



SJTU SPEECH LAB

上海交通大学智能语音实验室

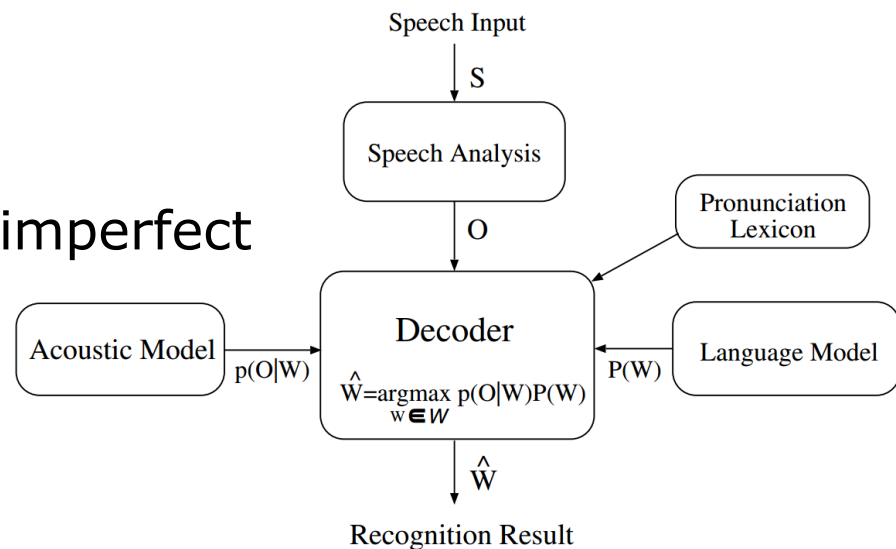
Confidence Measures for CTC-based Phone Synchronous Decoding

Zhehuai Chen, Yimeng Zhuang, Kai Yu

Introduction

ASR Decoding & Confidence Measure

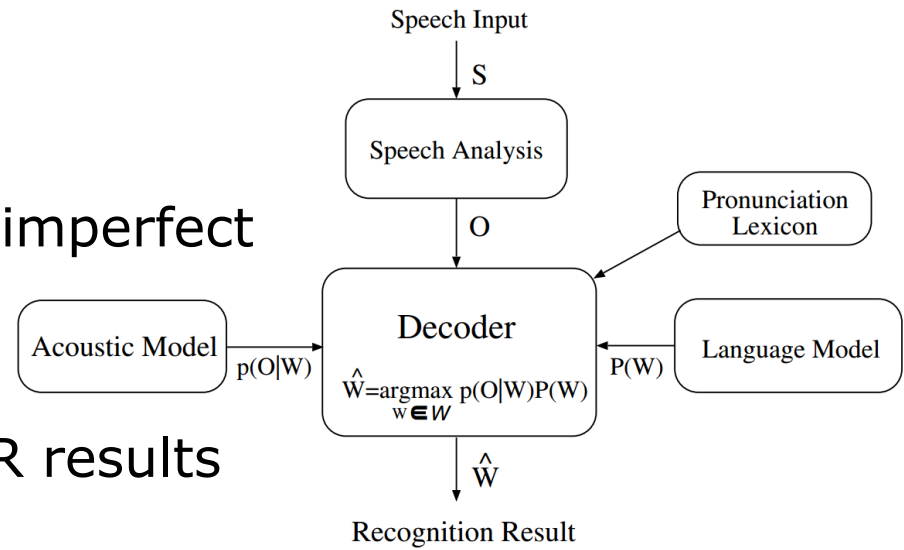
- ASR Decoding
 - Inference by AM/LM/lex ...
 - Model and search are both imperfect



Introduction

ASR Decoding & Confidence Measure

- ASR Decoding
 - Inference by AM/LM/lex ...
 - Model and search are both imperfect
- Confidence Measure (CM)
 - Reliability evaluation of ASR results
 - Traditional CM
 - Predictor features based CM
 - Acoustic score, duration, entropy ... (NOT ideal)
 - CRF, NN ... (need training stage; train \neq test)
 - Hypothesis Posterior based CM
 - Theoretically sounder



Introduction

Hypothesis Posterior based CM

- ASR as the *maximum a posterior* (MAP) decision process

$$\begin{aligned}\hat{W} &= \arg \max_{W \in \Sigma} p(W | X) \\ &= \arg \max_{W \in \Sigma} \frac{p(X | W) \cdot p(W)}{p(X)}\end{aligned}$$

$$p(X) = \sum_H p(X, H) = \sum_H p(H) \cdot p(X | H)$$

- H is from lattice/filler
 - Both imperfect

Introduction

Hypothesis Posterior based CM

- ASR as the *maximum a posterior* (MAP) decision process

$$\hat{W} = \arg \max_{W \in \Sigma} p(W | X)$$

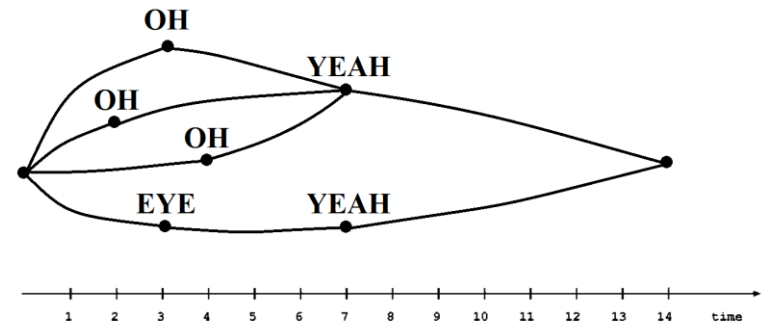
$$= \arg \max_{W \in \Sigma} \frac{p(X | W) \cdot p(W)}{p(X)}$$

$$p(X) = \sum_H p(X, H) = \sum_H p(H) \cdot p(X | H)$$

- H is from lattice/filler
 - Both imperfect

- **Lattice quality** is the bottleneck

- Not compact
 - Boundary unstable



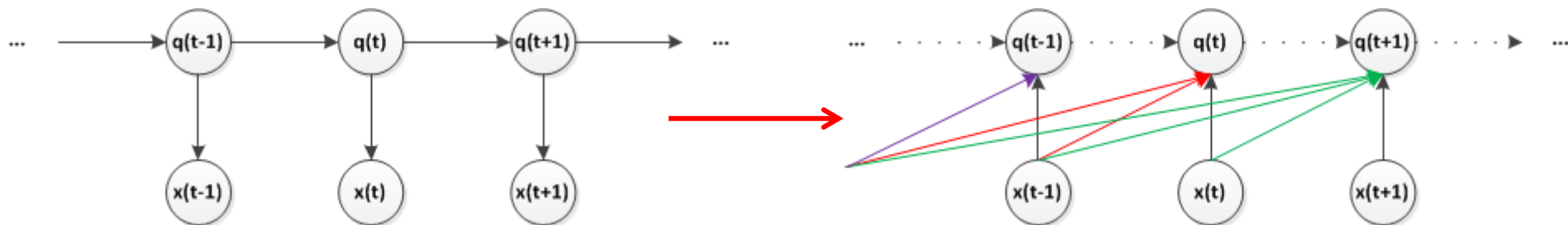
- Not precise
 - Beam prune

WE NEED NEW MODEL !

Introduction

from HMM to CTC acoustic model

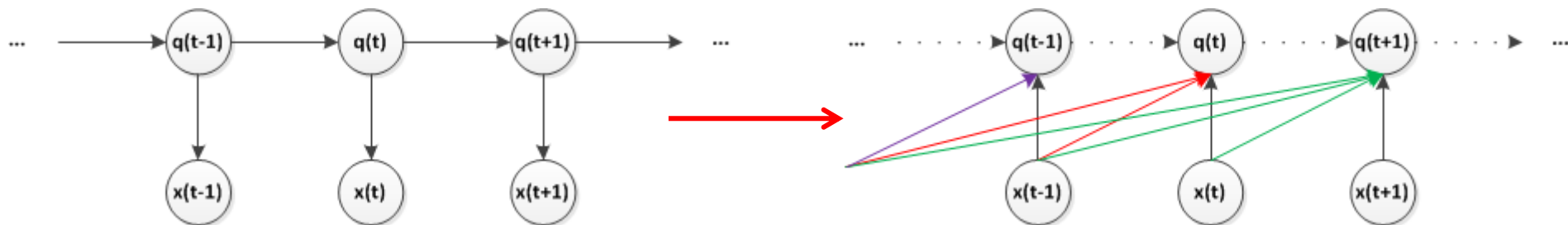
- From HMM to CTC: do better in *sequential modeling*



Introduction

from HMM to CTC acoustic model

- From HMM to CTC: do better in *sequential modeling*



- CTC model: learn the many-to-one function of \mathcal{B}

$$P(\mathbf{l}|\mathbf{x}) = \sum_{\pi \in \mathcal{B}^{-1}(\mathbf{l})} P(\pi|\mathbf{x}) = \sum_{\pi: \pi \in L', \mathcal{B}(\pi_{1:T}) = \mathbf{l}} \prod_{t=1}^T y_{\pi_t}^t \quad \mathcal{B} : L' \mapsto L$$

$$L' = L \cup \{\text{blank}\}$$

Introduction

from HMM to CTC acoustic model

- From HMM to CTC: do better in *sequential modeling*

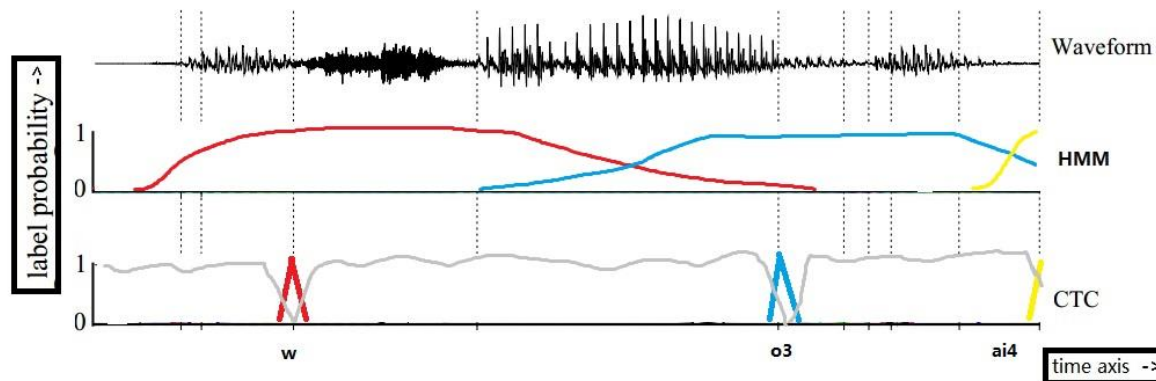


- CTC model: learn the many-to-one function of \mathcal{B}

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$$L' = L \cup \{\text{blank}\}$$

- peaky distribution and concentrated information output



Frame Sync. to Phone Sync.

■ frame synchronous Viterbi beam search in CTC

$$\mathbf{w}^* = \operatorname{argmax}_{\mathbf{w}} \{P(\mathbf{w})p(\mathbf{x}|\mathbf{w})\} = \operatorname{argmax}_{\mathbf{w}} \{P(\mathbf{w})p(\mathbf{x}|\mathbf{l}_{\mathbf{w}})\} \quad (1)$$

$$= \operatorname{argmax}_{\mathbf{w}} \left\{ P(\mathbf{w}) \max_{\mathbf{l}_{\mathbf{w}}} \frac{P(\mathbf{l}_{\mathbf{w}}|\mathbf{x})}{P(\mathbf{l}_{\mathbf{w}})} \right\} \quad (2)$$

$$\cong \operatorname{argmax}_{\mathbf{w}} \left\{ P(\mathbf{w}) \max_{\pi: \pi \in L', \mathcal{B}(\pi_{1:T})=\mathbf{l}_{\mathbf{w}}} \frac{1}{P(\mathbf{l}_{\mathbf{w}})} \prod_{t=1}^T y_{\pi_t}^t \right\} \quad (3)$$



Frame Sync. to Phone Sync.

- **frame synchronous Viterbi beam search in CTC**

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- **frame sync. to phone synchronous decoding**

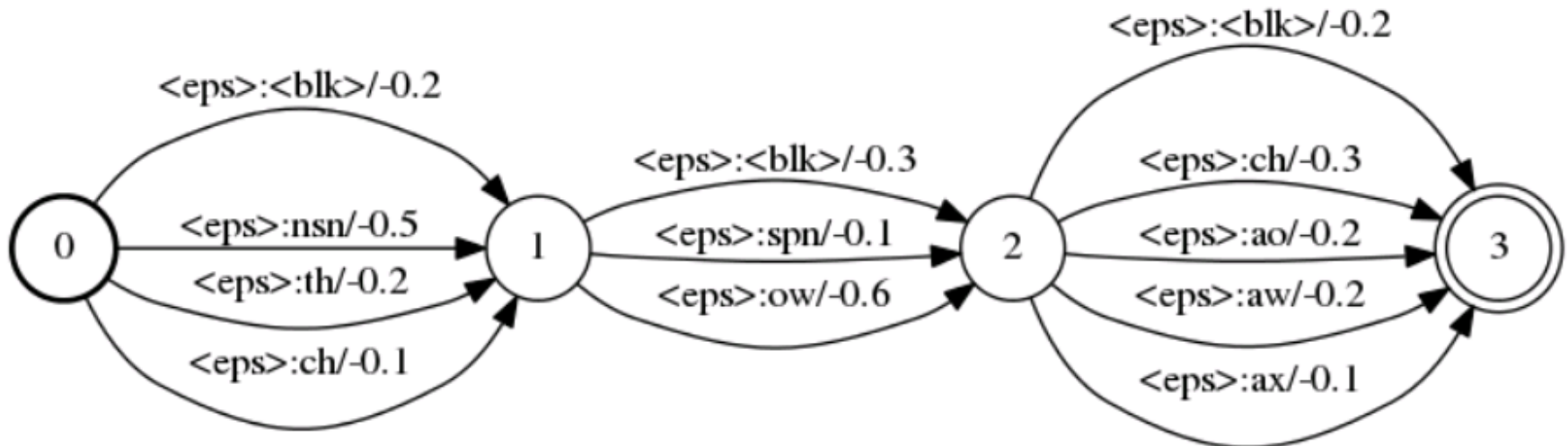
$$\mathbf{w}^* \cong \operatorname{argmax}_{\mathbf{w}} \left\{ P(\mathbf{w}) \max_{\pi: \pi \in L', \mathcal{B}(\pi_{1:T}) = \mathbf{l}_{\mathbf{w}}} \frac{1}{P(\mathbf{l}_{\mathbf{w}})} \left\{ \prod_{t \notin U} y_{\pi_t}^t \cdot \prod_{t \in U} y_{\text{blank}}^t \right\} \right\} \quad (4) \quad U = \{u : y_{\text{blank}}^u \simeq 1\} \quad (5)$$

$$= \operatorname{argmax}_{\mathbf{w}} \left\{ P(\mathbf{w}) \max_{\pi': \pi' \in L, \mathcal{B}(\pi'_{1:J}) = \mathbf{l}_{\mathbf{w}}} \frac{1}{P(\mathbf{l}_{\mathbf{w}})} \prod_{j=1}^J y_{\pi'_j}^{t_j} \right\} \quad (6) \quad J = T - |U| \quad (7)$$

CTC Lattice

- CTC Lattice - Extremely Compact Acoustic Information Preserver

Time	phone label : acoustic score
0.4s	< blk > : 0.2 nsn : 0.5 th : 0.2 ch : 0.1
0.9s	< blk > : 0.3 ow : 0.6 spn : 0.1
1.5s	< blk > : 0.2 ch : 0.3 ao : 0.2 aw : 0.2 ax : 0.1



Hypothesis Posterior CM

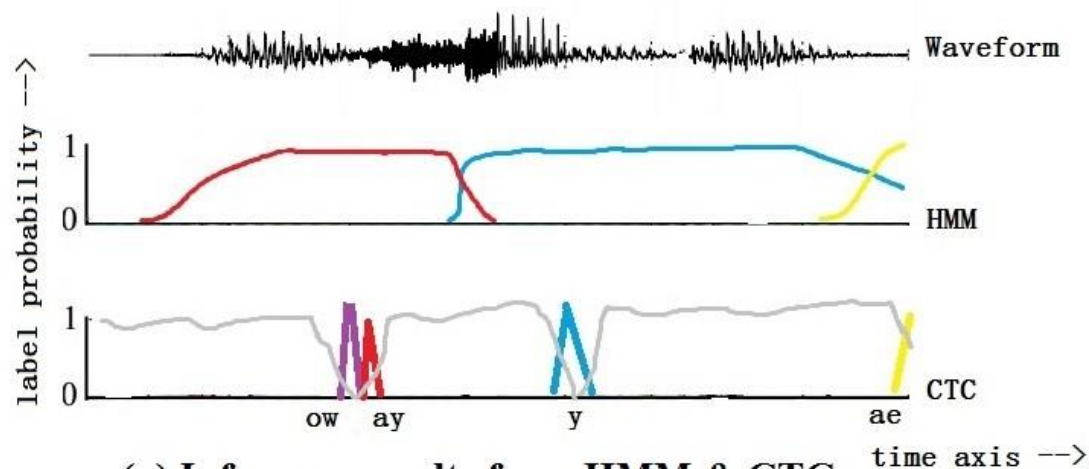
■ Procedure:

• Phone level CTC lattice

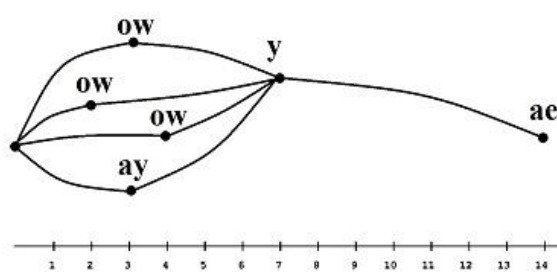
• Word Lattice

• Confusion Network

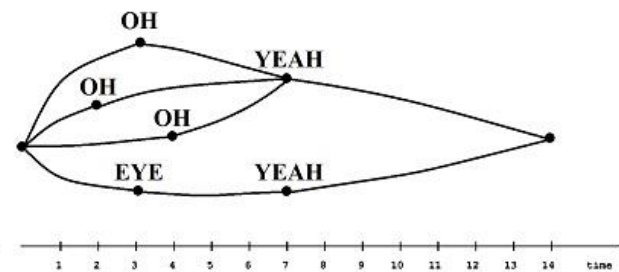
• Confidence Measure



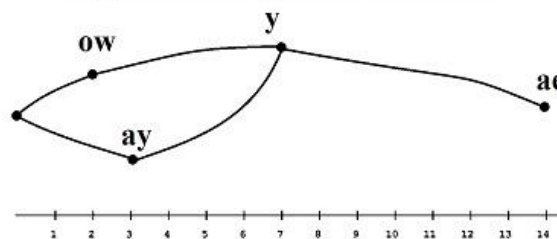
(a) Inference results from HMM & CTC



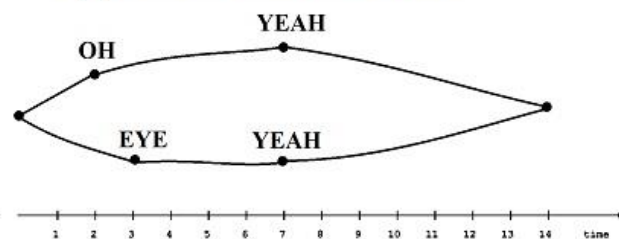
(b) HMM phone lattice



(c) HMM word lattice



(d) CTC phone lattice



(e) CTC word lattice

Experiment

- Setup
 - Swb 300h, 2-2.5M parameters, NIST hub5e-swb subset
 - details on our paper
- Baseline WER performance

Model Unit	AM	Decoding	WER
CD-state	DNN-HMM	FSD	16.7
CI-phone	LSTM-CTC	FSD	18.7
		PSD	18.8

- CM Evaluation: Normalised Cross Entropy (NCE)

$$NCE = \frac{H(\mathbf{C}) - H(\mathbf{C}|\mathbf{x})}{H(\mathbf{C})}$$

$H(\mathbf{C})$ corresponds to the entropy of the tag sequence,
 $H(\mathbf{C}|\mathbf{x})$ is the entropy of the confidence score sequence

- The higher the better

Experiment

- Hypothesis Posterior CM ¹

AM	Decoding	CM	NCE
DNN-HMM	FSD	CN	0.172
LSTM-CTC	FSD	CN	0.019
	PSD	CN	0.224
		AC+CN	0.230

- CN hypothesis posterior CM can't be directly applied to CI-phone-CTC model
 - Blank allocation problem:
 - e.g., ow <blk> ch <blk> <blk> <blk> ao <blk>

¹ We also derive a PSD version of predictor based CM, detail comparison can be referred to our paper.

Experiment

- Hypothesis Posterior CM ¹

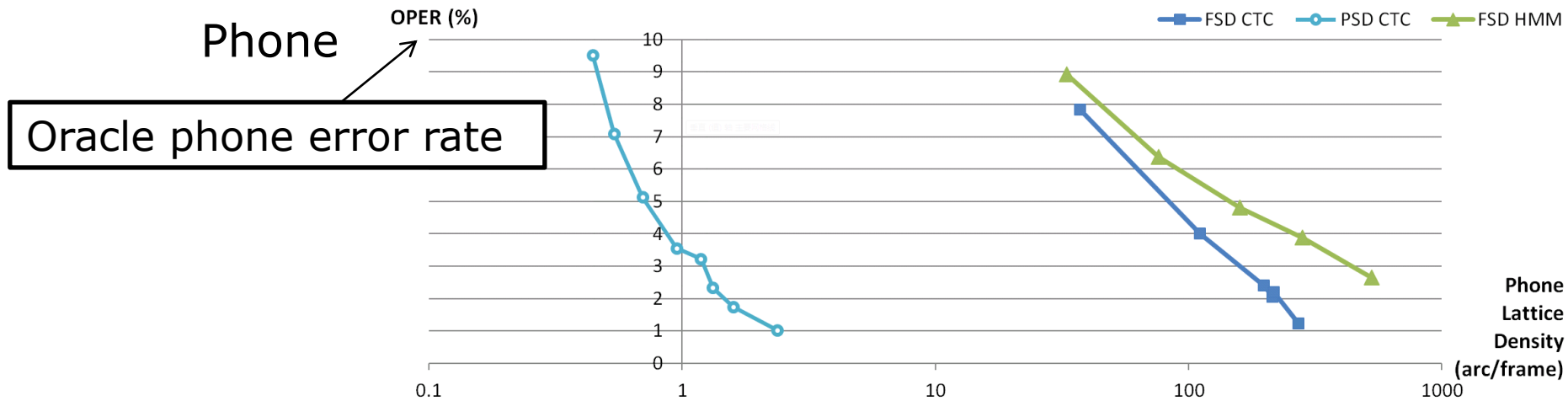
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- CN hypothesis posterior CM can't be directly applied to CI-phone-CTC model
 - Blank allocation problem:
 - e.g., ow <blk> ch <blk> <blk> <blk> ao <blk>
- In PSD, CN hypothesis posterior CM can be successfully applied
- Even with significantly better NCE: 0.224 → 0.172

¹ We also derive a PSD version of predictor based CM, detail comparison can be referred to our paper.

Experiment

- Reason of Better CM
 - Better lattice



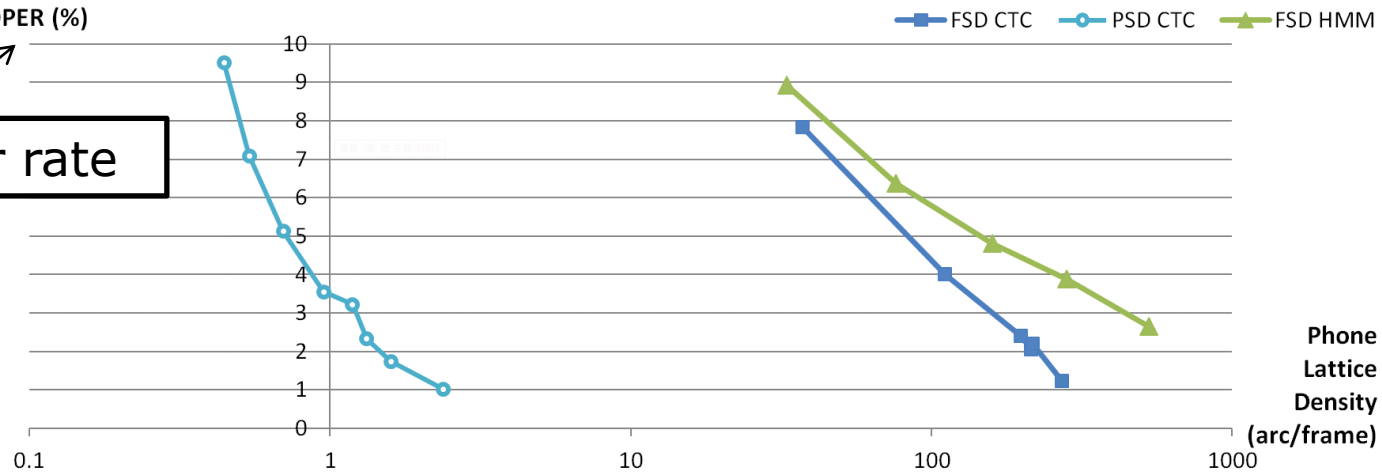
Experiment

- Reason of Better CM
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Phone OPER (%)

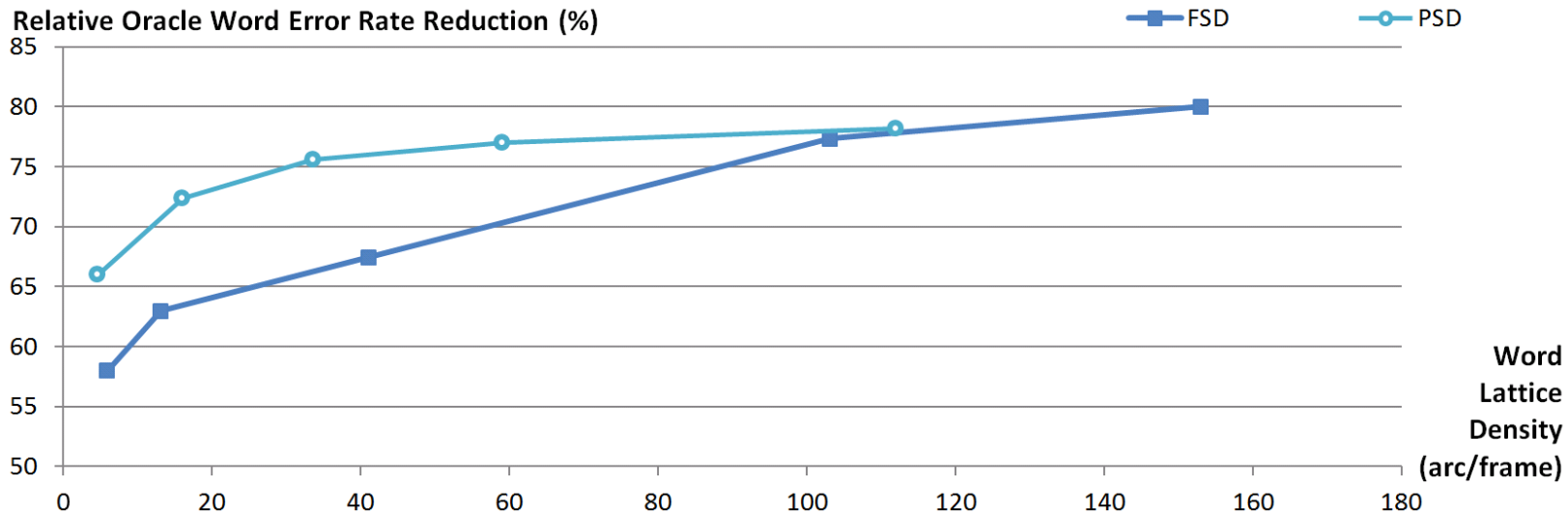
Oracle phone error rate

Word



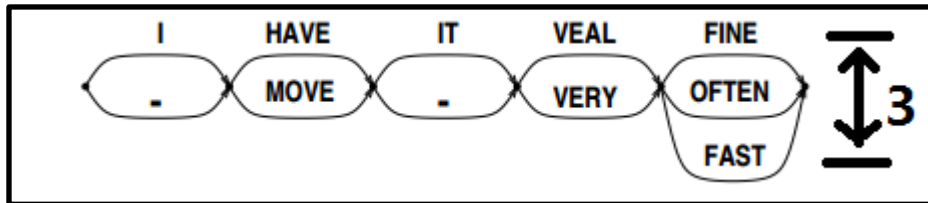
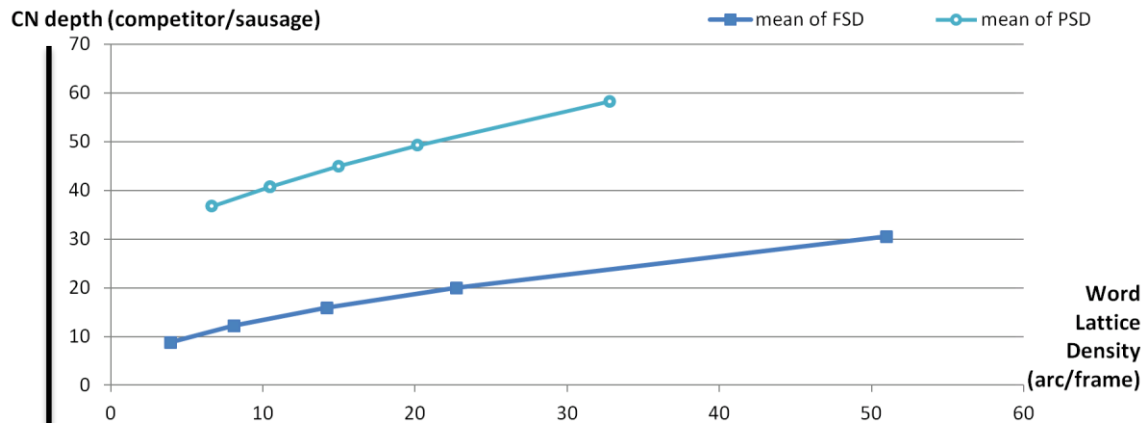
$$1 - \frac{OWER}{WER}$$

Relative Oracle Word Error Rate Reduction (%)



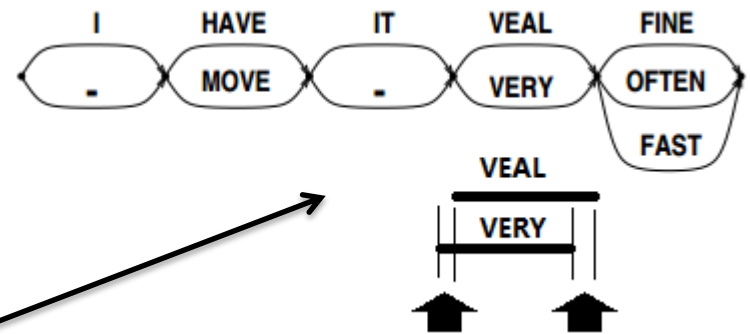
Experiment

- Reason of Better CM
 - Larger CN depth \rightarrow more competing information

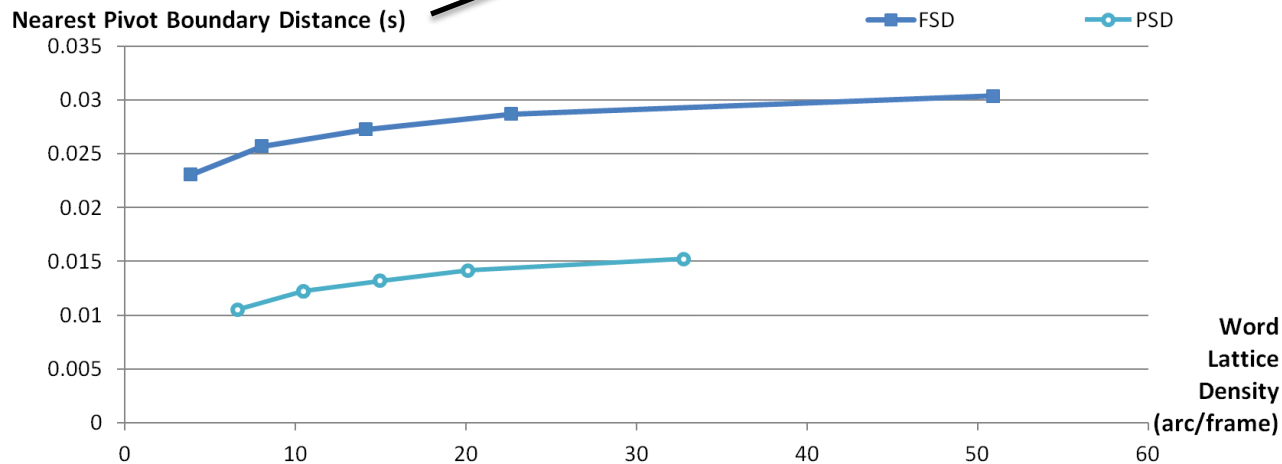


Experiment

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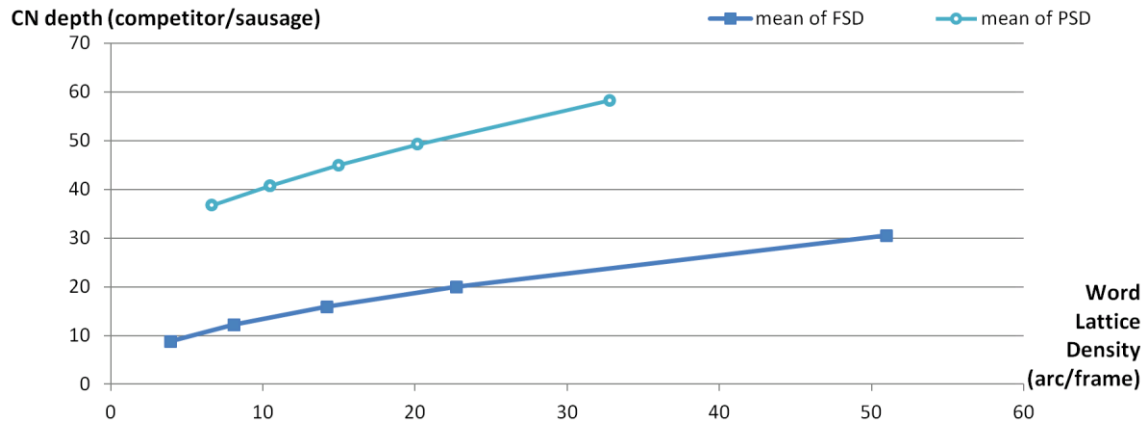


- Because of more stable boundary

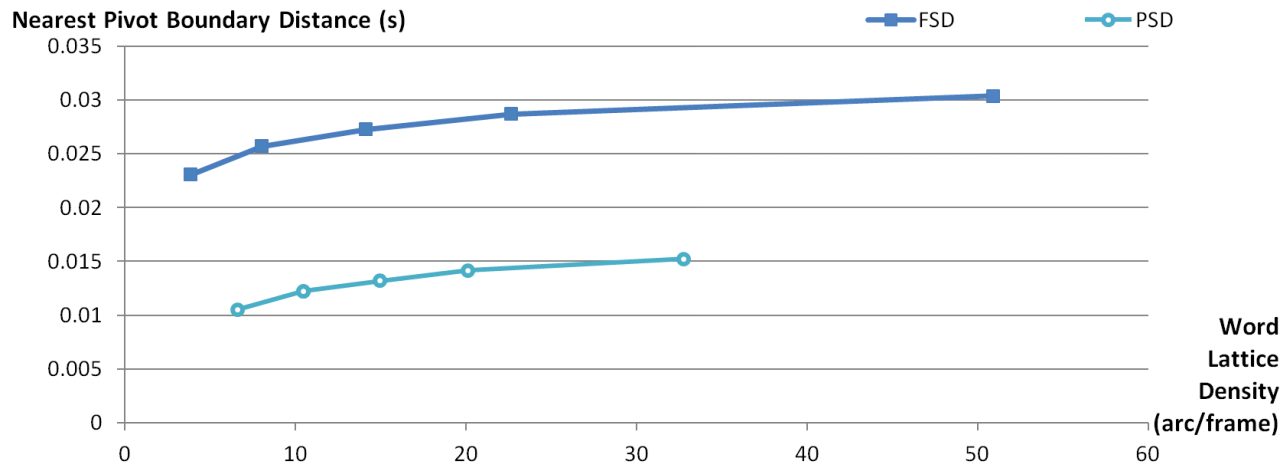


Experiment

- Reason of Better CM
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Summary

- The potential of **compact** and **precise** PSD CTC lattice in preserving acoustic information was utilized to form better CMs
- PSD version of predictor based CM was proposed with elaborate phonemic normalization and blank info (in paper)
- The characteristics of **lattice** and **confusion network** generated from **PSD** framework were carefully investigated, and CN hypothesis posterior CM was proposed
- The two types of CMs can be combined together as a pair of complements
- Future work: applying proposed CMs as predictors in model training framework