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ML Refresher - Classification Evaluation Metrics

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Confusion Matrix

What it is? A table used to describe the performance of a classification model.

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

- **TP**: Correctly predicted positive class.
- **TN**: Correctly predicted negative class.
- **FP**: Incorrectly predicted positive class (Type I error).
- **FN**: Incorrectly predicted negative class (Type II error).

Precision

$$\frac{TP}{TP + FP}$$

- **What is it?** The proportion of true positive predictions out of all positive predictions made
- **Use case:** Best for scenarios where the cost of false positives is high (e.g., spam detection).
- **Limitation:** Does not take into account false negatives, which can be significant in some contexts.

Recall

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

- **What is it?** The proportion of true positive predictions out of all actual positive instances
- **Use case:** Important in situations where missing a positive instance is costly (e.g., disease screening).
- **Limitation:** High recall can lead to low precision if many false positives are present.

Accuracy

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

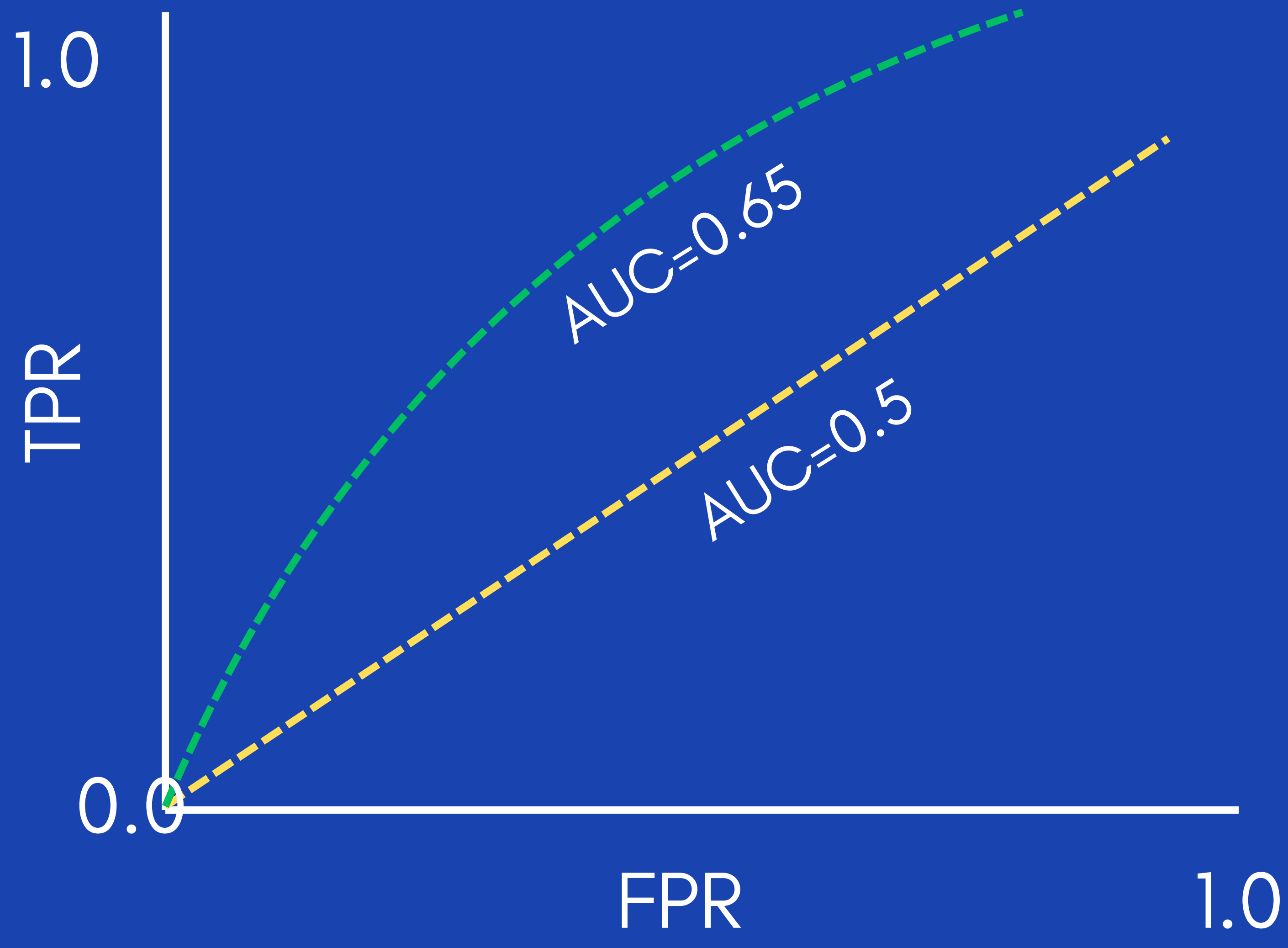
- **What is it?** The proportion of correct predictions out of all predictions.
- **Use case:** Best for balanced datasets where classes are equally distributed.
- **Limitation:** Misleading for imbalanced datasets (e.g. 95% accuracy if 95% of data belongs to one class).

F1-score

$$\frac{2 * Precision * Recall}{Precision + Recall}$$

- **What is it?** The harmonic mean of precision and recall, providing a balance between the two
- **Use case:** Useful in cases where you need a balance between precision and recall, especially in imbalanced datasets.
- **Limitation:** Can be misleading if the underlying distribution of classes is not considered, as it averages the performance.

AUC-ROC Curve



- **What is it?** The area under the receiver operating characteristic curve, representing the trade-off between true positive rate (recall) and false positive rate across different thresholds.
- **Use case:** Good for evaluating classifiers on imbalanced datasets, as it considers all classification thresholds.
- **Limitation:** AUC-ROC can be overly optimistic for highly imbalanced datasets and may not reflect practical performance.

Ponder Upon...

- What does an AUC-ROC score of 0.5 indicate about a model's performance, and how would you interpret an AUC of 0.8 versus 0.9?
- How do you interpret the shape of an ROC curve, and what does it indicate about a model's performance at various thresholds?
- In what scenarios might a model exhibit a high F1 score while having a low overall accuracy? Provide an example.
- How would you evaluate a classification model differently in a medical diagnosis context compared to a marketing context?
- How do you interpret a precision-recall curve, and how is it different from an ROC curve in terms of evaluating model performance?
- How does the distribution of classes in your dataset influence the evaluation metrics, and how can you mitigate the effects of an imbalanced dataset?
- Why is F1-score a harmonic mean of Precision and Recall and not AM or GM?

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