End-to-End Speech Translation

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EACL 2021

Speakers

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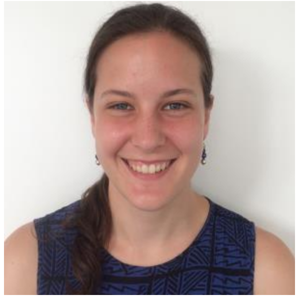

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		2.3:	Architecture & modifications
		2.4:	Output representations
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Sec 1:

Introduction

Task definition

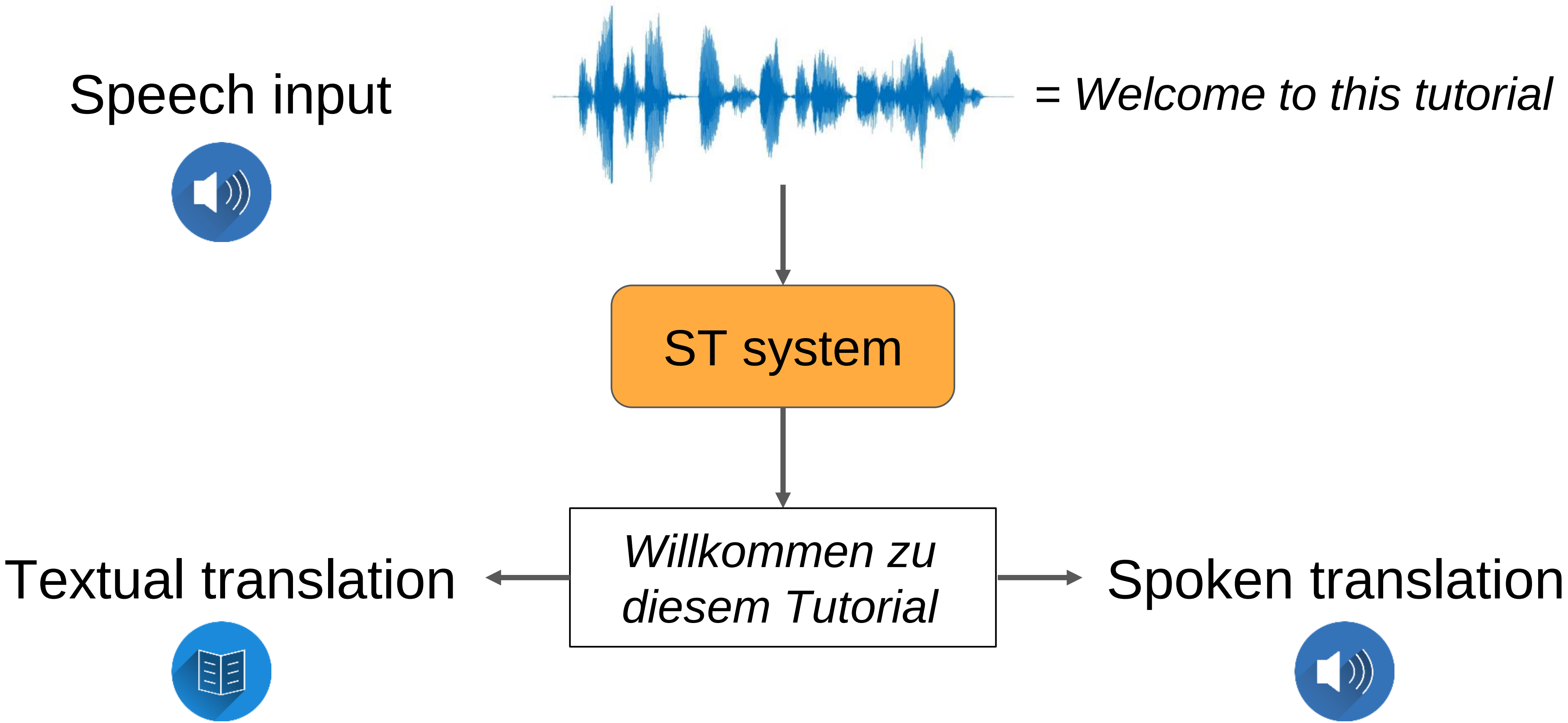
Challenges in translation of speech

Traditional cascade approaches

Sec 1.1

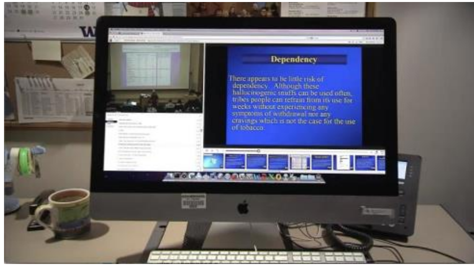
Task Definition

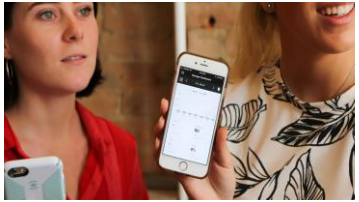
Speech Translation - Task



Speech Translation - Motivation

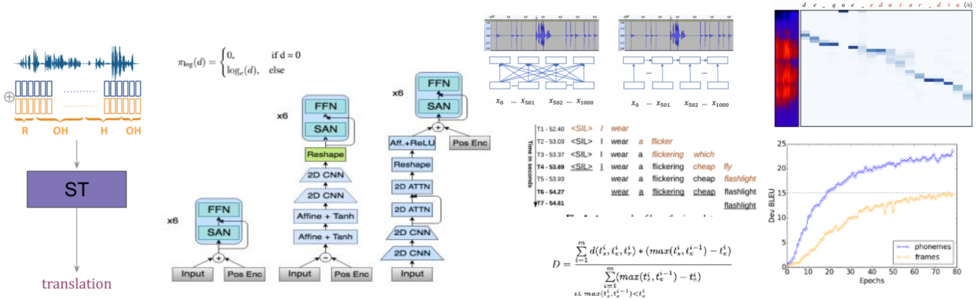
- Break language barriers to communicate, spread information and culture
  - Work
    - Meetings
  - Education and training
    - Lectures, conferences
  - Entertainment
    - Youtube, social media, cinema, tv
  - Everyday communication
    - Tourism, medical care, telephone conversations



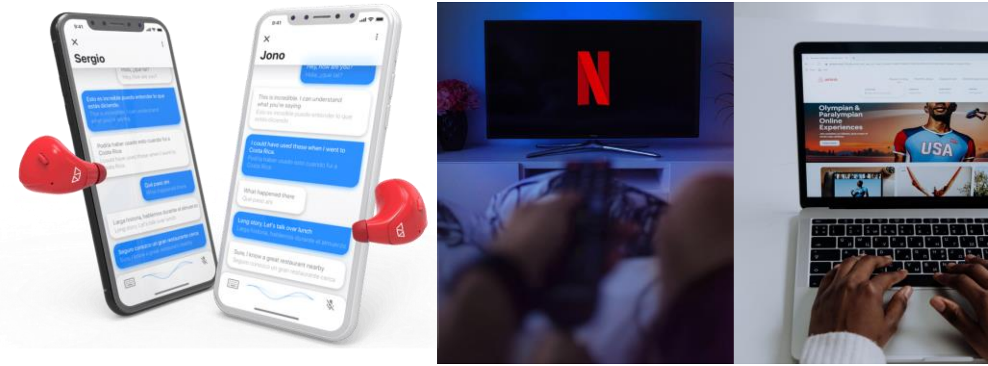


Speech Translation - Motivation

- Room for advanced research…
  - 99% of this tutorial



- …and for applications
  - Wearable devices
  - Video subtitling
  - Live captioning
  - Human-machine communication



Speech Translation - History (before e2e)

Late '80s: first proofs of concept

Constraints to control language ambiguity (phonetics, syntax, semantics)

- Restricted vocabulary
- Controlled speaking style
- Narrow domain
- Offline processing

'90s: Less constraints (vocabulary, speaking style)

First spontaneous ST systems (C-STAR, Verbmobil, Nespole,...)

2003-2006: Less constraints (domain)

First open-domain ST systems (STR-DUST, TC-STAR, GALE)

- different scenarios (broadcast news, parliamentary speeches, academic lectures)
- different languages (Zh, Ar, Es)

2006: Less constraints (operating conditions)

First simultaneous translator
(real-time translation of spontaneous lectures and presentations)

Speech Translation - History (the e2e era)

2005: first ST corpora

Small size/language coverage

2016-2017: first e2e ST models

(Duong et al., 2016, Berard et al., 2016, Weiss et al., 2017, ...)
encoder-decoder architectures based on RNNs

2018: first e2e models at IWSLT

8.7 BLEU points below cascade ST solutions on En-De

2019: significant gap reduction at IWSLT

1.6 BLEU points below cascade ST solutions on En-De

2019: ST adaptation of Transformer

(Di Gangi et al., 2019)

2019-2020: new ST corpora

Larger size/language coverage

2020: the gap almost closed?

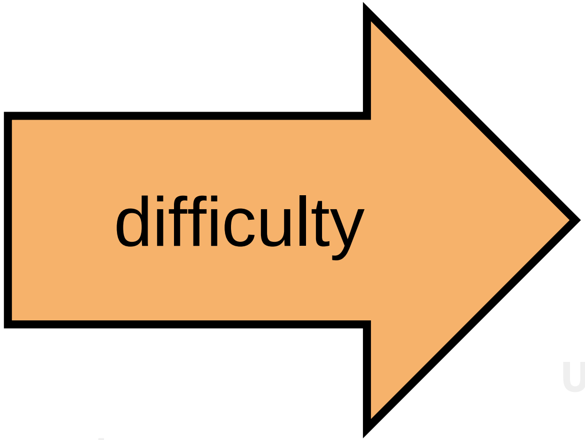
+0.24 BLEU on unsegmented En-De test data

Speech Translation - a Multi-faceted Problem

difficulty

Speech Translation - a Multi-faceted Problem

Offline	Simultaneous
Single-speaker	Multi-speaker
Clean audio	Noisy conditions
Restricted domain	Open domain
Resource-rich languages	Under-resourced languages
Low speaker variety (gender, accent, …)	High speaker variety
Unconstrained	Constrained (e.g. subtitling)
…	…



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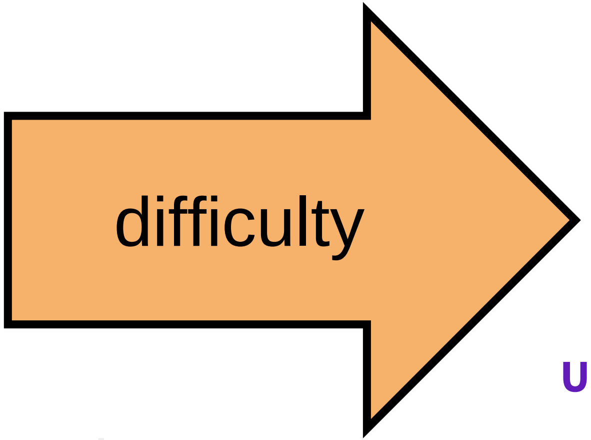

Speech Translation - a Multi-faceted Problem

Offline

Single-speaker

Clean audio

Restricted domain

Resource-rich languages

Low speaker variety (gender, accent, ...)

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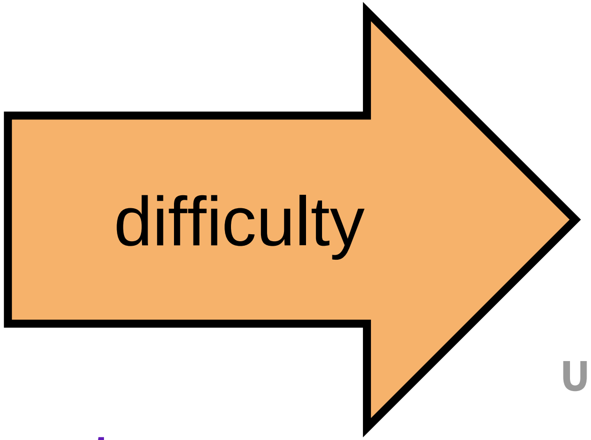

Simultaneous

Multi-speaker

Noisy conditions

Open domain

Under-resourced languages

High speaker variety

Constrained (e.g. subtitling)

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Sec 1.2

Challenges in Translation of Speech

Challenges in translation of speech

- Audio challenges
  - Multiple speaker
    - e.g. Meetings
    - Challenges:
      - Overlapping voice
  - Background noise
  - Audio segmentation

Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
    - Disfluencies
        - Hesitations: “uh”, “uhm”, “hmm”,
        - Discourse markers: “you know”, “I mean”,…
        - Repetitions: “It had, it had been a good day”
        - Corrections: “no, it cannot, I cannot go there”

    - No punctuation
        - Let’s eat Grandpa !
        - Let’s eat, Grandpa !

Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
- Error propagation
  - ASR errors worse after translation
    - More difficult to compensate by human
    - MT adds additional errors

Re**d**en (engl. speeches)

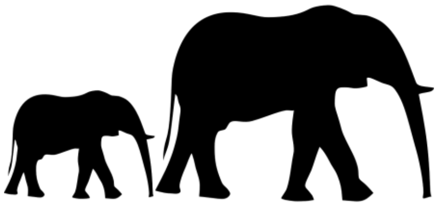
Re**b**en (engl. vines)

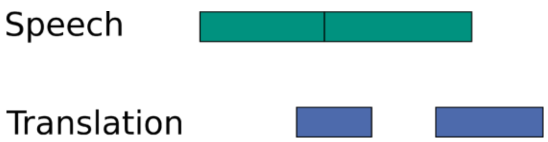
Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
- Error propagation
- Data
  - End-to-End data:
    - Growing amount but still limited
  - Integration of other data types
    - Speech transcripts
    - Parallel data

Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
- Error propagation
- Data
- Partial information
  - Online: Translate during production of speech
  - Generate translation before full sentence is known

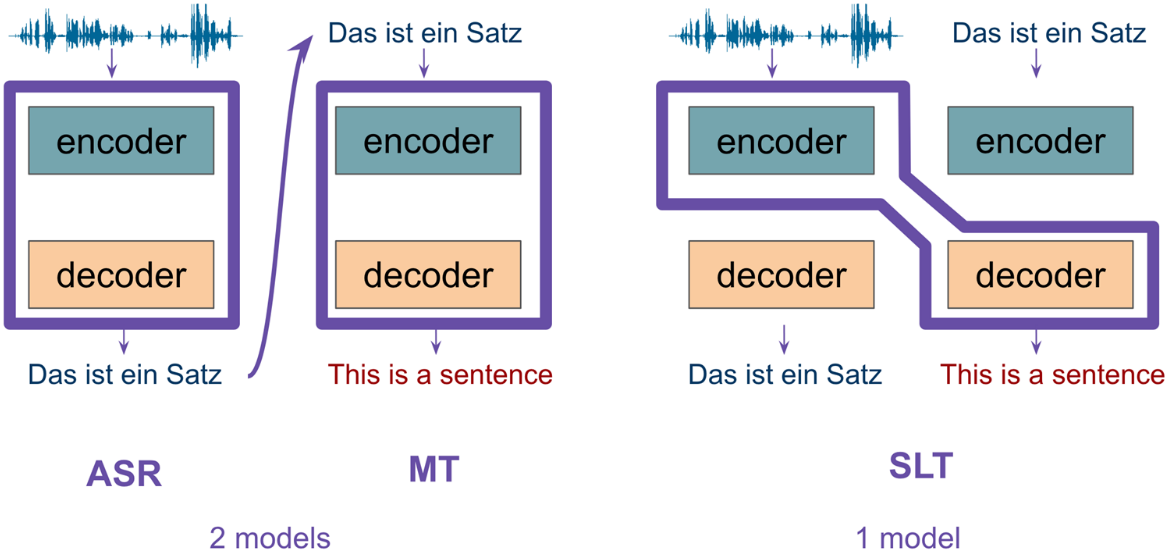




Sec 1.3

Traditional cascade approach

Traditional cascade approach



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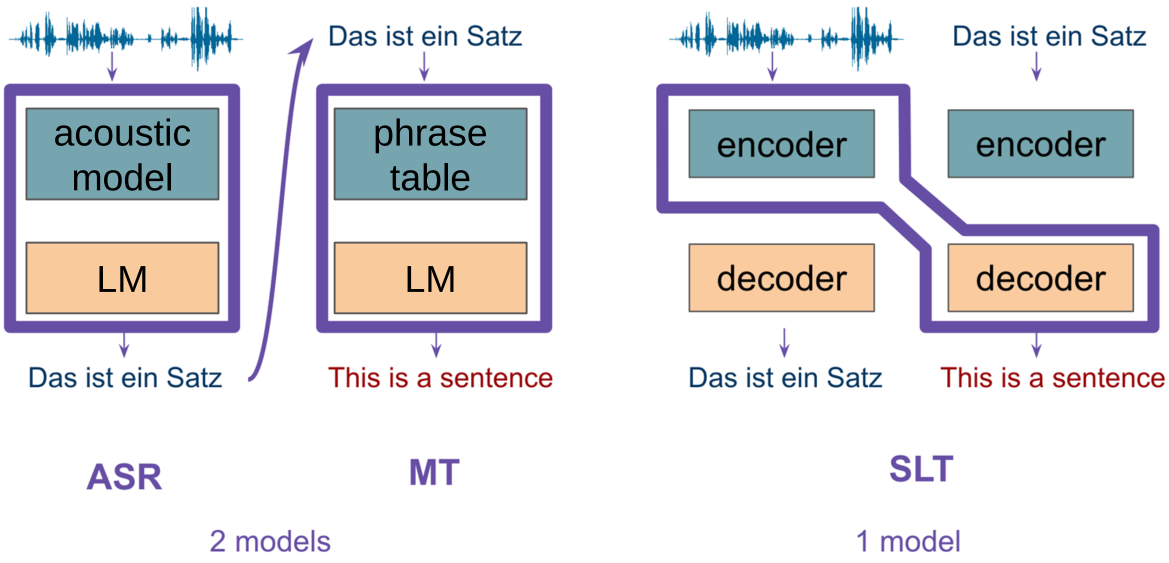


Modular, pipeline approach

ASR, MT: isolated objectives

(Waibel et al. 1991; Vidal, 1997; Ney, 1999; Saleem et al. 2004; Matusov et al. 2005; Bertoldi and Federico, 2005; Quan et al. 2005; Kumar et al. 2014; IWSLT Eval Campaigns 2004—)

Data Used

- Datasets with parallel speech + translations arose with E2E models
- Traditionally, cascades used separate datasets for their component models
- **IWSLT Evaluation Campaigns** (*2004-present*): ASR, MT, ST tasks

⊕ *many more data sources*

⊖ *data is from different domains*

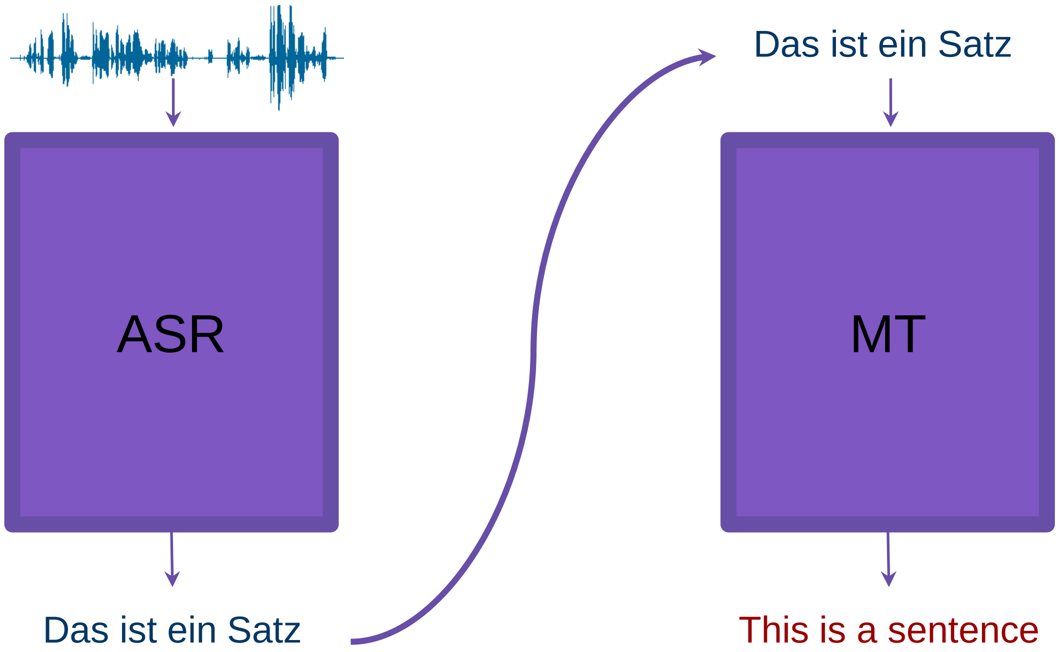
Modular Models

***Domain challenge*:** mismatch between ASR output and MT input

ASR output:
- lowercase, punctuation removed
- disfluencies (um, uh, …, repetitions, false starts)
- ASR errors

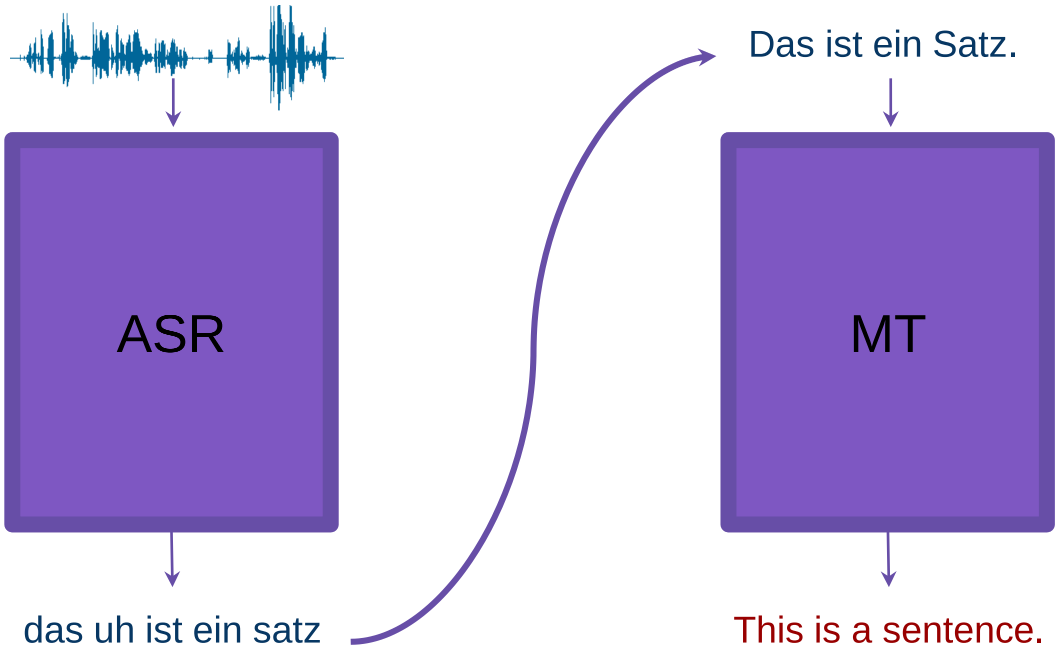
⟶ *Differing training data domains, train-test mismatch: requires adaptation!*

Modular Models



2 models

Modular Models



2 models

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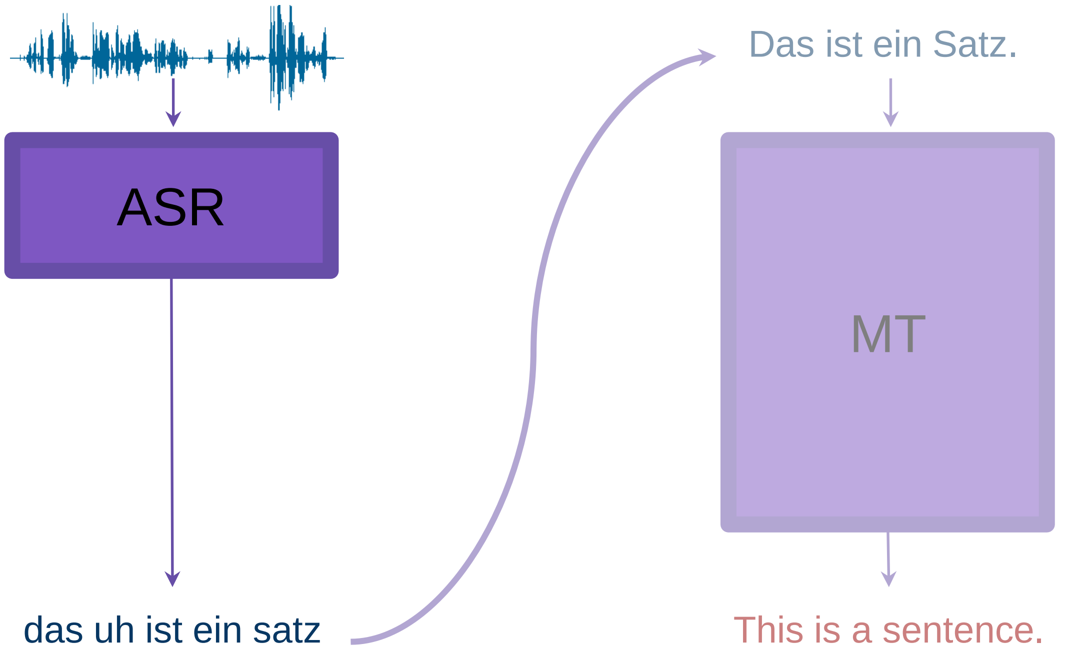
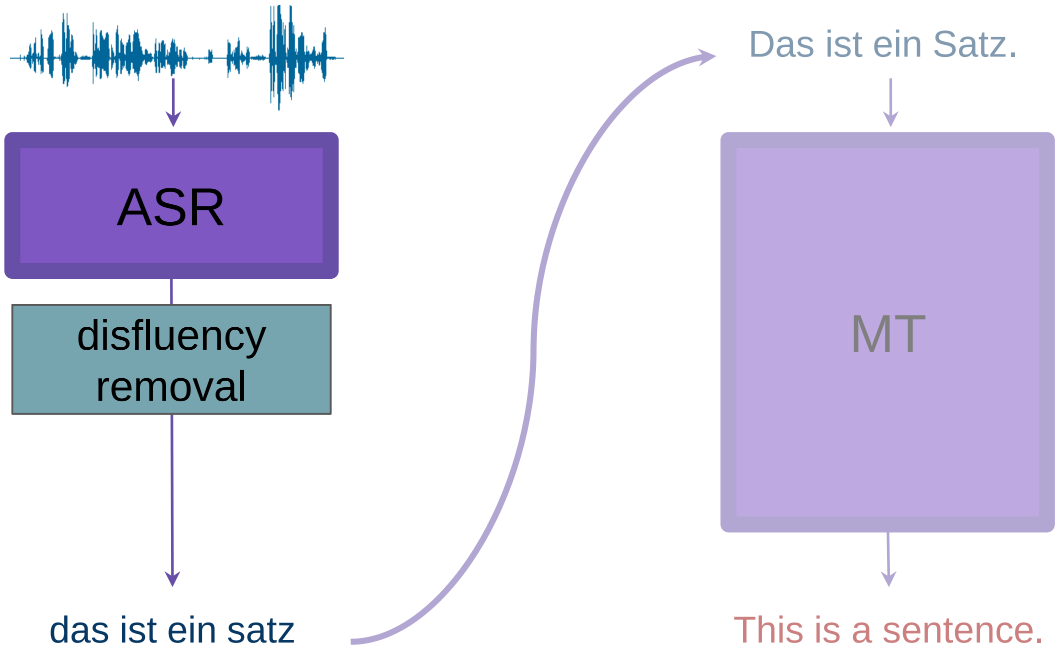
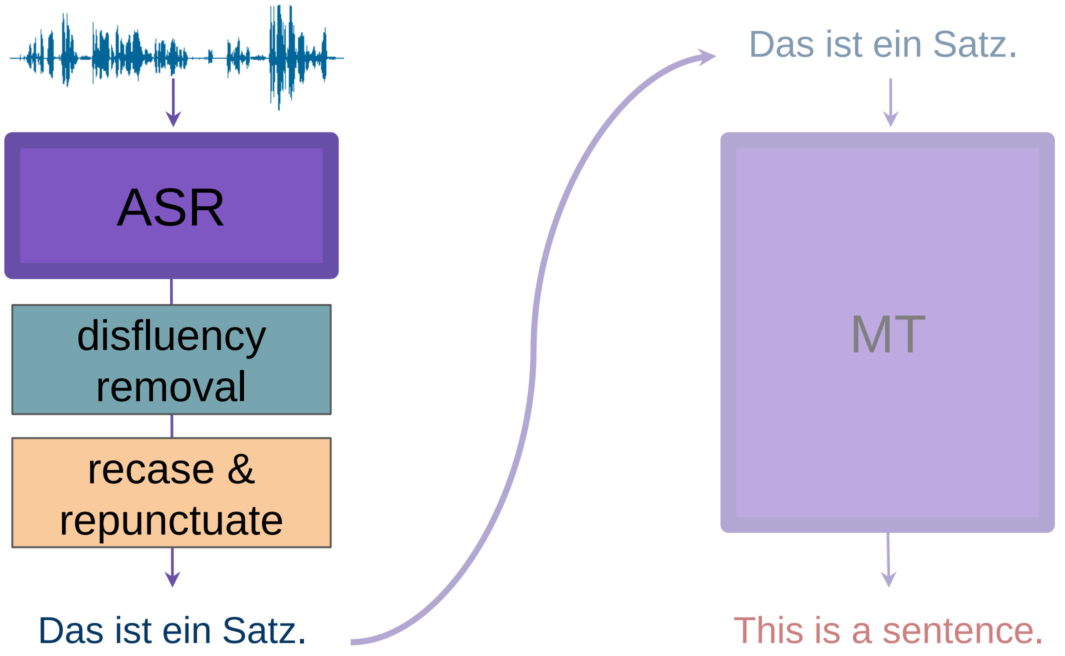


Modular Models



(Wang et al. 2010; Cho et al. 2013/2014)

Modular Models



(Cho et al. 2012; Cho et al. 2017)

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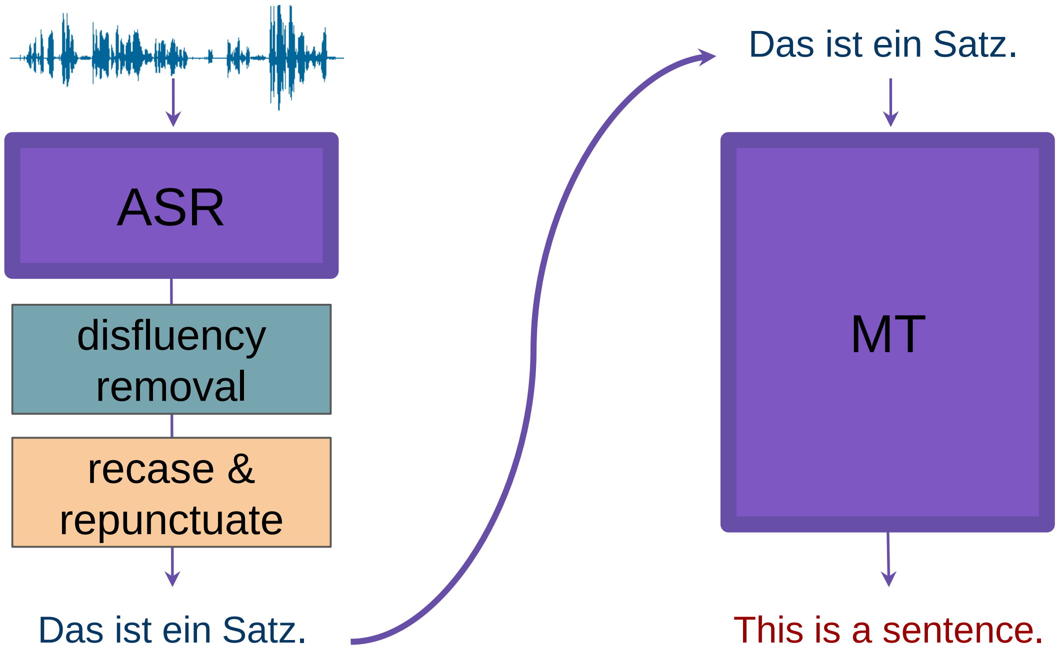

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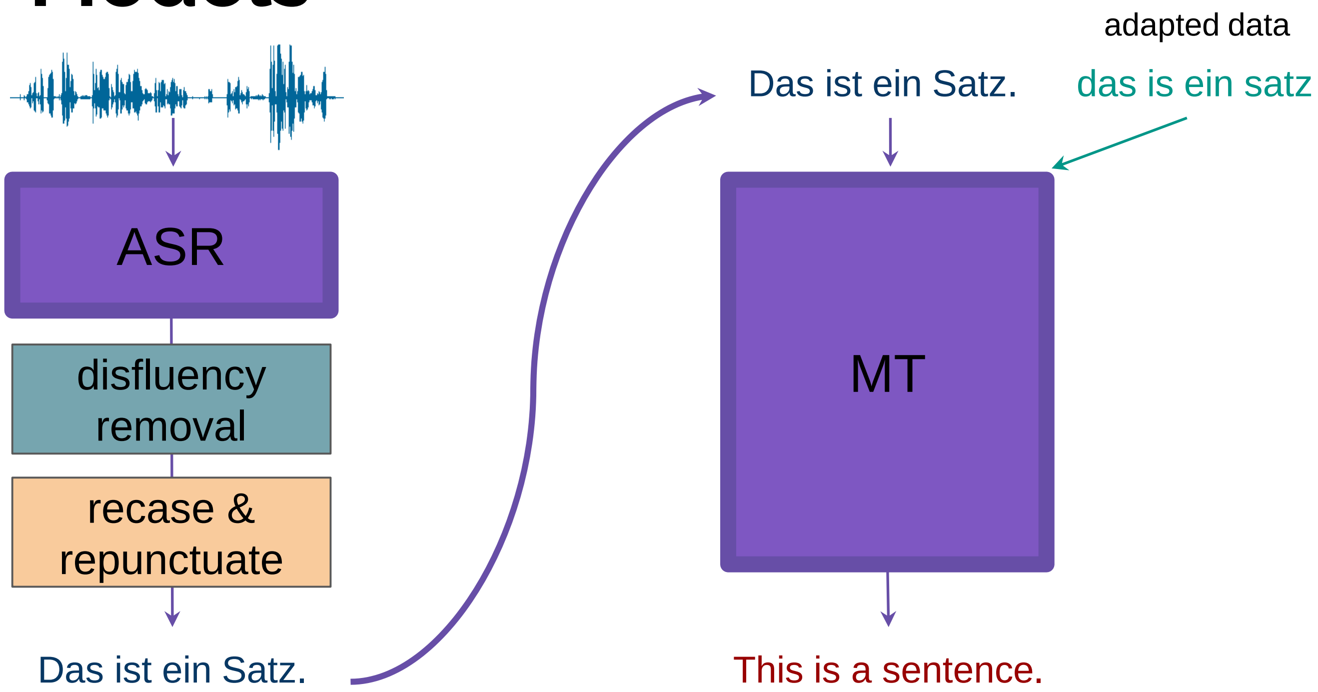
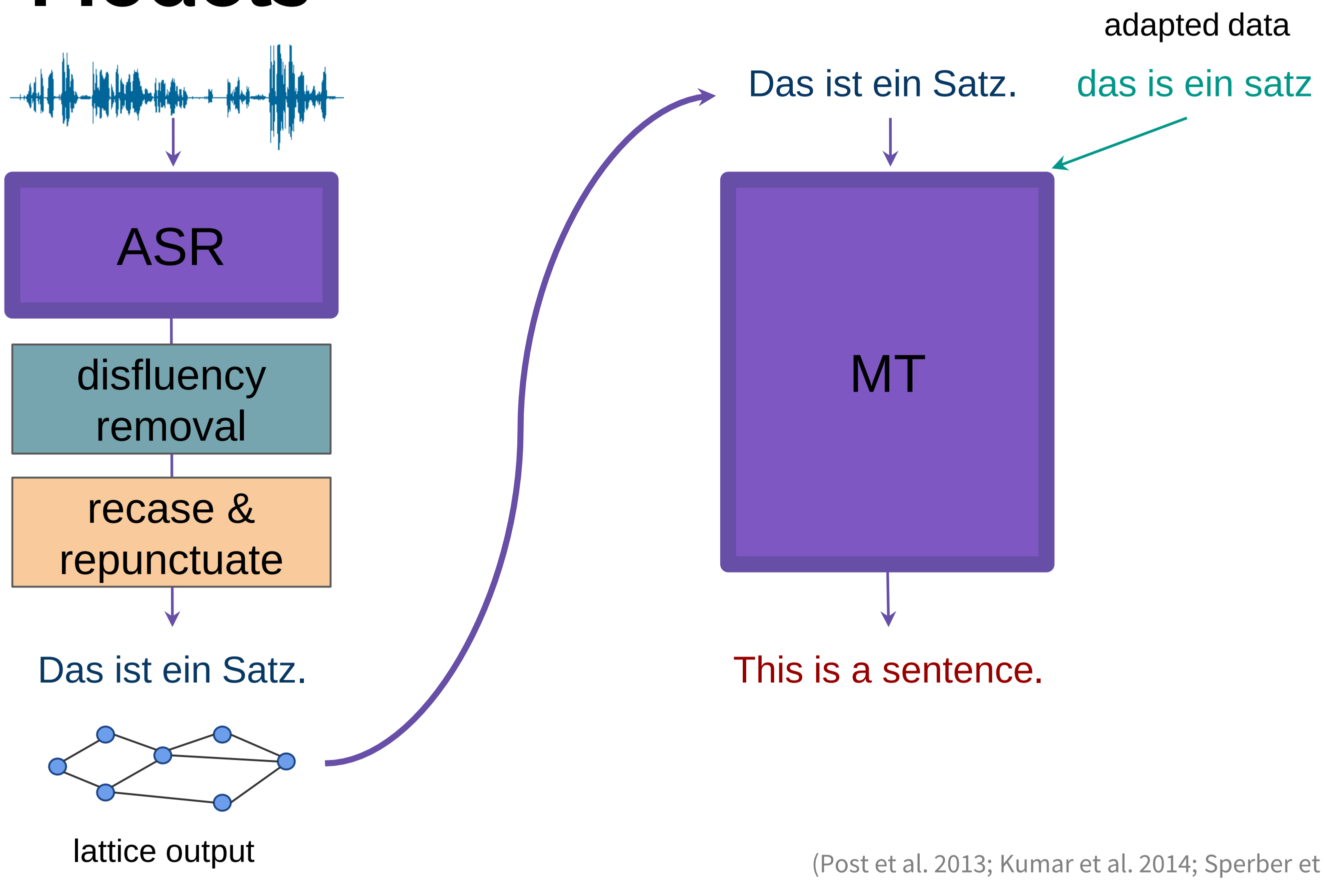


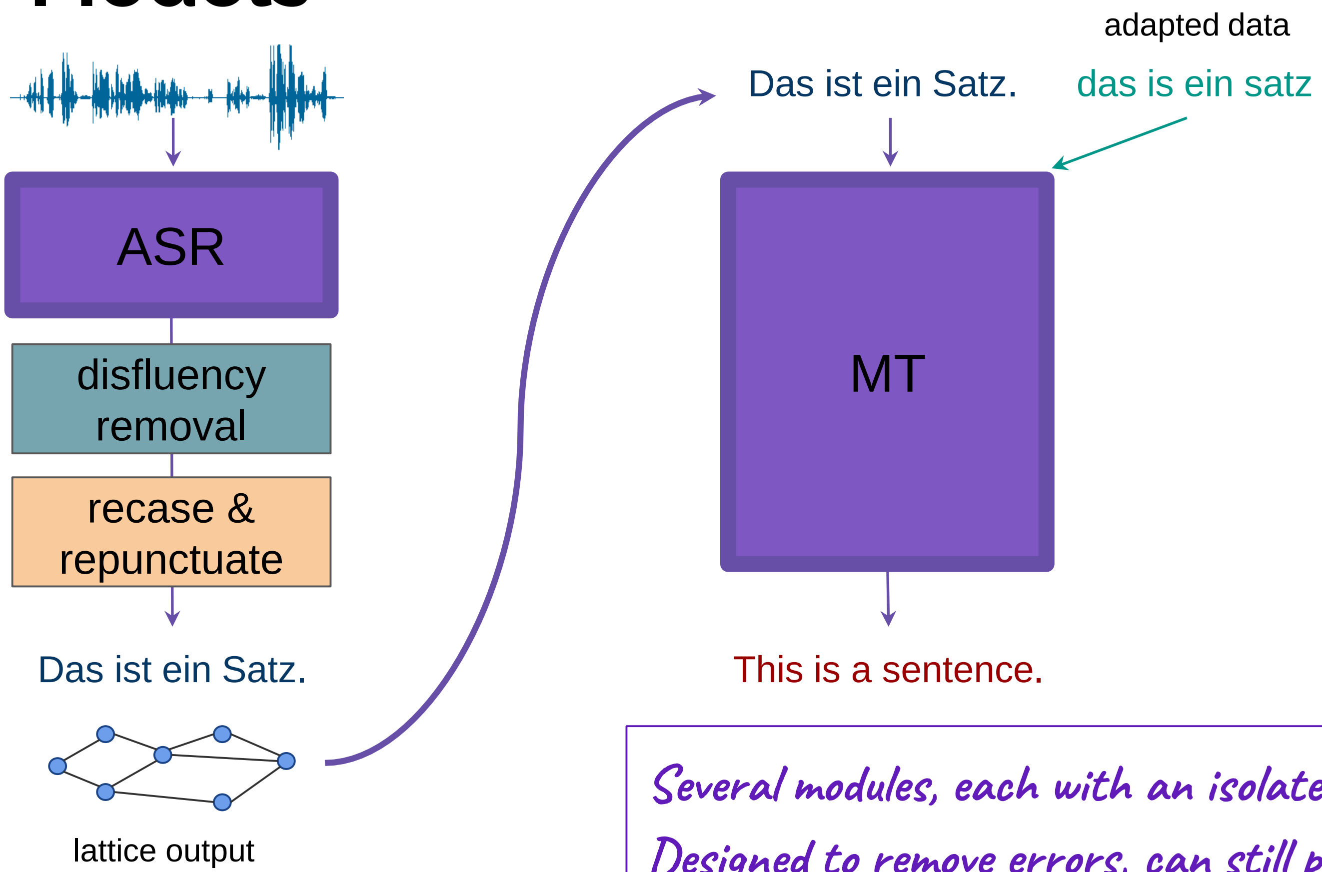
(Tsvetkov et al. 2014; Ruiz et al. 2015; Sperber et al. 2017)

Modular Models



(Post et al. 2013; Kumar et al. 2014; Sperber et al. 2017)

Modular Models



Several modules, each with an isolated task

Designed to remove errors, can still propagate

Sec 2:

End-to-End

Current state

Input representations

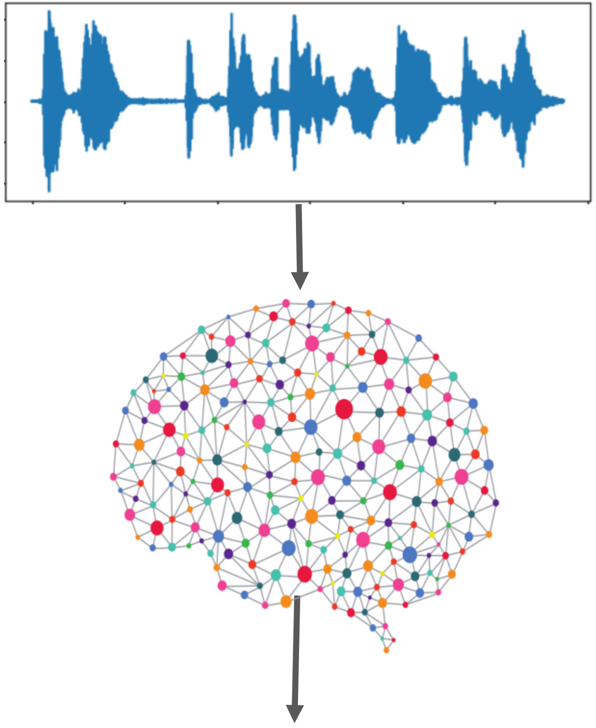
Architecture modifications

Output representations

Sec 2.1

Current state

End-to-end SLT (Bérard et al., 2016; Weiss et al., 2017)



What a wonderful tutorial!

Definition of end-to-end approach

IWSLT 2020 (Ansari et al., 2020)

End-to-end model:

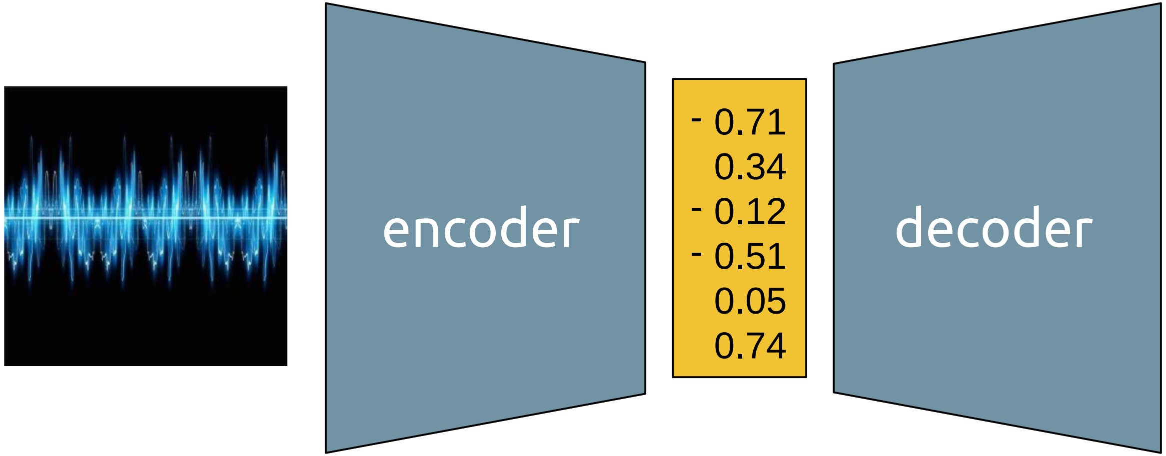
- No intermediate discrete representations (transcripts like in cascade or multiple hypotheses like in rover technique)
- All parameters/parts that are used during decoding need to be trained on the end2end task (may also be trained on other tasks → multitasking ok, LM rescoring is not ok)

Other definitions are possible depending on the application

end-to-end speech translation (e2e)

Spanish Audio

English
Translated text



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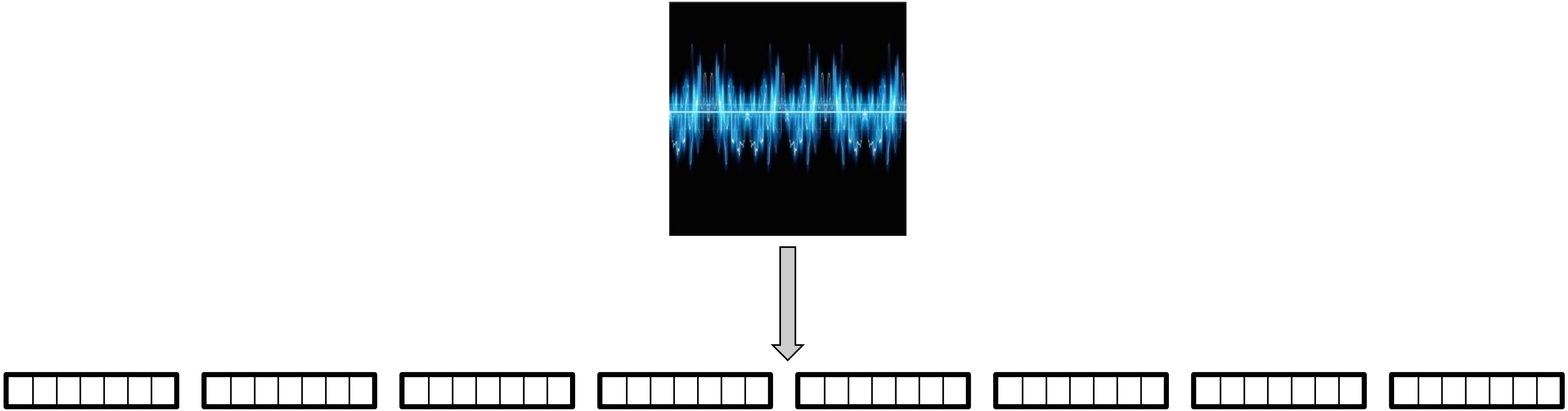
end-to-end speech translation (e2e)



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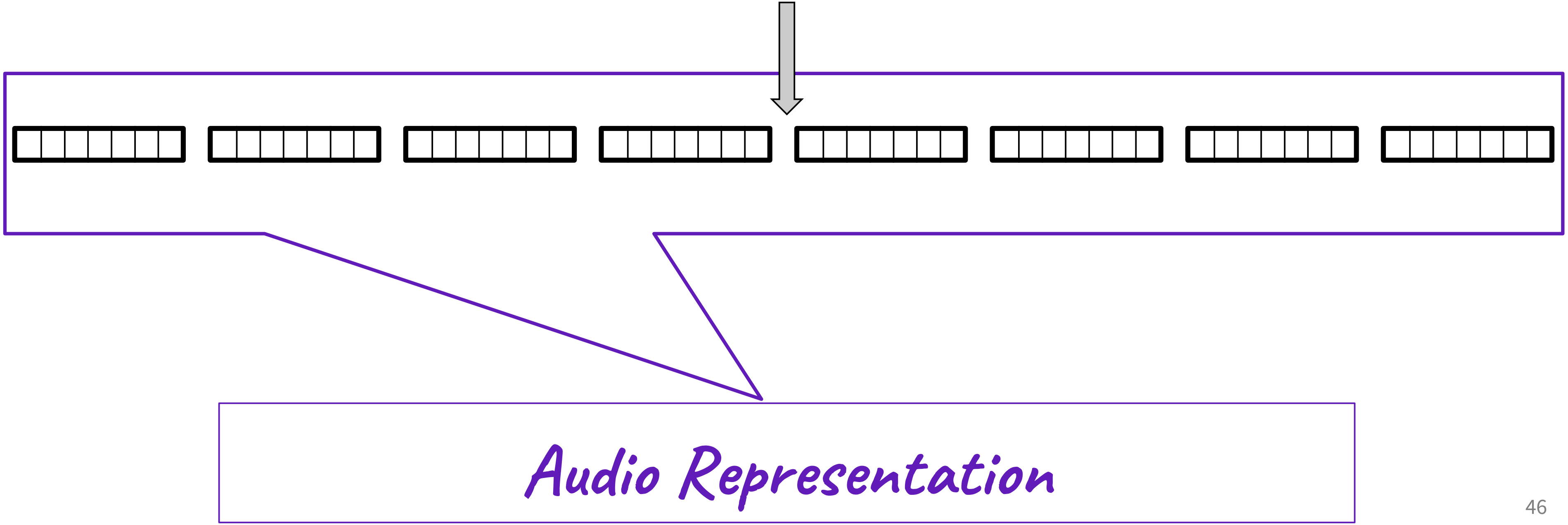
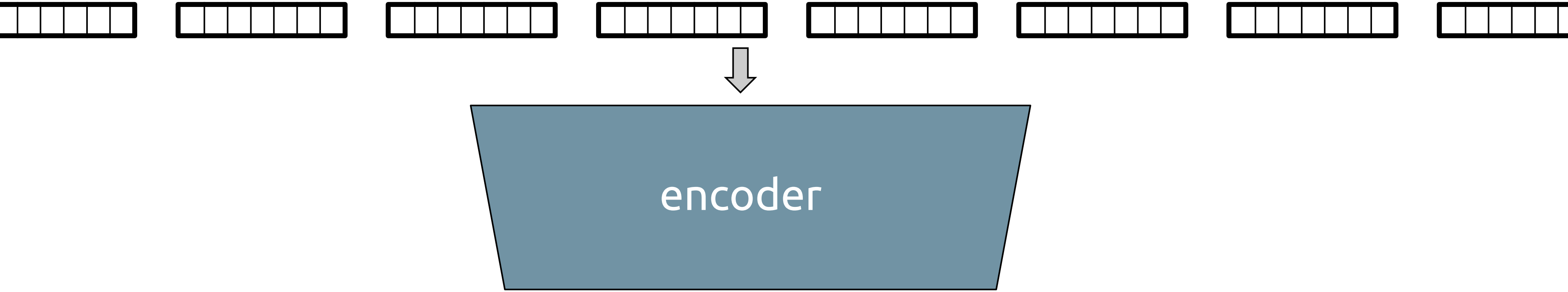


end-to-end speech translation (e2e)



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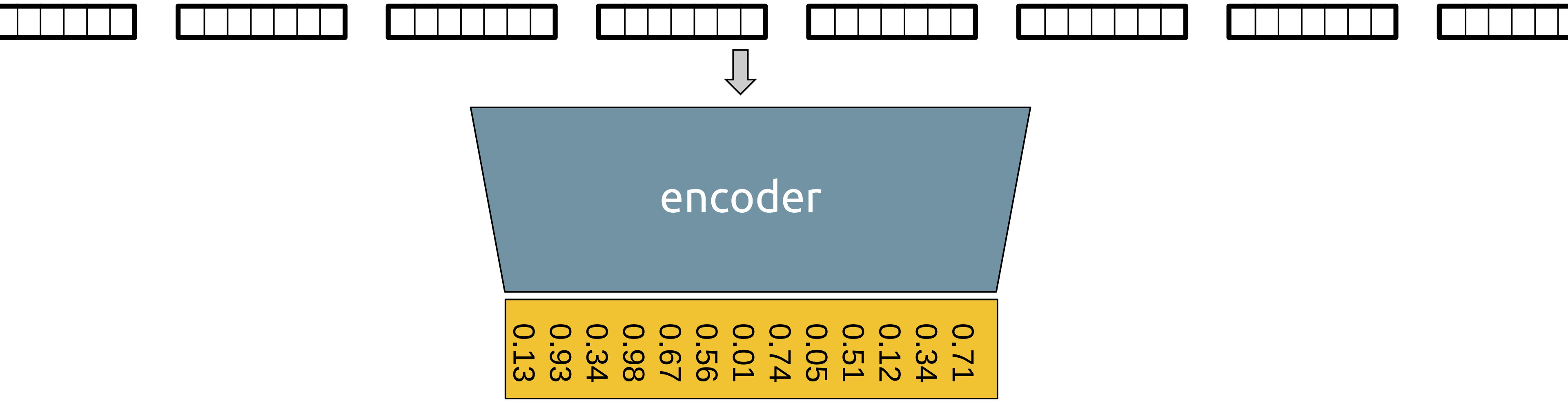

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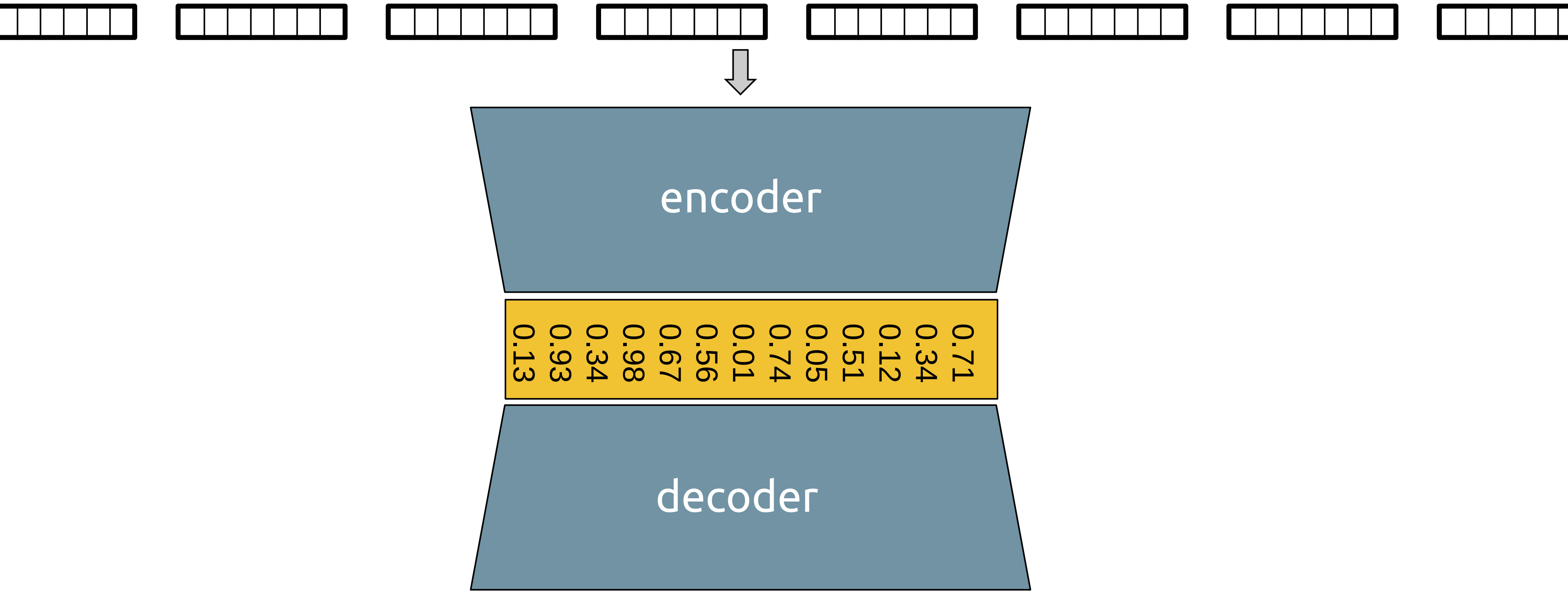

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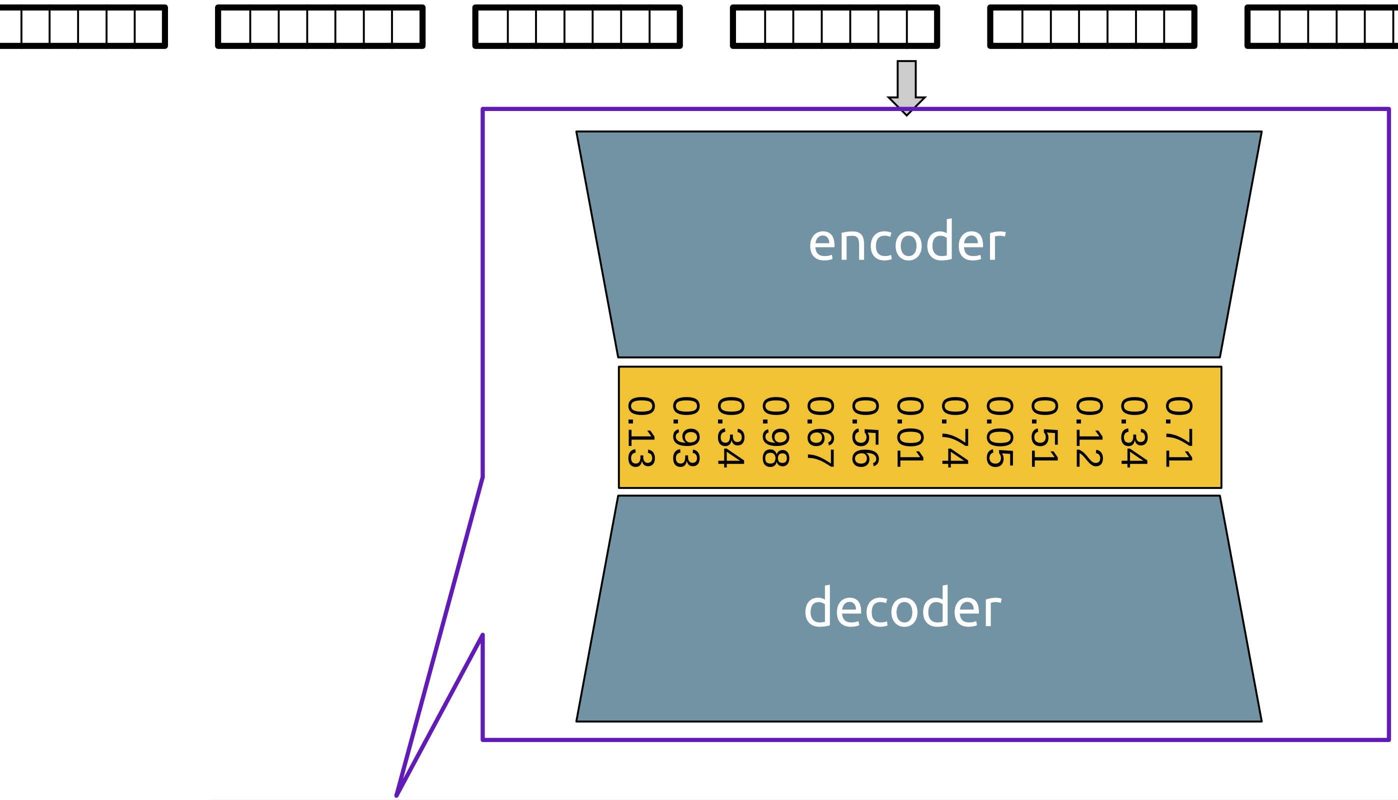
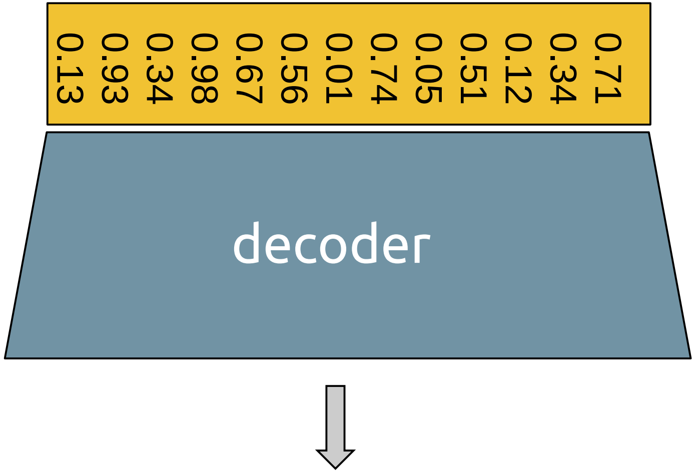


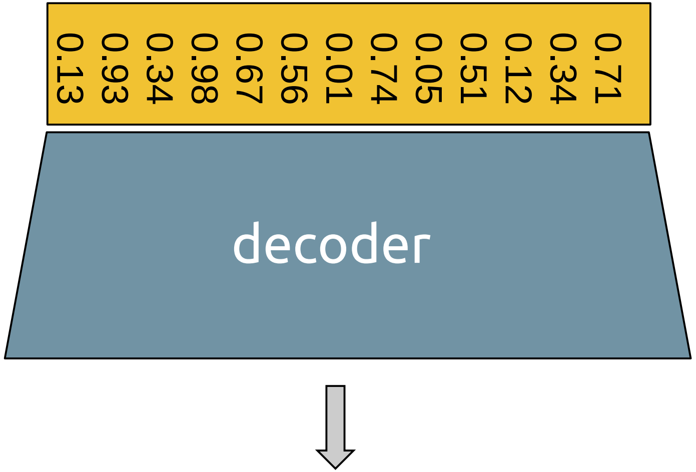
System Architectures

end-to-end speech translation (e2e)



W h a t <space> a <space> w o n d e r f u l <space> t u t o r i a l !

end-to-end speech translation (e2e)



Wh @at a w @on @der @fu @l tut @or @ial!

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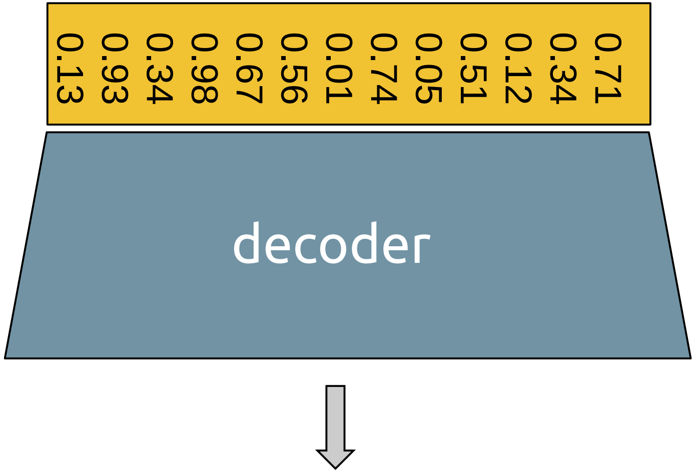

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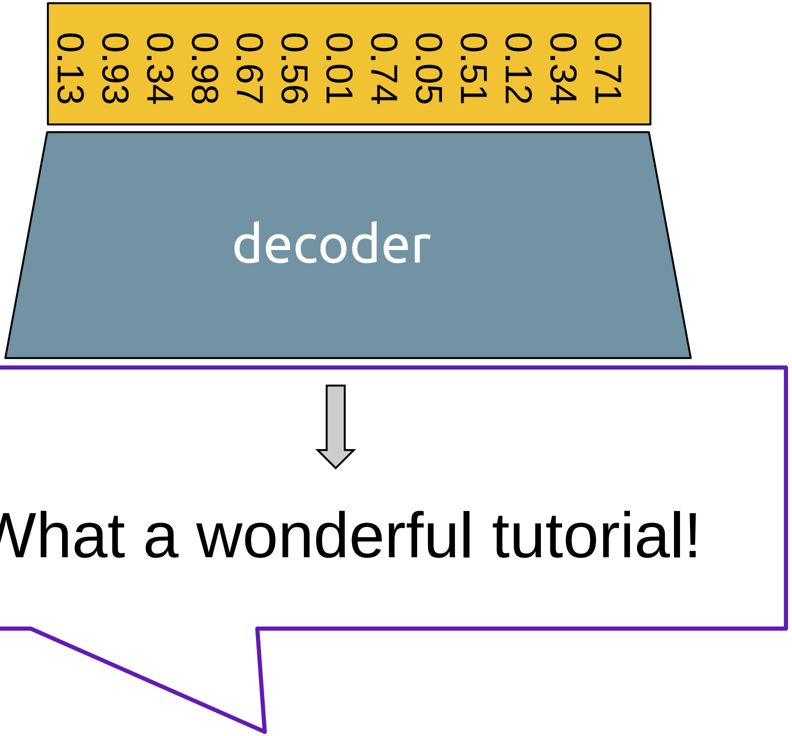
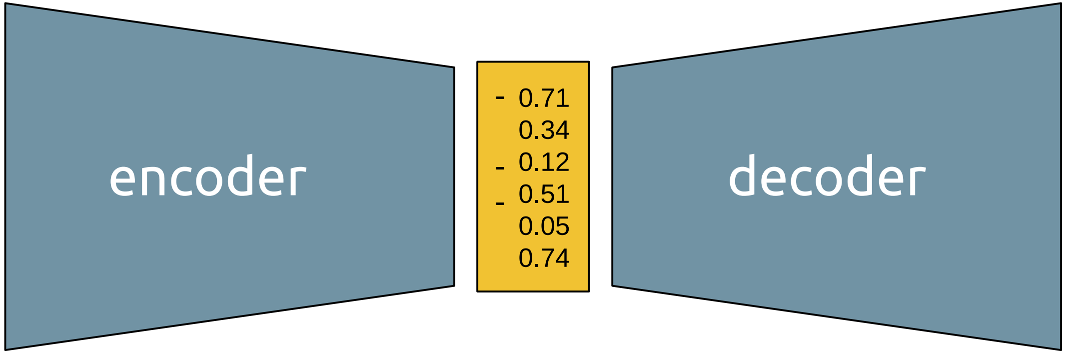


Output Representation

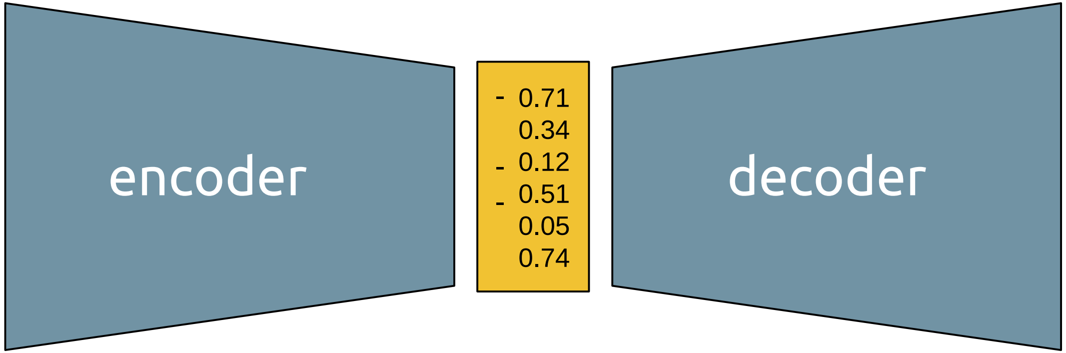
Sequence-to-Sequence Model



Pros:

- Direct access to the audio during translation
- No error propagation
- One system to maintain

Sequence-to-Sequence Model



Pros:

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Cons:

- Less consolidated technology
- Scarcity of training data
- Non-monotonic alignments audio-text

Cascade vs End-to-End Systems

Cascade

- ✓ Large corpora for ASR and MT
- ✓ Less complex tasks
- ✕ Error propagation
- ✕ Information loss
- ✕ Higher latency

End-to-End

- ✓ Access to all audio information
- ✓ Reduced latency
- ✓ Easier management
- ✕ Small corpora
- ✕ More complex task

Cascade vs End-to-End Systems

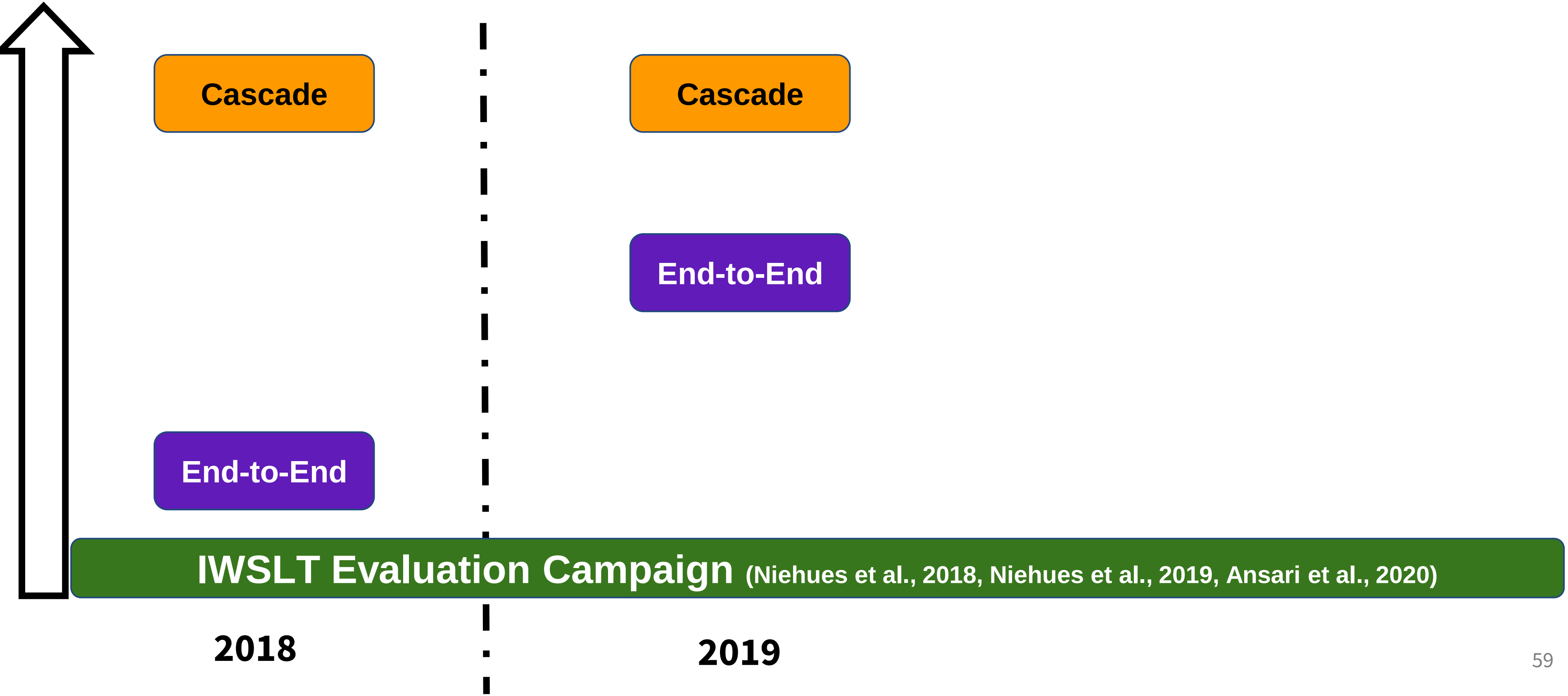
Cascade

End-to-End

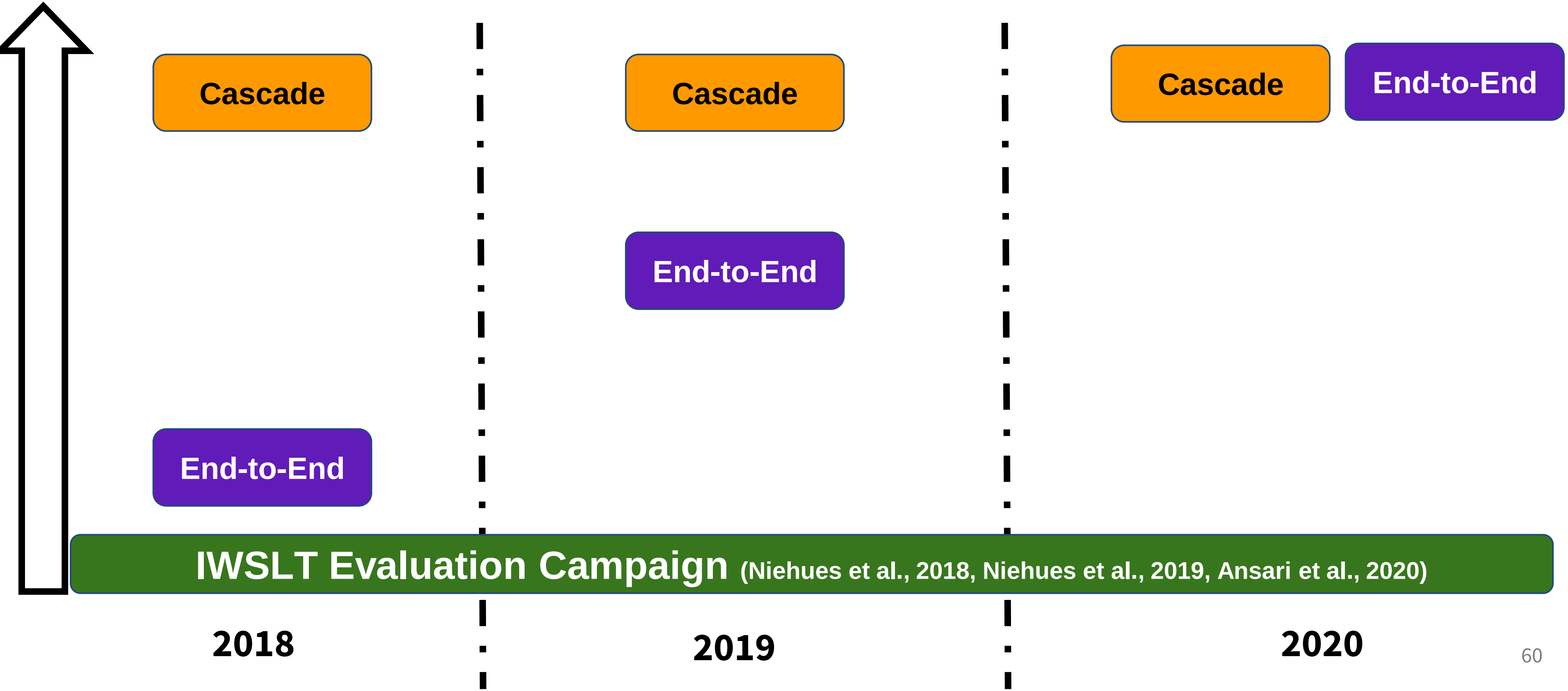
IWSLT Evaluation Campaign (Niehues et al., 2018, Niehues et al., 2019, Ansari et al., 2020)

2018

Cascade vs End-to-End Systems



Cascade vs End-to-End Systems



Cascade vs End-to-End Systems

Most of the papers (Weiss et al., 2017, Jia et al., 2019, Di Gangi et al., 2019) about end-to-end SLT system mention the following advantages over the cascade:

- No error propagation:

  End-to-end naturally avoids compounding errors between the ASR and MT systems.

Cascade vs End-to-End Systems

Most of the papers (Weiss et al., 2017, Jia et al., 2019, Di Gangi et al., 2019) about end-to-end SLT system mention the following advantages over the cascade:

- No error propagation:

  End-to-end naturally avoids compounding errors between the ASR and MT systems

- Direct access to the audio:

  End-to-end better manipulates paralinguistic and non-linguistic information during translation

The correctness of these statements taken for granted

Cascade vs End-to-End Systems

Key questions:

Is it true that end-to-end avoids error propagation?

To what extent does accessing the audio help? How? When?

Cascade vs End-to-End Systems

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Is it true that end-to-end avoids error propagation?

To what extent does accessing the audio help? How? When?

No answers in this tutorial!

No error propagation

Open issues:

- Overall translation quality is not enough to measure the reduction of error prop.

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- Not a consolidated architecture in end-to-end technology

No error propagation

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- Difficult to disentangle the impact of various components in e2e (two tasks collapsed into one)
- Not a consolidated architecture in end-to-end technology

Possible opening:

Sperber et al., (2019) consider the encoder output as an intermediate representation and pose the attention on the presence of errors in it

Direct access to the audio

Open issues:

- Better encoder technology results in better translation performance (not enough)

Direct access to the audio

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- Not clear what aspects of the audio can help (e.g. prosody, emotions, tone, pauses)

Direct access to the audio

Open issues:

- Better encoder technology results in better translation performance (not enough)
- Not clear what aspects of the audio can help (e.g. prosody, emotions, tone, pauses)
- Audio understanding capability can only be analyzed in the final translation (no transcripts)

Direct access to the audio

Open issues:

- Better encoder technology results in better translation performance (not enough)
- Not clear what aspects of the audio can help (e.g. prosody, emotions, tone, pauses)
- Audio understanding capability can only be analyzed in the final translation (no transcripts)
- Lack of *ad hoc* test sets to measure the impact of prosody, emotions, ...

Direct access to the audio

Open issues:

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- Not clear what aspects of the audio can help (e.g. prosody, emotions, tone, pauses)
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Possible openings:

Karakanta et al. (2020): the direct access to the audio pauses improves subtitles' quality

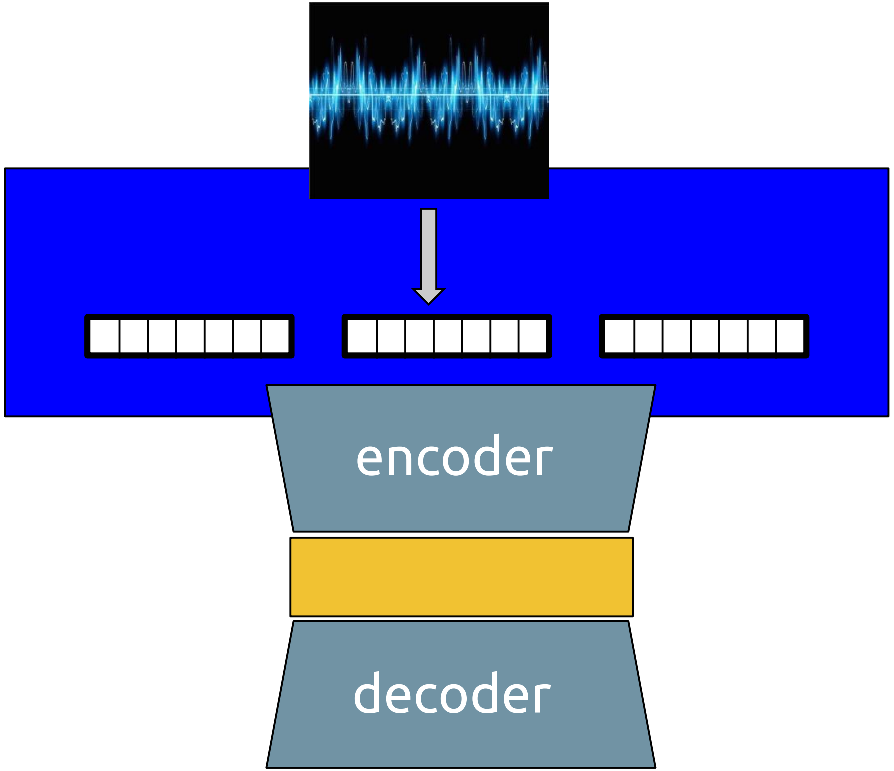
Gaido et al. (2020): vocal characteristics can guide e2e systems in modeling gender (but opens ethical issues!)

Sec 2.2

Input representations

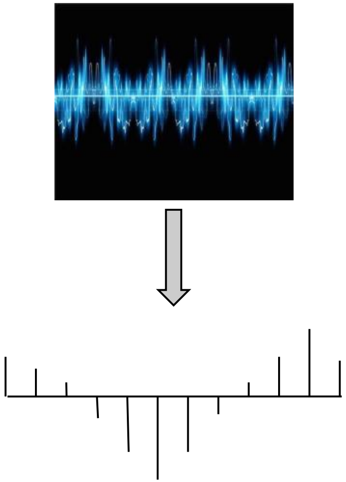
From text translation to speech translation

- Encoder-decoder models:
  - Can apply similar techniques
- Main differences to text translation
  - Input: Audio signal
    - Continuous
    - Longer



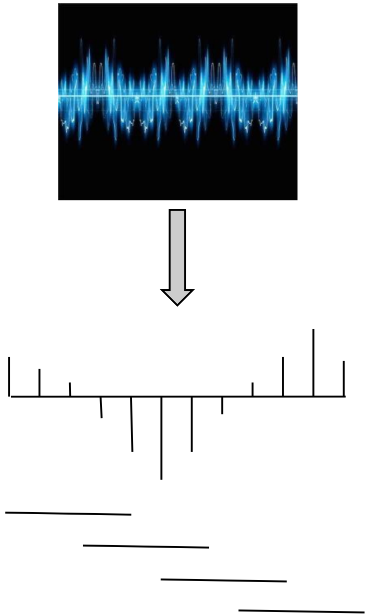
Audio representation

- Following best-practice from ASR
- Sampling
  - Measure Amplitude of signal at time t
  - Typically 16 kHz



Audio representation

- Following best-practice from ASR
- Sampling
  - Measure Amplitude of signal at time t
  - Typically 16 kHz
- Windowing
  - Split signal in different windows
    - Length: ~ 20-30 ms
    - Shift: ~ 10 ms
- Result:
  - One representation every 10 ms

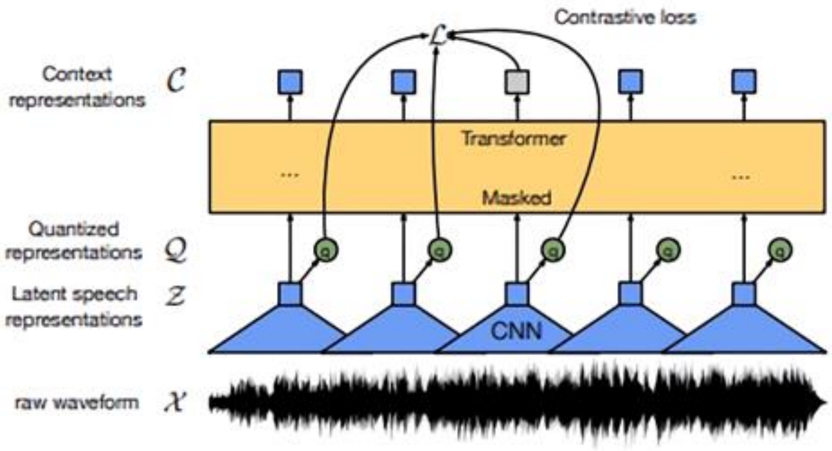


Audio representation

- Input features:
  - Signal processing:
    - Most common:
      - Mel-Frequency Cepstral Coefficients (MFCC)
      - Log mel-filterbank features (FBANK)
    - Idea:
      - Analyse frequencies of the signal
    - Steps:
      - Discrete Fourier Transformation
      - Mel filter-banks
      - Log scale
      - (Inverse Discrete Fourier Transformation)
    - Size:
      - 20-100 features per frame

Audio representation

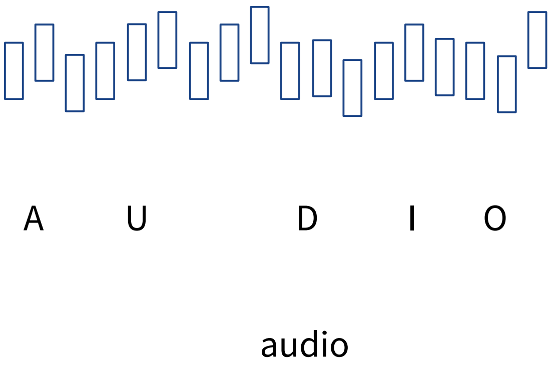
- Input features:
  - Signal processing:
  - Deep Learning:
    - Self-supervised Learning
      - Predict frame based on context
    - E.g. Wav2Vec 2.0 (Baevski et al., 2020)



Baevski et al. 2020

Challenges

- Variation
  - Many different ways to speech same sentence
  - Data augmentation
- Sequence Length
  - IWSLT test set 2020
    - Segments: 1804
    - Words: 32.795
    - Characters: 149.053
    - Features: 1.471.035
  - Architectural changes

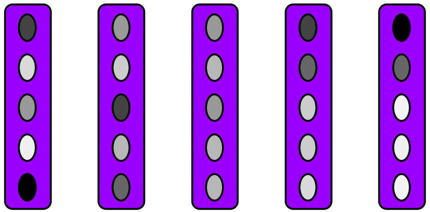


Data augmentation

- Limited training data
- Generate synthetic training data
- ASR investigated several possibilities
  - Noise injection (Hannun et al., 2014)
  - Speed perturbation (Ko et al., 2015)
- Successful technique in deep learning ASR
  - SpecAugment (Spark et al., 2019)
  - Also applied in ST (Bahar et al, 2019)

SpecAugment

- Directly applied on audio features
- Idea:
  - Mask information



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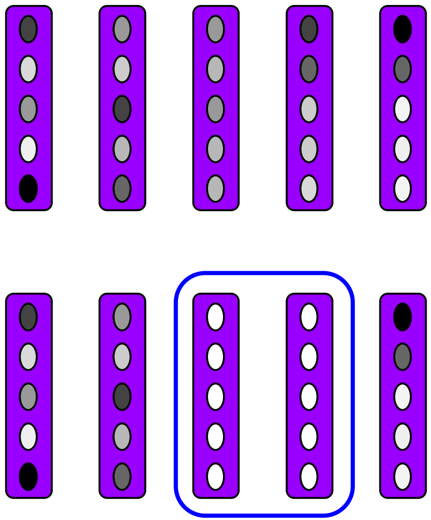
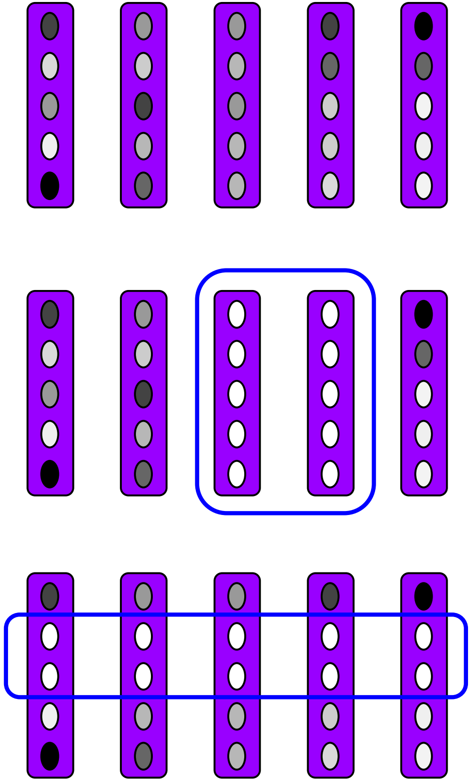


- *Time masking*
  - Set several consecutive feature vector to zero

SpecAugment

- Directly applied on audio features
- Idea:
  - Mask information

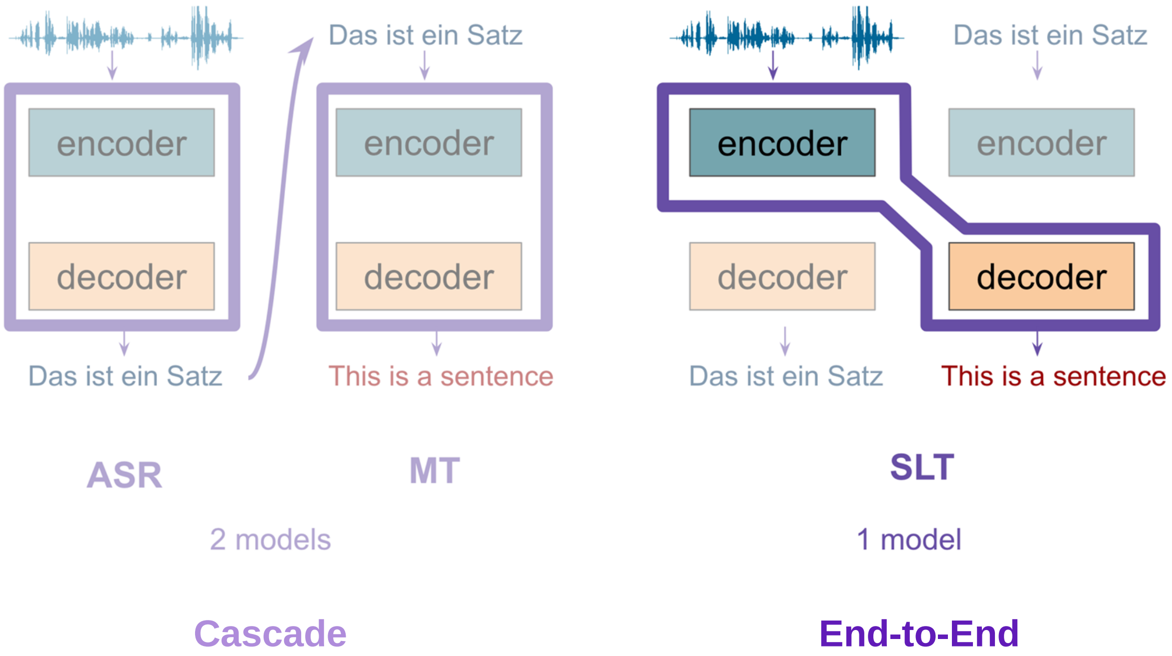


- *Time masking*
  - Set several consecutive feature vector to zero
- *Frequency masking*
  - Mask consecutive frequency channels

Sec 2.3

Architecture & Modifications

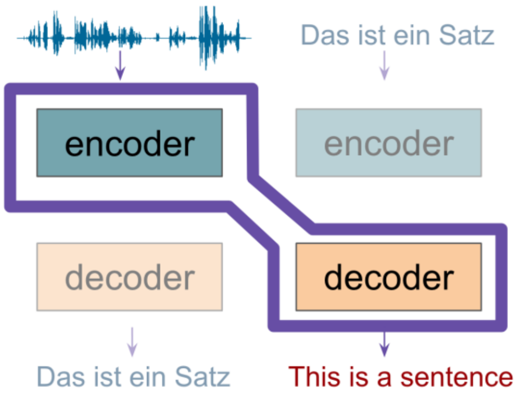
End-to-End Architecture



End-to-End Architecture

LSTM or Transformer
Encoder-Decoder Models

However, speech ≠ text

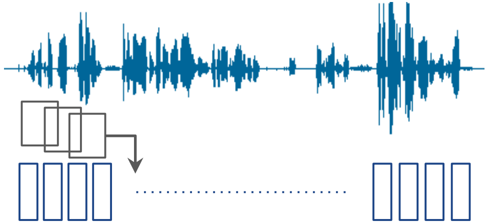


SLT

1 model

End-to-End

Speech vs. Text

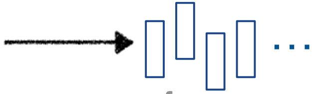


Discretized audio — speech frames

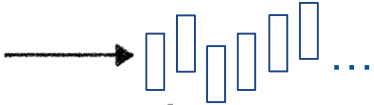
Speech features ~8-10x longer than
the equivalent character sequences

c h a r a c t e r s

SPEECH:

p 

frames

o 

frames

TEXT:

p → p

Each feature vector is unique,
Number of feature vectors per phone varies

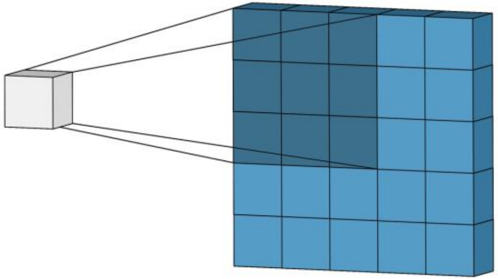
Challenges

- Sequence length:
  - increased memory requirements
  - greater distance between dependencies
- Redundancy:
  - adds task for model to learn
- Variation:
  - requires more data for model to learn correspondences

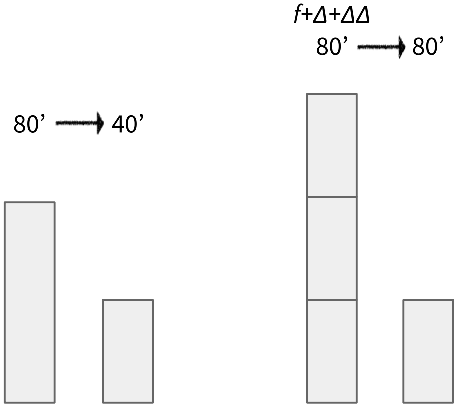
Dimensionality Reduction

Two directions: ① temporal and ② feature dimension

Convolutional layers enable *fixed-length downsampling*



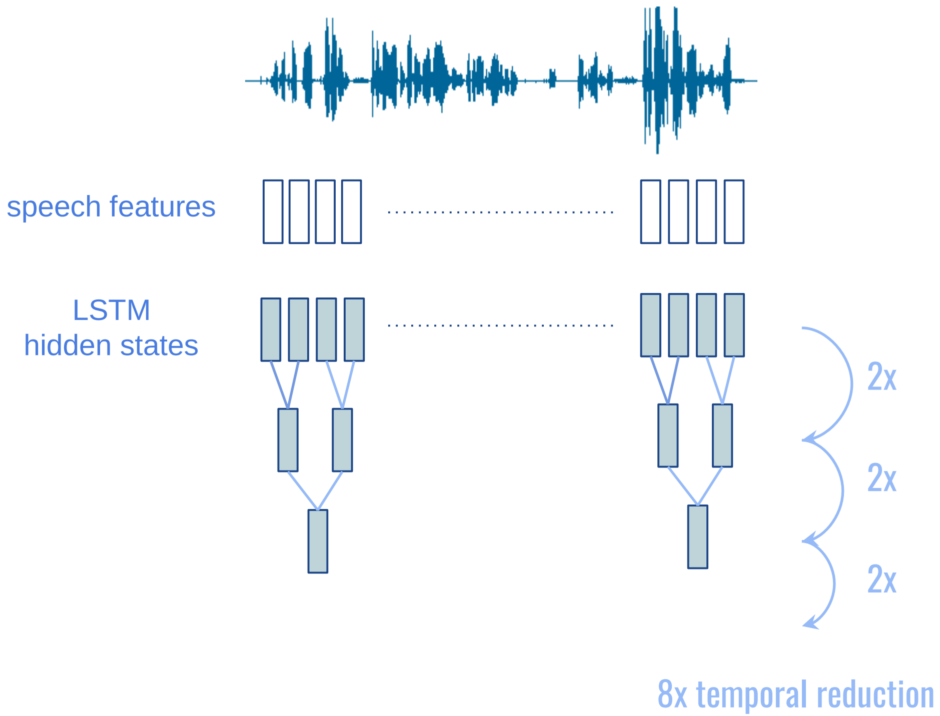
Scale sequence length and feature dimension linearly by a factor corresponding to the convolutional kernel size and stride length



Conv1D, ConvLSTM layers

(Weiss et al. 2017; Bansal et al. 2018)

Pyramidal Encoder



- Motivation: do not need attention to the granularity of speech features
- Reduce dimensionality *through* encoder

  - concatenation
  - sum
  - skip
  - linear projection

Linear projection, ASR:
(Zhang et al. 2017; Sperber et al. 2018)

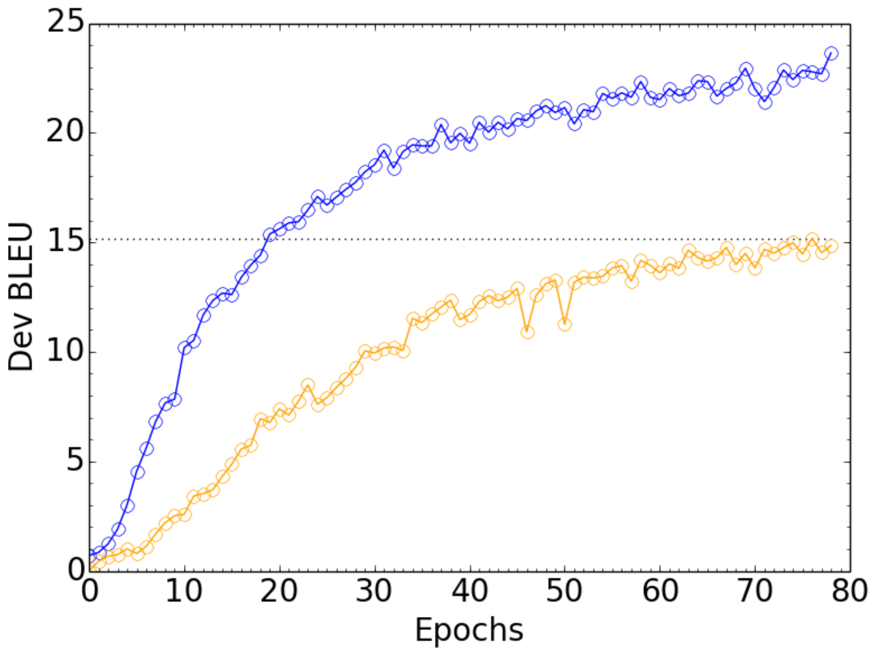
Pyramidal encoder in ST:
(Weiss et al. 2017; Salesky et al. 2019;
Sperber et al. 2019; Salesky et al. 2020)

Listen, Attend, and Spell
(Chan et al. 2015)

Dimensionality Reduction Impact

Improved training efficiency!

- Reduces memory footprint
- Faster convergence
- Improved results



(Salesky et al. 2019)

Encoder and Decoder Depth

MT: typically same depth for encoder and decoder

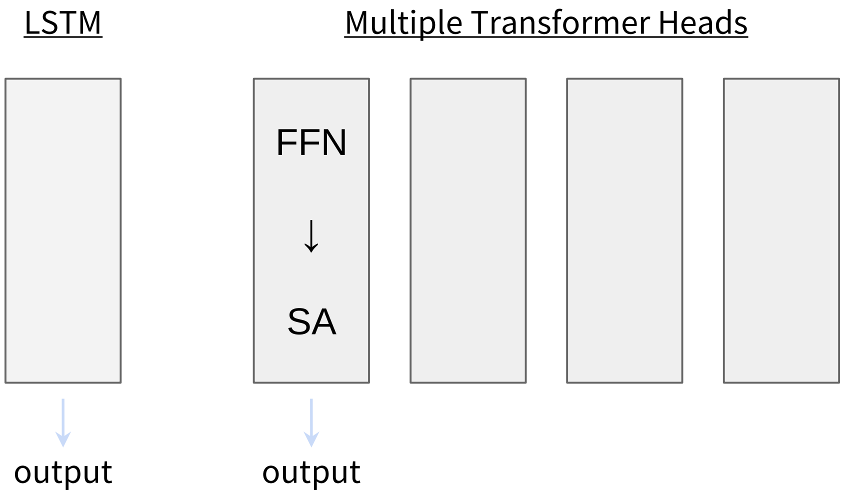
ST: empirically, deeper encoders than decoders perform better!

⟶ *more parameters allocated to learning more complicated associations between inputs*

Models	Test WER
CTC [19]	17.4
CTC/LM + speed perturbation [19]	13.7
12Enc-12Dec (Ours)	14.2
Stc. 12Enc-12Dec (Ours)	12.4
Stc. 24Enc-24Dec (Ours)	11.3
Stc. 36Enc-12Dec (Ours)	**10.6**

(Zhang et al. 2017; Pham et al. 2018)

LSTM → Transformer



Transformer-S

- 2D Convolutions
- Distance penalty for attention
- 2D self-attention

…

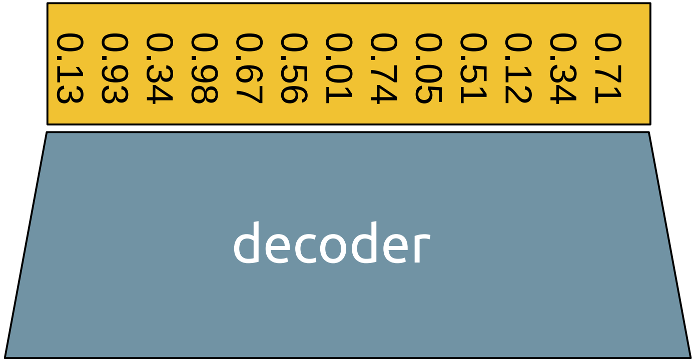
Conv-Transformer

(DiGangi et al. 2019; Huang et al. 2020)

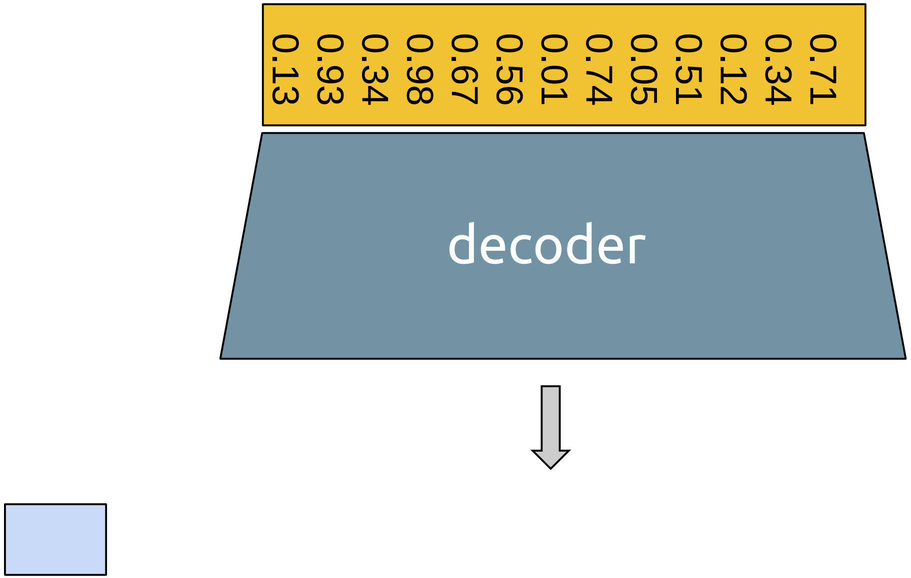
Sec 2.4

Output representations

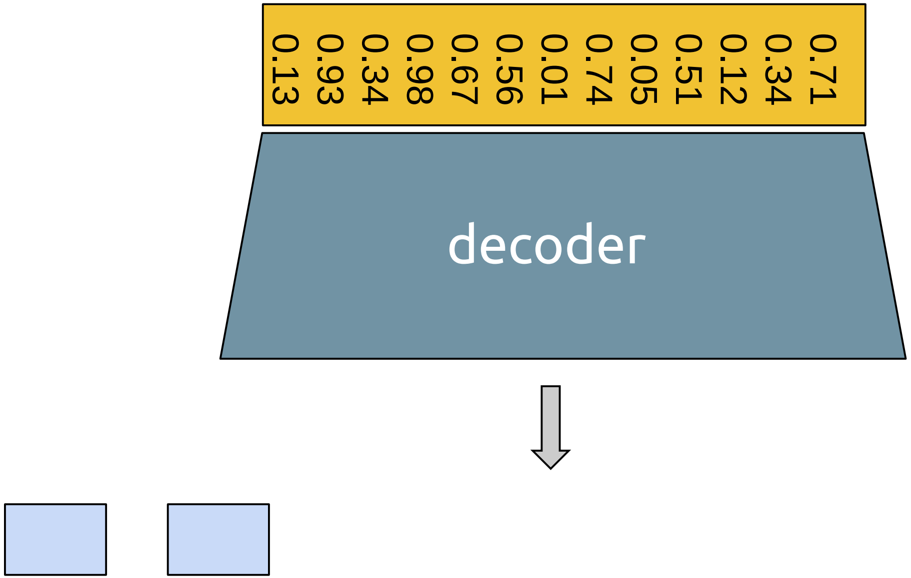
Output representation



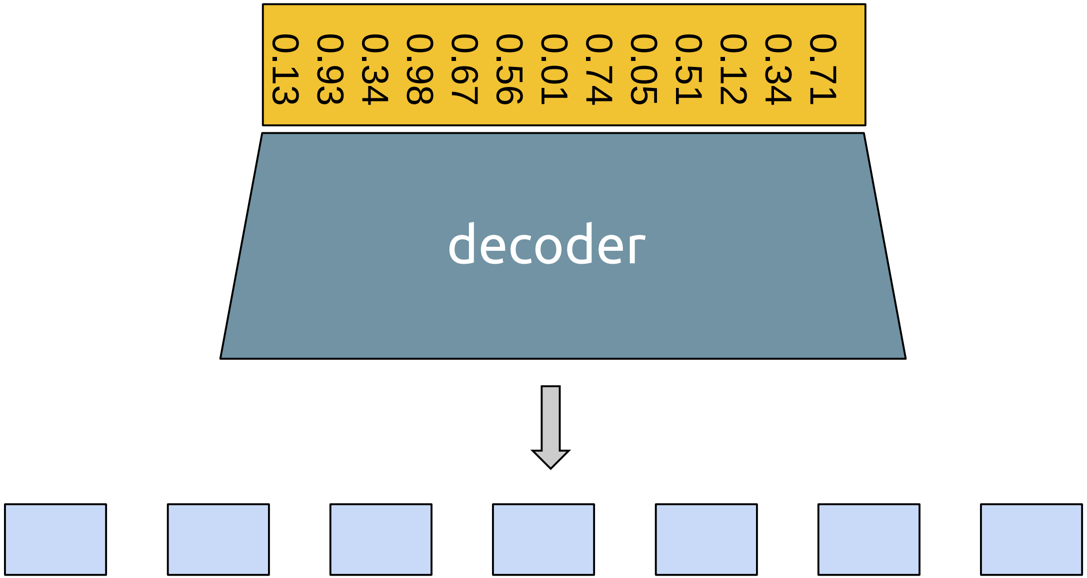
Output representation



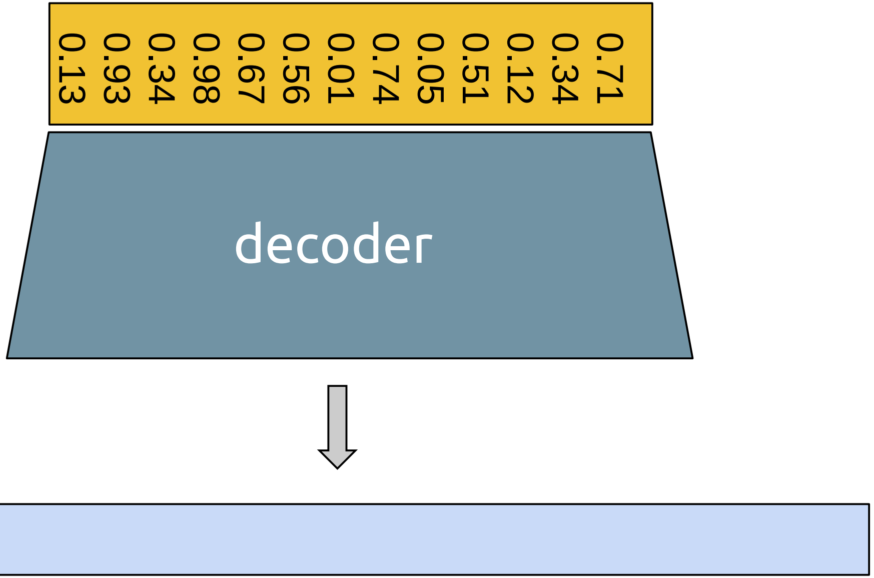
Output representation



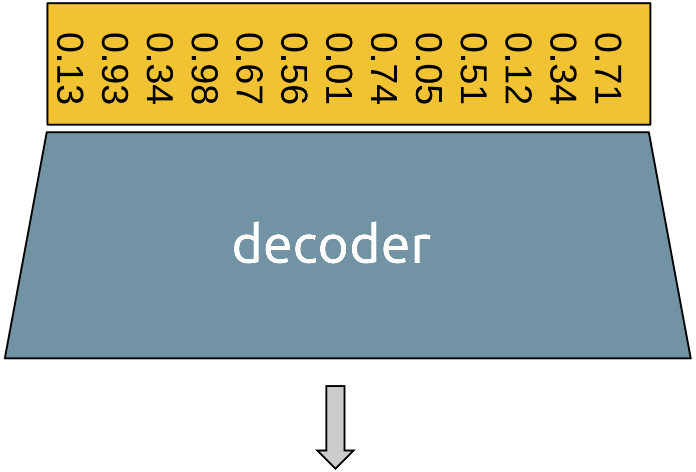
Output representation



Output representation



Output representation



What a wonderful tutorial!

Output representation

- Word (Bansal et al., 2018)
- Byte Pair Encoding (BPE) (Sperber et al., 2018)
- Character (Bérard et al., 2016; Weiss et al., 2017)

Output representation: Word

- Words as atomic unit
- Applicable only for small and high-repetitive datasets
- Tested in low-resource speech-to-text translation

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- Words as atomic unit
- Applicable only for small and high-repetitive datasets
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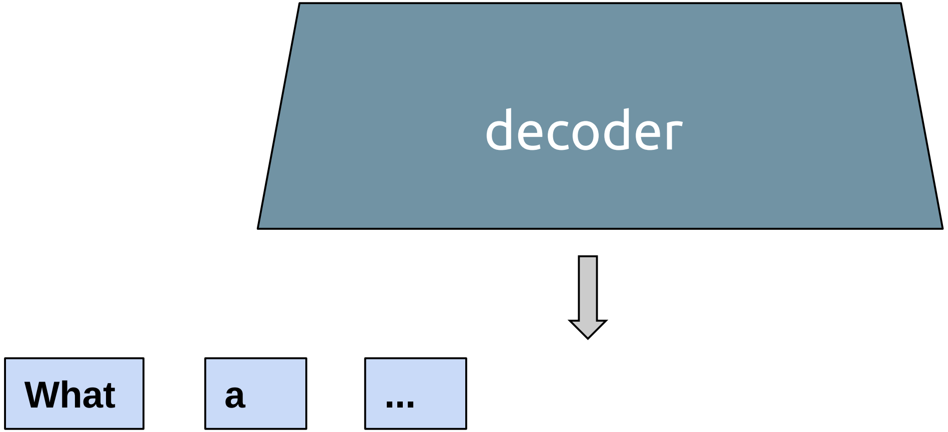

Output representation: BPE

- Introduced in Neural Machine Translation to fit a large vocabulary in memory
- Each target sentence splits in sub-word units
- Iterative approach merging the most frequently co-occurring characters or character sequences
- Widely used in several NLP tasks

Output representation: BPE

- Training and test data are split based on a learned vocabulary
- After translation, BPEs converted into words

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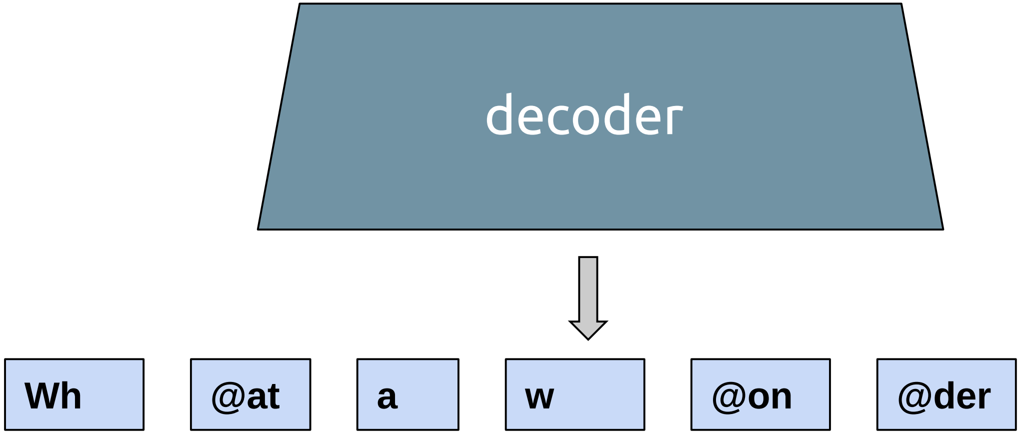
- Training and test data are split based on a learned vocabulary
- After translation, BPEs converted into words

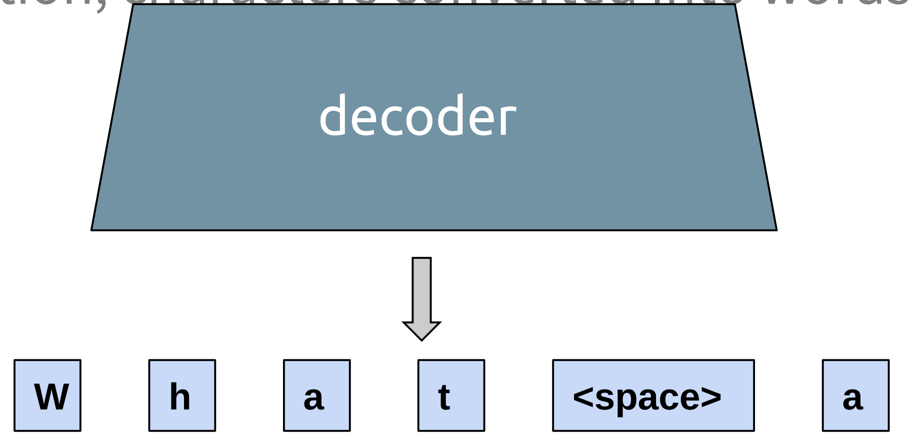


Output representation: Characters

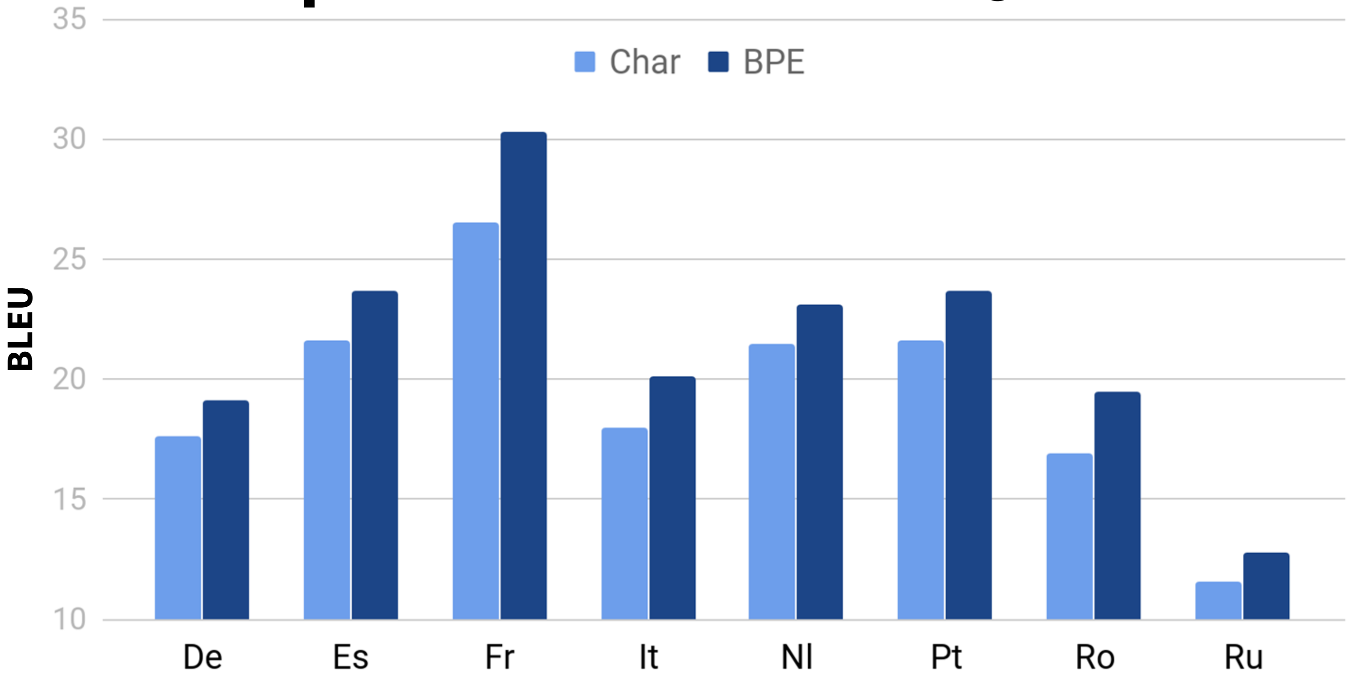
- Each sentence splits in characters with a special symbol for the empty space
- Training and test data are split
- After translation, characters converted into words

Output representation: Characters

- Each sentence splits in characters with a special symbol for the empty space
- Training and test data are split
- After translation, characters converted into words

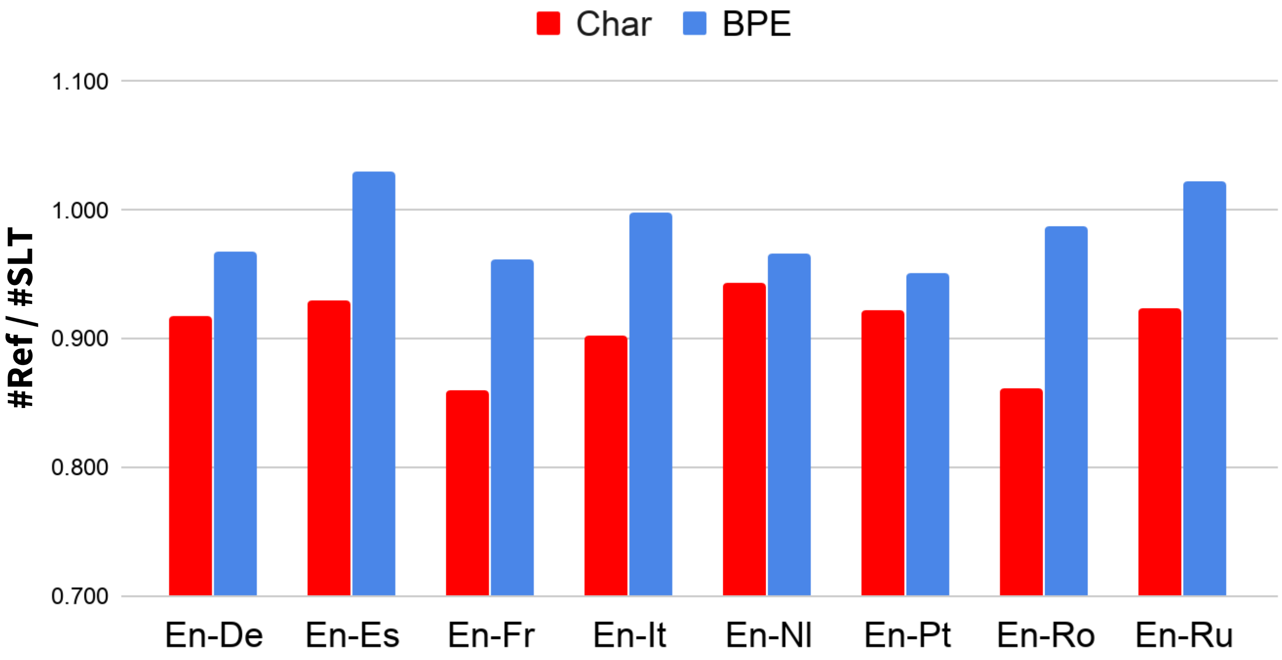


Translation performance (Di Gangi et al., 2020)



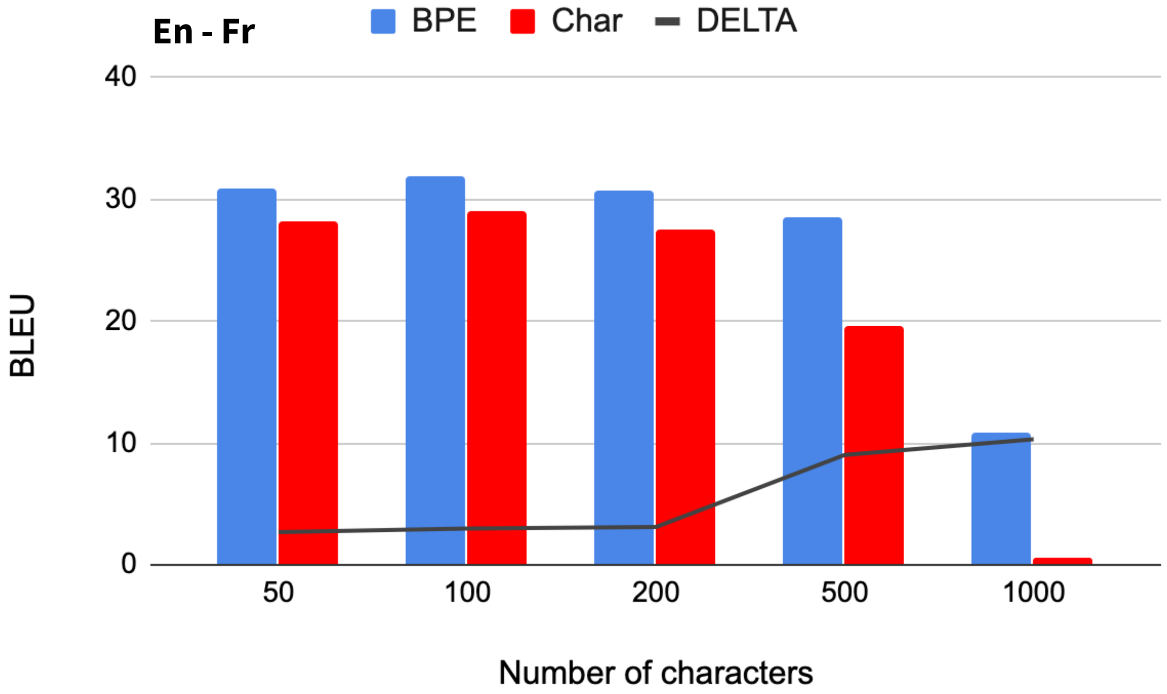
BPE outperforms Characters in all languages

Length comparison



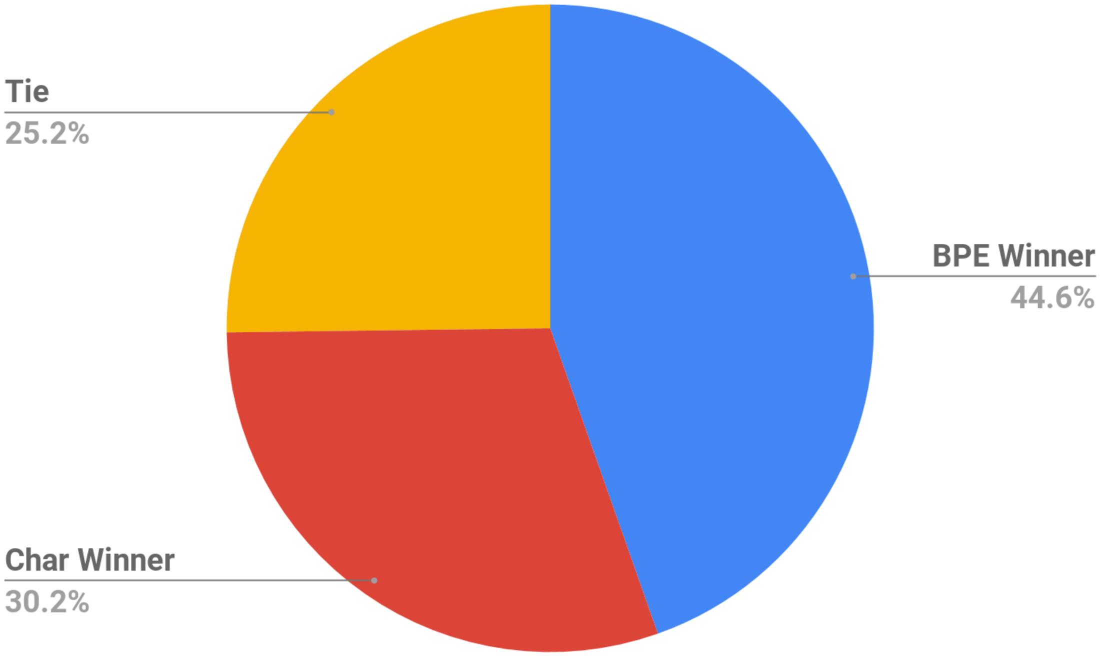
BPE produces longer sentences

Translation quality by sent. length



BPE better on longer sentences

Sentence Level Comparison



Chars better on lower quality translations

Sec 3:

Leveraging Data Sources

Available data

Techniques

Multi-task learning

Transfer learning and pretraining

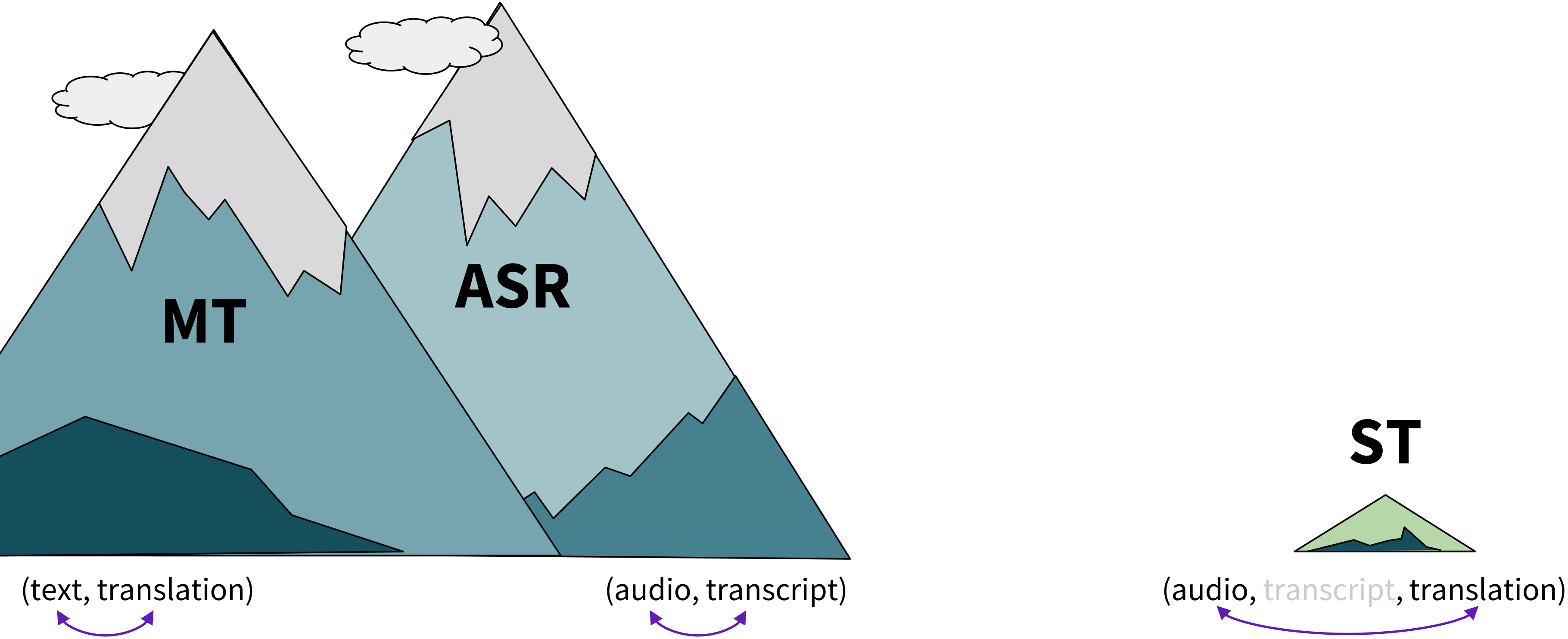
Knowledge distillation

Alternate data representations

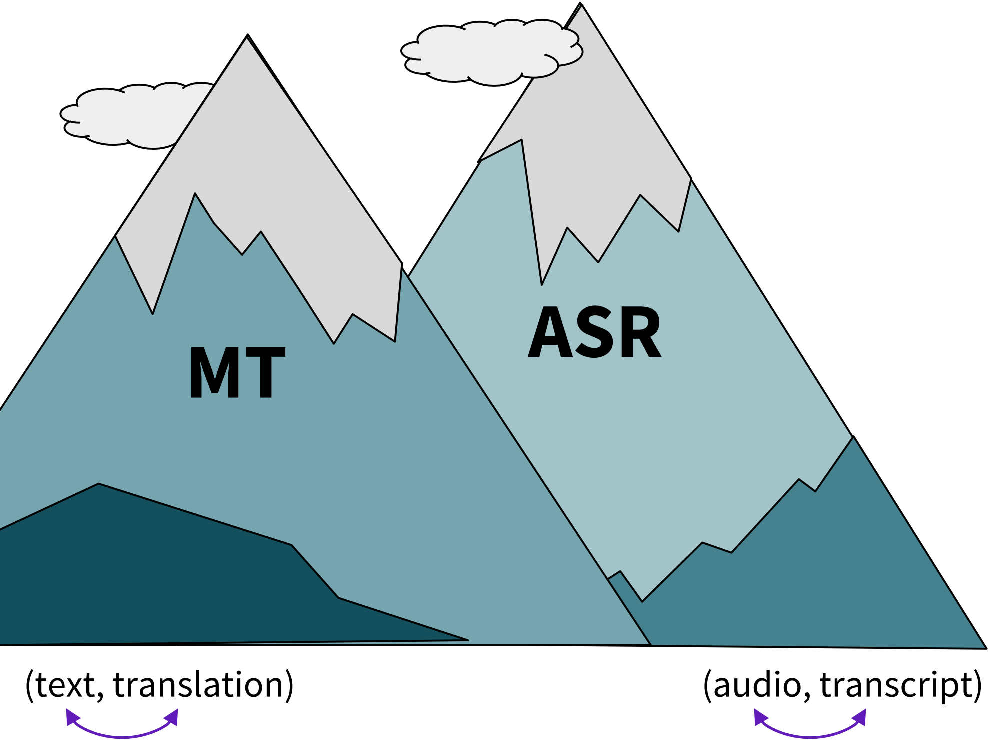
Sec 3.1

Available Data

Available data



Available data

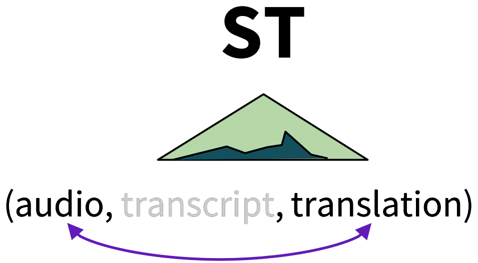


Question: Why so few data?

Answer: High creation costs!

1. Find good data (e.g. audio+transcr+transl., free)
2. Download and clean
3. Segment transcripts and translations
4. Align transcripts and translations
5. Align transcripts and audio
6. Filter wrong/poor alignments
7. Pack in suitable format, extract features

MuST-C (Cattoni et al., 2021)



Available data (≥ 20 hrs of speech)

(*no name*)	(Tohyama et al., 2005)	En↔Jp 182hrs	simult. interpret.
(*no name*)	(Paulik and Waibel, 2009)	En→Es 111 Es→En 105hrs	simult. interpret.
Fisher	(Post 2013)	Es→En 160hrs	phone conversations
STC	(Shimizu et al., 2014)	En↔Jp 22hrs	simult. interpret.
How2	(Sanabria et al., 2018)	En→Pt 300hrs	instructional videos
IWSLT 2018	(Niehues et al., 2018)	En→De 273hrs	TED talks
LIBRI-TRANS	(Kocabiyikoglu et al., 2018)	En→Fr 236hrs	read audiobooks
MuST-C	(Cattoni et al., 2021)	En→ 14 lang. (237-504hrs)	TED talks
CoVoST	(Wang et al., 2020)	En→15 lang. (929hrs), 21 lang.→En (30-311hrs)	read, Common Voice
Europarl-ST	(Iranzo-Sanchez et al., 2020)	9 lang. (72 dir., 10-90hrs)	EP proceedings
LibriVoxDeEn	(Beilharz et al., 2020)	De→En 100hrs	read audiobooks
MaSS	(Zanon Boito et a., 2020)	8 lang. (56 dir.) 20hrs	Bible readings
BSTC	(Baidu, 2020)	Zh→En 50hrs	simult. interpret.
Multilingual TEDx	(Salesky et al., 2021)	8 lang.→6 lang. 11-69hrs	TED talks

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Half of these corpora were built in the last 2 years

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Trend (1): increasing data size (>200 hours of translated speech)

Available data (≥ 20 hrs of speech)

(no name)	(Tohyama et al., 2005)	En↔Jp 182hrs	simult. interpret.
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Trend (2): more language directions

Available data (≥ 20 hrs of speech)

(no name)	(Tohyama et al., 2005)	En↔Jp 182hrs	simult. interpret.
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Fisher	(Post 2013)	Es→En 160hrs	phone conversations
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BSTC	(Baidu, 2020)	Zh→En 50hrs	simult. interpret.
Multilingual TEDx	(Salesky et al., 2021)	8 lang.→6 lang. 11-69hrs	TED talks

Trend (3): multilinguality + non-English speech

Available data (≥ 20 hrs of speech)

(no name)	(Tohyama et al., 2005)	En↔Jp 182hrs	simult. interpret.
(no name)	(Paulik and Waibel, 2009)	En→Es 111 Es→En 105hrs	simult. interpret.
Fisher	(Post 2013)	Es→En 160hrs	phone conversations
STC	(Shimizu et al., 2014)	En↔Jp 22hrs	simult. interpret.
How2	(Sanabria et al., 2018)	En→Pt 300hrs	instructional videos
IWSLT 2018	(Niehues et al., 2018)	En→De 273hrs	TED talks
LIBRI-TRANS	(Kocabiyikoglu et al., 2018)	En→Fr 236hrs	read audiobooks
MuST-C	(Cattoni et al., 2021)	En→ 14 lang. (237-504hrs)	TED talks
CoVoST	(Wang et al., 2020)	En→15 lang. (929hrs), 21 lang.→En (30-311hrs)	read, Common Voice
Europarl-ST	(Iranzo-Sanchez et al., 2020)	9 lang. (72 dir., 10-90hrs)	EP proceedings
LibriVoxDeEn	(Beilharz et al., 2020)	De→En 100hrs	read audiobooks
MaSS	(Zanon Boito et a., 2020)	8 lang. (56 dir.) 20hrs	Bible readings
BSTC	(Baidu, 2020)	Zh→En 50hrs	simult. interpret.
Multilingual TEDx	(Salesky et al., 2021)	8 lang.→6 lang. 11-69hrs	TED talks

Trend (4): same segmentation across datasets

Available data (≥ 20 hrs of speech)

(no name)	(Tohyama et al., 2005)	En↔Jp 182hrs	simult. interpret.
(no name)	(Paulik and Waibel, 2009)	En→Es 111 Es→En 105hrs	simult. interpret.
Fisher	(Post 2013)	Es→En 160hrs	phone conversations
STC	(Shimizu et al., 2014)	En↔Jp 22hrs	simult. interpret.
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MuST-C	(Cattoni et al., 2021)	En→ 14 lang. (237-504hrs)	TED talks
CoVoST	(Wang et al., 2020)	En→15 lang. (929hrs), 21 lang.→En (30-311hrs)	read, Common Voice
Europarl-ST	(Iranzo-Sanchez et al., 2020)	9 lang. (72 dir., 10-90hrs)	EP proceedings
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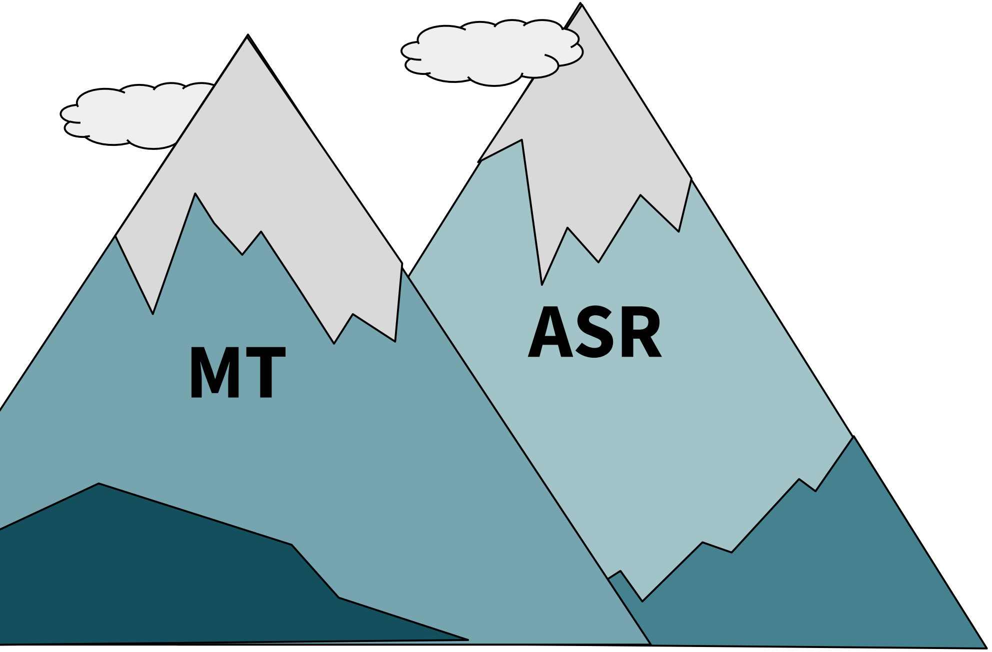
BSTC	(Baidu, 2020)	Zh→En 50hrs	simult. interpret.
Multilingual TEDx	(Salesky et al., 2021)	8 lang.→6 lang. 11-69hrs	TED talks

Trend (5): common test data across language pairs

Sec 3.2

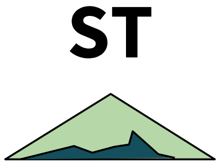
Techniques

Recap: Available data



(text, translation) (audio, transcript)

Can we make use of this large amount of data?



(audio, transcript, translation)

Multi-task learning

Definition:

“Multi-task learning improves generalization by leveraging the domain-specific information contained in the training signals of related tasks”

— Caruana, R. (1998)

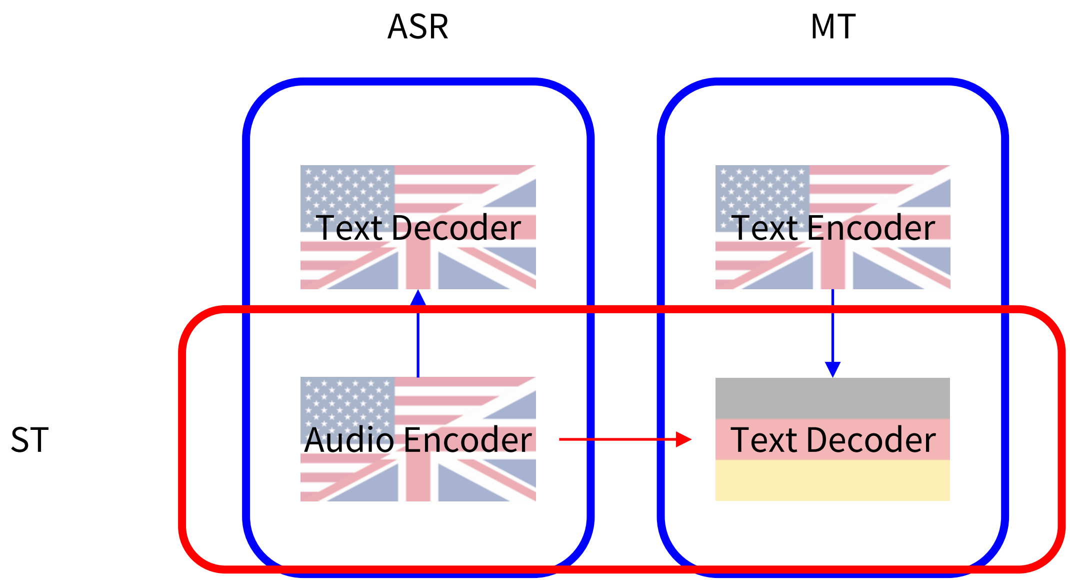
Transfer Learning

Definition:

“Transfer learning and domain adaptation refer to the situation where what has been learned in one setting … is exploited to improve generalization in another setting”

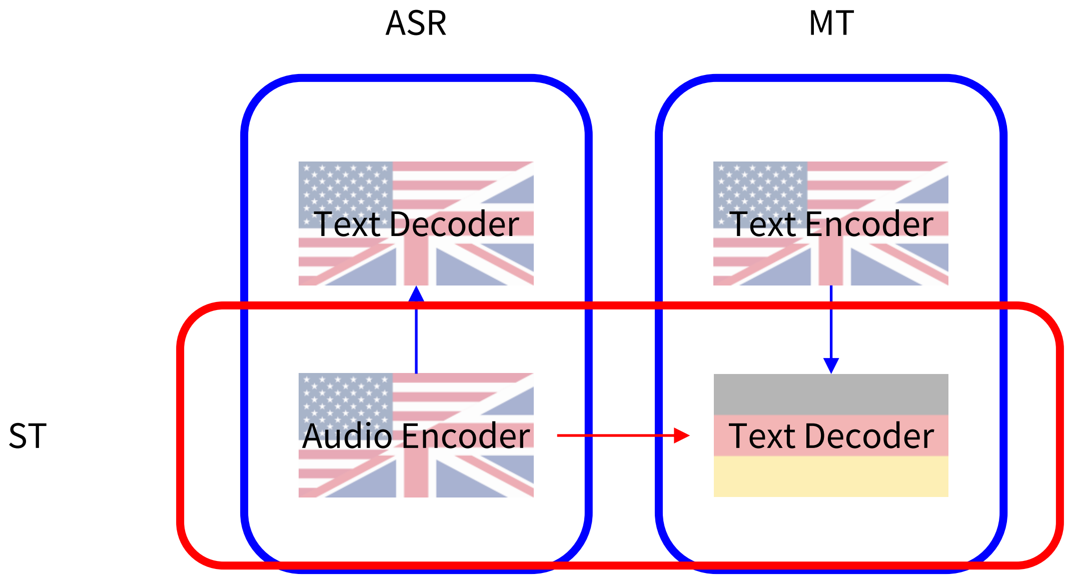
— Page 526, Deep Learning, 2016.

Setting


ASR
MT
Text Decoder
Text Encoder
ST
Audio Encoder
Text Decoder

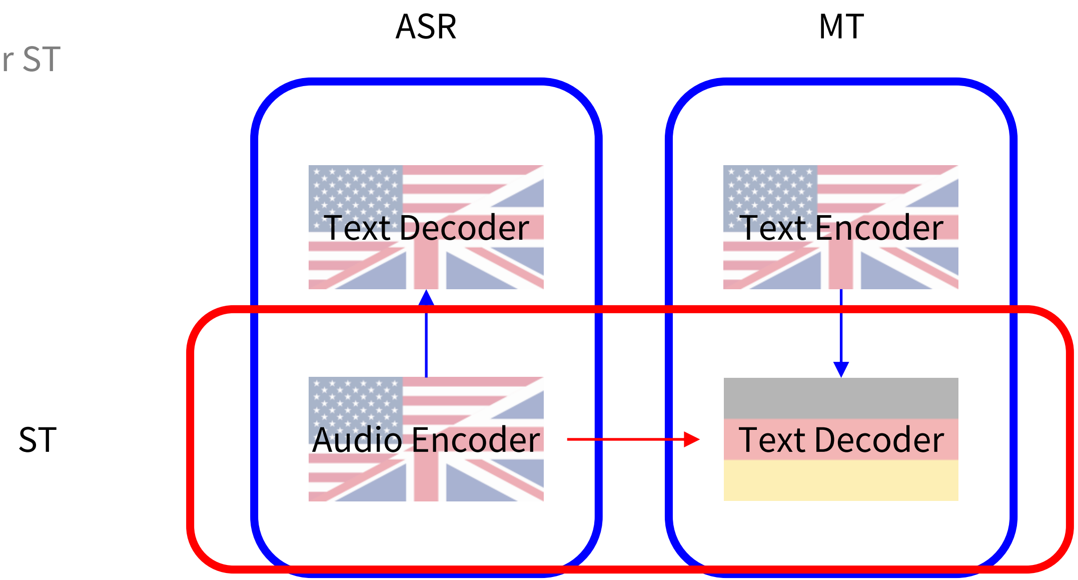
Setting

- Multi-task
  - Train all three tasks jointly



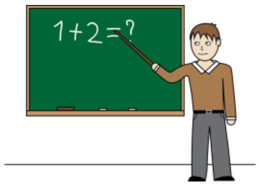
Setting

- Multi-task
- Pre-training
  - Train ASR and MT
  - Reuse part of the model for ST

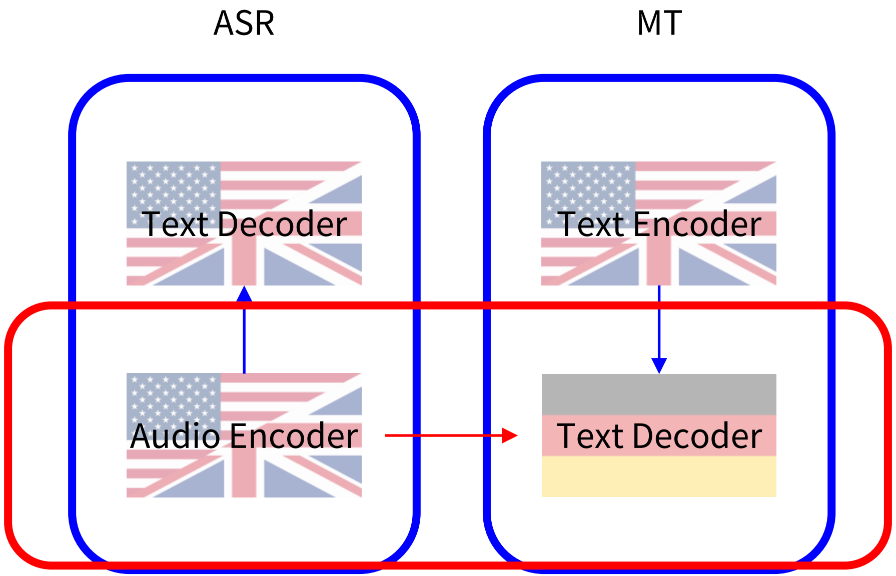


Setting

- Multi-task
- Pre-training
- Knowledge distillation
  - Take MT model
  - Train ST based on training signal from MT



ST

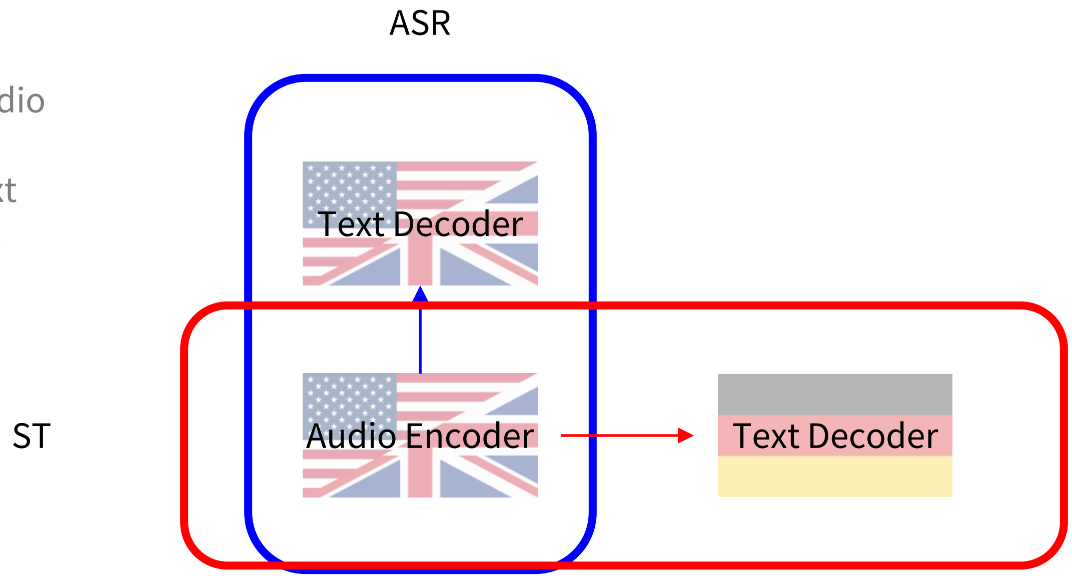


Sec 3.2.1

Multi-task Learning

Multi-task learning

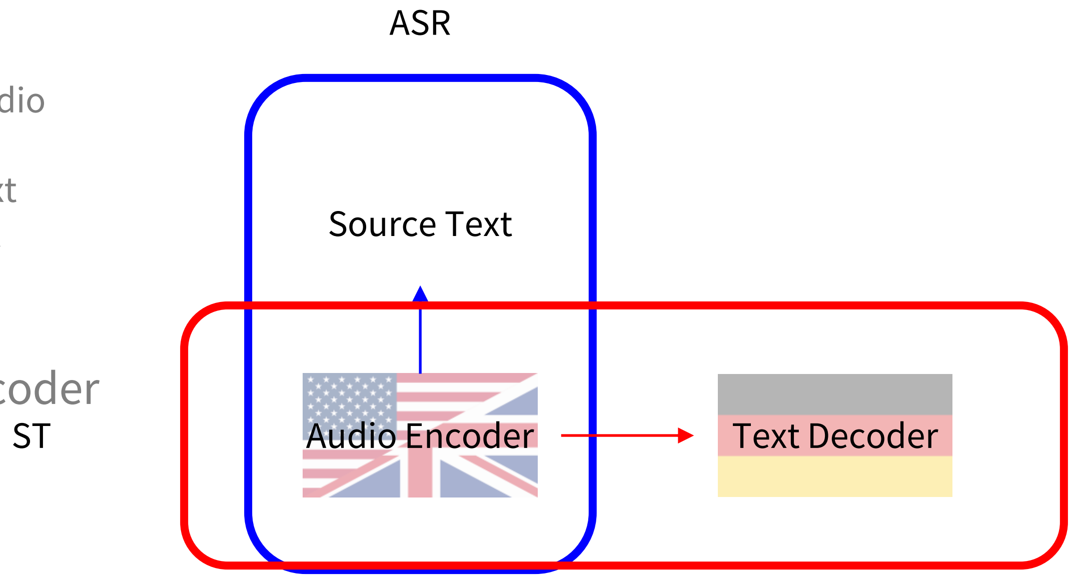
- Baseline
  - No changes to the architecture
- ST+ASR
  - One encoder
    - Source Language audio
  - Two decoder
    - Source Language text
    - Target language text
  - (Weis et al, 2017)



Multi-task learning

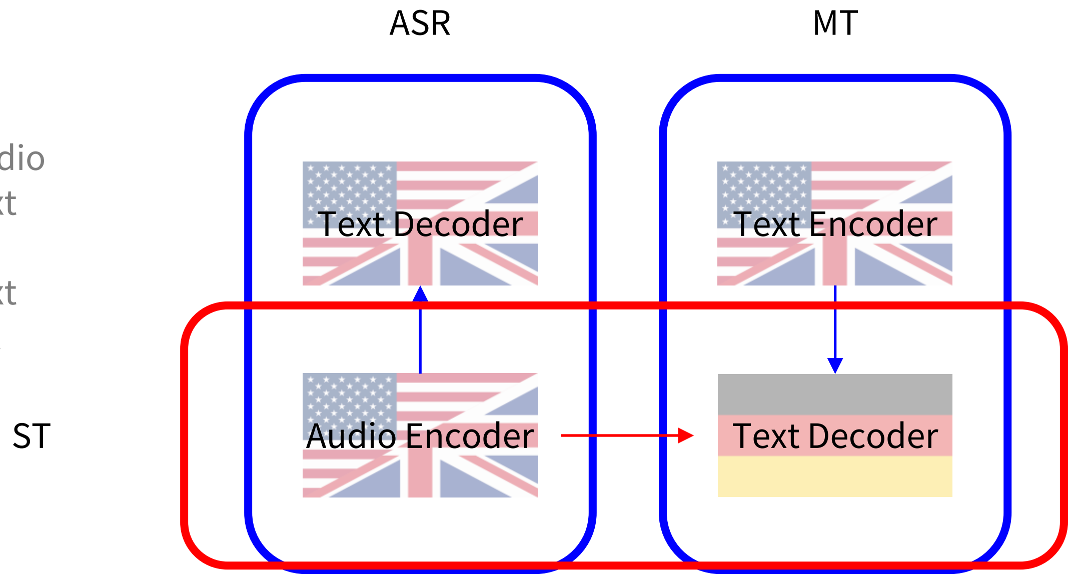
- Baseline
  - No changes to the architecture
- ST+ASR
  - One encoder
    - Source Language audio
  - Two decoder
    - Source Language text
    - Target language text
  - (Weis et al, 2017)

- ASR using CTC loss on encoder
  - (Hori et al, 2017)
  - (Bahra et al, 2019)



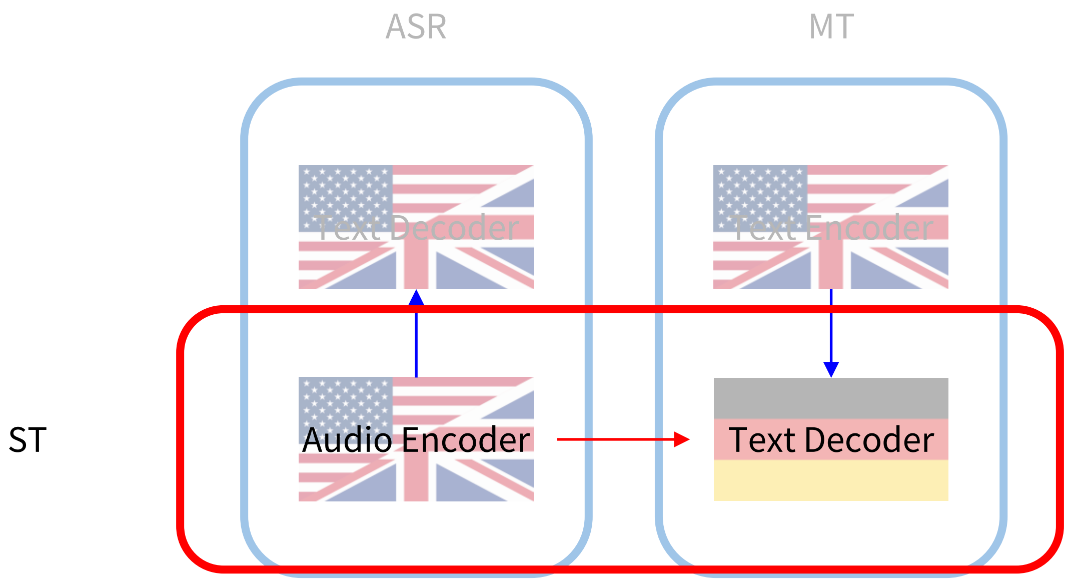
Multi-task learning

- Baseline
  - No changes to the architecture
- ST+ASR
- ST+ASR+MT
  - Two encoder
    - Source Language audio
    - Source Language text
  - Two decoder
    - Source Language text
    - Target language text
  - (Berard et al, 2018)



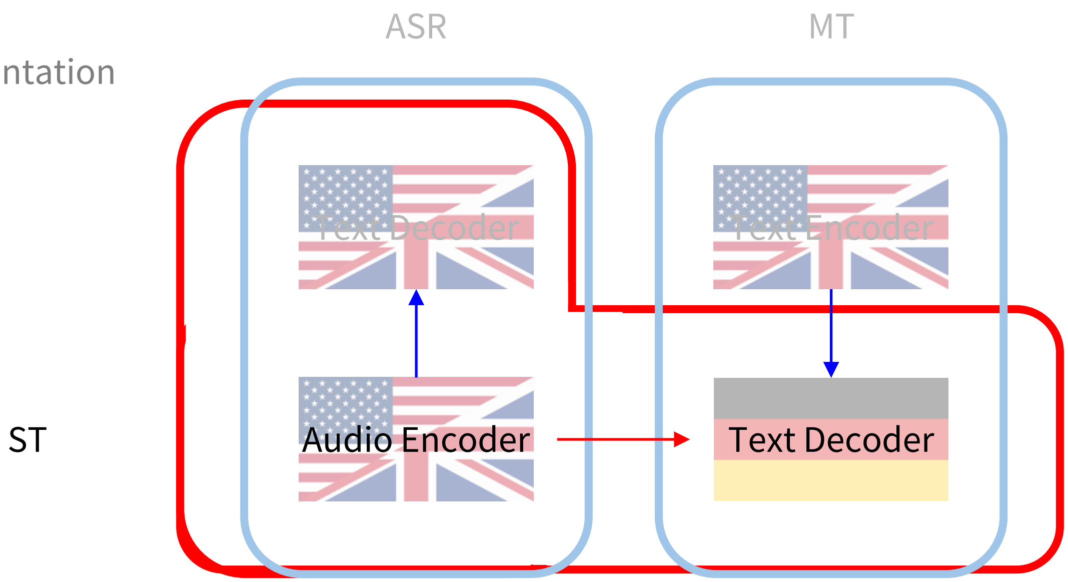
Multi-task learning

- Baseline
  - No changes to the architecture
- ST+ASR
- ST+ASR+MT
- Inference:
  - Direct translation
  - No use of additional parts



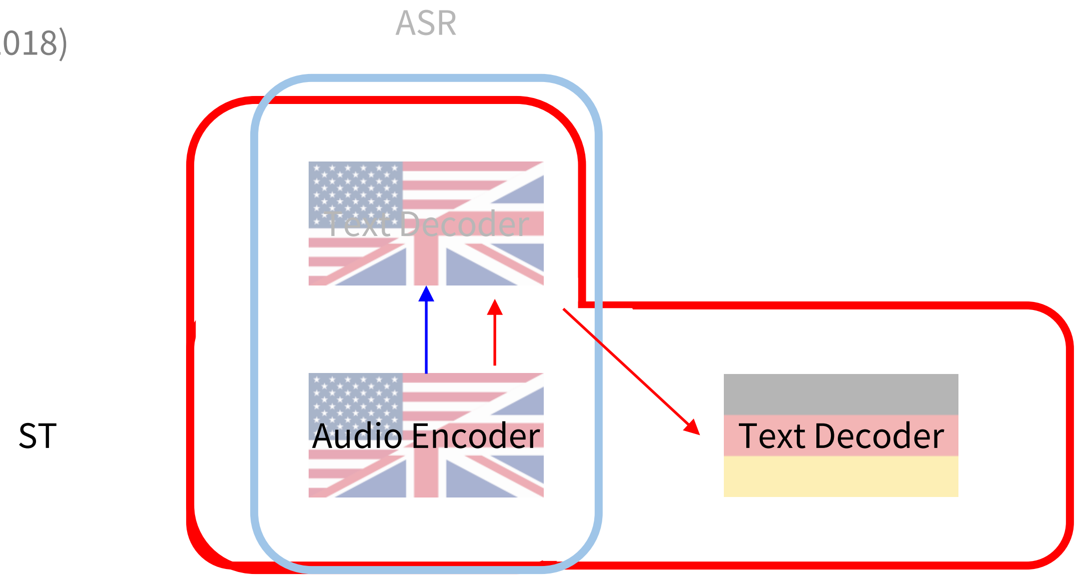
2-stage models

- Make use of additional model also during decoding
- *Simplify task*
  - using intermediate representation
- Comparison to cascade:
  - Full pipeline is trained
- Methods:
  - Adapt architecture
  - Preprocess data



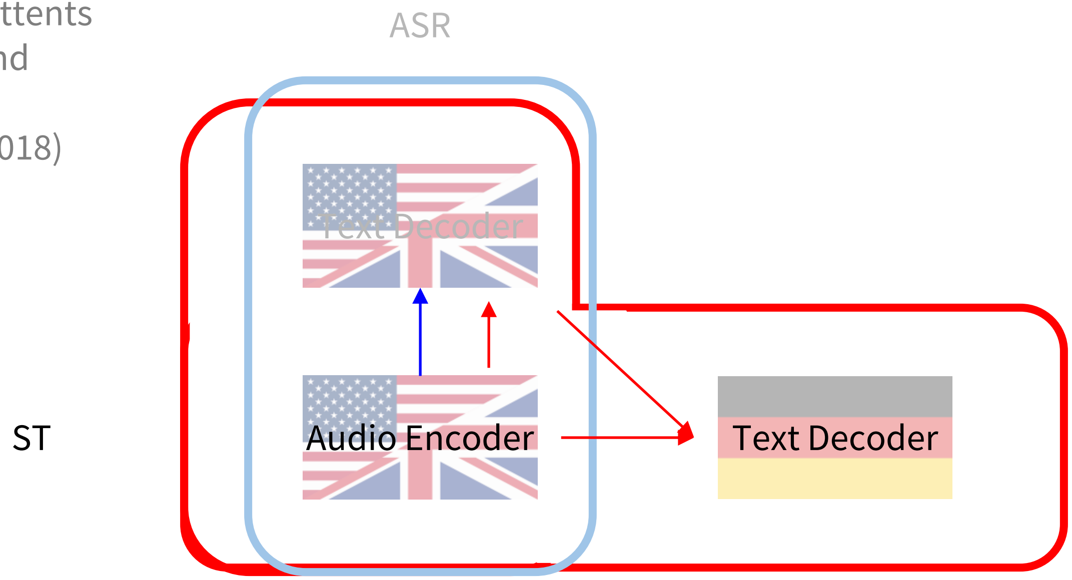
2-stage models

- Cascade:
  - Target language decoder attents to source text decoder
  - (Anastasopoulos Chiang, 2018)



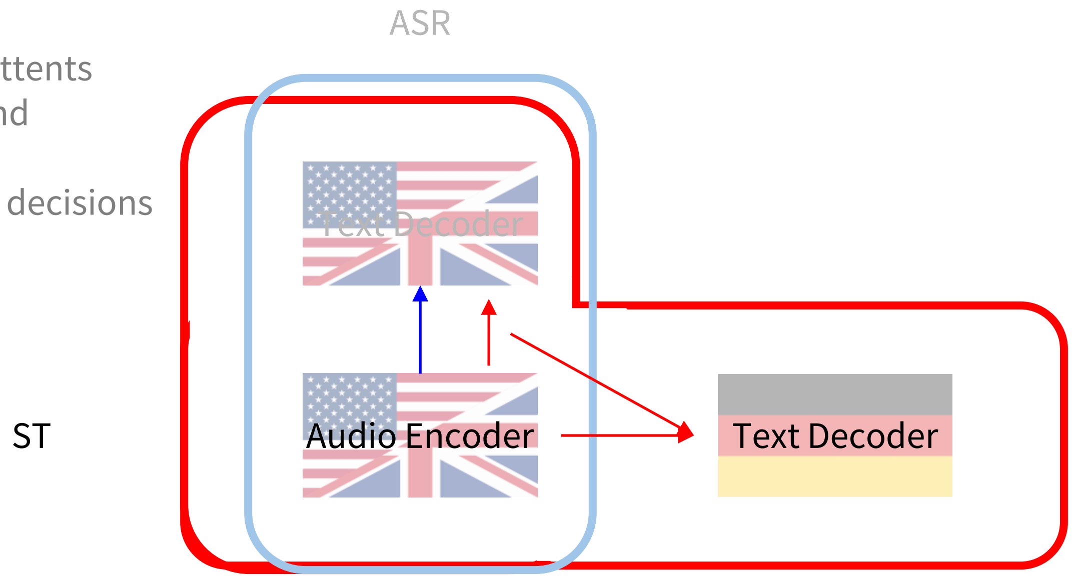
2-stage models

- Cascade:
- Triangle:
  - Target language decoder attents to source audio encoder and source text decoder
  - (Anastasopoulos Chiang, 2018)



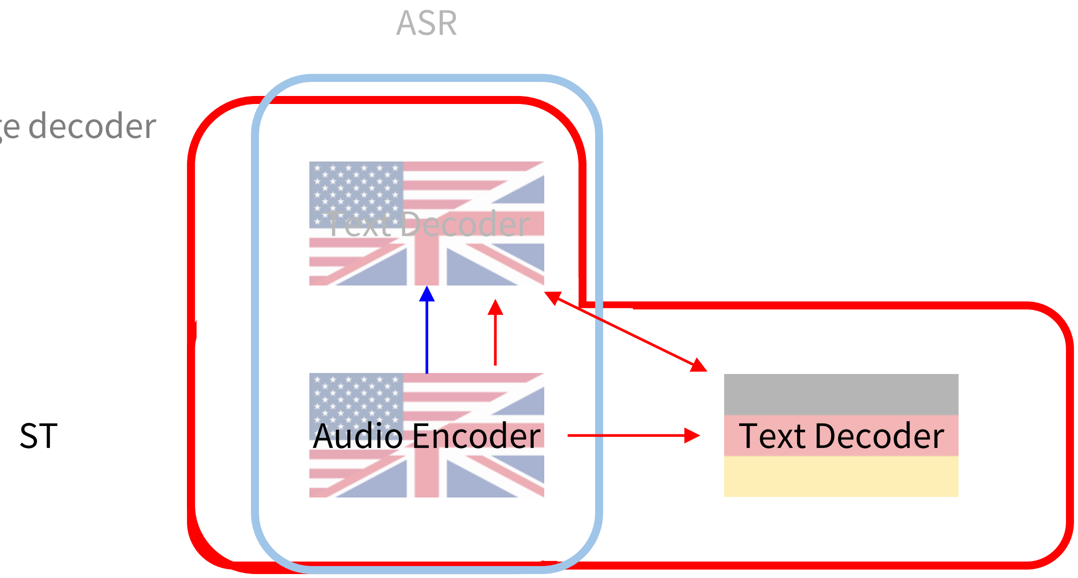
2-stage models

- Cascade:
- Triangle:
- Shared context vector
  - Target language decoder attents to source audio encoder and ASR context vectors
  - No direct influence of hard decisions of source text decoder
  - (Sperber et al, 2019)



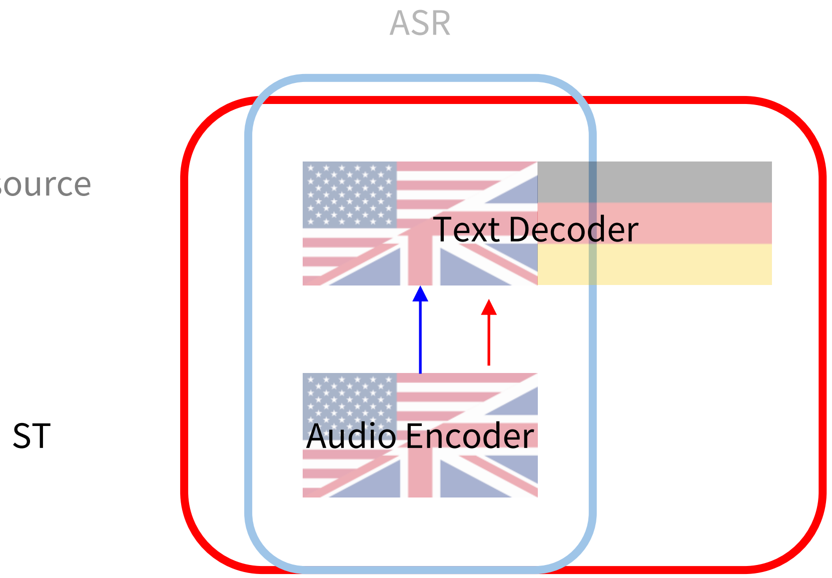
2-stage models

- Cascade:
- Triangle:
- Shared context vector
- Dual Decoder
  - Source and target language decoder run in parallel
  - Attend to each other
  - (Le et al, 2020)



2-stage models

- Cascade:
- Triangle:
- Shared context vector
- Dual Decoder
- Concat
  - Single decoder generates source and target language
  - Output is concatenation
  - (Sperber et al, 2020)



Sec 3.2.2

Transfer Learning & Pretraining

Pre-training SLT components

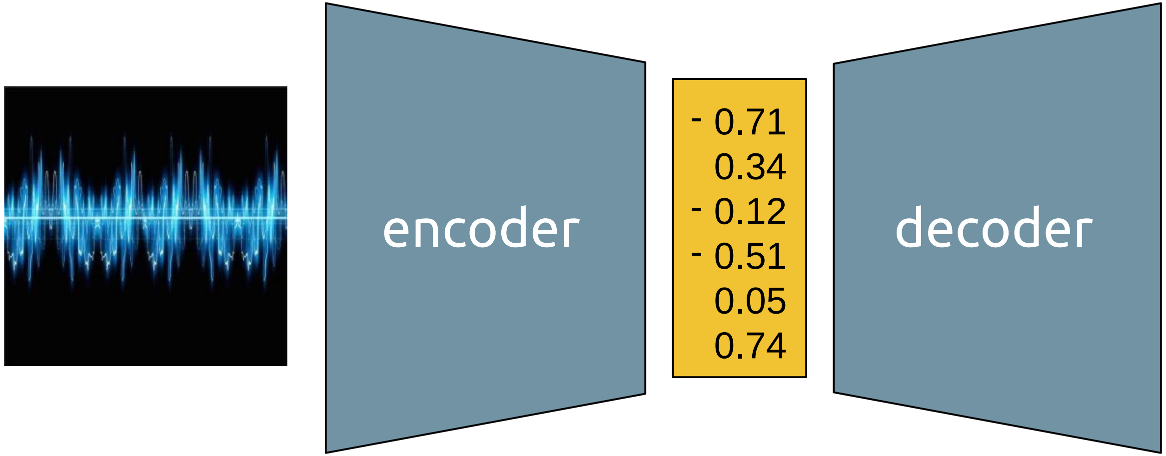
Pre-training components of the SLT systems on different tasks

- Encoder pre-training (Bansal et al., 2018) <--> Automatic Speech Recognition
- Decoder pre-training (Bérard et al., 2018) <--> Machine Translation

Encoder Pre-training

Spanish Audio

English text

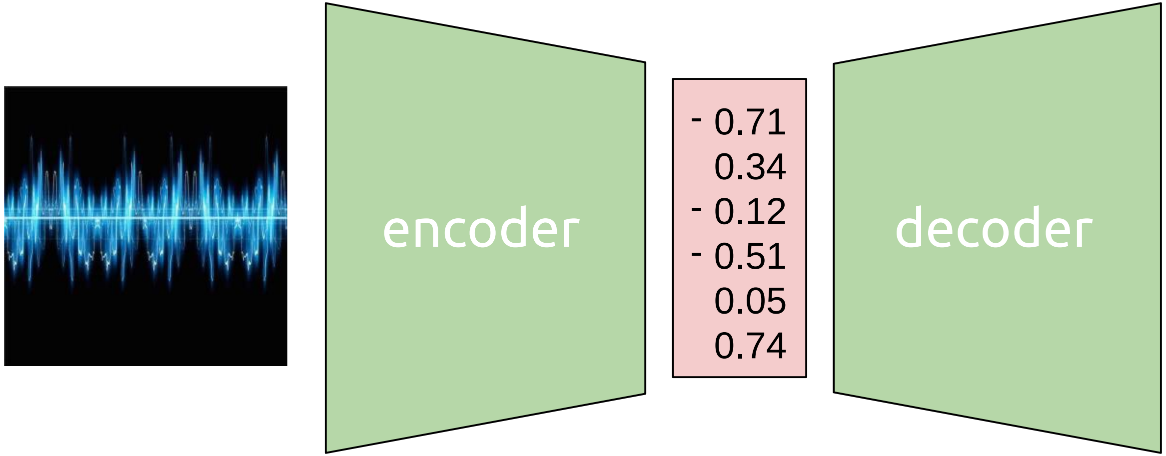


What a wonderful tutorial!

Encoder Pre-training

Spanish Audio

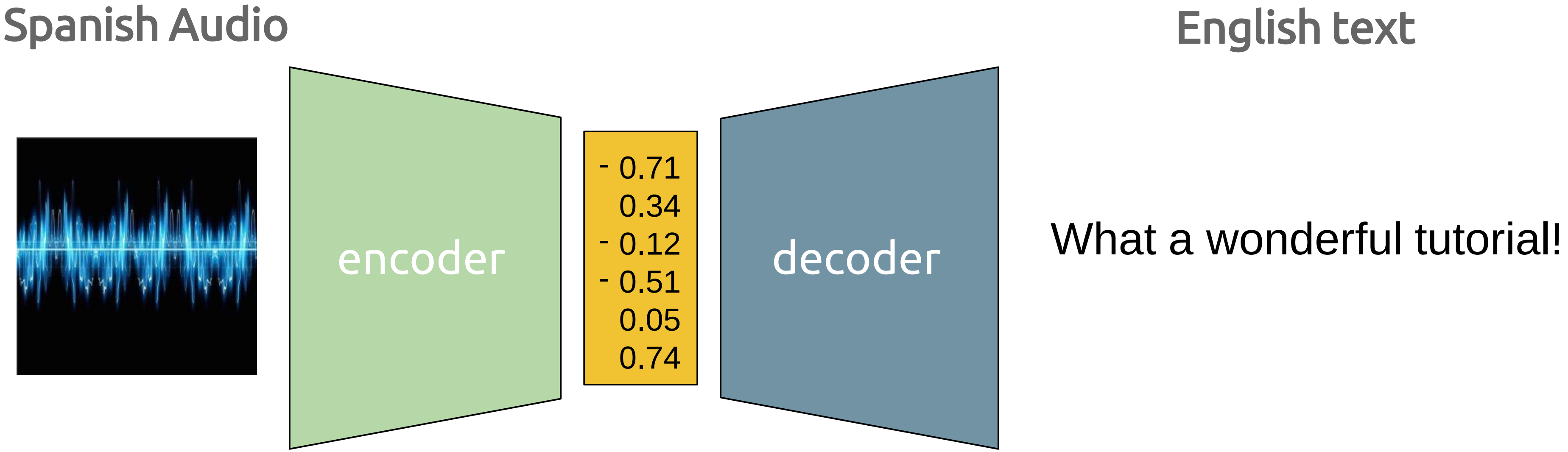
Spanish text



¡Qué maravilloso tutorial!

Training an ASR using the same SLT architecture

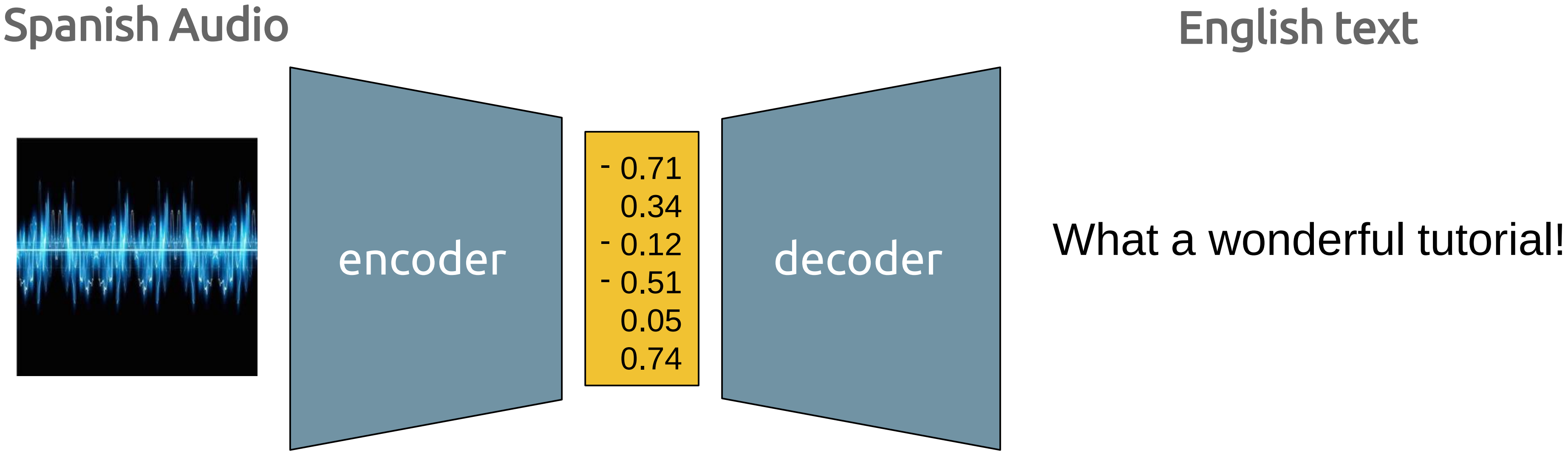
Encoder Pre-training



Training an ASR using the same SLT architecture

Training the SLT system initializing the encoder with the trained ASR encoder

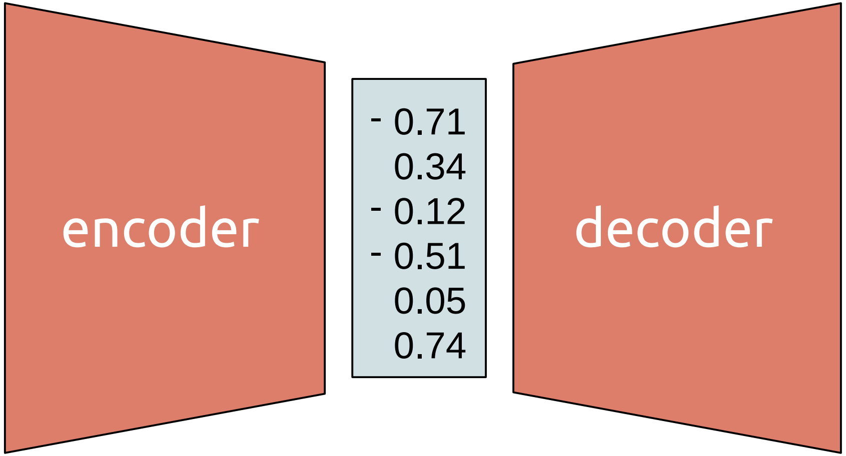
Decoder Pre-training



Decoder Pre-training

Spanish text

¡Qué maravilloso tutorial!



English text

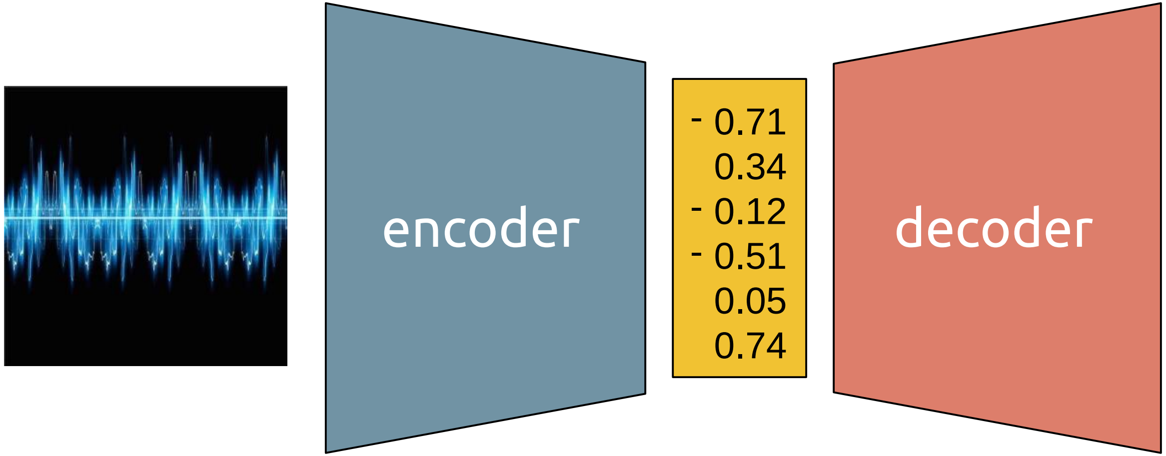
What a wonderful tutorial!

Training an MT system using the same SLT architecture

Decoder Pre-training

Spanish Audio

English text



What a wonderful tutorial!

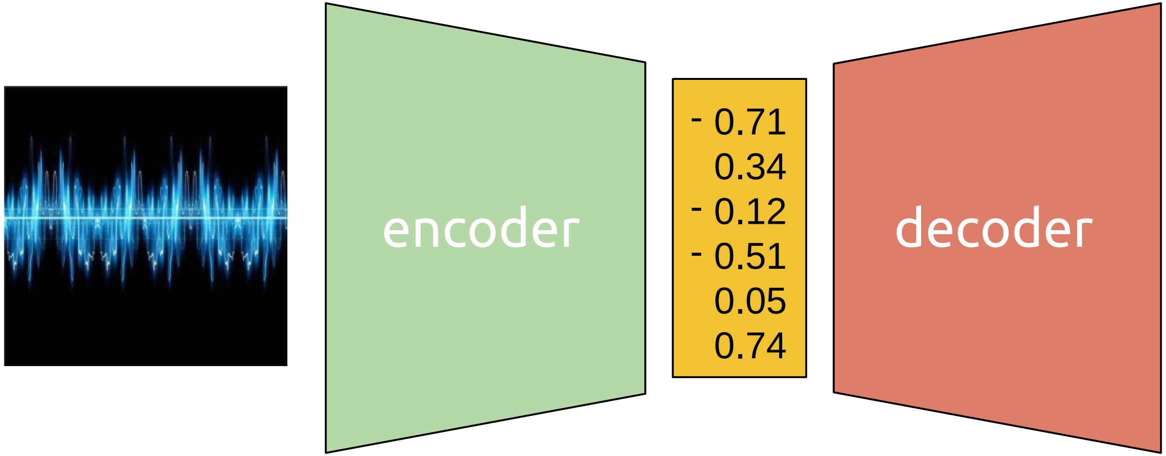
Training an MT system using the same SLT architecture

Training the SLT system initialising the decoder with the trained MT decoder

Encoder-Decoder Pre-training

Spanish Audio

English text



What a wonderful tutorial!

Training the SLT system initializing:

- the encoder with the trained ASR encoder
- the decoder with the trained MT decoder

Exploiting unlabelled data

Following the trends in MT and text generation, exploiting unlabelled data

Exploiting unlabelled data

Following the trends in MT and text generation, exploiting unlabelled data

Integration of:

- Encoder pre-training based on a general-purpose acoustic models: wav2vect (Ly et al., 2020)

- Decoder pre-training based on general-purpose language models: BERT or mBART (Wu et al., 2020)

Exploiting unlabelled data

Following the trends in MT and text generation, exploiting unlabelled data

Integration of:

- Encoder pre-training based on a general-purpose acoustic models: wav2vect (Ly et al., 2020)

- Decoder pre-training based on general-purpose language models: BERT or mBART (Wu et al., 2020)

Useful in low-resourced and zero-shot conditions

Sec 3.2.3

Knowledge Distillation

Knowledge distillation

E2E SLT

Knowledge distillation

E2E SLT
(Student)

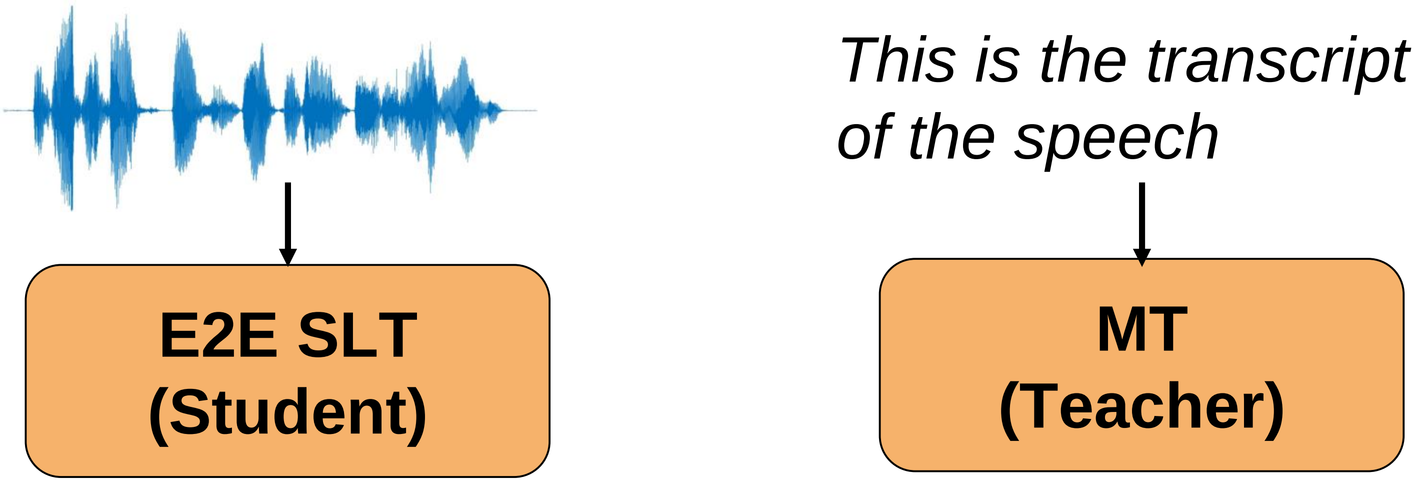
Knowledge distillation

Knowledge distillation

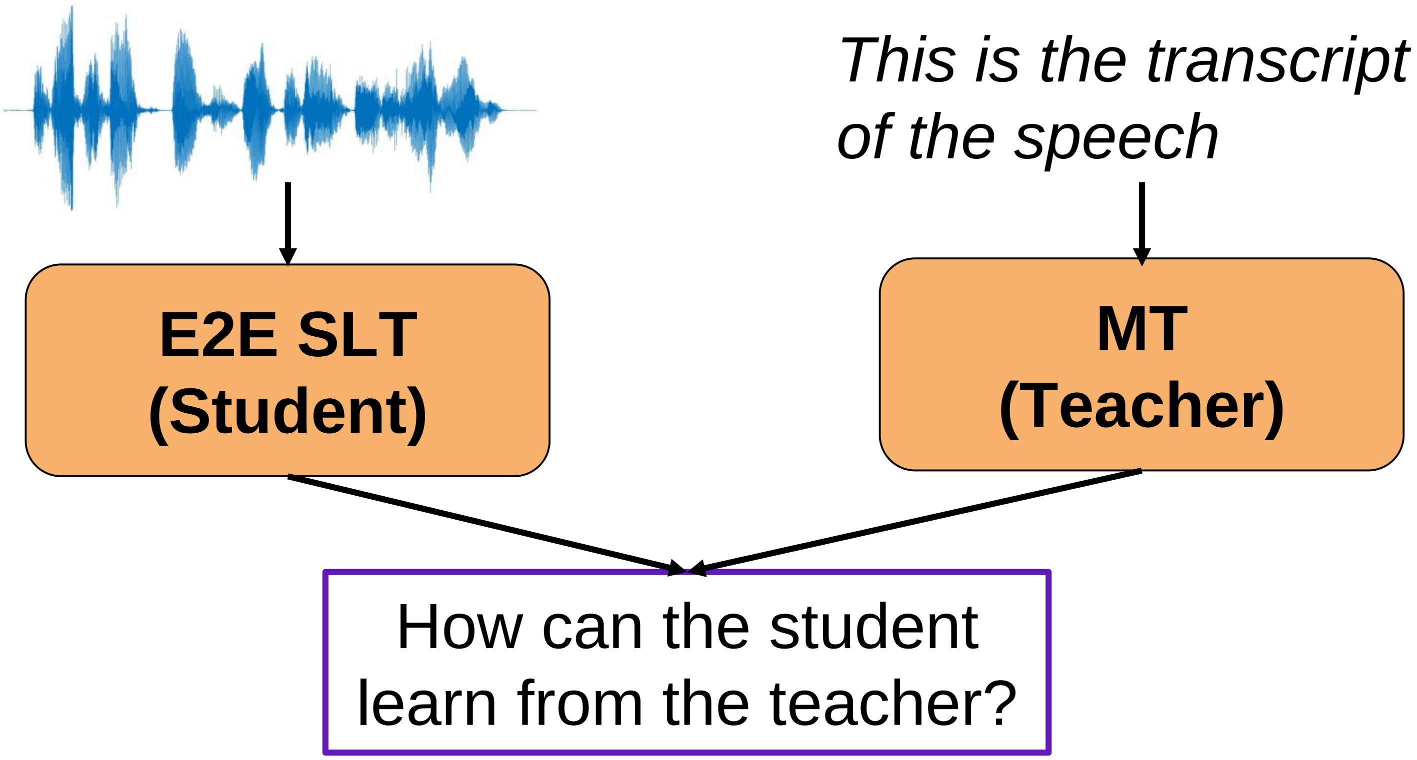
E2E SLT
(Student)

MT
(Teacher)

Knowledge distillation



Knowledge distillation



Knowledge Distillation

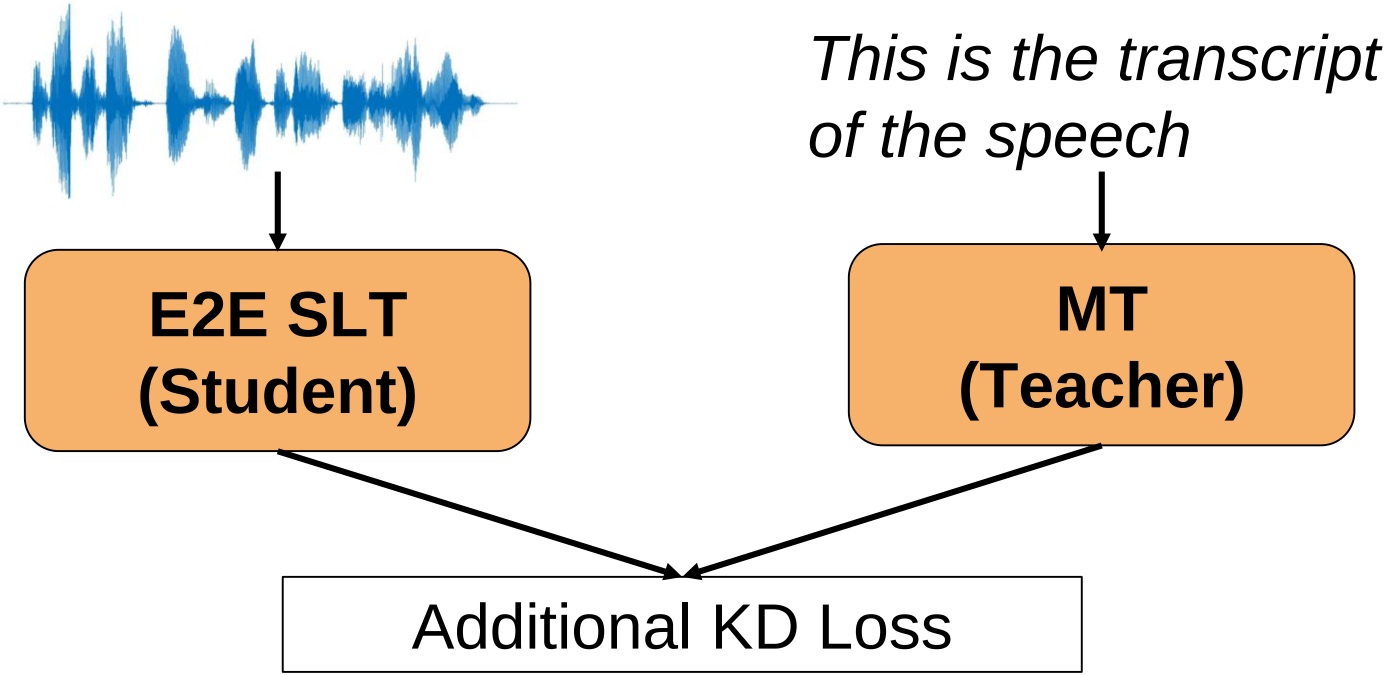
Knowledge distillation for sequences (Kim and Rush, 2016)

- Word-Level KD
- Sequence KD
- Sequence Interpolation KD

- Requirements:
  - ASR data
  - Pre-trained MT system

Word-Level KD

- Proposed by Liu et al. (2019)

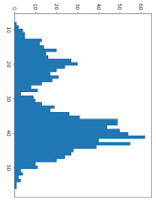


Word-Level KD

E2E SLT
(Student)

MT
(Teacher)

During training

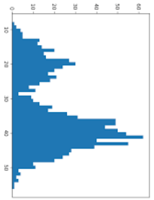


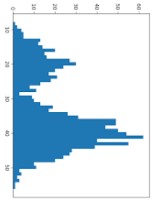
Word-Level KD

E2E SLT (Student)

MT (Teacher)

During training



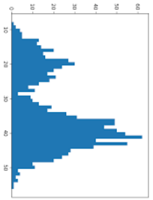


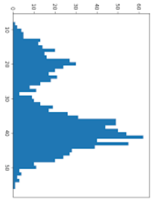
Word-Level KD

E2E SLT
(Student)

MT
(Teacher)

During training





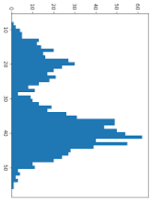
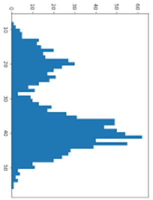
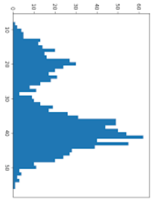
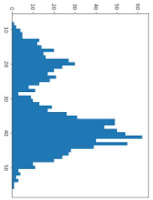
$KL(ST_1, MT_1)$

Word-Level KD

E2E SLT (Student)

MT (Teacher)

During training

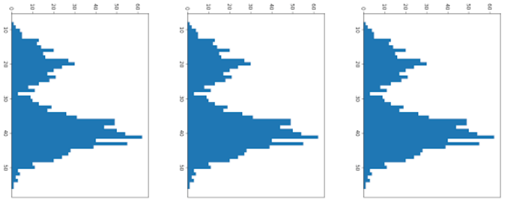
$KL(ST_1, MT_1)$ + $KL(ST_2, MT_2)$

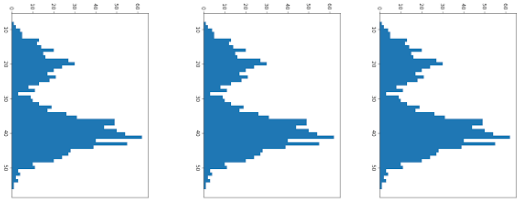
Word-Level KD

E2E SLT (Student)

MT (Teacher)

During training





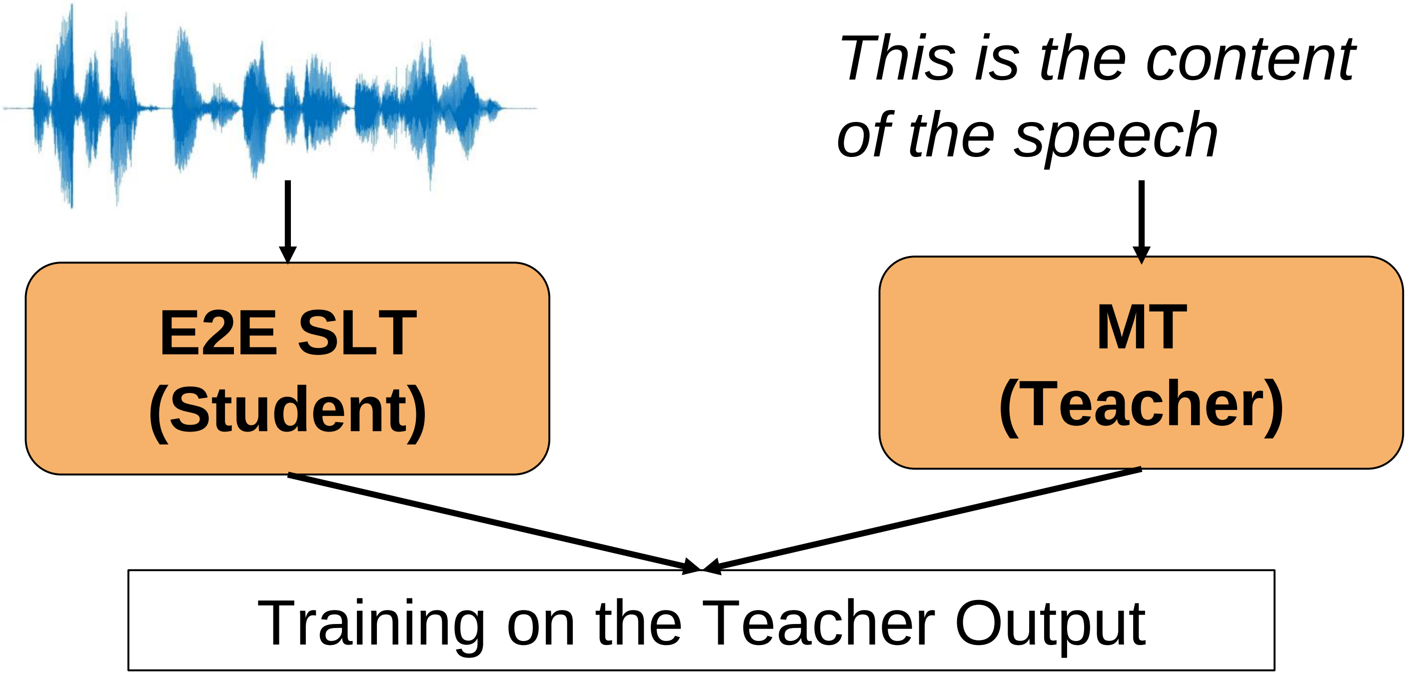
$KL(ST_1, MT_1)$ + $KL(ST_2, MT_2)$ + ...

Word-Level KD

- Training with SLT and KD losses
- Goal:
  - matching the output of SLT ground-truth
  - matching also the output probabilities of teacher model

Sequence Level KD (Seq-KD)

- The output of the teacher is used as reference



Sequence Level KD (Seq-KD)

- The output of the teacher is used as reference

This is the content of the speech

E2E SLT (Student)

MT (Teacher)

Questo e' il contenuto del discorso

Sequence Level KD (Seq-KD)

- The output of the teacher is used as reference

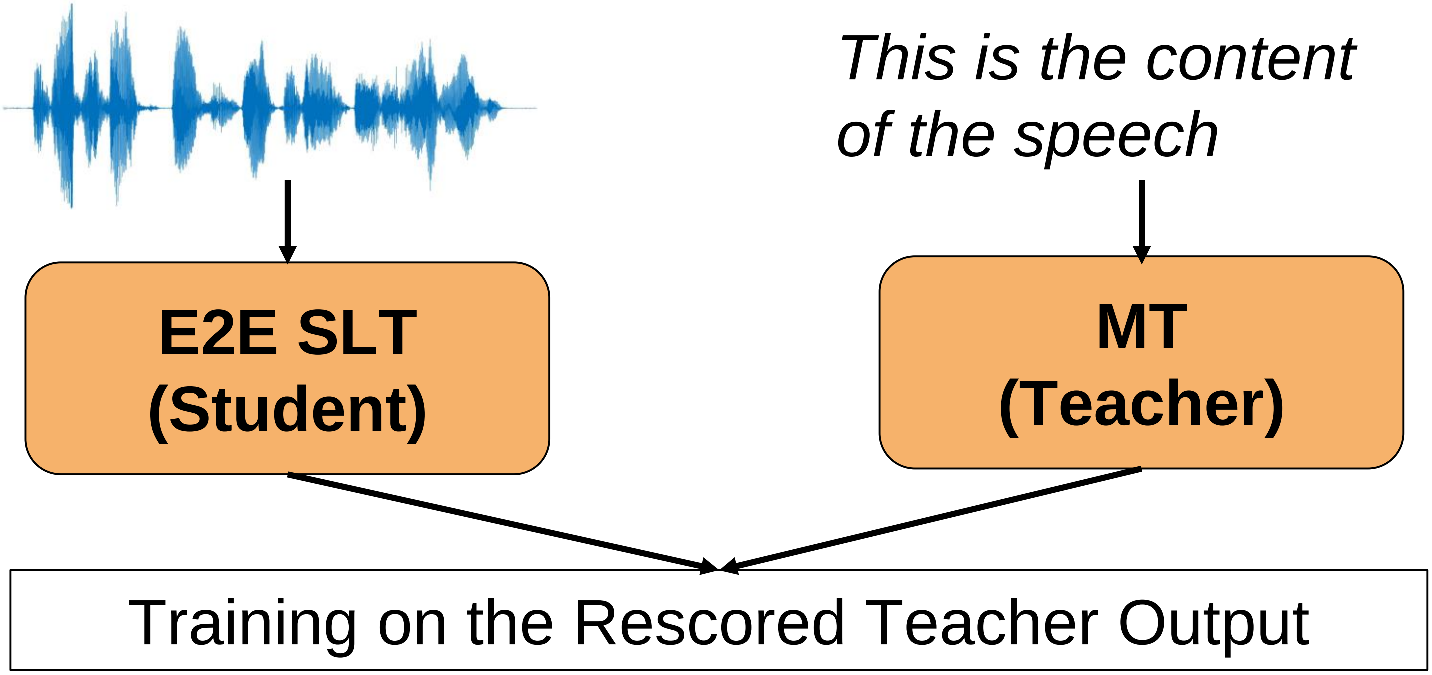
E2E SLT (Student)

MT (Teacher)

Questo e' il contenuto del discorso

Sequence Interpolation (Seq-Inter)

- The n-bests of the teacher are rescored



Sequence Interpolation (Seq-Inter)

- The n-bests of the teacher are rescored

E2E SLT
(Student)

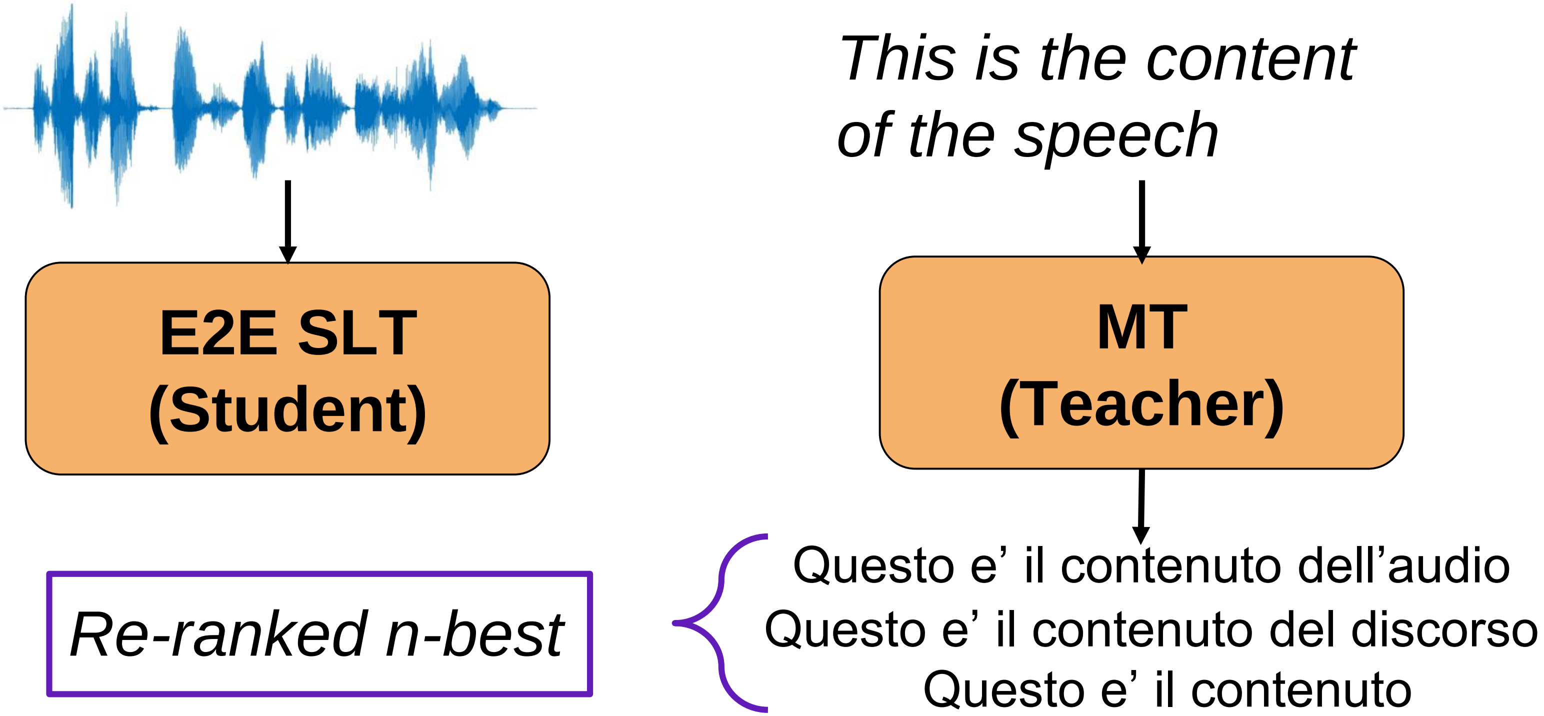
This is the content of the speech

MT
(Teacher)

Questo e' il contenuto del discorso
Questo e' il contenuto dell'audio
Questo e' il contenuto

Sequence Interpolation (Seq-Inter)

- The n-bests of the teacher are rescored



Sequence Interpolation (Seq-Inter)

- The n-bests of the teacher are rescored

E2E SLT (Student)

MT (Teacher)

Questo e’ il contenuto dell’audio

Sequence Interpolation (Seq-Inter)

How to rescore:

- BLEU using SLT data for which there is the reference
- Other methods: e.g. quality estimation (using ASR data)

Sequence Interpolation (Seq-Inter)

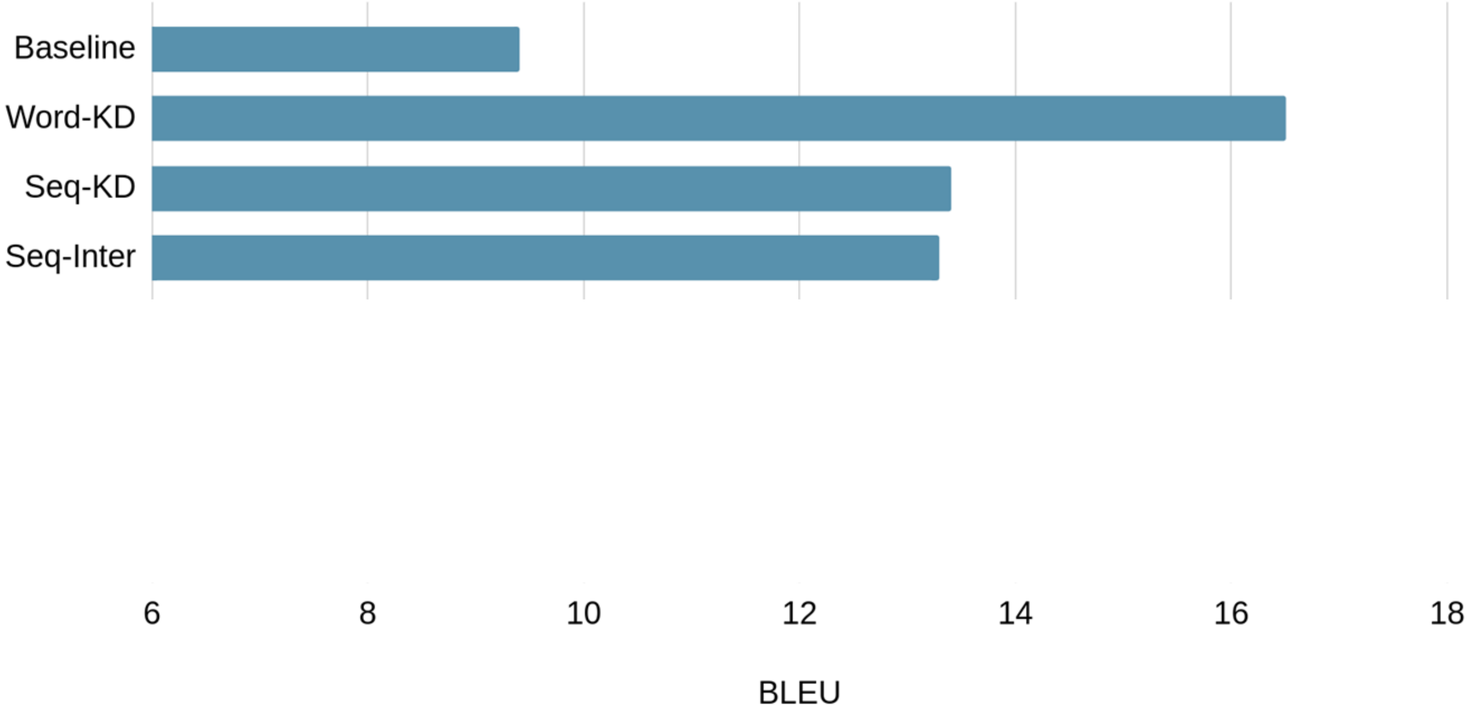
How to rescore:

- BLEU using SLT data for which there is the reference
- Other methods: e.g. quality estimation (using ASR data)

Goal:

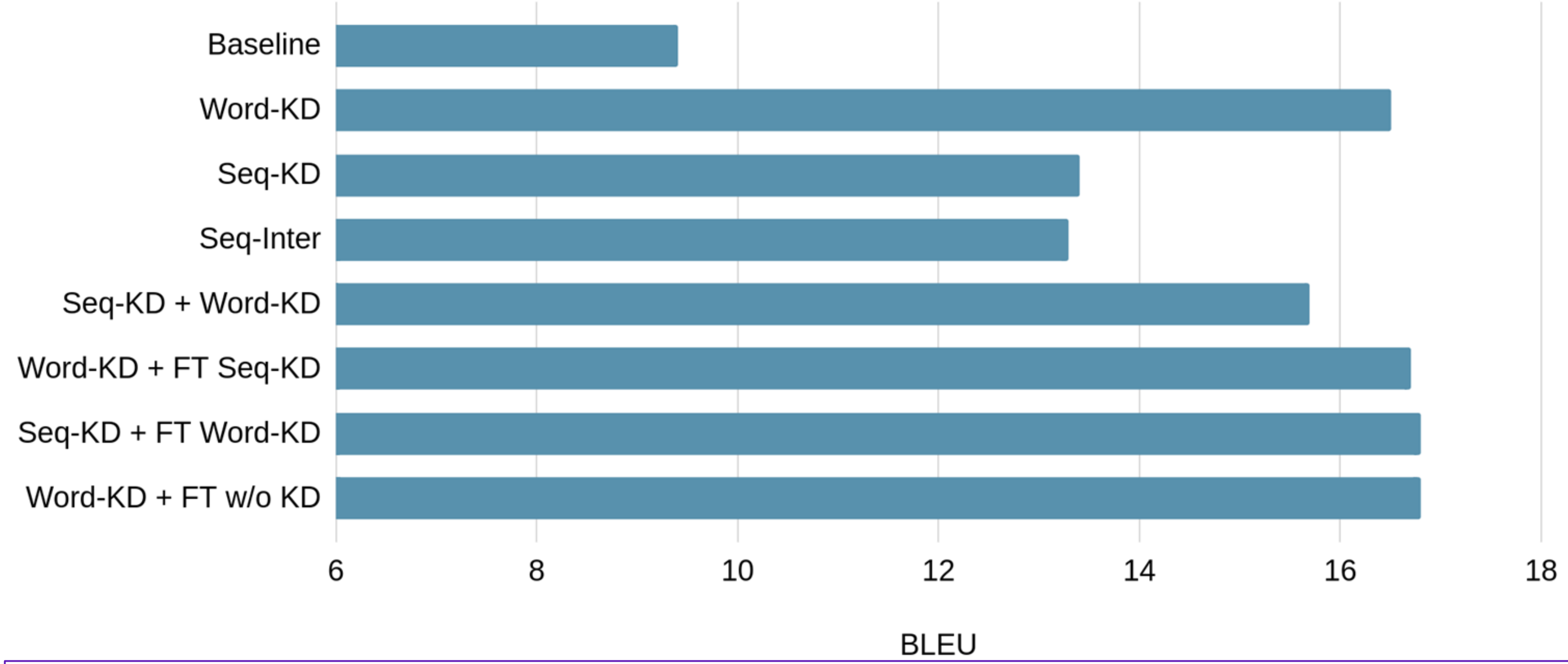
- To add knowledge from the teacher
- To reduce the lexical variability in the data (MT outputs have less variability)

KD Methods (Gaido et al., 2020)



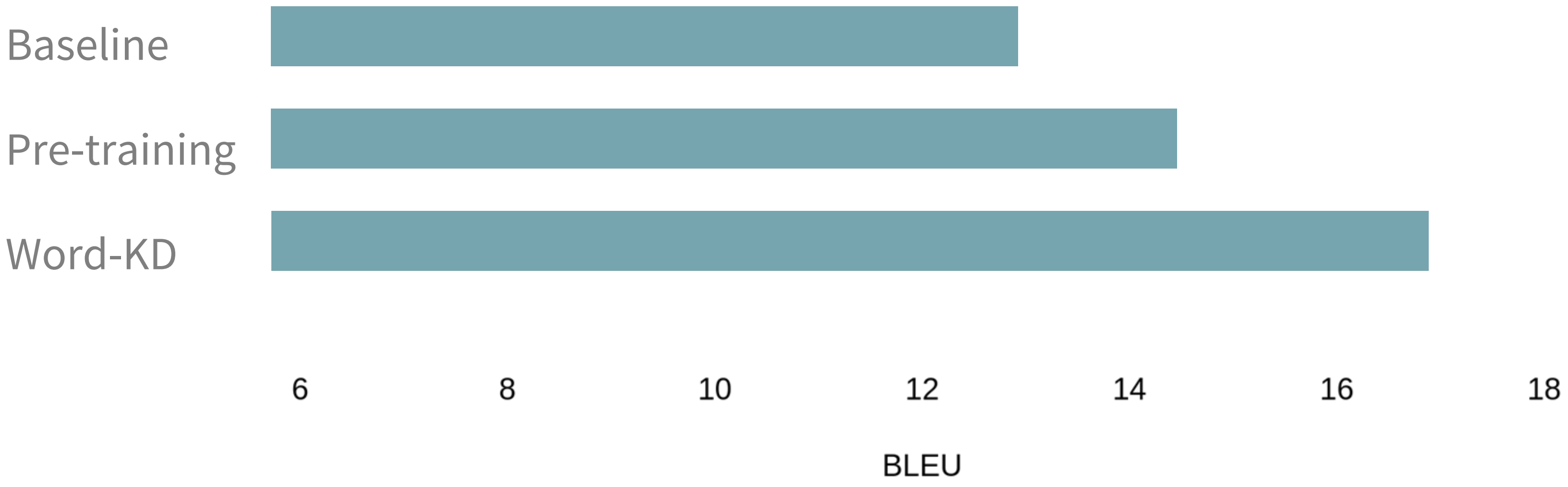
Word KD works the best

KD Methods (Gaido et al., 2020)



Word KD with a fine-tuning slightly improves over word KD

Pre-training vs KD (Liu et al., 2019)

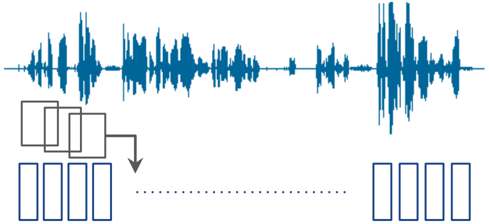


KD outperforms pre-training

Sec 3.3

Alternate Data Representations

[Recall] Speech vs. Text

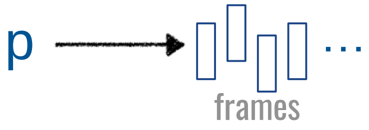


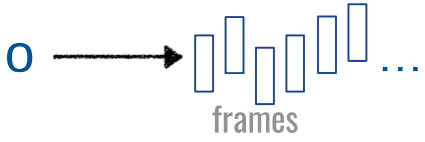
Discretized audio — speech frames

Speech features ~8-10x longer than
the equivalent character sequences

c h a r a c t e r s

SPEECH:





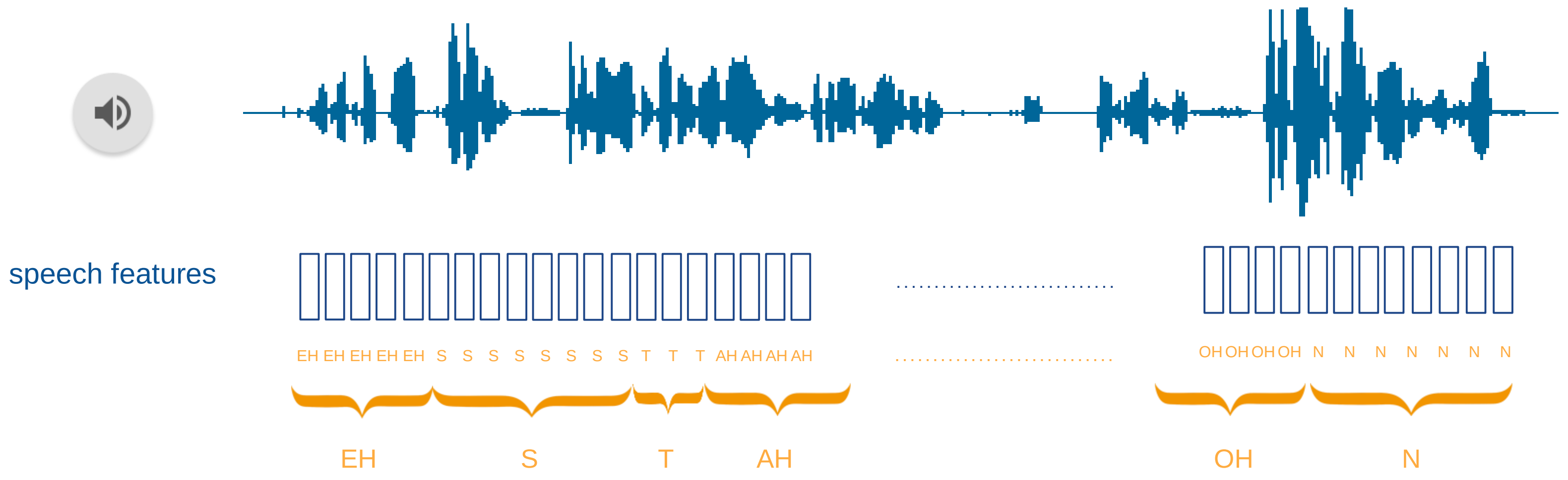
Each feature vector is unique,
Number of feature vectors per phone varies

TEXT: p → p

Challenges:

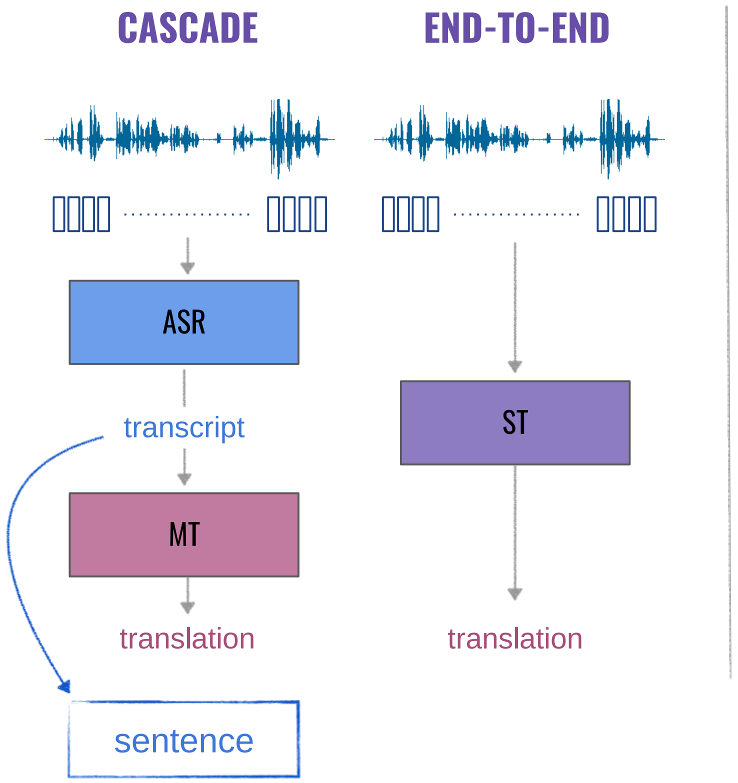
- *Sequence length*
- *Sequence redundancy*
- *Speech feature variation*

A Closer Look

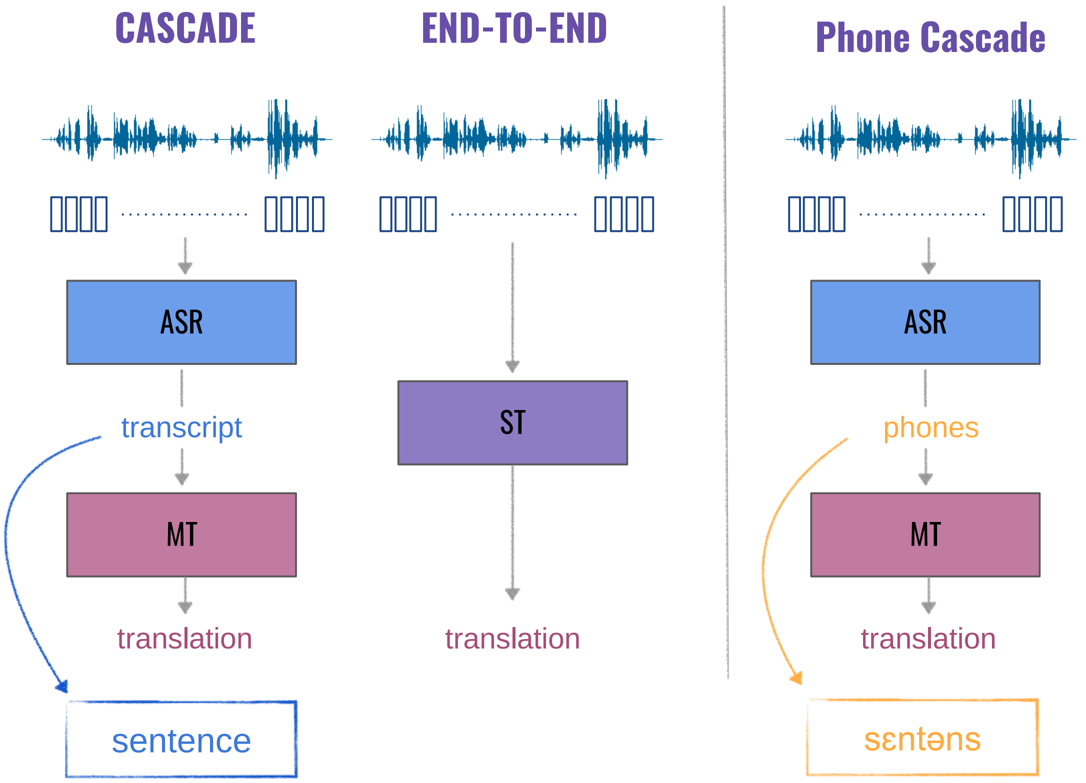


[Esta es una oración]

ST Architectures



ST Architectures



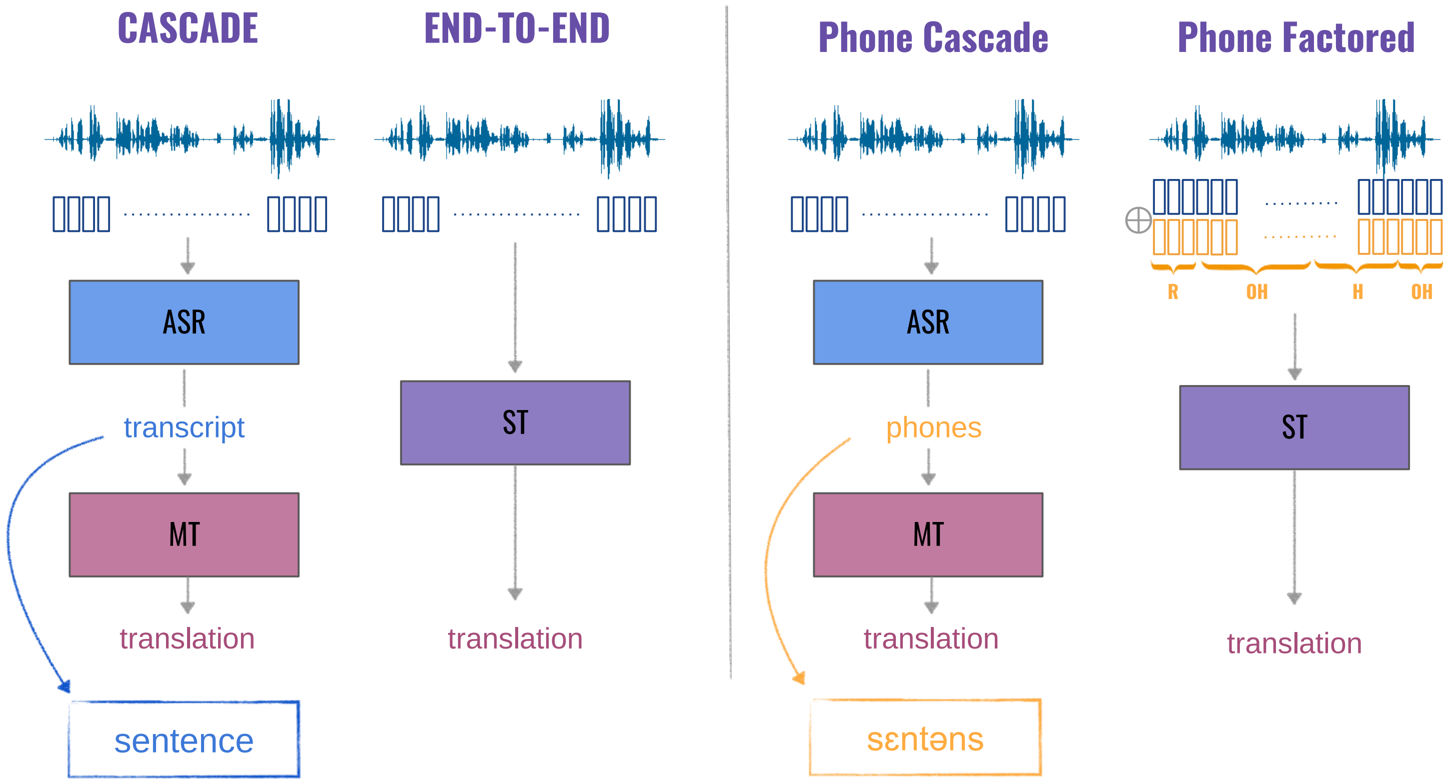
Recall: Redundancy

Translating redundant phone sequences: EH EH EH EH EH S S S S S S S S T T T AH AH AH AH

performs 13% worse than uniqued: EH S T AH

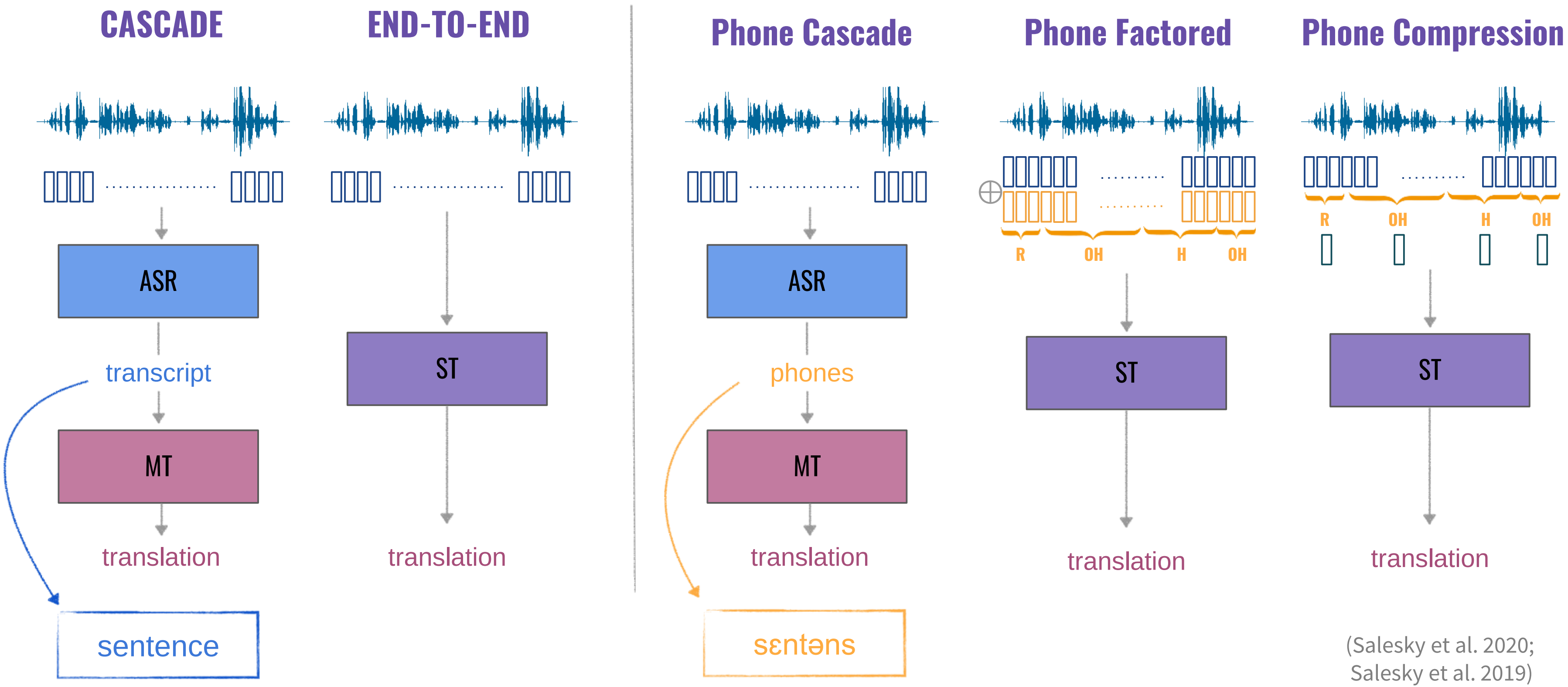
(Salesky et al. 2020)

ST Architectures



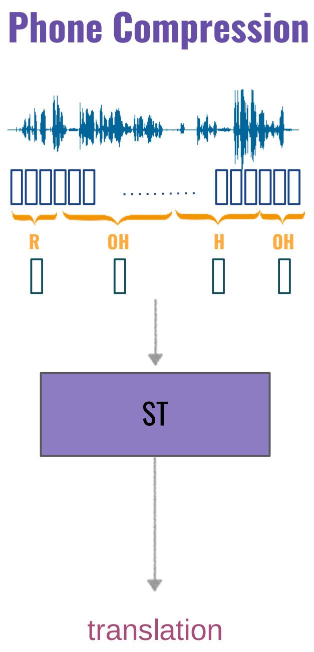
(Salesky et al. 2020)

ST Architectures



(Salesky et al. 2020; Salesky et al. 2019)

Methods



Detecting 'phone' units:

- ASR alignment* (Salesky et al. 2019)
- Adaptive feature selection (AFS)* (Zhang et al. 2020)
- CTC loss applied in encoder (Gaido et al. 2021)

  *require an additional model

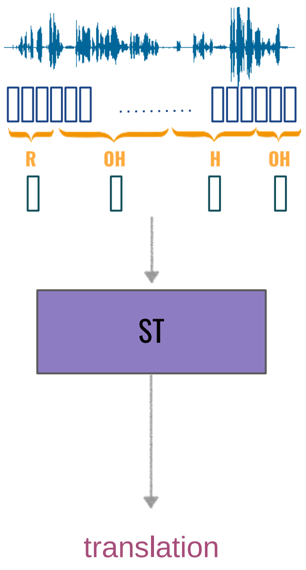
Compression:

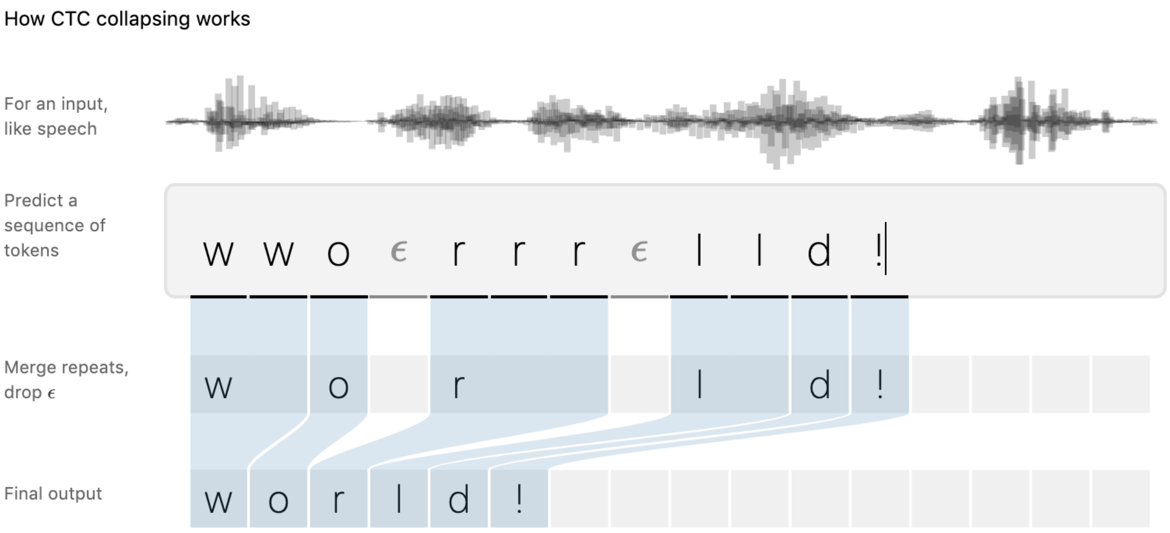
- Averaging
- Skip (select key-frame only)
- Softmax
- Weighted projection

(Salesky et al. 2019; Zhang et al. 2020; Gaido et al. 2021)

Methods

Phone Compression





(Hannun et al. 2017) — https://distill.pub/2017/ctc

Results

Larger datasets

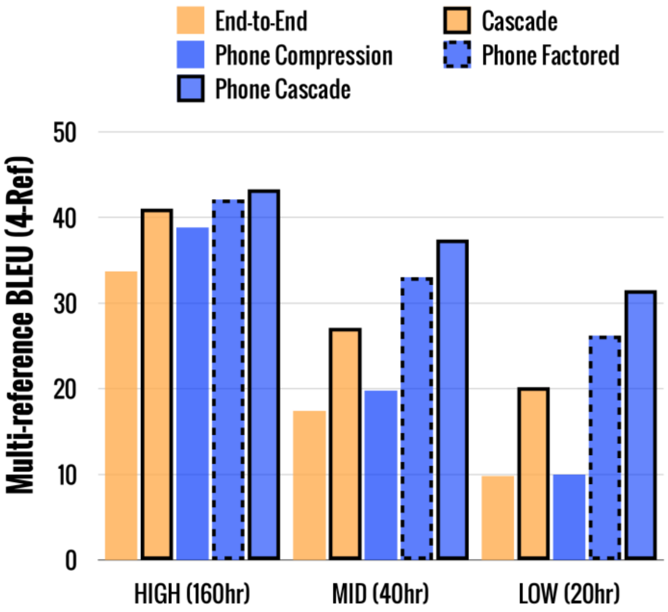
- Librispeech English—French
- MuST-C English—German+
- ~400 hours of speech with translations, transcripts

Performance Improvements

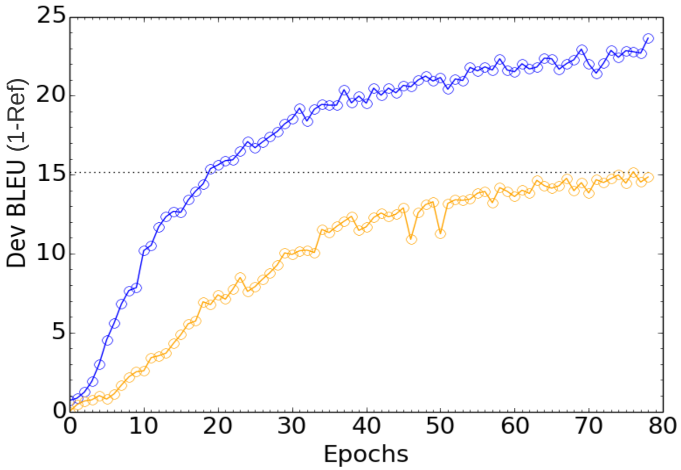
- Improvements of 1-2 BLEU
- Computation reduction:
  - *AFS*: temporal reduction by 80%
  - *CTC*: overall computation reduced by ~10%
- Training and inference time reductions

(Zhang et al. 2020; Gaido et al. 2021)

Results



Fisher Spanish—English
(160 hours)



(Salesky et al. 2019; Salesky et al. 2020)

Sec 4:

Evaluation

Automatic Metrics

Utterance segmentation

Mitigating error due to speaker variation

Sec 4.1

Automatic Metrics

Evaluation

- Motivated by evaluation in machine translation
  - Automatic evaluation
    - Cheap
    - Fast
  - Human evaluation
    - Gold standard
    - Subjective
    - Expensive, time-consuming

Automatic metrics

- Reuse Text MT-based metrics
    - BLEU
        - Compare reference translation to output
- Multi-task system
    - Word error rate (WER) of transcription
        - Single correct output
        - Often calculated ignoring punctuation and case

BLEU

- Compare Hypothesis to reference translation
    - Geometric mean of n-gram precision (1 to 4-grams)
    - Using case- and punctuation information

Reference: BLEU is a MT metric

Hypothesis: BLEU is my metric

BLEU

- Compare Hypothesis to reference translation
  - Geometric mean of n-gram precision (1 to 4-grams)
  - Using case- and punctuation information

Reference: BLEU is a MT metric

Hypothesis: BLEU is my metric

1-gram: 3/4
2-gram: 1/3
3-gram: 0/2
4-gram: 0/1

$$\text{BLEU} = \sqrt[4]{3/4*1/3*0*0*\text{BP}}$$

BLEU

- Compare Hypothesis to reference translation
  - Geometric mean of n-gram precision (1 to 4-grams)
  - Using case- and punctuation information
- Aggregated scores over large dataset
- "*Brevity penalty*" to account for recall

Reference: BLEU is a MT metric

Hypothesis: BLEU is my metric

1-gram: 3/4
2-gram: 1/3
3-gram: 0/2
4-gram: 0/1

BLEU = $\sqrt[4]{3/4*1/3*0*0*BP}$

Word error rate (WER)

- Align reference and hypothesis
  - Calculate insertions, deletions and substitutions
  - Divide by reference length

Reference: WER is an ASR metric

Hypothesis: WER is my *** metric

- Often ignoring case and punctuation

Word error rate (WER)

- Align reference and hypothesis
  - Calculate insertions, deletions and substitutions
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Reference: WER is an ASR metric

Hypothesis: WER is my *** metric

Alignment: S D

- Often ignoring case and punctuation

Word error rate (WER)

- Align reference and hypothesis
  - Calculate insertions, deletions and substitutions
  - Divide by reference length
- Often ignoring case and punctuation

Reference: WER is an ASR metric

Hypothesis: WER is my *** metric

Alignment: S D

$$\text{WER} = \frac{S+D+I}{N} = \frac{2}{5}$$

Sec 4.2

Utterance Segmentation

Utterance segmentation

SLT evaluation has an additional level of complexity compared to machine translation.

Utterance segmentation

SLT evaluation has an additional level of complexity compared to machine translation.

Machine Translation:

Document:

This is an audio signal. In the training data it was split using strong punctuation. Three sentences in total.

Utterance segmentation

SLT evaluation has an additional level of complexity compared to machine translation.

Machine Translation:

Document:

This is an audio signal. In the training data it was split using strong punctuation. Three sentences in total.

Source sentences:

This is an audio signal.

In the training data it was split using strong punctuation.

Three sentences in total!

Utterance segmentation

SLT evaluation has an additional level of complexity compared to machine translation.

Machine Translation:

Document:

This is an audio signal. In the training data it was split using strong punctuation. Three sentences in total.

Source sentences:

This is an audio signal.

In the training data it was split using strong punctuation.

Three sentences in total!

Reference sentence:

Questo e’ un segnale audio.

Nei dati di training e’ stato diviso usando la punteggiatura forte.

Tre frasi in totale!

Utterance segmentation

SLT evaluation has an additional level of complexity compared to machine translation.

Machine Translation:

Source sentences:	MT sentences:	Reference sentence:
This is an audio signal.	Questo è un segnale audio.	Questo e' un segnale audio.
In the training data it was split using strong punctuation.	Nei dati di allenamento è stato suddiviso utilizzando una forte punteggiatura.	Nei dati di training e' stato diviso usando la punteggiatura forte.
Three sentences in total!	3 frasi in totale!	Tre frasi in totale!

Utterance segmentation

SLT evaluation has an additional level of complexity compared to machine translation.

Machine Translation:

Source sentences:	MT sentences:	Reference sentence:
This is an audio signal.	Questo è un segnale audio.	Questo e' un segnale audio.
In the training data it was split using strong punctuation.	Nei dati di allenamento è stato suddiviso utilizzando una forte punteggiatura.	Nei dati di training e' stato diviso usando la punteggiatura forte.
Three sentences in total!	3 frasi in totale!	Tre frasi in totale!

Utterance segmentation

Spoken Language Translation:

Source input:

t h i s i s a n a u d i o s i g n a l i n t h e t r a i n i n g d a t a i t w a s s p l i t u s i n g s t r o n g p u n c t u a t i o n t h r e e s e n t e n c e s i n t o t a l

Utterance segmentation

Spoken Language Translation:

Source input:

t h i s i s a n a u d i o s i g n a l i n t h e t r a i n i n g d a t a i t w a s s p l i t u s i n g s t r o n g p u n c t u a t i o n t h r e e s e n t e n c e s i n t o t a l

Reference sentences:

This is an audio signal.

In the training data it was split using strong punctuation.

Three sentences in total!

Utterance segmentation

SLT outputs depend on the segmentation of the audio input:

This is an audio | Signal in the training data was split. | Using strong punctuation, 3 sentences in total!

Utterance segmentation

SLT outputs depend on the segmentation of the audio input:

This is an audio | Signal in the training data was split. | Using strong punctuation, 3 sentences in total!

This is an audio signal in the training data. | It was split using strong punctuation. | Three sentences in total!

Utterance segmentation

SLT outputs depend on the segmentation of the audio input:

This is an audio	Signal in the training data was split.	Using strong punctuation, 3 sentences in total!
This is an audio signal in the training data.	It was split using strong punctuation.	Three sentences in total!
This is a signal.	In the training data.	It was split in three sentences.

Utterance segmentation

SLT outputs depend on the segmentation of the audio input:

This is an audio / Signal in the training data was split. / Using strong punctuation, 3 sentences in total!

This is an audio signal in the training data. / It was split using strong punctuation. / Three sentences in total!

This is a signal. / In the training data. / It was split in three sentences.

This is / Signal. In the training data / it was split using strong punctuation. / Three sentences / in total!

Utterance segmentation

SLT outputs depend on the segmentation of the audio input:

This is an audio	Signal in the training data was split.	Using strong punctuation, 3 sentences in total!		
This is an audio signal in the training data.	It was split using strong punctuation.	Three sentences in total!		
This is a signal.	In the training data.	It was split in three sentences.		
This is	Signal. In the training data	it was split using strong punctuation.	Three sentences	in total!

Reference sentences:

This is an audio signal.	In the training data it was split using strong punctuation.	Three sentences in total!

SLT output - reference alignment

1. How to compare the automatically split SLT outputs with the manually split references?
2. How to compare different systems splitting the SLT outputs in different ways?

SLT output - reference alignment

1. How to compare the automatically split SLT outputs with the manually split references?
2. How to compare different systems splitting the SLT outputs in different ways?

Issues:

- Different number of sentences
- Truncated SLT sentences
- Insertion of additional text in the SLT outputs
- Missing large parts in the SLT outputs

Concatenation

SLT output:

This is	Signal. In the training data	it was split using strong punctuation.	Three sentences	in total!

Reference sentences:

This is an audio signal.	In the training data it was split using strong punctuation.	Three sentences in total!

Concatenation

SLT output:

This is Signal . In the training data it was split using strong punctuation . Three sentences in total !

Reference sentences:

This is an audio signal . In the training data it was split using strong punctuation . Three sentences in total !

The concatenated STL outputs (references) are considered as a single sentence.

Automatic metrics applied on two strings.

Much less precise than working at segment level, but fast to implement

Automatic re-segmentation algorithm

SLT output:

This is Signal . In the training data it was split using strong punctuation . Three sentences in total !

Reference sentences:

This is an audio signal . In the training data it was split using strong punctuation . Three sentences in total!

Automatic re-segmentation algorithm

SLT output:

This is Signal . In the training data it was split using strong punctuation . Three sentences in total !

Reference sentences:

This is an audio signal . <eos> In the training data it was split using strong punctuation . <eos> Three sentences in total ! <eos>

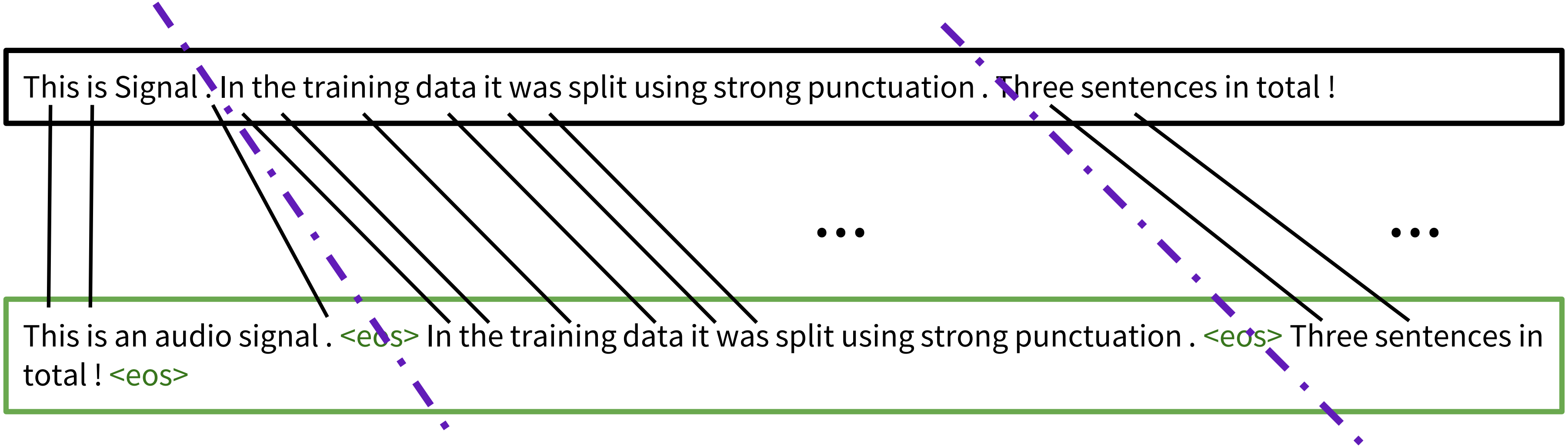
Automatic re-segmentation algorithm

This is Signal . In the training data it was split using strong punctuation . Three sentences in total !

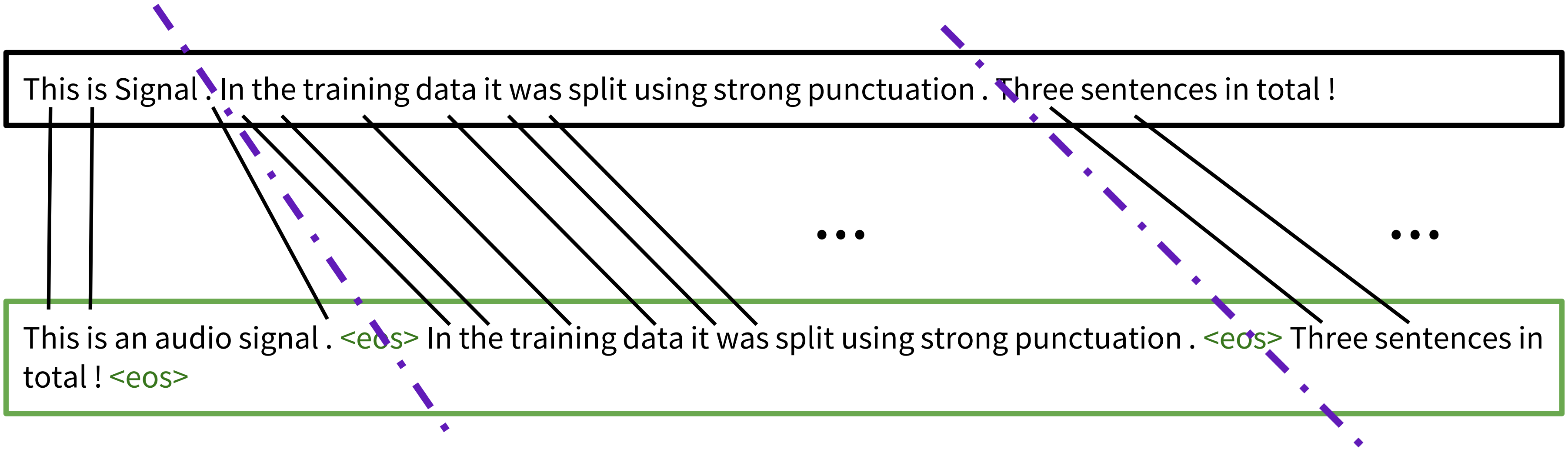
...   ...

This is an audio signal . <eos> In the training data it was split using strong punctuation . <eos> Three sentences in total ! <eos>

Automatic re-segmentation algorithm



Automatic re-segmentation algorithm



Based on the word alignments and <eos>, the SLT output and reference are segmented.

Alignment and segmentation in one step using the Levenshtein distance (Matuzov et al., 2015).

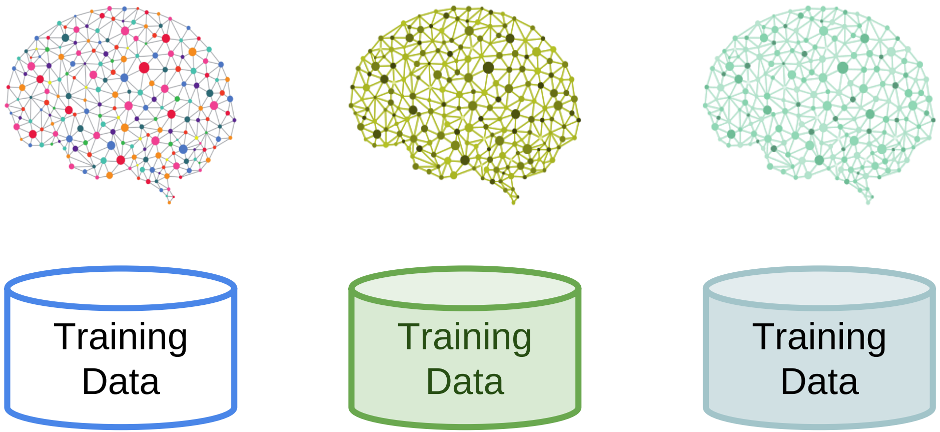
New segments used to compute the automatic metrics.

Sec 4.3

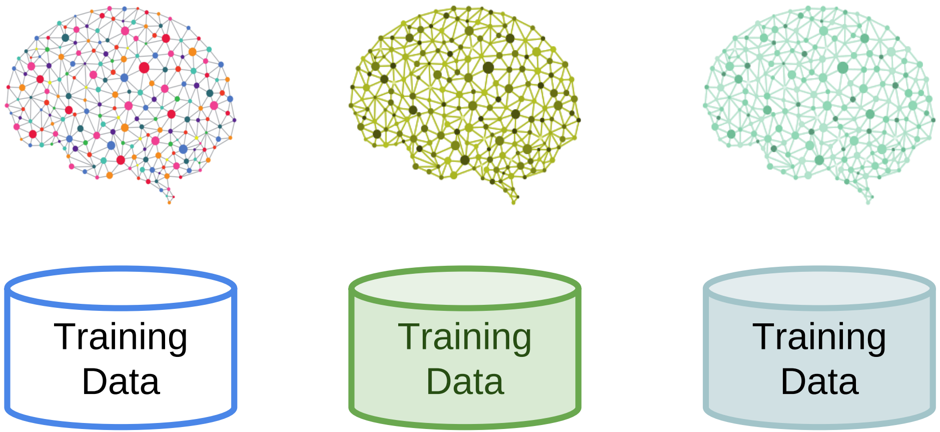
Mitigating error — Gender bias

Gender and data

Gender and data



Gender and data



- ~ 70% of the TED speakers is male
- Most of the ASR and MT data are generated by male speakers

Gender and translation

- How do languages convey the gender of a referred entity?

English:
Natural Gender Language

- Pronouns (he/she)
- Lexical gender (boy/girl)
- Gender-marked titles (actor/actress)

she is a good friend
he is a good friend

Italian/French:
Grammatical Gender Languages

- Overtly express feminine/masculine gender on numerous POS

è un**a** buon**a** amic**a** (Fem.)
è un_ buon_ amic**o**» (Masc.)

?

I'm a good friend

Gender bias: a technical and ethical problem

"I'm a good friend"	Correct Italian translation	Most probable automatic translation
M: *"Sono un_ buon_ amic**o**"*	✓	✓
F: *"Sono un**a** buon**a** amic**a**"*	✓	

Gender bias: a technical and ethical problem

“I’m a good friend”	Correct Italian translation	Most probable automatic translation
M: *“Sono un_ buon_ amic**o**”*	✓	✓
F: *“Sono un**a** buon**a** amic**a**”*	✓	

Independently from the speaker

Gender bias: a technical and ethical problem

"I'm a good friend"	Correct Italian translation	Most probable automatic translation
M: *"Sono un_ buon_ amic**o**"*	✓	✓
F: *"Sono un**a** buon**a** amic**a**"*	✓	

Independently from the speaker

Bias in the training data…
...pushes systems towards a "male default"…
...amplifying social asymmetries!

Gender bias and automatic translation

- **Machine Translation** (text-to-text)
  → textual input does NOT always provide gender clues

- **Speech Translation** (speech-to-text)
  → audio input can provide gender clues

I’m a good friend

I’m a good friend

Are ST systems able to exploit audio information to translate gender?

Gender bias and ST - exploiting audio features

- Bentivogli et al., "*Gender in Danger? Evaluating Speech Translation Technology on the MuST-SHE Corpus*", ACL 2020
  - **MuST-SHE: a benchmark for the analysis of gender translation in MT and ST**

- **Derived from MuST-C** (2 language directions En→It, En→Fr)
- **Gender-sensitive design**: each segment contains 1+ English gender-neutral word translated into the corresponding masculine/feminine target word(s)
- **2 gender phenomena**: info-in-audio (*I'm a good friend*), info-in-content (*she is a good...*)

Gender bias and ST - exploiting audio features

- Bentivogli et al., "*Gender in Danger? Evaluating Speech Translation Technology on the MuST-SHE Corpus*", ACL 2020
    - MuST-SHE: a benchmark for the analysis of gender translation in MT and ST
    - **Gender-sensitive evaluation methodology based on "gender swapping"**

- BLEU/Accuracy scores computed against **correct** and **wrong** references
    - Src: *I have been to London* (female speaker)
    - C-Ref: *Io sono stat**a** a Londra*,
    - W-Ref: *Io sono stat**o** a Londra*
- Difference between correct and wrong reference as a measure of gender translation performance (the higher the better -- lower bias!)

Gender bias and ST - exploiting audio features

- Bentivogli et al., "*Gender in Danger? Evaluating Speech Translation Technology on the MuST-SHE Corpus*", ACL 2020
    - MuST-SHE: a benchmark for the analysis of gender translation in MT and ST
    - Gender-sensitive evaluation methodology based on "gender swapping"
    - **Comparison between end-to-end and cascade ST approaches**

- Translation quality (BLEU): cascade better than e2e
- Gender translation (BLEU+gender swapping): the two perform on par
- Gender translation (Accuracy+gender swapping) on info-in-audio samples:
    - **e2e much better than simple cascade**
        - leveraging audio features ⇨ethical issues (vocally impaired, transgender)?

Gender bias and ST - exploiting speakers' info

- Gaido et al., "*Breeding Gender-aware Direct Speech Translation Systems*", Coling 2020
    - **MuST-Speakers: annotation of MuST-SHE with speakers' gender information**

Gender bias and ST - exploiting speakers' info

- Gaido et al., "*Breeding Gender-aware Direct Speech Translation Systems*", Coling 2020
  - MuST-Speakers: annotation of MuST-SHE with speakers' gender information
  - **Comparison of different e2e ST systems**

- **Base**: Generic, "gender-unaware" ST model
- **Multi-gender**: single model informed of the speaker's gender via pre-pended gender tokens
- **Gender-specialized**: two models, fine-tuned on utterances spoken by men/women
- Overall translation quality (BLEU): small differences
- Gender translation (Accuracy+gender swapping) on info-in-audio samples (*I'm a good friend*):
  - **Specialized >> Multi-gender >> Base**

Sec 5:

Advanced topics

Utterance segmentation

Multilingual ST

Under-resourced languages

Sec 5.1

Utterance Segmentation

Utterance segmentation - Problem

- **Mismatch between training and evaluation data**
  - Training corpora: "sentence-level" split of continuous speech

This is an audio signal.

In the training data it was split using strong punctuation.

Three sentences in total!

Utterance segmentation - Problem

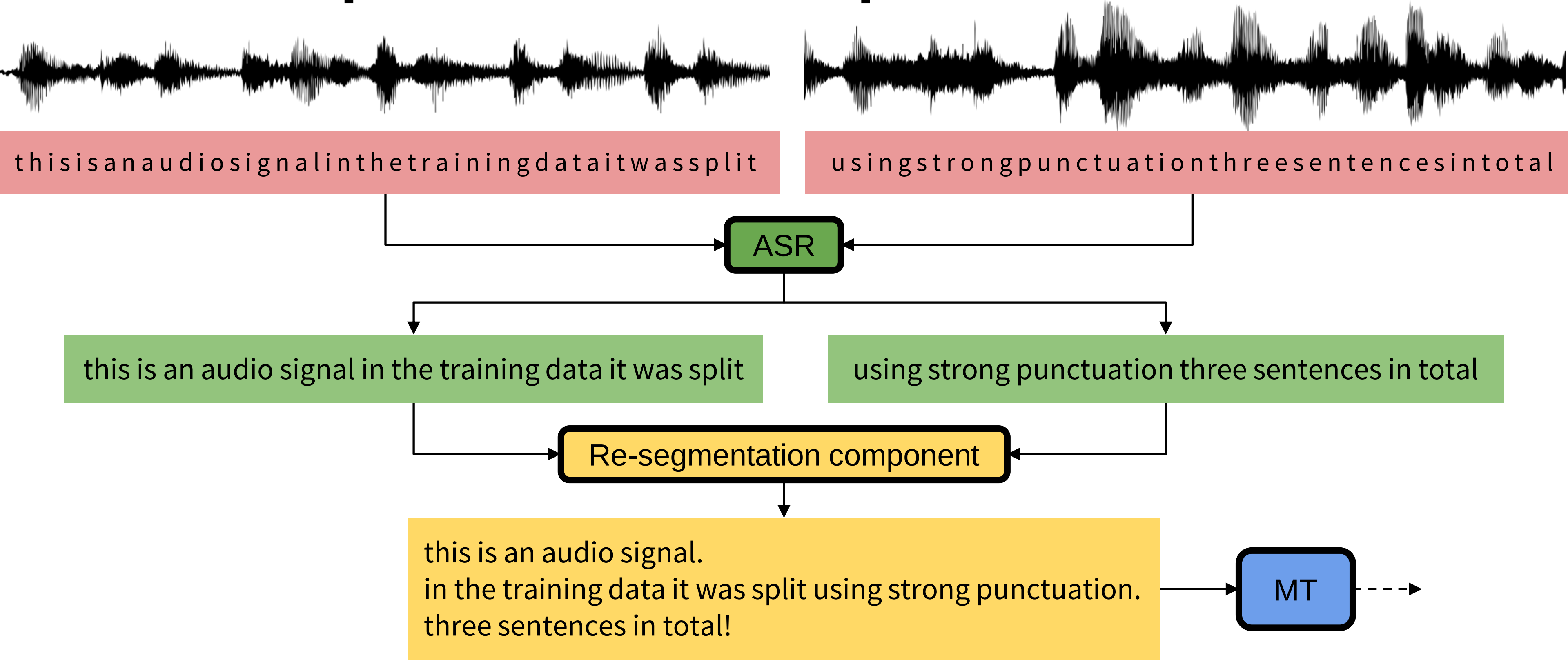
- **Mismatch between training and evaluation data**
  - Training corpora: “sentence-level” split of continuous speech

This is an audio signal. | In the training data it was split using strong punctuation. | Three sentences in total!

  - At run-time: unsegmented continuous speech

thisisanaudiosignalinthetrainingdataitwassplitusingstrongpunctuationthreesentencesintotal

How to split continuous speech in cascade ST?

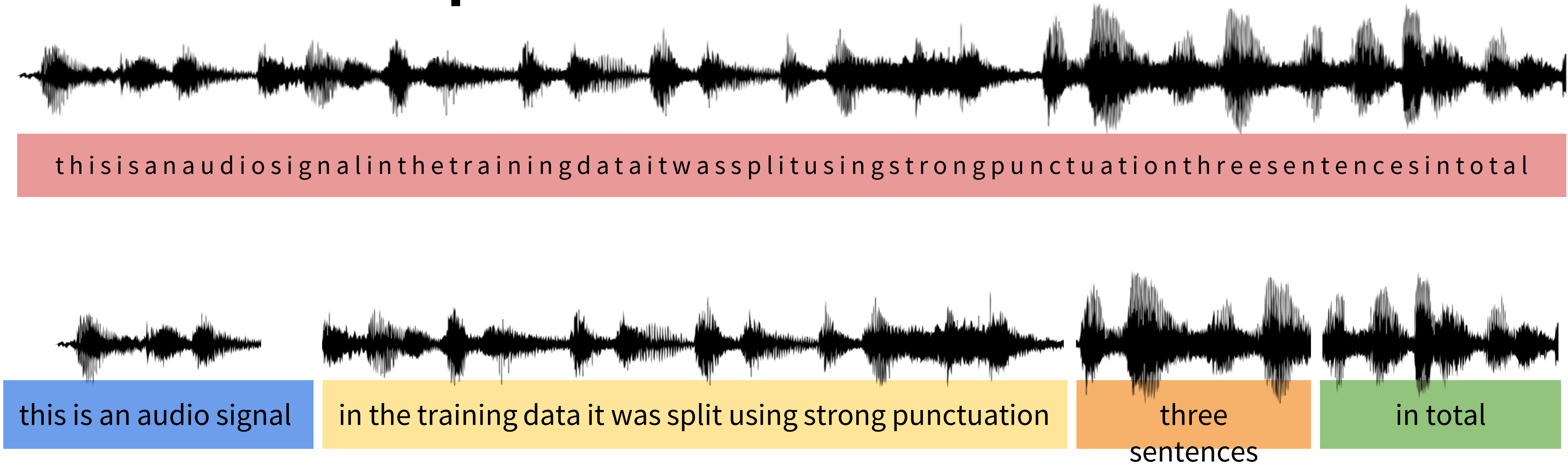


Matusov et al.: "*Automatic Sentence Segmentation and Punctuation Prediction for Spoken Language Translation*", IWSLT`06

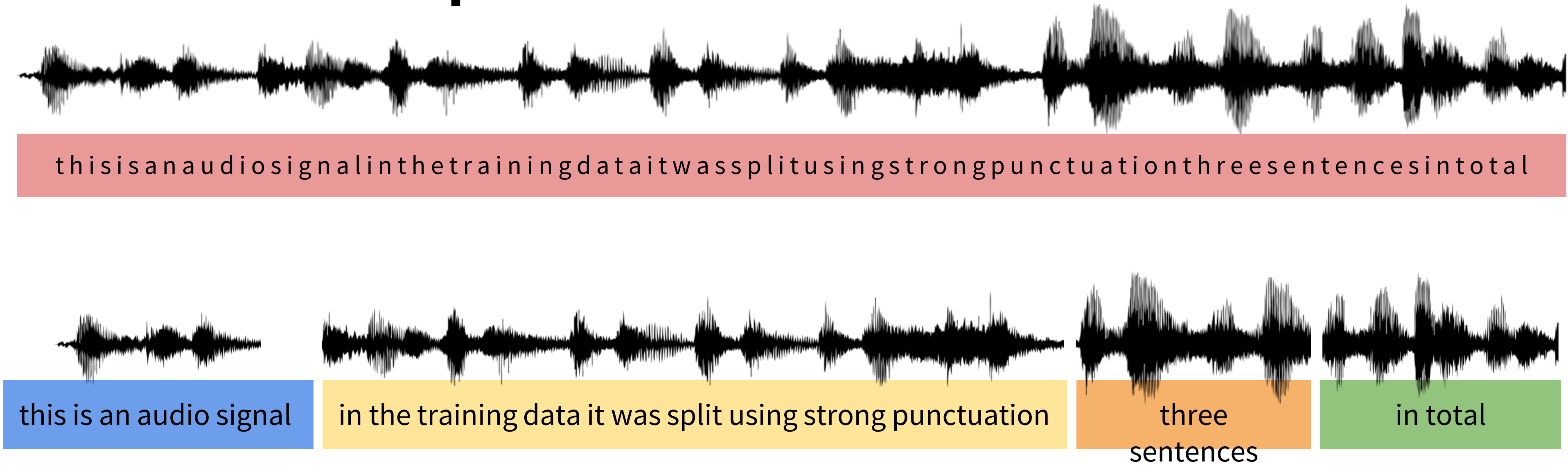
How to split continuous speech in e2e ST?

thisisanaudiosignalinthetrainingdataitwassplitusingstrongpunctuationthreesentencesintotal

Solution 1: Split on silences (via VAD)

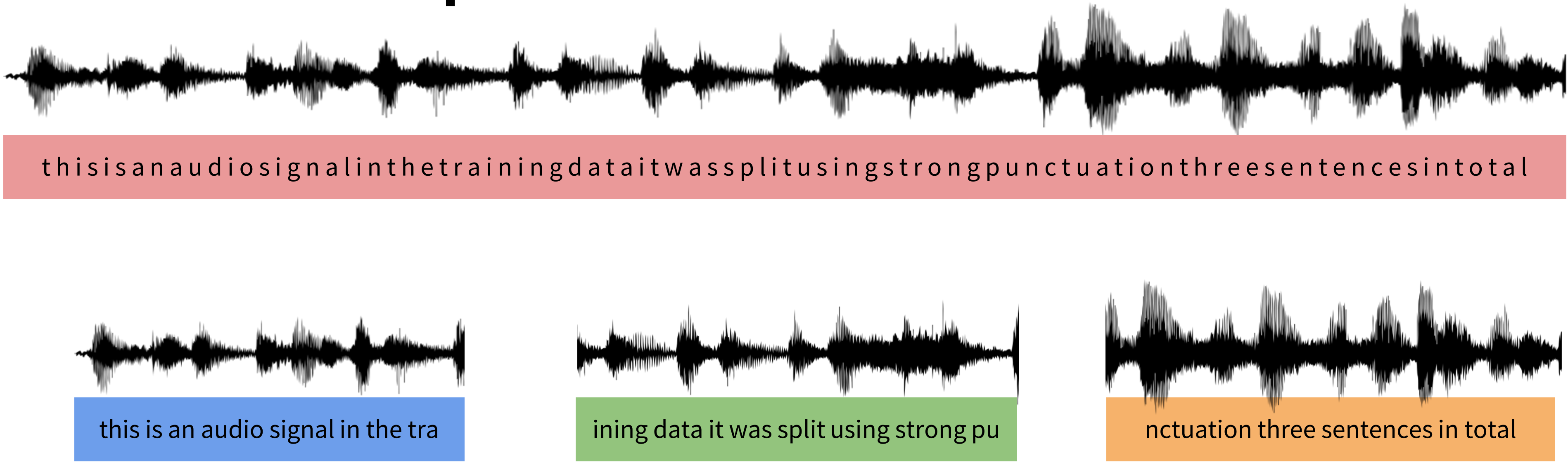


Solution 1: Split on silences (via VAD)

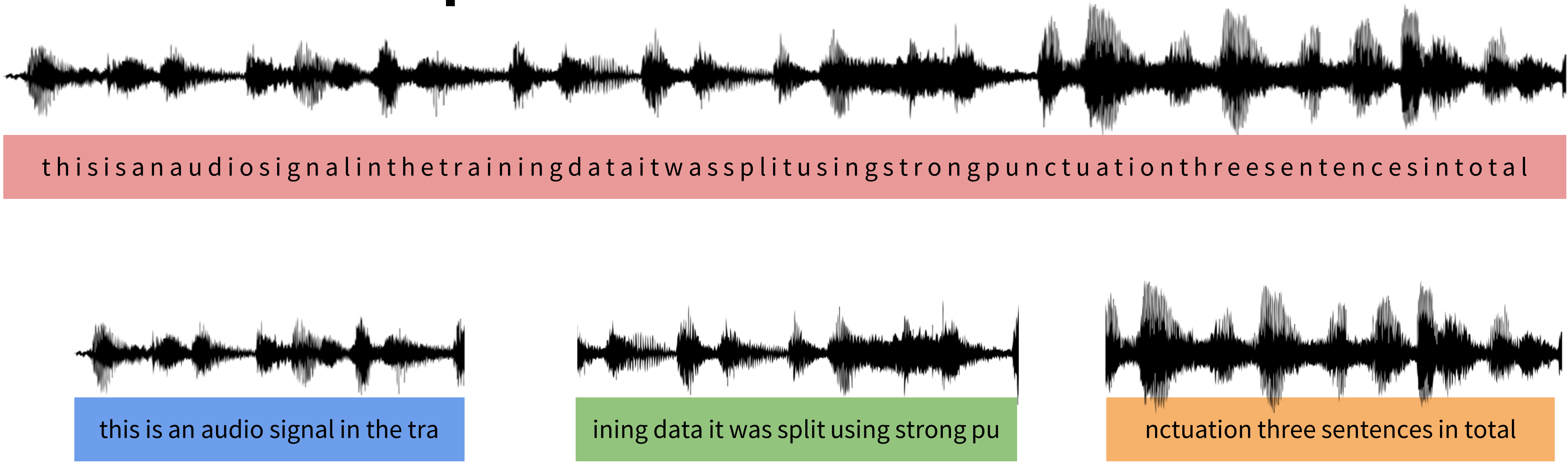


Advantage: silences as a proxy of sentence boundaries
Drawback: variable segments' length (including very short and very long ones)

Solution 2: Split based on fixed audio duration



Solution 2: Split based on fixed audio duration



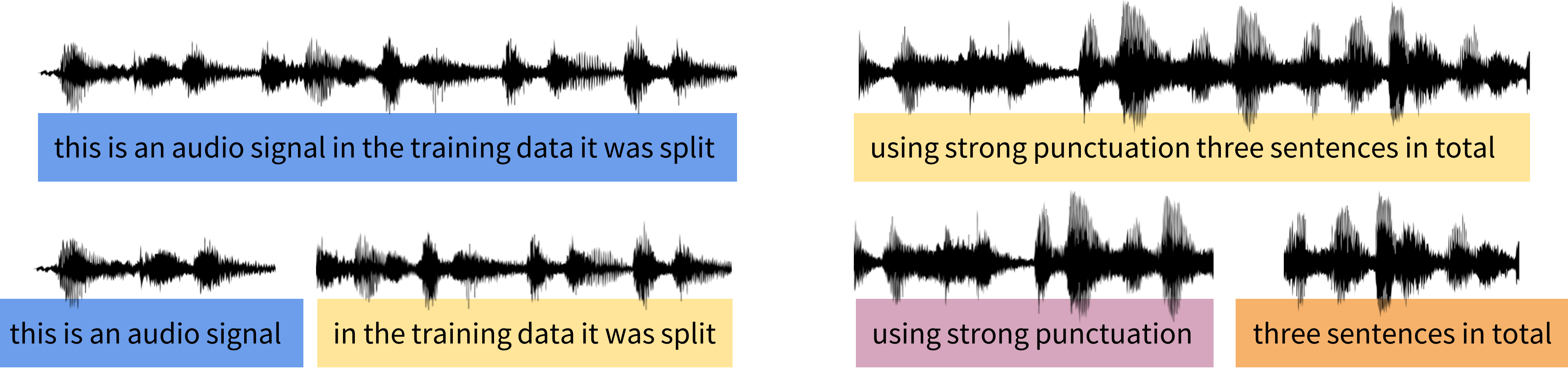
Advantage: uniform segment length

Drawback #1: split points are likely to break the input in critical positions

Drawback #2: non-speech frames are kept in the input

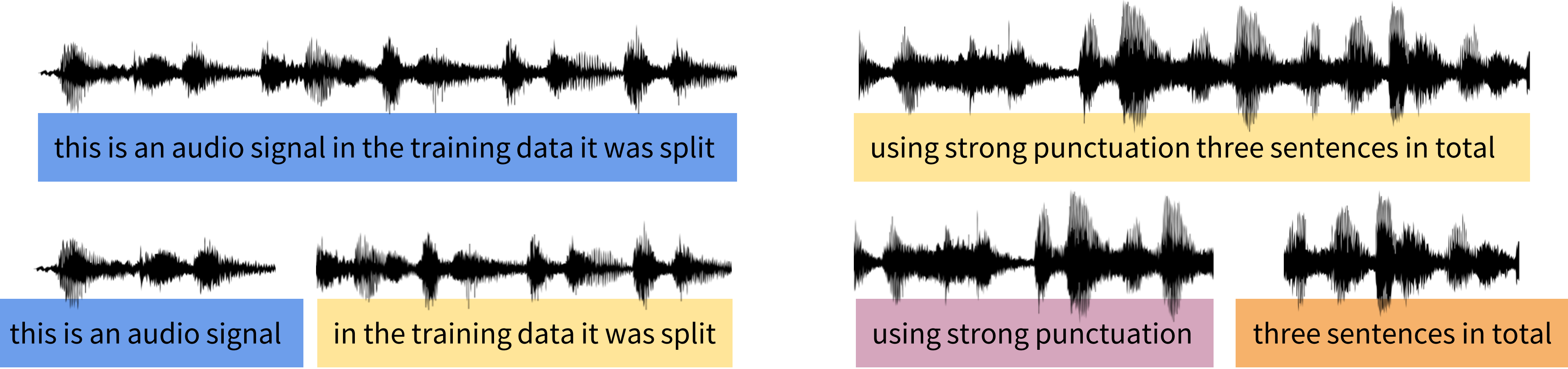
Solution 3: Split on silences & segments' length

Potapczyk and Przybysz: "*SRPOL's system for the IWSLT 2020 end-to-end speech translation task*", IWSLT 2020



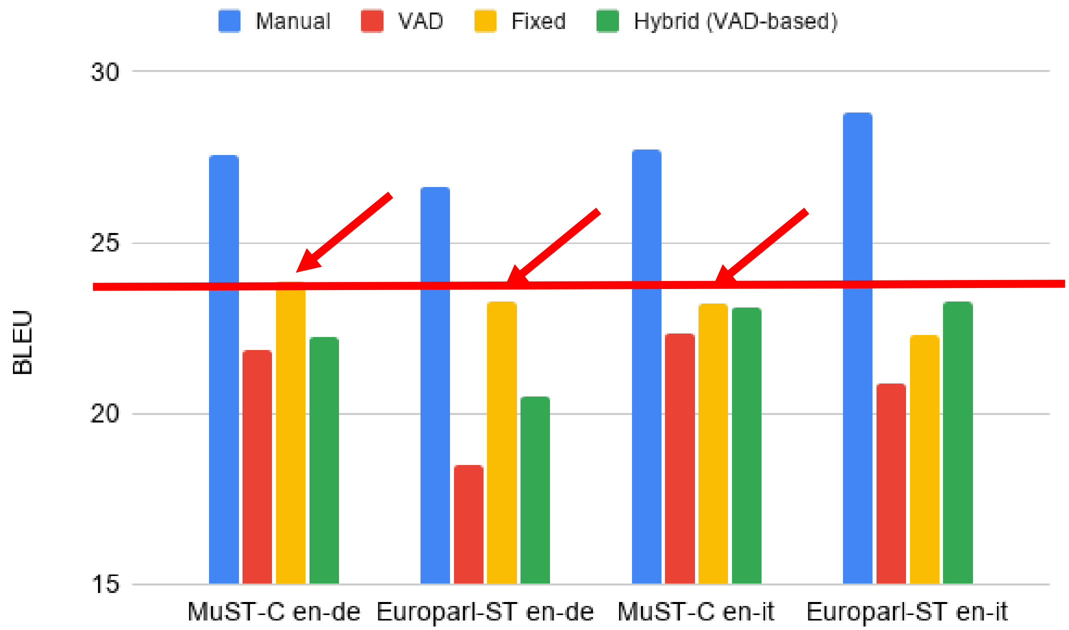
Solution 3: Split on silences & segments' length

Potapczyk and Przybysz: "*SRPOL's system for the IWSLT 2020 end-to-end speech translation task*", IWSLT 2020



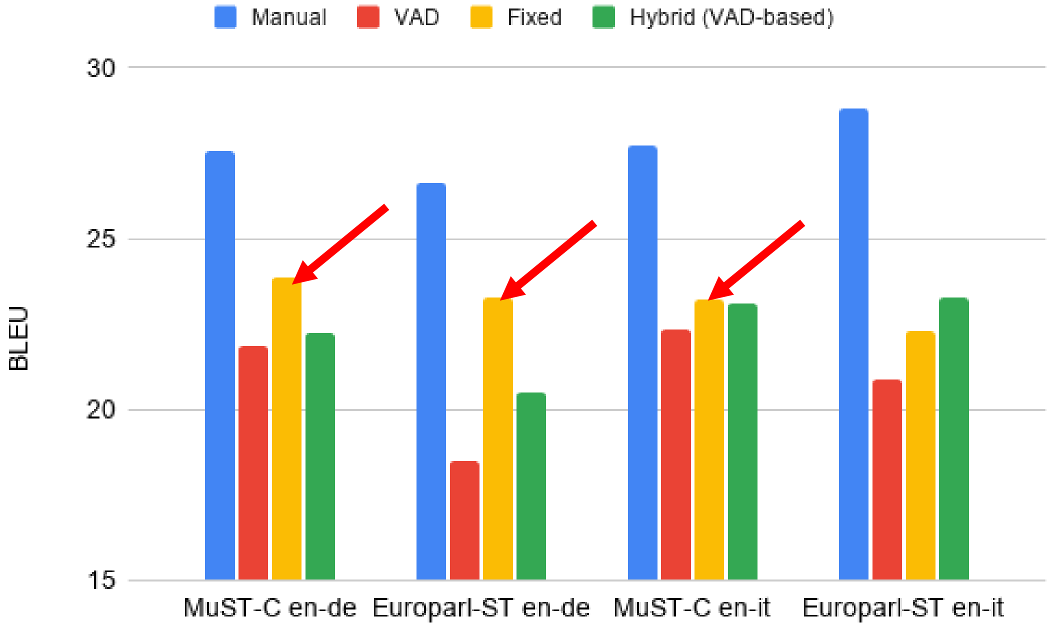
Advantages: closer to sentence-like splits, uniform segment length
Drawback #1: manually-detected silences (non scalable/reproducible)
Drawback #2: full audio required for splitting (not applicable to audio streams)

Utterance segmentation - An open problem



Large room for improvement compared to manual segmentation

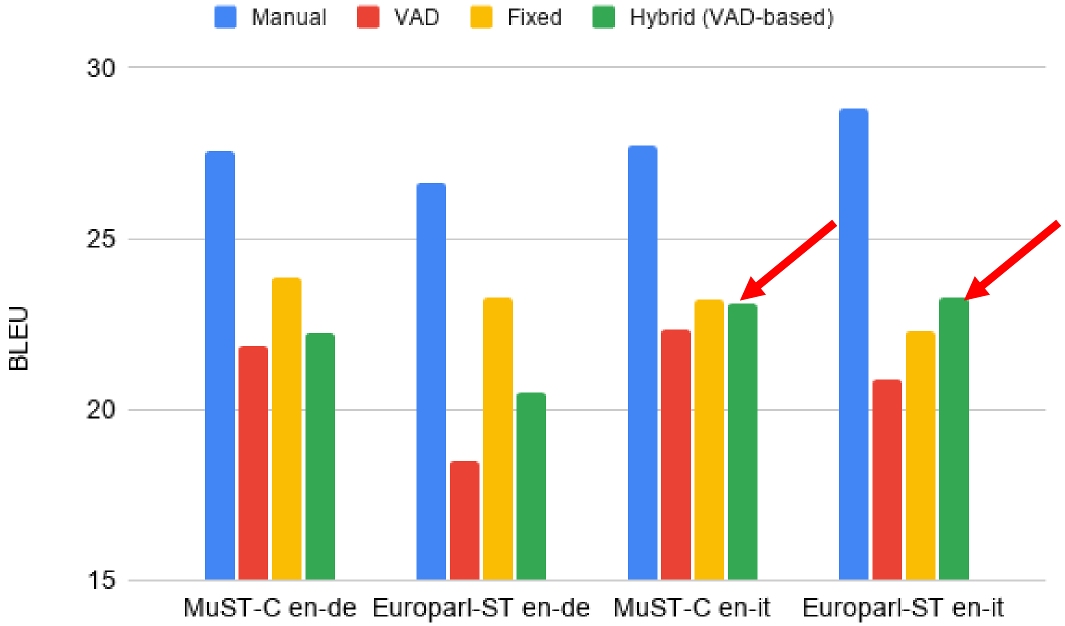
Utterance segmentation - An open problem



FIXED length surprisingly good

→ segments' length is more important than precise split times

Utterance segmentation - An open problem



Fully automatic hybrid segmentation?

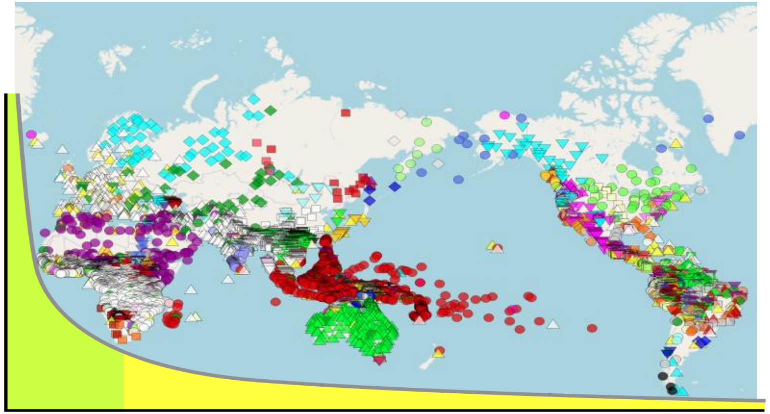
→ better than VAD, better than FIXED on one language pair

Sec 5.2

Multilingual ST

Multilingual ST

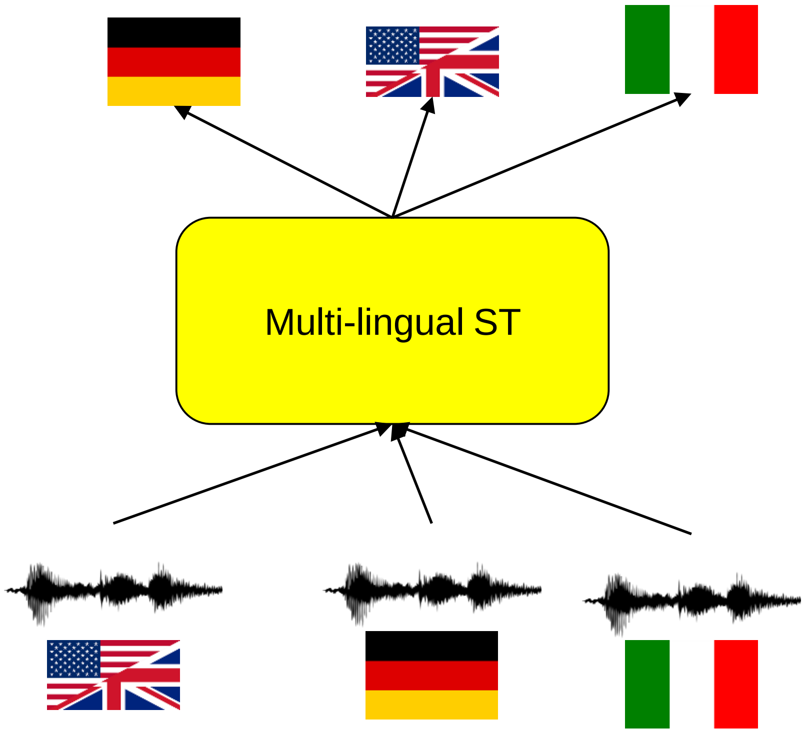
- Most research focuses on few languages
- More than *7,000 languages* in the world



- Challenges:
  - Scale to many languages
  - Limited resources

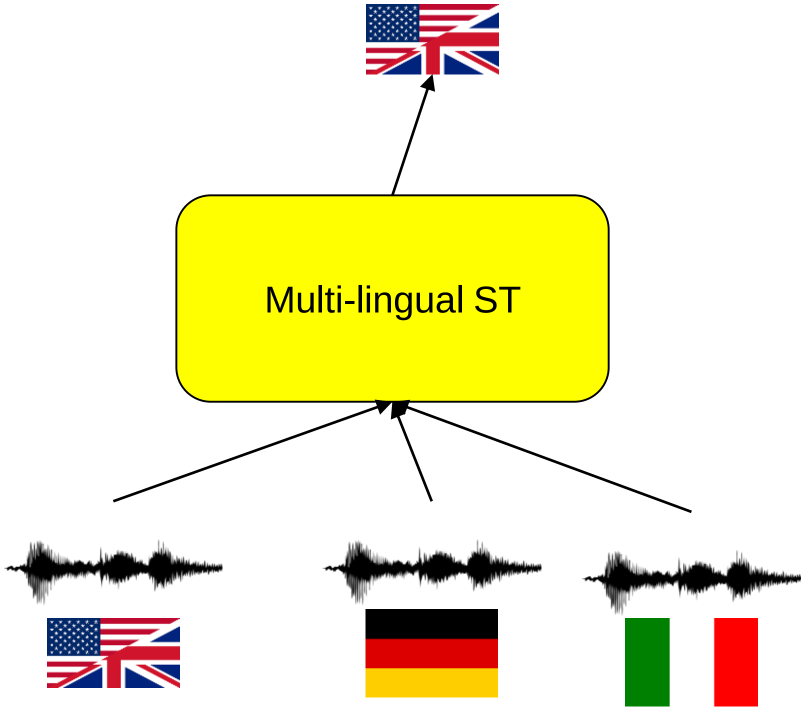
Multilingual ST

- Idea:
  - *Single model for many languages*
  - Motivated by text translation
- Advantages:
  - Less training data necessary
  - Handle several languages by single model
  - Zero-shot direction:
    - Translate between languages without training data



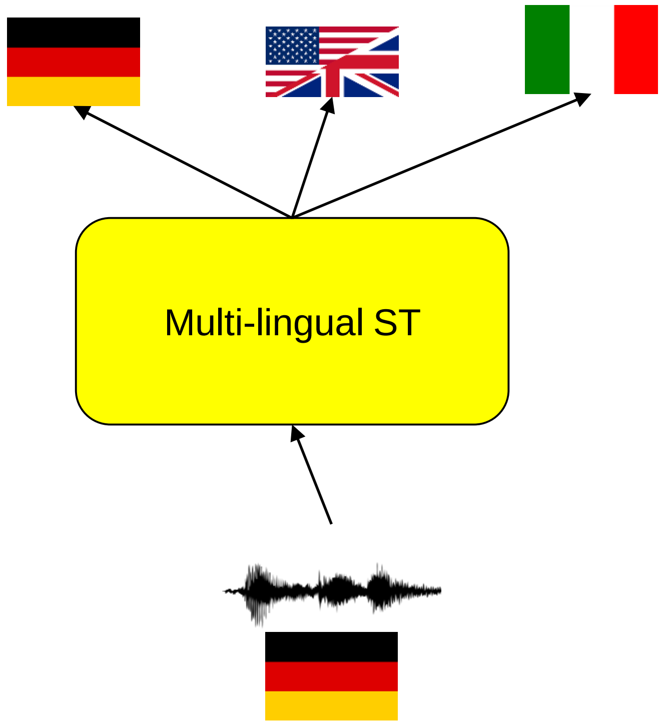
Multilingual ST

- Scenarios:
    - Many-to-One



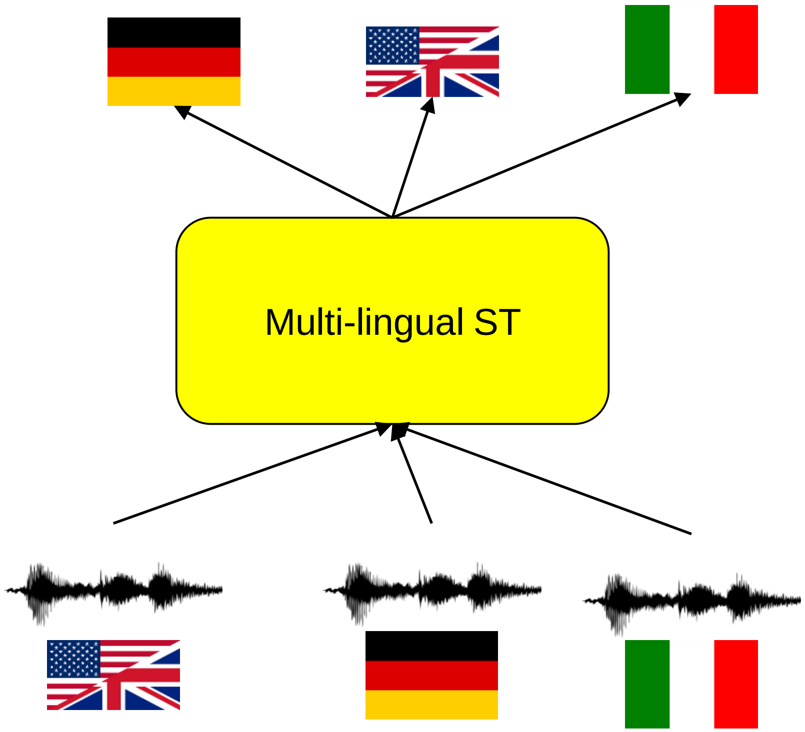
Multilingual ST

- Scenarios:
  - Many-to-One
  - One-to-Many



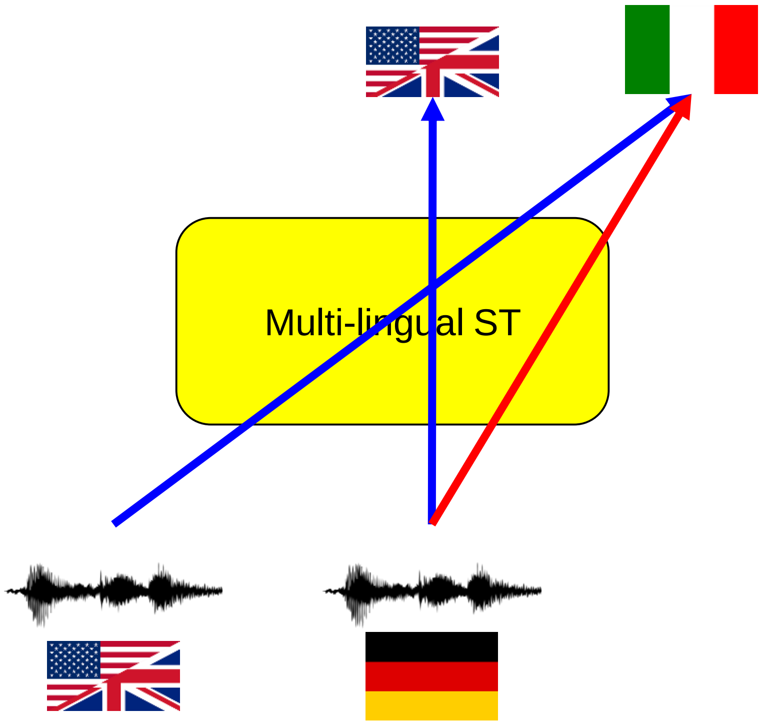
Multilingual ST

- Scenarios:
  - Many-to-One
  - One-to-Many
  - Many-to-Many



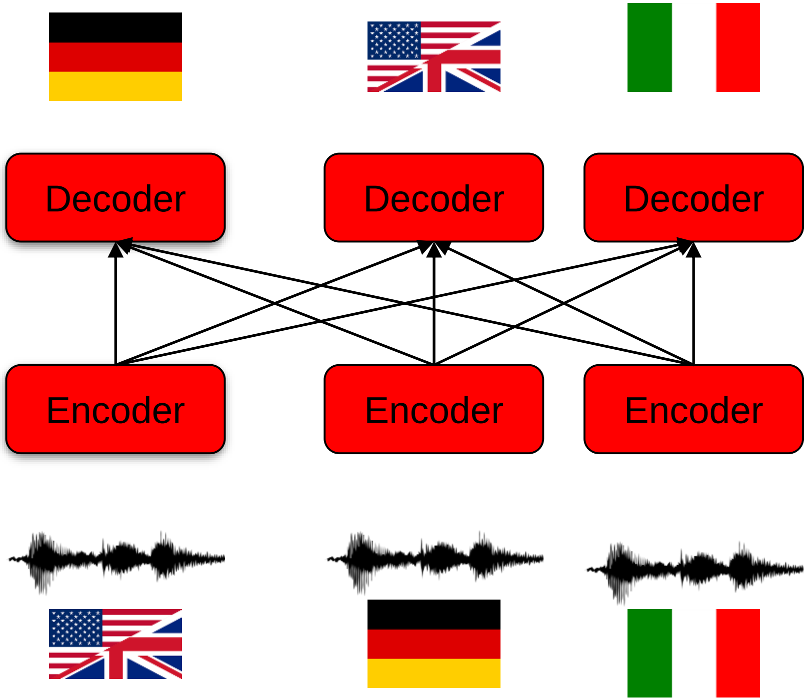
Multilingual ST

- Scenarios:
  - Many-to-One
  - One-to-Many
  - Many-to-Many
- Zero-shot:
  - No training data in test language pair



Training direction
Test direction

Multilingual ST - Architecture



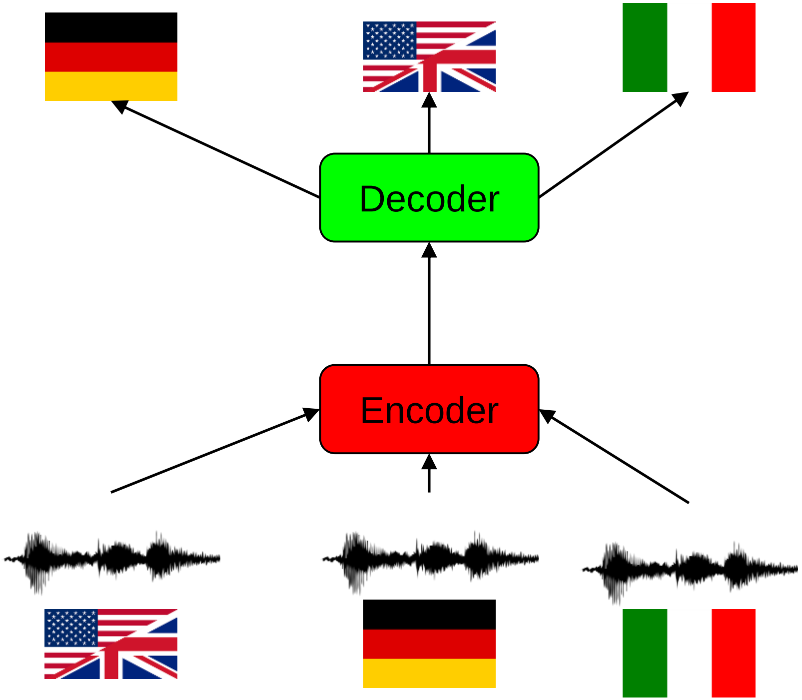
Individual encoder and decoder for each language

(e.g. Escolano et al. 2020)

Multilingual ST - Architecture

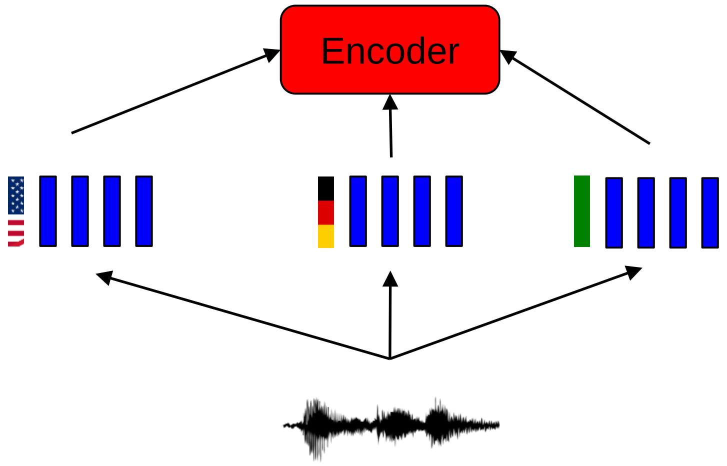
Joint encoder and decoder
Di Gangi et al., 2019
Inaguma et al., 2019

Challenge:
How to model different languages?



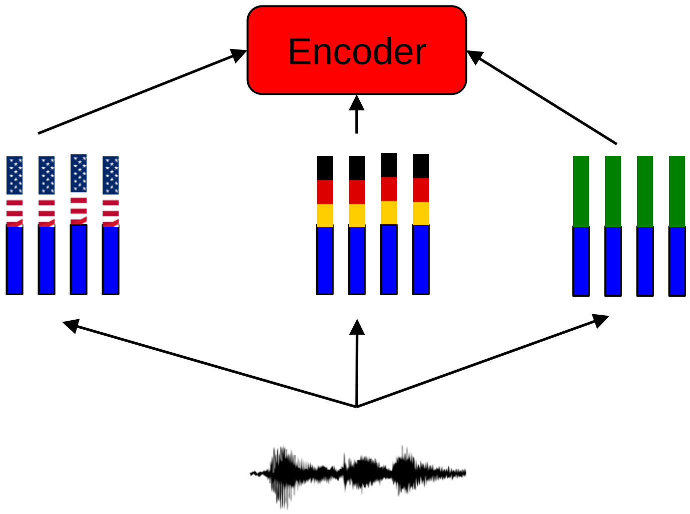
Multilingual ST - Language representation

- Encoder
    - Concat
        - Append learned language embedding for target language to audio features



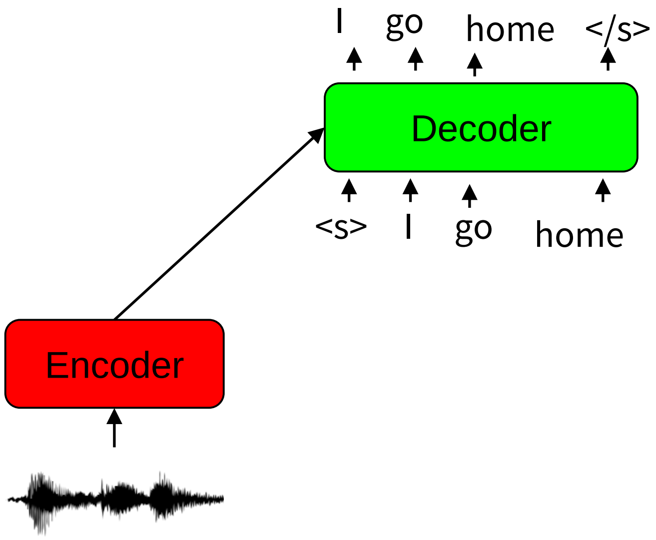
Multilingual ST - Language representation

- Encoder
  - Concat
    - Append learned language embedding for target language to audio features
  - Merge
    - Repeat language embedding for target language at each time step



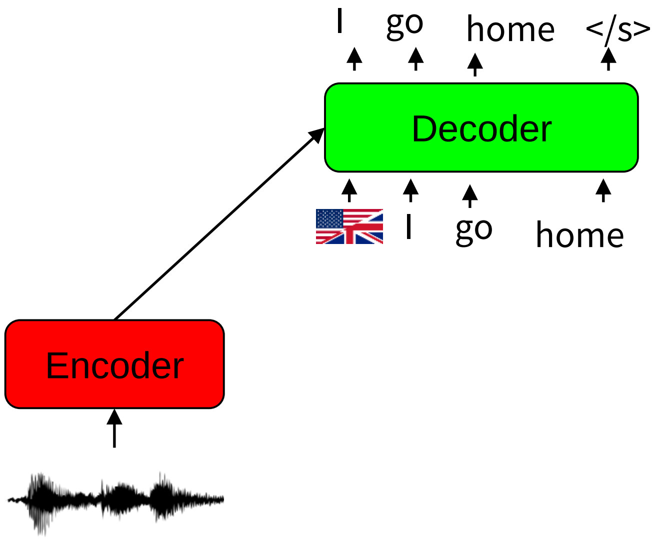
Multilingual ST - Language representation

- Encoder
- Decoder



Multilingual ST - Language representation

- Encoder
- Decoder
  - Replace Begin of sentence by sentence embedding

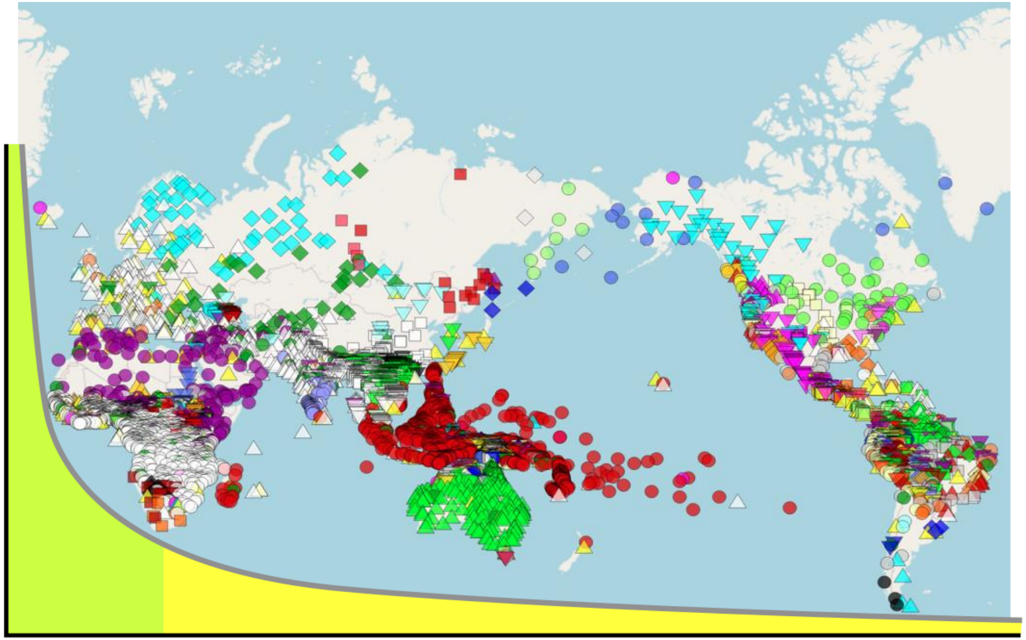


Sec 5.3

Under-resourced Languages

Under-resourced languages

More than 7,000 languages spoken today



Under-resourced languages

What makes a language under-resourced?

- Data availability: labeled data, unlabeled data, quality and representation
- Data domain: coverage and representation
- Noisy and/or opaque orthographies
- Unwritten languages
- Typological coverage:
  - Unique phonetic and phonological systems
  - Dialectal variation
  - Code-switching
  - Representation of non-native speakers

Taxonomy

0. Exceptionally limited resources: pretraining exacerbates situation

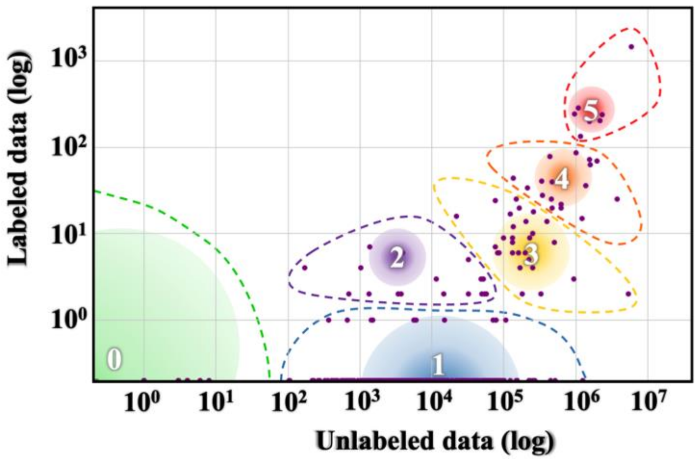
1. Some amount of unlabeled data

2. Small set of labeled data created

3. Unlabeled data enables pretraining, but limited labeled data

4. Large amount of unlabeled data, high quality but limited labeled

5. High-resource languages



Language resource distribution of Joshi et al. (2020). The size and colour of a circle represent the number of languages and speakers respectively in each category.
Colours (on the VIBGYOR spectrum; **V**iolet–**I**ndigo–**B**lue–**G**reen–**Y**ellow–**O**range–**R**ed) represent the total speaker population size from low (violet) to high (red).

(Joshi et al. 2020)

Languages: Examples

Class	5 Example Languages	#Langs	#Speakers	% of Total Langs
0	Dahalo, Warlpiri, Popoloca, Wallisian, Bora	2191	1.0B	88.17%
1	Cherokee, Fijian, Greenlandic, Bhojpuri, Navajo	222	1.0B	8.93%
2	Zulu, Konkani, Lao, Maltese, Irish	19	300M	0.76%
3	Indonesian, Ukranian, Cebuano, Afrikaans, Hebrew	28	1.1B	1.13%
4	Russian, Hungarian, Vietnamese, Dutch, Korean	18	1.6B	0.72%
5	English, Spanish, German, Japanese, French	7	2.5B	0.28%

Number of languages, number of speakers, and percentage of total languages for each language class

0. Dahalo:

Recorded Swadesh list

1. Cherokee:

Bible; 15k sentences parallel text; Tatoeba; Ubuntu

2. Zulu:

Recorded word lists; Tatoeba; Ubuntu

3. Cebuano:

Recorded word lists; BABEL; Bible; Wikipedia; Tatoeba; Ubuntu

4. Korean:

Bible; Wikipedia; OpenSLR 40, 58, 97; Tatoeba; Ubuntu

5. English:

∀

ST: Resources Required

Two steps where resources are required: ① for training and ② for corpus creation

Labeled data:
parallel speech and translations, segmented

Unlabeled data:
monolingual source language speech;
monolingual target language text

Pronunciation lexicons:
Use: alignment, hybrid ASR models; alternate data representations; CTC loss and/or compression

Availability:
MuST-C (1); mTEDx (8); CoVoST (21)

Bible (~1000); Wikipedia (285);
linguistic resources often <2 hours

Hand-created lexicons often unreleased;
Wikipron (117); Epitran (63)

(# source languages)

Pretrained Models

encoder

wav2vec 2.0 — XLSR

decoder

mBART

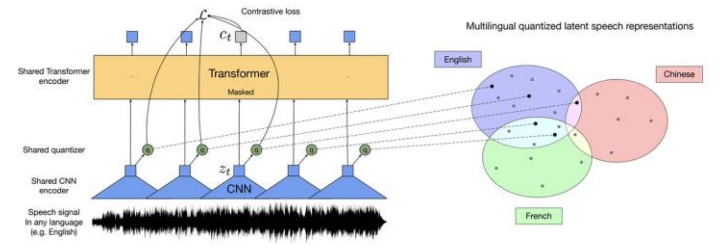


Figure 1: **The XLSR approach.** A shared quantization module over feature encoder representations produces multilingual quantized latent speech units whose embeddings are then used as targets for a single Transformer trained with contrastive learning. The model learns to share discrete tokens across languages, creating bridges across languages. Our approach is inspired by [15, 36] and builds on top of wav2vec 2.0 [6]. It requires only raw unsupervised speech audio from multiple languages.

(Baevski et al. 2020; Liu et al. 2020; Li et al. 2021)

Methods previously discussed:
pretraining + finetuning, knowledge distillation, alternate data representations

Dependences on shared features:
in-vocabulary orthography, phone inventories, use of same model architecture

Unless we assess on under-resourced languages, we will not know how well methods apply!

Sec 6:

Real-world Applications

Automatic generation of subtitles

Simultaneous translation

Sec 6.1

Automatic Generation of Subtitles

Automatic subtitling - Motivation

- Explosion of audio-visual content available (Cinema, OTT platforms, social media,...)
  - Need: offer high-quality subtitles into dozens of languages in a short time
  - Problem: human subtitling is slow and costly (1-15$/min)
  - Goal: automatic solutions to reduce human workload and costs

What is special about Subtitling?

- Importance of time
- Text needs to satisfy spatial and temporal constraints

In and out times based on speech rhythm

Length:
max. 2 lines (of ≈ length)
max. 42 characters/line

Reading speed:
max. 21 characters/second

Segmenting into proper subtitles

This kind of harassment keeps women <**eob**> from accessing the internet – <**eol**> essentially, knowledge. <**eob**>

```
10
00:00:31,066 --> 00:00:34,390
This kind of harassment keeps women
11
00:00:34,414 --> 00:00:36,191
from accessing the internet --
essentially, knowledge.
```

Segmenting into proper subtitles

This kind of harassment keeps women **<eol>** from accessing the internet – **<eob>** essentially, knowledge. **<eob>**

```
10
00:00:31,066 --> 00:00:34,390
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00:00:31,066 --> 00:00:34,390
This kind of harassment keeps women
from accessing the internet --
11
00:00:34,414 --> 00:00:36,191
essentially, knowledge.
```

Segmentation approaches

Manual template

This kind of harassment keeps women <eol> from accessing the internet – <eob>

MT

Ce harcèlement empêche les femmes <eol> d'accéder à Internet, <eob>

Segmentation approaches

Previous works focused only on length-matching given the template

(Matusov et al., 2019; Lakew et al., 2019)

Manual template

This kind of harassment keeps women <eol> from accessing the internet – <eob>

MT

Ce harcèlement empêche les femmes <eol> d'accéder à Internet, <eob>

Segmentation approaches

Manual template

This kind of harassment keeps women <eol> from accessing the internet – <eob>

MT

Cascade

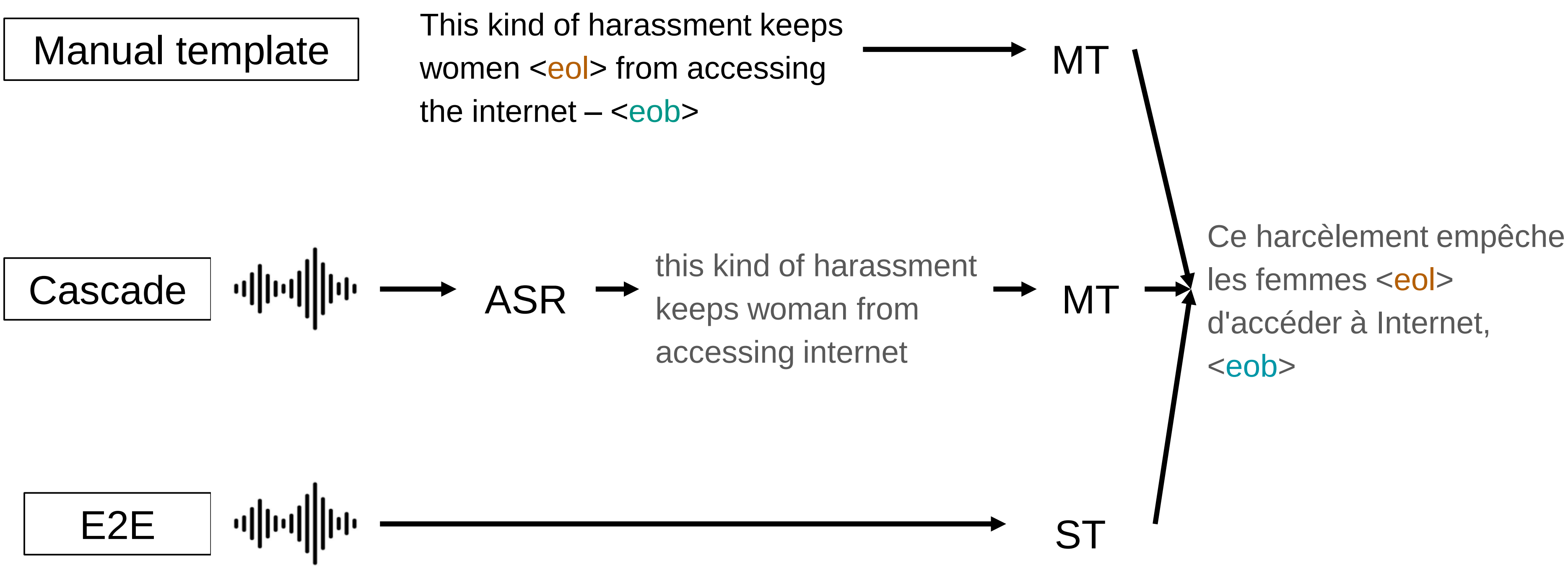
ASR

this kind of harassment keeps woman from accessing internet

MT

Ce harcèlement empêche les femmes <eol> d'accéder à Internet, <eob>

Segmentation approaches



Segmentation approaches

Manual template

This kind of harassment keeps women <eol> from accessing the internet – <eob> → MT

Costly!

Cascade → ASR → this kind of harassment keeps woman from accessing internet → MT

Audio info (e.g. duration) is lost

E2E → ST

Audio info (e.g. duration) is available to ST

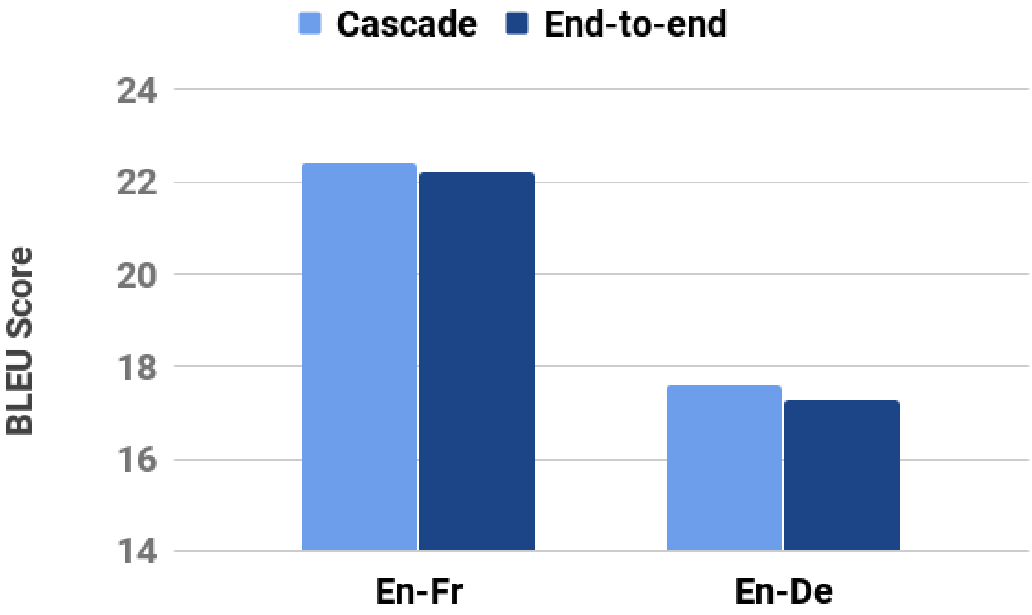
Ce harcèlement empêche les femmes <eol> d'accéder à Internet, <eob>

Automatic subtitling - Data

- **OpenSubtitles** (Lison and Tiedemann, 2016) -- 60 languages
  - Variable quality (professional/amateur subt., automatic sentence-level alignm.):
  - No information about subtitle breaks
  - No alignment with audio (mostly copyright-protected videos)
- **JESC** (Pryzant et al., 2018) -- Ja-En
  - Automatic alignments (caption level = only subtitles with matching timestamps)
  - No alignment with audio
- **Must-Cinema** (Karakanta et al., 2020) -- En→ 7 languages
  - Derived from MuST-C (TED talks)
  - Annotated with subtitle breaks
  - Audio-transcript-translation alignments

E2E subtitling: experiments on En-Fr/De

- **Doable?**
  - Translation quality

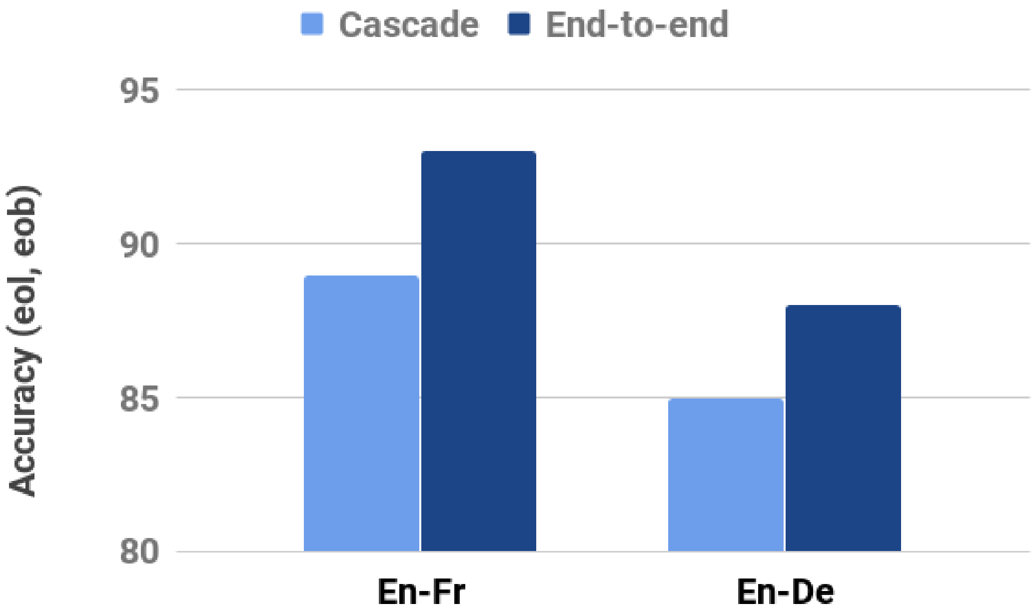


Karakanta et al., 2020 - IWSLT

No gap between Cascade and E2E

E2E subtitling: experiments on En-Fr/De

- **Effective?**
  - Segmentation (<eol> and <eob> insertion)



Karakanta et al., 2020 - IWSLT

E2E exploits acoustic information (pause duration) to insert breaks

Sec 6.2

Simultaneous ST

Simultaneous Translation

- Generate translation while speaker speaks
- Tradeoff:
  - *More context* improves speech translation
    - Wait as long as possible
  - *Low latency* is important for user experience
    - Generate translation as early as possible
- Challenge:
  - Different word order in the language
    - SOV vs SVO

German	Ich	melde	mich	zum	E2E	Tutorial	an
Gloss	I	register/ cancel	myself	to	E2E	tutorial	
English	I	????					

Simultaneous Translation

- Approaches:
  - Learn optimal segmentation strategies
    - Create segments that optimizing tradeoff between segment length and translation quality
    - Advantages:
      - No changes to the system
    - Disadvantage:
      - Shorter context during translation
  - Mainly used in cascaded approaches (e.g. Oda et al., 2014)

Example:

Ich melde mich

zur Konferenz an

Simultaneous Translation

- Approaches:
  - Learn optimal segmentation strategies
  - Re-translate / Iterative -update
    - Directly output first hypothesis
    - If more context is available:
      - Update with better hypothesis
    - Cascade
      - (Niehues et al, 2018; Arivazhagan et al, 2020)
    - End-to-end
      - (Weller et al, 2021)

Example:

Ich
I

Ich melde mich
I register

Ich melde mich von
I cancel my registration for

Re-translation

- Challenge:
  - Flickering
- Ideas:
  - Output masking
    - Do not output last tokens
  - Constrained decoding:
    - Fixed part of the previous translation

Example:

Ich

I

Ich melde mich

I register

Ich melde mich von

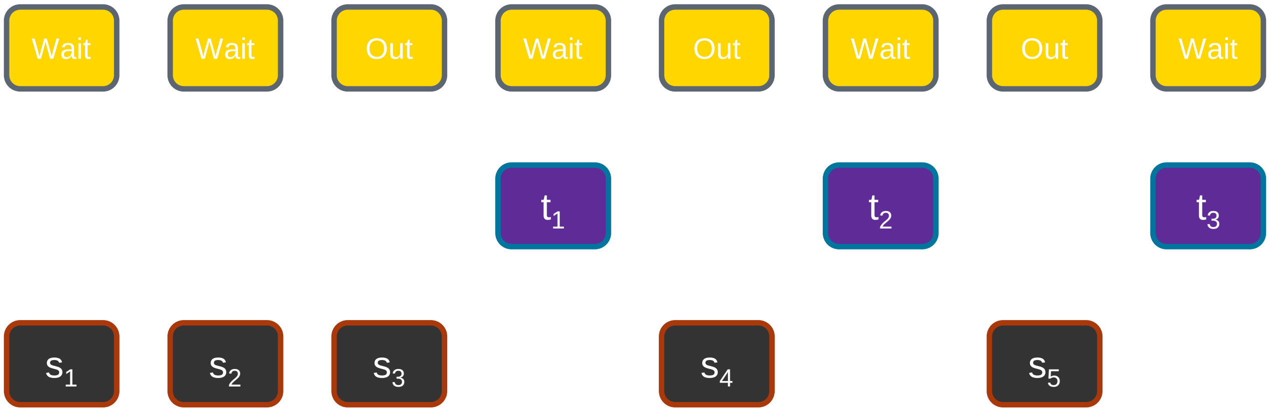
I cancel my registration for

Simultaneous Translation

- Approaches:
  - Learn optimal segmentation strategies
  - Re-translate
  - Stream decoding
    - Dynamically learn when to generate a translation
    - At each time step:
      - Decided to output word
      - Wait for additional input

Stream decoding

- Methods:
  - Fixed schedule (Ma et al, 2019)
    - Wait-k policy



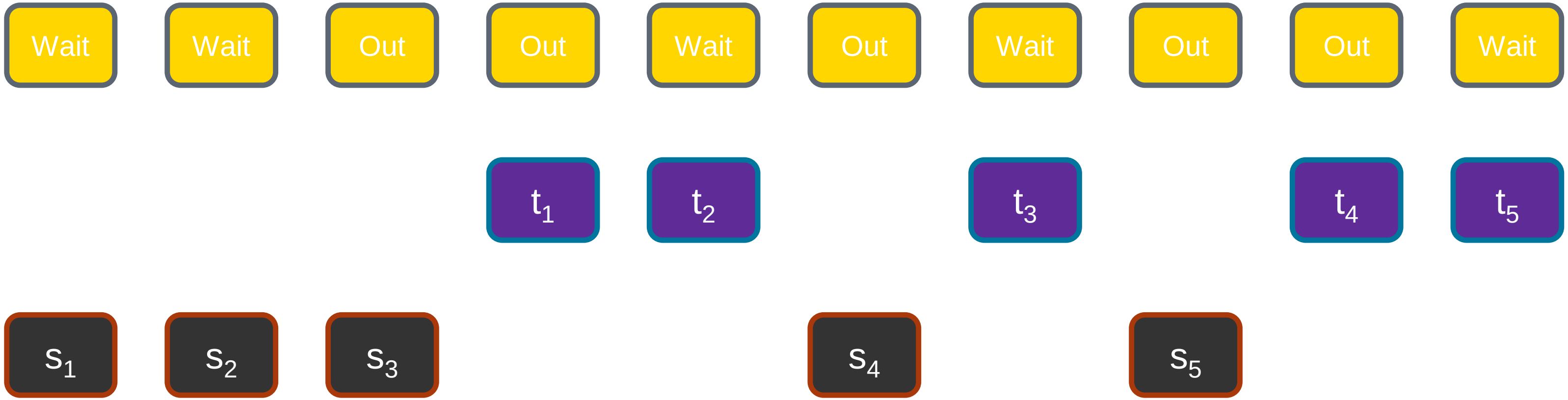
Stream decoding

- Challenges:
  - Assumes constant rate between input and output
    - Speaking speed varies

- Ideas:
  - Estimate word boundaries on the source side (Ma et al. 2020)
    - Predict using CTC Loss (Ren et al, 2020)

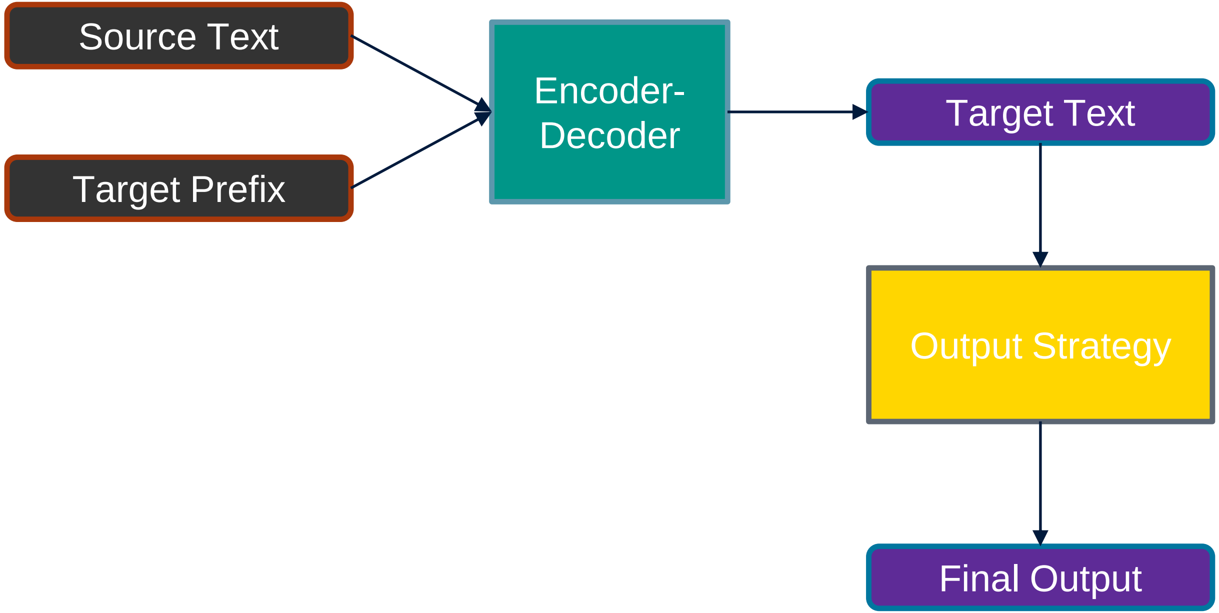
Stream decoding

- Methods:
  - Fixed schedule (Ma et al, 2019)
  - Dynamic decision (Cho et al, 2016; Gu et al, 2017; Dalvi et al, 2018)
    - End-to-end:
      - Estimate output probability based on confidence



Stream decoding using Retranslation

- Decoding with fixed target prefix



Stream decoding strategies

- Local agreement (Liu et al, 2020)
  - Output if previous and current output agree on prefix
  - Variation (Yao et al., 2020):
    - Predict the next source word instead of relying on the previous input

Input	Prefix	Target Text	Final Output
1	Ø	All model trains	Ø
1,2	Ø	All models art	All
1,2,3	All	All models are wrong	All models
1,2,3,4	All models		
…			

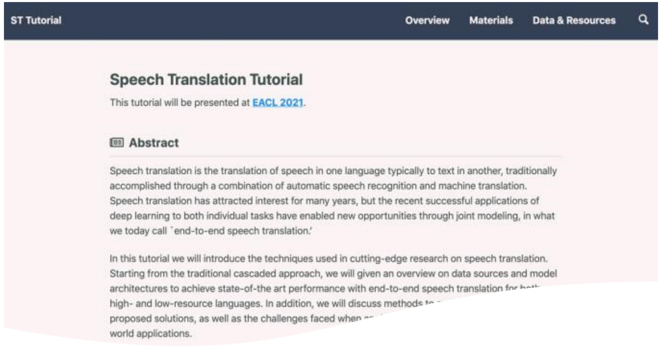
Sec 7:

Conclusion

Recap

- Introduction
- End-to-End Models
- Leveraging Data Sources
- Evaluation
- Advanced Topics
- Real-World

https://st-tutorial.github.io/



References

http://st-tutorial.github.io/materials

Links to:

- All cited papers in this tutorial: bibtex and links to papers
- Individual section videos and slides

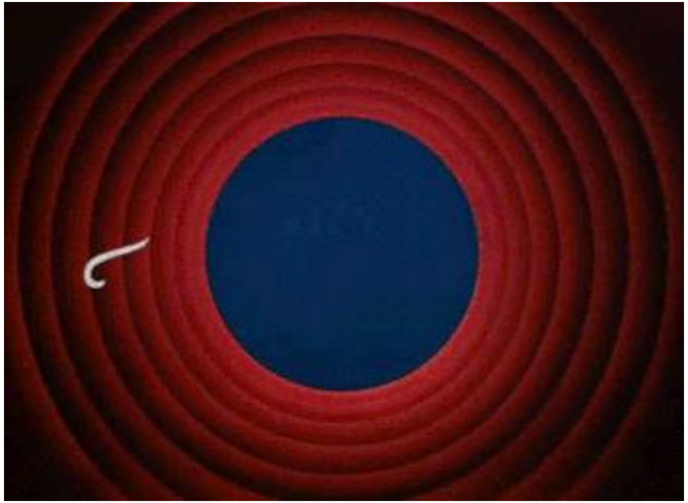
Resources

http://st-tutorial.github.io/resources

Links to:

- Available data
- Available toolkits and code
- ST communities:
  - SIGSLT
  - iwslt.org

Thank you!



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