Google

Story

An Aesop's Fable: The Boy Who Cried Wolf (*compressed*)

A shepherd boy gets bored tending the town's flock. To have some fun, he cries out, "Wolf!" even though no wolf is in sight. The villagers run to protect the flock, but then get really mad when they realize the boy was playing a joke on them.

[Iterate previous paragraph *N* times.]

One night, the shepherd boy sees a real wolf approaching the flock and calls out, "Wolf!" The villagers refuse to be fooled again and stay in their houses. The hungry wolf turns the flock into lamb chops. The town goes hungry. Panic ensues.

Let's make the following definitions:

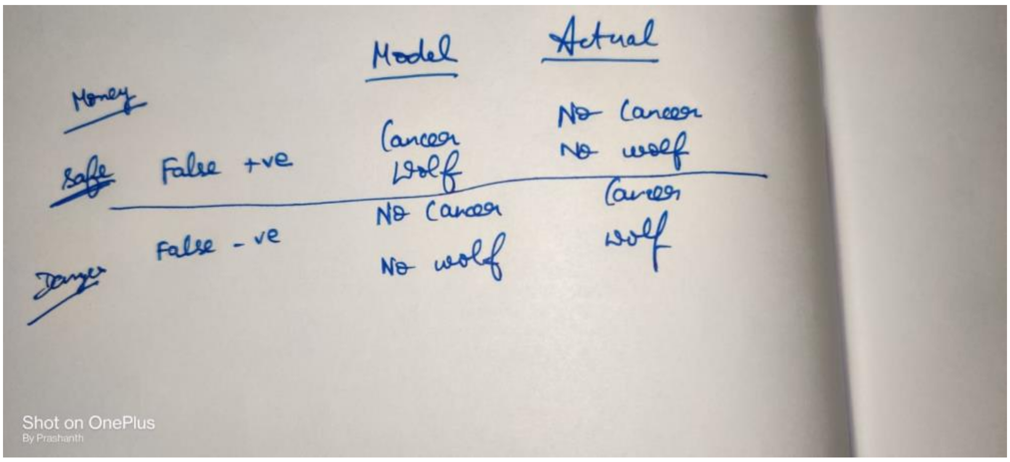
- "Wolf" is a **positive class**. நரி வருது
- "No wolf" is a **negative class**. நரி வரல

We can summarize our "wolf-prediction" model using a 2x2 confusion matrix that depicts all four possible outcomes:

True Positive (TP): • Reality: A wolf threatened. • Shepherd said: "Wolf." • Outcome: Shepherd is a hero.	**False Positive (FP):** • Reality: No wolf threatened. • Shepherd said: "Wolf." • Outcome: Villagers are angry at shepherd for waking them up.
False Negative (FN): • Reality: A wolf threatened. • Shepherd said: "No wolf." • Outcome: The wolf ate all the sheep.	**True Negative (TN):** • Reality: No wolf threatened. • Shepherd said: "No wolf." • Outcome: Everyone is fine.

A **true positive** is an outcome where the model *correctly* predicts the *positive* class. Similarly, a **true negative** is an outcome where the model *correctly* predicts the *negative* class.

A **false positive** is an outcome where the model *incorrectly* predicts the *positive* class. And a **false negative** is an outcome where the model *incorrectly* predicts the *negative* class.



Recall (Sensitivity)

(Sensitivity)

True Positive Recall

$\hookrightarrow \dfrac{TP}{TP + FN}$

	Actual	
Predicted	TP	FP
	FN	TN

False Positive Recall

$\hookrightarrow \dfrac{FP}{FP + TN}$

Same

Precision

	Actual	
Predicted	TP	FP
	FN	TN

Precision $\Rightarrow \dfrac{TP}{TP + FP}$

True Negative Rate

(Specificity)

$\hookrightarrow \dfrac{TN}{TN + FP}$

	Actual	
Predicted	TP	FP
	FN	TN

False Positive Rate

(1- specificity)

$\hookrightarrow \dfrac{FP}{FP + TN}$

Actual values

Predicted Values	Positive (1)	Negative (0)
Positive (1)	True Positive (TP)	False Positive (FP)
Negative (0)	False Negative (FN)	True Negative (TN)

*) Predicted & Actual values } Exactly corrected

True positive (TP) and True Negative (TN)

*) Predicted ✓ } False positive
Actual ×

*) Predicted × } False negative
Actual ✓

*) Predict whether a patient has cancer / not

should have more focus

False positive	False Negative
Model : Cancer Actual : No cancer	Model : No cancer Actual : Cancer
Person goes to the hospital and check ↳ Report (No cancer) Money is lost	Person thinks he is Not having cancer Later he dies Life is lost

Domain knowledge comes into picture

Accuracy

$$\text{Accuracy} \Rightarrow \frac{\text{True Positive (TP)} + \text{True Negative (TN)}}{TP + TN + FP + FN}$$

Recall / True Positive Recall:

$$\text{Recall} \Rightarrow \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}}$$

	Actual Positive	Negative
Predict Positive	TP	FP
Negative	FN	TN
	True +ve rate	False +ve rate

Recall / False Positive Recall:

$$\text{Recall} \Rightarrow \frac{\text{False Positive (FP)}}{\text{False Positive (FP)} + \text{True Negative (TN)}}$$

Balanced vs Imbalanced data-sets

	(+true) 1	0 (false)
Balanced data-sets	1000	900
Imbalanced data-sets	1000	100

↳ fraud detection
fraud transaction

*) We will use Up Sampling and create points.

*) Every disease related data-sets are imbalanced since everybody is not having disease.

Confusion Matrix

Recall (Sensitivity)

(Sensitivity)

True Positive Recall

$\hookrightarrow \frac{TP}{TP + FN}$

False Positive Recall

$\hookrightarrow \frac{FP}{FP + TN}$

	Actual	
Predicted (Machine)	TP	FP
	FN	TN

precision (impt)

False +ve ⇒ Type-1 error

False -ve ⇒ Type-2 error

recall (impt)

Precision

precision ⇒ $\frac{TP}{TP + FP}$

	Actual	
Predicted	TP	FP
	FN	TN

Same

email ⇒ precision

tumour ⇒ recall

$\boxed{\text{Precision} \propto \frac{1}{\text{recall}}}$

$\frac{TP}{TP + FP} \propto \frac{1}{\left(\frac{TP}{TP + FN}\right)}$

True Negative Rate

(Specificity)

$\hookrightarrow \frac{TN}{TN + FP}$

	Actual	
Predicted	TP	FP
	FN	TN

False Positive Rate

(1- specificity)

$\hookrightarrow \frac{FP}{FP + TN}$

	Model	Actual
False +ve ⇒	Cancer / Diff	No Cancer / No Diff
False -ve ⇒	No Cancer / No Diff	Cancer / Diff

F1 measure ⇒ $\frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$

↓

More important than accuracy with mean class distribution

[It uses Harmonic Mean in place of Arithmetic Mean by punishing the extreme values more]

Precision

Precision is defined as the ratio of correctly classified positive samples (True Positive) to a total number of classified positive samples *(either correctly or incorrectly).*

Recall

The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples.
The ***recall measures the model's ability to detect positive samples***. The higher the recall, the more positive samples detected.

Statistical Power

Statistical power, or the power of a hypothesis test is the probability that the test correctly rejects the null hypothesis.
More intuitively, the statistical power can be thought of as the probability of accepting an alternative hypothesis, when the alternative hypothesis is true.

True Positive

Patient having heart disease

Actual

Model

correctly predicted

↳ Patients with heart disease and correctly classified.

True Negative

Patient doesn't have heart disease

Actual

Model

correctly predicted

↳ Patients without heart disease and correctly classi

False Positive

Actual → Patient doesn't have heart disease.

Model → Patient have heart disease.

↳ This condition is not dangerous.

↳ Requires further diagnostics. (No issue in re-checking)

False Negative

Actual → Patient having heart disease

Model → Patient doesn't have heart disease

↳ This condition is extremely dangerous.

TP
TN

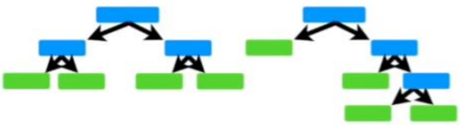
↳ The Numbers along the diagonal tells us how many times the samples are correctly classified.

↳ The Numbers that are Not along the diagonal are the samples that the algorithm messed up.

FP
FN

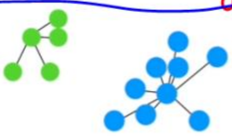
(Better Approach)

Random Forest (TP, TN) ✓



	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	142	22
Does Not Have Heart Disease	29	110

k-Nearest Neighbors (TP, TN) ×

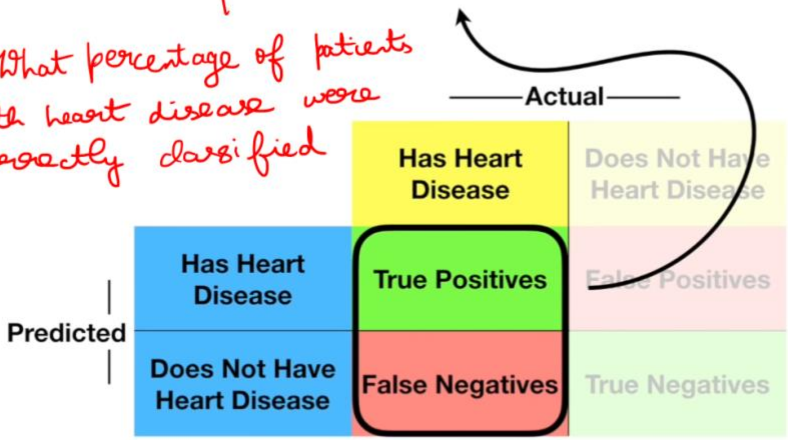


	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	107	53
Does Not Have Heart Disease	64	79

Sensitivity

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

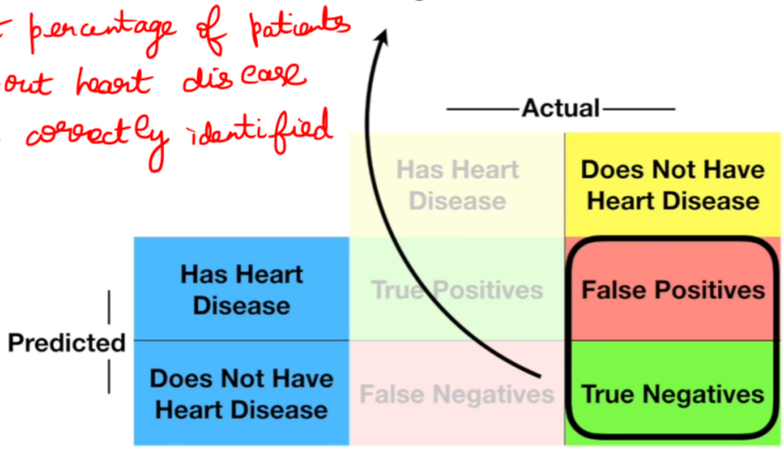
What percentage of patients with heart disease were correctly classified



Specificity

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

What percentage of patients without heart disease were correctly identified



Logistic Regression

	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	139 TP	20 FP
Does Not Have Heart Disease	32 FN	112 TN

$$\text{Specificity} \Rightarrow \frac{TN}{TN+FP} \Rightarrow \frac{112}{112+20} \Rightarrow \frac{112}{132} \Rightarrow 84\%$$

↳ 84% of people without heart-disease are correctly classified by the Logistic Regression model.

$$\text{Sensitivity} \Rightarrow \frac{TP}{TP+FN} \Rightarrow \frac{139}{139+32} \Rightarrow \frac{139}{171} \Rightarrow 81\%$$

↳ 81% of the people with heart disease are correctly classified by the Logistic Regression Model

Random Forest

		Actual: Has Heart Disease	Actual: Does Not Have Heart Disease
Predicted	Has Heart Disease	142 TP	22 FP
	Does Not Have Heart Disease	29 FN	110 TN

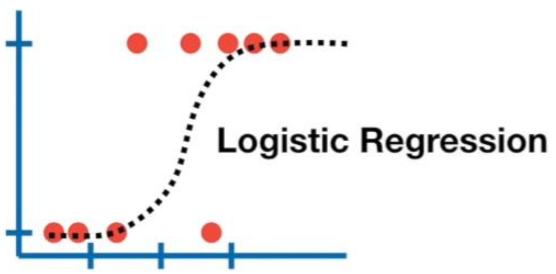
$$\text{Specificity} \Rightarrow \frac{TN}{TN+FP} \Rightarrow \frac{110}{110+22} \Rightarrow \frac{110}{132} \Rightarrow 0.83$$

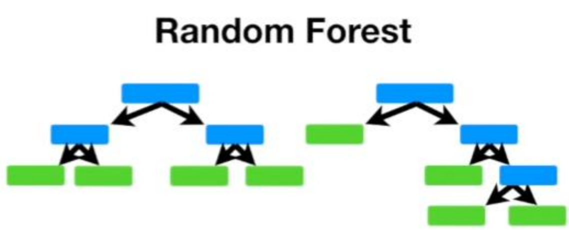
↳ 83% of people without heart-disease are correctly classified by the Random Forest Model

$$\text{Sensitivity} \Rightarrow \frac{TP}{TP+FN} \Rightarrow \frac{142}{142+29} \Rightarrow \frac{142}{171} \Rightarrow 0.83$$

↳ 83% of the people with heart disease are correctly classified by the Random Forest Model

Comparing both the confusion matrices





Sensitivity = 0.81

Specificity = 0.85

Sensitivity = 0.83

Specificity = 0.83

(0.81 < 0.83)

↳ Sensitivity ⇒ Random forest is better in identifying positives (patient with heart disease)

↳ Specificity ⇒ Logistic Regression is better in identifying the negatives (patients without heart disease)

(0.85 > 0.83)

Patients with heart disease (Important)
Patients without heart disease (Not Important)

} Random Forest is best

Patients with heart disease (Not Important)
Patients without heart disease (Important)

} Logistic Regression is best

Final thoughts

Spam mail detection → False Positive

Medical → False Negative

		Actual 1)	Actual 0)
Predicted	1)	TP	FP
	0)	FN	TN

1) Precision ⇒ TP / TP+FP

2) $\boxed{\text{Recall} \Rightarrow \text{TP / TP + FN}}$ → $\boxed{\text{True +ve Recall } \frac{TP}{TP+FN}}$ Left ↓

→ False +ve Recall $\frac{FP}{FP+TN}$ Right ↓

3) $\boxed{\text{Sensitivity} \Rightarrow \text{TP / TP+FN}}$ Left ↓

4) Specificity ⇒ TN / TN+FP Right ↑

5) (1 − Specificity) ⇒ $\frac{FP}{FP+TN}$ Right ↓

5) Accuracy ⇒ $\frac{TP + TN}{TP + TN + FP + FN}$

6) F1 score ⇒ $\frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$

7) (Rejecting NULL hypothesis when it is true)

Type-1 error ⇒ False Positive — Spam mail

Actual ⇒ Non spam
Predict ⇒ Spam } danger

8) (Failing to reject the NULL hypothesis when it is false)

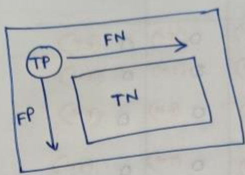
Type-2 error ⇒ False Negative

Medical

Actual ⇒ cancer
Predict ⇒ No cancer } danger

Calculate the Precision, Recall and Accuracy for below confusion matrix? What is the drawback of Accuracy metric?

	0	1	2	3	4	5	6	7	8	9
0	38	0	0	0	1	0	0	0	0	0
1	0	29	0	0	0	1	0	0	1	0
2	0	0	34	0	0	0	0	0	0	1
3	1	1	0	32	0	0	0	0	0	0
4	0	0	0	0	39	0	0	2	0	0
5	0	1	0	0	0	32	0	0	0	1
6	0	0	0	0	0	0	34	0	0	0
7	0	0	0	0	0	0	0	47	1	0
8	1	1	0	0	0	0	0	0	33	0
9	0	1	0	0	0	0	0	0	1	27



Feature - 0

TP ⇒ 38

FP ⇒ 2

TN ⇒ (33 + 34 + 32 + 39 + 33 + 34 + 49 + 36 + 29) ⇒ 319

FN ⇒ 1

$$TPR \Rightarrow \frac{TP}{TP + FN} \Rightarrow \frac{38}{38 + 1} \Rightarrow 0.97$$

$$FPR \Rightarrow \frac{FP}{FP + TN} \Rightarrow \frac{2}{2 + 319} \Rightarrow \frac{2}{321} \Rightarrow 0.00623$$

$$\boxed{(0.00623, 0.97)}$$

Feature - 5

TP ⇒ 32

FP ⇒ 0

TN ⇒ (34 + 47 + 35 + 27) ⇒ 143

FN ⇒ 1

$$TPR \Rightarrow \frac{TP}{TP + FN} \Rightarrow \frac{32}{32 + 1} \Rightarrow 32/33 \Rightarrow 0.96$$

$$FPR \Rightarrow \frac{FP}{FP + TN} \Rightarrow \frac{0}{0 + 143} \Rightarrow 0$$

$$\boxed{(0, 0.96)}$$

Area Under the Curve Problem

Play (actual)	Predicted Probability (y)	>0.25	>0.45	>0.65	>0.85
1) 1	0.30	1 (TP)	0 (FN)	0 (FN)	0 (FN)
2) 0	0.30	1 (FP)	0 (TN)	0 (TN)	0 (TN)
3) 1	0.40	1 (TP)	0 (FN)	0 (FN)	0 (FN)
4) 0	0.45	1 (FP)	0 (TN)	0 (TN)	0 (TN)
5) 0	0.50	1 (FP)	1 (FP)	0 (TN)	0 (TN)
6) 1	0.60	1 (TP)	1 (TP)	0 (FN)	0 (FN)
7) 1	0.70	1 (TP)	1 (TP)	1 (TP)	0 (FN)
		TP ⇒ ~~3~~ 4 FP ⇒ 3 TN ⇒ 0 FN ⇒ 0	TP ⇒ 2 FP ⇒ 1 TN ⇒ 2 FN ⇒ 2	TP ⇒ 1 FP ⇒ 0 TN ⇒ 3 FN ⇒ 3	TP ⇒ 0 FP ⇒ 0 TN ⇒ 3 FN ⇒ 4

Predict \ Actual	1)	0)
1)	TP	FP
0)	FN	TN

Actual - Predict
0 0 → TN
0 1 → FP
1 0 → FN
1 1 → TP

Predict - Actual
0 0 → TN
0 1 → FN
1 0 → FP
1 1 → TP

>0.25

$TPR \Rightarrow \frac{TP}{TP+FN} \Rightarrow \frac{4}{4+0} \Rightarrow 1$

(0.33, 1)

$FPR \Rightarrow \frac{FP}{FP+TN} \Rightarrow \frac{1}{1+2} \Rightarrow 1/3$

(0.33, 0.5)

>0.45

$TPR \Rightarrow \frac{TP}{TP+FN} \Rightarrow \frac{2}{2+2} \Rightarrow 2/4 \Rightarrow 1/2$ ‖ $FPR \Rightarrow \frac{FP}{FP+TN} \Rightarrow \frac{\cancel{0}\,1}{\cancel{0}+2} \Rightarrow 1/3$

(0, 0.25)

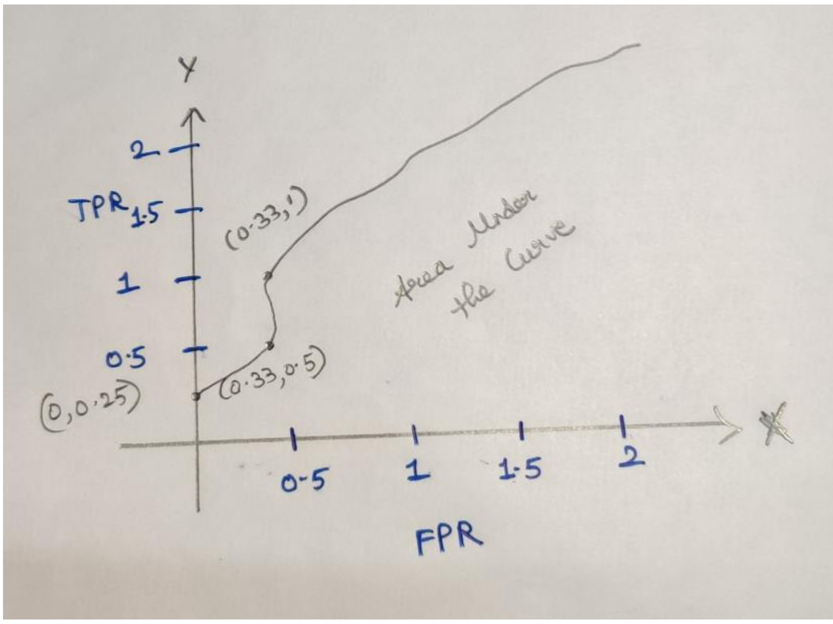
>0.65

$TPR \Rightarrow \frac{TP}{TP+FN} \Rightarrow \frac{1}{1+3} \Rightarrow 1/4$ ‖ $FPR \Rightarrow \frac{FP}{FP+TN} \Rightarrow \frac{0}{0+3} \Rightarrow 0$

(0, 0)

>0.85

$TPR \Rightarrow \frac{TP}{TP+FN} \Rightarrow \frac{0}{0+4} \Rightarrow 0$ ‖ $FPR \Rightarrow \frac{FP}{FP+TN} \Rightarrow \frac{0}{0+3} \Rightarrow 0$



https://developers.google.com/machine-learning/crash-course/classification/true-false-positive-negative