GPU Accelerated Machine Learning for Bond Price Prediction

Venkat Bala Rafael Nicolas Fermin Cota

R N

Motivation

Primary Goals

- · Demonstrate potential benefits of using GPUs over CPUs for machine learning
- · Exploit inherent parallelism to improve model performance
- · Real world application using a bond trade dataset

Highlights

Ensemble

- · Bagging: Train independent regressors on equal sized bags of samples
- · Generally, performance is superior to any single individual regressor
- · Scalable: Each individual model can be trained independently and in parallel

Hardware Specifications

- CPU: Intel(R) Xeon(R) CPU E5-2699 v4 @ 2.20GHz
- · GPU: GeForce GTX 1080 Ti
- RAM: 1 TB (DDR4 2400 MHZ)

Bond Trade Dataset

Feature Set

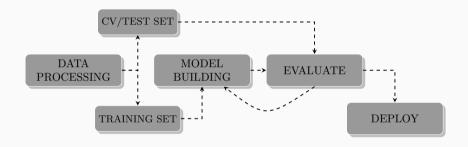
- 100+ features per trade
 - Trade Size/Historical Features
 - Coupon Rate/Time to Maturity
 - Bond Rating
 - · Trade Type: Buy/Sell
 - Reporting Delays
 - · Current Yield/Yield To Maturity

Response

Trade Price

Modeling Approach

The Machine Learning Pipeline



Accelerate each stage in the pipeline for maximum performance

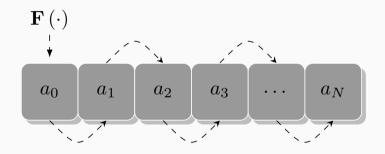
Data Preprocessing

Exposing Data Parallelism

- Important stage in the pipeline (Garbage In \rightarrow Garbage out)
- · Many models rely on input data being on the same scale
- Standardization, log transformations, imputations, polynomial/non-linear feature generation, etc.
- · Most cases, no data dependence so each operation can be executed independently
- Significant speedups can be obtained using GPUs, given sufficient data/computation

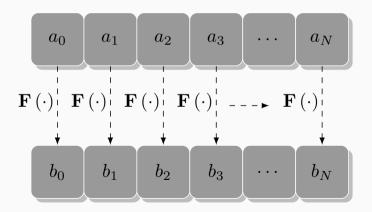
Data Preprocessing: Sequential Approach

Apply function $F(\cdot)$ sequentially to each element in a feature column



Data Preprocessing: Parallel Approach

Apply function $F(\cdot)$ in parallel to each element in a feature column



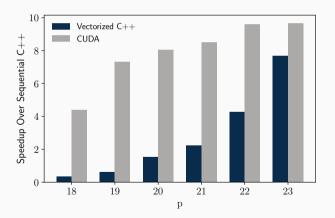
Programming Details

Implementation Basics

- Task is embarrassingly parallel
- Improve CPU code performance
 - Auto vectorizations + compiler optimizations
 - Using performance libraries (Intel MKL)
 - Adopting Threaded (OpenMP)/Distributed computing (MPI) approaches
- Great application case for GPUs
 - Offload computations onto the GPU via CUDA kernels
 - · Launch as many threads as there are data elements
 - · Launch several kernels concurrently using CUDA streams

Toy Example: Speedup Over Sequential C++

- Log transformation of an array of floats
- $N = 2^p$, Number of elements, $p = log_2(N)$



Bond Dataset Preprocessing

Applied Transformations

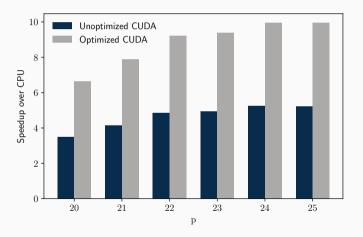
- · Log transformation of highly skewed features (Trade Size, Time to Maturity)
- Standardization (Trade Price & historical prices)
- Missing value imputation
- Winsorizing features to handle outliers
- · Feature generation (Price differences, Yield measurements)

Implementation Details

- · CPU: C++ implementation using Intel MKL/Armadillo
- · GPU: CUDA

GPU Speedup over CPU implementation

• Nearly 10x speedup obtained after CUDA optimizations



CUDA Optimizations

Standard Tricks

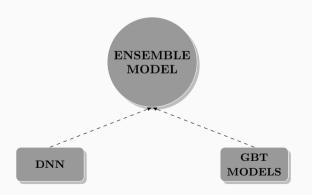
- Concurrent kernel executions of kernels using CUDA streams to maximizing GPU utilization
- Use of optimized libraries such as cuBLAS/Thrust
- Coalesced memory access
- Maximizing memory bandwidth for low arithmetic intensive operations
- · Caching using GPU shared memory

Model Building

Ensemble Model

Model Choices

· GBT: XGBoost, DNN: Tensorflow/Keras



Hyperparameter Tuning: Hyperopt

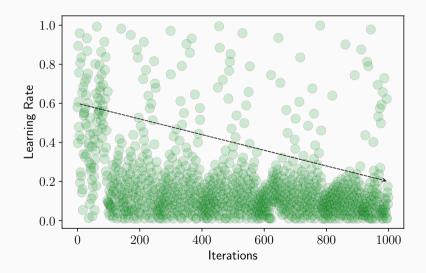
GBT: XGBoost

- Learning Rate
- Max depth
- · Minimum child weight
- · Subsample, Colsample-bytree
- Regularization parameters

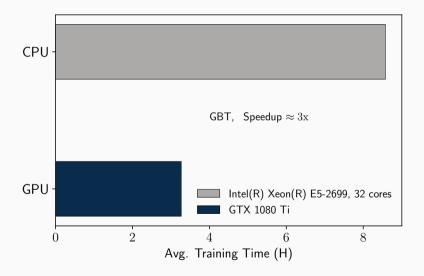
DNN: MLPs

- · Learning Rate/Decay Rate
- · Batch Size
- · Epochs
- Hidden layers/Layer width
- Activations/Dropouts

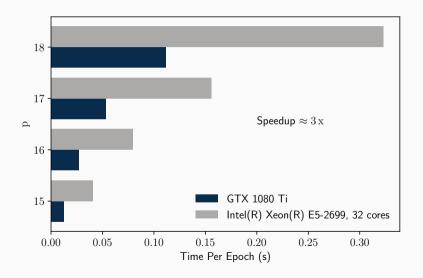
Hyperparameters Tuning: Hyperopt



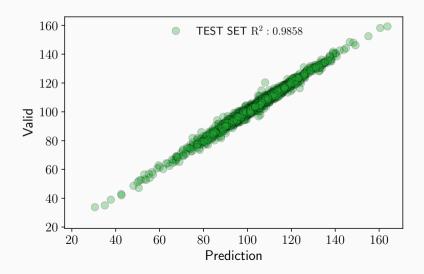
XGBoost: Training & Hyperparameter Optimization Time



TensorFlow/Keras Time Per Epoch



Model Test Set Performance





Summary

Summary

Final Remarks

- \cdot Leveraging the GPU computation power o dramatic speedups
- · Maximum performance when GPUs incorporated into every stage of the pipeline
- Ensembles: Bagging/Boosting to improve model accuracy/throughput
- Shorter training times allows more experimentation
- Extensive support available
- · Deploy this pipeline now in our in-house DGX-1

Questions?