Distributed Machine Learning

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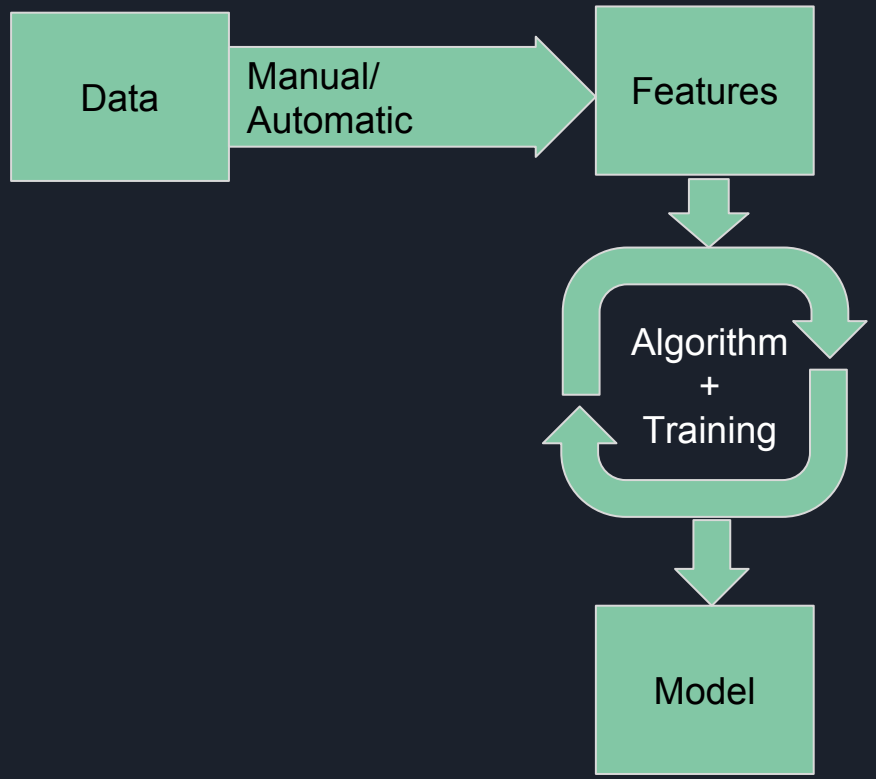
What is Machine Learning?

- Model
  - Computation architecture
  - Parameters
- Data
  - Training set
  - Features



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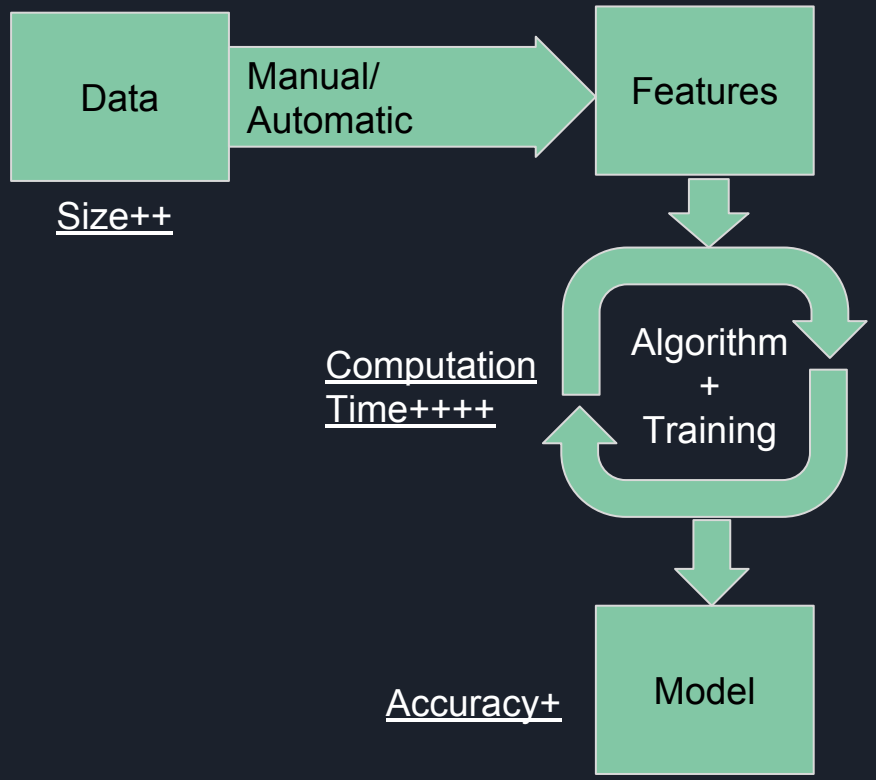


Motivations for DML

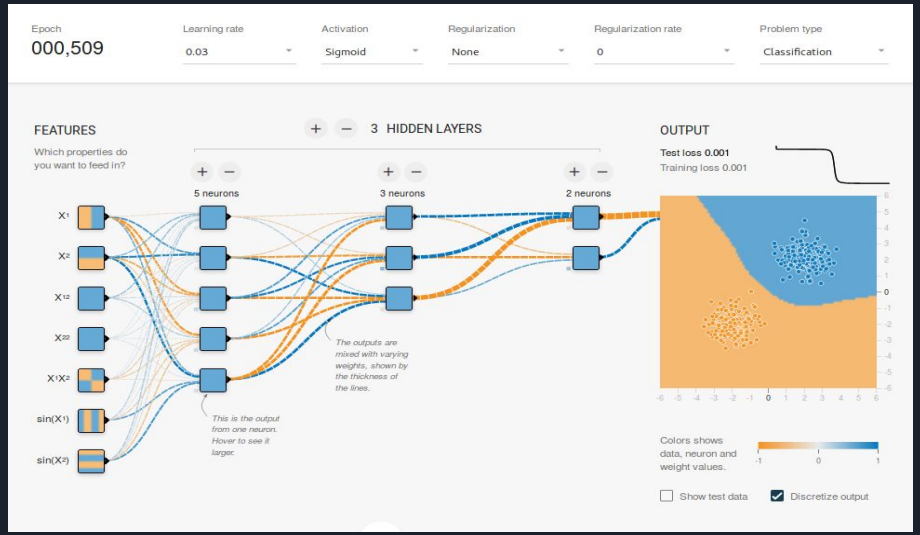
- Data size (TB - PB)
- Large Volume of Data increases Model accuracy
- A lot of Computations
- Data Locality
- Data privacy / security

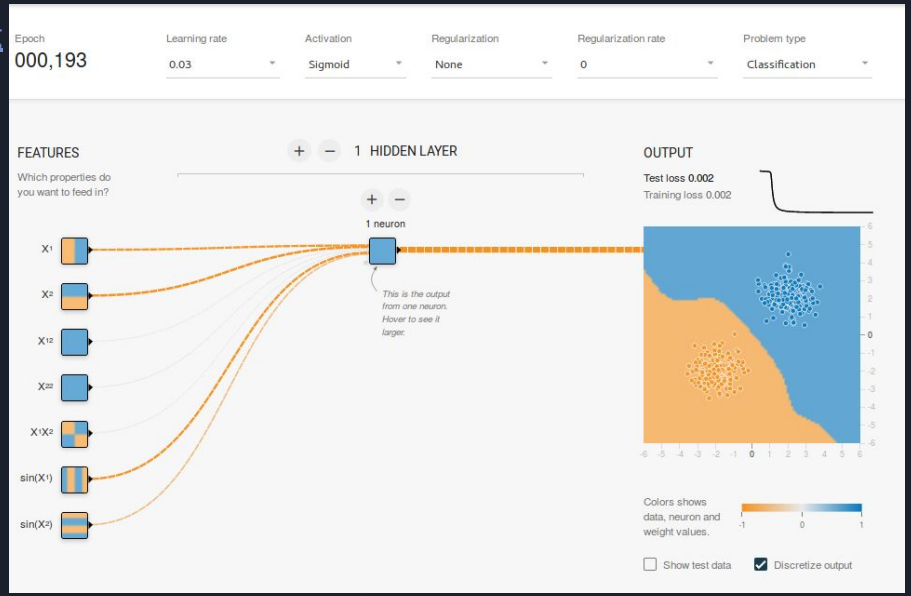
Challenges of DML

- Communication cost
  - Latency
  - Bandwidth
- Diverse Resource Capabilities
  - Differing CPU Threads
  - RAM available
  - Power Consumption
- Poor Resource Utilization
- Distribute data for workers
- Difficult to Develop
- Error Tolerance
- Current ML Algorithms are not naturally distributed
- Balancing consistency with performance and accuracy

Motivating Example

Neural Net http://playground.tensorflow.org





Strategies for DML

- Data Parallelism
  - Parameter server scheme
- Model Parallelism
  - Distributed networks (NN)
  - Pipelined computation
- Hybrid Approach

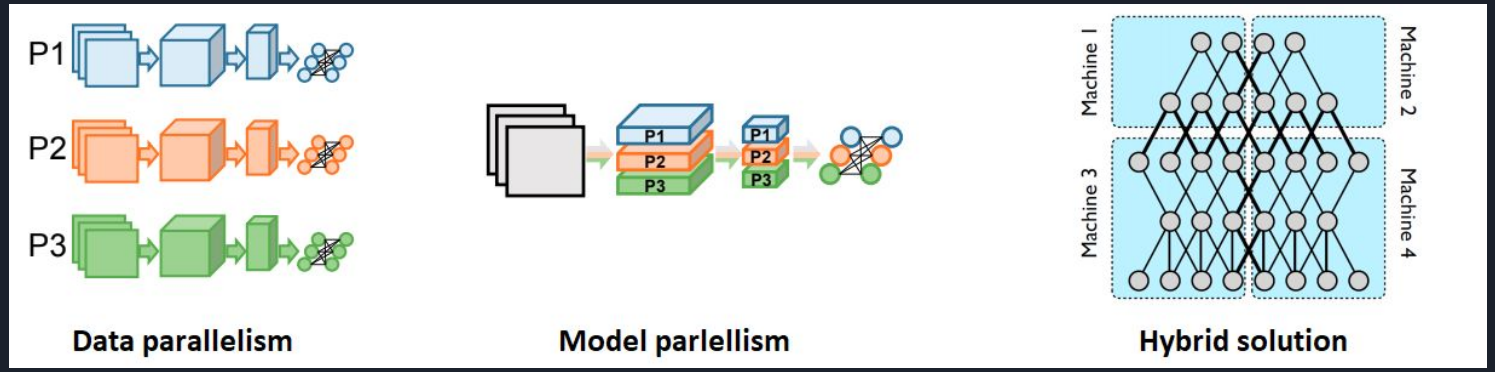
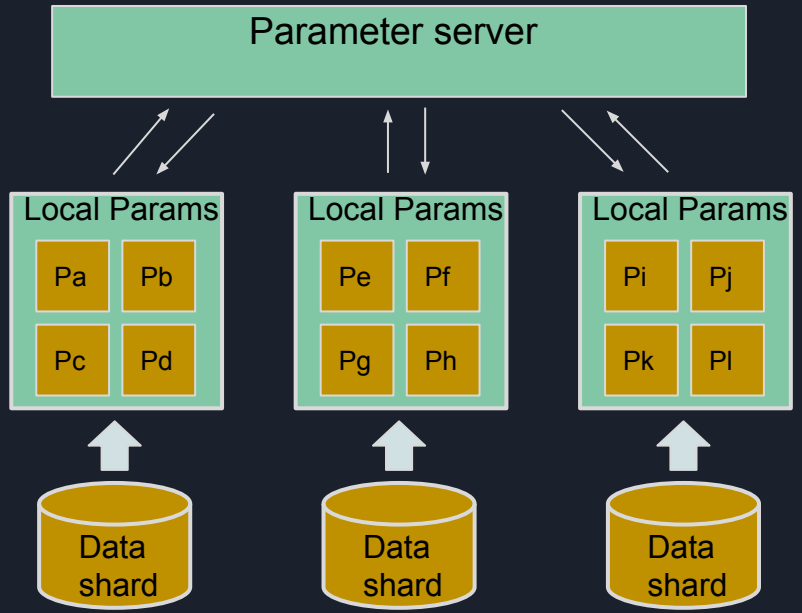


Image Courtesy of [3] TAL BEN-NUN and TORSTEN HOEFLER, ETH Zurich, Switzerland

Data-Parallel: Parameter-Server

- 1 point of reference for Global Model Parameters
- Each worker has a partition of the data and computes a partial update of all parameters
- Takes advantage of Error Tolerance in ML Algorithms



Parameter-Server: Synchronization

- Bulk Synchronous Parallel
  - Synchronize after each iteration
- Stale Synchronous Parallel
  - Synchronizes after the fastest node passes the slowest in s iterations
- Adaptive Synchronous Parallel
  - Zhang et al suggests changing the stale threshold based on CPU occupancy and have a minimum number of executions for the slowest [2]

Model Parallel: Distributed networks

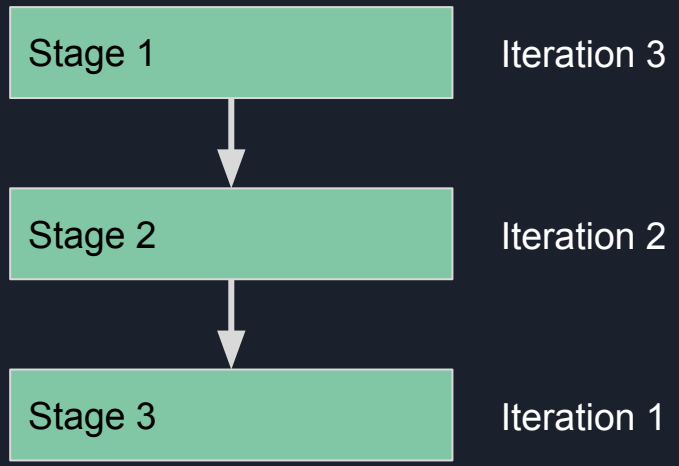
- Computation is divided among nodes
  - Different layers or parts of a layer in a NN
- Model is split among nodes
- Every node has access to the entire dataset
- Every node is responsible of its part of the parameter space
- Heavy communication is usually required
  - DDNN early exit [4]
- Issue: Under-utilized nodes

Model Parallel: Pipelined computation

- Overall computation in iterative steps
  - Layers of neural networks
- Subset of nodes responsible for part of computation
- Temporal division
  - One iteration goes through multiple stages in subsequent time intervals
- Easier communication
  - Messages flow from one stage to the next only
  - Simple synchronization
- Bigger throughput and latency
- Susceptible to bottlenecks

Pipelined computation

- 3 different iterations being executed at the same time
- One iteration goes through 3 seperate barrier-synchronized steps



Early Implementations

- Hand-crafted implementations
  - C++
  - MPI
- Distributed computing frameworks
  - MapReduce
- Adapting ML libraries to distributed computation
  - Caffe (DNN)
- Adapting distributed computation libraries to ML
- Simple strategies

DML-specific frameworks

- Specialized libraries
  - Spark/MLlib
  - TensorFlow
  - GraphLab
- Data flow paradigm
  - Execution DAG
  - Graph coloring
- Industrial solutions
  - Difficult to implement though
- Novel strategies
  - Hybrid parallelism
  - Parameter server variants
  - Relaxing consistency and accuracy for speed
  - Distributed gradient descent

Recent Developments

- Mature industrial solutions
  - Easier to set up production-level DML
- Novel systems
  - DDNN - edge computing
  - ASP
- Bridging the gap between ease of use and performance
  - MLI
  - MXNet

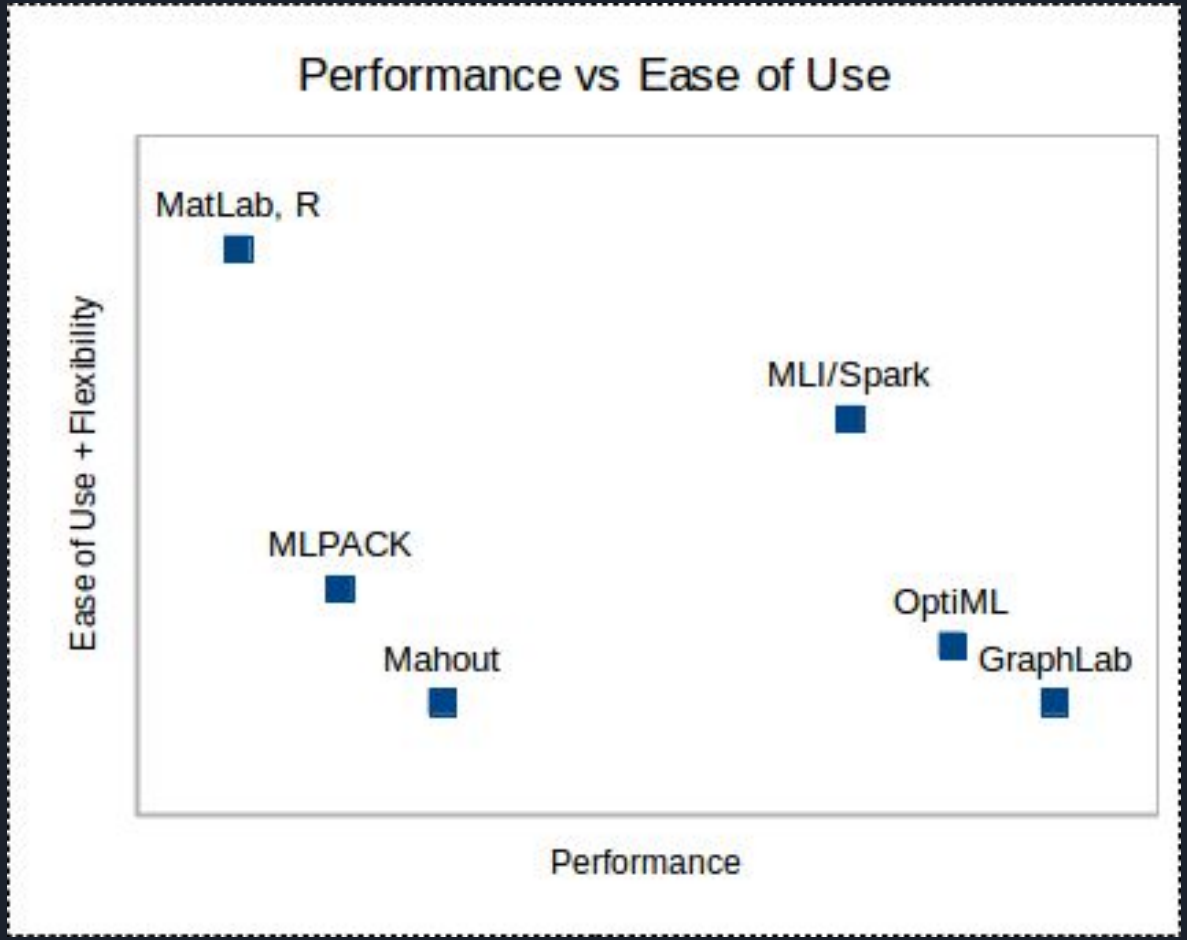


Image Recreated from: Sparks et al., MLI: An API for Distributed Machine Learning

Implementations

- Data-Parallel
  - Parameter Server
    - Petuum/PMLS - C++
    - YahooLDA
    - MXNet
- Model-Parallel
  - Strads
- Specialized libraries
  - GraphLab
  - Spark/MLLib
  - TensorFlow
  - PyTorch

Thank You
Any Questions?

References

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