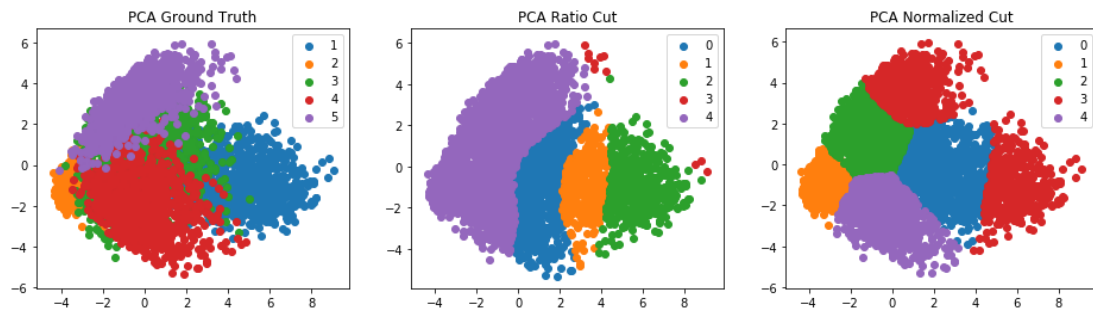


# Homework# 7

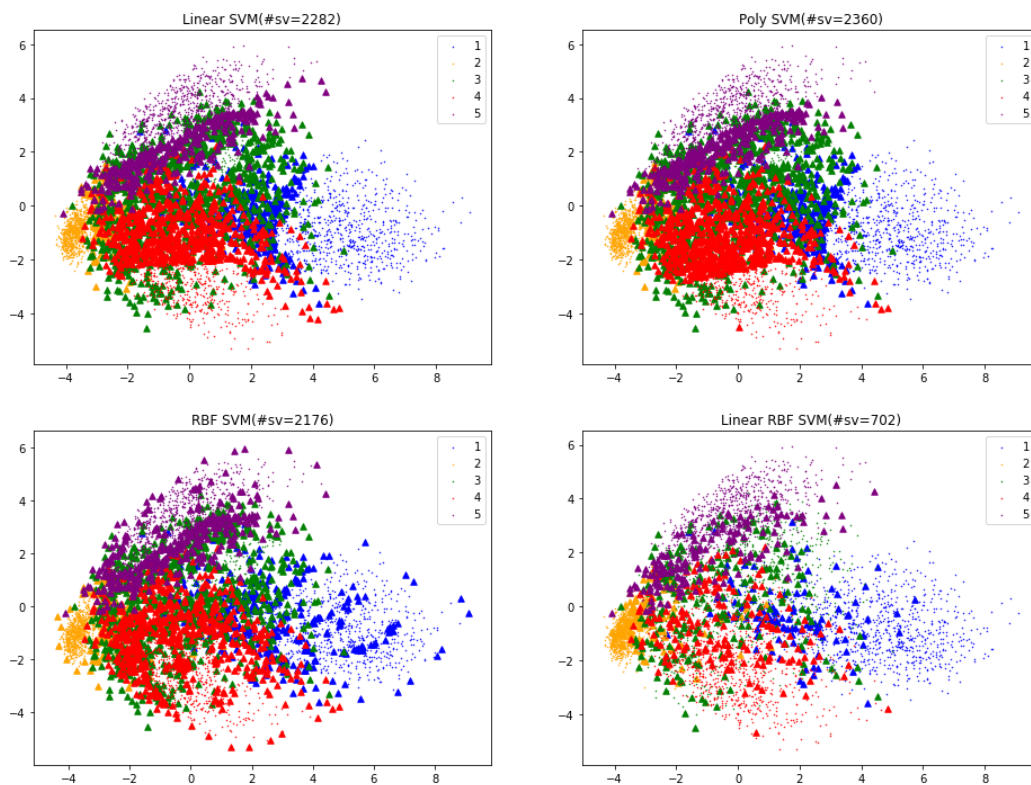
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## 1. PCA projection and clustering



可以發現 normalized cut 不同 cluster 間的個數較為平均。

## 2. PCA projection and SVM classification

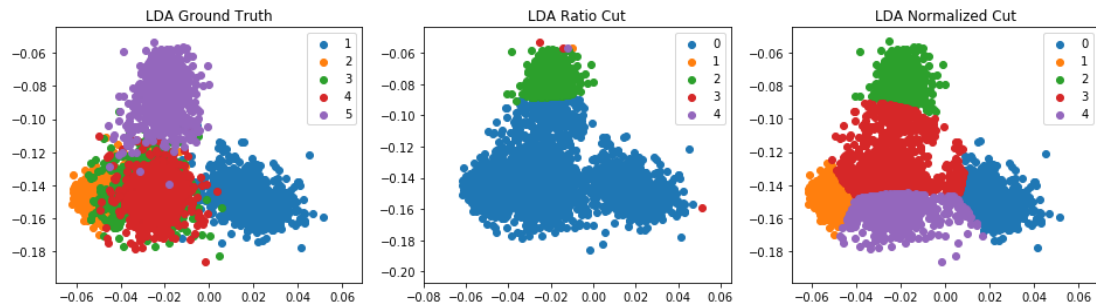


可以發現使用 Linear + RBF kernel 所用的 support vector 最少 (support vector 越少代表 overfitting 的風險越小)

此處 kernel 參數採用 default

(  $C=0$ ,  $degree=3$  for poly,  $coef0=0.0$ ,  $gamma = 1/784$  )

### 3. LDA projection



同上，可以發現 normalized cut 不同 cluster 間的個數較為平均。

### 4. EigenFace

Top 25 EigenFaces



Reconstruction



可以看到使用越多的 eigenFace 來重建，會越像本來的臉。

## Code Detail

### 0. Read Data

```
df_X = pd.read_csv('X_train.csv', header=None)
df_Y = pd.read_csv('T_train.csv', header=None)
|
X_train = df_X.values
Y_train = df_Y.values
Y_train = Y_train.reshape(Y_train.shape[0])
```

### 1. Use PCA to project all your data X\_train.csv onto 2D space

```
class PCA:
    def __init__(self, n_components=2):
        self.n_components = n_components

    def transform(self, X):
        X_high = np.copy(X)
        mean_mat = np.tile(self.mean_vec, (X.shape[0],1))
        diff_mat = X_high - mean_mat
        # Project from high to low
        X_low = np.matmul(diff_mat, self.W)
        return np.real(X_low)

    def fit(self, X):
        # Compute covariance matrix
        X_high = np.copy(X)
        mean_vec = np.mean(X_high, 0)
        mean_mat = np.tile(mean_vec, (X.shape[0],1))
        diff_mat = X_high - mean_mat
        cov_mat = np.cov(diff_mat.T)
        self.mean_vec = mean_vec

        # Compute eigenpairs of cov mat
        eigenValues, eigenVectors = np.linalg.eig(cov_mat)
        idx = eigenValues.argsort()[::-1]
        W = eigenVectors[:,idx][:, :self.n_components]
        W = W * -1
        self.W = W
        # Compute first-k eigenvector of covariance matrix
        return self

pca = PCA(n_components=2)
X_low_pca = pca.fit(X_train).transform(X_train)
```

## 2. Use LDA to project all your data X\_train.csv onto 2D space

```
class LDA:
    def __init__(self, n_components=2):
        self.n_components = n_components
        self.mean = 0
        self.std = 1

    def transform(self, X):
        X_high = np.copy(X)
        X_high = (X_high - self.mean) / self.std
        # Project from high to low
        X_low = np.matmul(X_high, self.W)
        return np.real(X_low)

    def fit(self, X, Y):
        N, dim = X.shape
        X_high = np.copy(X)
        self.mean = X_high.mean()
        self.std = X_high.std()
        X_high = (X_high - self.mean) / self.std
        # Compute mean for each class (mj, nj)
        mean_vectors = []
        for c in set(Y):
            mean_vectors.append( np.mean(X_high[Y==c], axis=0) )
        self.mean_vectors = mean_vectors

        # Compute within-class scatter
        SW = np.zeros( (dim,dim) )
        for c, mv in zip(set(Y), mean_vectors):
            within_class_scatter = np.zeros((dim, dim))
            for xi in X_high[Y==c]:
                xi = xi.reshape(-1, 1) # make vec to mat
                mj = mv.reshape(-1, 1) # make vec to mat
                within_class_scatter += np.matmul(xi-mj, (xi-mj).T)
            SW += within_class_scatter

        # Compute between-class scatter
        SB = np.zeros( (dim,dim) )
        m = np.mean(X_high, axis=0).reshape(-1, 1)
        for c, mv in zip(set(Y), mean_vectors):
            nj = X_high[Y==c].shape[0]
            mj = mv.reshape(-1, 1) # make vec to mat
            SB += nj * np.matmul((mj-m), (mj-m).T)

        # Compute W using first k eigenvector of inv(SW)*SB
        mat = np.dot(np.linalg.pinv(SW), SB)
        eigenValues, eigenVectors = np.linalg.eig(mat)
        idx = eigenValues.argsort()[::-1]
        eigenValues = eigenValues[idx]
        eigenVectors = eigenVectors[:,idx]
        W = np.real(eigenVectors[:, 0:self.n_components])
        W /= np.linalg.norm(W, axis=0)
        self.W = W
        return self

lda = LDA(n_components=2)
X_low_lda = lda.fit(X_train, Y_train).transform(X_train)
```

Compute Within-class  
scatter

Compute Within-class scatter

Compute first-k largest  
eigvector of  $\text{inv}(\text{SW}) * \text{SB}$

### 3. RatioCut

```
class Spectral_clustering_ratioCut:

    def __init__(self, n_cluster=2, gamma=1):
        self.n_cluster = n_cluster
        self.gamma = gamma

    def fit(self, X, kernel='rbf'):
        # 0. Define similarity matrix W and D
        W = []

        if kernel == 'linear':
            W = compute_linear_kernel(X)
        elif kernel == 'rbf':
            W = compute_RBF_kernel(X, self.gamma)
        elif kernel == 'rbf_linear':
            W = kernel = compute_linear_rbf_kernel(X, self.gamma)

        D = np.zeros((X.shape[0], X.shape[0]))
        for d in range(X.shape[0]):
            D[d][d] = W[d].sum()

        # 1. Graph Laplacian L = D - W
        L = D - W

        # Get first k eigenvector
        eigenValues, eigenVectors = LA.eig(L)
        idx = eigenValues.argsort()
        eigenValues = eigenValues[idx]
        eigenVectors = eigenVectors[:,idx]
        U = eigenVectors[:, 1:self.n_cluster+1]

        # Do k-means
        kmeans = k_means_clustering(k=self.n_cluster)
        membership = kmeans.fit(U)
        return membership
```

## 4. Normalized Cut

```
class Spectral_clustering_normCut:
    def __init__(self, n_cluster=2, gamma=1):
        self.n_cluster = n_cluster
        self.gamma = gamma

    def fit(self, X, kernel='rbf'):
        # 0. Define similarity matrix W and D
        W = []

        if kernel == 'linear':
            W = compute_linear_kernel(X)
        elif kernel == 'rbf':
            W = compute_RBF_kernel(X, self.gamma)
        elif kernel == 'rbf_linear':
            W = kernel = compute_linear_rbf_kernel(X, self.gamma)
        D = np.zeros((X.shape[0], X.shape[0]))
        for d in range(X.shape[0]):
            D[d][d] = W[d].sum()

        # 1. Graph Laplacian  $L = D - W$ ,  $L_{norm} = D^{(-1/2)} L D^{(-1/2)}$ 
        L = D - W
        D_inv_sqrt = np.linalg.pinv(sqrtm(D))
        L = np.matmul(np.matmul(D_inv_sqrt, L), D_inv_sqrt)

        # Get first k eigenvector
        eigenValues, eigenVectors = LA.eig(L)
        idx = eigenValues.argsort()
        eigenValues = eigenValues[idx]
        eigenVectors = eigenVectors[:,idx]
        U = eigenVectors[:, 1:self.n_cluster+1]

        # Do k-means
        kmeans = k_means_clustering(k=self.n_cluster)
        membership = kmeans.fit(U)
        return membership
```

## 5. SVM

```
from sklearn import svm
```

```
svm_linear = svm.SVC(kernel='linear')
svm_linear.fit(X_low_pca, Y_train)
y_pred_svm_linear = svm_linear.predict(X_low_pca)
sv_linear_index = svm_linear.support_
print(svm_linear.n_support_)
```

Linear SVM

```
svm_poly = svm.SVC(kernel='poly')
svm_poly.fit(X_low_pca, Y_train)
y_pred_poly_rbf = svm_poly.predict(X_low_pca)
sv_poly_index = svm_poly.support_
print(svm_poly.n_support_)
```

Poly SVM

```
svm_rbf = svm.SVC(kernel='rbf')
svm_rbf.fit(X_low_pca, Y_train)
y_pred_svm_rbf = svm_rbf.predict(X_low_pca)
sv_rbf_index = svm_rbf.support_
print(svm_rbf.n_support_)
```

RBF SVM

```
svm_linear_rbf = svm.SVC(kernel='precomputed')
kernel = compute_linear_rbf_kernel(X_train, gamma=1/784)
svm_linear_rbf.fit(kernel, Y_train)
# y_pred_svm_rbf = svm_linear_rbf.predict(X_low_pca)
sv_linear_rbf_index = svm_linear_rbf.support_
print(svm_linear_rbf.n_support_)
```

Linear + RBF SVM

## 6. EigenFaces

```
imgs = []
for dir_path in img_dirs:
    imgs += read_dir_imgs(dir_path)

imgs = np.array(imgs)
imgs = imgs.reshape( (prod(imgs.shape[:1]), prod(imgs.shape[1:])) ).T

mean_vector = imgs.mean(1)
mean_face = vec2img(mean_vector)
plt.imshow(mean_face, cmap = 'gray'), plt.show()

diff_imgs = imgs - np.tile(np.array([mean_vector]).T, (1, 400))
T_trans_T = np.cov(imgs.T)

eigenValues, eigenVectors = np.linalg.eig(T_trans_T)

idx = eigenValues.argsort()[::-1]
eigenValues = eigenValues[idx]
eigenVectors = eigenVectors[:,idx]
print(eigenVectors.shape)

k = 25
eigenValues = eigenValues[:k]
eigenVectors = eigenVectors[:, 0:k]

# get real eigen vector(eigen faces)
A = diff_imgs
eigenVectors = np.matmul(A, eigenVectors)
eigen_faces = np.copy(eigenVectors)
```

Read Images

Compute Mean Face  
And covariance matrix

Get 25 largest eigenvector  
And project mean face to  
eigenspace to get 25 eigen  
faces

For more detail, please check EigenFace.py and HW7.py