Authentication

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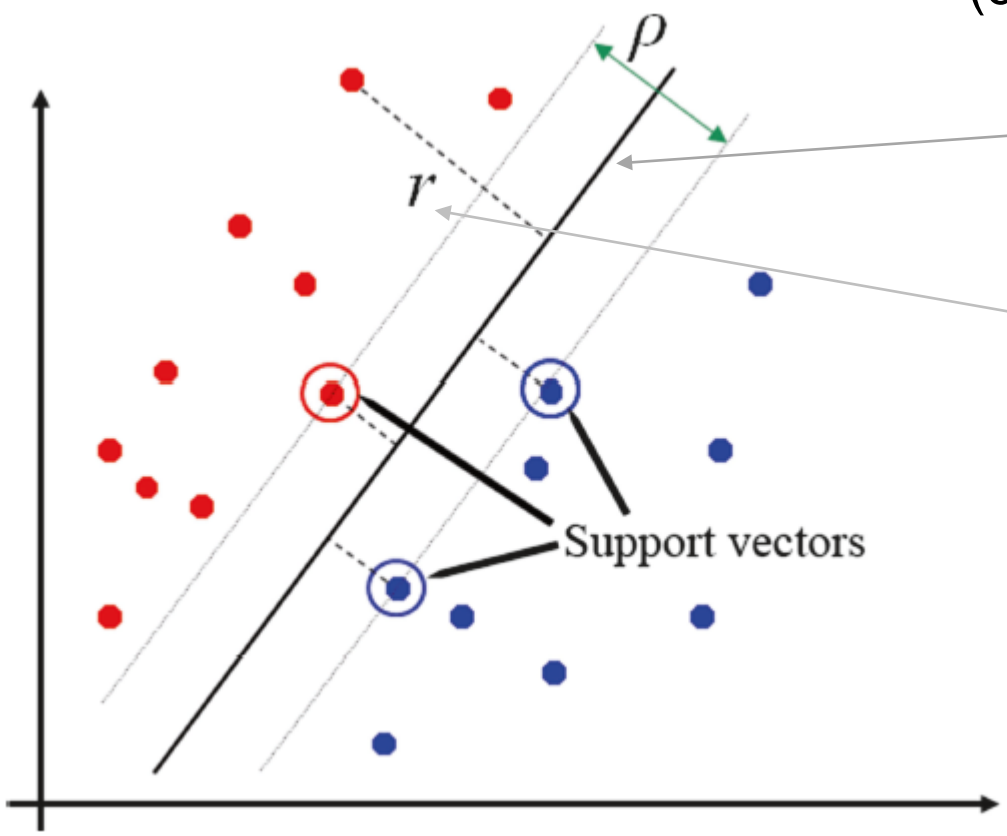
Excursus: Support-Vector-Machine



Support vectors and classification margin $\boldsymbol{\rho}$

separating hyperplane
(classification function) is:

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + b = 0$$

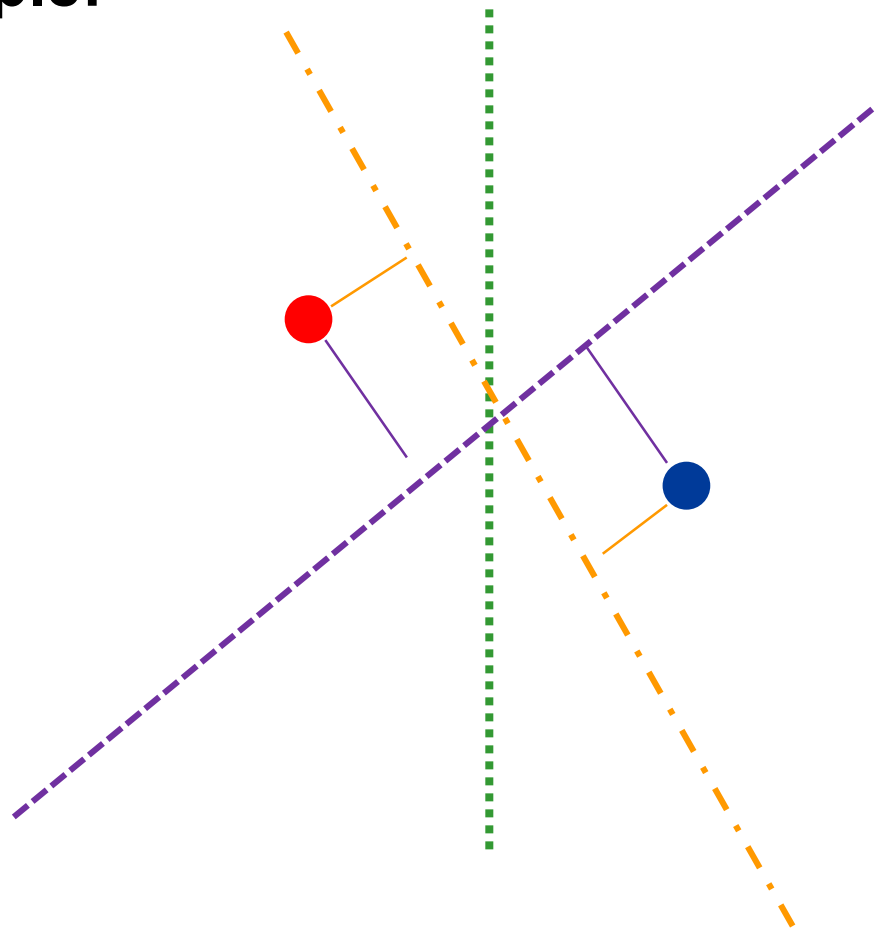
$$r = (\mathbf{w}^{\mathrm{T}}\mathbf{x} + b)/\|\mathbf{w}\|$$

margin is:

$$\boldsymbol{\rho} = \boldsymbol{max}_{\boldsymbol{w,b}} \ (\mathbf{w}^{\mathrm{T}}\mathbf{x} + b)/\|\mathbf{w}\|$$

Excursus: Support-Vector-Machine

Extreme example:



Learned before

Classification Methods:

- naïve Bayes
- support-vector-machine
- decision tree
- 3-nearest-neighbours
- LDA (good for Gaussian)

Feature Extraction and Feature Selection Methods:

- PCA (good for correlated features; bad for noisy data)
- LDA (good for Gaussian)

Lecture 7:

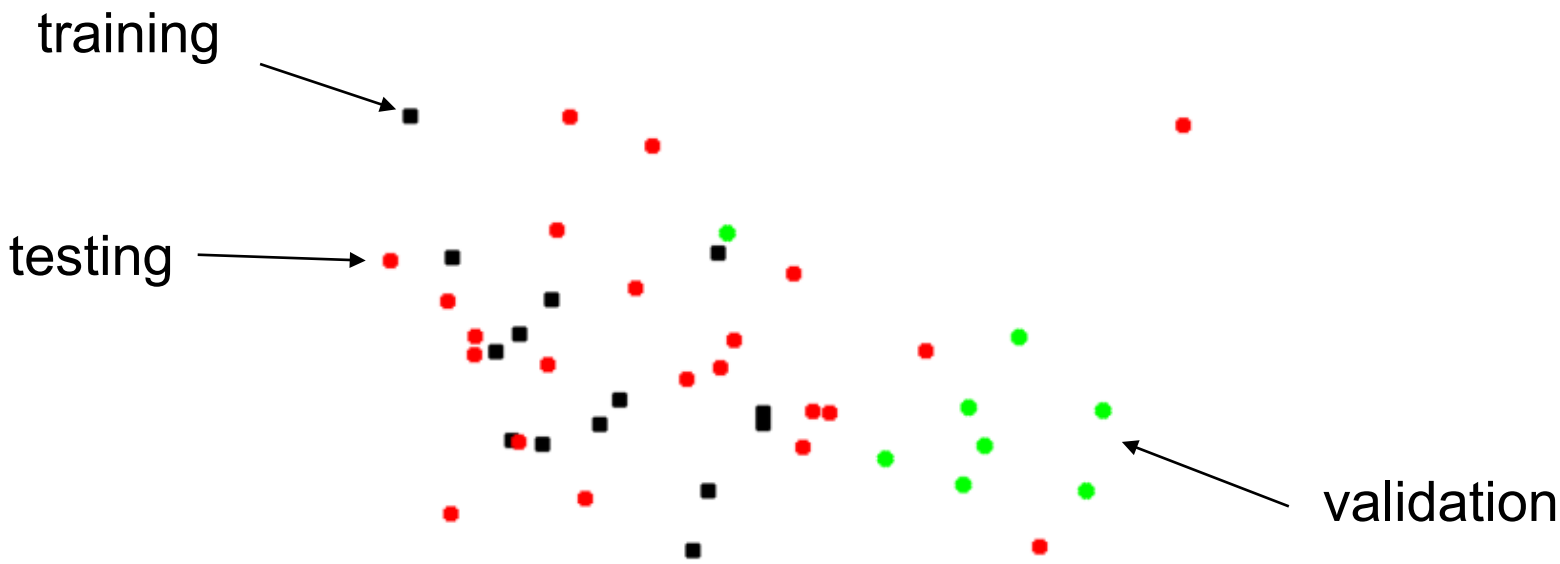
Estimating and Comparing Classifiers

Comparing Classifiers and No Free Lunch Theorem

No Free Lunch Theorem: there is **no one ideal solution** to the classification problem

Take into account: If we compare algorithms on a particular application, the comparison is only **true** for **that application** and **that dataset**

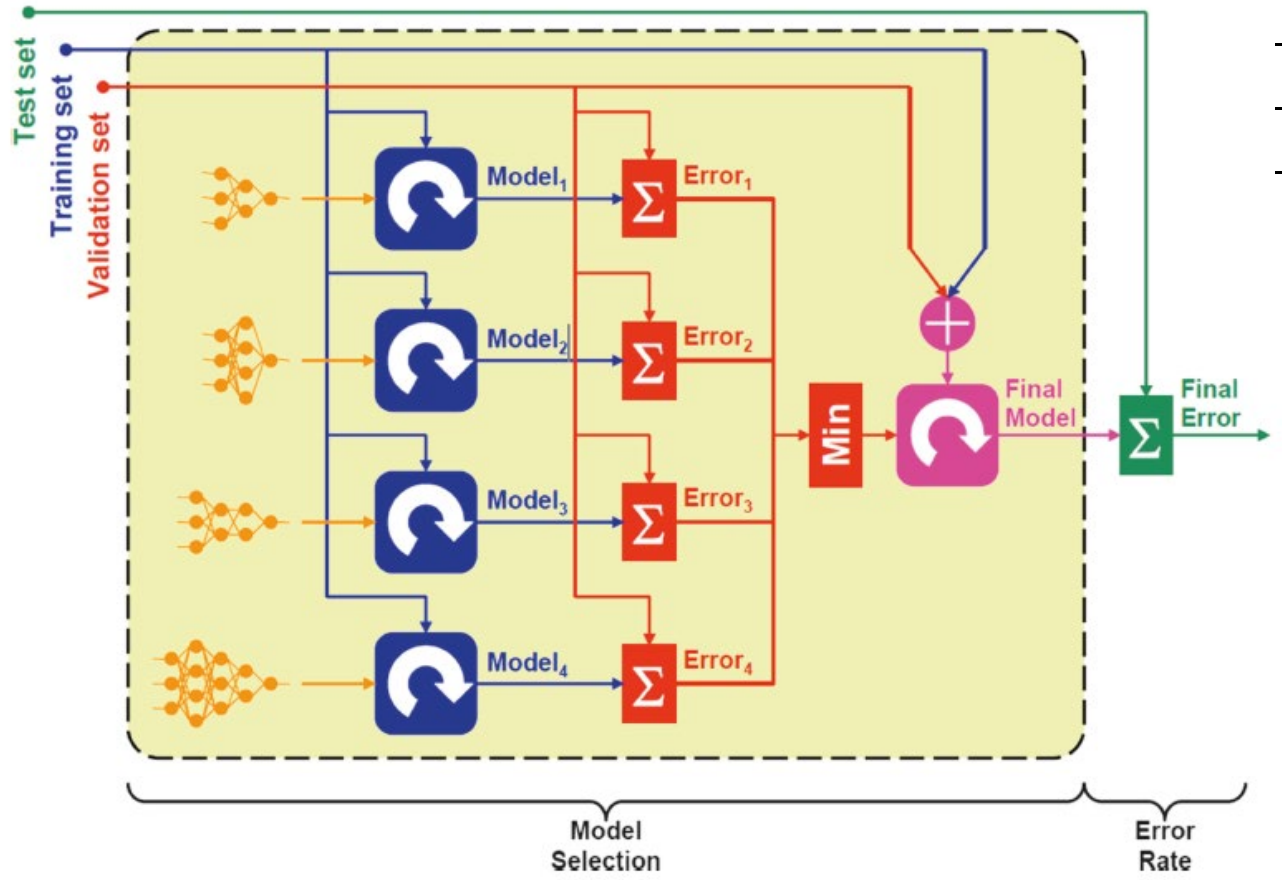
Comparing Classifiers and No Free Lunch Theorem



possible split of sample in subsets

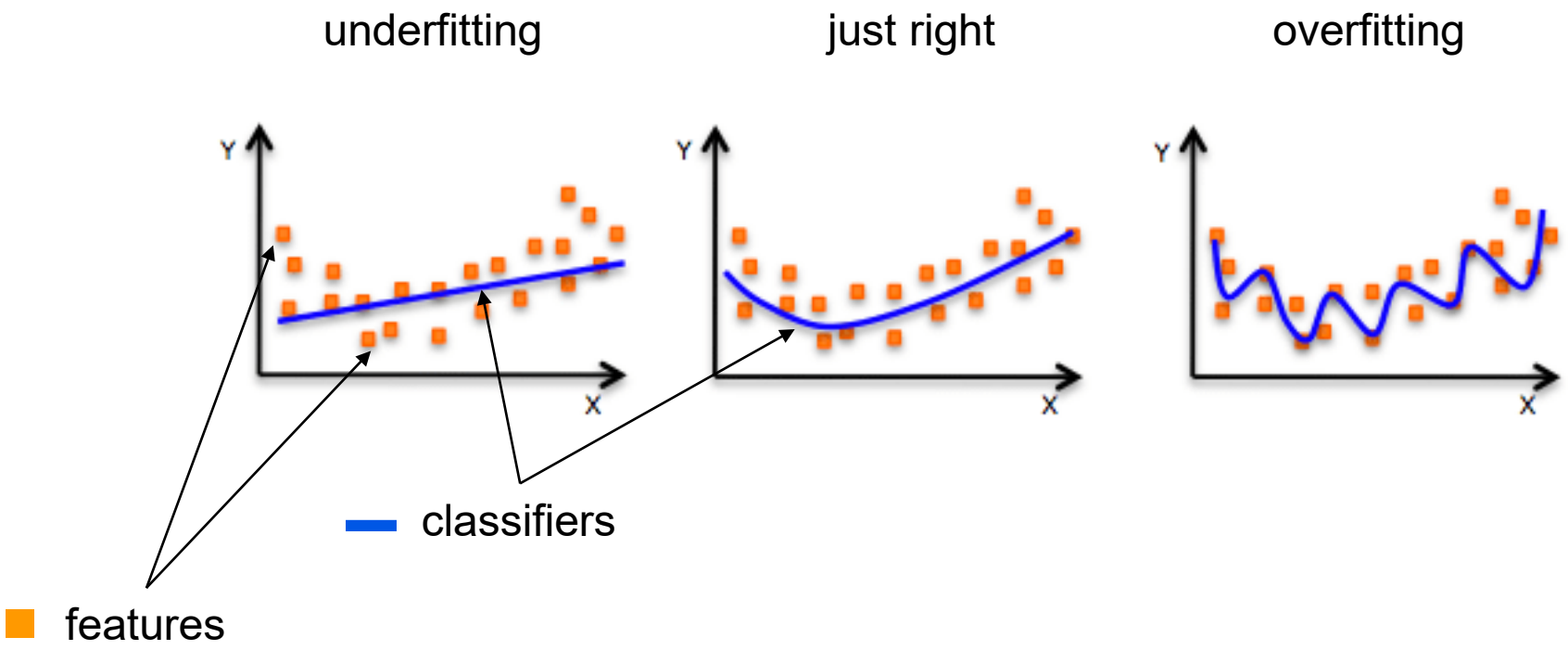
Comparing Classifiers and No Free Lunch Theorem

Model selection and error estimation using data split:



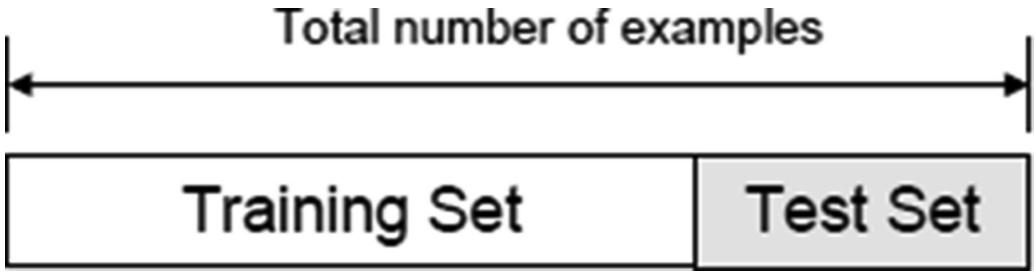
- train
- validation
- test

Cross-Validation and Resampling Methods



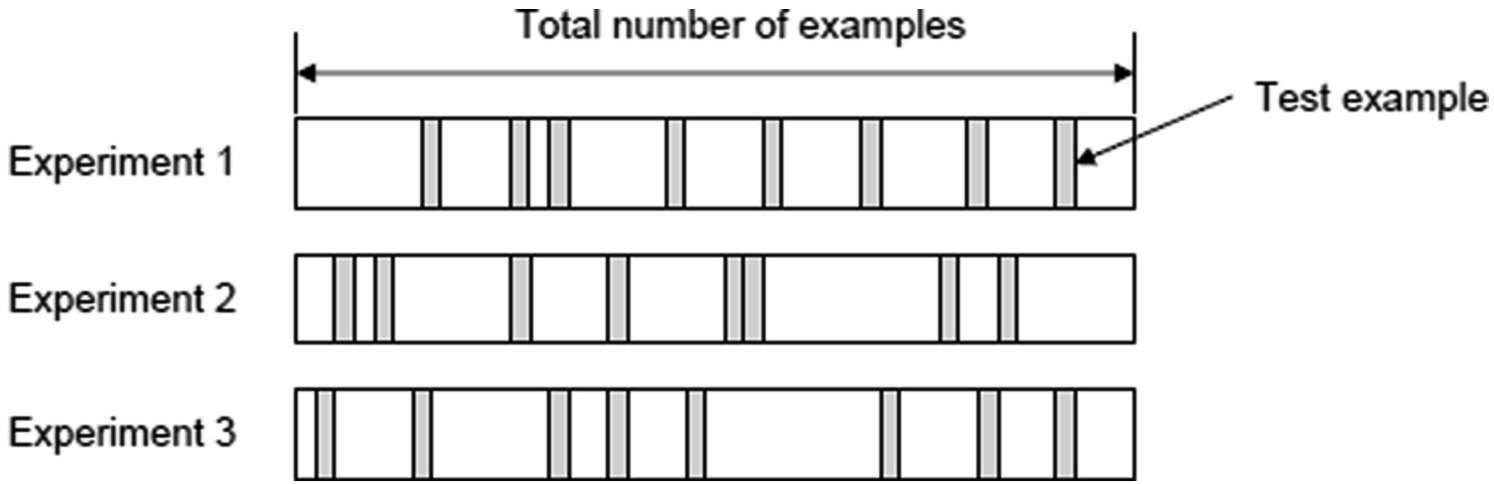
Cross-Validation and Resampling Methods

Holdout method



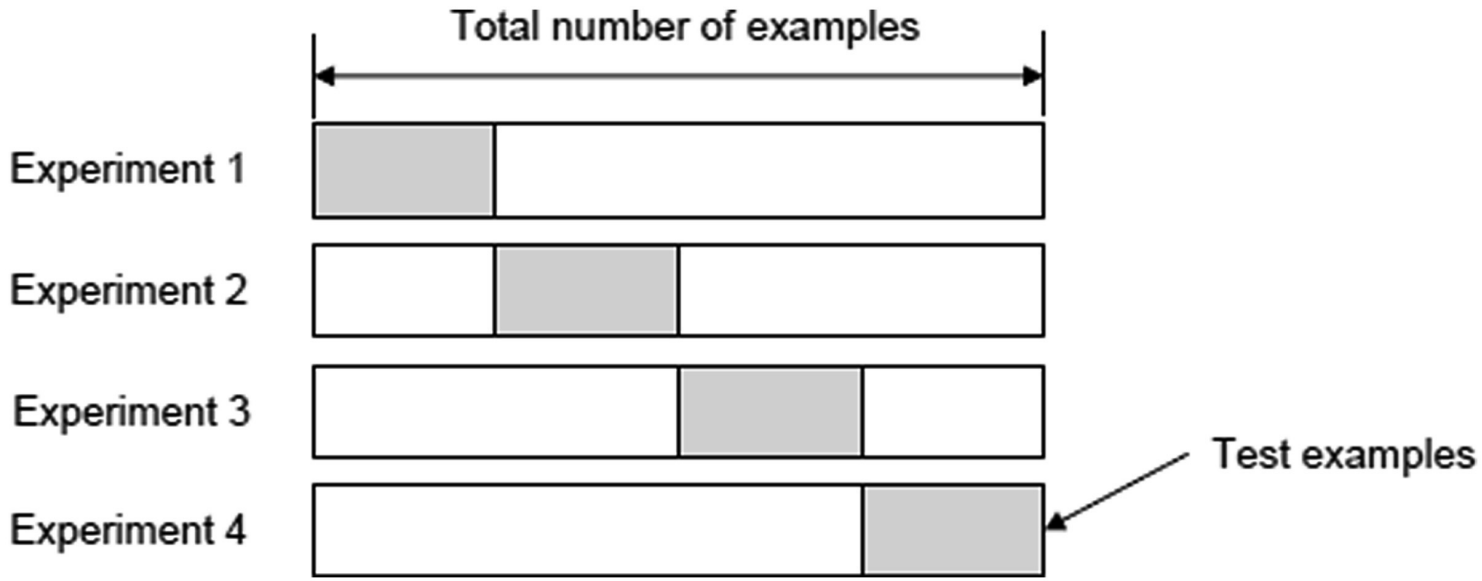
Cross-Validation and Resampling Methods

Random subsampling



Cross-Validation and Resampling Methods

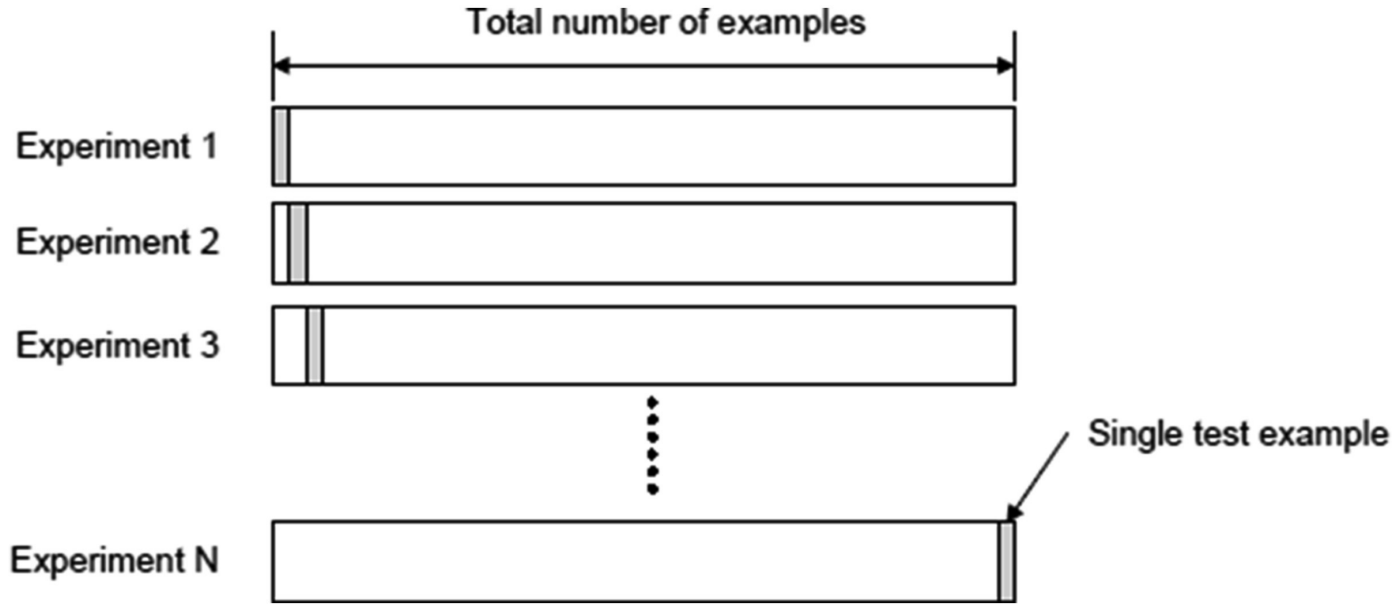
k-fold cross-validation



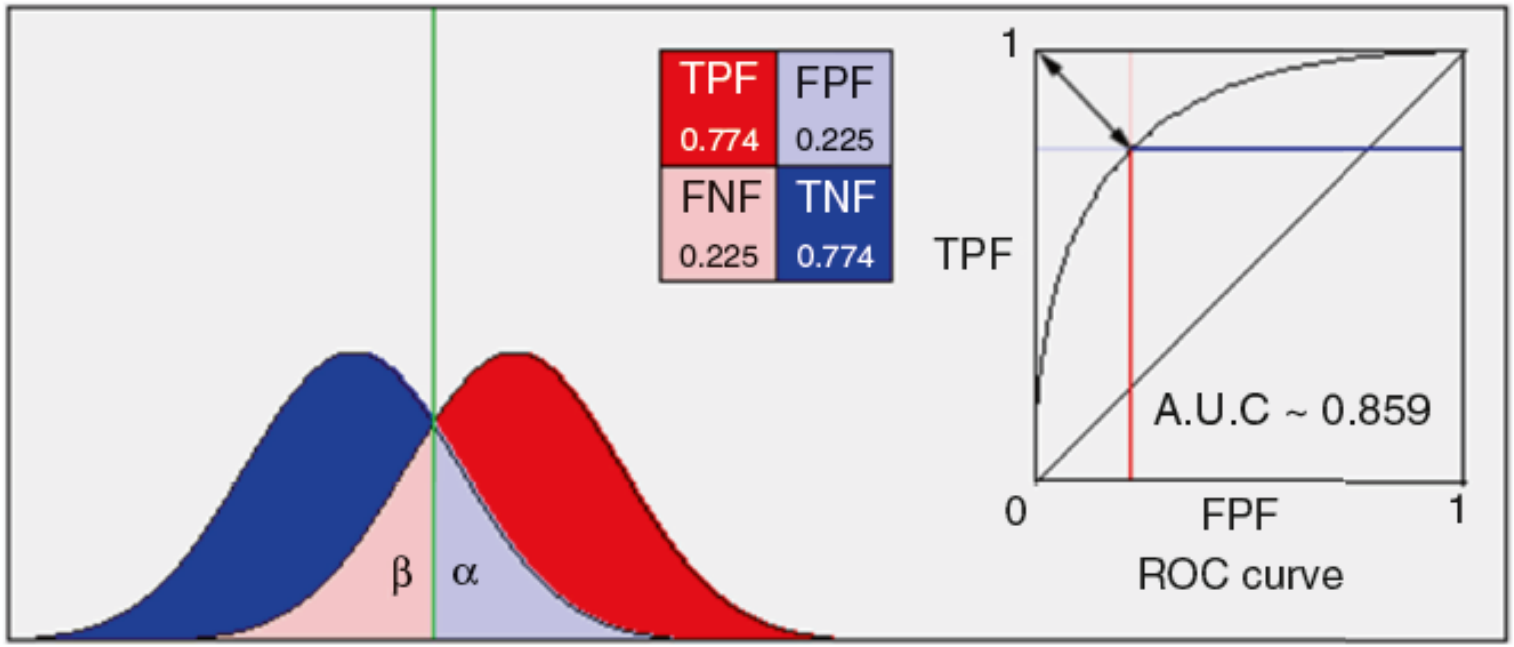
4-fold experiment

Cross-Validation and Resampling Methods

Leave-one-out



Measuring Classifier Performance



negatives **positives**

ω_1 ω_2

Measuring Classifier Performance

Predicted			
Actual	Positive	Negative	Total
Positive	TP	FN	p
Negative	FP	TN	n
Total	p'	n'	N

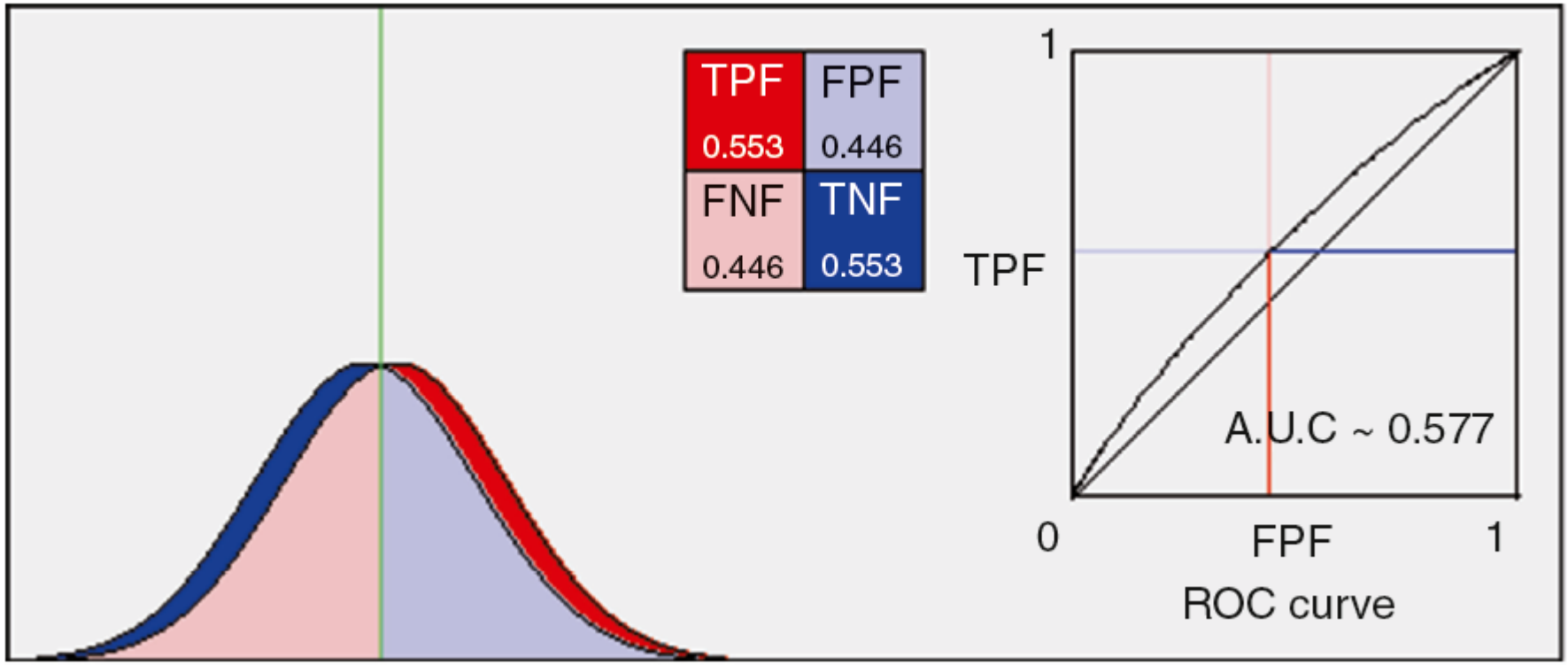
Confusion matrix for two classes

Measuring Classifier Performance

Name	Formula
(total) error	$(FP + FN)/N$ $(=\alpha + \beta)$
Accuracy	$(TP + TN)/N$ $[=1 - \text{(total) error}]$
FPF, false positive fraction (or FP rate)	FP/n (or α)
TPF, true positive fraction (or TP rate)	TP/p [or $(1 - \alpha)$]
Precision	TP/p'
Recall	TP/p (=TP fraction)
Sensitivity	TP/p (=TPF)
Specificity	TN/n (=TNF $= 1 -$ FPF)

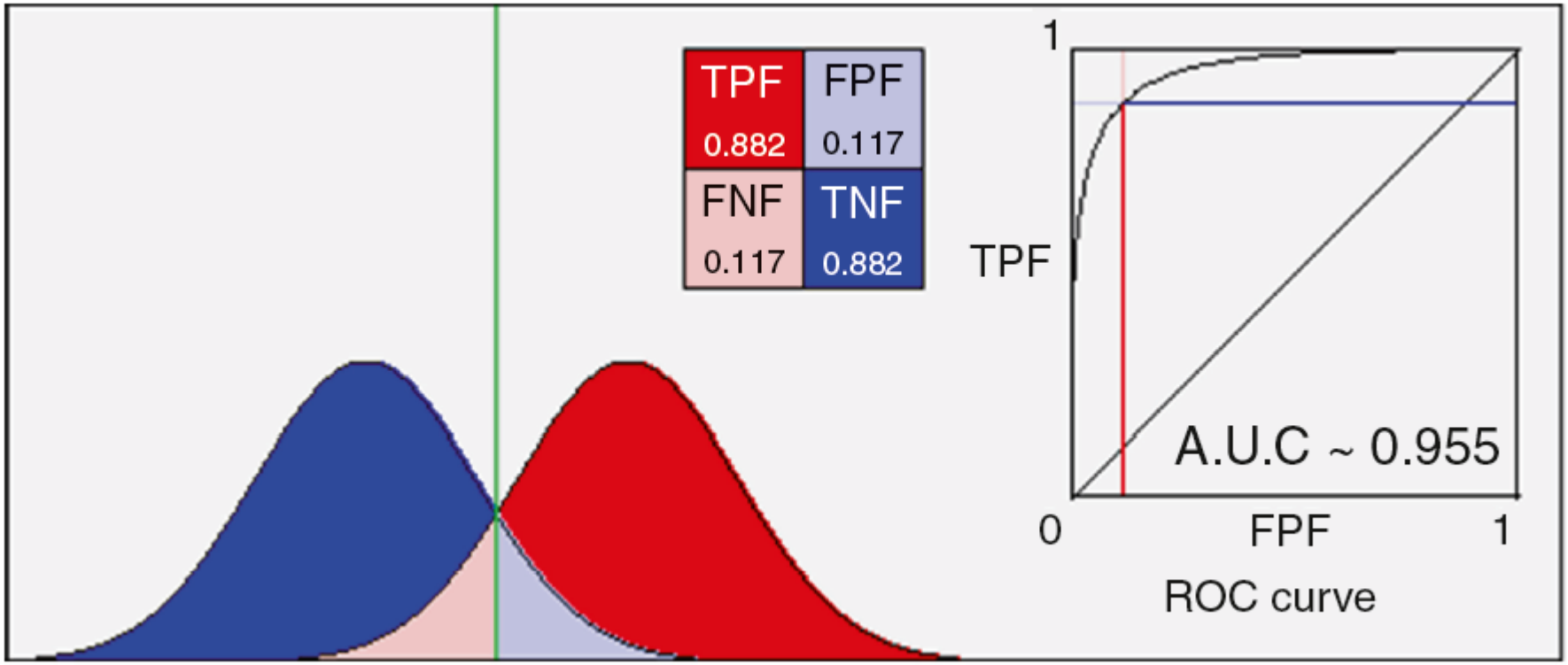
Performance measures used in two-class problems

Measuring Classifier Performance



Distributions with a lot of overlap result in a ROC plot, with an **AUC** close to $\mathbf{0.5}$

Measuring Classifier Performance



Distributions that are well-separated result in a ROC plot, with an **AUC** close to **1**

Comparing Classifiers

McNemar's test

e_{00}: number of examples misclassified by both	e_{01}: number of examples misclassified by 1 but not by 2
e_{10}: number of examples misclassified by 2 but not by 1	e_{11}: number of examples correctly classified by both

classifier 1 vs. classifier 2

same error: $e_{01} = e_{10}$

otherwise: $e_{01} \neq e_{10}$

Chi-square statistic: $\frac{(|e_{01} - e_{10}| - 1)^2}{e_{01} + e_{10}} \sim \chi_1^2 \quad > 3.84$

Comparing Classifiers

Further tests:

- $\mathbf{5 \times 2}$ cv Paired $\boldsymbol{t}$ Test
- $\mathbf{5 \times 2}$ cv Paired $\boldsymbol{F}$ Test

Summary

- Measuring of classifier performance
- Comparing classifiers

Homework: Exercises and Labs

for the next week prepare practical exercises and labs from **Exercises Lec 7** (you will find it in the donwload area)