

Speech to Text conversion of NPTEL Lectures using ASR-ESPNET

A Project Report

submitted by

POSINA SHANMUKA BHARATH KUMAR

*in partial fulfilment of the requirements
for the award of the degree of*

BACHELOR OF TECHNOLOGY



**DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY MADRAS.**

May 2019

THESIS CERTIFICATE

This is to certify that the thesis titled **Speech to Text conversion of NPTEL Lectures using ASR-ESPNET**, submitted by **Posina Shanmuka Bharath Kumar**, to the Indian Institute of Technology, Madras, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Prof. Umesh.S
Research Guide
Professor
Dept. of Electrical Engineering
IIT-Madras, 600 036

Place: Chennai

Date: 10th May, 2019

ACKNOWLEDGEMENTS

I take this opportunity to express my deepest gratitude to my project guide Prof. Umesh.S for his valuable guidance and motivation throughout the project. I am very grateful to him for providing his valuable time to guide me during the project. It is a privilege to be a student in IIT Madras. I express special thanks to all my teachers for all the academic insight obtained from them. I also acknowledge the excellent facilities provided by the institute to the students.

I am indebted to my parents and my brother for their unconditional love, support and guidance.

ABSTRACT

KEYWORDS: ASR-ESPNET

The National Programme on Technology Enhanced Learning (NPTEL) is an initiative in which several Indian Institutes of Technology (IIT Bombay, Delhi, Guwahati, Kanpur, Kharagpur, Madras and Roorkee) and the Indian Institute of Science (IISc, in Bangalore) are partners in creating complete, free and open course ware online for engineering, science and management subjects, and in training teachers in Indian technical institutions to help improve the overall quality of technical and professional education and the employ-ability of Indian graduates. The contents are, however, available free to everyone in the world and follow closely the curriculum design adopted by major technical universities in India and abroad.

Most of the lectures that are available on NPTEL are in English language. There are many students who struggle with English language while attending NPTEL lectures online. They might benefit if these lectures are translated into different languages. Currently We have Sophisticated Language models that we are capable of doing speech recognition very well and all that we need is Data to train them.

My project is a part of above main idea that helps to convert Audio to text of the lectures by using ASR-ESPNET. I trained and decoded the audio files using ESPNET architecture on a large dataset form the NPTEL websites and train them by using the time frame information available for each lecture in the form of “srt” files(subtitles file).

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ABBREVIATIONS

ASR	Automatic Speech Recognition
WER	Word Error Rate
CER	Character Error Rate
BLSTM	Bidirectional Long Short-Term Memory
RNN	Recurrent Neural Network

NOTATION

.srt	Subtitle file extension
.mp3	Audio file extension

CHAPTER 1

INTRODUCTION

1.1 ESPNET

ESPnet is an end-to-end speech processing toolkit, mainly focuses on end-to-end speech recognition and end-to-end text-to-speech. ESPnet uses chainer and pytorch as a main deep learning engine, and also follows Kaldi style data processing, feature extraction/-format, and recipes to provide a complete setup for speech recognition and other speech processing experiments.

Automatic speech recognition (ASR) becomes a mature technology with a lot of research and development efforts mainly in speech processing communities. This paper describes a new open source toolkit named ESPnet (End-to-end speech processing toolkit), which aims to provide a neural end-to-end platform for ASR and other speech processing. ESPnet provides a single neural network architecture to perform speech recognition in an end-to-end manner.

ESPnet fully utilizes benefits of two major end-to-end ASR implementations based on both connectionist temporal classification (CTC) and attention-based encoder-decoder network. Attention-based methods use an attention mechanism to perform alignment between acoustic frames and recognized symbols.

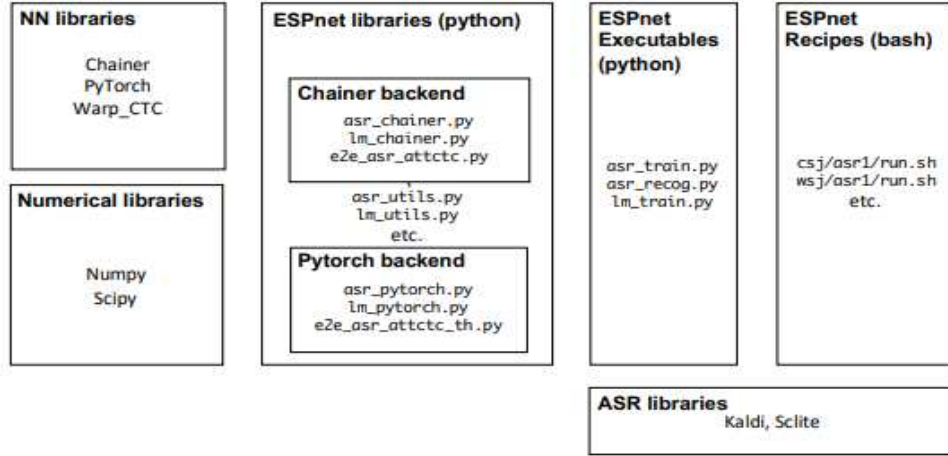


Figure 1.1: Software architecture of ESPnet

1.2 Functionality

Figure 1.1 shows a software architecture of ESPnet. In the ESPnet, main neural network training and recognition parts are written in python, which calls Chainer and PyTorch by switching the backend option.

1.2.1 Attention-based encoder-decoder

Encoder

The default encoder network is represented by bidirectional long short-term memory (BLSTM) with subsampling given T-length speech feature sequence $O_{1:T}$ to extract high-level feature sequence $h_{1:T'}$ as

$$h_{1:T'} = BLSTM(O_{1:T})(1.1)$$

where $T' < T$ in general due to the subsampling.

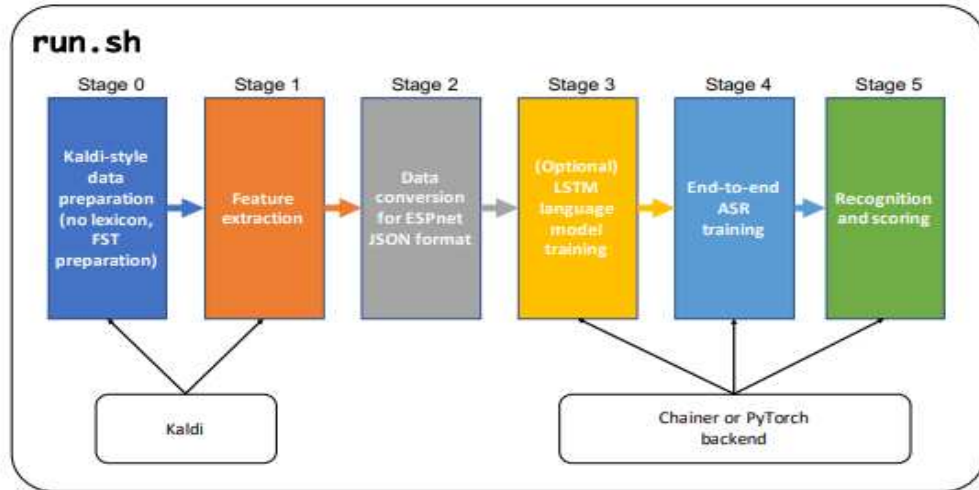


Figure 1.2: Flow of standard ESPnet `run.sh` code

1.3 `run.sh`

1.3.1 code

`run.sh` code is a shell script.

1.3.2 Standard flow

Figure 1.2 shows a flow of standard recipes in ESPnet. The standard recipe includes the following 5 stages in `run.sh`:

Stage 0(optional) - Data Download

This stage is for data download if we don't have data. We adopt the Kaldi data directory format, and we can simply use the Kaldi data preparation script.

stage 1: Feature Generation

We use the Kaldi feature extraction. Most of recipes use the 80-dimensional log Mel feature with the pitch feature (totally 83 dimensions). These features are stored in `fbank` directory.

stage 2: Dictionary and Json Data Preparation

This stage converts all the information including in the Kaldi data directory (transcriptions, speaker and language IDs, and input and output lengths) to one JSON file (`data.json`) except for input features.

stage 3: Network Training

Character-based BLSTM is trained by using either Chainer or PyTorch backend. Attention-based encoder-decoder is trained by using either Chainer or PyTorch backend.

stage 4: Decoding

After training the model, testing of model is done by decoding on separate data set. After decoding, results are produced in terms of WER(Word Error Rate), CER(Character Error Rate).

CHAPTER 2

Data Preprocessing before training

2.1 Introduction

Data required for model training are audio files(.wav format) and corresponding subtitle file(.srt file). These data can be downloaded from NPTEL website. But these audio files are mostly 50min - 1hour long files. For training we need audio files of length approximately 15 - 20sec and corresponding subtitle files. This segmentation is done by split_srt.py python code.

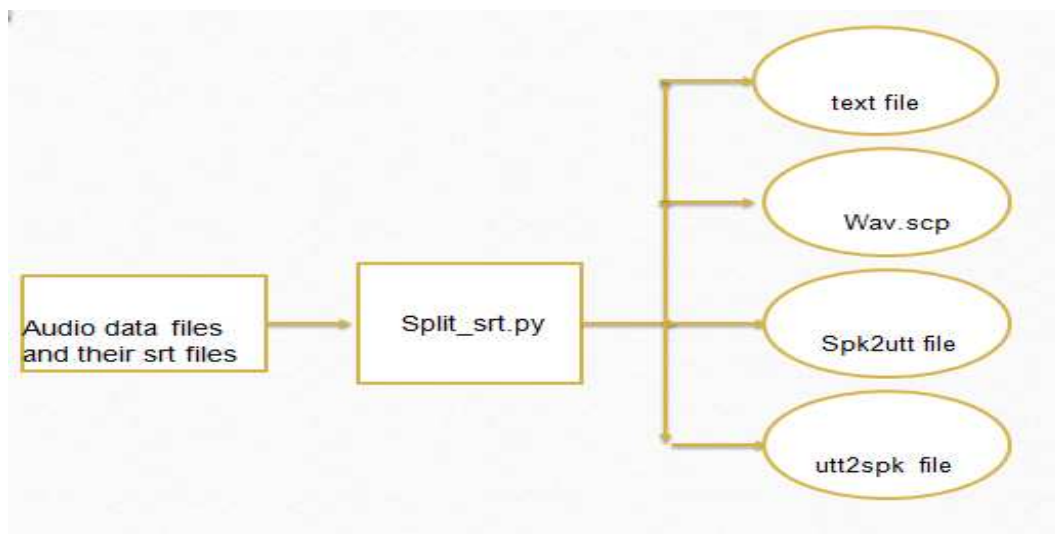


Figure 2.1: Flow chart of inputs and outputs of split-srt.py

2.2 Input formats required for model training

Model training requires certain formats of inputs. The following are required formats:

text.txt

This text file should contain Utterance ID followed by the text of segmented audio file.

An example line in text file :

mod01lec01_1006.72_1019.29 in India there are many factors that can influence the society

where,

mod01lec01_1006.72_1019.29 - Utterance ID

mod01lec01 - lecture number,

1006.72 - start time in seconds,

1019.29 - end time in seconds.

At last is the text data in that time segment.

wav.scp

The wav.scp file should contain Utterance ID followed by entire path of corresponding audio file.

An example line in wav.scp file :

mod01lec01_1006.72_1019.29 /speech/batch1/bharath/testnptel5/data/tr/
splitwav/ mod01lec01_1006.72_1019.29. wav

where,

mod01lec01_1006.72_1019.29 - Utterance ID

spk2utt file

The spk2utt file should contain Speaker ID followed by each Utterance ID.

utt2spk file

The utt2spk file should contain each Utterance ID followed by speaker ID.

where

Speaker ID: ID given to each speaker(in this case lecturer)

Utterance ID: ID give to each segmented audio file in the format of professor_name_course_start-time_end-time

2.3 Algorithm of split_str.py

The algorithm of split_srt.py code is as follows:

```
1 mp3_list = contains all the names of the mp3 files in the current
   folder.
2 extract_timeframes_text() : function that returns a list of timestamp
   information and corresponding text data from the given srt file.
3 time_framelist=contains the timestamps
4 text_list =contains the corresponding text data for each timestamp
5 Algo:
6 for mp3_file in mp3_list:
7     initialise time_framelen_tillnow=0
8     initialise prev_timestamp=0
9     initialise clip_start=0
10    time_framelist ,text_list =extract_timeframes_text(mp3_list+
        srt )
11    text=
12    for i in range(len(time_framelist)):
13        temp_timeframe_len=time_framelist[i]-prev_timestamp
14        if(temp_timeframe_len+time_framelen_tillnow <=15):
15            time_framelen_tillnow+=temp_timeframe_len
16            text+=text_list[i]
17        prev_timestamp=time_framelist[i]
18    else:
19        File.write(textfile , clip_start , prev_timestamp , text_list)
20        File.write(spk2_utt , clip_start , prev_timestamp)
21        File.write(utt2spk , clip_start , prev_timestamp)
```

```
22 File.write(wav.scp , clipped_paths_of_wav_files , clip_start ,
    prev_timestamp)
23 clip_start=prev_timestamp
24 time_framelen_tillnow=0
25 temp_timeframe_len=time_framelist[i]-prev_timestamp
26 time_framelen_tillnow+=temp_timeframe_len
27 prev_timestamp=time_framelist[i]
```

Note:

- Several corner cases and how the text , wav.scp ,spk2utt, utt2spk files were written were not addressed here.
- The clipped audio segments cannot directly be given as input to the espnet because they are generally sampled at different rates (40 to 45 kHz) which unnecessarily uses a lot of space so all the clipped audio segments are downsampled to 16 KHz using sox command in resample.sh code.
- All the clipped .wav files are indexed to a single speaker itself in spk2utt ,utt2spk files because we don't have the information about the course instructors for a course in the downloaded data. If so , then index each course by a different speaker.

2.4 Key procedures that are to be taken care of before running split_srt.py

There are some processes that are to be taken care of before running split_srt.py. They are as follows:

- Download mp3 files and the corresponding srt files for each lecture from NPTEL website.
- Preprocess the srt files to check for unusual tokens because they reduce the model performance.
- Naming for both mp3 and srt files of a lecture that is downloaded from NPTEL website should be same. This is the important one since it is assumed in the code.

After running split_srt.py, we get all the input files required for ESPnet model training. Train the ESPnet model using the input files.

CHAPTER 3

Model Performance after Training

After training the model, model is tested by decoding it with some data files. The results of decoding are as follows:

3.1 The model performance when trained for 8 hours data and tested for 1hour data using RNN model

3.1.1 Without text normalisation

Table 3.1: The model performance without text normalisation

Word error rate	Character error rate	Number of epochs
89.2	56.5	15

3.1.2 With text normalisation

Table 3.2: The model performance with text normalisation

Word error rate	Character error rate	Number of epochs
44.1	20.5	15

As we can see from Table3.1 and Table 3.2 that there is significant decrease in Word Error rate and Character Error Rate from training without normalisation to with normalisation. This is because in training without normalisation there will be capital letters and small letters and words using them. since there is less data and more targets hence WER and CER is high. Where as in the case of with normalisation, there will be only either Upper case or lower case words. Hence, WER and CER decreased greatly.

3.1.3 Observations

The word error rates have been same when we normalised the data into all capital letters to the case where data is normalised to all small letters.

3.2 The model performance when trained for 8 hrs data and tested for one hour data using BLSTM

Table 3.3: The model performance when trained for 8 hrs data and tested for one hour data using BLSTM

WER for validation	CER for validation	CER for training	Number of epochs
44.1	20.5	8.6	15

As we can see from Figure 3.1, the loss decreases with number of epochs. This is because since there is not lots of data, it requires lots of epochs. This effect can also be seen in Figure 3.2- Accuracy increases with number of epochs and from Figure 3.3- CER decreases with number of epochs.

3.3 The model performance when trained for 400 hrs data and tested for one hour data using BLSTM

Table 3.4: The model performance when trained for 400 hrs data and tested for one hour data using BLSTM

WER for validation	CER for validation	CER for training	Number of epochs
19.6	9.8	4.8	11

In this case, there is lots of data, so training doesn't require many number of epochs. This can be seen in Figure 3.4 loss increases with epochs, from Figure 3.5 accuracy decreases with number of epochs and from Figure 3.6 CER increases with number of epochs.

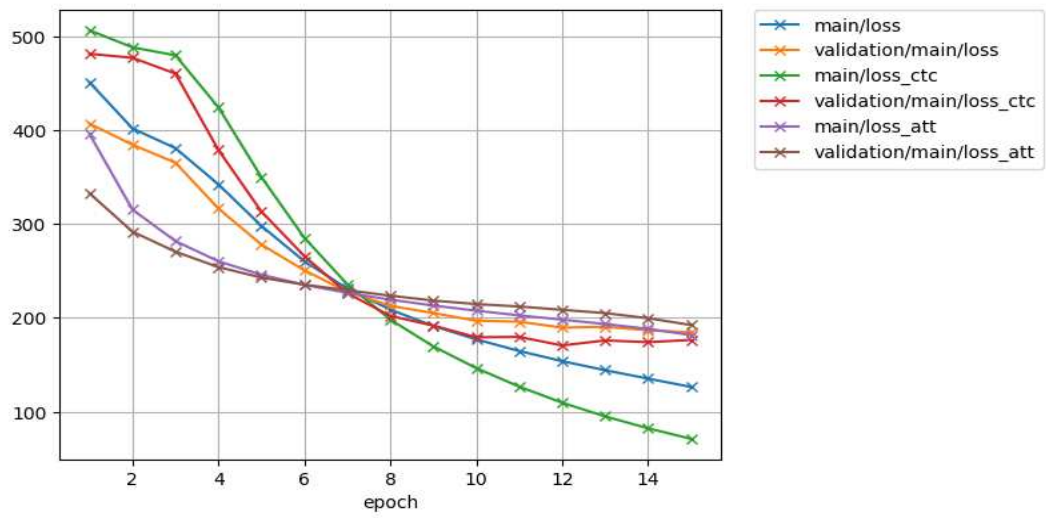


Figure 3.1: Loss vs Number of epochs

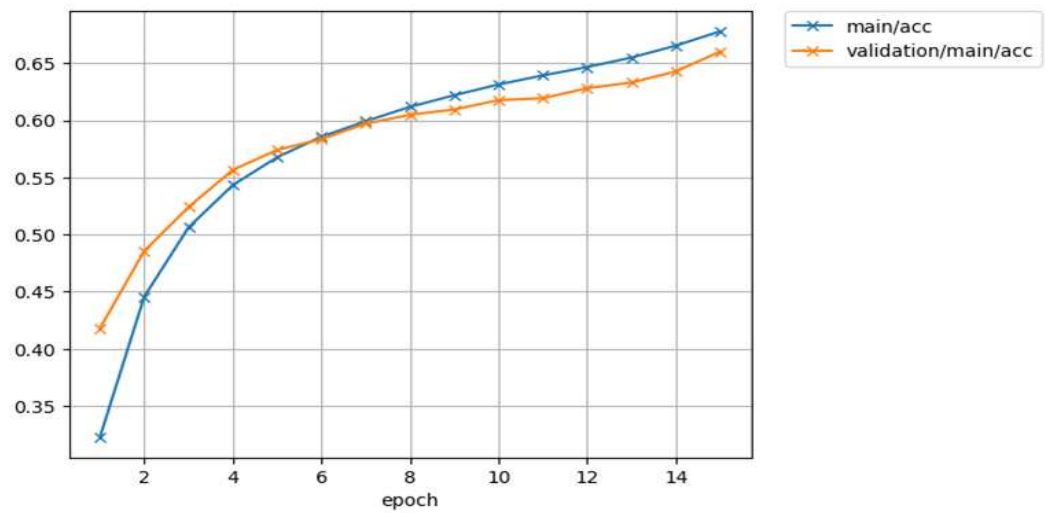


Figure 3.2: Accuracy vs Number of epochs

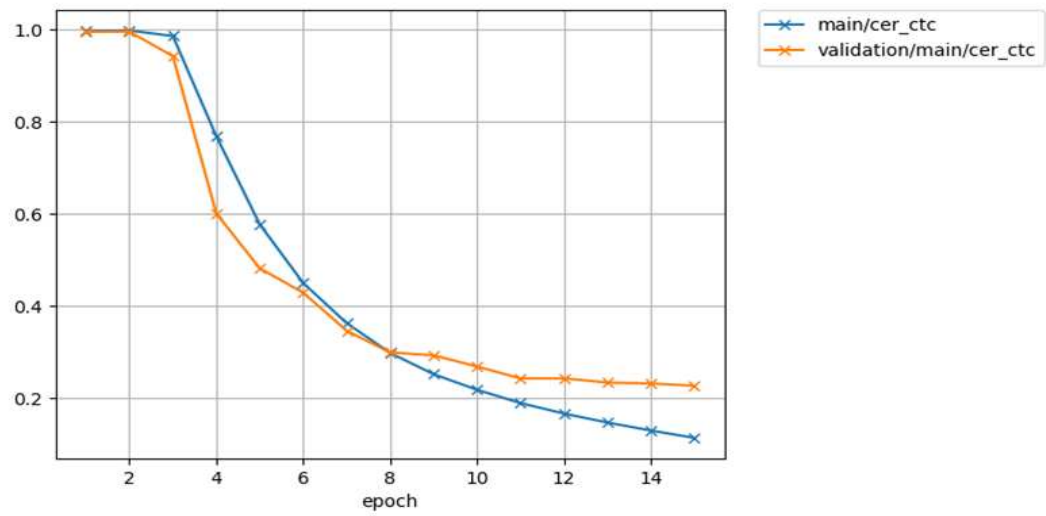


Figure 3.3: Character Error Rate vs Number of epochs

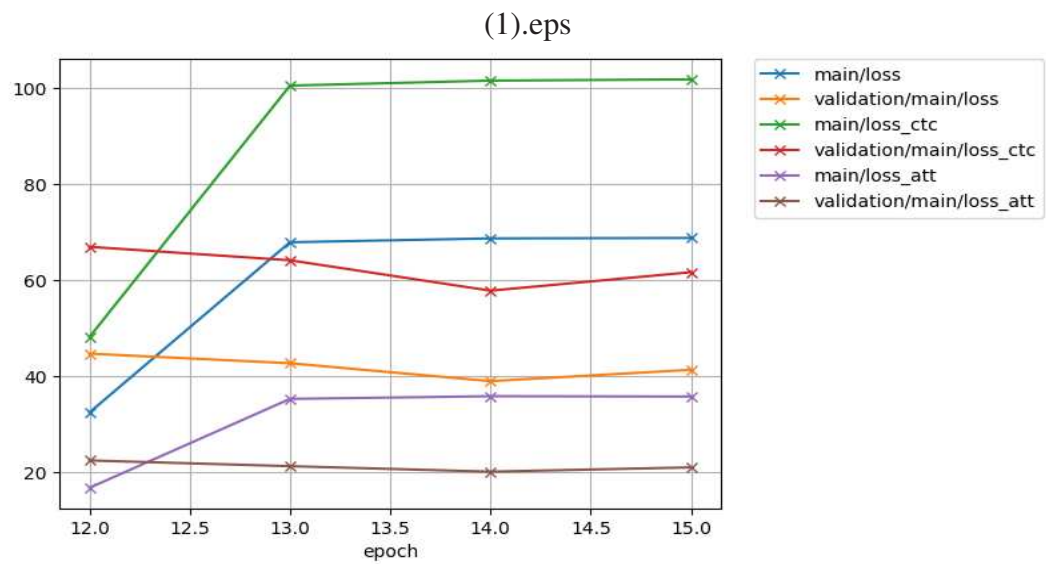


Figure 3.4: Loss vs Number of epochs

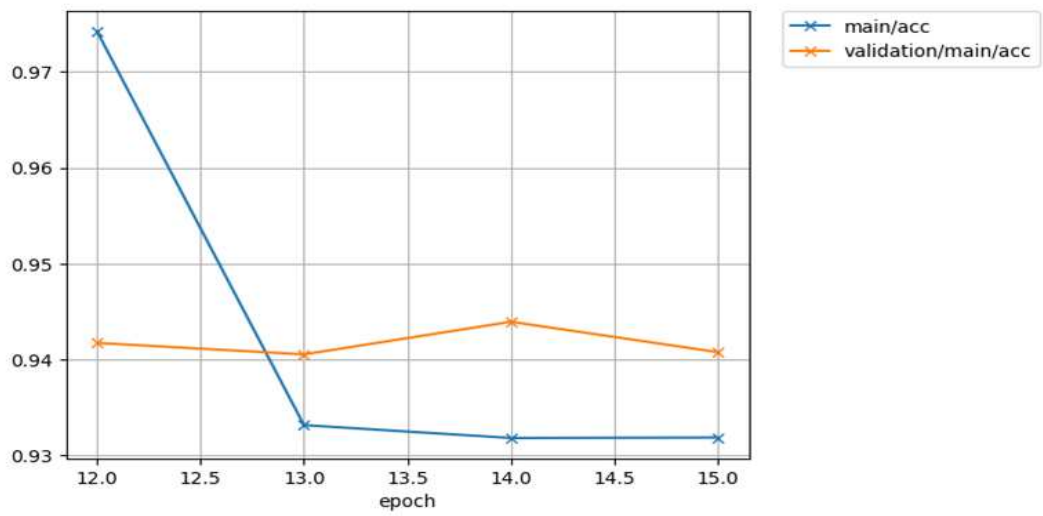


Figure 3.5: Accuracy vs Number of epochs

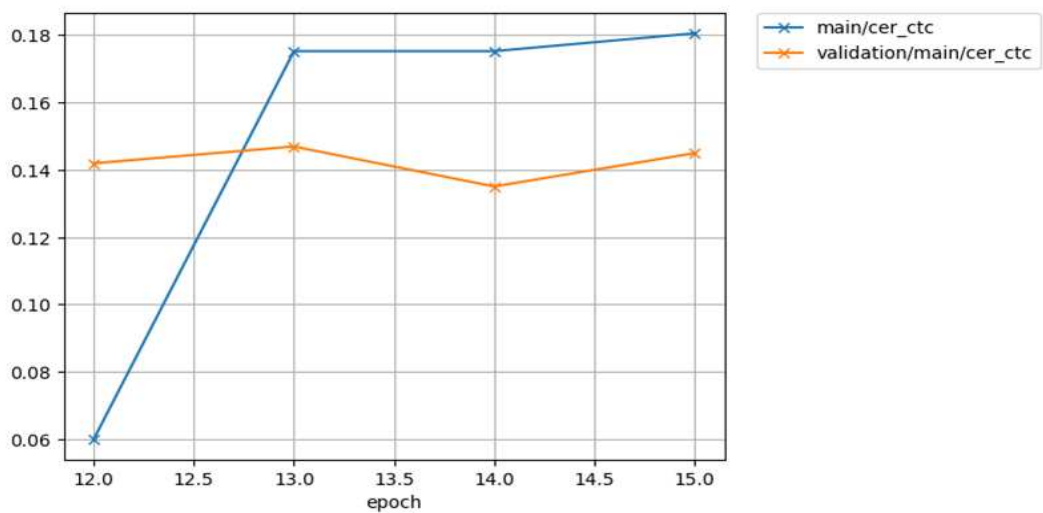


Figure 3.6: Character Error Rate vs Number of epochs

3.4 Observations

The following are the observations:

- As seen from the error plots above The training error continuously decreased with increase in the number of epochs for the case with 8 lectures because the data there is very less so it requires a large number of epochs to train that model.
- Contrary to which for the case with 400 lectures the validation loss is increasing after 11 epochs indicating over fitting which is expected.
- More the amount of data that we pour into the training of the rnn model in espnet. Better will be the word and character error rates as well that which is evident in a decrease of about 55.56% in the word error rates and a decrease of about 55.2% in the character error rate for the validation set than its predecessor model.

CHAPTER 4

Codes

The codes used in the project are written here.

4.1 run.sh

```
1 #!/bin/bash
2
3 # Copyright 2017 Johns Hopkins University (Shinji Watanabe)
4 # Apache 2.0 (http://www.apache.org/licenses/LICENSE-2.0)
5
6 . ./path.sh
7 . ./cmd.sh
8
9
10 # general configuration
11 backend=pytorch
12 stage=4          # start from -1 if you need to start from data download
13 stop_stage=100
14 ngpu=0           # number of gpus ("0" uses cpu, otherwise use gpu)
15 debugmode=1
16 dumpdir=dump     # directory to dump full features
17 N=0              # number of minibatches to be used (mainly for
                  # debugging). "0" uses all minibatches.
18 verbose=0        # verbose option
19 resume=          # Resume the training from snapshot
20
21 # feature configuration
22 do_delta=false
23
24 # network architecture
25 # encoder related
26 etype=vggblstm  # encoder architecture type
27 elayers=4
```

```

28 eunits=320
29 eprojs=320
30 subsample=1_2_2_1_1 # skip every n frame from input to nth layers
31 # decoder related
32 dlayers=1
33 dunits=300
34 # attention related
35 atype=location
36 aconv_chans=10
37 aconv_filts=100
38
39 # hybrid CTC/attention
40 mtlalpha=0.5
41
42 # minibatch related
43 batchsize=10 #30
44 maxlen_in=800 # if input length > maxlen_in, batchsize is
    automatically reduced
45 maxlen_out=150 # if output length > maxlen_out, batchsize is
    automatically reduced
46
47 # optimization related
48 sortagrad=0 # Feed samples from shortest to longest ; -1: enabled for
    all epochs, 0: disabled, other: enabled for 'other' epochs
49 opt=adadelta
50 epochs=15
51 patience=3
52
53 # decoding parameter
54 beam_size=20
55 penalty=0
56 maxlenratio=0.0
57 minlenratio=0.0
58 ctc_weight=0.3
59 recog_model=model.acc.best # set a model to be used for decoding: '
    model.acc.best' or 'model.loss.best'
60
61 # scheduled sampling option
62 samp_prob=0.0
63

```

```

64 # data
65 voxforge=downloads # original data directory to be stored
66 lang=en # de, en, es, fr, it, nl, pt, ru
67
68 # exp tag
69 tag="" # tag for managing experiments.
70
71 . utils/parse_options.sh || exit 1;
72
73 . ./path.sh
74 . ./cmd.sh
75
76 # Set bash to 'debug' mode, it will exit on :
77 # -e 'error', -u 'undefined variable', -o ... 'error in pipeline', -x
  'print commands',
78 set -e
79 set -u
80 set -o pipefail
81
82 train_set=tr_${lang}
83 train_dev=dt_${lang}
84 train_test=et_${lang}
85 recog_set="dt_${lang} et_${lang}"
86 #recog_set="dt_${lang}"
87 <<"over"
88 if [ ${stage} -le -1 ] && [ ${stop_stage} -ge -1 ]; then
89     echo "stage -1: Data Download"
90     local/getdata.sh ${lang} ${voxforge}
91 fi
92
93 if [ ${stage} -le 0 ] && [ ${stop_stage} -ge 0 ]; then
94     ### Task dependent. You have to make data the following
  preparation part by yourself.
95     ### But you can utilize Kaldi recipes in most cases
96     echo "stage 0: Data Preparation"
97     selected=${voxforge}/${lang}/extracted
98     # Initial normalization of the data
99     local/voxforge_data_prep.sh ${selected} ${lang}
100     local/voxforge_format_data.sh ${lang}
101 fi

```

```

102 over
103
104 feat_tr_dir=${dumpdir}/${train_set}/delta${do_delta}; mkdir -p ${
    feat_tr_dir}
105 feat_dt_dir=${dumpdir}/${train_dev}/delta${do_delta}; mkdir -p ${
    feat_dt_dir}
106 if [ ${stage} -le 1 ] && [ ${stop_stage} -ge 1 ]; then
107     ### Task dependent. You have to design training and dev sets by
    yourself.
108     ### But you can utilize Kaldi recipes in most cases
109     echo "stage 1: Feature Generation"
110     fbankdir=fbank
111
112     for x in ${train_dev} ${train_test} ${train_set}; do
113         utils/fix_data_dir.sh data/${x}
114         steps/make_fbank_pitch.sh --cmd "$train_cmd" --nj 10 --
            write_utt2num_frames true \
115             data/${x} exp/make_fbank/${x} ${fbankdir}
116     done
117     # compute global CMVN
118     compute-cmvn-stats scp:data/tr_${lang}/feats.scp data/tr_${lang}/
        cmvn.ark
119
120     dump.sh --cmd "$train_cmd" --nj 10 --do_delta $do_delta \
121         data/${train_set}/feats.scp data/${train_set}/cmvn.ark exp/
        dump_feats/train ${feat_tr_dir}
122     dump.sh --cmd "$train_cmd" --nj 4 --do_delta $do_delta \
123         data/${train_dev}/feats.scp data/${train_set}/cmvn.ark exp/
        dump_feats/dev ${feat_dt_dir}
124     for rtask in ${recog_set}; do
125         feat_recog_dir=${dumpdir}/${rtask}/delta${do_delta}; mkdir -p
            ${feat_recog_dir}
126         dump.sh --cmd "$train_cmd" --nj 4 --do_delta $do_delta \
127             data/${rtask}/feats.scp data/${train_set}/cmvn.ark exp/
            dump_feats/recog/${rtask} \
128             ${feat_recog_dir}
129     done
130 fi
131
132 dict=data/lang_1char/tr_${lang}_units.txt

```

```

133 echo "dictionary: ${dict}"
134 if [ ${stage} -le 2 ] && [ ${stop_stage} -ge 2 ]; then
135     ### Task dependent. You have to check non-linguistic symbols used
136     in the corpus.
137     echo "stage 2: Dictionary and Json Data Preparation"
138     mkdir -p data/lang_1char/
139     echo "<unk> 1" > ${dict} # <unk> must be 1, 0 will be used for "
140     blank" in CTC
141     text2token.py -s 1 -n 1 data/tr_${lang}/text | cut -f 2- -d" " |
142     tr " " "\n" \
143     | sort | uniq | grep -v -e '^\\s*$' | awk '{print $0 " " NR+1}' >>
144     ${dict}
145     wc -l ${dict}
146
147     # make json labels
148     data2json.sh --lang ${lang} --feat ${feat_tr_dir}/feats.scp \
149     data/tr_${lang} ${dict} > ${feat_tr_dir}/data.json
150     data2json.sh --lang ${lang} --feat ${feat_dt_dir}/feats.scp \
151     data/dt_${lang} ${dict} > ${feat_dt_dir}/data.json
152     for rtask in ${recog_set}; do
153         feat_recog_dir=${dumpdir}/${rtask}/delta${do_delta}
154         data2json.sh --feat ${feat_recog_dir}/feats.scp \
155         data/${rtask} ${dict} > ${feat_recog_dir}/data.json
156     done
157 fi
158
159
160
161
162
163
164 if [ -z ${tag} ]; then
165     expname=${train_set}_${backend}_${etype}_e${elayers}_subsample${
166     subsample}_unit${eunits}_proj${eprojs}_d${dlayers}_unit${dunits}_$
167     {atype}_aconvc${aconv_chans}_aconvf${aconv_filts}_mtlalpha${
168     mtlalpha}_${opt}_sampprob${samp_prob}_bs${batchsize}_mli${
169     maxlen_in}_mlo${maxlen_out}
170     if ${do_delta}; then
171         expname=${expname}_delta
172     fi
173 else
174     expname=${train_set}_${backend}_${tag}
175 fi

```

```

165 expdir=exp/${expname}
166 #mkdir -p ${expdir}
167
168 #exit 0
169 if [ ${stage} -le 3 ] && [ ${stop_stage} -ge 3 ]; then
170     mkdir -p ${expdir}
171     echo "stage 3: Network Training"
172     ${cuda_cmd} --gpu ${ngpu} ${expdir}/train.log \
173         asr_train.py \
174         --ngpu ${ngpu} \
175         --backend ${backend} \
176         --outdir ${expdir}/results \
177         --tensorboard-dir tensorboard/${expname} \
178         --debugmode ${debugmode} \
179         --dict ${dict} \
180         --debugdir ${expdir} \
181         --minibatches ${N} \
182         --verbose ${verbose} \
183         --resume ${resume} \
184         --train-json ${feat_tr_dir}/data.json \
185         --valid-json ${feat_dt_dir}/data.json \
186         --etype ${etype} \
187         --elayers ${elayers} \
188         --eunits ${eunits} \
189         --eprojs ${eprojs} \
190         --subsample ${subsample} \
191         --dlayers ${dlayers} \
192         --dunits ${dunits} \
193         --atype ${atype} \
194         --aconv-chans ${aconv_chans} \
195         --aconv-filts ${aconv_filts} \
196         --mtlalpha ${mtlalpha} \
197         --batch-size ${batchsize} \
198         --maxlen-in ${maxlen_in} \
199         --maxlen-out ${maxlen_out} \
200         --opt ${opt} \
201         --sortagrad ${sortagrad} \
202         --sampling-probability ${samp_prob} \
203         --epochs ${epochs} \
204         --patience ${patience}

```

```

205 fi
206
207
208 #exit 0
209 recog_set="et_${lang}"
210 if [ ${stage} -le 4 ] && [ ${stop_stage} -ge 4 ]; then
211     echo "stage 4: Decoding"
212     nj=10
213
214     pids=() # initialize pids
215     for rtask in ${recog_set}; do
216     (
217         decode_dir=decode_${rtask}_beam${beam_size}_e${recog_model}
218         _p${penalty}_len${minlenratio}-${maxlenratio}_ctcw${ctc_weight}
219         feat_recog_dir=${dumpdir}/${rtask}/delta${do_delta}
220         mkdir -p ${expdir}/${decode_dir}
221         # split data
222         splitjson.py --parts ${nj} ${feat_recog_dir}/data.json
223
224         ##### use CPU for decoding
225         ngpu=0
226
227         ${decode_cmd} JOB=1:${nj} ${expdir}/${decode_dir}/log/decode.
228         JOB.log \
229             asr_recog.py \
230             --ngpu ${ngpu} \
231             --backend ${backend} \
232             --debugmode ${debugmode} \
233             --verbose ${verbose} \
234             --recog-json ${feat_recog_dir}/split${nj}utt/data.JOB.
235         json \
236             --result-label ${expdir}/${decode_dir}/data.JOB.json \
237             --model ${expdir}/results/${recog_model} \
238             --beam-size ${beam_size} \
239             --penalty ${penalty} \
240             --maxlenratio ${maxlenratio} \
241             --minlenratio ${minlenratio} \
242             --ctc-weight ${ctc_weight}
243
244         score_sclite.sh --wer true ${expdir}/${decode_dir} ${dict}

```



```

242
243     ) &
244     pids+=($!) # store background pids
245     done
246     i=0; for pid in "${pids[@]"; do wait ${pid} || ((++i)); done
247     [ ${i} -gt 0 ] && echo "$0: ${i} background jobs are failed." &&
    false
248     echo "Finished"
249 fi

```

4.2 split_srt.py

```

1 import numpy as np
2 import os
3 import pydub
4 from pydub import AudioSegment
5 speaker="speakerid1"
6 uut_list=[]
7 current_directory = os.getcwd()
8 split_dir_name="splitwav2"      # temporary folder which contains .
    wavfiles downsampled to 16Khz and later saved to splitwav
9 final_directory = os.path.join(current_directory+"/"+split_dir_name)
10 #print(os.path.exists(final_directory))
11 if not os.path.exists(final_directory):
12     os.makedirs(final_directory)
13 outFileNames = os.getcwd()+"/" + "text"
14 outmp3FileName = os.getcwd() + "/" + "wav.scp"
15 with open(outmp3FileName, "w") as f1:
16     with open(outFileName, "w") as f:
17         for mp3_files in os.listdir(os.getcwd()):
18             if(".mp3" in mp3_files):
19                 sound = AudioSegment.from_mp3(mp3_files)
20
21                 file=mp3_files[:-4] + ".srt"
22                 timestamps=15.0 # duration of each audio file
23                 l=[]
24                 with open(file, "r", encoding="utf8") as fop:
25                     l=fop.read().splitlines()
26                     print(file)
27                 fop.close()

```

```

28         dictionary={}# contains all info of start time, end
time and text
29         k=1
30         file_length=len(l)
31         for i in range(-1,file_length):
32             temp=""
33             if(l[i]==" " or i==-1):
34                 i+=2
35                 if(i<file_length):
36                     temp_string=l[i]
37                     start_time=int(temp_string[0:2])*60*60+
int(temp_string[3:5])*60+int(temp_string[6:8])+int(temp_string
[9:12])*0.001
38                     loc=temp_string.find('>')
39                     loc+=2
40                     end_time=int(temp_string[loc+0:loc+2])
*60*60+int(temp_string[loc+3:loc+5])*60+int(temp_string[loc+6:loc
+8])+int(temp_string[loc+9:loc+12])*0.001
41                     i+=1
42
43             while(l[i]!=" "):
44                 temp+=l[i] + " "
45                 if(i+1 >= file_length):
46                     break #for loop index exceeding
47                 else:
48                     i=i+1
49
50
51             temp_list_for_dict=[]
52             temp_list_for_dict.append(end_time)
53             temp_list_for_dict.append(temp)
54             dictionary[start_time]=temp_list_for_dict
55
56
57         dict_keys=dictionary.keys()
58         dict_len=len(dict_keys)
59         temp_sum=0
60         j=1
61         print(len(sound))
62         lenth=len(sound)

```

```

63         temp_str=""
64         start=None
65         end=None
66         time=None
67         timeslots = []
68         listofkeys = list(dictionary)
69         for m in dict_keys:
70             start=float(m)
71             end=float(dictionary[m][0])
72             time=end-start
73             boolean = 0
74             if (temp_sum+time>timestamps):
75                 timeslots.append(float(m))
76                 l=len(timeslots)
77
78                 # if(l==1):
79                 #     outFileName = os.getcwd() + "\
Western_philosophy" + "_" + str(0) + "_" + str(timeslots[l-1]) + "
_.txt"
80
81                 # else:
82                 #     outFileName = os.getcwd() + "\
Western_philosophy" + "_" + str(timeslots[l-2]) + "_" + str(timeslots
[l-1]) + "_.txt"
82
83                 #outFile=open(outFileName, "w")
84                 f.write(mp3_files[: -4] + "_")
85                 if(l==1):
86                     f.write(str(listofkeys[0]) + "_" + str(
timeslots[l-1]) + "
") #Utterance ID
87                     uut_list.append(mp3_files[: -4] + "_" + str(
listofkeys[0]) + "_" + str(timeslots[l-1]))
88                 else:
89                     f.write(str(timeslots[l-2]) + "_" + str(
timeslots[l-1]) + "
")#Utterance ID
90                     uut_list.append(mp3_files[: -4] + "_" + str(
timeslots[l-2]) + "_" + str(timeslots[l-1]))
91                     f.write(temp_str.lower())# text
92                     f.write("\n")
93                     temp_str=dictionary[m][1]
94                     temp_sum=time
95                     j+=1

```

```

95         f1.write(mp3_files[: -4] + "_")
96         if(l==1): # because we know only end time. we
          didnt know start time. It can be pulled from listofkeys of
          dictionary
97             temp_audio_file=sound[ float( listofkeys
[0])*1000: float( timeslots[ l-1])*1000)# splitting audio according to
          start and end time
98             temp_audio_file.export( final_directory+"/
"+"Western_philosophy"+ "_" + mp3_files[: -4] + "_" + str(
listofkeys[0]) + "_" + str( timeslots[ l-1]) + "_wav", format="wav")
99             f1.write( str( listofkeys[0]) + "_" + str(
timeslots[ l-1]) + "          ")#for wav.scp
100             f1.write( os.getcwd()+ "/" +split_dir_name+"
"/+ "Western_philosophy"+ "_" + mp3_files[: -4] + "_" + str(
listofkeys[0]) + "_" + str( timeslots[ l-1]) + "_wav")#audio paths
          for wav.scp
101             f1.write("\n")
102         else:
103             temp_audio_file=sound[ float( timeslots[ l
-2])*1000: float( timeslots[ l-1])*1000]
104             temp_audio_file.export( final_directory+"/
"+"Western_philosophy"+ "_" + mp3_files[: -4] + "_" +str( timeslots[
l-2]) + "_" + str( timeslots[ l-1]) + "_wav", format="wav")
105             f1.write( str( timeslots[ l-2]) + "_" + str(
timeslots[ l-1]) + "          ")
106             f1.write( os.getcwd() + "/" +split_dir_name+
"/+ "Western_philosophy"+ "_" + mp3_files[: -4] + "_" +str(
timeslots[ l-2]) + "_" + str( timeslots[ l-1]) + "_wav")
107             f1.write("\n")
108         else:
109             if( boolean == 0):
110                 temp_str+=dictionary[m][1]
111                 temp_sum+=time
112                 boolean = 1
113             else:
114                 temp_str+=" " + dictionary[m][1]
115                 temp_sum+=time
116             f.write( mp3_files[: -4] + "_")#for last segment
117             f1.write( mp3_files[: -4] + "_")# for last split
118             if(l==1):

```

```

119         f.write(str(listofkeys[0]) + "_" + str(listofkeys
120 [len(listofkeys)-1]) + "
121         temp_audio_file=sound[float(listofkeys[0])*1000:
float(listofkeys[len(listofkeys)-1])*1000]
122         temp_audio_file.export(final_directory+"/"+
Western_philosophy" + "_" + mp3_files[:4] + "_" + str(listofkeys
123 [0]) + "_" + str(listofkeys[len(listofkeys)-1]) + "_wav",format="
wav")
124         f1.write(str(listofkeys[0]) + "_" + str(
listofkeys[len(listofkeys)-1]) + "
125         f1.write(os.getcwd()+"/"+split_dir_name+"/"+
Western_philosophy" + "_" + mp3_files[:4] + "_" + str(listofkeys
126 [0]) + "_" + str(listofkeys[len(listofkeys)-1]) + "_wav")
127         f1.write("\n")
128         uut_list.append(mp3_files[:4] + "_" + str(
listofkeys[0]) + "_" + str(listofkeys[len(listofkeys)-1]))
129     else:
130         f.write(str(timeslots[l-1]) + "_" + str(
listofkeys[len(listofkeys)-1]) + "
131         temp_audio_file=sound[float(timeslots[l-1])*1000:
float(listofkeys[len(listofkeys)-1])*1000]
132         temp_audio_file.export(final_directory+"/"+
Western_philosophy" + "_" + mp3_files[:4] + "_" + str(timeslots[l
133 -1]) + "_" + str(listofkeys[len(listofkeys)-1]) + "_wav",format="
wav")
134         f1.write(str(timeslots[l-1]) + "_" + str(
listofkeys[len(listofkeys)-1]) + "
135         f1.write(os.getcwd()+"/"+split_dir_name+"/"+
Western_philosophy" + "_" + mp3_files[:4] + "_" + str(timeslots[l
136 -1]) + "_" + str(listofkeys[len(listofkeys)-1]) + "_wav")
137         f1.write("\n")
138         uut_list.append(mp3_files[:4] + "_" + str(
timeslots[l-1]) + "_" + str(listofkeys[len(listofkeys)-1]))
139         f.write(temp_str.lower())
140         f.write("\n")
141     f.close()
142 f1.close
143 with open(os.getcwd()+"/"+utt2spk,"w") as uf:
144     for i in uut_list:
145         uf.write(i+" "+speaker+"\n")

```

```

141     uf.close()
142 with open(os.getcwd()+"/"+"spk2utt","w") as spf:
143     spf.write(speaker+" ")
144     for i in uut_list:
145         spf.write(i+" ")
146     spf.close()

```

4.3 resample.sh

This script calls the above split_srt.py and downsamples all audio files to $16Khz$.

```

1 #!/bin/bash
2 mkdir -p splitwav
3 python split_srt.py
4 for entry in `ls splitwav2/`; do
5     echo ${entry}
6     sox splitwav2/${entry} -r 16000 splitwav/${entry} #downsample the .
    wav files in splitwav2 created by split_srt.py and put them in
    splitwav
7 done
8 rm -r splitwav2

```

LIST OF PAPERS BASED ON THESIS

1. Takaaki Hori, Jaejin Cho, Shinji Watanabe END-TO-END SPEECH RECOGNITION WITH WORD-BASED RNN LANGUAGE MODELS *Journal*, 1, (Aug, 2018).
2. Thomas Zenkel, Matthias Sperber, Jan Niehues, Markus Müller, Ngoc-Quan Pham, Sebastian Stüker, Alex Waibel Open Source Toolkit for Speech to Text Translation (Oct 2018)