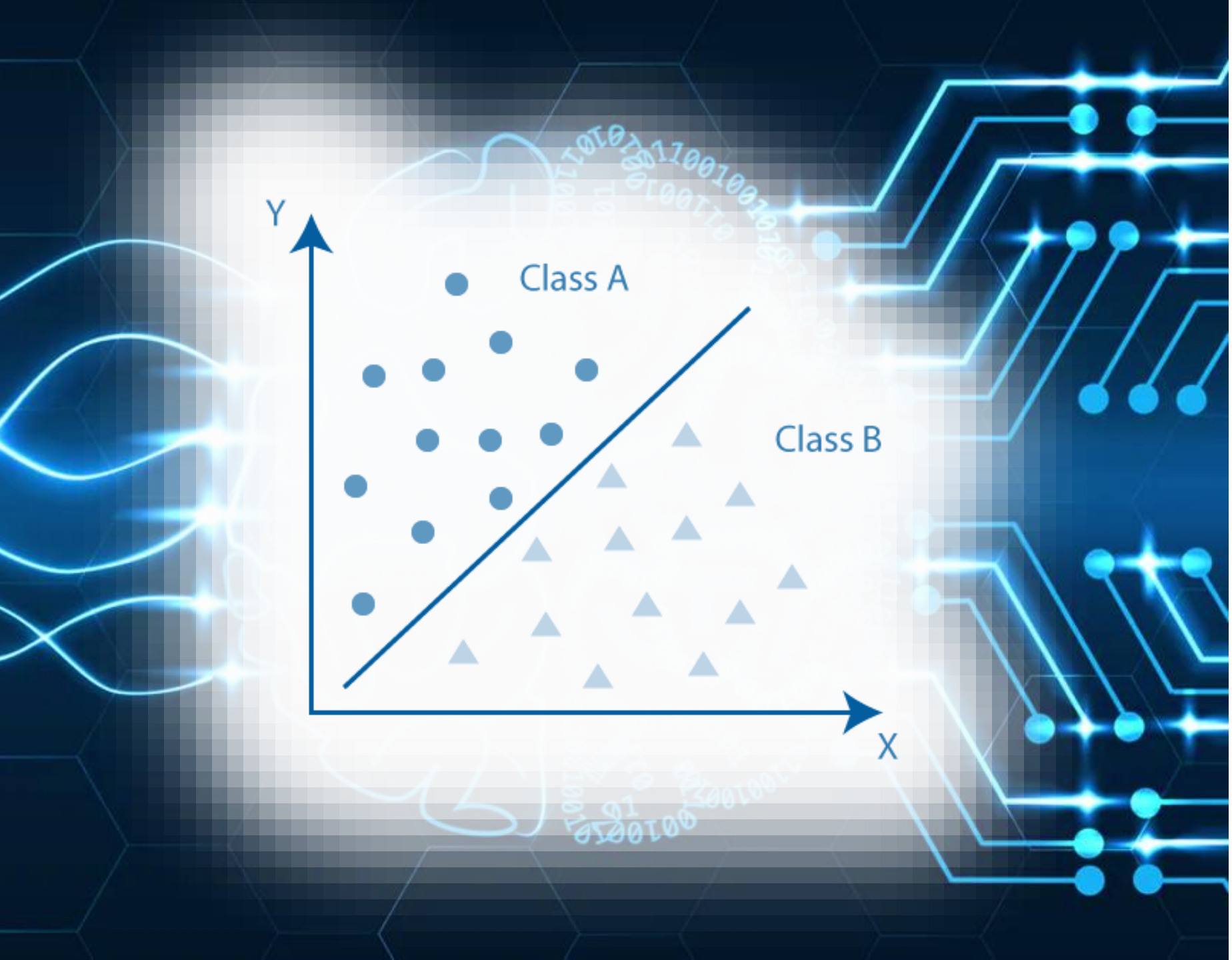

طبقه بندی
(Classification)

اسفند ۱۴۰۱

دانشکده مهندسی صنایع

دانشگاه صنعتی شریف

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Classification

In this chapter we will be using the MNIST dataset, which 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: whenever people come up with a new classification algorithm, they are curious to see how it will perform on MNIST, and anyone who learns Machine Learning tackles this dataset sooner or later.

MNIST

Scikit-Learn provides many helper functions to download popular datasets. MNIST is one of them. The following code fetches the MNIST dataset:

```
>>> 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'])
```

MNIST

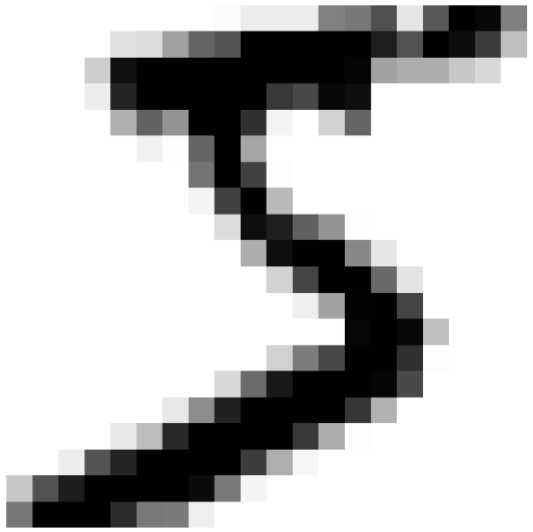
Datasets loaded by Scikit-Learn generally have a similar dictionary structure, including the following:

- A DESCR key describing the dataset
- A data key containing an array with one row per instance and one column per feature
- A target key containing an array with the labels

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

MNIST

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).
Let's take a peek at one digit from the dataset. All you need to do is grab an instance's feature vector, reshape it to a 28 × 28 array, and display it using Matplotlib's imshow() function:



MNIST

Figure 3-1. Digits from the MNIST dataset

MNIST

Note that the label is a string. Most ML algorithms expect numbers, so let's cast y to integer:

```
>>> y = y.astype(np.uint8)
```

But wait! You should always create a test set and set it aside before inspecting the data closely. 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):

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

MNIST

The training set is already shuffled for us, which is good because this guarantees that all cross-validation folds will be similar (you don't want one-fold to be missing some digits). Moreover, some learning algorithms are sensitive to the order of the training instances, and they perform poorly if they get many similar instances in a row. Shuffling the dataset ensures that this won't happen.

Training a Binary Classifier

Let’s simplify the problem for now and only try to identify one digit—for example, the number 5. This “5-detector” will be an example of a binary classifier, capable of distinguishing between just two classes, 5 and not-5. Let’s create the target vectors for this classification task:

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

Training a Binary Classifier

Now let's pick a classifier and train it. A good place to start is with a Stochastic Gradient Descent (SGD) classifier, using Scikit-Learn's SGDClassifier class. This classifier has the advantage of being capable of handling very large datasets efficiently. This is in part because SGD deals with training instances independently, one at a time (which also makes SGD well suited for online learning), as we will see later. Let's create an SGDClassifier and train it on the whole training set:

```
from sklearn.linear_model import SGDClassifier

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

Performance Measure

Evaluating a classifier is often significantly trickier than evaluating a regressor, so we will spend a large part of this chapter on this topic. There are many performance measures available, so get ready to learn many new concepts and acronyms!

Measuring Accuracy Using Cross-Validation

Let’s use the cross_val_score() function to evaluate our SGDClassifier model, using K-fold cross-validation with three folds.
Remember that K-fold cross-validation means splitting the training set into K folds (in this case, three), then making predictions and evaluating them on each fold using a model trained on the remaining folds as we did in the last chapter.

```
>>> 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])
```

Measuring Accuracy Using Cross-Validation

Wow! Above 93% accuracy (ratio of correct predictions) on all cross-validation folds? This looks amazing, doesn't it? Well, before you get too excited, let's look at a very dumb classifier that just classifies every single image in the "not-5" class:

```
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)
```

```
>>> never_5_clf = Never5Classifier()
>>> cross_val_score(never_5_clf, X_train, y_train_5, cv=3,
scoring="accuracy")
array([0.91125, 0.90855, 0.90915])
```

Measuring Accuracy Using Cross-Validation

That’s right, it has over 90% accuracy! This is simply because only about 10% of the images are 5s, so if you always guess that an image is not a 5, you will be right about 90% of the time. This demonstrates why accuracy is generally not the preferred performance measure for classifiers, especially when you are dealing with skewed datasets (i.e., when some classes are much more frequent than others).

```
>>> never_5_clf = Never5Classifier()
>>> cross_val_score(never_5_clf, X_train, y_train_5, cv=3,
scoring="accuracy")
array([0.91125, 0.90855, 0.90915])
```

Confusion Matrix

A much better way to evaluate the performance of a classifier is to look at the **confusion matrix**. The general idea is to count the number of times instances of class A are classified as class B. For example, to know the number of times the classifier confused images of 5s with 3s, you would look in the fifth row and third column of the confusion matrix. To compute the confusion matrix, you first need to have a set of predictions so that they can be compared to the actual targets. You could make predictions on the test set, but let's keep it untouched for now (remember that you want to use the test set only at the very end of your project, once you have a classifier that you are ready to launch). Instead, you can use the cross_val_predict() function:

```
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

Each row in a confusion matrix represents an actual class, while each column represents a predicted class.

The first row of this matrix considers non-5 images (the negative class): 53,057 of them were correctly classified as non-5s (they are called true negatives), while the remaining1,522 were wrongly classified as 5s (false positives).

The second row considers the images of 5s (the positive class): 1,325 were wrongly classified as non-5s (false negatives), while the remaining 4,096 were correctly classified as 5s (true positives).

A perfect classifier would have only true positives and true negatives, so its confusion matrix would have nonzero values only on its main diagonal (top left to bottom right):

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

```
>>> y_train_perfect_predictions = y_train_5  # pretend we reached
perfection
>>> confusion_matrix(y_train_5, y_train_perfect_predictions)
array([[54579,     0],
       [    0,  5421]])
```

Confusion Matrix

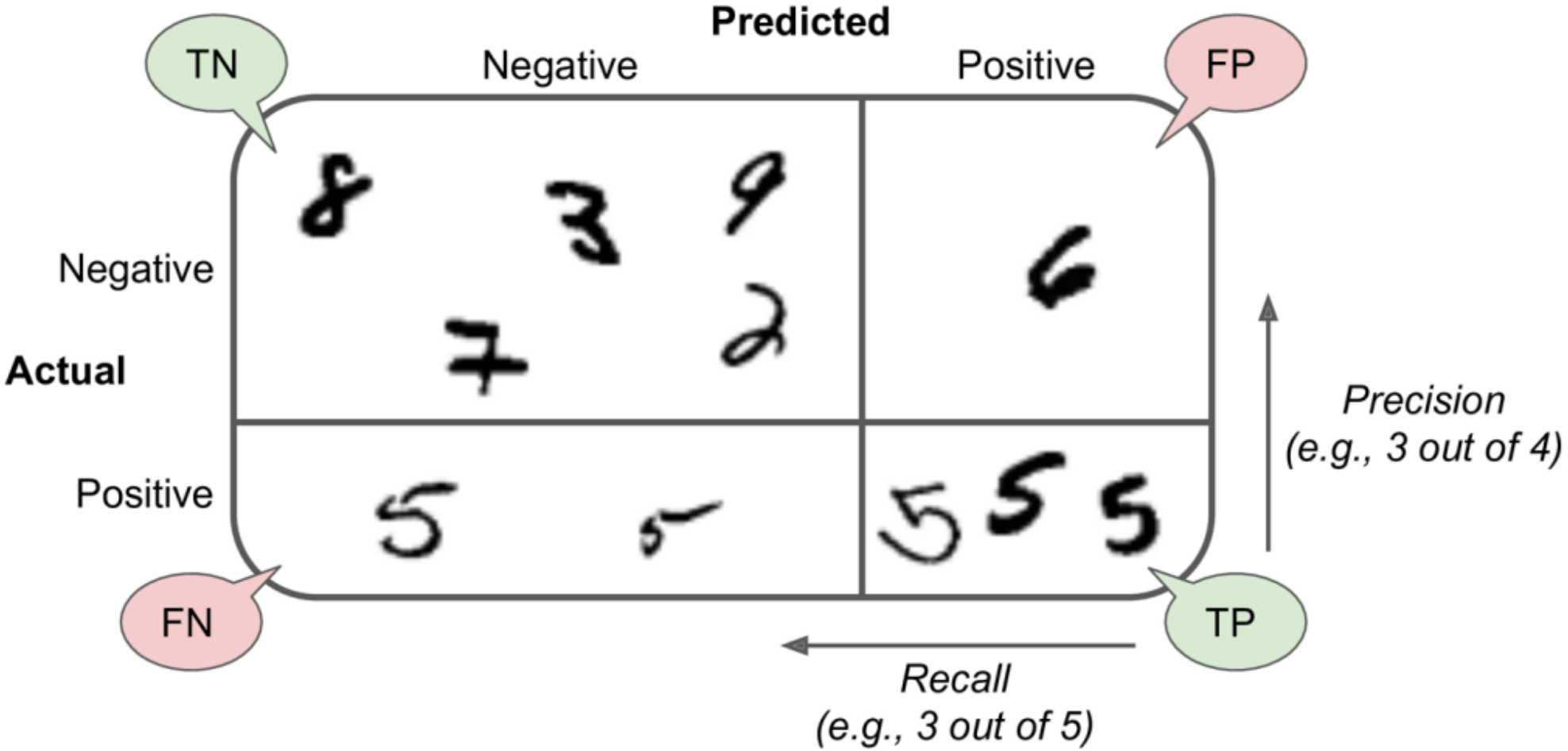


Figure 3-2. An illustrated confusion matrix shows examples of true negatives (top left), false positives (top right), false negatives (lower left), and true positives (lower right)

Precision, Recall, and F1 Score

It is often convenient to combine precision and recall into a single metric called the F1 score, in particular if you need a simple way to compare two classifiers. The F1 score is the harmonic mean of precision and recall (below Equation). Whereas the regular mean treats all values equally, the harmonic mean gives much more weight to low values. As a result, the classifier will only get a high F1 score if **both recall, and precision** are high.

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

```
>>> from sklearn.metrics import 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
```

Precision, Recall, and F1 Score

The F1 score favors classifiers that have similar precision and recall. This is **not** always what you want: in some contexts, you mostly care about precision, and in other contexts you really care about recall. For example, if you trained a classifier to detect videos that are safe for kids, you would probably prefer a classifier that rejects many good videos (**low recall**) but keeps only safe ones (**high precision**), rather than a classifier that has a much higher recall but lets a few really bad videos show up in your product. On the other hand, suppose you train a classifier to detect shoplifters in surveillance images: it is probably fine if your classifier has only **30% precision** as long as it has **99% recall**.

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

Precision/Recall Trade-off

Unfortunately, you can't have it both ways: increasing precision reduces recall, and vice versa. This is called the **precision/recall trade-off**.

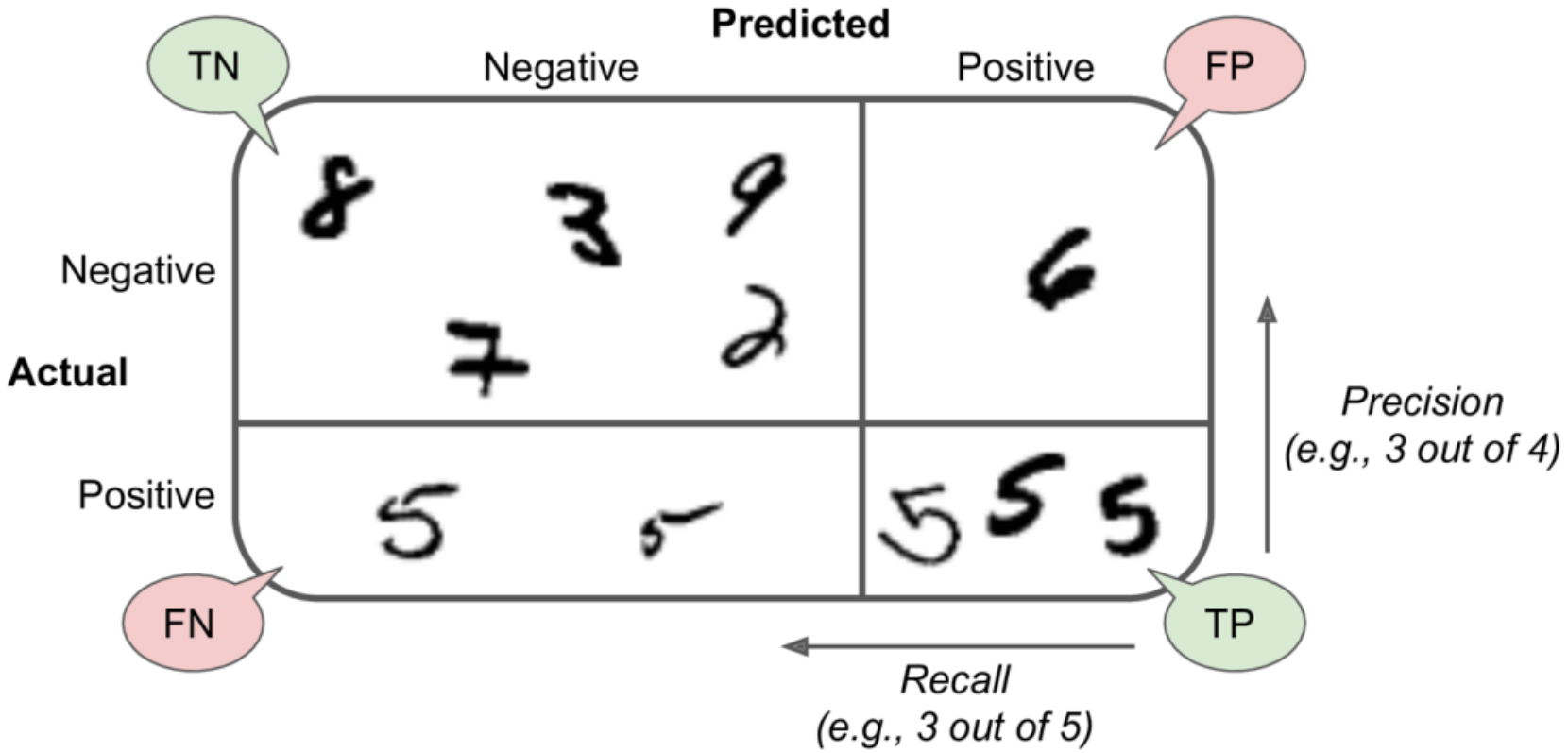


Figure 3-2. An illustrated confusion matrix shows examples of true negatives (top left), false positives (top right), false negatives (lower left), and true positives (lower right)

Precision/Recall Trade-off

To understand this trade-off, let's look at how the SGDClassifier makes its classification decisions. For each instance, it computes a score based on a decision function. If that score is greater than a threshold, it assigns the instance to the positive class; otherwise it assigns it to the negative class. Figure 3-3 shows a few digits positioned from the lowest score on the left to the highest score on the right.

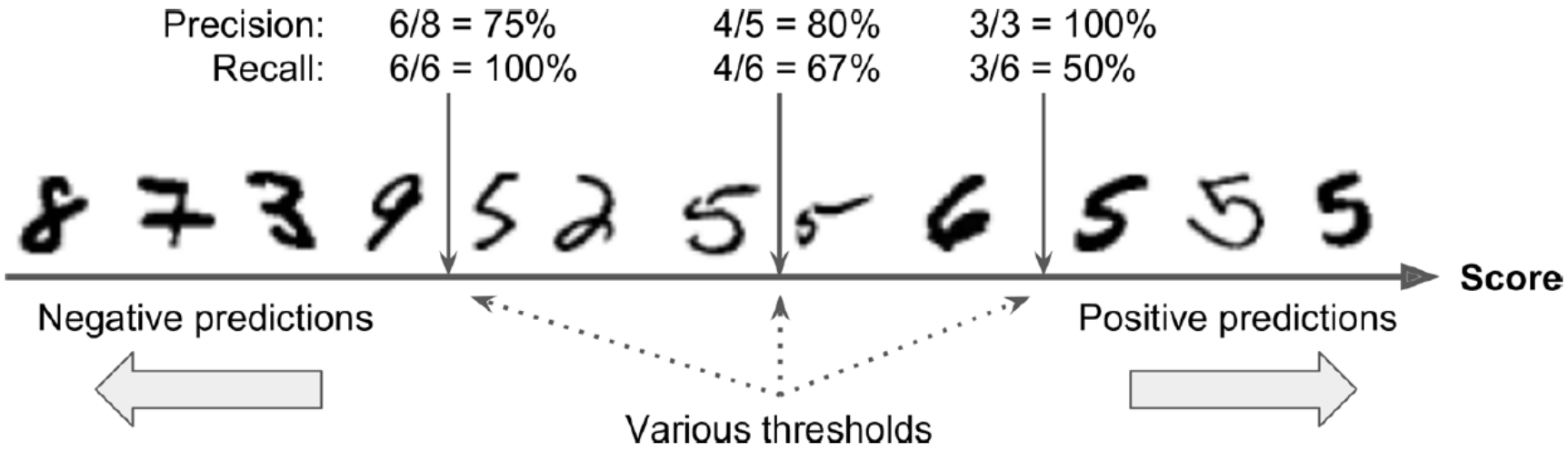


Figure 3-3. In this precision/recall trade-off, images are ranked by their classifier score, and those above the chosen decision threshold are considered positive; the higher the threshold, the lower the recall, but (in general) the higher the precision

Precision/Recall Trade-off

Suppose the decision threshold is positioned at the central arrow (between the two 5s): you will find 4 true positives (actual 5s) on the right of that threshold, and 1 false positive (actually a 6). Therefore, with that threshold, the precision is 80% (4 out of 5). But out of 6 actual 5s, the classifier only detects 4, so the recall is 67% (4 out of 6). If you raise the threshold (move it to the arrow on the right), the false positive (the 6) becomes a true negative, thereby increasing the precision (up to 100% in this case), but one true positive becomes a false negative, decreasing recall down to 50%. Conversely, lowering the threshold increases recall and reduces prec

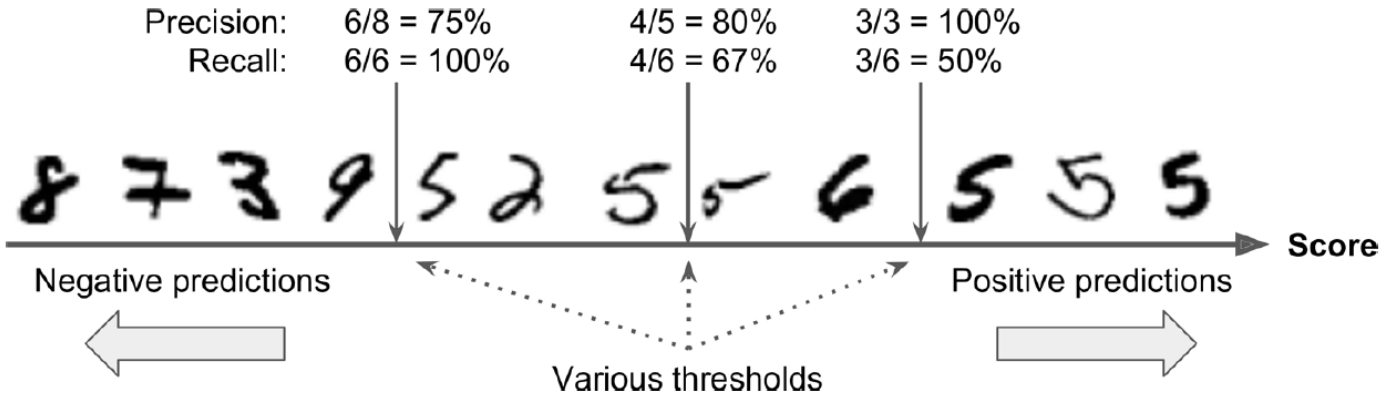


Figure 3-3. In this precision/recall trade-off, images are ranked by their classifier score, and those above the chosen decision threshold are considered positive; the higher the threshold, the lower the recall, but (in general) the higher the precision

Precision and Recall in Sklearn

Scikit-Learn does not let you set the threshold directly, but it does give you access to the decision scores that it uses to make predictions. Instead of calling the classifier's predict() method, you can call its decision_function() method, which returns a score for each instance, and then use any threshold you want to make predictions based on those scores:

```
>>> y_scores = sgd_clf.decision_function([some_digit])
>>> y_scores
array([2412.53175101])
>>> threshold = 0
>>> y_some_digit_pred = (y_scores > threshold)
array([ True])
```

Precision and Recall in Sklearn

The SGDClassifier uses a threshold equal to 0, so the previous code returns the same result as the predict() method (i.e., True). Let's raise the threshold:

```
>>> threshold = 8000
>>> y_some_digit_pred = (y_scores > threshold)
>>> y_some_digit_pred
array([False])
```

Precision and Recall in Sklearn

This confirms that **raising the threshold decreases recall.** The image actually, represents a 5, and the classifier detects it when the threshold is 0, but it misses it when the threshold is increased to 8,000.

How do you decide **which threshold** to use? First, use the cross_val_predict() function to get the scores of all instances in the training set, but this time specify that you want to return decision scores instead of predictions. With these scores, use the precision_recall_curve() function to compute precision and recall for all possible thresholds

```
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)
```

Precision/Recall Trade-off

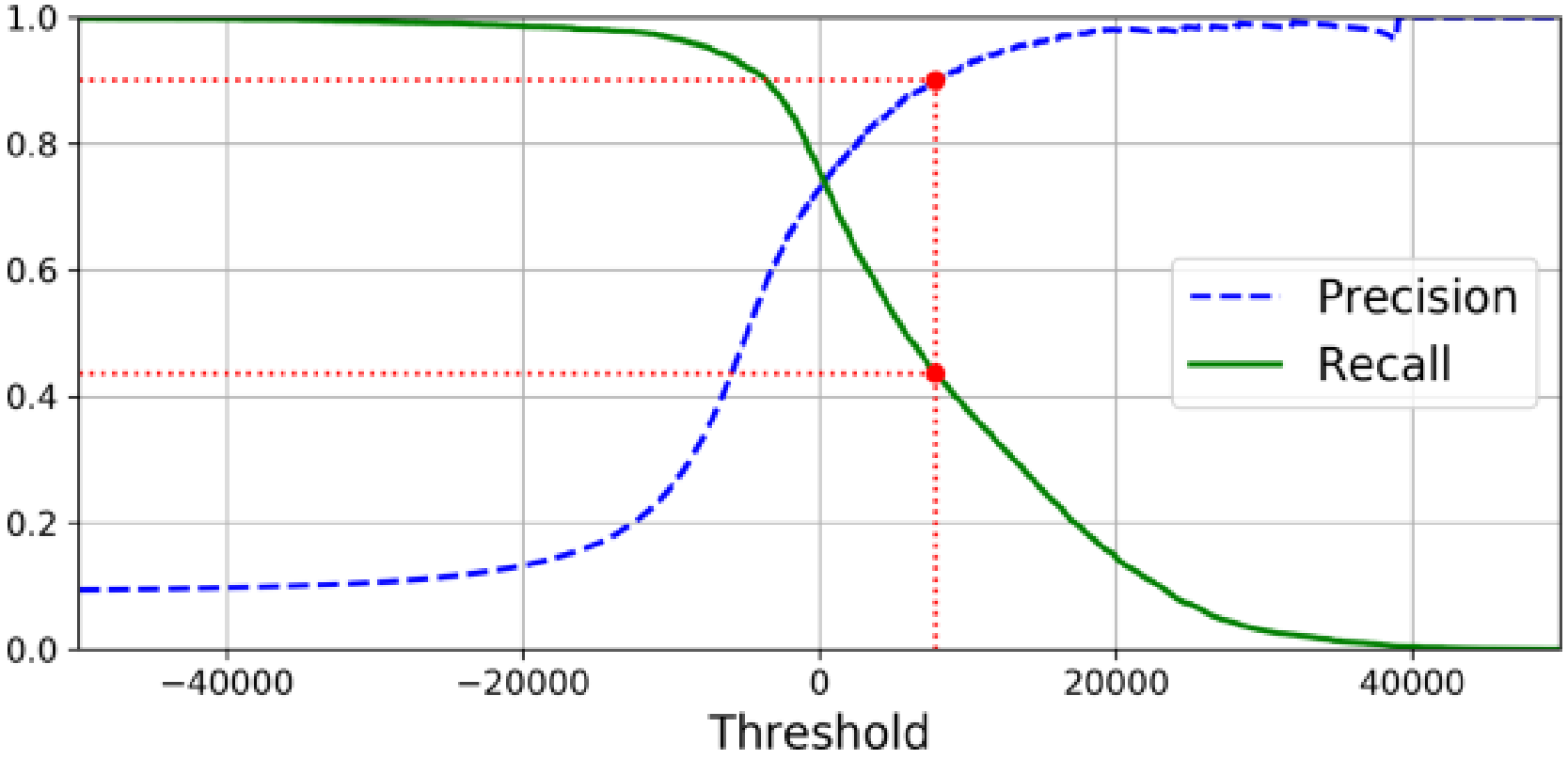


Figure 3-4. Precision and recall versus the decision threshold

Precision/Recall Trade-off

Another way to select a good precision/recall trade-off is to plot precision directly against recall, as shown in Figure 3-5 (the same threshold as earlier is highlighted).

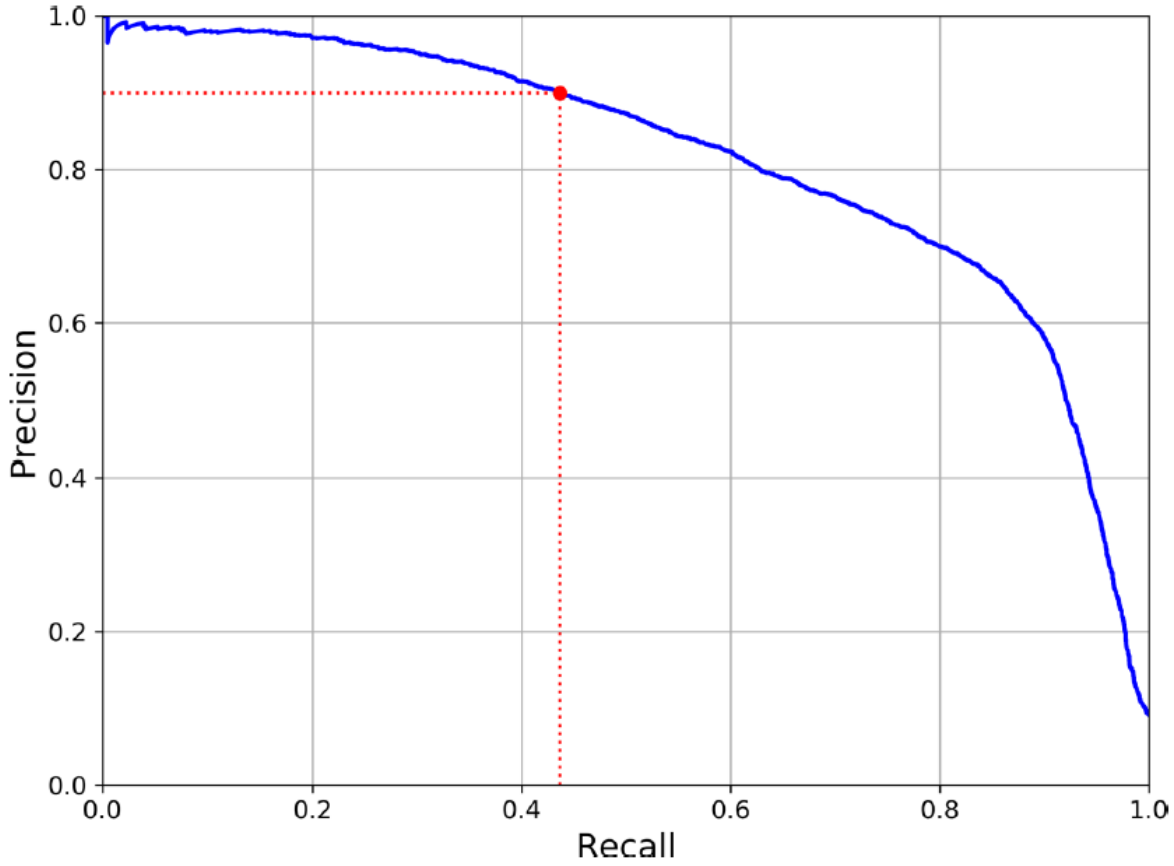


Figure 3-5. Precision versus recall

The ROC Curve

The **receiver operating characteristic (ROC)** curve is another common tool used with binary classifiers. It is very similar to the precision/recall curve, but instead of plotting precision versus recall, the ROC curve plots the **true positive rate** (another name for recall) against the **false positive rate** (FPR). The FPR is the ratio of negative instances that are incorrectly classified as positive. It is equal to 1 – the true negative rate (TNR), which is the ratio of negative instances that are correctly classified as negative. The TNR is also called **specificity.** Hence, the ROC curve plots **sensitivity (recall) versus 1 – specificity**. To plot the ROC curve, you first use the roc_curve() function to compute the TPR and FPR for various threshold values:

```
from sklearn.metrics import roc_curve

fpr, tpr, thresholds = roc_curve(y_train_5, y_scores)
```

The ROC Curve

Once again there is a trade-off: the higher the recall (TPR), the more false positives (FPR) the classifier produces. The dotted line represents the ROC curve of a purely random classifier; a good classifier stays as **far away** from that line as possible (toward the top-left corner).

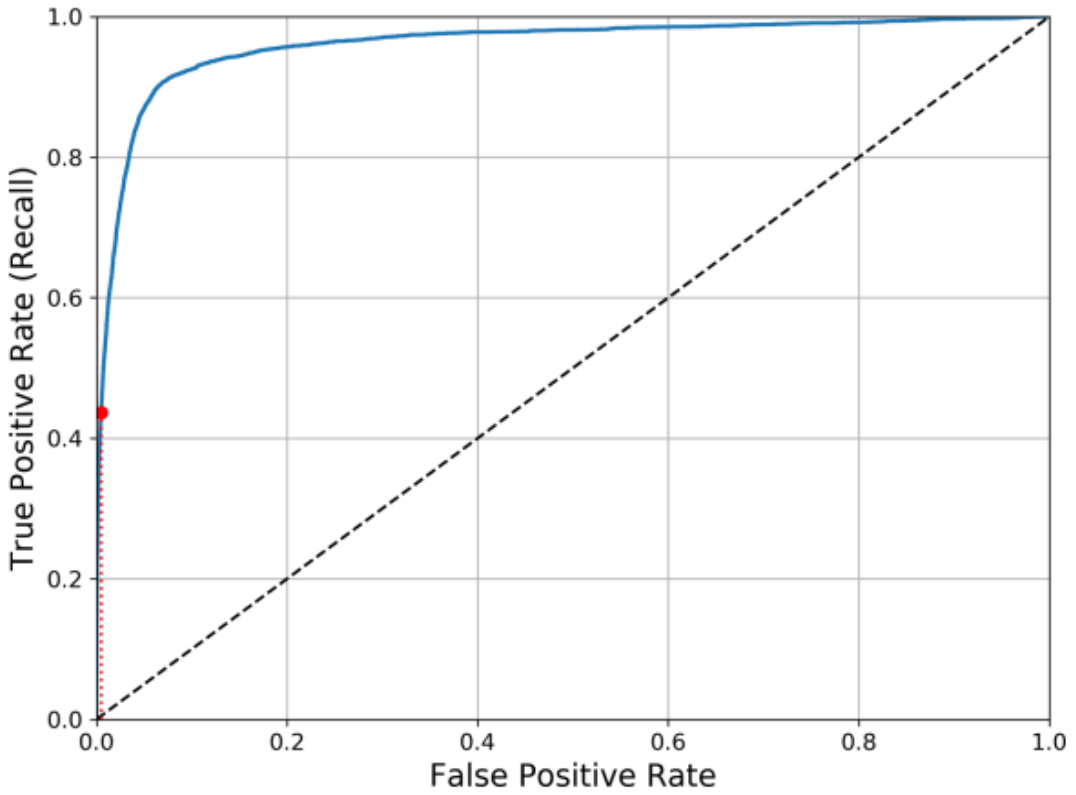


Figure 3-6. This ROC curve plots the false positive rate against the true positive rate for all possible thresholds; the red circle highlights the chosen ratio (at 43.68% recall)

The AUC

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**, whereas a purely random classifier will have a ROC AUC equal to **0.5**. Scikit-Learn provides a function to compute the ROC AUC:

```
>>> from sklearn.metrics import roc_auc_score
>>> roc_auc_score(y_train_5, y_scores)
0.9611778893101814
```

Compare ROC AUC Scores

Let's now train a **RandomForestClassifier** and compare its ROC curve and ROC AUC score to those of the **SGDClassifier**. First, you need to get scores for each instance in the training set. But due to the way it works, the RandomForestClassifier class does not have a decision_function() method. Instead, it has a predict_proba() method. Scikit-Learn classifiers generally have one or the other, or both. The predict_proba() method returns an array containing a row per instance and a column per class, each containing the probability that the given instance belongs to the given class (e.g., 70% chance that the image represents a 5):

```
from sklearn.ensemble import RandomForestClassifier

forest_clf = RandomForestClassifier(random_state=42)
y_probas_forest = cross_val_predict(forest_clf, X_train, y_train_5, cv=3,
                                    method="predict_proba")
```

Compare ROC AUC Scores

The roc_curve() function expects labels and scores, but instead of scores you can give it class probabilities. Let's use the positive class's probability as the score:

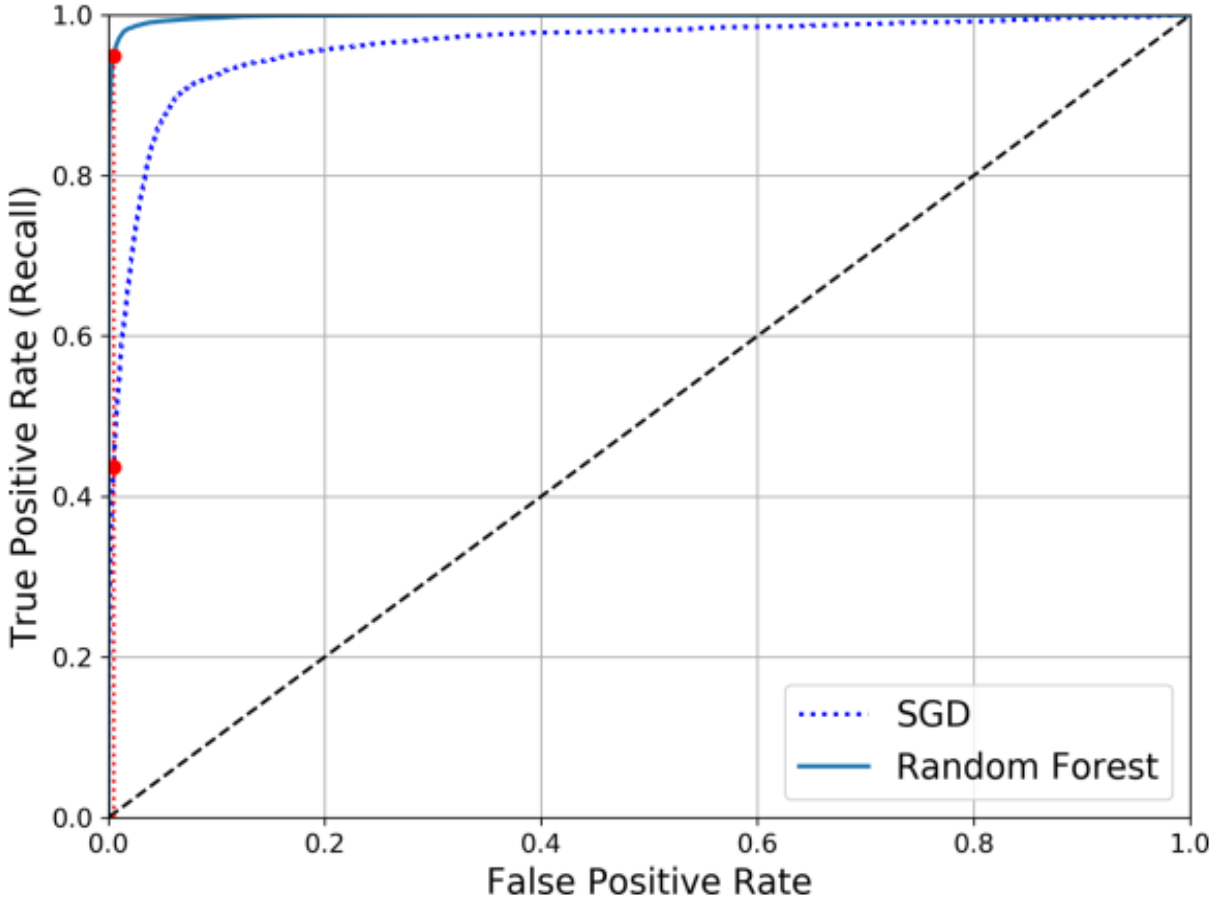


Figure 3-7. Comparing ROC curves: the Random Forest classifier is superior to the SGD classifier because its ROC curve is much closer to the top-left corner, and it has a greater AUC

Compare ROC AUC Scores

RandomForestClassifier’s ROC curve looks **much better** than the SGDClassifier’s.

It comes much closer to the top-left corner. As a result, its ROC AUC score is also significantly better:

```
>>> roc_auc_score(y_train_5, y_scores_forest)
0.9983436731328145
```

Multiclass Classification

You now know how to train binary classifiers, choose the appropriate metric for your task, evaluate your classifiers using cross-validation, select the precision/recall trade-off that fits your needs, and use ROC curves and ROC AUC scores to compare various models. Now let’s try to detect more than just the 5s.

Multiclass Classification

Whereas binary classifiers distinguish between two classes, multiclass classifiers (also called multinomial classifiers) can distinguish between more than two classes. Some algorithms (such as SGD classifiers, Random Forest classifiers, and naive Bayes classifiers) are capable of handling multiple classes natively. Others (such as Logistic Regression or Support Vector Machine classifiers) are strictly binary classifiers. However, there are various strategies that you can use to perform multiclass classification with multiple binary classifiers

Multiclass Classification

One way to create a system that can classify the digit images into 10 classes (from 0 to 9) is to train 10 binary classifiers, one for each digit (a 0-detector, a 1-detector, a 2-detector, and so on). Then when you want to classify an image, you get the decision score from each classifier for that image and you select the class whose classifier outputs the highest score. This is called the **one-versus-the-rest (OvR) strategy** (also called one- versus-all).

Multiclass Classification

Another strategy is to train a binary classifier for every pair of digits: one to distinguish 0s and 1s, another to distinguish 0s and 2s, another for 1s and 2s, and so on. This is called the **one-versus-one (OvO) strategy**. If there are N classes, you need to train **N × (N – 1) / 2** classifiers. For the MNIST problem, this means training 45 binary classifiers! When you want to classify an image, you have to 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 the part of the training set for the two classes that it must distinguish.

Multiclass Classification

Some algorithms (such as Support Vector Machine classifiers) scale poorly with the size of the training set. For these algorithms OvO is preferred because it is faster to train many classifiers on small training sets than to train few classifiers on large training sets. For most binary classification algorithms, however, OvR is preferred.

Multiclass Classification

Scikit-Learn detects when you try to use a binary classification algorithm for a multiclass classification task, and it automatically runs OvR or OvO, depending on the algorithm. Let's try this with a Support Vector Machine classifier (see Chapter 5), using the sklearn.svm.SVC class:

```
>>> from sklearn.svm import SVC
>>> svm_clf = SVC()
>>> svm_clf.fit(X_train, y_train) # y_train, not y_train_5
>>> svm_clf.predict([some_digit])
array([5], dtype=uint8)
```

This code trains the SVC on the training set using the original target classes from 0 to 9 (y_train), instead of the 5-versus-the-rest target classes (y_train_5). Then it makes a prediction (a correct one in this case). Under the hood, Scikit-Learn actually used the **OvO strategy**. It trained 45 binary classifiers, got their decision scores for the image, and selected the class that won the most duels.

Multiclass Classification

If you call the decision_function() method, you will see that it returns 10 scores per instance (instead of just 1). That's one score per class: The highest score is indeed the one corresponding to class 5

```
>>> some_digit_scores = svm_clf.decision_function([some_digit])
>>> some_digit_scores
array([[ 2.92492871,  7.02307409,  3.93648529,  0.90117363,  5.96945908,
         9.5       ,  1.90718593,  8.02755089, -0.13202708,
4.94216947]])

>>> np.argmax(some_digit_scores)
5
>>> svm_clf.classes_
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
>>> svm_clf.classes_[5]
5
```

Multiclass Classification

If you want to force Scikit-Learn to use one-versus-one or one-versus-the-rest, you can use the OneVsOneClassifier or OneVsRestClassifier classes. Simply create an instance and pass a classifier to its constructor (it does not even have to be a binary classifier).

Multiclass Classification

For example, this code creates a multiclass classifier using the OvR strategy, based on an SVC:

```
>>> from sklearn.multiclass import OneVsRestClassifier
>>> ovr_clf = OneVsRestClassifier(SVC())
>>> ovr_clf.fit(X_train, y_train)
>>> ovr_clf.predict([some_digit])
array([5], dtype=uint8)
>>> len(ovr_clf.estimators_)
10
>>> sgd_clf.fit(X_train, y_train)
>>> sgd_clf.predict([some_digit])
array([5], dtype=uint8)
>>> sgd_clf.decision_function([some_digit])
array([[-15955.22628, -38080.96296, -13326.66695,   573.52692,
-17680.68466,
         2412.53175, -25526.86498, -12290.15705, -7946.05205,
-10631.35889]])
>>> cross_val_score(sgd_clf, X_train, y_train, cv=3, scoring="accuracy")
array([0.8489802 , 0.87129356, 0.86988048])
```

Multiclass Classification

It gets over 84% on all test folds. If you used a random classifier, you would get 10% accuracy, so this is not such a bad score, but you can still do much better. Simply scaling the inputs increases accuracy above 89%:

```
>>> 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")
array([0.89707059, 0.8960948 , 0.90693604])
```

Error Analysis

If this were a real project, you would now follow the steps in your Machine Learning project checklist. You'd explore data preparation options, try out multiple models (shortlisting the best ones and fine-tuning their hyperparameters using GridSearchCV), and automate as much as possible. Here, we will assume that you have found a promising model and you want to find ways to improve it. One way to do this is to analyze the types of errors it makes.

Error Analysis

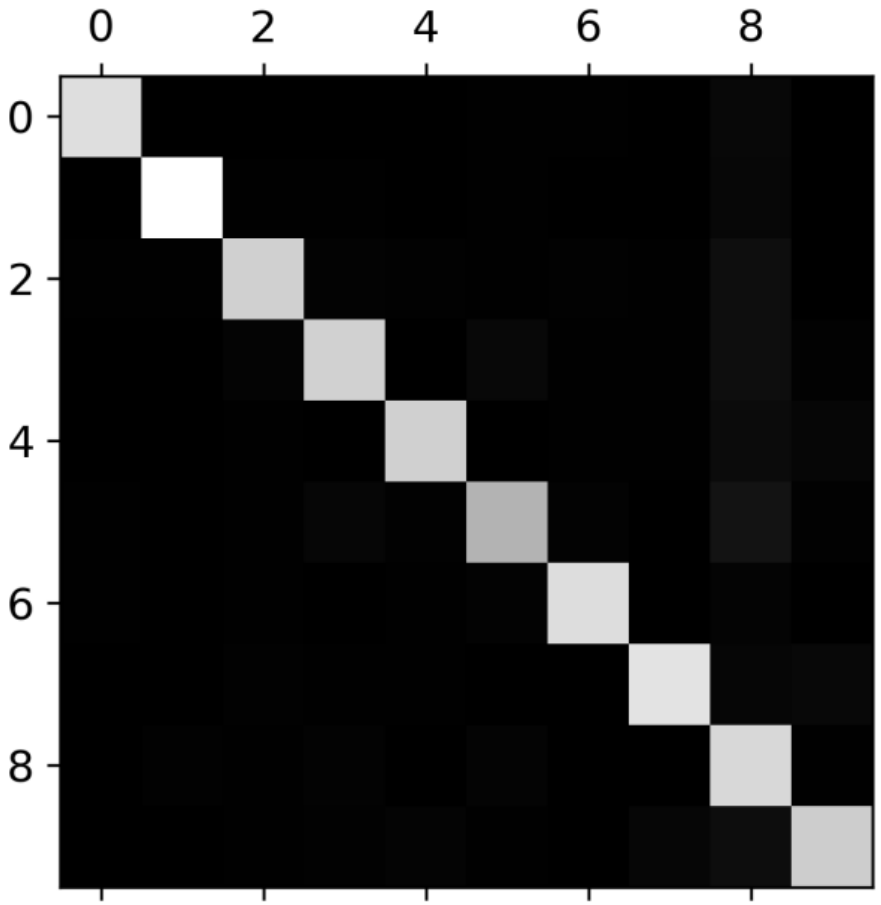
First, look at the **confusion matrix**.

You need to make predictions using the cross_val_predict() function, then call the confusion_matrix() function, just like you did earlier:

```
>>> 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]])
```

Error Analysis

That’s a lot of numbers. It’s often more convenient to look at an image representation of the confusion matrix, using Matplotlib’s matshow() function:

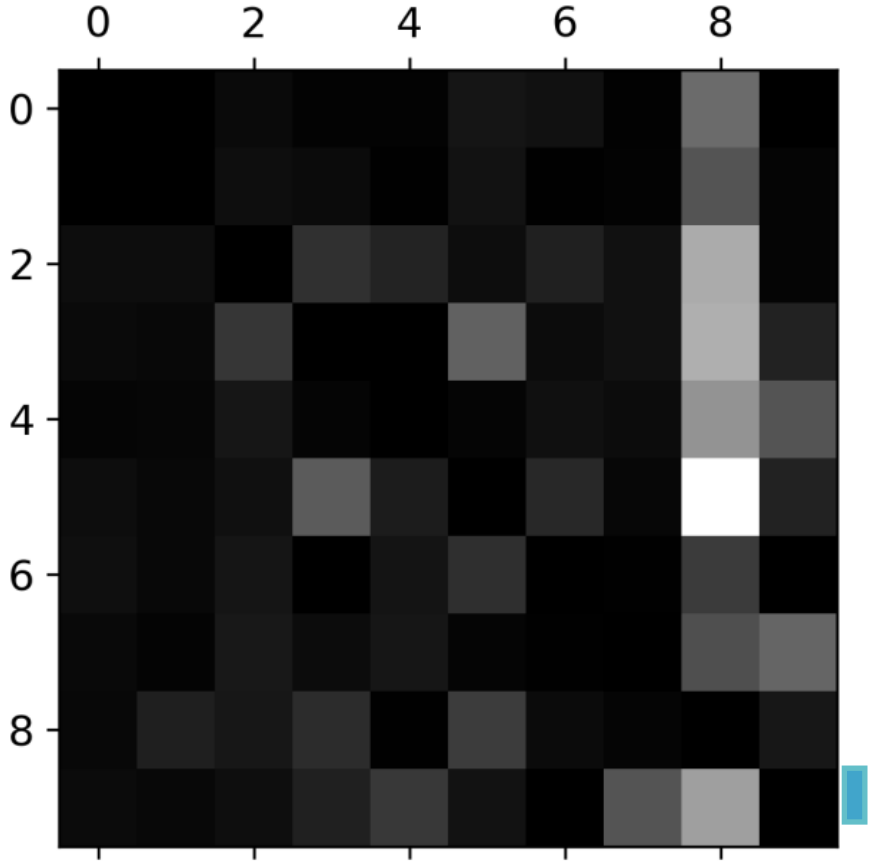


Error Analysis

Let’s focus the plot on the errors. First, you need to divide each value in the confusion matrix by the number of images in the corresponding class so that you can compare error rates instead of absolute numbers of errors (which would make abundant classes look unfairly bad). Fill the diagonal with zeros to keep only the errors, and plot the result:

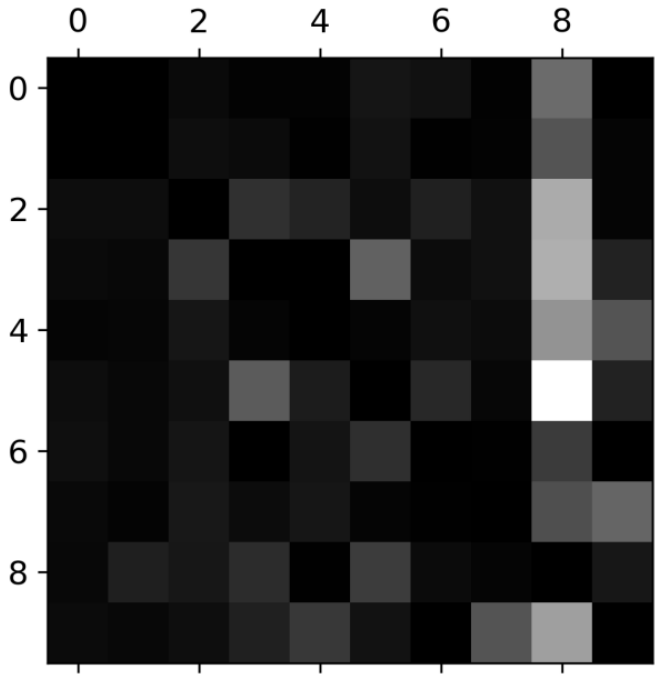
```
row_sums = conf_mx.sum(axis=1, keepdims=True)
norm_conf_mx = conf_mx / row_sums

np.fill_diagonal(norm_conf_mx, 0)
plt.matshow(norm_conf_mx, cmap=plt.cm.gray)
plt.show()
```



Error Analysis

The column for class 8 is quite bright, which tells you that many images get misclassified as 8s. However, the row for class 8 is not that bad, telling you that actual 8s in general get properly classified as 8s. As you can see, the confusion matrix is not necessarily symmetrical. You can also see that 3s and 5s often get confused (in both directions).



Multilabel Classification

Until now each instance has always been assigned to just one class. In some cases, you may want your classifier to **output multiple classes** for each instance. Consider a face-recognition classifier: what should it do if it recognizes several people in the same picture? It should attach one tag per person it recognizes. Say the classifier has been trained to recognize three faces, Alice, Bob, and Charlie. Then when the classifier is shown a picture of Alice and Charlie, it should output [1, 0, 1] (meaning "Alice yes, Bob no, Charlie yes"). Such a classification system that outputs multiple binary tags is called a **multilabel classification system**.

Multilabel Classification

We won't go into face recognition just yet, but let's look at a simpler example, just for illustration purposes: This code creates a y_multilabel array containing two target labels for each digit image: the first indicates whether or not the digit is large (7, 8, or 9), and the second indicates whether or not it is odd. The next lines create a KNeighborsClassifier instance (which supports multilabel classification, though not all classifiers do), and we train it using the multiple targets array. Now you can make a prediction, and notice that it outputs two labels:

```
from sklearn.neighbors import KNeighborsClassifier

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]])
```

Multilabel Classification

There are many ways to **evaluate a multilabel classifier**, and selecting the right metric really depends on your project. One approach is to measure the **F1 score** for each individual label (or any other binary classifier metric discussed earlier), then simply compute the average score. This code computes the average F1 score across all labels: This assumes that all labels are equally important, however, which may not be the case. In particular, if you have many more pictures of Alice than of Bob or Charlie, you may want to give more weight to the classifier's score on pictures of Alice. One simple option is to give each label a weight equal to its support (i.e., the number of instances with that target label). To do this, simply set average="weighted" in the preceding code

```
>>> y_train_knn_pred = cross_val_predict(knn_clf, X_train, y_multilabel,
cv=3)
>>> f1_score(y_multilabel, y_train_knn_pred, average="macro")
0.976410265560605
```

Multioutput Classification

The last type of classification task we are going to discuss here is called **multioutput–multiclass classification** (or simply 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). To illustrate this, let's build a system that removes noise from images. It will take as input a noisy digit image, and it will (hopefully) output a clean digit image, represented as an array of pixel intensities, just like the MNIST images. Notice that the classifier's output is multilabel (one label per pixel) and each label can have multiple values (pixel intensity ranges from 0 to 255).

Multioutput Classification

Let’s start by creating the training and test sets by taking the MNIST images and adding noise to their pixel intensities with NumPy’s randint() function. The target images will be the original images:

```
noise = np.random.randint(0, 100, (len(X_train), 784))
X_train_mod = X_train + noise
noise = np.random.randint(0, 100, (len(X_test), 784))
X_test_mod = X_test + noise
y_train_mod = X_train
y_test_mod = X_test
```

Multioutput Classification

On the left is the noisy input image, and on the right is the clean target image. Now let's train the classifier and make it clean this image:

```
knn_clf.fit(X_train_mod, y_train_mod)
clean_digit = knn_clf.predict([X_test_mod[some_index]])
plot_digit(clean_digit)
```

Multioutput Classification

Looks close enough to the target! This concludes our tour of classification. You should now know how to select good metrics for classification tasks, pick the appropriate precision/recall trade-off, compare classifiers, and more generally build good classification systems for a variety of tasks.