

## Computer Vision Applications

BY QUADEER SHAIKH

#### About me



#### **Work Experience**

- Risk Analyst
  - Morgan Stanley (Jan 2023 Present)
- Data Science Intern
  - AkzoNobel Coatings International B.V. Netherlands (Feb 2022 Dec 2022)
- Data Science Intern
  - EzeRx Health Tech Pvt. Ltd. (Jan 2022 July 2022)
- Associate Engineer
  - Tata Communications Ltd. (July 2019 Aug 2020)
- Network Automation and Analysis Engineer Intern
  - Cisco (June 2018 July 2018)

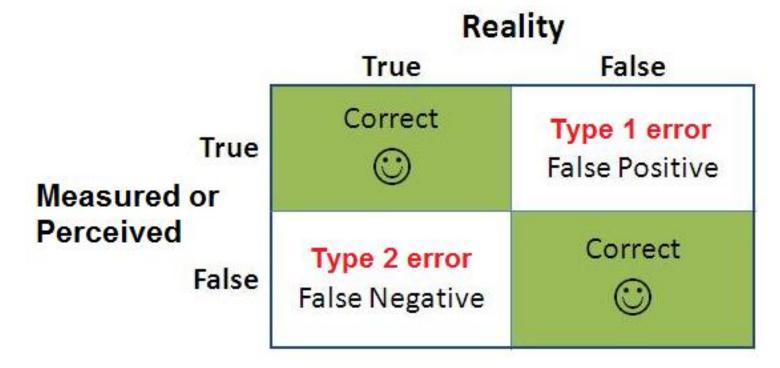
#### Education

- M.Tech Artificial Intelligence
  - NMIMS (2021 2023, currently pursuing)
- B.E. Computer Engineering
  - Mumbai University (2015 2019)

## Classification Models: Improvement and Usage in Video Processing Pipelines

### Type I and Type II Error

Which is more dangerous?



#### Type I and Type II Errors: Context Matters

You decide to get tested for COVID-19 based on mild symptoms. There are two errors that could potentially occur:

- Type I error (false positive): the test result says you have coronavirus, but you actually don't.
- Type II error (false negative): the test result says you don't have coronavirus, but you actually do.

You build a model for predicting if a credit card user is going to default or not. The bank that uses this model might want to take some precautionary measures based on the prediction.

- Type I error (false positive): the model result says user will default, but he actually doesn't.
- Type II error (false negative): the model result says user will not default, but he actually does.

### Confusion Matrix

Decide on the threshold value for classification based on the confusion matrix

	True	<u>Class</u>	
	T	F	
d Class	True Positives (TP)	False Positives	True Positive Rate (TPR) = $\frac{TP}{TP + FN}$
		(FP)	False Positive Rate (FPR) = $\frac{FP}{FP + TN}$
Acquire N	False Negatives (FN)	True Negatives (TN)	Accuracy $(ACC) = \frac{\text{FP + TN}}{\text{TP + FP + TN + FN}}$

#### Different Metrics for Classification

Recall Sensitivity True positive rate (TPR)	$\frac{TP}{FN + TP} = \frac{TP}{P}$
False positive rate (FPR) False alarm rate	$\frac{FP}{TN + FP} = \frac{FP}{N}$
Specificity True negative rate (TNR)	$\frac{TN}{TN + FP} = \frac{TN}{N} = 1 - FPR$
Precision	$\frac{TP}{TP + FP}$
False negative rate (FNR)	$\frac{FN}{FN + TP} = \frac{FN}{P}$
Accuracy	$\frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN}$

## ROC (Receiver Operating Characteristic) Curve (Binary Classification)

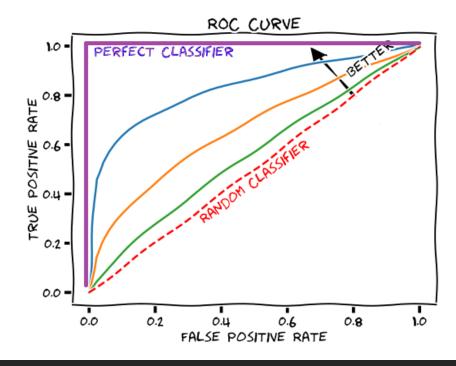
An **ROC curve** (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- True Positive Rate
- False Positive Rate

predicted→ real↓	Class_pos	Class_neg
Class_pos	TP	FN
Class_neg	FP	TN

TPR (sensitivity) = 
$$\frac{TP}{TP + FN}$$

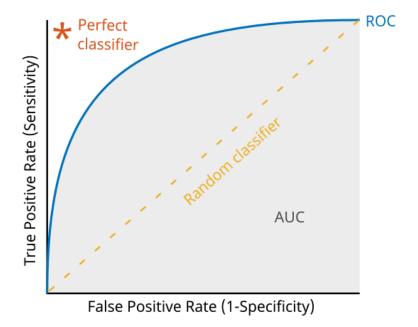
$$FPR (1-specificity) = \frac{FP}{TN + FP}$$



### AUC (Area Under ROC Curve)

AUC provides an aggregate measure of performance across all possible classification thresholds.

AUC ranges in value from 0 to 1. A model whose predictions are 100% wrong has an AUC of 0.0; one whose predictions are 100% correct has an AUC of 1.0.



#### Losses in Classification Models

**Binary Cross Entropy** 

$$L_{BCE} = -\frac{1}{n} \sum_{i=1}^{n} (Y_i \cdot \log \hat{Y}_i + (1 - Y_i) \cdot \log (1 - \hat{Y}_i))$$

Categorical Cross Entropy

$$ext{Loss} = -\sum_{i=1}^{ ext{output}} y_i \cdot \log \, \hat{y}_i$$

Why should one monitor validation loss while saving the best model instead of accuracy?

### Which Model is better?

Model 1		P(A)	P(B)	P(C)	GT(A)	GT(B)	GT(C)		Actual label	Predicted Label
	1	0.55	0.35	0.1	1	. C	) (	)	Α	Α
	2	0.3	0.5	0.2	0	1		)	В	В
	3	0.6	0.35	0.05	1	. C	) (	)	Α	Α
	4	0.3	0.3	0.4	0	C	) 1	Ĺ	С	С

Model 2		P(A)	P(B)	P(C)	GT(A)	GT(B)	GT(C)	Actual label	Predicted Label
	1	0.8	0.1	0.1	1	. C	0	Α	Α
	2	0.5	0.4	0.1	C	1	. 0	В	Α
	3	0.75	0.2	0.05	1	. C	0	Α	Α
	4	0.05	0.2	0.75	C	C	1	С	С

#### Which Model is better?

Space for Quadeer's lethal mathematical skillzzzz

# How to get more confident predictions?

#### Different Ensembling techniques

- 1. Bagging
- 2. Boosting
- 3. Stacking
- 4. Voting
  - i. Hard Voting: Takes the mode of predictions of different classifiers
  - ii. Soft Voting: Takes the probability average of different classifiers and then decides a class

## Video Processing Pipelines using Classification Models

#### Naïve Video Processing Pipeline

- 1. Give a video input source
- Read each frame of the video
- 3. Classify each frame in the video (Bottleneck)
- 4. Display the prediction on the video

## Video Processing Pipelines using Classification Models

### MULTI THREADING (AKA CONCURRENT PROCESSING)

- Multiple segments of a program/process is created to speed up the task at hand
- 2. Should be used when your task is I/O bound i.e. receiving an input continuously, processing it and then displaying it is a bottleneck.
- 3. E.g. You type sentences in a word file, and your spell check runs concurrently without blocking you from typing the next word.
- 4. E.g. Your model classifies each frame of the video and your program should not have to wait for fetching the next video frame thus blocking and slowing down the whole process

#### MULTIPROCESSING

- A program/process is subdivided into multiple processes that can speed up a task by running this multiple subdivided processes on different processors/CPU cores.
- 2. Should be used when your task is computationally heavy and requires a lot of processors for computation.
- 3. E.g. Utilizing multiple cores of a GPU to train your deep learning models

# Thank you

For any queries drop an email at: quadeershaikh15.8@gmail.com