To Detect Face And Calculate Screen Time Of Characters In a Video

INDEX

ABSTRACT

We present an end-to-end system for counting actor screen time in movies through detecting and clustering faces in a Video . We break the problem apart into two parts: face segmentation and facial recognition. Our data consists of trailers that we divide into different frames (images). Then, we solve the first part of the problem using state-of-the-art pre-trained models in order to detect bounding boxes around where the Actor faces are. Given this output, we feed the information into the second model which detects which Actor it is. We present results the show our quality predictions with different models.

INTRODUCTION

In the 4 minutes of Video from movie Jurrasic Park:, one of the highest grossing blockbuster of that time, which characters and stories were given the most minutes to deliver a performance worthy of entertainment news cycles, word of mouth reviews, and pop culture canon? To satisfy this curiosity, we apply deep learning and CNNs to Video to breakdown the screen time allocated to each actor or character. For our project, we will build an application to recognize faces and count how many seconds each character appears in a single video.

PROBLEM STATEMENT

As one of the most successful applications of image analysis and understanding, face recognition has recently gained significant attention, especially during the past several years. This is evidenced by the emergence of specific face recognition conferences such as AFGR and AVBPA, and systematic empirical evaluation of face recognition techniques (FRT), including the FERET and XM2VTS protocols. There are at least two reasons for such a trend: the first is the wide range of commercial and law enforcement applications and the second is the availability of feasible technologies after years of research.

A general statement of face recognition problem can be formulated as follows:
Given still or video images of a scene identify or verify one or more persons in the scene using a stored database of faces and calculate screen time of faces in video. The solution of the problem involves segmentation of faces (face detection) from cluttered scenes, feature extraction from the face region recognition or verification. In identification problems, the input to the system is an unknown face and the system reports back the decided identity from a database of known individuals, whereas in verification problems, the system needs to confirm or reject the claimed identity of the input face.

Proposed Suggestive Solution

1. Face Recognition in A video

Here we use technique called deep metric learning.

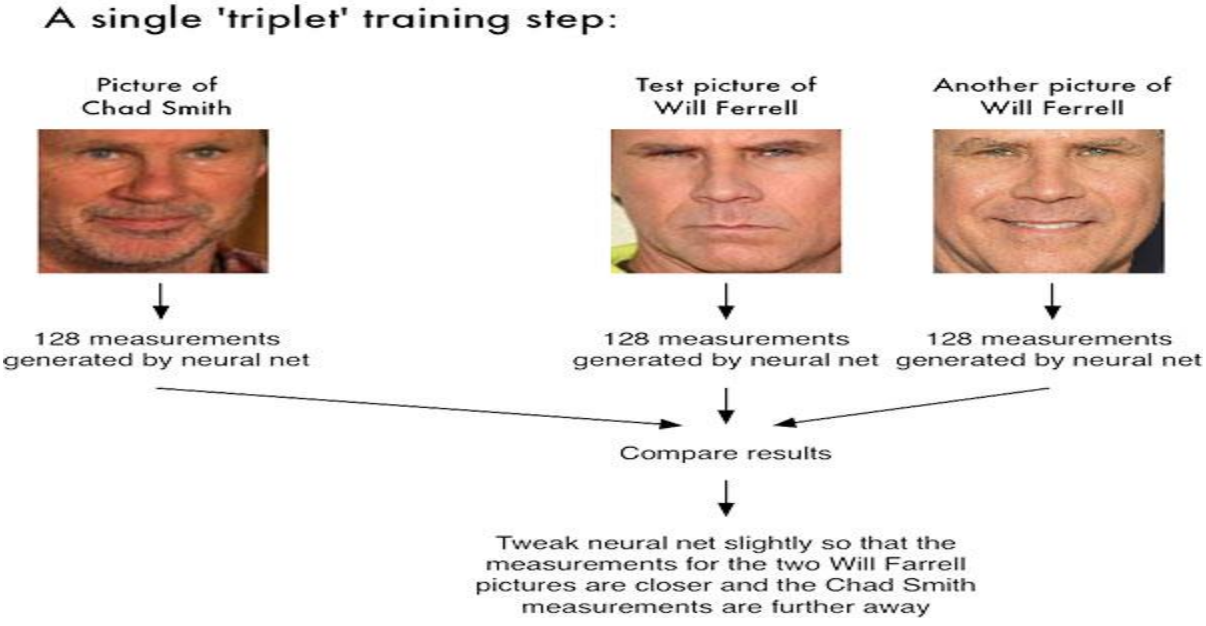
In, deep learning you know that we typically train a network to:

- Accept a single input image
- And output a classification/label for that image

However, deep metric learning is different.

instead, of trying to output a single label (or even the coordinates/bounding box of objects in an image), we are instead outputting a real-valued feature vector.

For the dlib facial recognition network, the output feature vector is 128-d (i.e., a list of 128 real-valued numbers) that is used to quantify the face. Training the network is done using triplets



2.Calculate Screen Time Of characters

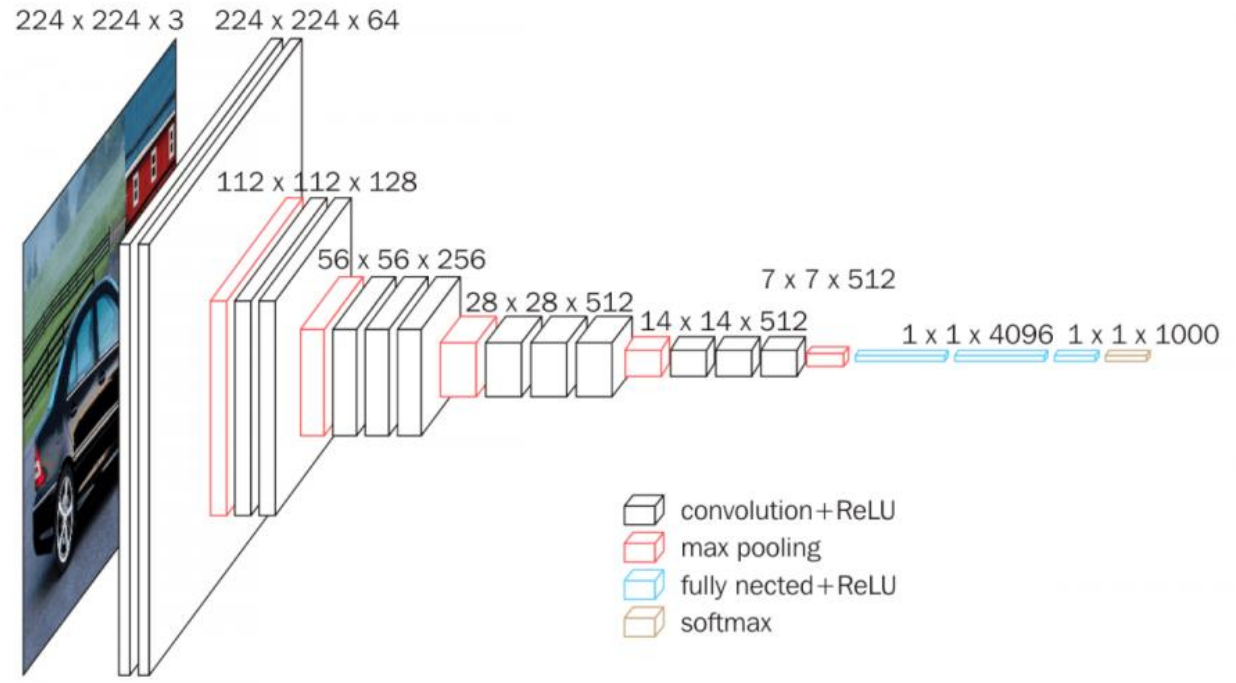
1 Preprocessing

Model should take images, not video, the first step is to convert movies into frames. Break down the video into frames taken one second apart. Then apply our deep learning model to each image in order to identify the faces that appear in each frame. The total screen time for each character is the sum of 1-second frames that they appear in.

2 Transfer Learning

Since we have only 4559 images, so it will be difficult to train a neural network with this little dataset. Here comes the concept of transfer learning.

With the help of transfer learning, we can use features generated by a model trained on a large dataset into our model. Here we will use VGG16 model trained on “imagenet” dataset. For this, we are using tensorflow high-level API Keras. With keras, you can directly import VGG16 model as shown in the code below.



VGG16 has around 138 million parameters. But in this project we will calculate screen time of only 2 actors. Therefore we are not including fully connected layers. After removing fully connected layers,we are left with 14 million parameters.

Since video is made up of 24 frames per second, we will count the number of frames which has been predicted for having “Alan Grant” in it and then divide it by 24 to count the number of seconds “Alan Grant” was on screen.

SYSTEM REQUIREMENTS

1 Hardware Requirements

- 4 GB RAM(min)
- Intel core processor(any processor ranging from i5 to i9)/Dual Core.
- 512 GB SSD/HDD(80 GB min).
- Camera.

1 Software Requirements

- Windows XP/7/8/10, Linux(Ubuntu)
- OpenCv
- Pandas
- Numpy
- Jupyter Notebook/Spyder
- Anaconda

PROJECT SNAPSHOTS

1.Face Recognition in Video

```
#%%
import face_recognition
import argparse
import imutils
import pickle
import time
import cv2

# construct the argument parser and parse the arguments
#%%
ap = argparse.ArgumentParser()
ap.add_argument("-e", "--encodings", required=True,
    help="path to serialized db of facial encodings")
ap.add_argument("-i", "--input", required=True,
    help="path to input video")
ap.add_argument("-o", "--output", type=str,
    help="path to output video")
ap.add_argument("-y", "--display", type=int, default=1,
    help="whether or not to display output frame to screen")
ap.add_argument("-d", "--detection-method", type=str, default="hog",
    help="face detection model to use: either `hog` or `cnn`")
args = vars(ap.parse_args())
```

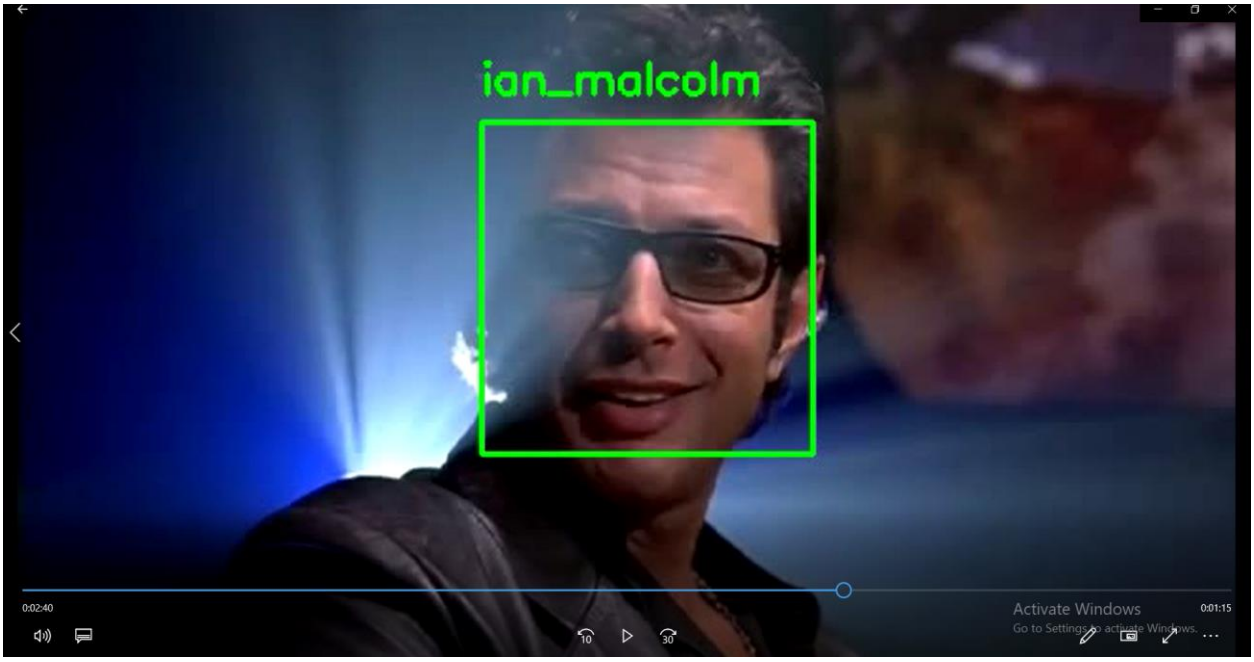
```
#%%
# load the known faces and embeddings
print("[INFO] loading encodings...")
data = pickle.loads(open(args["encodings"], "rb").read())

# initialize the pointer to the video file and the video writer
print("[INFO] processing video...")
stream = cv2.VideoCapture(args["input"])
writer = None

# loop over frames from the video file stream
while True:
    # grab the next frame
    (grabbed, frame) = stream.read()

    # if the frame was not grabbed, then we have reached the
    # end of the stream
    if not grabbed:
        break

    # convert the input frame from BGR to RGB then resize it to have
    # a width of 750px (to speedup processing)
    rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
    rgb = imutils.resize(frame, width=750)
    r = frame.shape[1] / float(rgb.shape[1])

    # detect the (x, y)-coordinates of the bounding boxes
    # corresponding to each face in the input frame, then compute
    # the facial embeddings for each face
    boxes = face_recognition.face_locations(rgb,
        model=args["detection_method"])
    encodings = face_recognition.face_encodings(rgb, boxes)
    names = []

    # loop over the facial embeddings
    for encoding in encodings:
        # attempt to match each face in the input image to our known
        # encodings
        matches = face_recognition.compare_faces(data["encodings"],
            encoding)
```

```
        name = "Unknown"

        # check to see if we have found a match
        if True in matches:
            # find the indexes of all matched faces then initialize a
            # dictionary to count the total number of times each face
            # was matched
            matchedIdxs = [i for (i, b) in enumerate(matches) if b]
            counts = {}

            # loop over the matched indexes and maintain a count for
            # each recognized face face
            for i in matchedIdxs:
                name = data["names"][i]
                counts[name] = counts.get(name, 0) + 1

            # determine the recognized face with the largest number
            # of votes (note: in the event of an unlikely tie Python
            # will select first entry in the dictionary)
            name = max(counts, key=counts.get)

        # update the list of names
        names.append(name)

    # loop over the recognized faces
    for ((top, right, bottom, left), name) in zip(boxes, names):
        # rescale the face coordinates
        top = int(top * r)
        right = int(right * r)
        bottom = int(bottom * r)
        left = int(left * r)

        # draw the predicted face name on the image
        cv2.rectangle(frame, (left, top), (right, bottom),
            (0, 255, 0), 2)
        y = top - 15 if top - 15 > 15 else top + 15
        cv2.putText(frame, name, (left, y), cv2.FONT_HERSHEY_SIMPLEX,
            0.75, (0, 255, 0), 2)

    # if the video writer is None *AND* we are supposed to write
```

```
    # if the writer is not None, write the frame with recognized
    # faces t odisk
    if writer is not None:
        writer.write(frame)

    # check to see if we are supposed to display the output frame to
    # the screen
    if args["display"] > 0:
        cv2.imshow("Frame", frame)
        key = cv2.waitKey(1) & 0xFF

        # if the `q` key was pressed, break from the loop
        if key == ord("q"):
            break

# close the video file pointers
stream.release()

# check to see if the video writer point needs to be released
if writer is not None:
    writer.release()
```


john_hammond
1995
1996
1997
lunch_scene_01


ian_malcolm
Unknown


ian_malcolm
0:02:40
0:01:15
Activate Windows
Go to Settings to activate Windows.


ellie_sattler
alan_grant
0:03:00
0:00:55
Activate Windows
Go to Settings to activate Windows.


alan_grant
0:03:14
0:00:41
Activate Windows
Go to Settings to activate Windows.

2.Calculate Screen time of Actors

```
[ ] from tqdm import tqdm
    import cv2
    import os
    import numpy as np
```

```
[ ] img_path = '/content/drive/MyDrive/Colab Notebooks/Minor Project/data'

    class1_data = []
    class2_data = []
    class3_data = []
    class4_data = []
    class5_data = []
    for classes in os.listdir(img_path):
            fin_path = os.path.join(img_path, classes)
            for fin_classes in tqdm(os.listdir(fin_path)):
                img = cv2.imread(os.path.join(fin_path, fin_classes))
                img = cv2.resize(img, (224,224))
                img = img/255.
                if classes == 'alan_grant':
                    class1_data.append(img)
                #elif classes == 'ellie_sattler':
                #    class2_data.append(img)
                elif classes == 'ian_malcom':
                    class3_data.append(img)
                #elif classes == 'john_hammond':
                #    class4_data.append(img)
                #elif classes == 'Unknown':
                 #   class5_data.append(img)

    class1_data = np.array(class1_data)
    #class2_data = np.array(class2_data)
    class3_data = np.array(class3_data)
    #class4_data = np.array(class4_data)
```

```
[ ] 100%|██████████| 1672/1672 [00:10<00:00, 159.48it/s]
    100%|██████████| 2461/2461 [00:15<00:00, 163.42it/s]
    100%|██████████| 3019/3019 [00:19<00:00, 151.21it/s]
    100%|██████████| 1194/1194 [00:07<00:00, 162.80it/s]
    100%|██████████| 1540/1540 [00:10<00:00, 152.07it/s]
```

```
[ ] from keras.applications import VGG16

    model = VGG16(include_top=False,input_shape = (224,224,3), weights='imagenet')
```

```
[ ] import tensorflow_addons as tfa
    tqdm_callback = tfa.callbacks.TQDMProgressBar()
    vgg_class1 = model.predict(class1_data,verbose = 1)
    #vgg_class2 = model.predict(class2_data)
    vgg_class3 = model.predict(class3_data,verbose = 1)
    #vgg_class4 = model.predict(class4_data)
    #vgg_class5 = model.predict(class5_data)
```

```
    49/49 [==============================] - 14s 118ms/step
    95/95 [==============================] - 11s 119ms/step
```

```
[ ] from keras.layers import Input, Dense, Dropout
    from keras.models import Model

    inputs = Input(shape=(7*7*512,))

    dense1 = Dense(1024, activation = 'relu')(inputs)
    drop1 = Dropout(0.5)(dense1)
    dense2 = Dense(512, activation = 'relu')(drop1)
    drop2 = Dropout(0.5)(dense2)
    outputs = Dense(1, activation = 'sigmoid')(drop2)

    model1 = Model(inputs, outputs)
    model1.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 25088)]           0
_________________________________________________________________
dense (Dense)                (None, 1024)              25691136
_________________________________________________________________
dropout (Dropout)            (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 513
=================================================================
Total params: 26,216,449
Trainable params: 26,216,449
Non-trainable params: 0
_________________________________________________________________
```

```
[ ] train_data = np.concatenate((vgg_class1[:1078], vgg_class3[:2113]), axis = 0)
    train_data = train_data.reshape(train_data.shape[0],7*7*512)

    valid_data = np.concatenate((vgg_class1[1078:], vgg_class3[2113:]), axis = 0)
    valid_data = valid_data.reshape(valid_data.shape[0],7*7*512)
```

```
[ ] train_label = np.array([0]*vgg_class1[:1078].shape[0] + [1]*vgg_class3[:2113].shape[0])
    valid_label = np.array([0]*vgg_class1[1078:].shape[0] + [1]*vgg_class3[2113:].shape[0])
```

```
[ ] import tensorflow as tf
    from keras.callbacks import ModelCheckpoint

    tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR)
    model1.compile(optimizer = 'sgd', loss = 'binary_crossentropy', metrics = ['accuracy'])

    filepath="best_model.hdf5"
    checkpoint = ModelCheckpoint(filepath, monitor='val_acc', verbose=1, save_best_only=True, mode='max')
    callbacks_list = [checkpoint]
```

```
[ ] model1.fit(train_data, train_label, epochs = 10, batch_size = 64, validation_data = (valid_data, valid_label), verbose = 1, callbacks = callbacks_list)
```

```
Epoch 1/10
20/20 [==============================] - 0s 19ms/step - loss: 0.5744 - acc: 0.7762 - val_loss: 0.3155 - val_acc: 0.8723
Epoch 2/10
20/20 [==============================] - 0s 9ms/step - loss: 0.1229 - acc: 0.9661 - val_loss: 0.0170 - val_acc: 1.0000
Epoch 3/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0399 - acc: 0.9984 - val_loss: 0.0083 - val_acc: 1.0000
Epoch 4/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0251 - acc: 0.9992 - val_loss: 0.0047 - val_acc: 1.0000
Epoch 5/10
20/20 [==============================] - 0s 10ms/step - loss: 0.0164 - acc: 1.0000 - val_loss: 0.0030 - val_acc: 1.0000
Epoch 6/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0129 - acc: 1.0000 - val_loss: 0.0023 - val_acc: 1.0000
Epoch 7/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0107 - acc: 1.0000 - val_loss: 0.0016 - val_acc: 1.0000
Epoch 8/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0089 - acc: 1.0000 - val_loss: 0.0012 - val_acc: 1.0000
Epoch 9/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0082 - acc: 1.0000 - val_loss: 0.0010 - val_acc: 1.0000
Epoch 10/10
20/20 [==============================] - 0s 9ms/step - loss: 0.0066 - acc: 1.0000 - val_loss: 8.2709e-04 - val_acc: 1.0000
```

```
len(ian_images)
```

```
[20] 3364
```

```
3364/30
```

```
[21] 112.13333333333334
```

To test our trained model and calculate the screen time, I have extracted images in “img” path. To calculate the screen time, first I have used the trained model to predict each image to find out which class it belongs, either “Ian_Malcom” or ”No_Ian_malcom". Since video is made up of 30 frames per second, we will count the number of frames which has been predicted for having “Ian or No Ian” in it and then divide it by 30 to count the number of seconds “Ian” was on screen.

Screen Time of Ian Malcom = 3364/30 = 112 seconds