Automatic Speech Recognition

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thanks to: Pavel Kveton, Michal Juza

THE MAMA AI

Outline

- Intro
- Conventional ASR
  - Front-end
  - Model
  - Decoder
- End-to-end ASR

Introduction

First commercial success in ASR:
Radio Rex (1920)

A celluloid dog released by a spring when triggered with a 500 Hz acoustic energy (roughly the first formant of the vowel [eh] in “Rex”).

"Humans evolved to optimally use the acoustic channel to communicate - why not to inspire by them?"

- Fletcher – temporal and frequency masking – 1950's
- Information about a phone spans 250 - 400 ms - coarticulation
- 4-7 frequency channels min. for intelligibility, >10 for fidelity
- modulations about 2-10Hz (peak at 4Hz ~ 250ms)
- auditory cortex response also in 2 - 20Hz range

Information in audio

Audio contains lots of information irrelevant for ASR:

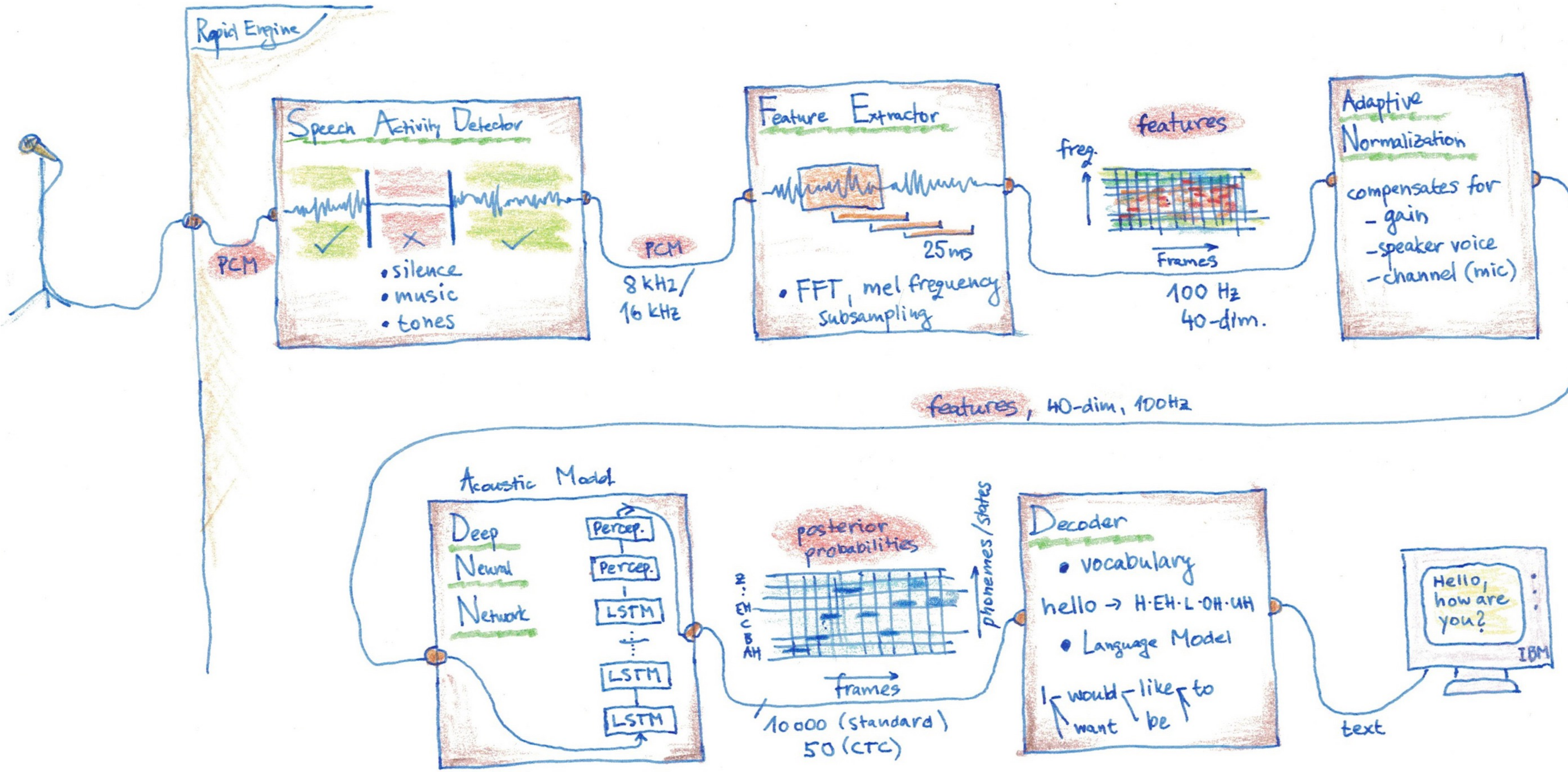
- Speaker identity (gender, age, speaking style, dialect)
- Speaker's state (emotions, health)
- Environment (ambient sounds, reverb/echo of the room)
- Distortions (noise, channel effects, distance)

How many bits per second we need:

- to store speech, we need about 64 kbps (8kHz, 8bits)
- low-bitrate audio codecs: down to 500 bps
- text: about 50 bps

... so ASR is an ultimate speech compressor.

Conventional ASR



Speech Activity Detector

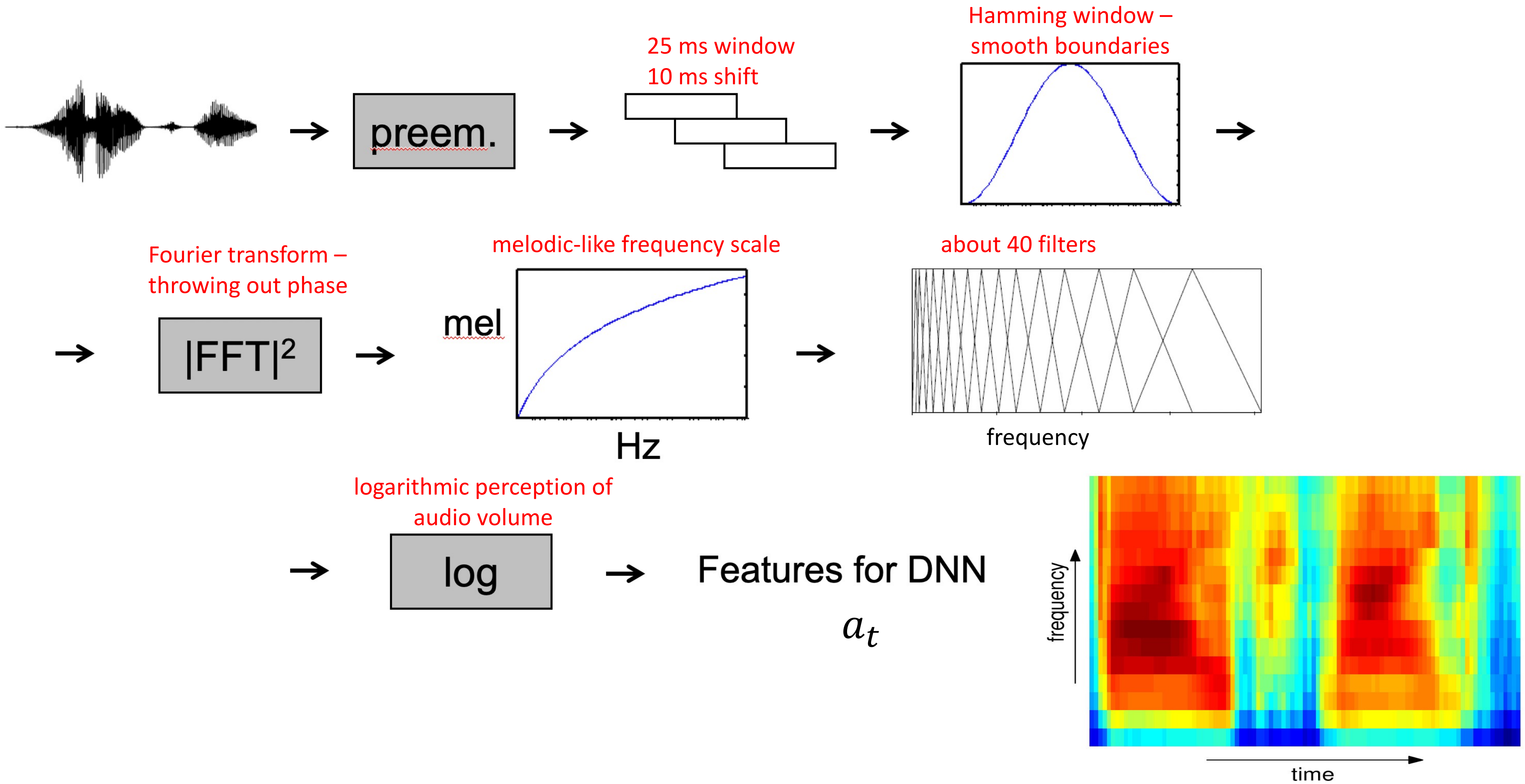
Goal:

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

Technologies:

- Energy-based
  - Track signal amplitude contours
  - Simple, for low-resource tasks
- Neural networks
  - A model trained on large corpora to tell speech from other sounds
  - Input features often shared with ASR
  - Accurate but more CPU-demanding

Features for ASR



Conventional speech model

$$P(T|A)$$

T ... text, A ... acoustics

- Unable to model P(T|A) directly, so using Bayes:

$$P(T|A) = \frac{P(A|T)P(T)}{P(A)}$$

  - P(A) constant, ignoring
  - P(A|T) ... acoustic model P_A
  - P(T) ... language model P_T

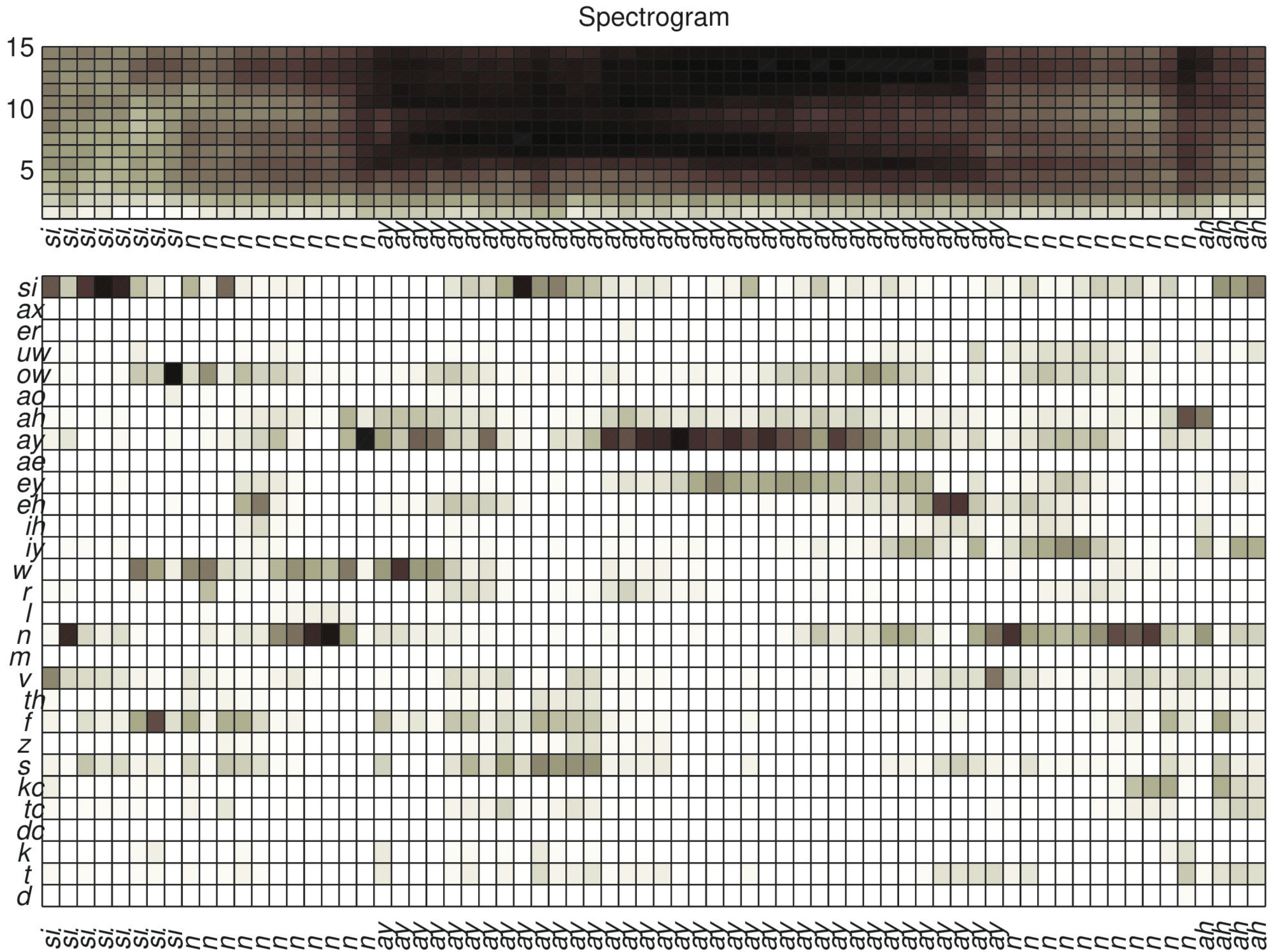
Acoustic model $P_A(A|T)$

- T... hypothesized sequence of acoustic units
- we assume independence between frames so that we can write

$$P(A|T) = \prod_i P_A(a_i\,|t_i) \qquad \text{i ... time}$$

- i ... time
- a_i ... feature vector
- t_i ... acoustic class (a phone or context-dependent phone)

features for the word "nine" – n-ay-n



Language model $P_{LM}(T)$

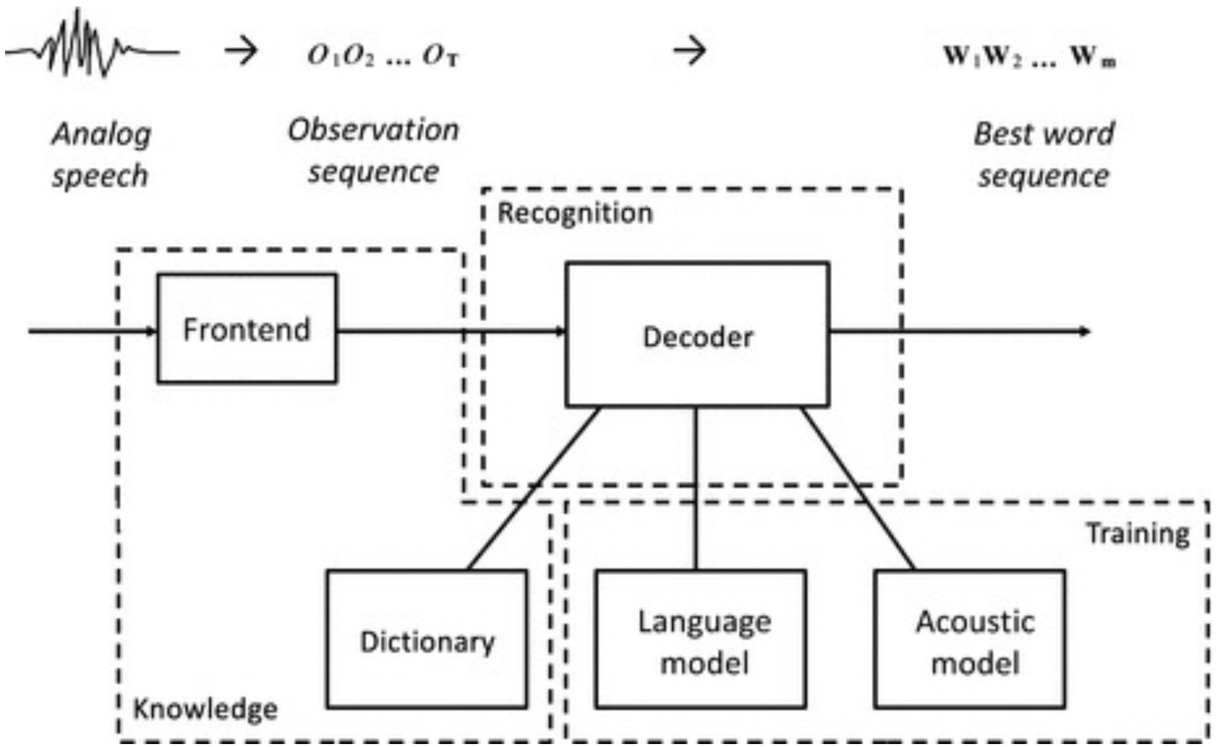
- T... sentence, consists of word sequence $w_1 \ldots w_N$
- sequence probability modelled with n-gram LM (or neural LMs)

$$P_{LM}(T) = \prod_i P(w_i \,|w_{i-1}, w_{i-2}, \ldots)$$

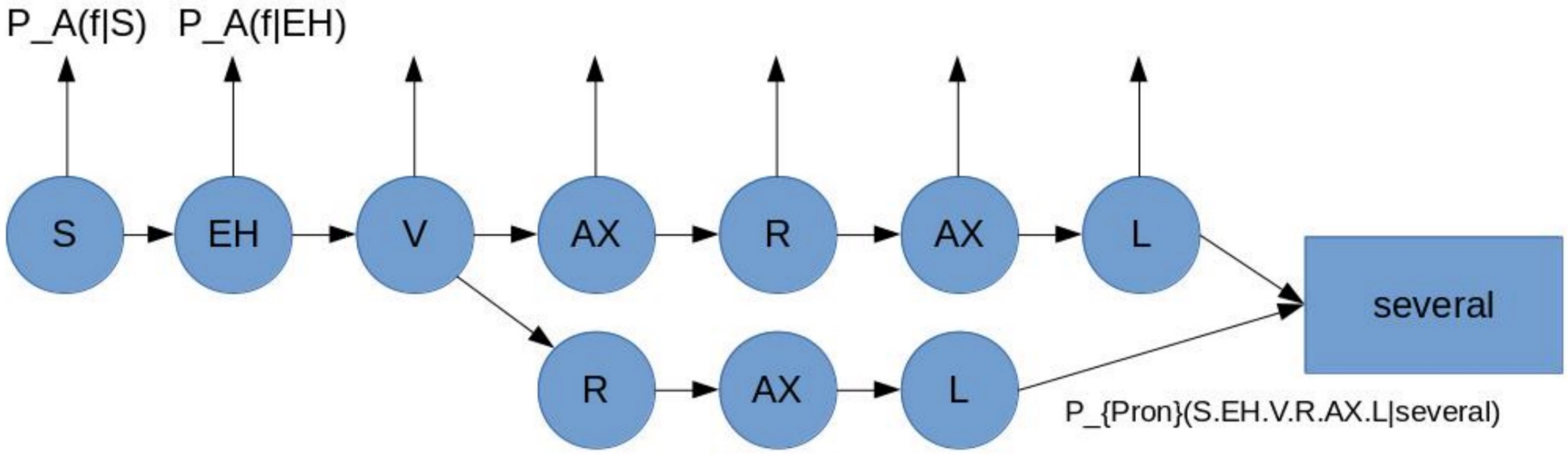
How to map words w_i to acoustic classes t_i ? → need Dictionary $P_{pron}(pron|w)$

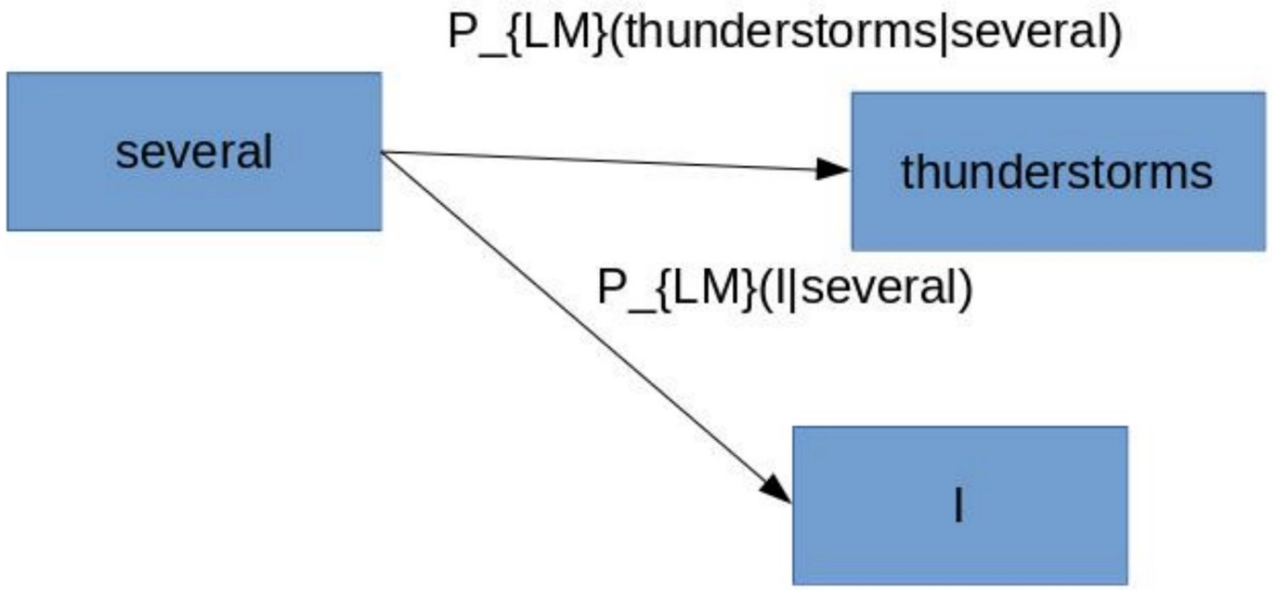
- "several" S EH V AX R AX L
- "several" S EH V R AX L

Decoder



- Why "decoder"? - the text has been *encoded* into acoustic signal (or features), now we attempt to *decode* it back
- Hidden Markov Models - decoding hidden message (sentence) from the sequence of features
- Dynamic programming (Viterbi) to find the best path through the FST (composed from AM, LM, Dictionary)

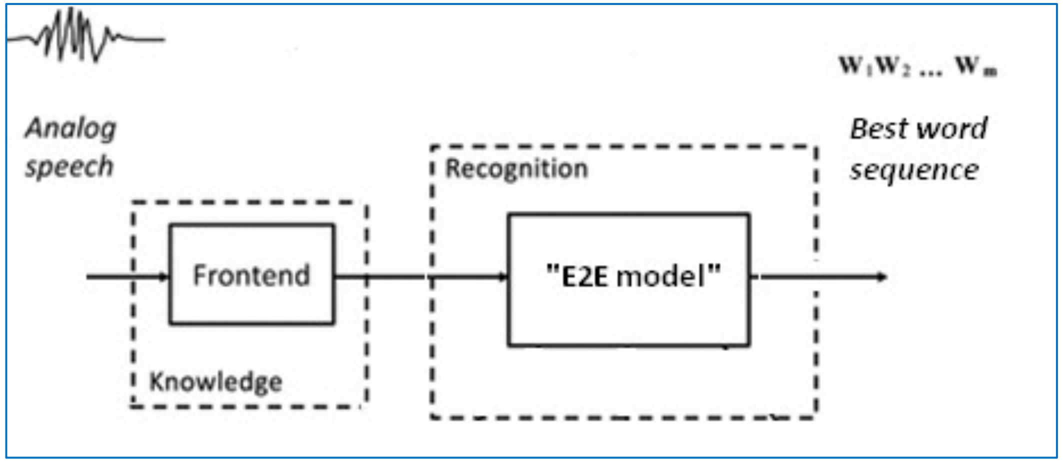

P_A(f|S)
P_A(f|EH)
S
EH
V
AX
R
AX
L
R
AX
L
several
P_{Pron}(S.EH.V.R.AX.L|several)


P_{LM}(thunderstorms|several)
several
thunderstorms
P_{LM}(I|several)
I

End-to-end (E2E) ASR

E2E model

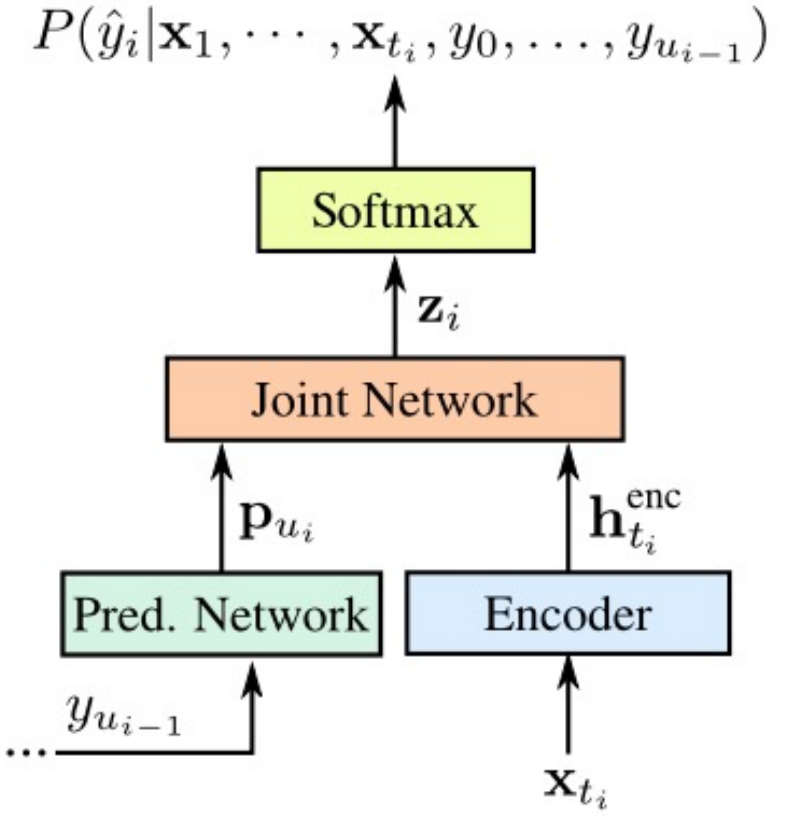
- Models $P(T|A)$ directly
- Able to predict per-frame probability of characters, sub-words or even words
- No need for Dictionary (pronunciation is not modelled explicitly)
- No separate acoustic model → no need for alignment between symbols and audio
- Decoder can be much simpler
- All you need to build the model is audio and its transcript



E2E model downsides

- **Inaccurate word/character time stamps**
  - because there is no explicit symbol alignment
- **Hard to add new words**
  - because there is no explicit Dictionary
  - on the other hand, E2E models generate characters so unknown words may decode well

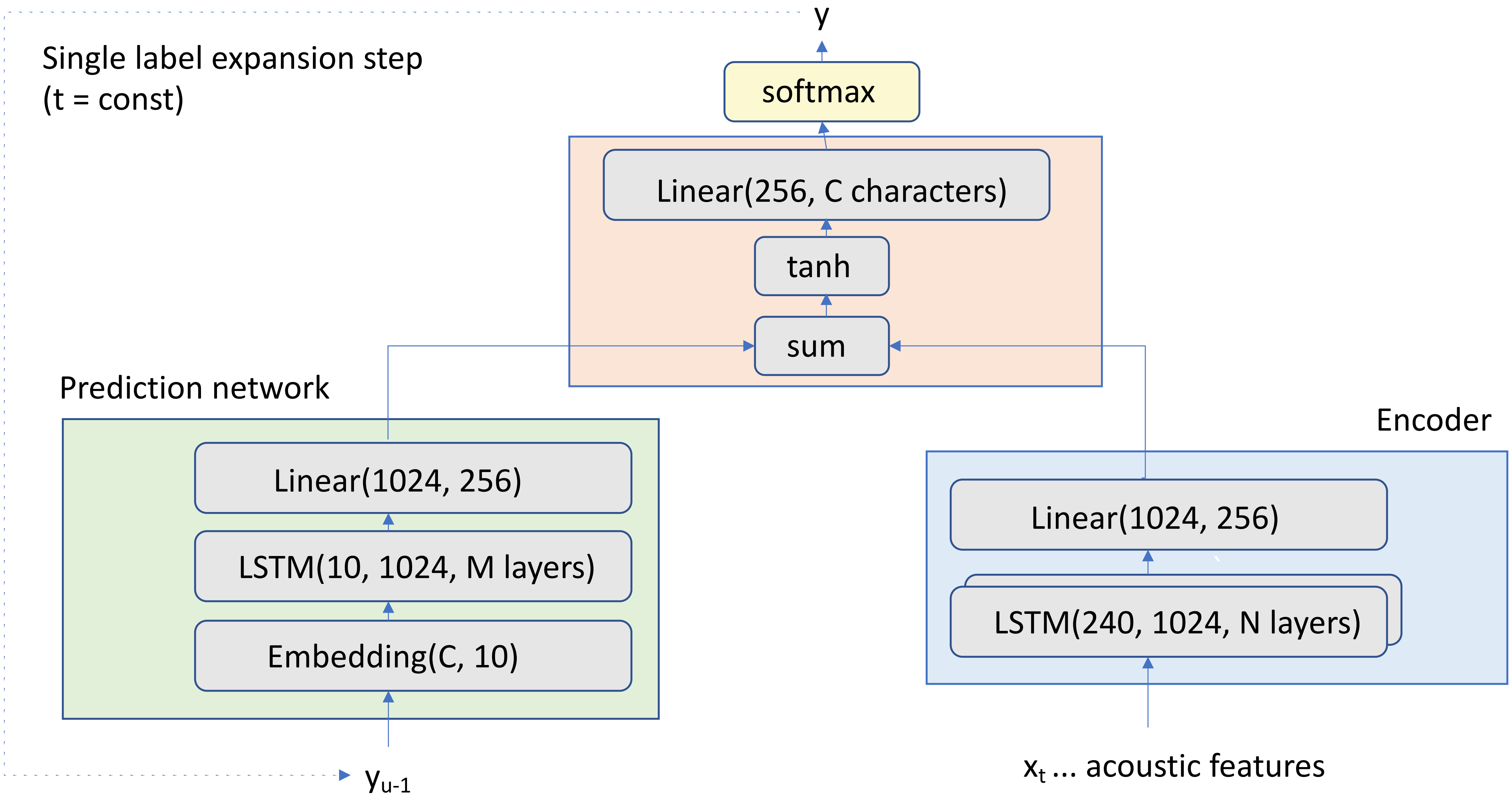
RNN-Transducer model



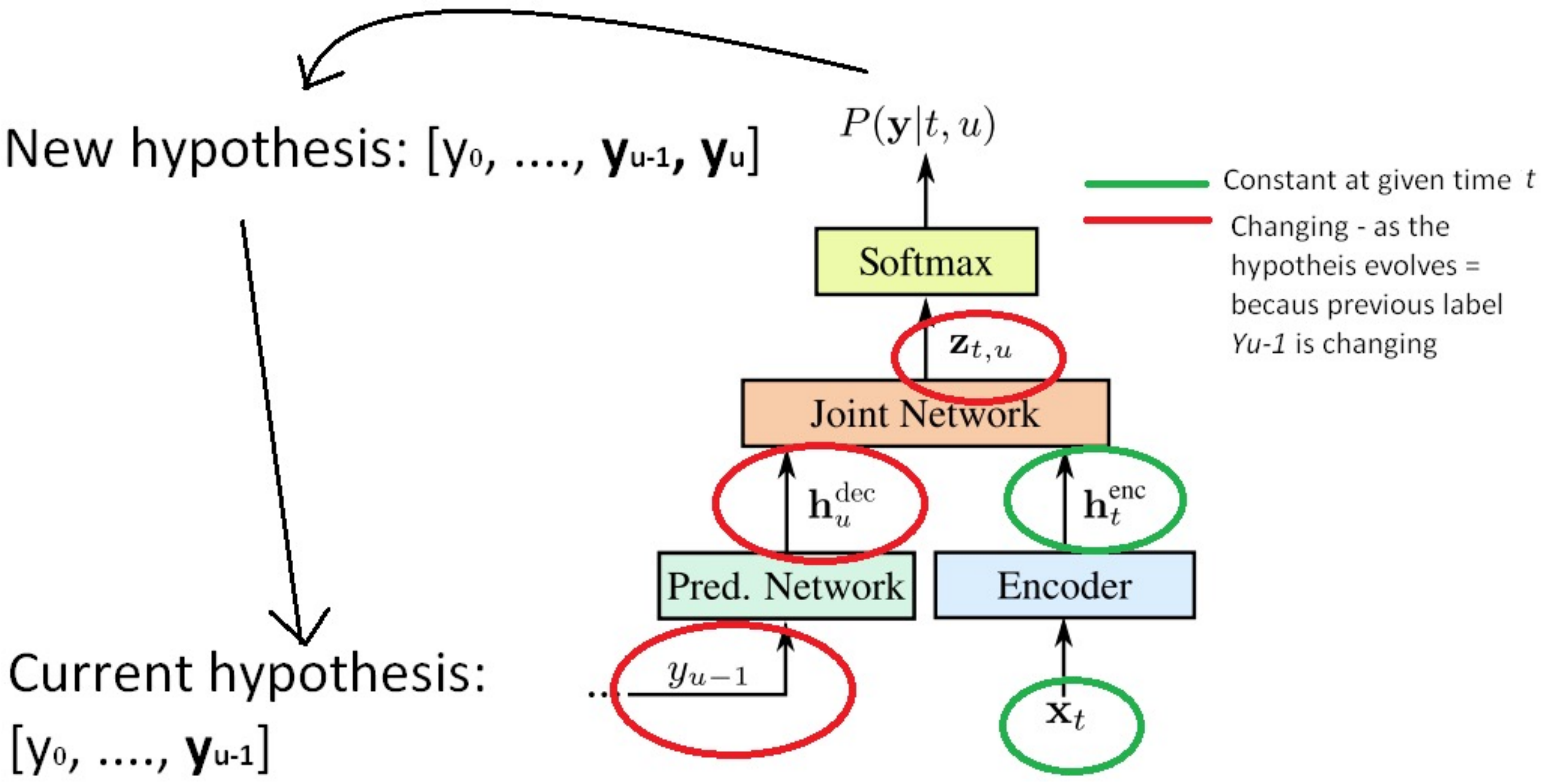
(b.) RNN-Transducer

* "Streaming End-to-end Speech Recognition for Mobile Devices", ICASSSP'19, Google

RNN-T model architecture – an example



RNN-T Decoding



- Beam search
- RNN-T gives *P(y|x,y_)*, where *y* is the next character, *x* are the audio frames so far, *y_* is the current hypothesis
- RNN-T does not always consume input (allows to decode multiple characters in a single frame)

RNN-T loss

- For each frame, NN outputs probabilities of characters + blank symbol
- We have the correct transcript in train time
- An alignment is a sequence of characters + blank symbols
- A consistent alignment is one consistent with the correct transcript, e.g.
  - Let's say we have 8 acoustic frames and a transcript "hello"
  - an alignment *"_ _ h e _ l _ l _ o _ _ _"* is consistent
  - so is *" _ h _ e _ _ l l o _ _ _ _ _"*
  - by definition, blank symbol means go to next frame
- RNN-T optimizes the sum of probabilities across *all* consistent alignments

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END