Machine Learning in Speech Processing: Speaker Diarization

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Introduction

Speech processing has been an important research area of computer science and signal processing for the last few decades. Recent advances in machine learning have had a profound impact on the field. Long gone are the days in which automatic transliteration used to be riddled with errors and accuracy problems, and you needed to manually train the model. These days, the latest version of Google Assistant can recognize speech on the device locally and instantaneously, without any internet connection. Cloud platforms even offer API endpoints for speech to text conversion, speaker identification, and dialogue labeling. It seems a solved problem. But is it? There are still plenty of challenges left to solve, like real-time multi-language translation, on-device translation, etc.

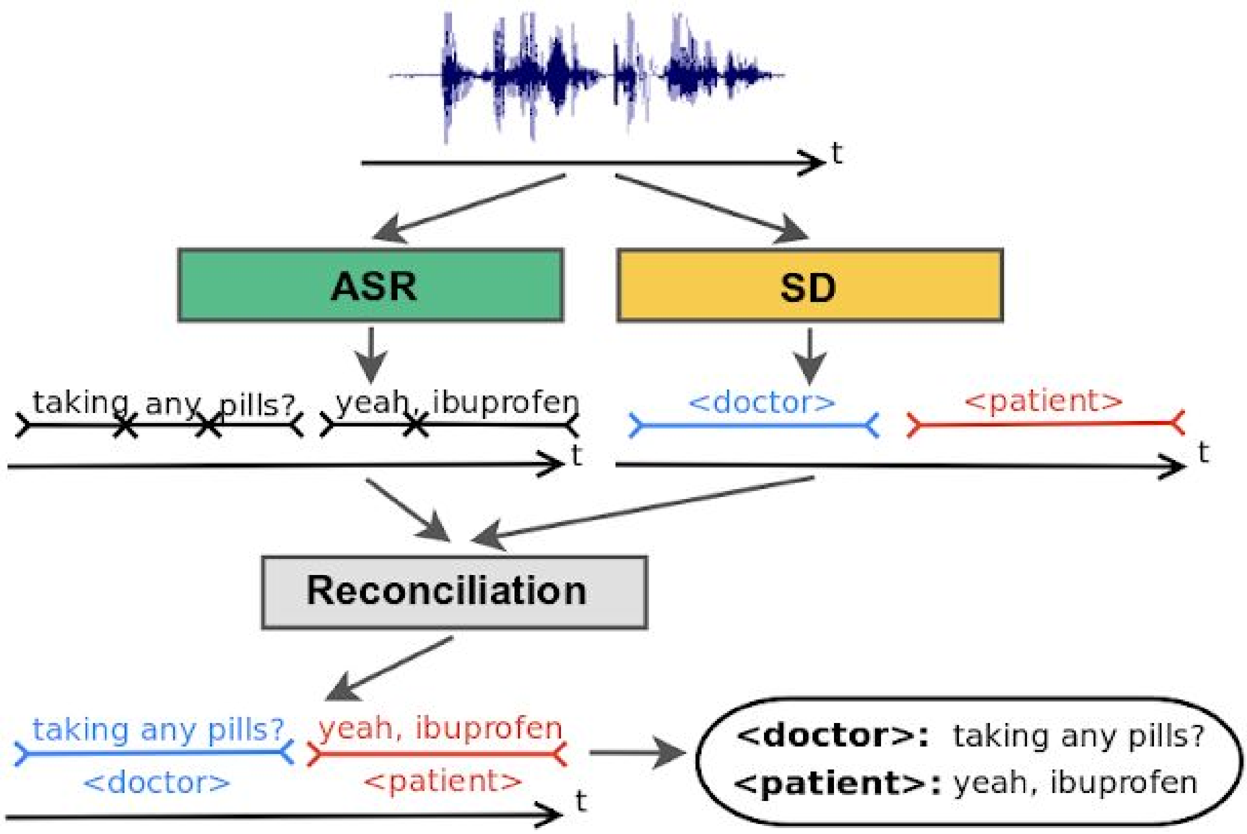
Analysis

Speaker diarization is the process of dividing an input audio stream into separate streams for each speaker[1]. In their seminal paper titled "Joint Speech Recognition and Speaker Diarization via Sequence Transduction"[2], the Google AI teams have demonstrated the suitability of a new neural network model, Recurrent Neural Network Transducer(RNN-T) to speaker diarization. Using this model, the team achieved a new performance breakthrough, from 20% to 2% in word diarization error rate, a factor of 10 improvement.

Conventional Speaker Diarization Systems

Ordinary speaker diarization frameworks depend on contrasts in how individuals sound acoustically to recognize the speakers in a sound sample. While male and female speakers can be recognized effectively from their pitch utilizing basic acoustic models (e.g., Gaussian blend models) in a solitary stage, speaker diarization frameworks utilize a multi-organize way to deal with speakers having a conceivably comparable pitch. First, a switch model separates the discussion into homogeneous fragments, ideally containing just a solitary speaker, in view of recognized vocal attributes. At that point, deep learning models are utilized to guide sections from every speaker to an inserting vector. Lastly, in a bunching stage, these embeddings are gathered to monitor a similar speaker over the discussion.

Mostly, the speaker diarization framework keeps running in parallel to the programmed discourse acknowledgment (ASR) framework and the yields of the two frameworks are consolidated to credit speaker names to the perceived words.

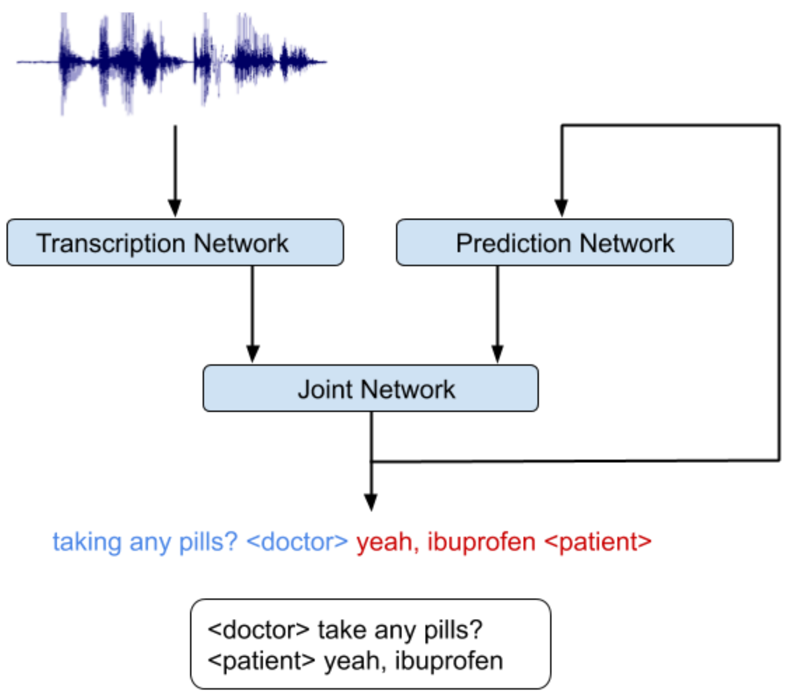


Conventional speaker diarization system infers speaker labels in the acoustic domain and then overlays the speaker labels on the words generated by a separate ASR system

An Integrated Speech Recognition and Speaker Diarization System

The group has built a novel and straightforward model that joins acoustic and semantic signs consistently as well as consolidates speaker diarization and discourse acknowledgment into a single framework.

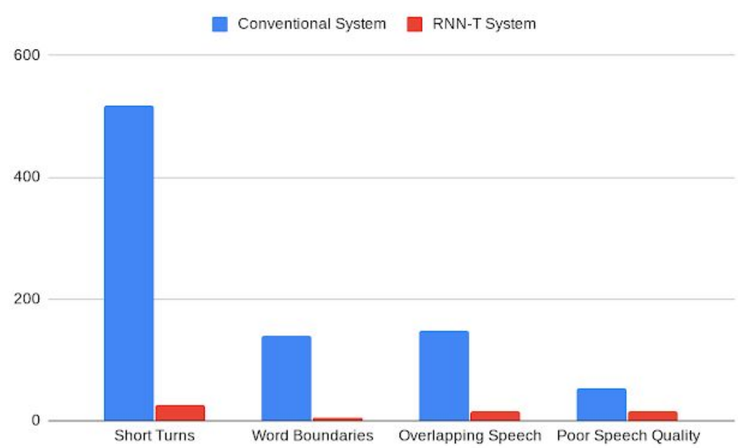
The key insight in the paper was to perceive that the RNN-T design is appropriate to incorporate acoustic and phonetic prompts. The RNN-T model comprises of three unique systems: (1) an interpretation organize (or encoder) that maps the acoustic casings to a dormant portrayal, (2) a forecast system that predicts the following objective mark given the past objective names, and (3) a joint system that consolidates the yield of the past two systems and produces a likelihood appropriation over the arrangement of yield names around them.



An integrated speech recognition and speaker diarization system where the system jointly infers who spoke when and what.

Training the RNN-T model on accelerators like graphical processing units (GPU) or tensor processing units (TPU) is complex as computation of the loss function requires running the forward-backward algorithm, which includes all possible alignments of the input and the output sequences. This can be resolved by recasting the problem as a sequence of matrix multiplications. The team also took advantage of an efficient implementation of the RNN-T loss in TensorFlow that allowed quick iterations of model development and trained a very deep network.

The integrated model can be trained just like a speech recognition system. The reference transcripts for training contain words spoken by a speaker followed by a tag that defines the role of the speaker. For example, “When is the meeting?” <CEO>, “It’s at 3 pm,” <Secretary>. Once the model is trained with examples of audio and corresponding reference transcripts, a user can feed in the recording of the conversation and expect to see an output in a similar form. The analyses in the paper show that improvements from the RNN-T system impact all categories of errors, including short speaker turns, splitting at the word boundaries, incorrect speaker assignment in the presence of overlapping speech, and poor audio quality. Moreover, the RNN-T system exhibited consistent performance across conversation with substantially lower variance in average error rate per conversation compared to the conventional system.



A comparison of errors committed by the conventional system vs. the RNN-T system, as categorized by human annotators.

Pros

This is a state of the art system with record-setting scores. The accuracy of this model is very high, with low error rates. This can have multiple applications, especially in workplace scenarios.

Cons

This is a computationally intensive model. The training of this model requires clusters of high-end GPUs or TPUs, thereby limiting its accessibility. No API exists as of now to leverage this model, and the code is not open source yet.

Recommendations

For understanding the basics of speaker diarization, follow the instructions to use the google cloud speech to text API at the website in the reference [5].

To run the model described in the paper, clone their github repo and follow the instructions in the readme file.

Conclusion

The pace of improvement in speech recognition has been astonishing to see as a result of applied machine learning. The accuracy will surely improve even further, perhaps even surpassing native human capabilities, in the future.

References

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[5] Separating different speakers in an audio recording
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Summaries of Teammates' Reports

#1 Amanda's Report - Deep Neural Network Architectures for Speech Recognition

- Recent developments in the Speech Recognition focus on applications of deep neural networks, moving away from traditional approaches like Gaussian Mixture Models and Hidden Markov Chains.
- Current research is focused on identifying the most optimal representations for the speech features, which can be used to obtain the best results.
- SincNet Architecture- Uses raw audio frames as input allows "the networks to "learn low-level speech representations of the waveforms", as opposed to networks that take input in the form of human-crafted features (such as Mel Frequency Cepstral Coefficients)."
- No need for human feature design, saving time.
- "Certain valuable traits, such as fundamental pitch and formant frequency information of the signal are maintained". The approach minimizes the number of parameters while preserving signal information, reducing compute complexity.
- By reducing learning complexity, the model becomes very efficient at learning features, leading to lower training times.
- Another approach by Seki et al involves a bank of Gaussian Filters, the approach being somewhat similar to the SincNet approach, reducing compute complexity by learning fewer parameters.
- 3D CNNs: This approach utilizes a 3-dimensional CNN, and uses MFEC inputs, instead of raw audio frames. The goal is to create a speaker model that is independent of the speaker setting, therefore accurately recognizing a word utterance irrespective of its intonation and other characteristics being somewhat different.

- While there is no consensus on any one model being the most optimal, deep learning approaches are currently state of the art. They are however computationally very intensive and may be accessible to only well-funded labs and teams.

#2 Shineun's Report - Deep Neural Network Architectures for Speech Recognition

- "Digital Speech Processing is a broad field of study that embraces: speech recognition, speech synthesis, speaker recognition, language identification, lip synchronization, and co-channel separation."
- Evolution of Algorithms: Kalman filters were the first algorithms used in digital speech processing. They consist of two steps, first determining the values for state variables, along with their uncertainties. In the next step, the algorithm updates these values using a weighted average, with more weight being assigned to estimates with higher certainty.
- Multi Speaker algorithms involve "multi-speaker detection, tracking, and segmentation of speakers".
- Problems faced by Kalman filters include speaker overlap and break and silences in the signal.
- To overcome these problems, Hidden Markov Models proposed which utilize parallel Kalman filters.
- APIs: Google speech to text API, Microsoft Speech Service API: Text-to-Speech, IBM Watson's Speaker Speech-to-Text API are a few public APIs for speech processing.
- The Google API implements an RNN to model speaker embeddings.
- It can recognize 120 different languages but is cost-prohibitive.
- The Microsoft Speech service API can recognize individual speakers in a conversation and is useful for the analysis of a multi-speaker environment.

- However individual speaker samples are required for each speaker in the environment and there are various format specifications that need to be conformed to.
- Each API is better suited to specific applications, with the Microsoft API more useful to enterprise users and the Google cloud API better suited for non-commercial applications.

#3 Yang's Report - Deep Neural Networks on Speech Processing

- In automatic speech recognition (ASR), modeling and algorithms are key areas of improvement.
- Hidden Markov Models based on Gaussian Mixture Models (GMM) have been the focus in ASR for decades.
- Deep Neural Networks have become the key focus area now.
- DNNs are strong at modeling data correlations.
- DNNs are however much more complex to implement than GMMs.
- For multitasking, DNNs are more efficient than GMMs.