Exploring the Performance of Machine Learning on Kove XPDs

Abstract

Machine learning is a common large-scale application. As HPC moves toward the exascale, the requirements of machine learning are only increasing. Memory consumption and computational load increase significantly as algorithms complexify but the predictive learning ability also increases with these factors. Thus, high-performance machine learning requires large, performant systems and extensive time.

Disaggregated memory is a technique similar to SAN in the 90s; here, memory is decoupled from the CPU. The benefits are myriad and hold under debate, but with disparity in resource demand caused by the memory wall problem, and given the memory requirements of larger systems, the performance of machine learning, machine memory may be an ideal setup for disaggregated memory systems.

To that end, this project works toward an understanding of the relationship between machine learning conditions and disaggregated memory setups to determine how machine learning might be made more performant at large scales in a disaggregated memory datacenter.

Machine Learning

Simple machine learning algorithms were trained and tested on engineered datasets. Algorithms were selected to be mathematically predictable but computationally diverse. Datasets were engineered for different features/class relationships, and all were widely configurable.

Algorithms

- AdaBoost
- Decision Trees
- K-nearest Neighbors (k = 3, 5)
- Naive Bayes
- Multilayer Perceptron Neural Network
- Random Forest

Datasets

- @-dimensions
- Binary classification
- Classes arranged on noisy, 10-dimenional hyperspheres
- Gaussian Quantiles
- Binary features
- Classes arranged on noisy, 10-dimenional hyperspheres
- Quantiles
- Binary features
- Classes arranged on noisy, 10-dimenional hyperspheres
- Moons
- Binary features
- Classes shaped like two adjacent crescents arranged to intersect given noise.

The RAM Area Network and Kove XPDs

Argonne National Laboratory (ANL) has a production setup for disaggregated memory. The network physical hierarchy includes the following: L1 cache, L2 cache, L3 cache, DDR3 bank of remote memory, with a bank of remote memory might dramatically change how batch size selection is configured. Further testing here is needed.

Experimental Configuration and Results

Tests were run settling the local RAM cache (the L4 cache) to different sizes. Results are presented as ratios of the resident set size (RSS) to the L4 cache size. This represents how much of the RSS was local. Results indicate the performance cost when using the disaggregated system as caused by the RSS / L4 cache size ratio.

For each dataset-algorithm combination, a constant overhead time to completion results from using disaggregated memory in this setup. The overhead cost holds constant with L4 cache size sufficient to hold only 30% of the RSS.

Major Conclusions

1. Using disaggregated memory in this experiment’s setup has an overhead cost in time to completion. Accuracy is unaffected.
2. The overhead cost plateaus for each dataset-algorithm combination regardless of the RSS / L4 ratio. It is not clear whether the RSS is a factor in the overhead cost.
3. The more computationally intensive the dataset-algorithm combination, the less the overhead is manifested.

Future Work

L4 Cache Size

To continue exploring the overhead plateau, additional tests should be run with L4 cache sizes below 30% of the RSS in each dataset-algorithm combination. These tests are currently underway.

Batch Size

Modern machine learning frequently depends on batch training. Here, subsets of the training dataset are processed per pass, and tuning this parameter often affects performance (time to completion and accuracy/wr). Use of disaggregated memory and the availability of a large bank of remote memory might dramatically change how batch size selection is configured. Further testing here is needed.

Resident Set Size

Modern machine learning frequently uses enormous datasets and complex algorithms designed to fit within the limits of the system. Testing should be performed where the resident set size is made one, two, and (if possible) three orders of magnitude larger.

Neural Networks and Deep Learning

Neural networks and deep learning are major topics in modern HPC and data science. Simple neural networks were tested in these experiments with the goal of understanding the effect of the size of the batch size. More complex neural networks should be trained and tested to understand if the above conclusions hold in the related but differing applications of machine learning.

XPD Configuration

Kove’s environment brings the user a wide variety of configuration options to control the behavior of paging to remote memory. In these tests, the L4 cache size parameter was held fixed. It is possible altering other settings could affect performance, likely reducing the overhead cost plateaus. These tests are currently underway with significant input from Kove developments.