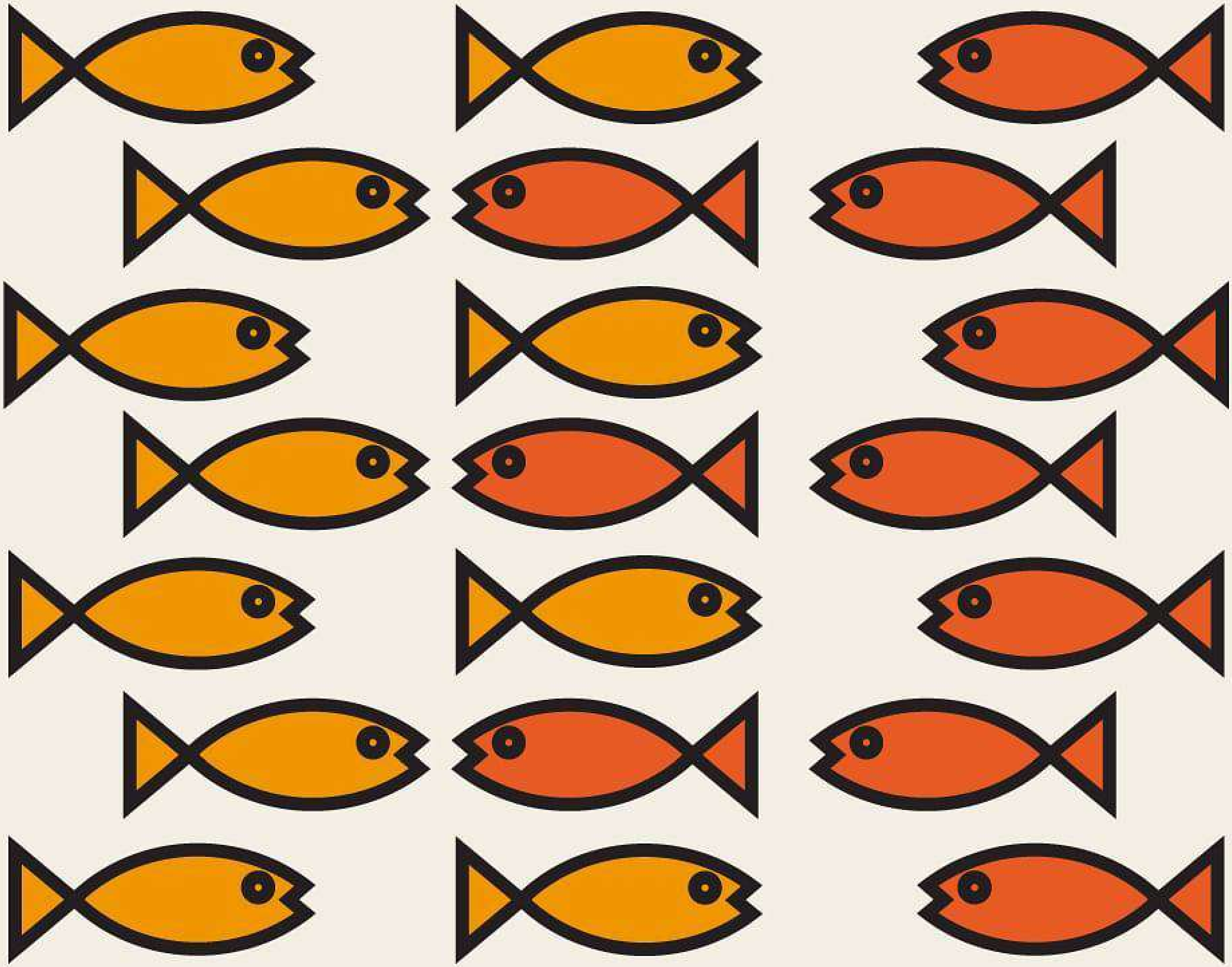
HOW TO EVALUATE CLASSIFICATION MODEL

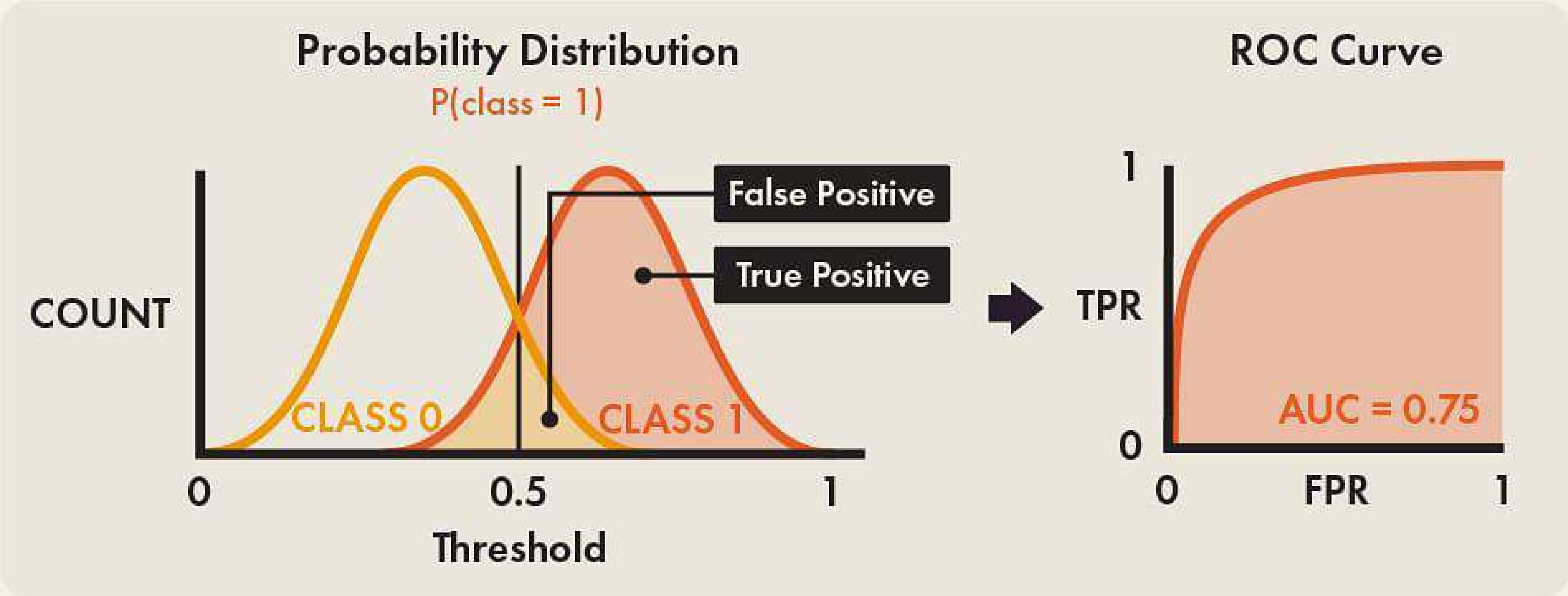


		PREDICTED CLASS	
		positive	negative
ACTUAL CLASS	positive	TP (ture positive)	FN (false negative)
	negative	FP (false positive)	TN (true negative)

precision	recall	f1
$\frac{TP}{TP+FP}$	$\frac{TP}{TP+FN}$	$2\,\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$

Confusion Matrics

We can use it to derive f1 score, It keeps a **balance** between Precision and Recall. when you have a data **imbalance** between positive and negative samples, you should use F1-score.



TPR
True Positive Rate

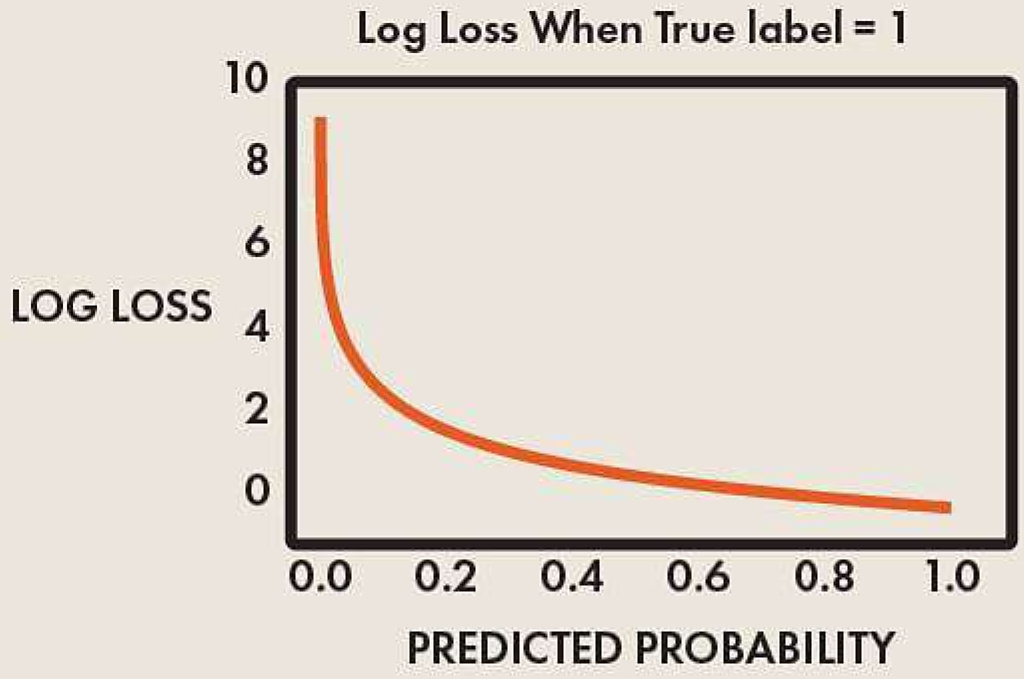
$$\frac{TP}{TP + FN}$$

FPR
False Positive Rate

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

Area Under Curve (AUC)

F1 score is applicable for any particular point on the ROC curve with different threshold. AUC (area under the ROC curve) indicates how well the probabilities from the positive classes are separated from the negative classes.



$$-(y \log(p) + (1 - y)\log(1 - p))$$

binary indicator (0 or 1) if class *c* label is the correct classification for observation *o*

predicted probability observation *o* is of class *c*

Binary Cross entropy

Cross-entropy loss, or log loss, measures the performance of a classification model whose output is a probability value between 0 and 1. Cross-entropy loss increases as the predicted probability diverges from the actual label.