

# F-Measures

**Prepared By:** Dr.Mydhili K Nair, Professor, ISE Dept, RIT  
**For:** Machine Learning Elective Class  
**Target Audience:** Sem 6 Students  
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# Performance Measures

## Classification:

- Simple Accuracy
- Precision
- Recall
- F-beta measure
- ROC (and AUC)

## Regression:

- Sum of Squares Error
- Mean Absolute Error
- RMS Error

# Accuracy as a Performance Measure

- What is 95% accuracy?
  - Classification: 95 / 100 shoes correctly classified
  - Regression: Predict 95/100 house prices correctly



\$600,000

\$400,000 ✗

\$599,999 ✗

# Limitations of Simple Accuracy

$$\text{Accuracy} = \frac{\text{No. Samples Predicted Correctly}}{\text{Total No. of Samples}}$$

What is wrong with this ?

9,990 Non-Nike

10 Nike

```
def classifier(shoe):  
    return False
```

$$\text{Accuracy} = \frac{9,990}{10,000} = 99.9\%$$



# Limitation with Accuracy

Is this tumor cancerous?







very few  
positive  
examples

most are  
negative  
examples

Class Imbalance  
Problem



	Diagnosed Sick	Diagnosed Healthy
Sick	True positive 	False Negative 
Healthy	False Positive 	True Negative 

$$\text{Accuracy} = \frac{1,000 + 8,000}{10,000} = 90\%$$

## Confusion Matrix







10,000  
Patients

(Actual)

Patients

(Predicted)	Diagnosis	
	Diagnosed sick	Diagnosed Healthy
Sick	1000 True positives	200 False Negatives
Healthy	800 False Positives	8000 True Negatives

	Sent to Spam Folder	Sent to Inbox
Spam	True Positives 	False Negatives 
Not Spam	False Positives 	True Negatives 

$$\text{Accuracy} = \frac{100 + 700}{1000} = 80\%$$

## Confusion Matrix



1,000  
e-mails

(Actual)

E-mail

(Predicted)	Folder	
	Spam Folder	Inbox
Spam	100 True positives	170 False Negatives
Not spam	30 False Positives	700 True Negatives





Diagnosed Sick

Diagnosed Healthy

Sick

**Error Rate is very high.  
(1-Accuracy Rate)  
i.e. Off-diagonal values**

False Negative



Healthy

False Positive





Sent to Spam Folder

Sent to Inbox

Spam

**Error Rate is very high.  
(1-Accuracy Rate)  
i.e. Off-diagonal values**

False  
Negatives



Not Spam

False  
Positives





- Simple Accuracy is excellent when we have a Balanced Data Set
- It fails when the Dataset is "Imbalanced".

# Precision and Recall as Performance Measure

# EVALUATION METRICS



	$p'$ (Predicted)	$n'$ (Predicted)
$p$ (Actual)	True Positive	False Negative
$n$ (Actual)	False Positive	True Negative



Medical Model

False positives ok  
False negatives **NOT** ok

Find all the sick people  
Ok if not all are sick

**High Recall Model**



	$p'$ (Predicted)	$n'$ (Predicted)
$p$ (Actual)	True Positive	False Negative
$n$ (Actual)	False Positive	True Negative



Spam Detector


False positives **NOT** ok  
False negatives ok

You don't necessarily need to find all spam  
But they better all be spam

**High Precision Model**



# Precision

E-mail	Folder	
	Spam Folder	Inbox
Spam	100	170
Not spam	30 	700

Precision: Out of the all the e-mails, sent to the spam inbox, how many were actually spam?

$$\text{Precision} = \frac{100}{100 + 30} = 76.9\%$$

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False Positives}}$$



# Recall

Folder

E-mail

	Spam Folder	Inbox
Spam	100	170
Not spam	30 	700

Recall: Out of the all the spam e-mails, how many were correctly sent to the spam folder?

$$\text{Recall} = \frac{100}{100 + 170} = 37\%$$

Recall =

$$\frac{\text{True positives}}{\text{True positives} + \text{False Negatives}}$$



# Precision

Patients

Diagnosis

	Diagnosed sick	Diagnosed Healthy
Sick	1000	200 ❌
Healthy	800	8000

Precision: Out of the patients we diagnosed with an illness, how many did we classify correctly?

$$\text{Precision} = \frac{1,000}{1,000 + 800} = 55.7\%$$

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False Positives}}$$





# Recall

Patients

Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1000	200 ❌
Is Healthy	800	8000

Recall: Out of the sick patients, how many did we correctly diagnose as sick?

$$\text{Recall} = \frac{1,000}{1,000 + 200} = 83.3\%$$

Recall =

$$\frac{\text{True positives}}{\text{True positives} + \text{False Negatives}}$$

# Precision and Recall



Medical Model

Precision: 55.7%

**Recall: 83.3%**



Spam Detector

**Precision: 76.9%**

Recall: 37%

# F-Measures as Performance Measure

- Used on imbalanced datasets
- Harmonic Mean of Precision & Recall
- Used because simple mean fails

# Measuring Machine Learning Models : F1 Score

## F-Measure

Precision



Recall

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

- $F_1$  : evenly weighted
- $F_2$  : weights Recall more
- $F_{0.5}$  : weights Precision more

# Credit Card Fraud



Model: All transactions are good.

Precision = 100%

$$\text{Recall} = \frac{0}{472} = 0\%$$

Average = 50%

# Credit Card Fraud



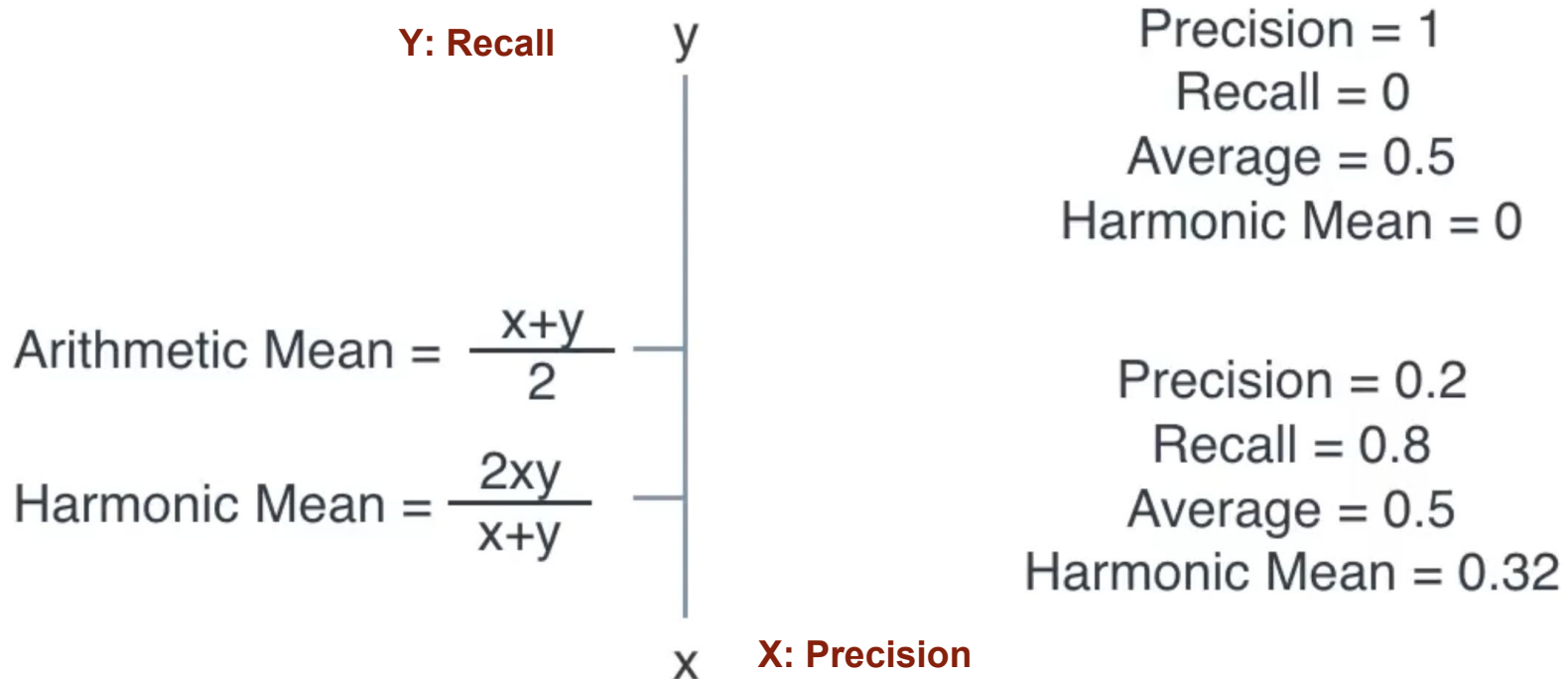
Model: All transactions are fraudulent.

$$\text{Precision} = \frac{472}{284,807} = .016\%$$

$$\text{Recall} = \frac{472}{472} = 100\%$$

Average = 50.008%

# Harmonic mean



~~Arithmetic Mean(Precision, Recall)~~  
F1 Score = Harmonic Mean(Precision, Recall)

# F1 Score



Medical Model

Precision = 55.7%

Recall = 83.3%

Average = 69.5%

$$\text{F1 Score} = \frac{2 \times 55.7 \times 83.3}{55.7 + 83.3} = 66.76\%$$

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$



# F1 Score



Spam Detector  
Model

Precision = 76.9%

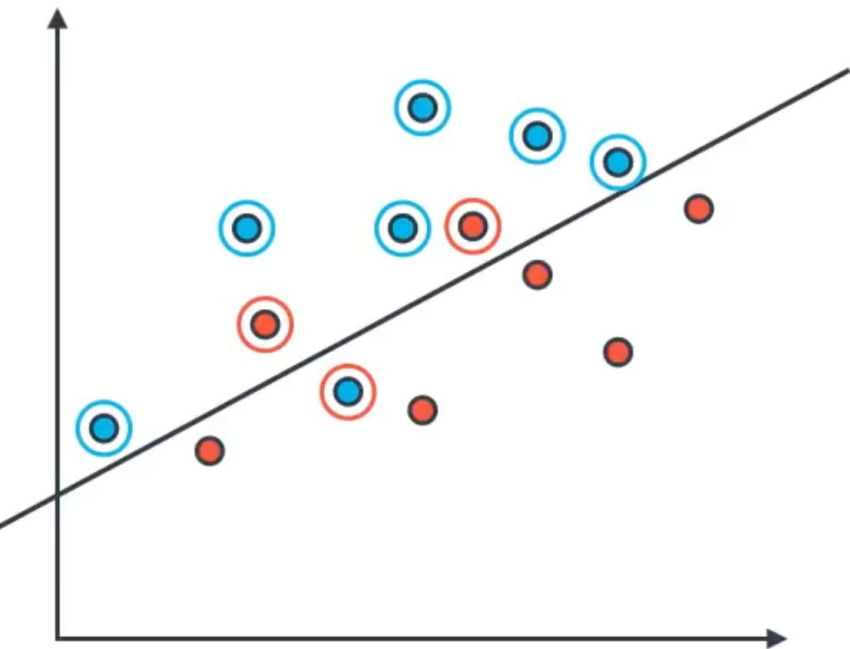
Recall = 37%

Average = 56.95%

$$\text{F1 Score} = \frac{2 \times 76.9 \times 37}{76.9 + 37} = 49.96\%$$

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

# F1 Score



Precision = 75%

Recall = 85.7%

Average = 80.35

$$\text{F1 Score} = \frac{2 \times 75 \times 85.7}{75 + 85.7} = 80\%$$

$F_{\beta}$  Score



**Precision**

**$F_{0.5}$  Score**

**$F_1$  Score**

**$F_2$  Score**



**Recall**



## Comparing Systems

System 1

- Precision: 70%
- Recall: 60%



System 2

- Precision: 80%
- Recall: 50%

$$F_{\beta} = \frac{1}{\beta \times \frac{1}{Precision} + (1 - \beta) \times \frac{1}{Recall}}$$

- Greater  $\beta$ , Greater importance to Precision

# Comparing Systems

System 1

- Precision: 70%
- Recall: 60%



System 2

- Precision: 80%
- Recall: 50%

$$F_{\beta} = \frac{1}{\beta \times \frac{1}{Precision} + (1 - \beta) \times \frac{1}{Recall}}$$

$$\beta = 0.95$$

0.6942



0.7766

$$\beta = 0.5$$

$$F_{\beta} = \frac{1}{0.5 \times \frac{1}{0.7} + (1 - 0.5) \times \frac{1}{0.6}} = 0.6461$$

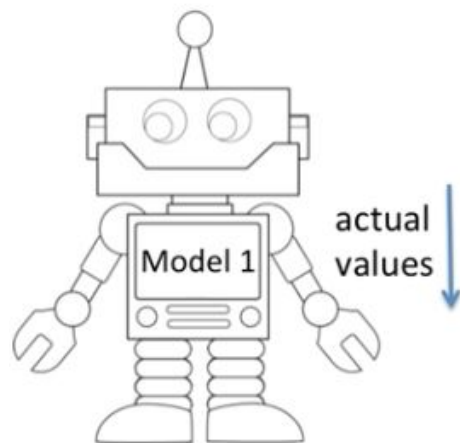


$$\beta = 0.5$$

$$F_{\beta} = \frac{1}{0.5 \times \frac{1}{0.8} + (1 - 0.5) \times \frac{1}{0.5}} = 0.6153$$

*F-Measure*

## F1 Score on imbalanced data

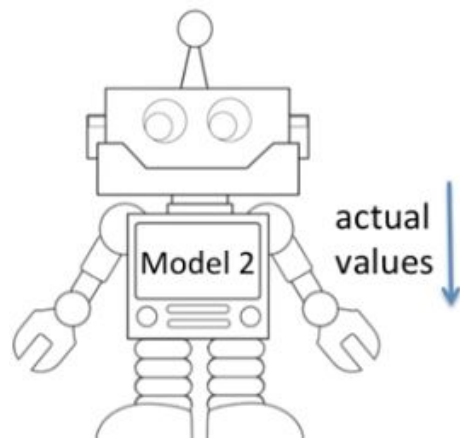


predictions →

	A	B	C	D
A	100	80	10	10
B	0	9	0	1
C	0	1	8	1
D	0	1	0	9

F1 Score = **0.601**

accuracy = 0.547



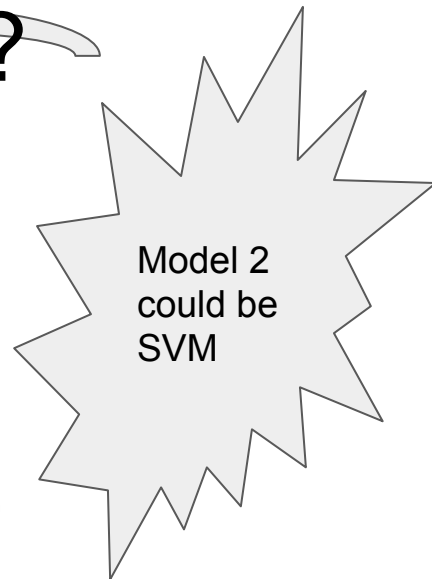
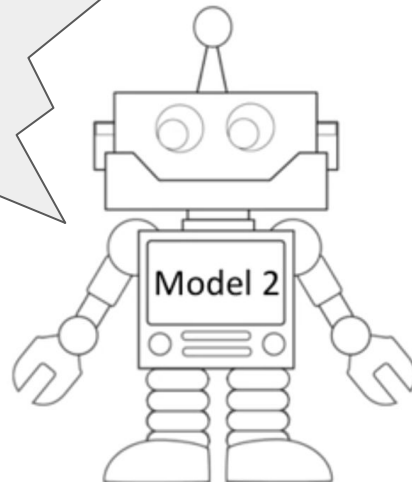
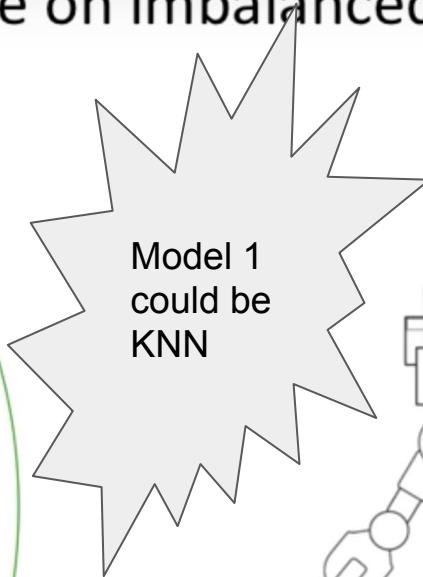
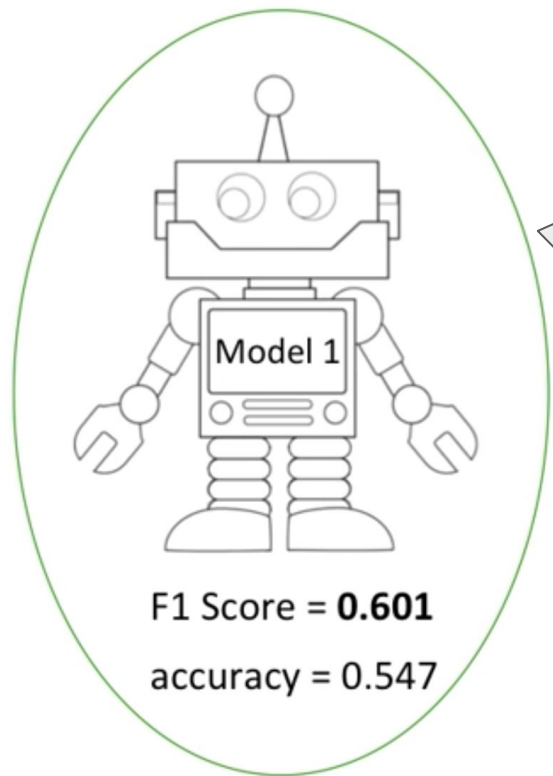
predictions →

	A	B	C	D
A	198	2	0	0
B	7	1	0	2
C	0	8	1	1
D	2	3	4	1

F1 Score = **0.342**

accuracy = 0.87

# F1 Score on imbalanced data



Which to  
choose ?


Model 1 predicts well on multiple class classification on imbalanced given data, and F1 score is the metric to quantify its performance.

# QUIZ


#1: FPR must be reduced -  
Precision must be high  
 $F_\beta$  where  $\beta$  must be high. So  $F_2$

In each of the following scenarios which choice of  $F_1$ ,  $F_{0.5}$  or  $F_2$  be the best choice of metric.

1. Cancer Detection: If someone is falsely diagnose we may do some extra tests. If someone who actually has cancer is not diagnosed they may die.



2. Convicting to Prison: People are innocent until proven guilty by US Law. We want to avoid false convictions. But we also want criminals to not run free.



#2: FNR must be reduced -  
Recall must be high  
 $F_\beta$  where  $\beta$  must be low. So  $F_{0.5}$