

CLASSIFICATION METRICS

INTRODUCTION

ADVANCED CLASSIFICATION METRICS

ADVANCED CLASSIFICATION METRICS

- ▶ While we've already discussed three different metrics to measure the effectiveness of a classification model, they've only given us an overall picture of how a model is performing.
- ▶ What if we wanted to know exactly how a classifier was performing (e.g. what is predicting correctly vs incorrectly)?

INTRODUCTION

Confusion Matrix

ADVANCED CLASSIFICATION METRICS

- ▶ We can use a confusion matrix to obtain more granular accuracy ratings for of each class by using the *true positive rate* and the *false positive rate*.

		<u>True class</u>	
		p	n
<u>Hypothesized class</u>	Y	True Positives	False Positives
	N	False Negatives	True Negatives
Column totals:		P	N

ADVANCED CLASSIFICATION METRICS

- ▶ The **true positive rate (TPR)** asks, “Out of all of the target classes, how many were accurately predicted to belong to that class?”
- ▶ Using our example, the TPR would be how often does our model correctly identify customer who will default on their credit card debt.

		<u>True class</u>	
		p	n
<u>Hypothesized class</u>	Y	True Positives	False Positives
	N	False Negatives	True Negatives
Column totals:		P	N

tp rate = $\frac{TP}{P}$

ADVANCED CLASSIFICATION METRICS

- ▶ The **false positive rate (FPR)** asks, “Out of all items not belonging to a class, how many were predicted as belonging to that target class label?”
- ▶ Using our example, the FPR would be how often the model predict that a customer will default when they end up not doing so.

		<u>True class</u>	
		p	n
<u>Hypothesized class</u>	Y	True Positives	False Positives
	N	False Negatives	True Negatives
Column totals:		P	N

fp rate = $\frac{FP}{N}$

ADVANCED CLASSIFICATION METRICS

- We can also measure the inverse of TPR/FPR or the false negative rate and the true negative rate (TNR).

		<u>True class</u>		
		p	n	
<u>Hypothesized class</u>	Y	True Positives	False Positives	$\frac{TN}{TN+FN}$
	N	False Negatives	True Negatives	
Column totals:		P	N	

		<u>True class</u>		
		p	n	
<u>Hypothesized class</u>	Y	True Positives	False Positives	$\frac{FN}{TN+FN}$
	N	False Negatives	True Negatives	
Column totals:		P	N	

ADVANCED CLASSIFICATION METRICS

- ▶ These rates gives us a much clearer pictures of where model predictions begin to fall apart and exactly what business cases are being mishandled.
- ▶ This allows us to adjust our models accordingly and use metrics that best align to our business needs.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{TN + FP} = 1 - TNR$$

$$TNR = \frac{TN}{TN + FP}$$

$$FNR = \frac{FN}{TP + FN} = 1 - TPR$$

ADVANCED CLASSIFICATION METRICS

- ▶ Ideally, our classifier would have a TPR approaching 1 and a FPR approaching 0. This would mean that our model is correctly predicting all customers who defaulted and not mistakenly predict that they wouldn't default.
- ▶ We can vary the classification threshold for our model to get different predictions, but how do we know if a model is better overall than other model?
- ▶ We can compare the FPR and TPR of the models, but it can often be difficult to optimize two numbers at once. *Can you think of any ways to combine our two metrics?*

AREA UNDER THE CURVE

- ▶ If we have a TPR of 1 (all positives are marked positive) and FPR of 0 (all negatives are not marked positive), we'd have an AUC of 1. This means everything was accurately predicted.
- ▶ If we have a TPR of 0 (all positives are not marked positive) and an FPR of 1 (all negatives are marked positive), we'd have an AUC of 0. This means nothing was predicted accurately.
- ▶ An AUC of 0.5 would suggest a model no better than random is an excellent benchmark to use for comparing predictions (e.g. is my AUC above 0.5?).

MORE CLASSIFICATION METRICS!

- ▶ There are several other common metrics that are similar to TPR and FPR that can also be useful.

		<u>True class</u>			
		p	n		
<u>Hypothesized class</u>	Y	True Positives	False Positives	$\text{fp rate} = \frac{FP}{N}$	$\text{tp rate} = \frac{TP}{P}$
	N	False Negatives	True Negatives	$\text{precision} = \frac{TP}{TP+FP}$	$\text{recall} = \frac{TP}{P}$
Column totals:		P	N	$\text{accuracy} = \frac{TP+TN}{P+N}$	
				$\text{F-measure} = \frac{2}{1/\text{precision} + 1/\text{recall}}$	

- ▶ Sklearn has

INTRODUCTION

Building a Confusion Matrix

HOW... MEASURE PERFORMANCE?

Confusion Matrix: table to describe the performance of a 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?*

CLASSIFICATION

CONFUSION MATRIX

n=165	Predicted: NO	Predicted: 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**?*
- *$(TP + TN) / total = 150 / 165 = 0.91$*

Misclassification Rate (Error Rate):

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

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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**?
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INTRODUCTION

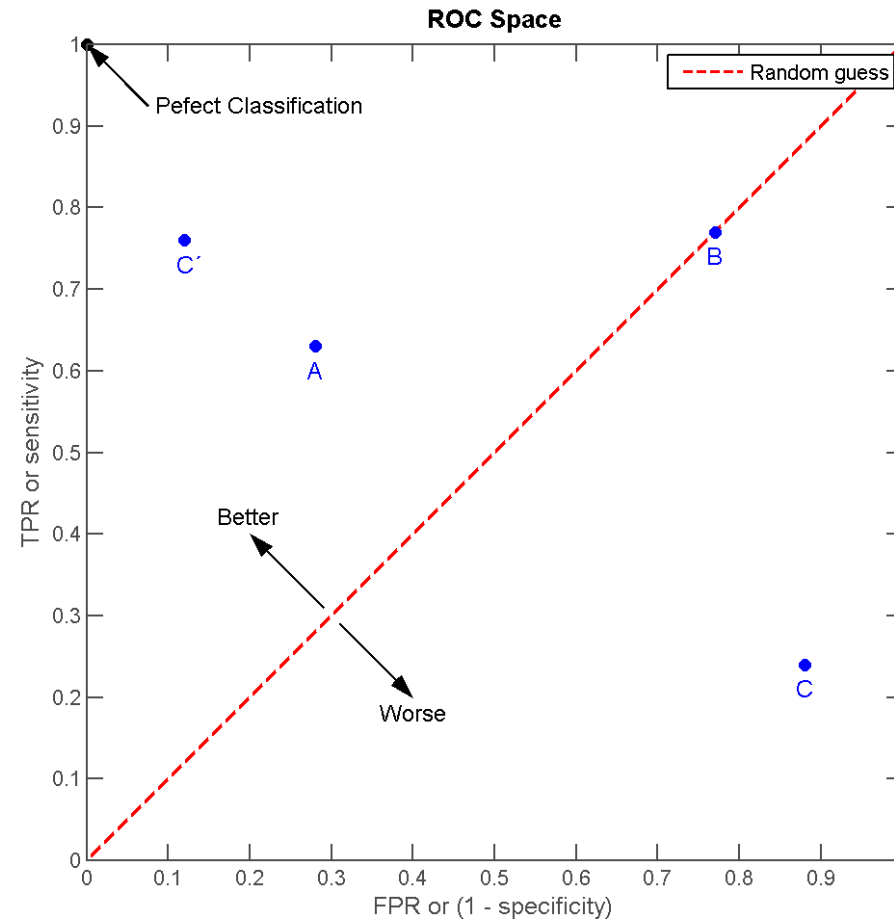
ROC AUC

THE ROC CURVE

- ▶ This is where the Receiver Operation Characteristic (ROC) curve comes in handy.
- ▶ The curve is created by plotting the TPR against the FPR at various model classification settings.
- ▶ Area Under the Curve (AUC) summarizes the impact of TPR and FPR in a single value.

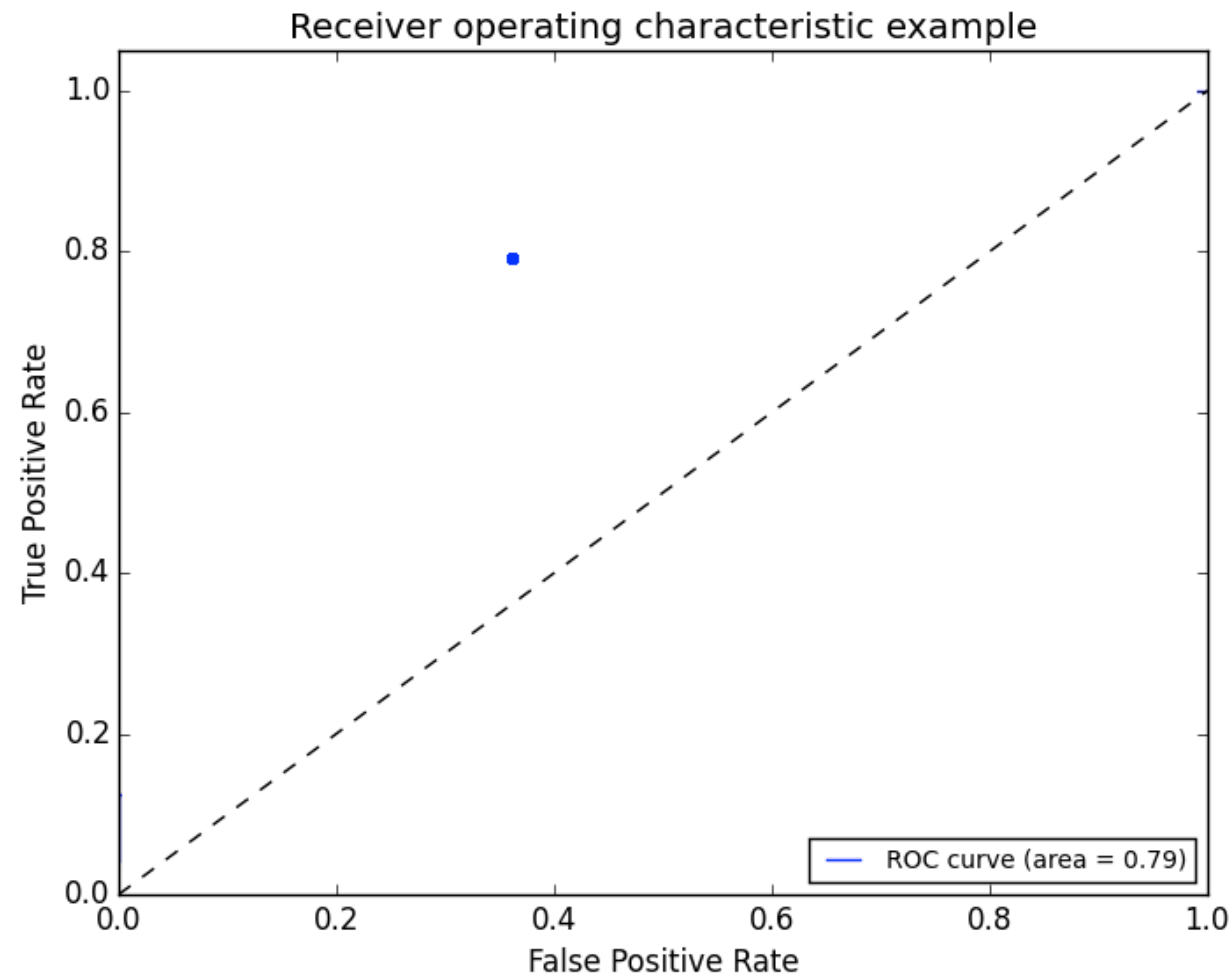
THE ROC CURVE

- There can be a variety of points on an ROC curve.



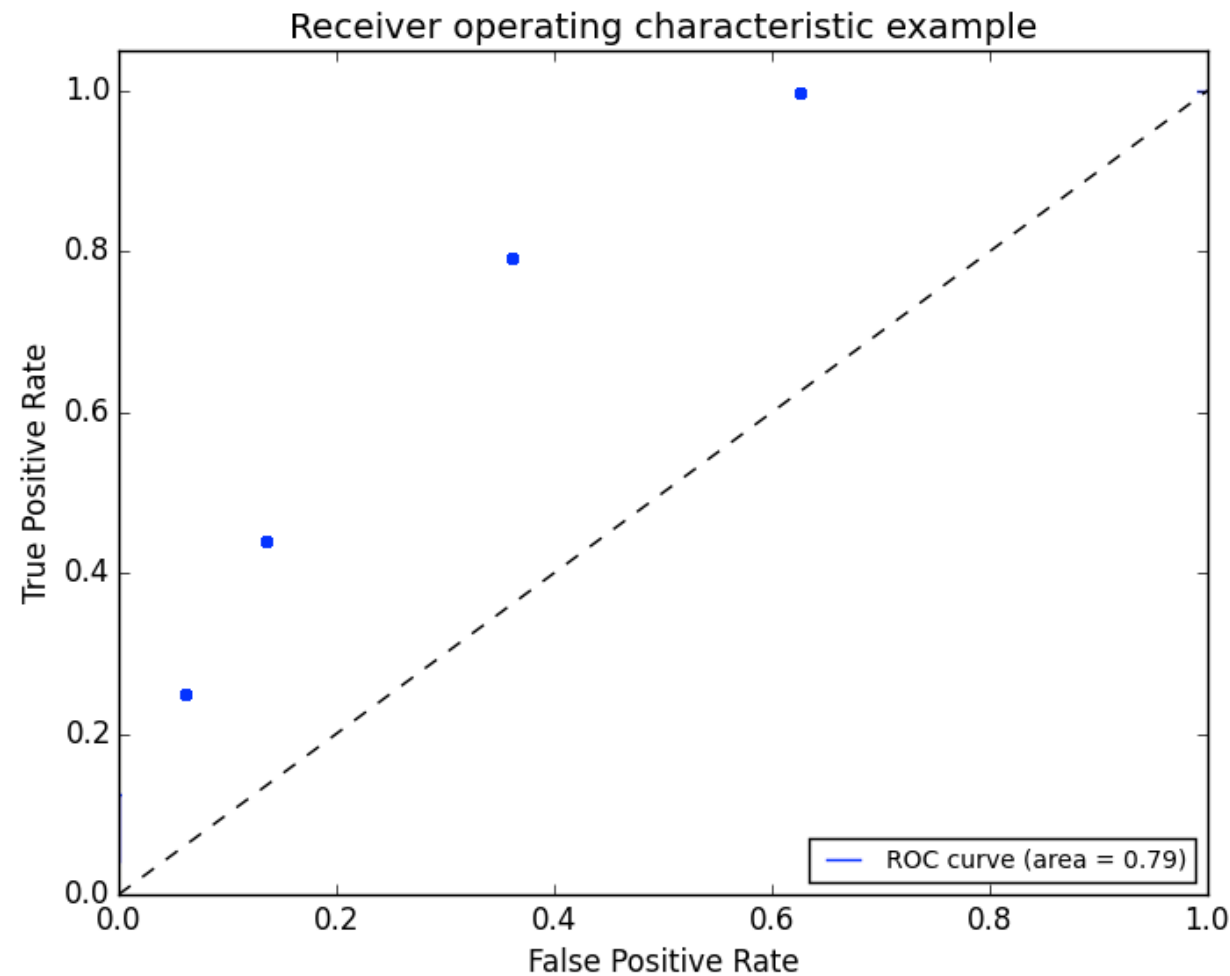
THE ROC CURVE

- We can begin by plotting an individual TPR/FPR pair for one threshold.



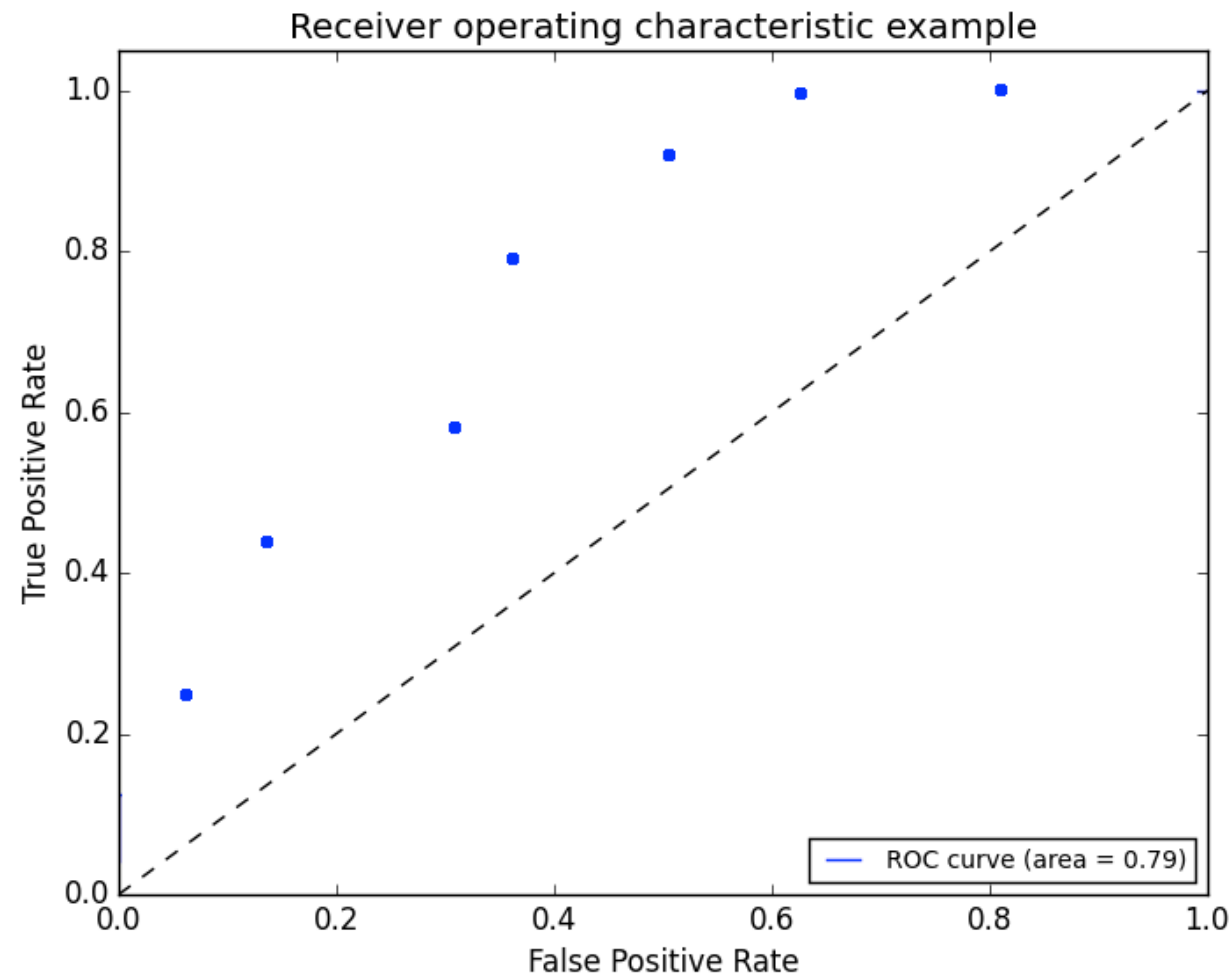
THE ROC CURVE

- We can continue adding pairs for different thresholds.



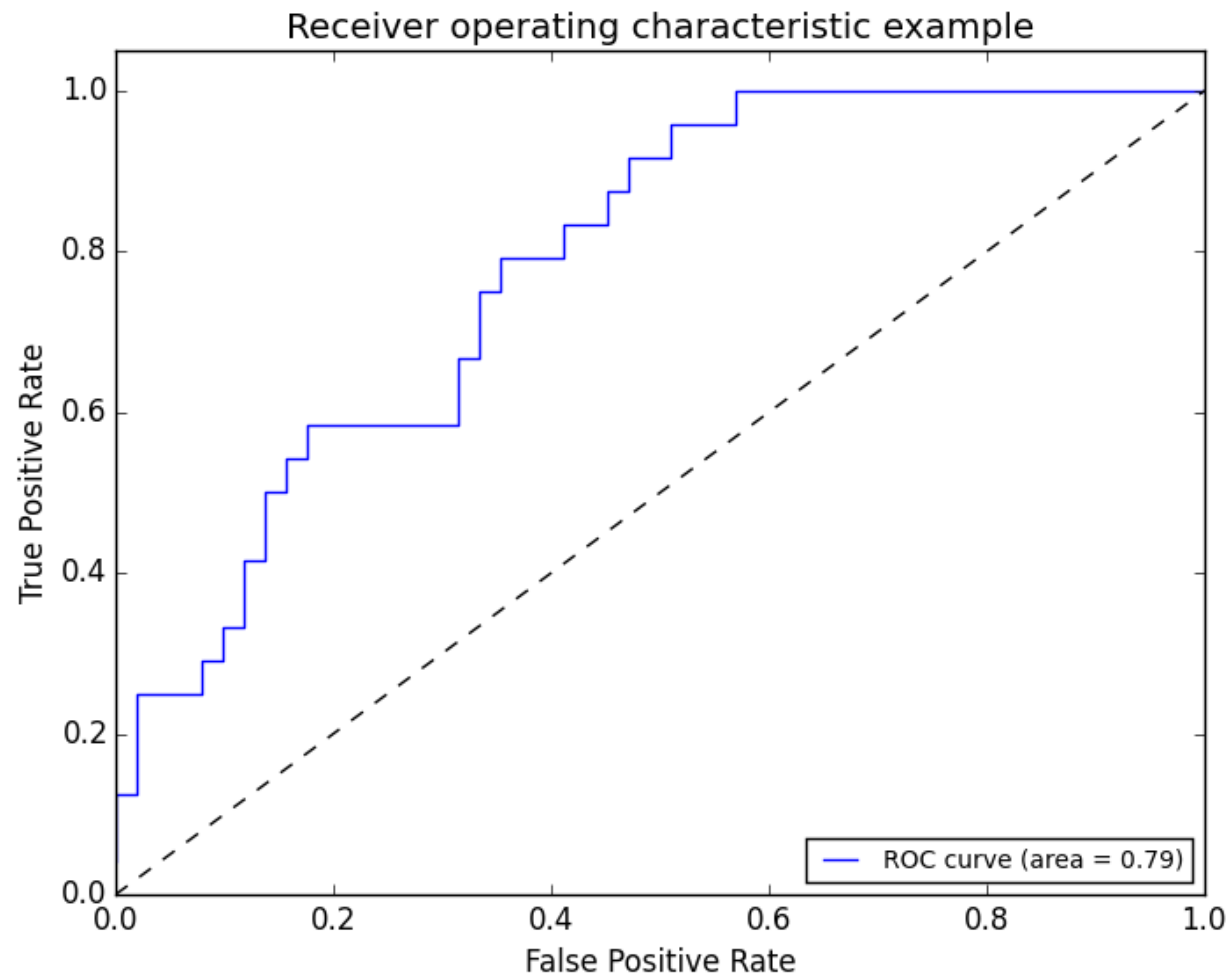
THE ROC CURVE

- We can continue adding pairs for even more thresholds.



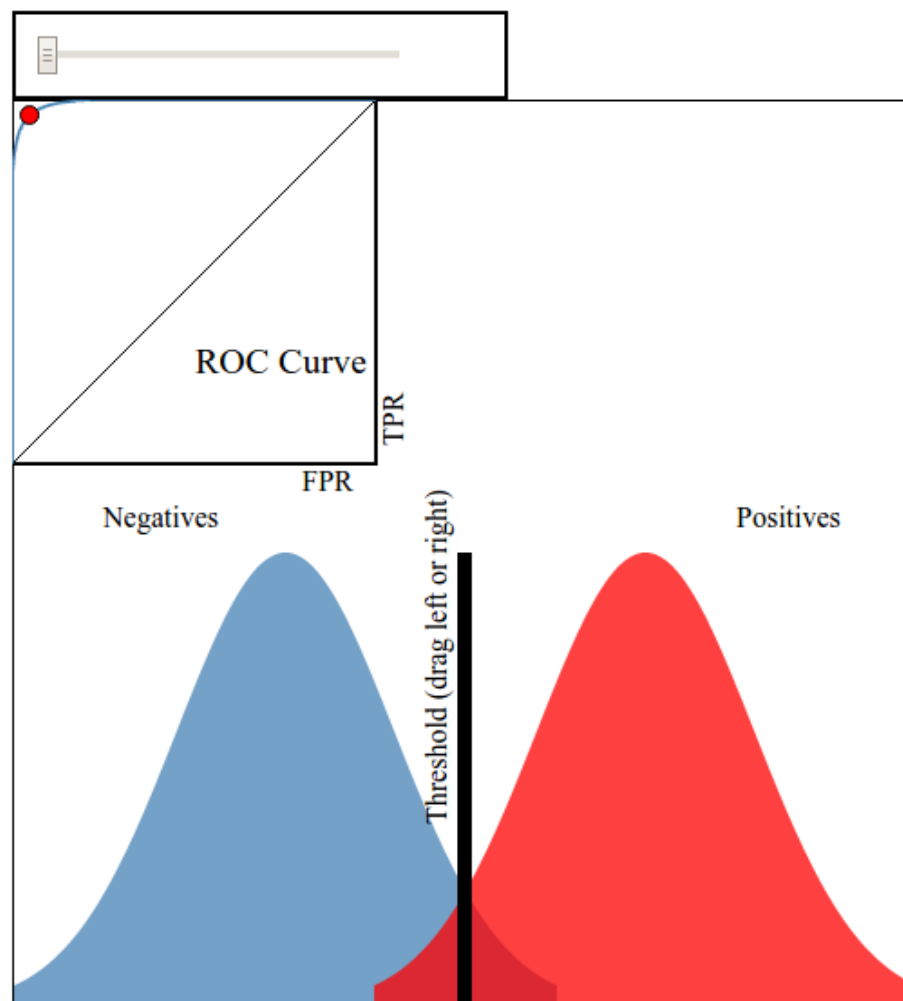
THE ROC CURVE

- Finally, we create a full “curve” that is described by both TPR and FPR.



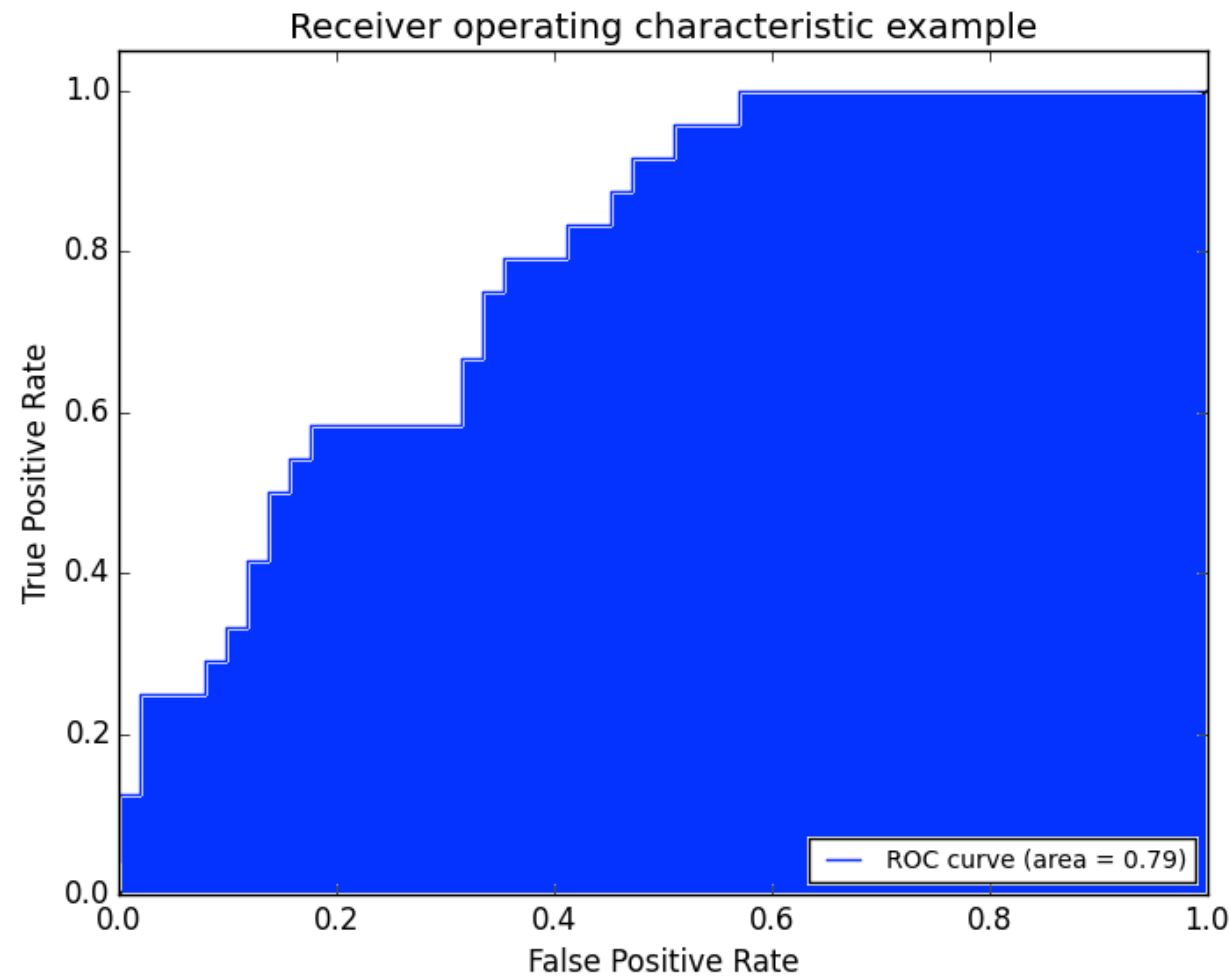
THE ROC CURVE

- ▶ This [interactive visualization](#) can help practice visualizing ROC curves.



AREA UNDER THE CURVE

- With this curve, we can find the Area Under the Curve (AUC).



RECEIVING OPERATOR CHARACTERISTIC (ROC) CURVE

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!

CLASSIFICATION

ROC CURVE / AUC

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5	0.99	Spam
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7	0.48	Spam
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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**?*

CLASSIFICATION

ROC CURVE / AUC

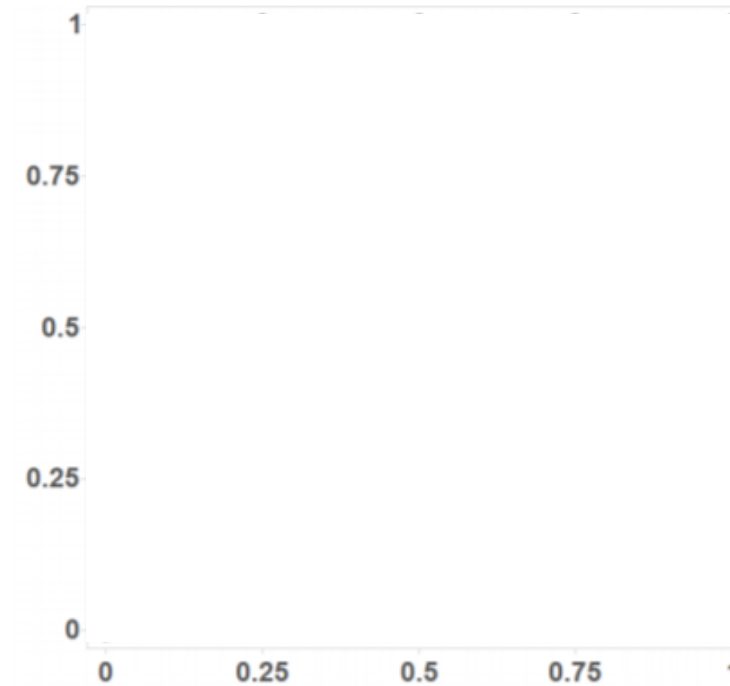
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	Predicted: NO	Predicted: YES	
Actual: NO			
Actual: YES			

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

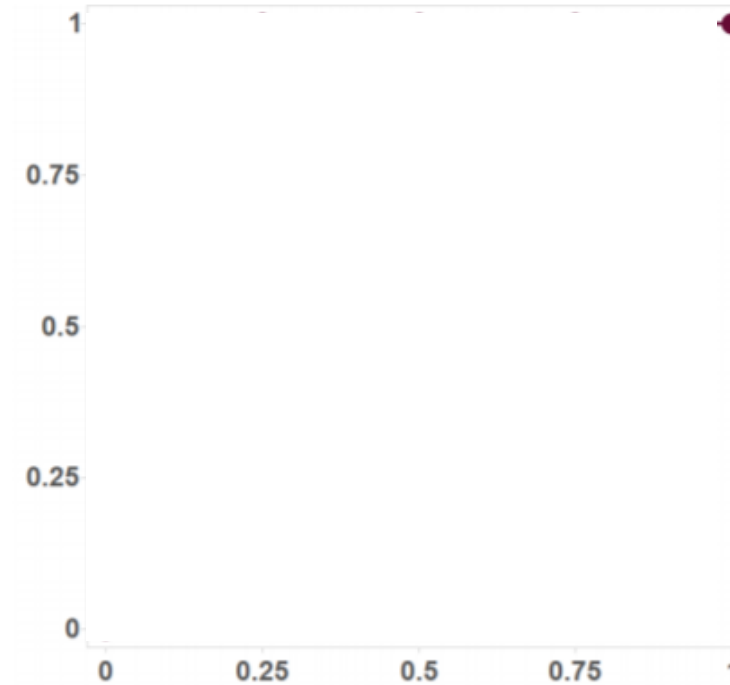
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	Predicted: NO	Predicted: YES	
Actual: NO	0	4	4
Actual: YES	0	4	4
	0	8	

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

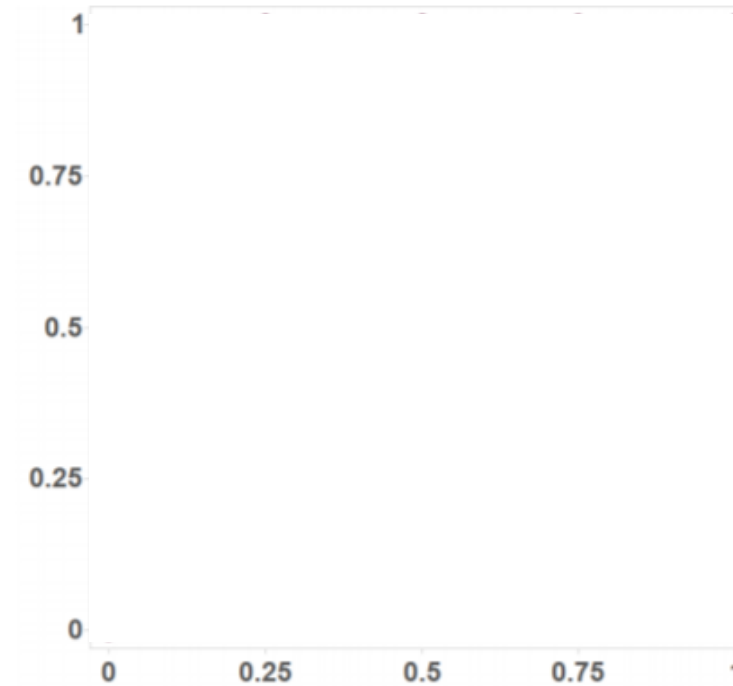
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TPR

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

ROC Curve



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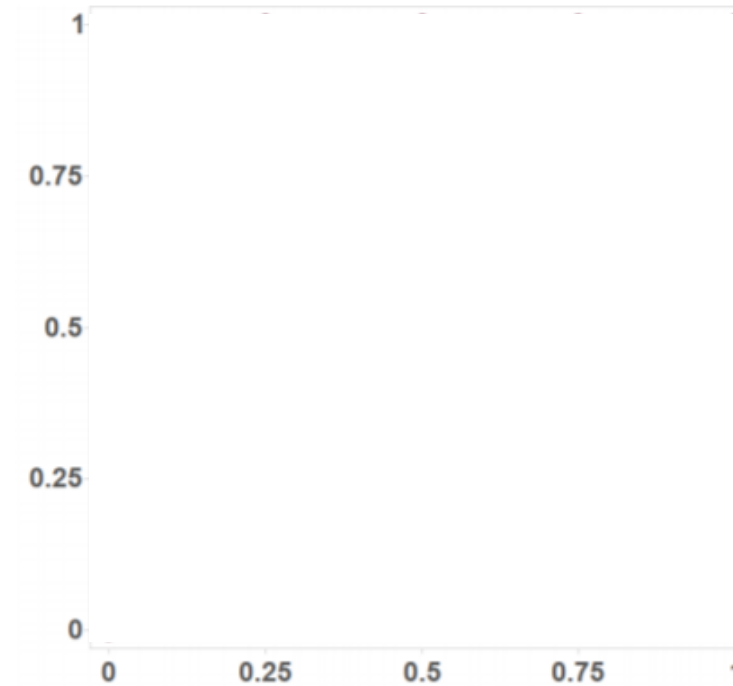
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ROC Curve



FPR

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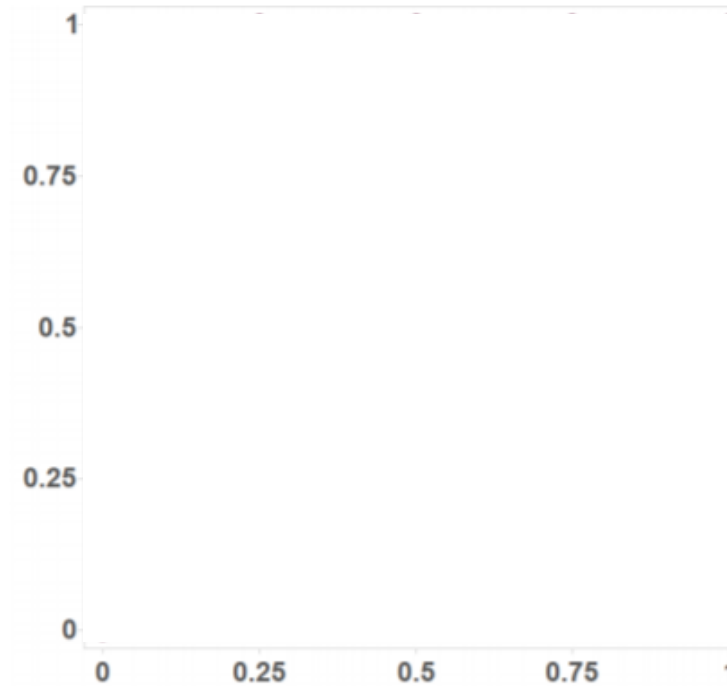
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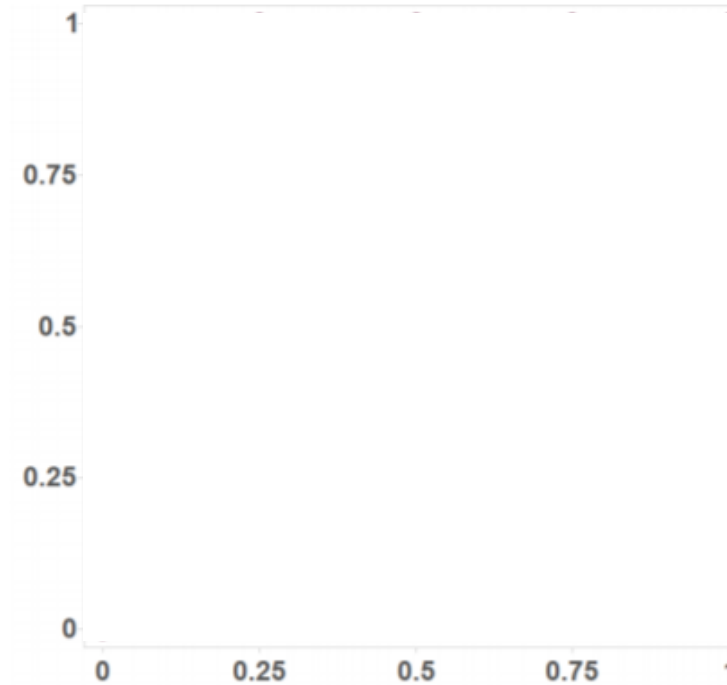
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Actual: YES		3	

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

CLASSIFICATION

ROC CURVE / AUC

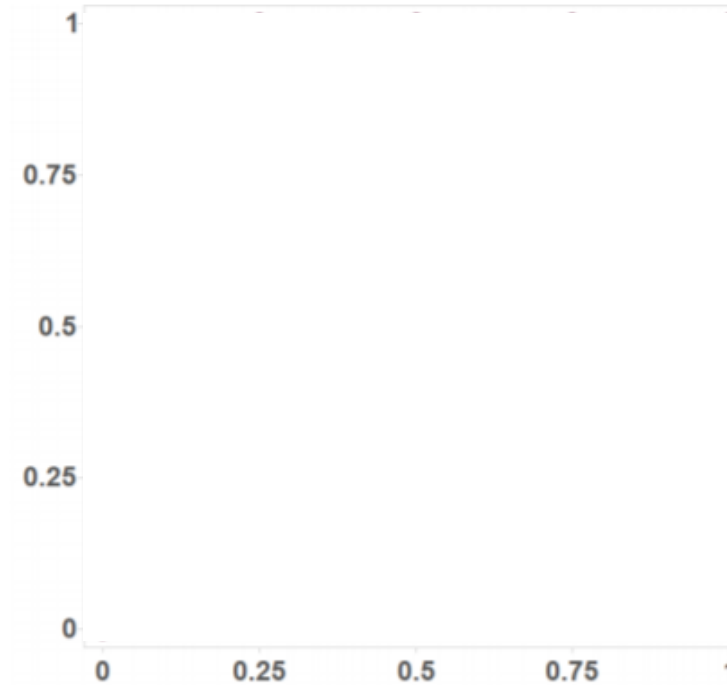
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES
Actual: NO		
Actual: YES		4

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

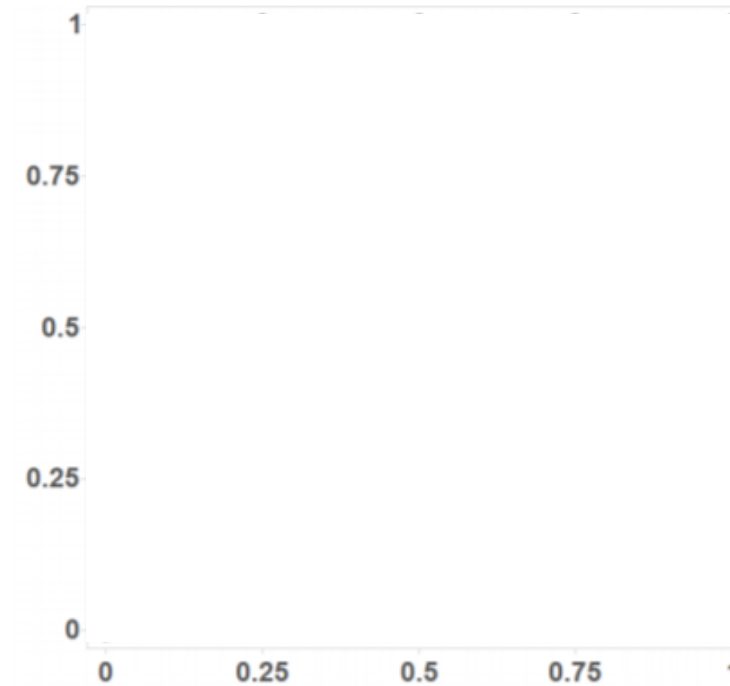
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES	
Actual: NO			
Actual: YES		5	

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

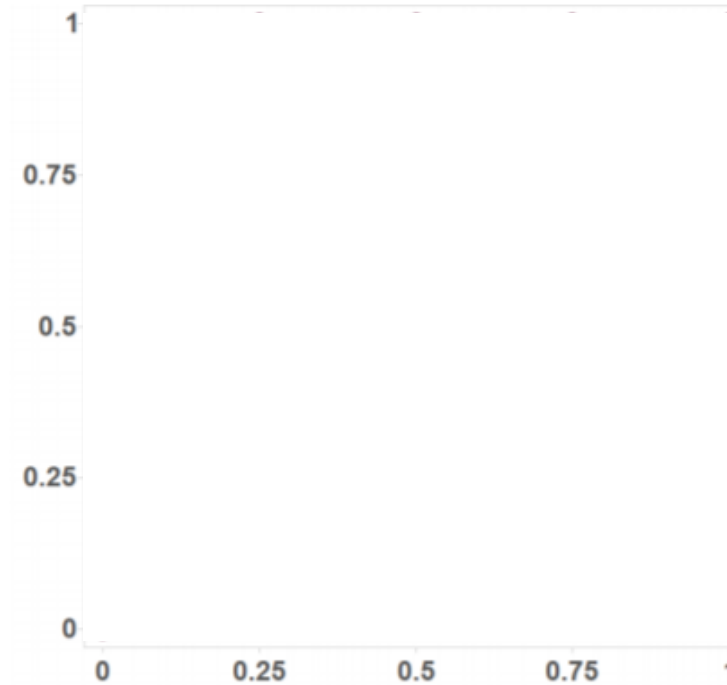
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES
Actual: NO		
Actual: YES		7

TPR

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

ROC Curve



FPR

CLASSIFICATION

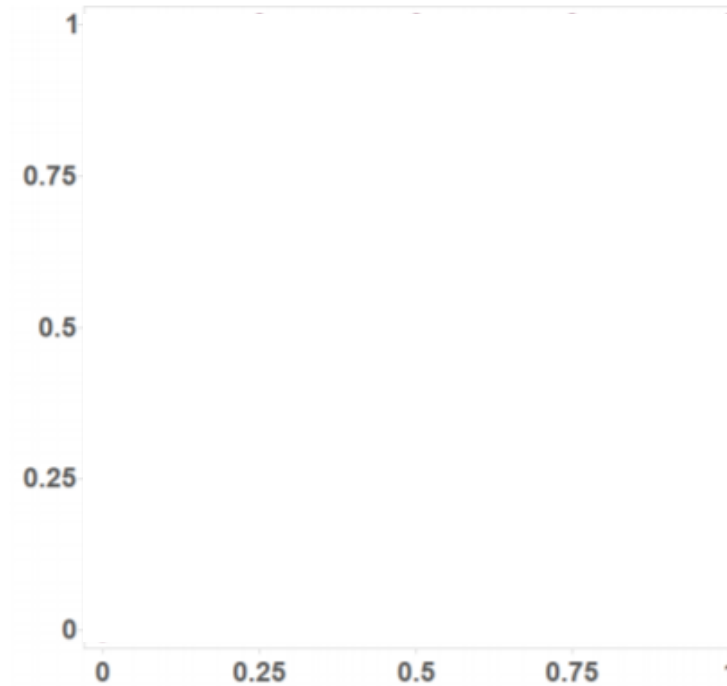
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO			
Actual: YES			
	1	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

ROC CURVE / AUC

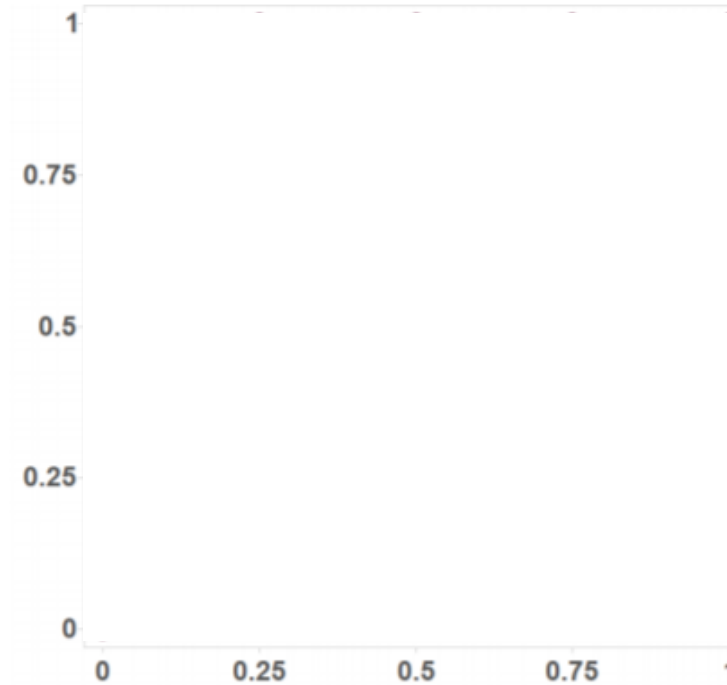
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES
Actual: NO		3
Actual: YES	1	7

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

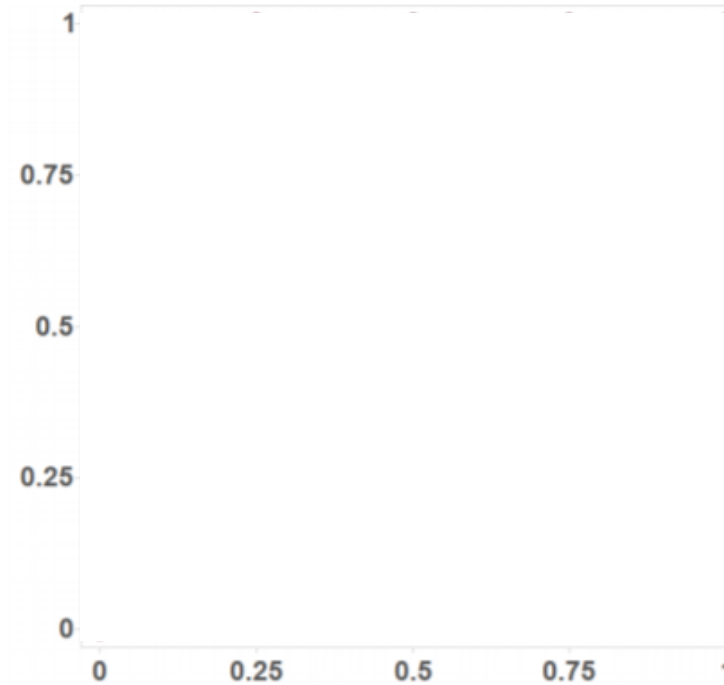
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES
Actual: NO	1	3
Actual: YES	1	7

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

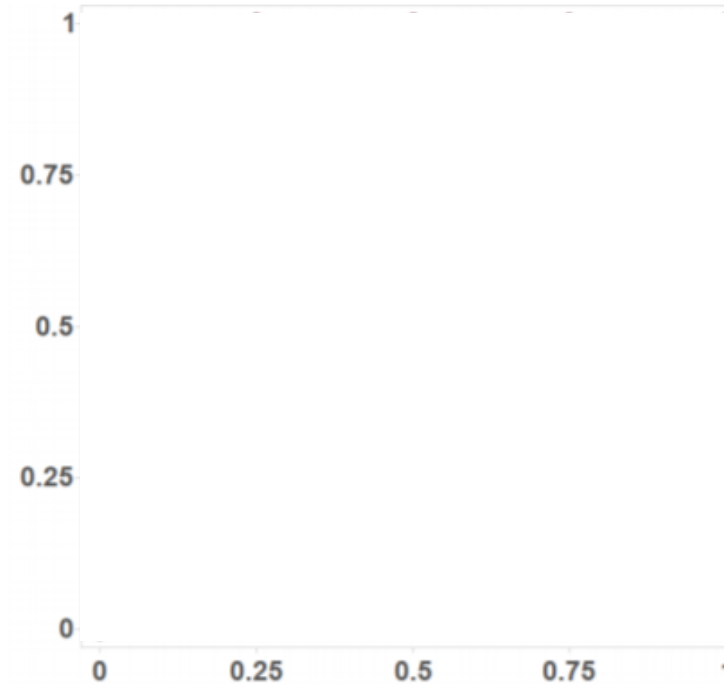
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	1	7	

TPR

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

ROC Curve



FPR

CLASSIFICATION

ROC CURVE / AUC

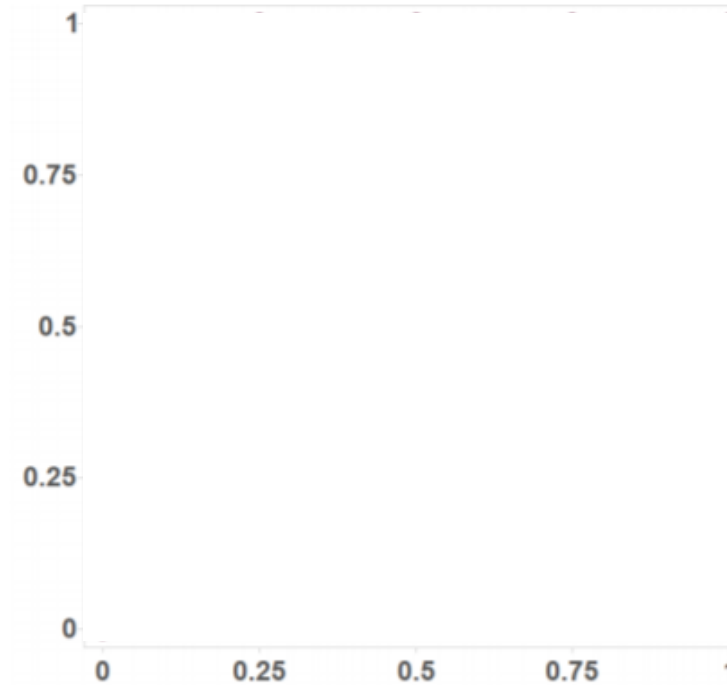
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	?		
	1	7	

TPR

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

ROC Curve



FPR

CLASSIFICATION

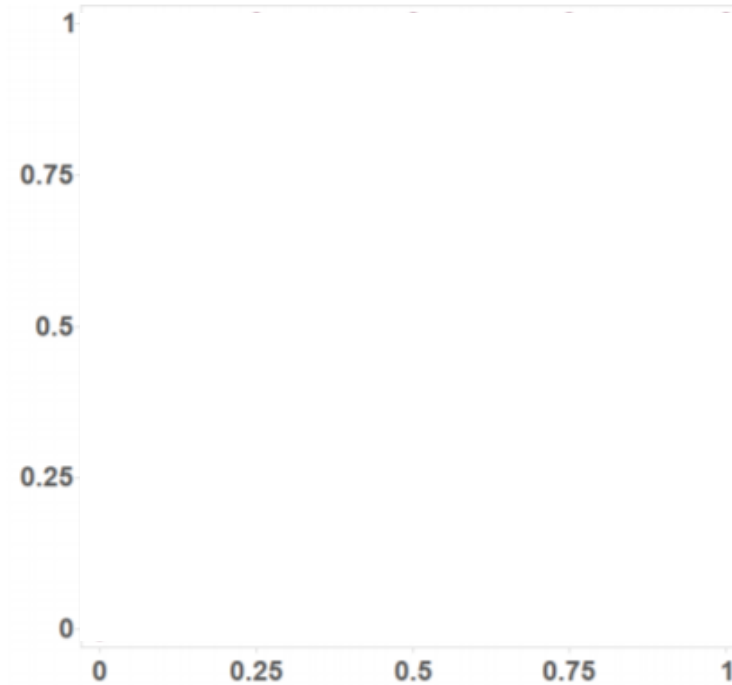
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

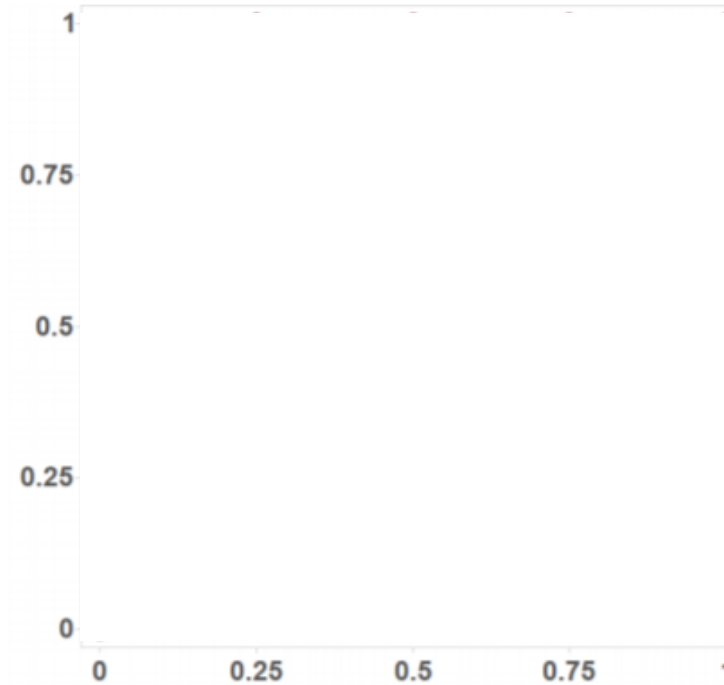
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	?	
	1	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

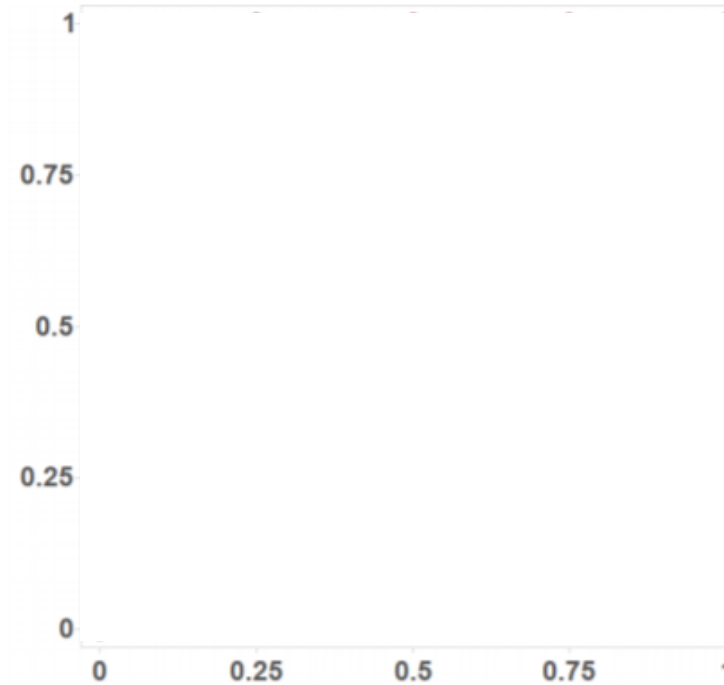
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	?	
	1	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

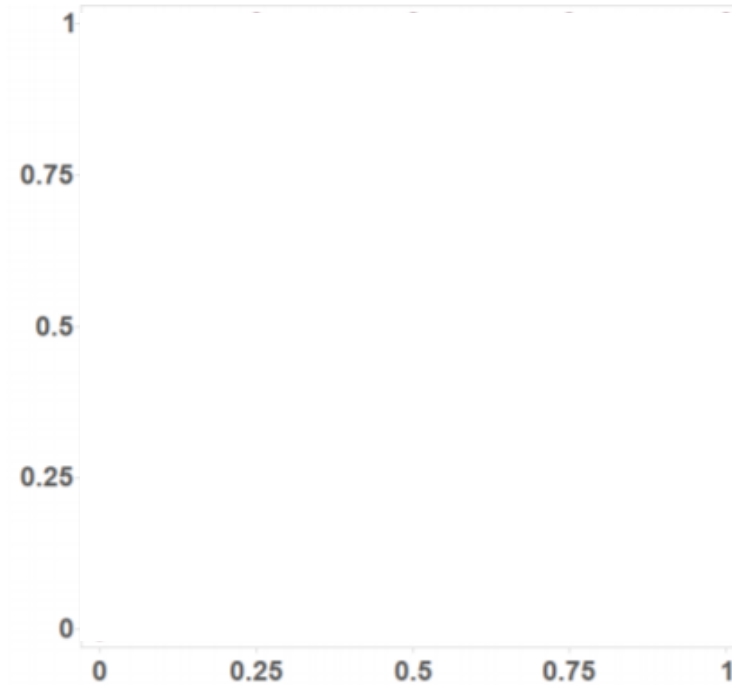
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	?	
	1	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

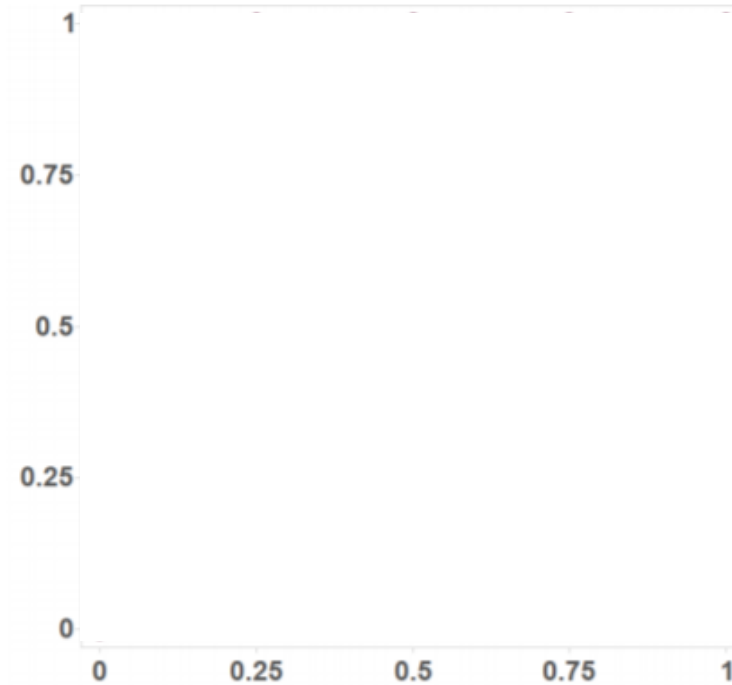
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	4	
	1	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

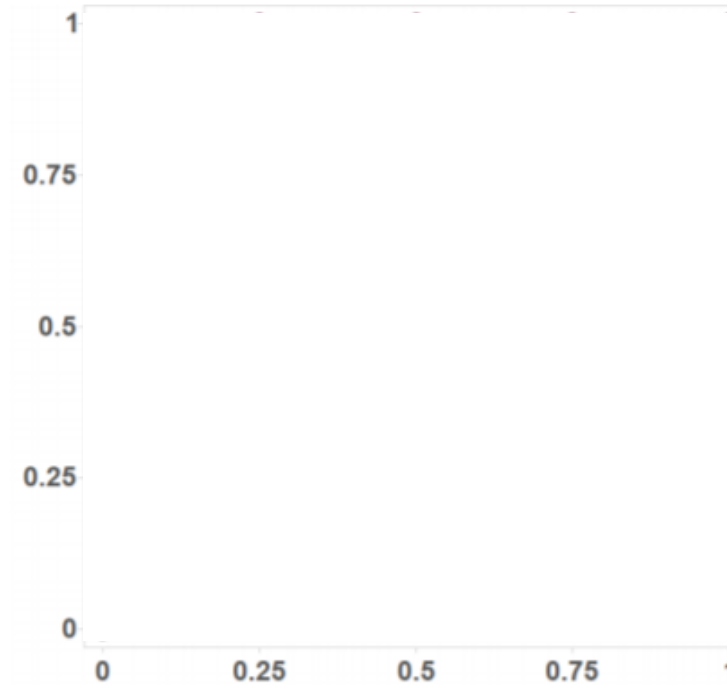
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	4	4
	1	7	

TPR

ROC Curve



FPR

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

CLASSIFICATION

ROC CURVE / AUC

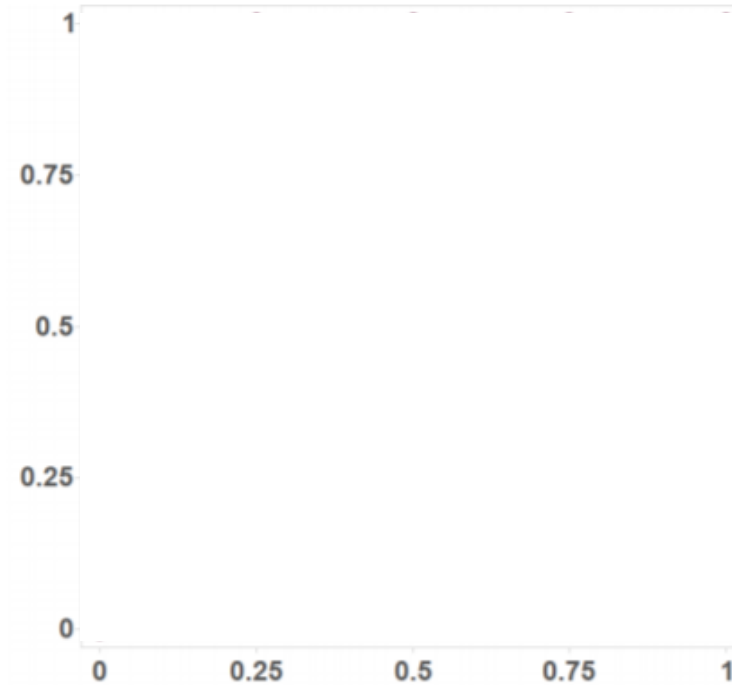
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	4	4
	1	7	

TPR

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

ROC Curve



FPR = $3/4 \rightarrow 0.75$

CLASSIFICATION

ROC CURVE / AUC

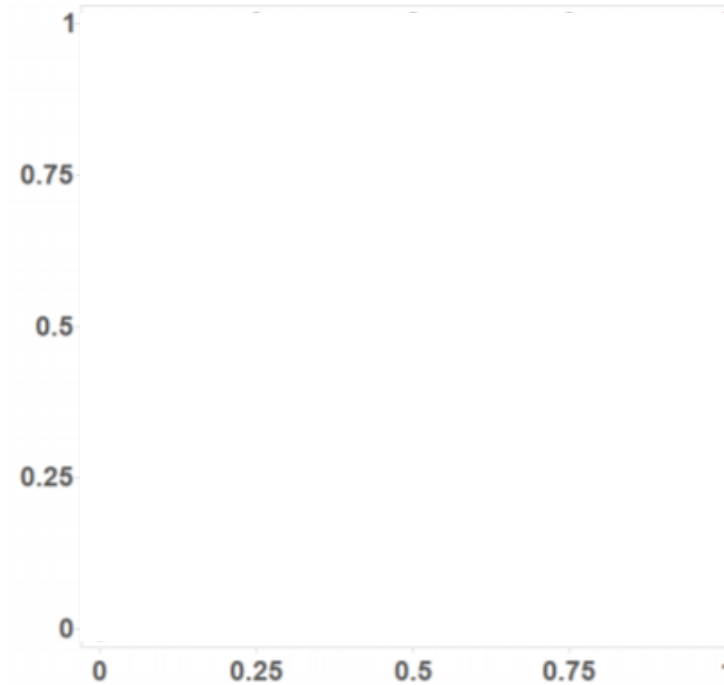
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	4	4
	1	7	

TPR

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

ROC Curve



FPR = $3/4 \rightarrow 0.75$

CLASSIFICATION

ROC CURVE / AUC

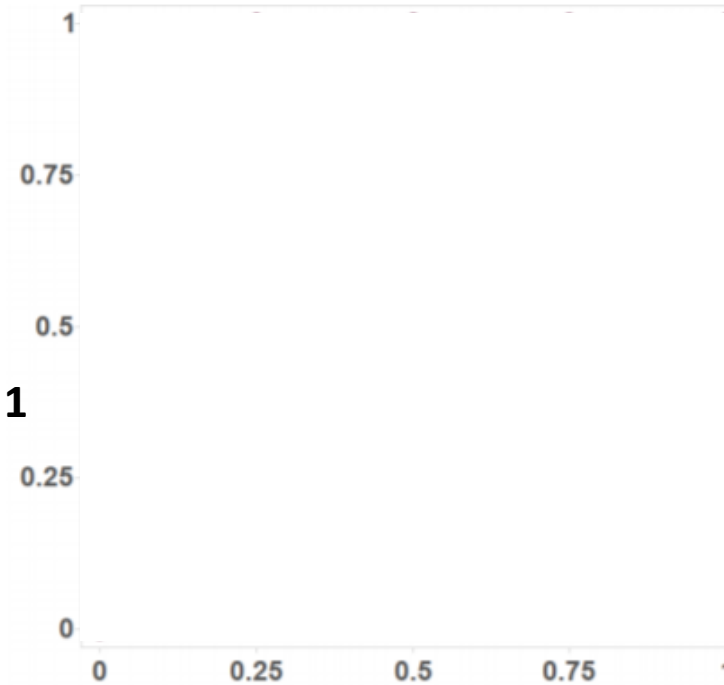
Email Number	Score	True Label
5	0.99	Spam
8	0.82	Spam
2	0.60	Spam
1	0.60	Ham
7	0.48	Spam
3	0.22	Ham
4	0.10	Ham
6	0.02	Ham

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	4	4
	1	7	

$$TPR = \frac{4}{4} \rightarrow 1$$

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

ROC Curve



FPR

CLASSIFICATION

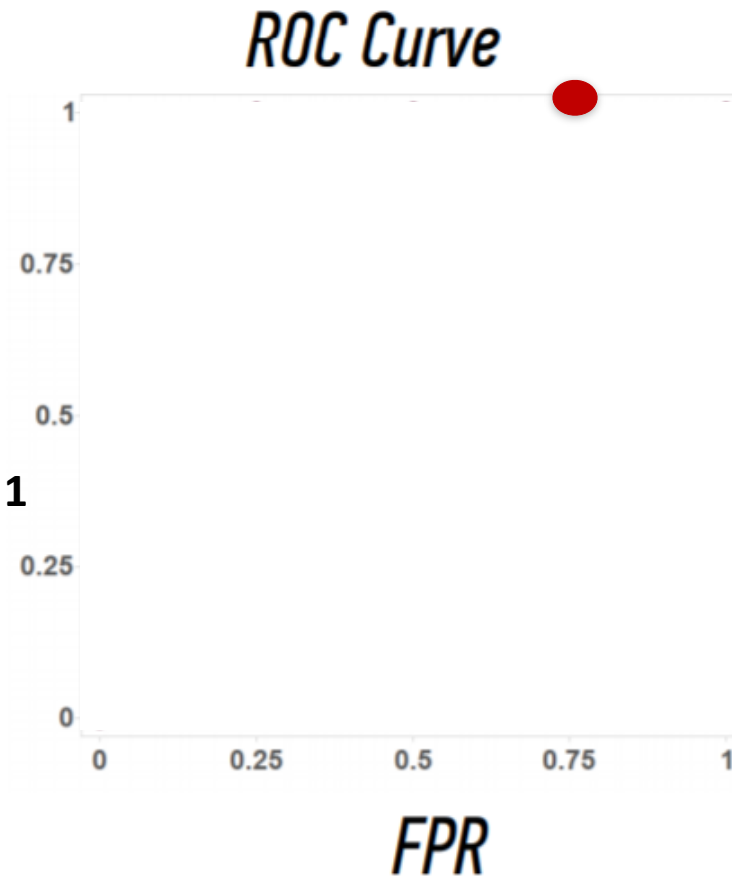
ROC CURVE / AUC

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

	Predicted: NO	Predicted: YES	
Actual: NO	1	3	4
Actual: YES	0	4	4
	1	7	

TPR
 $= 4/4 \rightarrow 1$

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

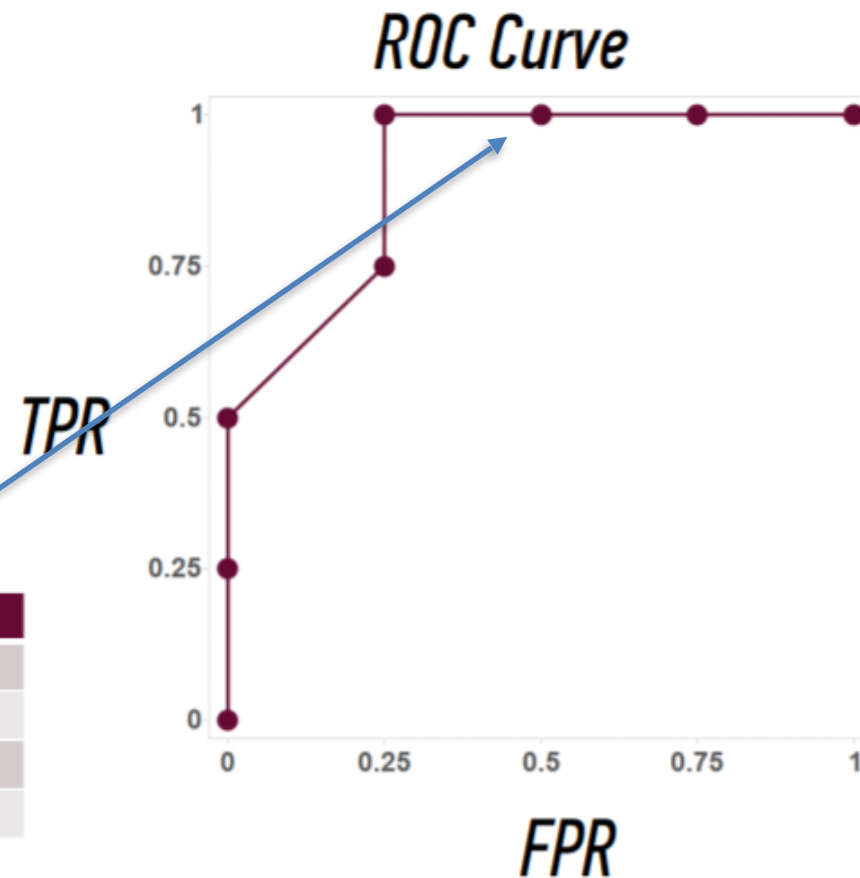


CLASSIFICATION

ROC CURVE / AUC

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

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

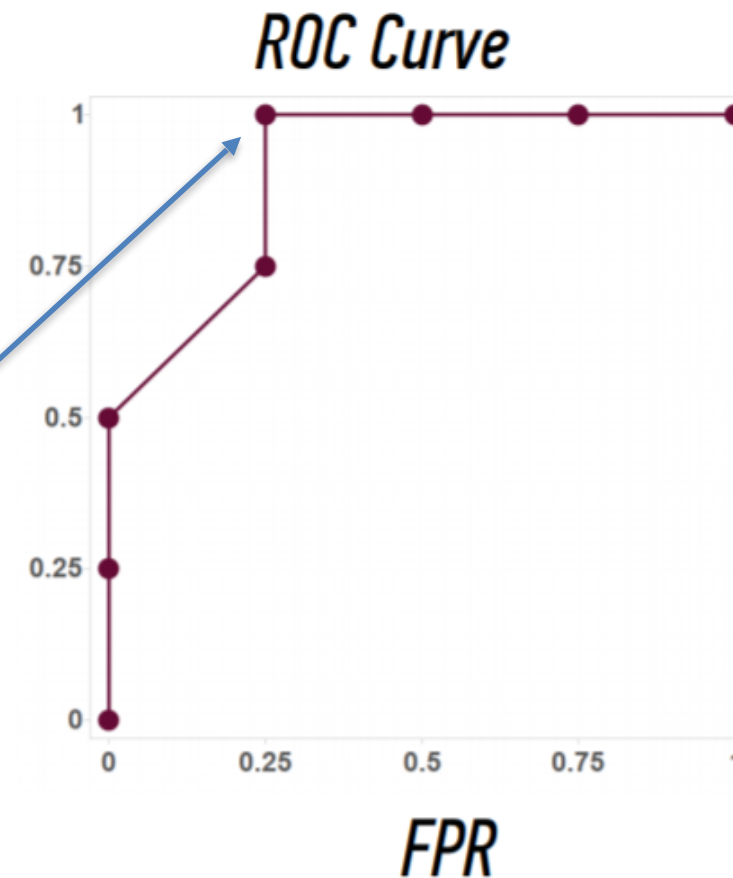


CLASSIFICATION

ROC CURVE / AUC

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

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

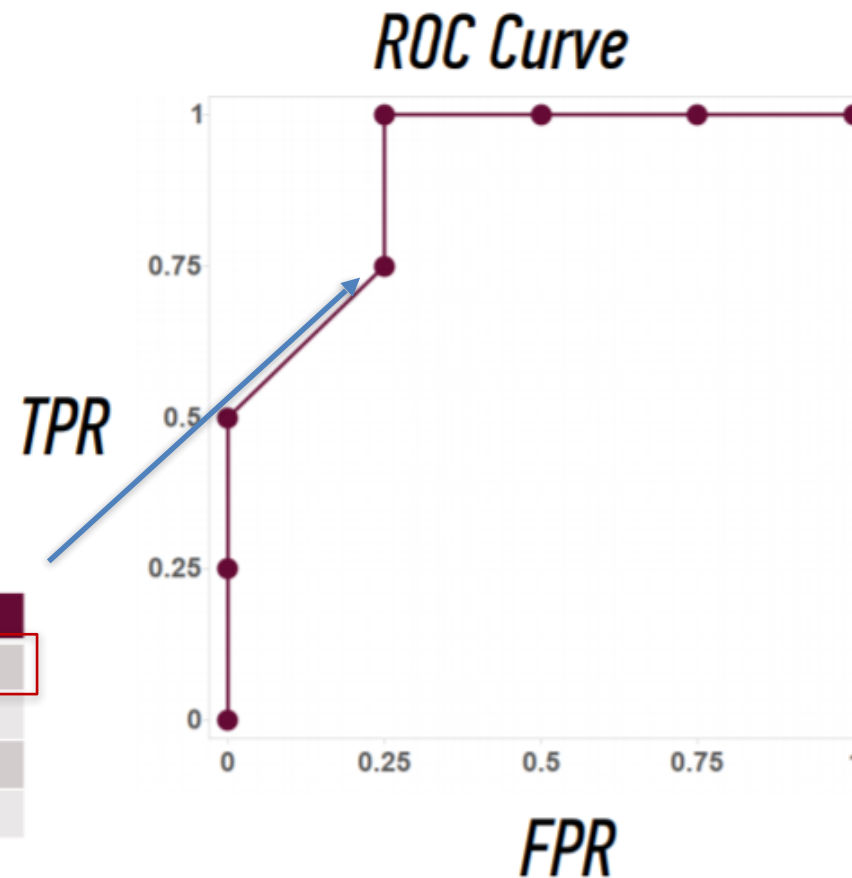


CLASSIFICATION

ROC CURVE / AUC

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

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

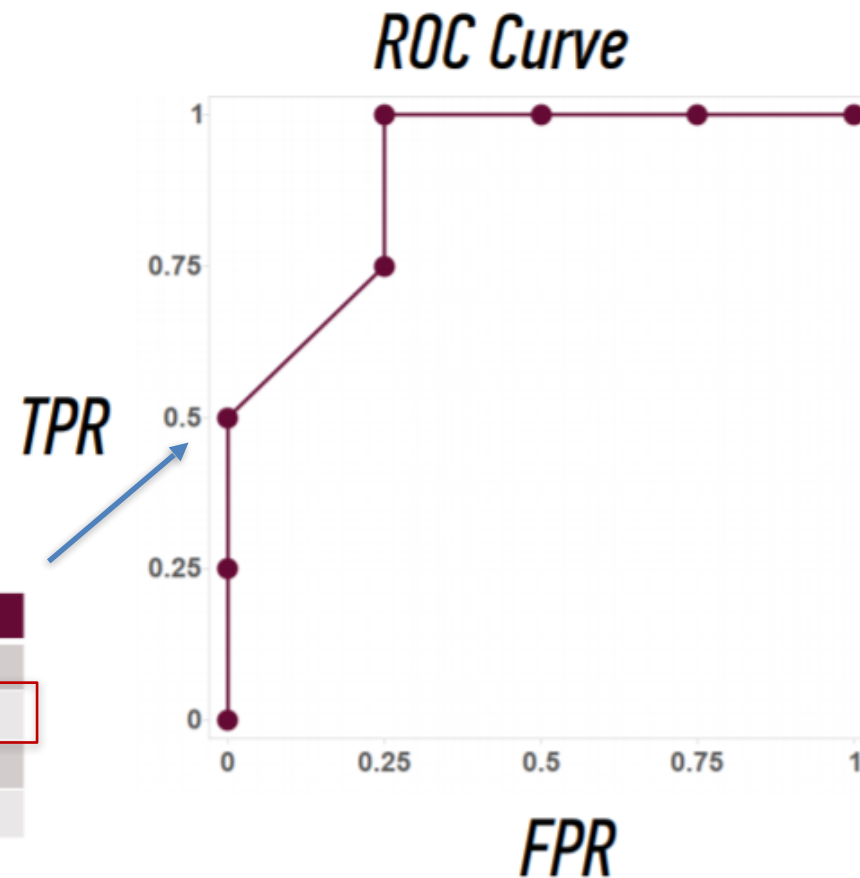


CLASSIFICATION

ROC CURVE / AUC

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

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

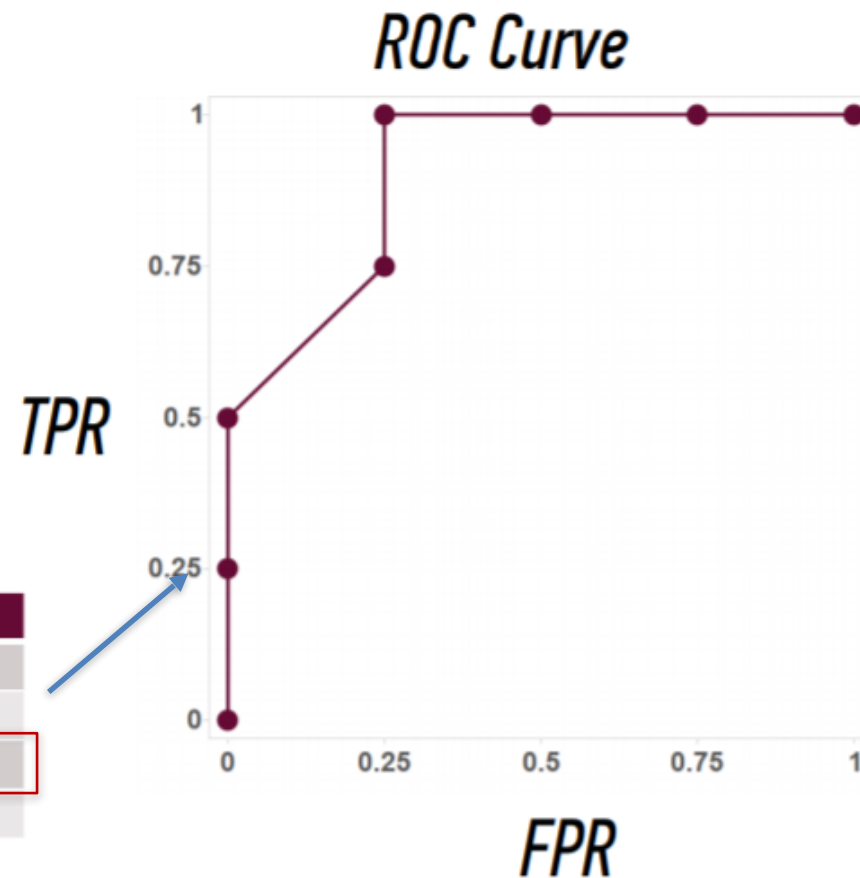


CLASSIFICATION

ROC CURVE / AUC

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

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

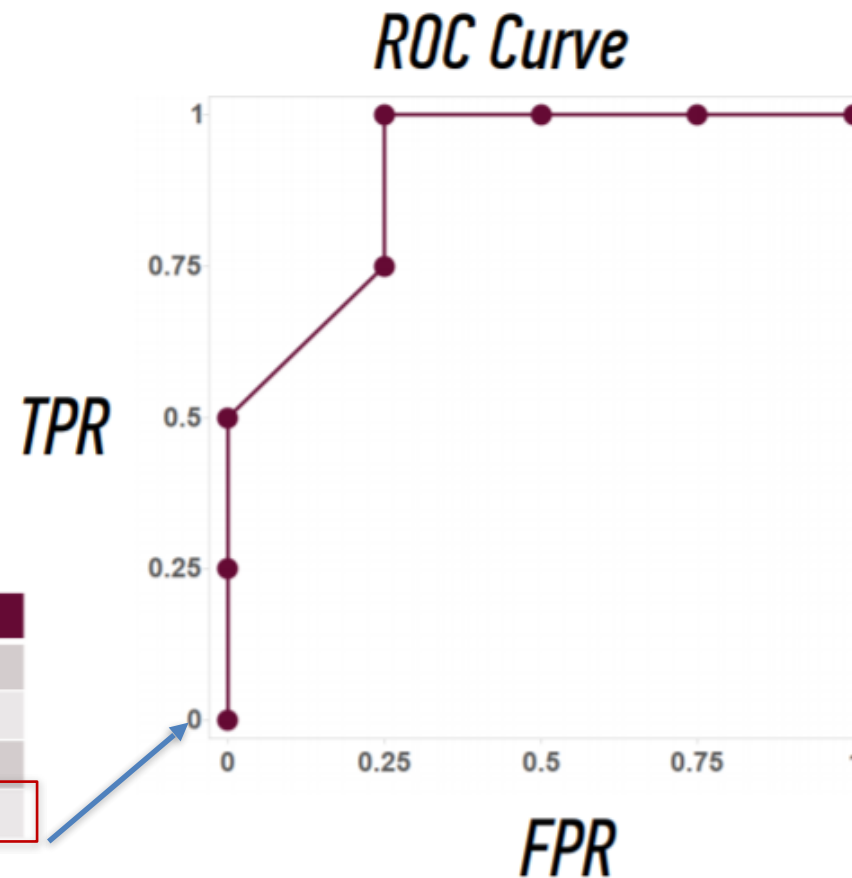


CLASSIFICATION

ROC CURVE / AUC

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

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



GUIDED PRACTICE

WHICH METRIC MATTERS?

ACTIVITY: WHICH METRIC MATTERS?



EXERCISE

DIRECTIONS (15 minutes)

While AUC seems like a “golden standard”, it could be *further* improved depending upon your problem. There will be instances where error in positive or negative matches will be very important. For each of the example on the next slide:

1. Write a confusion matrix: true positive, false positive, true negative, false negative. Then decide what each square represents for that specific example.
2. Define the *benefit* of a true positive and true negative and the *cost* of a false positive and false negative.

DELIVERABLE

Answers for each example

ACTIVITY: WHICH METRIC MATTERS?



DIRECTIONS (15 minutes)

Examples:

1. A test is developed for determining if a patient has cancer or not.
2. A newspaper company is targeting a marketing campaign for "at risk" users that may stop paying for the product soon.
3. You build a spam classifier for your email system.

DELIVERABLE

Answers for each example

CONFUSION VS ROC?

Discuss in your groups:

- ☐ What information do you take away from each of these evaluation techniques?
- ☐ What decisions can be made from each tool?