NPFL123 Dialogue Systems
11. Speech Recognition

https://ufal.cz/npfl123

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loosely based on earlier slides by Petr Fousek, Pavel Květoň, Michal Jůza

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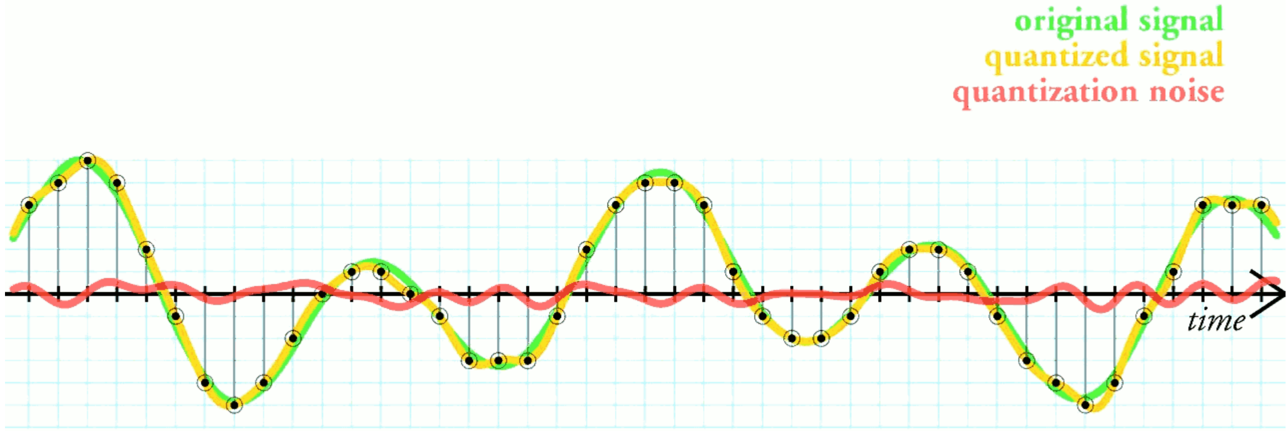
Speech recognition

- Task: convert audio (sound wave) → text
  - generally just words, no punctuation or capitalization used
- Audio: waveform
  - wave position in time (samples)
    - 8 kHz – 44 kHz frequency (telephone → CD quality)
    - 8-16 kHz mostly used for speech
  - quantized (=8-bit/16-bit number)
  - lot more than just words:
    - speaker identity (age, gender, dialect, speech defects), emotional state (pitch, loudness, health)
    - environment, noise (reverb, distance, channel effects)



https://en.wikipedia.org/wiki/Quantization_%28signal_processing%29

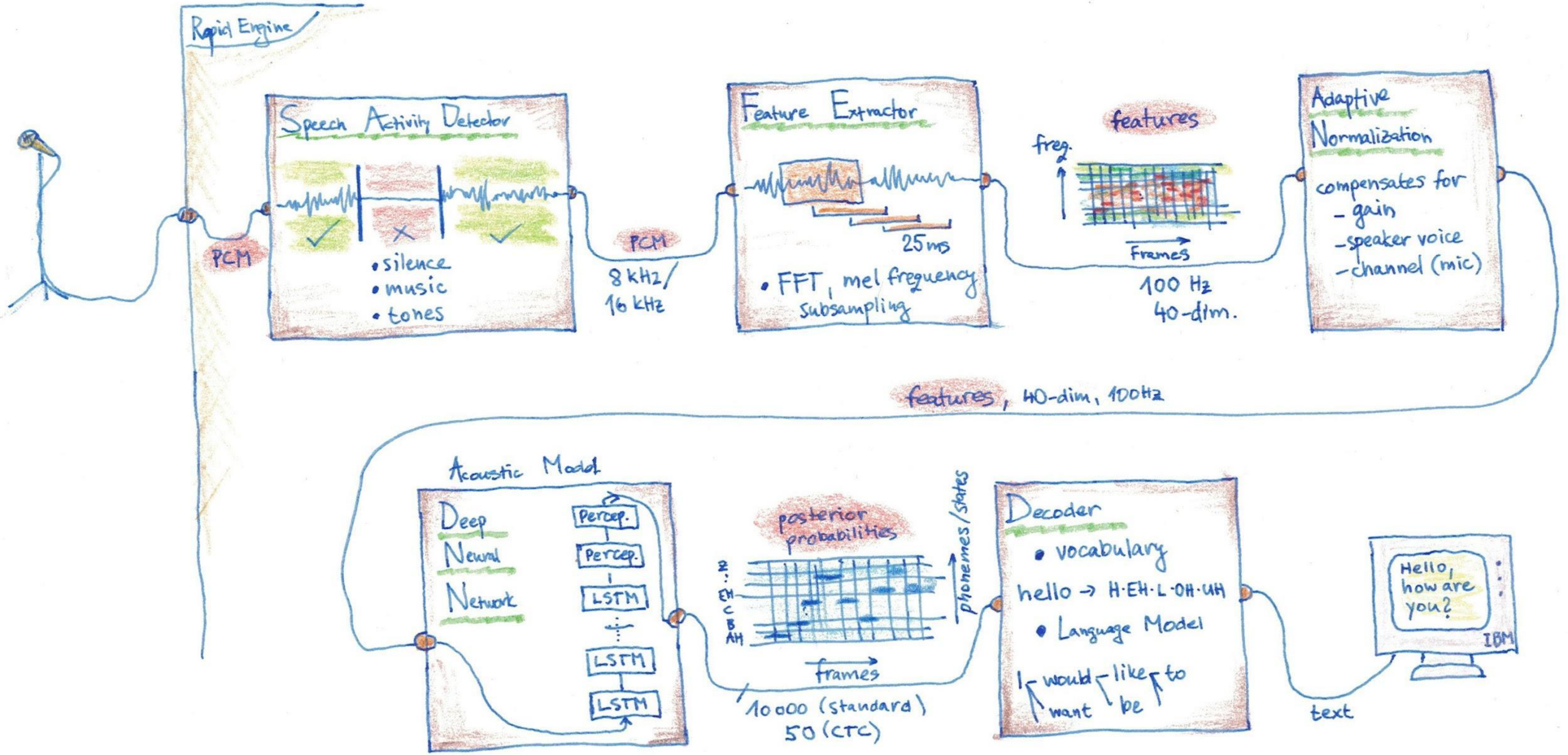
- ASR is basically very harsh lossy compression
  - from ~ 64 kbps (8 kHz, 8-bit) to ~ 50 bps (text)
  - for context, low-bitrate audio codecs are ~ 500 bps at least

ASR History

- First commercial success in “ASR”: Radio Rex (1920)
  - spring triggered by 500 Hz audio (~F1 formant of [ɛ] in “Rex”)
- 1950’-60’s – rule-based formant detection
  - digit recognition, isolated words
- 1970’s – first statistical modelling, HMMs
- 1980’s – larger models, adding language models
- 1990’s ~ first practically usable, large-vocab, continuous speech
- 2000’s – early neural approaches
- late 2010’s – fully neural, end-to-end ASR

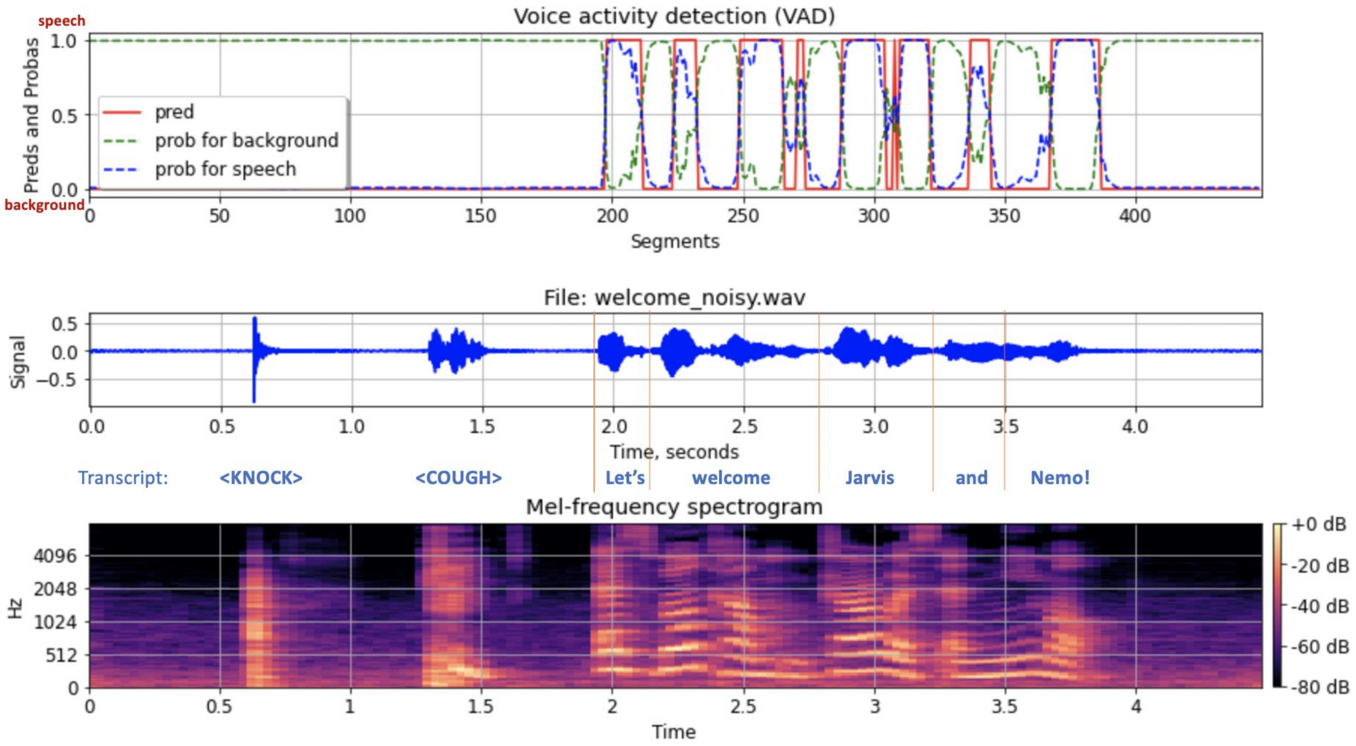
https://en.wikipedia.org/wiki/Speech_recognition

Conventional ASR



Speech Activity Detector

https://docs.nvidia.com/deeplearning/nemo/user-guide/docs/zh/latest/voice_activity_detection/tutorial.html



Preprocessing step in ASR

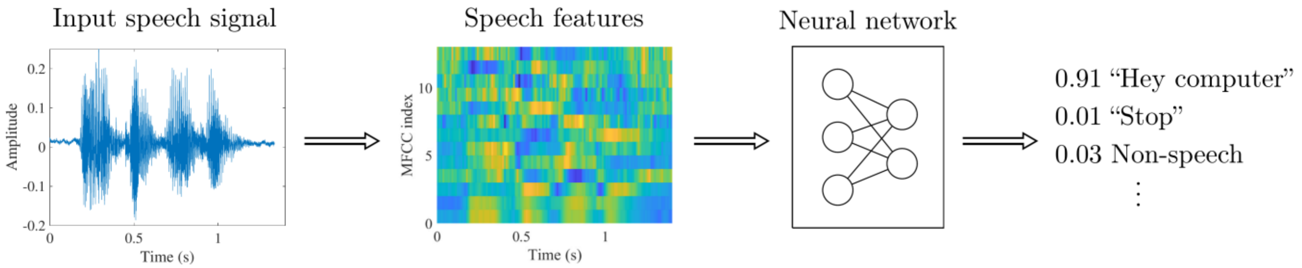
- Save CPU: run ASR only when there is speech
- Avoid confusing ASR with non-speech sounds

- Handcrafted (now obsolete)
  - Track signal amplitude contours
  - Simple, for low-resource tasks, assumes low noise
- Statistical / neural
  - Trained on large corpora to tell speech from other sounds – binary classifier
  - Input features same as ASR (→ →)
  - Accurate but more CPU-demanding
- basic smoothing needs to be applied

Wake words

- trigger to “start listening” (i.e. run full-scale ASR)
- simpler & more precise than VAD – detecting specific wake word
  - *OK Google, Alexa, Hey Siri*
  - simpler than to recognize that user is speaking to the system
  - simpler to distinguish from background noise
- basically a small-vocabulary ASR problem
  - ASR system running continuously
  - low-power, low-accuracy, but good enough for wake word

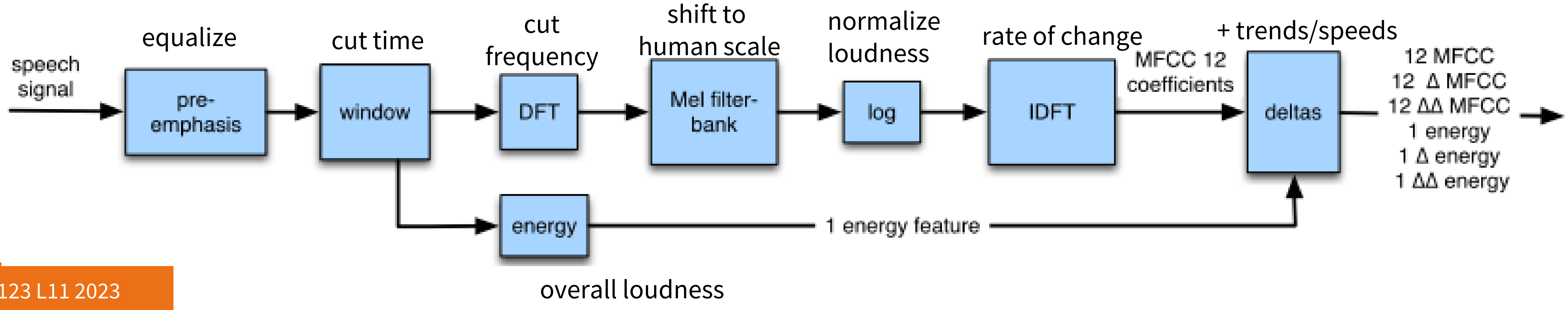
(small feed forward/convolutional)



https://speechprocessingbook.aalto.fi/Recognition/Wake-word_and_keyword_spotting.html

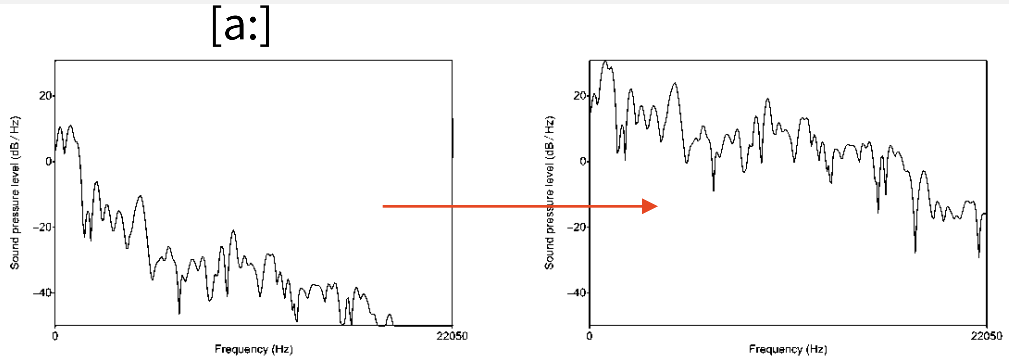
Features for ASR – Preprocessing

- In: Raw waveform ~ 1 number per 0.125 ms (8 kHz)
  - current pos. of the sound wave (~continuous) – sample, 8-bit/16-bit quantized
- Out: Mel Frequency Cepstral Coefficients ~ 40 features per 10 ms
  - step-wise (~discrete), dissected to frequency loudness & trends
- Inspired by humans:
  - information for 1 phone spans 250-400ms (coarticulation)
  - need to follow at least 4-7 freq. channels for intelligibility (10+ for better fidelity)
  - speech ~ 2-10 phones/sec (peak 4), auditory cortex reaction ~ 2-20 Hz

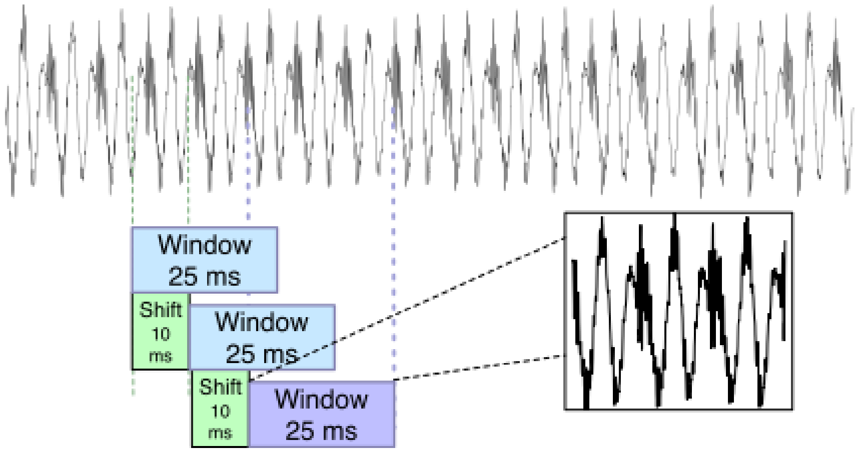


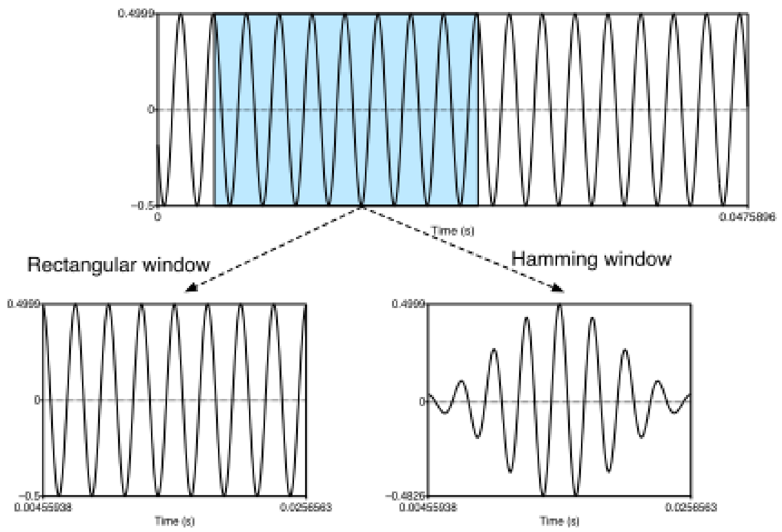
Features for ASR

- Preemphasis
  - boost higher frequencies (equalization)
- Windowing ~ frames
  - sliding: 25 ms / each 10 ms – overlapping
  - Hamming window – middle is emphasized
- Energy = overall loudness (+Δ, ΔΔ)



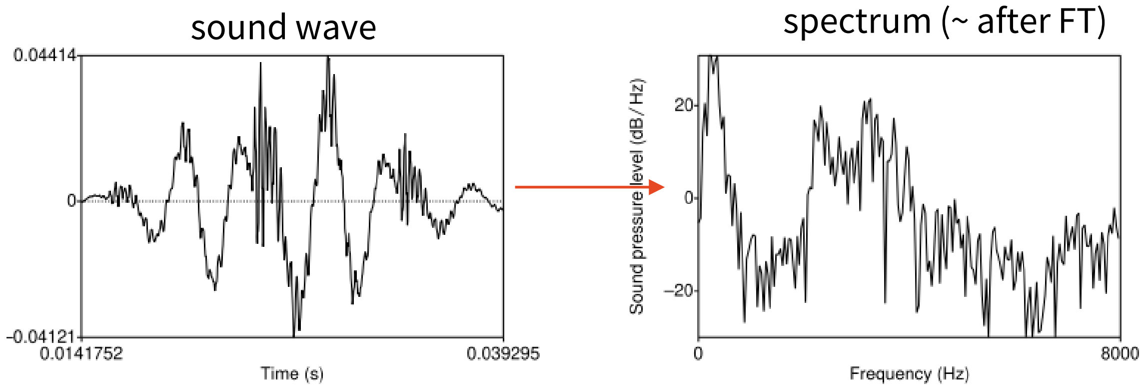
(Jurafsky & Martin, 2009)

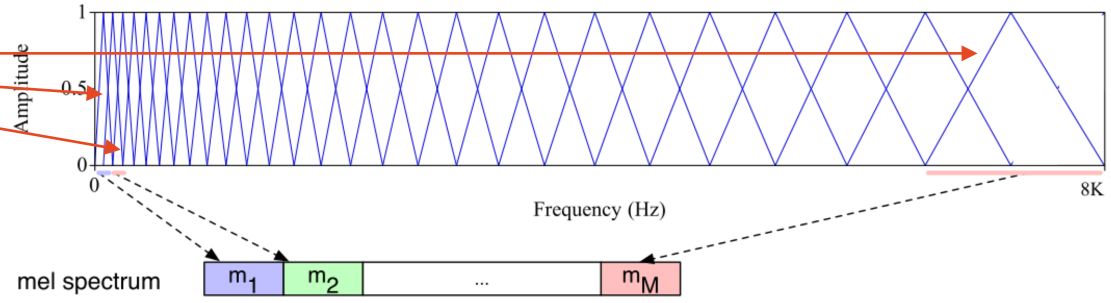


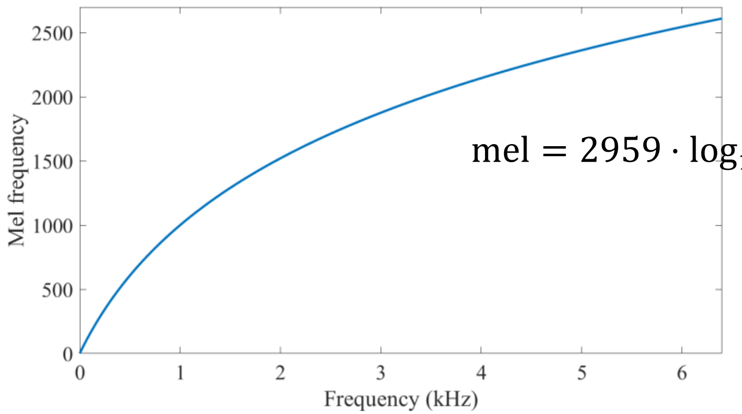


(Jurafsky & Martin, 2023)

- Spectrum – Fourier transform
  - loudness at different frequencies
- Mel bank filter
  - loudness at ~12-16 mel banks (i.e. frequency ranges)
    - using triangular frequency filters (sum everything within the filter)
    - ranges equal on mel scale (get wider in terms of normal frequency)
  - mel scale – logarithmic
    - corresponds to human perception of pitch







$$\text{mel} = 2959 \cdot \log_{10}\left(1 + \frac{\text{freq}}{700}\right)$$

Features for ASR

- Logarithmic volume
  - ~human-like, robust to loudness variation
- Cepstrum – another (inverse) Fourier transform
  - ~ "spectrum of log spectrum"
  - "rate of change in various spectral bands"
  - decorrelated (unlike filterbanks, which are overlapping)
  - slow changes – relevant to phones
    - ~ formants, other properties
    - usual speech: 2-10 phones per sec.
    - ~ only keep coeffs 2-13 (or thereabouts)
  - high range – harmonics (F0)
- Δ, ΔΔ: (× 3 features) – trends, speed of trends

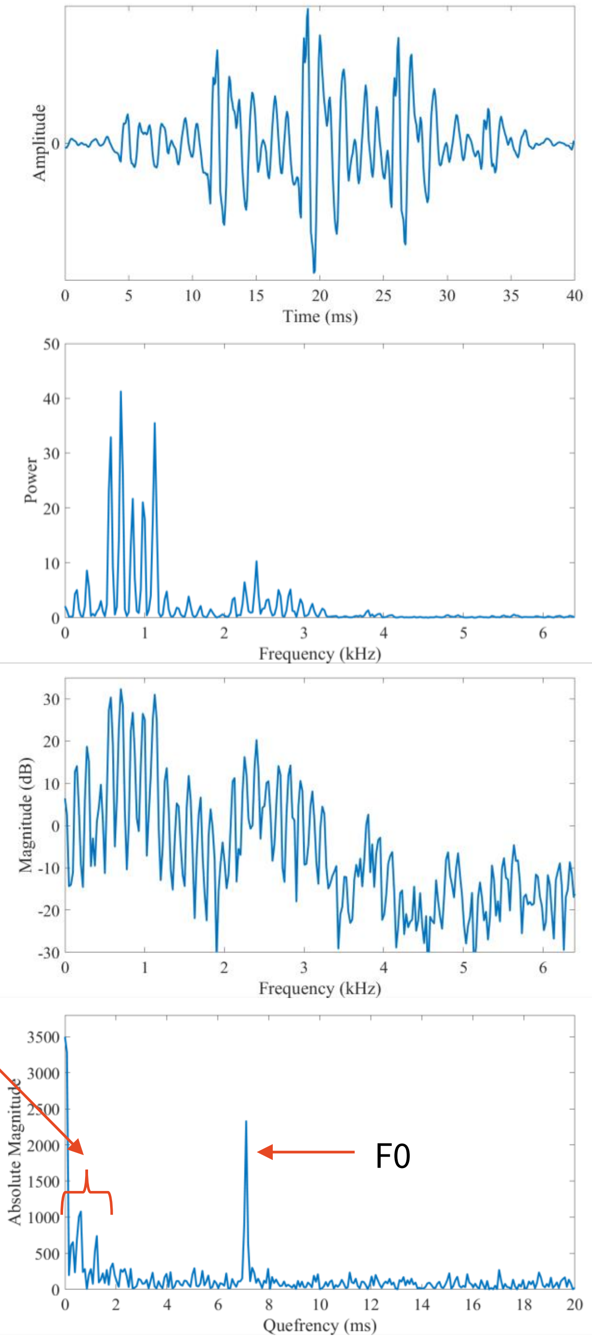
wave

spectrum

log spectrum

info about slowly changing
features of log spectrum
~ formants

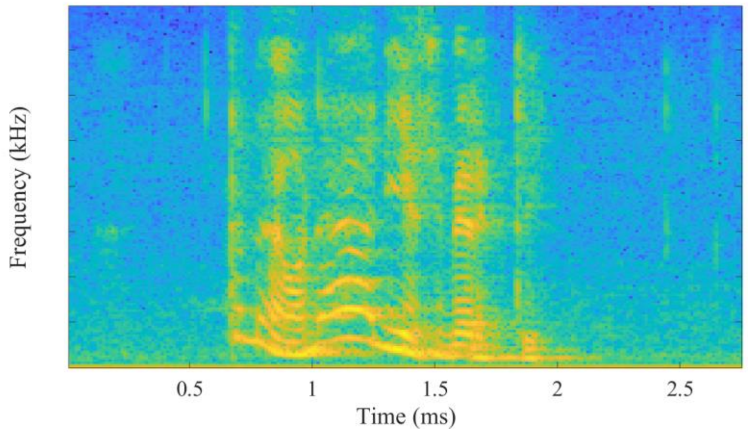
cepstrum



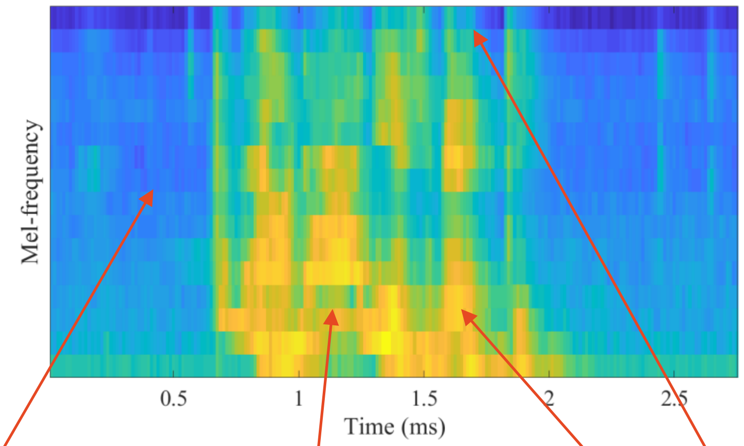
https://medium.com/@derutycsl/intuitive-understanding-of-mfccs-836d36a1f779
http://practicalcryptography.com/miscellaneous/machine-learning/guide-mel-frequency-cepstral-coefficients-mfccs/
https://medium.com/prathena/the-dummys-guide-to-mfcc-aceab2450fd
https://wiki.aalto.fi/display/ITSP/Cepstrum+and+MFCC

Features for ASR

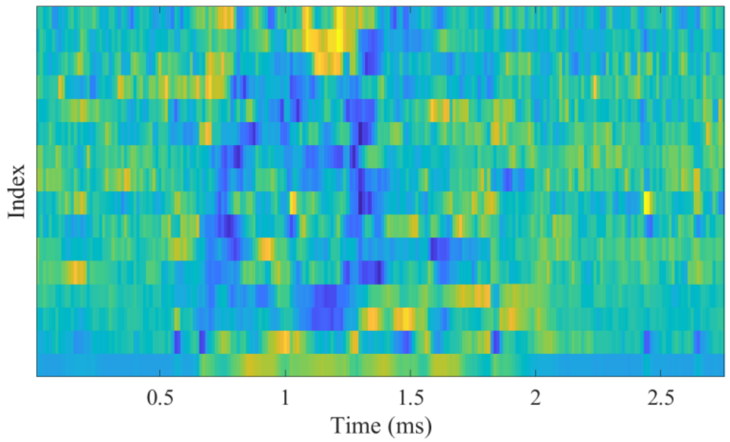
spectrogram



mel filtered spectrogram



MFCCs



less detail

general shape preserved

wider in low frequencies,
narrower in higher frequencies

hard to interpret,
uncorrelated

- MFCCs used mainly in older/low-resource systems
- newer: mel spectrograms (filterbank) / raw spectrograms / raw audio

https://wiki.aalto.fi/display/ITSP/Cepstrum+and+MFCC

Conventional ASR

- We want to model $P(\text{text}|\text{audio})$
- Can't model directly, so using Bayes:

$$P(\text{text}|\text{audio}) = \frac{P(\text{audio}|\text{text})P(\text{text})}{P(\text{audio})}$$

  - $P(\text{audio})$ is a constant, we're ignoring that
  - $P(\text{audio}|\text{text})$ ~ **acoustic model $\boldsymbol{P_A}$**
  - $P(\text{text})$ ~ **language model $\boldsymbol{P_T}$**
- **decoder** then combines information from both

Acoustic model

- $P_A = P(\text{audio}|\text{text})$, where
  - audio = ASR features, i.e. spectrograms
  - text = sequence of phone[me]s
- assuming independence between audio frames:

$$P(\text{audio}|\text{text}) = \prod_i P(a_i|t_i)$$

  - i – time (frame no.)
  - a_i – audio feature vector (~ spectrum)
  - t_i – acoustic class (~ phone[me], context-dependent phone)

Acoustic model

Spectrogram
(audio features)

true phones

silence

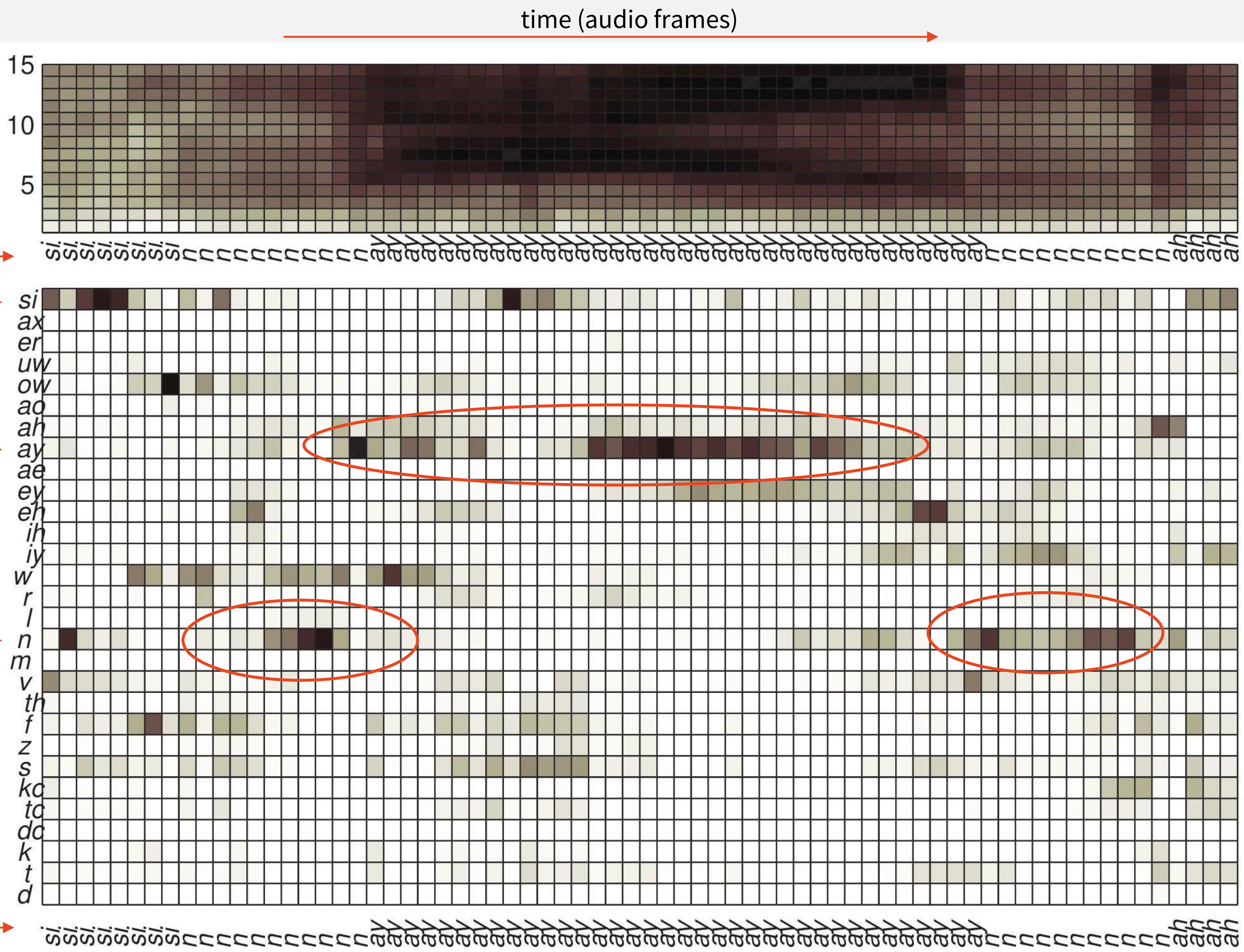
“nine”

[ai]

Acoustic model output
(phone posterior probs.)

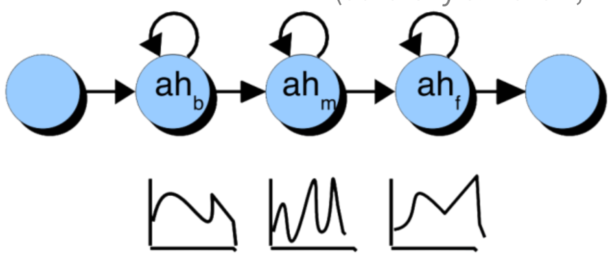
[n]

true phones

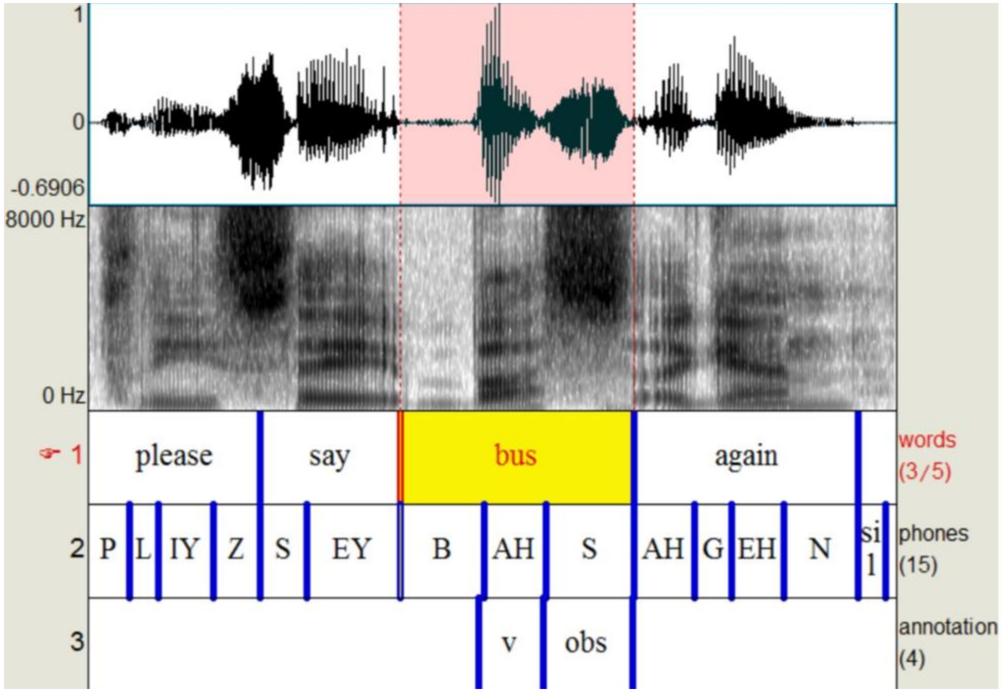


Acoustic model

(Jurafsky & Martin, 2009)



- Representing each phone by an HMM
  - start – mid – end, with loops (~ different lengths)
- Original: GMM – Gaussian mixtures
  - each HMM transition/emission is a multivariate Gaussian
  - clustering, as there are too many options
- Improvement: DNN
  (=feed forward neural net) instead of GMM
- Training – Baum Welch force-alignment
  - start from equal lengths of all phonemes, iteratively shift & increase likelihood
  - GMMs used to produce alignment to train DNN



Language model

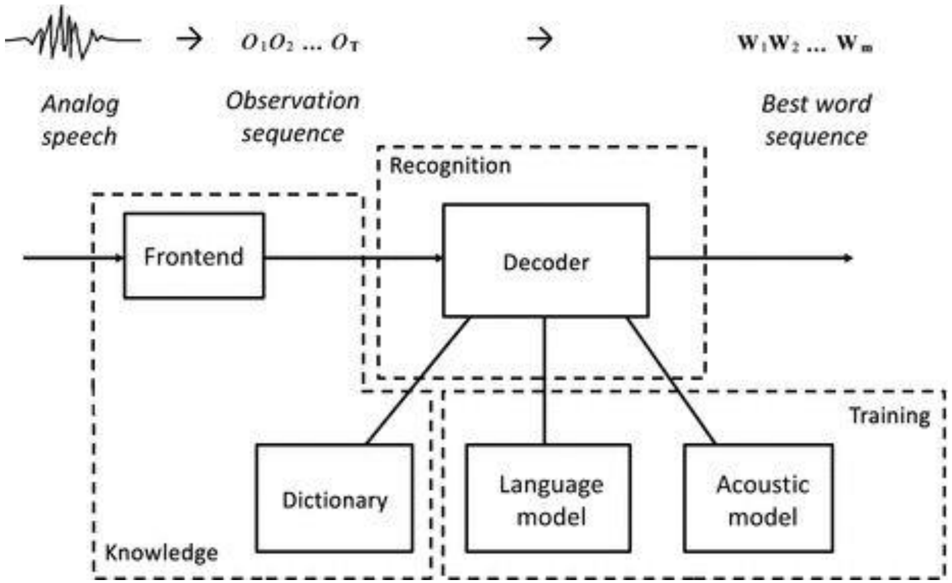
- $P(\text{text})$, where text ~ sentence, consisting of words $w_1, \ldots w_n$
- sequence probability modeled with a LM:

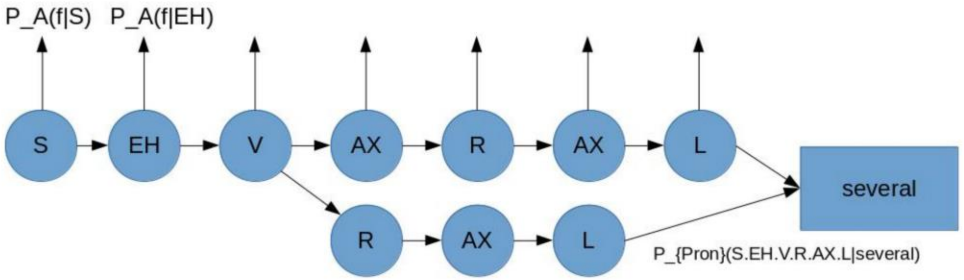
$$P_T(\text{text}) = \prod_i P(w_i | w_{i-1}, w_{i-2}, \ldots)$$

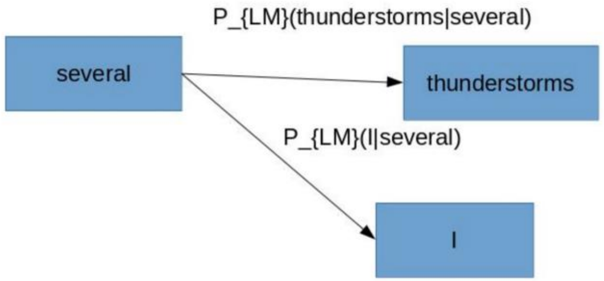
  - **words given preceding context**
  - traditionally n-gram LMs
  - more recently neural LMs
- Words w_i mapped to acoustic classes t_i using a pronouncing **dictionary**
  - or rules – essentially reverse of TTS's grapheme-to-phoneme conversion
  - multiple pronunciation variants considered
    e.g. S EH V AX R AX L ['sɛvəɹəl] vs. S EH V R AX L [‘sɛvɹəl]

Decoder

- Text *encoded* into acoustic signal / audio features → decoding back
- Hidden Markov Models
  - decoding word sequence from observed sequence of features
  - Dynamic programming (Viterbi)
  - Finding the best path through a finite state transducer
    composed of acoustic model & language model & pronouncing dictionary

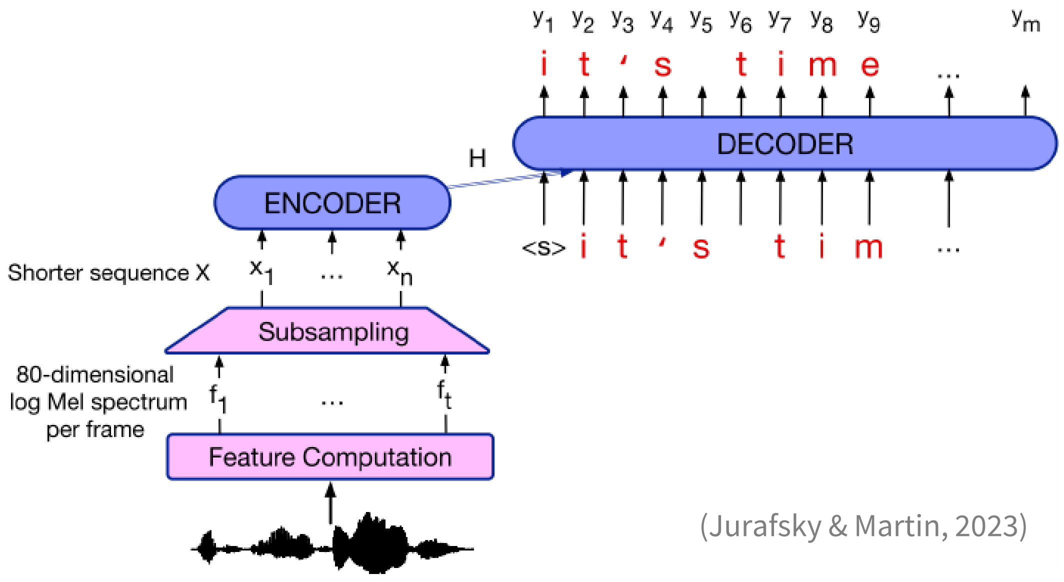






End-to-End ASR: Encoder-decoder

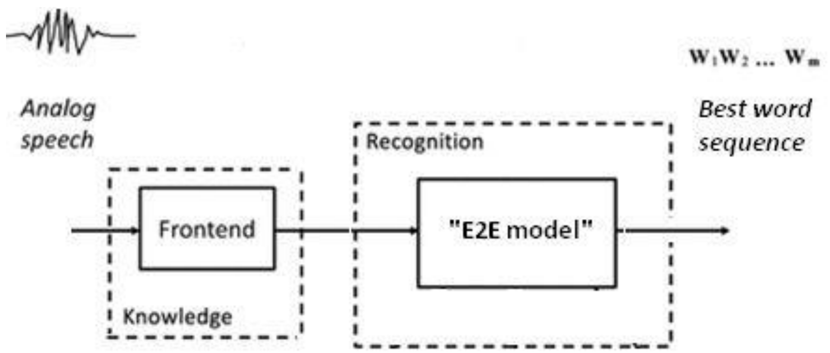
- Models $P(\text{text}|\text{audio})$ directly
- **Attention encoder-decoder** (AED) as in language tasks
  - a.k.a. listen-attend-spell (LAS)
  1. encode audio features
  2. decode text character-by-character
- RNN (LSTM) + attention / Transformer
- Audio is too fast/long → slowing it down ("low frame rate")
  - e.g. concatenate every 3 frames of audio ~ 40-dim → 120-dim at ⅓ speed
- Optional external language model: beam search & rerank



(Jurafsky & Martin, 2023)

Encoder-decoder ASR Pros & Cons

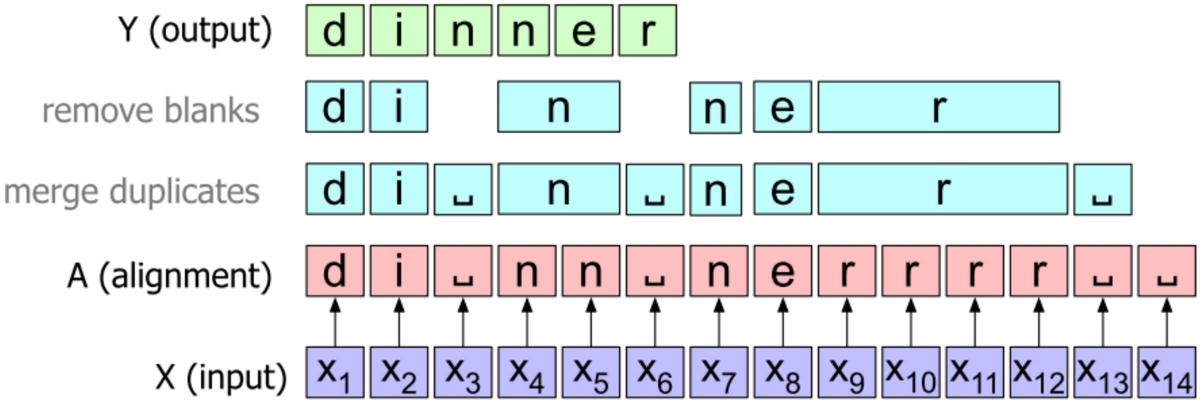
- Easier to train
  - pronunciation not modeled explicitly – direct audio to letter
  - no need to align phones & audio frames
  - audio & transcript is enough to train
- Easier to run – simpler decoder
- Inaccurate word/character timestamps
- Not low-latency
  - assuming whole sentence input → output
- Harder to customize: retrain everything
  - dictionary – unknown words may be guessed well as-is
  - language model – can use beam search & rescoring by an external LM



CTC (Connectionist Temporal Classification)

(Hannun, 2017)
https://distill.pub/2017/ctc/

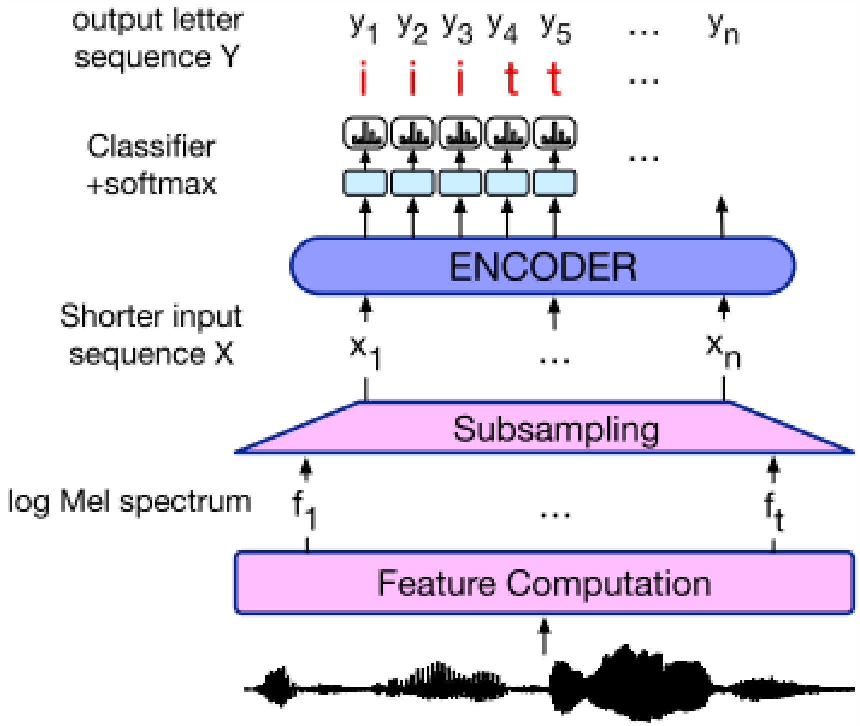
- Alt. idea: **predict something for every input frame**
  - **_/ε (“blank”)** for silence & double letters
  - collapse duplicates & remove blanks later
- Problem: many-to-one alignments
  - Many predicted sequences align to the same collapsed output
  - solution: clever summing
- training: minimizing **CTC loss**
  - sum over all possible alignments
  - computed by dynamic programming (forward-backward algorithm)
- inference: modified beam search
  - beam of output prefixes after collapsing



(Jurafsky & Martin, 2023)

CTC Model

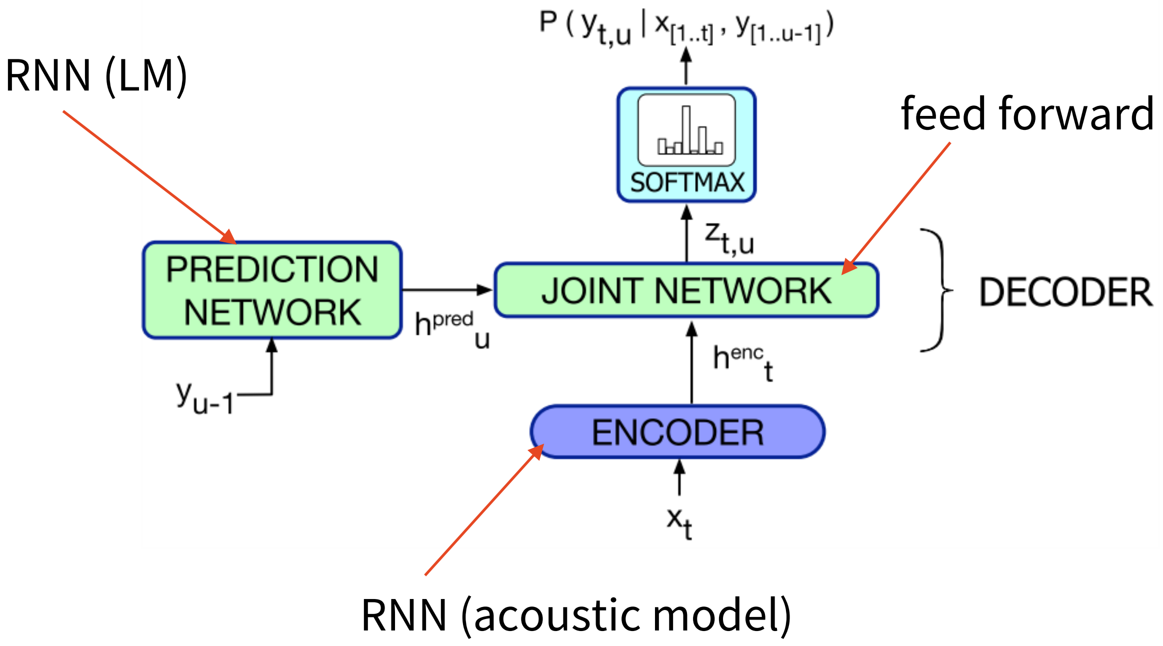
- Encoder + softmax classifier only
  - output something for every step
- Great for low latency
  - can work in parallel too
- Worse performance overall
  - strong assumption: outputs independent of each other (non-autoregressive)
- Can be combined with encoder-decoder
  - CTC as additional encoder loss
  - inference: combine probs. from both



(Jurafsky & Martin, 2023)

Transducers (RNN-T): Low-latency & accuracy

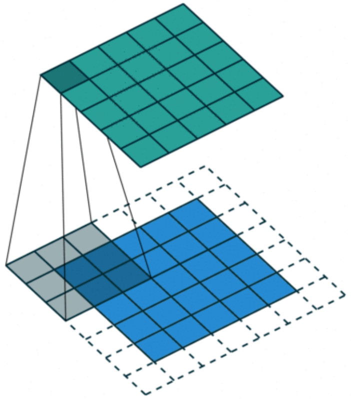
- Remove output independence
- Add RNN *prediction network* conditioned on prev. output
  - i.e. a language model component
- (RNN) acoustic model & RNN LM → joint (feed-forward) decoder
- Still predicts 1 output per frame
- All trained with CTC loss
  - You can retrain LM & keep acoustics
- Transformer variant (*s/RNN/Transformer/g*)



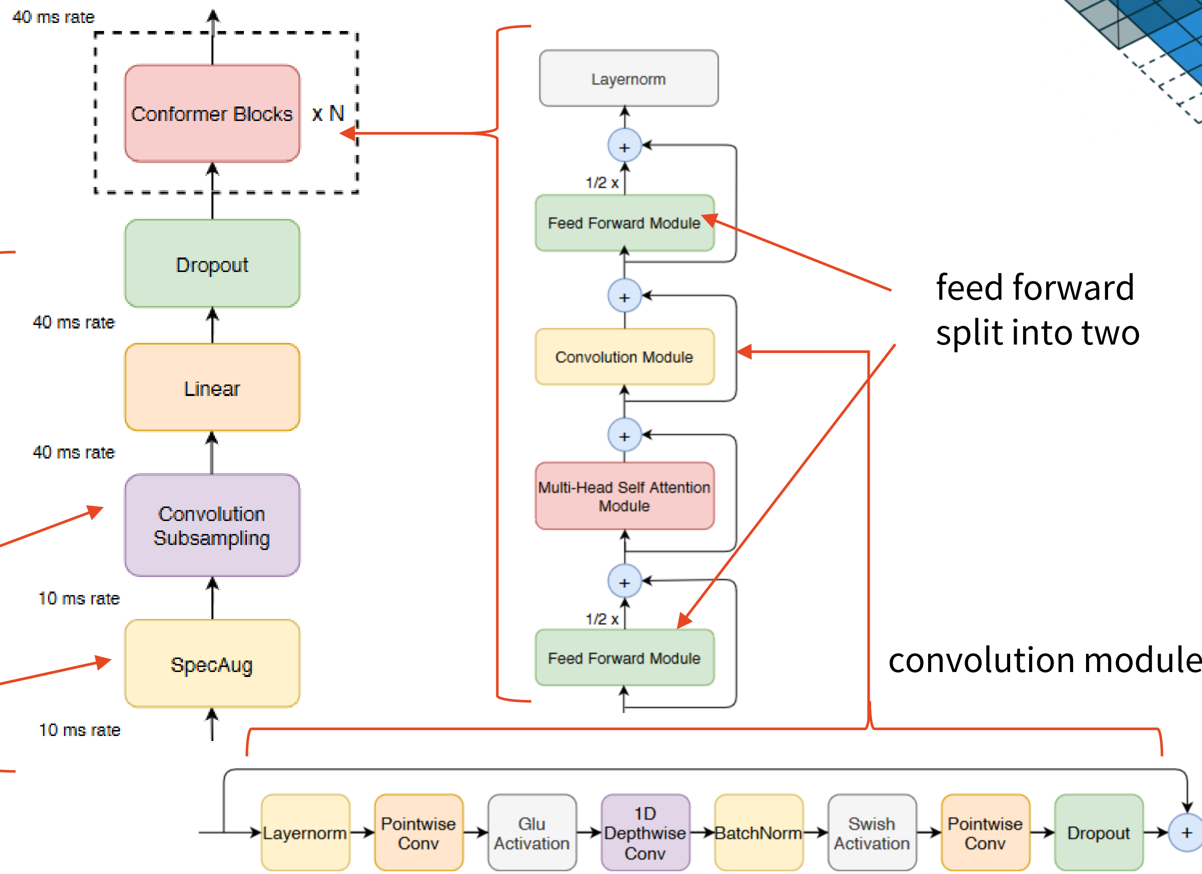
https://lorenlugosch.github.io/posts/2020/11/transducer/
(He et al., 2019) http://arxiv.org/abs/1811.06621
(Zhang et al., 2020) https://arxiv.org/abs/2002.02562

Conformer – better representation

https://towardsdatascience.com/types-of-convolutions-in-deep-learning-717013397f4d



- Transformer-like architecture, but with convolutions
  - CNN: applying same parameters (kernel) repeatedly over shifted inputs
- CNN for local interaction
- Transformer-like for global
- Used as acoustic model (encoder) in a Transducer



~embeddings

lower frame rate
by convolution (over time)

warping/masking
for robustness

feed forward
split into two

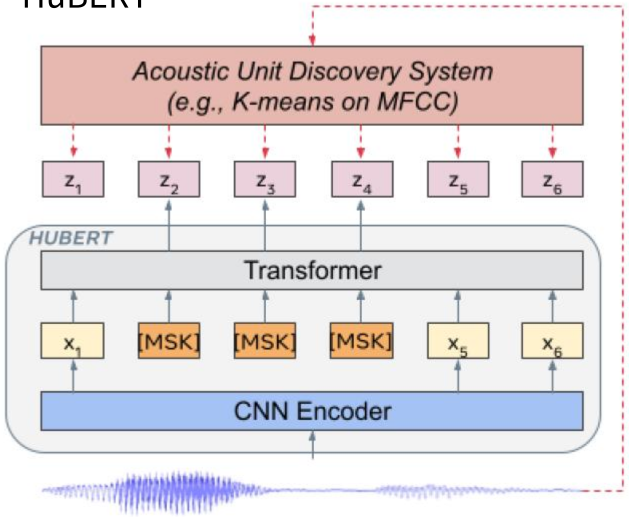
convolution module added

(Gulati et al., 2020) https://arxiv.org/abs/2005.08100

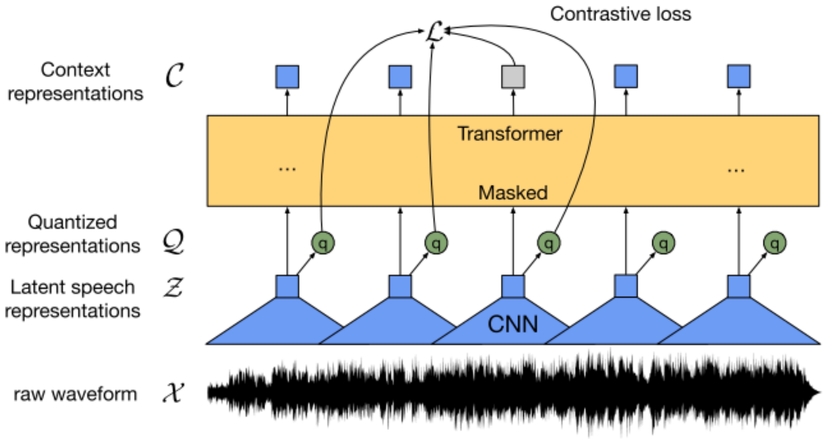
Self-supervised models

- Learning from large data without transcriptions
  - ~ 1000s of hours of audio
  - input: raw audio & convolutions
  - creating some inventory of pseudo-phonemes
    - HuBERT – clustering based on MFCC
    - Wav2Vec2 – jointly trained quantization
  - masking out some pseudo-phonemes
    & learning to predict them
- Finetuning on transcriptions (CTC loss)
  - works with ~ minutes of labeled data
- usable with Transducers / attention too

HuBERT



Wav2Vec2

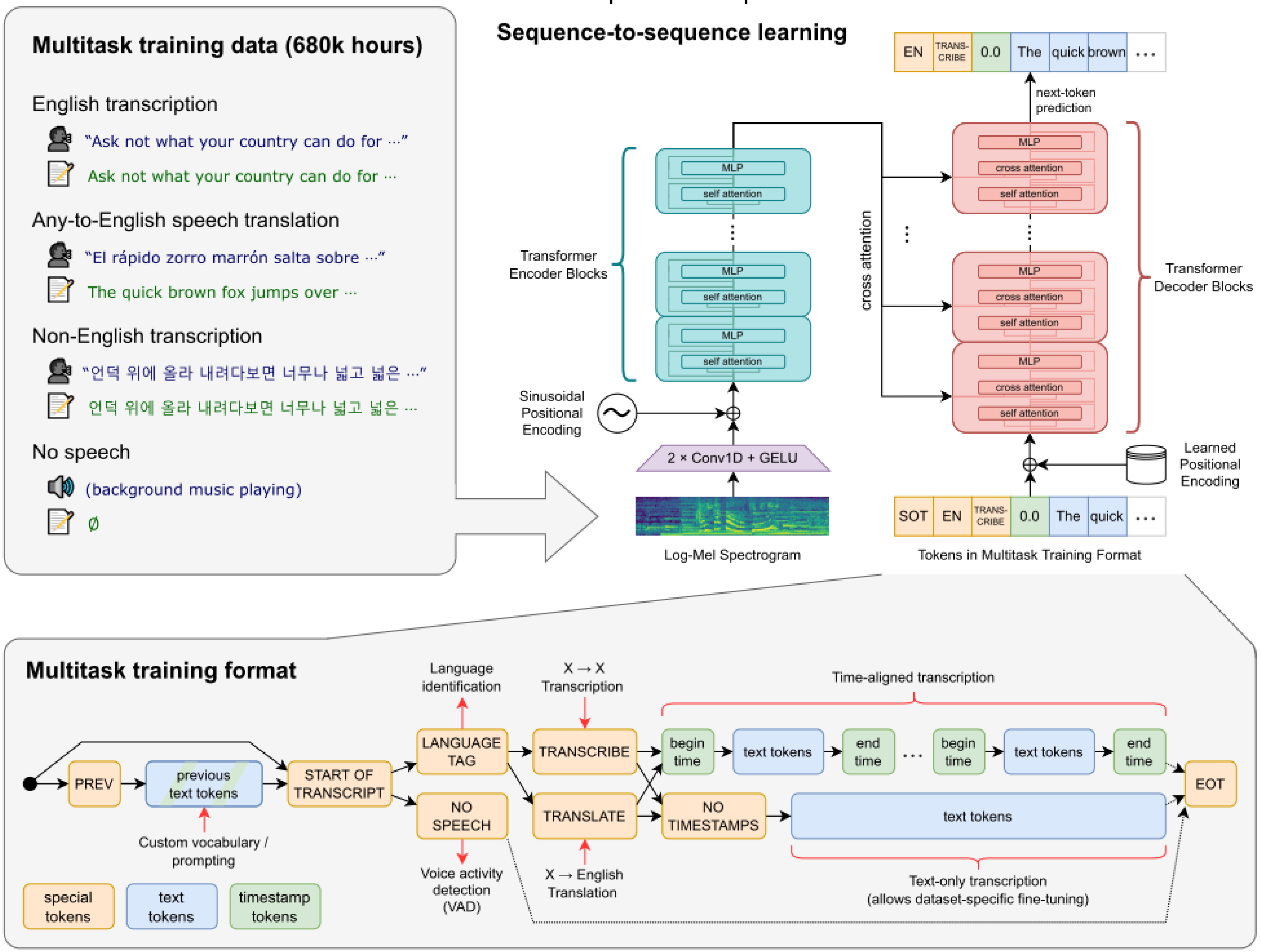


(Baevski et al., 2020) http://arxiv.org/abs/2006.11477
(Hsu et al., 2021) http://arxiv.org/abs/2106.07447

Weak supervision & multi-tasking

- Any transcriptions available
  - scraping the web (even low-quality)
- + speech translation
- + multiple languages
- aim: no finetuning

OpenAI Whisper



(Radford et al., 2022)
https://arxiv.org/abs/2212.04356

Challenges

- Human-human spontaneous speech harder than human-system
  - unscripted speech, disfluencies, repairs
  - stark topic shifts
- Specific domains
- Demographics
  - gender imbalances
  - non-native speech
- Language coverage
- Noise
- Latency/on-device

(Szymański et al., 2020) https://aclanthology.org/2020.findings-emnlp.295/

Summary

- VAD → features → ASR → text
- Features: MFCCs/filter banks/raw
- Traditional: separate acoustic & language models
- Neural:
  - Attention-based
  - CTC-based
  - Transducers
- Pretrained models
- Weak supervision

Thanks

Contact us:

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Skype/Meet/Zoom (by agreement)

Labs in 10 mins

Get these slides here:

http://ufal.cz/npfl123

References/Inspiration/Further:

- Jurafsky & Martin's Speech & Language Processing (3rd ed., 2023): https://web.stanford.edu/~jurafsky/slp3/16.pdf
- Jurafsky & Martin's Speech & Language Processing (2nd ed., 2009)
- https://en.wikipedia.org/wiki/Speech_recognition
- https://speechprocessingbook.aalto.fi/Recognition_tasks_in_speech_processing.html
- https://wiki.aalto.fi/display/ITSP/Introduction+to+Speech+Processing