

# Artificial Intelligence & Neural Networks

CSE-351

Lecture-10

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# Confusion Matrix

A confusion matrix is a table that is often used to describe the **performance of a classification model** (or “classifier”) on a set of test data for which the true values are known.

- It allows the visualization of the **performance of an algorithm**.
- We compare each class with every other class and see how many samples are misclassified.
- We actually come across several key metrics that are very important in the field of machine learning.

# Confusion Matrix Classification

Let's consider a **binary classification** case where the output is either **0** or **1**:

1. **True positives:** These are the samples for which we predicted 1 as the output and the ground truth is 1 too.
2. **True negatives:** These are the samples for which we predicted 0 as the output and the ground truth is 0 too.
3. **False positives:** These are the samples for which we predicted 1 as the output but the ground truth is 0. This is also known as a Type I error.
4. **False negatives:** These are the samples for which we predicted 0 as the output but the ground truth is 1. This is also known as a Type II error.

# Confusion Matrix Classification

## True Positive(TP):

- ▶ You projected positive and its turn out to be true. For example, you had predicted that France would win the world cup, and it won.

## True Negative(TN):

- ▶ When you predicted negative, and it's true. You had predicted that England would not win and it lost.

## False Positive(FP):

- ▶ Your prediction is positive, and it is false.
- ▶ You had predicted that England would win, but it lost.

## False Negative(FN):

- ▶ Your prediction is negative, and result it is also false.
- ▶ You had predicted that France would not win, but it won.

# Confusion Matrix Classification

		Predicted Class		
		Positive	Negative	
Actual Class	Positive	True Positive (TP)	False Negative (FN) <b>Type II Error</b>	<b>Sensitivity</b> $\frac{TP}{(TP + FN)}$
	Negative	False Positive (FP) <b>Type I Error</b>	True Negative (TN)	<b>Specificity</b> $\frac{TN}{(TN + FP)}$
		<b>Precision</b> $\frac{TP}{(TP + FP)}$	<b>Negative Predictive Value</b> $\frac{TN}{(TN + FN)}$	<b>Accuracy</b> $\frac{TP + TN}{(TP + TN + FP + FN)}$

# Example Scenario

- ▶ Suppose we have a binary classification problem to predict whether an email is **Spam** or **Not Spam**. Here, we have four outcomes in our confusion matrix:
- ▶ **True Positive (TP)**: Predicted Spam, and it is actually Spam.
- ▶ **True Negative (TN)**: Predicted Not Spam, and it is actually Not Spam.
- ▶ **False Positive (FP)**: Predicted Spam, but it is actually Not Spam (also known as a Type I error).
- ▶ **False Negative (FN)**: Predicted Not Spam, but it is actually Spam (also known as a Type II error).

# Example Scenario

Let's say we test our model with 10 emails, and we have the following results:

## Actual

Spam

Not Spam

Spam

Not Spam

Not Spam

Spam

Not Spam

Spam

Not Spam

Spam

## Predicted

Spam

Spam

Spam

Not Spam

Spam

Not Spam

Not Spam

Spam

Not Spam

Not Spam

## Calculate TP, TN, FP, FN

Based on the results above, we categorize each outcome:

**1. True Positives (TP):** Predicted Spam and actually Spam → 3

**2. True Negatives (TN):** Predicted Not Spam and actually Not Spam → 3

**3. False Positives (FP):** Predicted Spam but actually Not Spam → 2

**4. False Negatives (FN):** Predicted Not Spam but actually Spam → 2

# Example Scenario

## **Create the Confusion Matrix**

Using the counts from above, we can create the confusion matrix:

	Predicted: Spam	Predicted: Not Spam
Actual Spam	TP = 3	FN = 2
Actual Not Spam	FP = 2	TN = 3

- Confusion Matrix:

$$\begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix}$$



# Example Scenario

## Calculate Performance Metrics

Using the confusion matrix, we can calculate various metrics to evaluate the model's performance:

1. **Accuracy:** Measures the overall correctness of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{3 + 3}{3 + 3 + 2 + 2} = \frac{6}{10} = 0.6 (60\%)$$

2. **Precision:** Measures the accuracy of positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{3}{3 + 2} = \frac{3}{5} = 0.6 (60\%)$$

3. **Recall (Sensitivity):** Measures the ability to find all positive cases.

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{3}{3 + 2} = \frac{3}{5} = 0.6 (60\%)$$

4. **F1 Score:** The harmonic mean of Precision and Recall.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0.6 \times 0.6}{0.6 + 0.6} = 0.6 (60\%)$$

The background features abstract, overlapping green geometric shapes, primarily triangles and polygons, in various shades of green, creating a modern, layered effect on the right side of the slide.

Questions ??

The background features abstract, overlapping green geometric shapes, primarily triangles and polygons, in various shades of green, creating a modern and dynamic visual effect. The shapes are layered, with some appearing more prominent than others, and they extend from the right and bottom edges towards the center.

Thanks'