KALDI GPU ACCELERATION

GTC - March 2019

AGENDA

1) Brief introduction to speech processing
2) What we have done?
3) How can I use it?

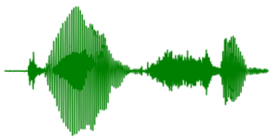
INTRODUCTION TO ASR

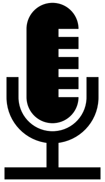
Translating Speech into Text

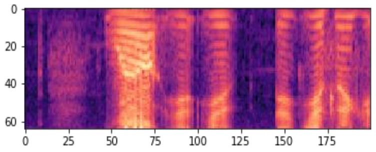
Speech Recognition: the process of taking a raw audio signal and transcribing to text

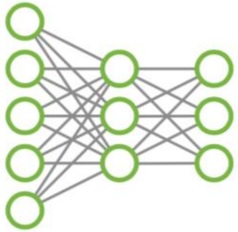
Use of Automatic Speech Recognition has exploded in the last ten years:

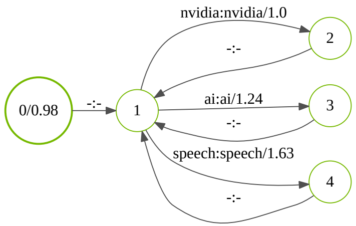
Personal assistants, Medical transcription, Call center analytics, Video search, etc











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SPEECH RECOGNITION

State of the Art

- Kaldi fuses known state-of-the-art techniques from speech recognition with deep learning
- Hybrid DL/ML approach continues to perform better than deep learning alone
- "Classical" ML Components:
    - Mel-Frequency Cepstral Coefficients (MFCC) features – represent audio as spectrum of spectrum
    - I-vectors – Uses factor analysis, Gaussian Mixture Models to learn speaker embedding – helps acoustic model adapt to variability in speakers
    - Predict phone states – HMM - Unlike "end-to-end" DL models, Kaldi Acoustic Models predict context-dependent phone substates as Hidden Markov Model (HMM) states
- Result is system that, to date, is more robust than DL-only approaches and typically requires less data to train

KALDI

Speech Processing Framework

Kaldi is a speech processing framework out of Johns Hopkins University

Uses a combination of DL and ML algorithms for speech processing

Started in 2009 with the intent to reduce the time and cost needed to build ASR systems

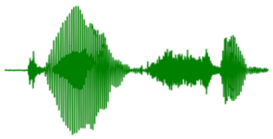
http://kaldi-asr.org/

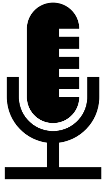
Maintained by Dan Povey

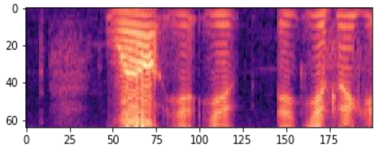
Considered state-of-the-art

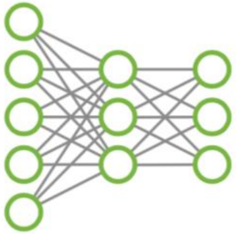
KALDI SPEECH PROCESSING PIPELINE

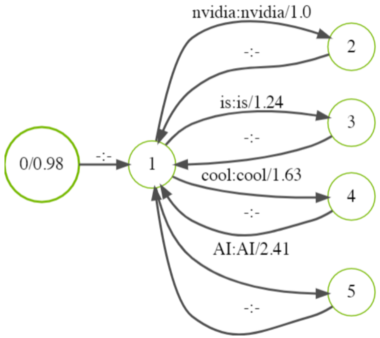
Raw Audio → Feature Extraction → Acoustic Model → Language Model → Output











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Kaldi Components:

MFCC & Ivectors

NNET3

Decoder

Lattice

FURTHER READING

“Speech Recognition with Kaldi Lectures.” *Dan Povey*, www.danielpovey.com/kaldi-lectures.html

Deller, John R., et al. *Discrete-Time Processing of Speech Signals*. Wiley IEEE Press Imprint, 1999.

WHAT HAVE WE DONE?

PREVIOUS WORK

Partnership between Johns Hopkins University and NVIDIA in October 2017

Goal: Accelerate Inference processing using GPUs

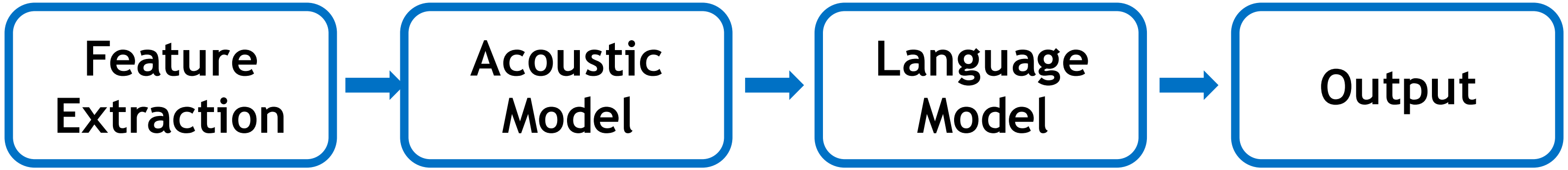
Used CPU for entire pipeline

NVIDIA Progress reports:

GTC On Demand: DC8189, S81034

https://on-demand-gtc.gputechconf.com/gtcnew/on-demand-gtc.php

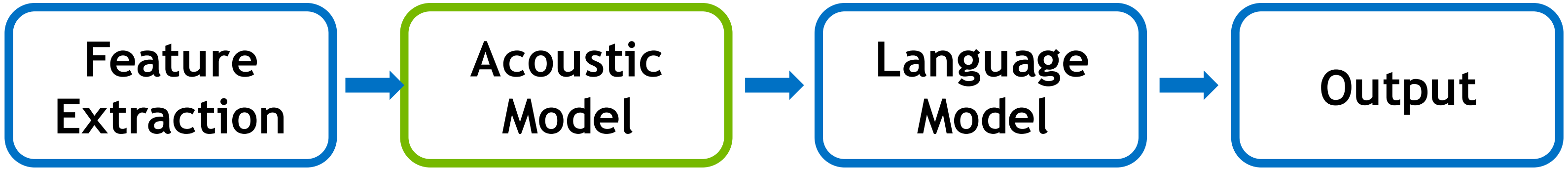
INITIAL WORK



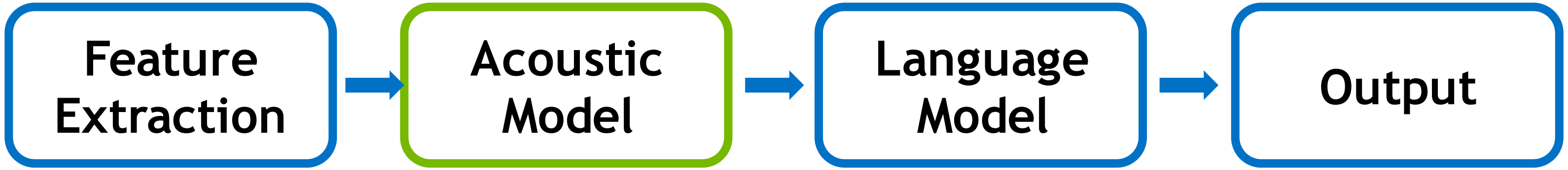
First Step: Move Acoustic Model to GPU

Was already implemented but not enabled, batch NNET3 added by Dan Povey

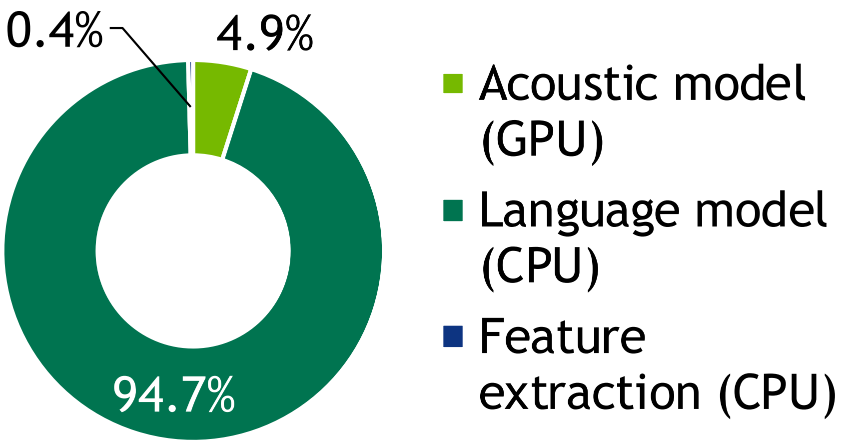
Enabled Tensor-Cores for NNET3 processing



INITIAL WORK



Early on it was clear that we needed to target language model decoding



LANGUAGE MODEL CHALLENGES

Dynamic Problem:

Amount of parallelism changes significantly throughout decode

Can have few or many candidates moving from frame to frame

Limited Parallelism:

Even when there are lots of candidates the amount of parallelism is orders of magnitude smaller than required to saturate a large GPU

Solution:

1) Use graph processing techniques and a GPU-friendly data layout to maximize parallelism while load balancing across threads (See previous talks)

2) Process batches of decodes at a time in a single pipeline

3) Use multiple threads for multiple batched-pipelines

CHALLENGES

Kaldi APIs are single threaded, single instance, and synchronous

Makes batching and multi-threading challenging

Solution:

Create a CUDA-enabled Decoder with asynchronous APIs

Master threads submit work and later wait for that work

Batching/Multi-threading occur transparently to the user

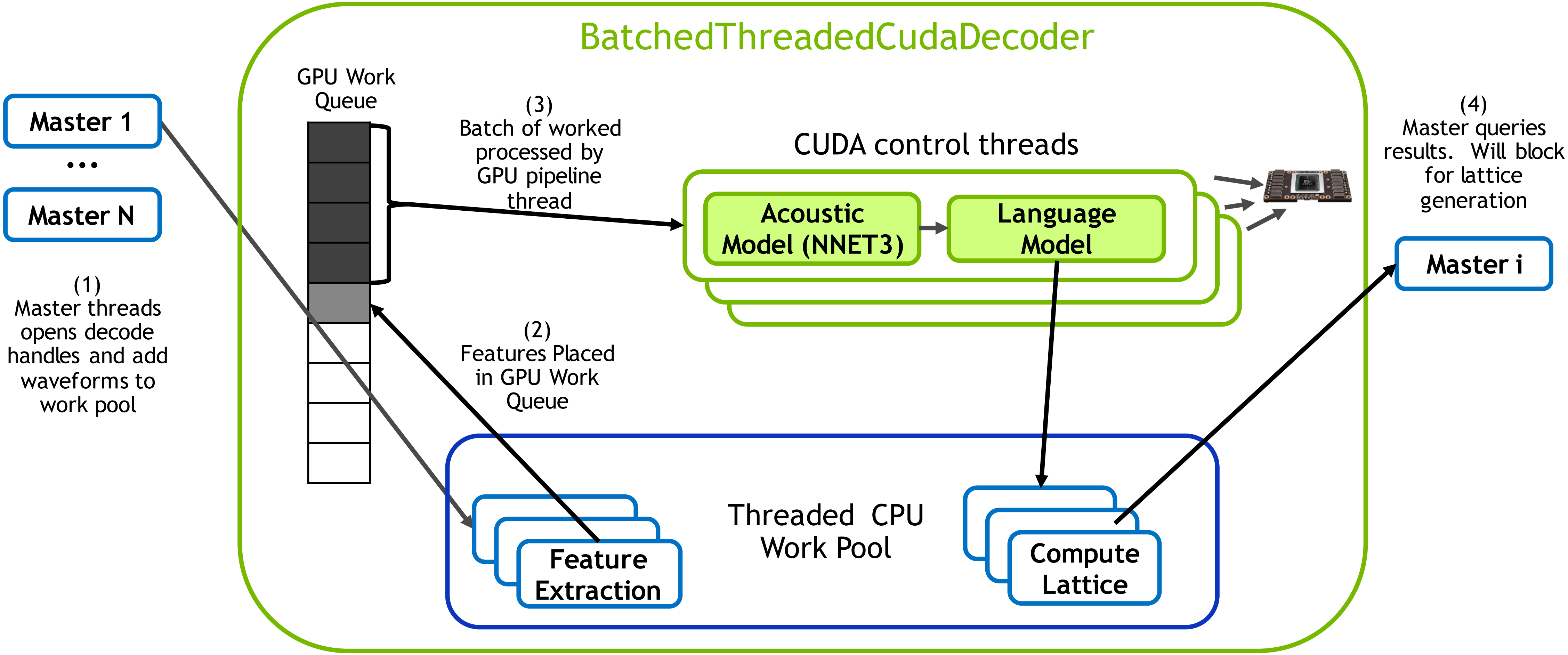
EXAMPLE DECODER USAGE

More Details: kaldi-src/cudadecoder/README

```
for ( … ) {
    …
    //Enqueue decode for unique "key"
    CudaDecoder.OpenDecodeHandle(key, wave_data);
    …
}

for ( … ) {
    …
    //Query results for "key"
    CudaDecoder.GetLattice(key, &lattice);
    …
}
```

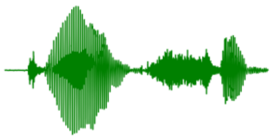
GPU ACCELERATED WORKFLOW

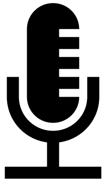


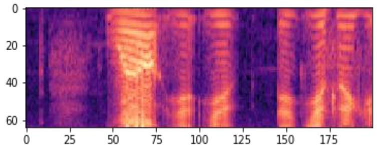
KALDI SPEECH PROCESSING PIPELINE

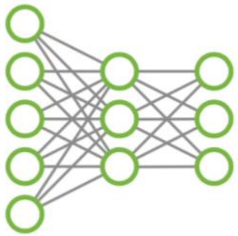
GPU Accelerated

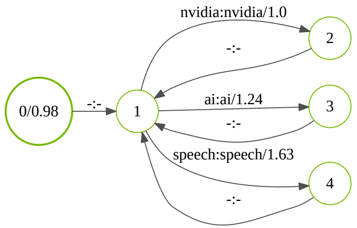
Raw Audio → Feature Extraction → Acoustic Model → Language Model → Output











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BENCHMARK DETAILS

LibriSpeech

Model:

LibriSpeech - TDNN: https://github.com/kaldi-asr/kaldi/tree/master/egs/librispeech

Data: LibriSpeech - Clean/Other: http://www.openslr.org/12/

Hardware:

CPU: 2x Intel Xeon Platinum 8168

NVIDIA GPUs: V100, T4, or Xavier AGX

Benchmarks:

CPU: online2-wav-nnet3-latgen-faster.cc (modified for multi-threading)

Online decoding disabled

GPU: batched-wav-nnet3-cuda.cc

2 GPU control threads, batch=100

TESLA V100

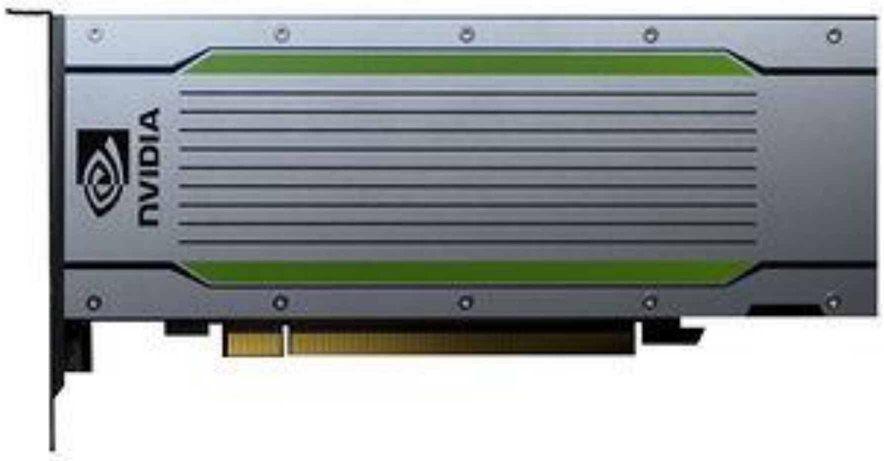
World's Most Advanced Data Center GPU

5,120 CUDA cores
640 Tensor cores
7.8 FP64 TFLOPS
15.7 FP32 TFLOPS
125 Tensor TFLOPS
20MB SM RF
16MB Cache
32 GB HBM2 @ 900GB/s
300GB/s NVLink

TESLA T4

World's most advanced scale-out GPU

2,560 CUDA Cores
320 Turing Tensor Cores
65 FP16 TFLOPS
130 INT8 TOPS
260 INT4 TOPS
16GB | 320GB/s
70 W



JETSON AGX XAVIER

World's first AI computer for Autonomous Machines

AI Server Performance in
30W • 15W • 10W

512 Volta CUDA Cores • 2x NVDLA

8 core CPU

32 DL TOPS • 750 Gbps SerDes

2x Xeon*: 2x Intel Xeon Platinum 8168, 410W, ~$13000
Xavier: AGX Devkit, 30W, $1299
T4*: PCI-E, (70+410)W, ~$(2000+13000)
V100*: SXM, (300W+410), ~$(9000+13000)

KALDI PERFORMANCE

1 GPU, LibriSpeech

Determinized Lattice Output
beam=10
lattice-beam=7
Uses all available HW threads

Hardware	Perf (RTFx)	WER	Perf	Perf/$	Perf/watt
LibriSpeech Model, Libri Clean Data					
2x Intel Xeon	381	5.5	1.0x	1.0x	1.0x
AGX Xavier	500	5.5	1.3x	13.1x	17.9x
Tesla T4	1635	5.5	4.3x	3.7x	3.7x
Tesla V100	3524	5.5	9.2x	5.5x	5.3x
LibriSpeech Model, Libri Other Data					
2x Intel Xeon	377	14.0	1.0x	1.0x	1.0x
AGX Xavier	450	14.0	1.2x	11.9x	16.3x
Tesla T4	1439	14.0	3.8x	3.3x	3.3x
Tesla V100	2854	14.0	7.6x	4.5x	4.4x

*Price/Power, not including, system, memory, storage, etc, price is an estimate

INCREASING VALUE

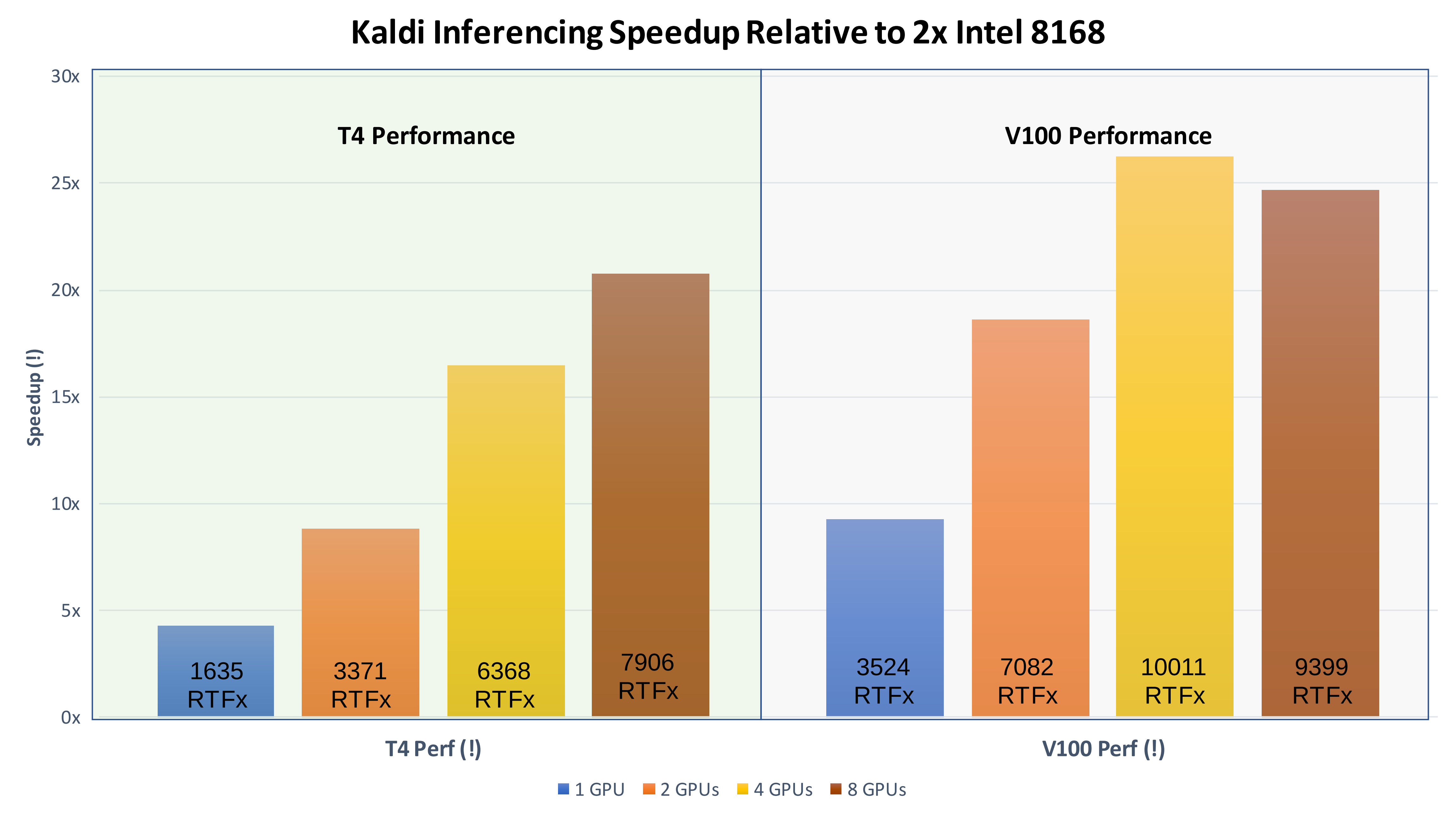
Amortizing System Cost

Adding more GPUs to a single system increases value

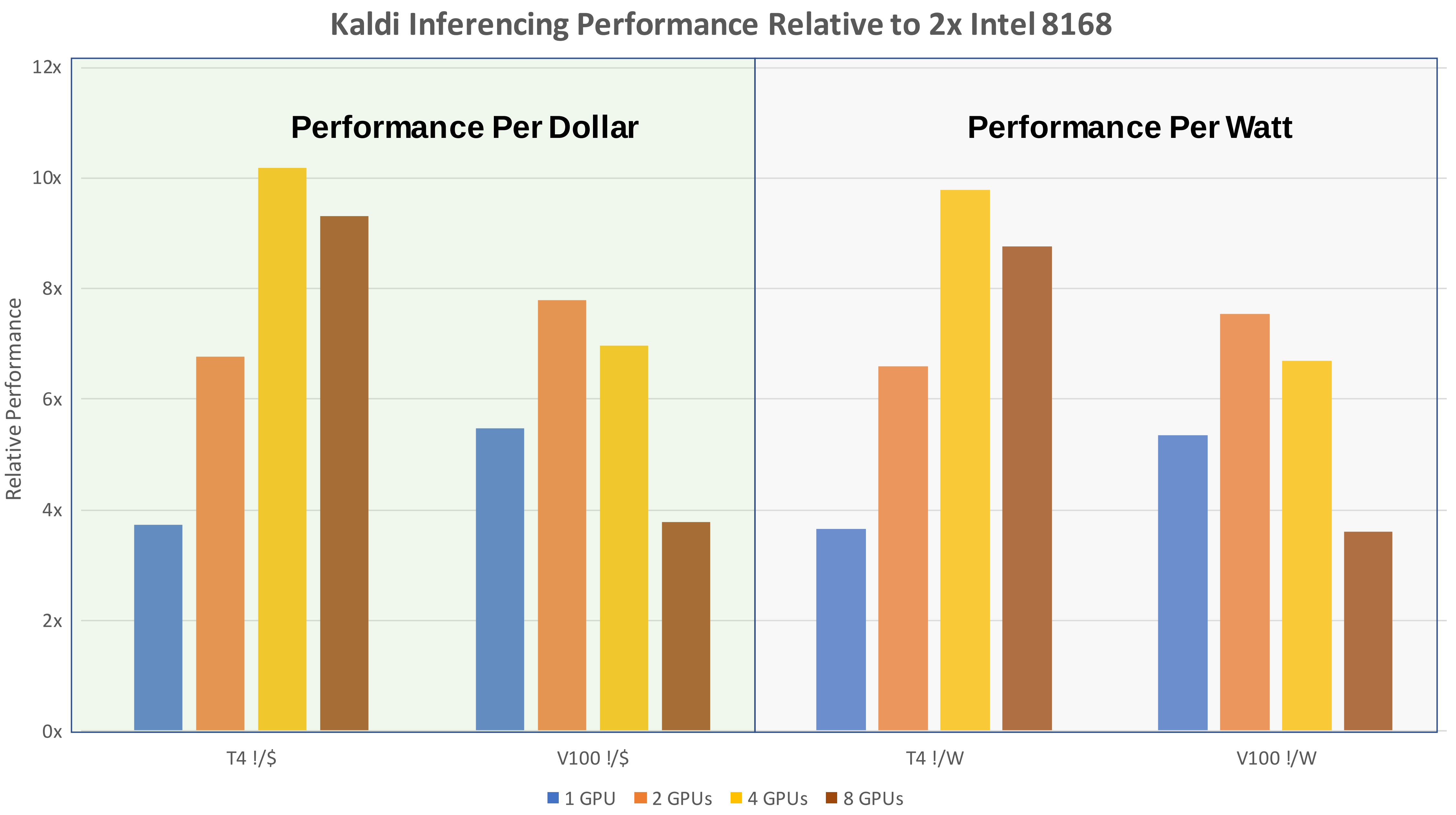
- Less system cost overhead
- Less system power overhead

Dense systems are the new norm:

- DGX1V: 8 V100s in a single node
- DGX-2: 16 V100s in a single node
- SuperMicro 4U SuperServer 6049GP-TRT: 20 T4s in a single node



Kaldi Inferencing Speedup Relative to 2x Intel 8168
T4 Performance
V100 Performance
Speedup (!)
30x
25x
20x
15x
10x
5x
0x
1635 RTFx
3371 RTFx
6368 RTFx
7906 RTFx
3524 RTFx
7082 RTFx
10011 RTFx
9399 RTFx
T4 Perf (!)
V100 Perf (!)
1 GPU
2 GPUs
4 GPUs
8 GPUs


Kaldi Inferencing Performance Relative to 2x Intel 8168
Performance Per Dollar
Performance Per Watt
Relative Performance
12x
10x
8x
6x
4x
2x
0x
T4 !/$
V100 !/$
T4 !/W
V100 !/W
1 GPU
2 GPUs
4 GPUs
8 GPUs

PERFORMANCE LIMITERS

Cannot feed the beast

- Feature Extraction and Determinization become bottlenecks
- CPU has a hard time keeping up with GPU performance

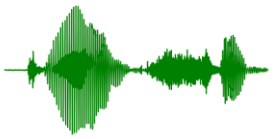
Small kernel launch overhead

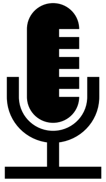
- Kernels typically only run for a few microseconds
- Launch latency can become dominant
- Avoid this by using larger batch sizes (larger memory GPUs are crucial)

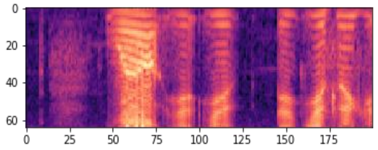
FUTURE WORK

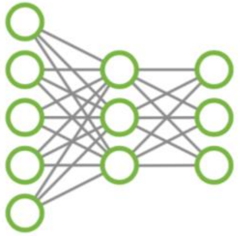
GPU Accelerated Feature Extraction

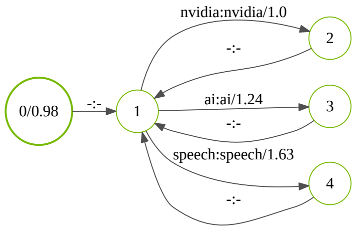
Raw Audio → **Feature Extraction** → **Acoustic Model** → **Language Model** → **Output**











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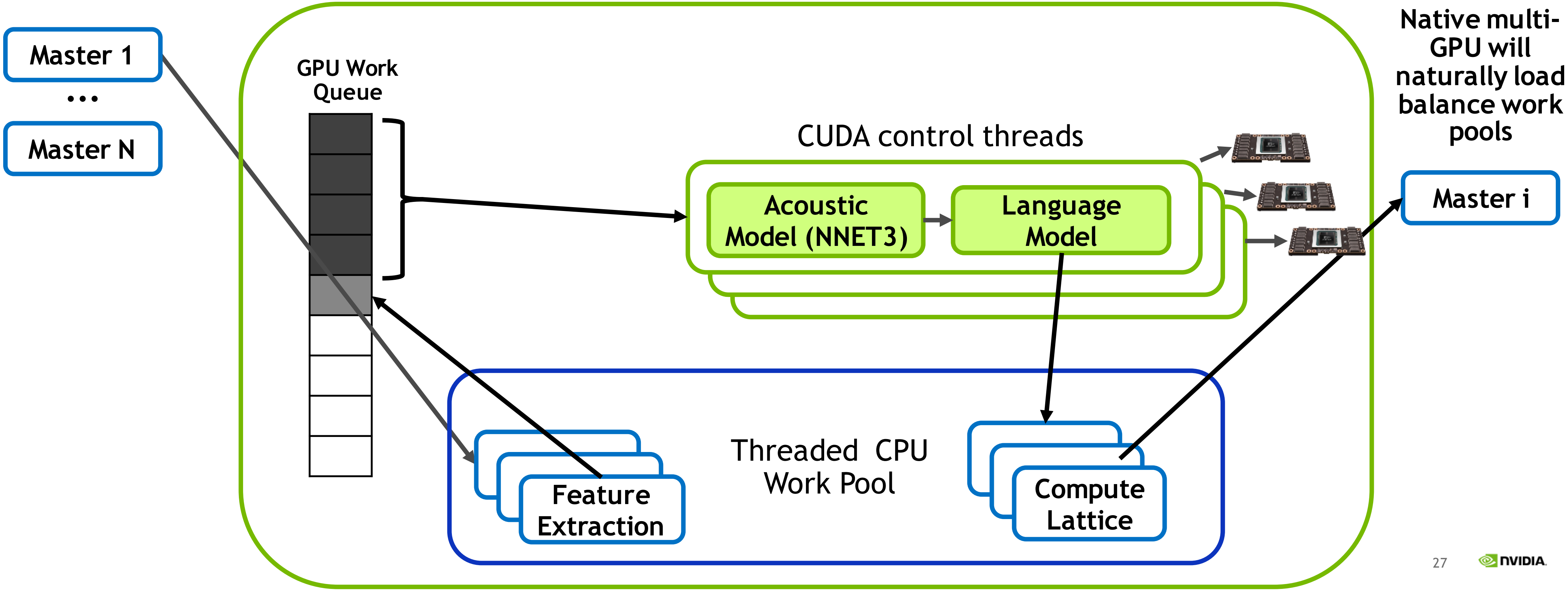
Feature Extraction on GPU is a natural next step: algorithms map well to GPUs

Allows us to increase density and therefore value

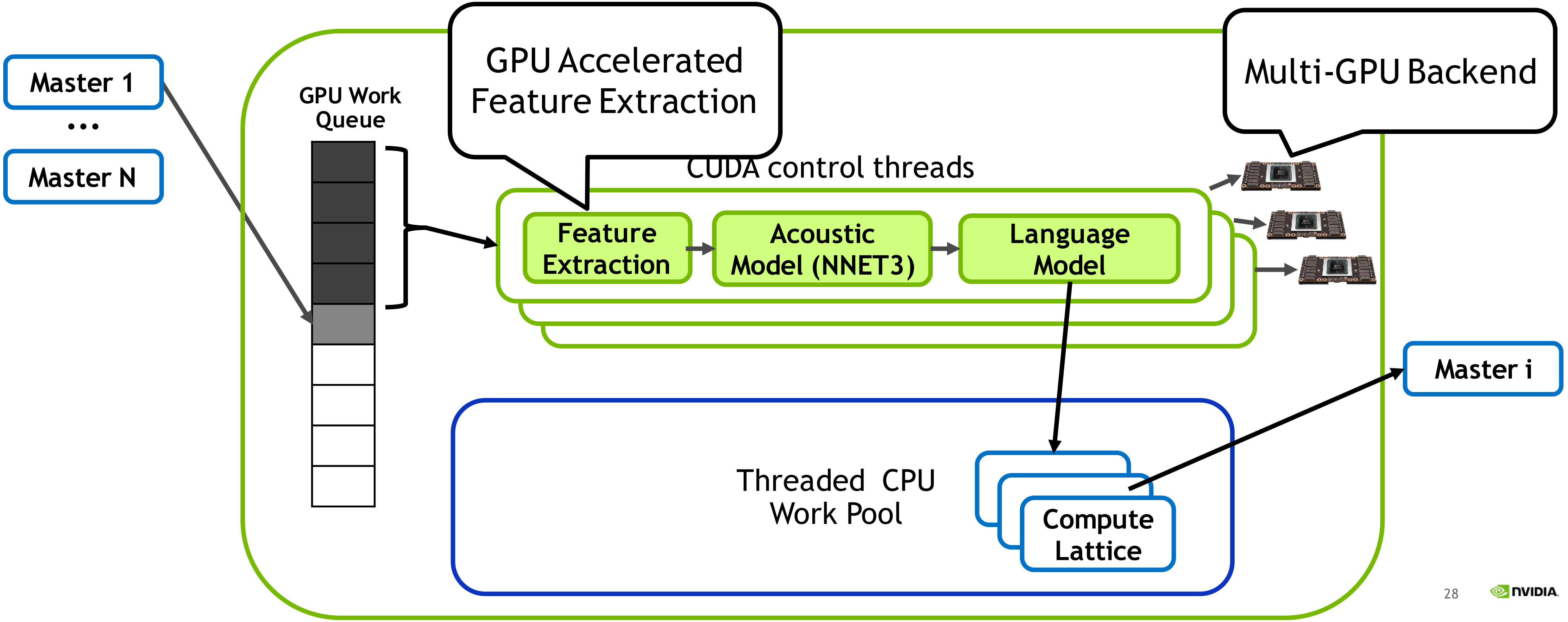
FUTURE WORK

Native Multi-GPU Support



FUTURE WORK

Where We Want To Be



HOW CAN I USE IT?

HOW TO GET STARTED

2 Methods

1) Download Kaldi, Pull in PR, Build yourself

   https://github.com/kaldi-asr/kaldi/pull/3114

2) Run NVIDIA GPU Cloud Container

   Get up and running in less than 10 minutes!

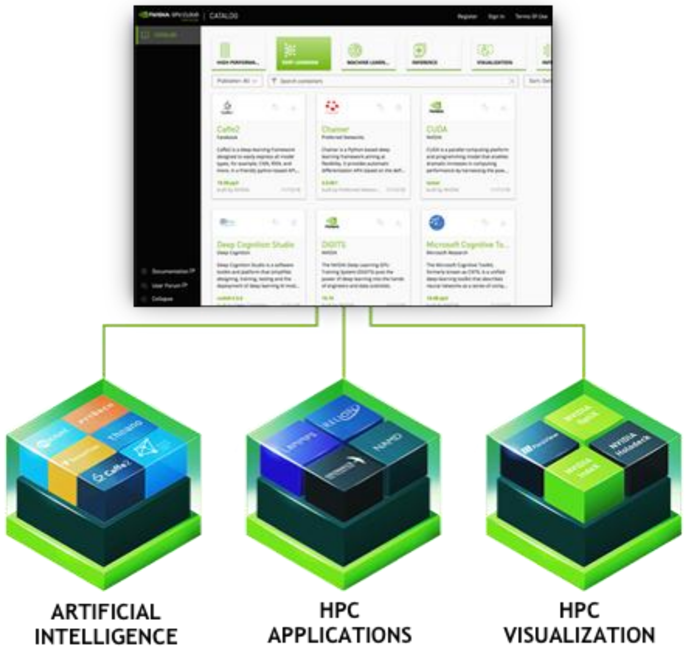
THE NGC CONTAINER REGISTRY

Simple Access to GPU-Accelerated Software

Discover over 40 GPU-Accelerated Containers
Spanning deep learning, machine learning, HPC applications, HPC visualization, and more

Innovate in Minutes, Not Weeks
Pre-configured, ready-to-run

Run Anywhere
The top cloud providers, NVIDIA DGX Systems, PCs and workstations with select NVIDIA GPUs, and NGC-Ready systems



NGC CONTAINER

Free & Easy

Get an NGC account: https://ngc.nvidia.com/signup

```
#login in to NGC, pull container, and run it
%> docker login nvcr.io
%> docker pull nvcr.io/nvidia/kaldi:19.03-py3
%> docker run --rm -it nvcr.io/nvidia/kaldi:19.03-py3

#prepare models and data
%> cd /workspace/nvidia-examples/librispeech
%> ./prepare_data.sh

#run benchmarks
%> ./run_benchmark.sh
%> ./run_multigpu_benchmark.sh 4
```

BENCHMARK OUTPUT

NGC Container

```
BENCHMARK SUMMARY:
  test_set: test_clean
    Overall: Aggregate Total Time: 55.1701 Total Audio: 194525 RealTimeX: 3525.91
      %WER 5.53 [ 2905 / 52576, 386 ins, 230 del, 2289 sub ]
      %SER 51.30 [ 1344 / 2620 ]
      Scored 2620 sentences, 0 not present in hyp.
  test_set: test_other
    Overall: Aggregate Total Time: 64.7724 Total Audio: 192296 RealTimeX: 2968.79
      %WER 13.97 [ 7314 / 52343, 850 ins, 730 del, 5734 sub ]
      %SER 73.94 [ 2173 / 2939 ]
      Scored 2939 sentences, 0 not present in hyp.
Running test_clean on 4 GPUs with 24 threads per GPU
GPU: 0 RTF: 2469.55
GPU: 1 RTF: 2472.81
GPU: 2 RTF: 2519.33
GPU: 3 RTF: 2515.81
Total RTF: 9977.50 Average RTF: 2494.3750
```

NVIDIA GPUS ARE ON EVERY CLOUD

Over 30 Offerings Across USA and China

	K520	K80	P40	M60	P4	P100	T4	V100	NGC
Alibaba Cloud					●	●		●	●
AWS	●	●		●				●	●
Baidu Cloud			●		●		●		
Google Cloud		●			●	●	●	●	●
IBM Cloud		●		●		●		●	
Microsoft Azure		●	●	●		●		●	●
Oracle Cloud						●		●	●
Tencent Cloud			●		●				

CONTAINER FUTURE WORK

Add more models

Add scripts to help users run quickly on their own models

NUMA pinning

Continue to update Kaldi source with latest updates

KALDI CHANGES

Source Layout

https://github.com/kaldi-asr/kaldi/pull/3114

Added two new directories to source tree

- cudadecoder/*:
  - Implements framework/library classes for use in applications
  - cudadecoder/README: Detailed documentation on how to use
- cudadecoderbin/*:
  - Binary example using cuda-accelerated decoder

TUNING PERFORMANCE

Functional Parameters

determinize-lattice:

determinize lattice in CPU pool or not

If not determinized in CPU pool master thread will determinize if GetLattice is called

beam:

width of beam during search

Smaller beam = faster but possibly less accuracy

lattice_beam:

width of lattice beam before determinization

Smaller beam = smaller lattice, less I/O, less determinization time

TUNING PERFORMANCE

GPU Performance

cuda-control-threads:

number of concurrent CPU threads controlling a single GPU pipeline

Typically 2-4 is ideal (more = more GPU memory and less batch size)

cuda-worker-threads:

number of CPU threads in the CPU workpool, should use all CPU resources available

max-batch-size:

maximum batch size per pipeline (more = more GPU memory and less control threads)

Want as large as memory allows (<200 is currently possible)

batch-drain-size:

how far to drain a batch before refilling (batches NNET3)

typically 20% of max-batch-size works well

cuda-use-tensor-cores:

Turn on Tensor Cores (FP16)

TUNING PERFORMANCE

Memory Utilization

max-outstanding-queue-length:

Length of GPU work queue, Consumes CPU memory only

ntokens-preallocated:

Preallocated host memory to store output, CPU memory only

Will grow dynamically if needed

max-tokens-per-frame:

Maximum tokens in GPU memory per frame

Cannot resize, will reduce accuracy if it fills up

max-active:

maximum number of arcs retained in a given frame (keeping only the max-active best ones)

Less = faster & less accurate

AUTHORS

Hugo Braun is a Senior AI Developer Technology Engineer at NVIDIA. With a background in mathematics and physics, he has been working on performance-oriented machine learning algorithms. His work at NVIDIA focuses on the design and implementation of high-performance GPU algorithms, specializing in deep learning and graph analytics. He holds a M.S. in Mathematics and Computer Science from Ecole Polytechnique, France.

Justin Luitjens is a Senior Developer Technology Engineer at NVIDIA. He has spent the last 16 years working on HPC applications with the last 8 focusing directly on CUDA acceleration at NVIDIA. He holds a Ph.D. in Scientific Computing from the University of Utah, a Bachelor of Science in Computer Science from Dakota State University and a Bachelor of Science in Mathematics for Information Systems from Dakota State University.

Ryan Leary is a Senior Applied Research Scientist specializing in speech recognition and natural language processing at NVIDIA. He has published research in peer-reviewed venues on machine learning techniques tailored for scalability and performance as well as natural language processing for health applications. He holds a M.S. in Electrical & Computer Engineering from Johns Hopkins University, and a Bachelor of Science in Computer Science from Rensselaer Polytechnic Institute.

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