Hands-on Classification

Describe the used dataset

- Name: MNIST
- Author: Yann LeCun, Corinna Cortes, Christopher J.C. Burges
- Content: 70,000 images of digits handwritten
- Source: MNIST Website

Get data

Download data

```
from sklearn.datasets import fetch_openml

mnist = fetch_openml('mnist_784', as_frame=False)        # as_frame=False: get data as Nump
mnist.DESCR
```

```
/usr/local/anaconda3/envs/dhuy/lib/python3.11/site-packages/sklearn/datasets/_openml.py:1022

The default value of `parser` will change from `'liac-arff'` to `'auto'` in 1.4. You can set

"**Author**: Yann LeCun, Corinna Cortes, Christopher J.C. Burges  \n**Source**: [MNIST Websi
```

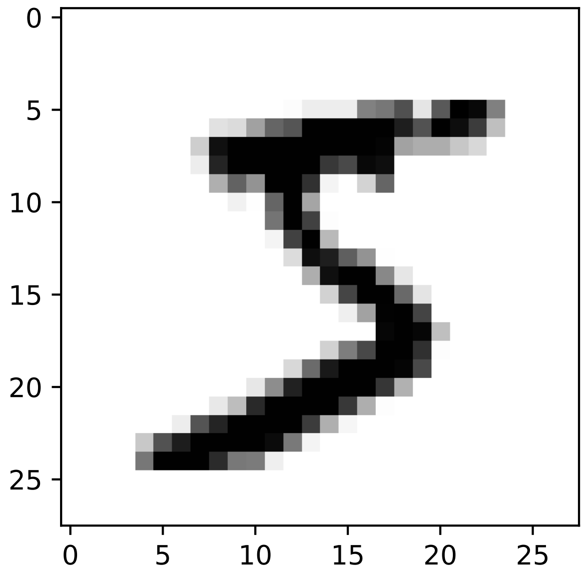
Quick Look

```
## Size of dataset

X,y = mnist.data, mnist.target
print(X.shape, y.shape)
```

```
(70000, 784) (70000,)
```

```
## Quick look

import matplotlib.pyplot as plt

def plot_digit(data):
    image = data.reshape(28,28)
```

```
    plt.imshow(image, cmap='binary')   # binary: grayscale color map from 0 (white) to 255

some_digit = X[0]    # Look at first digit
plot_digit(some_digit)
plt.show()
```



Create train, test set

```
## Split dataset into train set and test set as its describe (train: first 60000 images, t

X_train, X_test, y_train, y_test = X[:60000], X[60000:], y[:60000], y[60000:]
print(X_train.shape)
```

```
(60000, 784)
```

Create a Binary Classfier(5 or non-5)

```
## Target labels

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

Stochastic Gradient Descent

Train model

```
from sklearn.linear_model import SGDClassifier

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

sgd_clf.predict([some_digit])
```

```
array([ True])
```

Evaluate model

> Tip
>
> Metrics:
> - Accuracy
> - Confusion matrix: Precision, Recall (TPR), FPR, ROC, ROC AUC
> - Plot: Precision-Recall Curve, ROC Curve
>
> Use case:
> - Precision-Recall Curve: aim to care more about `false positives` than the `false negatives`
> - Otherwise: ROC Curve

Accuracy

```
from sklearn.model_selection import cross_val_score

cross_val_score(sgd_clf, X_train, y_train_5, cv=3, scoring='accuracy')
```

```
array([0.95035, 0.96035, 0.9604 ])
```

Warning

The accuracy scores are pretty good, but it may be due to the class imbalance. Let take a look at a Dummy Model which always classify as the most frequent class

```
## Dummy classifier

from sklearn.dummy import DummyClassifier
from sklearn.model_selection import cross_val_score

dummy_model = DummyClassifier(random_state=248)
cross_val_score(dummy_model, X_train, y_train_5, cv=3, scoring='accuracy')
```

```
array([0.90965, 0.90965, 0.90965])
```

! Important

The accuracy scores are over 90% because there's only about 10% of training set are 5 digit
=> With class imbalance, accuracy score is not a useful metric
=> We will use other metrics such as Precision, Recall, ROC Curve, AUC

Confusion Matrix

```
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix

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

```
array([[53892,   687],
       [ 1891,  3530]])
```

```
## Precision and Recall

from sklearn.metrics import precision_score, recall_score
```

```python
print(f'Precision scores: {precision_score(y_train_5, y_train_pred):.4f}')
print(f'Recall scores: {recall_score(y_train_5, y_train_pred):.4f}')
```

```
Precision scores: 0.8371
Recall scores: 0.6512
```

```python
## F1-score

from sklearn.metrics import f1_score

print(f'F1-score: {f1_score(y_train_5, y_train_pred):.4f}')
```

```
F1-score: 0.7325
```

Precision-Recall Trade-off

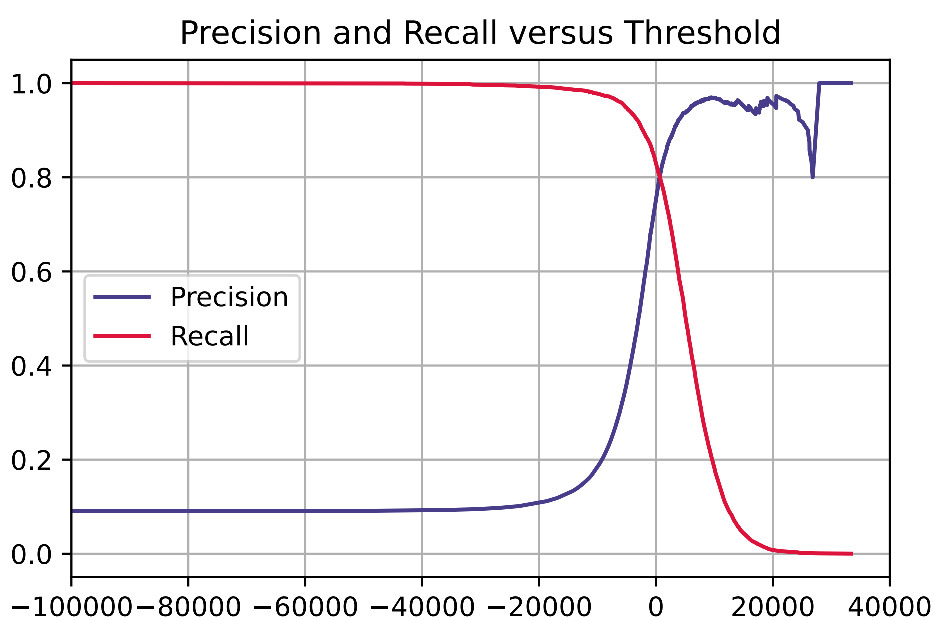
- Compute the scores of all instances in the training using *decision_function*
- Change the threshold to see the difference

```python
y_score = sgd_clf.decision_function([some_digit])

threshold = [0, 1000, 3000]
for thr in threshold:
    print(f'With threshold of {thr:4d}: predicted value is {y_score>thr}')
```

```
With threshold of    0: predicted value is [ True]
With threshold of 1000: predicted value is [ True]
With threshold of 3000: predicted value is [False]
```

> **!** Important
>
> **How to choose the suitable threshold?**
>
> - Use Precision-Recall Curve
> - precision_recall_curve: require *scores* computed from decision_function or *probabilities* from predict_proba

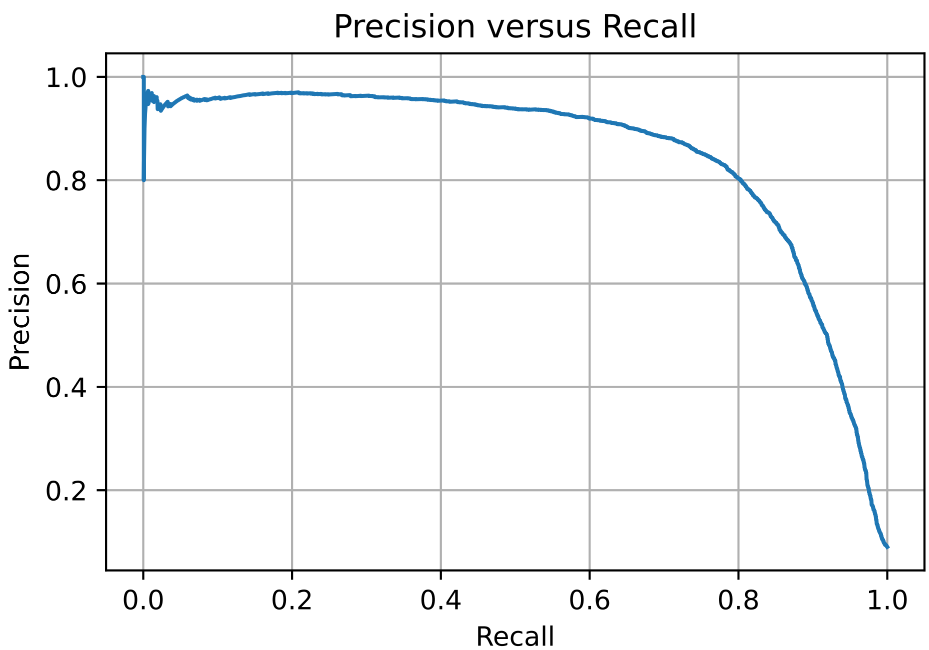
```
## Precision-Recall Curve


### Compute scores by decision_function

y_scores = cross_val_predict(sgd_clf, X_train, y_train_5, method='decision_function')

### Plot Precision-Recall Curve vs Threshold

from sklearn.metrics import precision_recall_curve

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

plt.plot(thresholds, precisions[:-1], label='Precision', color='darkslateblue')
plt.plot(thresholds, recalls[:-1], label='Recall', color='crimson')
plt.grid()
plt.legend(loc='center left')
plt.xlim([-100000,40000])
plt.title('Precision and Recall versus Threshold')
plt.show()
```



ℹ Note

The higher Precision, the lower Recall and vice versa

```
## Plot Precision versus Recall

plt.plot(recalls, precisions)
plt.title('Precision versus Recall')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.grid()

plt.show()
```



Tip

Depend on your project, you would trade between precision and recall

```
## Find Threshold of over 0.90 Precision
```

```
idx_90_precision = (precisions >= 0.90).argmax()
threshold_90_precision = thresholds[idx_90_precision]
threshold_90_precision
```

```
3045.9258227053647
```

```
y_train_90_precision = (y_scores > threshold_90_precision)

from sklearn.metrics import accuracy_score
print(f'Accuracy score: {accuracy_score(y_train_5, y_train_90_precision):.4f}')
print(f'Precision score: {precision_score(y_train_5, y_train_90_precision):.4f}')
print(f'Recall score: {recall_score(y_train_5, y_train_90_precision):.4f}')
print(f'F1 score: {f1_score(y_train_5, y_train_90_precision):.4f}')
```

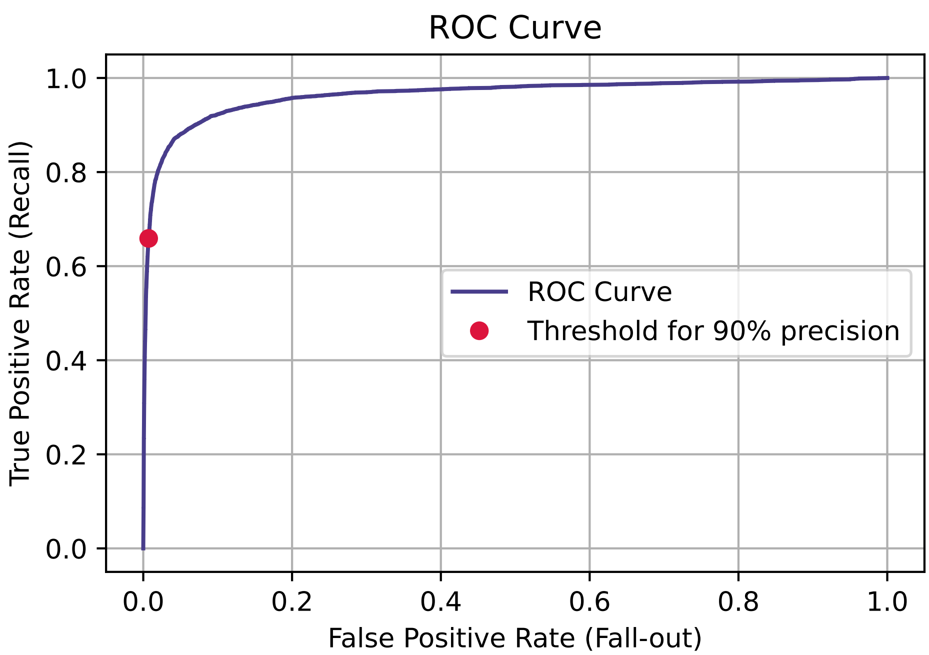
```
Accuracy score: 0.9626
Precision score: 0.9002
Recall score: 0.6587
F1 score: 0.7608
```

```
## ROC AUC

from sklearn.metrics import roc_auc_score, roc_curve

print(f'AUC score: {roc_auc_score(y_train_5, y_scores):.4f}')
```

```
AUC score: 0.9648
```

```
## ROC Curve

fpr, tpr, thresholds = roc_curve(y_train_5, y_scores)
idx_threshold_90_precision = (thresholds<=threshold_90_precision).argmax()      # threshol
fpr_90, tpr_90 = fpr[idx_threshold_90_precision], tpr[idx_threshold_90_precision]

plt.plot(fpr, tpr, label='ROC Curve', color='darkslateblue')
plt.plot([fpr_90], [tpr_90], 'o', label='Threshold for 90% precision', color='crimson')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate (Fall-out)')
plt.ylabel('True Positive Rate (Recall)')
```

```
plt.legend(loc='center right')
plt.grid()

plt.show()
```



> **! Important**
>
> Another trade-off: The higher TPR, the lower FPR and vice versa

Logistic Regression

```
from sklearn.linear_model import LogisticRegression

logistic = LogisticRegression(random_state=29)

y_pred_logis = cross_val_predict(logistic, X_train, y_train_5, cv=3, method='predict_proba
```

```
/usr/local/anaconda3/envs/dhuy/lib/python3.11/site-packages/sklearn/linear_model/_logistic.py
```

```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

/usr/local/anaconda3/envs/dhuy/lib/python3.11/site-packages/sklearn/linear_model/_logistic.py

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Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

```python
## Measure performance

threshold = 0.5
f1_logis = f1_score(y_train_5, y_pred_logis>=threshold)
auc_logis = roc_auc_score(y_train_5, y_pred_logis>=threshold)

print(f'F1 score Random Forest: {f1_logis:.4f}')
print(f'AUC Random Forest: {auc_logis:.4f}')
```

```
F1 score Random Forest: 0.8487
AUC Random Forest: 0.9004
```

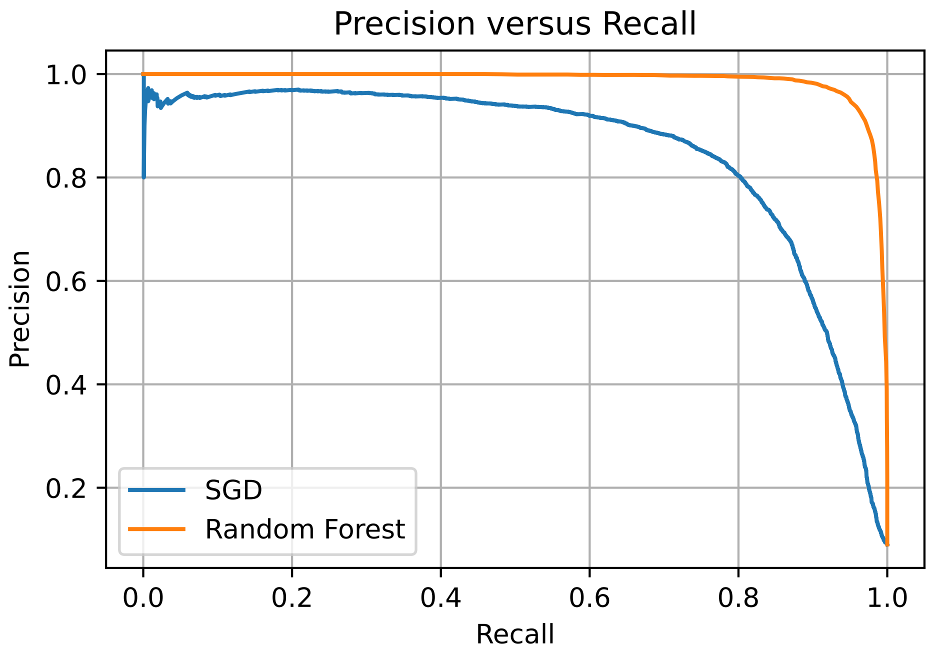
Random Forest

```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(random_state=42)

y_train_pred_rf = cross_val_predict(rf_clf, X_train, y_train_5, cv=3, method='predict_prob
```

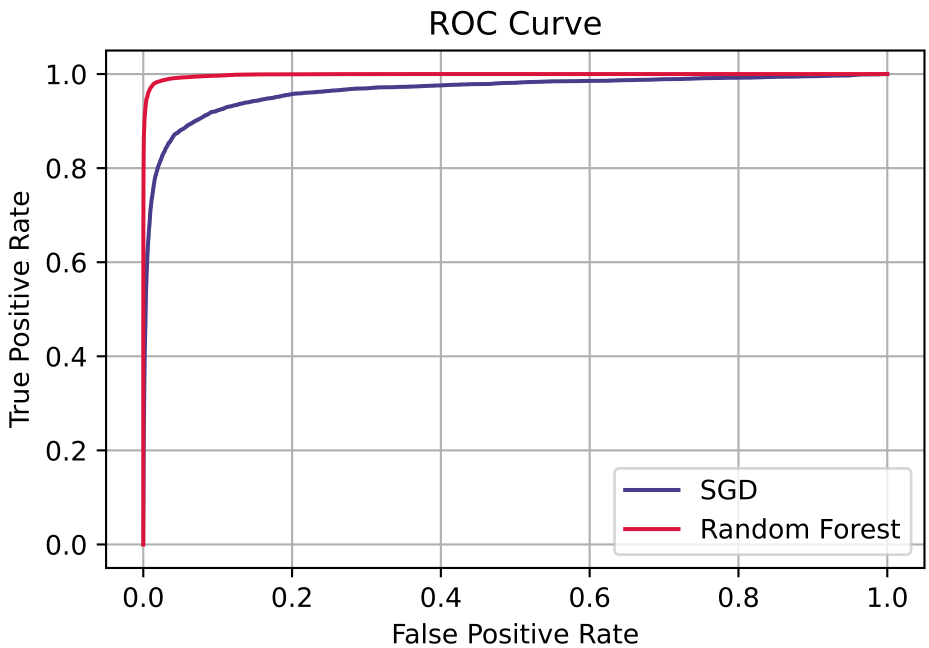
```
## Measure performance

threshold = 0.5
f1_rf = f1_score(y_train_5, y_train_pred_rf>=threshold)
auc_rf = roc_auc_score(y_train_5, y_train_pred_rf>=threshold)

print(f'F1 score Random Forest: {f1_rf:.4f}')
print(f'AUC Random Forest: {auc_rf:.4f}')
```

```
F1 score Random Forest: 0.9275
AUC Random Forest: 0.9358
```

```
## PR Curve

precisions_rf, recalls_rf, thresholds_rf = precision_recall_curve(y_train_5, y_train_pred_

plt.plot(recalls, precisions, "-", label='SGD')
plt.plot(recalls_rf, precisions_rf, label='Random Forest')
plt.title('Precision versus Recall')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.legend()
plt.grid()

plt.show()
```




```
## ROC Curve

fpr_rf, tpr_rf, thresholds = roc_curve(y_train_5, y_train_pred_rf)

plt.plot(fpr, tpr, label='SGD', color='darkslateblue')
plt.plot(fpr_rf, tpr_rf, label='Random Forest', color='crimson')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()

plt.show()
```



Multiclass Classification

- LogisticRegression, RandomForestClassifier, GaussianNB: *natively* handle Multiclass Classification
- SGDClassifier and SVC: *strictly* binary classifiers
  - `ovo`: one versus one strategy, preferred with scale poorly algorithms (i.e. SVC)
  - `ovr`: one versus rest strategy, preferred for almost algorithms

SVC

Default: ovo strategy

```
from sklearn.svm import SVC

svc_clf = SVC(random_state=42)
svc_clf.fit(X_train[:1000], y_train[:1000])
svc_clf.predict([some_digit])
```

```
array(['5'], dtype=object)
```

```python
## Scores from decision_function

some_digit_svc = svc_clf.decision_function([some_digit])
some_digit_svc.round(4)
```

```
array([[ 1.7583,  2.7496,  6.1381,  8.2854, -0.2873,  9.3012,  0.7423,
         3.7926,  7.2085,  4.8576]])
```

```python
## Class of highest score

idx_svc = some_digit_svc.argmax()
idx_svc
```

```
5
```

```python
## Classes of prediction
svc_clf.classes_[idx_svc]
```

```
'5'
```

Force: ovr strategy

```python
## Train model

from sklearn.multiclass import OneVsRestClassifier

ovr_svc_clf = OneVsRestClassifier(SVC(random_state=42))
ovr_svc_clf.fit(X[:1000], y_train[:1000])
ovr_svc_clf.predict([some_digit])
```

```
array(['5'], dtype='<U1')
```

```
## Compute scores

some_digit_ovr_svc = ovr_svc_clf.decision_function([some_digit])
some_digit_ovr_svc.round(4)
```

```
array([[-1.3439, -1.5195, -1.221 , -0.9294, -2.0057,  0.6077, -1.6226,
        -0.9998, -1.2764, -1.7031]])
```

```
## Class of hishest score

some_digit_ovr_svc.argmax()
```

```
5
```

```
## Extract classes

ovr_svc_clf.classes_
```

```
array(['0', '1', '2', '3', '4', '5', '6', '7', '8', '9'], dtype='<U1')
```

SGD

```
## Train model

from sklearn.linear_model import SGDClassifier

sgd_clf = SGDClassifier(random_state=42)
sgd_clf.fit(X_train, y_train)
sgd_clf.predict([some_digit])
```

```
array(['3'], dtype='<U1')
```

That's incorrect. As we can see,The Classifier is not very confident about its prediction.

```
## Compute scores
```

```python
sgd_clf.decision_function([some_digit])
```

```
array([[-31893.03095419, -34419.69069632,  -9530.63950739,
          1823.73154031, -22320.14822878,  -1385.80478895,
        -26188.91070951, -16147.51323997,  -4604.35491274,
        -12050.767298  ]])
```

We will use cross validation to evaluate our model

```python
cross_val_score(sgd_clf, X_train, y_train, cv=3, scoring='accuracy')
```

```
array([0.87365, 0.85835, 0.8689 ])
```

We can scale the data to get better result

```python
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')
```

```
array([0.8983, 0.891 , 0.9018])
```

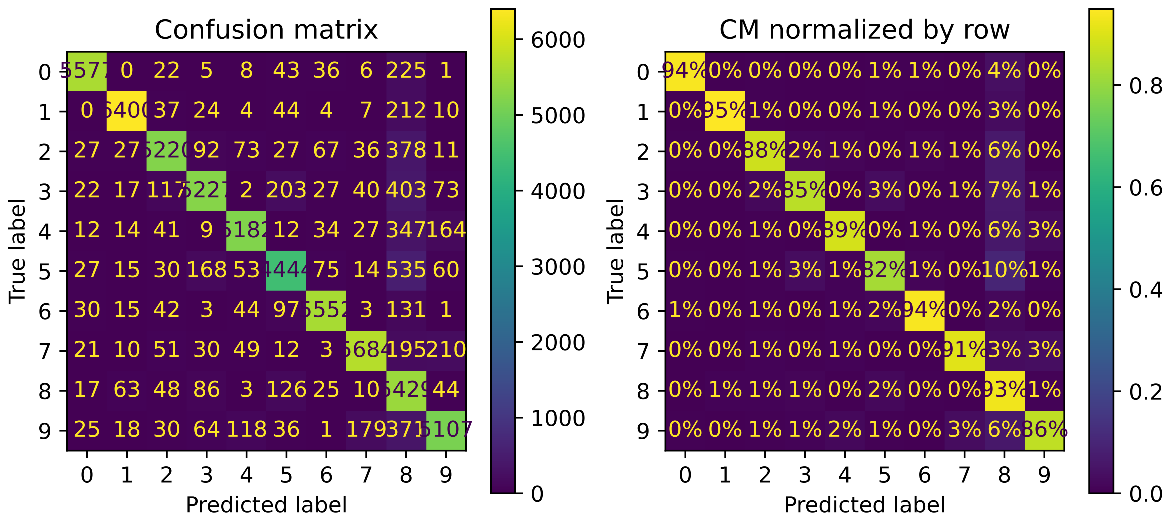
Let's look at the confusion matrix of our prediction

```python
## Predict using cross_val_predict

from sklearn.metrics import ConfusionMatrixDisplay

y_train_pred = cross_val_predict(sgd_clf, X_train_scaled, y_train, cv=3)
```

Confusion matrix with (right) and without (left) normalization.

```python
fig,ax = plt.subplots(1,2,figsize=(9, 4))

ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred, ax=ax[0])
ax[0].set_title("Confusion matrix")
ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred, ax=ax[1], normalize='true',
ax[1].set_title("CM normalized by row")
```

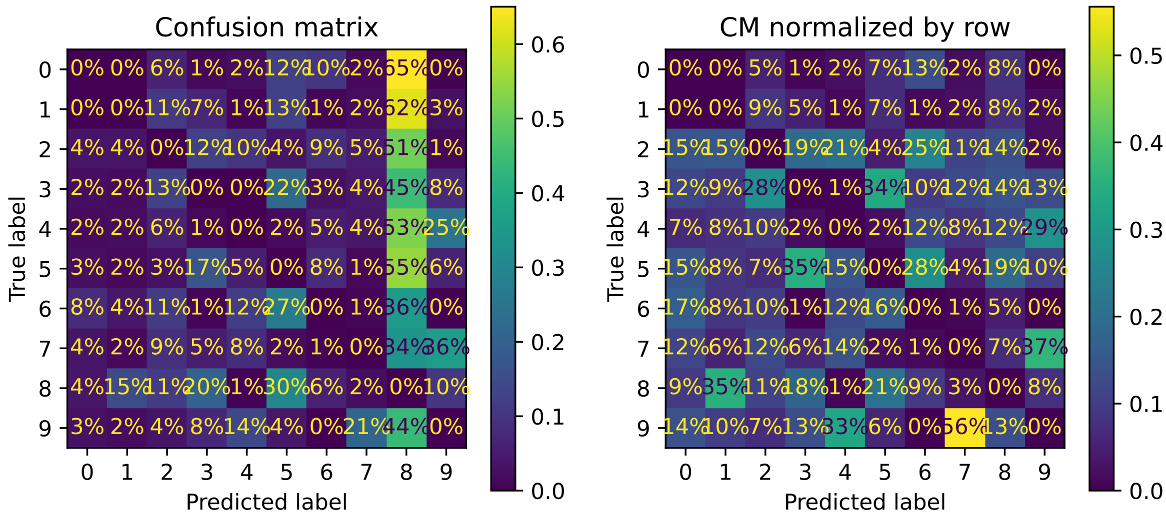
```
plt.show()
```



In row #5 and column #8 on the left plot, it's means 10% of true 5s is misclassified as 8s. Kinda hard to see the errors made by model. Therefore, we will put 0 weight on correct prediction (error plot).

Confustion matrix with error normalized by row (left) and by column (right) (normalize=['true','pred'])

```
fig,ax = plt.subplots(1,2,figsize=(9, 4))

sample_weight = (y_train != y_train_pred)

ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred, ax=ax[0],sample_weight=samp
ax[0].set_title("Confusion matrix")
ConfusionMatrixDisplay.from_predictions(y_train, y_train_pred, ax=ax[1],sample_weight=samp
ax[1].set_title("CM normalized by row")

plt.show()
```



In row #5 and column #8 on the left plot, it's means 55% of errors made on true 5s is misclassified as 8s.

In row #5 and column #8 on the right plot, it's means 19% of misclassified 8s are actually 5s.

Analyzing the made errors can help us gain insights and why the classifier failing

Multilabel Classification

Output is multilabel for each instances. For example, we will classify whether the digit is large (>7) and is odd

K Nearest Neighbors

```
## Train model

import numpy as np
from sklearn.neighbors import KNeighborsClassifier

y_train_large = (y_train >= '7')
y_train_odd = (y_train.astype('int8') % 2 == 1)
y_train_multilabel = np.c_[y_train_large, y_train_odd]
```

```python
knn = KNeighborsClassifier()
knn.fit(X_train_scaled, y_train_multilabel)
knn.predict([some_digit])
```

```
array([[False,  True]])
```

Compute average F1 score across all labels (equally important)

```python
## Evaluate model

y_train_pred_knn = cross_val_predict(knn, X_train_scaled, y_train, cv=3)
f1_score(y_train, y_train_pred_knn, average='macro')
```

```
0.9396793112547043
```

Another approach is to give each label a weight equal to its number of instances

```python
f1_score(y_train, y_train_pred_knn, average='weighted')
```

```
0.940171964265114
```

SVC

- SVC does not natively support multilabel classification. Therefore, there are 2 strategies:

1. Train one model per label. It turns out that it's hard to capture the dependencies between labels
2. Train models sequentially (ChainClassifier): using input features and all predictions of previous models in the chain

```python
from sklearn.multioutput import ClassifierChain

chain_clf = ClassifierChain(SVC(), cv=3, random_state=42)
chain_clf.fit(X_train_scaled[:2000], y_train_multilabel[:2000])
chain_clf.predict([some_digit])
```

```
array([[0., 1.]])
```

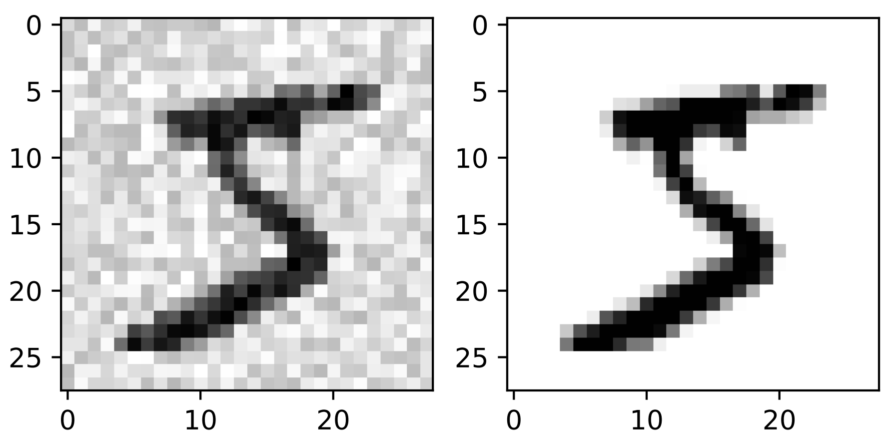
Multioutput Classification

- Multiclass-multilabel classification
- For example, we will build a model that removes noise from an digit image
- Output is a clean image 28x28: multilabel (one label per pixel) and multiclass (pixel intensity range from 0-255 per label)

```
## Create a noisy train set

np.random.seed(42)

noise = np.random.randint(0,100,(len(X_train), 28*28))
X_train_noise = X_train + noise
y_train_noise = X_train

noise = np.random.randint(0,100,(len(X_test), 28*28))
X_test_noise = X_test + noise
y_test_noise = X_test
```

Let's look at sample images

```
plt.subplot(1,2,1)
plot_digit(X_train_noise[0])
plt.subplot(1,2,2)
plot_digit(y_train_noise[0])

plt.show()
```



```
knn.fit(X_train_noise, y_train_noise)
y_pred_noise = knn.predict([X_train_noise[0]])
plot_digit(y_pred_noise)
```