# Neural Network Project Report 2

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#### **0** What Have Been Done This time

#### 0.1 Data set

I check the video clip one by one and surprisingly find that some of them are not the same as the label at all. So I trimmed the data by select some of videos in the original HMDB51 dataset. And this video may or may not have this properties:

1 the video is filmed from a camera which has a fixed view. (It's reasonable that the home monitor system capture the video from a video camera set at a fixed angle.)

2 people in this video shows most of their body. (Its's reasonable that the camera has a proper distance from the people.)

## 0.2 Preprocessing

I use the same down sample method to sample the data into a fixed size (100,100, 11) and we use these 11 frames to generate 10 frames of optical flow. The optical flow data of size (100, 100, 10) is used to be the input data for the neural network. Since the data size remain the same, the structure of neural network doesn't have to be change (of course this can be a very important method to improve the performance of the system). By using the optical follow, the impact of the background in the video is undermined. I think the better the optical flow is the better performance can be obtained. By doing this, the classifier starts to work rather than last time it didn't work for the test video at all.

#### 1 Topic

In this project I build a neural network and train it for the action recognition task. The dataset for training is HMDB51.

### 2 Dataset

HMDB51 is a dataset collected from various sources, mostly from movies, and a small proportion from public databases such as the Prelinger archive, YouTube and Google videos. The dataset contains 6849 clios distributed in 51 action categories, Each containing at least 101 clips. The actions categories can be grouped in five types:

- 1 general facial action smile, laugh, chew, talk.
- 2 Facial actions with object manipulation: smoke, eat, drink.
- 3 General body movements: cartwheel, clap hands, climb, etc.
- 4 Body movements with object interaction: brush hair, catch, draw sword, etc.
- 5 Body movements for human interaction: fencing, hug, kiss, etc.

My goal is to detect jump in the video and is classified as general body movements. In this case, some of the video of general body movements will be used to train the neural network. For this week's training, only jump and walk has been used for train the neural network.

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#### 3 DNN Model

In this project, I would like to design a 3D neural network for this action recognition task since I think neural network with a 3D convolutional kernel is intuitive for video processing. For the first week, the main goal is to make sure all the part of this project is working and the video data can be processed step by step as I want.

#### 3.1 Preprocess

The video clips for training quite short and its reasonable to sample it into same size so that the training can be done. In our case, the colored video is transferred into the gray scale video and we uniformly sample 10 frames for each video and the resolution is resized to 100 by 100. So for each video, the input data is of size (100,100,10,1).

We have 150 videos from both classes, jump and walk, and they are sampled and resized in the desired size. So the entire dataset is of size (300,100,100,10,1) and there will be a split for training and validation.

#### 3.2 3D-CNN Model

Input data is of shape (300,100,100,10,1)

Output data is a vector shows the binary classification result of shape (2,1)

Shape of each layer

Output of convolution layer: (96,96,6)

Output of the pooling layer:(32,32,2)

Flatten layer: (1536,1) Fully connect layer: (128,1)

### 4 Hyperparameters

The hyperparameter used in the training process: Batch Size 2 Epochs 15 Dropout 0.3

#### **5** Annotated Code

Import the necessary libraries

```
import cv2
     import math
     import matplotlib.pyplot as plt
     import pandas as pd
     from keras. preprocessing import image
     import numby as no
     from keras.utils import np_utils
     from skimage. transform import resize
     from keras. models import Sequential
     from keras.layers import Dense, Flatten, Dropout, Conv3D, MaxPooling3D, Activation
     from keras. layers. convolutional import Convolution3D, MaxPooling3D
     import os
     from sklearn.model_selection import train_test_split
     Using TensorFlow backend.
[2]: img_row = 100
     img_col = 100
     img_depth = 10
```

Read and preprocess of the training video

```
X tr = []
a = 0
listing = os. listdir('videofortraining/jump/')
for vid in listing:
   vid = 'videofortraining/jump/'+vid
    frames = []
    newDimension = (img_row,img_col)
    cap = cv2. VideoCapture(vid)
    ret, first_frame = cap.read()
    first_frame = cv2.resize(first_frame, newDimension, interpolation = cv2.INTER_AREA)
    prev_gray = cv2.cvtColor(first_frame, cv2.COLOR_BGR2GRAY)
    hsv = np. zeros_like(first_frame)
    hsv[...,1] = 255
    frameRate = cap.get(7)/(img_depth)
    #print(frameRate)
    newDimension = (img row, img col)
    a = a + frameRate
    frame_list = []
    for i in range (img_depth):
        f = math.floor((i + 1) * frameRate)
        frame_list.append(f)
    frame_list.append(int(cap.get(7)-2))
    while (cap.isOpened()):
       frameId = cap.get(1)
        ret, frame = cap.read()
        if (ret != True):
            hreak
        if frameId in frame_list:
            frame = cv2.resize(frame, newDimension, interpolation = cv2.INTER_AREA)
            gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
            flow = cv2.calcOpticalFlowFarneback(prev_gray, gray, None, 0.5, 3, 15, 3, 5, 1.2, 0)
            mag, ang = cv2. cartToPolar(flow[..., 0], flow[..., 1])
            hsv[...,0] = ang*180/np.pi/2
            hsv[..., 2] = cv2. normalize(mag, None, 0, 255, cv2. NORM_MINMAX)
            flow = cv2.cvtColor(hsv, cv2.COLOR_HSV2BGR)
            flow = cv2.cvtColor(flow,cv2.COLOR_BGR2GRAY)
            frames.append(flow)
            prev_gray = gray
    cap.release()
    cv2. destroyAllWindows()
    input=np.array(frames)
    ipt=np.rollaxis(np.rollaxis(input, 2, 0), 2, 0)
    print (ipt. shape)
    X_tr.append(ipt)
```

```
Hyperparameters
```

```
X_{tr} = np. array(X_{tr})
 print(X_tr.shape)
 (230, 100, 100, 10)
 num_sample = len(X_tr)
 label = np.ones((num_sample))
 label[0:115] = 0
 label[115:230] = 1
 print(label)
 train_data = [X_tr, label]
 (X_train, Y_train) = (train_data[0], train_data[1])
 train_set = np. zeros((num_sample, 1, img_row, img_col, img_depth))
 for sample in range(num_sample):
      train_set[sample][0][:][:][:] = X_train[sample][:][:][:]
 patch_size = 10
 #print(train_set.shape)
 batch_size = 1
 num class = 2
 num_{epoch} = 15
 Y_train = np_utils.to_categorical(Y_train, num_class)
 #print(Y_train)
 num_filter = [32, 32]
 num_pooling = [3,3]
 num_{conv} = [5, 5]
 train_set = train_set.astype('float32')
 train_set -= np.mean(train_set)
 train_set /= np.max(train_set)
Model
 mode1 = Sequentia1()
 model.add(Convolution3D(data_format = 'channels_first', filters = num_filter[0], kernel_size = (5, 5, 5), input_shape = (1, img_row, img_col, img_
 \verb|model.add(MaxPooling3D(pool_size = [3, 3, 3])||
 model.add(Dropout(0.5))
 model.add(Flatten())
 model. add(Dense(128, init = 'normal', activation = 'relu'))
 model.add(Dropout(0.5))
 model. add(Dense(2, init = 'normal'))
 model.add(Activation('softmax'))
 model.compile(loss = 'categorical_crossentropy', optimizer = 'RMSprop', metrics = ['accuracy'])
  /home/jasongao/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:7: UserWarning: Update your `Dense` call to the Keras 2 API:
  Dense(128, activation="relu", kernel_initializer="normal")
  import sys
  home/jasongao/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:9: UserWarning: Update your `Dense` call to the Keras 2 API:
  Dense(2, kernel_initializer="normal")
   if __name__ == '__main__'
 X train new, X val new, Y train new, Y val new = train test split(train set, Y train, test size = 0,2)
 hist = model.fit(X_train_new, Y_train_new, validation_data = (X_val_new, Y_val_new), batch_size = batch_size, nb_epoch = num_epoch, shuffle = Ti
```

#### Save the result and plot the curve

```
model_json = model.to_json()
with open("model.json", "w") as json_file:
    json_file.write(model_json)
model. save_weights("model_w. json")
train_loss=hist.history['loss']
val_loss=hist.history['val_loss']
train_acc=hist.history['accuracy']
val_acc=hist. history['val_accuracy']
xc=range(num_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'])
```

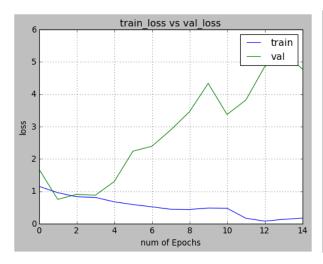
Load the test video and give a classification curve over time

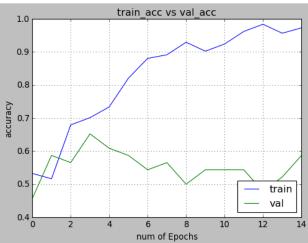
```
for video in range(5):
   vid = 'video_filmed/' + str(video) +'.MP4'
#for i in range(1).
   vid = 'video_filmed/' + str(1) +'.MP4'
   X_{TEST} = []
   frames = []
   count = 0
   cap = cv2. VideoCapture(vid)
   ret, first_frame = cap.read()
   first_frame = cv2.resize(first_frame, newDimension, interpolation = cv2.INTER_
   prev_gray = cv2.cvtColor(first_frame, cv2.COLOR_BGR2GRAY)
   hsv = np.zeros_like(first_frame)
hsv[...,1] = 255
   frameRate = round(cap.get(5))
   num_frame = round(cap.get(7))
   #print(frameRate)
   #print(num_frame)
   newDimension = (img_row, img_col)
   sample_rate = 0.2 * frameRate
   sample_frame = []
    sample_frame.append(0)
   while (s <= num_frame - 1 - img_depth * sample_rate);</pre>
        s += round(sample_rate)
        sample_frame.append(s)
    #print(sample_frame)
```

```
while (cap.isOpened()):
       frameId = cap.get(1)
       ret, frame = cap.read()
       if (ret != True):
           break
       if frameId in sample_frame:
           frame = cv2.resize(frame, newDimension, interpolation = cv2.INTER_AREA
           gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
           flow = cv2.calcOpticalFlowFarneback(prev_gray, gray, None, 0.5, 3, 15,
3, 5, 1.2, 0)
           mag, ang = cv2. cartToPolar(flow[..., 0], flow[..., 1])
           hsv[...,0] = ang*180/np.pi/2
           hsv[...,2] = cv2.normalize(mag, None, 0, 255, cv2.NORM_MINMAX)
           flow = cv2.cvtColor(hsv,cv2.COLOR_HSV2BGR)
           flow = cv2.cvtColor(flow, cv2.COLOR_BGR2GRAY)
           frames.append(flow)
           #plt.figure()
           #plt. imshow(flow)
           prev_gray = gray
           count +=1
   cap.release()
   cv2. destroyAllWindows()
   frames = np. array(frames)
   #print(frames, shape)
   for i in range(count-img_depth):
       frame_pack = []
       for j in range(img_depth):
           frame_pack.append(frames[i+j][:][:])
       X_TEST. append(frame_pack)
      #f = np. array(frame_pack)
      #print(f. shape)
   X_{TEST} = np. array(X_{TEST})
   X_TEST = np.rollaxis(np.rollaxis(X_TEST, 3, 1), 3, 1)
   #print(X_TEST. shape)
   TEST_set = np. zeros((count-img_depth, 1, img_row, img_col, img_depth))
   for sample in range(count-img_depth):
       TEST_set[sample][0][:][:][:] = X_TEST[sample][:][:][:]
   prediction = model.predict(TEST_set)
   time = []
   prob = []
   time_label = []
   for i in range(count-img_depth):
       time.append(i*0.2)
       prob. append(prediction[i][0])
       time_label.append([i*0.2, prediction[i][0]])
   plt.figure()
   plt.plot(time,prob)
   with open('time_label_op' + str(video), 'w') as f:
       json.dump(str(time_label),f)
```

### **6 Training and Testing Performance**

```
Train on 184 samples, validate on 46 samples
Epoch 1/15
                                               =] - 57s 311ms/step - loss: 1.1536 - accuracy: 0.5326 - val 1
184/184 [=
oss: 1.6904 - val accuracy: 0.4565
Epoch 2/15
                                               =] - 57s 310ms/step - loss: 0.9574 - accuracy: 0.5163 - val 1
184/184 [=
oss: 0.7503 - val accuracy: 0.5870
Epoch 3/15
184/184 [=
                                               =] - 57s 309ms/step - loss: 0.8319 - accuracy: 0.6793 - val 1
oss: 0.9058 - val accuracy: 0.5652
Epoch 4/15
                                               =] - 57s 310ms/step - loss: 0.8117 - accuracy: 0.7011 - val 1
184/184 [==
oss: 0.8780 - val accuracy: 0.6522
Epoch 5/15
                                               =] - 57s 310ms/step - loss: 0.6756 - accuracy: 0.7337 - val 1
184/184 [=
oss: 1.2986 - val accuracy: 0.6087
Epoch 6/15
184/184 [==
                                               =] - 58s 313ms/step - loss: 0.5898 - accuracy: 0.8207 - val 1
oss: 2.2406 - val accuracy: 0.5870
Epoch 7/15
                                               = ] - 57s 308ms/step - loss: 0.5212 - accuracy: 0.8804 - val 1
184/184 [=
oss: 2.3896 - val accuracy: 0.5435
Epoch 8/15
184/184 [=
                                               =] - 57s 309ms/step - loss: 0.4453 - accuracy: 0.8913 - val 1
oss: 2.8918 - val accuracy: 0.5652
Epoch 9/15
184/184 [=
                                               =] - 57s 309ms/step - loss: 0.4390 - accuracy: 0.9293 - val 1
oss: 3.4549 - val accuracy: 0.5000
Epoch 10/15
184/184 [=
                                               =] - 57s 309ms/step - loss: 0.4828 - accuracy: 0.9022 - val 1
oss: 4.3352 - val accuracy: 0.5435
Epoch 11/15
                                               =] - 57s 308ms/step - loss: 0.4770 - accuracy: 0.9239 - val 1
184/184 [==
oss: 3.3740 - val accuracy: 0.5435
Epoch 12/15
                                               =] - 57s 308ms/step - loss: 0.1675 - accuracy: 0.9620 - val 1
184/184 [==
oss: 3.8184 - val accuracy: 0.5435
Epoch 13/15
                                               =] - 57s 308ms/step - loss: 0.0777 - accuracy: 0.9837 - val 1
184/184 [==
oss: 4.8502 - val accuracy: 0.4783
Epoch 14/15
                                               =] - 57s 308ms/step - loss: 0.1340 - accuracy: 0.9565 - val 1
184/184 [==
oss: 5.2807 - val accuracy: 0.5217
Epoch 15/15
184/184 [=
                                               =] - 57s 308ms/step - loss: 0.1699 - accuracy: 0.9728 - val 1
oss: 4.7831 - val accuracy: 0.5870
```





## 7 Instruction on how to test the trained DNN

Install Dpendencies: python 3 Keras

Tensorflow

Anaconda