Dynamic Control Flow in Large-Scale Machine Learning, Yu et al. (2018)¹ Review

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Presentation Overview

- Motivation
- TensorFlow: a Data-Flow System
- Implementation Overview
- Evaluation
- Criticisms
- References

- Training and running of recurrence relations models (RNNs, Reinforcement Learning)
 - Static vs. Dynamic unrolling

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- Training on distributed computation units
 - Parallelism and asynchrony

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 - Static vs. Dynamic unrolling
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 - Parallelism and asynchrony
- Dynamic control flow
 - Ability to define models as general data flow constructs
- No existing dynamic control flow system supporting automatic differentiation

TensorFlow

• Data-flow system, not exclusively for machine-learning

TensorFlow

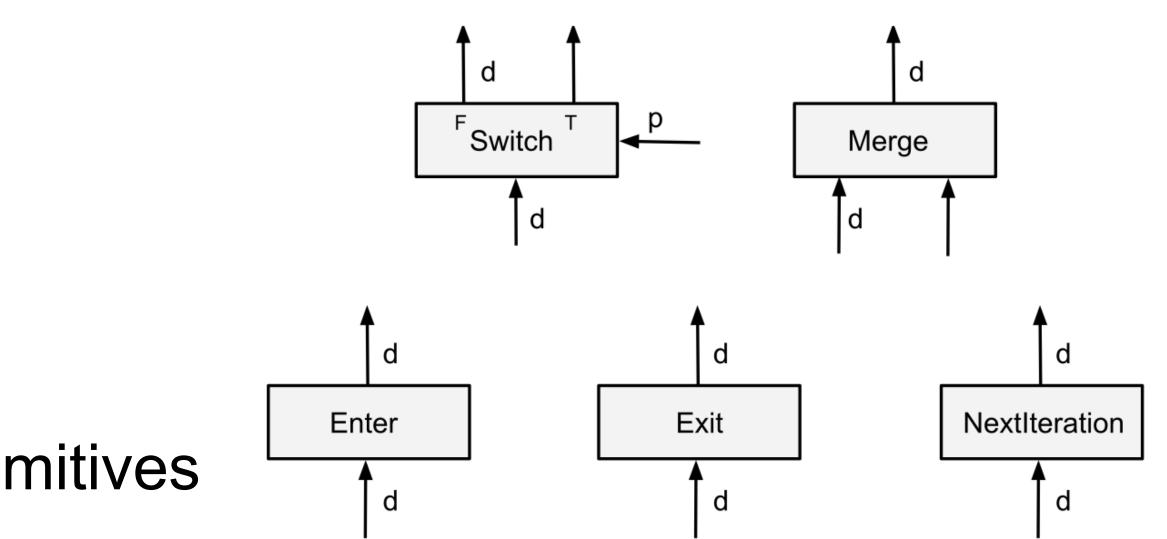
- Data-flow system, not exclusively for machine-learning
- Computations represented as directed dataflow graphs²

TensorFlow

- Data-flow system, not exclusively for machine-learning
- Computations represented as directed dataflow graphs²
- Built to support a wide variety of hardware (first major system to support computation mapping to multiple devices)²

Control Flow Operations

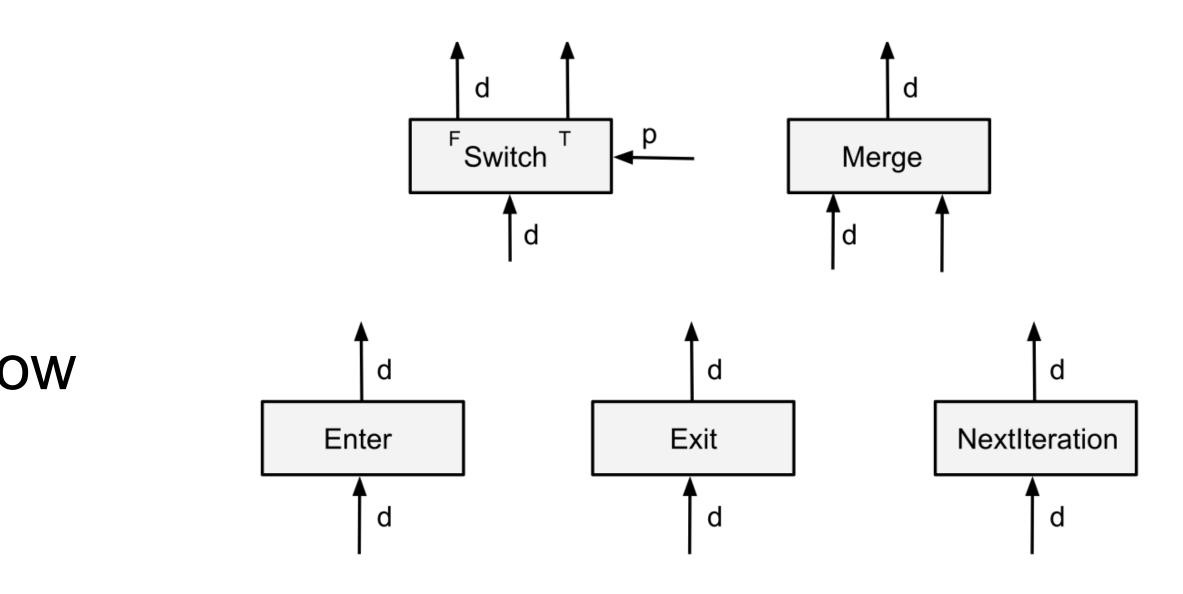
• Dynamic flow with basic graph primitives



"The Control Flow Primitives" ¹

Control Flow Operations

- Dynamic flow with basic TensorFlow primitives
 - while-loops, conditionals



"The Control Flow Primitives" ¹

Graph Partitioning

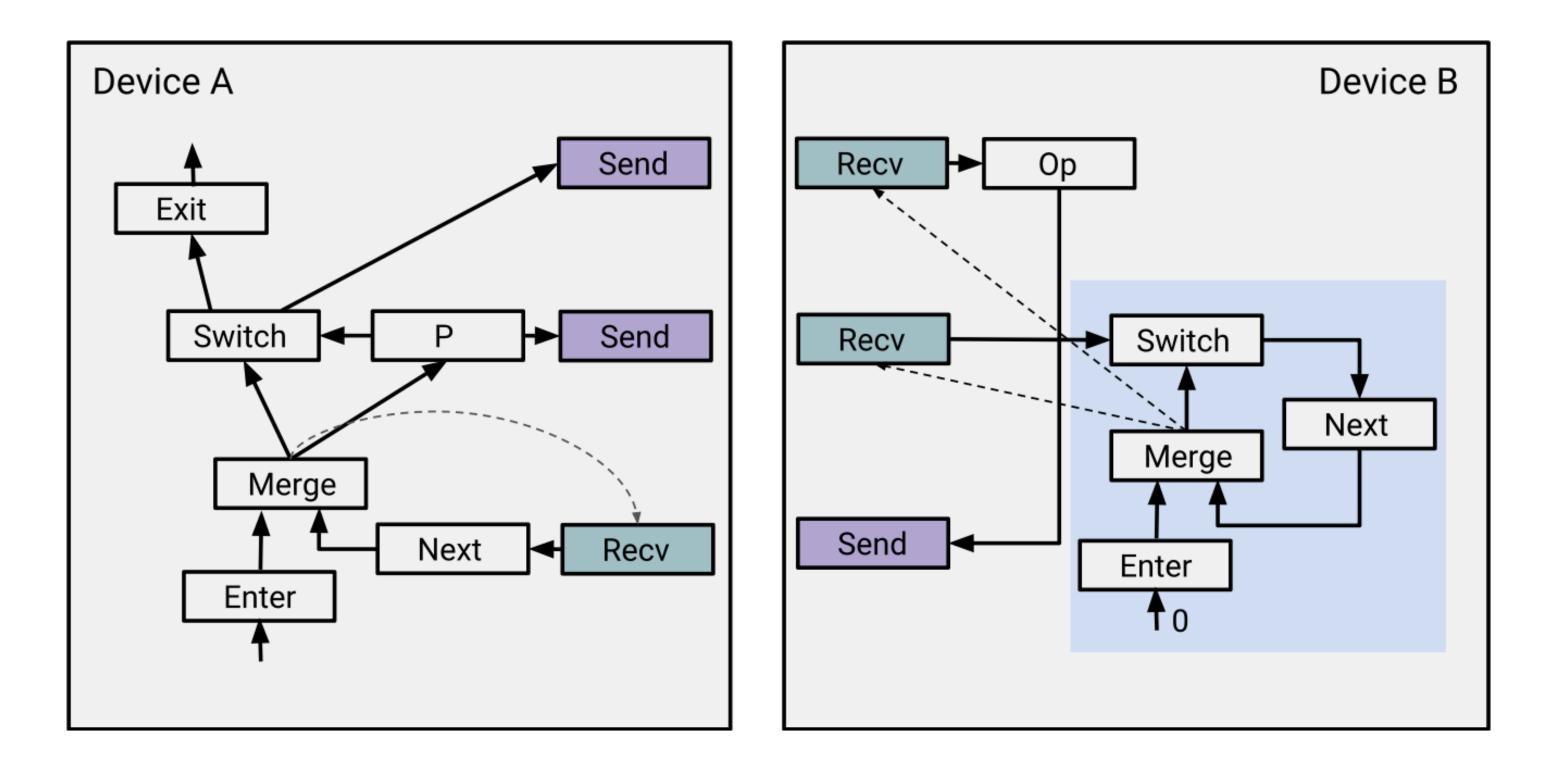
• Ability to split a graph into subgraphs

Graph Partitioning

- Ability to split a graph into subgraphs
- TensorFlow: running subgraphs on various devices

Direct cross-device communication

Send and Recv operations



"Distributed execution of a while-loop" ¹

Memory swapping

- Temporary use of abundant memory (GPU \leftrightarrow CPU)
- Dependent primarily on the parallel execution

Automatic Differentiation

- TensorFlow mechanisms
- Saving intermediate values (while-loops)
- Memory management (memory swapping)

Evaluation

• Good memory performance (memory swapping, distributed systems)

Evaluation

	Training time per loop iteration (ms), by sequence length						
Swap	100	200	500	600	700	900	1000
Disabled	5.81	5.78	5.75	OOM	OOM	OOM	OOM
Enabled	5.76	5.76	5.73	5.72	5.77	5.74	5.74

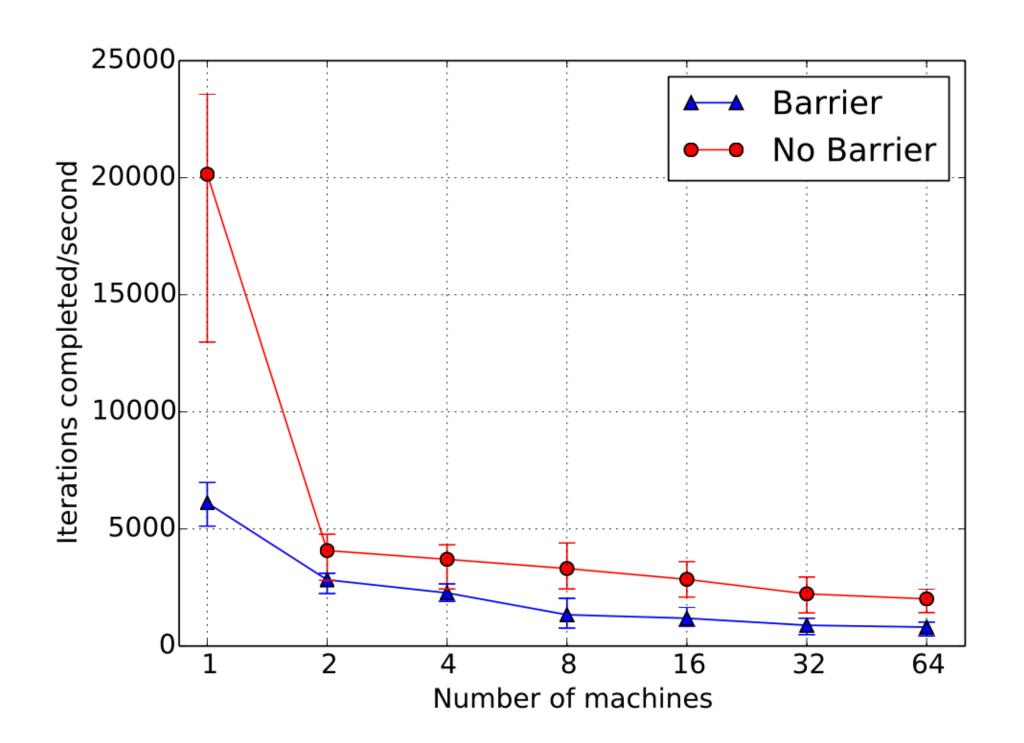
with increasing sequence lengths." ¹

Evaluation

"Training time per loop iteration for an LSTM model"

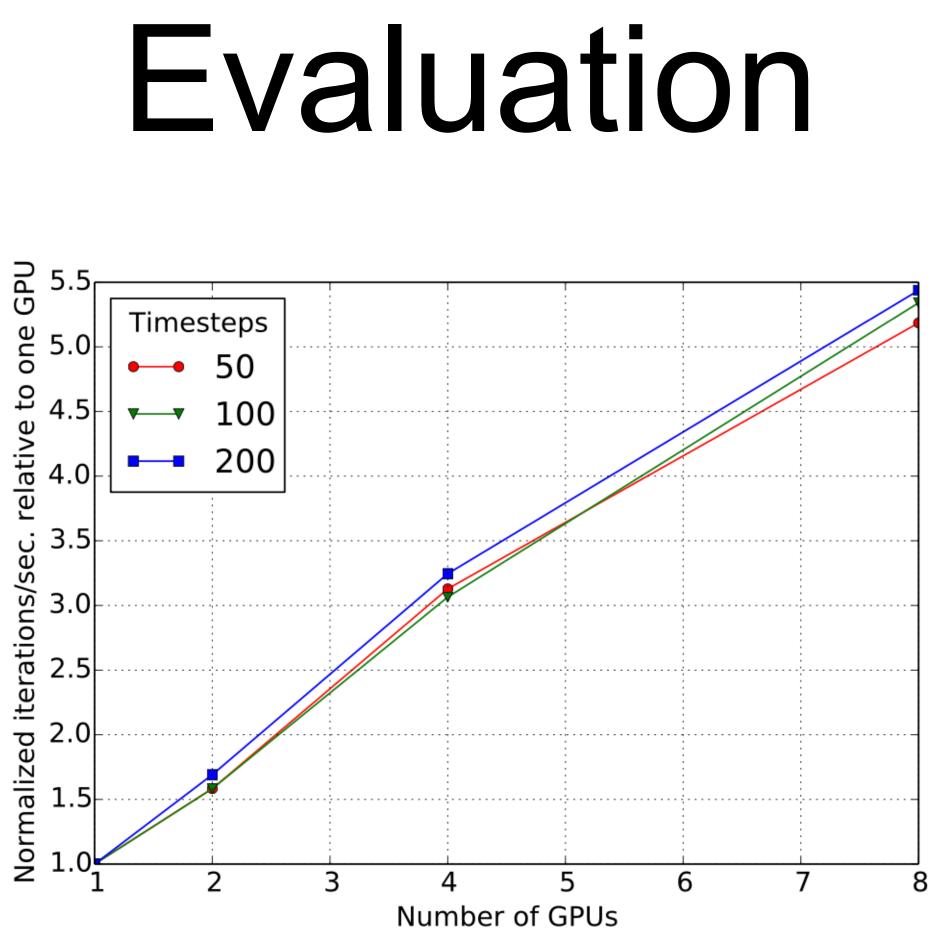
- Good memory performance (memory swapping, distributed systems)
- Mixed speed performance (overheads)

Evaluation



Evaluation

"Performance of a distributed while-loop with a trivial body on a GPU cluster"¹



(training)¹

"Parallel speedup for an 8-layer LSTM as we vary the number of GPUs from 1 to 8."

Analysis of 11.7 million machine-learning graphs:

- 65% contain conditional computation
- 5% contain one or more loop

Evaluation

• Limited discussion of alternative approaches

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- Limited testing approaches (only performance)

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- Limited testing approaches (only performance)
- Tested on limited and fairly homogenous distributed systems
- Limited discussion of implementation (graph semantics)

References

- Proceedings of the Thirteenth EuroSys Conference. 2018.
- ² Abadi, Martín, et al. "Tensorflow: Large-scale machine learning on

¹ - Yu, Yuan, et al. "Dynamic control flow in large-scale machine learning."

heterogeneous distributed systems." arXiv preprint arXiv:1603.04467. 2016.