Use-Case-1

November 11, 2024

1 Module 8: Dimensionality Reduction

1.1 Case Study – 1

1.1.1 Understand and practice principal component analysis using scikit learn.

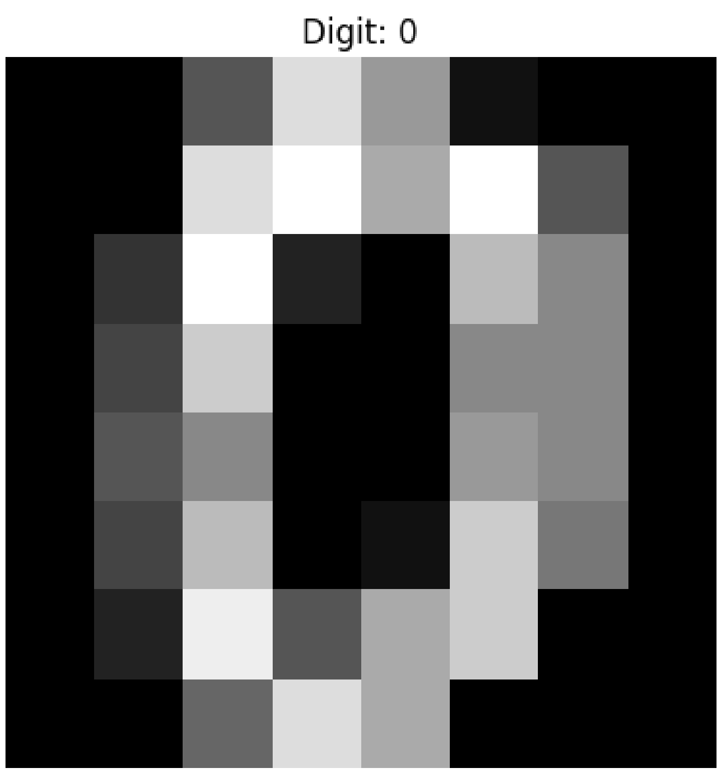
[19]:
```
# 1. Scikit learn comes with the pre-loaded dataset, load the digits dataset␣
↪from
# that collection and write a helper function to plot the image using␣
↪matplotlib.
# [Hint: Explore datasets module from scikit learn]

# Step 1: Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.decomposition import PCA
from sklearn.metrics import confusion_matrix
from sklearn.metrics import confusion_matrix

# 1.
# Step 2: Load the digits dataset
from sklearn.datasets import load_digits
digits = load_digits()
print(digits.DESCR)
print(digits.target_names[[0]])
print(digits.images[[0]])
```

```
.. _digits_dataset:

Optical recognition of handwritten digits dataset
--------------------------------------------------

**Data Set Characteristics:**
```

```
:Number of Instances: 1797
:Number of Attributes: 64
:Attribute Information: 8x8 image of integer pixels in the range 0..16.
:Missing Attribute Values: None
:Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)
:Date: July; 1998

This is a copy of the test set of the UCI ML hand-written digits datasets
https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digit
s

The data set contains images of hand-written digits: 10 classes where
each class refers to a digit.

Preprocessing programs made available by NIST were used to extract
normalized bitmaps of handwritten digits from a preprinted form. From a
total of 43 people, 30 contributed to the training set and different 13
to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of
4x4 and the number of on pixels are counted in each block. This generates
an input matrix of 8x8 where each element is an integer in the range
0..16. This reduces dimensionality and gives invariance to small
distortions.

For info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G.
T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C.
L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469,
1994.

.. dropdown:: References

  - C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their
    Applications to Handwritten Digit Recognition, MSc Thesis, Institute of
    Graduate Studies in Science and Engineering, Bogazici University.
  - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.
  - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.
    Linear dimensionalityreduction using relevance weighted LDA. School of
    Electrical and Electronic Engineering Nanyang Technological University.
    2005.
  - Claudio Gentile. A New Approximate Maximal Margin Classification
    Algorithm. NIPS. 2000.

[0]
[[[ 0.  0.  5. 13.  9.  1.  0.  0.]
  [ 0.  0. 13. 15. 10. 15.  5.  0.]
  [ 0.  3. 15.  2.  0. 11.  8.  0.]
  [ 0.  4. 12.  0.  0.  8.  8.  0.]
  [ 0.  5.  8.  0.  0.  9.  8.  0.]
```

```
 [ 0.  4. 11.  0.  1. 12.  7.  0.]
 [ 0.  2. 14.  5. 10. 12.  0.  0.]
 [ 0.  0.  6. 13. 10.  0.  0.  0.]]]
```

[67]:
```
# Helper function to plot an image
def plot_digit_image(index):
    # Select the image at the given index
    image = digits.images[index]
    label = digits.target[index]

    # Plot the image with matplotlib
    plt.imshow(image, cmap='gray')
    plt.title(f"Digit: {label}")
    plt.axis('off')
    plt.show()

# Test the function
plot_digit_image(0)
```



[22]:
```
# Load the digits dataset
x = digits.data  # The feature data
y = digits.target  # The target labels
```

```python
print(type(x))
#x

# Convert the features to a DataFrame
X_df = pd.DataFrame(digits.data, columns=[f'pixel_{i}' for i in range(digits.
↪data.shape[1])])

# Add the target as a new column
X_df['target'] = digits.target

# Display the first few rows
print(X_df.head(12))

# Display summary information about the DataFrame
print(X_df.info())

'''
We have 1,797 instances in total.
Each instance represents an 8x8 pixel grayscale image (so each image has 64␣
↪pixels in a flattened form).
The pixel values range from 0 to 16, where higher values indicate brighter␣
↪pixels.
The target variable represents the digit label (from 0 to 9) for each image,␣
↪which we want the model to classify.
'''
```

```
<class 'numpy.ndarray'>
    pixel_0  pixel_1  pixel_2  pixel_3  pixel_4  pixel_5  pixel_6  pixel_7  \
0       0.0      0.0      5.0     13.0      9.0      1.0      0.0      0.0
1       0.0      0.0      0.0     12.0     13.0      5.0      0.0      0.0
2       0.0      0.0      0.0      4.0     15.0     12.0      0.0      0.0
3       0.0      0.0      7.0     15.0     13.0      1.0      0.0      0.0
4       0.0      0.0      0.0      1.0     11.0      0.0      0.0      0.0
5       0.0      0.0     12.0     10.0      0.0      0.0      0.0      0.0
6       0.0      0.0      0.0     12.0     13.0      0.0      0.0      0.0
7       0.0      0.0      7.0      8.0     13.0     16.0     15.0      1.0
8       0.0      0.0      9.0     14.0      8.0      1.0      0.0      0.0
9       0.0      0.0     11.0     12.0      0.0      0.0      0.0      0.0
10      0.0      0.0      1.0      9.0     15.0     11.0      0.0      0.0
11      0.0      0.0      0.0      0.0     14.0     13.0      1.0      0.0

    pixel_8  pixel_9  …  pixel_55  pixel_56  pixel_57  pixel_58  pixel_59  \
0       0.0      0.0  …       0.0       0.0       0.0       6.0      13.0
1       0.0      0.0  …       0.0       0.0       0.0       0.0      11.0
2       0.0      0.0  …       0.0       0.0       0.0       0.0       3.0
3       0.0      8.0  …       0.0       0.0       0.0       7.0      13.0
4       0.0      0.0  …       0.0       0.0       0.0       0.0       2.0
```

```
5       0.0      0.0  …       0.0       0.0       0.0       9.0      16.0
6       0.0      0.0  …       0.0       0.0       0.0       1.0       9.0
7       0.0      0.0  …       0.0       0.0       0.0      13.0       5.0
8       0.0      0.0  …       0.0       0.0       0.0      11.0      16.0
9       0.0      2.0  …       0.0       0.0       0.0       9.0      12.0
10      0.0      0.0  …       0.0       0.0       0.0       1.0      10.0
11      0.0      0.0  …       0.0       0.0       0.0       0.0       1.0

    pixel_60  pixel_61  pixel_62  pixel_63  target
0       10.0       0.0       0.0       0.0       0
1       16.0      10.0       0.0       0.0       1
2       11.0      16.0       9.0       0.0       2
3       13.0       9.0       0.0       0.0       3
4       16.0       4.0       0.0       0.0       4
5       16.0      10.0       0.0       0.0       5
6       15.0      11.0       3.0       0.0       6
7        0.0       0.0       0.0       0.0       7
8       15.0      11.0       1.0       0.0       8
9       13.0       3.0       0.0       0.0       9
10      13.0       3.0       0.0       0.0       0
11      13.0      16.0       1.0       0.0       1

[12 rows x 65 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1797 entries, 0 to 1796
Data columns (total 65 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   pixel_0   1797 non-null   float64
 1   pixel_1   1797 non-null   float64
 2   pixel_2   1797 non-null   float64
 3   pixel_3   1797 non-null   float64
 4   pixel_4   1797 non-null   float64
 5   pixel_5   1797 non-null   float64
 6   pixel_6   1797 non-null   float64
 7   pixel_7   1797 non-null   float64
 8   pixel_8   1797 non-null   float64
 9   pixel_9   1797 non-null   float64
 10  pixel_10  1797 non-null   float64
 11  pixel_11  1797 non-null   float64
 12  pixel_12  1797 non-null   float64
 13  pixel_13  1797 non-null   float64
 14  pixel_14  1797 non-null   float64
 15  pixel_15  1797 non-null   float64
 16  pixel_16  1797 non-null   float64
 17  pixel_17  1797 non-null   float64
 18  pixel_18  1797 non-null   float64
 19  pixel_19  1797 non-null   float64
```

```
 20  pixel_20  1797 non-null   float64
 21  pixel_21  1797 non-null   float64
 22  pixel_22  1797 non-null   float64
 23  pixel_23  1797 non-null   float64
 24  pixel_24  1797 non-null   float64
 25  pixel_25  1797 non-null   float64
 26  pixel_26  1797 non-null   float64
 27  pixel_27  1797 non-null   float64
 28  pixel_28  1797 non-null   float64
 29  pixel_29  1797 non-null   float64
 30  pixel_30  1797 non-null   float64
 31  pixel_31  1797 non-null   float64
 32  pixel_32  1797 non-null   float64
 33  pixel_33  1797 non-null   float64
 34  pixel_34  1797 non-null   float64
 35  pixel_35  1797 non-null   float64
 36  pixel_36  1797 non-null   float64
 37  pixel_37  1797 non-null   float64
 38  pixel_38  1797 non-null   float64
 39  pixel_39  1797 non-null   float64
 40  pixel_40  1797 non-null   float64
 41  pixel_41  1797 non-null   float64
 42  pixel_42  1797 non-null   float64
 43  pixel_43  1797 non-null   float64
 44  pixel_44  1797 non-null   float64
 45  pixel_45  1797 non-null   float64
 46  pixel_46  1797 non-null   float64
 47  pixel_47  1797 non-null   float64
 48  pixel_48  1797 non-null   float64
 49  pixel_49  1797 non-null   float64
 50  pixel_50  1797 non-null   float64
 51  pixel_51  1797 non-null   float64
 52  pixel_52  1797 non-null   float64
 53  pixel_53  1797 non-null   float64
 54  pixel_54  1797 non-null   float64
 55  pixel_55  1797 non-null   float64
 56  pixel_56  1797 non-null   float64
 57  pixel_57  1797 non-null   float64
 58  pixel_58  1797 non-null   float64
 59  pixel_59  1797 non-null   float64
 60  pixel_60  1797 non-null   float64
 61  pixel_61  1797 non-null   float64
 62  pixel_62  1797 non-null   float64
 63  pixel_63  1797 non-null   float64
 64  target    1797 non-null   int64
dtypes: float64(64), int64(1)
memory usage: 912.7 KB
None
```

[22]: '\nWe have 1,797 instances in total.\nEach instance represents an 8x8 pixel grayscale image (so each image has 64 pixels in a flattened form).\nThe pixel values range from 0 to 16, where higher values indicate brighter pixels.\nThe target variable represents the digit label (from 0 to 9) for each image, which we want the model to classify.\n'

[23]:
```
# 2.
# Split the Dataset into Train and Test Sets
# 80-20 split for training and testing, as specified.
# Split the data: 80% for training, 20% for testing
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[24]:
```
# 2.
# Fit a Logistic Regression Model
# Initialize the Logistic Regression model
logistic_model = LogisticRegression(max_iter=10000, solver='lbfgs',␣
↪multi_class='auto')

# Fit the model to the training data
logistic_model.fit(x_train, y_train)
```

```
C:\Users\akram\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class'
was deprecated in version 1.5 and will be removed in 1.7. From then on, it will
always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
```

[24]: LogisticRegression(max_iter=10000, multi_class='auto')

[25]:
```
# 2.
# Make Predictions and Evaluate Accuracy
# After training the model, let's use it to predict the test set and then␣
↪calculate the accuracy.

# Predict on the test data
y_pred = logistic_model.predict(x_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of Logistic Regression Model: {accuracy * 100:.2f}%")
```

```
Accuracy of Logistic Regression Model: 97.50%
```

[9]:
```
# 3.
# Initialize PCA to retain 95% of the variance
pca = PCA(n_components=0.95)
```

```
# Fit and transform the data
x_pca = pca.fit_transform(x)
```

[28]:
```
x_pca
```

[28]:
```
array([[ -1.25946645, -21.27488348,   9.46305462, …,   3.67072108,
          0.9436689 ,   1.13250195],
       [  7.9576113 ,  20.76869896,  -4.43950604, …,   2.18261819,
          0.51022719,  -2.31354911],
       [  6.99192297,   9.95598641,  -2.95855808, …,   4.22882114,
         -2.1576573 ,  -0.8379578 ],
       …,
       [ 10.8012837 ,   6.96025223,  -5.59955453, …,  -3.56866194,
         -1.82444444,  -3.53885886],
       [ -4.87210009, -12.42395362,  10.17086635, …,   3.25330054,
         -0.95484174,   0.93895602],
       [ -0.34438963,  -6.36554919, -10.77370849, …,  -3.01636722,
         -1.29752723,  -2.58810313]])
```

[17]:
```
# 3.
# Number of components to explain 95% of the variance
num_components = pca.n_components_
print(f"Number of components to explain 95% of variance: {num_components}")
```

```
Number of components to explain 95% of variance: 29
```

[20]:
```
# Apply PCA to retain 95% of the variance
# Fitting PCA on the training data to find the principal components and then␣
↪transforming both x_train and x_test based on these components.
x_train_pca = pca.fit_transform(x_train)
x_test_pca = pca.transform(x_test)

# Fit logistic regression on the PCA-transformed data
# This part trains a logistic regression model on the reduced-dimensional data.
# Setting max_iter high ensures convergence, which is often necessary for␣
↪higher-dimensional data.
logistic_model_pca = LogisticRegression(max_iter=10000, solver='lbfgs',␣
↪multi_class='auto')
logistic_model_pca.fit(x_train_pca, y_train)

# Predict on the test data and calculate accuracy
y_pred_pca = logistic_model_pca.predict(x_test_pca)
accuracy_pca = accuracy_score(y_test, y_pred_pca)
print(f"Accuracy of Logistic Regression Model after PCA: {accuracy_pca * 100:.
↪2f}%")
# The accuracy of 95.83% indicates the model performs well even after␣
↪dimensionality reduction.
```

```
Accuracy of Logistic Regression Model after PCA: 95.83%
```

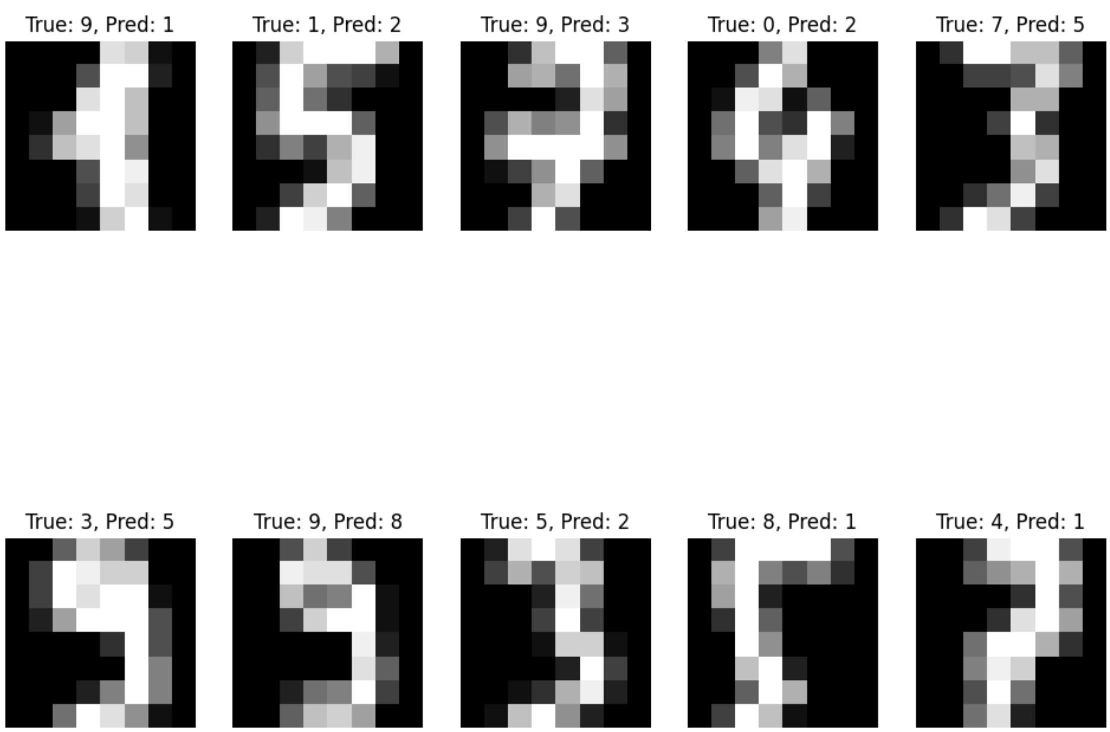
```
C:\Users\akram\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class'
was deprecated in version 1.5 and will be removed in 1.7. From then on, it will
always use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
```

[21]:

```python
# 4.
# Compute the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_pca)
print(conf_matrix)

# 5.
# Identifying Misclassified Instances
# Calculate the number of misclassified instances
misclassified_indices = np.where(y_test != y_pred_pca)[0]
print(misclassified_indices)
num_misclassified = len(misclassified_indices)
print(f"Number of misclassified instances: {num_misclassified}")


def plot_misclassified_images(X, y_true, y_pred, indices, num_samples=10):
    """
    Plots misclassified images with their true and predicted labels.

    Parameters:
    - X: The original feature data.
    - y_true: The true labels.
    - y_pred: The predicted labels.
    - indices: Indices of misclassified samples.
    - num_samples: Number of samples to plot.
    """
    plt.figure(figsize=(12, 10))

    # Limit to num_samples misclassified images for display
    for i, idx in enumerate(indices[:num_samples]):
        plt.subplot(2, 5, i + 1)
        plt.imshow(X_df.iloc[idx, :-1].values.reshape(8, 8), cmap='gray')
        plt.title(f"True: {y_true[idx]}, Pred: {y_pred[idx]}")
        plt.axis('off')

    plt.show()

# Plot misclassified images
plot_misclassified_images(x_test, y_test, y_pred_pca, misclassified_indices)
```

```
# Explanation: This part identifies the indices where the true labels (y_test)
↪do not match the predicted labels (y_pred_pca).
# Printing these indices and the count of misclassified samples (15) is helpful
↪for understanding model performance and potential misclassification patterns.
```

```
[[32  0  1  0  0  0  0  0  0  0]
 [ 0 27  1  0  0  0  0  0  0  0]
 [ 0  1 32  0  0  0  0  0  0  0]
 [ 0  0  0 33  0  1  0  0  0  0]
 [ 0  1  0  0 45  0  0  0  0  0]
 [ 0  0  1  0  0 44  1  0  0  1]
 [ 0  0  0  0  0  1 34  0  0  0]
 [ 0  0  0  0  0  1  0 33  0  0]
 [ 0  1  0  0  0  1  0  0 28  0]
 [ 0  1  0  1  0  0  0  0  1 37]]
[ 11  32  52 124 133 149 159 193 204 222 234 239 244 245 339]
Number of misclassified instances: 15
```



1.1.2 Explanation

- PCA Transformation: We transformed x into x_pca, which now has 29 features instead of 64.
- Training on Reduced Data: We used the reduced feature set to train the logistic regression model.

- Model Accuracy: Despite the reduction in dimensions, the model should achieve high accuracy because the PCA retained 95% of the information (variance) in the data.

1.1.3 Benefits of PCA in This Case

- Reduced Complexity: Fewer dimensions make the model simpler, potentially improving training speed and reducing the risk of overfitting.
- Retained Information: By retaining components that explain 95% of the variance, we ensure that most of the important information in the data is still available for the model.
- This is a common workflow in data science, where PCA helps reduce the dimensionality while preserving essential information, making the model efficient without losing accuracy significantly.

[ ]:

```

```