In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import numpy.random as npr
import cv2
from time import time
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# Load the dataset
X_train = np.load('Dataset/data_train.npy').T
t_train = np.load('Dataset/labels_train_corrected.npy')
X_test = np.load('Dataset/data_test.npy').T
t_test = np.load('Dataset/labels_test_corrected.npy')

X_train.shape, t_train.shape, X_test.shape, t_test.shape
```

Out[2]:
```
((6720, 90000), (6720,), (2880, 90000), (2880,))
```

In [3]:
```
# Reshape the training adn test data set
X_train_reshaped = np.zeros((6720, 2500))
X_test_reshaped = np.zeros((2880, 2500))

for i in range(len(X_train[:, 0])):
    im1 = X_train[i, :].reshape(300,300)
    res = cv2.resize(im1, dsize=(50, 50), interpolation=cv2.INTER_CUBIC)
    X_train_reshaped[i, :] = res.reshape(2500,)

for i in range(len(X_test[:, 0])):
    im1 = X_test[i, :].reshape(300,300)
    res = cv2.resize(im1, dsize=(50, 50), interpolation=cv2.INTER_CUBIC)
    X_test_reshaped[i, :] = res.reshape(2500,)

X_train_reshaped.shape, X_test_reshaped.shape
```

Out[3]:
```
((6720, 2500), (2880, 2500))
```

In [4]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from scipy import stats
from sklearn.model_selection import cross_val_score


# Define a function for evaluating performance
def Evaluate_performance(estimator, Name, confidence=True, X_train=X_train_reshaped

    t0 = time()
    y_train = estimator.predict(X_train)
    t1 = time()
    predict_train_time = t1 - t0

    t0 = time()
    y_test = estimator.predict(X_test)
    t1 = time()
    predict_test_time = t1 - t0

    # Accuracy
    train_accuracy = accuracy_score(t_train, y_train)
    test_accuracy = accuracy_score(t_test, y_test)

    if confidence == True:
        # 95% CI in training set
        scores = cross_val_score(estimator, X_train, t_train,
```

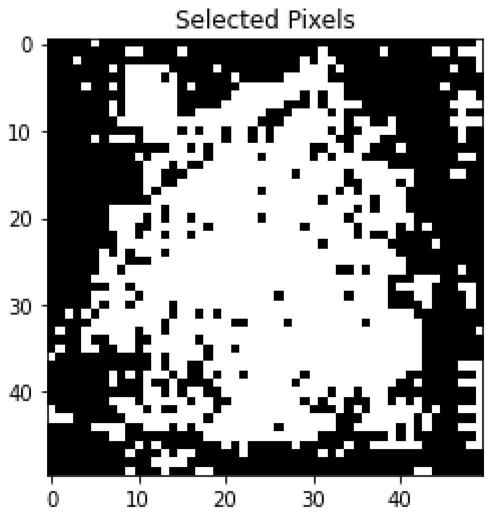
```
                            scoring=scoring,
                            cv=5)
        confidence_ = 0.95
        train_interval = stats.t.interval(confidence_,
                                          len(scores)-1,
                                          loc = scores.mean(),
                                          scale=scores.std(ddof=1)/np.sqrt(len(score

        # Accuracy and 95% CI in test set
        scores = cross_val_score(estimator, X_test, t_test,
                            scoring=scoring,
                            cv=5)
        confidence_ = 0.95
        test_interval = stats.t.interval(confidence_,
                                          len(scores)-1,
                                          loc = scores.mean(),
                                          scale=scores.std(ddof=1)/np.sqrt(len(score

    print('Performance of {}:\n'.format(Name))
    print('1. In training set: (time used in predict: {:.2f} sec)'.format(predict_tr
    print(classification_report(t_train, y_train))
    print('Accuracy: {}'.format(train_accuracy))
    if confidence == True:
        print('95% CI: {}\n'.format(train_interval))
    print('Confusion Matrix')
    print(confusion_matrix(t_train, y_train))

    print('\n ===================================================== \n')

    print('2. In test set: (time used in predict: {:.2f} sec)'.format(predict_test_t
    print(classification_report(t_test, y_test))
    print('Accuracy: {}'.format(test_accuracy))
    if confidence == True:
        print('95% CI: {}\n'.format(test_interval))
    print('Confusion Matrix')
    print(confusion_matrix(t_test, y_test))
```

- Identify which pixels are selected and displaymask examples from the training dataset.

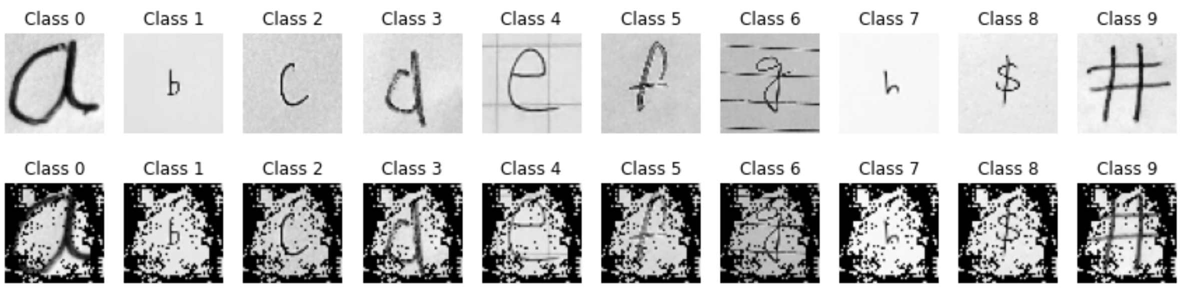
In [5]:
```
# Load the model
import joblib

rfe_lr = joblib.load('Model/rfe_lr_question1.pkl')
rfe_svm = joblib.load('Model/rfe_svm_question1.pkl')
```

In [6]:
```
# For Logistic Regression with RFE
pixels = rfe_lr.named_steps['RFE'].support_.reshape(50,50)
plt.imshow(pixels, cmap='gray')
plt.title('Selected Pixels')
```

Out[6]:
```
Text(0.5, 1.0, 'Selected Pixels')
```

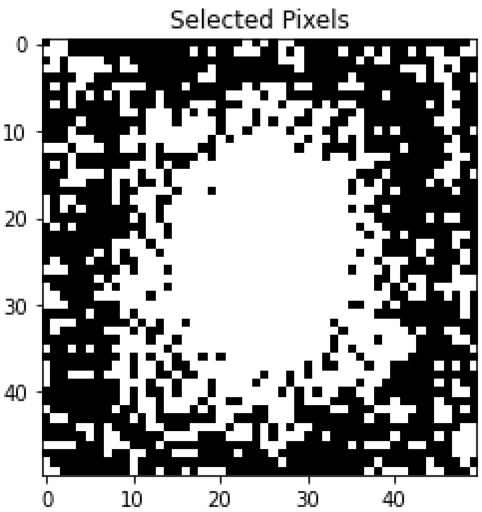


In [7]:
```
plt.figure(figsize=(15,15))
for i in range(10):
    index = np.where(t_train==i)
    plt.subplot(1,10,i+1)
    plt.imshow(X_train_reshaped[index[0][0], :].reshape(50,50), cmap='gray')
    plt.axis('off')
    plt.title('Class {:.0f}'.format(t_train[index[0][0]]))

plt.figure(figsize=(15,15))
for i in range(10):
    index = np.where(t_train==i)
    plt.subplot(1,10,i+1)
    plt.imshow(X_train_reshaped[index[0][0], :].reshape(50,50)*pixels, cmap='gray')
    plt.axis('off')
    plt.title('Class {:.0f}'.format(t_train[index[0][0]]))
```



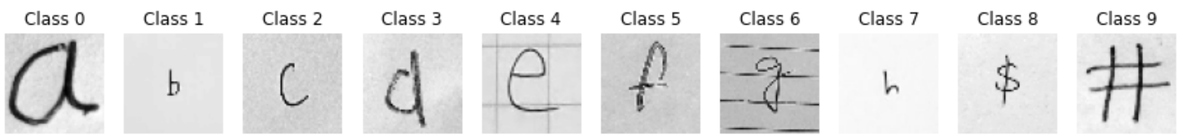
In [8]:
```
# For SVM with RFE
pixels = rfe_svm.named_steps['RFE'].support_.reshape(50,50)
plt.imshow(pixels, cmap='gray')
plt.title('Selected Pixels')
```

Out[8]:
```
Text(0.5, 1.0, 'Selected Pixels')
```



In [9]:

```python
plt.figure(figsize=(15,15))
for i in range(10):
    index = np.where(t_train==i)
    plt.subplot(1,10,i+1)
    plt.imshow(X_train_reshaped[index[0][0], :].reshape(50,50), cmap='gray')
    plt.axis('off')
    plt.title('Class {:.0f}'.format(t_train[index[0][0]]))

plt.figure(figsize=(15,15))
for i in range(10):
    index = np.where(t_train==i)
    plt.subplot(1,10,i+1)
    plt.imshow(X_train_reshaped[index[0][0], :].reshape(50,50)*pixels, cmap='gray')
    plt.axis('off')
    plt.title('Class {:.0f}'.format(t_train[index[0][0]]))
```



Question 2

- Was training faster using the reduced dataset?

When training the dataset with the 182 dimension's dataset, it took 8.76 seconds. When training the dataset with whole 2500 reshaped pixels, it took 76.26 seconds. Classifier with PCA is almost 10 times faster than the original classifier.

- Compare performances.

In [10]:

```python
# Load the model
svm_pca = joblib.load('Model/svm_pca_question2.pkl')
svm = joblib.load('Model/svm_question2.pkl')
```

In [11]:

```python
Evaluate_performance(estimator=svm_pca, confidence=True, Name='SVM with PCA')
```

Performance of SVM with PCA:

1. In training set: (time used in predict: 8.36 sec)

```
              precision    recall  f1-score   support

         0.0       0.60      0.64      0.62       686
         1.0       0.61      0.57      0.59       680
         2.0       0.44      0.78      0.57       680
         3.0       0.66      0.60      0.63       658
         4.0       0.69      0.56      0.62       656
         5.0       0.56      0.59      0.58       664
         6.0       0.68      0.65      0.66       671
         7.0       0.57      0.54      0.56       680
         8.0       0.72      0.55      0.63       672
         9.0       0.74      0.59      0.66       673

    accuracy                           0.61      6720
   macro avg       0.63      0.61      0.61      6720
weighted avg       0.63      0.61      0.61      6720
```

Accuracy: 0.6066964285714286
95% CI: (0.44942447657130097, 0.4776588567620324)

Confusion Matrix

```
[[436  26  62  32  24  25  22  35   4  20]
 [ 31 385 104  14  14  34  14  45  25  14]
 [ 23  16 532  16  26  16  10  25   2  14]
 [ 52  21  64 396  16  31  27  23  10  18]
 [ 27  28 116  28 365  34  15  22   6  15]
 [ 20  19  76  16  23 392  49  23  33  13]
 [ 32  19  57  19  10  35 435  22  32  10]
 [ 39  72  90  19  21  32  11 365  13  18]
 [ 25  35  33  29  11  68  45  34 372  20]
 [ 37  15  62  31  20  31  16  41  21 399]]
```

===

2. In test set: (time used in predict: 3.58 sec)

```
              precision    recall  f1-score   support

         0.0       0.45      0.50      0.48       274
         1.0       0.43      0.44      0.43       273
         2.0       0.35      0.69      0.47       285
         3.0       0.52      0.50      0.51       296
         4.0       0.60      0.40      0.48       309
         5.0       0.44      0.42      0.43       296
         6.0       0.54      0.52      0.53       291
         7.0       0.43      0.38      0.40       280
         8.0       0.58      0.42      0.48       291
         9.0       0.60      0.48      0.53       285

    accuracy                           0.47      2880
   macro avg       0.49      0.47      0.47      2880
weighted avg       0.50      0.47      0.48      2880
```

Accuracy: 0.47430555555555554
95% CI: (0.36523618896418947, 0.4007360332580328)

Confusion Matrix

```
[[138  12  41  19   4  15  10  18   5  12]
 [ 13 120  38  15  12  17   6  26  15  11]
 [ 15   7 196  12  19   5  14  12   0   5]
 [ 38  15  29 147   3  20  17  12   5  10]
 [ 20  21  67  16 125  21  10  18   2   9]
```

```
 [  8  22  45  15  11 125  26  14  23   7]
 [ 22  10  32  18   7  13 150  12  14  13]
 [ 18  45  52  10  10  12   5 107   9  12]
 [ 12  16  27  16   3  39  27  18 121  12]
 [ 21  11  26  15  14  18  15  13  15 137]]
```

In [12]:

```
Evaluate_performance(estimator=svm, confidence=True, Name='SVM without PCA')
```

Performance of SVM without PCA:

1. In training set: (time used in predict: 86.77 sec)

	precision	recall	f1-score	support
0.0	0.67	0.68	0.68	686
1.0	0.67	0.63	0.65	680
2.0	0.46	0.82	0.59	680
3.0	0.71	0.64	0.67	658
4.0	0.74	0.61	0.67	656
5.0	0.62	0.64	0.63	664
6.0	0.73	0.70	0.71	671
7.0	0.63	0.60	0.62	680
8.0	0.78	0.61	0.68	672
9.0	0.78	0.63	0.70	673
accuracy			0.66	6720
macro avg	0.68	0.66	0.66	6720
weighted avg	0.68	0.66	0.66	6720

Accuracy: 0.65625
95% CI: (0.43644462129632317, 0.4599839501322484)

Confusion Matrix

```
[[468  20  58  28  23  22  17  30   3  17]
 [ 20 427  92  13   8  31  13  42  22  12]
 [ 18  14 560  12  19   9   9  22   2  15]
 [ 39  21  65 423  12  30  21  23   8  16]
 [ 22  19 108  23 398  33  17  19   5  12]
 [ 21  20  81  10  17 423  38  18  24  12]
 [ 21  17  58  14   7  31 467  23  25   8]
 [ 31  53  86  20  24  20  10 410  13  13]
 [ 20  36  36  28  12  48  38  29 408  17]
 [ 35  13  64  26  19  30  14  34  12 426]]
```

===

2. In test set: (time used in predict: 34.87 sec)

	precision	recall	f1-score	support
0.0	0.42	0.49	0.45	274
1.0	0.44	0.42	0.43	273
2.0	0.34	0.70	0.46	285
3.0	0.53	0.48	0.50	296
4.0	0.57	0.39	0.46	309
5.0	0.42	0.40	0.41	296
6.0	0.52	0.51	0.51	291
7.0	0.44	0.39	0.42	280
8.0	0.59	0.42	0.49	291
9.0	0.59	0.48	0.53	285
accuracy			0.47	2880
macro avg	0.49	0.47	0.47	2880
weighted avg	0.49	0.47	0.47	2880

Accuracy: 0.46631944444444445
95% CI: (0.35006720212576103, 0.39159946454090566)

Confusion Matrix

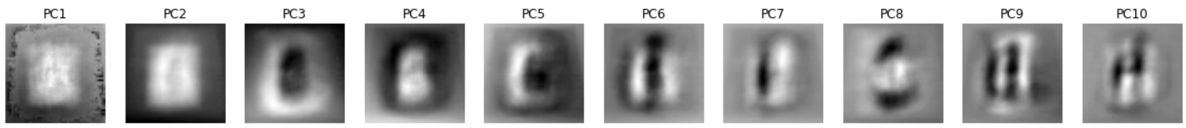
```
[[133  10  44  20   9  15  12  15   6  10]
 [ 14 116  45  11  10  15   7  25  17  13]
 [ 12   5 199  10  18   7  14  14   0   6]
 [ 41  13  30 142   4  21  16  13   6  10]
 [ 23  18  72  15 119  24  13  15   2   8]
```

```
 [ 12  29  46  15   8 118  26  12  21   9]
 [ 22   9  35  18   8  13 147  11  14  14]
 [ 20  39  55   8  11  13   4 110   8  12]
 [ 14  13  30  13   4  33  28  21 123  12]
 [ 23  10  27  15  16  20  14  14  10 136]]
```

From the performance, we can see svm classifier without PCA has better accuracy in training data set, but in test data set, the accuracies are almost the same.

- Visualize the top 10 eigenvectors. Discuss what they represent.

In [13]:
```python
plt.figure(figsize=(20,5))
for i in range(10):
    plt.subplot(1,10,i+1)
    plt.imshow(svm_pca.named_steps['PCA'].components_[i,:].reshape(50,50), cmap='gra
    plt.title('PC'+str(i+1)); plt.axis('off');
```



They represent the 10 maximum variance direction in the data. They are also the outline handwritten characters.

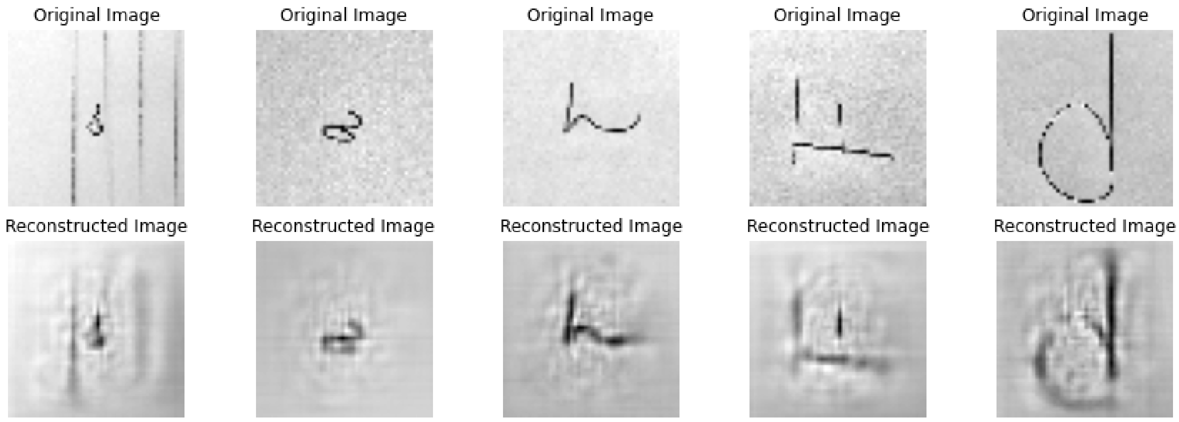
- Visualize examples of image reconstruction from PCA projections.

In [14]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA

# Recall that the number of components we choose is 182
pca_pipe = Pipeline([('scaler', MinMaxScaler()),
                     ('PCA', PCA(n_components=182))])

pca_pipe.fit(X_train_reshaped)
```

Out[14]:
```
▸ Pipeline
  ▸ MinMaxScaler
  ▸ PCA
```

In [15]:
```python
ypca_test = pca_pipe.transform(X_test_reshaped)
X_test_reconstructed =  pca_pipe.inverse_transform(ypca_test)

# Visualization
N = 5
idx = np.random.choice(range(X_test_reconstructed.shape[0]), size=N, replace=False)

fig = plt.figure(figsize=(15, 5))

j=1
for i in range(N):
    fig.add_subplot(2,N,j)
    plt.imshow(X_test_reshaped[idx[i], :].reshape(50,50), cmap='gray')
    plt.axis('off')
```

```
    plt.title('Original Image')

    fig.add_subplot(2,N,j+N)
    plt.imshow(X_test_reconstructed[idx[i], :].reshape(50,50), cmap='gray')
    plt.axis('off')
    plt.title('Reconstructed Image')

    j += 1
```



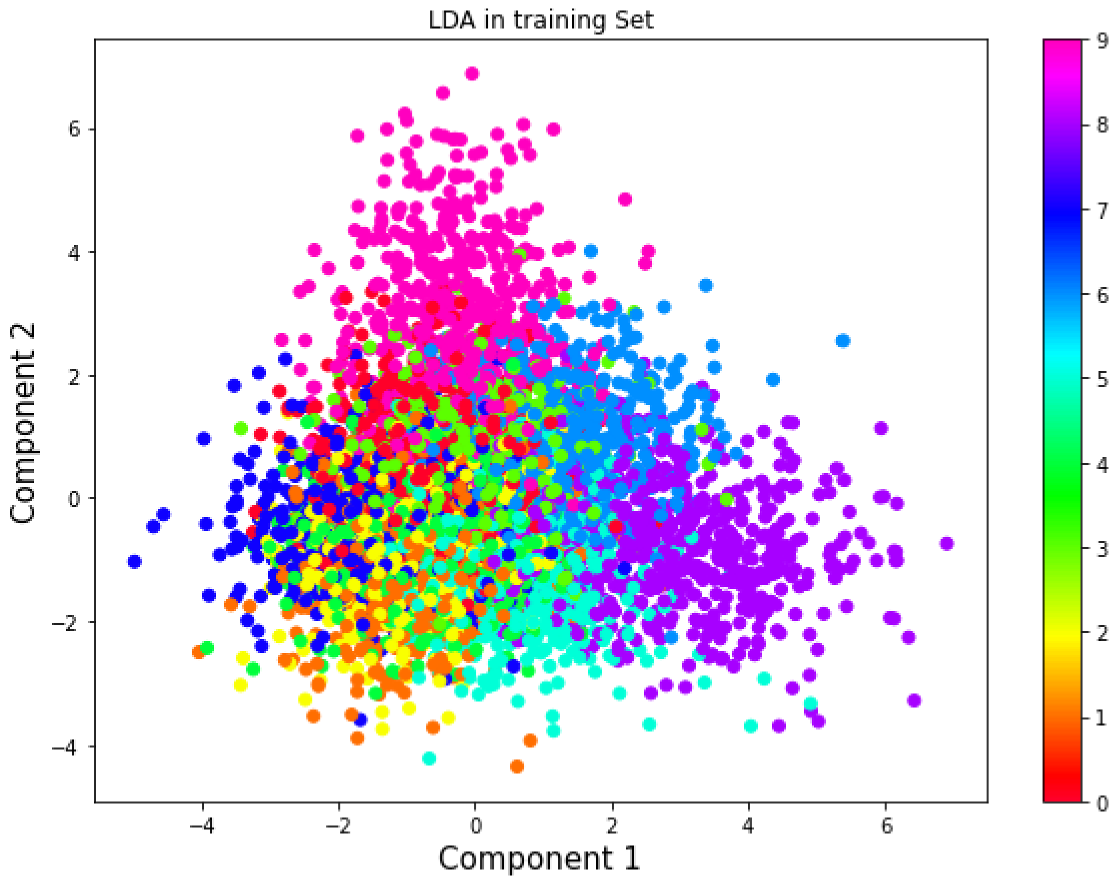
Question 3

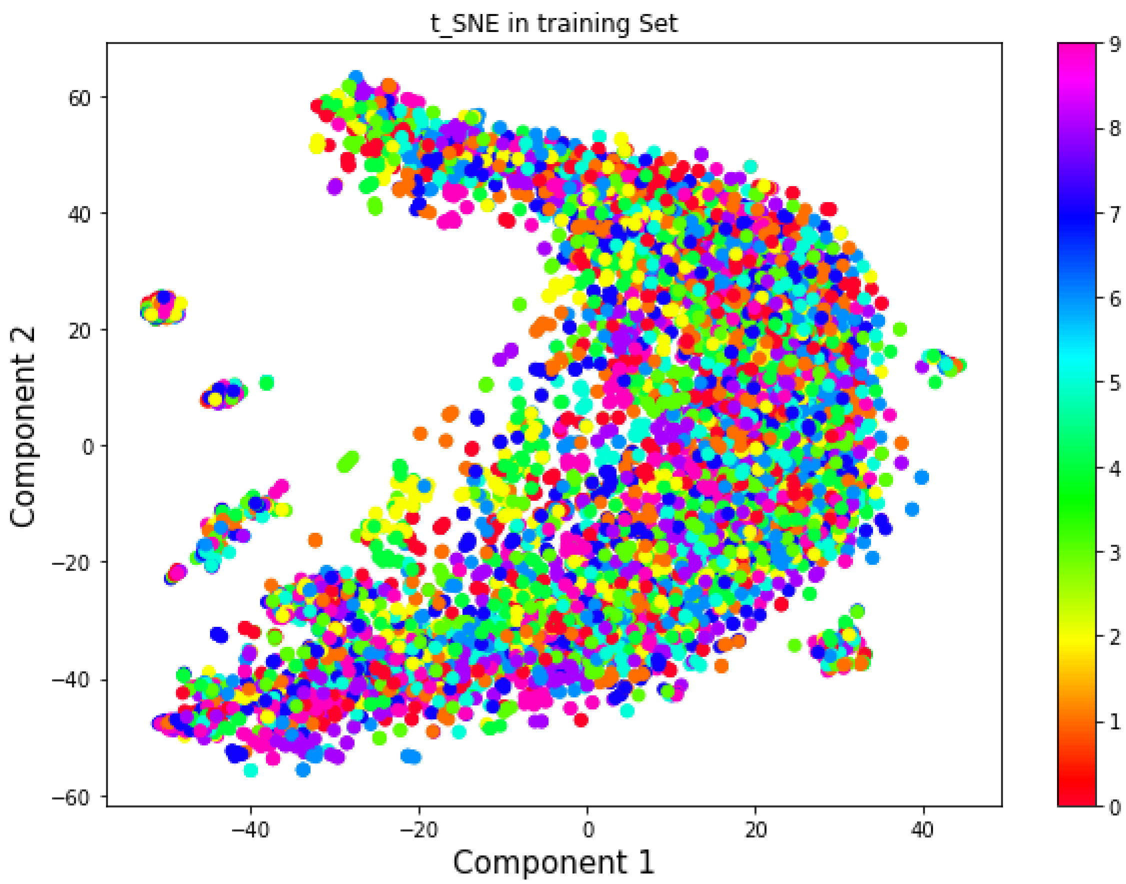
- Visualize the dataset, be sure to color-code each point to its corresponding target label.

In [16]:
```
# Load the dataset
X_lda = np.load('Dataset/data_train_lda_question3.npy')
X_tsne = np.load('Dataset/data_train_tsne_question3.npy')
lda = joblib.load('Model/lda_question3.pkl')
tsne = joblib.load('Model/tsne_question3.pkl')

X_lda.shape, X_tsne.shape
```

Out[16]:
```
((6720, 2), (6720, 2))
```

In [17]:
```
#Visualization in training set
## Visualization for LDA
plt.figure(figsize=(10,7))
plt.scatter(X_lda[:,0], X_lda[:,1], c=t_train, cmap=plt.cm.gist_rainbow)
plt.xlabel('Component 1', size=15)
plt.ylabel('Component 2', size=15)
plt.title('LDA in training Set')
plt.colorbar()

## Visualization for t_SNE
plt.figure(figsize=(10,7))
plt.scatter(X_tsne[:,0], X_tsne[:,1], c=t_train, cmap=plt.cm.gist_rainbow)
plt.xlabel('Component 1', size=15)
plt.ylabel('Component 2', size=15)
plt.title('t_SNE in training Set')
plt.colorbar();
```



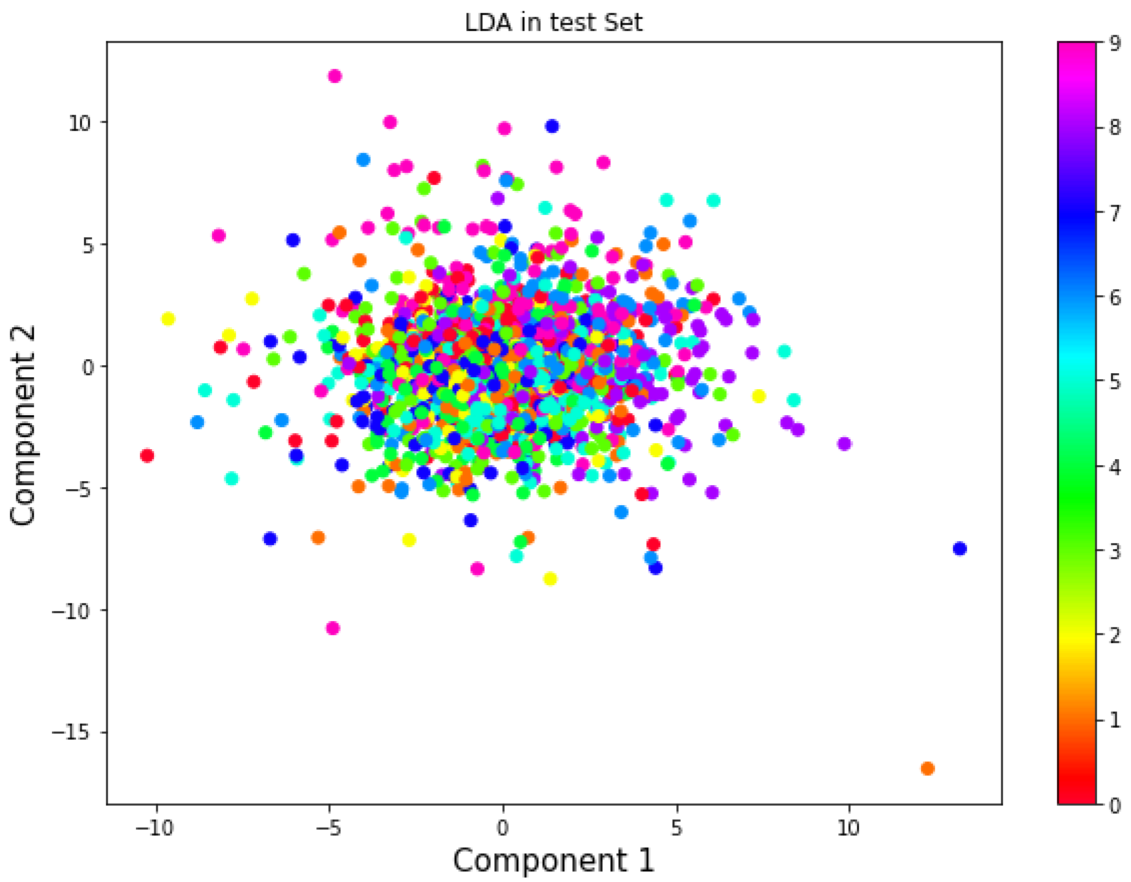


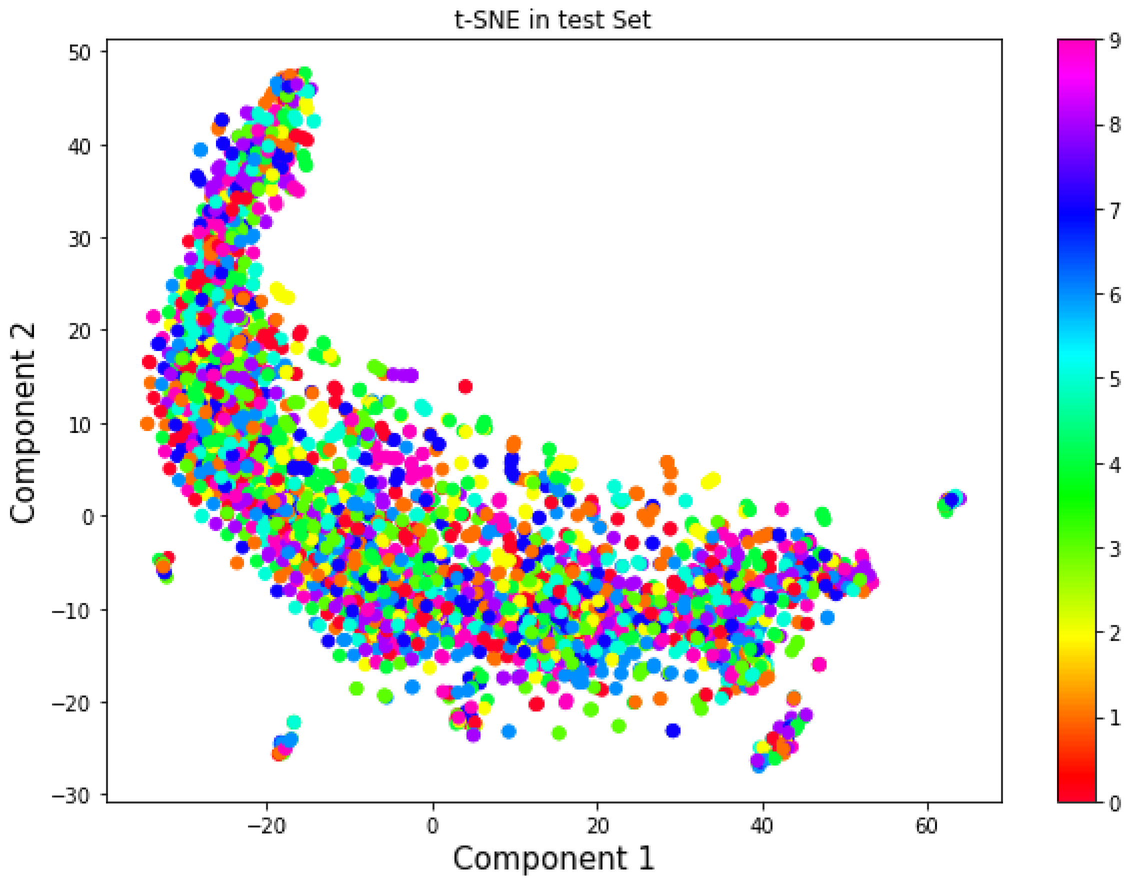
In [18]:

```
# Visualization in test set
ylda = lda.transform(X_test_reshaped)
ytsne = tsne.fit_transform(X_test_reshaped)

## Visualization for LDA
plt.figure(figsize=(10,7))
plt.scatter(ylda[:,0], ylda[:,1], c=t_test, cmap=plt.cm.gist_rainbow)
```

```python
plt.xlabel('Component 1', size=15)
plt.ylabel('Component 2', size=15)
plt.title('LDA in test Set')
plt.colorbar()

## Visualization for LDA
plt.figure(figsize=(10,7))
plt.scatter(ytsne[:,0], ytsne[:,1], c=t_test, cmap=plt.cm.gist_rainbow)
plt.xlabel('Component 1', size=15)
plt.ylabel('Component 2', size=15)
plt.title('t-SNE in test Set')
plt.colorbar()
```

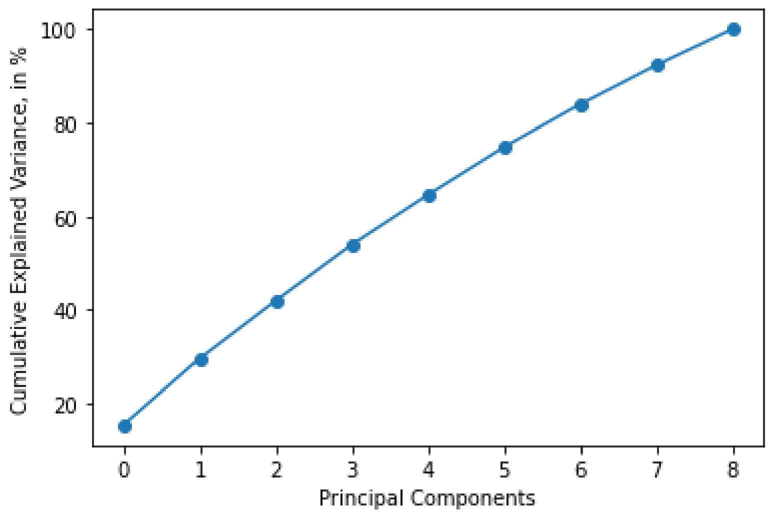
Out[18]: <matplotlib.colorbar.Colorbar at 0x2b6df8124130>





- How many features would you select? Why?

In [19]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.manifold import TSNE

lda = Pipeline([('scaler', MinMaxScaler()),
                ('features_selector', LDA(n_components=9))])

lda.fit(X_train_reshaped, t_train)

plt.plot(100*np.cumsum(lda.named_steps['features_selector'].explained_variance_ratio
plt.xlabel('Principal Components',size=10)
plt.ylabel('Cumulative Explained Variance, in %', size=10);
```



In [20]:
```
lda_num_to_choose = np.where(np.cumsum(lda.named_steps['features_selector'].explain
print('For LDA, I select {} features.'.format(lda_num_to_choose))
print('This is because when 8 features are selected, the explained varianced is abov
```

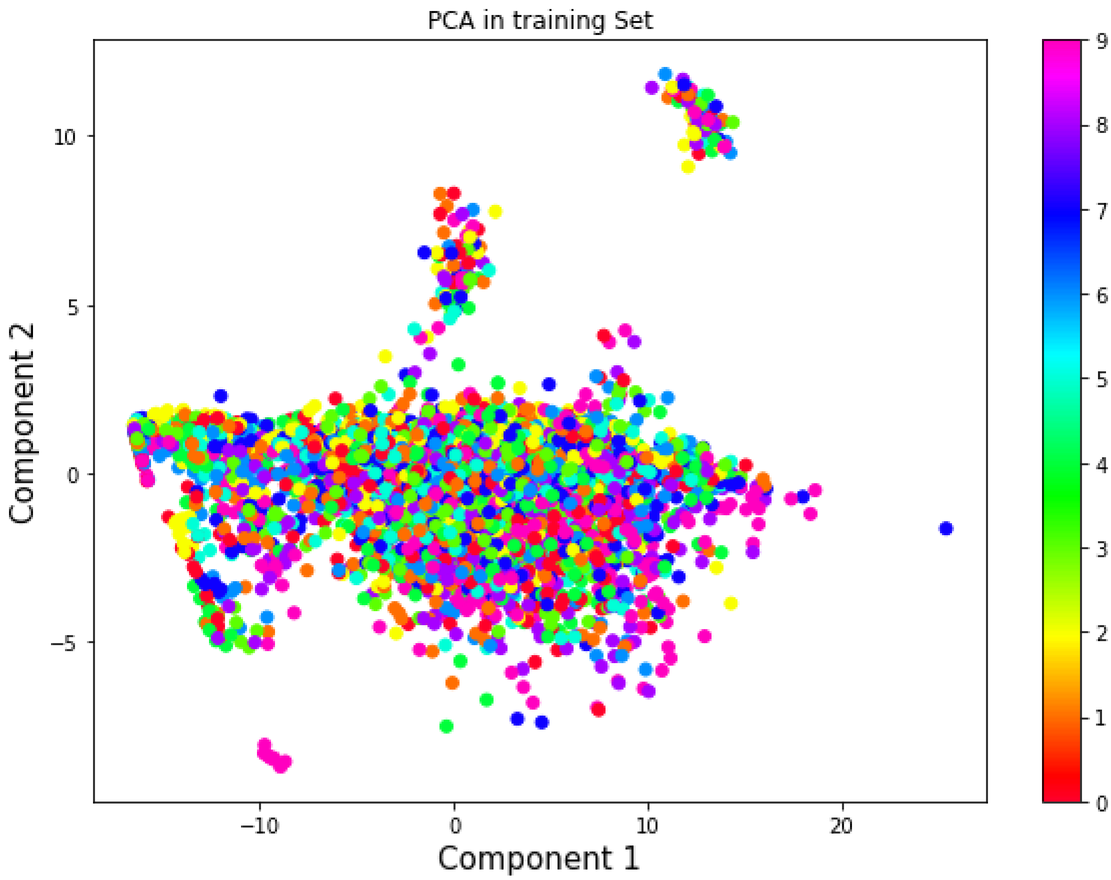
```
For LDA, I select 8 features.
This is because when 8 features are selected, the explained varianced is above 90%
```

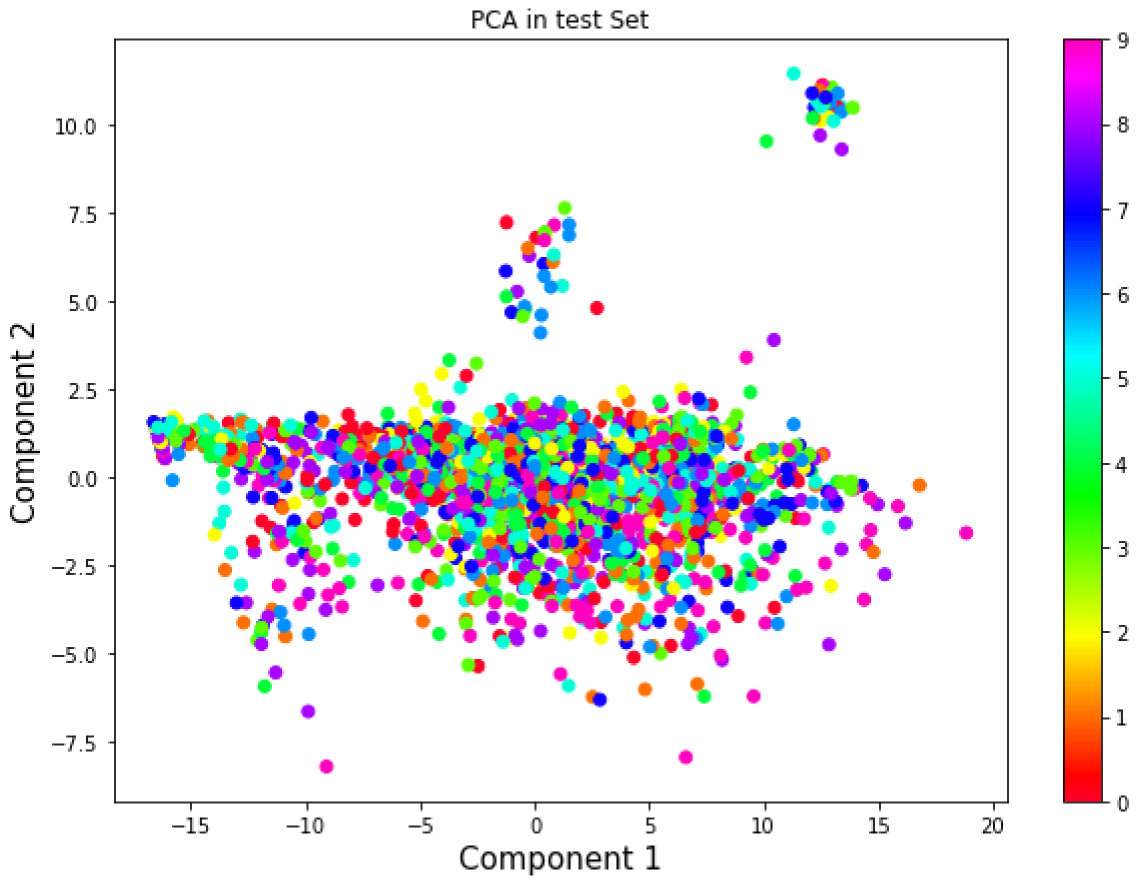
For t_SNE, which is used for visualization, its numbers of components can only be setted in 2 and 3.

- Visualize and compare the 2-dimensional projections with PCA. Discuss your observations.

In [21]:
```
X_pca = np.load('Dataset/data_train_pca_question3.npy')
pca = joblib.load('Model/pca_question3.pkl')

# For training
plt.figure(figsize=(10,7))
plt.scatter(X_pca[:,0], X_pca[:,1], c=t_train, cmap=plt.cm.gist_rainbow)
plt.xlabel('Component 1', size=15)
plt.ylabel('Component 2', size=15)
plt.title('PCA in training Set')
plt.colorbar()

# For test
ypca = pca.transform(X_test_reshaped)

plt.figure(figsize=(10,7))
plt.scatter(ypca[:,0], ypca[:,1], c=t_test, cmap=plt.cm.gist_rainbow)
plt.xlabel('Component 1', size=15)
plt.ylabel('Component 2', size=15)
plt.title('PCA in test Set')
plt.colorbar()
```

Out[21]: <matplotlib.colorbar.Colorbar at 0x2b6df92f2980>





From the three figures above, we can see the LDA has the best performance. It has distinct clusters for some classes. Compared to LDA, PCA and t_SNE cannot clearly classify the classes.

Question 4

- Which manifold learning algorithm would you select?

In [22]:

```
# Load the model
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.manifold import MDS, Isomap
from sklearn.manifold import LocallyLinearEmbedding as LLE
import warnings
import joblib
warnings.filterwarnings("ignore")

class Custom_MDS(BaseEstimator, TransformerMixin):

    def __init__(self, n_components=2):
        self.n_components = n_components
        self.mds = MDS(n_components=self.n_components)

    def fit(self, X, y=None):
        self.mds.fit_transform(X, y)
        return self

    def transform(self, X, y=None):
        self.embedding_ = self.mds.fit_transform(X,y)
        return self.embedding_

    def fit_transform(self, X, y=None):
```

```
        self.mds.fit_transform(X, y)
        self.embedding_ = self.mds.fit_transform(X,y)
        return self.embedding_

svm_mds = joblib.load('Model/svm_mds_question4.pkl')
svm_isomap = joblib.load('Model/svm_isomap_question4.pkl')
svm_lle = joblib.load('Model/svm_lle_question4.pkl')
```

In [23]:

```
# Performance of MSD
Evaluate_performance(estimator=svm_mds, Name='SVM classifier with MDS', confidence=F
```

```
Performance of SVM classifier with MDS:

1. In training set: (time used in predict: 1467.02 sec)
              precision    recall  f1-score   support

         0.0       0.08      0.07      0.08       686
         1.0       0.12      0.11      0.11       680
         2.0       0.12      0.10      0.11       680
         3.0       0.09      0.17      0.12       658
         4.0       0.12      0.08      0.09       656
         5.0       0.08      0.06      0.07       664
         6.0       0.10      0.06      0.07       671
         7.0       0.10      0.06      0.07       680
         8.0       0.10      0.19      0.13       672
         9.0       0.14      0.13      0.14       673

    accuracy                           0.10      6720
   macro avg       0.10      0.10      0.10      6720
weighted avg       0.10      0.10      0.10      6720

Accuracy: 0.10357142857142858
Confusion Matrix
[[ 50  68  61 154  44  55  36  47 107  64]
 [ 63  73  61 133  33  52  33  29 132  71]
 [ 61  59  71 132  31  55  35  43 140  53]
 [ 53  61  49 112  48  51  47  51 128  58]
 [ 69  51  56 128  51  43  47  43 115  53]
 [ 69  55  57 115  35  38  43  37 147  68]
 [ 70  70  73 107  40  40  40  41 127  63]
 [ 62  62  49 133  40  63  32  41 144  54]
 [ 66  45  59 125  40  38  55  46 131  67]
 [ 68  68  61  89  57  39  41  39 122  89]]

 =====================================================

2. In test set: (time used in predict: 256.86 sec)
              precision    recall  f1-score   support

         0.0       0.12      0.07      0.09       274
         1.0       0.09      0.10      0.09       273
         2.0       0.20      0.19      0.19       285
         3.0       0.10      0.27      0.15       296
         4.0       0.13      0.05      0.07       309
         5.0       0.10      0.17      0.13       296
         6.0       0.10      0.05      0.06       291
         7.0       0.14      0.05      0.07       280
         8.0       0.12      0.10      0.11       291
         9.0       0.10      0.08      0.09       285

    accuracy                           0.11      2880
   macro avg       0.12      0.11      0.11      2880
weighted avg       0.12      0.11      0.11      2880

Accuracy: 0.11388888888888889
Confusion Matrix
[[ 19  30  25  58   9  61  20   5  25  22]
 [ 17  26  22  73   7  51  19  12  18  28]
 [ 13  33  55  67  12  52  12   8  16  17]
 [ 18  21  32  81  20  53  17   8  27  19]
 [ 21  32  37  72  16  66  10   5  19  31]
 [ 17  28  30  75  16  51   9  10  27  33]
 [  9  32  22  99  12  39  14  16  33  15]
 [ 14  26  27  77  12  47  14  14  28  21]
```

```
 [ 12  26  18 105   8  44  13   9  29  27]
 [ 21  27  14  95   8  52  19  12  14  23]]
```

In [24]:
```
# Performance of Isomap
Evaluate_performance(estimator=svm_isomap, Name='SVM classifier with Isomap', confid
```

Performance of SVM classifier with Isomap:

1. In training set: (time used in predict: 13.79 sec)

	precision	recall	f1-score	support
0.0	0.31	0.44	0.37	686
1.0	0.36	0.37	0.36	680
2.0	0.33	0.56	0.41	680
3.0	0.41	0.28	0.33	658
4.0	0.45	0.29	0.35	656
5.0	0.32	0.36	0.34	664
6.0	0.32	0.28	0.30	671
7.0	0.45	0.33	0.38	680
8.0	0.46	0.40	0.43	672
9.0	0.45	0.39	0.42	673
accuracy			0.37	6720
macro avg	0.39	0.37	0.37	6720
weighted avg	0.39	0.37	0.37	6720

Accuracy: 0.371875
Confusion Matrix

```
[[303  36  82  36  28  49  52  27  32  41]
 [ 73 253 100  16  25  52  30  55  28  48]
 [ 69  39 378  19  54  40  25  22  16  18]
 [ 85  44 102 186  17  54  59  24  48  39]
 [ 73  48 141  25 191  59  42  26  17  34]
 [ 63  50  85  28  26 237  44  37  65  29]
 [102  41  84  43  28  72 190  25  51  35]
 [ 75 100  74  26  23  54  40 226  26  36]
 [ 50  58  45  37  10  77  57  27 270  41]
 [ 76  38  62  41  24  44  50  38  35 265]]
```

===

2. In test set: (time used in predict: 6.02 sec)

	precision	recall	f1-score	support
0.0	0.21	0.32	0.25	274
1.0	0.28	0.30	0.29	273
2.0	0.26	0.47	0.34	285
3.0	0.19	0.12	0.15	296
4.0	0.27	0.16	0.20	309
5.0	0.19	0.21	0.20	296
6.0	0.26	0.25	0.26	291
7.0	0.32	0.23	0.27	280
8.0	0.31	0.26	0.28	291
9.0	0.32	0.26	0.29	285
accuracy			0.26	2880
macro avg	0.26	0.26	0.25	2880
weighted avg	0.26	0.26	0.25	2880

Accuracy: 0.25625
Confusion Matrix

```
[[ 87  16  35  19  15  26  27  12  23  14]
 [ 21  82  54  19  13  13  12  19  20  20]
 [ 38  10 134   7  35  25  14  10   3   9]
 [ 45  27  37  36  15  32  38  18  31  17]
 [ 46  24  86  15  50  32  21   9  13  13]
 [ 39  40  43  20   9  62  22  14  32  15]
 [ 48  13  27  15  11  37  73  17  23  27]
 [ 26  38  41  19  16  25  22  63   9  21]
```

```
 [ 28  17  27  20   8  39  36  15  76  25]
 [ 36  30  29  19  15  28  16  18  19  75]]
```

In [25]:

```
# Performance of LLE
Evaluate_performance(estimator=svm_lle, Name='SVM classifier with LLE', confidence=F
```

```
Performance of SVM classifier with LLE:

1. In training set: (time used in predict: 13.07 sec)
              precision    recall  f1-score   support

         0.0       0.24      0.35      0.28       686
         1.0       0.28      0.34      0.31       680
         2.0       0.38      0.32      0.35       680
         3.0       0.22      0.26      0.24       658
         4.0       0.36      0.21      0.27       656
         5.0       0.25      0.29      0.27       664
         6.0       0.30      0.24      0.27       671
         7.0       0.36      0.19      0.25       680
         8.0       0.31      0.38      0.34       672
         9.0       0.30      0.30      0.30       673

    accuracy                           0.29      6720
   macro avg       0.30      0.29      0.29      6720
weighted avg       0.30      0.29      0.29      6720

Accuracy: 0.2876488095238095
Confusion Matrix
[[239  67  53  70  38  40  35  19  59  66]
 [ 86 232  42  56  17  54  30  45  66  52]
 [ 80  62 218  73  72  44  38  24  34  35]
 [105  43  35 169  28  52  46  22  99  59]
 [ 73  62  98  74 141  77  39  21  23  48]
 [ 74  84  27  55  13 192  59  26  84  50]
 [102  55  33  69  28  71 160  24  81  48]
 [ 98 103  38  75  22  59  44 129  50  62]
 [ 84  60  10  50  10  94  32  23 253  56]
 [ 71  71  23  71  22  71  50  29  65 200]]

 =====================================================

2. In test set: (time used in predict: 5.59 sec)
              precision    recall  f1-score   support

         0.0       0.18      0.28      0.22       274
         1.0       0.21      0.26      0.23       273
         2.0       0.27      0.23      0.25       285
         3.0       0.16      0.20      0.18       296
         4.0       0.28      0.14      0.19       309
         5.0       0.15      0.17      0.16       296
         6.0       0.20      0.18      0.19       291
         7.0       0.22      0.12      0.16       280
         8.0       0.23      0.26      0.24       291
         9.0       0.23      0.24      0.23       285

    accuracy                           0.21      2880
   macro avg       0.21      0.21      0.20      2880
weighted avg       0.21      0.21      0.20      2880

Accuracy: 0.20520833333333333
Confusion Matrix
[[77 24 21 36 17 19 20 12 26 22]
 [31 72 21 35 11 28 13 12 25 25]
 [38 24 65 33 33 27 21 15 17 12]
 [48 31 22 58 11 18 24 14 46 24]
 [44 32 37 36 43 37 34 15 16 15]
 [45 48 14 36  3 49 27  8 42 24]
 [48 19 16 30 14 35 51 13 33 32]
 [38 46 25 25  7 32 18 34 22 33]
```

```
 [33 26  7 32  6 37 24 15 75 36]
 [34 29  9 37  9 37 24 17 22 67]]
```

From the evaluation above, I will select ISOMAP as my dimensinality reduction algorithm. This is because ISOMAP has the highest accuracy score in both training set and test set, and it takes lower time on training.

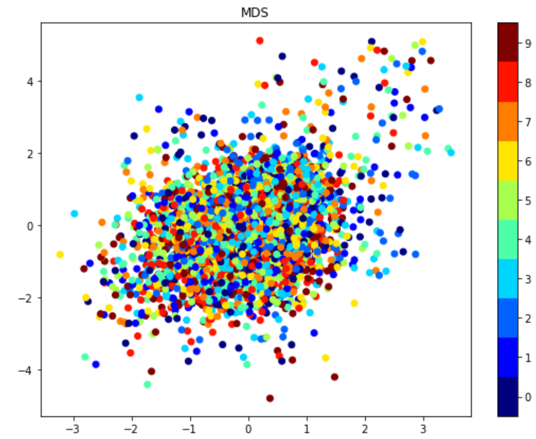
- Visualize and interprEvaluate_performancest 2 dimensions in the manifold learning algorithm you train.

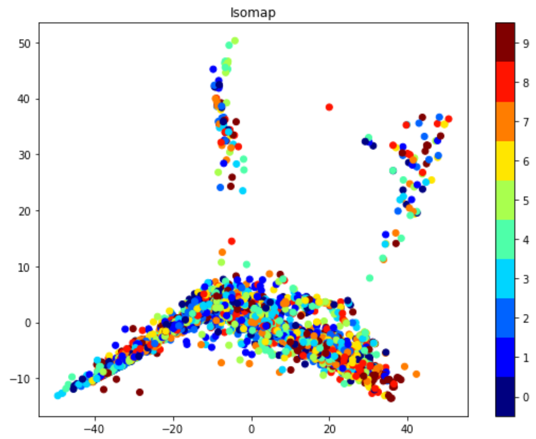
In [27]:

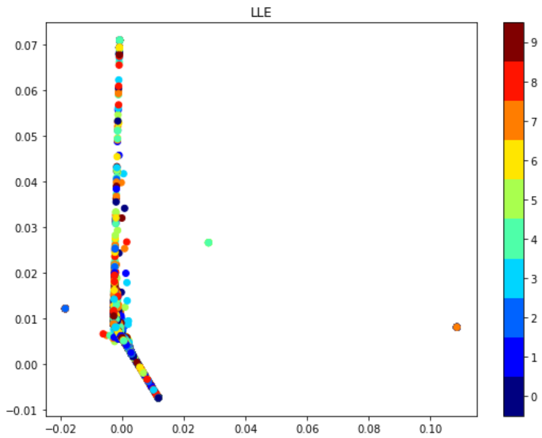
```
plt.figure(figsize=(20,15))

# Load the model
svm_mds = joblib.load('Model/svm_mds_question4.pkl')
svm_isomap = joblib.load('Model/svm_isomap_question4.pkl')
svm_lle = joblib.load('Model/svm_lle_question4.pkl')

# MDS
proj = svm_mds.named_steps['features_selector'].embedding_
plt.subplot(2,2,1)
plt.scatter(proj[:, 0], proj[:, 1], c=t_train, cmap=plt.cm.get_cmap('jet', 10))
plt.colorbar(ticks=range(10))
plt.clim(-0.5, 9.5);
plt.title('MDS')

# Isomap
proj = svm_isomap.named_steps['features_selector'].embedding_
plt.subplot(2,2,2)
plt.scatter(proj[:, 0], proj[:, 1], c=t_train, cmap=plt.cm.get_cmap('jet', 10))
plt.colorbar(ticks=range(10))
plt.clim(-0.5, 9.5)
plt.title('Isomap')

# LLE
proj = svm_lle.named_steps['features_selector'].embedding_
plt.subplot(2,2,3)
plt.scatter(proj[:, 0], proj[:, 1], c=t_train, cmap=plt.cm.get_cmap('jet', 10))
plt.colorbar(ticks=range(10))
plt.clim(-0.5, 9.5)
plt.title('LLE')
```

Out[27]:

```
Text(0.5, 1.0, 'LLE')
```

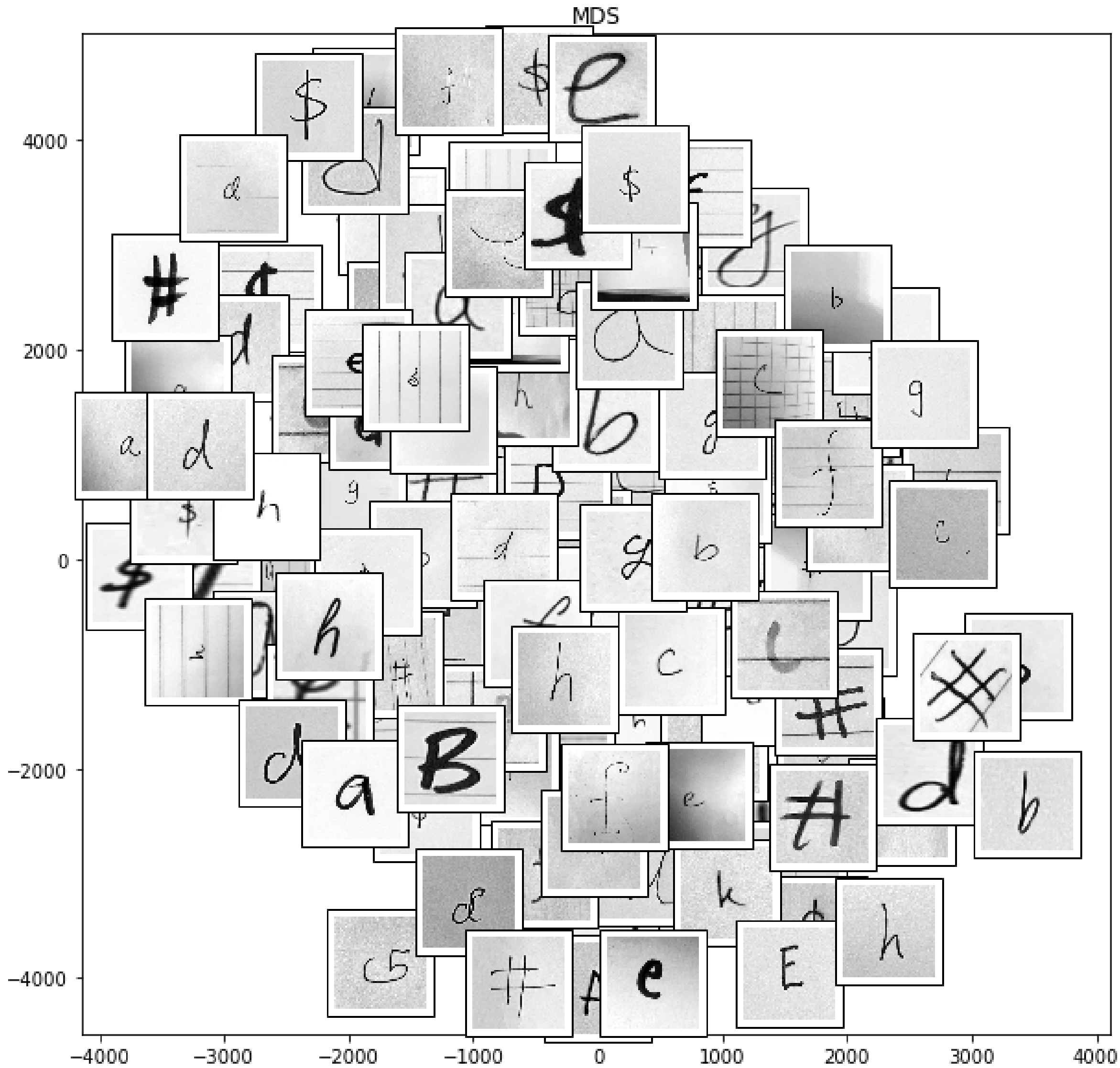


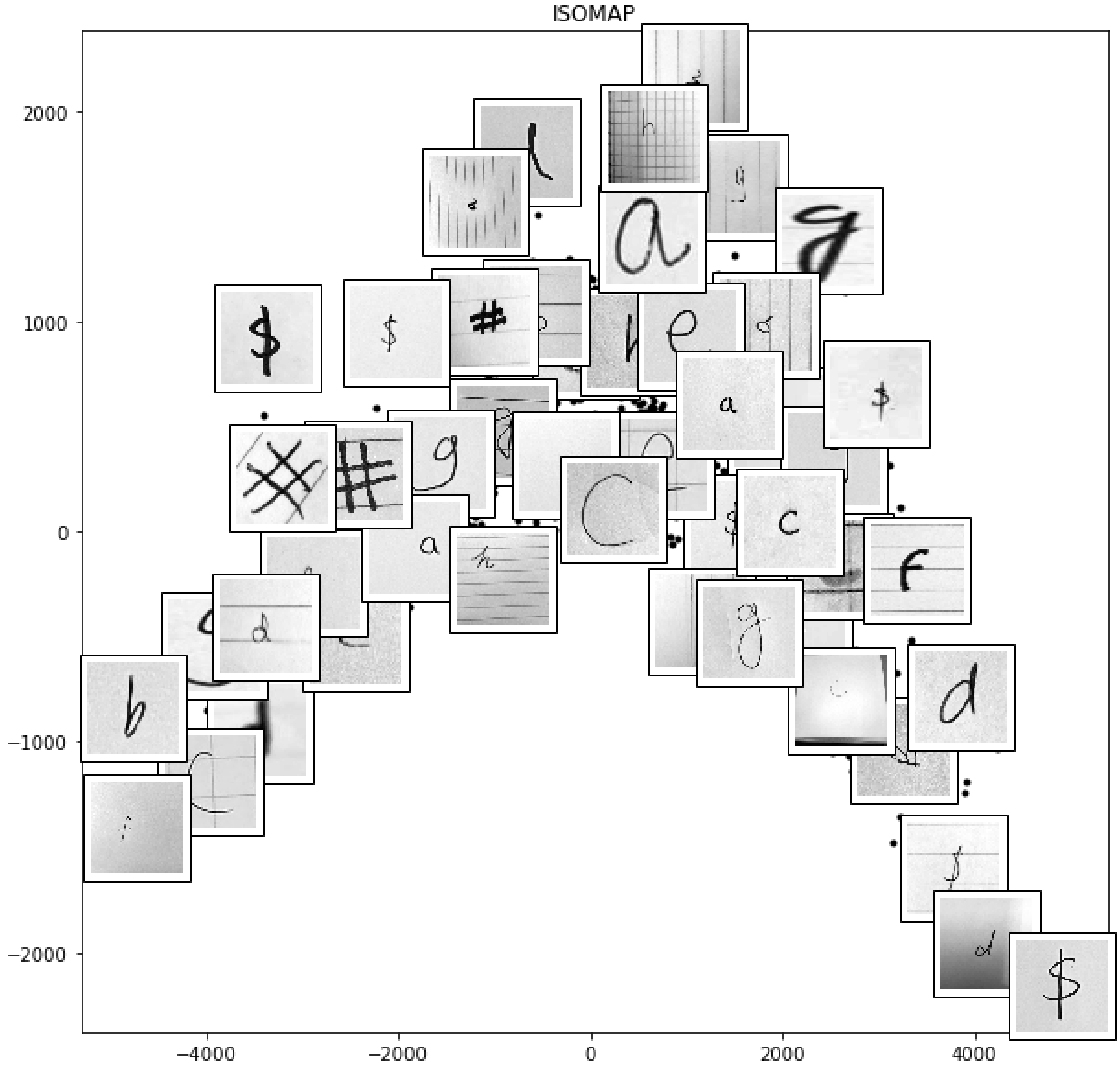


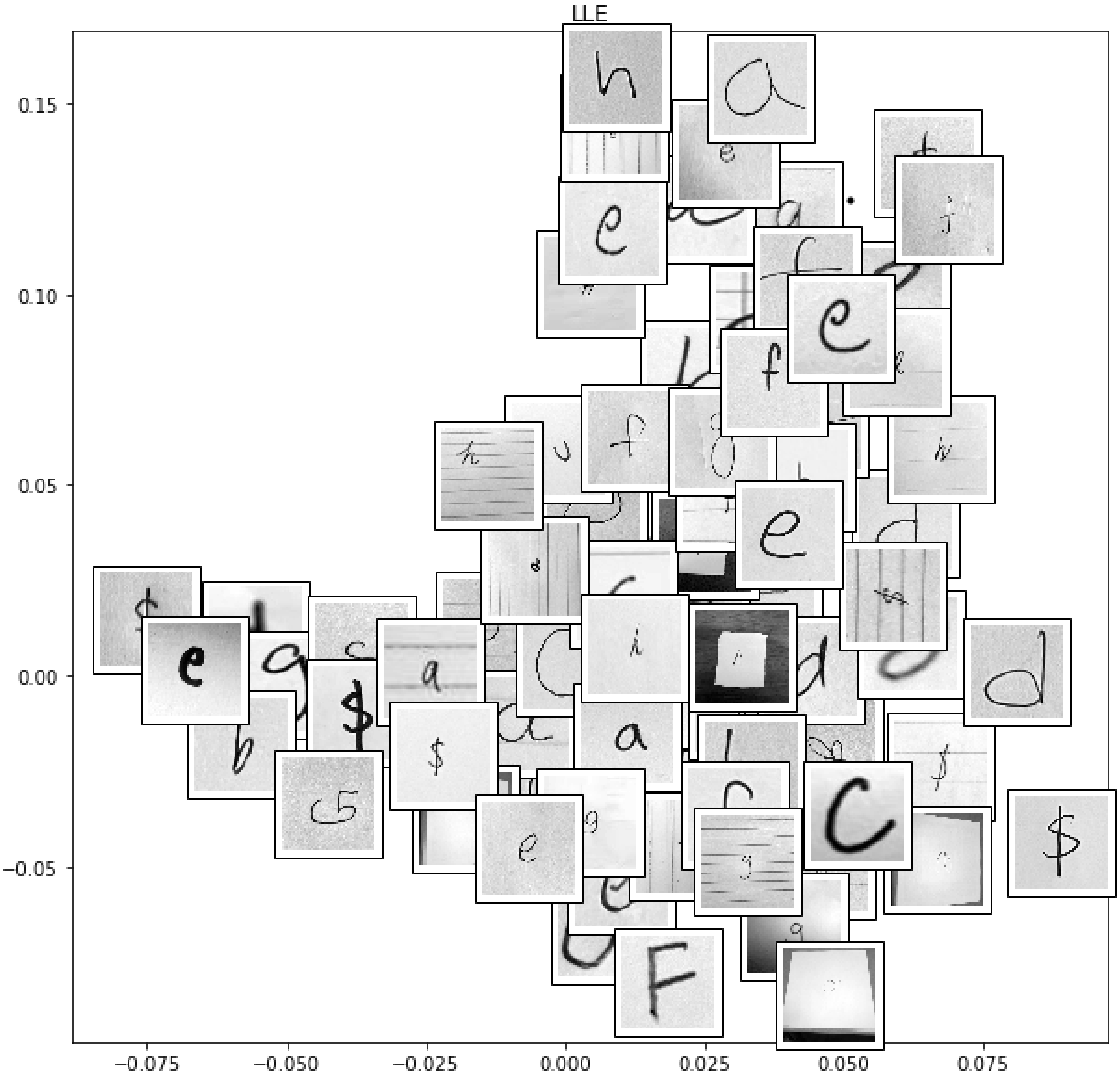


In [28]:
```
from matplotlib import offsetbox
def plot_components(data, model, images=None, ax=None,
                    thumb_frac=0.05, cmap='gray'):
    ax = ax or plt.gca()

    proj = model.fit_transform(data)
    ax.plot(proj[:, 0], proj[:, 1], '.k')

    if images is not None:
        min_dist_2 = (thumb_frac * max(proj.max(0) - proj.min(0))) ** 2
        shown_images = np.array([2 * proj.max(0)])
        for i in range(data.shape[0]):
            dist = np.sum((proj[i] - shown_images) ** 2, 1)
            if np.min(dist) < min_dist_2:
                # don't show points that are too close
                continue
            shown_images = np.vstack([shown_images, proj[i]])
            imagebox = offsetbox.AnnotationBbox(
                offsetbox.OffsetImage(images[i], cmap=cmap),
                                      proj[i])
            ax.add_artist(imagebox)

#%%
data = X_train_reshaped[::6]

# MDS
fig, ax = plt.subplots(figsize=(10, 10))
model = MDS(n_components=2)
plot_components(data, model, images=X_train_reshaped.reshape((-1, 50, 50)),
                ax=ax, thumb_frac=0.05, cmap='gray')
plt.title('MDS')

# ISOMAP
fig, ax = plt.subplots(figsize=(10, 10))
model = Isomap(n_components=2, n_neighbors=100)
```

```
plot_components(data, model, images=X_train_reshaped.reshape((-1, 50, 50)),
                ax=ax, thumb_frac=0.05, cmap='gray')
plt.title('ISOMAP')

# LLE
fig, ax = plt.subplots(figsize=(10, 10))
model = LLE(n_components=2, n_neighbors=100)
plot_components(data, model, images=X_train_reshaped.reshape((-1, 50, 50)),
                ax=ax, thumb_frac=0.05, cmap='gray')
plt.title('LLE');
```




ISOMAP
2000
1000
0
−1000
−2000
−4000
−2000
0
2000
4000



In [ ]: