Module No. 01

Performance Measures

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Confusion Matrix

Understand some basic terminologies

- Now we know what is classification, how classifiers works so we may built a classification model
- For example, suppose you used sales data to build a classifier to predict customer purchasing behaviour
- In this example we would like to analyse how our model can predict the purchasing behaviour of future customers.(data on which classifier has not been trained)
- We may built different classifiers and we can compare their accuracy/performance by applying various evaluation matrices

Class-Labeled Training Tuples from the *AllElectronics* Customer Database

RID	*age*	*income*	*student*	*credit_rating*	*Class: buys_computer*
1	youth	high	no	fair	no
2	youth	high	no	excellent	no
3	middle_aged	high	no	fair	yes
4	senior	medium	no	fair	yes
5	senior	low	yes	fair	yes
6	senior	low	yes	excellent	no
7	middle_aged	low	yes	excellent	yes
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes
10	senior	medium	yes	fair	yes
11	youth	medium	yes	excellent	yes
12	middle_aged	medium	no	excellent	yes
13	middle_aged	high	yes	fair	yes
14	senior	medium	no	excellent	no

Confusion Matrix

Understand some basic terminologies

- MODEL : a model is created by applying an algorithms(or statistical calculations) to data to generate predictions/classifications of new data.
- Given data set is partitioned into subsets

  Training data set

  Testing data set
- Training data set: training data set is used to derive the model or train the model
- Testing data set: the models accuracy is estimated by using testing data set

ML Confusion Matrix

Understand some basic terminologies

- **Positive tuples** : positive tuples of the class attribute (in our last example positive tuples are *buys_computer= yes)*
- **Negative tuples** : negative tuples of the class attribute (in our last example negative tuples are *buys_computer= no)*
- Suppose we use our classifier on a test set of labeled tuples.
- P is the number of positive tuples and N is the number of negative tuples.
- For each tuple, we compare the classifier's class attribute prediction with the tuple's known class attribute value.

Confusion Matrix

There are four additional terms we need to know that are

- **True positives (TP):** These refer to the positive tuples that were correctly labeled by the classifier. Let TP be the number of true positives.
- **True negatives (TN):** These are the negative tuples that were correctly labeled by the classifier. Let TN be the number of true negatives.
- **False positives (FP):** These are the negative tuples that were incorrectly labeled as positive (e.g., tuples of class *buys_computer=no* for which the classifier predicted *buys_computer=yes*). Let FP be the number of false positives.
- **False negatives (FN):** These are the positive tuples that were mislabeled as negative (e.g., tuples of class *buys_computer=yes* for which the classifier predicted *buys_computer=no*). Let FN be the number of false negatives.

ML Confusion Matrix

Labeled Samples:

RID	age	income	student	credit_rating	buys_computer
1	youth	high	no	fair	no
2	youth	high	no	excellent	no
3	middle_aged	high	no	fair	yes
4	senior	medium	no	fair	yes
5	senior	low	yes	fair	yes
6	senior	low	yes	excellent	no
7	middle_aged	low	yes	excellent	yes
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes
10	senior	medium	yes	fair	yes
11	youth	medium	yes	excellent	yes
12	middle_aged	medium	no	excellent	yes
13	middle_aged	high	yes	fair	yes
14	senior	medium	no	excellent	no

Classification Model

Classification Results

RID	age	income	student	credit_rating	buys_computer
1	youth	high	no	fair	no yes
2	youth	high	no	excellent	no
3	middle_aged	high	no	fair	yes no
4	senior	medium	no	fair	yes
5	senior	low	yes	fair	yes
6	senior	low	yes	excellent	no yes
7	middle_aged	low	yes	excellent	yes
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes no
10	senior	medium	yes	fair	yes
11	youth	medium	yes	excellent	yes
12	middle_aged	medium	no	excellent	yes
13	middle_aged	high	yes	fair	yes no
14	senior	medium	no	excellent	no

TP= TN= FP= FN=

ML Confusion Matrix

Confusion Matrix

- The confusion matrix is a useful tool for analyzing how well your classifier can recognize tuples of different classes.
- TP and TN tell us when the classifier is getting things right, while FP and FN tell us when the classifier is getting things wrong.

		Predicted class		
		yes	*no*	Total
Actual class	*yes*	*TP*	*FN*	*P*
	no	*FP*	*TN*	*N*
	Total	P'	N'	$P + N$

Confusion matrix, shown with totals for positive and negative tuples.

Confusion Matrix

Precision — Out of all the examples that predicted as positive, how many are really positive?

Recall — Out of all the positive examples, how many are predicted as positive?

Specificity — Out of all the people that do **not** have the disease, how many got negative results?

Sensitivity — Out of all the people that have the disease, how many got positive test results?

Confusion Matrix

Confusion Matrix

- E.g. suppose in a data set of the customers who buys the computer, there are total 10000 tuples, out of that 7000 are positive and 3000 are negative and our model has predicated 6954 are positive and 2588 are negative, so prepare confusion matrix

Predicted class

Actual class	yes	no	Total
yes	TP	FN	P
no	FP	TN	N
Total	P'	N'	$P+N$

Classes	$buys\_computer = yes$	$buys\_computer = no$	Total
$buys\_computer = yes$	6954		7000
$buys\_computer = no$		2588	3000
Total			10,000

Confusion matrix for the classes $buys\_computer = yes$ and $buys\_computer = no$,

ML Confusion Matrix

Confusion Matrix

- E.g. suppose in a data set of the customers who buys the computer, there are total 10000 tuples, out of that 7000 are positive and 3000 are negative and our model has predicated 6954 are positive and 2588 are negative, so the confusion matrix will be

Classes	buys_computer = yes	buys_computer = no	Total
buys_computer = yes	6954	46	7000
buys_computer = no	412	2588	3000
Total	7366	2634	10,000

Confusion matrix for the classes *buys_computer* = *yes* and *buys_computer* = *no*,

Confusion Matrix

PREDICTED

ACTUAL

	DOG	CAT	RABBIT	TOTAL
DOG	25	5	10	40
CAT	0	30	4	34
RABBIT	4	10	20	34
TOTAL	29	45	34	

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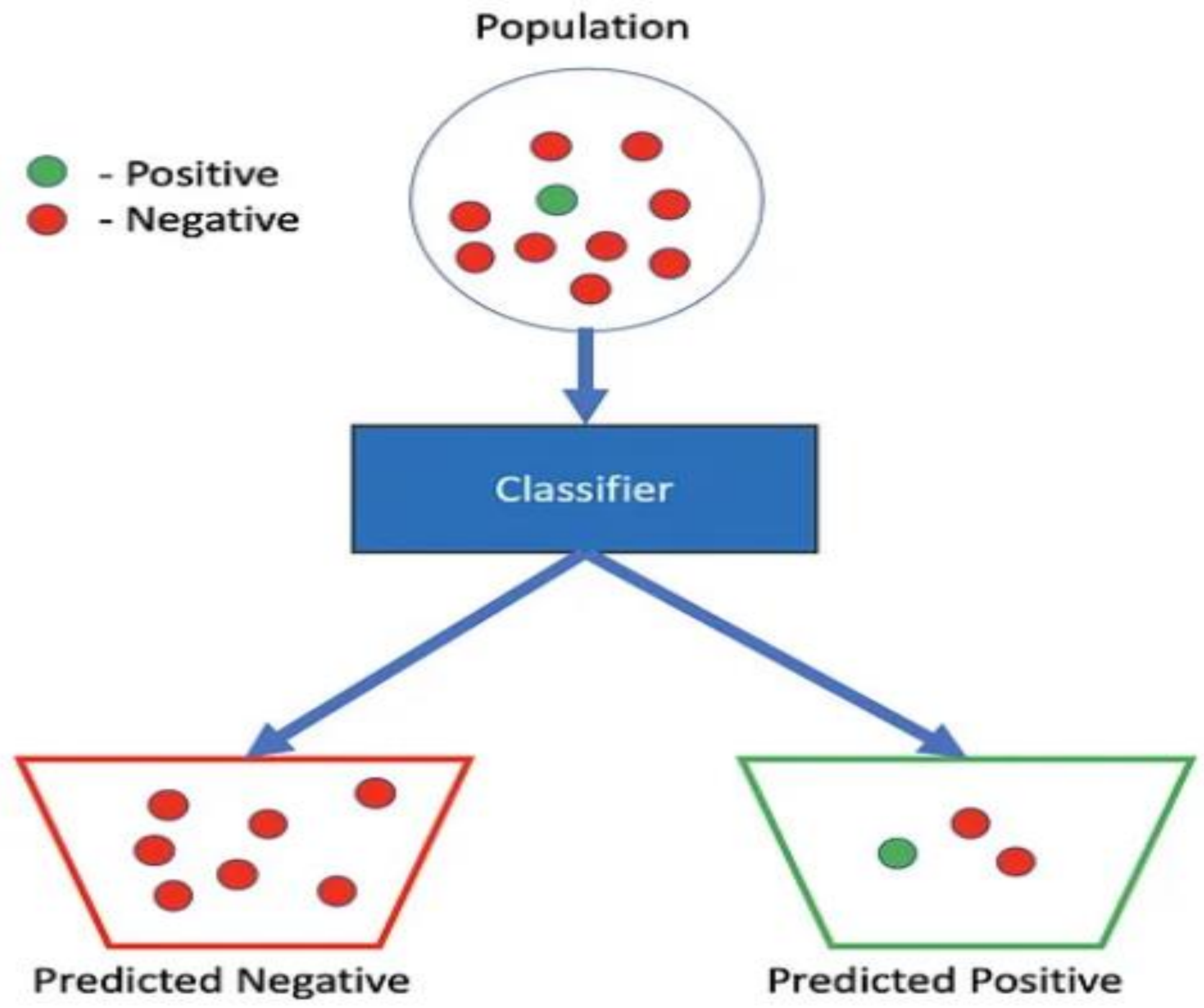
Confusion Matrix



Confusion Matrix

Classifiers performance evaluation measures

Measure	Formula
accuracy	$\frac{TP+TN}{P+N}$
error rate	$\frac{FP+FN}{P+N}$
sensitivity, true positive rate	$\frac{TP}{P}$
specificity, true negative rate	$\frac{TN}{N}$
precision	$\frac{TP}{TP+FP}$

Evaluation measures. Note that some measures are known by more than one name. TP, TN, FP, P, N refer to the number of true positive, true negative, false positive, positive, and negative samples, respectively

ML Confusion Matrix

Find all evaluation measures for the following confusion matrix

Classes	*buys_computer = yes*	*buys_computer = no*	*Total*
buys_computer = yes	6954	46	7000
buys_computer = no	412	2588	3000
Total	7366	2634	10,000

Confusion matrix for the classes *buys_computer = yes* and *buys_computer = no*,

ML Confusion Matrix

Find all evaluation measures for the following confusion matrix

- E.g. suppose in a data set of the cancer, there are total 10000 tuples, out of that 300 are positive and 9700 are negative and our model has predicated 90 are positive and 9560 are negative, so prepare confusion matrix and Find all evaluation measures for the confusion matrix

Predicted class

Actual class	yes	no	Total
yes	TP	FN	P
no	FP	TN	N
Total	P'	N'	P + N

Classes	Cancer = yes	bu; Cancer = no	Total
Cancer = yes			
Cancer = no			
Total			

Confusion Matrix

Find all evaluation measures for the following confusion matrix

- We have a data-set where we are predicting number of people who have more than Rs 1000 in their bank account. Consider a data-set with 200 observations i.e. n=200

Predicted class

Actual class	yes	no	Total
yes	$TP = 125$	$FN = 5$	P
no	$FP = 10$	$TN = 60$	N
Total	P'	N'	$P + N$

- Out of 200 cases, our classification model predicted “YES” 135 times, and “NO” 65 times *
- Out of 200 cases, our classification model predicted “YES” 125 times, and “NO” 65 times.
- Out of 200 cases, our classification model predicted “YES” 135 times, and “NO” 60 times.
- Out of 200 cases, our classification model predicted “YES” 135 times, and “NO” 5 times.

Confusion Matrix

Evaluation measures for the confusion matrix

1. Accuracy:
2. Error rate:
3. Sensitivity: ability to correctly label the positive as positive
4. Specificity: ability to correctly label the negative as negative
5. Precision: % of positive tuples labelled as positive

ML ROC Curves

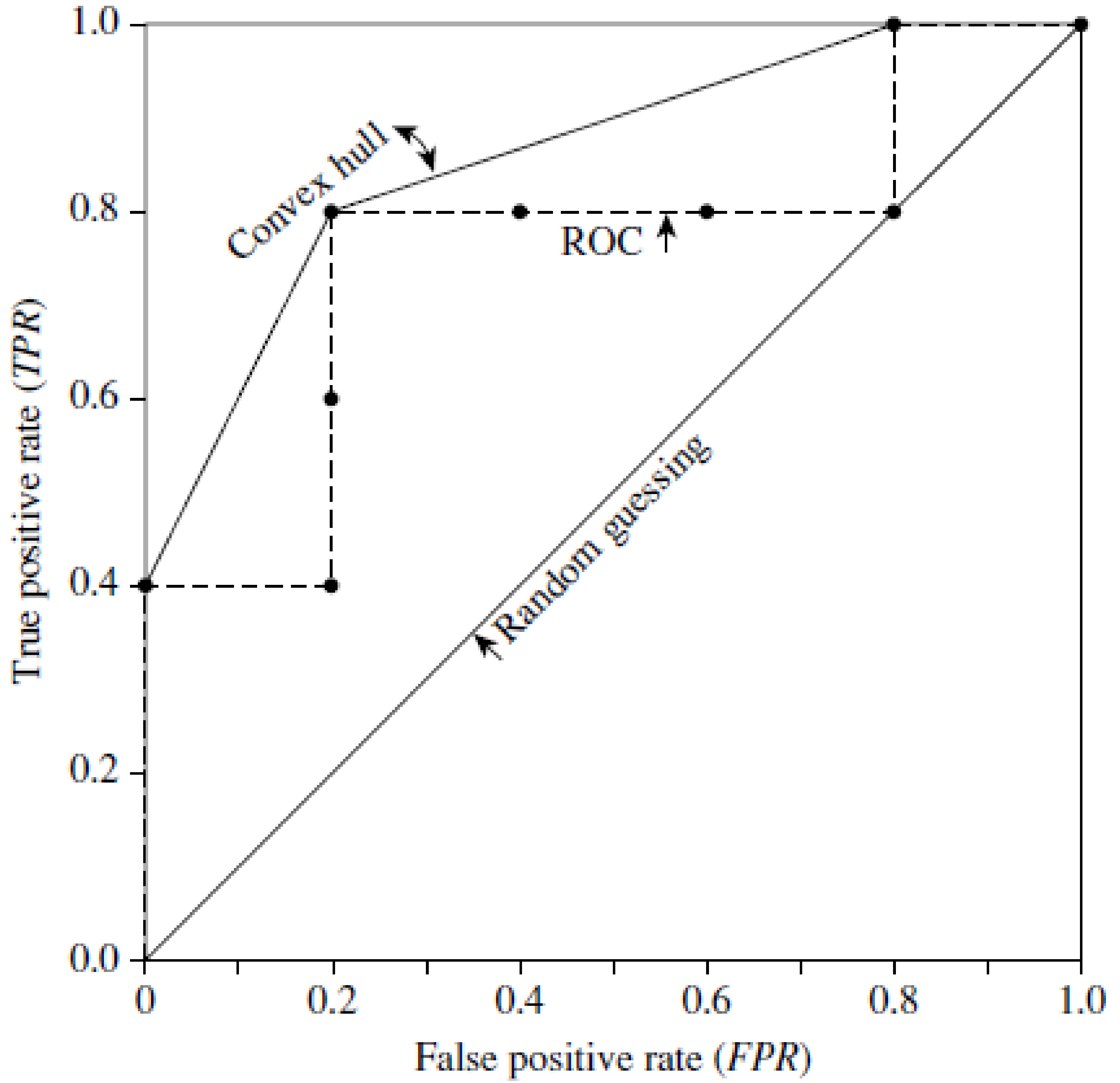
ROC Curves (Receiver operating characteristic curves)

- Useful visual tool for comparing two classification models
- An ROC curve for a given model shows the trade-off between the true positive rate (TPR: Sensitivity) and the false positive rate (FPR: Specificity)
- TPR is the proportion of positive (or “yes”) tuples that are correctly labeled by the model; FPR is the proportion of negative (or “no”) tuples that are mislabelled as positive

ROC Curves

ROC Curves (Receiver operating characteristic curves)

- The vertical axis represents TPR
- The horizontal axis represents FPR
- If we have a true positive then TPR increase we move up and plot a point
- If the model classifies a negative tuple as positive, FPR increase we move right and plot a point
- The area under the ROC curve is a measure of the accuracy of the model



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ROC Curves

ROC Curves (Receiver operating characteristic curves)

Tuple #	Class	Prob.	TP	FP	TN	FN	TPR	FPR
1	P	0.90	1	0	5	4	0.2	0
2	P	0.80	2	0	5	3	0.4	0
3	N	0.70	2	1	4	3	0.4	0.2
4	P	0.60	3	1	4	2	0.6	0.2
5	P	0.55	4	1	4	1	0.8	0.2
6	N	0.54	4	2	3	1	0.8	0.4
7	N	0.53	4	3	2	1	0.8	0.6
8	N	0.51	4	4	1	1	0.8	0.8
9	P	0.50	5	4	0	1	1.0	0.8
10	N	0.40	5	5	0	0	1.0	1.0

Tuples sorted by decreasing score, where the score is the value returned by a probabilistic classifier.

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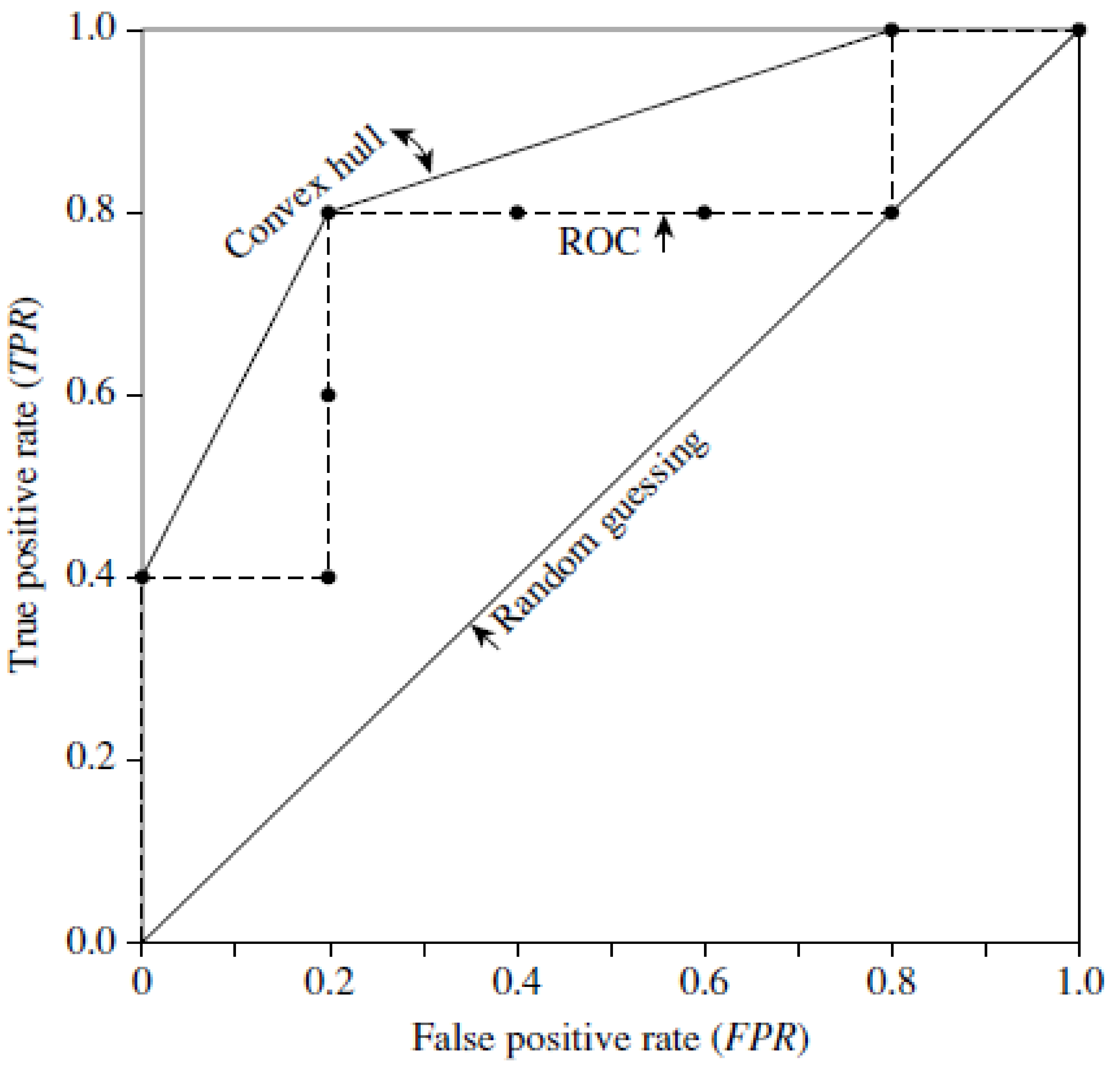
ML ROC Curves

ROC Curves
(Receiver operating
characteristic curves)

Tuple #	Class	Prob.	TP	FP	TN	FN	TPR	FPR
1	P	0.90	1	0	5	4	0.2	0
2	P	0.80	2	0	5	3	0.4	0
3	N	0.70	2	1	4	3	0.4	0.2
4	P	0.60	3	1	4	2	0.6	0.2
5	P	0.55	4	1	4	1	0.8	0.2
6	N	0.54	4	2	3	1	0.8	0.4
7	N	0.53	4	3	2	1	0.8	0.6
8	N	0.51	4	4	1	1	0.8	0.8
9	P	0.50	5	4	0	1	1.0	0.8
10	N	0.40	5	5	0	0	1.0	1.0



ROC Curve for the data given in last table

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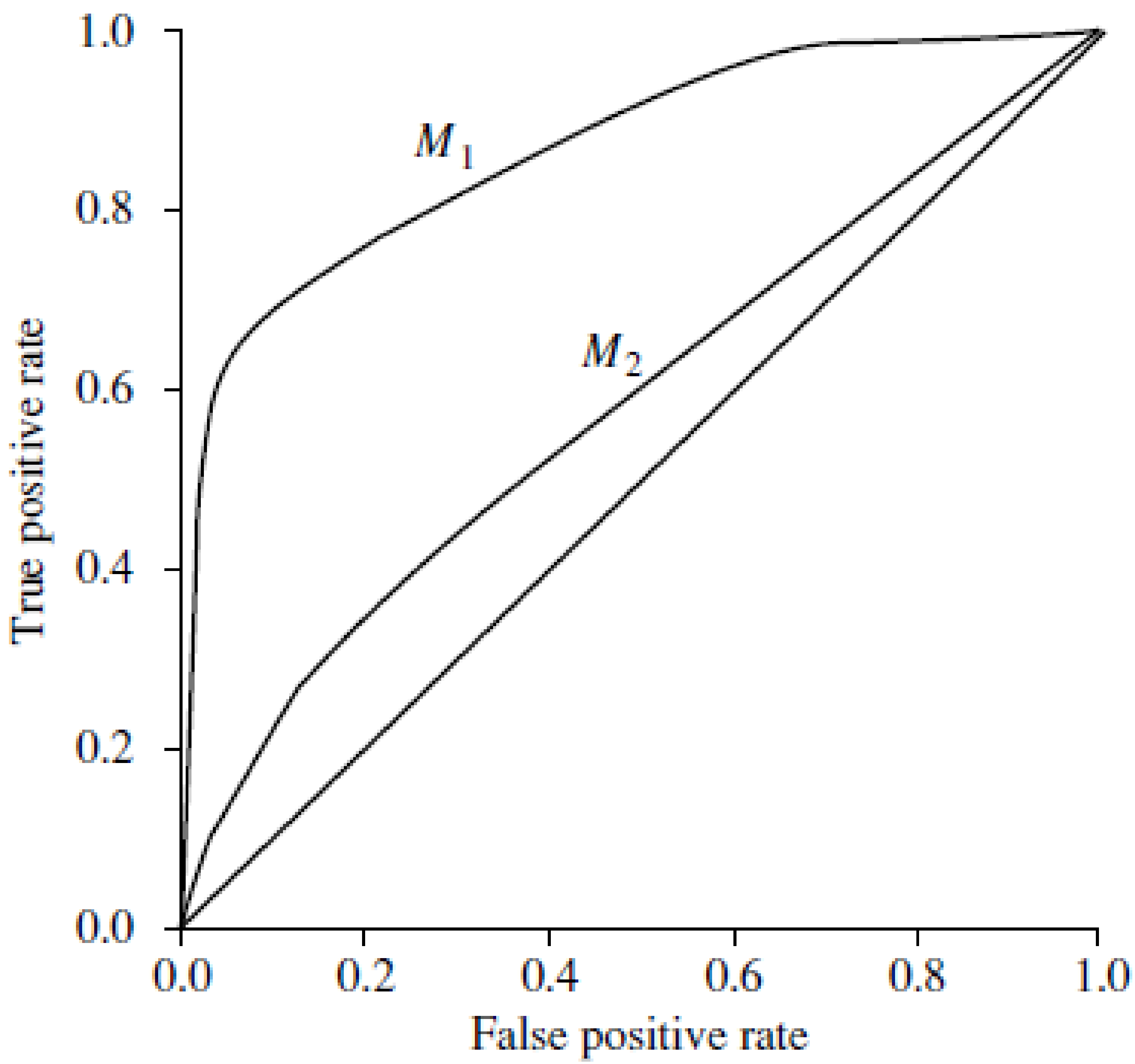
ROC Curves



ROC curves of two classification models, M_1 and M_2.