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tags :

- Machine Learning
- Hands on ML - book

Chapter 3 - Hands on

- **MNIST**
  - The `sklearn.datasets` package offers three main types of functions:
    - `fetch_*` **functions** (e.g., `fetch_openml()`): Download real-world datasets.
    - `load_*` **functions**: Load built-in small toy datasets (no internet needed).
    - `make_*` **functions**: Generate synthetic datasets for testing.
  - Generated datasets usually come as `(X, y)` NumPy arrays, while others are returned as `Bunch` objects (dictionary-like), typically containing:
    - `"DESCR"` : Dataset description
    - `"data"` : Input features (2D array)
    - `"target"` : Labels (1D array)
  - The `fetch_openml()` function typically returns inputs as a Pandas DataFrame and labels as a Series. However, for image datasets like MNIST, it's better to set `as_frame=False` to get NumPy arrays, which are more suitable for image data.

    ```
    from sklearn.datasets import fetch_openml
    mnist = fetch_openml('mnist_784', as_frame=False)
    X, y = mnist.data, mnist.target # X.shape->(70000, 784) y.shape->
    (70000,)
    ```

  - Each of the 70,000 MNIST images has 784 features (28×28 pixels), where each feature represents a pixel's intensity from 0 (white) to 255 (black). To visualize an image, reshape its feature vector to 28×28 and display it using `matplotlib.pyplot.imshow()` with `cmap="binary"` for grayscale. Here's a sample function:

    ```
    def plot_digit(image_data):
          image = image_data.reshape(28, 28)
          plt.imshow(image, cmap="binary")
          plt.axis("off")
    ```

```
some_digit = X[0]
plot_digit(some_digit)
plt.show()
```

Training a Binary Classifier

- To build a simple digit classifier, we focus on detecting the number **5**, turning it into a **binary classification** problem (5 vs. not 5). We create target labels using:
- Then, we use Scikit-Learn's `SGDClassifier`, which is efficient for large datasets and supports online learning:

```
from sklearn.linear_model import SGDClassifier
y_train_5 = (y_train == '5')
y_test_5 = (y_test == '5')

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

sgd_clf.predict([some_digit])  # Output: array([True])
```

Performance Measures

Measuring Accuracy Using Cross-Validation

- To evaluate the **SGDClassifier**, we use **3-fold cross-validation** with `cross_val_score`, which gives over **95% accuracy**—seemingly impressive

```
cross_val_score(sgd_clf, X_train, y_train_5, cv=3, scoring="accuracy")
# Output: array([0.95035, 0.96035, 0.9604 ])
```

- However, a **DummyClassifier** that always predicts "not 5" still achieves **over 90% accuracy**, because only ~10% of the data are actually 5s:

```
cross_val_score(dummy_clf, X_train, y_train_5, cv=3, scoring="accuracy")
# Output: array([0.90965, 0.90965, 0.90965])
```

- **Conclusion**: Accuracy can be misleading on **imbalanced datasets**. A better alternative for evaluation is the **confusion matrix**, which gives more insight into model performance.

- **IMPLEMENTING CROSS-VALIDATION**
  - To manually implement **cross-validation** with more control, you can use `StratifiedKFold`, which ensures each fold has a representative class distribution. Here's the process:
    1. Use `StratifiedKFold(n_splits=3)` to split the data into 3 balanced folds.
    2. For each fold:
       - Clone the classifier.
       - Train on the training folds.
       - Predict on the test fold.
       - Calculate and print the accuracy.
       This replicates what `cross_val_score()` does, but allows customization. Example output:
       `0.95035`, `0.96035`, `0.9604` — matching the automated method.

```
from sklearn.model_selection import StratifiedKFold
from sklearn.base import clone
skfolds = StratifiedKFold(n_splits=3) # add shuffle=True if the dataset
is not already shuffled
for train_index, test_index in skfolds.split(X_train, y_train_5):
    clone_clf = clone(sgd_clf)
    X_train_folds = X_train[train_index]
    y_train_folds = y_train_5[train_index]
    X_test_fold = X_train[test_index]
    y_test_fold = y_train_5[test_index]
    clone_clf.fit(X_train_folds, y_train_folds)
    y_pred = clone_clf.predict(X_test_fold)
    n_correct = sum(y_pred == y_test_fold)
    print(n_correct / len(y_pred)) # prints 0.95035, 0.96035, and
0.9604
```

Confusion Matrices

- A **confusion matrix** shows how often instances of class **A** are predicted as class **B**.
- You use it to evaluate classification performance in more detail than accuracy.
- **Code to build it:**

```
from sklearn.model_selection import cross_val_predict
y_train_pred = cross_val_predict(sgd_clf, X_train, y_train_5, cv=3) #it is
1d array contain 1 value for each instance, we pass the label to train the
model
```

```python
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_train_5, y_train_pred)

[[53892   687]   # Non-5s: 53892 correct (TN), 687 mistaken as 5s (FP)
 [1891   3530]]  # 5s: 1891 missed (FN), 3530 correct (TP)
```

- **Interpretation**:
  - Rows = actual class
  - Columns = predicted class
  - Diagonal = correct predictions
  - Off-diagonal = errors (false positives/negatives)
- A **perfect classifier** would have only true positives and true negatives
- While the **confusion matrix** is detailed, you might want simpler metrics:
  - **Precision** (a.k.a. positive prediction accuracy):
    - $\text{Precision} = \frac{TP}{TP+FP}$
    - Measures how **many predicted positives are actually correct**.
    - A model can get **100% precision** by making **very few positive predictions**—but it may miss many actual positives.
  - **Recall** (a.k.a. sensitivity or true positive rate):
    - $\text{Recall} = \frac{TP}{TP+FN}$
    - Measures how **many actual positives the model correctly detects**.
    - High recall means **fewer false negatives**.

Precision and Recall

- After evaluating the 5-detector using accuracy, it's time to dig deeper using **precision**, **recall**, and the **F1 score**.
- **Metrics:**
  - **Precision**:
    - $\text{Precision} = \frac{TP}{TP+FP} = 0.837$
      $\rightarrow$ Of all predicted 5s, **83.7% were correct**.
  - **Recall**:
    - $\text{Recall} = \frac{TP}{TP+FN} = 0.651$
      $\rightarrow$ The model found **65.1% of actual 5s**.
- **F1 Score** (harmonic mean of precision and recall):

$$F_1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = 0.733$$

  - Balances both precision and recall.

    - Favors models with **similar** values for both.
- You **can't maximize both** at the same time.
    - Choose based on context:
        - **High precision, low recall**: Good for **kid-safe content filters**.
        - **High recall, low precision**: Okay for **shoplifter detection**, where missing one is worse than a false alarm.

The Precision/Recall Trade-off

- **SGDClassifier** computes a **decision score** for each input.
- If the score is **above a threshold**, it predicts **positive** (e.g., “5”); otherwise, **negative**.
- **Raising the threshold**:
    - ✅ Increases **precision** (fewer false positives)
    - ❌ Decreases **recall** (more false negatives)
- **Lowering the threshold**:
    - ✅ Increases **recall**
    - ❌ Decreases **precision**
- **Example:**
    - If threshold is at default `0`: prediction is **True** (high recall).
    - Raising it to `3000`: prediction becomes **False** (misses a correct 5 → lower recall).
- **How to Tune the Threshold:**
    1. **Get decision scores** (instead of predictions):

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

    2. **Compute precision and recall for all thresholds**:

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

    3. **Visualize** precision & recall against thresholds:

    ```
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
    ```

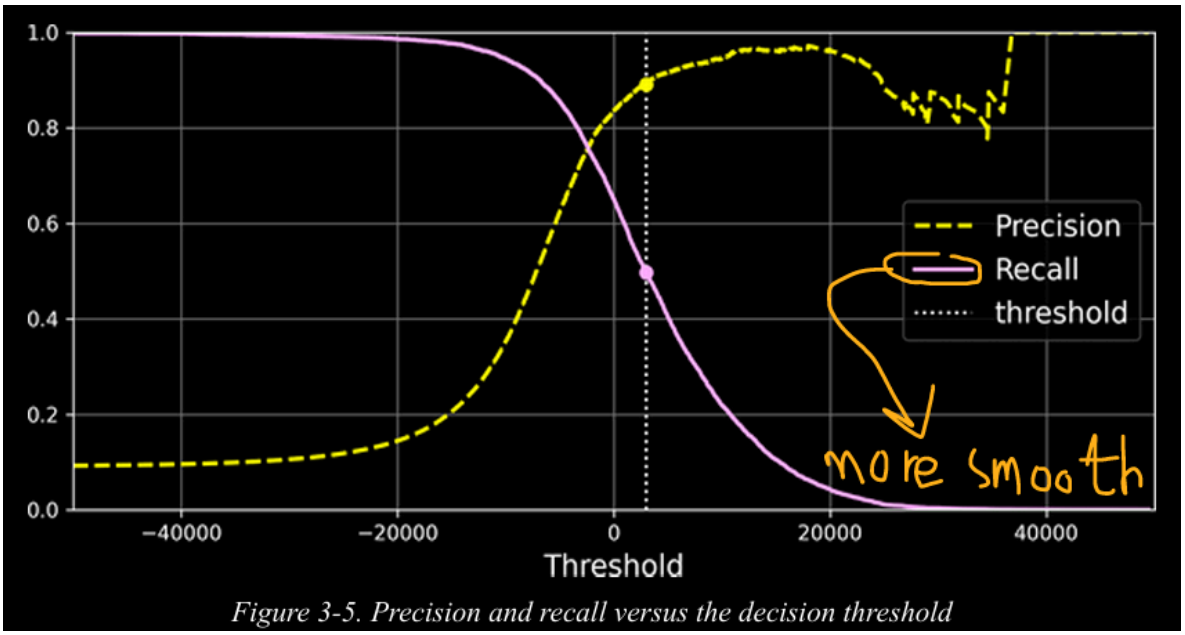


Figure 3-5. Precision and recall versus the decision threshold

4. **Or plot precision directly vs. recall** to spot the sweet spot before a sharp drop in precision.

```
plt.plot(recalls, precisions, linewidth=2, label="Precision/Recall
curve")
#[...] beautify the figure: add labels, grid, legend, arrow, and text
plt.show()
```

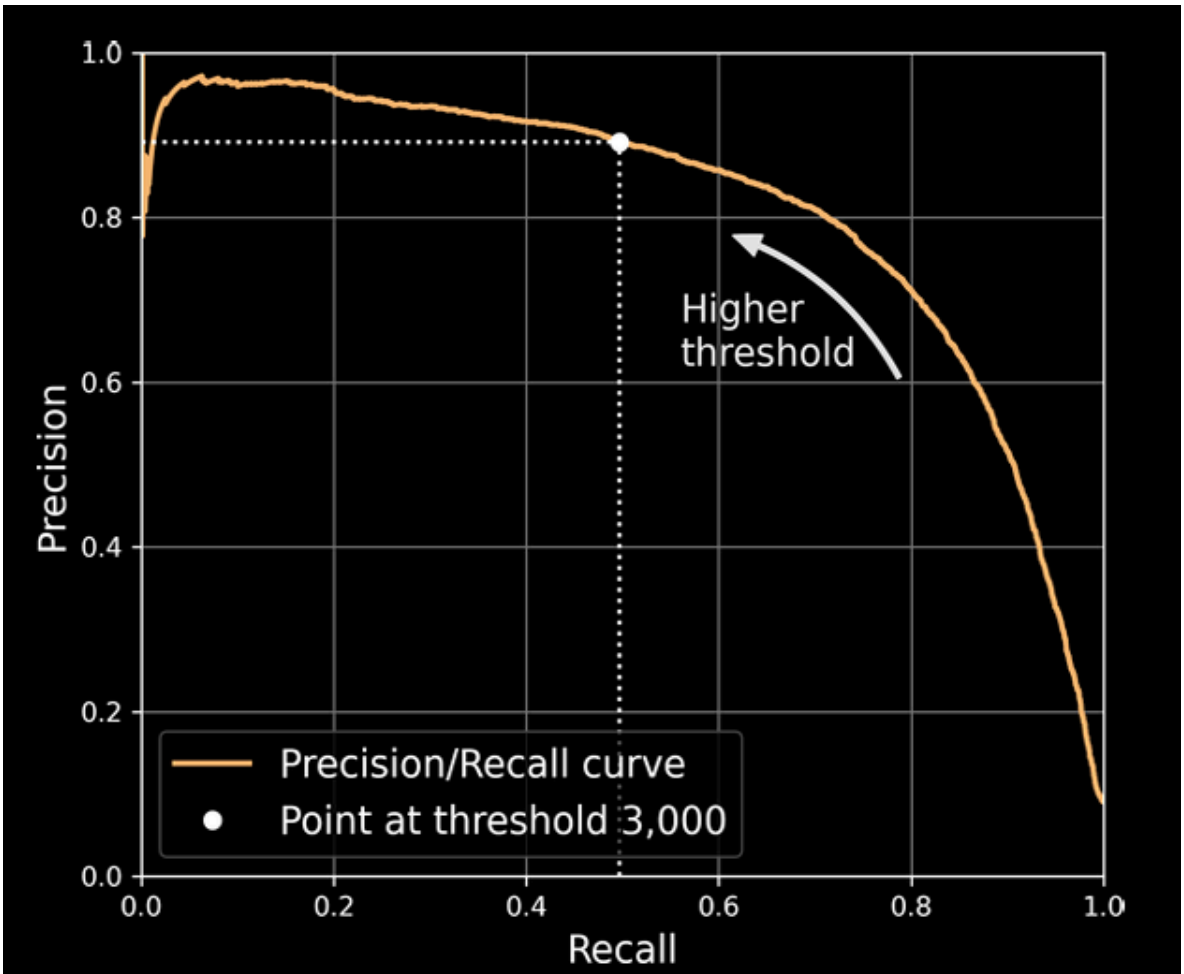
- 

Figure 3-6. Precision versus recall

- Key Insight:
  - There's **no universal best threshold**.
  - Choose it based on **what matters more**:
    - **Precision**: when **false positives are costly** (e.g., kid-safe content).
    - **Recall**: when **missing positives is worse** (e.g., medical diagnosis or shoplifter detection).
- You can **tune your classifier** to reach **90% precision** by:

```
idx = (precisions >= 0.90).argmax()
threshold = thresholds[idx]
y_pred_90 = (y_scores >= threshold)
# hecking performance Precision: 90% and Recall: Only ~48%
```

The ROC Curve

- It plots **True Positive Rate (TPR)** = **Recall** vs **False Positive Rate (FPR)**.
- FPR = 1 - Specificity = fraction of **negatives misclassified as positives**.

- How is it constructed? (code)

```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_train_5, y_scores)

#plotting
idx_for_threshold_at_90 = (thresholds <=
threshold_for_90_precision).argmax()
tpr_90, fpr_90 = tpr[idx_for_threshold_at_90], fpr[idx_for_threshold_at_90]
plt.plot(fpr, tpr, linewidth=2, label="ROC curve") plt.plot([0, 1], [0, 1],
'k:', label="Random classifier's ROC curve")
plt.plot([fpr_90], [tpr_90], "ko", label="Threshold for 90% precision")
# [...] beautify the figure: add labels, grid, legend, arrow, and text
plt.show()
```

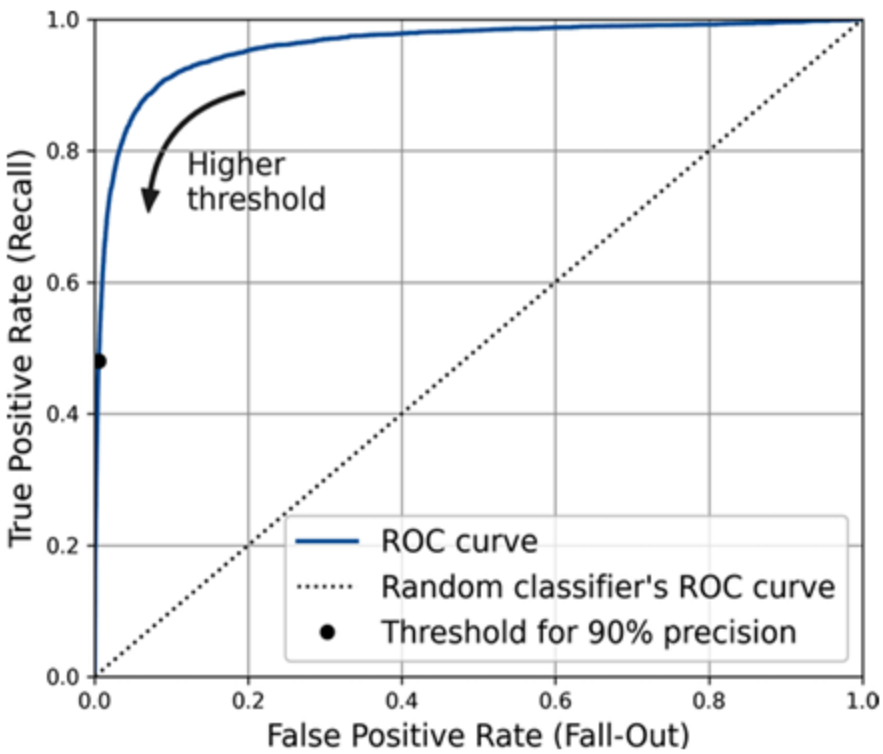


Figure 3-7. A ROC curve plotting the false positive rate against the true positive rate for all possible thresholds; the black circle highlights the chosen ratio (at 90% precision and 48% recall)

- A **great classifier** hugs the **top-left corner** (high recall, low FPR).
- The **farther above the diagonal** it is, the better.

- AUC (Area Under the Curve):

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

- Value close to **1.0** = excellent classifier.

    - Value **0.5** = random guessing.
- **Choosing Between ROC and PR Curves**
    - Use **PR curve** when:
        - The **positive class is rare**.
        - You care **more about false positives** than false negatives.
    - Use **ROC curve** otherwise.
    - ROC AUC can be misleading if positives are rare—it might look good even if the model isn't.
    - PR curve gives a more honest view in such cases.
- **Random Forest vs SGD Classifier (on PR Curve)**
    1. **RandomForestClassifier**:
        - Doesn't use `decision_function()` like SGD.
        - Use `predict_proba()` to get probability scores instead.
        - Use the **positive class probability** as the score for PR/ROC analysis.

```
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")

y_probas_forest[:2]
# array([[0.11, 0.89],
#        [0.99, 0.01]])  First image: 89% likely to be positive, Second
image: 99% likely to be negative.
```

- **Warning About Probabilities**
    - These are **estimated probabilities**, not guaranteed.
    - For example, samples predicted with 50–60% confidence were actually positive **94% of the time** → model underestimated.
    - Some models can also be **overconfident**.
    - Use `sklearn.calibration` to fix this and make probabilities more accurate.
- **Evaluating with PR Curve**
    - Use `precision_recall_curve()` on `y_scores_forest = y_probas_forest[:, 1]`.
    - Plot both **Random Forest** and **SGD** PR curves for comparison.

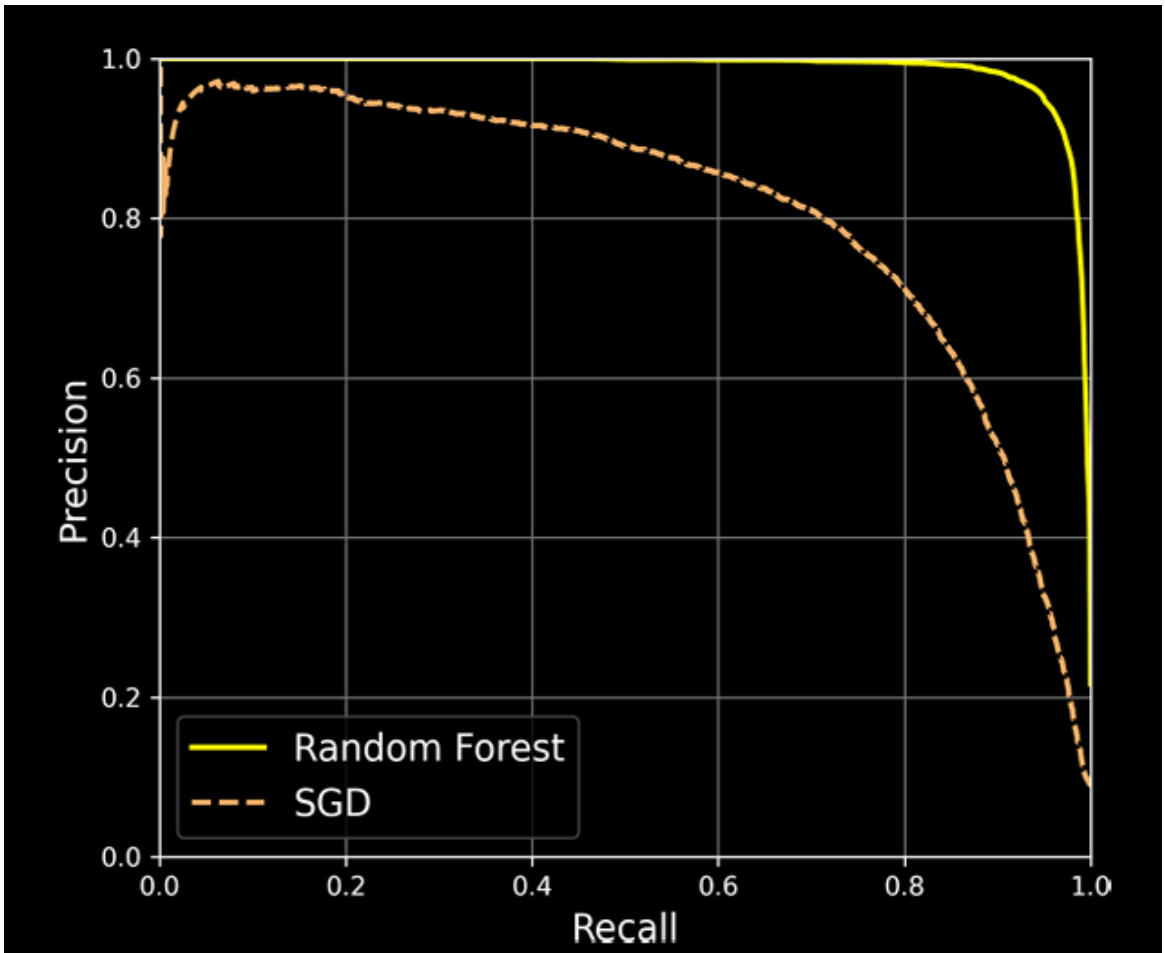
- 

Figure 3-8. Comparing PR curves: the random forest classifier is superior to the SGD classifier because its PR curve is much closer to the top-right corner, and it has a greater AUC

  - Random Forest performs much better:
    - Closer PR curve to the top-right corner.
    - **F1 score**: `0.924`
    - **ROC AUC score**: `0.998`
    - **Precision ≈** `99.1%`, **Recall ≈** `86.6%`

Multiclass Classification

- What is Multiclass Classification?
  - Unlike binary classification (2 classes), **multiclass classification** handles **more than two** classes (e.g., digits 0–9).
- Built-in Support
  - Some classifiers (like `LogisticRegression`, `RandomForestClassifier`) support multiclass natively.
  - Others (like `SGDClassifier`, `SVC`) only support binary classification—but **Scikit-Learn** handles multiclass automatically using two strategies:
- Strategies for Multiclass with Binary Classifiers
  1. **One-vs-Rest (OvR / OvA)**

    - Train **one binary classifier per class**.
    - Classify by picking the classifier with the **highest decision score**.
  2. **One-vs-One (OvO)**
    - Train a binary classifier for **every pair of classes**.
    - For 10 classes (MNIST): **45 classifiers** → `10 × 9 / 2`.
    - Each classifier "votes"; the class with **most wins** is chosen.
- Example: `SVC` with OvO
  - `SVC` scales poorly with large datasets, so **OvO is used by default**.

```
svm_clf = SVC(random_state=42)
svm_clf.fit(X_train[:2000], y_train[:2000])
```

    - It trains **45 classifiers** internally for 10 classes.
- When you predict, it:
  - Runs the sample through all 45 classifiers.
  - Collects **10 class scores** using `decision_function()` — one score per class (based on votes).
  - Picks the class with the **highest score**.

```
some_digit_scores = svm_clf.decision_function([some_digit])
class_id = some_digit_scores.argmax()
svm_clf.classes_[class_id]  # gives predicted class
```

  - Even though OvO uses many classifiers, **you still get one score per class**.
- You can **manually choose** One-vs-One (OvO) or One-vs-Rest (OvR) using:
  - `OneVsOneClassifier`
  - `OneVsRestClassifier`

```
from sklearn.multiclass import OneVsRestClassifier
ovr_clf = OneVsRestClassifier(SVC(random_state=42))
ovr_clf.fit(X_train[:2000], y_train[:2000]) #This trains **10 classifiers**
(one for each class).
ovr_clf.predict([some_digit])  # Output: '5'
```

- Using SGDClassifier for Multiclass

```
sgd_clf = SGDClassifier(random_state=42)
sgd_clf.fit(X_train, y_train)
sgd_clf.predict([some_digit])  # Output: '3' (could be wrong)
```

```
cross_val_score(sgd_clf, X_train, y_train, cv=3, scoring="accuracy")
# → ~86% accuracy (better than random guessing, which is 10%)
```

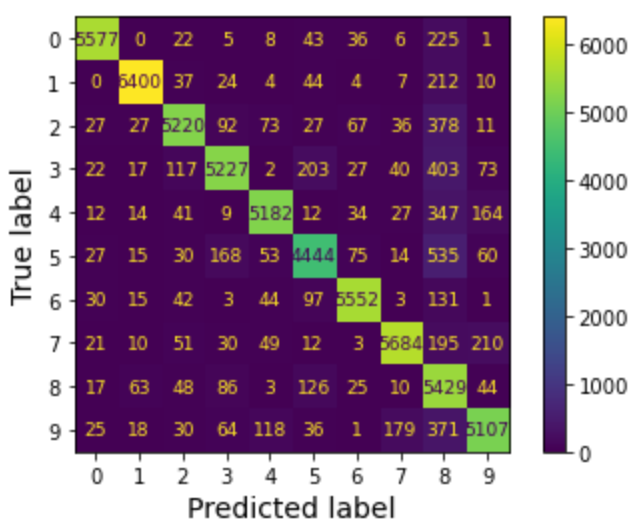
- `SGDClassifier` uses **OvR** by default.
- `decision_function([some_digit])` returns **10 confidence scores**, one per class.
- Boosting Accuracy with Scaling:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train.astype("float64"))
cross_val_score(sgd_clf, X_train_scaled, y_train, cv=3,
scoring="accuracy")
# → ~89–90% accuracy
```

Error Analysis

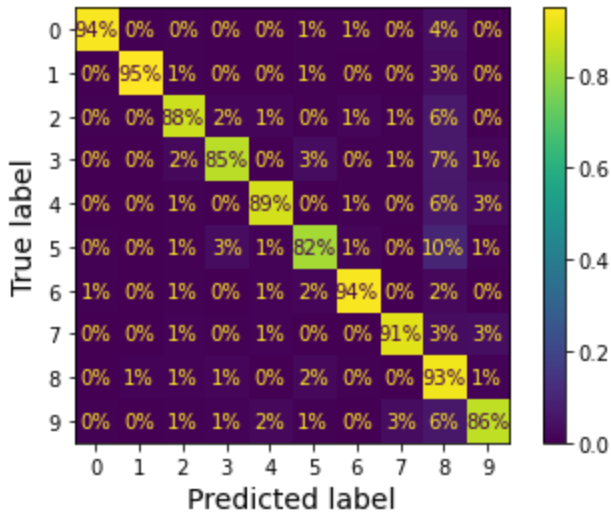
- Once you've trained a promising model, analyze **what types of mistakes it makes** to improve it.
- Confusion Matrix
  - Use `cross_val_predict()` to get predictions.
  - Plot the confusion matrix using:

```
from sklearn.metrics import ConfusionMatrixDisplay
y_train_pred = cross_val_predict(sgd_clf, X_train_scaled, y_train, cv=3)
ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred)
plt.show()
```



- Normalized Confusion Matrix

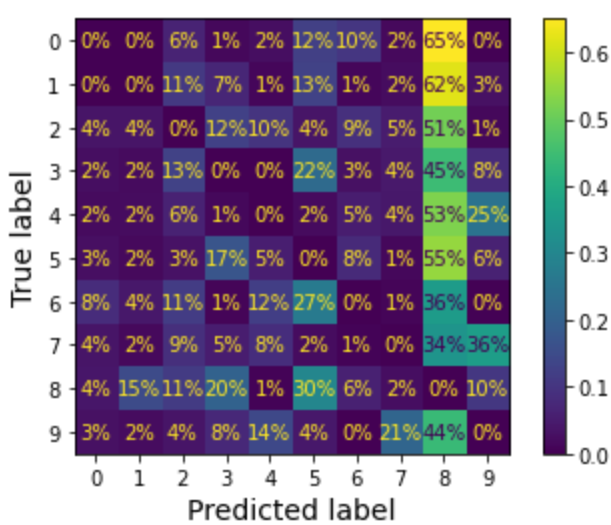
```
ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred,
                                        normalize="true",
                                        values_format=".0%")
```

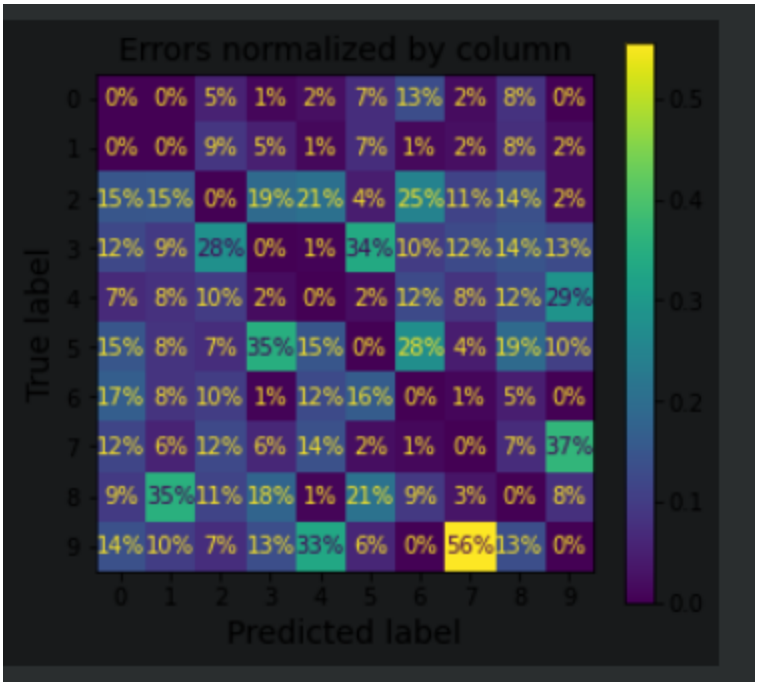


- **Example finding: Only 82% of digit 5s are correctly predicted.**
  - 10% of 5s were misclassified as 8s.
  - Only 2% of 8s were misclassified as 5s → **asymmetrical errors**.

- Highlight Only the Errors(To make misclassifications more visible)

```
sample_weight = (y_train_pred != y_train)
ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred,
                                        sample_weight=sample_weight,
                                        normalize="true",
                                        values_format=".0%")
```



- **Column-Normalized Confusion Matrix**
  - Use `normalize="pred"` to normalize **by column**:
    - Shows **what predicted class the errors are going to**.
    - Example: 56% of **predicted 7s** are actually **9s**.
  - 

- Error Analysis:
  - Use a **confusion matrix** to find common mistakes (e.g., many digits misclassified as 8).
  - Improve accuracy by:
    - Adding **more training data** for confusing digits.
    - **Engineering features** (e.g., count loops in digits).
    - **Preprocessing images** to highlight important patterns.
  - **Visualize errors** (like 3s vs 5s) to see where and why mistakes happen.
  - **SGDClassifier is linear**, so it's sensitive to small changes like shifts or rotations.
  - **Best fix**: Use **data augmentation**—add rotated/shifted versions of training images to improve model robustness.

Multilabel Classification

- In **multilabel classification**, each input can be assigned **multiple binary labels** (not just one class).

```
y_train_large = (y_train >= '7')        # True if digit is 7, 8, or 9
y_train_odd = (y_train.astype('int8') % 2 == 1)  # True if digit is odd
y_multilabel = np.c_[y_train_large, y_train_odd]
```

    - This creates **two labels per digit**:
    - Then trains a `KNeighborsClassifier` with these multilabels.
    - Prediction Example

```
knn_clf.predict([some_digit]) → [[False, True]]
```

        - → The digit is not large but it is odd (like 5).
- Evaluation
    - Use **F1 score** with `average="macro"` to give equal weight to each label:

```
f1_score(y_multilabel, y_train_knn_pred, average="macro")
```

    - → `average="weighted"` gives more weight to labels with more examples.
- **When Classifier Doesn't Support Multilabels**
    - Train one model per label (but they won't communicate).
    - A better option: use `ClassifierChain`.
- ClassifierChain
    - Organizes models **in a chain** so later models use predictions from earlier ones.
    - Use `cv` to get clean predictions during training.

```
chain_clf = ClassifierChain(SVC(), cv=3, random_state=42)
chain_clf.fit(X_train[:2000], y_multilabel[:2000])
chain_clf.predict([some_digit])  → [[0., 1.]]
```

Multioutput Classification

- **What is Multioutput Classification?**
    - A **generalization of multilabel classification**.
    - Each label can have **more than two values** (i.e., it's multiclass per output).
    - Example: A system that removes noise from images.
- **Noise Removal Example**
    - Input: **Noisy MNIST digit** image (added random noise to each pixel).
    - Output: **Clean digit** image (original pixel intensities).
    - Each pixel is a label, and its value ranges from 0–255 → **multioutput multiclass**.
- code

```
noise = np.random.randint(0, 100, (len(X_train), 784))
X_train_mod = X_train + noise       # Noisy inputs
y_train_mod = X_train               # Clean targets
```

- Trained a **KNeighborsClassifier** to predict clean images from noisy ones:

```
knn_clf.fit(X_train_mod, y_train_mod)
clean_digit = knn_clf.predict([X_test_mod[0]])
```

Resources :

-

Related notes :

-

References :

- **Internal :**
  -
  -
  -
- **External :**
  - notebook ofthe chapter
    - hegab videos
  - the book
  -