

Breast Cancer Detection Using Classification Models

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2022-12-01

Project Description:

The project is a classifier problem. The Data set contains the different dependent features to predict the Breast Cancer whether it is Benign or Malignant. The Data set is taken from the study done by University of California at Irvine from there ML Data Set Repository.

Reading the Data File

```
Data=read.table("data.csv", header = TRUE, sep = ",")
```

Checking if any null records are present in Data Set

```
sum(is.na(Data))
```

```
## [1] 0
```

The dataset is almost equally distributed for both Malignant and Benign cases

```
table(Data$diagnosis)
```

```
##  
##    B    M  
## 357 212
```

Displaying the Data Set

```
head(Data)
```

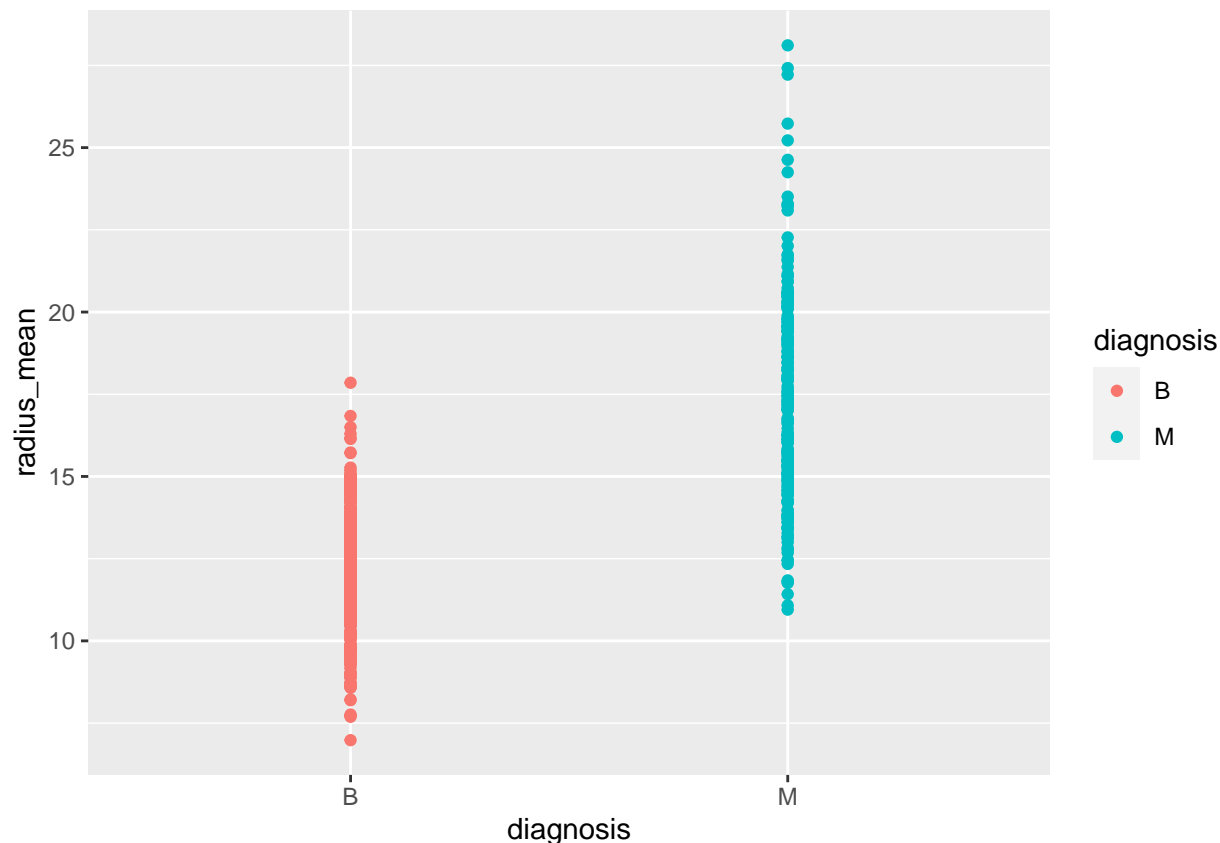
```
##           id diagnosis radius_mean texture_mean perimeter_mean area_mean  
## 1    842302         M      17.99      10.38         122.80      1001.0  
## 2    842517         M      20.57      17.77         132.90      1326.0  
## 3  84300903         M      19.69      21.25         130.00      1203.0  
## 4  84348301         M      11.42      20.38          77.58       386.1  
## 5  84358402         M      20.29      14.34         135.10      1297.0  
## 6    843786         M      12.45      15.70          82.57       477.1  
## smoothness_mean compactness_mean concavity_mean concave.points_mean  
## 1         0.11840         0.27760         0.3001         0.14710  
## 2         0.08474         0.07864         0.0869         0.07017  
## 3         0.10960         0.15990         0.1974         0.12790  
## 4         0.14250         0.28390         0.2414         0.10520
```

```
## 5      0.10030      0.13280      0.1980      0.10430
## 6      0.12780      0.17000      0.1578      0.08089
## symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se
## 1      0.2419      0.07871      1.0950      0.9053      8.589
## 2      0.1812      0.05667      0.5435      0.7339      3.398
## 3      0.2069      0.05999      0.7456      0.7869      4.585
## 4      0.2597      0.09744      0.4956      1.1560      3.445
## 5      0.1809      0.05883      0.7572      0.7813      5.438
## 6      0.2087      0.07613      0.3345      0.8902      2.217
## area_se smoothness_se compactness_se concavity_se concave.points_se
## 1 153.40      0.006399      0.04904      0.05373      0.01587
## 2  74.08      0.005225      0.01308      0.01860      0.01340
## 3  94.03      0.006150      0.04006      0.03832      0.02058
## 4  27.23      0.009110      0.07458      0.05661      0.01867
## 5  94.44      0.011490      0.02461      0.05688      0.01885
## 6  27.19      0.007510      0.03345      0.03672      0.01137
## symmetry_se fractal_dimension_se radius_worst texture_worst perimeter_worst
## 1  0.03003      0.006193      25.38      17.33      184.60
## 2  0.01389      0.003532      24.99      23.41      158.80
## 3  0.02250      0.004571      23.57      25.53      152.50
## 4  0.05963      0.009208      14.91      26.50      98.87
## 5  0.01756      0.005115      22.54      16.67      152.20
## 6  0.02165      0.005082      15.47      23.75      103.40
## area_worst smoothness_worst compactness_worst concavity_worst
## 1 2019.0      0.1622      0.6656      0.7119
## 2 1956.0      0.1238      0.1866      0.2416
## 3 1709.0      0.1444      0.4245      0.4504
## 4  567.7      0.2098      0.8663      0.6869
## 5 1575.0      0.1374      0.2050      0.4000
## 6  741.6      0.1791      0.5249      0.5355
## concave.points_worst symmetry_worst fractal_dimension_worst
## 1      0.2654      0.4601      0.11890
## 2      0.1860      0.2750      0.08902
## 3      0.2430      0.3613      0.08758
## 4      0.2575      0.6638      0.17300
## 5      0.1625      0.2364      0.07678
## 6      0.1741      0.3985      0.12440
```

Displaying the classifier data with one of the feature. The graph displays radius_mean, a feature from our data set to visualize the classifier problem.

```
library(ggplot2)

# Scatter plot by group
ggplot(Data, aes(x = diagnosis, y = radius_mean, color = diagnosis)) +
  geom_point()
```



We can see that there is a column called 'id' in our dataset which we don't require for training our model. Dropping the column 'id'. From the data we can see that the records of the dependent variable contain mainly mean, standard error, and worst features.

Exploratory Data Analysis :

```
summary(Data)
```

```
##          id          diagnosis      radius_mean      texture_mean
## Min.      :    8670  Length:569      Min.      : 6.981  Min.      : 9.71
## 1st Qu.:   869218  Class :character  1st Qu.:11.700  1st Qu.:16.17
## Median :   906024  Mode  :character  Median :13.370  Median :18.84
## Mean      : 30371831                      Mean      :14.127  Mean      :19.29
## 3rd Qu.:   8813129                      3rd Qu.:15.780  3rd Qu.:21.80
## Max.      :911320502                      Max.      :28.110  Max.      :39.28
## perimeter_mean  area_mean  smoothness_mean  compactness_mean
## Min.      : 43.79  Min.      : 143.5  Min.      :0.05263  Min.      :0.01938
## 1st Qu.: 75.17  1st Qu.: 420.3  1st Qu.:0.08637  1st Qu.:0.06492
## Median : 86.24  Median : 551.1  Median :0.09587  Median :0.09263
## Mean      : 91.97  Mean      : 654.9  Mean      :0.09636  Mean      :0.10434
## 3rd Qu.:104.10  3rd Qu.: 782.7  3rd Qu.:0.10530  3rd Qu.:0.13040
## Max.      :188.50  Max.      :2501.0  Max.      :0.16340  Max.      :0.34540
## concavity_mean  concave.points_mean  symmetry_mean  fractal_dimension_mean
## Min.      :0.00000  Min.      :0.00000  Min.      :0.1060  Min.      :0.04996
## 1st Qu.:0.02956  1st Qu.:0.02031  1st Qu.:0.1619  1st Qu.:0.05770
## Median :0.06154  Median :0.03350  Median :0.1792  Median :0.06154
```

```
## Mean :0.08880 Mean :0.04892 Mean :0.1812 Mean :0.06280
## 3rd Qu.:0.13070 3rd Qu.:0.07400 3rd Qu.:0.1957 3rd Qu.:0.06612
## Max. :0.42680 Max. :0.20120 Max. :0.3040 Max. :0.09744
## radius_se texture_se perimeter_se area_se
## Min. :0.1115 Min. :0.3602 Min. : 0.757 Min. : 6.802
## 1st Qu.:0.2324 1st Qu.:0.8339 1st Qu.: 1.606 1st Qu.: 17.850
## Median :0.3242 Median :1.1080 Median : 2.287 Median : 24.530
## Mean :0.4052 Mean :1.2169 Mean : 2.866 Mean : 40.337
## 3rd Qu.:0.4789 3rd Qu.:1.4740 3rd Qu.: 3.357 3rd Qu.: 45.190
## Max. :2.8730 Max. :4.8850 Max. :21.980 Max. :542.200
## smoothness_se compactness_se concavity_se concave.points_se
## Min. :0.001713 Min. :0.002252 Min. :0.00000 Min. :0.000000
## 1st Qu.:0.005169 1st Qu.:0.013080 1st Qu.:0.01509 1st Qu.:0.007638
## Median :0.006380 Median :0.020450 Median :0.02589 Median :0.010930
## Mean :0.007041 Mean :0.025478 Mean :0.03189 Mean :0.011796
## 3rd Qu.:0.008146 3rd Qu.:0.032450 3rd Qu.:0.04205 3rd Qu.:0.014710
## Max. :0.031130 Max. :0.135400 Max. :0.39600 Max. :0.052790
## symmetry_se fractal_dimension_se radius_worst texture_worst
## Min. :0.007882 Min. :0.0008948 Min. : 7.93 Min. :12.02
## 1st Qu.:0.015160 1st Qu.:0.0022480 1st Qu.:13.01 1st Qu.:21.08
## Median :0.018730 Median :0.0031870 Median :14.97 Median :25.41
## Mean :0.020542 Mean :0.0037949 Mean :16.27 Mean :25.68
## 3rd Qu.:0.023480 3rd Qu.:0.0045580 3rd Qu.:18.79 3rd Qu.:29.72
## Max. :0.078950 Max. :0.0298400 Max. :36.04 Max. :49.54
## perimeter_worst area_worst smoothness_worst compactness_worst
## Min. : 50.41 Min. : 185.2 Min. :0.07117 Min. :0.02729
## 1st Qu.: 84.11 1st Qu.: 515.3 1st Qu.:0.11660 1st Qu.:0.14720
## Median : 97.66 Median : 686.5 Median :0.13130 Median :0.21190
## Mean :107.26 Mean : 880.6 Mean :0.13237 Mean :0.25427
## 3rd Qu.:125.40 3rd Qu.:1084.0 3rd Qu.:0.14600 3rd Qu.:0.33910
## Max. :251.20 Max. :4254.0 Max. :0.22260 Max. :1.05800
## concavity_worst concave.points_worst symmetry_worst fractal_dimension_worst
## Min. :0.0000 Min. :0.00000 Min. :0.1565 Min. :0.05504
## 1st Qu.:0.1145 1st Qu.:0.06493 1st Qu.:0.2504 1st Qu.:0.07146
## Median :0.2267 Median :0.09993 Median :0.2822 Median :0.08004
## Mean :0.2722 Mean :0.11461 Mean :0.2901 Mean :0.08395
## 3rd Qu.:0.3829 3rd Qu.:0.16140 3rd Qu.:0.3179 3rd Qu.:0.09208
## Max. :1.2520 Max. :0.29100 Max. :0.6638 Max. :0.20750
```

```
table(Data$diagnosis)
```

```
##
## B M
## 357 212
```

```
Data=subset(Data,select=(-1))
```

Grouping the dependent variables into the groups for easily analyzing them.

```
meanIdx = grepl('mean', colnames(Data))
```

```
seIdx = grepl('se',colnames(Data))
```

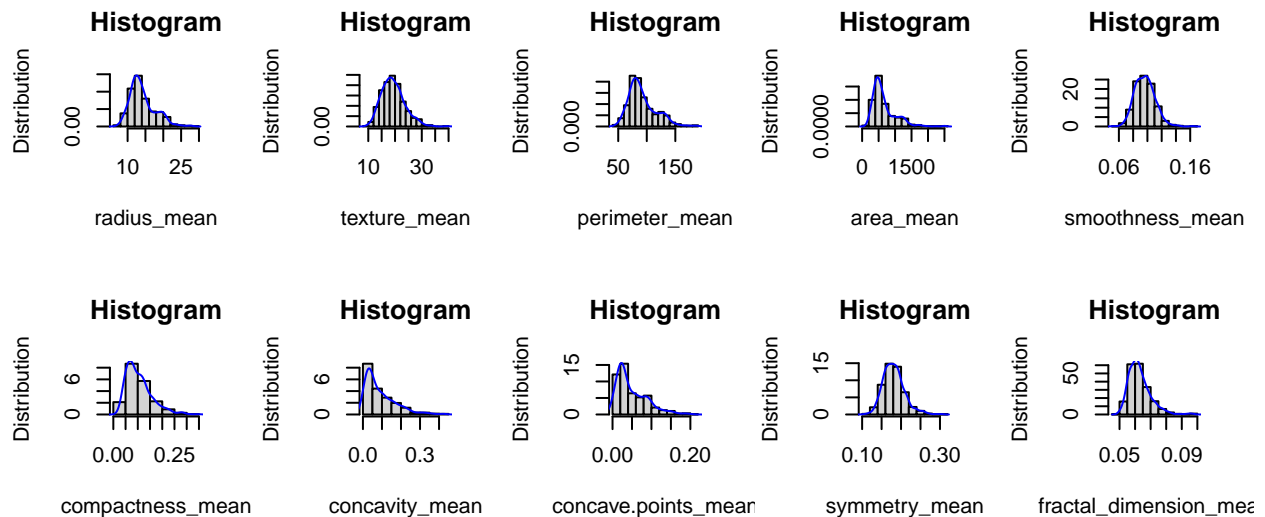
```
worstIdx= grep('worst',colnames(Data))
```

Plotting the Histograms and observing the distribution for mean group data. We can see that some of the features like symmetric mean, smoothness mean, texture mean are uniform. Other features a little skewed distributions.

```
meanData=Data[meanIdx]

par(mfrow=c(3,5))

for(i in 1:ncol(meanData)) {      # for-loop over columns
  set.seed(seed = 49078)
  x <- meanData[, i]
  hist(main="Histogram", ylab="Distribution",xlab=colnames(meanData)[i],x = x, freq = FALSE)
  lines(x = density(x = x), col = "blue")
}
```



Plotting the Histograms and observing the distribution for standard error group data. Almost all the distributions of this group is appearing skewed.

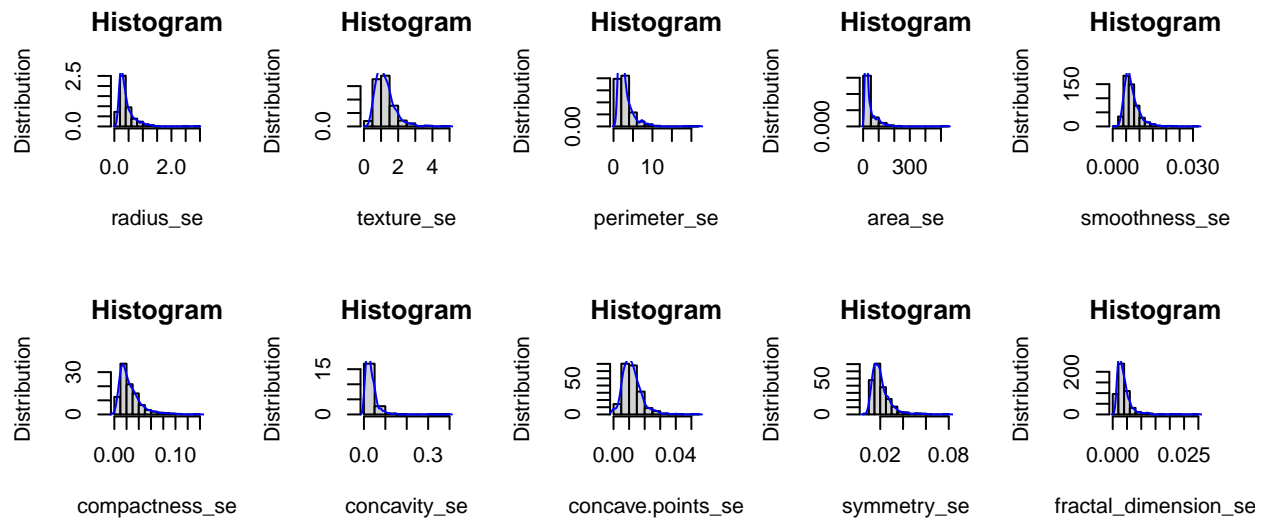
```
seData=Data[seIdx]

par(mfrow=c(3,5))
for(i in 1:ncol(seData)) {      # for-loop over columns
  set.seed(seed = 49078)
```

```

x <- seData[, i]
hist(main="Histogram", ylab="Distribution", xlab=colnames(seData)[i], x = x, freq = FALSE)
lines(x = density(x = x), col = "blue")
}

```



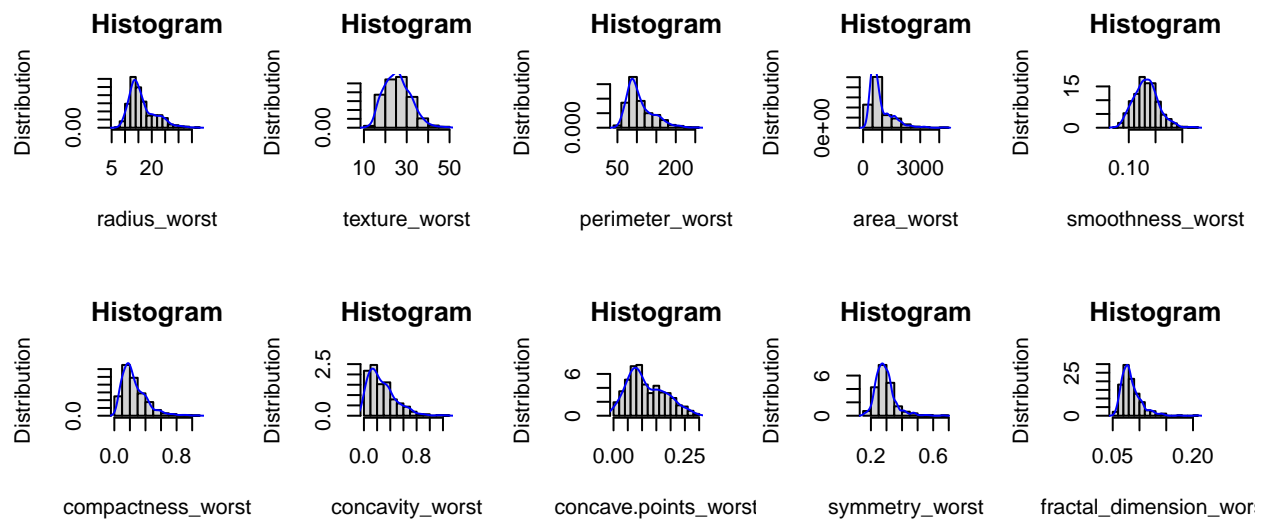
Plotting the Histograms and observing the distribution for worst group data. Almost all the distributions of this group is appearing skewed.

```

worstData=Data[worstIdx]

par(mfrow=c(3,5))
for(i in 1:ncol(worstData)) {      # for-loop over columns
  set.seed(seed = 49078)
  x <- worstData[, i]
  hist(main="Histogram", ylab="Distribution", xlab=colnames(worstData)[i], x = x, freq = FALSE)
  lines(x = density(x = x), col = "blue")
}

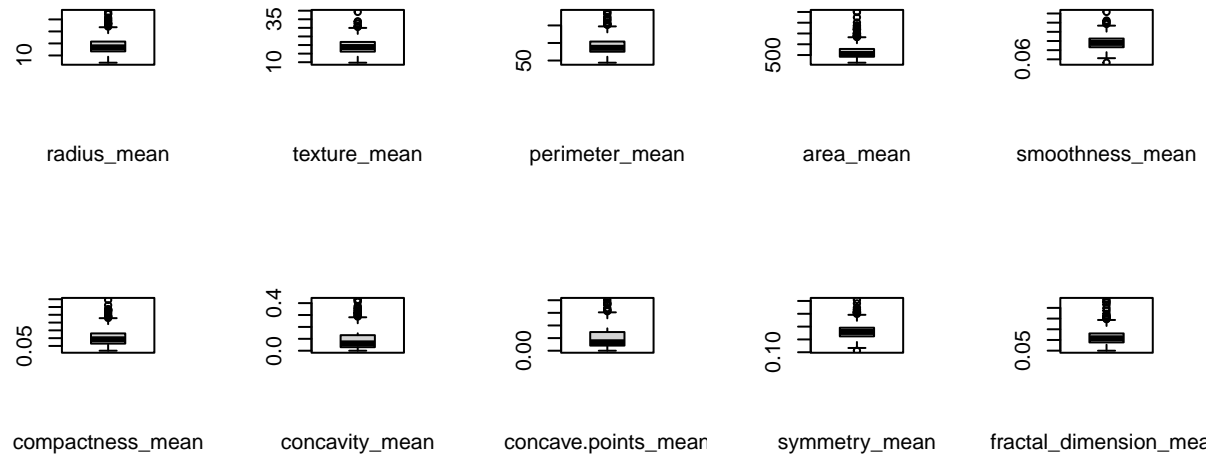
```



Plotting boxplots to see the outliers in mean data. Most of the dependent variables has outliers.

```
par(mfrow=c(3,5))

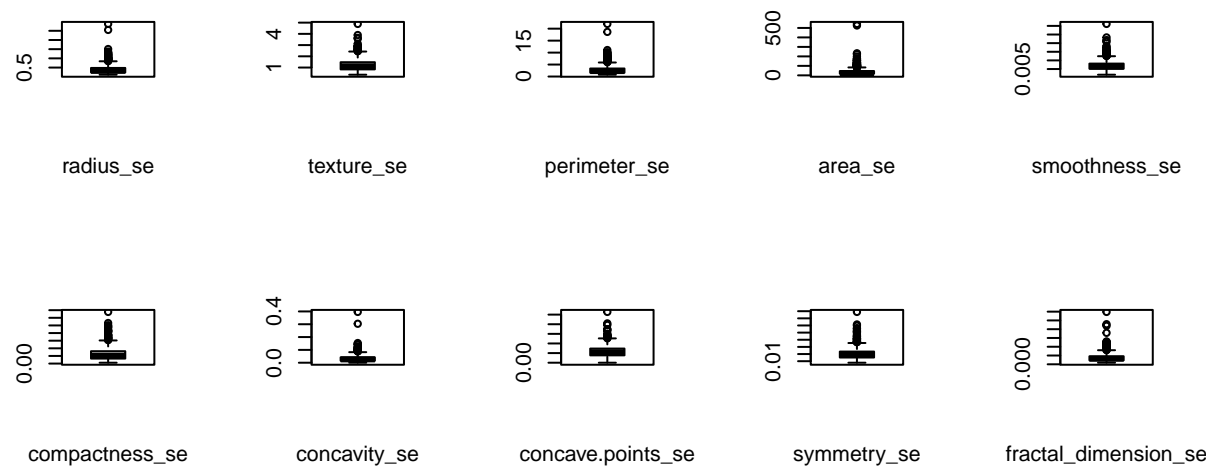
for(i in 1:ncol(meanData)) {      # for-loop over columns
  set.seed(seed = 49078)
  x <- meanData[, i]
  boxplot(xlab=colnames(meanData)[i], x = x, freq = FALSE)
}
```



Plotting boxplots to see the outliers in se data. Most of the dependent variables has outliers.

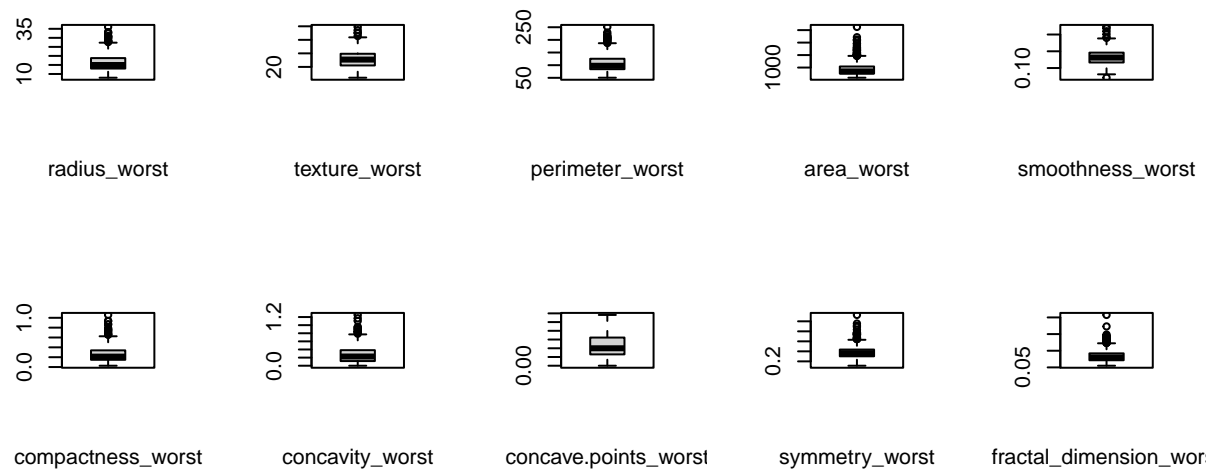
```
par(mfrow=c(3,5))

for(i in 1:ncol(seData)) {      # for-loop over columns
  set.seed(seed = 49078)
  x <- seData[, i]
  boxplot(xlab=colnames(seData)[i], x = x, freq = FALSE)
}
```

Plotting boxplots to see the outliers in worst data. Most of the dependent variables has outliers.

```
par(mfrow=c(3,5))
for(i in 1:ncol(worstData)) {      # for-loop over columns
  set.seed(seed = 49078)
  x <- worstData[ , i]
  boxplot(xlab=colnames(worstData)[i], x = x, freq = FALSE)
}
```



Checking the correlation of data set with the Dependent variable diagnosis we can see only few columns are correlated with diagnosis. We will use this columns to build our model in classification.

```
Data$diagnosis <- ifelse(Data$diagnosis=='M', 1, 0)
library(reshape2)

df=abs(cor(Data[-1:-2],Data[2]))>0.7
df=melt(df)
df[df$value==TRUE,-2]
```

```
##           Var1 value
## 2    perimeter_mean TRUE
## 3         area_mean TRUE
## 7 concave.points_mean TRUE
## 13        area_se  TRUE
## 20    radius_worst TRUE
## 22    perimeter_worst TRUE
## 23        area_worst TRUE
## 27 concave.points_worst TRUE
```

```
df$var2==TRUE
```

```
## logical(0)
```

Dividing and splitting the data into train and test data sets

```

# perimeter_mean+ area_worst+ radius_mean
library(caTools)
# Splitting dataset
split <- sample.split(Data, SplitRatio = 0.8)
split

```

```

## [1] FALSE TRUE TRUE FALSE TRUE TRUE FALSE TRUE TRUE TRUE TRUE TRUE
## [13] TRUE TRUE FALSE TRUE TRUE TRUE FALSE TRUE TRUE TRUE TRUE TRUE
## [25] TRUE FALSE TRUE FALSE TRUE TRUE TRUE

```

```

train_reg <- subset(Data, split == "TRUE")
test_reg <- subset(Data, split == "FALSE")

```

Implementing SVM Classifier

```

library(e1071)

classifier = svm(diagnosis~concave.points_worst+ perimeter_worst+ concave.points_mean+ radius_worst+ ar

Y_predicion = predict(classifier, newdata = test_reg)

ConMat=table(test_reg$diagnosis, Y_predicion)
print("confusionMatrix")

```

```
## [1] "confusionMatrix"
```

ConMat

```

##      Y_predicion
##      0  1
## 0 81  2
## 1  2 44

```

```

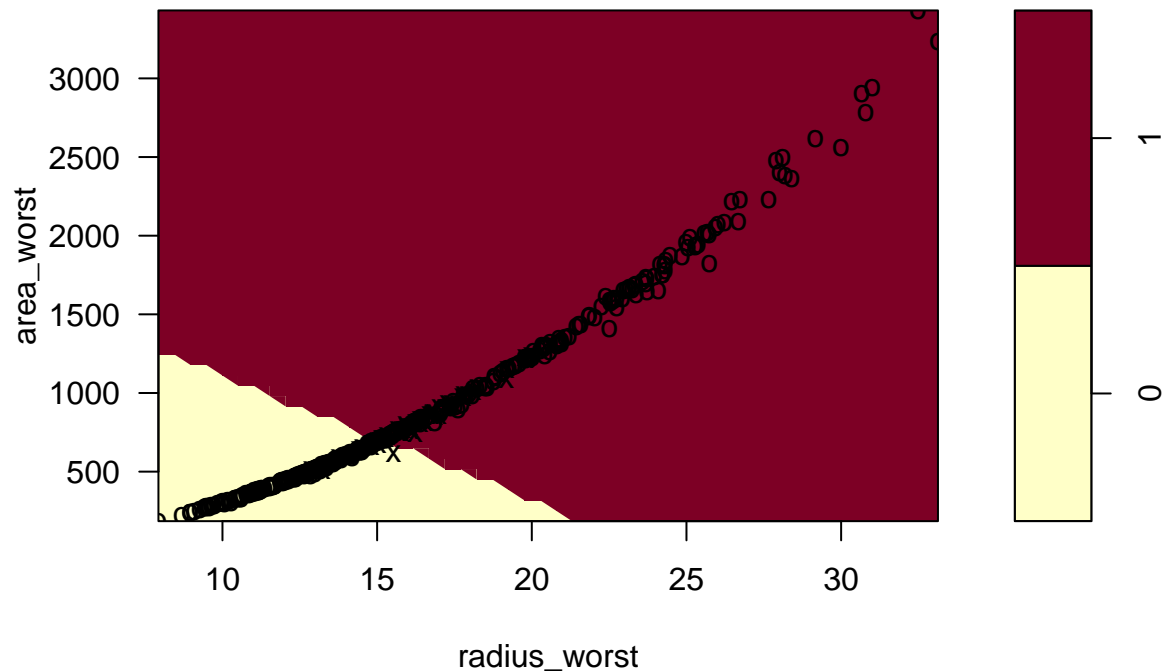
missing_classerr <- mean(Y_predicion != test_reg$diagnosis)
print(paste('Accuracy =', 1-missing_classerr))

```

```
## [1] "Accuracy = 0.968992248062015"
```

```
plot(classifier, train_reg,area_worst~radius_worst)
```

SVM classification plot



Implementing KNN Classifier

```
library(class)

knnModel=knn(train=train_reg, test=test_reg, cl=train_reg$diagnosis, k=21)

# Notice that I am only getting 2 dimensions

plot_predictions=data.frame(test_reg$diagnosis
, test_reg$concave.points_worst
, test_reg$perimeter_worst
, test_reg$concave.points_mean
, test_reg$radius_worst
, test_reg$area_mean
, test_reg$perimeter_mean
, test_reg$area_worst
, test_reg$radius_mean, predicted=knnModel)

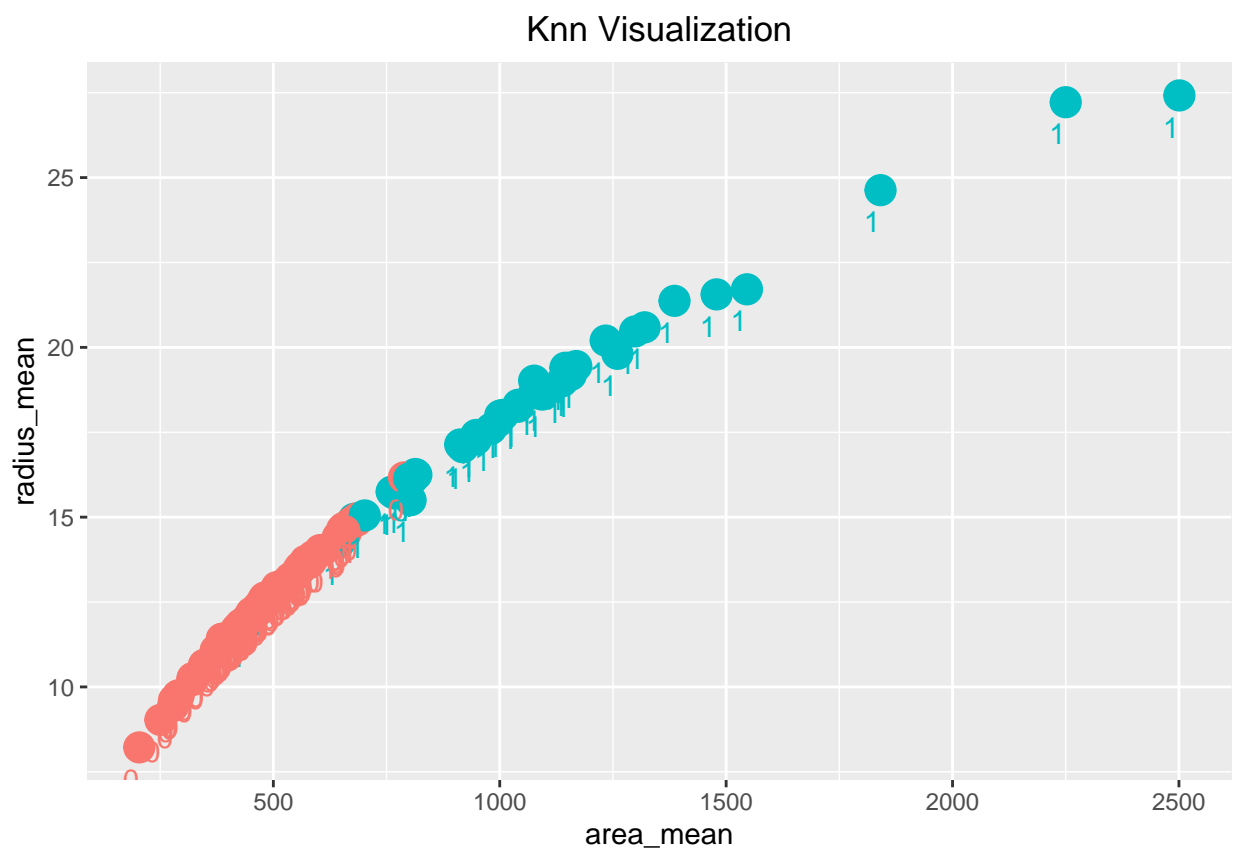
colnames(plot_predictions) <- c("diagnosis",
                               "concave.points_worst",
                               "perimeter_worst",
                               "concave.points_mean",
                               "radius_worst",
```

```

        "area_mean",
        "perimeter_mean",
        "area_worst",
        "radius_mean",
        'predicted')
# Visualize the KNN algorithm results.
library(ggplot2)

ggplot(plot_predictions, aes(area_mean, radius_mean, color = predicted, fill = predicted)) +
  geom_point(size = 5) +
  geom_text(aes(label=diagnosis),hjust=1, vjust=2) +
  ggtitle("Knn Visualization") +
  theme(plot.title = element_text(hjust = 0.5)) +
  theme(legend.position = "none")

```



```

confMatrix=table(test_reg$diagnosis, knnModel)
print("confusionMatrix")

```

```
## [1] "confusionMatrix"
```

```
confMatrix
```

```
##      knnModel
##      0  1

```

```
##    0 82  1
##    1  5 41
```

```
missing_classerr <- mean(test_reg$diagnosis != knnModel)
print(paste('Accuracy =', 1-missing_classerr))
```

```
## [1] "Accuracy = 0.953488372093023"
```

Implementing logistic regression

```
# Training model
logistic_model <- glm(diagnosis~concave.points_worst+ perimeter_worst+ concave.points_mean
                      + radius_worst+ area_mean+ perimeter_mean+ area_worst+ radius_mean
                      ,family=binomial("logit"),data = train_reg)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
predictData=predict(logistic_model,data.frame(concave.points_worst=test_reg$concave.points_worst,perimeter_worst=test_reg$perimeter_worst,area_mean=test_reg$area_mean,area_worst=test_reg$area_worst,radius_mean=test_reg$radius_mean,radius_worst=test_reg$radius_worst))

library(InformationValue)

origTest=test_reg$diagnosis

#find optimal cutoff probability to use to maximize accuracy
optimal <- optimalCutoff(test_reg, predictData)[1]
optimal
```

```
## [1] 0.63
```

```
predictDif <- ifelse(predictData>optimal, 0, 1)

library(ggplot2)

print("confusionMatrix")
```

```
## [1] "confusionMatrix"
```

```
table(origTest, predictDif)
```

```
##      predictDif
## origTest  0  1
##      0  0 83
##      1 44  2
```

```
missing_classerr <- mean(predictDif != origTest)
print(paste('Accuracy =', 1 - missing_classerr))
```

```
## [1] "Accuracy = 0.0155038759689923"
```

```
ggplot(Data, aes(x=radius_mean, y=diagnosis)) + geom_point() +
  stat_smooth(method="glm", color="red", se=FALSE,
             method.args = list(family=binomial))
```

```
## 'geom_smooth()' using formula = 'y ~ x'
```

