# Classification

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Reference: *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* by Aurélien Géron (O'Reilly). 2019, 978-1-492-03264-9.

# Introduction

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

https://youtu.be/Lf2bCQIktTo

# Outline

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

# 1. MNIST Dataset

- MNIST is a set of 70,000 small images of handwritten digits.
- Available from [mldata.org](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

```
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:]
```

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# 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])
```

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# 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

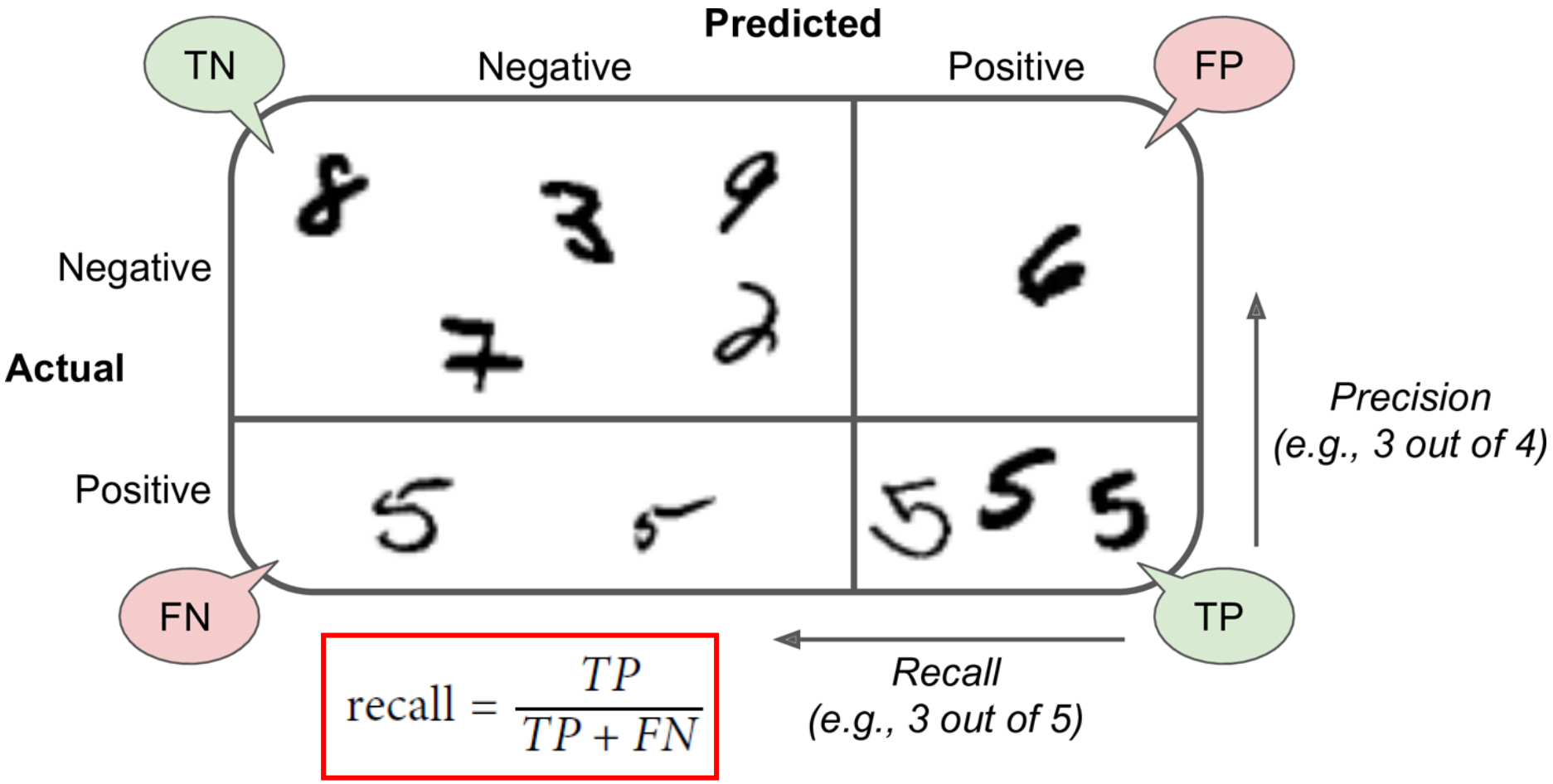
- Use cross_val_predict() to predict the targets of the entire training set.

```
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**

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

**Recall**

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

```
>>> 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

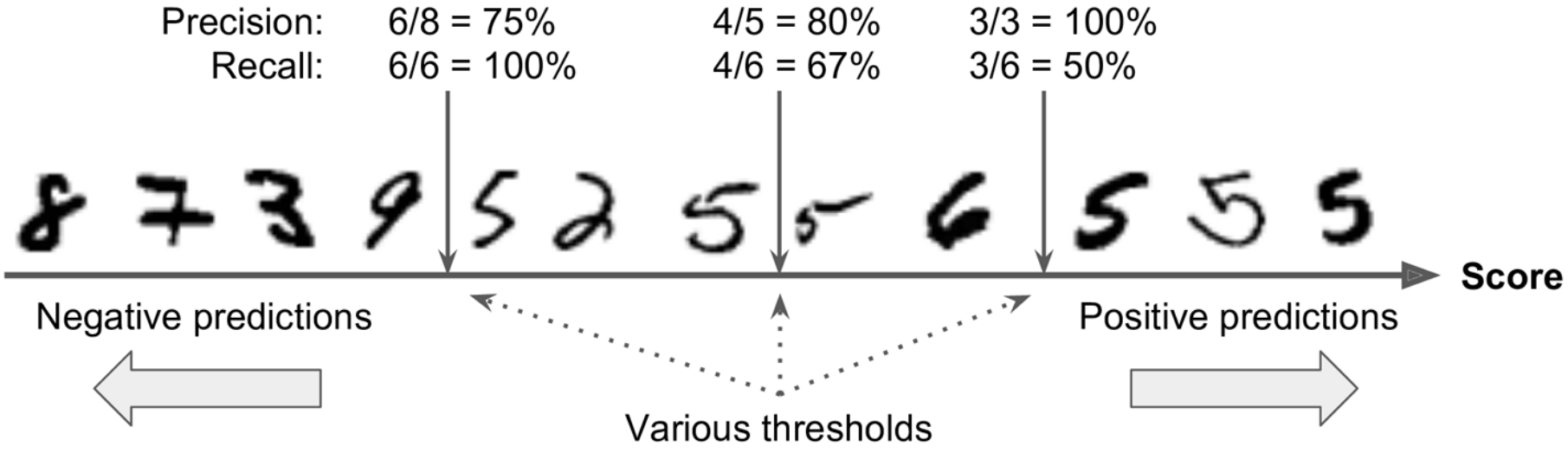
- The F1 Score combines the precision and recall in one metric (harmonic mean).

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

```
>>> 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.

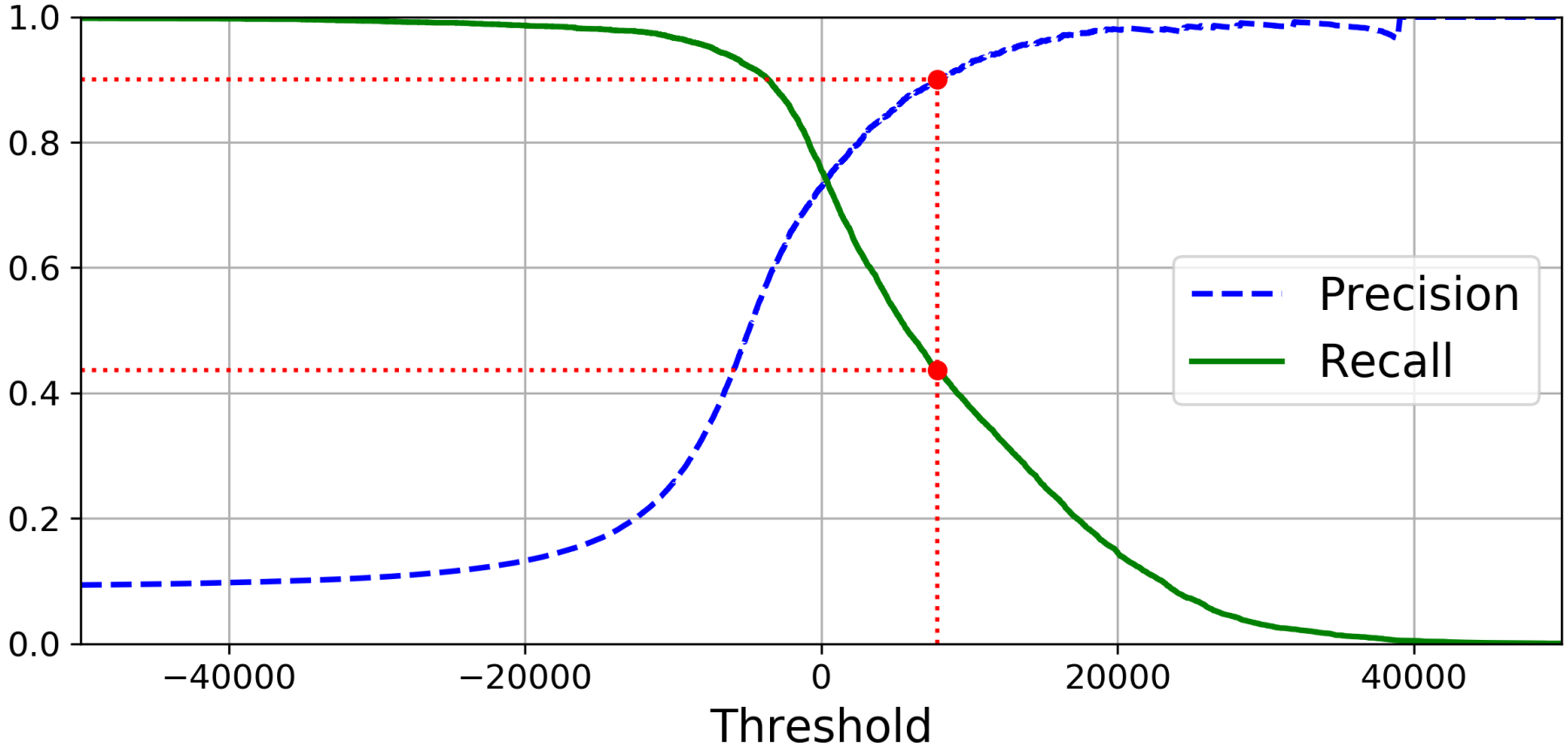
```
y_scores = cross_val_predict(sgd_clf, X_train, y_train_5, cv=3,
                             method="decision_function")
```

- 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

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# 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.

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# 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

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# 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).