

# Score Normalisation

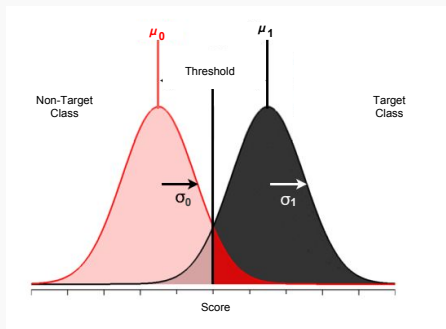
**Pattern Recognition, Jul-Nov 2019**

Indian Institute of Technology Madras

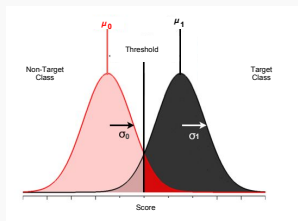
August 26, 2019

# Target and Non-Target scores

- ▶ In any N class problem, the class which is of interest can be considered as target class and all the other classes can be pooled together and called as non-target class.
- ▶ The scores for the target and non target classes form a gaussian distribution as shown in the below figure.



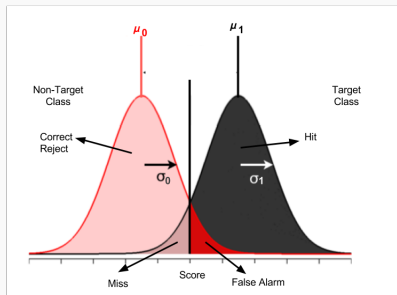
# Confusion Matrix



Based on the threshold chosen on the score, every test example may result in one of the following four outcomes of confusion matrix.

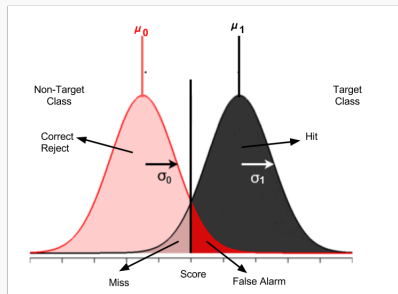
		Ground Truth	
		Target	Non- Target
Model Prediction	Target	HIT (True Positive)	False Alarm (False Positive)
	Non-Target	Miss (False Negative)	Correct Reject (True Negative)

# Confusion Matrix



		Ground Truth	
		Target	Non- Target
Model Prediction	Target	HIT (True Positive)	False Alarm (False Positive)
	Non-Target	Miss (False Negative)	Correct Reject (True Negative)

# Confusion Matrix



- For an ideal case, we would like the area under the curve to be minimum for "False Alarm" and "Miss". i.e., the means of the target and non-target scores should be far apart from each other.

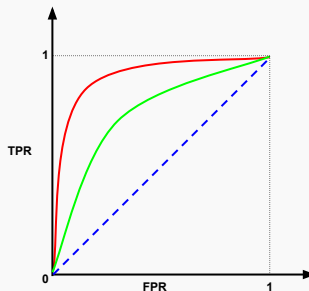
# Measures of error from confusion matrix

- ▶ True positive rate or Recall  $TPR = \frac{TP}{TP+FN}$
- ▶ False positive rate  $FPR = \frac{FP}{FP+TN}$
- ▶ Accuracy =  $\frac{TP+FP}{TP+FN+FP+TN}$
- ▶ Precision or positive predictive value =  $\frac{TP}{TP+FP}$
- ▶ F Measure =  $2 \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$
- ▶ For other error measures based on confusion matrix, please refer this wiki:  
[https://en.wikipedia.org/wiki/Confusion\\_matrix](https://en.wikipedia.org/wiki/Confusion_matrix)

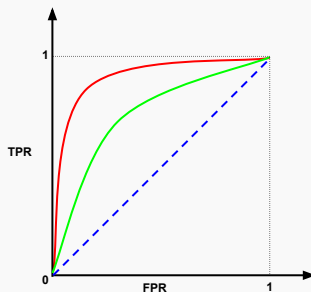
# Receiver operating characteristic

## Definition

In a ROC curve the true positive rate is plotted in function of the false positive rate for various decision threshold on the score



# Receiver operating characteristic



In the above figure,

- ▶ The blue line denotes a random system.
- ▶ The red line denotes best system.



## Detection error tradeoff curves (DET Curve)

- ▶ DET assumes that target and not target score follows a gaussian distribution

$$\text{True Negative} \sim \mathcal{N}(\mu_0, \sigma_0) \quad (1)$$

$$\text{True Positive} \sim \mathcal{N}(\mu_1, \sigma_1) \quad (2)$$

$$(3)$$

- ▶ Therefore, the probability of miss(m) and false alarm(fa) can be written as:

$$P_m(t) = \int_{-\infty}^t e^{-\frac{(x-\mu_1)^2}{\sigma_1^2}} dx = \phi\left(\frac{t - \mu_1}{\sigma_1}\right) \quad (4)$$

$$P_{fa}(t) = \int_t^{\infty} e^{-\frac{(x-\mu_0)^2}{\sigma_0^2}} dx = \phi\left(\frac{\mu_0 - t}{\sigma_0}\right) \quad (5)$$

## Detection error tradeoff curves (DET Curve)

- ▶ Equation 4 and 5 can be rewritten as:

$$\frac{t - \mu_1}{\sigma_1} = \phi^{-1}(P_m(t)) \quad (6)$$

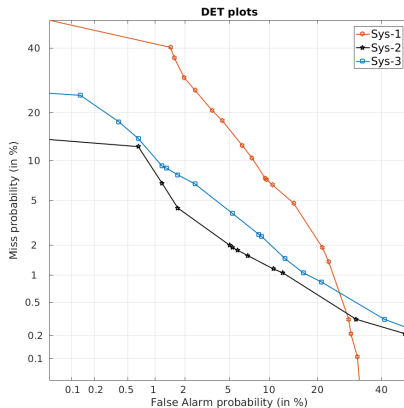
$$\frac{\mu_0 - t}{\sigma_1} = \phi^{-1}(P_{fa}(t)) \quad (7)$$

- ▶ Equating for  $t$  we get:

$$\phi^{-1}(P_m(t)) = \frac{-\sigma_0}{-\sigma_1} \phi^{-1}(P_{fa}(t)) + \frac{\mu_0 - \mu_1}{\sigma_1} \quad (8)$$

- ▶ Equation 8 denotes the probability of miss as a linear function of probability of false alarm. The plot of  $\phi^{-1}(P_m(t))$  vs  $\phi^{-1}(P_{fa}(t))$  is called as the DET curve.

# Example of DET curve



# Normalization using an impostor model

- ▶ Let  $\log(P(W_i|\theta))$  be the likelihood of the observation points  $\theta$  belonging to the class  $w_i$
- ▶ The normalized likelihood is given by

$$\log(P(W_i|\theta)) = \log(P(\theta|W_i)) - \log(P(\theta|W_N))$$

$W_N$  : Cohort model

- ▶ In place of a cohort model, a world model can also be used
- ▶ A world model is trained using data from all the classes

# Z-norm

- ▶ For each class  $W_i$ , a set of  $N$  cohort models are chosen
- ▶ These models are also called as Impostor models
- ▶ For each class, impostor mean ( $\mu_I$ ) and standard deviation ( $\sigma_I$ ) are calculated
- ▶ For the test sample, the new normalized score is computed as

$$S = \frac{\log(P(W_i|\theta)) - \mu_I}{\sigma_I}$$

# T-norm

- ▶ Performing Z-norm is not adequate if there is a variability between the train and test
- ▶ In Test norm (T-norm), the mean and standard deviation are calculated during testing

$$S_T = \frac{\log(P(W_i|\theta)) - \mu'_l}{\sigma'_l}$$