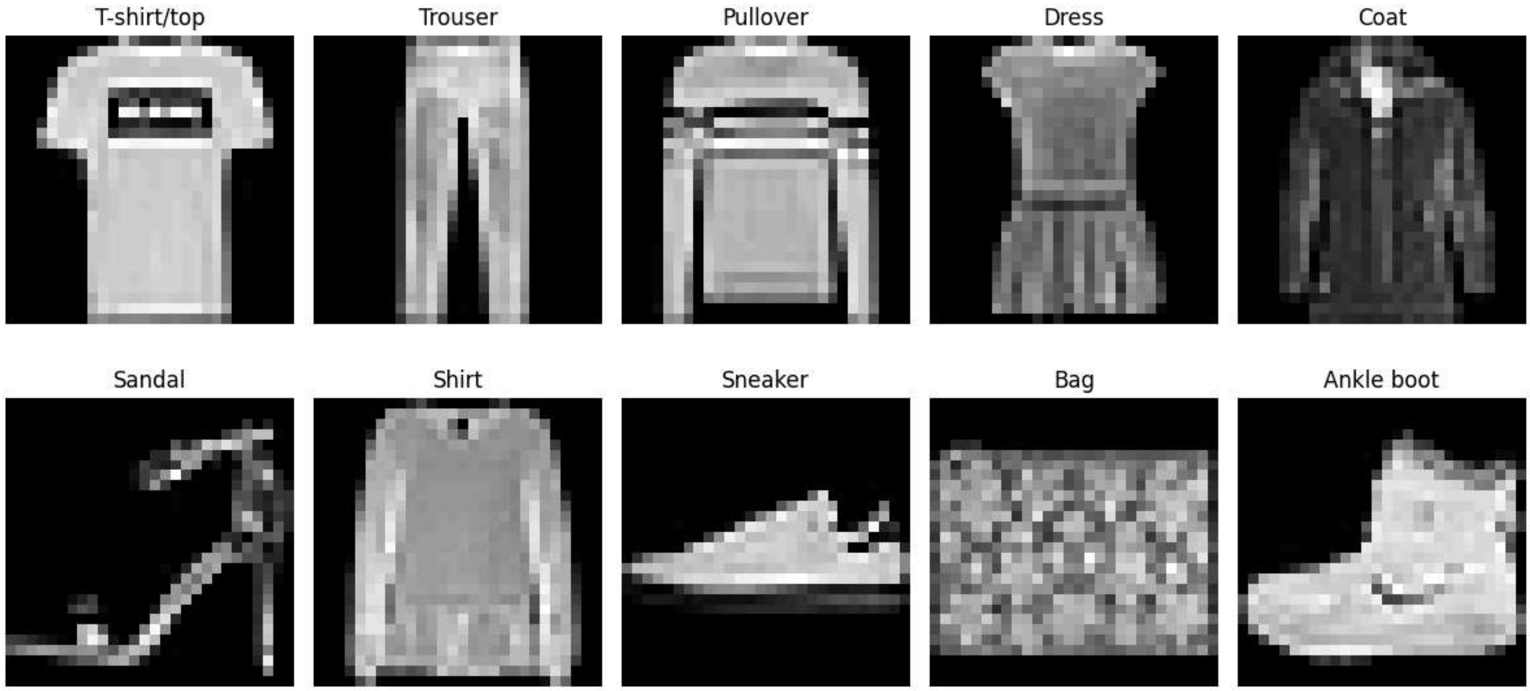
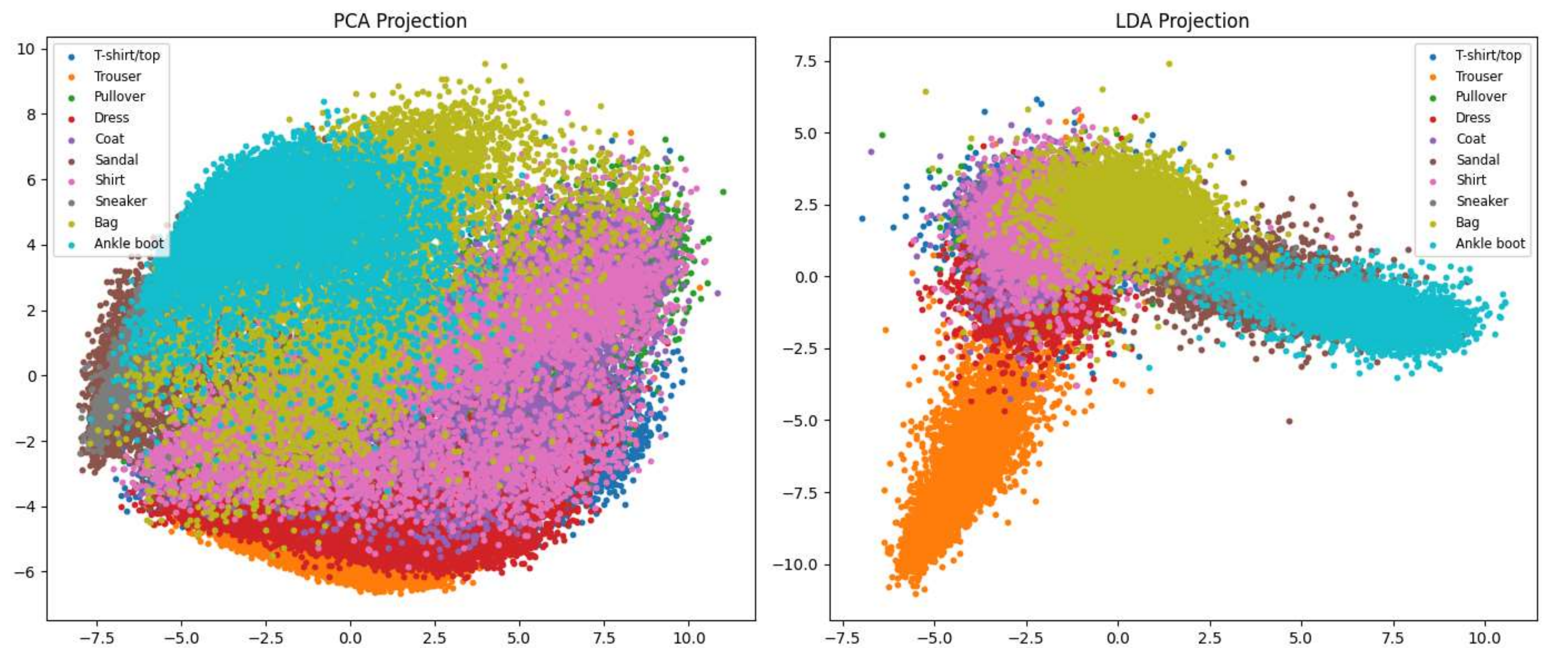
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.datasets import fetch_openml
from sklearn.preprocessing import MinMaxScaler

# 1. Load the Dataset
print("Loading Fashion-MNIST dataset...")
X, y = fetch_openml('Fashion-MNIST', version=1, return_X_y=True, as_frame=False)
y = y.astype(int)

# 2. Preprocess the Data
print("Normalizing data and visualizing samples...")
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# Visualize one image per category
categories = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
              'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
plt.figure(figsize=(12, 6))
for i in range(10):
    idx = np.where(y == i)[0][0]
    plt.subplot(2, 5, i+1)
    plt.imshow(X[idx].reshape(28, 28), cmap='gray')
    plt.title(categories[i])
    plt.axis('off')
plt.tight_layout()
plt.show()

# 3. Apply PCA
print("Applying PCA...")
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# 4. Apply LDA
print("Applying LDA...")
lda = LDA(n_components=2)
X_lda = lda.fit_transform(X_scaled, y)

# 5. Visualize PCA and LDA Results
print("Plotting results...")
fig, axs = plt.subplots(1, 2, figsize=(14, 6))

# PCA Plot
for i in range(10):
    axs[0].scatter(X_pca[y == i, 0], X_pca[y == i, 1], label=categories[i], s=10)
axs[0].set_title('PCA Projection')
axs[0].legend(loc='best', fontsize='small')

# LDA Plot
for i in range(10):
    axs[1].scatter(X_lda[y == i, 0], X_lda[y == i, 1], label=categories[i], s=10)
axs[1].set_title('LDA Projection')
axs[1].legend(loc='best', fontsize='small')

plt.tight_layout()
plt.show()

# 6. Analysis and Discussion
report = """
Analysis & Discussion:

1. **Category Separation:**
   - In the PCA plot, some categories overlap significantly, e.g., 'Shirt', 'T-shirt/top', 'Pullover'.
   - In the LDA plot, class separation is more distinct due to label supervision.

2. **Comparison:**
   - **PCA** is unsupervised and tries to maximize variance without considering class labels. Thus, categories may overlap.
   - **LDA** is supervised and maximizes class separability. It shows clearer boundaries.

3. **When to use PCA vs LDA:**
   - Use **PCA** when there are no labels or when you want to reduce noise and compress data.
   - Use **LDA** when class labels are available and your goal is classification or visualization of class separation.
"""

print(report)
```

Loading Fashion-MNIST dataset...
Normalizing data and visualizing samples...



Applying PCA...
Applying LDA...
Plotting results...



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