

Integration of speech separation, diarization, and recognition for multi-speaker meetings:

System description, comparison, and analysis

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Multi-speaker meeting transcription

Input: recordings. **Output: speaker-attributed transcription**

10 min to **1-2 hours**



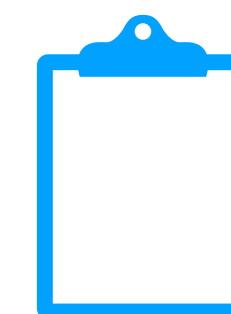
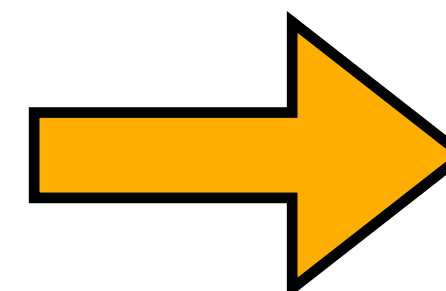
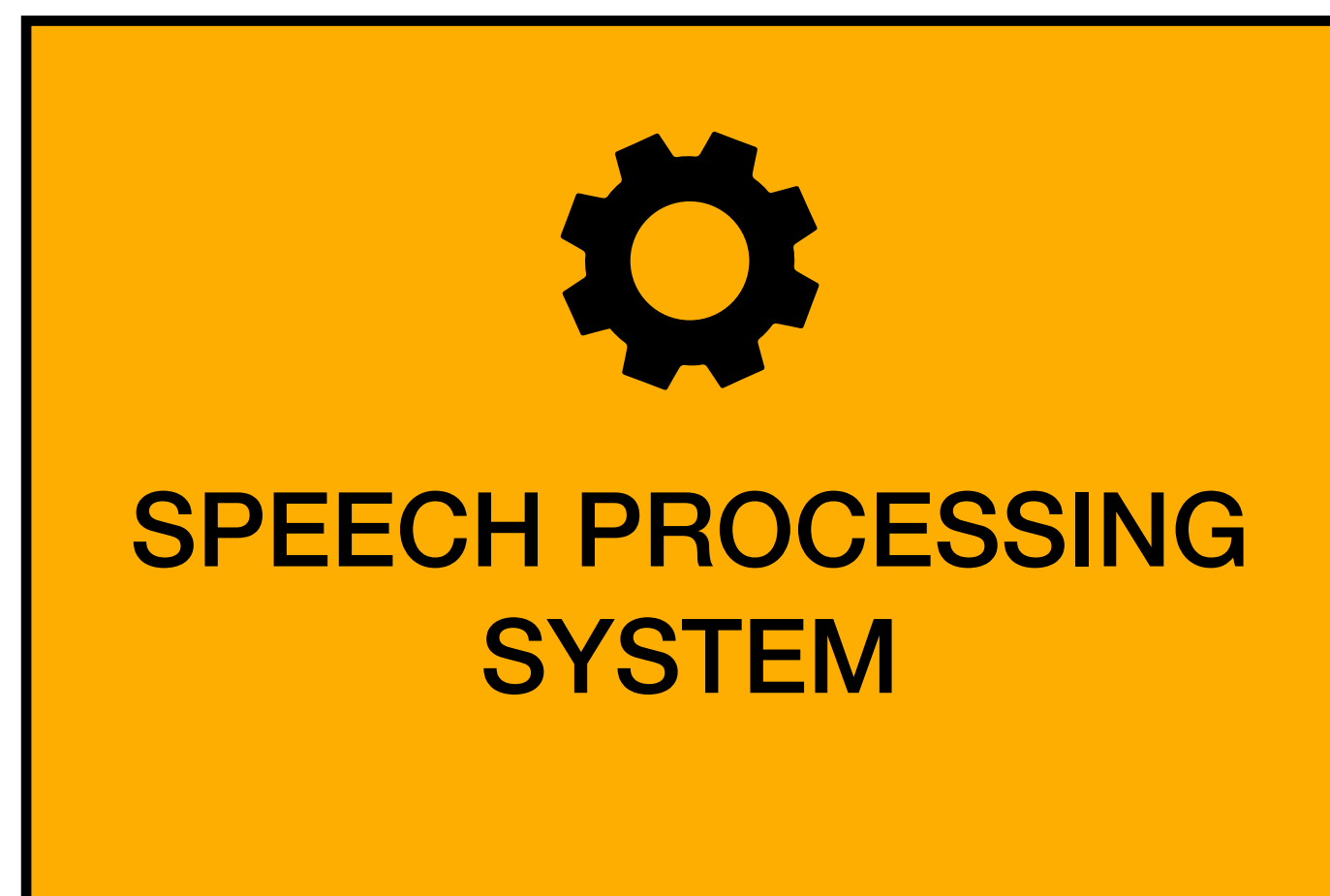
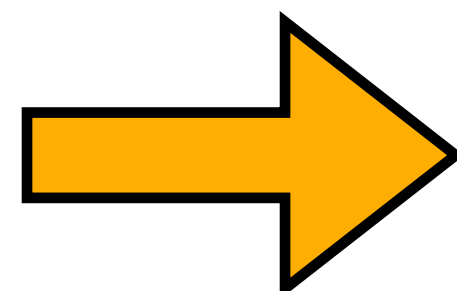
2-10 speakers



Typically **20% overlap**



Single/multi microphone



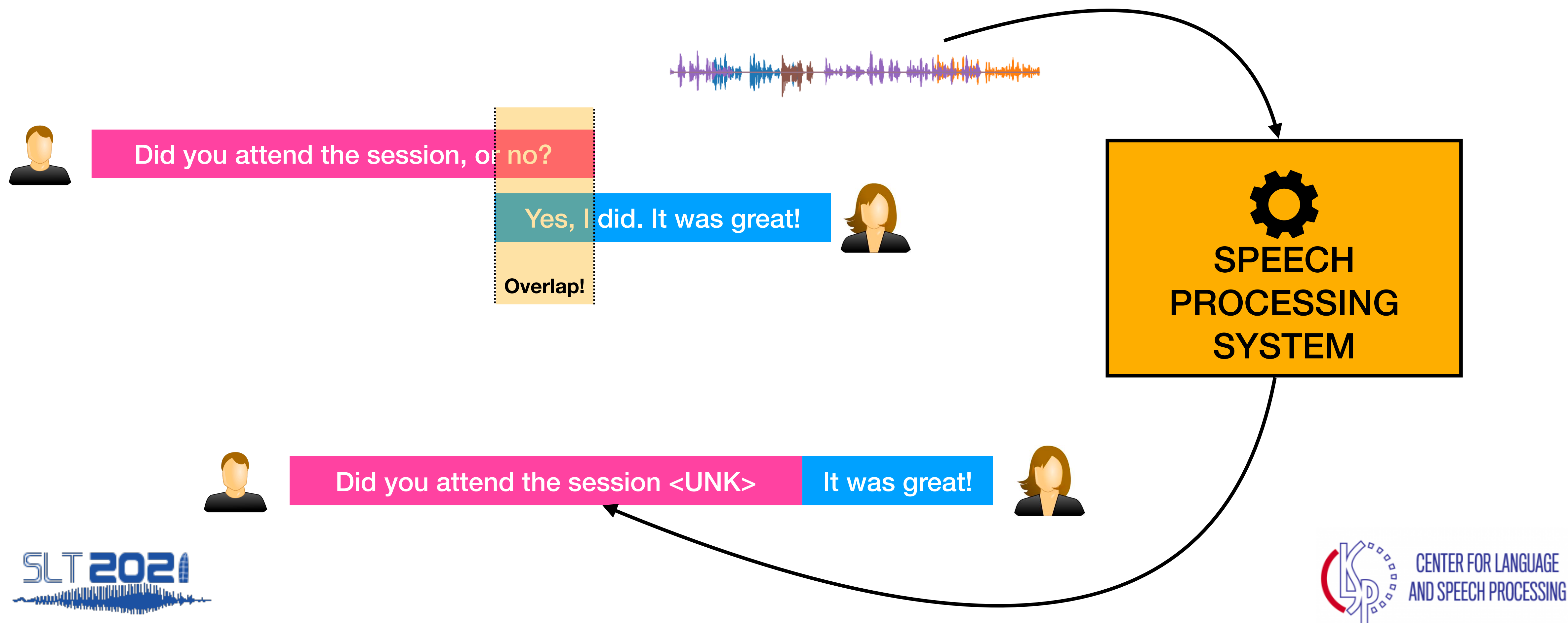
WHO said **WHAT** and **WHEN**

Speech recognition

Speaker diarization

Why is it difficult?

Overlapping speech affects both ASR and diarization outputs



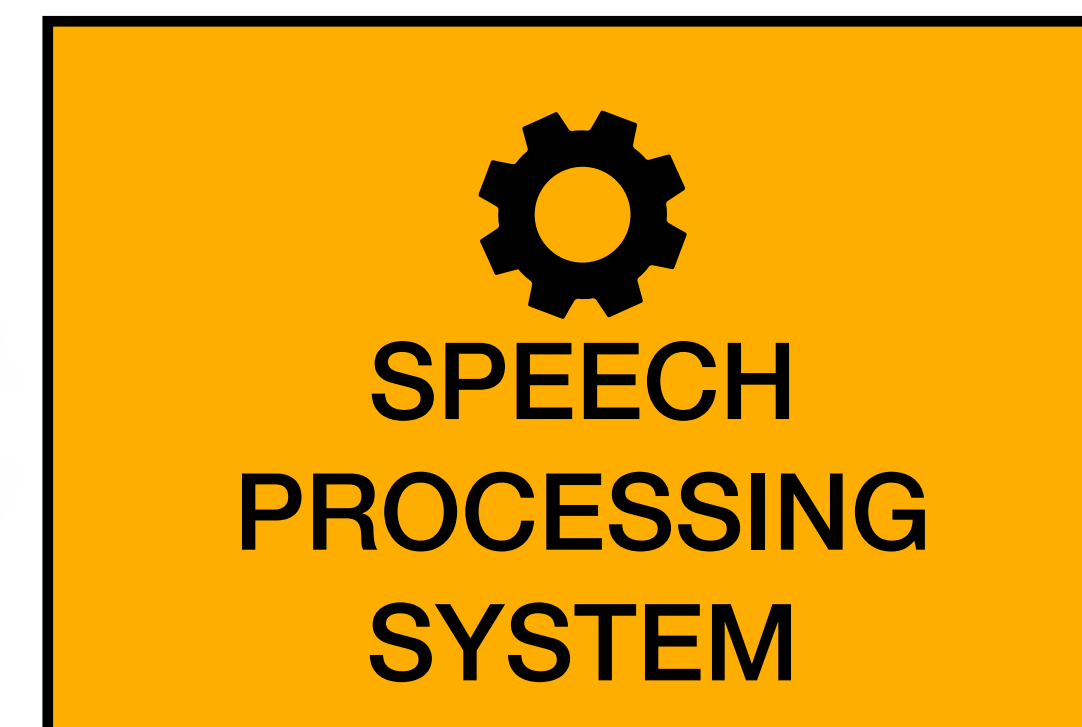
Why is it difficult?

Overlapping speech affects both ASR and diarization outputs



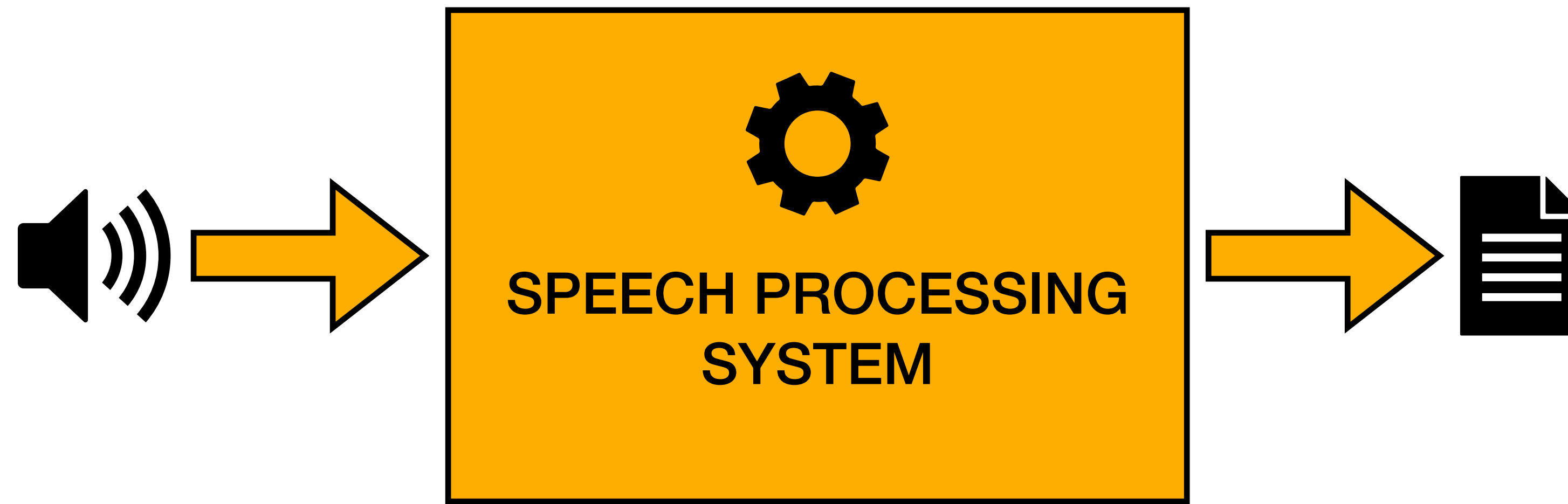
The diagram illustrates the difficulty of ASR and diarization in the presence of overlapping speech. At the top, a waveform shows two overlapping speech signals. Below, a speaker icon asks, "Did you attend the session ~~over~~?" and another speaker icon responds, "Yes, I did. It was great!". A large red 'X' is placed over the first speaker's text, indicating a failure. A dashed box contains two bullet points: "ASR models are typically trained on single-speaker utterances" and "Conventional clustering-based diarization systems assume single-speaker segments". Below this, the same scenario is shown with ASR outputs: the first speaker's text is "Did you attend the session <UNK>" and the second's is "It was great!".

- ASR models are typically trained on single-speaker utterances
- Conventional clustering-based diarization systems assume single-speaker segments



One possible solution

Separate the speech before applying diarization and ASR



We study this integration extensively...

...on the **LibriCSS dataset***



10 min “mini-sessions”



8 speakers per recording



0–40% overlap ratio



7-microphone circular array

*MORE ON THIS LATER

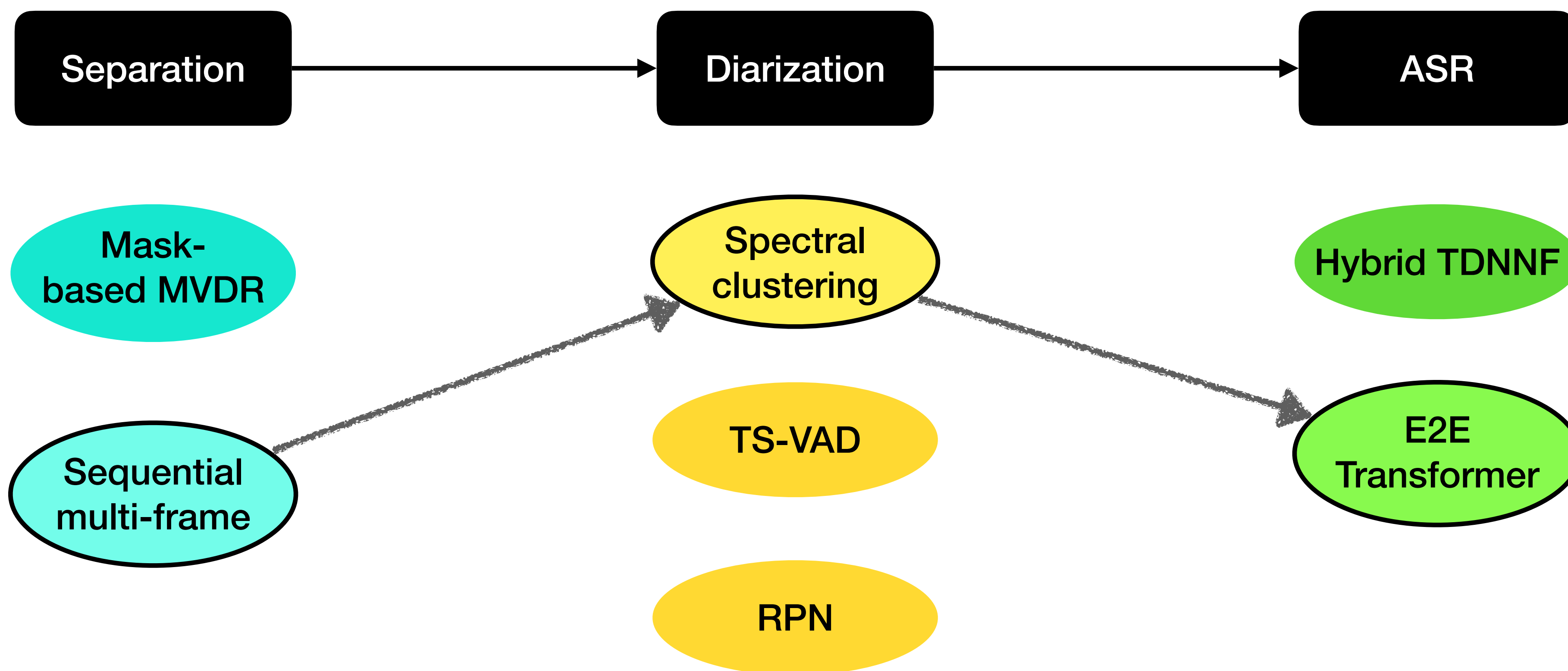


Zhuo Chen, Takuya Yoshioka, Liang Lu, Tianyan Zhou, Zhong Meng, Yi Luo, J. Wu, and Jinyu Li,
“Continuous speech separation: Dataset and analysis,” ICASSP 2020.



Our final pipeline

Final cpWER = **12.7%** (compared with **27.1%** for “no separation” baseline)

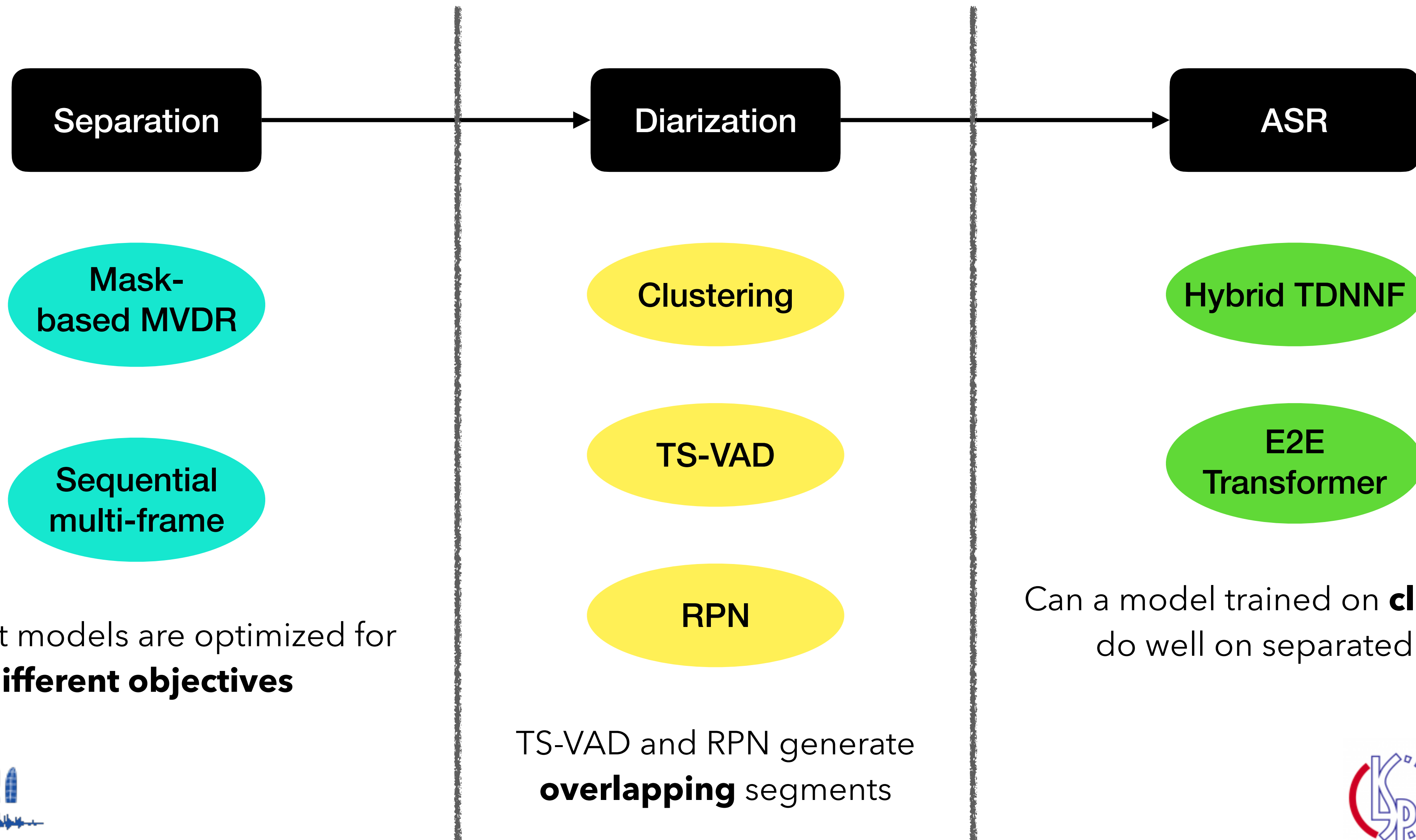


End of Highlight

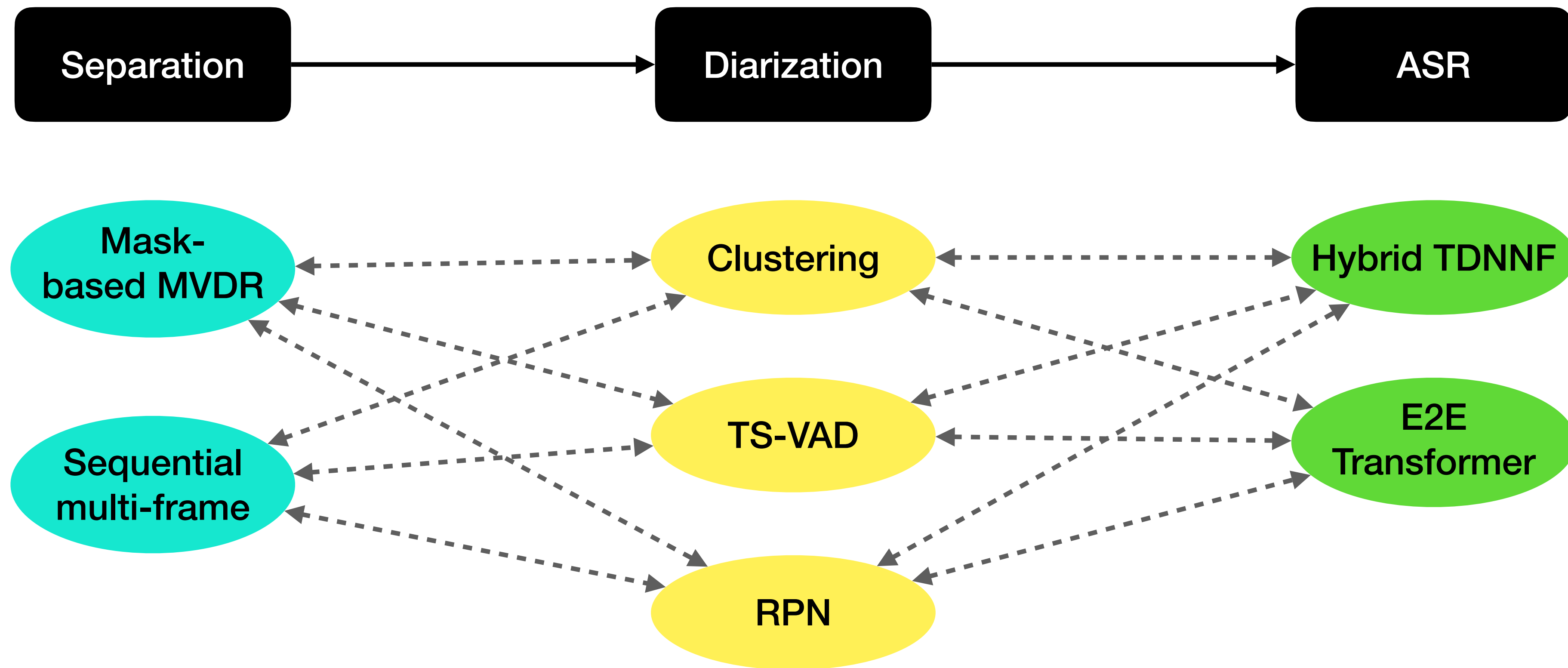
Overview

- **Modular pipeline: Too many options!**
- **Related Work: Integrated pipelines in literature**
- **More on the dataset (LibriCSS) and the metric (cpWER)**
- **Results and Discussion:**
 - **The separation component**
 - **The diarization component**
 - **The ASR component**
- **Where does your model fit in?**

What components should you choose?



What components should you choose?



How do the components **interact** among themselves?

CHiME-6 and CSS

Different orders of the 3 main components

CHiME-6 Track 2



CSS pipeline



This work



CHiME-6 and CSS

Diarization: Overlap-aware? Across streams?

CHiME-6 Track 2



CSS pipeline



This work



CHiME-6 and CSS

Separation: informed?

CHiME-6 Track 2



CSS pipeline



This work



CHiME-6 and CSS

ASR: using speaker information?

CHiME-6 Track 2



CSS pipeline

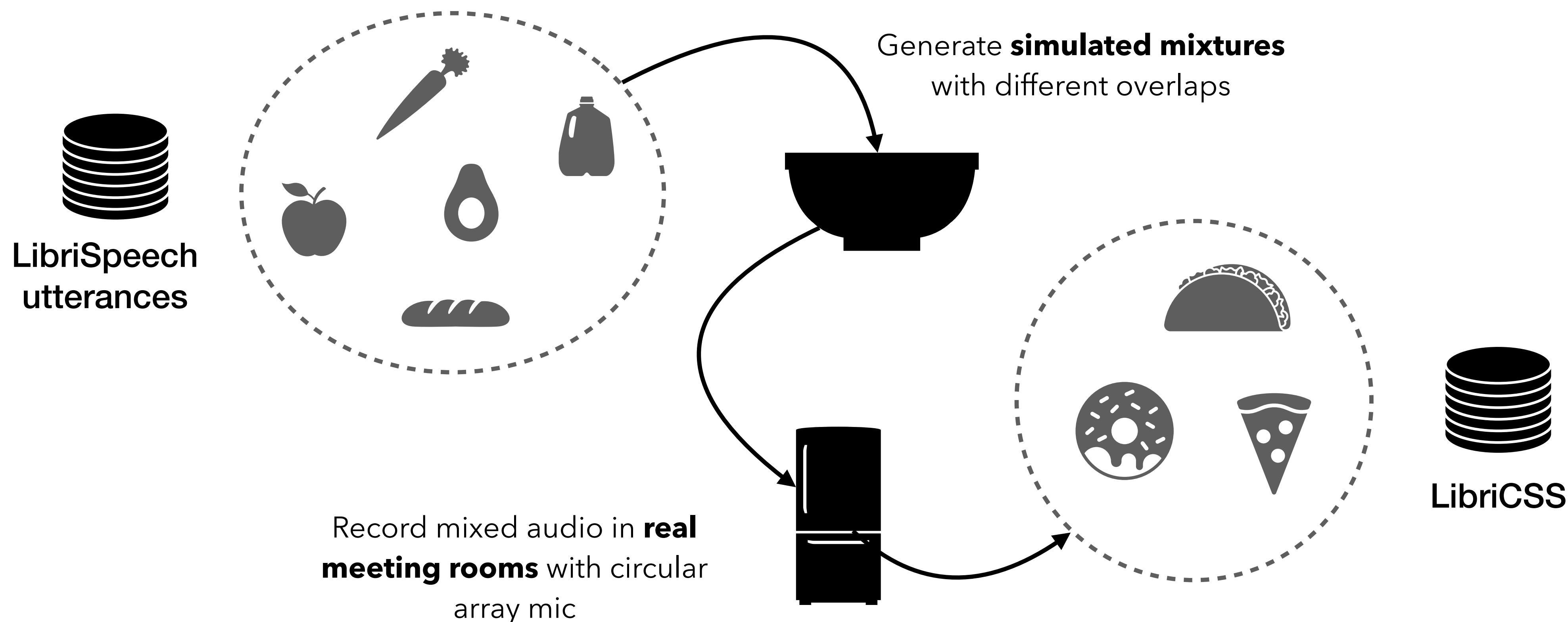


This work



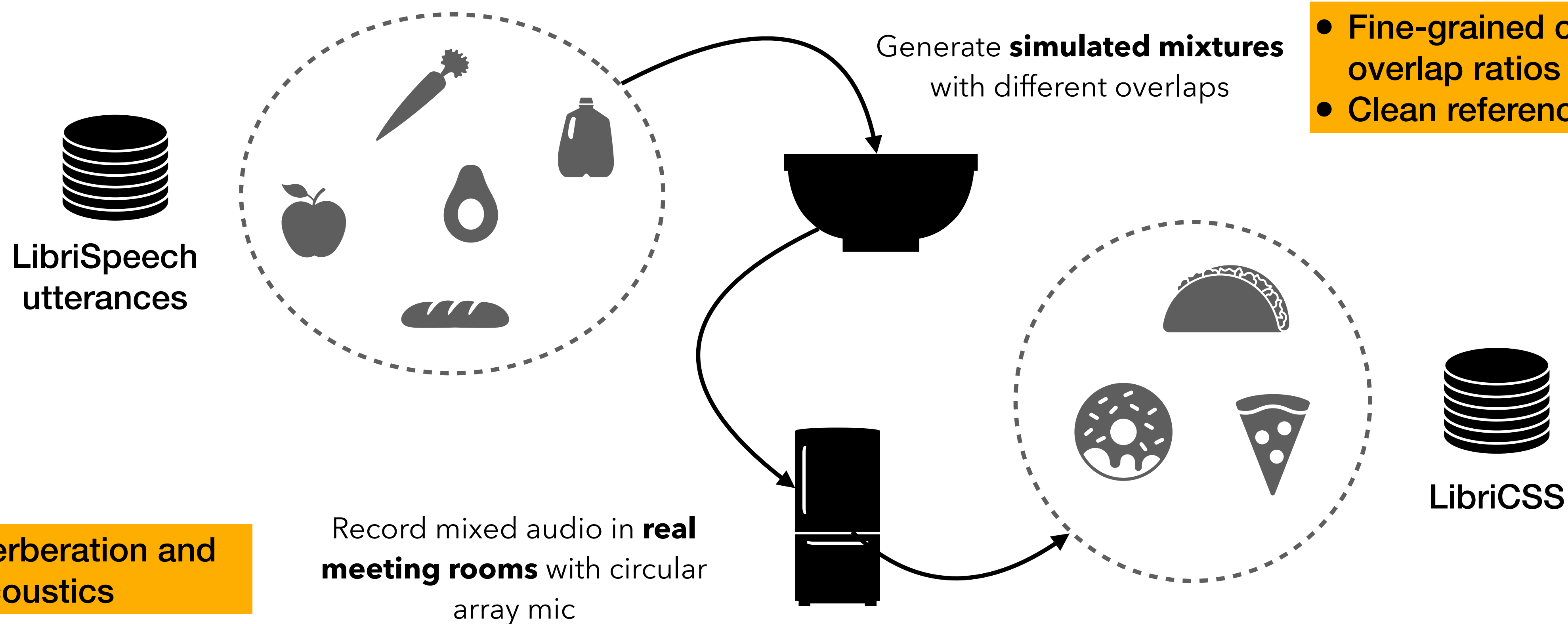
More about LibriCSS

“Real recordings of simulated conversations”



More about LibriCSS

Why is it useful?



More about cpWER

Metric for “who spoke what”

cpWER = concatenated minimum-permutation word error rate

Concatenate all utterances of a speaker in reference and hypothesis

Score all pairs of reference and hypothesis speakers

Find permutation that **minimizes the total WER**
(linear sum assignment)

Speech separation results

SDR is not related to cpWER results

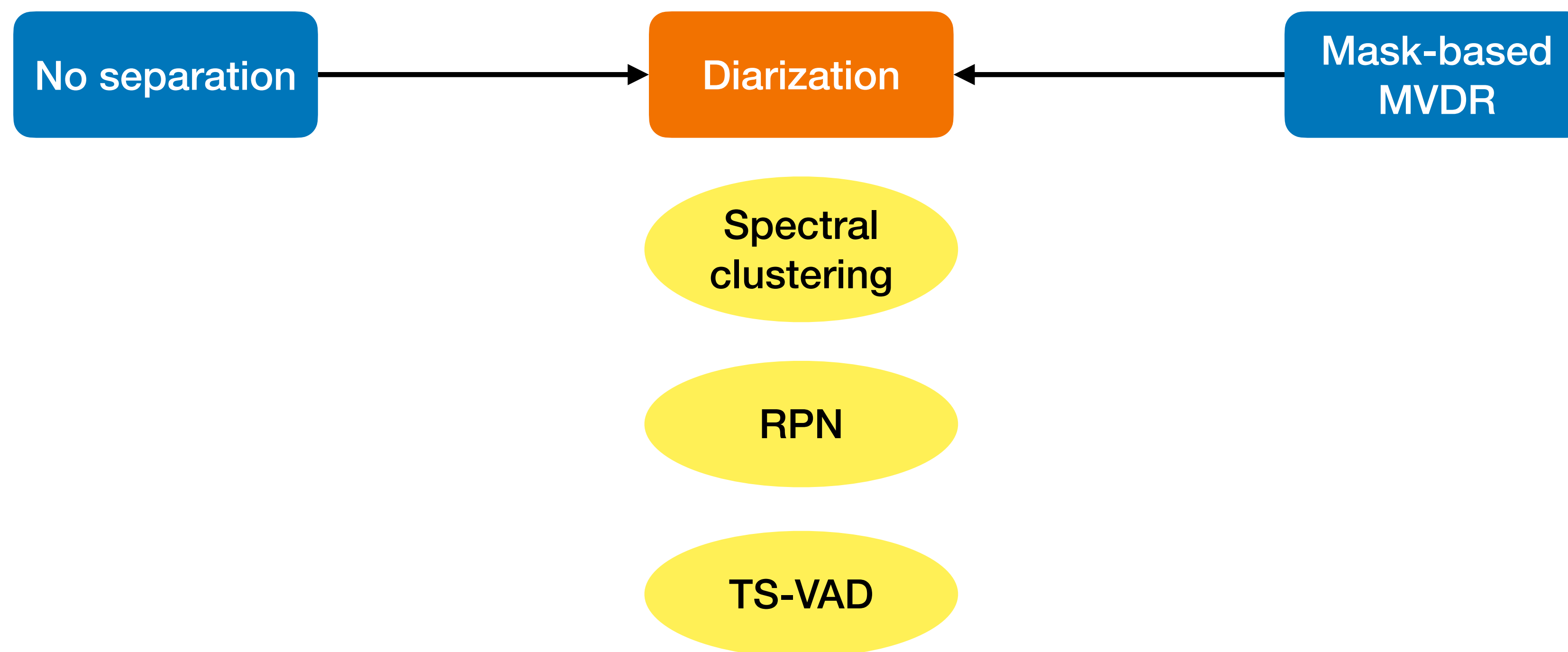
		Separation SDR	Spectral clustering DER	Hybrid TDNNF cpWER
No separation		-	18.3	31.0
Mask-based MVDR	2.4s chunks; 2 streams	5.8	13.9	22.8
Sequential multi-frame	10s chunks; 3 streams	14.1	14.1	19.3

Takuya Yoshioka, Hakan Erdogan, Zhuo Chen, and Fil Alleva, "Multi-microphone neural speech separation for farfield multi-talker speech recognition," ICASSP 2018

Zhong-Qiu Wang, Hakan Erdogan, Scott Wisdom, Kevin Wilson, Desh Raj, Shinji Watanabe, Zhuo Chen, and John R. Hershey, "Sequential multi-frame neural beamforming for speech separation and enhancement," IEEE SLT 2021.

Diarization results

Clustering-based vs. supervised methods



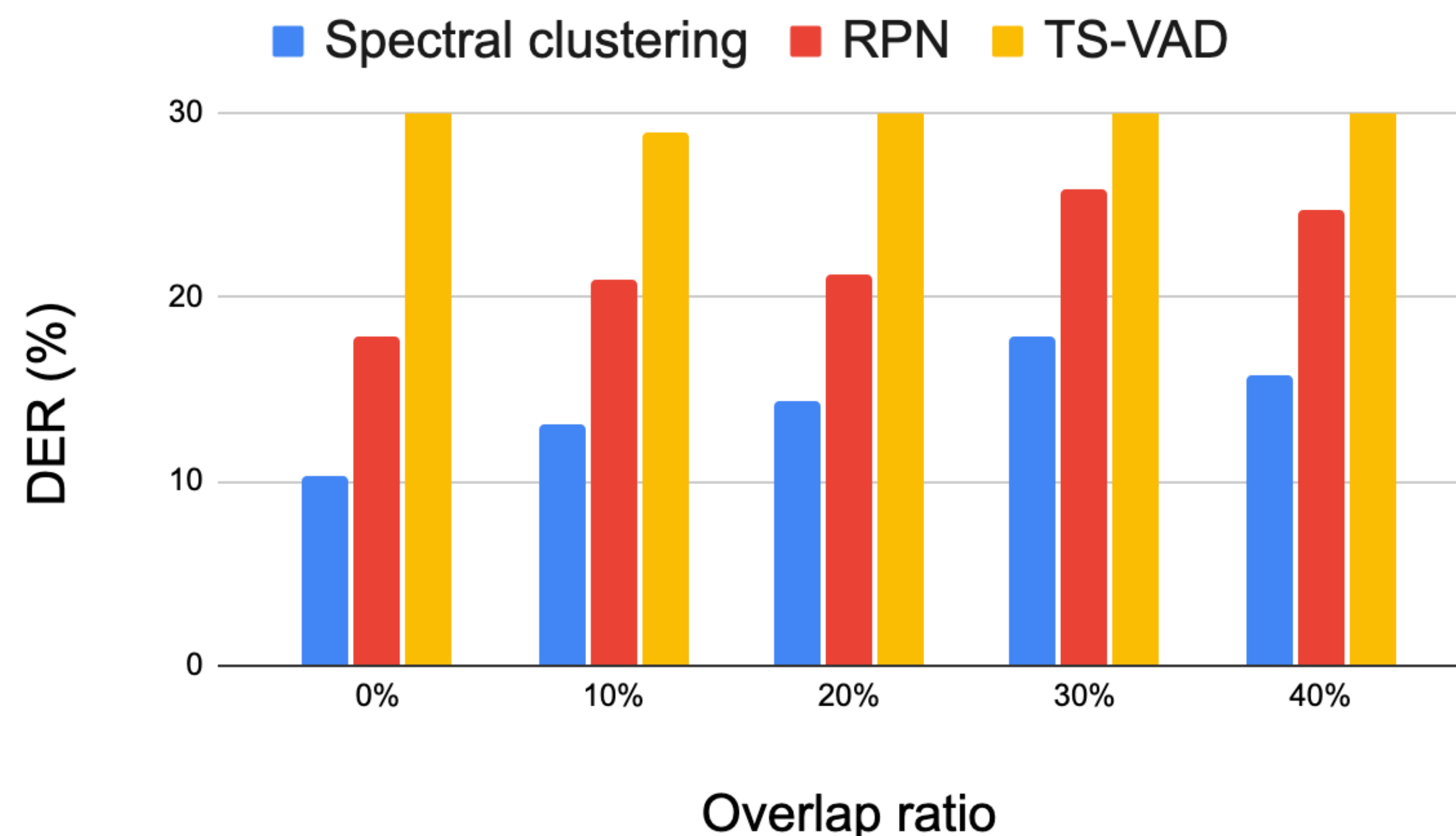
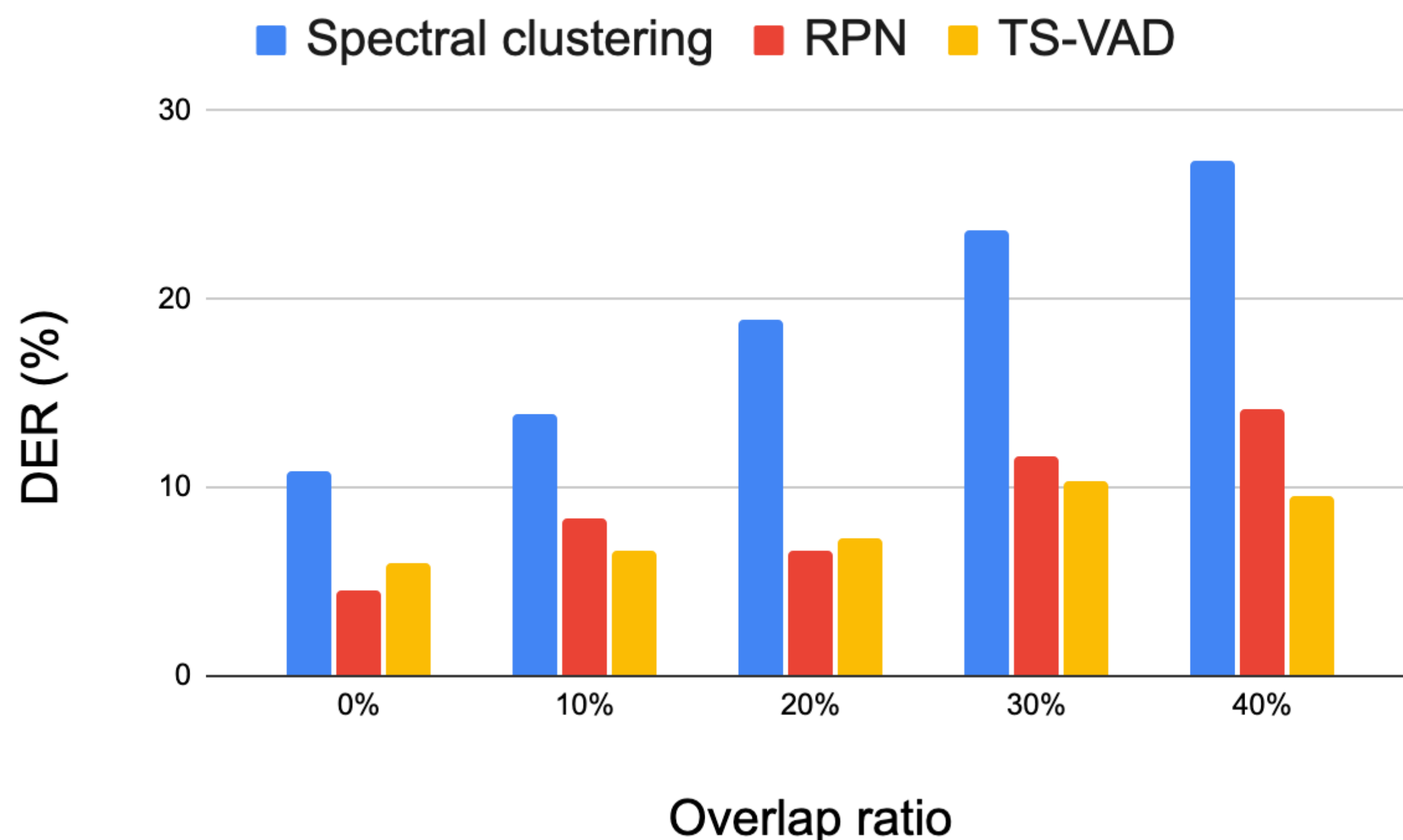
Park et al., "Auto-tuning spectral clustering for speaker diarization using normalized maximum eigengap," IEEE Signal Processing Letters, 2020.

Huang et al., "Speaker diarization with region proposal network," ICASSP 2020.

Medennikov, et al., "Target speaker voice activity detection: a novel approach for multispeaker diarization in a dinner party scenario," Interspeech 2020.

Diarization results

Dichotomy between performance on mixed and separated audio



ASR results

Hybrid TDNNF and End-to-end Transformer models



 **KALDI** **TDNNF**

 **ESPnet** **Transformer**



Daniel Povey, Gaofeng Cheng, Yiming Wang, Ke Li, Hainan Xu, Mahsa Yarmohammadi, and Sanjeev Khudanpur, "Semiorthogonal low-rank matrix factorization for deep neural networks," Interspeech 2018.

Shigeki Karita, Nanxin Chen, Tomoki Hayashi, Takaaki Hori, Hirofumi Inaguma, Ziyang Jiang, Masao Someki, Nelson Enrique Yalta Soplin, Ryuichi Yamamoto, Xiaofei Wang, et al., "A comparative study on transformer vs RNN in speech applications," IEEE ASRU 2019.



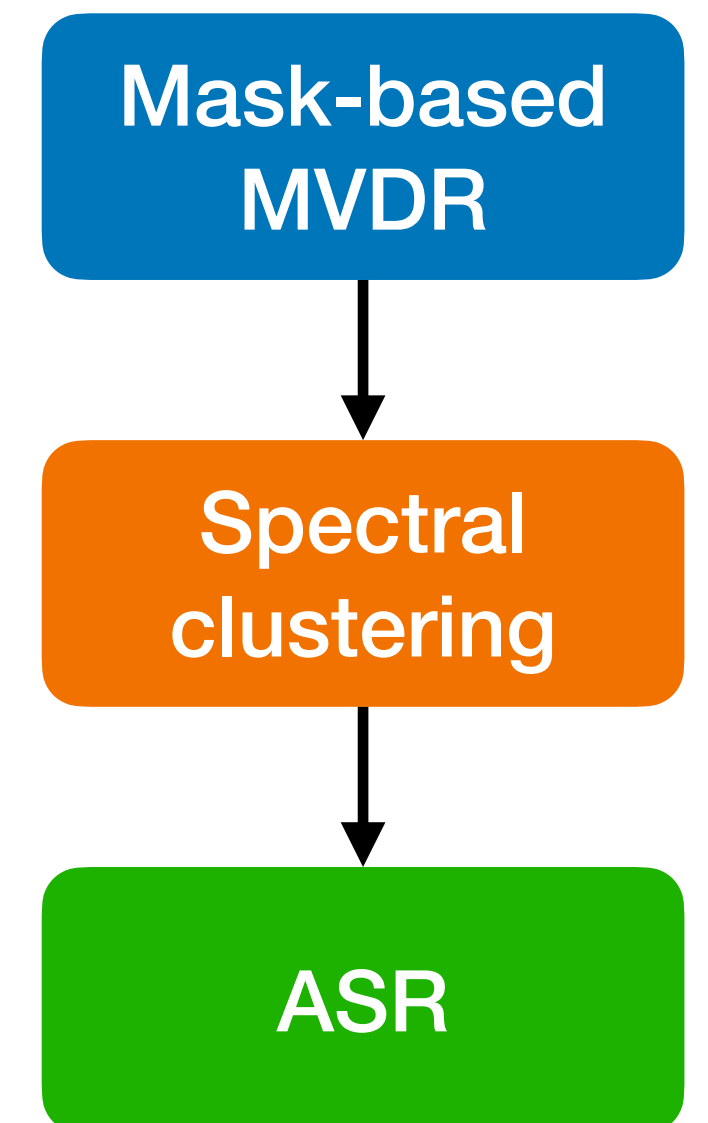
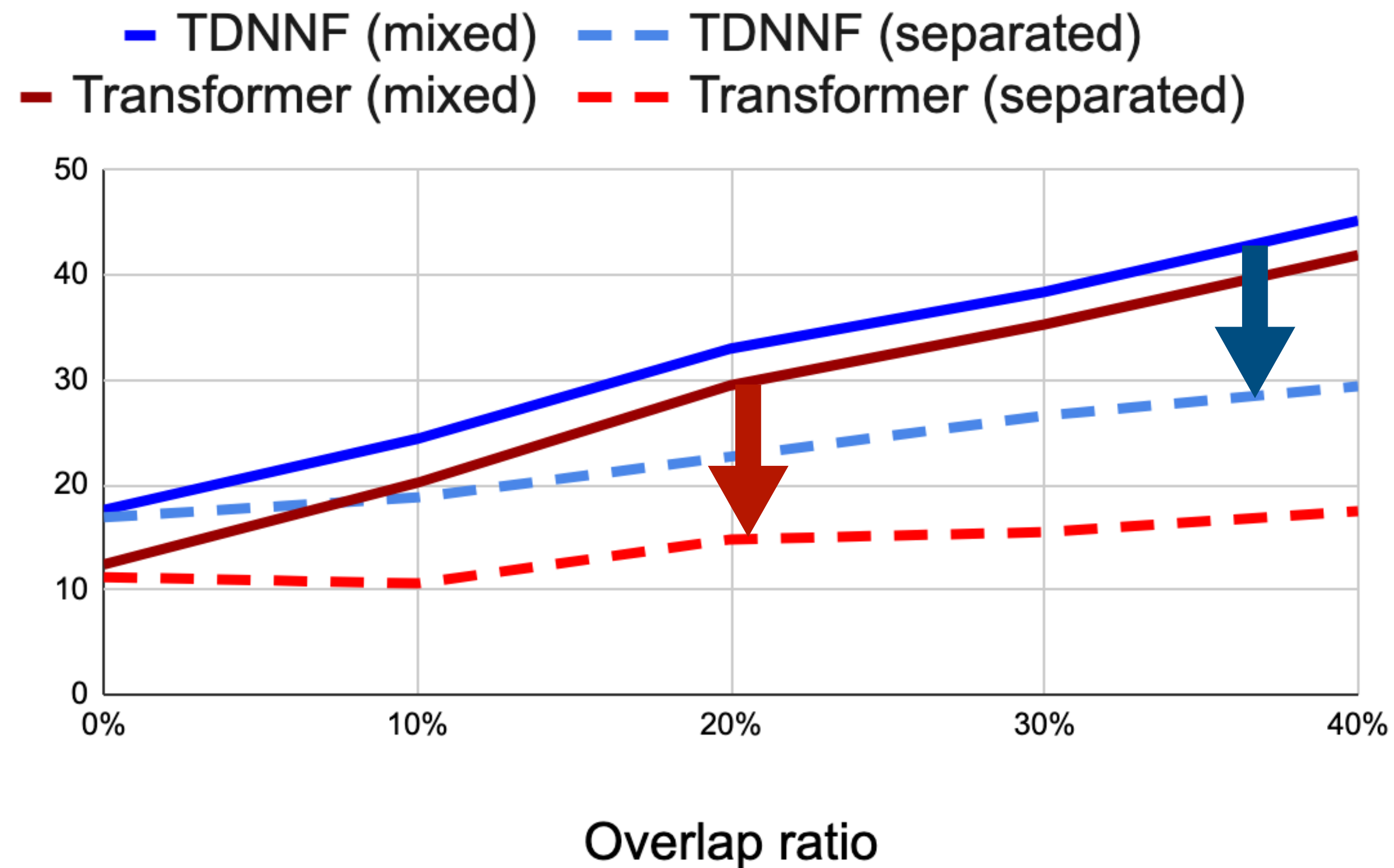
ASR results

Performance on clean and separated audio are correlated



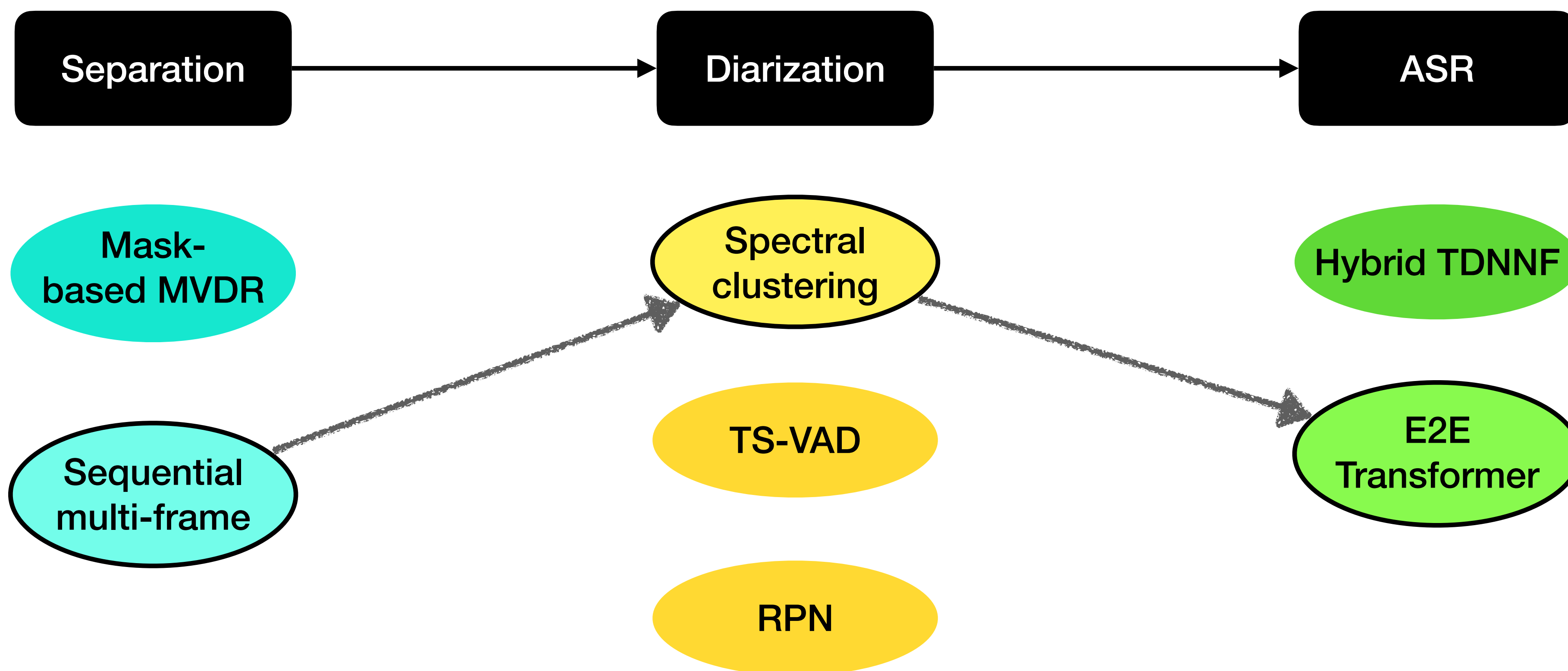
Performance on
LibriSpeech:

TDNNF **3.8%**
Transformer **2.2%**



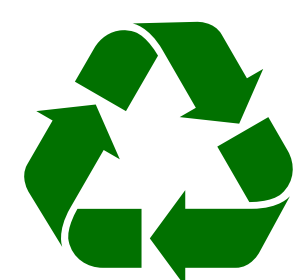
Our final pipeline

Final cpWER = **12.7%** (compared with **27.1%** for “no separation” baseline)



How to use this research?

Plug in your component in the pipeline to get cpWER results



✓ Mask-based MVDR

✓ Clustering

✓ Hybrid TDNNF



✓ Sequential multi-frame

⚙ TS-VAD

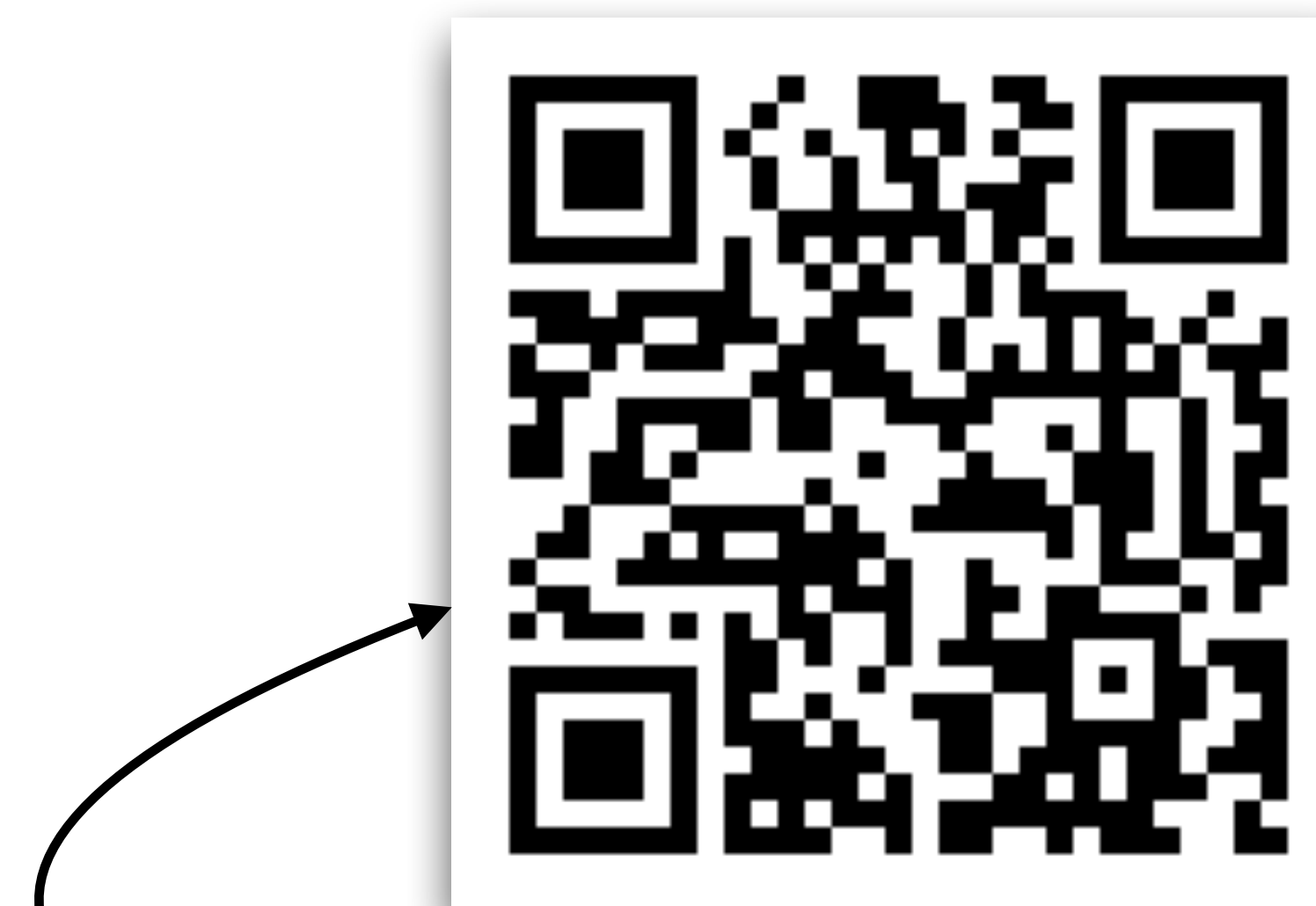
✓ E2E Transformer



⚙ RPN

How to use this research?

Details available on project page



Scan me!

Acknowledgments:

The work reported here was started at JSALT 2020 at JHU, with support from Microsoft, Amazon, and Google.

