Introduction to Data Mining

Chapter 6

Classification:

Alternative Techniques

Source: revised from slides provided by Tan, Steinbach, Karpatne, and Kumar

Measures of Classification Performance

Class Imbalance Problem

Lots of datasets face the problem that the classes are skewed (more records from one class than another)

- Credit card fraud
- Intrusion detection
- Defective products in manufacturing assembly line

Challenges

Difficult to find sufficiently many labeled samples of a rare class

Evaluation measures such as accuracy is not well-suited for imbalanced class

Confusion Matrix

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)

Accuracy

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

Most widely-used metric:

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

Problem with Accuracy

Consider a 2-class problem

- Number of Class NO examples = 990
- Number of Class YES examples = 10

If a model predicts everything to be class NO, accuracy is 990/1000 = 99 %

- This is misleading because the model does not detect any class YES example
- Detecting the rare class is usually more interesting (e.g., frauds, intrusions, defects, etc)

Alternative Measures

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

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

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

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

Alternative Measures

	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	10	0
Class=No	10	980

$$\text{Precision (p)} = \frac{10}{10+10} = 0.5$$

$$\text{Recall (r)} = \frac{10}{10+0} = 1$$

$$\text{F - measure (F)} = \frac{2*1*0.5}{1+0.5} = 0.62$$

$$\text{Accuracy} = \frac{990}{1000} = 0.99$$

Alternative Measures

	PREDICTED CLASS	
	Class=Yes	Class=No
ACTUAL CLASS Class=Yes	10	0
ACTUAL CLASS Class=No	10	980

$$\text{Precision (p)} = \frac{10}{10+10} = 0.5$$

$$\text{Recall (r)} = \frac{10}{10+0} = 1$$

$$\text{F - measure (F)} = \frac{2*1*0.5}{1+0.5} = 0.62$$

$$\text{Accuracy} = \frac{990}{1000} = 0.99$$

	PREDICTED CLASS	
	Class=Yes	Class=No
ACTUAL CLASS Class=Yes	1	9
ACTUAL CLASS Class=No	0	990

$$\text{Precision (p)} = \frac{1}{1+0} = 1$$

$$\text{Recall (r)} = \frac{1}{1+9} = 0.1$$

$$\text{F - measure (F)} = \frac{2*0.1*1}{1+0.1} = 0.18$$

$$\text{Accuracy} = \frac{991}{1000} = 0.991$$

Alternative Measures

	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	40	10
Class=No	10	40

$$\text{Precision (p)} = 0.8$$

$$\text{Recall (r)} = 0.8$$

$$\text{F - measure (F)} = 0.8$$

$$\text{Accuracy} = 0.8$$

Alternative Measures

	PREDICTED CLASS	
	Class=Yes	Class=No
ACTUAL CLASS Class=Yes	40	10
ACTUAL CLASS Class=No	10	40

$$\text{Precision (p)} = 0.8$$
$$\text{Recall (r)} = 0.8$$
$$\text{F - measure (F)} = 0.8$$
$$\text{Accuracy} = 0.8$$

	PREDICTED CLASS	
	Class=Yes	Class=No
ACTUAL CLASS Class=Yes	40	10
ACTUAL CLASS Class=No	1000	4000

$$\text{Precision (p)} =\sim 0.04$$
$$\text{Recall (r)} = 0.8$$
$$\text{F - measure (F)} =\sim 0.08$$
$$\text{Accuracy} =\sim 0.8$$

Measures of Classification Performance

	PREDICTED CLASS		
ACTUAL CLASS		Yes	No
	Yes	TP	FN
	No	FP	TN

α **is the probability that we reject the null hypothesis when it is true. This is a Type I error or a false positive (FP).**

β **is the probability that we accept the null hypothesis when it is false. This is a Type II error or a false negative (FN).**

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

$$ErrorRate = 1 - accuracy$$

$$Precision = Positive\ Predictive\ Value = \frac{TP}{TP + FP}$$

$$Recall = Sensitivity = TP\ Rate = \frac{TP}{TP + FN}$$

$$Specificity = TN\ Rate = \frac{TN}{TN + FP}$$

$$FP\ Rate = \alpha = \frac{FP}{TN + FP} = 1 - specificity$$

$$FN\ Rate = \beta = \frac{FN}{FN + TP} = 1 - sensitivity$$

$$Power = sensitivity = 1 - \beta$$

Alternative Measures

	PREDICTED CLASS	
	Class=Yes	Class=No
ACTUAL CLASS: Class=Yes	40	10
ACTUAL CLASS: Class=No	10	40

$$\text{Precision (p)} = 0.8$$
$$\text{TPR} = \text{Recall (r)} = 0.8$$
$$\text{FPR} = 0.2$$
$$\text{F - measure (F)} = 0.8$$
$$\text{Accuracy} = 0.8$$

	PREDICTED CLASS	
	Class=Yes	Class=No
ACTUAL CLASS: Class=Yes	40	10
ACTUAL CLASS: Class=No	1000	4000

$$\text{Precision (p)} =\sim 0.04$$
$$\text{TPR} = \text{Recall (r)} = 0.8$$
$$\text{FPR} = 0.2$$
$$\text{F - measure (F)} =\sim 0.08$$
$$\text{Accuracy} =\sim 0.8$$

Alternative Measures

	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	10	40
Class=No	10	40

$$Precision\ (p) = 0.5$$
$$TPR = Recall\ (r) = 0.2$$
$$FPR = 0.2$$

	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	25	25
Class=No	25	25

$$Precision\ (p) = 0.5$$
$$TPR = Recall\ (r) = 0.5$$
$$FPR = 0.5$$

	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	40	10
Class=No	40	10

$$Precision\ (p) = 0.5$$
$$TPR = Recall\ (r) = 0.8$$
$$FPR = 0.8$$

ROC (Receiver Operating Characteristic)

- A graphical approach for displaying trade-off between detection rate and false alarm rate
- Developed in 1950s for signal detection theory to analyze noisy signals
- ROC curve plots TPR against FPR
  - Performance of a model represented as a point in an ROC curve
  - Changing the threshold parameter of classifier changes the location of the point

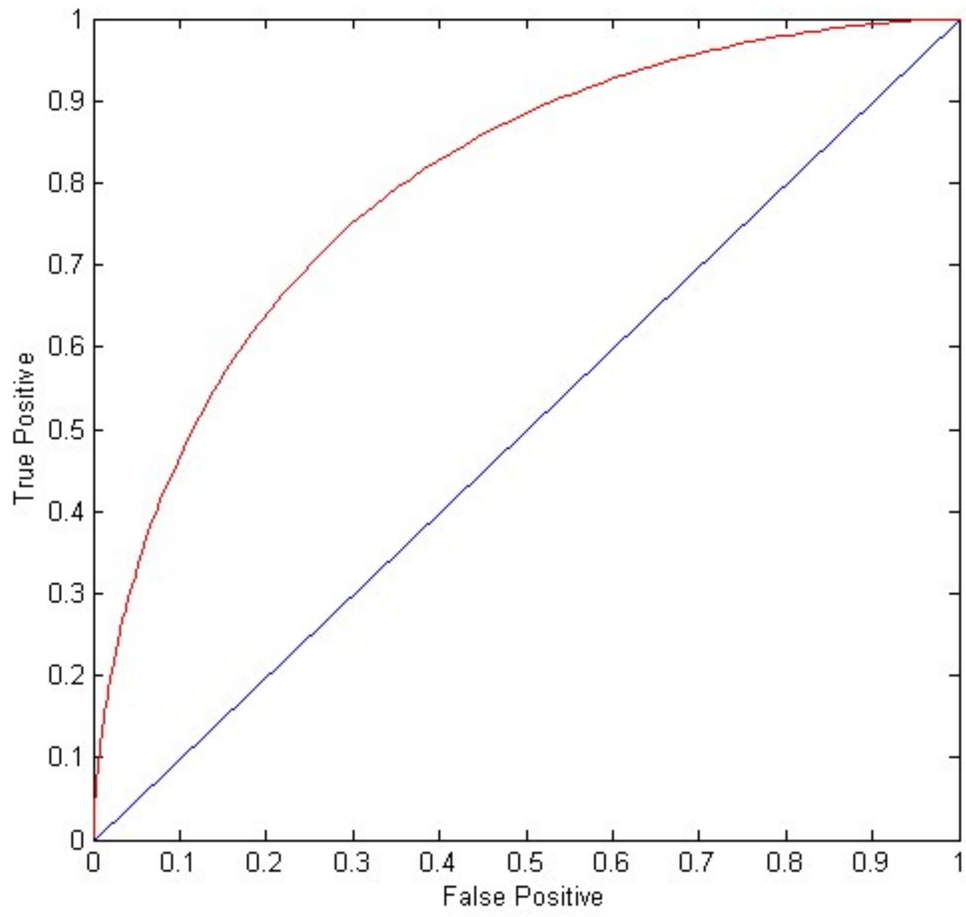
ROC Curve

(TPR,FPR):

(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

ROC (Receiver Operating Characteristic)

To draw ROC curve, classifier must produce continuous-valued output

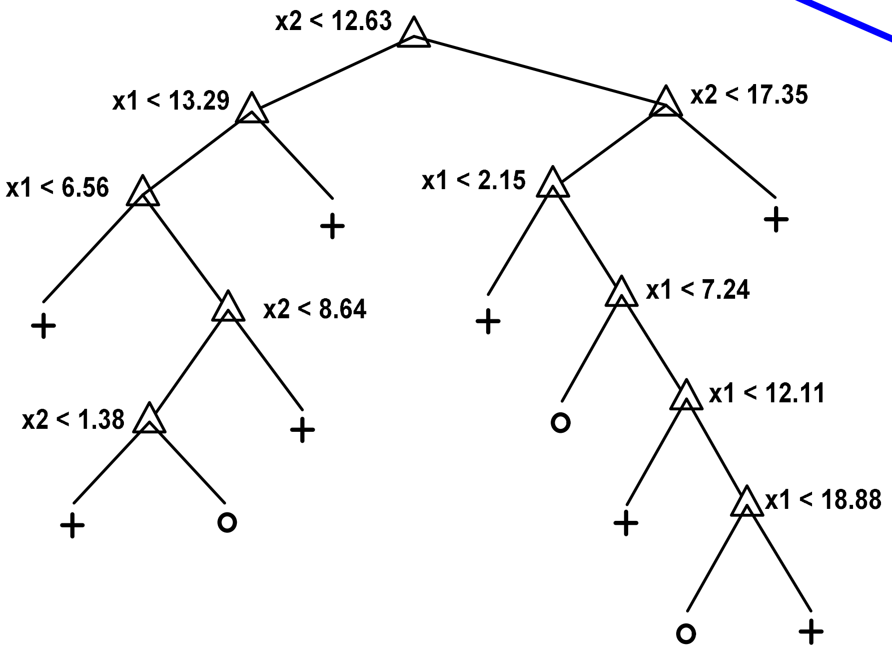
- Outputs are used to rank test records, from the most likely positive class record to the least likely positive class record

Many classifiers produce only discrete outputs (i.e., predicted class)

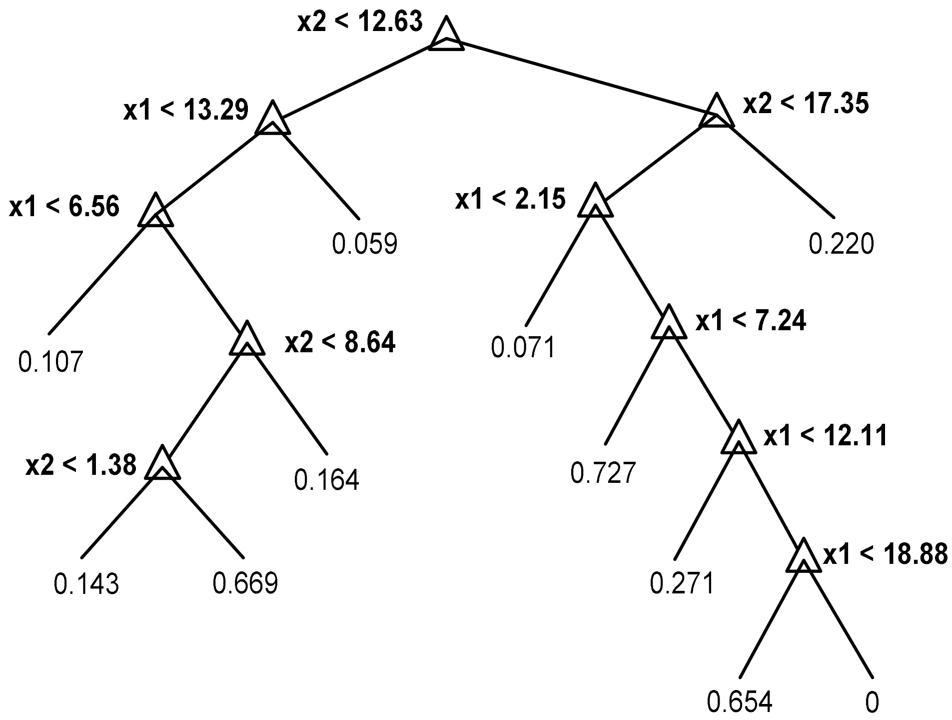
- How to get continuous-valued outputs?
  - Decision trees, rule-based classifiers, neural networks, Bayesian classifiers, k-nearest neighbors, SVM

Example: Decision Trees

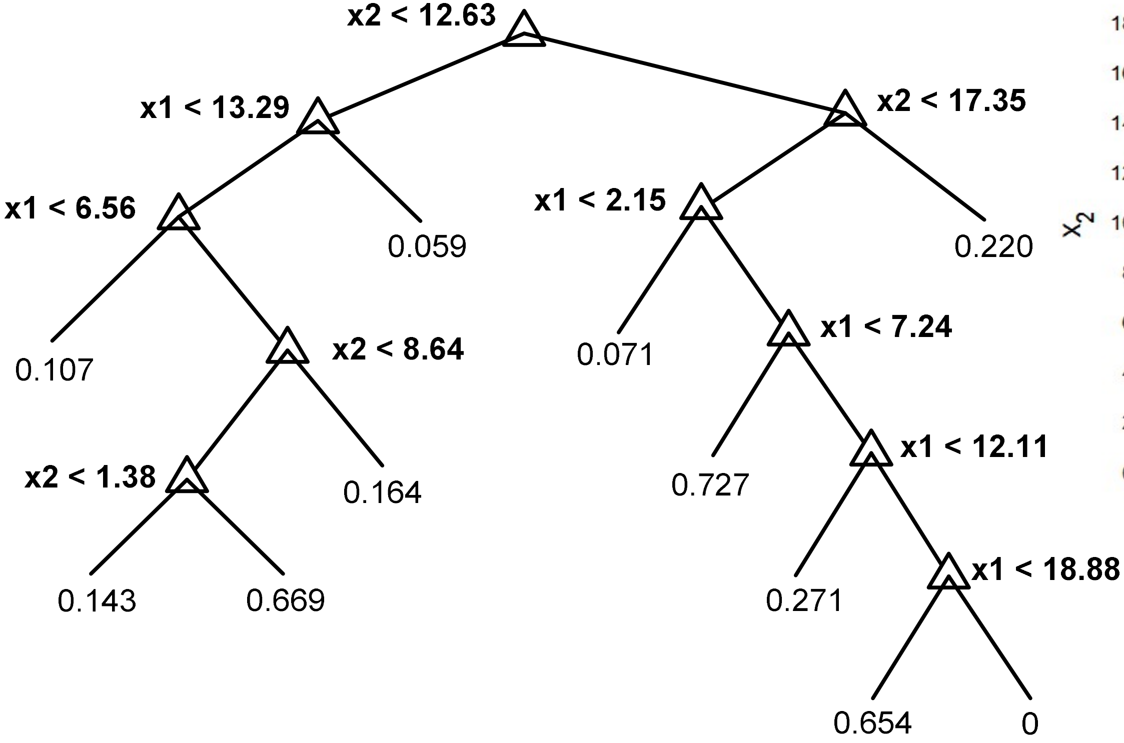
Decision Tree

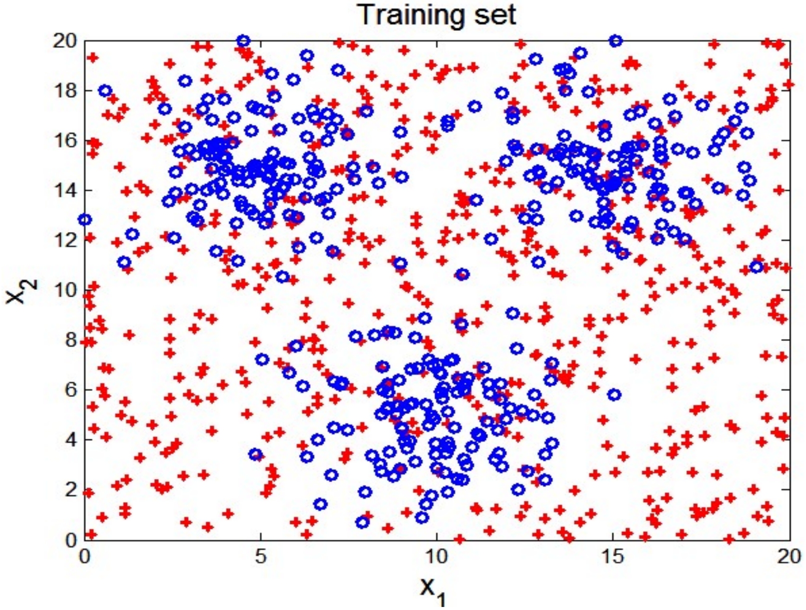


Continuous-valued outputs



ROC Curve Example



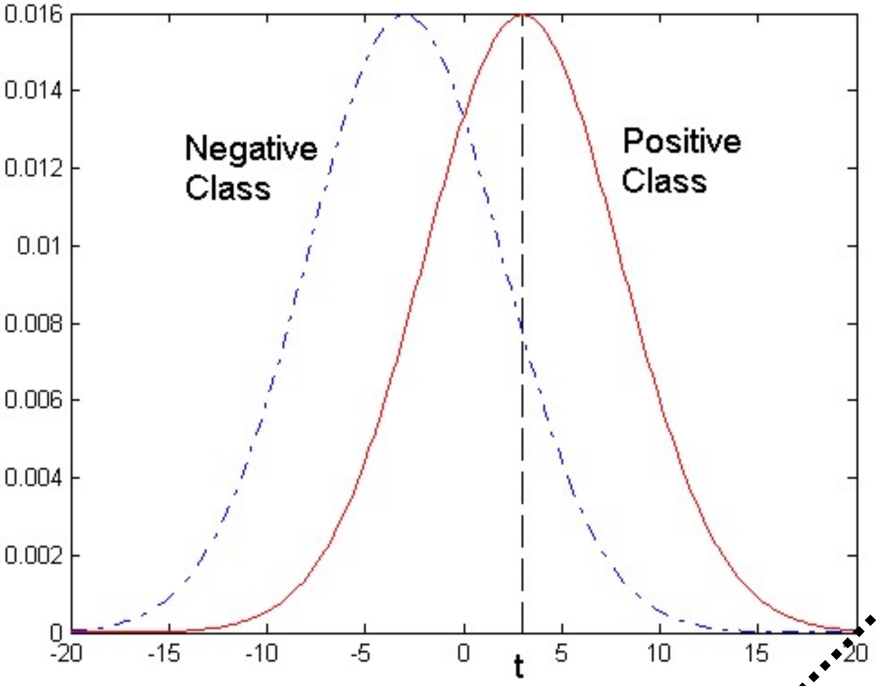


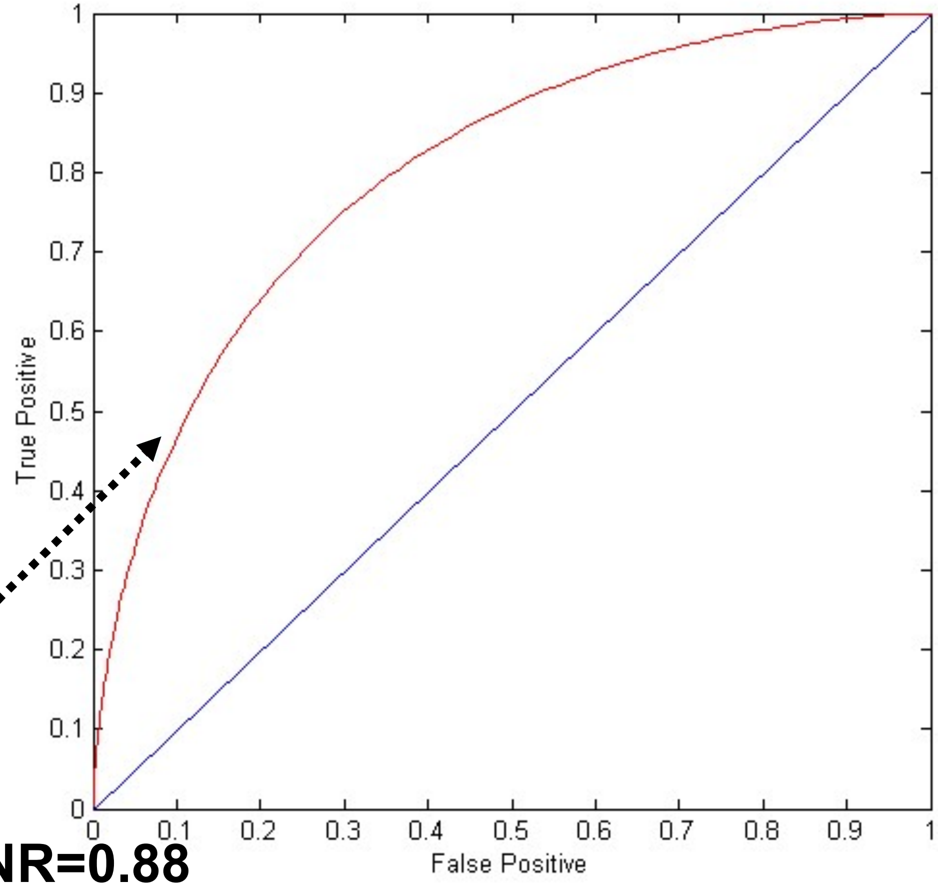
$\alpha = 0.3$		Predicted Class	
		Class o	Class +
Actual Class	Class o	645	209
	Class +	298	948

$\alpha = 0.7$		Predicted Class	
		Class o	Class +
Actual Class	Class o	181	673
	Class +	78	1168

ROC Curve Example

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

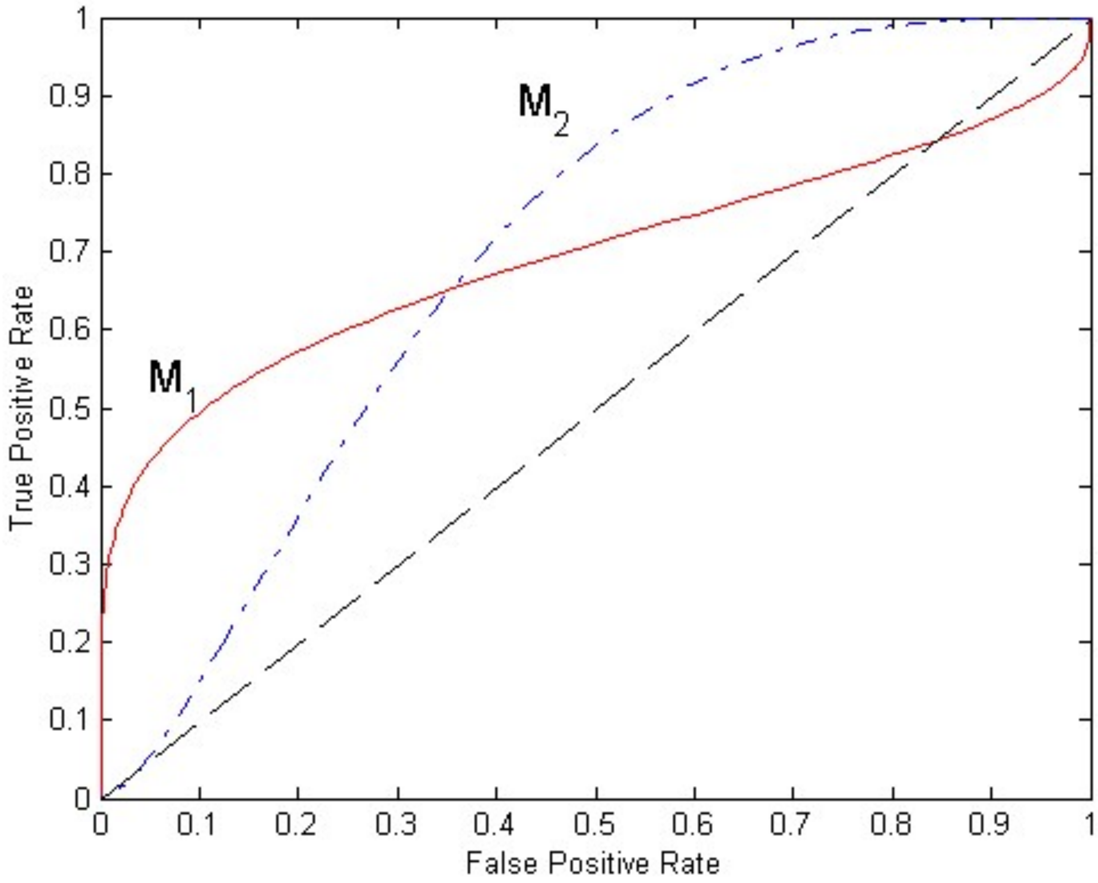




At threshold t:

TPR=0.5, FNR=0.5, FPR=0.12, TNR=0.88

Using ROC for Model Comparison



No model consistently outperform 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

How to Construct an ROC curve

Instance	Score	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

- Use a classifier that produces a continuous-valued score for each instance
  - The more likely it is for the instance to be in the + class, the higher the score
- Sort the instances in decreasing order according to the score
- Apply a threshold at each unique value of the score
- Count the number of TP, FP, TN, FN at each threshold
  - TPR = TP/(TP+FN)
  - FPR = FP/(FP + TN)

How to construct an ROC curve

Class	+	-	+	-	-	-	+	-	+	+	
Threshold >=	0.25	0.43	0.53	0.76	0.85	0.85	0.85	0.87	0.93	0.95	1.00
TP	5	4	4	3	3	3	3	2	2	1	0
FP	5	5	4	4	3	2	1	1	0	0	0
TN	0	0	1	1	2	3	4	4	5	5	5
FN	0	1	1	2	2	2	2	3	3	4	5
TPR	1	0.8	0.8	0.6	0.6	0.6	0.6	0.4	0.4	0.2	0
FPR	1	1	0.8	0.8	0.6	0.4	0.2	0.2	0	0	0

ROC Curve: