GeePS: Scalable deep learning on distributed GPUs with a GPU-specialized parameter server

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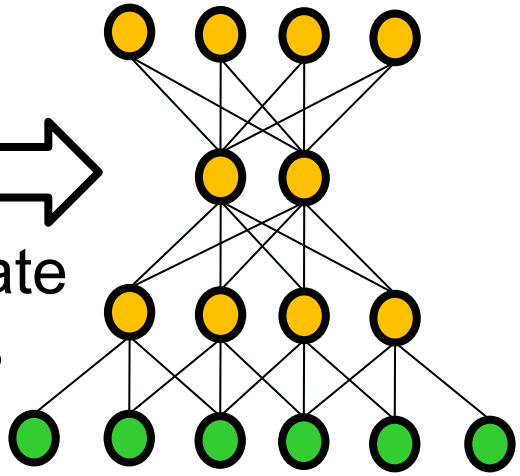
Image classification w/ deep learning

Training data:
images w/ labels

Machine learning
program

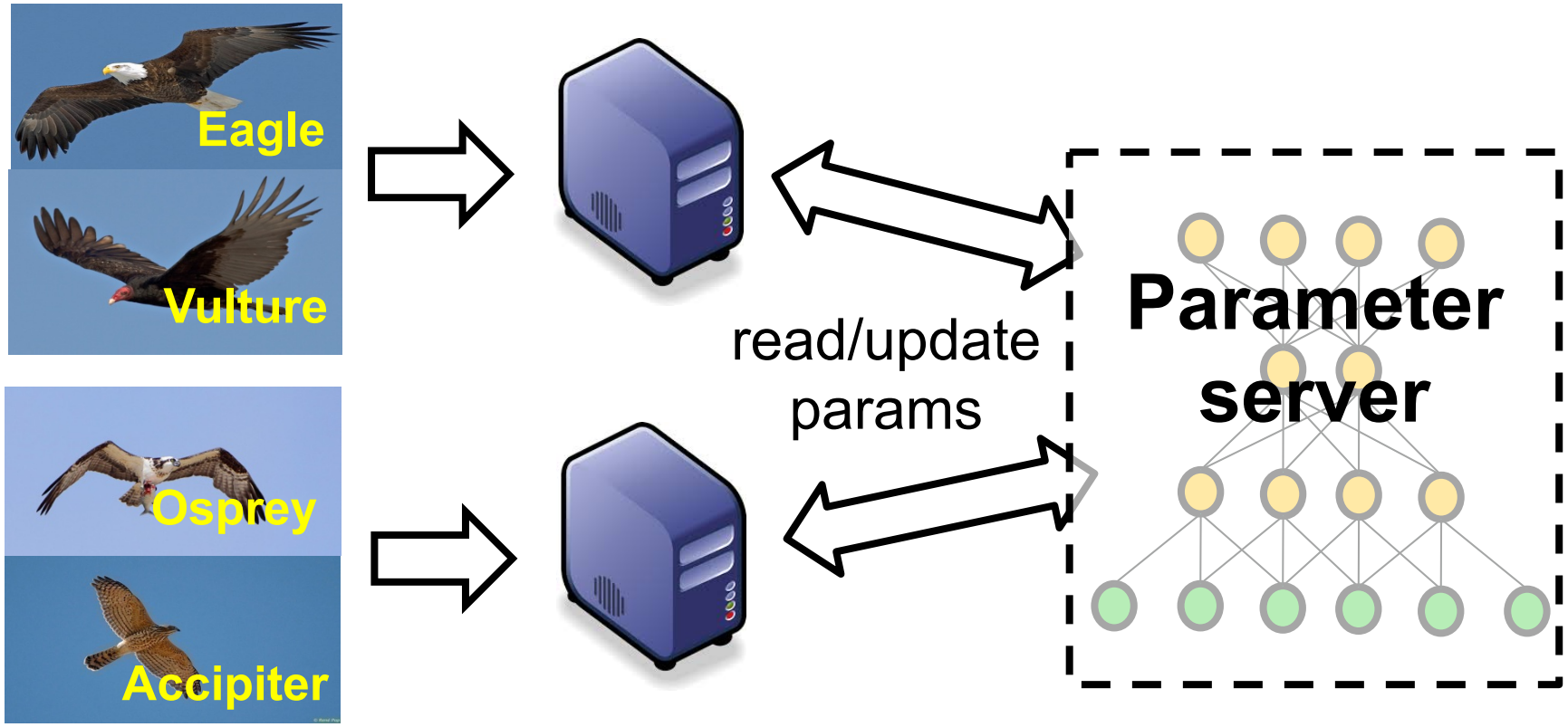
read/update
params

Deep neural network:
interconnected neurons



Model parameters:
connection weights
(solution)

Distributed deep learning

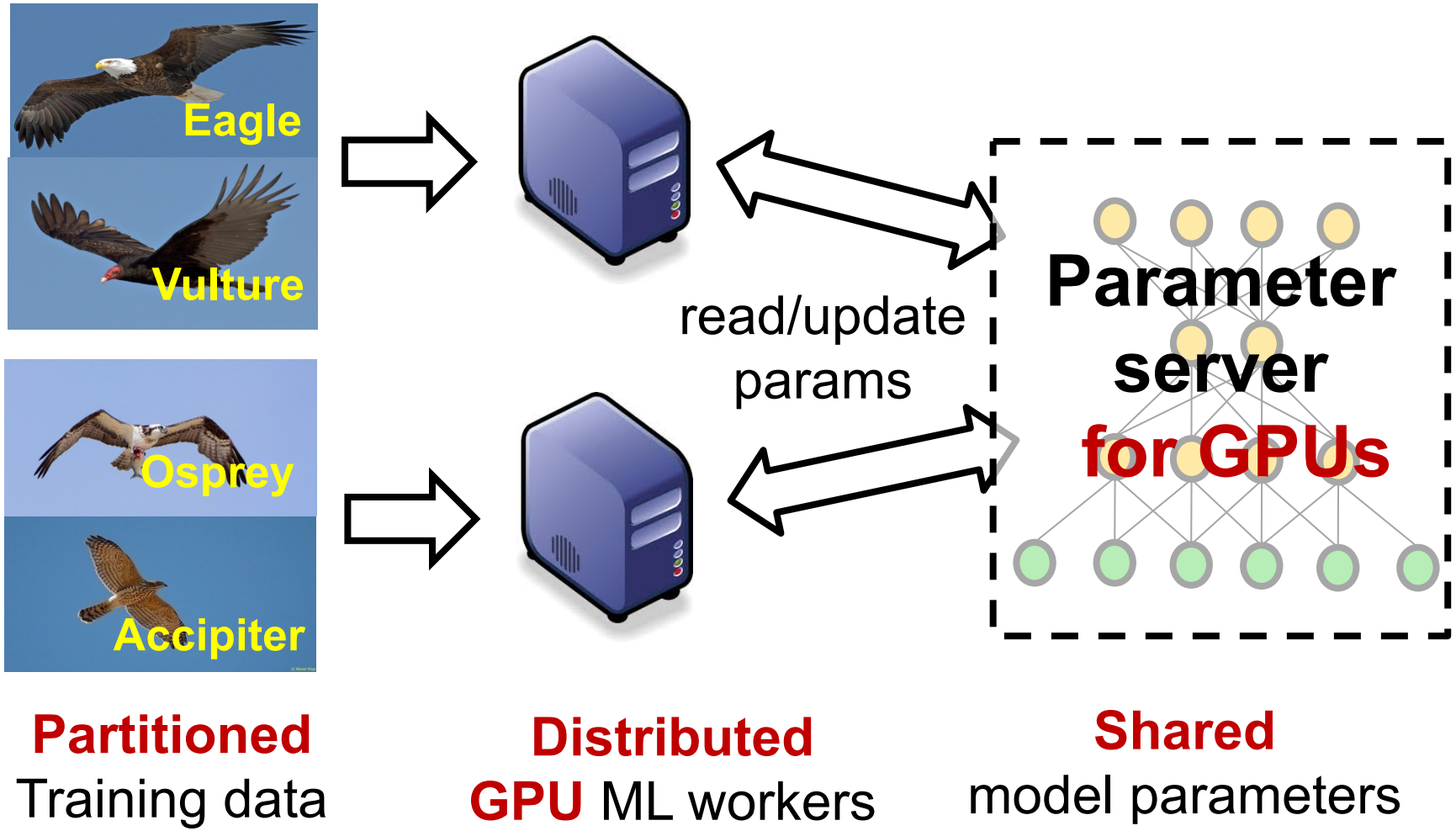


Partitioned
Training data

Distributed
ML workers

Shared
model parameters

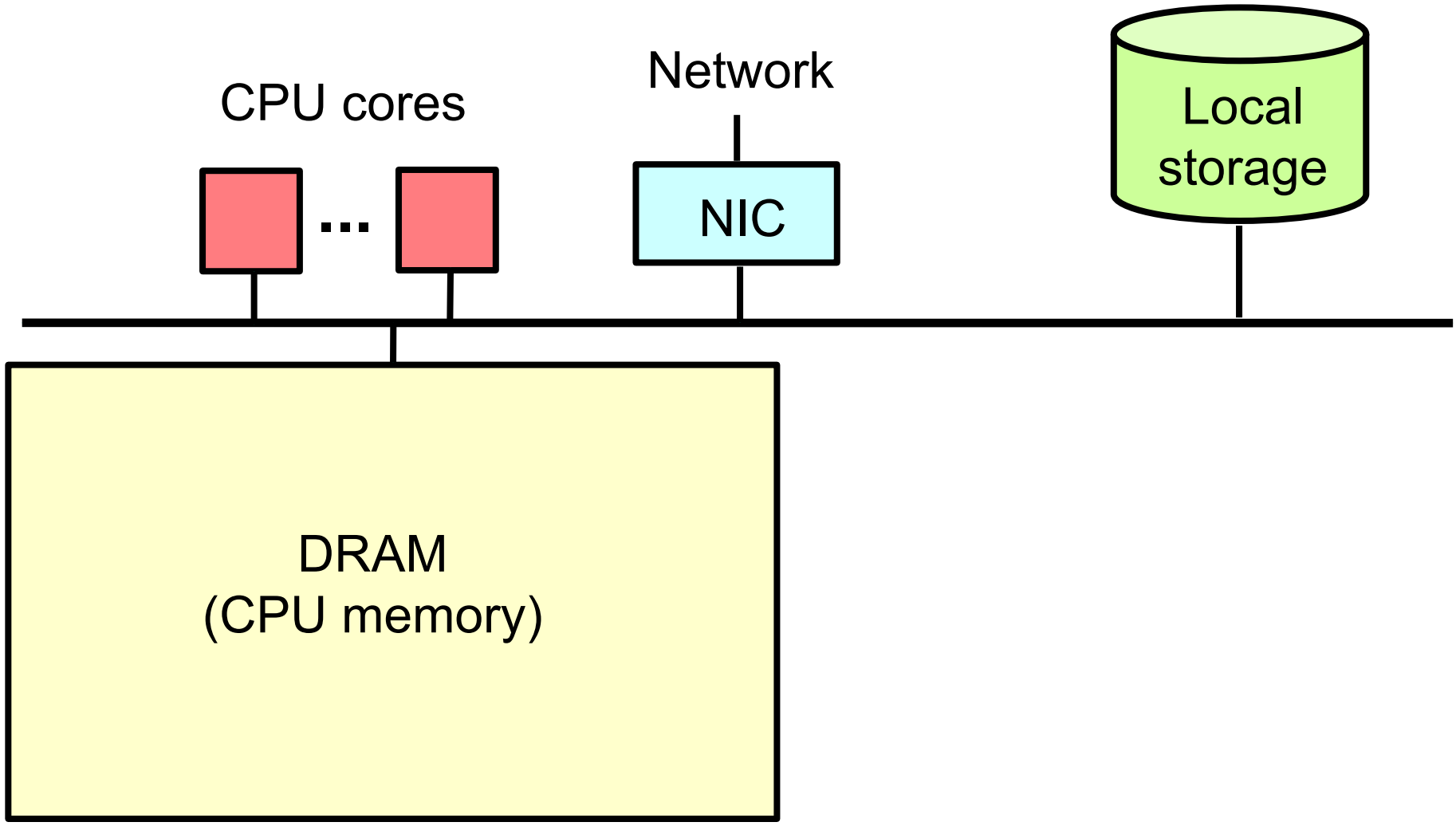
Distributed deep learning



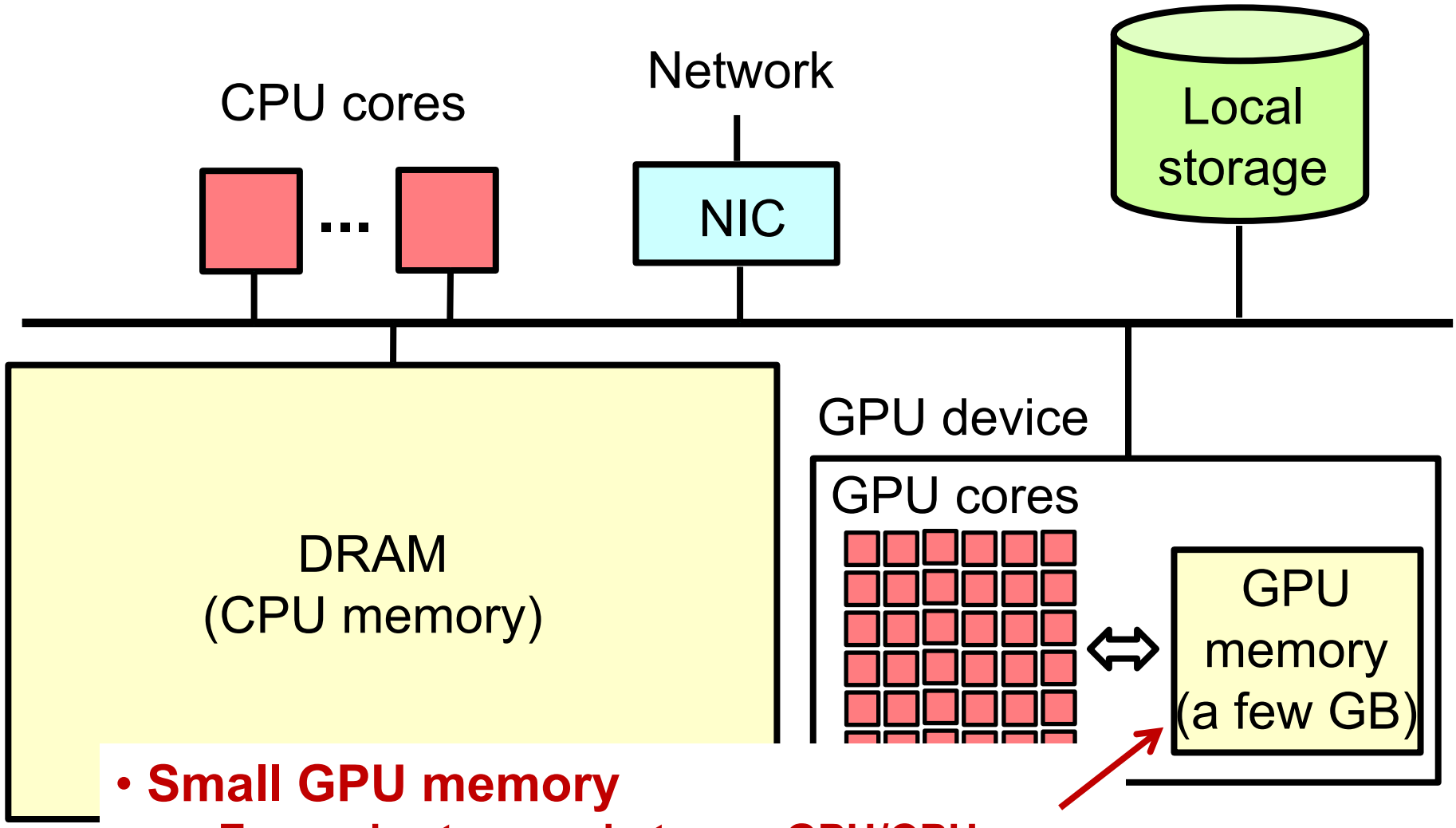
Outline

- Background
  - Deep learning with GPUs
  - Parallel ML using parameter servers
- GeePS: GPU-specialized parameter server
- Experiment results

A machine with no GPU

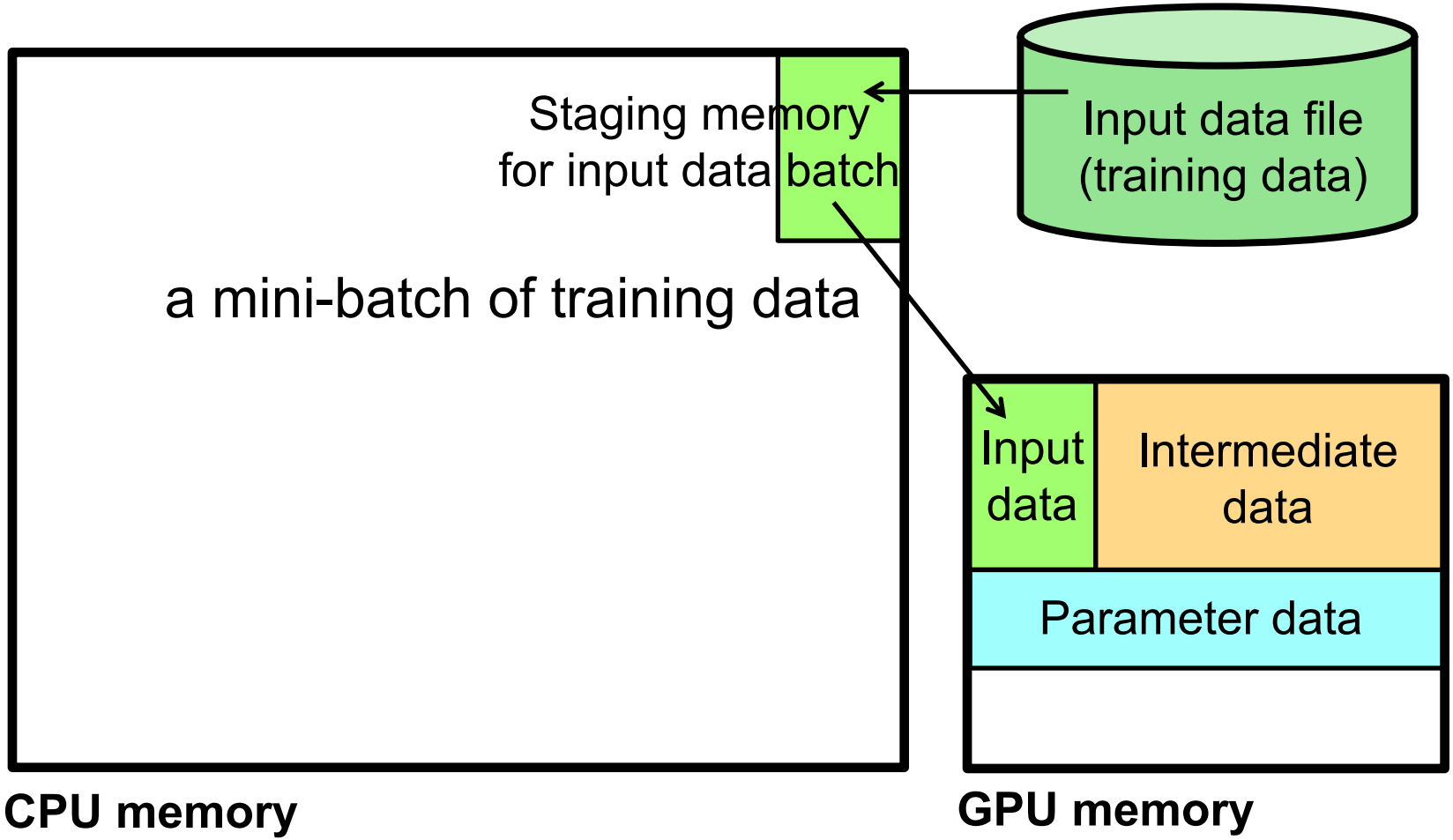


A machine with a GPU device

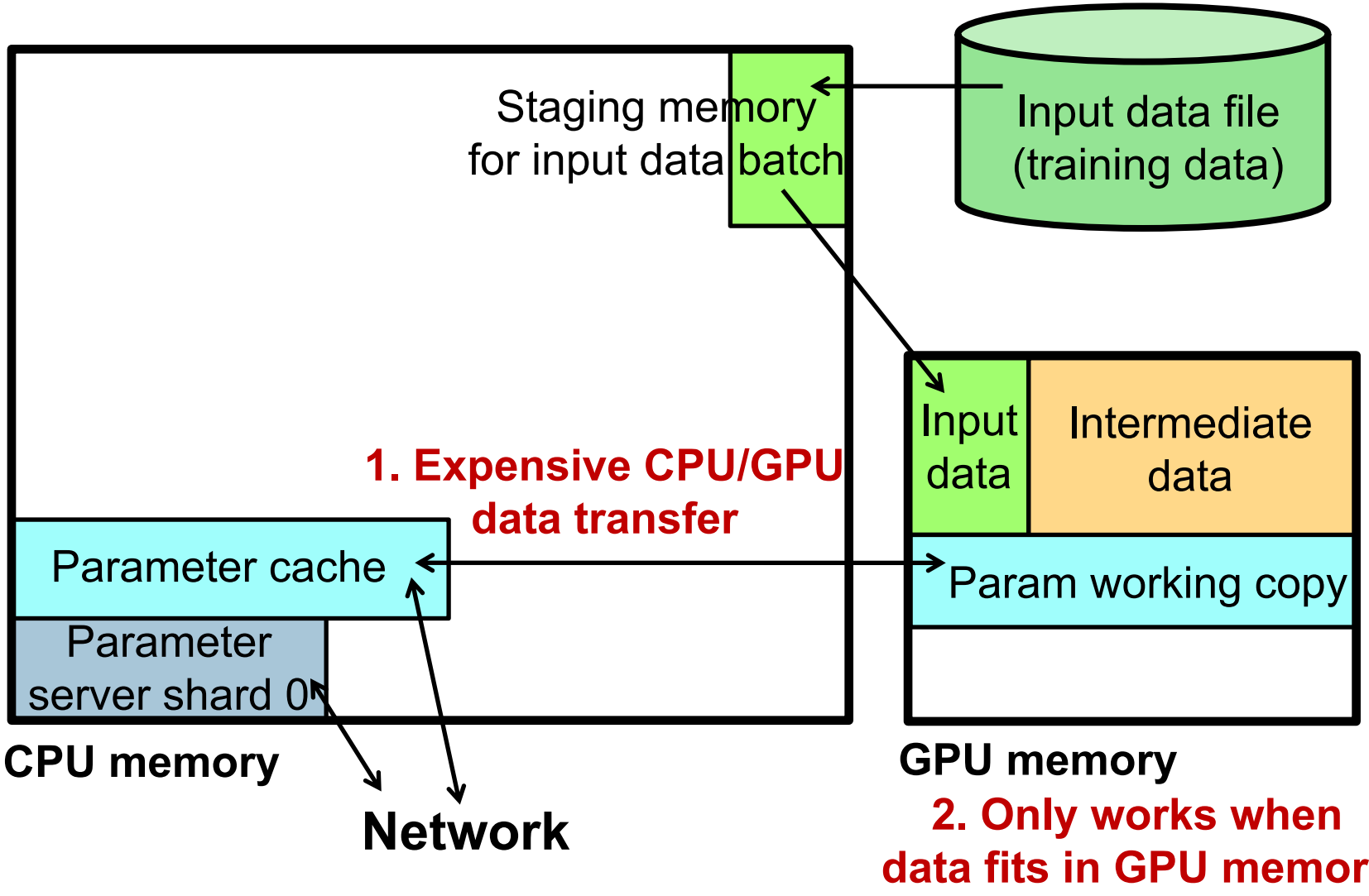


- **Small GPU memory**
  - **Expensive to copy between GPU/CPU mem**

Single GPU machine learning



Multi-GPU ML via CPU param. serv.



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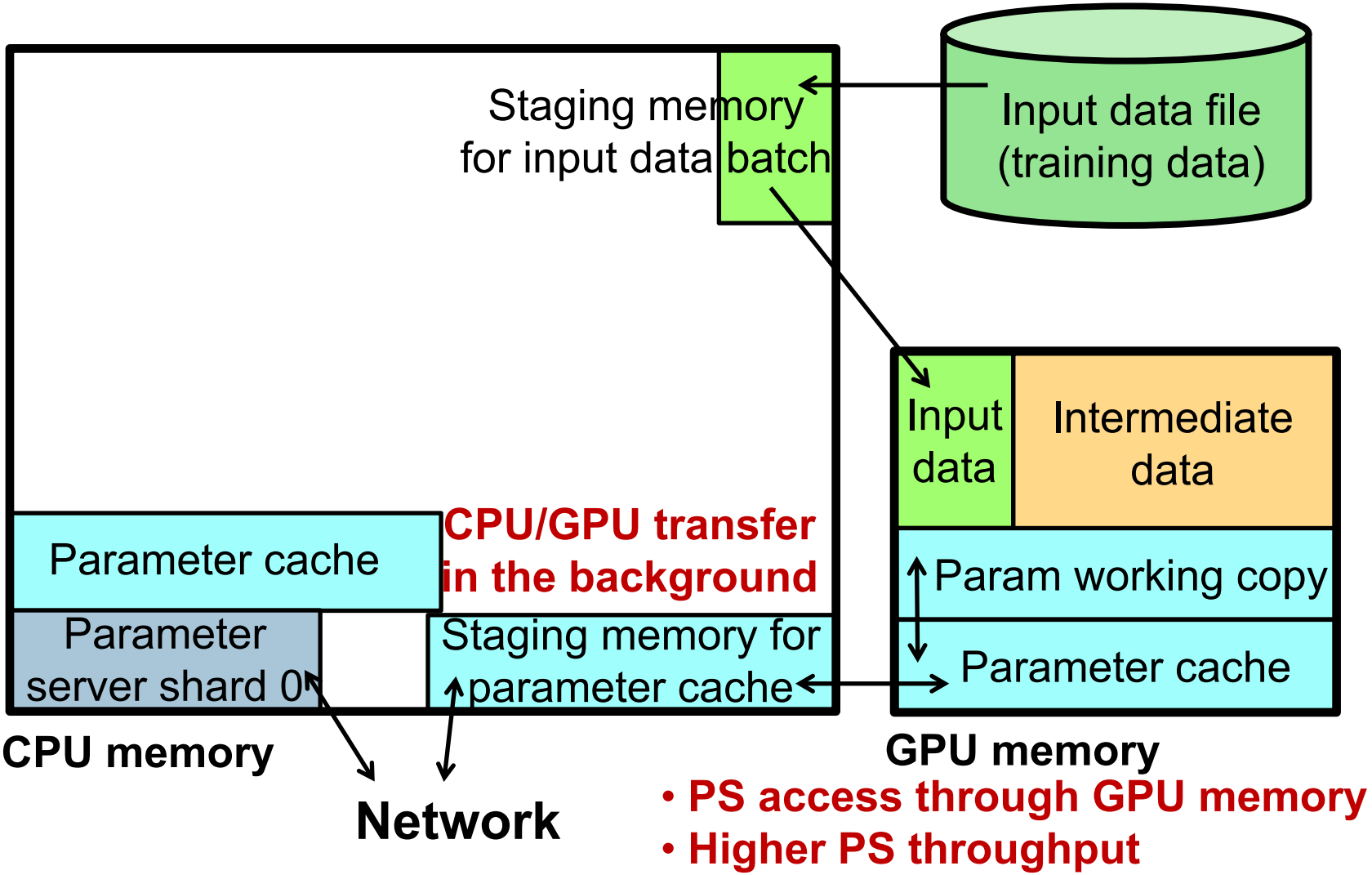
- Background
  - Deep learning with GPUs
  - Parallel ML using parameter servers

- GeePS: GPU-specialized parameter server
  - Maintaining the parameter cache in GPU memory
  - Batch access with GPU cores for higher throughput
  - Managing limited GPU device memory

- Experiment results

Multi-GPU ML via GeePS



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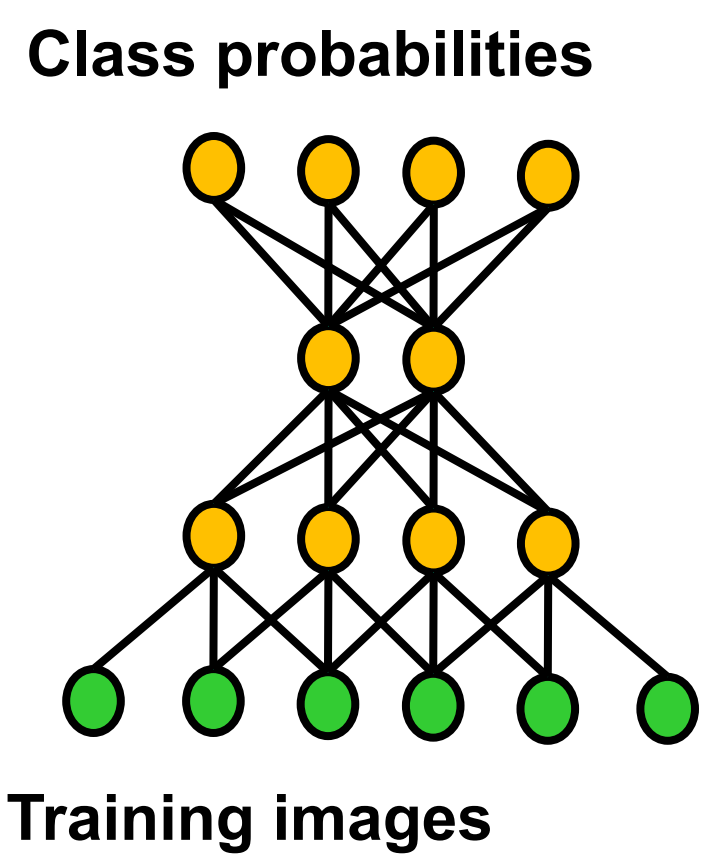
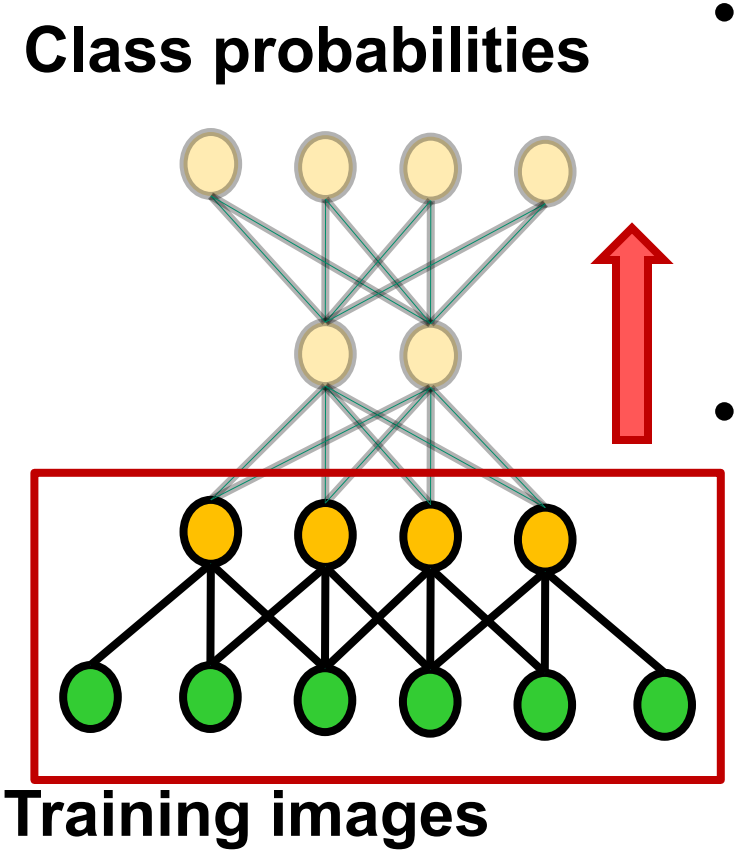
Layer-by-layer computation for DNN



- For each iteration (mini-batch)
  - A forward pass
  - Then a backward pass
- Each time only data of two layers are used

Layer-by-layer computation for DNN



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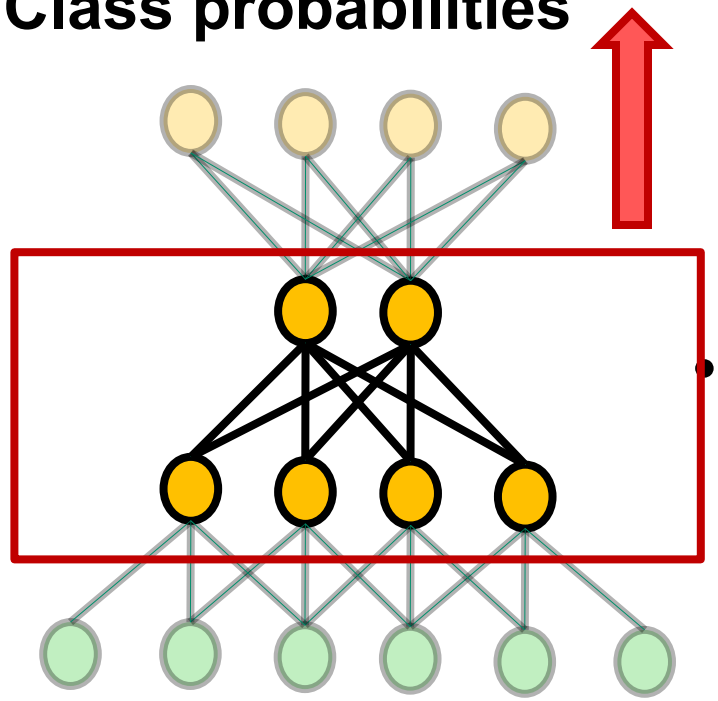

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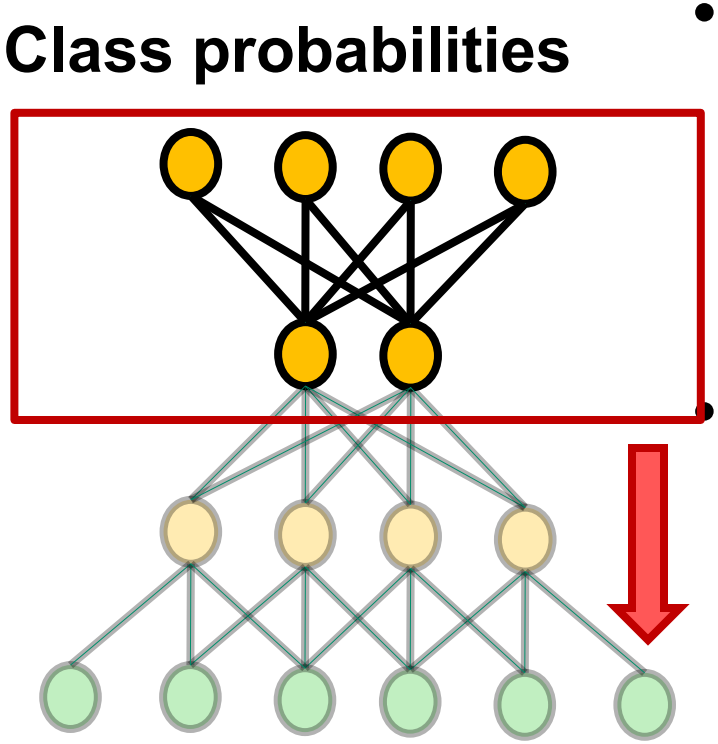

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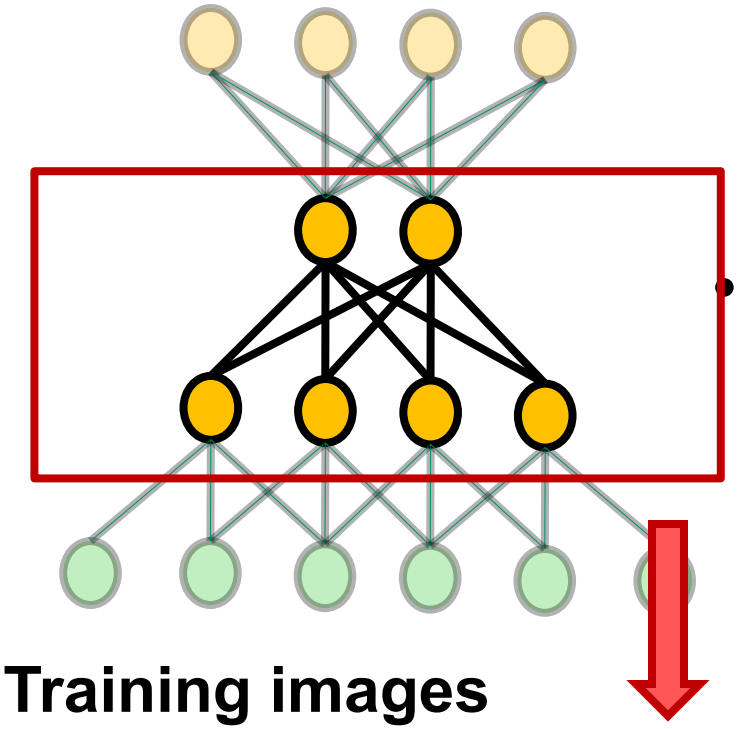

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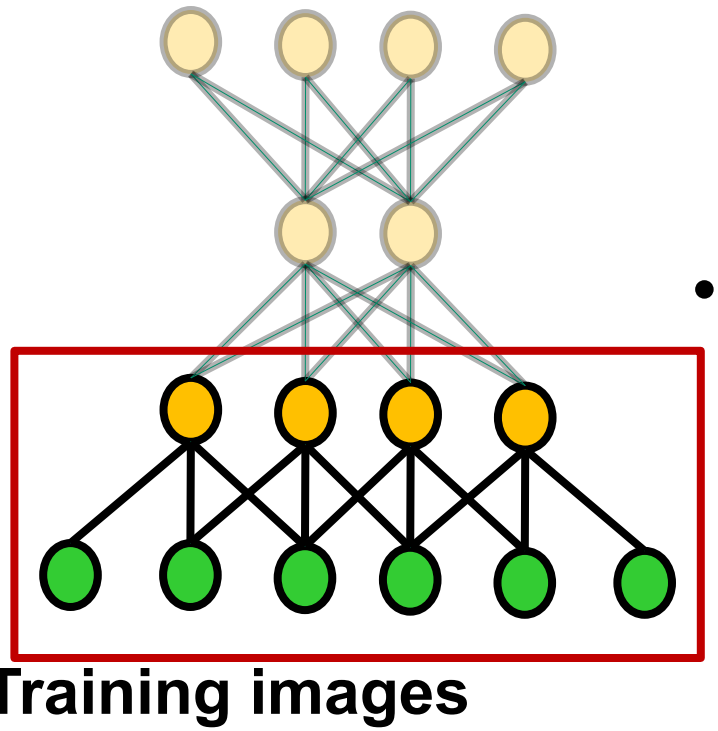
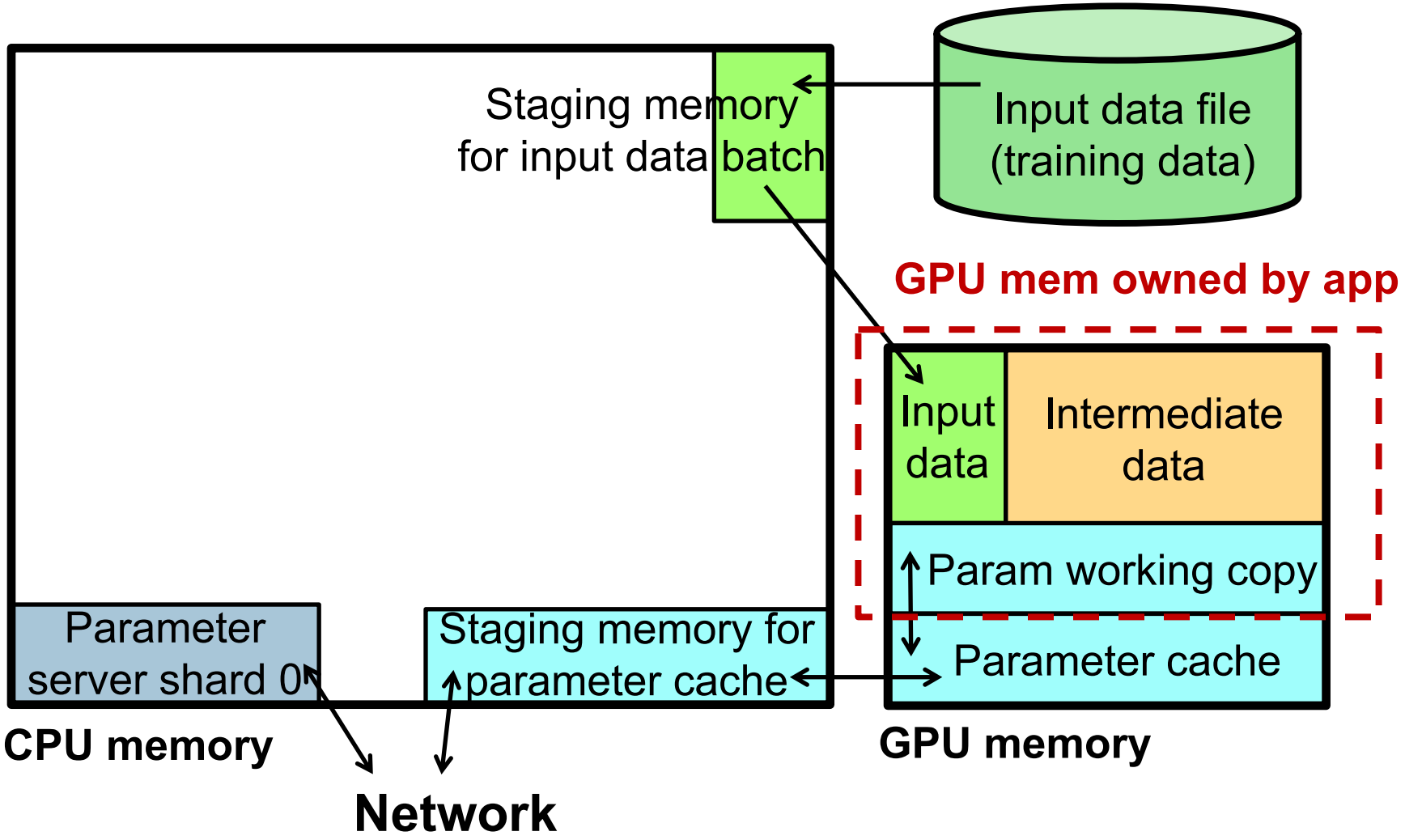
Layer-by-layer computation for DNN



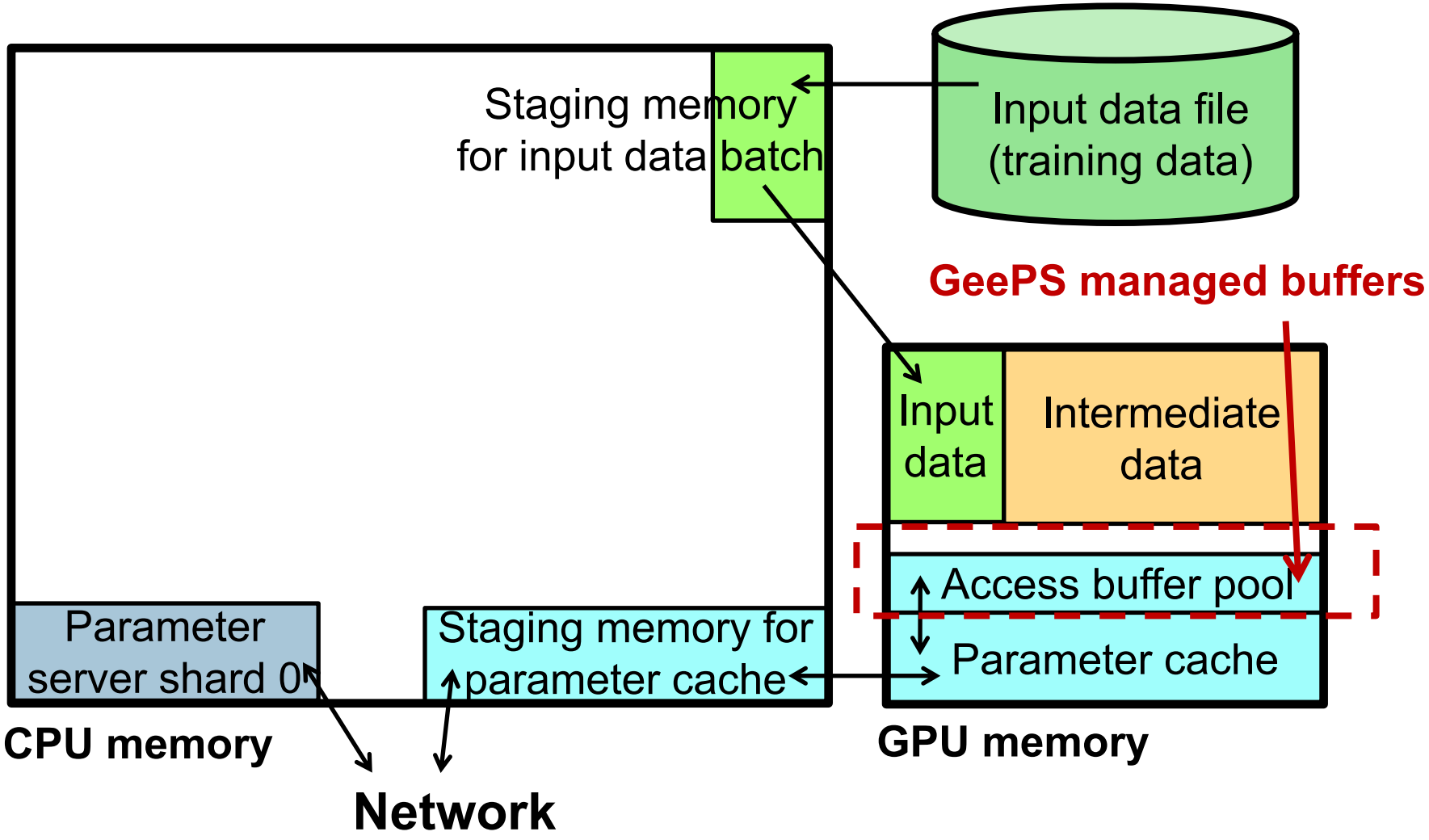
- For each iteration (mini-batch)
  - A forward pass
  - Then a backward pass
- Each time only data of two layers are used

- **Use GPU mem as a cache to keep actively used data**
- **Store the remaining in CPU mem**

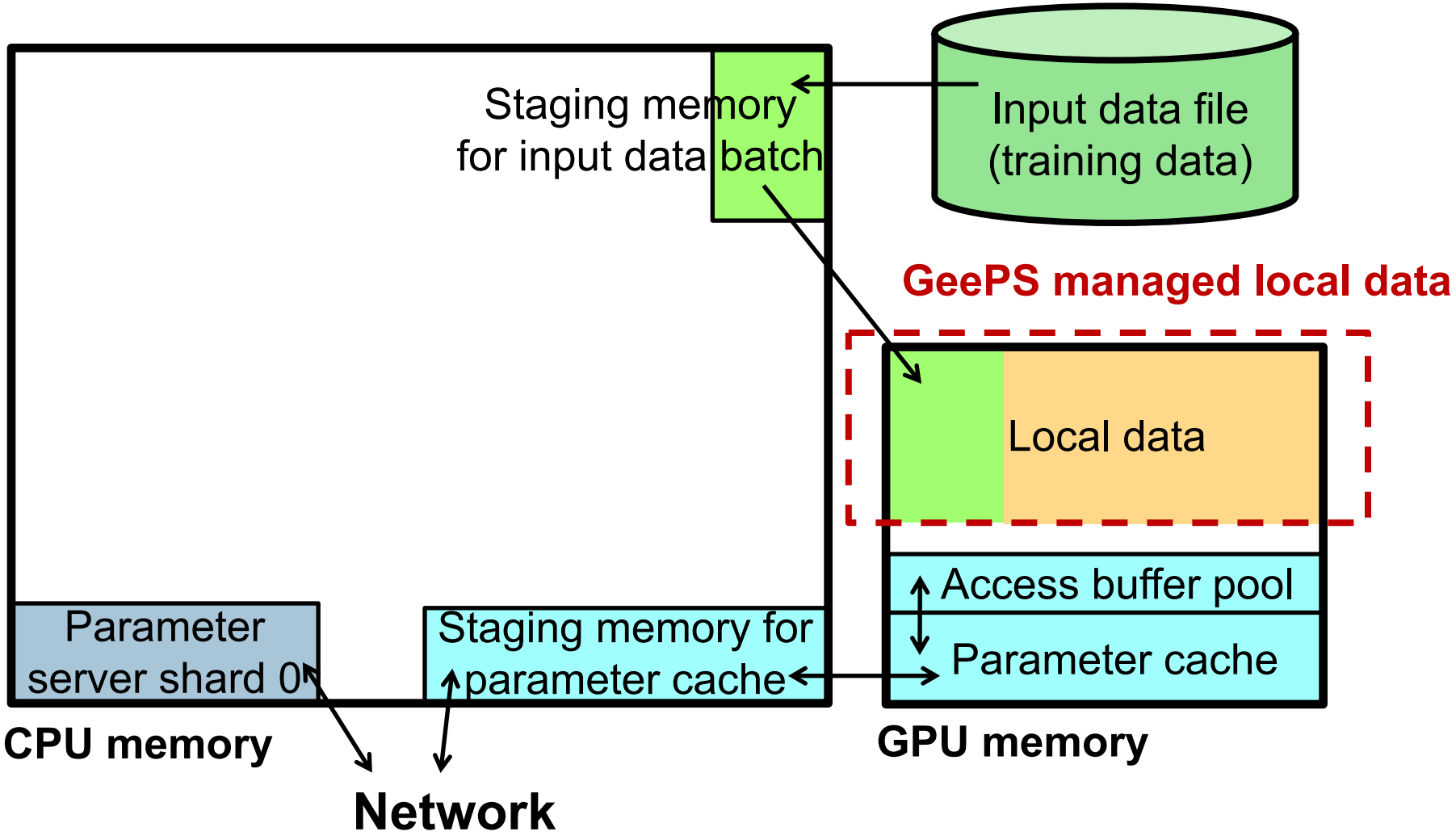
GPU memory management



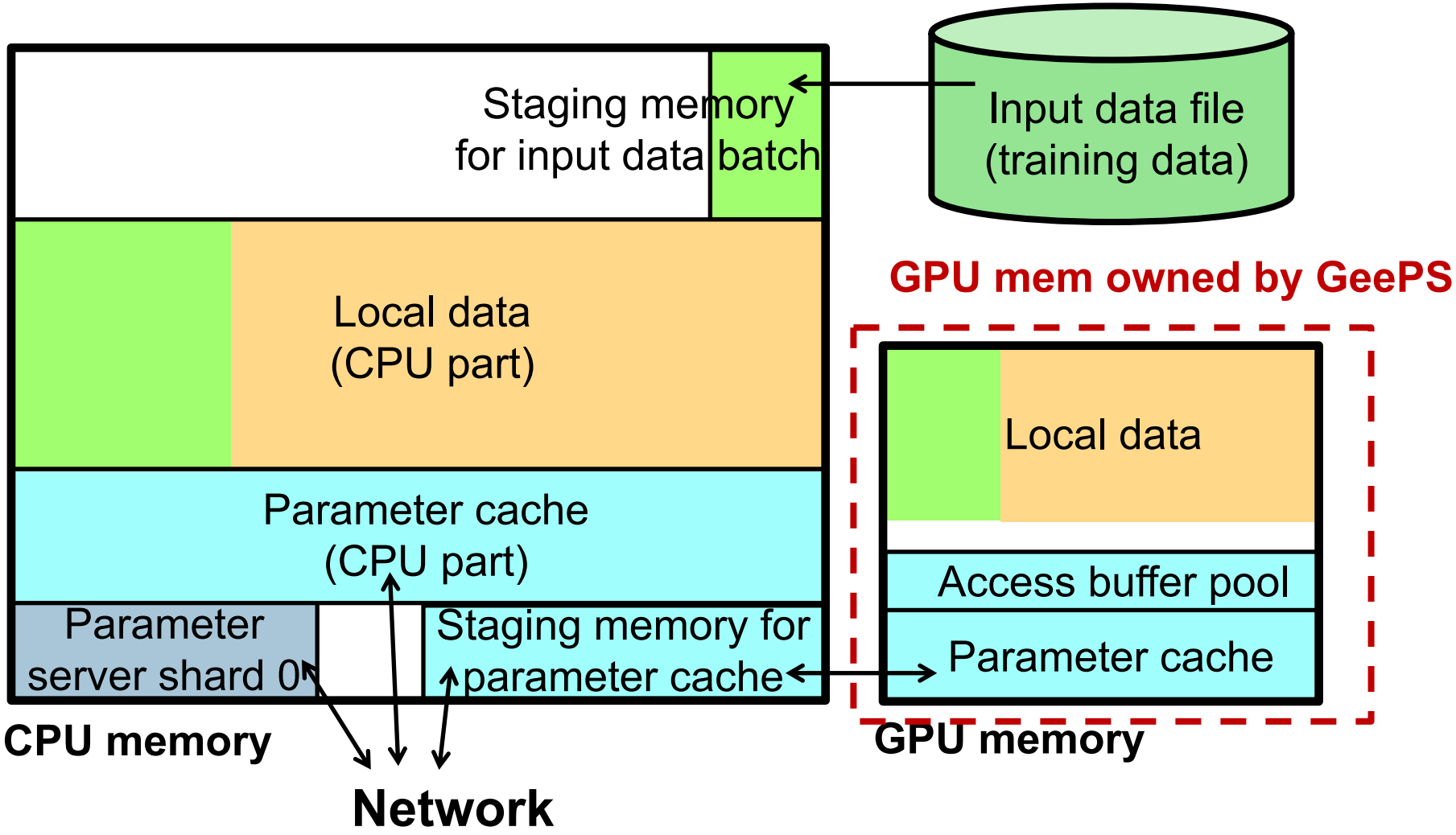
GeePS-managed buffers



GeePS manages local data also



Use CPU memory when not fit



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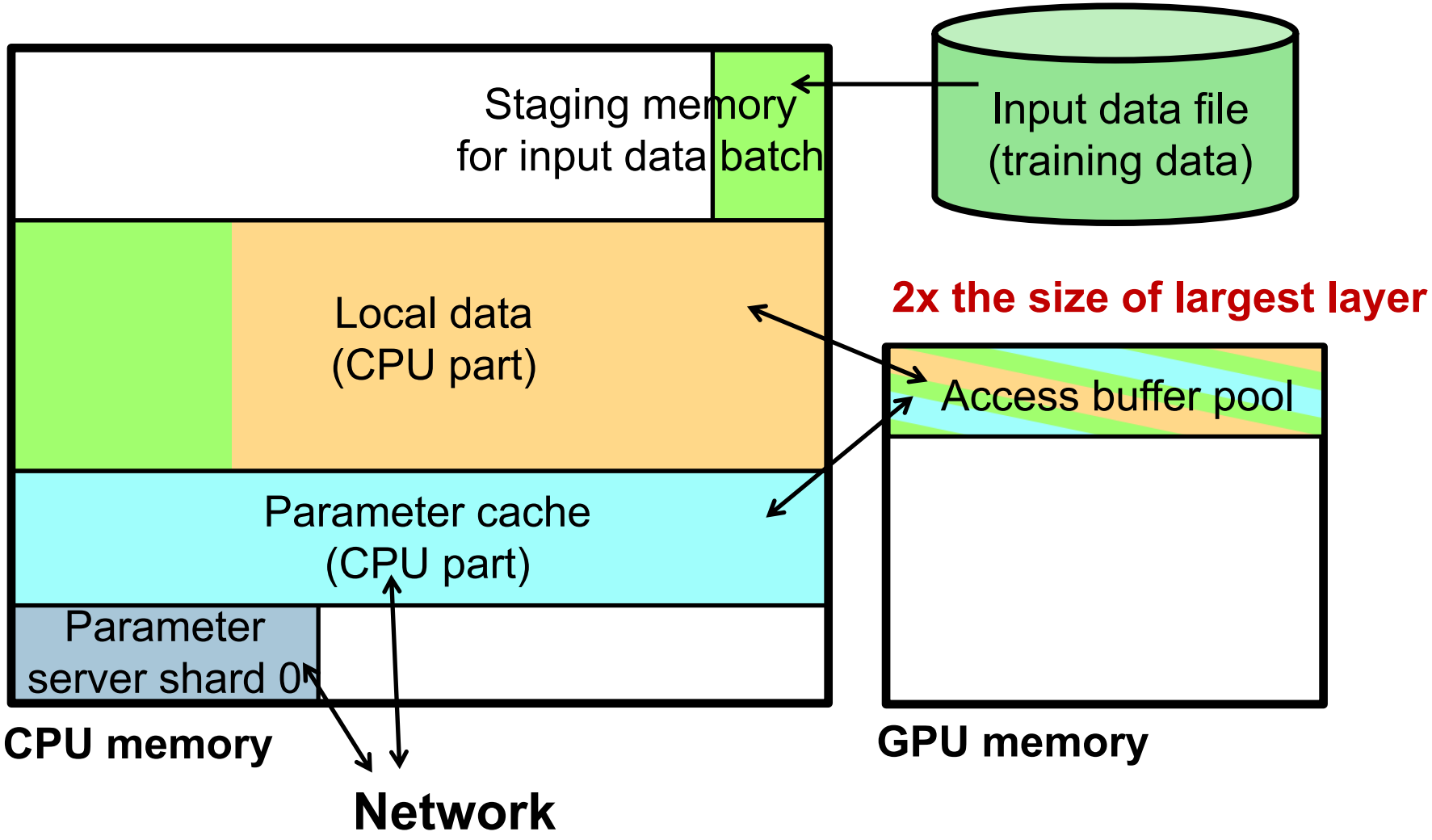

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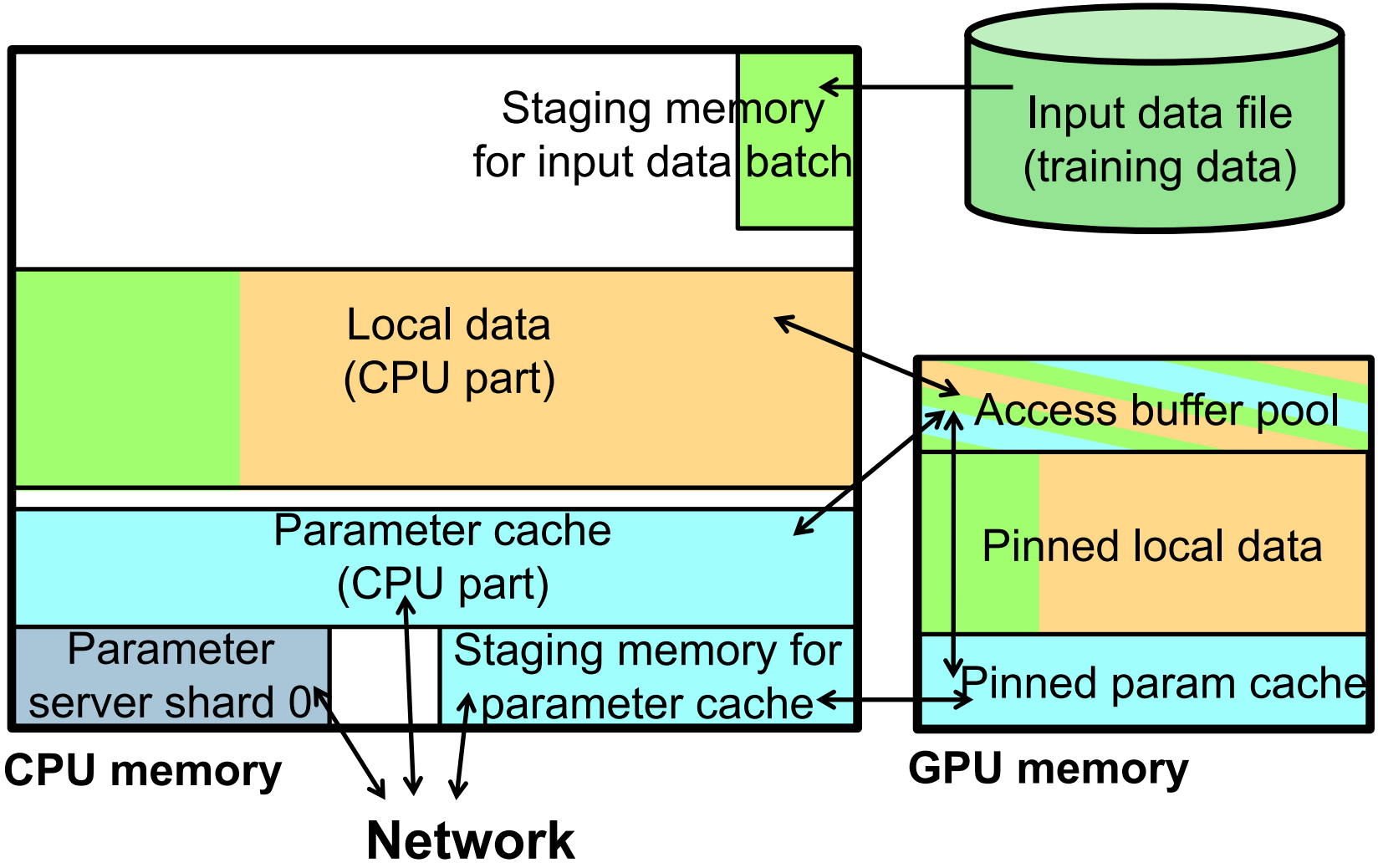

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  - Maintaining the parameter cache in GPU memory
  - Batch access with GPU cores for higher throughput
  - Managing limited GPU device memory
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Experimental setups

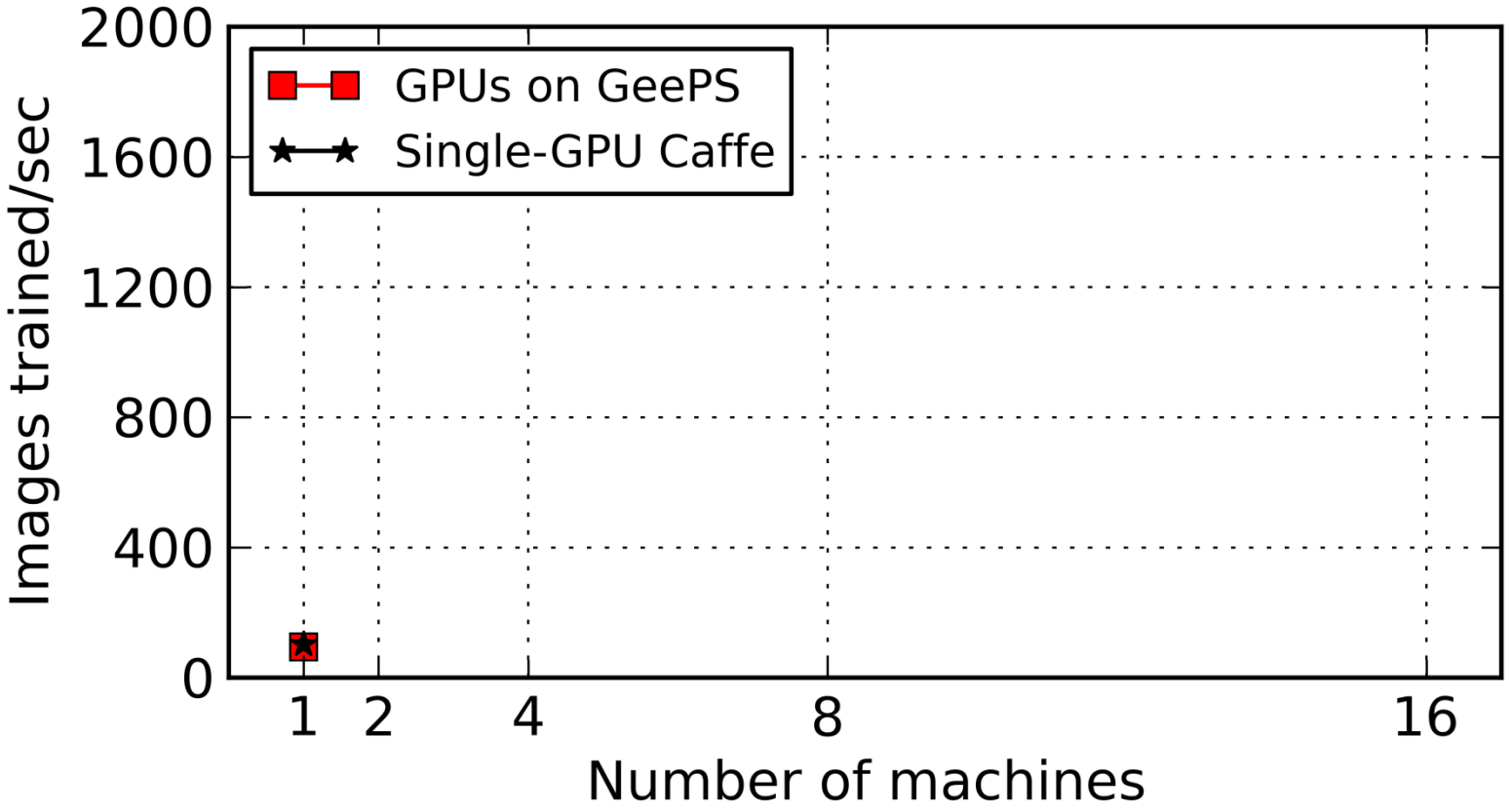
- Cluster information
  - Tesla K20C GPUs with 5 GB GPU memory
- Dataset and model
  - ImageNet: 7 million training images in 22,000 classes
  - Model: AlexNet
    - 25 layers, 2.4 billion conns
    - total memory consumption 4.5 GB

System setups

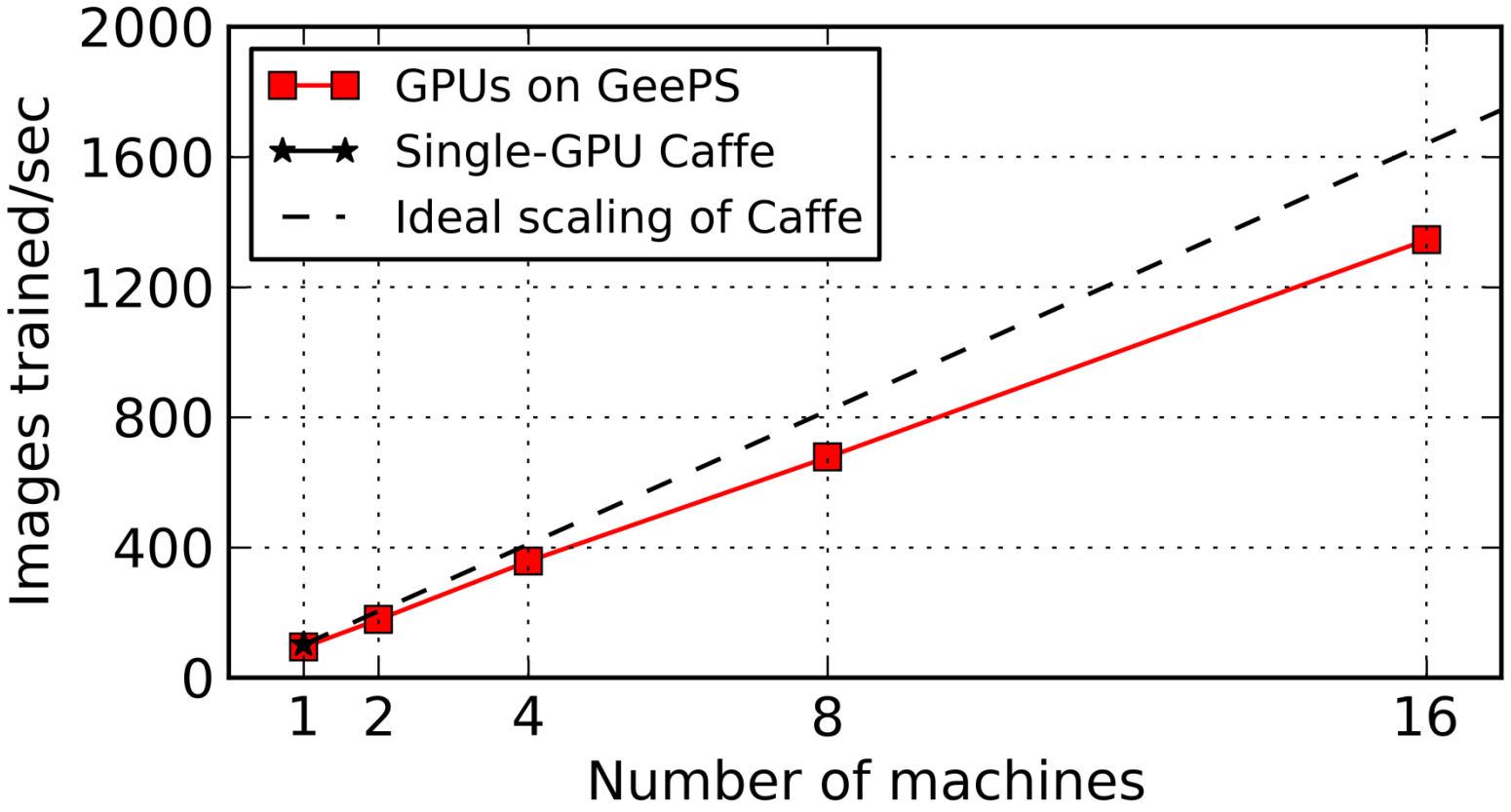
- GeePS-Caffe setups
  - Caffe: single-machine GPU deep learning system
  - GeePS-Caffe: Caffe linked with GeePS

- Baselines
  - The original unmodified Caffe
  - Caffe linked with CPU-based PS (IterStore [Cui SoCC'14])

Training throughput

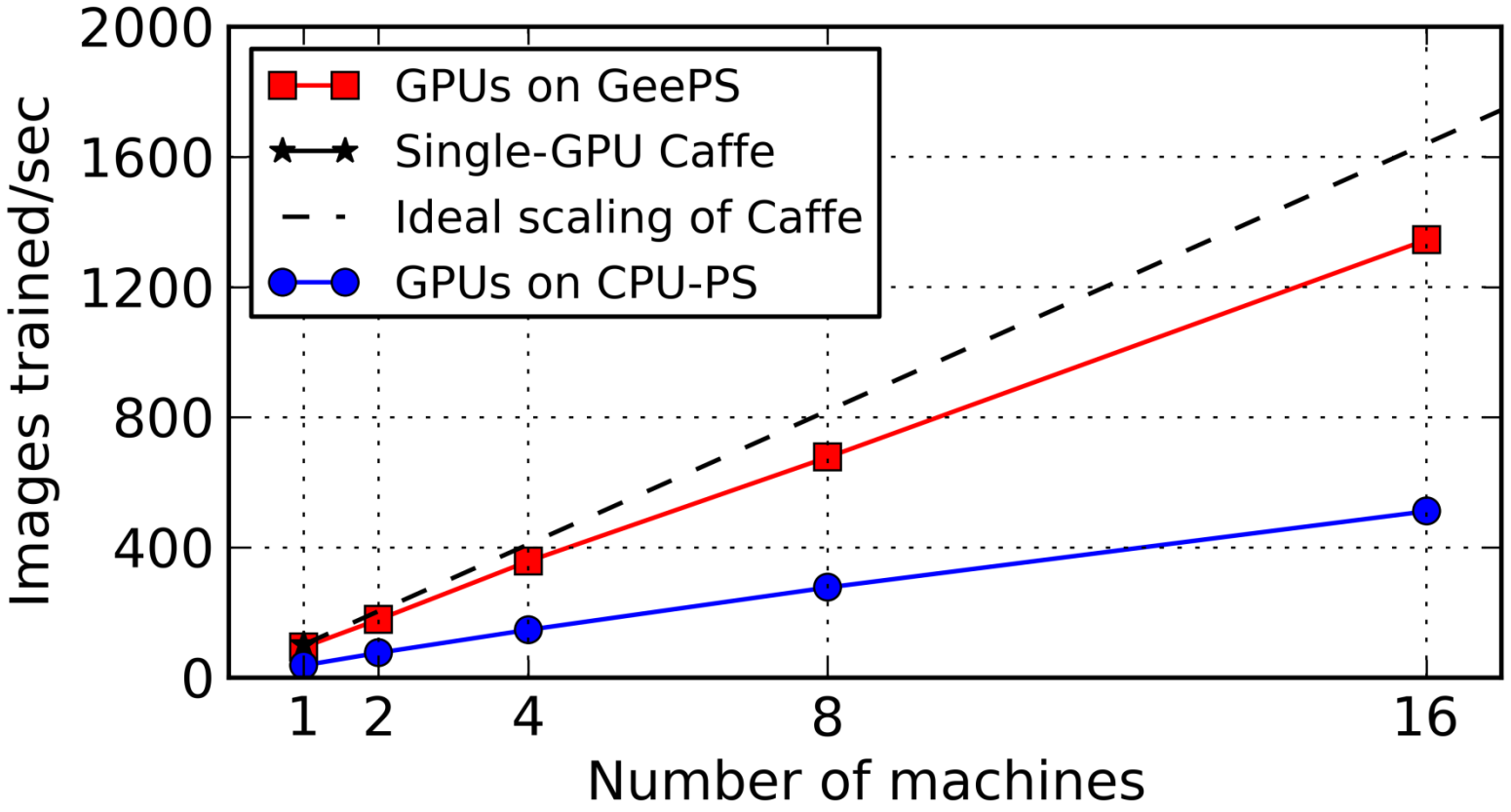


Training throughput



- **GeePS scales close to linear with more machines**
  - **with 16 machines, it runs 13x faster than Caffe**
  - **only 8% GPU stall time**

Training throughput



- **GeePS is much faster than CPU-based PS**
  - **2.6x higher throughput**
  - **reduces GPU stall time from 65% to 8%**

More results in the paper

- Good scalability and convergence speed for
  - GoogLeNet network
  - RNN network for video classification

- Handle problems larger than GPU memory
  - Only 27% reduction in throughput with 35% memory
    - 3x bigger problems with little overhead
  - Handle models as large as 20 GB
  - Support 4x longer videos for video classification

Conclusion

- GPU-specialized parameter server for GPU ML
  - 13x throughput speedup using 16 machines
  - 2x faster compared to CPU-based PS

- Managing limited GPU memory
  - By managing GPU memory inside GeePS as a cache
  - Efficiently handle problems larger than GPU memory

→ Enable use of data-parallel PS model

References

- **[IterStore]** H. Cui, A. Tumanov, J. Wei, L. Xu, W. Dai, J. Haber-Kucharsky, Q. Ho, G. R. Ganger, P. B. Gibbons, G. A. Gibson, and E. P. Xing. Exploiting iterative-ness for parallel ML computations. In ACM SoCC, 2014.
- **[Caffe]** Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. arXiv preprint arXiv:1408.5093, 2014.
- **[ImageNet]** J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In IEEE CVPR, 2009.
- **[ProjectAdam]** T. Chilimbi, Y. Suzue, J. Apacible, and K. Kalyanaraman. Project Adam: Building an efficient and scalable deep learning training system. In USENIX OSDI, 2014.

Additional related work

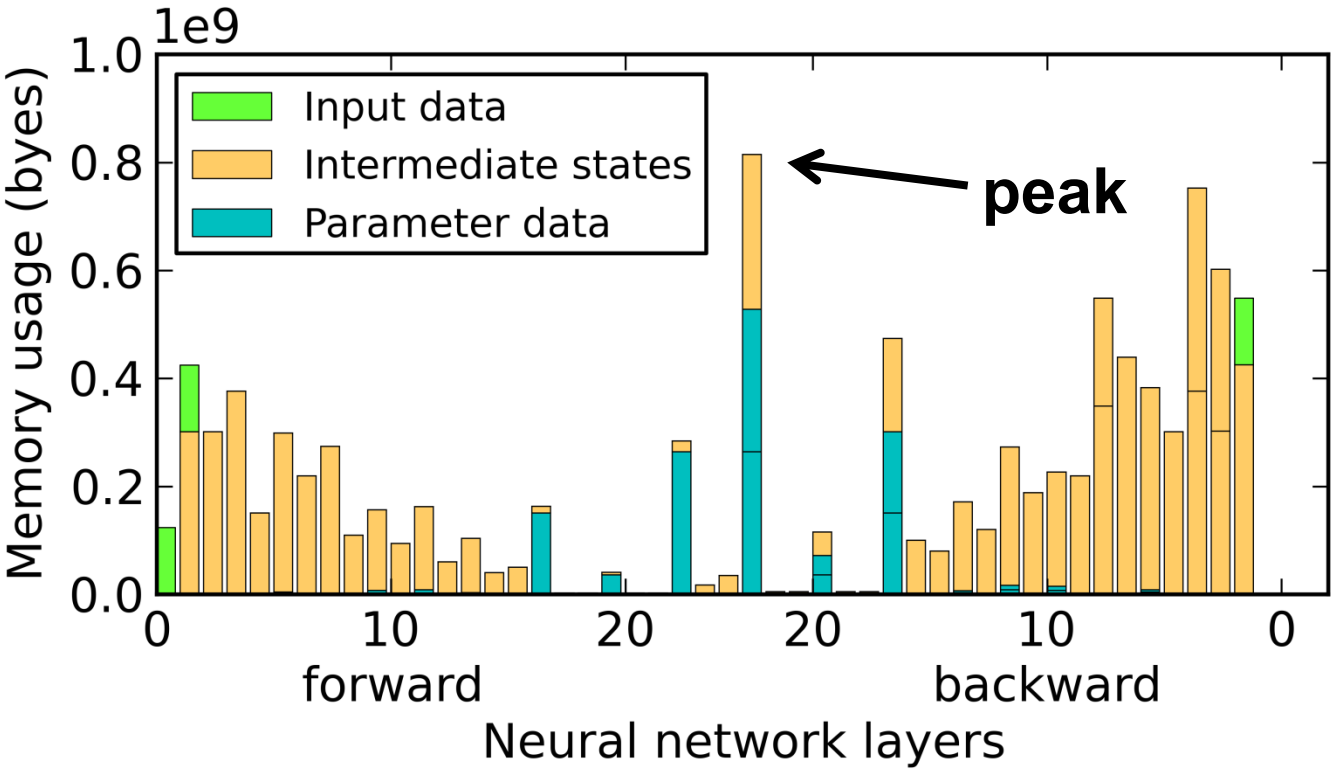
- T. Chen, et al. MXNet: A flexible and efficient machine learning library for heterogeneous distributed systems. arXiv preprint arXiv:1512.01274, 2015.
- H. Zhang, et al. Poseidon: A system architecture for efficient GPU-based deep learning on multiple machines. arXiv preprint arXiv:1512.06216, 2015.
- A. Krizhevsky, I. Sutskever, and G. E. Hinton. ImageNet classification with deep convolutional neural networks. In NIPS, 2012.
- J. Dean, et al. Large scale distributed deep networks. In NIPS, 2012.
- C. Szegedy, et al. Going deeper with convolutions. arXiv preprint arXiv:1409.4842, 2014.
- R. Wu, S. Yan, Y. Shan, Q. Dang, and G. Sun. Deep image: Scaling up image recognition. arXiv preprint arXiv:1501.02876, 2015.
- A. Coates, B. Huval, T.Wang, D.Wu, B. Catanzaro, and N. Andrew. Deep learning with COTS HPC systems. In ICML, 2013.

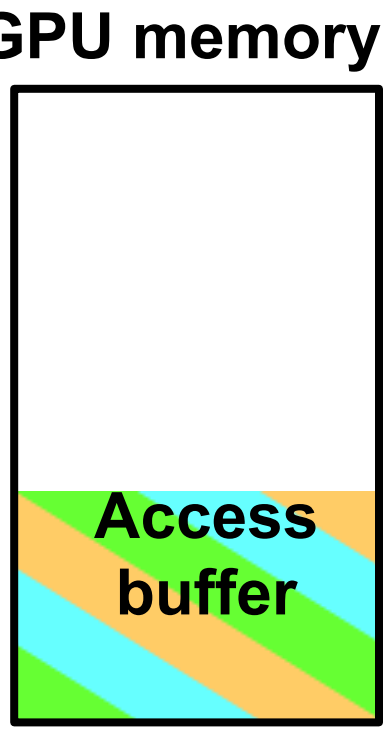
Backup Slides

Interface to GeePS-managed buffer

- Read
  - Buffer “allocated” by GeePS
  - Data copied to buffer
- PostRead
  - Buffer reclaimed
- PreUpdate
  - Buffer “allocated” by GeePS
- Update
  - Updates applied to data
  - Buffer reclaimed

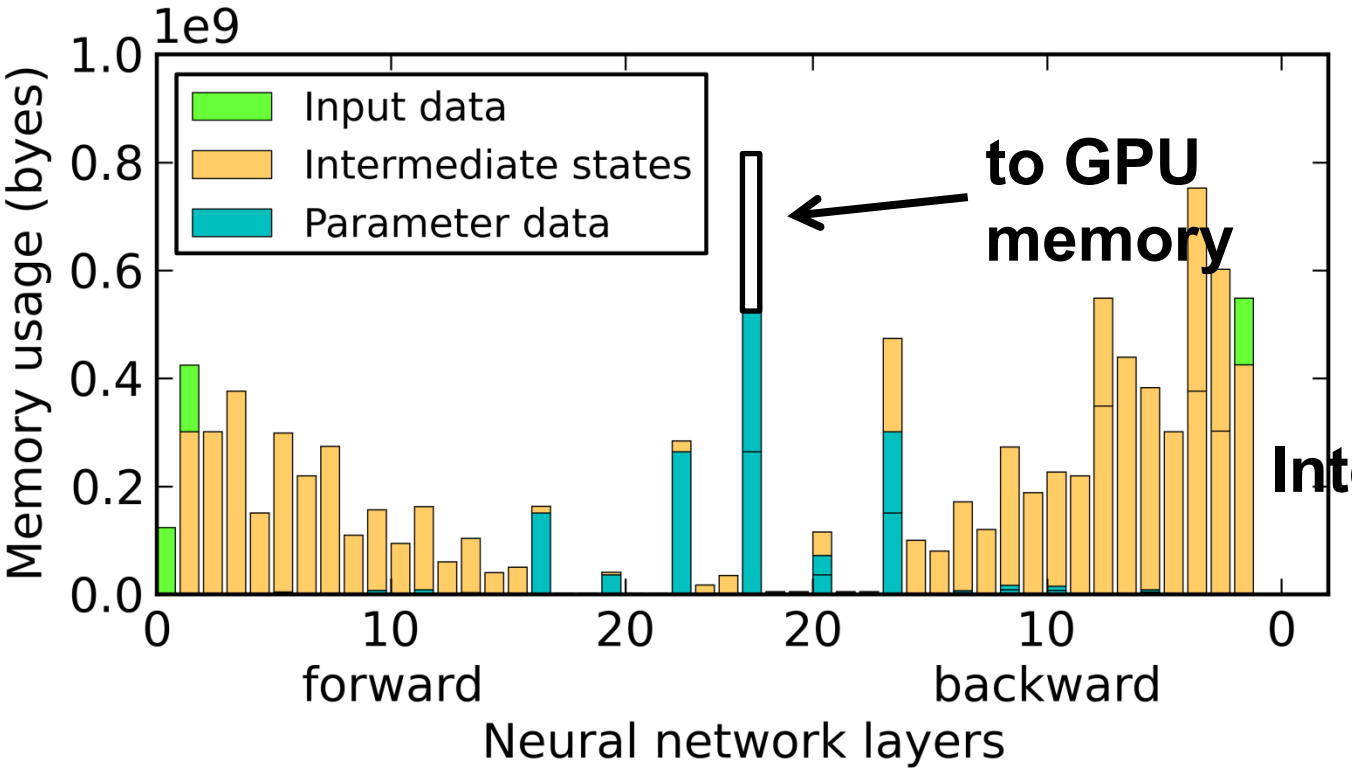
Data placement policy

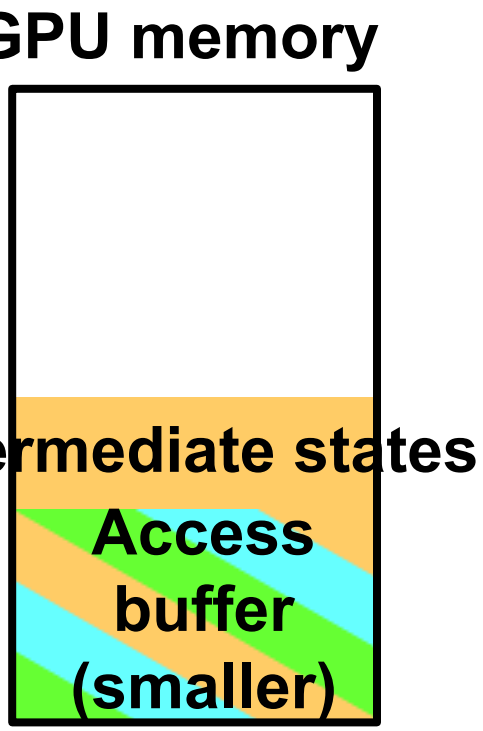




- **Pin as much local data as can in GPU memory**
  - **Select local data that causes peak usage**

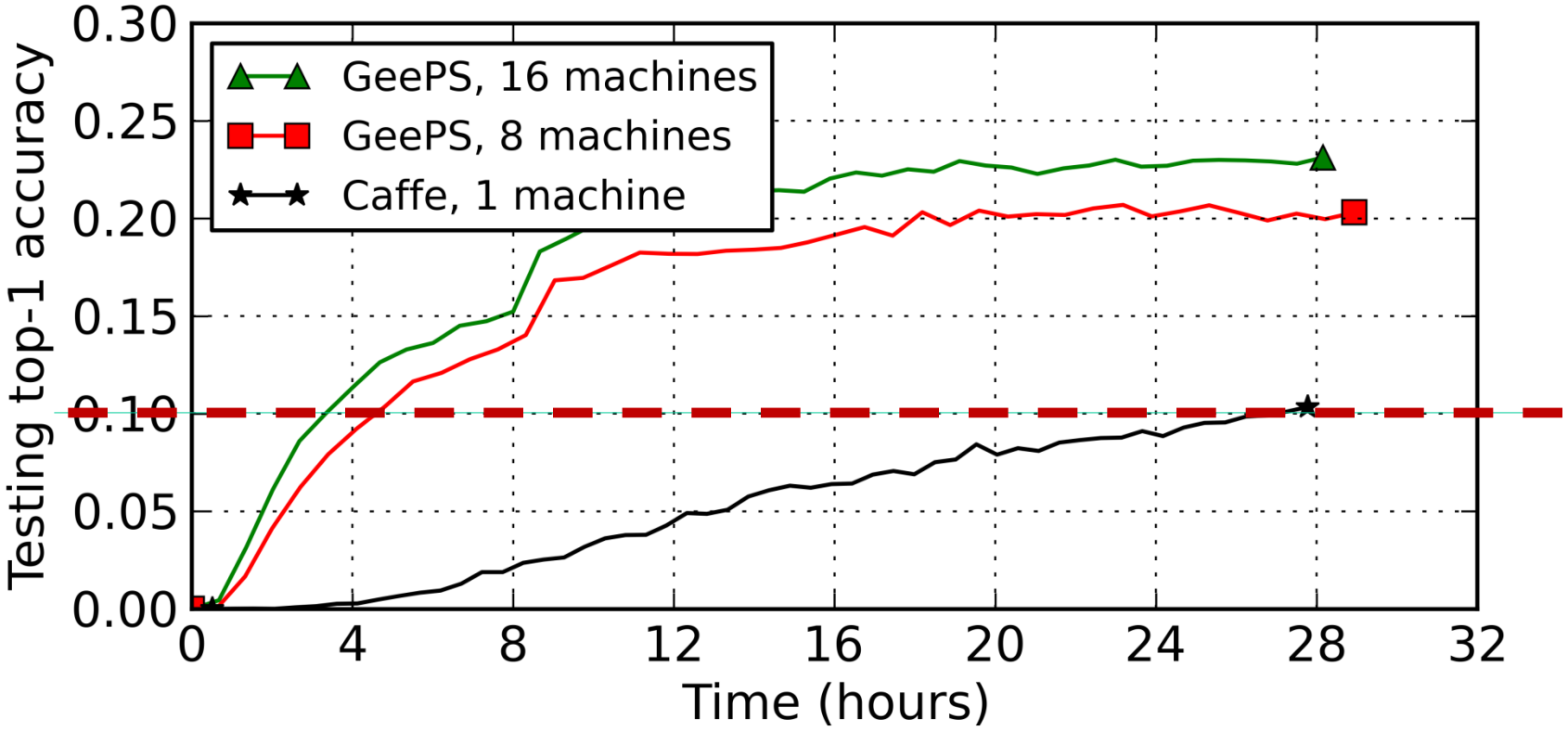
Data placement policy





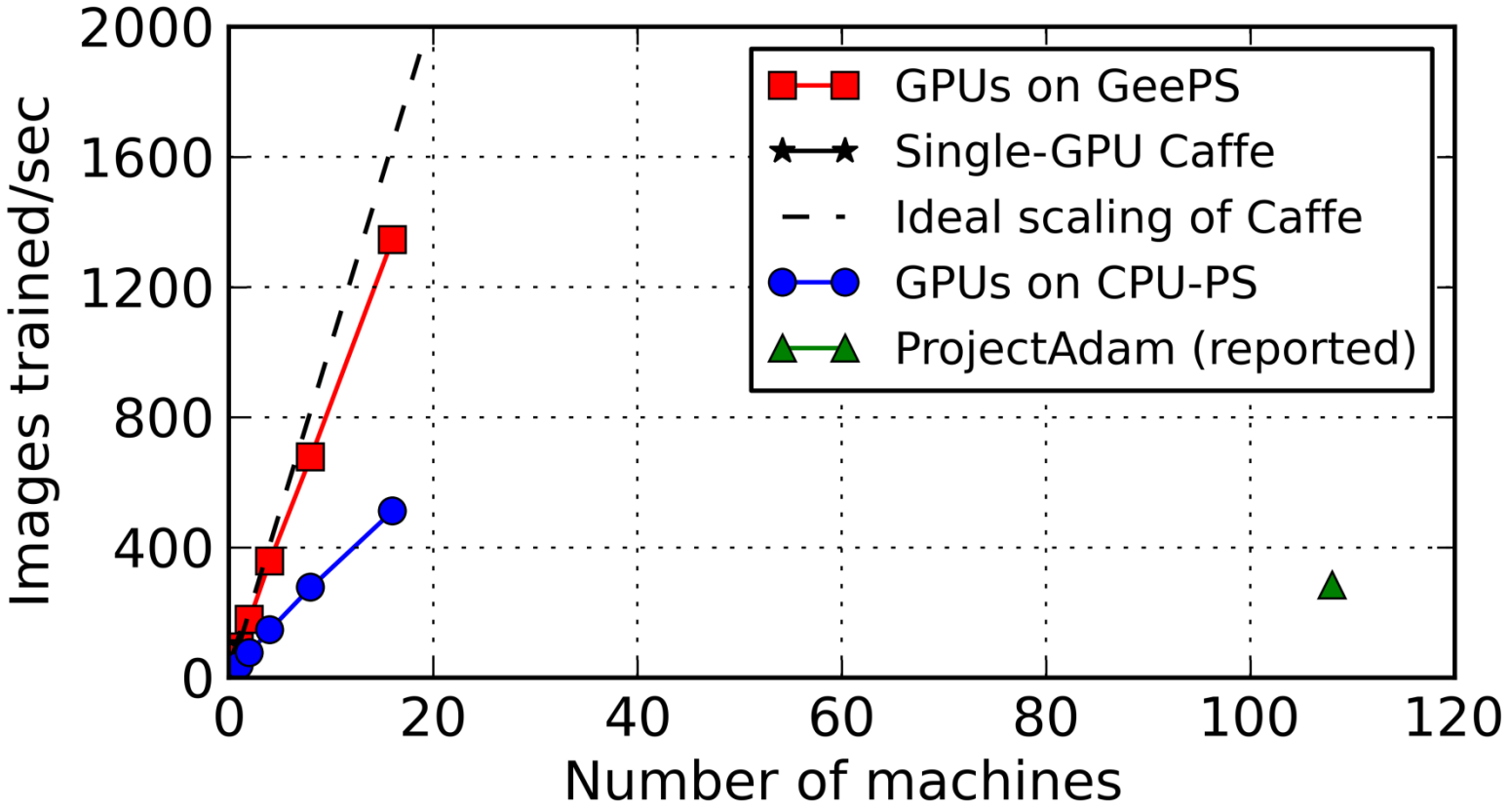
Pin as much local data as can in GPU memory
Select local data that causes peak usage

Image classification accuracy

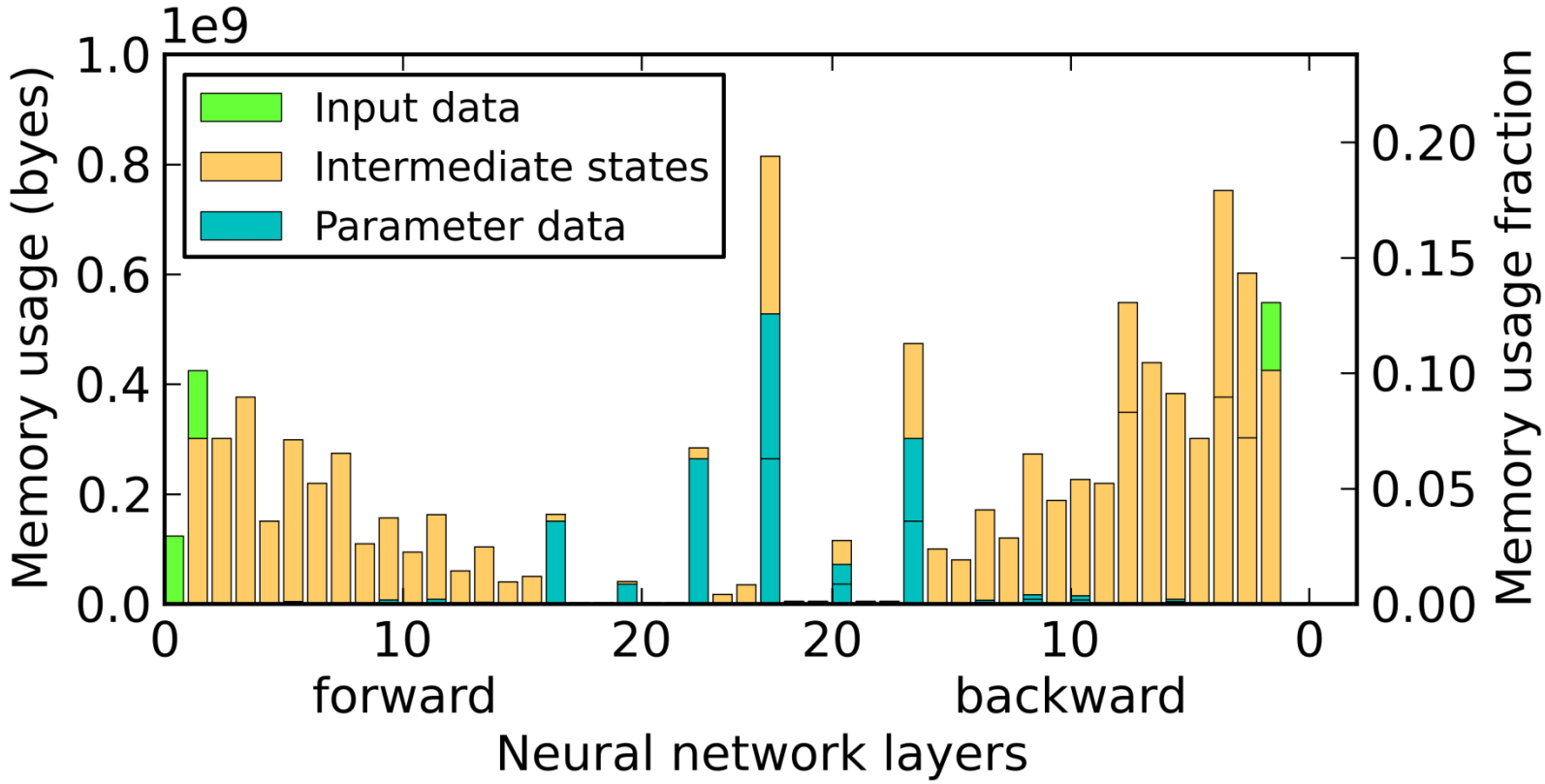


- **To reach 10% classification accuracy:**
  - **6x faster with 8 machines**
  - **8x faster with 16 machines**

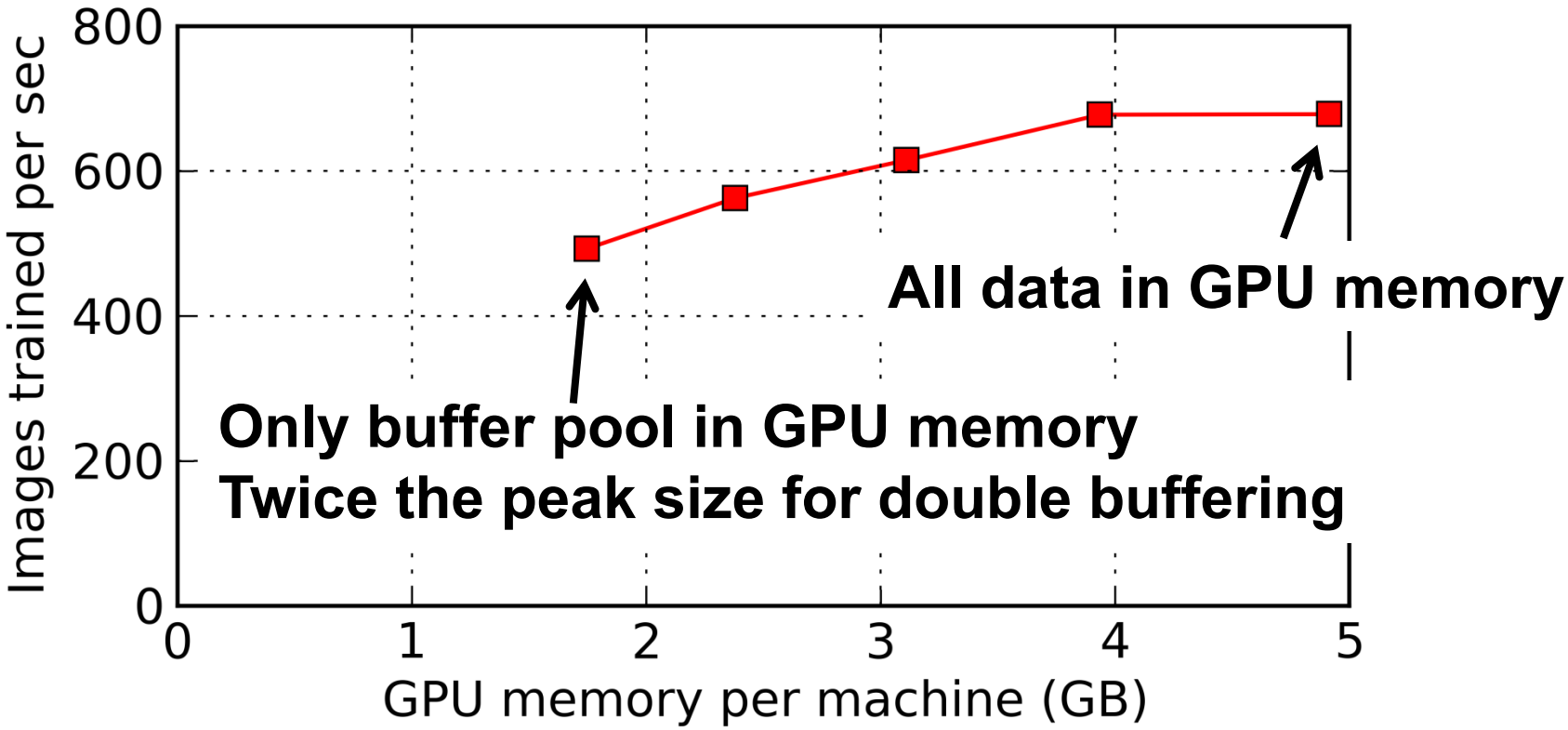
Training throughput (more)



Per-layer memory usage

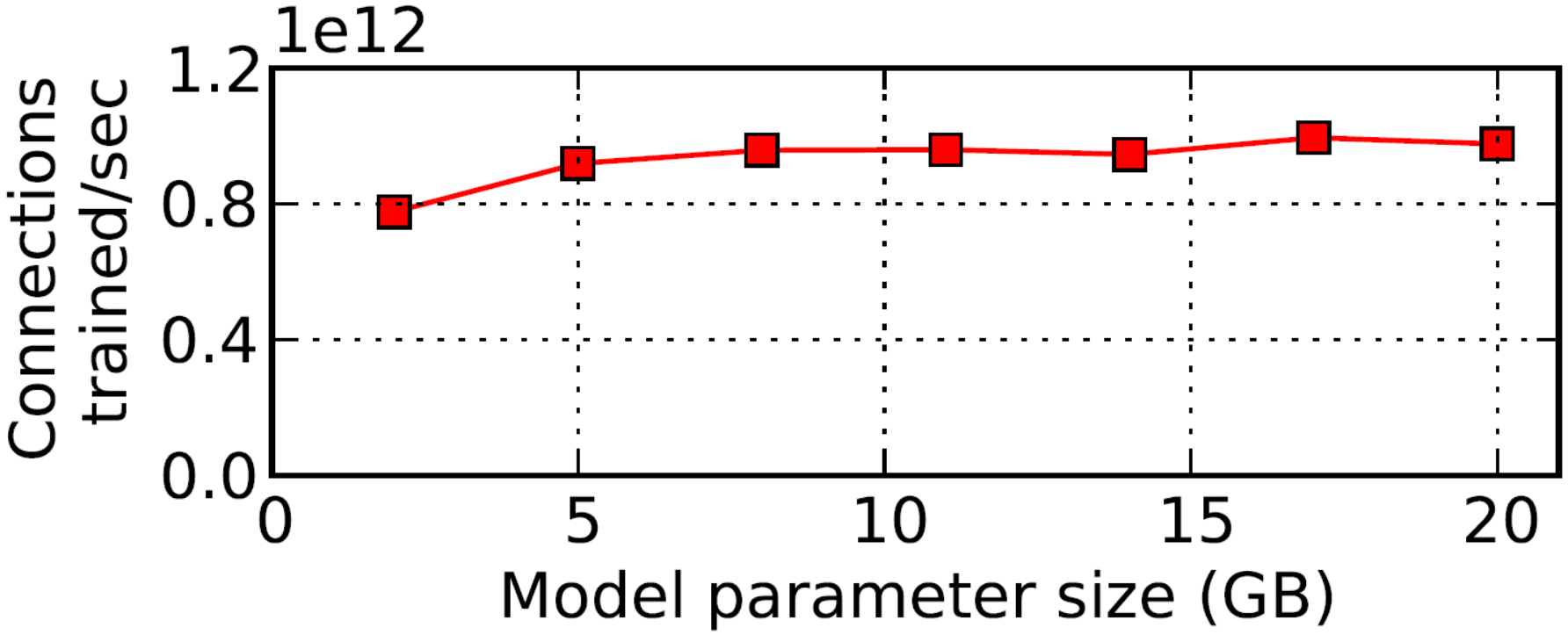


Throughput vs. memory budget



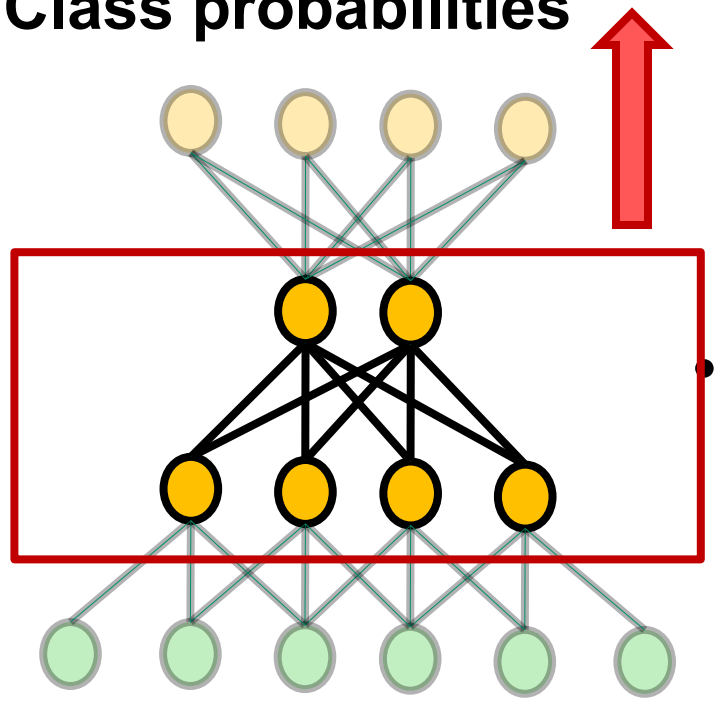
- **Only 27% reduction in throughput with 35% memory**
- **Can do 3x bigger problems with little overhead**

Larger models



- **Models up to 20 GB**

Layer-by-layer computation for DNN



- For each iteration (mini-batch)
  - A forward pass
  - Then a backward pass
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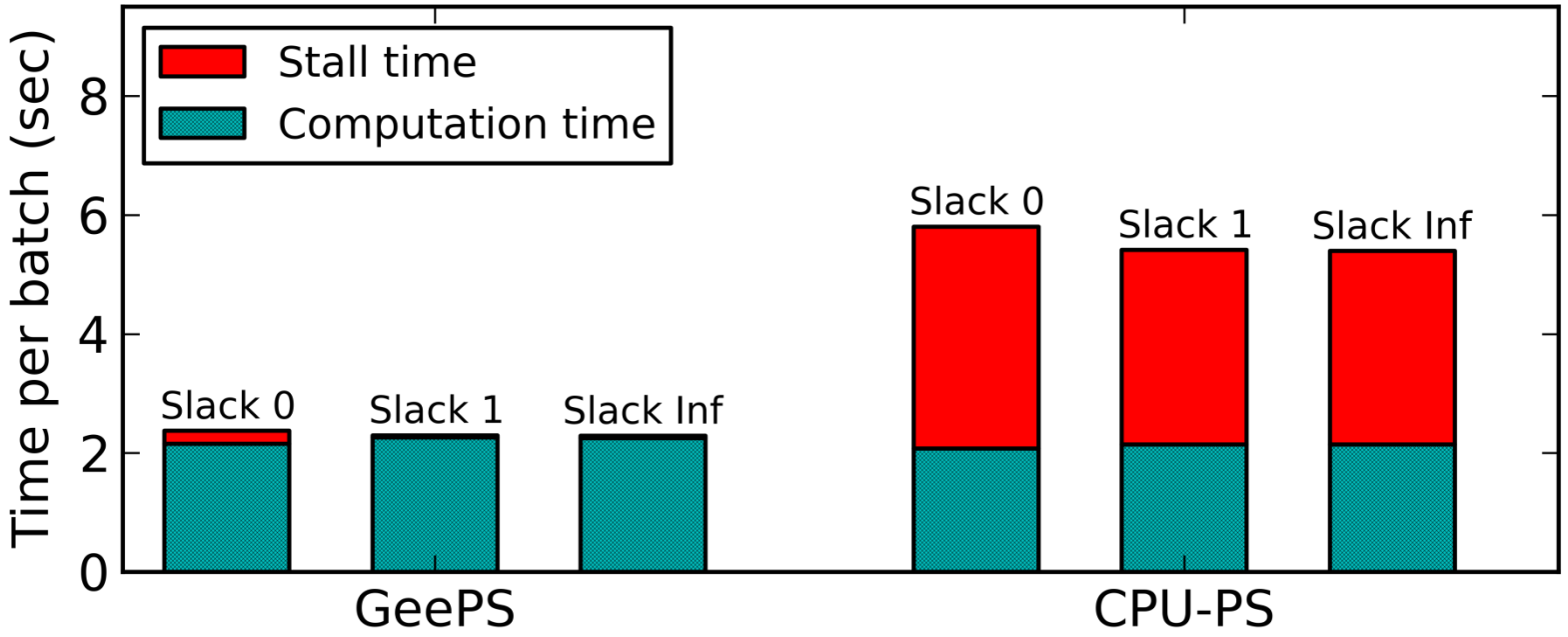
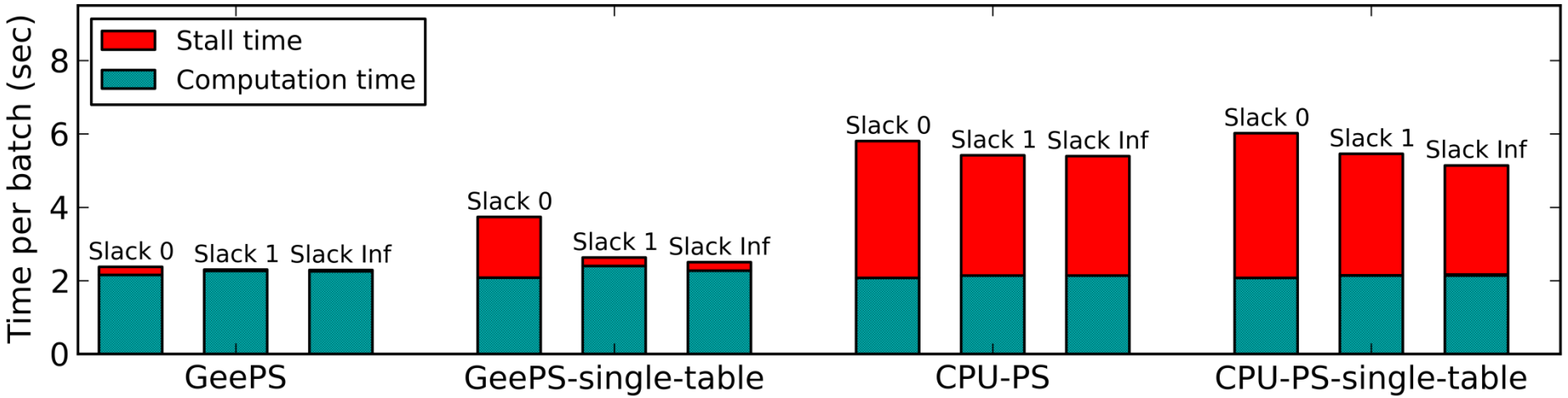
Computation vs. stall times



• Even for slack 0, updates of a layer can be sent to other machines before the updates of other layers finish

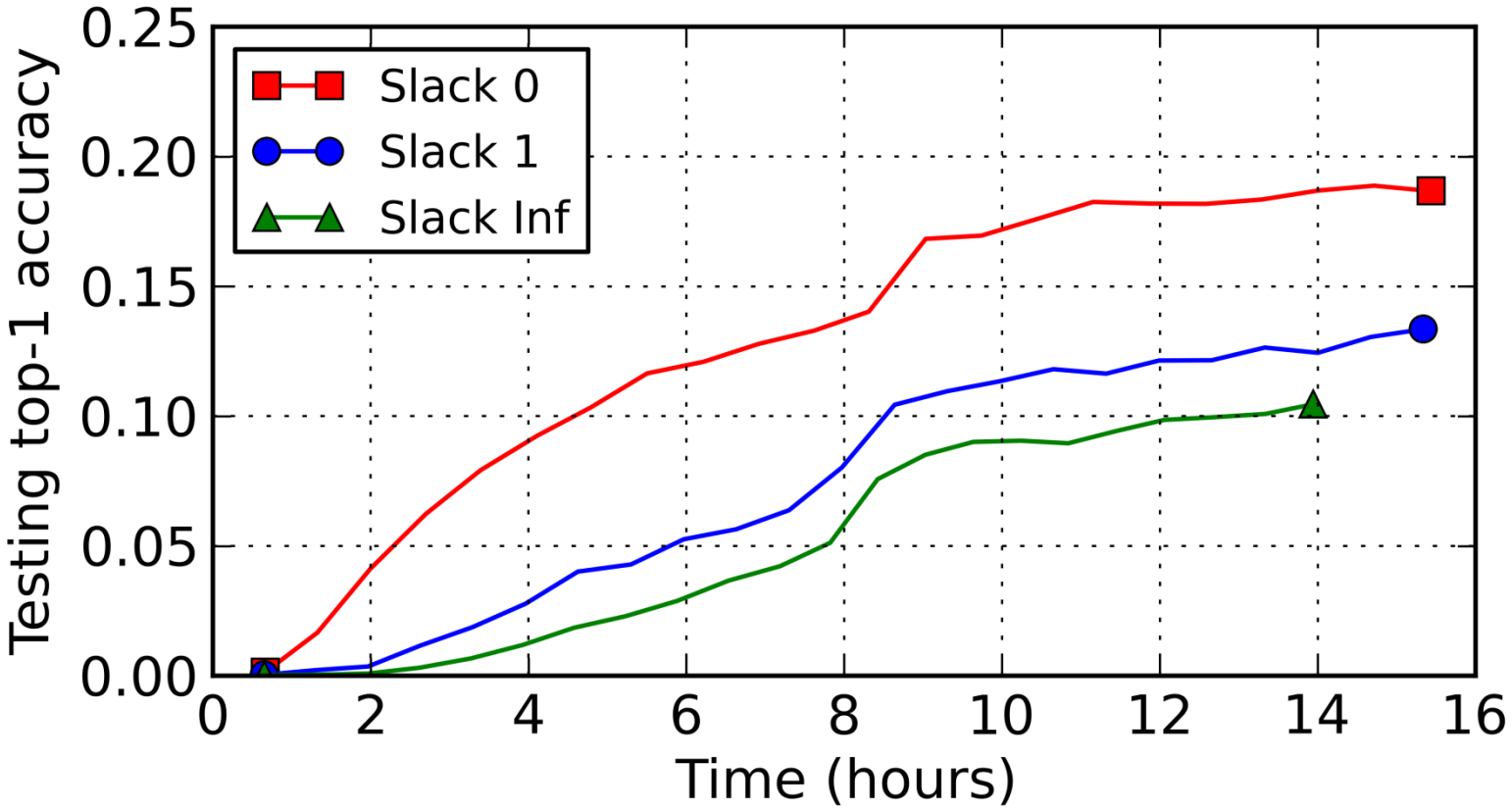
• CPU-PS has much overhead of transferring data between GPU/CPU memory in the foreground

Computation vs. stall times (more)



- GeePS and CPU-PS: updates of each layer are sent in distinct batches
- Single-table: updates of all layers are sent in a single batch

Convergence with data staleness



- The data staleness sweet spot is Slack 0
  - because the GPUs perform huge amount of computation every clock