GPU-Accelerated Large Vocabulary Continuous Speech Recognition for Scalable Distributed Speech Recognition

Jungsuk Kim lan Lane

Electrical and Computer Engineering
Carnegie Mellon University

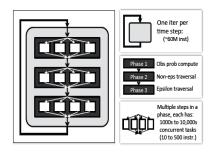
Overview

- Introduction
- Background
 - Weighted Finite State Transducers in Speech Recognition
- Proposed Approach
 - GPU-Accelerated scalable DSR
- Evaluation
- Conclusion

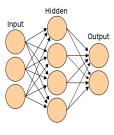
- Voice interfaces a core technology for User Interaction
 - Mobile devices, Smart TVs, In-Vehicle Systems, ...
- For a captivating User Experience, Voice UI must be:
 - Robust
 - Acoustic robustness
 - Linguistics robustness
 - Responsive
 - Low latency
 - Adaptive
 - User and Task adaptation

- → Large Acoustic Models
- → Large Vocabulary Recognition
- → Faster than real-time search

- Large models critical for accurate speech recognition:
 - Large acoustic models Tens of Millions of parameters
 - Large vocabulary → Millions of words
 - Large language model → Billions of n-gram entries (>= 20GB)
 - Examples include:
 - Acoustic modeling for telephony [Mass 2014] or Youtube [Bacchiani 2014]
 - ~200M parameter Deep Neural Networks
 - Language model rescoring for Voice Search [Schalkwyk 2010]
 - 1.2M vocabulary, 5-gram LM, <u>12.7B</u> n-gram entries



Speech recognition contains many highly parallel tasks

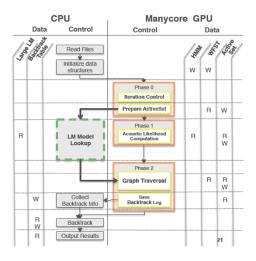


Large Models
More Accurate



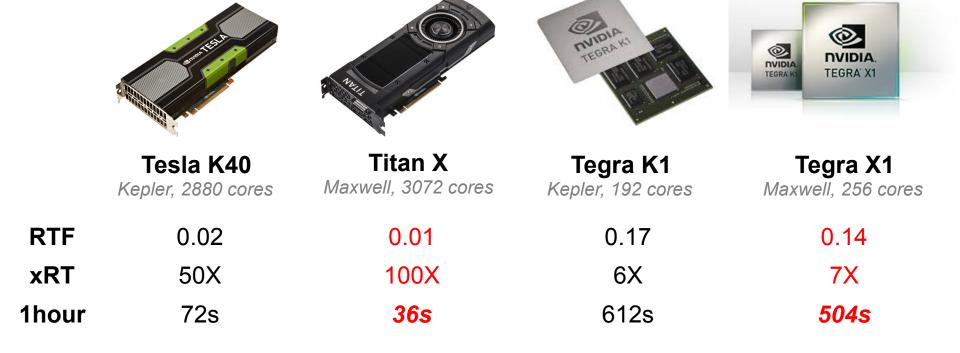
Graphic Processing Units
(SIMT, ~3000 cores, <24GB)
optimized for parallel

computing



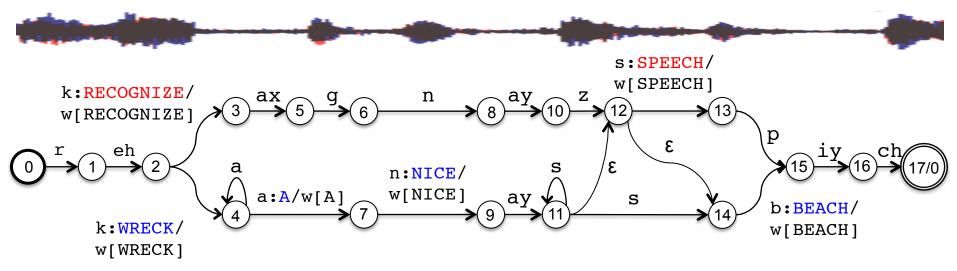
ASR engine designed specifically for GPUs

- 1 Million Vocabulary (3-gram)
- **30 Million** parameter Deep Neural Network

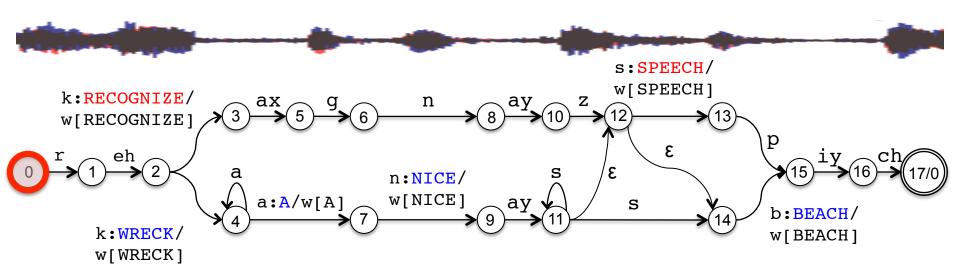


Background

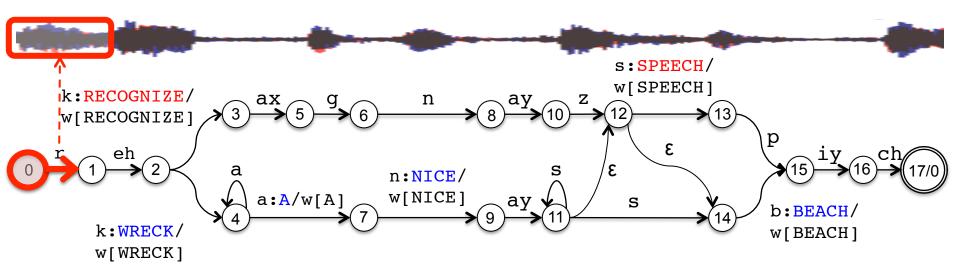
Weighted Finite State Transducers (WFSTs) in Speech Recognition



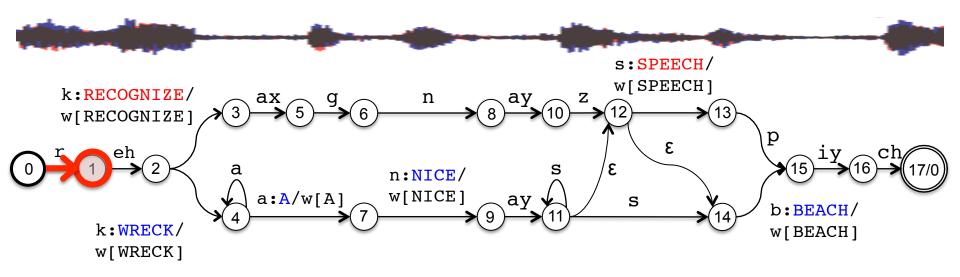
- "Recognize speech" v.s. "Wreck a nice beach"...
- Search is performed in 3 phases.
 - Phase 0: Active Set Preparation.
 - Phase 1: Acoustic Score Computation.
 - Phase 2: WFST Search.



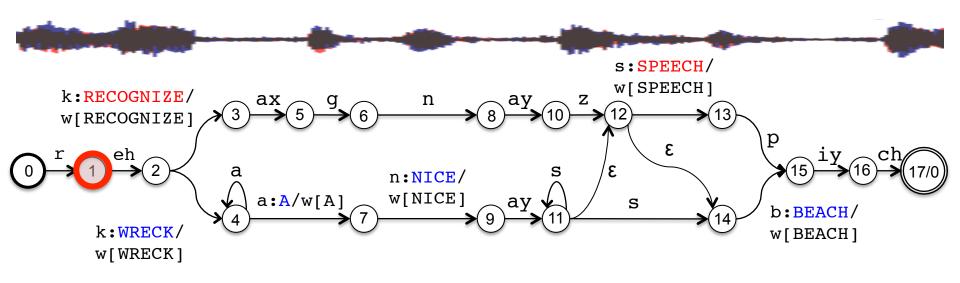
- Phase 0: Active Set Preparation
 - Collect active hypotheses from previous frame.



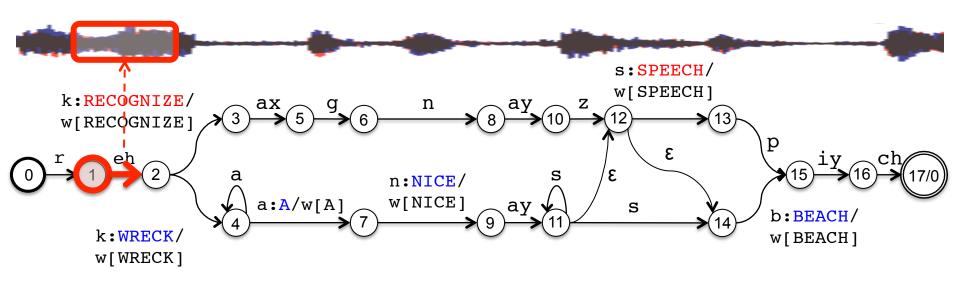
- Phase 1: Acoustic Score Computation
 - Compute acoustic similarity between given speech and phonetic models using Deep Neural Network



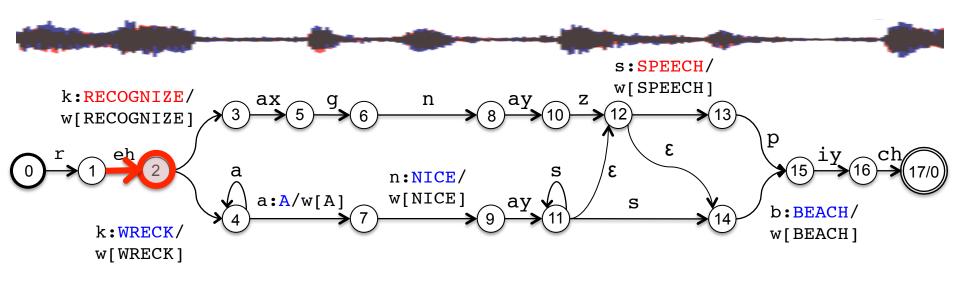
- Phase 2: WFST Search
 - Perform frame synchronous Viterbi beam search on WFST network.
 - If multiple transitions have same next state s, then the most likely (minimum score) hypothesis is retained (i.e. state 12, 14, 15...)



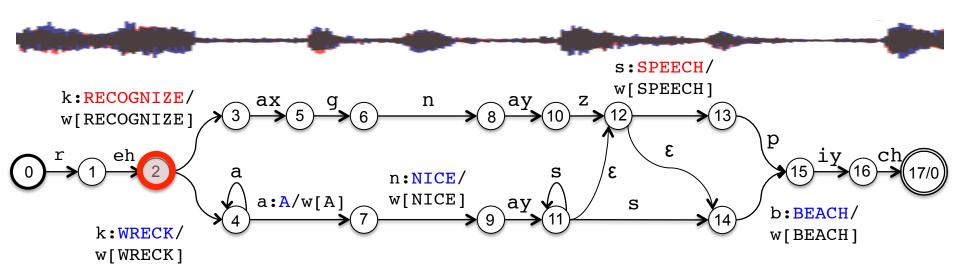
- Iterate these 3 phases until input audio ends.
- Phase 0: Active Set Preparation



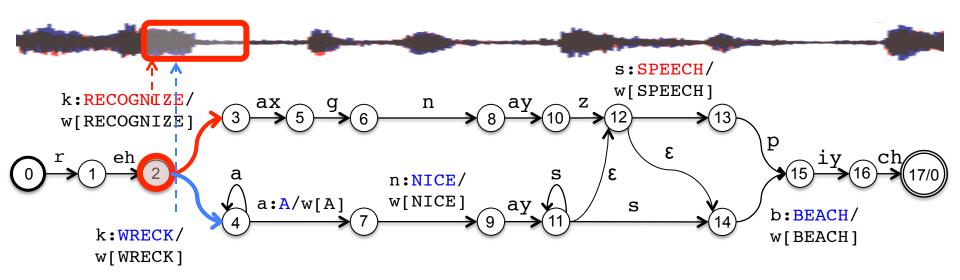
Phase 1: Acoustic Score Computation



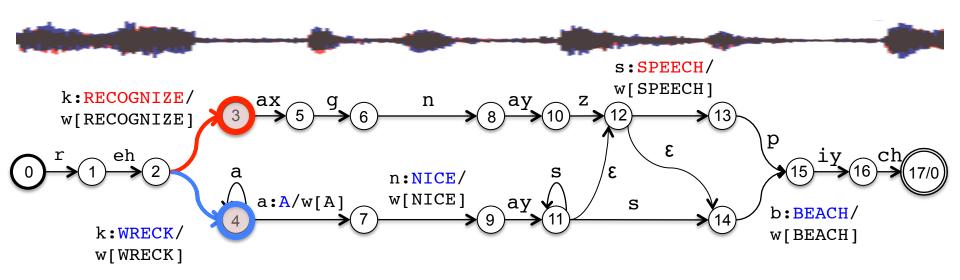
Phase 2: WFST Search



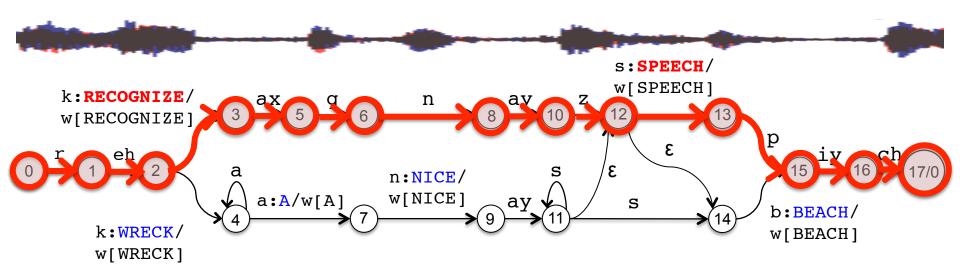
Phase 0: Active Set Preparation



Phase 1: Acoustic Score Computation



Phase 2: WFST Search

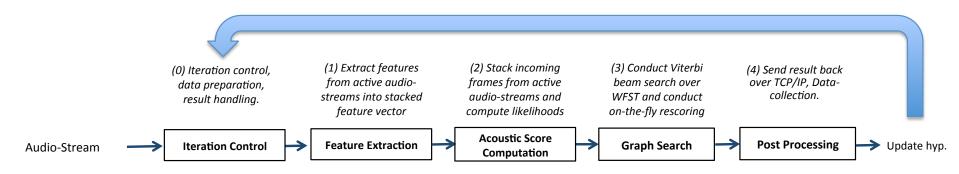


- Recognized result is an output symbol sequence over the best path.
 - Result: "RECOGNIZE SPEECH"

Proposed Approach

GPU-Accelerated Scalable DSR

Distributed Speech Recognition (DSR)



Iteration control

- Allocate or deallocate data structures.
- Terminate decoding task.

Feature extraction

- Receive audio and extract feature for current iteration (batch).
- Speaker dependent adaptation.

Acoustic score computation

Deep Neural Network (Forward Propagation).

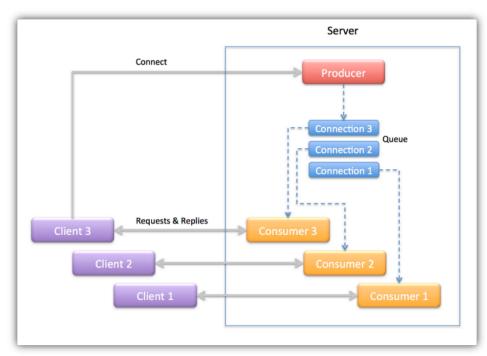
Graph search

- Conduct frame synchronous WFST search.
- End-of-utterance detection.

Post processing

- Output (Lattice) processing.
- Sending result back to client.

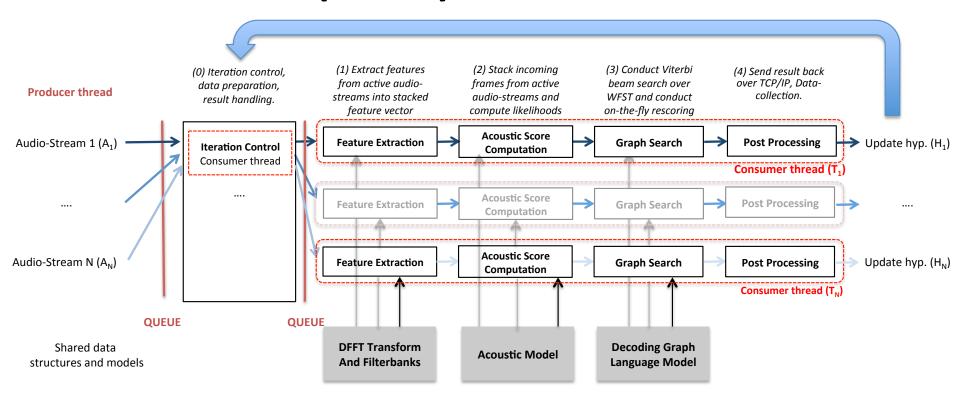
Producer/Consumer design pattern



Producer-Consumer multi-threaded model

- Master/Slave pattern.
- Decuple processes that produce and consume data at different rates.
- Advantages:
 - Enhanced data sharing
 - Processes can run in different speeds.
 - Buffered communication between processes.

Architecture 1 (Naïve)



Architecture 1 (Naïve)

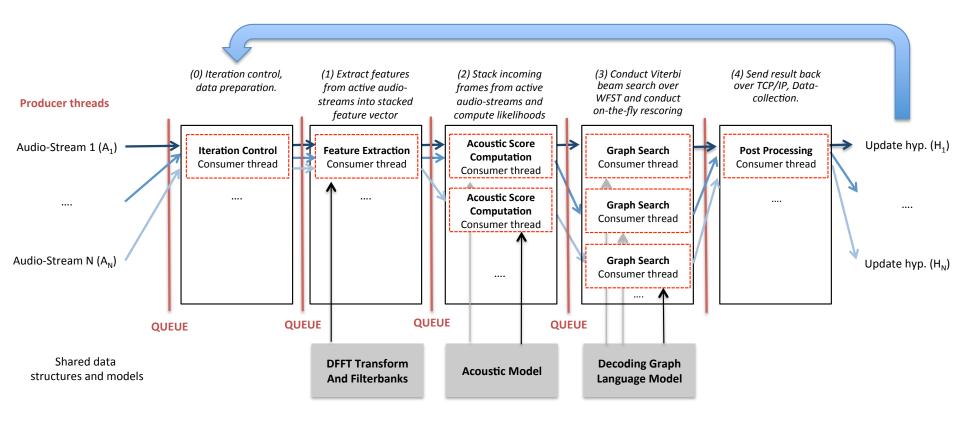
Pros.

- Maximum decoding performance.
- Simple thread management.

Cons.

- Low throughput and GPU utilization if batch size is small.
- Number of consumer threads can be limited by GPU (by maximum inflight kernels)
- Not suitable for many CPU + single GPU configuration.

Architecture 2



Architecture 2

Pros.

- More scalable and configurable structure.
- Can assign more threads to bottleneck phase.
- interleaving frames from multiple tasks.
- Can achieve maximum utilization of GPU.

Cons.

- Complex threads configuration.
- More queuing overheads
- Expected relatively <u>higher latency</u> compared to "structure 1"

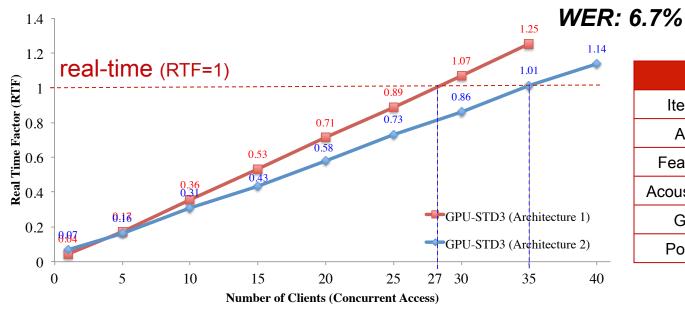
Evaluation Results

GPU-Accelerated Scalable DSR

Evaluation Setup

- Language Model:
 - 1 Million Vocab. 3-gram (10.1M n-gram)
- Acoustic Model:
 - DNN: (in) 253 X 2048 X 2048 X 2048 X 2048 X 2048 X 3432 (out)
- Feature type:
 - 23th Filterbank coefficient with CMVN
- <u>Evaluation Set:</u>
 - WSJ eval92 (20K, 333 utts.)
- Platform:
 - Core i7-2600K + NVIDIA Tesla K40

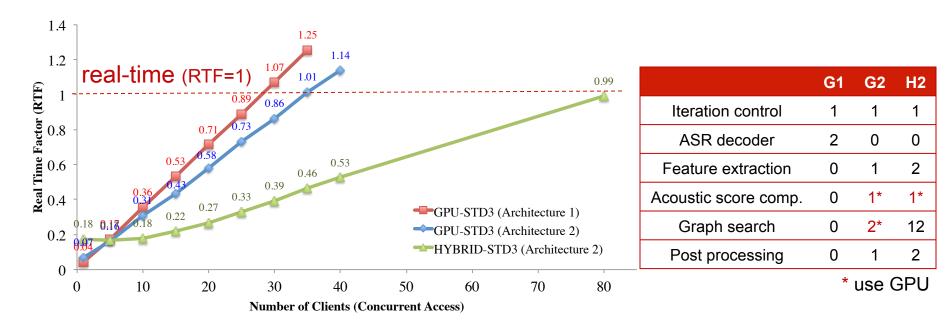
Evaluation Results



	G1	G2
Iteration control	1	1
ASR decoder	2*	0
Feature extraction	0	1
Acoustic score comp.	0	1*
Graph search	0	2*
Post processing	0	2
	* use	GPU

- GPU only configuration (G1, G2): 1 Tesla K40.
- Architecture 2 improves speed by 0.24 RTF (N=35)
- "Architecture 2" processes 35 concurrent audio streams in real-time.

Evaluation Results



- *Hybrid configuration* (H2): 1 GPU + 2 CPU (16 cores).
- "Architecture 2" processes 80 concurrent audio streams in real-time.

Conclusion

GPU-Accelerated Scalable DSR

Conclusions

- Proposed scalable and configurable DSR server architecture.
- "Architecture 2" was able to process ...
 - 40 concurrent audio streams in real-time with 1 GPU (K40c)
 - 80 concurrent audio streams in real-time with 1 GPU + 16 CPU cores.
- Performance can be improved further
 - Lock-free task queue.
 - Optimal / Adaptive Thread configuration.
 - Smart task scheduling.

References

References

1999

[Mass, 2010] Andrew L. Maas, Awni Y. Hannun, Christopher T. Lengerich, Peng Qi, Daniel Jurafsky, and Andrew Y. Ng. "Increasing Deep Neural Network Acoustic Model Size for Large Vocabulary Continuous Speech Recognition", ArXiv: 1406.7806 [cs.CL], 2010

[Schalkwyk, 2010] J. Schalkwyk, D. Beeferman, F.Beaufays, B. Byrne, C.chelba, M. Cohen, M. Kamvar, and B. Stropek, Google Search by Voice: A case study, Springer, 2010

[Bacchiani, 2014] M. Bacchiani, David Rybach, "Context Dependent State Tying For Speech Recognition Using Deep Neural Network Acoustic Models," in Proc. ICASSP, 2014, pp.230-234.

[Mohri, 2002] M. Mohri, F. Pereira, and M. Riley, "Weighted Finite-State Transducers in Speech Recognition," *Computer Speech and Language*, vol. 16, no. 1, pp. 69-88, 2002

[Kanthak, 2002] S. Kanthak, H. Ney, M. Riley, and M. Mohri. A comparison of two LVR search optimization techniques. In Proc. ICSLP, pp. 1309-1312, 2002.

[Chong, 2009] J. Chong, E. Gonina, Y. Yi, and K. Keutzer, "A Fully Data Parallel WFST-based Large Vocabulary Continuous Speech Recognition on a Graphix Processing Unit," in *Proc. Interspeech*, Sep. 2009, pp. 1183-1186. [Ljolje, 1999] A. Ljolje, F. Pereira, and M. Riley, "Efficient general lattice generation and rescoring," in *Proc. Eurospeech*,

[Hori, 2007] T.Hori, C.Hori, Y.Minami, and A.Nakamura, "EfficientWFST-BasedOne-Pass Decoding With On-The-Fly Hypothesis Rescoring in Extremely Large Vocabulary Continuous Speech Recognition," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 15, no. 4, pp. 1352 –1365, may 2007.

Q&A

Thank you for your attention.