Topic – 05
Part-1
Classification & more

Binary Classification

Like the name suggests, Binary Classification are problems where there can be two classes and the instances are classified in one of these Class.

It shouldn't be mixed up with **Binary-label** classification where two-labels are to be predicted for each instance.

For example:

- Support Vector Machine
- Linear Classifiers

Problems where the Decision is - True/False, Right/Wrong, Yes/No - Binary

Let's say, we are developing an AI, which will replace the Umpires in Cricket. It will analyze all the Video Feeds and give decisions.

Now, at first, we will train our AI so that it can look into all the LBWs and based on that give decisions.

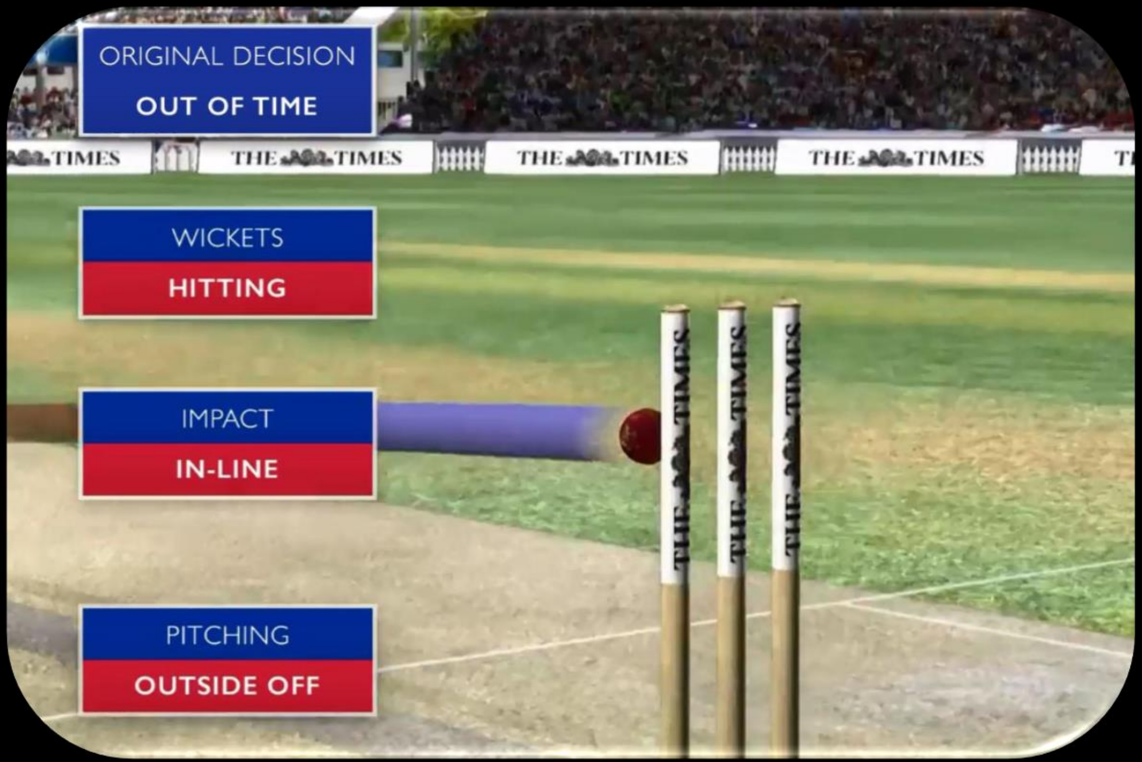
We will look into 1,00,000 cases, where the Umpires have given OUTS and NOT OUTS.

Among them, 50,000 will be OUTS and 50,000 will be NOT OUTS

80% Data (80,000) will be used for Training and 20% Data (20,000) will be used for Testing

True Positive (TP)

If the AI ***CORRECTLY/TRUELY*** gives the Decision as ***OUT***, which is ***OUT*** in reality, then the decision is ***TRUE POSITIVE***



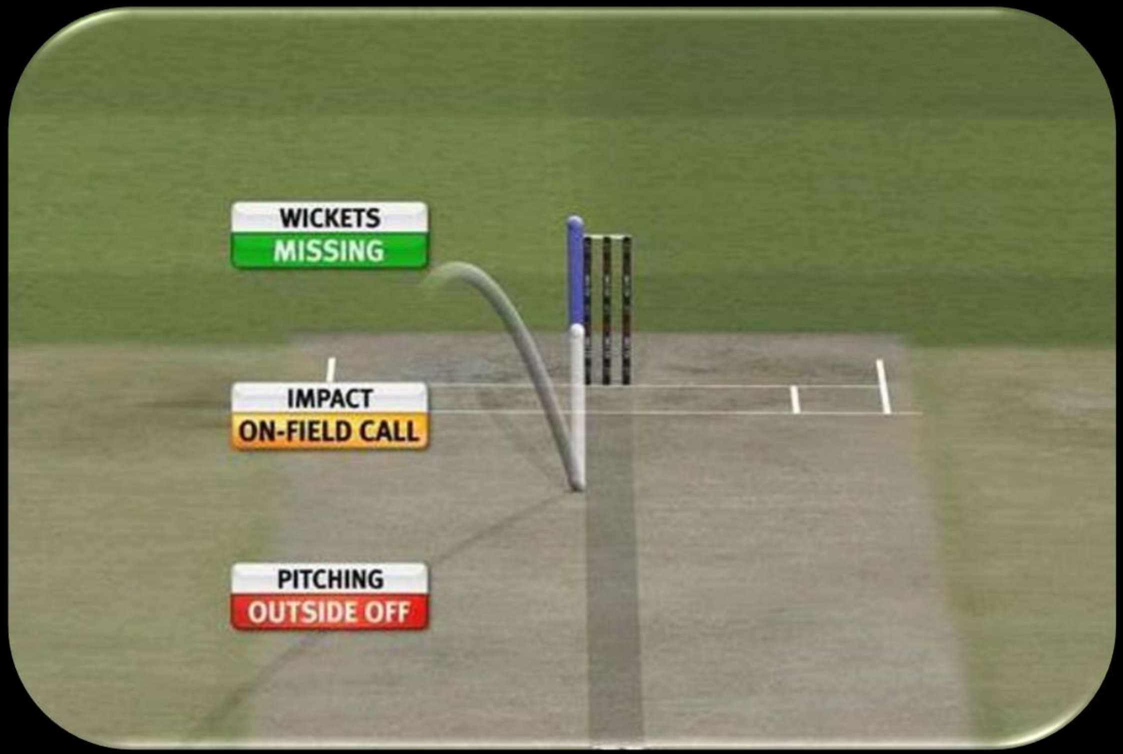
True Positive Cont.

In the time of Testing, if the AI Successfully recognizes 9,700 samples as OUT from all the samples which are OUT in reality, then –

True Positive = 9,700

True Negative (TN)

If the AI ***CORRECTLY/TRUELY*** gives the Decision as ***NOT OUT***, which is ***NOT OUT*** in reality, then the decision is ***TRUE NEGATIVE***



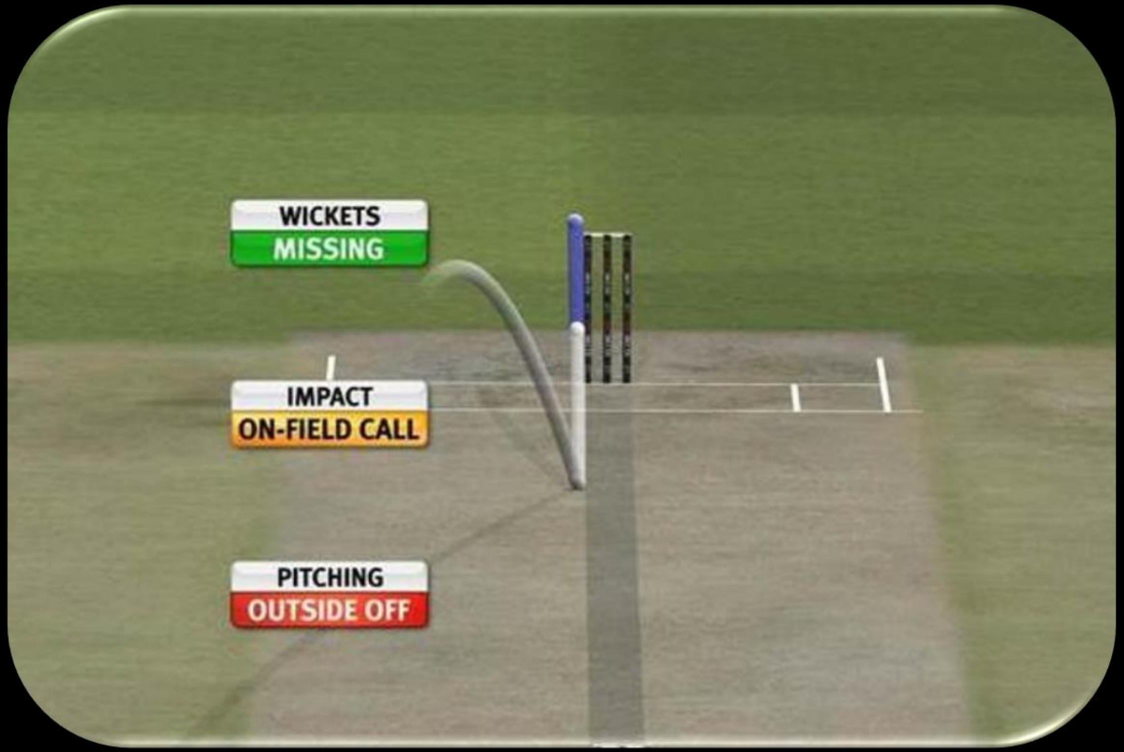
True Negative Cont.

In the time of Testing, if the AI Successfully recognizes 9,500 samples as **NOT OUT** from all the samples which are NOT OUT in reality, then –

True Negative = 9,500

False Positive (FP)

If the AI ***WRONGLY/FALSELY*** gives the Decision as ***OUT***, which is ***NOT OUT*** in reality, then the decision is ***FALSE POSITIVE***



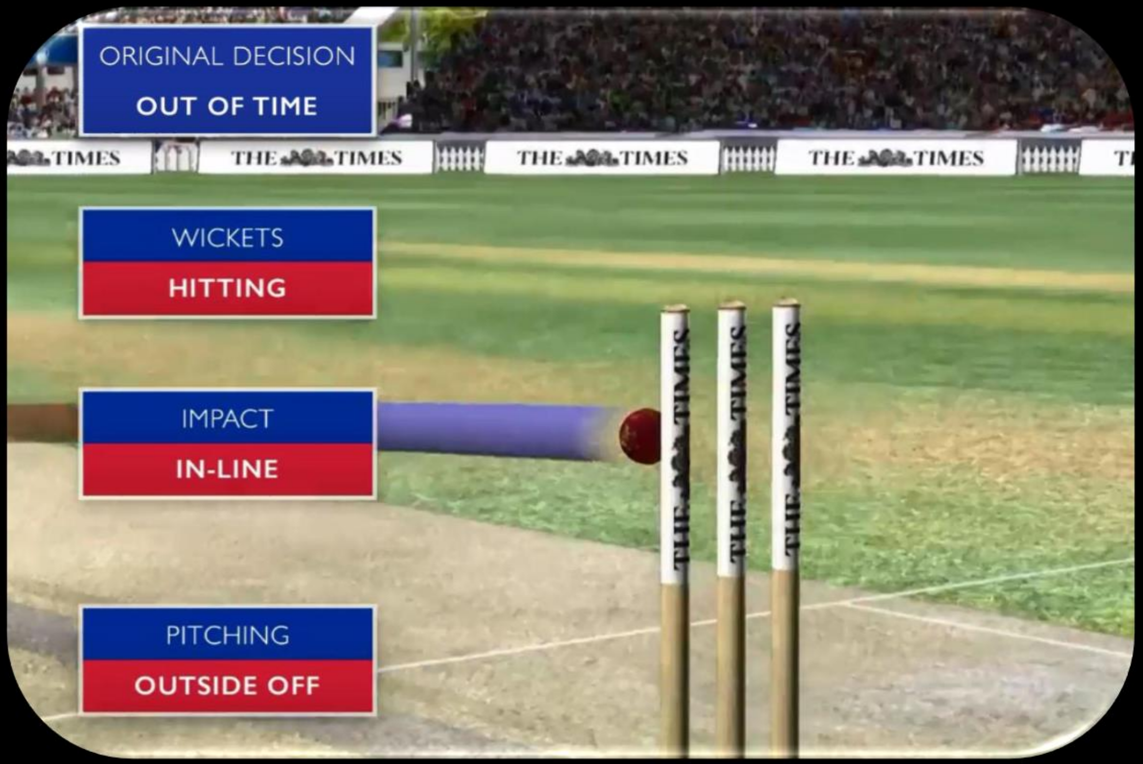
False Positive Cont.

In the time of Testing, if the AI Wrongly recognizes 500 samples as OUT from all the samples which are NOT OUT in reality, then –

False Positive = 500

False Negative (FN)

If the AI ***WRONGLY/FALSELY*** gives the Decision as ***NOT OUT***, which is ***OUT*** in reality, then the decision is ***FALSE NEGATIVE***



False Negative Cont.

In the time of Testing, if the AI Wrongly recognizes 300 samples as NOT OUT from all the samples which are OUT in reality, then –

False Negative = 300

Precision (aka Positive Predictive Value)

Here, TP = 9,700, TN = 9,500, FP = 500, FN = 300

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{Actual Results}}$$

$$\text{Precision} = \frac{9700}{9700 + 500} = 0.951$$

Recall (aka Sensitivity aka True Positive Rate (TPR))

Here, TP = 9,700, TN = 9,500, FP = 500, FN = 300

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{Actual Positives}}$$

$$\text{Recall} = \frac{9700}{9700 + 300} = 0.97$$

The higher the Recall (TPR), the more False Positives (FPR) the classifier produces

False Positive Rate (FPR)

Here, TP = 9,700, TN = 9,500, FP = 500, FN = 300

$$FPR = \frac{\text{False Positive}}{\text{False Positive + True Negative}}$$

$$FPR = \frac{\text{False Positive}}{\text{Actual Negatives}}$$

$$FPR = \frac{500}{500 + 9500} = 0.05$$

Accuracy

Here, TP = 9,700, TN = 9,500, FP = 500, FN = 300

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total}}$$

$$\text{Accuracy} = \frac{9700 + 9500}{20000} = 0.96$$

$$= 0.96 * 100\ \% = 96\%$$

F1-score

Here, TP = 9,700, TN = 9,500, FP = 500, FN = 300.

F1-score is the harmonic mean of precision and recall.

$$\text{F1-score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{F1-score} = 2 * \frac{0.951 * 0.97}{0.951 + 0.97}$$

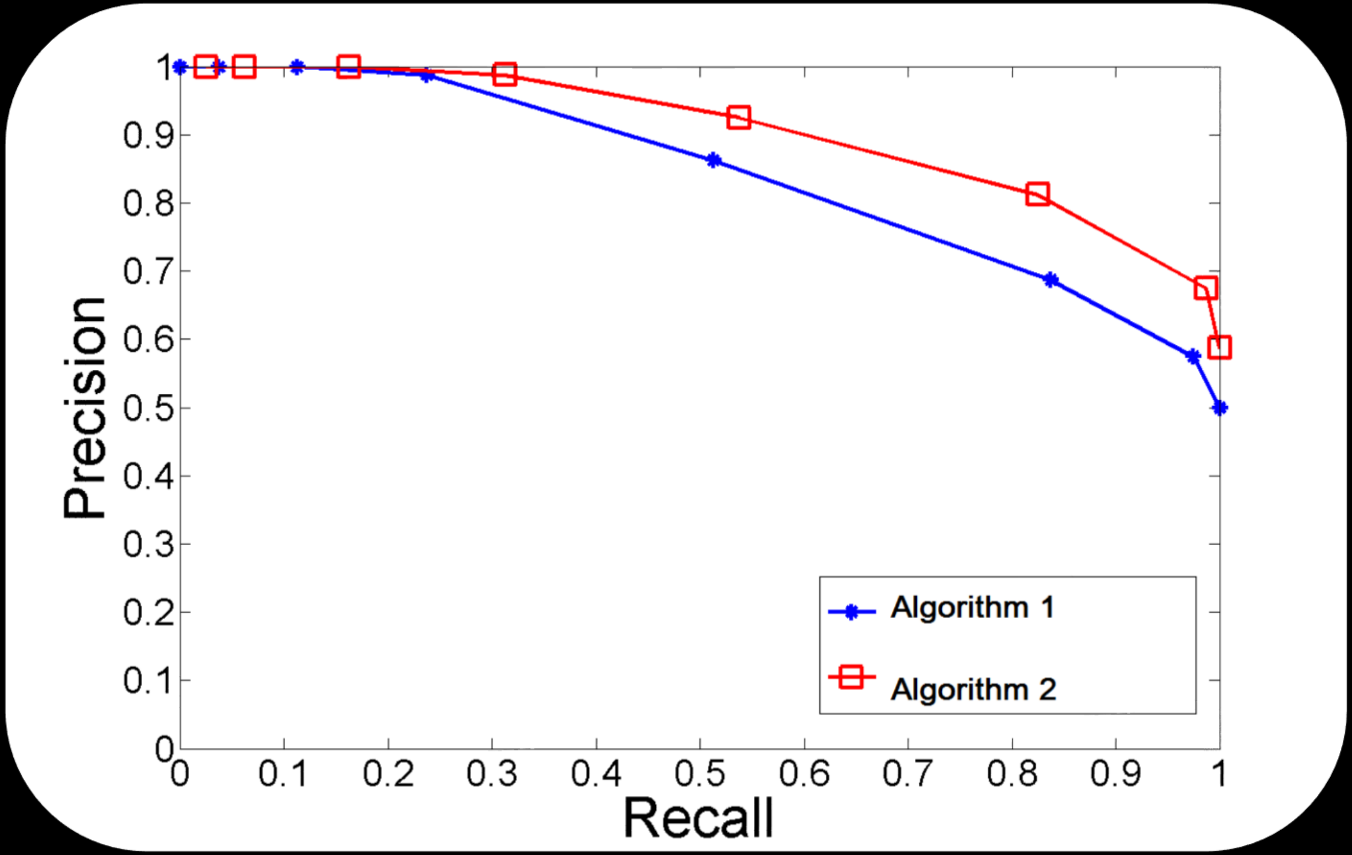
$$\text{F1-score} = 0.96 = 0.96 * 100\ \% = 96\%$$

Precision vs Recall Curve

A precision-recall curve is a plot of the precision (y-axis) and the recall (x-axis) for different thresholds.

Precision-Recall curves should be used when there is a moderate to large class imbalance. A high-precision classifier is not very useful if its recall is too low.

If someone says “let’s reach 99% precision,” you should ask, “at what recall?”



ROC (Receiver Operating Characteristic) Curve

ROC Curve is very similar to the Precision vs Recall curve, but instead of plotting precision versus recall, the ROC curve plots the TPR against the FPR. The FPR is the ratio of negative instances that are incorrectly classified as positive.