Automatic Speech Recognition

13 & 20 Feb 2025

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Text To Speech

Part 1:
ASR Fundamentals

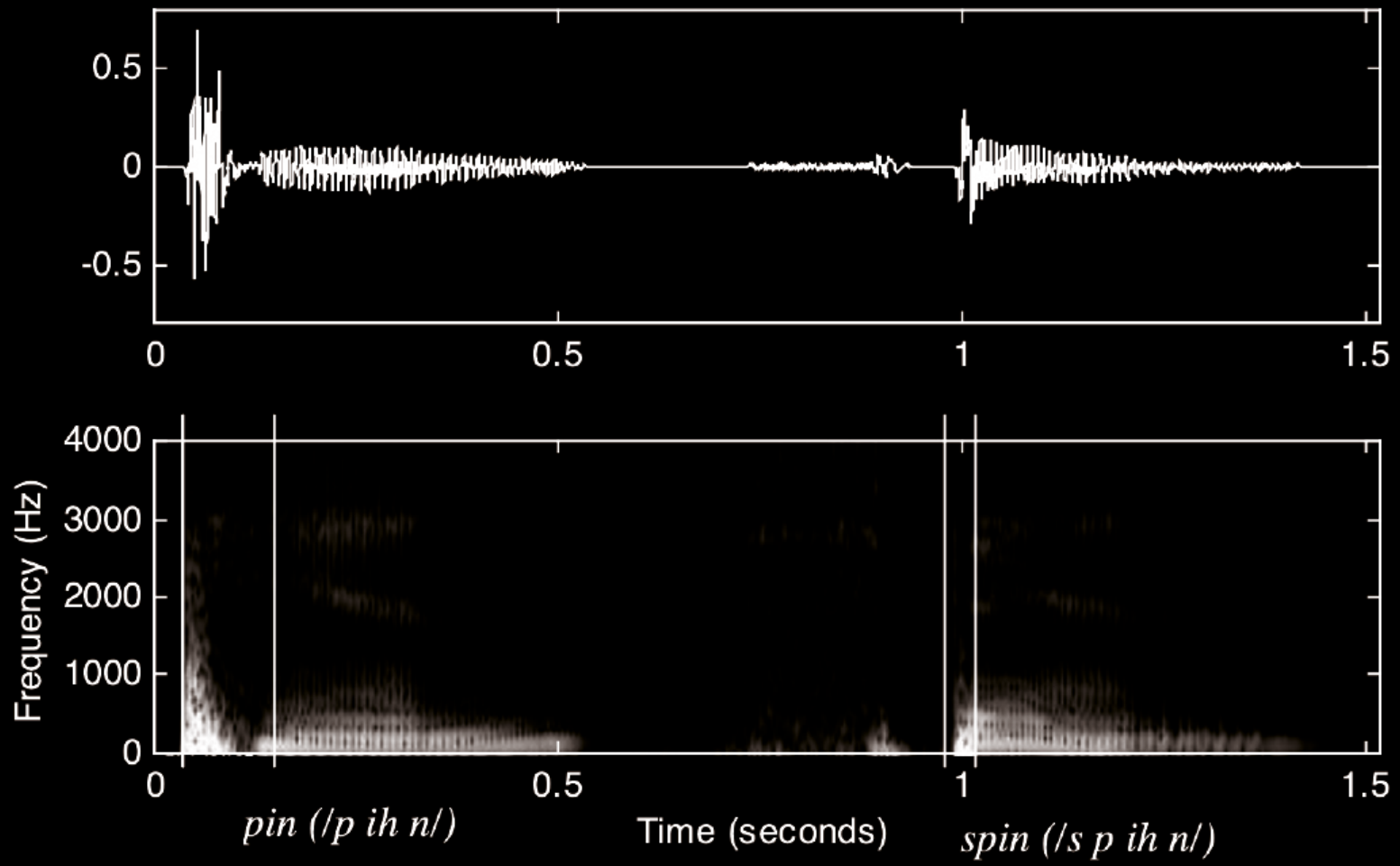
ASR types

- fixed commands
- grammars (e.g. date)
- continuous speech recognition (huge vocabulary)

What is ASR

- The aim is to decode the acoustic signal O into a word sequence $\hat{W}$ which is hopefully close to the original word sequence W.
- We need an acoustic model: our knowledge about acoustics, phonetics, microphone, environment, speakers, dialects, etc.
- And a language model that knows about words (and non-words), how they co-occur and form sequences (utterances)

Challenge: context variability



Variability in speech

- context variability (pin vs spin), coarticulation
- style variability
- speaker variability
- environment variability

Formal definition

Formal definition

- We can observe the set of parameters O (observations) for the acoustic signal.
- In the following equation acoustic model would be responsible for P(O|W) and language model for P(W)

$$W = \arg\max_{W} P(W|O) = \arg\max_{W} \frac{P(O|W)P(W)}{P(O)} = \arg\max_{W} P(O|W)P(W)$$

But how do we calculate P(O|W)?

- Can we use words?

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- Can we use words? Yes, but then there will be a huge range of observations.
- Can we minimise the number of possible observations? Yes, by selecting some smaller phonetic units.

Why word is not a good unit:

- New task can have new words but we won't have any training data.
- There are too many words, and each of them has too many acoustic realisations.

Good unit is:

- accurate, in order to represent acoustic realisation in different contexts
- trainable, we should have enough data to estimate the parameters of the unit
- generalisable, so new words could be derived from our units

What about phonemes?

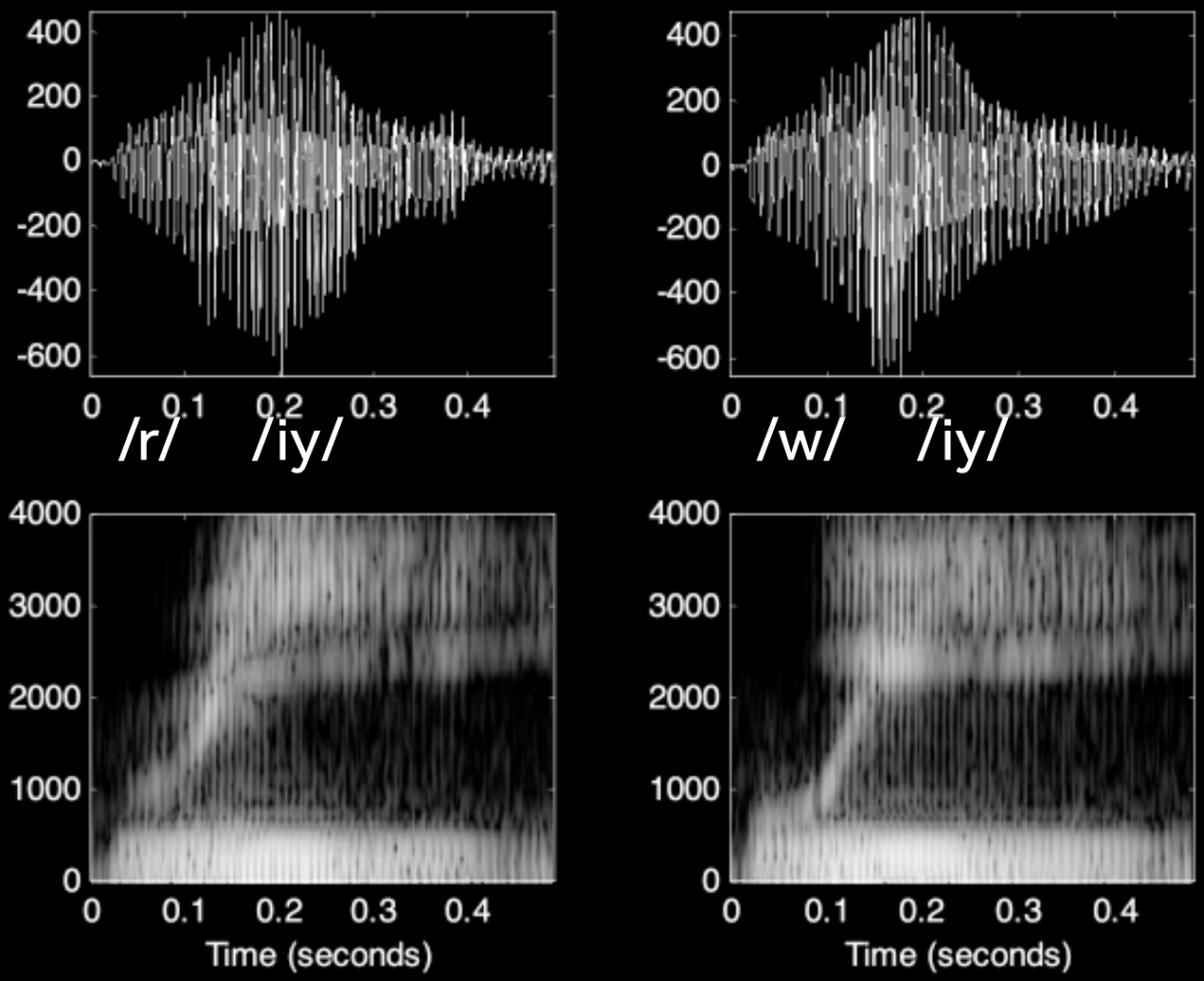
What about phonemes?

- Just 50 phones in English, no problem to train. And they are vocabulary-independent.
- But phonemes are not produced independently, they are context-dependent, so they can over-generalise.
- For some languages we can use syllables (1200 in Chinese, 50 in Japanese) but for English (30k+) training is challenging.

How can we capture context dependency?

- A triphone phonetic model: it takes into consideration the left and the right contexts.
- They capture coarticulation of a phone in all possible contexts.

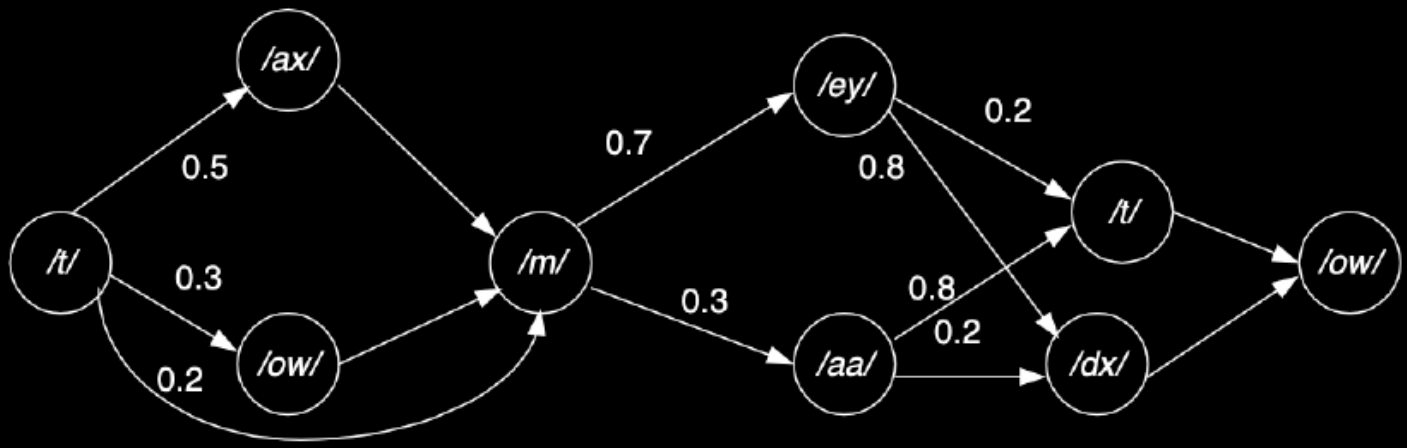
Different but similar



Different but similar

- It is desirable to find instances of similar contexts and merge them.
- This would lead to a much more managable number of models that can be trained.

Word modelling



Feature extraction

Feature extraction I: windowing

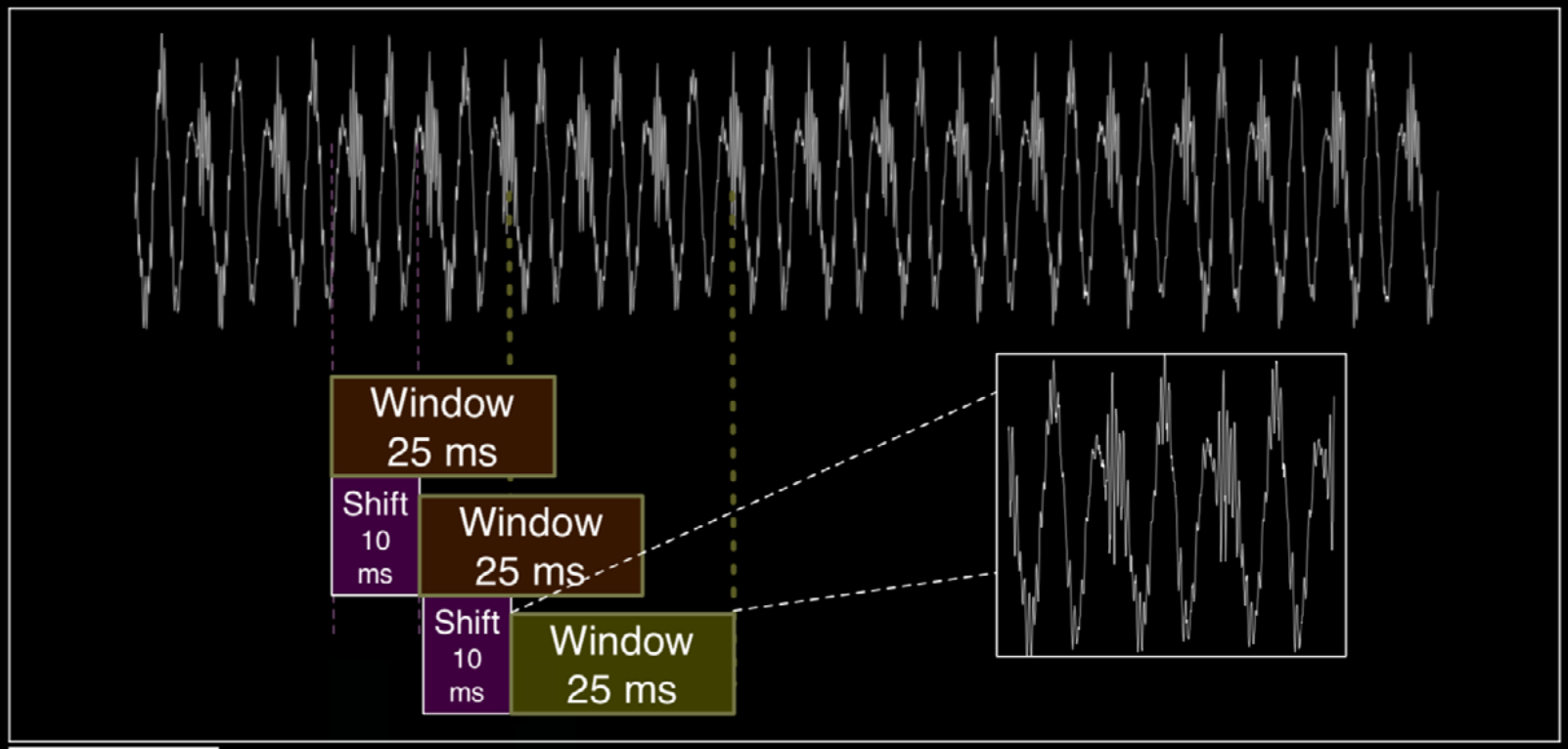


Figure 26.2 Windowing, showing a 25 ms rectangular window with a 10ms stride.

Hamming window

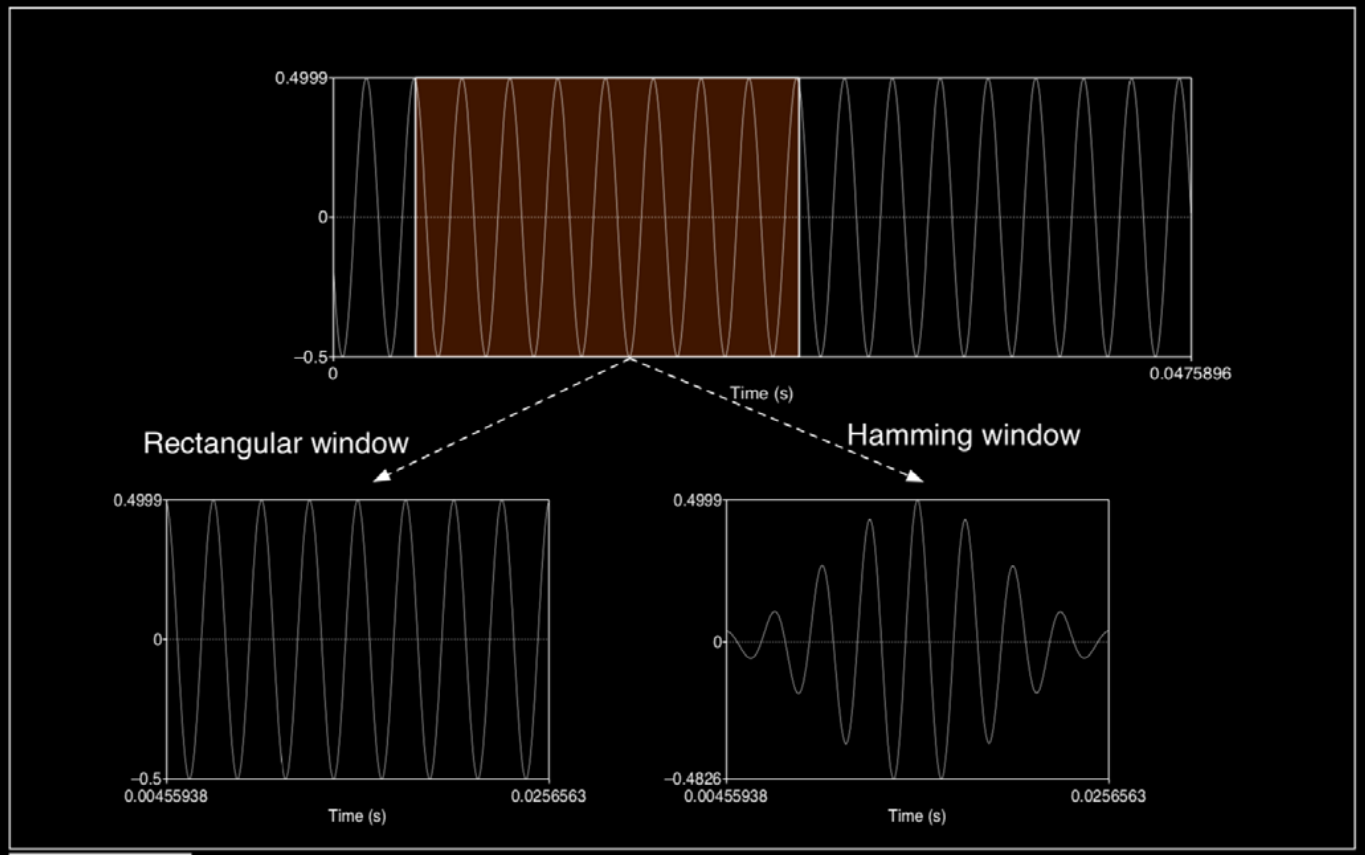


Figure 26.3 Windowing a sine wave with the rectangular or Hamming windows.

Discrete Fourier Transform (DFT)

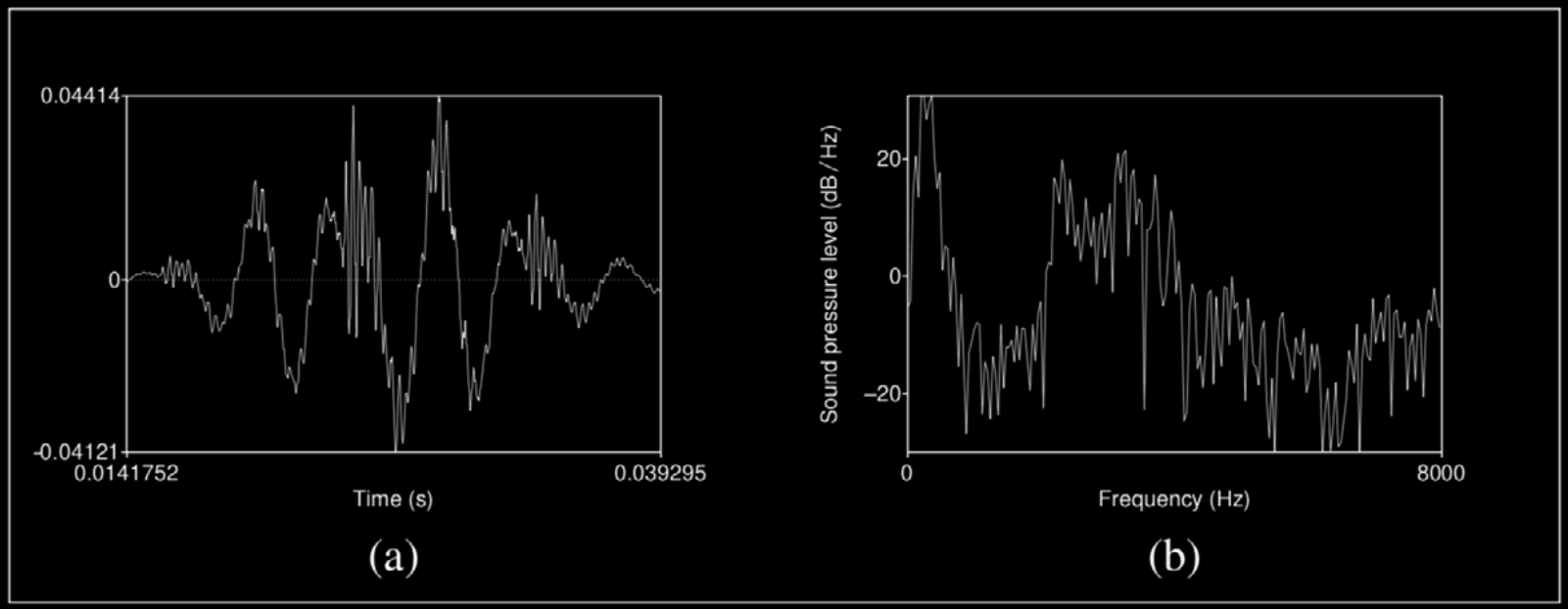


Figure 26.4 (a) A 25 ms Hamming-windowed portion of a signal from the vowel [iy] and (b) its spectrum computed by a DFT.

Mel filter bank

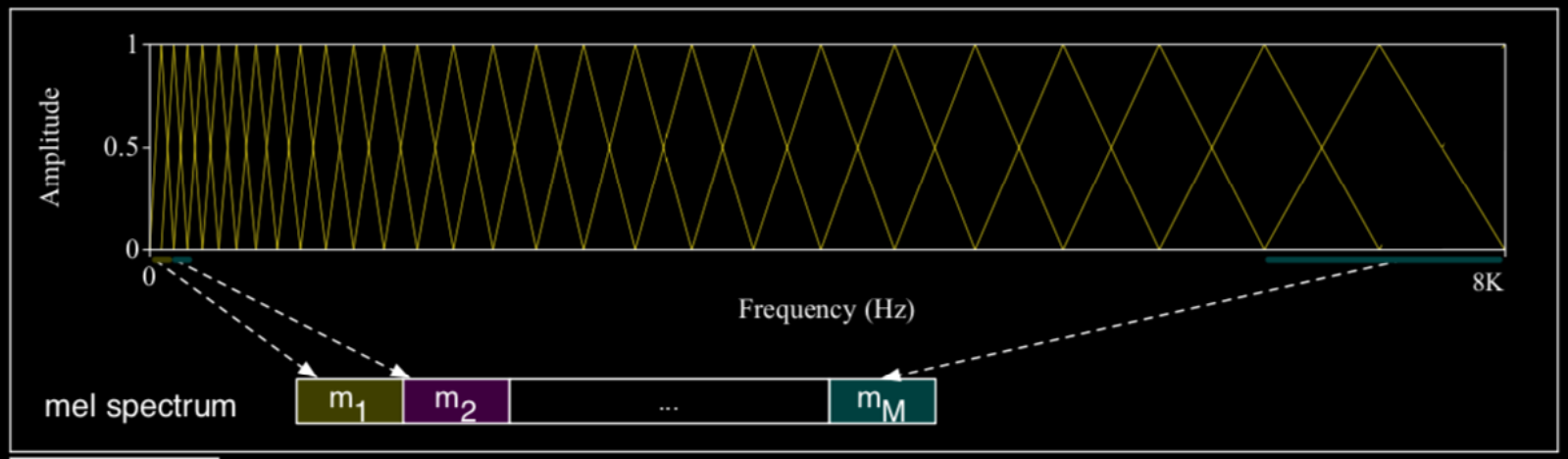


Figure 26.5 The mel filter bank (Davis and Mermelstein, 1980). Each triangular filter, spaced logarithmically along the mel scale, collects energy from a given frequency range.

ASR architecture

- frames (width: 25ms, shift: 10ms), feature extraction, Hamming window
- Mel-frequency cepstral coefficients (MFCCs) are used as an input to individual Gaussian distribution for each phone
- encoder models
- decoding is integral path: the process which transforms the signal into word hypotheses.

Encoder-decoder architecture

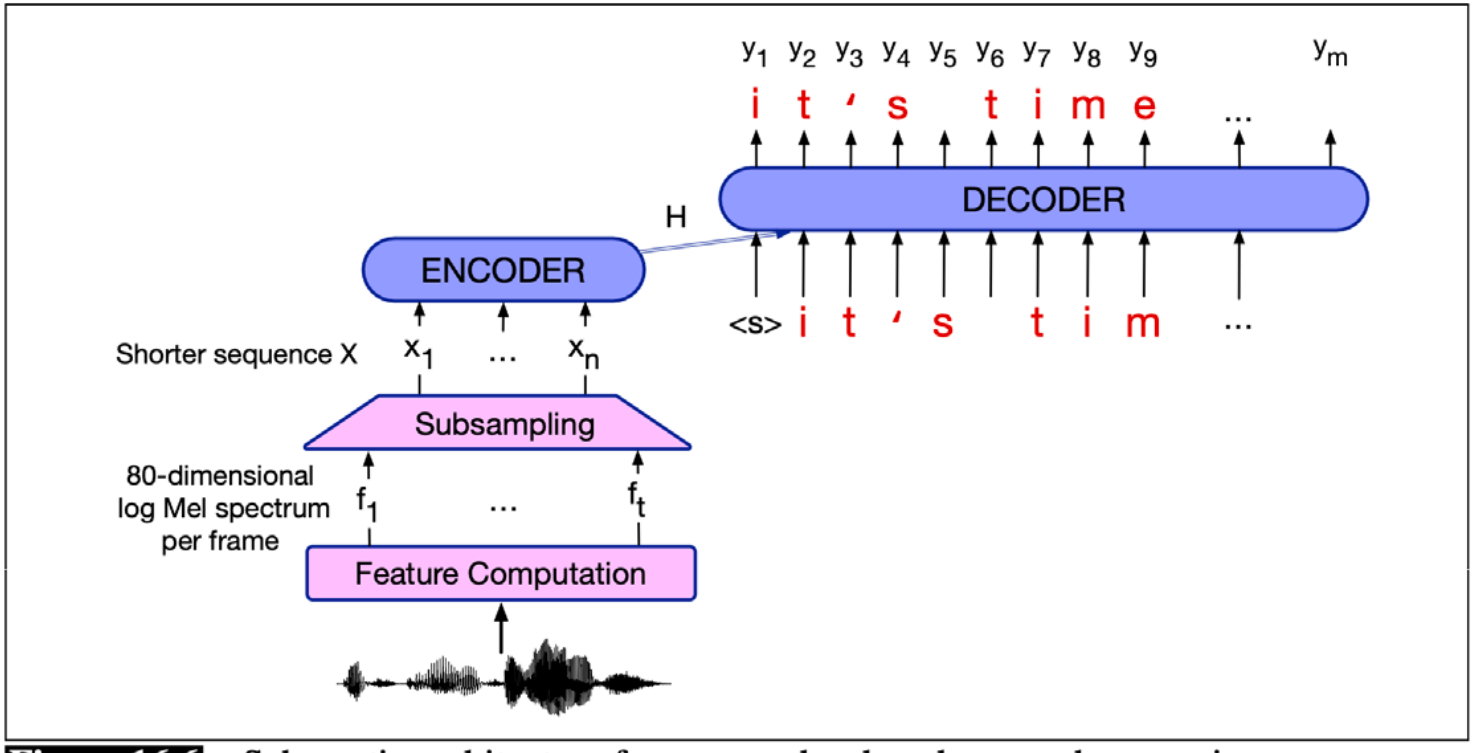


Figure 16.6 Schematic architecture for an encoder-decoder speech recognizer.

Connectionist Temporal Classification (CTC)

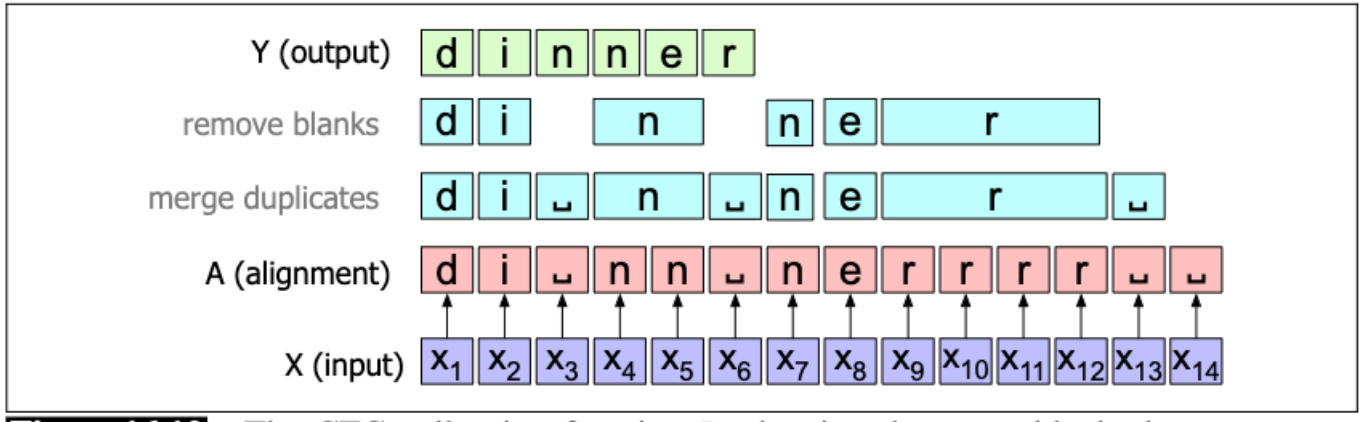
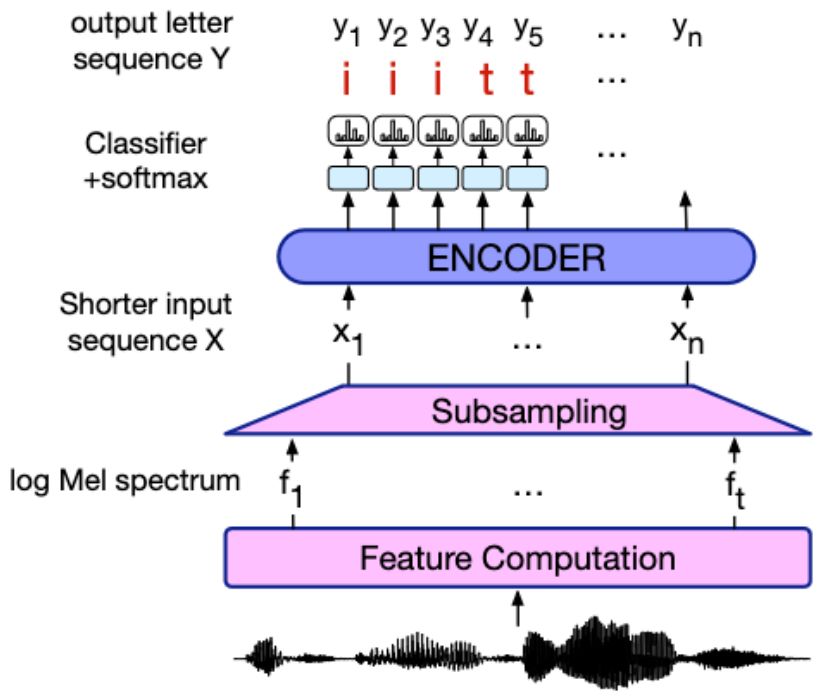


Figure 16.10 The CTC collapsing function B, showing the space blank character ␣; repeated (consecutive) characters in an alignment A are removed to form the output Y.

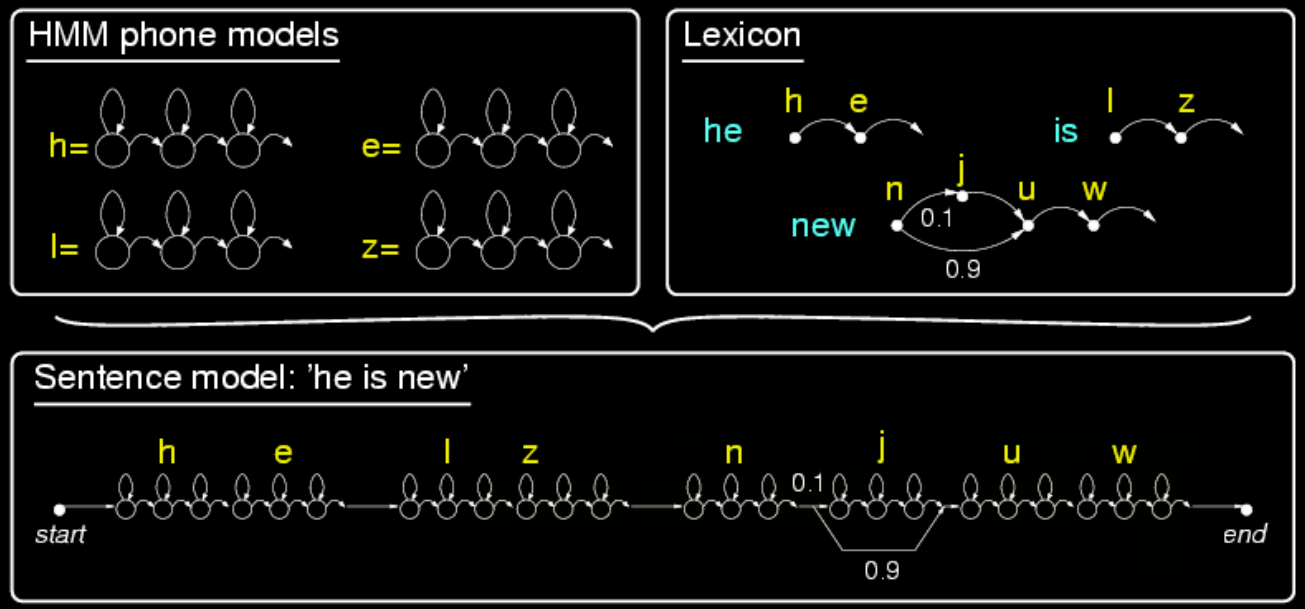
Connectionist Temporal Classification (CTC)



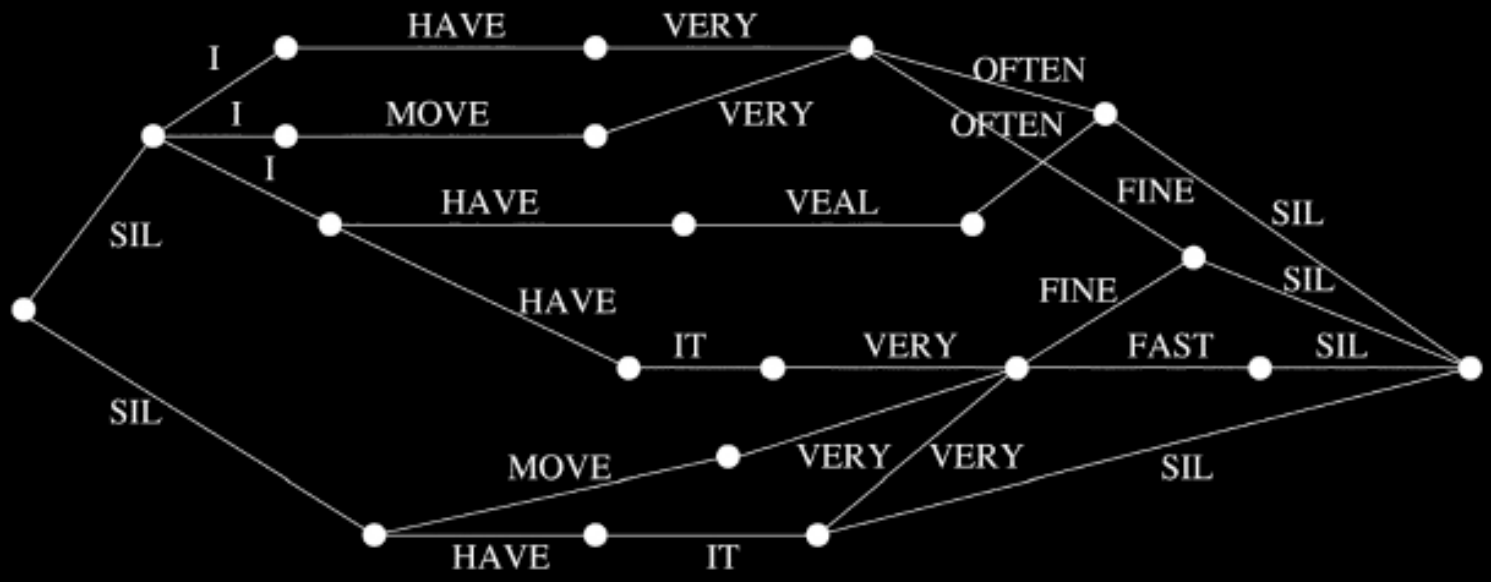
ASR decoding:

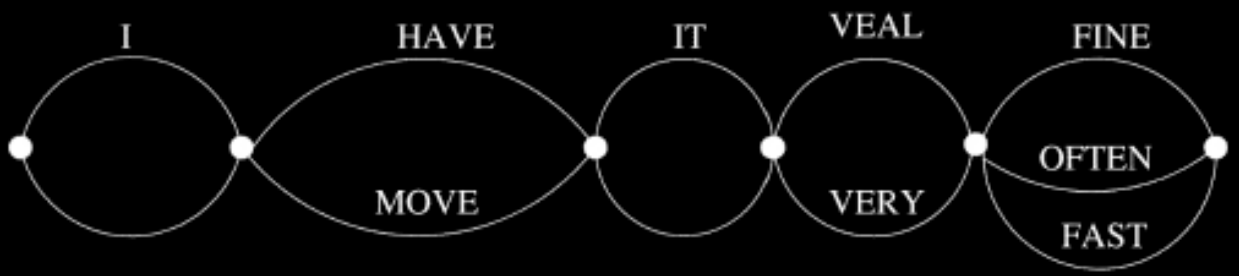
- Using Viterbi or other methods, multiple ‘top’ hypotheses can remain
- The possible outcomes can be stored in a word-confusion network (sausage) or a lattice.

From phonemes to sentences



Word lattice and confusion network





ASR evaluation

- Levenshtein distance/alignment
- Word-error rate (WER)

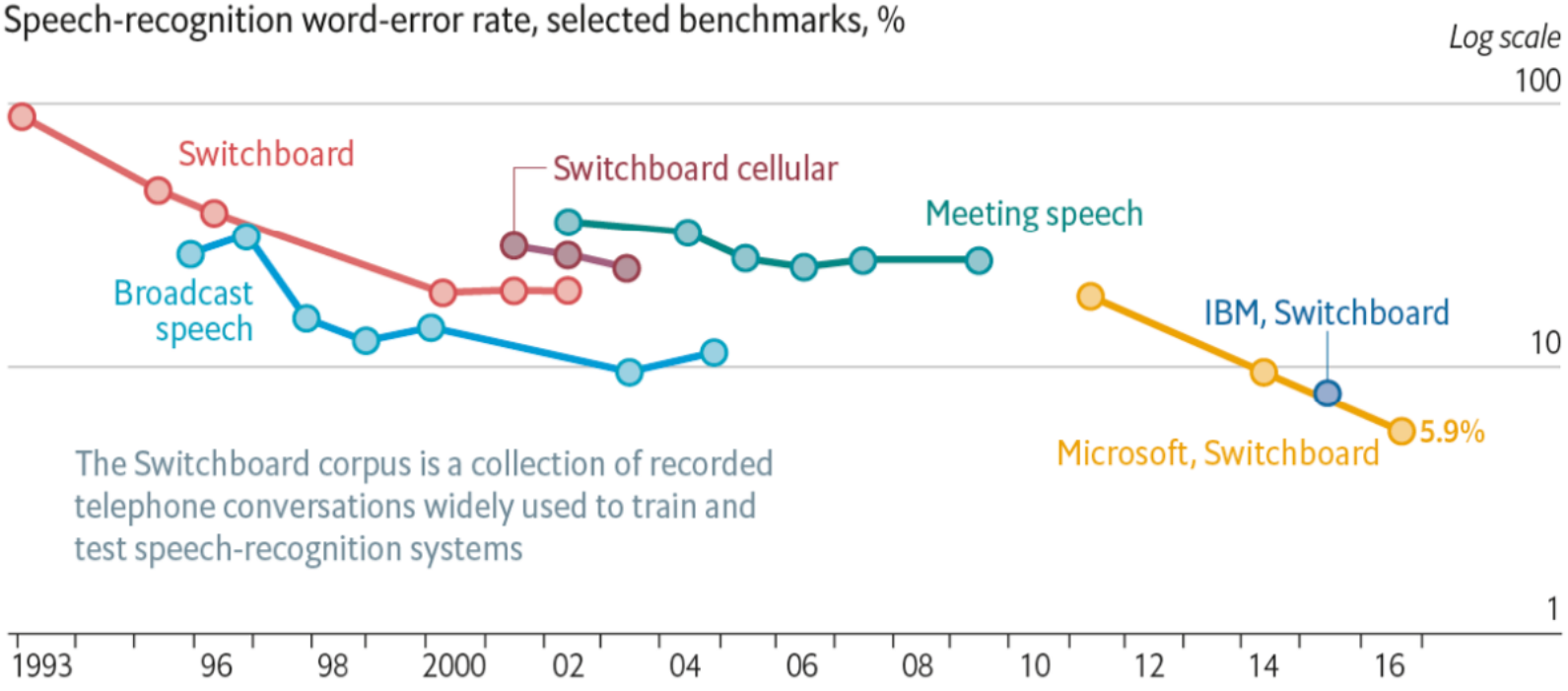
$$WER = (I + S + D) / N$$

English Tasks	**WER%**
LibriSpeech audiobooks 960hour clean	1.4
LibriSpeech audiobooks 960hour other	2.6
Switchboard telephone conversations between strangers	5.8
CALLHOME telephone conversations between family	11.0
Sociolinguistic interviews, CORAAL (AAL)	27.0
CHiMe5 dinner parties with body-worn microphones	47.9
CHiMe5 dinner parties with distant microphones	81.3
Chinese (Mandarin) Tasks	**CER%**
AISHELL-1 Mandarin read speech corpus	6.7
HKUST Mandarin Chinese telephone conversations	23.5

Figure 16.1 Rough Word Error Rates (WER = % of words misrecognized) reported around 2020 for ASR on various American English recognition tasks, and character error rates (CER) for two Chinese recognition tasks.

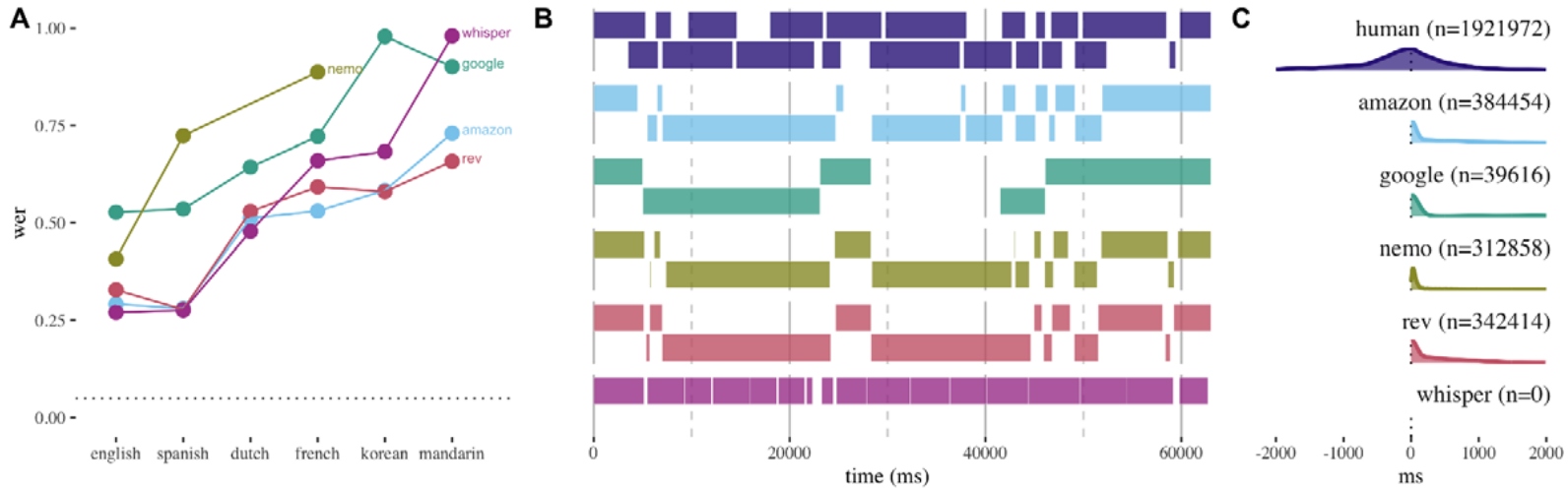
Loud and clear

Speech-recognition word-error rate, selected benchmarks, %



Sources: Microsoft; research papers

ASR and conversation



A Word error rates (WER) for five speech-to-text systems in six languages. **B** One minute of English conversation as annotated by human transcribers (top) and by five speech-to-text systems, showing that while most do some diarization, all underestimate the number of transitions and none represent overlapping turns (Whisper offers no diarization). **C** Speaker transitions and distribution of floor transfer offset times (all languages), showing that even ASR systems that support diarization do not represent overlapping annotations in their output.

Liesenfeld, A., Lopez, A., & Dingemanse, M. (2023). The timing bottleneck: Why timing and overlap are mission-critical for conversational user interfaces, speech recognition and dialogue systems. Proceedings of the 24th Annual SIGdial Meeting on Discourse and Dialogue, 482–495.

Incremental ASR

Incrementality in ASR

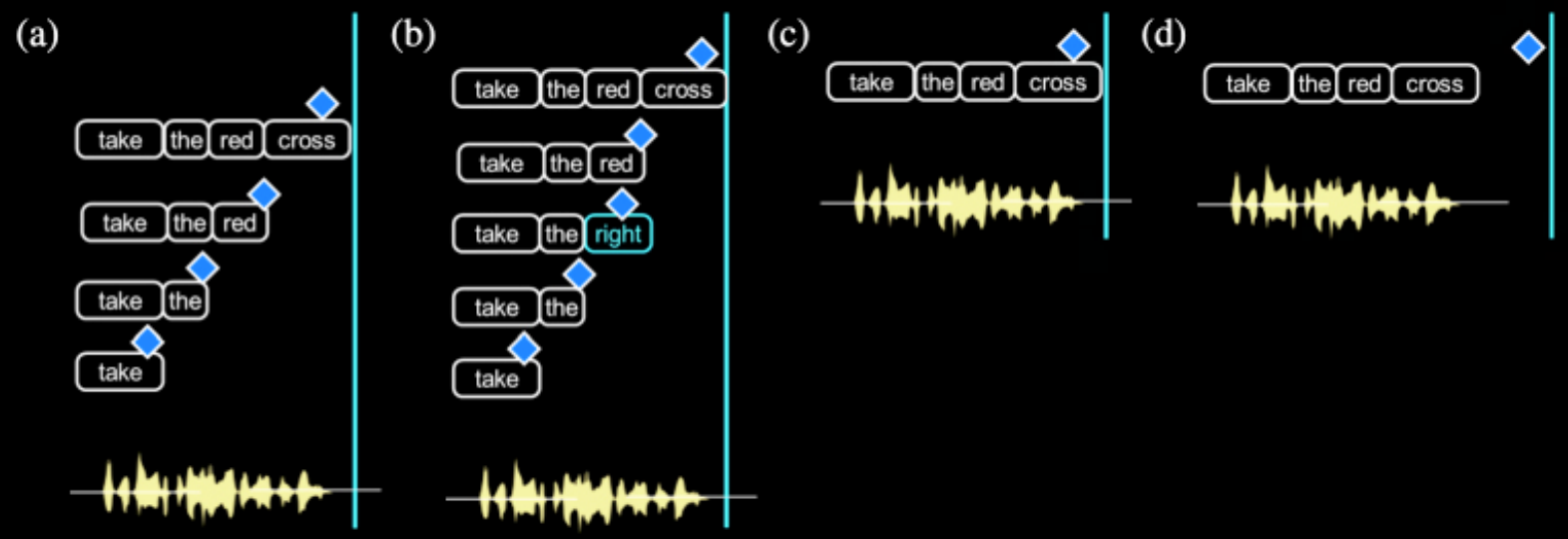


Fig. 1 Incrementality in ASR: vertical line indicates current time, diamond the time of update. (a) perfect output, (b) unstable output, (c) non-incremental but timely, (d) non-incremental and latent.

Incrementalising ASR

- We need incremental ASR, which would require incrementalising all the internal processes.
- We need incremental LMs and AMs, in order to get the best sequences unit-by-unit.
- It is critical that ASR will provide timing for recognised words in a timely manner.

ASR should support disfluencies

> “have the engine [take the oranges to Elmira, + { um, I mean, } take them to Corning] ” (Core and Schubert 1999)

- ‘um’ and ‘uh’ should be considered English words
- it is important to have access to “the oranges” in ASR output
- incremental disfluency detector (Hough and Purver, 2014)

Incremental evaluation I (Baumann et al., 2017)

Utterance-level Accuracy and Disfluency Suitability

- WER disfluency gain to determine how much of disfluent material is recovered

Incremental evaluation II

Timing: first occurence (FO) and final decision (FD):

- FO is the time between the (true) beginning of a word and the first time it occurs in the output (regardless if it is afterwards changed)
- FD is the time between the (true) end of a word and the time when the recognizer decides on the word, without later revising it anymore.

Incremental evaluation III

Diachronic Evolution: how often consuming processors have to re-consider their output and for how long hypotheses are likely to still change.

- stability of the hypotheses. For words that are added and later revoked or substituted we measure the “survival time” and report aggregated plots of word survival rate (WSR) after a certain age.

Systems

- Off-the-shelf web-based ASR models have improved to a very good overall accuracy level. They can also be fine-tuned.
- Web Speech API and ponyfilling
- Training your ASR for your language/ domain to improve accuracy can reap rewards (Sphinx, Kaldi).

Part 2:
TTS Fundamentals

TTS challenges

- coarticulation
- Text normalisation
- Homography
- Code-switching (and borrowed words)
- Morphology

Text normalisation

- abbreviations and acronyms: Dr., DC, NASA, COVID-19
- number formats, e.g. IBM 370, dates, times and currencies
- ~ Ü * ″ UPPER CASE :-)

Homograph normalisation

- Homograph variation can often be resolved on PoS (grammatical) category, e.g. object, bass, absent, -ate.
- But sometimes PoS does not help, e.g. read, kinda
- Variation of dialects
- Rate of speech (e.g. ‘g’ in recognise)

What is TTS

- text and phonetic analysis, grapheme-to-phoneme, morphology
- prosody generation/modification
- speech synthesis

ALGORITHM 14.4 MORPHOLOGICAL ANALYSIS

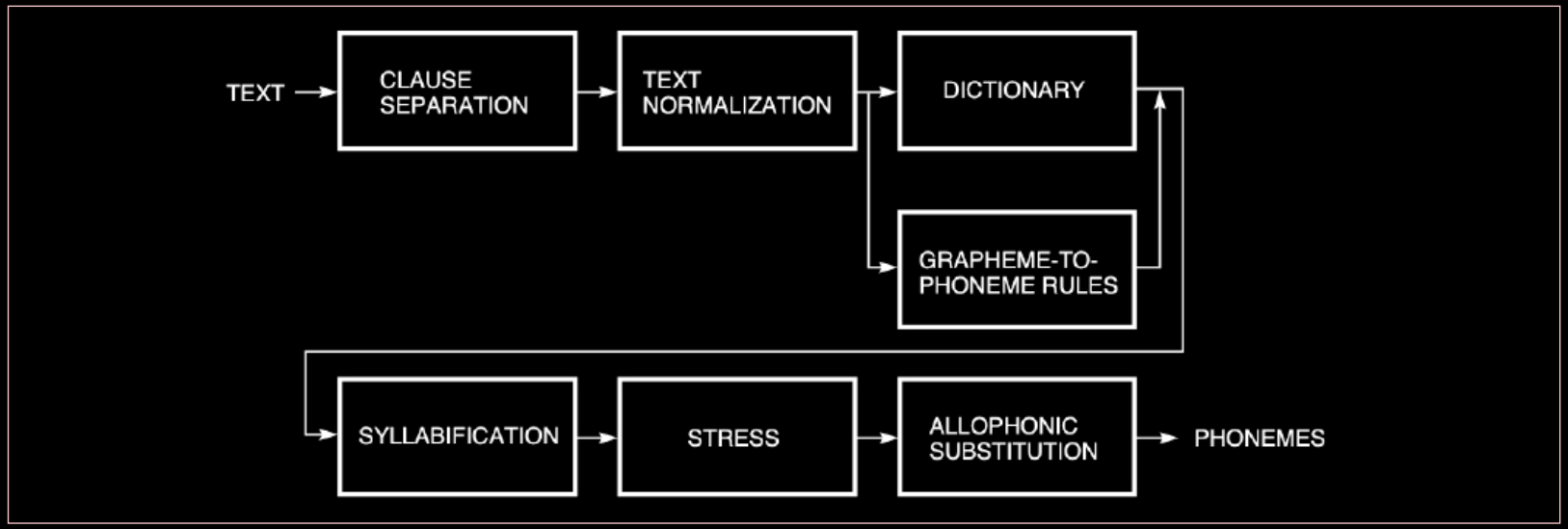
1. **Dictionary Lookup**
   Look up word w in lexicon
   If found
      Output attributes of the found lexical entry and exit
2. **Suffix Stripping**
   If word ends in –s, -'s, -ing, -ed, -est, -ment, etc
      Strip the suffix from word w to form u
   If stripped form u found in lexicon
      Output attributes of the stem and suffix and exit
3. **Prefix Stripping**
   If word begins with *in-*, *un-*, *non-*, *pre-*, *sub-*, etc
      Strip the prefix from word w to form u
   If stripped form u found in lexicon
      Output attributes of the prefix and stem and exit
4. **Compound word decomposition**
   If detect word-medial case differences within word w
      Break word w into a multiple words u_1, u_2, u_3, …according to case changes
      For words u_1, u_2, u_3, **goto 1**.
   Else if word w can be decomposed into two nouns u_1, u_2
      Output attributes of the u_1, u_2 and exit
5. Pass word w to letter-to-sound module

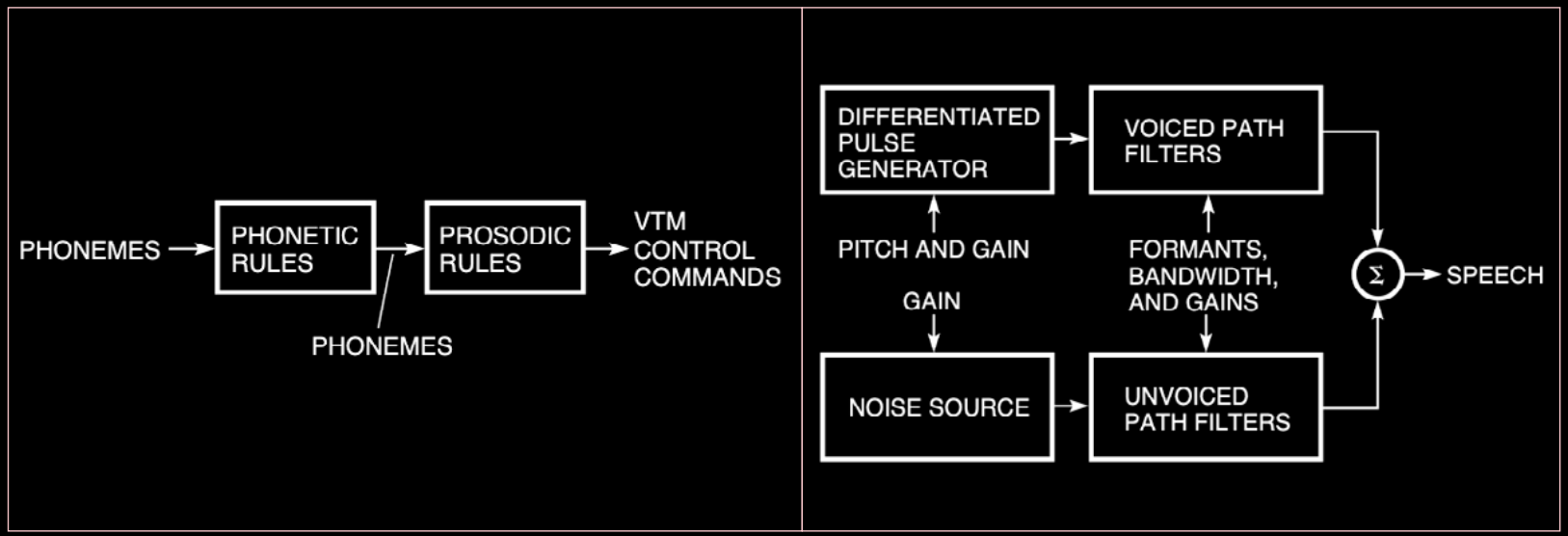
Prosody

- speaking style (character and emotion)
- symbolic prosody (pauses, punctuation)
- accent and stress
- tone (e.g. yn- vs. wh-questions)

Speech synthesis

- Articulatory synthesis
- Rule-based formant synthesis
- Concatenative synthesis
- Statistical parametric synthesis (generative synthesis)
- Deep learning-based synthesis


TEXT
CLAUSE SEPARATION
TEXT NORMALIZATION
DICTIONARY
GRAPHEME-TO-PHONEME RULES
SYLLABIFICATION
STRESS
ALLOPHONIC SUBSTITUTION
PHONEMES


PHONEMES
PHONETIC RULES
PROSODIC RULES
VTM CONTROL COMMANDS
PHONEMES
DIFFERENTIATED PULSE GENERATOR
VOICED PATH FILTERS
PITCH AND GAIN
FORMANTS, BANDWIDTH, AND GAINS
Σ
SPEECH
GAIN
NOISE SOURCE
UNVOICED PATH FILTERS

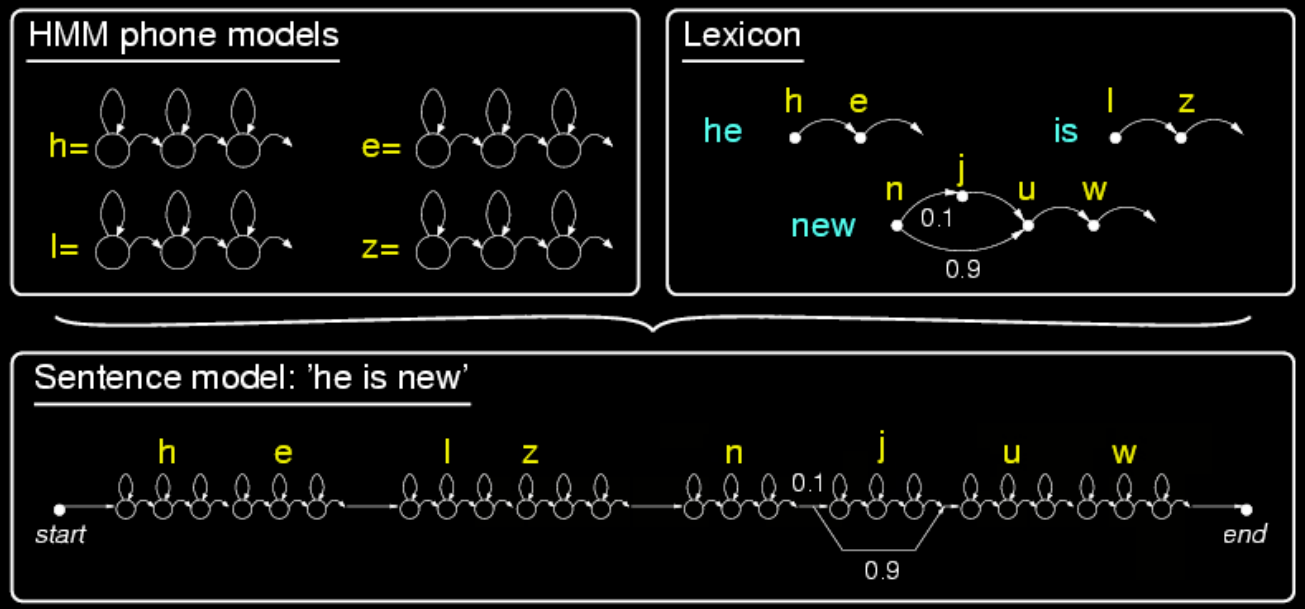
Concatenative synthesis (unit-selection)

- Searches for the best sequence of (variably sized) units of speech in a large, annotated corpus of recordings, aiming to find a sequence that closely matches the target sequence.
- Sounds good if you fit the bits well. Also can be tuned.
- Can be really expensive to build: need professional speakers, many hours of stable recordings.

Statistical parametric speech synthesis

- Essentially, reproduces the speech signal.
- Break speech into several factors and represent them as numbers.
- Learns the model from data.
- From the model we can generate a spectrogram and then create a waveform.

HMM: from phonemes to sentences



HMM speech synthesis

- a) sequence model: a weighted finite state network of states and transitions, and 2) observation model: multivariate Gaussian distribution in each state.
- Generates most likely sequence for the given phoneme(s).
- A global optimisation then computes a stream of vocoding features that optimise both HMM emission probabilities and continuity constraints.

Neural speech synthesis

- Essentially it is a type of statistical parametric speech synthesis
- text to features and then features to sound (neural vocoder)
- sequence2sequence models (e.g. RNN, GRU), Tacotron2
- e.g. LPCNet, WaveNet

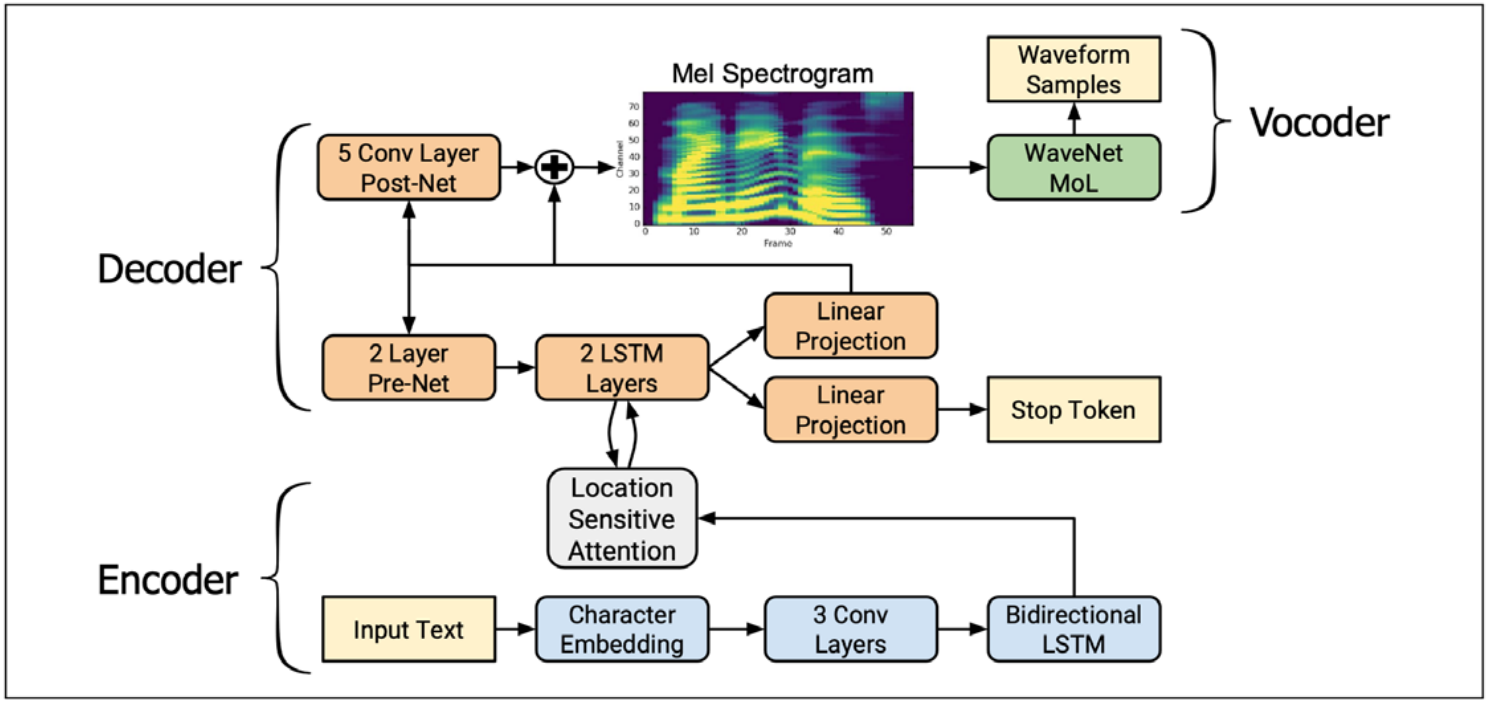


Figure 16.14 The Tacotron2 architecture: An encoder-decoder maps from graphemes to mel spectrograms, followed by a vocoder that maps to wavefiles. Figure modified from Shen et al. (2018).

Some advanced matters

- adapting voices, by changing a few parameters in the model
- repairing voices
- Simon King - Using Speech Synthesis to give Everyone their own Voice: https://youtu.be/xzL-pxcpo-E
- Incrementality: INPRO_iSS https://www.youtube.com/watch?v=kwNvcUXfD7Y

Evaluation

- Intelligibility tests, e.g. rhyme tests
- Quality tests: mean opinion scores (MOS) and preference test
- Functional tests
- Automated tests, mainly for letter-to-sound or prosody