Assignment 2

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1 Task1

1.1 data describe

Cardiovascular diseases (CVDs) is the leading cause of mortality in India. Ischemic heart disease and stroke are the predominant causes and are responsible for nearly 80% of CVD deaths.

```
dt <- read.csv("heart1.csv",na.strings = "?")
dt <- na.omit(dt) # handle NA
head(dt)
age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal target
1  63   1  3     145  233  1      0     150    0     2.3    0  0    1      1
2  37   1  2     130  250  0      1     187    0     3.5    0  0    2      1
3  41   0  1     130  204  0      0     172    0     1.4    2  0    2      1
4  56   1  1     120  236  0      1     178    0     0.8    2  0    2      1
5  57   0  0     120  354  0      1     163    1     0.6    2  0    2      1
6  57   1  0     140  192  0      1     148    0     0.4    1  0    1      1
```

This database contains 14 attributes. The "target" field refers to the presence of CVD in the patient. It is integer valued 0 (no presence) or 1 (presence). Next we look in detail at the data characteristics of each attribute.
Age: Age in years
Sex: (1 = male; 0 = female)
CP:Chest pain type(1-typical angina, 2-atypical angina, 3-non-anginal pain, 4-asymptomatic)
trestbps:Resting blood pressure (in mm Hg on admission to the hospital)
Chol:Serum cholestoral in mg/dl
Fbs:Indicator of whether fasting blood sugar>120 mg/dl (1-true; 0-false)
restecg:Resting electrocardiographic results
exang:Exercise induced angina (1-yes; 0-no)
oldpeak:ST depression induced by exercise relative to rest
slope:Slope of the peak exercise ST segment (1-upsloping, 2-flat, 3-downsloping)
ca:Number of major vessels (0-3) colored by flourosopy
thal:Summary of heart condition(3 = normal, 6 = fixed defect, 7=reversable defect)
target:the "The Disease Diagnosis" field refers to the presence of heart disease in the patient(0-No presence,1-Presence)

```
<- summary(dt)
age       sex    cp        trestbps        chol      fbs    restecg   thalach    exang
     oldpeak
Min.  :29.00  0: 96  0:143  Min.  : 94.0  Min.  :126.0  0:258  0:147  Min.  : 71.0  0:204  Min.
       :0.00
1st Qu.:47.50 1:207  1: 50  1st Qu.:120.0 1st Qu.:211.0 1: 45 1:152  1st Qu.:133.5 1: 99  1st
     Qu.:0.00
Median :55.00        2: 87  Median :130.0 Median :240.0       2:  4  Median :153.0
     Median :0.80
Mean  :54.37         3: 23  Mean  :131.6  Mean  :246.3               Mean  :149.6         Mean
       :1.04
3rd Qu.:61.00               3rd Qu.:140.0 3rd Qu.:274.5              3rd Qu.:166.0        3rd
     Qu.:1.60
Max.  :77.00                Max.  :200.0  Max.  :564.0               Max.  :202.0         Max.
       :6.20

slope       ca        thal      target
0: 21  Min.  :0.0000  0:  2  Min.  :0.0000
1:140  1st Qu.:0.0000 1: 18  1st Qu.:0.0000
2:142  Median :0.0000 2:166  Median :1.0000
       Mean  :0.7294  3:117  Mean  :0.5446
       3rd Qu.:1.0000        3rd Qu.:1.0000
       Max.  :4.0000         Max.  :1.0000
```

1.2 logistic regression

By looking at the details of each data item in the dataset, it was found that the values of age as well as maximum heart rate were quite different and needed to be processed for both data items.

```
summary(dt$age)
dt$age<-cut(as.numeric(dt$age),breaks=3,labels=c("low1","normal1","high1"))
levels(dt$age)
table(dt$age)
> summary(dt$age)
   Min. 1st Qu. Median  Mean 3rd Qu.  Max.
  29.00  47.50  55.00  54.37  61.00  77.00
> dt$age<-cut(as.numeric(dt$age),breaks = 3,labels=c("low1","normal1","high1"))
> levels(dt$age)
[1] "low1"  "normal1" "high1"
> table(dt$age)

   low1 normal1 high1
     64     168     71
> summary(dt$chol)
Min. 1st Qu. Median  Mean 3rd Qu.  Max.
126.0  211.0  240.0  246.3  274.5  564.0
> dt$chol<-cut(as.numeric(dt$chol),breaks =3,labels=c("low","normal","high"))
> levels(dt$chol)
[1] "low"   "normal" "high"
> table(dt$chol)

low normal high
222    80     1
```

Dividing the data set into training and test sets according to a 7 to 3 ratio

```
  > samp<-sample(2,nrow(dt),replace = T,prob = c(0.7,0.3))
> training<-dt[samp==1,]
> test<-dt[samp==2,]
> head(training)
     age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal target
1   high1  1  3      145   low  1       0     150     0     2.3     0  0    1      1
```

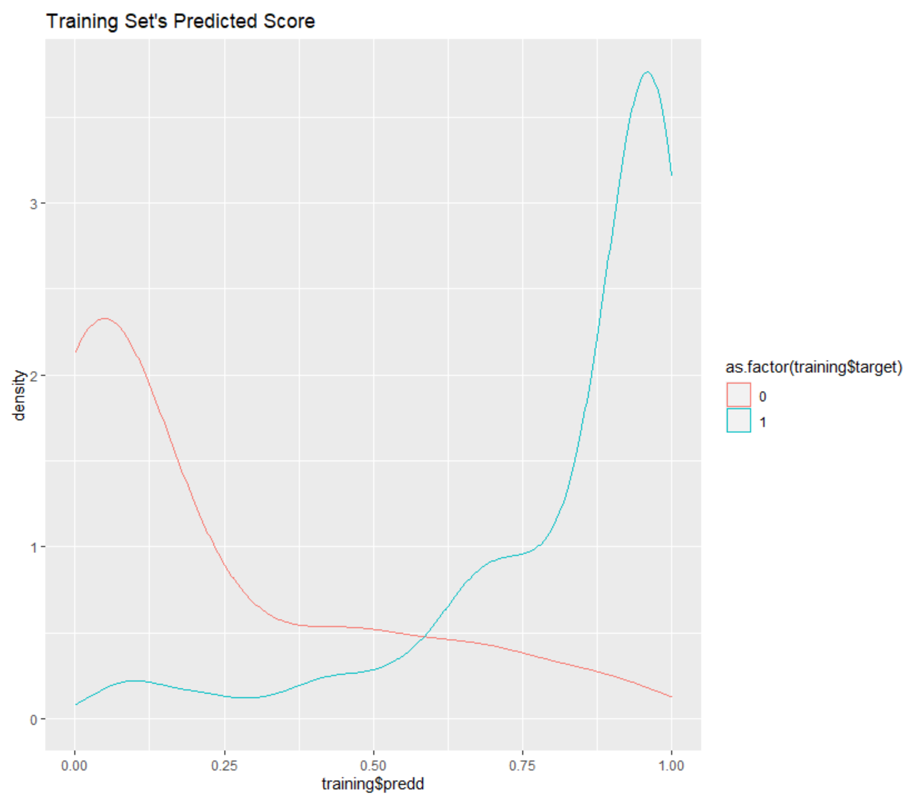
```
3   low1  0  1     130   low  0      0    172    0    1.4    2  0    2     1
4 normal1  1  1     120   low  0      1    178    0    0.8    2  0    2     1
5 normal1  0  0     120 normal  0      1    163    1    0.6    2  0    2     1
6 normal1  1  0     140   low  0      1    148    0    0.4    1  0    1     1
7 normal1  0  1     140 normal  0      0    153    0    1.3    1  0    2     1
> head(test)
      age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal target
2    low1   1  2      130   low  0       1     187     0     3.5     0  0    2      1
18  high1   0  3      150   low  0       1     114     0     2.6     0  0    2      1
25   low1   1  3      140   low  0       1     178     1     1.4     2  0    3      1
29  high1   0  2      140 normal  1       0     157     0     0.8     2  1    2      1
36 normal1  0  2      142   low  0       0     160     1     1.4     0  0    2      1
38 normal1  1  2      150   low  0       0     165     0     1.6     2  0    3      1
> colSums(is.na(test))
    age      sex       cp trestbps     chol      fbs  restecg  thalach    exang  oldpeak    slope       ca
         thal   target
      0        0        0        0        0        0        0        0        0        0        0        0
            0        0
```

Next, a logistic regression prediction model is built using the training set data

```
> mod<-glm(target~.,data = training,family = binomial('logit'))
> summary(mod)

Call:
glm(formula = target ~ ., family = binomial("logit"), data = training)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6397  -0.3260  0.1472   0.4614   2.4521

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   1.43597    3.14892   0.456  0.64838
agenormal1   -1.08551    0.66165  -1.641  0.10088
agehigh1      0.19073    0.82340   0.232  0.81682
sex1         -1.27014    0.63533  -1.999  0.04559 *
cp1           1.07789    0.64981   1.659  0.09716 .
cp2           1.76202    0.59697   2.952  0.00316 **
cp3           2.33462    0.87380   2.672  0.00754 **
trestbps     -0.02011    0.01359  -1.480  0.13899
cholnormal   -0.87024    0.56281  -1.546  0.12204
cholhigh     13.46342 1455.39800   0.009  0.99262
fbs1          1.40058    0.78331   1.788  0.07377 .
restecg1      0.75994    0.47349   1.605  0.10850
restecg2      0.18667    3.24270   0.058  0.95409
thalach       0.01516    0.01288   1.177  0.23910
exang1       -1.06170    0.53172  -1.997  0.04585 *
oldpeak      -0.52696    0.26619  -1.980  0.04774 *
slope1       -0.74014    1.04764  -0.706  0.47989
slope2        0.01442    1.13336   0.013  0.98985
ca           -0.57276    0.23372  -2.451  0.01426 *
thal1         1.48527    2.16992   0.684  0.49367
thal2         1.70341    1.83567   0.928  0.35343
thal3         0.18380    1.87081   0.098  0.92174
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '’. 0.1 '’1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 292.99 on 213 degrees of freedom
Residual deviance: 134.65 on 192 degrees of freedom
AIC: 178.65

Number of Fisher Scoring iterations: 14
```

After getting the training model, we need to evaluate the suitability of the model for the scenario by the following metrics

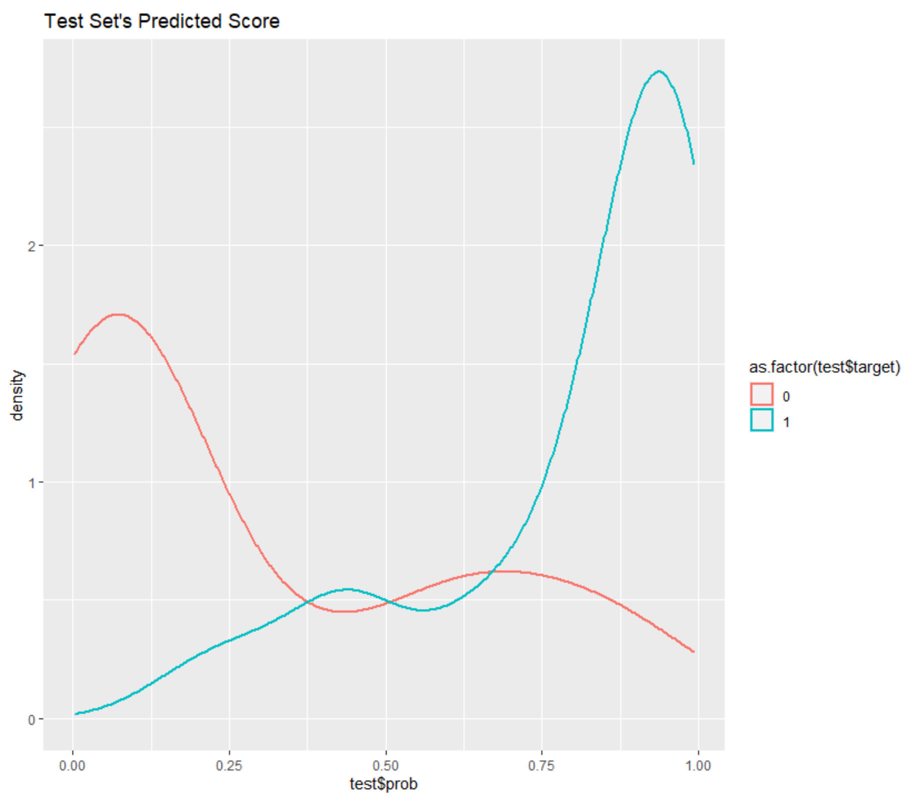
```
predicted<-predict(mod,training,type ="response")
training$predd<-round(predicted,3)
View(training)
ggplot( training, aes( training$predd, color = as.factor(training$target) ) ) +
  geom_density( ) +
  ggtitle( "Training Set's Predicted Score" )
training$predw<-ifelse(training$predd>0.46,1,0)
```




```
> training$predw<-ifelse(training$predd>0.46,1,0)
> confusn<-confusionMatrix(training$target,training$predw,threshold = 0.46)
> confusn
   0   1
0 74  11
1 19 110
> confusn<-as.matrix(confusn)
> AccuracyRate <- sum(diag(confusn))/sum(confusn)
> AccuracyRate
[1] 0.8598131
```

Similarly, we need to evaluate this model in the test set

```
> test$prob <- predict(mod,test,type = "response")
> View(test)
> ggplot( test, aes( test$prob, color = as.factor(test$target) ) ) + geom_density( size = 1
     ) + ggtitle( "Test Set's Predicted Score" )
> test$predc<-ifelse(test$prob>0.475,1,0)
> confusn<-confusionMatrix(test$target,test$predc,threshold = 0.475)
> confusn
   0  1
0 31  7
1 14 37
> class(confusn)
[1] "data.frame"
> confusn<-as.matrix(confusn)
> AccuracyRate <- sum(diag(confusn))/sum(confusn)
> AccuracyRate
[1] 0.7640449
```



The evaluation summary of logistic regression can be seen below

```
  > Confusion
        Actual
Predicted 0 1
       0 31 7
       1 14 37
> AccuracyRate
[1] 0.7640449
```

```
> plot(rocCurve)
> rocCurve$sensitivities
[1] 1.0000000 0.6888889 0.0000000
> rocCurve$specificities
[1] 0.0000000 0.8409091 1.0000000
> rocCurve$au
Area under the curve: 0.7649
```

1.3 Decision Tree

The decision tree algorithm is a method of approximating the value of a discrete function. It is a typical classification method. It first processes the data, uses induction algorithms to generate readable rules and decision trees, and then uses decisions to analyze new data. In essence, a decision tree is a process of classifying data through a series of rules.

The decision tree algorithm constructs a decision tree to discover the classification rules contained in the data. How to construct a high-precision, small-scale decision tree is the core content of the decision tree algorithm. The decision tree construction can be done in two steps. The first step is to generate a decision tree: the process of generating a decision tree from the training sample set. In general, the training sample data set is a data set that has a history and a certain degree of comprehensiveness according to actual needs, and is used for data analysis and processing. The second step, the pruning of the decision tree: The pruning of the decision tree is the process of testing, correcting and pruning the decision tree generated in the previous stage, mainly using a new sample data set (called a test data set) The data verifies the preliminary rules generated during the decision tree generation process, and prunes those branches that affect the accuracy of the pre-balance.

We divided the original data set into two parts, using two-thirds of the data as the training set and the other third as the test set.

```
> data<-read.csv("./heart.csv", head = TRUE, fileEncoding = 'GBK')
> set.seed(1)
> sub<-sample(1:nrow(data),round(nrow(data)*2/3))
> data_train<-data[sub,]
> data_test<-data[-sub,]
> dim(data_train)
[1] 202 14
> dim(data_test)
[1] 101 14
```

Then we build a decision tree model and evaluate the model.

```
> library(rpart)
> dt_model = rpart(target~., data = data_train,method = "class",parms = list(split="
     information"))
> summary(dt_model)
Call:
rpart(formula = target ~ ., data = data_train, method = "class",
   parms = list(split = "information"))
  n= 202

          CP nsplit rel error xerror      xstd
1 0.50000000      0 1.0000000 1.0000000 0.07541752
2 0.05319149      1 0.5000000 0.5000000 0.06388682
```

```
3 0.04255319   3 0.3936170 0.5000000 0.06388682
4 0.01773050   4 0.3510638 0.5000000 0.06388682
5 0.01595745   7 0.2978723 0.5212766 0.06480973
6 0.01000000   9 0.2659574 0.5212766 0.06480973

Variable importance
     cp thalach    thal   exang oldpeak     age     sex   slope    chol      ca trestbps
     21      18      15      11       8       7       7       5       3       3       3

Node number 1: 202 observations,    complexity param=0.5
  predicted class=1  expected loss=0.4653465  P(node) =1
    class counts:    94   108
   probabilities: 0.465 0.535
  left son=2 (95 obs) right son=3 (107 obs)
  Primary splits:
      cp    < 0.5  to the left,  improve=30.14774, (0 missing)
      thal  < 2.5  to the right, improve=25.50801, (0 missing)
      exang < 0.5  to the right, improve=21.12757, (0 missing)
      slope < 1.5  to the left,  improve=15.34173, (0 missing)
      ca    < 0.5  to the right, improve=14.98973, (0 missing)
  Surrogate splits:
      exang   < 0.5   to the right, agree=0.748, adj=0.463, (0 split)
      thalach < 143.5 to the left,  agree=0.703, adj=0.368, (0 split)
      thal    < 2.5   to the right, agree=0.663, adj=0.284, (0 split)
      oldpeak < 1.85  to the right, agree=0.624, adj=0.200, (0 split)
      slope   < 1.5   to the left,  agree=0.624, adj=0.200, (0 split)

Node number 2: 95 observations,    complexity param=0.05319149
  predicted class=0  expected loss=0.2526316  P(node) =0.470297
    class counts:    71    24
   probabilities: 0.747 0.253
  left son=4 (54 obs) right son=5 (41 obs)
  Primary splits:
      thal    < 2.5  to the right, improve=13.701710, (0 missing)
      ca      < 0.5  to the right, improve= 7.720223, (0 missing)
      exang   < 0.5  to the right, improve= 7.709513, (0 missing)
      sex     < 0.5  to the right, improve= 6.603312, (0 missing)
      oldpeak < 0.7  to the right, improve= 6.334665, (0 missing)
  Surrogate splits:
      sex      < 0.5  to the right, agree=0.705, adj=0.317, (0 split)
      trestbps < 116  to the right, agree=0.674, adj=0.244, (0 split)
      exang    < 0.5  to the right, agree=0.642, adj=0.171, (0 split)
      oldpeak  < 0.05 to the right, agree=0.632, adj=0.146, (0 split)
      age      < 61.5 to the left,  agree=0.621, adj=0.122, (0 split)

Node number 3: 107 observations,    complexity param=0.0177305
  predicted class=1  expected loss=0.2149533  P(node) =0.529703
    class counts:    23    84
   probabilities: 0.215 0.785
  left son=6 (84 obs) right son=7 (23 obs)
  Primary splits:
      age     < 44.5 to the right, improve=6.378769, (0 missing)
      sex     < 0.5  to the right, improve=5.146720, (0 missing)
      slope   < 1.5  to the left,  improve=4.543258, (0 missing)
      oldpeak < 0.75 to the right, improve=4.230748, (0 missing)
      thal    < 2.5  to the right, improve=3.621652, (0 missing)
  Surrogate splits:
      thalach < 181  to the left,  agree=0.841, adj=0.261, (0 split)

Node number 4: 54 observations
  predicted class=0  expected loss=0.05555556  P(node) =0.2673267
    class counts:    51     3
   probabilities: 0.944 0.056

Node number 5: 41 observations,    complexity param=0.05319149
  predicted class=1  expected loss=0.4878049  P(node) =0.2029703
    class counts:    20    21
   probabilities: 0.488 0.512
```

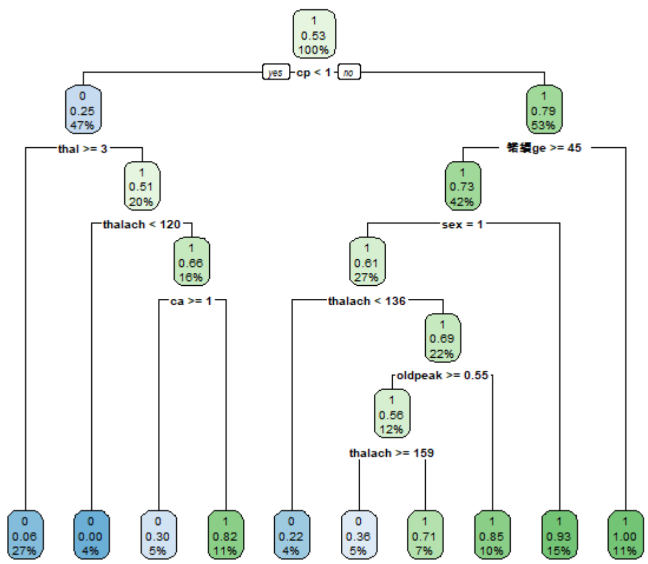
```
  left son=10 (9 obs) right son=11 (32 obs)
  Primary splits:
      thalach < 120 to the left, improve=7.815108, (0 missing)
      ca      < 0.5  to the right, improve=6.988807, (0 missing)
      exang   < 0.5  to the right, improve=5.670943, (0 missing)
      slope   < 1.5  to the left, improve=3.074021, (0 missing)
      sex     < 0.5  to the right, improve=2.822754, (0 missing)
  Surrogate splits:
      oldpeak < 3.1 to the right, agree=0.805, adj=0.111, (0 split)

Node number 6: 84 observations,    complexity param=0.0177305
  predicted class=1  expected loss=0.2738095  P(node) =0.4158416
    class counts:    23    61
   probabilities: 0.274 0.726 
  left son=12 (54 obs) right son=13 (30 obs)
  Primary splits:
      sex     < 0.5  to the right, improve=5.875620, (0 missing)
      slope   < 1.5  to the left, improve=3.827789, (0 missing)
      oldpeak < 0.7  to the right, improve=2.782247, (0 missing)
      age < 56.5 to the right, improve=2.433472, (0 missing)
      thal    < 2.5  to the right, improve=2.361801, (0 missing)
  Surrogate splits:
      chol    < 282.5 to the left, agree=0.75, adj=0.300, (0 split)
      age < 64.5 to the left, agree=0.69, adj=0.133, (0 split)
      thalach < 118 to the right, agree=0.69, adj=0.133, (0 split)

Node number 7: 23 observations
  predicted class=1  expected loss=0  P(node) =0.1138614
    class counts:     0    23
   probabilities: 0.000 1.000 

Node number 10: 9 observations
  predicted class=0  expected loss=0  P(node) =0.04455446
    class counts:     9     0
   probabilities: 1.000 0.000 

Node number 11: 32 observations,    complexity param=0.04255319
  predicted class=1  expected loss=0.34375  P(node) =0.1584158
    class counts:    11    21
   probabilities: 0.344 0.656 
  left son=22 (10 obs) right son=23 (22 obs)
  Primary splits:
      ca      < 0.5  to the right, improve=4.0520220, (0 missing)
      exang   < 0.5  to the right, improve=3.1562630, (0 missing)
      sex     < 0.5  to the right, improve=1.3529580, (0 missing)
      chol    < 280.5 to the right, improve=0.9875400, (0 missing)
      thalach < 133.5 to the right, improve=0.8956238, (0 missing)
  Surrogate splits:
      chol    < 280.5 to the right, agree=0.844, adj=0.5, (0 split)
      age < 66.5 to the right, agree=0.750, adj=0.2, (0 split)
      oldpeak < 1.8 to the right, agree=0.719, adj=0.1, (0 split)

Node number 12: 54 observations,    complexity param=0.0177305
  predicted class=1  expected loss=0.3888889  P(node) =0.2673267
    class counts:    21    33
   probabilities: 0.389 0.611 
  left son=24 (9 obs) right son=25 (45 obs)
  Primary splits:
      thalach < 135.5 to the left, improve=3.418656, (0 missing)
      oldpeak < 0.7 to the right, improve=3.235388, (0 missing)
      age < 56.5 to the right, improve=2.703478, (0 missing)
      chol    < 273.5 to the right, improve=2.543589, (0 missing)
      fbs     < 0.5  to the left, improve=2.077240, (0 missing)
  Surrogate splits:
      chol < 180 to the left, agree=0.870, adj=0.222, (0 split)
      thal < 1.5 to the left, agree=0.852, adj=0.111, (0 split)

Node number 13: 30 observations
```

```
  predicted class=1 expected loss=0.06666667 P(node) =0.1485149
    class counts:   2    28
   probabilities: 0.067 0.933 

Node number 22: 10 observations
  predicted class=0 expected loss=0.3 P(node) =0.04950495
    class counts:   7     3
   probabilities: 0.700 0.300 

Node number 23: 22 observations
  predicted class=1 expected loss=0.1818182 P(node) =0.1089109
    class counts:   4    18
   probabilities: 0.182 0.818 

Node number 24: 9 observations
  predicted class=0 expected loss=0.2222222 P(node) =0.04455446
    class counts:   7     2
   probabilities: 0.778 0.222 

Node number 25: 45 observations,    complexity param=0.01595745
  predicted class=1 expected loss=0.3111111 P(node) =0.2227723
    class counts:  14    31
   probabilities: 0.311 0.689 
  left son=50 (25 obs) right son=51 (20 obs)
  Primary splits:
      oldpeak < 0.55 to the right, improve=2.296979, (0 missing)
      age   < 56.5 to the right, improve=2.114354, (0 missing)
      trestbps < 131 to the right, improve=1.626569, (0 missing)
      chol    < 223.5 to the right, improve=1.539977, (0 missing)
      fbs     < 0.5  to the left,  improve=1.467395, (0 missing)
  Surrogate splits:
      slope   < 1.5  to the left,  agree=0.756, adj=0.45, (0 split)
      age   < 57.5 to the right, agree=0.689, adj=0.30, (0 split)
      cp      < 1.5  to the right, agree=0.644, adj=0.20, (0 split)
      trestbps < 131 to the right, agree=0.622, adj=0.15, (0 split)
      chol    < 223.5 to the right, agree=0.600, adj=0.10, (0 split)

Node number 50: 25 observations,    complexity param=0.01595745
  predicted class=1 expected loss=0.44 P(node) =0.1237624
    class counts:  11    14
   probabilities: 0.440 0.560 
  left son=100 (11 obs) right son=101 (14 obs)
  Primary splits:
      thalach < 159  to the right, improve=1.5621710, (0 missing)
      trestbps < 131 to the right, improve=1.1420530, (0 missing)
      fbs     < 0.5  to the left,  improve=0.8954905, (0 missing)
      ca      < 0.5  to the right, improve=0.8185171, (0 missing)
      chol    < 236.5 to the left,  improve=0.6757523, (0 missing)
  Surrogate splits:
      age   < 58.5 to the left,  agree=0.76, adj=0.455, (0 split)
      trestbps < 139 to the left,  agree=0.68, adj=0.273, (0 split)
      chol    < 279.5 to the right, agree=0.68, adj=0.273, (0 split)
      cp      < 1.5  to the left,  agree=0.64, adj=0.182, (0 split)
      ca      < 0.5  to the right, agree=0.64, adj=0.182, (0 split)

Node number 51: 20 observations
  predicted class=1 expected loss=0.15 P(node) =0.0990099
    class counts:   3    17
   probabilities: 0.150 0.850 

Node number 100: 11 observations
  predicted class=0 expected loss=0.3636364 P(node) =0.05445545
    class counts:   7     4
   probabilities: 0.636 0.364 

Node number 101: 14 observations
  predicted class=1 expected loss=0.2857143 P(node) =0.06930693
    class counts:   4    10
```

```
  probabilities: 0.286 0.714
```

Draw the decision tree.

```
> library(rpart.plot)
> rpart.plot(dt_model)
```



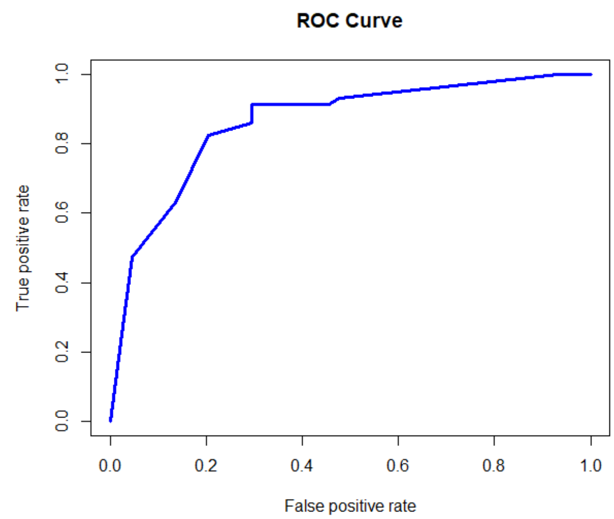
Using the trained model to predict the test data.

```
> test_predict=predict(dt_model,newdata = data_test,type="class")
> test_predict
  3   4   5   6   7   8  10  11  12  18  21  23  32  35  38  46  47  52  54  55  58  59  62  63  66  67  68
       69  74  76  81  82  91  94  95  96  97
  1   0   1   1   1   1   0   1   1   1   0   1   0   0   0   1   1   1   1   1   1   1   1   1   1   1   1
          1   1   1   1   1   1   1   1   0   1
101 109 112 114 119 120 123 125 128 132 134 142 146 148 153 154 155 157 161 164 166 168 169
      171 177 179 182 183 188 199 200 203 205 207 208 209 210
  1   1   1   0   1   1   1   1   1   1   1   1   1   1   1   1   1   1   0   0   0   1   0   0   0
          1   0   0   0   0   0   0   0   1   0
212 214 215 216 219 229 235 238 241 243 249 250 251 260 264 266 272 276 278 280 281 288 289
      295 296 298 303
  0   0   0   0   0   1   0   0   0   0   1   1   0   1   0   0   1   0   1   0   1   1   0   1   0   0   1
Levels: 0 1
> test_confusion=table(test_predict, data_test$target, dnn = c("Predicted", "Actual"))
> test_confusion
         Actual
Predicted  0  1
        0 31  8
        1 13 49
> acc <- sum(diag(test_confusion)) / sum(test_confusion)
> acc
[1] 0.7920792
```

Draw the ROC curve and calculate the AUC.

```
> library(ROCR)
> test.pred<-prediction(test.predict[,2],data_test$target)
> test.perf<-performance(test.pred,"tpr","fpr")
> View(test.perf)
> plot(test.perf,main="ROC Curve",col = "blue", lty = 1, lwd = 3)
> auc_ROCR <- performance(test.pred, measure = "auc")
> auc_ROCR
A performance instance
  'Area under the ROC curve'
> auc_ROCR <- auc_ROCR@y.values[[1]]
> auc_ROCR
[1] 0.8598485
```

The AUC is 0.8598485.



1.4 Random Forest

In machine learning, a random forest is a classifier containing multiple decision trees, and the output category is determined by the mode of the category output by the individual trees. Leo Breiman and Adele Cutler developed an algorithm to infer random forests. And ”Random Forests” is their trademark. This term is derived from random decision forests proposed by Tin Kam Ho of Bell Labs in 1995. This method combines Breimans’ ”Bootstrap aggregating” idea and Ho’s ”random subspace method” to build a set of decision trees.

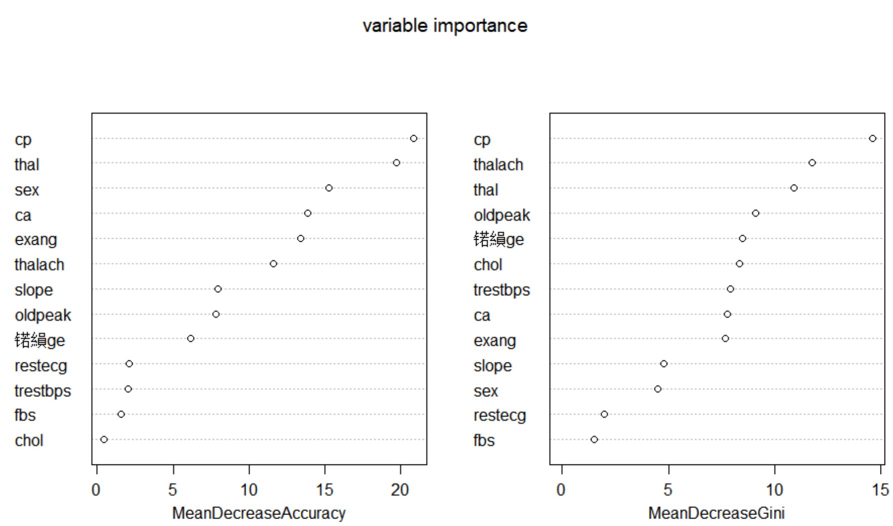
We divided the original data set into two parts, using two-thirds of the data as the training set and the other third as the test set.

```
> data<-read.csv("./heart.csv", head = TRUE, fileEncoding = 'GBK')
> set.seed(1)
> sub<-sample(1:nrow(data),round(nrow(data)*2/3))
> data_train<-data[sub,]
> data_test<-data[-sub,]
```

```
> dim(data_train)
[1] 202 14
> dim(data_test)
[1] 101 14
```

Constructing a random forest and see the importance of each attribute.

```
> data_train$target = as.factor(data_train$target)
> data_test$target = as.factor(data_test$target)
> heart_randomforest <- randomForest(target ~ .,data = data_train,ntree =500,mtry=3,
     importance=TRUE ,proximity=TRUE)
> wine_randomforest$importance
> heart_randomforest$importance
                    0           1 MeanDecreaseAccuracy MeanDecreaseGini
age   0.0044937516 0.011962156    0.0086940003      8.478937
sex      0.0145044314 0.028124986    0.0218931544      4.485431
cp       0.0574064595 0.040003224    0.0477923304     14.602807
trestbps 0.0012780918 0.004201236    0.0027883228      7.904588
chol    -0.0042746775 0.004597818    0.0006192567      8.319724
fbs      0.0003928993 0.001395237    0.0009719512      1.478607
restecg  0.0021038577 0.001391102    0.0016794871      1.961444
thalach  0.0125979001 0.026459197    0.0200311648     11.766105
exang    0.0257168826 0.018111586    0.0217800801      7.691388
oldpeak  0.0174696577 0.009578546    0.0130692595      9.089572
slope    0.0138465158 0.009035109    0.0110925198      4.770929
ca       0.0144427976 0.025380724    0.0201100161      7.771338
thal     0.0363102817 0.043796083    0.0402148715     10.913105
> varImpPlot(heart_randomforest, main = "variable importance")
```

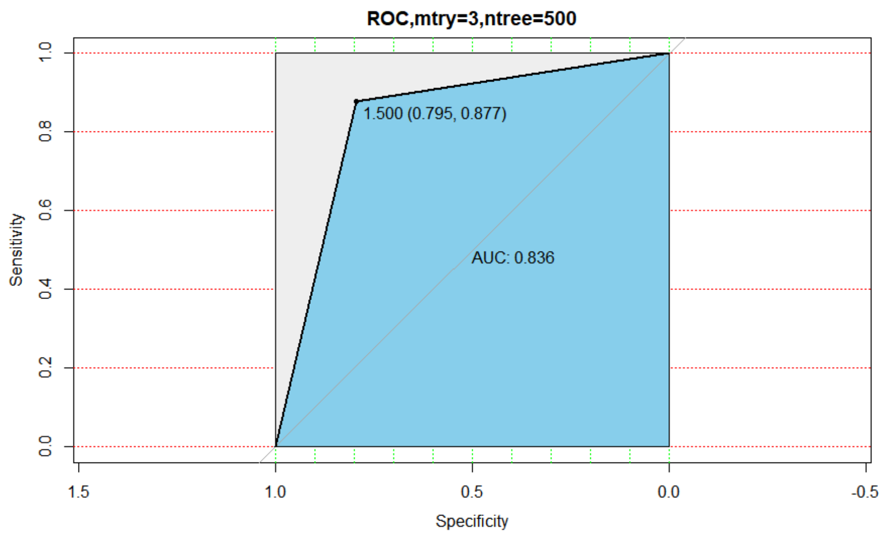


Predicting test data with the trained model

```
> pre_ran <- predict(heart_randomforest,newdata=data_test)
> obs_p_ran = data.frame(prob=pre_ran,obs=data_test$target)
> table(data_test$target,pre_ran,dnn=c("True","Predict"))
    Predict
True  0  1
   0 35  9
```

```
  1  7 50
> test_confusion=table(data_test$target,pre_ran,dnn=c("True","Predict"))
> acc <- sum(diag(test_confusion)) / sum(test_confusion)
> acc
[1] 0.8415842
```

ROC curve and AUC value



1.5 discuss

Result	Logistic Regression	Decision Tree	Random forest
Accurancy	0.764	0.792	0.841
AUC	0.765	0.859	0.836

For bicategorization problems logistic regression is a frequently used method, the logistic regression algorithm is to find a hyperplane in the sample data, which can then be accurately separated into categories and be able to classify the corresponding new data features.
The tree model is processed one feature at a time, before the linear model is where all features are given weights and summed to get a new value. The difference between decision tree and logistic regression is that logistic regression converts all the features into probability and divides them into one category if they are greater than a probability threshold and another category if they are less than a probability threshold, while decision tree divides each feature into one category. Also logistic regression can only find a linear partition (between input feature x and logit is linear, unless a multidimensional mapping of x is performed), while decision tree can find a non-linear partition.

The tree model is closer to the human mind, which can produce visual classification rules, and the resulting model is interpretable (can extract rules). The functions fitted by the tree model are actually step functions of the partitioning interval.
In spite of pruning and other methods, one tree is still definitely not as good as multiple trees, hence the random forest, which addresses the weakness of decision tree generalization.
Based on the predictions for this heart problem dataset, we can find that:
1. logistic regression is better at analyzing the overall structure of data than decision trees, while decision trees are better at analyzing the local structure than logistic regression. (2) Logistic regression is good at analyzing linear relationships, while decision trees have a poor grasp of linear relationships. Although dealing with nonlinear relationships is the strength of decision trees, many nonlinear relationships can be approximated entirely by linear relationships and work well. Linear relationships have many advantages in practice: they are concise, easy to understand, and can prevent overfitting of the data to some extent. 3. logistic regression is sensitive and susceptible to extreme values, and decision trees perform better in this respect.

2 Task2

2.1 Describe the Reuters-21578 corpus

Reuters-21578 is a test collection for text classification research that is a multi-class, multi-label dataset. This dataset contains 90 classes, 7769 training files, and 3019 test files is a ModApte subdirectory of the Reuters-21578 benchmark. The Reuters-21578 dataset was originally collected and tagged by the Carnegie Group and Reuters in 1987 during the development of the CONSTRUE text classification system, and later by AT&T Labs Research in September 1997. released in February, with David D. Lewis as the lead publisher

2.2 Describe how each document is represented in your implementation.

```
> data(Reuters21578)
> class(Reuters21578)
[1] "VCorpus" "Corpus"
> head(Reuters21578)
<<VCorpus>>
Metadata: corpus specific: 0, document level (indexed): 0
Content: documents: 6
> summary(Reuters21578)
    Length Class           Mode
1   2      PlainTextDocument list
2   2      PlainTextDocument list
3   2      PlainTextDocument list
4   2      PlainTextDocument list
5   2      PlainTextDocument list
...
```

We import the Reuters-21578 as Vcorpus, which contains Metadata and Content. The metadata attribute contains author, datetime stamp, description, heading id, language, origin, lewissplit, cgisplit, oldid, topics_cat, places, people, orgs, exchanges. The content is the raw data.

The data structure in the tm package that mainly manages documents is called Corpus, which represents a collection of documents. The corpus is divided into a dynamic corpus (Volatile Corpus) and a static corpus (Permanent Corpus). A dynamic corpus will be stored in memory as an R object and can be generated by either VCorpus() or Corpus(). The dynamic corpus, on the other hand, is stored as an R external file and can be generated using the PCorpus() function.

2.3 Describe the whole procedure on applying LDA to this corpus to perform topic modeling.

1. Import the dataset
2. Pre-processing the dataset, including transforming the content to lower case, striping whitespace, removing stopwords, punctuation and numbers, and steming document.
3. Calculate the BOW/TF-IDF document term matrix, “bowdtm“ and “tfidfdtm“
4. Reducing the dimension with “tfidfdtm“
5. Calculate the word cloud with “bowdtm“
6. Apply LDA analysis.

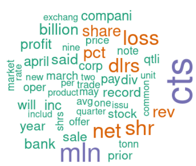
2.4 Describe the parameter setting that you use in the LDA and explain their meanings.

```
result <- LDA(bowdtm, k, method="Gibbs", control=list(iter = 25, verbose = 25, alpha = 0.1)
     )
```

- “bowdtm“: The document term matrix with BOW method.
- “k“: number of topics
- “method=Gibbs“: Applying Gibbs sampling
- “control=list(iter = 25, verbose = 25, alpha = 0.1)“: inference via 25 iterations.

2.5 Describe the output of your code and visualize the obtained topics in appropriate ways

... Draw the Word cloud.



Draw the word cloud from the TF-IDF document term matrix

```
 > bowdtm <- bowdtm[slam::row_sums(bowdtm) > 0, ]
> k <- 20
> result <- LDA(bowdtm, k, method="Gibbs", control=list(iter = 25, verbose = 25, alpha =
    0.1))
K = 20; V = 32697; M = 19042
Sampling 25 iterations!
Iteration 25 ...
Gibbs sampling completed!
> result
A LDA_Gibbs topic model with 20 topics.
> terms(result, 10)
     Topic 1  Topic 2  Topic 3  Topic 4  Topic 5  Topic 6  Topic 7  Topic 8    Topic 9   Topic
         10 Topic 11 Topic 12 Topic 13 Topic 14 Topic 15
 [1,] "said"  "said"   "said"   "said"    "dlrs"   "billion" "said" "tonn"      "bank"    "said"
       "said"   "oil"    "said"   "pct"    "said"
 [2,] "govern" "will"  "trade"  "trade"   "mln"    "bank"   "market" "said"     "said"    "share"
       "reuter"  "said"   "export" "will"  "share"
 [3,] "econom" "compani" "japan" "reuter" "said" "pct"    "rate"   "mln"      "debt"    "
      compani" "mine" "price"  "will"   "issu"  "stock"
 [4,] "japan" "new"    "offici" "futur"  "year"   "franc"  "dollar" "wheat"    "loan"    "stock"
       "gold"   "gas"    "produc" "said"  "compani"
 [5,] "offici" "reuter" "state" "price" "quarter" "said" "bank"   "export"   "billion" "
      reuter" "will"  "barrel" "price" "mln"   "inc"
 [6,] "minist" "car"   "import" "pct"    "compani" "year" "trade" "reuter"    "dlrs"    "court"
       "compani" "product" "coffe" "bond" "dlrs"
 [7,] "year"  "trade"  "japanes" "new"    "sale"   "mln"    "analyst" "agricultur" "will" "offer
      " "ton"   "mln"    "reuter" "dlrs" "offer"
 [8,] "will"  "motor"  "unit"   "cent"    "earn"   "reuter" "currenc" "year"    "interest" "file
      " "oper"   "compani" "meet" "rate"  "will"
 [9,] "west"  "exchang" "will" "tonn"    "share"  "foreign" "dealer" "grain"    "countri" "board
      " "ounc"   "dlrs"   "countri" "reuter" "reuter"
[10,] "japanes" "market" "reuter" "contract" "report" "mark" "exchang" "crop" "new"   "inc"
       "power"  "will"   "quota"  "manag" "common"
     Topic 16 Topic 17 Topic 18 Topic 19 Topic 20
 [1,] "said"  "said"   "said"   "mln"    "pct"
 [2,] "tax"   "compani" "compani" "cts" "year"
 [3,] "billion" "dlrs" "will"   "net"    "said"
 [4,] "budget" "reuter" "reuter" "loss" "billion"
```

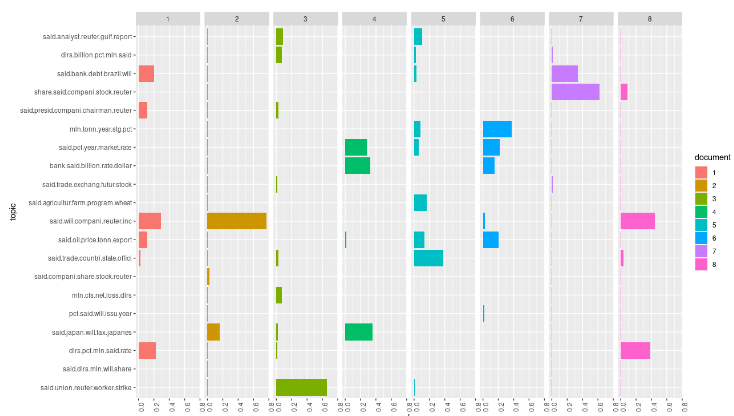
```
 [5,] "bill"  "share"  "inc"    "dlrs"  "februari"
 [6,] "stg"   "mln"    "corp"   "shr"   "januari"
 [7,] "hous"  "corp"   "system" "reuter" "rose"
 [8,] "dlrs"  "inc"    "new"    "profit" "rise"
 [9,] "reuter" "group" "servic" "rev"   "last"
[10,] "bank"  "will"   "comput" "oper"  "month"
```

We should remove empty rows in “bowdtm“ and set number of topics to 20. Then we can compute the LDA model, inferencing via 25 iterations of Gibbs sampling.

We can see the 10 most likely terms within the term probabilities beta of the inferred topics.

We took eight sample documents and get topic proportions form example documents.

```
examples <- c(2, 100, 200, 400, 800, 1000, 1200, 1400)
lapply(pre_process_reuters[examples], as.character)

theta <- tmposterior$topics
N <- length(examples)

tpExamples <- theta[examples,]
colnames(tpExamples) <- nameOfTopics
vizDataFrame <- melt(cbind(data.frame(tpExamples), document = factor(1:N)), variable.name =
      "topic", id.vars = "document")
vizDataFrame
```



3 Task3

3.1 Data mining and cleaning

This data comes from Twitter sentiment analysis in kaggle, From a data set of nearly one million, 13,700 comments about Alan bryd were selected. Among these data, 9,700 positive sentiment data. 4000 negative emotion data. In order to balance the data set, 4000 positive sentiment data and 4000 negative sentiment data were extracted.

id	comment
0	gone to work miss me k leave me love er some shit
0	gone to work... mondays- wednesdays always suck! hope it goes by fast so I can come home to my
0	gonig to do some homework not fun. not fun at all.
0	gonig to work in like 20 mins. it upsets me
0	Gonna attempt to leave my phone in living room on charger and go to sleep alone. wish me luck!! N
0	Have to take my 10 yearold German Shepherd to vet tomorrow
0	Have to take the dog a walk now. And it's raning boo.
0	Have to throw some of her stuffs. Luggages are too full!
0	Have to trash all the carpet that was put in 1.5 years ago
0	Have to wait 3 weeks to find out if I am pregnant or not..
0	Have to wait another day to get the album
0	have to wait for hot water until monday
0	Have to wait for the maintenance guy today. Pipes in building getting a makeover and bathroom sinl
0	Have to wait til Wednesday to get internet back, they sent us the wrong modem
0	Have to wait 'till tomorrow to get my iPhone 3G S They're getting a shipment in around 12 tomorrov
0	Have to wait two weeks for my cord thankfully I had a great experience with Apple support. Thanks
0	have to wait until june 4 to see mtv award cause here in panama didnt transmited tonightt
0	Have to wear the penalty sombrero for the rest of the afternoon after losing in foosball
0	have to work 2night
0	have to work a double today
0	have to work at budabing's at 8 but i feel miserable
0	Have to work now... it will be a hard and long day and then preparing all for the painter on Monday.
0	have to work this arvo
0	have to work todayy oh well ill twitter in the back room ilec ilec ilec
0	Have to work tomorrow.. yay me
0	Have to work until 3am at the bar! Ughh why Im I doing this
0	Have to write a college application. Then i have to go to spanish.
0	Have to write up my case study today and it has to be in tomorrow god damn twitter made me forge
0	have too changes in my life
0	have too many things going on in my life and my mind that I can't seem to get a good nights rest.
0	have too much on my mind & cant sleep
0	Have torn the ligaments in my ankle and now walk like a pleb! xXxc
0	have totally failed one of my chemistry exams
0	have tried half an onion, warm oil, pain meds and nothing is helping my little girls sore ear any hoo
0	Have tried to be nice about it, but that term and "retard" really really hurt sometimes
0	Have u ever been so high your voice sounds 1000x's louder than it really is...?
0	Have u ever been spooked so bad u didnt wanna move at all.... that me right now!
0	Have u ever done somethin' you thought at the time was right, but afterwards realised u wer dead w
0	Have u ever realized that something u never imagined u would need is the one thing u want the mos
0	have u every created an elaborate query from the master database, forget to set the limiter and exe
0	Gonna be a great message at NorthPoint today but I couldn't find my journal this morning.
0	Gonna be a long day here @ home - Everton lost to Chelsea.
0	Gonna be a long day. Working until 7.
0	gonna be all alone tonite I want my girl to come by
0	Gonna be another hot day! We will have water shortage if it doesn't rain soon
0	Gonna be hard but Rpattz and I have to quit smoking. http://bit.ly/90DqI =1

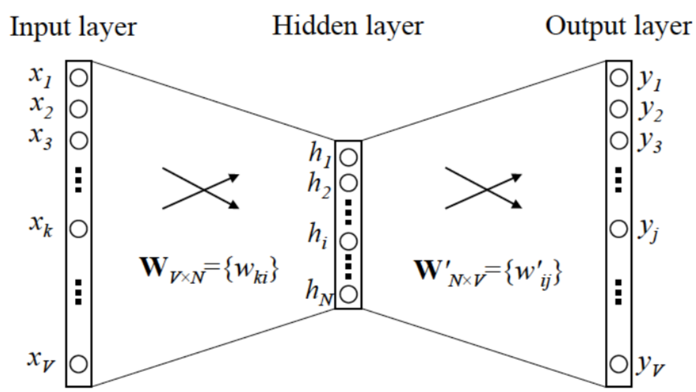
There are most characters in the comments, such as emoji, @ other users and some garbled characters are inconsistent in capitalization

1	Finished my paper!!!!!!!!!! But............ smh
1	first days are always good..wish my dentist gave me more hours though
1	fone off....cant talk 2 my love....imu marcus!!!!!
1	for the fact that *I* didn't get any work done, not that you all did.
1	forgot XBL was off today, was about to check to see if a game was on XBLA that I wanted to buy
1	found a mosquito bite. (Those tend to get really swollen and red for me) Distracting myself with
1	Found a way to make this Private woot woot
1	Four more fake people added me. Is this why people don't like Twitter?
1	frank iero should be the sexiest vegetarian 2009.
1	french lost, #fb
1	fuck man .i hate this. =O. work suckss :'(
1	fuck you, :]
1	- fuck, my money is running out & i have no jobs...
1	fuck. I am an ugly person.
1	fucking rur mom
1	- Fwd: Good Morn,happy birthday ! regardless of what ppl said yesterday,they don't realize what
1	gah. so much less ok than i was trying to tell myself i was.
1	GCSE's clearly suck.
1	- Geez Chelsea already scored against Everton 1-0
1	gerald lost a friend............idk what to say........this is like day 2 of crazy events.......
1	getting "goodbye" e-mails from #Iran #iranelection
1	-- getting a Mani + Pedi with the husband!
1	getting a webcam today.
1	- Getting ready to leave for Spring City, TN - @EzraJane I'm going to miss your show tonight...

So a series of data cleaning operations are used to clean the data.

```
data=pd.read_csv("AlanBryd.csv").astype(str)
'''
clean the dataset
'''


def remove_pattern(input_txt, pattern):
    r = re.findall(pattern, input_txt)
    for i in r:
        input_txt = re.sub(i, '', input_txt)

    return input_txt
data['comment'] = np.vectorize(remove_pattern)(data['comment'], "@[\w]*")
data['comment']= data['comment'].str.replace("[^a-zA-Z#]", " ")
data['comment'] = data['comment'].apply(lambda x: ' '.join([w for w in x.split() if len(w)>3]))




text = data['comment']
sentences = []
```

3.2 Use word2vec to build word vectors



Use word2vec's word vector for word embedding as input to the model

```
text = data['comment']
sentences = []
for item in text:
    sentence = str(item).split(' ')
    sentences.append(sentence)
#训练
model = word2vec.Word2Vec(sentences, size = 200)

def buildWordVector(imdb_w2v, text, size):
    vec = np.zeros(size).reshape((1, size))
    count = 0.
    #print text
    for word in text.split():
        #print word
        try:
            vec += imdb_w2v[word].reshape((1, size))
            count += 1.
        except KeyError:
            print (word)
            continue
    if count != 0:
        vec /= count
    return vec
result = buildWordVector(model, data.loc[1]['comment'] , 200)
for i in range(1,len(data)):
    result = np.concatenate((result, buildWordVector(model, data.loc[i]['comment'] , 200)), axis = 0)
#读取出数据
#把series 转换成dataframe格式，并且将200维的特征都赋值

vectors = pd.DataFrame(result)
```

3.3 model using and result

3.3.1 GBDT

theory of GBDT

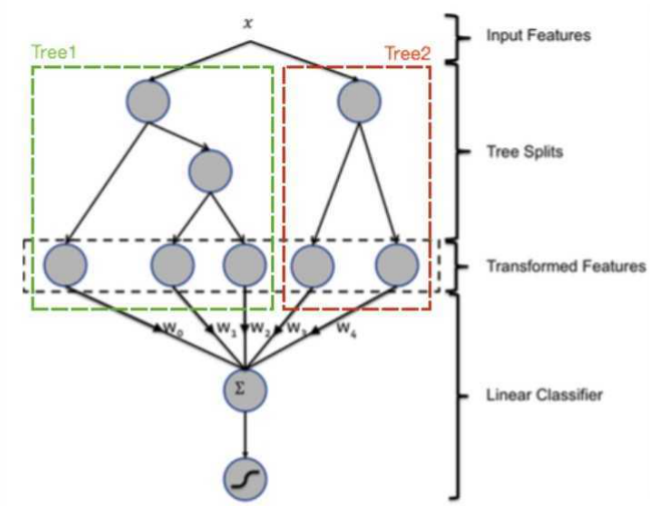
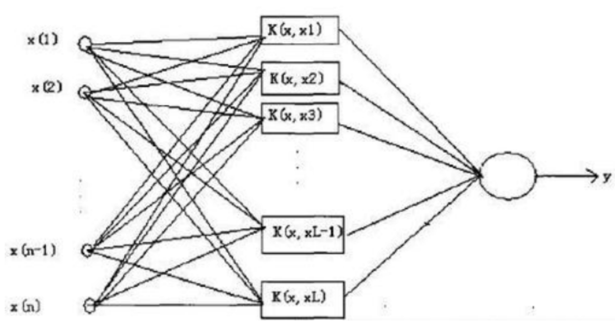


Figure 1: Hybrid model structure. Input features are transformed by means of boosted decision trees. The output of each individual tree is treated as a categorical input feature to a sparse linear classifier. Boosted decision trees prove to be very powerful feature transforms.

Parameters of gbdt:
$n_estimators = 1000$, $subsample = 0.8$, $loss =' deviance'$, $max_features =' sqrt'$,

3.3.2 SVM

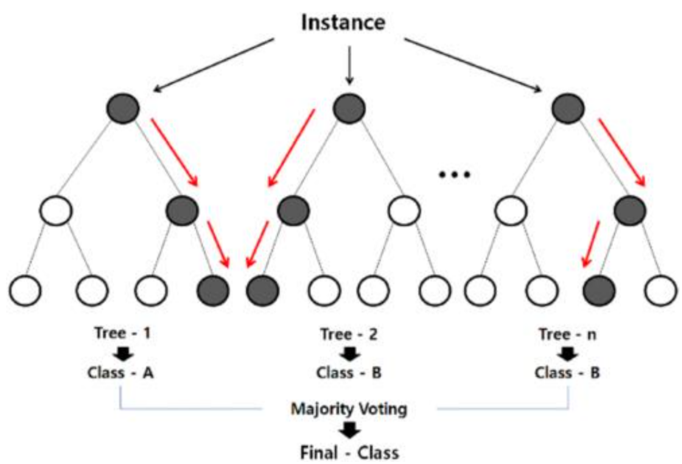
theory of SVM



Parameters of SVM: $kernel = \text{‘}rbf\text{’}degree = 3$

3.3.3 RandomForest

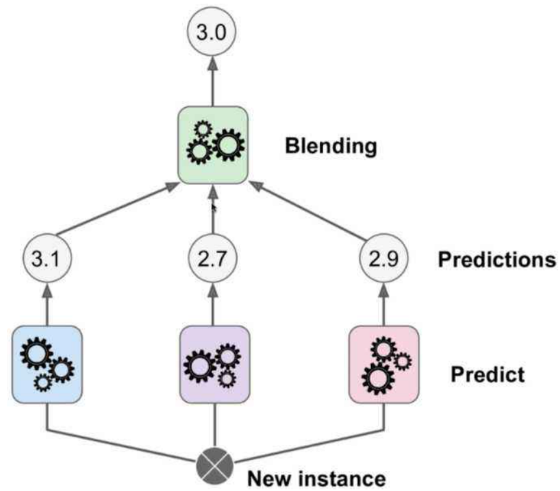
theory of RF



Parameters of RF:$oob_score = True, n_estimators = 400, max_features =' sqrt',$

3.3.4 ExtraTrees

theory of ET

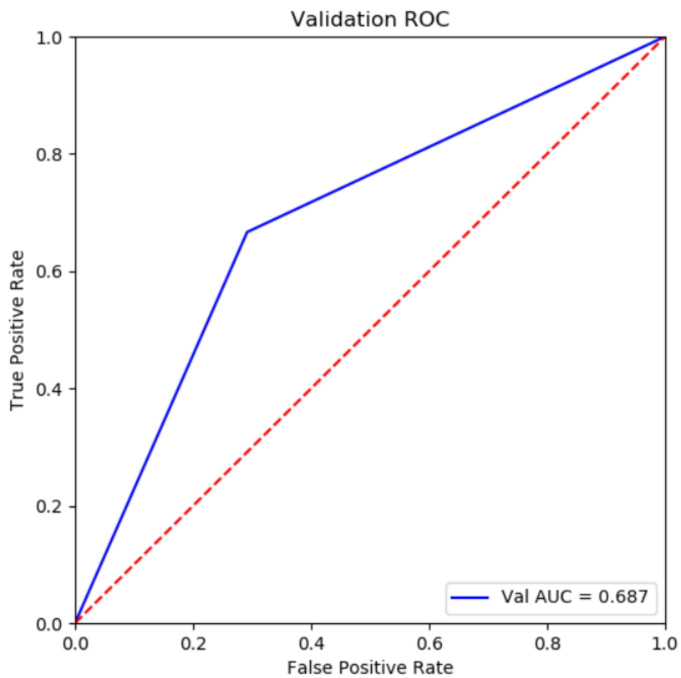


Parameter of ET: $criterion = gini, maxfeatures = log, maxdepth = 50$

3.3.5 Result

```
gbdt score:
model train err is 0.053545
auc is  0.6888644488777488
precision is  0.6891532910703071
recall is  0.6888644488777488
 test err is  0.310948905109489
svm score:
model train err is 0.446049
auc is  0.5516693095981039
precision is  0.5811703096539163
recall is  0.5516693095981039
 test err is  0.44525547445255476
RF score:
model train err is 0.015252
auc is  0.6916253175780518
precision is  0.6925907836786455
recall is  0.6916253175780518
 test err is  0.30802919708029197
ET score:
model train err is 0.015252
auc is  0.6756043219033654
precision is  0.6801474018098703
recall is  0.6756043219033654
 test err is  0.3236009732360097
staking(GBDT ET RF - LR) score:
model train err is 0.015252
auc is  0.6864247105563797
precision is  0.6970203449083667
recall is  0.6864247105563797
 test err is  0.3124087591240876
```

According to the picture above,The expressive power of gbdt is better than other models in all aspects, and the mathematical model in machine learning can fit the features well when the data set is not large. Compared with other tree models, GBDT has a stronger ability to fit data by calculating residuals. The auc figure of GBDT is :



4 contribution

Wangzhihui Mei: 25%
Hongyi Huang: 25%
Chang Xu: 25%
Zijia He: 25%