1. Introduction

In this article, the emotion distribution learning to determine the emotion distribution for the given images is proposed. Here a current state-of-the-art algorithm model which have the distribution specific loss is considered as a reference and proper modelling of the correlation for the image emotion distribution learning is added as the additional feature. For a particular image, the emotion recognized will vary when the model used in it varies. So here the graph convolutional network is used for capturing the hidden relationship in the graph data which will be formed by converting each pixel into the graph with equivalent number of nodes. This emotion correlation matrix represents the probability distribution of the particular emotion from which any test data can be recognized.

In [48]:

```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import matplotlib.pyplot as plt
import os
import cv2 as cv
import random
from sklearn.preprocessing import LabelEncoder
import glob
import time
import pickle
import pandas as pd
from pathlib import Path
from keras.preprocessing.image import img_to_array
from sklearn.preprocessing import LabelBinarizer
from sklearn.model selection import train test split
import tensorflow as tf
import keras.backend as K
from keras.layers import Input, Dense, Flatten
from keras.models import Model
from keras.callbacks import EarlyStopping
from keras.regularizers import 12
from sklearn.model selection import train test split
from spektral.layers import GraphConv, GlobalAvgPool, EdgeConditionedConv
from spektral.utils import Batch, batch_iterator
from spektral.utils import label_to_one_hot, normalized_laplacian
from spektral.layers.ops import sp_matrix_to_sp_tensor
import graph
import networkx as nx
import scipy.sparse as sp
from spektral.datasets import mnist
from keras.layers import MaxPooling2D, Reshape
from spektral.layers import GraphConv, ChebConv
from spektral.utils import localpooling filter
from tensorflow.keras.optimizers import Adam
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from utilities import generate graph, create graph
```

In [49]:

```
train_path = 'C:\\Users\\ACER\\Desktop\\Emotion_detection\\train_trim'
# Parameters
user_reguralization_rate = 5e-4
user_model_learning_rate = 0.03
user_model_batch = 32
epochs = 80
print(train_path)
```

C:\Users\ACER\Desktop\Emotion_detection\train_trim

In [50]:

```
# folder preprocessing
def check_folder_path(path):
    if not Path.is dir(path):
        raise ValueError("argument is not directory")
   yield from filter(Path.is_dir, path.iterdir())
def check depth(path, depth):
    if 0 > depth:
        raise ValueError("depth smaller 0")
    if 0 == depth:
        yield from check_folder_path(path)
    else:
        for folder in check_folder_path(path):
            yield from check_depth(folder, depth - 1)
def check_files(path):
    if not Path.is_dir(path):
        raise ValueError("argument is not a directory")
    yield from filter(Path.is file, path.iterdir())
def sum_file_size(filepaths):
    return sum([filep.stat().st_size for filep in filepaths])
def convert_image_to_array(image_dir):
    try:
        image = cv.imread(image_dir)
        if image is not None:
            image1 = cv.resize(image, default_image_size)
            gray = cv.cvtColor(image1, cv.COLOR BGR2GRAY)
            return img_to_array(gray).flatten()
        else:
            return np.array([])
    except Exception as e:
        print(f"Error : {e}")
        return None
def graph convolution one layer model(A, N=28 * 28, F=1,n out=10,12 reg=user reguraliza
tion rate,
                     learning_rate=user_model_learning_rate,
                     ):
    Creating a simple single layer GCN
    L = localpooling filter(A)
    X in = Input(shape=(N, F)) # N=nodes and F=features dimension
    A in = Input(tensor=sp matrix to sp tensor(L))
```

```
10/27/21, 7:55 PM
       graph_conv = GraphConv(10,
                               activation='relu',
                               kernel regularizer=12(12 reg),
                               use_bias=True)([X_in, A_in])
       fc = Flatten()(graph_conv)
       output = Dense(n_out, activation='softmax')(fc)
       # Build model
       model = Model(inputs=[X_in, A_in], outputs=output)
       model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['a
   ccuracy'])
       return model
   def graph_convolution_network(A, N=28 * 28, F=1,
           n out=10,
           12_reg=user_reguralization_rate,
           learning_rate=user_model_learning_rate,
           ):
       .. .. ..
       Creating two Layer GCN
       L = localpooling_filter(A)
       X_in = Input(shape=(N, F))
       A_in = Input(tensor=sp_matrix_to_sp_tensor(L))
       graph_conv = GraphConv(32,
                               activation='relu',
                               kernel_regularizer=12(12_reg),
                               use_bias=True)([X_in, A_in])
       graph_conv = GraphConv(32,
                               activation='relu',
                               kernel_regularizer=12(12_reg),
                               use_bias=True)([graph_conv, A_in])
       rs = Reshape((28, 28, 32))(graph_conv)
       pooled = MaxPooling2D(pool_size=(2, 2))(rs)
       flatten = Flatten()(pooled)
       fc = Dense(512, activation='relu')(flatten)
       output = Dense(n_out, activation='softmax')(fc)
       # Build model
       model = Model(inputs=[X_in, A_in], outputs=output)
       model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['a
   ccuracy'])
       return model
```

In [51]:

```
image list, label list = [], []
train_labels = os.listdir(train_path) # take training path labels
num_labels=len(train_labels)
print(num labels)
train_labels.sort() # sort the labels
print(train_labels) # primt the lables
labels = [] # create label variables so as to decode text to number
total = 0 # initialize
tot_file = [] # initialize
count = 1 # start count to check number of images
i = 0
j = 0
k = 0
print(Path.cwd()) # gives the current path
for folder in check_depth(Path.cwd(), 1):
    # first loop will pick the first foldend then next folder
    files = list(check_files(folder)) # list all files in folder
    file = len(files) # length of files
    tot_file.append(file) # because we are running for all folder
    # we are appending all files in tot_file at the end we
    # shall get the list of number of files in the folder
    # we are doing this because every folder has different number of files
    # at the end when we are trainig all class of disease have to be
    # trained equally, hence find the least number of images in the folder
    # and then train accordingly
    total_size = sum_file_size(files)
    # total size of files
    count = count + 1 # check total number of files executed
    print(f'{folder}:filecount:{len(files)},total size:{total_size}')
tot_file.sort() # sort files based on ascending order
num = int(tot_file[1]) # Index 0 is junkhence extract index 1
print('tOTAL FILE:', tot file)
print(num)
images_per_class = 3200 # consider number of images per class
# %%START WITH TRAINING
# for tr_name in range(0,2):
count = 0
default image size = tuple((28, 28))
for count in range(0, len(train labels)):
    tr_name = count
    dir = train path + '\\' + train labels[tr name]
      print(dir)
    current_label = train_labels[tr_name]
    print("[STATUS] processed folder: {}".format(current_label))
    k = 1
   file sub folder = os.listdir(dir)
      print(file_sub_folder)
    for x in range(0, images_per_class):
        file = dir + '\\' + file_sub_folder[x]
#
          print(file)
        image_list.append(convert_image_to_array(file))
        label list.append(current label)
        i += 1
```

```
k += 1
    count = count + 1
print("[STATUS] training labels{}".format(np.array(label_list).shape))
labelEncoder = LabelEncoder()
image_size = len(image_list)
image_labels = labelEncoder.fit_transform(label_list)

np_image_list = np.array(image_list, dtype=np.float32) / 225.0
print("[INFO] Spliting data to train, test")
X_train, X_test, y_train, y_test = train_test_split(np_image_list, image_labels, test_s ize=0.2, random_state=42)
X_val = X_test
y_val = y_test
```

```
4
['angry', 'happy', 'sad', 'surprise']
C:\Users\ACER\Desktop\Emotion detection
C:\Users\ACER\Desktop\Emotion detection\.idea\inspectionProfiles:filecoun
t:1,total size:174
C:\Users\ACER\Desktop\Emotion detection\gcn1\conda-meta:filecount:61,total
size:11459445
C:\Users\ACER\Desktop\Emotion_detection\gcn1\DLLs:filecount:34,total size:
C:\Users\ACER\Desktop\Emotion_detection\gcn1\include:filecount:102,total s
ize:656144
C:\Users\ACER\Desktop\Emotion detection\gcn1\Lib:filecount:172,total size:
C:\Users\ACER\Desktop\Emotion_detection\gcn1\Library:filecount:0,total siz
e:0
C:\Users\ACER\Desktop\Emotion_detection\gcn1\libs:filecount:3,total size:5
C:\Users\ACER\Desktop\Emotion_detection\gcn1\Scripts:filecount:83,total si
ze:13221247
C:\Users\ACER\Desktop\Emotion detection\gcn1\share:filecount:0,total size:
C:\Users\ACER\Desktop\Emotion_detection\gcn1\sip:filecount:0,total size:0
C:\Users\ACER\Desktop\Emotion_detection\gcn1\tcl:filecount:6,total size:16
C:\Users\ACER\Desktop\Emotion_detection\gcn1\Tools:filecount:0,total size:
C:\Users\ACER\Desktop\Emotion_detection\train\angry:filecount:3993,total s
ize:6332643
C:\Users\ACER\Desktop\Emotion_detection\train\happy:filecount:7164,total s
ize:11296707
C:\Users\ACER\Desktop\Emotion detection\train\neutral:filecount:4982,total
size:7740763
C:\Users\ACER\Desktop\Emotion_detection\train\sad:filecount:4938,total siz
e:7640144
C:\Users\ACER\Desktop\Emotion_detection\train\surprise:filecount:3205,tota
l size:5182401
C:\Users\ACER\Desktop\Emotion_detection\train_trim\angry:filecount:3993,to
tal size:6332643
C:\Users\ACER\Desktop\Emotion_detection\train_trim\happy:filecount:7164,to
tal size:11296707
C:\Users\ACER\Desktop\Emotion_detection\train_trim\sad:filecount:4938,tota
l size:7640144
C:\Users\ACER\Desktop\Emotion detection\train trim\surprise:filecount:320
5, total size: 5182401
tOTAL FILE: [0, 0, 0, 0, 1, 3, 6, 34, 61, 83, 102, 172, 3205, 3205, 3993,
3993, 4938, 4938, 4982, 7164, 7164]
[STATUS] processed folder: angry
[STATUS] processed folder: happy
[STATUS] processed folder: sad
[STATUS] processed folder: surprise
[STATUS] training labels(12800,)
[INFO] Spliting data to train, test
```

In [52]:

```
gen_random_seed = 2000
os.environ['PYTHONHASHSEED']=str(gen_random_seed)
random.seed(gen_random_seed)
np.random.seed(gen_random_seed)
tf.compat.v1.random.set_random_seed(gen_random_seed)

session_conf = tf.compat.v1.ConfigProto(intra_op_parallelism_threads=1, inter_op_parallelism_threads=1)
sess = tf.compat.v1.Session(graph=tf.compat.v1.get_default_graph(), config=session_conf
)
K.set_session(sess)
```

Splitting the dataset

In [53]:

```
X_train, X_val, X_test = X_train[..., None], X_val[..., None], X_test[..., None]
N = X_train.shape[-2]  # Number of nodes in the graphs
F = X_train.shape[-1]  # Node features dimensionality
n_out = 10  # Dimension of the target
print(X_train.shape, y_train.shape)
print(X_val.shape, y_val.shape)
print(X_test.shape, y_test.shape)

(10240, 784, 1) (10240,)
(2560, 784, 1) (2560,)
(2560, 784, 1) (2560,)
```

Creating graph with same dimension of images

- 1. Create a grid the same orientation as the training picture.
- 2. Find the embedding of the grid.
- 3. Generate the compressed sparse row (CSR) matrix.
- 4. Create two graph object with the CSR matrix. One is a complete graph and another one is after removing all the nodes without edges.
- 5. Find the degree matrix for the graph and repeat the steps for that matrix.

In [54]:

```
A = generate graph(28, 8)
plt.imshow(A.todense())
fig, ax = plt.subplots(figsize=(8, 8))
ax = create_graph(A, ax=ax, size_factor=1)
ax = create_graph(A, ax=ax, size_factor=1, spring_layout=True)
fig, axes = plt.subplots(figsize=(20, 5), ncols=4)
axes[2].imshow(A.todense())
# degree matrix D
D = A.sum(axis=0).reshape(28, 28)
axes[3].imshow(D)
axes[0] = create_graph(A, ax=axes[0], size_factor=1)
axes[1] = create_graph(A, ax=axes[1], size_factor=1, spring_layout=True)
fig.tight_layout()
threshold = 0.25 # to reduce the noise for averaged signals
# threshold = 0.5
d_emotion_graphs = {} # to collect feature graphs from each class
```

3198 > 3136 edges

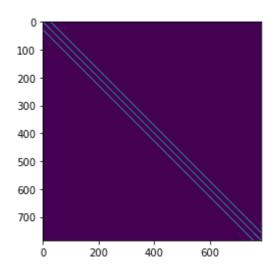
Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198

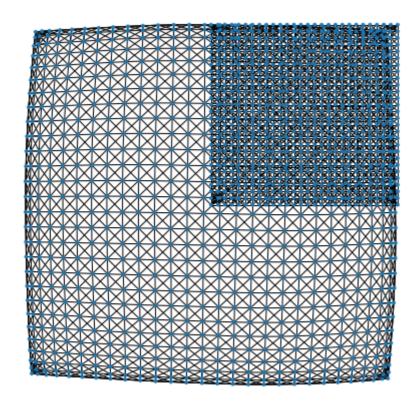
After removing nodes without edges:

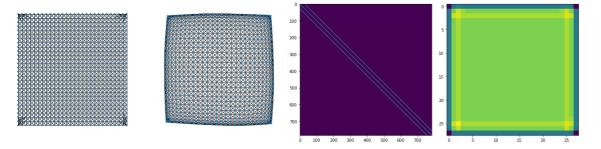
Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198

After removing nodes without edges:

Number of nodes: 784; Number of edges: 3198







Creating sample graphs for each class of emotions

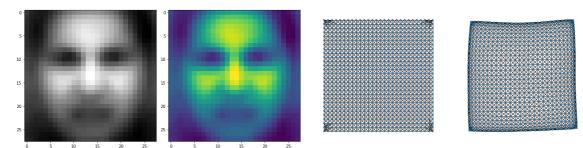
In [55]:

```
for i in range(num labels):
   mask = y_train == i
    fig, axes = plt.subplots(figsize=(20, 5), ncols=4)
    x_train_i_avg = X_train[mask].mean(axis=0).flatten()
    axes[0].imshow(x_train_i_avg.reshape(28, 28),cmap='gray')
    # threshold the averages of pixels
    x_train_i_avg[x_train_i_avg < threshold] = 0</pre>
    axes[1].imshow(x_train_i_avg.reshape(28, 28))
    # a sparse diag matrix with the intensities values on the diagnoal
   A_diag_i = sp.diags(x_train_i_avg, dtype=np.float32).tolil()
    A_i = A.dot(A_diag_i)
   d_emotion_graphs[i] = A i
    axes[2] = create_graph(A_i, ax=axes[2], size_factor=1)
    axes[3] = create_graph(A_i, ax=axes[3], size_factor=1, spring_layout=True)
    fig.tight_layout()
    plt.show()
```

Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198

After removing nodes without edges:

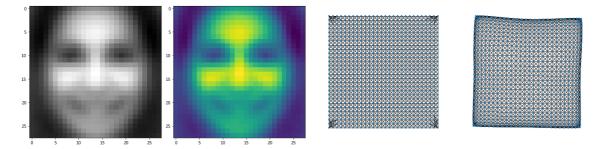
Number of nodes: 784; Number of edges: 3198



Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198

After removing nodes without edges:

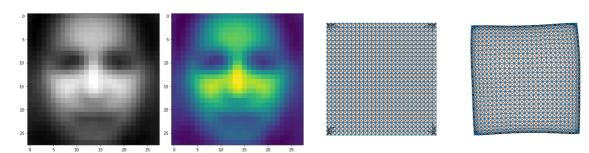
Number of nodes: 784; Number of edges: 3198



Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198

After removing nodes without edges:

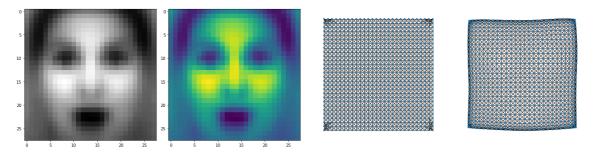
Number of nodes: 784; Number of edges: 3198



Number of nodes: 784; Number of edges: 3198 Number of nodes: 784; Number of edges: 3198

After removing nodes without edges:

Number of nodes: 784; Number of edges: 3198



Training the data with single layer GCN

In [56]:

```
# -----graph convolution one layer model-----
print("======== -graph_convolution_one_layer_model- ========")
test_scores = []
model_full_grid = graph_convolution_one_layer_model(A)
model_full_grid.summary()
validation_data = (X_val, y_val)
model_full_grid.fit(X_train,
                   y_train,
                   batch_size=user_model_batch,
                   validation data=validation data,
                   epochs=epochs)
print('Evaluating model.')
eval_results = model_full_grid.evaluate(X_test,
                             y_test,
                             batch_size=user_model_batch)
print('loss:{}\n'
      'acc: {}'.format(*eval_results))
test_scores.append({
    'model': 'graph_convolution_one_layer_model',
    'accuracy': eval_results[1]
})
```

======= -graph_convolution_one_layer_model- ======== Model: "model_12"

Layer (type) to	Output Shape	Param #	Connected
			========
input_22 (InputLayer)	(None, 784, 1)	0	
input_23 (InputLayer)	(784, 784)	0	
graph_conv_13 (GraphConv) [0][0]	(None, 784, 10)	20	input_22
[0][0]			input_23
flatten_12 (Flatten) v_13[0][0]	(None, 7840)	0	graph_con
dense_15 (Dense) 2[0][0]	(None, 10)	78410	flatten_1
		=======	========
Total params: 78,430 Trainable params: 78,430 Non-trainable params: 0			
Train on 10240 samples, validate	to on 2560 samples		
Epoch 1/80 10240/10240 [====================================] - 7s 6		loss: 1.338
10240/10240 [====================================	-	•	loss: 1.235
10240/10240 [====================================	-	•	loss: 1.206
10240/10240 [====================================	-	•	loss: 1.191
10240/10240 [====================================			loss: 1.180
10240/10240 [====================================	-	•	
Epoch 7/80 10240/10240 [====================================			loss: 1.163
Epoch 8/80 10240/10240 [====================================	-	•	loss: 1.156
Epoch 9/80 10240/10240 [====================================	=====] - 5s 4	80us/step -	loss: 1.151

```
9 - acc: 0.5040 - val_loss: 1.2080 - val_acc: 0.4570
Epoch 10/80
10240/10240 [============= ] - 5s 493us/step - loss: 1.149
1 - acc: 0.4993 - val loss: 1.1806 - val acc: 0.4836
10240/10240 [=============== ] - 5s 490us/step - loss: 1.143
8 - acc: 0.5064 - val_loss: 1.2008 - val_acc: 0.4668
Epoch 12/80
10240/10240 [============= ] - 5s 480us/step - loss: 1.137
6 - acc: 0.5110 - val_loss: 1.1724 - val_acc: 0.4832
Epoch 13/80
10240/10240 [============== ] - 5s 482us/step - loss: 1.131
0 - acc: 0.5141 - val_loss: 1.1739 - val_acc: 0.4781
Epoch 14/80
9 - acc: 0.5084 - val loss: 1.1723 - val acc: 0.4934
Epoch 15/80
10240/10240 [==============] - 5s 481us/step - loss: 1.122
9 - acc: 0.5157 - val_loss: 1.2045 - val_acc: 0.4688
Epoch 16/80
5 - acc: 0.5149 - val_loss: 1.1822 - val_acc: 0.4754
Epoch 17/80
10240/10240 [============== ] - 5s 504us/step - loss: 1.118
7 - acc: 0.5169 - val_loss: 1.1701 - val_acc: 0.4855
Epoch 18/80
10240/10240 [============= ] - 5s 482us/step - loss: 1.113
3 - acc: 0.5257 - val_loss: 1.1968 - val_acc: 0.4777
Epoch 19/80
10240/10240 [============== ] - 5s 482us/step - loss: 1.111
0 - acc: 0.5225 - val_loss: 1.1755 - val_acc: 0.4891
Epoch 20/80
3 - acc: 0.5243 - val_loss: 1.1644 - val_acc: 0.4969
Epoch 21/80
8 - acc: 0.5259 - val_loss: 1.1764 - val_acc: 0.4793
Epoch 22/80
10240/10240 [==============] - 5s 482us/step - loss: 1.104
1 - acc: 0.5309 - val_loss: 1.1884 - val_acc: 0.4809
Epoch 23/80
7 - acc: 0.5265 - val_loss: 1.1813 - val_acc: 0.4879
Epoch 24/80
6 - acc: 0.5352 - val loss: 1.1873 - val acc: 0.4852
0 - acc: 0.5278 - val_loss: 1.1776 - val_acc: 0.4828
Epoch 26/80
0 - acc: 0.5339 - val_loss: 1.1764 - val_acc: 0.4859
Epoch 27/80
8 - acc: 0.5353 - val_loss: 1.1928 - val_acc: 0.4723
Epoch 28/80
0 - acc: 0.5434 - val loss: 1.1925 - val acc: 0.4852
Epoch 29/80
6 - acc: 0.5389 - val_loss: 1.1851 - val_acc: 0.4793
```

```
Epoch 30/80
2 - acc: 0.5455 - val loss: 1.1719 - val acc: 0.4852
Epoch 31/80
6 - acc: 0.5423 - val_loss: 1.1840 - val_acc: 0.4844
Epoch 32/80
10240/10240 [============== ] - 5s 498us/step - loss: 1.079
6 - acc: 0.5427 - val loss: 1.2289 - val acc: 0.4605
Epoch 33/80
8 - acc: 0.5485 - val_loss: 1.1965 - val_acc: 0.4777
Epoch 34/80
0 - acc: 0.5485 - val_loss: 1.2115 - val_acc: 0.4695
Epoch 35/80
4 - acc: 0.5481 - val_loss: 1.1795 - val_acc: 0.4754
Epoch 36/80
4 - acc: 0.5481 - val_loss: 1.1782 - val_acc: 0.4895
Epoch 37/80
10240/10240 [============= ] - 5s 484us/step - loss: 1.065
6 - acc: 0.5521 - val loss: 1.2112 - val acc: 0.4734
Epoch 38/80
7 - acc: 0.5491 - val loss: 1.2076 - val acc: 0.4793
Epoch 39/80
7 - acc: 0.5502 - val_loss: 1.1824 - val_acc: 0.4809
4 - acc: 0.5589 - val_loss: 1.1873 - val_acc: 0.4813
Epoch 41/80
1 - acc: 0.5551 - val_loss: 1.2026 - val_acc: 0.4852
Epoch 42/80
7 - acc: 0.5613 - val_loss: 1.2087 - val_acc: 0.4813
1 - acc: 0.5550 - val_loss: 1.2014 - val_acc: 0.4793
Epoch 44/80
0 - acc: 0.5598 - val loss: 1.1908 - val acc: 0.4859
Epoch 45/80
6 - acc: 0.5601 - val_loss: 1.1990 - val_acc: 0.4816
Epoch 46/80
7 - acc: 0.5568 - val loss: 1.1854 - val acc: 0.4906
Epoch 47/80
2 - acc: 0.5637 - val loss: 1.1897 - val acc: 0.4793
Epoch 48/80
8 - acc: 0.5644 - val loss: 1.2327 - val acc: 0.4727
Epoch 49/80
0 - acc: 0.5649 - val loss: 1.2093 - val acc: 0.4789
Epoch 50/80
```

```
10240/10240 [============== ] - 5s 475us/step - loss: 1.046
1 - acc: 0.5586 - val_loss: 1.1936 - val_acc: 0.4820
Epoch 51/80
10240/10240 [============= ] - 5s 474us/step - loss: 1.042
8 - acc: 0.5631 - val_loss: 1.1947 - val_acc: 0.4832
Epoch 52/80
9 - acc: 0.5655 - val_loss: 1.2188 - val_acc: 0.4859
Epoch 53/80
7 - acc: 0.5697 - val_loss: 1.1966 - val_acc: 0.4867
Epoch 54/80
6 - acc: 0.5643 - val_loss: 1.2030 - val_acc: 0.4805
Epoch 55/80
6 - acc: 0.5685 - val_loss: 1.2075 - val_acc: 0.4785
Epoch 56/80
8 - acc: 0.5682 - val_loss: 1.1943 - val_acc: 0.4797
Epoch 57/80
9 - acc: 0.5643 - val_loss: 1.2084 - val_acc: 0.4813
Epoch 58/80
0 - acc: 0.5753 - val_loss: 1.2129 - val_acc: 0.4750
Epoch 59/80
10240/10240 [============== ] - 5s 506us/step - loss: 1.034
7 - acc: 0.5675 - val_loss: 1.2397 - val_acc: 0.4688
Epoch 60/80
9 - acc: 0.5753 - val_loss: 1.2202 - val_acc: 0.4867
Epoch 61/80
10240/10240 [============= ] - 5s 497us/step - loss: 1.027
1 - acc: 0.5712 - val_loss: 1.2081 - val_acc: 0.4828
Epoch 62/80
10240/10240 [============== ] - 5s 486us/step - loss: 1.029
9 - acc: 0.5726 - val_loss: 1.2089 - val_acc: 0.4875
Epoch 63/80
9 - acc: 0.5736 - val_loss: 1.2152 - val_acc: 0.4781
Epoch 64/80
4 - acc: 0.5762 - val_loss: 1.2052 - val_acc: 0.4832
Epoch 65/80
7 - acc: 0.5809 - val loss: 1.2648 - val acc: 0.4617
Epoch 66/80
4 - acc: 0.5794 - val_loss: 1.2048 - val_acc: 0.4871
Epoch 67/80
3 - acc: 0.5775 - val_loss: 1.2313 - val_acc: 0.4766
Epoch 68/80
6 - acc: 0.5833 - val_loss: 1.2150 - val_acc: 0.4801
Epoch 69/80
3 - acc: 0.5805 - val_loss: 1.2071 - val_acc: 0.4965
Epoch 70/80
```

```
5 - acc: 0.5800 - val_loss: 1.2189 - val_acc: 0.4801
Epoch 71/80
10240/10240 [============== ] - 5s 495us/step - loss: 1.014
4 - acc: 0.5810 - val loss: 1.2051 - val acc: 0.4879
2 - acc: 0.5819 - val_loss: 1.2326 - val_acc: 0.4805
Epoch 73/80
10240/10240 [============= ] - 5s 474us/step - loss: 1.011
1 - acc: 0.5842 - val loss: 1.2444 - val acc: 0.4840
Epoch 74/80
10240/10240 [============== ] - 5s 490us/step - loss: 1.012
1 - acc: 0.5856 - val_loss: 1.2140 - val_acc: 0.4891
Epoch 75/80
10240/10240 [============== ] - 5s 476us/step - loss: 1.013
8 - acc: 0.5859 - val loss: 1.2213 - val acc: 0.4883
Epoch 76/80
10240/10240 [==============] - 5s 473us/step - loss: 1.008
5 - acc: 0.5843 - val_loss: 1.2068 - val_acc: 0.4848
Epoch 77/80
10240/10240 [============== ] - 5s 474us/step - loss: 1.007
2 - acc: 0.5849 - val_loss: 1.2134 - val_acc: 0.4895
Epoch 78/80
3 - acc: 0.5909 - val_loss: 1.2080 - val_acc: 0.4887
Epoch 79/80
9 - acc: 0.5889 - val_loss: 1.2220 - val_acc: 0.4723
Epoch 80/80
10240/10240 [============== ] - 5s 474us/step - loss: 1.000
3 - acc: 0.5886 - val_loss: 1.2392 - val_acc: 0.4805
Evaluating model.
2560/2560 [=========== ] - 0s 183us/step
loss:1.2392246305942536
acc: 0.48046875
```

Training the data with multi layer GCN

In [57]:

```
# -----graph convolution multi layer model-----
print("======== -graph_convolution_multi_layer_model- ========")
test_scores = []
model_full_grid = graph_convolution_network(A)
model_full_grid.summary()
validation_data = (X_val, y_val)
model_full_grid.fit(X_train,
                   y_train,
                   batch_size=user_model_batch,
                   validation data=validation data,
                   epochs=epochs)
print('Evaluating model.')
eval_results = model_full_grid.evaluate(X_test,
                             y_test,
                             batch_size=user_model_batch)
print('loss:{}\n'
      'acc: {}'.format(*eval_results))
test_scores.append({
    'model': 'graph_convolution_multi_layer_model',
    'accuracy': eval_results[1]
})
```

======= -graph convolution multi layer model- ======== Model: "model 13" Layer (type) Output Shape Param # Connect ed to input_24 (InputLayer) (None, 784, 1) input 25 (InputLayer) (784, 784)0 graph_conv_14 (GraphConv) (None, 784, 32) 64 input_2 4[0][0] input_2 5[0][0] graph_conv_15 (GraphConv) (None, 784, 32) 1056 graph_c onv_14[0][0] input_2 5[0][0] reshape_3 (Reshape) (None, 28, 28, 32) graph_c onv_15[0][0] max_pooling2d_3 (MaxPooling2D) (None, 14, 14, 32) reshape _3[0][0] flatten_13 (Flatten) (None, 6272) max_poo ling2d_3[0][0] dense_16 (Dense) (None, 512) 3211776 flatten _13[0][0] dense 17 (Dense) (None, 10) 5130 dense 1 6[0][0] Total params: 3,218,026 Trainable params: 3,218,026 Non-trainable params: 0 Train on 10240 samples, validate on 2560 samples Epoch 1/80 79 - acc: 0.3723 - val loss: 1.2564 - val acc: 0.4250 Epoch 2/80 93 - acc: 0.4494 - val_loss: 1.2324 - val_acc: 0.4207 Epoch 3/80 53 - acc: 0.4743 - val_loss: 1.1982 - val_acc: 0.4680

```
Epoch 4/80
05 - acc: 0.4908 - val loss: 1.1821 - val acc: 0.4727
Epoch 5/80
10240/10240 [============== ] - 61s 6ms/step - loss: 1.13
63 - acc: 0.5068 - val_loss: 1.1649 - val_acc: 0.4832
Epoch 6/80
97 - acc: 0.5166 - val loss: 1.2203 - val acc: 0.4516
Epoch 7/80
11 - acc: 0.5237 - val_loss: 1.2069 - val_acc: 0.4734
Epoch 8/80
10240/10240 [============= ] - 61s 6ms/step - loss: 1.07
74 - acc: 0.5385 - val_loss: 1.1475 - val_acc: 0.4934
Epoch 9/80
42 - acc: 0.5419 - val_loss: 1.1572 - val_acc: 0.4883
Epoch 10/80
10240/10240 [============= ] - 61s 6ms/step - loss: 1.02
77 - acc: 0.5640 - val_loss: 1.1376 - val_acc: 0.5020
Epoch 11/80
59 - acc: 0.5797 - val loss: 1.1461 - val acc: 0.5062
Epoch 12/80
07 - acc: 0.5914 - val loss: 1.1634 - val acc: 0.4938
Epoch 13/80
20 - acc: 0.6081 - val_loss: 1.1302 - val_acc: 0.5094
86 - acc: 0.6191 - val_loss: 1.1663 - val_acc: 0.5109
Epoch 15/80
81 - acc: 0.6426 - val_loss: 1.1650 - val_acc: 0.5129
Epoch 16/80
10240/10240 [=============== ] - 61s 6ms/step - loss: 0.84
44 - acc: 0.6562 - val_loss: 1.1968 - val_acc: 0.5098
50 - acc: 0.6697 - val_loss: 1.2036 - val_acc: 0.5090s: 0.8061 -
Epoch 18/80
10240/10240 [============== ] - 61s 6ms/step - loss: 0.77
48 - acc: 0.6937 - val loss: 1.2115 - val acc: 0.5098
Epoch 19/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.72
86 - acc: 0.7125 - val_loss: 1.2511 - val_acc: 0.50271
Epoch 20/80
28 - acc: 0.7253 - val loss: 1.2751 - val acc: 0.5195
Epoch 21/80
04 - acc: 0.7538 - val_loss: 1.2873 - val_acc: 0.5184
Epoch 22/80
94 - acc: 0.7745 - val loss: 1.3813 - val acc: 0.5137
Epoch 23/80
59 - acc: 0.7935 - val loss: 1.4076 - val acc: 0.5199
Epoch 24/80
```

```
30 - acc: 0.8149 - val loss: 1.4890 - val acc: 0.5199
Epoch 25/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.47
36 - acc: 0.8296 - val loss: 1.5443 - val acc: 0.5188
Epoch 26/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.44
99 - acc: 0.8400 - val_loss: 1.5596 - val_acc: 0.5105
Epoch 27/80
73 - acc: 0.8675 - val_loss: 1.7113 - val_acc: 0.5219
Epoch 28/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.35
40 - acc: 0.8803 - val_loss: 1.8195 - val_acc: 0.5074
Epoch 29/80
88 - acc: 0.8959 - val_loss: 1.8452 - val_acc: 0.5230
Epoch 30/80
58 - acc: 0.9074 - val_loss: 1.9602 - val_acc: 0.5164
Epoch 31/80
75 - acc: 0.9212 - val_loss: 2.0505 - val_acc: 0.5098: 0.2434 - ETA: 1s
- loss: 0.2456 - a
Epoch 32/80
08 - acc: 0.9265 - val loss: 2.1508 - val acc: 0.5258
Epoch 33/80
10240/10240 [==============] - 62s 6ms/step - loss: 0.20
14 - acc: 0.9413 - val_loss: 2.2546 - val_acc: 0.5137
Epoch 34/80
91 - acc: 0.9441 - val_loss: 2.2878 - val_acc: 0.5211
Epoch 35/80
23 - acc: 0.9507 - val_loss: 2.4490 - val_acc: 0.5281
Epoch 36/80
87 - acc: 0.9605 - val_loss: 2.5448 - val_acc: 0.5215
07 - acc: 0.9595 - val_loss: 2.5540 - val_acc: 0.5285
Epoch 38/80
31 - acc: 0.9669 - val loss: 2.6885 - val acc: 0.5238
Epoch 39/80
19 - acc: 0.9698 - val_loss: 2.7687 - val_acc: 0.5277
Epoch 40/80
64 - acc: 0.9691 - val loss: 2.8236 - val acc: 0.5176
Epoch 41/80
02 - acc: 0.9685 - val_loss: 2.8247 - val_acc: 0.5230
Epoch 42/80
10240/10240 [============== ] - 60s 6ms/step - loss: 0.12
18 - acc: 0.9690 - val loss: 2.8291 - val acc: 0.5195
Epoch 43/80
46 - acc: 0.9718 - val loss: 3.0301 - val acc: 0.5188
Epoch 44/80
```

```
52 - acc: 0.9832 - val_loss: 3.0354 - val_acc: 0.5180
Epoch 45/80
54 - acc: 0.9804 - val loss: 3.0900 - val acc: 0.5258
Epoch 46/80
56 - acc: 0.9654 - val_loss: 2.9120 - val_acc: 0.5246
Epoch 47/80
58 - acc: 0.9781 - val_loss: 3.1255 - val_acc: 0.5207
Epoch 48/80
86 - acc: 0.9886 - val_loss: 3.1843 - val_acc: 0.5219
Epoch 49/80
92 - acc: 0.9778 - val_loss: 3.1549 - val_acc: 0.5223
Epoch 50/80
10240/10240 [============== ] - 59s 6ms/step - loss: 0.07
52 - acc: 0.9857 - val_loss: 3.2917 - val_acc: 0.5191
Epoch 51/80
52 - acc: 0.9768 - val_loss: 3.3177 - val_acc: 0.5031
Epoch 52/80
64 - acc: 0.9615 - val_loss: 3.1806 - val_acc: 0.5152
Epoch 53/80
20 - acc: 0.9827 - val_loss: 3.2101 - val_acc: 0.5273
Epoch 54/80
48 - acc: 0.9885 - val_loss: 3.1744 - val_acc: 0.5238
Epoch 55/80
10240/10240 [============= ] - 60s 6ms/step - loss: 0.06
33 - acc: 0.9884 - val_loss: 3.3135 - val_acc: 0.5227
Epoch 56/80
73 - acc: 0.9791 - val_loss: 3.2164 - val_acc: 0.5266
Epoch 57/80
90 - acc: 0.9869 - val_loss: 3.3388 - val_acc: 0.5152
Epoch 58/80
23 - acc: 0.9857 - val_loss: 3.2813 - val_acc: 0.5293
Epoch 59/80
21 - acc: 0.9889 - val loss: 3.3823 - val acc: 0.5227
Epoch 60/80
02 - acc: 0.9825 - val_loss: 3.3445 - val_acc: 0.5082
Epoch 61/80
89 - acc: 0.9749 - val loss: 3.3139 - val acc: 0.5305
10240/10240 [============== ] - 62s 6ms/step - loss: 0.04
61 - acc: 0.9945 - val_loss: 3.4244 - val_acc: 0.5270
Epoch 63/80
07 - acc: 0.9850 - val_loss: 3.4401 - val_acc: 0.5121
Epoch 64/80
```

```
01 - acc: 0.9897 - val_loss: 3.3461 - val_acc: 0.5262
Epoch 65/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.06
44 - acc: 0.9859 - val loss: 3.3416 - val acc: 0.5250
51 - acc: 0.9817 - val_loss: 3.3186 - val_acc: 0.5273
Epoch 67/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.04
19 - acc: 0.9954 - val loss: 3.4118 - val acc: 0.5293
Epoch 68/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.04
61 - acc: 0.9937 - val_loss: 3.4408 - val_acc: 0.5336
Epoch 69/80
04 - acc: 0.9710 - val loss: 3.5225 - val acc: 0.5246
Epoch 70/80
28 - acc: 0.9836 - val_loss: 3.3697 - val_acc: 0.5289
Epoch 71/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.04
04 - acc: 0.9947 - val_loss: 3.4486 - val_acc: 0.5309
Epoch 72/80
60 - acc: 0.9964 - val_loss: 3.4153 - val_acc: 0.5383
Epoch 73/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.04
33 - acc: 0.9941 - val_loss: 3.4759 - val_acc: 0.5289
Epoch 74/80
10240/10240 [============== ] - 61s 6ms/step - loss: 0.05
12 - acc: 0.9903 - val_loss: 3.5384 - val_acc: 0.5273
Epoch 75/80
46 - acc: 0.9643 - val_loss: 3.5233 - val_acc: 0.5105
Epoch 76/80
21 - acc: 0.9872 - val_loss: 3.3795 - val_acc: 0.5227
Epoch 77/80
10240/10240 [=============] - 61s 6ms/step - loss: 0.02
95 - acc: 0.9976 - val loss: 3.4397 - val acc: 0.5340
Epoch 78/80
38 - acc: 0.9968 - val_loss: 3.4095 - val_acc: 0.5340
Epoch 79/80
10240/10240 [============= ] - 61s 6ms/step - loss: 0.04
49 - acc: 0.9925 - val loss: 3.5892 - val acc: 0.5230
Epoch 80/80
55 - acc: 0.9688 - val loss: 3.3730 - val acc: 0.5219
Evaluating model.
2560/2560 [=========== ] - 3s 1ms/step
loss:3.373025028407574
acc: 0.521875
```

Training the data with fully connected GCN

In [58]:

```
A0 = sp.csr matrix(A.shape, dtype=np.float32)
print(A0.shape, A0.nnz)
model_no_graph = graph_convolution_one_layer_model(A0)
model no graph.summary()
model_no_graph.fit(X_train,
                    batch_size=user_model_batch,
                    validation_data=validation_data,
                    epochs=epochs)
print('Evaluating model.')
eval_results = model_no_graph.evaluate(X_test,
                              y_test,
                              batch_size=user_model_batch)
print('loss: {}\n'
      'acc: {}'.format(*eval_results))
test_scores.append({
    'model': 'GCN graph',
    'accuracy': eval_results[1]
})
def fc_model(N=28 * 28, F=1,
             n_out=10,
             12_reg=user_reguralization_rate,
             learning_rate=user_model_learning_rate):
    '''-connected model classification.
    X in = Input(shape=(N, F))
    fc = Dense(10, activation='relu',
               kernel_regularizer=12(12_reg),
               use_bias=True)(Flatten()(X_in))
    output = Dense(n_out, activation='softmax')(fc)
    # Build model
    model = Model(inputs=X_in, outputs=output)
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['a
ccuracy'])
    return model
model_fc = fc_model()
model_fc.summary()
model fc.fit(X train,
                    y train,
                    batch_size=user_model_batch,
                    validation data=validation data,
                    epochs=epochs)
```

(784, 784) 0 Model: "model_14"

Layer (type) to		Param #	
input_26 (InputLayer)	(None, 784, 1)	0	
input_27 (InputLayer)	(784, 784)	0	
graph_conv_16 (GraphConv) [0][0]	(None, 784, 10)	20	input_26
[0][0]			input_27
flatten_14 (Flatten) v_16[0][0]	(None, 7840)	0	graph_con
dense_18 (Dense) 4[0][0] =================================	(None, 10)	78410	flatten_1
Train on 10240 samples, validate Epoch 1/80 10240/10240 [====================================	======] - 6s .2614 - val_acc: 0.43	352	
10240/10240 [====================================	.2253 - val_acc: 0.45 ======] - 4s	666 421us/step -	
10240/10240 [====================================	.2232 - val_acc: 0.46 ======] - 4s	625 427us/step -	
Epoch 6/80 10240/10240 [====================================	.1976 - val_acc: 0.46] - 4s	389us/step -	
8 - acc: 0.4924 - val_loss: 1 Epoch 8/80 10240/10240 [====================================	- ======] - 4s .1880 - val_acc: 0.47	389us/step - 734	
10240/10240 [====================================	-	•	loss: 1.146

```
Epoch 10/80
6 - acc: 0.5070 - val loss: 1.1935 - val acc: 0.4750
Epoch 11/80
10240/10240 [============= ] - 4s 391us/step - loss: 1.135
7 - acc: 0.5054 - val_loss: 1.1990 - val_acc: 0.4777
10240/10240 [============== ] - 4s 391us/step - loss: 1.126
9 - acc: 0.5134 - val loss: 1.2451 - val acc: 0.4574
Epoch 13/80
8 - acc: 0.5088 - val_loss: 1.2044 - val_acc: 0.4699
Epoch 14/80
0 - acc: 0.5120 - val_loss: 1.1957 - val_acc: 0.4645
Epoch 15/80
0 - acc: 0.5259 - val_loss: 1.1920 - val_acc: 0.4691
Epoch 16/80
7 - acc: 0.5175 - val_loss: 1.1798 - val_acc: 0.4848
Epoch 17/80
10240/10240 [============= ] - 4s 416us/step - loss: 1.104
1 - acc: 0.5289 - val loss: 1.1990 - val acc: 0.4691
Epoch 18/80
2 - acc: 0.5239 - val loss: 1.1936 - val acc: 0.4797
Epoch 19/80
0 - acc: 0.5290 - val_loss: 1.1892 - val_acc: 0.4742
6 - acc: 0.5305 - val_loss: 1.2019 - val_acc: 0.4699
Epoch 21/80
7 - acc: 0.5319 - val_loss: 1.1842 - val_acc: 0.4809
Epoch 22/80
5 - acc: 0.5343 - val_loss: 1.2270 - val_acc: 0.4578
2 - acc: 0.5394 - val_loss: 1.2369 - val_acc: 0.4711
Epoch 24/80
5 - acc: 0.5386 - val loss: 1.1792 - val acc: 0.4719
Epoch 25/80
0 - acc: 0.5396 - val_loss: 1.2101 - val_acc: 0.4629
Epoch 26/80
1 - acc: 0.5427 - val loss: 1.1897 - val acc: 0.4855
Epoch 27/80
0 - acc: 0.5450 - val loss: 1.1931 - val acc: 0.4781
Epoch 28/80
5 - acc: 0.5475 - val loss: 1.1961 - val acc: 0.4703
Epoch 29/80
8 - acc: 0.5500 - val loss: 1.1983 - val acc: 0.4684
Epoch 30/80
```

```
10240/10240 [============== ] - 4s 394us/step - loss: 1.060
5 - acc: 0.5455 - val_loss: 1.1859 - val_acc: 0.4734
Epoch 31/80
8 - acc: 0.5523 - val_loss: 1.2992 - val_acc: 0.4539
Epoch 32/80
1 - acc: 0.5538 - val_loss: 1.1762 - val_acc: 0.4844
Epoch 33/80
10240/10240 [============= ] - 4s 434us/step - loss: 1.055
5 - acc: 0.5563 - val_loss: 1.1868 - val_acc: 0.4805
Epoch 34/80
4 - acc: 0.5536 - val_loss: 1.2018 - val_acc: 0.4770
Epoch 35/80
2 - acc: 0.5548 - val_loss: 1.2061 - val_acc: 0.4727
Epoch 36/80
2 - acc: 0.5640 - val_loss: 1.2140 - val_acc: 0.4727
Epoch 37/80
8 - acc: 0.5604 - val_loss: 1.1940 - val_acc: 0.4801
Epoch 38/80
8 - acc: 0.5646 - val_loss: 1.2052 - val_acc: 0.4824
Epoch 39/80
7 - acc: 0.5652 - val_loss: 1.1945 - val_acc: 0.4781
Epoch 40/80
4 - acc: 0.5681 - val_loss: 1.2073 - val_acc: 0.4785
Epoch 41/80
10240/10240 [============== ] - 4s 397us/step - loss: 1.033
8 - acc: 0.5666 - val_loss: 1.2028 - val_acc: 0.4742
Epoch 42/80
3 - acc: 0.5696 - val_loss: 1.2004 - val_acc: 0.4785
Epoch 43/80
4 - acc: 0.5707 - val_loss: 1.2327 - val_acc: 0.4699
Epoch 44/80
6 - acc: 0.5660 - val_loss: 1.2598 - val_acc: 0.4582
Epoch 45/80
4 - acc: 0.5727 - val_loss: 1.2061 - val_acc: 0.4715
Epoch 46/80
0 - acc: 0.5771 - val_loss: 1.1972 - val_acc: 0.4801
Epoch 47/80
7 - acc: 0.5755 - val_loss: 1.2462 - val_acc: 0.4754
Epoch 48/80
7 - acc: 0.5739 - val_loss: 1.2126 - val_acc: 0.4750
Epoch 49/80
7 - acc: 0.5756 - val_loss: 1.2036 - val_acc: 0.4852
Epoch 50/80
```

```
8 - acc: 0.5784 - val_loss: 1.2660 - val_acc: 0.4621
Epoch 51/80
10240/10240 [============= ] - 4s 384us/step - loss: 1.005
9 - acc: 0.5836 - val loss: 1.2342 - val acc: 0.4770
8 - acc: 0.5875 - val_loss: 1.1995 - val_acc: 0.4789
Epoch 53/80
10240/10240 [============= ] - 4s 386us/step - loss: 1.004
4 - acc: 0.5803 - val_loss: 1.2469 - val_acc: 0.4668
Epoch 54/80
10240/10240 [============= ] - 4s 386us/step - loss: 0.999
9 - acc: 0.5876 - val_loss: 1.1998 - val_acc: 0.4773
Epoch 55/80
6 - acc: 0.5852 - val loss: 1.2293 - val acc: 0.4797
Epoch 56/80
6 - acc: 0.5867 - val_loss: 1.2548 - val_acc: 0.4680
Epoch 57/80
5 - acc: 0.5918 - val_loss: 1.2144 - val_acc: 0.4824
Epoch 58/80
1 - acc: 0.5940 - val_loss: 1.2169 - val_acc: 0.4863
Epoch 59/80
9 - acc: 0.5876 - val_loss: 1.2958 - val_acc: 0.4637
Epoch 60/80
10240/10240 [============= ] - 4s 406us/step - loss: 0.989
8 - acc: 0.5901 - val_loss: 1.3097 - val_acc: 0.4484
Epoch 61/80
0 - acc: 0.5932 - val_loss: 1.2245 - val_acc: 0.4746
Epoch 62/80
2 - acc: 0.5947 - val_loss: 1.2262 - val_acc: 0.4789
Epoch 63/80
10240/10240 [============== ] - 4s 384us/step - loss: 0.979
8 - acc: 0.5900 - val loss: 1.2410 - val acc: 0.4805
Epoch 64/80
8 - acc: 0.5940 - val_loss: 1.2333 - val_acc: 0.4754
Epoch 65/80
3 - acc: 0.5969 - val loss: 1.2525 - val acc: 0.4699
1 - acc: 0.5964 - val_loss: 1.2170 - val_acc: 0.4754
Epoch 67/80
3 - acc: 0.6049 - val_loss: 1.2782 - val_acc: 0.4703
Epoch 68/80
3 - acc: 0.5974 - val_loss: 1.2615 - val_acc: 0.4730
Epoch 69/80
3 - acc: 0.5968 - val loss: 1.2473 - val acc: 0.4668
Epoch 70/80
6 - acc: 0.6037 - val_loss: 1.2613 - val_acc: 0.4645
```

```
Epoch 71/80
6 - acc: 0.6054 - val loss: 1.2382 - val acc: 0.4719
Epoch 72/80
2 - acc: 0.6063 - val_loss: 1.2794 - val_acc: 0.4695
Epoch 73/80
8 - acc: 0.6004 - val loss: 1.2753 - val acc: 0.4582
Epoch 74/80
2 - acc: 0.6022 - val_loss: 1.2677 - val_acc: 0.4750
Epoch 75/80
10240/10240 [============== ] - 4s 384us/step - loss: 0.970
4 - acc: 0.6033 - val_loss: 1.2389 - val_acc: 0.4867
Epoch 76/80
7 - acc: 0.6093 - val_loss: 1.2898 - val_acc: 0.4617
Epoch 77/80
9 - acc: 0.6020 - val_loss: 1.2408 - val_acc: 0.4789
Epoch 78/80
0 - acc: 0.6082 - val loss: 1.2838 - val acc: 0.4711
Epoch 79/80
7 - acc: 0.6085 - val loss: 1.2603 - val acc: 0.4723
Epoch 80/80
4 - acc: 0.6116 - val_loss: 1.2470 - val_acc: 0.4738
Evaluating model.
2560/2560 [=========== ] - 0s 160us/step
loss: 1.2469926431775094
acc: 0.473828125
Model: "model_15"
Layer (type)
                Output Shape
                               Param #
______
input_28 (InputLayer)
                (None, 784, 1)
flatten 15 (Flatten)
                (None, 784)
dense 19 (Dense)
                (None, 10)
                                7850
dense 20 (Dense)
                (None, 10)
                                110
______
Total params: 7,960
Trainable params: 7,960
Non-trainable params: 0
Train on 10240 samples, validate on 2560 samples
Epoch 1/80
7 - acc: 0.3212 - val_loss: 1.3156 - val_acc: 0.3719
Epoch 2/80
```

file:///C:/Users/REVANTH/Downloads/main_gcn_emotion.html

Epoch 3/80

Epoch 4/80

- acc: 0.3964 - val loss: 1.2885 - val acc: 0.3984

- acc: 0.4240 - val loss: 1.2609 - val acc: 0.4258

```
- acc: 0.4374 - val_loss: 1.2441 - val_acc: 0.4297
10240/10240 [============= ] - 1s 69us/step - loss: 1.2320
- acc: 0.4439 - val_loss: 1.2396 - val_acc: 0.4465
Epoch 6/80
- acc: 0.4574 - val_loss: 1.2560 - val_acc: 0.4230
Epoch 7/80
- acc: 0.4728 - val_loss: 1.2511 - val_acc: 0.4547
Epoch 8/80
- acc: 0.4677 - val_loss: 1.2251 - val_acc: 0.4453
Epoch 9/80
10240/10240 [============= ] - 1s 70us/step - loss: 1.1964
- acc: 0.4747 - val_loss: 1.2274 - val_acc: 0.4535
Epoch 10/80
10240/10240 [============== ] - 1s 67us/step - loss: 1.1953
- acc: 0.4770 - val_loss: 1.2208 - val_acc: 0.4578
Epoch 11/80
- acc: 0.4844 - val_loss: 1.2261 - val_acc: 0.4582
Epoch 12/80
- acc: 0.4812 - val_loss: 1.2051 - val_acc: 0.4629
Epoch 13/80
10240/10240 [============= ] - 1s 70us/step - loss: 1.1767
- acc: 0.4894 - val_loss: 1.2438 - val_acc: 0.4578s - loss: 1.1771 - acc:
0.48
Epoch 14/80
- acc: 0.4881 - val_loss: 1.2179 - val_acc: 0.4570
Epoch 15/80
- acc: 0.4932 - val_loss: 1.2096 - val_acc: 0.4684
Epoch 16/80
- acc: 0.4908 - val_loss: 1.2500 - val_acc: 0.4453
- acc: 0.4965 - val_loss: 1.2190 - val_acc: 0.4535
Epoch 18/80
10240/10240 [============== ] - 1s 92us/step - loss: 1.1638
- acc: 0.5017 - val loss: 1.2285 - val acc: 0.4539
Epoch 19/80
- acc: 0.4961 - val_loss: 1.2014 - val_acc: 0.4723
Epoch 20/80
- acc: 0.4971 - val loss: 1.2254 - val acc: 0.4539
Epoch 21/80
- acc: 0.4962 - val_loss: 1.2010 - val_acc: 0.4719
Epoch 22/80
- acc: 0.5002 - val loss: 1.2223 - val acc: 0.4527
Epoch 23/80
- acc: 0.5009 - val loss: 1.2046 - val acc: 0.4594
Epoch 24/80
```

```
- acc: 0.4998 - val_loss: 1.2045 - val_acc: 0.4758
Epoch 25/80
10240/10240 [============= ] - 1s 68us/step - loss: 1.1495
- acc: 0.5044 - val_loss: 1.2177 - val_acc: 0.4688
Epoch 26/80
10240/10240 [============= ] - 1s 67us/step - loss: 1.1479
- acc: 0.5091 - val_loss: 1.2108 - val_acc: 0.4605
Epoch 27/80
- acc: 0.5001 - val_loss: 1.2056 - val_acc: 0.4734
Epoch 28/80
- acc: 0.5088 - val_loss: 1.2025 - val_acc: 0.4695
Epoch 29/80
- acc: 0.5104 - val_loss: 1.2344 - val_acc: 0.4586 loss: 1.1477 - acc: 0.5
Epoch 30/80
10240/10240 [============== ] - 1s 67us/step - loss: 1.1460
- acc: 0.5111 - val_loss: 1.1968 - val_acc: 0.4793
Epoch 31/80
- acc: 0.5088 - val_loss: 1.2130 - val_acc: 0.4645
Epoch 32/80
10240/10240 [============== ] - 1s 69us/step - loss: 1.1444
- acc: 0.5116 - val loss: 1.2090 - val acc: 0.4691
Epoch 33/80
- acc: 0.5107 - val_loss: 1.2070 - val_acc: 0.4785
- acc: 0.5144 - val_loss: 1.2051 - val_acc: 0.4781
Epoch 35/80
- acc: 0.5177 - val_loss: 1.2017 - val_acc: 0.4773
Epoch 36/80
- acc: 0.5133 - val_loss: 1.2087 - val_acc: 0.4652
- acc: 0.5088 - val_loss: 1.2535 - val_acc: 0.4488
Epoch 38/80
- acc: 0.5101 - val loss: 1.2074 - val acc: 0.4645
Epoch 39/80
- acc: 0.5097 - val_loss: 1.2098 - val_acc: 0.4676
Epoch 40/80
- acc: 0.5154 - val loss: 1.2010 - val acc: 0.4656
Epoch 41/80
- acc: 0.5159 - val loss: 1.2068 - val acc: 0.4699
Epoch 42/80
10240/10240 [============== ] - 1s 67us/step - loss: 1.1384
- acc: 0.5153 - val loss: 1.1972 - val acc: 0.4762
Epoch 43/80
- acc: 0.5124 - val_loss: 1.2015 - val_acc: 0.4773
Epoch 44/80
```

```
- acc: 0.5163 - val_loss: 1.2066 - val_acc: 0.4781
Epoch 45/80
10240/10240 [============= ] - 1s 67us/step - loss: 1.1334
- acc: 0.5141 - val_loss: 1.1924 - val_acc: 0.4859
Epoch 46/80
- acc: 0.5194 - val_loss: 1.2077 - val_acc: 0.4664
Epoch 47/80
- acc: 0.5210 - val_loss: 1.2529 - val_acc: 0.4637
Epoch 48/80
- acc: 0.5144 - val_loss: 1.1998 - val_acc: 0.4871
Epoch 49/80
- acc: 0.5208 - val_loss: 1.2198 - val_acc: 0.4578
Epoch 50/80
- acc: 0.5224 - val_loss: 1.2198 - val_acc: 0.4680 - loss: 1.1257 - acc:
0.522
Epoch 51/80
10240/10240 [============== ] - 1s 67us/step - loss: 1.1309
- acc: 0.5228 - val_loss: 1.2114 - val_acc: 0.4820
Epoch 52/80
10240/10240 [============== ] - 1s 67us/step - loss: 1.1294
- acc: 0.5200 - val loss: 1.2065 - val acc: 0.4840
Epoch 53/80
- acc: 0.5178 - val_loss: 1.2108 - val_acc: 0.4832s - loss: 1.1259 - acc:
0.517
Epoch 54/80
10240/10240 [============= ] - 1s 67us/step - loss: 1.1274
- acc: 0.5204 - val_loss: 1.2101 - val_acc: 0.4527
Epoch 55/80
- acc: 0.5170 - val_loss: 1.1972 - val_acc: 0.4742
Epoch 56/80
10240/10240 [============== ] - 1s 70us/step - loss: 1.1285
- acc: 0.5231 - val_loss: 1.2863 - val_acc: 0.4324 0s - loss: 1.1202 - ac
Epoch 57/80
- acc: 0.5221 - val_loss: 1.2086 - val_acc: 0.4598
Epoch 58/80
- acc: 0.5224 - val loss: 1.2048 - val acc: 0.4543
10240/10240 [==============] - 1s 67us/step - loss: 1.1233
- acc: 0.5236 - val_loss: 1.2514 - val_acc: 0.4418
Epoch 60/80
- acc: 0.5263 - val_loss: 1.2498 - val_acc: 0.4445
Epoch 61/80
- acc: 0.5308 - val_loss: 1.2121 - val_acc: 0.4648
Epoch 62/80
10240/10240 [============== ] - 1s 70us/step - loss: 1.1131
- acc: 0.5259 - val_loss: 1.2137 - val_acc: 0.4676
Epoch 63/80
- acc: 0.5276 - val_loss: 1.1929 - val_acc: 0.4754
```

```
Epoch 64/80
- acc: 0.5312 - val loss: 1.2039 - val acc: 0.4820
Epoch 65/80
- acc: 0.5274 - val_loss: 1.2155 - val_acc: 0.4605
Epoch 66/80
10240/10240 [============== ] - 1s 69us/step - loss: 1.1024
- acc: 0.5321 - val loss: 1.1948 - val acc: 0.4871
Epoch 67/80
- acc: 0.5346 - val_loss: 1.2184 - val_acc: 0.4770
Epoch 68/80
10240/10240 [============== ] - 1s 70us/step - loss: 1.1148
- acc: 0.5296 - val loss: 1.2049 - val acc: 0.4840
Epoch 69/80
- acc: 0.5304 - val_loss: 1.1900 - val_acc: 0.4738
Epoch 70/80
- acc: 0.5214 - val_loss: 1.1885 - val_acc: 0.4770
Epoch 71/80
- acc: 0.5282 - val_loss: 1.1955 - val_acc: 0.4707s - loss: 1.1041 - acc:
0.5
Epoch 72/80
10240/10240 [============= ] - 1s 69us/step - loss: 1.1004
- acc: 0.5379 - val_loss: 1.2396 - val_acc: 0.4449s - loss: 1.0980 - acc:
Epoch 73/80
10240/10240 [==============] - 1s 71us/step - loss: 1.1024
- acc: 0.5311 - val_loss: 1.1952 - val acc: 0.4766
Epoch 74/80
- acc: 0.5279 - val_loss: 1.2187 - val_acc: 0.4734
Epoch 75/80
- acc: 0.5373 - val_loss: 1.2006 - val_acc: 0.4547
Epoch 76/80
10240/10240 [============== ] - 1s 70us/step - loss: 1.1071
- acc: 0.5298 - val loss: 1.1993 - val acc: 0.4727
Epoch 77/80
- acc: 0.5262 - val_loss: 1.2140 - val_acc: 0.4625
Epoch 78/80
- acc: 0.5316 - val loss: 1.2088 - val acc: 0.4781
Epoch 79/80
10240/10240 [==============] - 1s 67us/step - loss: 1.0978
- acc: 0.5294 - val loss: 1.2037 - val acc: 0.4785
Epoch 80/80
- acc: 0.5294 - val loss: 1.1917 - val acc: 0.4793
4
```

Out[58]:

<keras.callbacks.History at 0x1f487826ba8>

In [59]:

```
# Evaluate model
print('Evaluating model.')
eval_results = model_fc.evaluate(X_test,
                             batch_size=user_model_batch)
print('Done.\n'
      'Test loss: {}\n'
      'Test acc: {}'.format(*eval_results))
test_scores.append({
    'model': 'connected model',
    'accuracy': eval_results[1]
})
Evaluating model.
2560/2560 [=========== ] - 0s 47us/step
```

Test loss: 1.1917159155011177 Test acc: 0.479296875

Training each class separately with single layer GCN

In [60]:

```
0 6396
Train on 10240 samples, validate on 2560 samples
Epoch 1/80
2 - acc: 0.3524 - val_loss: 1.3057 - val_acc: 0.3859
Epoch 2/80
5 - acc: 0.4275 - val_loss: 1.2619 - val_acc: 0.4344
Epoch 3/80
10240/10240 [============== ] - 5s 443us/step - loss: 1.220
5 - acc: 0.4528 - val_loss: 1.2168 - val_acc: 0.4637
Epoch 4/80
10240/10240 [============= ] - 4s 421us/step - loss: 1.204
4 - acc: 0.4639 - val_loss: 1.2485 - val_acc: 0.4414
2 - acc: 0.4703 - val_loss: 1.2721 - val_acc: 0.4523
Epoch 6/80
5 - acc: 0.4752 - val loss: 1.2030 - val acc: 0.4582
Epoch 7/80
5 - acc: 0.4787 - val_loss: 1.2115 - val_acc: 0.4656
Epoch 8/80
8 - acc: 0.4874 - val_loss: 1.1913 - val_acc: 0.4703
Epoch 9/80
8 - acc: 0.4895 - val_loss: 1.2267 - val_acc: 0.4633
Epoch 10/80
10240/10240 [============= ] - 5s 444us/step - loss: 1.167
5 - acc: 0.4879 - val_loss: 1.2095 - val_acc: 0.4648
Epoch 11/80
10240/10240 [============= ] - 4s 423us/step - loss: 1.165
8 - acc: 0.4923 - val_loss: 1.1943 - val_acc: 0.4680
Epoch 12/80
5 - acc: 0.4897 - val_loss: 1.2237 - val_acc: 0.4582
Epoch 13/80
1 - acc: 0.4954 - val_loss: 1.2168 - val_acc: 0.4617
Epoch 14/80
0 - acc: 0.5006 - val_loss: 1.2021 - val_acc: 0.4777
Epoch 15/80
7 - acc: 0.4956 - val_loss: 1.1982 - val_acc: 0.4629
Epoch 16/80
1 - acc: 0.4985 - val loss: 1.1895 - val acc: 0.4840
Epoch 17/80
3 - acc: 0.5014 - val_loss: 1.1827 - val_acc: 0.4805
Epoch 18/80
10240/10240 [============= ] - 4s 435us/step - loss: 1.152
3 - acc: 0.4990 - val_loss: 1.1977 - val_acc: 0.4664
1 - acc: 0.5091 - val_loss: 1.1949 - val_acc: 0.4688
Epoch 20/80
```

```
5 - acc: 0.5017 - val_loss: 1.2447 - val_acc: 0.4484
Epoch 21/80
10240/10240 [============== ] - 5s 441us/step - loss: 1.143
9 - acc: 0.5032 - val loss: 1.1847 - val acc: 0.4875
10240/10240 [=============== ] - 4s 421us/step - loss: 1.142
4 - acc: 0.5029 - val_loss: 1.1823 - val_acc: 0.4813
Epoch 23/80
10240/10240 [============= ] - 4s 425us/step - loss: 1.141
0 - acc: 0.5012 - val_loss: 1.1875 - val_acc: 0.4801
Epoch 24/80
10240/10240 [============== ] - 4s 423us/step - loss: 1.139
2 - acc: 0.5072 - val_loss: 1.1911 - val_acc: 0.4883
Epoch 25/80
10240/10240 [============== ] - 5s 446us/step - loss: 1.139
9 - acc: 0.5080 - val loss: 1.1969 - val acc: 0.4730
Epoch 26/80
10240/10240 [==============] - 4s 423us/step - loss: 1.132
4 - acc: 0.5141 - val_loss: 1.1857 - val_acc: 0.4824
Epoch 27/80
5 - acc: 0.5116 - val_loss: 1.1733 - val_acc: 0.4914
Epoch 28/80
5 - acc: 0.5067 - val_loss: 1.1955 - val_acc: 0.4777
Epoch 29/80
10240/10240 [============== ] - 5s 464us/step - loss: 1.131
3 - acc: 0.5103 - val_loss: 1.2245 - val_acc: 0.4625
Epoch 30/80
10240/10240 [============== ] - 5s 447us/step - loss: 1.128
2 - acc: 0.5123 - val_loss: 1.2216 - val_acc: 0.4703
Epoch 31/80
1 - acc: 0.5083 - val_loss: 1.1808 - val_acc: 0.4719
Epoch 32/80
8 - acc: 0.5110 - val_loss: 1.1954 - val_acc: 0.4793
Epoch 33/80
10240/10240 [=============== ] - 4s 425us/step - loss: 1.124
3 - acc: 0.5112 - val_loss: 1.1742 - val_acc: 0.4863
Epoch 34/80
2 - acc: 0.5186 - val_loss: 1.1897 - val_acc: 0.4824
Epoch 35/80
4 - acc: 0.5135 - val loss: 1.2051 - val acc: 0.4727
3 - acc: 0.5169 - val_loss: 1.1690 - val_acc: 0.4945
Epoch 37/80
5 - acc: 0.5146 - val_loss: 1.1700 - val_acc: 0.4961
Epoch 38/80
1 - acc: 0.5197 - val_loss: 1.1848 - val_acc: 0.4844
Epoch 39/80
4 - acc: 0.5174 - val loss: 1.1883 - val acc: 0.4758
Epoch 40/80
0 - acc: 0.5224 - val_loss: 1.1677 - val_acc: 0.4926
```

```
Epoch 41/80
3 - acc: 0.5204 - val loss: 1.1708 - val acc: 0.4773
Epoch 42/80
7 - acc: 0.5170 - val_loss: 1.1998 - val_acc: 0.4656
Epoch 43/80
10240/10240 [============== ] - 5s 448us/step - loss: 1.109
4 - acc: 0.5233 - val loss: 1.1734 - val acc: 0.4836
Epoch 44/80
0 - acc: 0.5247 - val_loss: 1.2025 - val_acc: 0.4754
Epoch 45/80
7 - acc: 0.5242 - val_loss: 1.1644 - val_acc: 0.4844
Epoch 46/80
5 - acc: 0.5239 - val_loss: 1.1682 - val_acc: 0.4855
Epoch 47/80
4 - acc: 0.5277 - val_loss: 1.1758 - val_acc: 0.4844
Epoch 48/80
10240/10240 [============= ] - 4s 428us/step - loss: 1.098
4 - acc: 0.5286 - val_loss: 1.2196 - val acc: 0.4703
Epoch 49/80
3 - acc: 0.5259 - val loss: 1.1618 - val acc: 0.4863
Epoch 50/80
6 - acc: 0.5237 - val_loss: 1.1642 - val_acc: 0.4832
1 - acc: 0.5266 - val_loss: 1.1886 - val_acc: 0.4832
Epoch 52/80
0 - acc: 0.5318 - val_loss: 1.1881 - val_acc: 0.4723
Epoch 53/80
2 - acc: 0.5307 - val_loss: 1.1769 - val_acc: 0.4879
6 - acc: 0.5305 - val_loss: 1.1675 - val_acc: 0.4852
Epoch 55/80
8 - acc: 0.5356 - val loss: 1.1906 - val acc: 0.4773
Epoch 56/80
6 - acc: 0.5303 - val_loss: 1.1764 - val_acc: 0.4906
Epoch 57/80
5 - acc: 0.5409 - val loss: 1.1765 - val acc: 0.4828
Epoch 58/80
2 - acc: 0.5326 - val loss: 1.1848 - val acc: 0.4758
Epoch 59/80
3 - acc: 0.5333 - val loss: 1.1695 - val acc: 0.4906
Epoch 60/80
3 - acc: 0.5355 - val loss: 1.1787 - val acc: 0.4820
Epoch 61/80
```

```
0 - acc: 0.5344 - val loss: 1.1651 - val acc: 0.4844
Epoch 62/80
0 - acc: 0.5390 - val loss: 1.1870 - val acc: 0.4867
Epoch 63/80
9 - acc: 0.5418 - val_loss: 1.1868 - val_acc: 0.4762
Epoch 64/80
6 - acc: 0.5326 - val_loss: 1.1660 - val_acc: 0.4898
Epoch 65/80
4 - acc: 0.5418 - val_loss: 1.1988 - val_acc: 0.4836
Epoch 66/80
5 - acc: 0.5319 - val_loss: 1.1820 - val_acc: 0.4859
Epoch 67/80
0 - acc: 0.5401 - val_loss: 1.1698 - val_acc: 0.4789
Epoch 68/80
2 - acc: 0.5418 - val_loss: 1.1786 - val_acc: 0.4773
Epoch 69/80
5 - acc: 0.5410 - val_loss: 1.1888 - val_acc: 0.4824
Epoch 70/80
8 - acc: 0.5433 - val_loss: 1.1748 - val_acc: 0.4875
Epoch 71/80
4 - acc: 0.5448 - val_loss: 1.1739 - val_acc: 0.4910
8 - acc: 0.5432 - val_loss: 1.1709 - val_acc: 0.4863
Epoch 73/80
0 - acc: 0.5411 - val_loss: 1.1716 - val_acc: 0.4906
Epoch 74/80
10240/10240 [============= ] - 4s 430us/step - loss: 1.071
7 - acc: 0.5404 - val_loss: 1.1839 - val_acc: 0.4797
Epoch 75/80
7 - acc: 0.5415 - val_loss: 1.1852 - val_acc: 0.4707
Epoch 76/80
5 - acc: 0.5483 - val loss: 1.1902 - val acc: 0.4816
Epoch 77/80
9 - acc: 0.5514 - val_loss: 1.1769 - val_acc: 0.4867
Epoch 78/80
2 - acc: 0.5486 - val loss: 1.1854 - val acc: 0.4855
Epoch 79/80
9 - acc: 0.5476 - val_loss: 1.1820 - val_acc: 0.4910
Epoch 80/80
10240/10240 [=============== ] - 4s 426us/step - loss: 1.067
9 - acc: 0.5450 - val_loss: 1.1815 - val_acc: 0.4816
1 6396
Train on 10240 samples, validate on 2560 samples
```

```
Epoch 1/80
1 - acc: 0.3713 - val loss: 1.2828 - val acc: 0.3922
Epoch 2/80
10240/10240 [============= ] - 5s 442us/step - loss: 1.226
9 - acc: 0.4474 - val_loss: 1.2215 - val_acc: 0.4621
10240/10240 [============== ] - 4s 436us/step - loss: 1.209
4 - acc: 0.4570 - val loss: 1.2172 - val acc: 0.4605
Epoch 4/80
3 - acc: 0.4729 - val_loss: 1.2048 - val_acc: 0.4613
Epoch 5/80
3 - acc: 0.4782 - val loss: 1.2405 - val acc: 0.4414
Epoch 6/80
1 - acc: 0.4809 - val_loss: 1.2179 - val_acc: 0.4555
Epoch 7/80
6 - acc: 0.4798 - val_loss: 1.2531 - val_acc: 0.4305
Epoch 8/80
10240/10240 [============= ] - 4s 423us/step - loss: 1.161
9 - acc: 0.4938 - val loss: 1.2072 - val acc: 0.4656
Epoch 9/80
4 - acc: 0.4970 - val loss: 1.2053 - val acc: 0.4680
Epoch 10/80
3 - acc: 0.4942 - val_loss: 1.1840 - val_acc: 0.4855
Epoch 11/80
9 - acc: 0.4971 - val_loss: 1.1834 - val_acc: 0.4707
Epoch 12/80
9 - acc: 0.5008 - val_loss: 1.1743 - val_acc: 0.4828
Epoch 13/80
1 - acc: 0.5011 - val_loss: 1.1988 - val_acc: 0.4664
9 - acc: 0.5069 - val_loss: 1.1867 - val_acc: 0.4734
Epoch 15/80
4 - acc: 0.5104 - val loss: 1.1718 - val acc: 0.4879
Epoch 16/80
8 - acc: 0.5099 - val_loss: 1.1871 - val_acc: 0.4836
Epoch 17/80
3 - acc: 0.5045 - val loss: 1.1693 - val acc: 0.4777
Epoch 18/80
9 - acc: 0.5164 - val loss: 1.2015 - val acc: 0.4676
Epoch 19/80
7 - acc: 0.5160 - val loss: 1.1886 - val acc: 0.4699
Epoch 20/80
3 - acc: 0.5200 - val loss: 1.1648 - val acc: 0.4926
Epoch 21/80
```

```
10240/10240 [============== ] - 4s 425us/step - loss: 1.112
7 - acc: 0.5141 - val_loss: 1.2114 - val_acc: 0.4746
Epoch 22/80
8 - acc: 0.5201 - val loss: 1.1624 - val acc: 0.4844
Epoch 23/80
0 - acc: 0.5222 - val_loss: 1.1938 - val_acc: 0.4809
Epoch 24/80
3 - acc: 0.5272 - val_loss: 1.1756 - val_acc: 0.4797
Epoch 25/80
7 - acc: 0.5259 - val_loss: 1.1707 - val_acc: 0.4859
Epoch 26/80
0 - acc: 0.5338 - val_loss: 1.1780 - val_acc: 0.4859
Epoch 27/80
6 - acc: 0.5274 - val_loss: 1.1767 - val_acc: 0.4785
Epoch 28/80
9 - acc: 0.5307 - val_loss: 1.1684 - val_acc: 0.4973
Epoch 29/80
2 - acc: 0.5328 - val_loss: 1.1701 - val_acc: 0.4832
Epoch 30/80
6 - acc: 0.5313 - val_loss: 1.1744 - val_acc: 0.4902
Epoch 31/80
10240/10240 [============== ] - 5s 449us/step - loss: 1.086
4 - acc: 0.5373 - val_loss: 1.1856 - val_acc: 0.4887
Epoch 32/80
10240/10240 [============= ] - 4s 421us/step - loss: 1.083
1 - acc: 0.5384 - val_loss: 1.1746 - val_acc: 0.4844
Epoch 33/80
10240/10240 [============== ] - 4s 423us/step - loss: 1.082
2 - acc: 0.5401 - val_loss: 1.1736 - val_acc: 0.4918
Epoch 34/80
7 - acc: 0.5416 - val_loss: 1.1831 - val_acc: 0.4891
Epoch 35/80
9 - acc: 0.5468 - val_loss: 1.1937 - val_acc: 0.4840
Epoch 36/80
4 - acc: 0.5460 - val loss: 1.1810 - val acc: 0.4883
Epoch 37/80
6 - acc: 0.5439 - val_loss: 1.1655 - val_acc: 0.4914
Epoch 38/80
8 - acc: 0.5428 - val loss: 1.1715 - val acc: 0.4887
Epoch 39/80
0 - acc: 0.5509 - val_loss: 1.1744 - val_acc: 0.4867
Epoch 40/80
3 - acc: 0.5492 - val_loss: 1.2104 - val_acc: 0.4672
Epoch 41/80
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3 - acc: 0.5498 - val_loss: 1.1776 - val_acc: 0.4852
Epoch 42/80
10240/10240 [============== ] - 5s 460us/step - loss: 1.061
6 - acc: 0.5525 - val loss: 1.1961 - val acc: 0.4785
Epoch 43/80
10240/10240 [============== ] - 5s 444us/step - loss: 1.059
9 - acc: 0.5568 - val_loss: 1.1831 - val_acc: 0.4887
Epoch 44/80
10240/10240 [============= ] - 4s 419us/step - loss: 1.055
4 - acc: 0.5547 - val_loss: 1.1762 - val_acc: 0.4879
Epoch 45/80
10240/10240 [============== ] - 4s 410us/step - loss: 1.058
2 - acc: 0.5542 - val_loss: 1.1946 - val_acc: 0.4832
Epoch 46/80
5 - acc: 0.5544 - val loss: 1.2043 - val acc: 0.4793
Epoch 47/80
6 - acc: 0.5600 - val_loss: 1.1839 - val_acc: 0.4938
Epoch 48/80
4 - acc: 0.5616 - val_loss: 1.2117 - val_acc: 0.4758
Epoch 49/80
10240/10240 [============== ] - 4s 413us/step - loss: 1.048
3 - acc: 0.5619 - val_loss: 1.1847 - val_acc: 0.4852
Epoch 50/80
1 - acc: 0.5645 - val_loss: 1.2154 - val_acc: 0.4770
Epoch 51/80
10240/10240 [============= ] - 4s 410us/step - loss: 1.047
1 - acc: 0.5626 - val_loss: 1.1833 - val_acc: 0.4855
Epoch 52/80
4 - acc: 0.5636 - val_loss: 1.1987 - val_acc: 0.4777
Epoch 53/80
6 - acc: 0.5643 - val_loss: 1.1843 - val_acc: 0.4852
Epoch 54/80
10240/10240 [============== ] - 4s 412us/step - loss: 1.044
1 - acc: 0.5677 - val_loss: 1.1994 - val_acc: 0.4898
Epoch 55/80
9 - acc: 0.5639 - val_loss: 1.1971 - val_acc: 0.4820
Epoch 56/80
6 - acc: 0.5667 - val loss: 1.1845 - val acc: 0.4840
1 - acc: 0.5668 - val_loss: 1.1852 - val_acc: 0.4809
Epoch 58/80
1 - acc: 0.5716 - val_loss: 1.2057 - val_acc: 0.4887
Epoch 59/80
9 - acc: 0.5709 - val_loss: 1.2246 - val_acc: 0.4754
Epoch 60/80
9 - acc: 0.5753 - val loss: 1.1899 - val acc: 0.4867
Epoch 61/80
5 - acc: 0.5691 - val_loss: 1.2100 - val_acc: 0.4738
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Epoch 62/80
7 - acc: 0.5714 - val loss: 1.2158 - val acc: 0.4742
Epoch 63/80
8 - acc: 0.5752 - val_loss: 1.2046 - val_acc: 0.4848
Epoch 64/80
3 - acc: 0.5756 - val loss: 1.2096 - val acc: 0.4711
Epoch 65/80
10240/10240 [============= ] - 4s 424us/step - loss: 1.024
6 - acc: 0.5748 - val_loss: 1.1967 - val_acc: 0.4875
Epoch 66/80
8 - acc: 0.5773 - val_loss: 1.1910 - val_acc: 0.4875
Epoch 67/80
2 - acc: 0.5792 - val_loss: 1.2057 - val_acc: 0.4898
Epoch 68/80
0 - acc: 0.5763 - val_loss: 1.2613 - val_acc: 0.4652
Epoch 69/80
10240/10240 [============= ] - 4s 413us/step - loss: 1.018
1 - acc: 0.5760 - val_loss: 1.2042 - val_acc: 0.4820
Epoch 70/80
3 - acc: 0.5813 - val loss: 1.2254 - val acc: 0.4777
Epoch 71/80
0 - acc: 0.5822 - val_loss: 1.2229 - val_acc: 0.4793
9 - acc: 0.5829 - val_loss: 1.2033 - val_acc: 0.4844
Epoch 73/80
7 - acc: 0.5798 - val_loss: 1.2088 - val_acc: 0.4828
Epoch 74/80
10240/10240 [============= ] - 4s 412us/step - loss: 1.011
0 - acc: 0.5800 - val_loss: 1.2045 - val_acc: 0.4867
Epoch 75/80
6 - acc: 0.5882 - val_loss: 1.2058 - val_acc: 0.4813
Epoch 76/80
2 - acc: 0.5851 - val loss: 1.2150 - val acc: 0.4770
Epoch 77/80
1 - acc: 0.5839 - val_loss: 1.2123 - val_acc: 0.4891
Epoch 78/80
2 - acc: 0.5864 - val_loss: 1.2169 - val_acc: 0.4844
Epoch 79/80
7 - acc: 0.5880 - val_loss: 1.2126 - val_acc: 0.4832
Epoch 80/80
10240/10240 [============== ] - 4s 424us/step - loss: 1.007
1 - acc: 0.5890 - val loss: 1.2232 - val acc: 0.4797
2 6396
Train on 10240 samples, validate on 2560 samples
Epoch 1/80
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5 - acc: 0.3607 - val_loss: 1.2777 - val_acc: 0.4121
Epoch 2/80
10240/10240 [============== ] - 4s 417us/step - loss: 1.238
3 - acc: 0.4383 - val loss: 1.2324 - val acc: 0.4465
10240/10240 [============== ] - 5s 441us/step - loss: 1.210
6 - acc: 0.4576 - val_loss: 1.2159 - val_acc: 0.4543
Epoch 4/80
10240/10240 [============= ] - 4s 417us/step - loss: 1.197
5 - acc: 0.4754 - val_loss: 1.2500 - val_acc: 0.4559
Epoch 5/80
10240/10240 [============== ] - 4s 423us/step - loss: 1.189
6 - acc: 0.4724 - val_loss: 1.2193 - val_acc: 0.4484
Epoch 6/80
0 - acc: 0.4752 - val loss: 1.2262 - val acc: 0.4492
Epoch 7/80
10240/10240 [=============] - 4s 430us/step - loss: 1.183
9 - acc: 0.4797 - val_loss: 1.2103 - val_acc: 0.4551
Epoch 8/80
10240/10240 [============== ] - 4s 420us/step - loss: 1.174
8 - acc: 0.4929 - val_loss: 1.2135 - val_acc: 0.4551
Epoch 9/80
1 - acc: 0.4885 - val_loss: 1.2322 - val_acc: 0.4586
Epoch 10/80
10240/10240 [============== ] - 5s 439us/step - loss: 1.173
5 - acc: 0.4887 - val_loss: 1.2012 - val_acc: 0.4734
Epoch 11/80
10240/10240 [============== ] - 4s 418us/step - loss: 1.164
3 - acc: 0.4870 - val_loss: 1.1900 - val_acc: 0.4738
Epoch 12/80
8 - acc: 0.4905 - val_loss: 1.1945 - val_acc: 0.4609
Epoch 13/80
1 - acc: 0.4938 - val_loss: 1.1940 - val_acc: 0.4664
Epoch 14/80
2 - acc: 0.4956 - val_loss: 1.1916 - val_acc: 0.4727
Epoch 15/80
3 - acc: 0.5006 - val_loss: 1.1977 - val_acc: 0.4746
Epoch 16/80
7 - acc: 0.5053 - val loss: 1.1809 - val acc: 0.4805
6 - acc: 0.5078 - val_loss: 1.1777 - val_acc: 0.4789
Epoch 18/80
0 - acc: 0.5079 - val_loss: 1.1737 - val_acc: 0.4820
Epoch 19/80
4 - acc: 0.5099 - val_loss: 1.1825 - val_acc: 0.4797
Epoch 20/80
7 - acc: 0.5112 - val loss: 1.1893 - val acc: 0.4820
Epoch 21/80
6 - acc: 0.5131 - val_loss: 1.1814 - val_acc: 0.4766
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Epoch 22/80
3 - acc: 0.5146 - val loss: 1.1689 - val acc: 0.4746
Epoch 23/80
1 - acc: 0.5153 - val_loss: 1.1887 - val_acc: 0.4785
10240/10240 [============== ] - 4s 415us/step - loss: 1.123
7 - acc: 0.5106 - val loss: 1.1855 - val acc: 0.4727
Epoch 25/80
4 - acc: 0.5203 - val_loss: 1.1900 - val_acc: 0.4727
Epoch 26/80
9 - acc: 0.5233 - val_loss: 1.1767 - val_acc: 0.4797
Epoch 27/80
4 - acc: 0.5213 - val_loss: 1.1690 - val_acc: 0.4770
Epoch 28/80
10240/10240 [============= ] - 4s 417us/step - loss: 1.109
7 - acc: 0.5256 - val_loss: 1.1801 - val_acc: 0.4809
Epoch 29/80
1 - acc: 0.5177 - val loss: 1.1714 - val acc: 0.4770
Epoch 30/80
6 - acc: 0.5256 - val loss: 1.1976 - val acc: 0.4805
Epoch 31/80
4 - acc: 0.5239 - val_loss: 1.1885 - val_acc: 0.4770
0 - acc: 0.5299 - val_loss: 1.1987 - val_acc: 0.4719
Epoch 33/80
3 - acc: 0.5248 - val_loss: 1.1989 - val_acc: 0.4680
Epoch 34/80
10240/10240 [============== ] - 4s 415us/step - loss: 1.098
6 - acc: 0.5307 - val_loss: 1.1761 - val_acc: 0.4813
9 - acc: 0.5321 - val_loss: 1.1758 - val_acc: 0.4805
Epoch 36/80
5 - acc: 0.5301 - val loss: 1.1754 - val acc: 0.4809
Epoch 37/80
9 - acc: 0.5396 - val_loss: 1.1695 - val_acc: 0.4922
Epoch 38/80
2 - acc: 0.5380 - val loss: 1.1792 - val acc: 0.4848
Epoch 39/80
2 - acc: 0.5326 - val loss: 1.1675 - val acc: 0.4961
Epoch 40/80
0 - acc: 0.5387 - val loss: 1.1873 - val acc: 0.4793
Epoch 41/80
8 - acc: 0.5422 - val loss: 1.1646 - val acc: 0.4801
Epoch 42/80
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10240/10240 [============== ] - 4s 415us/step - loss: 1.086
6 - acc: 0.5392 - val_loss: 1.1805 - val_acc: 0.4813
Epoch 43/80
4 - acc: 0.5425 - val loss: 1.1711 - val acc: 0.4797
Epoch 44/80
6 - acc: 0.5450 - val_loss: 1.1697 - val_acc: 0.4867
Epoch 45/80
2 - acc: 0.5467 - val_loss: 1.1642 - val_acc: 0.4887
Epoch 46/80
1 - acc: 0.5432 - val_loss: 1.1757 - val_acc: 0.4945
Epoch 47/80
2 - acc: 0.5487 - val_loss: 1.1654 - val_acc: 0.4902
Epoch 48/80
8 - acc: 0.5519 - val_loss: 1.1751 - val_acc: 0.4859
Epoch 49/80
7 - acc: 0.5513 - val_loss: 1.1712 - val_acc: 0.4906
Epoch 50/80
9 - acc: 0.5523 - val_loss: 1.1777 - val_acc: 0.4789
Epoch 51/80
5 - acc: 0.5514 - val_loss: 1.1697 - val_acc: 0.4848
Epoch 52/80
10240/10240 [=============== ] - 5s 441us/step - loss: 1.059
2 - acc: 0.5528 - val_loss: 1.1711 - val_acc: 0.4820
10240/10240 [============= ] - 4s 433us/step - loss: 1.059
1 - acc: 0.5535 - val_loss: 1.1874 - val_acc: 0.4871
Epoch 54/80
10240/10240 [============== ] - 5s 452us/step - loss: 1.058
8 - acc: 0.5539 - val_loss: 1.1874 - val_acc: 0.4809
Epoch 55/80
6 - acc: 0.5544 - val_loss: 1.1933 - val_acc: 0.4762
Epoch 56/80
9 - acc: 0.5630 - val_loss: 1.1933 - val_acc: 0.4836
Epoch 57/80
3 - acc: 0.5600 - val loss: 1.1723 - val acc: 0.4844
Epoch 58/80
4 - acc: 0.5645 - val_loss: 1.1890 - val_acc: 0.4793
Epoch 59/80
6 - acc: 0.5620 - val_loss: 1.1815 - val_acc: 0.4875
Epoch 60/80
2 - acc: 0.5650 - val_loss: 1.1854 - val_acc: 0.4836
Epoch 61/80
2 - acc: 0.5689 - val_loss: 1.1773 - val_acc: 0.4977
Epoch 62/80
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0 - acc: 0.5682 - val_loss: 1.1794 - val_acc: 0.4898
Epoch 63/80
10240/10240 [============= ] - 4s 431us/step - loss: 1.039
7 - acc: 0.5651 - val loss: 1.1861 - val acc: 0.4852
Epoch 64/80
6 - acc: 0.5715 - val_loss: 1.1828 - val_acc: 0.4848
Epoch 65/80
6 - acc: 0.5717 - val_loss: 1.1859 - val_acc: 0.4820
Epoch 66/80
10240/10240 [============= ] - 4s 435us/step - loss: 1.035
5 - acc: 0.5716 - val_loss: 1.1802 - val_acc: 0.4918
Epoch 67/80
6 - acc: 0.5767 - val loss: 1.2002 - val acc: 0.4809
Epoch 68/80
10240/10240 [==============] - 5s 454us/step - loss: 1.032
2 - acc: 0.5711 - val_loss: 1.1934 - val_acc: 0.4910
Epoch 69/80
2 - acc: 0.5745 - val_loss: 1.1871 - val_acc: 0.4914
Epoch 70/80
2 - acc: 0.5782 - val_loss: 1.1841 - val_acc: 0.4836
Epoch 71/80
8 - acc: 0.5742 - val_loss: 1.2052 - val_acc: 0.4875
Epoch 72/80
10240/10240 [============= ] - 5s 451us/step - loss: 1.025
7 - acc: 0.5745 - val_loss: 1.1868 - val acc: 0.4918
Epoch 73/80
9 - acc: 0.5769 - val_loss: 1.1855 - val_acc: 0.4840
Epoch 74/80
2 - acc: 0.5768 - val_loss: 1.1824 - val_acc: 0.4926
Epoch 75/80
10240/10240 [============== ] - 4s 436us/step - loss: 1.025
2 - acc: 0.5759 - val_loss: 1.1926 - val_acc: 0.4852
Epoch 76/80
4 - acc: 0.5793 - val_loss: 1.1999 - val_acc: 0.4801
Epoch 77/80
9 - acc: 0.5797 - val loss: 1.2022 - val acc: 0.4848
9 - acc: 0.5810 - val loss: 1.1850 - val acc: 0.4891
Epoch 79/80
1 - acc: 0.5820 - val loss: 1.2168 - val acc: 0.4797
Epoch 80/80
7 - acc: 0.5837 - val_loss: 1.2359 - val_acc: 0.4742
3 6396
Train on 10240 samples, validate on 2560 samples
Epoch 1/80
9 - acc: 0.3711 - val loss: 1.2470 - val acc: 0.4371
Epoch 2/80
```

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10240/10240 [============== ] - 5s 458us/step - loss: 1.236
9 - acc: 0.4510 - val_loss: 1.2437 - val_acc: 0.4398
0 - acc: 0.4647 - val loss: 1.2245 - val acc: 0.4508
Epoch 4/80
3 - acc: 0.4707 - val_loss: 1.2614 - val_acc: 0.4117
Epoch 5/80
7 - acc: 0.4775 - val_loss: 1.2296 - val_acc: 0.4523
Epoch 6/80
6 - acc: 0.4787 - val_loss: 1.1977 - val_acc: 0.4746
Epoch 7/80
3 - acc: 0.4781 - val_loss: 1.2070 - val_acc: 0.4535
Epoch 8/80
9 - acc: 0.4859 - val_loss: 1.2196 - val_acc: 0.4594
Epoch 9/80
7 - acc: 0.4875 - val_loss: 1.2037 - val_acc: 0.4559
Epoch 10/80
5 - acc: 0.4931 - val_loss: 1.1809 - val_acc: 0.4801
Epoch 11/80
4 - acc: 0.4898 - val_loss: 1.1854 - val_acc: 0.472388 - acc: 0.4
Epoch 12/80
3 - acc: 0.5008 - val_loss: 1.1909 - val_acc: 0.4711
10240/10240 [============= ] - 5s 491us/step - loss: 1.152
3 - acc: 0.4990 - val_loss: 1.1772 - val_acc: 0.4840
Epoch 14/80
10240/10240 [============== ] - 5s 454us/step - loss: 1.149
4 - acc: 0.5021 - val_loss: 1.2001 - val_acc: 0.4680
Epoch 15/80
1 - acc: 0.4986 - val_loss: 1.1944 - val_acc: 0.4727
Epoch 16/80
2 - acc: 0.5078 - val_loss: 1.1975 - val_acc: 0.4773
Epoch 17/80
6 - acc: 0.5101 - val loss: 1.2033 - val acc: 0.4668
Epoch 18/80
8 - acc: 0.5060 - val_loss: 1.2065 - val_acc: 0.4734
Epoch 19/80
9 - acc: 0.5122 - val loss: 1.2111 - val acc: 0.4656
Epoch 20/80
4 - acc: 0.5160 - val_loss: 1.1710 - val_acc: 0.4715
Epoch 21/80
5 - acc: 0.5188 - val_loss: 1.1772 - val_acc: 0.4773
Epoch 22/80
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7 - acc: 0.5160 - val_loss: 1.1951 - val_acc: 0.4695
Epoch 23/80
10240/10240 [============== ] - 5s 475us/step - loss: 1.124
1 - acc: 0.5136 - val loss: 1.2355 - val acc: 0.4539
Epoch 24/80
9 - acc: 0.5121 - val_loss: 1.2158 - val_acc: 0.4535
Epoch 25/80
10240/10240 [============== ] - 5s 451us/step - loss: 1.112
0 - acc: 0.5222 - val_loss: 1.1791 - val_acc: 0.4785
Epoch 26/80
10240/10240 [============== ] - 5s 473us/step - loss: 1.114
7 - acc: 0.5221 - val_loss: 1.1712 - val_acc: 0.4887
Epoch 27/80
0 - acc: 0.5230 - val loss: 1.1887 - val acc: 0.4789
Epoch 28/80
10240/10240 [=============] - 5s 454us/step - loss: 1.113
3 - acc: 0.5206 - val_loss: 1.2175 - val_acc: 0.4727
Epoch 29/80
3 - acc: 0.5248 - val_loss: 1.1846 - val_acc: 0.4750
Epoch 30/80
10240/10240 [============== ] - 5s 473us/step - loss: 1.110
4 - acc: 0.5173 - val_loss: 1.2130 - val_acc: 0.4738
Epoch 31/80
10240/10240 [============= ] - 5s 451us/step - loss: 1.102
3 - acc: 0.5324 - val_loss: 1.1726 - val_acc: 0.4813
Epoch 32/80
10240/10240 [============== ] - 5s 469us/step - loss: 1.101
4 - acc: 0.5303 - val_loss: 1.2153 - val_acc: 0.4652
Epoch 33/80
0 - acc: 0.5327 - val_loss: 1.1677 - val_acc: 0.4828
Epoch 34/80
6 - acc: 0.5333 - val_loss: 1.1849 - val_acc: 0.4758
Epoch 35/80
10240/10240 [============== ] - 5s 454us/step - loss: 1.090
3 - acc: 0.5383 - val_loss: 1.1882 - val_acc: 0.4770
Epoch 36/80
0 - acc: 0.5372 - val_loss: 1.1764 - val_acc: 0.4766
Epoch 37/80
2 - acc: 0.5330 - val loss: 1.1775 - val acc: 0.4859
6 - acc: 0.5344 - val_loss: 1.1870 - val_acc: 0.4719
Epoch 39/80
2 - acc: 0.5356 - val_loss: 1.1886 - val_acc: 0.4828
Epoch 40/80
7 - acc: 0.5398 - val_loss: 1.1727 - val_acc: 0.4887
Epoch 41/80
0 - acc: 0.5422 - val loss: 1.1878 - val acc: 0.4777
Epoch 42/80
8 - acc: 0.5433 - val_loss: 1.1735 - val_acc: 0.4871
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Epoch 43/80
5 - acc: 0.5408 - val loss: 1.1796 - val acc: 0.4832
Epoch 44/80
2 - acc: 0.5434 - val_loss: 1.2104 - val_acc: 0.4758
Epoch 45/80
10240/10240 [============== ] - 5s 456us/step - loss: 1.078
4 - acc: 0.5429 - val loss: 1.1822 - val acc: 0.4695
Epoch 46/80
1 - acc: 0.5483 - val_loss: 1.1937 - val_acc: 0.4785
Epoch 47/80
4 - acc: 0.5420 - val_loss: 1.1876 - val_acc: 0.4828
Epoch 48/80
9 - acc: 0.5457 - val_loss: 1.2113 - val_acc: 0.4629
Epoch 49/80
5 - acc: 0.5479 - val_loss: 1.1734 - val_acc: 0.4859
Epoch 50/80
10240/10240 [============= ] - 5s 478us/step - loss: 1.070
8 - acc: 0.5483 - val loss: 1.1688 - val acc: 0.4867
Epoch 51/80
5 - acc: 0.5516 - val loss: 1.1822 - val acc: 0.4832
Epoch 52/80
3 - acc: 0.5487 - val_loss: 1.1701 - val_acc: 0.4918
7 - acc: 0.5494 - val_loss: 1.1867 - val_acc: 0.4801
Epoch 54/80
4 - acc: 0.5560 - val_loss: 1.1754 - val_acc: 0.4875
Epoch 55/80
8 - acc: 0.5539 - val_loss: 1.1753 - val_acc: 0.4820
0 - acc: 0.5553 - val_loss: 1.1850 - val_acc: 0.4832- loss: 1.0602
Epoch 57/80
3 - acc: 0.5563 - val loss: 1.1938 - val acc: 0.4832
Epoch 58/80
8 - acc: 0.5488 - val_loss: 1.2381 - val_acc: 0.4727
Epoch 59/80
3 - acc: 0.5582 - val loss: 1.1804 - val acc: 0.4887
Epoch 60/80
2 - acc: 0.5610 - val loss: 1.2688 - val acc: 0.4590
Epoch 61/80
1 - acc: 0.5600 - val loss: 1.1988 - val acc: 0.4832
Epoch 62/80
5 - acc: 0.5607 - val loss: 1.2176 - val acc: 0.4680
Epoch 63/80
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7 - acc: 0.5604 - val loss: 1.1700 - val acc: 0.4879
Epoch 64/80
1 - acc: 0.5519 - val loss: 1.2035 - val acc: 0.4832
Epoch 65/80
1 - acc: 0.5605 - val_loss: 1.2123 - val_acc: 0.4711
Epoch 66/80
0 - acc: 0.5642 - val_loss: 1.1850 - val_acc: 0.4844
Epoch 67/80
6 - acc: 0.5588 - val_loss: 1.1961 - val_acc: 0.4820
Epoch 68/80
0 - acc: 0.5632 - val loss: 1.1887 - val acc: 0.4922
Epoch 69/80
6 - acc: 0.5653 - val_loss: 1.1817 - val_acc: 0.4922
Epoch 70/80
2 - acc: 0.5611 - val_loss: 1.1829 - val_acc: 0.4938
Epoch 71/80
5 - acc: 0.5632 - val_loss: 1.1831 - val_acc: 0.4891
Epoch 72/80
9 - acc: 0.5698 - val_loss: 1.1879 - val_acc: 0.4816
Epoch 73/80
2 - acc: 0.5699 - val_loss: 1.1978 - val_acc: 0.4855
9 - acc: 0.5667 - val loss: 1.2100 - val acc: 0.4789
Epoch 75/80
9 - acc: 0.5720 - val_loss: 1.1932 - val_acc: 0.4922
Epoch 76/80
10240/10240 [============= ] - 5s 456us/step - loss: 1.033
8 - acc: 0.5687 - val_loss: 1.2150 - val_acc: 0.4820
Epoch 77/80
1 - acc: 0.5719 - val_loss: 1.1890 - val_acc: 0.4934
Epoch 78/80
6 - acc: 0.5626 - val loss: 1.2119 - val acc: 0.4793
Epoch 79/80
3 - acc: 0.5713 - val_loss: 1.2015 - val_acc: 0.4738
Epoch 80/80
4 - acc: 0.5666 - val loss: 1.2215 - val acc: 0.4680
```

In [61]:

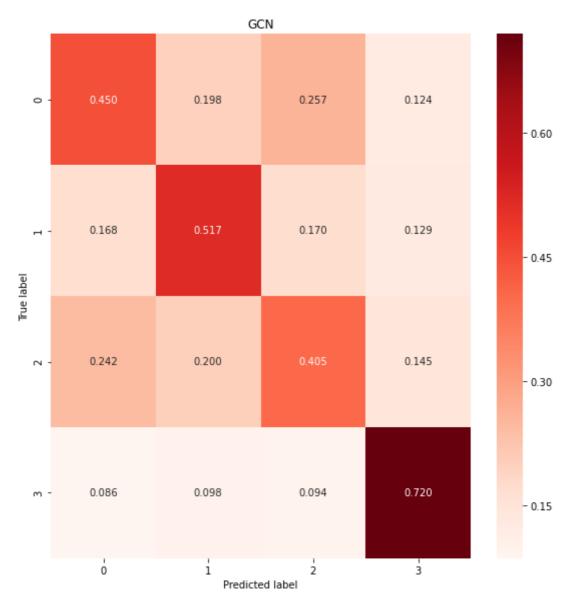
```
2560/2560 [=========== ] - 0s 148us/step
Emotion angry
Test loss: 1.1814735934138298
Test acc: 0.481640625
2560/2560 [=========== ] - 0s 145us/step
Emotion happy
Test loss: 1.2232192665338517
Test acc: 0.4796875
2560/2560 [=========== ] - Os 141us/step
Emotion sad
Test loss: 1.2358716316521168
Test acc: 0.47421875
2560/2560 [=========== ] - 0s 145us/step
Emotion surprise
Test loss: 1.2215377621352672
Test acc: 0.46796875
```

In [62]:

```
def plot confusion matrix(cm, classes=list(range(num labels))):
    cm_df = pd.DataFrame(cm, index=classes, columns=classes)
    fig, ax = plt.subplots(figsize=(8, 8))
    ax = sns.heatmap(cm_df,
                     fmt='.3f',
                     annot=True, cmap='Reds', ax=ax)
    ax.set_ylabel('True label')
    ax.set_xlabel('Predicted label')
    fig.tight_layout()
    return fig
y_test_preds = model_full_grid.predict(X_test)
print(y_test_preds.shape)
cm = metrics.confusion_matrix(y_test, np.argmax(y_test_preds, axis=1))
fig = plot_confusion_matrix(cm/cm.sum(axis=1))
fig.get_axes()[0].set_title('GCN');
for i in range(0,num_labels):
    print("Emotion mapping {} : {} ".format(i,train_labels[i]))
```

(2560, 10)

Emotion mapping 0 : angry
Emotion mapping 1 : happy
Emotion mapping 2 : sad
Emotion mapping 3 : surprise

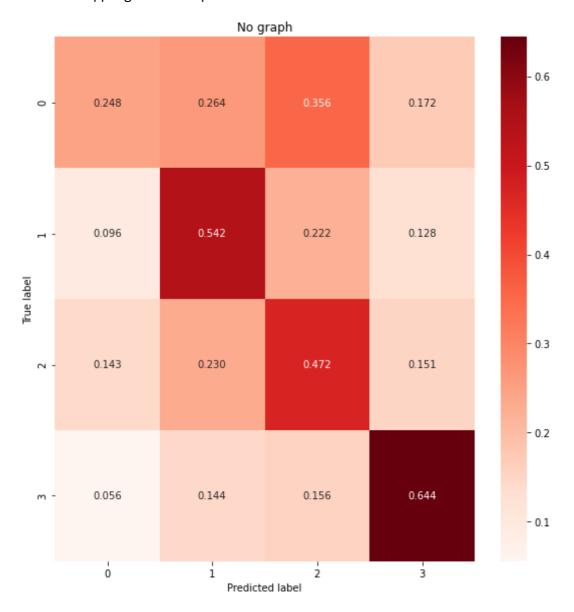


In [63]:

```
y_test_preds = model_no_graph.predict(X_test)
print(y_test_preds.shape)
cm = metrics.confusion_matrix(y_test, np.argmax(y_test_preds, axis=1))
fig = plot_confusion_matrix(cm/cm.sum(axis=1))
fig.get_axes()[0].set_title('No graph');
for i in range(0,num_labels):
    print("Emotion mapping {} : {} ".format(i,train_labels[i]))
```

(2560, 10)

Emotion mapping 0 : angry
Emotion mapping 1 : happy
Emotion mapping 2 : sad
Emotion mapping 3 : surprise



```
In [64]:
```

```
acc_df = {}
for model_name, model in d_emotion_models.items():

    y_test_preds = model.predict(X_test)
    cm = metrics.confusion_matrix(y_test, np.argmax(y_test_preds, axis=1))

    acc_per_classes = np.diag(cm/cm.sum(axis=1))

acc_df[model_name] = acc_per_classes
```

Finding the distribution

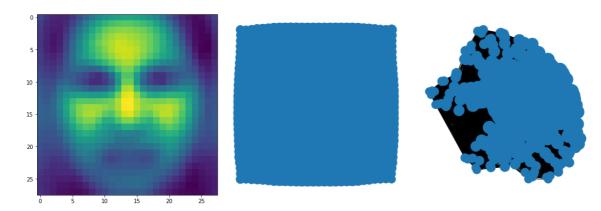
In [65]:

```
d_emotion_corr_graphs = {}
for i in range(num_labels):
    mask = y_train == i
    dist = metrics.pairwise_distances(X_train[mask].reshape(-1, 784).T, metric='cosine'
, n_jobs=-2)
    W = sp.coo_matrix(1 - dist, dtype=np.float32)
    # No self-connections.
   W.setdiag(0)
    # Non-directed graph.
    bigger = W.T > W
    W = W - W.multiply(bigger) + W.T.multiply(bigger)
    assert W.nnz % 2 == 0
    assert np.abs(W - W.T).mean() < 1e-10</pre>
    assert type(W) is sp.csr.csr_matrix
    fig, axes = plt.subplots(figsize=(15, 5), ncols=3)
    x_train_i_avg = X_train[mask].mean(axis=0).flatten()
    axes[0].imshow(x_train_i_avg.reshape(28, 28))
    # thresholding
    W = W.multiply(W > 0.8)
    d_emotion_corr_graphs[i] = W
    axes[1] = create_graph(W, ax=axes[1], size_factor=1)
    axes[2] = create_graph(W, ax=axes[2], size_factor=1, spring_layout=True)
    fig.tight_layout()
    plt.show()
```

Number of nodes: 784; Number of edges: 250706 Number of nodes: 784; Number of edges: 250706

After removing nodes without edges:

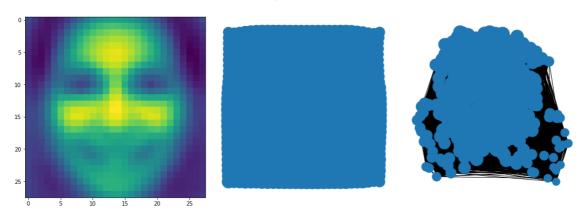
Number of nodes: 784; Number of edges: 250706



Number of nodes: 784; Number of edges: 267144 Number of nodes: 784; Number of edges: 267144

After removing nodes without edges:

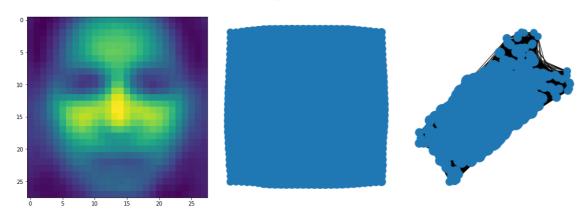
Number of nodes: 784; Number of edges: 267144



Number of nodes: 784; Number of edges: 242263 Number of nodes: 784; Number of edges: 242263

After removing nodes without edges:

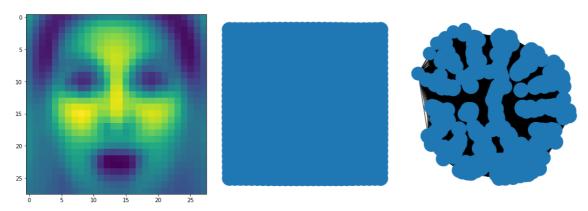
Number of nodes: 784; Number of edges: 242263



Number of nodes: 784; Number of edges: 300470 Number of nodes: 784; Number of edges: 300470

After removing nodes without edges:

Number of nodes: 784; Number of edges: 300470



In [66]:

```
fig, axes = plt.subplots(figsize=(20, 6), nrows=3, ncols=num_labels)
for i in range(num_labels):
    mask = y_train == i
    x_train_i_avg = X_train[mask].mean(axis=0).flatten()
    axes[0, i].imshow(x_train_i_avg.reshape(28, 28))
    axes[0, i].axis('off')
    axes[1, i] = create_graph(d_emotion_graphs[i], ax=axes[1, i], size_factor=0.2)
    axes[2, i] = create_graph(d_emotion_corr_graphs[i], ax=axes[2, i], size_factor=0.2)
fig.tight_layout()
fig.subplots_adjust(wspace=0, hspace=0)
Number of nodes: 784; Number of edges: 3198
Number of nodes: 784; Number of edges: 250706
Number of nodes: 784; Number of edges: 3198
Number of nodes: 784; Number of edges: 267144
Number of nodes: 784; Number of edges: 3198
Number of nodes: 784; Number of edges: 242263
Number of nodes: 784; Number of edges: 3198
Number of nodes: 784; Number of edges: 300470
```

In [67]:

```
y_test_preds = model_full_grid.predict(X_test)
cm = metrics.confusion_matrix(y_test, np.argmax(y_test_preds, axis=1))
acc_per_class_full_model = np.diag(cm/cm.sum(axis=1))
acc_per_class_full_model
for i in range(0,num_labels):
    print("Emotion efficency : {} :{} ".format(train_labels[i],acc_per_class_full_model
[i]))
```

Emotion efficency : angry :0.4496240601503759

Emotion efficency: happy:0.5168

Emotion efficency : sad :0.4047244094488189 Emotion efficency : surprise :0.7196850393700788

In []: