

# MP4

November 5, 2025

## 1 AI 221: Machine Exercise 4 - Handwritten Digits Analysis

This exercise focuses on dimensionality reduction and classification techniques applied to the 8x8 handwritten digits dataset from sklearn.

## 2 Dataset Preparation

This section contains the loading the handwritten digits and showing random samples.

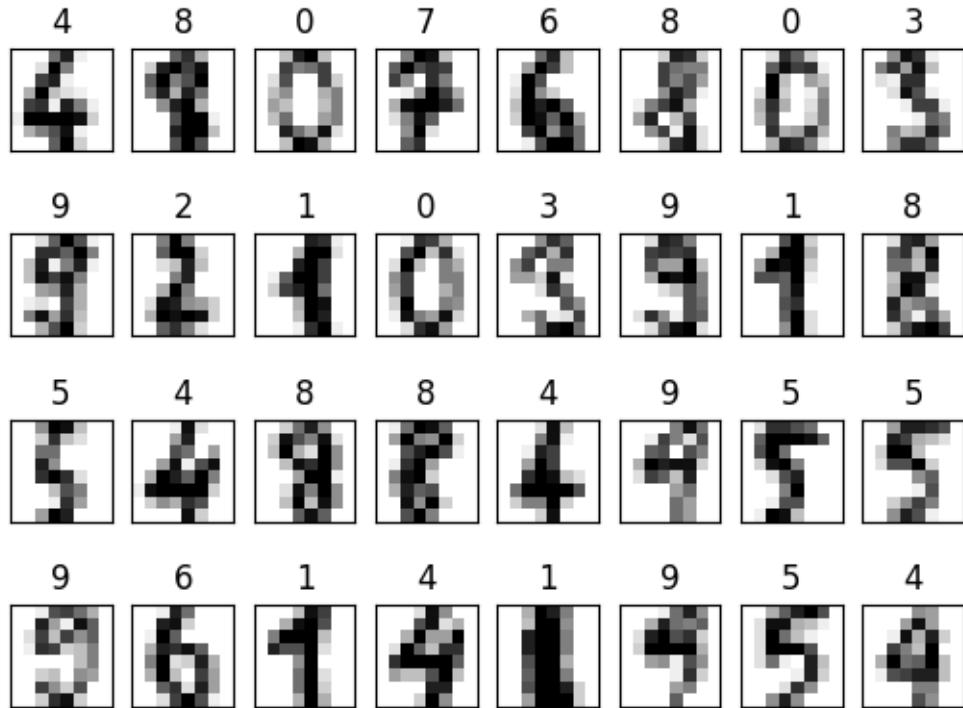
```
[1]: from sklearn.datasets import load_digits
import matplotlib.pyplot as plt
import numpy as np
import random
X, y = load_digits(return_X_y=True)
print(X.shape)
random.seed(0)

rows, cols = 4, 8
fig, ax = plt.subplots(rows, cols, sharex='col', sharey='row',
                      subplot_kw=dict(xticks=[], yticks=[]))

for row in range(rows):
    for col in range(cols):
        n = np.random.randint(1796)+1      # show random samples
        im = ax[row, col].imshow(X[n].reshape((8,8)), cmap=plt.cm.binary)
        ax[row, col].set_title(y[n])
        im.set_clim(0, 16)
        #print(X[n])

plt.show()
```

(1797, 64)



### 3 Exercises

This section contains the core implementations of Machine Exercise 4 and is subdivided in to 3 subsections;

- Part A: Dimensionality Reduction Visualization
- Part B: Variance Analysis
- Part C: Classification Comparison

#### 3.1 Part A: Dimensionality Reduction Visualization

##### 3.1.1 Tasks:

1. Load and preprocess data:
  - Import digits dataset from `sklearn.datasets`
  - Apply StandardScaler normalization
2. Implement 6 dimensionality reduction techniques:
  - Local Linear Embedding (`n_neighbors=200, random_state=0`)
  - t-SNE (`perplexity=50, random_state=0`)
  - Isomap (`n_neighbors=200`)
  - Laplacian Eigenmap (`n_neighbors=200`)
  - Kernel PCA (`kernel='rbf', gamma=0.01`)
  - PCA
3. Visualization requirements:

- Project data to 2D for each method
- Color points by digit labels
- Compare clustering quality

### **3.1.2 Local Linear Embedding (n\_neighbors = 200, random\_state=0)**

### **3.1.3 t-SNE (perplexity = 50, random\_state = 0)**

### **3.1.4 Isomap (n\_neighbors=200)**

### **3.1.5 Laplacian Eigenmap (n\_neighbors=200)**

### **3.1.6 Kernel PCA (kernel='rbf', gamma=0.01)**

### **3.1.7 PCA**

### **3.1.8 Results**

Which of the methods produced clear clusters of data points?

## **3.2 Part B: Variance Analysis [10 pts]**

### **3.2.1 Task Breakdown:**

1. Generate CPV (Cumulative Percent Variance) plots for:
  - Kernel PCA
  - Standard PCA
2. Analysis requirements:
  - Determine number of components for 95% variance retention
  - Compare results between KPCA and PCA

### **3.2.2 Kernel PCA**

### **3.2.3 Standard PCA**

### **3.2.4 Results**

This section contains relevant inf

## **3.3 Part C: Classification Comparison [60 pts]**

### **3.3.1 Data Preparation:**

- Split data: 70% training, 30% testing
- Ensure stratified sampling by class label

### **3.3.2 Classification Methods:**

1. Method 1: Kernel PCA Pipeline [20 pts]
  - StandardScaler
  - Kernel PCA (kernel='sigmoid', n\_components=40)
  - SVC (default parameters)
  - Report accuracy and F1-score
2. Method 2: LDA Pipeline [20 pts]

- StandardScaler
  - LDA (n\_components=9)
  - SVC (default parameters)
  - Report accuracy and F1-score
  - Explain LDA component limitation
3. Method 3: Baseline SVC [20 pts]
- StandardScaler
  - SVC (default parameters)
  - No dimensionality reduction
  - Report accuracy and F1-score

### **3.3.3 Analysis Requirements:**

- Compare performance metrics
- Explain best performing method
- Discuss trade-offs

### **3.3.4 Kernel PCA Pipeline**

- StandardScaler
- Kernel PCA (kernel='sigmoid', n\_components=40)
- SVC (default parameters)
- Report accuracy and F1-score

### **3.3.5 LDA Pipeline [20 pts]**

- StandardScaler
- LDA (n\_components=9)
- SVC (default parameters)
- Report accuracy and F1-score
- Explain LDA component limitation

### **3.3.6 Baseline SVC [20 pts]**

- StandardScaler
- SVC (default parameters)
- No dimensionality reduction
- Report accuracy and F1-score

## **3.4 Submission Guidelines**

1. Format Requirements:
  - Submit as PDF file
  - Export from Jupyter Notebook
  - Highlight final answers clearly
2. Code Organization:
  - Clear section headers
  - Well-documented implementations
  - Proper visualization labels

3. Analysis Documentation:
  - Detailed explanations for each part
  - Comparative analysis between methods
  - Clear conclusions and insights
4. Submit through UVLE platform