TensorFlow: A System for Large-Scale Machine Learning

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Background

- Motivation:
  - Improvement to DistBelief for large-scale distributed computing
  - DistBelief: Parameter server architecture – stateless worker, stateful parameter server
  - Also allow training and using models on smaller scale machines (single GPU machines and mobile CPUs)
  - More flexibility to model training

Related works

- DistBelief:
  - Limitations of parameter server architecture
  - Lack of flexibility to refine optimisation functions
  - Fixed execution pattern – fails for more advanced models
- Single-machine frameworks:
  - Caffe – difficult to add new layers
  - Theano – similar structure
  - Torch – less portable
- Batch dataflow systems:
  - Require data to be immutable
  - Update step must process larger batches slowing convergence

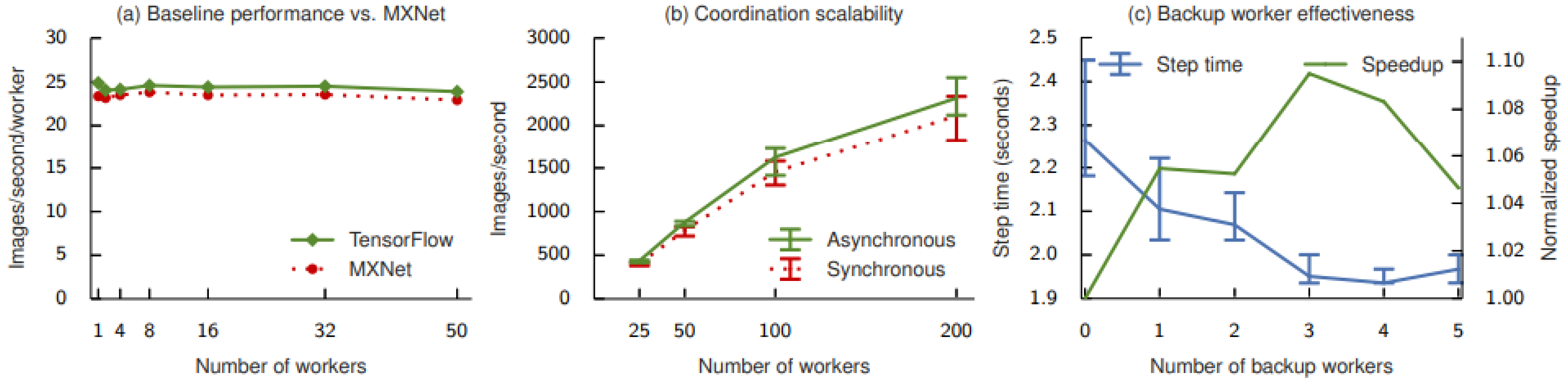
Approach

- Model represents individual mathematical operators
- Deferred execution
  - 1st phase defines program as a symbolic dataflow graph
  - 2nd phase executes an optimised version of the program

Evaluation

Library	Training step time (ms)			
	AlexNet	Overfeat	OxfordNet	GoogleNet
Caffe [38]	324	823	1068	1935
Neon [58]	87	**211**	**320**	**270**
Torch [17]	**81**	268	529	470
TensorFlow	**81**	279	540	445

- Similar performance to MXNet
- Neon and Caffe optimised differently
- Torch and TensorFlow use the same version of cuDNN
- Evaluation of Language Modelling not compared against other systems



Strength and Weaknesses

- Strength:
  - Distributable
  - Optimised for large-scale model training

- Weaknesses:
  - Static dataflow graph implementation limits training of deep reinforcement learning algorithms
    - PyTorch seems to be the more popular tool for this

Impact

- Widely adopted in the industry for machine learning engineering
- Used in many research projects

References

1. M. Abadi et al. Tensorflow: A system for large-scale machine learning. OSDI, 2016.