

TaigaHasegawaHW2

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1

```
#read the file
es_trades=read.csv("ES_Trades.csv")
```

```
#where the symbol is ESU13
esu13=es_trades[es_trades$Symbol=="ESU13",]
```

```
#show the first 6 rows
head(esu13)
```

```
##   Symbol      Date      Time  Price Volume Market.Flag
## 1  ESU13 09/01/2013 17:00:00.083 1640.25      8         E
## 2  ESU13 09/01/2013 17:00:00.083 1640.25      1         E
## 3  ESU13 09/01/2013 17:00:00.083 1640.25      2         E
## 4  ESU13 09/01/2013 17:00:00.083 1640.25      1         E
## 5  ESU13 09/01/2013 17:00:00.083 1640.25      1         E
## 6  ESU13 09/01/2013 17:00:00.083 1640.25     12         E
##   Sales.Condition Exclude.Record.Flag Unfiltered.Price
## 1                0                NA             1640.25
## 2                0                NA             1640.25
## 3                0                NA             1640.25
## 4                0                NA             1640.25
## 5                0                NA             1640.25
## 6                0                NA             1640.25
```

```
#define dollar bars
dollarBars <- function(dat, nvol)
{
  n=cumsum(esu13$Unfiltered.Price)
  winIdx <- as.factor(floor(n/nvol))
  H <- aggregate(dat$Unfiltered.Price, by = list(winIdx), max)$x
  L <- aggregate(dat$Unfiltered.Price, by = list(winIdx), min)$x
  O <- aggregate(dat$Unfiltered.Price, by = list(winIdx), function(x){x[1]})$x
  C <- aggregate(dat$Unfiltered.Price, by = list(winIdx), function(x){x[length(x)]})$x
  list(H=H,L=L,O=O,C=C)
}
```

```
#implementing the dollar bar
dollar_bar=dollarBars(esu13,1000000)
length(dollar_bar$H)
```

```
## [1] 5572
```

When the threshold is 1,000,000, we have 5572 dollar bars.

2

```
#define cusum filter
istar_CUSUM <- function(yvec, h)
{
  S_pos <- S_neg <- 0
  istar <- NULL
  yminusEy <- diff(yvec)
  n <- length(yminusEy)
  for(i in 1:n)
  {
    S_pos <- max(0, S_pos + yminusEy[i])
    S_neg <- min(0, S_neg + yminusEy[i])
    if(max(S_pos, -S_neg) >= h) # note that Snippet 2.4 in AFML does not follow the definition of S_t
    {
      istar <- c(istar, i)
      S_pos <- S_neg <- 0
    }
  }
  return(istar)
}
```

```
i_CUSUM <- istar_CUSUM(dollar_bar$C, h=3)
```

```
i_CUSUM
```

```
## [1] 13 27 48 67 78 92 111 141 155 161 167 184 195 214
## [15] 244 317 337 363 381 431 450 479 496 521 565 638 667 687
## [29] 700 714 727 755 771 791 810 825 843 909 921 960 991 1005
## [43] 1053 1063 1088 1106 1124 1151 1187 1260 1316 1344 1448 1513 1521 1590
## [57] 1606 1633 1639 1647 1661 1682 1704 1731 1754 1784 1865 1964 2081 2106
## [71] 2156 2168 2177 2193 2222 2236 2262 2282 2313 2333 2376 2391 2416 2425
## [85] 2440 2456 2485 2529 2552 2567 2580 2594 2617 2647 2707 2738 2756 2786
## [99] 2810 2928 2951 2986 3044 3071 3132 3154 3177 3205 3219 3250 3268 3295
## [113] 3317 3354 3397 3514 3551 3624 3650 3778 3784 3800 3818 3832 3860 3941
## [127] 3984 4098 4172 4194 4255 4392 4493 4496 4511 4535 4561 4616 4665 4725
## [141] 4795 4834 4951 5076 5123 5166 5212 5271 5332 5368 5402 5436 5484 5510
## [155] 5557
```

When h is 3, we have 155 feature bars and it is reasonable.

3

```
#define the triple barrier method
#return the dataframe
label_meta=function(x,events,ptSl){
  t0 <- events$t0
  t1 <- events$t1
  trgt <- events$trgt
  side <- events$side
  u <- ptSl[1]
  l <- ptSl[2]
  rstlist=data.frame()
  for (i in 1:dim(events)[1]){
```

```

i_trgt=trgt[i]
i_x=x[t0[i]:t1[i]]
i_side=side[i]
if(i_side==0){
  up <- i_trgt*u
  lo <- i_trgt*l
  isup <- (i_x/i_x[1]-1) >= up
  islo <- -(i_x/i_x[1]-1) >= lo
  T_up <- ifelse(sum(isup)>0, min(which(isup)), Inf)
  T_lo <- ifelse(sum(islo)>0, min(which(islo)), Inf)
  ret <- i_x[min(T_up, T_lo, length(i_x))] / i_x[1] - 1
  rst <- c(T_up, T_lo, length(i_x), ret)
}else if(i_side==1){
  up <- i_trgt*u
  isup <- (i_x/i_x[1]-1) >= up
  T_up <- ifelse(sum(isup)>0, min(which(isup)), Inf)
  T_lo <- Inf
  ret <- i_x[min(T_up, T_lo, length(i_x))] / i_x[1] - 1
  rst <- c(T_up, T_lo, length(i_x), ret)
}else{
  lo <- i_trgt*l
  islo <- -(i_x/i_x[1]-1) >= lo
  T_up <- Inf
  T_lo <- ifelse(sum(islo)>0, min(which(islo)), Inf)
  ret <- i_x[min(T_up, T_lo, length(i_x))] / i_x[1] - 1
  rst <- c(T_up, T_lo, length(i_x), ret)
}
rstlist=rbind(rstlist,rst)
}
colnames(rstlist)=c("T_up","T_lo","length","ret")
return(rstlist)
}

```

```

#where ptSl=[1,1] and t1=70
n_event=length(i_CUSUM)
events <- data.frame(t0=i_CUSUM+1, t1 = i_CUSUM+70, trgt = rep(0.002, n_event), side=rep(0,n_event))
x=dollar_bar$C
ptSl=c(1,1)
triplebarrier=label_meta(x,events,ptSl)
triplebarrier

```

##	T_up	T_lo	length	ret
## 1	36	Inf	70	0.0021302495
## 2	40	Inf	70	0.0021289538
## 3	Inf	Inf	70	0.0001518372
## 4	Inf	Inf	70	-0.0010615711
## 5	Inf	Inf	70	-0.0015192950
## 6	Inf	51	70	-0.0022751403
## 7	Inf	32	70	-0.0024264483
## 8	Inf	Inf	70	-0.0006077180
## 9	7	Inf	70	0.0024356828
## 10	Inf	7	70	-0.0021260440
## 11	18	Inf	70	0.0021305737
## 12	Inf	12	70	-0.0022779043

## 13	20	Inf	70	0.0021308980
## 14	46	Inf	70	0.0021263670
## 15	Inf	Inf	70	-0.0009097801
## 16	Inf	Inf	70	-0.0007593014
## 17	34	Inf	70	0.0021279830
## 18	Inf	28	70	-0.0021241086
## 19	Inf	Inf	70	-0.0004557885
## 20	Inf	48	70	-0.0021247534
## 21	Inf	46	70	-0.0021279830
## 22	Inf	22	70	-0.0021296015
## 23	Inf	70	70	-0.0024379095
## 24	Inf	Inf	70	-0.0001526019
## 25	Inf	Inf	70	0.0004582251
## 26	Inf	38	70	-0.0021396913
## 27	Inf	Inf	70	0.0000000000
## 28	Inf	56	70	-0.0021403455
## 29	Inf	Inf	70	0.0006126512
## 30	Inf	29	70	-0.0021403455
## 31	Inf	Inf	70	0.0003063256
## 32	Inf	27	70	-0.0021410002
## 33	70	Inf	70	0.0021446078
## 34	64	29	70	-0.0021416552
## 35	31	Inf	70	0.0022981462
## 36	27	Inf	70	0.0022953328
## 37	Inf	Inf	70	0.0013748854
## 38	Inf	15	70	-0.0021347972
## 39	Inf	Inf	70	0.0019862490
## 40	35	Inf	70	0.0021367521
## 41	Inf	Inf	70	-0.0015246227
## 42	Inf	64	70	-0.0021354484
## 43	Inf	11	70	-0.0022865854
## 44	66	Inf	70	0.0021390374
## 45	65	Inf	70	0.0021361001
## 46	23	Inf	70	0.0021390374
## 47	30	Inf	70	0.0022883295
## 48	43	Inf	70	0.0021318715
## 49	Inf	Inf	70	0.0012159903
## 50	Inf	Inf	70	0.0018206645
## 51	55	Inf	70	0.0021212121
## 52	Inf	Inf	70	0.0004539952
## 53	Inf	Inf	70	0.0013623978
## 54	Inf	13	70	-0.0021160822
## 55	Inf	Inf	70	-0.0009085403
## 56	23	Inf	70	0.0021218551
## 57	44	Inf	70	0.0022692890
## 58	Inf	31	70	-0.0022651767
## 59	11	Inf	70	0.0024209411
## 60	Inf	17	70	-0.0021144842
## 61	Inf	Inf	70	0.0003025261
## 62	Inf	Inf	70	0.0003023432
## 63	Inf	36	70	-0.0022655188
## 64	35	Inf	70	0.0021183235
## 65	33	Inf	70	0.0021154427
## 66	Inf	Inf	70	-0.0004524887

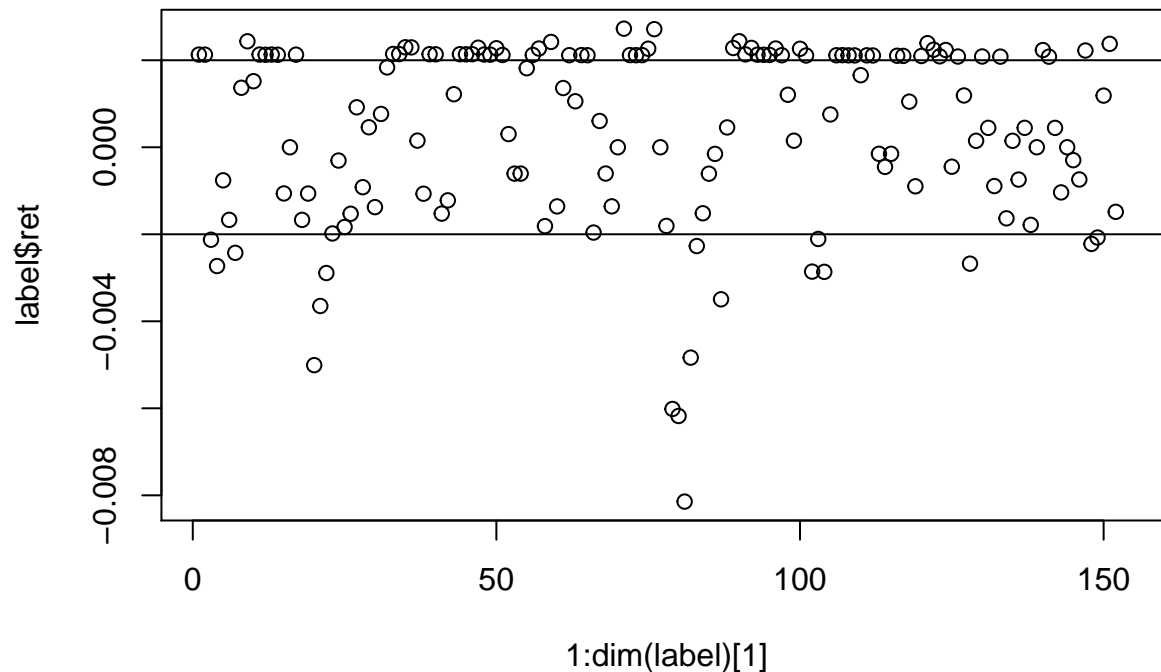
## 67	Inf	Inf	70	-0.0001510574
## 68	Inf	Inf	70	-0.0007548309
## 69	Inf	54	70	-0.0022638092
## 70	Inf	53	70	-0.0024191110
## 71	26	Inf	70	0.0027256208
## 72	14	Inf	70	0.0021186441
## 73	60	Inf	70	0.0021160822
## 74	36	Inf	70	0.0021180030
## 75	20	Inf	70	0.0022655188
## 76	30	Inf	70	0.0027149321
## 77	Inf	Inf	70	0.0000000000
## 78	Inf	Inf	70	-0.0006025004
## 79	Inf	30	70	-0.0021052632
## 80	Inf	52	70	-0.0021090690
## 81	Inf	18	70	-0.0021112954
## 82	Inf	27	70	-0.0022662034
## 83	Inf	22	70	-0.0022706630
## 84	Inf	32	70	-0.0022747953
## 85	Inf	22	70	-0.0022768670
## 86	Inf	Inf	70	0.0010639915
## 87	Inf	Inf	70	-0.0012152514
## 88	Inf	41	70	-0.0021276596
## 89	Inf	26	70	-0.0024334601
## 90	60	Inf	70	0.0024364245
## 91	18	Inf	70	0.0021351228
## 92	33	Inf	70	0.0022838002
## 93	48	Inf	70	0.0021279830
## 94	Inf	Inf	70	0.0016699560
## 95	40	Inf	70	0.0021215336
## 96	46	Inf	70	0.0022699758
## 97	41	Inf	70	0.0021154427
## 98	Inf	Inf	70	0.0010561255
## 99	Inf	Inf	70	-0.0001506478
## 100	34	Inf	70	0.0022634676
## 101	41	Inf	70	0.0021093868
## 102	Inf	Inf	70	-0.0007521059
## 103	Inf	42	70	-0.0021074816
## 104	Inf	Inf	70	-0.0004521477
## 105	Inf	Inf	70	-0.0009059339
## 106	68	Inf	70	0.0021148036
## 107	29	Inf	70	0.0021173624
## 108	Inf	Inf	70	0.0009055237
## 109	Inf	Inf	70	0.0001507841
## 110	Inf	20	70	-0.0021090690
## 111	33	Inf	70	0.0021128886
## 112	56	Inf	70	0.0021097046
## 113	Inf	Inf	70	0.0007521059
## 114	Inf	Inf	70	-0.0007515407
## 115	Inf	Inf	70	-0.0003008424
## 116	Inf	Inf	70	0.0010518407
## 117	Inf	Inf	70	0.0003000300
## 118	Inf	Inf	70	0.0011988611
## 119	Inf	Inf	70	-0.0010469638
## 120	7	Inf	70	0.0020976925

```
## 121 37 Inf 70 0.0023923445
## 122 21 Inf 70 0.0022424877
## 123 33 Inf 70 0.0020904883
## 124 43 Inf 70 0.0022358027
## 125 Inf Inf 70 0.0001488982
## 126 Inf Inf 70 0.0011918951
## 127 Inf Inf 70 0.0002976190
## 128 Inf Inf 70 -0.0008916630
## 129 Inf Inf 70 -0.0001488317
## 130 65 Inf 70 0.0020867491
## 131 Inf Inf 70 0.0007439369
## 132 Inf Inf 70 0.0002972210
## 133 4 Inf 70 0.0020833333
## 134 Inf 23 70 -0.0020790021
## 135 Inf Inf 70 -0.0001487652
## 136 Inf 49 70 -0.0020793109
## 137 Inf Inf 70 0.0014880952
## 138 Inf 52 70 -0.0020805469
## 139 Inf Inf 70 -0.0005954153
## 140 Inf Inf 70 0.0014896470
## 141 47 Inf 70 0.0020820940
## 142 Inf Inf 70 0.0008906041
## 143 Inf Inf 70 -0.0005928561
## 144 Inf Inf 70 -0.0008888889
## 145 Inf Inf 70 0.0007410701
## 146 Inf 55 70 -0.0020719254
## 147 Inf Inf 70 0.0008895478
## 148 Inf Inf 70 -0.0013327410
## 149 Inf 68 70 -0.0020746888
## 150 Inf Inf 70 0.0001484340
## 151 43 Inf 70 0.0023770614
## 152 Inf Inf 70 -0.0004451699
## 153 Inf Inf 70 -0.0002968680
## 154 NA NA 70 NA
## 155 NA NA 70 NA
```

4

```
#where ptSl=[1,0] and t1=100
events <- data.frame(t0=i_CUSUM+1, t1 = i_CUSUM+100, trgt = rep(0.002, n_event), side=rep(1,n_event))
ptSl=c(1,0)
label=label_meta(x,events,ptSl)

#plot the rst and threshold
plot(1:dim(label)[1],label$ret)
abline(h=events$trgt[1])
abline(h=-events$trgt[1])
```



```
#calculatet the features from feature bars
```

```
iTmp <- c(0, i_CUSUM)
fMat0 <- t(sapply(1:(length(i_CUSUM)),
  function(i){
    winTmp <- x[(iTmp[i]+1):(iTmp[i+1])]
    C <- winTmp[length(winTmp)]
    SD <- sd(winTmp)
    return(c(C,SD))
  })
))
```

```
#change into the dataframe
```

```
fMat0 <- data.frame(fMat0)
names(fMat0) <- c("Close", "SD")
X_train=fMat0
```

```
#labeling
```

```
Y_train <- rep(0, n_event)
Y_train[label$ret>=events$trgt*ptSl[1]] <- 1
```

```
#linear regression
```

```
fit1 <- glm(Y_train ~ X_train$Close + X_train$SD, family = "binomial")
summary(fit1)
```

```
##
## Call:
## glm(formula = Y_train ~ X_train$Close + X_train$SD, family = "binomial")
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.3142  -1.0677  -0.8107   1.2260   1.6758
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept) 35.92470 18.29996 1.963 0.0496 *
## X_train$Close -0.02223 0.01093 -2.034 0.0420 *
## X_train$SD 0.74561 1.48766 0.501 0.6162
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 210.83 on 154 degrees of freedom
## Residual deviance: 205.75 on 152 degrees of freedom
## AIC: 211.75
##
## Number of Fisher Scoring iterations: 4
```

I used the close price and standard deviation as predictors. The result showed that close price and intercept is significant with p value less than 5%.

Next I used only close price as predictors.

```
fit2 <- glm(Y_train ~ X_train$Close, family = "binomial")
summary(fit2)

##
## Call:
## glm(formula = Y_train ~ X_train$Close, family = "binomial")
##
## Deviance Residuals:
##    Min       1Q   Median       3Q      Max
## -1.267  -1.061  -0.809   1.228   1.637
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  37.97554   17.85390   2.127  0.0334 *
## X_train$Close -0.02313    0.01079  -2.145  0.0320 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 210.83 on 154 degrees of freedom
## Residual deviance: 206.00 on 153 degrees of freedom
## AIC: 210
##
## Number of Fisher Scoring iterations: 4
```

Close price and intercept was still significant.

I predicted the outcome, using close price as predictors and made the confusion matrix.

```
pred <- predict(fit2, type="response")
#confusion matrix
table(Y_train, pred > 0.5)

##
## Y_train FALSE TRUE
##      0      75      15
##      1      53      12
```


I couldn't categorize well when the true label is 1.

ROC shows that the closer the ROC curve is to upper left corner, the higher the overall accuracy of the test is. The below ROC was almost straight line and it was difficult to tell which point was the highest accuracy but 0.7 true positive rate and 0.5 false positive seemed to be good.

```
library(ROCR)
```

```
## Loading required package: gplots
```

```
##
```

```
## Attaching package: 'gplots'
```

```
## The following object is masked from 'package:stats':
```

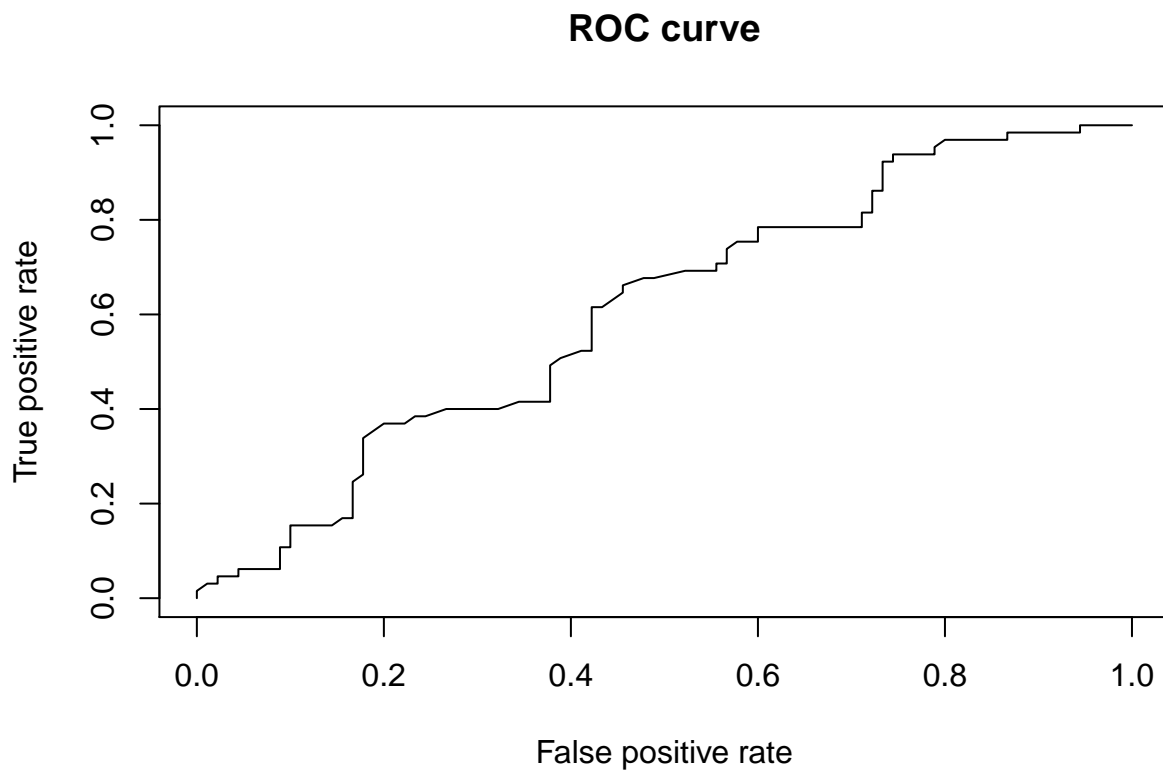
```
##
```

```
## lowess
```

```
ROC <- prediction(pred, Y_train)
```

```
ROC_perf <- performance(ROC, 'tpr', 'fpr')
```

```
plot(ROC_perf, main = "ROC curve")
```



higher the AUC value is, the more accurate the model is. In this case, the AUC is 0.6073504.

```
AUC <- performance(ROC, "auc")
```

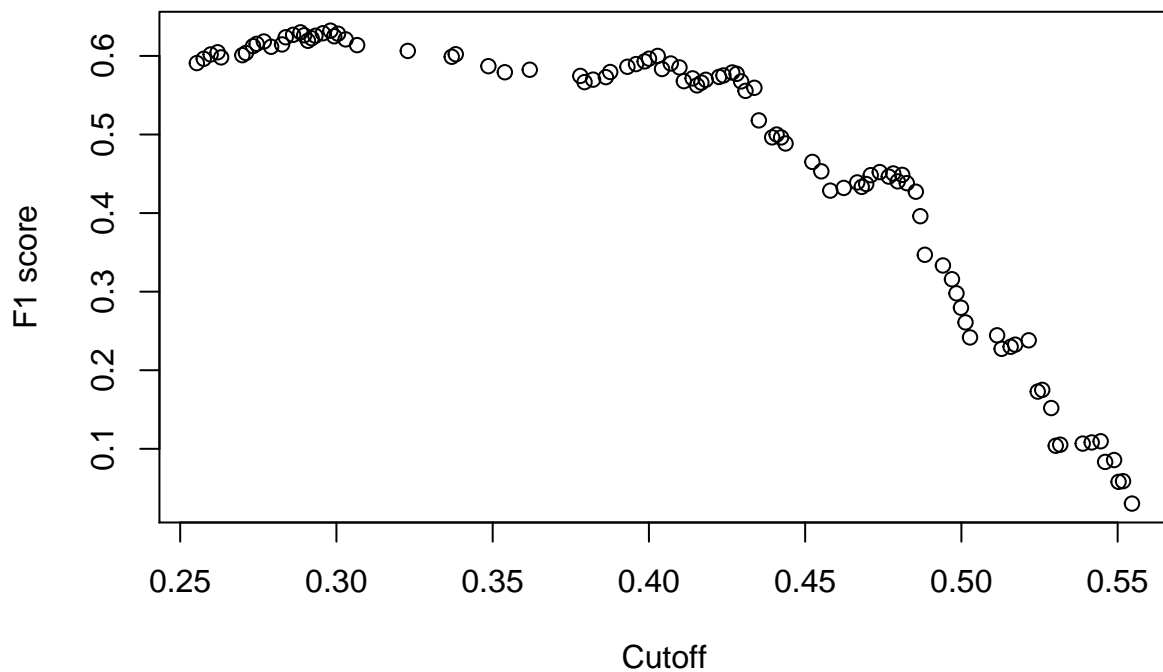
```
AUC@y.values[[1]]
```

```
## [1] 0.6073504
```

The below F1 score plot showed F1 score at every cutoff point .

```
F1 <- performance(ROC, 'f')
```

```
plot(F1@y.values[[1]][-1]~F1@x.values[[1]][-1], xlab="Cutoff", ylab="F1 score")
```



```
optCut <- F1@x.values[[1]][-1][which.max(F1@y.values[[1]][-1])]
```

When the cutoff point was 0.2980931, the f1 score was the highest. At this cutoff point, the confusion matrix was like below. we could classify the label 1 very well.

```
table(Y_train, pred >= optCut)
```

```
##
## Y_train FALSE TRUE
##      0      23      67
##      1       4      61
```