Knowledge Discovery and Data Mining

Unit # 5

Acknowledgement

- Most of the slides in this presentation are taken from course slides provided by
  - Han and Kimber (Data Mining Concepts and Techniques) and
  - Tan, Steinbach and Kumar (Introduction to Data Mining)

Accuracy or Error Rates

- Partition: Training-and-testing
  - use two independent data sets, e.g., training set (2/3), test set(1/3)
  - used for data set with large number of examples

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	
		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)

Metrics for Performance Evaluation…

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

- Most widely-used metric:

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

Limitation of Accuracy

- Consider a 2-class problem
  - Number of Class 0 examples = 9990
  - Number of Class 1 examples = 10
- If model predicts everything to be class 0, accuracy is 9990/10000 = 99.9 %
  - Accuracy is misleading because model does not detect any class 1 example

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

Cost Matrix (Cont'd)

	PREDICTED CLASS		
ACTUAL CLASS		True	False
	True	10	5
	False	1	14

	PREDICTED CLASS		
ACTUAL CLASS		True	False
	True	10	3
	False	3	14

	PREDICTED CLASS		
ACTUAL CLASS		True	False
	True	10	6
	False	0	14

All three confusion matrices have the same accuracy value, i.e., **24 / 30**

What if the cost of misclassification is not the same for both type of errors?

Cost Matrix (Cont'd)

	PREDICTED CLASS		
		True	False
ACTUAL CLASS	True	10	5x5
	False	1	14

	PREDICTED CLASS		
		True	False
ACTUAL CLASS	True	10	3x5
	False	3	14

	PREDICTED CLASS		
		True	False
ACTUAL CLASS	True	10	6x5
	False	0	14

Suppose the cost of misclassifying True as False is 5 while the cost of misclassifying False as True is 1.

Accuracy values are:
24/50, 24/42, 24/54

Cost Matrix (Cont'd)

	PREDICTED CLASS		
		True	False
ACTUAL CLASS	True	10	5x4
	False	1	14

	PREDICTED CLASS		
		True	False
ACTUAL CLASS	True	10	3x4
	False	3	14

	PREDICTED CLASS		
		True	False
ACTUAL CLASS	True	10	6x4
	False	0	14

Suppose the cost of misclassifying True as False is **4** while the cost of misclassifying False as True is 1.

Accuracy values are:
24/45, 24/39, 24/48

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(Yes|Yes) & C(Yes|No)
- Recall is biased towards C(Yes|Yes) & C(No|Yes)
- F-measure is biased towards all except C(No|No)

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

Recall and Precision

Actual	Prediction
T	T
T	F
F	T
F	F
F	T
T	T
T	T
T	F
F	T
T	T

Recall and Precision

Actual	Prediction
T	T
T	F
F	T
F	F
F	T
T	T
T	T
T	F
F	T
T	T

- Recall = 4 / 6

Recall and Precision

Actual	Prediction
T	T
T	F
F	T
F	F
F	T
T	T
T	T
T	F
F	T
T	T

- Recall = 4 / 6
- Precision = 4 / 7
- F-Measure = 8 / 13

Terminology

- True Positive: The number of positive examples correctly predicted by the classification model.
- False Negative: The number of positive examples wrongly predicted as negative by the classification model.
- False Positive: The number of negative examples wrongly predicted as positive by the classification model.
- True Negative: The number of negative examples correctly predicted by the classification model.

Terminology (Cont'd)

- The true positive rate (TPR) or sensitivity is defined as TPR = TP / (TP + FN).
- The true negative rate (TNR) or specificity is defined as TNR = TN / (TN + FP).
- The false positive rate (FPR) is defined as FPR = FP / (TN + FP).
- The false negative rate (FNR) is defined as FNR = FN / (TP + FN).

ROC (Receiver Operating Characteristic)

- Developed in 1950s for signal detection theory to analyze noisy signals
  - Characterize the trade-off between positive hits and false alarms
- ROC curve plots TPR (on the y-axis) against FPR (on the x-axis)
- Remember that TPR represents “sensitivity” while FPR represents “100 – specificity”.

How to Construct an ROC curve

Instance	P(+|A)	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	+

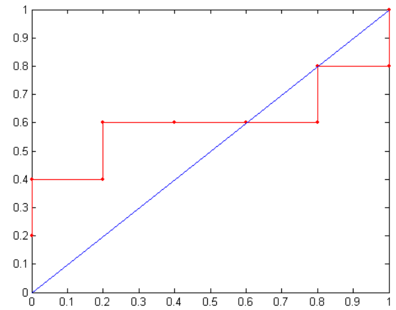
- Use classifier that produces posterior probability for each test instance P(+|A)
- Sort the instances according to P(+|A) in decreasing order
- Apply threshold at each unique value of P(+|A)
- Count the number of TP, FP, TN, FN at each threshold
- TP rate, TPR = TP/(TP+FN)
- FP rate, FPR = FP/(FP + TN)

How to construct an ROC curve

Threshold >=

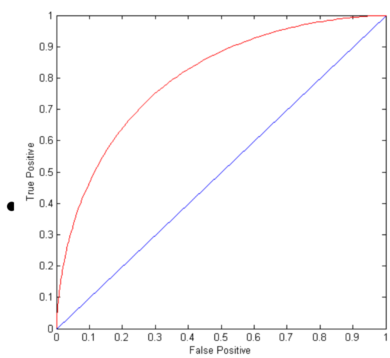
Class	+	-	+	-	-	-	+	-	+	+	
	0.25	0.43	0.53	0.76	0.85	0.85	0.85	0.87	0.93	0.95	1.00
TP	5	4	4	3	3	3	3	2	2	1	0
FP	5	5	4	4	3	2	1	1	0	0	0
TN	0	0	1	1	2	3	4	4	5	5	5
FN	0	1	1	2	2	2	2	3	3	4	5
TPR	1	0.8	0.8	0.6	0.6	0.6	0.6	0.4	0.4	0.2	0
FPR	1	1	0.8	0.8	0.6	0.4	0.2	0.2	0	0	0

ROC Curve:



ROC Curve

- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.
- The area under the curve is a measure of text accuracy.



Lift and Gain Charts

- Very commonly used in the marketing research.
- **Lift** is a measure of the effectiveness of a predictive model calculated as the ratio between the results obtained with and without the predictive model.
- A lift chart consists of a lift curve and a baseline
- The greater the area between the lift curve and the baseline, the better the model

Example

http://www2.cs.uregina.ca/~dbd/cs831/notes/lift_chart/lift_chart.html

- Using the response model P(x)=100-AGE(x) for customer x and the data table, construct the cumulative gains and lift charts. Ties in ranking should be arbitrarily broken by assigning a higher rank to who appears first in the table.

Customer Name	*Height*	*Age*	*Actual Response*
Alan	70	39	N
Bob	72	21	Y
Jessica	65	25	Y
Elizabeth	62	30	Y
Hilary	67	19	Y
Fred	69	48	N
Alex	65	12	Y
Margot	63	51	N
Sean	71	65	Y
Chris	73	42	N
Philip	75	20	Y
Catherine	70	23	N
Amy	69	13	N
Erin	68	35	Y
Trent	72	55	N
Preston	68	25	N
John	64	76	N
Nancy	64	24	Y
Kim	72	31	N
Laura	62	29	Y

Example: Steps 1 & 2

1. Calculate P(*x*) for each person *x*
2. Order the people according to rank P(*x*)

Customer Name	*P(x)*	*Actual Response*
Alex	88	Y
Amy	87	N
Hilary	81	Y
Philip	80	Y
Bob	79	Y
Catherine	77	N
Nancy	76	Y
Jessica	75	Y
Preston	75	N
Laura	71	Y
Elizabeth	70	Y
Kim	69	N
Erin	65	Y
Alan	61	N
Chris	58	N
Fred	52	N
Margot	49	N
Trent	45	N
Sean	35	Y
John	24	N

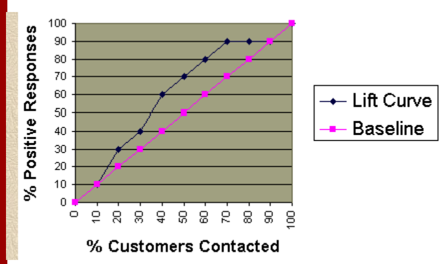
Example: Step 3

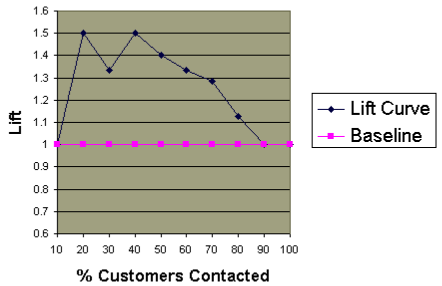
- Calculate the percentage of total responses for each cutoff point
  - Response Rate = Number of Responses / Total Number of Responses (10)

Total Customers Contacted	Number of Responses	Response Rate
2	1	10%
4	3	30%
6	4	40%
8	6	60%
10	7	70%
12	8	80%
14	9	90%
16	9	90%
18	9	90%
20	10	100%

Example: Gains and Lift Charts

- To plot life chart, calculate the points on the lift curve by determining the ratio between the result predicted by our model and the result using no model.





Practice Exercises

- Draw gains and lift charts of data set given on slide 18 .
- Draw ROC for data set given in slide 23.
- Apply supervised and unsupervised discretization techniques on “Attribute 2” of data set given on slide 35 of Unit # 3.
- Form decision trees using Entropy, Gini and Gain_ratio as splitting criteria on the above data set (after discretization).