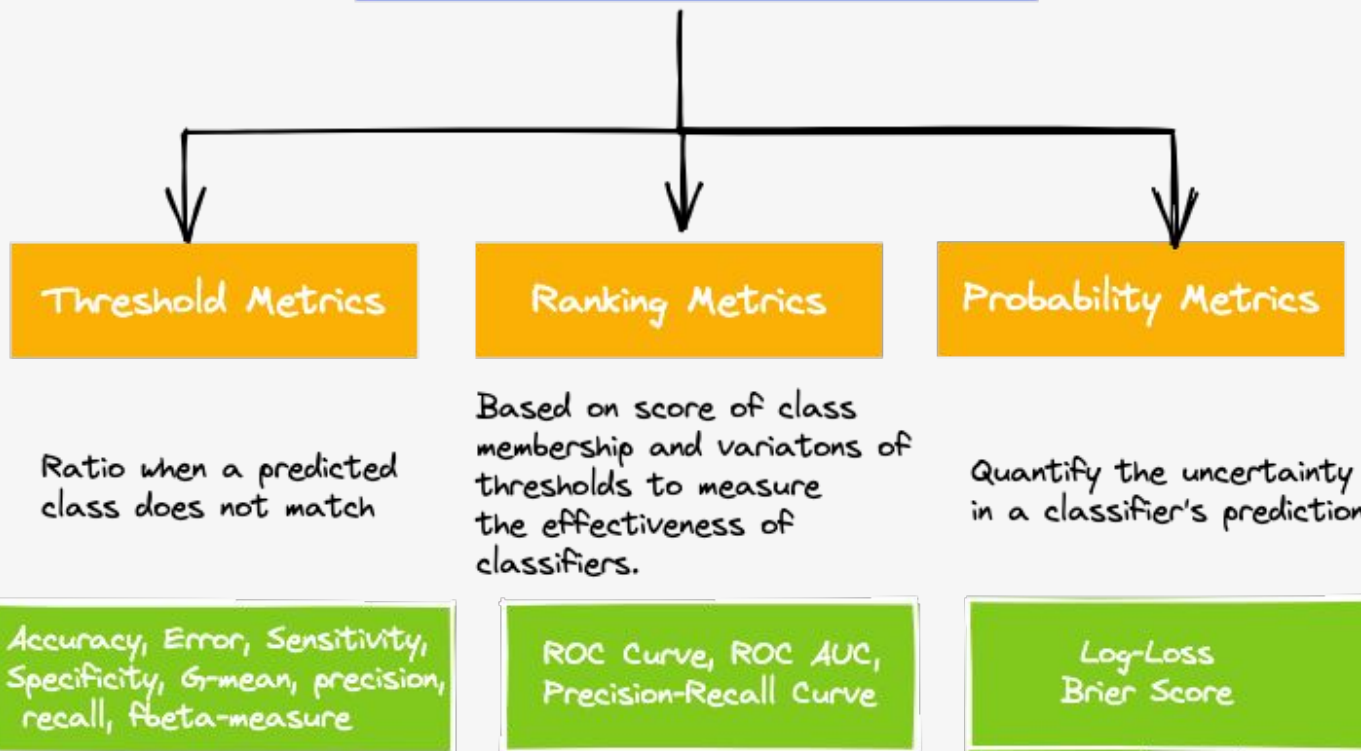


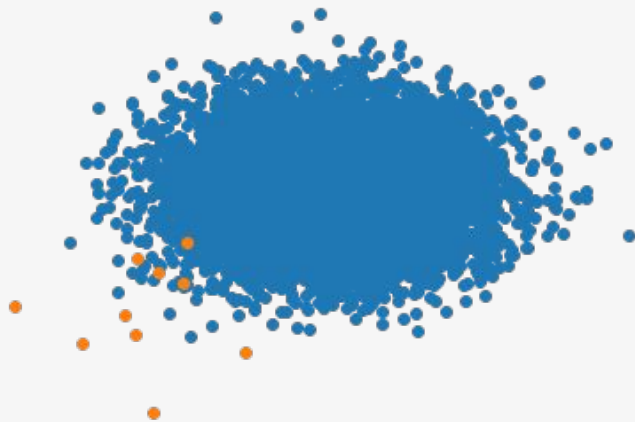
# Machine Learning Evaluation Metrics



# Taxonomy of Classifier Evaluation Metrics



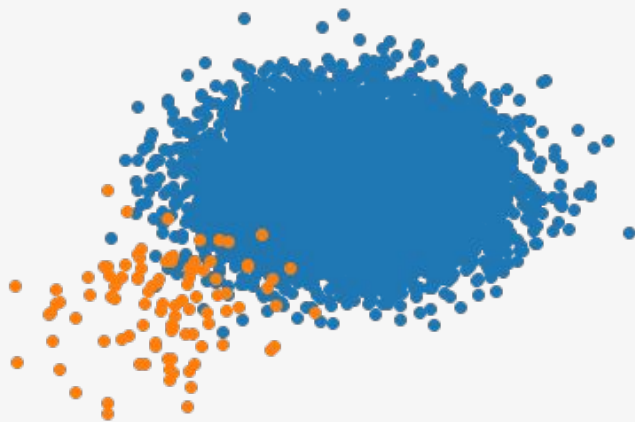
Imbalanced 1:1000



Imbalanced 1:10



Imbalanced 1:100

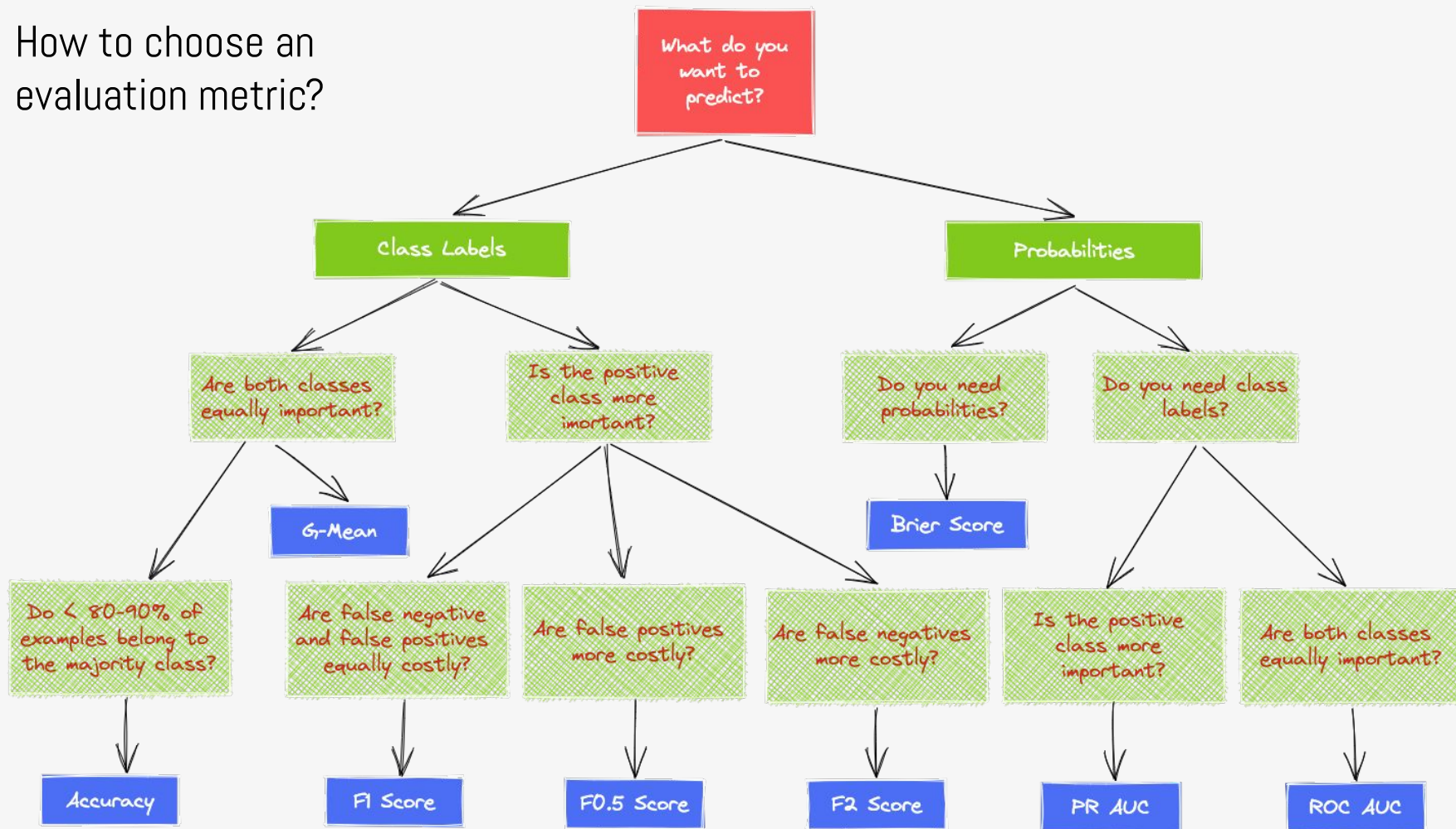


Imbalanced 1:2











# How to choose an evaluation metric?

4



# Confusion Matrix

Expected

		Positive class (1)		Negative class (0)	
Predicted	Negative class (0)	True Positive (TP)		False Positive (FP)	
		Predicted	Expected	Predicted	Expected
					
Predicted	Positive class (1)	False Negative (FN)		True Negative (TN)	
		Predicted	Expected	Predicted	Expected
					

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

$$\text{Error} = 1 - \text{Accuracy}$$

# Confusion Matrix

Expected

Positive class (1)

Negative class (0)

Predicted

Positive class (1)  
Negative class (0)

True Positive (TP)

Predicted



Expected



False Positive (FP)

Predicted



Expected



False Negative (FN)

Predicted



Expected



True Negative (TN)

Predicted



Expected



$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{FP + TN}$$

$$G\text{-mean} = \sqrt{\text{Sensitivity} \times \text{Specificity}}$$



# Confusion Matrix

Expected

Positive class (1)

Negative class (0)

Predicted  
Positive class (1)  
Negative class (0)

True Positive (TP)

Predicted



Expected



False Positive (FP)

Predicted



Expected



False Negative (FN)

Predicted



Expected



True Negative (TN)

Predicted



Expected



$$\text{Precision} = \frac{TP}{TP + FP}$$

(positive predictive value - PPV)

$$\text{Precision} = \frac{TN}{TN + FN}$$









(negative predictive value - NPV)

$$\text{Recall} = \frac{TP}{TP + FN}$$



# Confusion Matrix

Expected

		Positive Class (1)		Negative Class (0)	
Predicted	Positive class (1)	<b>True Positive (TP)</b> Predicted:  Expected: 		<b>False Positive (FP)</b> Predicted:  Expected: 	
	Negative class (0)	<b>False Negative (FN)</b> Predicted:  Expected: 		<b>True Negative (TN)</b> Predicted:  Expected: 	

$$F_{\text{beta-measure}} = \frac{(1 + \beta^2) \times \text{Precision} \times \text{Recall}}{\beta^2 \times \text{Precision} + \text{Recall}}$$

$$\beta == \begin{cases} 0.5, \text{ more weight on precision} \\ 1.0, \text{ balance on weight PR and RE} \\ 2.0, \text{ less weight on precision} \end{cases}$$

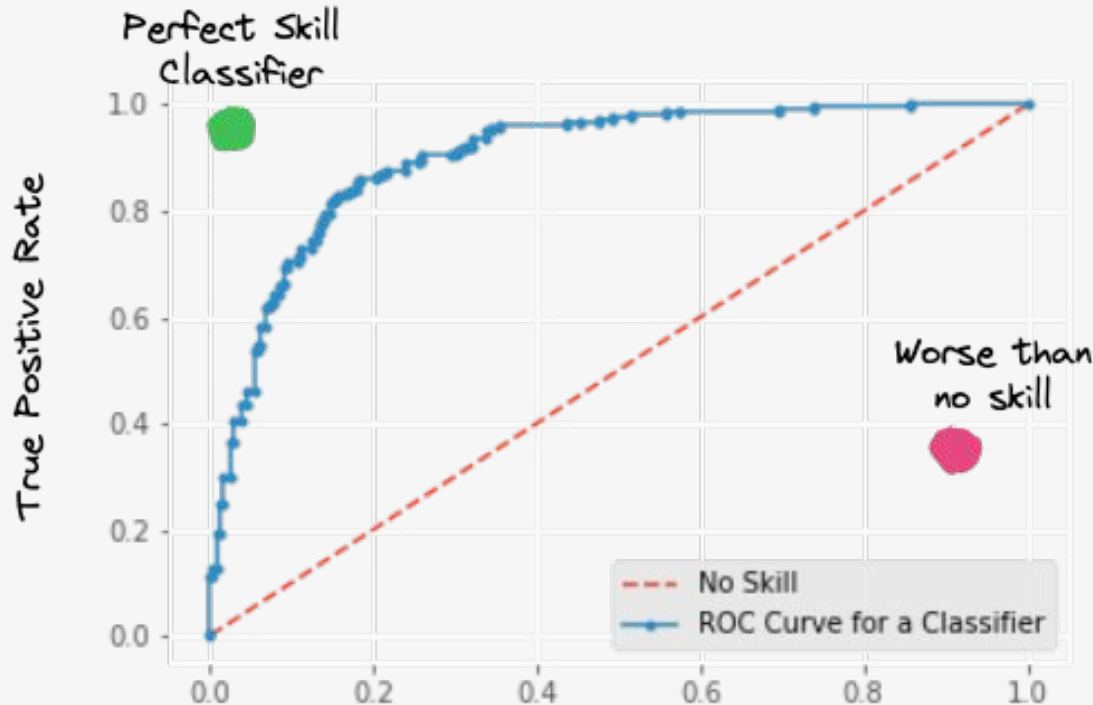


Rank metrics are more concerned with evaluating classifiers based on **how effective** they are at separating classes.

These metrics require that a **classifier predicts a score** or a probability of class membership. From this score, **different thresholds** can be applied to **test the effectiveness of classifiers**. Those models that maintain a good score across a range of thresholds will have good class separation and will be ranked higher.

# Receiver Operating Characteristic (ROC)

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



Expected

Positive class (1)

Negative class (0)

Predicted

	Positive class (1)		Negative class (0)	
	Predicted	Expected	Predicted	Expected
Positive class (1)	True Positive (TP) 😊	😊	False Positive (FP) 😊	😞
Negative class (0)	False Negative (FN) 😞	😊	True Negative (TN) 😊	😞

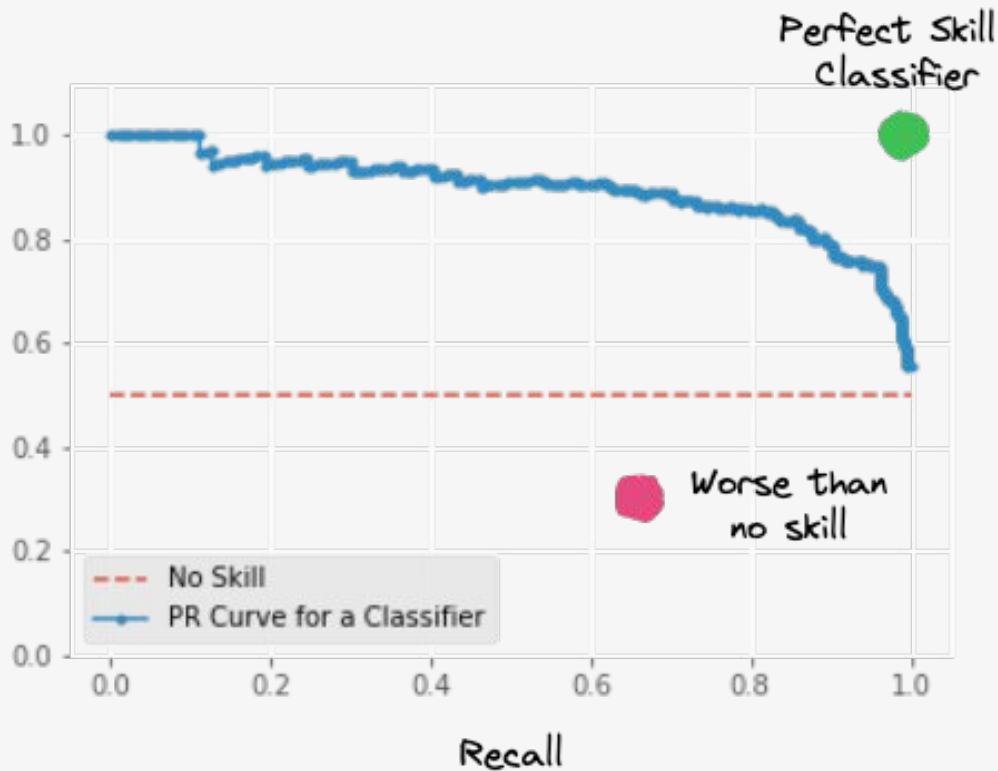
False Positive Rate

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

# Precision-Recall (PR) Curve

$$\text{Precision} = \frac{TP}{TP + FP}$$

Precision



Expected

Positive class (1)

Negative class (0)

Predicted	True Positive (TP)		False Positive (FP)	
	Predicted	Expected	Predicted	Expected
	😊	😊	😊	😞
Negative class (0)	False Negative (FN)		True Negative (TN)	
	Predicted	Expected	Predicted	Expected
	😞	😊	😞	😞

$$\text{Recall} = \frac{TP}{TP + FN}$$