Topic : Neural Network for Image Classification

Objective for this template:

1. To introduce participants to the basic pipeline for Image classification using a multinomial logistic regression.
2. Use tensorflow to build a simple sequential neural network that implements a multinomial logistic regression.
3. Demonstrate the process of training the model and evaluating its performance

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Permission granted to use template for educational purposes so long as this heading is not removed.

Step 1:

```
#KERAS
import tensorflow as tf
from tensorflow import keras
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation, Flatten
from keras.layers.convolutional import Convolution2D, MaxPooling2D
from tensorflow.keras.optimizers import SGD,RMSprop,Adam
from keras.utils import np_utils

import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import os
from PIL import Image
from numpy import *
# SKLEARN
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix

# input image dimensions
img_rows, img_cols = 200, 200

# number of channels
img_channels = 1

from google.colab import drive
drive.mount('/content/gdrive')

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

```
ModuleNotFoundError                       Traceback (most recent call
last)
~\AppData\Local\Temp/ipykernel_9916/3060666491.py in <module>
     25 img_channels = 1
     26
---> 27 from google.colab import drive
     28 drive.mount('/content/gdrive')

ModuleNotFoundError: No module named 'google.colab'
```

Step 2: Setup directory for raw and resized data

```
path1 = "/content/gdrive/My Drive/input_data"    #path of folder of
images
path2 = "/content/gdrive/My Drive/resized_data"  #path of folder to
save images
print("Directory path is set")
```

```
Directory path is set
```

Step 3 : Check number of raw images stored in input directory

```
listing = os.listdir(path1)
num_samples=size(listing)
print ("Total number of raw images is {}".format(num_samples))
```

```
Total number of rw images s 80
```

Step 4: Resize images and convert to grayscale

```
for file in listing:
    im = Image.open(path1 + '/' + file)
    img = im.resize((img_rows,img_cols))
    gray = img.convert('L')
                #need to do some more processing here
    gray.save(path2 +'/' +  file, "JPEG")

imlist = os.listdir(path2)
print ("Raw images converted to following filenames
{}".format(imlist))
```

```
Raw images converted to following filenames ['Comfort_002.jpg',
'Comfort_003.jpg', 'Comfort_007.jpg', 'Comfort_004.jpg',
'Comfort_009.jpg', 'Comfort_005.jpg', 'Comfort_008.jpg',
'Comfort_001.jpg', 'Comfort_010.jpg', 'Comfort_006.jpg',
'Comfort_019.jpg', 'Comfort_017.jpg', 'Comfort_018.jpg',
'Comfort_016.jpg', 'Comfort_013.jpg', 'Comfort_014.jpg',
'Comfort_020.jpg', 'Comfort_011.jpg', 'Comfort_012.jpg',
'Comfort_015.jpg', 'discomfort_020.JPG', 'discomfort_015.JPG',
'discomfort_017.JPG', 'discomfort_014.JPG', 'discomfort_018.JPG',
'discomfort_013.JPG', 'discomfort_019.JPG', 'discomfort_012.JPG',
'discomfort_016.JPG', 'discomfort_008.JPG', 'discomfort_007.JPG',
```

```
'discomfort_009.JPG', 'discomfort_011.JPG', 'discomfort_010.JPG',
'discomfort_005.JPG', 'discomfort_003.JPG', 'discomfort_004.JPG',
'discomfort_006.JPG', 'discomfort_002.JPG', 'discomfort_001.JPG',
'distressed_017.JPG', 'distressed_020.JPG', 'distressed_019.JPG',
'distressed_013.JPG', 'distressed_018.JPG', 'distressed_015.JPG',
'distressed_014.JPG', 'distressed_016.JPG', 'distressed_012.JPG',
'distressed_010.JPG', 'distressed_011.JPG', 'distressed_009.JPG',
'distressed_004.JPG', 'distressed_007.JPG', 'distressed_005.JPG',
'distressed_006.JPG', 'distressed_003.JPG', 'distressed_008.JPG',
'distressed_002.JPG', 'distressed_001.JPG', 'Pleasure_001.jpg',
'Pleasure_020.jpg', 'Pleasure_014.jpg', 'Pleasure_015.jpg',
'Pleasure_016.jpg', 'Pleasure_013.jpg', 'Pleasure_019.jpg',
'Pleasure_017.jpg', 'Pleasure_018.jpg', 'Pleasure_012.jpg',
'Pleasure_011.jpg', 'Pleasure_010.jpg', 'Pleasure_009.jpg',
'Pleasure_003.jpg', 'Pleasure_006.jpg', 'Pleasure_004.jpg',
'Pleasure_007.jpg', 'Pleasure_008.jpg', 'Pleasure_005.jpg',
'Pleasure_002.jpg']
```

Step 5 : Check number of resized images for use as input

```
im1 = array(Image.open(path2 + '/'+ imlist[0]))
# open one image to get size
m,n = im1.shape[0:2] # get the size of the images
imnbr = len(imlist) # get the number of images

print(imnbr)
print ("Total number of processed images is {}".format(imnbr))
```

```
80
Total number of processed images is 80
```

Step 6: Apply one hot encoding and generate label the images

```
# create matrix to store all flattened images
immatrix = array([array(Image.open(path2+ '/' + im2)).flatten() for
im2 in imlist],'f')

print("Matrix shape is {}".format(immatrix.shape))
print(immatrix)

label=np.ones((num_samples,),dtype = int)
label[0:20]=0
label[20:40]=1
label[40:]=2

print("Label shape is {}".format(label.shape))
print(label)
```

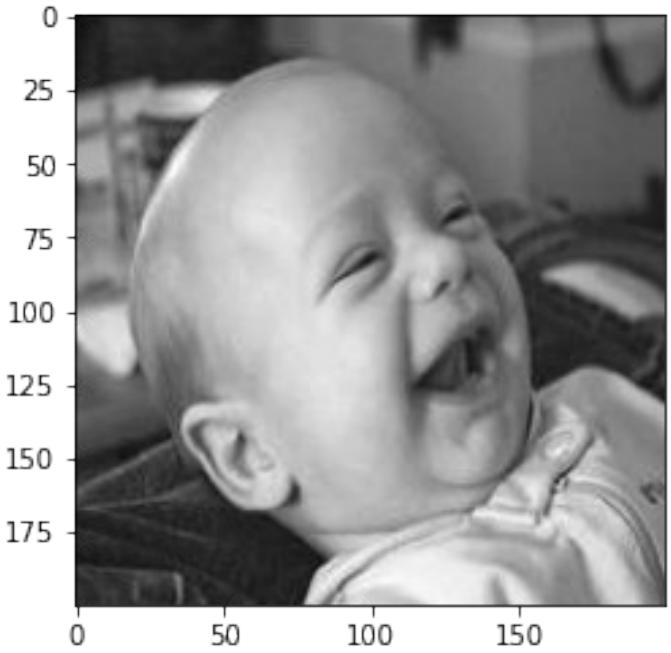
```
Matrix shape is (80, 40000)
[[  3.   4.   4. ... 154. 156. 154.]
 [255. 255. 255. ... 244. 244. 244.]
```

```
 [227. 227. 227. ... 232. 231. 230.]
 ...
 [237. 237. 237. ... 184. 181. 179.]
 [237. 237. 237. ... 245. 246. 247.]
 [217. 217. 218. ... 222. 210. 198.]]
Label shape is (80,)
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2]
```

Step 7: Attach labels to data matrix

```
data,Label = shuffle(immatrix,label, random_state=2)
train_data = [data,Label]

img=immatrix[67].reshape(img_rows,img_cols)
plt.imshow(img)
plt.imshow(img,cmap='gray')
print (train_data)
```

```
[array([[243., 241., 237., ..., 168., 173., 178.],
       [255., 255., 255., ..., 246., 246., 246.],
       [255., 255., 255., ..., 253., 255., 255.],
       ...,
       [179., 175., 170., ..., 216., 216., 216.],
       [227., 228., 230., ..., 242., 241., 241.],
       [224., 223., 221., ..., 207., 207., 206.]], dtype=float32),
array([1, 1, 1, 2, 2, 2, 2, 2, 1, 0, 1, 1, 2, 0, 2, 2, 2, 0, 1, 2, 2,
2,
       1, 2, 1, 0, 2, 2, 0, 2, 0, 0, 1, 2, 2, 0, 2, 0, 2, 2, 0, 2, 2,
1,
       2, 0, 2, 0, 0, 2, 0, 2, 0, 2, 2, 1, 0, 0, 1, 2, 1, 2, 2, 2, 2,
0,
       1, 1, 1, 1, 2, 2, 2, 1, 0, 2, 1, 2, 0, 2])]
```



Step 8: Generate training and testing data

```
(X, y) = (train_data[0],train_data[1])
print(X)
print(y)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=4)

print('X_train :', X_train)
print('y_train :', y_train)
print('X_test :', X_test)
print('y_test :', y_test)

X_train = X_train.reshape(X_train.shape[0], img_rows, img_cols, 1)
X_test = X_test.reshape(X_test.shape[0], img_rows, img_cols, 1)

X_train = X_train.astype('float32')
X_test = X_test.astype('float32')

X_train /= 255
X_test /= 255

print('X_train shape:', X_train.shape)
print('y_train shape:', y_train.shape)
print('X_test shape:', X_test.shape)
print('y_test shape:', y_test.shape)
print(X_train.shape[0], 'train samples')
print(X_test.shape[0], 'test samples')
```

```
[[243. 241. 237. ... 168. 173. 178.]
 [255. 255. 255. ... 246. 246. 246.]
 [255. 255. 255. ... 253. 255. 255.]
 ...
 [179. 175. 170. ... 216. 216. 216.]
 [227. 228. 230. ... 242. 241. 241.]
 [224. 223. 221. ... 207. 207. 206.]]
[1 1 1 2 2 2 2 2 1 0 1 1 2 0 2 2 2 0 1 2 2 2 1 2 1 0 2 2 0 2 0 0 1 2 2
0 2
 0 2 2 0 2 2 1 2 0 2 0 0 2 0 2 0 2 2 1 0 0 1 2 1 2 2 2 2 0 1 1 1 1 2 2
2 1
 0 2 1 2 0 2]
X_train : [[175. 184. 189. ... 250. 246. 243.]
 [181. 181. 181. ... 200. 203. 204.]
 [ 45.  45.  42. ... 142. 139. 138.]
 ...
 [143. 132. 108. ... 233. 233. 233.]
 [142. 141. 135. ...  66.  65.  68.]
 [244. 244. 243. ... 172. 169. 168.]]
y_train : [2 2 2 2 1 0 2 2 0 1 1 1 2 1 2 1 0 2 2 0 0 0 0 2 2 2 0 0 2 2
0 1 2 2 2 1 0
 2 2 1 2 0 1 1 2 2 1 2 0 2 2 0 2 0 2 0 1 0 0 2 1 1 1 2]
X_test : [[206. 208. 211. ...  46.  89. 152.]
 [228. 228. 228. ... 231. 230. 229.]
 [167. 168. 163. ...  64.  66.  67.]
 ...
 [ 18.  19.  20. ...  97.  71.  73.]
 [222. 217. 209. ... 245. 240. 236.]
 [186. 187. 188. ... 229. 229. 229.]]
y_test : [1 2 1 2 2 1 1 2 2 0 2 0 2 2 2 2]
X_train shape: (64, 200, 200, 1)
y_train shape: (64,)
X_test shape: (16, 200, 200, 1)
y_test shape: (16,)
64 train samples
16 test samples
```

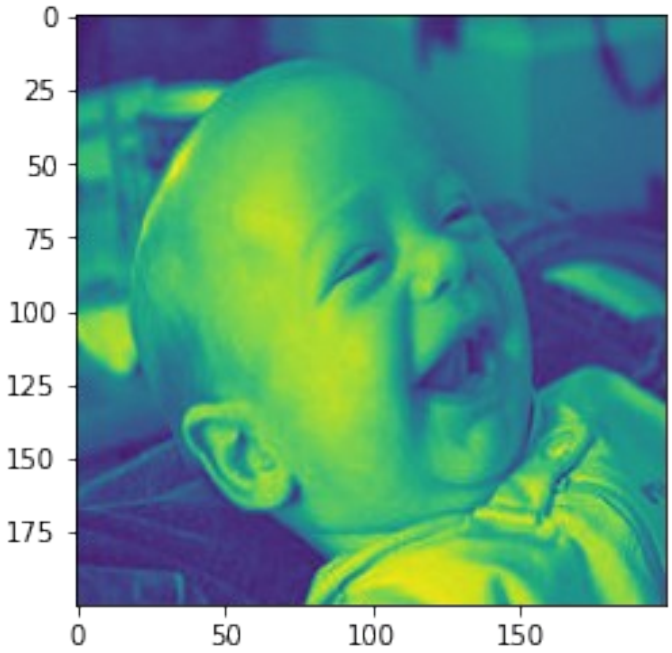
Step 9: Convert output to categorical form and test input data

```
print(y_train)
print(y_test)
# convert class vectors to binary class matrices
Y_train = np_utils.to_categorical(y_train, nb_classes)
Y_test = np_utils.to_categorical(y_test, nb_classes)

print(Y_train)
print(Y_test)


i = 10
```

```
img=immatrix[67].reshape(img_rows,img_cols)
plt.imshow(img)
print("label of this image is: ", Y_train[i,:])
```

```
[2 2 2 2 1 0 2 2 0 1 1 1 2 1 2 1 0 2 2 0 0 0 0 2 2 2 0 0 2 2 0 1 2 2 2
1 0
 2 2 1 2 0 1 1 2 2 1 2 0 2 2 0 2 0 2 0 1 0 0 2 1 1 1 2]
[1 2 1 2 2 1 1 2 2 0 2 0 2 2 2 2]
[[0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 1. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 1. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 1. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
```

```
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 1. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
[[0. 1. 0.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]]
label of this image is:  [0. 1. 0.]
```



Step 10.1 Using Feedforward NN model

```
model = tf.keras.Sequential()

layer_0 = tf.keras.layers.Flatten(input_shape=(1, img_rows, img_cols))
layer_1 = tf.keras.layers.Dense(units=128, activation="relu")
layer_2 = tf.keras.layers.Dense(units=128, activation="relu")
layer_3 = tf.keras.layers.Dense(units=128, activation="relu")
layer_4 = tf.keras.layers.Dense(units=10, activation="softmax")

model.add(layer_0)
model.add(layer_1)
model.add(layer_2)
model.add(layer_3)
model.add(layer_4)
model.summary()
model.compile(optimizer=keras.optimizers.Adadelta(learning_rate=0.0001
),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_2 (Flatten)          (None, 40000)             0
_________________________________________________________________
dense_8 (Dense)              (None, 128)               5120128
_________________________________________________________________
dense_9 (Dense)              (None, 128)               16512
```

```
_________________________________________________________________
dense_10 (Dense)             (None, 128)               16512
_________________________________________________________________
dense_11 (Dense)             (None, 10)                1290
=================================================================
Total params: 5,154,442
Trainable params: 5,154,442
Non-trainable params: 0
_________________________________________________________________
```

Step 10.2: Using Convolutional Neural Network model

```
# number of convolutional filters to use
nb_filters = 32
# size of pooling area for max pooling
nb_pool = 2
# convolution kernel size
nb_conv = 3

#batch_size to train
batch_size = 32
# number of output classes
nb_classes = 3
# number of epochs to train
nb_epoch = 20

model = Sequential()

model.add(Convolution2D(nb_filters, nb_conv, nb_conv,
border_mode='valid', input_shape=(img_rows, img_cols, 1))) #,
activation = 'relu', data_format='channels_first'))
convout1 = Activation('relu')
model.add(convout1)
model.add(Convolution2D(nb_filters, nb_conv, nb_conv))
convout2 = Activation('relu')
model.add(convout2)
model.add(MaxPooling2D(pool_size=(nb_pool, nb_pool)))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(128))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(nb_classes))
model.add(Activation('softmax'))
model.compile(optimizer=keras.optimizers.Adadelta(learning_rate=0.0001
),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:17:
UserWarning: Update your `Conv2D` call to the Keras 2 API: `Conv2D(32,
(3, 3), input_shape=(200, 200,..., padding="valid")`
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:20:
UserWarning: Update your `Conv2D` call to the Keras 2 API: `Conv2D(32,
(3, 3))`
```

Step 12: Train the model and gather training history data

```
hist = model.fit(X_train, Y_train, batch_size=batch_size,
epochs=nb_epoch, verbose=1, validation_data=(X_test, Y_test))
```

```
Train on 64 samples, validate on 16 samples
Epoch 1/20
64/64 [==============================] - 7s 112ms/step - loss: 1.0909
- accuracy: 0.3750 - val_loss: 1.0642 - val_accuracy: 0.6250
Epoch 2/20
64/64 [==============================] - 7s 102ms/step - loss: 1.0852
- accuracy: 0.3125 - val_loss: 1.0624 - val_accuracy: 0.6250
Epoch 3/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0820
- accuracy: 0.3750 - val_loss: 1.0610 - val_accuracy: 0.6250
Epoch 4/20
64/64 [==============================] - 7s 102ms/step - loss: 1.1044
- accuracy: 0.3906 - val_loss: 1.0598 - val_accuracy: 0.6250
Epoch 5/20
64/64 [==============================] - 7s 102ms/step - loss: 1.0908
- accuracy: 0.4375 - val_loss: 1.0589 - val_accuracy: 0.6250
Epoch 6/20
64/64 [==============================] - 7s 104ms/step - loss: 1.0935
- accuracy: 0.4375 - val_loss: 1.0577 - val_accuracy: 0.6250
Epoch 7/20
64/64 [==============================] - 7s 102ms/step - loss: 1.0942
- accuracy: 0.2812 - val_loss: 1.0567 - val_accuracy: 0.6250
Epoch 8/20
64/64 [==============================] - 7s 103ms/step - loss: 1.1090
- accuracy: 0.2969 - val_loss: 1.0559 - val_accuracy: 0.6250
Epoch 9/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0710
- accuracy: 0.4062 - val_loss: 1.0548 - val_accuracy: 0.6250
Epoch 10/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0874
- accuracy: 0.3906 - val_loss: 1.0533 - val_accuracy: 0.6250
Epoch 11/20
64/64 [==============================] - 7s 102ms/step - loss: 1.1113
- accuracy: 0.3125 - val_loss: 1.0526 - val_accuracy: 0.6250
Epoch 12/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0765
- accuracy: 0.4375 - val_loss: 1.0514 - val_accuracy: 0.6250
Epoch 13/20
64/64 [==============================] - 7s 102ms/step - loss: 1.0966
```

```
- accuracy: 0.4219 - val_loss: 1.0503 - val_accuracy: 0.6250
Epoch 14/20
64/64 [==============================] - 7s 102ms/step - loss: 1.1085
- accuracy: 0.3438 - val_loss: 1.0495 - val_accuracy: 0.6250
Epoch 15/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0943
- accuracy: 0.3594 - val_loss: 1.0485 - val_accuracy: 0.6250
Epoch 16/20
64/64 [==============================] - 7s 102ms/step - loss: 1.0956
- accuracy: 0.3750 - val_loss: 1.0478 - val_accuracy: 0.6250
Epoch 17/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0816
- accuracy: 0.4219 - val_loss: 1.0469 - val_accuracy: 0.6250
Epoch 18/20
64/64 [==============================] - 7s 102ms/step - loss: 1.1022
- accuracy: 0.4375 - val_loss: 1.0462 - val_accuracy: 0.6250
Epoch 19/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0750
- accuracy: 0.4062 - val_loss: 1.0454 - val_accuracy: 0.6250
Epoch 20/20
64/64 [==============================] - 7s 103ms/step - loss: 1.0873
- accuracy: 0.4531 - val_loss: 1.0447 - val_accuracy: 0.6250
```

Step 13: Display results of performance assessment metrics

```
score = model.evaluate(X_test, Y_test, verbose=0)
print(model.metrics_names)
print(score)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

print(Y_test)
Y_pred = model.predict_classes(X_test)
print(Y_pred)
#y_pred = np.argmax(Y_pred, axis=1)
print(y_pred)
target_names = ['class 0(Comfort)', 'class 1(Discomfort)', 'class
2(HORSES)']
print("Performance report: \
n",classification_report(np.argmax(Y_test,axis=1),
y_pred,target_names=target_names))
print("Confusion Matrix: \
n",confusion_matrix(np.argmax(Y_test,axis=1), y_pred))


['loss', 'accuracy']
[1.0446850061416626, 0.625]
Test loss: 1.0446850061416626
Test accuracy: 0.625
[[0. 1. 0.]
 [0. 0. 1.]
```

```
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 1. 0.]
 [0. 1. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [1. 0. 0.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]
 [0. 0. 1.]]
[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
Performance report:
                     precision    recall  f1-score   support

   class 0(Comfort)       0.12      1.00      0.22         2
class 1(Discomfort)       0.00      0.00      0.00         4
    class 2(HORSES)       0.00      0.00      0.00        10

           accuracy                           0.12        16
          macro avg       0.04      0.33      0.07        16
       weighted avg       0.02      0.12      0.03        16

Confusion Matrix:
 [[ 2  0  0]
 [ 4  0  0]
 [10  0  0]]

/usr/local/lib/python3.6/dist-packages/sklearn/metrics/
_classification.py:1272: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

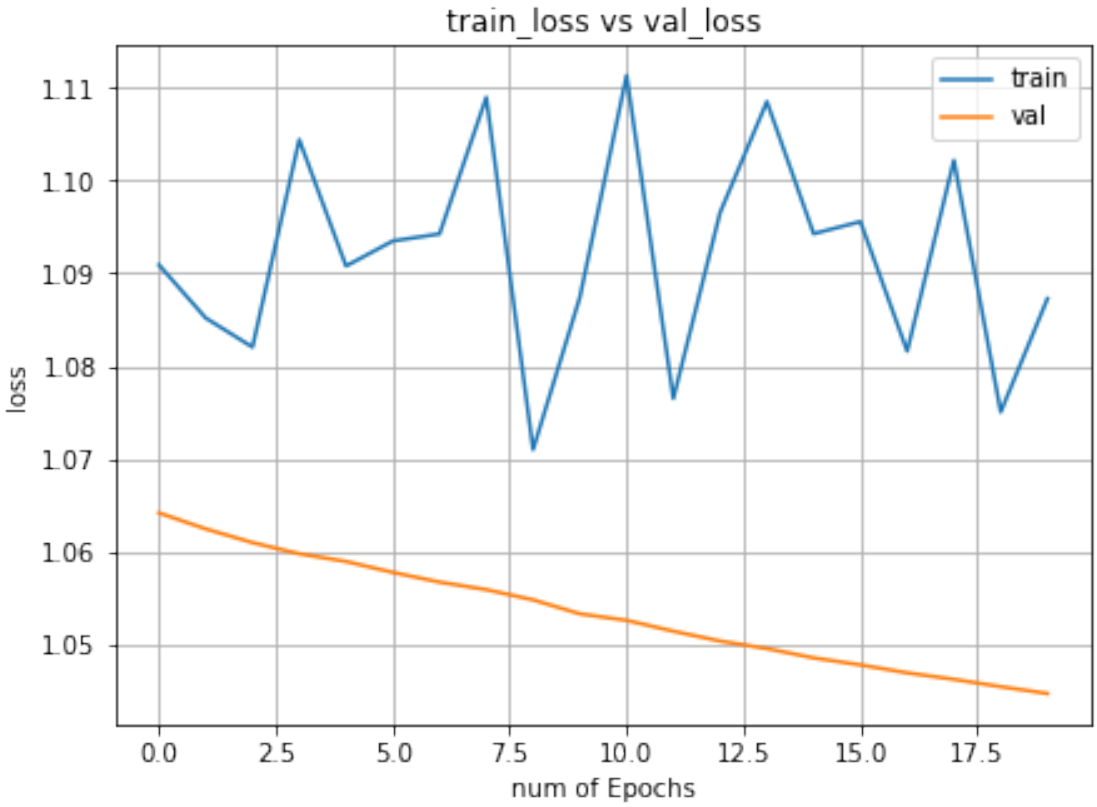
Other things we can do:

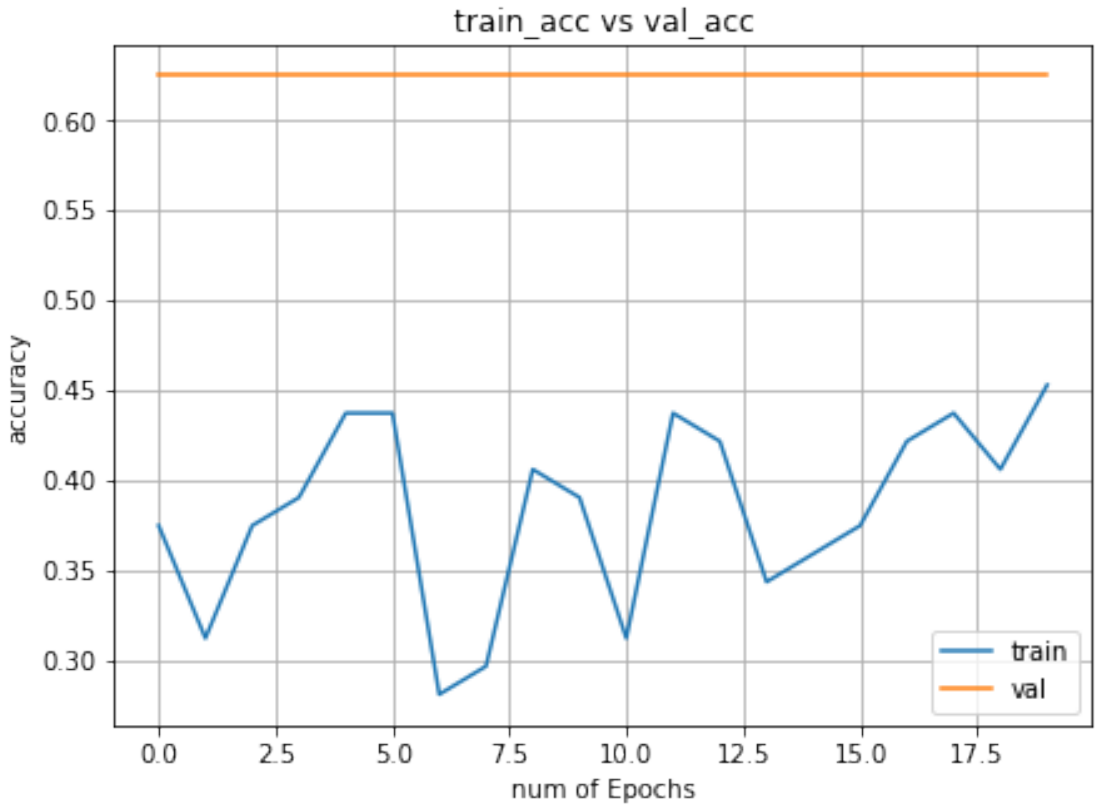
Analyze training statistics

```
train_loss=hist.history['loss']
val_loss=hist.history['val_loss']
train_acc=hist.history['accuracy']
val_acc=hist.history['val_accuracy']
xc=range(nb_epoch)

plt.figure(1,figsize=(7,5))
plt.plot(xc,train_loss)
plt.plot(xc,val_loss)
```

```
plt.xlabel('num of Epochs')
plt.ylabel('loss')
plt.title('train_loss vs val_loss')
plt.grid(True)
plt.legend(['train','val'])
#print (plt.style.available # use bmh, classic,ggplot for big
pictures)
#plt.style.use(['classic'])

plt.figure(2,figsize=(7,5))
plt.plot(xc,train_acc)
plt.plot(xc,val_acc)
plt.xlabel('num of Epochs')
plt.ylabel('accuracy')
plt.title('train_acc vs val_acc')
plt.grid(True)
plt.legend(['train','val'],loc=4)
#print plt.style.available # use bmh, classic,ggplot for big pictures
#plt.style.use(['classic'])
```

```
<matplotlib.legend.Legend at 0x7f270c707a90>
```




train_acc vs val_acc
0.60
0.55
0.50
0.45
0.40
0.35
0.30
accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
num of Epochs
train
val