Speech Translation

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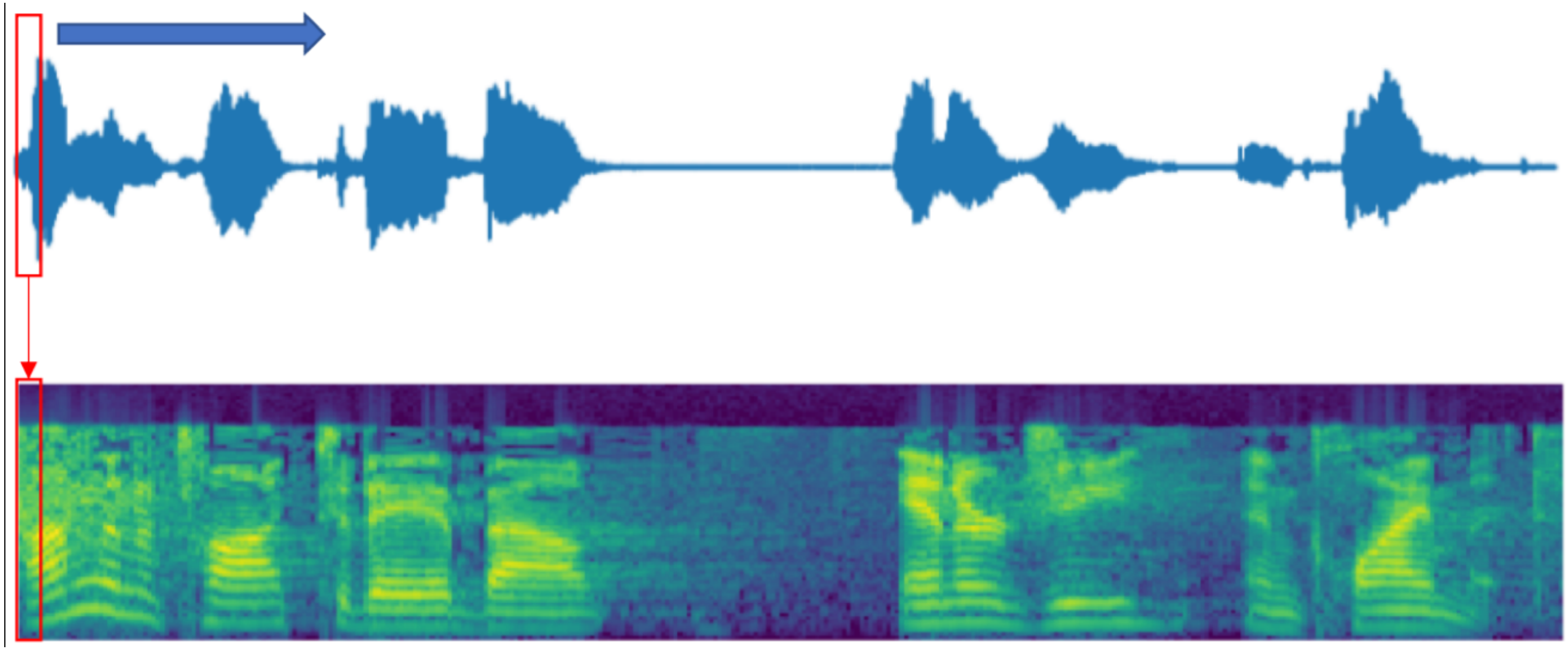
based on slides from Xutai Ma

14 November 2023

What is Speech?



- Spectrogram: Loudness at different sound frequencies and time steps
- Typically segmented into, say, 50 frames per second (50Hz)

⇒ can be used in sequence models

What Makes Speech Hard?

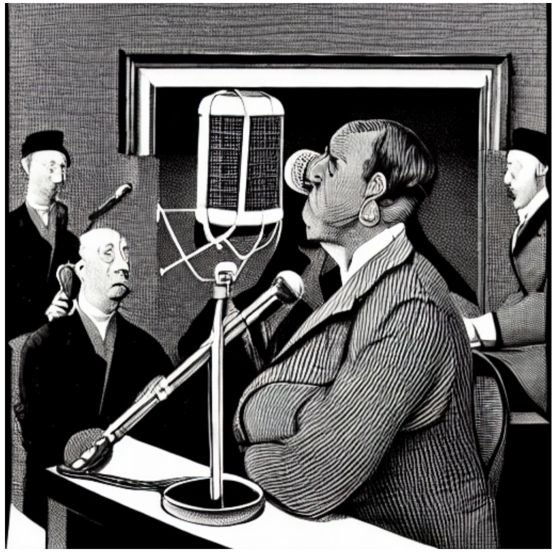
- Disfluent language
  - Ungrammatical languages, restarts, repetitions
  - Pauses, filler words (”ah”, ”hm”, ”like”),

- Noise
  - background sounds, reverberation, etc.
  - cocktail party effect

- Recording conditions
  - sampling rate
  - which sound frequencies are filtered out
  - microphone placement, possibly multiple microphones

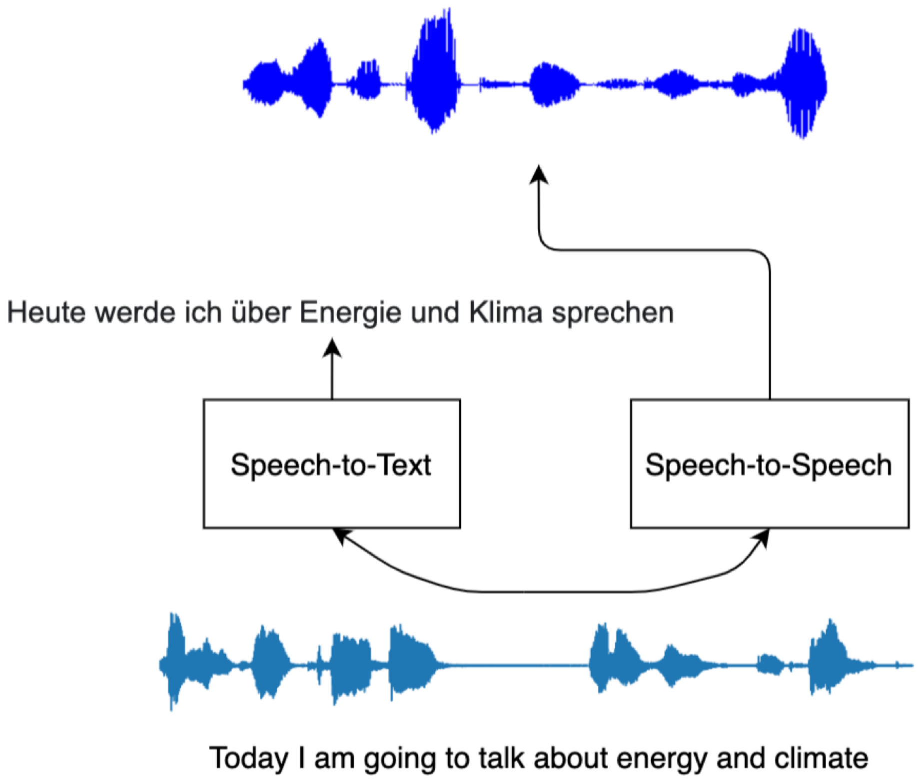
- More variety
  - different speakers
  - more spoken language varieties
  - tone, emotional content not captured in text

- Less data (also more privacy concerns about data)



Introduction

- What is speech translation?
  - Translate speech in source language to text / speech in target language



Introduction

Why/Where do we need speech translation?

- International conferences (e.g., UN, EU)
- Live video translation (e.g., YouTube, streaming)
- Personal translator (e.g., international travels)
  - Google translate (Conversation)

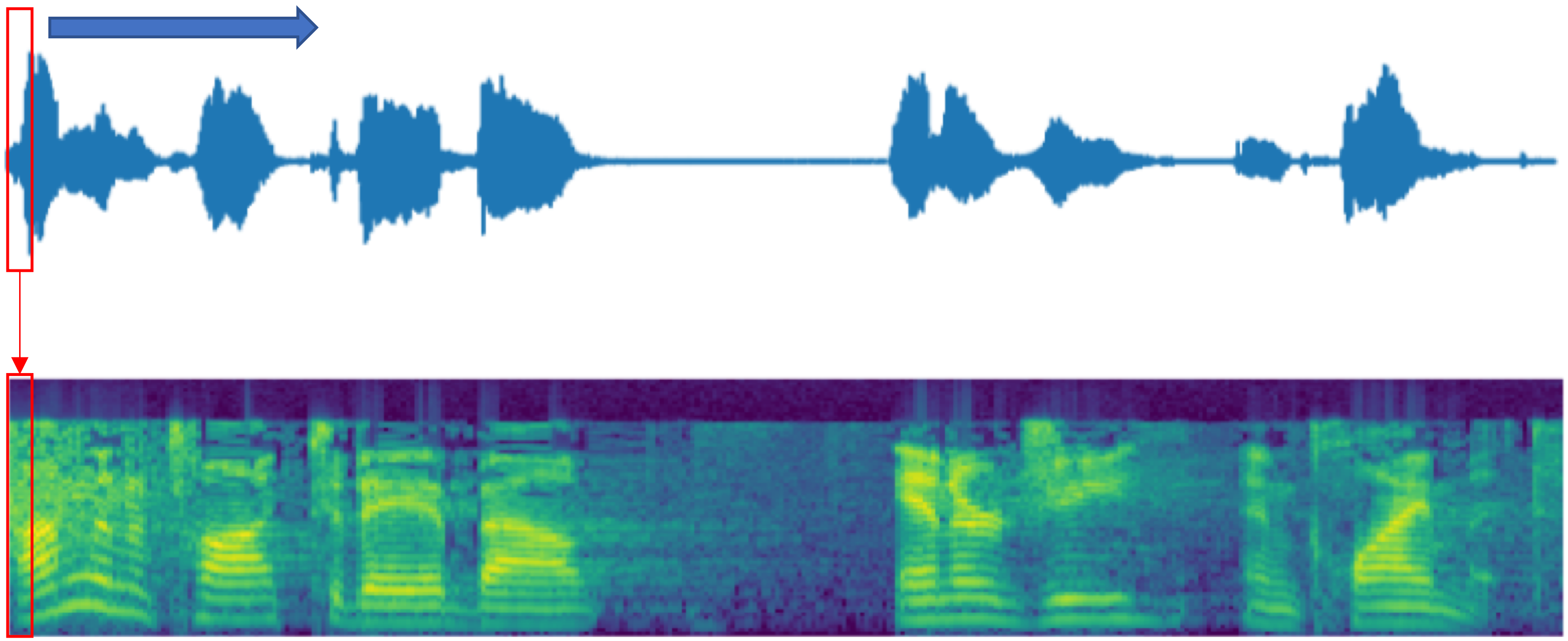
speech recognition

Background:
Speech Processing and Recognition

- Speech Processing
  - How to represent speech → feature extraction
- Automatic Speech Recognition (ASR)
  - Transcribe speech to text in one language
  - Seq2seq task, but input and output have the same order

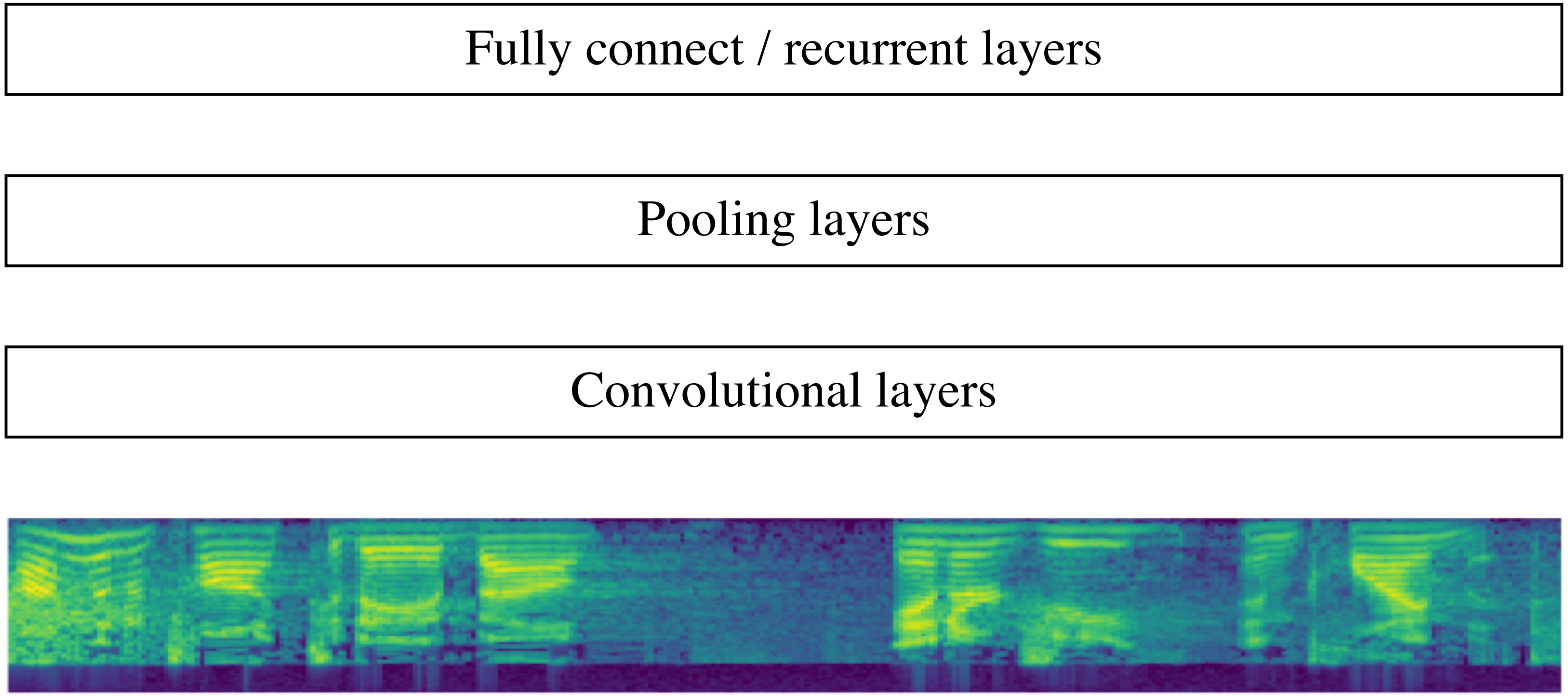
Feature Extractions

- Short-Term Spectrum
  - (Mel-frequency cepstral coefficients) MFCC
- Convert speech samples to sequence of vectors



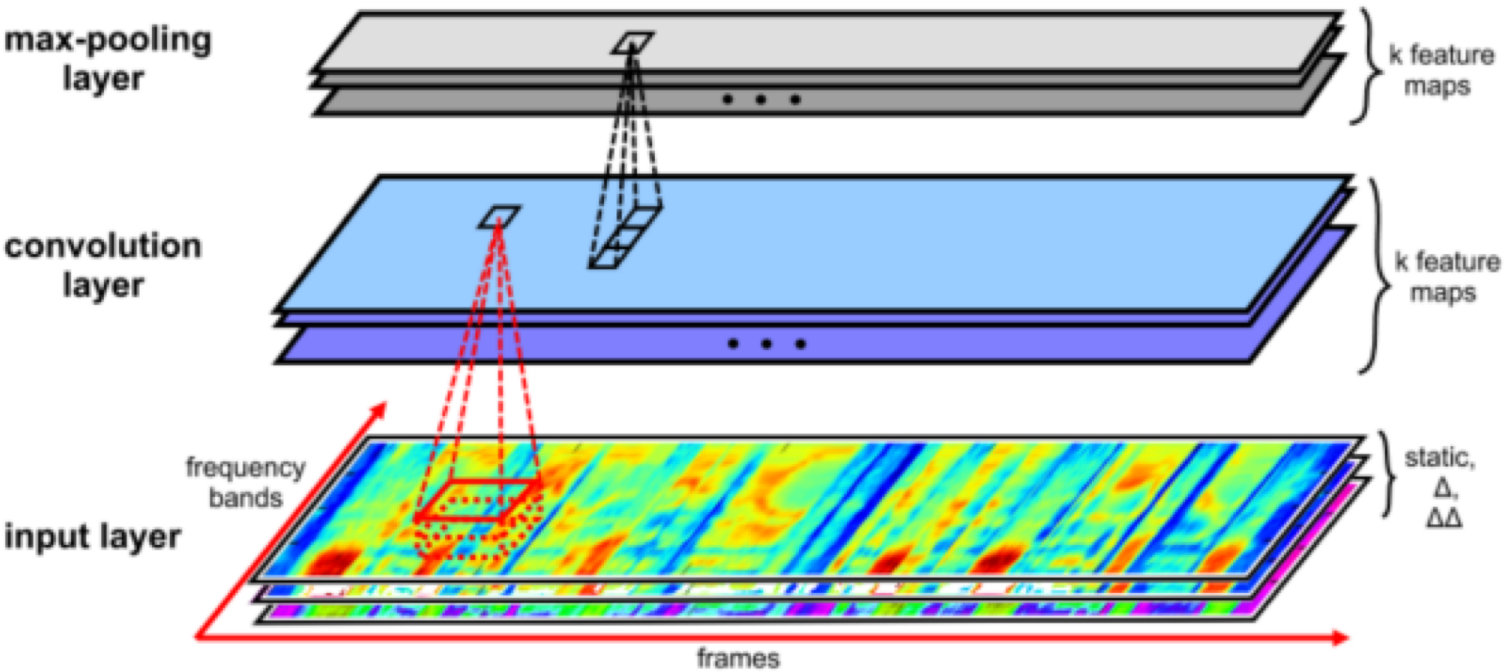
Automatic Speech Recognition

- Acoustic Model
  - Neural-based models



Automatic Speech Recognition

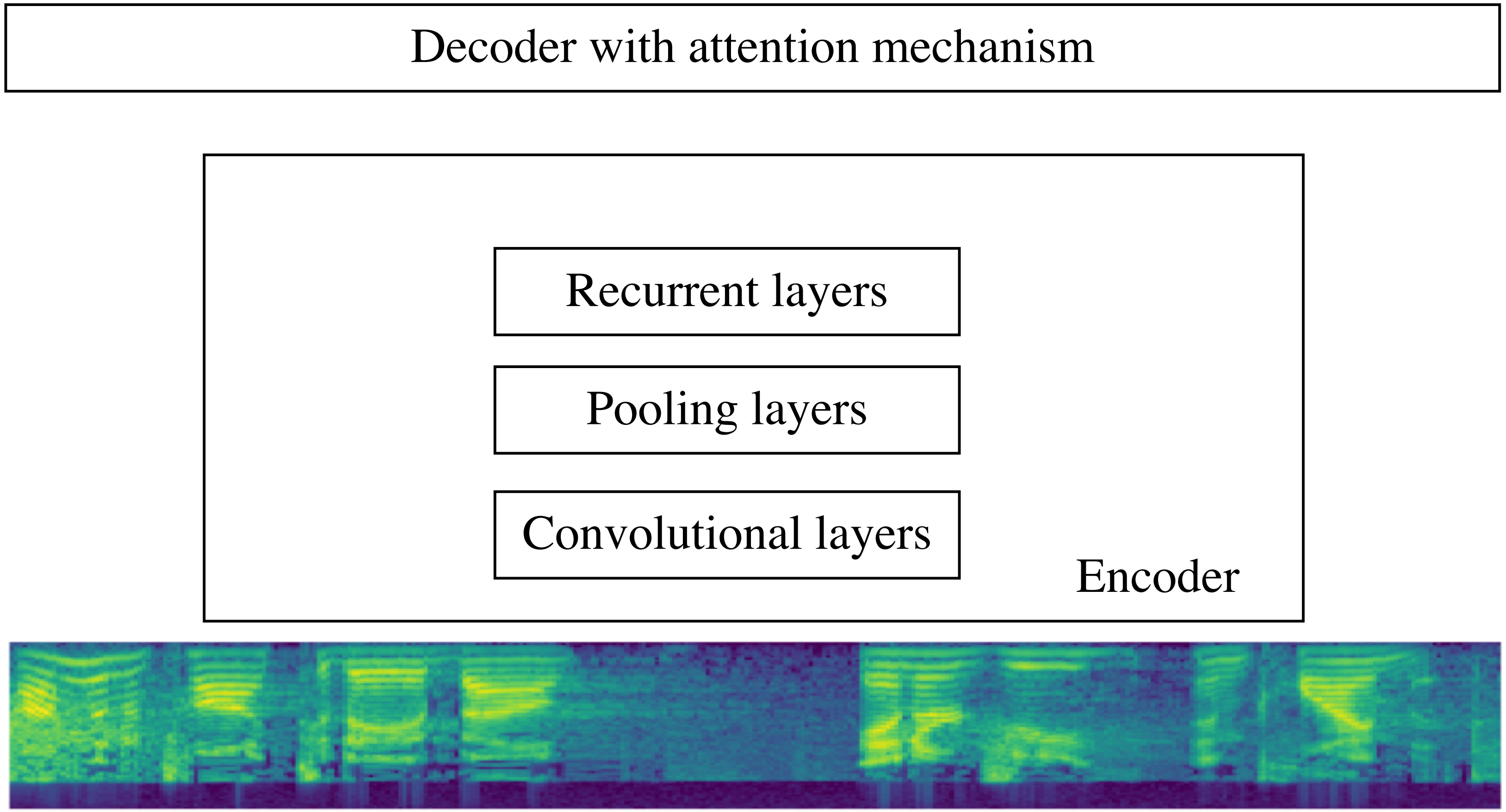
- Convolutional layers



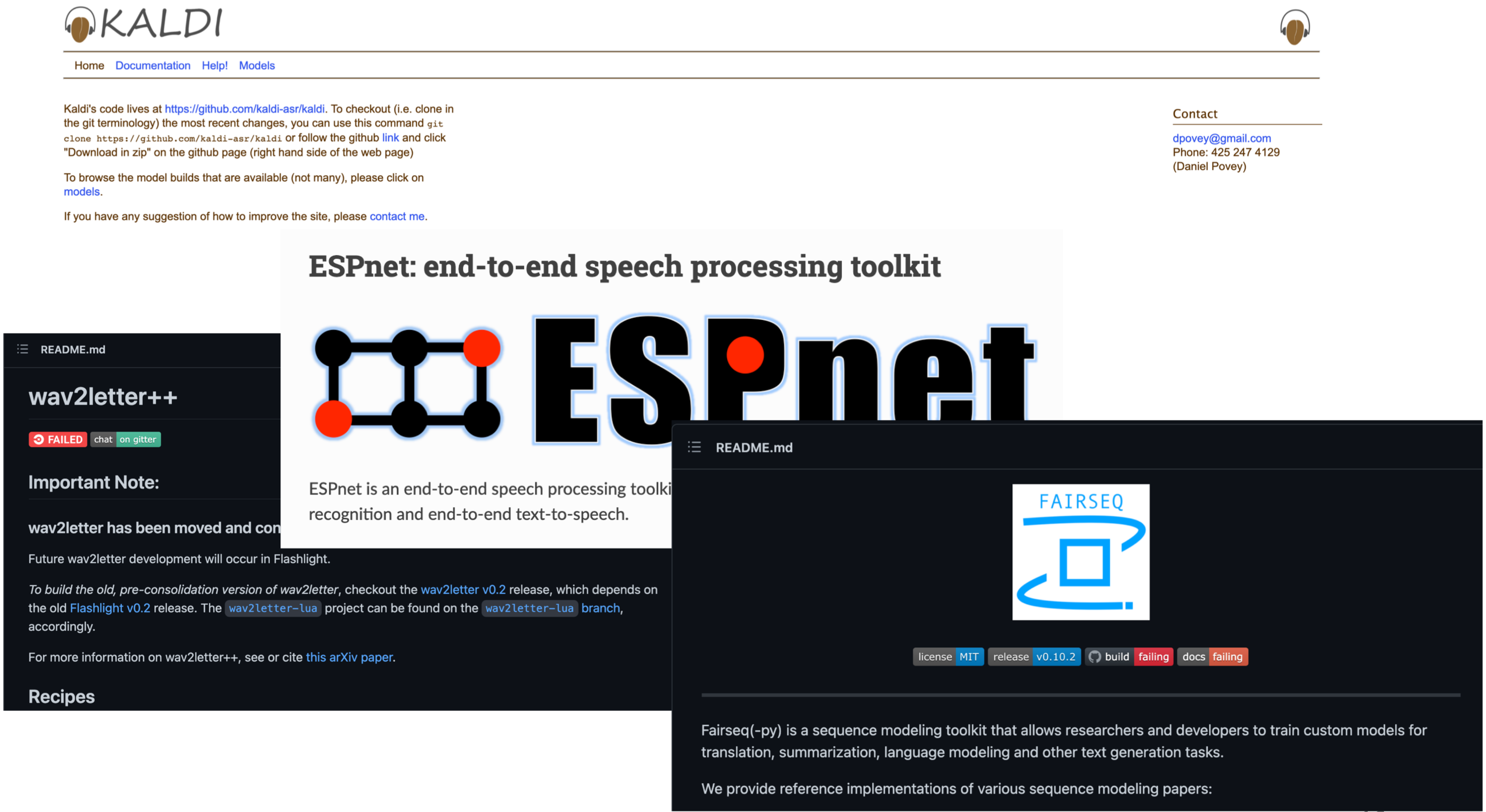
Zhang, Ying, et al. "Towards end-to-end speech recognition with deep convolutional neural networks." *arXiv preprint arXiv:1701.02720* (2017).

Automatic Speech Recognition

- Seq2Seq model

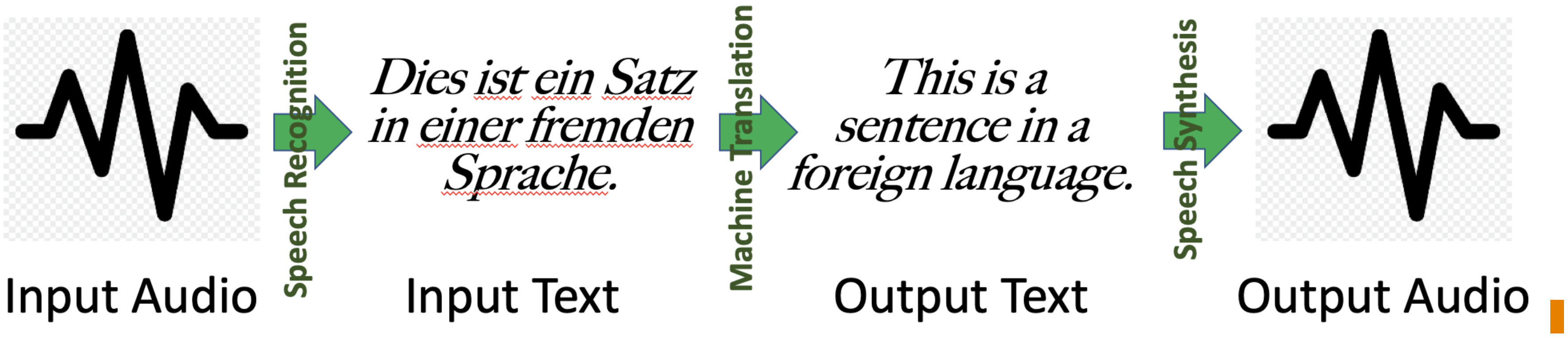


Automatic Speech Recognition



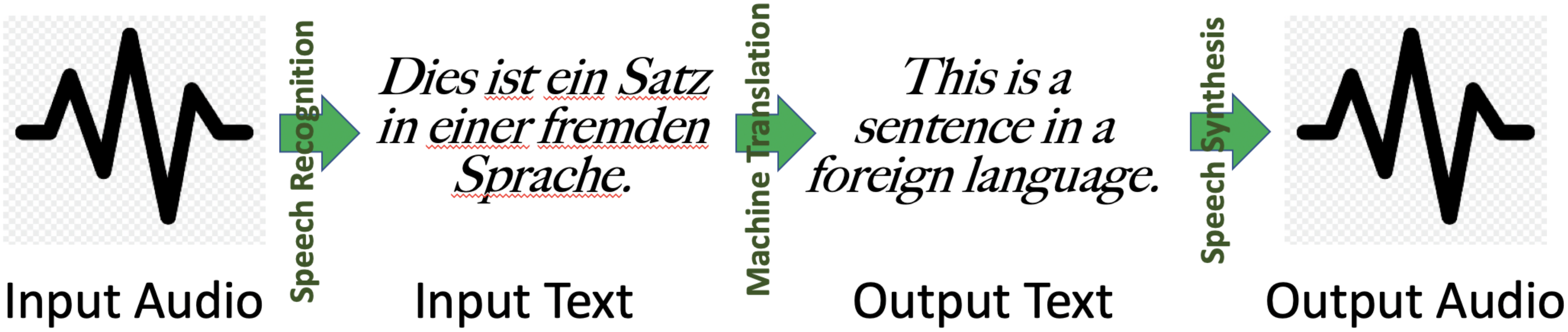
speech translation

Cascaded Speech Translation



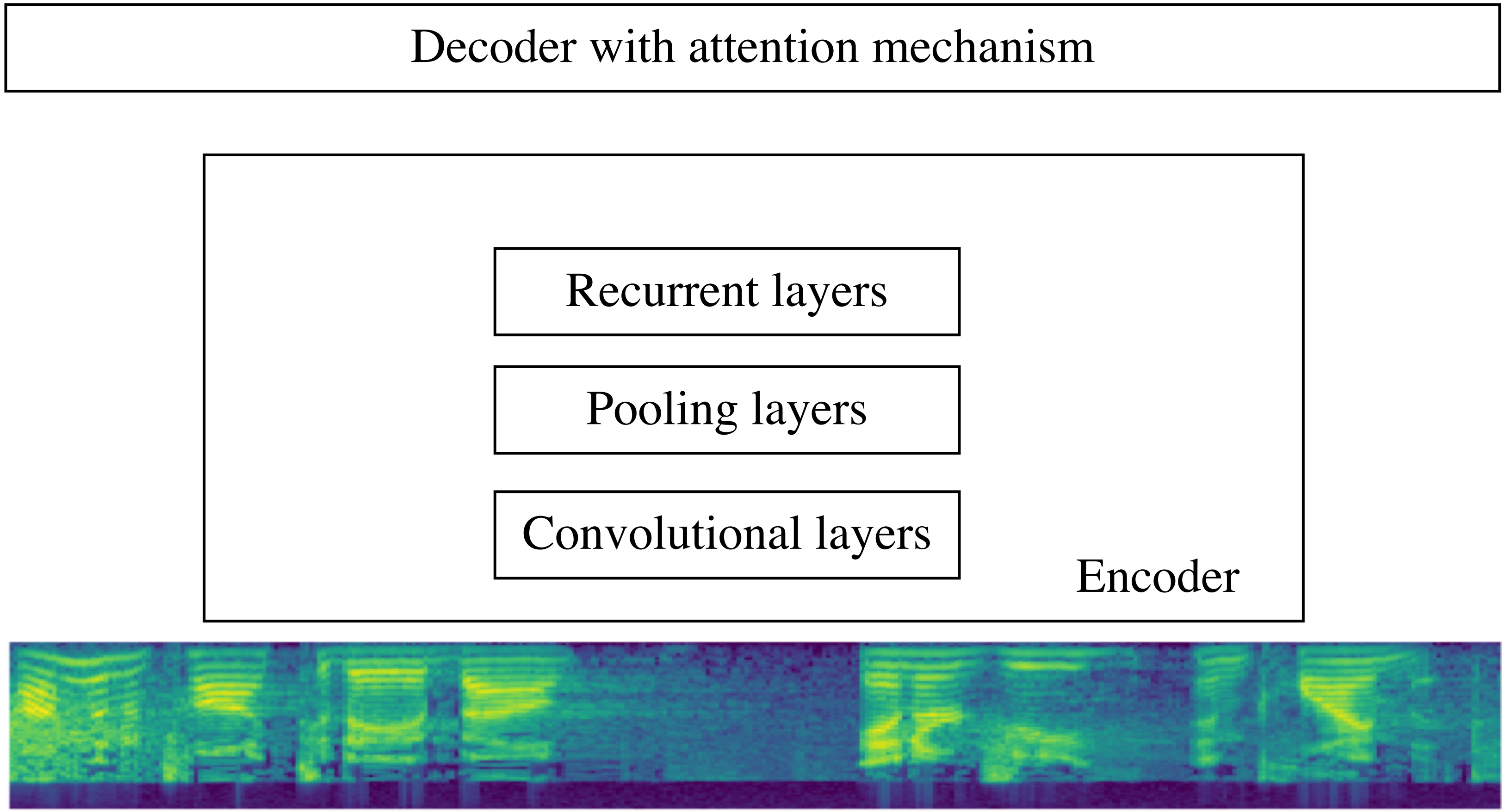
- Synchronize tokenization schemes
- Pass lattices between steps
- Main concern: error propagation

End-to-End Systems

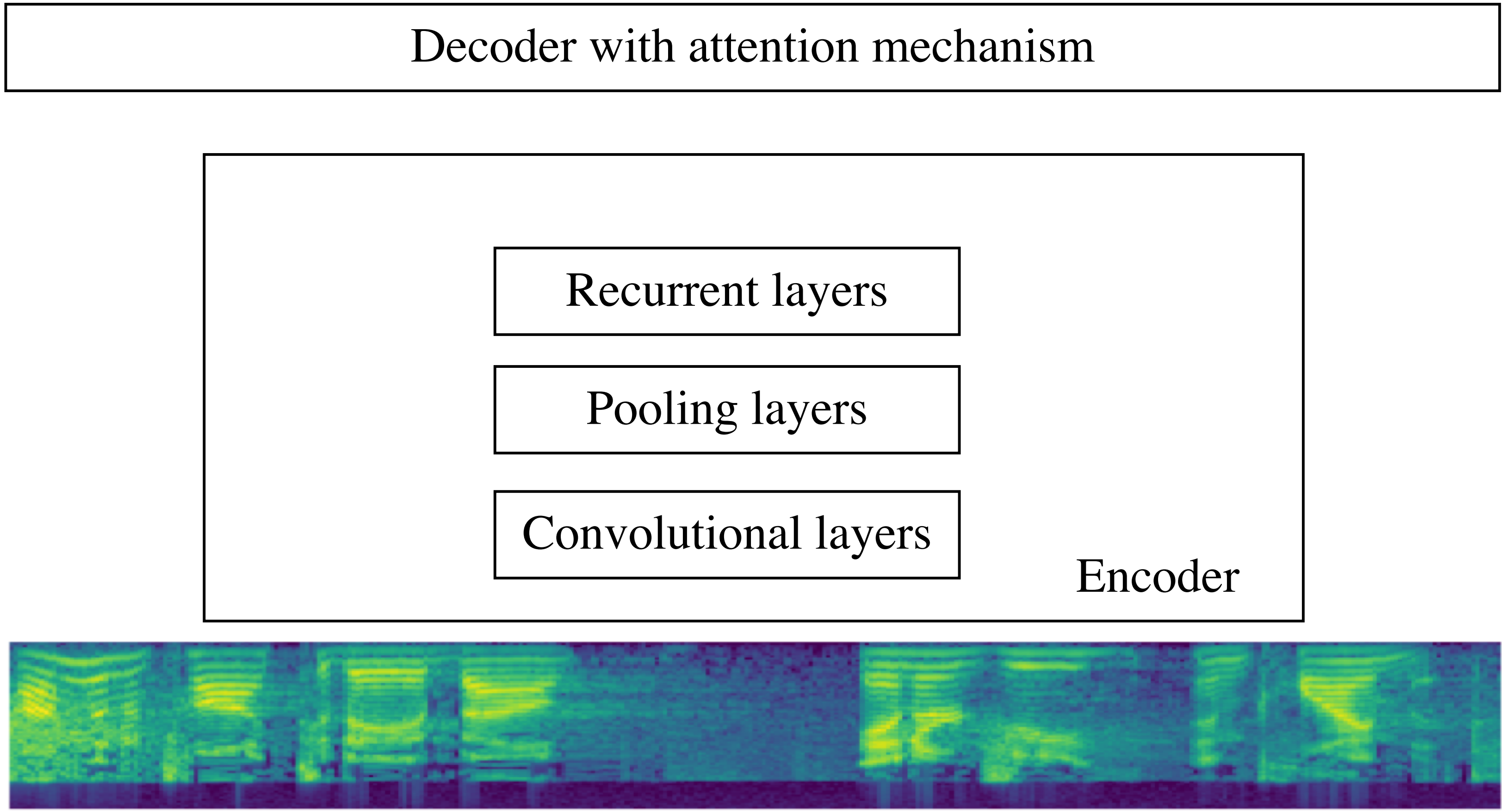


Moving towards end-to-end systems:

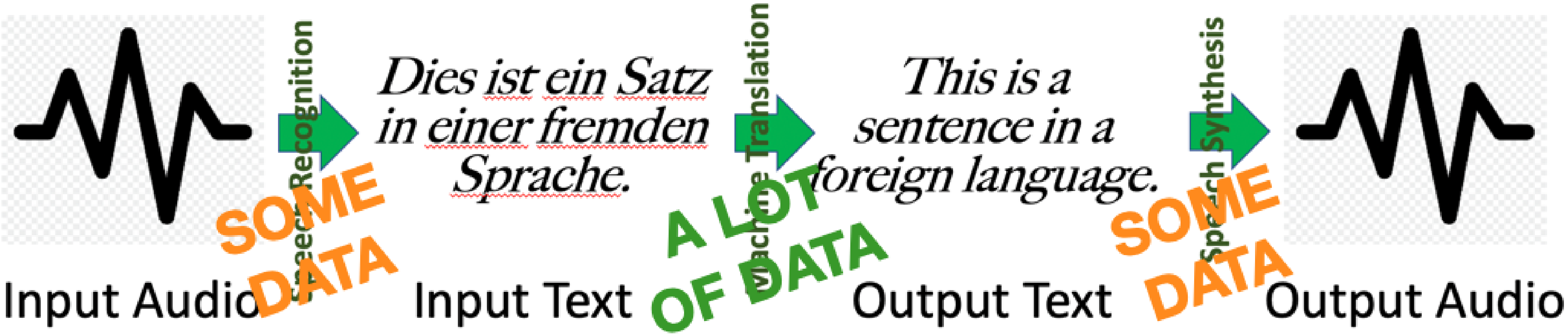
Automatic Speech Recognition



End-to-End Speech Translation

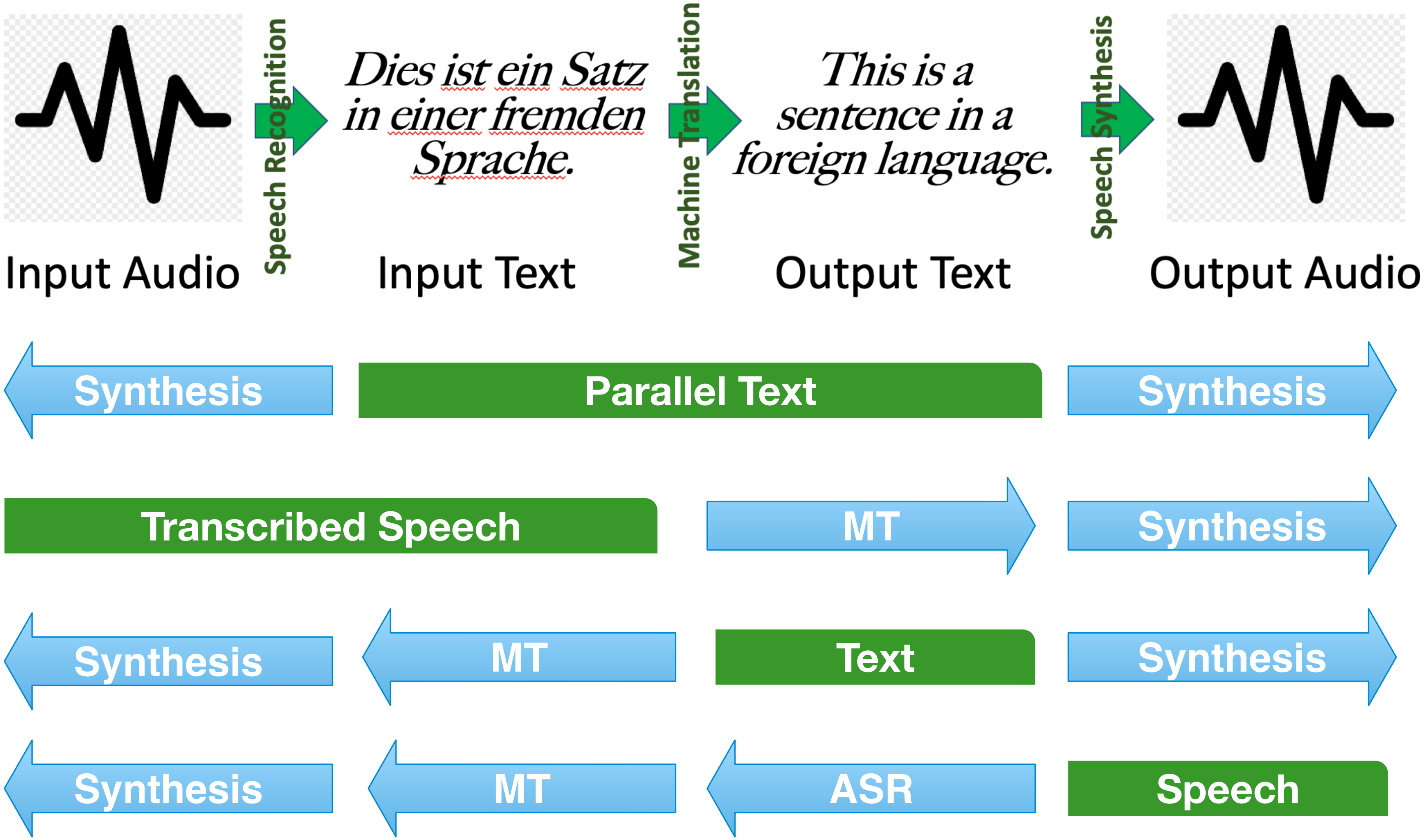


The Data Aspect

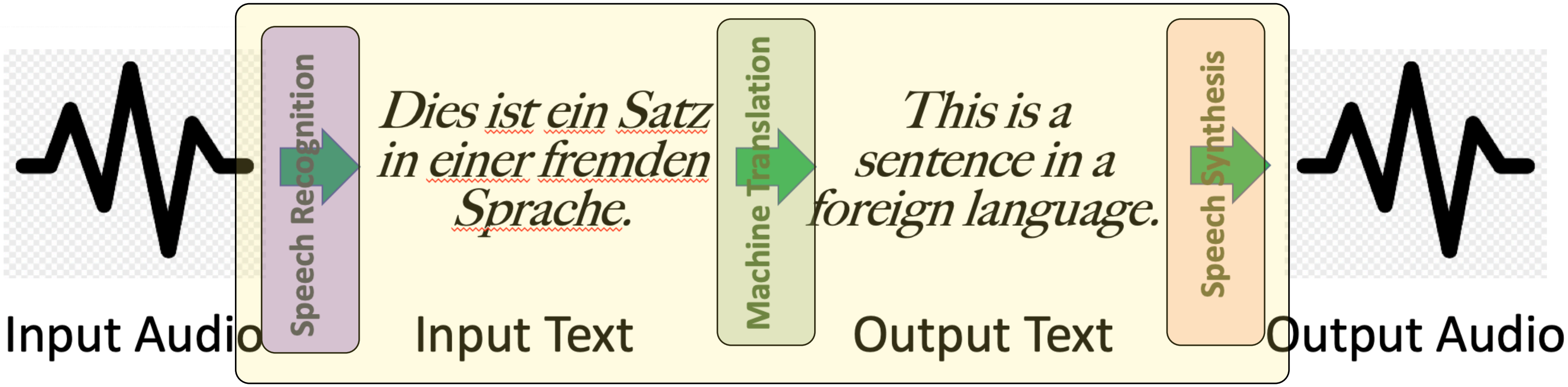


Moving towards end-to-end systems:

Data Augmentation



Pretraining Components

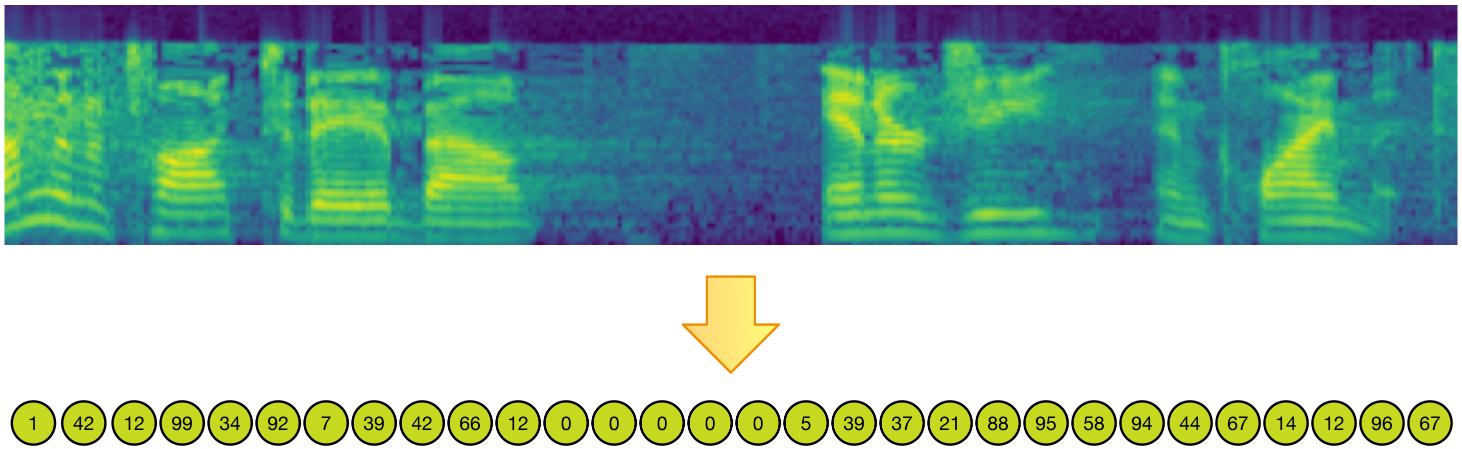


- Train components of the model separately
- Connect components
- Fine-tune on end-to-end data

speech tokens

Speech Tokens

- Goal: Represent speech as a sequence of discrete tokens



- Two Methods
  - Semantic tokens: wav2vec-BERT
  - Acoustic tokens: SpeechStream / SpeechStorm

Semantic and Acoustic Tokens

- Generating with semantic vs. acoustic tokens

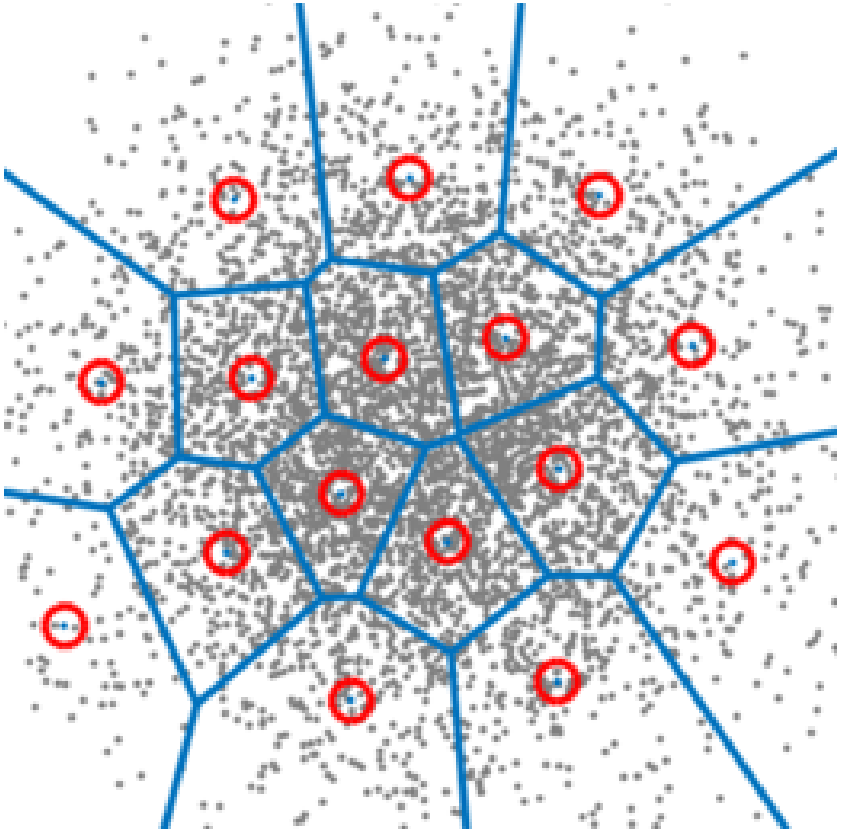
	Acoustic	Semantic
Reconstruction	-	+
Phonetic discriminability	+	-

- Training model only on acoustic tokens creates “babbling”: no meaningful words

Speech Tokens by Vector Quantization

- Input: high dimensional vector corresponding to a speech frame

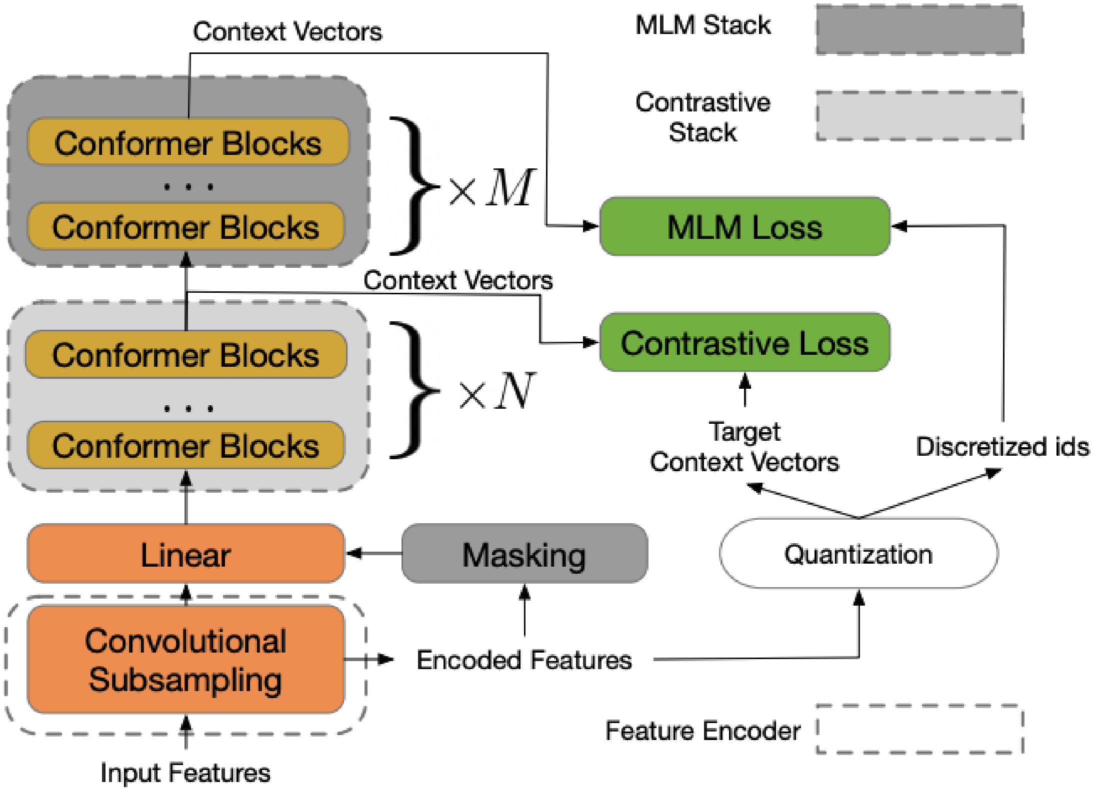
- K-Means Clustering



- Token is cluster ID

Wav2Vec-BERT

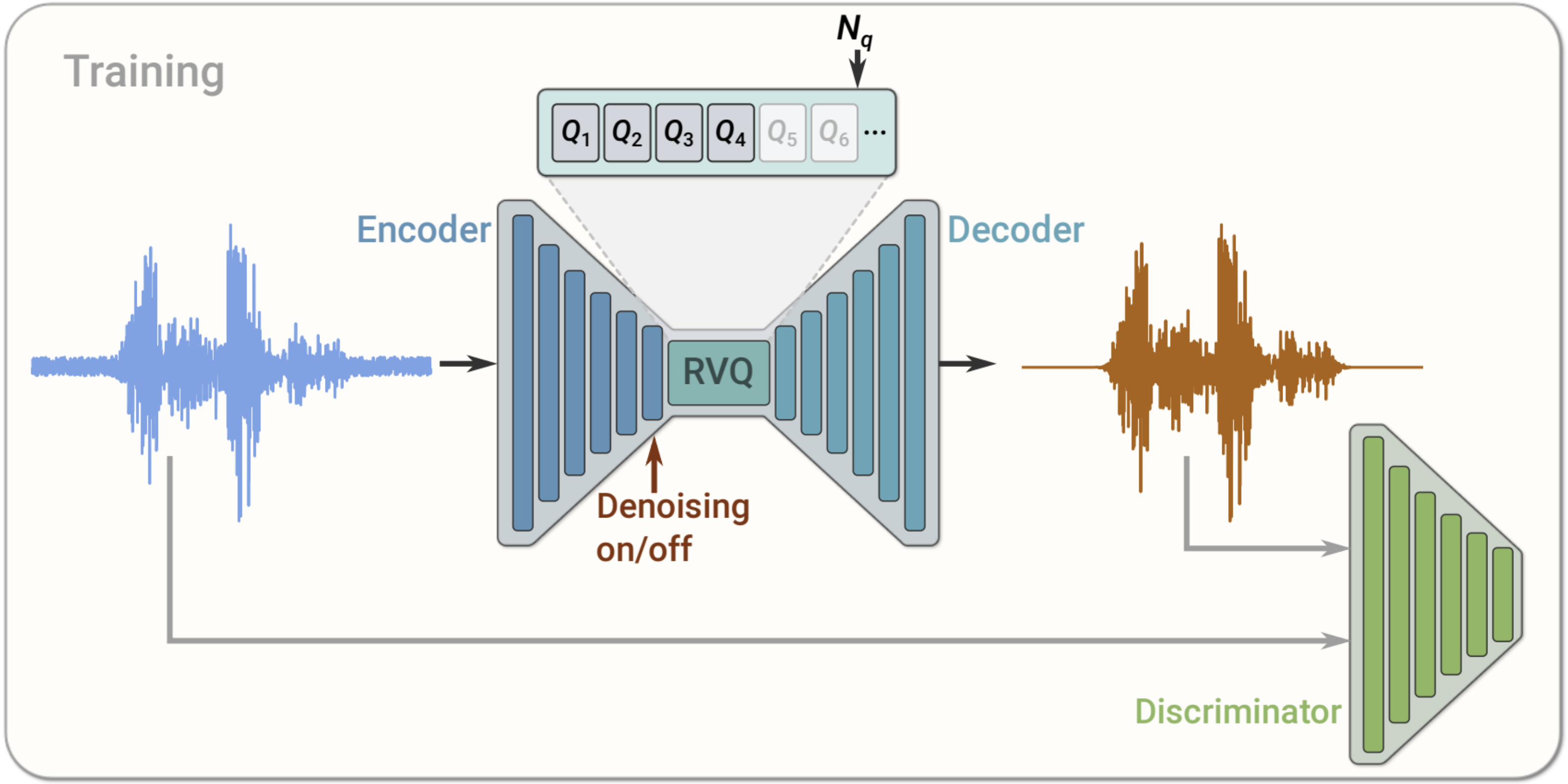
- Pre-trained model for speech, optimizing
  - masked language model loss on discrete tokens
  - contrastive loss: detect true vector from distractors (from same utterance)
  - also: codebook diversity loss (encourage uniform use of codes)



- Iteration between k-means clustering and retraining representations

SpeechStream

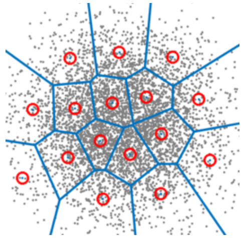
- A neural audio codec: goal is compression for transmitting less data



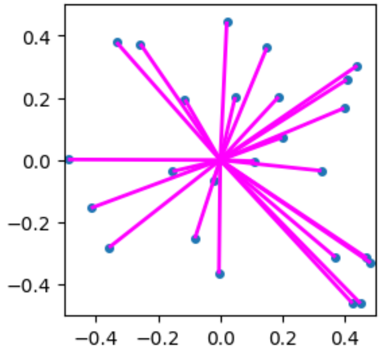
- Trained with reconstruction loss and discriminative training

Residual Vector Quantization

- Vector Quantization: K-Means Clustering ($\rightarrow$ token is cluster ID)



- Subtract centroid from **all** data points

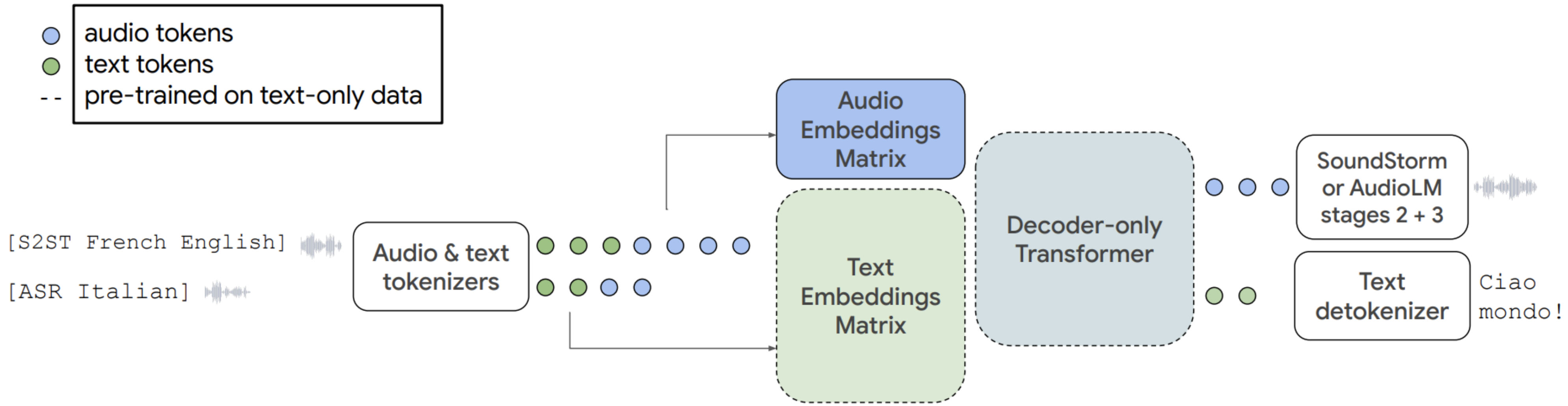


- Quantize **all** data points again (not hierarchical), rinse and repeat

(images from https://drscotthawley.github.io/blog/posts/2023-06-12-RVQ.html)

audiopalm (google)

AudioPaLM



- Step 1: Pretrained PaLM
- Step 2: Fine-Tuning on Speech Data (ASR, S2ST, S2TT, MT, TTS)

AudioPaLM Training

- Pre-trained PaLM

- Pre-trained Audio $\rightarrow$ audio tokens (wav2vec-BERT)

- Extend embedding matrix with speech tokens
  - audio embeddings initialized randomly
  - train all parameters with text+speech data

- Decode audio tokens
  - autoregressive as in AudioLM
  - non-autoregressive as in SoundStorm
  - prepend with 3 seconds of audio of desired speaker

Presenting Task Data

- Tasks
  - ASR: audio $\rightarrow$ text
  - AST (S2TT): audio $\rightarrow$ translated text
  - S2ST: audio $\rightarrow$ translated audio
  - MT: text $\rightarrow$ translated text
  - TTS: text $\rightarrow$ audio

- Task label at beginning of input, including languages
  e.g., `[S2ST English French]`
  - natural language prompts: no difference
  - naming language helpful for low resource languages
  - also combined labels: `[ASR AST S2ST English French]`

SpeechStorm

- Creating audio signal from semantic audio tokens (from wav2vec-BERT)

- Predict acoustic audio tokens
  - 50 Hertz (code rate 20 per second)
  - 12 quantization levels
  - 1024 vocabulary (clusters) per level

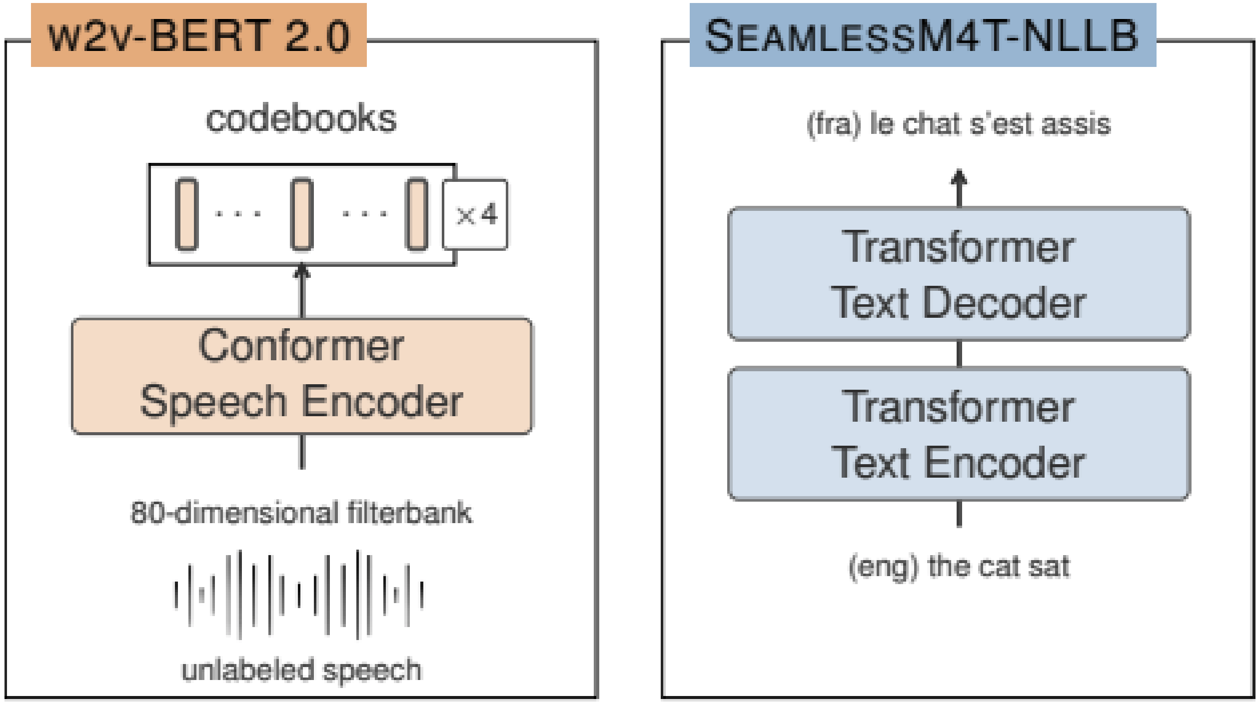
- Prepend speaker-specific audio tokens

- Predict waveforms with conformers & all that good stuff

- Non-autoregressive decoding

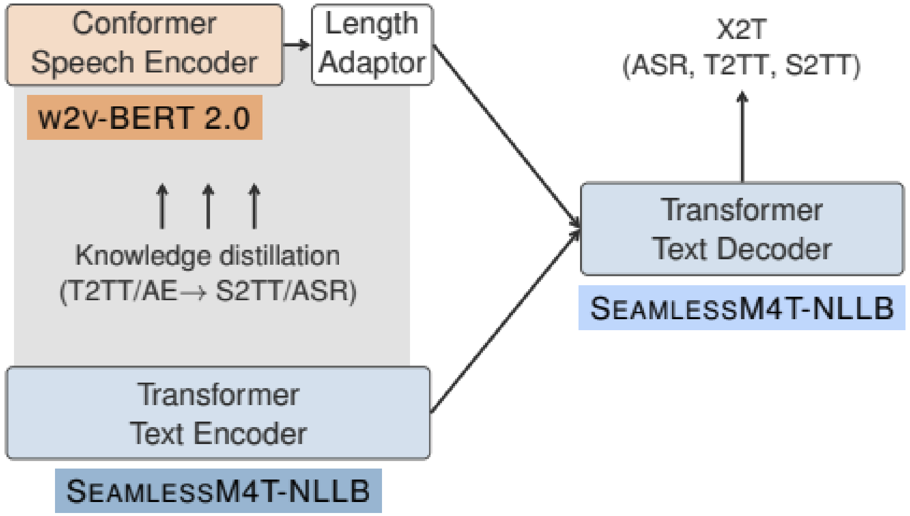
seamless4mt (meta)

Pretrained Models



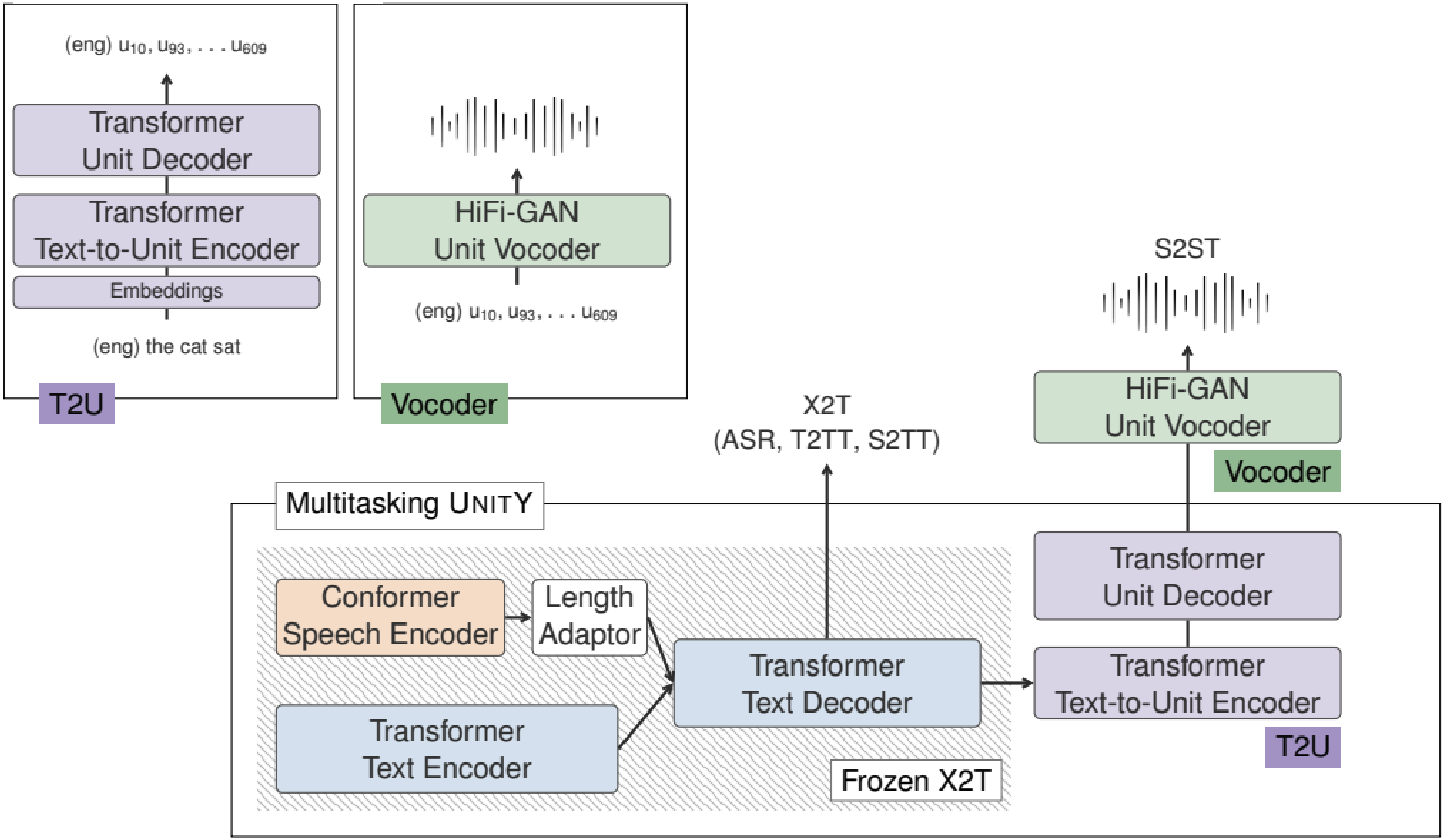
- w2v-BERT 2.0: speech tokenizer
- NLLB: multilingual text translation model

Speech-to-Text Training



- Multi-task training: T2T, S2T, ASR
- Additional training objective:
  For (speech, transcription, translation) triples T2T and S2T should agree

Speech-to-Speech Training



simultaneous speech translation

Simultaneous Speech Translation

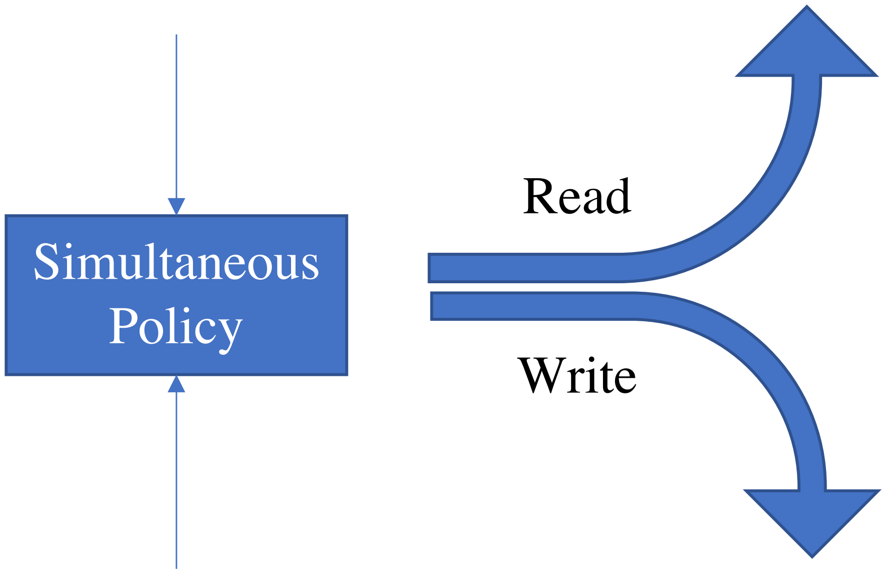
- Start the translation before read all the input speech

I am going to talk today about energy and climate.

Heute spreche ich zu Ihnen über Energie und Klima.

Simultaneous Speech Translation

Input I am going to talk today about energy and climate.

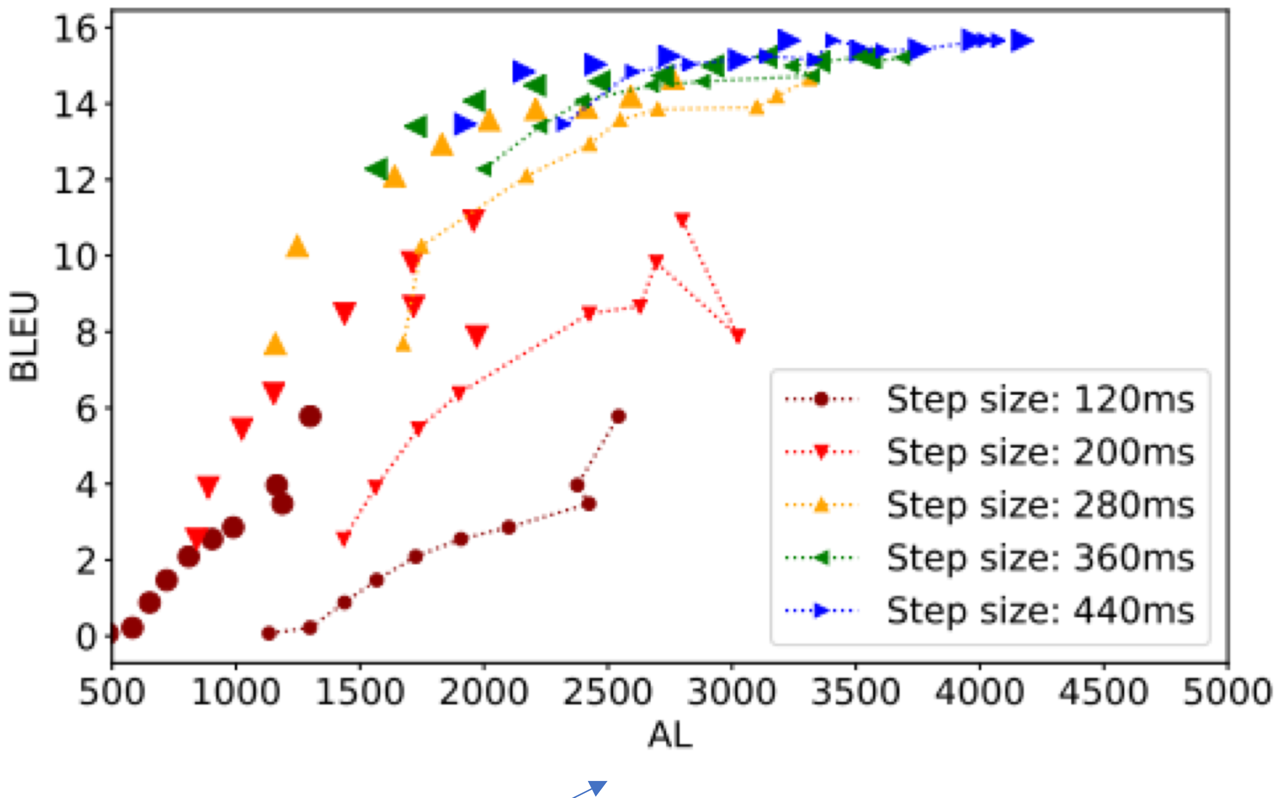


Output Heute spreche ich zu Ihnen über Energie und Klima.

Simultaneous Translation Policies

- Reinforcement learning (Gu et al. 2017; Luo et al. 2017; Lawson et al. 2018)
  - Less stable learning process.
- Fixed policy (Cho and Esipova 2016; Ma et al. 2019a)
  - Weaker performance, for instance Wait-K (Ma et al. 2019a).
- Monotonic attention (Raffel et al., 2017; Arivazha-gan et al., 2019; Ma et al., 2020)
  - The State of the art for the task.

Quality-Latency Trade-off



The lagging behind an oracle/perfect system

Thank You

questions?