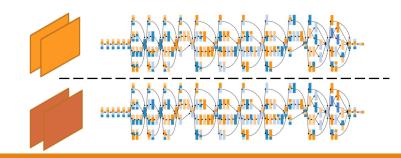
Beyond Data and Model Parallelism for Deep Neural Networks

ZHIHAO JIA, MATEI ZAHARIA, ALEX AIKEN SYSML 2019 PRESENTED BY JULIUS LISCHEID

Existing Parallelisation Approaches (1/2)

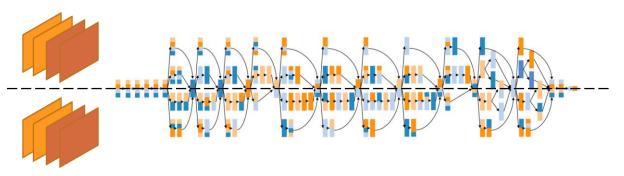
DATA PARALLELISM

- •Replica of neural network on each device
- •Each device processes subset of training data
- •After each iteration, parameters are synchronised
- •Works well for compute-heavy operations with few parameters (e.g. convolutions)



MODEL PARALLELISM

- •Disjoint subsets of neural network assigned to devices
- •No parameter synchronisation, but requires data transfers between operations



Existing Parallelisation Approaches (2/2)

EXPERT-DESIGNED STRATEGIES

AUTOMATED FRAMEWORKS

- •A. Krizhevsky. One weird trick for parallelizing convolutional neural networks. CoRR 2014.
 - Data parallelism for convolutional layers, model parallelism for fully-connected layers
- •Y. Wu et al. Google's neural machine translation system: bridging the gap between human and machine translation. CoRR 2016.
 - Data parallelism for compute nodes, model parallelism for intra-node computation

- •A. Mirhoseini et al. Device Placement Optimization with Reinforcement Learning. ICML 2017.
 - Reinforment learning for model parallelism
- •Z. Jia et al. Exploring hidden dimensions in parallelizing convolutional neural networks. CoRR 2018.
 - Dynamic Programming for parallelisation of DNNs with linear computation graphs
- •D. Narayanan et al. PipeDream: generalized pipeline parallelism for DNN training. SOSP 2019.

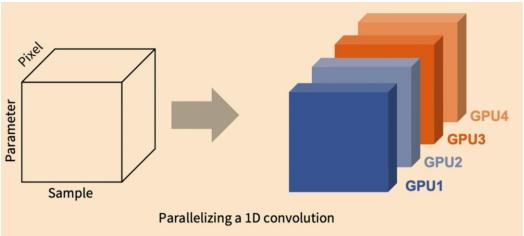
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The SOAP Search Space

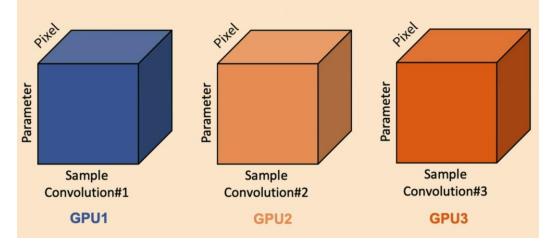
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Samples (data parallelism)

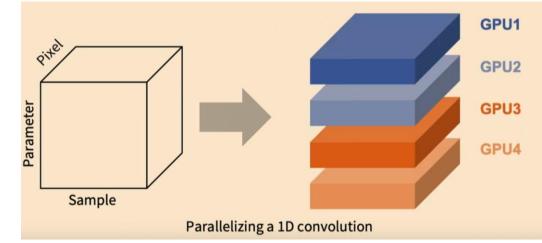
Attributes (e.g. pixels)



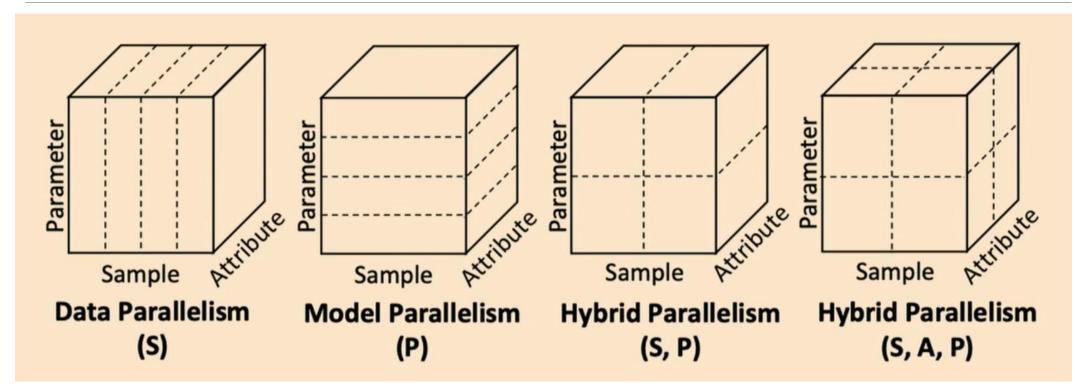
Operators (model parallelism)



Parameters (≈model parallelism)

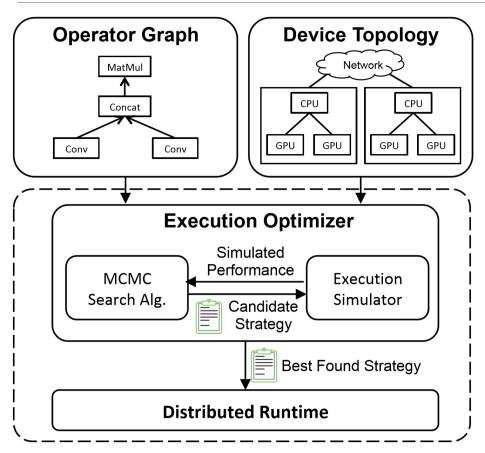


Hybrid Parallelism in SOAP



Example parallelization strategies for 1D convolution

FlexFlow



- •Trying out strategies on hardware is expensive due to long iteration times
- Execution Optimizer uses simulator instead
 - Measures operator runtime on hardware
 - Estimates runtime of parallelisation strategies
 - Delta simulation algorithm uses incremental updates for acceleration

•Execution optimizer explores search space with Markov Chain Monte Carlo algorithm

Evaluation (1/2)

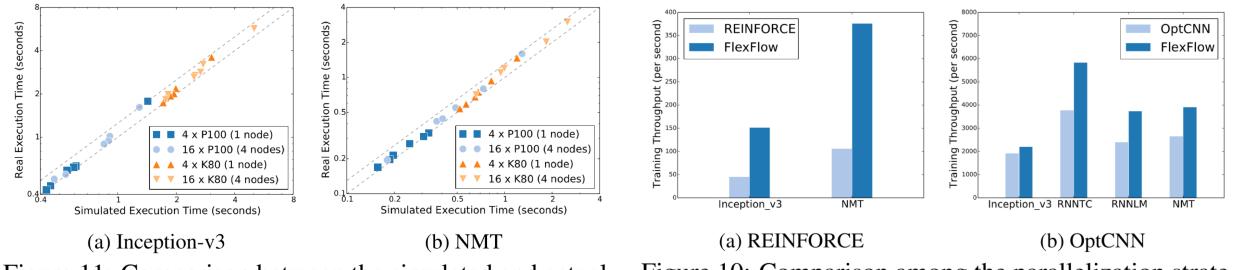


Figure 11: Comparison between the simulated and actual execution time for different DNNs and device topologies.

Figure 10: Comparison among the parallelization strategies found by different automated frameworks.

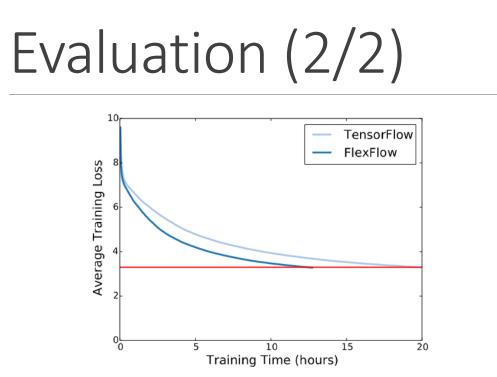
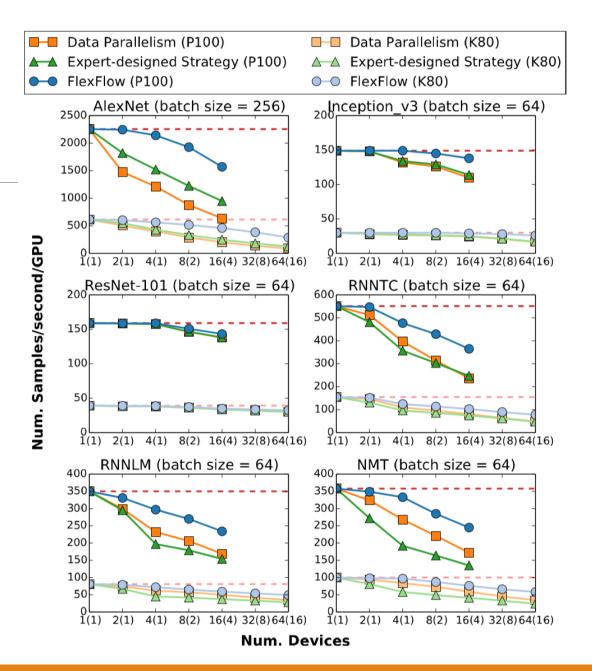


Figure 9: Training curves of Inception-v3 in different systems. The model is trained on 16 P100 GPUs (4 nodes).



Review (1/2)

STRENGTHS/AGREEMENTS

- •Expands search space for parallelisation strategies
- Proposes a way to efficiently explore that search space
- Leads to an actual speed-up

WEAKNESSES/DISAGREEMENTS

- •Unclear how much SOAP and execution optimiser contribute to training acceleration
- •Usefulness of Attribute dimension is questionable
- •More end-to-end performance benchmarks would have been useful

Review (2/2)

KEY TAKEAWAYS

- •Training performance of parallelisation strategies can be efficiently and accurately predicted
- •The resulting speed-up allows for the exploration of a wider search space

POTENTIAL IMPACT

- •Usage of other search algorithms to explore parallelisation search space in simulation
- •Combination of parallelisation search space with computation graph substitutions (compare Tim's presentation next week)

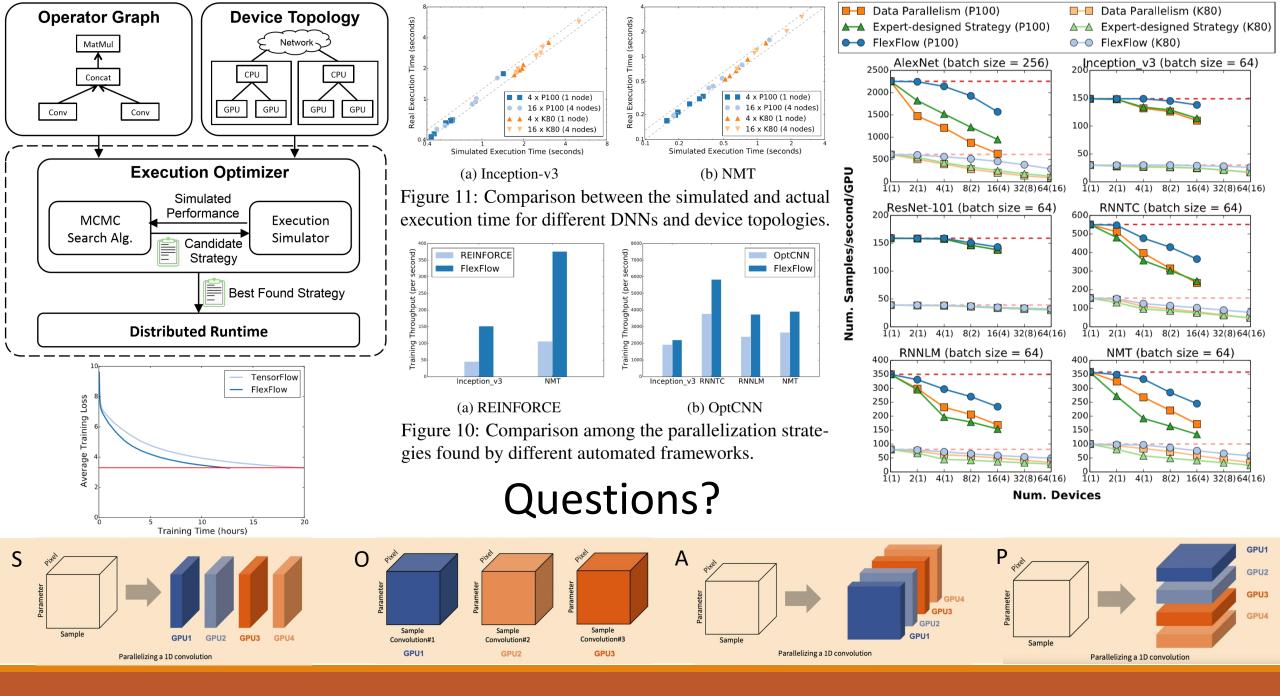


Image Citations

Images with beige background retrieved from Jia Zhihao's SysML 19 talk: <u>https://www.youtube.com/watch?v=81l6kkV-OkE</u>

All other images extracted from Z. Jia, M. Zaharia, and A. Aiken: Beyond Data and Model Parallelism for Deep Neural Networks, SYSML, 2019.