



# Classification

Certificate Course on Artificial Intelligence & Deep Learning  
by IIT Roorkee





# Agenda

- Introduction
- Build Model with MNIST Dataset
- Performance Measures
  - Cross Validation
  - Confusion Matrix
  - Precision & Recall
  - Precision/Recall Trade-off
  - ROC Curve
- Type of Classification
  - Multi Class
  - Multi Label
  - Multi Output

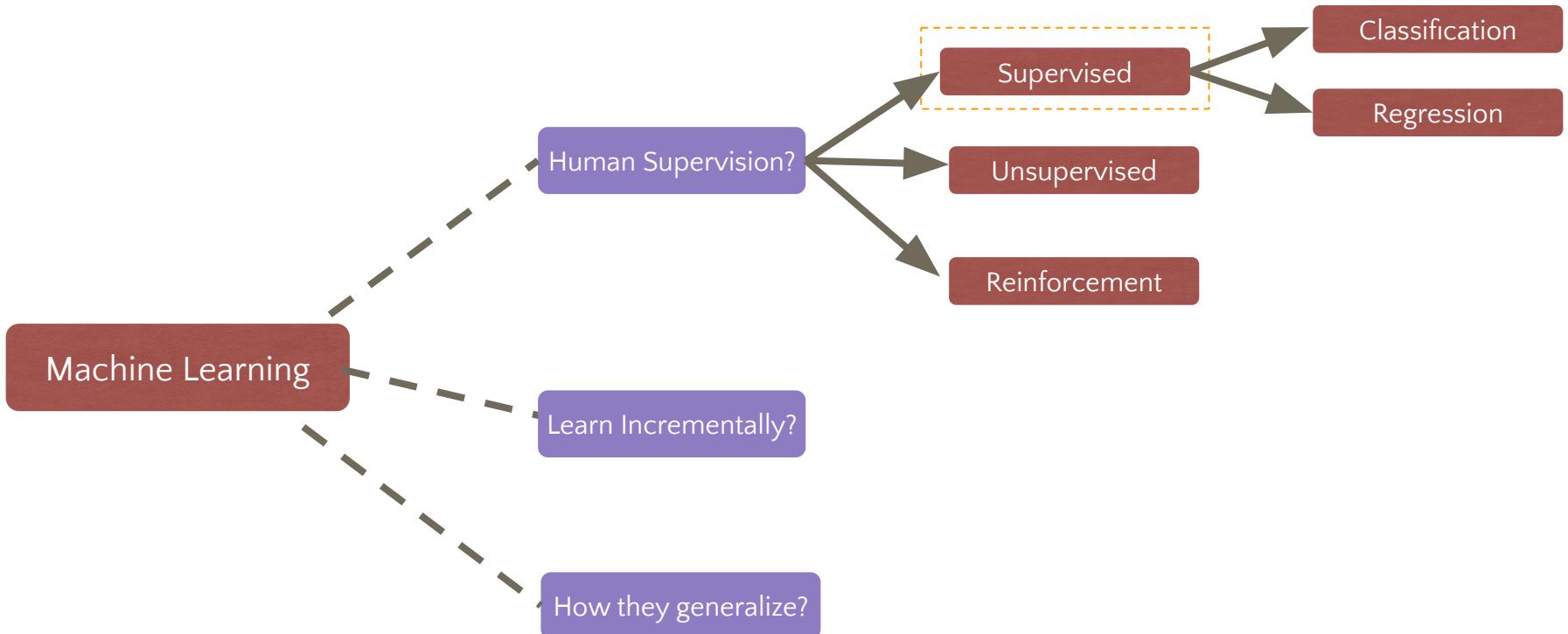


# Agenda

- Ask questions
- Teaching Assistants will be there to help you out
- Post your questions on forum
  - [discuss.cloudxlab.com](https://discuss.cloudxlab.com)



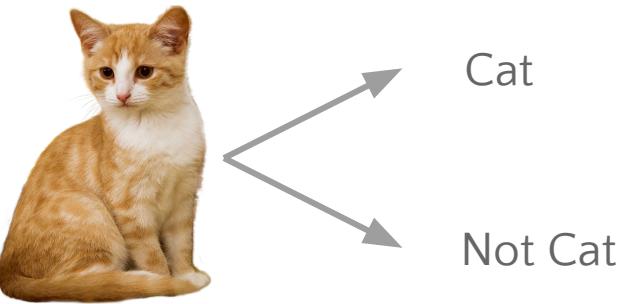
# What is Classification ?



# What is Classification?: Definition

Classification is the task of

- Identifying to which category a new observation belongs
- Since labeled data is available (value of output variable), it's a supervised classification.



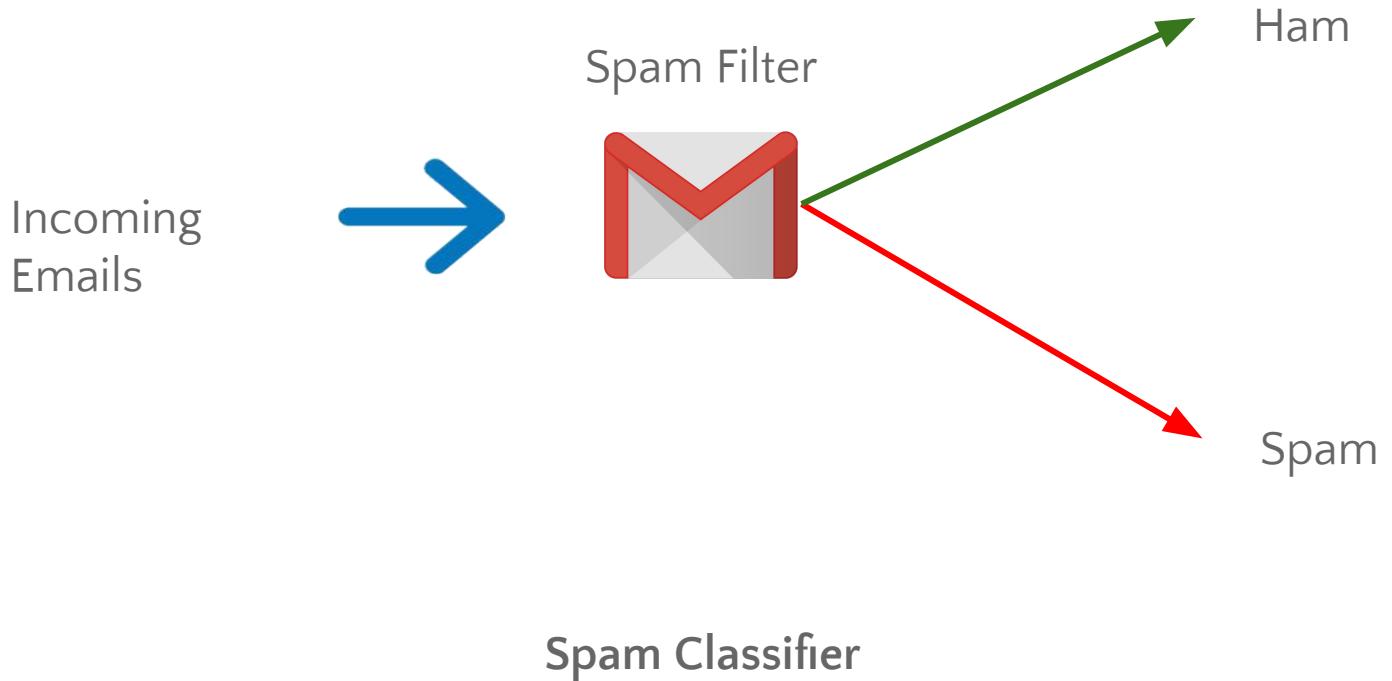
Another example:  
 $C_2 = \{\text{Cat, Dog}\}$

**Cat or Not Cat Classifier**

$$C_1 = \{\text{Cat, Not Cat}\}$$

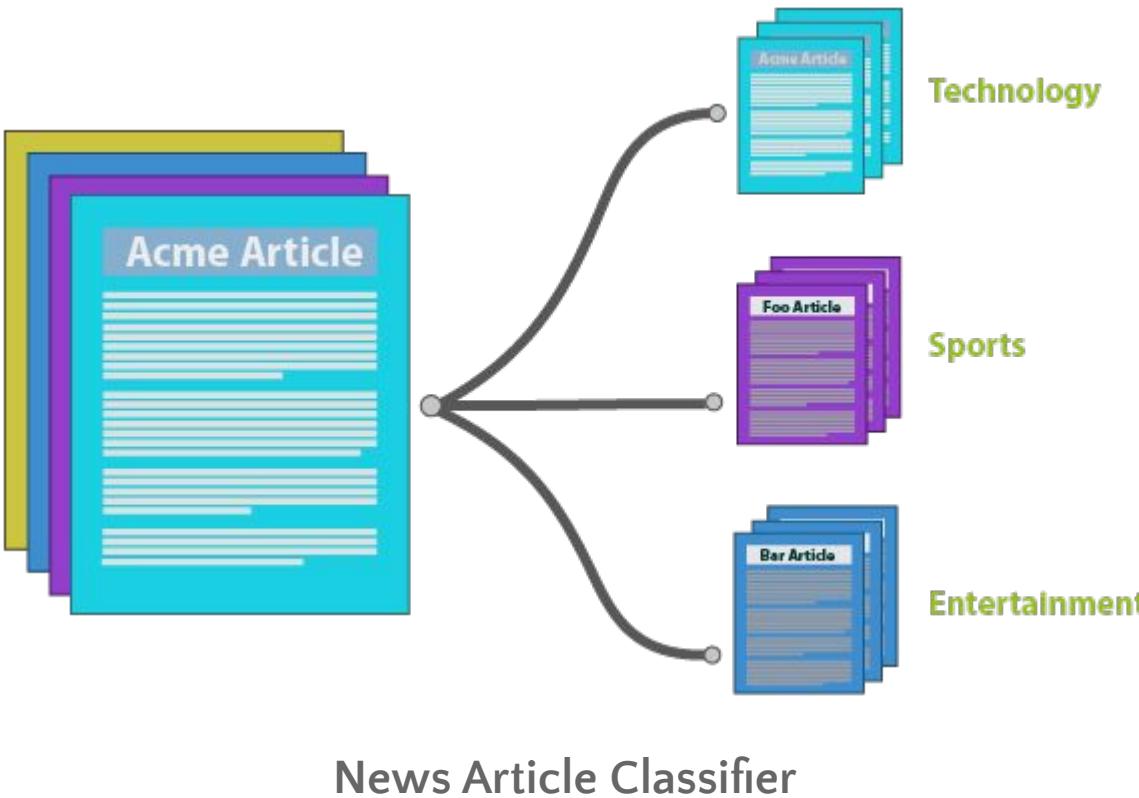


# What is Classification?: Example-1





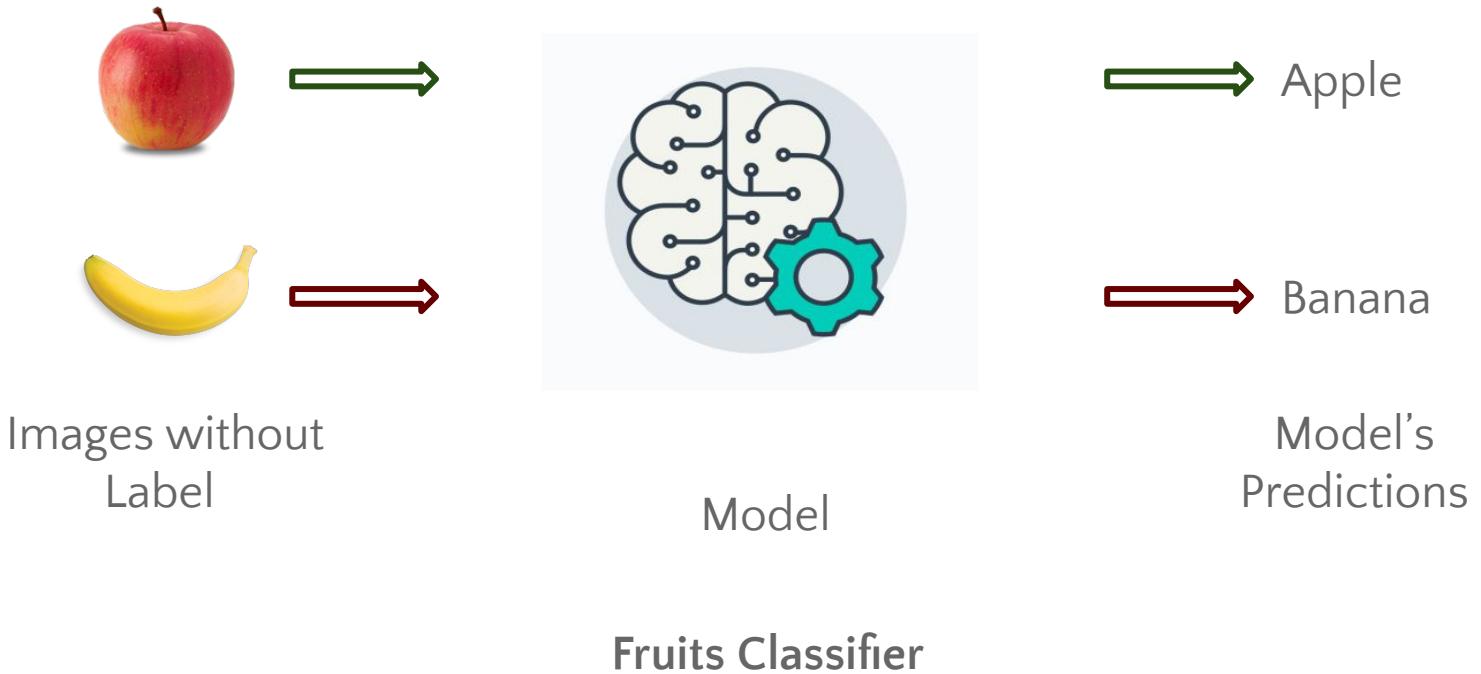
# What is Classification ? Example-2



News Article Classifier



# What is Classification?: Prediction





# So how does classification training works?

Labeled  
Images  
for  
Building  
Model



Apple



Banana



Apple



Kiwi



Grapes



Labeled  
Images  
for  
Building  
Model



Apple



Banana



Apple



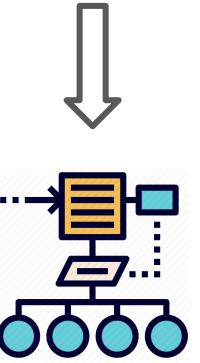
Kiwi



Grapes



## Training Phase



Algorithm

Labeled  
Images  
for  
Building  
Model



Apple



Banana



Apple



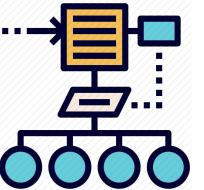
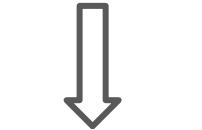
Kiwi



Grapes



## Training Phase



Algorithm



Model



# Predictions



Images without  
Label



Model

Fruits Classifier

→ Apple

→ Banana

Model's  
Predictions



# So how do we train the model in classification?



# Labeled Images for Building Model



Apple



Banana



Apple



Kiwi



Grapes

Img-1	....	...	.....				Apple
Img-2							Banana
Img-3							Apple

Feature Matrix (X)

Label  
Vector (Y)



# Train-test Split

Labeled  
Images  
for  
Building  
Model



Apple



Banana



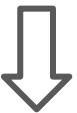
Apple



Kiwi



Grapes



Split images into training and test set



Training Set - 80% Data

Test Set - 20% Data

# Labeled Images for Building Model



Apple



Banana



Apple



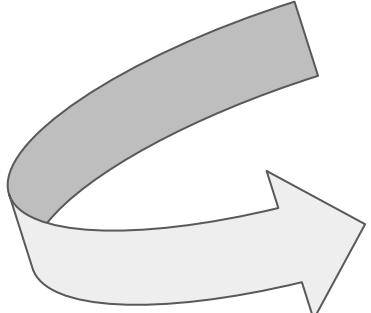
Kiwi



Grapes



Split images into training and test set



Using training set we  
build the model



# Labeled Images for Building Model



Apple



Banana



Apple



Kiwi



Grapes



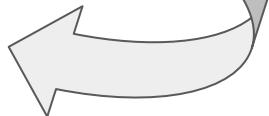
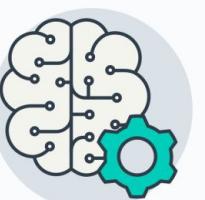
Split images into training and test set



Training Set - 80% Data

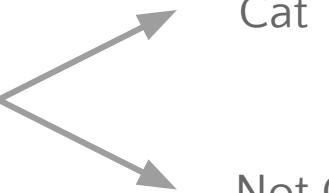
Test Set - 20% Data

Using test set we evaluate  
performance of model

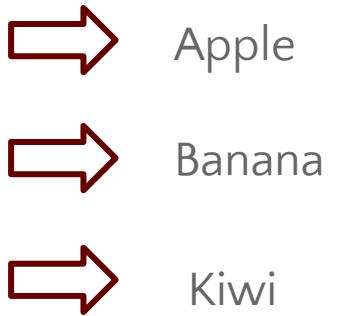




# Classification Types



Binary Classification -  
Two Classes



Multi Class Classification -  
Multiple Classes

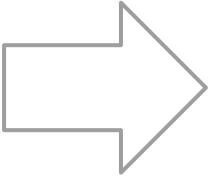


The goal of this session is to build a model to  
classify handwritten digits

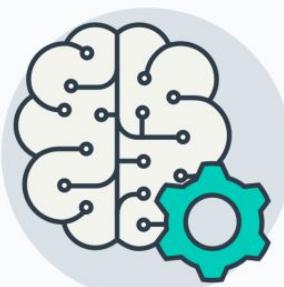


# Handwritten Digits Classifier

5



Input image



Model



Model classifies the image  
into one of the digits between  
0 and 9

0
1
2
3
4
5
6
7
8
9

Model's  
prediction

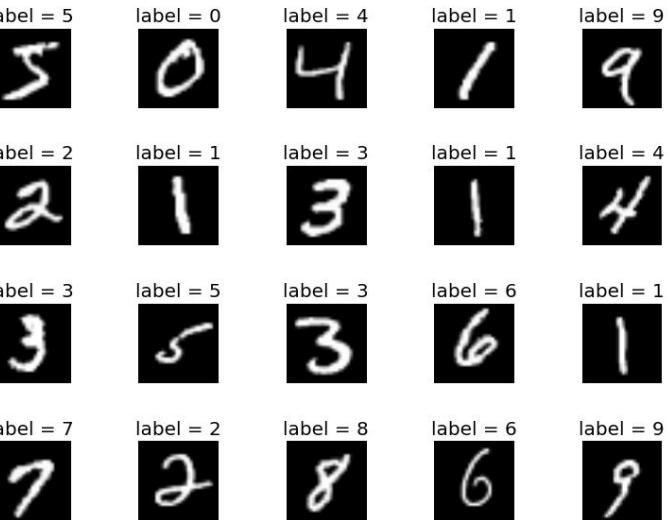
Multiclass Classification



# Handwritten Digits Classifier - Dataset

Source: <http://yann.lecun.com/exdb/mnist/>

- In this problem, we will use MNIST dataset
  - Set of 70,000 small images
  - Each image is grayscale (black & white)
  - 28 by 28 pixels (total 784 pixels for an image)
  - The digits have been size-normalized and centered in a fixed-size image.

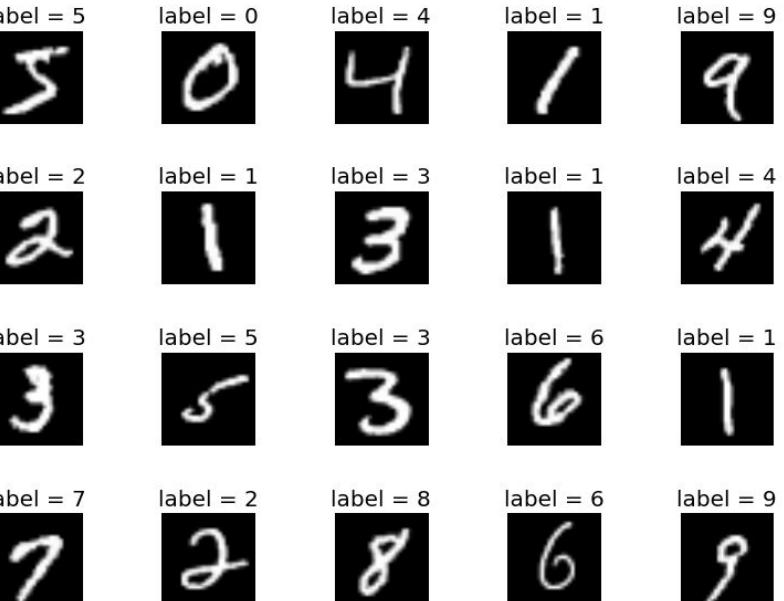


MNIST Dataset  
(Modified National Institute of  
Standards and Technology)



# Handwritten Digits Classifier - Dataset

- Handwritten by high school students and employees of the US Census Bureau.
- Each image is labeled with the digit it represents.

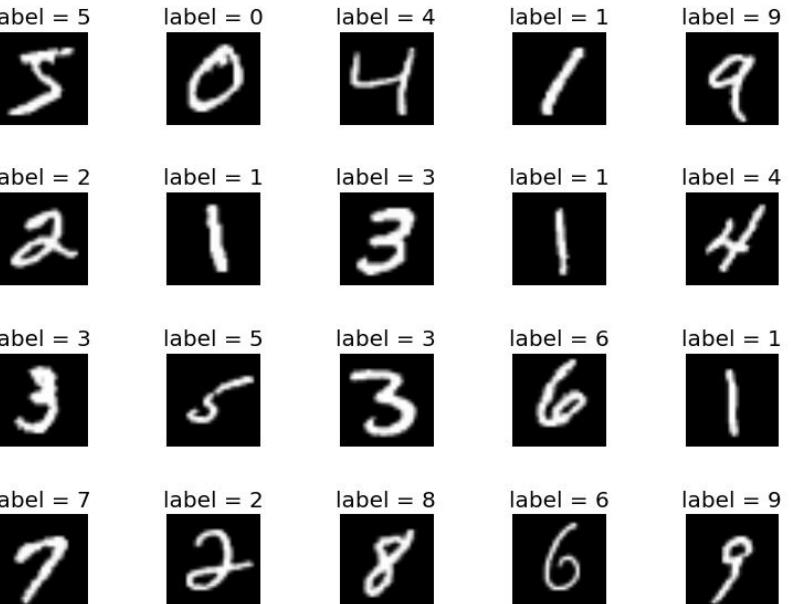


Every Image has Label Associated



# Handwritten Digits Classifier - Dataset

- MNIST dataset is also called
  - “Hello World” of Machine Learning
- We have to build a model using this labelled dataset



Every Image has Label Associated



# Handwritten Digits Classifier - Dataset

- Let's get the data and explore it
  - Go to Jupyter
  - Open New Terminal
  - Switch to the repository
    - `cd iitr-deep-learning-spl-tf2`
  - Get the latest code
    - `git pull origin master`



# Handwritten Digits Classifier - Dataset

## Fetch the Data

```
>>> from sklearn.datasets import fetch_openml  
>>> mnist = fetch_openml('mnist_784', version=1)  
>>> X, y = mnist["data"], mnist["target"]
```



# Handwritten Digits Classifier - Dataset

So how do we start the training process?



# Handwritten Digits Classifier - Training Process

label = 5	label = 0	label = 4	label = 1	label = 9
label = 2	label = 1	label = 3	label = 1	label = 4
label = 3	label = 5	label = 3	label = 6	label = 1
label = 7	label = 2	label = 8	label = 6	label = 9

???



Tabular form -  
Rows and Columns



# Handwritten Digits Classifier - Training Process

label = 5	label = 0	label = 4	label = 1	label = 9
label = 2	label = 1	label = 3	label = 1	label = 4
label = 3	label = 5	label = 3	label = 6	label = 1
label = 7	label = 2	label = 8	label = 6	label = 9

???



Instances, Features  
and Labels?



# Handwritten Digits Classifier - Training Process

label = 5



label = 0



label = 4



label = 1



label = 9



label = 2



label = 1



label = 3



label = 1



label = 4



label = 3



label = 5



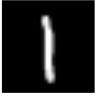
label = 3



label = 6



label = 1



label = 7



label = 2



label = 8



label = 6



label = 9

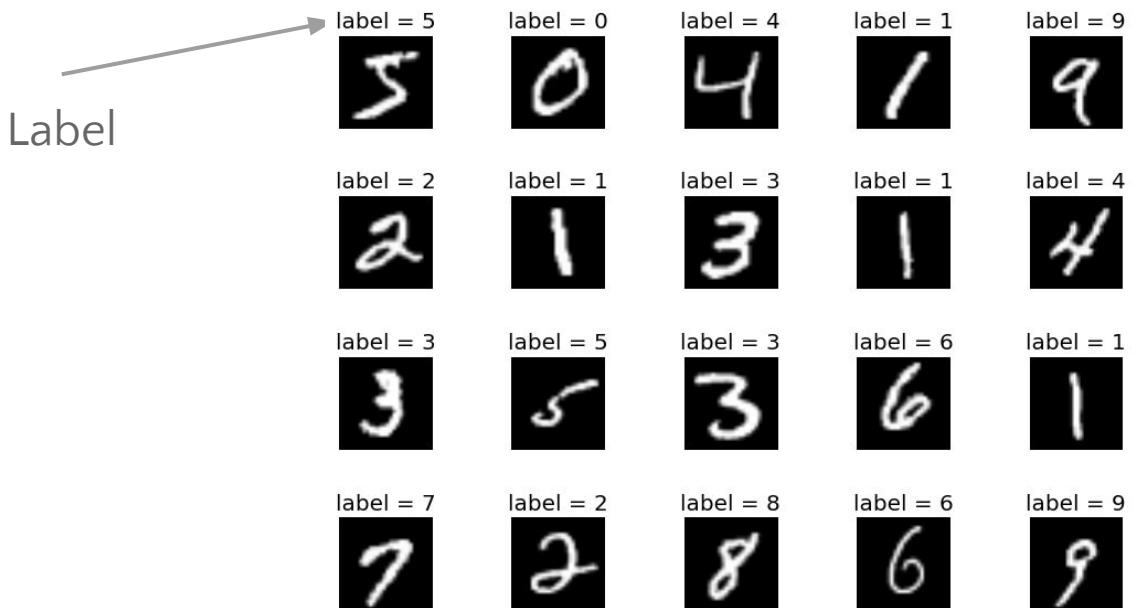


Total number of instances are  
seventy thousand

Each image is an instance



# Handwritten Digits Classifier - Training Process





# Handwritten Digits Classifier - Training Process

label = 5



label = 0



label = 4



label = 1



label = 9



label = 2



label = 1



label = 3



label = 1



label = 4



label = 3



label = 5



label = 3



label = 6



label = 1



label = 7



label = 2



label = 8



label = 6



label = 9



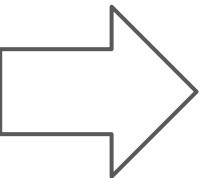
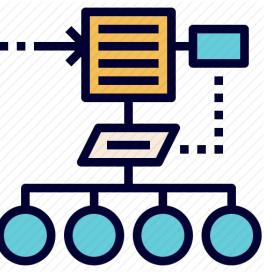
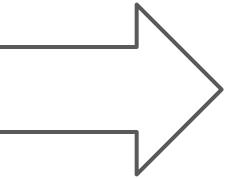
Features?





# Handwritten Digits Classifier - Training Process

label = 5	label = 0	label = 4	label = 1	label = 9
5	0	4	1	9
label = 2	label = 1	label = 3	label = 1	label = 4
2	1	3	1	4
label = 3	label = 5	label = 3	label = 6	label = 1
3	5	3	6	1
label = 7	label = 2	label = 8	label = 6	label = 9
7	2	8	6	9



Model

Input data in tabular form -  
Includes both features and  
labels

Algorithm



# Fetching MNIST dataset in Scikit-Learn

## How to visualize a tabular entry into image form

```
>>> %matplotlib inline  
>>> import matplotlib as mpl  
>>> import matplotlib.pyplot as plt  
  
>>> some_digit = X[0]  
>>> some_digit_image = some_digit.reshape(28, 28)  
>>> plt.imshow(some_digit_image, cmap=mpl.cm.binary)  
>>> plt.axis("off")  
>>> plt.show()
```



Switch to Notebook



# Fetching MNIST dataset in Scikit-Learn

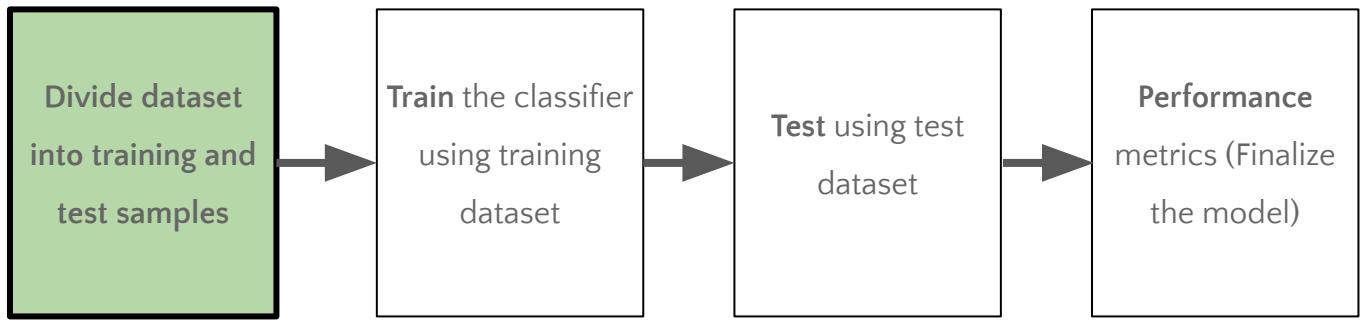
Looking at one of the data samples



Switch to Notebook

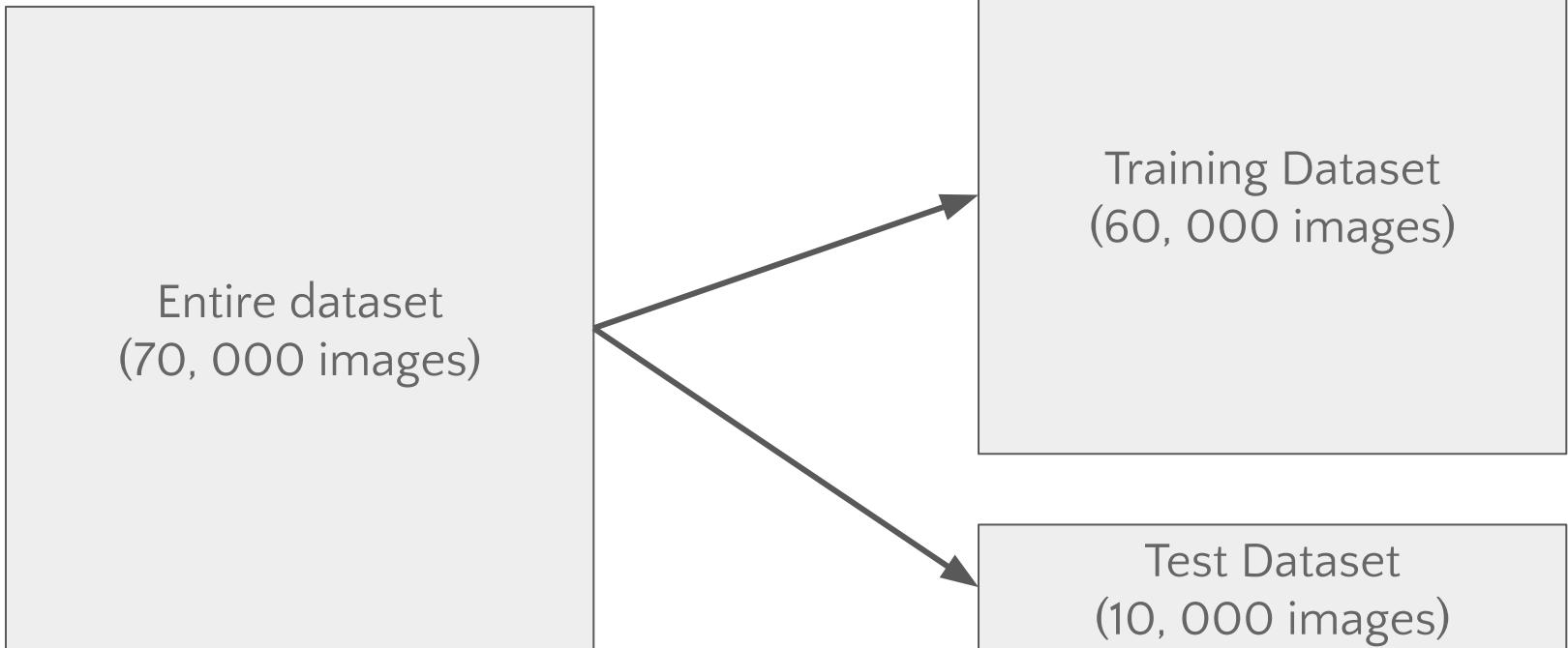


# Handwritten Digits Classifier - Training Process - Steps





# Training and Test dataset





# Dividing dataset into training and test samples

Dividing dataset into training and test in python:

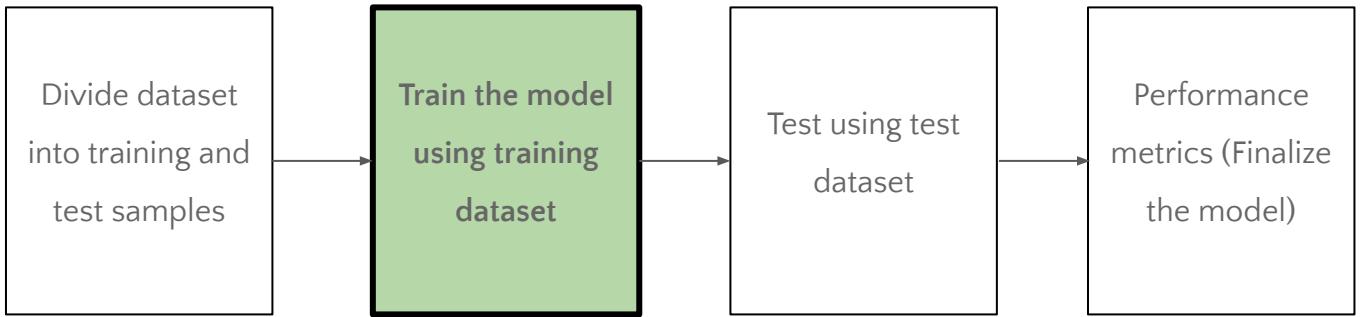
```
>>> X_train, X_test, y_train, y_test = X[:60000], X[60000:], y[:60000], y[60000:]
```



Switch to Notebook

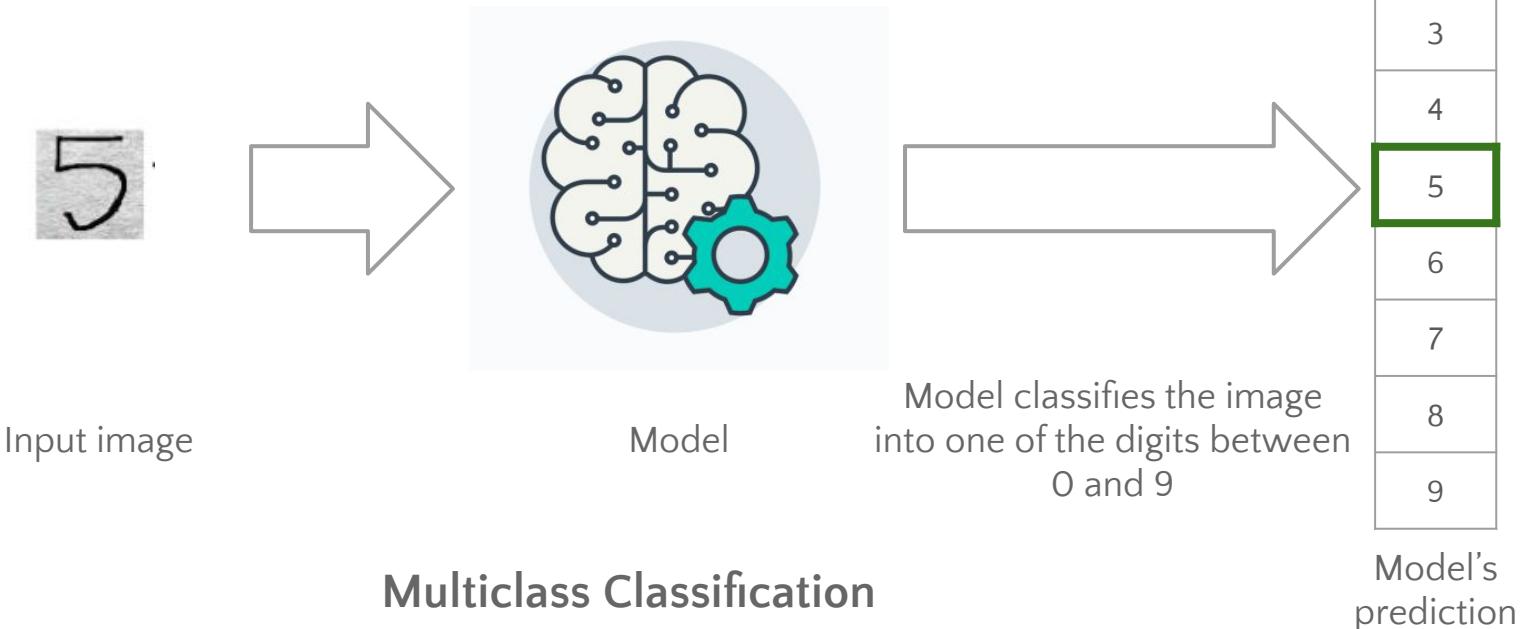


# Steps





# Train the Classifier using Training Dataset





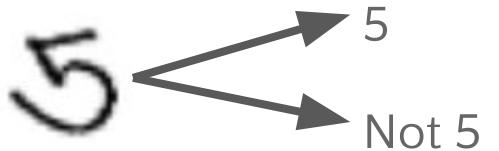
# Train the Classifier using Training Dataset

For simplicity, let's first train a binary classifier instead of multiclass classifier



# Train the Classifier using Training Dataset

We will train a binary classifier called 5-detector



Input: Image      Output: Classification

## 5 - Detector



# Train the Classifier using Training Dataset

Lets change our training and test set labels in MNIST to train 5 detector

```
>>> y_train_5 = (y_train == 5) # True for all 5s, False for all other digits  
>>> y_test_5 = (y_test == 5) # True for all 5s, False for all other digits
```



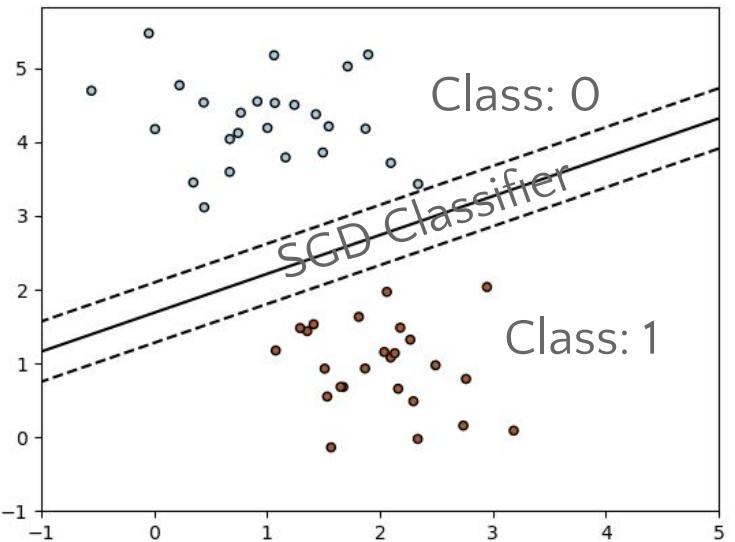
# Train the Classifier using Training Dataset

We are going to use: Stochastic Gradient Descent (SGD)  
Classifier (a linear classifier)

# SGD - Stochastic Gradient Descent Classifier

For the two-dimensional (2 features) training dataset,

- Trying to estimate the coefficients of the line ( $WX+b$ ) which can be
- $W$ -weights vector to feature matrix  $X$ ,  $b$ - bias (from which point in  $Y$  the line should start at  $x=0$ )
- Best-fitted dividing the two categories





# SGD - Stochastic Gradient Descent Classifier

- Stochastic Gradient Descent (SGD) Classifier
  - Capable of handling large datasets
  - Well suited for online training



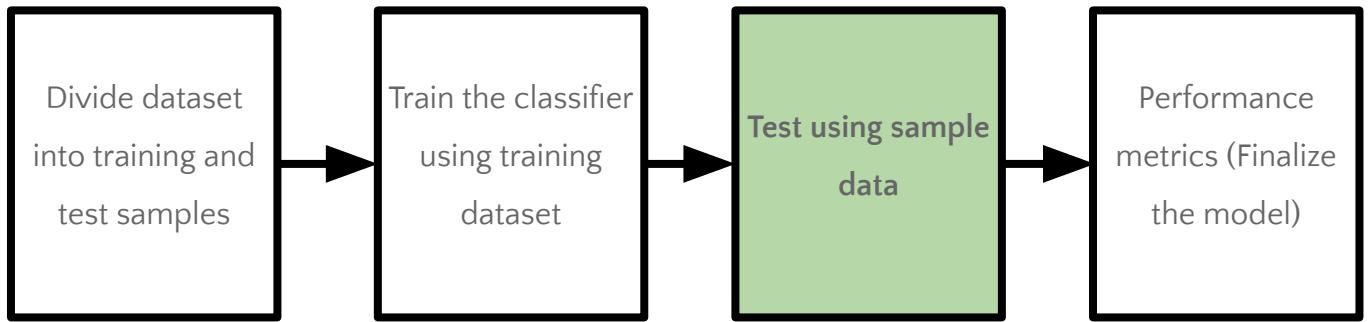
# Training SGDClassifier

Original problem: '5' and 'Not 5' classifier

```
>>> from sklearn.linear_model import SGDClassifier  
  
>>> sgd_clf = SGDClassifier(random_state=42) #initialize the model  
>>> sgd_clf.fit(X_train, y_train_5) #fit the model
```



# Steps





# Testing SGDClassifier

- First image stores the digit 5 and the classifier correctly classifies it as ‘True’

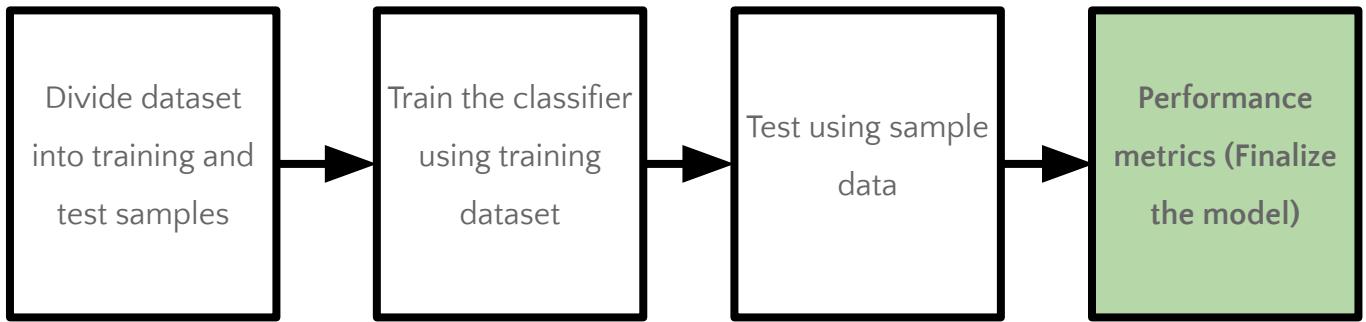
```
>>> some_digit = X[0] # Taking the First image
>>> sgd_clf.predict([some_digit])
array([True], dtype=bool)
```



# Pause for Questions



# Steps





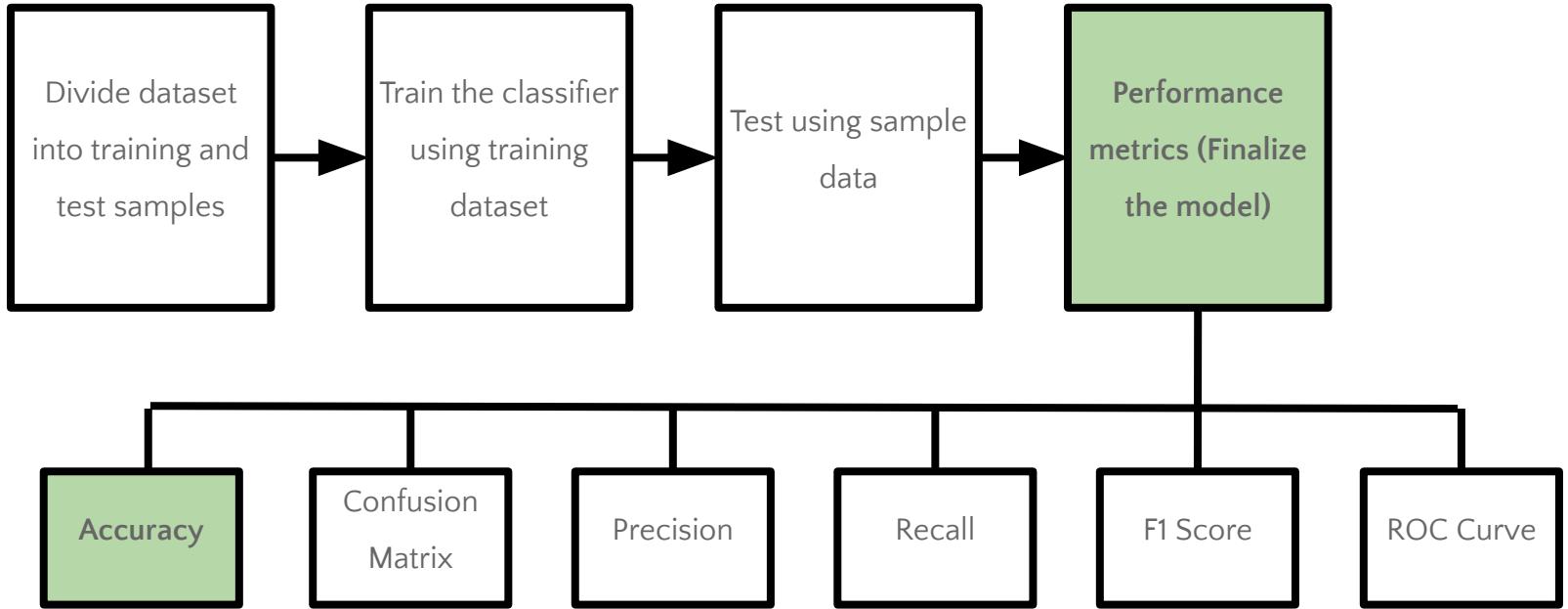
# Measuring Performance of Classifier

- Accuracy
- Confusion Matrix
  - Precision
  - Recall
  - F1 score
- ROC Curve





# Steps





# Performance Measures - Test Data Vs Cross-Validation

Case-1: Measure performance on test data: Report accuracy on test data only

Case-2: Measure performance on different splits (folds) of the entire data (Cross-validation): Report the combined accuracy





# Performance Measures - Test Data Vs Cross-Validation

## cross\_val\_score

As discussed in end-to-end project session, `cross_val_score()` function in scikit-learn can be used to perform cross validation

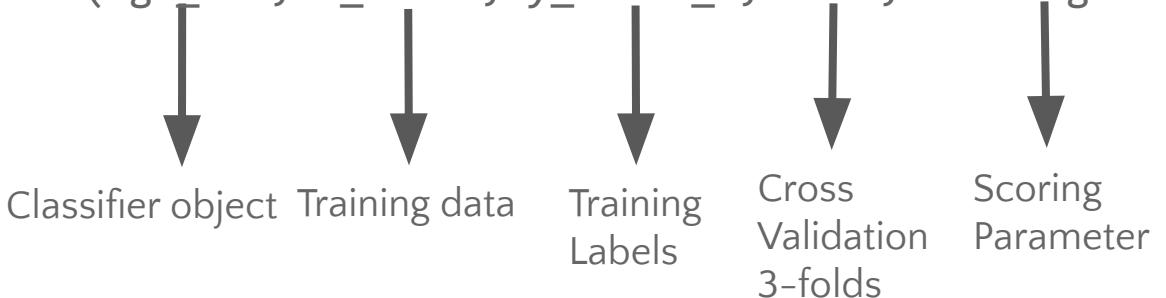


# Performance Measures - Cross Validation

## Initiating cross validation method

```
>>> from sklearn.model_selection import cross_val_score
```

```
>>> cross_val_score(sgd_clf, X_train, y_train_5, cv=3, scoring="accuracy")
```



The scoring attribute can be “f1” for f-score or any other metric suitable to your model.

Refer: [https://scikit-learn.org/stable/modules/model\\_evaluation.html](https://scikit-learn.org/stable/modules/model_evaluation.html)



Switch to Notebook



# Performance Measures - Cross Validation

```
>>> array([0.95035, 0.96035, 0.9604 ])
```

- The resulting accuracy is above 95 % for each of the folds



# Performance Measures - Cross Validation

Is the accuracy of 95% good enough?



## Performance Measures - Cross Validation

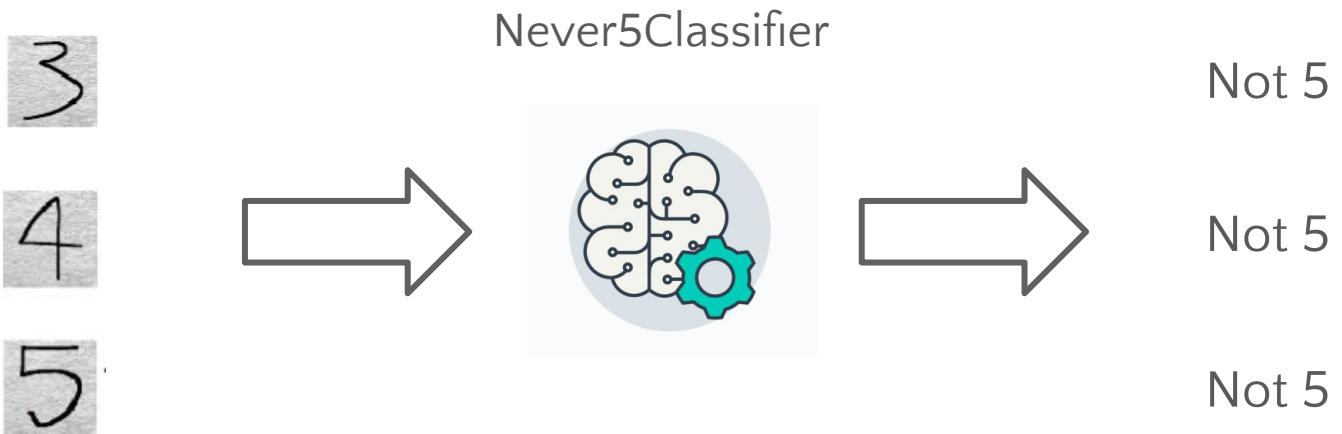
Is the accuracy of 95% good enough?

Let's see



# Performance Measures - Cross Validation

For Now Let's Build Another Classifier - Never5Classifier - Which classifies every image as “Not 5”





# Performance Measures - Cross Validation

## Never5Classifier

```
>>> from sklearn.base import BaseEstimator  
>>> class Never5Classifier(BaseEstimator):  
    def fit(self, X, y=None):  
        pass  
    def predict(self, X):  
        return np.zeros((len(X), 1), dtype=bool)
```



Switch to Notebook



# Performing Cross validation in Scikit learn

**Calculating accuracy using cross\_val\_score**

```
>>> never_5_clf = Never5Classifier()  
>>> cross_val_score(never_5_clf, X_train, y_train_5, cv=3, scoring="accuracy")
```



**Switch to Notebook**



# Performing Cross validation in Scikit learn

Accuracy = 95 %

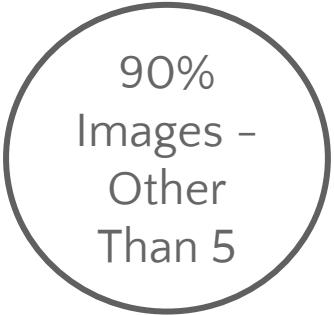
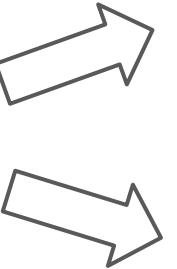
SGDClassifier

Accuracy = 90 %

Dumb Classifier -  
Never5 Classifier



# Skewed Dataset



Skewed Dataset  
(Number of  
instances are not  
equal)

Class Imbalance



## Model's Prediction

Not 5



Not 5



Dumb Classifier -  
Classifies every  
image as "Not 5"

Accuracy → 90%



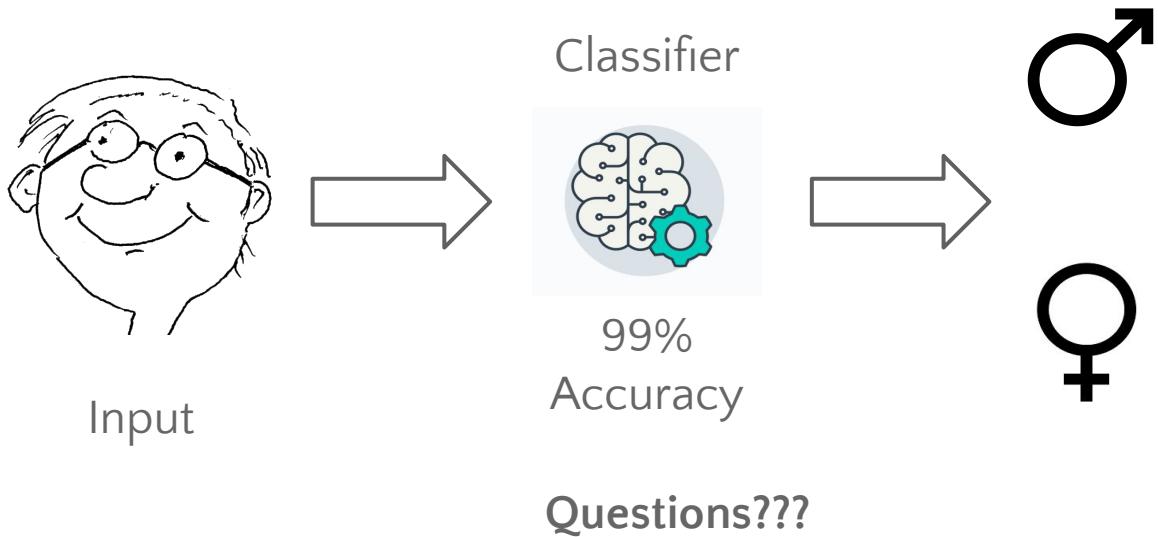


# Learnings??

- Accuracy may not be a good performance measure when dealing with skewed datasets



Question - Let's say your friend has built a model which classify an image into a male or female with 99% accuracy. What questions you will ask your friend to make sure his model is fine?



# Labeled Images for Building Model



Male



Male



Male



Female



Male



%  
Males  
???

%  
Females  
???

Question – Percentage of males and females in training dataset

# Labeled Images for Building Model



Male



Male



Male



Female



Male



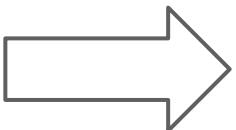
80%  
Males

20%  
Females

Your friend answers 80% male and 20% females



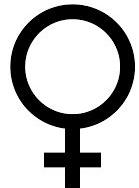
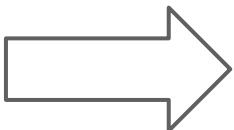
Input



X  
Classifier



99%  
Accuracy



Since dataset is skewed hence you will not  
trust his model



# Performing Cross validation in Scikit learn

Accuracy = 95 %

SGDClassifier

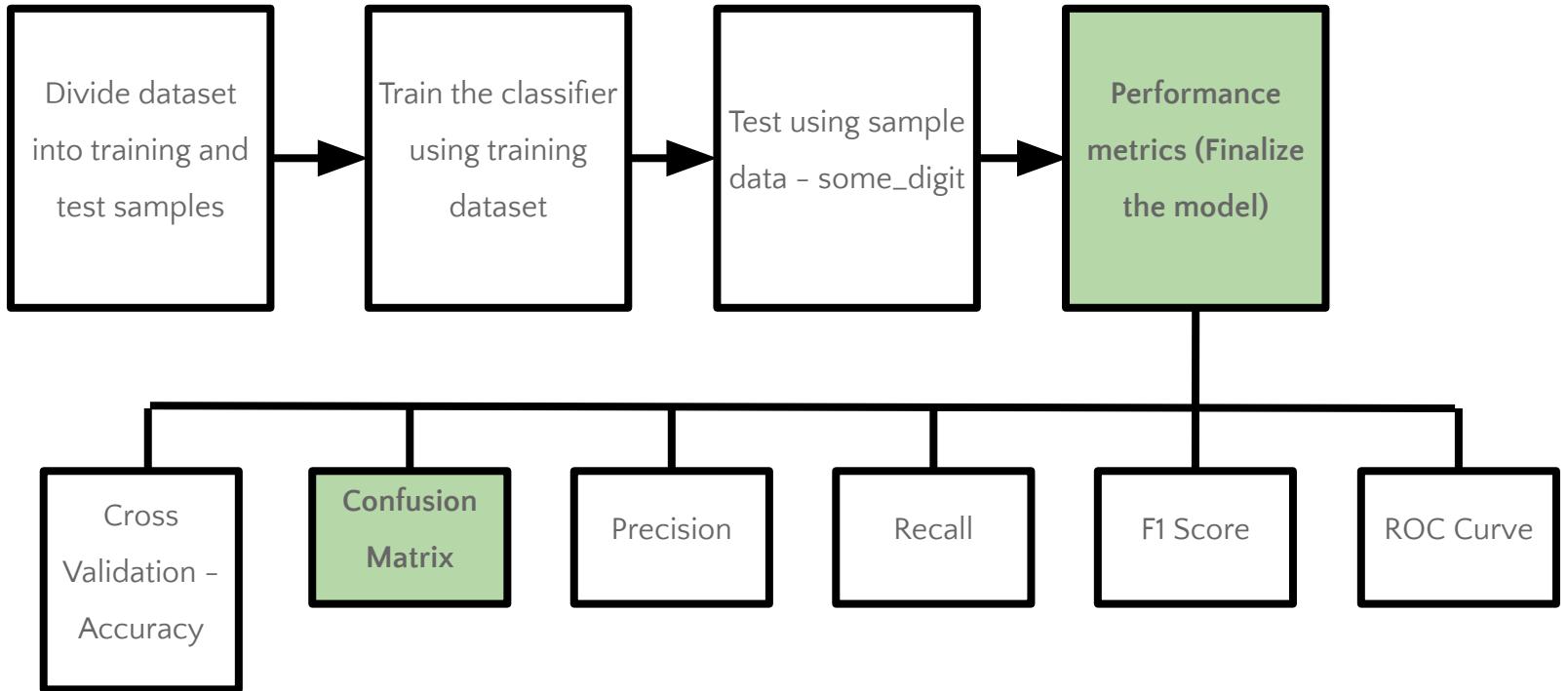
Accuracy = 90 %

Dumb Classifier -  
Never5 Classifier

We need a better measure of performance for the classifier



# Steps





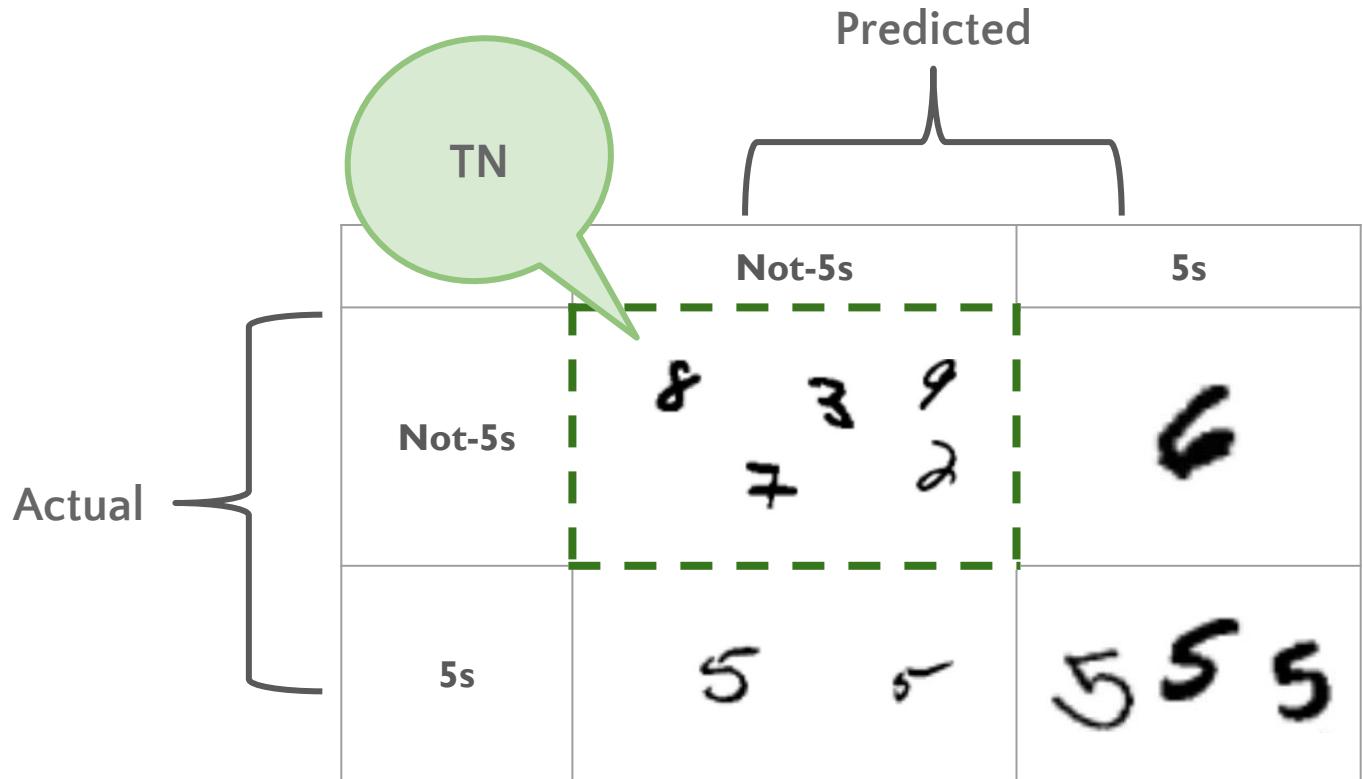
# Performance Measures - Confusion Matrix

		Predicted YES	Predicted NO	
Actual YES	TP	620	FN	380
	FP	180	TN	8820

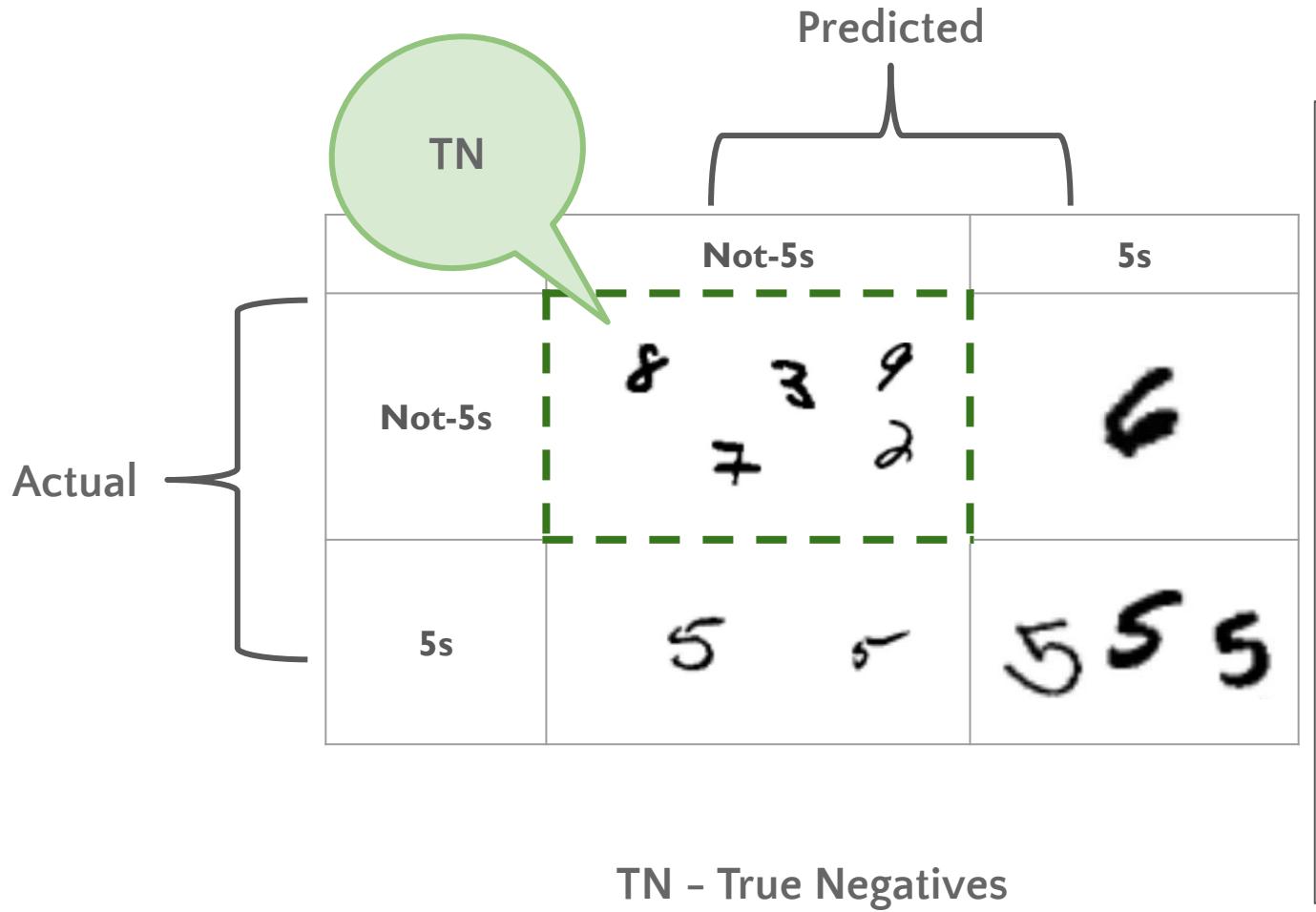


		Predicted	
		Not-5s	5s
Actual	Not-5s	8 3 9 7 2	6
	5s	5 5	5 5 5

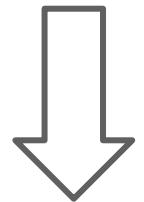
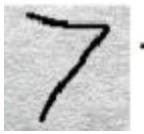
Sample Confusion Matrix of 5-Detector



TN - True Negatives

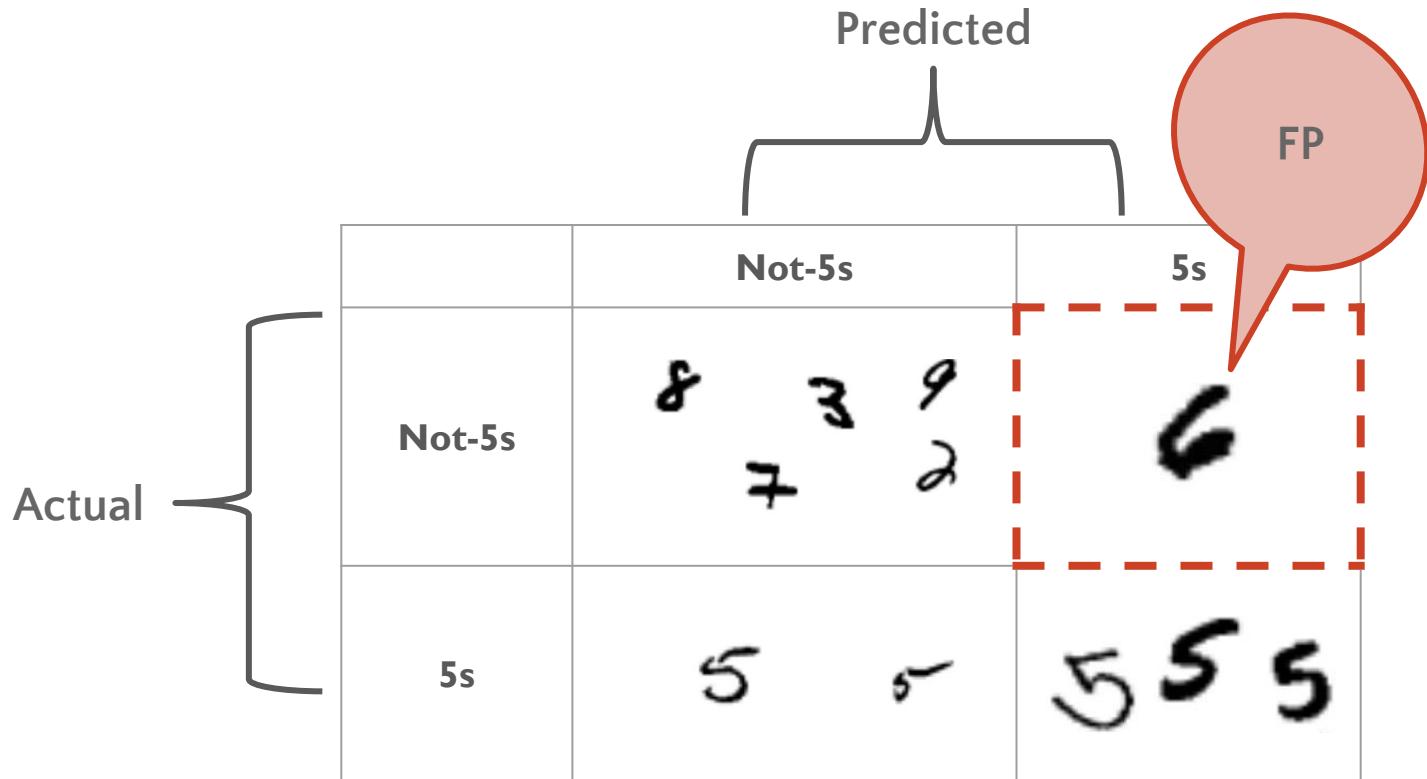


( Actual Image )

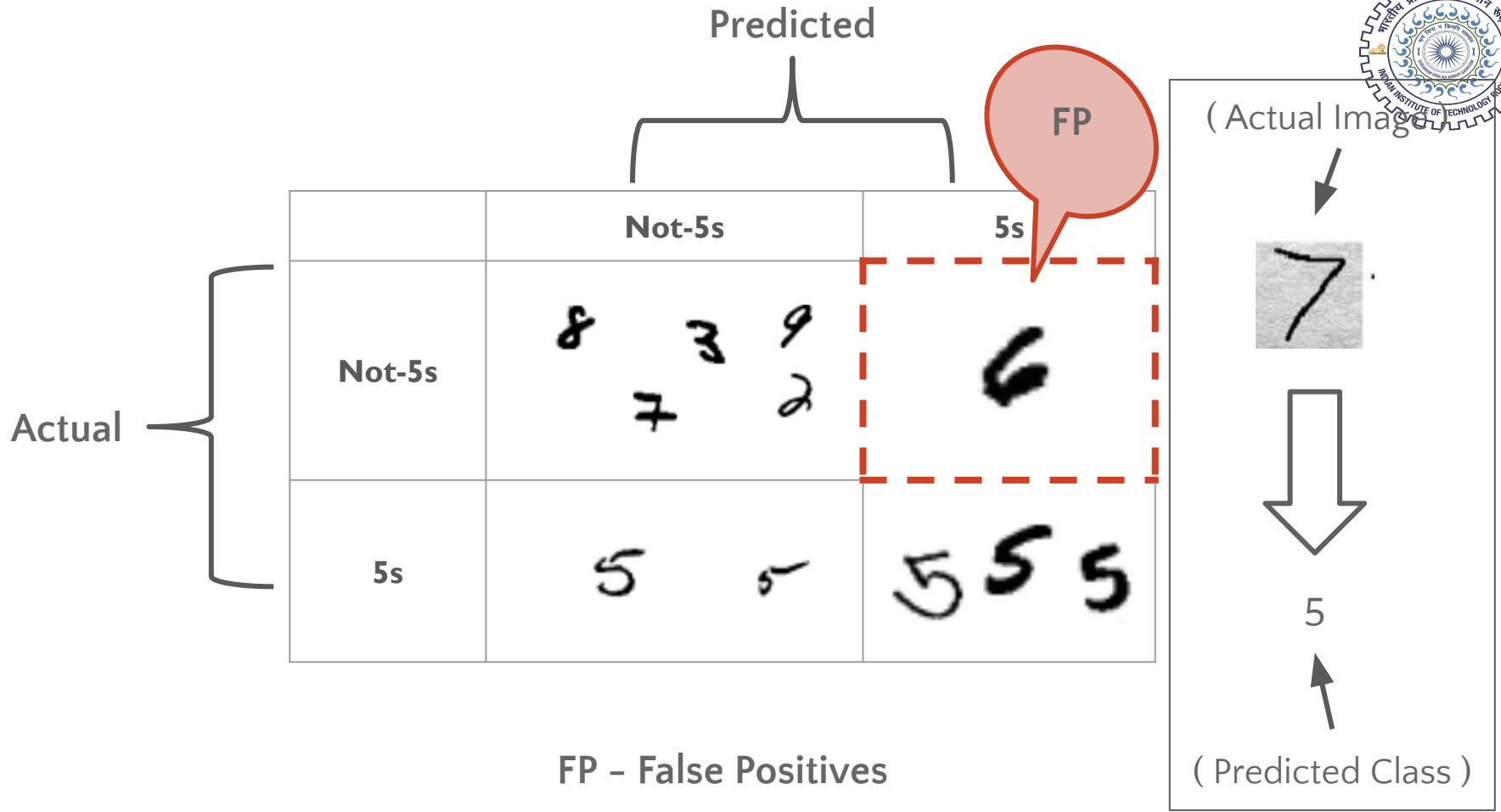


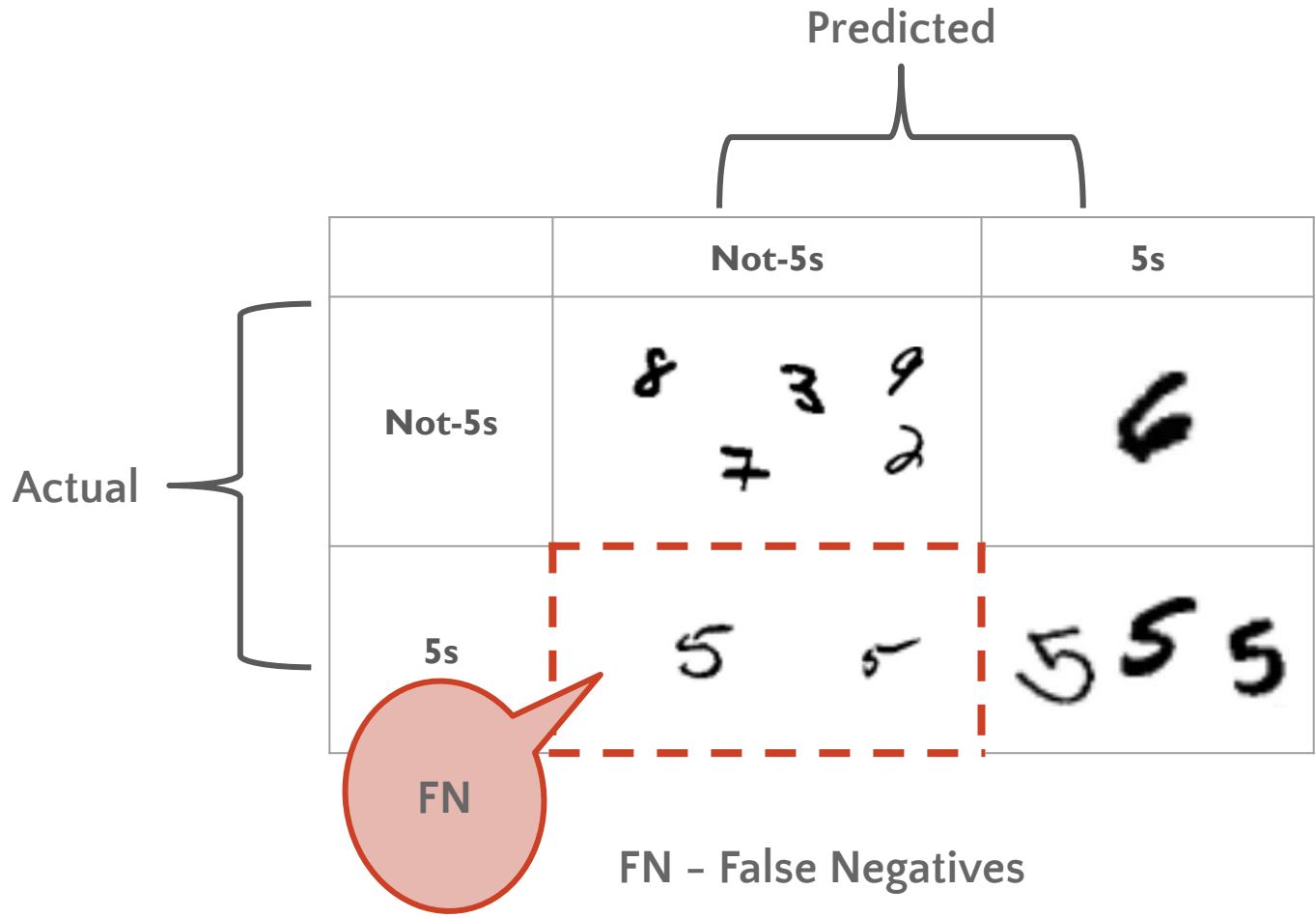
Not 5

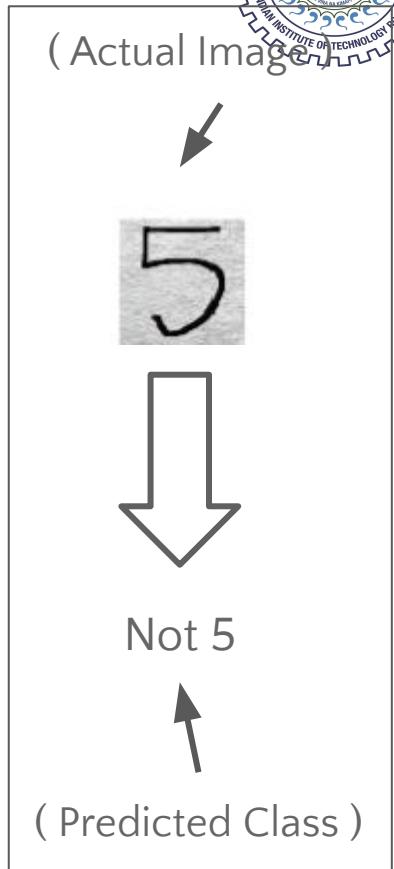
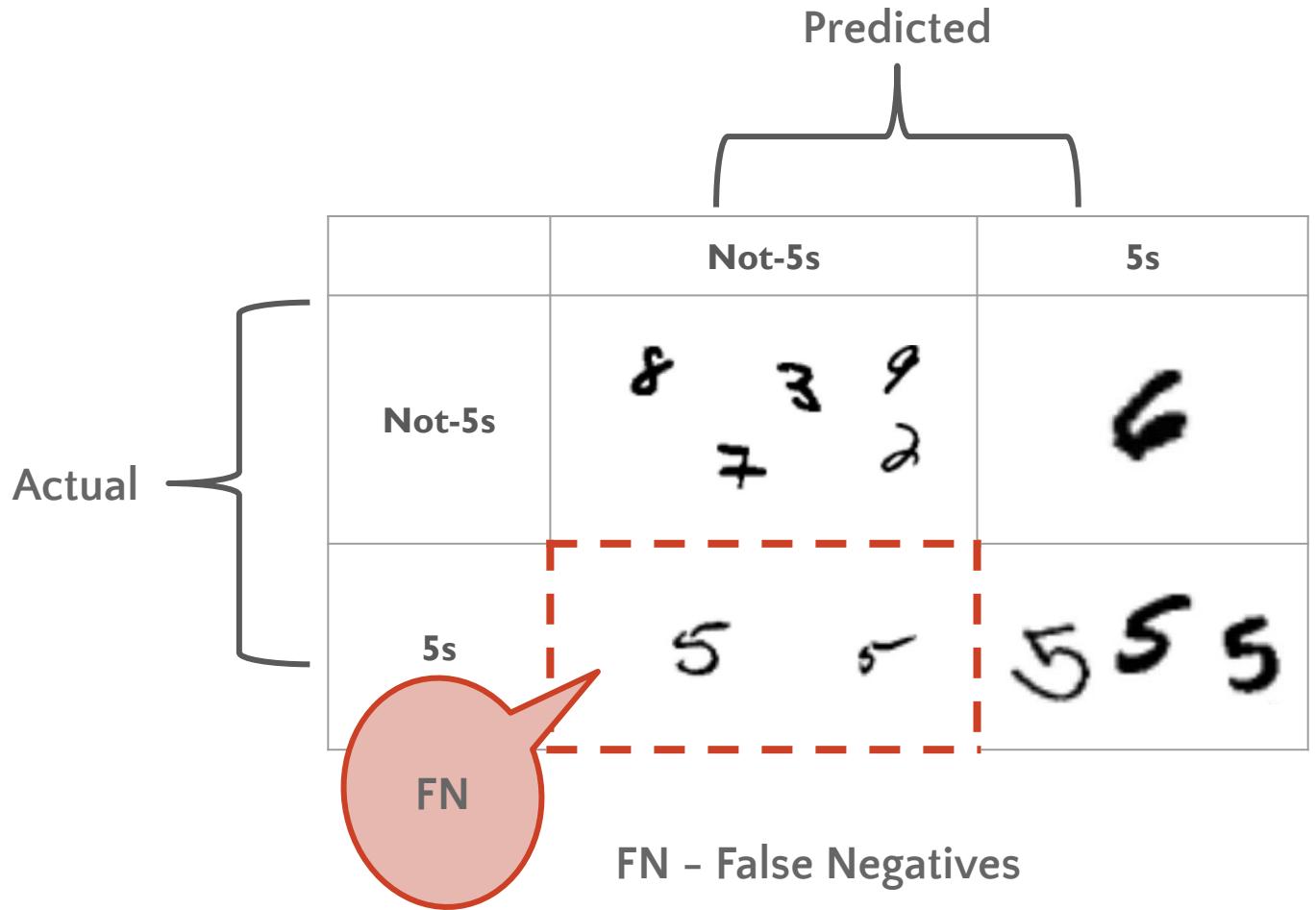
( Predicted Class )

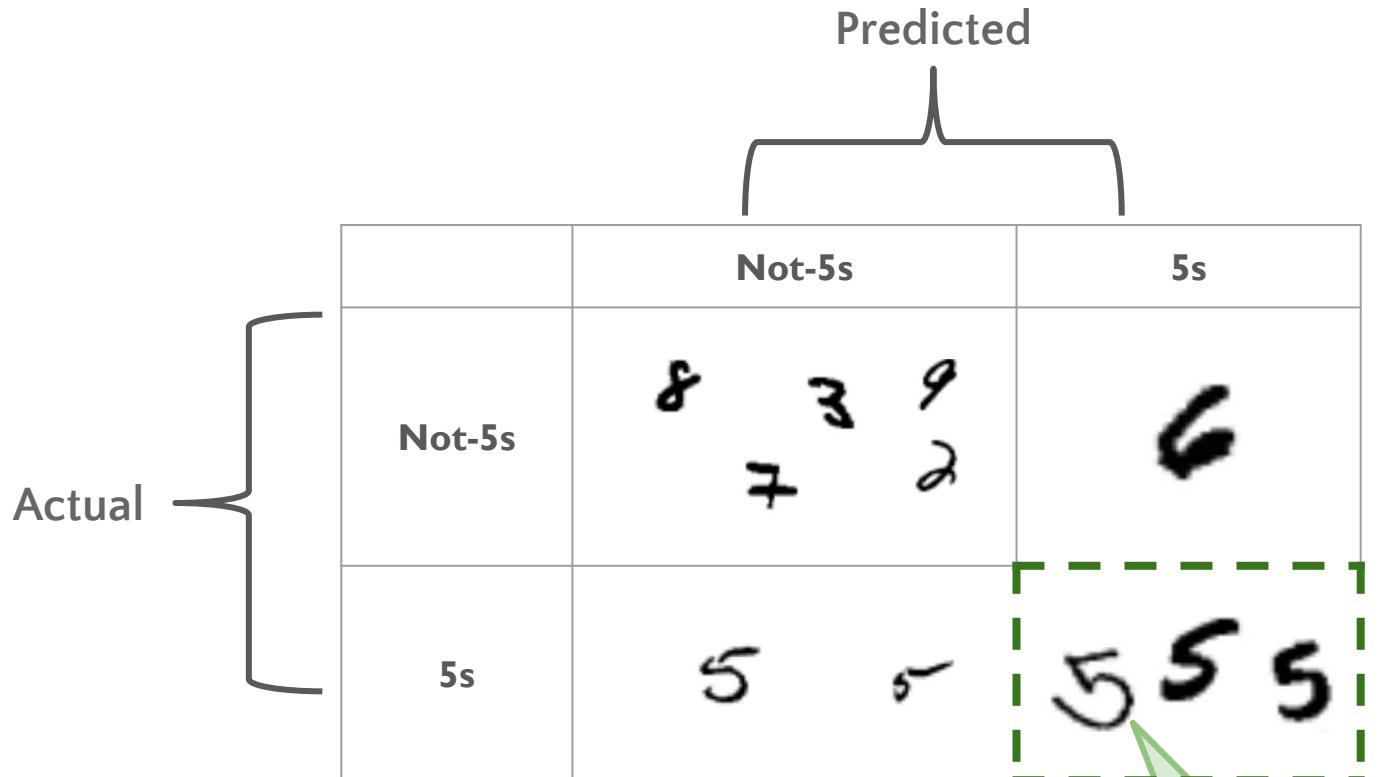


FP - False Positives

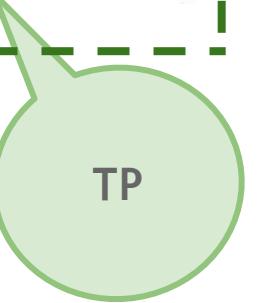


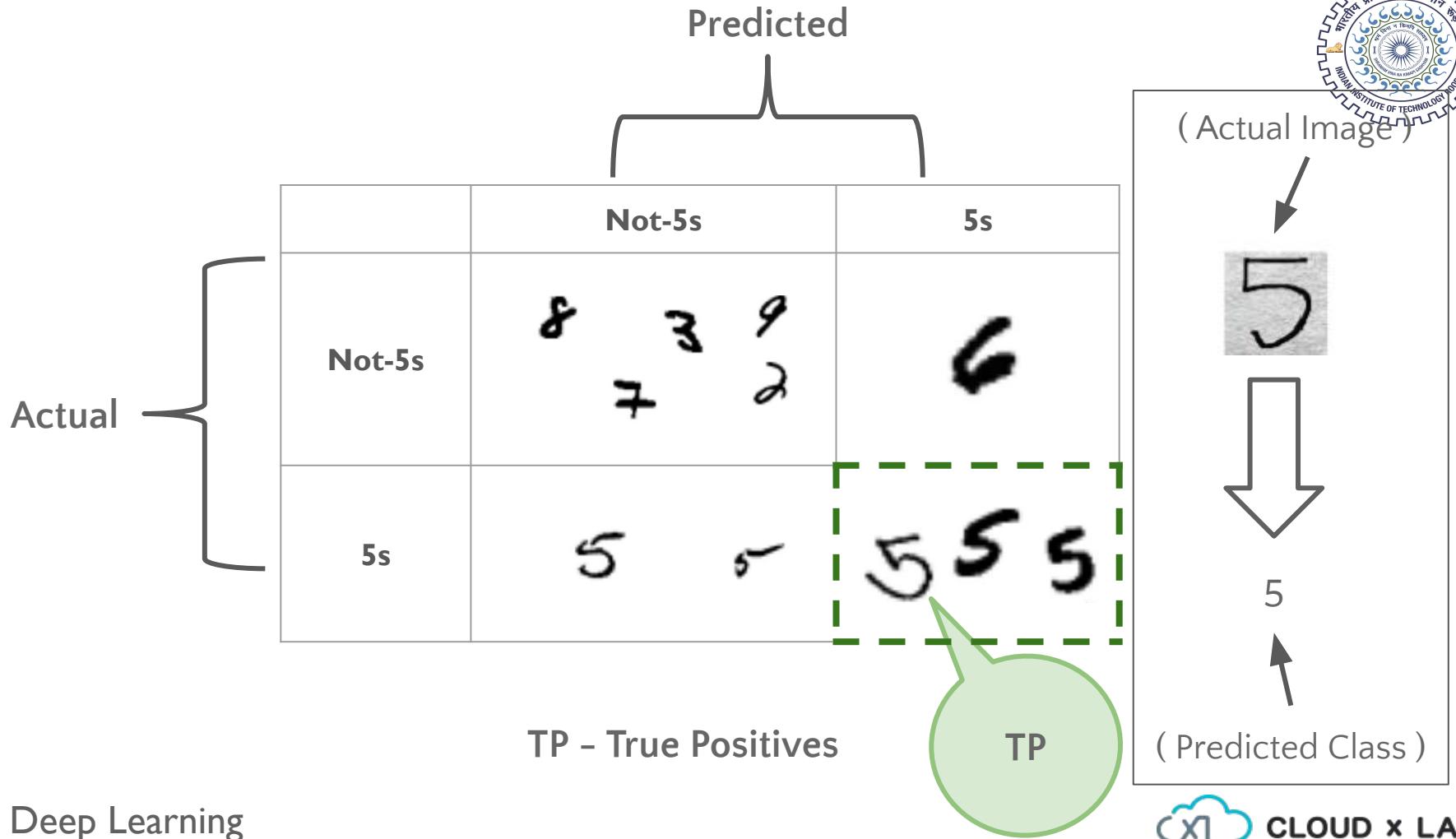


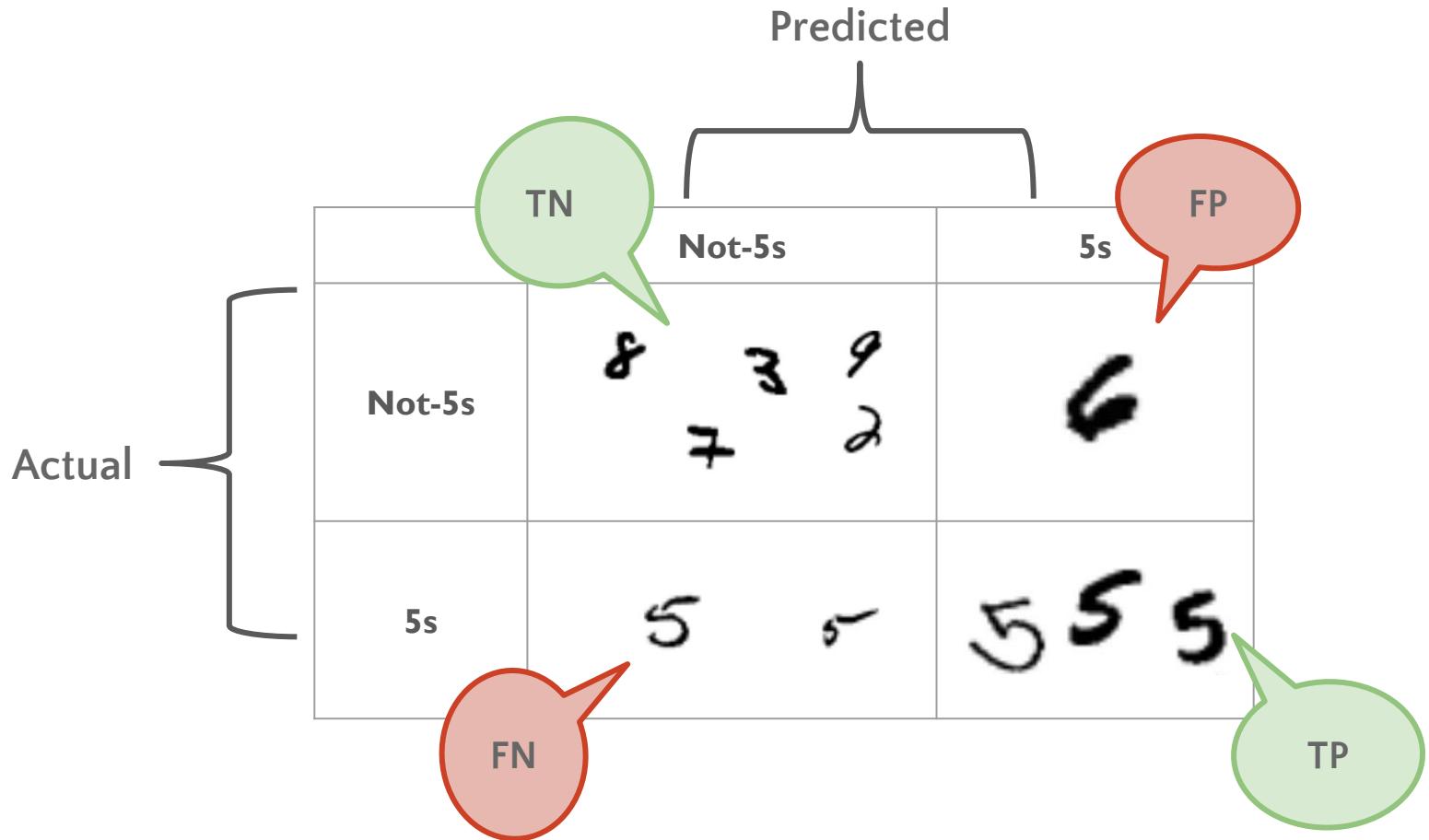




TP - True Positives

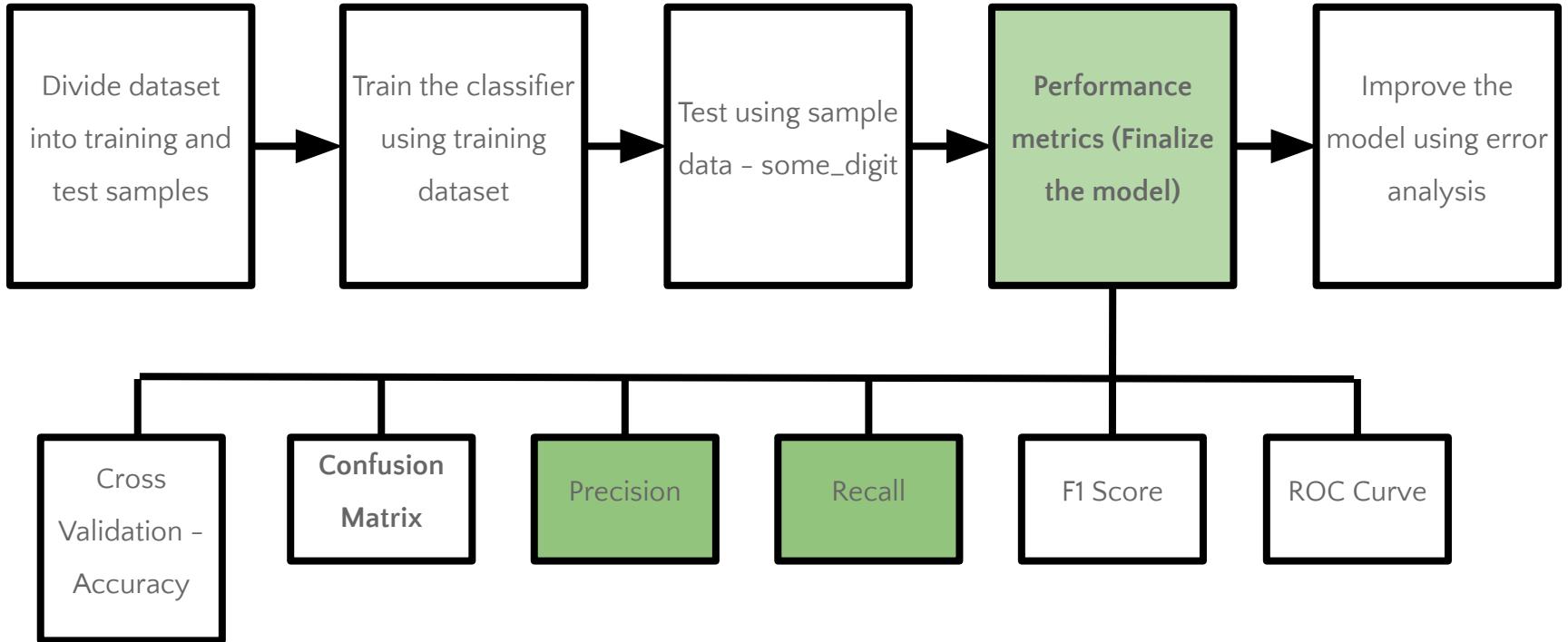








# Steps





# Pause for Questions



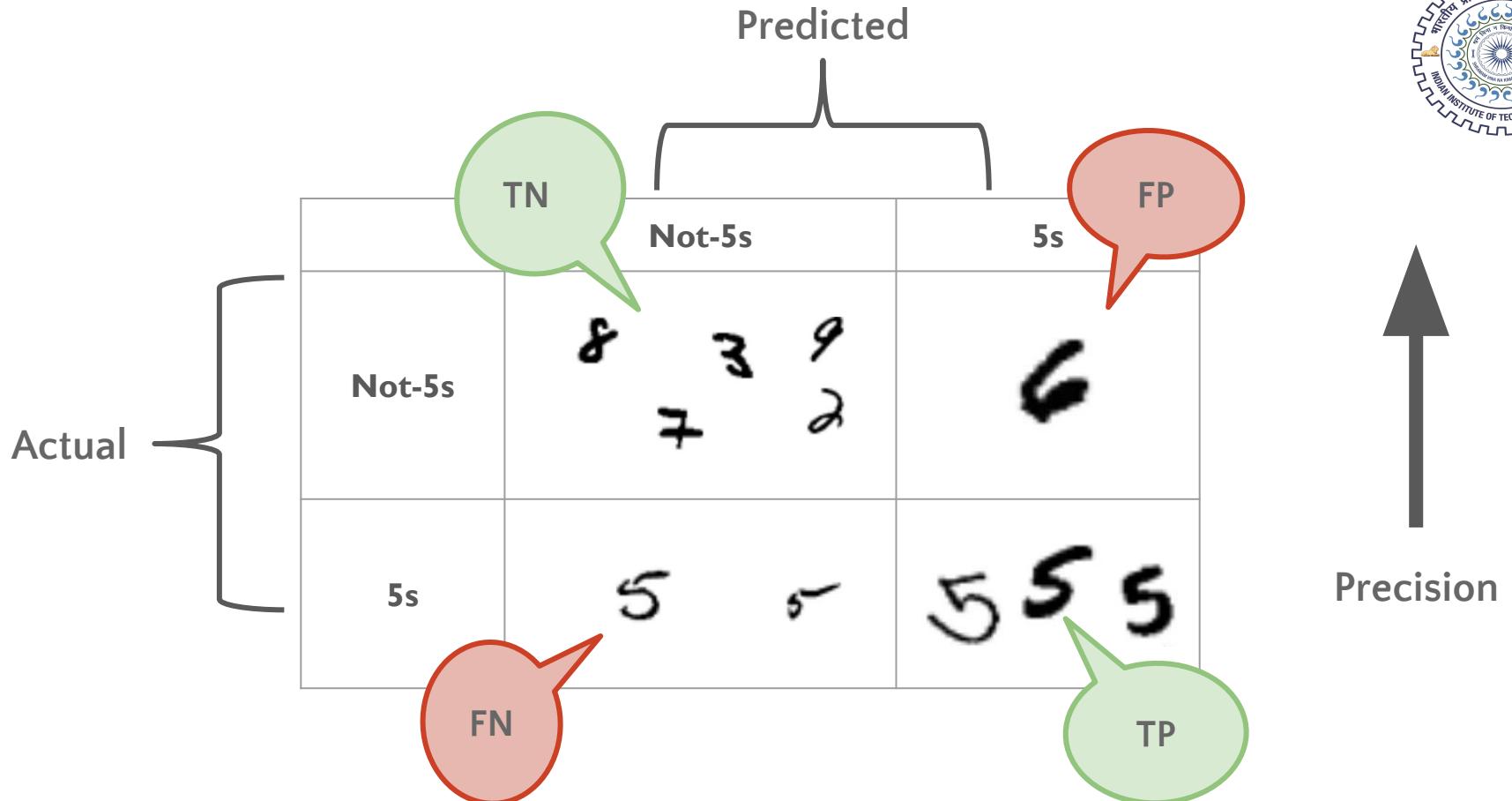
# Precision and Recall



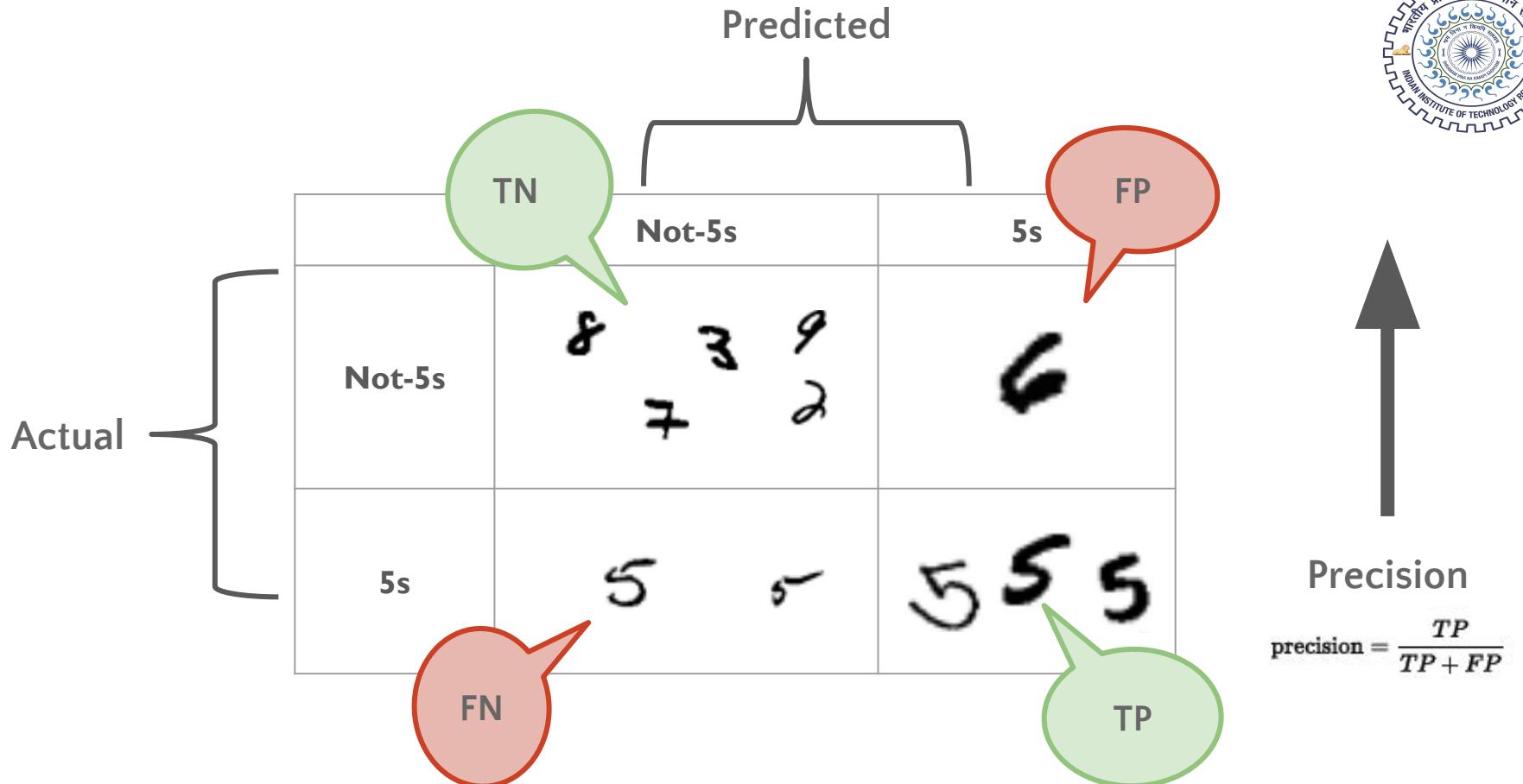
# Performance Measures - Precision



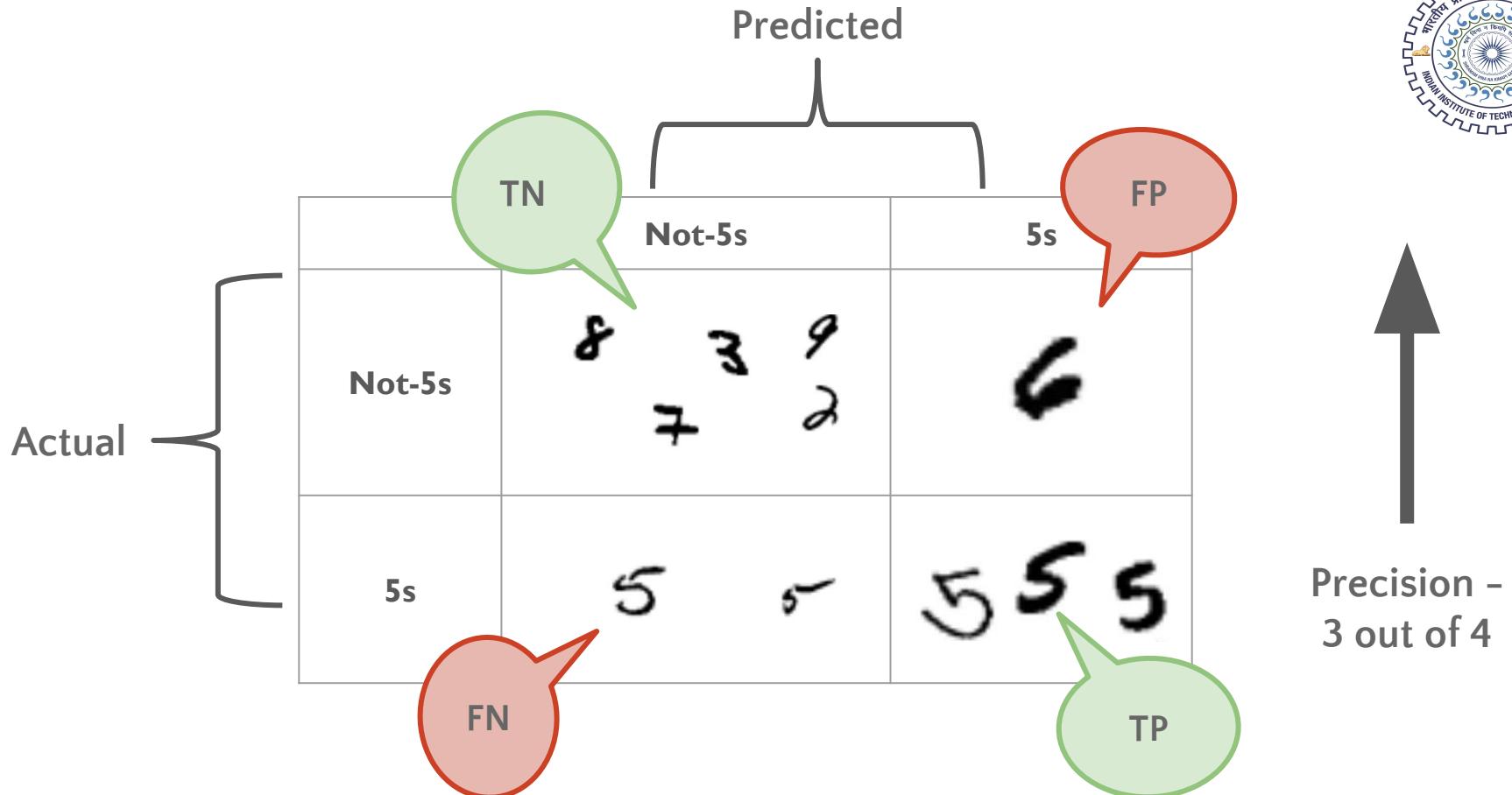
Precision means lack of mistakes



what proportion of images that were classified as 5s were actually 5



what proportion of images that were classified as 5s were actually 5



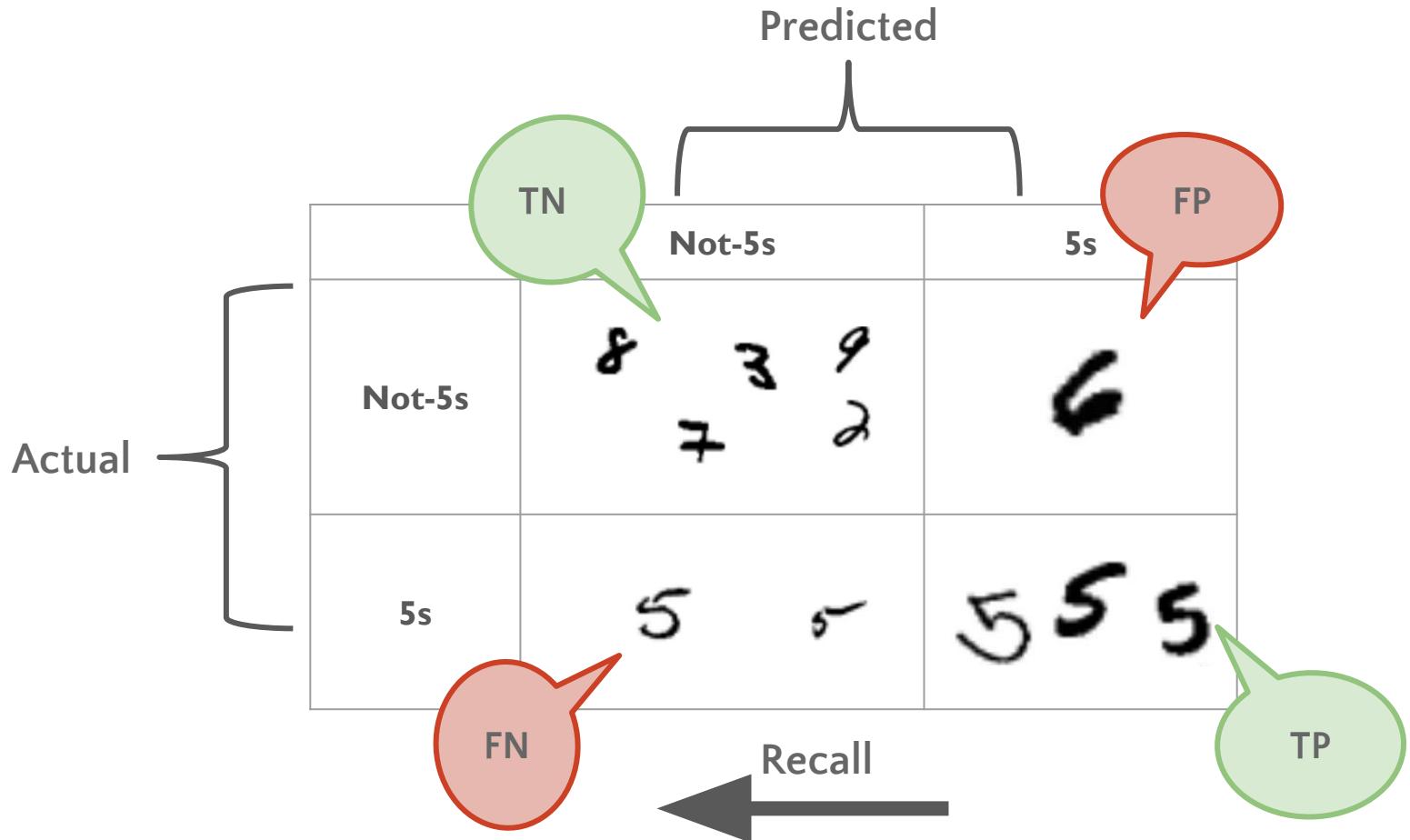
what proportion of images that were classified as 5s were actually 5



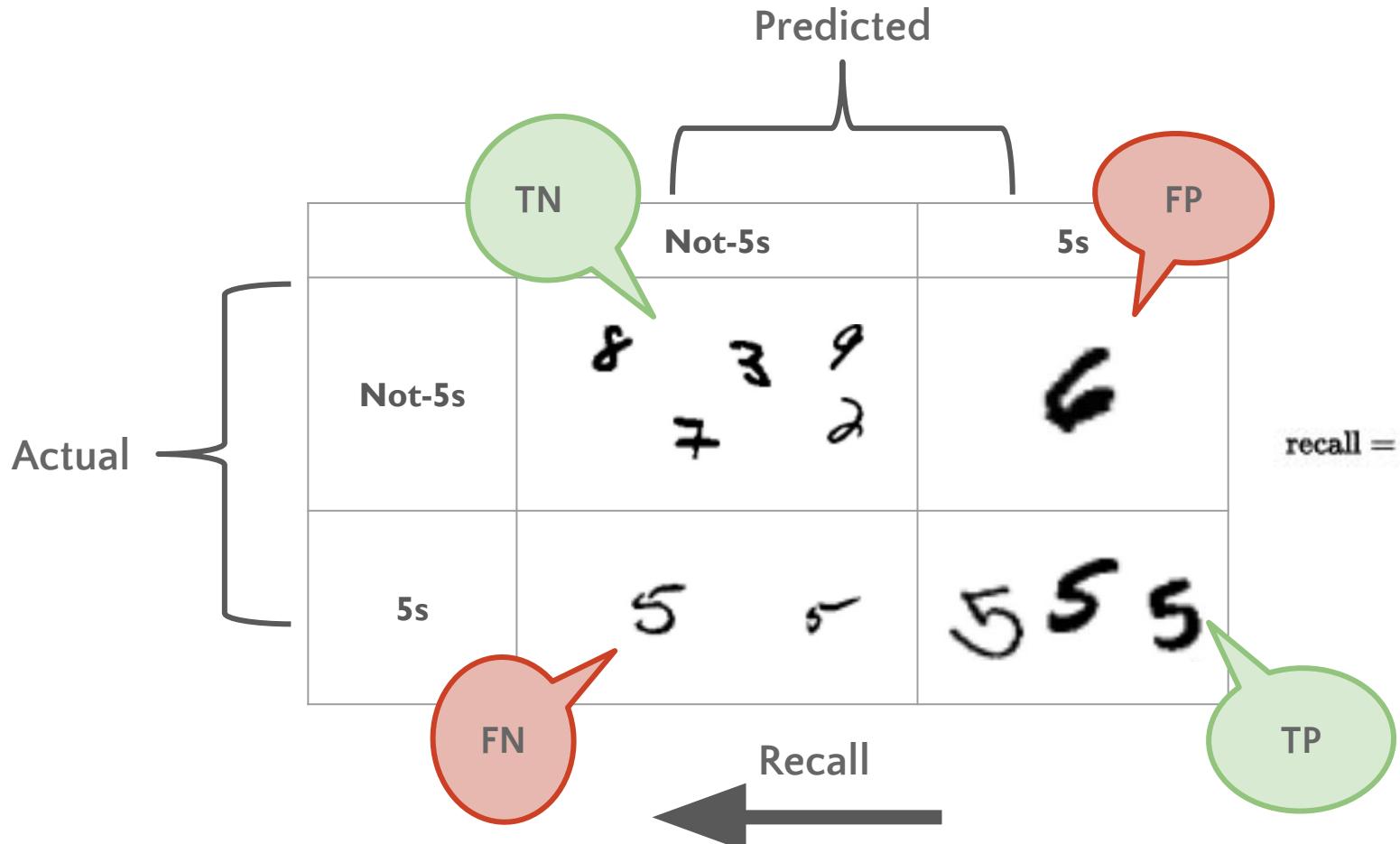
# Performance Measures - Recall



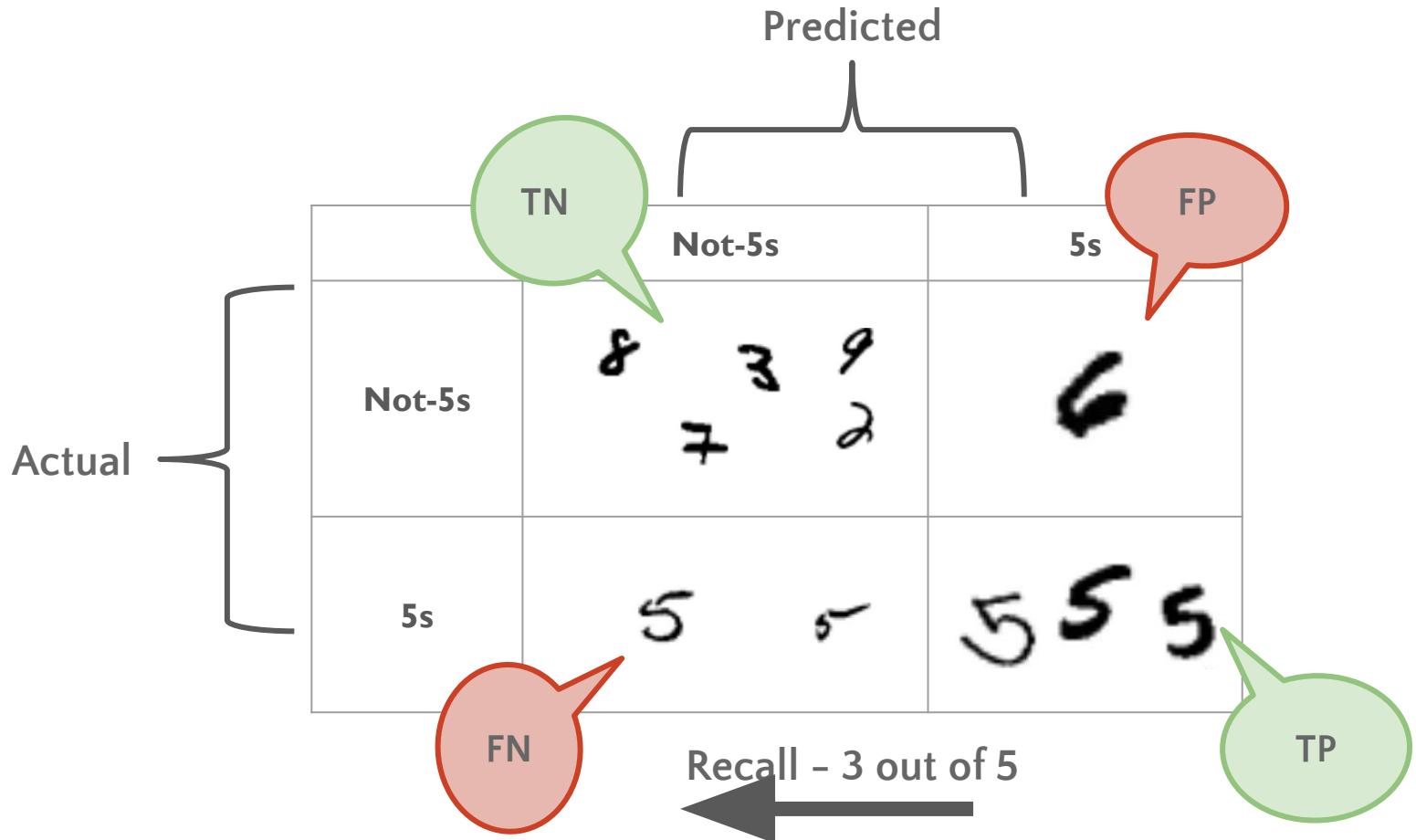
Recall means remember something learnt in past



what proportion of images that were actually 5 were predicted as class 5



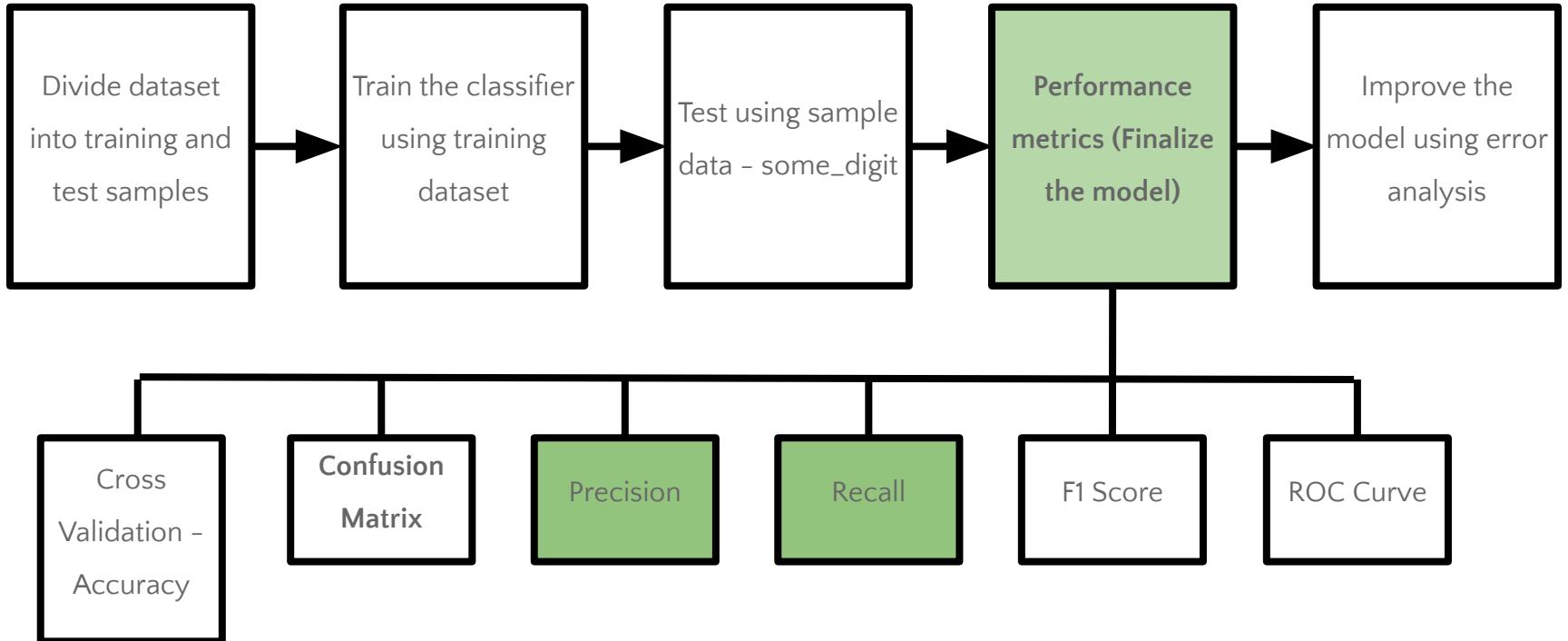
what proportion of images that were actually 5 were predicted as class 5



what proportion of images that were actually 5 were predicted as class 5



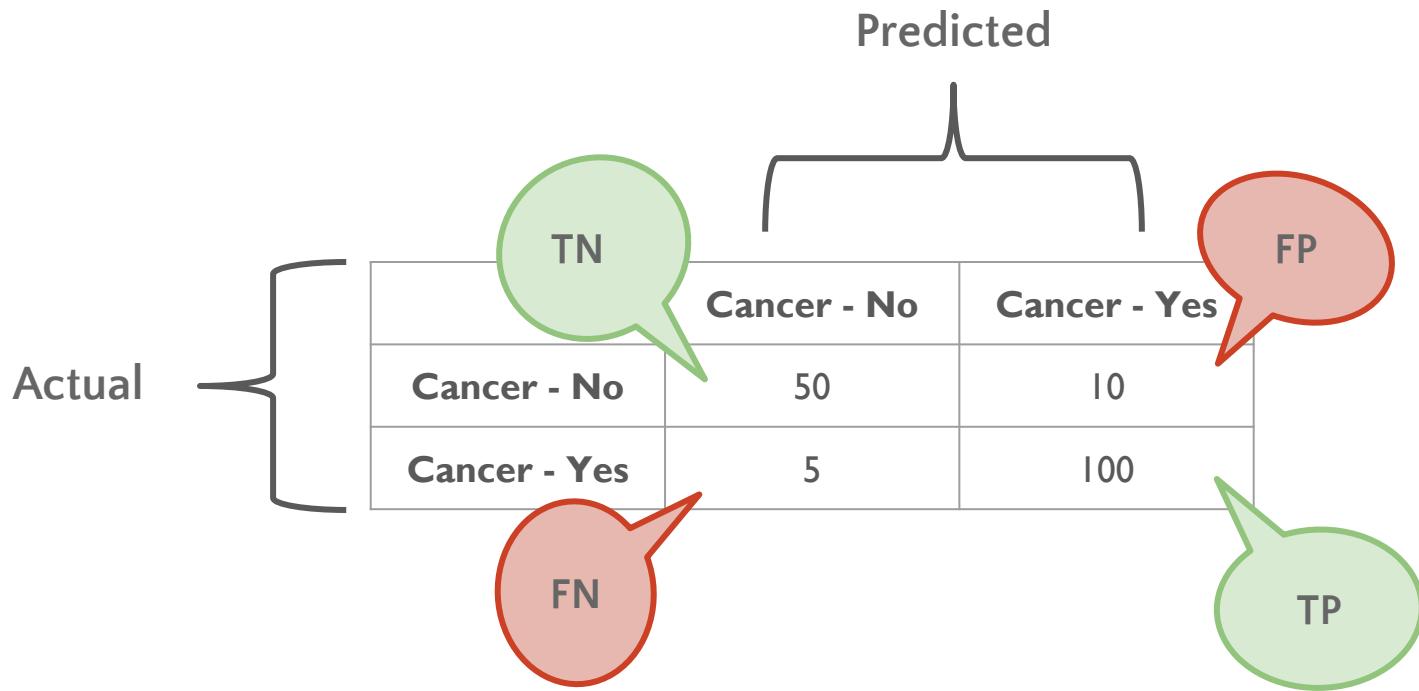
# Steps





Let's see one more example of confusion matrix of model predicting if someone has cancer or not

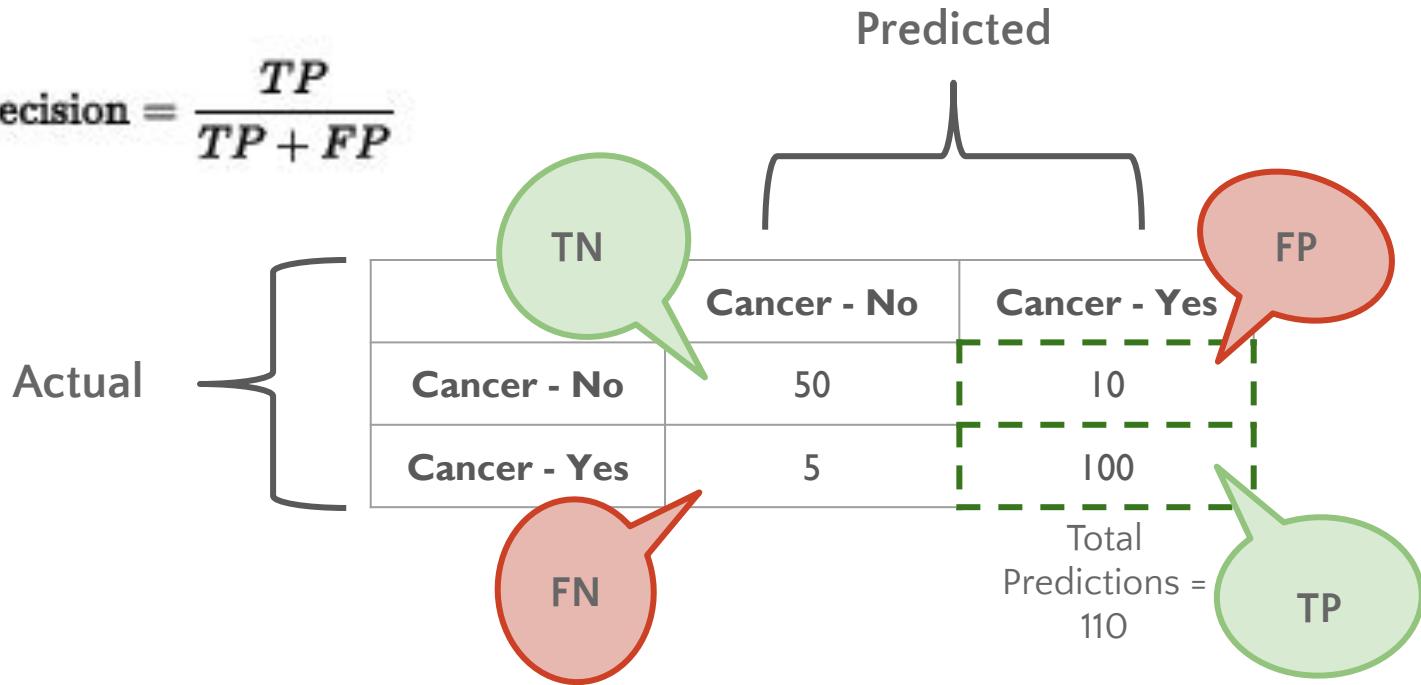
# Performance Measures - Confusion Matrix



What is Precision?

# Performance Measures - Confusion Matrix

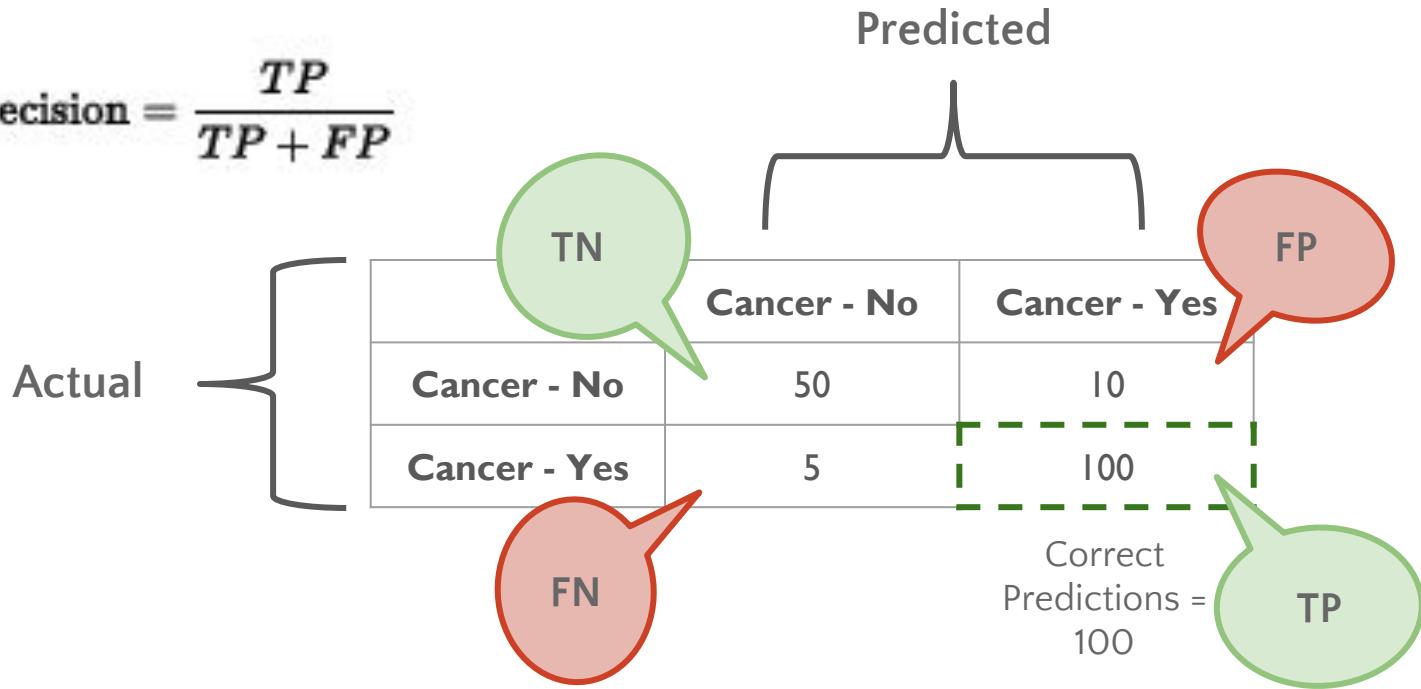
$$\text{precision} = \frac{TP}{TP + FP}$$



What is Precision?

# Performance Measures - Confusion Matrix

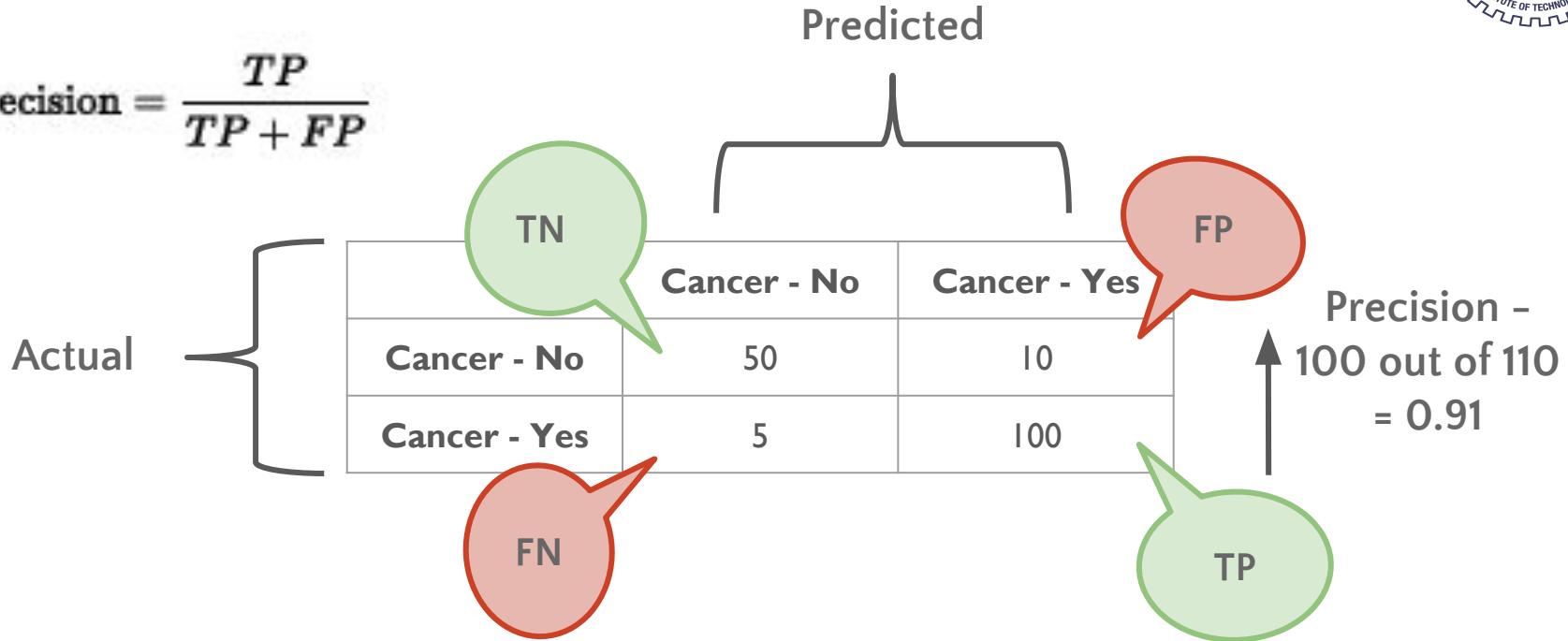
$$\text{precision} = \frac{TP}{TP + FP}$$



## What is Precision?

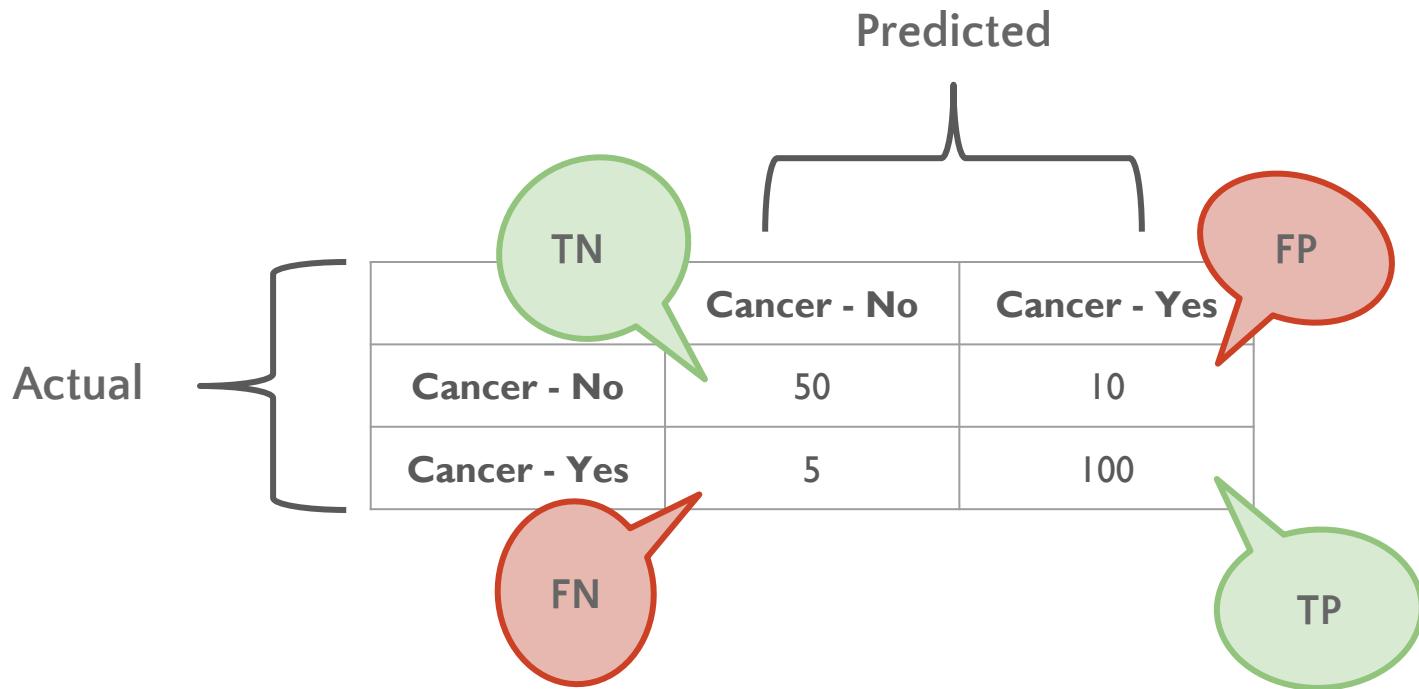
# Performance Measures - Confusion Matrix

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



What is Precision?

# Performance Measures - Confusion Matrix



What is Recall?

# Performance Measures - Confusion Matrix

Predicted

$$\text{recall} = \frac{TP}{TP + FN}$$

Actual

		Predicted	
		Cancer - No	Cancer - Yes
Actual	Cancer - No	50	10
	Cancer - Yes	5	100

Total Patients Having Cancer = 105

FN

TP

## What is Recall?



# Performance Measures - Confusion Matrix

Predicted

$$\text{recall} = \frac{TP}{TP + FN}$$

Actual

		Predicted	
		Cancer - No	Cancer - Yes
Actual	Cancer - No	50	10
	Cancer - Yes	5	100

FN

TN

FP

TP

Model's Predictions as  
Having Cancer = 100

## What is Recall?

# Performance Measures - Confusion Matrix

$$\text{recall} = \frac{TP}{TP + FN}$$

Actual

		Predicted	
		Cancer - No	Cancer - Yes
Actual	Cancer - No	50	10
	Cancer - Yes	5	100

FN

TP

Recall - 100 out of 105  
= 0.95

What is Recall?



# Performance Measures - Confusion Matrix

```
# Get the predicted values
```

```
>>> from sklearn.model_selection import cross_val_predict  
>>> y_train_pred = cross_val_predict(sgd_clf, X_train, y_train_5, cv=3)
```

```
# Confusion matrix of 5-detector
```

```
>>> from sklearn.metrics import confusion_matrix array([[53892,    687],  
>>> confusion_matrix(y_train_5, y_train_pred)           [ 1891,   3530]])
```

## Confusion Matrix of 5-detector



# Performance Measures - Confusion Matrix

```
# Get Precision Score of 5-detector
```

```
>>> from sklearn.metrics import precision_score, recall_score  
>>> precision_score(y_train_5, y_train_pred)
```

Precision Score of 5-detector



# Performance Measures - Confusion Matrix

```
# Get Recall Score of 5-detector  
  
>>> recall_score(y_train_5, y_train_pred)
```

**Recall Score of 5-detector**



# Performance Measures - Confusion Matrix

Precision = 83 %

Correct only  
83% of time

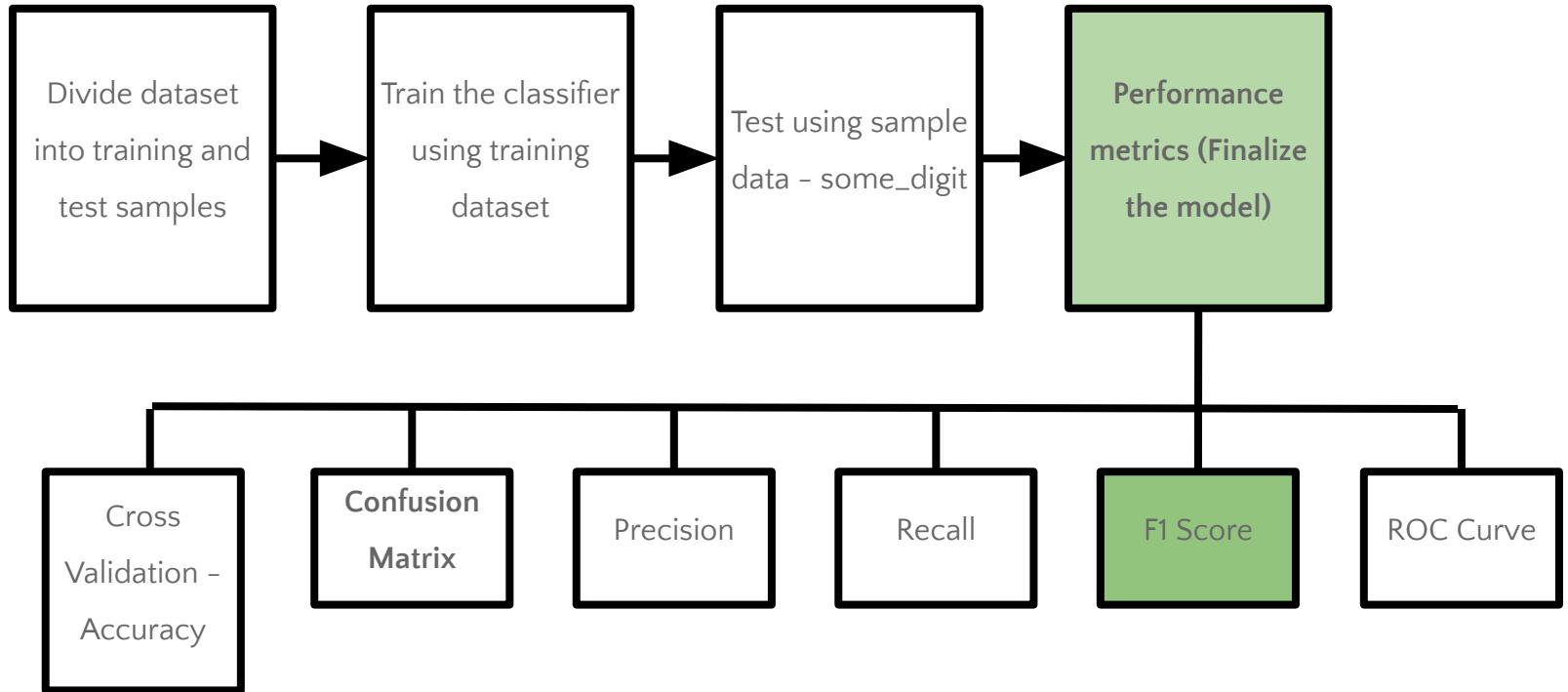
Recall = 65 %

Detects only  
65% of 5s

Precision / Recall Score of 5-detector



# Steps





# Performance Measures - F1 Score

- Instead of computing precision and recall every time
- We prefer a single metric which combines both precision and recall
- This single metric is f1 score



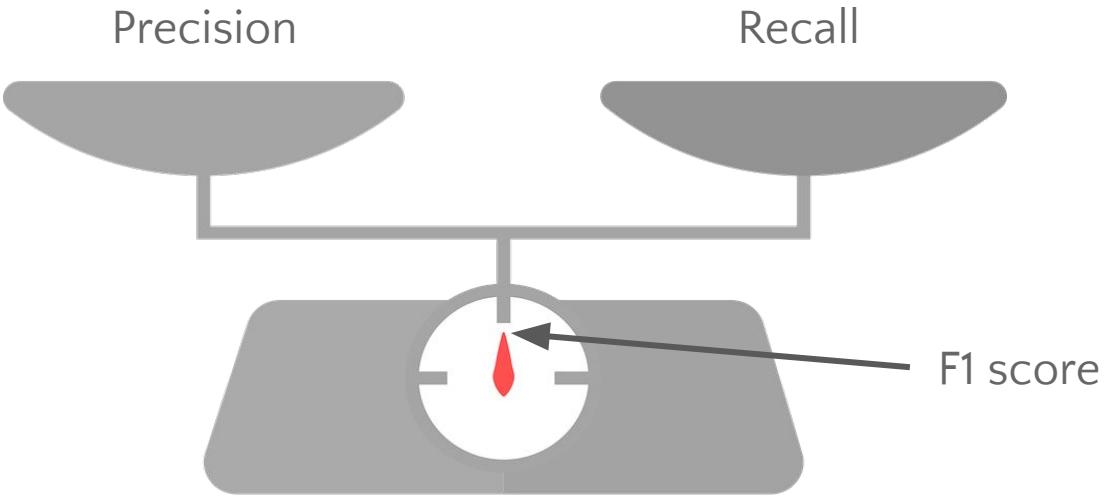
## Performance Measures - F1 Score

- F1 score is harmonic mean of precision and recall

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



# Performance Measures - F1 Score



F1 score is high when both **Precision** and **Recall** are almost similar



# Performance Measures - F1 Score

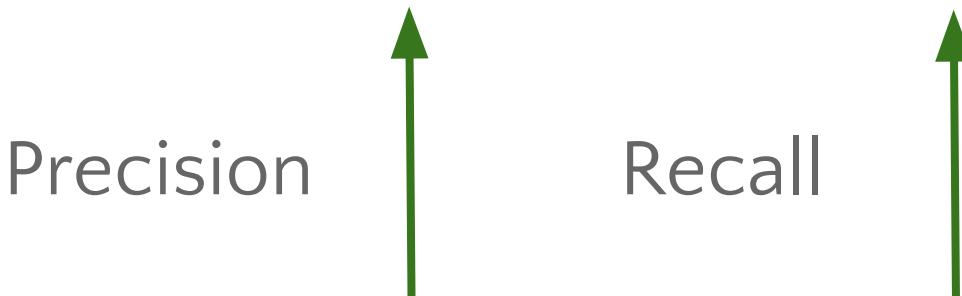
```
# Get f1 score of 5-detector  
  
>>> from sklearn.metrics import f1_score  
>>> f1_score(y_train_5, y_train_pred)
```

**F1 Score of 5-detector**



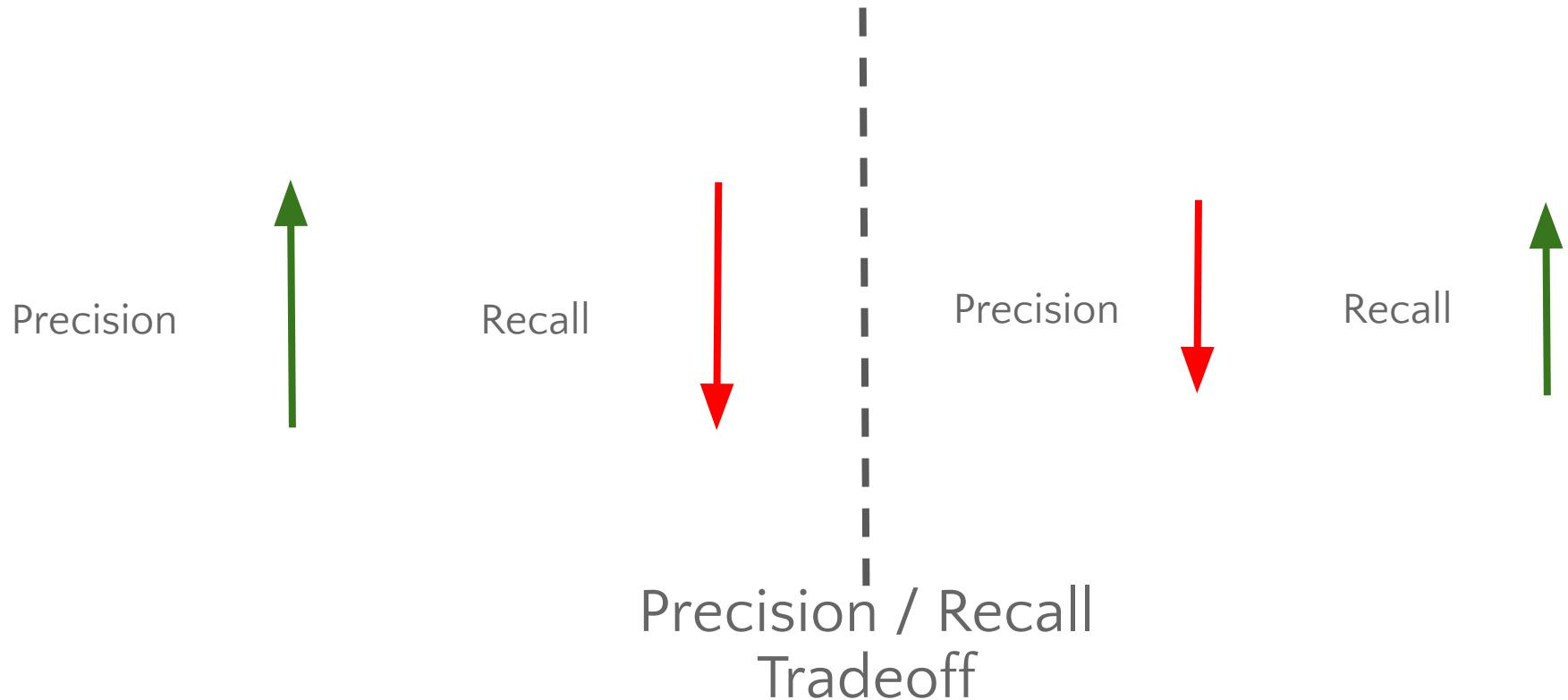
## Performance Measures - Precision / Recall Tradeoff

Now you may think that we can have both high precision and high recall in a model. But unfortunately, we can't have both high precision and high recall at the same time.





# Performance Measures - Precision / Recall Tradeoff





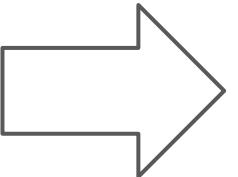
# Performance Measures - Precision / Recall Tradeoff

To understand this tradeoff, lets see how SGDClassifier works



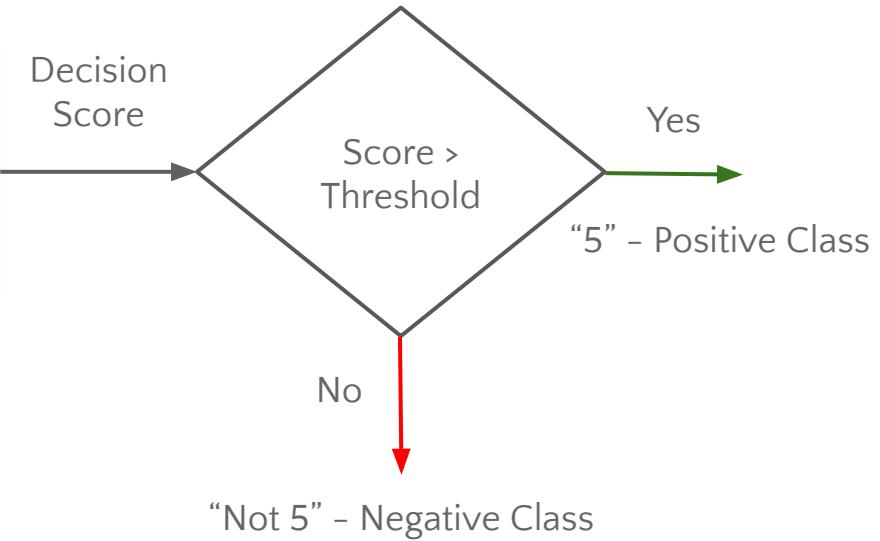
# Performance Measures - Precision / Recall Tradeoff

5



Training Set

model



Threshold - decided by the classification algorithm



# Precision / Recall Tradeoff - Thresholds

- Scikit enables the user to get the scores from the classifier

Calculating the decision function score for the SGDClassifier

```
>>> y_scores = sgd_clf.decision_function([some_digit])
>>> y_scores
array([2164.22030239])
```



# Precision / Recall Tradeoff

Increasing precision reduces recall and vice-versa

Raising the threshold, decreases recall

- For '5' and 'Not 5' classifier
  - For threshold = 0, classifier correctly classifies 5 as 5

```
>>> threshold = 0
>>> y_some_digit_pred = (y_scores > threshold)
>>> y_some_digit_pred
array([ True])
```

Run it on Notebook



# Precision / Recall Tradeoff

Increasing precision reduces recall and vice-versa

Raising the threshold, decreases recall

- For '5' and 'Not 5' classifier
  - For threshold = 0, classifier correctly classifies 5 as 5
  - For threshold = 8000, classifier incorrectly classifies digit 5 as not 5

```
# Setting the threshold to 8000
>>> threshold = 8000
>>> y_some_digit_pred = (y_scores > threshold)
>>> y_some_digit_pred
array([False])
```

Run it on Notebook

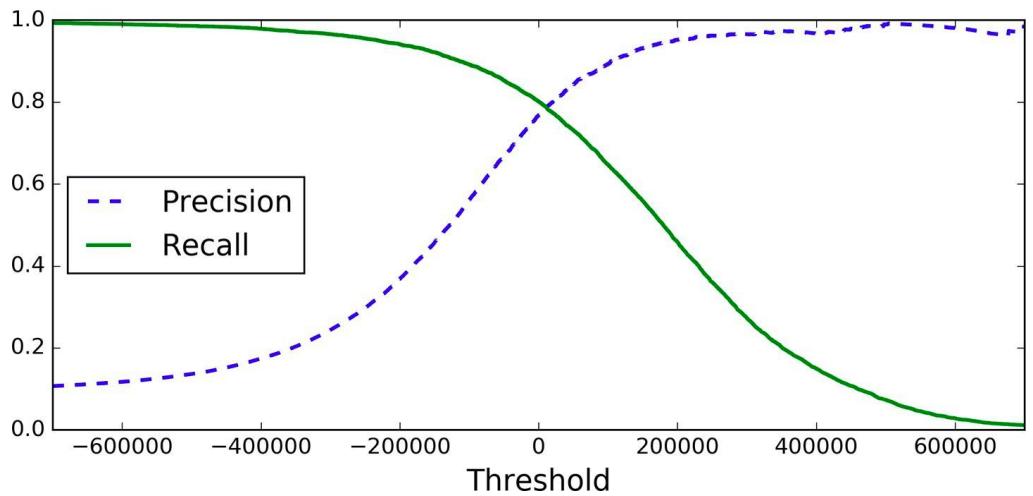


# Review of Precision/ Recall Tradeoff

- Hence, by selecting an appropriate threshold, the user can obtain the desired precision. However, the best precision may not have the best recall.



# Precision / Recall Curve

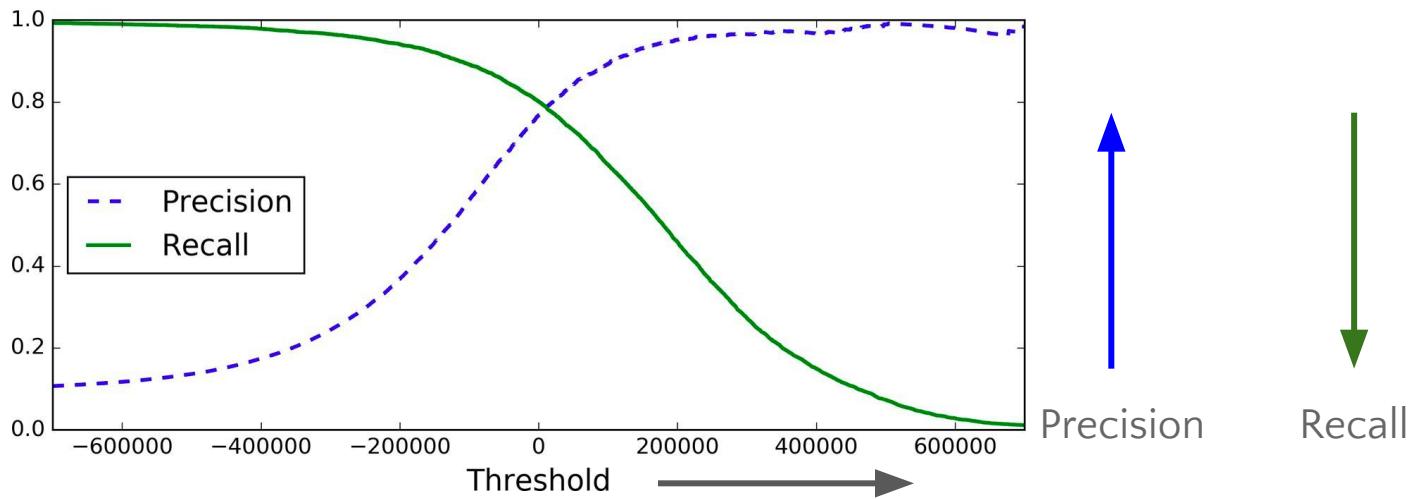


Precision and recall versus the decision threshold

Precision Recall Curve of 5-detector

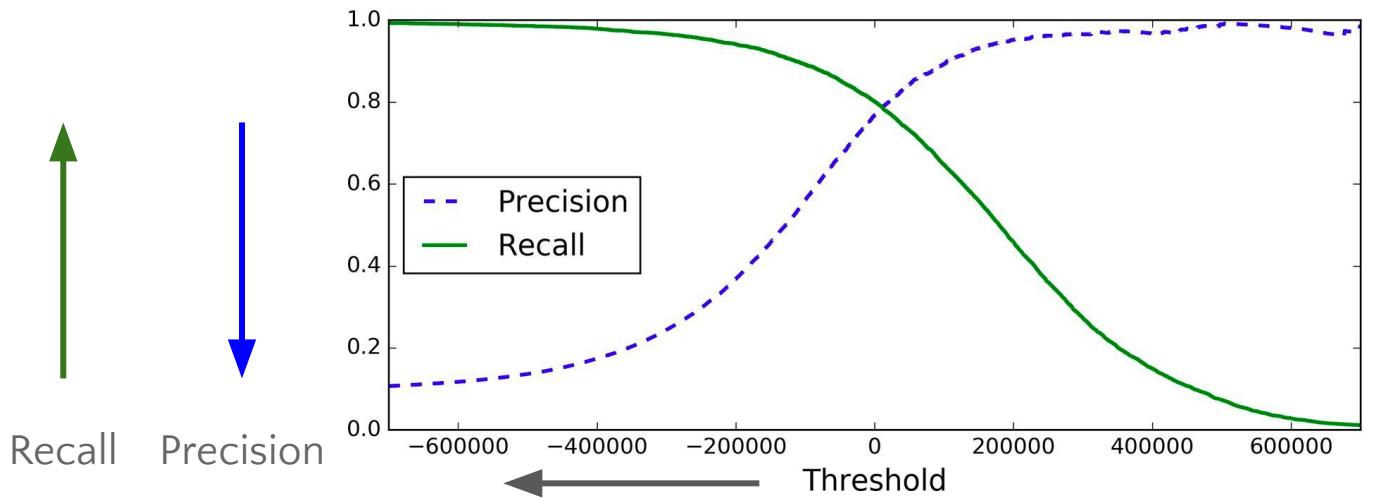


# Precision / Recall Curve



Precision and recall versus the decision threshold

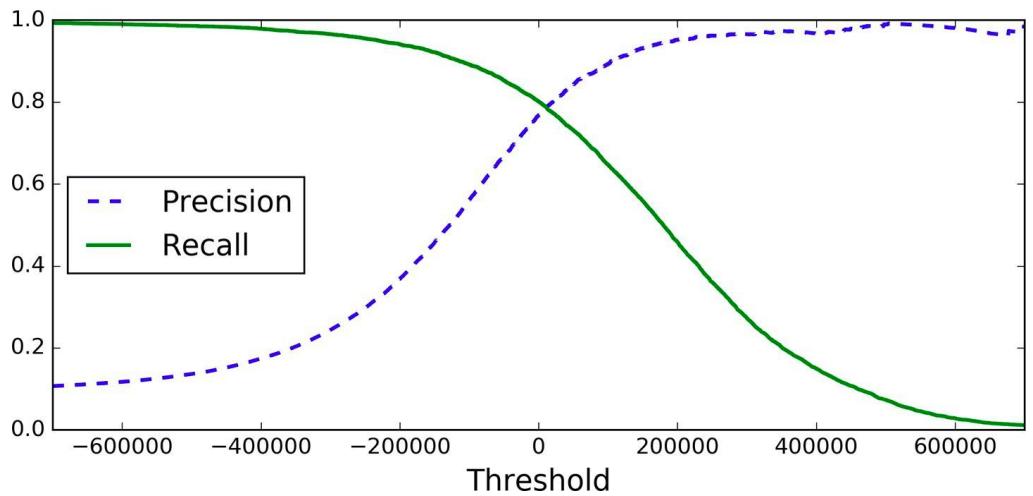
# Precision / Recall Curve



Precision and recall versus the decision threshold

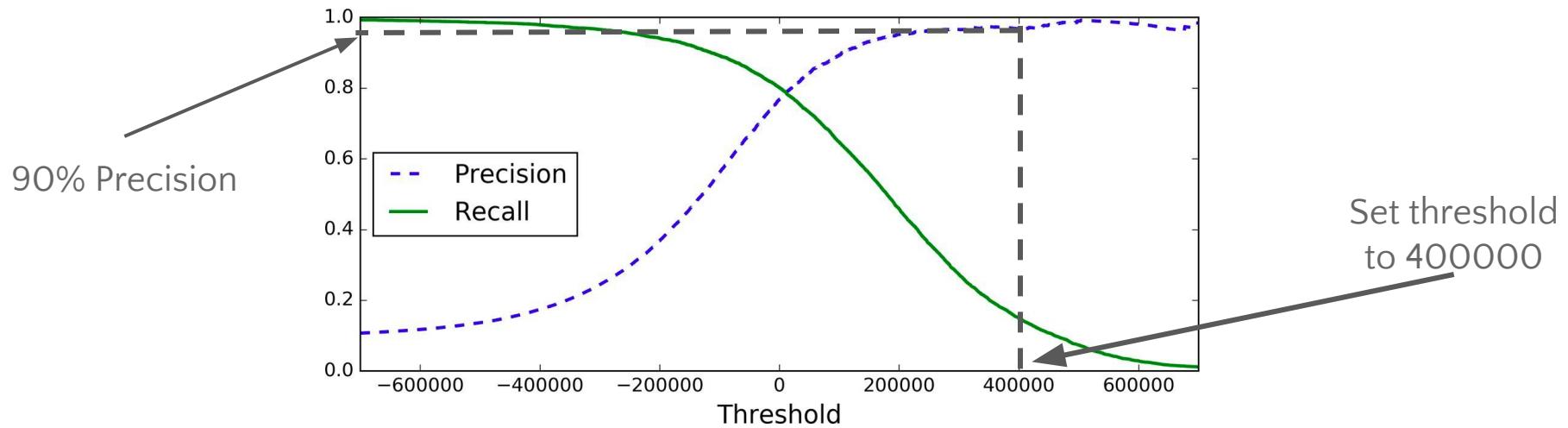


# Precision / Recall Curve



Which threshold value to use?

# Precision / Recall Curve





# Precision / Recall Curve Using Scikit-learn

## Plot Precision / Recall Curve

- Get the scores of all the training dataset using `cross_val_predict` with `decision_function` as function
- Compute the precision and recall for all possible thresholds using `precision_recall_curve()`
- Plot both precision and recall for the thresholds using `matplotlib`
- Select the threshold value that gives the best precision/ recall tradeoff to the task at hand.



# Precision / Recall Curve Using Scikit-learn

- Calculating precision/ recall curve using Scikit-Learn

```
>>> y_scores = cross_val_predict(sgd_clf, X_train, y_train_5, cv=3,
method="decision_function")
```

```
>>> from sklearn.metrics import precision_recall_curve
precisions, recalls, thresholds = precision_recall_curve(y_train_5,
y_scores)
```

Run it on Notebook



# Precision / Recall Curve Using Scikit-learn

- Plotting precision/ recall curve using Scikit-Learn

```
>>> def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision", linewidth=2)
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall", linewidth=2)
    plt.legend(loc="center right", fontsize=16)
    plt.xlabel("Threshold", fontsize=16)
    plt.grid(True)
    plt.axis([-50000, 50000, 0, 1])

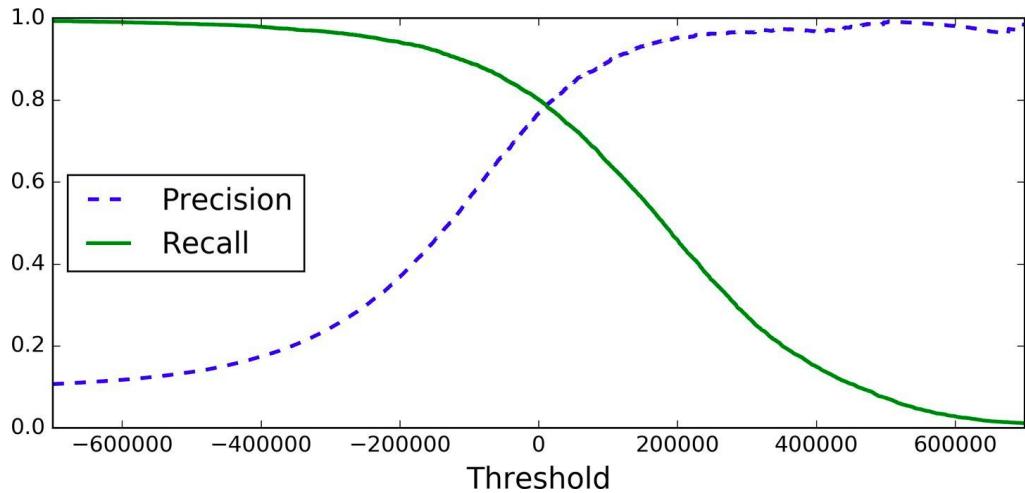
plt.figure(figsize=(8, 4))

>>> plot_precision_recall_vs_threshold(precisions, recalls, thresholds)
>>> plt.show()
```

Run it on Notebook

# Precision / Recall Curve

- Plotting precision/ recall curve using Scikit-Learn

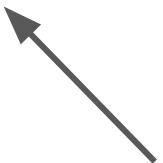




# Building model with desired precision

- So let's say you want to build a classifier with 90% precision
  - Then first select the threshold value which gives you 90% precision
  - Then build classifier using this threshold

```
>>> threshold_90_precision = thresholds[np.argmax(precisions >= 0.90)]  
>>> y_train_pred_90 = (y_scores >= threshold_90_precision)
```



This classifier will give 90%  
precision

Run it on Notebook



# Building model with desired precision

- Verify it

```
>>> precision_score(y_train_5, y_train_pred_90)  
0.9000380083618396
```

```
>>> recall_score(y_train_5, y_train_pred_90)  
0.4368197749492714
```

Run it on Notebook

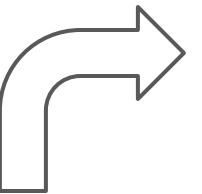


# Pause for Questions



Boss

AI & Deep Learning



I want a model with  
99% precision

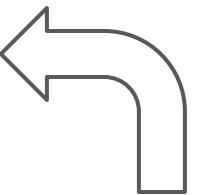


ML Engineer



Boss

AI & Deep Learning



At what recall? :)



ML Engineer



Say we have to build a model which detects if a video is safe for kids or not.

Question - High Precision or High Recall?



# High Precision or High Recall?

High precision means if the model classifies video 4 and video 6 as safe for kids, they are actually safe for kids.



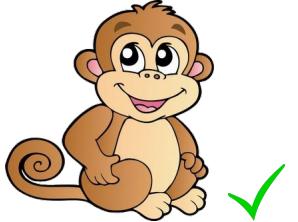
1 - Not Safe



2 - Safe



3 - Not Safe



4 - Safe



5 - Not Safe



6 - Safe

High Precision

# High Precision or High Recall?

In high precision, we are okay if the model is not able to classify video 2 as safe for kids but whichever videos it classifies as safe for kids they are actually safe.



1 - Not Safe



2 - Safe



3 - Not Safe



4 - Safe



5 - Not Safe



6 - Safe

High Precision



# High Precision or High Recall?

We would prefer a model which has high precision and low recall. It is okay if the model rejects many good videos but keeps only really safe ones



1 - Not Safe



2 - Safe



3 - Not Safe



4 - Safe



5 - Not Safe



6 - Safe

High Precision, Low Recall ✓



Say we have to build a model which detects shoplifters on the basis of surveillance image. In case, someone is marked as shoplifter, we manually examine.

Question – High Precision or High Recall?





# High Precision or High Recall?

We would prefer the model to have high recall even if the precision is low because our goal is to catch almost all the shoplifters.



High Recall

# High Precision or High Recall?

In the high recall, the security guard might catch and examine some non shoplifters also but we will achieve our goal of catching almost all the shoplifters.



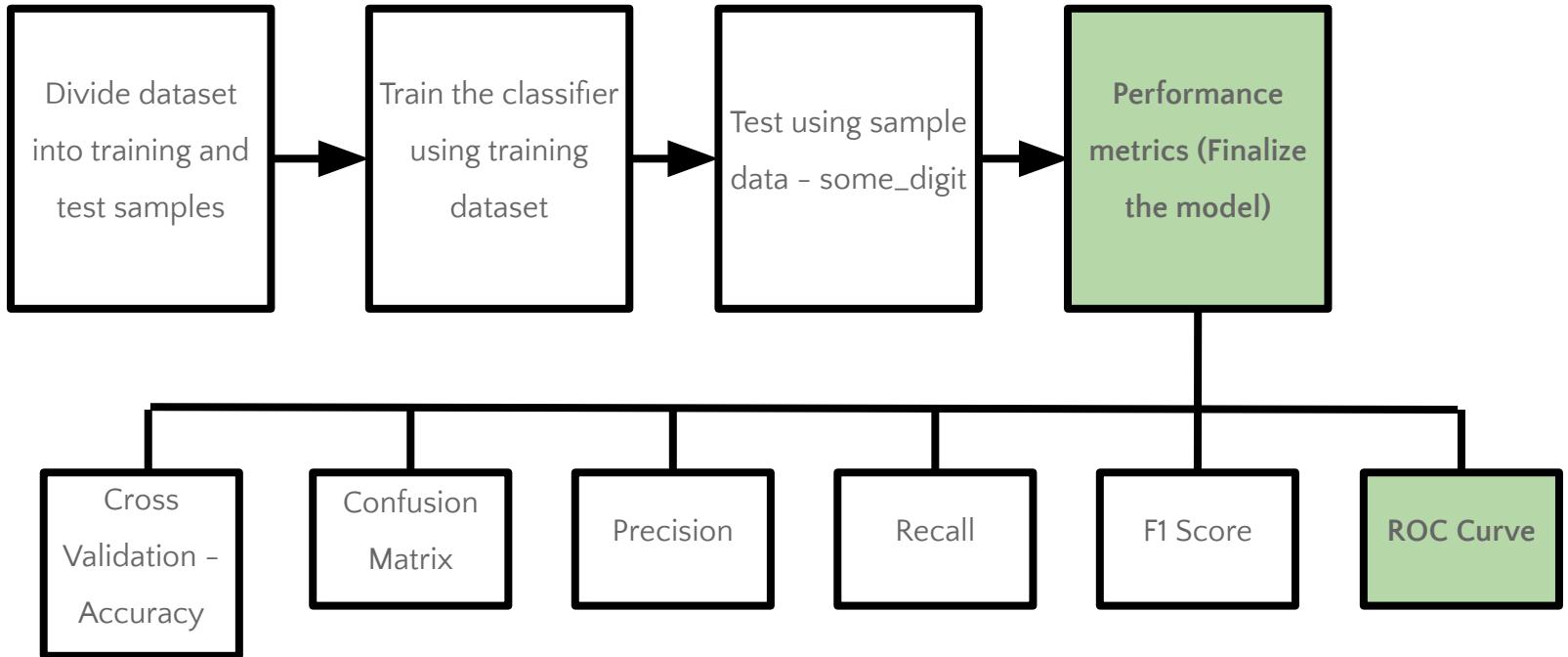
High Recall



# Pause for Questions



# Steps





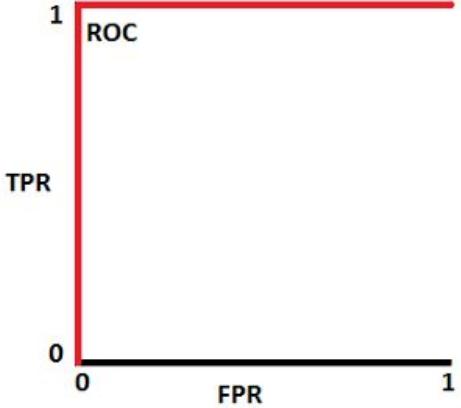
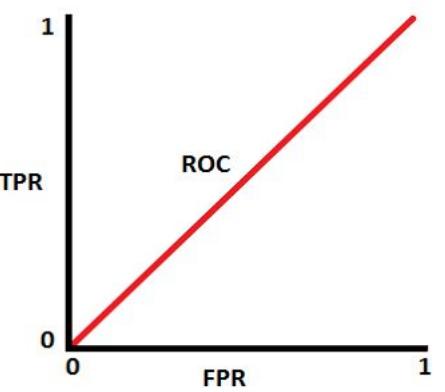
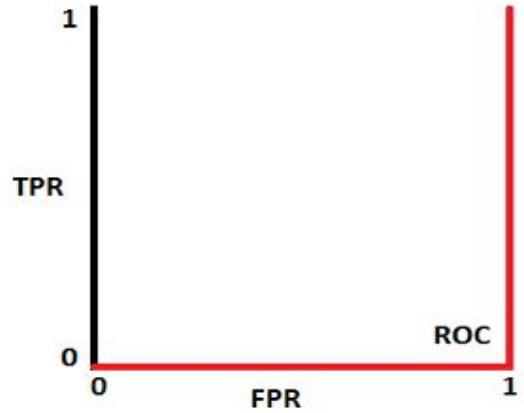
# The ROC (Receiver Operating Characteristic) Curve



# Performance Measures – ROC Curve

- Is helpful in comparing performances of different models
- Provides a tradeoff between true positives and false positives like precision/recall curve
- ROC is a probability curve and AUC represents degree or measure of separability.
- Let see ROC Curve of two different models
  - SGD Classifier
  - Random Forest Classifier
- Before that lets learn about “Area Under the Curve”

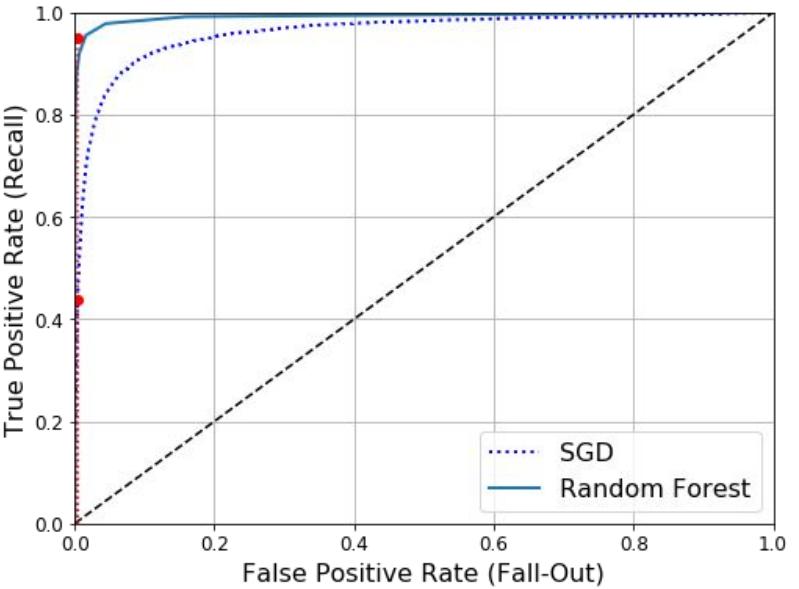
# Performance Measures – ROC Curve



- A model is reciprocating the classes is represented at the point (1,0), ROC travels from bottom left to bottom right and, then to the top right and has an AUC of 0.
- A model with no skill is represented at the point (0.5, 0.5), ROC travels by a diagonal line from the bottom left of the plot to the top right and has an AUC of 0.5.
- Perfect skill Model is represented at a point (0,1), ROC travels from bottom left to top left, then across the top to the top right and has an AUC of 1.

# Performance Measures – ROC Curve

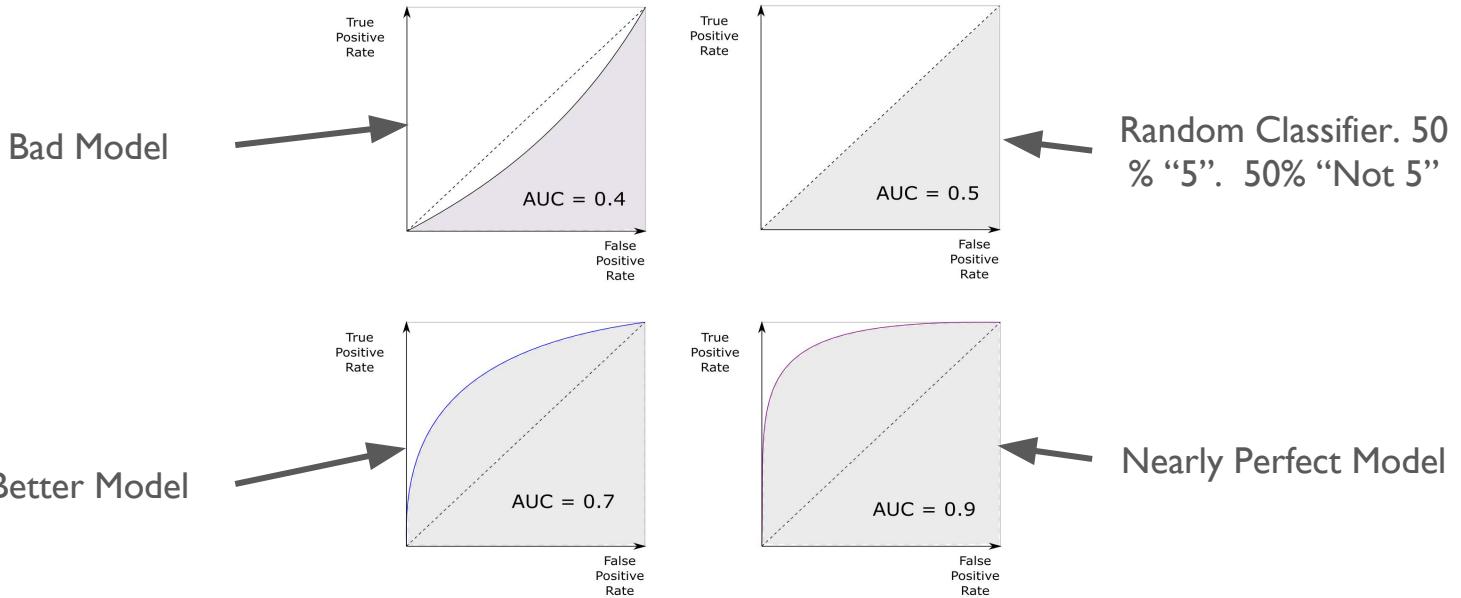
Area Under the Curve is higher for Random Forest, so its better model than SGD



ROC Curve of 5 Detector for SGD and Random Forest

# Performance Measures – ROC Curve

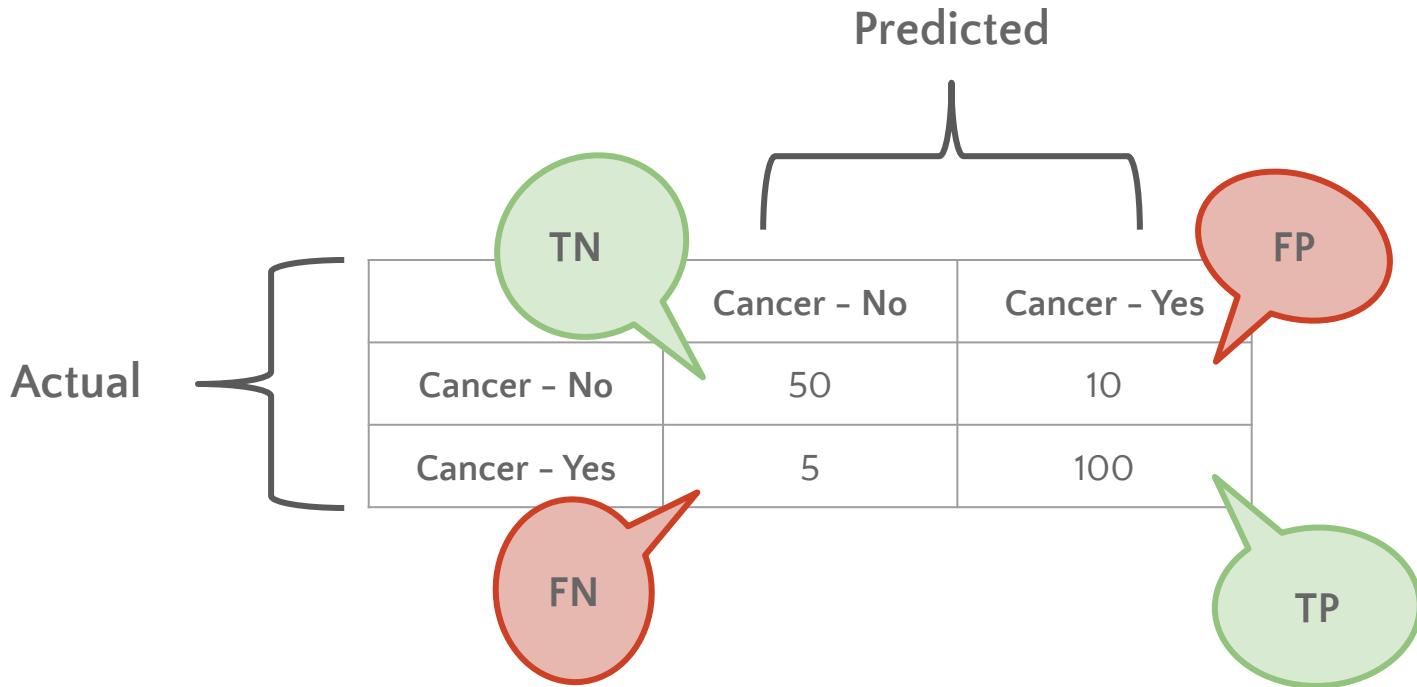
Higher the area under the curve, better the model is



AUC - Area Under the Curve

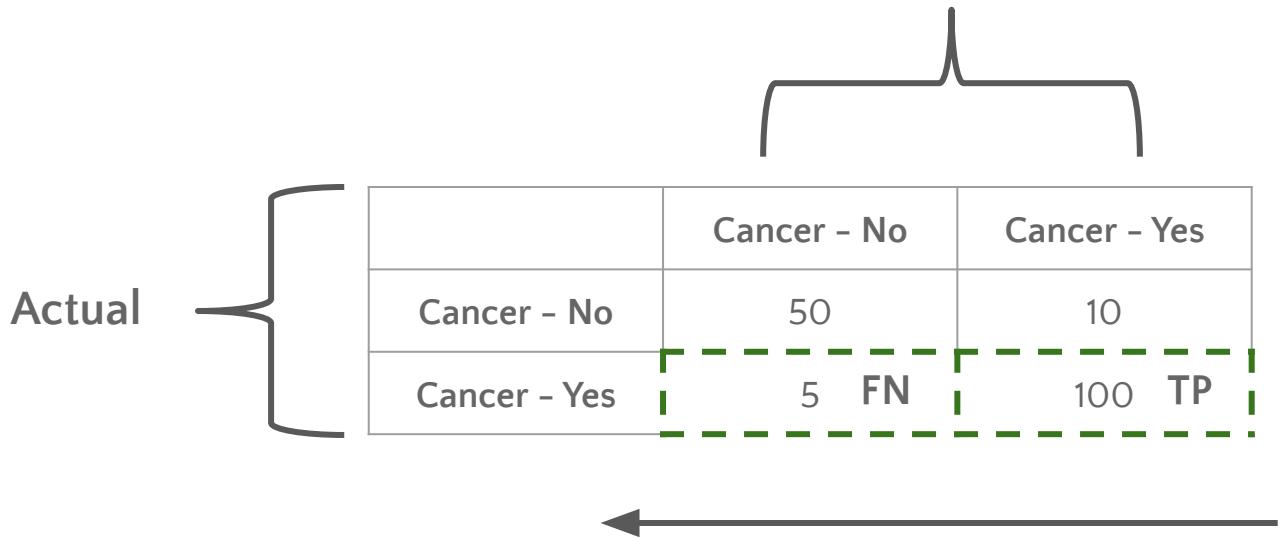


# Performance Measures – ROC Curve



# Performance Measures – ROC Curve

Predicted

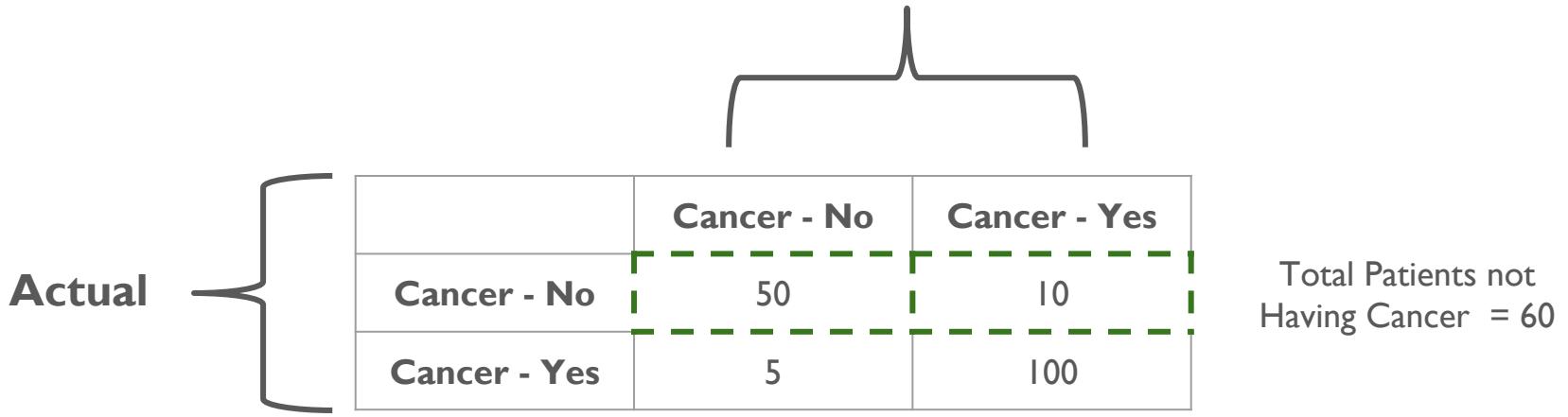


Recall or True Positive Rate = 100 out of 105 = 0.95



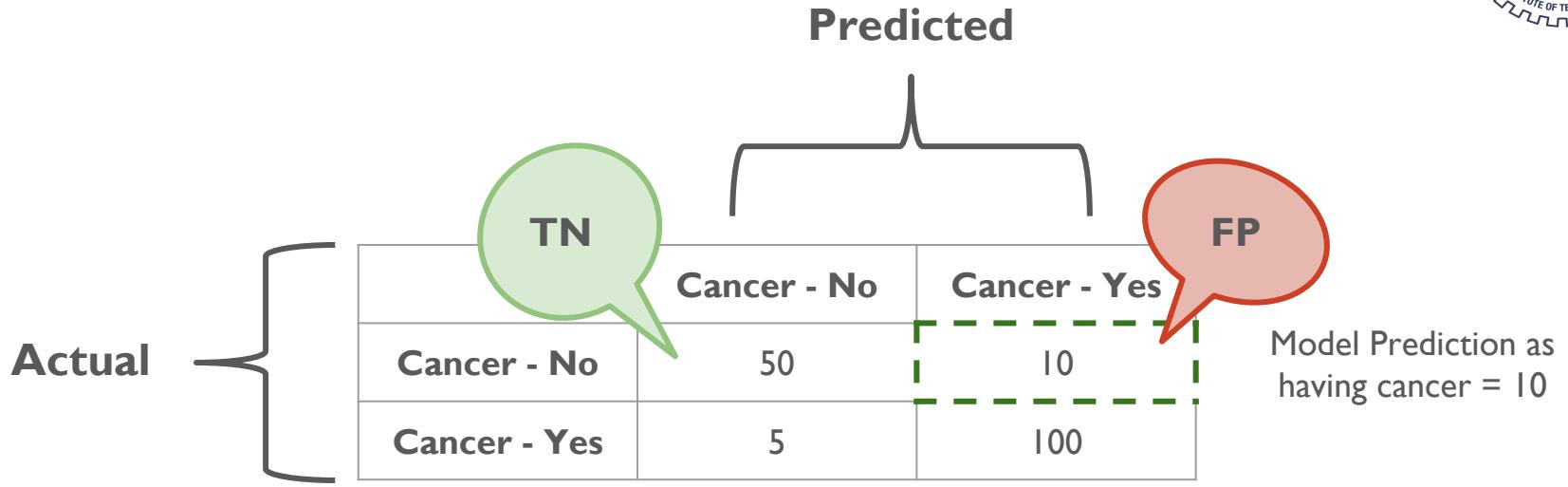
# Performance Measures – ROC Curve

Predicted



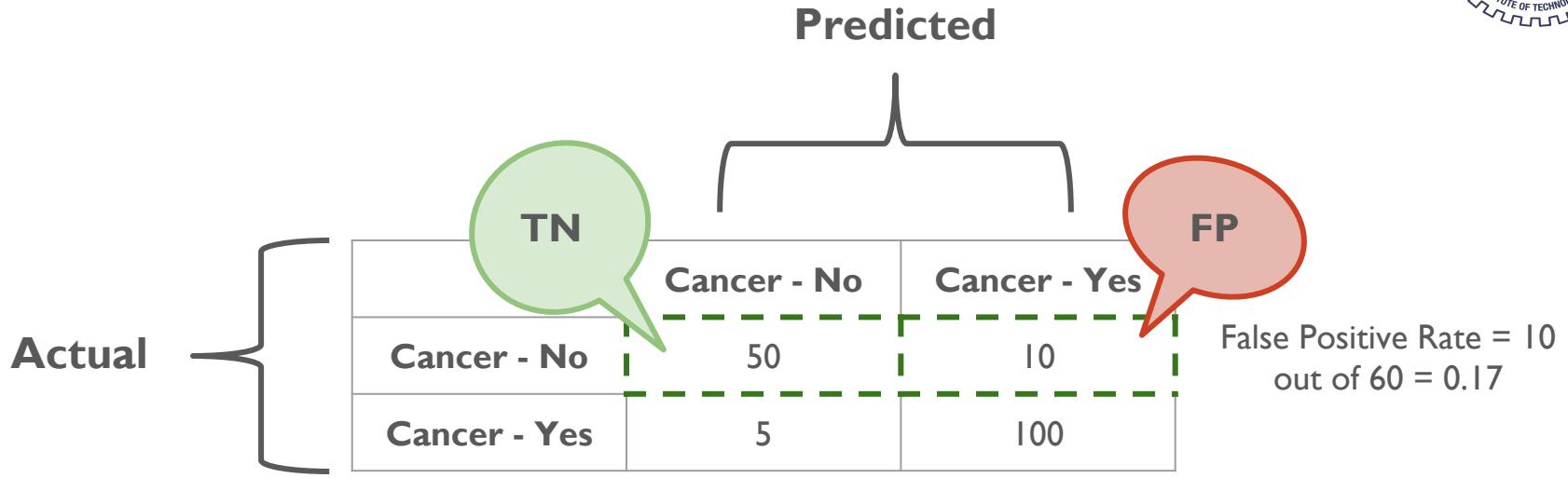
False Positive Rate tells us what proportion of patients that actually were not having cancer are classified as having cancer by the model.

# Performance Measures - ROC Curve

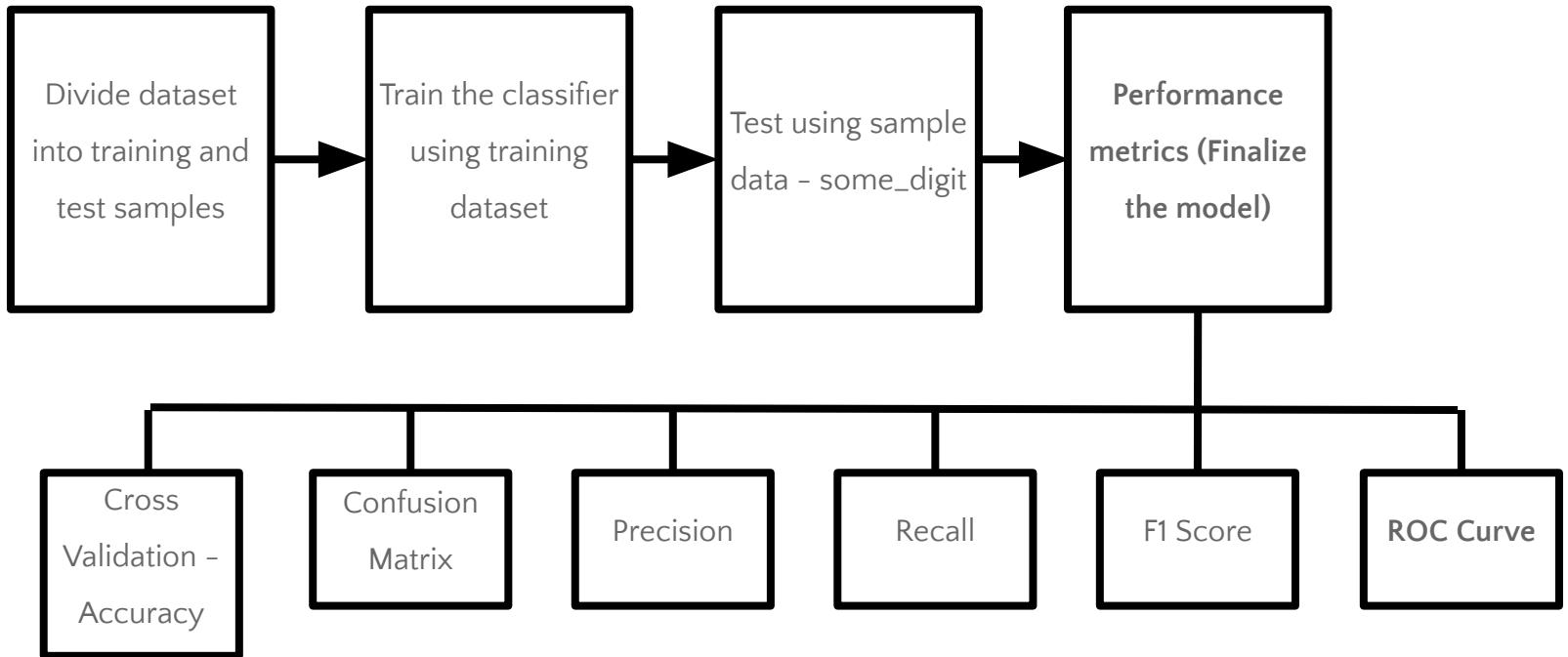


False Positive Rate tells us what proportion of patients that actually were not having cancer are classified as having cancer by the model.

# Performance Measures - ROC Curve



False Positive Rate tells us what proportion of patients that actually were not having cancer are classified as having cancer by the model.





# Multiclass Classification

So far we have discussed 5-detector. Let's come back to the original problem



# Multiclass Classification

Classify Handwritten Digits – Which is a MultiClass Problem

7 → 7    5 → 5

8 → 8    3 → 3

2 → 2    4 → 4



# Multiclass Classification

## Multiclass Classifier Using SGDClassifier

```
>>> sgd_clf.fit(X_train, y_train)  
>>> sgd_clf.predict([some_digit])
```



# Multiclass Classification

## Check Accuracy Using Cross Validation

```
>>> cross_val_score(sgd_clf, X_train, y_train, cv=3,  
scoring="accuracy")
```



# Multiclass Classification

## Improving Accuracy by Scaling the Features

```
>>> from sklearn.preprocessing import StandardScaler  
>>> scaler = StandardScaler()  
>>> X_train_scaled = scaler.fit_transform(X_train.astype(np.float64))  
>>> cross_val_score(sgd_clf, X_train_scaled, y_train, cv=3,  
scoring="accuracy")
```



# What do we do next?

Completed:

- Binary Classification
- Multi-class Classification

Next:

- Multi-label Classification
- Multi-output Classification



# Multilabel Classification

Output multiple classes



## 4. **Raging Bull** (1980)

R | 129 min | Biography, Drama, Sport

★ 8.2 ⭐ Rate

89 Metascore

The life of boxer **Jake LaMotta**, as the violence and temper that leads him to the top in the ring destroys his life outside of it.

Director: **Martin Scorsese** | Stars: **Robert De Niro, Cathy Moriarty, Joe Pesci, Frank Vincent**

Votes: 281,713 | Gross: \$23.38M



Multiple  
Classes

BioGraphy	1
Drama	1
Sport	1
Sci-fi	0

Categories in which model  
is trained



# Multilabel Classification

Output multiple classes



Multiple  
Classes

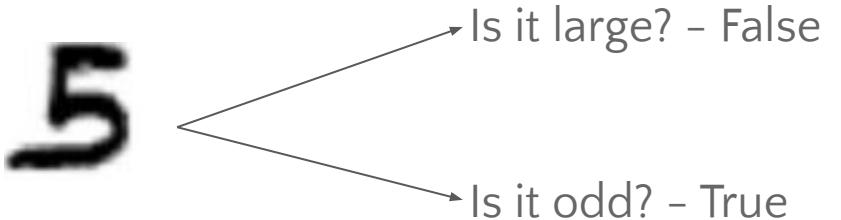
BioGraphy	0
Drama	1
Sport	0
Sci-fi	0

Categories in which model  
is trained



# Multilabel Classification

- Build a model to classify an image into two classes
  - Greater than or equal to 7
  - Is Odd

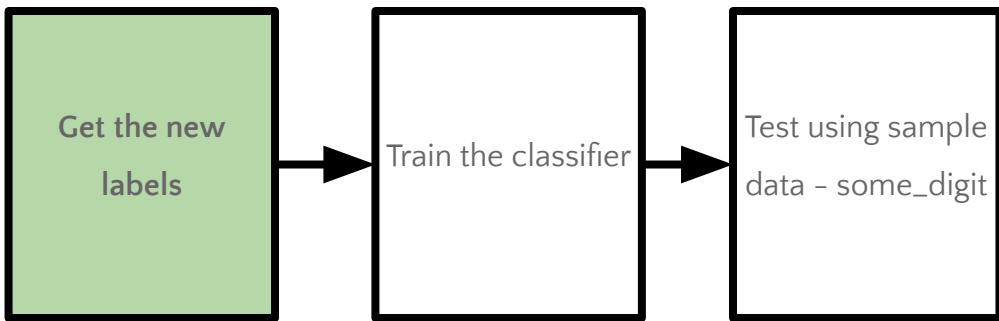


Classifier's output will be - [False, True]



# Multilabel Classification – Example

- Classification of image into whether [large, odd], how do we do it?





# Multilabel Classification – Example

- Step 1: Get the new labels

```
>>> y_train_large = (y_train >= 7)
>>> y_train_odd = (y_train % 2 == 1)
>>> y_multilabel = np.c_[y_train_large, y_train_odd]

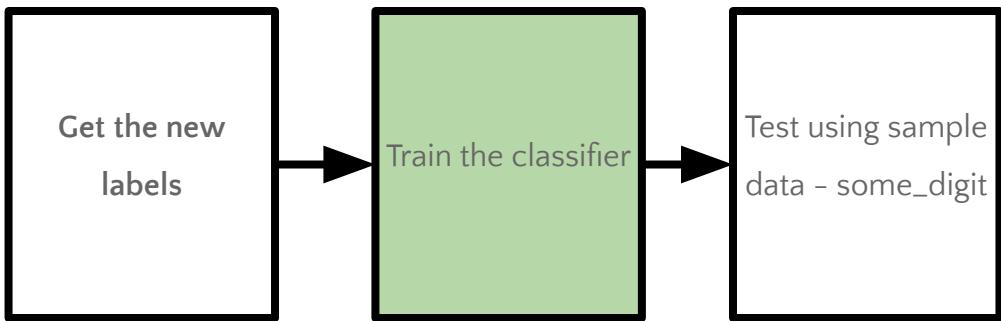
# np.c_ is used to concatenate the two arrays element wise
```

Run it on Notebook



# Multilabel Classification

- Step 2: Train the model
  - KNeighbors Classifier supports multi-label, classification



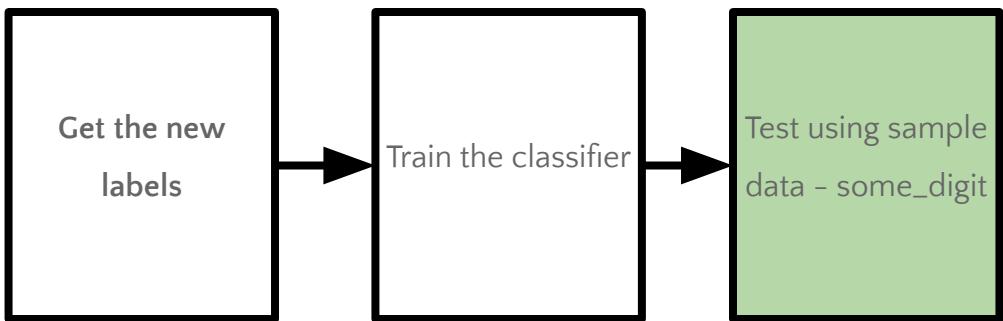
```
>>> from sklearn.neighbors import KNeighborsClassifier  
>>> knn_clf = KNeighborsClassifier()  
>>> knn_clf.fit(X_train, y_multilabel)
```

Run it on Notebook



# Multilabel Classification

- Step 3: Test it



```
>>> knn_clf.predict([some_digit])
array([[False, True]], dtype=bool)
```

- Digit 5 is not large (i.e. it's not 7 or 8 or 9) but is odd



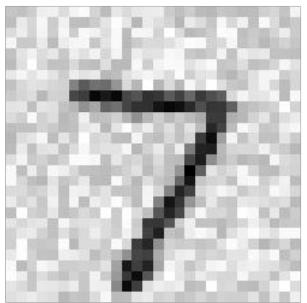
# Multioutput Classification

- It is simply a generalization of multilabel classification where each label can be multiclass (i.e., it can have more than two possible values)
- Multi-output classification example - **Removing noise from images**



# Multioutput Classification

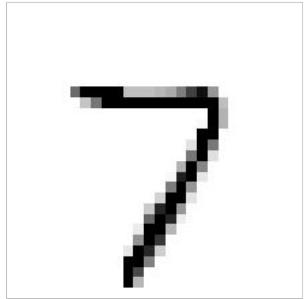
- We'll build a model that removes noise from images. It will take as input a noisy digit image, and it will output a clean digit image, represented as an array of pixel intensities, just like the MNIST images.



Input Image with  
Noise



Model

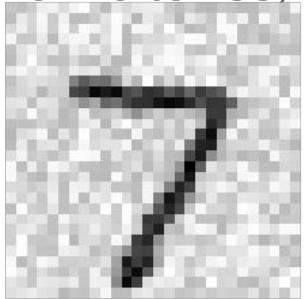


Cleaned Image



# Multioutput Classification

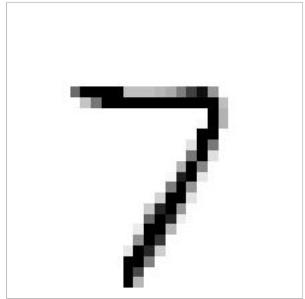
- Notice that the models' output is
  - Multilabel** (one label per pixel) - so 784 labels //we want values for all labels to be predicted together
  - Multiclass**: And each label can have **multiple values** (pixel intensity ranges from 0 to 255) - 256 classes.



Input Image with  
Noise



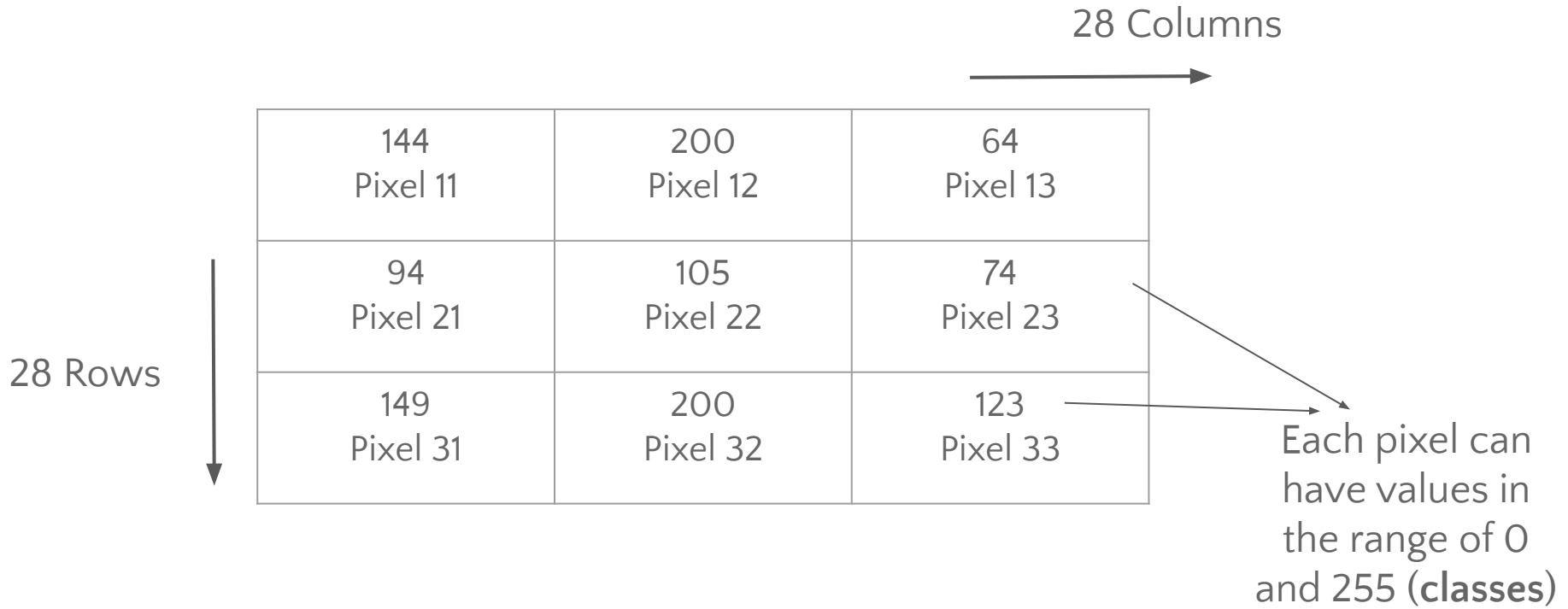
Model



Cleaned Image



# Multioutput Classification





# Multioutput Classification

Hands-on - image noise removal

- Adding noise to the training set #to make our data noisy

```
>>> import numpy.random as rnd  
>>> noise_train = rnd.randint(0, 100, (len(X_train), 784))  
>>> X_train_mod = X_train + noise_train
```

Run it on Notebook



# Multioutput Classification

Hands-on - image noise removal

- Adding noise to the test set

```
>>> noise_test = rnd.randint(0, 100, (len(X_test), 784))  
>>> X_test_mod = X_test + noise_test
```

Run it on Notebook



# Multioutput Classification

Hands-on - image noise removal

- Setting clean image as the label (`y_train` and `y_test`)

```
>>> y_train_mod = X_train  
>>> y_test_mod = X_test
```

Run it on Notebook



# Multioutput Classification

Hands-on - image noise removal

- Let's view the noise image at index 0

```
>>> some_index = 0  
>>> plot_digit(X_test_mod[some_index])
```

Run it on Notebook



# Multioutput Classification

Hands-on - image noise removal

- Clean the image using the KNN Classifier

```
>>> knn_clf.fit(X_train_mod, y_train_mod)
```

Run it on Notebook



# Multioutput Classification

Hands-on - image noise removal

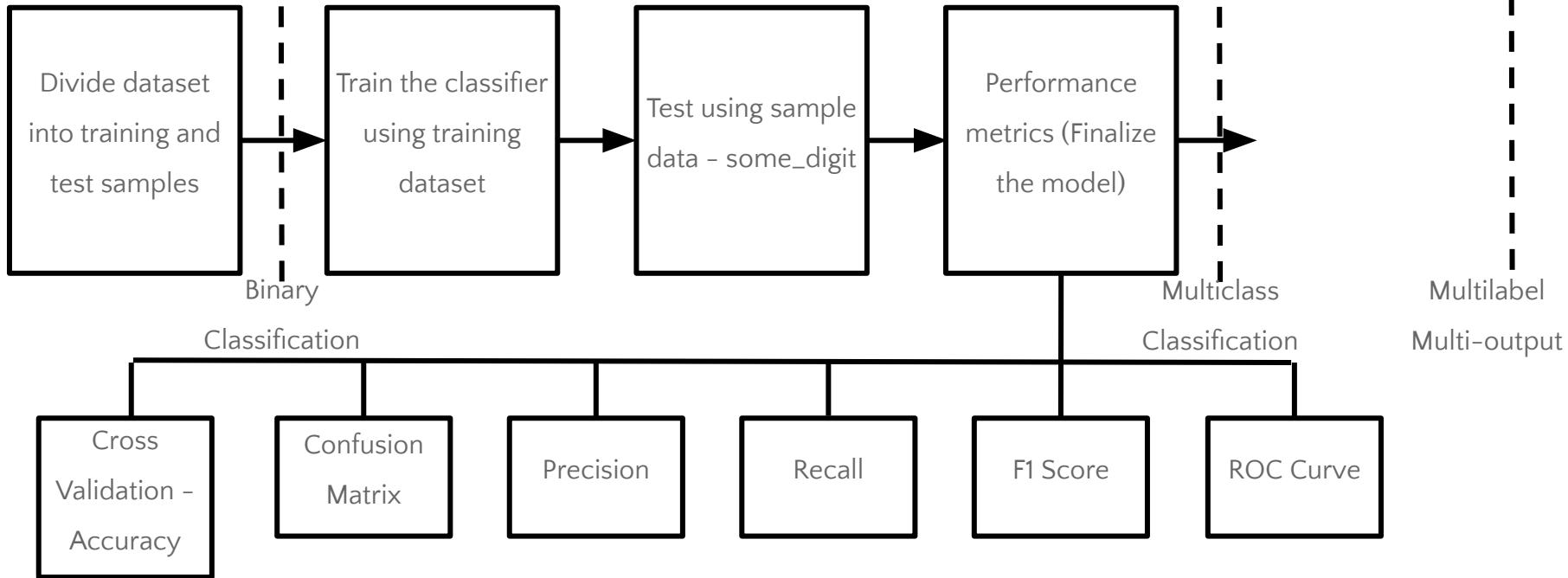
- View cleaned image at index 0

```
>>> clean_digit = knn_clf.predict([X_test_mod[some_index]])  
>>> plot_digit(clean_digit)
```

Run it on Notebook



# Review till now?





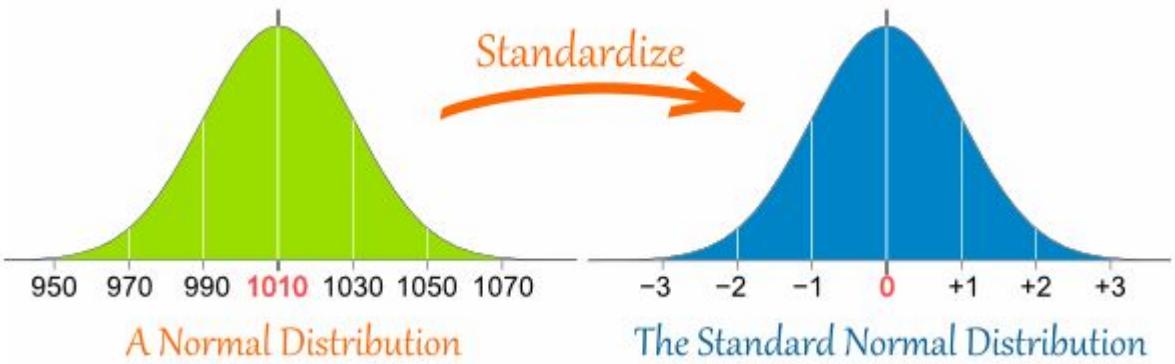
# Questions?

<https://discuss.cloudxlab.com>

reachus@cloudxlab.com



# Feature Scaling – Standardization



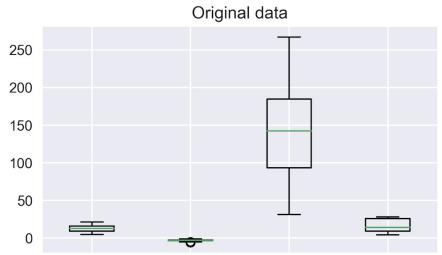
$$\bar{x} = 0 \text{ and } \sigma = 1$$

Zero Mean

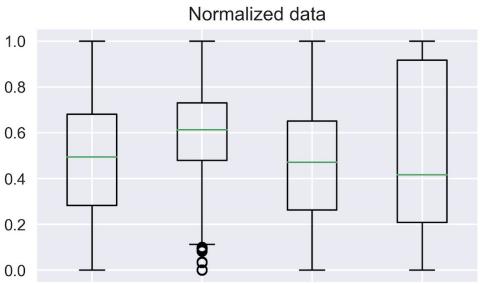
Unit Standard Deviation



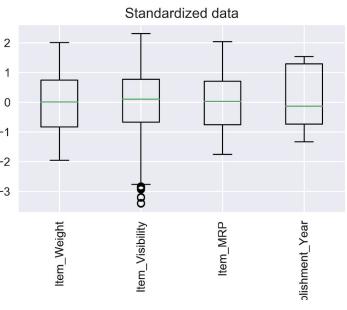
# Feature Scaling - Standardization



Original Data



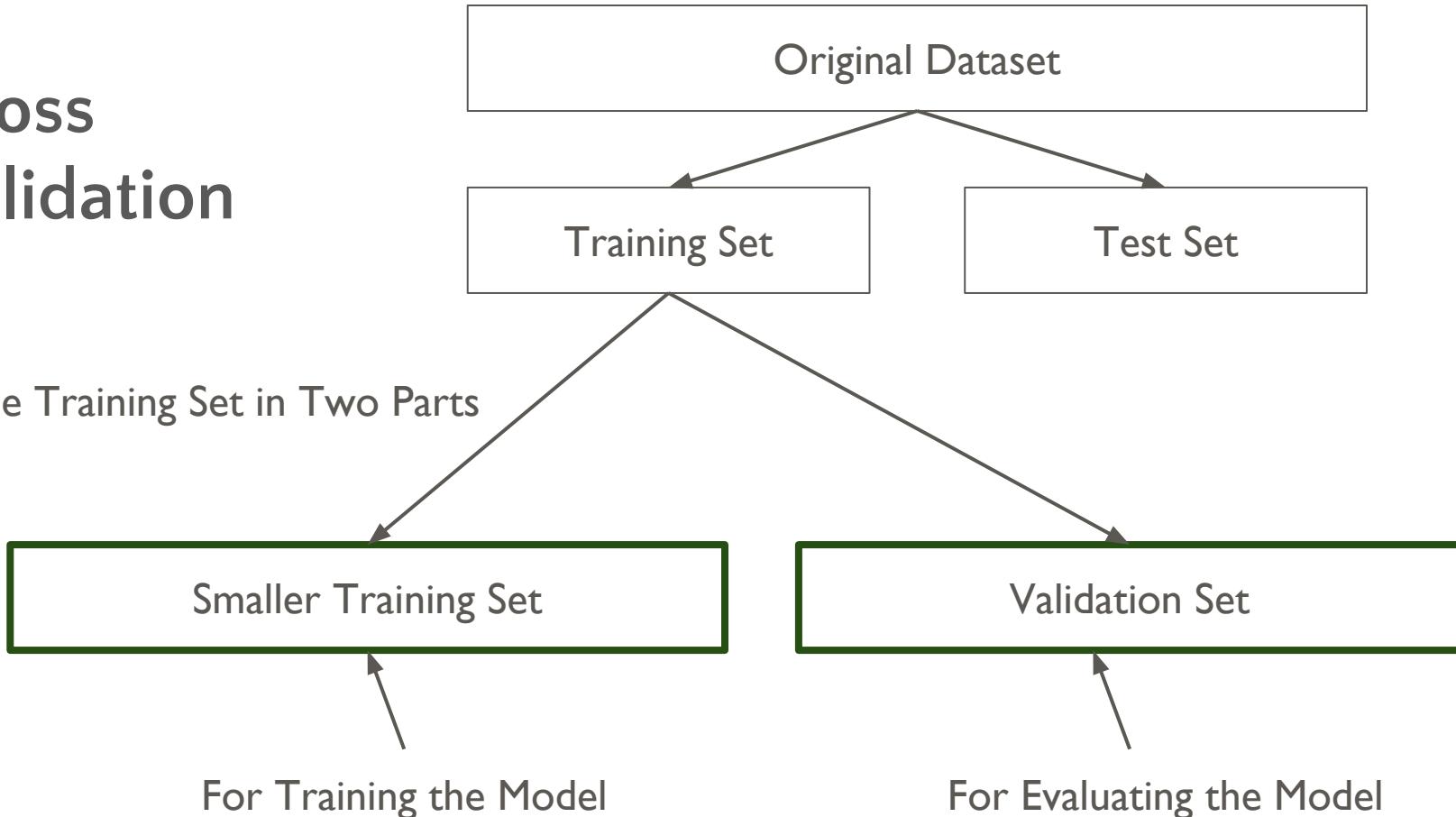
Normalized  
Data



Standardized  
Data

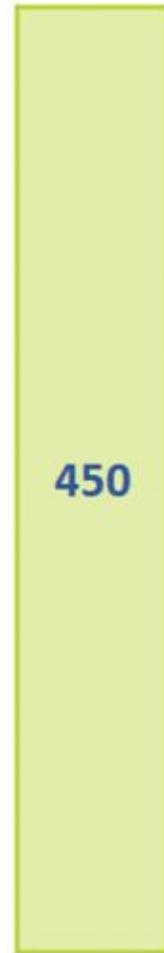
# Cross Validation

Divide Training Set in Two Parts



# Cross Validation

With 10  
Folds





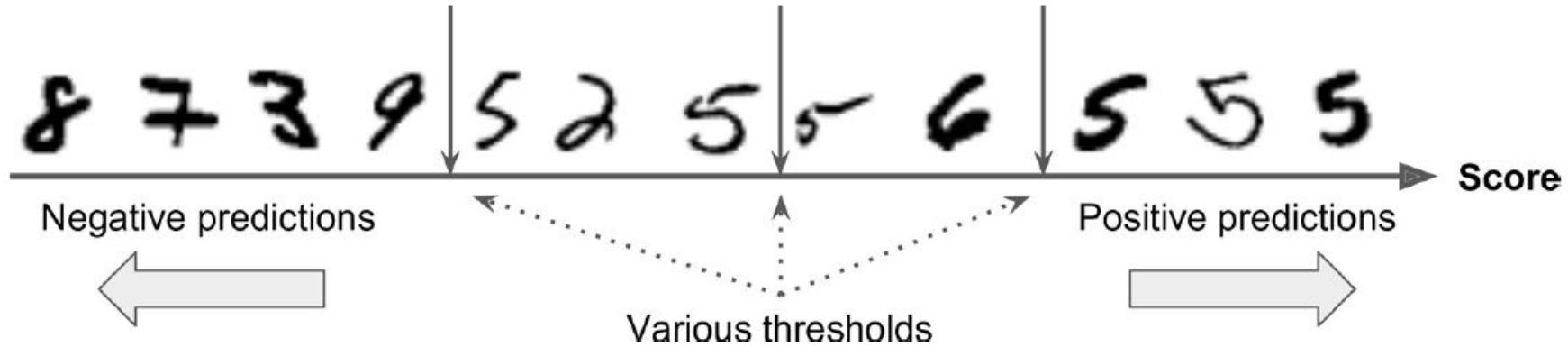
# Performance Measures – ROC Curve

- ROC Curve Similar to F1 score but uses a different metric
- Uses True Positive Rate (TPR) = Recall =  $TP / (TP + FN)$
- False Positive Rate (FPR) =  $FP / (FP + TN)$   
= 1 – True Negative Rate (TNR)
- $TNR = TN / (FP + TN)$

Receiver Operating Characteristics (ROC) plots:  
TPR versus FPR



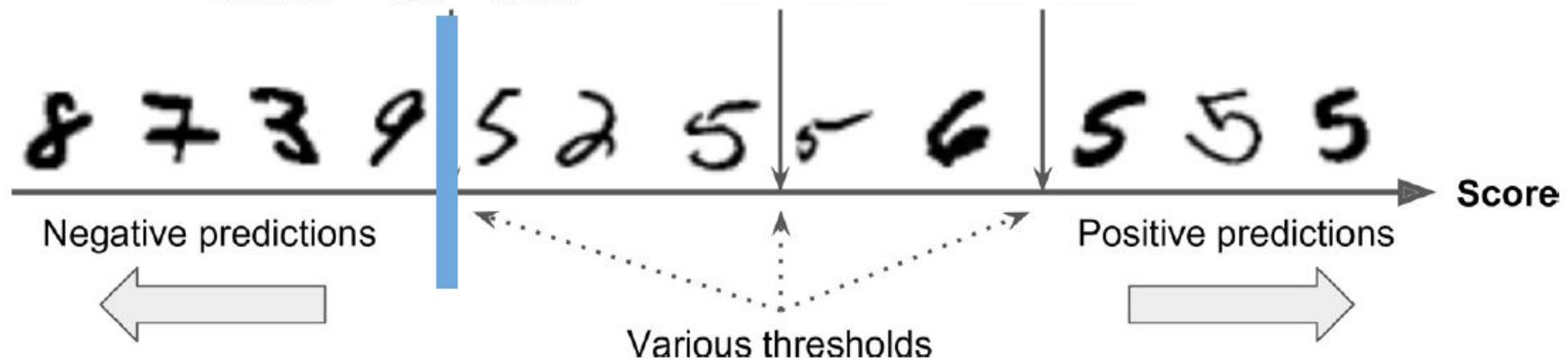
# Precision / Recall Tradeoff - Thresholds



Thresholds can be set to achieve certain precision and recall as required

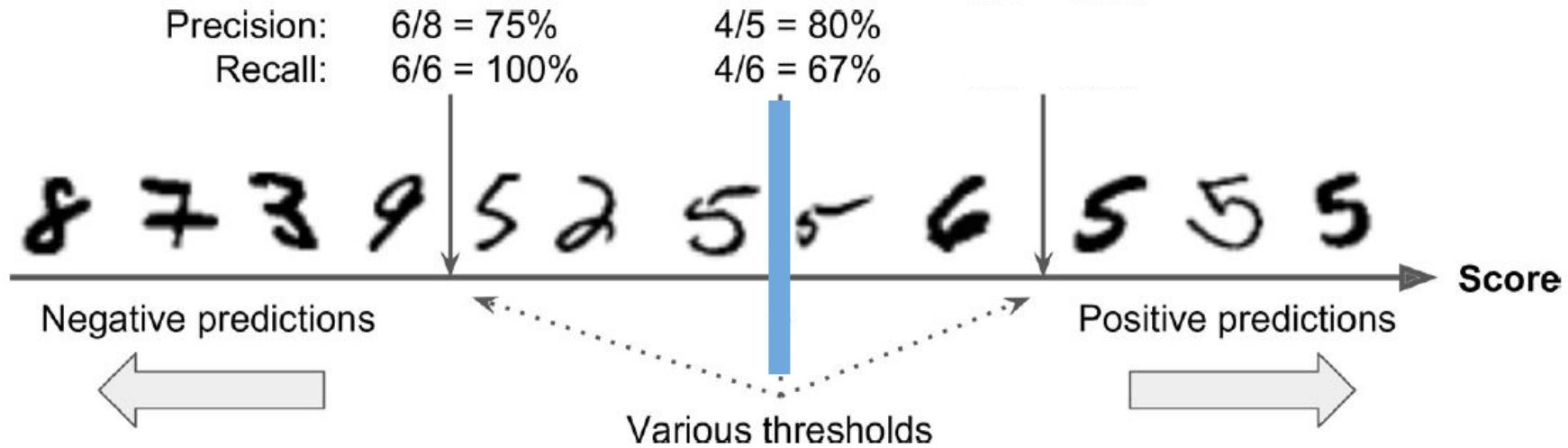
# Precision / Recall Tradeoff

Precision:  $6/8 = 75\%$   
Recall:  $6/6 = 100\%$



In this precision/recall trade-off, images are ranked by their classifier score, and those above the chosen decision threshold are considered positive; the higher the threshold, the lower the recall, but (in general) the higher the precision

# Precision / Recall Tradeoff



In this precision/recall trade-off, images are ranked by their classifier score, and those above the chosen decision threshold are considered positive; the higher the threshold, the lower the recall, but (in general) the higher the precision

# Precision / Recall Tradeoff

Precision:

$$6/8 = 75\%$$

Recall:

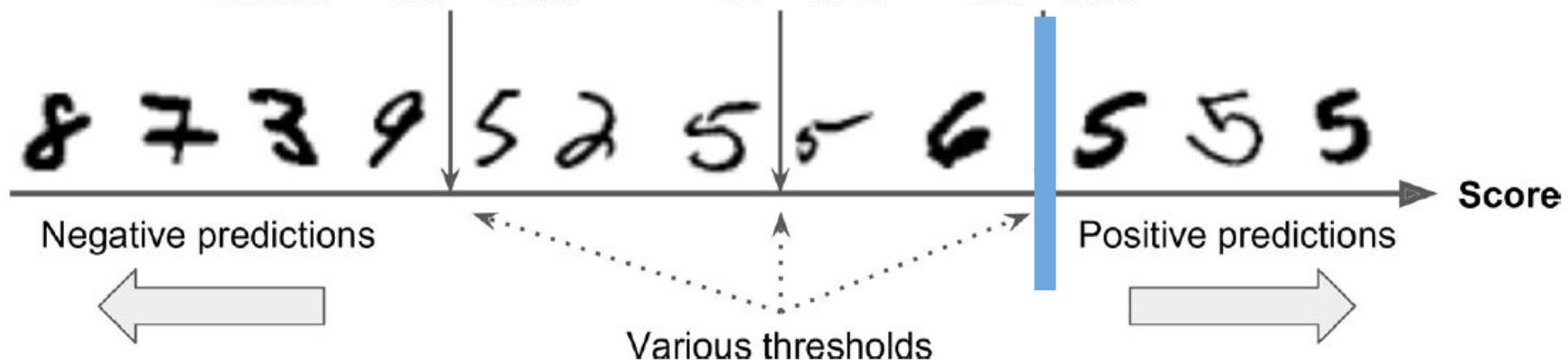
$$6/6 = 100\%$$

$$4/5 = 80\%$$

$$4/6 = 67\%$$

$$3/3 = 100\%$$

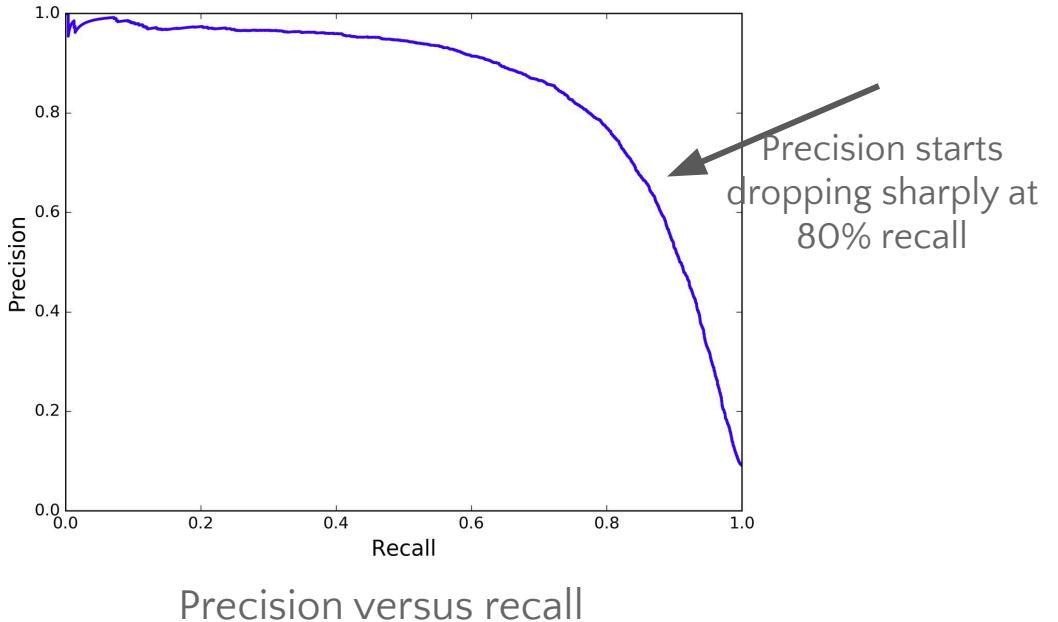
$$3/6 = 50\%$$



In this precision/recall trade-off, images are ranked by their classifier score, and those above the chosen decision threshold are considered positive; the higher the threshold, the lower the recall, but (in general) the higher the precision

# Precision vs Recall Curve

- Another way to select a good precision/recall tradeoff is to
  - plot precision directly against recall.





# Precision vs Recall Curve

- Another way to select a good precision/recall tradeoff is to
  - plot **precision directly against recall**.

```
>>> def plot_precision_vs_recall(precisions, recalls):  
    plt.plot(recalls, precisions, "b-", linewidth=2)  
    plt.xlabel("Recall", fontsize=16)  
    plt.ylabel("Precision", fontsize=16)  
    plt.axis([0, 1, 0, 1])  
    plt.grid(True)  
  
>>> plt.figure(figsize=(8, 6))  
>>> plot_precision_vs_recall(precisions, recalls)  
>>> plt.show()
```

Run it on Notebook



# Another Example of Multioutput Classification

A	B	C	D	E	F	G
5	133.5	27	284	638	31	220
5	111.9	27	285	702	36	230
5	99.3	25	310	713	39	227
5	102.5	25	311	670	34	218
5	114.8	25	312	685	34	222

F, 37  
C, 26



## Performance Measures - F1 Score

F1 Score



**Recall** is really small compared to **Precision**

F1 score will be closer to the smaller number than the bigger one

## Performance Measures - F1 Score

F1 Score



**Recall** is really small compared to **Precision**

Hence F1 score is closer to Recall than Precision



# High Precision or High Recall?

High recall means the model will try to maximize the number of videos that are classified as safe.



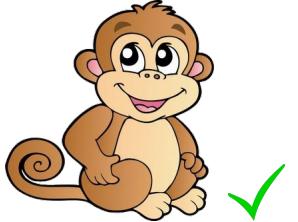
1 - Not Safe



2 - Safe



3 - Not Safe



4 - Safe



5 - Not Safe



6 - Safe

High Recall

# High Precision or High Recall?

In high recall model may mistake while classifying video as safe. This is because recall is more about classifying all the “safe for kids” videos as “safe” rather than classifying all the videos correctly.



1 - Not Safe



2 - Safe



3 - Not Safe



4 - Safe



5 - Not Safe



6 - Safe

High Recall