



# Alpa Automating Inter- and Intra-Operator Parallelism for Distributed Deep Learning



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# Background


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# Large Models Enable Breakthroughs in Machine Learning

AI

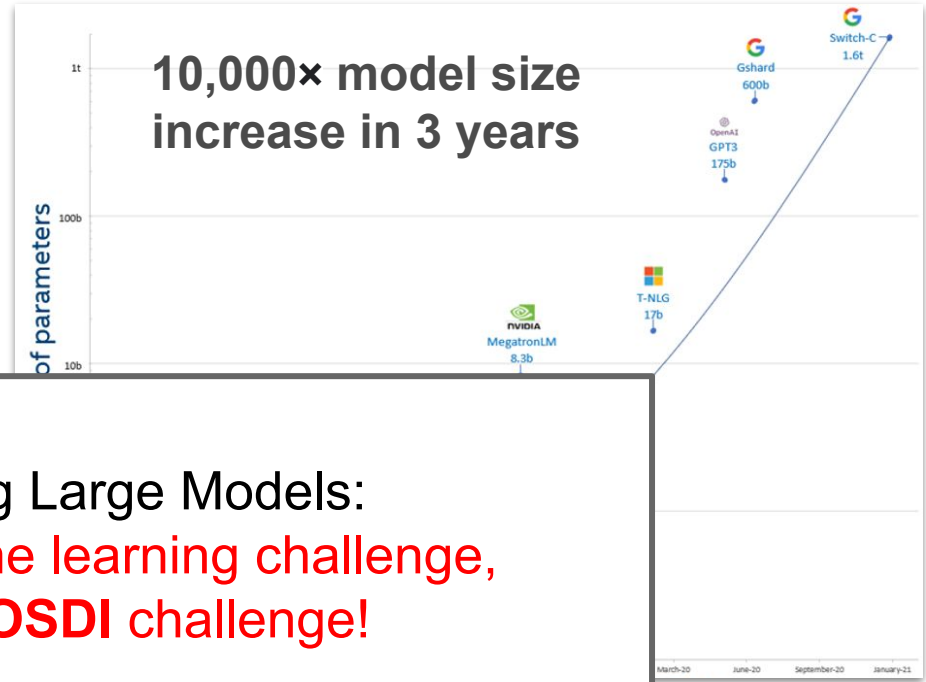
OpenAI debuts gigantic GPT-3 language model with **175 billion parameters**

KHARI JOHNSON @KHARIJOHNSON MAY 29, 2020 8:34 AM



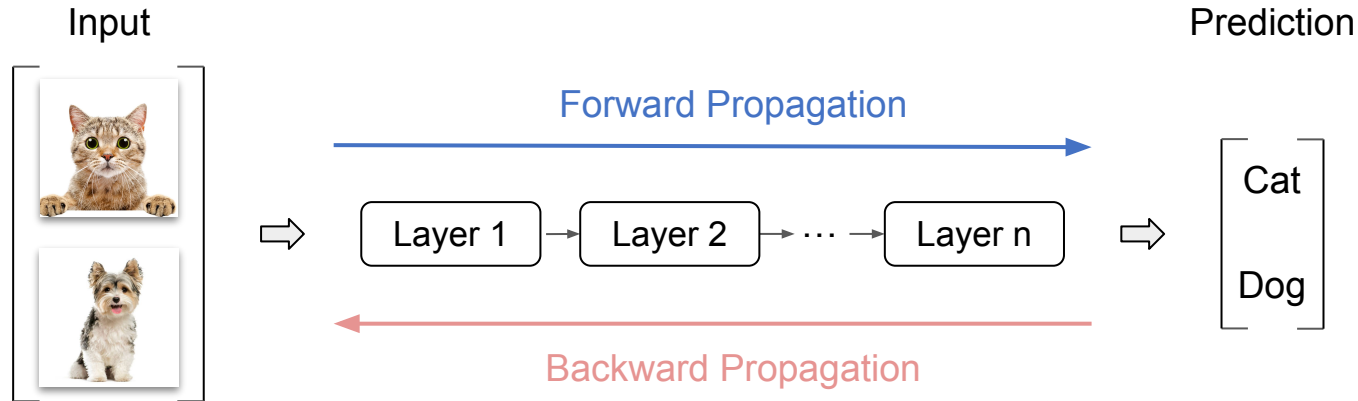
OpenAI booth at NeurIPS 2019 in Vancouver, Canada  
Image Credit: Khari Johnson / VentureBeat

A team of more than 30 OpenAI researchers has been capable of achieving state-of-the-art results on a wide range of processing tasks that range from language translation to SAT questions. GPT-3 has a whopping 175 billion



Training Large Models:  
**Not a machine learning challenge,  
but an **OSDI** challenge!**

# What are System Challenges?



1. What if the **input dataset** is very large?

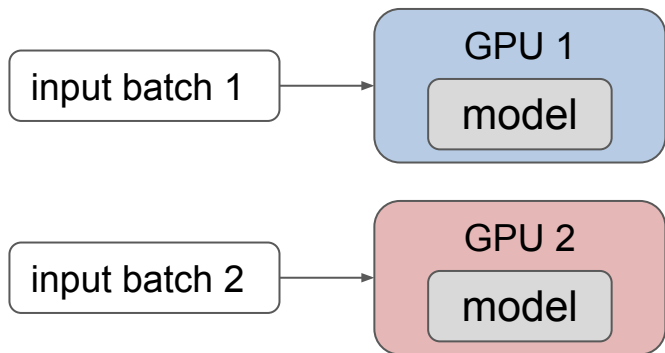
2. What if the **model** is very large?

# What are System Challenges?

1. What if the input dataset is very large?

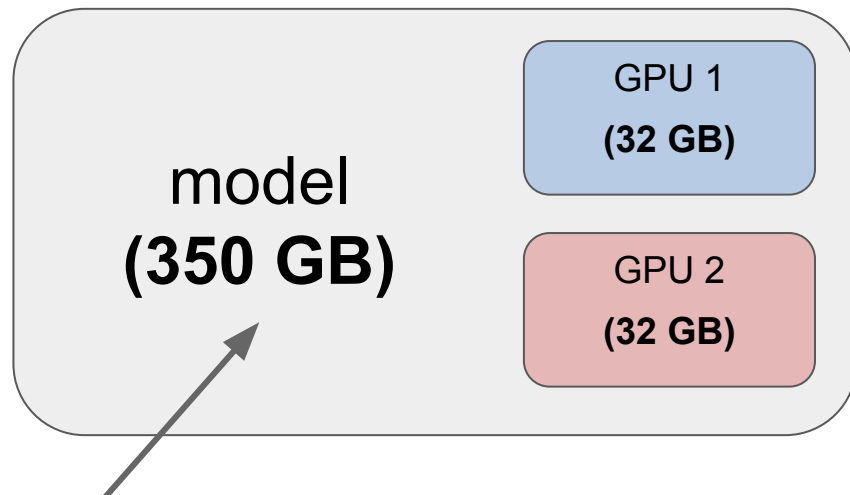
😊 **Easy.**

Use data parallelism: partition input data and replicate the model



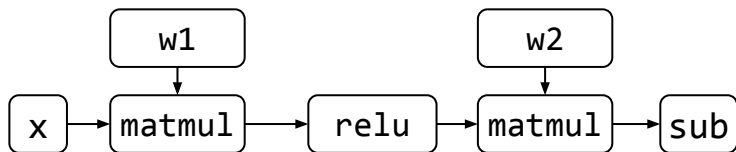
2. What if the model is very large?

😡 **Hard !!**

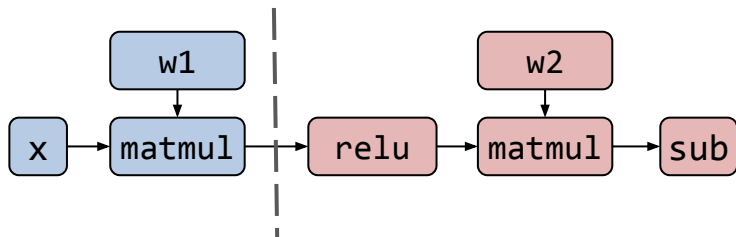


**Challenge:** How to partition a computational graph?

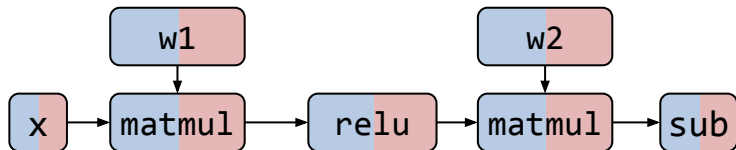
# Partition Computational Graphs



## Strategy 1: Inter-operator Parallelism



## Strategy 2: Intra-operator Parallelism

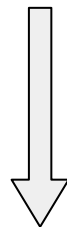
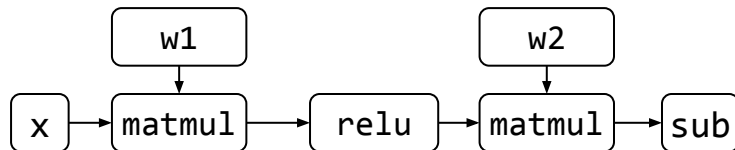


## Trade-off

	Inter-operator Parallelism	Intra-operator Parallelism
Communication	Less	More
Device Idle Time	More	Less



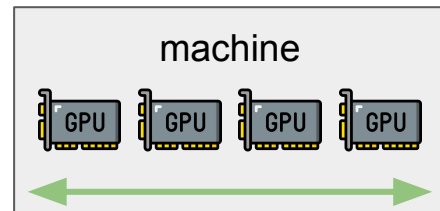
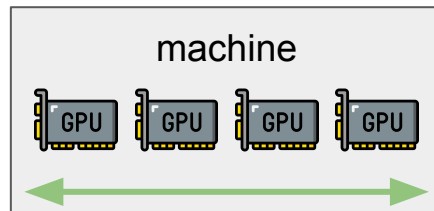
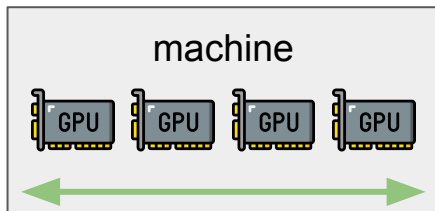
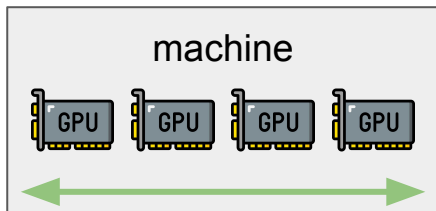
# Network Topology



**Challenge:** How to handle heterogeneous network topology?

↔ Fast connections

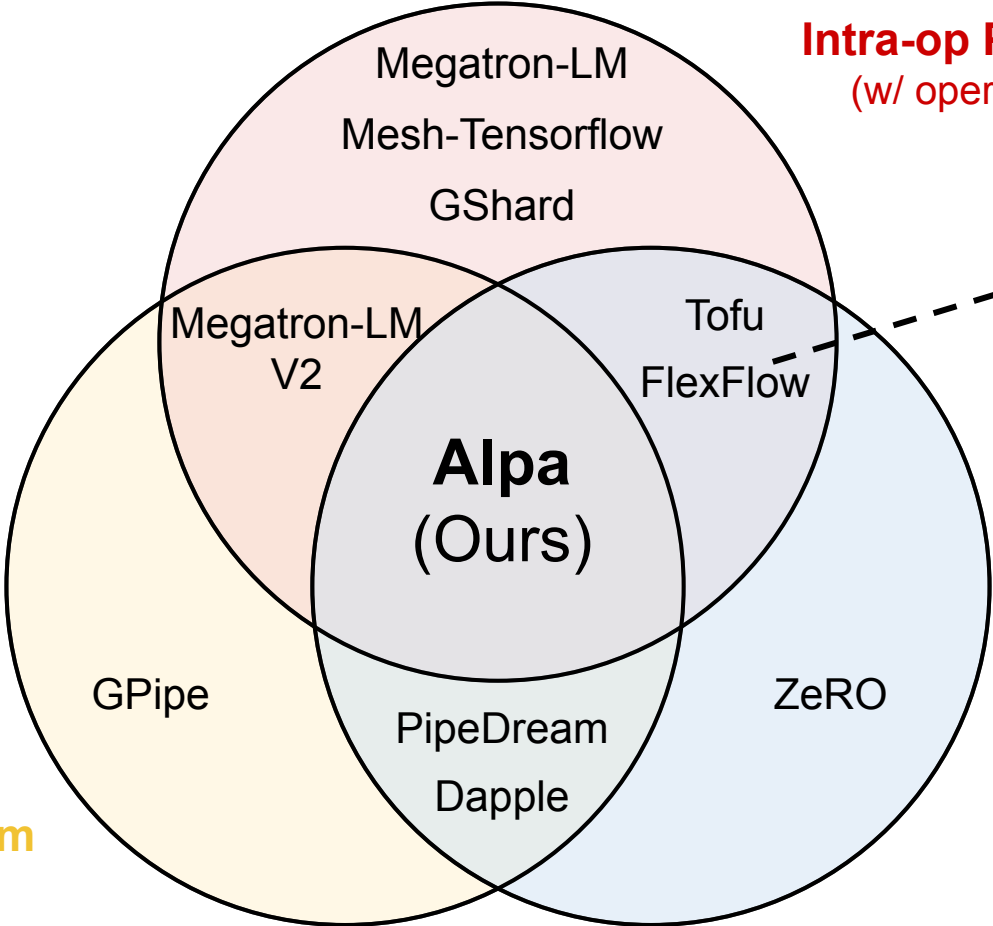
↔ Slow connections





# Prior Works

**Inter-op Parallelism**  
(w/ pipeline)



**Intra-op Parallelism**  
(w/ operator-level)

**Automatic**

Unity [OSDI'22]

# Alpa Compiler

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A unified **compiler** that **automatically** finds and executes the best **Inter-op** and **Intra-op** parallelism for **large** deep learning models.

# Alpa User API

`@alpa.parallelize`

Distribute the training function  
with a simple decorator



```
@alpa.parallelize
def train_step(model_state, batch):
    def loss_func(params):
        out = model_state.forward(params, batch["x"])
        return np.mean((out - batch["y"]) ** 2)

    grads = grad(loss_func)(state.params)
    new_model_state = model_state.apply_gradient(grads)
    return new_model_state

# A typical JAX training loop
model_state = create_train_state()
for batch in data_loader:
    model_state = train_step(model_state, batch)
```

# Alpa's Main Contributions



Two-level hierarchical space of parallelism techniques.

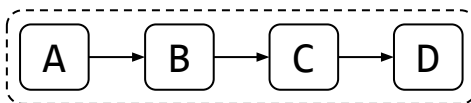


Effective optimization algorithms at each level.

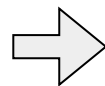
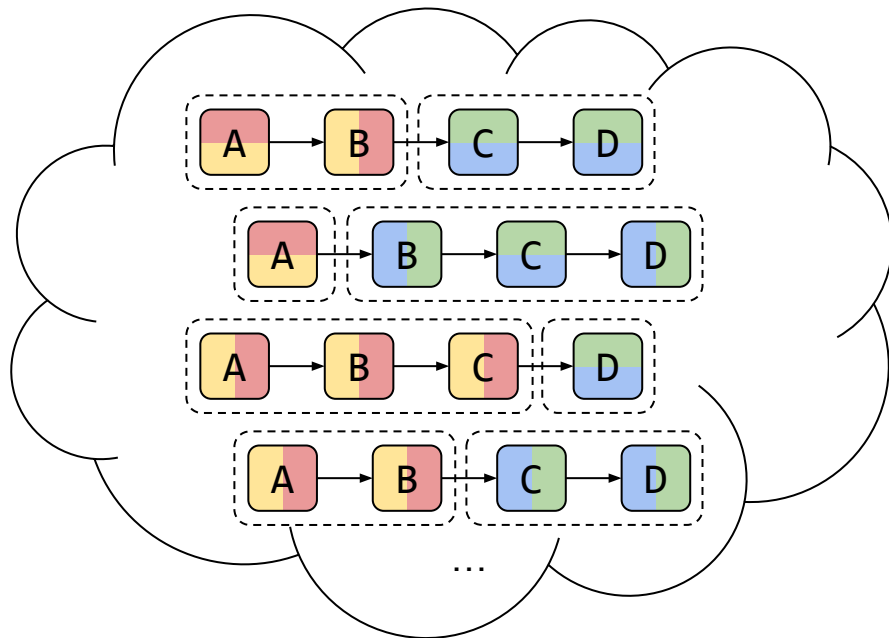


Efficient compiler and runtime system implementation.

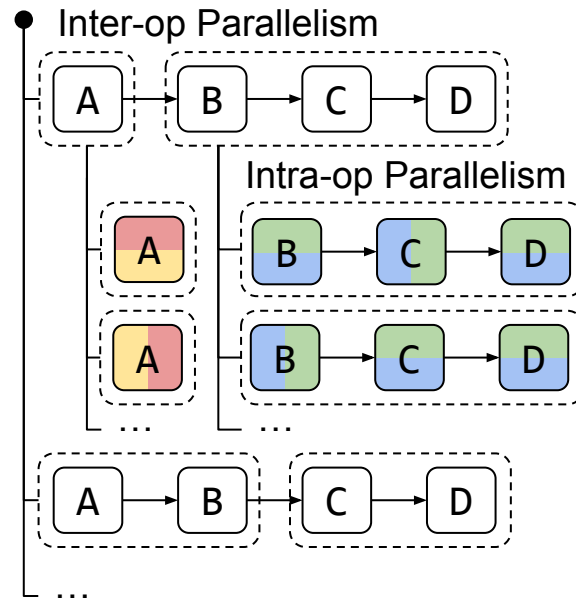
# Computational Graph



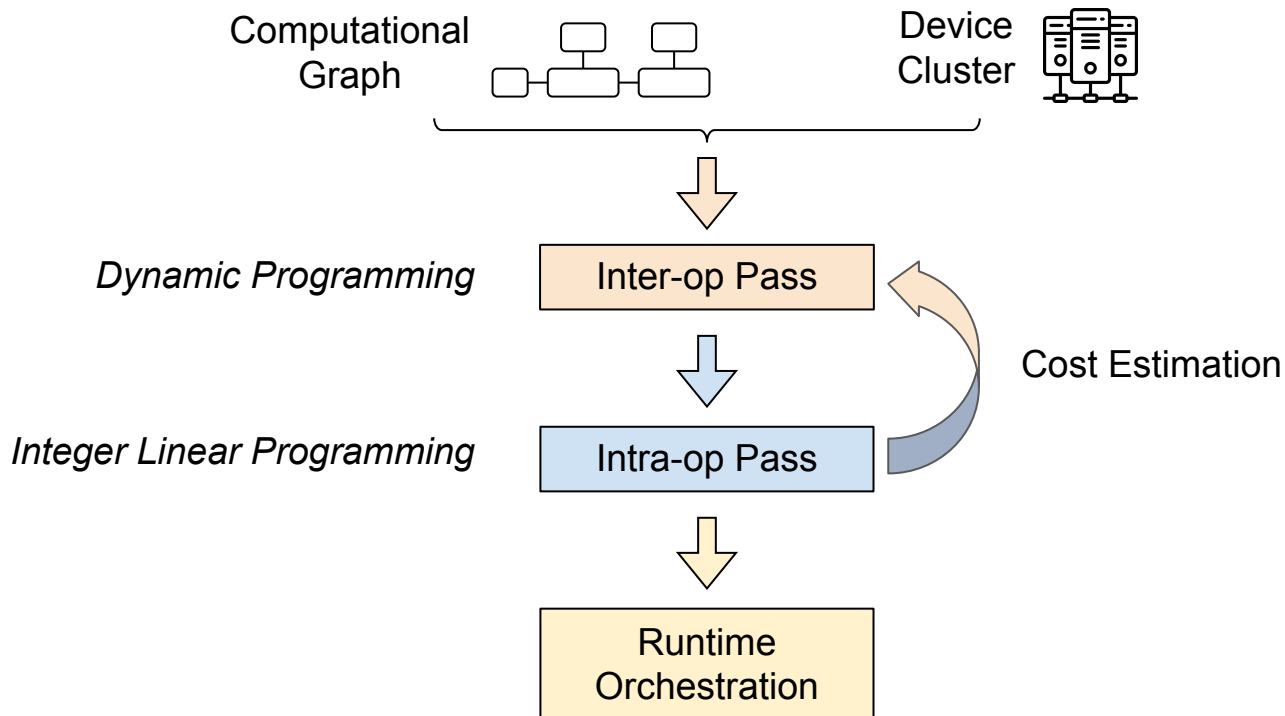
## Whole Search Space



## Alpha Hierarchical Space

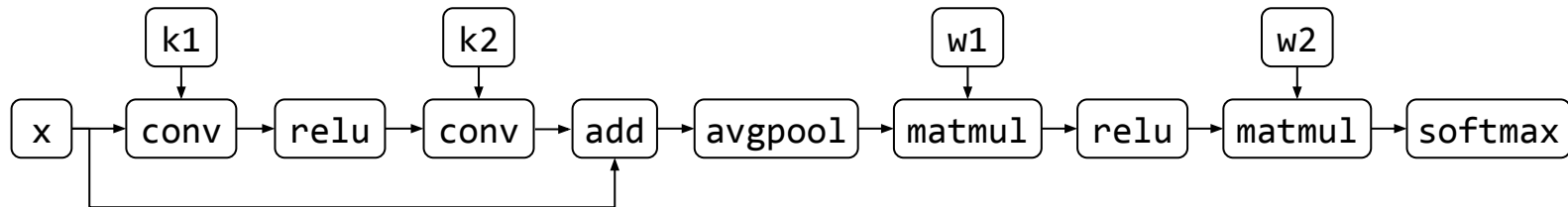


# Alpa Compiler: Hierarchical Optimization



# Inter-op Pass

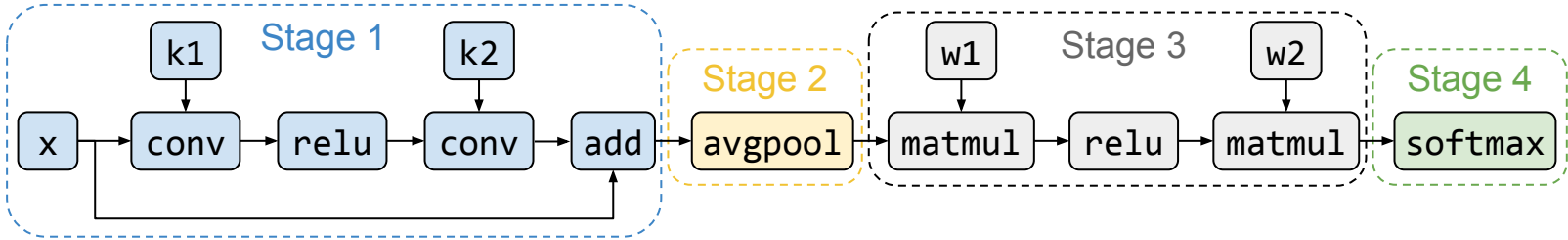
## Computational Graph



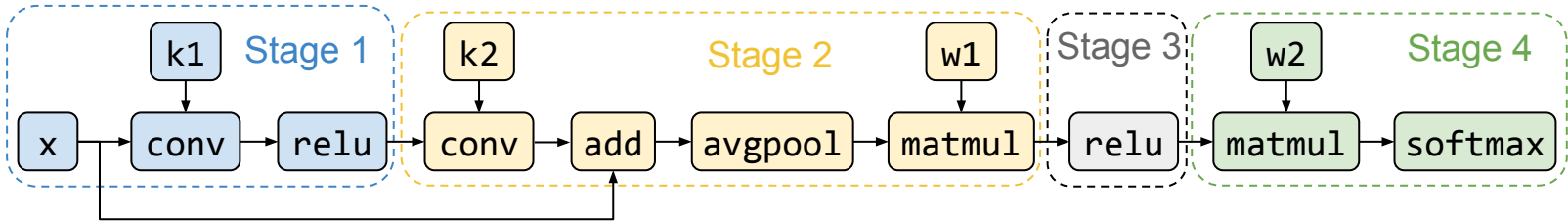


# Inter-op Pass

Graph Partitioning



or

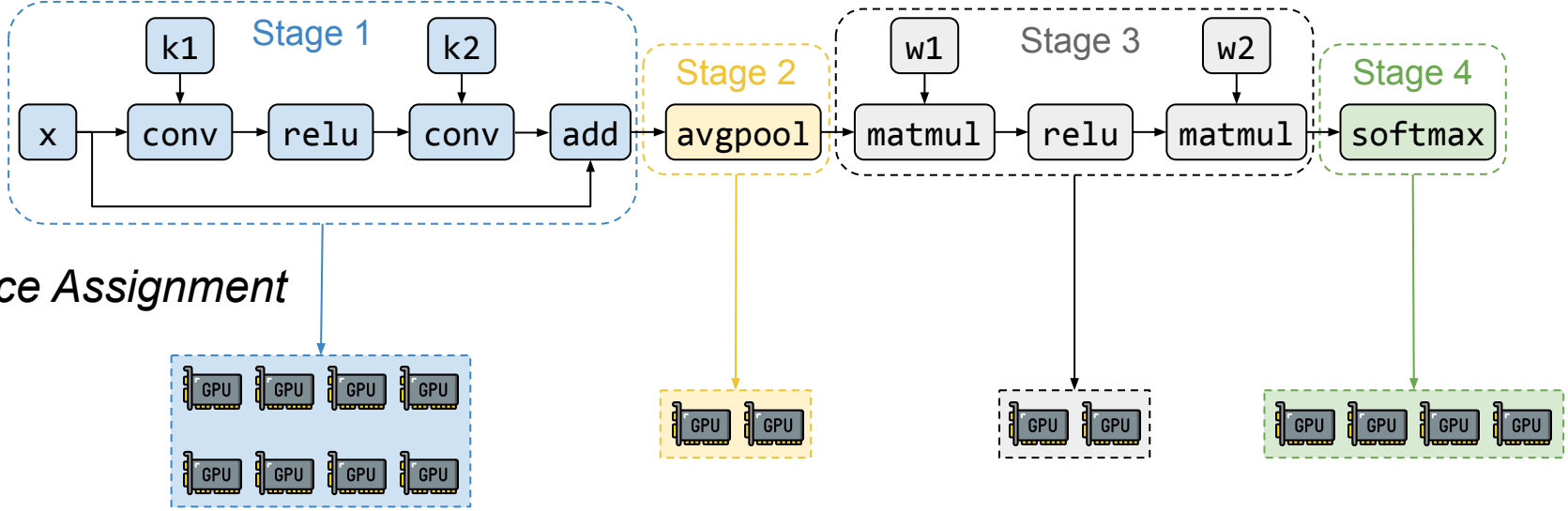


or

...

# Inter-op Pass

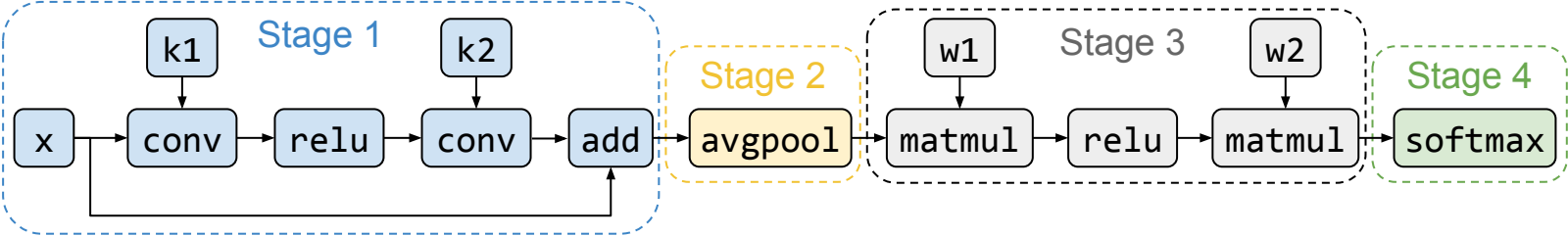
## Partitioned Computational Graph



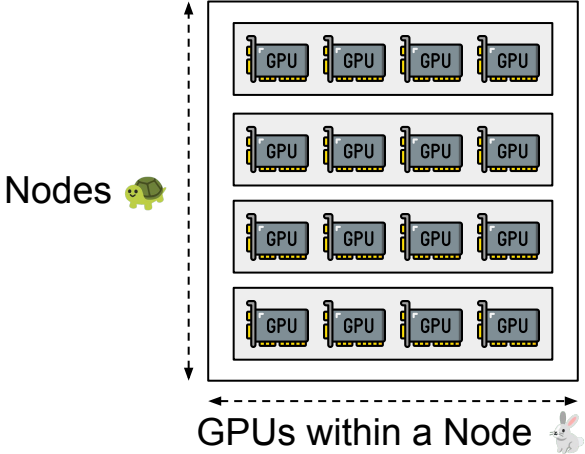
*Device Assignment*

# Inter-op Pass

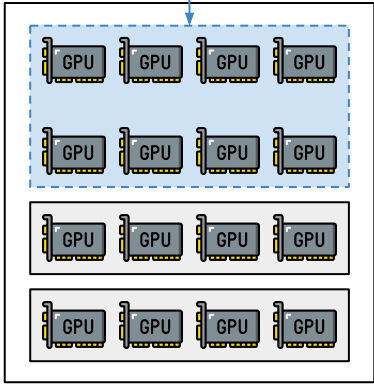
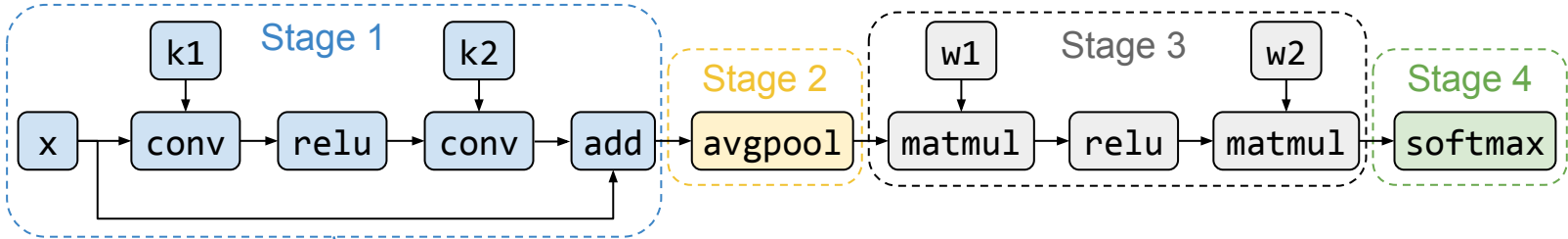
## Partitioned Computational Graph



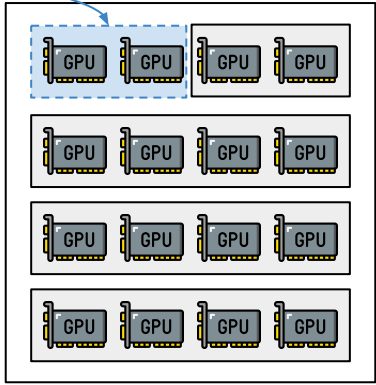
## Cluster (2D Device Mesh)



# Inter-op Pass



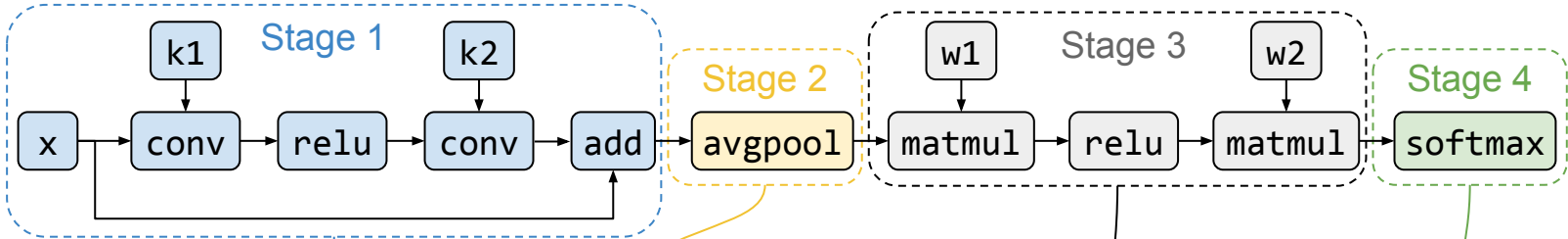
or



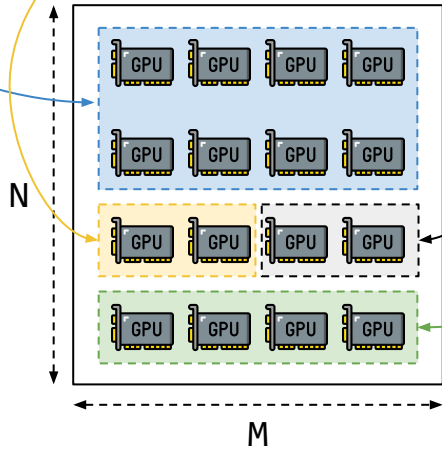
or

...

# Inter-op Pass

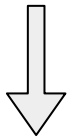
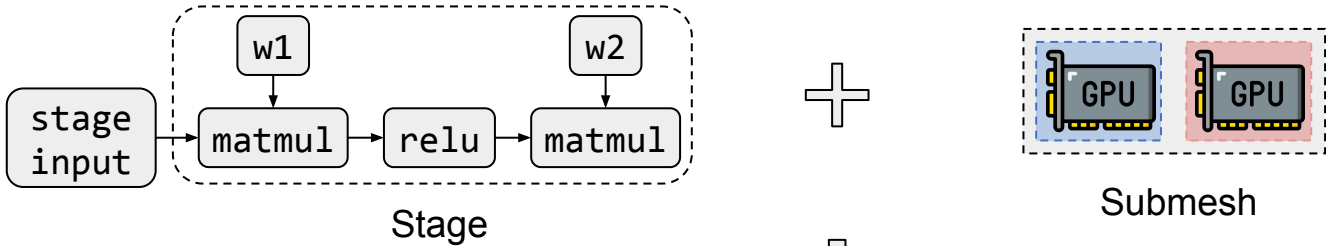


Solved together by  
**Dynamic Programming**

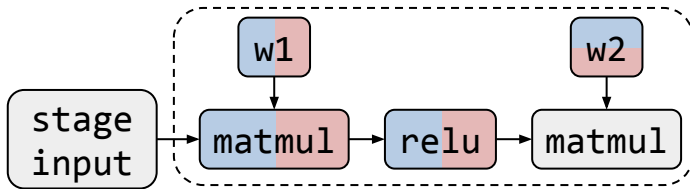


More details on the DP algorithm can be found in the paper.

# Intra-op Pass



*Solved by*  
**Integer Linear  
Programming**



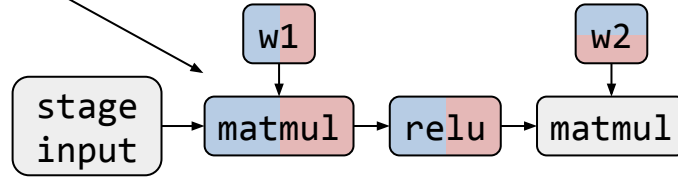
Stage with intra-operator  
parallelization

# Intra-op Pass

## Integer Linear Programming Formulation

### Decision vector

Parallel strategies of each operator



**Minimize** Computation cost + Communication cost

More details on the ILP algorithm can be found in the paper.

# Compilation Time Optimization

Communication-aware  
operator clustering in  
ILP & DP

Early stopping in DP

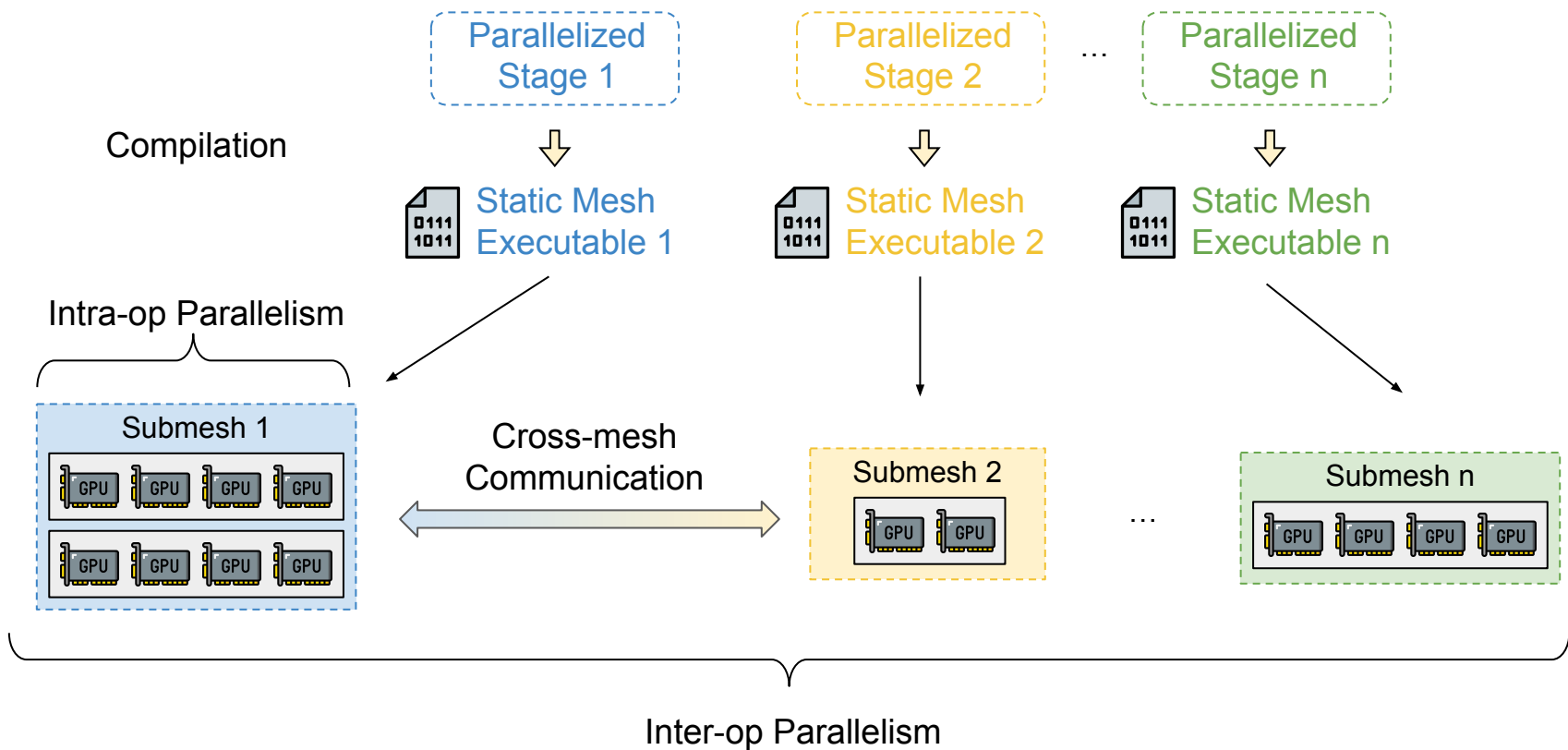
Distributed  
Compilation

**Alpa Compilation Time:** < 40 min for the largest experiment.

- Can be further reduced by at least 50% with search space pruning.



# Runtime Orchestration

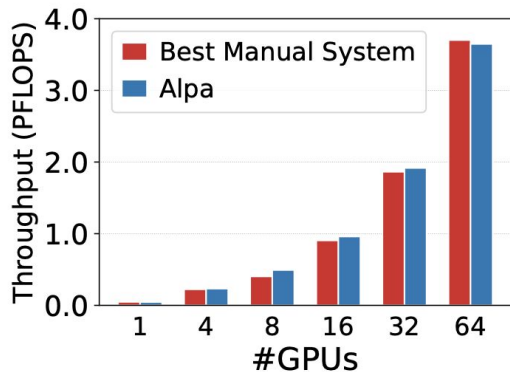


# Evaluation

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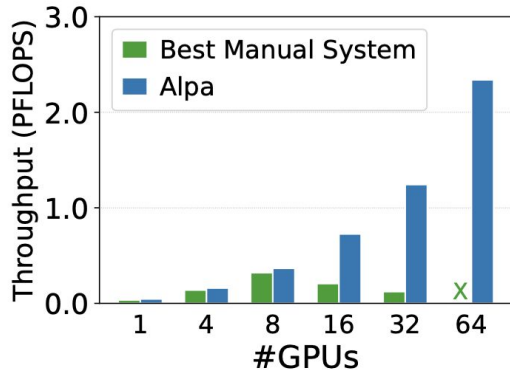
# Evaluation: Comparing with Previous Works

## GPT (up to 39B)



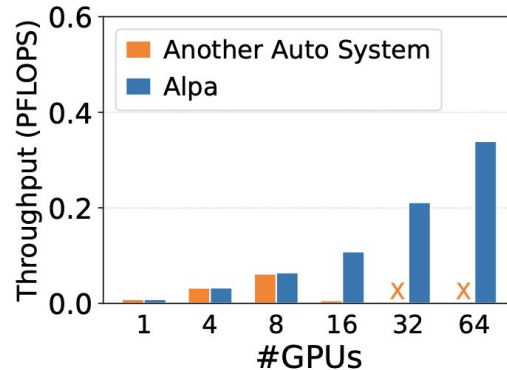
Match specialized manual systems.

## GShard MoE (up to 70B)



Outperform the manual baseline by up to 8x.

## Wide-ResNet (up to 13B)

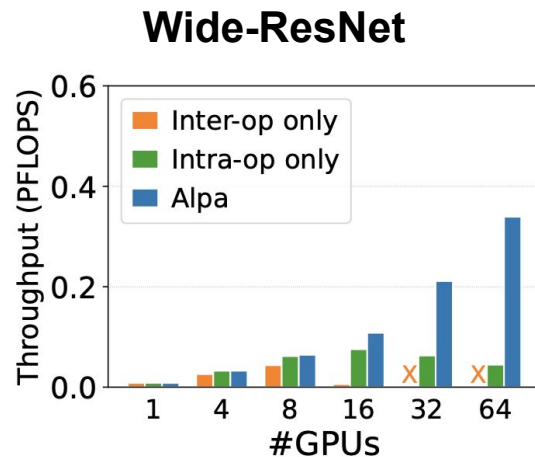
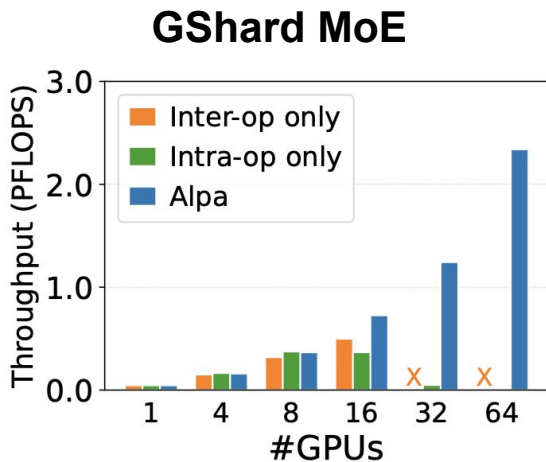
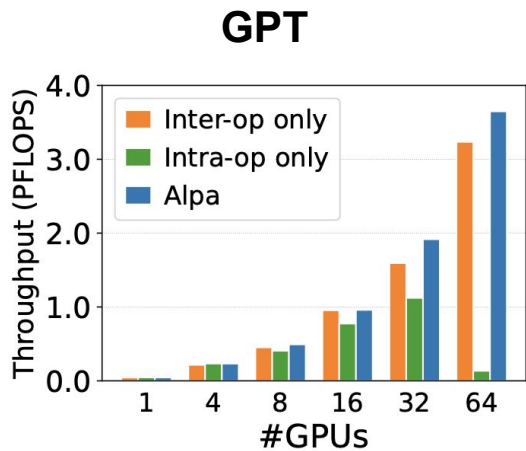


Generalize to models without manual plans.

*Weak scaling results where the model size grow with #GPUs.*

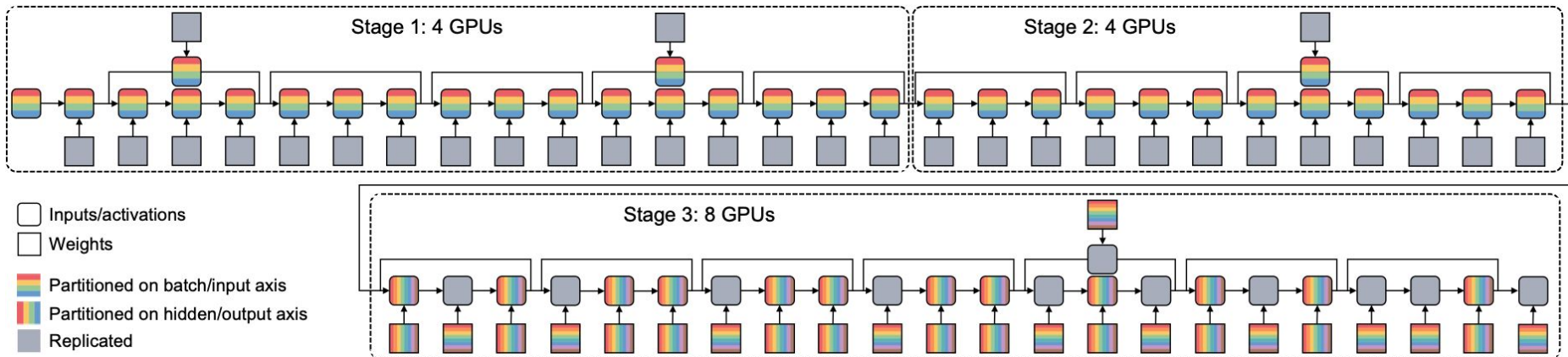
*Evaluated on 8 AWS EC2 p3.16xlarge nodes with 8 16GB V100s each (64 GPUs in total).*

# Evaluation: Ablation Study with Inter-op and Intra-op Only



Combining inter- and intra-operator parallelism scales to more devices.

# Case Study: Wide-ResNet Partition on 16 GPUs.



[@alpa.parallelize](#): automatic model-parallel training



Hierarchical view: [inter-op](#) and [intra-op](#)



Match or outperform specialized systems



Generalizes to new models

Alpa



[alpa.ai](https://github.com/alpa-ai/alpa)



Star

390