TensorFlow: A System for Large-Scale Machine Learning

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Predecessors to TensorFlow

- **MapReduce**: Early batch data processing system, TensorFlow extends to more complex algorithms.
  - MapReduce used reactive backup workers, TensorFlow uses backup workers proactively.
- **Naiad**: Single optimized static data flow graph and some control flow (looping, branching) in TensorFlow are similar to Naiad.
- **DistBelief**: Google’s earlier machine learning system.
  - Parameter server architecture from DistBelief is largely used again in TensorFlow.
  - TensorFlow is more flexible and faster on a variety of problems.
Major Accomplishments

- Scalability across heterogeneous devices
  - Separating workload distribution from the implementation of computations allows the same node of data flow graph to be executed on a variety of different kernels/devices.

- Performance on a single device and distributed systems
  - Compared to DistBelief, TensorFlow scales down much better, while maintaining and improving large system performance

- Flexibility for new NN layers and optimization algorithms
  - Abstraction of computations allows new algorithms to be swapped in easily.
Data Flow Graph

- Nodes represent an operation
- Edges represent a tensor of data that will flow between nodes
- Variables can be used to store global data, e.g. current model parameters
- Queues also implement state, and help synchronize operations such as data fetching and computations
- Any subgraph can be executed by itself since data flow is separated
Data Flow Graph Generation

Implementation Details
Distributed Workload

- **Client**: programmer interface that allows the graph, or a subgraph to be run.
- **Master**: main organizational process. Does not handle scheduling, this is implemented by blocking queues.
- **Worker Processes**: processes responsible for handling node computations on any of the hardware devices available.
Basic Data Flow

• With a single device, nodes are put in a ready queue when the number of unexecuted dependencies reaches 0.
• Using heuristics and a greedy algorithm, the algorithm simulates the graph execution and assigns nodes to different devices when multiple are available.
• On a single machine, TensorFlow has adequate training speed. One of the main challenges the authors faced was the ability to scale up and down.

<table>
<thead>
<tr>
<th>Library</th>
<th>Training step time (ms)</th>
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<tbody>
<tr>
<td></td>
<td>AlexNet</td>
</tr>
<tr>
<td>Caffe [38]</td>
<td>324</td>
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<tr>
<td>Neon [58]</td>
<td>87</td>
</tr>
<tr>
<td>Torch [17]</td>
<td>81</td>
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<tr>
<td>TensorFlow</td>
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</tbody>
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Distributed Data Flow

- Greedy algorithm incorporates time to send data between machines. Tensors are sent between machines only once even if multiple nodes use the same data.
- User-level checkpointing achieves fault tolerance which is necessary when training for a long time period on a cluster.
- Asynchronous training uses stale parameters, so TensorFlow begins to use synchronous training as well using blocking queues. Backup workers are required to mitigate the effect of lagging processes.
- Backup workers train on different data to take advantage of SGD batching. Reduces the effect of a lagging node, number of workers is optimized.
Major Benefits

• Much easier to experiment than previous systems.
• Abstracted computation kernels is a clever way to solve the heterogeneous device problem.
• Ability to scale up and scale down by balancing overhead computations is impressive.
• Backup processes are well optimized to minimize resource consumption and the effect of lagging workers.
Major Criticisms

- Static data flow graph makes reinforcement learning and recurrent neural networks difficult to implement.
- Authors stated the goal of making their ML platform more accessible, but TensorFlow still requires a lot of manual tuning.
- Too generic? TensorFlow works with a lot of languages and libraries, but doesn’t fit in with any. Depending where a piece was implemented, the performance can be hard to predict. (C++ vs Python)
- Minimal comparison to other systems for large scale distributed machine learning.
- Is the balance between large and small scale abilities at the cost of being really good at either one?