

# Confusion Matrix

# Confusion matrix

- A confusion matrix is a table that categorizes predictions according to whether they match the actual value in the data.
- One of the table's dimensions indicates the possible categories of predicted values while the other dimension indicates the same for actual values.

## Two Classes

Predicted Class

A

B

Actual  
Class

A



B



## Three Classes

Predicted Class

A

B

C

Actual  
Class

A



B







C









- When the predicted value is the same as the actual value, this is a correct classification. Correct predictions fall on the diagonal in the confusion matrix (denoted by O).
- The off-diagonal matrix cells (denoted by X) indicate the cases where the predicted value differs from the actual value. These are incorrect predictions.
- Performance measures for classification models are based on the counts of predictions falling on and off the diagonal in these tables:

**Two Classes**

		Predicted Class	
		A	B
Actual Class	A		
	B		

### Three Classes

		Predicted Class		
		A	B	C
Actual Class	A			
	B			
	C			

- The most common performance measures consider the model's ability to discern one class versus all others. The class of interest is known as the **positive class**, while all others are known as **negative class**.
- The relationship between positive class and negative class predictions can be depicted as a 2 x 2 confusion matrix that tabulates whether predictions fall into one of four categories:
  - **True Positive (TP):** Correctly classified as the class of interest
  - **True Negative (TN):** Correctly classified as not the class of interest
  - **False Positive (FP):** Incorrectly classified as the class of interest
  - **False Negative (FN):** Incorrectly classified as not the class of interest

# Confusion Matrix -Problem

- Suppose 10000 patients get tested for flu; out of them, 9000 are actually healthy and 1000 are actually sick. For the sick people, a test was positive for 620 and negative for 380. For the healthy people, the same test was positive for 180 and negative for 8820. Construct a confusion matrix for the data.

	Predicted YES	Predicted NO
Actual YES	TP=620	FN=380
Actual NO	FP=180	TN=8820

# Using confusion matrices to measure performance

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

- In this formula, the terms TP, TN, FP, and FN refer to the number of times the model's predictions fell into each of these categories. Therefore, the accuracy is the proportion that represents the number of true positives and true negatives divided by the total number of predictions.
- The error rate, or the proportion of incorrectly classified examples, is specified as:

$$\begin{aligned}\text{error rate} &= \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \\ &= 1 - \text{accuracy}\end{aligned}$$

# Sensitivity

- The sensitivity of a model (also called the true positive rate), measures the proportion of positive examples that were correctly classified.
- Therefore, as shown in the following formula, it is calculated as the number of true positives divided by the total number of positives in the data—those correctly classified (the true positives), as well as those incorrectly classified (the false negatives).
  - $\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$



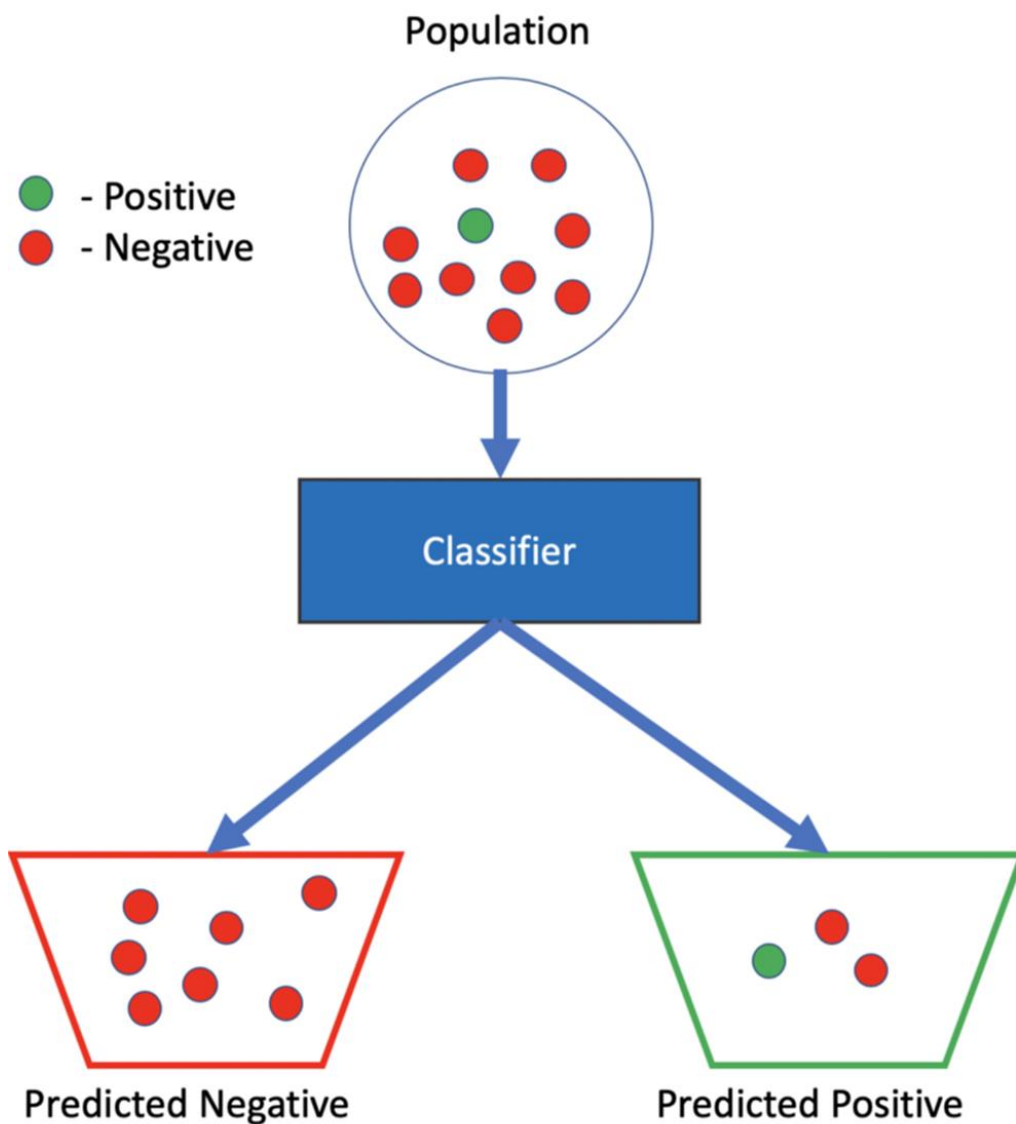
# Specificity

- The specificity of a model (also called the true negative rate), measures the proportion of negative examples that were correctly classified. As with sensitivity, this is computed as the number of true negatives divided by the total number of negatives—the true negatives plus the false positives.
  - $\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$

# Precision and recall

- The two other performance measures that are closely related to sensitivity and specificity are: **precision and recall**.
- The precision (also known as the positive predictive value) is defined as the proportion of positive examples that are truly positive; in other words, when a model predicts the positive class, how often is it correct
- In the context of information retrieval, this would be similar to a search engine such as Google returning unrelated results.

- Precision =  $TP / (TP + FP)$
- Recall is a **measure of how complete the results are**. As shown in the following formula, this is defined as the number of true positives over the total number of positives.
- Recall =  $TP / (TP + FN)$



		Real	
		Positive	Negative
Predicted	Positive	1	2
	Negative	0	7

$$\text{precision} = \frac{tp}{tp + fp} = \frac{1}{3} = 33\%$$

$$\text{recall} = \frac{tp}{tp + fn} = \frac{1}{1} = 100\%$$

$$\text{specificity} = \frac{tn}{tn + fp} = \frac{7}{9} = 78\%$$

$$\text{sensitivity} = \text{recall} = 100\%$$

# F-measure

- A measure of model performance that combines precision and recall into a single number is known as the F-measure (also sometimes called the F1 score or the F-score).
- The F-measure combines precision and recall using the harmonic mean.
  - $F - \text{measure} = 2 \times \text{precision} \times \text{recall} / (\text{recall} + \text{precision})$

# Confusion Matrix- Common Metrics

		PREDICTED	
		Positive	Negative
ACTUAL	Positive	TRUE POSITIVE	FALSE NEGATIVE
	Negative	FALSE POSITIVE	TRUE NEGATIVE

$$\text{Predictive Accuracy} = \frac{TP + TN}{TP + FN + TN + FP}$$

# Common measures of Evaluation

Precision =

$$\begin{aligned} \text{Precision (+ve), } Pp &= \frac{TP}{TP + FP} \\ \text{Precision (-ve), } Pn &= \frac{TN}{TN + FN} \end{aligned}$$

Recall =

$$\begin{aligned} \text{Recall (+ve), } Rp &= \frac{TP}{TP + FN} \\ \text{Recall (-ve), } Rn &= \frac{TN}{TN + FP} \end{aligned}$$

$$F - \text{Score} = \frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})}$$

		PREDICTED	
		Positive	Negative
ACTUAL	Positive	TRUE POSITIVE	FALSE NEGATIVE
	Negative	FALSE POSITIVE	TRUE NEGATIVE



```
print(confusion_matrix(y_test, y_pred))  
print(classification_report(y_test, y_pred))
```



```
[[13  0  0]  
 [ 0 20  1]  
 [ 0  0 11]]
```

	precision	recall	f1-score	support
Setosa	1.00	1.00	1.00	13
Versicolor	1.00	0.95	0.98	21
Virginica	0.92	1.00	0.96	11
accuracy			0.98	45
macro avg	0.97	0.98	0.98	45
weighted avg	0.98	0.98	0.98	45



	Predicted				Total (Actual)
		Setosa	Versicolor	Virginica	
Actual	Setosa	13	0	0	13
	Versicolor	0	20	1	21
	Virginica	0	0	11	11
	Total (Predicted)	13	20	12	

Accuracy	$= (13+20+11)/(13+20+1+11)$	0.977778
Precision (Setosa)	$= 13/13$	1
Precision (Versicolor)	$= 20/20$	1
Precision (Setosa)	$= 11/12$	0.916667
Recall (Setosa)	$= 13/13$	1
Recall (Versicolor)	$= 20/21$	0.952381
Recall (Virginica)	$= 11/11$	1

# Confusion Matrix -Problem

- Suppose 10000 patients get tested for flu; out of them, 9000 are actually healthy and 1000 are actually sick. For the sick people, a test was positive for 620 and negative for 380. For the healthy people, the same test was positive for 180 and negative for 8820. Construct a confusion matrix for the data and compute the precision and recall for the data

	Predicted YES	Predicted NO
Actual YES	TP=620	FN=380
Actual NO	FP=180	TN=8820

- Precision=  $TP/(TP+FP)$

In the example:  $620/(620+180)=0.775$

- Recall =  $TP/(TP+FN)$

In the example:  $620/(620+380)=0.62$

	Predicted YES	Predicted NO
Actual YES	TP=620	FN=380
Actual NO	FP=180	TN=8820

# Confusion Matrix –Problem2

2. Suppose that among 1000 samples 28 are actually fraud. When it undergone for a classification test, 10 fraud data classified correctly and the remaining predicted as negative. For fair transactions 950 classified correctly. Construct a confusion matrix and compute accuracy, precision and recall for this fraud detection data.