COSC 522 – Machine Learning

Performance Evaluation

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Roadmap

- Module 1: Baysian Decision Theory (Maximum Posterior Probability or MPP)
  - Parametric
  - Non-parametric
  - In-depth: the three cases – parametric (e.g., pdf is Gaussian)
    - Minimum Euclidean Distance Classifier – linear machine (features are independent, covariance matrices from different classes are the same, pdf is Gaussian)
    - Minimum Mahalanobis Distance Classifier – linear machine (~~features are independent~~, covariance matrices from different classes are the same, pdf is Gaussian)
    - Quadratic Machine (~~features are independent~~, ~~covariance matrices from different classes are the same~~, pdf is Gaussian)

$$P(w_j|x) = \frac{p(x|w_j)P(w_j)}{p(x)}$$

- Module 2: Connection-based Neural Networks
  - Perceptron
  - BPNN and MLP (multi-layer perceptron)

Test 1

  - Kernel Methods
  - SVM
- Module 3: Regression
  - Linear Regression
  - Logistic Regression
- Module 4: Unsupervised Learning
  - Assume k is known (k-means, wta)
  - Hierarchical methods (Agglomerative clustering)
- Module 5: Pre-processing: Dimensionality Reduction
  - Supervised (FLD)
  - Unsupervised (PCA)
- Module 6: Post-processing
  - Performance Evaluation
  - Fusion

A recurring theme

- Objective function (cost function)
- Optimization method
- Distance metrics

Questions

AICIP RESEARCH

- What are TP, TN, FP, FN?
- What are sensitivity and specificity? What are their relationship to TP, TN, FP, and FN?
- What are precision and recall? What are their relationship to TP, TN, FP, and FN?
- What is confusion matrix? How can you derive TP, TN, FP, and FN from a confusion matrix?

- What is ROC curve?
- What does each axis mean? What are the relationship of the axes?
- How to draw an ROC curve?
- Which curve is optimal on an ROC plot?

- What is cross-validation? Why do we need it?

PART I: METRICS

Performance Metrics

- Often used in automatic target recognition and medical diagnosis
- True positive
  - The object is there and our classifier says it is there
- True negative
  - The object is not there and our classifier says it is not there
- False negative (false misses)
  - The object is there and our classifier says it is not there
- False positive (false hits)
  - The object is not there and our classifier says it is there

AICIP RESEARCH

Performance Metrics (cont'd)

- Sensitivity
  - Probability of a true-positive = TP/(TP+FN)
- Specificity
  - Probability of a true-negative = TN/(TN+FP)
- The probability of a correct decision = (TP+TN)/N, where N is the total number of samples

Performance Metrics (cont'd)

- Precision = TP/(TP+FP)
  - What proportion of positive identifications was actually correct?
- Recall = TP/(TP+FN)
  - What proportion of actual positives was correctly identified?
- Accuracy = (TP+TN)/(TP+TN+FP+FN)

Performance Metrics (cont'd)

- Confusion matrix
- Example: 3-class classification problem (AAV, DW, HMV)

	AAV	DW	HMV
AAV	894	329	143
DW	99	411	274
HMV	98	42	713

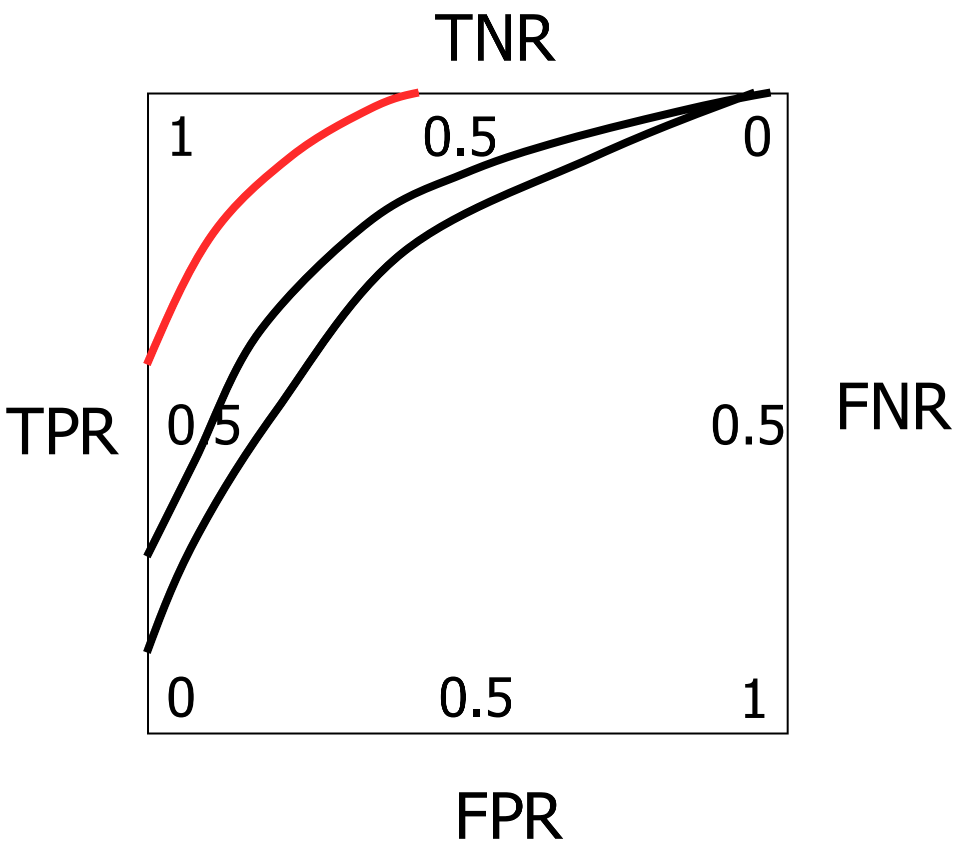
The real class is DW, the classifier says it's HMV

PART II: ROC CURVE AND CROSS VALIDATION

Parameters vs. Performance

- Once we have designed our classifier, we invariably have some parameters we'd like to adjust. E.g.,
  - Prior probability
- The optimal classifier is one with sensitivity as close to 100% as possible, and at the same time with specificity as close to 100% as possible

ROC – Receiver Operating Characteristic

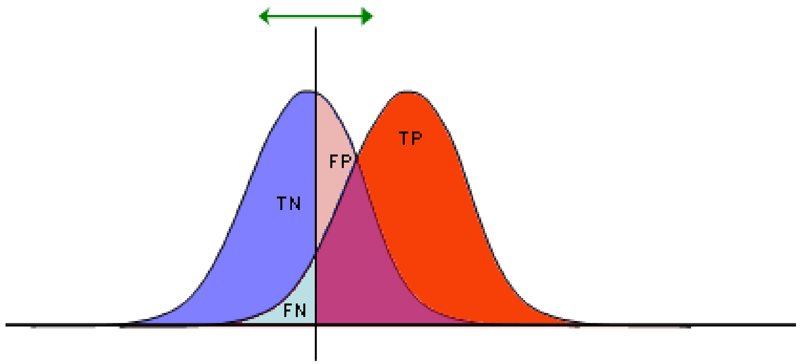


- Each curve represents the performance of a particular classifier as some parameter is varied over its range
- Of the three curves, the one with the sharpest bend, which passes closest to the upper left corner, is the best
- Calculate the area above the curve, the one with the smallest area is the best

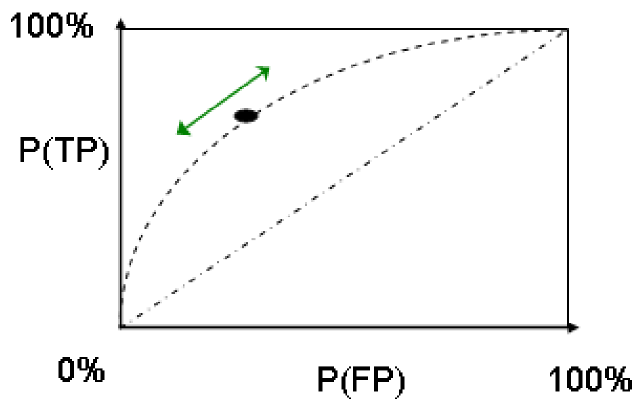
- TPR: TP out of the total actual positives (Sensitivity or Recall)
- FPR: FP out of the total actual negatives (1-Specificity)

- **AUC** (Area Under the Curve)

ROC (cont'd)



TP	FP
FN	TN
1	1



http://en.wikipedia.org/wiki/Receiver_operating_characteristic

Determine ROC from Test Data

- Apparent error rate vs. true error rate
  - Apparent error rate: counting the number of elements in the training set that are misclassified. However, this error rate leads to an optimistic result since the classifier has been designed to minimize the number of misclassifications of the training set
- Solutions???

Solution 1 – Separating the training set and the test set

- Divide the training set into two parts (randomly) and build the classifier using half of the data, then test the classifier on the other half. This other half is called the validation set.
- Clarification: training set, test set, validation set

Solution 2 – The Leave-One-Out Approach

- Assume there are n points in the training set.
- Remove point 1 from the set and design the classifier (determine the pdf) using the other n-1 points. Then test the classifier on point 1.
- Repeat for all points.
- The resulting error rate can be shown to be an almost unbiased estimate of the expected true error rate
- This requires we design n classifiers. However, we only need to do it once.

m-Fold Cross Validation

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- A generalization to both solution 1 and 2.
- The training set is randomly divided into m disjoint sets of equal size. The classifier is trained m times, each time with a different set held out as a validation set
- For example, when m = 3,
  - m1+m2 as training, test on m3
  - m1+m3 as training, test on m2
  - m2+m3 as training, test on m1
- When m=2, it is solution 1
- When m=n, it is solution 2 (n is the number of samples in the original training set)

The Train-Validation-Test Scheme

- Data set is divided into
  - training set (use label information to train)
  - validation set (use label information to evaluate)
  - test set (not seen during training)