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MOTIVATION

Task: Speech recognition

Problem

Hypothesis-level combination requires all models to use the same input time segmentations.

Proposal

Allow different time segmentations between models by splitting and re-joining the hypothesis *N*-best lists.

Applications

Allow combinations between:

- Different voice activity detection front-ends.
- Different unsynchronised recording devices.
- Overlapping inference.
- 1st pass used to refine time segmentation of 2nd pass.



MEETING TRANSCRIPTION SETUP

1st pass streaming ASR \rightarrow **diarisation** \rightarrow **2nd pass offline ASR**

- 1st pass ASR uses VAD segments.
- 2nd pass ASR uses per-speaker segments from diarisation.
- Want to combine 1st pass and 2nd pass hypotheses.

Data:

- *dev* 51 meetings, 23 hours
- eval 60 meetings, 35 hours
- Average of 7 participants per meeting

Ensemble combination between different time segmentations

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MULTI-PASS COMBINATION

CONFUSION NETWORK SPLITTING



Steps:

- 1. Convert *N*-best list into confusion network.
- 2. Estimate start and end times of confusion sets.
- 3. Estimate confusion set speaker from 1-best hypothesis.
- 4. Split up confusion network into separate confusion sets.
- 5. Re-join consecutive confusion sets of the same speaker.
- 6. Do Confusion Network Combination (CNC). **Advantages:**
- 1-best is preserved after re-joining. **Disadvantages:**
- Confusion set times are approximate.
- Context of language model scores is not preserved.

N-BEST LIST SPLITTING



Steps:

- 1. Distribute hypothesis scores to words.
- 2. Estimate speakers for *N*-best words from 1-best hypothesis.
- 3. Split up the *N*-best lists.
- 4. Re-join *N*-best lists according to segment time and speaker.
- 5. Do Minimum Bayes' Risk (MBR) combination. **Advantages:**
- Exact word start and end times are preserved.
- Context of language model scores is preserved. **Disadvantages:**
- Hypothesis rank order may not be preserved after re-joining.



- **Steps:**
- 1. Convert *N*-best list into prefix and suffix trees.
- 2. Push weights to branches.

Split	Per-word scores	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
	average	20.55

- 1st pass streaming hybr 2nd pass offline hybrid
- 2nd pass offline LAS
- CNC streaming hybrid CNC streaming hybrid MBR streaming hybrid MBR streaming hybrid MBR offline hybrid + o

- Hybrid + LAS outperforms hybrid + hybrid.

- 0.5	ļ	brown, 0.625	cat, 1	0.5
	a, 0.8		cat, 1	
- 0.2	the, 0.2	bound, 0.375 brown, 1	mat, 1	0.2
	a, 0.894	(b) Forward prefi brown, 0.625	x tree cat, 0.894	
at, 0.8	a, 0.894	bound, 0.375	cat, 0.894	0.5
at, 0.2	the, 0.447	brown, 1	mat, 0.447	0.3
	(d) A	• verage scores from	n both trees	, 0.2

HYPOTHESIS SCORES TO WORD SCORES

• Black-box speech recogniser may not produce per-word scores. • Want to estimate per-word scores from per-hypothesis scores.

3. Take log-average of scores from prefix and suffix trees.

EXPERIMENTS

Distribution of hypothesis scores to words, on 1st pass *eval*

• Best performance with average of prefix and suffix trees. **Multi-pass combination** (Speaker-attributed WER (%))

	dev	eval
orid	21.43	20.43
1	19.93	19.13
	19.91	19.04
l + offline hybrid	20.01	19.10
l + offline LAS	19.71	18.71
l + offline hybrid	19.83	19.00
l + offline LAS	19.30	18.43
offline LAS	19.11	18.24

• *N*-best list splitting outperforms confusion network splitting. • Combination with no increase in 2nd pass computational cost.

CONCLUSION

• Distribute hypothesis scores to words using trees. • Combine different time segments by splitting *N*-best lists.