Metrics

Machine Learning

Metrics

- Metrics are problem and domain specific
- Find a single number metric to compare models
- Be cautious of metrics others used

Accuracy in classification

- Accuracy measures closeness to true values
- Accuracy = correctly classified / total classified
- Error = misclassified / total classified
- Accuracy is useful in supervised classification problems
- Error is useful in regression problems

Minimal Accuracy

Higher than chance accuracy

For example 20% accuracy in a classifier with five classes means that classifier is not working.

Confusion matrix

Visualization of where classifier makes mistakes

Confusion Matrix

1	5	0	0	0	0	100%
	20.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0	1	1	0	0	50.0%
	0.0%	4.0%	4.0%	0.0%	0.0%	50.0%
: Class	0	0	4	0	0	100%
	0.0%	0.0%	16.0%	0.0%	0.0%	0.0%
4 Output	0	0	0	5	4	55.6%
	0.0%	0.0%	0.0%	20.0%	16.0%	44.4%
5	0	4	0	0	1	20.0%
	0.0%	16.0%	0.0%	0.0%	4.0%	80.0%
	100%	<mark>20.0%</mark>	80.0%	100%	20.0%	64.0%
	0.0%	80.0%	20.0%	0.0%	80.0%	36.0%
	1	2	3 Target	4 Class	5	

Error

Useful in regression problems Usually mean squared error:

MSE =
$$\frac{1}{n} \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2$$
.

Learning curve



training set size

- See how much training data you need
- How training improves accuracy
- Sanity check of algorithm
- Spot overfiting

Binary Classifier Metrics

	True label is positive	True label is negative
Prediction is positive	True Positive (TP)	False positive (FP)
Prediction is negative	False negative (FN)	True negative (TN)

F1 Measure = 2 * (precision * recall) / (precision + recall)

Useful in situations with skewed classes (e.g cancer)

ROC curves

- Receiver operating characteristic
- Visualize performance of binary classifier
- Plots tradeoff between recall and specificity





Validation

Machine Learning

Overfitting

- Big issue in machine learning
- Balance with underfitting
- Happens when test accuracy starts to diverge from training accuracy

Overfitting



Image from http://en.wikipedia.org/wiki/File:Overfitting_svg.svg

Separating data

Typically split 70% training, 30% evaluation Random split

In Sklearn:

x_train, x_test, y_train, y_test = cross_validation.train_test_split(data, labels, test_size=0.1, random_state=0)

Cross-validation

- Used to detect overfitting
- Cross validation allows use of full data set for training.
- Number of different cross-validation methods
- K-fold is most common

K-fold cross validation

- Divides dataset into K randomly selected subsets
- Each fold one subset is used for validation, and rest for training.
- 10-fold cross validation is common
- Variants: Leave-one-out (LOO), Stratified Kfold

Cross validation in Python

To construct cross validation object

- kf = cross_validation.KFold(n, n_folds = 10)
- n = number of elements
- n_folds = number of folds

To get the scores

cross_validation.cross_val_score(clf, data, labels, kf)

Model Selection

Machine Learning

Brute force approach

- Grid search of parameters such as gamma in SVM
- Can take a long time
- Cross-validation is performed on each iteration
- Some score function is computed

AIC / BIC

- Akaike/Bayesian information criterion
- Smaller is better
- Used to find "best" (most appropriate) model
- BIC penalizes complexity more

AIC =
$$-2 \ln L + 2k$$

BIC = $-2 \ln L + k \ln N$
of data points