

# Understanding and Optimizing GPU Energy Consumption of DNN Training

Jae-Won Chung October 7<sup>th</sup>, 2022

Work done in collaboration with Jie You and Mosharaf Chowdhury

To appear at NSDI '23

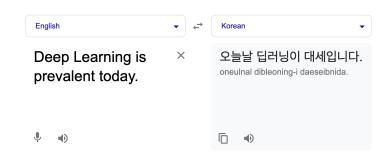




### Deep Learning is Prevalent Today

Image processing
Speech recognition
Machine translation
Intelligent assistants
Autonomous driving
Search
Video analytics











### DNN Energy Consumption is Skyrocketing

DNN

• Re-training is commonplace (e.g. every hour)<sup>3</sup>



GPU

- Dominant power consumer in servers (~70%)<sup>1</sup>
- Training GPT-3 == 120 years of electricity for a household<sup>2</sup>



Energy

• Performance optimizations oblivious of energy impact

### Existing Efforts are not Practical Enough

DNN

New energy-efficient DNN architectures
 SqueezeNext (CVPRW '18), ChamNet (CVPR '19), SkyNet (MLSys '20)



GPU

New energy-efficient HW architectures
 TPU (ISCA '17), EDEN (MICRO '19), LNPU (ISSCC '19)



Energy

- Offline profiling and power model fitting
- Confined to GPU power configuration knobs
   MPC (HPCA '17), ODPP (CCGRID '20), GPOEO (TPDS '22)

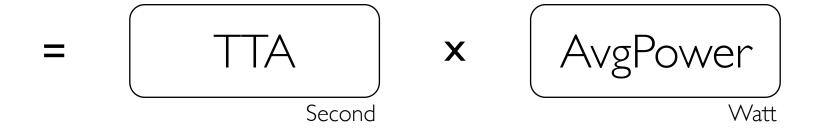
### Understanding GPU Energy Consumption

#### Energy to Accuracy (ETA)

- Energy needed to reach the user-specified target accuracy
- Energy-counterpart of Time to Accuracy (TTA)

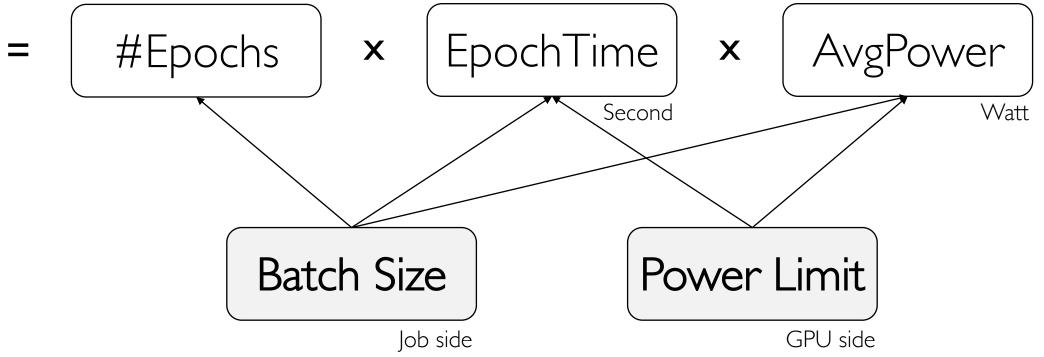
# Understanding GPU Energy Consumption





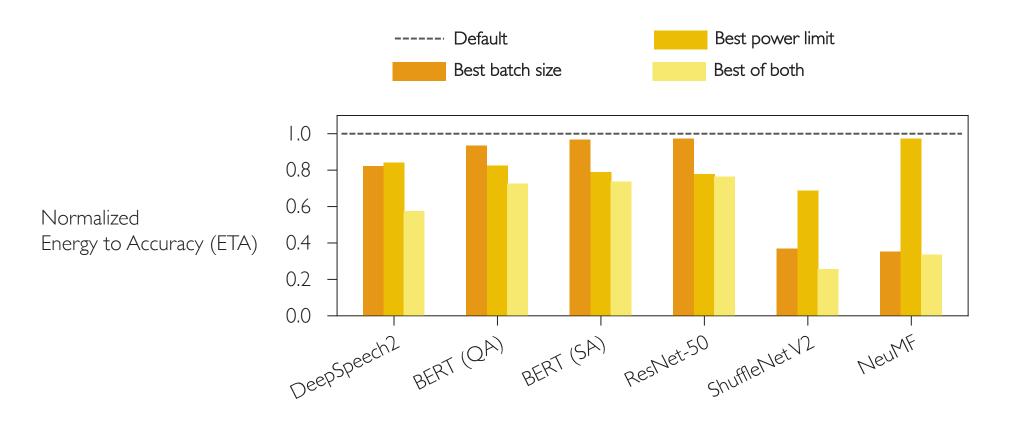
# Understanding GPU Energy Consumption





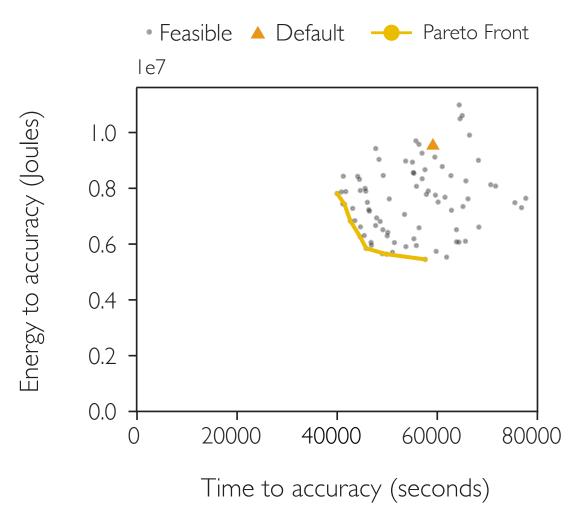
# Opportunity for Energy Savings

#### Sweep of feasible batch sizes and power limits

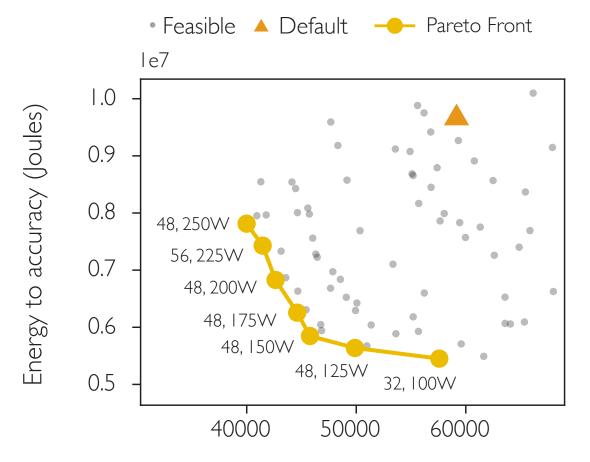


24 ~ 75% energy reduction

Measured on an NVIDIA VI00 GPU. Training terminates when the DNN reaches its original target accuracy.

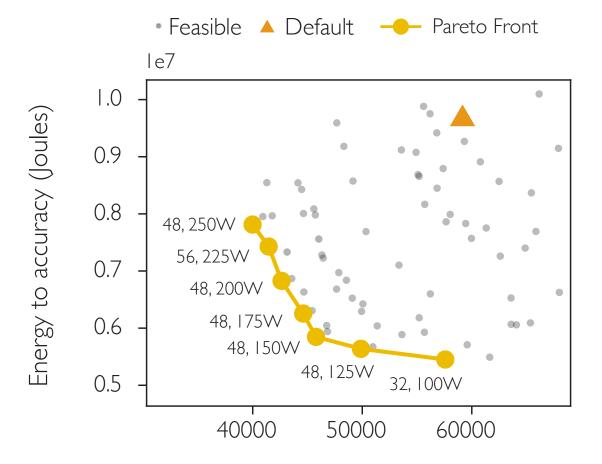


Results from training DeepSpeech2 on LibriSpeech on an NVIDIA V100 GPU. Similar trends found over 6 DL workloads and 4 GPU generations.



- I. Time and energy minimized by different knobs
- 2. Efficient time and energy show a trade-off

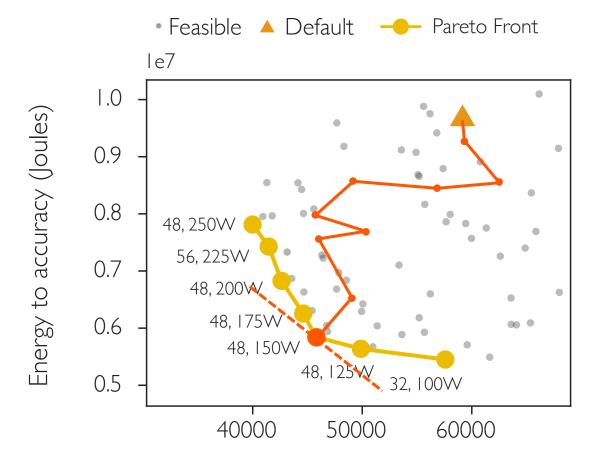
Time to accuracy (seconds)



Which yellow point is the best?

 $Cost = \frac{\eta}{\eta} \cdot ETA + (1 - \frac{\eta}{\eta}) \cdot MaxPower \cdot TTA$ 

Time to accuracy (seconds)



Which yellow point is the best?

 $Cost = \frac{\eta}{\eta} \cdot ETA + (1 - \frac{\eta}{\eta}) \cdot MaxPower \cdot TTA$ 

Time to accuracy (seconds)

### Challenge #1: Average Power

#### GPU is a black box



- Confidential hardware architecture
- Unknown internal voltage/frequency control algorithm

#### Power modelling lacks practicality

- Requires offline profiling
- Does not generalize to other DNNs and GPUs

# Challenge #2:Time to Accuracy (TTA)

#### Difficult to predict number of epochs



- Batch size affects model accuracy
- We would be solving HPO if we can predict TTA

#### DNN training is stochastic

- Parameter initialization and batch order are random
- TTA varies even when we train with the same config



# An Energy Optimization Framework for DNN Training

#### Optimizes the cost

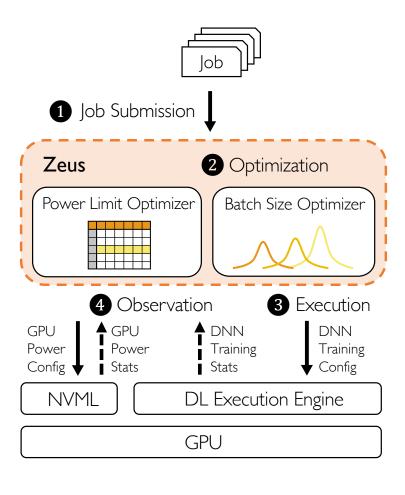
- of an arbitrary DNN model
- on an arbitrary GPU type
- in an efficient manner

#### without any

- offline profiling,
- hardware modification, or
- accuracy degradation

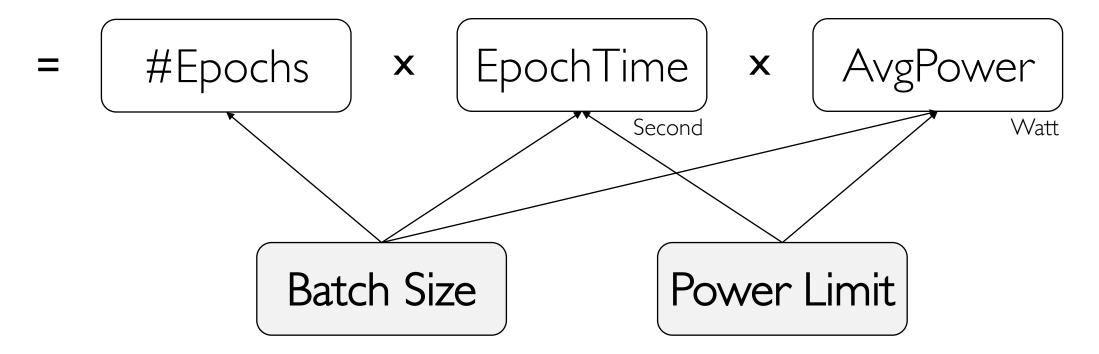
### Overall Workflow

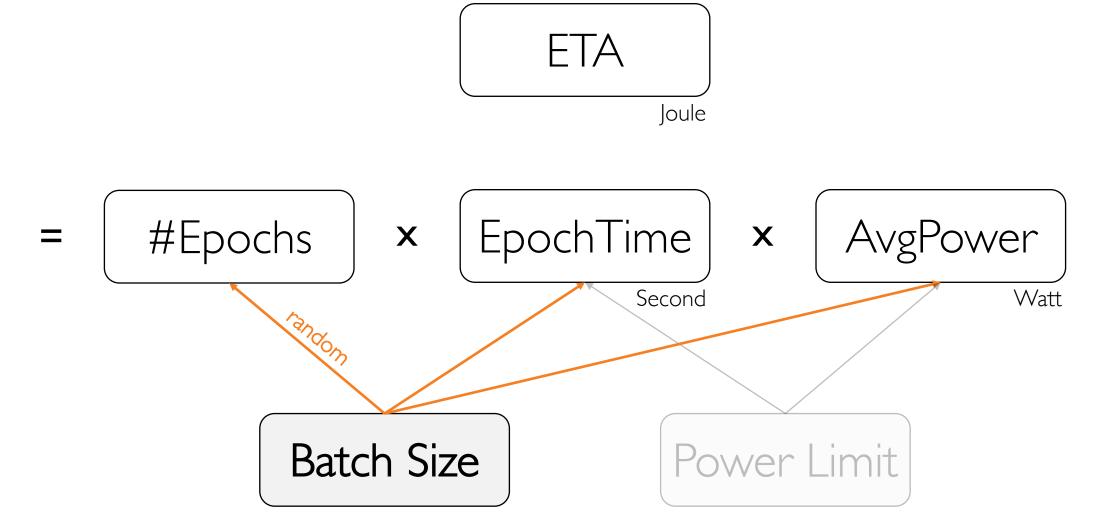
#### Re-training jobs are opportunity for exploration!



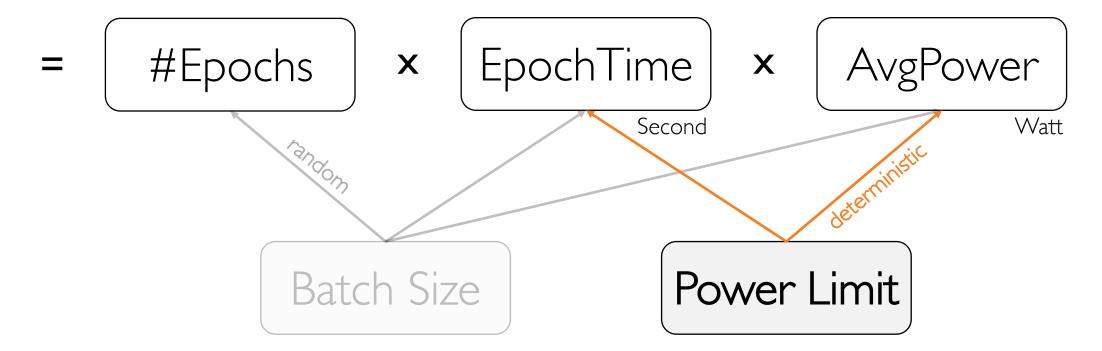
- I. Decoupling
- 2. Power Limit Optimizer
- 3. Batch Size Optimizer

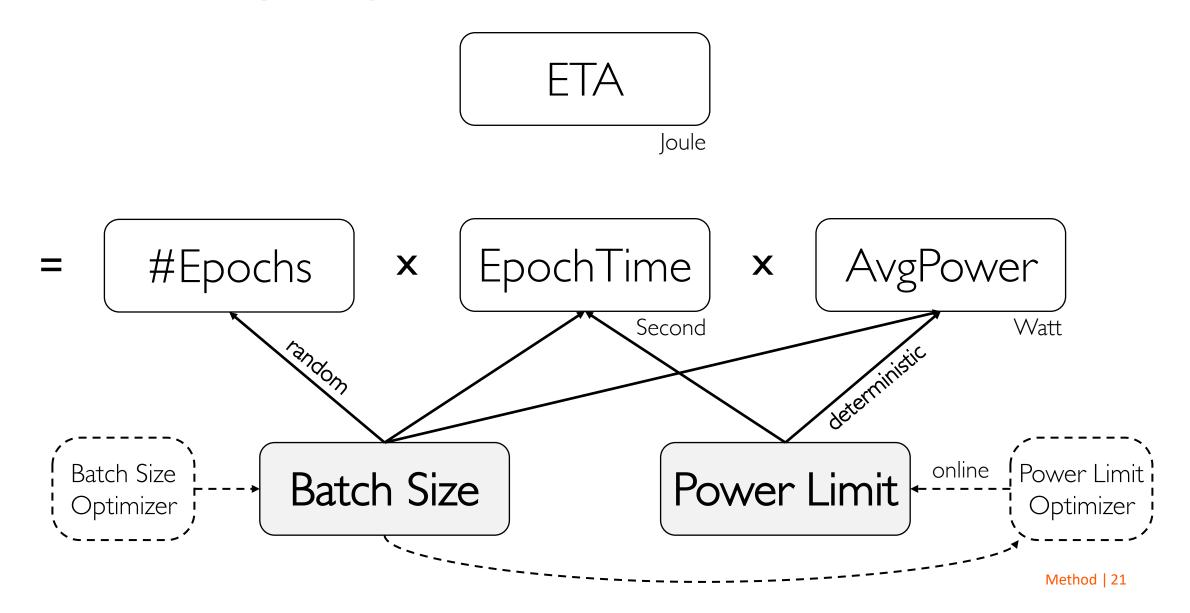












### 2. Power Limit Optimizer

#### Just-in-time online profiler

- Profiles the power and throughput of each power limit
- Five seconds per power limit is enough

#### Low overhead

- Profile only once for each batch size
- Profiling contributes to the training process

### 3. Batch Size Optimizer

#### A good solution must

- I. incorporate the stochasticity of DNN training, and
- 2. intelligently trade-off exploration and exploitation

#### Multi-Armed Bandit

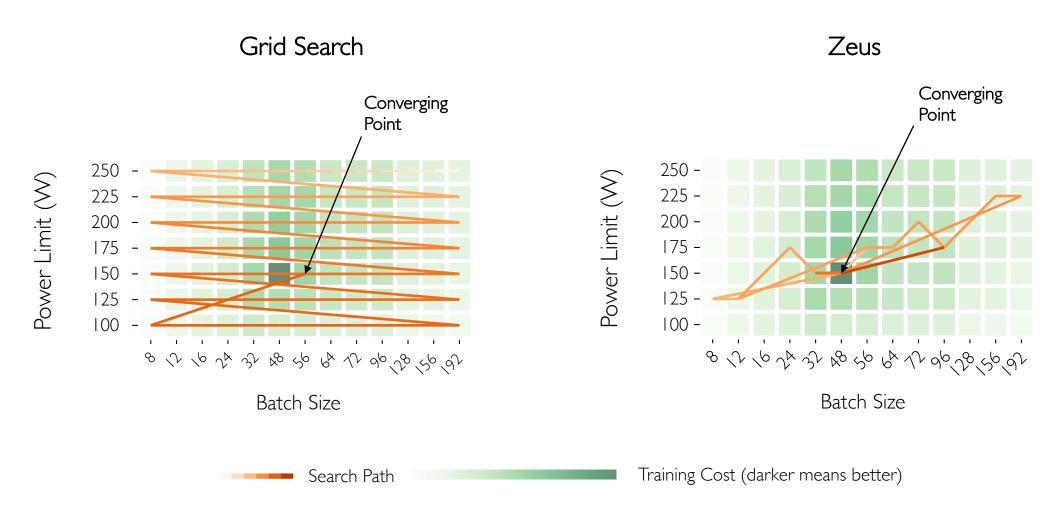
 $Cost = \frac{\eta}{\eta} \cdot ETA + (1 - \frac{\eta}{\eta}) \cdot MaxPower \cdot TTA$ 

- I. Models cost as a Gaussian random variable
- 2. Automatically controls exploration and exploitation

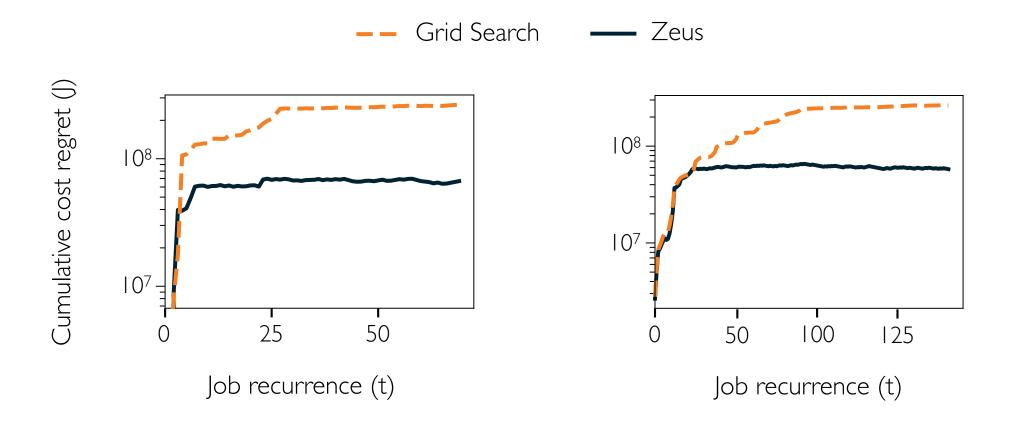
### Workloads and GPU Generations

Task	Dataset	DNN	GPU	Arch
Speech Recognition	LibriSpeech	DeepSpeech2	NVIDIA A40	Ampere
Question Answering	SQuAD	BERT	NVIDIA V I 00	Volta
Sentiment Analysis	Sentiment I 40	BERT	NVIDIA RTX6000	Turing
Image Classification	ImageNet	ResNet-50	NVIDIA P100	Pascal
Image Classification	CIFAR-100	ShuffleNet-v2		
Recommendation	MovieLens-IM	NeuMF		

### Zeus in Action



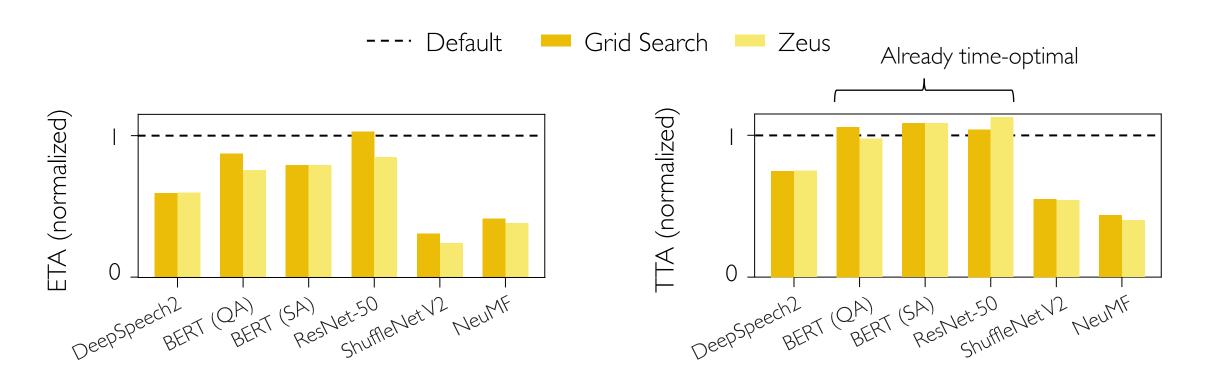
# Zeus Quickly Converges to the Optimum



ResNet50 trained on ImageNet on an NVIDIA VI00 GPU

DeepSpeech2 trained on LibriSpeech on an NVIDIA VI00 GPU

### Zeus Leads to Large Benefits



15 ~ 76% energy reduction Up to 60% time reduction

### Conclusion

Works on arbitrary DNN models



Works without modifying existing hardware



Energy

- Fully online with JIT profiling and MAB
- Jointly optimizes both job- and GPU-side configurations



https://ml.energy/zeus