National College Ireland

Configuration Manual

MSc Research Project Data Analytics

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Configuration Manual

Donovan Michael Jeremiah x18181562

1 Introduction

The configuration manual is part of the project code for the paper titled 'Detecting Depression from Speech with Residual Learning'. It contains system setup, and the explanation of the preprocessing steps and neural network models that were implemented as part of the research project.

2 System Setup

The preprocessing steps, model execution and evaluation of the 3 models (Base-CNN, AlexNet, and ResNet-18) used in this research was executed on Google Colab as the local system environment (laptop) did not meet the recommended system requirements for the project.

2.1 Hardware

- **Environment:** Google Colaboratory's online cloud-based Jupyter notebook environment.
- Processor: NVIDIA Tesla P100 GPU, 16GB
- **RAM:** 25 GB
- Operating System: Ubuntu 18.04.3 LTS
- Disk Storage: 150 GB
- Google Drive Storage: 200 GB

2.2 Software

- Jupyter Notebook (Google Colab)
- Python Version: 3.6.9
- Keras Version: 2.4.3
- Tensorflow: 2.3.0

2.3 Main Packages Used

Preprocessing:

- import numpy as np
- import pandas as pd
- pyAudioAnalysis
- scipy.io.wavfile
- wave

Neural Network Models:

- \bullet keras
- $\bullet~{\rm tensorflow}$
- \bullet sklearn

3 Data Collection

The data¹ used in this project is the Wizard-of-Oz interviews from the Distress Analysis Interview Corpus (DAIC-WOZ). It was from obtained from the University of Southern California's Institute for Creative Technologies. The official documentation² for the DAIC-WOZ database is found at its homepage.

It consists of 189 .wav audio files of interview sessions between Ellie, a virtual interviewer (who is controlled by a human in another room) and the participant.

The data must be downloaded and placed in google drive. Its appropriate path must be placed in the AUDIO_FOLDER_PATH variable of the **config.py** file as seen below.

<pre>SRC_PATH = "/content/drive/My Drive/Projects/depression-detection"</pre>
AUDIO_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/audio" INTERIM_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/interim" PROCESSED_513_125_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5 PROCESSED_513_513_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5 PROCESSED_513_125_15P_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5 PROCESSED_513_513_15P_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5 PROCESSED_513_513_15P_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5 PROCESSED_513_513_15P_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5 PROCESSED_513_125_20P_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/processed/5
PROCESSED_513_513_20P_FOLDER_PATH = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/process
TRAIN_SPLIT_CSV = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/train_split_Depression_AVU TEST_SPLIT_CSV = "/content/drive/My Drive/Projects/datasets/DAIC-WOZ/dev_split_Depression_AVEC20
<pre>PLOTS_DATA = "/content/drive/My Drive/Projects/depression-detection/plots"</pre>

Figure 1: config.py

¹https://dcapswoz.ict.usc.edu/

²https://dcapswoz.ict.usc.edu/wwwutil_files/DAICWOZDepression_Documentation.pdf

My Drive > ··· > DAIC-WOZ > audio -

Name 1	Owner	Last modified	File size
300_AUDIO.wav	me	Dec 27, 2019 me	20 MB
301_AUDIO.wav	me	Dec 27, 2019 me	25 MB
302_AUDIO.wav	me	Dec 27, 2019 me	23 MB
303_AUDIO.wav	me	Dec 27, 2019 me	30 MB
304_AUDIO.wav	me	Dec 27, 2019 me	24 MB
305_AUDIO.wav	me	Dec 27, 2019 me	52 MB
306_AUDIO.wav	me	Dec 27, 2019 me	26 MB
307_AUDIO.wav	me	Dec 27, 2019 me	38 MB
308_AUDIO.wav	me	Dec 27, 2019 me	26 MB

Figure 2: Audio files from DAIC-WOZ.

4 Preprocessing

4.1 Audio Segmentation

Figure 3: segmentation.py

4.2 Spectrogram Extraction

Figure 4: spectrograms.py

```
def logscale spec(spec, sr=44100, factor=20.):
    timebins, freqbins = np.shape(spec)
    scale = np.linspace(0, 1, freqbins) ** factor
    scale *= (freqbins-1)/max(scale)
    scale = np.unique(np.round(scale))
    newspec = np.complex128(np.zeros([timebins, len(scale)]))
    scale = scale.astype(int)
    for i in range(0, len(scale)):
        if i == len(scale)-1:
            newspec[:, i] = np.sum(spec[:, scale[i]:], axis=1)
            newspec[:, i] = np.sum(spec[:, scale[i]:scale[i+1]], axis=1)
    allfreqs = np.abs(np.fft.fftfreq(freqbins*2, 1./sr)[:freqbins+1])
    freqs = []
for i in range(0, len(scale)):
        if i == len(scale)-1:
            freqs += [np.mean(allfreqs[scale[i]:])]
        else:
            freqs += [np.mean(allfreqs[scale[i]:scale[i+1]])]
    return newspec, freqs
```

Figure 5: Log scaling of spectrograms (spectrograms.py).

My Drive > ··· > interim > P304 ~		⊕ ≙ ⊚	⊡ :
Name 1	Owner	Last modified	File size
P304_no_silence.png	me	Jul 25, 2020 me	3 MB
P304_no_silence.wav	me	Jul 2, 2020 me	11 MB

Figure 6: Segmented audio from previous step and spectrograms.

4.3 Exclusion of Shorter Interviews

```
start = time.time()
#depressed dict, normal dict = spd.build class dictionaries(cfg.INTERIM FOLDER
end = time.time()
print("*** Time Taken (in mins): " + str(round((end - start)/60,2)))
# Compute Quartiles to check if we can omit some (short) interviews
# in an attempt to increase the equal no. of samples taken from
# each participant.
df n len = pd.DataFrame(columns=['id', 'length'])
for x in normal dict.items():
  row = {'id':x[0], 'length':x[1].shape[1]}
  #print("P: " + str(x[0]) + " | Length: " + str(x[1].shape[1]))
 df n len = df n len.append(row, ignore index=True)
df n len.length.guantile([0.15,0.25,0.50,0.75,0.90])
# for depressed participants...
df d len = pd.DataFrame(columns=['id', 'length'])
for x in depressed dict.items():
  row = {'id':x[0], 'length':x[1].shape[1]}
  df d len = df d len.append(row, ignore index=True)
print("Note: Approx... 31.2 length = 1 second in interview clip.")
print("**** Intervew length quartiles for normal participants: ")
print(df n len.length.guantile([0.15,0.20,0.25,0.50,0.75,0.90]))
```

Figure 7: Code to see what interviews to exclude (main.ipynb).

4.4 Random Undersampling

```
def get_random_samples(matrix, n_samples, crop_width):
    """
    Get N random samples with width of crop_width from the numpy matrix
    representing the participant's audio spectrogram.
    """
    # crop full spectrogram into segments of width = crop_width
    clipped_mat = matrix[:, (matrix.shape[1] % crop_width):]
    n_splits = clipped_mat.shape[1] / crop_width
    cropped_sample_ls = np.split(clipped_mat, n_splits, axis=1)
    # get random samples
    samples = random.sample(cropped_sample_ls, n_samples)
    return samples
```

Figure 8: Fixed no. of random samples taken from each participant's spectrogram $(random_s ampling.py)$.

4.5 Preprocess input for Neural Networks

```
# retrieve spectrogram matrices from .npz files...
#path = cfg.PROCESSED 513 125 20P FOLDER PATH
path = cfg.PROCESSED 513 125 FOLDER PATH # change path accordingly to use diff
# PROCESSED 513 513 15P FOLDER PATH
X_train = np.load(path + '/train_samples.npz')
y train = np.load(path + '/train labels.npz')
X test = np.load(path + '/test samples.npz')
y_test = np.load(path + '/test_labels.npz')
X_train, y_train, X_test, y_test = \
        X_train['arr_0'], y_train['arr_0'], X_test['arr_0'], y_test['arr_0']
nb classes = 2
print('Processing images for Keras...')
X train, X test, y train, y test = cnn.prep train test(X train, y train,
                                                    X test, y test,
                                                    nb classes=nb classes)
# 513x125x1 for spectrogram with crop size of 125 pixels
img_rows, img_cols, img_depth = X_train.shape[1], X_train.shape[2], 1
# reshape image input for Keras
X train, X test, input shape = cnn.keras img prep(X train, X test, img depth,
                                              img_rows, img cols)
```

Figure 9: Preprocess the input for Keras models (Base-CNN, AlexNet, ResNet-18) (main.ipynb).

5 Neural Network Models

5.1 Base-CNN

```
model = Sequential()
model.add(MaxPooling2D(pool size=(4, 3), strides=(1, 3)))
model.add(Conv2D(32, (1, 3), padding='valid', strides=1,
         input shape=input shape, activation='relu'))
model.add(MaxPooling2D(pool size=(1, 3), strides=(1, 3)))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(nb classes))
model.add(Activation('sigmoid')) # DJ
model.compile(loss='binary crossentropy',
             optimizer=Adam(lr=0.001),
             metrics=['accuracy'])
lrr = ReduceLROnPlateau(monitor='val accuracy', factor=.01, pati
history = model.fit(X train, y train,
                   batch_size=batch size,
                  epochs=epochs,
                  verbose=0,
                   validation data=(X test, y test),
                   callbacks=[lrr])
```

Figure 10: Implementation of Base-CNN (cnn.py)

```
for train, val in kfold.split(np.zeros(ZX train.shape[0]), Zy label):
   #if fold no != 4:
       #fold no = fold no + 1
       #continue
   fold no = fold no + 1
   # create fold to use
   train X, val X = ZX train[train], ZX_train[val]
   train y, val y = Zy train[train], Zy train[val]
   print(f'Train** N: {str(np.count_nonzero(Zy_label[train] == 0))} D:
   print(f'Valid** N: {str(np.count nonzero(Zy label[val] == 0))} D: {
   input shape = (train X.shape[1], train X.shape[2], 1)
   start = time.time()
   model, history = cnn.cnn(train X, train y, val X, val y, batch size
                    nb classes, epochs, input shape)
   end = time.time()
   print("*** Time Taken (in mins): " + str(round((end - start)/60,2))
   # Evaluate accuracy on test and train sets
   e.accuracy(model, train X, val X, train y, val y, met)
   y test pred proba, conf matrix = e.performance(model, train X, val >
   e.additional metrics(conf matrix, met)
```

Figure 11: Base-CNN with K-fold (main.ipynb)

5.2 AlexNet



Figure 12: Implementation of AlexNet ($alexnet_1.py$)



Figure 13: AlexNet with K-fold (main.ipynb)

5.3 ResNet-18

```
if K.image_data_format() == 'channels_last':
        input_shape = (input_shape[1], input_shape[2], input_shape[0])
    block_fn = _get_block(block_fn)
    input = Input(shape=input shape)
    conv1 = _conv_bn_relu(filters=64, kernel_size=(7, 7), strides=(2, 2))(input)
pool1 = MaxPooling2D(pool_size=(3, 3), strides=(2, 2), padding="same")(conv1)
    block = pool1
filters = 64
for i, r in enumerate(repetitions):
        block = _residual_block(block_fn, filters=filters, repetitions=r, is_first_l
filters *= 2
    block = _bn_relu(block)
    block shape = K.int shape(block)
   flatten1 = Flatten()(pool2)
    model = Model(inputs=input, outputs=dense)
    return model
@staticmethod
def build_resnet_18(input_shape, num_outputs):
    return ResnetBuilder.build(input_shape, num_outputs, basic_block, [2, 2, 2, 2])
```

Figure 14: Implementation of ResNet-18 (resnet₁.py)

```
fold_no = 1
```

```
for train, val in kfold.split(np.zeros(ZX train.shape[0]), Zy label):
   fold no = fold no + 1
   # create fold to use
   train X, val X = ZX train[train], ZX train[val]
   train_y, val_y = Zy train[train], Zy train[val]
   print(f'Train** N: {str(np.count nonzero(Zy label[train] == 0))} D:
   print(f'Valid** N: {str(np.count nonzero(Zy label[val] == 0))} D: {
   input shape = (1, train X.shape[1], train X.shape[2])
   optimizer = Adam(lr=learning rate)
   #optimizer = RMSprop(lr=learning rate)
   lr reducer = ReduceLROnPlateau(factor=np.sqrt(0.1), cooldown=0, pat
   # must give input shape as (img channels, img rows, img cols), resr
   model = resnet 1.ResnetBuilder.build resnet 18(input shape, nb clas
   model.compile(loss='binary_crossentropy',
                 optimizer=optimizer,
                 metrics=['accuracy'])
   start = time.time()
   history = model.fit(train X, train y,
                 batch size=batch size,
                 epochs=epochs,
                 validation data=(val X, val y),
                 verbose=0,
```

Figure 15: ResNet-18 with K-fold (main.ipynb)

6 Evaluation



Figure 16: Calculates Confusion Matrix and metrics like precision, recall, and f1-score (evaluate.py)