

Classification

Part 4

Dr. Sanjay Ranka

Professor

Computer and Information Science and Engineering

University of Florida, Gainesville

Model Evaluation

- Metrics for Performance Evaluation
 - How to evaluate the performance of a model
- Methods for Performance Evaluation
 - How to obtain reliable estimates
- Methods for Model Comparison
 - How to compare the relative performance among competing models

Metrics for Performance Evaluation

- Focus on the predictive capability of a model
 - Rather than how fast it takes to classify or build models, scalability, etc.
- Confusion Matrix:

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive)
b: FN (false negative)
c: FP (false positive)
d: TN (true negative)

Metrics for Performance Evaluation

ACTUAL CLASS	PREDICTED CLASS		
		Class=Yes	Class=No
	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

- Most widely-used metric:

$$\text{Accuracy} = \frac{a + d}{a + b + c + d} = \frac{TP + TN}{TP + TN + FP + FN}$$

Cost Matrix

	PREDICTED CLASS		
ACTUAL CLASS	C(i j)	Class=Yes	Class=No
	Class=Yes	C(Yes Yes)	C(No Yes)
	Class=No	C(Yes No)	C(No No)

$C(i | j)$: Cost of misclassifying class j example as class i

- Accuracy is a useful measure if
 - $C(\text{Yes} | \text{No}) = C(\text{No} | \text{Yes})$ and $C(\text{Yes} | \text{Yes}) = C(\text{No} | \text{No})$
 - $P(\text{Yes}) = P(\text{No})$ (class distribution are equal)

Cost vs. Accuracy

Cost Matrix	PREDICTED CLASS		
	C(i j)	+	-
	+	-1	100
	-	1	0

Model M_1	PREDICTED CLASS		
ACTUAL CLASS	C(i j)	+	-
	+	150	40
	-	60	250

Accuracy = 80%

Cost = 3910

Model M_2	PREDICTED CLASS		
ACTUAL CLASS	C(i j)	+	-
	+	250	45
	-	5	200

Accuracy = 90%

Cost = 4255

Cost-Sensitive Measures

$$\text{Precision (p)} = \frac{a}{a + c}$$

$$\text{Recall (r)} = \frac{a}{a + b}$$

$$\text{F - measure (F)} = \frac{2rp}{r + p} = \frac{2a}{2a + b + c}$$

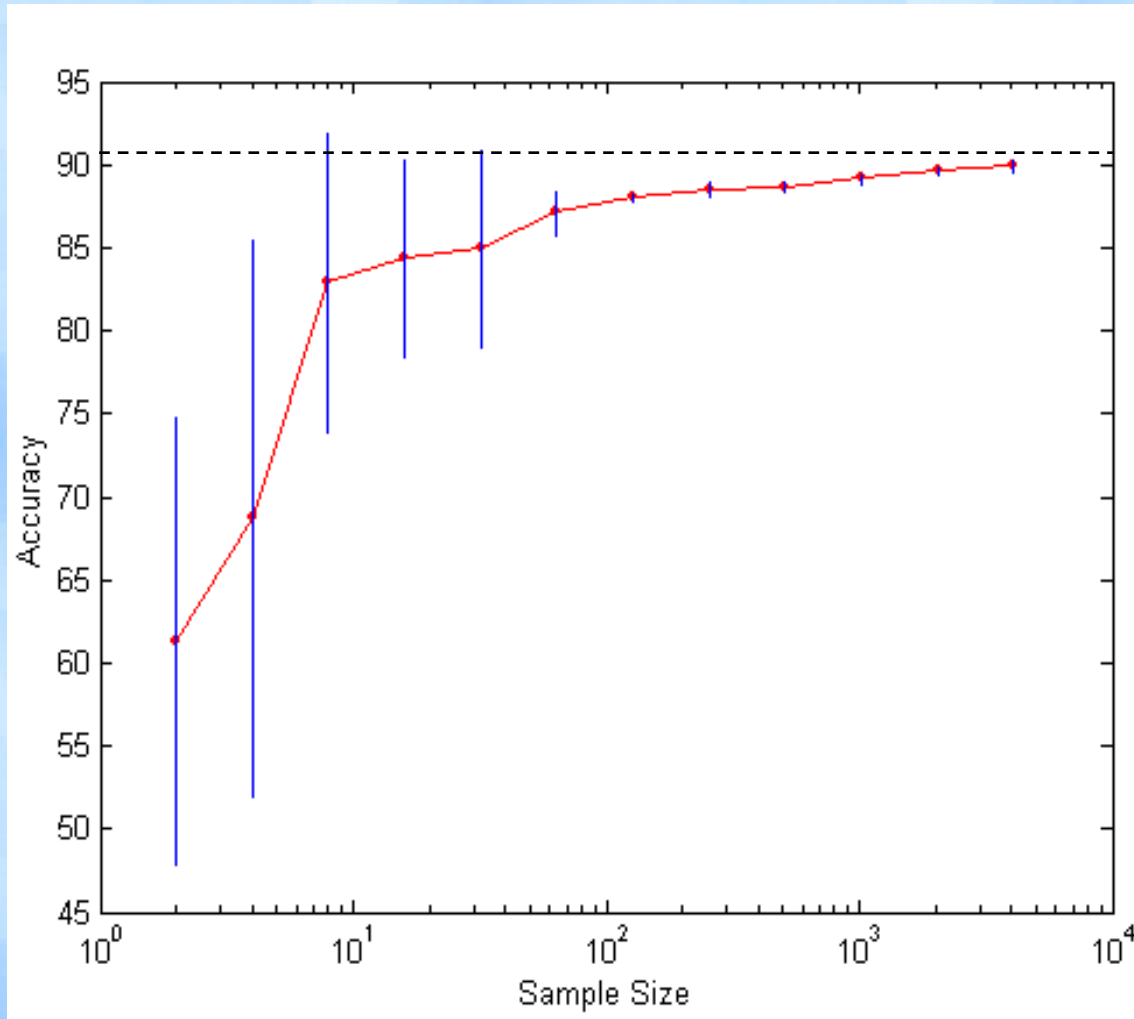
- Precision is biased towards $C(\text{Yes} | \text{Yes})$ & $C(\text{Yes} | \text{No})$
- Recall is biased towards $C(\text{Yes} | \text{Yes})$ & $C(\text{No} | \text{Yes})$
- F-measure is biased towards all except $C(\text{No} | \text{No})$

$$\text{Weighted Accuracy} = \frac{w_1 a + w_4 d}{w_1 a + w_2 b + w_3 c + w_4 d}$$

Methods for Performance Evaluation

- How to obtain a reliable estimate of performance
- Performance of a model may depend on other factors besides the learning algorithm:
 - Class distribution
 - Cost of misclassification
 - Size of training and test sets

Learning Curve



- Learning curve shows how accuracy changes with varying sample size
- Requires a sampling schedule for creating a learning curve
 - Arithmetic sampling
 - Geometric sampling
- Effect of small sample size
 - Bias in the estimate
 - Variance of the estimate

Methods for Estimation

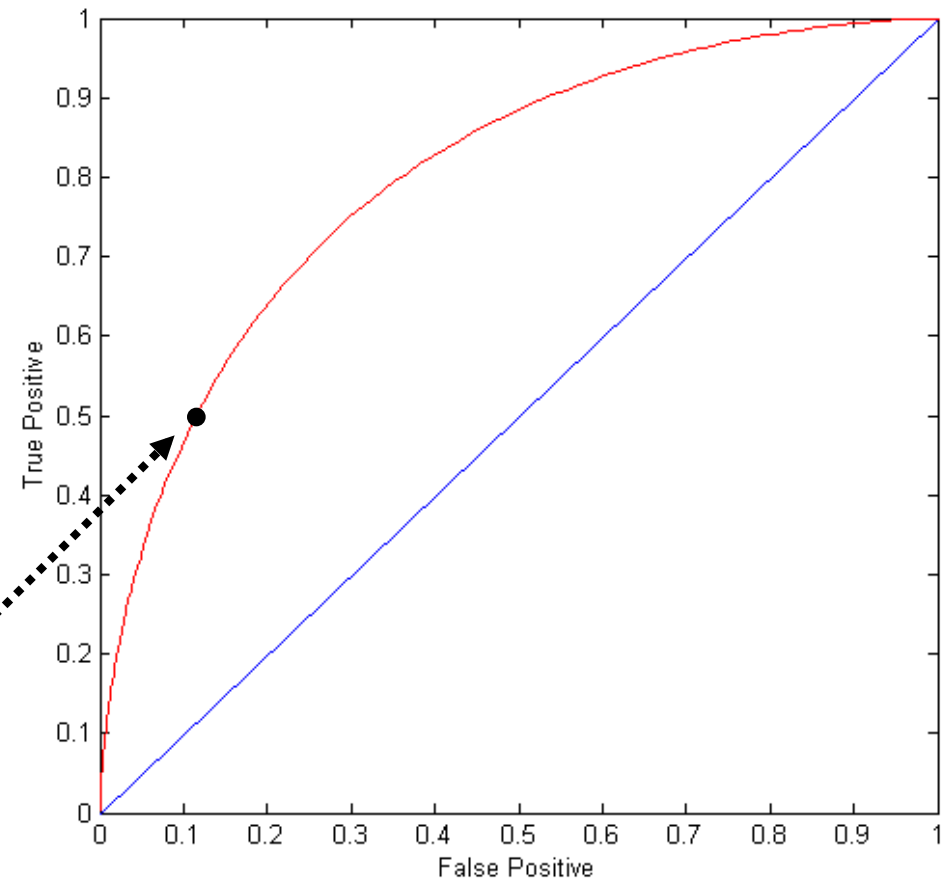
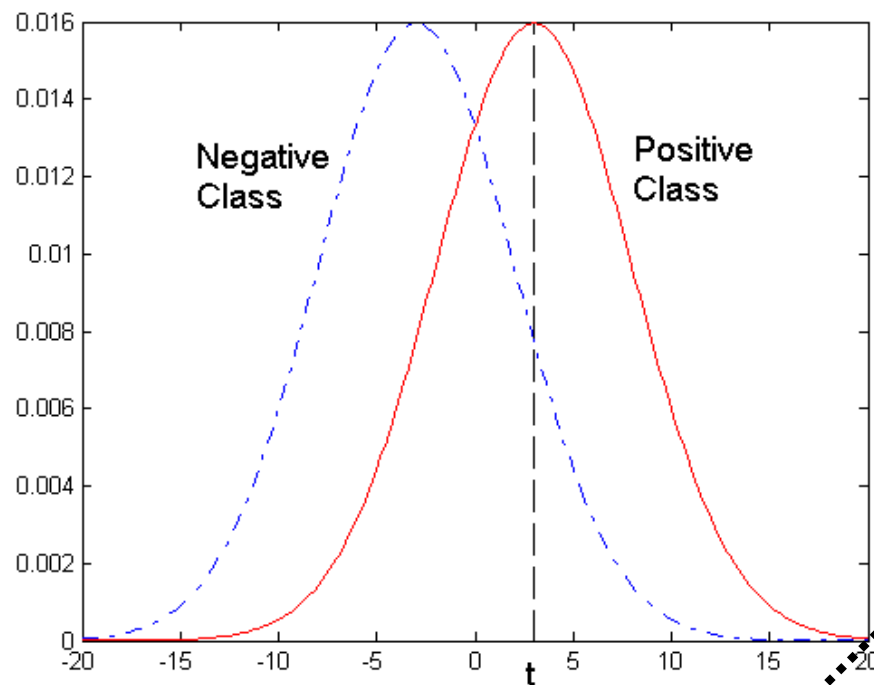
- Holdout
 - Reserve $2/3$ for training and $1/3$ for testing
- Random sub-sampling
 - Repeated holdout
- Cross validation
 - Partition data into k disjoint subsets
 - k -fold: train on $k-1$ partitions, test on the remaining one
 - Leave-one-out: $k=n$
- Stratified sampling
 - Over-sampling vs. Under-sampling
- Bootstrap
 - Sampling with replacement

Receiver Operating Characteristic (ROC)

- Developed in 1950s for signal detection theory to analyze noisy signals
 - Characterize the trade-off between positive hits and false alarms
- ROC curve plots TP (on the y-axis) against FP (on the x-axis)
- Performance of each classifier represented as a point on the ROC curve
 - changing the threshold of algorithm, sample distribution or cost matrix changes the location of the point

ROC Curve

- 1-dimensional data set containing 2 classes (positive and negative)
- Any point located at $x > t$ is classified as positive



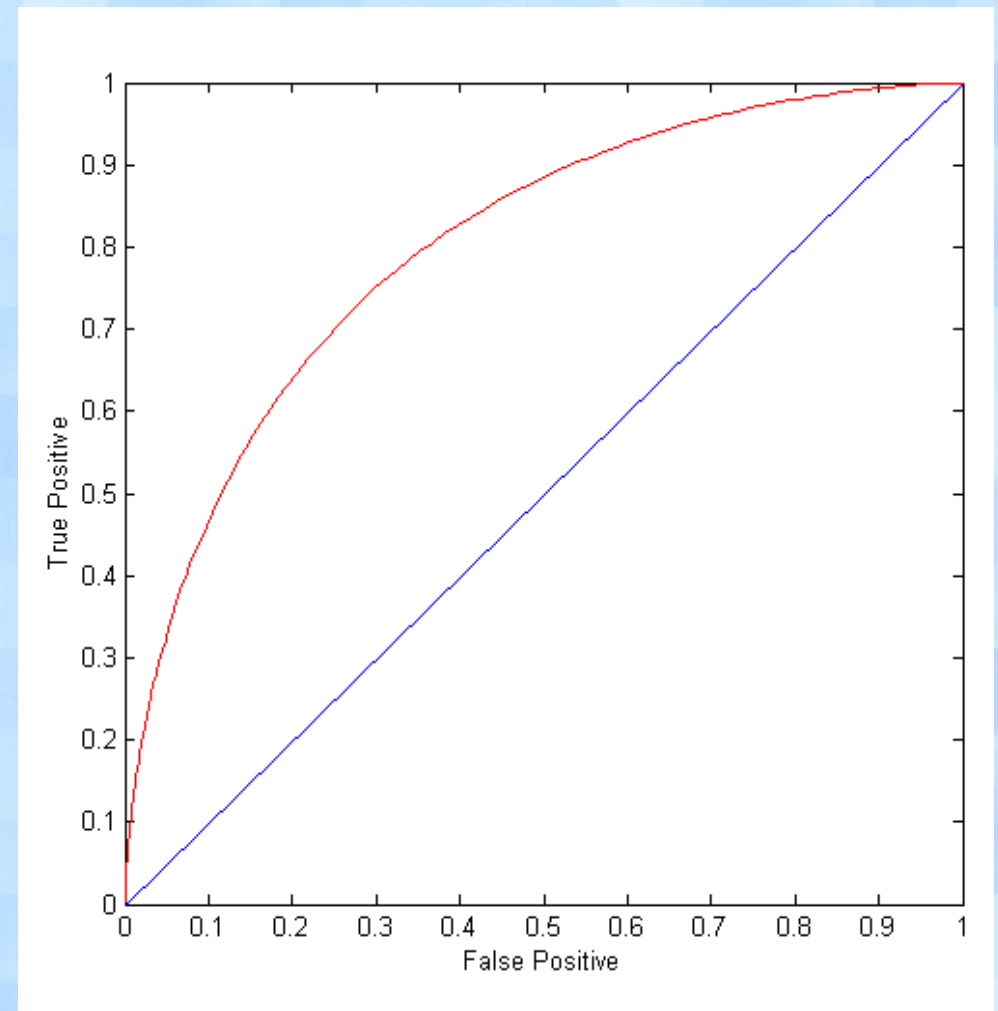
At threshold t :

TP=0.5, FN=0.5, FP=0.12, FN=0.88

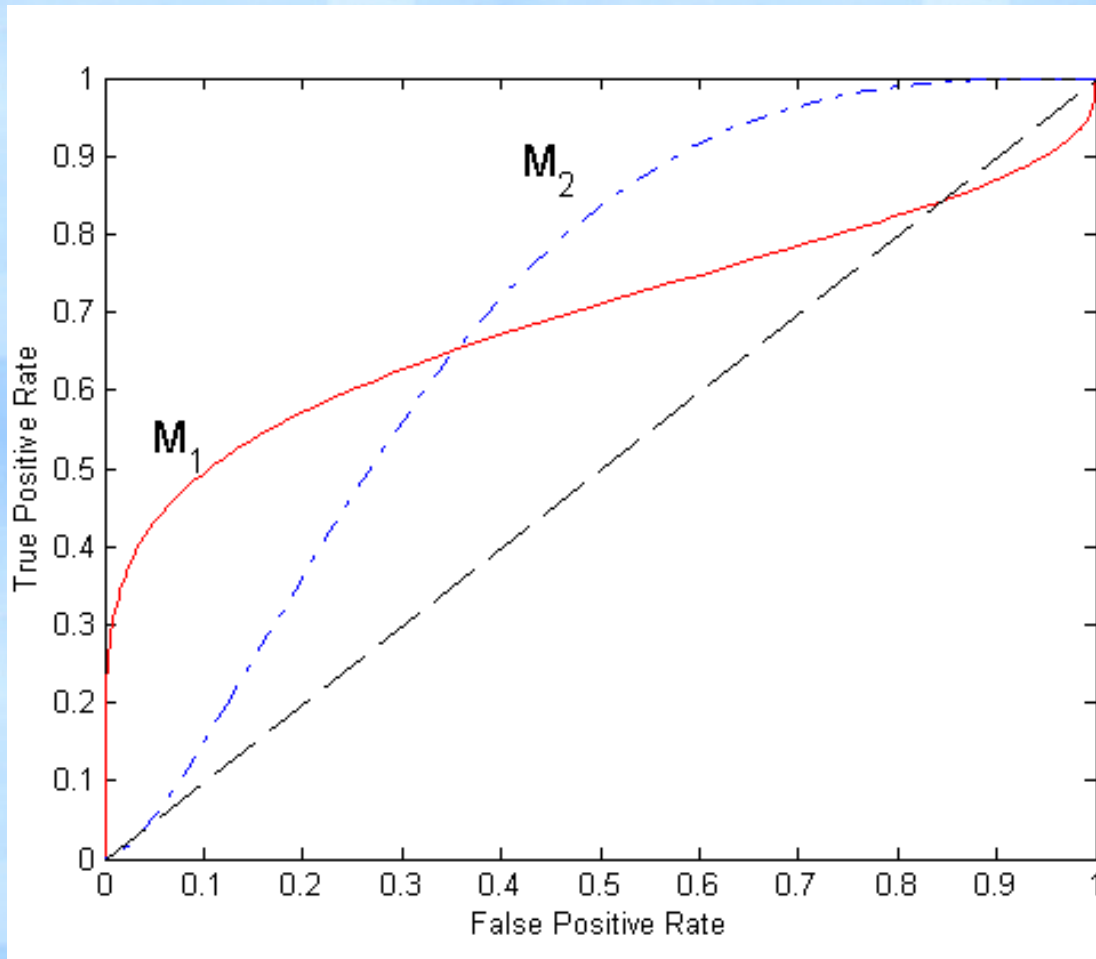
ROC Curve

(TP,FP):

- (0,0): declare everything to be negative class
- (1,1): declare everything to be positive class
- (1,0): ideal
- Diagonal line:
 - Random guessing
 - Below diagonal line:
 - prediction is opposite of the true class



Using ROC for Model Comparison



- No model consistently outperforms the other
 - M_1 is better for small FPR
 - M_2 is better for large FPR
- Area under the ROC curve
 - Ideal, area = 1
 - Random guess, area = 0.5