

**COURSE NAME: ARTIFICIAL INTELLIGENCE**  
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**SYED TANGIM PASHA**  
**LECTURER,**

**DEPARTMENT OF COMPUTING AND INFORMATION SYSTEM (CIS)**  
**DAFFODIL INTERNATIONAL UNIVERSITY (DIU)**  
**DHAKA, BANGLADESH**

# CONFUSION MATRIX

- **Confusion Matrix:** A confusion matrix is a performance measurement for machine learning algorithms.

	Predicted class		
	Class = Yes	Class = No	
Actual Class	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

# TRUE POSITIVE, TRUE NEGATIVE

- **True Positive (TP):** These are the correctly predicted positive values which means that the value of actual class is yes and the value of predicted class is also yes. Example: If actual class value indicates that this passenger survived and predicted class tells you the same thing.
- **True Negative (TN):** These are the correctly predicted negative values which means that the value of actual class is no and value of predicted class is also no. Example: if actual class says this passenger did not survive and predicted class tells you the same thing.

	Predicted class		
	Class = Yes	Class = No	
Actual Class	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

# FALSE POSITIVE, FALSE NEGATIVE

- **False Positive (FP):** When actual class is no and predicted class is yes. Example: if actual class says this passenger did not survive but predicted class tells you that this passenger will survive.
- **False Negative (FN):** When actual class is yes but predicted class is no. Example: if actual class indicates that this passenger survived and predicted class tells you that passenger will die.

	Predicted class		
	Class = Yes	Class = No	
Actual Class	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

# PRECISION

- **Precision:** Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. High precision relates to the low false positive rate.
- **Example:** you would want greater precision is **spam filters**. A greater number of false positives in a spam filter would mean that one or more important emails could be tagged as spam and moved in spam folders.

$$\textit{precision} = \frac{TP}{TP + FP}$$

$$\textit{recall} = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times \textit{precision} \times \textit{recall}}{\textit{precision} + \textit{recall}}$$

$$\textit{accuracy} = \frac{TP + TN}{TP + FN + TN + FP}$$

$$\textit{specificity} = \frac{TN}{TN + FP}$$

# RECALL

- **Recall:** Recall is the ratio of correctly predicted positive observations to the all observations in actual class-yes.
- **Example:** In medical diagnosis, the recall score should be extremely high otherwise greater number of false negative would prove to be fatal for life of patients.

$$\begin{aligned} \textit{precision} &= \frac{TP}{TP + FP} \\ \textit{recall} &= \frac{TP}{TP + FN} \\ \textit{F1} &= \frac{2 \times \textit{precision} \times \textit{recall}}{\textit{precision} + \textit{recall}} \\ \textit{accuracy} &= \frac{TP + TN}{TP + FN + TN + FP} \\ \textit{specificity} &= \frac{TN}{TN + FP} \end{aligned}$$

# F1 SCORE

- **F1-Score:** F1 score is the weighted average of Precision and Recall. That is, a good F1 Score means that you have low false positive and low false negatives. An F1 score is considered perfect when it's 1, while the model is a total failure when it's 0.

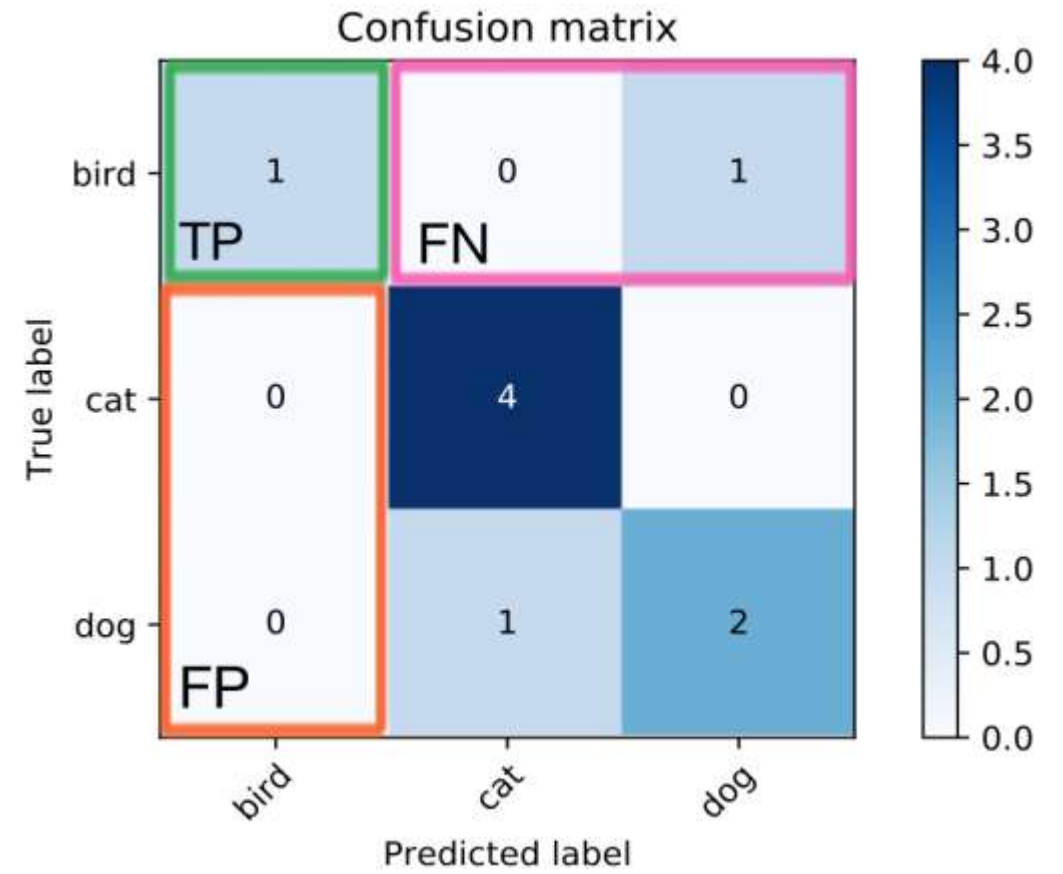
$$\begin{aligned} \textit{precision} &= \frac{TP}{TP + FP} \\ \textit{recall} &= \frac{TP}{TP + FN} \\ \textit{F1} &= \frac{2 \times \textit{precision} \times \textit{recall}}{\textit{precision} + \textit{recall}} \\ \textit{accuracy} &= \frac{TP + TN}{TP + FN + TN + FP} \\ \textit{specificity} &= \frac{TN}{TN + FP} \end{aligned}$$

# ACCURACY

- **Accuracy:** Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations.
- Accuracy can tell us immediately whether a model is being trained correctly and how it perform generally.

$$\begin{aligned} \textit{precision} &= \frac{TP}{TP + FP} \\ \textit{recall} &= \frac{TP}{TP + FN} \\ \textit{F1} &= \frac{2 \times \textit{precision} \times \textit{recall}}{\textit{precision} + \textit{recall}} \\ \textit{accuracy} &= \frac{TP + TN}{TP + FN + TN + FP} \\ \textit{specificity} &= \frac{TN}{TN + FP} \end{aligned}$$

# KNN



# EXAMPLE



**TRUE POSITIVE**



**FALSE NEGATIVE**



**FALSE POSITIVE**



**TRUE NEGATIVE**

# EXAMPLE

- We will now go back to the earlier example of classifying **100** people (which includes **40 pregnant women** and the remaining **60 are not pregnant** women and men with a fat belly) as pregnant or not pregnant. Out of 40 pregnant women **30 pregnant women are classified correctly** and the remaining **10 pregnant women are classified as not pregnant** by the machine learning algorithm. On the other hand, out of 60 people in the not pregnant category, **55 are classified as not pregnant** and the remaining **5 are classified as pregnant**.

	Predicted Positives	Predicted Negatives
Positives	True Positives	False Negatives
Negatives	False Positives	True Negatives

# EXAMPLE

- $TN = 55, FP = 5, FN = 10, TP = 30$

- $PRECISION = TP / (TP + FP) = 30 / (30 + 5) = 0.857$

- $RECALL = TP / (TP + FN) = 30 / (30 + 10) = 0.75$

- $F1-SCORE = 2 * (PRECISION * RECALL) /$   
 $(PRECISION + RECALL) =$   
 $2 * (0.857 * 0.75) / (0.857 + 0.75) = 0.799$

- $ACCURACY = (TN + TP) / (TN + FP + TP + FN) =$   
 $(55 + 30) / (55 + 5 + 30 + 10) = 0.85$