How Walmart Improves Forecast Accuracy with NVIDIA GPUs

Walmart

Smart Forecasting

March 19, 2019

Agenda

- Walmart's forecasting problem
- Initial (non-GPU) approach
  - Algorithms
  - Pipeline
- Integrating GPUs into every aspect of the solution
  - History cleansing
  - Feature engineering
  - Off-the-shelf algorithms
  - In-house algorithms
- Benefits – translating speed into forecast accuracy

Walmart

- Over $500B annual sales (over $330B in the U.S.)
- Over 11,000 stores worldwide (over 4700 stores in the U.S.)

- Over 90% of the population in the U.S. lives within 10 miles of a Walmart store

- The largest grocer in the U.S.

- The largest commercial producer of solar power in the U.S.

Problem description

- Short-term: forecast weekly demand for all item x store combinations in the U. S.
  - Purpose:
    - Inventory control (short horizons, e.g., 0-3 weeks)
    - Purchase / vendor production planning (longer horizons)
  - Scope:
    - Size: 500M item x store combinations
    - Forecast horizon: 0 – 52 weeks
    - Frequency: every week

- Longer term: forecast daily demand for everything, everywhere.

- Pipeline constraints
  - Approximately 12 hour window to perform all forecasting (scoring) tasks
  - Approximately 3 days to perform all training tasks

Pre-existing system

- COTS (Commercial Off The Shelf) solution integrated with Walmart replenishment and other downstream systems
- Uses Lewandowski (Holt-Winters with "secret sauce" added) to forecast U.S. –wide sales on a weekly basis
- Forecasts are then allocated down to the store level
- Works quite well – it beat three out of four external vendor solutions in out-of-sample testing during our RFP for a new forecasting system
- … still used for about 80% of store-item combinations, expect to be fully replaced by end of the year.

History cleansing

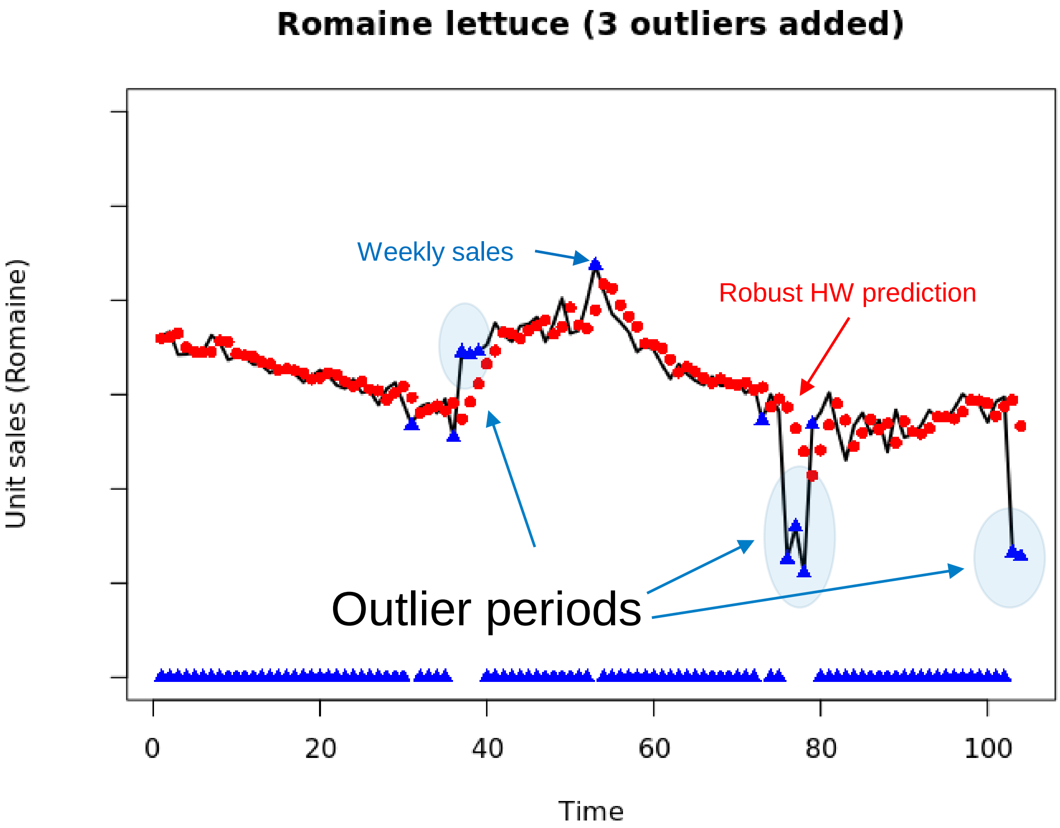
- Most machine learning algorithms are not robust in a formal sense, resulting in:

Garbage in, garbage out

- Three approaches:
  - Build robust ML algorithms (best)
  - Clean the data before giving it to the non-robust ML algorithms that exist today
  - Hope that your data is better than everyone else’s data (worst)

- We’ve taken the second approach, but are thinking about the first.

Identifying outliers using robust time series – U. S. Romaine sales



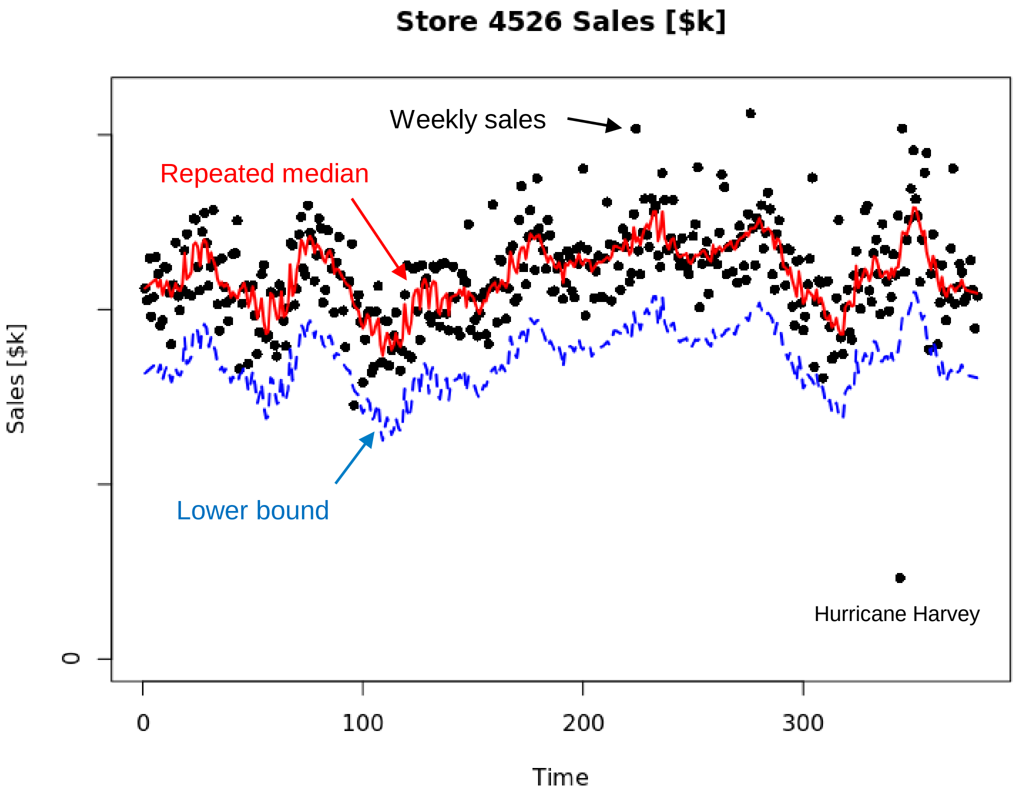
We show two years of weekly sales + a robust Holt-Winters time series model.

We've constructed an artificial three-week drop in sales for demonstration purposes.

Outlier identification occurs as part of the estimation process.

Imputation uses a separate algorithm.

Identifying store closures using repeated median estimators

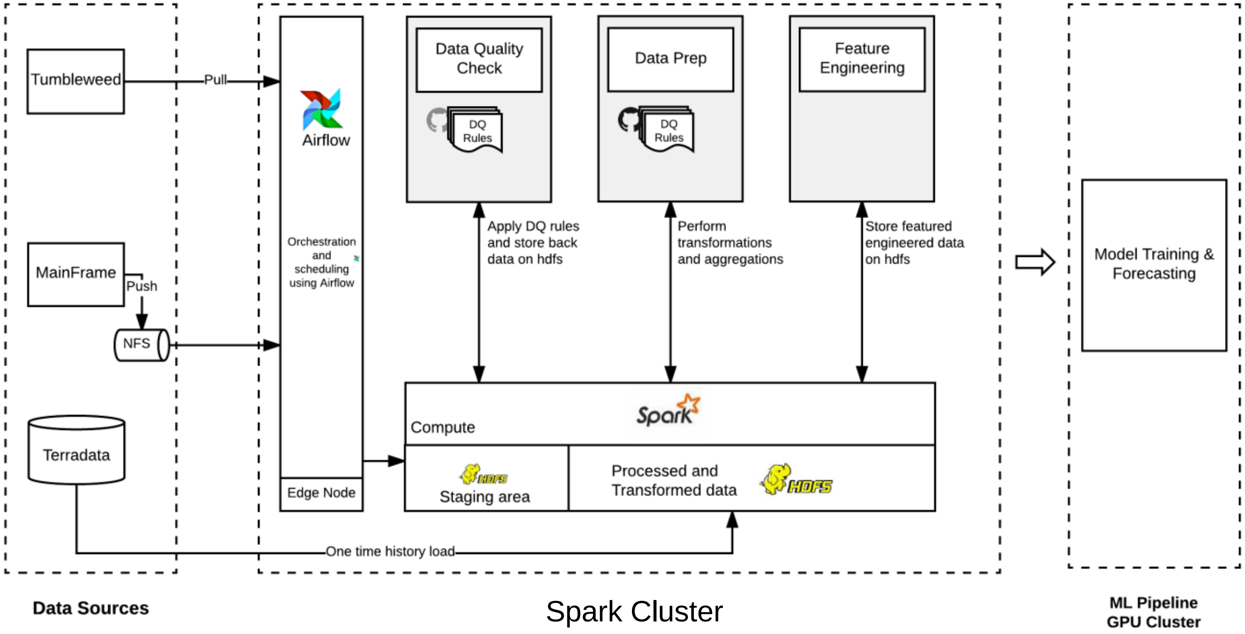


Hurricane Harvey stands out clearly in this plot.

Our GPU-based implementation of the (computationally intensive) RM estimator offers runtime reductions of **> 40-1** over parallelized CPU-based implementations using 48 CPU cores.

Feature Engineering

Initial architecture



Feature engineering - Roadblock

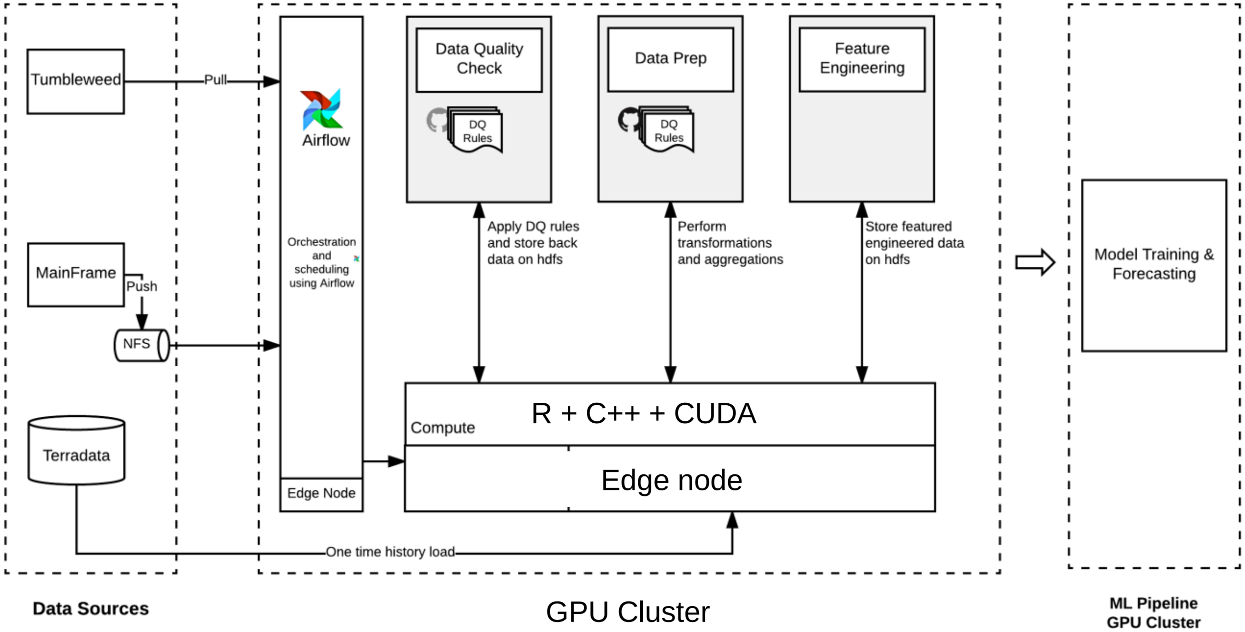
- Initial FE strategy:
  - Extract raw data from databases
  - FE execute on Spark / Scala (giving us scalability)
  - Push features to GPU machines for consumption by algorithms

- As the volume of data grew, the Spark processes began to fail erratically
  - Appeared to be a memory issue internal to Spark – nondeterministic feature outputs and crashes
  - Six+ weeks of debugging / restructuring code had essentially no effect

- Eventually, we were unable to complete any FE processes at all

Revised Feature Engineering Pipeline

- Spark code ported to R / C++ / CUDA

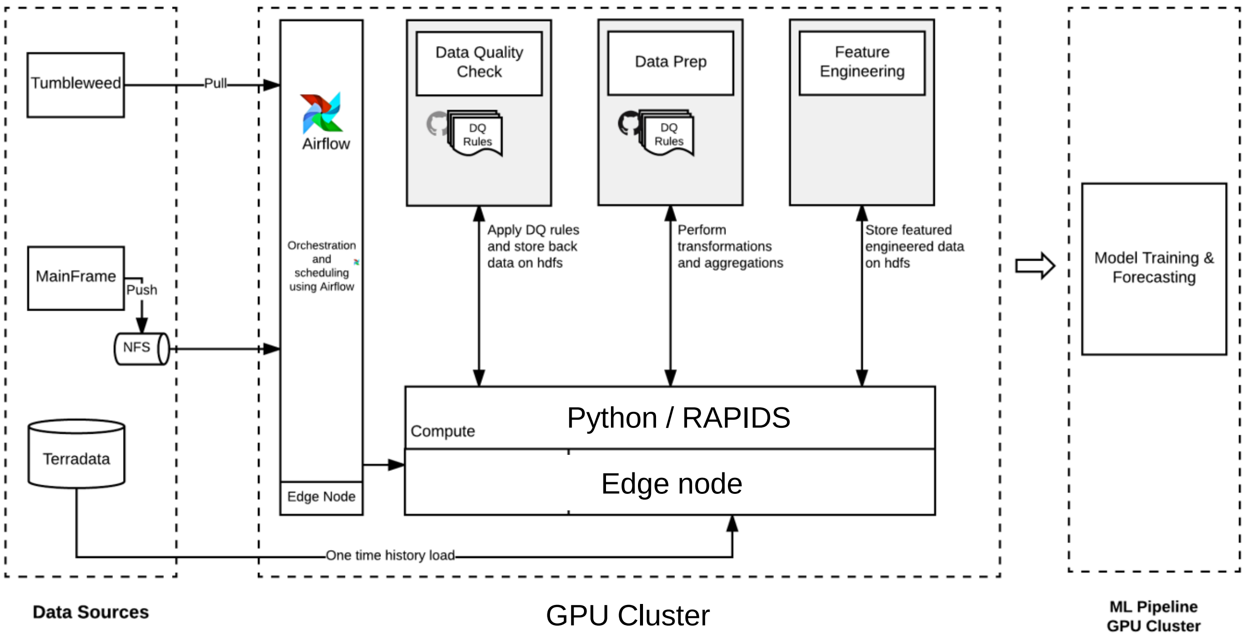


- Port took 2 weeks + 1 week code cleanup
- Performance was essentially the same as the Spark cluster
- CUDA code runtime reduction of ~**50-100x** relative to C++ parallelized on 48 CPU cores
- With a full port to CUDA, we'd expect ~**4x reduction** in FE computation runtime over today
- Reliability has been essentially 100%!

GPU Cluster: 14 SuperMicro servers with 4x P100 NVIDIA GPU cards

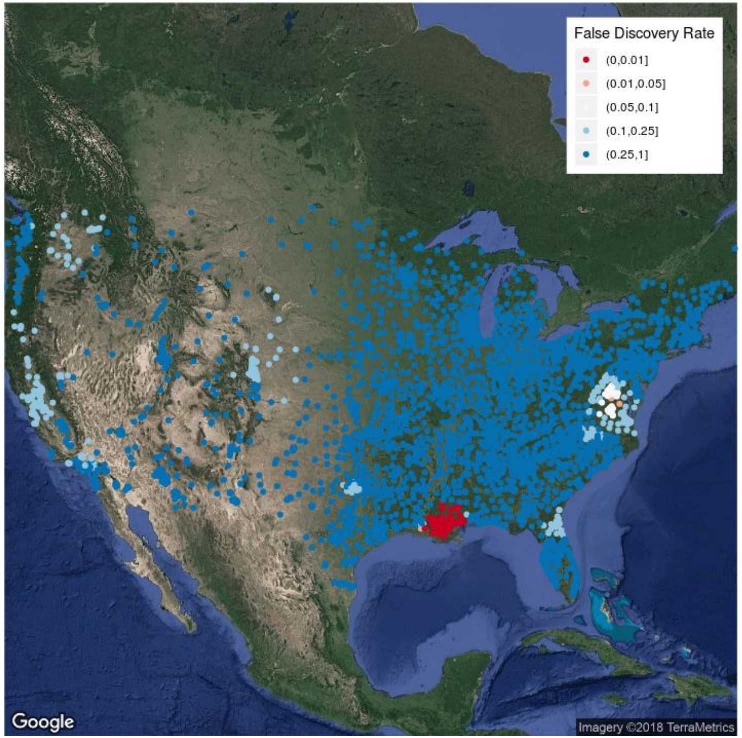
Future Revised Feature Engineering Pipeline

- R / C++ / CUDA code ported to Python / RAPIDS



- Walmart is working with NVIDIA to ensure RAPIDS functionality encompasses our use cases
- Our in-house testing indicates **very significant** runtime reductions are almost assured – exceeding what we could do on our own
- Implementation expected in June – August timeframe

Better Features - detection of spatial anomalies



Spatial anomaly detection using:

- k-NN estimation of store unit lift
- G* z-score estimate of spatial autocorrelation
- False Discovery Rate

Takes about 2 minutes to run on a single CPU – obviously infeasible to use this for our problem

k-NN is part of RAPIDS; early tests indicate a runtime reduction of > 100x by switching to the RAPIDS implementation.

The rest of the calculations will have to be ported to CUDA by us.

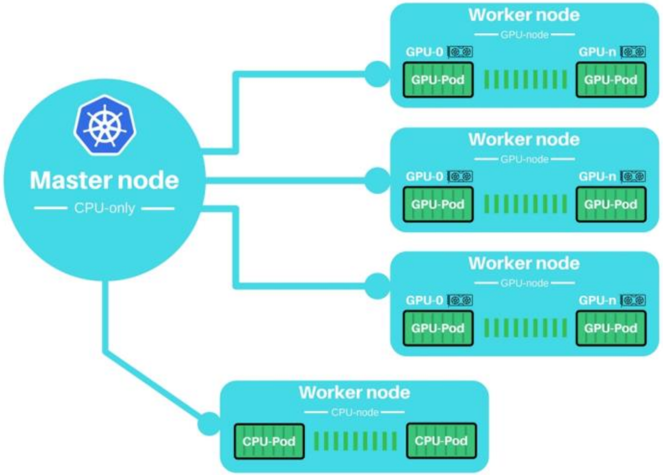
Algorithm Technology

- Gradient Boosting Machine
- State Space model
- Random Forests
- … others …
- Ensembling

Production configuration

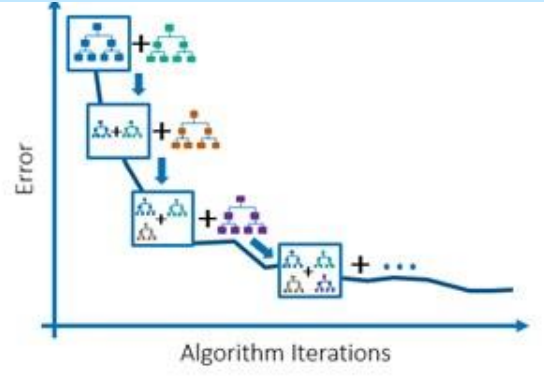
Our training and scoring are run on a cluster of 14 SuperMicro servers each with 4x P100 NVIDIA GPU cards

- Kubernetes manages Dockerized production processes.
- Each server can run four groups of store-item combinations in parallel, one on each GPU card.
- For CPU-only models, our parallelization limits us to one group per server at a time.



Forecasting Algorithms – the two mainstays

Gradient Boosting Machine

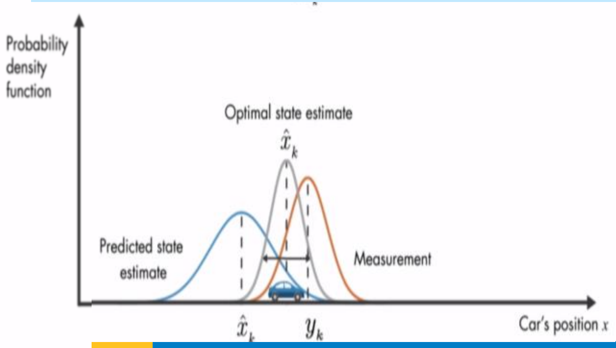


- **Gradient boosting** is a machine learning technique for regression and classification problems.
- GBM prediction models are an ensemble of hundreds of weak decision tree prediction models
- Each weak model tries to predict the errors from the cumulation of all the previous prediction models
- Features (such as Events, Promotions, SNAP calendar, etc.) are directly added as regressors
- Interactions between the regressors are also detected by the boosting machine and automatically incorporated in the model
- Mostly works by reducing the bias of the forecasts for small subsets of the data

Pros

- Ability to easily incorporate external factors (features) influencing demand
- The algorithm infers the relationships between demand and features automatically

State Space Model



- Defines a set of equations to describe hidden states (e.g. demand level, trend, and seasonality) and observations
- The **Kalman Filter** is an algorithm for estimating parameters in a linear state-space system. It sequentially updates our best estimates for the states after having the "observations" (sales) and other features (such as price), and is very fast.
- “Linearizes” features before incorporating them

Pros

- Can forecast for any horizon using a single model
- Can work seamlessly even if some of the data is missing – it just iterates over the gap.
- Very fast.

Walmart

Gradient Boosting Machine

- Underlying engine: NVIDIA's XGBoost / GPU code
  - Both R package and Python library
  - Can be called from C/C++ as well
  - Performance comparison:
    - Pascal P100 (16GB memory) vs 48 CPU cores (out of 56) on a Supermicro box
    - Typical category size (700K rows, 400 features)
    - GPU speedup of ~25x.

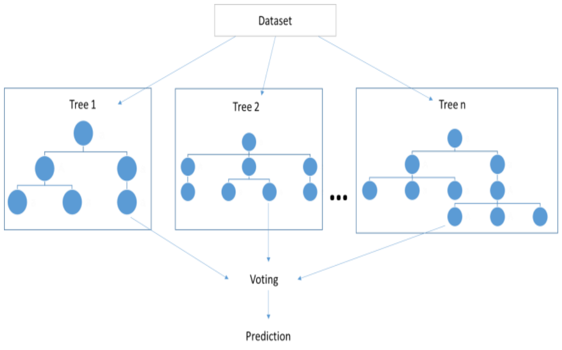
- Features
  - Lagged demands -> level, trends, seasonal factors
  - Holidays, other U. S. – wide events (e.g., Super Bowl weekend)
  - (lots of) other features

State space model

- State space (DLM) model adapted from one developed for e-Commerce
- Generates forecasts for a cluster of items at all stores at once
- Multiple control parameterizations of model treated as an ensemble of models and a weighted average is returned as the forecast
- Used for all long-horizon forecasts and about 30% of short-horizon forecasts
- Implemented in TensorFlow (port from C++)
  - GPU version of TensorFlow did not offer much speed improvement over CPU version (< 2x)
- Uses Kalman Filtering for updating state parameters
  - Preliminary tests indicate RAPIDS Kalman Filter routine is far faster than what we are using today

Forecasting Algorithms – the next wave

Random Forests

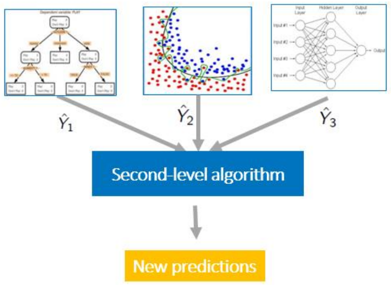


- **Random Forests** is a machine learning technique for regression and classification problems.
- RF prediction models are an ensemble of hundreds of strong (deep) decision tree prediction models averaged together
- Each strong model tries to predict the errors from a random sample of the data
- More randomization is added by selecting a subset of features to be evaluated at each node
- Features (such as Events, Promotions, SNAP calendar, etc.) are directly added as regressors
- Interactions between the regressors are also detected by the deep tree and automatically incorporated in the model
- Mostly works by averaging out model- and dataset- specific overfitting of the forecasts

Pros

- Ability to easily incorporate external factors (features) influencing demand
- The algorithm infers the relationships between demand and features automatically

Ensembles



- Uses forecasts generated by different models, possibly along with other features, as predictors in a “final stage” model
- Can be as simple as a weighted average of different predictors or much more complex
- Mostly works by averaging out model-specific overfitting of the data

Pros

- Typically superior to “pick the best model” approaches
- Almost always offers at least some improvement over any individual forecast

Random Forests

- Underlying engine: scikit-learn's random forest algorithm
  - Many other random forest implementations exist; this one works well for us…
  - However, scikit-learn's implementation is too slow for scoring given our time window
  - Developed custom CUDA code to score using the model object returned by Python:
    - GPU speedup of > 300x relative to scikit-learn (> 50x including file i/o)
    - Makes Random Forests a practical alternative to our GBM and State Space models
- NVIDIA is developing a GPU-based random forest implementation using some of our data for test purposes
- Features - uses the same feature set as the GBM; this will likely change

Ensembling

- Ensembling implemented as weighted averages of different models' predictions
  - Analysis to determine weights done separately
  - Reduces scoring time, increases forecast stability

- Weighted averages of a small number of large vectors is an ideal task for CUDA

- However, in this case, the CPU performs well too:
  - Large numbers of fast operations on localizable memory
  - No transfer of data to and from the GPU (about half the time in our tests)

- The advantage of the GPU is < 2x.

- With NVLINK and a newer generation of GPU card, it would be perhaps 4x.

Benefits

- Runtime improvements enable:
  - Better history cleansing algorithms
  - Better and more comprehensive feature engineering
  - A broader suite of forecasting algorithms

- However, incremental improvements do little. We need **large** improvements to be able to revolutionize the forecasting pipeline.

- With RAPIDS and CUDA, we've been able to implement a forecasting pipeline that:

reduces overall forecast error by ~ 1.7 percentage points

relative to the reduction in forecast error that would have been possible with CPU-only code.

And… we're not done yet!

Thank you, NVIDIA!