L03_dummy_classifier

February 13, 2026

1 LO3 - Classification

1.0.1 Qa Load and display the MNIST data

[1]:
```
import numpy as np

def MNIST_GetDataSet(action,print):
    if action==1:
        from sklearn.datasets import fetch_openml
        # Load data from https://www.openml.org/d/554
        X, y = fetch_openml('mnist_784',return_X_y=True, cache=True) # Returns␣
 ↪two distinct values, saves locally to avoid reloading
        # Convert to [0;1] via scaling
        X = X / 255.
        if print==1:
            %matplotlib inline
            def MNIST_PlotDigit(data):
             import matplotlib
             import matplotlib.pyplot as plt
             image = data.reshape(28, 28)
             plt.imshow(image, cmap = matplotlib.cm.binary,␣
 ↪interpolation="nearest")
             plt.axis("off")
        # Force the first row of X to be a generic array instead of pandas␣
 ↪formatting, also serves as a test for working import of data.
             MNIST_PlotDigit(X.to_numpy()[0])
        else:
           pass

        return X, y

    else:
        pass

MNIST_GetDataSet(1,1)
```

```
[1]: (       pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  pixel8  pixel9
    \
     0         0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     1         0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     2         0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     3         0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     4         0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     …        …      …      …      …      …      …      …      …      …
     69995     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     69996     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     69997     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     69998     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
     69999     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

            pixel10  …  pixel775  pixel776  pixel777  pixel778  pixel779  \
     0          0.0  …       0.0       0.0       0.0       0.0       0.0
     1          0.0  …       0.0       0.0       0.0       0.0       0.0
     2          0.0  …       0.0       0.0       0.0       0.0       0.0
     3          0.0  …       0.0       0.0       0.0       0.0       0.0
     4          0.0  …       0.0       0.0       0.0       0.0       0.0
     …          …  …       …       …       …       …       …
     69995      0.0  …       0.0       0.0       0.0       0.0       0.0
     69996      0.0  …       0.0       0.0       0.0       0.0       0.0
     69997      0.0  …       0.0       0.0       0.0       0.0       0.0
     69998      0.0  …       0.0       0.0       0.0       0.0       0.0
     69999      0.0  …       0.0       0.0       0.0       0.0       0.0

            pixel780  pixel781  pixel782  pixel783  pixel784
     0           0.0       0.0       0.0       0.0       0.0
     1           0.0       0.0       0.0       0.0       0.0
     2           0.0       0.0       0.0       0.0       0.0
     3           0.0       0.0       0.0       0.0       0.0
     4           0.0       0.0       0.0       0.0       0.0
     …           …       …       …       …       …
     69995       0.0       0.0       0.0       0.0       0.0
     69996       0.0       0.0       0.0       0.0       0.0
     69997       0.0       0.0       0.0       0.0       0.0
     69998       0.0       0.0       0.0       0.0       0.0
     69999       0.0       0.0       0.0       0.0       0.0

     [70000 rows x 784 columns],
     0        5
     1        0
     2        4
     3        1
     4        9
             ..
```

```
69995    2
69996    3
69997    4
69998    5
69999    6
Name: class, Length: 70000, dtype: category
Categories (10, object): ['0', '1', '2', '3', …, '6', '7', '8', '9'])
```

1.0.2 Qb Add a Stochastic Gradient Decent [SGD] Classifier

[2]:
```python
# 1. Imports
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import train_test_split
SGDC = SGDClassifier()
X, y = MNIST_GetDataSet(1,0)

print(f"X.shape={X.shape}") # print X.shape= (70000, 28, 28)
if X.ndim==3:
    print("reshaping X..")
    assert y.ndim==1
    X = X.reshape((X.shape[0],X.shape[1]*X.shape[2]))
assert X.ndim==2
print(f"X.shape={X.shape}") # X.shape= (70000, 784)
```

```
X.shape=(70000, 784)
X.shape=(70000, 784)
```

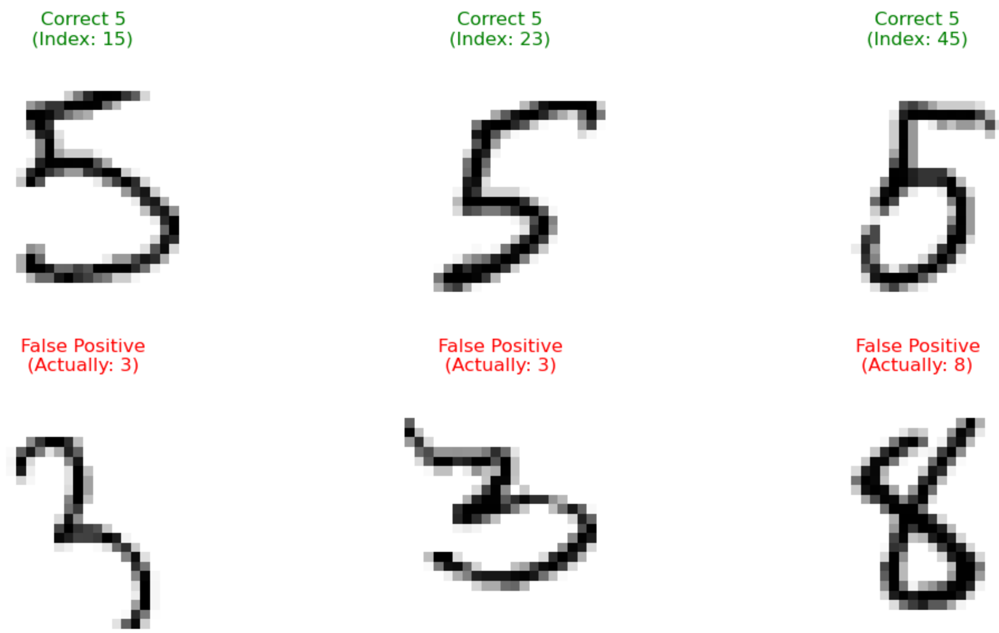
[7]:
```python
#Split into the first 60000 of X and y to train and the rest is test
X_train, X_test = X[:60000], X[60000:]
y_train, y_test = y[:60000], y[60000:]

# The binary y classification
y_train_5 = (y_train == '5')
y_test_5 = (y_test == '5')

# Ensuring the numbers are the correct type of array
X_test_np = X_test.to_numpy()
y_test_np = y_test_5.to_numpy()

#Fit
print("Training the model...")
SGD = SGDC.fit(X_train, y_train_5)

#Predict
y_test_pred = SGDC.predict(X_test_np)
```

```python
import matplotlib.pyplot as plt


tp_indices = np.where((y_test_pred == True) & (y_test_np == True))[0]

fp_indices = np.where((y_test_pred == True) & (y_test_np == False))[0]

print(f"Found {len(tp_indices)} correct 5s and {len(fp_indices)} false␣
↪positives.")

# --- 3. Plotting Function ---
def plot_digit(data, ax):
    image = data.reshape(28, 28)
    ax.imshow(image, cmap = plt.cm.binary, interpolation="nearest")
    ax.axis("off")

plt.figure(figsize=(12, 6))

for i in range(3):
    ax = plt.subplot(2, 3, i + 1)
    if i < len(tp_indices):
        idx = tp_indices[i]
        plot_digit(X_test_np[idx], ax)
        ax.set_title(f"Correct 5\n(Index: {idx})", color="green")

for i in range(3):
    ax = plt.subplot(2, 3, i + 4)
    if i < len(fp_indices):
        idx = fp_indices[i]
        plot_digit(X_test_np[idx], ax)
        original_label = y_test.iloc[idx] if hasattr(y_test, 'iloc') else␣
↪y_test[idx]
        ax.set_title(f"False Positive\n(Actually: {original_label})",␣
↪color="red")

plt.tight_layout()
plt.show()
```

```
Training the model…
```

```
c:\ProgramData\anaconda3\Lib\site-packages\sklearn\utils\validation.py:2749:
UserWarning: X does not have valid feature names, but SGDClassifier was fitted
with feature names
  warnings.warn(
```

```
Found 728 correct 5s and 67 false positives.
```



1.0.3 Qc Implement a dummy binary classifier

[4]:
```python
from sklearn.base import BaseEstimator

class DummyClassifier(BaseEstimator):
    def fit(self, X, y=None):
        # This model doesn't "learn" anything, so fit does nothing.
        # It just returns self to be compatible with sklearn pipelines.
        return self

    def predict(self, X):
        # Create a list of "False" (zeros) that is the same length as X
        return np.zeros((len(X), 1), dtype=bool)

# Running and evaluating
from sklearn.metrics import accuracy_score

# Create the model
dummy_clf = DummyClassifier()

# "Train" it (it learns nothing)
dummy_clf.fit(X_train, y_train_5)

# (This will just generate 10,000 "False" values)
y_dummy_pred = dummy_clf.predict(X_test)
```

```
# We are comparing our "All False" guesses against the Real answers
score = accuracy_score(y_test_5, y_dummy_pred)

print(f"Dummy Classifier Accuracy: {score}")
```

```
Dummy Classifier Accuracy: 0.9108
```

So we see a classifier with an accuracy of over 91%, incredible. One of the best classifiers I have ever made. Although all it really tells us is that aboubt 91,08% of the set is not the number 5. And so if we were to test it on a set mostly consisting of 5s then it would have an accuracy of nearly zero.

1.0.4 Qd Multiclass Classification

[5]:
```
# Random forrest multiclassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Create the model
rf_clf = RandomForestClassifier(n_estimators=10)

# Train (Fit)
print("Training Random Forest...")
rf_clf.fit(X_train, y_train)

# Predict & Evaluate
y_pred_rf = rf_clf.predict(X_test)
print(f"Random Forest Accuracy: {accuracy_score(y_test, y_pred_rf)}")

# SVM multiclassifier
from sklearn.svm import LinearSVC

svm_clf = LinearSVC(dual="auto")

print("Training Linear SVM...")
svm_clf.fit(X_train, y_train)

y_pred_svm = svm_clf.predict(X_test)
print(f"SVM Accuracy: {accuracy_score(y_test, y_pred_svm)}")


# Dummy classifier on full set

from sklearn.metrics import accuracy_score

# Create the model
dummy_clf = DummyClassifier()
```

```python
# "Train" it (it learns nothing)
dummy_clf.fit(X_train, y_train)

# (This will just generate 10,000 "False" values)
y_dummy_pred = dummy_clf.predict(X_test)
print("y_dummy_pred = ",y_dummy_pred)

# We are comparing our "All False" guesses against the Real answers
score = accuracy_score(y_test, y_dummy_pred)

print(f"Dummy Classifier Accuracy: {score}")
```

```
Training Random Forest…
Random Forest Accuracy: 0.9453
Training Linear SVM…
SVM Accuracy: 0.9183
y_dummy_pred =  [[False]
 [False]
 [False]
 …
 [False]
 [False]
 [False]]
Dummy Classifier Accuracy: 0.0
```

With the random forrest classifier getting an accuracy of 0.946 and that with n=10 is quite impressive, it even does it faster than the linear SVM. The dummy classifier, since it always predicts "False" and there is bound to be a number drawn, we get an accuracy of 0, but it does run!

1.0.5 Qe Conclusion

It is clear that it matters greatly how one chooses to organize one's data and what critereas are measured. There are some logical pitfalls one should be aware of like that of the dummyclassifier having an accuracy of ~90% but not predicting any numbers correctly in fact. It is analog to the way some statistics are presented where things can be made to look either really good or horrific depending on the way one chooses to present and sort in the data. The random forrest classifier took quite a long time with n=1000, so it was changed to n=10 which ran much faster and reached a very acceptable accuracy score. The SVM model also run pretty fast but ultimately yielded a little lower accuracy, still above 90% so depending on usecase still very much usable.

Remember that a broken clock is right twice a day. One could aslo say that a binary classifier saying whether a letter is a B or not will have a 100% accuracy if tested on the MNIST data set.