CSCE633 Homework 01

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Question 1: Maximum likelihood estimate

(a.i) Show that $\hat{\mu} = \frac{\sum\limits_{n=1}^{N} x_n}{N}$ and $\hat{\sigma}^2 = \frac{\sum\limits_{n=1}^{N} (x_n - \hat{\mu})^2}{N}$

Answer:

Assume $\chi = \{x_1, x_2, ..., x_N\}$, function $L(\mu, \sigma^2|\chi)$ is the likelihood function defined as follow:

$$L(\mu, \sigma^2|\chi) = \prod_{n=1}^{N} P(x_n|\mu, \sigma^2) \overset{x_n \sim N(\mu,\sigma^2)}{=} \prod_{n=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\Big(- \frac{(x_n - \mu)^2}{2\sigma^2}\Big)$$

Then the following equivalent formula can be obtained:

$$\max_{\mu,\sigma} L(\mu, \sigma^2|\chi) \Longleftrightarrow \max_{\mu,\sigma} \log\Big(L(\mu, \sigma^2|\chi)\Big) \Longleftrightarrow \max_{\mu,\sigma} \sum_{n=1}^{N} \Big[\log(\frac{1}{\sqrt{2\pi}}) - \log\sigma + \Big(-\frac{(x_n - \mu)^2}{2\sigma^2}\Big)\Big]$$

$$\Longleftrightarrow \max_{\mu,\sigma} N\log(\frac{1}{\sqrt{2\pi}}) - N\log\sigma - \sum_{n=1}^{N} \frac{(x_n - \mu)^2}{2\sigma^2} \Longleftrightarrow \min_{\mu,\sigma} N\log\sigma + \sum_{n=1}^{N} \frac{(x_n - \mu)^2}{2\sigma^2}$$

Suppose $f(\mu, \sigma) = N\log\sigma + \sum\limits_{n=1}^{N} \frac{(x_n-\mu)^2}{2\sigma^2}$, then the following formula can be obtained:

$$\begin{aligned}
\frac{\partial f}{\partial \mu} &= \sum_{n=1}^{N} \frac{\mu - x_n}{\sigma^2} &&= \frac{N}{\sigma^2} \cdot \Big(\mu - \frac{\sum\limits_{n=1}^{N} x_n}{N}\Big) \\
\frac{\partial f}{\partial \sigma} &= \frac{N}{\sigma} - \sum_{n=1}^{N} \frac{(x_n-\mu)^2}{\sigma^3} &&= \frac{N}{\sigma^3} \cdot \Big(\sigma^2 - \frac{\sum\limits_{n=1}^{N} (x_n-\mu)^2}{N}\Big)
\end{aligned}$$

Set $\frac{\partial f}{\partial \mu} = 0$, $\frac{\partial f}{\partial \sigma} = 0$, suppose $\hat{\mu}, \hat{\sigma} \in \arg\max\limits_{\mu,\sigma} L(\mu, \sigma^2|\chi)$,finally, we can get $\hat{\mu} = \frac{\sum\limits_{n=1}^{N} x_n}{N}$ and $\hat{\sigma}^2 = \frac{\sum\limits_{n=1}^{N} (x_n-\hat{\mu})^2}{N}$

(a.ii) Using the data in $Q1\_data.csv$ and above formula, estimate μ, σ^2

Answer:

μ	1.0711573934217282
σ^2	0.08840831592001618

Table 1: Results

The corresponding code is shown as follow:

```
import numpy as np
import xlrd

# Give the location of the file
filename = ("/content/drive/My ...
     Drive/2020_FALL/CSCE633/HomeWork/HW03/Q1_Data.xlsx")
data_file = xlrd.open_workbook(filename)  # Open File "to read"
data = data_file.sheet_by_index(0)
data = np.array(data.col_values(0))
#print(data.shape)
mu = np.mean(data)
sigma_squra = np.mean((data-mu)*(data-mu))
print(mu,sigma_squra,np.std(data)**2)
```

(b) Multinomial distribution: Compute the maximum likelihood estimate of ϕ

Answer:

According to multinomial distribution's definition, $(Y_1, Y_2, Y_3) \sim Multinomia(\theta_1, \theta_2, \theta_3, N)$, where $\theta_1 := (1-\phi)^2, \theta_2 = \phi^2, \theta_3 = 2\phi(1-\phi), N = N_1 + N_2 + N_3$. Suppose $y = (N_1, N_2, N_3)$, then the corresponding likelihood function $L(\phi|N_1, N_2, N_3) := L(\theta_1, \theta_2, \theta_3|y, N)$ can be defined as follow:

$$
\begin{aligned}
L(\phi|N_1, N_2, N_3) &= L(\theta_1, \theta_2, \theta_3|y, N) := p(y|\theta_1, \theta_2, \theta_3, N) \\
&= \tfrac{(N_1+N_2+N_3)!}{N_1!N_2!N_3!}(1-\phi)^{2N_1}\phi^{2N_2}(2\phi(1-\phi))^{N_3} \\
&= \tfrac{2^{N_3}(N_1+N_2+N_3)!}{N_1!N_2!N_3!}(1-\phi)^{2N_1+N_3}\phi^{2N_2+N_3}
\end{aligned}
$$

Then the following equivalent formula can be obtained:

$$
\begin{aligned}
\max_{\phi} L(\phi|N_1, N_2, N_3) &\iff \max_{\phi} \log\Big(L(\phi|N_1, N_2, N_3)\Big) \\
&\iff \max_{\phi} \log \tfrac{2^{N_3}(N_1+N_2+N_3)!}{N_1!N_2!N_3!} + (2N_1 + N_3)\log(1-\phi) + (2N_2 + N_3)\log\phi \\
&\iff \max_{\phi} (2N_1 + N_3)\log(1-\phi) + (2N_2 + N_3)\log\phi
\end{aligned}
$$

Suppose $f(\phi) := (2N_1 + N_3)\log(1-\phi) + (2N_2 + N_3)\log\phi$, then

$$
\begin{aligned}
\frac{\partial f}{\partial \phi} &= -\tfrac{2N_1+N_3}{1-\phi} + \tfrac{2N_2+N_3}{\phi} \\
&= \tfrac{1}{\phi(1-\phi)}\Big(-2N_1\phi - N_3\phi + 2N_2 + N_3 - 2N_2\phi - N_3\phi \Big) \\
&= \tfrac{1}{\phi(1-\phi)}\Big(2N_2 + N_3 - 2(N_1+N_2+N_3)\phi \Big) \\
&= \tfrac{2(N_1+N_2+N_3)}{\phi(1-\phi)}\Big(\tfrac{2N_2+N_3}{2(N_1+N_2+N_3)} - \phi \Big)
\end{aligned}
$$

Set $\frac{\partial f}{\partial \phi} = 0$, we have $\phi = \frac{2N_2+N_3}{2(N_1+N_2+N_3)}$

Question 2: Machine learning for facial recognition

(a) Visualization:

Answer:

The code for plotting is as follow:

Listing 1: Visualization

```
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
import numpy as np

labelMap = {0:"Angry", 1:"Disgust", 2:"Fear", 3:"Happy", ...
    4:"Sad", 5:"Surprise", 6:"Neutral"}

def funcPlot(images_set,labels_set,dataName):
  fig = plt.figure(figsize=[25,25])
  index = 0
  plot_num = 0
  for i in range(len(images_set)):
    if labels_set[i] == index:
      a = fig.add_subplot(4,4,plot_num+1)
      _ = plt.imshow(images_set[i])
      a.set_title("label:{},emotion:{}\n Visualizing a random ...
          image ({}th) from {} dataset".format(
          labels_set[i],labelMap[labels_set[i]],i+1,dataName))
      plot_num +=1
      if plot_num%2 ==0:
        index +=1
    if index ==7:
      break
  plt.show()
funcPlot(train_images,train_labels,'train')
```

The plot is shown as follow:

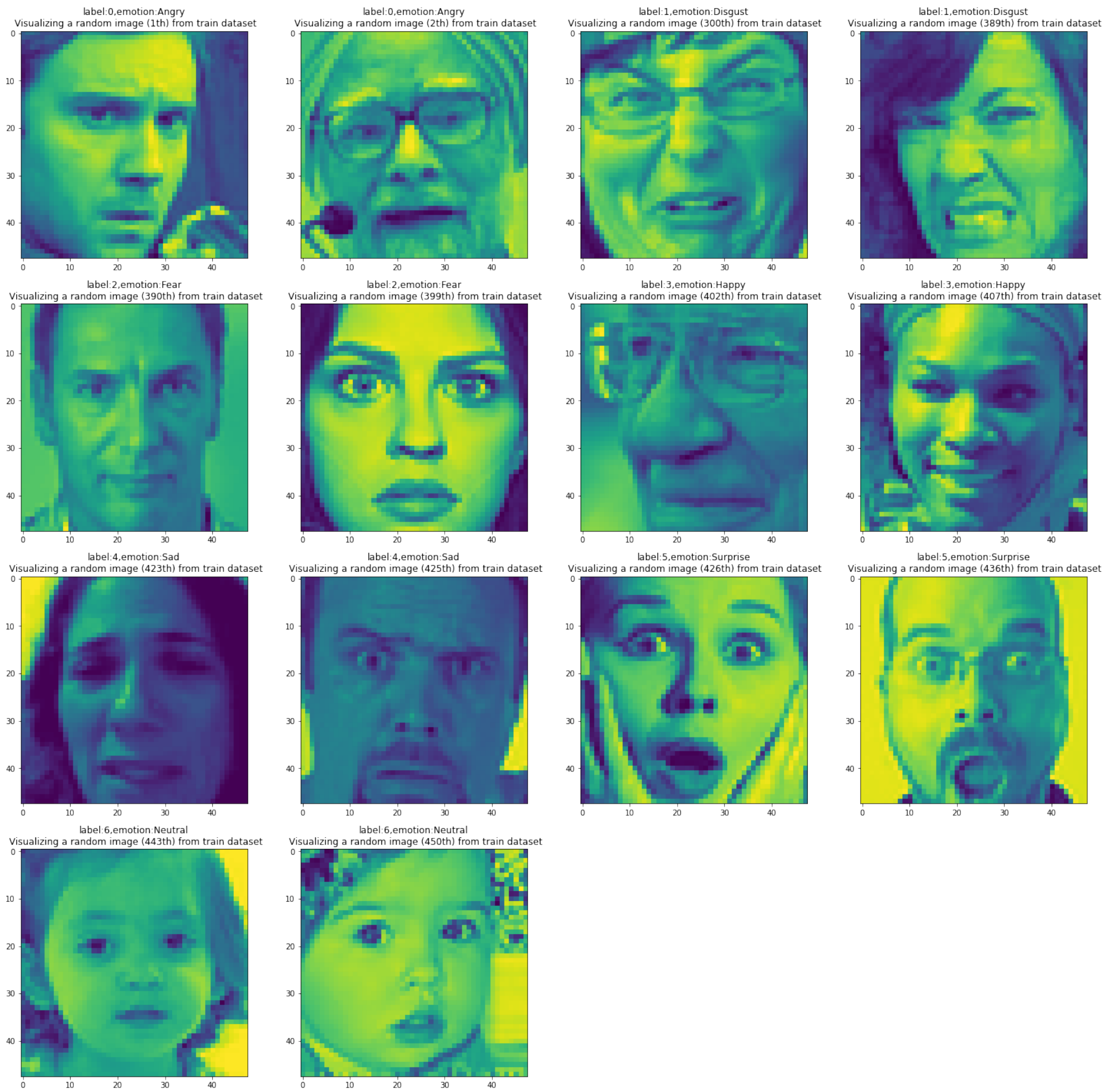


Figure 1: Visualization

(b) Data exploration:

Answer:

The code is as follow:

```
num_emotion = []
for i in range(7):
  num_tep = np.count_nonzero(train_labels==i)
  num_emotion.append(num_tep)
  print(i,labelMap[i],num_tep)
print(len(train_labels),sum(num_emotion))
```

The results are shown as follow:

label	emotion	number
0	Angry	3995
1	Disgust	436
2	Fear	4097
3	Happy	7215
4	Sad	4830
5	Surprise	3171
6	Neutral	4965

Table 2: Count the number of samples per emotion in the training data.

(c) Image classification with FNNS:

(c.i)

- Experiment on #layers,#nodes per layer,activation function,dropout,weight regularization.
- Report classification accuracy on the training and validation sets, running time and #parameters.
- Plot the cross-entropy loss over the number of iterations during training for 2-3 hyper-parameter combinations.

Answer:

Before the construction of FNN or CNN, data preprocessing is needed to improve traning performance. The code is as follow:

Listing 2: Data Preporcessing

```
# tf.image.per_image_standardization
def np_per_image_standardization(ImageData):
  N = 48*48
  N = 1/np.sqrt(N)
  ImageData = np.array(ImageData,dtype=float)
```

```
  for i in range(len(ImageData)):
    mean = np.mean(ImageData[i])
    stddev = np.std(ImageData[i])
    adjusted_stddev = max(stddev,N)
    #image_tep = (ImageData[i] - mean)/adjusted_stddev
    #print(image_tep)
    ImageData[i] = (ImageData[i] - mean)/adjusted_stddev
    #print(ImageData[i])
  return ImageData
#print(np_per_image_standardization(train_images[0:2])[1])
train_image = np_per_image_standardization(train_images)
valid_image = np_per_image_standardization(valid_images)
test_image = np_per_image_standardization(test_images)
```

Here, we need to set following hyper parameters:

- N = # layers $\in \{2, 3, 4, 5, 6\}$
- n = # nodes or initial layers $\in \{48 * 48, 48 * 48/2, 24 * 24\}$
- af = activation function $\in \{'relu', 'sigmoid', 'tanh'\}$
- dp = dropout ration $\in \{0.001, 0.01\}$
- wr = weight regularization $\in \{0.2, 0.3, 0.4\}$

To experiment on the above parameter, the following FNN structure is needed:

```
 ----------------------------------------------------------------
Layer (type)          Input Shape               Output Shape
=================================================================
1 layer (Dense)       (None, 48*48)             (None,n)
 ----------------------------------------------------------------
2 layer (Dense)       (None, n)                 (None,n/2)
 ----------------------------------------------------------------
...                   ...                       ...
 ----------------------------------------------------------------
N-2 layer (Dense)     (None, n/((2)^(N-4)))     (None, n/((2)^(N-3)))
 ----------------------------------------------------------------
dropout (Dropout)     (None, n/((2)^(N-3)))     (None, n/((2)^(N-3)))
 ----------------------------------------------------------------
N layer (Dense)       (None, n/((2)^(N-3)))     (None, 7)
=================================================================
```

Namely, always use only one dropout layer, and the dropout ratio is related to dp. The code for FNN is as follow. In the following code $epoch = 30, batch\_size = 256, lr = 0.01, momentum = 0.9$ and SGD is chosen as the optimal method.

- Input: $num\_layers, num\_nodes, act\_func, dropout\_ratio, regulaize\_ratio$ are related to the above hyper parameters.
- Input: $train\_status = True$ means using training data set for training, validation data set for fitting the model; $train\_status = False$ means using training and validation data set for training model, testing data set for evaluation the model.

- Output: When $train\_status = True$, output 'training accuracy','validation accuracy','running time','number of parameters'; when $train\_status = False$, output 'testing loss','testing accuracy'.

Listing 3: FNN

```
def funcFnn(num_layers,num_nodes,act_func, dropout_ratio, ...
    regulaize_ratio,train_status = True):
  #num_layers = 2,3,4,5,6
  #num_does = 48*48,48*48/2,24*24
  #act_func = 'relu' or 'sigmoid' or 'tanh'
  #dropout_ratio = 0.2,0.3,0.4
  #regulaize_ratio = 0.001,0.01
  #  Define a Feed-Forward Model
  model = Sequential()
  nodes_tep = num_nodes
  for i in range(num_layers-1):
    if i != num_layers-2:
      model.add(Dense(nodes_tep,
                activation=act_func,
                input_shape=(48*48,),
                name="{}_hidden_layer".format(i+1)))
      nodes_tep = nodes_tep//2
    else:
      if i == 0:#no drop out, layer number =2
        model.add(Dense(nodes_tep,
                  activation=act_func,
                  input_shape=(48*48,),
                  name="{}_hidden_layer".format(i+1)))
      else:
        model.add(Dropout(dropout_ratio))
  model.add(Dense(7,
                  activation='softmax',
                  name="{}_hidden_layer".format(num_layers)))

  #  Validate your Model Architecture
  print(model.summary())

  # Compile model
  opt = SGD(lr=0.01, momentum=0.9, decay=regulaize_ratio)
  model.compile(optimizer=opt,
                loss='categorical_crossentropy',
                metrics=['accuracy'],)

  if train_status == True:
    # Train model
    time1 = time.time()
    training = model.fit(flatten_train_images,
                         to_categorical(train_labels),
                         epochs=30,
                         batch_size=256,
                         validation_data=(flatten_valid_images,
                                          to_categorical(valid_labels)))
    time2 = time.time() -time1
    funcPlot_ce(training.history['accuracy'],training.history['val_accuracy'],
                training.history['loss'],training.history['val_loss'],
```

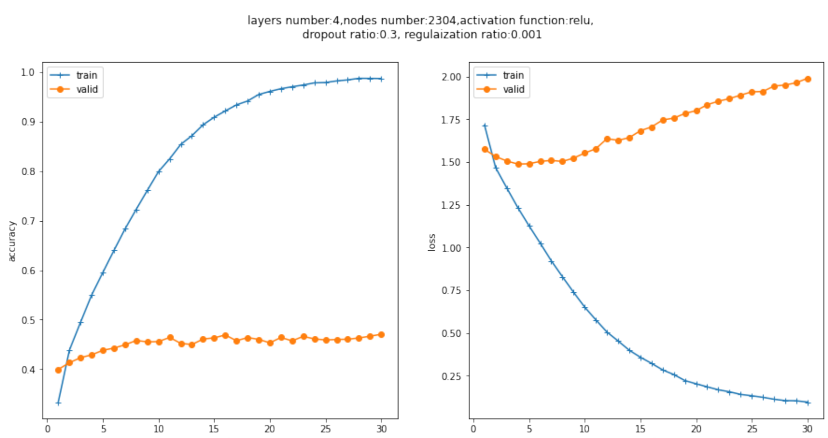
```
                   num_layers,num_nodes,act_func,
                   dropout_ratio,regulaize_ratio)
    return [training.history['accuracy'],
            training.history['val_accuracy']],
            time2,model.count_params()
  else:
    # Test model
    training = model.fit(np.vstack([flatten_train_images,
                                    flatten_valid_images]),
                         to_categorical(np.hstack([train_labels,
                                                   valid_labels])),
                         epochs=30,
                         batch_size=256,
                         )
    performance = model.evaluate(flatten_test_images,
                                 to_categorical(test_labels))
    return performance
```

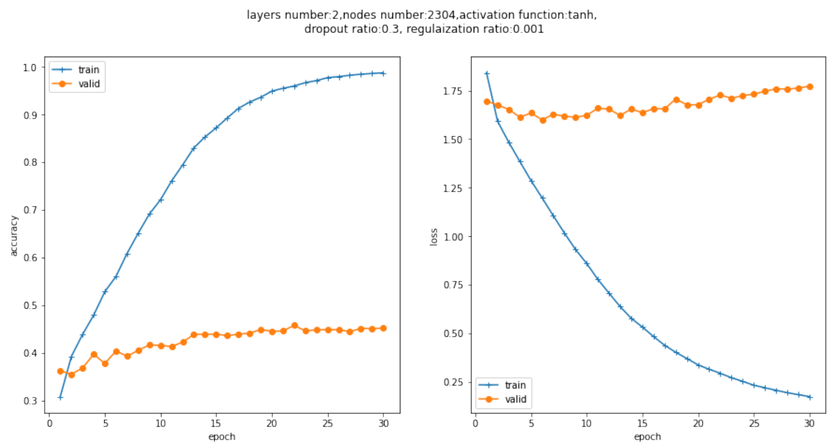
The full results are shown in Appendix-'fnn results'. In this section only the best parameter combination is shown(here, 'best' mean the highest valid accuracy and the lowest time):

#layers	#initial nodes	activate function	dropout ratio	weight ratio
4	2304	'relu'	0.3	0.001
	training accuracy	validation accuracy	running time	#parameters
	0.9864153861999512	0.47060462832450867	21.376885414123535	7974151

Table 3: FNN Best Results

The plots are shown as follow:





(c.ii)Run the best model in (c.i) on the testing set. Report the emotion classification accuracy on the testing set.

Answer: The code is as follow:

```
performance =funcFnn(4,2304,'relu',0.3, 0.001,train_status=False)
#2304 ['relu', 0.001, 0.3, 4]
```

The results are shown as follow:

train loss	train acc	test loss	test acc
0.1054	0.9846	1.8753	0.4831

Table 4: FNN Testing

(d) Image classification with CNNS:

(d.i)

- Experiment on #layers,filter size,stride size,activation function,dropout,weight regularization.
- Report classification accuracy on the training and validation sets, running time and #parameters.
- How do these metrics compare to the FNN.

Answer:

Here, we need to set following hyper parameters:

- N = # layers $\in \{7, 10\}$ for stride 1 and 7 for stride 2
- fs = filter size $\in \{3, 5\}$
- ss = stride size $\in \{1, 2\}$
- af = activation function $\in \{'relu',' sigmoid',' tanh'\}$
- dp = dropout ration $\in \{0.001, 0.01\}$
- wr = weight regularization $\in \{0.2, 0.3, 0.4\}$

To experiment on the above parameter, the following CNN structure for stride 1 (take $N = 10$ as an example)is needed:

```
----------------------------------------------------------------
Layer (type)        Input Shape             Output Shape
================================================================
1 layer (Conv2D)    (None, 48, 48, 1)       (None, 48, 48, 32)
----------------------------------------------------------------
2 layer (Conv2D)    (None, 48, 48, 32)      (None, 48, 48, 32)
----------------------------------------------------------------
max_pooling2d       (None, 48, 48, 32)      (None, 24, 24, 32)
----------------------------------------------------------------
4 layer (Conv2D)    (None, 24, 24, 32)      (None, 24, 24, 64)
----------------------------------------------------------------
5 layer (Conv2D)    (None, 24, 24, 64)      (None, 24, 24, 64)
----------------------------------------------------------------
max_pooling2d       (None, 24, 24, 64)      (None, 12, 12, 64)
----------------------------------------------------------------
flatten (Flatten)   (None, 12, 12, 64)      (None, 12*12*64)
----------------------------------------------------------------
8 layer (Dense)     (None, 12*12*64)        (None, 512)
----------------------------------------------------------------
dropout (Dropout)   (None, 512)             (None, 512)
----------------------------------------------------------------
10 layer(Dense)     (None, 512)             (None, 7)
================================================================
```

the following CNN structure for stride 2 is needed:

```
 ----------------------------------------------------------------
Layer (type)         Input Shape             Output Shape
=================================================================
1 layer (Conv2D)     (None, 48, 48, 1)       (None, 24, 24, 32)
 ----------------------------------------------------------------
2 layer (Conv2D)     (None, 24, 24, 32)      (None, 12, 12, 32)
 ----------------------------------------------------------------
max_pooling2d        (None, 12, 12, 32)      (None, 6, 6, 32)
 ----------------------------------------------------------------
flatten (Flatten)    (None, 6, 6, 32)        (None, 6*6*32)
 ----------------------------------------------------------------
5 layer (Dense)      (None, 6*6*32)          (None, 512)
 ----------------------------------------------------------------
dropout (Dropout)    (None, 512)             (None, 512)
 ----------------------------------------------------------------
7 layer(Dense)      (None, 512)             (None, 7)
=================================================================
```

Namely, always use only one dropout layer, and the dropout ratio is related to *dp*. The code for FNN is as follow. In the following code $epoch = 30, batch\_size = 256, lr = 0.01, momentum = 0.9$ and SGD is chosen as the optimal method.

- Input: $num\_layers, num\_nodes, act\_func, dropout\_ratio, regulaize\_ratio$ are related to the above hyper parameters.
- Input: $train\_status = True$ means using training data set for training, validation data set for fitting the model; $train\_status = False$ means using training and validation data set for training model, testing data set for evaluation the model.
- Output: When $train\_status = True$, output 'training accuracy','validation accuracy','running time','number of parameters'; when $train\_status = False$, output 'testing loss','testing accuracy'.

Listing 4: CNN

```
def funcCnn(num_layers,filter_size,stride_size,act_func, ...
    dropout_ratio, regulaize_ratio,train_status = True):
  #num_layers =  4+ 3,+6, or 4+ 3
  #stride_size = 1        or 2
  #filter_size = 3 or 5
  #act_func = 'relu' or 'sigmoid' or 'tanh'
  #dropout_ratio = 0.2,0.3,0.4
  #regulaize_ratio = 0.001,0.01
  #  Define a Feed-Forward Model
  model = Sequential()
  nodes_tep = 32
  for i in range((num_layers-4)//3):
    if i==0:
      model.add(Conv2D(nodes_tep,
                       kernel_size = filter_size,
                       activation=act_func,
                       input_shape=(48,48,1),
```

```
                        strides=(stride_size,stride_size),
                        padding = 'same',
                        name="{}_hidden_layer".format(i*3+1)))
      model.add(Conv2D(nodes_tep,
                        kernel_size = filter_size,
                        activation=act_func,
                        strides=(stride_size,stride_size),
                        padding='same',
                        name="{}_hidden_layer".format(i*3+2)))
      model.add(MaxPooling2D(pool_size=(2,2)))
      nodes_tep = nodes_tep*2
    else:
      model.add(Conv2D(nodes_tep,
                        kernel_size = filter_size,
                        activation=act_func,
                        strides=(stride_size,stride_size),
                        padding = 'same',
                        name="{}_hidden_layer".format(i*3+1)))
      model.add(Conv2D(nodes_tep,
                        kernel_size = filter_size,
                        activation=act_func,
                        strides=(stride_size,stride_size),
                        padding='same',
                        name="{}_hidden_layer".format(i*3+2)))
      model.add(MaxPooling2D(pool_size=(2,2)))
      nodes_tep = nodes_tep*2
  model.add(Flatten())
  model.add(Dense(512,
            activation=act_func,
            name="{}_hidden_layer".format(num_layers-2)))
  model.add(Dropout(dropout_ratio))
  model.add(Dense(7,
            activation='softmax',
            name="{}_hidden_layer".format(num_layers)))
  #  Validate your Model Architecture
  print(model.summary())

  # Compile model
  opt = SGD(lr=0.01, momentum=0.9, decay=regulaize_ratio)
  model.compile(optimizer=opt,
                loss='categorical_crossentropy',
                metrics=['accuracy'],)

  if train_status == True:
    # Train model
    time1 = time.time()
    training = model.fit(train_images_3d,
                         to_categorical(train_labels),
                         epochs=30,
                         batch_size=256,
                         validation_data=(valid_images_3d,
                                          to_categorical(valid_labels)))
    time2 = time.time() -time1
    funcPlot_ce_3d(training.history['accuracy'],training.history['val_accuracy'],
                training.history['loss'],training.history['val_loss'],
                num_layers,filter_size,stride_size,act_func,
                dropout_ratio,regulaize_ratio)
```

```
    return [training.history['accuracy'],
            training.history['val_accuracy']],
            time2,model.count_params()
  else:
    # Test model
      training = model.fit(np.vstack([train_images_3d,
                                      valid_images_3d]),
                           to_categorical(np.hstack([train_labels,
                                                     valid_labels])),
                           epochs=30,
                           batch_size=256,
                           )
      performance = model.evaluate(test_images_3d ,
                        to_categorical(test_labels))
      return performance
```

The full results are shown in Appendix-'cnn results'. In this section only the best parameter combination is shown(here, 'best' mean the highest valid accuracy and the lowest time):

#layers	stride	filter	activate function	dropout ratio	weight ratio
10	1	5	'relu'	0.3	0.001
		training accuracy	validation accuracy	running time	#parameters
		0.9803197383880615	0.5717470049858093	160.68341517448425	4902887

Table 5: CNN Best Results

From the data set in appendix, the following comparison results with FNN can be obtained:

- Train accuracy of cnn is a little bit larger than that of fnn in total.
- Valid accuracy of cnn is larger than that of fnn. In fnn, the top 10 largest numbers is between [0.45,0.49], while that in cnn is [0.55,0.58]
- Time of cnn is more longer than that of fnn. Running time of fnn is within 50, while cnn's occurs over 100.
- The number of parameter in cnn is usually 2 or 3 times larger than that of fnn.

(d.ii)Run the best model in (d.i) on the testing set. Report the emotion classification accuracy on the testing set. How does this compare to FNN?

Answer: The code is as follow:

```
performance =funcCnn(10,5,1,'relu',0.3, 0.001,train_status=False)
```

The results are shown as follow:

train loss	train acc	test loss	test acc
0.0615	0.9805	2.1902	0.6013

Table 6: CNN Testing

By comparing with FNN, the following results can be obtained:

- The testing accuracy of CNN(over 0.55) is larger than that of FNN(less than 0.5).

(e) Bayesian optimization for hyper-parameter tuning:

- Use publicly available libraries to perform a Bayesian optimization on the hyper-parameter space using the validation set.
- Report the emotion classification accuracy on the testing set

Answer:
The code is as follow:
First the model of CNN is re-defined.

Listing 5: CNN model

```
def  black_box_function(num_layers,filter_size,stride_size, ...
    dropout_ratio, regulaize_ratio,act_func='relu',train_status ...
    = True):
  num_layers = int(num_layers)
  filter_size = int(filter_size)
  stride_size = int(stride_size)
  model = Sequential()
  nodes_tep = 32
  for i in range((num_layers-4)//3):
    if i==0:
      model.add(Conv2D(nodes_tep,
                        kernel_size = filter_size,
                        activation=act_func,
                        input_shape=(48,48,1),
                        strides=(stride_size,stride_size),
                        padding = 'same',
                        name="{}_hidden_layer".format(i*3+1)))
      model.add(Conv2D(nodes_tep,
                        kernel_size = filter_size,
                        activation=act_func,
                        strides=(stride_size,stride_size),
                        padding='same',
                        name="{}_hidden_layer".format(i*3+2)))
      model.add(MaxPooling2D(pool_size=(2,2)))
      nodes_tep = nodes_tep*2
    else:
      model.add(Conv2D(nodes_tep,
                        kernel_size = filter_size,
                        activation=act_func,
                        strides=(stride_size,stride_size),
```

```
                           padding = 'same',
                           name="{}_hidden_layer".format(i*3+1)))
        model.add(Conv2D(nodes_tep,
                           kernel_size = filter_size,
                           activation=act_func,
                           strides=(stride_size,stride_size),
                           padding='same',
                           name="{}_hidden_layer".format(i*3+2)))
        model.add(MaxPooling2D(pool_size=(2,2)))
        nodes_tep = nodes_tep*2
    model.add(Flatten())
    model.add(Dense(512,
              activation=act_func,
              name="{}_hidden_layer".format(num_layers-2)))
    model.add(Dropout(dropout_ratio))
    model.add(Dense(7,
              activation='softmax',
              name="{}_hidden_layer".format(num_layers)))
    #  Validate your Model Architecture
    print(model.summary())

    # Compile model
    opt = SGD(lr=0.01, momentum=0.9, decay=regulaize_ratio)
    model.compile(optimizer=opt,
                  loss='categorical_crossentropy',
                  metrics=['accuracy'],)

    if train_status == True:
      # Train model
      time1 = time.time()
      training = model.fit(train_images_3d,
                             to_categorical(train_labels),
                             epochs=30,
                             batch_size=256,
                             validation_data=(valid_images_3d,
                                              to_categorical(valid_labels)))
      time2 = time.time() -time1
      funcPlot_ce_3d(training.history['accuracy'],training.history['val_accuracy'],
                  training.history['loss'],training.history['val_loss'],
                  num_layers,filter_size,stride_size,act_func,
                  dropout_ratio,regulaize_ratio)

      return training.history['val_accuracy'][-1]
    else:
      # Test model
        training = model.fit(np.vstack([train_images_3d,
                                         valid_images_3d]),
                             to_categorical(np.hstack([train_labels,
                                                       valid_labels])),
                             epochs=30,
                             batch_size=256,
                             )
        performance = model.evaluate(test_images_3d ,
                                  to_categorical(test_labels))
        return performance
```

Next, the Bayesian Optimization is used.

Listing 6: Bayesian Optimization

```
from bayes_opt import BayesianOptimization
###################Hyperparameter Setting######################
pbounds = {'num_layers':(7,10),
            'filter_size':(3,5),
            'stride_size':(1,2),
            'dropout_ratio':(0.2,0.4),
            'regulaize_ratio':(0.001,0.01)}#'act_func':'relu'

optimizer = BayesianOptimization(
    f=black_box_function,
    pbounds=pbounds,
    verbose=2, # verbose = 1 prints only when a maximum is observed
    random_state=1,
)

optimizer.maximize(
    init_points=5,
    n_iter=5,
)
black_box_function(optimizer.max['params']['num_layers'],
                   optimizer.max['params']['filter_size'],
                   optimizer.max['params']['stride_size'],
                   optimizer.max['params']['dropout_ratio'],
                   optimizer.max['params']['regulaize_ratio'],
                   act_func='relu',train_status = False)
```

The results of best parameter are as follow:

#layers	stride	filter	activate function	dropout ratio	weight ratio
10	1	5	'relu'	0.4	0.001

Table 7: New Method CNN Best parameter Results

The results of testing is shown as follow:

train loss	train acc	test loss	test acc
0.0955	0.9684	2.2181	0.5904

Table 8: New method CNN Testing

Appendix

Listing 7: fnn results

```
#nodes, [act, regular, drop, #layer], Training acc, Validation ...
    acc, Length of time, #parameters
2304 ['relu', 0.001, 0.2, 2] 0.9947403073310852 ...
    0.45388686656951904 18.317853212356567 5326855
2304 ['relu', 0.001, 0.2, 3] 0.9230206608772278 ...
    0.4494287967681885 17.613085746765137 5326855
2304 ['relu', 0.001, 0.2, 4] 0.9939043521881104 ...
    0.47088325023651123 21.377570629119873 7974151
2304 ['relu', 0.001, 0.2, 5] 0.9969347715377808 ...
    0.4555586576461792 22.753923654556274 8634247
2304 ['relu', 0.001, 0.2, 6] 0.9973527193069458 ...
    0.4527723491191864 23.634246110916138 8798407
2304 ['relu', 0.001, 0.3, 2] 0.994078516960144 ...
    0.4421844482421875 17.041662454605103 5326855
2304 ['relu', 0.001, 0.3, 3] 0.8790971636772156 ...
    0.45026469230651855 17.583329916000366 5326855
2304 ['relu', 0.001, 0.3, 4] 0.9864153861999512 ...
    0.47060462832450867 21.376885414123535 7974151
2304 ['relu', 0.001, 0.3, 5] 0.9964122772216797 ...
    0.45444414019584656 22.792892932891846 8634247
2304 ['relu', 0.001, 0.3, 6] 0.9969347715377808 ...
    0.45583727955818176 23.252522945404053 8798407
2304 ['relu', 0.001, 0.4, 2] 0.9949841499328613 ...
    0.4508219659328461 17.14392066001892 5326855
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    0.4399554133415222 17.782411336898804 5326855
2304 ['relu', 0.01, 0.2, 3] 0.6340172290802002 ...
    0.4366118609905243 17.4662344455719 5326855
2304 ['relu', 0.01, 0.2, 4] 0.7470827698707581 ...
    0.43911951780319214 21.563490629196167 7974151
2304 ['relu', 0.01, 0.2, 5] 0.8092584013938904 ...
    0.4430203437805176 22.881914377212524 8634247
2304 ['relu', 0.01, 0.2, 6] 0.875404953956604 ...
    0.43466147780418396 23.304298162460327 8798407
2304 ['relu', 0.01, 0.3, 2] 0.7416141033172607 ...
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2304 ['relu', 0.01, 0.3, 3] 0.5961893200874329 ...
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2304 ['relu', 0.01, 0.3, 5] 0.7554076910018921 ...
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2304 ['relu', 0.01, 0.3, 6] 0.8361141085624695 ...
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```

```
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```

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```

```
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    15.693447589874268 1331719
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```

```
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```

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Listing 8: cnn results

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