# Strong Scaling and Weak Scaling Results

Lokesh Mohanty (lokeshm@iisc.ac.in)

November 2022

# 1 Shared-Memory Parallel Algorithms for Fully Dynamic Maintenance of 2-Connected Components

Reference: C. A. Haryan, G. Ramakrishna, K. Kothapalli and D. S. Banerjee, "Shared-Memory Parallel Algorithms for Fully Dynamic Maintenance of 2-Connected Components," 2022 IEEE International Parallel and Distributed Processing Symposium (IPDPS), 2022, pp. 1195-1205, doi: 10.1109/IPDPS53621.2022.00119.

### **Strong Scaling**

• Application: Fully Dynamic Maintenance of 2 connected components

• Number of cores: 128

• Kind of scaling: Linear

• Speedup: 4

### Weak Scaling

- Application: Fully Dynamic Maintenance of 2 connected components
- **Methodology**: decrease batch size while keeping the number of threads fixed.
- Number of cores: 128
- Comments: Incremental batch exhibits good weak-scaling property as its run time decreases proportionately as the batch size decreases while keeping the number of threads fixed.

## 2 AxoNN: An asynchronous, message-driven parallel framework for extreme-scale deep learning

Reference: S. Singh and A. Bhatele, "AxoNN: An asynchronous, message-driven parallel framework for extreme-scale deep learning," 2022 IEEE International Parallel and Distributed Processing Symposium (IPDPS), 2022, pp. 606-616, doi: 10.1109/IPDPS53621.2022.00065.

## **Strong Scaling**

• **Application**: Message driven parallel framework for exteme-scale deep learning

• Number of cores: 384 GPU

• Kind of scaling: Linear

• Speedup: 4

## Weak Scaling

• **Application**: Message driven parallel framework for exteme-scale deep learning

• Methodology: optimal number of GPU for the data size

• Number of cores: 384 GPU

• Comments: Data parallelism is embarrassingly parallel, this ends up substantially improving AxoNN's performance

# 3 High-Performance Parallel Graph Coloring with Strong Guarantees on Work, Depth, and Quality

Reference: M. Besta, A. Carigiet, K. Janda, Z. Vonarburg-Shmaria, L. Gianinazzi and T. Hoefler, "High-Performance Parallel Graph Coloring with Strong Guarantees on Work, Depth, and Quality," SC20: International Conference for High Performance Computing, Networking, Storage and Analysis, 2020, pp. 1-17, doi: 10.1109/SC41405.2020.00103.

## **Strong Scaling**

• Application: Graph coloring

• Number of cores: 32

• Kind of scaling: Linear

• Speedup: 1.7

#### Weak Scaling

• Application: Graph coloring

• **Methodology**: Kronecker graphs of the increasing sizes by varying the number of edges/vertex

• Number of cores: 32

• Comments: From the weak scaling graph we can tell that the application has bad weak scaling since the time increases with increases in problem size and threads due to memory bottleneck

# 4 Distributed-Memory Parallel Symmetric Nonnegative Matrix Factorization

Reference: S. Eswar, K. Hayashi, G. Ballard, R. Kannan, R. Vuduc and H. Park, "Distributed-Memory Parallel Symmetric Nonnegative Matrix Factorization," SC20: International Conference for High Performance Computing, Networking, Storage and Analysis, 2020, pp. 1-14, doi: 10.1109/SC41405.2020.00078.

#### **Strong Scaling**

• **Application**: Distributed-memory parallel symmetric non-negative matrix factorization

• Number of cores: 4096

• **Kind of scaling**: Linear at low data size, slightly super linear for large data

• **Speedup**: 4505.6

#### Weak Scaling

• **Application**: Distributed-memory parallel symmetric non-negative matrix factorization

• **Methodology**: Matrix dimensions are increased proportionally to the square root of the number of nodes as we scale up

• Number of cores: 4096

• Comments: It is expected that the computation will be bottlenecked by matrix multiplication call which is confirmed by the observation on results of weak scaling

# 5 A Parallel Framework for Constraint-Based Bayesian Network Learning via Markov Blanket Discovery

Reference: A. Srivastava, S. P. Chockalingam and S. Aluru, "A Parallel Framework for Constraint-Based Bayesian Network Learning via Markov Blanket Discovery," SC20: International Conference for High Performance Computing, Networking, Storage and Analysis, 2020, pp. 1-15, doi: 10.1109/SC41405.2020.00011.

#### **Strong Scaling**

• Application: Constraint-based Bayesian Network Learning

• Number of cores: 1024

• Kind of scaling: Linear

• **Speedup**: 845

## Weak Scaling

• Application: Constraint-based Bayesian Network Learning

• Methodology: Approximately same work load per core

• Number of cores: 1024

• Comments: Degradation in scaling efficiency is due to communication overhead being the limiting factor for weak scaling