Simple predictive models: Linear and logistic regression

Montserrat Guillen

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Contents

In this document we continue with simple Data Analysis linked to the article by S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014. The two datasets ontain similar information, but not exactly the same.. Here we will analyse the smaller data set (called **bank.csv**). The file can be downloaded from: https://archive.ics.uci.edu/ml/datasets/bank+marketing

or (for this course)

http://www.ub.edu/rfa/docs/DATA/bank.csv

We will see linear regression and logistic regression.

Introduction

Here we set up some options for the Rmarkdown ouput. We want to see the R programme (echo=TRUE), but sometime we do not want to see the output, then we set include=FALSE.

Reading the data

Here we read the data and check the names.

```
# read data
#setwd("..")
mydata <- read.csv2("bank.csv", header=TRUE, sep=";", dec=".")
n.var <- names(mydata)
glimpse(mydata)
```

```
## Observations: 4,521
## Variables: 17
## $ age       <int> 30, 33, 35, 30, 59, 35, 36, 39, 41, 43, 39, 43, 36, ...
```

```
## $ job       <fctr> unemployed, services, management, management, blue-...
## $ marital   <fctr> married, married, single, married, married, single,...
## $ education <fctr> primary, secondary, tertiary, tertiary, secondary, ...
## $ default   <fctr> no, no, no, no, no, no, no, no, no, no, no, no, no,...
## $ balance   <int> 1787, 4789, 1350, 1476, 0, 747, 307, 147, 221, -88, ...
## $ housing   <fctr> no, yes, yes, yes, yes, no, yes, yes, yes, yes, yes...
## $ loan      <fctr> no, yes, no, yes, no, no, no, no, no, yes, no, no, ...
## $ contact   <fctr> cellular, cellular, cellular, unknown, unknown, cel...
## $ day       <int> 19, 11, 16, 3, 5, 23, 14, 6, 14, 17, 20, 17, 13, 30,...
## $ month     <fctr> oct, may, apr, jun, may, feb, may, may, may, apr, m...
## $ duration  <int> 79, 220, 185, 199, 226, 141, 341, 151, 57, 313, 273,...
## $ campaign  <int> 1, 1, 1, 4, 1, 2, 1, 2, 2, 1, 1, 2, 2, 1, 1, 2, 5, 1...
## $ pdays     <int> -1, 339, 330, -1, -1, 176, 330, -1, -1, 147, -1, -1,...
## $ previous  <int> 0, 4, 1, 0, 0, 3, 2, 0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 2...
## $ poutcome  <fctr> unknown, failure, failure, unknown, unknown, failur...
## $ y         <fctr> no, no, no, no, no, no, no, no, no, no, no, no, no,...
```

We have previously analysed the data. Just recall that the data contain 4521 cases and 17 variables. The variable names are: age, job, marital, education, default, balance, housing, loan, contact, day, month, duration, campaign, pdays, previous, poutcome, y.

Linear regression

We will study the duration of the telephone call as a function of age.

Linear model (quantitative regressors)

We introduce two variables: **age**, **balance** and days since last call (**pdays**).

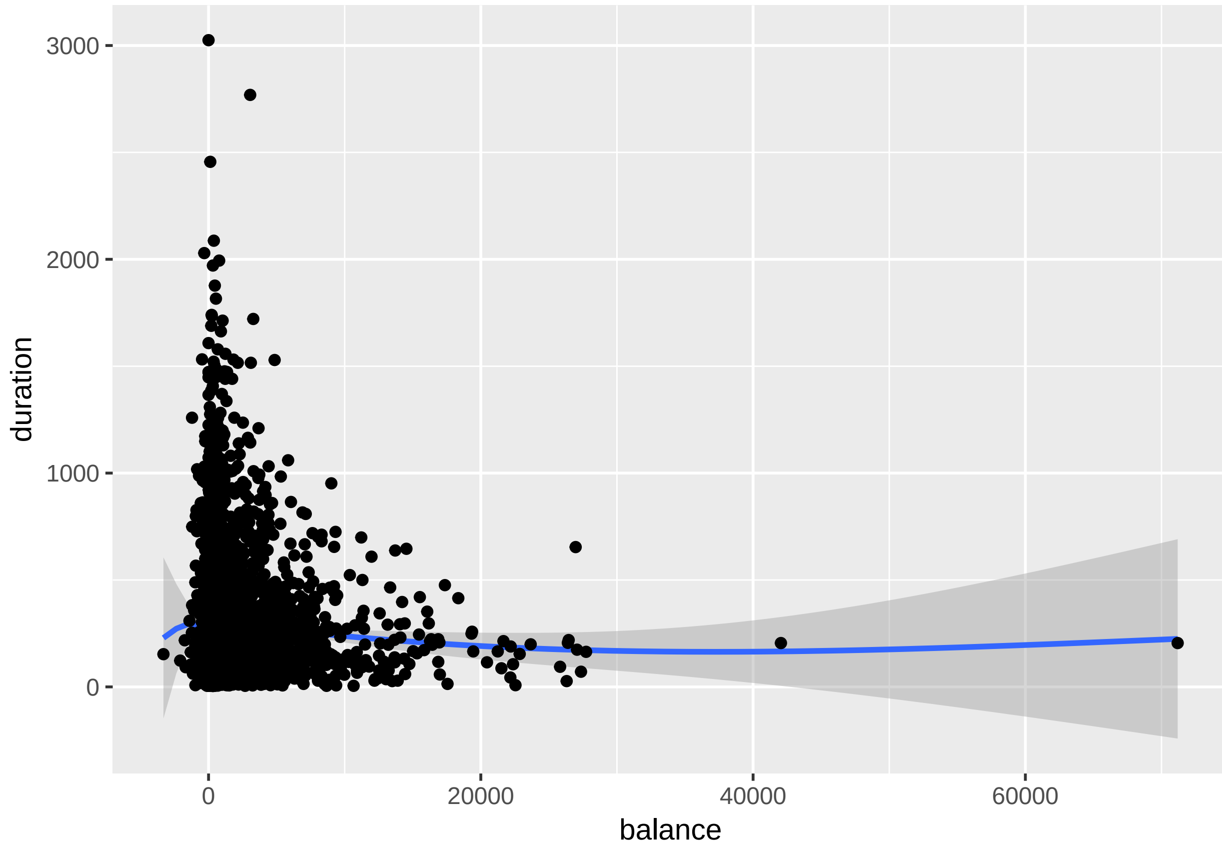
```r
# Model estimation
attach(mydata)

Model.1.1<- lm(duration~age+ balance+pdays, data=mydata )
summary(Model.1.1)
```

```
##
## Call:
## lm(formula = duration ~ age + balance + pdays, data = mydata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -281.86 -159.95  -78.95   64.60 2760.60
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 265.782426  15.635701  16.998   <2e-16 ***
## age          -0.022964   0.366818  -0.063    0.950
## balance      -0.001379   0.001289  -1.070    0.285
## pdays         0.027311   0.038614   0.707    0.479
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 259.9 on 4517 degrees of freedom
## Multiple R-squared:  0.0003662,  Adjusted R-squared:  -0.0002977
## F-statistic: 0.5515 on 3 and 4517 DF,  p-value: 0.6471
```

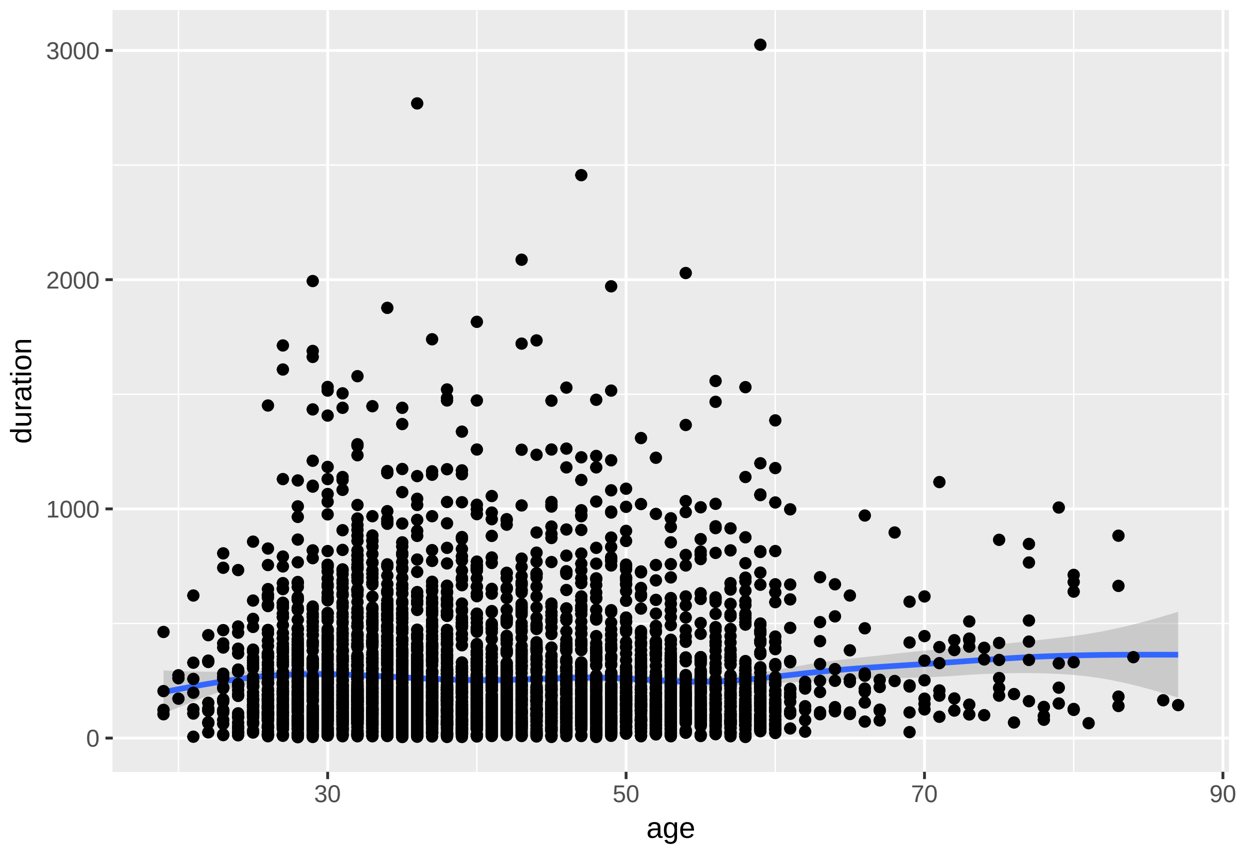
```r
qplot(balance,duration, data = mydata,geom = c("smooth", "point"))
```

```
## `geom_smooth()` using method = 'gam'
```



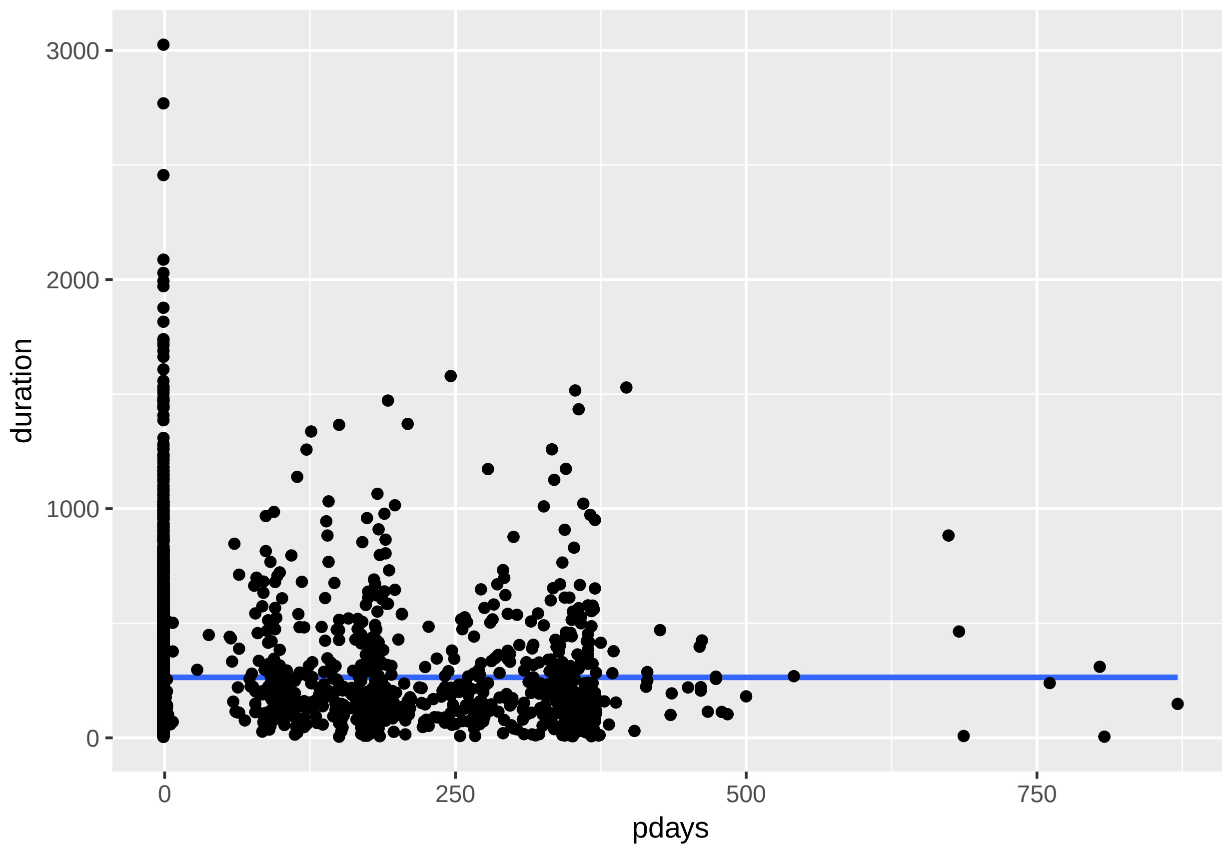

```r
qplot(age,duration, data = mydata,geom = c("smooth", "point"))
```

```
## `geom_smooth()` using method = 'gam'
```




```
qplot(pdays, duration, data = mydata,geom = c("smooth", "point"))
```

```
## `geom_smooth()` using method = 'gam'
```



The goodness-of-fit coefficient is 0.00037

Linear model (quantitative and qualitative regressors)

We now also include **month**, **loan** (yes/no) and **contact** (telephone/cellular/other).

```
monthR=relevel(month, ref = 'mar')
loanR=relevel(loan, ref = 'no')
contactR=relevel(contact, ref = 'telephone')

Model.1.2<- lm(duration~age+ balance+factor(monthR)+factor(loanR)+factor(contactR), data=mydata )
summary(Model.1.2)
```

```
##
## Call:
## lm(formula = duration ~ age + balance + factor(monthR) + factor(loanR) +
##     factor(contactR), data = mydata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -353.60 -158.81  -78.40   62.85 2746.30
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)              171.242123  44.030023   3.889 0.000102 ***
## age                        0.197277   0.377299   0.523 0.601092
```

```
## balance                    -0.001513   0.001311  -1.154 0.248443
## factor(monthR)apr          92.949051  40.207779   2.312 0.020838 *
## factor(monthR)aug          40.641928  38.611697   1.053 0.292590
## factor(monthR)dec         218.572502  68.940605   3.170 0.001532 **
## factor(monthR)feb          54.871529  41.062446   1.336 0.181520
## factor(monthR)jan          68.562270  42.866071   1.599 0.109790
## factor(monthR)jul          72.012452  38.542344   1.868 0.061771 .
## factor(monthR)jun          52.273360  40.104623   1.303 0.192496
## factor(monthR)may          66.457346  38.499819   1.726 0.084385 .
## factor(monthR)nov          73.249744  39.458837   1.856 0.063468 .
## factor(monthR)oct          73.640188  47.112642   1.563 0.118107
## factor(monthR)sep          14.211828  51.794399   0.274 0.783798
## factor(loanR)yes           -7.471544  10.950277  -0.682 0.495075
## factor(contactR)cellular  27.257131  16.167606   1.686 0.091882 .
## factor(contactR)unknown   24.269113  19.035798   1.275 0.202403
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 259.5 on 4504 degrees of freedom
## Multiple R-squared:  0.005938,   Adjusted R-squared:  0.002407
## F-statistic: 1.682 on 16 and 4504 DF,  p-value: 0.04299
```

Compare goodnes-of-fit

```r
summary(Model.1.1)$adj.r.squared*100
```

```
## [1] -0.02977405
```

```r
summary(Model.1.2)$adj.r.squared*100
```

```
## [1] 0.2406728
```

The goodness-of-fit coefficient is in the first model -3e-04 and in the second model 0.0024.

Prediction

Assume we have a new observation and want to predict the duration pf the call.

```r
newdata=data.frame(age=30, balance=100.0, monthR='jun', loanR='yes', contactR='cellular', pdays=30)
predict(Model.1.1, newdata)
```

```
##        1
## 265.7749
```

```r
predict(Model.1.2, newdata)
```

```
##        1
## 249.0681
```

Logistic regression model

Estimation of the model

We estimate the model for the dependent variable **y** = **Term Diposit**. We only consider age and duration of the call.

```
Model.2.1=glm(y~age+duration, family=binomial)
summary(Model.2.1)
```

```
##
## Call:
## glm(formula = y ~ age + duration, family = binomial)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.9345  -0.4331  -0.3550  -0.3053   2.5960
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.8606442  0.2141070  -18.03  < 2e-16 ***
## age          0.0144683  0.0046083    3.14  0.00169 **
## duration     0.0035526  0.0001713   20.73  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3231.0  on 4520  degrees of freedom
## Residual deviance: 2692.1  on 4518  degrees of freedom
## AIC: 2698.1
##
## Number of Fisher Scoring iterations: 5
```

Prediction with this model

```
newdata=data.frame(age=30, balance=100.0, monthR='jun', loanR='yes', contactR='cellular', pdays=30, dura

predict(Model.2.1, newdata, type="response")
```

```
##          1
## 0.07320616
```

The prediction for that custmer and the logistic model is 0.073.

Improve the model

We can improve the model now with more information

```
Model.2.2=glm(y~age+duration+factor(month), family=binomial)
summary(Model.2.2)
```

```
##
## Call:
## glm(formula = y ~ age + duration + factor(month), family = binomial)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.1203  -0.4102  -0.3028  -0.2340   2.8635
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -3.0065925  0.2583671 -11.637  < 2e-16 ***
## age               0.0049704  0.0047033   1.057 0.290612
## duration          0.0039210  0.0001856  21.131  < 2e-16 ***
## factor(month)aug -0.3975137  0.2136124  -1.861 0.062757 .
## factor(month)dec  1.0696658  0.5424684   1.972 0.048627 *
## factor(month)feb  0.0273859  0.2553147   0.107 0.914580
## factor(month)jan -0.6592617  0.3442742  -1.915 0.055501 .
## factor(month)jul -1.0758984  0.2245574  -4.791 1.66e-06 ***
## factor(month)jun -0.7430330  0.2331552  -3.187 0.001438 **
## factor(month)mar  1.7134677  0.3447136   4.971 6.67e-07 ***
## factor(month)may -1.3384223  0.2038424  -6.566 5.17e-11 ***
## factor(month)nov -0.8687405  0.2532264  -3.431 0.000602 ***
## factor(month)oct  1.5898738  0.2928645   5.429 5.68e-08 ***
## factor(month)sep  1.1940001  0.3496861   3.414 0.000639 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3231.0  on 4520  degrees of freedom
## Residual deviance: 2465.5  on 4507  degrees of freedom
## AIC: 2493.5
##
## Number of Fisher Scoring iterations: 6
```

The Akaike Information Criterion (AIC) in the first model was 2698 ans now it is 2494.

ROC curve

Predictive performance

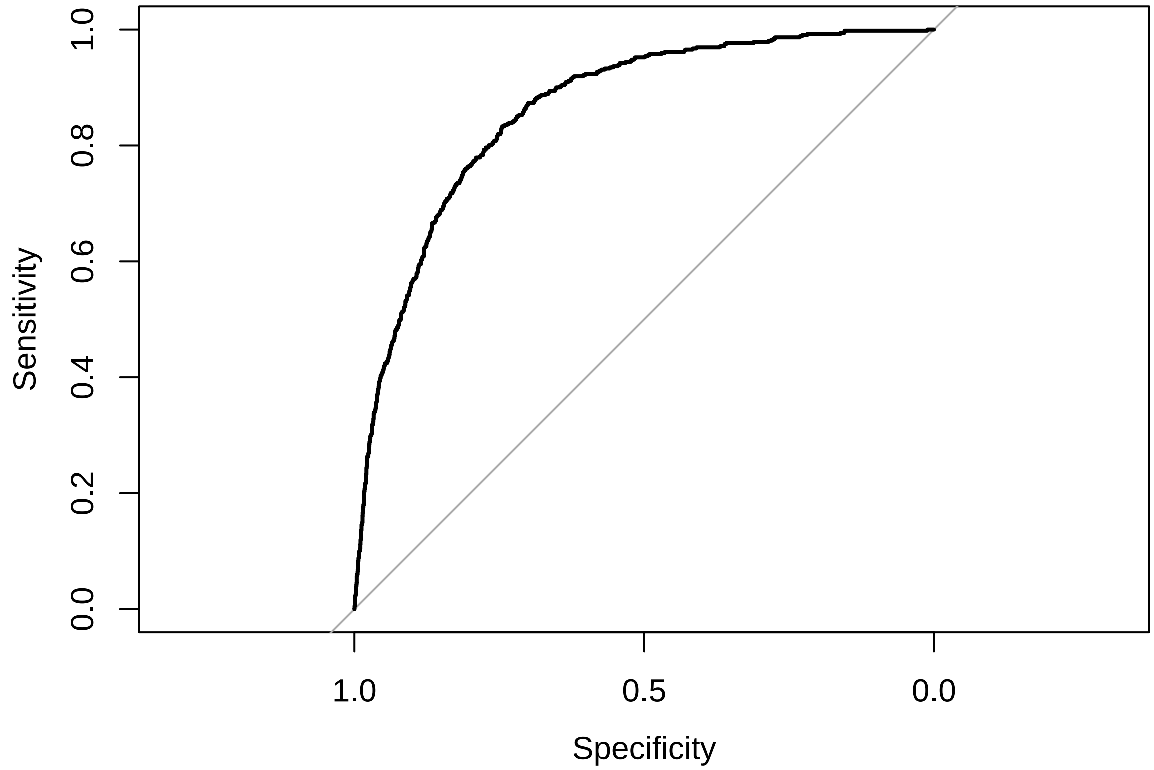
```
#install.packages("pROC")
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
prob=predict(Model.2.2,type=c("response"))
mydata$prob=prob
g=roc(y,prob, data=mydata)
plot(g)
```




```r
auc(g)
```

```
## Area under the curve: 0.8618
```

The AUROC is 0.86.