Automatic Speech Recognition

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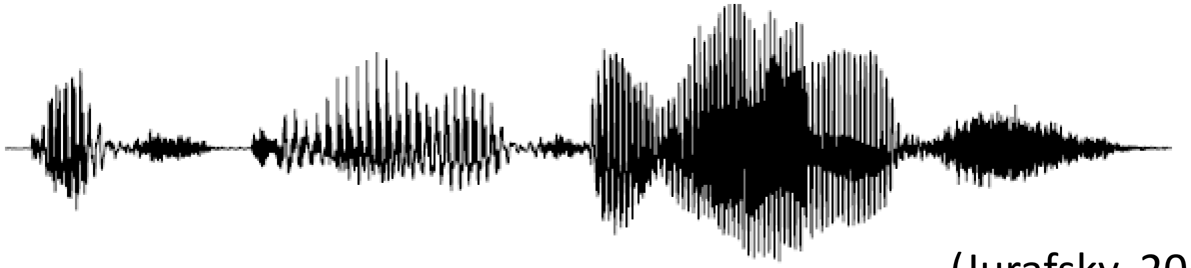
Overview

- What is ASR?
- Use Case
- History
- ASR Task
- Typical Architecture
- Evaluation
- Problem and Challenge
- Future

What is ASR?

- Definition
  - The conversion of speech into text (Foteini, 2020)
  - Map any waveform to the appropriate string of words (Jurafsky, 2020)



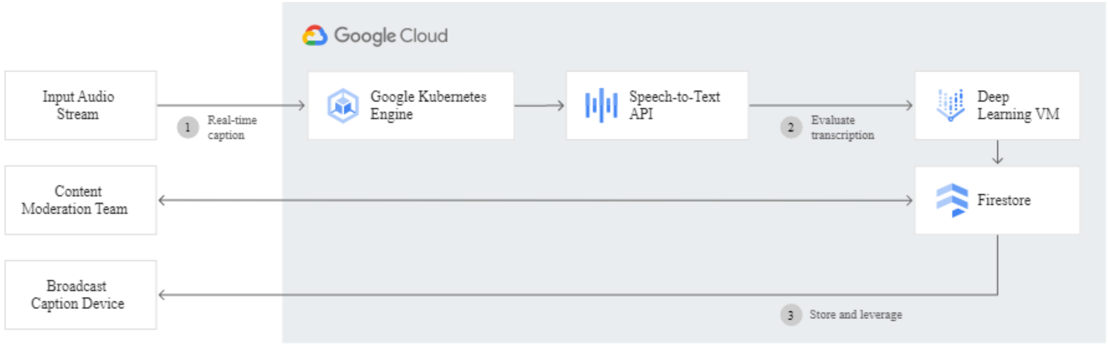
(Jurafsky, 2020)

It's time for lunch!

Use Case

- Human-machine communication for personal use
  - Communicating with smart home appliances
  - Generating captions for audio or video text

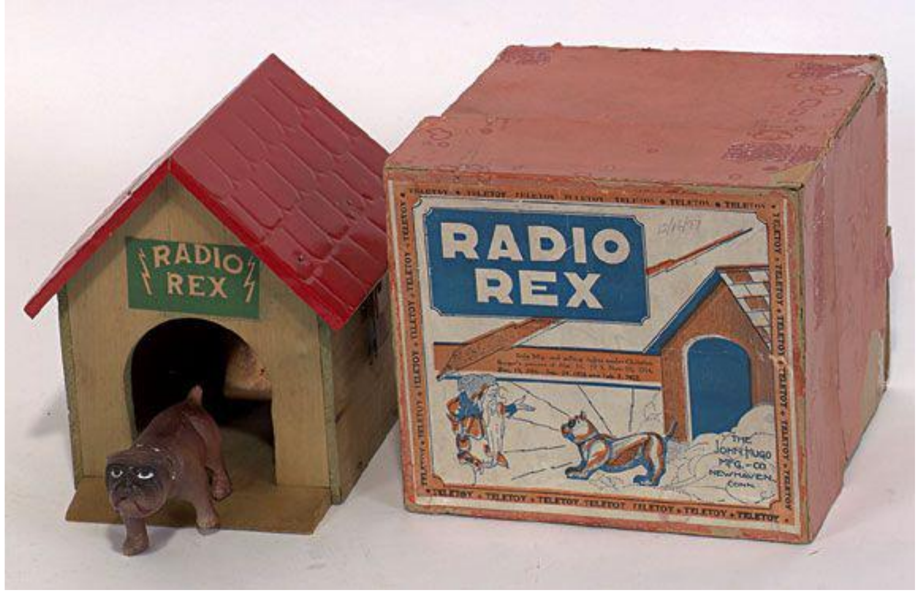
- Industrial Use
  - Industrial machine guidance with voice commands
  - Automatic telephone communication
  - Communication with automotive systems
  - Military vehicles
  - Communication with health care
  - Aerospace



(Google, use case for transcribing multimedia content)

History –The first “Speech Recognition”

- “Radio Rex” (1920s)
  - The first machine that recognize speech
  - Dog “Rex” comes by the spring was released by 500 Hz acoustic energy by the vowel [eh] in “Rex”



(Jurafsky, 2020)

2’ 55 https://youtu.be/AdUi_St-BdM?t=175

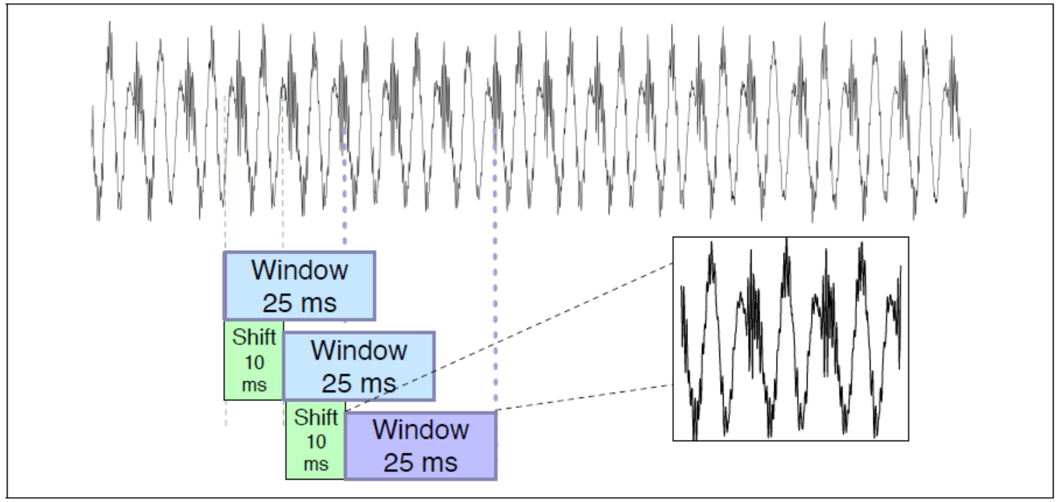
ASR Task

Breaks down waveform into very small window, where it represents a phoneme

Convert the analog waveform representations into a digital signal

Transform the digital signal into a sequence of acoustic feature vectors

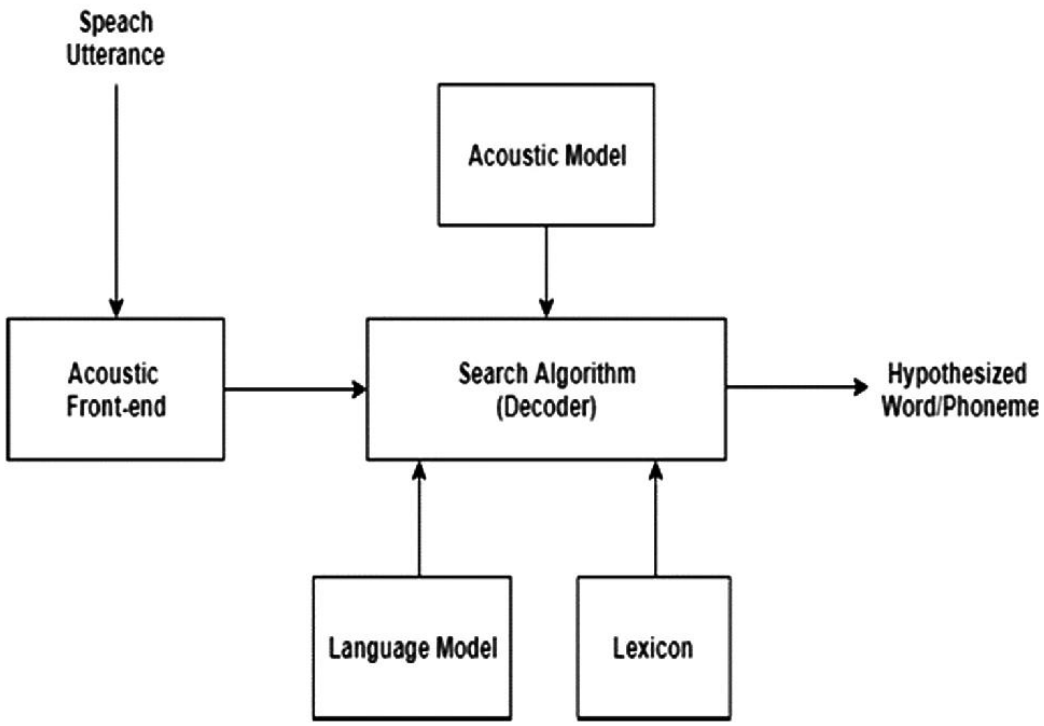
Use Algorithm to find the most probable word fit in that language.



(Jurafsky, 2020)

Architecture

- Acoustic front-end
  - Extract useful features from speech
- Language Model
  - Gives the limitation of the sequence of the given words
- Lexicon
  - Includes vocabulary
- Search Algorithm (Decoder)
  - Produce the hypothesized word/phoneme
- Acoustic Model
  - Contains Statistical representation of each sounds that makes up a word

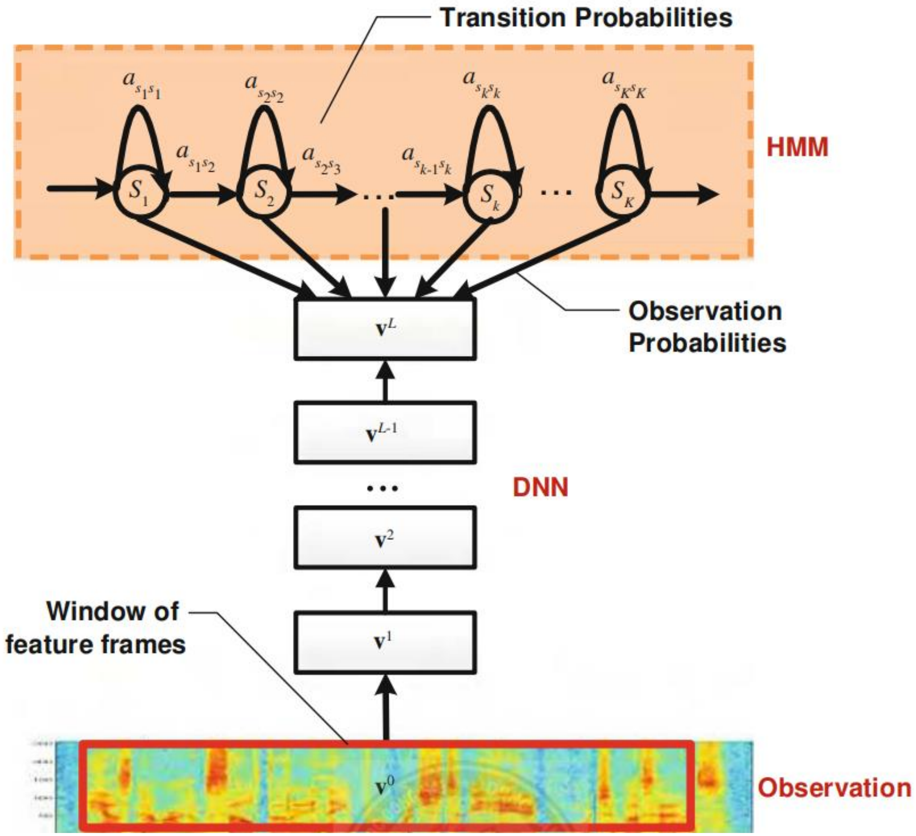


(Foteini, 2020)

Brain Part -Hybrid DNN-HMM-

- Deep Neural Network model (DNN)
  - Strong leaning power / Overfitting
- Hidden Markov Model (HMM)
  - Sequential modeling ability and flexibility
- Combining DNN-HMM approaches with end-to-end systems
  - HMMs : models the dynamics of the speech signal
  - DNNs: estimate the observation probabilities

(Rista A, 2020)



(Yu and Deng, 2015)

Evaluation

- WER (word error rate) = the distance between the word sequence that produces an ASR and the reference series. (Opposite of Accuracy)
  - Types of Error
    - Substitution : A word in the reference sequence is transcribed as a different word (S) (ex: “shipping” → “sipping”)
    - Deletion : A word is completely missing (D)
    - Insertion : The appearance of a word in the transcription that has no correspondent in the reference word sequence (I) (ex: hostess →host is)

$$WER = \frac{(S+D+I)}{N_1} = \frac{(S+D+I)}{(H+S+D)}$$ (H = Total number of success, N1 = total number of reference words)

  - Google Speech to Text (Foteini, 2020)
    - 2013 ⇒ 23 %
    - 2015 ⇒ 8 %

(Foteini, 2020)

Problem and Challenge

- Handling with variabilities of linguistic attributes, speaker and channel (Rista A, 2020)
  - Different Phonetic attributes in each language
  - Adverse environment conditions (clean, noisy)
  - Speed of utterance
  - Accent / Dialect
- Low resource Language (Koenecke et al., 2020)
- Overlapping issues when multiple people speaks at the same time (Anguraj et al., 2022)

Corpora

- **Switchboard corpus**
  - Telephone conversations between strangers
  - Contains 2430 conversations averaging 6 minutes each, totaling 240 hours of 8 kHz speech and about 3 million words (Godfrey et al., 1992).
  - Advantage of an enormous amount of auxiliary hand-done linguistic labeling, including parses, dialogue act tags, phonetic and prosodic labeling, and discourse and information structure
- **CORAAL**
  - Collection of over 150 sociolinguistic interviews with African American speakers
  - With the goal of studying African American Language (AAL)
  - Many variations of language used in African American communities (Kendall and Farrington, 2020)

Future ASR

"Real time recognition with

100% accuracy,

all words that are intelligibly spoken by any person,

independent of vocabulary size,

noise,

speaker characteristics or accent"

(IANCU B, 2019)

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Sources for the image and the video

- https://cloud.google.com/speech-to-text?hl=ja
- https://youtu.be/AdUi_St-BdM?t=175