On Speaker Attribution with SURT

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Meta

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Motivation

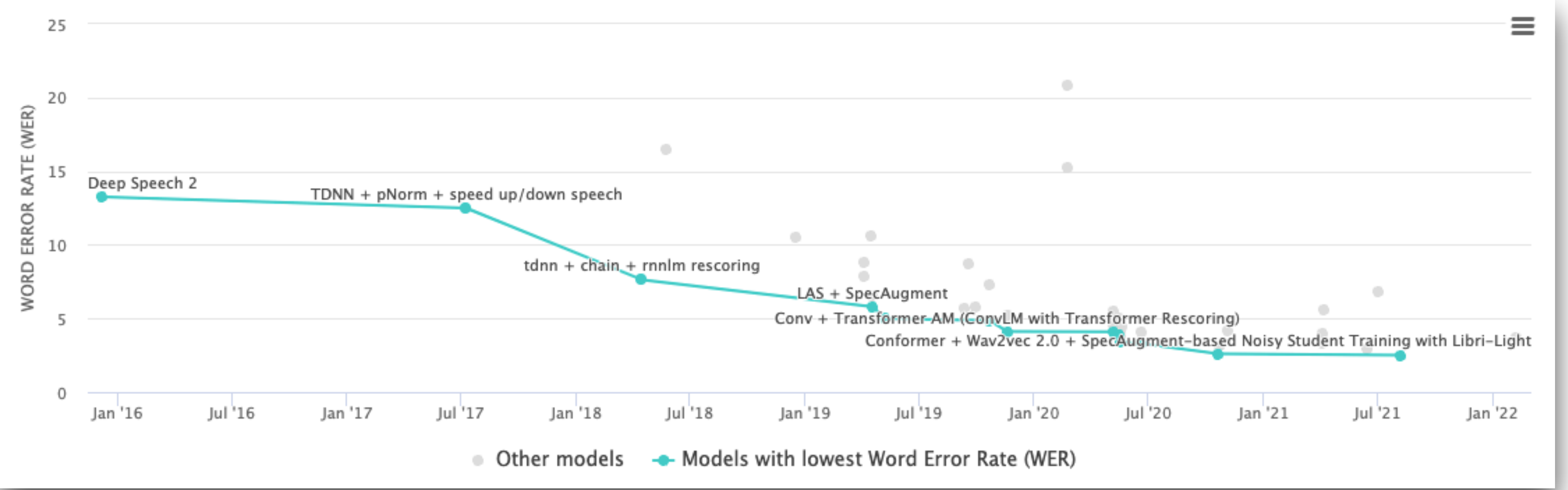
OCTOBER 20, 2020

AI outperforms humans in speech recognition

by Monika Landgraf, Karlsruhe Institute of Technology

Microsoft claims new speech recognition record, achieving a super-human 5.1% error rate

BY TODD BISHOP on August 20, 2017 at 7:44 pm



https://paperswithcode.com/sota/speech-recognition-on-librispeech-test-other

Motivation

Single-user applications

Smart Assistants

Language Learning

Customer Service

Voice-based Search

Multi-user applications

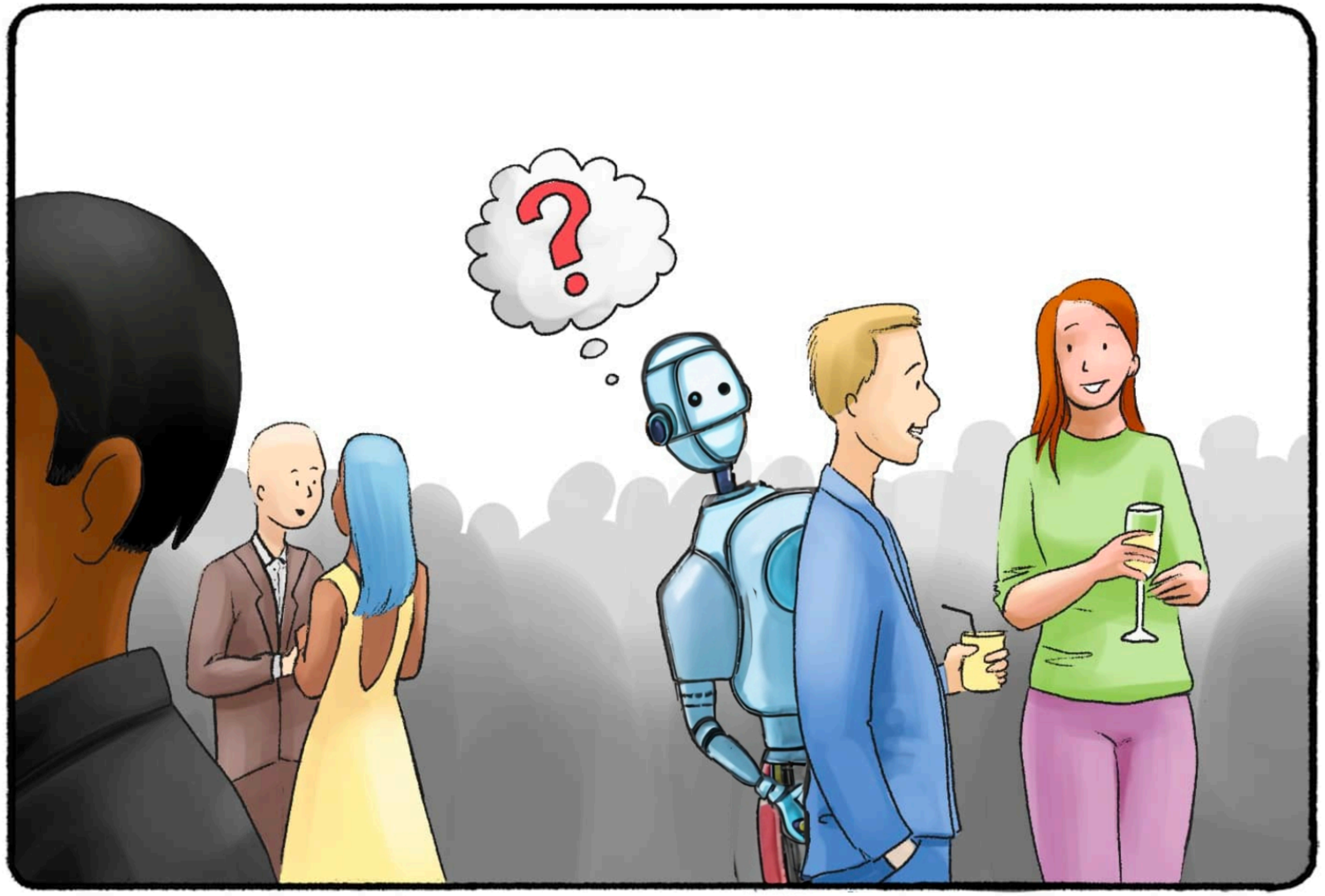
Meeting summaries

Collaborative Learning

Child language development

Motivation

The Cocktail Party Problem



Outline of the talk

1. Problem statement: “who spoke what?”
2. Modular system and its Limitations
3. Streaming Unmixing and Recognition Transducer (SURT)
4. Speaker-attributed transcription with SURT
5. Conclusion

Problem Statement

Multi-talker speaker-attributed ASR

- **Input:** long unsegmented (possibly multi-channel) recording containing multiple speakers.
- **Output:**
  - Transcription of the recording (speech recognition)
  - Speaker attribution (diarization)
  - Additional constraints: streaming, i.e., real-time transcription
- We specifically look at “meetings”: AMI, ICSI

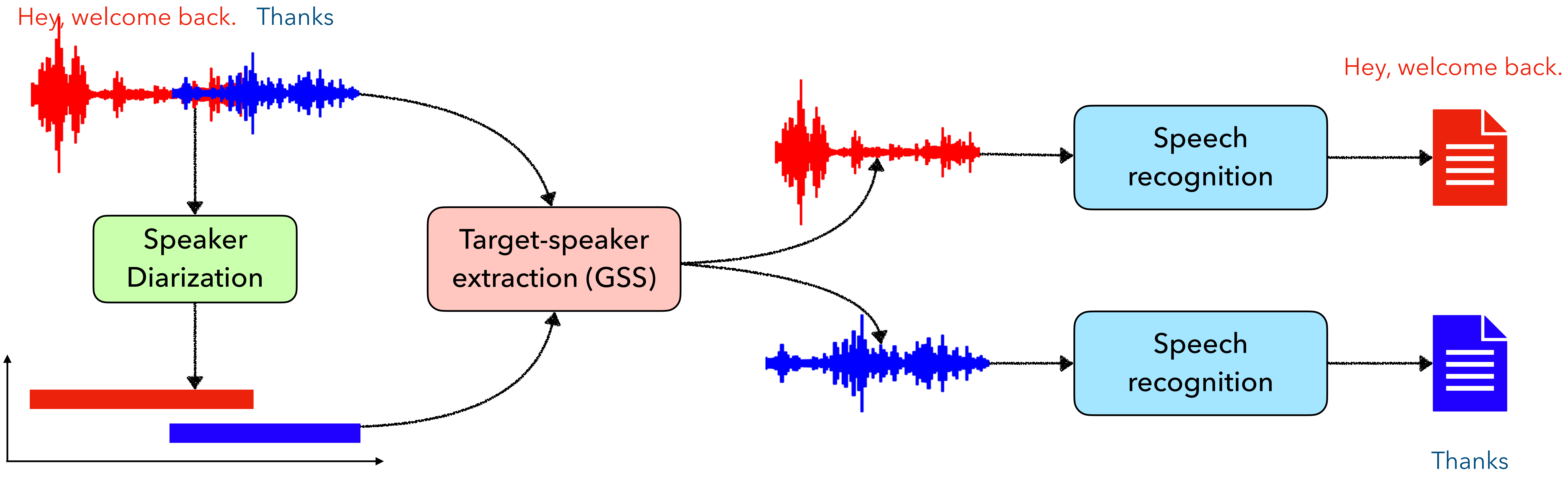
Problem Statement

Evaluation metrics

- *Speech Recognition*
  - Word error rate (**WER**) = insertion + deletion + substitution (Levenshtein distance)
- *Speaker Diarization*
  - Diarization error rate (**DER**) = missed speech + false alarm + speaker confusion
  - Word diarization error rate (**WDER**) = % of correctly recognized words attributed to the wrong speaker
- *Multi-talker ASR*
  - **ORC-WER**: WER for overlapping speech **without** speaker attribution
  - **cpWER**: WER for overlapping speech **with** speaker attribution

Modular system

Pipeline from the CHiME challenge



Shinji Watanabe, et al. CHiME-6 Challenge: Tackling Multi-speaker Speech Recognition for Unsegmented Recordings. *CHiME Workshop, 2020*.

Desh Raj, et al. GPU-accelerated Guided Source Separation for Meeting Transcription. *Interspeech, 2023*.

Modular system

Limitations

- Modules are independently optimized for different objectives
- Higher accumulated **latency**
- **Error propagation** through modules
- Requires more engineering efforts to maintain

- Cannot be used for streaming or single-channel inputs

Continuous, streaming, multi-talker ASR

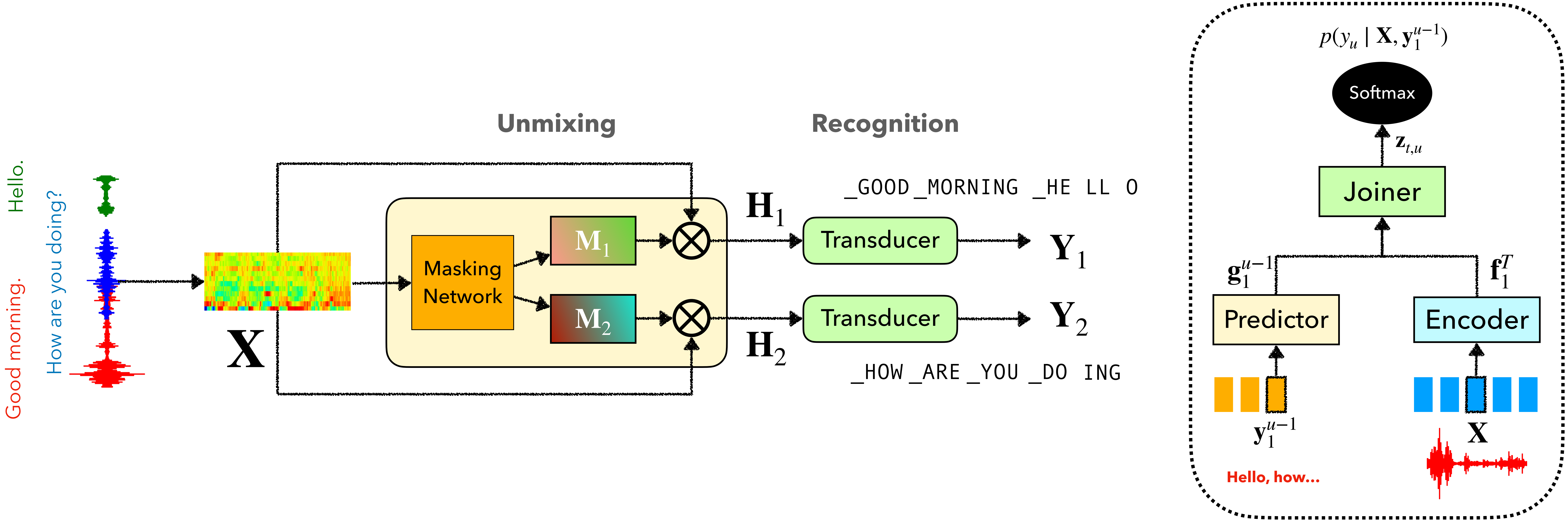
Definitions

- **Continuous:** does not rely on external segmentation
- **Streaming:** does not use right context; overlapping speech is transcribed simultaneously

Desh Raj, et al. Continuous Streaming Multi-Talker ASR with Dual-Path Transducers. *IEEE ICASSP, 2022*.

Desh Raj, et al. SURT 2.0: Advances in Transducer-Based Multi-Talker Speech Recognition. *IEEE/ACM TASLP, vol. 31, 2023*.

Streaming Unmixing and Recognition Transducer (SURT)



- To solve the **permutation problem**, assign utterances to first available channel in order of start time

$$\mathscr{L}_{\text{heat}}(\mathbf{y}_{1:N}, \mathbf{X}; \Theta) = -\log P_{\Theta}(\mathbf{Y}_1 \mid \mathbf{X}) - \log P_{\Theta}(\mathbf{Y}_2 \mid \mathbf{X})$$

Streaming Unmixing and Recognition Transducer (SURT)

Results on real meetings (AMI and ICSI)

AMI	
Close-talk WER (%)	35.1
Far-field WER (%)	44.6

Overlap ratio = 21.6%

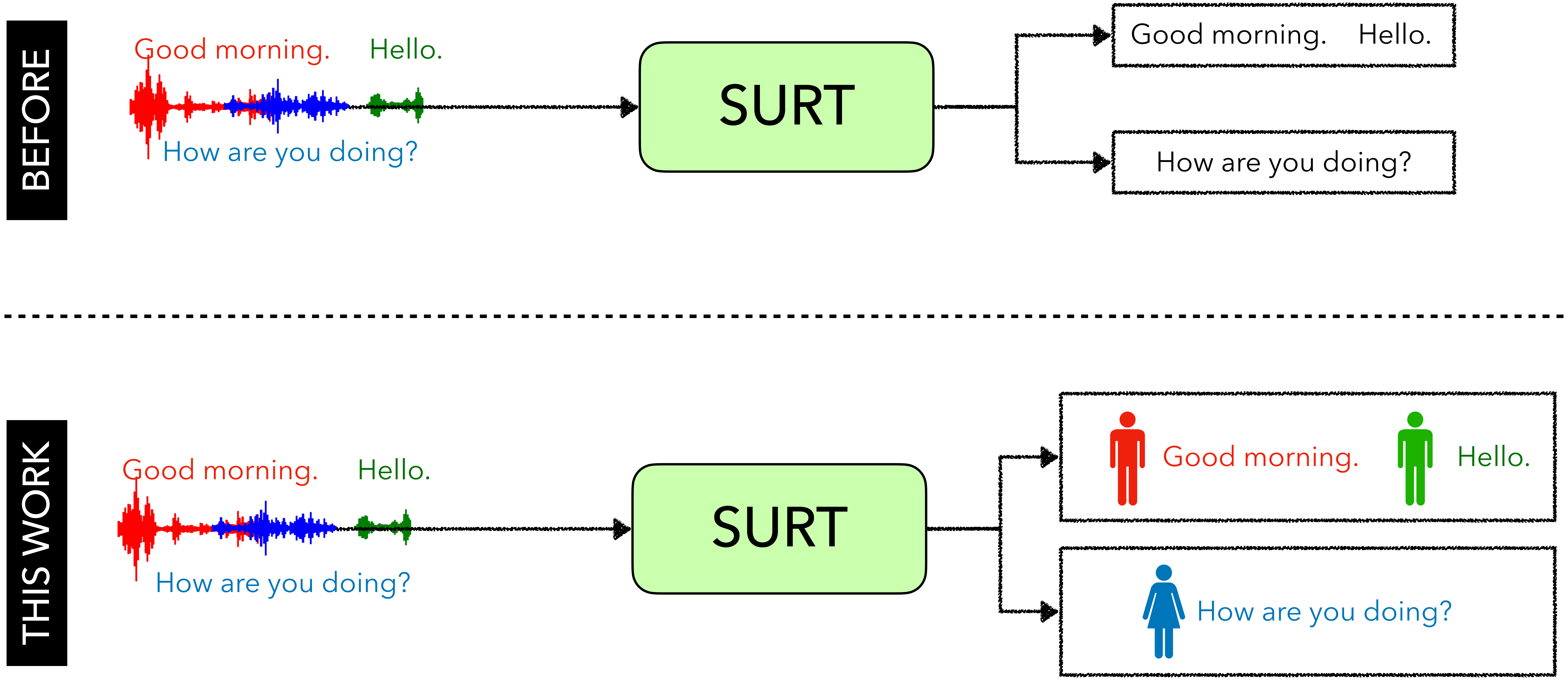
ICSI	
Close-talk WER (%)	24.4
Far-field WER (%)	32.2

Overlap ratio = 11.1%

- Results in terms of ORC-WER (speaker-agnostic).
- As a comparison, a single-speaker model for AMI gets ~18% (close-talk) and 32% (far-field).

Speaker attribution with SURT

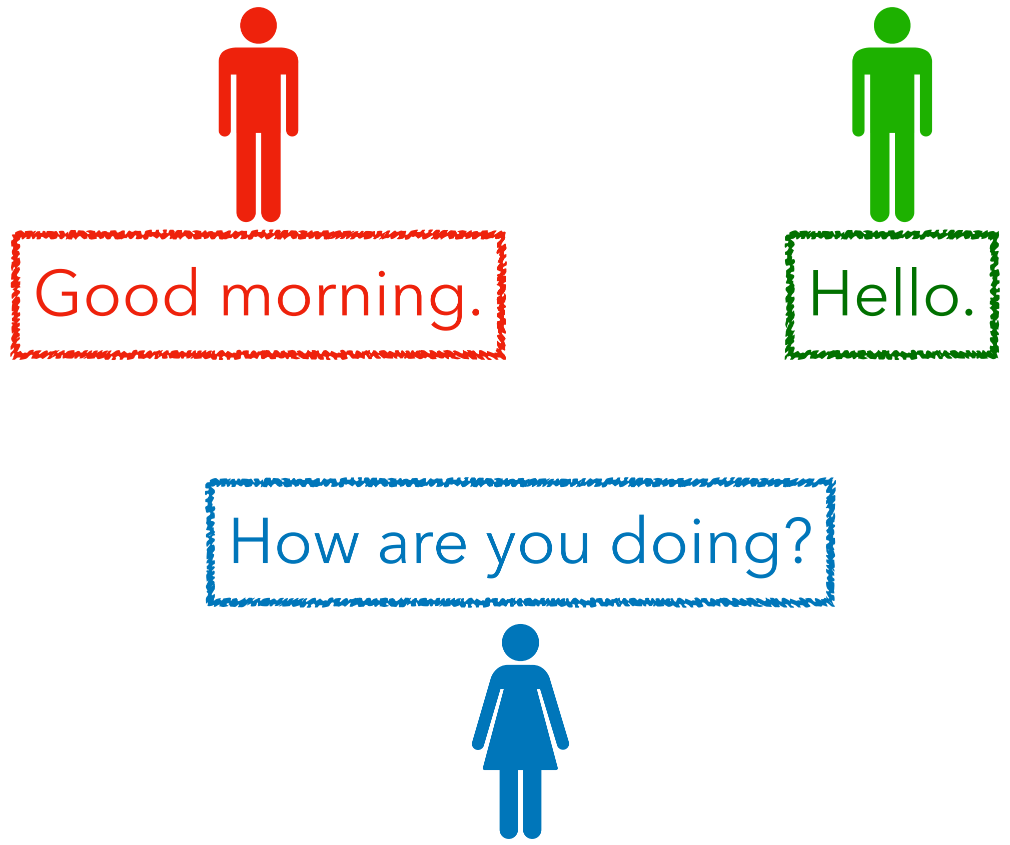
How to predict speaker labels with ASR tokens?



Speaker attribution with SURT

Heuristic error assignment training for speakers

- Use the same 2-branch strategy, but predict speaker labels instead of ASR tokens
- Speakers are ordered in their relative order of appearance
- *How to do both tasks jointly?*

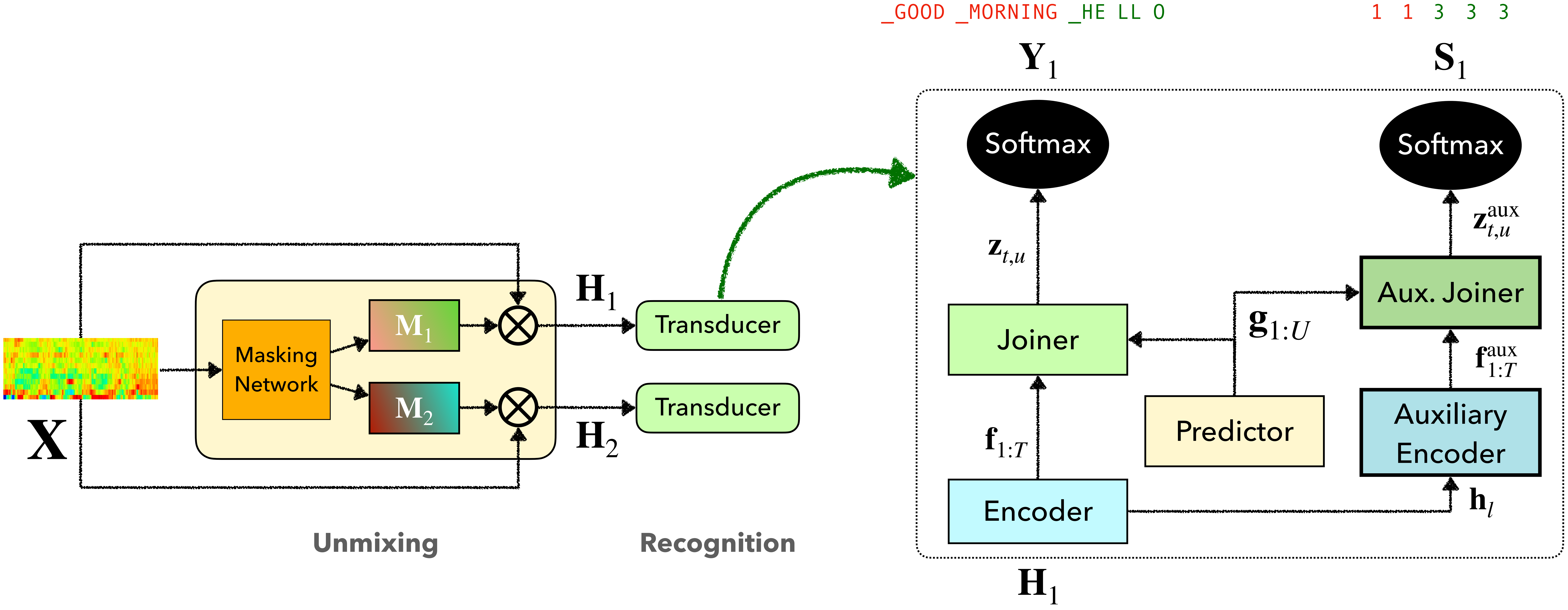


$\mathbf{Y}_1$	_GOOD	_MORNING	_HE	LL	O
$\mathbf{S}_1$	1	1	3	3	3

$\mathbf{Y}_2$	_HOW	_ARE	_YOU	_DO	ING
$\mathbf{S}_2$	2	2	2	2	2

Speaker attribution with SURT

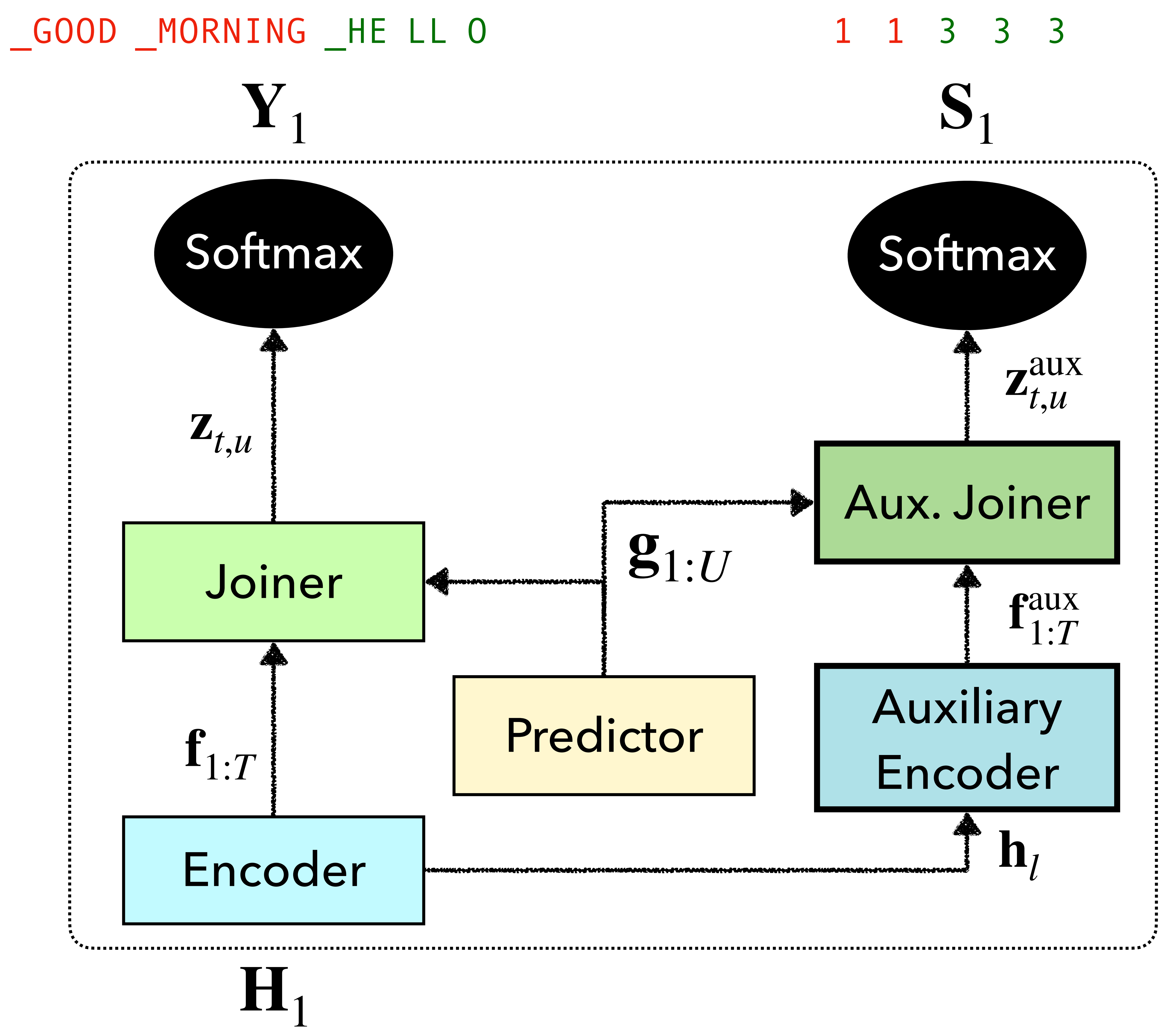
Auxiliary speaker encoder



Speaker attribution with SURT

Synchronizing speaker labels with ASR tokens

- At inference time, it is not necessary that both output streams emit same number of tokens.
- Even if they do, they may not be frame synchronous.



$\mathbf{Y}_1$	<blk>	_GOOD	_MORNING	<blk>	_HE	<blk>	LL	O
$\mathbf{S}_1$	<blk>	1	<blk>	1	<blk>	3	<blk>	3

Speaker attribution with SURT

Hybrid autoregressive transducer (HAT)

RNN-Transducer

$$P(\mathbf{a}_t \mid \mathbf{f}_1^t, \mathbf{g}_1^{u(t)-1}) = \mathrm{Softmax}(\mathbf{z}_{\mathrm{t,u}})$$

- Multinomial distribution over blank and non-blank tokens
- Cannot model blank probability separately

HAT

$$P(\mathbf{a}_t \mid \mathbf{f}_1^t, \mathbf{g}_1^{u(t)-1}) = \begin{cases} b_{t,u}, & \text{if } \mathbf{a}_t = \phi, \\ (1 - b_{t,u})\ \mathrm{Softmax}(\mathbf{z}_{\mathrm{t,u}}[1:]), & \text{otherwise} \end{cases} \qquad b_{t,u} = \sigma(\mathbf{z}_{t,u}[0])$$

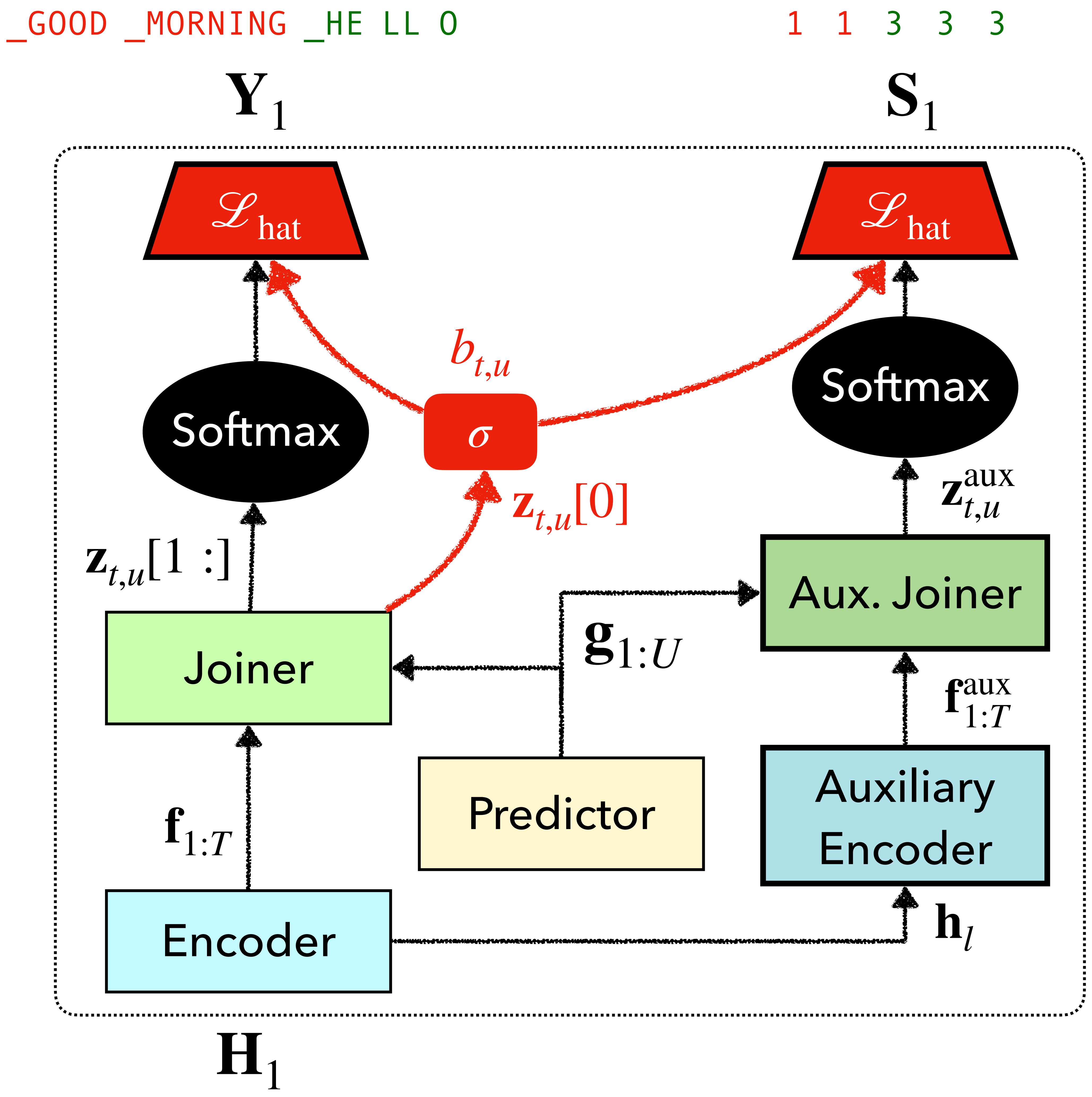
- Bernoulli distribution for blank; multinomial over non-blank tokens
- Probability of blank given directly by $b_{t,u}$

Ehsan Variani, et al. Hybrid Autoregressive Transducer (HAT). *IEEE ICASSP 2020*.

Speaker attribution with SURT

Synchronization by sharing `<blk>`

- If ASR branch emits `<blk>` do the same for speaker branch
- This is achieved by using HAT-style blank factorization, and sharing blank logit between ASR and speaker branch



Speaker attribution with SURT

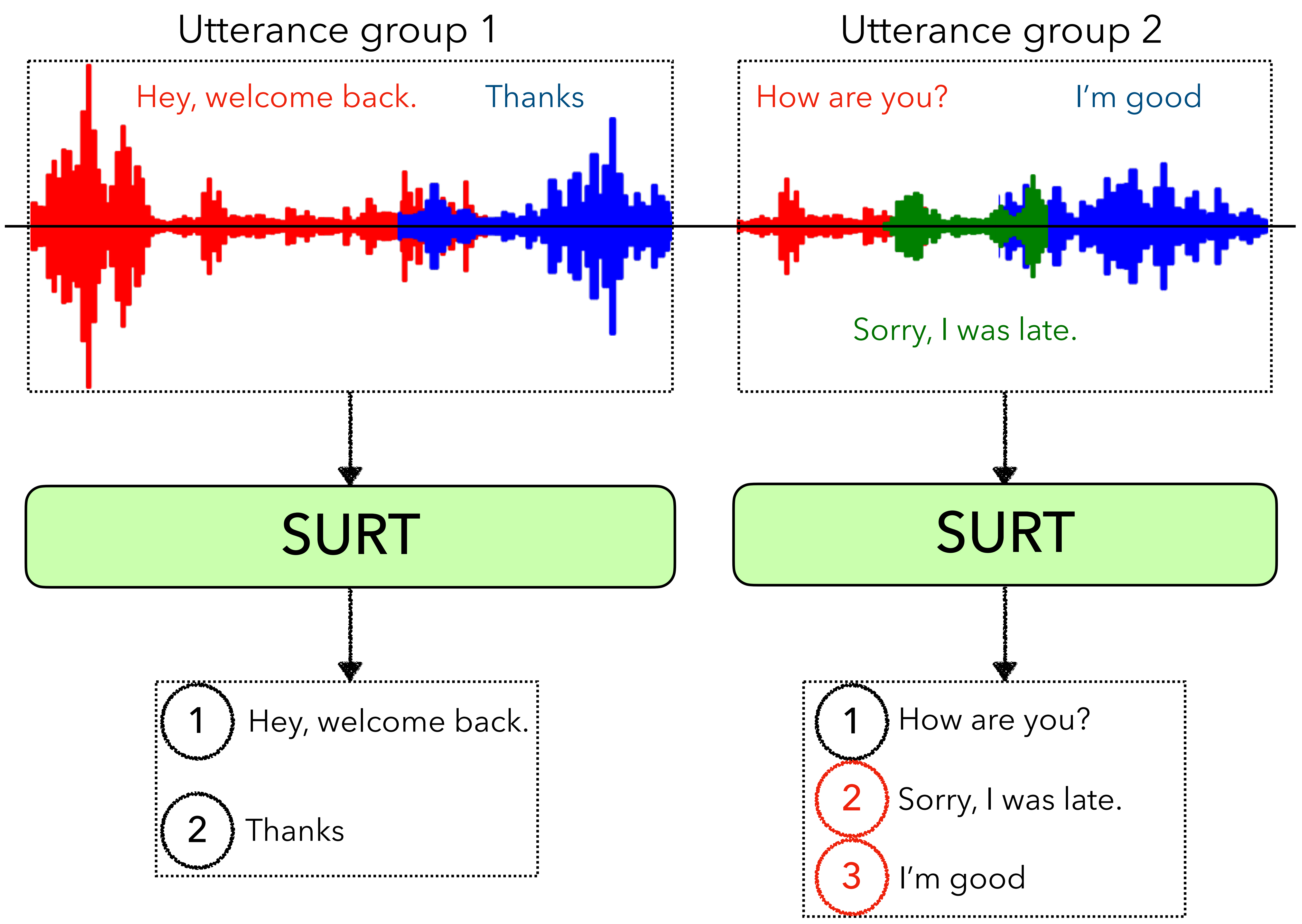
Results on AMI (evaluation on utterance groups)

Utterance group = set of utterances connected by overlaps or short pauses

	Streaming			Offline
Mic Setting	**ORC-WER**	**WDER**	**cpWER**	**Modular System cpWER**
Close-talk	34.9	9.3	42.3	–
Far-field	43.2	10.9	50.3	38.5

Speaker attribution with SURT

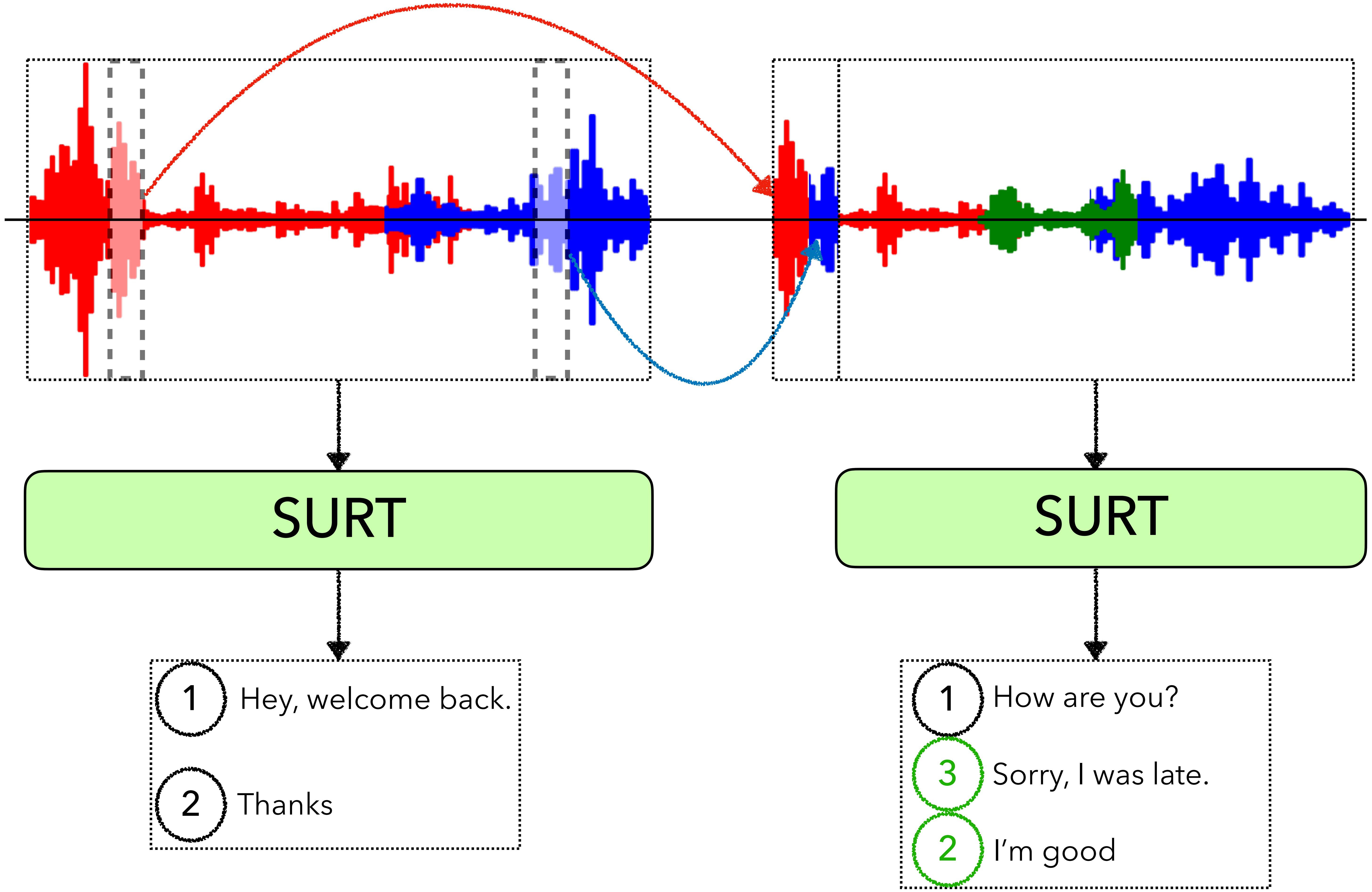
From utterance groups to full sessions



- How to maintain relative speaker labels when processing different utterance groups within the same session?

Speaker attribution with SURT

Speaker prefixing approach



- Extract high-confidence frames of predicted speakers and prefix them in front of current input.
- Remove prefixed part from encoder representation.

Summary

- **We showed that the same models that do transcription can also do speaker attribution with small changes!**
- For more results and analysis, please refer to our paper.
- Reviewer #5: *"I assume the authors are very eager to have these results published in Odyssey since a different (and longer) format would probably have suited this content better."*

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Extra Slides

Speaker attribution with SURT

Joint vs. sequential training

Experiments on simulated LibriSpeech mixtures

Method	ORC-WER	WDER	cpWER
✓ **Sequential**	8.5	**4.0**	**15.0**
Joint	**8.4**	4.5	**15.0**
Sequential + joint	9.2	4.3	15.3

Speaker attribution with SURT

Where to branch out of the main encoder?

Experiments on simulated LibriSpeech mixtures

Main Encoder Block	WDER	cpWER
Block 0 (after embedding layer)	5.4	16.7
Block 1	**4.0**	**15.0**
Block 2	6.7	19.6
Block 3	8.4	23.4

Speaker attribution with SURT

Evaluation on AMI IHM-Mix setting

"Enrollment" = using small chunk from speaker's enrollment speech for prefixing

Evaluation	Method	cpWER
Utterance group	SURT w/o speaker prefix	42.3
Full session	SURT w/o speaker prefix	100.1
	SURT w/ speaker prefix (128 frames = 1.28s per speaker)	82.8
	+ enrollment	53.8