Untitled

September 19, 2018

In [62]:
```
# import the necessary packages
from keras.models import Sequential
from keras.layers.normalization import BatchNormalization
from keras.layers.convolutional import Conv2D
from keras.layers.convolutional import MaxPooling2D
from keras.layers.core import Activation
from keras.layers.core import Flatten
from keras.layers.core import Dropout
from keras.layers.core import Dense
from keras import backend as K

class SmallerVGGNet:
#@staticmethod
     def build(width, height, depth, classes, finalAct="softmax"):
# initialize the model along with the input shape to be
# "channels last" and the channels dimension itself
        model = Sequential()
        inputShape = (height, width, depth)
        chanDim = -1

# if we are using "channels first", update the input shape
# and channels dimension
        if K.image_data_format() == "channels_first":
            inputShape = (depth, height, width)
            chanDim = 1

# CONV => RELU => POOL
        model.add(Conv2D(32, (3, 3), padding="same",
             input_shape=inputShape))
        model.add(Activation("relu"))
        model.add(BatchNormalization(axis=chanDim))
        model.add(MaxPooling2D(pool_size=(3, 3)))
        model.add(Dropout(0.25))

# (CONV => RELU) * 2 => POOL
        model.add(Conv2D(64, (3, 3), padding="same"))
        model.add(Activation("relu"))
        model.add(BatchNormalization(axis=chanDim))
```

```
            model.add(Conv2D(64, (3, 3), padding="same"))
            model.add(Activation("relu"))
            model.add(BatchNormalization(axis=chanDim))
            model.add(MaxPooling2D(pool_size=(2, 2)))
            model.add(Dropout(0.25))

        # (CONV => RELU) * 2 => POOL
            model.add(Conv2D(128, (3, 3), padding="same"))
            model.add(Activation("relu"))
            model.add(BatchNormalization(axis=chanDim))
            model.add(Conv2D(128, (3, 3), padding="same"))
            model.add(Activation("relu"))
            model.add(BatchNormalization(axis=chanDim))
            model.add(MaxPooling2D(pool_size=(2, 2)))
            model.add(Dropout(0.25))

        # first (and only) set of FC => RELU layers
            model.add(Flatten())
            model.add(Dense(1024))
            model.add(Activation("relu"))
            model.add(BatchNormalization())
            model.add(Dropout(0.5))

        # softmax classifier
            model.add(Dense(classes))
            model.add(Activation(sigmoid))

        # return the constructed network architecture
            return model
```

In [63]:
```
# set the matplotlib backend so figures can be saved in the background
import matplotlib
matplotlib.use("Agg")

# import the necessary packages
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam
from keras.preprocessing.image import img_to_array
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.model_selection import train_test_split
from pyimagesearch.smallervggnet import SmallerVGGNet
import matplotlib.pyplot as plt
from imutils import paths
import numpy as np
import argparse
import random
import pickle
import cv2
```

```
         import os
```

In [64]:
```
from glob import glob
```

In [65]:
```
# construct the argument parse and parse the arguments
ap = argparse.ArgumentParser()
#ap.add_argument("-data_dir", type=str, default='--D:/MultipleLabels/keras-multi-labe
#ap.add_argument("-model_dir", type=str, default='--D:/MultipleLabels/keras-multi-lab
ap.add_argument("-data_dir", type=str, default='--/keras-multi-label/dataset/') #, he
ap.add_argument("-model_dir", type=str, default='--/keras-multi-label/fashion.model');

args = vars(ap.parse_args())
%tb
```

```
usage: __main__.py [-h] [-data_dir DATA_DIR] [-model_dir MODEL_DIR]
__main__.py: error: unrecognized arguments: -f C:\Users\mahmo\AppData\Roaming\jupyter\runtime\k



        An exception has occurred, use %tb to see the full traceback.


        SystemExit: 2



C:\Users\mahmo\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2918: UserWarning:
  warn("To exit: use 'exit', 'quit', or Ctrl-D.", stacklevel=1)
```

In [66]:
```
# initialize the number of epochs to train for, initial learning rate,
# batch size, and image dimensions
EPOCHS = 75
INIT_LR = 1e-3
BS = 32
IMAGE_DIMS = (96, 96, 3)
```

1 grab the image paths and randomly shuffle them

print("[INFO] loading images...") imagePaths = sorted(list(paths.list_images('dataset//'))) imagePaths = sorted(list(paths.list_images() random.seed(42) random.shuffle(imagePaths)

2 initialize the data and labels

data = [] labels = []

In [67]:
```
imagePaths = sorted(list(glob("dataset/*/*")))
data = []
labels = []
```

In [68]:
```
#imagePathes
```

In [69]:
```
import re
```

In [70]:
```
# loop over the input images
parser=argparse.ArgumentParser()

for imagePath in imagePaths:
    # load the image, pre-process it, and store it in the data list
    image = cv2.imread(imagePath)
    image = cv2.resize(image, (IMAGE_DIMS[1], IMAGE_DIMS[0]))
    image = img_to_array(image)
    data.append(image)

     # extract set of class labels from the image path and update the
    # labels list
    l = label = imagePath.split(os.path.sep)[-2].split("_")
   # l = label = imagePath.split(os.path.split)[0].split('/')[1].split('_')
    labels.append(l)
```

In [71]:
```
labels
```

Out[71]:
```
[['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
 ['black', 'jeans'],
```

```
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ['blue', 'jeans'],
          ...]
```

```
In [72]: len(labels)
```

```
Out[72]: 2167
```

```
In [73]: data = np.array(data, dtype="float") / 255.0
         labels = np.array(labels)
         print("[INFO] data matrix: {} images ({:.2f}MB)".format(
         len(imagePaths), data.nbytes / (1024 * 1000.0)))
```

```
[INFO] data matrix: 2167 images (468.07MB)
```

```
In [74]: # binarize the labels using scikit-learn's special multi-label
         # binarizer implementation
         print("[INFO] class labels:")
         mlb = MultiLabelBinarizer()
         labels = mlb.fit_transform(labels)

         # loop over each of the possible class labels and show them
         for (i, label) in enumerate(mlb.classes_):
             print("{}. {}".format(i + 1, label))
```

```
[INFO] class labels:
1. black
2. blue
3. dress
4. jeans
5. red
6. shirt
```

```
In [75]: labels
```

```
Out[75]: array([[1, 0, 0, 1, 0, 0],
                [1, 0, 0, 1, 0, 0],
```

```
                [1, 0, 0, 1, 0, 0],
                ...,
                [0, 0, 0, 0, 1, 1],
                [0, 0, 0, 0, 1, 1],
                [0, 0, 0, 0, 1, 1]])
```

from sklearn.preprocessing import MultiLabelBinarizer labels2 = [("blue", "jeans"),("blue", "dress"),("red", "dress"),("red", "shirt"),("blue", "shirt"),("black", "jeans")] mlb = MultiLabelBinarizer() mlb.fit(labels2) MultiLabelBinarizer(classes=None, sparse_output=False) mlb.classes_
mlb.transform([("red", "dress")])

```
In [76]: print(data.shape)

         print(type(data))
         print(type(labels))
         print(labels.shape)

(2167, 96, 96, 3)
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
(2167, 6)


In [77]: # partition the data into training and testing splits using 80% of
         # the data for training and the remaining 20% for testing
         (trainX, testX, trainY, testY) = train_test_split(data,labels, test_size=0.2, random_s

         # construct the image generator for data augmentation
         aug = ImageDataGenerator(rotation_range=25, width_shift_range=0.1,height_shift_range=0

In [99]: type(aug)

Out[99]: keras.preprocessing.image.ImageDataGenerator

In [78]: print("[INFO] compiling model...")
         model = SmallerVGGNet.build(
         width=IMAGE_DIMS[1], height=IMAGE_DIMS[0],
         depth=IMAGE_DIMS[2], classes=len(mlb.classes_),
         finalAct="sigmoid")

         # initialize the optimizer
         opt = Adam(lr=INIT_LR, decay=INIT_LR / EPOCHS)

[INFO] compiling model...


In [81]: # compile the model using binary cross-entropy rather than
         # categorical cross-entropy -- this may seem counterintuitive for
         # multi-label classification, but keep in mind that the goal here
```

```
        # is to treat each output label as an independent Bernoulli
        # distribution
        model.compile(loss="binary_crossentropy", optimizer=opt,
        metrics=["accuracy"])

        # train the network
        print("[INFO] training network...")
        H = model.fit_generator(
            aug.flow(trainX, trainY, batch_size=BS),
            validation_data=(testX, testY),
            steps_per_epoch=len(trainX) // BS,
            epochs=EPOCHS, verbose=1)
```

```
[INFO] training network...
Epoch 1/75
54/54 [==============================] - 11s 210ms/step - loss: 0.3309 - acc: 0.8647 - val_loss
Epoch 2/75
54/54 [==============================] - 5s 91ms/step - loss: 0.1672 - acc: 0.9392 - val_loss:
Epoch 3/75
54/54 [==============================] - 5s 90ms/step - loss: 0.1467 - acc: 0.9468 - val_loss:
Epoch 4/75
54/54 [==============================] - 5s 91ms/step - loss: 0.1463 - acc: 0.9477 - val_loss:
Epoch 5/75
54/54 [==============================] - 5s 90ms/step - loss: 0.1351 - acc: 0.9522 - val_loss:
Epoch 6/75
54/54 [==============================] - 5s 90ms/step - loss: 0.1135 - acc: 0.9623 - val_loss:
Epoch 7/75
54/54 [==============================] - 5s 91ms/step - loss: 0.1083 - acc: 0.9607 - val_loss:
Epoch 8/75
54/54 [==============================] - 5s 90ms/step - loss: 0.1182 - acc: 0.9605 - val_loss:
Epoch 9/75
54/54 [==============================] - 5s 90ms/step - loss: 0.1021 - acc: 0.9623 - val_loss:
Epoch 10/75
54/54 [==============================] - 5s 90ms/step - loss: 0.1059 - acc: 0.9655 - val_loss:
Epoch 11/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0822 - acc: 0.9703 - val_loss:
Epoch 12/75
54/54 [==============================] - 5s 96ms/step - loss: 0.0781 - acc: 0.9730 - val_loss:
Epoch 13/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0978 - acc: 0.9672 - val_loss:
Epoch 14/75
54/54 [==============================] - 6s 103ms/step - loss: 0.1060 - acc: 0.9632 - val_loss
Epoch 15/75
54/54 [==============================] - 5s 93ms/step - loss: 0.0862 - acc: 0.9691 - val_loss:
Epoch 16/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0893 - acc: 0.9684 - val_loss:
Epoch 17/75
54/54 [==============================] - 6s 115ms/step - loss: 0.0971 - acc: 0.9713 - val_loss
```

```
Epoch 18/75
54/54 [==============================] - 5s 93ms/step - loss: 0.1356 - acc: 0.9606 - val_loss:
Epoch 19/75
54/54 [==============================] - 6s 114ms/step - loss: 0.1389 - acc: 0.9523 - val_loss
Epoch 20/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0944 - acc: 0.9652 - val_loss:
Epoch 21/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0802 - acc: 0.9721 - val_loss:
Epoch 22/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0823 - acc: 0.9701 - val_loss:
Epoch 23/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0890 - acc: 0.9687 - val_loss:
Epoch 24/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0815 - acc: 0.9715 - val_loss:
Epoch 25/75
54/54 [==============================] - 5s 93ms/step - loss: 0.0828 - acc: 0.9699 - val_loss:
Epoch 26/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0781 - acc: 0.9703 - val_loss:
Epoch 27/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0892 - acc: 0.9716 - val_loss:
Epoch 28/75
54/54 [==============================] - 5s 93ms/step - loss: 0.0831 - acc: 0.9698 - val_loss:
Epoch 29/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0641 - acc: 0.9771 - val_loss:
Epoch 30/75
54/54 [==============================] - 6s 113ms/step - loss: 0.0784 - acc: 0.9760 - val_loss
Epoch 31/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0737 - acc: 0.9747 - val_loss:
Epoch 32/75
54/54 [==============================] - 6s 104ms/step - loss: 0.0635 - acc: 0.9799 - val_loss
Epoch 33/75
54/54 [==============================] - 5s 99ms/step - loss: 0.0819 - acc: 0.9737 - val_loss:
Epoch 34/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0752 - acc: 0.9754 - val_loss:
Epoch 35/75
54/54 [==============================] - 5s 93ms/step - loss: 0.0513 - acc: 0.9800 - val_loss:
Epoch 36/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0586 - acc: 0.9790 - val_loss:
Epoch 37/75
54/54 [==============================] - 6s 118ms/step - loss: 0.0520 - acc: 0.9830 - val_loss
Epoch 38/75
54/54 [==============================] - 6s 108ms/step - loss: 0.0664 - acc: 0.9764 - val_loss
Epoch 39/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0540 - acc: 0.9797 - val_loss:
Epoch 40/75
54/54 [==============================] - 5s 94ms/step - loss: 0.0595 - acc: 0.9808 - val_loss:
Epoch 41/75
54/54 [==============================] - 6s 102ms/step - loss: 0.0425 - acc: 0.9858 - val_loss
```

```
Epoch 42/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0375 - acc: 0.9868 - val_loss:
Epoch 43/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0489 - acc: 0.9840 - val_loss:
Epoch 44/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0463 - acc: 0.9835 - val_loss:
Epoch 45/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0434 - acc: 0.9837 - val_loss:
Epoch 46/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0631 - acc: 0.9780 - val_loss:
Epoch 47/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0571 - acc: 0.9800 - val_loss:
Epoch 48/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0487 - acc: 0.9824 - val_loss:
Epoch 49/75
54/54 [==============================] - 6s 115ms/step - loss: 0.0475 - acc: 0.9849 - val_loss
Epoch 50/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0588 - acc: 0.9789 - val_loss:
Epoch 51/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0417 - acc: 0.9856 - val_loss:
Epoch 52/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0444 - acc: 0.9840 - val_loss:
Epoch 53/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0476 - acc: 0.9834 - val_loss:
Epoch 54/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0436 - acc: 0.9856 - val_loss:
Epoch 55/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0396 - acc: 0.9861 - val_loss:
Epoch 56/75
54/54 [==============================] - 5s 101ms/step - loss: 0.0601 - acc: 0.9794 - val_loss
Epoch 57/75
54/54 [==============================] - 5s 95ms/step - loss: 0.0484 - acc: 0.9846 - val_loss:
Epoch 58/75
54/54 [==============================] - 5s 101ms/step - loss: 0.0568 - acc: 0.9804 - val_loss
Epoch 59/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0420 - acc: 0.9863 - val_loss:
Epoch 60/75
54/54 [==============================] - 5s 91ms/step - loss: 0.0442 - acc: 0.9851 - val_loss:
Epoch 61/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0450 - acc: 0.9831 - val_loss:
Epoch 62/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0456 - acc: 0.9855 - val_loss:
Epoch 63/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0433 - acc: 0.9853 - val_loss:
Epoch 64/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0403 - acc: 0.9875 - val_loss:
Epoch 65/75
54/54 [==============================] - 5s 90ms/step - loss: 0.0417 - acc: 0.9849 - val_loss:
```

```
Epoch 66/75
54/54 [==============================] - 6s 108ms/step - loss: 0.0286 - acc: 0.9893 - val_loss
Epoch 67/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0412 - acc: 0.9867 - val_loss:
Epoch 68/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0424 - acc: 0.9870 - val_loss:
Epoch 69/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0417 - acc: 0.9850 - val_loss:
Epoch 70/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0415 - acc: 0.9845 - val_loss:
Epoch 71/75
54/54 [==============================] - 5s 92ms/step - loss: 0.0331 - acc: 0.9883 - val_loss:
Epoch 72/75
54/54 [==============================] - 5s 89ms/step - loss: 0.0366 - acc: 0.9874 - val_loss:
Epoch 73/75
54/54 [==============================] - 6s 109ms/step - loss: 0.0571 - acc: 0.9797 - val_loss
Epoch 74/75
54/54 [==============================] - 6s 106ms/step - loss: 0.0747 - acc: 0.9788 - val_loss
Epoch 75/75
54/54 [==============================] - 5s 95ms/step - loss: 0.0552 - acc: 0.9819 - val_loss:
```

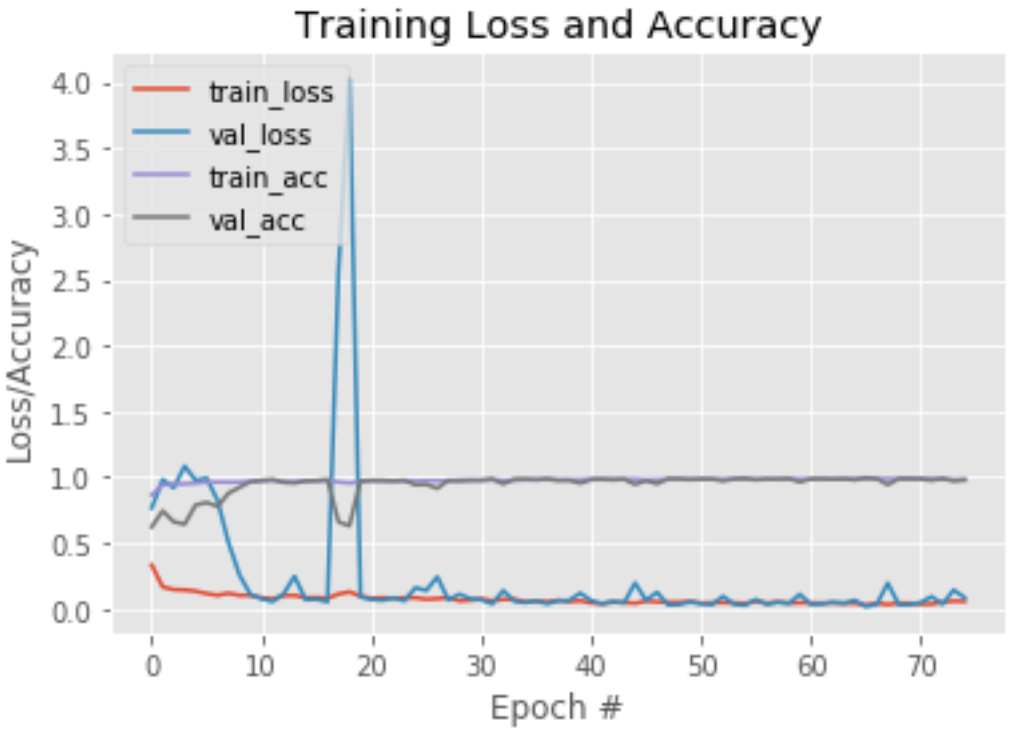
In [82]:
```
# save the model to disk
print("[INFO] serializing network...")
model.save(args["model"])

# save the multi-label binarizer to disk
print("[INFO] serializing label binarizer...")
f = open(args["labelbin"], "wb")
f.write(pickle.dumps(mlb))
f.close()
```

```
[INFO] serializing network...
```

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-82-5af681a77637> in <module>()
  1 # save the model to disk
  2 print("[INFO] serializing network...")
----> 3 model.save(args["model"])
  4
  5 # save the multi-label binarizer to disk
```

```
NameError: name 'args' is not defined
```

In [86]:
```
# plot the training loss and accuracy
%matplotlib inline
plt.style.use("ggplot")
plt.figure()
N = EPOCHS
plt.plot(np.arange(0, N), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, N), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, N), H.history["acc"], label="train_acc")
plt.plot(np.arange(0, N), H.history["val_acc"], label="val_acc")
plt.title("Training Loss and Accuracy")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend(loc="upper left")
#plt.savefig(args["plot"])
plt.show()
```



In [89]:
```
pred=model.predict(testX)
```

In [90]:
```
pred
```

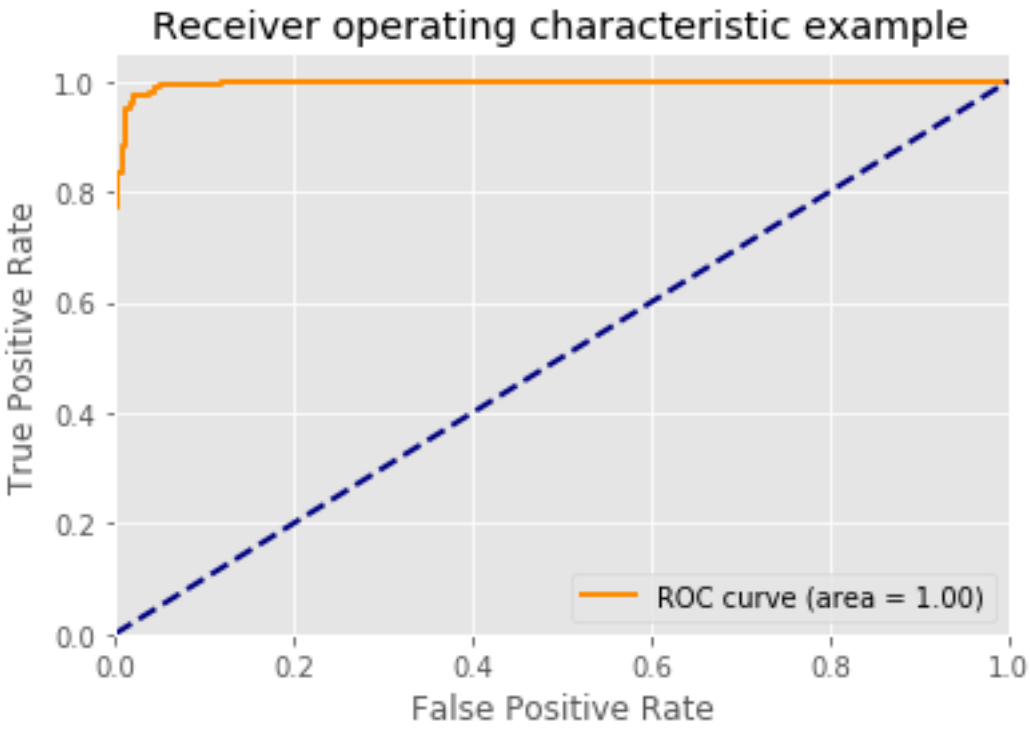
Out[90]:
```
array([[2.7967994e-07, 2.8758905e-05, 9.9998784e-01, 1.8953782e-06,
        9.9999905e-01, 1.6993548e-06],
```

```
                [3.8726458e-07, 1.4320040e-05, 9.9624276e-01, 1.0497152e-04,
                 1.0000000e+00, 1.6722931e-03],
                [2.8229690e-06, 1.1650398e-03, 9.9971253e-01, 2.8170980e-05,
                 9.9982280e-01, 2.8528821e-05],
                ...,
                [5.3812691e-04, 9.9998820e-01, 3.6258844e-01, 3.8932837e-04,
                 9.8860955e-09, 7.7784568e-01],
                [9.9998248e-01, 5.2561722e-05, 9.5061360e-08, 1.0000000e+00,
                 3.7664769e-10, 1.8038398e-05],
                [8.1040402e-05, 3.7716335e-04, 2.2128897e-05, 1.0002643e-03,
                 9.9999690e-01, 9.9987793e-01]], dtype=float32)
```

```
In [97]: print(__doc__)

         import numpy as np
         import matplotlib.pyplot as plt
         from itertools import cycle

         from sklearn import svm, datasets
         from sklearn.metrics import roc_curve, auc
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import label_binarize
         from sklearn.multiclass import OneVsRestClassifier
         from scipy import interp

         n_classes = 6#y.shape[1]
         # Compute ROC curve and ROC area for each class
         fpr = dict()
         tpr = dict()
         roc_auc = dict()
         for i in range(n_classes):
             fpr[i], tpr[i], _ = roc_curve(testY[:, i], pred[:, i])
             roc_auc[i] = auc(fpr[i], tpr[i])

         # Compute micro-average ROC curve and ROC area
         fpr["micro"], tpr["micro"], _ = roc_curve(testY.ravel(), pred.ravel())
         roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])


# Import some data to play with
iris = datasets.load_iris()
X = iris.data
y = iris.target

# Binarize the output
y = label_binarize(y, classes=[0, 1, 2])
n_classes = y.shape[1]
```

```
# Add noisy features to make the problem harder
random_state = np.random.RandomState(0)
n_samples, n_features = X.shape
X = np.c_[X, random_state.randn(n_samples, 200 * n_features)]

# shuffle and split training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.5,
                                                    random_state=0)

# Learn to predict each class against the other
classifier = OneVsRestClassifier(svm.SVC(kernel='linear', probability=True,
                                 random_state=random_state))
y_score = classifier.fit(X_train, y_train).decision_function(X_test)
```

```
In [98]: plt.figure()
         lw = 2
         plt.plot(fpr[2], tpr[2], color='darkorange',
                  lw=lw, label='ROC curve (area = %0.2f)' % roc_auc[2])
         plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver operating characteristic example')
         plt.legend(loc="lower right")
         plt.show()
```



In [95]:
```
# Compute macro-average ROC curve and ROC area

# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(fpr["micro"], tpr["micro"],
         label='micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["micro"]),
         color='deeppink', linestyle=':', linewidth=4)
```

```
plt.plot(fpr["macro"], tpr["macro"],
         label='macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["macro"]),
         color='navy', linestyle=':', linewidth=4)

colors = cycle(['aqua', 'darkorange', 'cornflowerblue'])
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=lw,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Some extension of Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.show()
```