

DATA SCIENCE

MODEL EVALUATION METRICS FOR CLASSIFICATION

Confusion Matrix: table to describe the performance of classifier

n=165	Predicted: NO	Predicted: YES
	Actual: NO	Actual: YES
	50	10
	5	100

Example: Test for presence of disease

NO = negative test = False = 0

YES = positive test = True = 1

- How many classes are there?
- How many patients?
- How many times is disease predicted?
- How many patients actually have the disease?

CONFUSION MATRIX

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n=165	Predicted:		
	NO	YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Basic Terminology:

- True Positives (TP)
- True Negatives (TN)
- False Positives (FP)
- False Negatives (FN)

Accuracy:

- Overall, how often is it **correct**?
- $(TP + TN) / \text{total} = 150/165 = 0.91$

Misclassification Rate (Error Rate):

- Overall, how often is it **wrong**?
- $(FP + FN) / \text{total} = 15/165 = 0.09$

CONFUSION MATRIX

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n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

False Positive Rate:

- When actual value is **negative**, how often is prediction **wrong**?
- $FP / \text{actual no} = 10/60 = 0.17$

Sensitivity:

- When actual value is **positive**, how often is prediction **correct**?
- $TP / \text{actual yes} = 100/105 = 0.95$
- “True Positive Rate” or “Recall”

Specificity:

- When actual value is **negative**, how often is prediction **correct**?
- $TN / \text{actual no} = 50/60 = 0.83$

Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

Every email is assigned a “spamminess” score by our classification algorithm. To actually make our predictions, we choose a numeric cutoff for classifying as spam.

An ROC Curve will help us to visualize how well our classifier is doing without having to choose a cutoff!

Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

The ROC plots the True Positive Rate (TRP) on the y-axis against the False Positive Rate (FPR) on the x-axis.

TPR: When actual value is **spam**, how often is prediction **correct**?

FPR: When actual value is **ham**, how often is prediction **wrong**?

Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
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1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

TPR: When actual value is **spam**, how often is prediction **correct**?

FPR: When actual value is **ham**, how often is prediction **wrong**?

Cutoff	TPR (y)	FPR (x)	Cutoff	TPR (y)	FPR (x)
0			0.50		
0.05			0.65		
0.15			0.85		
0.25			1		

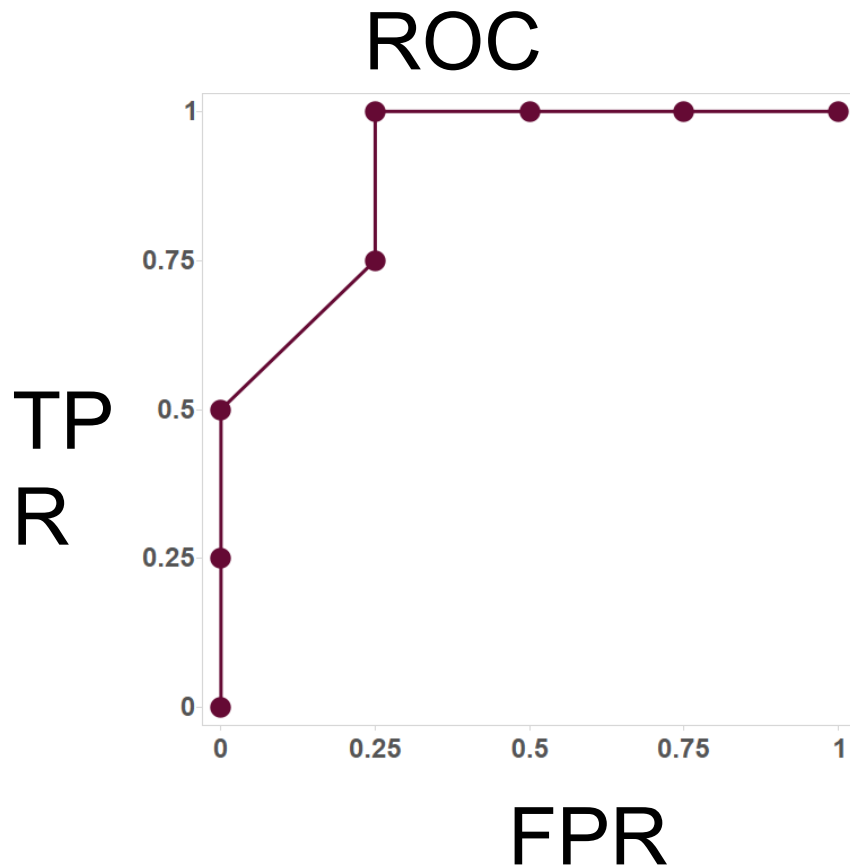
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6	0.02	Ham

TPR: When actual value is **spam**, how often is prediction **correct**?

FPR: When actual value is **ham**, how often is prediction **wrong**?

Cutoff	TPR (y)	FPR (x)	Cutoff	TPR (y)	FPR (x)
0	1	1	0.50	0.75	0.25
0.05	1	0.75	0.65	0.5	0
0.15	1	0.5	0.85	0.25	0
0.25	1	0.25	1	0	0

Email Number	Score	True Label
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7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham



Email Number	Score	True Label
5	0.99	Spam
8	0.98	Spam
2	0.97	Spam
1	0.97	Ham
7	0.96	Spam
3	0.95	Ham
4	0.94	Ham
6	0.93	Ham

Q: Would the ROC Curve (and AUC) change if the **scores** changed but the **ordering** remained the same?

A: Not at all! The ROC Curve is only sensitive to **rank ordering** and does not require **calibrated scores**.