Inception-Style Networks and the Labeled Faces in the Wild Dataset

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Background

Convolutional Neural Network Layers

Dense

Dense layers are fully connected. Every input is connected to every node.

Convolutional

Convolutional layers take the dot product of a n by m sized filter and a section of the same sized section of the input. The filter is applied across the input, moving across the matrix with a stride determining the distance the filter moves as the input is convolved.

Pooling

Pooling layers pull out the average or maximum importance elements from the input. This reduces the dimesionality of the input without reducing the risk of overfitting and maintaining the relative position of significant features,

Normalization

Inputs to neural nets or outputs of other layers, such as convolutional layers may have very large or very small magnitude which can disproportional blow up weights as the model is trained. Normalization layers keep all inputs between 0 and 1.

Inception-Style Deep Neural Nets

Inception v1

The philosophy behind the inception networks is that as neural networks get deeper, they must also get broader to prevent “bottle necking” or information loss over dimension reduction [3]. The Inception Network combines differently sized convolutional layers to great effect. Images of the same class may have important characteristics of different sizes [3]. The unique nature of a inception module is the combination of 1x1, 3x3, 5x5, and max pooling layers in parallel, taking from the same input, then concatenating them, thereby letting the network decide whether large features or small features are important. Further, inception modules use 1x1 matrices for dimension reduction to reduce computational complexity. An n x n convolution can be factored into two separate convolutions of size 1 x n and n x 1. This is done to reduce the computational complexity of large dimensional convolution operations. This works because Since inception is a very deep network, it has an issue of vanishing gradient. To prevent stagnation in the middle of the network, auxiliary classifiers consisting of average pooling, convolutional, filter concatenation, and softmax activation layers [3].

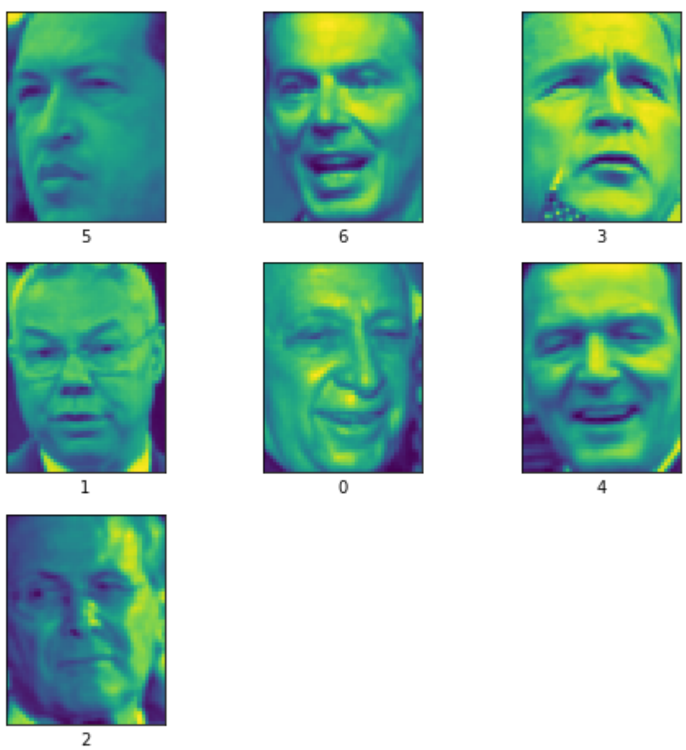
Inception v3

Inception version three adds 4 improvements over Inception V1. Firstly, they added was 7x7 factorized convolutional layers. This allows the network to learn even more advanced features than with a maximum convolution size of 5x5. Secondly, they implemented the RMSProp optimizer [2]. RMSProp is useful because training gradients can have a variety of slopes, so adjusting the learning rate makes learning more efficient [4]. Thirdly, they used label smoothing to prevent overfitting. label

In [93]:

```
from sklearn.datasets import fetch_lfw_people
import matplotlib.pyplot as plt
import math


lfw_people = fetch_lfw_people(min_faces_per_person=70)

n_samples, h, w = lfw_people.images.shape

def plot_images(images, labels):
    imgs = []
    l = []
    for label, im in zip(labels, images):
        if label not in l:
            l.append(label)
            imgs.append(im)

    fig=plt.figure(figsize=(8, 8))
    columns = int(math.sqrt(len(imgs))) + 1
    rows = columns

    for (name, (i, im)) in zip(l, enumerate(imgs)):
        fig.add_subplot(rows, columns, i + 1, xlabel=name, xticks=[], yticks=[]
)
        plt.imshow(im)
    print(images.shape)
    plt.show()

plot_images(lfw_people.images, lfw_people.target)
```

```
(1288, 62, 47)
```



SciKitLearn SVM

To get a comparison of techniques on this dataset, the student ran the example designed by Scikit-learn.

Methods

This example uses a support vector machine for classification, grid search to optimize the gamma and C penalty parameter. The principle component analysis of the faces or "eigenfaces" are taken to reduce the dimensionality of the faces while keeping important features.

Results & Discussion

Code

In [1]:
```
from time import time
import logging
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import fetch_lfw_people
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.decomposition import PCA
from sklearn.svm import SVC

def svm_ex():
    print(__doc__)

    # Display progress logs on stdout
    logging.basicConfig(level=logging.INFO, format='%(asctime)s %(message)s')


    # #########################################################################
####
    # Download the data, if not already on disk and load it as numpy arrays

    lfw_people = fetch_lfw_people(min_faces_per_person=70, resize=0.4)

    # introspect the images arrays to find the shapes (for plotting)
    n_samples, h, w = lfw_people.images.shape

    # for machine learning we use the 2 data directly (as relative pixel
    # positions info is ignored by this model)
    X = lfw_people.data
    n_features = X.shape[1]

    # the label to predict is the id of the person
    y = lfw_people.target
    target_names = lfw_people.target_names
    n_classes = target_names.shape[0]

    print("Total dataset size:")
    print("n_samples: %d" % n_samples)
    print("n_features: %d" % n_features)
    print("n_classes: %d" % n_classes)


    # #########################################################################
####
    # Split into a training set and a test set using a stratified k fold

    # split into a training and testing set
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.25, random_state=42)


    # #########################################################################
####
    # Compute a PCA (eigenfaces) on the face dataset (treated as unlabeled
    # dataset): unsupervised feature extraction / dimensionality reduction
    n_components = 150

    print("Extracting the top %d eigenfaces from %d faces"
          % (n_components, X_train.shape[0]))
    t0 = time()
    pca = PCA(n_components=n_components, svd_solver='randomized',
```

```
Automatically created module for IPython interactive environment
Total dataset size:
n_samples: 1288
n_features: 1850
n_classes: 7
Extracting the top 150 eigenfaces from 966 faces
done in 0.668s
Projecting the input data on the eigenfaces orthonormal basis
done in 0.020s
Fitting the classifier to the training set
done in 43.970s
Best estimator found by grid search:
SVC(C=1000.0, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
Predicting people's names on the test set
done in 0.048s
                   precision    recall  f1-score   support

     Ariel Sharon       0.86      0.46      0.60        13
     Colin Powell       0.80      0.87      0.83        60
  Donald Rumsfeld       0.89      0.63      0.74        27
    George W Bush       0.84      0.98      0.90       146
Gerhard Schroeder       0.95      0.80      0.87        25
      Hugo Chavez       0.89      0.53      0.67        15
       Tony Blair       0.97      0.81      0.88        36

        micro avg       0.85      0.85      0.85       322
        macro avg       0.89      0.73      0.78       322
     weighted avg       0.86      0.85      0.85       322

[[  6   2   0   5   0   0   0]
 [  1  52   1   5   0   1   0]
 [  0   2  17   8   0   0   0]
 [  0   3   0 143   0   0   0]
 [  0   1   0   3  20   0   1]
 [  0   4   0   2   1   8   0]
 [  0   1   1   5   0   0  29]]

<Figure size 720x720 with 12 Axes>

<Figure size 720x720 with 12 Axes>
```

This approach works well. Indeed, the f-scores of the classification of each class is within 0.60-0.90 and the weighted average of 0.85.

Network used for MNIST

The use on a basic, shallow CNN was considered. The network designed for the MNIST example used in class was adapted to the LFW set.

Methods

The network is sequential model consisting of three convolution layers interspersed with max pooling layers. The output is flattened and run through a hidden dense layer and finally classified with the output dense layer. The learning is optimized with stochastic gradient descent. The loss function used was catagorical crossentropy. The model was trained with a batch sized 32 and 100 epochs.

Results & Discussion

Code

In [94]:
```
import numpy as np
from keras import layers
from keras import models
from sklearn.datasets import fetch_lfw_people
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical

def mnist_net_ex():
    print(__doc__)

    # Display progress logs on stdout
    #logging.basicConfig(level=logging.INFO, format='%(asctime)s %(message)s')


    ##########################################################################
####
    # Download the data, if not already on disk and load it as numpy arrays

    lfw_people = fetch_lfw_people(min_faces_per_person=70, resize=1)

    # introspect the images arrays to find the shapes (for plotting)
    n_samples, h, w = lfw_people.images.shape

    # for machine learning we use the 2 data directly (as relative pixel
    # positions info is ignored by this model)
    X = lfw_people.images
    n_features = X.shape[1]

    # the label to predict is the id of the person
    y = lfw_people.target

    target_names = lfw_people.target_names
    n_classes = target_names.shape[0]
    print("Total dataset size:")
    print("n_samples: %d" % n_samples)
    print("n_features: %d" % n_features)
    print("n_classes: %d" % n_classes)
    print('target names:\n', target_names)

    y = to_categorical(y, num_classes=n_classes)
    X = X.reshape(n_samples, h, w, 1)

    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.25)

    model = models.Sequential()

    # Configure a convnet with 3 layers of convolutions and max pooling.
    model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(h, w, 1
)))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation='relu'))

    # Add layers to flatten the 2D image and then do a 7-way classification.
    model.add(layers.Flatten())
    model.add(layers.Dense(64, activation='relu'))
    model.add(layers.Dense(n_classes, activation='softmax'))

    model.summary()

    model.compile(optimizer='SGD',
```

```
Automatically created module for IPython interactive environment
Total dataset size:
n_samples: 1288
n_features: 125
n_classes: 7
target names:
 ['Ariel Sharon' 'Colin Powell' 'Donald Rumsfeld' 'George W Bush'
 'Gerhard Schroeder' 'Hugo Chavez' 'Tony Blair']
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_519 (Conv2D)          (None, 123, 92, 32)       320
_________________________________________________________________
max_pooling2d_37 (MaxPooling (None, 61, 46, 32)        0
_________________________________________________________________
conv2d_520 (Conv2D)          (None, 59, 44, 64)        18496
_________________________________________________________________
max_pooling2d_38 (MaxPooling (None, 29, 22, 64)        0
_________________________________________________________________
conv2d_521 (Conv2D)          (None, 27, 20, 64)        36928
_________________________________________________________________
flatten_8 (Flatten)          (None, 34560)             0
_________________________________________________________________
dense_25 (Dense)             (None, 64)                2211904
_________________________________________________________________
dense_26 (Dense)             (None, 7)                 455
=================================================================
Total params: 2,268,103
Trainable params: 2,268,103
Non-trainable params: 0
_________________________________________________________________
Epoch 1/10
966/966 [==============================] - 19s 20ms/step - loss: 13.1476 - acc:
0.1781
Epoch 2/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 3/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 4/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 5/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 6/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 7/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 8/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 9/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
Epoch 10/10
966/966 [==============================] - 12s 12ms/step - loss: 13.1648 - acc:
0.1832
322/322 [==============================] - 4s 14ms/step
[13.164779994798744, 0.18322981366459629]
```

The maximum accuracy achieved was 0.29 on the 19 class subset after training for 100 epochs. Training for 10 epochs resulted in an accuracy of 0.26. After looking at a sample of the faces which were incorrectly identified, the student noticed that 5 of the seven viewed had glasses.

Inception V3

The motivation behind this experiment was to replicate the architecture used by the FaceNet team [7]. However, the student did not implement the triplet loss function used by Schroff et. al. The student implemented this network following

Methods

The student used the same LFW subsets of 7 classes and 19 classes. The base model was pretrained on the Imagenet dataset using weights downloaded through the Keras API which contains images of different concepts, so it contains many non-face images. Initial tinkering suggested that keeping the pretrained weights resulted in higher accuracy. One of the difficulties faced by the student was the input of the Inception V3 network. The network requires an input with three color channels; however, the LFW images are encoded in greyscale. This dimension mismatch was corrected with the sklearn-image function grey2rgb(X) which duplicates the elements across the three color channels.

Results & Discussion

Code

In [87]:
```
from __future__ import print_function

from time import time
import logging
import matplotlib.pyplot as plt
import numpy as np
from skimage import color
from sklearn.model_selection import train_test_split
from sklearn.datasets import fetch_lfw_people
from keras.applications.inception_v3 import InceptionV3
from keras.models import Model
from keras.layers import Dense, GlobalAveragePooling2D
from keras.preprocessing.image import ImageDataGenerator
from keras.utils.np_utils import to_categorical


print(__doc__)

# Display progress logs on stdout
logging.basicConfig(level=logging.INFO, format='%(asctime)s %(message)s')


###############################################################################
# Download the data, if not already on disk and load it as numpy arrays

lfw_people = fetch_lfw_people(min_faces_per_person=70, resize=1)

# introspect the images arrays to find the shapes (for plotting)
n_samples, h, w = lfw_people.images.shape

print(lfw_people.images.shape)
# for machine learning we use the 2 data directly (as relative pixel
# positions info is ignored by this model)
X = lfw_people.images
n_features = X.shape[1]

# the label to predict is the id of the person
y = lfw_people.target

target_names = lfw_people.target_names
n_classes = target_names.shape[0]
print("Total dataset size:")
print("n_samples: %d" % n_samples)
print("n_features: %d" % n_features)
print("n_classes: %d" % n_classes)

X_3chan = color.grey2rgb(X)
y = to_categorical(y, num_classes=n_classes)

X_train, X_test, y_train, y_test = train_test_split(
    X_3chan, y, test_size=0.25)

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)

base_model = InceptionV3(weights="imagenet", include_top=False, input_shape=(h,
w,3))

# add a global spatial average pooling layer
x = base_model.output
x = GlobalAveragePooling2D()(x)
```

```
Automatically created module for IPython interactive environment
(1288, 125, 94)
Total dataset size:
n_samples: 1288
n_features: 125
n_classes: 7
(966, 125, 94, 3)
(966, 7)
(322, 125, 94, 3)
(322, 7)
Epoch 1/10
31/30 [==============================] - 27s 857ms/step - loss: 2.5072 - acc: 0
.3547
Epoch 2/10
31/30 [==============================] - 13s 424ms/step - loss: 1.7321 - acc: 0
.3777
Epoch 3/10
31/30 [==============================] - 13s 435ms/step - loss: 1.6555 - acc: 0
.4324
Epoch 4/10
31/30 [==============================] - 14s 436ms/step - loss: 1.6238 - acc: 0
.4506
Epoch 5/10
31/30 [==============================] - 16s 509ms/step - loss: 1.5664 - acc: 0
.4659
Epoch 6/10
31/30 [==============================] - 18s 571ms/step - loss: 1.5249 - acc: 0
.4718
Epoch 7/10
31/30 [==============================] - 17s 552ms/step - loss: 1.5220 - acc: 0
.4659
Epoch 8/10
31/30 [==============================] - 18s 593ms/step - loss: 1.4905 - acc: 0
.4603
Epoch 9/10
31/30 [==============================] - 14s 448ms/step - loss: 1.4921 - acc: 0
.4839
Epoch 10/10
31/30 [==============================] - 14s 463ms/step - loss: 1.4797 - acc: 0
.4685
0 input_6
1 conv2d_425
2 batch_normalization_404
3 activation_403
4 conv2d_426
5 batch_normalization_405
6 activation_404
7 conv2d_427
8 batch_normalization_406
9 activation_405
10 max_pooling2d_33
11 conv2d_428
12 batch_normalization_407
13 activation_406
14 conv2d_429
15 batch_normalization_408
16 activation_407
17 max_pooling2d_34
18 conv2d_433
19 batch_normalization_412
20 activation_411
21 conv2d_431
22 conv2d_434
```

Training for 100 epochs on the 19 class subset resulted in an accuracy of 0.27. However, the accuracy achieved on the training set was much higher. This suggests overfitting. To correct this, the student used image augmentation to inflate the training set. The augmentation used a rotation range of 20 degrees, a width shift of 0.2, a height shift of 0.2, and horizontal flip enabled. The model was retrained with the augmentation data generator, but the accuracy neither improved nor reduced. Training the model without the pretrained weights, with the 7 or 19 class subsets for 10 epochs resulted in a decrease in accuracy. The non-pretrained model was trained with a 158 class set over 100 epochs. This resulted in an accuracy of 0.12.

Conclusion

The best results were achieved on the 7 class subset with the SVM, with an average f1 score of 0.85. With the 7 class subset, both the MNIST style net and the inception v3 network at best achieved an accuracy of 0.4 - 0.45. The student could not determine the exact reason the SVM outperformed either the MNIST style or the inception network. It is possible better accuracy was achieved because the SVM classifies each sample pair pairwise. The SVM example also used a gridsearch to optimize the hyperperameters, where the other two networks were hand tuned.

Bibliography

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7. Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.