Aalto University

End-to-end speech recognition using lattice-free MMI

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Outline

End-to-end speech recognition

E2E models directly transcribe speech to text without requiring predefined alignment between acoustic frames and characters

- Single model is used
- New training methods are needed

The MMI method

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- We use an objective function that optimizes some criteria associated with the task -> discriminative

The MMI method in details

$$F_{MMI}(\lambda) = \sum_{u \in U} log \frac{P_\lambda(O_u|H_{w_u})P(w_u)}{\sum_{\hat{w}} P_\lambda(O_u|H_{\hat{w}_u})P(\hat{w}_u)}$$

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The numerator simply calculates the probability of the correct transcription (w_u) using the model (λ).

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  - N-best list (less used since it is too crude)

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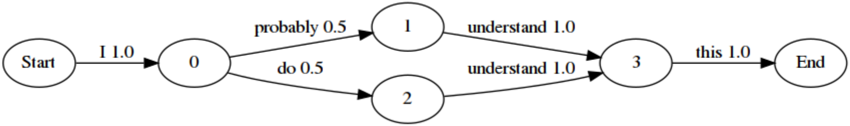
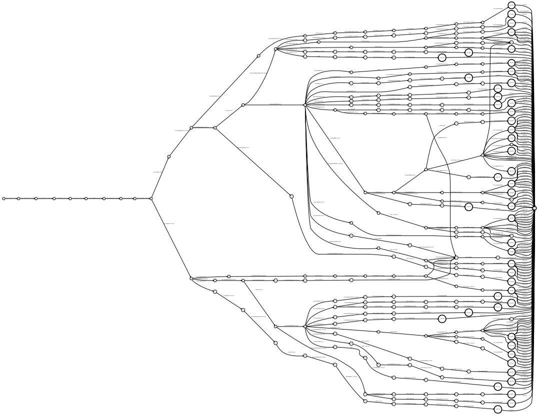
  - Lattice structure

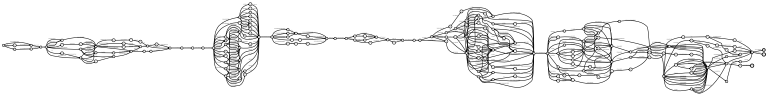
Lattice


Start
I 1.0
0
probably 0.5
do 0.5
1
2
understand 1.0
understand 1.0
3
this 1.0
End

Lattice



Lattice



MMI loss function

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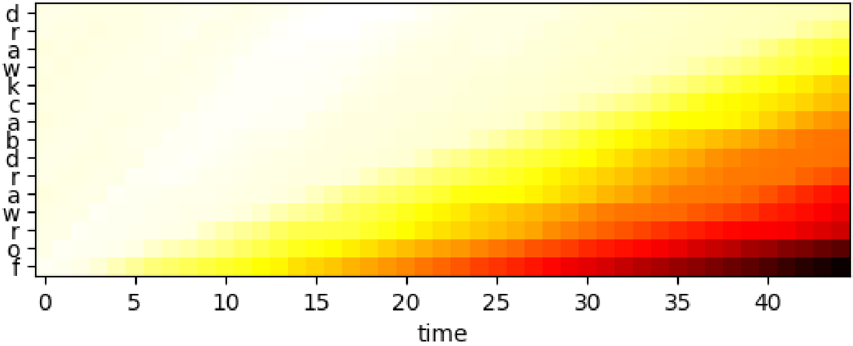
where γ is the forward-backward algorithm.

Forward-backward algorithm

- The goal is to find the alignment between the text and the audio



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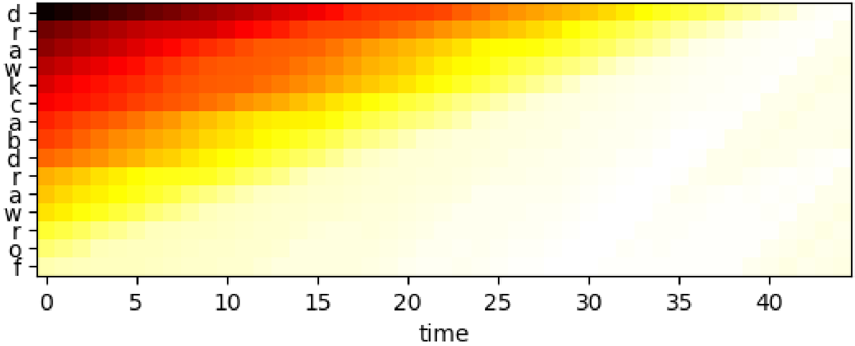

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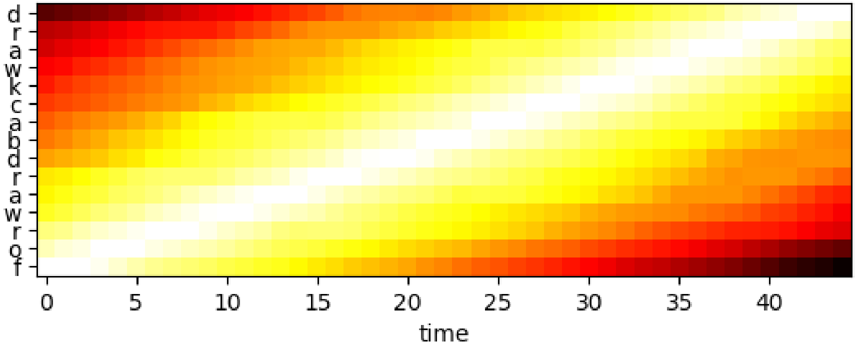

Relation to CTC

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Relation to CTC

- Using the numerator is quite similiar to CTC
- The differences between CTC and MMI:
  - No decoding in CTC
  - CTC uses fixed and uniform state priors, observation priors, and transition probabilities
  - Different topology (blank label)

Lattice-free MMI

Problems:

- Requires initialization with a trained model
- Unique lattice for each utterance
- Computationally expensive

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Solution:

- Represent the denominator as a graph
- Fit the graph in the GPU

Decoder graph

Notations

H=HMM state graph, C=context-dependency, L=the lexicon, G=the language model

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- LF-MMI uses HCP

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Additional trick: chunks of 1-1.5 seconds are used instead of the entire utterance (alignment is needed)

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End-to-end version

- In LF-MMI tied bi-phone or triphone HMM states are used -> alignments needed
- E2E solution: monophones or full bi-phones
- Phone language model for the denominator graph is estimated using the training transcriptions
- Composite HMM (with self-loops) as the numerator graph
    - No prior alignment
    - No restriction on the self-loops

Tree-free full bi-phone

Separate HMM model for each and every possible pair of phonemes.

Tree-free full bi-phone

Separate HMM model for each and every possible pair of phonemes.

- The tree is not pruned at all -> no need for alignments
- Some bi-phones never occurs in the training data -> the network learns to ignore them.

Results

Table 5: *Comparison of WER for character-based end-to-end LF-MMI (EE-LF-MMI) and related methods on WSJ.*

Method	Parameters	Lexicon	LM	WER
Phone CTC [4]	–	Y	Word NG	7.3
Attention [35]	6.6M	Y	Word NG	6.7
EE-LF-MMI	8.2M	Y	Word NG	**4.1**
EE-LF-MMI no-SP	8.2M	Y	Word NG	5.3
EE-LF-MMI	8.2M	N	Char NG	5.4

Results

Method	Params	Lex.	LM	SW	CH	Tot†
CTC [32]	50M	N	Char NG	13.8	21.8	17.8
Attention* [33]	100M	N	N	8.6	17.8	13.2
RNN-T* [33]	120M	N	N	**8.5**	**16.4**	**12.5**
EE-LF-MMI	26M	N	Char NG	12.1	21.7	16.9
EE-LF-MMI	26M	N	Char RNN	12.0	21.9	17.0
CTC [32]	50M	Y	Word NG	11.3	18.7	15.0
RNN-T* [33]	120M	Y	Word NG	8.1	17.5	12.8
EE-LF-MMI	26M	Y	Word NG	9.3	18.6	14.0
EE-LF-MMI no-SP	26M	Y	Word NG	9.7	19.0	14.4
CTC [32]	50M	Y	Word RNN	10.2	17.7	14.0
EE-LF-MMI	26M	Y	Word RNN	8.0	17.6	12.8
Phone CTC [34]	–	Y	Word NG	10.2	16.5	13.3
Phone EE-LF-MMI	26M	Y	Word NG	8.6	15.5	12.0
Phone EE-LF-MMI	26M	Y	Word RNN	**7.5**	**14.6**	**11.0**

* These use data augmentation by adding background noise.
† The total eval2000 WER for CTC and Attention is the average of SW and CH (as it is not reported).

Summary

- MMI is a sequence-discriminative loss function
- The LF version tries to reduce the space and time complexity
- E2E LF-MMI requires a lot of modifications
  - Biphones
  - Composite HMM (numerator graph)
  - Phone language model

References

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- Povey, D., Peddinti, V., Galvez, D., Ghahremani, P., Manohar, V., Na, X., Wang, Y., Khudanpur, S. (2016) Purely Sequence-Trained Neural Networks for ASR Based on Lattice-Free MMI. Proc. Interspeech 2016, 2751-2755.
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