Load Required Packages

In [55]:
```
import os,sys
import pandas as pd
import scipy.io
import numpy as np
from scipy.spatial.distance import pdist
import time
import math
import keras
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from sklearn import ensemble
from sklearn.metrics import accuracy_score, make_scorer, classification_report
from statistics import mean
from sklearn.ensemble import GradientBoostingClassifier
import PIL
from PIL import Image
from scipy.io import loadmat
from sklearn.model_selection import train_test_split, cross_validate,GridSearc
hCV
from keras.layers import Dense, Activation, Flatten, Input, Dropout
from keras.layers import BatchNormalization
from keras.models import Model
from keras import initializers
from keras.optimizers import Adam
from keras.utils import to_categorical
```

Part I Baseline Model: GBM

1. Provide directories for training/testing images.

In [56]:
```
root = sys.path[0]
train_dir =  os.path.join(root,  '../data/train_set')
train_image_dir =  os.path.join(train_dir, 'images')
train_pt_dir =  os.path.join(train_dir, 'points' )
train_label_path =  os.path.join(train_dir,  "label.csv")
```

2. Train/Test Split Feature Extraction

In [57]:
```
info = pd.read_csv(train_label_path)
# read mat file and store coordinates in mat
m = []
for idx in info['Index']:
    file = "%04d.mat"%(idx)
    m.append( scipy.io.loadmat( os.path.join( train_pt_dir, file ) ))

mat = [x[[i for i in x.keys() if not i in ['__header__', '__version__', '__globals__']][0]] for x in m]
c = np.array([pdist(x) for x in mat[0:]])
```

In [58]:
```
train_idx, test_idx = train_test_split(info['Index'], test_size=0.2, random_state=123)
```

In [62]:
```
start_time_test=time.time()
train_features=np.array([pdist(mat[i-1]) for i in train_idx ])
print("baseline train features extracting takes %s seconds" % round((time.time() - start_time_test),3))
start_time_train=time.time()
test_features=np.array(([pdist(mat[i-1]) for i in test_idx ]))
print("base line test features extracting takes %s seconds" % round((time.time() - start_time_train),3))
train_labels=info.emotion_idx[train_idx-1]
test_labels=info.emotion_idx[test_idx-1]
print(train_features.shape,train_labels.shape)
```

```
baseline train features extracting takes 0.093 seconds
base line test features extracting takes 0.021 seconds
(2000, 3003) (2000,)
```

3. Train a Baseline GBM model with training features and responses

In [63]:
```
#baseline GBM

baseline = GradientBoostingClassifier(learning_rate=0.1, n_estimators=100,max_
depth=3, min_samples_split=2, min_samples_leaf=1, subsample=1,max_features='sq
rt', random_state=10)
start_time=time.time()
baseline.fit(train_features, train_labels)
print("training  model takes %s seconds" % round((time.time() - start_time),3
))
predictors=list(train_features)


print('Accuracy of the GBM on test set: {:.3f}'.format(baseline.score(test_fea
tures,test_labels)))
start_time1 = time.time()
pred=baseline.predict(test_features)
print("testing model takes %s seconds" % round((time.time() - start_time1),3))
print(classification_report(test_labels, pred))
```

```
training  model takes 66.134 seconds
Accuracy of the GBM on test set: 0.440
testing model takes 0.044 seconds
              precision    recall  f1-score   support

           1       0.50      0.56      0.53        18
           2       0.65      0.68      0.67        19
           3       0.40      0.56      0.47        25
           4       0.50      0.52      0.51        21
           5       0.58      0.61      0.59        18
           6       0.63      0.46      0.53        26
           7       0.40      0.50      0.44        20
           8       0.73      0.69      0.71        16
           9       0.78      0.56      0.65        25
          10       0.45      0.45      0.45        20
          11       0.41      0.50      0.45        24
          12       0.44      0.25      0.32        32
          13       0.12      0.17      0.14        24
          14       0.54      0.57      0.55        23
          15       0.59      0.45      0.51        22
          16       0.73      0.73      0.73        22
          17       0.37      0.42      0.39        26
          18       0.31      0.23      0.26        22
          19       0.23      0.22      0.22        23
          20       0.17      0.30      0.21        20
          21       0.46      0.32      0.38        34
          22       0.25      0.20      0.22        20

    accuracy                           0.44       500
   macro avg       0.47      0.45      0.45       500
weighted avg       0.46      0.44      0.44       500
```

4. Parameter tuning

4.1 parameter tuning Learning_rate,n_estimator

In [9]:
```
#parameter tuning Learning_rate,n_estimator
#p_test3 = {'learning_rate':[0.1,0.05], 'n_estimators':[50,100,250,500,750,100
0,1250,1500,1750]}

#tuning = GridSearchCV(estimator =GradientBoostingClassifier(max_depth=4, min_
samples_split=2, min_samples_leaf=1, subsample=1,max_features='sqrt', random_s
tate=10),
#                param_grid = p_test3, scoring='accuracy',n_jobs=4,iid=False,
 cv=5)
#tuning.fit(train_features,train_labels)
#tuning.cv_results_, tuning.best_params_, tuning.best_score_
```

4.2 Tuning Max_depth, Min_samples_split

In [10]:
```
#param_test2 = {'max_depth':range(1,16,2), 'min_samples_split':range(2,102,2
0)}
#tuning2 = GridSearchCV(estimator = GradientBoostingClassifier(learning_rate=
0.05, n_estimators=500, max_features='sqrt', subsample=1, random_state=10),
#param_grid = param_test2, scoring='accuracy',n_jobs=4,iid=False, cv=5)
#tuning2.fit(train_features,train_labels)
#tuning2.cv_results_, tuning2.best_params_, tuning2.best_score_
```

4.3 Parameter Tuning:min_samples_split,min_samples_leaf

In [11]:
```
#param_test3 = {'min_samples_split':range(2,102,20), 'min_samples_leaf':range
(30,71,10)}
#tuning3 = GridSearchCV(estimator = GradientBoostingClassifier(learning_rate=
0.05, n_estimators=500,max_depth=5,min_samples_split=62,max_features='sqrt', s
ubsample=1, random_state=10),
#param_grid = param_test3,scoring='accuracy',n_jobs=4,iid=False, cv=5)
#tuning3.fit(train_features, train_labels)
#tuning3.cv_results_, tuning3.best_params_, tuning3.best_score_
```

4.4 Parameter Tuning Max_features

In [12]:
```
#param_test4 = {'max_features':range(7,20,2)}
#tuning4 = GridSearchCV(estimator = GradientBoostingClassifier(learning_rate=
0.05, n_estimators=500,max_depth=5, min_samples_split=62, min_samples_leaf=30,
subsample=0.8, random_state=10),
#param_grid = param_test4, scoring='accuracy',n_jobs=4,iid=False, cv=5)
#tuning4.fit(train_features,train_labels)
#tuning4.cv_results_, tuning4.best_params_, tuning4.best_score_
```

4.5 Parameter Tuning Subsample

In [13]:
```
#param_test5 = {'subsample':[0.6,0.7,0.75,0.8,0.85,0.9,1.0]}
#tuning5 = GridSearchCV(estimator = GradientBoostingClassifier(learning_rate=
0.05, n_estimators=500,max_depth=5,min_samples_split=62, min_samples_leaf=30,r
andom_state=10,max_features='sqrt'),
#param_grid = param_test5, scoring='accuracy',n_jobs=4,iid=False, cv=5)
#tuning5.fit(train_features,train_labels)
#tuning5.cv_results_, tuning5.best_params_, tuning5.best_score_
```

5. Final Parameter set at: learning_rate=0.05, n_estimators=500,max_depth=5,min_samples_split=62, min_samples_leaf=30,random_state=10,max_features='sqrt',subsample=1.0

In [64]:
```
baseline_tune=GradientBoostingClassifier(learning_rate=0.05, n_estimators=500,
max_depth=5,min_samples_split=62, min_samples_leaf=30,random_state=10,max_feat
ures='sqrt',subsample=1.0)
start_time=time.time()
baseline_tune.fit(train_features, train_labels)
print("training  model takes %s seconds" % round((time.time() - start_time),3
))
predictors=list(train_features)

print('Accuracy of the GBM on test set: {:.3f}'.format(baseline_tune.score(tes
t_features,test_labels)))
start_time1 = time.time()
pred=baseline_tune.predict(test_features)
print("testing model takes %s seconds" % round((time.time() - start_time1),3))
print(classification_report(test_labels, pred))
```

```
training  model takes 254.984 seconds
Accuracy of the GBM on test set: 0.486
testing model takes 0.165 seconds
              precision    recall  f1-score   support

           1       0.57      0.72      0.63        18
           2       0.70      0.84      0.76        19
           3       0.41      0.52      0.46        25
           4       0.43      0.57      0.49        21
           5       0.57      0.72      0.63        18
           6       0.72      0.50      0.59        26
           7       0.58      0.55      0.56        20
           8       0.75      0.75      0.75        16
           9       0.80      0.64      0.71        25
          10       0.41      0.45      0.43        20
          11       0.48      0.67      0.56        24
          12       0.44      0.34      0.39        32
          13       0.22      0.21      0.21        24
          14       0.52      0.65      0.58        23
          15       0.61      0.50      0.55        22
          16       0.80      0.73      0.76        22
          17       0.29      0.31      0.30        26
          18       0.26      0.23      0.24        22
          19       0.26      0.26      0.26        23
          20       0.24      0.30      0.27        20
          21       0.52      0.38      0.44        34
          22       0.38      0.15      0.21        20

    accuracy                           0.49       500
   macro avg       0.50      0.50      0.49       500
weighted avg       0.49      0.49      0.48       500
```

Increase accuracy from 0.440 to 0.486 after tuning

Part II Advanced Model: Densely-connected Neural Networks

Procedure

BatchNorm -> Densely-connected NN -> ReLu -> Dropout -> BatchNorm -> Densely-connected NN -> ReLu -> Dropout -> Densely-connected NN -> ReLu -> Dropout -> Densely-connected NN -> ReLu -> Densely-connected NN -> Softmax -> Output

1. Provide directories for training/testing images.

In [65]:
```
"""
Path
"""
DATA_PATH = "../data/train_set"
POINTS_FOLDER = os.path.join(DATA_PATH, "points")
LABELS_FOLDER = DATA_PATH
```

2. Train/Test Split Feature Extraction

In [66]:
```
def read_labels():
    labels_df = pd.read_csv(os.path.join(LABELS_FOLDER, 'label.csv'))
    labels_df = labels_df.loc[:,['emotion_idx','emotion_cat','type']]
    return labels_df

def read_points():
    files = [file for file in os.listdir(POINTS_FOLDER) if file.endswith('.ma
t')]
    files.sort()

    face_points = np.zeros((len(files), 78, 2))
    for index, filename in enumerate(files):
        face_points_dict = loadmat(os.path.join(POINTS_FOLDER, filename))

        face_points[index] = face_points_dict.get('faceCoordinatesUnwarped',
face_points_dict.get('faceCoordinates2'))
    return face_points

points = read_points()
labels = read_labels()

### train test split
X_points_train, X_points_test, y_train, y_test = train_test_split(points,label
s,test_size=0.2, random_state=666)

### Feature Extraction time on training set:
feature_training_start = time.time()
X_train = np.zeros((X_points_train.shape[0], 3003))
for i in range(X_points_train.shape[0]):
    current = X_points_train[i]
    X_train[i,] = pdist(current)
feature_training_end = time.time()
y_train = y_train['emotion_idx']
y_train = to_categorical(y_train)[:,1:]
print("Feature Extraction time on training set:","%s seconds"%(feature_trainin
g_end - feature_training_start))

### Feature Extraction time on test set:
feature_test_start = time.time()
X_test = np.zeros((X_points_test.shape[0], 3003))
for i in range(X_points_test.shape[0]):
    current = X_points_test[i]
    X_test[i,] = pdist(current)
feature_test_end = time.time()
y_test = y_test['emotion_idx']
y_test = to_categorical(y_test)[:,1:]
print("Feature Extraction time on test set:","%s seconds"%(feature_test_end -
feature_test_start))
```

```
Feature Extraction time on training set: 0.08642888069152832 seconds
Feature Extraction time on test set: 0.022643089294433594 seconds
```

3. Train model

In [67]:
```
input_shape = [3003]
input_layer = Input(input_shape)
x = BatchNormalization(momentum = 0.88)(input_layer)
x = Dense(22*10,activation='relu',kernel_initializer=initializers.glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = BatchNormalization()(x)
x = Dense(22*8,activation='relu',kernel_initializer=initializers.glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = Dense(22*4,activation='relu',kernel_initializer=initializers.glorot_normal(seed=4))(x)
x = Dropout(0.25)(x)
x = Dense(22*2,activation='relu',kernel_initializer=initializers.glorot_normal(seed=4))(x)
output_layer = Dense(22,activation='softmax',kernel_initializer=initializers.glorot_normal(seed=4))(x)
model2 = Model(input_layer,output_layer)
```

In [68]:
```
start_time = time.time()
model2.compile(loss='categorical_crossentropy',optimizer = Adam(lr=0.001),metr
ics=['accuracy'])
model_history = model2.fit(X_train,y_train,epochs = 40,validation_data=[X_test
,y_test])
print("training  model takes %s seconds" % round((time.time() - start_time),3
))
```

```
Train on 2000 samples, validate on 500 samples
Epoch 1/40
2000/2000 [==============================] - 5s 3ms/step - loss: 3.0269 - acc
uracy: 0.0990 - val_loss: 2.7920 - val_accuracy: 0.1700
Epoch 2/40
2000/2000 [==============================] - 2s 1ms/step - loss: 2.6582 - acc
uracy: 0.1660 - val_loss: 2.3423 - val_accuracy: 0.2420
Epoch 3/40
2000/2000 [==============================] - 2s 1ms/step - loss: 2.3774 - acc
uracy: 0.2375 - val_loss: 2.0918 - val_accuracy: 0.2940
Epoch 4/40
2000/2000 [==============================] - 3s 1ms/step - loss: 2.1810 - acc
uracy: 0.2610 - val_loss: 1.9944 - val_accuracy: 0.3140
Epoch 5/40
2000/2000 [==============================] - 3s 1ms/step - loss: 2.0409 - acc
uracy: 0.3195 - val_loss: 1.7949 - val_accuracy: 0.3840
Epoch 6/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.9855 - acc
uracy: 0.3100 - val_loss: 1.7787 - val_accuracy: 0.3800
Epoch 7/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.9317 - acc
uracy: 0.3510 - val_loss: 1.7717 - val_accuracy: 0.3820
Epoch 8/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.8672 - acc
uracy: 0.3780 - val_loss: 1.6792 - val_accuracy: 0.4240
Epoch 9/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.8162 - acc
uracy: 0.3970 - val_loss: 1.6650 - val_accuracy: 0.4280
Epoch 10/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.7853 - acc
uracy: 0.4020 - val_loss: 1.6706 - val_accuracy: 0.4480
Epoch 11/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.7429 - acc
uracy: 0.4315 - val_loss: 1.5854 - val_accuracy: 0.4700
Epoch 12/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.6919 - acc
uracy: 0.4270 - val_loss: 1.5941 - val_accuracy: 0.4500
Epoch 13/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.6461 - acc
uracy: 0.4455 - val_loss: 1.5573 - val_accuracy: 0.4700
Epoch 14/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.5596 - acc
uracy: 0.4700 - val_loss: 1.5451 - val_accuracy: 0.4920
Epoch 15/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.5842 - acc
uracy: 0.4600 - val_loss: 1.5445 - val_accuracy: 0.4620
Epoch 16/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.5176 - acc
uracy: 0.4805 - val_loss: 1.5046 - val_accuracy: 0.4680
Epoch 17/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.5125 - acc
uracy: 0.4795 - val_loss: 1.5085 - val_accuracy: 0.5040
Epoch 18/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.4849 - acc
uracy: 0.4895 - val_loss: 1.4787 - val_accuracy: 0.4660
Epoch 19/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.4105 - acc
```

```
uracy: 0.5050 - val_loss: 1.5293 - val_accuracy: 0.4600
Epoch 20/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.4444 - acc
uracy: 0.4955 - val_loss: 1.4738 - val_accuracy: 0.4840
Epoch 21/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.4051 - acc
uracy: 0.5125 - val_loss: 1.5263 - val_accuracy: 0.4680
Epoch 22/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.3799 - acc
uracy: 0.5200 - val_loss: 1.4523 - val_accuracy: 0.4920
Epoch 23/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.3800 - acc
uracy: 0.5315 - val_loss: 1.4510 - val_accuracy: 0.4880
Epoch 24/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.3305 - acc
uracy: 0.5455 - val_loss: 1.4100 - val_accuracy: 0.5020
Epoch 25/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.3163 - acc
uracy: 0.5465 - val_loss: 1.3894 - val_accuracy: 0.5340
Epoch 26/40
2000/2000 [==============================] - 4s 2ms/step - loss: 1.3285 - acc
uracy: 0.5475 - val_loss: 1.4608 - val_accuracy: 0.4880
Epoch 27/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.3028 - acc
uracy: 0.5470 - val_loss: 1.4193 - val_accuracy: 0.5060
Epoch 28/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.3025 - acc
uracy: 0.5550 - val_loss: 1.4377 - val_accuracy: 0.5080
Epoch 29/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.2296 - acc
uracy: 0.5820 - val_loss: 1.4006 - val_accuracy: 0.5140
Epoch 30/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.3002 - acc
uracy: 0.5545 - val_loss: 1.4246 - val_accuracy: 0.5040
Epoch 31/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.2375 - acc
uracy: 0.5850 - val_loss: 1.4244 - val_accuracy: 0.5320
Epoch 32/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.1772 - acc
uracy: 0.5880 - val_loss: 1.3912 - val_accuracy: 0.5380
Epoch 33/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.2212 - acc
uracy: 0.5955 - val_loss: 1.4758 - val_accuracy: 0.5160
Epoch 34/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.2519 - acc
uracy: 0.5840 - val_loss: 1.4336 - val_accuracy: 0.5080
Epoch 35/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.1852 - acc
uracy: 0.5950 - val_loss: 1.3802 - val_accuracy: 0.5300
Epoch 36/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.1838 - acc
uracy: 0.6030 - val_loss: 1.4425 - val_accuracy: 0.5080
Epoch 37/40
2000/2000 [==============================] - 2s 1ms/step - loss: 1.1977 - acc
uracy: 0.5910 - val_loss: 1.4042 - val_accuracy: 0.5200
Epoch 38/40
2000/2000 [==============================] - 4s 2ms/step - loss: 1.1580 - acc
```

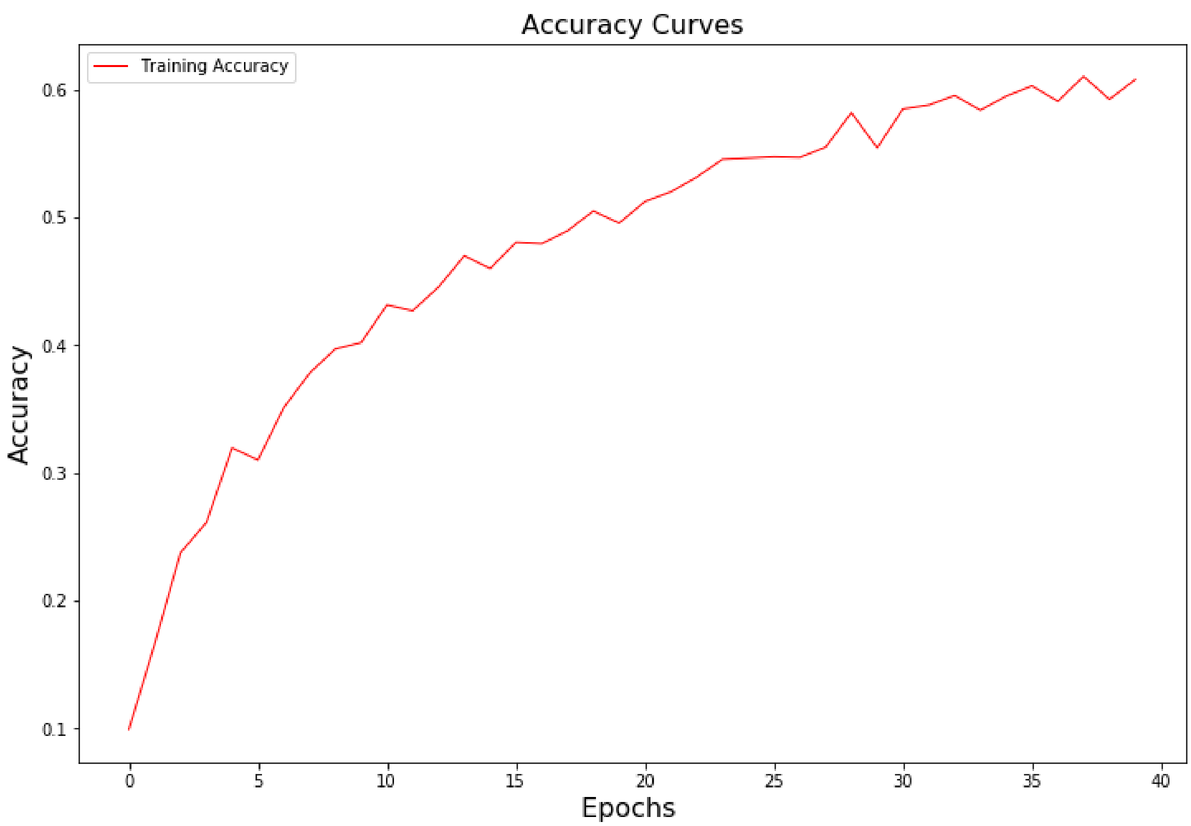
```
uracy: 0.6105 - val_loss: 1.4683 - val_accuracy: 0.4900
Epoch 39/40
2000/2000 [==============================] - 3s 2ms/step - loss: 1.1638 - acc
uracy: 0.5925 - val_loss: 1.3911 - val_accuracy: 0.5280
Epoch 40/40
2000/2000 [==============================] - 3s 1ms/step - loss: 1.1302 - acc
uracy: 0.6080 - val_loss: 1.3925 - val_accuracy: 0.5260
training  model takes 118.991 seconds
```

In [69]:

```
fig, ax = plt.subplots(figsize=[12,8])
ax.plot(model_history.history['accuracy'],'r',linewidth=1.0, label = 'Training
Accuracy')
ax.legend()
plt.xlabel('Epochs ',fontsize=16)
plt.ylabel('Accuracy',fontsize=16)
plt.title('Accuracy Curves',fontsize=16)
```

Out[69]:

```
Text(0.5, 1.0, 'Accuracy Curves')
```



4. Test accuracy

In [70]:

```
preds = model2.evaluate(X_test, y_test)
print ("Loss = " + str(preds[0]))
print ("Test Accuracy = " + str(preds[1]))
```

```
500/500 [==============================] - 0s 416us/step
Loss = 1.3924654483795167
Test Accuracy = 0.5260000228881836
```

5. Predicted label

In [71]:
```
y_predict = []
for i in model2.predict(X_test):
    y_predict.append(np.argmax(i) + 1)
np.array(y_predict)
```

Out[71]:
```
array([13,  6,  6, 11, 22, 19, 11, 11, 13, 15,  4, 17, 22, 18, 13,  8, 10,
       20,  4,  4, 16,  5,  3,  1,  3, 14,  7,  3, 22, 14,  5, 19, 17,  7,
       16, 17, 22,  2,  4,  2, 10, 11,  4, 11, 16, 17, 17, 16, 21,  5, 12,
       15,  3, 15, 21, 19,  3,  3,  5,  4,  4,  2,  4, 21,  9, 13,  3, 21,
        5, 15, 17, 12, 16,  2, 22,  1,  2,  6, 12,  5, 12,  1,  7, 19, 14,
       20, 11, 21, 20, 22,  3, 15, 20, 15,  7,  7,  8,  1, 14,  2, 20,  2,
       22,  4, 16,  9, 12, 21,  1, 17,  1, 17, 12, 13,  7, 10, 22, 21, 18,
       21,  1, 17,  4,  2, 17, 13, 19,  4,  8,  4, 10,  7, 12, 10, 15, 18,
       14,  4, 20, 21, 21, 14, 12, 14,  3, 10, 10, 15, 17, 10,  4, 19, 22,
        1, 14,  5, 16, 17,  1, 10, 21, 10, 20,  3, 21, 16,  4,  5, 15, 19,
        4,  4, 14, 19, 19, 15, 14, 22, 16, 10, 12, 21,  3, 12,  1, 11,  5,
       19,  7,  5, 13,  5,  3,  3,  4, 11, 19, 16, 14,  9, 14, 14, 17, 17,
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