Classification

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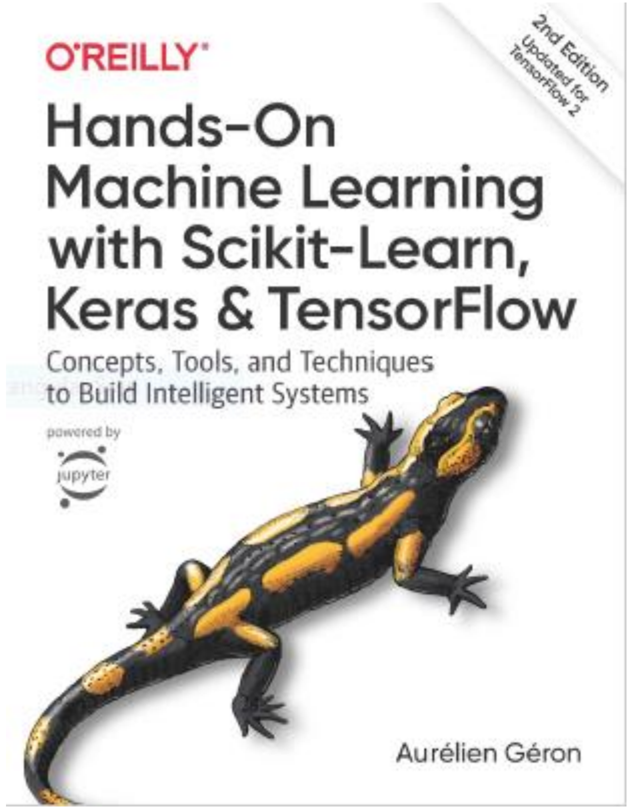
Reference

- Chapter 3: **Classification**



- Aurélien Géron, **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**, O'Reilly, 2nd Edition, 2019
  - Material: https://github.com/ageron/handson-ml2

Introduction

- YouTube Video: **Machine Learning - Supervised Learning Classification** from Cognitive Class

https://youtu.be/Lf2bCQIktTo

Outline

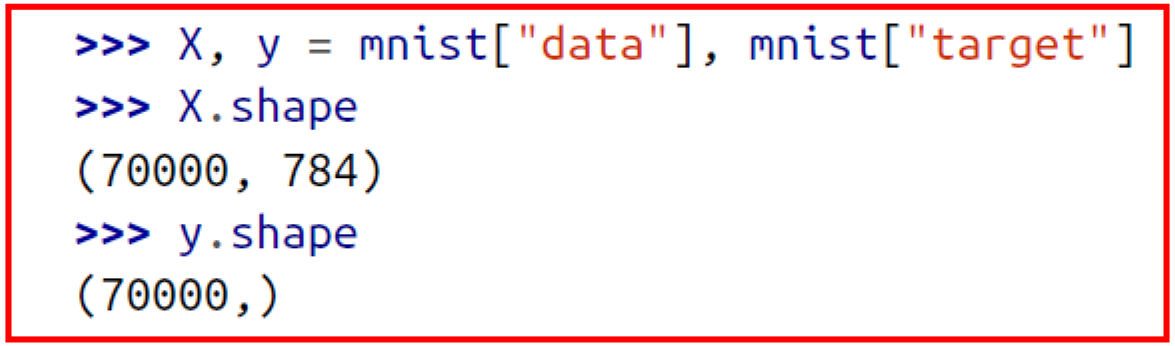
1. MNIST Dataset

- **MNIST** is a set of 70,000 small images of **handwritten digits**.
- Available from mldata.org
- **Scikit-Learn** provides **download** functions.

1.1. Get the Data

```
>>> from sklearn.datasets import fetch_openml
>>> mnist = fetch_openml('mnist_784', version=1)
>>> mnist.keys()
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'details',
           'categories', 'url'])
```

1.2. Extract Features and Labels



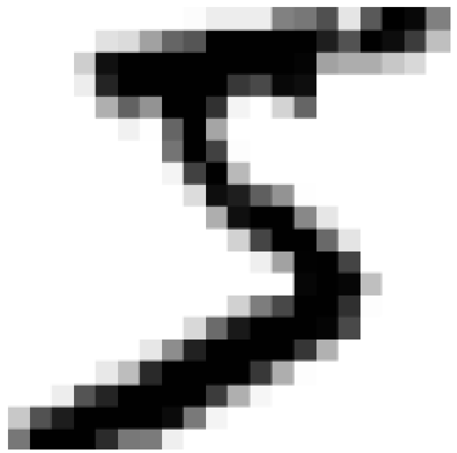
```
>>> X, y = mnist["data"], mnist["target"]
>>> X.shape
(70000, 784)
>>> y.shape
(70000,)
```

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**).

1.3. Examine One Image

```python
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, interpolation="nearest")
plt.axis("off")
plt.show()
```

```
>>> y[0]
'5'
```



1.4. Split the Data

- The MNIST dataset is actually already split into a **training set** (the first 60,000 images) and a **test set** (the last 10,000 images).
- The training set is **already shuffled**.

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

Outline

2. Training a Binary Classifier

- A binary classifier can classify **two classes**.
- For example, classifier for the number 5, capable of distinguishing between two classes, **5** and **not-5**.

```
y_train_5 = (y_train == 5)
y_test_5 = (y_test == 5)
```

True for all 5s, False for all other digits.

```
from sklearn.linear_model import SGDClassifier

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

Stochastic Gradient Descent (SGD) classifier

```
>>> sgd_clf.predict([some_digit])
array([ True])
```

Outline

3. Performance Measures

- **Accuracy**: Ratio of correct predictions
- **Confusion matrix**
- **Precision** and **recall**
- **F1 Score**
- **Precision/recall tradeoff**

3.1. Accuracy

```
y_pred = clone_clf.predict(X_test_fold)
n_correct = sum(y_pred == y_test_fold)
print(n_correct / len(y_pred))
```

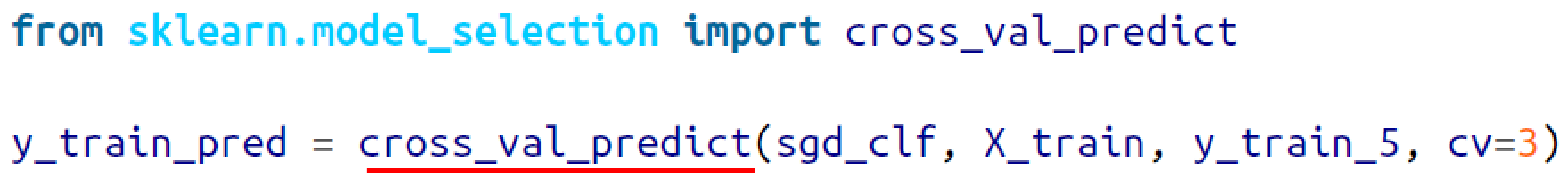
Example how to find the accuracy.

```
>>> from sklearn.model_selection import cross_val_score
>>> cross_val_score(sgd_clf, X_train, y_train_5, cv=3, scoring="accuracy")
array([0.96355, 0.93795, 0.95615])
```

Using the **`cross_val_score()`** function to find the accuracy on three folds

3.1. Accuracy

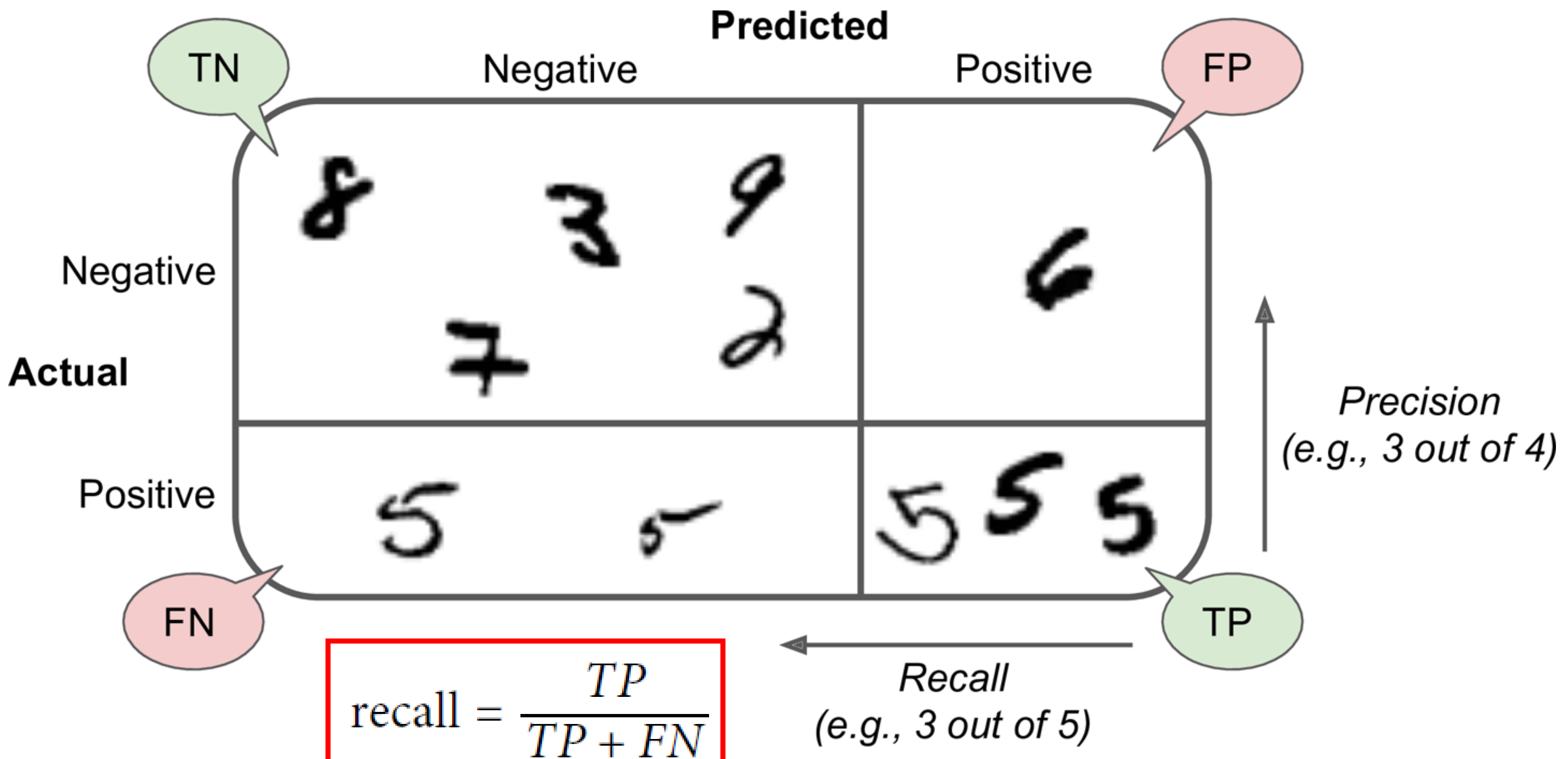
- Use **cross_val_predict()** to predict the targets of the entire training set.



```
from sklearn.model_selection import cross_val_predict

y_train_pred = cross_val_predict(sgd_clf, X_train, y_train_5, cv=3)
```

3.2. Confusion Matrix

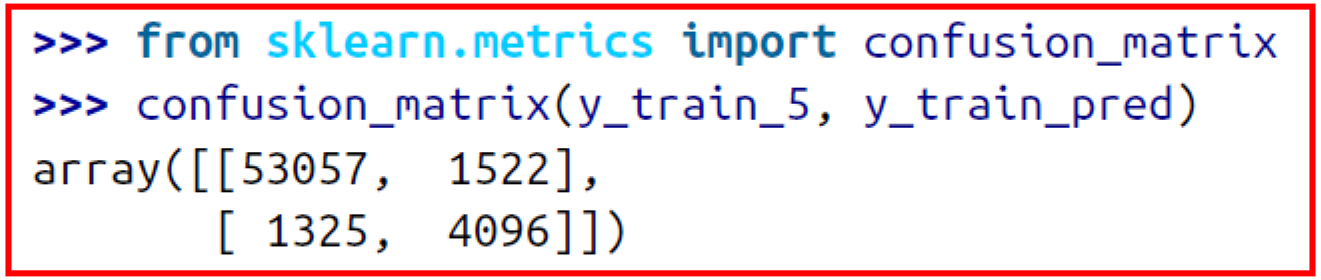
$$\text{precision} = \frac{TP}{TP + FP}$$



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

3.2. Confusion Matrix

- Scikit Learn has a function for finding the **confusion matrix**.



```
>>> from sklearn.metrics import confusion_matrix
>>> confusion_matrix(y_train_5, y_train_pred)
array([[53057,  1522],
       [ 1325,  4096]])
```

- The first row is for the non-5s (the **negative** class):
  - 53,057 correctly classified (**true negatives**)
  - 1,522 wrongly classified (**false positives**)
- The second row is for the 5s (the **positive** class):
  - 1,325 wrongly classified (**false negatives**)
  - 4,096 correctly classified (**true positives**)

3.3. Precision and Recall

Precision

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

Recall

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

```
>>> from sklearn.metrics import precision_score, recall_score
>>> precision_score(y_train_5, y_train_pred) # == 4096 / (4096 + 1522)
0.7290850836596654
>>> recall_score(y_train_5, y_train_pred) # == 4096 / (4096 + 1325)
0.7555801512636044
```

The precision and recall are smaller than the accuracy. Why?

3.4. F1 Score

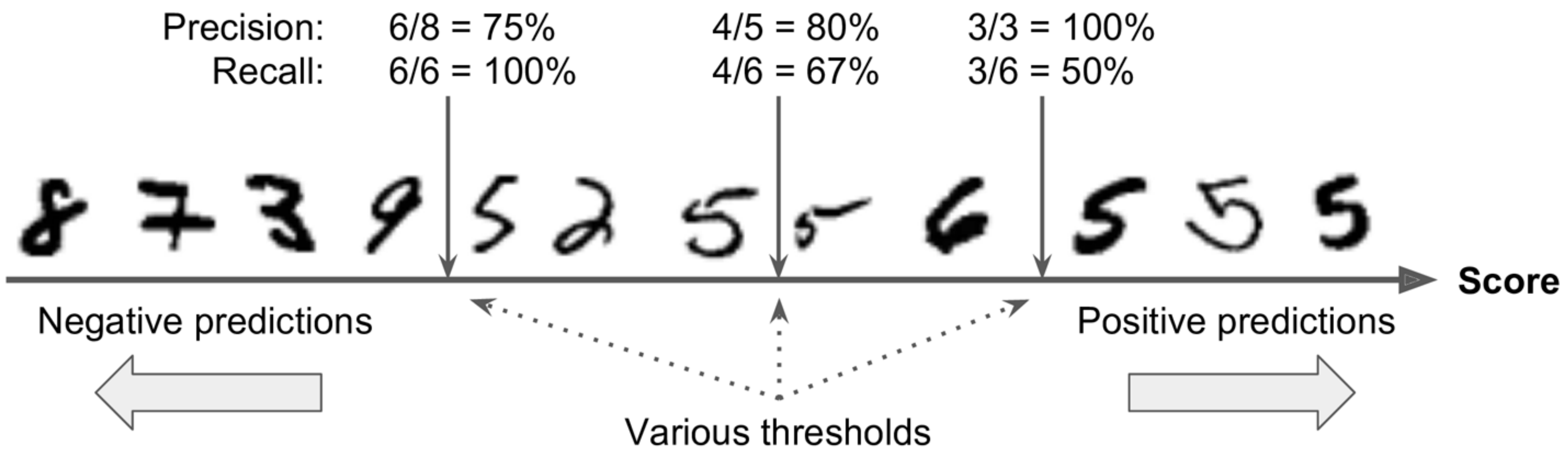
- The F1 Score combines the precision and recall in one metric (**harmonic mean**).

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

```
>>> from sklearn.metrics import f1_score
>>> f1_score(y_train_5, y_train_pred)
0.7420962043663375
```

3.5. Precision/Recall Tradeoff

- **Increase** the **decision threshold** to improve the precision when it is **bad** to have FP.
- **Decrease** the decision threshold to improve the recall when it is **important not to miss FN**.



3.5. Precision/Recall Tradeoff

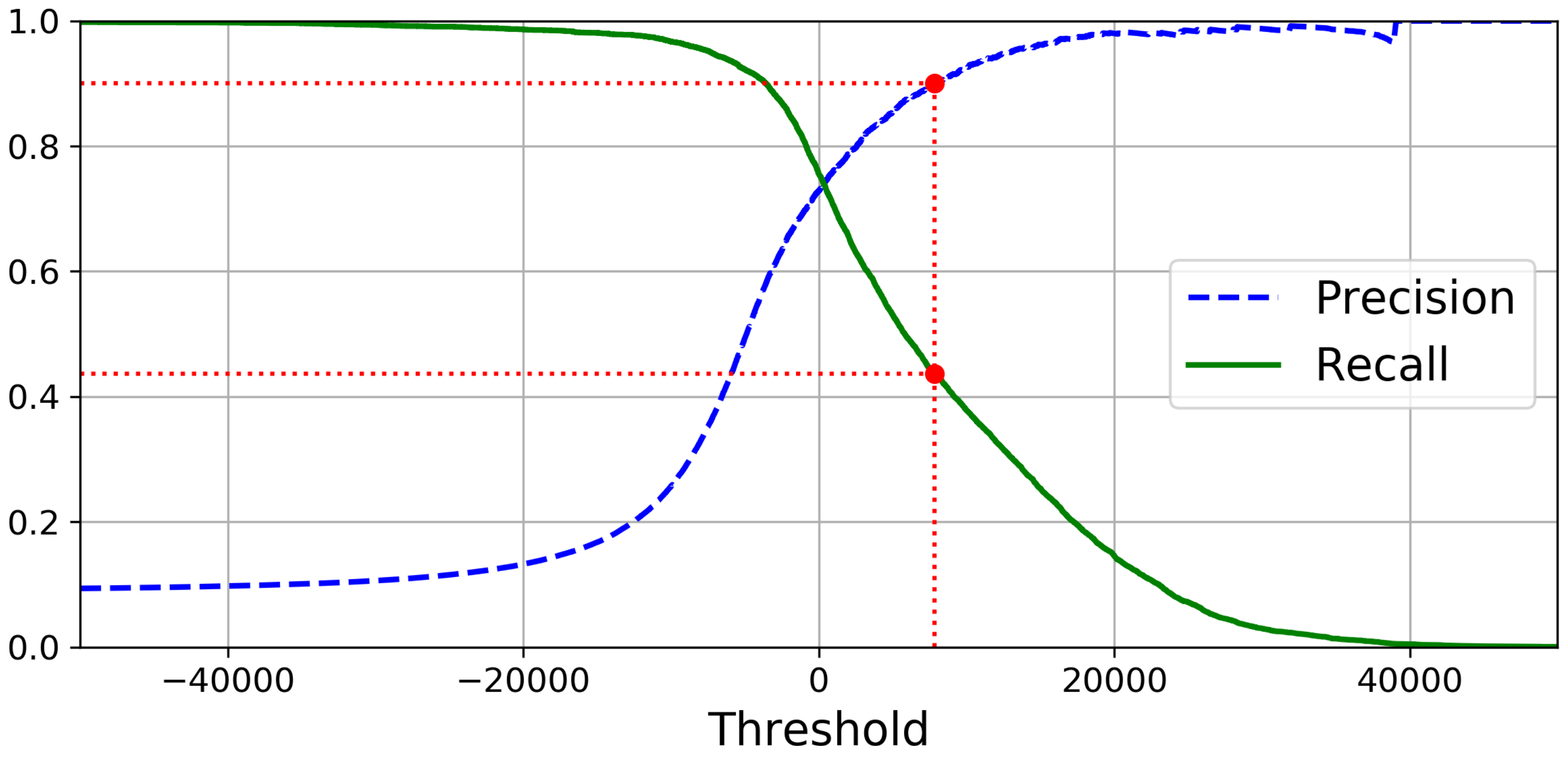
- The function **cross_val_predict()** can return **decision scores** instead of predictions.

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

- These scores can be used to compute precision and recall for all possible thresholds using the **precision_recall_curve()** function.

```
from sklearn.metrics import precision_recall_curve

precisions, recalls, thresholds = precision_recall_curve(y_train_5, y_scores)
```

3.5. Precision/Recall Tradeoff



3.5. Precision/Recall Tradeoff

- For **larger precision**, **increase the threshold**, and **decrease it** for **larger recall**.
- **Example**: To get 90% precision.

The first threshold with precision ≥ 90%

```
threshold_90_precision = thresholds[np.argmax(precisions >= 0.90)] # ~7816

y_train_pred_90 = (y_scores >= threshold_90_precision)

>>> precision_score(y_train_5, y_train_pred_90)
0.9000380083618396
>>> recall_score(y_train_5, y_train_pred_90)
0.4368197749492714
```

True when score ≥ new threshold

Outline

1. MNIST dataset
2. Training a binary classifier
3. Performance measures
4. Multiclass classification
5. Multilabel classification
6. Exercise

4. Multiclass Classification

- Multiclass classifiers can distinguish between **more than two classes**.
- Some **algorithms** (such as Random Forest classifiers or Naive Bayes classifiers) are **capable of handling multiple classes** directly.
- **Others** (such as Support Vector Machine classifiers or Linear classifiers) are **strictly binary classifiers**.
- There are **two main strategies** to perform multiclass classification using multiple binary classifiers.

4.1. One-versus-All (OvA) Strategy

- For example, classify the digit images into 10 classes (from 0 to 9) to **train 10 binary classifiers**, one for each digit (a 0-detector, a 1-detector, a 2-detector, and so on).
- Then to classify an image, get the decision score from each classifier for that image and select the class whose classifier outputs the **highest score**.

4.2. One-versus-One (OvO) Strategy

- Train a binary classifier **for every pair** of digits.
- If there are N classes, need **N × (N – 1) / 2** classifiers. For MNIST, **need 45 classifiers**.
- To classify an image, run the image through all 45 classifiers and see which class **wins the most duels**.
- The main advantage of **OvO** is that each classifier only needs to be **trained on a subset** of the training set.
- OvO is preferred for algorithms (such as **Support Vector Machine**) that scale poorly with the size of the training set.

4.3. Scikit Learn Support of Multiclass Classification

- **Scikit-Learn** detects when you try to use a binary classification algorithm for a multiclass classification task, and it automatically runs **OvA** (except for **SVM** classifiers for which it uses **OvO**).

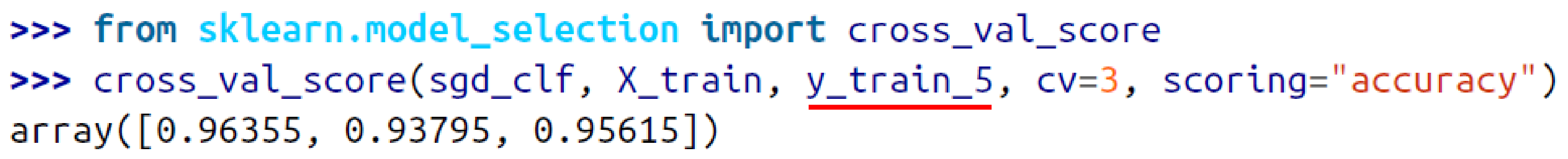
```
>>> sgd_clf.fit(X_train, y_train)  # y_train, not y_train_5
>>> sgd_clf.predict([some_digit])
array([5], dtype=uint8)
```

```
from sklearn.ensemble import RandomForestClassifier

forest_clf = RandomForestClassifier(random_state=42)

>>> forest_clf.fit(X_train, y_train)
>>> forest_clf.predict([some_digit])
array([5], dtype=uint8)
```

Better classifier than SGD

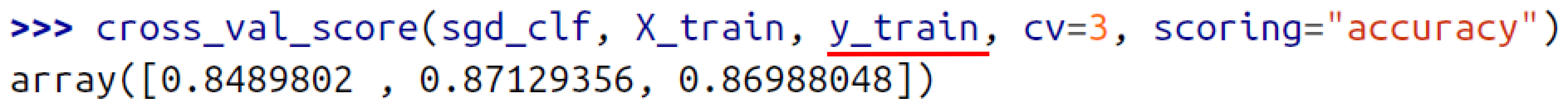
4.3. Scikit Learn Support of Multiclass Classification

- Note that the multiclass task is harder than the binary task.
- **Binary task**



```
>>> from sklearn.model_selection import cross_val_score
>>> cross_val_score(sgd_clf, X_train, y_train_5, cv=3, scoring="accuracy")
array([0.96355, 0.93795, 0.95615])
```

- **Multiclass task**



```
>>> cross_val_score(sgd_clf, X_train, y_train, cv=3, scoring="accuracy")
array([0.8489802 , 0.87129356, 0.86988048])
```

4.4. Error Analysis

```
>>> 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([[5578,    0,   22,    7,    8,   45,   35,    5,  222,    1],
       [   0, 6410,   35,   26,    4,   44,    4,    8,  198,   13],
       [  28,   27, 5232,  100,   74,   27,   68,   37,  354,   11],
       [  23,   18,  115, 5254,    2,  209,   26,   38,  373,   73],
       [  11,   14,   45,   12, 5219,   11,   33,   26,  299,  172],
       [  26,   16,   31,  173,   54, 4484,   76,   14,  482,   65],
       [  31,   17,   45,    2,   42,   98, 5556,    3,  123,    1],
       [  20,   10,   53,   27,   50,   13,    3, 5696,  173,  220],
       [  17,   64,   47,   91,    3,  125,   24,   11, 5421,   48],
       [  24,   18,   29,   67,  116,   39,    1,  174,  329, 5152]])
```

Many images are misclassified as 8s.

Outline

5. Multilabel Classification

- Classifiers that output **multiple classes for each instance**.

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

knn_clf = KNeighborsClassifier()
knn_clf.fit(X_train, y_multilabel)

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

Popular algorithm

Summary

1. MNIST dataset
2. Training a binary classifier
3. Performance measures
4. Multiclass classification
5. Multilabel classification
6. Exercise

Exercise

- Try to build a classifier for the MNIST dataset that achieves over 97% accuracy on the test set. Hint: the `KNeighborsClassifier` works quite well for this task; you just need to find good hyperparameter values (try a grid search on the `weights` and `n_neighbors` hyperparameters).