

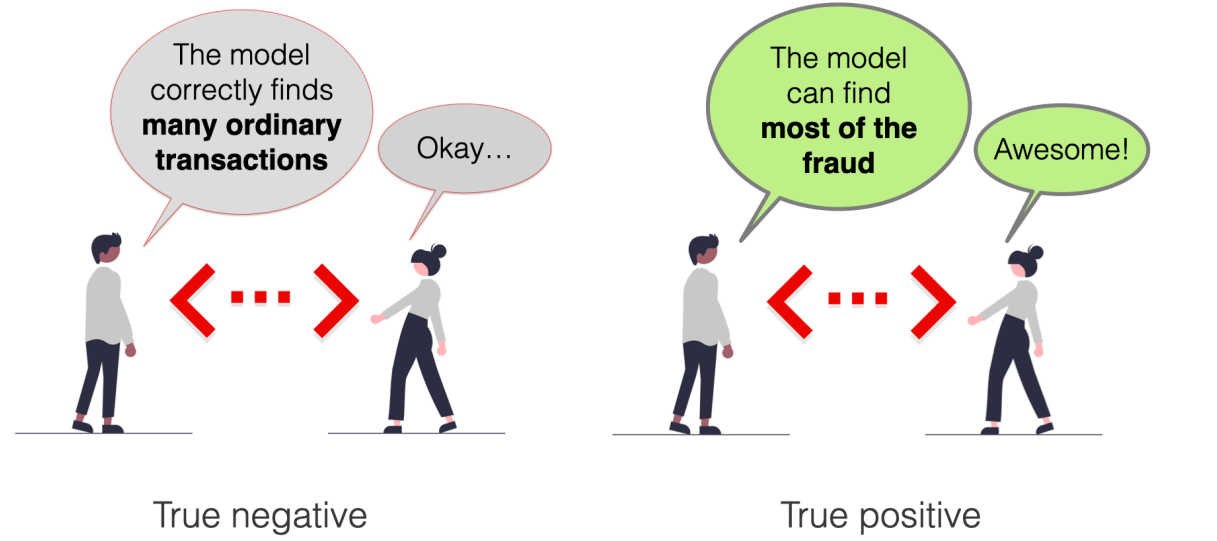
Evaluation metrics for classification problems

Fraud detection: Is it a fraudulent transaction?

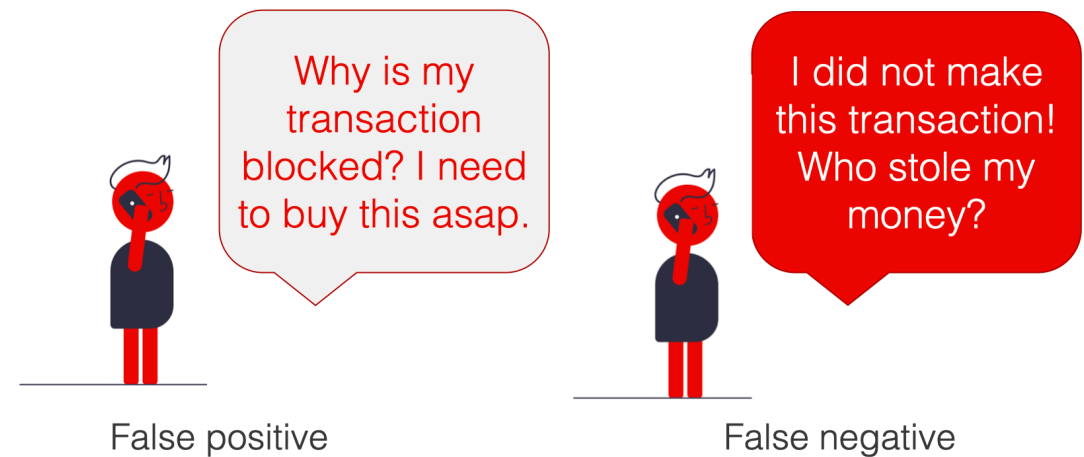
	Predicted	Actual	Correct?
1.	Not fraud	Not fraud	✓
2.	Not fraud	Not fraud	✓
3.	Not fraud	Fraud	✗
4.	Fraud	Fraud	✓
...			
n.	Fraud	Not fraud	✗



	Predicted	Actual	
1.	Not fraud	Not fraud	True Negative
2.	Not fraud	Not fraud	
3.	Not fraud	Fraud	True Positive
4.	Fraud	Fraud	
n.	Fraud	Not fraud	

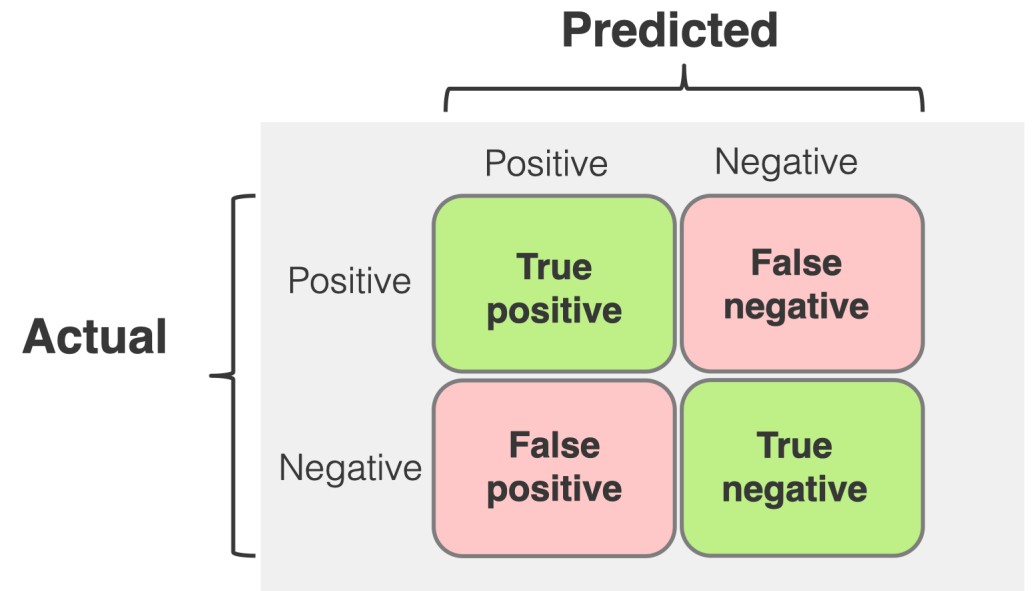


	Predicted	Actual	
1.	Not fraud	Not fraud	
2.	Not fraud	Not fraud	
3.	Not fraud	Fraud	False Negative
4.	Fraud	Fraud	
n.	Fraud	Not fraud	False Positive



Confusion matrix

- **True positive (TP)**: correctly predicted positive
- **True negative (TN)**: correctly predicted negative
- **False positive (FP)**: incorrectly predicted positive
- **False negative (FN)**: incorrectly predicted negative



Spam detection: Is it a spam email?

		Predicted	
		Spam	Non-spam
Actual	Spam	600 (True positive)	300 (False negative)
	Non-spam	100 (False positive)	9000 (True negative)



Accuracy































$$\frac{\text{correct predictions}}{\text{total predictions}}$$

Accuracy

		Predicted	
		Spam	Not
Actual	Spam	600 (TP)	300 (FN)
	Not	100 (FP)	9000 (TN)

Accuracy = $\frac{\text{True predictions (TP + TN)}}{\text{All predictions (TP + TN + FP + FN)}}$

A constant prediction: right in 8 out of 10 cases

Predicted Class										
Actual Class										
Classification Quality										

Accuracy paradox

A model that predicts all negative will have high accuracy on an imbalanced dataset.

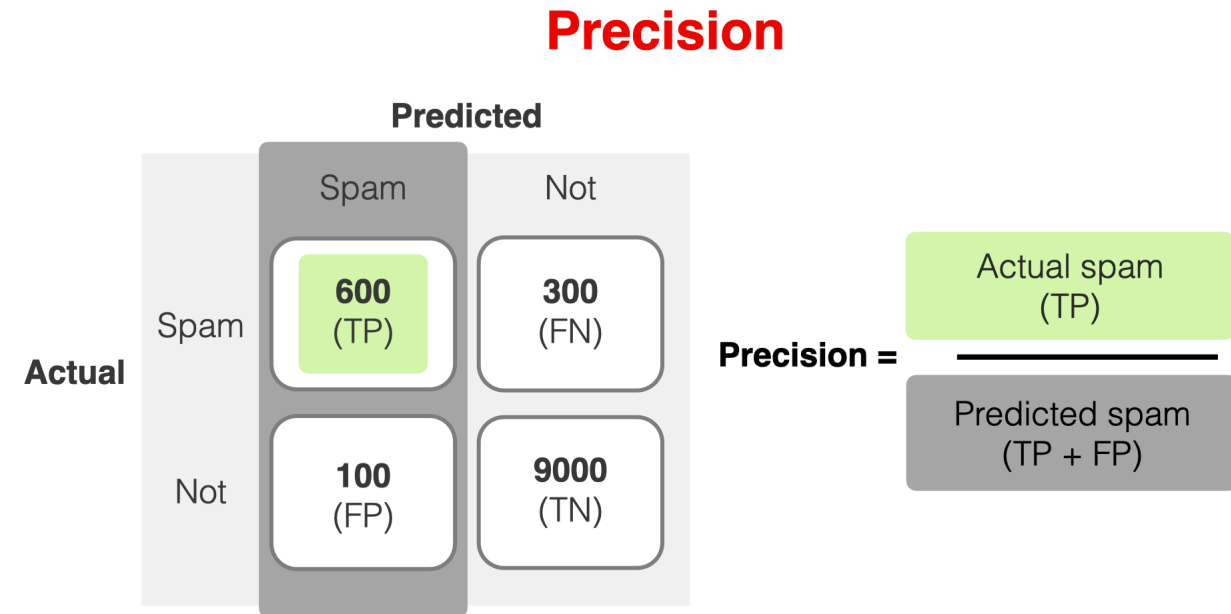
Predicting frequent class (negative samples) adds little value

Precision

$$\frac{\text{correctly predicted positive}}{\text{predicted positive}}$$

Use when FP is costly

- FP , Precision 

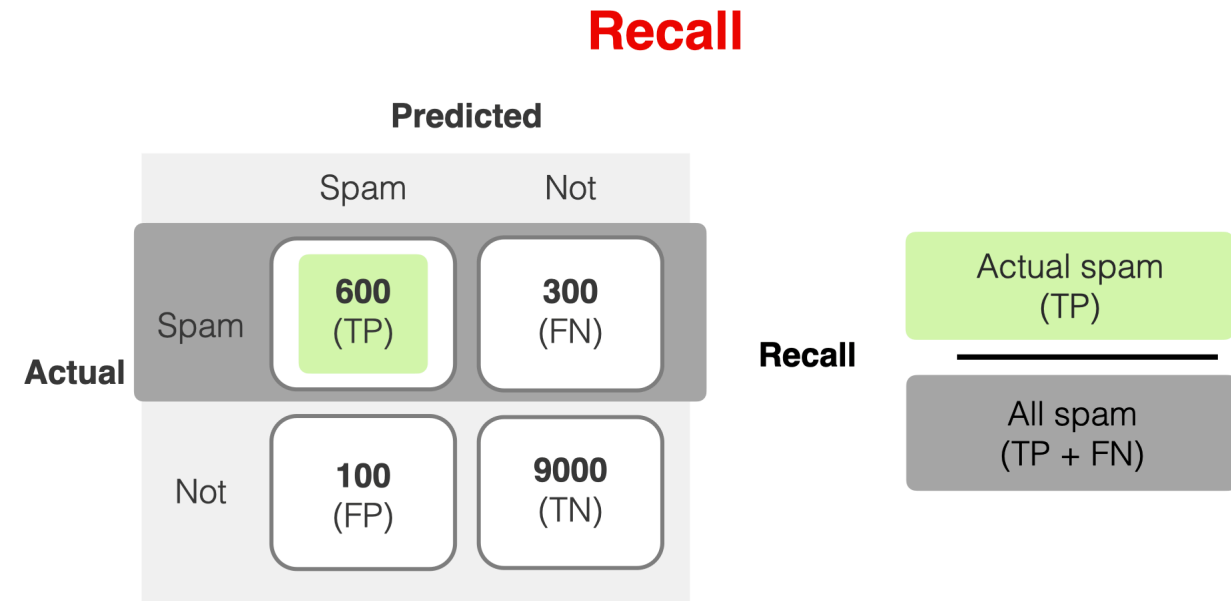


Recall

$$\frac{\text{correctly predicted positive}}{\text{actual positive}}$$

Use when FN is costly

- FN , Recall 



Classification threshold changes the confusion matrix

		Predicted	
		Spam	Not
Actual	Spam	800 (TP)	100 (FN)
	Not	500 (FP)	8600 (TN)

Threshold: 0.5

		Predicted	
		Spam	Not
Actual	Spam	600 (TP)	300 (FN)
	Not	100 (FP)	9000 (TN)

Threshold: 0.8



		Predicted	
		Spam	Not
Actual	Spam	200 (TP)	700 (FN)
	Not	10 (FP)	9090 (TN)

Threshold: 0.95





Precision-recall tradeoff

Increase threshold:

- More conservative: fewer positive predictions, but mostly right
- When in doubt, predict negative ($y=0$)
- Precision , Recall 

Decrease threshold:

- More aggressive: more positive predictions, but more mistakes
- When in doubt, predict positive ($y=1$)
- Precision , Recall 

Visualizing the confusion matrix

https://developers-dot-devsite-v2-prod.appspot.com/machine-learning/crash-course/classification/accuracy-precision-recall_48d642036b6a12f05752bd92fcdf132b3f73d1d61a0897727e060c27ed347370.frame

Optimize for precision or recall

FP is costly: optimize for precision

FN is costly: optimize for recall

Fraud detection:

- FP: non-fraudulent transaction is classified as fraudulent
- FN: fraudulent transaction is classified as non-fraudulent

Propensity to buy:

- FP: non-buyer is classified as buyer
- FN: buyer is classified as non-buyer

F1 score

$$2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Use when you want a single metric that balances precision and recall.



Validate on different evaluation metrics

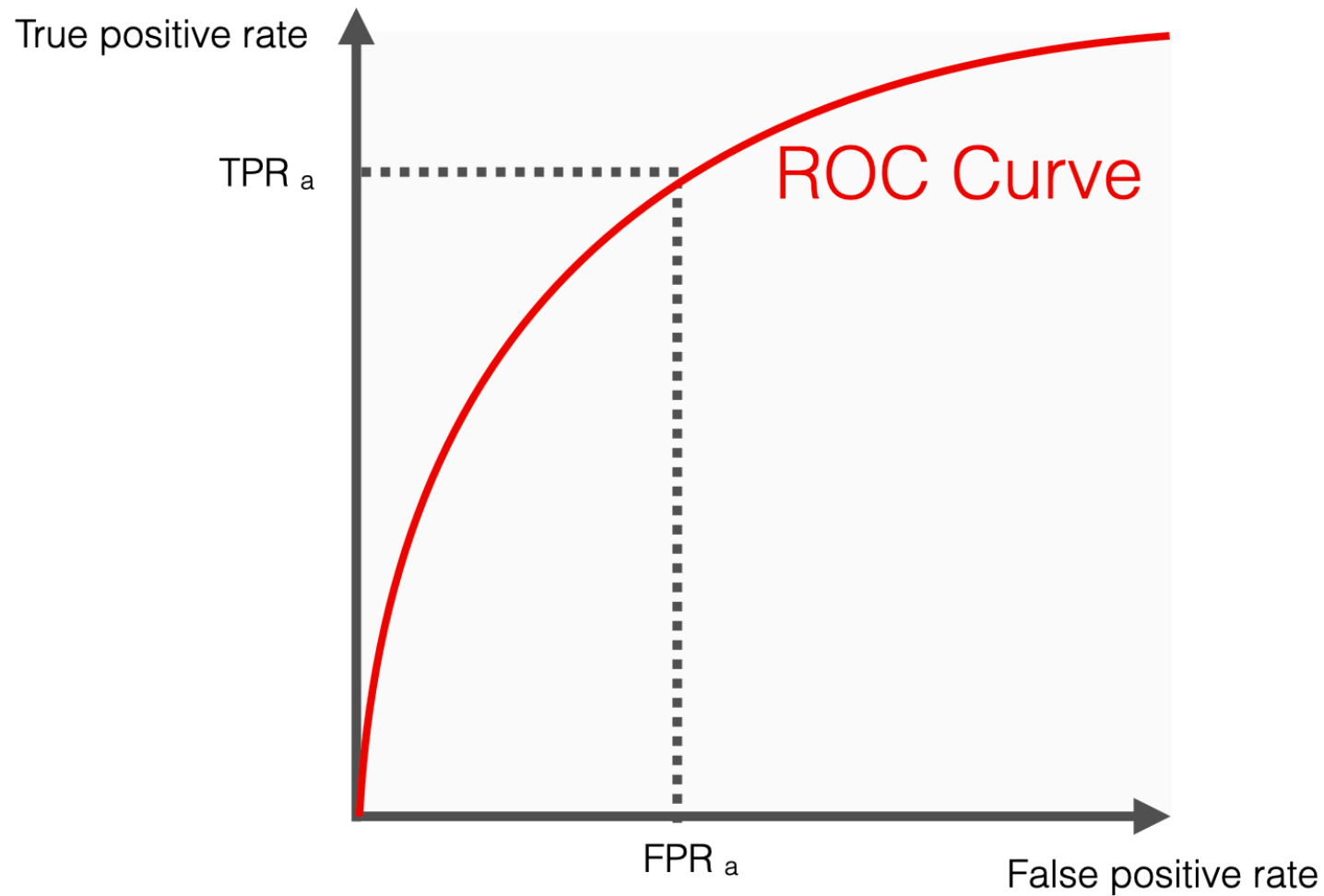
ROC and ROC-AUC

ROC: Receiver-operating characteristic curve

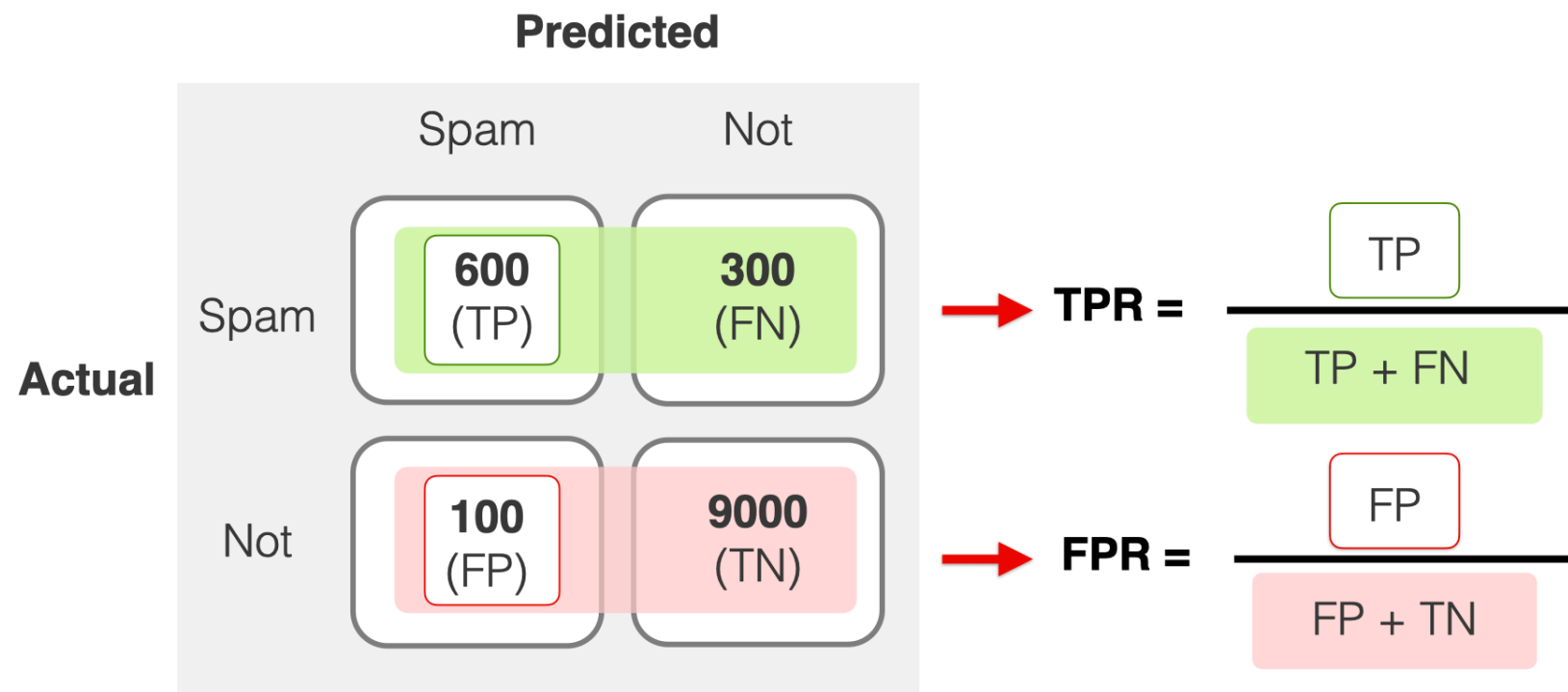
- shows the performance of a binary classifier with ***different thresholds***

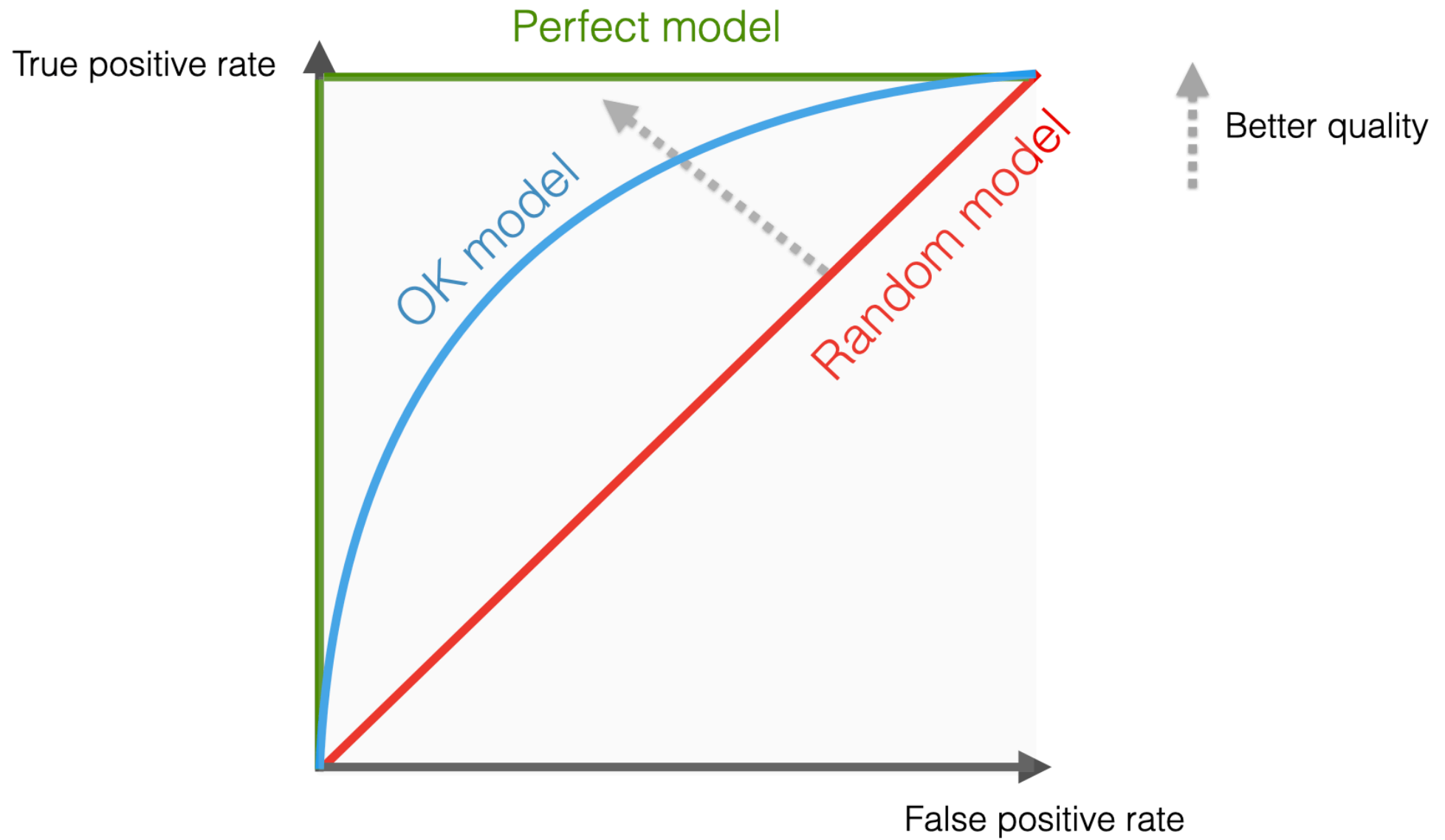
ROC-AUC: Area under the ROC curve

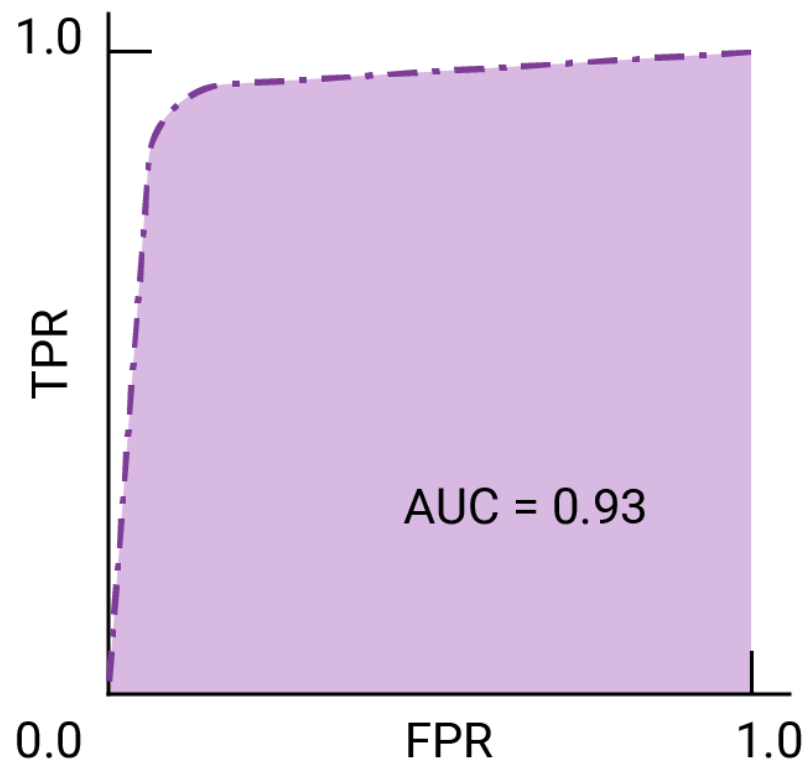
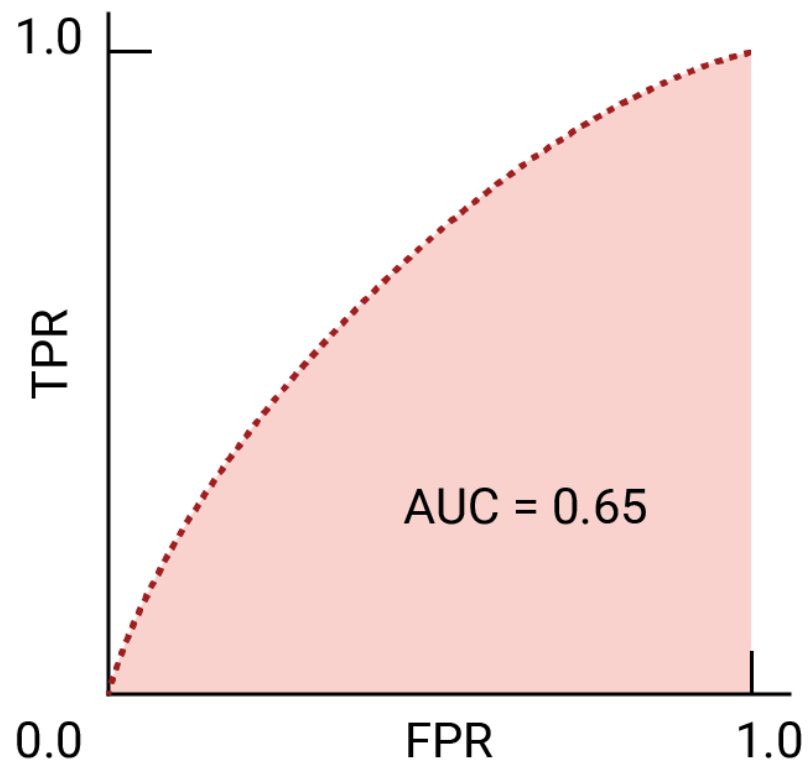
- Relative scores to discriminate between positive or negative instances across all classification thresholds.



TPR and FPR







When to use ROC-AUC

ROC-AUC: a single metric that summarizes the model performance across all thresholds

Useful:

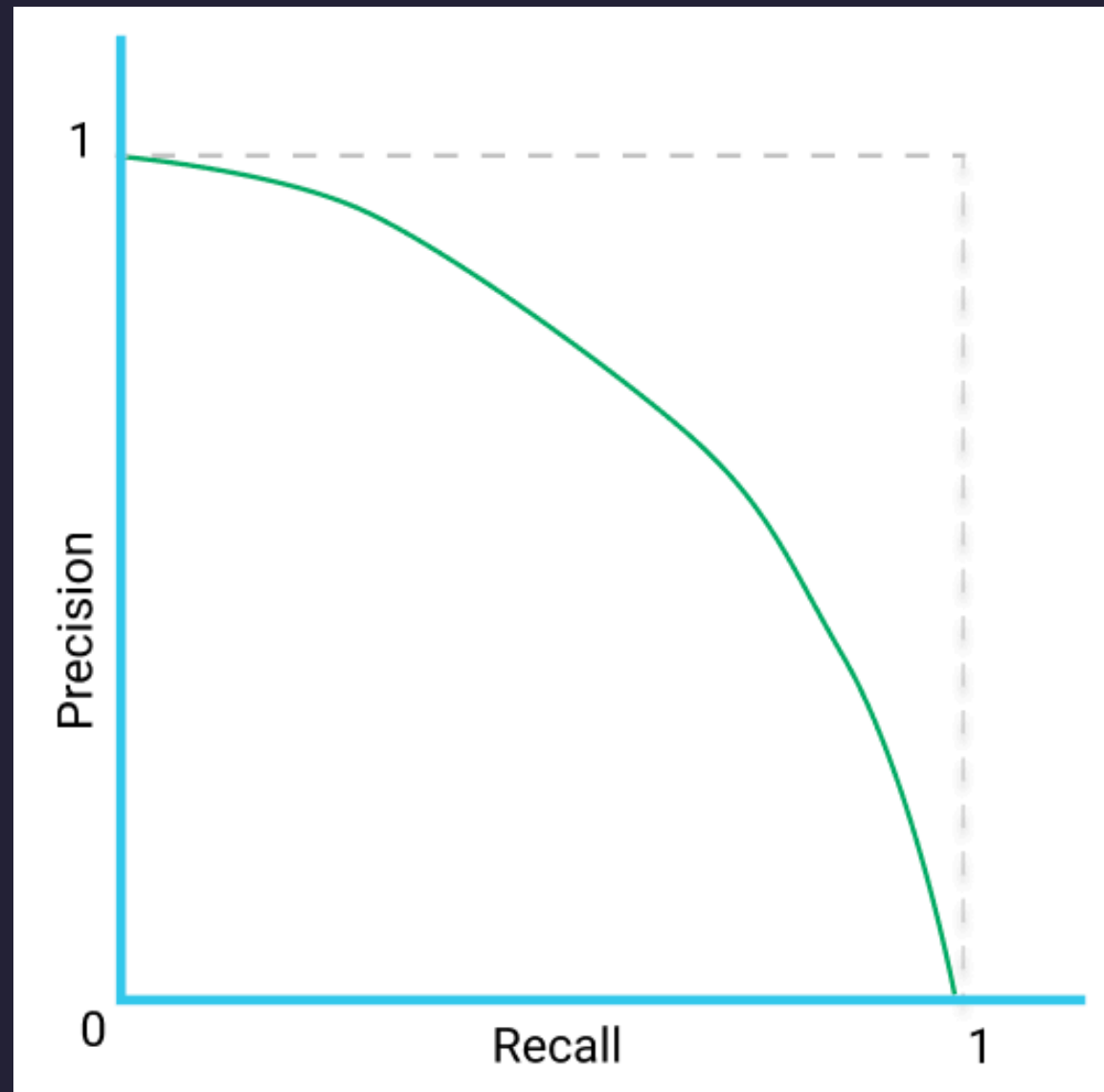
- for model comparison
- when the costs of errors are similar
- when the data is balanced

Less useful :

- when you care about different costs of error
- when the data is heavily imbalanced

Precision-recall (PR) curve

- For imbalanced datasets, use PR curve instead of ROC curve
- Precision vs. Recall across all thresholds
- Precision-recall tradeoff
- PR AUC: Area under the PR curve



ROC and PR curves