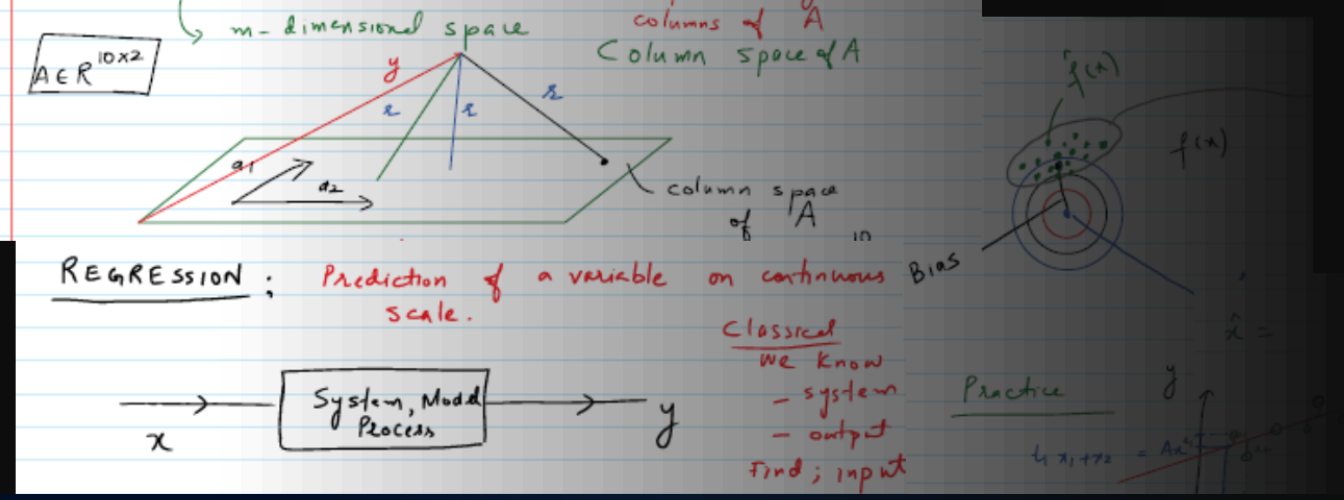


# Machine Learning

## EE514 – CS535

### Analysis and Evaluation of Classifier's Performance and Multi-class Classification


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LUMS
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# Outline

- Classification Accuracy (0/1 Loss)
- TP, TN, FP and FN
- Confusion Matrix
- Sensitivity, Specificity, Precision Trade-offs, ROC, AUC
- F1-Score and Matthew's Correlation Coefficient
- Multi-class Classification, Evaluation, Micro, Macro Averaging

# Evaluation of Classification Performance

## Classification Accuracy, Misclassification Rate (0/1 Loss):

$$\mathcal{L}_{0/1}(h) = \frac{1}{n}\sum_{i=1}^{n} 1 - \delta_{h(\mathbf{x_i})-y_i}$$

$$\delta_k = \begin{cases} 1, & k = 0 \\ 0 & \text{otherwise} \end{cases}$$

- For each test-point, the loss is either 0 or 1; whether the prediction is correct or incorrect.
- Averaged over n data-points, this loss is a 'Misclassification Rate'.

## Interpretation:

- Misclassification Rate: Estimate of the probability that a point is incorrectly classified.
- Accuracy = 1- Misclassification rate

## Issue:

- Not meaningful when the classes are imbalanced or skewed.

# Evaluation of Classification Performance

## Classification Accuracy (0/1 Loss):

**Example:**

- Predict if a bowler will not bowl a **no-ball**?
  - Assuming 15 no-balls in an inning, a **model that says 'Yes' all the time** will have **95%** accuracy.
  - Using accuracy as performance metric, we can say that a model is very accurate, but it is not useful or valuable in fact.

**Why?**

- Total points: 315 (assuming other balls are legal ☺)
- No-ball label: Class 0 (4.76% are from this class)
- Not a no-ball label: Class 1 (95.24% are from this class)

**Imbalanced Classes**

# Evaluation of Classification Performance

## TP, TN, FP and FN:

- *Consider a binary classification problem.*

$$D = \{(\mathbf{x_1}, y_1), (\mathbf{x_2}, y_2), \ldots, (\mathbf{x_n}, y_n)\} \subseteq \mathcal{X}^d \times \mathcal{Y}$$

$\mathcal{Y} = \{0, 1\}$ (Referring 0 as Negative, 1 as Positive)

$y$ - Actual labels, Ground truth, Gold labels or Standards

We have a classifier (hypothesis function) $h(\mathbf{x}) = \hat{y}$.

$y, \hat{y}$ - Positive (1) or Negative (0)

$\hat{y}$ - True if $\hat{y} = y$, False if $\hat{y} \neq y$

# Evaluation of Classification Performance

## TP, TN, FP and FN:

- TP - True Positive
  - Number of points with $y = 1$ and are classified as $\hat{y} = 1$
- TN - True Negative
  - Number of points with $y = 0$ and are classified as $\hat{y} = 0$
- FP - False Positive
  - Number of points with $y = 0$ and are classified as $\hat{y} = 1$
- FN - False Negative
  - Number of points with $y = 1$ and are classified as $\hat{y} = 0$

# Evaluation of Classification Performance

## TP, TN, FP and FN:

**Example:**

- Predict if a bowler will not bowl a **no-ball**?
  - 15 no-balls in an inning (Total balls: 315)
  - Bowl no-ball (Class 0), Bowl regular ball (Class 1)
  - Model(*) predicted 10 no-balls (8 correct predictions, 2 incorrect)

- TP - True Positive
- TN - True Negative
- FP - False Positive
- FN - False Negative

- TP - 298
- TN - 8
- FP - 7
- FN - 2

* Assume you have a model that has been observing the bowlers for the last 15 years and used these observations for learning.

# Evaluation of Classification Performance

## Confusion Matrix (Contingency Table):

- (TP; TN; FP; FN); usefully summarized in a table, referred to as confusion matrix:
  - the rows correspond to predicted class ($\hat{y}$)
  - and the columns to true class ($y$)

| | | Actual Labels | | |
|---|---|---|---|---|
| | | **1 (Positive)** | **0 (Negative)** | Total |
| Predicted Labels | **1 (Positive)** | **TP** | **FP** | Predicted Total Positives |
| | **0 (Negative)** | **FN** | **TN** | Predicted Total Negatives |
| | Total | P= TP+FN Actual Total Positives | N= P+TN Actual Total Negatives | |

# Evaluation of Classification Performance

## Confusion Matrix:

**Example:**

- Disease Detection :

Given pathology reports and scans, predict heart disease

- Yes: 1, No: 0

| | | Actual Labels | | |
|---|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) | Total |
| Predicted Labels | 1 (Positive) | TP = 100 | FP = 10 | 110 |
| | 0 (Negative) | FN = 5 | TN = 50 | 55 |
| | Total | P = 105 | N = 60 | |

**Interpretation:**

Out of 165 cases

- Predicted: "Yes" 110 times, and "No" 55 times
- In reality: "Yes" 105 times, and "No" 60 times

# Evaluation of Classification Performance

## Confusion Matrix:

**Example:**

- Predict if a bowler will not bowl a **no-ball**?

| | | Actual Labels | | |
|---|---|---|---|---|
| | | **1 (Positive)** | **0 (Negative)** | Total |
| Predicted Labels | **1 (Positive)** | **TP = 298** | **FP = 7** | 305 |
| | **0 (Negative)** | **FN = 2** | **TN = 8** | 10 |
| | Total | P = 300 | N = 15 | |

**Interpretation:**

Out of 315 balls, we had 15 no-balls.

- Model predicted 305 regular balls and 10 no-balls (8 correct predictions, 2 incorrect).

# Evaluation of Classification Performance

## Confusion Matrix:

| | | Actual Labels | | |
|---|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) | Total |
| Predicted Labels | 1 (Positive) | TP | FP | Predicted Total Positives |
| | 0 (Negative) | FN | TN | Predicted Total Negatives |
| | Total | P= TP+FN Actual Total Positives | N= P+TN Actual Total Negatives | |

## Metrics using Confusion Matrix:

- **Accuracy**: *Overall, how frequently is the classifier correct?*

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total}} = \frac{\text{TP} + \text{TN}}{\text{P} + \text{N}}$$

- ***Misclassification or Error Rate***: *Overall, how frequently is it wrong?*

$$1 - \text{Accuracy} = \frac{\text{FP} + \text{FN}}{\text{Total}} = \frac{\text{FP} + \text{FN}}{\text{P} + \text{N}}$$

- ***Sensitivity or Recall or True Positive Rate (TPR)***: *How often does it predict Positive when it is actually Positive?*

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$

# Evaluation of Classification Performance

## Confusion Matrix:

| | | Actual Labels | | |
|---|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) | Total |
| Predicted Labels | 1 (Positive) | TP | FP | Predicted Total Positives |
| | 0 (Negative) | FN | TN | Predicted Total Negatives |
| | Total | P= TP+FN Actual Total Positives | N= P+TN Actual Total Negatives | |

## Metrics using Confusion Matrix:

- **False Positive Rate:** Actual Negative, how often does it predict Positive?

$$FPR = \frac{\text{FP}}{\text{TN} + \text{FP}} = \frac{\text{FP}}{\text{N}}$$

- **Specificity or True Negative Rate (TNR):** When it's actually Negative, how often does it predict Negative?

$$TNR = S_p = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{\text{TN}}{\text{N}} = 1 - FPR$$

- **Precision:** When it predicts Positive, how often is it Positive?

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

# Evaluation of Classification Performance

## Confusion Matrix Metrics:

| | | Actual Labels | | |
|---|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) | Total |
| Predicted Labels | 1 (Positive) | TP | FP | *Predicted Total Positives* |
| | 0 (Negative) | FN | TN | *Predicted Total Negatives* |
| | Total | P= TP+FN *Actual Total Positives* | N= P+TN *Actual Total Negatives* | |

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\frac{\text{TN}}{\text{TN} + \text{FN}}$$ Negative Predicted Value

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$

$$TNR = S_p = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{\text{TN}}{\text{N}}$$

# Evaluation of Classification Performance

## Confusion Matrix:

| | | Actual Labels | | |
|---|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) | Total |
| Predicted Labels | 1 (Positive) | TP = 100 | FP = 10 | 110 |
| | 0 (Negative) | FN = 5 | TN = 50 | 55 |
| | Total | P = 105 | N = 60 | |

## Metrics using Confusion Matrix (Example: Disease Prediction):

- **Accuracy**: *Disease/Healthy prediction accuracy*

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total}} = \frac{\text{TP} + \text{TN}}{\text{P} + \text{N}}$$ **= (100+50)/165 = 0.91**

- **Misclassification or Error Rate**: *Disease/Healthy prediction accuracy*

$$1 - \text{Accuracy} = \frac{\text{FP} + \text{FN}}{\text{Total}} = \frac{\text{FP} + \text{FN}}{\text{P} + \text{N}}$$ **= (10+5)/165 = 0.09**

- **Sensitivity or Recall or True Positive Rate (TPR)**: *When it's positive, how often does the model detected disease?*

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$ **= 100/105 = 0.95**

# Evaluation of Classification Performance

## Confusion Matrix:

| | | Actual Labels | | |
|---|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) | Total |
| Predicted Labels | 1 (Positive) | TP = 100 | FP = 10 | 110 |
| | 0 (Negative) | FN = 5 | TN = 50 | 55 |
| | Total | P = 105 | N = 60 | |

## Metrics using Confusion Matrix (Example: Disease Prediction):

- **False Positive Rate:** Actually heathy, how often does it predict yes?

$$FPR = \frac{\text{FP}}{\text{TN} + \text{FP}} = \frac{\text{FP}}{\text{N}}$$ **= 10/60 = 0.17**

- **Specificity or True Negative Rate (TNR):** When it's actually health, how often does it predict healthy?

$$TNR = S_p = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{\text{TN}}{\text{N}}$$ **= 50/60 = 0.83**

- **Precision:** When it predicts disease, how often is it correct?

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$ **= 100/110 = 0.91**

# Evaluation of Classification Performance

## Confusion Matrix:

| | Actual Labels | | |
|---|---|---|---|
| Predicted Labels | | 1 (Positive) | 0 (Negative) |
| | 1 (Positive) | TP | FP |
| | 0 (Negative) | FN | TN |

## Metrics using Confusion Matrix:

*When to use which?*

- *Disease Detection: We do not want FN*

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$

- *Fraud Detection: We do not want FP*

$$TNR = S_p = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{\text{TN}}{\text{N}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

# Outline

- Classification Accuracy (0/1 Loss)
- TP, TN, FP and FN
- Confusion Matrix
- Sensitivity, Specificity, Precision Trade-offs, ROC, AUC
- F1-Score and Matthew's Correlation Coefficient
- Multi-class Classification, Evaluation, Micro, Macro Averaging

# Evaluation of Classification Performance

## Confusion Matrix:

## Precision and Sensitivity (Recall) Trade-off:

- Disease Detection:

**Sensitivity or Recall**

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$

**Precision**

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- Recall or Sensitivity ($S_e$); how good we are at detecting diseased people.
- **Precision:** How many have been correctly diagnosed as unhealthy.
- If we have diagnosed everyone unhealthy, $S_e$=1 (diagnose all unhealthy people correctly) but **Precision may be low** (because TN=0 that increases the value of FP).

| | Actual Labels | | |
|---|---|---|---|
| | | 1 (Positive) | 0 (Negative) |
| Predicted Labels | 1 (Positive) | TP | FP |
| | 0 (Negative) | FN | TN |

- We want high **Precision** and high $S_e$ (=1, Ideally).
- We should combine precision and sensitivity to evaluate the performance of classifier.
  - F1-Score

# Evaluation of Classification Performance

## Confusion Matrix:

## Sensitivity and Specificity Trade-off:

- Disease Detection:

**Sensitivity or Recall**

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$

**Specificity**

$$TNR = S_p = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{\text{TN}}{\text{N}}$$

- $S_p$ and $S_e$; how good we are at detecting **healthy** and **diseased** people, respectively.

- If we have diagnosed everyone healthy, $S_p$=1 (diagnose all healthy people correctly) but $S_e$=0 (diagnose all unhealthy people incorrectly)

- **Ideally:** we want $S_p$= $S_e$= 1 (perfect sensitivity and specificity) but unrealistic.

# Evaluation of Classification Performance

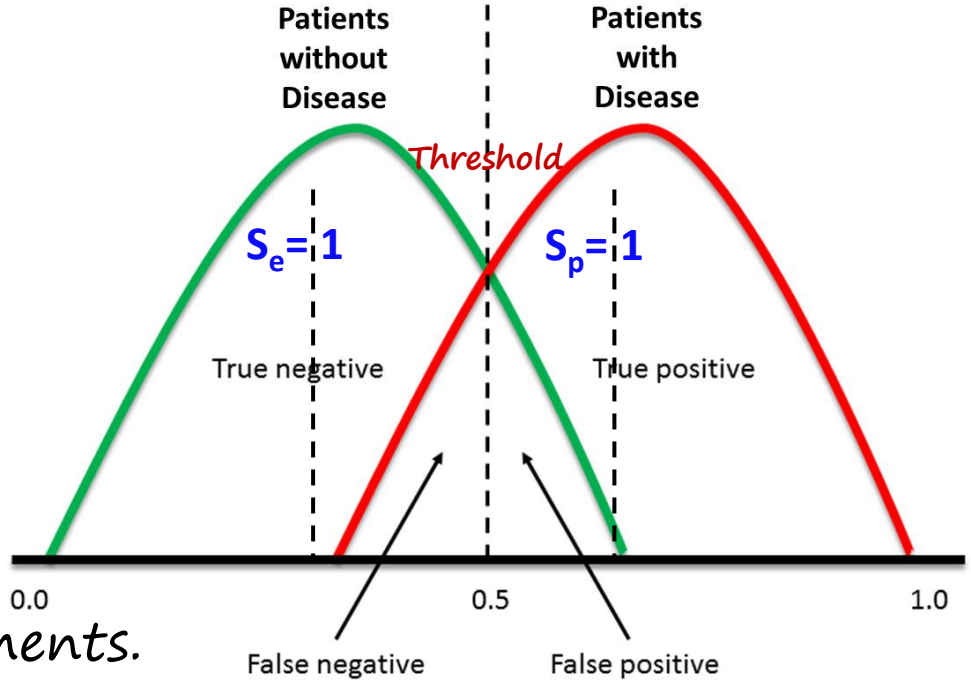
## Confusion Matrix:

## Sensitivity and Specificity Trade-off:

$$TNR = S_p = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{\text{TN}}{\text{N}} \qquad TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}}$$

**How optimal a pair of sensitivity, specificity values is?**

- Is $S_p$= 0.8, $S_e$= 0.7 better than $S_p$= 0.7, $S_e$= 0.8?




- The answer depends on the application.
- In disease diagnosis;
  - happy to reduce $S_p$ in order to increase $S_e$.
- In other applications, we may have different requirements.
- Trade-off is better explained by ROC curve and AUC.

# Evaluation of Classification Performance

## Confusion Matrix:

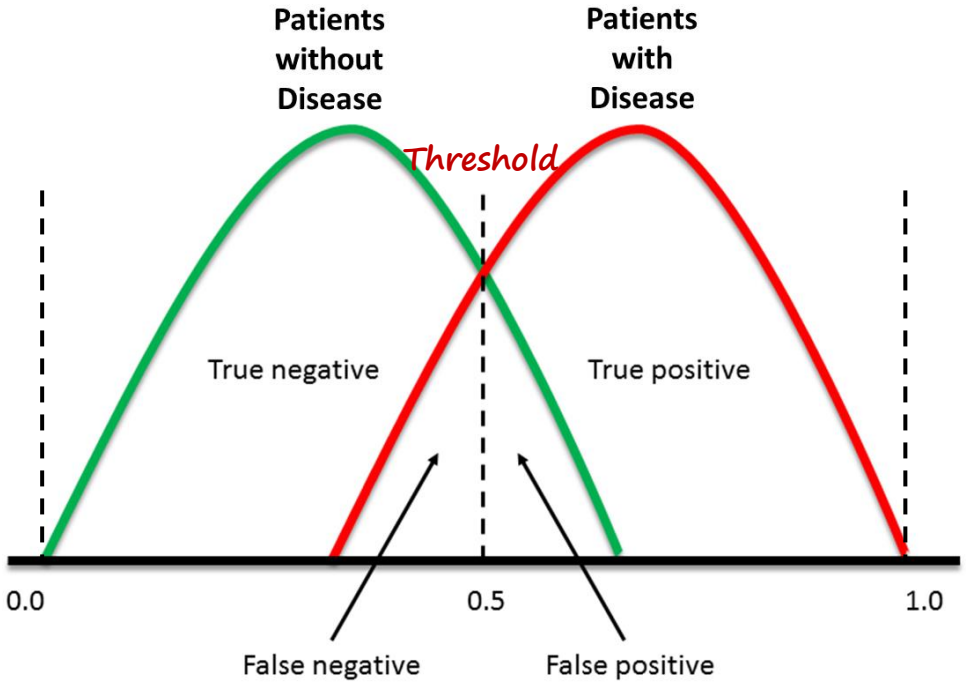
## ROC (Receiver Operating Characteristic) Curve:

- Plot of TPR (Sensitivity) against FPR (1 – Specificity) for different values of threshold.

- Also referred to as Sensitivity-(1-Specificity) plot.

- Threshold of 0.0, every case is diagnosed as positive.
  - $S_e$= TPR = 1
  - FPR = 1
  - $S_p$= 0

- Threshold of 1.0, every case is diagnosed as negative.
  - $S_e$= TPR = 0
  - FPR = 0
  - $S_p$= 1



# Evaluation of Classification Performance

## Confusion Matrix:

## ROC Curve and AUC:

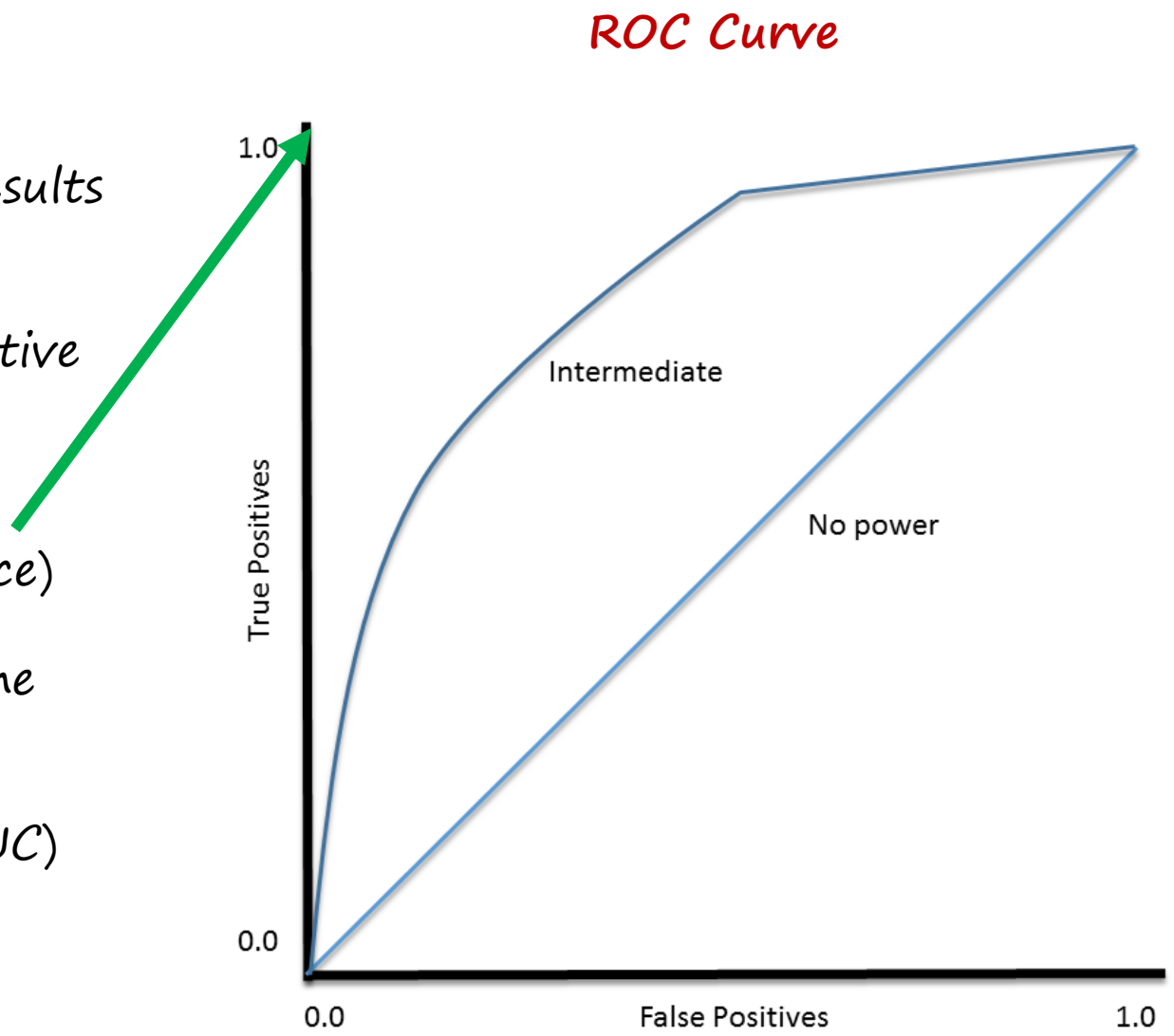
- TPR (Sensitivity): how many correct positive results occur among all positive samples.

- FPR (1 – Specificity): how many incorrect positive results occur among all negative samples.

- The best possible prediction method
  - $S_e = S_p = 1$ (Upper left corner of ROC space)

- Random guess; a point along a diagonal line (the so-called line of no-discrimination), No Power!

- Area Under the ROC Curve, abbreviated as (AUC) quantifies the power of the classifier.



# Outline

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# Evaluation of Classification Performance

## F1-Score:

- We observed trade-off between recall and precision.

$$TPR = S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{P}} \qquad \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- Higher levels of recall may be obtained at the price of lower values of precision.

- We need to define a single measure that combines recall and precision or other metrics to evaluate the performance of a classifier.

- Some combined measures:
  - F1 Score
  - Matthew's Correlation Coefficient
  - 11-point average precision
  - The Breakeven point

# Evaluation of Classification Performance

## F1 Score:

- One measure that assesses recall and precision trade-off is weighted harmonic mean (HM) of recall and precision, that is,

$$F_\beta = \frac{1+\beta^2}{\frac{1}{\text{Precision}} + \frac{\beta^2}{\text{Recall}}}, \quad \beta \geq 0$$

For $\beta = 1$, we have harmonic mean of precision and recall, that is,

$$F_1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2(\text{Precision})(\text{Recall})}{(\text{Precision}) + (\text{Recall})} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}$$

# Evaluation of Classification Performance

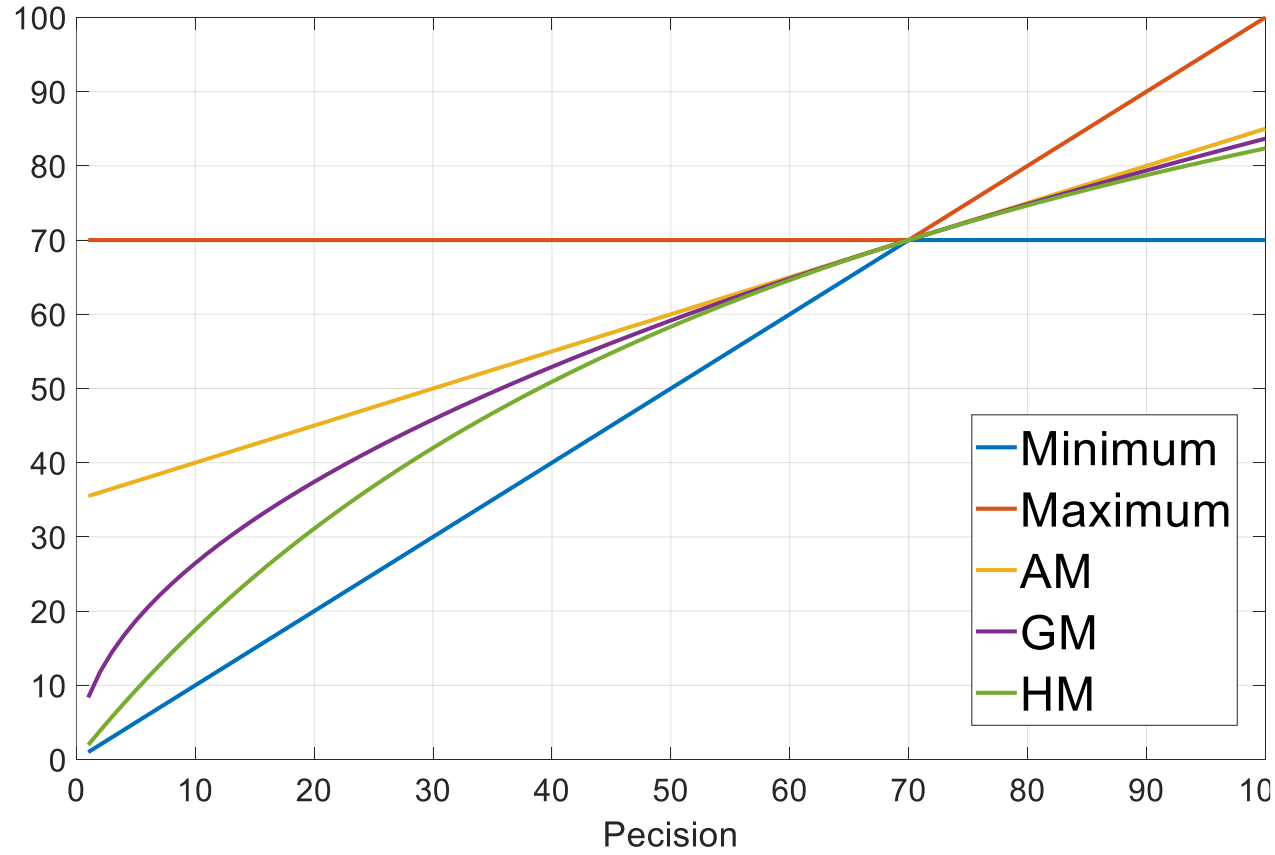
## F1 Score:

## Why harmonic mean?

- We could also use arithmetic mean (AM) or geometric mean (GM).
- HM is preferred as it penalizes model the most; a conservative average, that is, for two real positive numbers, we have

$$\mathrm{HM} \leq \mathrm{GM} \leq \mathrm{AM}$$

- Improvement in HM implies improvement in AM or GM.




**Different means, minimum and maximum against precision. Recall=70% is fixed.**

# Evaluation of Classification Performance

## Matthew's Correlation Coefficient (MCC):

- Precision, Recall and F1-score are asymmetric. Get a different result if the classes are switched.

- Matthew's correlation coefficient determines the correlation between true class and predicted class. The higher the correlation between true and predicted values, the better the prediction.

- Defined as $$\mathrm{MCC} = \frac{(\mathrm{TP})(\mathrm{TN}) - (\mathrm{FP})(\mathrm{FN})}{\sqrt{(\mathrm{TP}+\mathrm{FN})(\mathrm{TP}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})}}, \quad |\mathrm{MCC}| \leq 1$$

- MCC=1 when FP = FN = 0 (Perfect classification)
- MCC=-1 when TP = TN = 0 (Perfect misclassification)
- MCC=0; Performance of classifier is not better than a random classifier (flip coin)
- MCC is symmetric by design

# Evaluation of Classification Performance

## 11-point Average Precision:

- Adjust threshold of the classifier such that the recall takes the following 11 values 0.0, 0.1., …, 0.9, 1.0.

- For each value of the recall, determine the precision and find the average value of precision, referred to as average precision (AP).

- This is just uniformly-spaced sampling of Precision-Recall curve and taking average value.

## The Breakeven Point:

- Compute precision as a function of recall for different values of thresholds.

- When Precision = Recall, we have a breakeven.

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- Multi-class Classification, Evaluation, Micro, Macro Averaging

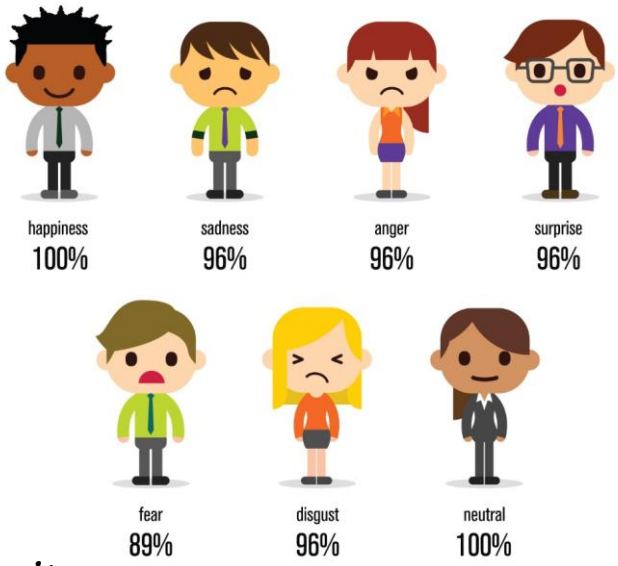
# Multi-Class Classification

## Formulation:

- We assume we have training data $D$ given by

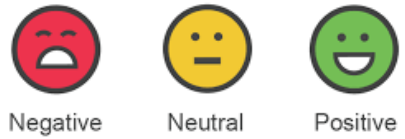
$$D = \{(\mathbf{x_1}, y_1), (\mathbf{x_2}, y_2), \ldots, (\mathbf{x_n}, y_n)\} \subseteq \mathcal{X}^d \times \mathcal{Y}$$

- $\mathcal{Y} = \{1, 2, \ldots, M\}$ (M-class classification)




## Examples:

- *Emotion Detection.*
- *Vehicle Type, Make, model, color of the vehicle from the images streamed by safe city camera.*
- *Speaker Identification from Speech Signal.*
- *State (rest, ramp-up, normal, ramp-down) of the process machine in the plant.*
- *Sentiment Analysis (Categories: Positive, Negative, Neutral), Text Analysis.*
- *Take an image of the sky and determine the pollution level (healthy, moderate, hazard).*
- *Record Home WiFi signals and identify the type of appliance being operated.*



# Multi-Class Classification

## Implementation (Possible options using binary classifiers):

### Option 1: Build a one-vs-all (OvA) one-vs-rest (OvR) classifier:

Train $M$ different binary classifiers $h_1(\mathbf{x}), h_2(\mathbf{x}), \ldots, h_M(\mathbf{x})$.

Classifier $h_i(\mathbf{x})$ is trained to classify if $\mathbf{x}$ belongs to $i$-th class or not.

For a new test point $\mathbf{z}$, get scores for each classifier, that is, $s_i = h_i(\mathbf{z})$.

For example, $s_i$ can be assigned the probability that $\mathbf{z}$ belongs to class $i$.

Predict the label as $\hat{y} = \max_{i=1,2,\ldots,M} s_i$

### Option 2: Build an all-vs-all classifier:

Train $\binom{M}{2} = \frac{(M)(M-1)}{2}$ different binary classifiers $h_{i,j}(\mathbf{x})$, $i, j = 1, 2, \ldots, k$

Classifier $h_{i,j}(\mathbf{x})$ is trained to classify if $\mathbf{x}$ belongs to $i$-th class or $j$-th class.

For a new test point $\mathbf{z}$, get scores for each classifier, that is, $s_{i,j} = h_{i,j}(\mathbf{z})$. For example, $s_{i,j} = 1$ if $\mathbf{z}$ is likely class $i$ or 0 if $\mathbf{z}$ is likely class $j$.

Predict the label $\hat{y}$ that has been predicted multiple times.

*There can be other options…*

# Evaluation of Classification Performance

## Multiclass Classification:

- How do we define the measures for the evaluation of the performance of multi-class classifier?

- Macro-averaging: We compute performance for each class and then average.

- Micro-averaging: Compute confusion matrix after collecting decisions for all classes and then evaluate.

# Evaluation of Classification Performance

## Multiclass Classification:

### Confusion Matrix

- Predict if a bowler will bowl a **no-ball, wide bowl, regular bowl?**
  - 15 no-balls, 20 wide-balls in an inning (Total balls: 335)
  - Model Predictions:

| Classifier Output \ Actual | No-ball | Wide-ball | Regular ball | Precision |
|---|---|---|---|---|
| No-ball | 8 | 5 | 20 | $\frac{8}{8+5+20}$ |
| Wide-ball | 2 | 10 | 10 | $\frac{10}{2+10+10}$ |
| Regular ball | 5 | 5 | 270 | $\frac{270}{5+5+270}$ |
| Recall | $\frac{8}{8+2+5}$ | $\frac{10}{5+10+5}$ | $\frac{270}{20+10+270}$ | |

# Evaluation of Classification Performance

## Multiclass Classification:

### Confusion Matrix – Recall and Precision:

$C_{i,j}$ represents the entry of the confusion matrix at $i$-th row and $j$-th column.

## Recall

- For i-th class, recall represents the fraction of data-points classified correctly, that is,

$$\text{Recall}_i = \frac{C_{i,i}}{\sum_{i=1}^{M} C_{i,j}}$$

## Precision

- For i-th class, precision represents the fraction of data-points predicted to be in class i are actually in the i-th class, that is,

$$\text{Precision}_i = \frac{C_{i,i}}{\sum_{j=1}^{M} C_{i,j}}$$

## Accuracy

- Fraction of data points classified correctly, that is,

$$\text{Accuracy} = \frac{\sum_{i=1} C_{i,i}}{\sum_{i=1} \sum_{j=1}^{M} C_{i,j}}$$

| | No-ball | Wide-ball | Regular ball |
|---|---|---|---|
| No-ball | 8 | 5 | 20 |
| Wide-ball | 2 | 10 | 10 |
| Regular ball | 5 | 5 | 270 |

# Evaluation of Classification Performance

## Multiclass Classification:

### Confusion Matrix – Macro-Averaging:

- We compute performance for each class and then average.

| | No-ball | Wide-ball | Regular ball |
|---|---|---|---|
| No-ball | 8 | 5 | 20 |
| Wide-ball | 2 | 10 | 10 |
| Regular ball | 5 | 5 | 270 |

### Confusion Matrix – Each Class:

| Classifier Output | Actual: No-ball | Actual: Not a No-ball |
|---|---|---|
| No-ball | 8 | 25 |
| Not a no-ball | 7 | 295 |

| Classifier Output | Actual: Wide | Actual: Not Wide |
|---|---|---|
| Wide | 10 | 12 |
| Not Wide | 10 | 303 |

| Classifier Output | Actual: Regular | Actual: Not Regular |
|---|---|---|
| Regular | 270 | 10 |
| Not Regular | 30 | 25 |

Recall $\frac{8}{8+7} = 0.53$ $\frac{10}{20} = 0.50$ $\frac{270}{300} = 0.90$

Macro-average Recall: $\frac{0.53+0.50+0.90}{3} = 0.64$

# Evaluation of Classification Performance

## Multiclass Classification:

### Confusion Matrix – Micro-Averaging:

- Compute confusion matrix after collecting decisions for all classes and then evaluate.

| | True | False |
|---|---|---|
| True | 288 | 47 |
| False | 47 | 623 |

Micro-average Recall:

$$\frac{288}{335} = 0.86$$

### Confusion Matrix – Each Class:

| Classifier Output | Actual: No-ball | Actual: Not a No-ball |
|---|---|---|
| No-ball | 8 | 25 |
| Not a no-ball | 7 | 295 |

| | Actual: Wide | Actual: Not Wide |
|---|---|---|
| Wide | 10 | 12 |
| Not Wide | 10 | 303 |

| | Actual: Regular | Actual: Not Regular |
|---|---|---|
| Regular | 270 | 10 |
| Not Regular | 30 | 25 |

# Evaluation of Classification Performance

## Multiclass Classification:

## Micro-Averaging vs Macro Averaging:

- Note Micro-average recall= Micro-average precision = F1 Score = Accuracy (computed from confusion matrix)
  - Micro-average is termed as a global metric.
  - Consequently, it is not a good measure when classes are not balanced.

- Macro-average is relatively a better as we can see a zoomed-in picture before averaging.

- Note Macro-averaging does not take class imbalance into account.
  - **Weighted-averaging**; Similar to Macro averaging but takes a weighted mean instead where weight for each class is the total number of data-points of that class.

Weighted-average Recall: $\frac{(15\times0.53)+(20\times0.50)+(300\times0.90)}{15+20+300} = 0.86$

# Evaluation of Classification Performance

**References:**

- KM 5.7.2