A baseline model for computationally inexpensive speech recognition for Kazakh using the Coqui STT framework

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Abstract

Mobile devices are transforming the way people interact with computers, and speech interfaces to applications are ever more important. Automatic Speech Recognition systems recently published are very accurate, but often require powerful machinery (specialised Graphical Processing Units) for inference, which makes them impractical to run on commodity devices, especially in streaming mode. Impressed by the accuracy of, but dissatisfied with the inference times of the baseline Kazakh ASR model of (Khassanov et al., 2021) when not using a GPU, we trained a new baseline acoustic model (on the same dataset as the aforementioned paper) and three language models for use with the Coqui STT framework. Results look promising, but further epochs of training and parameter sweeping or, alternatively, limiting the vocabulary that the ASR system must support, is needed to reach a production-level accuracy.

1 Introduction

1.1 Rationale

Smartphones are widespread, and speech interfaces to applications are becoming more and more important.

The performance of speech-to-text applications, as measured by word error rate (WER) and character error rate (CER), is getting closer and closer to 0%\(^1\). However, best performing systems require powerful machinery (read: Graphical Processing Units, GPUs) not found on commodity computers both for training models (which is justifiable), but often also for inference, which makes them impractical to run on low-power devices such as smartphones.

Often speech data is processed through APIs of big companies. At the same time, companies having access to and collecting large amounts of sensitive data is not without concerns, and many people, all other things being equal, would prefer their speech-to-text or text-to-speech applications be libre/open-source software that run locally, on their devices, without sending private data off to someone else’s server. Depending on the volume of speech/text data to be processed, cost of using APIs can also be an issue.

Needless to say, state-of-the art automatic speech recognition (ASR) systems are data-driven, and their accuracy is a function of the amount of speech data available to train them. Fortunately, new datasets are constantly emerging. So, in September 2020, a large speech corpus of Kazakh\(^2\), available under a Creative Commons Attribution 4.0 International license\(^3\), was first presented (Khassanov et al., 2021)\(^4\). As of June 2021, in version 1.1, the corpus contains 332 hours of read speech and is, to our knowledge, the largest speech corpus of Kazakh published. In addition, authors of the corpus trained ASR models on it, and made them publicly available\(^5\). We wrote a simple web interface to the best performing model of (Khassanov et al., 2021) and packaged it into a Docker image\(^6\). The model is very accurate (indeed, if not in terms of word error rate (WER), at least in terms of character error rate (CER) we consider it state of the art or very close to it) but we weren’t satisfied with inference times when not using a GPU. It is not surprising that a deep

\(^1\)https://nlpprogress.com/english/automatic_speech_recognition.html

\(^2\)A Turkic language mainly spoken in Kazakhstan and other Central Asian republics, China and Russia by about 13 million people (Eberhard et al., 2021)

\(^3\)https://creativecommons.org/licenses/by/4.0/

\(^4\)The corpus is available at https://doi.org/10.48342/gkg9-gn84. We deducted its first publication date from the following preprint: https://arxiv.org/abs/2009.10334

\(^5\)https://github.com/IS2AI/ISSAI_Saida_Kazakh_ASR

\(^6\)Available at http://taruen.com/hub.html
learning-based model is relatively slow when not utilising a special GPU, yet we wanted to be able to deploy the Kazakh ASR system on commodity machines, including smartphones, and use it in streaming mode.

### 1.2 Objectives

Thus the main objective of our study was to train and deploy an ASR system known to be fast enough on computers without a specialised GPU, and see how it performs in terms of accuracy and speed.

### 2 Experimental

#### 2.1 Acoustic model

We trained a baseline acoustic model for Kazakh using the Coqui STT framework\(^7\) on the corpus published by (Khassanov et al., 2021) (version 1.1, 332 hours of speech).

Except for the batch size, hyperparameters and number of training epochs were identical to that described in the “Baseline models” section of (Tyers and Meyer, 2021), which in turn were based on (Ardíla et al., 2020). Concretely, version 0.9.3 of the English model\(^8\) served as the source model for transfer learning. We dropped 2 final layers of it. Dropout was set to 0.05, learning rate to 0.001 and SpecAugment (Park et al., 2019) option was turned off. With these settings, we trained a model for 25 epochs, without early stopping. Training was done on a single g1.1 machine of the Yandex Data Sphere service\(^9\). The train, dev and test batch sizes was empirically set to 9, which kept the GPU utilisation oscillating between approximately 75-95%.

We made use of the scripts and the Docker file from the commonvoice-docker repository\(^10\) of (Tyers and Meyer, 2021) almost as is. We had to tweak the docker file slightly to accommodate for details how the Yandex Datasphere works.

The train/dev/test split was kept as released by (Khassanov et al., 2021) (see Table 1 of the cited paper).

\(^7\)https://github.com/coqui-ai/STT, version 0.9.3  
\(^8\)https://github.com/coqui-ai/STT/releases/tag/v0.9.3  
\(^9\)https://cloud.yandex.com/en/services/datasphere  
\(^10\)https://github.com/ftyers/commonvoice-docker/  

The csv files of the corpus were converted to the format Coqui STT expects.

Besides this technical conversion, there was one more minor change: approximately 20 cases were found where a Latin character (from Extended Latin character set) was typed instead of a letter of the Cyrillic Kazakh alphabet (as the rest of the transcriptions in the corpus are written in)\(^11\). All occurrences of these Latin characters were replaced with corresponding Cyrillic characters\(^12\). The reason for this change is that when training a Coqui STT model one has to specify the alphabet (character set) that the resulting model should recognise, and transcriptions should contain only the characters specified in the alphabet. Our target alphabet consisted only of the letters of the Cyrillic Kazakh alphabet, so that we had to pre-process the transcriptions of the corpus making sure that it contains only Cyrillic Kazakh letters.

#### 2.2 Language models

In ASR, an acoustic model can be and usually is complemented with a language model (LM). An LM supported by Coqui STT can be trained effectively without a GPU and independently from training the acoustic model using the kenlm tool (Heafield, 2011)\(^13\). All in all we built and tested three language models. The first one was made only on transcriptions from the train and dev sets of the speech corpus (about 1.6 million tokens in total). In addition, two larger LMs were constructed, which did not include any transcriptions from the speech corpus so that no bias is created. The first of these larger LMs was trained on the fiction texts scraped from the kitap.kz website on October 2017. The second was trained on the union of the same fiction texts with a collection of news texts\(^14\) and a snapshot of Kazakh Wikipedia. Both corpora were pre-processed with the covo utility\(^15\) of (Tyers and Meyer, 2021). After pre-processing, the fiction corpus contained about 20 million, the fiction+news+wikipedia corpus about

\(^11\)e.g. U+0259 instead of the correct U+04D9  
\(^12\)There was also a company name which in other circumstances would be fine to spell with Latin characters, but for the reason explained above, we have re-written it in all-Cyrillic as well.  
\(^13\)https://kheafield.com/code/kenlm  
\(^14\)Sources include egemen.kz, today.kz, akorda.kz, nur.kz and several others.  
\(^15\)https://github.com/ftyers/commonvoice-utils. Concretely, texts were piped through two commands: covo segment kk followed by covo norm kk
on the test but in the range of , Khassanov et al. shows WER and CER for each of the with the GPU , 2021 . In short, we can con-

1 We evaluated the acoustic model, as well the acoustic model only and acoustic model combined with ei-

er of the 31 languages that ( ) were 0.931289039105002 and 1.1834137581510284, respectively . The

default alpha and default beta values hard-coded for all experiments of (Tyers and Meyer, 2021), hard-coded because it’s as-

sumed that these two values (if they are in a reasonable range) don’t affect the accuracy by much to justify optimising them for all of the 31 languages that (Tyers and Meyer, 2021) trained ASR models for. But to be on the safe side, we also let the lm_optimizer.py script calculate the values of default_alpha and default_beta it deems optimal. Optimal default_alpha and default_beta were set to 1.2143912484271524 and 2.1012243193402487, respectively. The default_alpha, default_beta values of scorers of (Tyers and Meyer, 2021) were 0.931289039105002 and 1.1834137581510284, respectively.

Three language models times two sets of (default_alpha, default_beta) values resulted in 6 scorers to evaluate. We had evaluated all 7 seven cases (i.e. acoustic model only and acoustic model combined with ei-

er of the 6 scorers), but there was no difference in results in terms of WER/CER when using the “optimal” values versus values taken from (Tyers and Meyer, 2021), so we don’t discuss them any further.

16When “packaging” a language model for using it with Coqui STT (let’s call the resulting package a “scorer” to differentiate the two), it’s possible to specify the so-called default_alpha and default_beta values. We had 2 sets of those. The first were the default_alpha and the default_beta values hard-coded for all experiments of (Tyers and Meyer, 2021), hard-coded because it’s assumed that these two values (if they are in a reasonable range) don’t affect the accuracy by much to justify optimizing them for all of the 31 languages that (Tyers and Meyer, 2021) trained ASR models for. But to be on the safe side, we also let the lm_optimizer.py script calculate the values of default_alpha and default_beta it deems optimal. Optimal default_alpha and default_beta were set to 1.2143912484271524 and 2.1012243193402487, respectively. The default_alpha, default_beta values of scorers of (Tyers and Meyer, 2021) were 0.931289039105002 and 1.1834137581510284, respectively.

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17An Intel(R) Core(TM) i7-4700MQ CPU @ 2.40GHz with 12 GB of memory.
After 25 epochs of training (which is to be expected), so we hope that further training combined with parameter sweeping and the SpecAugment feature will decrease the error rates. The reason for limiting ourselves to 25 epochs was mainly due to the cost of training. At the time we did not have access to a GPU server of our own, but now we do, and are working towards training for more epochs and finding optimal parameters.

5 Related work and frameworks

For an overview of works on Kazakh speech recognition and synthesis and available speech corpora, we refer the reader to Section 2 of (Khassanov et al., 2021).

As for more recent developments, it is worth mentioning that since January 2021 Common Voice (Ardila et al., 2020) – a relatively new, multilingual dataset with the goal of collecting speech data for all languages and releasing the data into public domain – also includes Kazakh. Common Voice releases have been happening twice a year, and Kazakh is expected to land in the mid-year release of 2021, albeit the amount of data in Kazakh will probably be only moderate by then.

On a related note, any non-English language is often called ‘low-resourced’ in the literature (Hämäläinen, 2021), but calling Kazakh low-resourced now that there is a 332 hours-big freely available corpus (at least in the context of speech recognition) would be an injustice to its authors and many other researchers who have worked on Kazakh, so we refrain from calling it that. Besides, transfer learning, pre-training and other methods of that kind are blurring the distinction between what is “low-resourced“ and what is “high-resourced” even more.

There are many ASR tool kits to choose from. If we consider our desiderata of running ASR models on low-power devices, both Vosk20 and Coqui STT would have probably been equally valid choices. A more thorough comparative study of frameworks is left for future work. Our experience with Coqui STT was that is has a supportive community around it and an easy-to-follow documentation.

6 Conclusion

To our knowledge, we have presented the first ASR system for Kazakh usable on commodity (read: non GPU) computers in streaming mode. Our acoustic model and language models (scorers) can be downloaded from the following URL: https://drive.google.com/drive/folders/10mME4_sy2-xW739fm7zRLr0cqyYS0ArY?usp=sharing

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