Classification

Eltecon Data Science Course by Emarsys

János Divényi

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Goal of the lesson

- introduce **decision trees** as nonlinear classifiers
- measure the performance of classification models by the **ROC curve**

Section 1

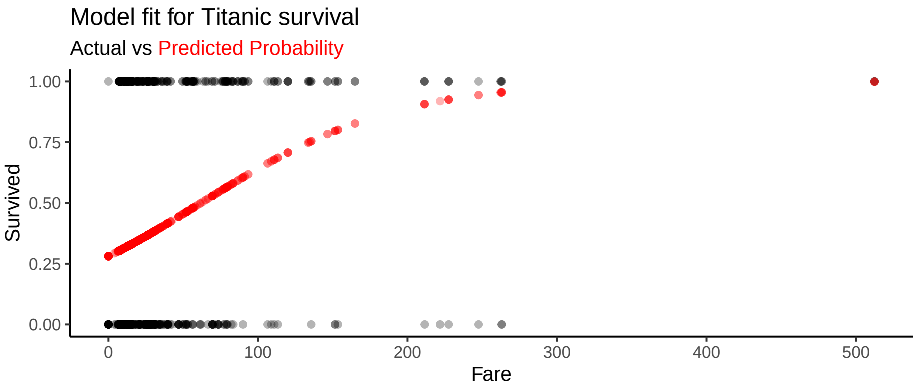
Classification

Recap: logistic regression to predict Titanic-survival

```
model <- glm(
    Survived ~ Fare,
    data = titanic_train,
    family = binomial(link = "logit")
)
```

```
predicted_prob <- predict.glm(
  model,
  newdata = titanic_train,
  type = "response"
)
```

Predictive fit



Evaluating binary models - Accuracy

```
calculateAccuracy <- function(actual, predicted) {
    N <- length(actual)
    accuracy <- sum(actual == predicted) / N

    return(accuracy)
}
```

```
predicted_class <- ifelse(predicted_prob > 0.5, 1, 0)
calculateAccuracy(titanic_train$Survived, predicted_class)
```

```
## [1] 0.6655443
```

Evaluating binary models - Confusion Matrix

```
table(
  titanic_train$Survived,
  predicted_class,
  dnn = c("actual", "predicted")
)
```

```
##        predicted
## actual    0   1
##       0 511  38
##       1 260  82
```

Non-linear classification: Decision Tree

Visual explanation by r2d3

Quiz

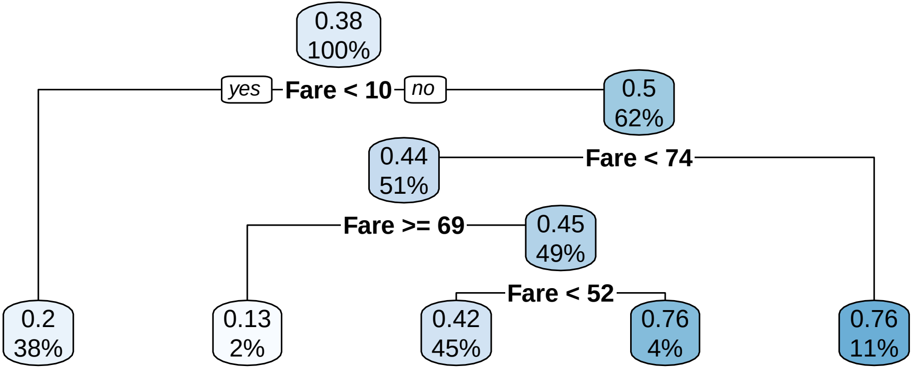
Estimate a decision tree model

```r
tree_model <- rpart(
    Survived ~ Fare, data = titanic_train
)
```

```
## n= 891
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
##  1) root 891 210.727300 0.3838384
##    2) Fare< 10.48125 339  53.758110 0.1976401 *
##    3) Fare>=10.48125 552 137.998200 0.4981884
##      6) Fare< 74.375 455 112.206600 0.4417582
##       12) Fare>=69.425 15   1.733333 0.1333333 *
##       13) Fare< 69.425 440 108.997700 0.4522727
##         26) Fare< 52.2771 403  98.441690 0.4243176 *
##         27) Fare>=52.2771 37   6.810811 0.7567568 *
##      7) Fare>=74.375 97  17.546390 0.7628866 *
```

Visualize

```
rpart.plot(tree_model)
```



Evaluate

```
predicted_prob_tree <- predict(tree_model, newdata = titanic_train)
calculateAccuracy(titanic_train$Survived, predicted_prob_tree > 0.5)
```

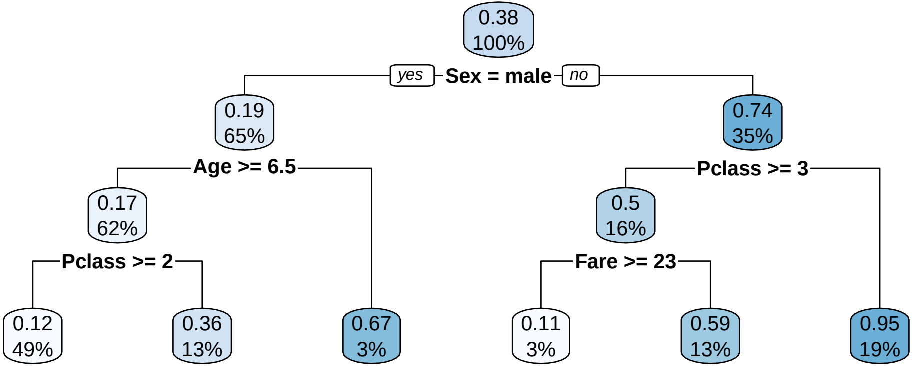
```
## [1] 0.694725
```

```
table(
  titanic_train$Survived,
  predicted_prob_tree > 0.5,
  dnn = c("actual", "predicted")
)
```

```
##       predicted
## actual FALSE TRUE
##      0   517   32
##      1   240  102
```

Include other variables

```
extended_tree <- rpart(
    Survived ~ Fare + Sex + Age + Pclass, data = titanic_trai
)
rpart.plot(extended_tree)
```



Including more variable helps

```
calculateAccuracy(
    titanic_train$Survived,
    predict(extended_tree) > 0.5
)
```

```
## [1] 0.8193042
```

Including more variable helps

```r
calculateAccuracy(
    titanic_train$Survived,
    predict(extended_tree) > 0.5
)
```

```
## [1] 0.8193042
```

. . . or does it?

Including more variables helps

```
calculateAccuracy(
    titanic_train$Survived,
    predict(extended_tree) > 0.5
)
```

```
## [1] 0.8193042
```

. . . or does it?

Recall: we have to evaluate the performance on a **different set of data** to avoid overfitting

Classify spam by decision trees

Recall from week 4

```
data <- fread("../week4/data/spam_clean.csv")

# Separate train-test set
train_proportion <- 0.8
n <- nrow(data)
set.seed(20211020)
train_index <- sample(1:n, floor(n * train_proportion))

data_to_use <- data[, -c(2, 50:400)]  # exclude columns to speed up
data_train <- data_to_use[train_index,]
data_test <- data_to_use[-train_index,]
```

Estimate logistic regression as benchmark

```
spam_logit <- glm(
    is_spam ~ .,
    data = data_train,
    family = binomial(link = "logit")
)
```

Accuracy evaluated on a test set:

```
predicted_probs <- predict(spam_logit, newdata = data_test, ty
calculateAccuracy(
    data_test$is_spam,
    predicted_probs > 0.5
)
```

```
## [1] 0.9533632
```

Tree model

Let's try to do this in R!

Enter your estimated accuracy on the test set into Socrative (up to the second digit).

Tree model

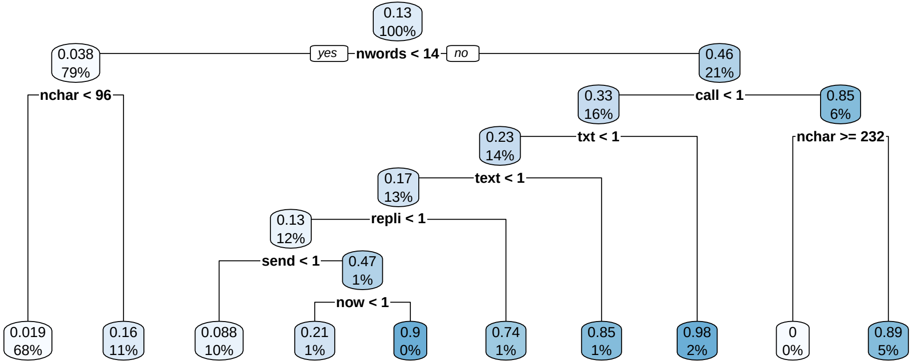
```r
spam_tree <- rpart(
    is_spam ~ .,
    data = data_train
)
```

```r
predicted_probs <- predict(spam_tree, newdata = data_test)
calculateAccuracy(
    data_test$is_spam,
    predicted_probs > 0.5
)
```

```
## [1] 0.9372197
```

Performs worse but is easier to interpret

```
rpart.plot(spam_tree)
```



Tree "pruning"

Additional leaves *always* improve the accuracy on the *train* set.

How to avoid overfitting?

Tree "pruning"

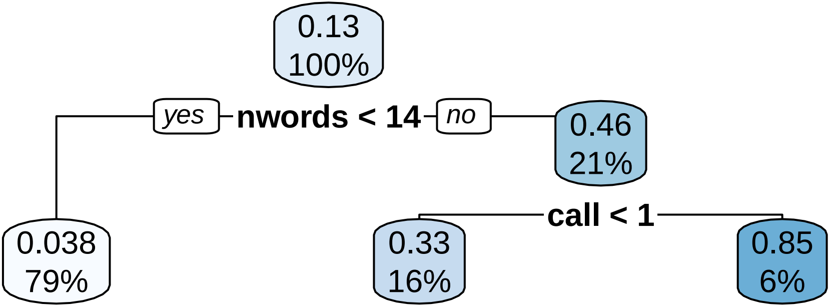
Additional leaves *always* improve the accuracy on the *train* set.

How to avoid overfitting? **Regularisation**

Tree "pruning"

The complexity parameter (cp) controls the penalty for more leaves.

```
rpart.plot(prune(spam_tree, cp = 0.1))
```



Overfitting

Estimate a "full" tree

```
spam_full_tree <- rpart(
    is_spam ~ .,
    data = data_train,
    control = rpart.control(
        minsplit = 2, minbucket = 1, cp = 0
    )
)
```

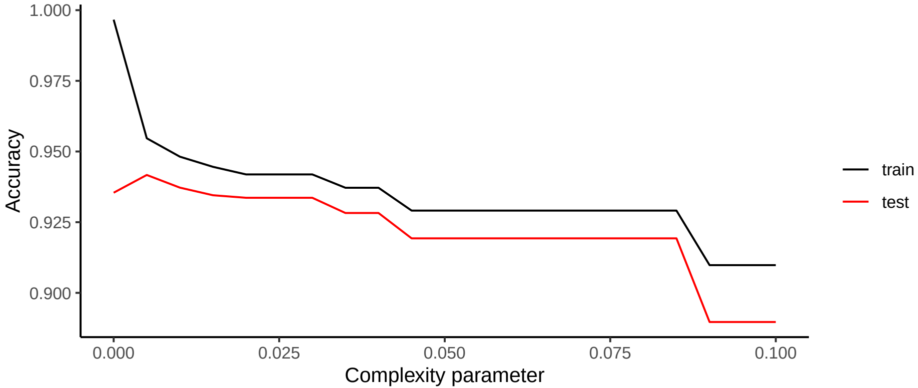
```
calculateAccuracy(
    data_train$is_spam,
    predict(spam_full_tree) > 0.5
)
```

```
## [1] 0.9966345
```

Compare performance on train and test set

```
accuracy_by_params <- map_df(seq(0, 0.1, 0.005), ~{
    pruned_tree <- prune(spam_full_tree, cp = .x)
    data.table(
        cp = .x,
        train = calculateAccuracy(data_train$is_spam, predict(pruned_tree, data_tra
        test = calculateAccuracy(data_test$is_spam, predict(pruned_tree, data_test)
    )
})
```

Compare performance on train and test set



Section 2

Evaluate binary classification performance

Accuracy might not be that informative

- *"PCR-tests have above 95% accuracy".* - What does that mean?

Accuracy might not be that informative

- *"PCR-tests have above 95% accuracy".* - What does that mean?
- I can always deliver a 99%+ accurate model to predict who will buy – until the purchase rate remains below 1% as usual (predicting no one will buy)

Accuracy might not be that informative

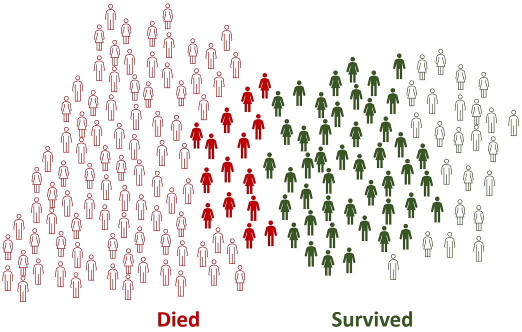
- *"PCR-tests have above 95% accuracy".* - What does that mean?
- I can always deliver a 99%+ accurate model to predict who will buy – until the purchase rate remains below 1% as usual (predicting no one will buy)
- Confusion matrix provides more detailed information by comparing actual and predicted labels

Confusion matrix

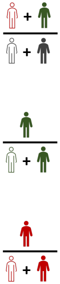
Recall the confusion matrix of the Titanic prediction task using the logistic regression model:

```
##        predicted
## actual FALSE TRUE
##      0   511   38
##      1   260   82
```

True Positive and False Positive Rate



predicted to survive



Accuracy

True Positive Rate

False Positive Rate

True Positive and False Positive Rate

Recall the confusion matrix of the Titanic prediction task using the glm:

```
##       predicted
## actual FALSE TRUE
##      0   511   38
##      1   260   82
```

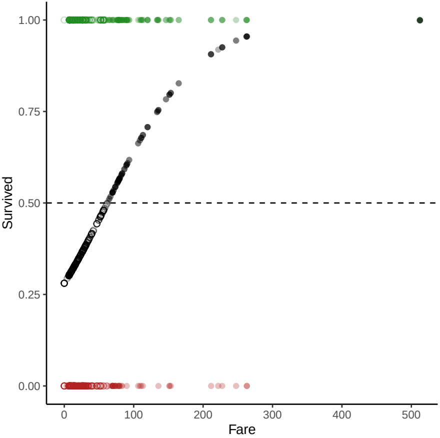
- True Positive Rate: `82/(260 + 82) = 23.98%`
- False Positive Rate: `38/(511 + 38) = 6.9%`

There is a trade-off between TPR and FPR

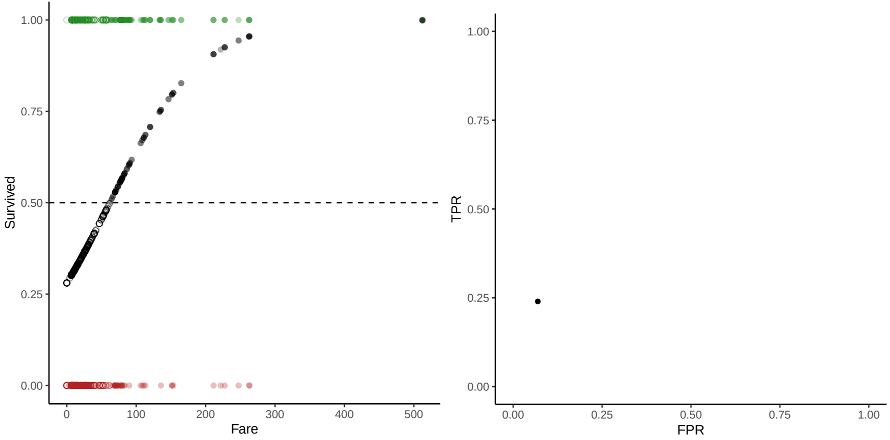
- Getting easier* about classifying someone as positive (or as a survivor) would definitely increase TPR - but also the FPR
  - It is easy to reach 100% true positive rate: just predict positive for everyone
- This trade-off is expressed by the ROC curve

* just decrease the probability cutoff that we defaulted to 0.5

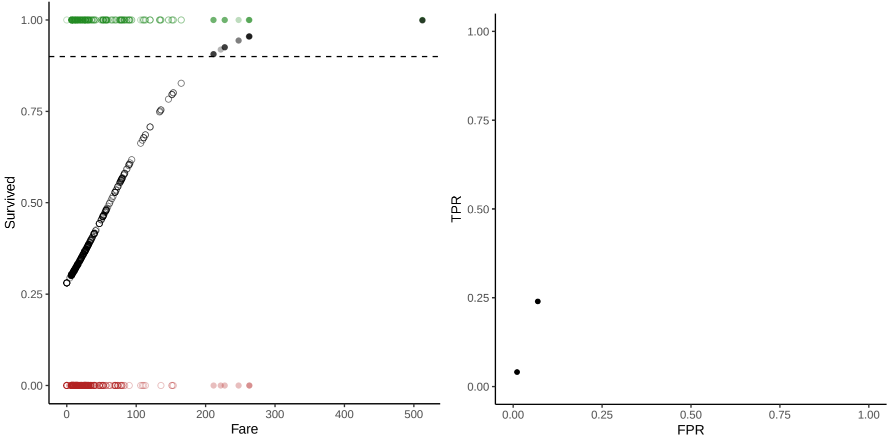
ROC plot



ROC plot

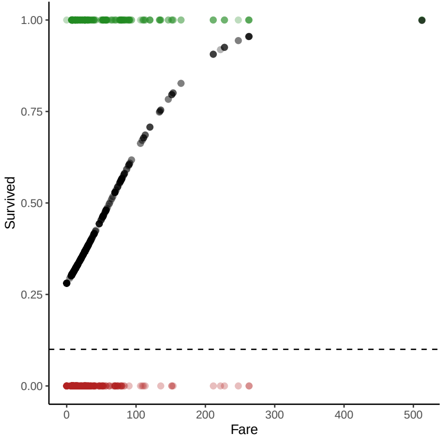

1.00
0.75
0.50
0.25
0.00
Survived
0
100
200
300
400
500
Fare
1.00
0.75
0.50
0.25
0.00
TPR
0.00
0.25
0.50
0.75
1.00
FPR

ROC plot



Survived
1.00
0.75
0.50
0.25
0.00
0
100
200
300
400
500
Fare
TPR
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
FPR

ROC plot


Survived
1.00
0.75
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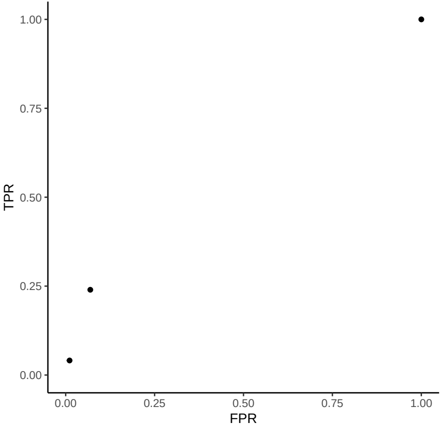
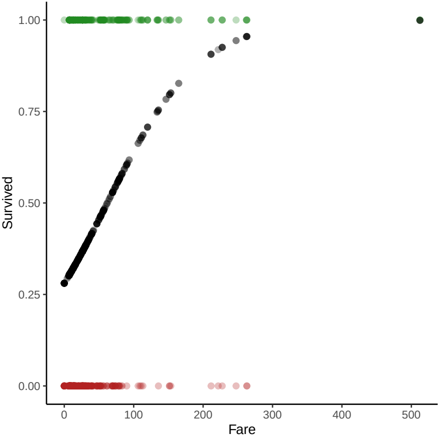
0
100
200
300
400
500
Fare


TPR
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
FPR

ROC plot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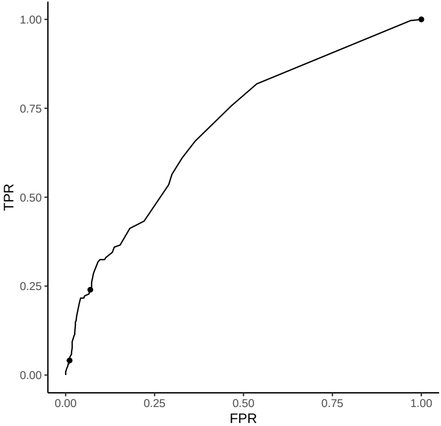
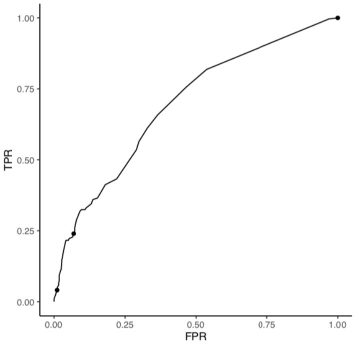
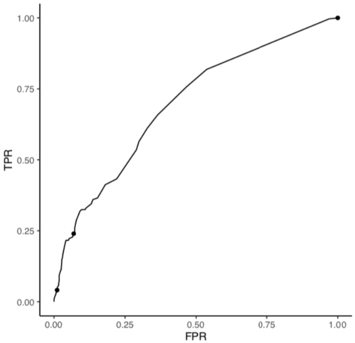
1.00
0.75
0.50
0.25
0.00
0
100
200
300
400
500
Fare

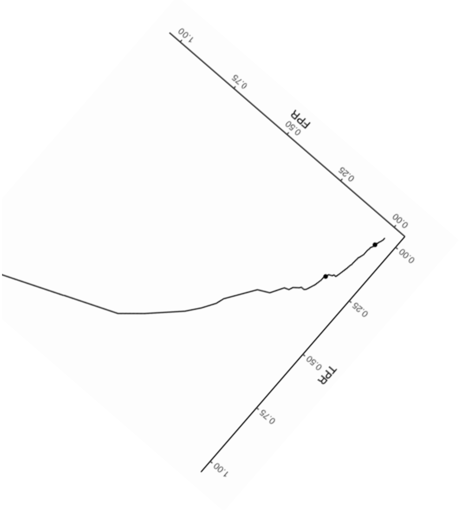

TPR
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
FPR

ROC plot

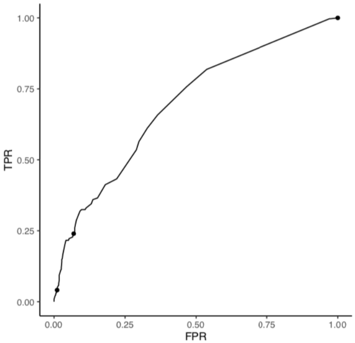


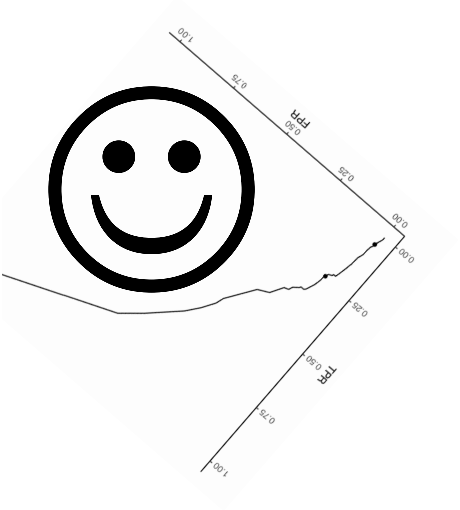
ROC plot





ROC plot





Quiz

ROC plot for spam prediction - live coding

Homework

- Figure out a research question based on the EDA that you are doing for Nov 3

Resources

- Gareth J., Witten D., Hastie T. and Tibshirani R.: An Introduction to Statistical Learning Chapter 8.
- Machine Learning meets economics: https://blog.mldb.ai/blog/posts/2016/01/ml-meets-economics/
- FPR, TPR: https://www.youtube.com/watch?v=sunUKFXMHGk (StatQuest)
- ROC curve: https://www.youtube.com/watch?v=4jRBRDbJemM (StatQuest)

Thank you & Feedback