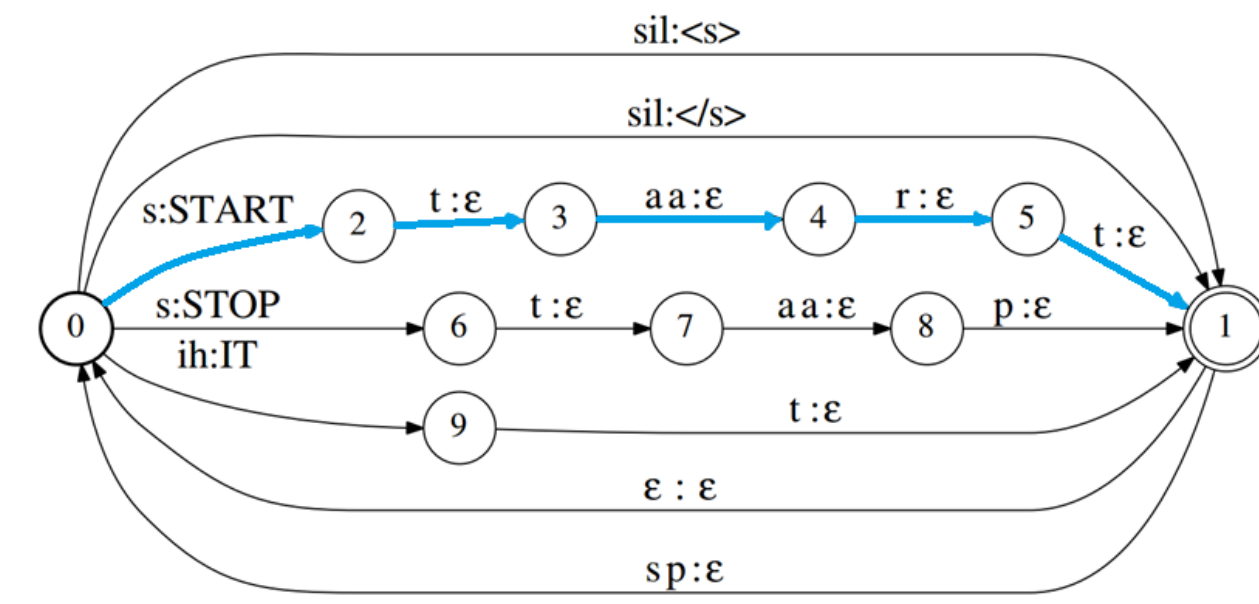


Linguistic Search Optimization for Deep Learning Based Speech Recognition

Zhehuai Chen

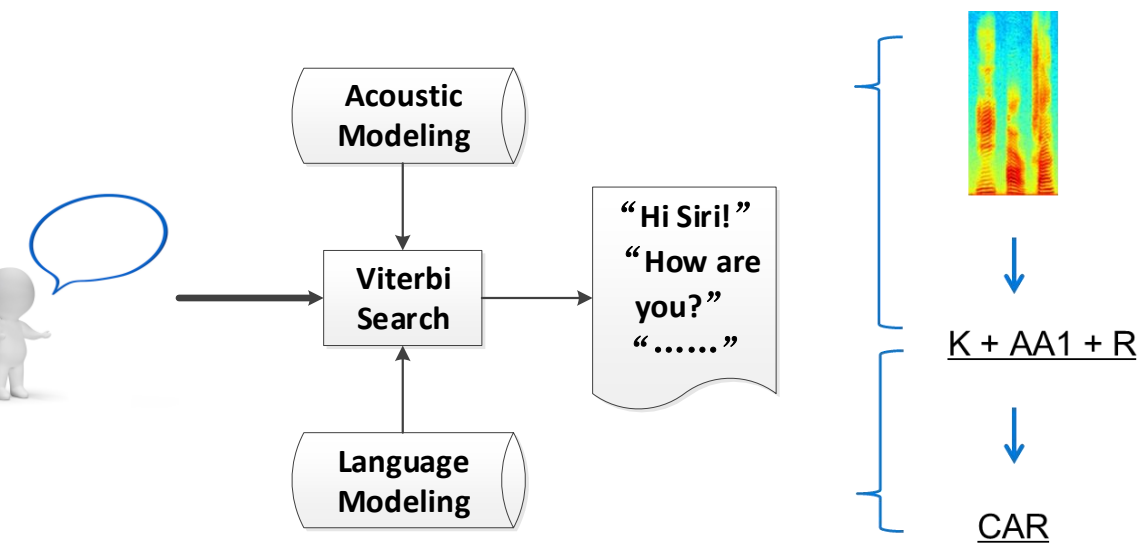
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Overview

- Problem:** Linguistic search takes over 50% computation in Automatic Speech Recognition (ASR).
- Approach:**
 - Reduce the **Search Complexity** by **End-to-end Modeling**
 - Accelerate the **Search Speed** using **Parallel Computing**
- Experiments & Discussion:** 5 times and 50 times speedup respectively; able to combine



Frame Sync. To Phone Sync.

- Frame synchronous Viterbi beam search in CTC**

$$w^* = \underset{w}{\operatorname{argmax}} \{P(w)p(x|w)\} = \underset{w}{\operatorname{argmax}} \{P(w)p(x|l_w)\}$$

$$= \underset{w}{\operatorname{argmax}} \left\{ P(w) \max_{l_w} \frac{P(l_w|x)}{P(l_w)} \right\}$$

$$\cong \underset{w}{\operatorname{argmax}} \left\{ P(w) \max_{\pi: \pi \in L', B(\pi_{1:T})=l_w} \frac{1}{P(l_w)} \prod_{t=1}^T y_{\pi_t}^t \right\}$$

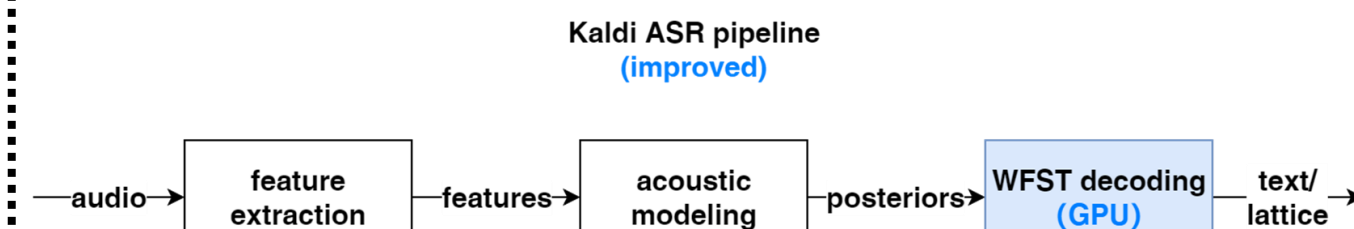
$\pi_{1:T} = (\pi_1, \dots, \pi_T)$ is the frame-wise decoding path
 l_w is phone sequence corresponding to w in dictionary
 $l \in L$ and L is the phone set
 $l \in L'$ and $L' = L \cup \{\text{blank}\}$
- Frame synchronous to phone synchronous decoding**

$$w^* \cong \underset{w}{\operatorname{argmax}} \left\{ P(w) \max_{\pi: \pi \in L', B(\pi_{1:T})=l_w} \frac{1}{P(l_w)} \left\{ \prod_{t \notin U} y_{\pi_t}^t \cdot \prod_{t \in U} y_{\text{blank}}^t \right\} \right\}$$

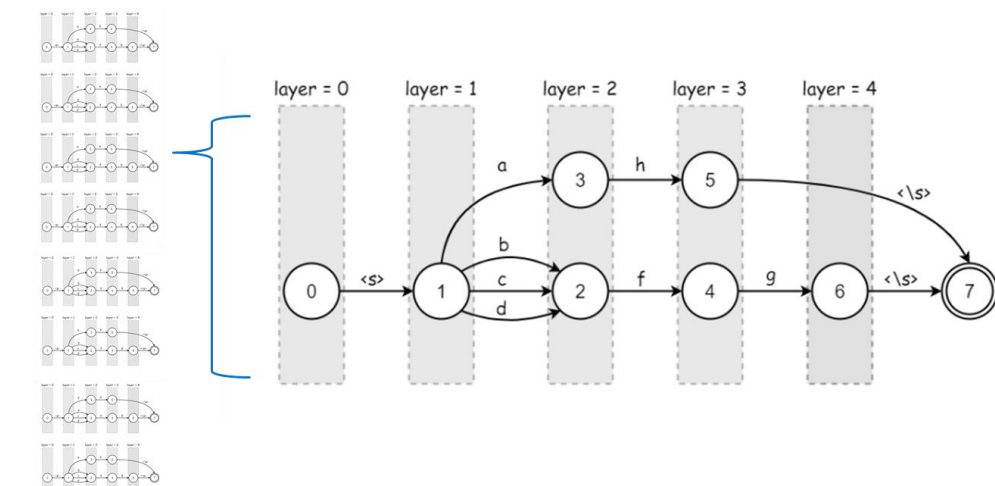
$$= \underset{w}{\operatorname{argmax}} \left\{ P(w) \max_{\pi': \pi' \in L, B(\pi'_{1:J})=l_w} \frac{1}{P(l_w)} \prod_{j=1}^J y_{\pi'_j}^{t_j} \right\}$$

$U = \{u : y_{\text{blank}}^u \approx 1\}$ is the set of common blank time indexes
 $J = T - |U|$ is the number of output phone labels

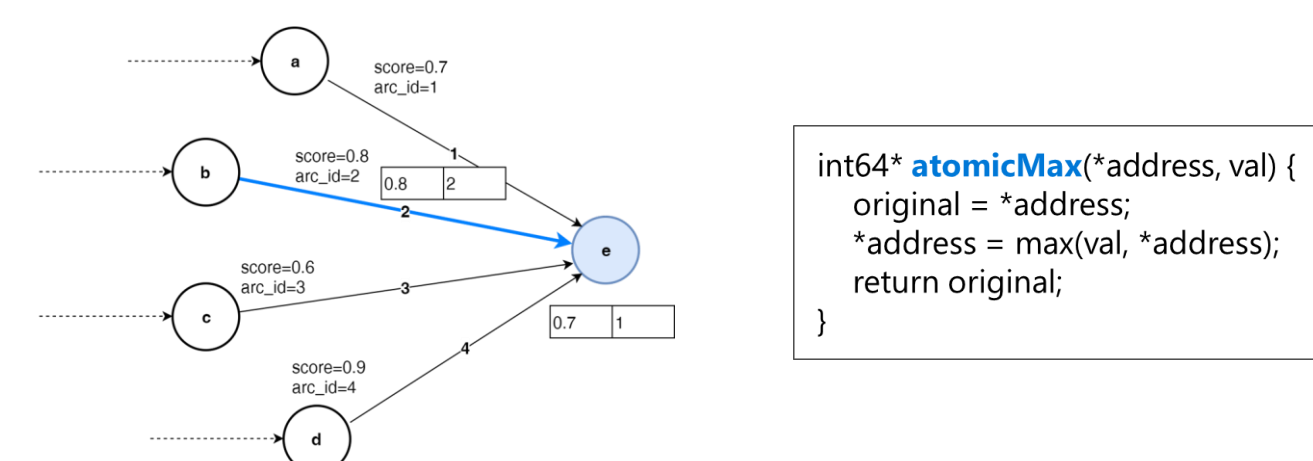
Parallel Viterbi Decoding



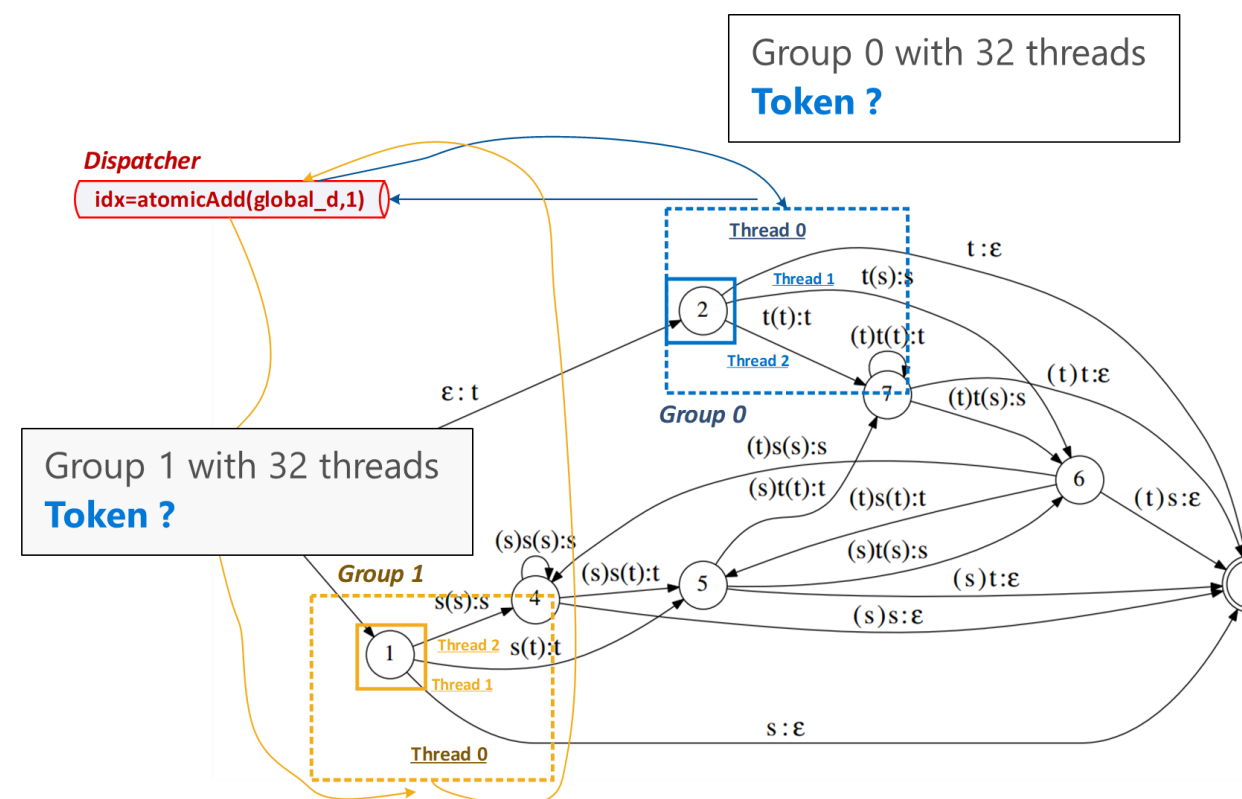
- Three levels of parallelism: future, history, utterance**



- Atomic Token Recombination**



- Dynamic Load Balancing**



- Lattice Processing**

- Linkedlist \rightarrow vector
- Atomic operations e.g. memory allocation
- Parallel lattice pruning

Experiments

- Experimental Setup**

- Switchboard 300 hours corpus, Cross Entropy & LF-MMI acoustic models (AM)
- 30k-vocabulary, several tri-gram language models (LM)
- Baseline: Kaldi 1-best decoder, Kaldi lattice decoder
- GPU Optimization: Fast memcpy; merge GPU kernels by adding grid sync.; etc. (rel. 20% speedup)
- <https://github.com/chenzhehuai/kaldi/tree/gpu-decoder>

subset	performance		search speed-up			
	FSD \rightarrow PSD	WER Δ (%)	FSD \rightarrow PSD	SRTF Δ (%)	FSD \rightarrow PSD	#AT Δ (%)
swb	18.7	+0.5	0.075	-71	2221	-77
callhm	33.3	+0.0	0.073	-70	2211	-77

- 3 times speedup from end-to-end modeling**

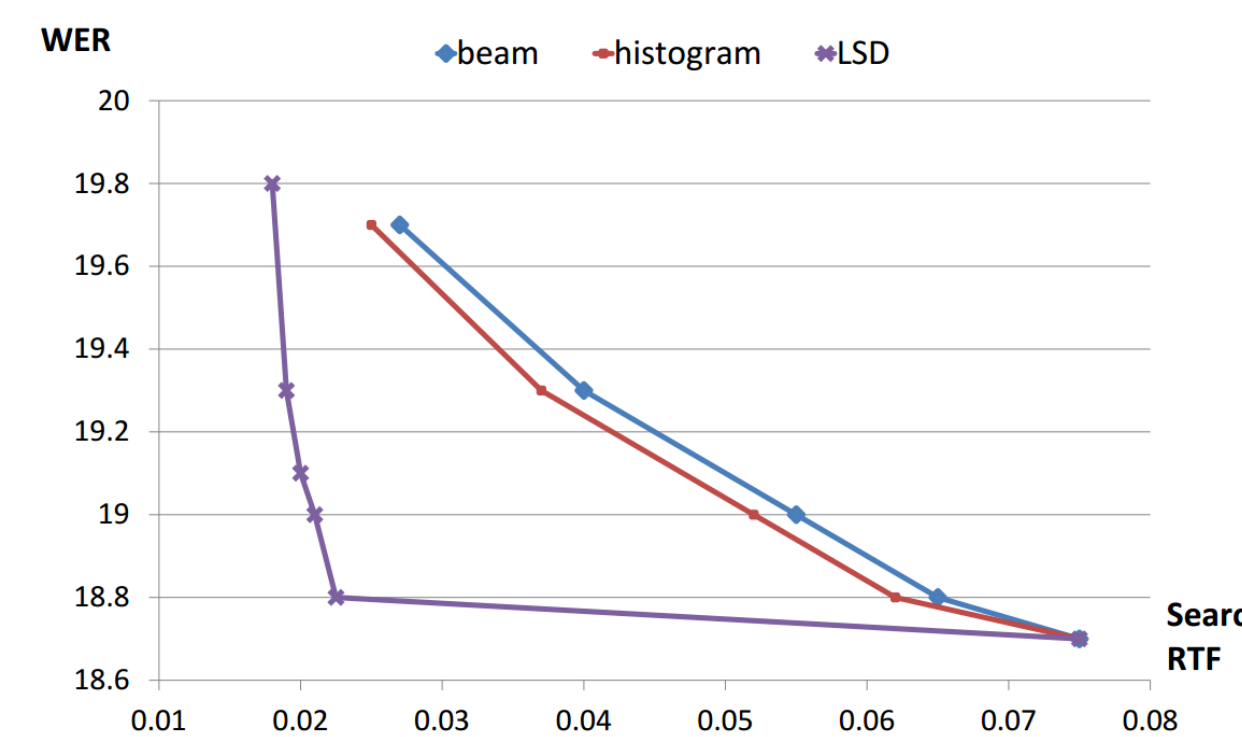
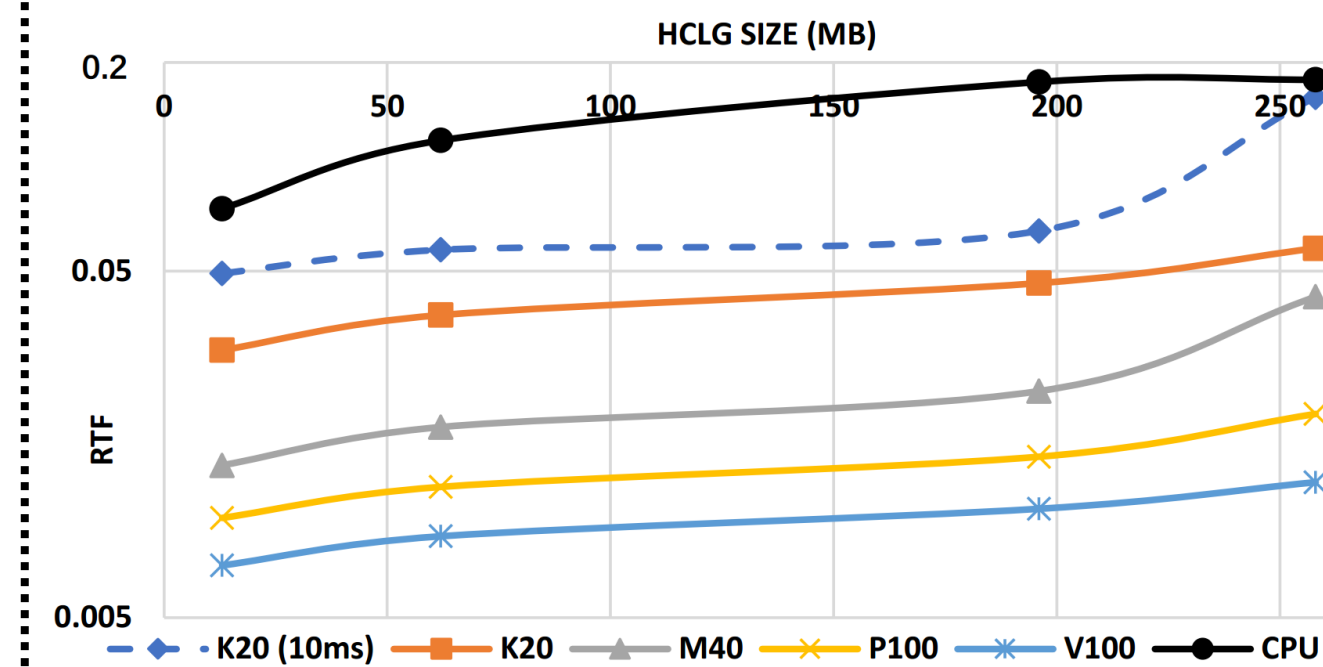


Table 2: Speedup of the Proposed Method (beam=14).

system	1-best		+ lattice	
	RTF	Δ	RTF	Δ
CPU	0.16	1.0X	0.27	1.0X
+ 8-sequence (1 socket)	-	-	0.15	1.8X
GPU	0.016	10X	0.080	3.3X
+ atomic operation	0.015	11X	0.077	3.5X
+ dyn. load balancing	0.011	15X	0.075	3.6X
+ lattice prune	-	-	0.028	9.7X
+ 8-sequence (MPS)	0.0035	46X	0.0080	34X

- 34 times speedup from parallel computing**

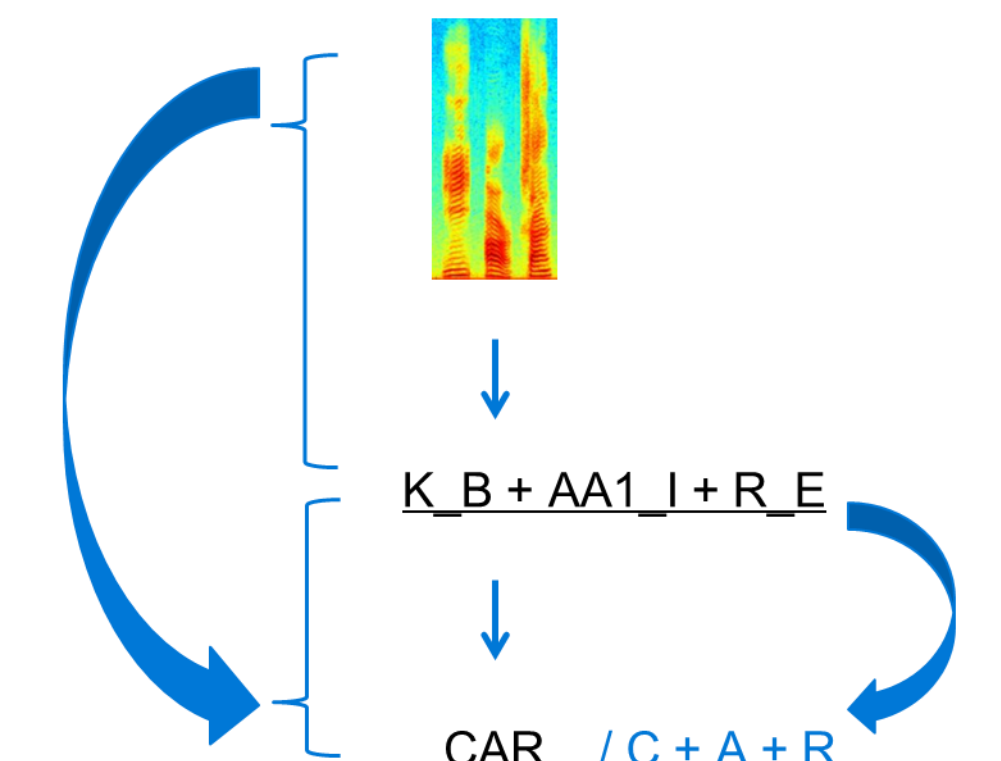


- Varieties of GPU arch., WFST sizes and acoustic models.**

Conclusions

- General speedup of linguistic search in speech recognition**

End-to-end Modeling



Parallel Computing

- Future works:**
 - Inspire more researches in GPU decoding
 - Combination of Both Techniques