26/3/24

1) Accuracy

$$Acc = \frac{100+50}{165} = 0.91$$

Confusion matrix

n=165		Pred NO	Pred YES
Actual	NO	50	10
	YES	5	100

Pool of 100 patients. Predict if they have cancer

	n=100	Predicted NO	Predicted YES
Actual	NO	94 TN	1 FP
	YES	3 FN	2 TP

Here, false negative is major concern as patient might die.

Accuracy: $\frac{TP+TN}{P+N}$

Sensitivity / Recall / TPR : $\frac{TP}{P}$

Precision : $\frac{TP}{TP+FP}$

False positive rate = $\frac{FP}{N}$

Recall = $\frac{2}{5}$ = 40%.

Here, P = 5 (Total patients having cancer)
(FN+TP)

Here, recall is more important than Precision.

Example

→ Sometimes, there is cost for each error

FP: cost of preventive measures
FN: cost of recovery

→ High precision, low recall (20%)
Rejects 80% of good fruit, but whatever it picks, those fruits are good.

2] F1-score : A unified measure

$$F_1 = \frac{2}{\frac{1}{\text{recall}} + \frac{1}{\text{precision}}}$$

Heavily penalizes extreme recall & precision scores.

macro F1 – normal mean
micro F1 – weighted mean

LCA can be used as a proxy to measure severity of mistakes of a model

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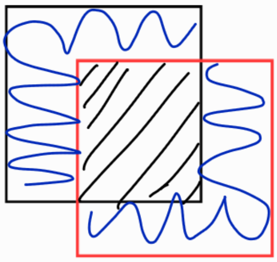
Metrics in Object Detection Problems

GT



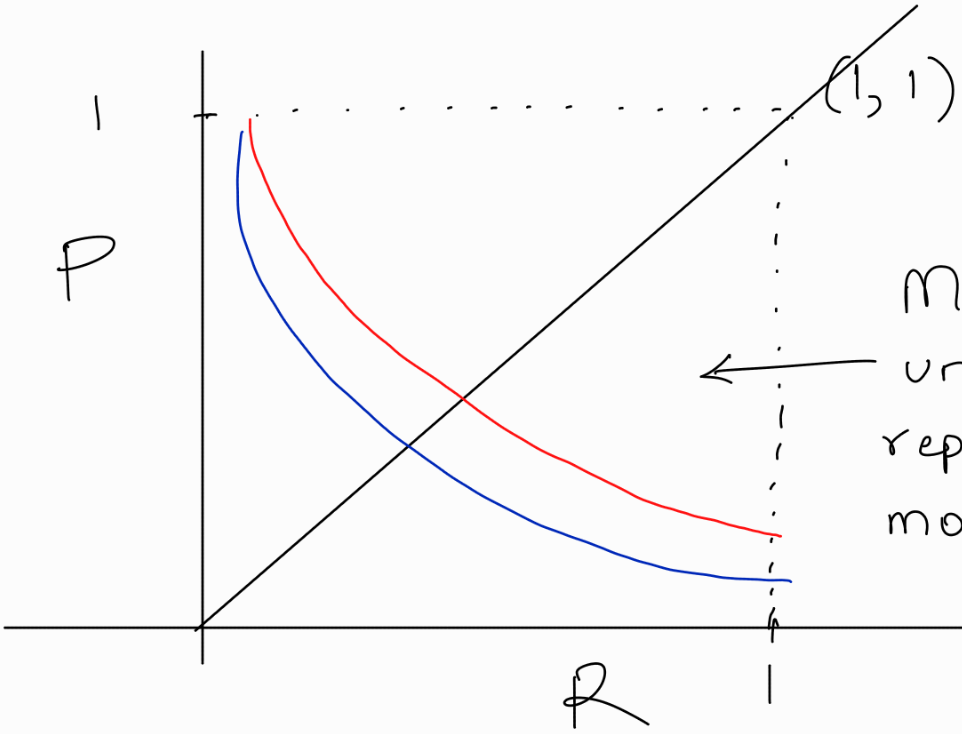
Predicted

$$IOU = \frac{A \cap B}{A \cup B}$$

$$\underbrace{IOU \geq 0.5 = \text{good}}_{\text{usually}}$$

Low IOU = High recall

High IOU = Low recall, $\underbrace{\text{high precision}}_{\text{I will only predict when the boxes overlap almost exactly.}}$



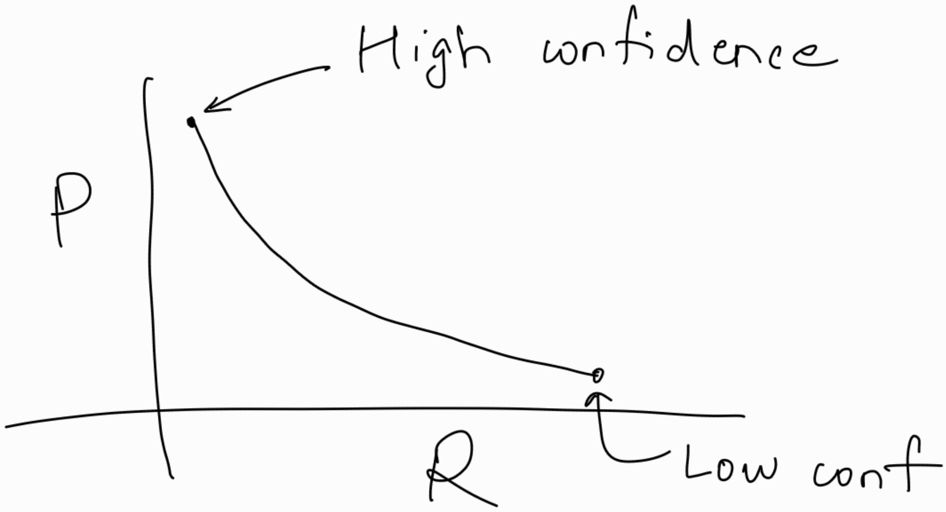
More area under curve represents better model

AP > 0.5
(avg precision)

Red model better than blue model

Consider car object detection:

Every car is detected, but some objects which are not cars may also be detected as cars. This is high recall, low precision.



AP graph

We fix IOU and vary confidence