

Classification – Performance metrics

- Accuracy
- Sensitivity
- Specificity
- Precision
- Recall
- F1 measure
- True positive rate (TPR)
- False negative rate (FNR)
- ROC
- AUC

Confusion Matrix

- Square matrix that contains all the possible classes in both the horizontal and vertical directions and list the classes along the top of a table as the predicted outputs, and then down the left-hand side as the targets.
- Example :

Outputs			
	C_1	C_2	C_3
C_1	5	1	0
C_2	1	4	1
C_3	2	0	4

- Accuracy?

Confusion matrix – Binary class

- Confusion matrix of binary class

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN) Type II Error
	Negative	False Positive (FP) Type I Error	True Negative (TN)

- Accuracy ???

Confusion matrix – Binary class with metrics

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

Sensitivity and Specificity

- Sensitivity (also known as the true positive rate) is the ratio of the number of correct positive examples to the number classified as positive
- Specificity is the same ratio for negative examples.

$$\text{Sensitivity} = \frac{\#TP}{\#TP + \#FN}$$

$$\text{Specificity} = \frac{\#TN}{\#TN + \#FP}$$

Precision and Recall

- Precision is the ratio of correct positive examples to the number of actual positive examples
- **Recall** is the ratio of the number of correct positive examples out of those that were classified as positive, which is the same as **sensitivity**

$$\text{Precision} = \frac{\#TP}{\#TP + \#FP}$$

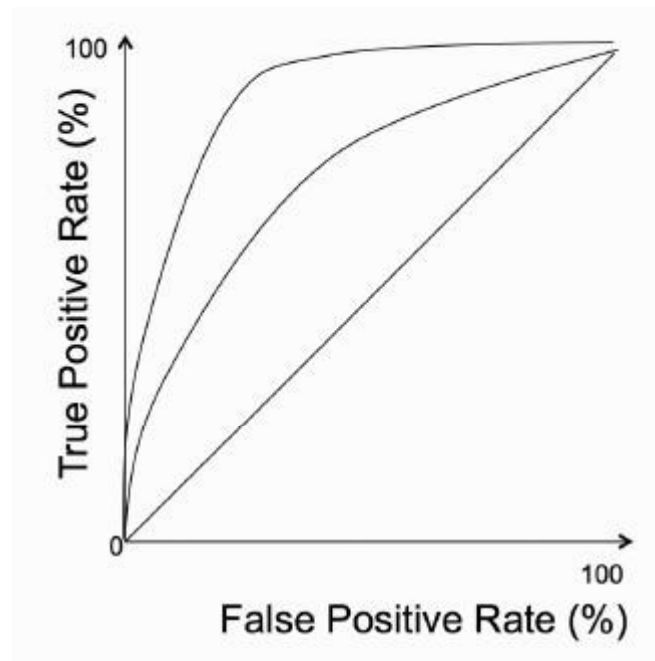
$$\text{Recall} = \frac{\#TP}{\#TP + \#FN}$$

F1 measure

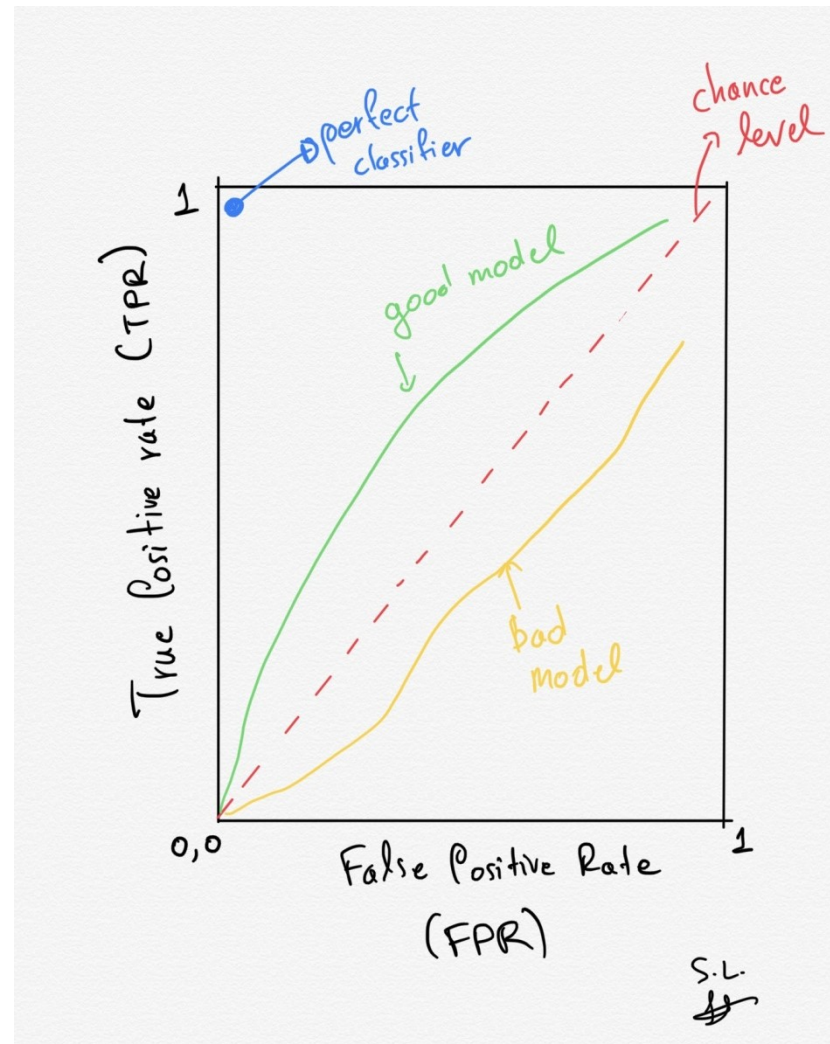
- Precision and recall are to some extent inversely related, in that if the number of false positives increases, then the number of false negatives often decreases, and vice versa.
- They can be combined to give a single measure, the *F1 measure*, which can be written in terms of precision and recall as:

$$F_1 = 2 \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Receiver Operator Characteristic (ROC) Curve



Receiver Operator Characteristic (ROC) Curve



ROC - AUC

- TPR - Sensitivity
- FPR - (1-specificity)
- With imbalanced datasets, the Area Under the Curve (AUC) score is calculated from ROC and is a very useful metric in imbalanced datasets.
- The AUC (area under the curve) indicates if the curve is above or below the diagonal (chance level). AUC ranges in value from 0 to 1. A model whose predictions are 100% wrong has an AUC of 0.0 and one whose predictions are 100% correct has an AUC of 1.0.

Performance metrics – overall

		True condition			
Total population		Condition positive	Condition negative	$Prevalence = \frac{\Sigma \text{Condition positive}}{\Sigma \text{Total population}}$	$Accuracy (ACC) = \frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$
Predicted condition	Predicted condition positive	True positive	False positive, Type I error	$Positive \text{ predictive value (PPV), Precision} = \frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$	$False \text{ discovery rate (FDR)} = \frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$
	Predicted condition negative	False negative, Type II error	True negative	$False \text{ omission rate (FOR)} = \frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$	$Negative \text{ predictive value (NPV)} = \frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$
		$True \text{ positive rate (TPR), Recall, Sensitivity, probability of detection, Power} = \frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	$False \text{ positive rate (FPR), Fall-out, probability of false alarm} = \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	$Positive \text{ likelihood ratio (LR+)} = \frac{TPR}{FPR}$	$Diagnostic \text{ odds ratio (DOR)} = \frac{LR+}{LR-}$
	$False \text{ negative rate (FNR), Miss rate} = \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	$Specificity (SPC), Selectivity, True negative rate (TNR) = \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	$Negative \text{ likelihood ratio (LR-)} = \frac{FNR}{TNR}$	$F_1 \text{ score} = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$	













https://en.wikipedia.org/wiki/Sensitivity_and_specificity

Accuracy Metrics – overall - Example

		Patients with bowel cancer (as confirmed on endoscopy)			
		Condition positive	Condition negative	Prevalence = (TP + FN) / Total_Population = (20 + 10) / 2030 ≈ 1.48%	Accuracy (ACC) = (TP + TN) / Total_Population = (20 + 1820) / 2030 ≈ 90.64%
Fecal occult blood screen test outcome	Test outcome positive	True positive (TP) = 20 (2030 × 1.48% × 67%)	False positive (FP) = 180 (2030 × (100 – 1.48%) × (100 – 91%))	Positive predictive value (PPV), Precision = TP / (TP + FP) = 20 / (20 + 180) = 10%	False discovery rate (FDR) = FP / (TP + FP) = 180 / (20 + 180) = 90.0%
	Test outcome negative	False negative (FN) = 10 (2030 × 1.48% × (100 – 67%))	True negative (TN) = 1820 (2030 × (100 – 1.48%) × 91%)	False omission rate (FOR) = FN / (FN + TN) = 10 / (10 + 1820) ≈ 0.55%	Negative predictive value (NPV) = TN / (FN + TN) = 1820 / (10 + 1820) ≈ 99.45%
		TPR, Recall, Sensitivity = TP / (TP + FN) = 20 / (20 + 10) ≈ 66.7%	False positive rate (FPR), Fall-out, probability of false alarm = FP / (FP + TN) = 180 / (180 + 1820) = 9.0%	Positive likelihood ratio (LR+) = $\frac{TPR}{FPR}$ = (20 / 30) / (180 / 2000) ≈ 7.41	Diagnostic odds ratio (DOR) = $\frac{LR+}{LR-}$ ≈ 20.2
		False negative rate (FNR), Miss rate = FN / (TP + FN) = 10 / (20 + 10) ≈ 33.3%	Specificity, Selectivity, True negative rate (TNR) = TN / (FP + TN) = 1820 / (180 + 1820) = 91%	Negative likelihood ratio (LR-) = $\frac{FNR}{TNR}$ = (10 / 30) / (1820 / 2000) ≈ 0.366	
					F ₁ score = 2 × $\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ ≈ 0.174

https://en.wikipedia.org/wiki/Sensitivity_and_specificity

Check your understanding...

	Predicted class POSITIVE (spam )	Predicted class NEGATIVE (normal )
Actual class POSITIVE (spam )	TRUE POSITIVE (TP)   320	FALSE NEGATIVE (FN)   43
Actual class NEGATIVE (normal )	FALSE POSITIVE (FP)   20	TRUE NEGATIVE (TN)   538

Multiclass Classification – metrics

	Predicted class POSITIVE (spam 📧)	Predicted class NEGATIVE (ad 📧)	Predicted class NEGATIVE (normal 📧)
Actual class POSITIVE (spam 📧)	TRUE POSITIVES 📧 📧 27	FALSE NEGATIVES 📧 📧 286 📧 📧 40	
Actual class NEGATIVE (ad 📧)	📧 📧 1 FALSE POSITIVES	📧 📧 37 TRUE NEGATIVES	📧 📧 9 TRUE NEGATIVES
Actual class NEGATIVE (normal 📧)	📧 📧 5 FALSE POSITIVES	📧 📧 16 TRUE NEGATIVES	📧 📧 500 TRUE NEGATIVES

Multiclass Classification – metrics

- **True Positives**, i.e. where the actual and predicted class is spam
- **False Negatives**, where the actual class is spam, and the predicted class is normal or ad
- **False Positives**, where the actual class is normal or ad, and the predicted class is spam
- **True Negatives**, where the actual class is ad or normal, and the predicted class is ad or normal. An incorrect prediction inside the negative class is still considered as a true negative

Source: <https://towardsdatascience.com/confusion-matrix-and-class-statistics-68b79f4f510b>

Check your understanding...

Find the value of following performance metrics

- What is contingency table?
- What is error matrix?
- Accuracy
- Sensitivity - True positive rate (TPR) - Recall
- Specificity
- Precision
- F1 measure
- False negative rate (FNR) – Miss rate

