Classifier evaluation

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Confusion matrix

Confusion matrix $M = \{m_{ij}\}_{i,j=1}^{C}$ shows the number of ω_i class objects predicted as belonging to class ω_j.

$$
\begin{array}{c}
 \\
\text{True classes}
\end{array}
\begin{array}{c}
 \\
\begin{array}{c} 1 \\ 2 \\ \vdots \\ C \end{array}
\end{array}
\overset{\displaystyle \text{Forecasted classes}}{\overset{\displaystyle 1 \quad 2 \quad \cdots \quad C}{
\begin{bmatrix}
n_{11} & n_{12} & & \\
n_{21} & n_{22} & & \\
 & & \ddots & \\
 & & & n_{CC}
\end{bmatrix}}}
$$

Diagonal elements correspond to correct classifications and off-diagonal elements - to incorrect classifications.
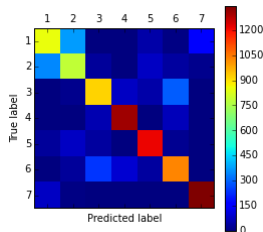
Example of confusion matrix visualization

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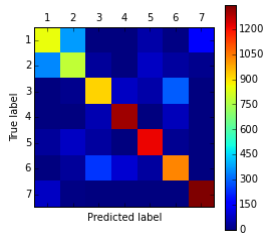
Example of confusion matrix visualization

Example of confusion matrix visualization

- We see here that errors here are concentrated at distinguishing between classes 1 and 2.
- We can
  - unite classes 1 and 2 into new class «1+2»
  - then solve 6-class classification problem
  - separate classes 1 and 2 for all objects assigned to class «1+2» with a separate classifier.

2 class case

Confusion matrix:

Prediction

		+	-
	+	TP (true positives)	FN (false negatives)
True class	-	FP (false positives)	TN (true negatives)

P and N - number of observations of positive and negative class.

$$P = TP + FN, \quad N = TN + FP$$

2 class case

Confusion matrix:

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True class	+	TP (true positives)	FN (false negatives)
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P and N - number of observations of positive and negative class.

$$P = TP + FN, \quad N = TN + FP$$

Accuracy:	$\frac{TP+TN}{P+N}$
Error rate:	1-accuracy$=\frac{FP+FN}{P+N}$

2 class case

Confusion matrix:

Prediction

True class		+	-
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$$P = TP + FN, \quad N = TN + FP$$

Accuracy:	$\frac{TP+TN}{P+N}$
Error rate:	1-accuracy=$\frac{FP+FN}{P+N}$

Not informative for skewed classes and one class of interest!

"Positive class" quality metrics

FPR (error rate on negatives):	$\frac{FP}{N}$
TPR (correct rate on positives):	$\frac{TP}{P}$
Precision:	$\frac{TP}{TP+FP}$
Recall:	$\frac{TP}{P}$
F-measure:	$\dfrac{2}{\frac{1}{Precision}+\frac{1}{Recall}}$
Weighted F-measure:	$\dfrac{1}{\frac{\beta^2}{1+\beta^2}\frac{1}{Precision}+\frac{1}{1+\beta^2}\frac{1}{Recall}}$

Class label versus class probability evaluation[1]

- **Discriminability quality measures** evaluate class label prediction.
  - examples: error rate, precision, recall, etc..

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[1]Give example when class labels are predicted optimally, but class probabilities - not.

Class label versus class probability evaluation[1]

- **Discriminability quality measures** evaluate class label prediction.
  - examples: error rate, precision, recall, etc..
- **Reliability quality measures** evaluate class probability prediction.
  - Example: probability likelihood:

$$\prod_{i=1}^{N} \widehat{p}(y_i|x_i)$$

  - Brier score:

$$\frac{1}{N} \sum_{n=1}^{N} \sum_{c=1}^{C} \left(\mathbb{I}[y_n = c] - \widehat{p}(y = c|x_n) \right)^2$$

[1]Give example when class labels are predicted optimally, but class probabilities - not.

Table of Contents

Discriminant decision rules

- Decision rule based on discriminant functions:
  - predict $y = +1 \iff g_{+1}(x) - g_{-1}(x) > \mu$
  - predict $y = +1 \iff g_{+1}(x)/g_{-1}(x) > \mu$ (for $g_{+1}(x) > 0$, $g_{-1}(x) > 0$)
- Decision rule based on probabilities:
 - predict $y = +1 \iff P(y = +1|x) > \mu$

ROC curve[2]

- ROC curve - is a function TPR(FPR).
- It shows how the probability of correct classification on positive classes ("recognition rate") changes with probability of incorrect classification on negative classes ("false alarm").
- It is build as a set of points $TPR(\mu)$, $FPR(\mu)$.
- If $\mu \downarrow$, the algorithm predicts ω_1 more often and
  - TPR=$1 - \varepsilon_1 \uparrow$
  - FPR=$\varepsilon_2 \uparrow$
- Characterizes classification accuracy for different μ.
  - more concave ROC curves are better

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[2]Prove that diagonal ROC corresponds to random assignment of ω_1 and ω_2 with probabilities p and $1 - p$.

Comparison of classifiers using ROC curves
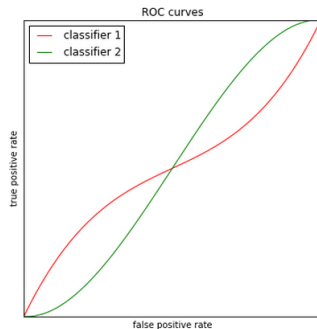
Comparison of classifiers using ROC curves
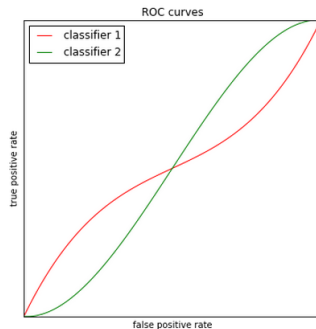
How to compare different classifiers?

Area under the curve

- AUC - area under the ROC curve:
  - global quality characteristic for different μ
  - AUC$\in [0, 1]$
    - AUC=0.5 - equivalent to random guessing
    - AUC=1 - no errors classification.
  - AUC property: it is equal to probability that for 2 random objects $x_1 \in \omega_1$ and $x_2 \in \omega_2$ it will hold that: $\widehat{p}(\omega_1|x_1) > \widehat{p}(\omega_2|x)$