In [1]:
```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import KFold, ShuffleSplit, StratifiedKFold, GridSe
from sklearn.metrics import confusion_matrix, roc_curve, classification_report
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score
from sklearn.manifold import MDS, Isomap
from sklearn.manifold import LocallyLinearEmbedding as LLE
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.manifold import TSNE
import joblib, random
from matplotlib import offsetbox
```

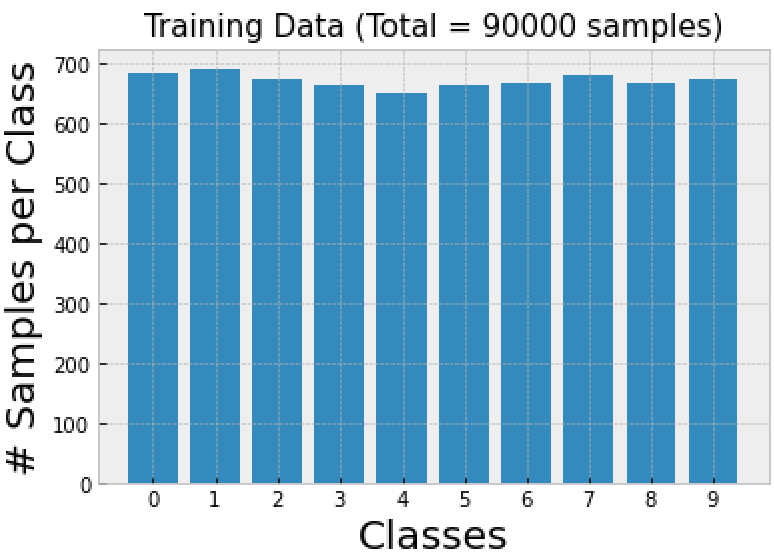
In [2]:
```
class_names = ['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', '$', '#']
```

In [3]:
```
import numpy as np
import pandas as pd
import numpy.random as npr
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('bmh')

# Loading Training Data
X_train = np.load('Data/data_train.npy').T
t_train = np.load('Data/labels_train.npy')

print(X_train.shape, t_train.shape)
```

```
(6720, 90000) (6720,)
```

In [4]:
```
from PIL import Image
import cv2
```

In [5]:
```
# Counting number samples per class
vals, counts = np.unique(t_train, return_counts=True)

plt.bar(vals, counts)
plt.xticks(range(10),range(10))
plt.xlabel('Classes',size=20)
plt.ylabel('# Samples per Class', size=20)
plt.title('Training Data (Total = '+str(X_train.shape[1])+' samples)',size=15);
```



In [6]:
```
#Resizing the image since kernel was dying.

NEW_SIZE = (50,50)
INTERPOLATION = cv2.INTER_CUBIC
data = []

for i in range(6720):
    img = X_train[i,:].reshape(300,300)
    img = cv2.resize(img, NEW_SIZE[::-1], interpolation=INTERPOLATION)
    data.append(img.flatten())

X_train_resized = np.array(data)
X_train_resized.shape
```

Out[6]: (6720, 2500)

Project Solution

Estimator 1: Logistic Regression

In [7]:
```
lr = LogisticRegression(penalty='l1', solver='liblinear', multi_class='auto')

pipe = Pipeline(steps=[('scaler', MinMaxScaler()),
                        ('RFE',RFE(estimator = lr, step = 500)),
                      ('LR', lr)])
# Creating Validation sets
cv = StratifiedKFold(n_splits=5, shuffle=True)

# Grid Search
# Cvals=np.arange(0.01,1,0.01) #L-1 penalty in Logistic Regression
n_features=[1000,1500] # number of features to keep

# Parameter Grid Search
param_grid = {'RFE__n_features_to_select': n_features}
grid_search = GridSearchCV(pipe, param_grid=param_grid, cv=cv, scoring='accuracy

# Train the model
grid_search.fit(X_train_resized, t_train)

# # Apply the best hyperpameter values
```

```python
print(grid_search.best_params_)
pipe.set_params(**grid_search.best_params_)

# # Train the final model with these hyperparameter values
pipe.fit(X_train_resized,t_train)
y_train=pipe.predict(X_train_resized)
print('\nTraining Set Performance for Logistic Regression Classifier')
print('Accuracy Score:', accuracy_score(t_train, y_train))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train))
print('\nPerformance Report: ')
print(classification_report(t_train,y_train))

joblib.dump(pipe, 'Models/LR_RFE1.pkl')
```

```
{'RFE__n_features_to_select': 1000}


Training Set Performance for Logistic Regression Classifier
Accuracy Score: 61.011904761904766 %
Confusion Matrix:
[[424  27  48  41  24  20  26  39  15  21]
 [ 24 400  40  25  15  32  29  70  29  26]
 [ 22  30 465  28  32  18  21  19  11  27]
 [ 60  22  36 400  21  19  29  28  20  30]
 [ 14  29  70  28 364  40  22  32  25  27]
 [ 25  30  33  33  33 382  38  34  36  19]
 [ 30  24  29  24  25  24 420  17  53  23]
 [ 34  49  47  21  26  13  18 436  18  20]
 [ 27  34  21  24  14  39  47  28 395  39]
 [ 22  27  23  25  27  30  29  35  42 414]]
Performance Report:
              precision    recall  f1-score   support

         0.0       0.62      0.62      0.62       685
         1.0       0.60      0.58      0.59       690
         2.0       0.57      0.69      0.63       673
         3.0       0.62      0.60      0.61       665
         4.0       0.63      0.56      0.59       651
         5.0       0.62      0.58      0.60       663
         6.0       0.62      0.63      0.62       669
         7.0       0.59      0.64      0.61       682
         8.0       0.61      0.59      0.60       668
         9.0       0.64      0.61      0.63       674

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

In [35]:
```python
lr = LogisticRegression(solver='liblinear', multi_class='auto')

pipe = Pipeline(steps=[('scaler', MinMaxScaler()),
                       ('RFE',RFE(estimator = lr, step = 500))])
# Creating Validation sets
cv = StratifiedKFold(n_splits=5, shuffle=True)
```

```
# Grid Search
# Cvals=np.arange(0.01,1,0.01) #L-1 penalty in Logistic Regression
n_features=[600,700] # number of features to keep

# Parameter Grid Search
param_grid = {'RFE__n_features_to_select': n_features}
grid_search = GridSearchCV(pipe, param_grid=param_grid, cv=cv, scoring='accuracy

# Train the model
grid_search.fit(X_train_resized, t_train)

# # Apply the best hyperpameter values
print(grid_search.best_params_)
pipe.set_params(**grid_search.best_params_)

# # Train the final model with these hyperparameter values
pipe.fit(X_train_resized,t_train)
y_train=pipe.predict(X_train_resized)
print('\nTraining Set Performance for Logistic Regression Classifier')
print('Accuracy Score:', accuracy_score(t_train, y_train))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train))
print('\nPerformance Report: ')
print(classification_report(t_train,y_train))

joblib.dump(pipe, 'Models/LR_RFE1.pkl')
```

```
{'RFE__n_features_to_select': 700}

Training Set Performance for Logistic Regression Classifier
Accuracy Score: 0.5985119047619047
Confusion Matrix:
[[403  28  47  43  36  16  33  47  15  17]
 [ 34 390  45  22  20  31  34  59  33  22]
 [ 18  33 475  25  33  13  24  17  13  22]
 [ 54  27  31 393  19  25  32  31  20  33]
 [ 15  37  78  28 346  32  26  37  25  27]
 [ 20  31  32  34  32 387  34  27  49  17]
 [ 31  21  31  24  16  25 400  22  66  33]
 [ 35  43  49  19  24  19  18 428  21  26]
 [ 18  31  24  23  18  52  46  34 393  29]
 [ 24  27  29  27  21  26  32  40  41 407]]

Performance Report:
              precision    recall  f1-score   support

         0.0       0.62      0.59      0.60       685
         1.0       0.58      0.57      0.57       690
         2.0       0.56      0.71      0.63       673
         3.0       0.62      0.59      0.60       665
         4.0       0.61      0.53      0.57       651
         5.0       0.62      0.58      0.60       663
         6.0       0.59      0.60      0.59       669
         7.0       0.58      0.63      0.60       682
         8.0       0.58      0.59      0.58       668
         9.0       0.64      0.60      0.62       674

    accuracy                           0.60      6720
   macro avg       0.60      0.60      0.60      6720
weighted avg       0.60      0.60      0.60      6720
```

Out[35]: ['Models/LR_RFE1.pkl']

In [ ]:

Estimator 2: Random Forest

In [7]:

```python
rf = RandomForestClassifier(n_estimators = 50, max_depth = 3)

pipe = Pipeline(steps=[('scaler', MinMaxScaler()),
                       ('RFE',RFE(estimator = rf, n_features_to_select = 1000))]
# Creating Validation sets
cv = StratifiedKFold(n_splits=5, shuffle=True)

# n_features=[1000] # number of features to keep

# Parameter Grid Search
# param_grid = {'RFE__n_features_to_select': n_features,
#               'Random_For__n_estimators': [100],
#              'Random_For__max_depth': [2]
#               }
# grid_search = GridSearchCV(pipe, param_grid=param_grid, scoring='accuracy')

# Train the model
# grid_search.fit(X_train_resized, t_train)
```

```python
pipe.fit(X_train_resized, t_train)

# # Apply the best hyperpameter values
# print(grid_search.best_params_)
# pipe.set_params(**grid_search.best_params_)

# Train the final model with these hyperparameter values
# pipe.fit(X_train_resized,t_train)
y_train_rf=pipe.predict(X_train_resized)
print('\n\nTraining Set Performance for Random Forest Classifier')
print('Accuracy Score:', accuracy_score(t_train, y_train_rf))

print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train_rf))
print('Performance Report: ')
print(classification_report(t_train,y_train_rf))
print('\n\n')

joblib.dump(pipe, 'Models/Random_Forest_RFE1.pkl')
```

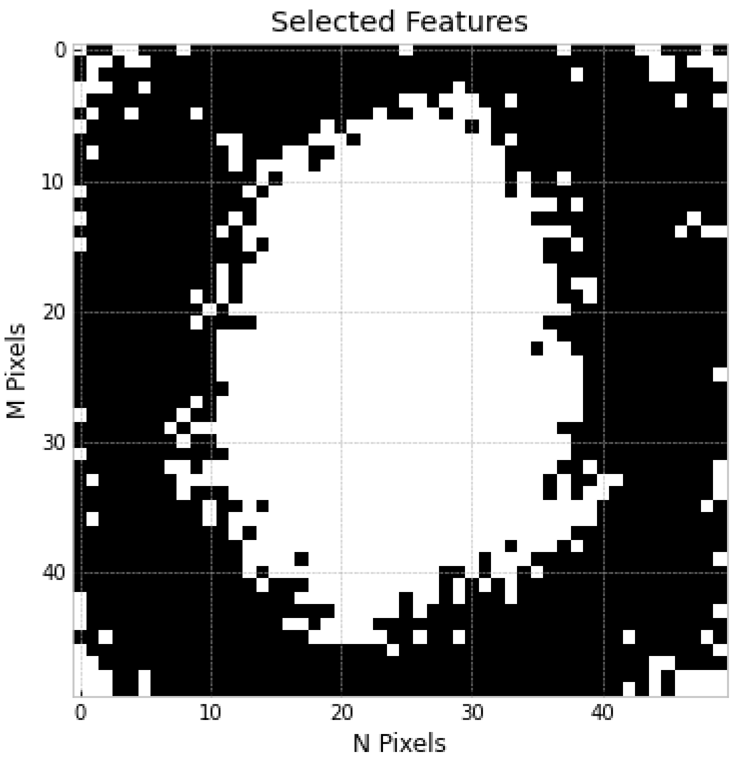
```
Training Set Performance for Random Forest Classifier
Accuracy Score: 1.0
Confusion Matrix:
[[685   0   0   0   0   0   0   0   0   0]
 [  0 690   0   0   0   0   0   0   0   0]
 [  0   0 673   0   0   0   0   0   0   0]
 [  0   0   0 665   0   0   0   0   0   0]
 [  0   0   0   0 651   0   0   0   0   0]
 [  0   0   0   0   0 663   0   0   0   0]
 [  0   0   0   0   0   0 669   0   0   0]
 [  0   0   0   0   0   0   0 682   0   0]
 [  0   0   0   0   0   0   0   0 668   0]
 [  0   0   0   0   0   0   0   0   0 674]]
Performance Report:
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00       685
         1.0       1.00      1.00      1.00       690
         2.0       1.00      1.00      1.00       673
         3.0       1.00      1.00      1.00       665
         4.0       1.00      1.00      1.00       651
         5.0       1.00      1.00      1.00       663
         6.0       1.00      1.00      1.00       669
         7.0       1.00      1.00      1.00       682
         8.0       1.00      1.00      1.00       668
         9.0       1.00      1.00      1.00       674

    accuracy                           1.00      6720
   macro avg       1.00      1.00      1.00      6720
weighted avg       1.00      1.00      1.00      6720
```

Out[7]: ['Models/Random_Forest_RFE1.pkl']

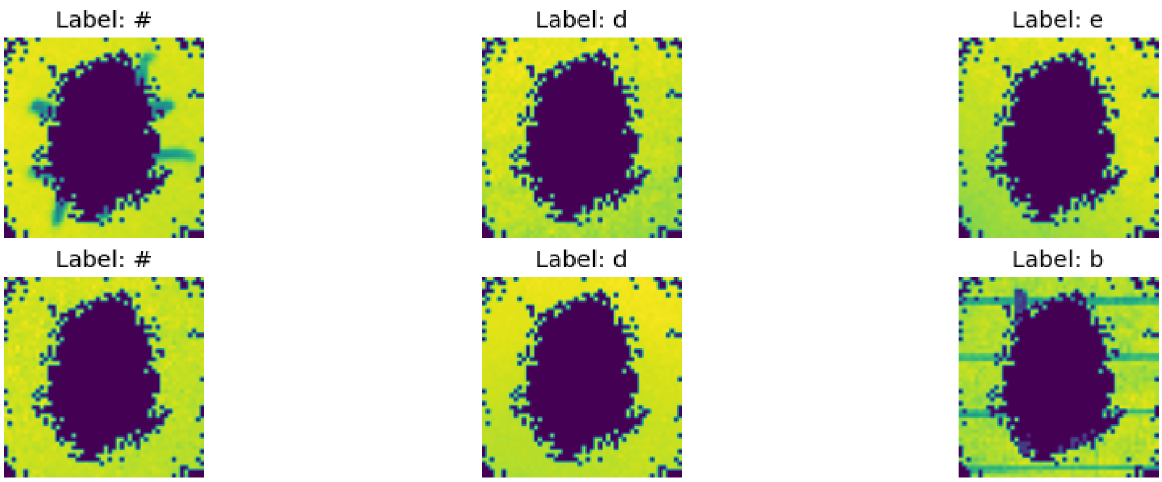
In [19]:
```python
pipe = joblib.load('Models/Random_Forest_RFE1.pkl')
```

```
#Following pixels were selected
np.where(pipe.named_steps['RFE'].support_== True)[0]
```

In [53]:
```
#Plot of selected pixels
plt.figure(figsize=(10, 6))
plt.title(f"Selected Features")
plt.imshow(pipe.named_steps['RFE'].support_.reshape(50,50), cmap='gray')
plt.xlabel("N Pixels")
plt.ylabel("M Pixels")
plt.show()
```



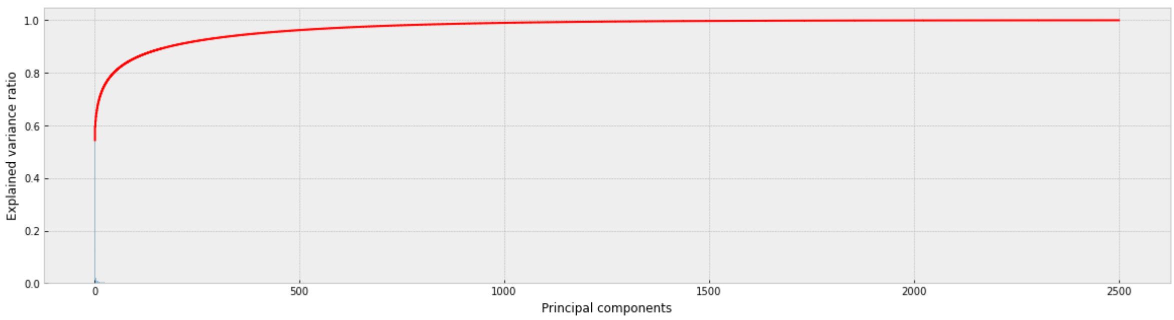
In [73]:
```
# Displaying mask examples from training set
fig = plt.figure(figsize=(15,5))
X_train_mask = X_train_resized
for i in range(6):
    fig.add_subplot(2,3,i+1)
    num_im = random.randint(0, 6720)
    mask = np.where(pipe.named_steps['RFE'].support_ == 0, X_train_mask[num_im],
    plt.imshow(mask.reshape(50,50))
    plt.axis('off')
    plt.title(f"Label: {class_names[int(t_train[num_im])]}");
```



2. Principal Component Analysis

In [51]:
```
pipe = Pipeline([('mixmax', MinMaxScaler()),
              ('pca',PCA())])

pipe.fit(X_train_resized)

variance_ratio = pipe.named_steps['pca'].explained_variance_ratio_

cumulative_variance_ratio = np.cumsum(variance_ratio)

plt.figure(figsize=(20,5))
plt.step(range(1,2501),cumulative_variance_ratio,c='r')
plt.bar(range(1,2501),variance_ratio, alpha=0.5)
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components')
```

Out[51]:
```
Text(0.5, 0, 'Principal components')
```



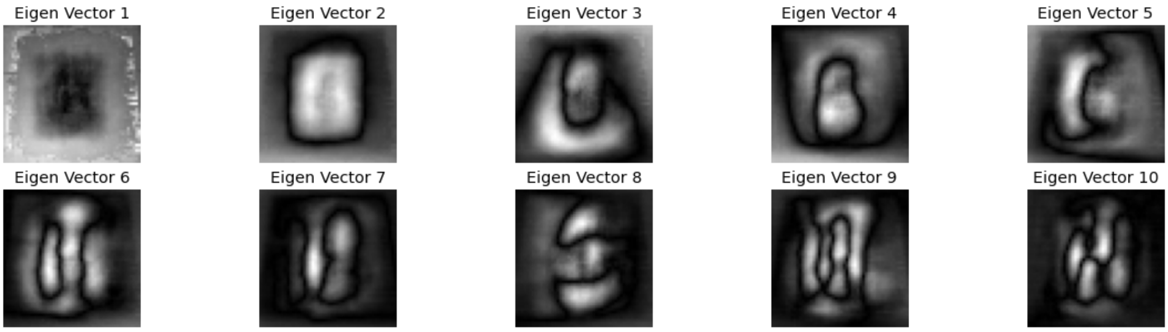
In [31]:
```
# A = pipe.named_steps['pca'].components_[:182]

np.where(cumulative_variance_ratio >=0.9)[0][0]
```

Out[31]:
```
182
```

In [32]:
```
pipe.named_steps['pca'].components_
```

Out[32]:
```
array([[-1.90309277e-02, -1.91422112e-02, -1.94262531e-02, ...,
        -2.16543685e-02, -2.11928025e-02, -2.09317017e-02],
       [-1.68069975e-02, -1.63535750e-02, -1.60390628e-02, ...,
        -2.41394974e-02, -2.36709081e-02, -2.31665969e-02],
       [-3.18281580e-02, -3.15941100e-02, -3.11099902e-02, ...,
        -5.91480505e-03, -6.32462965e-03, -6.74655004e-03],
       ...,
       [-3.35989151e-02,  3.38045017e-02,  3.84399611e-02, ...,
        -1.47148576e-02,  2.81596679e-02, -2.45394369e-02],
       [ 5.96386936e-03,  1.15246399e-02,  5.15875126e-03, ...,
         2.09217403e-02,  8.07471553e-03, -1.95319838e-02],
       [-8.76327890e-03,  2.68130505e-03, -1.29099927e-02, ...,
         4.64509109e-02,  8.86826779e-05, -3.11850227e-02]])
```

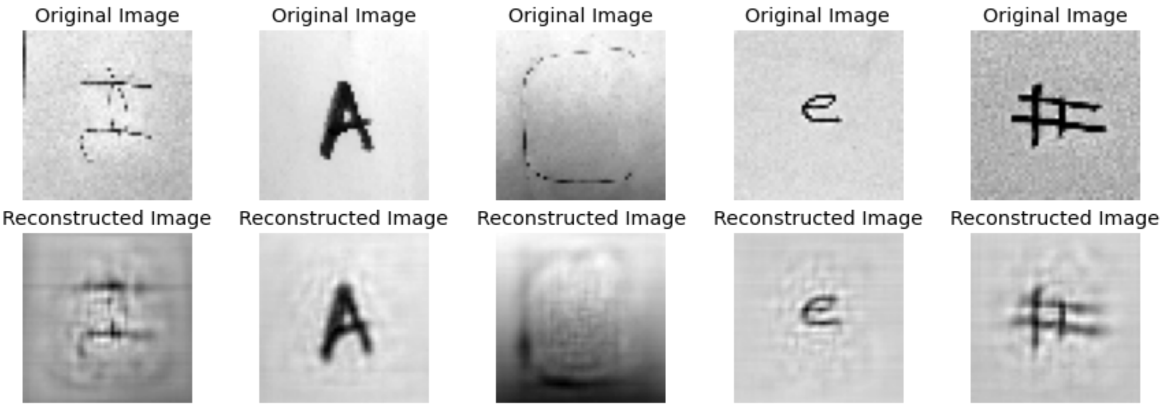
In [65]:
```python
#Visualization of Eigen vectors
grid_loc = 1
plt.figure(figsize=(20,5))
for i in range(10):
    plt.subplot(2,5,grid_loc)
    plt.imshow(abs(pipe.named_steps['pca'].components_[i,:].reshape(50,50)),cmap
    plt.title(f"Eigen Vector {grid_loc}")
    plt.axis('off')
    grid_loc+=1
```



In [34]:
```python
#Reconstruction from Eigen Vectors
N_eigenvectors = 182 # 90 percent variance

pipe = Pipeline([('scaler', MinMaxScaler()),
                 ('pca', PCA(n_components=N_eigenvectors))])
# pipe.fit(X_train_resized)
ypca = pipe.fit_transform(X_train_resized)
X_reconst = pipe.inverse_transform(ypca)

#Increase N for more images
N = 5

fig = plt.figure(figsize=(15,5))
idx = np.random.choice(range(X_reconst.shape[0]),replace=False,size=N)
j=1
for i in range(N):
    fig.add_subplot(2,N,j)
    plt.imshow(X_train_resized[idx[i],:].reshape(50,50), cmap='gray')
    plt.axis('off')
    plt.title('Original Image');

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

```
    j+=1

joblib.dump(pipe, 'Models/PCA2.pkl')
```

Out[34]: ['Models/PCA2.pkl']



In [35]:
```
from sklearn.linear_model import LogisticRegression

pipe1 = Pipeline([('scaler1', MinMaxScaler()),
                   ('pca1', PCA(n_components=182)),   #90% explained variance co
                 ('LR1',LogisticRegression(max_iter = 800))])

pipe2 = Pipeline([('scaler2', MinMaxScaler()),
                 ('LR2',LogisticRegression(max_iter = 800))])
```

In [36]:
```
# Training with PCA
pipe1.fit(X_train_resized,t_train)
y_train1 = pipe1.predict(X_train_resized)

joblib.dump(pipe1, 'Models/LR_PCA2.pkl')
```

Out[36]: ['Models/LR_PCA2.pkl']

In [37]:
```
# Training without PCA
pipe2.fit(X_train_resized,t_train)
y_train2 = pipe2.predict(X_train_resized)

joblib.dump(pipe2, 'Models/LR_NOPCA2.pkl')
```

```
/apps/python/3.10/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:
444: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[37]: ['Models/LR_NOPCA2.pkl']

In [38]:
```
# Training Performance of both the models

print('Training Set Performance for model with PCA')
print('Accuracy Score:', accuracy_score(t_train, y_train1))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train1))
```

```python
print('\nPerformance Report: ')
print(classification_report(t_train,y_train1))
print('\n\n')
```

```
Training Set Performance for model with PCA
Accuracy Score: 0.4928571428571429
Confusion Matrix:
[[338  29  48  49  43  20  47  62  19  30]
 [ 38 323  71  30  17  23  31  89  38  30]
 [ 22  37 439  30  48  18  25  32   8  14]
 [ 68  30  49 323  24  27  45  40  20  39]
 [ 18  33 113  45 291  39  36  20  26  30]
 [ 22  29  47  35  50 304  59  39  54  24]
 [ 29  27  38  40  30  39 335  31  69  31]
 [ 48  70  55  27  32  13  25 361  20  31]
 [ 30  49  26  38  18  70  71  44 279  43]
 [ 33  25  42  36  44  40  36  45  54 319]]

Performance Report:
              precision    recall  f1-score   support

         0.0       0.52      0.49      0.51       685
         1.0       0.50      0.47      0.48       690
         2.0       0.47      0.65      0.55       673
         3.0       0.49      0.49      0.49       665
         4.0       0.49      0.45      0.47       651
         5.0       0.51      0.46      0.48       663
         6.0       0.47      0.50      0.49       669
         7.0       0.47      0.53      0.50       682
         8.0       0.48      0.42      0.44       668
         9.0       0.54      0.47      0.50       674

    accuracy                           0.49      6720
   macro avg       0.49      0.49      0.49      6720
weighted avg       0.49      0.49      0.49      6720
```

In [39]:

```python
print('\n\n Training Set Performance for model without PCA')
print('Accuracy Score:', accuracy_score(t_train, y_train2))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train2))
print('\nPerformance Report: ')
print(classification_report(t_train,y_train2))
print('\n\n')
```

```
 Training Set Performance for model without PCA
Accuracy Score: 0.7532738095238095
Confusion Matrix:
[[526  16  25  22  19  11  22  27   6  11]
 [  9 505  30  12  12  19  21  46  18  18]
 [ 14  19 543  16  20   8  19  14   7  13]
 [ 40  14  22 488  13  15  19  18  14  22]
 [ 16  16  38  17 469  18  22  20  16  19]
 [ 21  16  30  16  20 481  26  22  19  12]
 [ 19  11  14  10   9  23 533  10  28  12]
 [ 24  34  28  20  16   9  17 512   9  13]
 [ 16  14  18  23  14  25  30  24 486  18]
 [ 14  13   6  12  17  24  16  25  28 519]]

Performance Report:
              precision    recall  f1-score   support

         0.0       0.75      0.77      0.76       685
         1.0       0.77      0.73      0.75       690
         2.0       0.72      0.81      0.76       673
         3.0       0.77      0.73      0.75       665
         4.0       0.77      0.72      0.74       651
         5.0       0.76      0.73      0.74       663
         6.0       0.74      0.80      0.76       669
         7.0       0.71      0.75      0.73       682
         8.0       0.77      0.73      0.75       668
         9.0       0.79      0.77      0.78       674

    accuracy                           0.75      6720
   macro avg       0.75      0.75      0.75      6720
weighted avg       0.75      0.75      0.75      6720
```

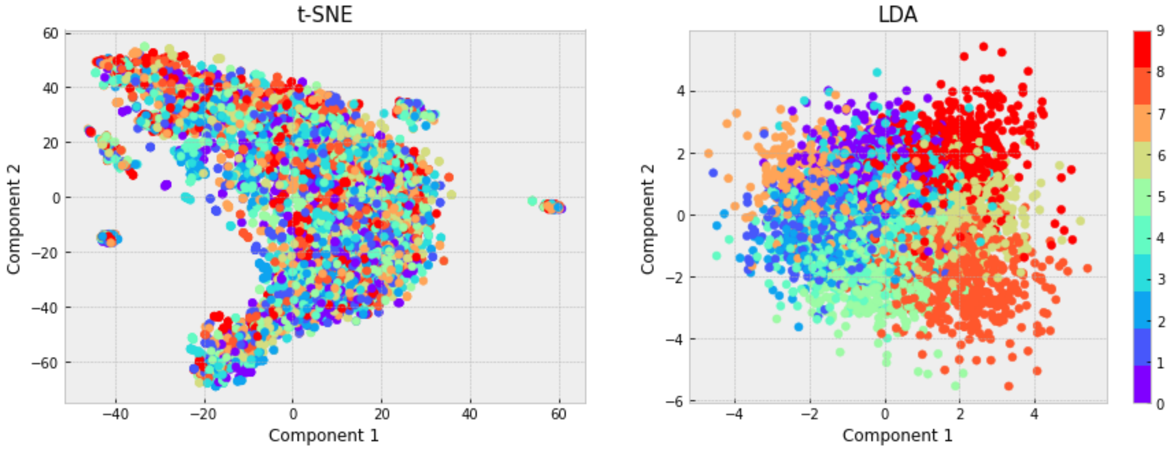
3. Fisher's LDA and t-SNE

In [52]:

```
#Fisher's LDA
lda = LDA(n_components=2)
lda.fit(X_train_resized, t_train)
y_train_lda = lda.transform(X_train_resized)

#t-SNE
tSNE = TSNE(n_components=2,learning_rate='auto', init='random')

y_train_sne = tSNE.fit_transform(X_train_resized)

#Visualize the dataset, be sure to color-code each point to its corresponding ta
plt.figure(figsize=(15,5))
plt.subplot(1,2,1); plt.title('t-SNE', fontsize=15)
plt.scatter(y_train_sne[:,0], y_train_sne[:,1], c=t_train, cmap=plt.cm.get_cmap(
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.subplot(1,2,2); plt.title('LDA', fontsize=15)
plt.scatter(y_train_lda[:,0], y_train_lda[:,1], c=t_train, cmap=plt.cm.get_cmap(
plt.xlabel("Component 1")
```

```
plt.ylabel("Component 2")
plt.colorbar();
```

```
/scratch/local/15693744/ipykernel_4102909/2594853714.py:21: MatplotlibDeprecation
Warning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since
3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar();
```



In [53]:
```
#Grid Search to find number of features?
cv = StratifiedKFold(n_splits=5, shuffle=True)
#Fisher's LDA

# lda_num_feat = LDA()

pipe_LDA = Pipeline([('scaler', MinMaxScaler()),
                     ('LDA', LDA()),
                     ('LR', LogisticRegression())])

param_grid = {'LDA__n_components': [2,4,6,8]}

grid_search_lda = GridSearchCV(pipe_LDA, param_grid=param_grid, cv=cv, scoring='

# Train the model
grid_search_lda.fit(X_train_resized, t_train)

# # Apply the best hyperpameter values
print("Best number of features for Fisher's LDA:", grid_search_lda.best_params_)
pipe_LDA.set_params(**grid_search_lda.best_params_)
```

```
Best number of features for Fisher's LDA: {'LDA__n_components': 8}
```

Out[53]:

```
Pipeline
  MinMaxScaler
  LinearDiscriminantAnalysis
  LogisticRegression
```

In [54]:
```
lda_num_feat = LDA(n_components = 8)
y_train_lda = lda_num_feat.fit_transform(X_train_resized, t_train)

joblib.dump(lda_num_feat, 'Models/LR_LDA3.pkl')
```

Out[54]: ['Models/LR_LDA3.pkl']

In [55]:
```
# Define a function to perform dimensionality reduction with varying n_component
def find_n_components_tsne(n_components_list, X_train, t_train):
    best_accuracy = 0
    accuracy = 0
    results = []
    for n_components in n_components_list:
        tsne = TSNE(n_components = n_components, learning_rate='auto', init='ran
        X_train_reduced = tsne.fit_transform(X_train)

        # Train a classifier (Random Forest in this case)
        clf = LogisticRegression(penalty='l1', solver='liblinear', multi_class='
        clf.fit(X_train_reduced, t_train)

        # Make predictions on the test set
        y_pred = clf.predict(X_train_reduced)

        # Calculate accuracy and store the result
        accuracy = accuracy_score(t_train, y_pred)
        if best_accuracy < accuracy:
            best_accuracy = accuracy
            best_component = n_components

    results.append(best_component)
    return results
```

In [56]:
```
#tsne ----------- NOT SURE-----------------------
# param_grid = {'tSNE__n_components': [2,4,6,8]}

# tsne = TSNE(learning_rate='auto', init='random')

# pipe_sne = Pipeline([('scaler', MinMaxScaler()),
#                       ('LR', LogisticRegression())])

# grid_search_sne = GridSearchCV(pipe_sne, param_grid=param_grid, cv=cv, scoring

# # Train the model
# grid_search_sne.fit(X_train_resized, t_train)

# # # Apply the best hyperpameter values
# print("Best number of features for t-SNE:",grid_search_sne.best_params_)
# pipe_sne.set_params(**grid_search_sne.best_params_)



n_components_list = [1,2,3]
results = find_n_components_tsne(n_components_list, X_train_resized, t_train)

print("Number of Components:", results[0])

tsne = TSNE(n_components = results[0], learning_rate='auto', init='random')

joblib.dump(tsne, 'Models/LR_tSNE3.pkl')
```

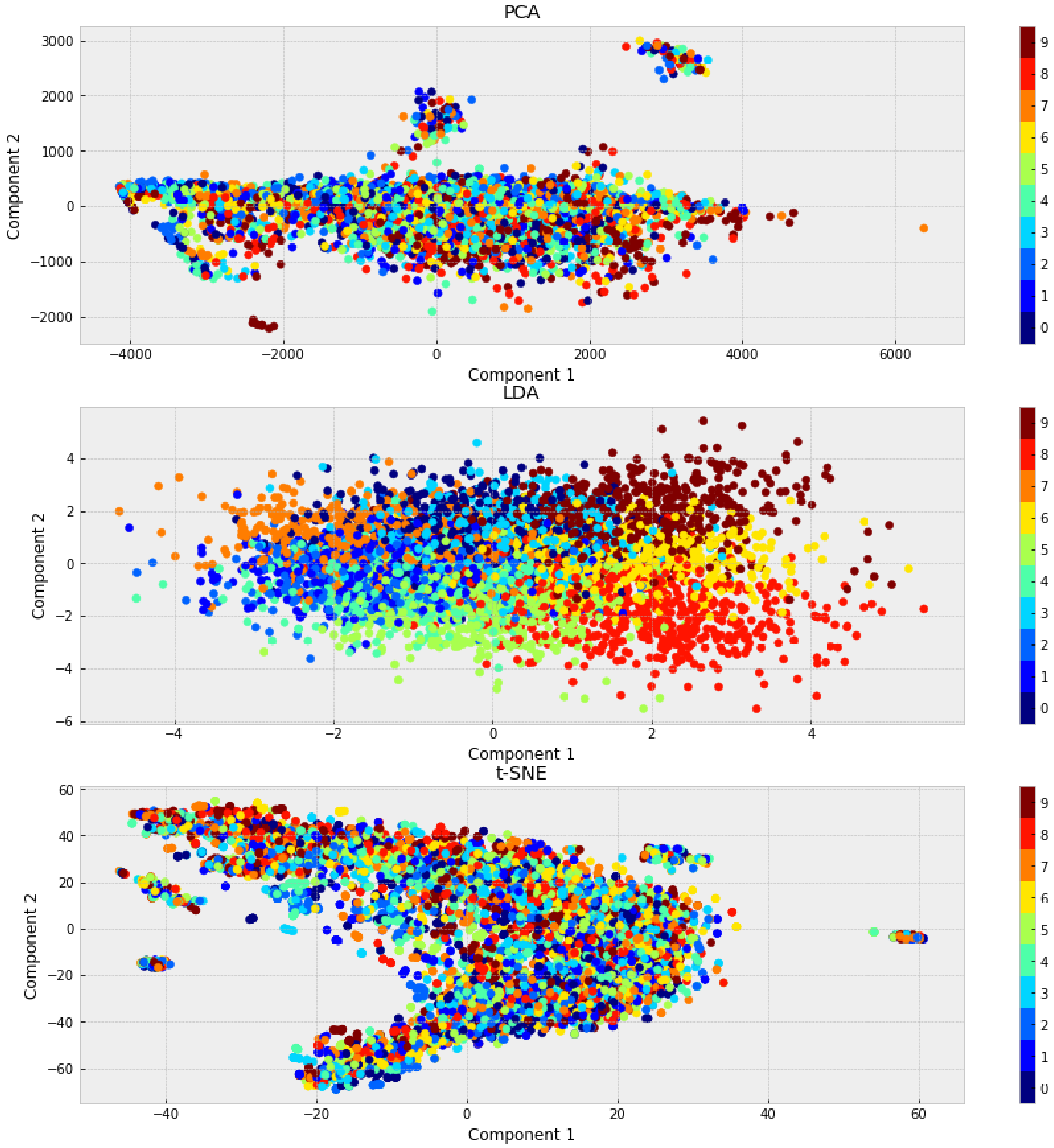
```
Number of Components: 3
```

Out[56]: ['Models/LR_tSNE3.pkl']

In [59]:

```python
#Visualization and comparison with PCA

pca = PCA(n_components=2)
y_train_pca = pca.fit_transform(X_train_resized)

#PCA plot
plt.figure(figsize=(15,15))
plt.subplot(3,1,1)
plt.scatter(y_train_pca[:, 0], y_train_pca[:, 1], c=t_train, cmap=plt.cm.get_cma
plt.colorbar(ticks=range(10))
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.clim(-0.5, 9.5); plt.title('PCA')

#FLDA plot
plt.subplot(3,1,2)
plt.scatter(y_train_lda[:, 0], y_train_lda[:, 1], c=t_train, cmap=plt.cm.get_cma
plt.colorbar(ticks=range(10))
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.clim(-0.5, 9.5); plt.title('LDA')

#tSNE
plt.subplot(3,1,3)
plt.scatter(y_train_sne[:, 0], y_train_sne[:, 1], c=t_train, cmap=plt.cm.get_cma
plt.colorbar(ticks=range(10))
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.clim(-0.5, 9.5); plt.title('t-SNE');
```

```
/scratch/local/15693744/ipykernel_4102909/1468947823.py:10: MatplotlibDeprecation
Warning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since
3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar(ticks=range(10))
/scratch/local/15693744/ipykernel_4102909/1468947823.py:18: MatplotlibDeprecation
Warning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since
3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar(ticks=range(10))
/scratch/local/15693744/ipykernel_4102909/1468947823.py:26: MatplotlibDeprecation
Warning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since
3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar(ticks=range(10))
```



4. Manifold Learning Algorithms

In [10]:
```
#MDS
mds = MDS(n_components=300, dissimilarity='euclidean')


pipe = Pipeline([('scaler', MinMaxScaler()),
                 ('LR', LogisticRegression(solver='liblinear', multi_class=

X_train_mds = mds.fit_transform(X_train_resized)
pipe.fit(X_train_mds,t_train)
y_train_mds = pipe.predict(X_train_mds)


joblib.dump(mds, 'Models/MDS4.pkl')
joblib.dump(pipe, 'Models/MDSclf.pkl')
```

Out[10]:
```
['Models/MDSclf.pkl']
```

In [11]:
```
iso = Isomap(n_components=182, n_neighbors = 10)

X_train_iso = iso.fit_transform(X_train_resized)
pipe.fit(X_train_iso,t_train)
y_train_iso = pipe.predict(X_train_iso)

joblib.dump(iso, 'Models/Isomap4.pkl')
joblib.dump(pipe, 'Models/isoclf.pkl')
```

```
/apps/python/3.10/lib/python3.10/site-packages/sklearn/manifold/_isomap.py:348: UserWarning: The number of connected components of the neighbors graph is 3 > 1. Completing the graph to fit Isomap might be slow. Increase the number of neighbors to avoid this issue.
  self._fit_transform(X)
/apps/python/3.10/lib/python3.10/site-packages/scipy/sparse/_index.py:103: SparseEfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive. lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
/apps/python/3.10/lib/python3.10/site-packages/scipy/sparse/_index.py:103: SparseEfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive. lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
/apps/python/3.10/lib/python3.10/site-packages/scipy/sparse/_index.py:103: SparseEfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive. lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
```

Out[11]: ['Models/isoclf.pkl']

In [12]:
```
#LLE

lle = LLE(n_components=182, n_neighbors=10)

X_train_lle = lle.fit_transform(X_train_resized)
pipe.fit(X_train_lle,t_train)
y_train_lle = pipe.predict(X_train_lle)

joblib.dump(lle, 'Models/LLE4.pkl')
joblib.dump(pipe, 'Models/lleclf.pkl')
```

Out[12]: ['Models/lleclf.pkl']

In [10]:
```
#Algorithm to select
#Classification report

print('\n\n Training Set Performance for MDS')
print('Accuracy Score:', accuracy_score(t_train, y_train_mds))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train_mds))
print('\nPerformance Report: ')
print(classification_report(t_train,y_train_mds))
print('\n\n')


print('\n\n Training Set Performance for LLE')
print('Accuracy Score:', accuracy_score(t_train, y_train_lle))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train_lle))
print('\nPerformance Report: ')
```

```
print(classification_report(t_train,y_train_lle))
print('\n\n')


print('\n\n Training Set Performance for ISOMAP')
print('Accuracy Score:', accuracy_score(t_train, y_train_iso))
print('Confusion Matrix:')
print(confusion_matrix(t_train,y_train_iso))
print('\nPerformance Report: ')
print(classification_report(t_train,y_train_iso))
print('\n\n')
```

```
 Training Set Performance for MDS
Accuracy Score: 0.26264880952380953
Confusion Matrix:
[[160  62  71  57  38  55  73  54  42  73]
 [ 60 158  91  49  43  47  52  75  71  44]
 [ 58  54 260  40  52  47  45  60  20  37]
 [ 55  44  86 133  35  35  85  53  73  66]
 [ 54  68  91  55 140  44  53  50  34  62]
 [ 41  53  73  34  46 155  55  70  89  47]
 [ 71  42  67  66  40  51 161  36  82  53]
 [ 53  82  92  42  40  44  51 161  57  60]
 [ 43  41  49  41  29  48  52  49 246  70]
 [ 62  51  62  44  35  46  49  45  89 191]]

Performance Report:
              precision    recall  f1-score   support

         0.0       0.24      0.23      0.24       685
         1.0       0.24      0.23      0.23       690
         2.0       0.28      0.39      0.32       673
         3.0       0.24      0.20      0.22       665
         4.0       0.28      0.22      0.24       651
         5.0       0.27      0.23      0.25       663
         6.0       0.24      0.24      0.24       669
         7.0       0.25      0.24      0.24       682
         8.0       0.31      0.37      0.33       668
         9.0       0.27      0.28      0.28       674

    accuracy                           0.26      6720
   macro avg       0.26      0.26      0.26      6720
weighted avg       0.26      0.26      0.26      6720
```

```
 Training Set Performance for LLE
Accuracy Score: 0.34092261904761906
Confusion Matrix:
[[237  32  89  66  38  24  66  42  41  50]
 [ 43 201  93  35  37  39  42 118  39  43]
 [ 34  36 371  30  72  24  28  27  24  27]
 [ 67  33  68 204  28  36  75  32  68  54]
 [ 44  49 158  37 177  37  53  32  25  39]
 [ 32  65  81  37  29 179  53  45 102  40]
 [ 50  37  68  72  26  40 224  25  73  54]
 [ 42  93  75  46  29  39  42 232  40  44]
 [ 40  43  42  49  22  58  51  41 258  64]
 [ 61  42  67  39  31  47  62  47  70 208]]

Performance Report:
              precision    recall  f1-score   support

         0.0       0.36      0.35      0.36       685
         1.0       0.32      0.29      0.30       690
         2.0       0.33      0.55      0.42       673
         3.0       0.33      0.31      0.32       665
         4.0       0.36      0.27      0.31       651
```

```
         5.0       0.34      0.27      0.30       663
         6.0       0.32      0.33      0.33       669
         7.0       0.36      0.34      0.35       682
         8.0       0.35      0.39      0.37       668
         9.0       0.33      0.31      0.32       674

    accuracy                           0.34      6720
   macro avg       0.34      0.34      0.34      6720
weighted avg       0.34      0.34      0.34      6720
```

```
 Training Set Performance for ISOMAP
Accuracy Score: 0.3568452380952381
Confusion Matrix:
[[255  43  66  67  34  26  68  33  42  51]
 [ 48 227  66  42  24  40  42 108  39  54]
 [ 48  44 308  37  76  31  49  32  12  36]
 [ 70  41  55 239  20  37  56  45  51  51]
 [ 47  32 116  47 202  38  63  33  20  53]
 [ 36  53  62  51  30 187  73  55  69  47]
 [ 90  38  54  55  22  42 232  37  47  52]
 [ 45  93  61  47  23  38  57 230  33  55]
 [ 39  55  39  42  17  60  62  36 250  68]
 [ 46  44  49  52  15  29  61  50  60 268]]

Performance Report:
              precision    recall  f1-score   support

         0.0       0.35      0.37      0.36       685
         1.0       0.34      0.33      0.33       690
         2.0       0.35      0.46      0.40       673
         3.0       0.35      0.36      0.36       665
         4.0       0.44      0.31      0.36       651
         5.0       0.35      0.28      0.31       663
         6.0       0.30      0.35      0.32       669
         7.0       0.35      0.34      0.34       682
         8.0       0.40      0.37      0.39       668
         9.0       0.36      0.40      0.38       674

    accuracy                           0.36      6720
   macro avg       0.36      0.36      0.36      6720
weighted avg       0.36      0.36      0.36      6720
```

In [28]:

```
#Training for 2D visualizations

#MDS
mds = MDS(n_components=2, dissimilarity='euclidean')
X_train_mds = mds.fit_transform(X_train_resized)
# joblib.dump(mds, 'Models/MDS4.pkl')

#Isomap
iso = Isomap(n_components=2)
```

```
X_train_iso = iso.fit_transform(X_train_resized)
# joblib.dump(iso, 'Models/Isomap4.pkl')

#LLE
lle = LLE(n_components=2, n_neighbors=10)
X_train_lle = lle.fit_transform(X_train_resized)
# joblib.dump(lle, 'Models/LLE4.pkl')
```

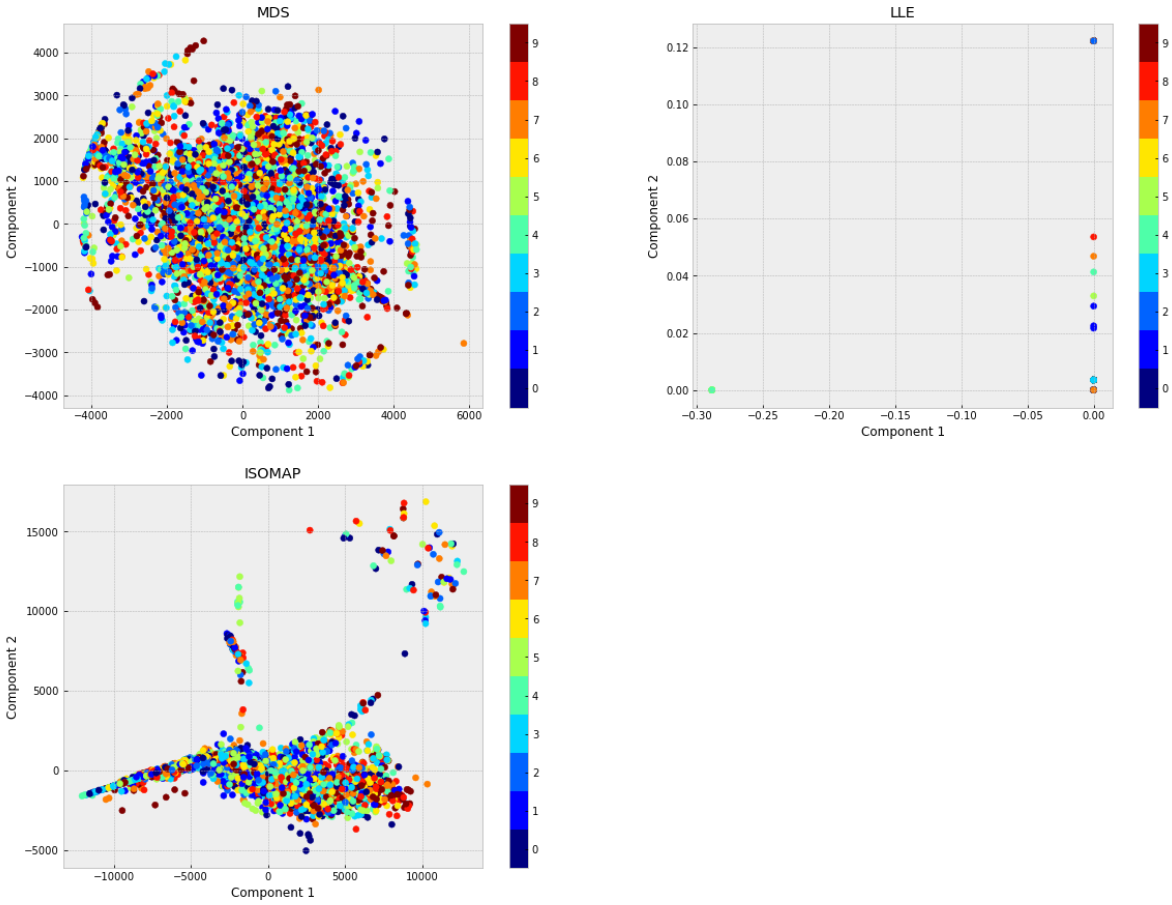
```
/apps/python/3.10/lib/python3.10/site-packages/sklearn/manifold/_isomap.py:348: U
serWarning: The number of connected components of the neighbors graph is 3 > 1. C
ompleting the graph to fit Isomap might be slow. Increase the number of neighbors
to avoid this issue.
  self._fit_transform(X)
/apps/python/3.10/lib/python3.10/site-packages/scipy/sparse/_index.py:103: Sparse
EfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive.
lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
/apps/python/3.10/lib/python3.10/site-packages/scipy/sparse/_index.py:103: Sparse
EfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive.
lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
/apps/python/3.10/lib/python3.10/site-packages/scipy/sparse/_index.py:103: Sparse
EfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive.
lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
```

In [60]:

```
#Visualization of the three Algorithms

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

#MDS
plt.subplot(2,2,1)
plt.scatter(X_train_mds[:, 0], X_train_mds[:, 1], c=t_train, cmap=plt.cm.get_cma
plt.colorbar(ticks=range(10))
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.clim(-0.5, 9.5); plt.title('MDS')

#LLE
plt.subplot(2,2,2)
plt.scatter(X_train_lle[:, 0], X_train_lle[:, 1], c=t_train, cmap=plt.cm.get_cma
plt.colorbar(ticks=range(10))
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.clim(-0.5, 9.5); plt.title('LLE')

#Isomap
plt.subplot(2,2,3)
plt.scatter(X_train_iso[:, 0], X_train_iso[:, 1], c=t_train, cmap=plt.cm.get_cma
plt.colorbar(ticks=range(10))
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.clim(-0.5, 9.5); plt.title('ISOMAP')
```

```
/scratch/local/15693744/ipykernel_4102909/3281107350.py:8: MatplotlibDeprecationWarning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since 3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar(ticks=range(10))
/scratch/local/15693744/ipykernel_4102909/3281107350.py:16: MatplotlibDeprecationWarning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since 3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar(ticks=range(10))
/scratch/local/15693744/ipykernel_4102909/3281107350.py:24: MatplotlibDeprecationWarning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since 3.5 and will be removed two minor releases later; please call grid(False) first.
  plt.colorbar(ticks=range(10))
```

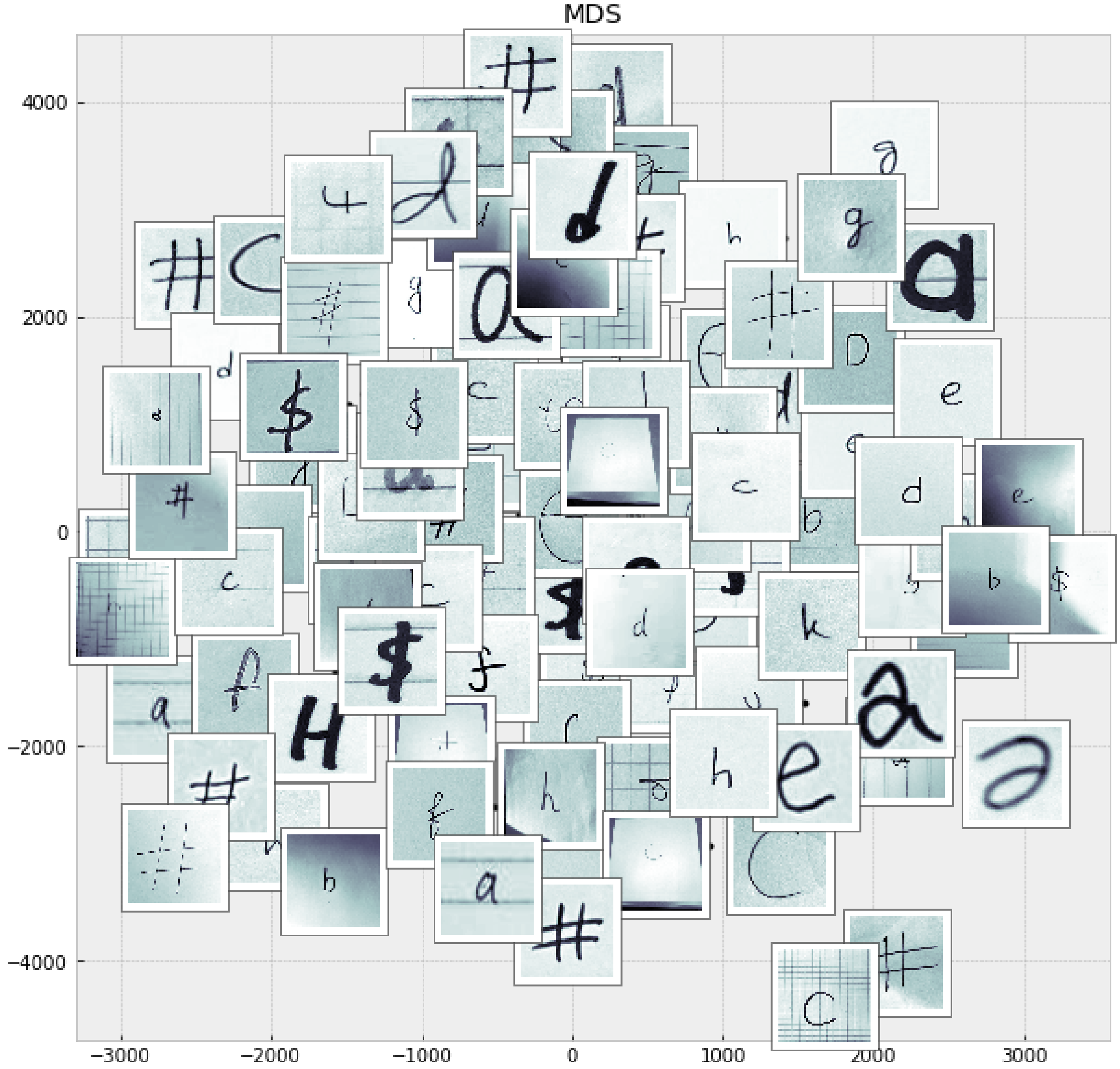
Out[60]: `Text(0.5, 1.0, 'ISOMAP')`

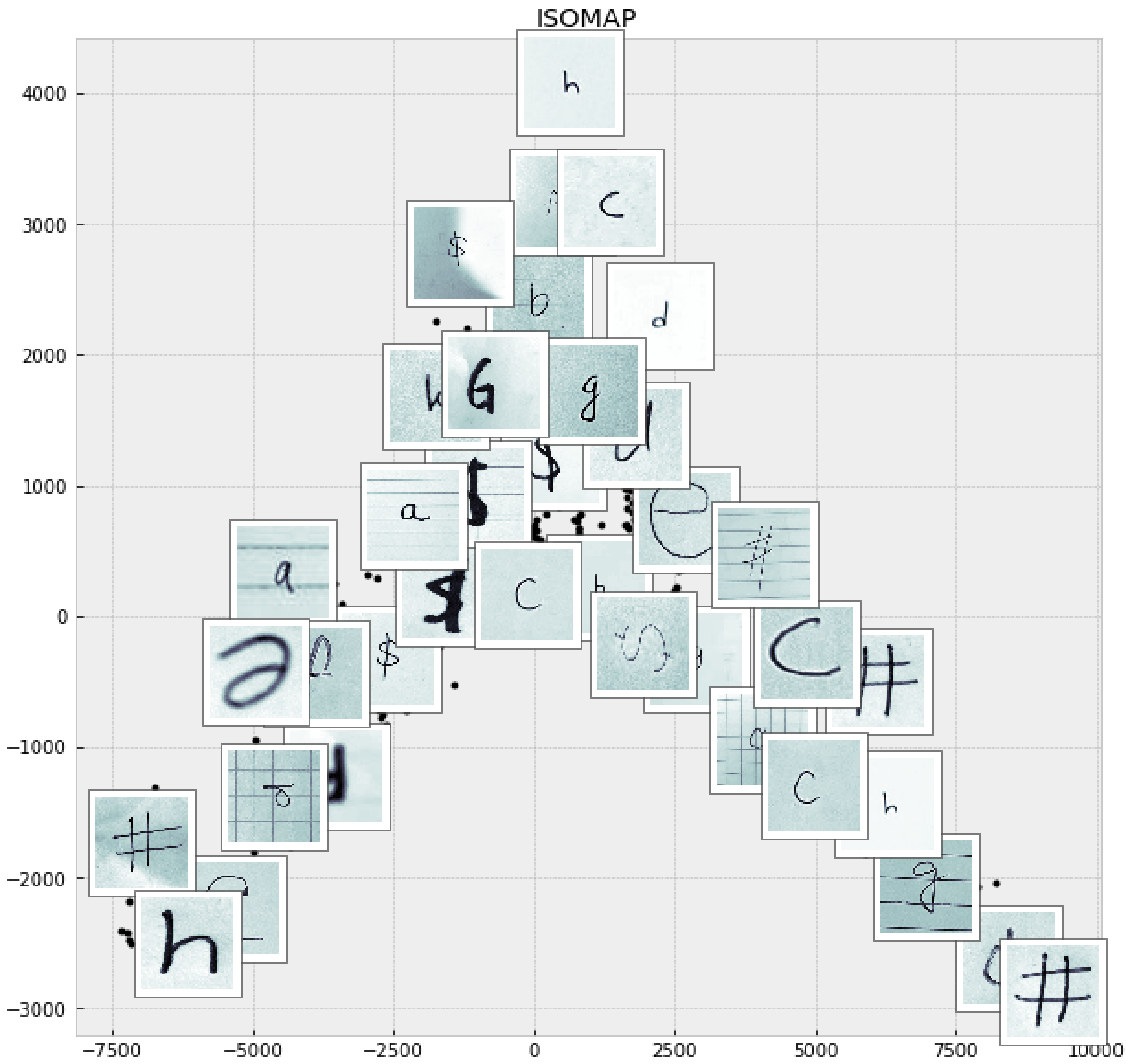


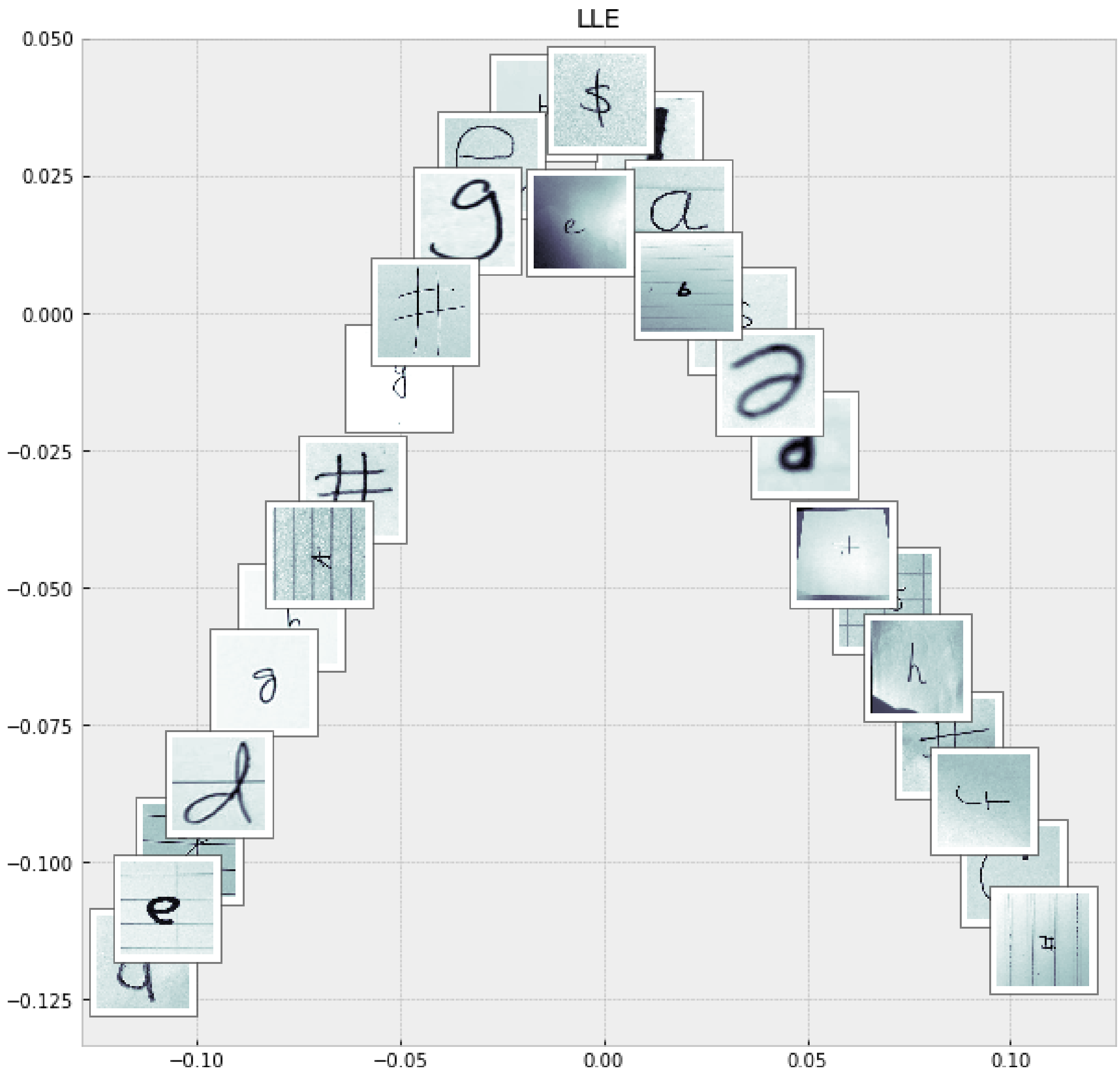
In [29]:

```python
#Visualizing data to see what the algorithms are considering important in the fi

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_resized[::15]

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

# ISOMAP
fig, ax = plt.subplots(figsize=(10, 10))
# isomap = Isomap(n_components=2)
plot_components(data, iso, images=X_train_resized.reshape((-1, 50, 50)),
                ax=ax, thumb_frac=0.05, cmap='bone')
plt.title('ISOMAP')

# LLE
fig, ax = plt.subplots(figsize=(10, 10))
# lle = LLE(n_components=2)
plot_components(data, lle, images=X_train_resized.reshape((-1, 50, 50)),
                ax=ax, thumb_frac=0.05, cmap='bone')
plt.title('LLE');
```


MDS
4000
2000
0
−2000
−4000
−3000
−2000
−1000
0
1000
2000
3000


ISOMAP
4000
3000
2000
1000
0
−1000
−2000
−3000
−7500
−5000
−2500
0
2500
5000
7500
10000


LLE
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.10
−0.05
0.00
0.05
0.10

In [ ]:

In [ ]: