Data Mining

Imbalanced Class Problem

Class Imbalance Problem

- Lots of classification problems where the classes are skewed (more records from one class than another)
  - Credit card fraud
  - Intrusion detection
  - Defective products in manufacturing assembly line

Challenges

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

- Detecting the rare class is like finding needle in a haystack

Confusion Matrix

- Confusion Matrix:

	PREDICTED CLASS	
		Class=Yes	Class=No
ACTUAL CLASS	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	

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

- Most widely-used metric:

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

Problem with Accuracy

- Consider a 2-class problem
  - Number of Class 0 examples = 9990
  - Number of Class 1 examples = 10

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

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

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

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

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

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

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

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

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

	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	1	9
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		
		Class=Yes	Class=No
ACTUAL CLASS	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	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	40	10
Class=No	10	40

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

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

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

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

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

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

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

ROC (Receiver Operating Characteristic)

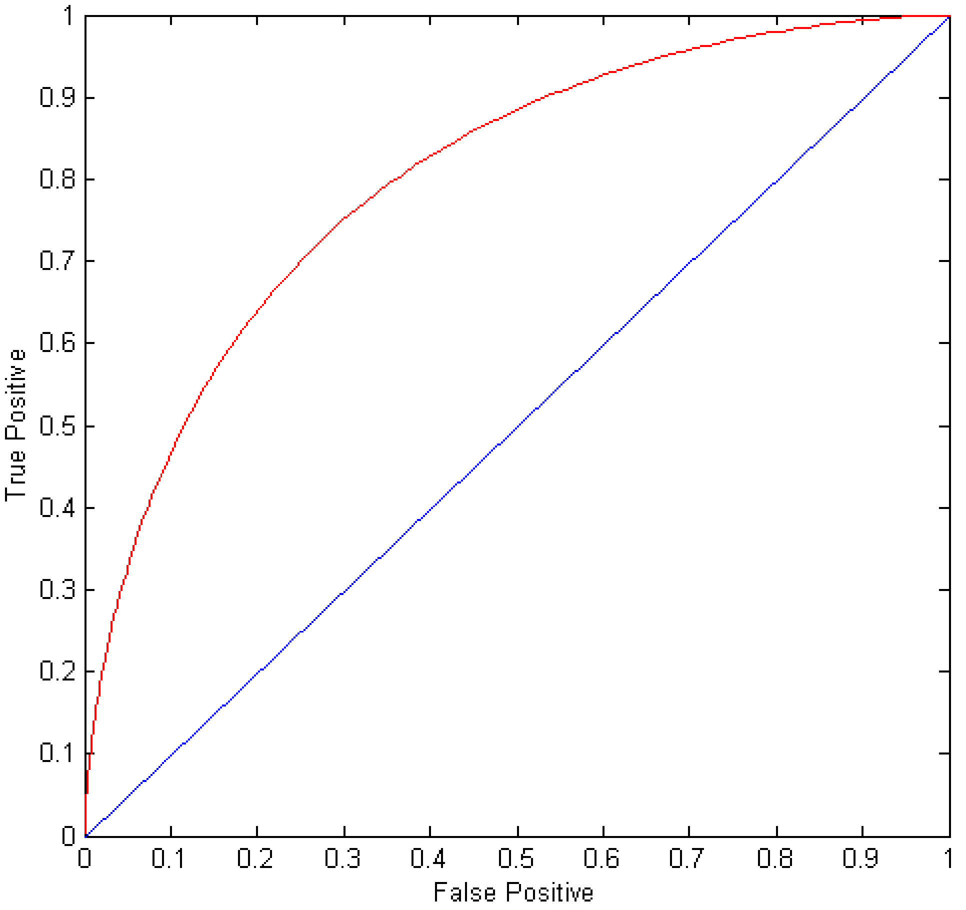
- A graphical approach for displaying trade-off between detection rate and false alarm rate
- Developed in 1950s for signal detection theory to analyze noisy signals
- ROC curve plots TPR against FPR
  - Performance of a model represented as a point in an ROC curve
  - Changing the threshold parameter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



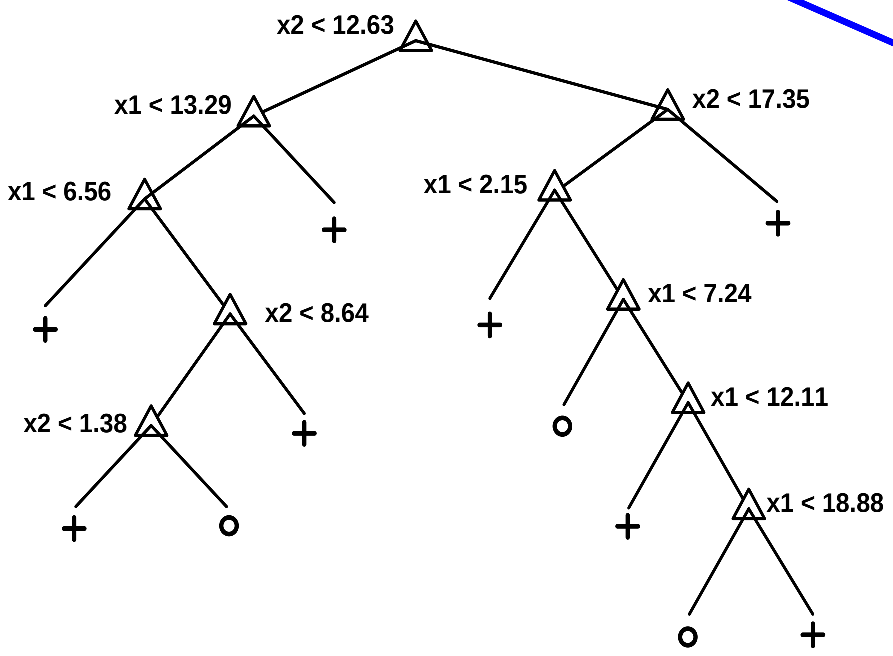
ROC (Receiver Operating Characteristic)

- 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

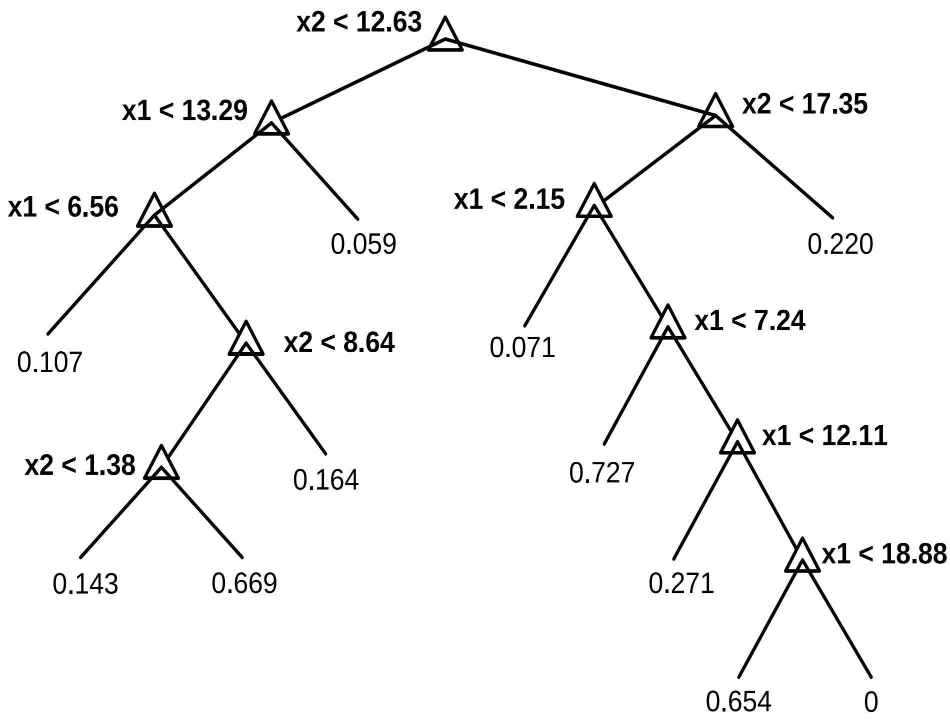
- Many classifiers produce only discrete outputs (i.e., predicted class)
  - How to get continuous-valued outputs?
    - Decision trees, rule-based classifiers, neural networks, Bayesian classifiers, k-nearest neighbors, SVM

Example: Decision Trees

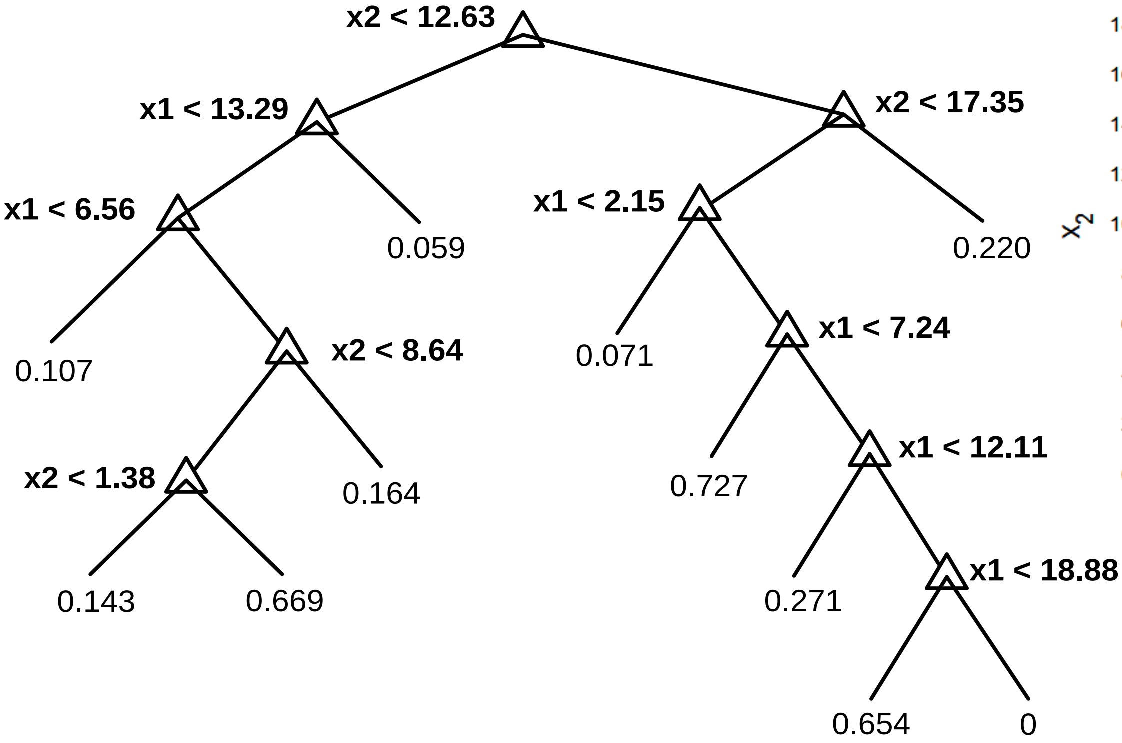
Decision Tree

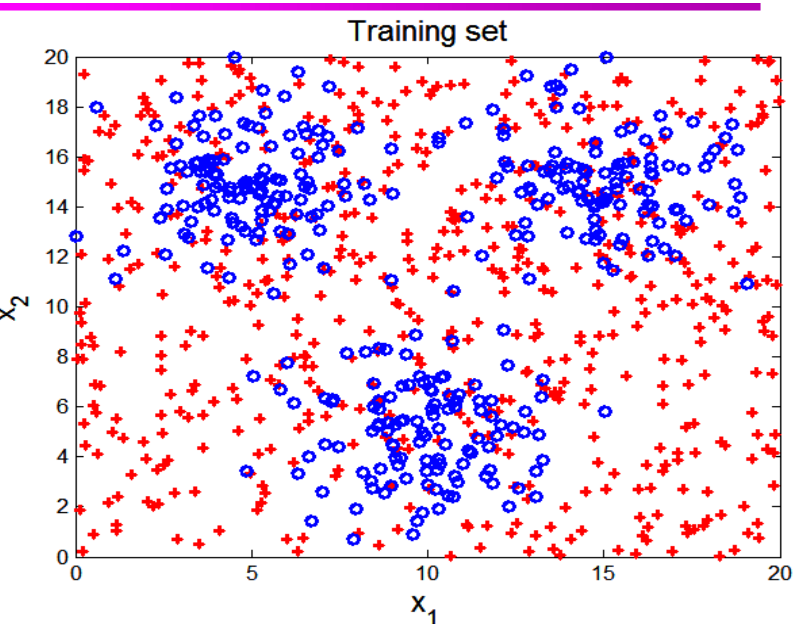


Continuous-valued outputs



ROC Curve Example





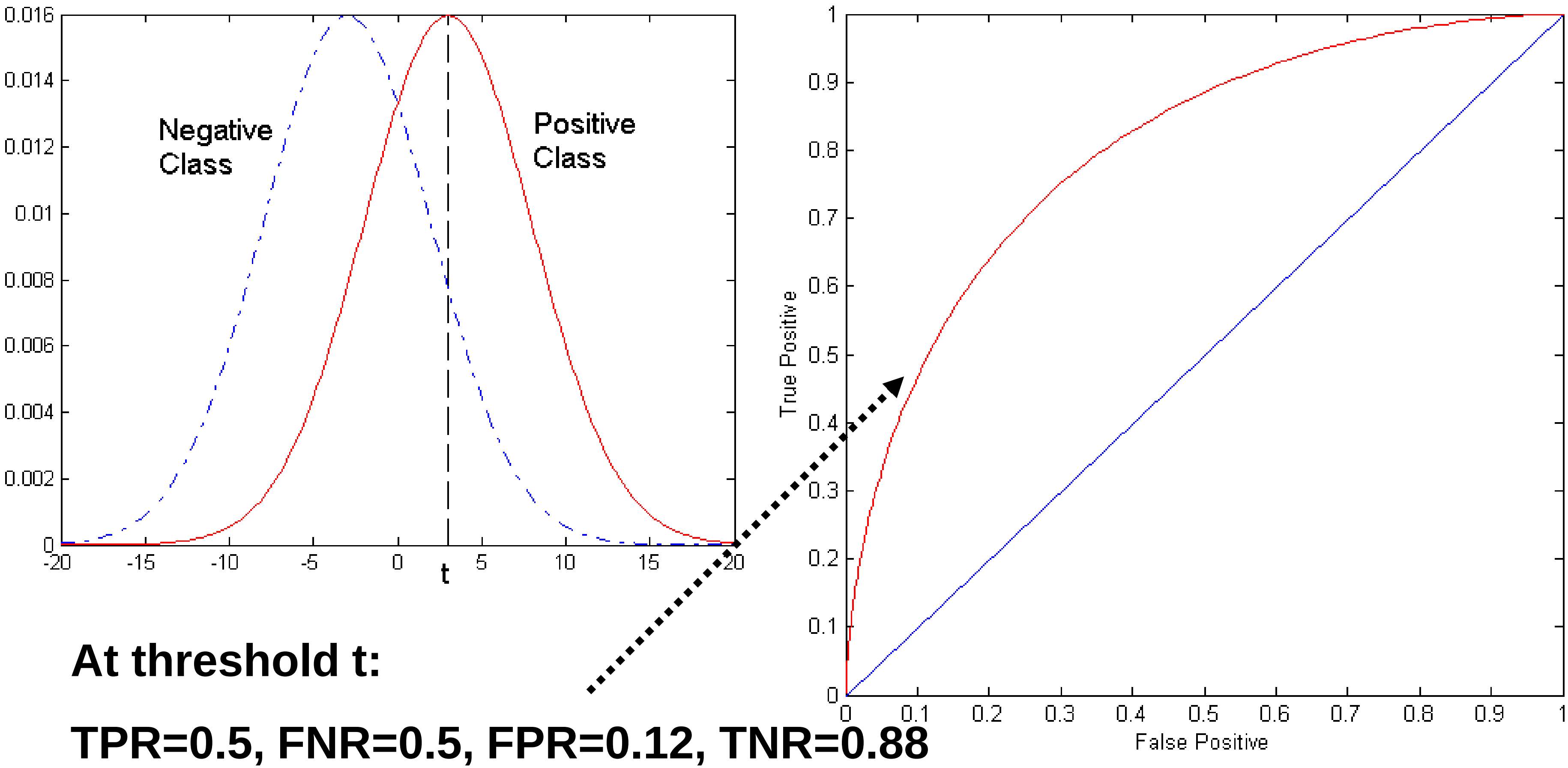
$\alpha = 0.3$		Predicted Class	
		Class o	Class +
Actual Class	Class o	645	209
	Class +	298	948

$\alpha = 0.7$		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)

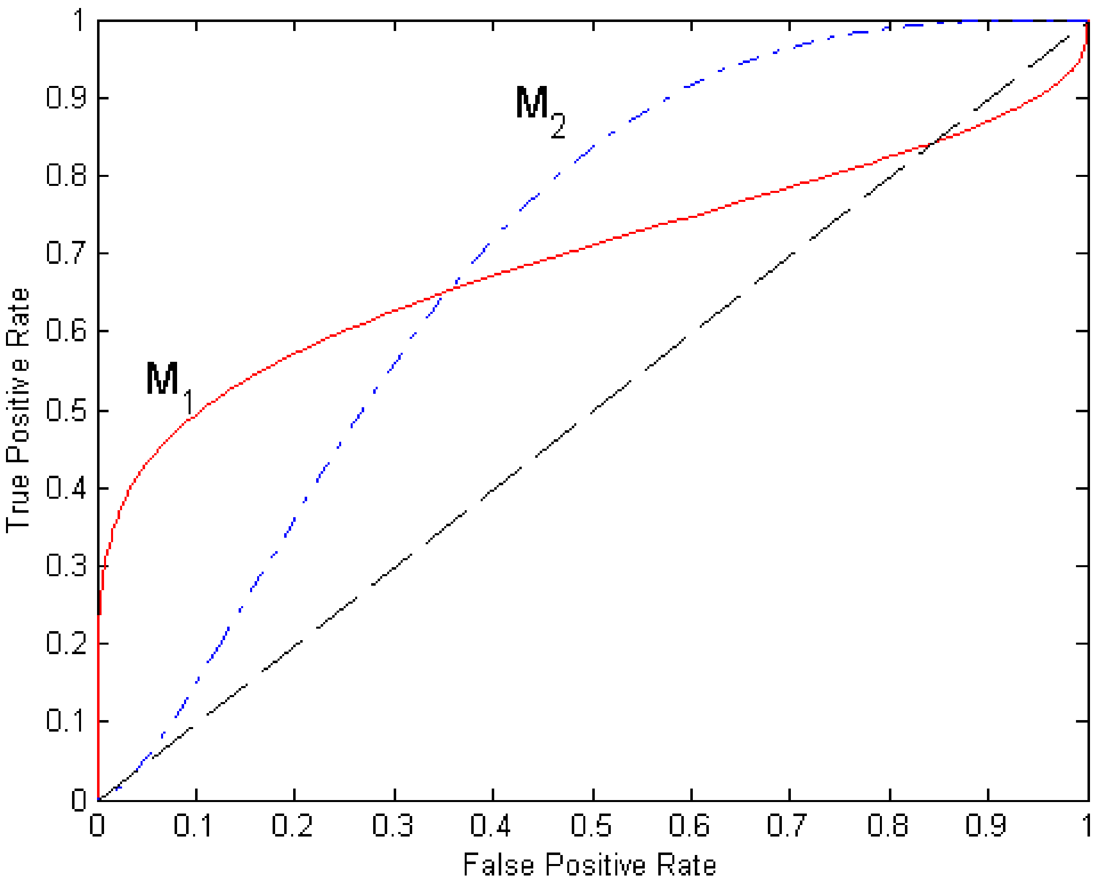
- Any points located at x > t is classified as positive



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

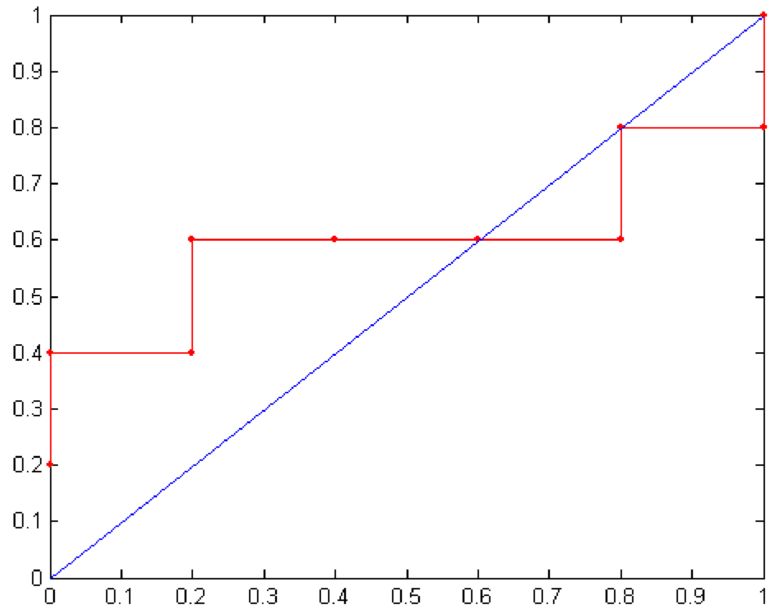
Instance	Score	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

- 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:



Handling Class Imbalanced Problem

- Class-based ordering (e.g. RIPPER)
  – Rules for rare class have higher priority

- Cost-sensitive classification
  – Misclassifying rare class as majority class is more expensive than misclassifying majority as rare class

- Sampling-based approaches

Cost Matrix

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	f(Yes, Yes)	f(Yes,No)
	Class=No	f(No, Yes)	f(No, No)

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

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

$$\text{Cost} = \sum C(i, j) \times f(i, j)$$

Computing Cost of Classification

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

Model M_1	PREDICTED CLASS		
ACTUAL CLASS		+	-
	+	150	40
	-	60	250

Model M_2	PREDICTED CLASS		
ACTUAL CLASS		+	-
	+	250	45
	-	5	200

Accuracy = 80%

Cost = 3910

Accuracy = 90%

Cost = 4255

Cost Sensitive Classification

- Example: Bayesian classifer
  - Given a test record x:
    - Compute p(i|x) for each class *i*
    - Decision rule: classify node as class k if

$$k = \arg\max_i p(i \mid x)$$

  - For 2-class, classify x as + if p(+|x) > p(-|x)
    - This decision rule implicitly assumes that C(+|+) = C(-|-) = 0 and C(+|-) = C(-|+)

Cost Sensitive Classification

- General decision rule:
  - Classify test record x as class k if

$$k = \arg\min_{j} \sum_{i} p(i \mid x) \times C(i, j)$$

- 2-class:
  - Cost(+) = p(+|x) C(+,+) + p(-|x) C(-,+)
  - Cost(-) = p(+|x) C(+,-) + p(-|x) C(-,-)
  - Decision rule: classify x as + if Cost(+) < Cost(-)
    - if C(+,+) = C(-,-) = 0:

$$p(+ \mid x) > \frac{C(-,+)}{C(-,+) + C(+,-)}$$

Sampling-based Approaches

- Modify the distribution of training data so that rare class is well-represented in training set
  - Undersample the majority class
  - Oversample the rare class

- Advantages and disadvantages