DATA MINING 2
Performance Evaluation

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Slides edited from Tan, Steinbach, Kumar, Introduction to Data Mining

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https://www.wooclap.com/DM2EVAL

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

Most widely-used metric:

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

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	
C(i|j)	**Class=Yes**	**Class=No**
ACTUAL CLASS — Class=Yes	C(Yes|Yes)	C(No|Yes)
ACTUAL CLASS — Class=No	C(Yes|No)	C(No|No)

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

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 vs Accuracy

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

Cost	PREDICTED CLASS	
ACTUAL CLASS	Class=Yes	Class=No
Class=Yes	p	q
Class=No	q	p

Accuracy is proportional to cost if

1. C(Yes|No)=C(No|Yes) = q
2. C(Yes|Yes)=C(No|No) = p

$N = a + b + c + d$

$\text{Accuracy} = (a + d)/N$

$$\begin{aligned} \text{Cost} &= p\,(a + d) + q\,(b + c) \\ &= p\,(a + d) + q\,(N - a - d) \\ &= q\,N - (q - p)(a + d) \\ &= N\,[q - (q-p) \times \text{Accuracy}] \end{aligned}$$

Cost-Sensitive Measures

$$\text{Precision (p)} = \frac{TP}{TP + FP}$$

$$\text{Recall (r)} = \frac{TP}{TP + FN}$$

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

- 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)

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

Data Partitioning

Dataset

Train | Test — Holdout (e.g.70/30)

Train the model for final testing

Train | Validation | Test

Train the model for parameter selection

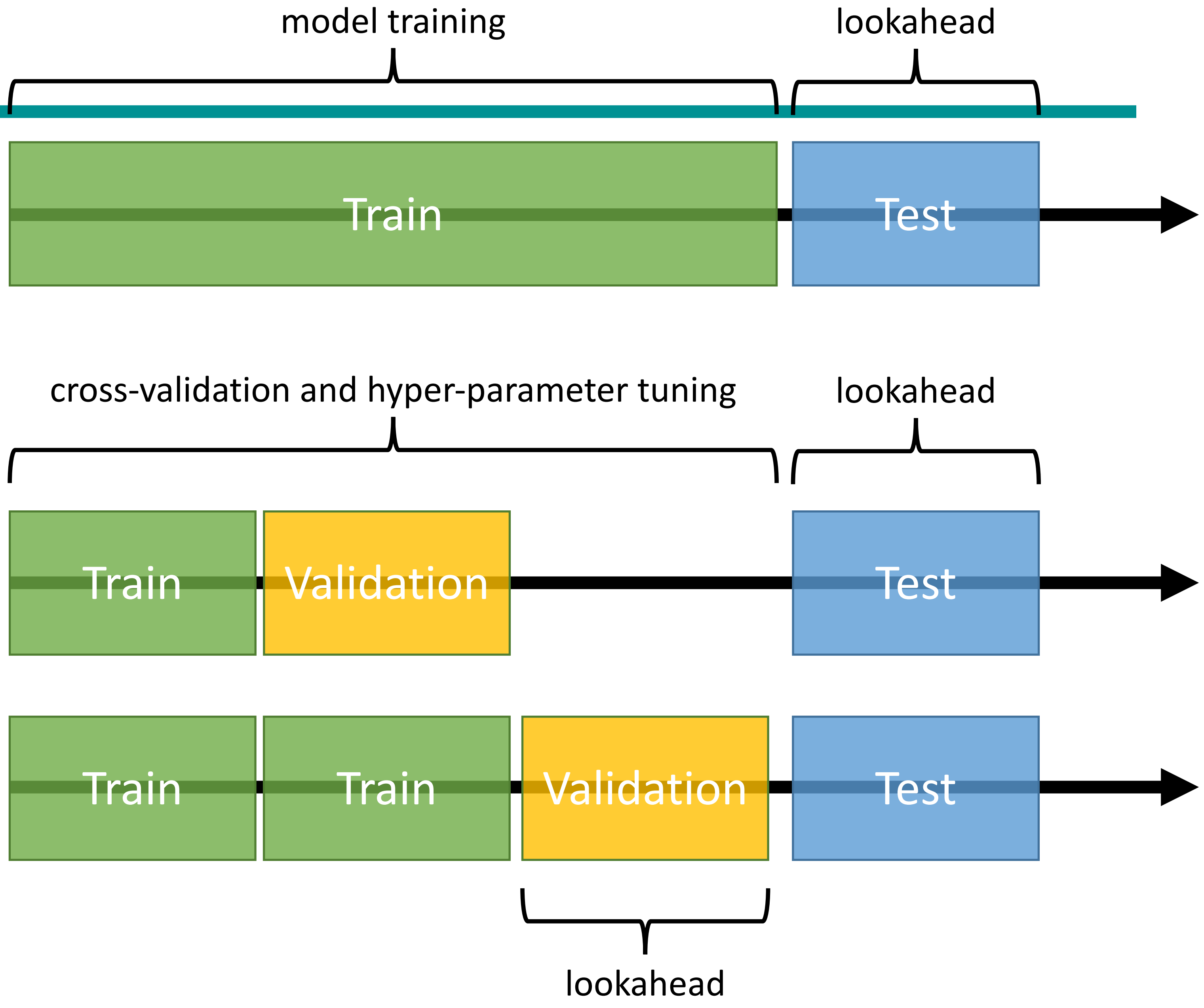
Validate the model (early stopping, parameter selection, etc.)

- Test the model
- Compare different models once parameters have been selected

Test

Cross Validation (check potential dataset bias)

Cross Validation Considering Time



ROC (Receiver Operating Characteristic)

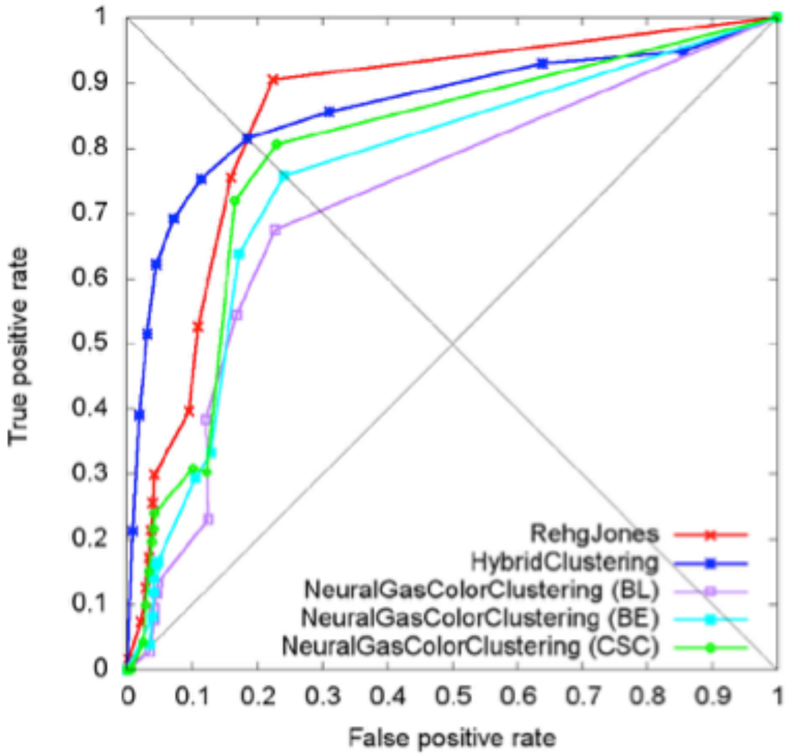
- Developed in 1950s for signal detection theory to analyze noisy signals
  - Characterize the trade-off between positive hits and false alarms

- ROC curve plots TPR (on the y-axis) against FPR (on the x-axis)

- **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

Receiver Operating Characteristic Curve

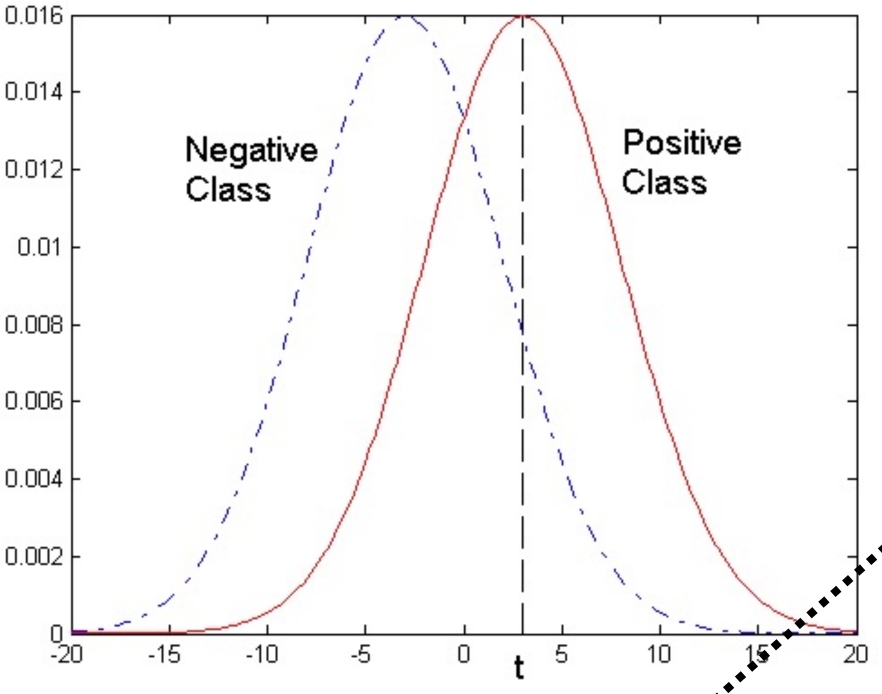
- It illustrates the ability of a binary classifier as its discrimination threshold THR is varied.
- The ***ROC*** curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various THR.
- The TPR = TP / (TP + FN) is also known as ***sensitivity***, ***recall*** or probability of detection.
- The FPR = FP / (TN + FP) is also known as probability of ***false alarm*** and can be calculated as (1 – specificity).

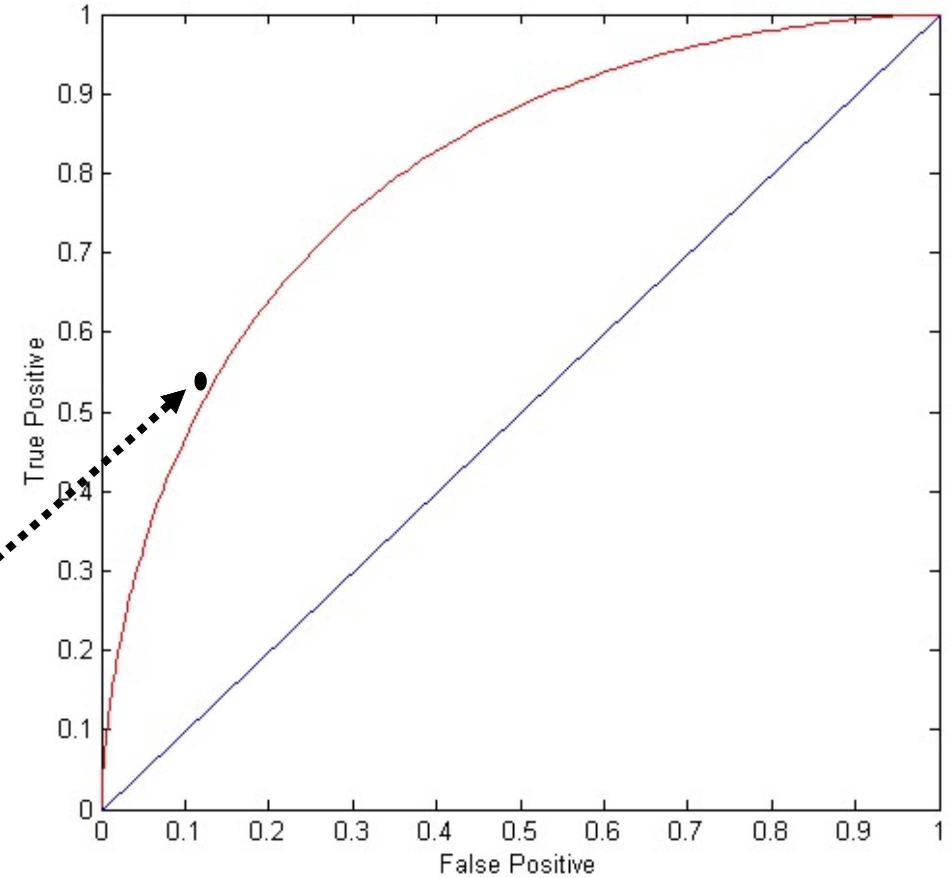


https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5

ROC Curve

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





At threshold t:

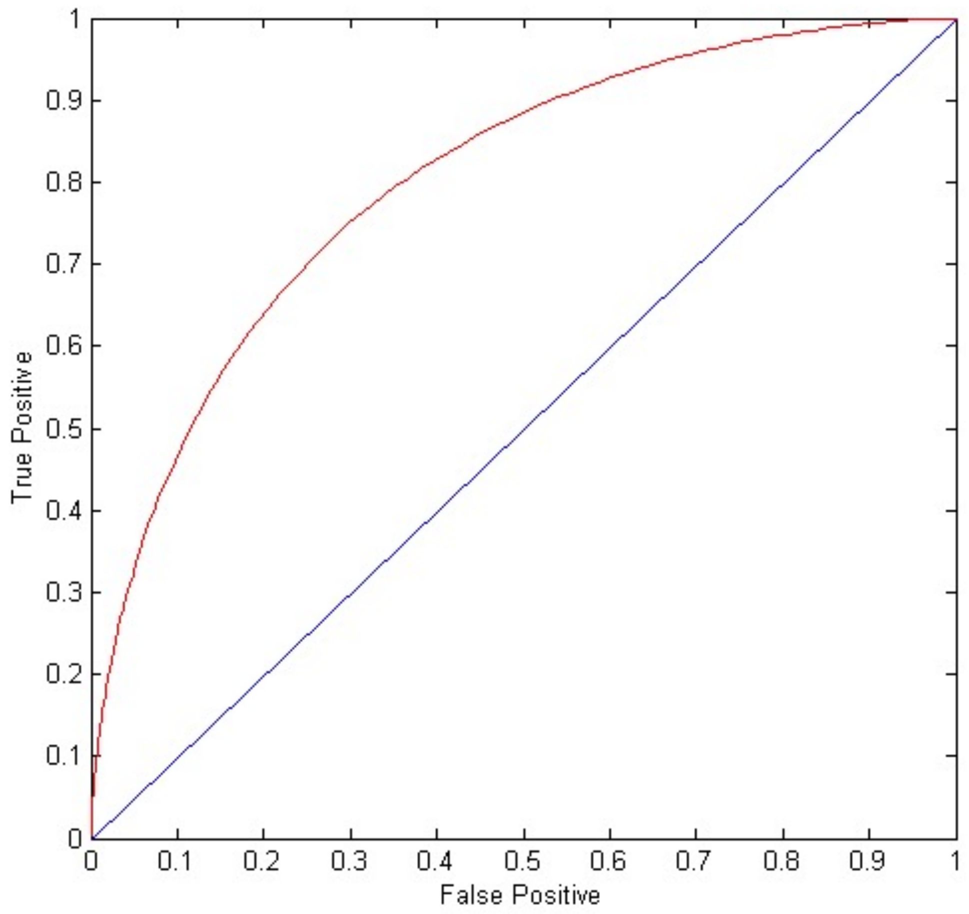
TP=0.5, FN=0.5, FP=0.12, FN=0.88

ROC Curve

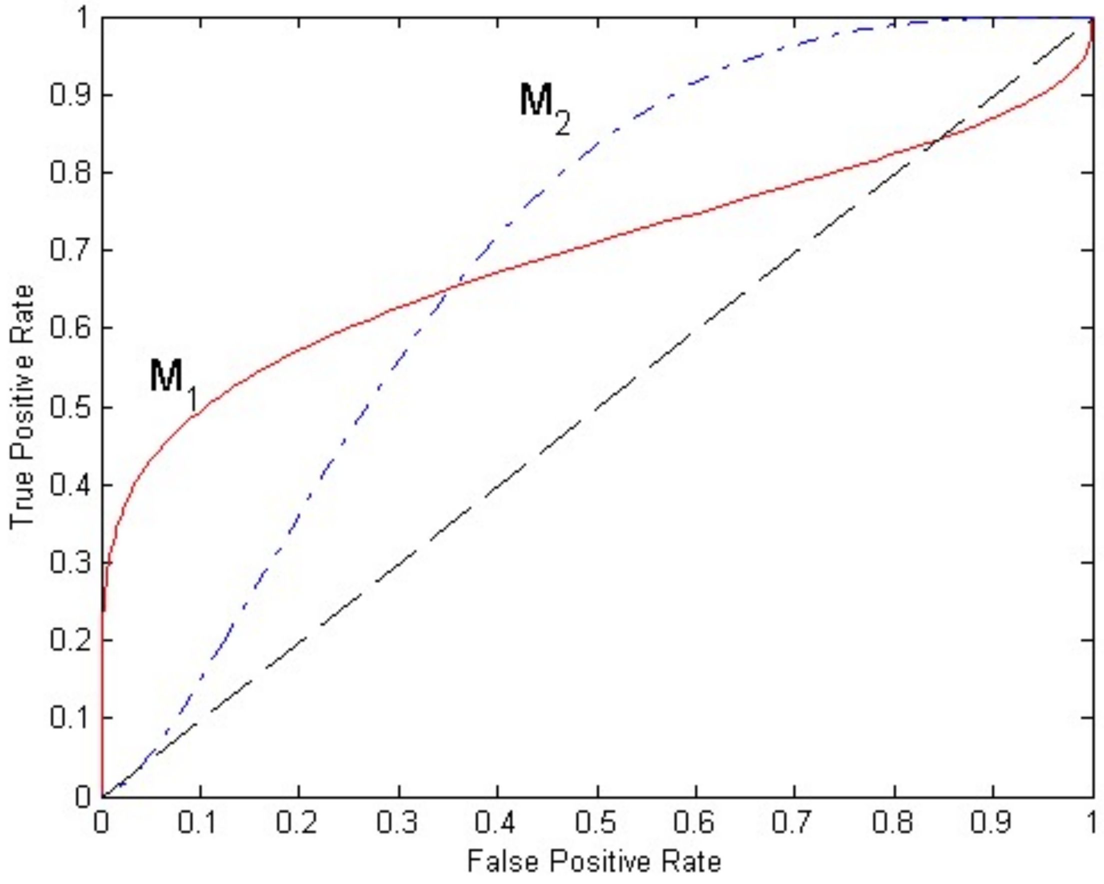
(TP,FP):

- (0,0): declare everything
  to be negative class
- (1,1): declare everything
  to be positive class
- (0,1): ideal

- Diagonal line:
  - Random guessing
  - Below diagonal line:
    - prediction is opposite of the true class



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 a ROC curve

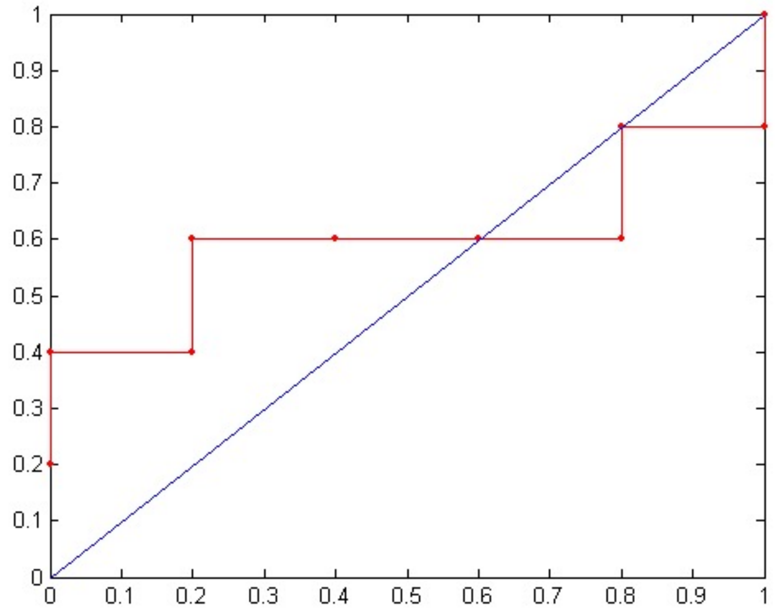
Instance	P(+|A)	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

- 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

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:



Lift Chart

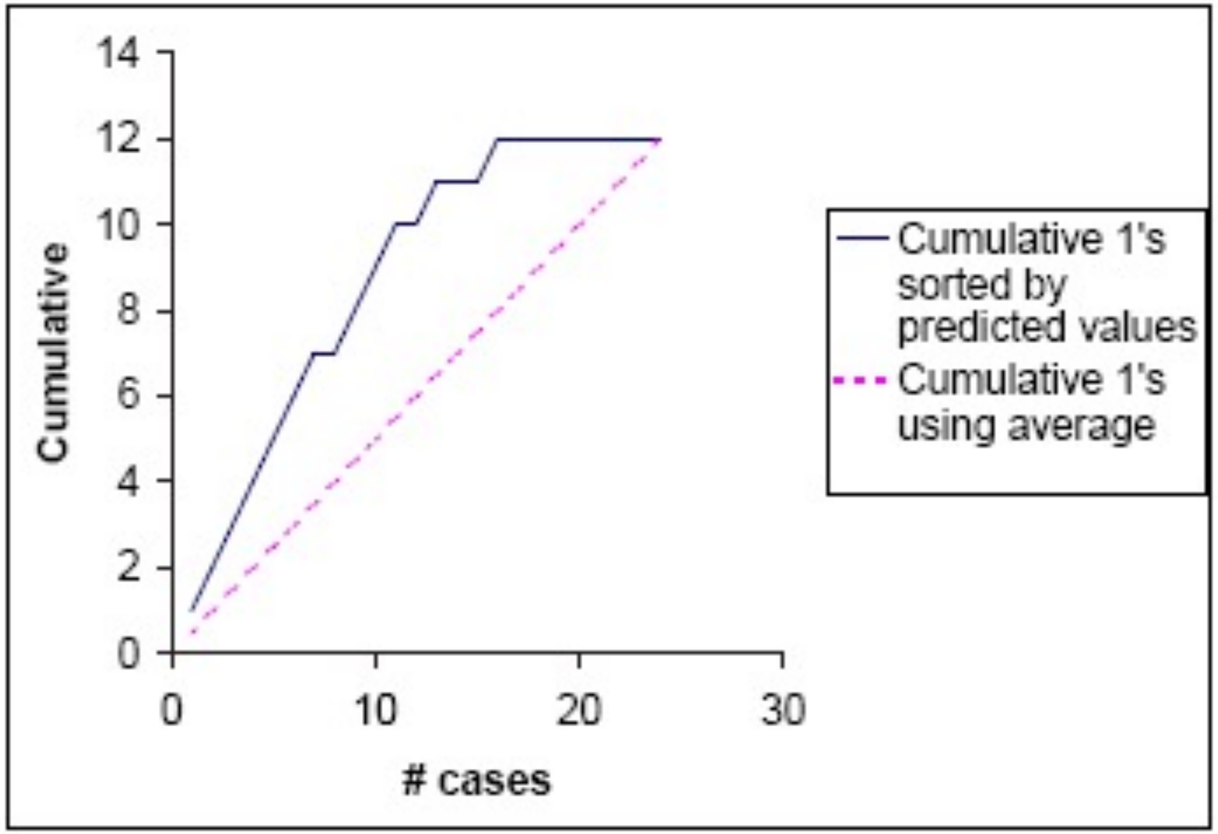
http://www2.cs.uregina.ca/~dbd/cs831/notes/lift_chart/lift_chart.html
http://mlwiki.org/index.php/Cumulative_Gain_Chart

- The lift curve is a popular technique in direct marketing.
- The input is a dataset that has been "scored'' by appending to each case the estimated probability that it will belong to a given class.
- The cumulative ***lift chart*** (also called ***gains chart***) is constructed with the cumulative number of cases (descending order of probability) on the x-axis and the cumulative number of true positives on the y-axis.
- The dashed line is a reference line. For any given number of cases (the x-axis value), it represents the expected number of positives we would predict if we did not have a model but simply selected cases at random. It provides a benchmark against which we can see performance of the model.

Notice: "Lift chart" is a rather general term, often used to identify also other kinds of plots. Don't get confused!

Lift Chart – Example

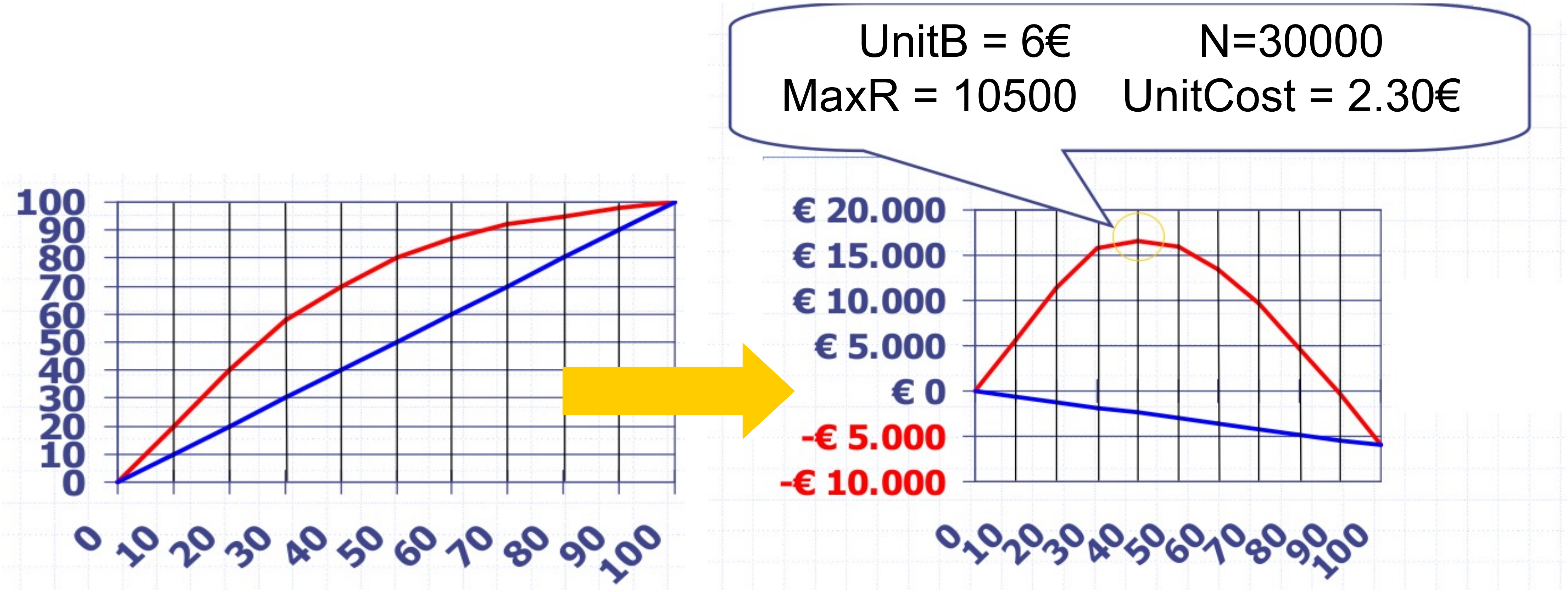
Serial no.	Predicted prob of 1	Actual Class	Cumulative Actual class
1	0.995976726	1	1
2	0.987533139	1	2
3	0.984456382	1	3
4	0.980439587	1	4
5	0.948110638	1	5
6	0.889297203	1	6
7	0.847631864	1	7
8	0.762806287	0	7
9	0.706991915	1	8
10	0.680754087	1	9
11	0.656343749	1	10
12	0.622419543	0	10
13	0.505506928	1	11
14	0.47134045	0	11
15	0.337117362	0	11
16	0.21796781	1	12
17	0.199240432	0	12
18	0.149482655	0	12
19	0.047962588	0	12
20	0.038341401	0	12
21	0.024850999	0	12
22	0.021806029	0	12
23	0.016129906	0	12
24	0.003559986	0	12



Lift Chart – Application Example

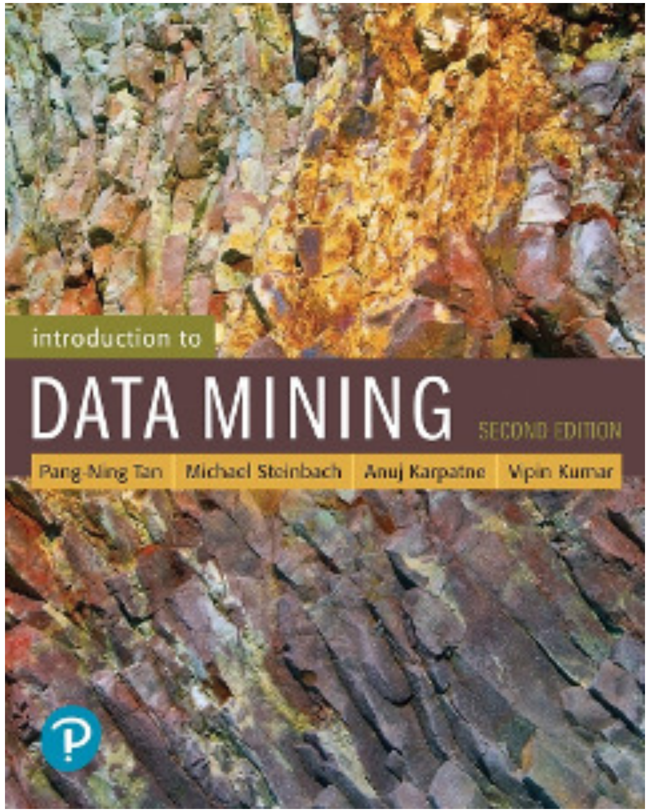
- From Lift chart we can easily derive an "economical value" plot, e.g. in target marketing.
- Given our predictive model, how many customers should we target to maximize income?
- Profit = UnitB*MaxR*Lift(X) - UnitCost*N*X/100
- UnitB = unit benefit, UnitCost = unit postal cost
- N = total customers
- MaxR = expected potential respondents in all population (N)
- Lift(X) = lift chart value for X, in [0,..,1]

Lift Chart – Application Example



References

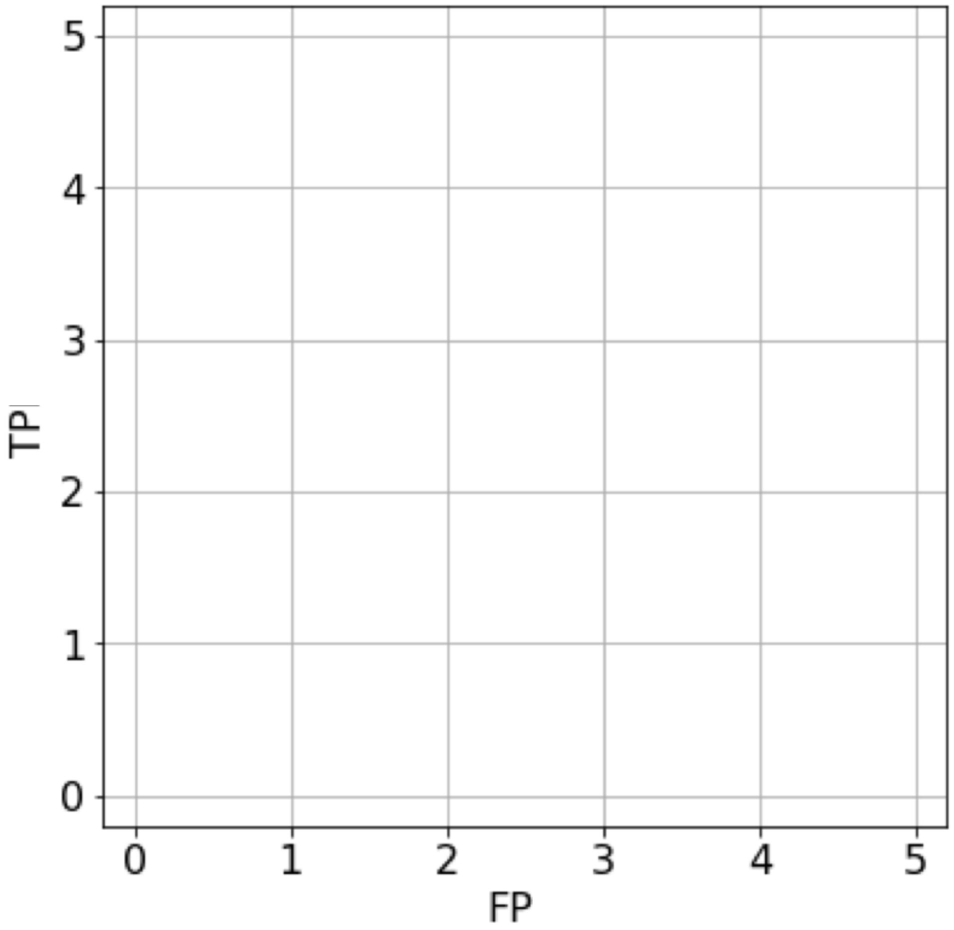
- Chapter 3. Classification: Basic Concepts and Techniques.



Exercises – ROC & Lift Chart

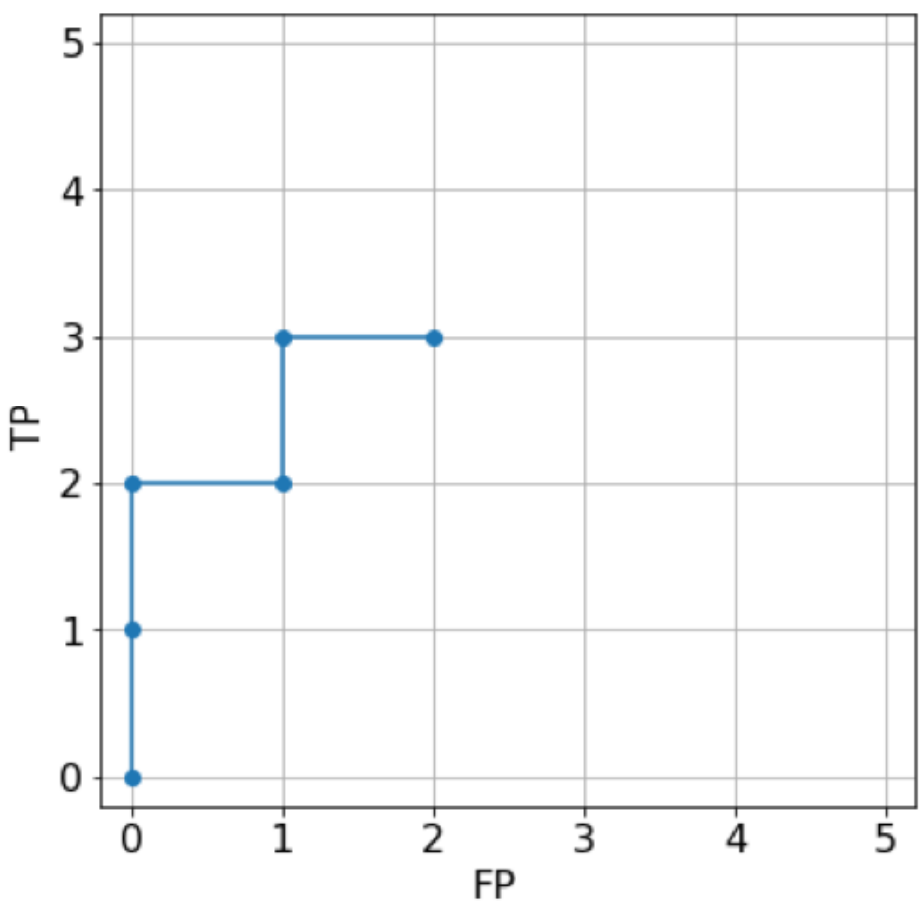
ROC Exercise

Predicted	Real	Score
No	Yes	0.8
No	No	0.4
Yes	No	0.7
Yes	Yes	0.9
Yes	Yes	0.6



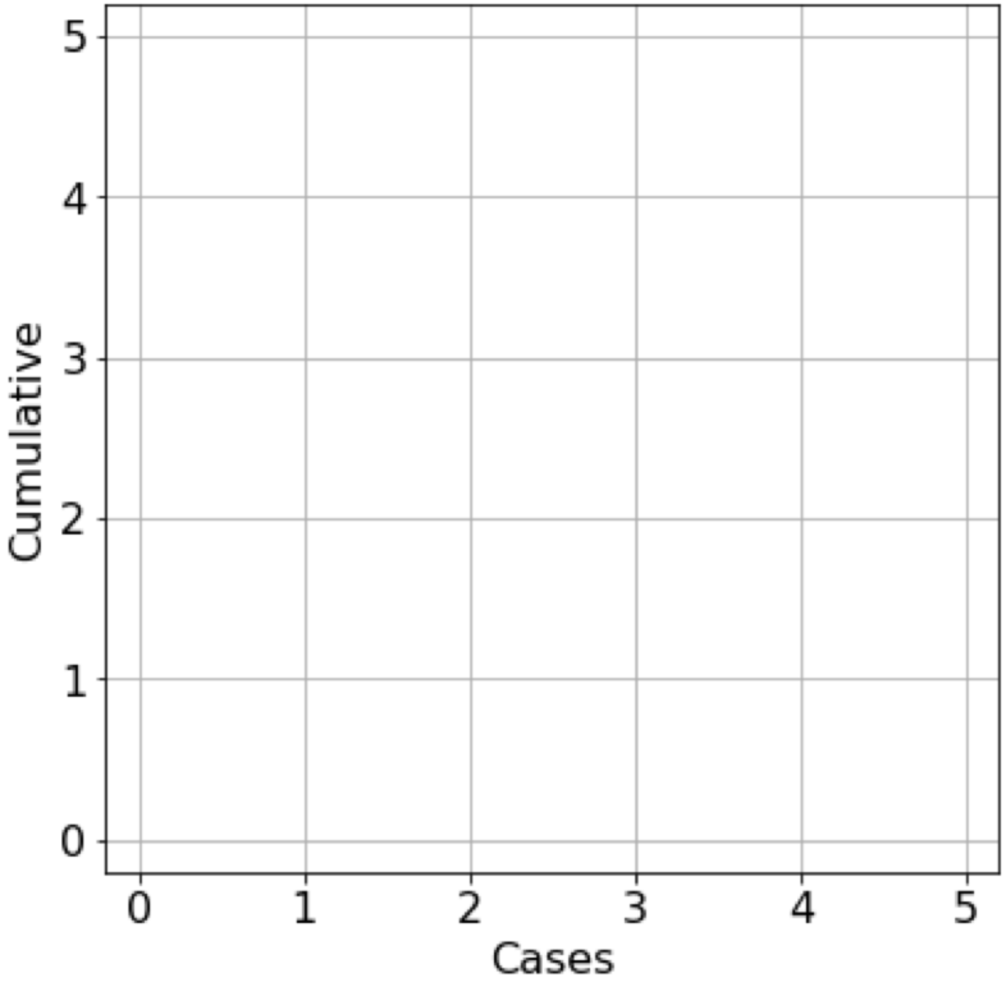
ROC Exercise Solution

Predicted	Real	Score	FP	TP
Yes	Yes	0.9	0	1
No	Yes	0.8	0	2
Yes	No	0.7	1	2
Yes	Yes	0.6	1	3
No	No	0.4	2	3



Lift Exercise

Real	Score
Yes	0.8
No	0.4
No	0.7
Yes	0.9
Yes	0.6



Lift Exercise Solution

Real	Score	Cases	Cumulative
Yes	0.9	0	1
Yes	0.8	1	2
No	0.7	2	2
Yes	0.6	3	3
No	0.4	4	3