A GPU Inference System Scheduling Algorithm with Asynchronous Data Transfer

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Background

- Deep Learning Inference
  - Small jobs, High concurrence, Low latency
  - Strong correlation with actual applications
  - Low attention compare with training
- General Purpose GPU computing
  - Widely used in Deep Learning
  - Suitable for computing intensive jobs
  - Somewhat different from CPU when it comes to scheduling jobs

Related Works

- Clipper[crankshaw2017clipper]
  - Dynamic match the batch size of inference jobs.
- LASER[agarwal2014laser]
  - Presented by LinkedIn for online advertising using cache system.
- FLEP[wu2017flep]
  - Accelerate GPU utilization ratio through kernel preemption and kernels scheduling with interruption skills.

Related Works

- [tanasic2014enabling]
  - Use s set of hardware extensions to support multi-programmed GPU workloads.
- Anakin[Baidu org]
  - Automatic graph fusion, memory reuse, assembly level optimization.

Motivation

- No model can describe inference jobs' processing mode quantitatively.
- Computation and data transmission execute serially, leading to low GPU utilization ratio.
- Question:
  - How to quantitatively analysis the relationship between concurrency and latency?
  - How to make full use of GPUs with their characteristics?

Model

- Latency: batch filling time + GPU processing time

$$L_i(n) = \max\left(F_i(n), P_{i-1}(m)\right) + P_i(n)$$

- batch filling time: batch size / concurrency

$$F(n) = n/C_t$$

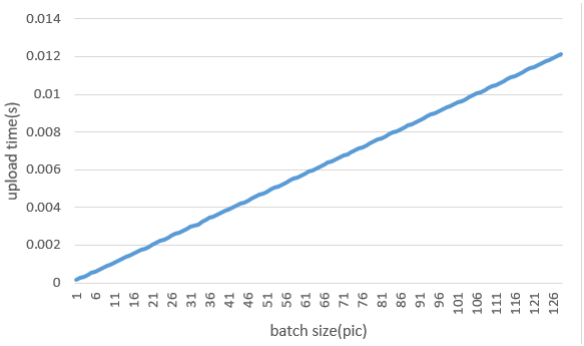
- GPU processing time: upload time + calculation time + download time, linear with data size(batch size).

$$P(n) = T_{up}(n) + T_{calc}(n) + T_{down}(n)$$

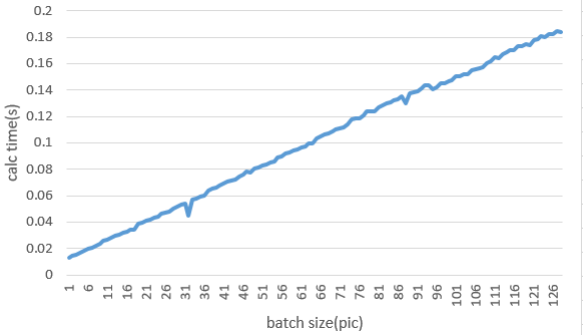
Model

- The relationship between batch size and upload time, calculation time and download time.

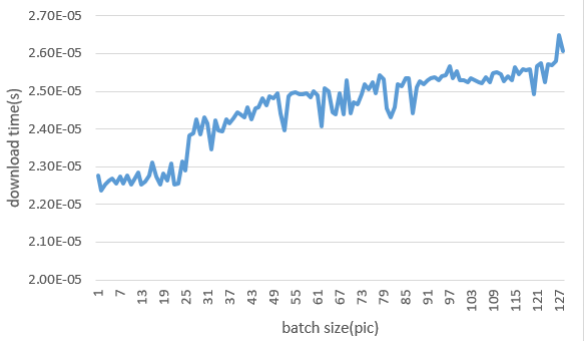
$$P(n) = kn + b$$



Upload time



Calculation time



Download time

Model

- Batch size selection:

$$n = \frac{bC_t}{1 - kC_t}$$

- Upper bound of concurrency

$$C_t = 1/k$$

- Limits of concurrency with given latency upper bound and batch size selection.

$$C_t = \frac{1}{k} - \frac{2b}{k} * \frac{1}{L}, \qquad n = \frac{L - 2b}{2k}$$

Model

- If job scheduling system supports GPU data transfer and computation asynchronous execution.

$$L_i'(n) = \max\left(F_i(n) + T_{up,i}(n), P_{i-1}(m)\right) + T_{calc,i}(n)$$

- Batch size selection:

$$n = \frac{(b_{calc} - b_{up})C_t}{1 - (k_{calc} - k_{up})C_t}$$

- Upper bound of concurrency

$$C_t = 1/(k_{calc} - k_{up})$$

Model

- Limits of concurrency with given latency upper bound and batch size selection

$$C_t = \frac{1}{k_{calc} - k_{up}} - \frac{2b_{calc}}{k_{calc} - k_{up}} * \frac{1}{L}$$

$$n = \frac{L - 2b_{calc}}{2k_{calc}}$$

- The time to upload new batch to GPU memory.

$$Up_{i+1} = Down_{i-1} - T_{down,i-1} + T_{calc,\,i} - T_{up,\,i+1}$$

Scheduling Algorithm

- Start two CUDA stream to use up the asynchronous capability of GPU.
- Select two different batch sizes to initial the model's parameters.
- Scheduling algorithm records recent several batches' GPU time, and updates the parameters.
- Calculate batch size according to real time concurrency and latency requested, and upload it to GPU memory ahead of last batch returning to host memory.

Scheduling Algorithm

- When concurrency increases
  - Batch will be filled ahead of schedule
  - Upload current filled batch
  - Update concurrency
  - Select new batch size with new concurrency, the remaining time of current processing batch and the GPU processing time of newly uploaded batch
  - Scheduling System adapts to new concurrency dynamically.

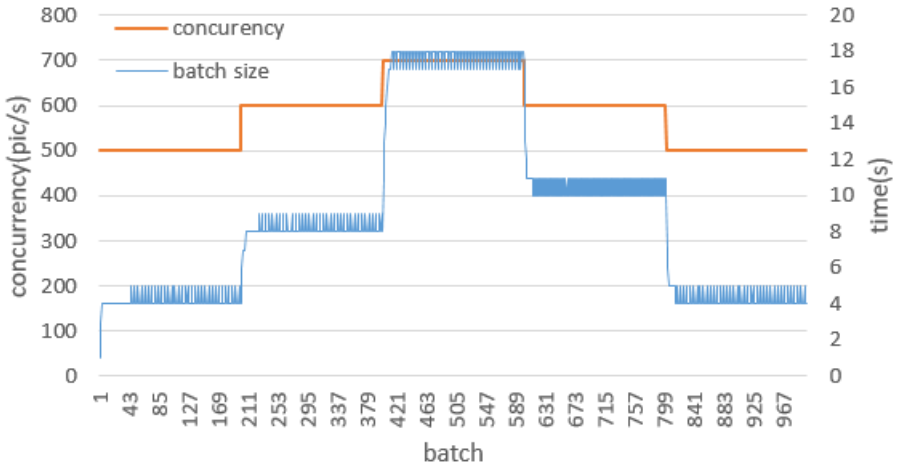
Scheduling Algorithm

- When concurrency decreases
  - Batch will not be filled when it's time to upload it.
  - Force the completion of the batch filling phase and upload the smaller batch.
  - Update concurrency
  - Select new batch size with new concurrency and the calculation time of newly uploaded batch
  - Scheduling System adapts to new concurrency dynamically.

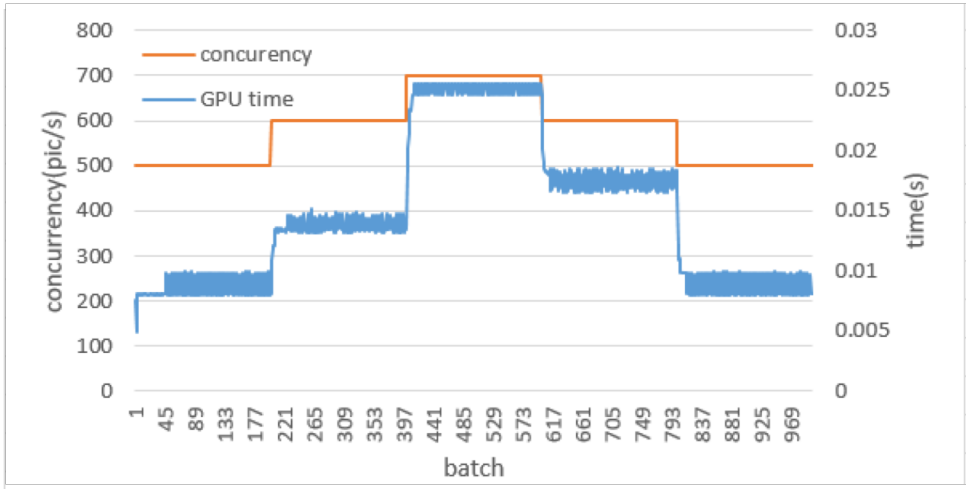
Experiments(environment)

CPU	Intel(R) Core(TM) i5-8600 CPU @ 3.10GHz
Memory	32GB
GPU	GTX 1080Ti
GPU memory	11GB
Operation System	Ubuntu 16.04
Platform	PyTorch 1.0.0
Model	ResNet-50
Dataset	CIFAR10

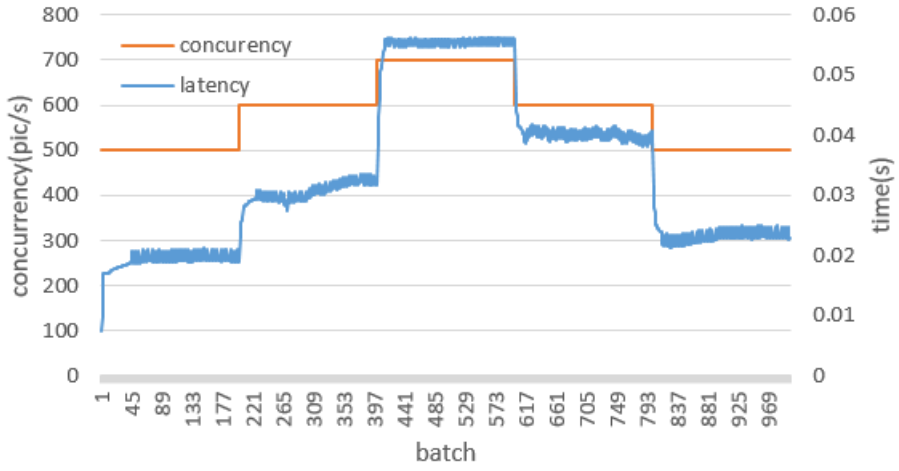
Experiments(concurrency changing)



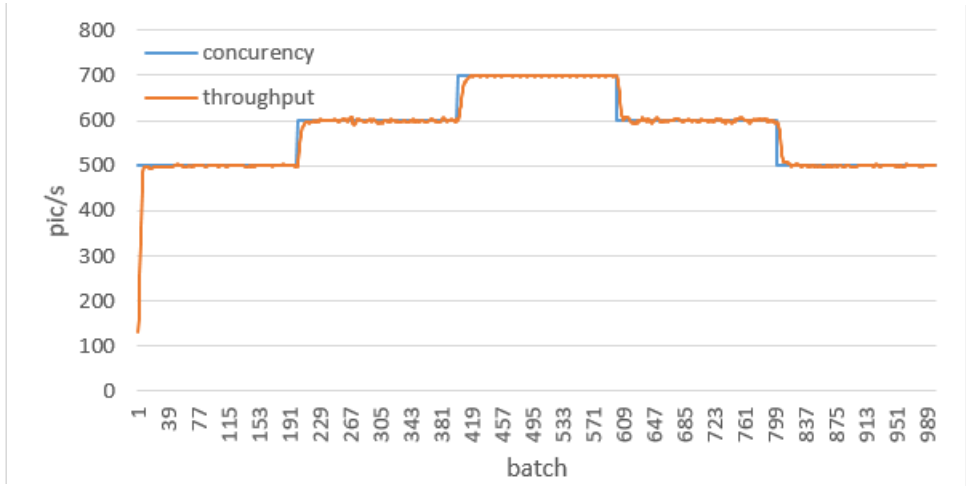
batch size



GPU processing time

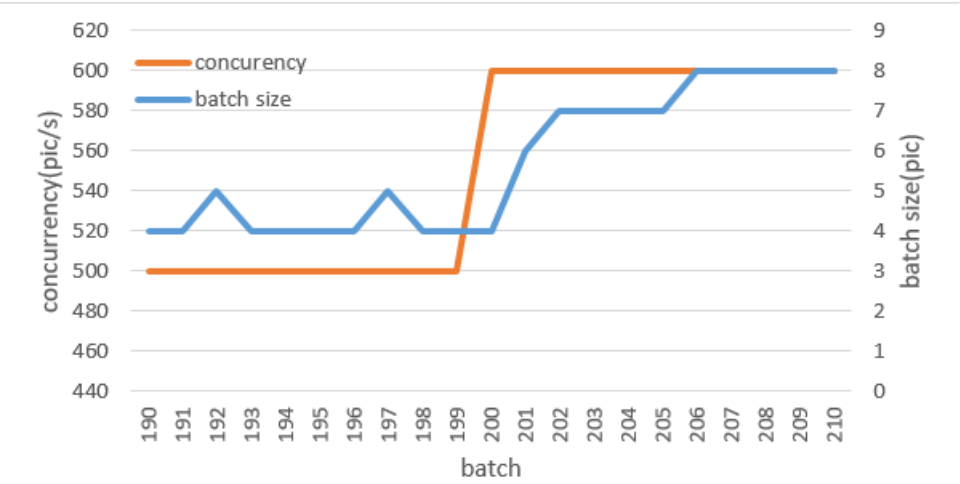


latency

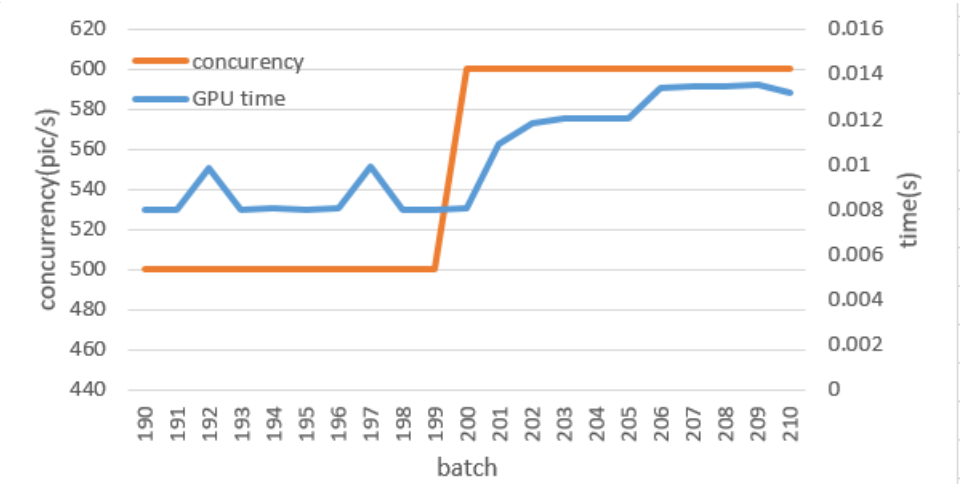


throughput

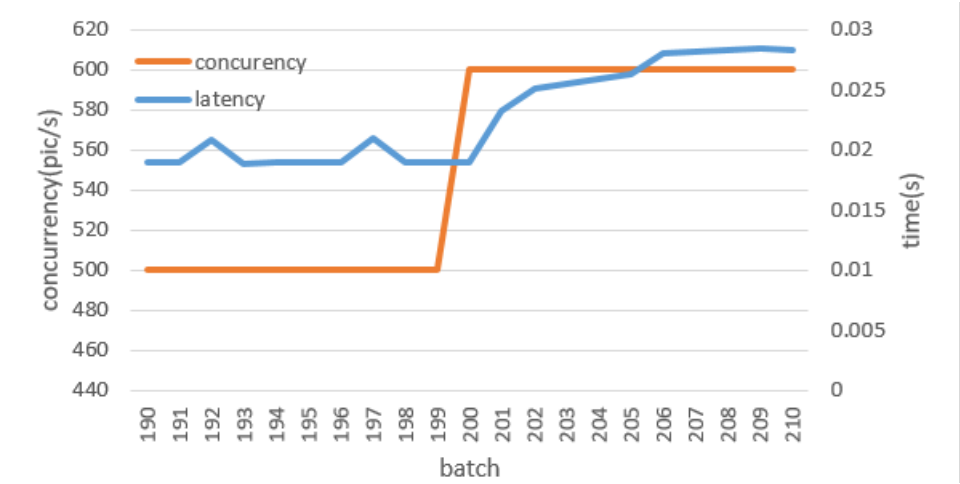
Experiments(concurrency increasing)



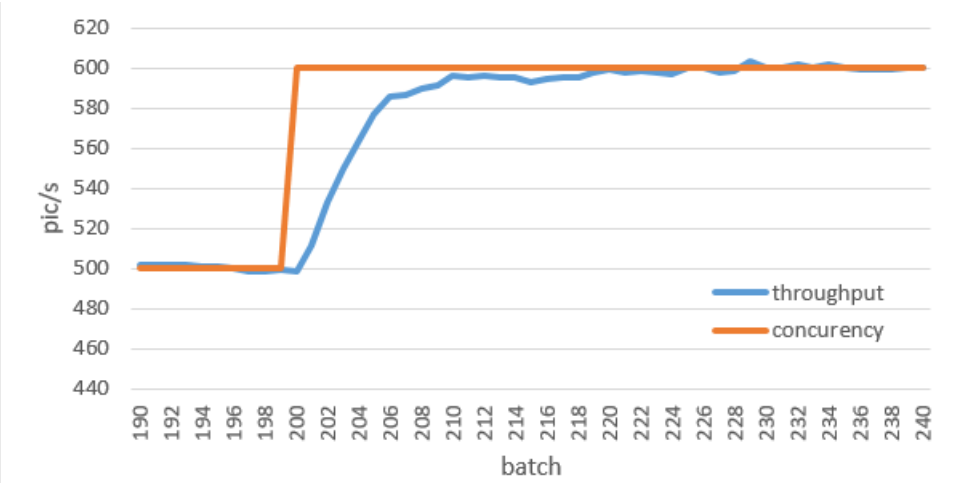
batch size



GPU processing time



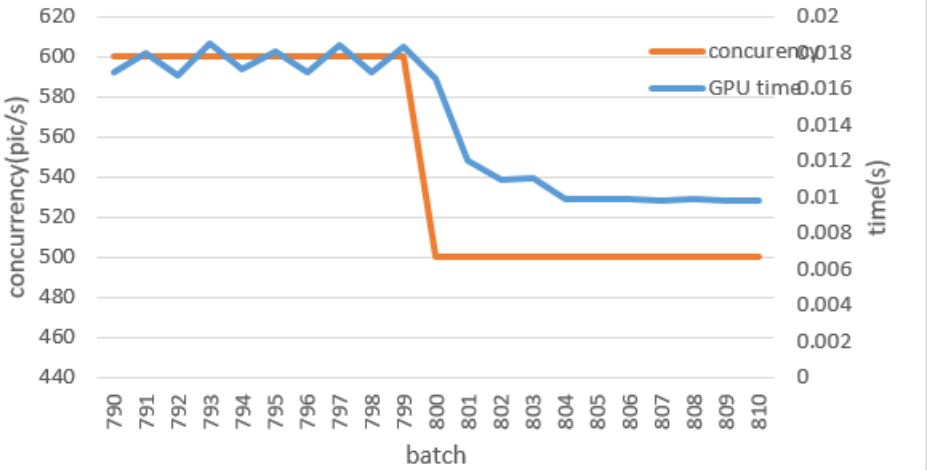
latency



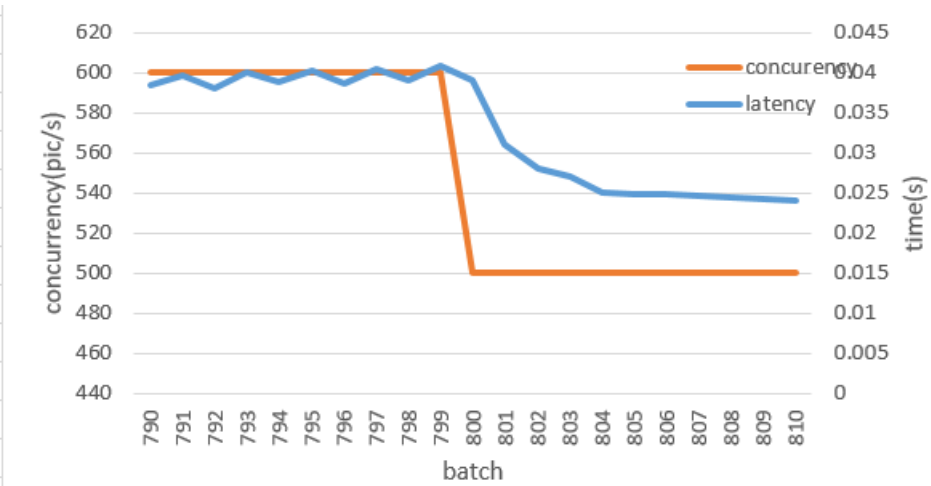
throughput

Experiments(concurrency decreasing)

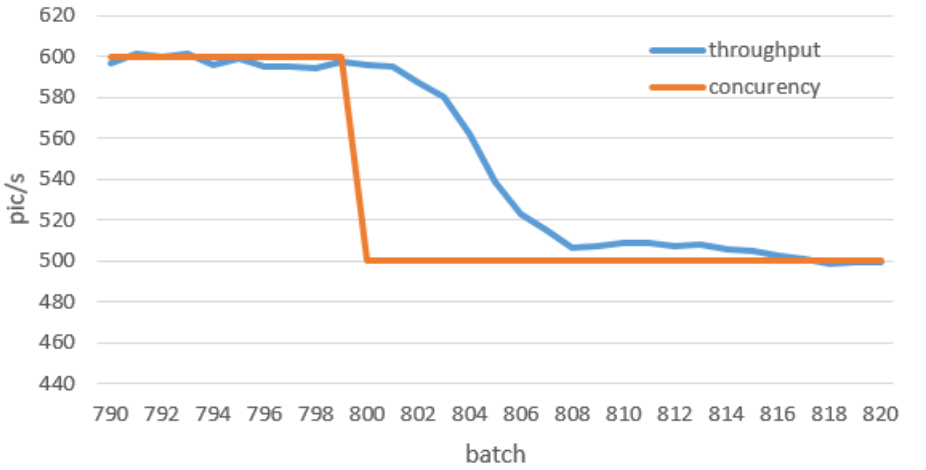
batch size



GPU processing time

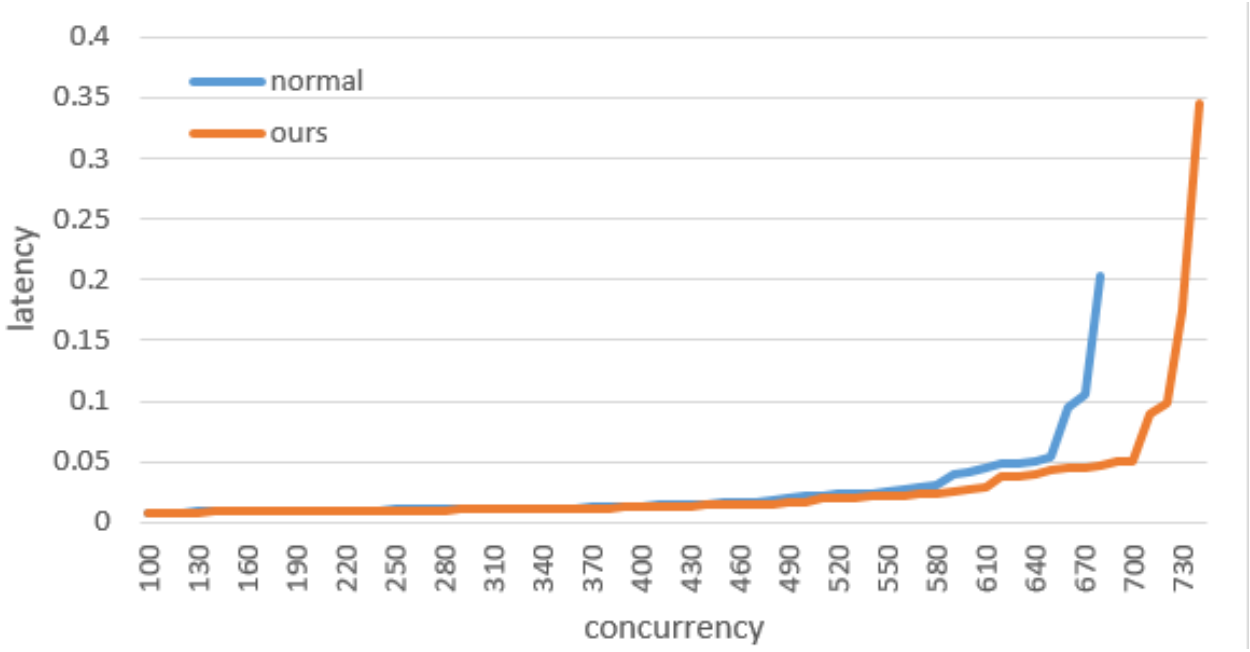


latency



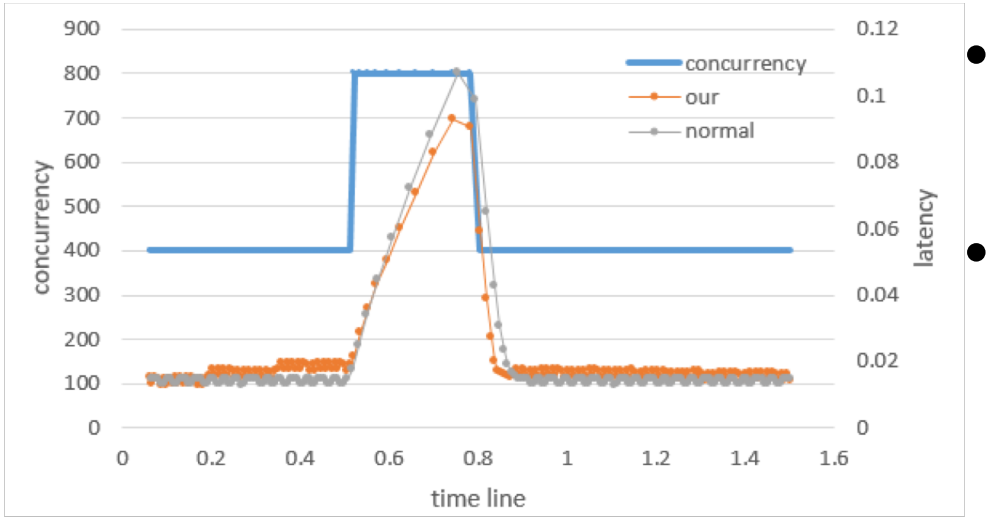
throughput

Experiments(concurrency-latency)

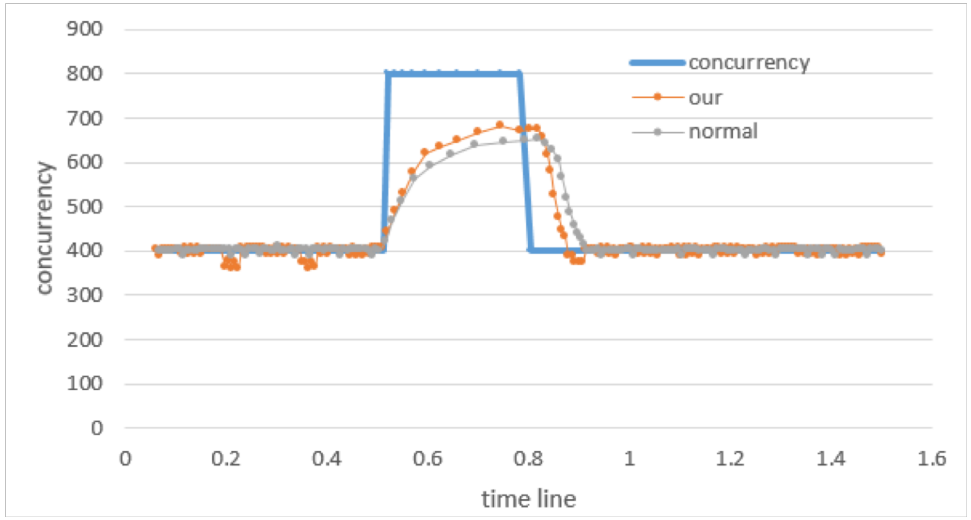


- Latency surges when concurrency increases under baseline and our scheduling algorithm.
- Our algorithm can slow down the increase of latency evidently(The larger the concurrency, the more obvious the effect).

Experiments(peak clipping)



latency



throughput

- Double the concurrency and keep 0.3s.
- Our algorithm can reduce the peak of batch size and job latency.
- Our algorithm can clip the peak of concurrency and smooth the throughput.

Conclusion

- Improve the processing capacity of the system by 9%.
- Reduces the latency by 3%-76% under different concurrency.
- Reduce the peak of latency by 16% when concurrency bursts from 400pic/s to 800pic/s for 0.3 second.
- Clip the peak of concurrency and smooth the throughput.

Future Work

- Is this method feasible in distributed system which have network communication delay?

- In deep learning training, we can also increase GPU utilization rate by making data transfer and computing asynchronously.

Q & A

Thanks!