## **ML INFOSEC**

6: Performance Measures

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# The setting

- A set of samples X
- A decomposition

$$X = X_{+} \dot{\cup} X_{-}, \quad P = |X_{+}|, N = |X_{-}|$$

into sets of samples marked "positive" and "negative", resp.

- A classifier  $C: X \to \{0, 1\}$
- A decomposion of *X* induced by *C*:

$$X = \hat{X}_{+} \dot{\cup} \hat{X}_{-}$$

with

$$\hat{X}_{+} = \{ x \in X \mid C(x) = 1 \}$$

and

$$\hat{X}_{-} = \{ x \in X \mid C(x) = 0 \}$$



# True/False Positive/Negatives

Set of **True Positives**:  $X_+ \cap \hat{X}_+$ 

$$TP = |X_+ \cap \hat{X}_+|$$

Set of **True Negatives**:  $X_- \cap \hat{X}_-$ 

$$TN = |X_- \cap \hat{X}_-|$$

Set of **False Positives**:  $X_- \cap \hat{X}_+$ 

$$FP = |X_- \cap \hat{X}_+|$$

Set of **False Negatives**:  $X_+ \cap \hat{X}_-$ 

$$FN = |X_+ \cap \hat{X}_-|$$

# The confusion matrix

	Positive samples (MW)	Negative samples (BW)
Classified as pos.	TP	FP
Classified as neg.	FN	TN

## Parameters I

#### Base rate

$$BR = \frac{|X_+|}{|X|} = \frac{P}{P+N}$$

#### Accuracy

$$\mathsf{accuracy} = \frac{|X_+ \cap \hat{X}_+| + |X_- \cap \hat{X}_-|}{|X|} = \frac{\mathit{TP} + \mathit{TN}}{\mathit{P} + \mathit{N}}$$

#### Precision

$$precision = \frac{|X_{+} \cap \hat{X}_{+}|}{|\hat{X}_{+}|} = \frac{TP}{TP + FP}$$

## Parameters II

## Sensitivity = Recall = True Positive Rate

$$TPR = \frac{|X_+ \cap \hat{X}_+|}{|X_+|} = \frac{TP}{P} = \frac{TP}{TP + FN}$$

## Specificity = True Negative Rate

$$TNR = \frac{|X_- \cap \hat{X}_-|}{|X_-|} = \frac{TN}{N} = \frac{TN}{TN + FP}$$

#### False Positive Rate

$$FPR = \frac{|X_{-} \cap \hat{X}_{+}|}{|X_{-}|} = \frac{FP}{N} = 1 - TNR$$

## Parameters III

#### Remark 1

We may assume that  $TPR \ge FPR$  because otherwise we can replace C by 1-C.

#### Remark 2

$$\mathsf{precision} = \frac{\mathit{TPR} \times \mathit{BR}}{\mathit{TPR} \times \mathit{BR} + \mathit{FPR} \times (1 - \mathit{BR})}$$

## Example: Let TPR = 0.8 and FPR = 0.1:

BR	Precision	
0.5	0.8889	
0.1	0.4706	
0.01	0.0748	

# Scoring I

In general, classifiers are derived from score functions

$$S: X \rightarrow [0,1].$$

For each **threshold**  $\tau \in [0,1]$  the score function S induces a classifier

$$C_{\tau}(x) = \left\{ egin{array}{ll} 1, & S(x) \geq \tau \ 0, & S(x) < \tau, \end{array} 
ight.$$

on X.  $\hat{X}_+$  and  $\hat{X}_-$  depend on au:

$$\hat{X}_{+}(\tau) = \{x \in X \mid S(x) > \tau\},\$$

$$\hat{X}_{-}(\tau) = \{ x \in X \mid S(x) \le \tau \},$$

so do all parameters introduced above.

# Scoring II

The functions

$$[0,1] 
ightarrow au \mapsto TPR( au) \in [0,1]$$

and

$$[0,1] 
ightarrow ag{FPR}( au) \in [0,1]$$

are decreasing with

$$TPR(1) = 0, FPR(1) = 0$$

The curve

$$[0,1]\ni\tau\mapsto(\mathit{FPR}(\tau),\mathit{TPR}(\tau))\in[0,1]\times[0,1]$$

is called **Receiver Operating Characteristic** (ROC) curve. The area under [this] curve (AUC) is called ROC-AUC and is another performace measure (the closer to 1 the better).



# Receiver Operating Characteristic (ROC) - Area under curve (AUC)

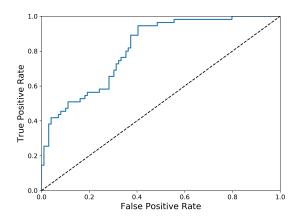


Figure: ROC curve: Gaussian Naive Bayes, Pima diabetes dataset