Finding the right cut-off: the strategy curve

Constructing a confusion matrix

```
> predict(log_reg_model, newdata = test_set, type = "response")

 1          2         3          4         5          …
0.08825517 0.3502768 0.28632298 0.1657199 0.11264550    …



> predict(class_tree, new data = test_set)
          0         1
1 0.7873134 0.2126866
2 0.6250000 0.3750000
3 0.6250000 0.3750000
4 0.7873134 0.2126866
5 0.5756867 0.4243133
```

Cut-off?

```
> pred_log_regression_model <- predict(log_reg_model, newdata = test_set,
type = "response")

> cutoff <- 0.14

> class_pred_logit <- ifelse(pred_log_regression_model > cutoff, 1, 0)
```

?

A certain strategy...

```
> log_model_full <- glm(loan_status ~ ., family = "binomial", data = training_set)
> predictions_all_full<- predict(log_reg_model, newdata = test_set, type = “response")

> cutoff <- quantile(predictions_all_full, 0.8)
  cutoff
      80%
0.1600124

> pred_full_20 <- ifelse(predictions_all_full > cutoff, 1, 0)
```

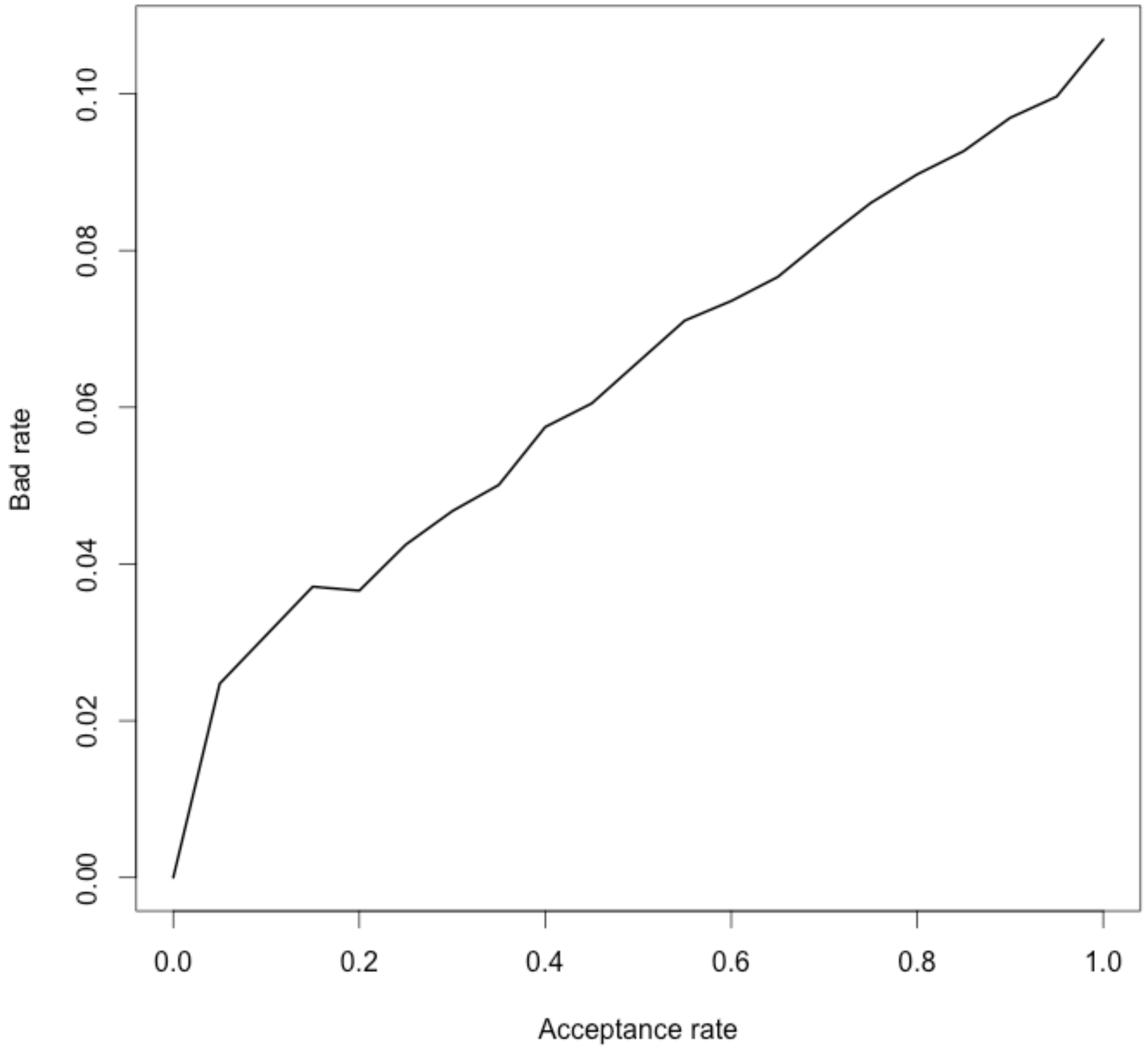
A certain strategy (continued)

```
> true_and_predval <- cbind(test_set$loan_status, pred_full_20)
  true_and_predval

     test_set$loan_status    pred_full_20
1                0                     0
2                0                     0
3                0                     1
4                0                     0
5                0                     1
…                …                     …


> accepted_loans <- pred_and_trueval[pred_full_20 == 0,1]

> bad_rate <- sum(accepted_loans)/length(accepted_loans)
> bad_rate
[1] 0.08972541
```

The strategy table

```
        accept_rate  cutoff  bad_rate
 [1,]         1.00   0.5142   0.1069
 [2,]         0.95   0.2122   0.0997
 [3,]         0.90   0.1890   0.0969
 [4,]         0.85   0.1714   0.0927
 [5,]         0.80   0.1600   0.0897
 [6,]         0.75   0.1471   0.0861
 [7,]         0.70   0.1362   0.0815
 [8,]         0.65   0.1268   0.0766
  …            …       …        …
[16,]         0.25   0.0644   0.0425
[17,]         0.20   0.0590   0.0366
[18,]         0.15   0.0551   0.0371
[19,]         0.10   0.0512   0.0309
[20,]         0.05   0.0453   0.0247
[21,]         0.00   0.0000   0.0000
```

The strategy curve



Let’s practice!

Let's practice!

The ROC-curve

Until now

- strategy table/curve : still make assumption
- what is “overall” best model?

Confusion matrix

model prediction

actual loan status

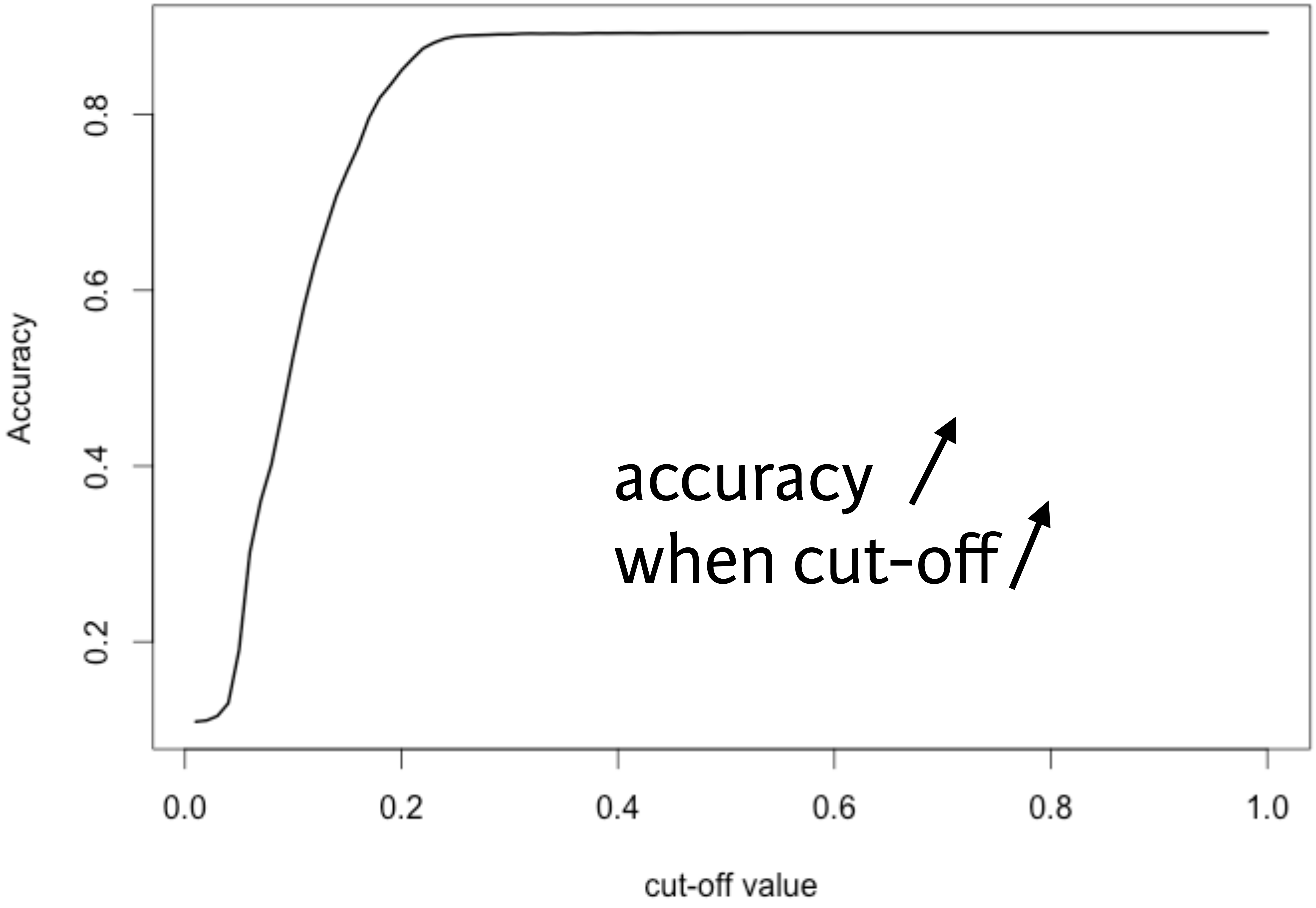
	no default (0)	default (1)
no default (0)	**TN**	**FP**
default (1)	**FN**	**TP**

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

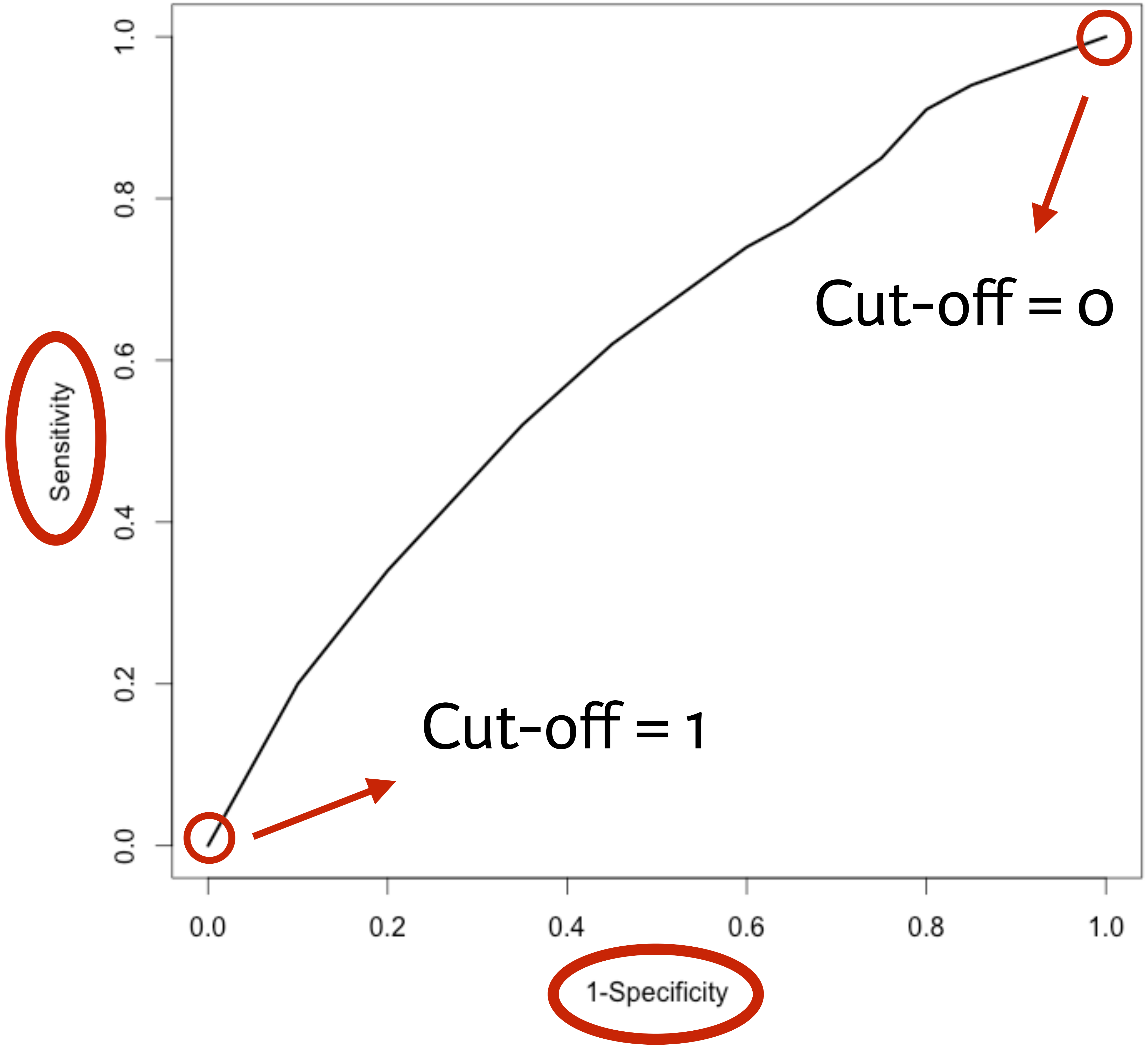
Accuracy?



$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

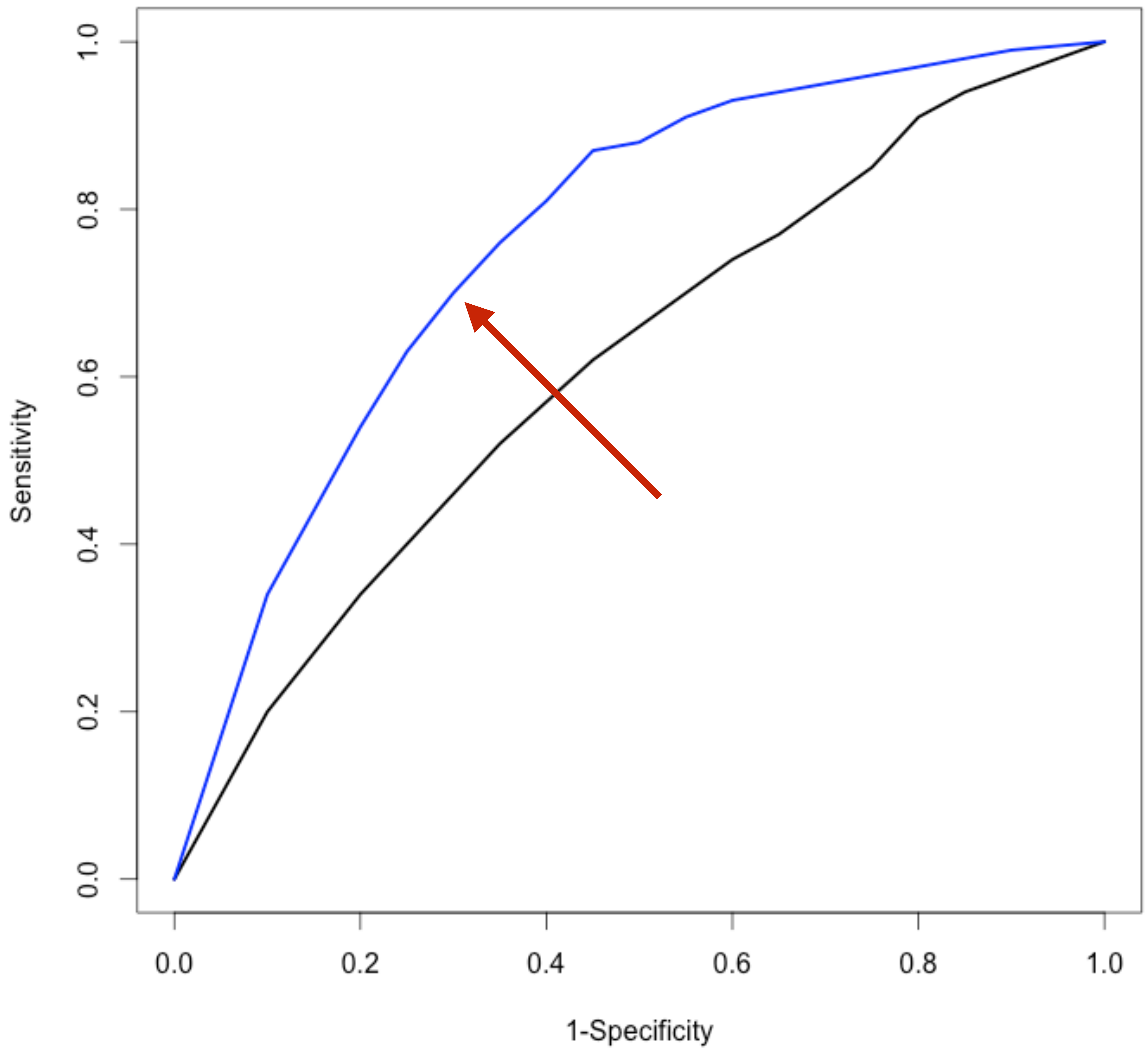
The ROC-curve



$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

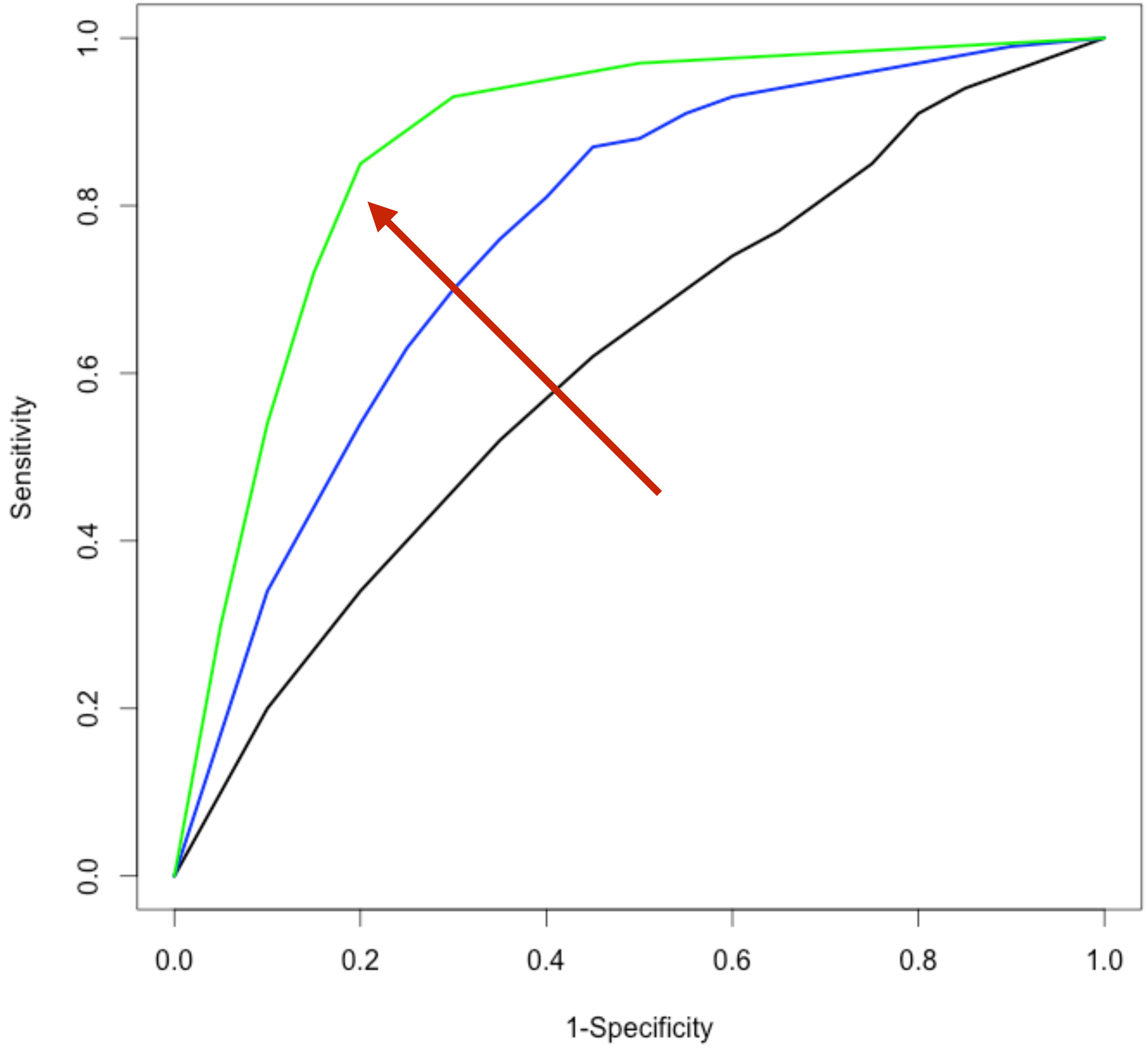
The ROC-curve



$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

The ROC-curve



$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

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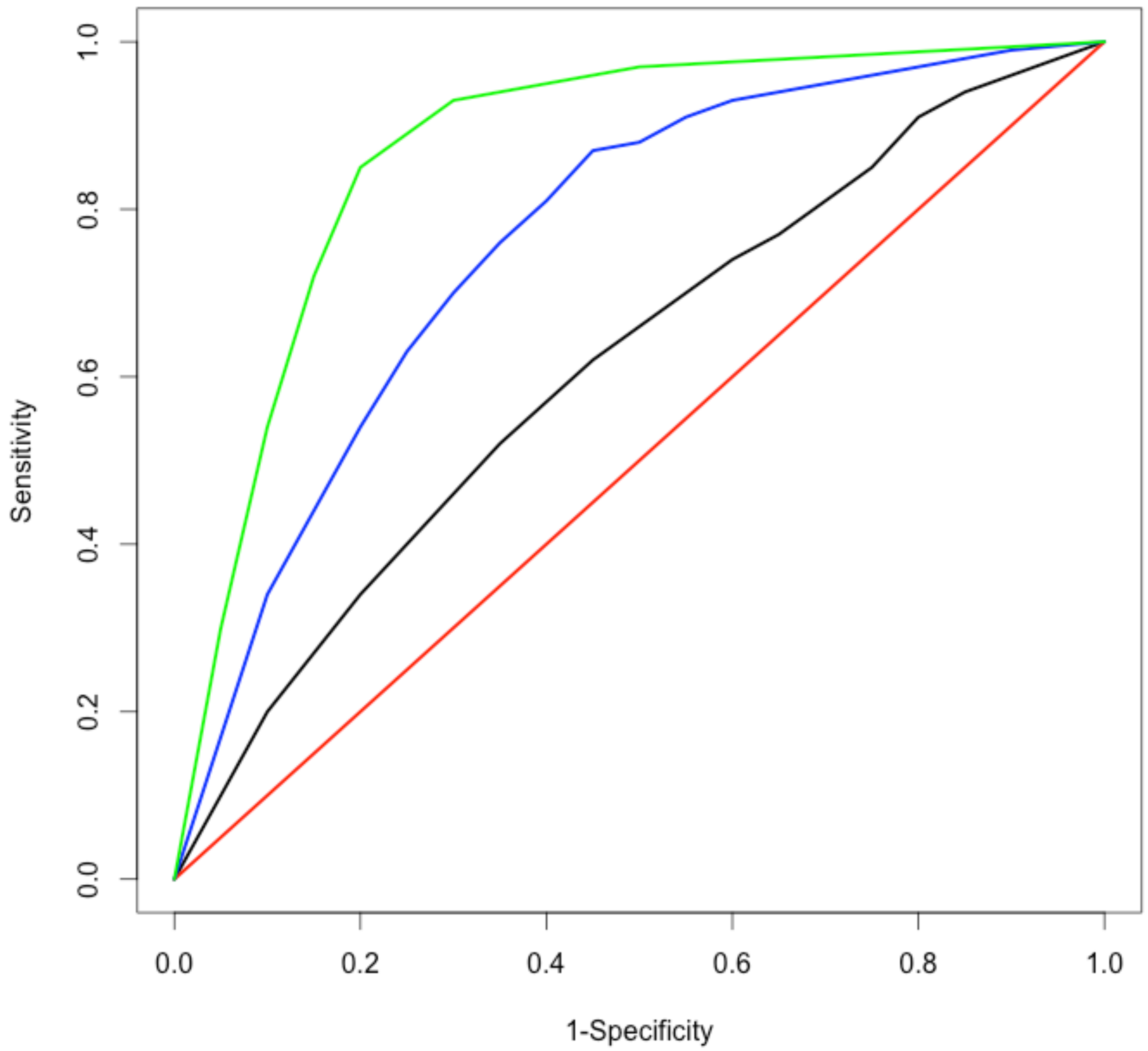
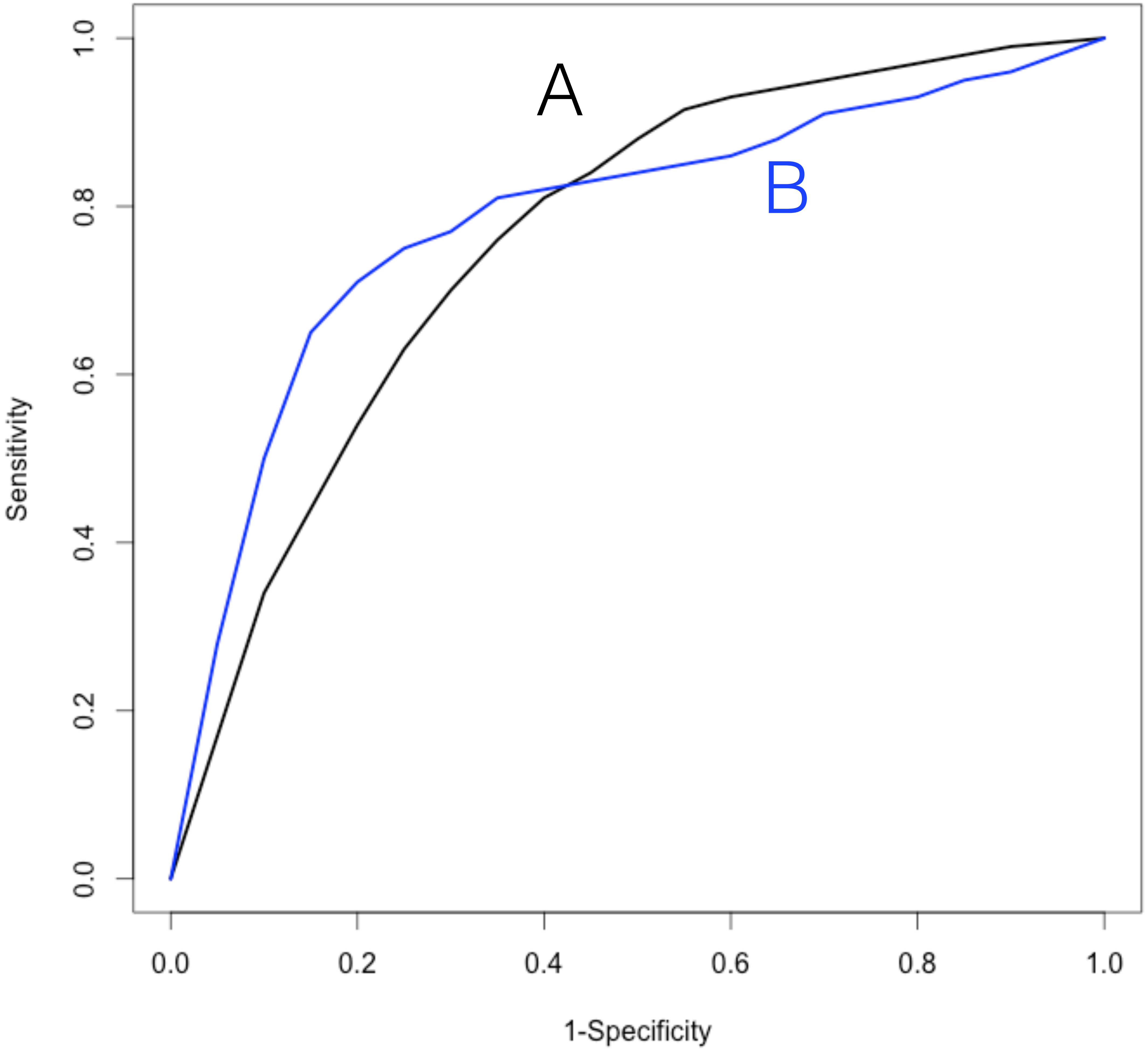
The ROC-curve



$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Which one is better?



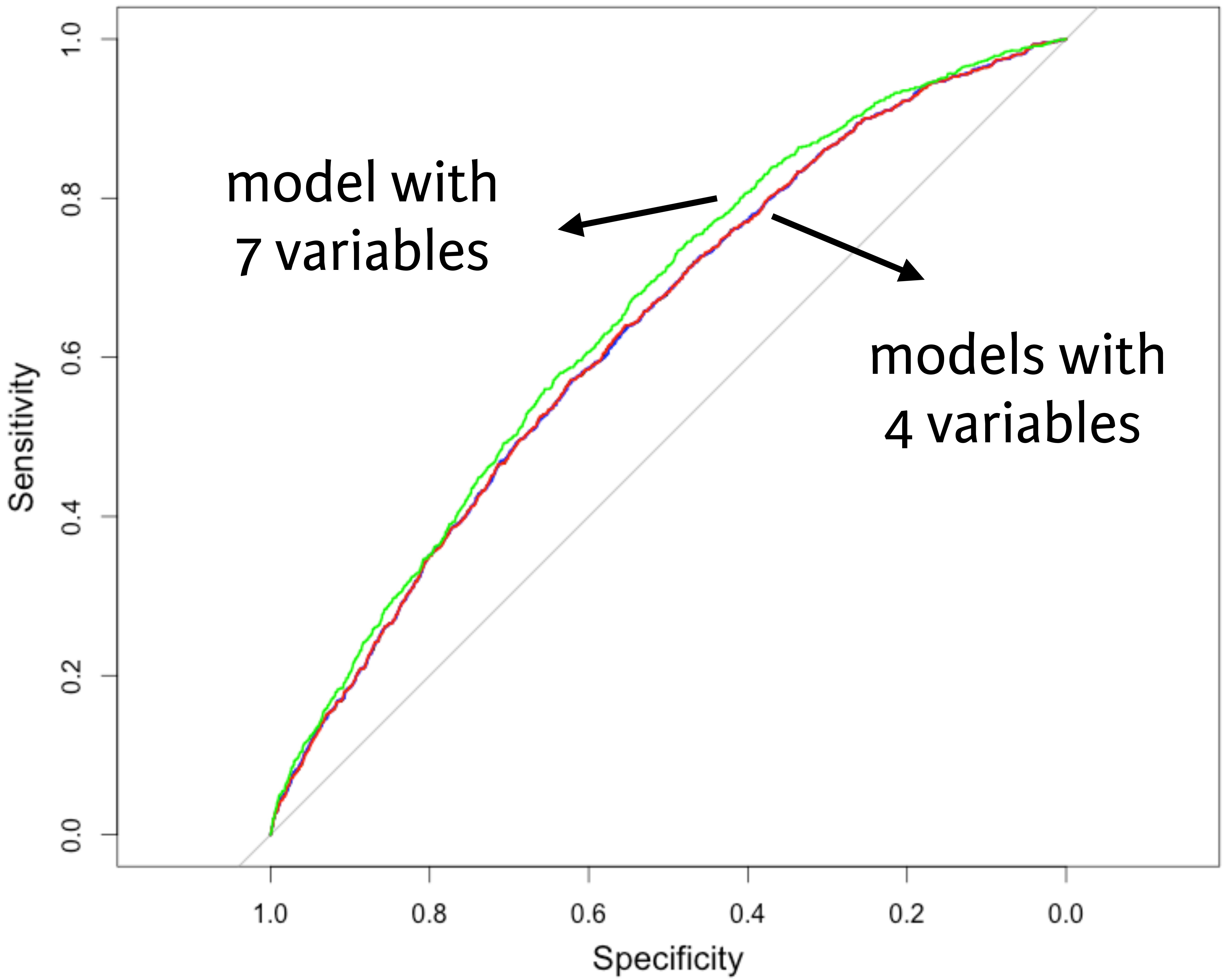
AUC ROC-curve A = 0.75

AUC ROC-curve B = 0.78

Let’s practice!

Input selection based on the AUC

ROC curves for 4 logistic regression models



AUC-based pruning

1) Start with a model including all variables (in our case, 7) and compute AUC

```
> log_model_full <- glm(loan_status ~ loan_amnt + grade + home_ownership +
annual_inc + age + emp_cat + ir_cat, family = "binomial", data = training_set)

> predictions_model_full <- predict(log_model_full, newdata = test_set, type =
“response")

> AUC_model_full <- auc(test_set$loan_status, predictions_model_full)
Area under the curve: 0.6512
```

AUC-based pruning

2) Build 7 new models, where each time one of the variables is removed, and make PD-predictions using the test set

```
log_1_remove_amnt <- glm(loan_status ~ grade + home_ownership + annual_inc + age
+ emp_cat + ir_cat, family = "binomial", data = training_set)

log_1_remove_grade <- glm(loan_status ~ loan_amnt + home_ownership + annual_inc +
age + emp_cat + ir_cat, family = "binomial", data = training_set)

log_1_remove_home <- glm(loan_status ~ loan_amnt + grade + annual_inc + age +
emp_cat + ir_cat, family = "binomial", data = training_set)

…

pred_1_remove_amnt <- predict(log_1_remove_amnt, newdata = test_set, type =
"response")
pred_1_remove_grade <- predict(log_1_remove_grade, newdata = test_set, type =
"response")
pred_1_remove_home <- predict(log_1_remove_home, newdata = test_set, type =
"response")
…
```

AUC-based pruning

3) Keep the model that led to the best AUC (AUC full model: 0.6512)

```
> auc(test_set$loan_status, pred_1_remove_amnt)
Area under the curve: 0.6514

> auc(test_set$loan_status, pred_1_remove_grade)
Area under the curve: 0.6438

> auc(test_set$loan_status, pred_1_remove_home)
Area under the curve: 0.6537

…
```

Remove variable “home_ownership”

4) Repeat until AUC decreases (significantly)

Let's practice!

Course wrap-up

Other methods

- Discriminant analysis
- Random forest
- Neural networks
- Support vector machines

But... very classification-focused

- Timing aspect is neglected
- New popular method: survival analysis
    - PD’s that change over time
    - time-varying covariates can be included

The end!