Model Evaluation

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Introduction

Protocol

Introduction

Protocol



- Protocol
- Performance metrics

How well is learning model doing?

- How the model generalizes on unseen data
- High generalization accuracy or low generalization error
- Error on the training data is not a good indicator of performance on future data
- New data (unseen data) will probably not be exactly the same as the training data!
- Overfitting: the model fits the training data too precisely usually leads to poor results on new data
- Underfitting: the model does not fit the training data well enough usually leads to poor results on training and test data



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Possible evaluation measures

- Classification Accuracy
- Total cost/benefit different errors involve different costs
- Lift and ROC curves
- Error in numeric predictions
- How reliable are the predicted results ?

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- Natural performance measure for classification problems: error rate
 - Success: example's class is predicted correctly
 - Error: example's class is predicted incorrectly
 - Error rate: proportion of errors made over the whole set of examples
- Training set error rate: is way too optimistic!

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Given dataset: trainset, testset

- Using **trainset** to build model **M**
- Reporting the result on **testset** using resulting model **M**



Protocol: cross-validation

■ *k*-fold (dataset, #examples > 300)



• it = k

train train train train train train train train train



Protocol: cross-validation

Given dataset

Protocol: hold-out

• Randomly split **dataset** into training set (2/3 for **trainset**) and test sets (1/3 for **testset**)

Protocol leave-1-out

• *k*-fold: **k** = #examples

Protocol bootstrap .632

- Bootstrap **B**: sampling with replacement from **dataset**
- Out-of-bag **OOB**: examples in **dataset** are left out of the bootstrap **B**
- Err(M, dataset) = 0,382 Err(M, OOB) + 0,632 Err(M, B)

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Confusion matrix (C) for k classes

prediction=>	1	•••	k
1			
•••			
k			

- C[i, j]: #examples in class i are predicted in class j
 C[i, i]: #examples in class i are correctly predicted
 Accuracy for class i: C[i,i] / C[i,]
- \Box Global accuracy: $\sum C[i,i] / C$

Protocol

<u>Performance metrics</u>

Confusion matrix (C) for 2 classes $(+1/-1)^{-1}$

Prediction =>	+1	-1
+1	TP	FN
-1	FP	TN

$$prec = \frac{tp}{tp + fp}$$
$$rec = \frac{tp}{tp + fn} = \frac{tp}{pos}$$

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 Confusion matrix (C) for 2 classes (+1/-1)

Prediction =>	+1	-1
+1	ТР	FN
-1	FP	TN

$$acc = \frac{tp + tn}{tp + fn + tn + fp} = \frac{tp + tn}{pos + neg}$$
$$F1 = \frac{2 \times prec \times rec}{prec + rec}$$
$$bep = \frac{prec + rec}{2}$$



Classification of imbalanced datasets

Imbalanced dataset

- Proportion of positive class < 10% (minority class)
- Proportion of negative class > 90% (majority class)
- Classification of imbalanced datasets
 - Model misclassifies minority class
 - Performance metrics: F1, ROC (Receiver Operating Characteristic)



ROC

Receiver Operating Characteristic

- How much model is capable of distinguishing between classes
- ROC curve (2D plot): fpr (false positive rate) on x-axis, tpr (true positive rate) on y-axis
- O(0, 1): ideal point idéal (perfect classification)
- Diagonal (tpr = fpr): random guess
- Performance: Area under the ROC curve (AUC)

$$tpr = \frac{tp}{tp + fn} = \frac{tp}{pos}$$

$$fpr = \frac{fp}{fp + tn} = \frac{fp}{neg} \qquad 16$$

- Protocole de test
- Mesures de la performance

ROC





ROC



