Contents

Introduction

In this assignment, we will present the Automatic Speech Recognition (ASR) task. The main goal of this task is to assign a sequence of words, letters or phonemes to a given input, which is usually audio features. In particular, we will use an already **built** recognition system based in End-to-end deep learning. We will use *ESPNet (End-to-end Speech Processing Toolkit).* The code that we will use was provided by Beltrán Labrador and Doroteo Torre, and can be found in this Google Colab notebook.

Setting the environment up

To test ESPNet, we will use the dataset `TIMIT`, which contains 6300 phrases, divided in 10 phrases of each of the 630 speakers from the 8 main different US dialect regions. The phrases are also divided in male and female speakers. It is also important to remark that the division in train/test splits is done in a way that:

- A speaker appears rather in the train or in the test split separately, but not in both at the same time.
- The phrases of the test set are **not** in the train set.

The first task will simply consists on looking at the content of the files that the `TIMIT` corpus provides and understanding these files.

Questions.

- *Check the content of the .txt, .wrd and .phn files listening to the audio (.wav file) with a few examples. Comment how it was done and the results obtained.*

  To check the content of the files, we can use `bash` commands. After loading the dataset in Google Colab, we store it in the `content/timit/TIMIT` folder, in which we can find the `TRAIN/TEST` folders. Having a look at the official documentation and to the assignment documentation, we observe that we have the folders have the following structure:

  ```
  <DIALECT>/<SEX><SPEAKER_ID>/<SENTENCE_ID>.<FILE_TYPE>
  ```

  We can list the different users of any of the regions and select one of them to observe his or her data. For convenience, we firstly use the code provided to examine the data of the user `DR1/FCJF0`, meaning that it is an user from the first dialect region, and it is a female. We select the audio `SX397` and then we show the *spelling* of the phrase.

  ```
  !cat /content/timit/TIMIT/TRAIN/DR1/FCJF0/SX397.TXT
  ```

  ```
  0 39220 Tim takes Sheila to see movies twice a week.
  ```

  We appreciate that this audio consist uniquely on one phrase. If we use

```
Ipython.display.audio('path_to_the_audio')
```

(where the path in this case is */content/timit/TIMIT/TRAIN/DR1/FCJF0/SX397.WAV*), we listen to the audio and verify that the spelling is correct. We can also check the *aligned word-level transcription*:

```
!cat /content/timit/TIMIT/TRAIN/DR1/FCJF0/SX397.WRD

 2240 5540 tim
 5540 8610 takes
 8610 14707 sheila
 14707 15791 to
 15791 19735 see
 19735 26402 movies
 26402 31210 twice
 31210 31791 a
 31791 37180 week
```

Which indicates exactly the steps of time where the words happen, and we can lastly observe the phonetic transcription:

```
!cat /content/timit/TIMIT/TRAIN/DR1/FCJF0/SX397.PHN

0 2240 h#
2240 2940 t
2940 4469 ih
4469 5540 m
5540 5860 tcl
5860 6570 t
6570 8211 ey
8211 8610 kcl
8610 11112 sh
...
```

Since this is the provided example, we repeat the process with a different example to check that everything is correct in another case. We use the same region and female speaker. We select the sentence id: SX307. We show the spelling transcription and the word-level transcription:

```
!cat /content/timit/TIMIT/TRAIN/DR1/FCJF0/SX307.TXT
!echo "-----"
!cat /content/timit/TIMIT/TRAIN/DR1/FCJF0/SX307.WRD

0 23143 The meeting is now adjourned.
-----
1960 2616 the
2616 8293 meeting
8293 10160 is
10960 13707 now
13707 20887 adjourned
```

Which shows the content of the phrase. Lastly, we have played the audio as we have explained before to check that the phrase is correct. We detect a little bit of noise on the speaker, but the words can be understood correctly.

- *Explore the documentation of the TIMIT corpus and find information associated to the speakers. Can you think of any other applications of this corpus further from the training and evaluation of Speech Recognition systems?*

We consider the folder structure mentioned before to give an answer to this. we find that we have audios classified by *sex* and *speaker*. Thanks to this, we could definitely use this corpus to build a *male/female* recognition system or even a **speaker recognition system**. However, the available data for this kind of tasks would probably too low since this dataset is not focused on this task.

Also, we know that we have both the **aligned word transcription** and the **aligned phonetic transcription** available, which could help us to create a **event detection system** with the capability of detecting the

event: *Speech*. However, it would be this unique event since it is the only one labeled in this dataset, so it would not be very useful, although this dataset could be joined with other events datasets to improve the event detection system.

Lastly, in this file of the documentation, we observe that we can find more information about the speakers such as the race, birth date or education level. All this information could be use to perform different classification tasks, as we mentioned before with the sex. The birth date could be used for a regression problem using audio.

ESPNet in Bash

In this section, we will use ESPNet in `Bash` to evaluate a STT system using end-to-end neural networks. We will use the previously presented corpus. The structure of stages that will have to be followed in order to train the system is presented in Figure 1

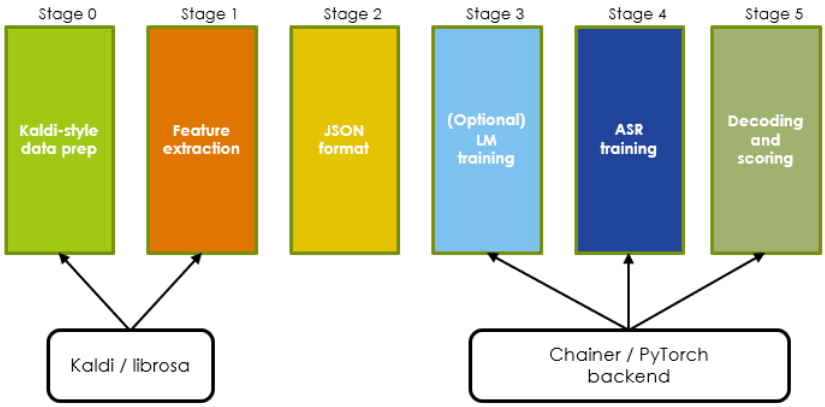


Figure 1: Stages of the complete recipe.

2.1 Directory tree and KALDI recipes

- *Which file(s) should be modified to change...:*
  - The DNN backbone: The DNN backbone is specified in the file:

    `espnet/egs/timit/asr1/conf/train.yaml`

    If we explore this file, we can see that we can specify the *encoder* architecture, the *decoder* architecture and also the attention related layers and hybrid CTC/attention parameters.
  - The Seq-to-seq mapping used: In the script

    `espnet/egs/timit/asr1/run.sh`

    We can find the parameter `trans_type` which indicates if we want to do the Seq-to-seq mapping in the character level or in the phoneme level. This is the parameter that we should modify.

    This parameter has certain value when we download the code.However, we must be careful, since in the Jupyter notebook, this parameter is manually changed using the `sed` bash command:

    ```
    !sed "s#trans_type=char#trans_type=phn#g" espnet/egs/timit/asr1/run.sh.orig > espnet/egs/timi
    ```

- *Comparing the obtained results in phoneme recognition and character recognition in the TIMIT corpus, which one do you consider more precise?*

  The results are shown in a `Markdown` file. In this file, the number of files, words, the percentage of correct tokens, percentage of substitutions/deletions/insertions and the error rate are shown.

  For each of the cases (phoneme/character) a few different configurations of encoder, decoder and attention type are displayed. We resume the most most relevant information in Table 1.

Transcription type	Encoder	Attention type	Decoder	Accuracy on tokens	Error on tokens
Phonemes	vggbgrup	coverage_location	gru	82.1	21.4
	bgrup	**coverage_location**	**lstm**	**82.7**	**20.2**
	bgrup	location	gru	82.5	20.5
Characters	vggbgrup	location	lstm	69.6	38.2
	vggbgrup	location2d	gru	72.0	34.0
	bgrup	coverage_location	lstm	72.8	33.7

Table 1: Results on Phonemes and Characters recognition.

The results show that, in general, this system is **more capable of recognizing the phonemes** than the characters. There is a difference of about 10% in accuracy and more than 15% in the error rates. Recall that the error rates do not have to sum 100%, since the error percentage can be higher than 100%. In particular, in the shown cases, we obtain that the best performing system for phoneme recognition uses `bgrup` as the encoder, an `lstm` as decoder, and uses `coverage_location` as the attention type, obtaining an accuracy of 82.7% on tokens and an error of 20%.

2.2 Data

In this section we will prepare the data for the training of the system.
Questions.

- *What are the names of the three subsets of `TIMIT` that are used? How many phrases does each of them have?*

  The subsets and the number of phrases are summarized in Table 2.

Subset name	Number of phrases	Mean duration	Min Duration	Max duration
train_wav	3696	3.063	0.915	7.788
dev_wav	400	3.08	1.09	7.43
test_wav	192	3.03	1.30	6.21

Table 2: Information about the used `TIMIT` subsets.

- *What are the "FBANK" features?*
  FBANK (Mel-filter bank coefficients) features are extracted from the raw audios. They can be compared with the known MFCCs(Mel Frequency Cepstral Coefficients), which are obtained using the FBANKS and the DCT. This is shown in [1]. The difference in the process can be observed in Figure 2.

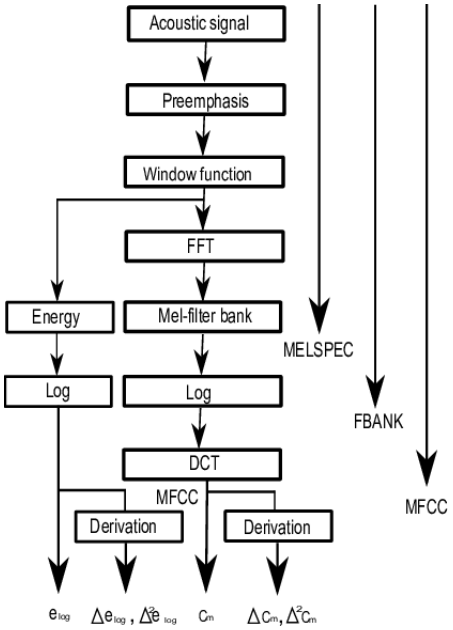


Figure 2: Obtention of FBANK and MFCCs.

- *What does the acronym "CMVN" shown in the computational logs mean?*

  We have found in Wikipedia that this acronym stands for **Cepstral Mean and Variance Normalization**, which is a computationally efficient normalization used in robust speech recognition. This technique minimizes distortion by noise contamination, leading to **robust feature extraction**, linearly transforming the Cepstral coefficients.

2.3 Training the neural networks.

It is time to train the model and check its performance.

Question.

Examine the file `train.yalm` *and try to identify which parameter should be modified in order to change:*

- *Number of encoder layers*: This is specified in the variable `elayers`.
- *Encoder type*: This parameter is stored in the variable `etype`
- *Number of units per encoder layer*: It can be found in the variable `eunits`.
- *Encoder attention type*: The variable `atype` indicates this.
- *Number of units in encoder*: This is stored in the variable `dunits`.

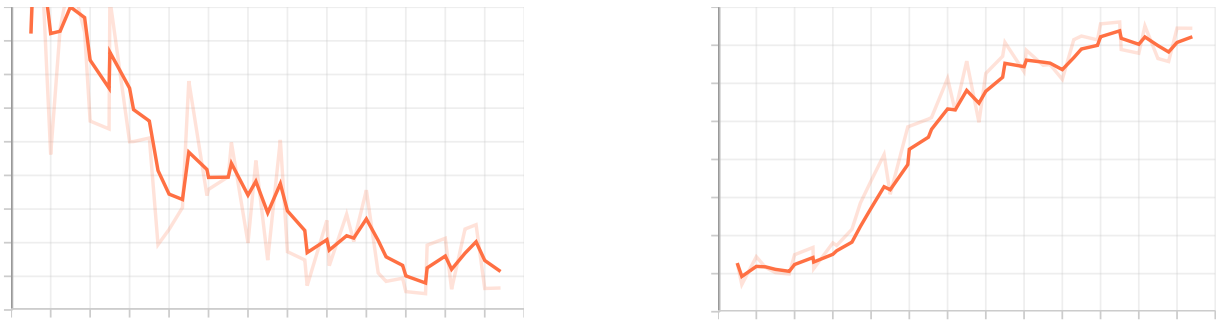
The variable names are self-explicative and the file `train.yalm` is properly commented so finding the answers was easy. Usually, variables related to the encoder start with `e`, the attention variables start with `a` and the decoder variables begin with `d`, making the script intuitive.

Tensorboard can be used to graphically analyze the evolution of the training.

Questions.

- *Can you identify the parameters that correspond to the CTC (Connectionst temporal classification) and attention?*
  Attention parameters are those starting with an `a`. We found the parameters `atype`,`adim`, `aconv-chans` and `aconv-filts`. Lastly, we find the parameter `mtalpha`, which controls the tradeoff between CTC and attention. This parameter is in the interval $[0, 1]$ and if it value is 0.0, the model only uses attention. Contrary, if $mtalpha = 1.0$, the model only uses CTC.
- *Check the evolution of the different parameters and the evolution in train and validation. Do you consider that the training has worked correctly?*

  Let us show a few charts and comment them one by one. Legends and axis are not shown since Tensorboard does not directly provide them.



(a) Main loss

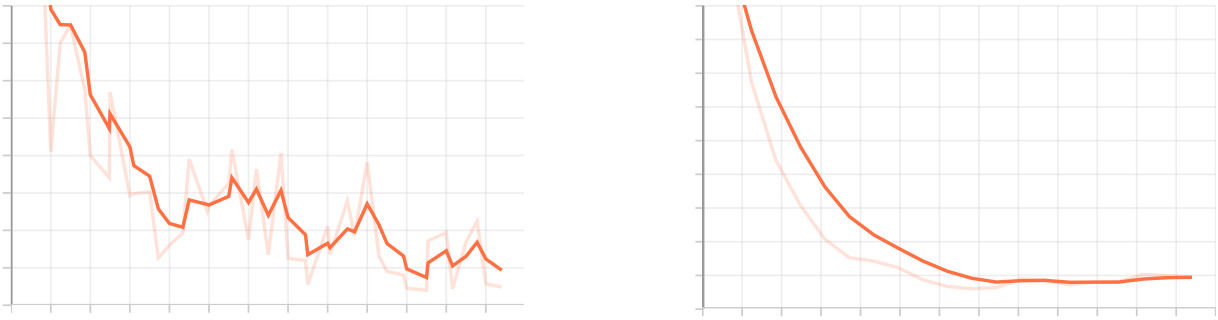
(b) Main accuracy

Figure 3: Tensorboard main loss and acc.

As we appreciate in Figure 3a, the model is training properly since the loss is reduced with the number of iterations. However, it is shown that the loss still has a high value (around 10) and that the curve

has not flattened yet, so more training could be done.

Figure 4 shows that the CTC is also properly trained, although more training could also be used. We see that the spikes in the main loss are quite big, while the validation loss is very smooth. We observe that the CTC loss does not decrease more after a few steps of training.

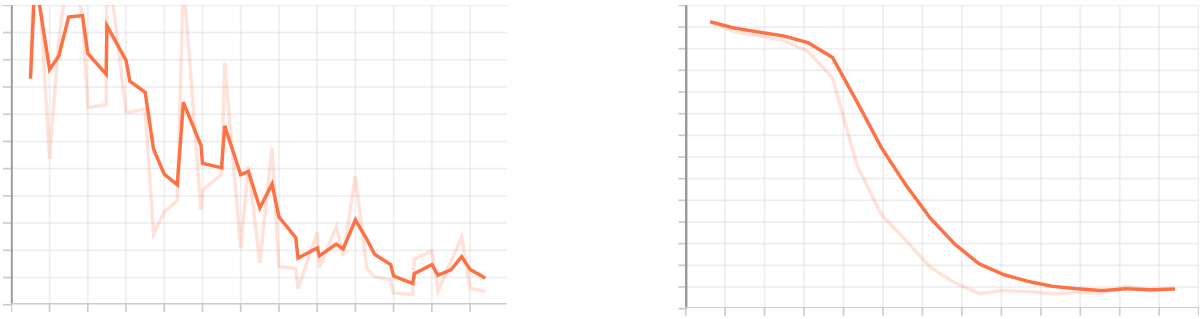


(a) Main loss in CTC

(b) Validation loss in CTC.

Figure 4: CTC graphics.

Lastly, in Figure 5, attention losses are shown. As we can see, the attention loss in the validation set starts to decrease a little bit later than the validation loss in CTC. The main losses have similar decreases. Lastly, the validation attention loss also stops decreasing after a certain number of iterations.



(a) Main loss in Attention

(b) Validation loss in Attention.

Figure 5: Attention graphics.

ESPNet also generates charts about the training process.

Questions.

- *Can you observe any difference between the evolutions associated to CTC and attention? Why?*

All the losses are represented in Figure 6.

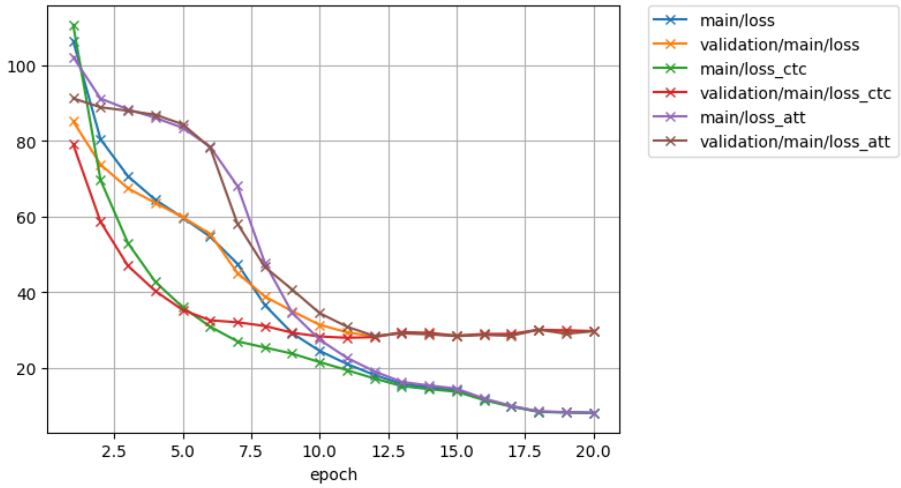
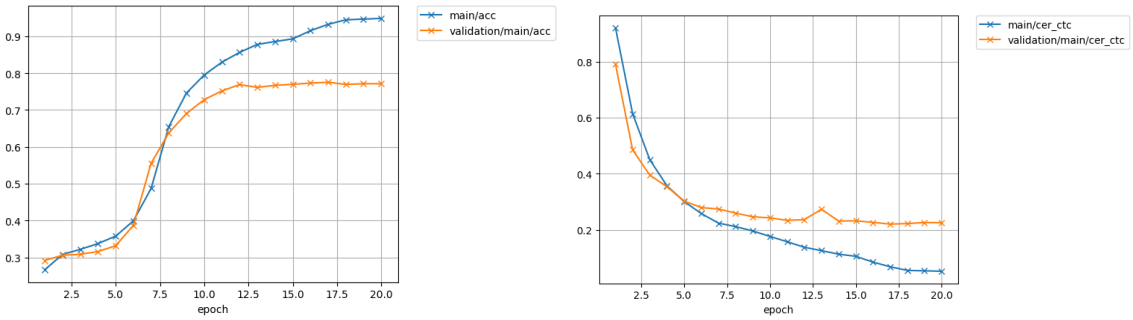


Figure 6: All losses of the training represented for the 20 epochs.

Firstly, we must note that although in the chart indicates `CER`, in our system we evaluated the `PER`, so our comments will mention this metric. This said, the results are the same as the previous ones. As we can see in the Figure 6, the **CTC** loss has a faster decrease in the first few epochs, where the **Attention** loss struggles to descend. After these epochs, both losses get really close and we could say they are almost the same. Since we specified that the CTC and attention have the same importance (using the parameter `ctc-weight`) and they have different losses, an explanation could be that the system is firstly minimizing the CTC loss and after that it starts minimizing the attention loss.

Also, we observe in Figure 7 that both accuracy and PER have similar behaviors. After approximately 10 epochs, the train accuracy continues increasing (and the PER continues decreasing), while the validation accuracy remains constant (and the validation PER also remains constant). This is some kind of overfitting in which the system **keeps learning the training data but does not improve in the validation set**. This may mean that the train and validation sets are not equally representative.



(a) Accuracy

(b) PER.

Figure 7: ESPNet generated graphs.

- *What is the final approximated PER in train and validation? Why are the results different?*

  We observe in Figure `fig:ESPNET:per` that the approximated results are:

	PER
Train	~ 0.06
Validation	~ 0.2

Table 3: PER results.

As we have already commented, this means that our model is learning the training set way better that it is generalizing to the validation set. However, we remark that the behavior is strange since the PER does not increase in the validation set when the model "overfits" (it is not strictly overfitting since the PER is not increasing), but stays constant.

2.4 Recognition and evaluation

In this section, we will examine the file `decode.yalm` and answer some questions about it.
Questions.

- *What does the parameter* `beam-size` *do?*

  The parameter `beam-size` controls the number of hypotheses kept during the Beam Search (found in the documentation of the `beam search` implementation). **Beam search** is a heuristic search algorithm that explores a graph exploring the most promising node in a limited set. In this sense, it is a *greedy* algorithm, reducing the memory requirements. It uses breadth-first search to build its search tree.

- *What does the parameter* `ctc-weight` *do?*

  We found in this section of the documentation that we can vary this parameter to switch the model's **decoding** mode from CTC, attention and hybrid. An example is the following code (extracted from the documentation):

```
# hybrid CTC/attention (default)
ctc-weight: 0.3
beam-size: 10

# CTC
ctc-weight: 1.0
## for best path decoding
api: v1 # default setting (can be omitted)
## for prefix search decoding w/ beam search
api: v2
beam-size: 10

# attention
ctc-weight: 0.0
beam-size: 10
maxlenratio: 0.8
minlenratio: 0.3
```

Lastly, we can execute the recognition script.

Question. *Why do two different results appear? What do they mean? Do they behave as expected?*

If we have a look at the output of the command that executes the ASR decoding, we find two different lines right before the results:

```
write a CER (or TER) result in exp/train_nodev_pytorch_train/decode_test_decode/result.txt
---
write a CER (or TER) result in exp/train_nodev_pytorch_train/decode_train_dev_decode/result.txt
```

As it is indicated, the first one is writing on the file the error in the `test` partition, while the second one is writing the result on `train and dev` partitions. We can say that the results behave **as expected**, since the error in the test partition is a little bit higher than the error in the train set, as it usually happens.

2.5 Checking the evaluation results

Lastly we show that the results can be shown in detail. Let us look at the output of an specific example (the result is tiny, it can be zoomed):

```
!tail -n 7 espnet/egs/timit/asr1/exp/train_nodev_pytorch_train/decode_test_decode/result.txt
---
id: (mwew0-mwew0_sx371)
Scores: (#C #S #D #I) 34 6 0 0
REF:  <space> r AY <space> n aw m EY n AA <space> b iy DH ih <space> b EH s <space> t ay M  f er <space> b ih z n ih s <space> m er <space> jh er z <space>
HYP:  <space> r EH <space> n aw m IH n AH <space> b iy DX ih <space> b OW s <space> t ay AE f er <space> b ih z n ih s <space> m er <space> jh er z <space>
Eval:         S               S   S             S             S               S
```

As we can see, the Substitutions/Deletions and Insertions are shown in detail.
Question. *Can you manually compute the PER for the previous alignment? What is the PER for this file?*
Using the expression of the PER, we obtain that:

$$PER = \frac{S+D+I}{S+D+I+C} \cdot 100\% = \frac{6}{40} \cdot 100\% = 15\%.$$

References

[1] Eva Vozáriková et al. “Comparison of Different Feature Types for Acoustic Event Detection System”. In: vol. 368. June 2013, pp. 288–297. ISBN: 978-3-642-38558-2 (Print) 978-3-642-38559-9 (Online). DOI: 10.1007/978-3-642-38559-9_25.