Model Evaluation and Metrics

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Topics

- Regression
  - RMSE – Root Mean Squared Error
- Classification
  - Confusion matrix
  - ROC Curve

Root Mean Squared Error

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

- Used for regression problems
- Square root of the mean of the squared errors
- Easily interpretable (in the “y” units)
- “Punishes” larger errors
- Other: *absolute error*

Root Mean Squared Error

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

Example:
y_true = [100, 50, 30]
y_preds = [90, 50, 50]
RMSE = np.sqrt((10**2 + 0**2 + 20**2) / 3) = 12.88

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?

Confusion Matrix: table to describe the performance of a classifier

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: table to describe the performance of a classifier

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

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 “spam” 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 visualize how well our classifier is doing without having to choose a cutoff!

ROC Curve

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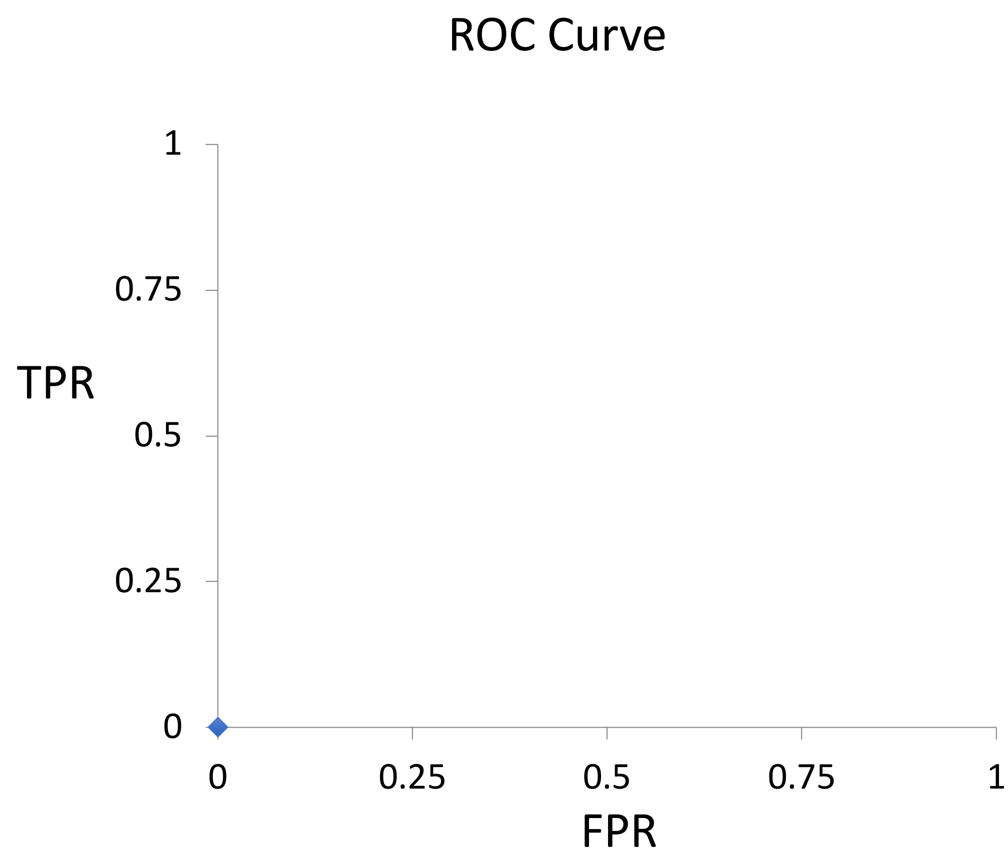

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TPR: When actual value is **spam**, how often is prediction **correct**?

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**		

ROC Curve

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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

ROC Curve

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**.