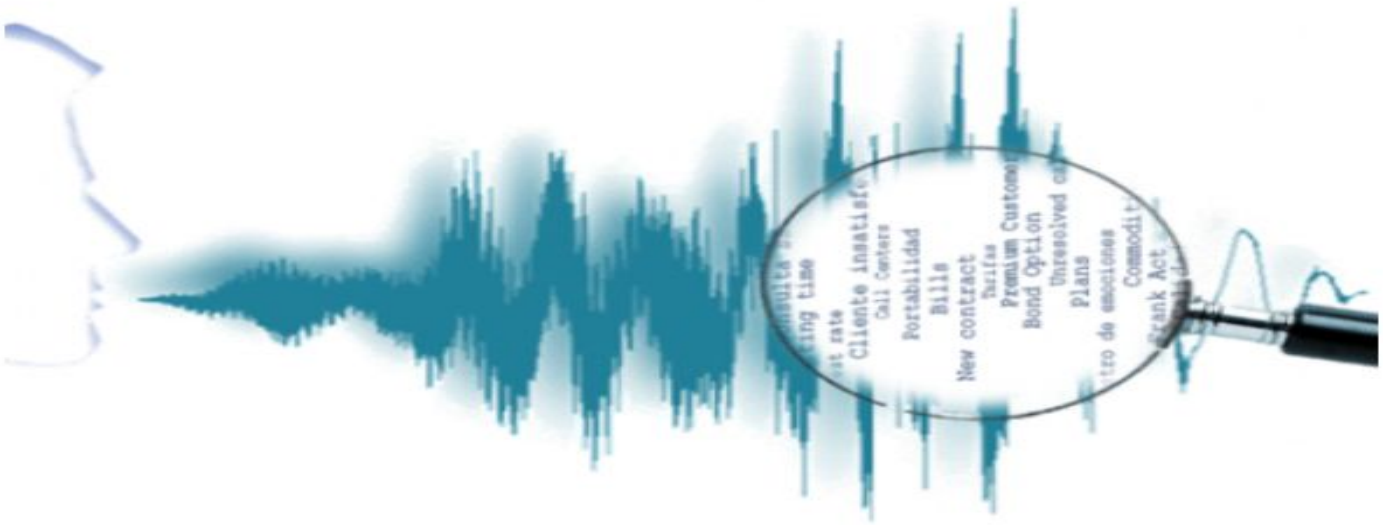


Comparison of Voice-to-Text Neural Networks

DATS 6203 : Final Project

Anamay Agnihotri • *Tanaya Kavathekar* • *Alex Cohen*

Outline

- Introduction
- Defining the Problem
- Data Sources and Collection
- Understanding the Networks
- Experiment Methodology
- Preliminary Results
- Final Results and Contributions
- Conclusion and Next Steps

Translating audio to text is a complex problem

- Audio data is extremely complex, relying on the translation from physical speech to electrical signals to encoded ones and zeros computers can interpret
- Variability in speech and acoustics, attributable to different languages, pronunciations and accents, along with lack of extensively labelled training data, make generalizable systems difficult.
- Speech recognition systems have become commonplace, with implementations like Siri, Alexa, Amazon's Echo, and Google Home becoming a part of people's everyday lives.
- Each implementation presumably has its own proprietary model architectures, which have been worked on for years and trained over 1000s of hours of data.

Problem Statement

Can open source Voice-to-Text neural architectures, either through pretrained models or transfer learning, compete with the proprietary, broadly developed translation models of tech giants like Google?

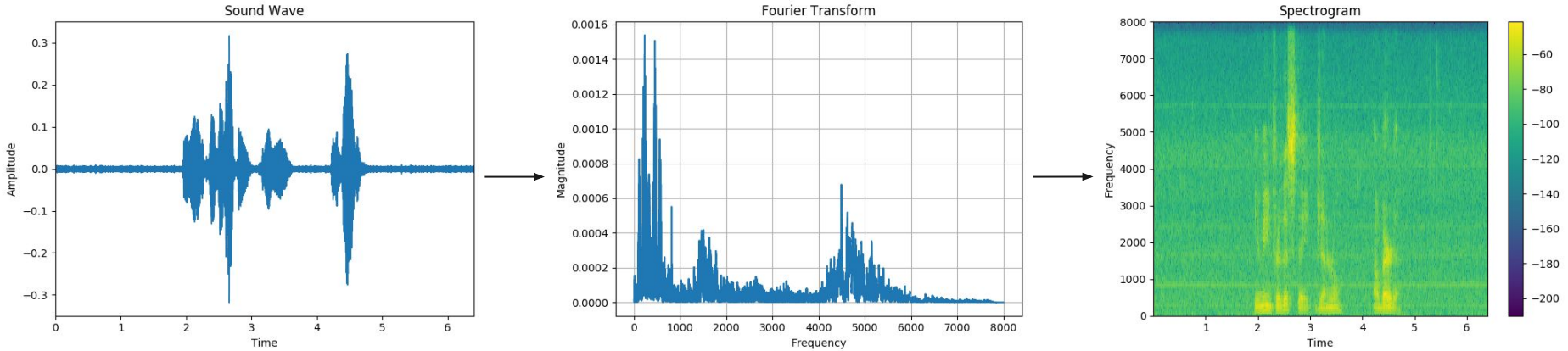
Data Sources

DeepSpeech 2

- An end-to-end, automatic speech recognition pipeline developed by researchers at **Baidu**, an AI organization.
- The DeepSpeech2 used here follows the **pytorch** implementation of github user **SeanNaren,** an ML research engineer from the UK.
- The repository has three pretrained models based on the following data sources:
    - **An4**: an alphanumeric database of census responses compiled by Carnegie Mellon University
    - **LibriSpeech**: A large-scale corpus of 1000 hours of English audio-book recordings
    - **TED-LIUM**: a collection of 1495 recorded and transcribed TED talks
- **Voxforge** data, a cleaned and accented English audiobook dataset from LibriVox , was used for the model evaluation and all transfer learning purposes.

Data Manipulation

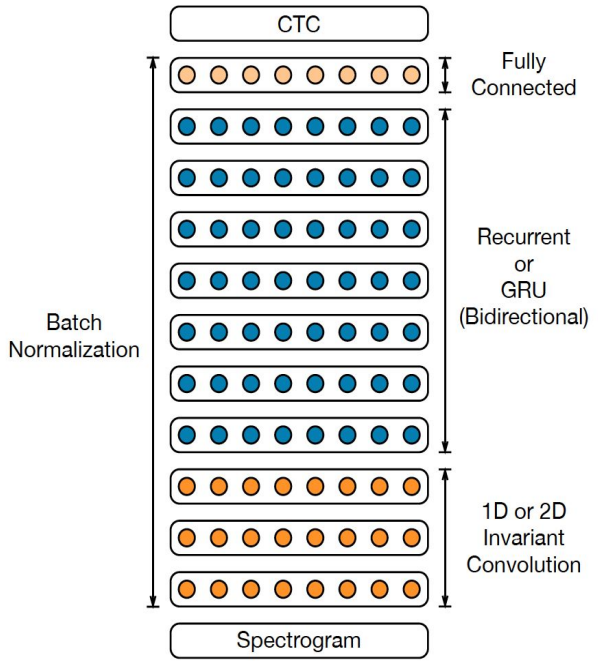
- All of the data came in the form of wav files (similar to an MP3 file), yet need to be converted to an input format the networks can understand
- Data transformations involved conversion using a Fourier Transformation and decomposition into magnitude and phase elements (done using the popular audio package LibRosa) to create a Spectrogram, which would be used as input to the DeepSpeech model



Text: 'YOU MEAN FOR THIS STATE GENERAL ALBERTA'

Understanding the DeepSpeech Network

- Inputs: Spectrograms of power normalized audio clips
- Outputs: graphemes (units of language). {a,b..z, apostrophes, spaces, blank}
- Hidden activation : clipped ReLU/hardtanh ⟶ σ(x) = min(max(x,0),20)
- Subsampling by striding in the convolutional layers - not good for english models.
- Output layer uses softmax activation, computing the probability distribution for each grapheme per time step. $$p(\ell_t = k|x) = \frac{\exp(w_k^L \cdot h_t^{L-1})}{\sum_j \exp(w_j^L \cdot h_t^{L-1})}$$
- 2D convolutions are used to convolve along (normalize) both the frequency and time axes
- Batch normalization improves speed of convergence without loss in generalization performance.



Understanding the DeepSpeech Network (Continued)

- Loss function: Connectionist Temporal Classification (CTC) loss

$$\mathcal{L}(x, y; \theta) = -\log \sum_{\ell \in \text{Align}(x,y)} \prod_{t}^{T} p_{\text{ctc}}(\ell_t | x; \theta).$$

- CTC loss is used in problems where having aligned data is an issue.
- Probability of each possible text alignment (path) is the product of the predicted probability of each character in that path.
- This alignment probability is summed up for all possible alignments of the label text. The negative logarithm of this summation is defined as the performance index, which is back-propagated.
- Optimizer: Synchronous SGD (reproducible, deterministic)

Google’s Speech-to-Text API

- Google Speech-to-Text enables developers to convert audio to text by applying powerful neural network model.
- Recognizes more than 120 languages and can process real-time streaming or prerecorded audio.
- Ideal for quick prototyping for complex speech tasks like separating multiple speakers, detecting speaker language and transcribing over multiple channels (audio sources).
- Each API request returns multiple transcriptions, sorted by their confidence.
- Enable the API and obtain a private key (credentials) for a given service/billing account.
- Easy to use and reliable REST API.

Experiment

- Use the pre-trained models (an4, LibriSpeech, and TED-LIUM) to transcribe 500 test audio files from the Voxforge dataset.
- Use different parameter tunings (transfer learning) to train the pre-trained models on other Voxforge files and transcribe the same 500 test audio files.
- Use the Google Cloud Speech-to-Text API to transcribe the same 500 test audio files.
- Calculate the Character Error Rate (CER) and Word Error Rate (WER) for all models to compare and contrast performance.

Preliminary Results

Model	WER	CER	Eval time
An4 - Pretrained	10.05%	30.80%	~4 mins
LibriSpeech - Pretrained	2.27%	4.28%	~4 mins
TED-LIUM - Pretrained	4.86%	9.23%	~4 mins
Google Speech-to-Text	1.61%	3.73%	~8 mins

Transfer learning approaches

Trained a librispeech pre-trained model on Voxforge dataset with different parameter settings:

- Default settings: batch size =20, lr = 3e-4, learning-anneal = 1.1, momentum = 0.9
- Using 500 random sampled files with more than 1 sec and less than 15 secs audio file
  - hidden layers =5, hidden size of RNNs = 500, RNN type = GRU
  - hidden layers =5, hidden size of RNNs = 500, RNN type = LSTM
  - hidden layers =5, hidden size of RNNs = 1000, RNN type = LSTM
- Using 7636 sampled with more than 1 sec and less than 15 secs audio file
  - hidden layers =5, hidden size of RNNs = 1000, RNN type = LSTM

Final Results

Model	WER	CER	Eval time
LibriSpeech - Pretrained	2.27%	4.28%	~4 mins
LibriSpeech - Pretrained -Transfer Learning (GRU)	3.09%	6.09%	~4 mins
LibriSpeech - Pretrained -Transfer Learning (LSTM)	3.15%	6.35%	~4 mins
LibriSpeech - Pretrained -Transfer Learning (LSTM+1000)	3.14%	6.31%	~4 mins
LibriSpeech - Pretrained -Transfer Learning (LSTM+1000)	1.66%	3.00%	~4 mins
Google Speech-to-Text	1.61%	3.73%	~8 mins

Key contributions

- Strip and reformat the original source code (rewriting arguments, re-defining classes, etc.)
- Simplified code base to meet project requirements and increase ease of use/understanding
    - Updated with significant commenting to explain most existing lines of code
- Developed model evaluation comparison scripts, rewriting target metric code
- Conducted informed parameter tuning and transfer learning to fit the context of the Voxforge dataset, generating four new transfer-learning models
- Developed Google API transcription code

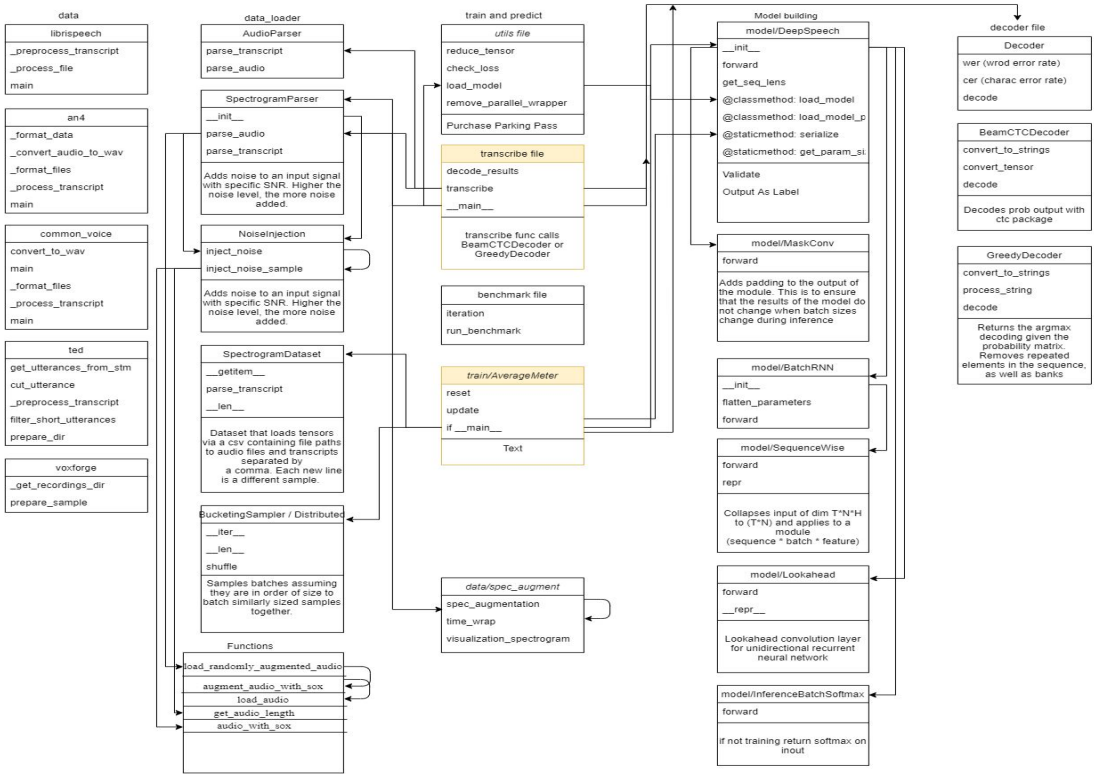
Conclusion and Next Steps

- The generalized Google Speech-to-text model outperforms the pre-trained DeepSpeech2 models.
- Our customized transfer learning approaches with the bi-directional LSTMs performed **marginally** better the Google API service on our test set, however may not be as generalizable.
- Next Step: Creating a model trained on all three datasets simultaneously to increase variety of audio data
- Next Step: Using data augmentation techniques in transfer learning models to increase robustness and generalizability.
- Next Step: Parallelization of GPU computing using CUDA could scale the transfer learning to larger datasets.
- Next Step: Incorporate training visualization that could better guide the transfer learning tunings.

Thank you!


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

Appendix


data
librispeech
_preprocess_transcript
_process_file
main
an4
_format_data
_convert_audio_to_wav
_format_files
_process_transcript
main
common_voice
convert_to_wav
main
_format_files
_process_transcript
main
ted
get_utterances_from_stm
cut_utterance
_preprocess_transcript
filter_short_utterances
prepare_dir
voxforge
_get_recordings_dir
prepare_sample
data_loader
AudioParser
parse_transcript
parse_audio
SpectrogramParser
__init__
parse_audio
parse_transcript
Adds noise to an input signal with specific SNR. Higher the noise level, the more noise added.
NoiseInjection
inject_noise
inject_noise_sample
Adds noise to an input signal with specific SNR. Higher the noise level, the more noise added.
SpectrogramDataset
__getitem__
parse_transcript
__len__
Dataset that loads tensors via a csv containing file paths to audio files and transcripts separated by a comma. Each new line is a different sample.
BucketingSampler / DistributedBucketingSampler
__iter__
__len__
shuffle
Samples batches assuming they are in order of size to batch similarly sized samples together.
Functions
load_randomly_augmented_audio
augment_audio_with_sox
load_audio
get_audio_length
audio_with_sox
train and predict
utils file
reduce_tensor
check_loss
load_model
remove_parallel_wrapper
Purchase Parking Pass
transcribe file
decode_results
transcribe
__main__
transcribe func calls BeamCTCDecoder or GreedyDecoder
benchmark file
iteration
run_benchmark
train/AverageMeter
reset
update
if __main__
Text
data/spec_augment
spec_augmentation
time_wrap
visualization_spectrogram
Model building
model/DeepSpeech
__init__
forward
get_seq_lens
@classmethod: load_model
@classmethod: load_model_p
@staticmethod: serialize
@staticmethod: get_param_si
Validate
Output As Label
model/MaskConv
forward
Adds padding to the output of the module. This is to ensure that the results of the model do not change when batch sizes change during inference
model/BatchRNN
__init__
flatten_parameters
forward
model/SequenceWise
forward
repr
Collapses input of dim T*N*H to (T*N) and applies to a module (sequence * batch * feature)
model/Lookahead
forward
__repr__
Lookahead convolution layer for unidirectional recurrent neural network
model/InferenceBatchSoftmax
forward
if not training return softmax on inout
decoder file
Decoder
wer (wrod error rate)
cer (charac error rate)
decode
BeamCTCDecoder
convert_to_strings
convert_tensor
decode
Decodes prob output with ctc package
GreedyDecoder
convert_to_strings
process_string
decode
Returns the argmax decoding given the probability matrix. Removes repeated elements in the sequence, as well as banks