Lab09a_pca_NN_CNN_partial

April 30, 2018

1 Lab 9a: PCA for Face Recognition

Following the demo for this unit, we will explore further the use of PCA for feature dimension reduction for classification. We will use a 2-layer neural net on the PCA coefficients. We will practice optimizing the classification parameters (the number of PCA components and the number of hidden nodes in the NN classifier). We will furthermore compare this approach with using convolutional neural net on raw images.

Through the lab, you will learn to:

- Perform PCA on the a face dataset to find the PC components
- Evaluate the effect of using different nubmer of principle components for data representation and classification.
- Optimize the number of PC coefficients and classifier parameters together to maximize classification accuracy.
- Understand the impact of training data size on the feature and classification method selection.

```
In [1]: import numpy as np
        import matplotlib
        import matplotlib.pyplot as plt

In [3]: # Import the flw_people dataset.
        # Select only those people with at least 100 instances
        # Reduce the face image size by 0.4

# TO DO
        from sklearn.datasets import fetch_lfw_people
        lfw_people = fetch_lfw_people(min_faces_per_person=100, resize=0.4)

Downloading LFW metadata: https://ndownloader.figshare.com/files/5976012

Downloading LFW metadata: https://ndownloader.figshare.com/files/5976009

Downloading LFW metadata: https://ndownloader.figshare.com/files/5976006

Downloading LFW data (~200MB): https://ndownloader.figshare.com/files/5976015
```

In [4]: # Save the face images in a datamatrix X and the labels and corresponding names in a d
Furthermore, determine the number of samples and the image size

```
# Determine the number of different faces (number of classes)
        # TO DO
        n_samples, h, w = lfw_people.images.shape
        npix = h*w
        # Data in 2D form
        X = lfw_people.data
        n_features = X.shape[1]
        # Labels of images
        y = lfw_people.target
        target_names = lfw_people.target_names
        n_classes = target_names.shape[0]
        print("Image size = {0:d} x {1:d} = {2:d} pixels".format(h,w,npix))
        print("Number faces = {0:d}".format(n_samples))
        print("Number classes = {0:d}".format(n_classes))
Image size = 50 \times 37 = 1850 pixels
Number faces = 1140
Number classes = 5
In [6]: # Plot some sample images to make sure your data load is correct
        def plt_face(x):
            h = 50
            w = 37
            plt.imshow(x.reshape((h, w)), cmap=plt.cm.gray)
            plt.xticks([])
            plt.yticks([])
        I = np.random.permutation(n_samples)
        plt.figure(figsize=(10,20))
        nplt = 4;
        for i in range(nplt):
            ind = I[i]
            plt.subplot(1,nplt,i+1)
            plt_face(X[ind])
            plt.title(target_names[y[ind]])
                                            Gerhard Schroeder
       George W Bush
                          George W Bush
                                                                George W Bush
```

```
In [7]: # Split the data into a training set and test set with 50% data for training.
        # Use "stratify" option to make sure the training data and test data have same
        # proportion of images from different faces
        # print the number of samples in the training data
        # TO DO
        from sklearn.model_selection import train_test_split
        # split into a training and testing set
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, stratify=y,test_size=0.5)
        n_samples_train = X_train.shape[0]
        print("Number faces in training data = {0:d}".format(n_samples_train))
Number faces in training data = 570
In [8]: # Perfom PCA on the training data to derive the principle components (PCs) and the PCA
        # You can directly use the PCA class in PCA package or use SVD.
        # Remember that you need to remove the mean from the data first
        # Also you should rescale the PCs so that the PCA coefficients all have unit variance
        # Determine the total number of PCs
        # TO DO
        from sklearn.model_selection import GridSearchCV
        from sklearn.svm import SVC
        n_samples, _ = X_train.shape
        Xtr_mean = np.mean(X_train,0)
        Xtr = X_train - Xtr_mean[None,:]
        Utr,Str,Vtr = np.linalg.svd(Xtr, full_matrices=False)
        print("The total number of PCs is %d." % Vtr.shape[0])
```

First let us construct a 2-layer neural net classifier that uses npc= 100 PCA coefficients to classify the faces. Set up your training and testing data to contain npc PCA coefficients using the previously determined principle components. You should directly use matrix multiplication (i.e. projecting original data to the first 100 principle components you found previously) to find the coefficients rather then using the pca.transform() method.

The total number of PCs is 570.

```
Xts = X_test - Xtr_mean[None,:]
Xts_pca = Xts.dot(eigenface.T)
Xts_pca_s = Xts_pca / Str[None,:npc] * np.sqrt(n_samples)
```

Now set up and compile a NN model with number of hidden nodes nnode=100 and a output layer, and then fit the model to the training data. Use 'relu' for the activation for the hidden layer and use 'softmax' for the output layer. Using sparse_categorical_crossentropy for the loss. Use accuracy as the metrics. You can choose to do a small number of epochs (=10) with batch size =100. Determine the accuracy on the validation set.

```
In [15]: # TO DO
       import keras
       from keras.models import Model, Sequential
       from keras.layers import Dense, Activation
       from keras.layers import Dropout, Flatten
       from keras.layers import Conv2D, MaxPooling2D
       import keras.backend as K
       K.clear_session()
       nin = Xtr_pca.shape[1] # dimension of input data
       nh = 100 # number of hidden units
       nout = int(np.max(y_train)+1) # number of outputs
       model = Sequential()
       model.add(Dense(nh, input_shape=(nin,), activation='relu', name='hidden'))
       model.add(Dense(nout, activation='softmax', name='output'))
       model.summary()
Layer (type)
              Output Shape
                                          Param #
______
hidden (Dense)
                      (None, 100)
                                          10100
_____
output (Dense) (None, 5)
                                          505
______
Total params: 10,605
Trainable params: 10,605
Non-trainable params: 0
```

Now try to identify the best number of PCs and the best number of hidden nodes in the NN classifer that can achieve the highest validation accuracy. You can set the range of PCs and nubmer of hidden nodes as below.

```
nnodes = [50,100,150,200,250], npcs = [50,100,150,200]
```

```
loss='sparse_categorical_crossentropy',
                 metrics=['accuracy'])
    hist = model.fit(Xtr_pca_s, y_train, epochs=10, batch_size=100)
    nnodes = [50, 100, 150, 200, 250]
    npcs = [50, 100, 150, 200]
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
In [19]: # Loop through the combinations to find the accuracy for each combination
    # For each possible combination of `nnode` and `npc`, set up and fit the model
    # using features containing only coefficents corresponding to npc coefficients.
    # TO DO
    result = np.zeros((len(npcs),len(nnodes)))
    loss_hist = []
    train_acc_hist = []
    val_acc_hist = []
    for i,npc in enumerate(npcs):
       for j,nnode in enumerate(nnodes):
         K.clear_session()
         eigenface = Vtr[:npc,:]
         Xtr_pca = X_train.dot(eigenface.T)
         Xtr_pca_s = Xtr_pca / Str[None,:npc] * np.sqrt(n_samples)
         Xts = X_test - Xtr_mean[None,:]
         Xts_pca = Xts.dot(eigenface.T)
         Xts_pca_s = Xts_pca / Str[None,:npc] * np.sqrt(n_samples)
         nin = Xtr_pca.shape[1] # dimension of input data
```

```
nout = int(np.max(y_train)+1)
                   model = Sequential()
                   model.add(Dense(nh, input_shape=(nin,), activation='relu', name='hidden'))
                   model.add(Dense(nout, activation='softmax', name='output'))
                   opt = optimizers.Adam(lr=0.01, beta_1=0.9, beta_2=0.999, epsilon=1e-08,decay=
                   model.compile(optimizer=opt,loss='sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',metrics=['sparse_categorical_crossentropy',m
                   hist = model.fit(Xtr_pca_s, y_train, epochs=10, batch_size=100,
                                       validation_data=(Xts_pca_s, y_test),shuffle=True)
                   result[i][j] = hist.history['val_acc'][-1]
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
```

nh = nnode # number of hidden units

```
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
```

```
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 2/10
Epoch 3/10
```

```
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
```

```
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
```

```
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Train on 570 samples, validate on 570 samples
```

Epoch 2/10

```
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
```

```
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
```

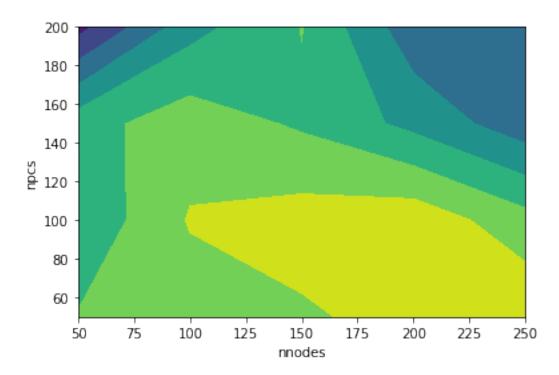
```
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 570 samples, validate on 570 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
```

```
In [30]: # Determine the npc and nnode that provides the highest validation accuracy
    # TO DO
    highest_accuracy = result[0][0]
    opt_npc_index = 0
    opt_nnode_index = 0
    for i in range(0,len(npcs)):
        for j in range(0,len(nnodes)):
            if result[i][j] > highest_accuracy:
                  highest_accuracy = result[i][j]
                  opt_npc_index = i
                  opt_nnode_index = j
        print("The best npc is %d, and the best nnode is %d." % (npcs[opt_npc_index],nnodes[opt_npc])
The best npc is 50, and the best nnode is 250.
The best validation accuracy is 0.792982.
```

In [31]: # Produce a contour plot of the accuracy using different nnode and npc combincations # TO DO

```
# plt.contourf ...
grid_x, grid_y = np.mgrid[50:250:50, 50:300:50]
plt.contourf(grid_y,grid_x,result)
plt.xlabel("nnodes")
plt.ylabel("npcs")
```

Out[31]: Text(0,0.5,'npcs')



1.1 Now let us compare the PCA+NN with applying a CNN on the raw image data only.

Note that you should scale your image data to between 0 and 1. And you should reshape your training and testing data according to image width and height

```
In [35]: # Data preparation for input to CNN
        # TO DO
        Xtr_cnn = X_train.astype("float32")/255
        Xts_cnn = X_test.astype("float32")/255
        Xtr_cnn = np.reshape(Xtr_cnn, (len(Xtr_cnn),h,w,1))
        Xts_cnn = np.reshape(Xts_cnn, (len(X)-len(Xtr_cnn),h,w,1))
In [36]: # Set up a CNN model
        # You can use 2 conv2D layer, each with kernel size of 5x5, each followed by a pooling
        # For this part, let both conv2D layer generate 16 channels.
        # The Conv layer should be followed by a flatten layer and two dense layers.
        # The first dense layer should produce 200 outputs.
        # The last dense layer is the output layer with n_classes output using 'softmax' acti
        # Print model summary to verify it follows the desired structure and compile the mode
        # TO DO
        model = Sequential()
        model.add(Conv2D(16, (5, 5),
                       padding='valid',
                        input_shape=Xtr_cnn.shape[1:],
                       activation='relu'))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Conv2D(16, (5, 5), padding='valid', activation='relu'))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Flatten())
        model.add(Dense(200, activation='relu'))
        model.add(Dense(nout, activation='softmax')) # TO DO
        print(model.summary())
Layer (type) Output Shape Param #
______
                         (None, 46, 33, 16)
conv2d_1 (Conv2D)
                                                  416
max_pooling2d_1 (MaxPooling2 (None, 23, 16, 16) 0
conv2d_2 (Conv2D) (None, 19, 12, 16)
                                                 6416
max_pooling2d_2 (MaxPooling2 (None, 9, 6, 16) 0
```

```
-----
                       173000
dense_1 (Dense)
            (None, 200)
dense 2 (Dense) (None, 5)
                       1005
______
Total params: 180,837
Trainable params: 180,837
Non-trainable params: 0
None
In [37]: # Fit the model using batch size=100, epochs = 40
   # Print the accuracy on the validation set
   # TO DO
   opt = optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0)
   # Let's train the model using Adam
   model.compile(loss='sparse_categorical_crossentropy',
              optimizer=opt,metrics=['accuracy'])
   hist_basic = model.fit(Xtr_cnn, y_train,batch_size=100,epochs=40,
             validation_data=(Xts_cnn, y_test),shuffle=True)
   print("The accuracy on validation set is:")
   print(hist_basic.history['val_acc'])
Train on 570 samples, validate on 570 samples
Epoch 1/40
Epoch 2/40
Epoch 3/40
Epoch 4/40
Epoch 5/40
Epoch 6/40
Epoch 7/40
Epoch 8/40
Epoch 9/40
Epoch 10/40
Epoch 11/40
```

flatten_1 (Flatten)

(None, 864)

```
Epoch 12/40
Epoch 13/40
Epoch 14/40
Epoch 15/40
Epoch 16/40
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
Epoch 33/40
Epoch 34/40
Epoch 35/40
```

How do the result compared with the PCA+NN method? (If you did right, they should be similar, with PCA+NN being slightly better. If you used more training data (e.g. 75%) and you trained the CNN with more epochs, CNN method may get better).

A: PCA+NN method is slightly better with validation accuracy around 0.83, CNN method is with validation accuracy around 0.79.

1.2 Repeat the above using a small dataset

Instead of using 50% of the total data for training, let us assume you have only 10% of the total data for training. Repeat both the PCA+NN and the CNN method, to see which one gives you better results.

Note that with only 10% data for training, the range of the npc has to be set to be below the total number of training samples.

For the CNN model, because you have small number of training samples, you cannot train a network with a large number of parameters reliably. Instead of producing 16 channels for each of the two conv2D layers, configure the model to produce only 8 channels each.

```
In [41]: ## TO DO
         X_train, X_test, y_train, y_test = train_test_split(
             X, y, stratify=y,test_size=0.5)
         X_train, X_test, y_train, y_test = train_test_split(X, y, stratify = y,test_size=0.9)
         n_samples, _ = X_train.shape
         Xtr_mean = np.mean(X_train,0)
         Xtr = X_train - Xtr_mean[None,:]
         Utr,Str,Vtr = np.linalg.svd(Xtr, full_matrices=False)
         nnodes = [50, 100, 150, 200, 250]
         npcs = [50,60,70,80,90,100]
         result = np.zeros((len(npcs),len(nnodes)))
         loss_hist = []
         train_acc_hist = []
         val_acc_hist = []
         for i,npc in enumerate(npcs):
             for j,nnode in enumerate(nnodes):
```

```
Xtr_pca_s = Xtr_pca / Str[None,:npc] * np.sqrt(n_samples)
          Xts = X_test - Xtr_mean[None,:]
          Xts_pca = Xts.dot(eigenface.T)
          Xts_pca_s = Xts_pca / Str[None,:npc] * np.sqrt(n_samples)
          nin = Xtr_pca.shape[1] # dimension of input data
          nh = nnode # number of hidden units
          nout = int(np.max(y_train)+1)
          model = Sequential()
          model.add(Dense(nh, input_shape=(nin,), activation='relu', name='hidden'))
          model.add(Dense(nout, activation='softmax', name='output'))
          opt = optimizers.Adam(lr=0.01, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay
          model.compile(optimizer=opt,loss='sparse_categorical_crossentropy',
                   metrics=['accuracy'])
          hist = model.fit(Xtr_pca_s, y_train, epochs=10, batch_size=100,
                     validation_data=(Xts_pca_s, y_test))
          result[i][j] = hist.history['val_acc'][-1]
     highest_accuracy = result[0][0]
     opt_npc_index = 0
     opt_nnode_index = 0
     for i in range(0,len(npcs)):
        for j in range(0,len(nnodes)):
          if result[i][j] > highest_accuracy:
             highest_accuracy = result[i][j]
             opt_npc_index = i
             opt_nnode_index = j
     print("The best npc is %d, and the best nnode is %d." % (npcs[opt_npc_index],nnodes[ortine])
     print("The best validation accuracy is %f." % highest_accuracy)
Train on 114 samples, validate on 1026 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
```

K.clear_session()

eigenface = Vtr[:npc,:]

Xtr_pca = Xtr.dot(eigenface.T)

```
Epoch 9/10
Epoch 10/10
Train on 114 samples, validate on 1026 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 114 samples, validate on 1026 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 10/10
Train on 114 samples, validate on 1026 samples
Epoch 1/10
```

```
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 114 samples, validate on 1026 samples
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
Train on 114 samples, validate on 1026 samples
Epoch 1/10
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Train on 114 samples, validate on 1026 samples
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Train on 114 samples, validate on 1026 samples
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The best npc is 60, and the best nnode is 200.
The best validation accuracy is 0.734893.
```

```
model.add(Conv2D(8, (5, 5),
           padding='valid',
           input_shape=Xtr_cnn.shape[1:],
           activation='relu'))
   model.add(MaxPooling2D(pool size=(2, 2)))
   model.add(Conv2D(8, (5, 5), padding='valid', activation='relu'))
   model.add(MaxPooling2D(pool size=(2, 2)))
   model.add(Flatten())
   model.add(Dense(200, activation='relu'))
   model.add(Dense(nout, activation='softmax'))
   opt = optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0)
   # Let's train the model using Adam
   model.compile(loss='sparse_categorical_crossentropy',
          optimizer=opt,
          metrics=['accuracy'])
   hist_basic = model.fit(Xtr_cnn, y_train,batch_size=100,epochs=40,
              validation_data=(Xts_cnn, y_test),shuffle=True)
   print("The accuracy on validation set is:")
   print(hist_basic.history['val_acc'])
Train on 114 samples, validate on 1026 samples
Epoch 1/40
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Epoch 12/40
Epoch 13/40
Epoch 14/40
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Epoch 36/40
Epoch 37/40
Epoch 38/40
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Q: How does CNN compare with PCA+NN with the small training set? Why? A:The validation accuracy CNN gets is much smaller than that of PCA+NN. It probably because of its smaller training data set.