

```
In [1]: from google.colab import drive  
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force\_remount=True).

This is an interesting task, I have experienced a lot, including writing code with colab, because the caltech256 data set is particularly large, split it into four 4GB files by pickle, and then to shorten the time of each raw data read, first time When reading, the data is saved to a CSV file, so that when the program is tested later, it can be read directly from the CSV file, but the CSV file is particularly large, and the x\_train.csv file size is 16 GB, which directly causes the RAM to explode, and then more I tried to directly read the data in the pickle file, split it into the train and test parts, and finally run the program. The RAM usage is 25.33GB, and the total RAM is only 25.51GB. And because of the excessive use of colab GPU resources, Google has blocked the account. But in the end, after asking classmates and Dr.yang, as well as online to find a solution, finally successfully used the VGG16 to train the caltech256 data set.

**There are two parts : the first one is training from scratch the accuracy is 24% the second one is training from pre-trained the accuracy is 55.7%**

```
In [6]: !/opt/bin/nvidia-smi
```

```
Sun Nov 10 22:24:40 2019
+-----+
+-----+
| NVIDIA-SMI 418.67      Driver Version: 418.67      CUDA Version: 10.1
|
|-----+-----+-----+
+-----+
| GPU   Name               Persistence-M| Bus-Id        Disp.A | Volatile Uncorr.
ECC |
| Fan   Temp   Perf   Pwr:Usage/Cap|      Memory-Usage | GPU-Util  Comput
e M. |
|=====+=====+=====+
=====|
|    0   Tesla P100-PCIE...    Off   | 00000000:00:04.0 Off |
0 |
| N/A    34C    P0      25W / 250W |      0MiB / 16280MiB |      0%      Def
ault |
+-----+-----+-----+
+-----+

+-----+
+-----+
| Processes:                                     GPU Me
mory |
| GPU           PID    Type    Process name                     Usage
|
|=====+=====+=====+
=====|
|   No running processes found
|
+-----+
+-----+
```

## Load the dataset from pickle file

By [http://places2.csail.mit.edu/PAMI\\_places](http://places2.csail.mit.edu/PAMI_places) ([http://places2.csail.mit.edu/PAMI\\_places](http://places2.csail.mit.edu/PAMI_places)) (given by Dr.yang) and reference code ,learning the method to generate the training and testing dataset.

```
In [0]: import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tarfile
import cv2
import pickle
%matplotlib inline
import tarfile
%matplotlib inline
```

load the picklepath from google drive

```
In [0]: import os
picklepath = '/content/drive/My Drive/Colab Notebooks/VGG16_Practice/pickle'
os.chdir(picklepath)
```

Using data\_process.ipynb divide data to four pickle file , so I should load those file

```
In [0]: import pickle
pickle_in = open("pickle_all_images_df1.pickle", "rb")
all_images_df1 = pickle.load(pickle_in)
```

```
In [0]: pickle_in = open("pickle_all_images_df2.pickle", "rb")
all_images_df2 = pickle.load(pickle_in)
```

```
In [0]: pickle_in = open("pickle_all_images_df3.pickle", "rb")
all_images_df3 = pickle.load(pickle_in)
```

```
In [0]: pickle_in = open("pickle_all_classes.pickle", "rb")
all_classes = pickle.load(pickle_in)
```

set the img size is 128

```
In [0]: img_size = 128
```

concatenate those four array together

```
In [0]: all_images = np.concatenate((all_images_df1, all_images_df2, all_images_df3))
```

```
In [10]: all_images.shape
```

```
Out[10]: (30607, 49152)
```

del those pre-data, in order to release RAM

```
In [0]: del all_images_df1
del all_images_df2
del all_images_df3
```

```
In [12]: all_images.shape
```

```
Out[12]: (30607, 49152)
```

```
In [0]: all_images.shape
```

```
In [0]: # train_total = np.concatenate((train_x, train_y), axis=1)
# test_total = np.concatenate((test_x, test_y), axis=1)
# df_train = pd.DataFrame(train_total)
# df_test = pd.DataFrame(test_total)
```

using pandas to implement one hot encode

```
In [0]: all_classes = pd.get_dummies(all_classes)
```

```
In [14]: all_classes.shape
```

```
Out[14]: (30607, 257)
```

```
In [0]: all_images = np.array(all_images)
```

```
In [16]: all_images.shape
```

```
Out[16]: (30607, 49152)
```

split all\_images to X\_train part and X\_test part. split all\_classes to y\_train part and y\_test part

```
In [0]: from sklearn.model_selection import train_test_split  
X_train, X_test, y_train, y_test = train_test_split(all_images, all_classes
```

```
In [19]: X_train.shape
```

```
Out[19]: (27546, 49152)
```

```
In [15]: X_test.shape
```

```
Out[15]: (3061, 49152)
```

```
In [23]: y_train.shape
```

```
Out[23]: (27546, 257)
```

```
In [24]: y_test.shape
```

```
Out[24]: (3061, 257)
```

```
In [0]: X_train[0].shape
```

Because using VGG16 network,so I should fit the dimension,so using reshape method to change dimension

```
In [0]: X_train = X_train.reshape(-1,img_size,img_size,3)
```

```
In [21]: X_train.shape
```

```
Out[21]: (27546, 128, 128, 3)
```

```
In [0]: X_test = X_test.reshape(-1,img_size,img_size,3)
```

```
In [21]: X_test.shape
```

```
Out[21]: (3061, 128, 128, 3)
```

## Save X\_train, X\_test, y\_train, y\_test to CSV file

```
In [0]: df_x_train = pd.DataFrame(X_train)
df_x_test = pd.DataFrame(X_test)
df_y_train = pd.DataFrame(y_train)
df_y_test = pd.DataFrame(y_test)
```

```
In [0]: df_x_train.to_csv('/content/drive/My Drive/Colab Notebooks/VGG16_Practice/x_train.csv')
```

```
In [0]: df_x_test.to_csv('/content/drive/My Drive/Colab Notebooks/VGG16_Practice/x_test.csv')
```

```
In [0]: df_y_train.to_csv('/content/drive/My Drive/Colab Notebooks/VGG16_Practice/y_train.csv')
```

```
In [0]: df_y_test.to_csv('/content/drive/My Drive/Colab Notebooks/VGG16_Practice/y_test.csv')
```

```
In [0]: del df_x_train
del df_x_test
del df_y_train
del df_y_test
```

```
In [0]:
```

Type *Markdown* and LaTeX:  $\alpha^2$

## Load train\_x test\_x train\_y test\_y from CSV

```
In [0]: import numpy as np
import pandas as pd
```

```
In [0]: train_x = pd.read_csv('/Users/wangxiang/Code/Jupyter/VGG16_Practice/pickle/train_x.csv')
```

```
In [0]: test_x = pd.read_csv('/Users/wangxiang/Code/Jupyter/VGG16_Practice/pickle/test_x.csv')
```

```
In [0]: train_y = pd.read_csv('/Users/wangxiang/Code/Jupyter/VGG16_Practice/pickle/train_y.csv')
```

```
In [0]: test_y = pd.read_csv('/Users/wangxiang/Code/Jupyter/VGG16_Practice/pickle/test_y.csv')
```

```
In [0]: train_x = train_x.values
(train_x.shape)
```

```
In [0]: # X_train = [cv2.cvtColor(cv2.resize(i,(224,224)), cv2.COLOR_GRAY2BGR) for
# X_train = np.concatenate([arr[np.newaxis] for arr in X_train]).astype('fl

# X_test = [cv2.cvtColor(cv2.resize(i,(224,224)), cv2.COLOR_GRAY2BGR) for
# X_test = np.concatenate([arr[np.newaxis] for arr in X_test] ).astype('fl

# print("X_train shape :",X_train.shape)
# print("X_test shape:",X_test.shape)
```

## Normalize the images Section

If you execute the following code, the accuracy will be reduced to 10%

```
In [22]: from tensorflow.keras.applications.vgg16 import preprocess_input

X_test = preprocess_input(X_test)
X_train = preprocess_input(X_train)
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.

We recommend you [upgrade \(https://www.tensorflow.org/guide/migrate\)](https://www.tensorflow.org/guide/migrate) now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: [more info \(https://colab.research.google.com/notebooks/tensorflow\\_version.ipynb\)](https://colab.research.google.com/notebooks/tensorflow_version.ipynb).

## VGG16 from Scratch

this part using VGG16 model without weights

```
In [0]: import os
import keras
from keras.models import Model
from keras.layers import Dense,Flatten,Dropout
from keras import datasets
from keras.applications.vgg16 import VGG16
```

Setting weights=None and layer.trainable=True,which is important

```
In [42]: model = VGG16(weights=None, include_top=False, input_shape=(128,128,3), cla
for layer in model.layers:
    layer.trainable=True
print(model.summary())
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
=====		
input_3 (InputLayer)	(None, 128, 128, 3)	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
=====		
Total params: 14,714,688		
Trainable params: 14,714,688		
Non-trainable params: 0		

None

Setting top-layer:add three Dense layer,especially the last Dense layer is softmax layer with 257 neruons to classify label

```
In [0]: from keras.layers import Flatten, Dense
        from keras.models import Model

x = model.get_layer('block5_pool').output
x = Flatten(name='flatten')(x)
x = Dense(512, activation='relu', name='fc1')(x)
x = Dense(4096, activation='relu', name='fc2')(x)
x = Dense(257, activation='softmax', name='predictions')(x)

model_caltech_vgg = Model(inputs=model.input, outputs=x)
```



```
In [44]: model_caltech_vgg.summary()
```

Model: "model\_3"

Layer (type)	Output Shape	Param #
=====		
input_3 (InputLayer)	(None, 128, 128, 3)	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
flatten (Flatten)	(None, 8192)	0
fc1 (Dense)	(None, 512)	4194816
fc2 (Dense)	(None, 4096)	2101248
predictions (Dense)	(None, 257)	1052929
=====		
Total params: 22,063,681		
Trainable params: 22,063,681		
Non-trainable params: 0		

```
In [0]: def learning_rate_schedule(epoch):  
        if epoch <= 10:  
            return 1e-4 # 0.00001  
        elif epoch <= 20:  
            return 1e-5  
        elif epoch <= 30:  
            return 1e-6  
        else:  
            return 1e-7  
        return LR
```

```
In [0]: from keras import optimizers  
        from keras.callbacks import EarlyStopping
```

setting epochs=30 and each batch\_size=32

```
In [47]: model_caltech_vgg.compile(
    loss='categorical_crossentropy',
    optimizer=optimizers.adam(lr=0.0001), metrics=['accuracy']
)
keras.callbacks.LearningRateScheduler(learning_rate_scheduler)
history = model_caltech_vgg.fit(
    X_train, y_train,
    batch_size=32, shuffle=True, epochs=30,
    validation_data=(X_test, y_test)
)
```

Train on 27546 samples, validate on 3061 samples

Epoch 1/30

27546/27546 [=====] - 88s 3ms/step - loss: 5.224  
0 - acc: 0.0565 - val\_loss: 4.9047 - val\_acc: 0.0856

Epoch 2/30

27546/27546 [=====] - 83s 3ms/step - loss: 4.614  
6 - acc: 0.1212 - val\_loss: 4.4271 - val\_acc: 0.1297

Epoch 3/30

27546/27546 [=====] - 82s 3ms/step - loss: 4.149  
2 - acc: 0.1747 - val\_loss: 4.0834 - val\_acc: 0.1875

Epoch 4/30

27546/27546 [=====] - 82s 3ms/step - loss: 3.757  
0 - acc: 0.2279 - val\_loss: 3.9624 - val\_acc: 0.2130

Epoch 5/30

27546/27546 [=====] - 82s 3ms/step - loss: 3.378  
5 - acc: 0.2803 - val\_loss: 3.8363 - val\_acc: 0.2411

Epoch 6/30

27546/27546 [=====] - 82s 3ms/step - loss: 2.928  
6 - acc: 0.3484 - val\_loss: 3.7786 - val\_acc: 0.2509

Epoch 7/30

27546/27546 [=====] - 83s 3ms/step - loss: 2.388  
8 - acc: 0.4405 - val\_loss: 3.9854 - val\_acc: 0.2594

Epoch 8/30

27546/27546 [=====] - 82s 3ms/step - loss: 1.720  
1 - acc: 0.5657 - val\_loss: 4.5628 - val\_acc: 0.2496

Epoch 9/30

27546/27546 [=====] - 82s 3ms/step - loss: 1.020  
9 - acc: 0.7243 - val\_loss: 5.6658 - val\_acc: 0.2440

Epoch 10/30

27546/27546 [=====] - 82s 3ms/step - loss: 0.580  
4 - acc: 0.8357 - val\_loss: 6.6711 - val\_acc: 0.2346

Epoch 11/30

27546/27546 [=====] - 82s 3ms/step - loss: 0.360  
9 - acc: 0.8962 - val\_loss: 7.1479 - val\_acc: 0.2375

Epoch 12/30

27546/27546 [=====] - 82s 3ms/step - loss: 0.268  
9 - acc: 0.9194 - val\_loss: 7.7502 - val\_acc: 0.2418

Epoch 13/30

27546/27546 [=====] - 82s 3ms/step - loss: 0.218  
6 - acc: 0.9343 - val\_loss: 8.2997 - val\_acc: 0.2372

Epoch 14/30

27546/27546 [=====] - 82s 3ms/step - loss: 0.197  
2 - acc: 0.9431 - val\_loss: 7.3544 - val\_acc: 0.2395

Epoch 15/30

27546/27546 [=====] - 82s 3ms/step - loss: 0.168

```
1 - acc: 0.9511 - val_loss: 8.3142 - val_acc: 0.2414
Epoch 16/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.160
8 - acc: 0.9526 - val_loss: 8.1826 - val_acc: 0.2401
Epoch 17/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.142
2 - acc: 0.9602 - val_loss: 8.4789 - val_acc: 0.2372
Epoch 18/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.144
1 - acc: 0.9593 - val_loss: 7.8706 - val_acc: 0.2421
Epoch 19/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.116
9 - acc: 0.9653 - val_loss: 8.1067 - val_acc: 0.2382
Epoch 20/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.136
1 - acc: 0.9603 - val_loss: 8.0828 - val_acc: 0.2398
Epoch 21/30
27546/27546 [=====] - 83s 3ms/step - loss: 0.103
1 - acc: 0.9703 - val_loss: 8.2957 - val_acc: 0.2336
Epoch 22/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.112
4 - acc: 0.9674 - val_loss: 8.2640 - val_acc: 0.2293
Epoch 23/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.102
9 - acc: 0.9713 - val_loss: 8.2929 - val_acc: 0.2418
Epoch 24/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.091
9 - acc: 0.9726 - val_loss: 8.0287 - val_acc: 0.2421
Epoch 25/30
27546/27546 [=====] - 82s 3ms/step - loss: 0.090
8 - acc: 0.9731 - val_loss: 8.0642 - val_acc: 0.2418
Epoch 26/30
27546/27546 [=====] - 83s 3ms/step - loss: 0.084
3 - acc: 0.9757 - val_loss: 8.3474 - val_acc: 0.2437
Epoch 27/30
27546/27546 [=====] - 83s 3ms/step - loss: 0.089
7 - acc: 0.9738 - val_loss: 8.8847 - val_acc: 0.2470
Epoch 28/30
27546/27546 [=====] - 83s 3ms/step - loss: 0.084
9 - acc: 0.9763 - val_loss: 8.5041 - val_acc: 0.2385
Epoch 29/30
27546/27546 [=====] - 83s 3ms/step - loss: 0.077
2 - acc: 0.9787 - val_loss: 8.0128 - val_acc: 0.2440
Epoch 30/30
27546/27546 [=====] - 83s 3ms/step - loss: 0.075
0 - acc: 0.9785 - val_loss: 8.0370 - val_acc: 0.2404
```

**By train 30 epochs the VGG16 from scratch model give me 28.29% testing accuracy**

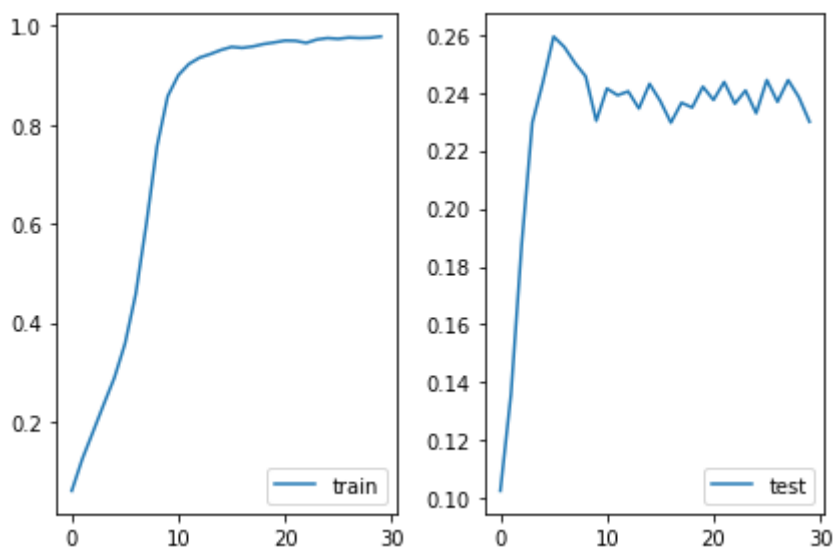
```
In [31]: import matplotlib.pyplot as plt
import numpy as np

plt.subplot(1, 2, 1)
plt.plot(history.history['acc'])
plt.legend(['train'], loc='lower right')

plt.subplot(1, 2, 2)
plt.plot(history.history['val_acc'])
plt.legend(['test'], loc='lower right')

plt.tight_layout()

plt.show()
```



## VGG16 Pre-trained

this part using VGG16 pre-trained model and run 3 times

```
In [32]: model = VGG16(weights='imagenet', include_top=False, input_shape=(128,128,3))

for layer in model.layers:
    layer.trainable = False
print(model.summary())
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	(None, 128, 128, 3)	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
=====		
Total params: 14,714,688		
Trainable params: 0		
Non-trainable params: 14,714,688		
None		

Setting top layer : three Dense layer and last layer is softmax layer

```
In [0]: from keras.layers import Flatten, Dense
        from keras.models import Model

x = model.get_layer('block5_pool').output
x = Flatten(name='flatten')(x)
x = Dense(512, activation='relu', name='fc1')(x)
x = Dense(4096, activation='relu', name='fc2')(x)
x = Dense(257, activation='softmax', name='predictions')(x)
model_updated = Model(inputs=model.input, outputs=x)
#model_caltech_vgg_pre = Model(inputs=model.input, outputs=x)
```

```
In [0]: def learning_rate_schedule(epoch):
        if epoch <= 10:
            return 1e-4 # 0.00001
        elif epoch <= 20:
            return 1e-5
        elif epoch <= 30:
            return 1e-6
        else:
            return 1e-7
        return LR
```

save weights for each time

```
In [0]: model_updated.save_weights('model_caltech_initial.h5')
```

```
In [0]: from keras import optimizers
        from keras.callbacks import EarlyStopping
```

```
In [39]: model_updated.save_weights('model_caltech_initial.h5')
training_runs = []
for i in range(3):
    #model_updated.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])
    model_updated.compile(loss='mean_squared_error', optimizer=optimizers.adam(1e-4),
                           metrics=['accuracy'], callbacks=[keras.callbacks.LearningRateScheduler(learning_rate_schedule)])
    history = model_updated.fit(X_train, y_train, batch_size=32, shuffle=True, verbose=1)
    training_runs.append(history)
model_updated.get_weights()
if i == 2:
    model_updated.save_weights('model1.h5')
else:
    model_updated.load_weights('model_caltech_initial.h5')
print()
```

Train on 27546 samples, validate on 3061 samples

Epoch 1/10

27546/27546 [=====] - 38s 1ms/step - loss: 0.0036 - acc: 0.1293 - val\_loss: 0.0034 - val\_acc: 0.1973

Epoch 2/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0031 - acc: 0.3033 - val\_loss: 0.0029 - val\_acc: 0.3728

Epoch 3/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0026 - acc: 0.4542 - val\_loss: 0.0025 - val\_acc: 0.4655

Epoch 4/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0022 - acc: 0.5458 - val\_loss: 0.0024 - val\_acc: 0.4959

Epoch 5/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0019 - acc: 0.6105 - val\_loss: 0.0022 - val\_acc: 0.5407

Epoch 6/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0017 - acc: 0.6597 - val\_loss: 0.0022 - val\_acc: 0.5534

Epoch 7/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0015 - acc: 0.6986 - val\_loss: 0.0022 - val\_acc: 0.5616

Epoch 8/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0013 - acc: 0.7338 - val\_loss: 0.0022 - val\_acc: 0.5583

Epoch 9/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0012 - acc: 0.7620 - val\_loss: 0.0022 - val\_acc: 0.5691

Epoch 10/10

27546/27546 [=====] - 35s 1ms/step - loss: 0.0011 - acc: 0.7874 - val\_loss: 0.0021 - val\_acc: 0.5773

Train on 27546 samples, validate on 3061 samples

Epoch 1/10

27546/27546 [=====] - 37s 1ms/step - loss: 0.0036 - acc: 0.1350 - val\_loss: 0.0034 - val\_acc: 0.2078

Epoch 2/10

27546/27546 [=====] - 34s 1ms/step - loss: 0.0031 - acc: 0.3099 - val\_loss: 0.0029 - val\_acc: 0.3665

Epoch 3/10

27546/27546 [=====] - 33s 1ms/step - loss: 0.0025 - acc: 0.4573 - val\_loss: 0.0026 - val\_acc: 0.4721



```
Epoch 4/10
27546/27546 [=====] - 33s 1ms/step - loss: 0.002
2 - acc: 0.5517 - val_loss: 0.0024 - val_acc: 0.5051
Epoch 5/10
27546/27546 [=====] - 33s 1ms/step - loss: 0.001
9 - acc: 0.6150 - val_loss: 0.0023 - val_acc: 0.5201
Epoch 6/10
27546/27546 [=====] - 33s 1ms/step - loss: 0.001
7 - acc: 0.6646 - val_loss: 0.0022 - val_acc: 0.5524
Epoch 7/10
27546/27546 [=====] - 34s 1ms/step - loss: 0.001
5 - acc: 0.7020 - val_loss: 0.0022 - val_acc: 0.5449
Epoch 8/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
3 - acc: 0.7356 - val_loss: 0.0022 - val_acc: 0.5603
Epoch 9/10
27546/27546 [=====] - 34s 1ms/step - loss: 0.001
2 - acc: 0.7667 - val_loss: 0.0022 - val_acc: 0.5590
Epoch 10/10
27546/27546 [=====] - 33s 1ms/step - loss: 0.001
1 - acc: 0.7900 - val_loss: 0.0022 - val_acc: 0.5678

Train on 27546 samples, validate on 3061 samples
Epoch 1/10
27546/27546 [=====] - 38s 1ms/step - loss: 0.003
6 - acc: 0.1298 - val_loss: 0.0034 - val_acc: 0.1931
Epoch 2/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.003
1 - acc: 0.3035 - val_loss: 0.0029 - val_acc: 0.3662
Epoch 3/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.002
6 - acc: 0.4511 - val_loss: 0.0025 - val_acc: 0.4750
Epoch 4/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.002
2 - acc: 0.5441 - val_loss: 0.0024 - val_acc: 0.5041
Epoch 5/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
9 - acc: 0.6093 - val_loss: 0.0023 - val_acc: 0.5361
Epoch 6/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
7 - acc: 0.6622 - val_loss: 0.0022 - val_acc: 0.5377
Epoch 7/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
5 - acc: 0.7003 - val_loss: 0.0022 - val_acc: 0.5550
Epoch 8/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
3 - acc: 0.7335 - val_loss: 0.0022 - val_acc: 0.5658
Epoch 9/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
2 - acc: 0.7620 - val_loss: 0.0022 - val_acc: 0.5691
Epoch 10/10
27546/27546 [=====] - 35s 1ms/step - loss: 0.001
1 - acc: 0.7877 - val_loss: 0.0022 - val_acc: 0.5596
```

```

In [40]: port matplotlib.pyplot as plt
port numpy as np

t.subplot(2, 3, 1)
t.plot(training_runs[0].history['acc'])
t.legend(['train'], loc='lower right')

t.subplot(2, 3, 2)
t.plot(training_runs[1].history['acc'])
t.legend(['train'], loc='lower right')

t.subplot(2, 3, 3)
t.plot(training_runs[2].history['acc'])
t.legend(['train'], loc='lower right')

t.subplot(2, 3, 4)
t.plot(training_runs[0].history['val_acc'])
t.legend(['test'], loc='lower right')

t.subplot(2, 3, 5)
t.plot(training_runs[1].history['val_acc'])
t.legend(['test'], loc='lower right')

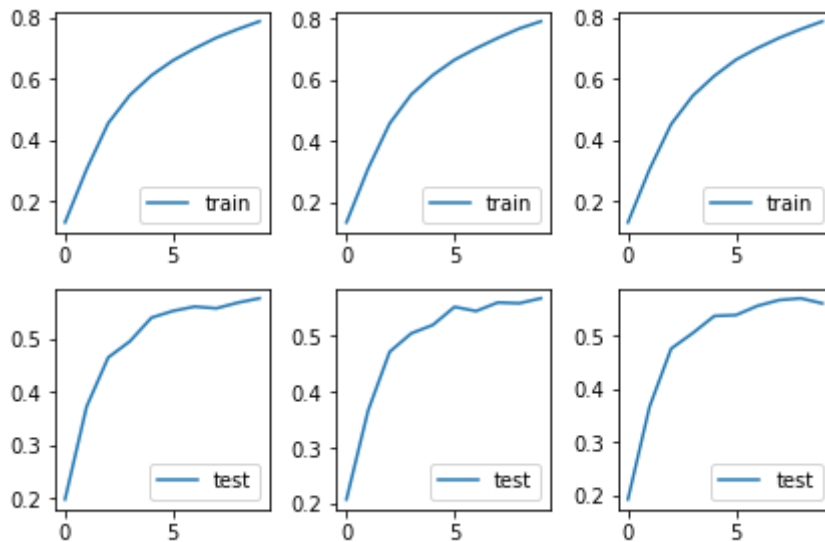
t.subplot(2, 3, 6)
t.plot(training_runs[2].history['val_acc'])
t.legend(['test'], loc='lower right')

t.tight_layout()

t.show()

int("Average training accuracy: {}".format(np.mean([training_runs[0].history
                                                    training_runs[1].history[
int("Average testing accuracy: {}".format(np.mean([training_runs[0].history[
                                                    training_runs[1].history[

```



Average training accuracy: 0.7883661269576123  
 Average testing accuracy: 0.5682238921106063

**By Using pre trained model run three times ,The best tesing accuracy performace for each run time is : 56.39% 55.90% 55.05% and average testing accuracy is 55.77%**