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Ensemble combination between different time segmentations

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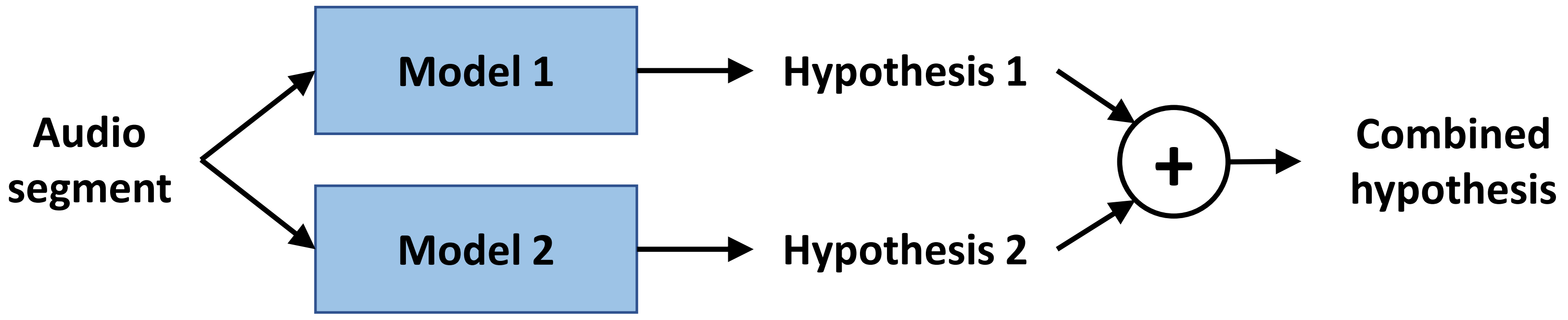
Ensemble combination



- Hypothesis-level combination assumes that all models use the same input time segments.

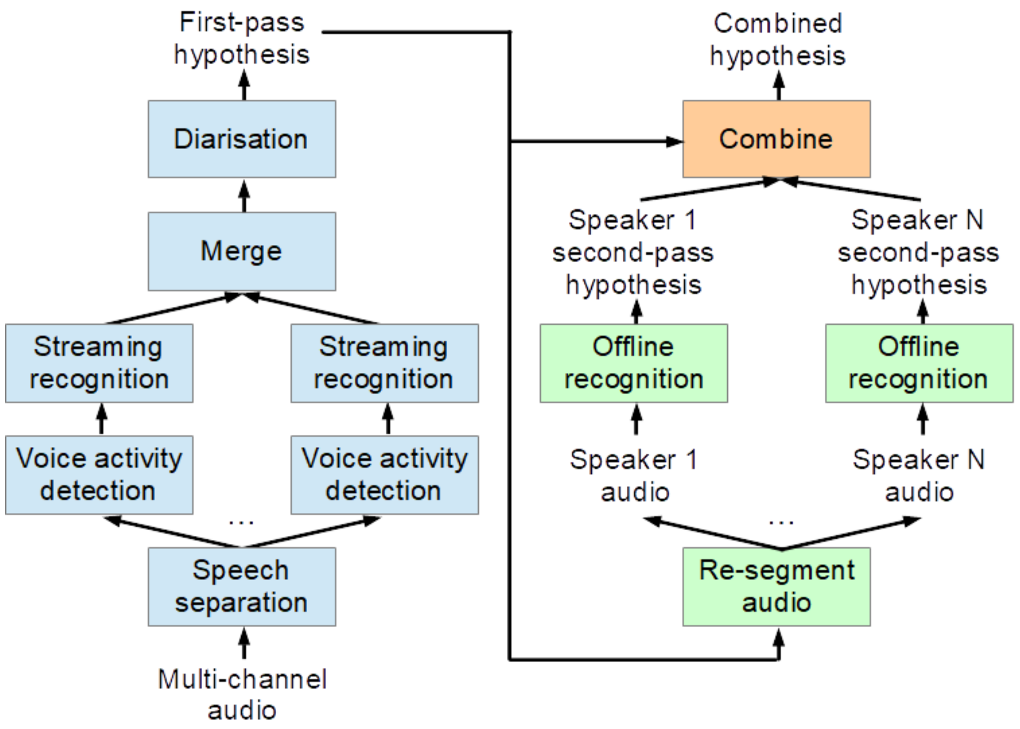
Propose:

- Method to allow different input segmentation times between models.

Applications for different time segmentations

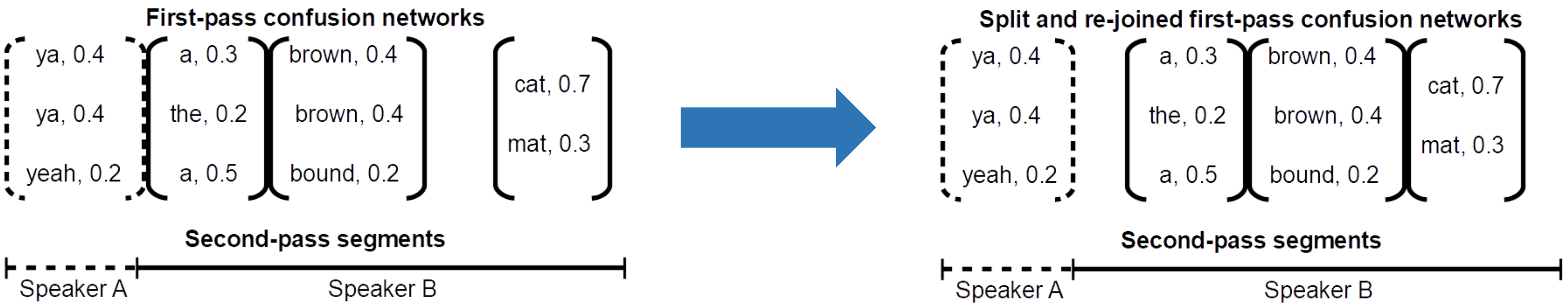
- Combination between different time segmentations can be used for:
  - Different VAD front-ends for each model.
  - Audio from multiple unsynchronised recording devices.
  - Overlapping inference.
  - Using a 1st pass ASR to refine the time segmentations for a 2nd pass ASR.

Meeting transcription setup



- 1st pass streaming ASR -> diarisation -> 2nd pass offline ASR
- 1st pass ASR uses VAD segments.
- 2nd pass ASR uses per-speaker segments.
- Want to combine 1st pass and 2nd pass ASR hypotheses to improve 2nd pass performance.

Confusion network splitting



1. Convert N-best list into confusion network.
2. Estimate start and end times of each confusion set.
3. Estimate the speaker ID for each confusion set from the 1-best hypothesis.
4. Split up confusion network into separate confusion sets.
5. Re-join consecutive confusion sets to match time segments.
6. Do Confusion Network Combination (CNC) between all models.

T. Yoshioka et. al., "*Meeting transcription using virtual microphone arrays*", Tech. Rep., Microsoft, May 2019

Confusion network splitting

Advantages:

- 1-best is preserved after splitting and re-joining.

Disadvantages:

- Start and end times of each confusion set are approximate.
- Word sequence context of language model scores is not preserved.

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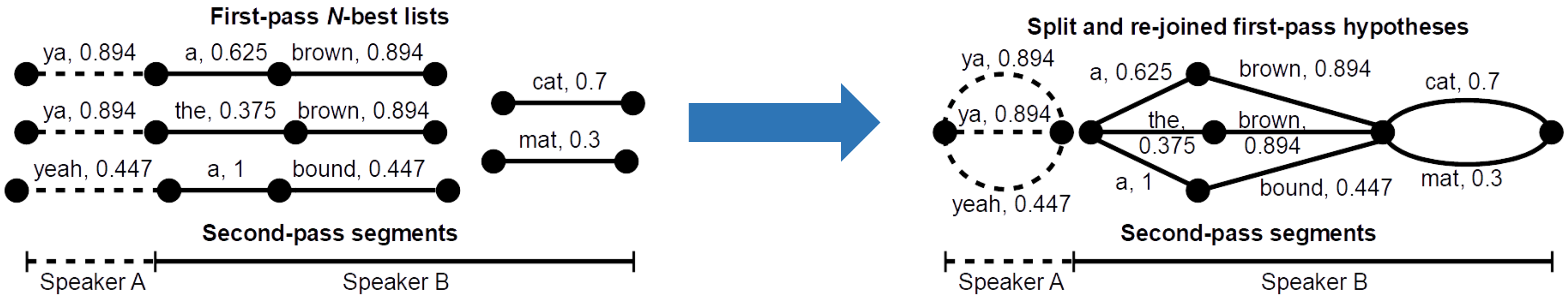
N-best list splitting



1. Distribute hypothesis scores to words.
2. Estimate the speaker ID for each N-best word from the 1-best hypothesis.
3. Split up the N-best lists.
4. Re-join N-best lists according to segment times.
5. Do Minimum Bayes' Risk (MBR) combination between all models.

N-best list splitting

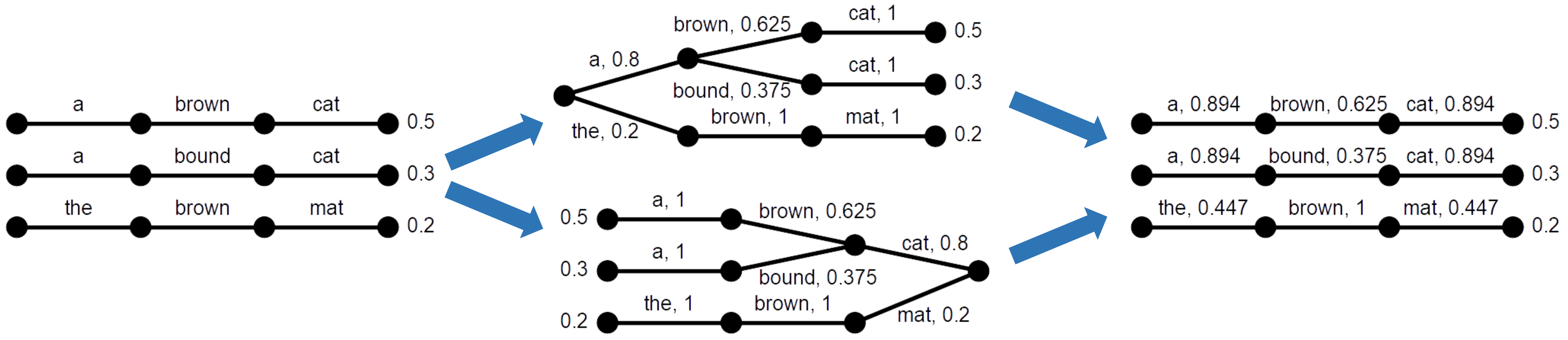
Advantages:

- Exact word start and end times are preserved from ASR decoding.
- Word sequence context of language model scores is preserved.

Disadvantages:

- 1-best may not be preserved after splitting and re-joining.

Distribute hypothesis scores to words



- Black-box ASR system may only produce per-hypothesis scores.
- Estimate per-word scores by:
  1. Convert N-best list to prefix and suffix trees.
  2. Push weights to branches.
  3. Take log-average of per-word scores from prefix and suffix trees.
- Prefix and suffix trees concentrate weights at opposite ends.

Experiments

Dataset:

- Internal Microsoft meetings.
- *dev* set: 51 meetings, 23 hours
- *eval* set: 60 meetings, 35 hours
- *Average of 7 participants per meeting.*

Speaker-attributed WER Metric:

- For each speaker, compute the WER of that speaker’s hypothesis vs reference.
- Average the WERs over all speakers.

Experiments

Models:

- **1st pass hybrid:** streaming latency-controlled and layer-trajectory BLSTM.
- **2nd pass hybrid:** ensemble of 2 offline BLSTMs.
- **2nd pass LAS:** offline BLSTM encoder, LSTM decoder.
- **Hybrid LM:** 5-gram + NNLM

N-best list size: 16

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Score distribution method

- Distribute hypothesis-level scores to words for streaming 1st pass model.
- Split and re-join 1st pass N-best lists to match 2nd pass segments.

Split	Per-word scores	*eval* Speaker-attributed WER (%)
no	original	20.43
yes	original	22.09
	language model re-score	22.09
	prefix tree	20.62
	suffix tree	20.60
	log-average	20.55

- After splitting, log-average between prefix and suffix trees performs best.
- Splitting yields degradation.

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Multi-pass combination

- Single model performance.

		Speaker-attributed WER (%)	
Segments	**Model**	***dev***	***eval***
1st pass	streaming hybrid	21.43	20.43
2nd pass	streaming hybrid	20.87	19.96
	offline hybrid	19.93	19.13
	offline LAS	19.91	19.04

- Offline model outperforms streaming model.
- 2nd pass segments yield gains over 1st pass segments for the same model.

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Multi-pass combination

Single model

Segments	Model	Speaker-attributed WER (%) *dev*	*eval*
1st pass	streaming hybrid	21.43	20.43
2nd pass	streaming hybrid	20.87	19.96
	offline hybrid	19.93	19.13
	offline LAS	19.91	19.04

Combination between 1st and 2nd pass hypotheses

Combination	Speaker-attributed WER (%) *dev*	*eval*
CNC streaming hybrid + offline hybrid	20.01	19.10
CNC streaming hybrid + offline LAS	19.71	18.71
MBR streaming hybrid + offline hybrid	19.83	19.00
MBR streaming hybrid + offline LAS	19.30	18.43
MBR offline hybrid + offline LAS	19.11	18.24

- MBR with N-best splitting outperforms CNC with confusion network splitting.
- Offline hybrid + offline LAS performs best, but is computationally expensive.
- Streaming hybrid + offline LAS yields reasonable gains, with only single model in 2nd pass.
- Hybrid + LAS outperforms hybrid + hybrid, suggesting greater diversity.
- Streaming hybrid (on 2nd pass segments) + offline hybrid *eval* WER = 18.37 %.

Summary

- **Proposed:**
  - Allow different time segments in combination by splitting and re-joining of N-best lists.
  - Estimate per-word scores from per-hypothesis scores using trees.

- Improve 2^{nd} pass performance without additional computational cost.

- Showed that hybrid + LAS outperforms hybrid + hybrid.