My Solution for Sainya Ranakshetram AI challenge

1. How to View my Solution

A. README.md

This is a README.md file for my solution for sainya-ranakshetram AI challenge. This README.md file is written in Markdown format. You can read more about Markdown format here. There are Two ways in which you can read this README.md file

Option 1: Read this README.md file on using grip (GitHub markdown previewer)

To render this readme.md , open the terminal and cd into this directory and run the following command in a bash shell to install grip

```
cd wheels
pip install 'grip-4.6.1-py3-none-any.whl' --no-index --find-links '.'
cd ..
```

Then Run to view this README.md file in your browser

```
grip
```

which will give the following output:

```
* Serving Flask app 'grip.app'
* Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use
a production WSGI server instead.
* Running on http://localhost:6419
Press CTRL+C to quit
```

Click on the link http://localhost:6419 to view the rendered README.md file.

Incase you are running this solution on a remote server, you can forward the port 6419 to a remote tunnel using ngork tunneling service. To do so, run the following command in a bash shell: Make sure an account is created on ngrok.com Then by going to your ngrok dashboard , you can get your auth token and run the following command in a bash shell:

```
ngrok authtoken <your-authtoken>
```

Then run the following command in a bash shell to forward the port 6419 to a remote tunnel:

```
ngrok http 6419
```

this will give the following output:

```
Check which logged users are accessing your tunnels in real time
https://ngrok.com/s/app-users

Session Status                online
Account                       Your Email (Plan: Free)
Version                       3.1.0
Region                        United States (us)
Latency                       17ms
Web Interface                 http://127.0.0.1:4040
Forwarding                    UrlHere -> http://localhost:6419

Connections                   ttl     opn     rt1     rt5     p50     p90
                              3       0       0.01    0.01    0.00    0.00
```

The Url will be in the front of Forwarding area will have your unique url. Click on the link to view the rendered README.md file.

Option 2: Read README.pdf

You can open a rendered pdf of README.md By opening the file README.pdf in this directory.

Option 3 : GitHub Repository

if you want to view this README.md file on GitHub, you can go to the following repo which is similar to this directory.

NOTE: : if you want view the transcripts of all the audio files provided in the dataset made by my solution you can open the folder transcripts_result in this directory or repo. The files are named according to the audio file name.

2. How to Run my solution

Step 1 : Make sure All requirements are installed

Docker

To check this run the following command in a bash shell

```
docker --version
```

If this command runs successfully then you have docker installed on your system. If your docker version is less than 19.03.8 use nvidia-docker instead of docker as an alias for docker. It is recommended to use docker version 19.03.8 or higher.

If the above command fails, then you need to install docker on your system. You can install docker by running the following command in a bash shell:

```
bash install_docker.sh
```

Which will install docker on your system

Drivers and Compute Requirements

This Docker image requires the Nvidia Drivers which support CUDA 11.0. The oldest driver you can use is 450.36.06. You can check your driver version by running the following command in a bash shell. It is recommended to update your drivers to the latest version for best performance and compatibility.

This Repo requires an Nvidia GPU with a minimum of 10GB of memory to run to fit the transcription model

To learn more about the Docker image requirements visit [here]

```
nvidia-smi
```

Audio File Requirements

The Audio File passes should be in either of the following formats:

- .wav
- .mp3
- .m4a
- .flac
- .ogg
- .aac
- .avi

more might be supported but these are the ones that I have tested.

Step 2 : Clone the Docker container

To clone the docker container run the following command in a bash shell

```
docker pull mithilaidocker/audiotranscribe:master
```

Step 3 : Run the Docker container

To run the docker container enter the following command in a bash shell

```
docker run --gpus all \
  --ipc=host \
  --ulimit memlock=-1 \
  --net="host" \
  --ulimit stack=67108864 \
  -it -v "/home/":/home \
  --rm mithilaidocker/audiotranscribe:master
```

nvidia docker command will be

```
nvidia-docker run --ipc=host \
  --ulimit memlock=-1 \
  --net="host" \
  --ulimit stack=67108864 \
  -it -v "/home/":/home \
  --rm mithilaidocker/audiotranscribe:master
```

By running this command you will enter the docker container. In case you get the following error `docker: Cannot connect to the Docker daemon at unix:///home/xx/.docker/desktop/docker.sock. Is the docker daemon running?` Run the Command with sudo

Step 4 : Run the Solution

Option 1 : Using the GUI in the form of a Flask Web Server

Step 1 : Run the Flask Web Server

To Run the flask app for the solution run the following command in a bash shell.(Make sure you are in the `/app` dir)

```
root@xx:/app  python -m flask run --host 0.0.0.0
```

This will run the flask app which contains the solution. The command will give the following output

```
* Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use
a production WSGI server instead.
* Running on all addresses (0.0.0.0)
* Running on http://127.0.0.1:5000
* Running on http://10.42.32.18:5000 #Use the url printed here.  It would be
different depending upon your IP address
Press CTRL+C to quit
```

Important: Make sure to Keep running the flask app in the background. If you close the terminal the flask app will stop

If you are seeing this solution on the same machine as the server then you can access the solution at http://127.0.0.1:5000. In case you running this solution on a remote server you will need to forward the port 5000 to your local machine. To do this we can use ngrok (*already installed on the docker image*) to forward the port 5000 to our local machine. To do this run the following command in a bash shell. Make sure you have added your ngrok auth token to the docker image. It is explained in the section above in Section 1.A Option 1 : Read README.md

```
ngrok http 5000
```

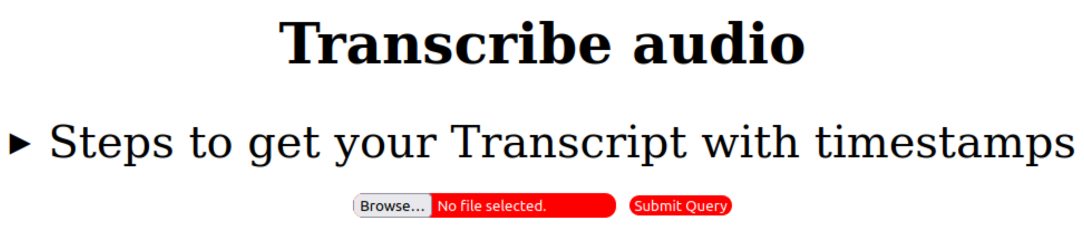
Which will Give the following output

```
Check which logged users are accessing your tunnels in real time
https://ngrok.com/s/app-users

Session Status                online
Account                       Your Email (Plan: Free)
Version                       3.1.0
Region                        United States (us)
Latency                       17ms
Web Interface                 http://127.0.0.1:4040
Forwarding                    https://88ee-172-83-13-4.ngrok.io ->
http://localhost:6419

Connections                   ttl     opn     rt1     rt5     p50     p90
                              3       0       0.01    0.01    0.00    0.00
```

The link will be in the front of Forwarding area will have your unique url. Click on the link to view the rendered solution.

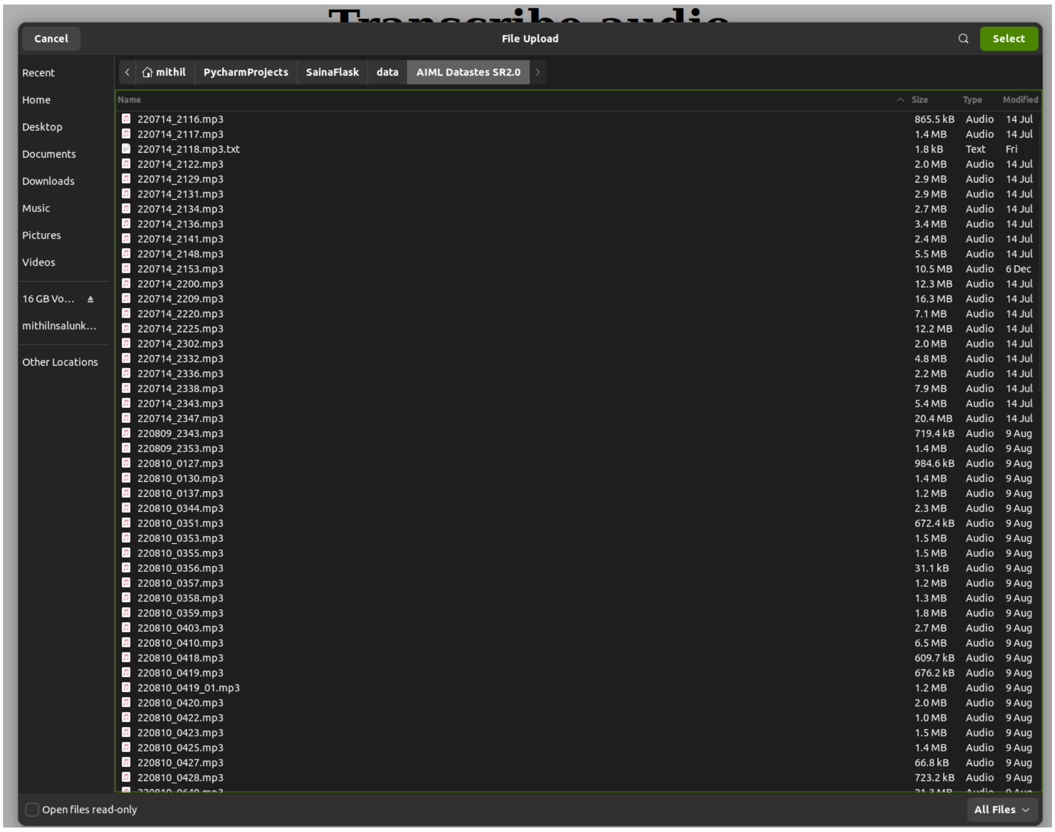
Step 2 : How to use the Flask App

Upon opening the url you will be greeted with the following page



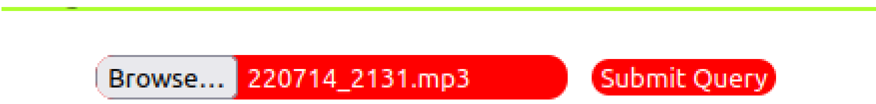
Steps To Transcribe The Audio File are following from here

1. Click on the `Choose File` or the `Browse` button to select the audio file you want to transcribe. The following window will open on Linux



2. Select the audio file which are in the supported audio formats you want to transcribe and click on `Select` (or any other button you get depending upon your os).

3. The file name will be displayed in the `File Name` text box Example -



4. Click on the `Submit Query` button to start the transcription process.

   NOTE: The Submit Query Button can have a different name depending upon the browser you are using. For example in Firefox it is `Submit Query` but in Chrome it is `Submit`

5. The transcription process will take some time depending upon the length of the audio file and the type of GPU you have. It is important not close the web page once clicking upon the `Submit Query` button. Once the process is complete you will be greeted with the result page. Let us take an example of the following audio file. [221001_0134.mp3]

6. The result page will look like this for the following audio file is transcribed

```
00:00.000 --> 00:12.000 Text: Alpha 1 for Alpha 3, Alpha 3 over
00:12.000 --> 00:16.000 Text: Alpha 3, Walekum Assalam
00:16.000 --> 00:23.000 Text: Alpha 1, Faheed Bhai was saying that we have to load our things one night before
00:23.000 --> 00:28.000 Text: and then there will be no movement till Friday prayer
00:28.000 --> 00:37.000 Text: Alpha 3, we will decide the date in the evening
00:37.000 --> 00:46.000 Text: Alpha 1, contact Alpha 3
00:46.000 --> 00:58.000 Text: Alpha 3, I will do it today and will inform you in the evening
00:58.000 --> 01:18.000 Text: Alpha 1, Khuda Hafiz
```

   the format of the timestamp is `Start - HH:MM:SS:MS --> End HH:MM:SS:MS : Transcript` where MS is the milliseconds

7. The Transcript will be saved in the `transcripts` subdirectory in the app directory of the docker container. The file name will be the same as the audio file name with the extension `.txt`. So for the above example the transcript will be saved in the `/transcripts/221001_0134.txt` file.

8. You can print the txt file following command in the docker container

```
root@xx:/app# cat transcripts_result/YourAudioFile.txt
```

With the 221001_0134.txt file being the name of the audio file you want to transcribe.

Option 2 : Using the CLI

Using the CLI is much more straightforward. To run the CLI for the solution run the following command in a bash shell.(Make sure you are in the `/app` dir)

```
root@xx:/app#  python model.py --path your_audio_file
```

Let us use the same file we used above for the flask App as an example [221001_0134.mp3]() so here the command will be

```
root@xx:/app#  python model.py --path 221001_0134.mp3
```

which would give us the following output

```
Transcribing... 221001_0134.mp3
Detecting language using up to the first 30 seconds. Use $(--language) to specify
the language
Detected language: Urdu
[00:00.000 -- Alpha 1 for Alpha 3, Alpha 3 over >00:12.000]
[00:12.000 -- Alpha 3, Walekum Assalam >00:16.000]
[00:16.000 -- Alpha 1, Faheed Bhai was saying that we have to load our things one
night before >00:23.000]
[00:23.000 -- and then there will be no movement till Friday prayer >00:28.000]
[00:28.000 -- Alpha 3, we will decide the date in the evening >00:37.000]
[00:37.000 -- Alpha 1, contact Alpha 3 >00:46.000]
```

```
[00:46.000 -- Alpha 3, I will do it today and will inform you in the evening
>00:58.000]
[00:58.000 -- Alpha 1, Khuda Hafiz >01:18.000]
Transcription complete. Saved it to transcripts_result/221001_0134.txt
```

the format of the timestamp is `Start - MM:SS:MS --> End MM:SS:MS : Transcript`

the transcript will be saved in the `transcripts` subdirectory in the app directory of the docker container. The file name will be the same as the audio file name with the extension `.txt`. So for the above example the transcript will be saved in the `transcripts/221001_0134.txt` file. You can print the txt file following command in the docker container

```
root@xx:/app# cat transcripts_result/YourAudioFile.txt
```

so here the YourAudioFile.txt will be the name of the audio file we are transcribing so for the above example it will be 221001_0134.txt

NOTE: You can also pass multiple paths to the `--path` argument. For example if you want to transcribe 2 audio

```
root@xx:/app# python model.py --path 221001_0134.mp3 221001_0135.mp3
```

3. What is my solution

3.1. Problem statement

The challenge aims to develop a software-based tool that is able to ingest radio audio recordings (non HiFi) in common format of (.wav, FLAC, MP3 (high bit rate) etc.) containing information in a mix of English and Hindi (Hinglish) with limited use of local slang's and create an extract transcript information output in textual format. This problem intrinsically contains the task of cleaning of raw audio signals, shaping of signals and creating algo specific data required by the NLP engine.

3.2 Transcribing and Translating Noise-filled Audio Recordings Containing Multiple Languages and Dialects: A Unique and Difficult Challenge

As we embark on the challenge of transcribing and translating audio recordings that are full of noise and contain a mix of multiple languages and dialects, we quickly realize that we're facing a unique and difficult task. Not only are the audio files we're working with low quality, with a high percentage of noise relative to signal, but they also contain slang's and local words that aren't present in any dataset and can't be easily translated using standard language models.

And even when we are able to translate words, we face the added challenge of context-dependent translations that don't always have a straightforward one-to-one correspondence. For example, the word "Bhai" could be translated as "Brother" or "Friend" depending on the context.

But that's not all - we also need to provide timestamps for the words in the audio file, a critical feature that will help users navigate and find the specific parts of the audio file they're looking for. All of these challenges combine to make this task a truly distinctive and challenging one, but with the right tools and approaches, we're confident we can rise to the challenge and deliver the best possible results.

3.3 Model Selection

As we set out to solve the challenge of transcribing and translating audio recordings that have been distorted and compressed for transmission over the airwaves, it quickly becomes apparent that we need a model that is up to the task. The input audio will be of low quality, with a restricted frequency range and the added complications of channel noise, dialects and slang's. To successfully extract and transcribe this information, we need a model that is capable of handling these challenges and producing high-quality results.

One of the key challenges we face in this task is the high level of noise and low signal-to-noise ratio in the audio recordings we're working with. This can make it difficult to accurately transcribe and translate the content of the audio files, as the noise can obscure the words and make them harder to understand.Since the model is likely to come across a diverse set of languages and dialects in production,a robust Zero-Shot model is the only feasible solution. That's where OpenAI Whisper Large-V2 comes in. Whisper Large-V2 is a state-of-the-art machine learning model that has been specifically designed to excel at handling audio files with high levels of noise and low signal-to-noise ratios. Its extensive training on a dataset of 680,000 hours of audio in 100 languages (as a point of comparison, GigaSpeech , which comes 2nd place to Whisper in terms of training data is trained on only 44,000 hours of audio), including non-ideal, noisy samples, has prepared it to tackle the unique challenges of our task.

But the benefits of Whisper Large-V2 don't end there. It is also a zero-shot learning model, meaning that it can perform tasks and make predictions without the need for any fine-tuning or additional training on specific datasets.Since the model is likely to come across a diverse set of languages and dialects in production,a robust Zero-Shot model is the ideal approach. This makes it a highly efficient and effective choice for our needs, as we can rely on it to deliver reliable results from the get-go, without the need to invest time and resources into adapting it to the specifics of our task. In fact, Whisper Large has a SOTA (state-of-the-art) performance in this type of scenario, making it the ideal model for transcribing and translating audio files that are full of noise and contain a mix of multiple languages and dialects.

Whisper Large-V2 has been trained for 2.5 times more epochs than Whisper Large-V1, with SpecAugment, stochastic depth, and BPE dropout for regularization. Other than the training procedure, the model architecture and size remained the same as the original large model

Whisper is also the most robust model for dataset with uncommon words as show in the last picture making it the best choice for transcribing and translating slang`s. Quoting the official paper "The results show that Whisper performs better than the compared models on most datasets, especially on the dataset which are heavy with uncommon words."

But why did we choose the large-v2 version of Whisper instead of the medium or small models? The answer is simple: the large version provides the best balance of accuracy and

speed for our needs. While the medium and small models may be able to handle some tasks required for this challenge, they don't offer the same level of proficiency as the large model. Plus, the large model is able to run efficiently on a GPU, making it a convenient and resource-saving choice. Overall, OpenAI Whisper Large-V2 is an excellent choice for our task of transcribing and translating audio recordings. Its extensive training, zero-shot learning capabilities, and proficiency in handling multiple languages make it well-suited to the novel challenges of this task, and its large size ensures that it delivers the best possible balance of accuracy and speed. We can trust Whisper Large-V2 to deliver reliable, high-quality results efficiently and effectively, making it the ideal model for this challenge

Some figures from the official paper which shows the performance of the model

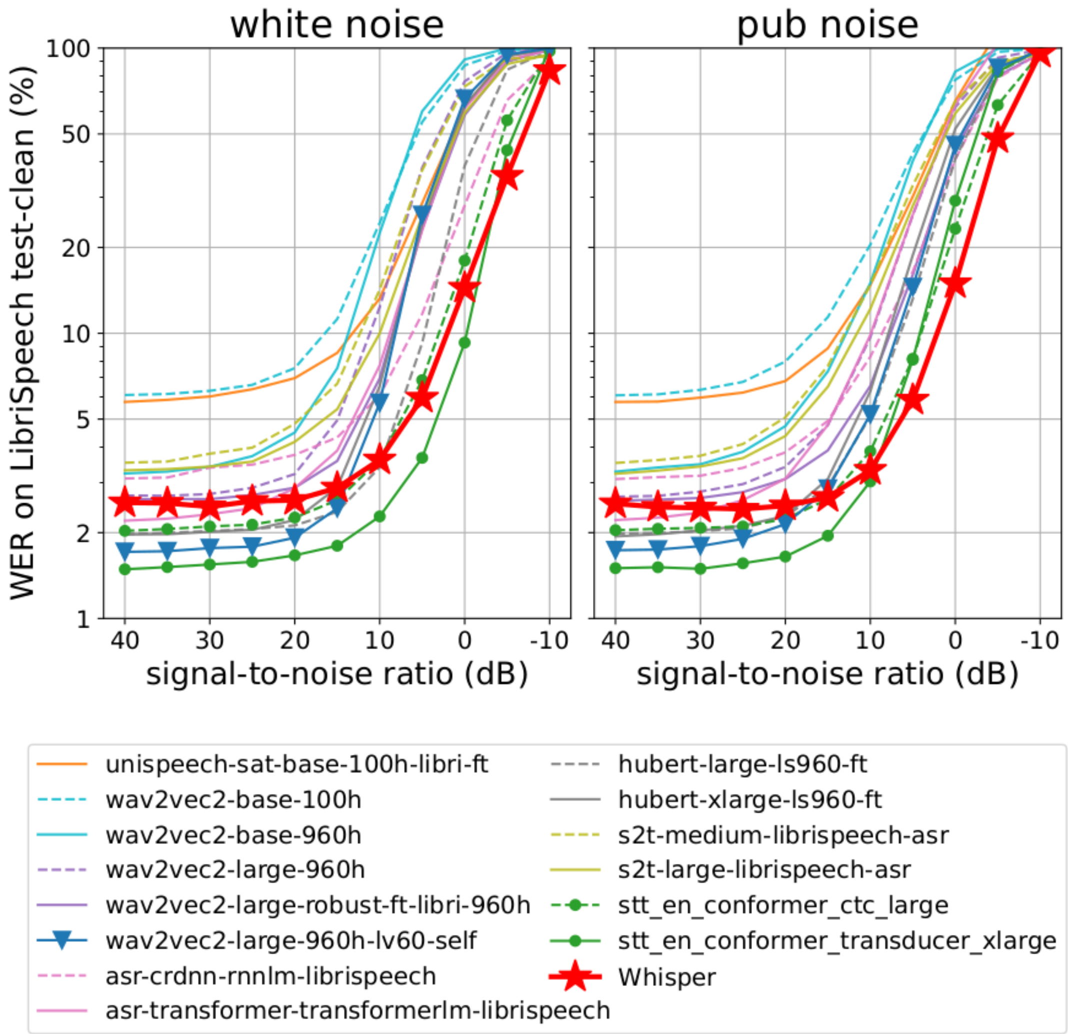


Figure 5. **WER on LibriSpeech test-clean as a function of SNR under additive white noise (left) and pub noise (right).** The accuracy of LibriSpeech-trained models degrade faster than the best Whisper model (★). NVIDIA STT models (●) perform best under low noise but are outperformed by Whisper under high noise (SNR $<$ 10 dB). The second-best model under low noise (▼) is fine-tuned on LibriSpeech only and degrades even more quickly.

X → English	High	Mid	Low	All
XMEF-X	34.2	20.2	5.9	14.7
XLS-R (2B)	36.1	27.7	15.1	22.1
mSLAM-CTC (2B)	37.8	29.6	18.5	24.8
Maestro	**38.2**	31.3	18.4	25.2
Zero-Shot Whisper	36.2	**32.6**	**25.2**	**29.1**

Table 4. **X→en Speech translation performance.** Zero-shot Whisper outperforms existing models on CoVoST2 in the overall, medium, and low resource settings but still moderately under-performs on high-resource languages compared to prior directly supervised work.

NOTE: Since all the languages in this dataset come under low-resource or mid-resource this is not a problem

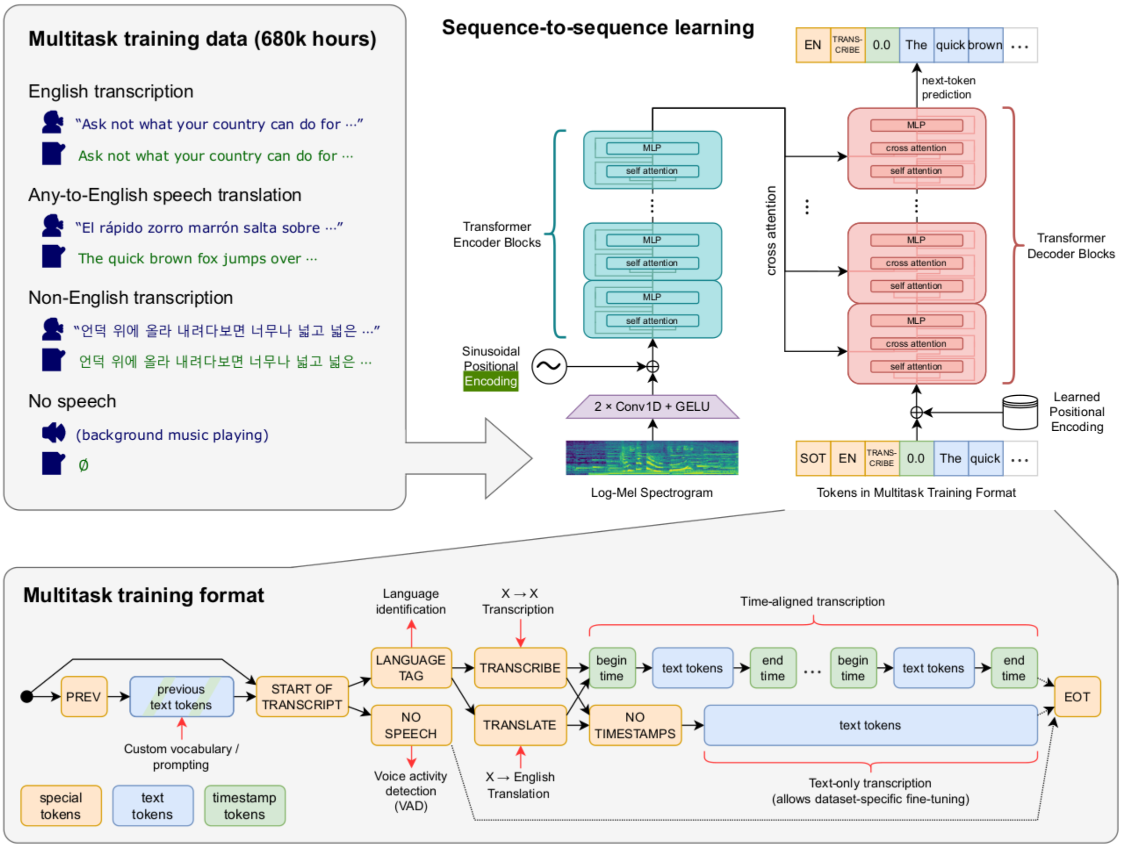


Figure 1. **Overview of our approach.** A sequence-to-sequence Transformer model is trained on many different speech processing tasks, including multilingual speech recognition, speech translation, spoken language identification, and voice activity detection. All of these tasks are jointly represented as a sequence of tokens to be predicted by the decoder, allowing for a single model to replace many different stages of a traditional speech processing pipeline. The multitask training format uses a set of special tokens that serve as task specifiers or classification targets, as further explained in Section 2.3.