

MLRF Lecture 05

J. Chazalon, LRDE/EPITA, 2019

Classifier evaluation

Lecture 05 part 04

Data to test generalization

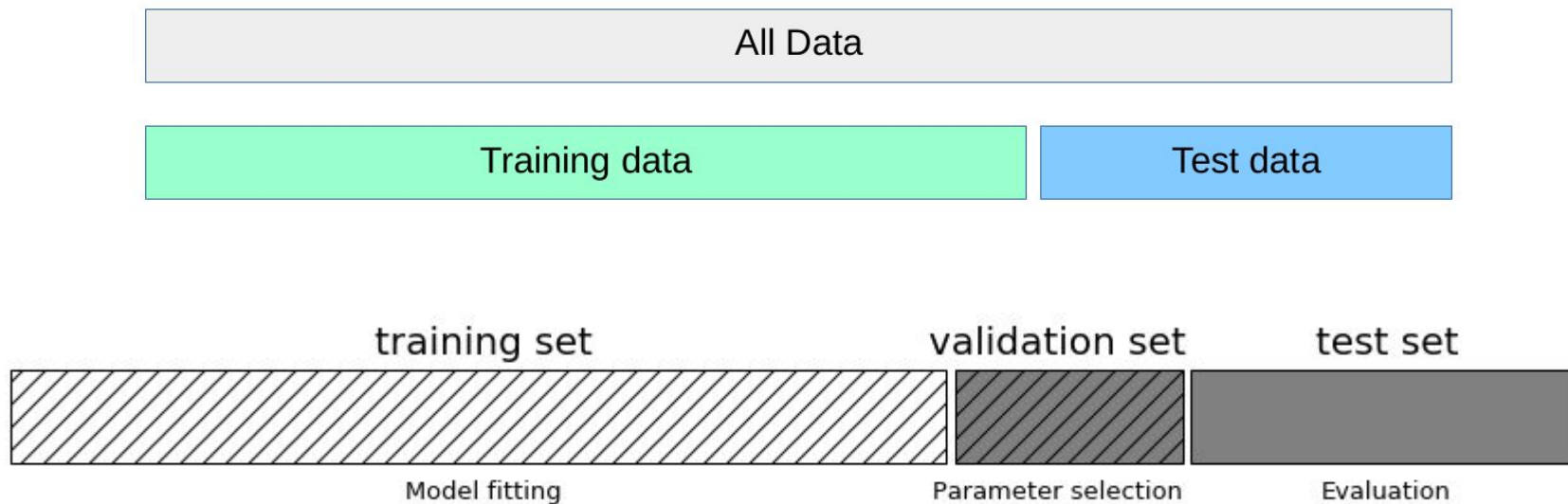
Bootstrap

Draw randomly with replacement samples of n units from the training set.

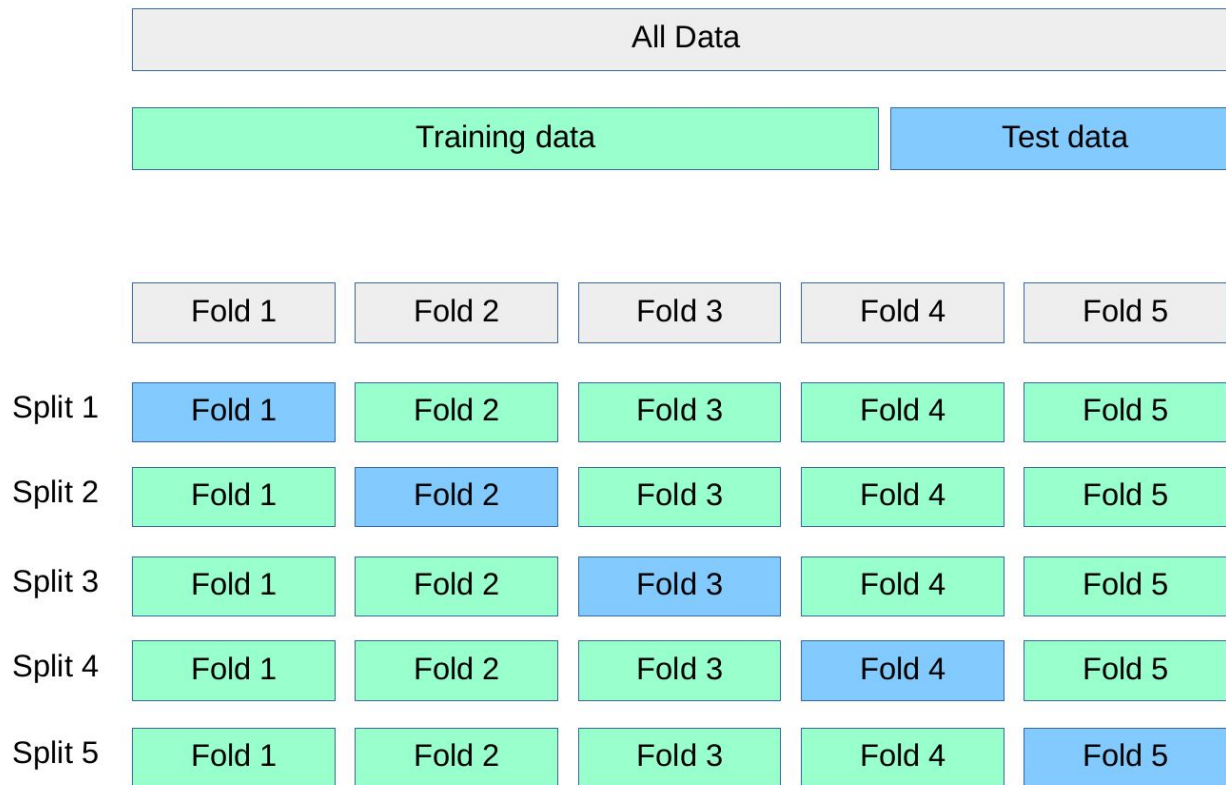
We can estimate the variance of estimators we use in the classification rule.

Holdout

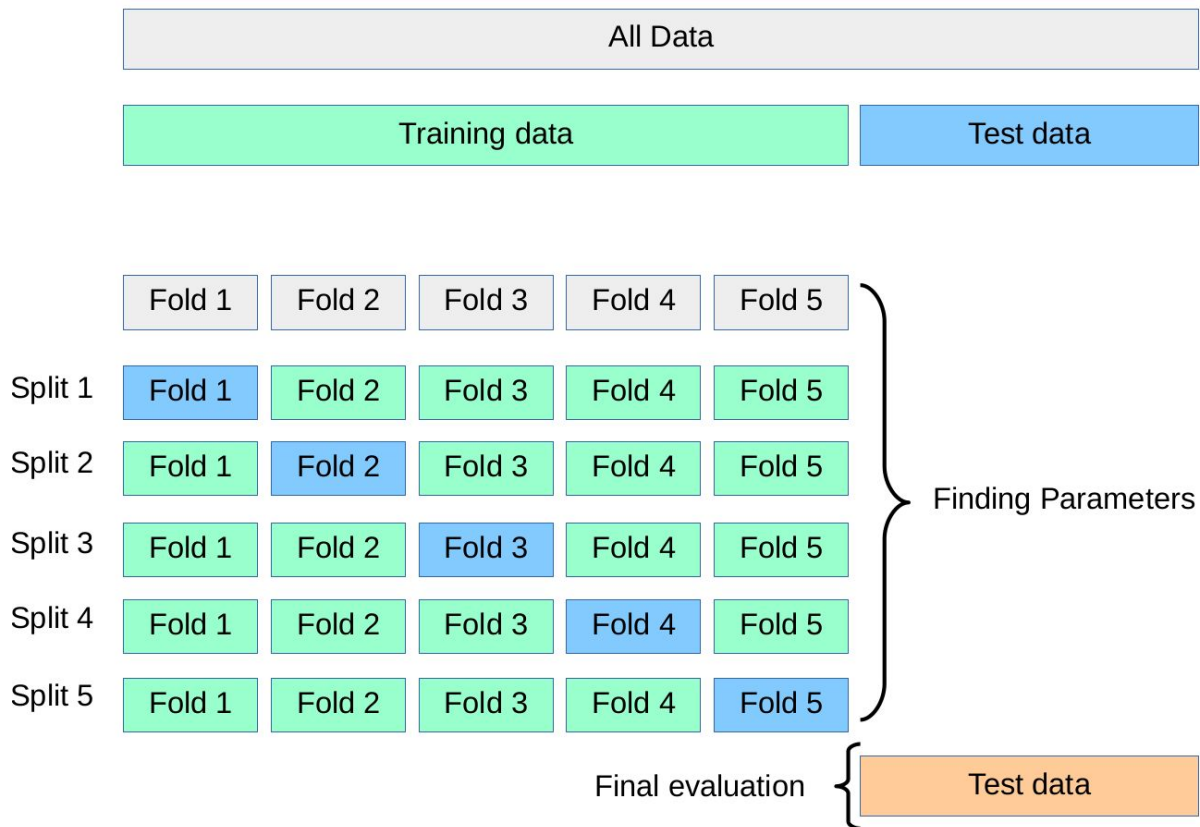
Just keep a part of the dataset for later validation/testing.



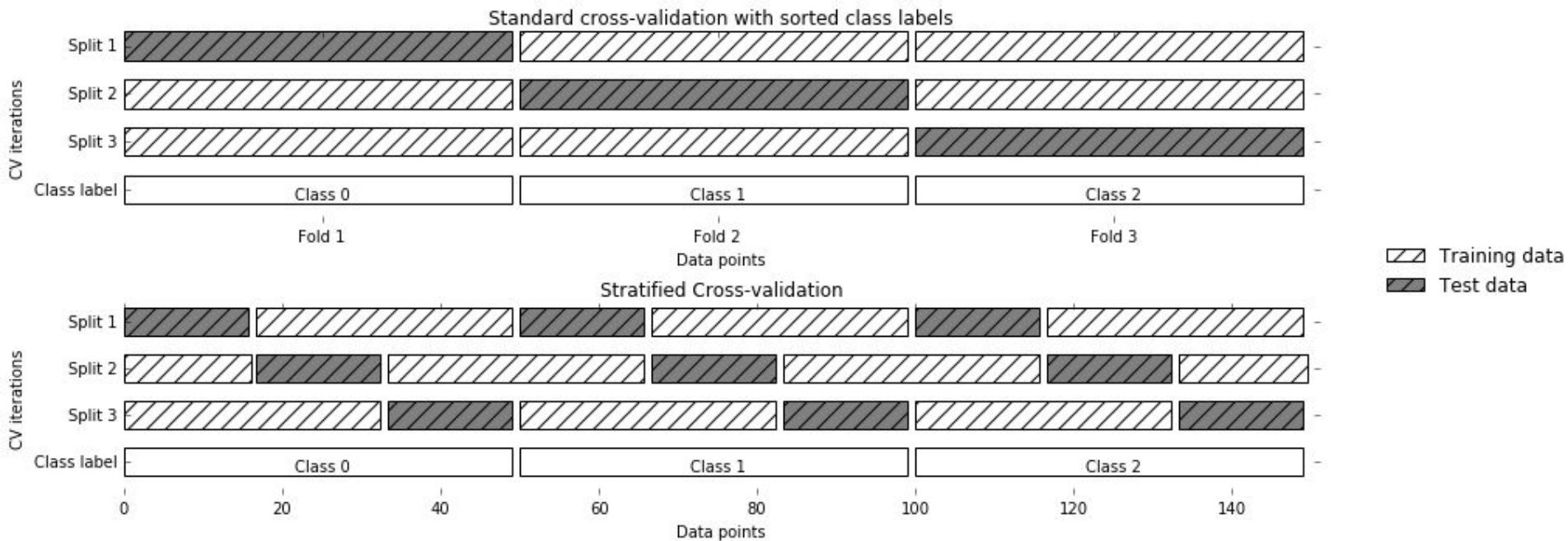
Cross validation



Cross validation with meta parameter tuning



StratifiedKFold (best)



Stratified: Ensure relative class frequencies in each fold reflect relative class frequencies on the whole dataset.

Metrics

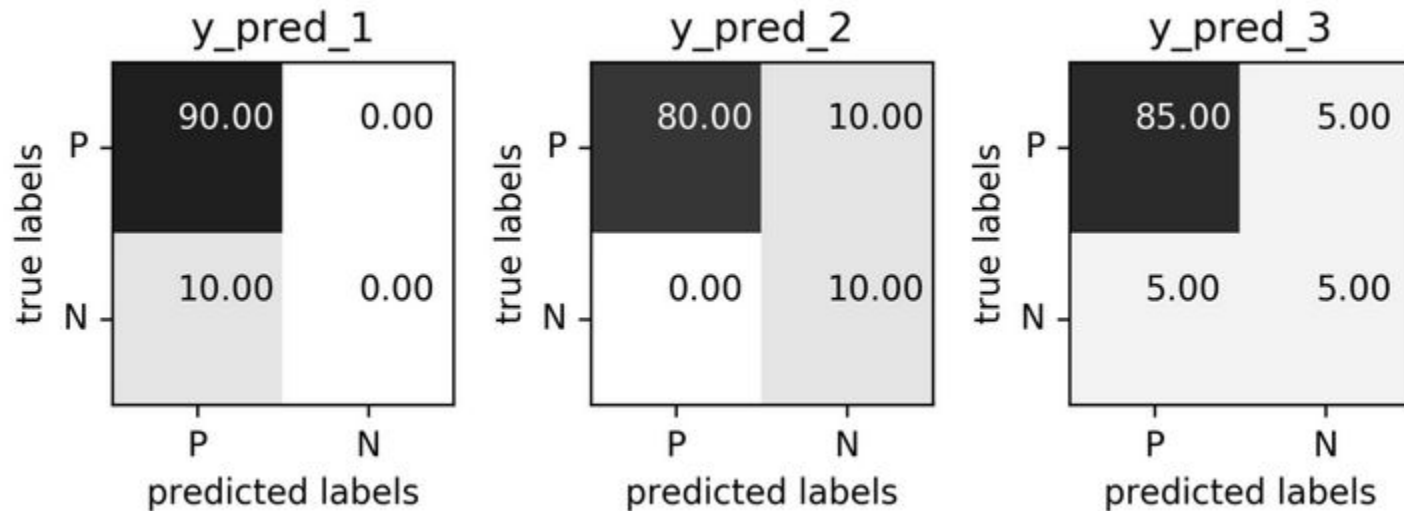
Confusion matrix and Accuracy

negative class	TN	FP
positive class	FN	TP
	predicted negative	predicted positive

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

Problems with Accuracy

All the following classifiers have a 90% accuracy



Do all errors have the same cost?

Precision, recall, F-score

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Positive Predicted Value (PPV)

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

Sensitivity, coverage, true positive rate.

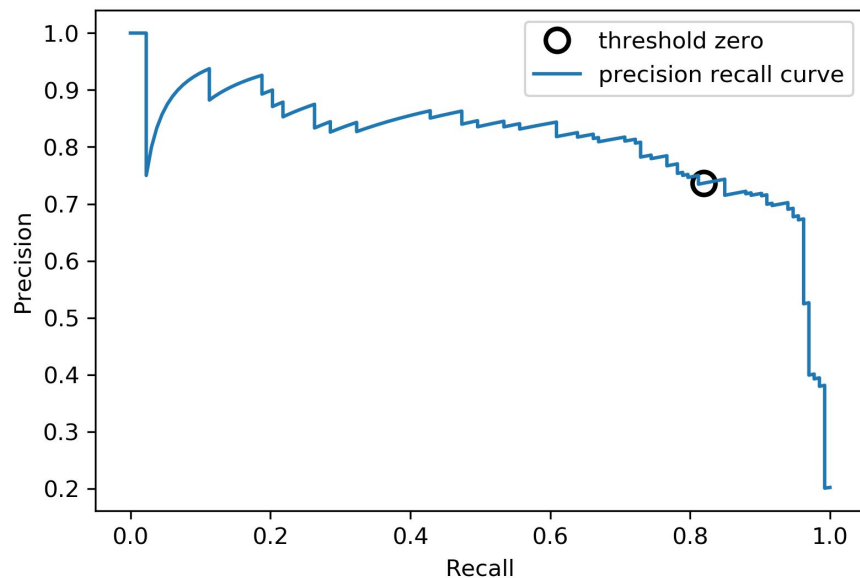
$$F = 2 \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Harmonic mean of precision and recall

Plotting a Precision/Recall for classification data

For binary classification

Instead of $\hat{y} = \operatorname{argmax}_y p(y|x)$, take all possible thresholds for $p(y|x)$.



TPR, FPR, ROC

ROC: “Receiver Operating Characteristic”

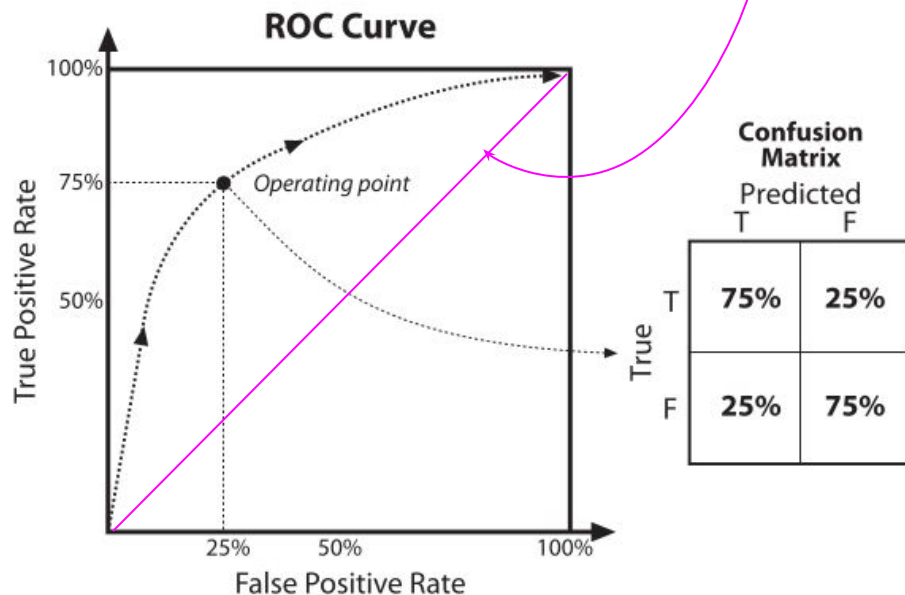
Kind of signal/noise measure under various tunings

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \text{recall}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} = \text{noise}$$

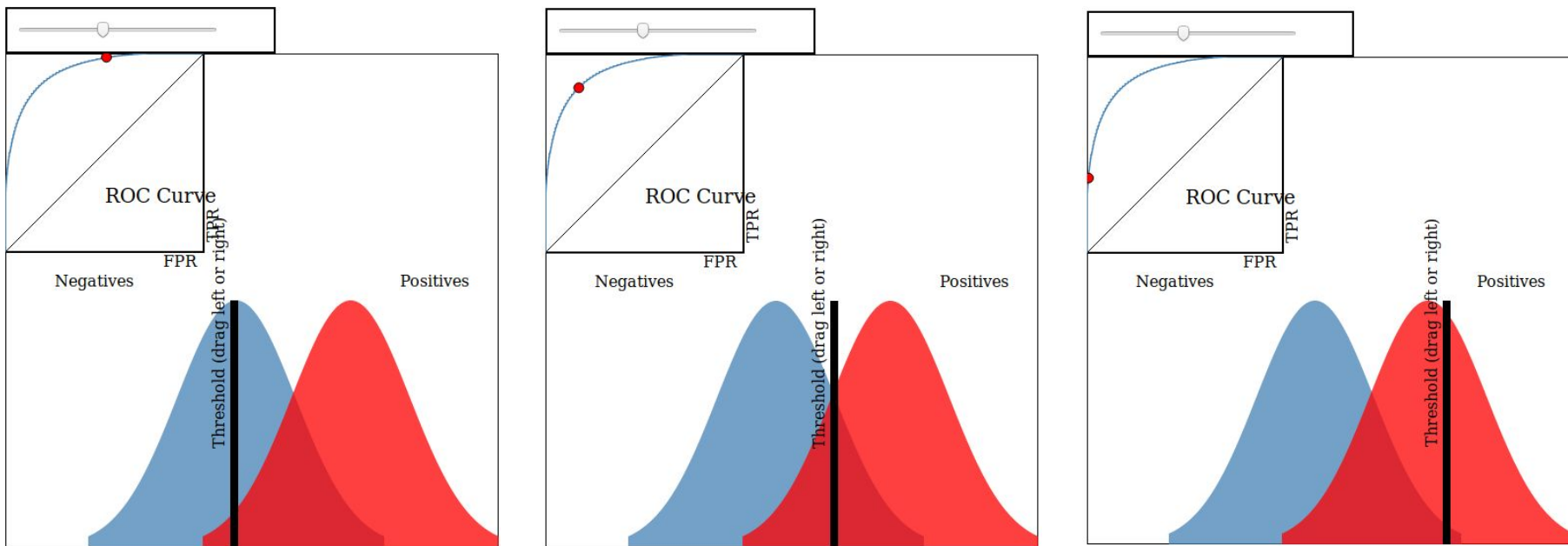
Common measure:

Area under the curve (AUC)



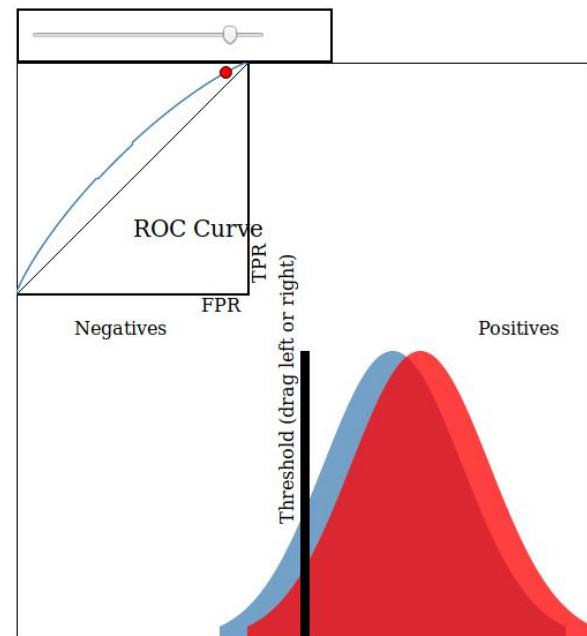
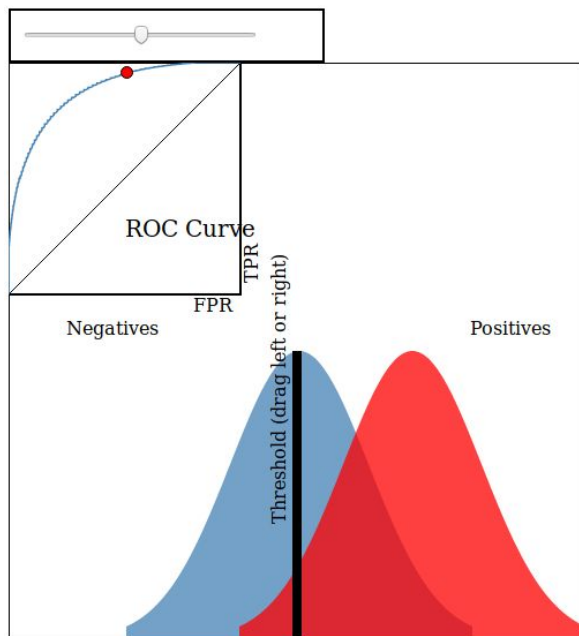
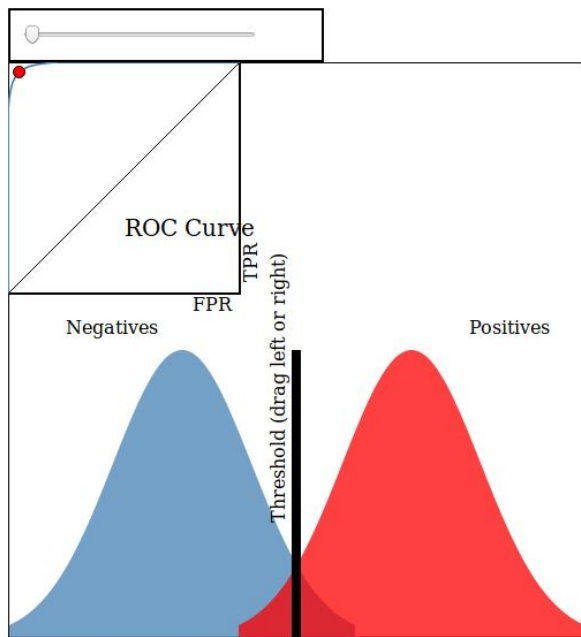
More about ROC curves: adjusting the threshold

<http://www.navan.name/roc/>



More about ROC curves: class overlap

<http://www.navan.name/roc/>



More about ROC curves

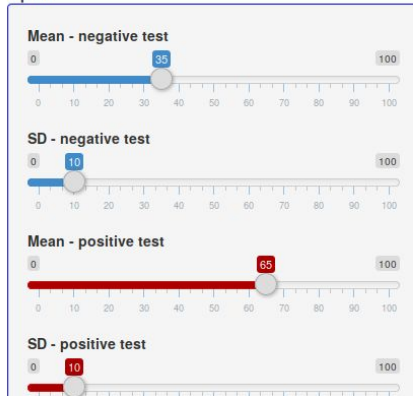
<https://kennis-research.shinyapps.io/ROC-Curves/>

Receiver Operating Characteristic (ROC) Curves

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A receiver operating characteristic (ROC) is a graph that illustrates the performance of a binary classifier as its discrimination threshold (cutoff) is changed. The curve is created by plotting the **true positive rate (TPR)** against the **false positive rate (FPR)** at various cutoff settings. The true-positive rate is known as sensitivity, the false-positive rate is known as the fall-out and is calculated as $(1 - \text{specificity})$. The ROC curve is thus a plot of the true positives (TPR) versus the false positives (FPR). The ROC curve can be generated by plotting the cumulative distribution function (area under the probability distribution from $-\infty$ to $+\infty$) of the correct detection probability in the y-axis versus the cumulative distribution function of the false-alarm probability in x-axis. For information on ROC curves click [here](#) for the *Wikipedia* page.

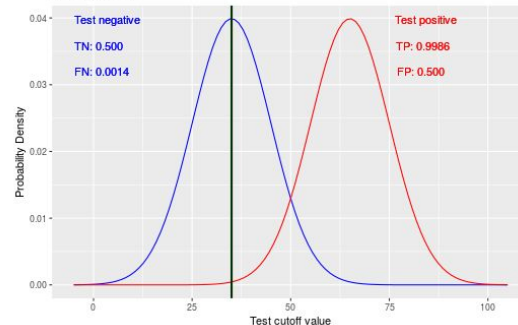
Inputs



Parameters Table

Parameter	Value
True Negatives	0.5
False Negatives	0.0014
True Positives	0.9986
False Positives	0.5
Cutoff	35
Intersection Point	50
Sensitivity	0.9986
Specificity	0.5
Positive Predictive value	0.6664
Negative Predictive value	0.9972
False Positive rate	0.5
False Negative rate	0.0014

Distributions



ROC curve



Missing things

Missing things

Cost of misclassification

Multiclass classification evaluation

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