GENERAL ASSEMBLY

DATA SCIENCE

MODEL EVALUATION METRICS

Regression:

- *Root Mean Squared Error*

Classification:

- *Confusion Matrix*
- *ROC Curve (and AUC)*

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- *Used for regression problems*
- *Square root of the mean of the squared errors*
- *Easily interpretable (in the "y" units)*
- *"Punishes" larger errors*

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Example #1

$$y = [100, 50, 30]$$

$$\hat{y} = [90, 60, 40]$$

$$RMSE = \sqrt{\frac{10^2 + 10^2 + 10^2}{3}} = 10$$

Example #2

$$y = [100, 50, 30]$$

$$\hat{y} = [100, 50, 60]$$

$$RMSE = \sqrt{\frac{0^2 + 0^2 + 30^2}{3}} = 17.32$$

Confusion Matrix: table to describe the performance of a classifier

n=165	Predicted: NO	Predicted: YES
Actual: NO	50	10
Actual: YES	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?*

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*

CONFUSION MATRIX

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

Sensitivity:

- *When actual value is **positive**, how often is prediction **correct**?*
- *TP / actual yes = 100/105 = 0.95*
- *"True Positive Rate" or "Recall"*

False Positive Rate:

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

Specificity:

- *When actual value is **negative**, how often is prediction **correct**?*
- *TN / 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
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1	0.60	Ham
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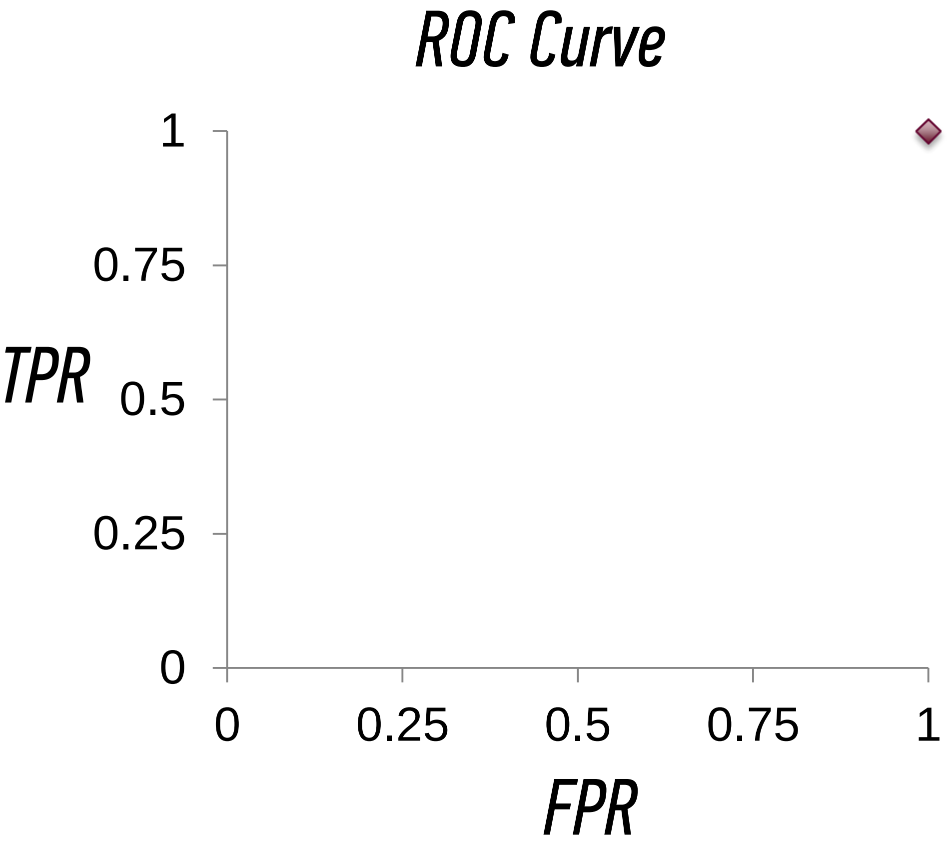
6	0.02	Ham



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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**		

Email Number	Score	True Label
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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	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
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**.*