UNIVERSITY OF TORONTO
SCHOOL OF CONTINUING STUDIES

3253 Analytic Techniques and Machine Learning

Module 3: Classification

Course Plan

Module Titles
Module 1 – Introduction to Machine Learning
Module 2 – End to End Machine Learning Project
Current Focus: Module 3 – Classification
Module 4 – Clustering and Unsupervised Learning
Module 5 – Training Models and Feature Selection
Module 6 – Support Vector Machines
Module 7 – Decision Trees and Ensemble Learning
Module 8 – Dimensionality Reduction
Module 9 – Introduction to TensorFlow
Module 10 – Introduction to Deep Learning and Deep Neural Networks
Module 11 – Distributing TensorFlow, CNNs and RNNs
Module 12 – Final Assignment and Presentations (no content)

Learning Outcomes for this Module

- Develop experience with binary classification
- Use performance measures to evaluate classifiers
- Extend the techniques to multiclass classification

Topics for this Module

- **3.1** The MNIST dataset
- **3.2** Binary classification
- **3.3** Precision and recall
- **3.4** ROC curves
- **3.5** Multi-class classification
- **3.6** Evaluating classifiers
- **3.7** Resources and Wrap-up

Module 3 – Section 1

The MNIST Dataset

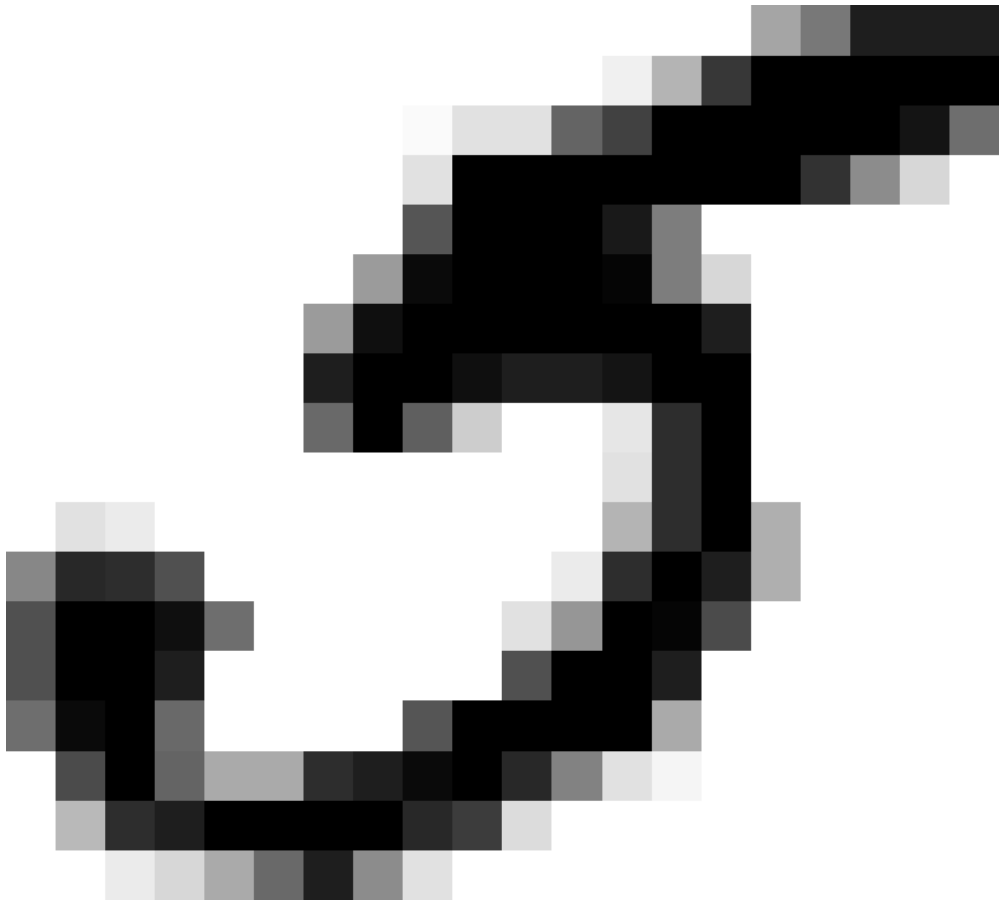
Hand Written Digit Recognition

MNIST dataset is a set of 70,000 small images of digits handwritten by high school students and employees of the US Census Bureau.

Each image is labeled with the digit it represents.

This set has been studied so much that it is often called the “Hello World” of Machine Learning:

Hand Written Digit Recognition (cont'd)



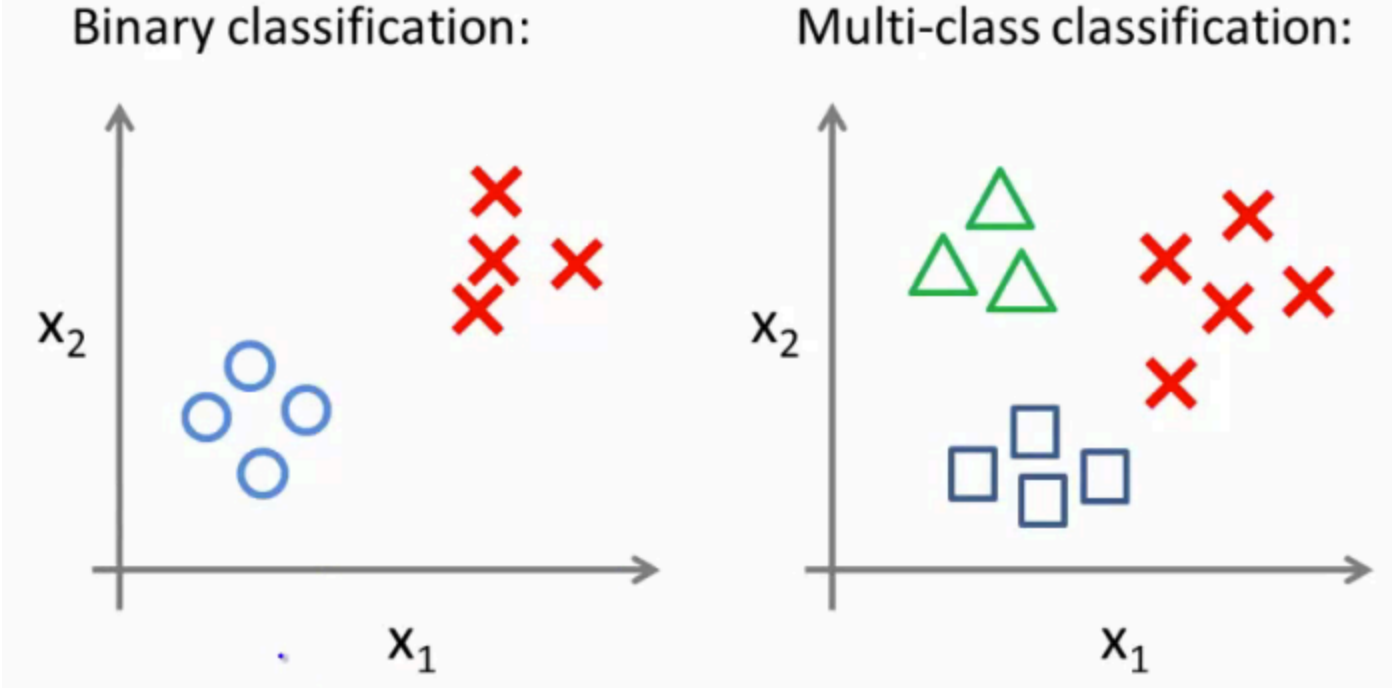
There are 70,000 images, and each image has 784 features.

This is because each image is 28×28 pixels, and each feature simply represents one pixel's intensity, from 0 (white) to 255 (black).

Module 3 – Section 2

Binary Classification

Binary Classification



5, Not-5 Classification

Split data

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

Shuffle data

```
shuffle_index = np.random.permutation(60000)
X_train, y_train = X_train[shuffle_index], y_train[shuffle_index]
```

Set Labels

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

5, Not-5 Classification

Train Classifier

```
from sklearn.linear_model import SGDClassifier

sgd_clf = SGDClassifier(random_state=42)
sgd_clf.fit(X_train, y_train_5)
```

Evaluate Performance

```
>>> from sklearn.model_selection import cross_val_score
>>> cross_val_score(sgd_clf, X_train, y_train_5, cv=3, scoring="accuracy")
array([ 0.9502 ,  0.96565,  0.96495])
```

Never 5 Classifier

Set Output to 0 (Not 5)

```
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)
```

Evaluate Performance

```
>>> never_5_clf = Never5Classifier()
>>> cross_val_score(never_5_clf, X_train, y_train_5, cv=3, scoring="accuracy")
array([ 0.909  ,  0.90715,  0.9128 ])
```

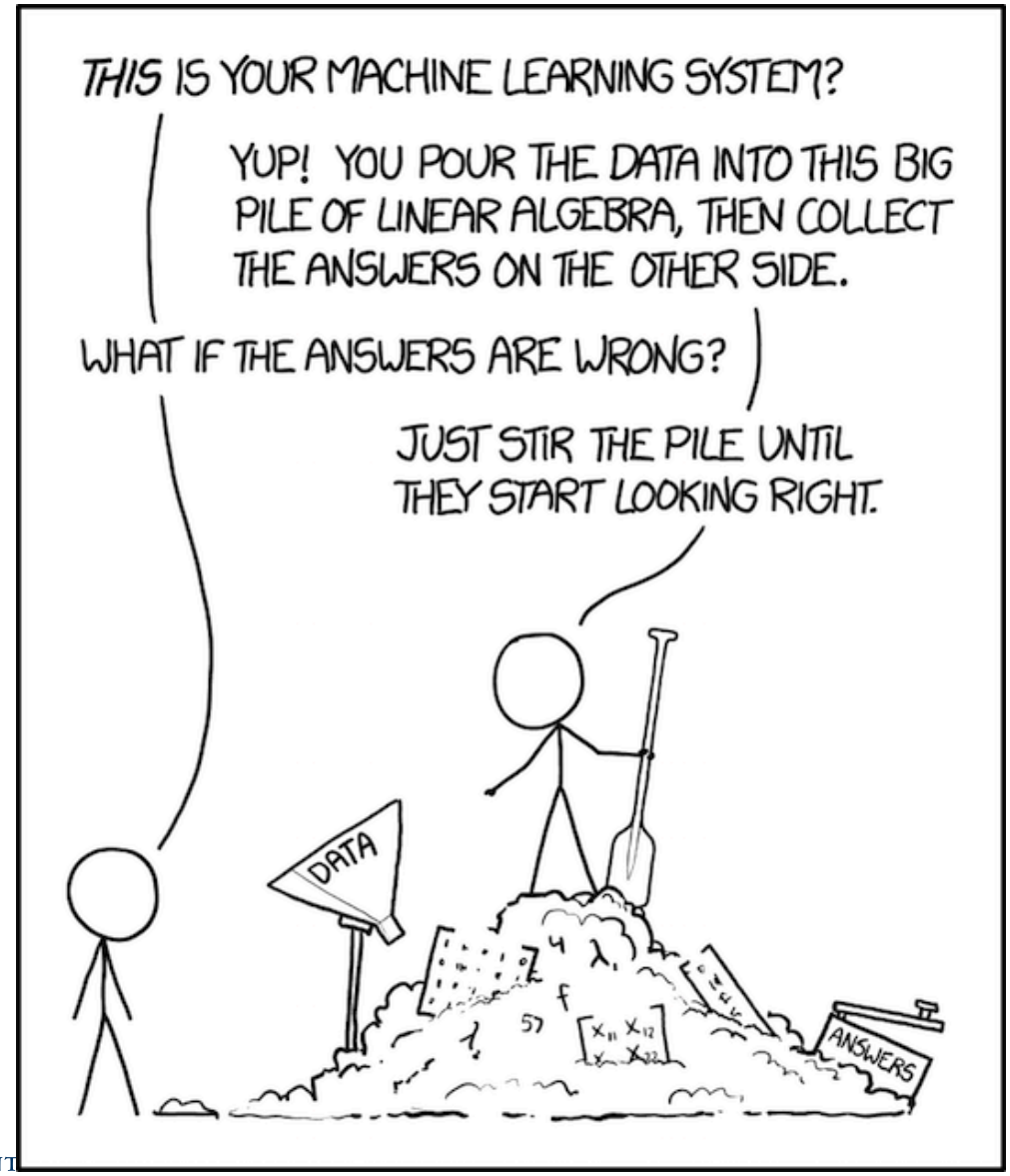
Binary Classification

		True Condition	
	Total Population	Condition Positive	Condition Negative
Test Outcome	Test Outcome Positive	True Positive	False Positve (Type I error)
	Test Outcome Negative	False Negative (Type II error)	True Negative

Module 3 – Section 3

Sensitivity & Specificity

This is your ML system?



Sensitivity, Specificity, Accuracy

$$\text{Sensitivity} = \frac{TP}{P} = \frac{TP}{TP+FN}$$

Out of all positive classes, what % correctly predicted

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

Out of all negative classes, what % correctly predicted

$$\text{Accuracy} = \frac{T}{T+F} = \frac{TP+TN}{TP+TN+FP+FN}$$

What percentage of predictions are correct?

Example

In our telco dataset, there are 900 negative customers (not churn) and 100 positive case (churn).

Model predicted that no one churns.

Calculate the Accuracy

$$\text{Accuracy} = \frac{T}{T+F} = \frac{TP+TN}{TP+TN+FP+FN}$$

Accuracy for imbalanced data

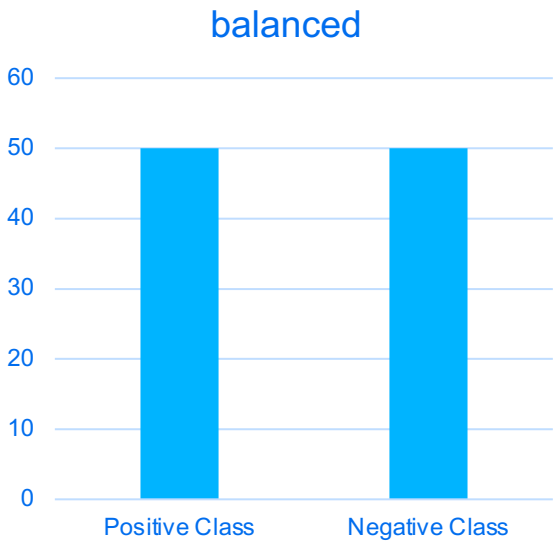
Accuracy = 90%

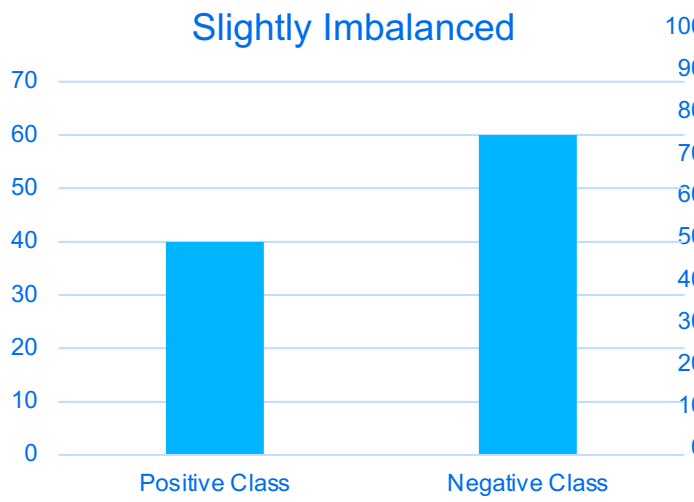
Is it you???

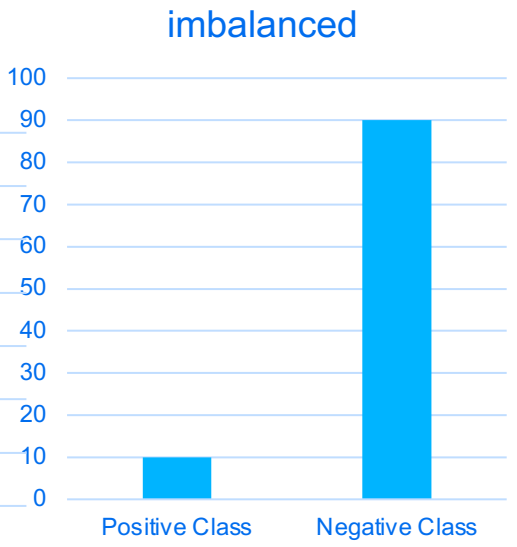
Why & when to use Sensitivity, Specificity, Accuracy?

Why: Easy to understand and communicate with business

When: You have a balance dataset in which your predicting label has relatively same number of instance of each class







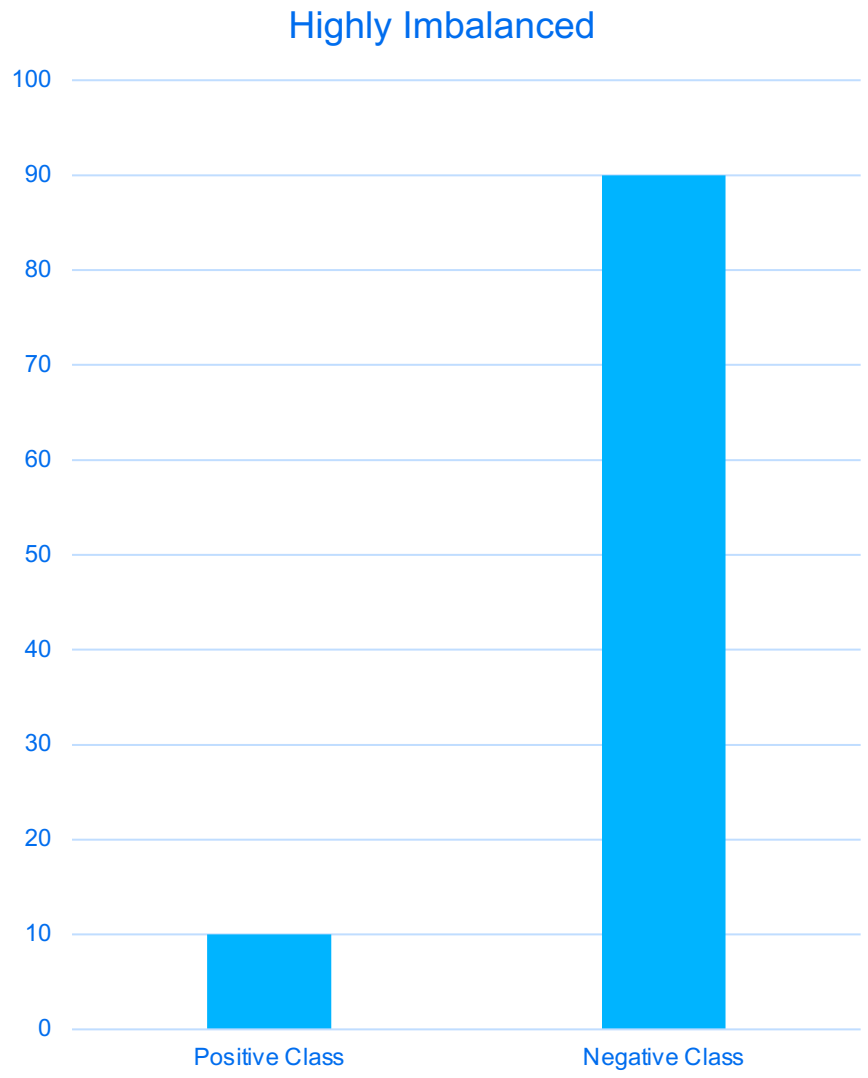
Module 3 – Section 4

Precision and Recall

What if you data is highly imbalanced?

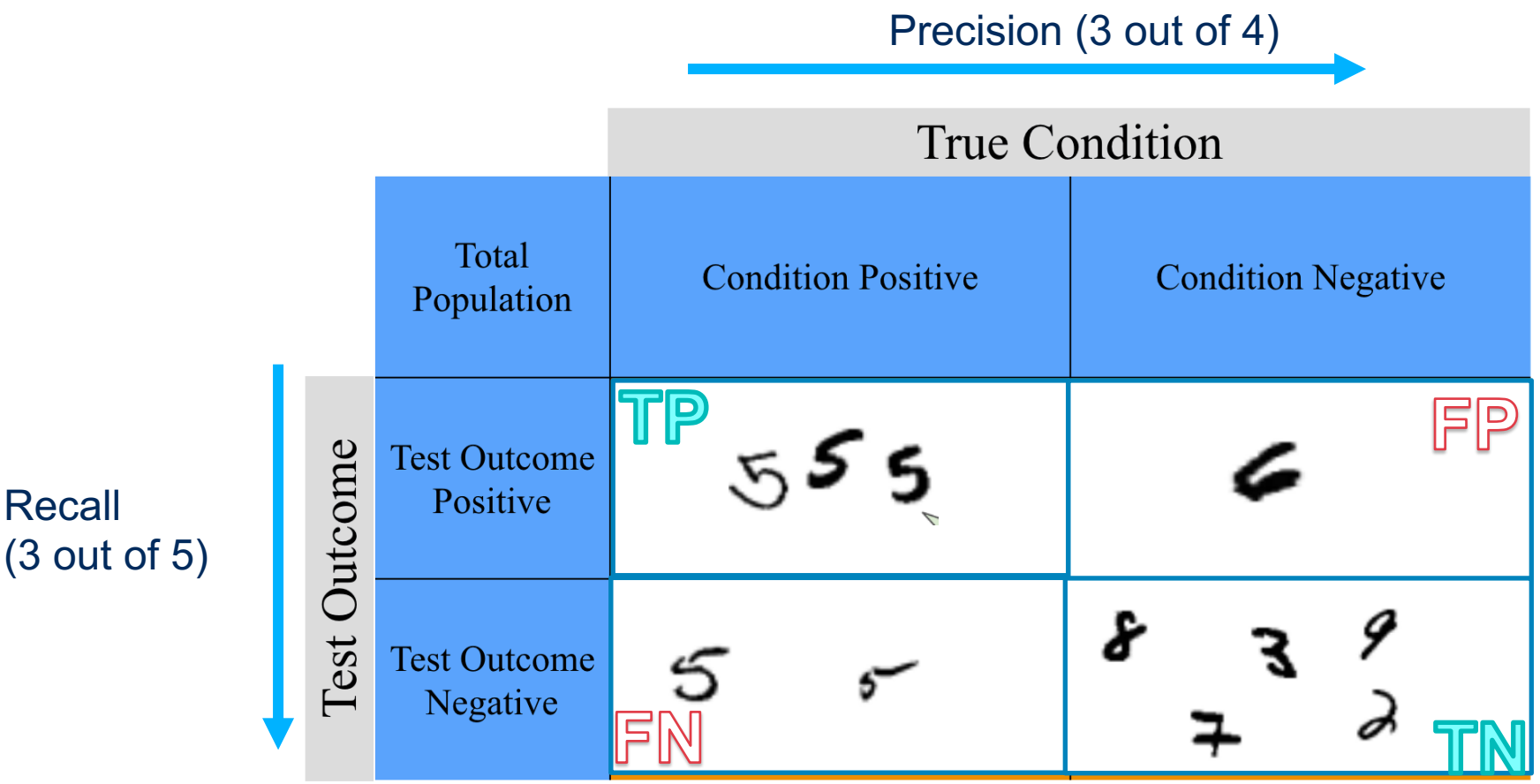
Example:

- 90% of customers are not churning
- 10% of customers are churning!



Example: Hand Written Digit Recognition

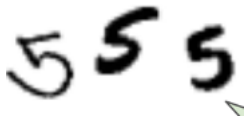
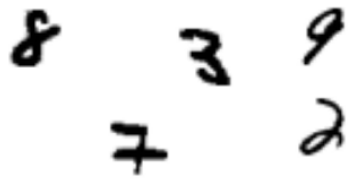
Let's assume below is the confusion matrix for a model

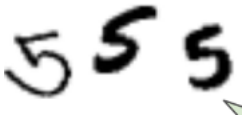


Example: Hand Written Digit Recognition

Precision (3 out of 4)

Recall
(3 out of 5)

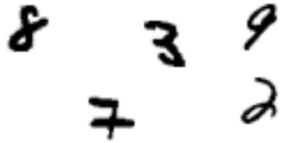
Total Population	True Condition: Condition Positive	True Condition: Condition Negative
Test Outcome: Test Outcome Positive	TP 	FP 
Test Outcome: Test Outcome Negative	FN 	TN 



Model: 5, actual: 5

Model: 5, actual: 6

Model: Not 5, actual: 5



Model: not 5, actual: not 5

Precision, Recall Calculation

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

the accuracy of the positive predictions

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

the ratio of positive instances that are correctly detected by the classifier

Precision, Recall Calculation

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

the accuracy of the positive predictions

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

the ratio of positive instances that are correctly detected by the classifier

$$F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = \frac{TP}{TP + \frac{FN + FP}{2}}$$

harmonic mean of precision and recall

F1 Score is harmonic mean!

$$F1 = \frac{2 * precision * recall}{precision + recall}$$

$$F1 = \frac{2 \times 0.3 \times 0.1}{0.3 + 0.1} \quad \therefore F1=0.15$$

Harmonic mean is conservative mean compared to Arithmetic meand and geometric mean.

It means that Harmonic mean is nearest to the smallest of the input numbers.

Explain Precision recall to business

Precision: Out of all ‘positive’ predictions, how many are actually positive?

Recall: Out of all ‘positive’ cases, how many captured by model?

Question: Look at below example and answer

Saeid built a churn model for a telecom with below numbers:

Recall = 91%.
Precision = 75%

Explain Precision recall to business

Precision: Out of all ‘positive’ predictions, how many are actually positive?

Recall: Out of all ‘positive’ cases, how many captured by model?

Question: Look at below example and answer

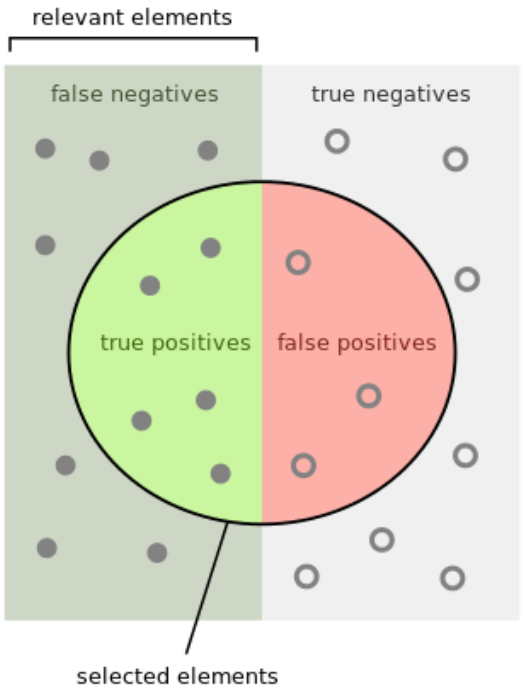
Saeid built a churn model for a telecom with below numbers:

Recall = 91%.	91% of churners are captured by model
Precision = 75%	75% of what Saeid predicted are churner

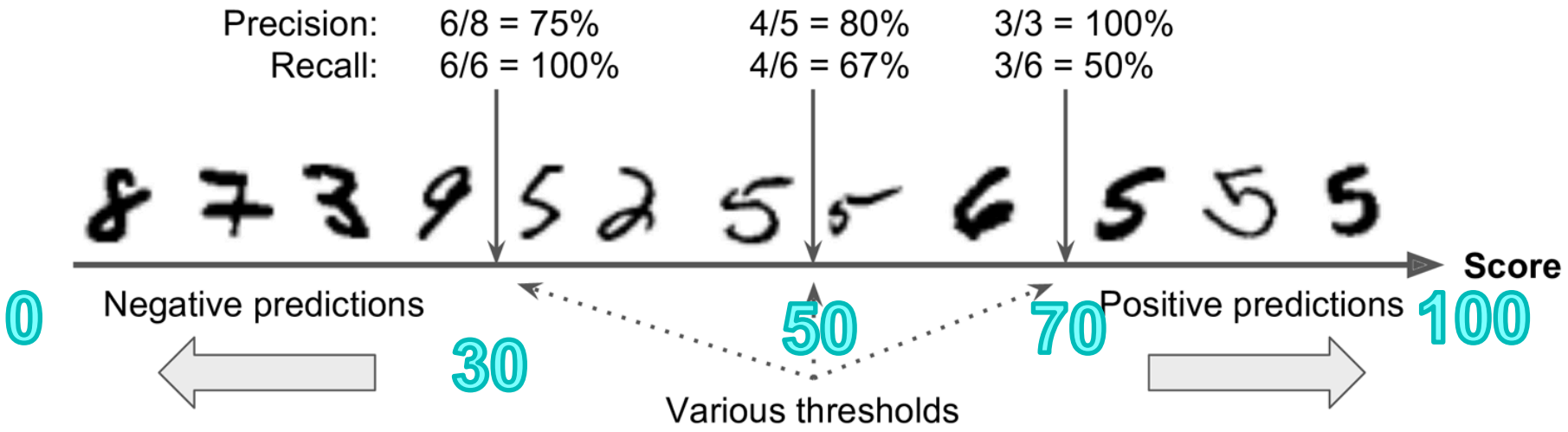
Further intuition into Precision & Recall

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

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



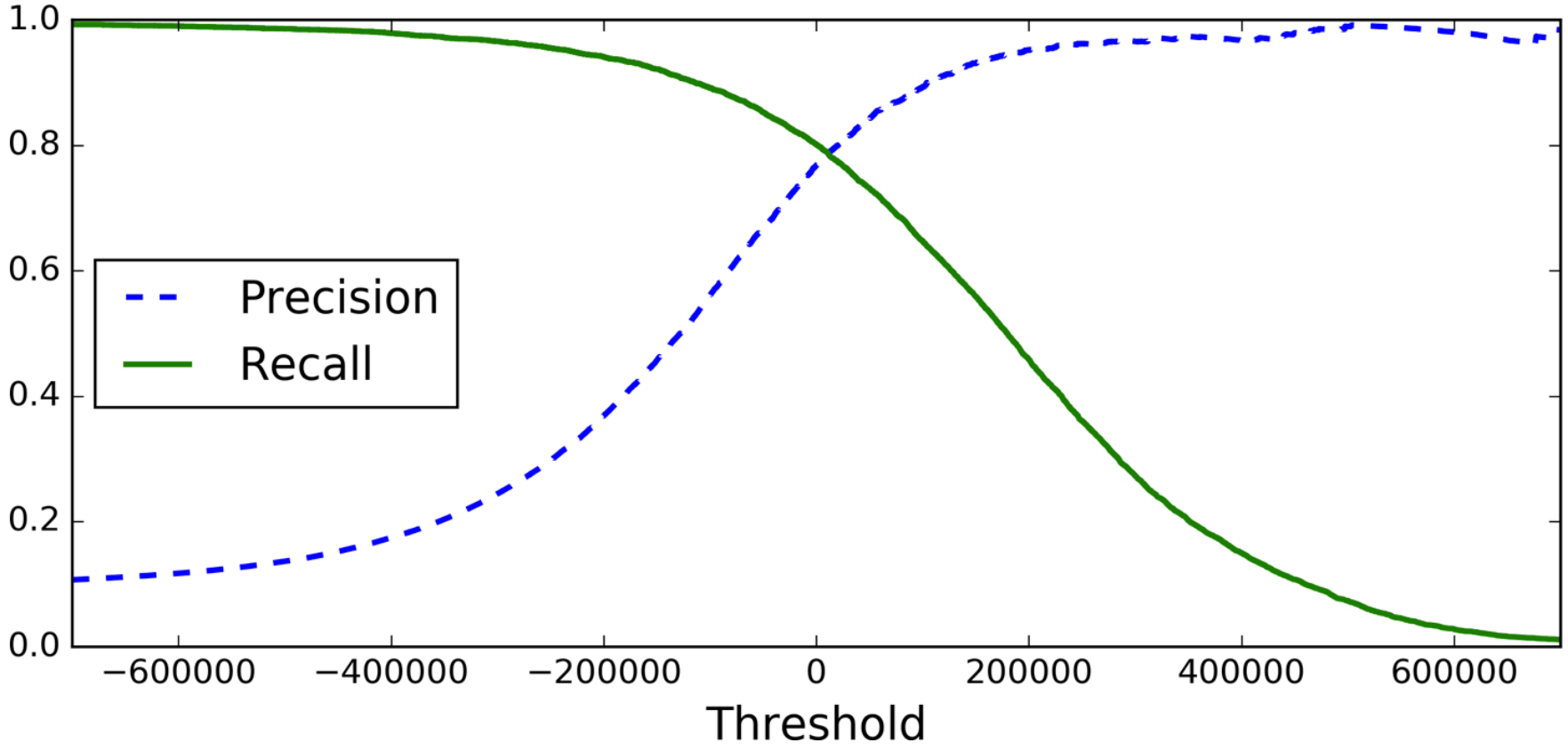
Precision Recall Tradeoff



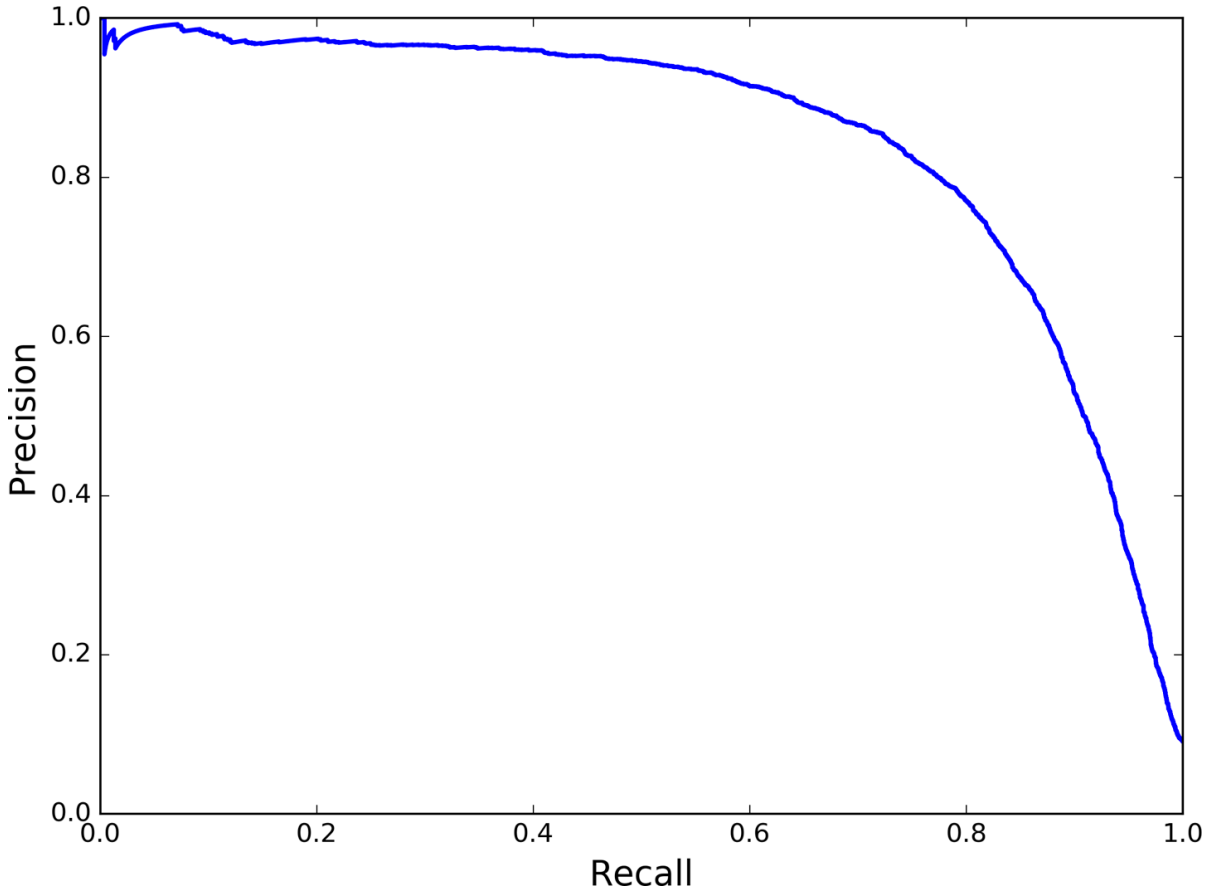
For each instance, the classifier computes a score based on a decision function (lets assume [0-100].
If that score is greater than a threshold, it assigns the instance to the positive class, or else it assigns it to the negative class.

Precision Recall Tradeoff (cont'd)

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



Precision Recall Tradeoff (cont'd)

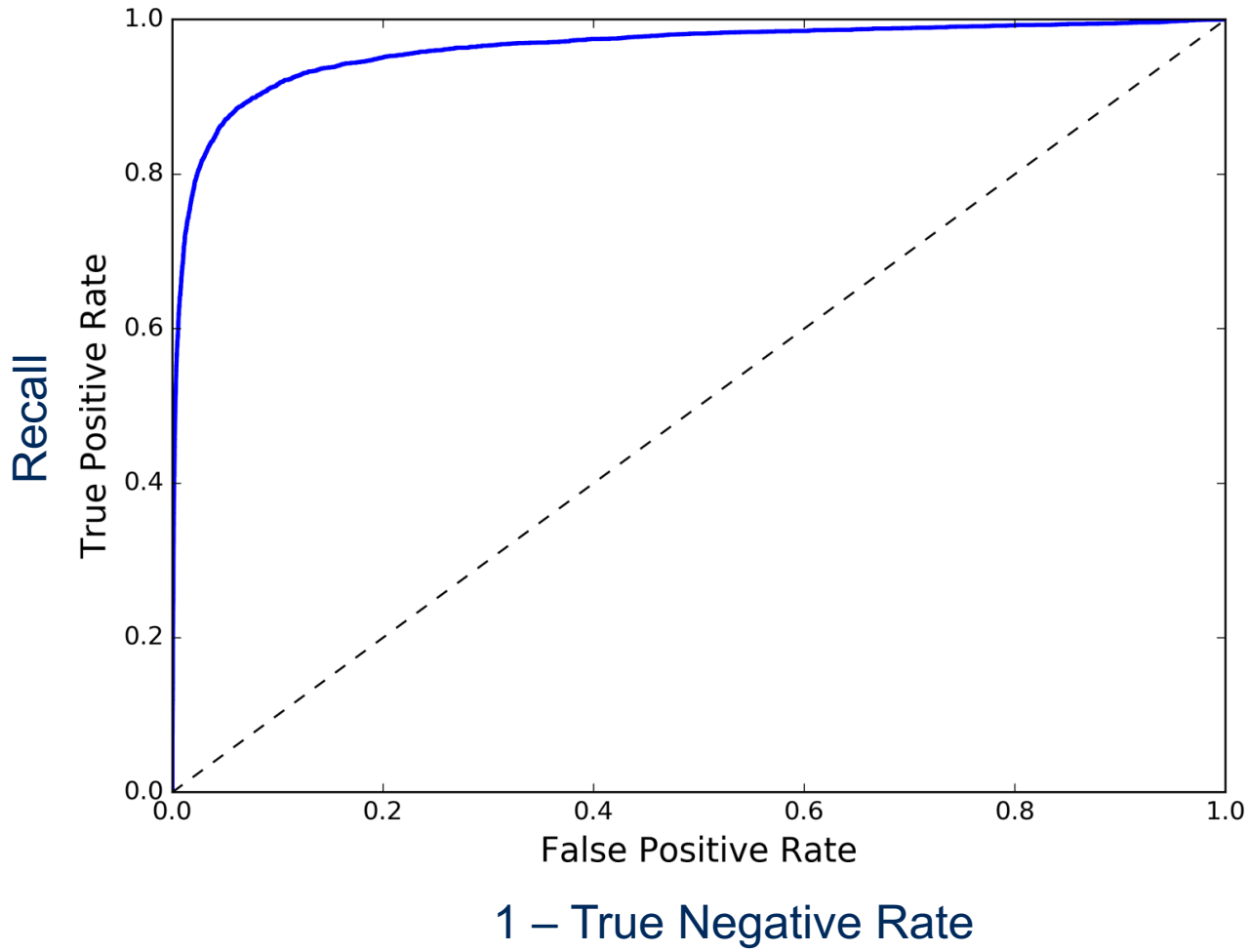


If someone says "let's reach 99% precision," you should ask, "at what recall?"

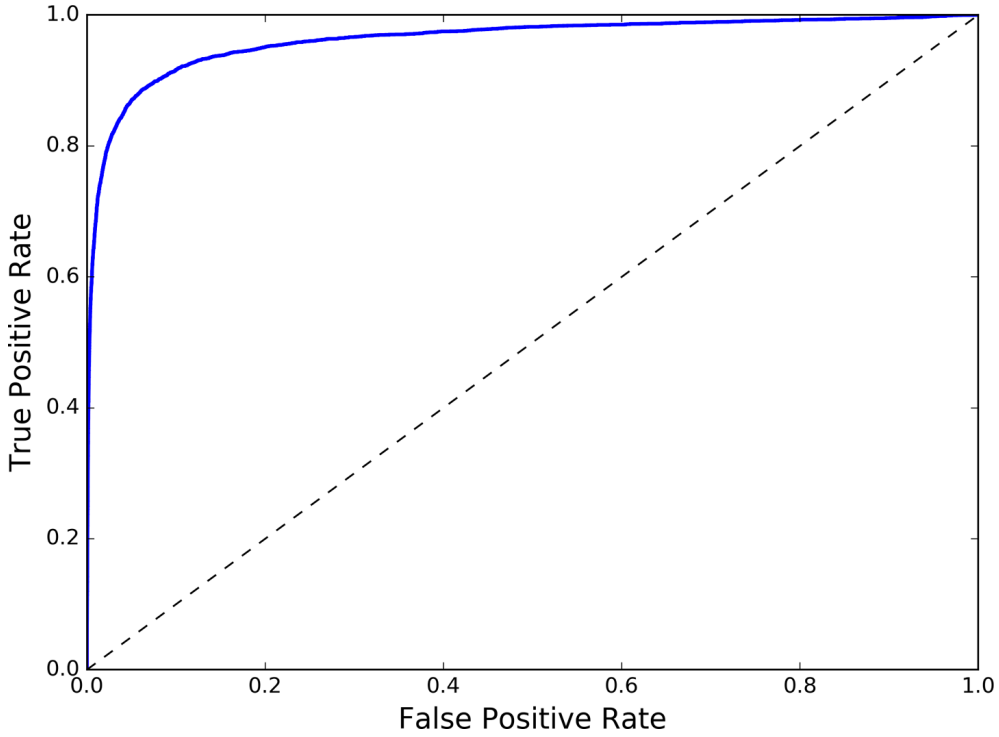
Module 3 – Section 5

ROC Curves

ROC Curve

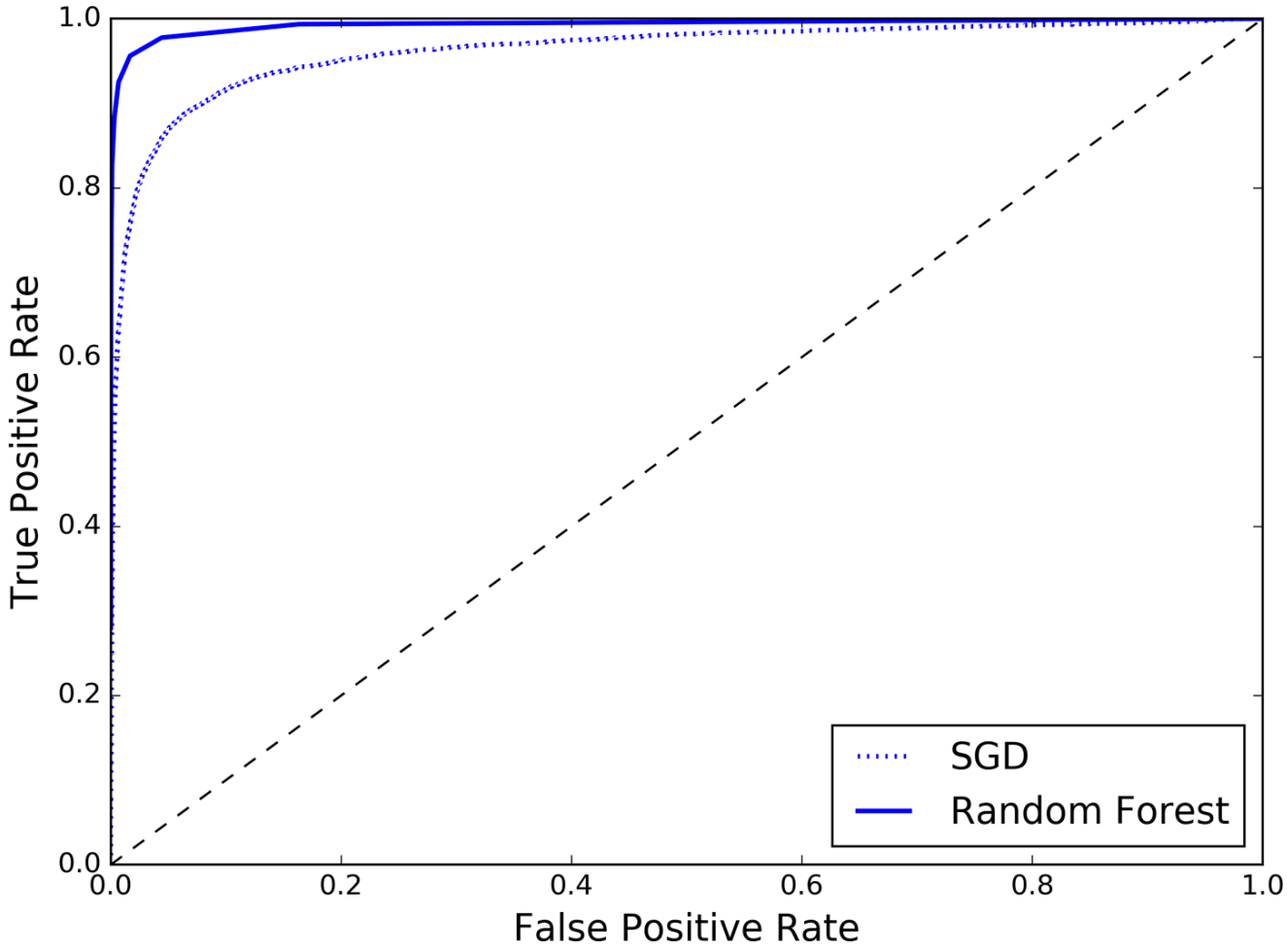

Recall
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
1 – True Negative Rate

ROC Curve (cont'd)



- One way to compare classifiers is to measure the area under the curve (AUC).
- A perfect classifier will have a ROC AUC equal to 1.
- A purely random classifier will have a ROC AUC equal to 0.5.
- Scikit-Learn provides a function to compute the ROC AUC.

Comparing ROC Curves



Module 3 – Section 6

Multi-class Classification

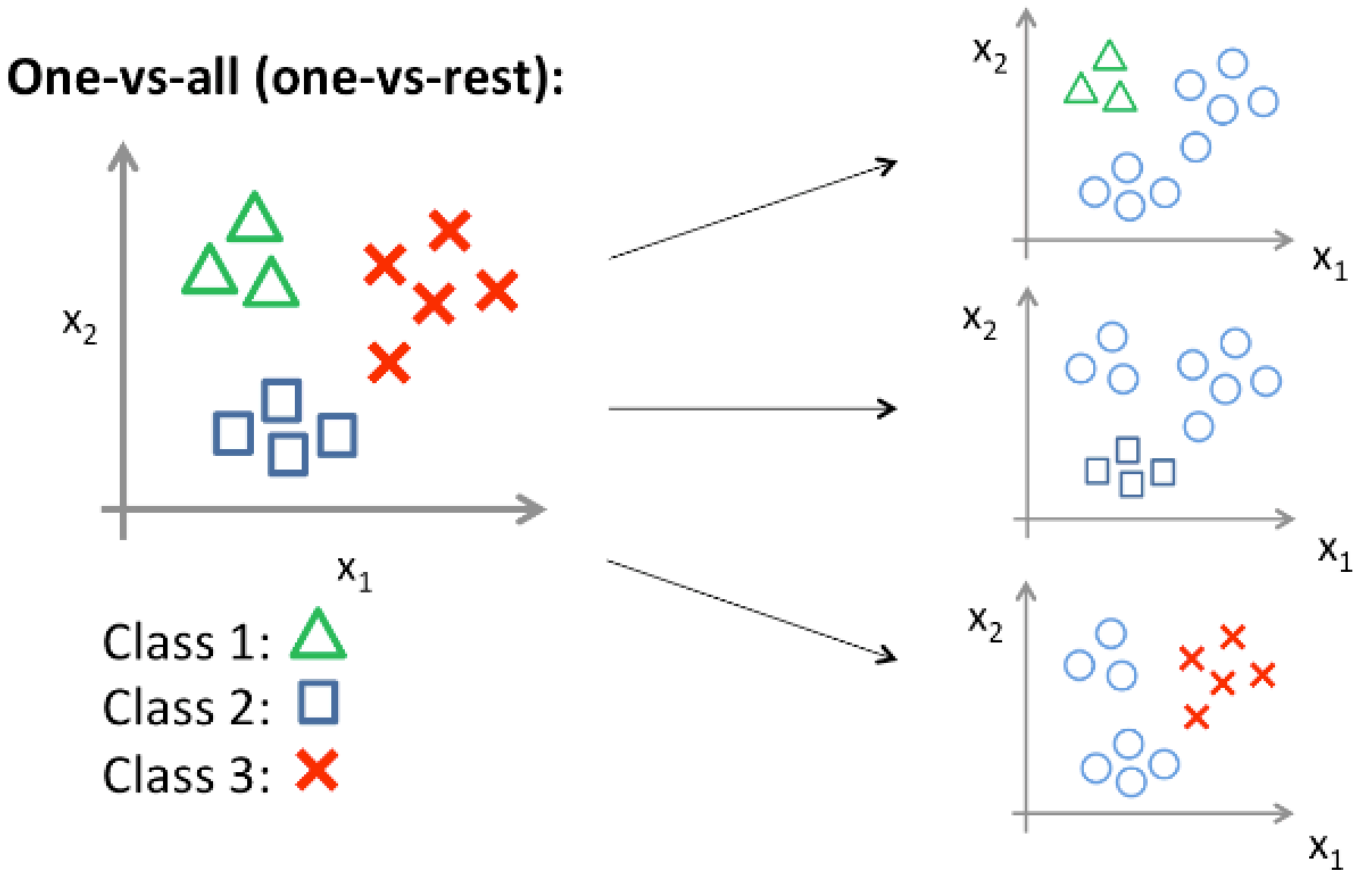
Multi-class Classification

- Distinguish between two or more classes

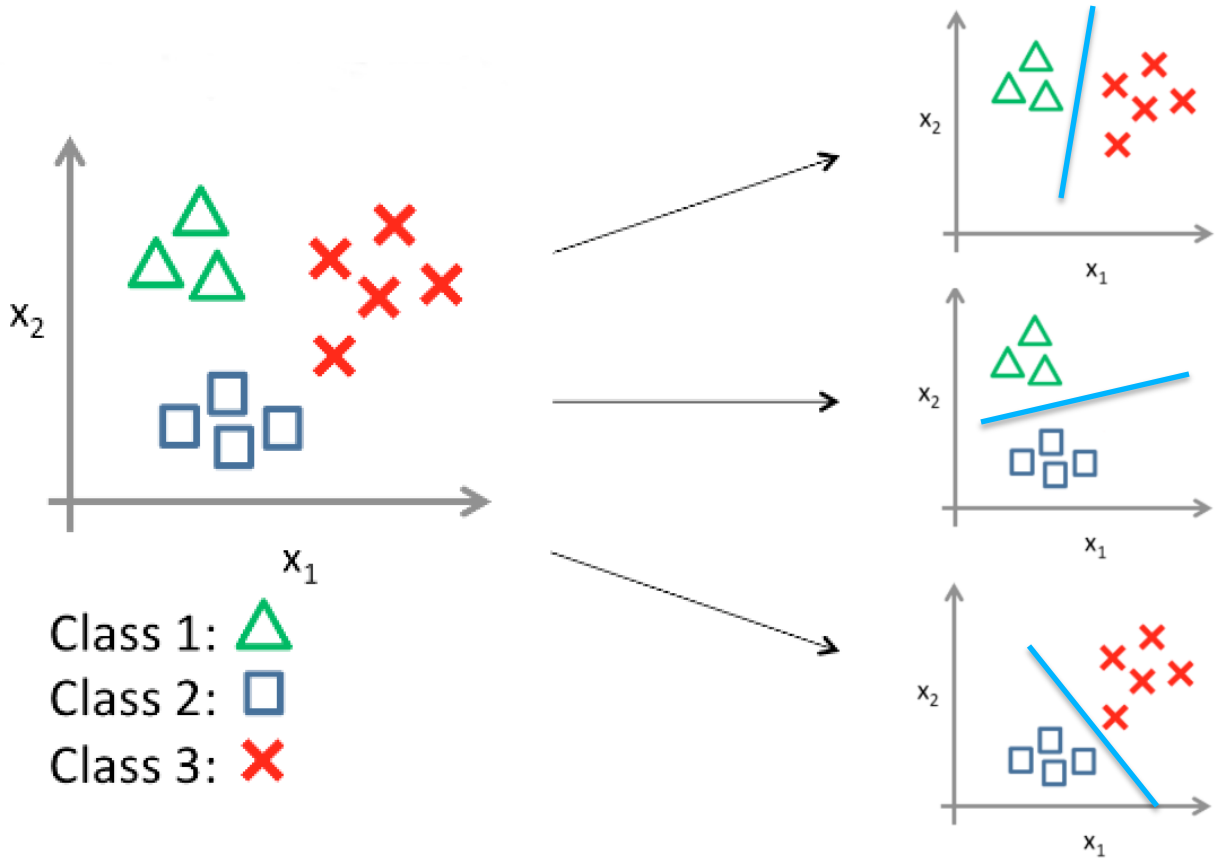
- One way to create a system that can classify n-classes is to train n-binary classifiers, one for each class. Then when you want to classify a new instance, you get the decision score from each classifier and select the class with the highest score.
  (one-versus-all (OvA) strategy)

- Another way is to train a binary classifier for every pair of classes. This is called the one-versus-one (OvO) strategy. If there are N classes, you need to train N × (N – 1) / 2 classifiers.

One-vs-all Classifier



One-vs-one Classifier



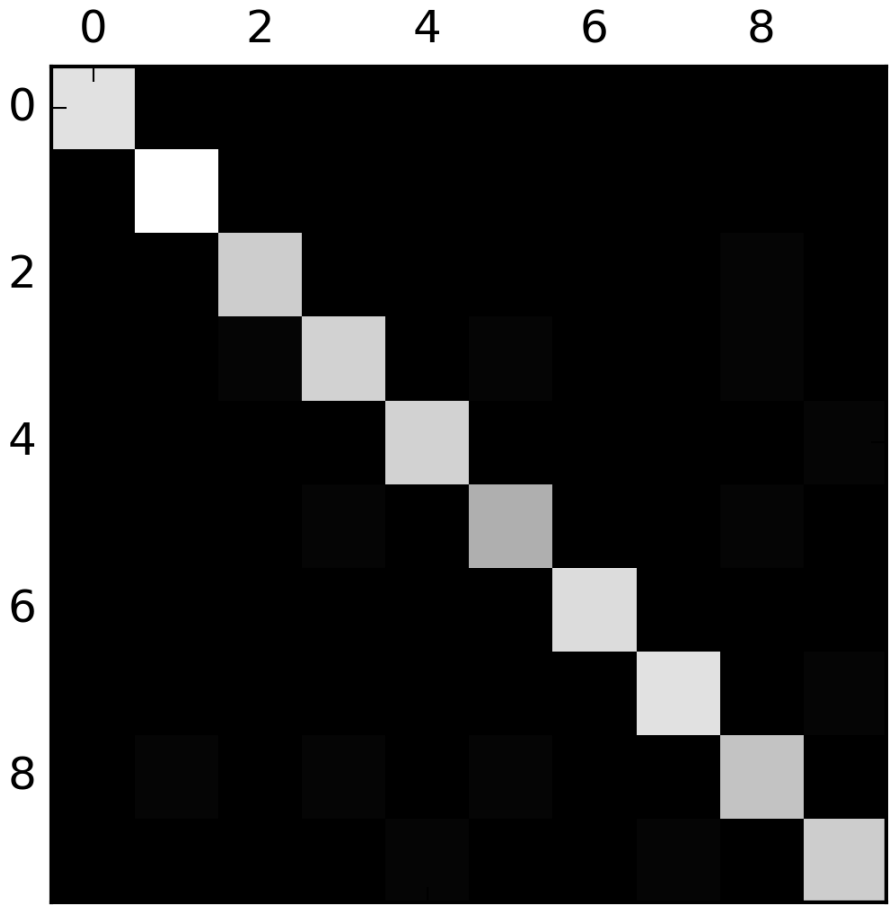
Module 3 – Section 7

Evaluating Classifiers

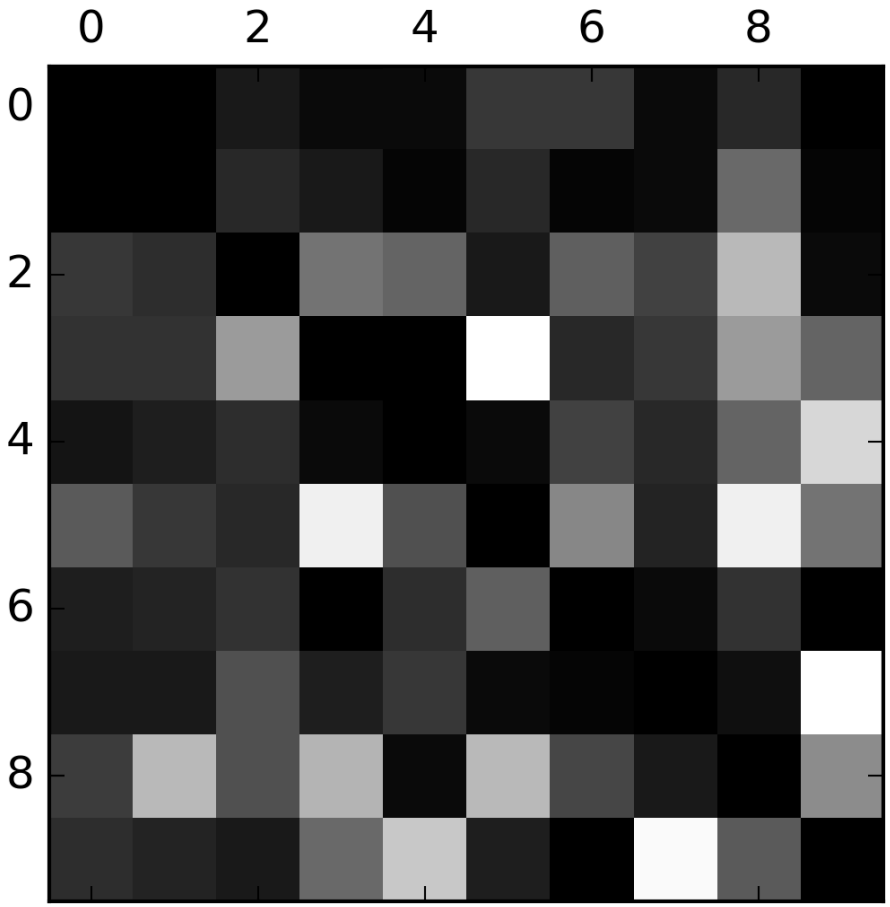
Multi-Dimensional Confusion Matrix

```
>>> y_train_pred = cross_val_predict(sgd_clf, X_train_scaled, y_train, cv=3)
>>> conf_mx = confusion_matrix(y_train, y_train_pred)
>>> conf_mx
array([[5725,    3,   24,    9,   10,   49,   50,   10,   39,    4],
       [   2, 6493,   43,   25,    7,   40,    5,   10,  109,    8],
       [  51,   41, 5321,  104,   89,   26,   87,   60,  166,   13],
       [  47,   46,  141, 5342,    1,  231,   40,   50,  141,   92],
       [  19,   29,   41,   10, 5366,    9,   56,   37,   86,  189],
       [  73,   45,   36,  193,   64, 4582,  111,   30,  193,   94],
       [  29,   34,   44,    2,   42,   85, 5627,   10,   45,    0],
       [  25,   24,   74,   32,   54,   12,    6, 5787,   15,  236],
       [  52,  161,   73,  156,   10,  163,   61,   25, 5027,  123],
       [  43,   35,   26,   92,  178,   28,    2,  223,   82, 5240]])
```

Multi-Dimensional Confusion Matrix (cont'd)

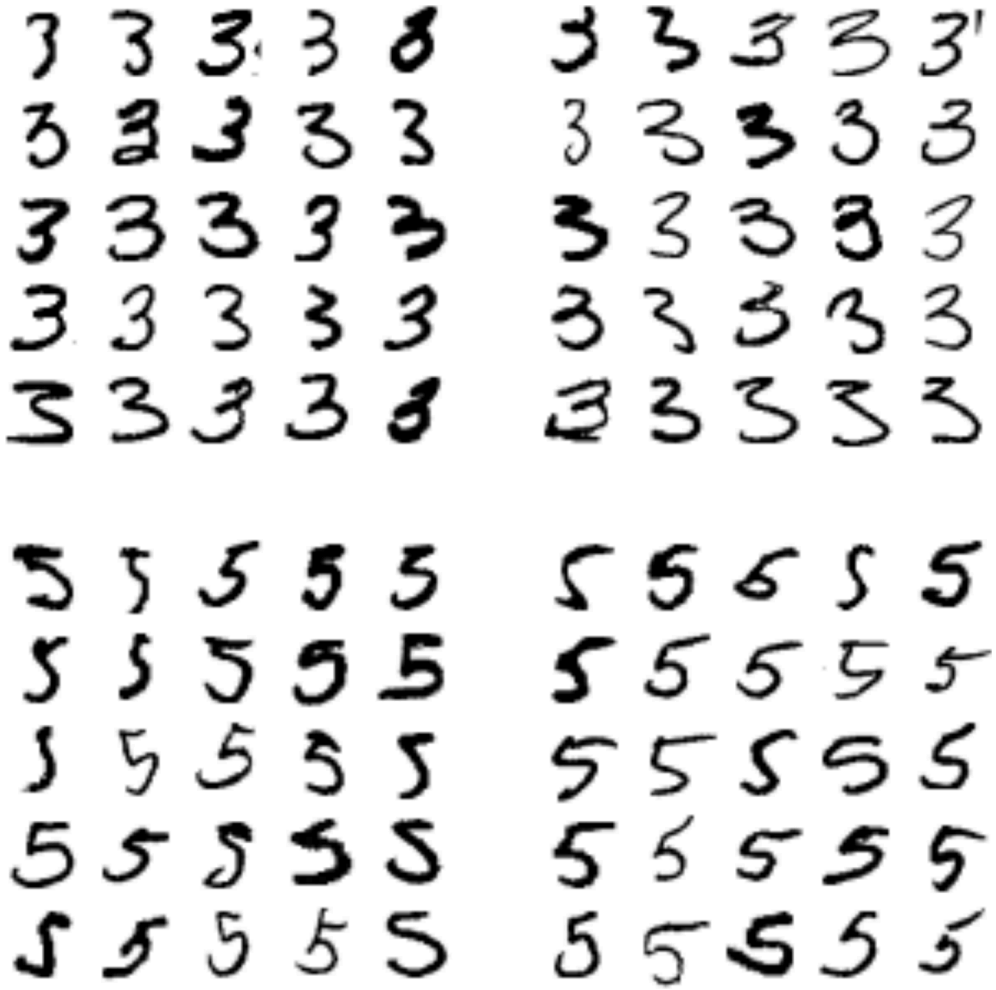


Multi-Dimensional Error Analysis



Divide each value in the confusion matrix by the number of images in the corresponding class

Multi-Dimensional Error Analysis (cont'd)



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Module 3 – Section 8

Resources and Wrap-up

Next Class

- Unsupervised methods
- Clustering

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