
- Random Forest

CHAPTER

SEVEN

DIMENSION REDUCTION ALGORITHMS

7.1 What is dimension reduction?

In machine learning and statistics, dimensionality reduction or dimension reduction is the process of reducing the number of random variables under consideration, via obtaining a set "uncorrelated" principle variables. It can be divided into feature selection and feature extraction. https://en.wikipedia.org/wiki/Dimensionality_reduction

7.2 Singular Value Decomposition (SVD)

At here, I will recall the three types of the SVD method, since some authors confused the definitions of these SVD method. SVD method is important for the the dimension reduction algorithms, such as Truncated Singular Value Decomposition (tSVD) can be used to do the dimension reduction directly, and the Full Rank Singular Value Decomposition (SVD) can be applied to do Principal Component Analysis (PCA), since PCA is a specific case of SVD.

1. **Full Rank Singular Value Decomposition (SVD)**

   Suppose $\mathbf{X} \in \mathbb{R}^{n\times p}$, $(p < n)$, then

   $$\underbrace{\mathbf{X}}_{n\times p} = \underbrace{\mathbf{U}}_{n\times n}\underbrace{\mathbf{\Sigma}}_{n\times p}\underbrace{\mathbf{V}^T}_{p\times p},$$

   is called a full rank **SVD** of $\mathbf{X}$ and

   - σ_i– Sigular calues and $\mathbf{\Sigma} = diag(\sigma_1, \sigma_2, \cdots, \sigma_p) \in \mathbb{R}^{n\times p}$
   - u_i– left singular vectors, $\mathbf{U} = [u_1, u_2, \cdots, u_n]$ and $\mathbf{U}$ is unitary.
   - v_i– right singular vectors, $\mathbf{V} = [v_1, v_2, \cdots, v_p]$ and $\mathbf{V}$ is unitary.

2. **Reduced Singular Value Decomposition (rSVD)**

   Suppose $\mathbf{X} \in \mathbb{R}^{n\times p}$, $(n < p)$, then

   $$\underbrace{\mathbf{X}}_{n\times p} = \underbrace{\hat{\mathbf{U}}}_{n\times p}\underbrace{\hat{\mathbf{\Sigma}}}_{p\times p}\underbrace{\hat{\mathbf{V}}^T}_{p\times p},$$

   is called a Reduced Singular Value Decomposition **rSVD** of $\mathbf{X}$ and

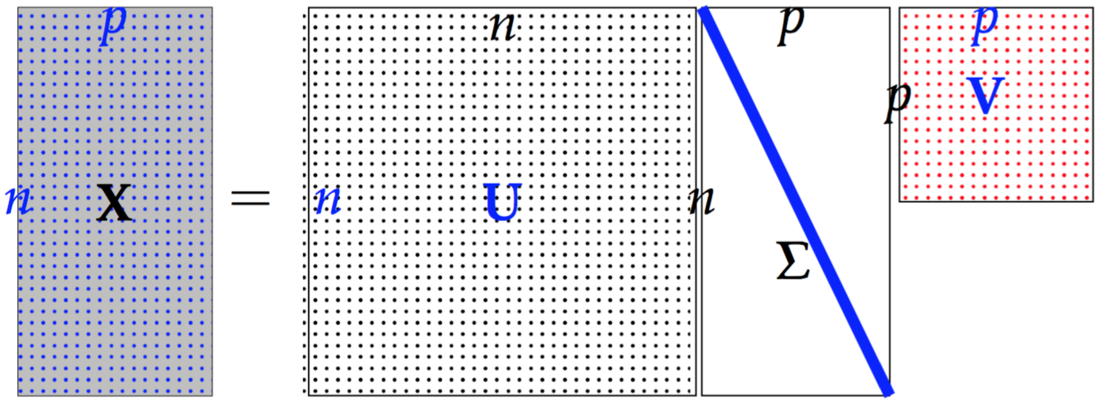


Fig. 1: Singular Value Decomposition

- σ_i– Sigular calues and $\hat{\mathbf{\Sigma}} = diag(\sigma_1, \sigma_2, \cdots, \sigma_p) \in \mathbb{R}^{p\times p}$
- u_i– left singular vectors, $\hat{\mathbf{U}} = [u_1, u_2, \cdots, u_p]$ is column-orthonormal matrix.
- v_i– right singular vectors, $\hat{\mathbf{V}} = [v_1, v_2, \cdots, v_p]$ is column-orthonormal matrix.

3. **Truncated Singular Value Decomposition (tSVD)**

   Suppose $\mathbf{X} \in \mathbb{R}^{n\times p}$, $(r < p)$, then

$$\underbrace{\mathbf{X}}_{n\times p} = \underbrace{\hat{\mathbf{U}}}_{n\times r} \underbrace{\hat{\mathbf{\Sigma}}}_{r\times r} \underbrace{\hat{\mathbf{V}}^T}_{r\times p}, \tag{7.1}$$

   is called a Truncated Singular Value Decomposition **tSVD** of $\mathbf{X}$ and

   - σ_i– Sigular calues and $\hat{\mathbf{\Sigma}} = diag(\sigma_1, \sigma_2, \cdots, \sigma_r) \in \mathbb{R}^{r\times r}$
   - u_i– left singular vectors, $\hat{\mathbf{U}} = [u_1, u_2, \cdots, u_r]$ is column-orthonormal matrix.
   - v_i– right singular vectors, $\hat{\mathbf{V}} = [v_1, v_2, \cdots, v_p]$ is column-orthonormal matrix.

Figure *Truncated Singular Value Decomposition* indictes that the the dimension of $\hat{\mathbf{U}}$ is smaller than $\mathbf{X}$. We can use this property to do the dimension reduction. But, usually, we will use SVD to compute the Principal Components. We will learn more details in next section.

7.3 Principal Component Analysis (PCA)

Usually, there are two ways to implement the PCA. Principal Component Analysis (PCA) is a specific case of SVD.

$$\underbrace{\mathbf{X}}_{n\times p} = \hat{\mathbf{U}} \tag{7.2}$$

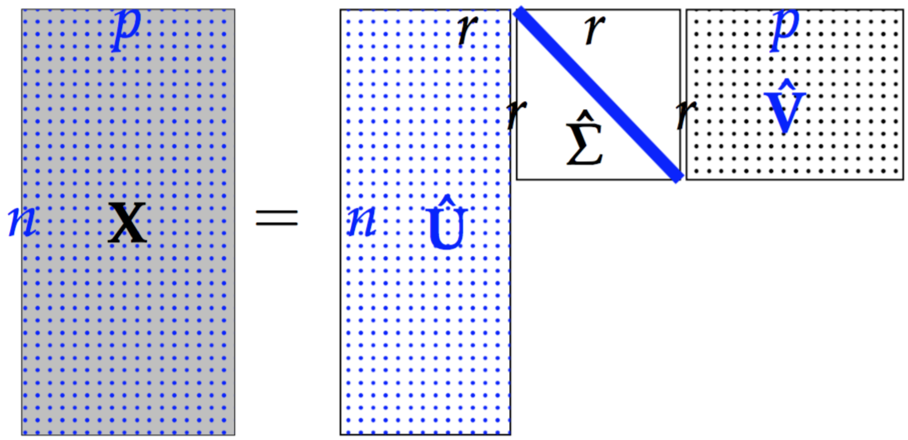


Fig. 2: Truncated Singular Value Decomposition

7.4 Independent Component Analysis (ICA)

7.5 Nonnegative matrix factorization (NMF)

TO DO. . . . . .

CHAPTER

EIGHT

REGRESSION ALGORITHM

Note: A journey of a thousand miles begins with a single step – old Chinese proverb

In statistical modeling, regression analysis focuses on investigating the relationship between a dependent variable and one or more independent variables. Wikipedia Regression analysis

In data mining, Regression is a model to represent the relationship between the value of lable (or target, it is numerical variable) and on one or more features (or predictors they can be numerical and categorical variables).

8.1 Ordinary Least Squares Regression (OLSR)

8.1.1 Introduction

Given that a data set $\{\, x_{i1}, \ldots, x_{in}, y_i\}_{i=1}^m$ which contains n features (variables) and m samples (data points), in simple linear regression model for modeling m data points with one independent variable: x_{i1}, the formula is given by:

$$y_i = \beta_0 + \beta_1 x_{i1}, \text{where}, i = 1, \cdots m.$$

In matrix notation, the data set is written as $\mathbf{X} = [\mathbf{X}_1, \cdots, \mathbf{X}_n]$ with $\mathbf{X}_i = \{x_{\cdot i}\}_{i=1}^n$, $\mathbf{y} = \{y_i\}_{i=1}^m$ and $\boldsymbol{\beta}^\top = \{\beta_i\}_{i=1}^m$. Then the normal equations are written as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta}.$$

8.1.2 How to solve it?

1. Direct Methods (For more information please refer to my Prelim Notes for Numerical Analysis)

   - For squared or rectangular matrices

    - Singular Value Decomposition
    - Gram-Schmidt orthogonalization
    - QR Decomposition
  - For squared matrices
    - LU Decomposition
    - Cholesky Decomposition
    - Regular Splittings

2. Iterative Methods
  - Stationary cases iterative method
    - Jacobi Method
    - Gauss-Seidel Method
    - Richardson Method
    - Successive Over Relaxation (SOR) Method
  - Dynamic cases iterative method
    - Chebyshev iterative Method
    - Minimal residuals Method
    - Minimal correction iterative method
    - Steepest Descent Method
    - Conjugate Gradients Method

8.2 Linear Regression (LR)

TO DO . . . ..

CHAPTER

NINE

CLASSIFICATION ALGORITHMS

9.1 Logistic Regression (LR)

9.2 k-Nearest Neighbour (kNN)

9.3 Linear Discriminant Analysis (LDA)

9.4 Quadratic Discriminant Analysis (QDA)

TO DO . . . ..

CHAPTER

TEN

REGULARIZATION ALGORITHMS

10.1 Subset Selection (SubS)

10.2 Ridge Regression (Ridge)

10.3 Least Absolute Shrinkage and Selection Operator (lASSO)

TO DO . . . ..

CHAPTER

ELEVEN

RESAMPLING ALGORITHMS

TO DO . . . ..

CHAPTER

TWELVE

DEVELOPING YOUR OWN R PACKAGES

TO DO……

CHAPTER THIRTEEN

DEVELOPING YOUR OWN PYTHON PACKAGES

```
Using Spark defined in the SPARK_HOME=/Users/~/spark environmental property

Python 3.7.1 (default, Dec 14 2018, 13:28:58)
[Clang 4.0.1 (tags/RELEASE_401/final)] :: Anaconda, Inc. on darwin
Type "help", "copyright", "credits" or "license" for more information.
2019-02-15 14:08:30 WARN  NativeCodeLoader:62 - Unable to load native-hadoop
↪library for your platform... using builtin-java classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use
↪setLogLevel(newLevel).
2019-02-15 14:08:31 WARN  Utils:66 - Service 'SparkUI' could not bind on port
↪4040. Attempting port 4041.
2019-02-15 14:08:31 WARN  Utils:66 - Service 'SparkUI' could not bind on port
↪4041. Attempting port 4042.
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 2.4.0
      /_/

Using Python version 3.7.1 (default, Dec 14 2018 13:28:58)
SparkSession available as 'spark'.
>>>
```

TO DO. . . . . .

INDEX