Automatic Speech Recognition with Sequence to Sequence Transformers

Name: Ilan Motiei
TAU Email: ilanmotiei@mail.tau.ac.il
Email: ilanmotiei1@gmail.com
ID: 212649701

Abstract

Similarly to previous works of Google's 'Magenta' team that used a seq2seq transformer from the NLP domain for the music transcription task [1] [2] - I have re-implemented the work for the ASR task.

Problem Description

Developing an ASR system using an 'off-the-shelf' seq2seq transformer from the NLP domain. An advantage of using an encoder-decoder transformer which auto-regressively generates the tokens, is that the model is less prone to spelling errors, and when trained extensively, may not need an additional language model on-top to perform well, in contrast to classical CTC models.

Method

Dataset:

'LibriSpeech' which contains:

- For training: 960h of spoken english audio along with transcriptions.
- For validating: 20h " ".
- For testing: 20h " ".

[1] SEQUENCE-TO-SEQUENCE PIANO TRANSCRIPTION WITH TRANSFORMERS
[2] MT3: MULTI-TASK MULTITRACK MUSIC TRANSCRIPTION

Model:
The network used is the T5 seq2seq transformer model. Specifically, I used the T5-small version, which has 60M parameters.
A log-mel-spectrogram is given to the model as input, with 512 mel-bins to match the embedding dimension of the original T5 model (which was trained on NLP tasks).

Because the space complexity of the model is quadratic in the input length, the input length in the original T5 is limited to 512, and as mentioned - so it is here.

Training:
In order to train the model, in each epoch, we iterate over all the files, and for each batch of files, we crop a random slice of 5 seconds of audio from each one, (which results in spectrograms with 500 time-steps), along with the corresponding transcription (which is determined by forced alignment with the Montreal Forced Aligner tool).
We enter the 500 spectrogram feature vectors into the T5 model, and the model is trained to minimize the cross-entropy loss between its prediction and the ground truth prediction.
As usual - teacher forcing is used when training.

Inference:
At inference time, we extract the spectrogram of the whole audio file to be transcribed, divide it into chunks of 512 (model's max input size), insert each to the model, which auto-regressively generates a list of the characters (tokens) spoken in each audio chunk, using beam search with a beam size of 4. In the end we concatenate the transcriptions of the model from all the chunks together for getting the final transcription.

Additional details:
Spectrograms were generated using torchaudio with a window size of 400 (25ms), and a hop length (stride) of 160 (10ms).

SpecAugment method was when training.
I.e. each spectrogram had a 50% chance of being augmented, in the following way:

- Between 1 to 80 of the frequencies (bins) in the spectrogram are masked (the amount is chosen randomly at each time and uniformly).
- Between 0% to 5% of the time vectors in the spectrogram are being masked (again, the amount is chosen randomly and uniformly).

Code Explanation

Framework: Pytorch.

My code (Link):

The repository also contains instructions on how to evaluate the model on LibriSpeech's test-sets, and for plotting the learning curves of the training process.

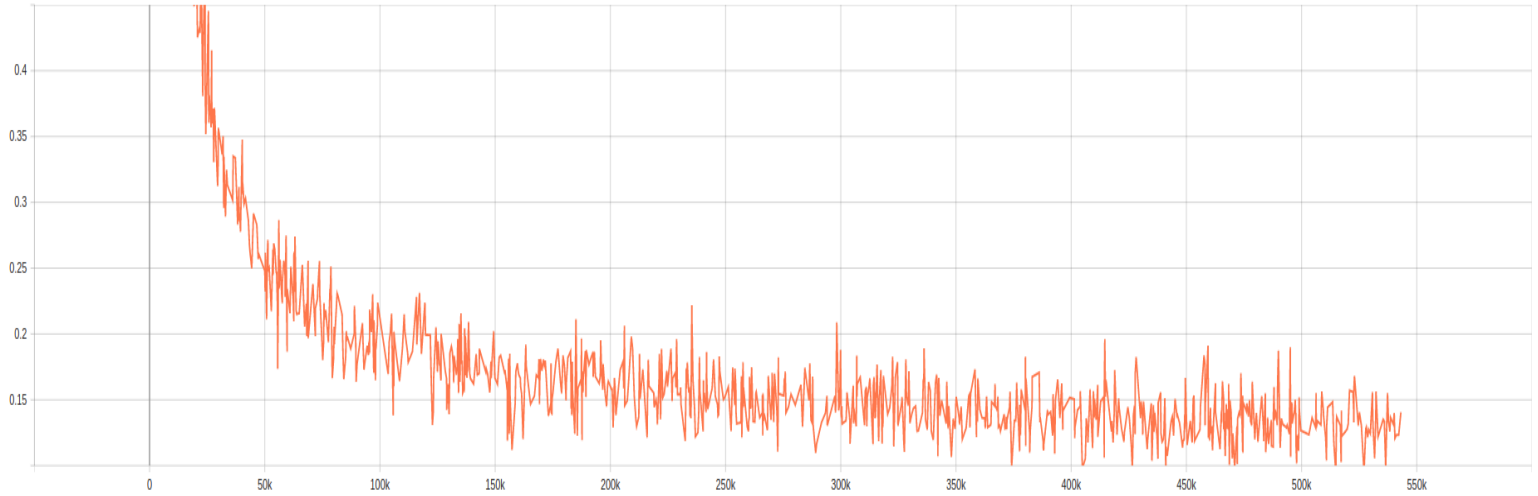
- dataset.py - contains utils for loading the data of LibriSpeech.
- dataset_stats.py - contains utils for measuring some statistics about the dataset.
- model.py - contains the model. For convenience the model is not a torch.nn.Module object, but pytorch_lightning.LightningModule object, which already contains utilities for fast training, checkpointing, and validating of the model.
- params.py - configurations for the experiments.
- preprocess.py - utils for combining between the alignments of the Montreal Forced Aligner to the LibriSpeech dataset.
- main.py - contains the training code. Running this file, (with no additional parameters), will start the training.
- eval.py - script for measuring model's performance on every subset of LibriSpeech after training.

Existing code:

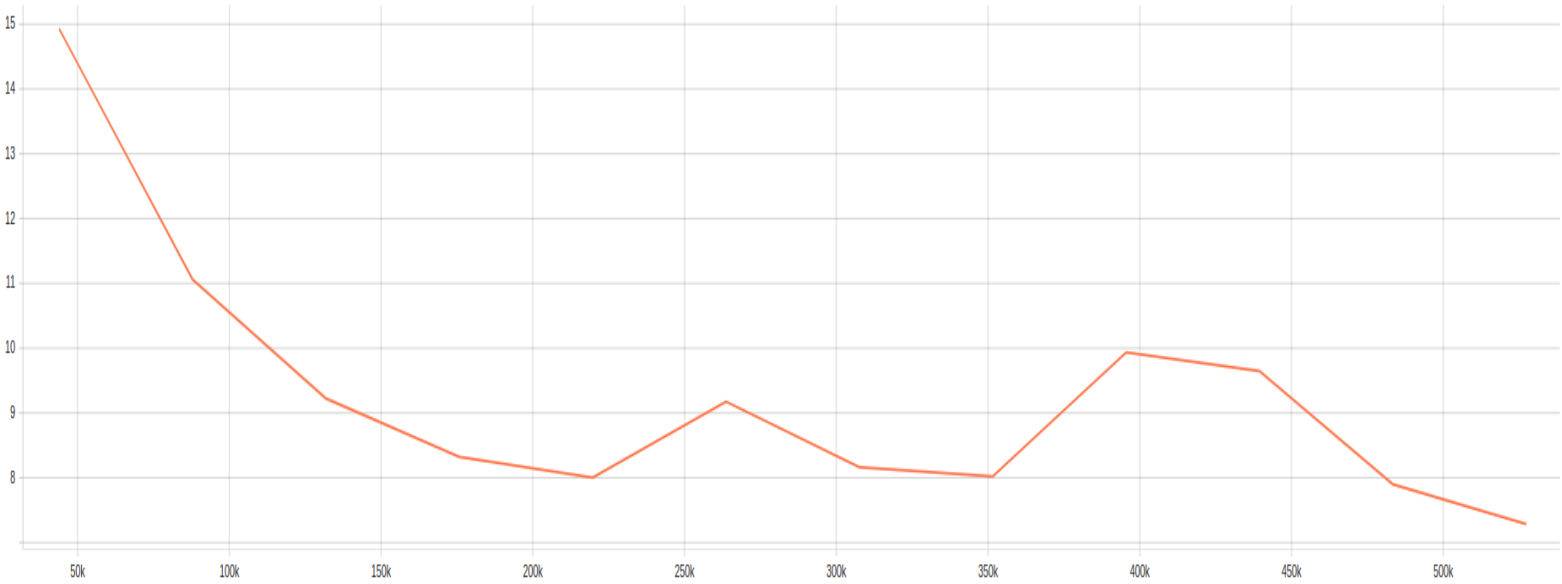
The alignments were taken from this repo (specifically ‘condensed format’ alignments were taken).

Results

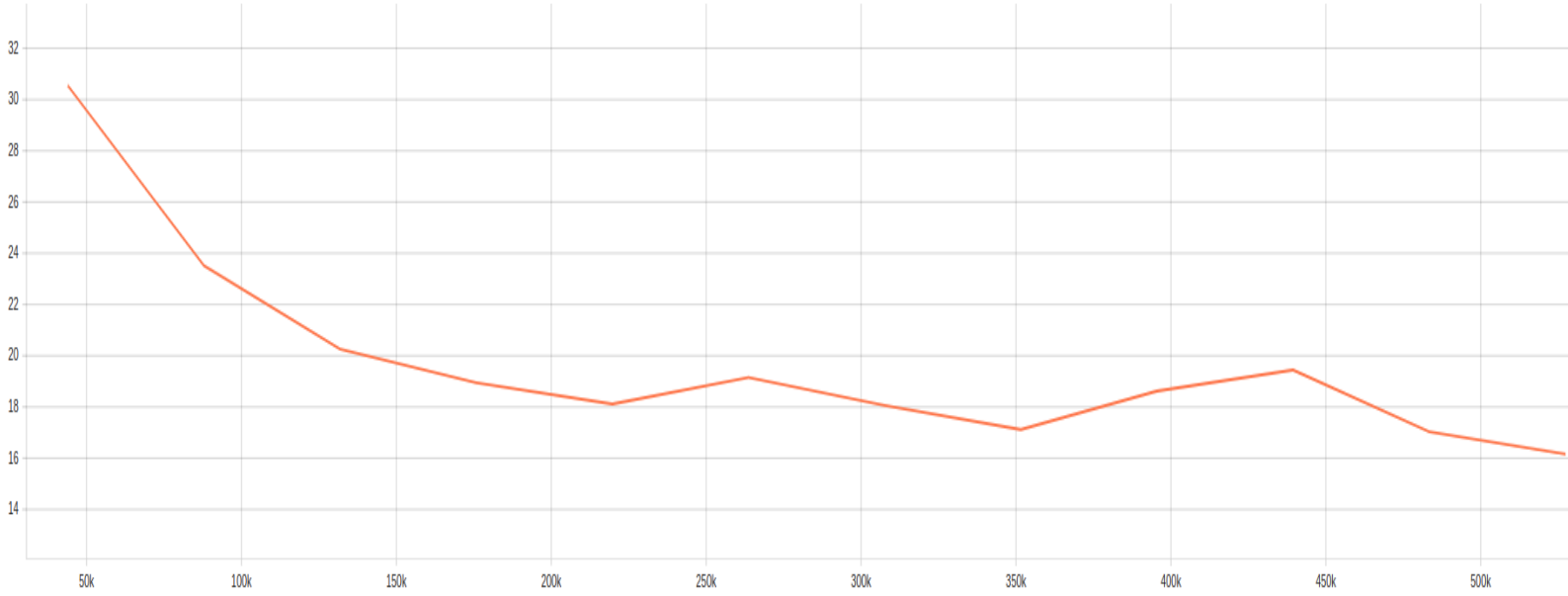
Training Loss



Validation CER



Validation WER



Validation set used: ‘dev-clean’.

My Model’s results:

Set / Metric	CER	WER
DEV-CLEAN	7.39	16.29
DEV-OTHER	15.06	28.95
TEST-CLEAN	7.06	15.75
TEST-OTHER	17.02	32.25

Current SOTA results

TEST-CLEAN	-	1.4
TEST-OTHER	-	2.5

Wav2Letter (uses a variant of the CTC loss, called ASG)

	CER	WER
DEV-CLEAN	6.9	-
DEV-OTHER	6.9	7.2

The model was trained on a single Nvidia RTX 3090 for ~550k steps (1.5 days). Although the model actually performs well, when comparing it to the current SOTA system, the results are much worse.

Related Work & Future Research

This work uses forced alignments for training. However, the only purpose we need those alignments here is because of the T5 model's quadratic memory cost in the input length, which limits us such that we can't use long spectrograms as input for the model. Therefore, the alignments don't have to be as accurate as in other works, which (implicitly) strongly rely on good alignments. Furthemore, we can potentially remove the need for alignments, if we'll use a version of the T5 model with sparse-attention, by being able to input a spectrogram of a whole audio file to the model when training.

There are many other works that overcome the need for the alignments for creating an ASR system. CTC loss models and their variations were the most popular ones until some years ago. They are trained with a loss objective which sums over the errors of all possible alignments of the gt text with respect to the predicted text. If the sum of the losses over the alignments is low - the model will give high probability for the ground truth text. However, CTC models are known for their high dependence on language models to perform well. This is due to the implicit assumption that hides behind the objective they are trained with - the labels are independent of each other given the input. This causes the model to make spelling errors, which are corrected by the language model.

This type of model also needs a beam-search decoding procedure at inference time to perform well.

Recently the Transductor model showed better results than the CTC models. It includes 3 different networks that are trained jointly. It has shown not only great results, but also the ability to run fast also on mobile devices. However, training 3 networks jointly opens a door for a lot of bugs and therefore this type of model is much harder to implement and maintain than the CTC models and my proposed model.

My proposed seq2seq T5 model has the advantage of modeling the probability of the next token conditioned on the input, but also on the previous predicted token. Therefore it is much less prone to spelling errors than the CTC models, and may not need a language model to perform well, but only a beam-search decoding procedure.

based on the graphs that I presented, as the WER and CER errors were both in a descending trend, training the model with more compute power or starting to train the model from a pre trained checkpoint that already encodes audio in a powerful way, such as Magenta's MT3, may give us competitive results compared to CTC models.

In addition, as I've already mentioned, by replacing the quadratic attention that the original T5 uses by a sparse one, we remove our need for any kind of alignment, and can create a very simple and potentially powerful model for the ASR task - which wouldn't need any alignments, any language model on top, will consist of one network, and will be trained with a simple cross-entropy loss objective.

Conclusions

Using an off-the-shelf NLP seq2seq model, I showed how to build an ASR system. Although the system may be applicable as a 'toy' one, the results are currently much worse than those of the SOTA, but probably can be improved a lot using more compute power or an available pre-trained

checkpoint of the MT3 model. This system can be extended to a much simpler model as described above, those enabling creating an ASR system in the simplest way that has ever been seen, which will ease the implementation and the maintenance of it.