



# ICTSS00120 - Artificial Intelligence Skill Set

## Evaluation Metrics

Lecturer: Jordan Hill

## Learning Objectives

- Understand the key evaluation metrics for machine learning models.
- Learn how to calculate and interpret each metric.
- Relate the metrics to the spam detection example from the lab.
- Appreciate the importance of different metrics in different contexts.

# **Key Evaluation Metrics: An Overview**

- 1. Accuracy**
- 2. Precision**
- 3. Recall**
- 4. F1 Score**
- 5. Confusion Matrix**

These metrics are essential for evaluating the performance of your machine learning models. Let's dive into each one in detail.

## Starting definitions

- TP (True Positives): The number of instances correctly predicted as positive.
- TN (True Negatives): The number of instances correctly predicted as negative.
- FP (False Positives): The number of instances incorrectly predicted as positive.
- FN (False Negatives): The number of instances incorrectly predicted as negative.

# Accuracy

## Definition:

- The ratio of correctly predicted instances to the total instances.

## Formula:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

## Usage:

- Provides a single measurement of the model's performance.
- Useful when the class distribution is balanced.



# Precision

**Definition:**

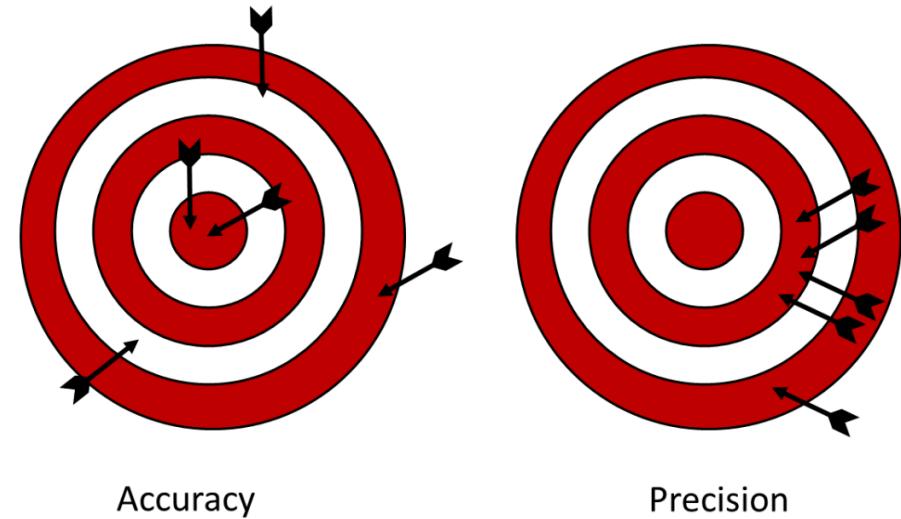
- The ratio of true positive predictions to the sum of true positive and false positive predictions.

**Formula:**

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

**Usage:**

- Indicates how many positive predictions were actually correct.
- Important in contexts where the cost of false positives



## Recall (Sensitivity, True Positive Rate)

### Definition:

- The ratio of true positive predictions to the sum of true positive and false negative predictions.

### Formula:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

### Usage:

- Indicates how many actual positives were captured by the model.
- Critical in contexts where catching all positive cases is important.

# F1 Score

## Definition:

- The harmonic mean of precision and recall.

## Formula:

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

## Usage:

- Provides a single metric that balances precision and recall.
- Useful when you need a balance between precision and recall.

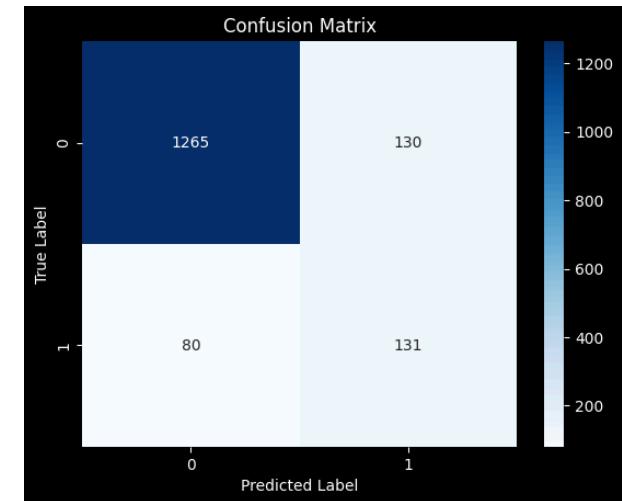
# Confusion Matrix

## Definition:

- A table used to describe the performance of a classification model on a set of test data for which the true values are known.

## Components:

- **True Positive (TP)**: Correctly predicted positive instances.
- **True Negative (TN)**: Correctly predicted negative instances.
- **False Positive (FP)**: Incorrectly predicted as positive (Type I error).
- **False Negative (FN)**: Incorrectly predicted as negative (Type II error).



## Example: Confusion Matrix in Spam Detection

### Initial SVM Result:

Confusion Matrix:

```
[[1200 195]
 [ 43 168]]
```

Precision: 0.46

Recall: 0.80

F1 Score: 0.59

- **TN (1200)**: Ham correctly identified as Ham.
- **FP (195)**: Ham incorrectly identified as Spam.
- **FN (43)**: Spam incorrectly identified as Ham.
- **TP (168)**: Spam correctly identified as Spam.

## Accuracy in Spam Detection

**Formula:**

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

**Result:**

$$\text{Accuracy} = \frac{1200+168}{1200+168+195+43} \approx 0.85$$

**Interpretation:**

85% of the time, the classifier made correct predictions, but this metric alone does not provide a full picture, especially with imbalanced classes.

## Precision in Spam Detection

**Formula:**

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

**Result:**

$$\text{Precision} = \frac{168}{168+195} \approx 0.46$$

**Interpretation:**

Only 46% of the messages identified as spam were actually spam. Indicates high false positive rate.

## Recall in Spam Detection

**Formula:**

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

**Result:**

$$\text{Recall} = \frac{168}{168+43} \approx 0.80$$

**Interpretation:**

80% of the actual spam messages were correctly identified as spam. Indicates high sensitivity to capturing spam.

# F1 Score in Spam Detection

**Formula:**

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

**Result:**

$$\text{F1 Score} = \frac{2 \cdot 0.46 \cdot 0.80}{0.46 + 0.80} \approx 0.59$$

**Interpretation:**

Balances the precision and recall. Useful in this context where both false positives and false negatives are important.

## Why Use Multiple Metrics?

- **Accuracy**: Good for balanced datasets but not informative for imbalanced classes.
- **Precision**: Important when the cost of false positives is high.
- **Recall**: Critical when the cost of false negatives is high.
- **F1 Score**: Provides a balance between precision and recall.
- **Confusion Matrix**: Offers a complete view of model performance.

Using multiple metrics provides a more comprehensive evaluation of the model's performance and helps in understanding its strengths and weaknesses.

## Questions & Discussion

### Q&A:

- Any questions about the evaluation metrics?
- How would you apply these metrics to other types of classification problems?

Contact: [jordan.hill@nmtafe.wa.edu.au](mailto:jordan.hill@nmtafe.wa.edu.au)