Gemel: Model Merging for Memory-Efficient, Real-Time Video Analytics at the Edge

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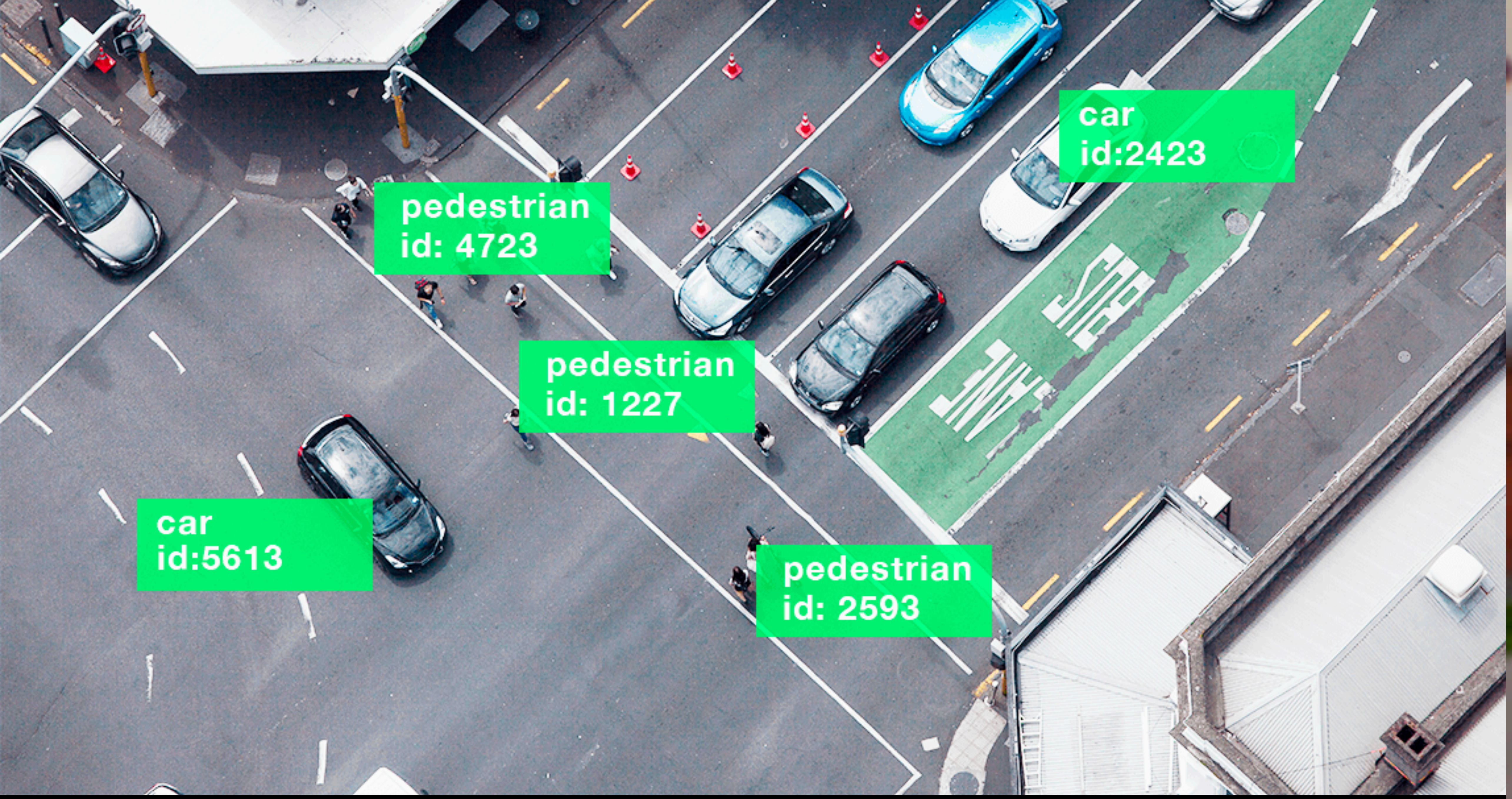
April 18, 2023

NSDI 2023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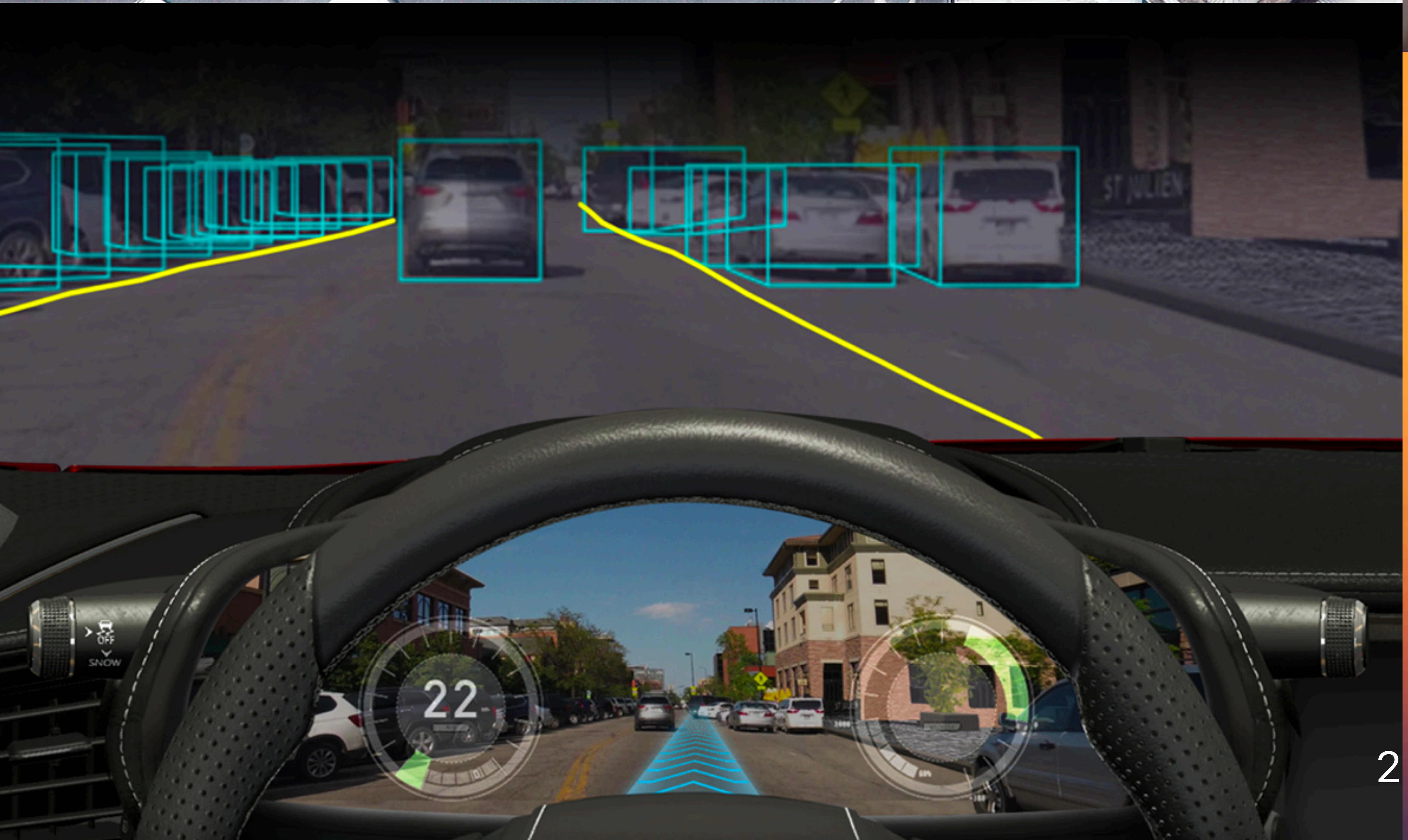
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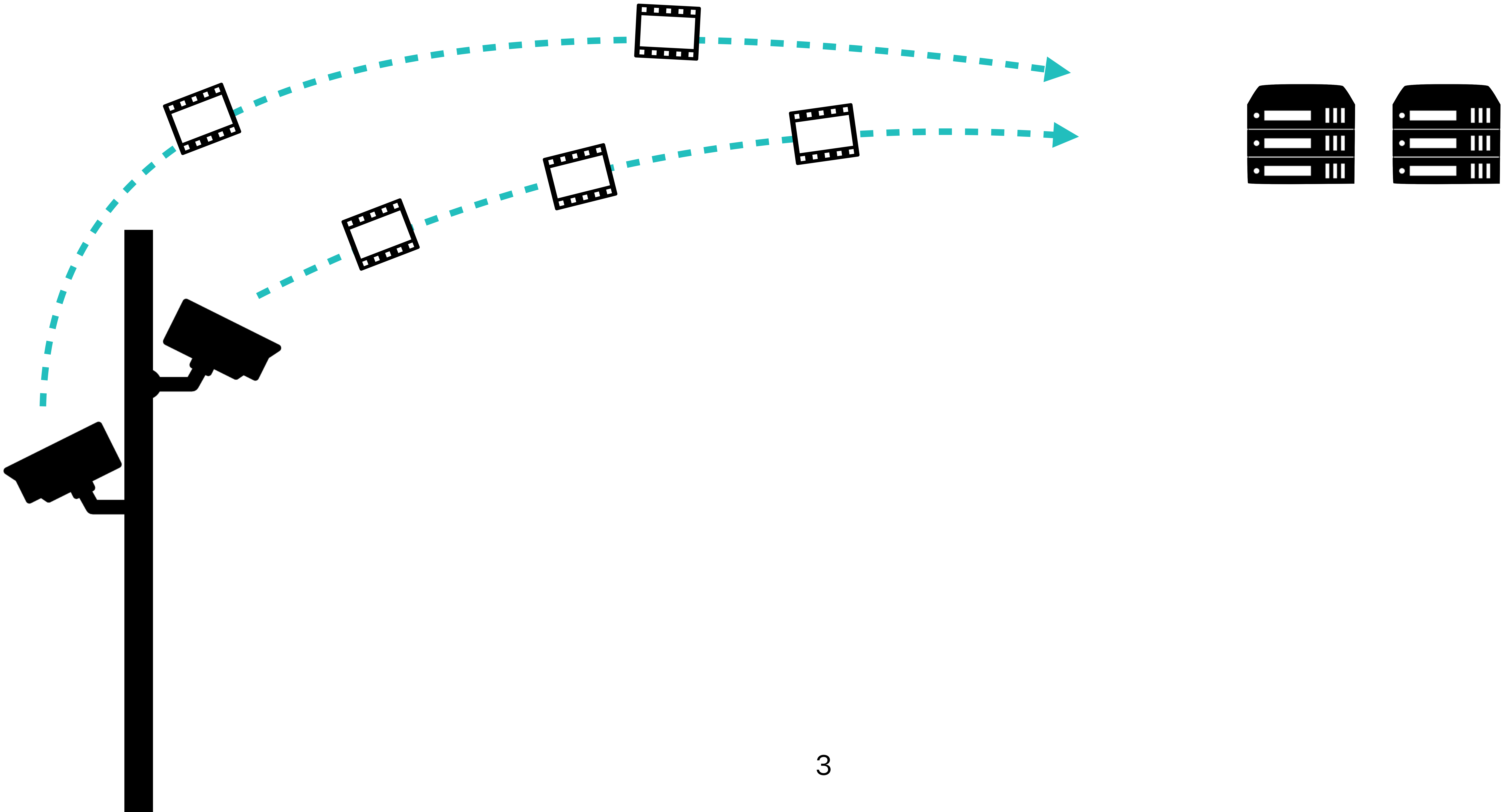
Live Video Analytics Pipeline



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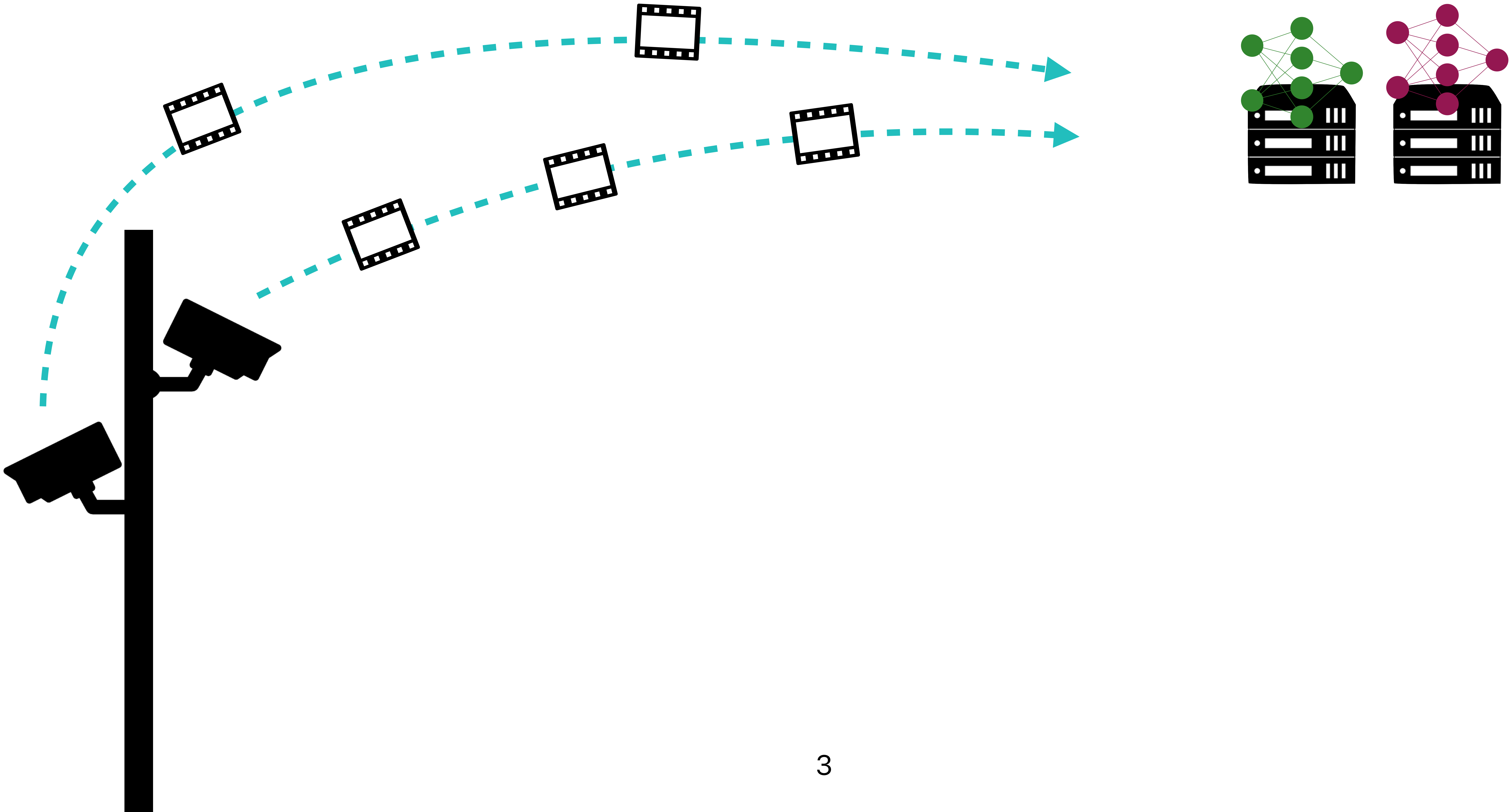

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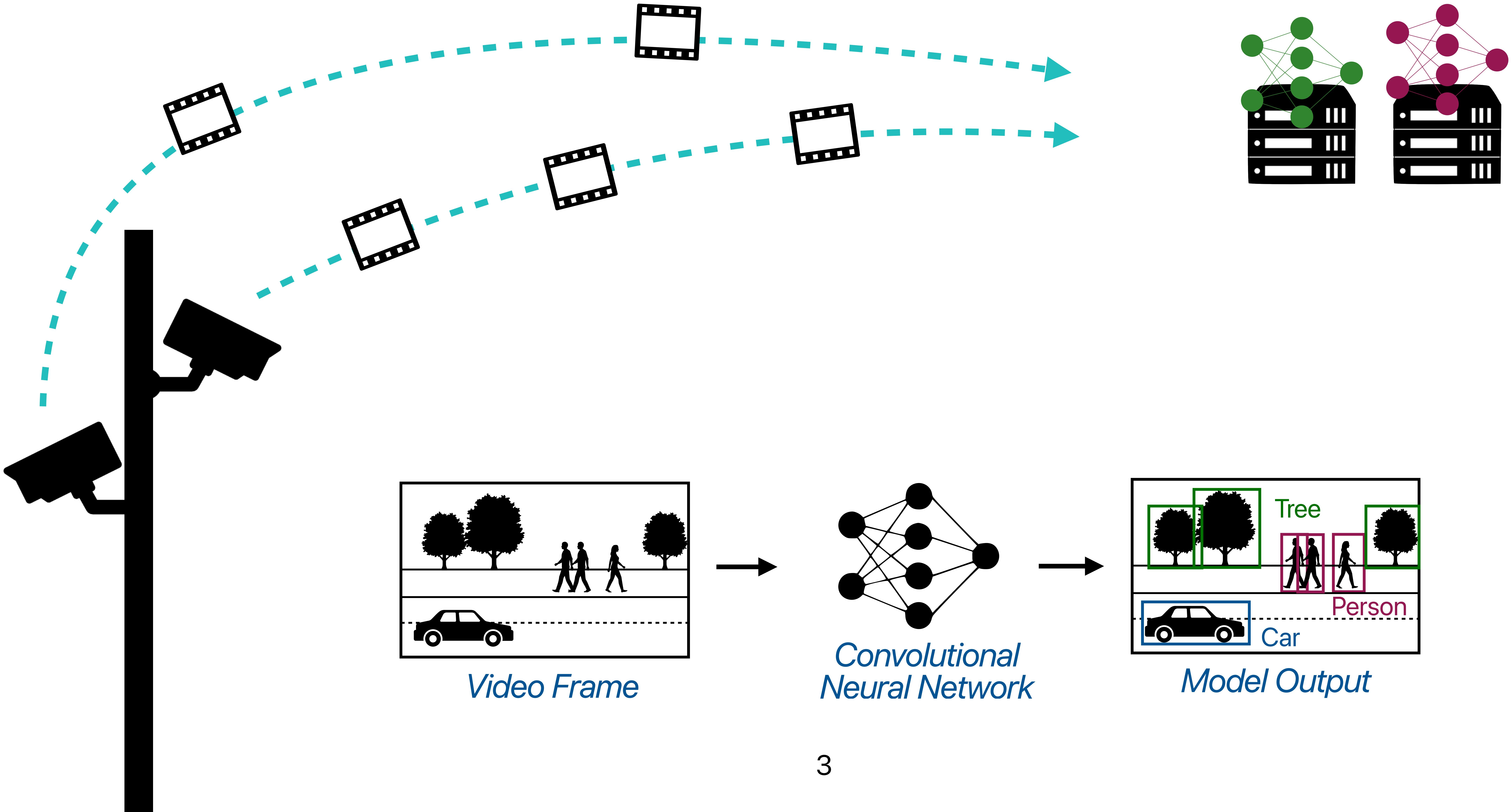

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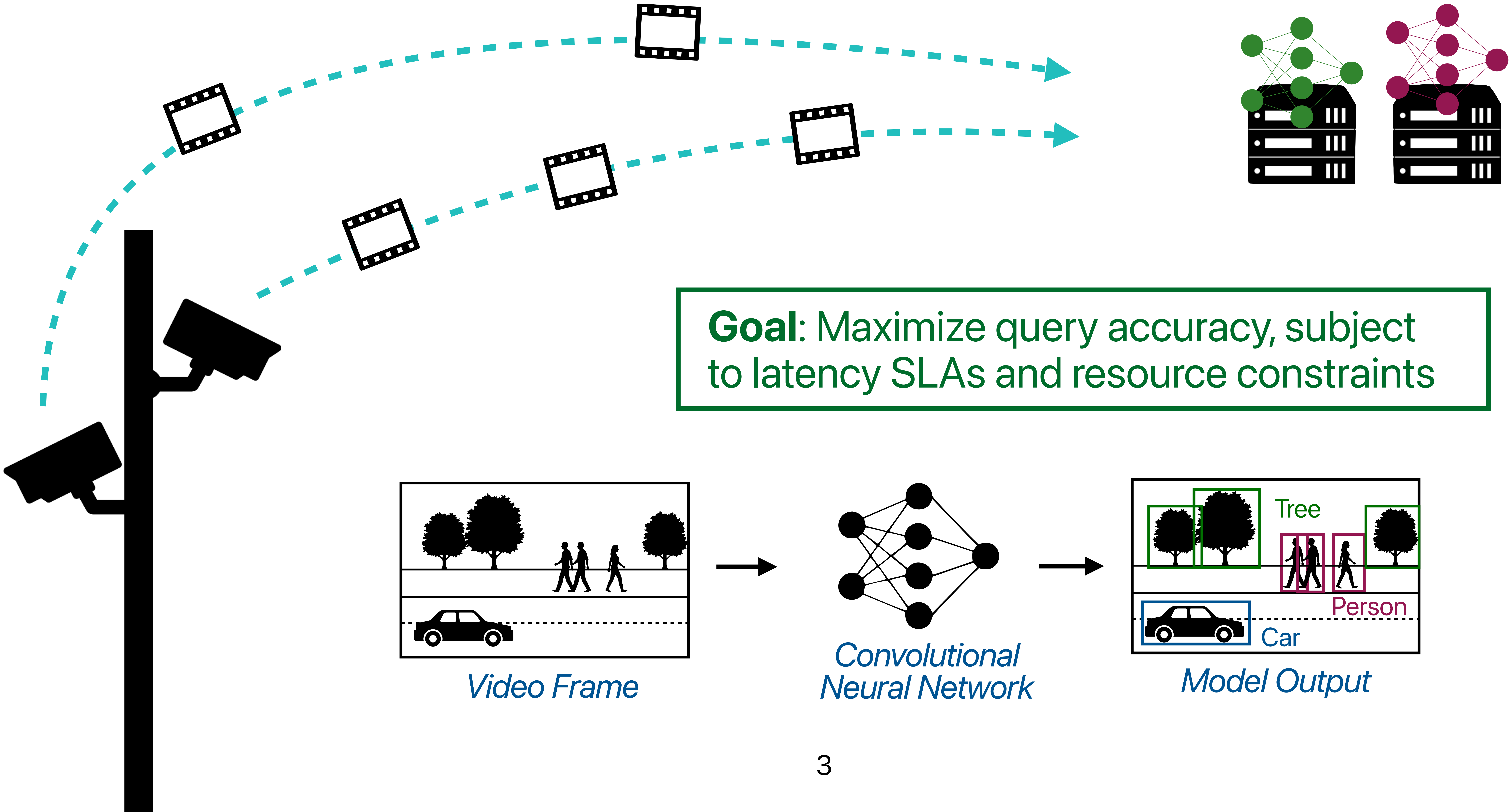
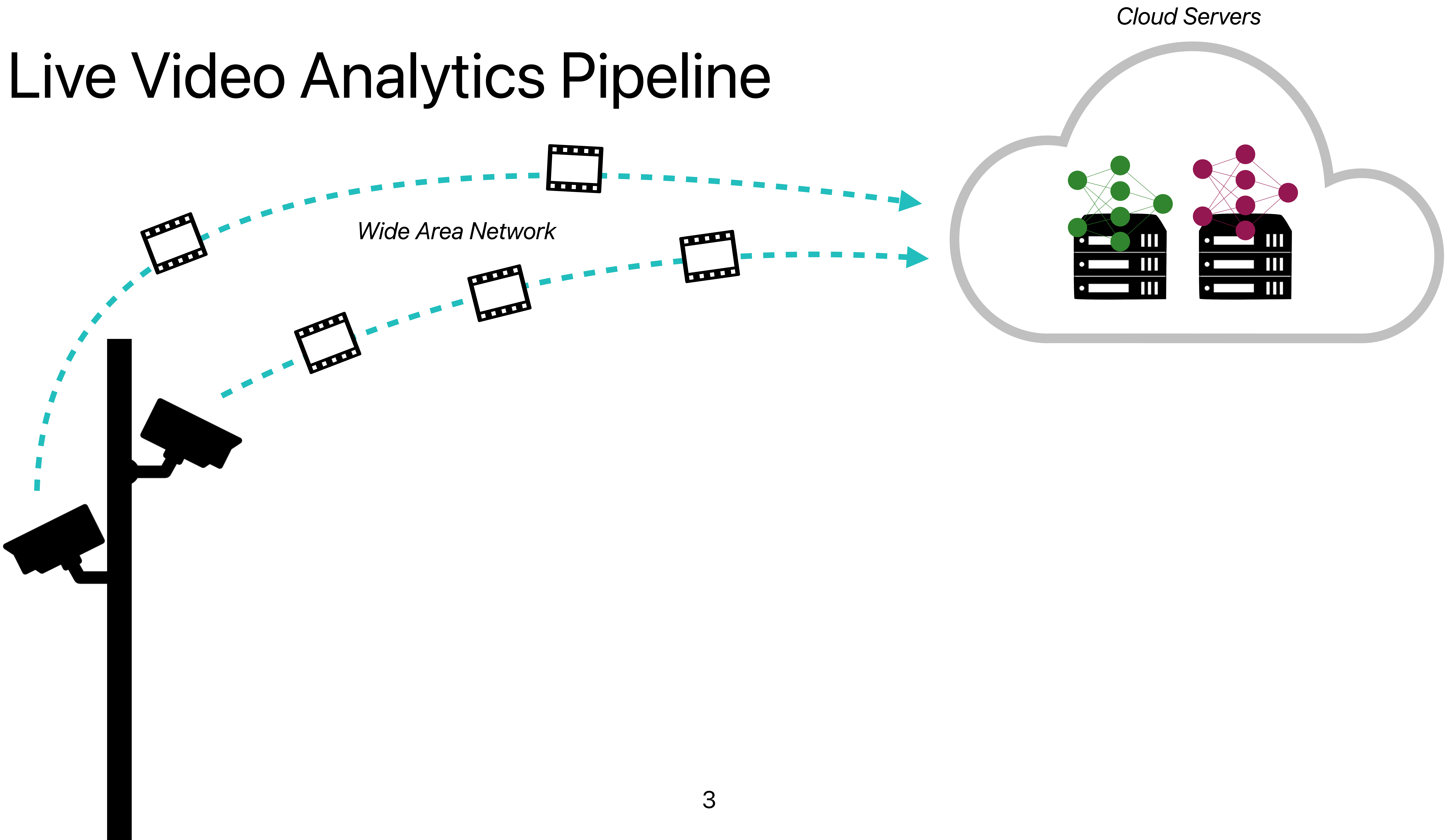
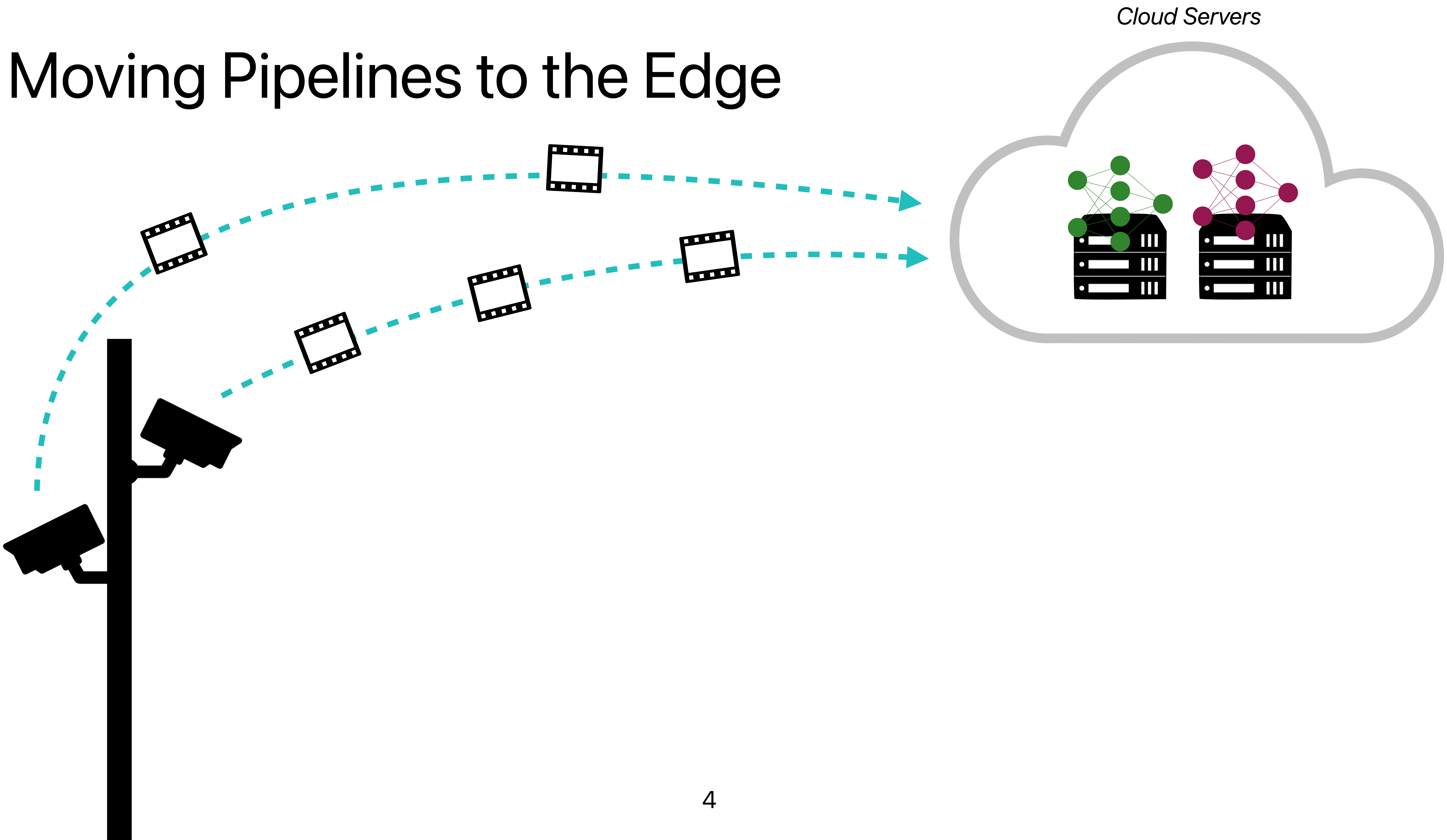


Goal: Maximize query accuracy, subject to latency SLAs and resource constraints

Live Video Analytics Pipeline



Moving Pipelines to the Edge



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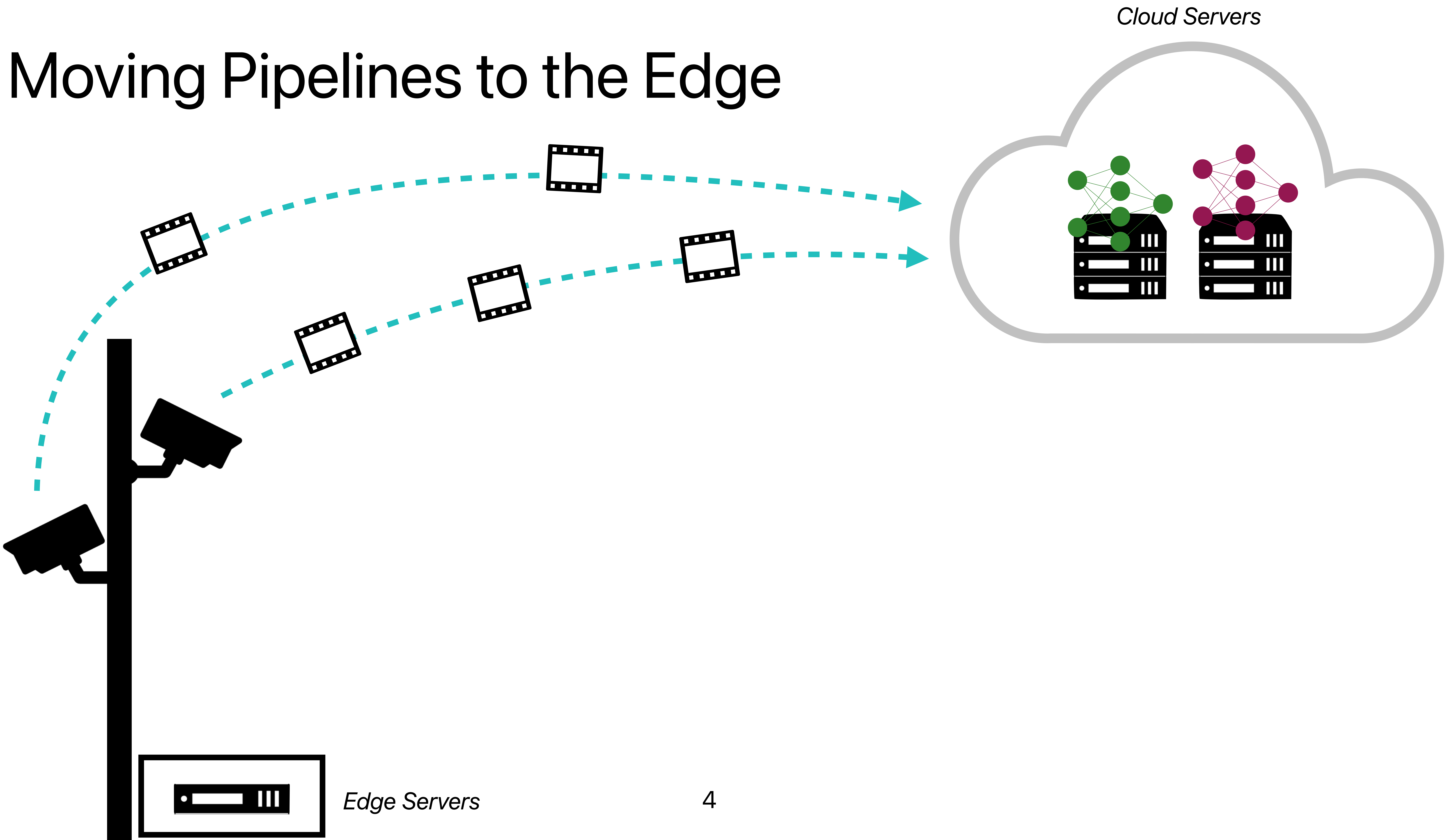

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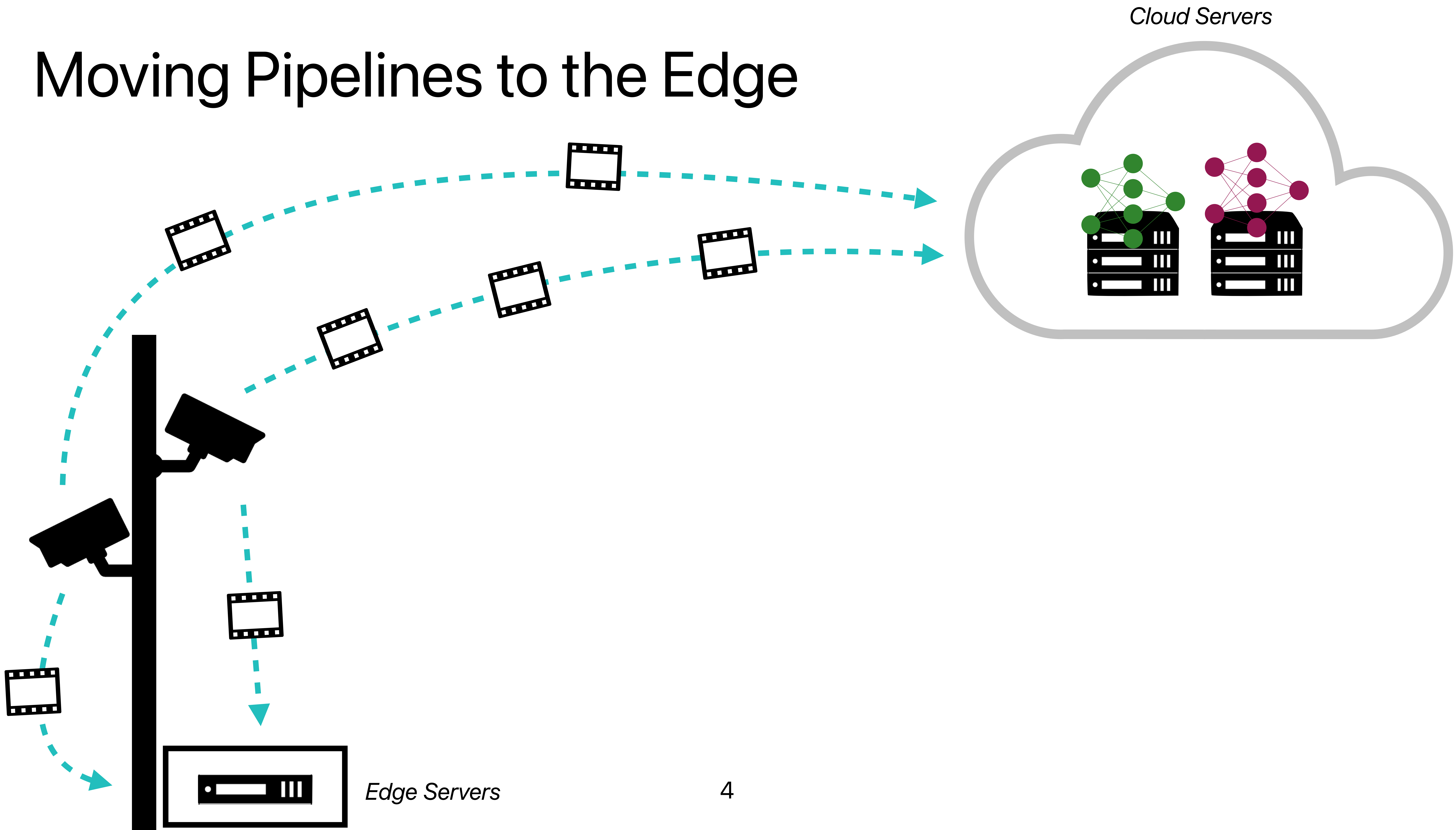

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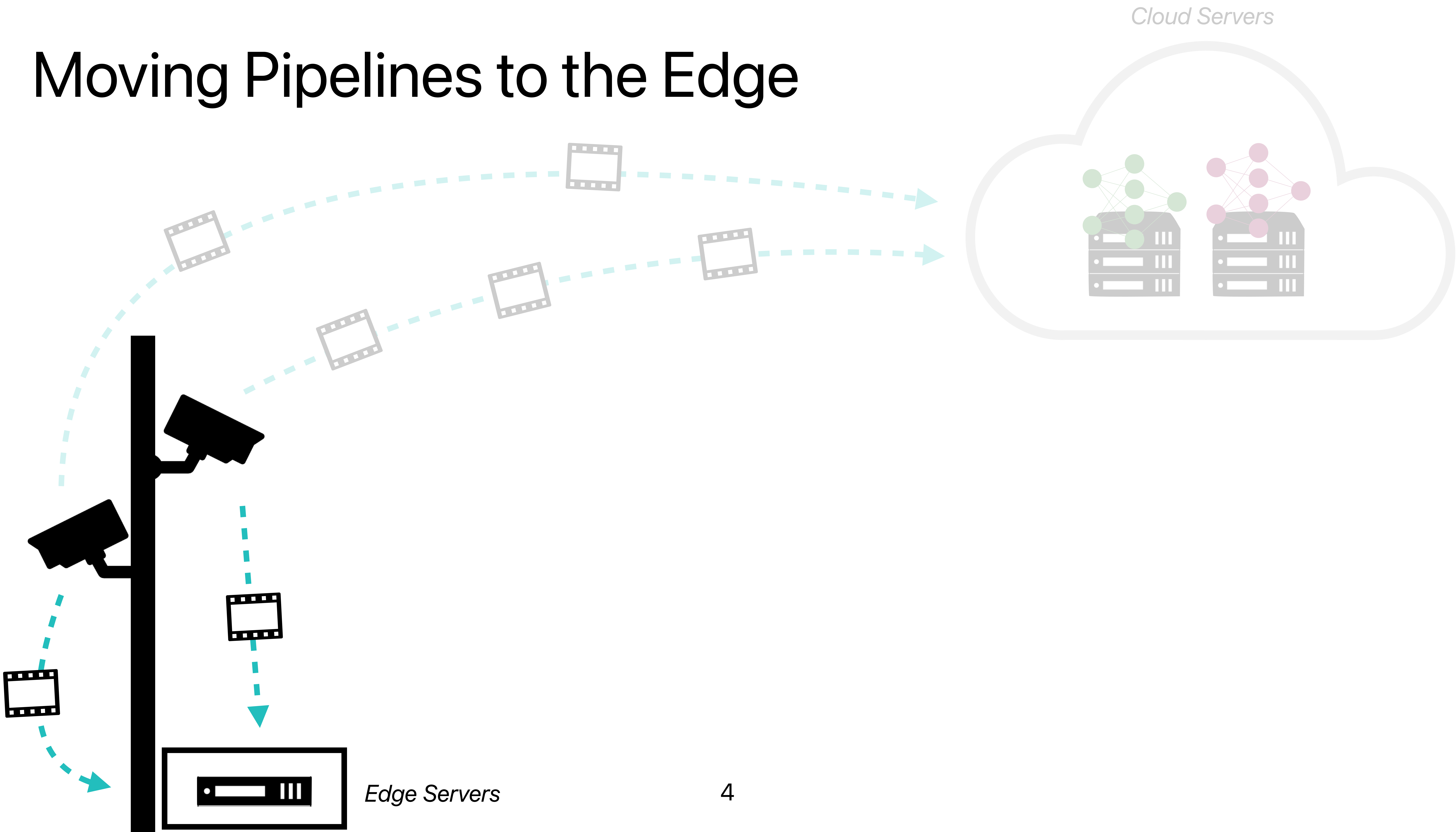

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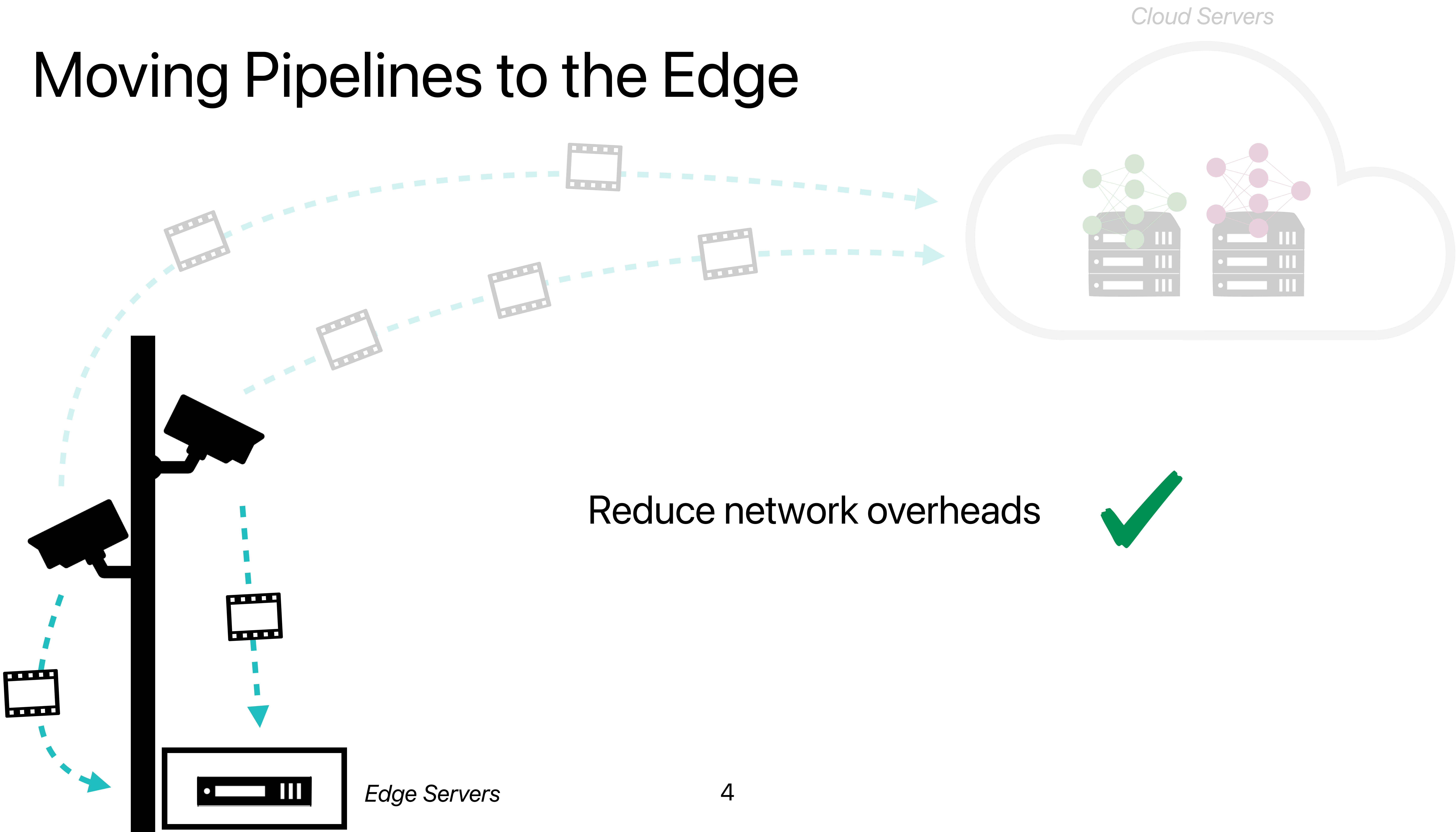
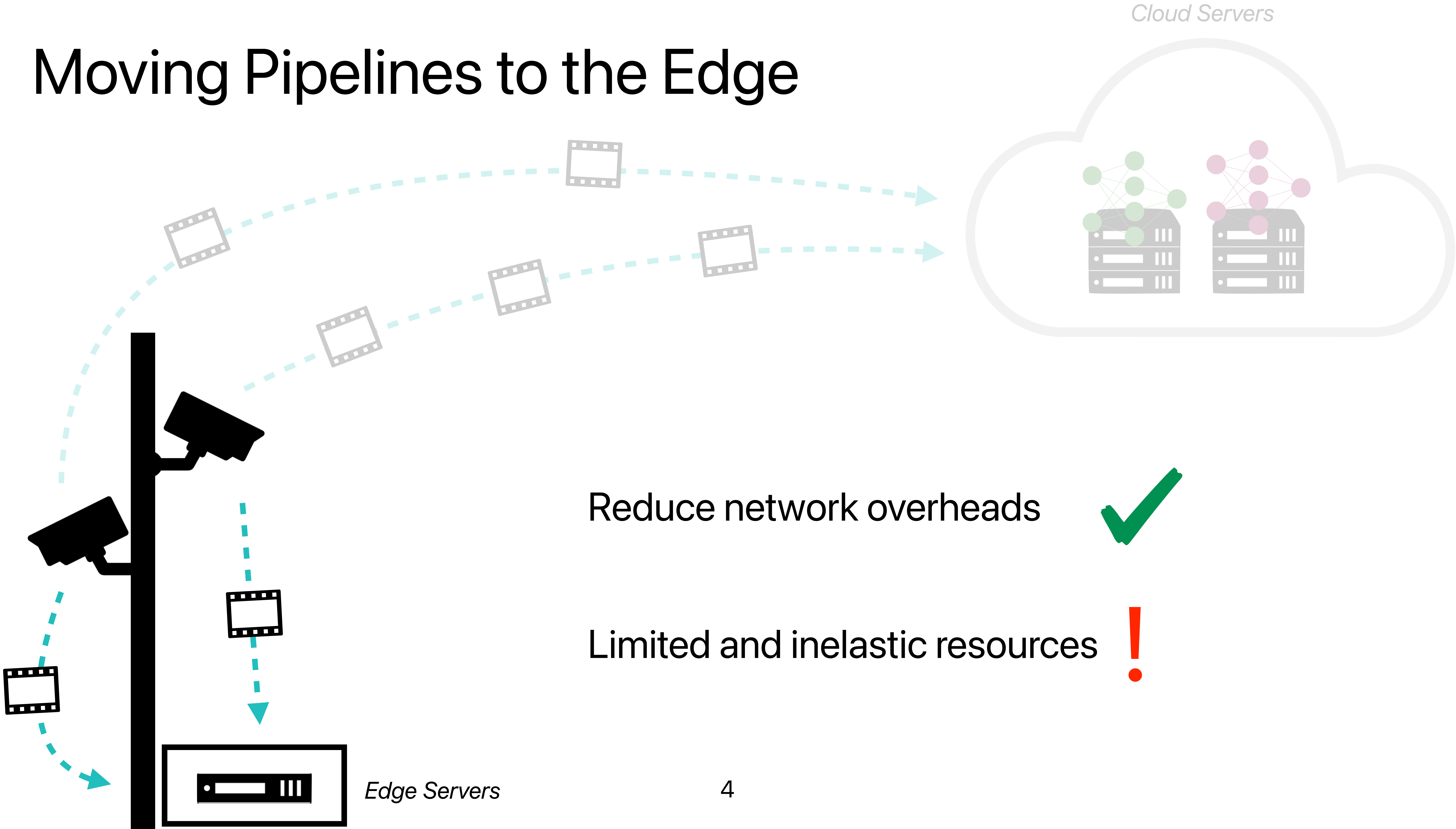


Reduce network overheads ✓

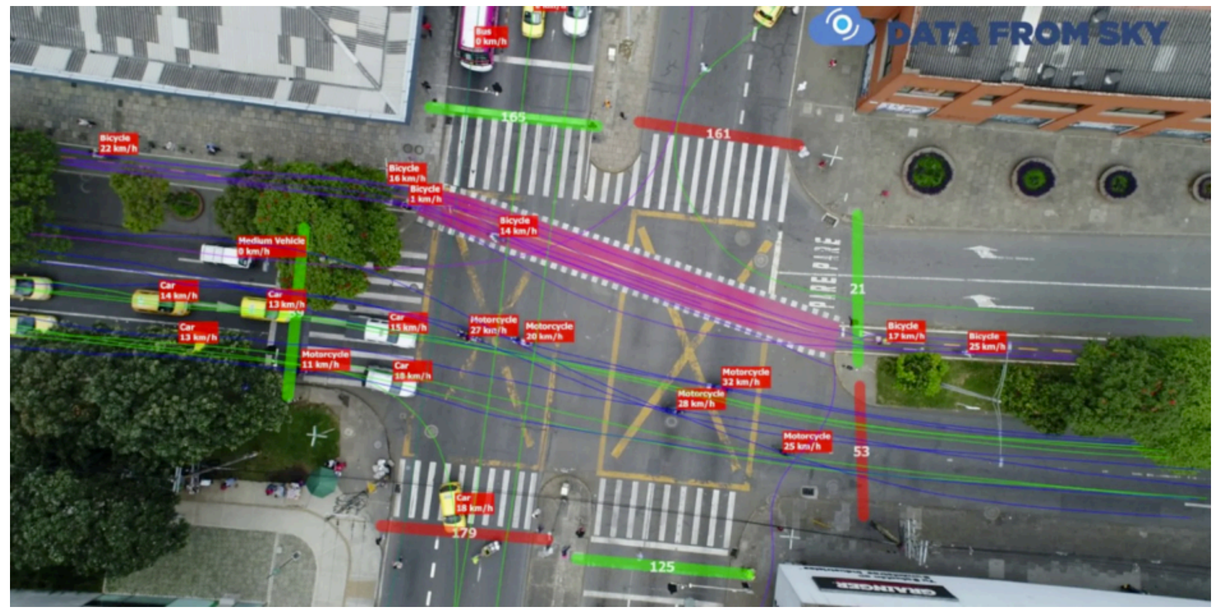
Moving Pipelines to the Edge



Reduce network overheads

Limited and inelastic resources

Edge Workloads in the Wild



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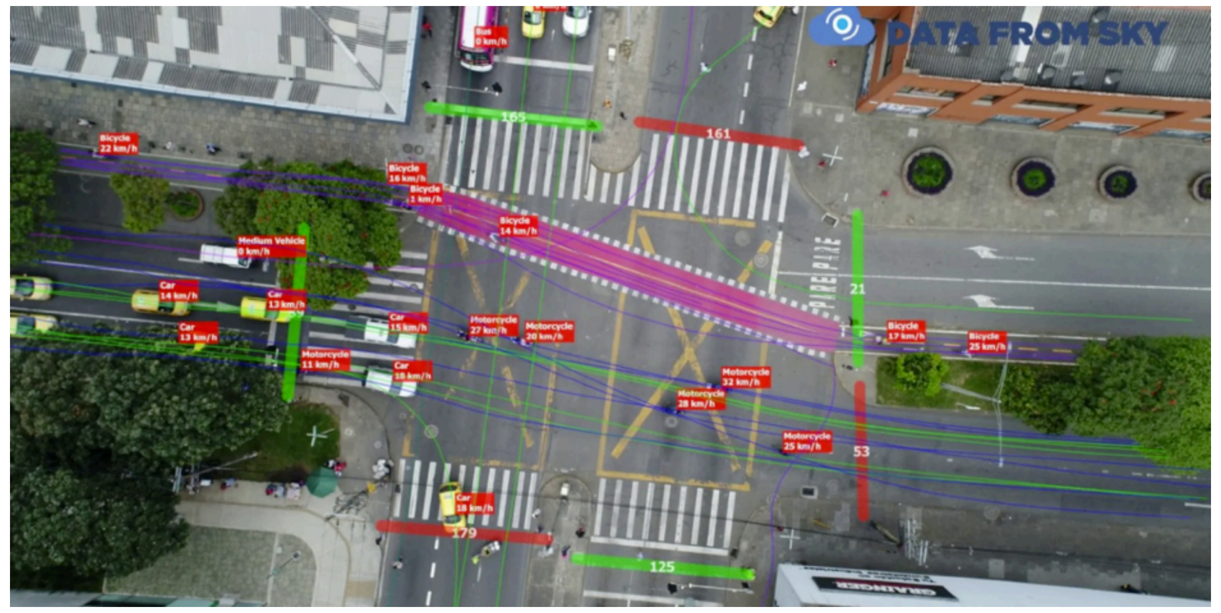

Pilot video analytics deployment across 2 major US cities, targeted at road traffic monitoring

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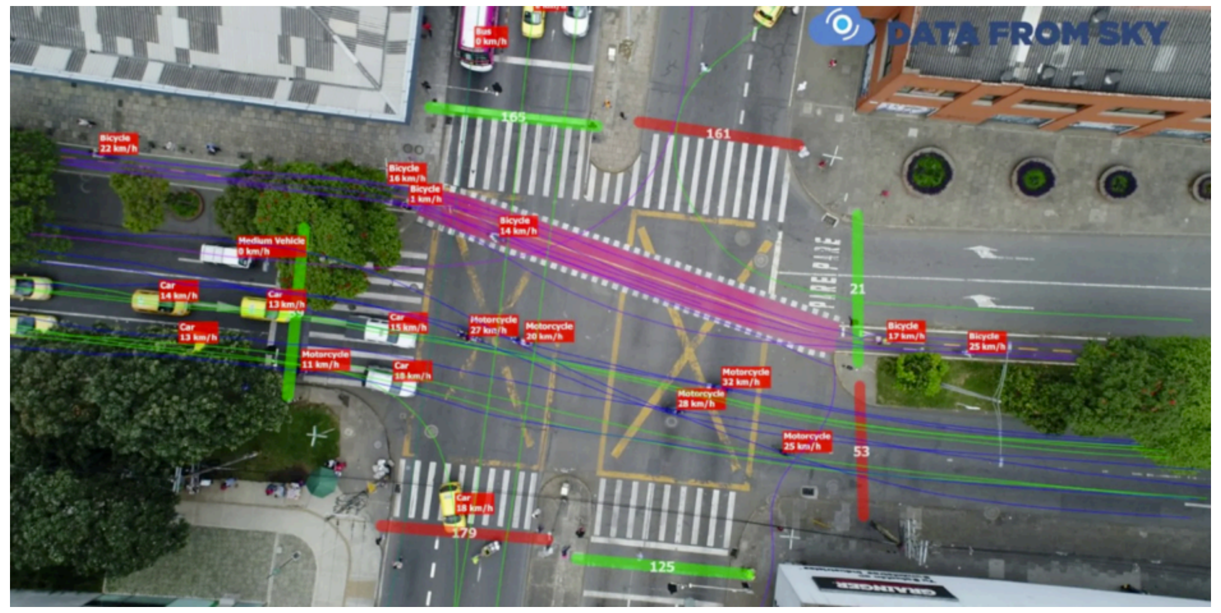

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Query: <camera feed, model, task>

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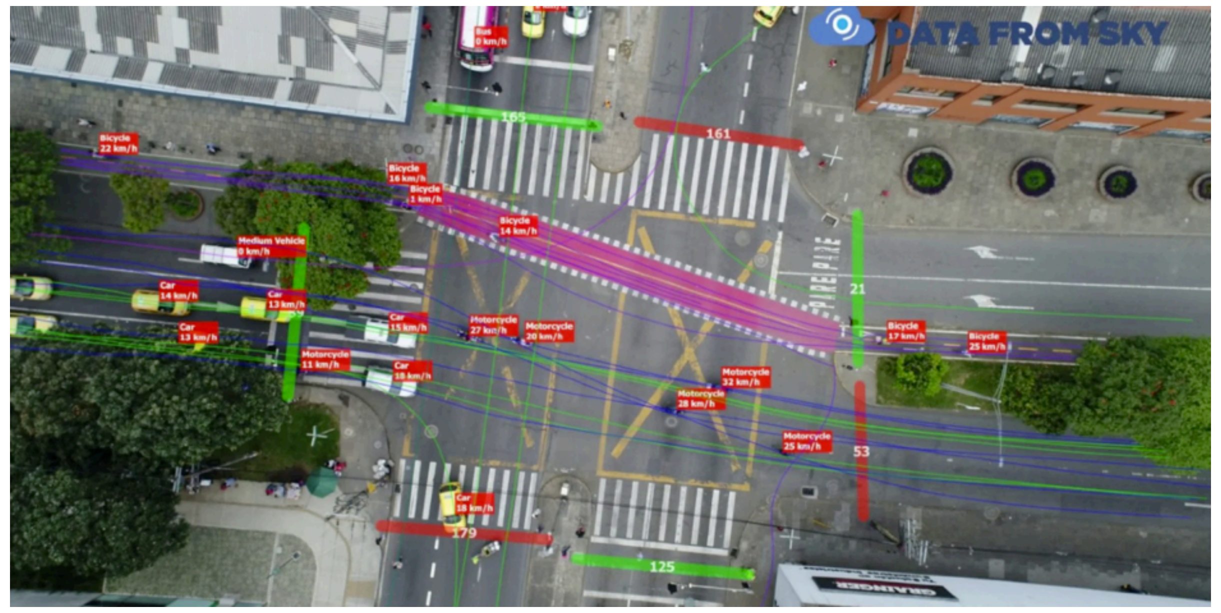


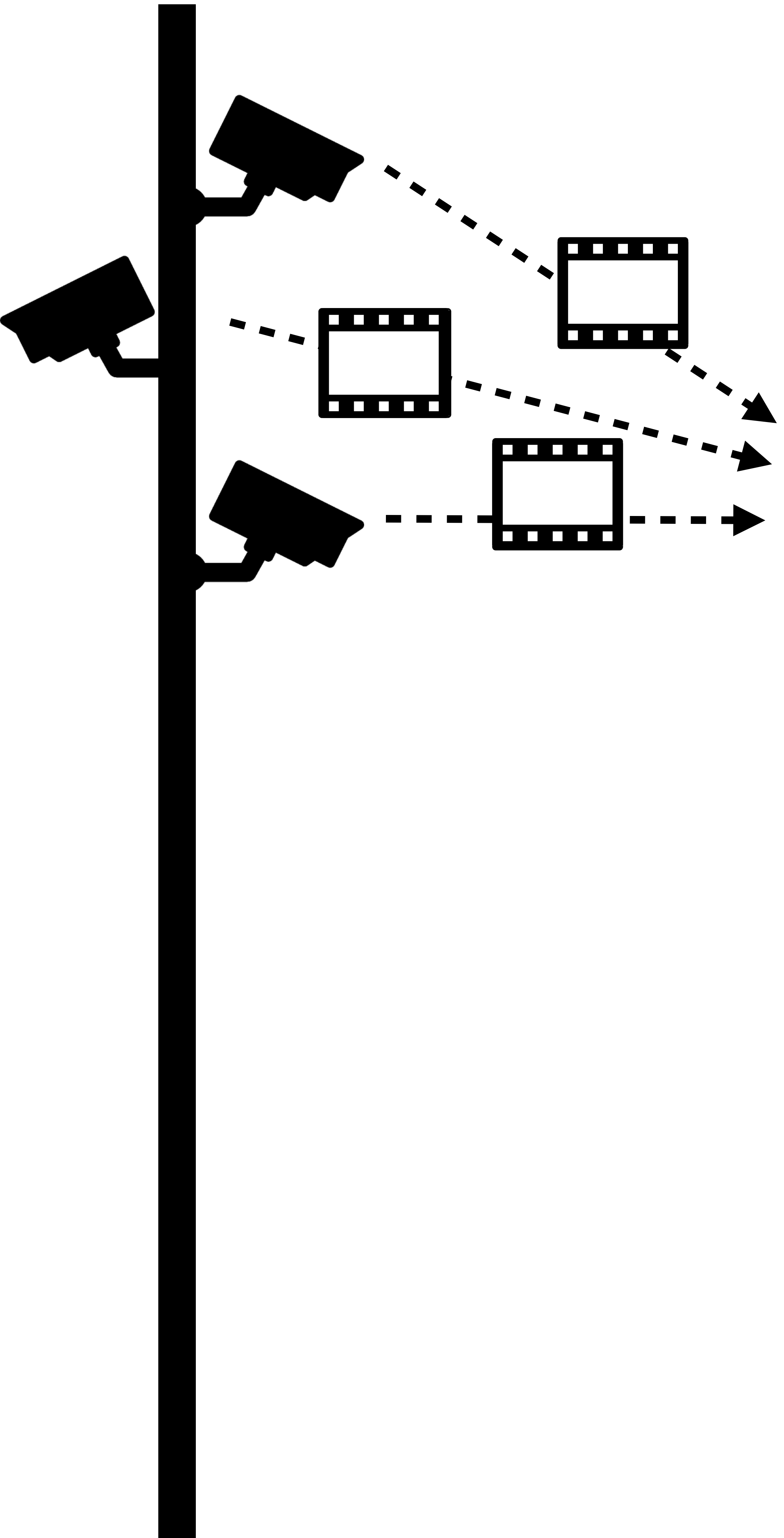
Pilot video analytics deployment across 2 major US cities, targeted at road traffic monitoring

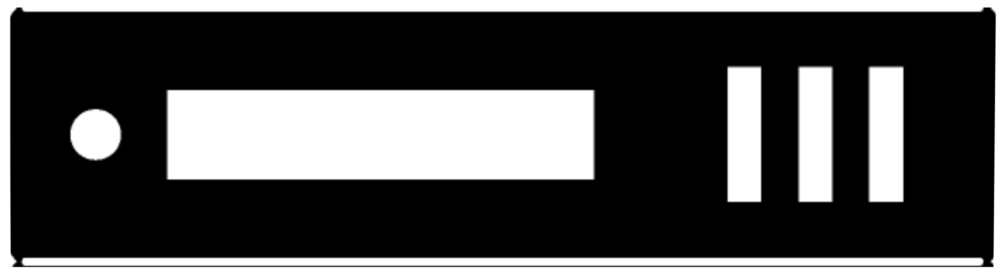
Query: <camera feed, model, task>

Sample Workload

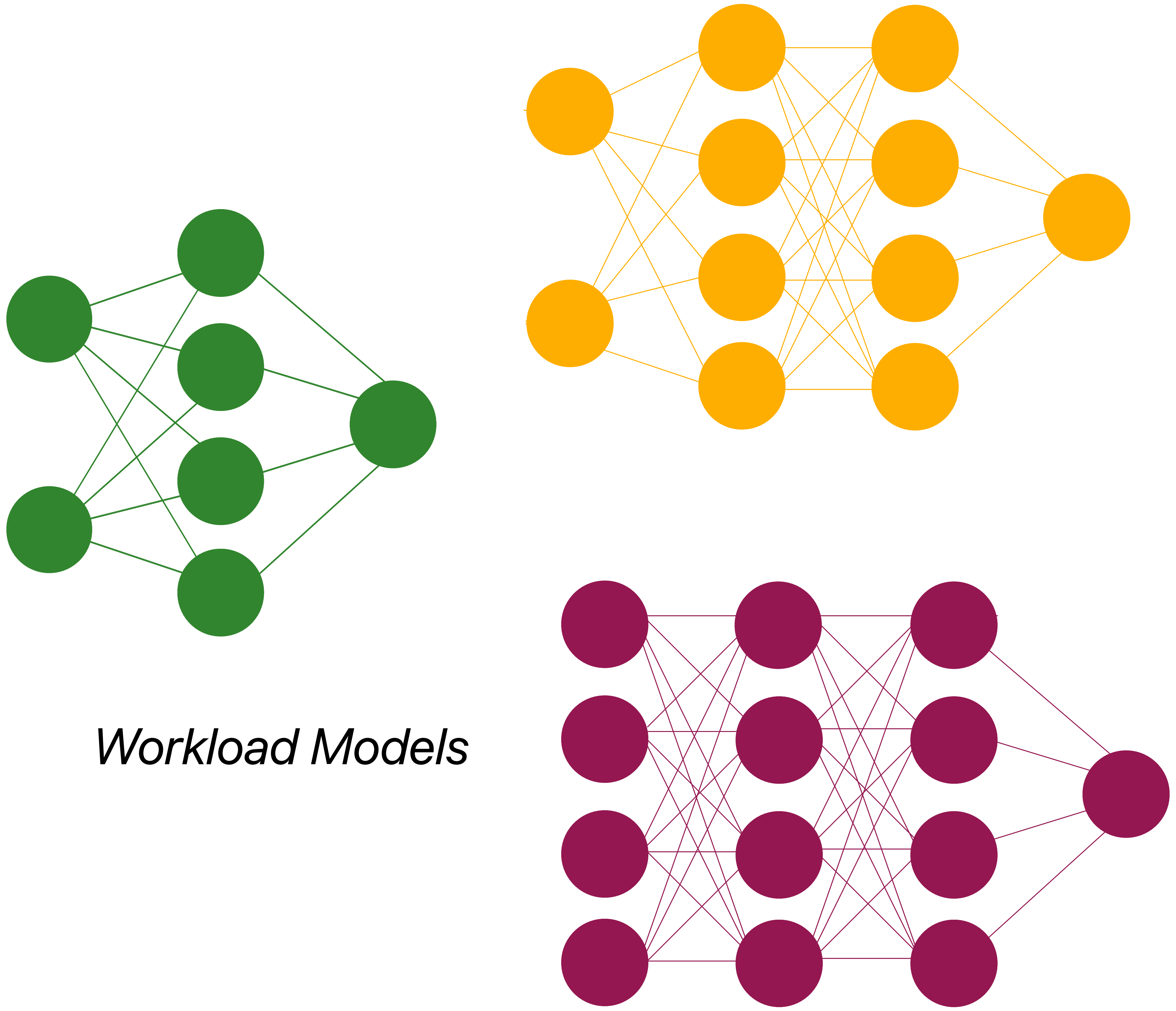
Query #	Camera Feed	Model Architecture	Task Description
1	3	FRCNN-R50	Object detection of cars
2	1	YOLOv3	Object detection of people
3	1	Inception	Binary Classification of people, vehicles
4	6	ResNet50	Binary Classification of cars, buses, trucks
5	3	Tiny-YOLOv3	Object Detection of people
…	…	…	…

Executing Edge Workloads



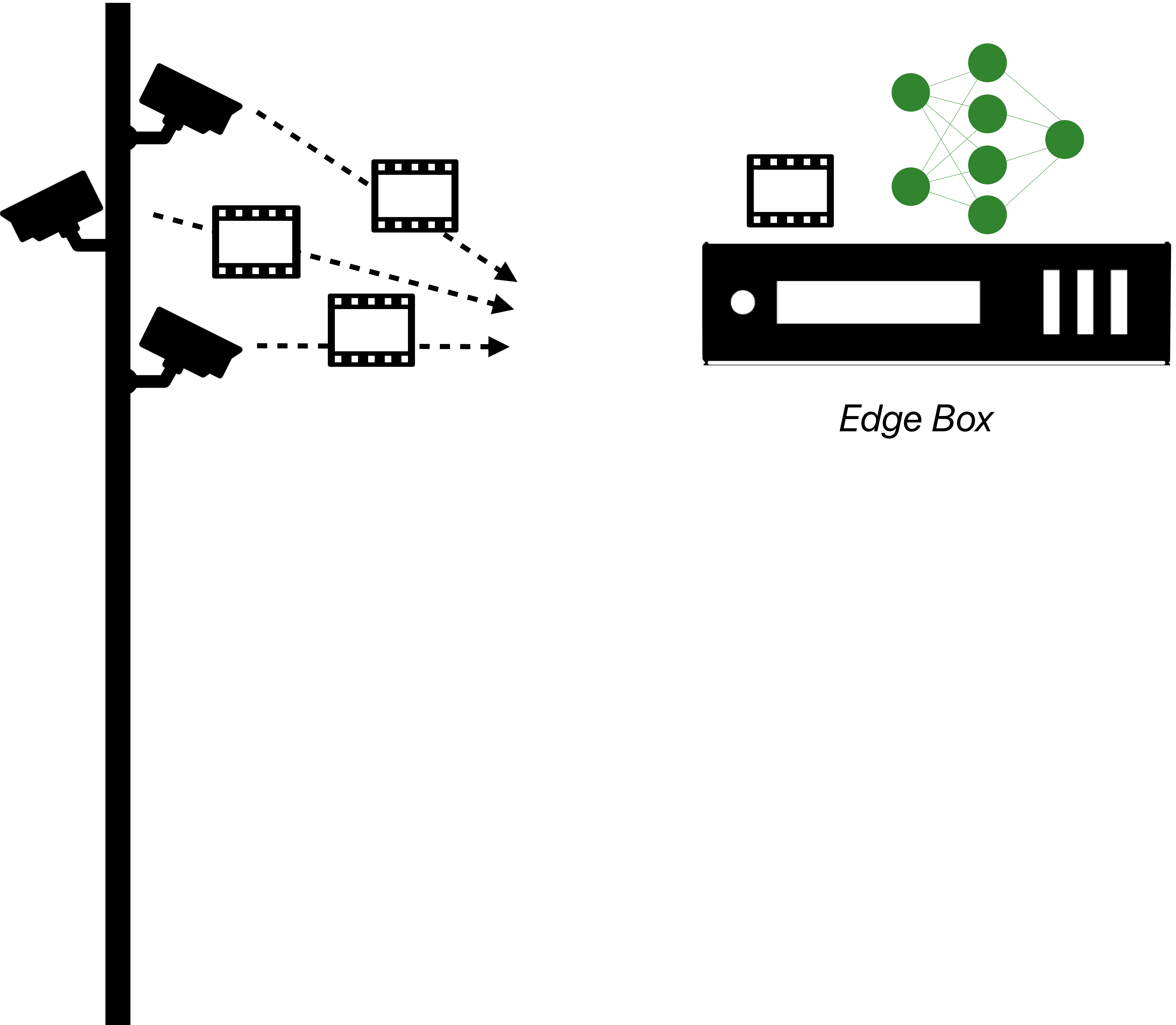


Edge Box



Workload Models

Executing Edge Workloads



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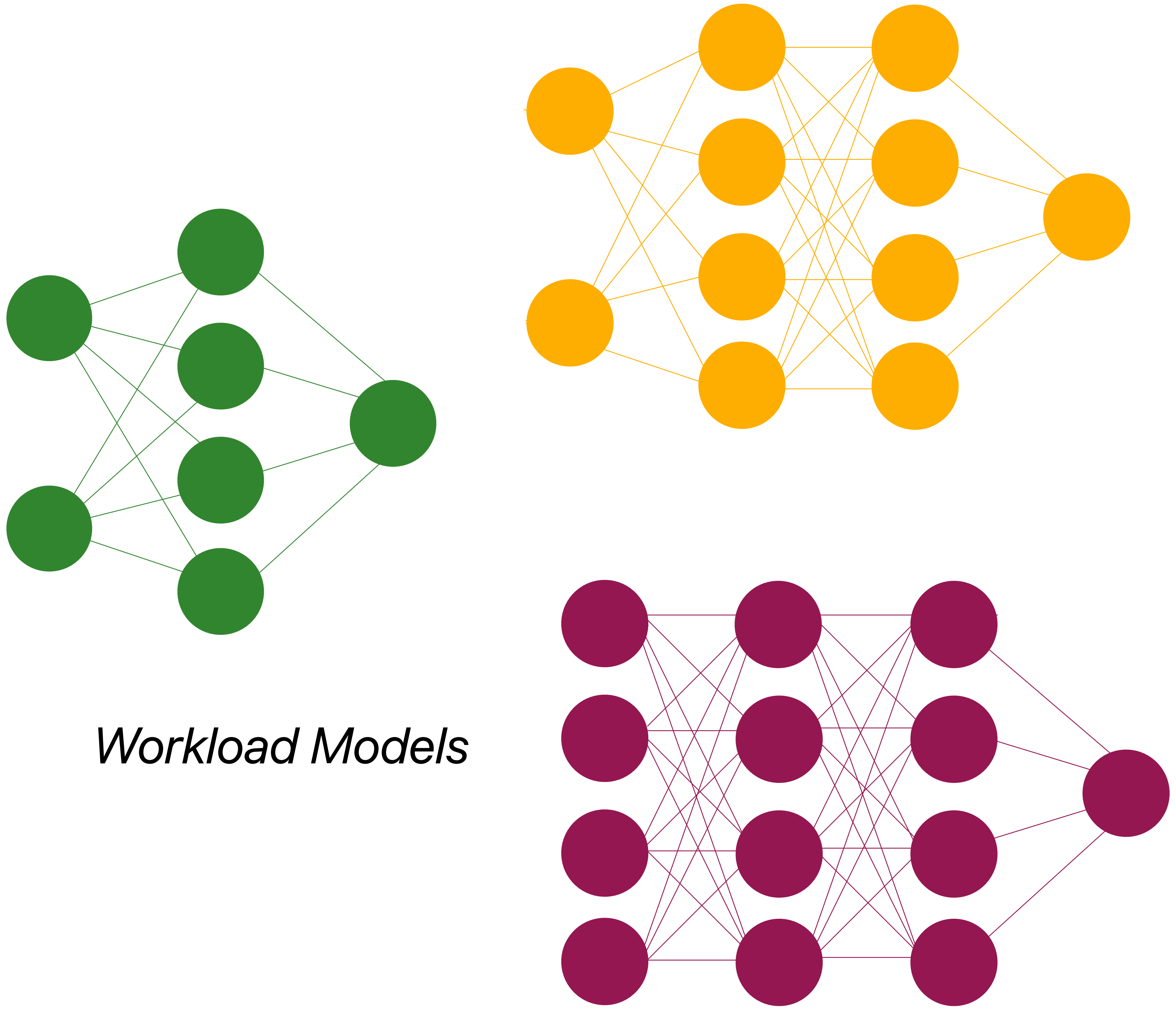

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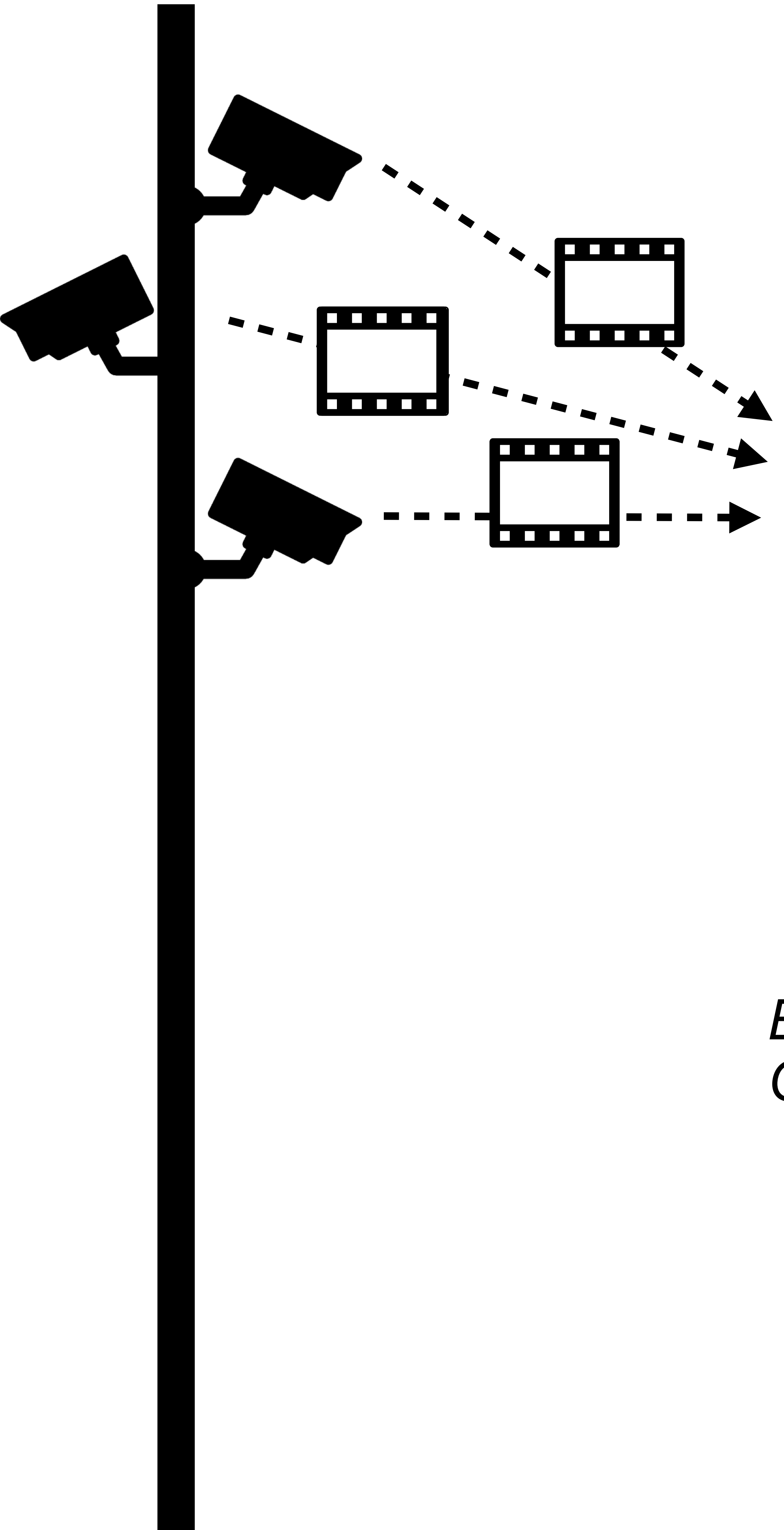

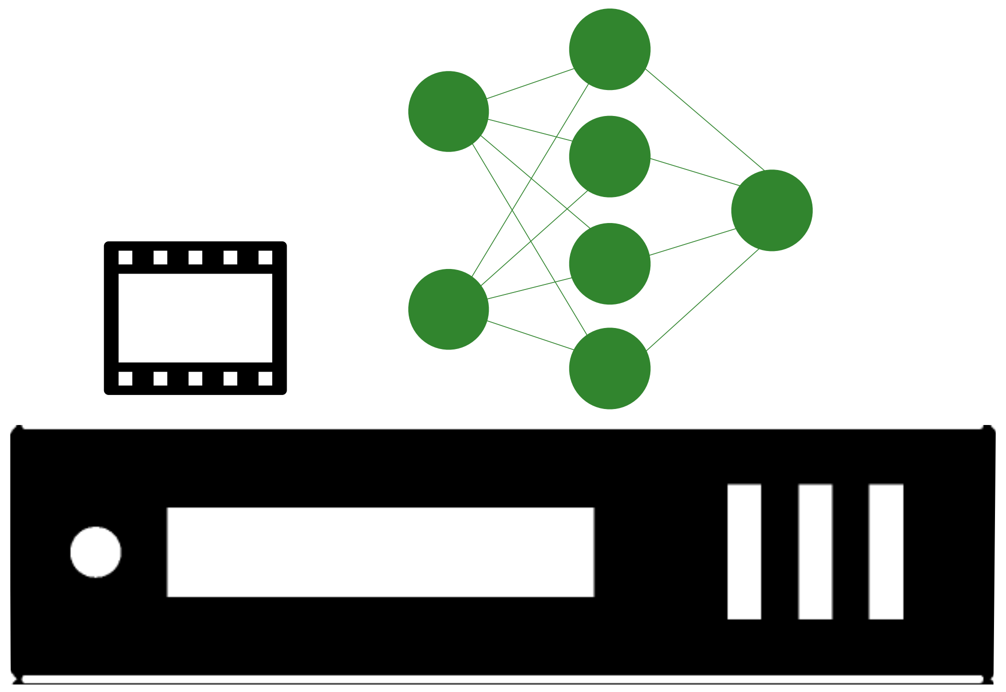

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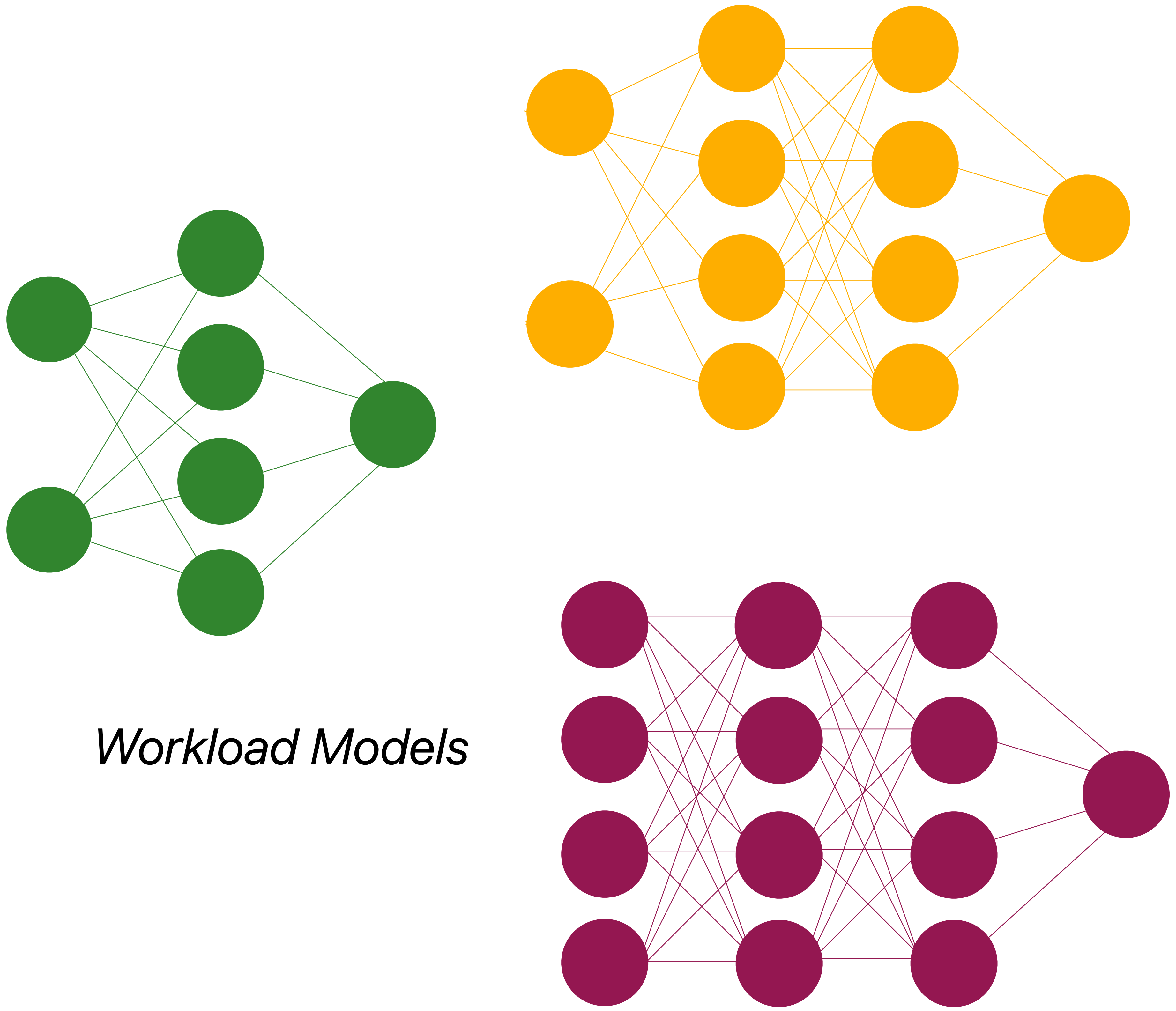
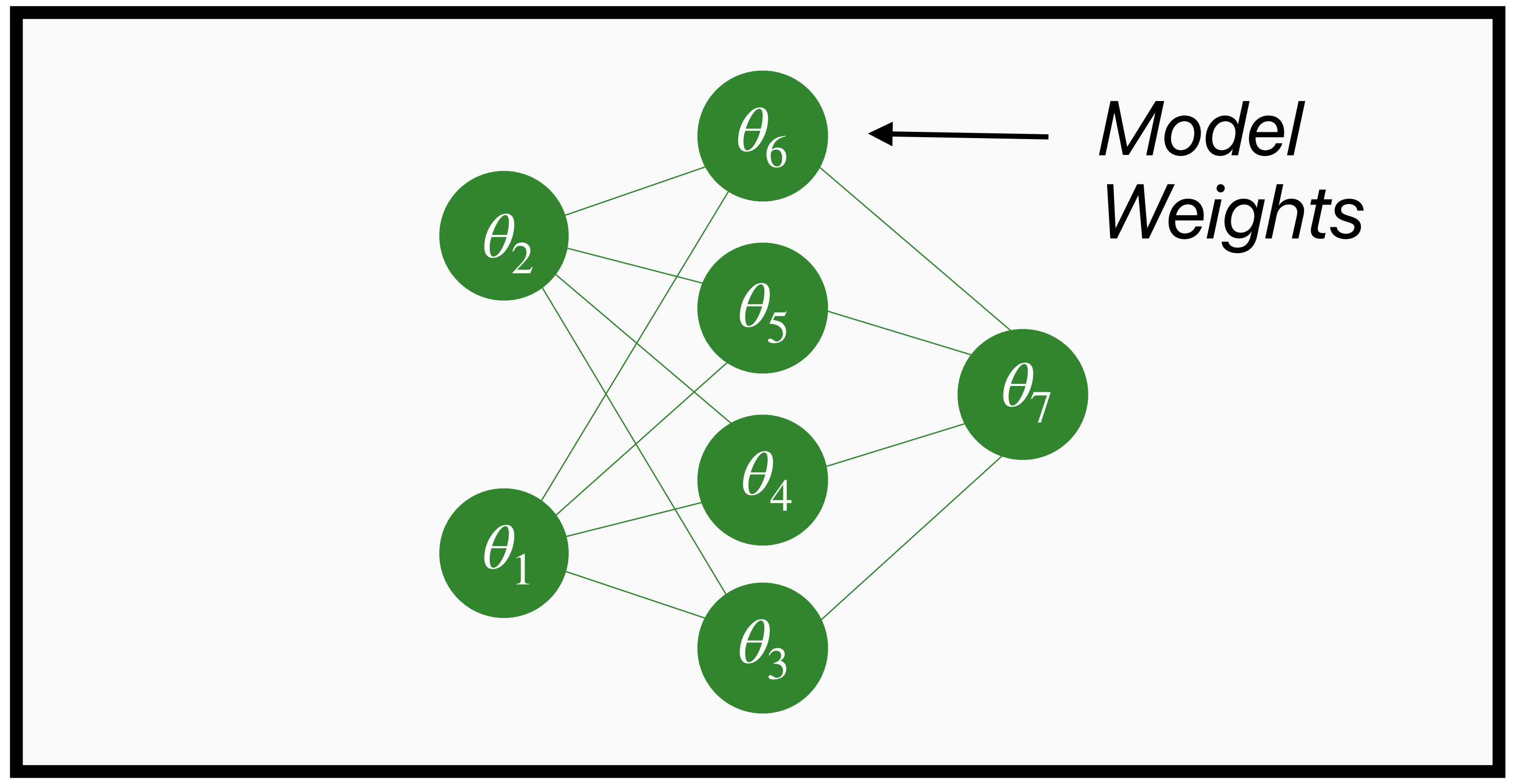


Edge Box
GPU Memory



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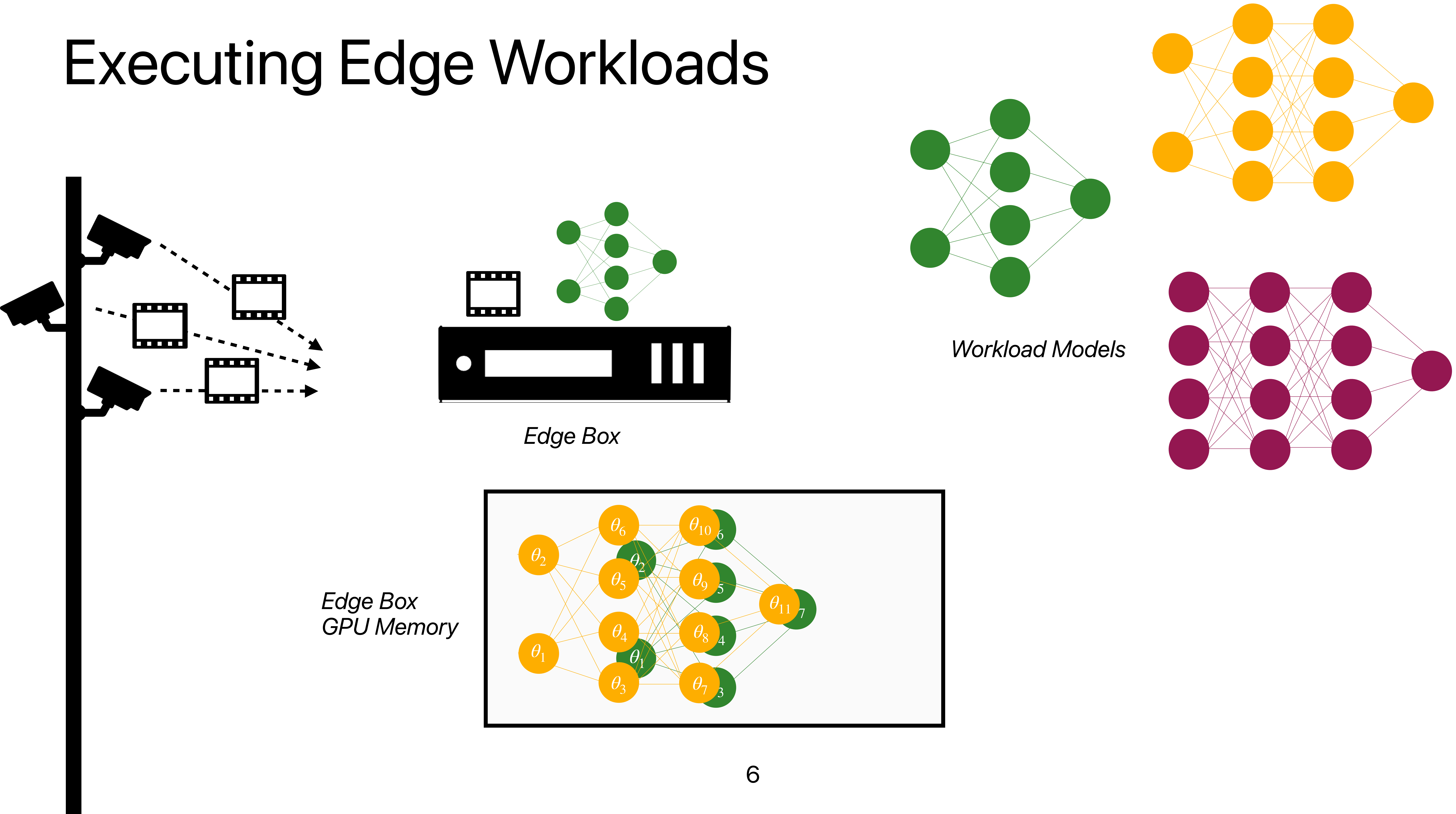

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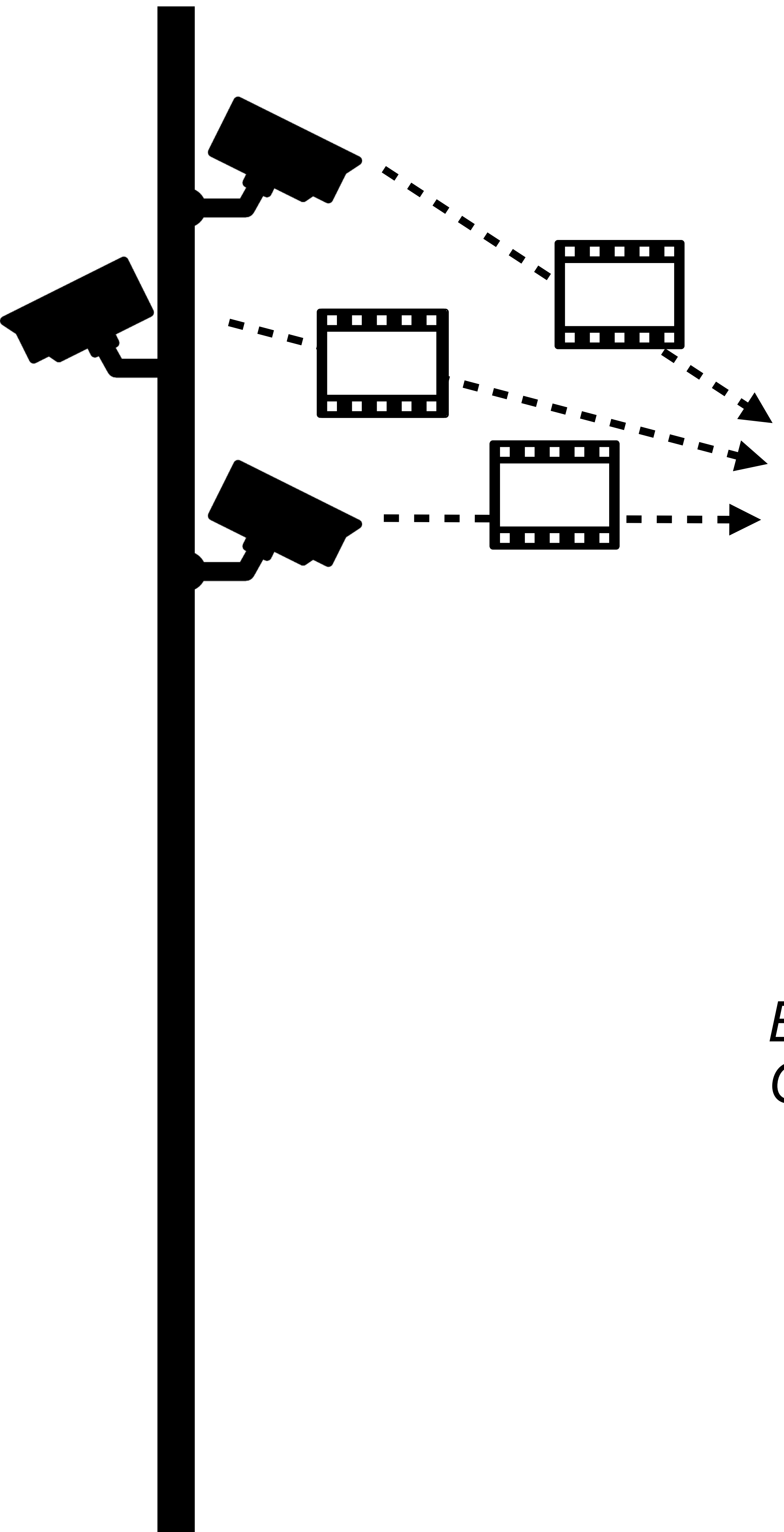

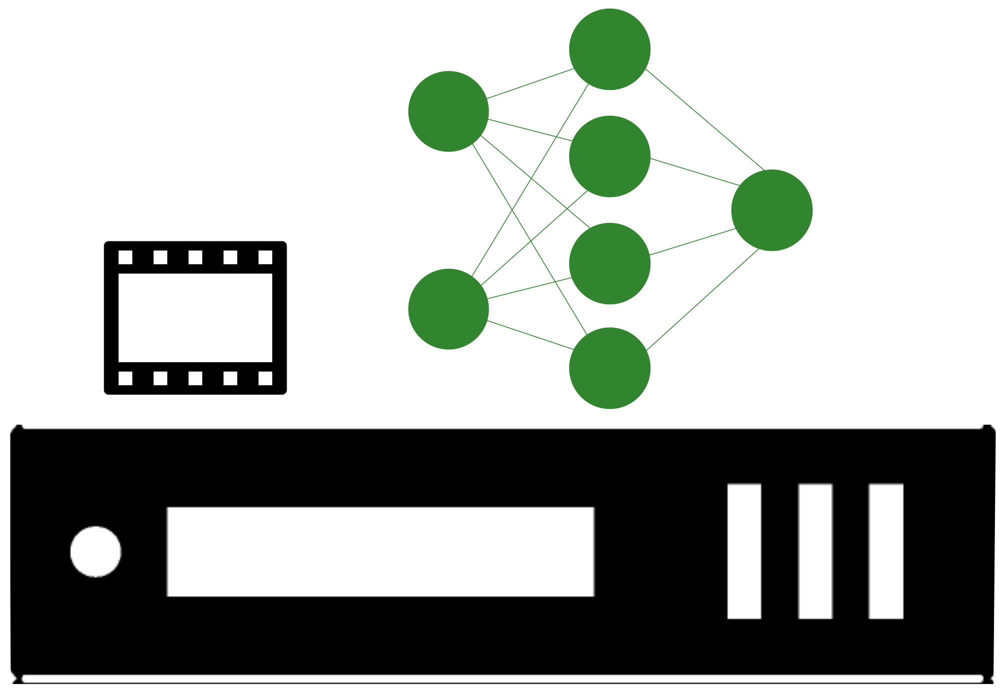

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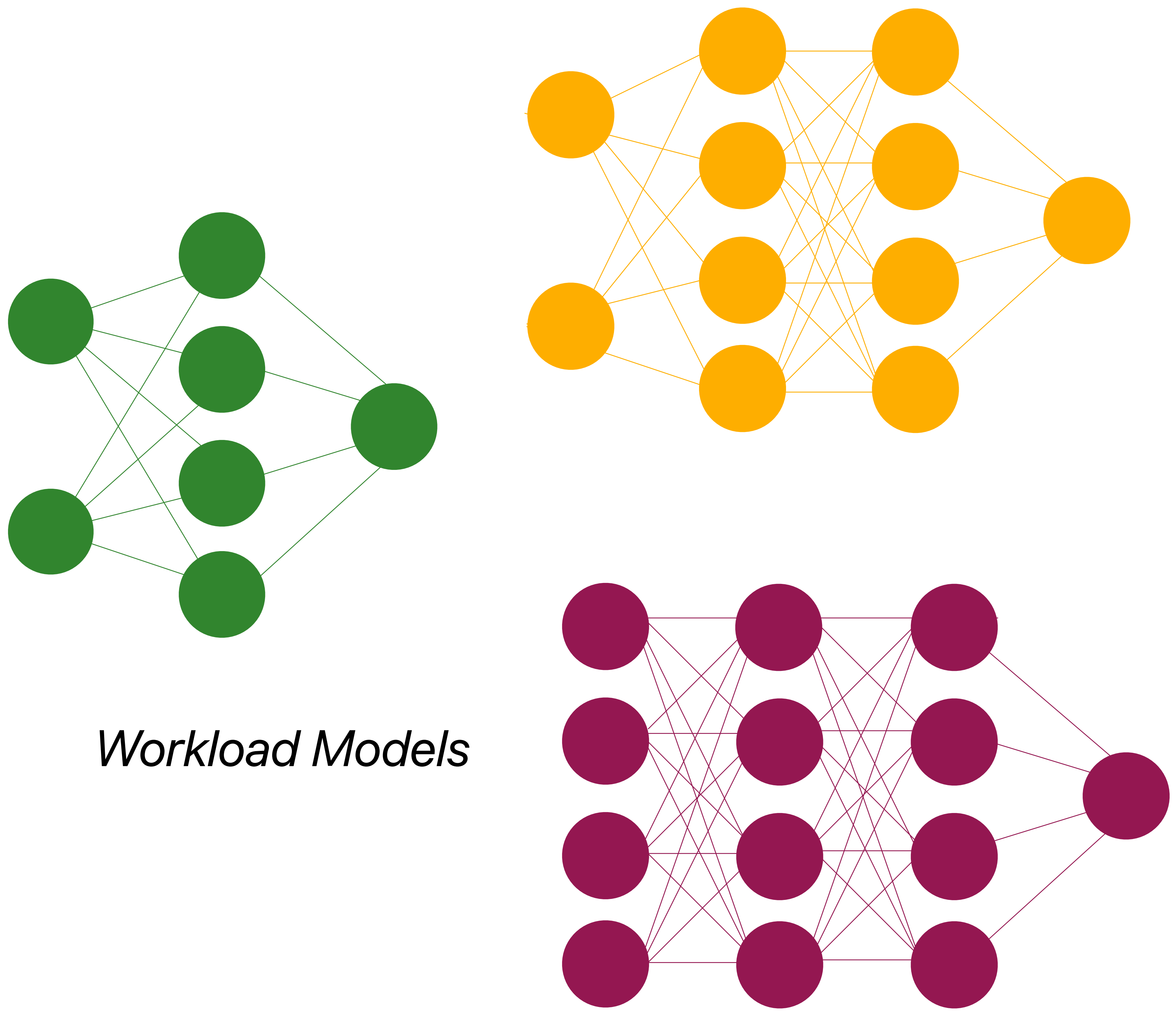
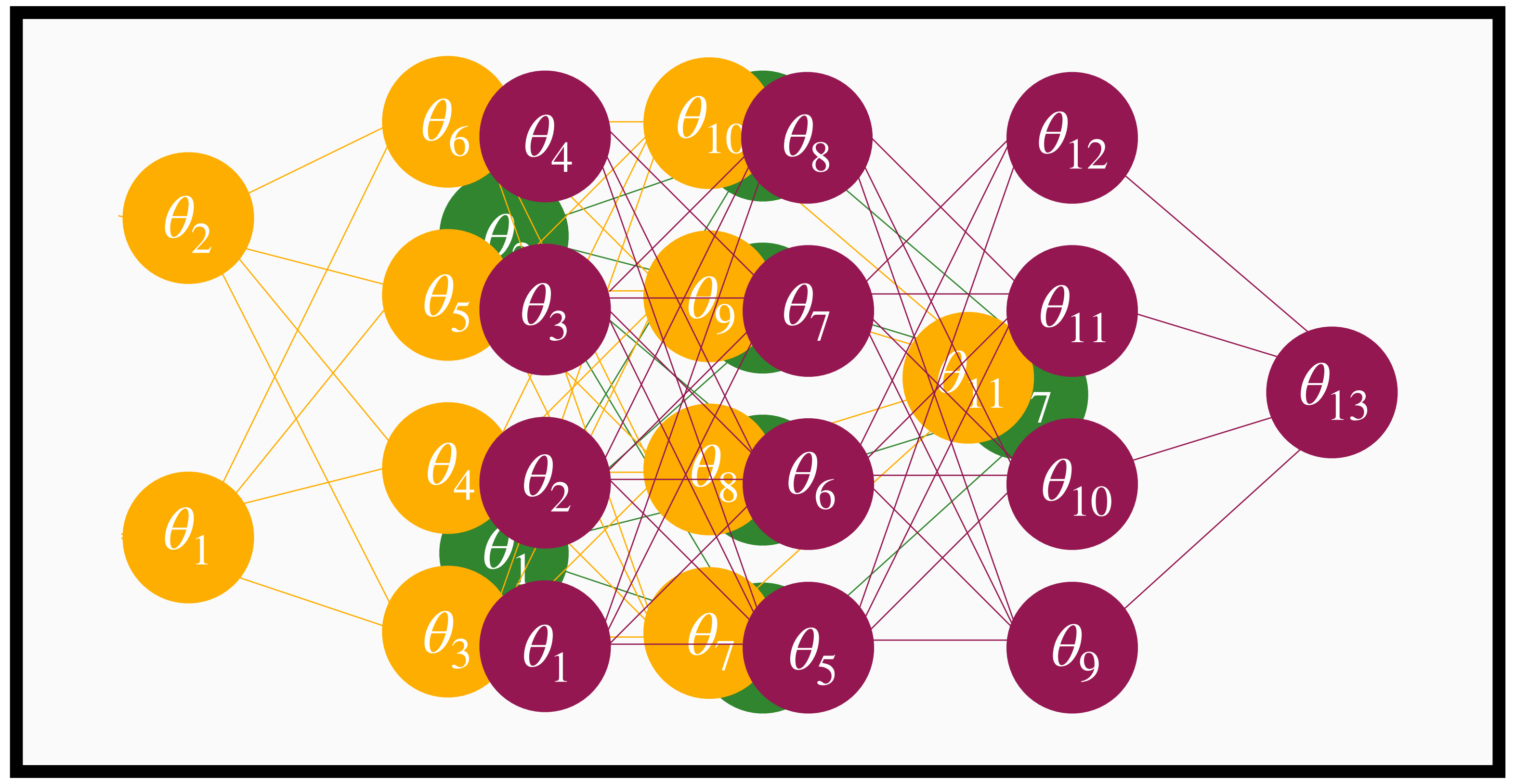
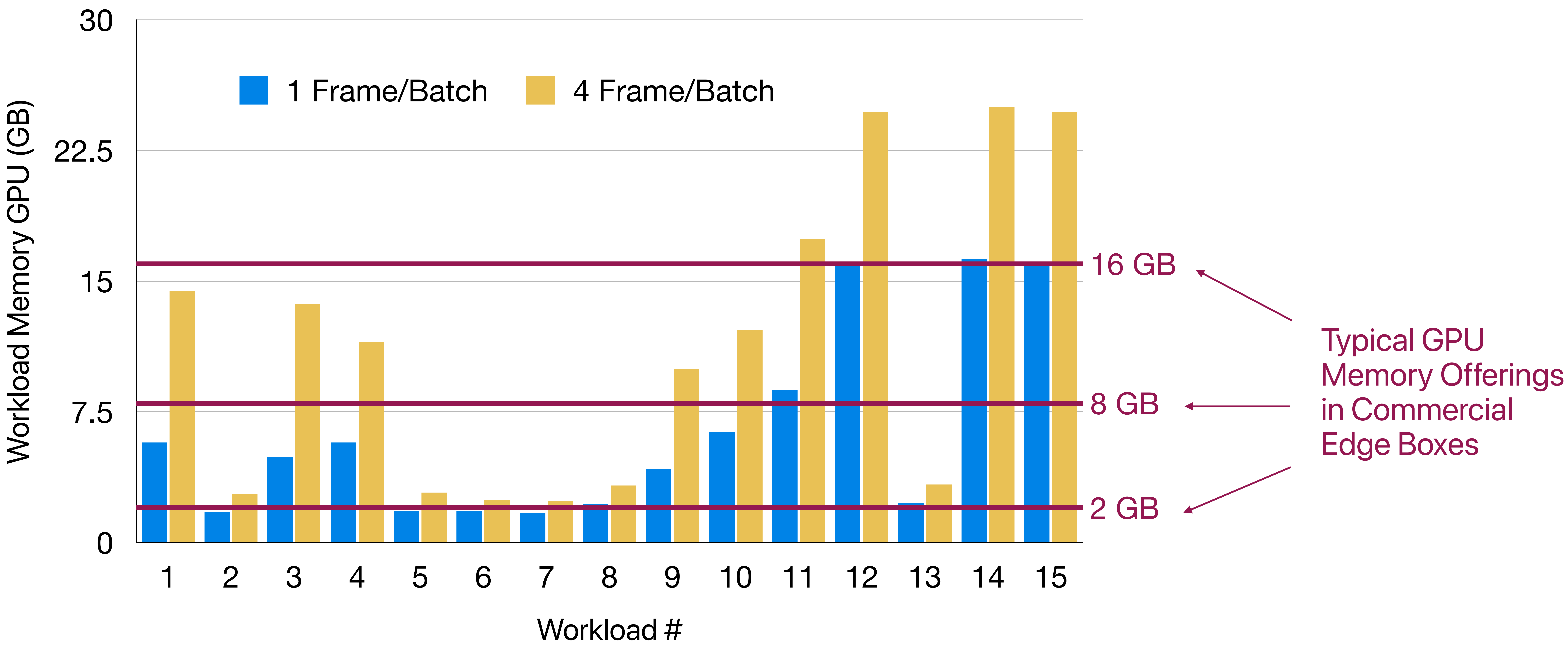


Workload Models

Edge Box
GPU Memory



Workloads are Outgrowing Edge GPU Memory



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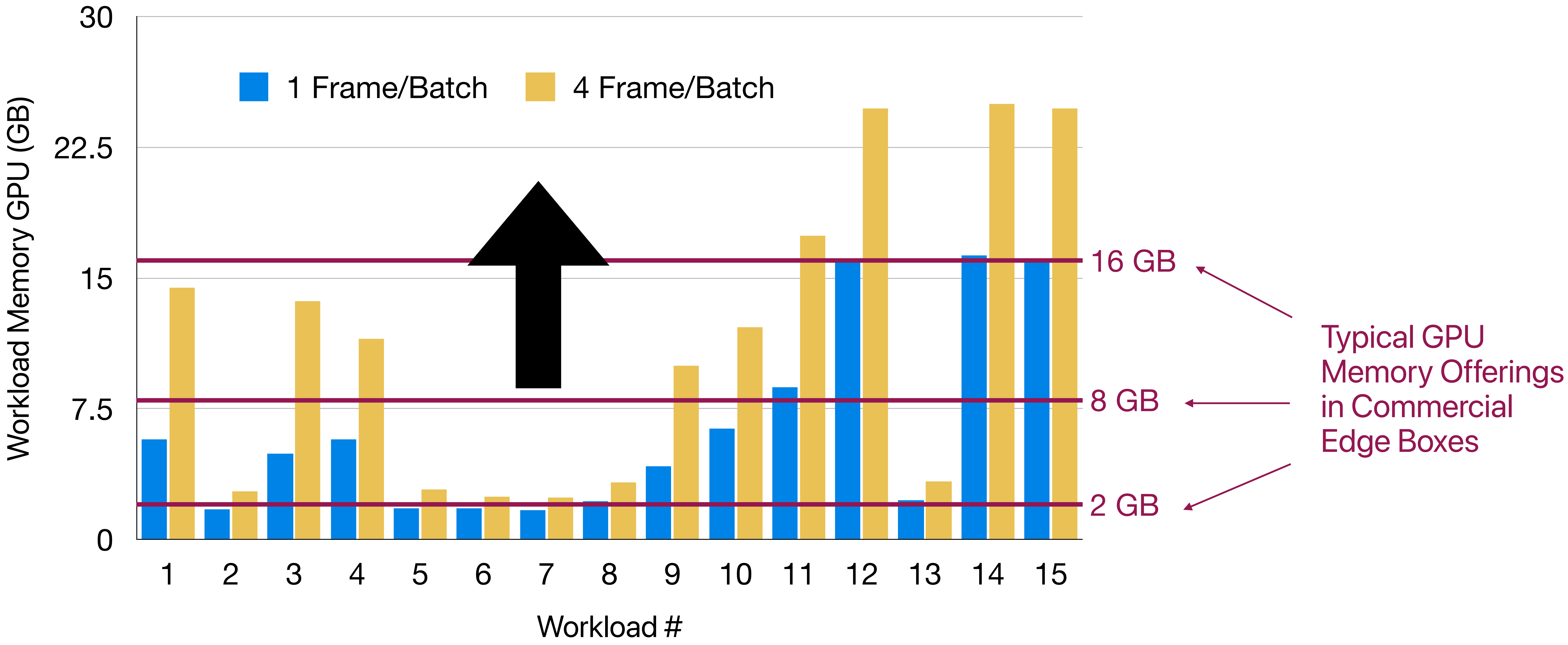
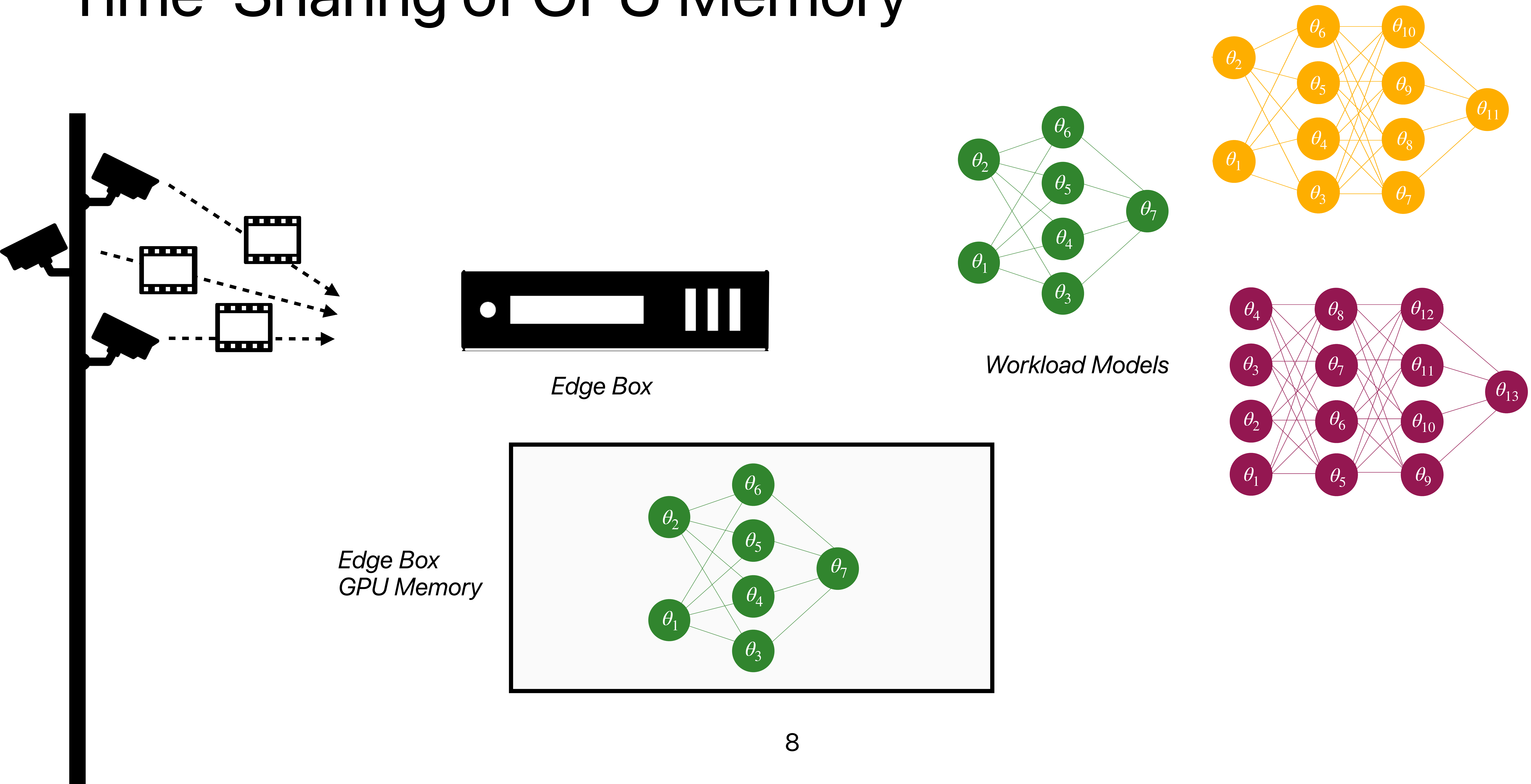


Time-Sharing of GPU Memory



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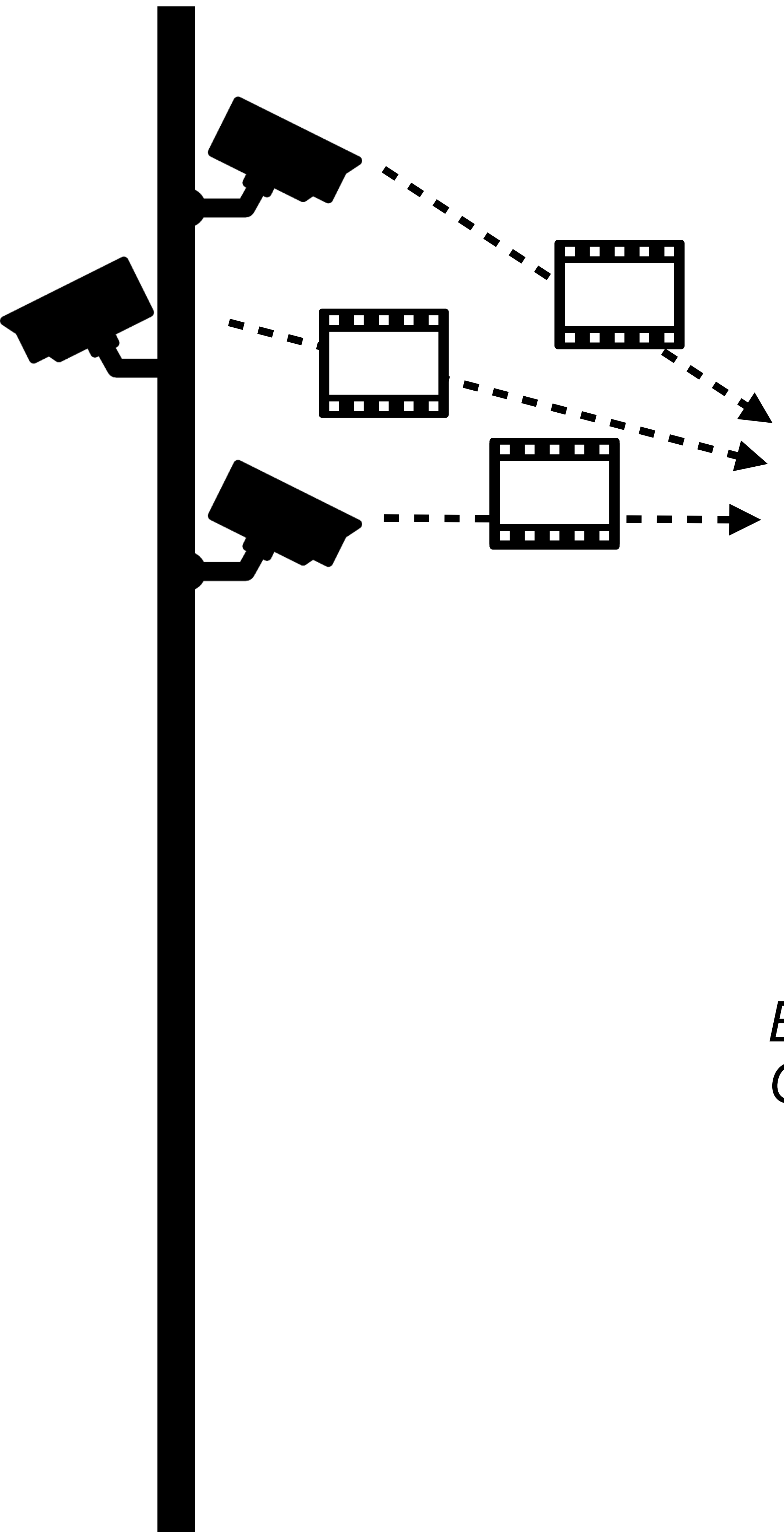

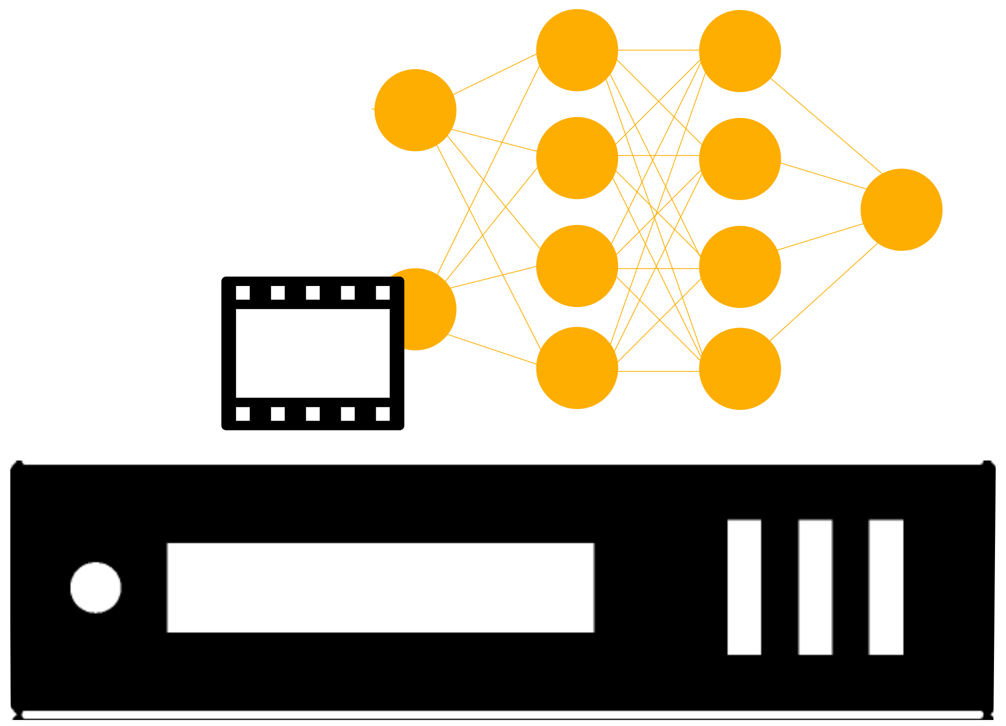

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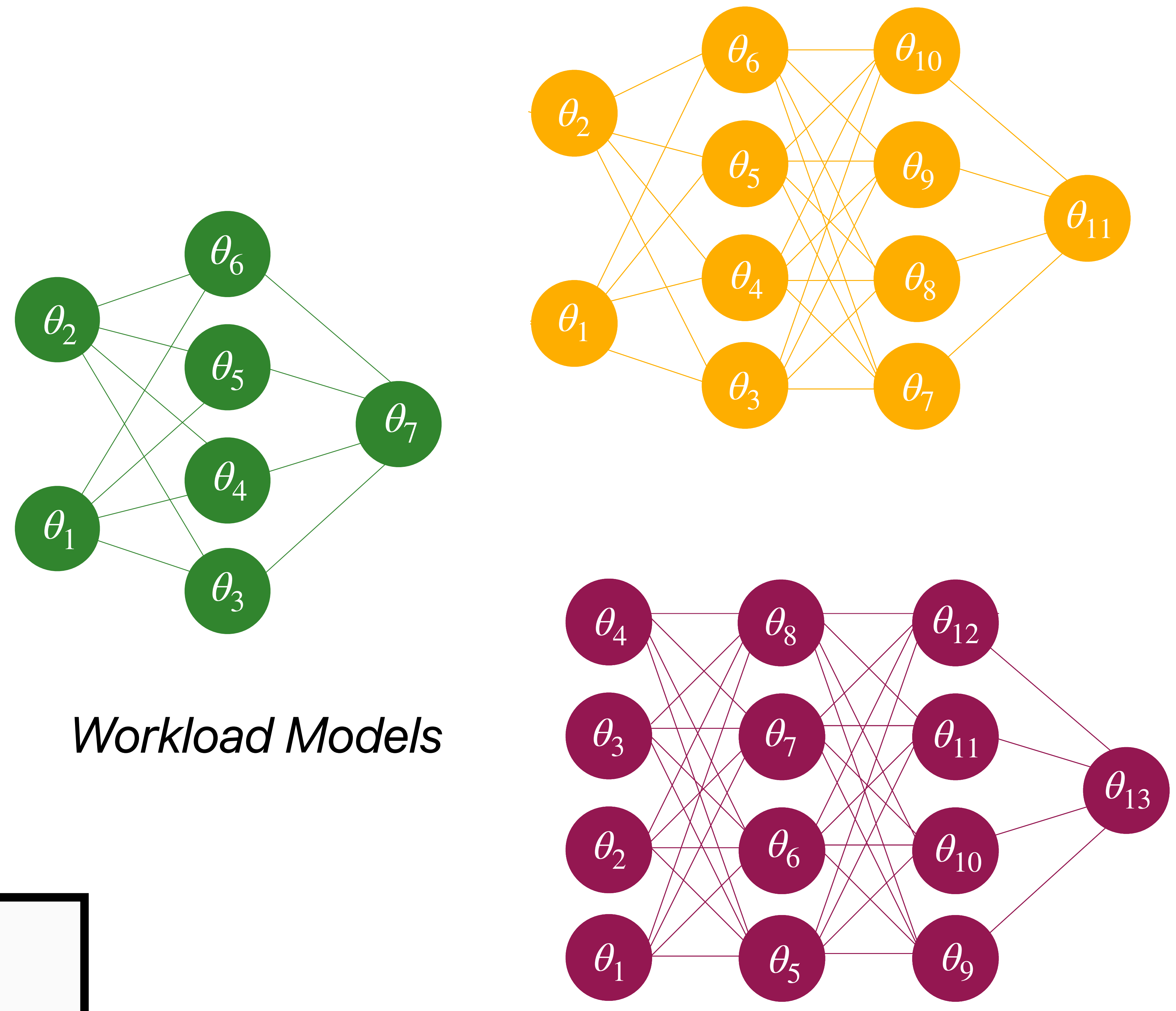

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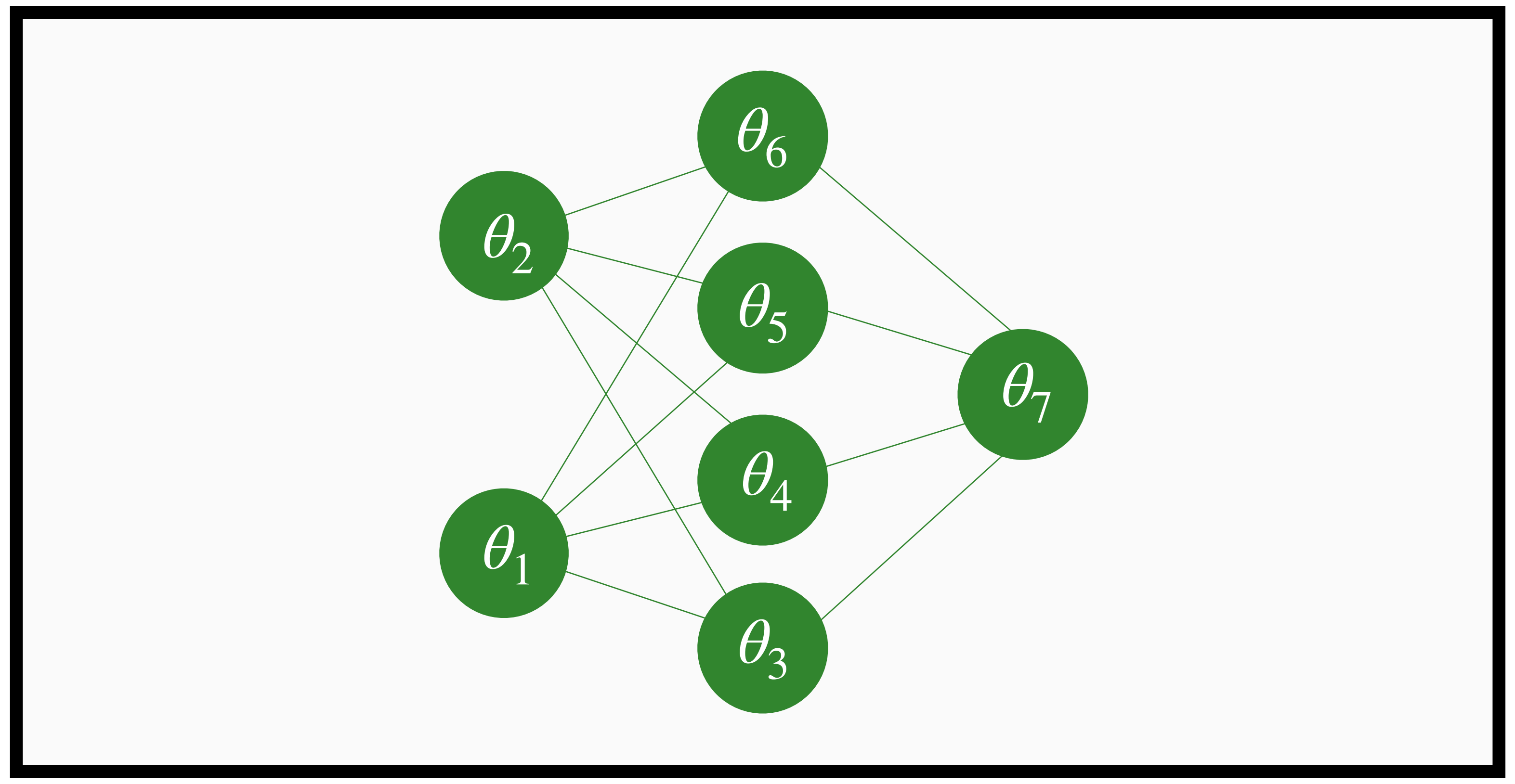

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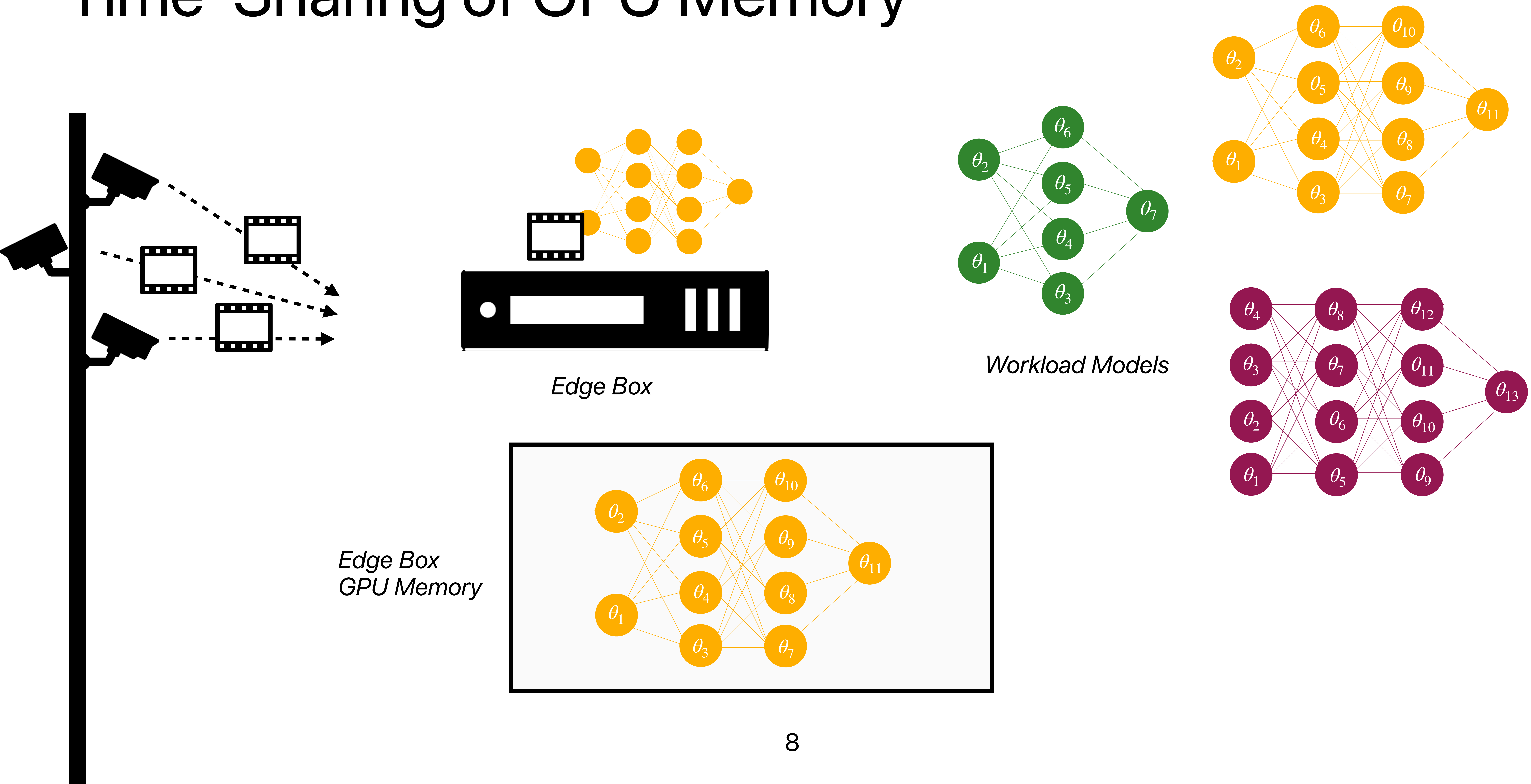

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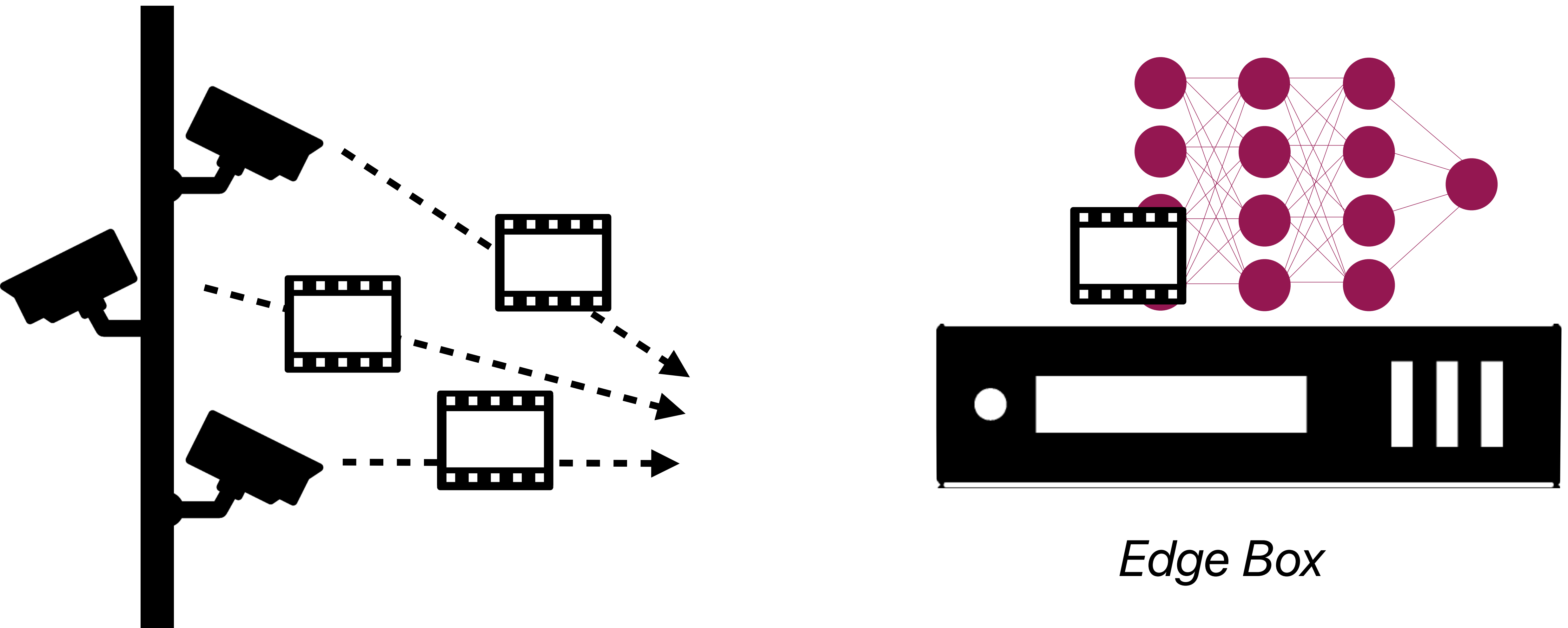

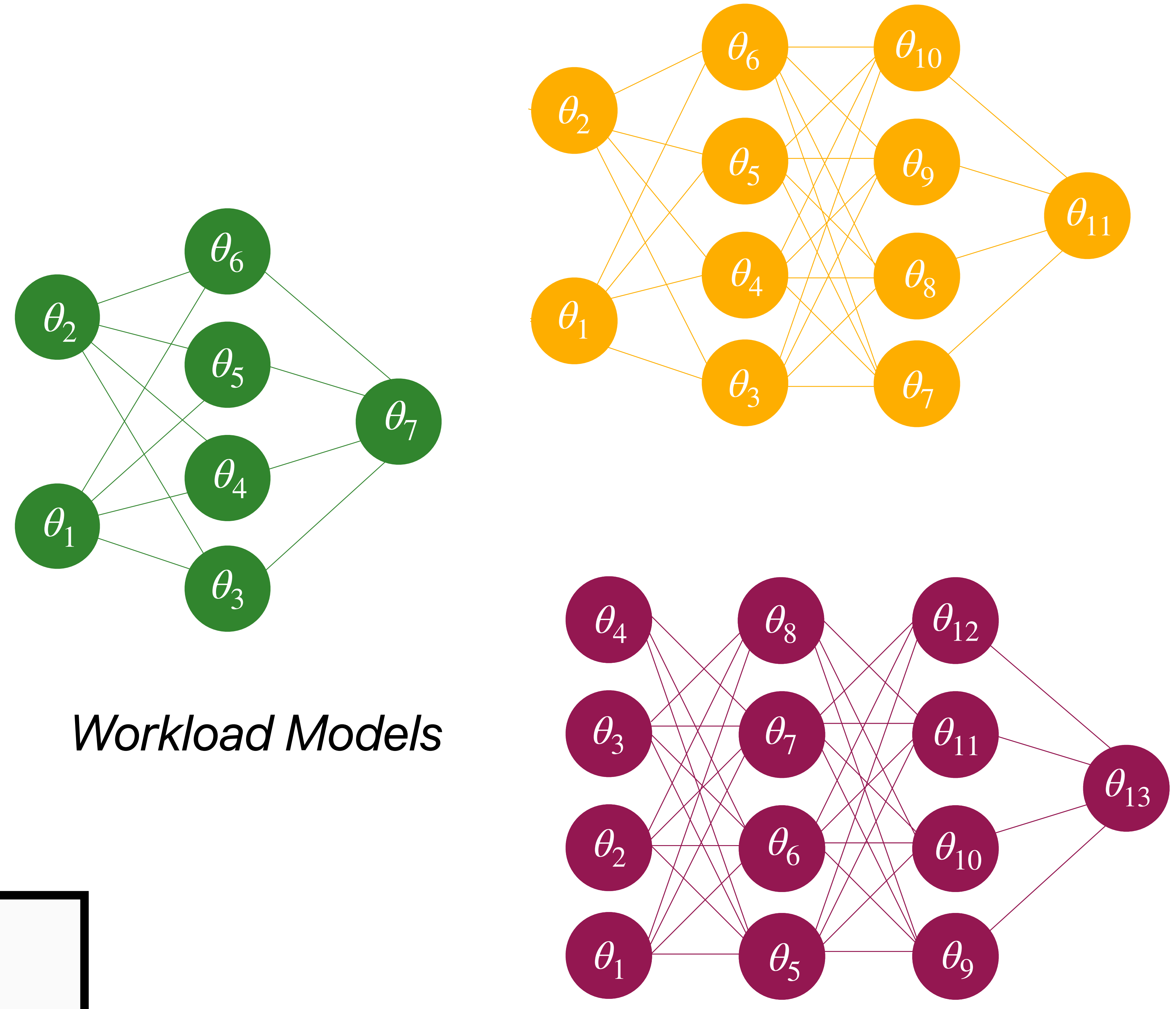

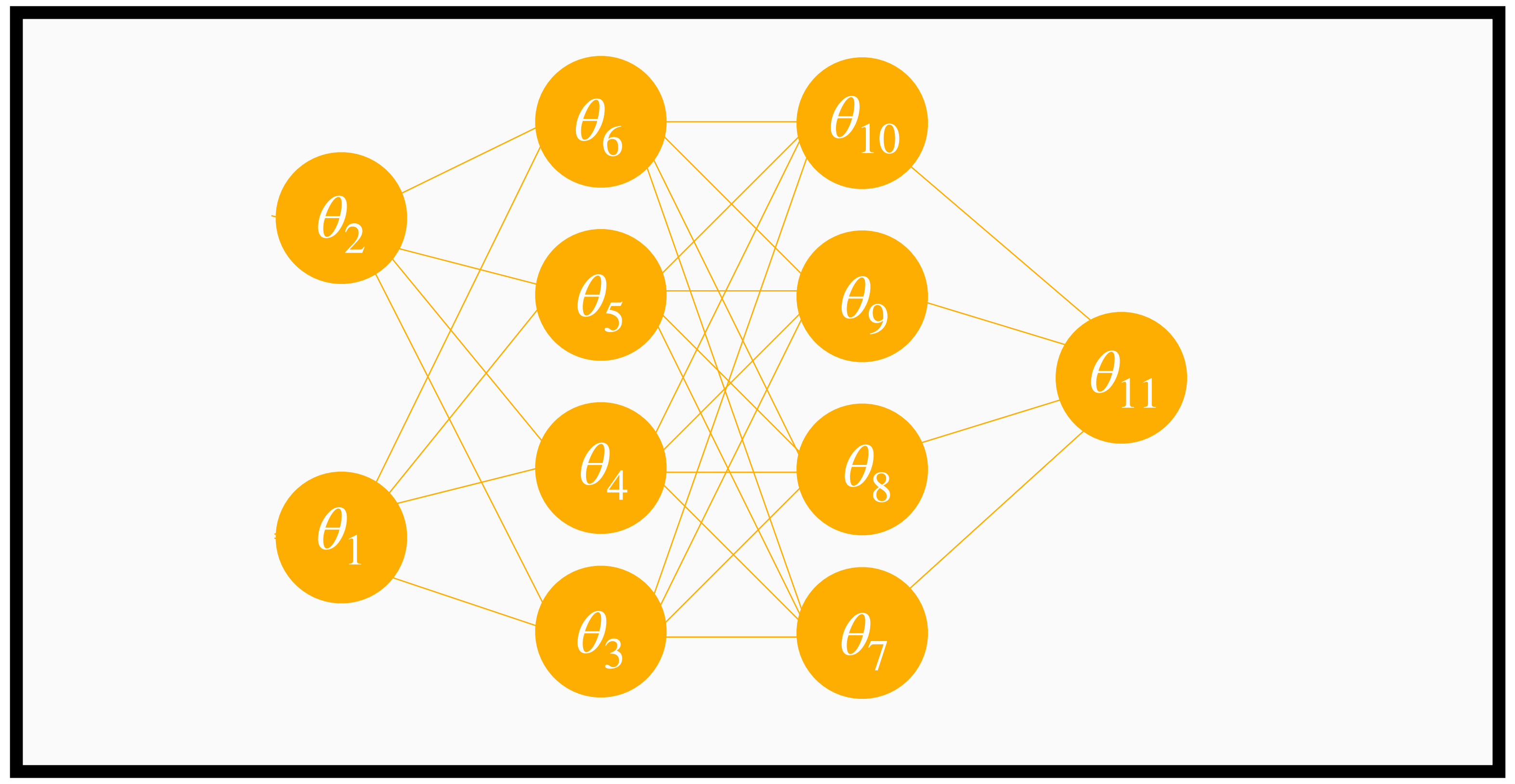

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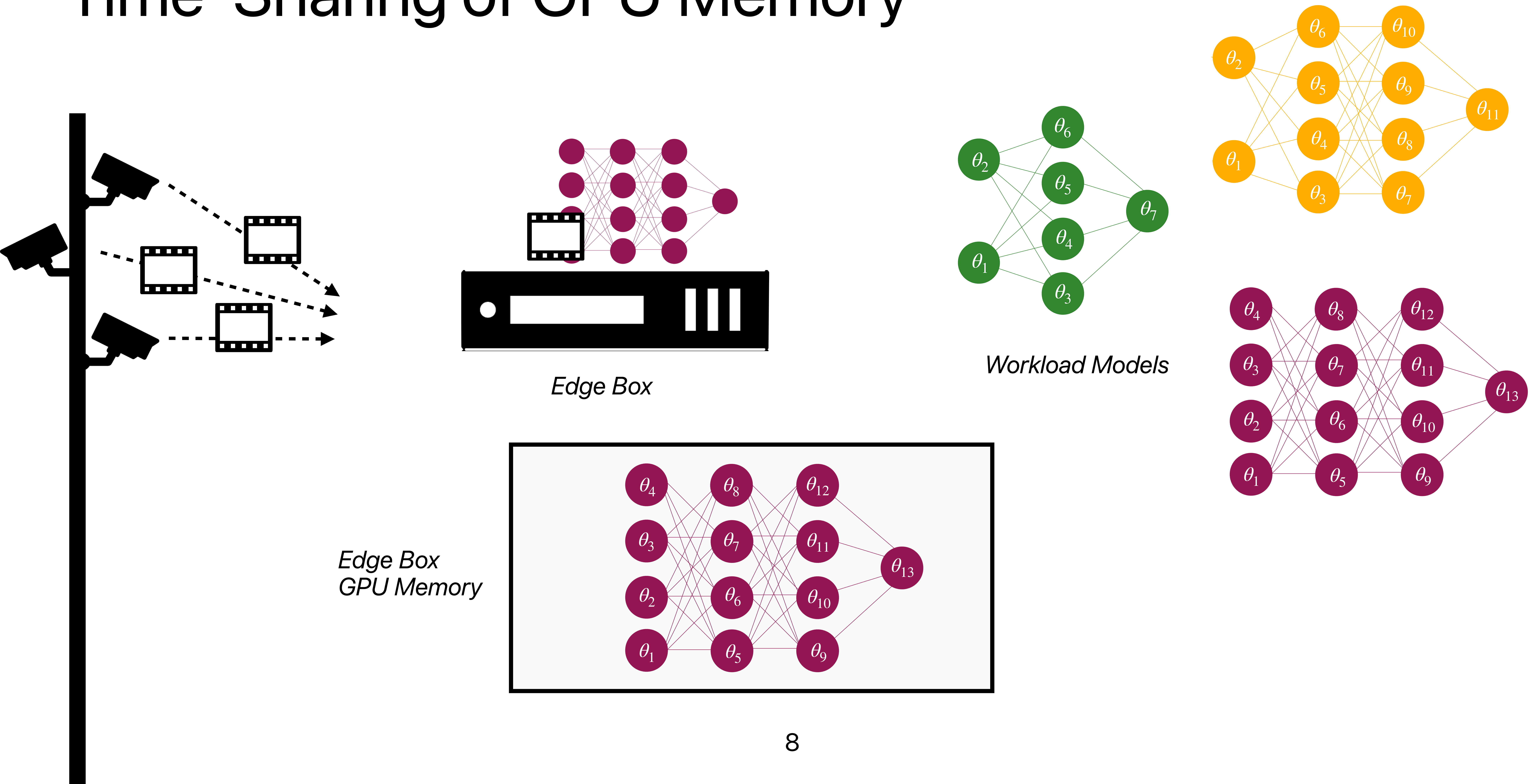

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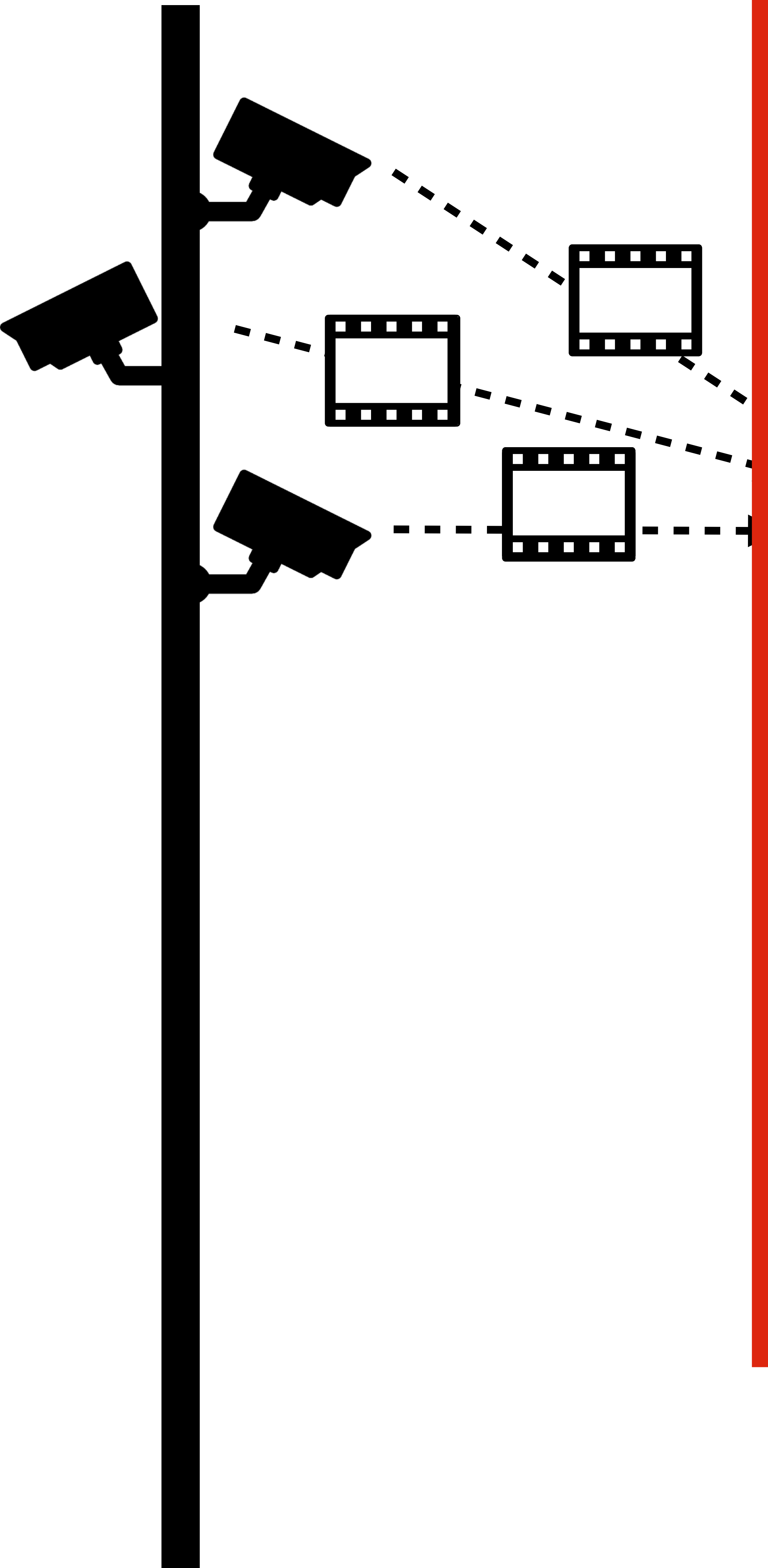
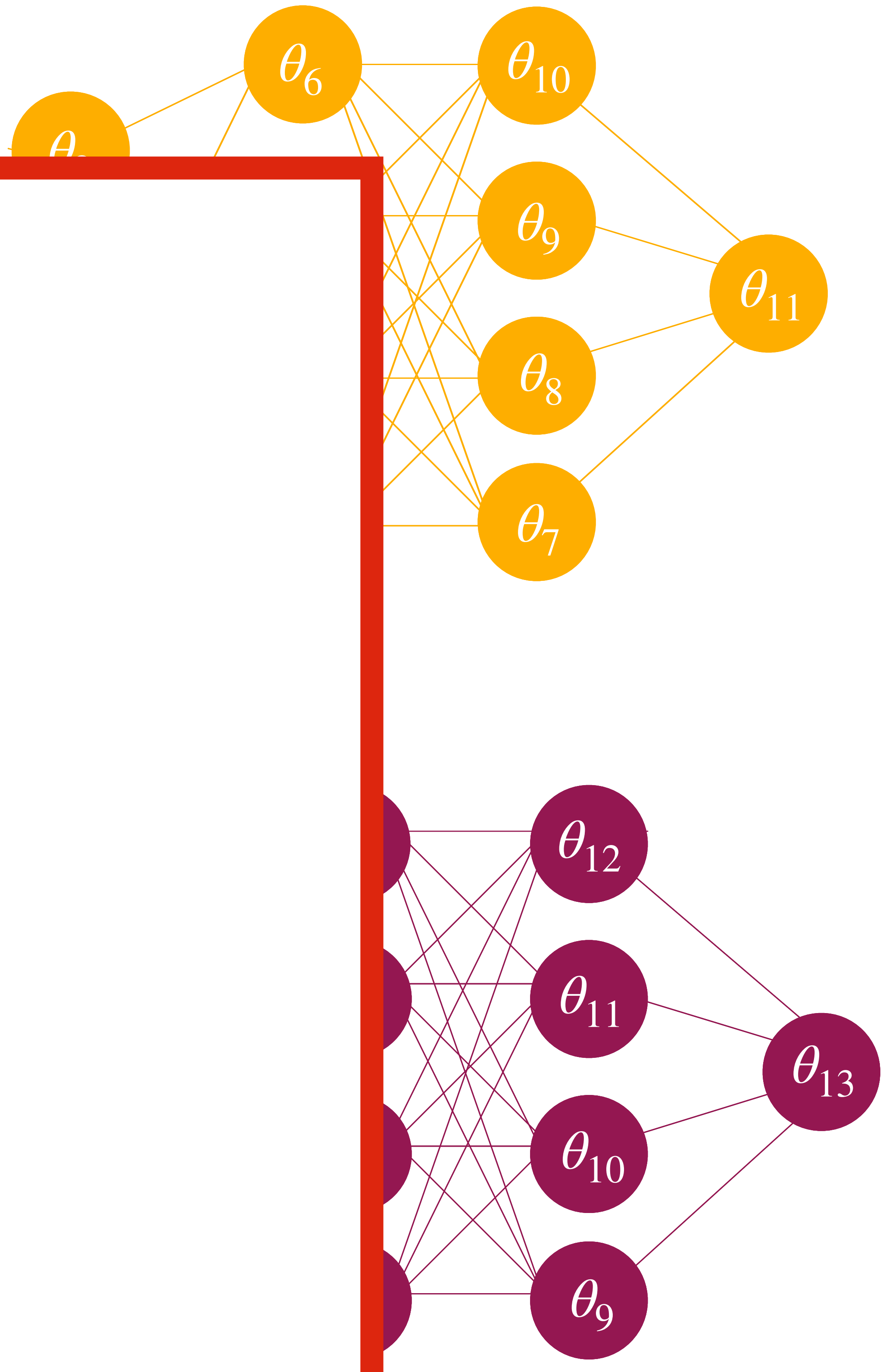


Skipped processing of 19-84% of frames and accuracy drops up to 43%



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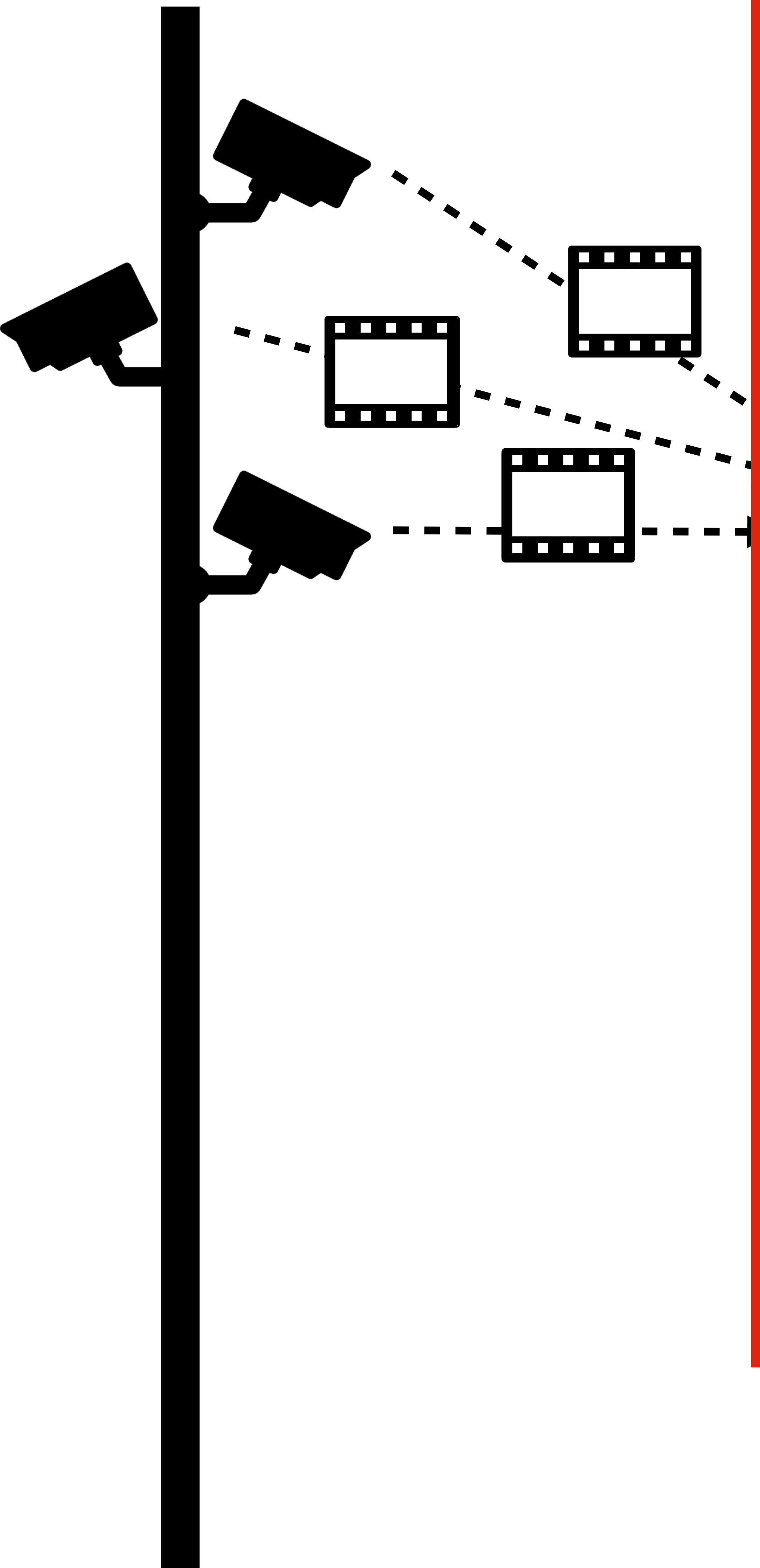

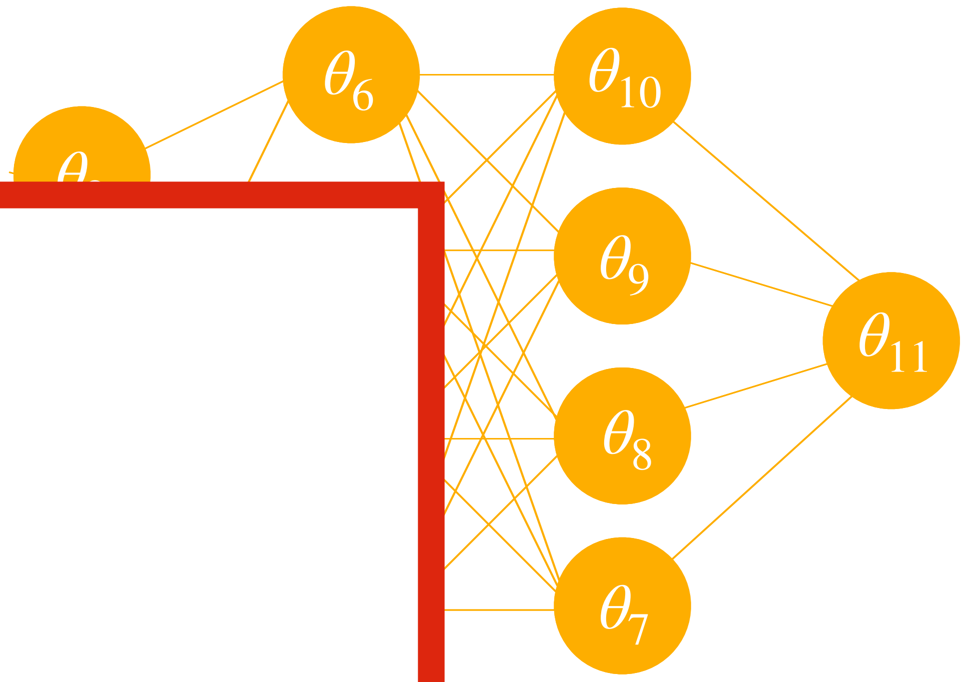

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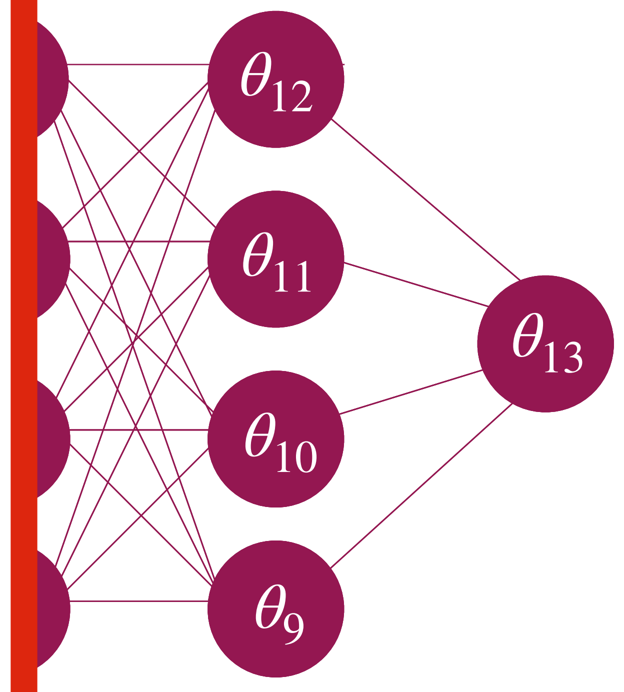
Model	**Loading Time** (ms)	**Run Time** (ms)
YOLOv3	49.5	17.0
ResNet152	73.3	24.8
ResNet50	27.1	8.4
VGG16	72.2	2.1
Tiny YOLOv3	6.7	3.0

Repeatedly loading models into GPU memory is *slow*



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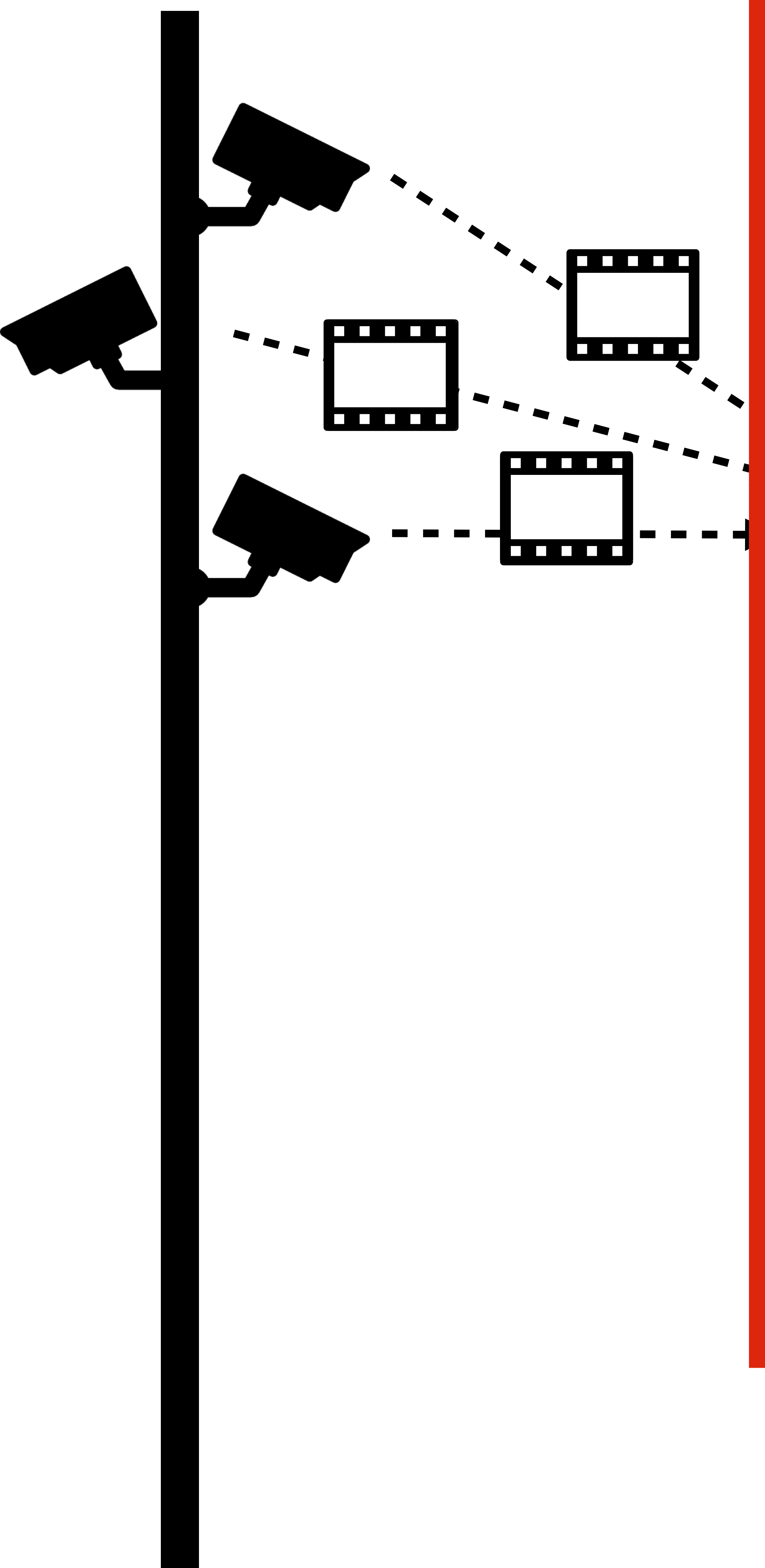

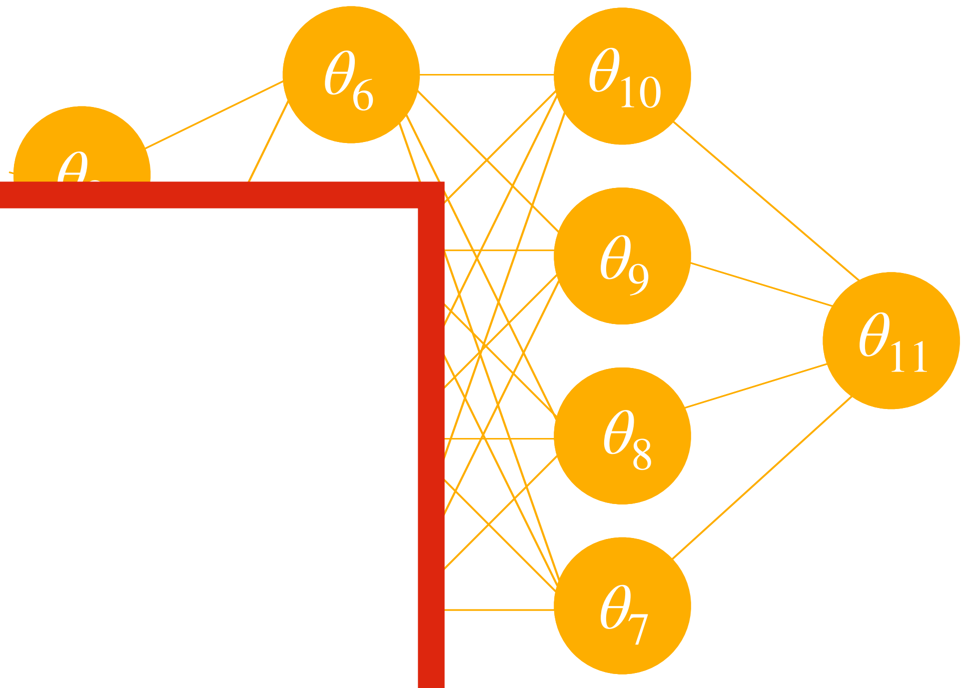

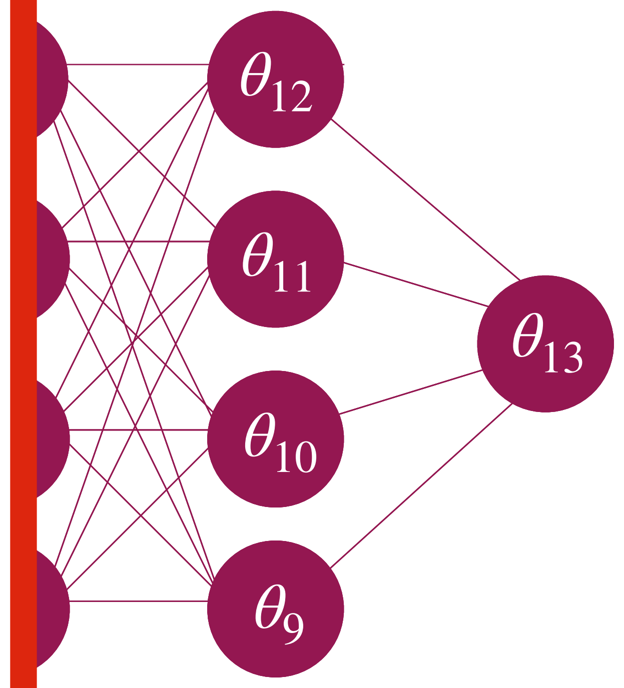

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Implication: cannot keep up with frame rate and must drop frames due to SLA violations

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How to reduce GPU memory bottlenecks in edge video analytics?

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Opportunity: reduce memory overheads by exploiting redundancies *across* models

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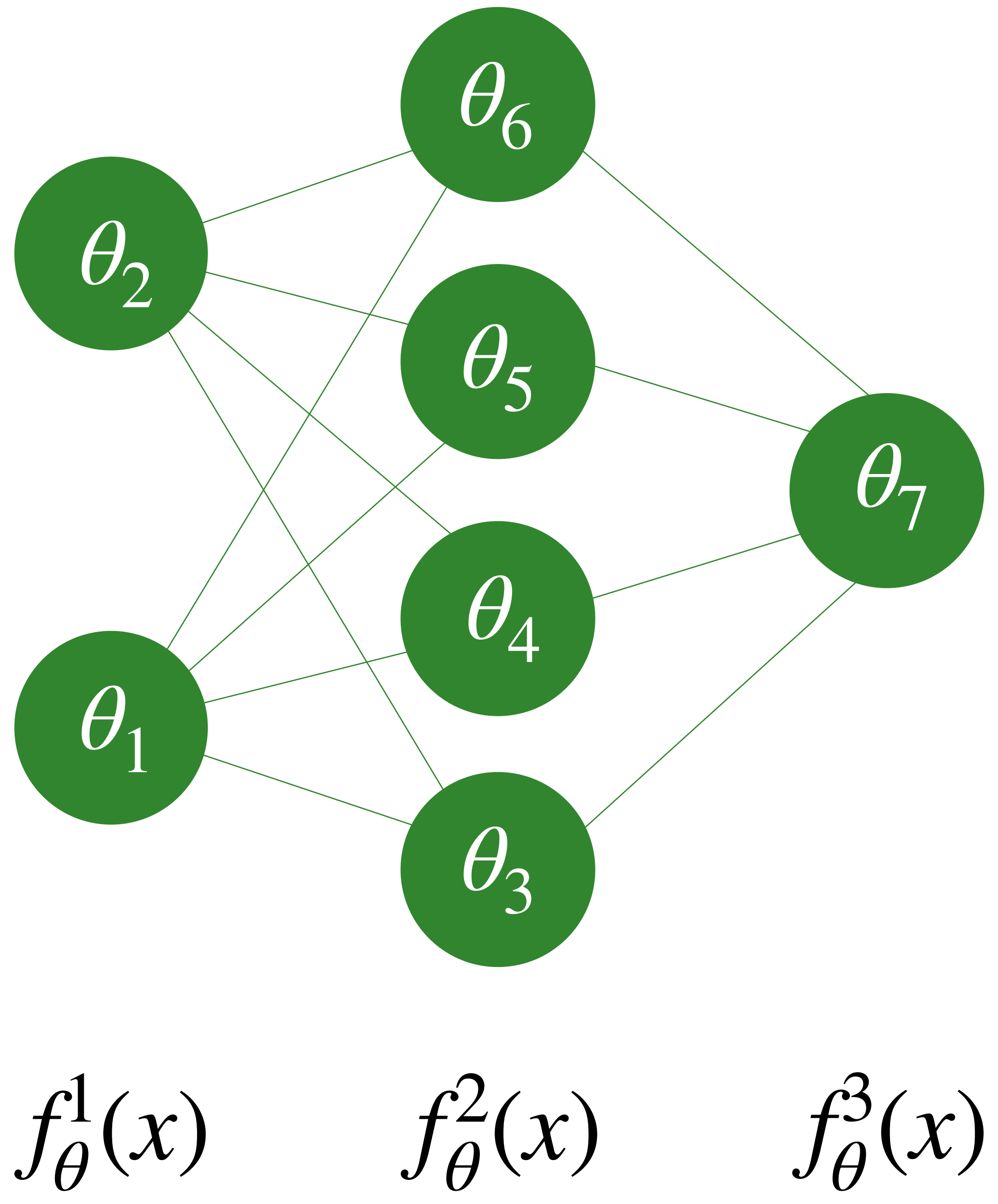
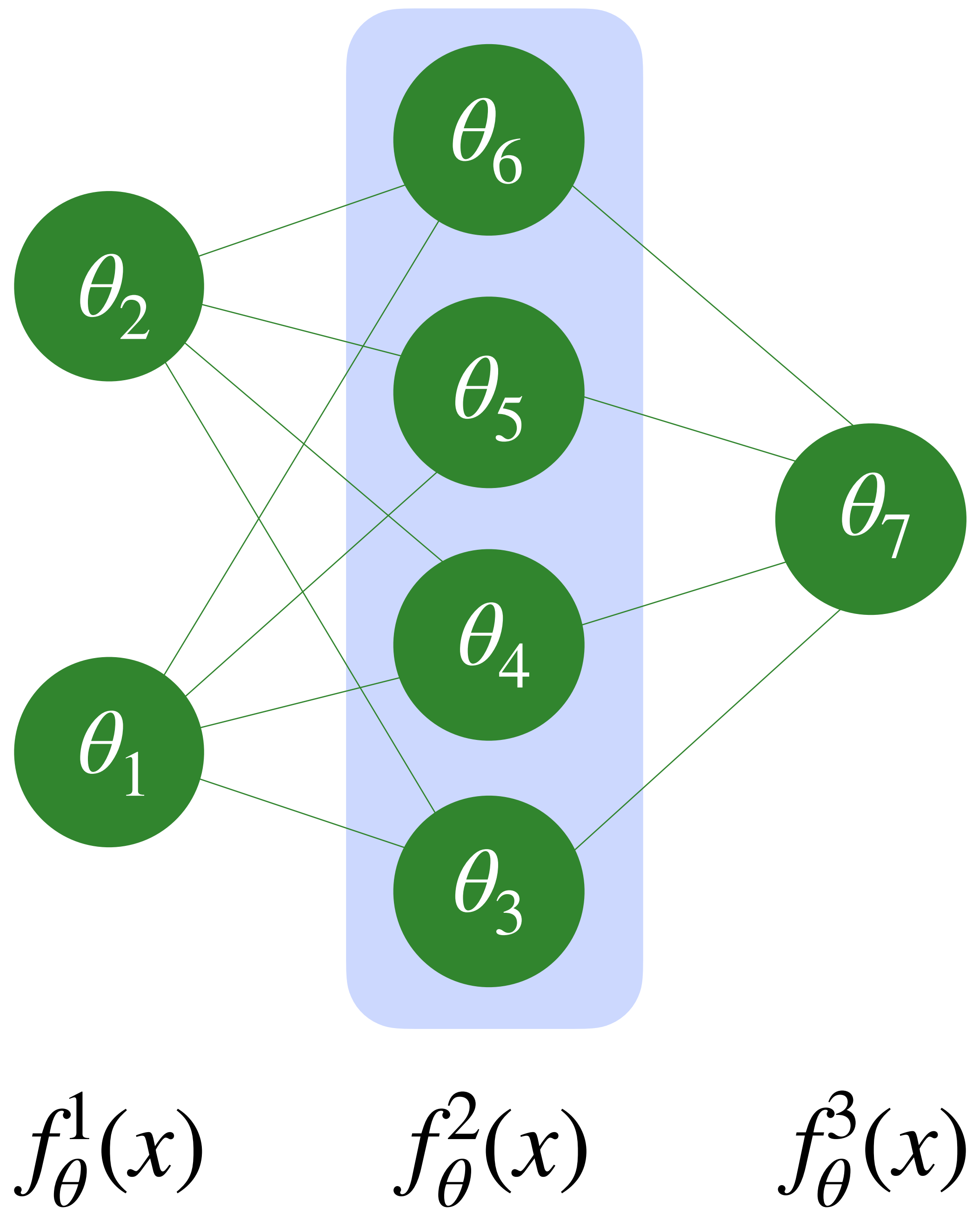
Observation: despite workload diversity, models often share many *layer definitions*

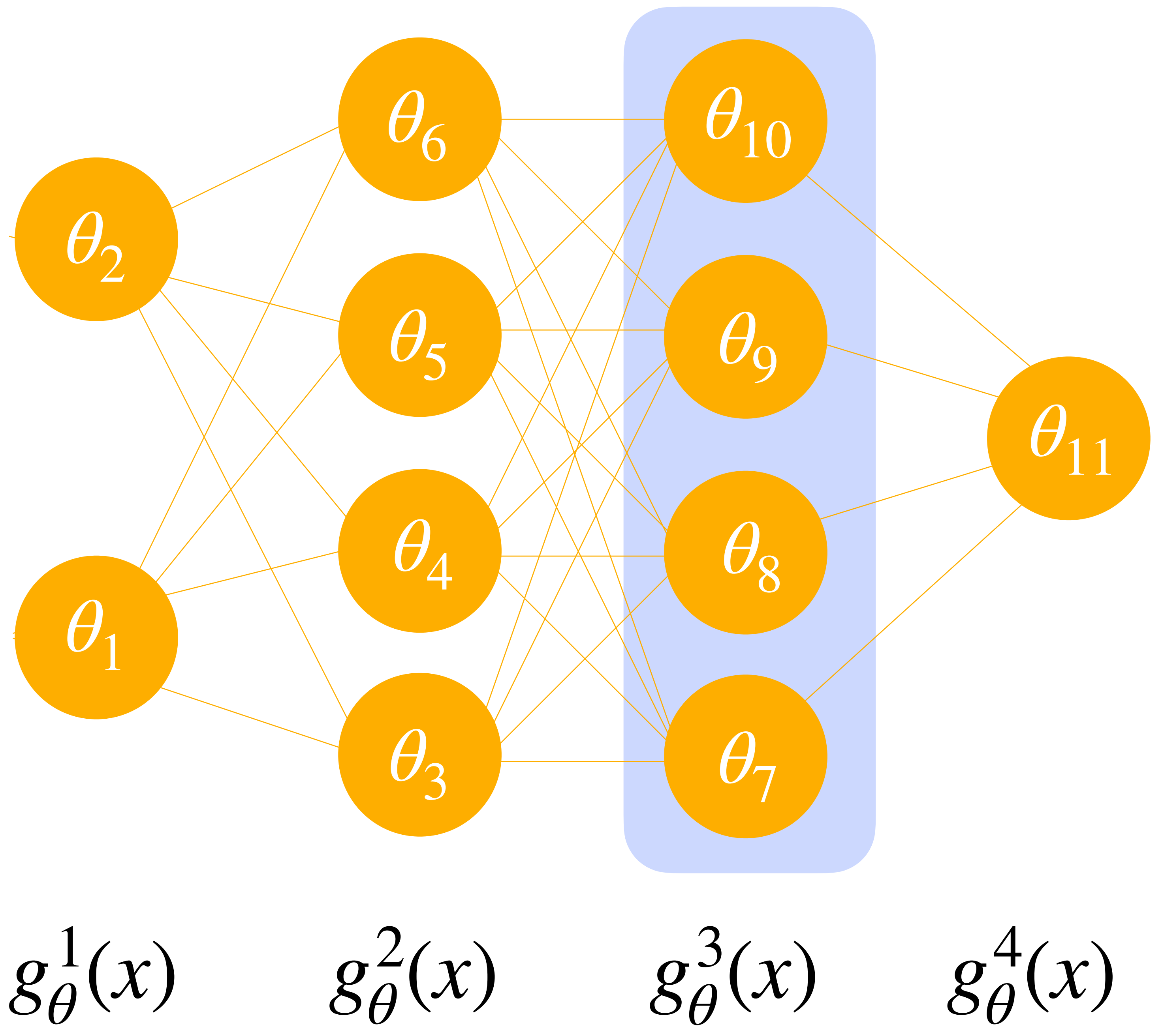
Shared Layer Definitions Across Models



Shared Layer Definitions Across Models

$$f_\theta^2(x) \equiv g_\theta^3(x)$$

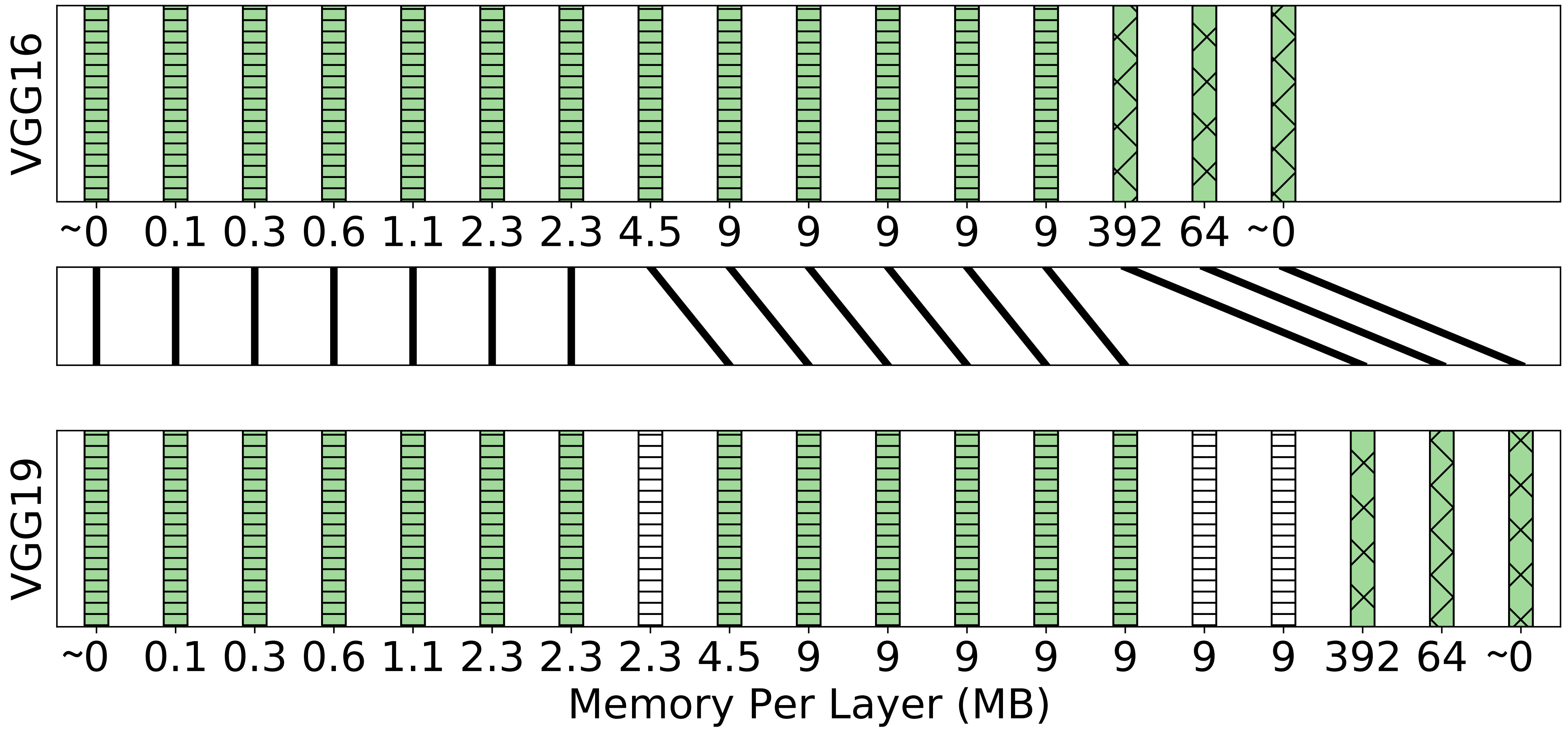




Shared layer definitions appear in…

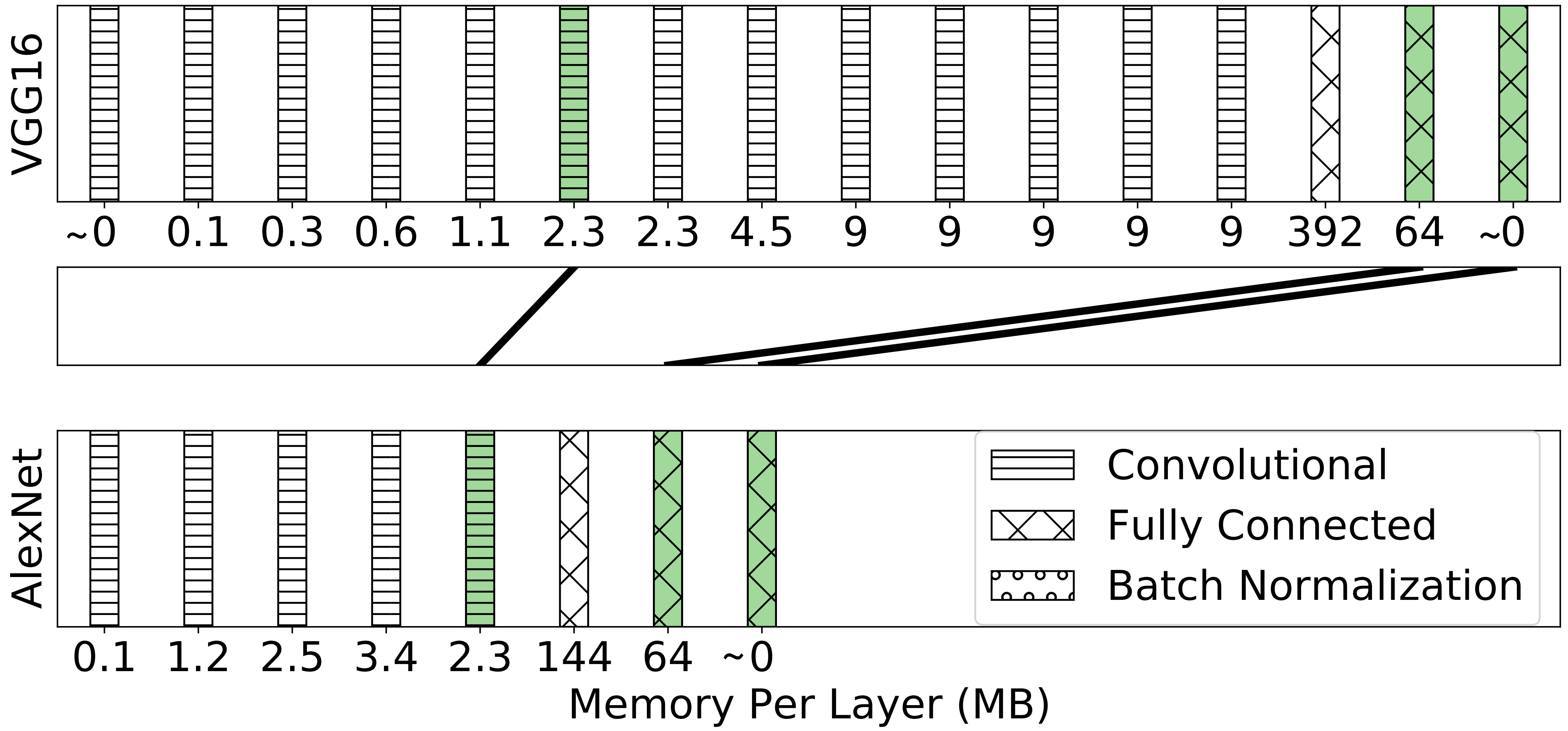
Models from the Same Architecture Family

e.g., VGG16 & VGG19



Models from Different Architecture Families

e.g., VGG16 & AlexNet



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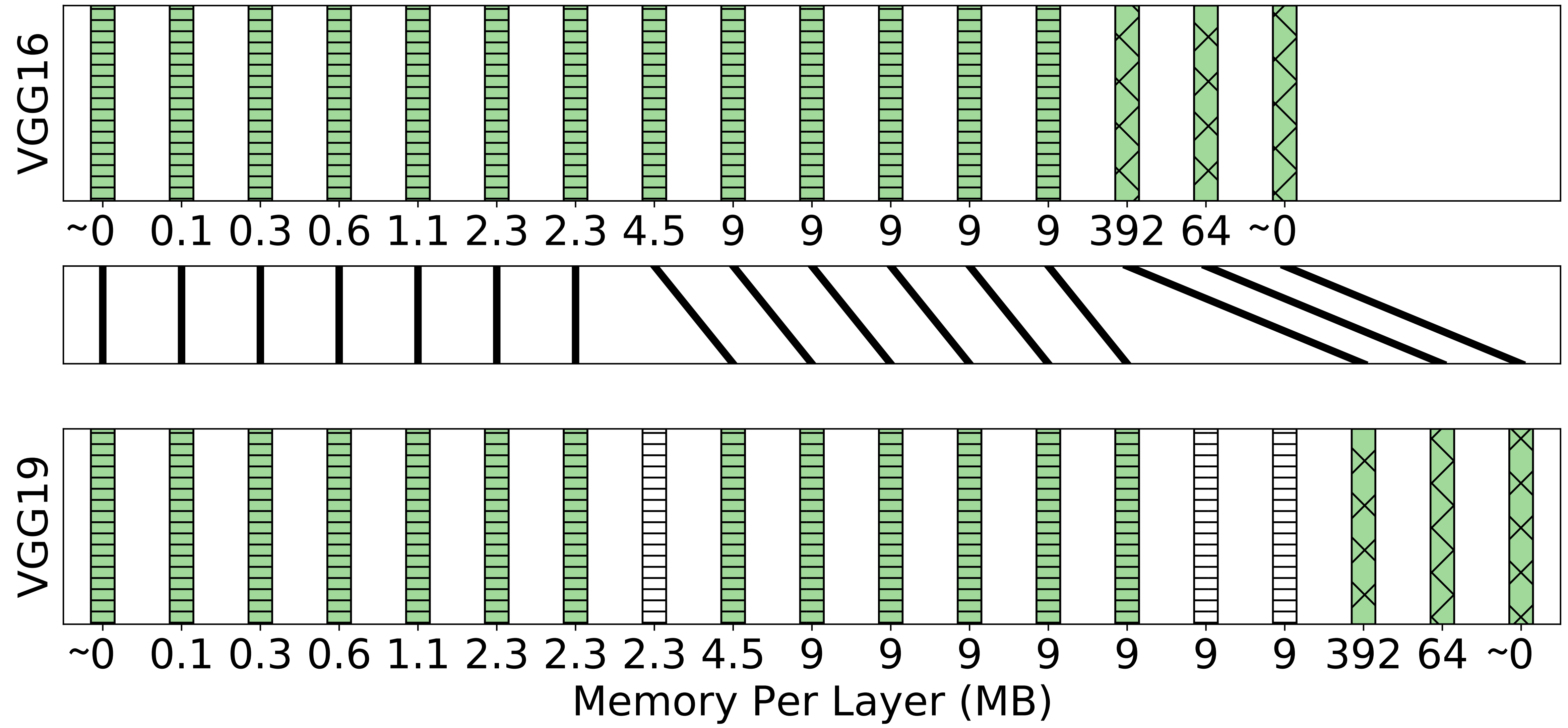

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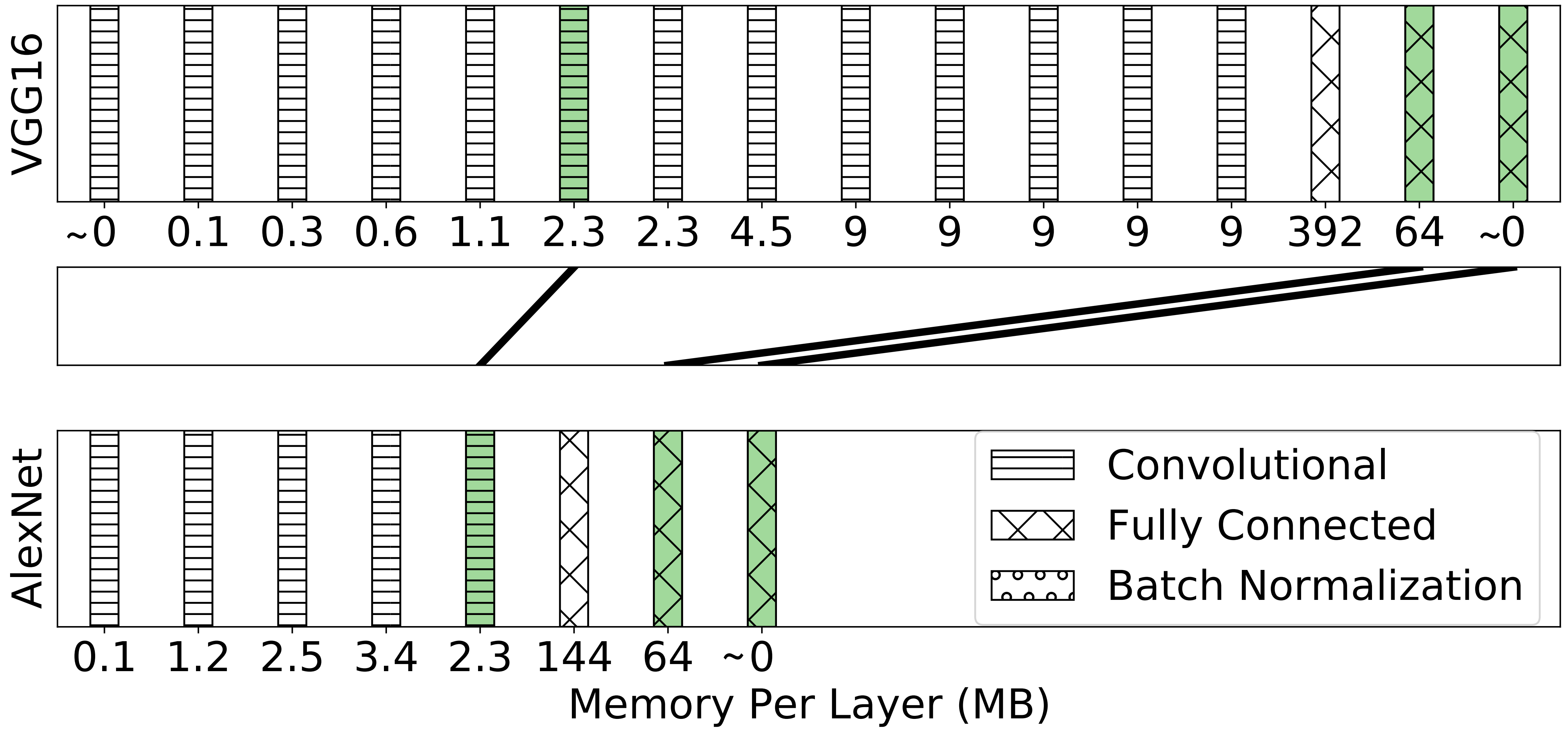
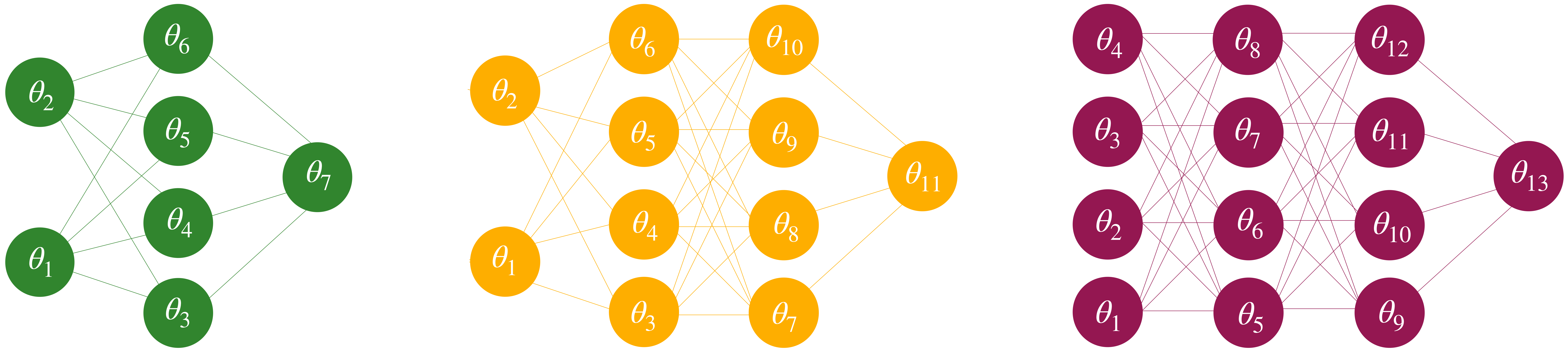


Across 24 different architectures, 43% of all pairs of different models have shared layers

Idea: Find unified weights for shared layers



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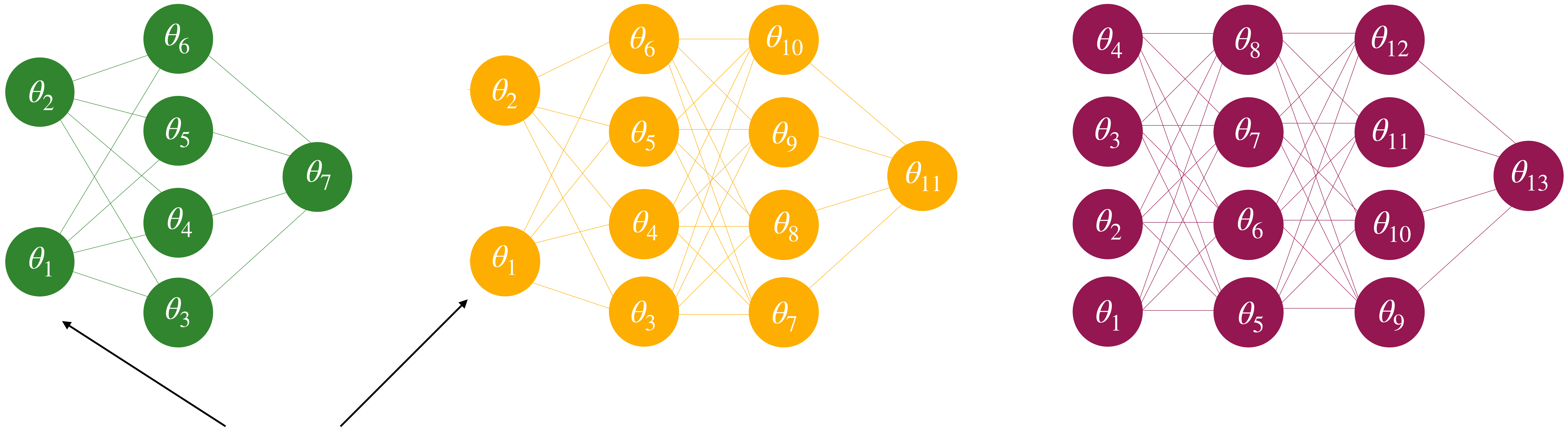
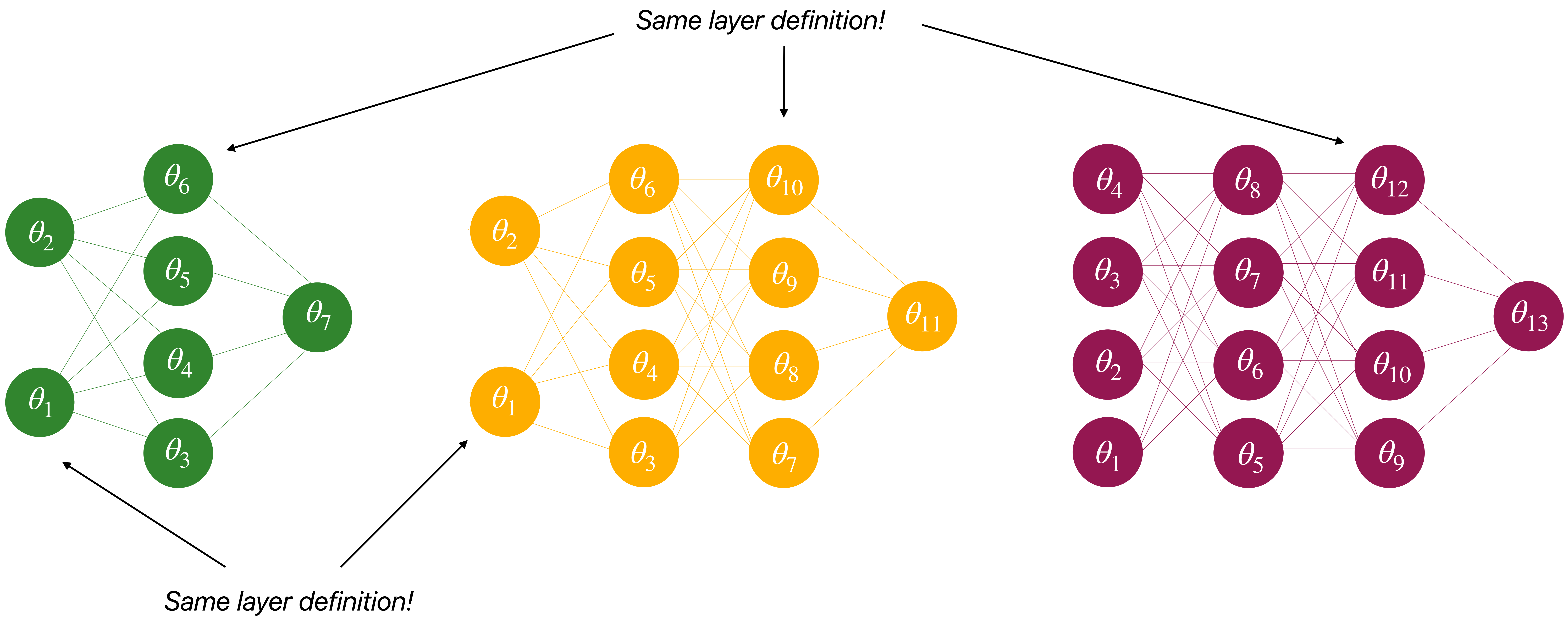


Same layer definition!

Idea: Find unified weights for shared layers



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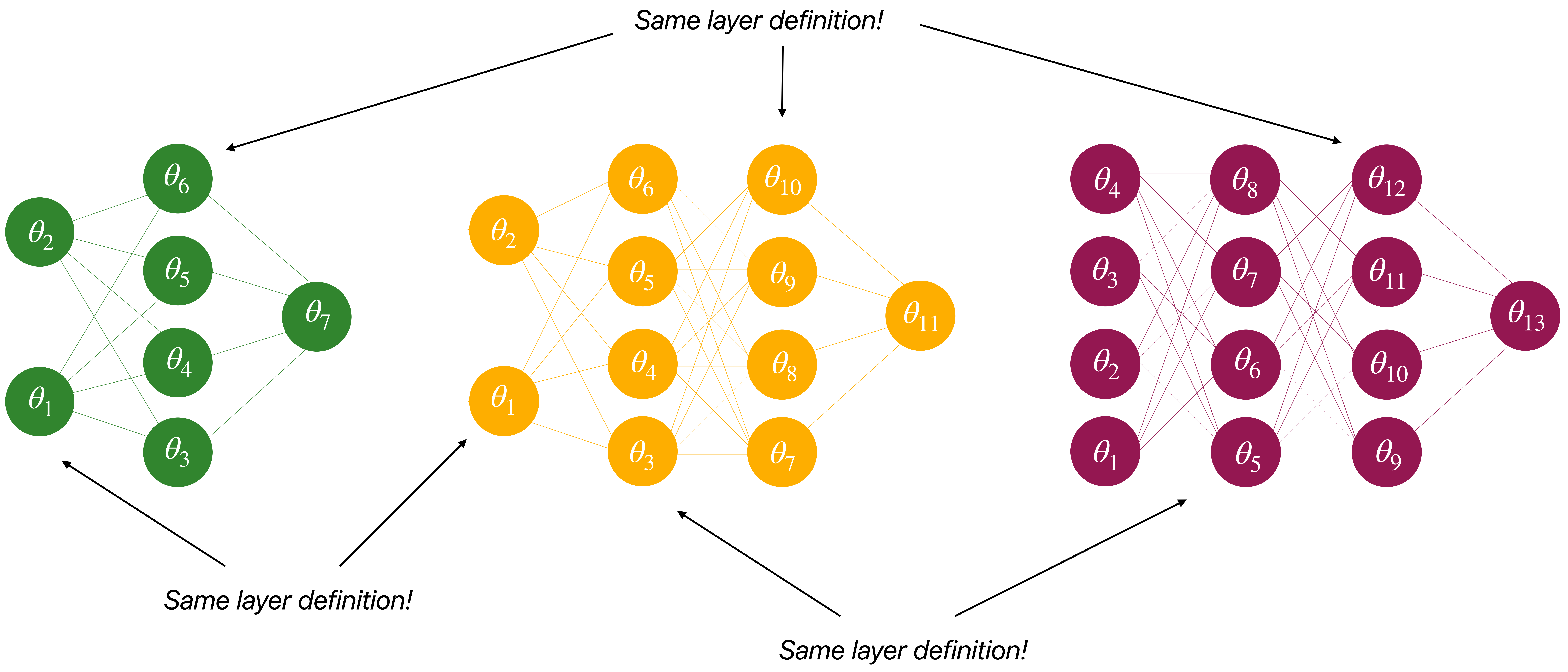

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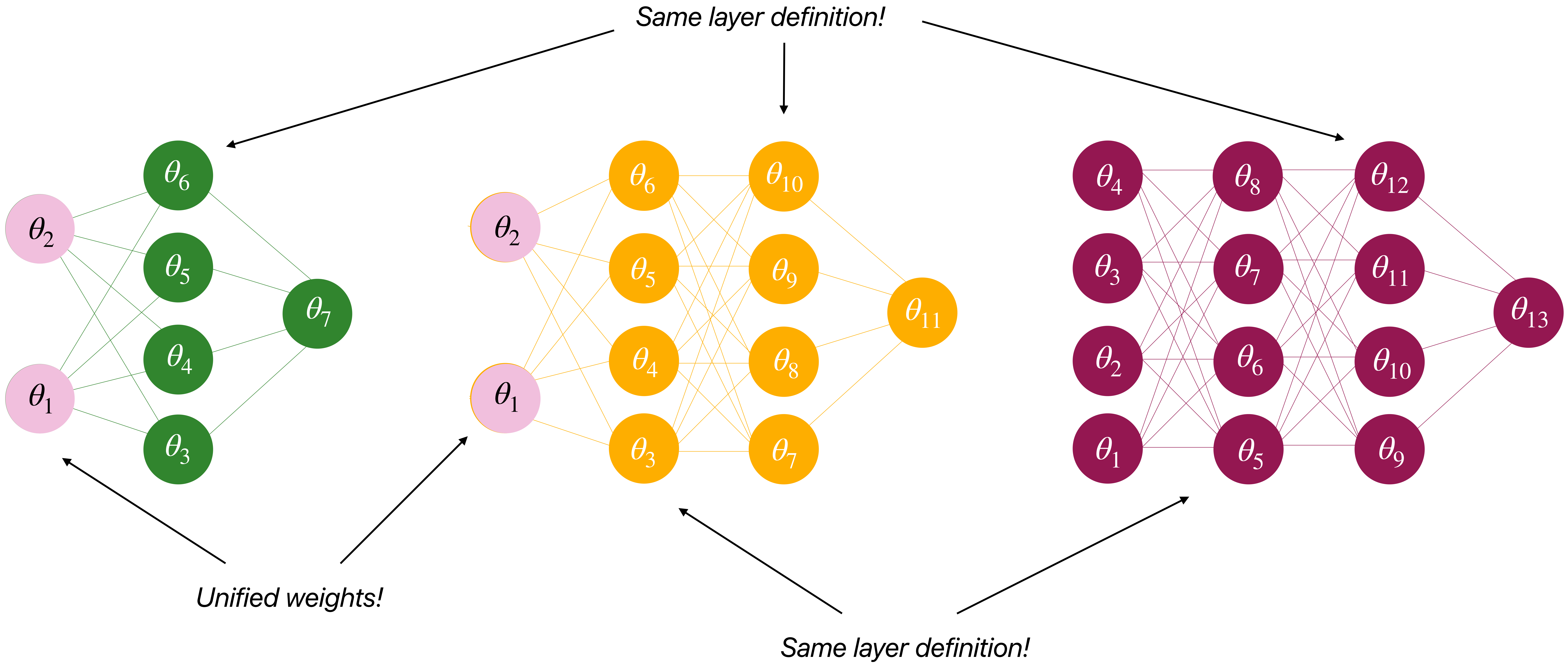

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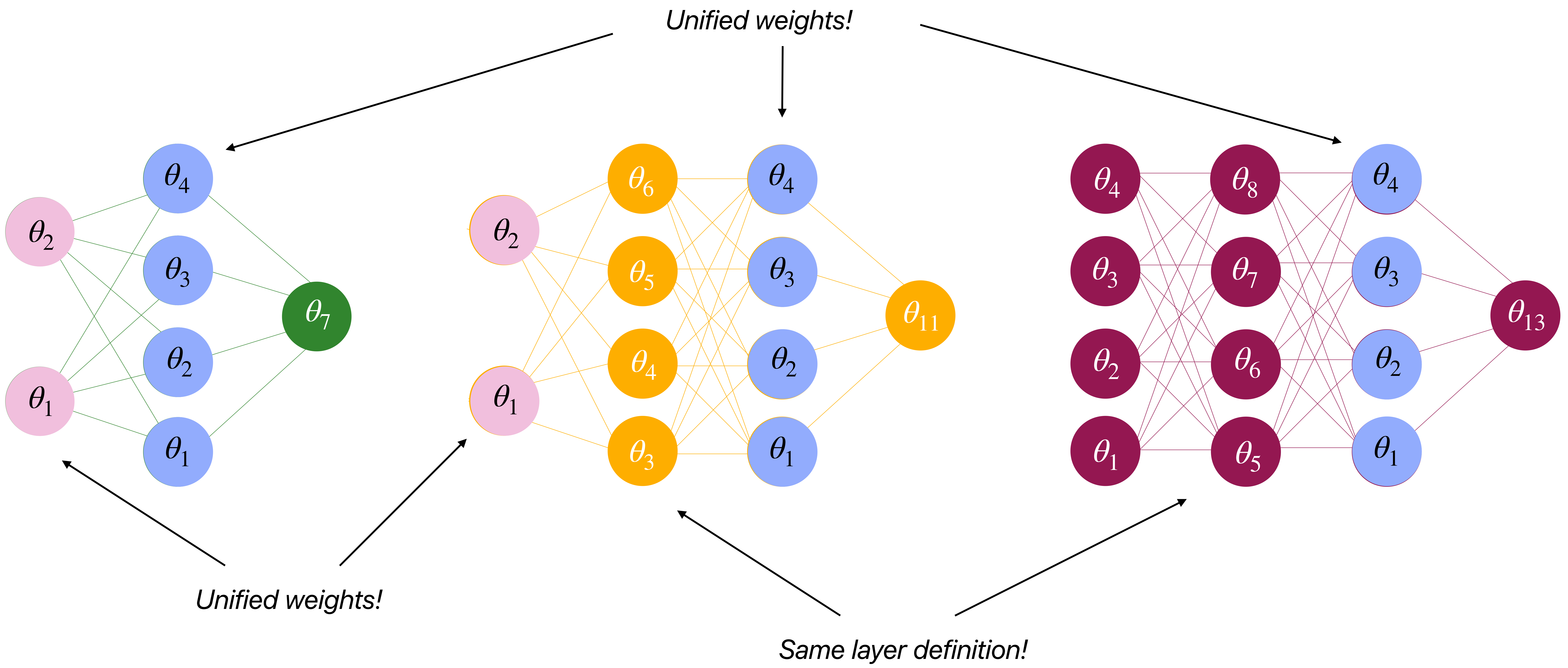

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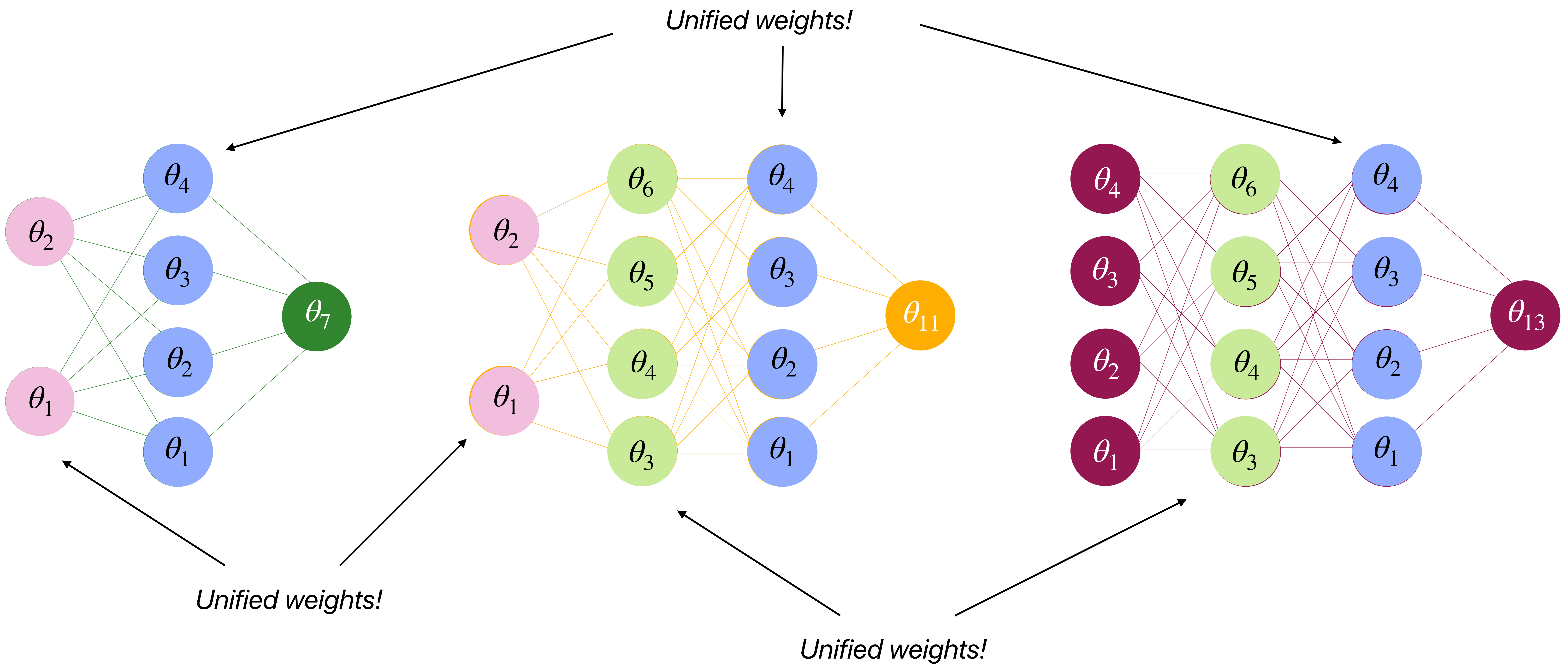
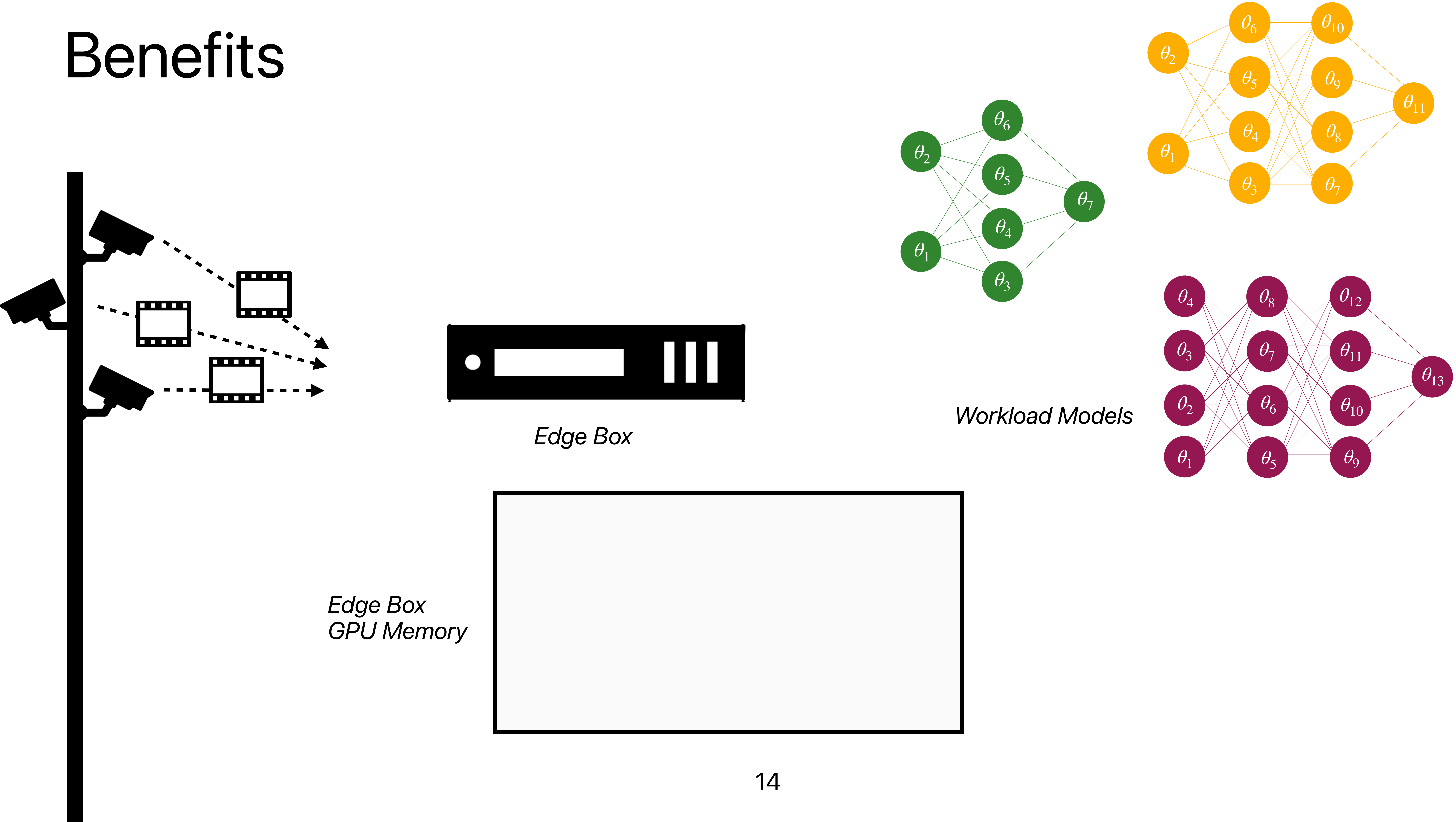


Benefits



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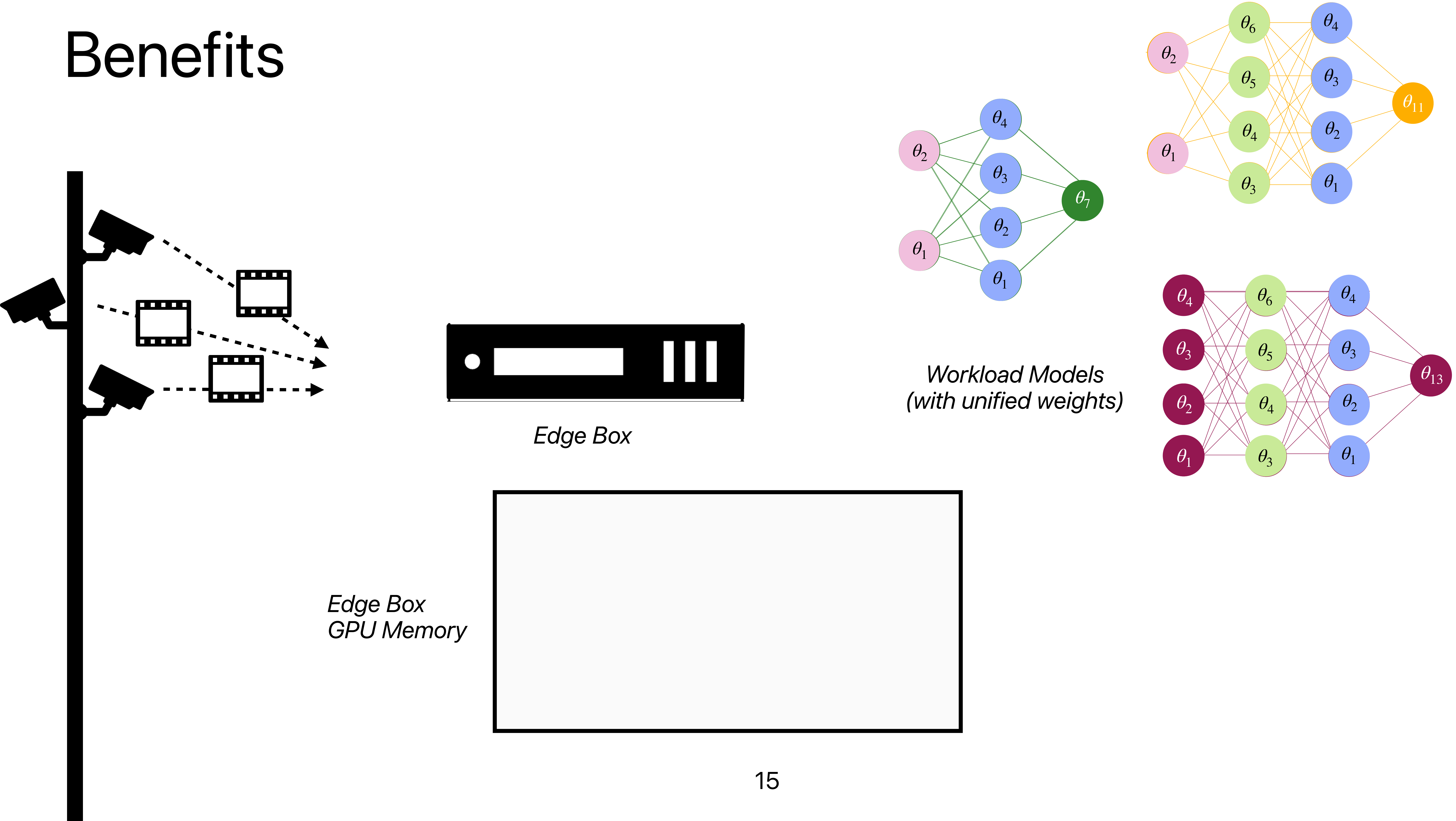
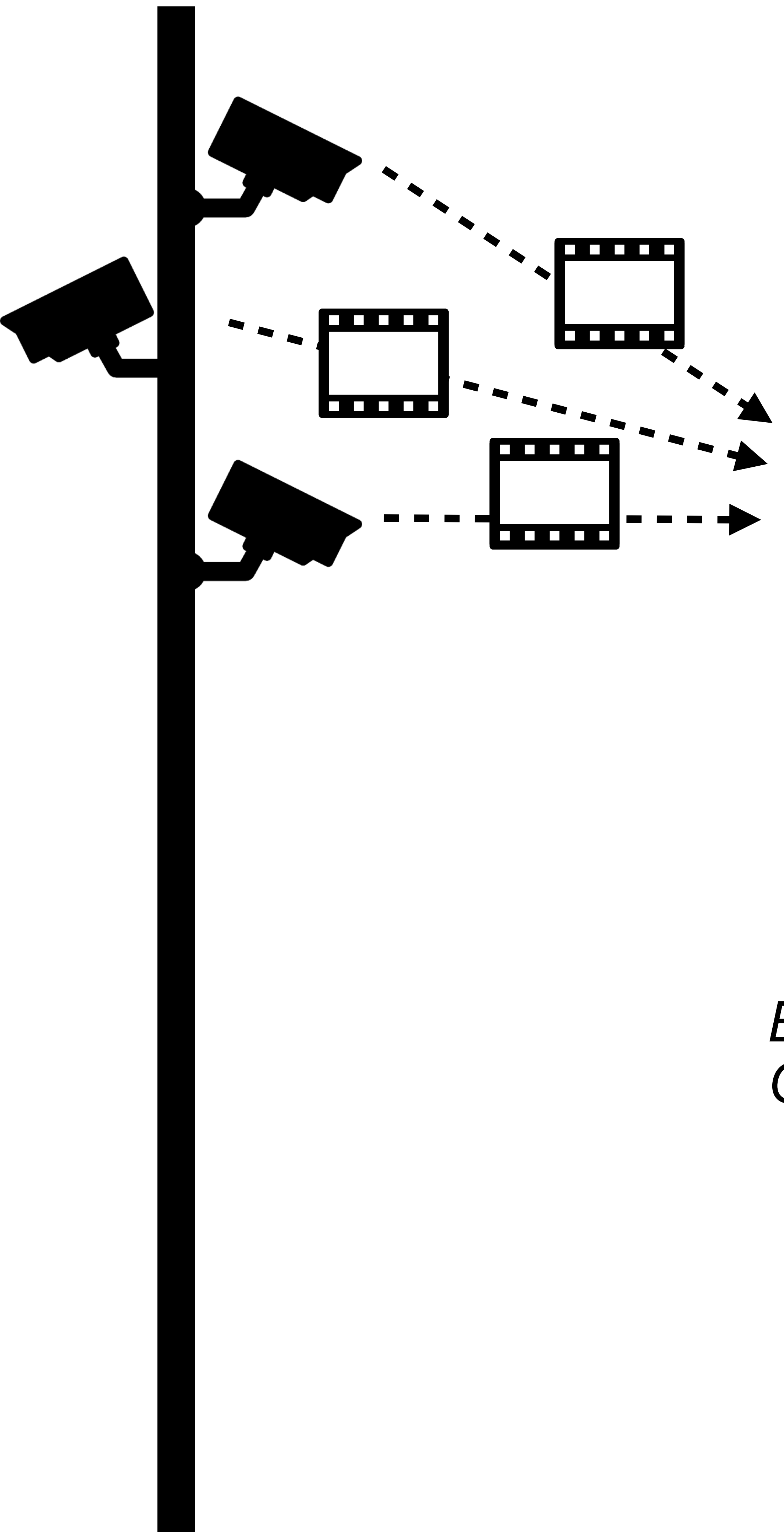
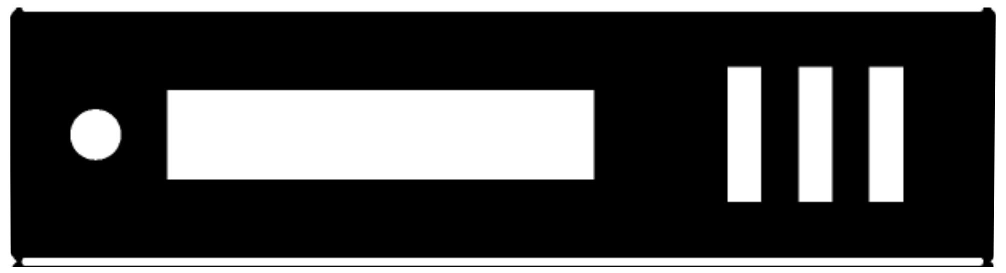

Edge Box
Workload Models
(with unified weights)
Edge Box
GPU Memory

Benefits





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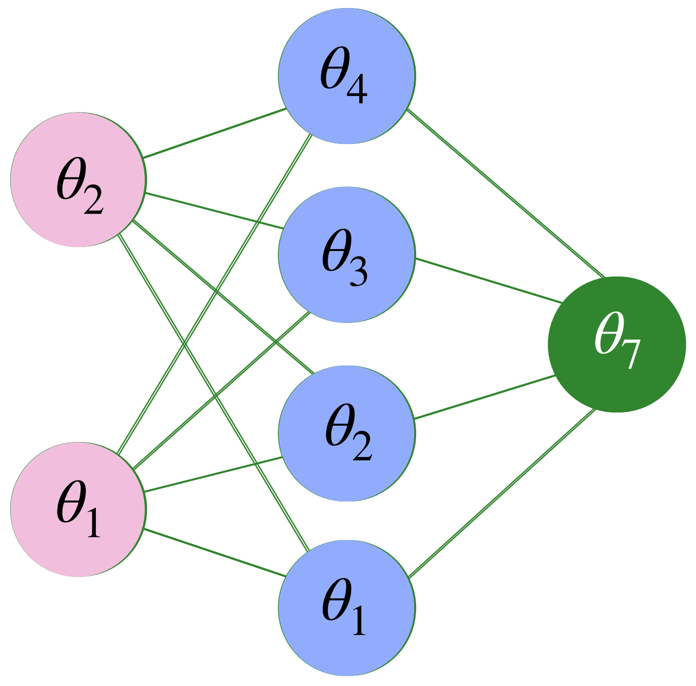

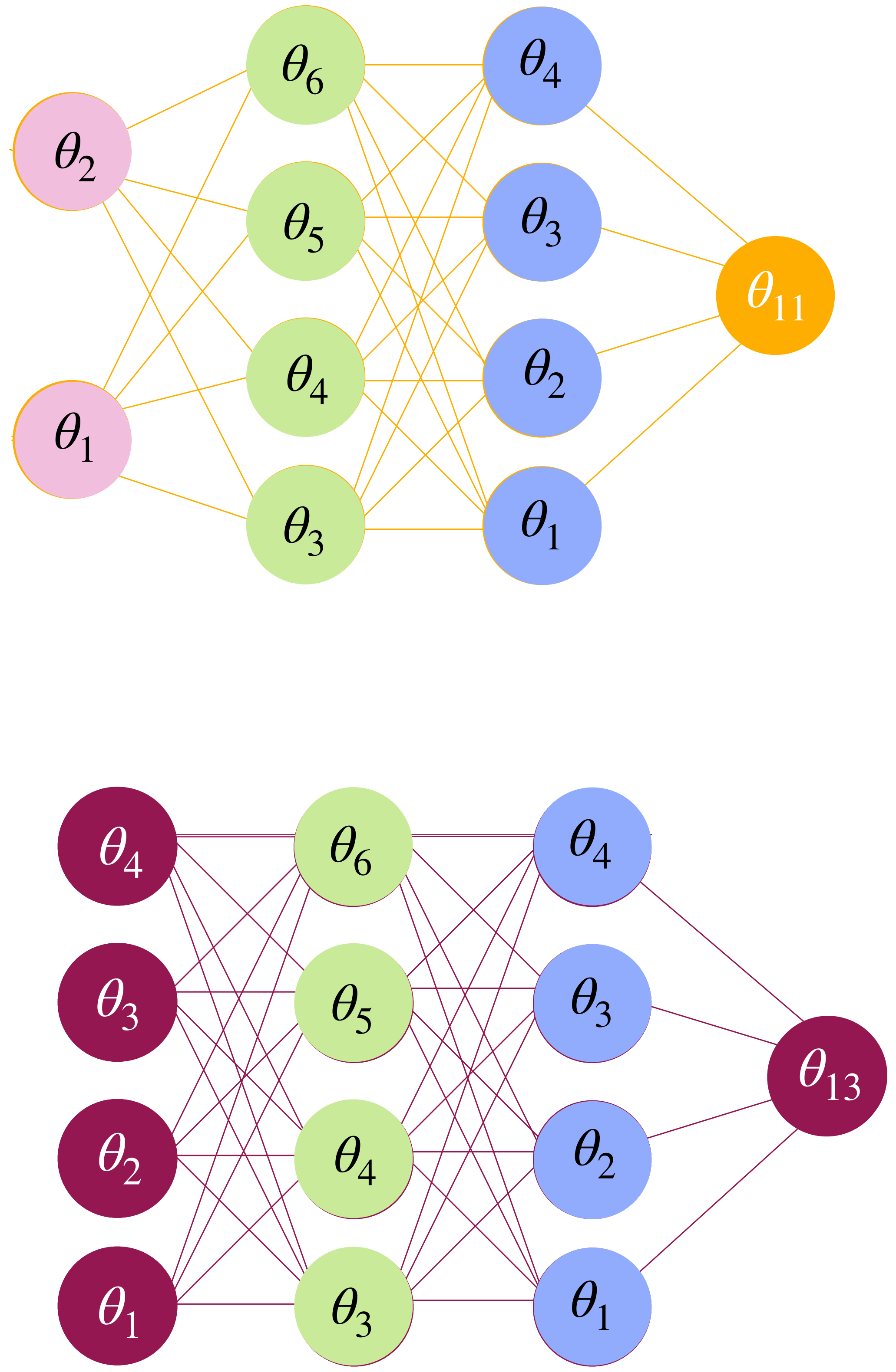

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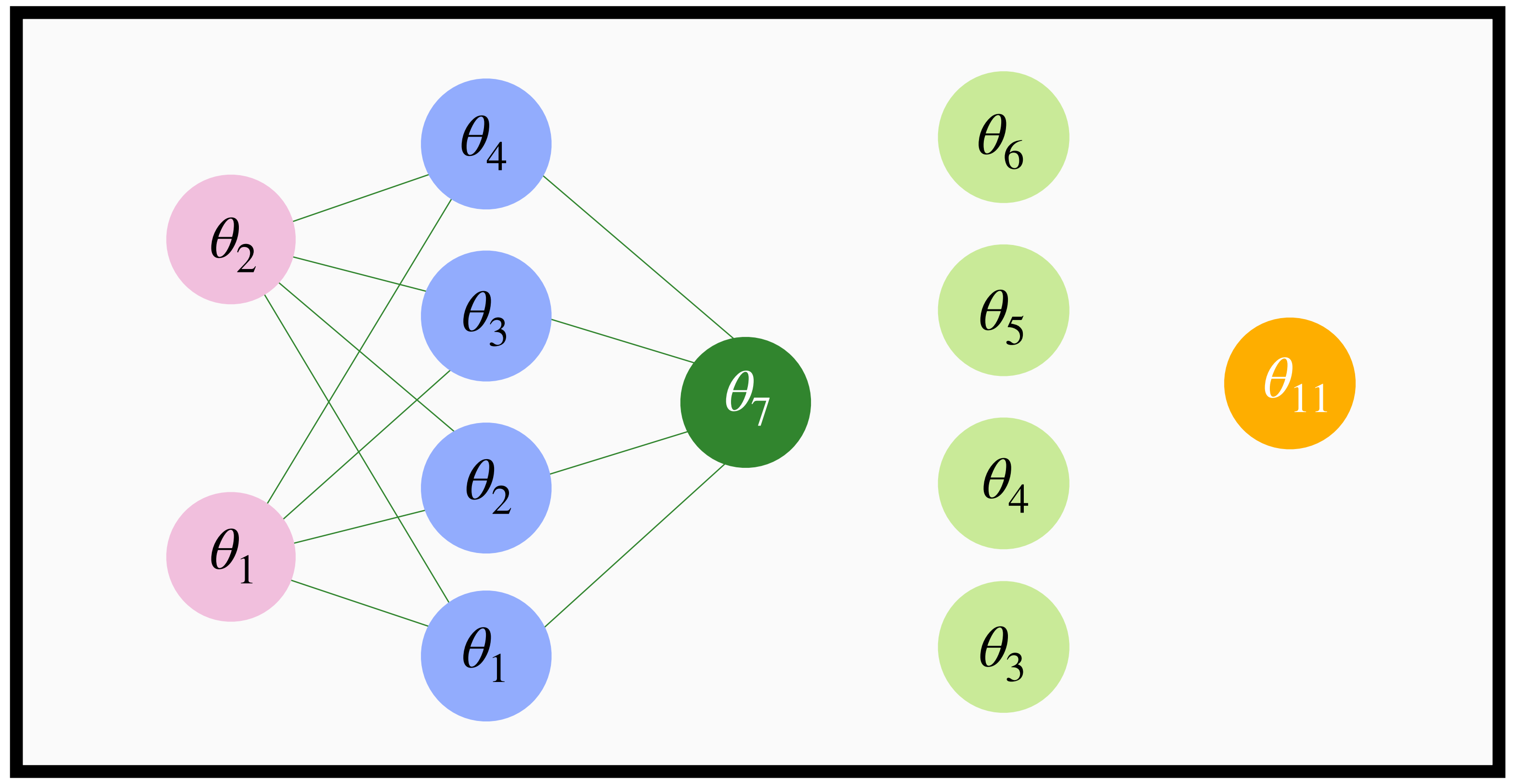
Edge Box
GPU Memory



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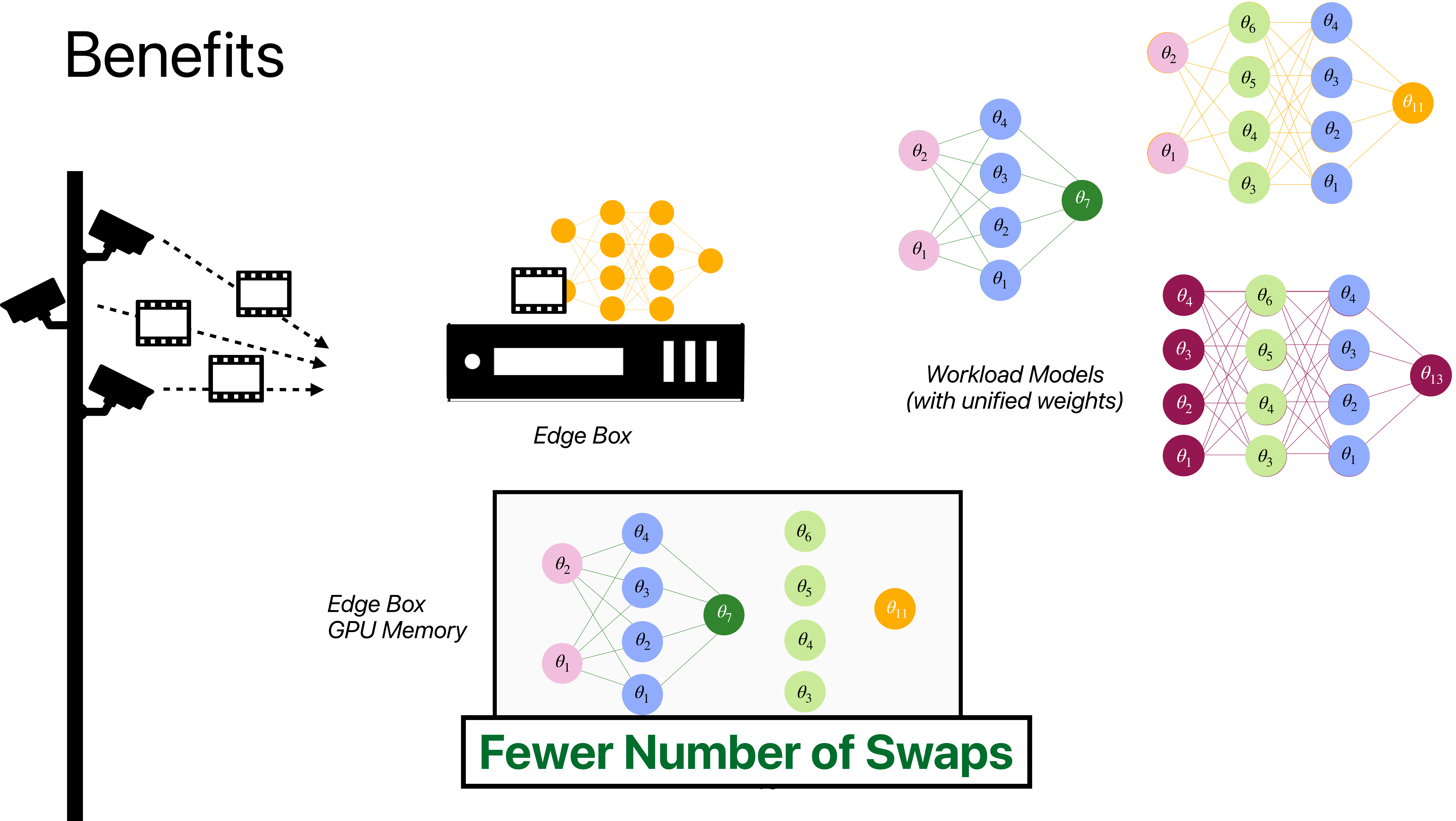

Edge Box
Workload Models
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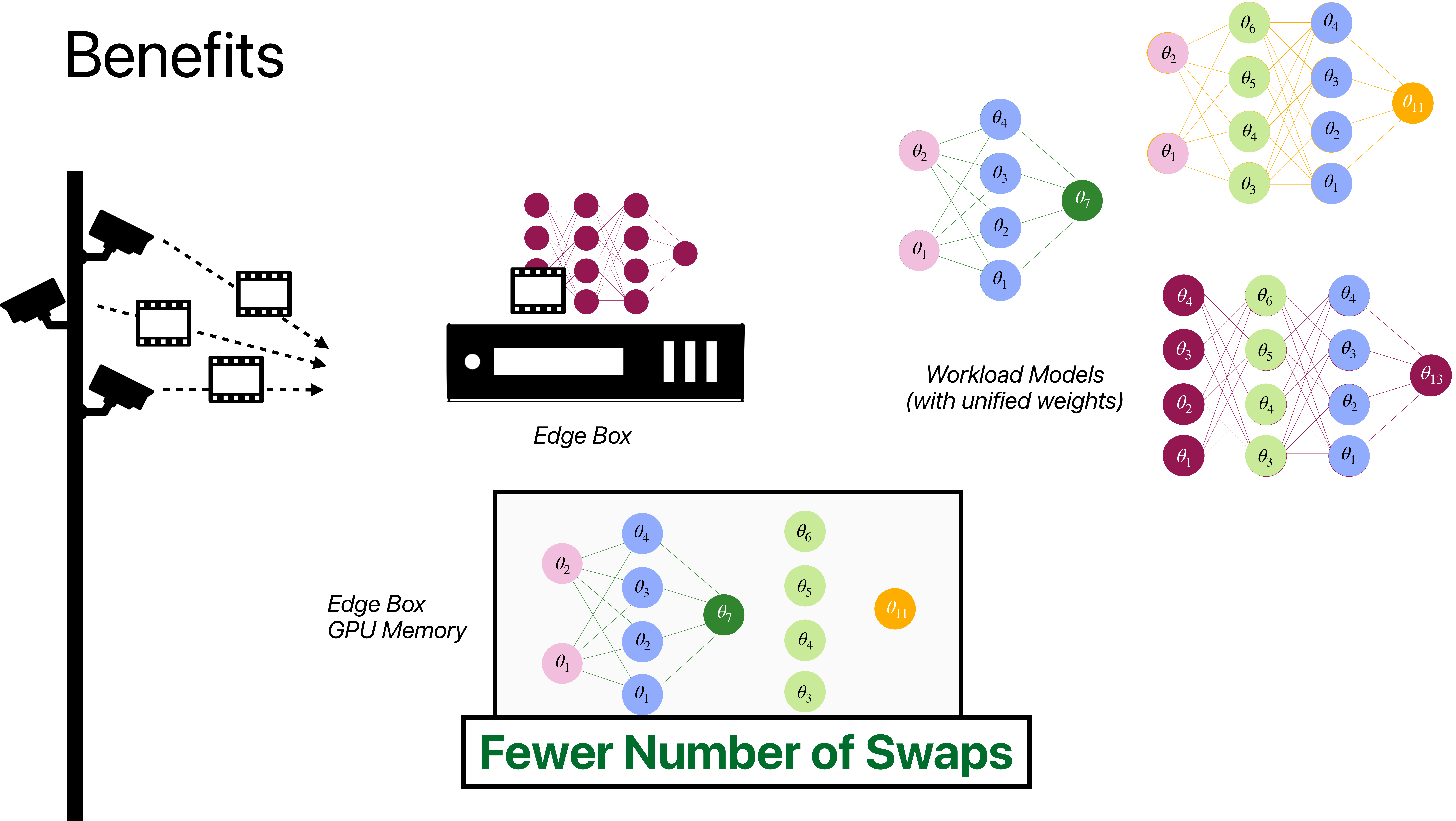
Edge Box
GPU Memory
Fewer Number of Swaps

Benefits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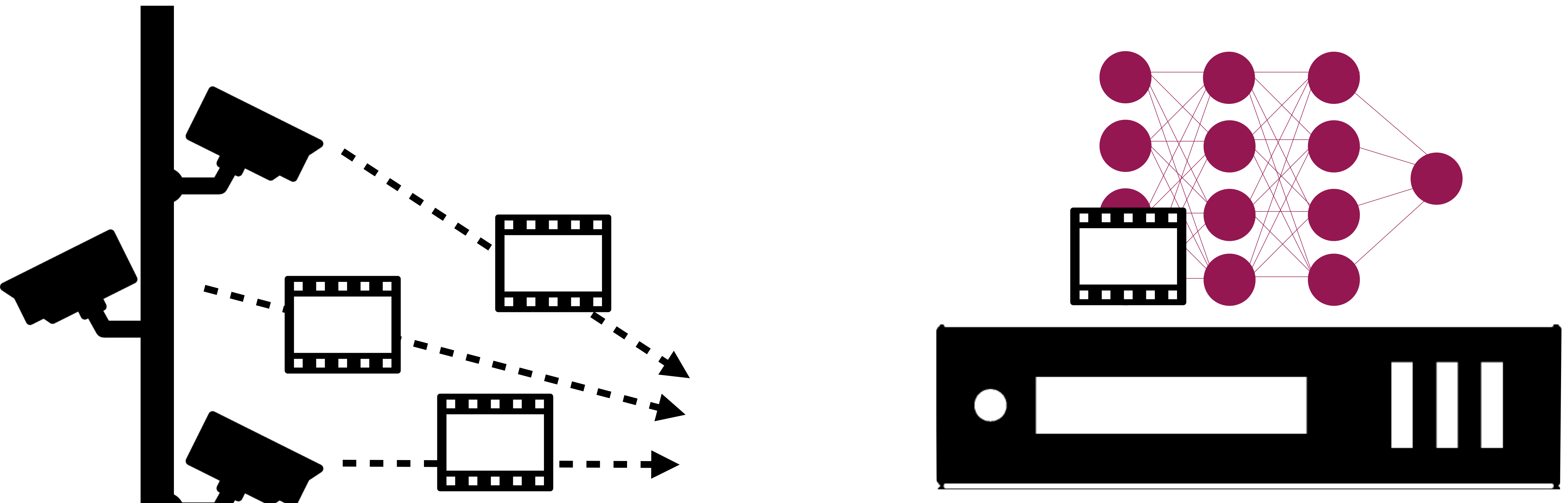

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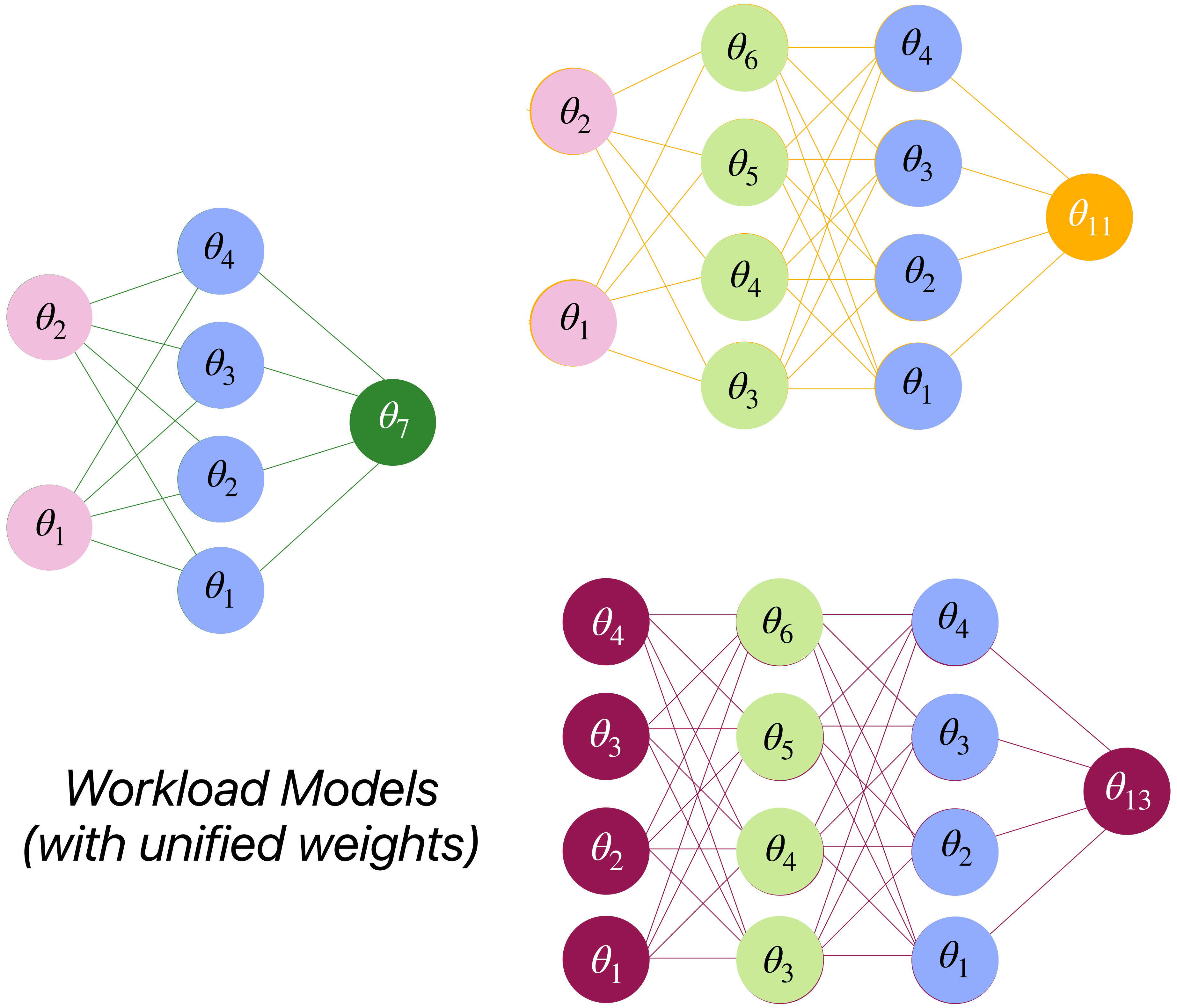

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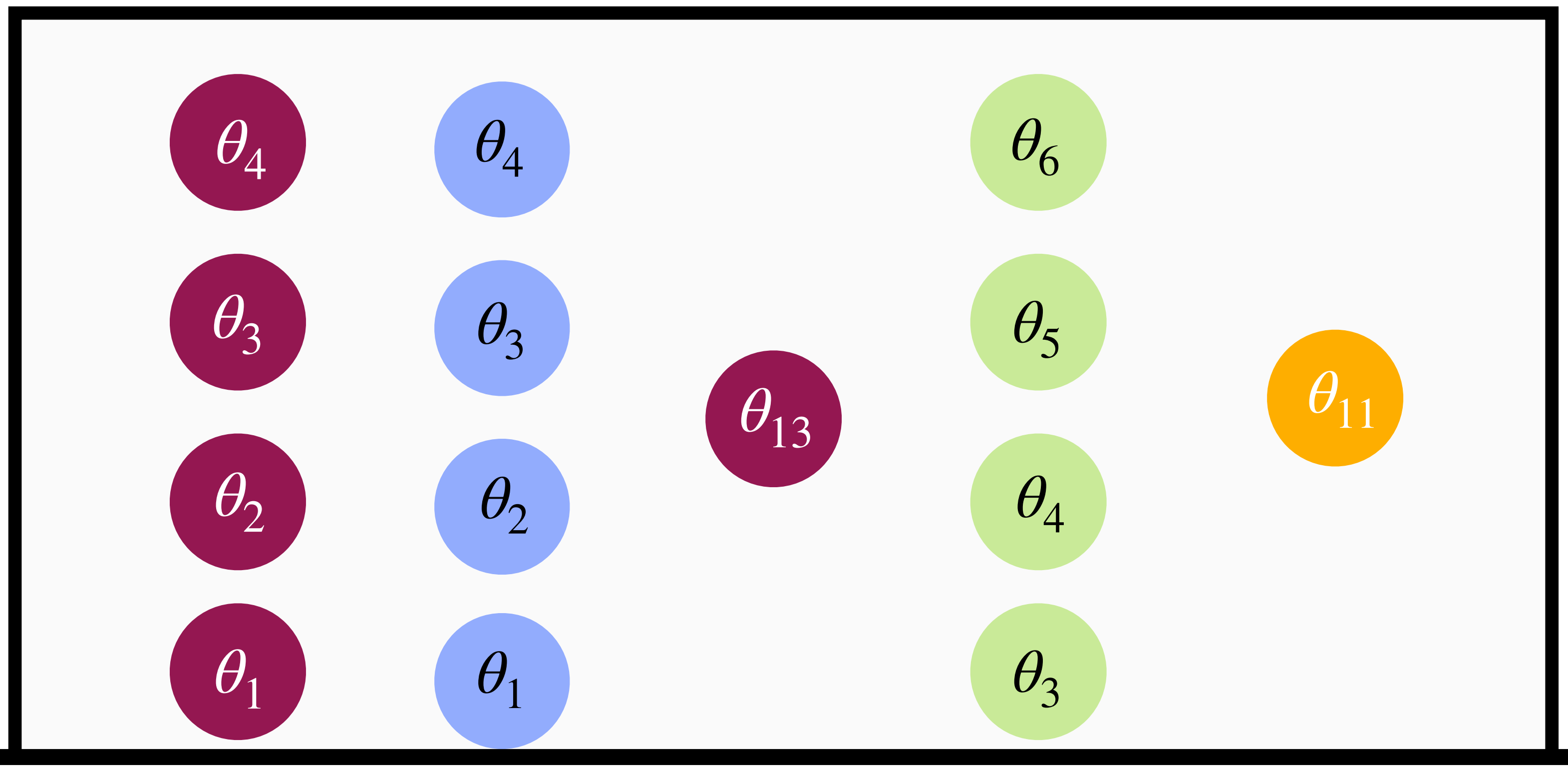
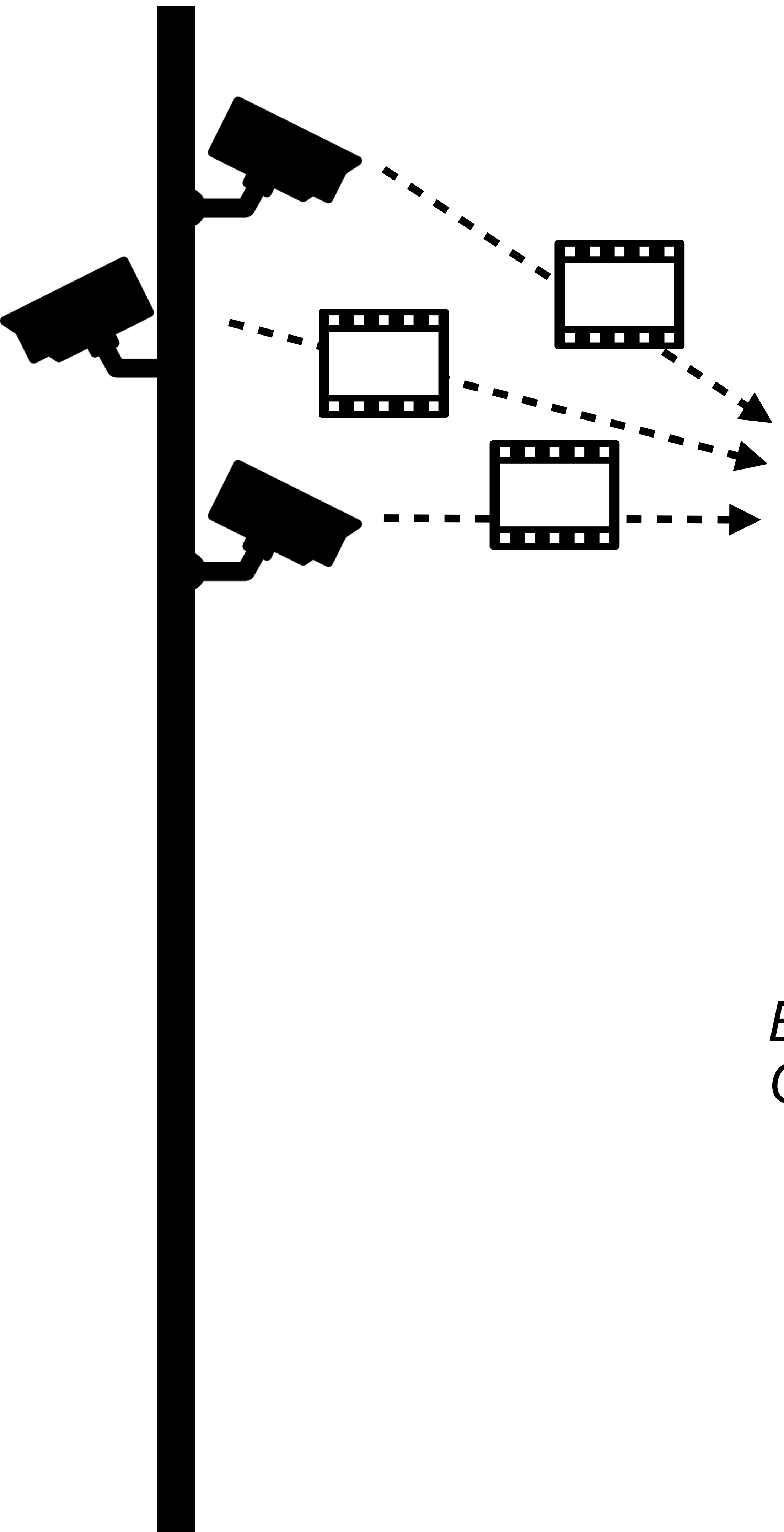


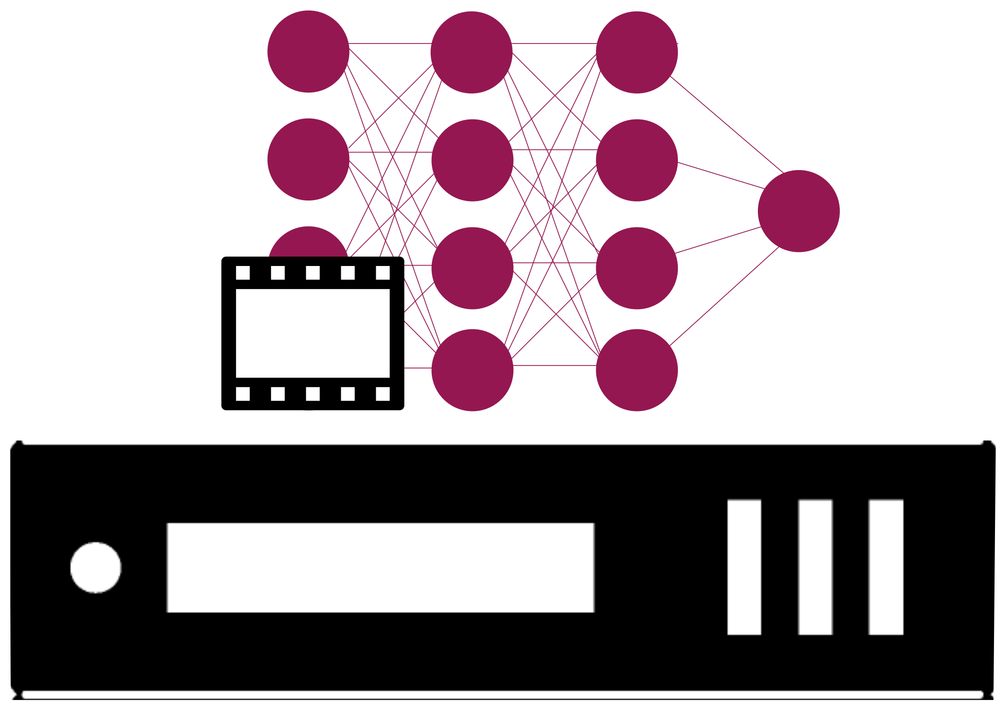
Fewer Number of Swaps

Remaining Swaps are Faster

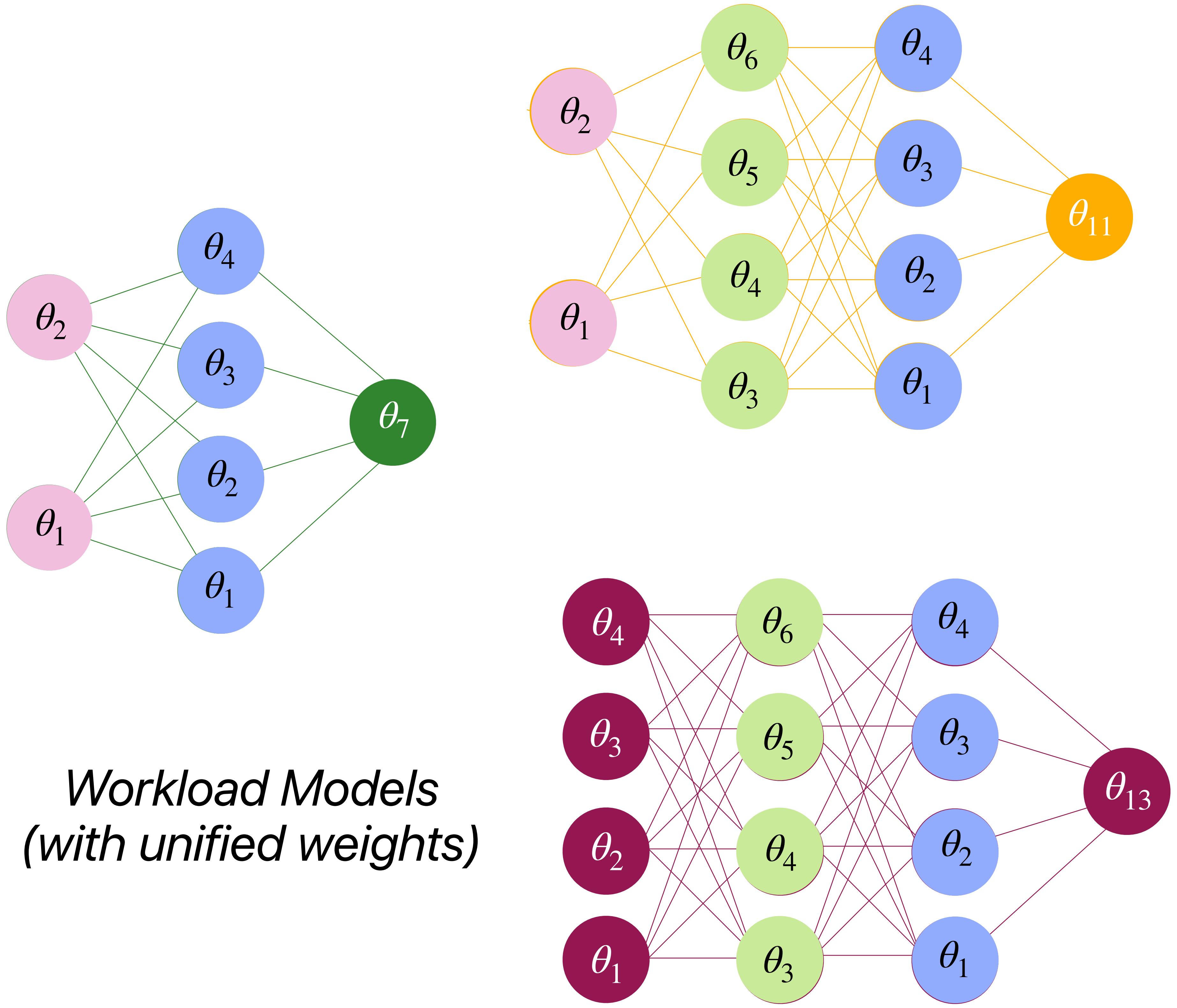
Benefits

Reduce per-workload memory usage by 17-86%



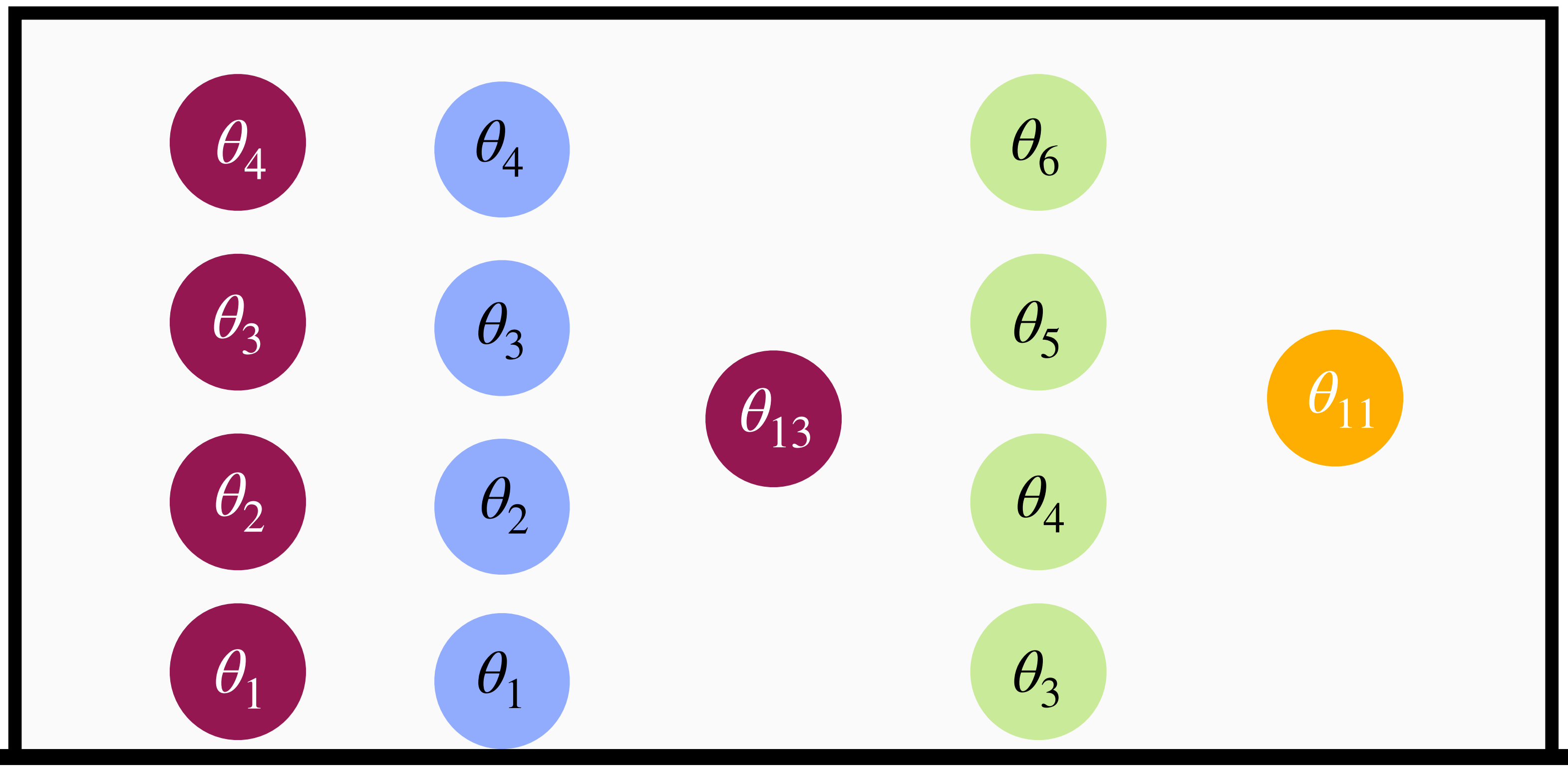


Edge Box



Workload Models (with unified weights)

Edge Box GPU Memory



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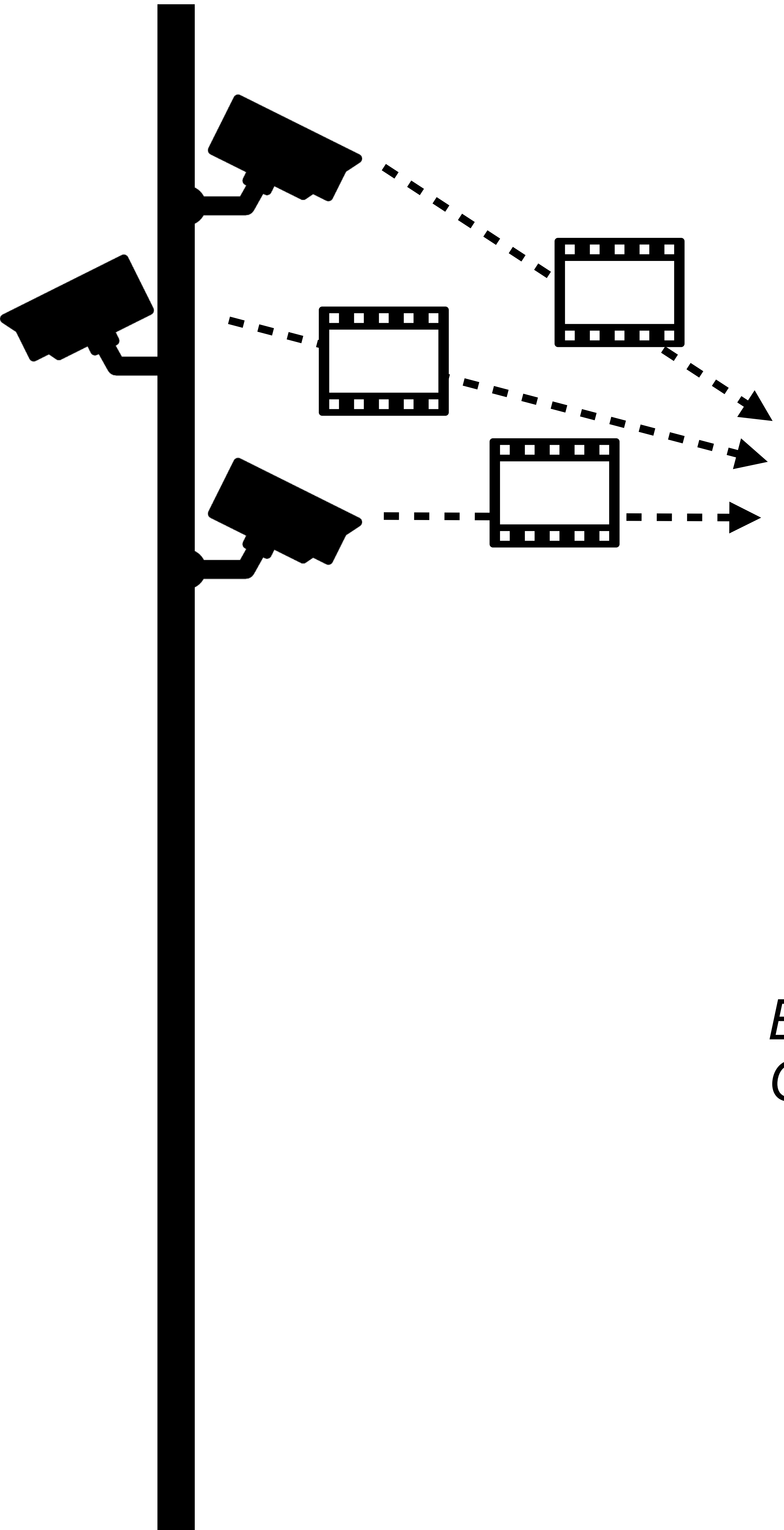
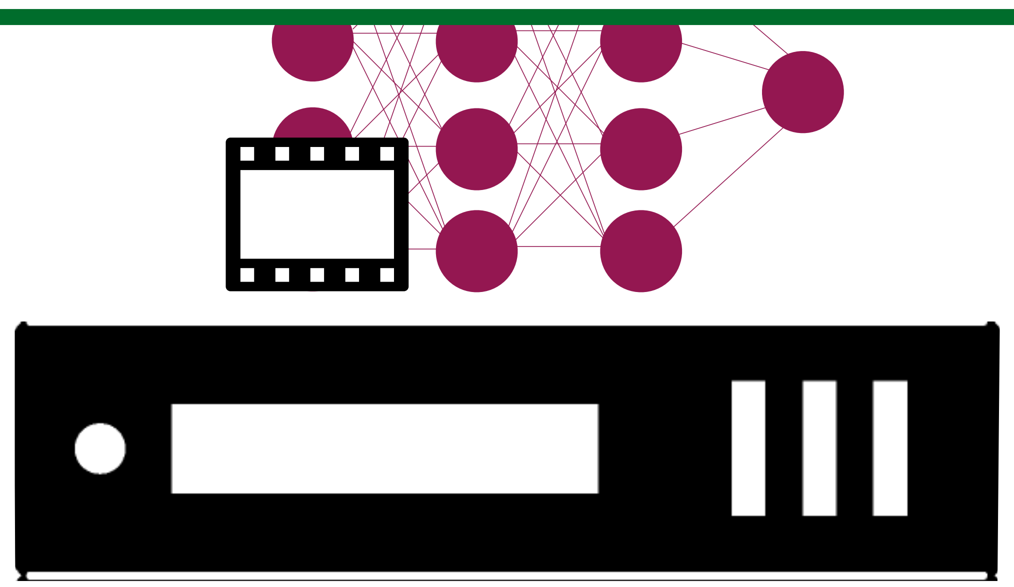
Process 29-61% more frames!





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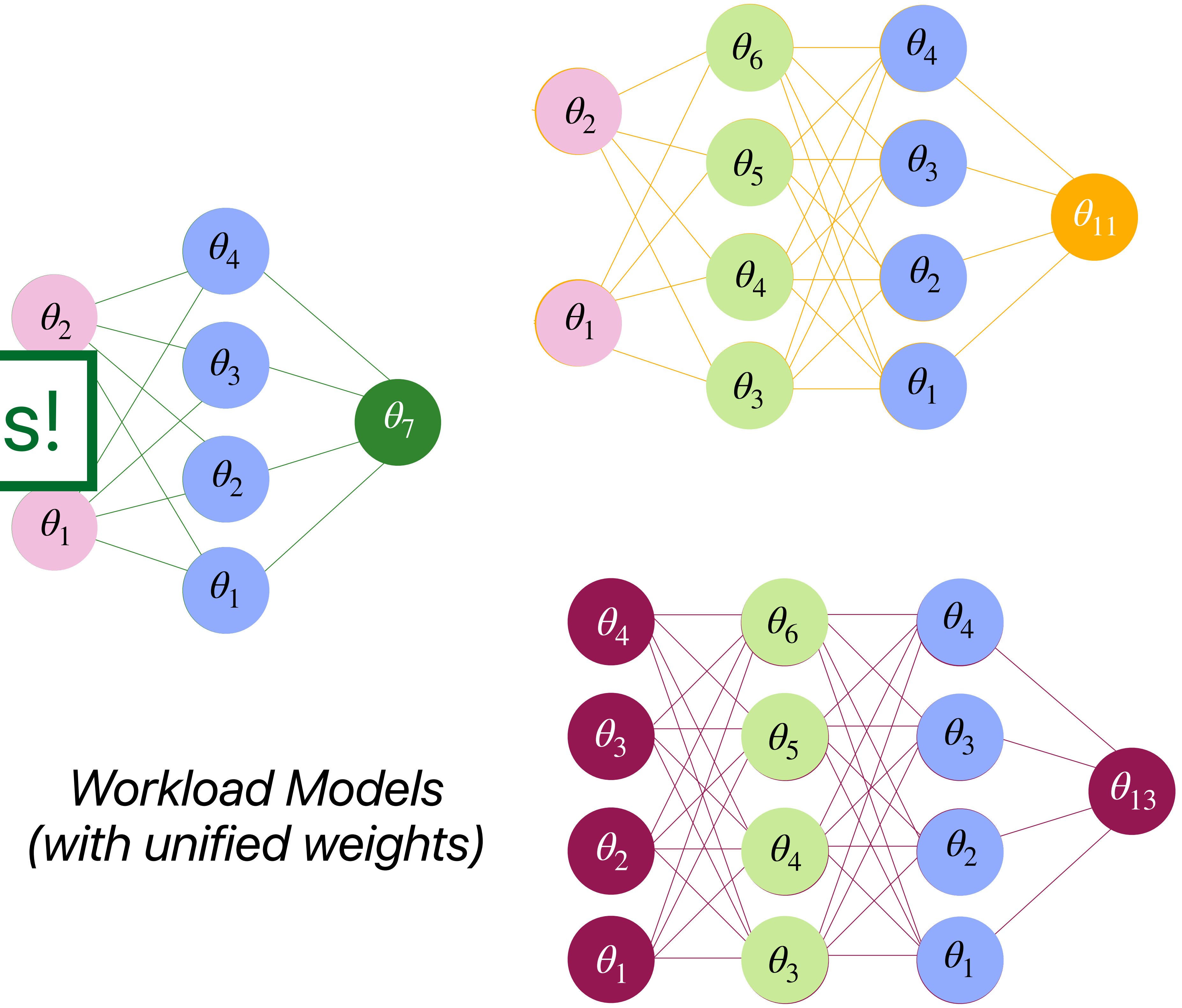

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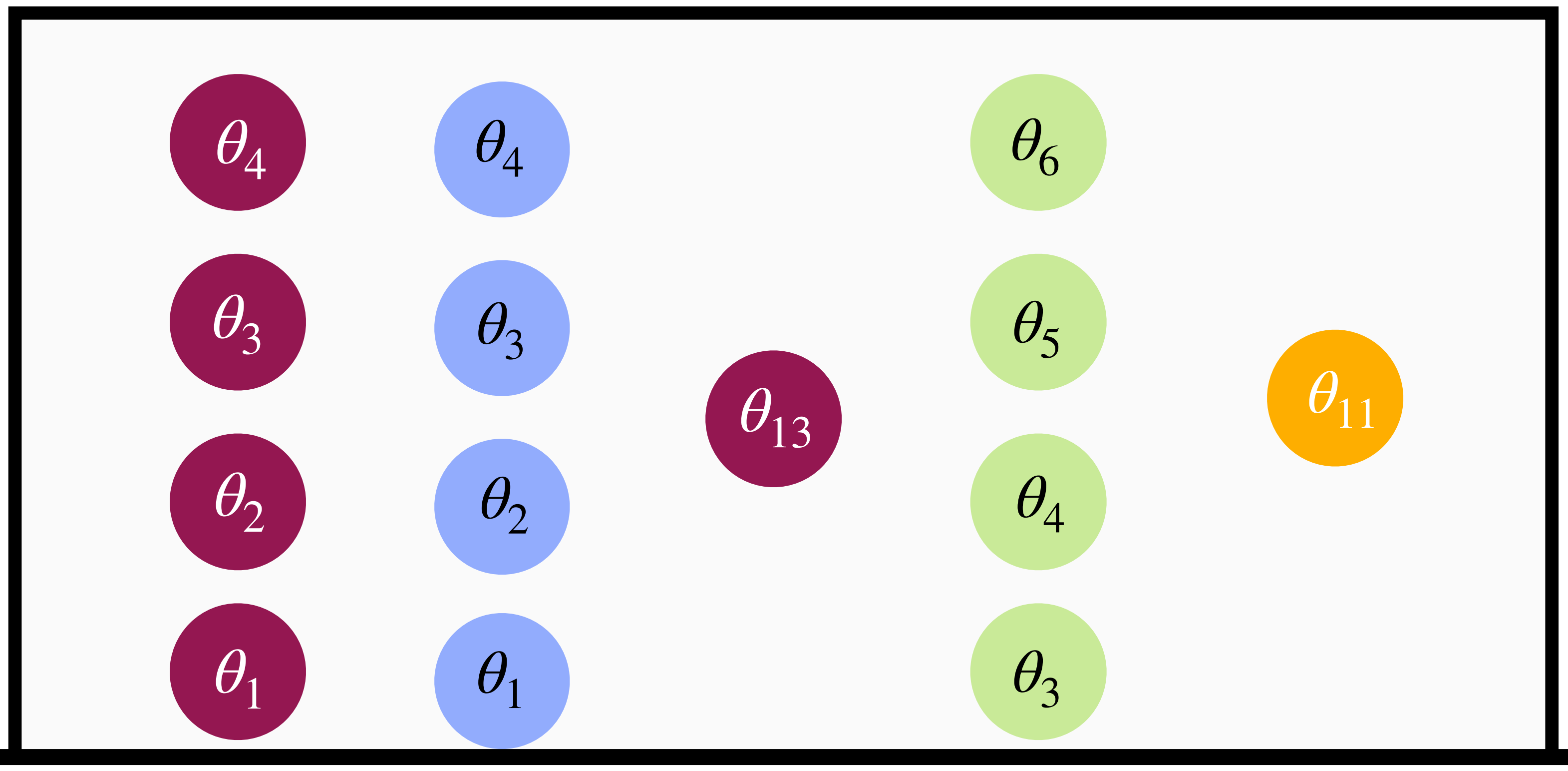

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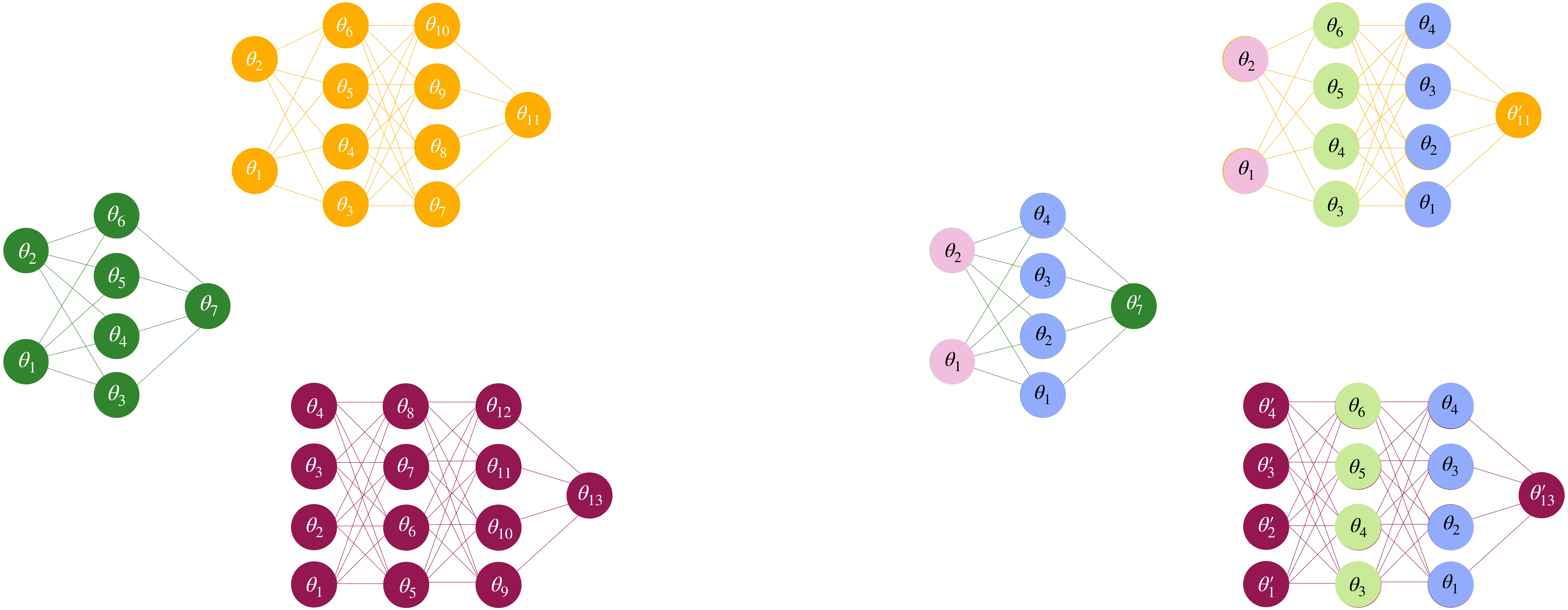
Model Merging



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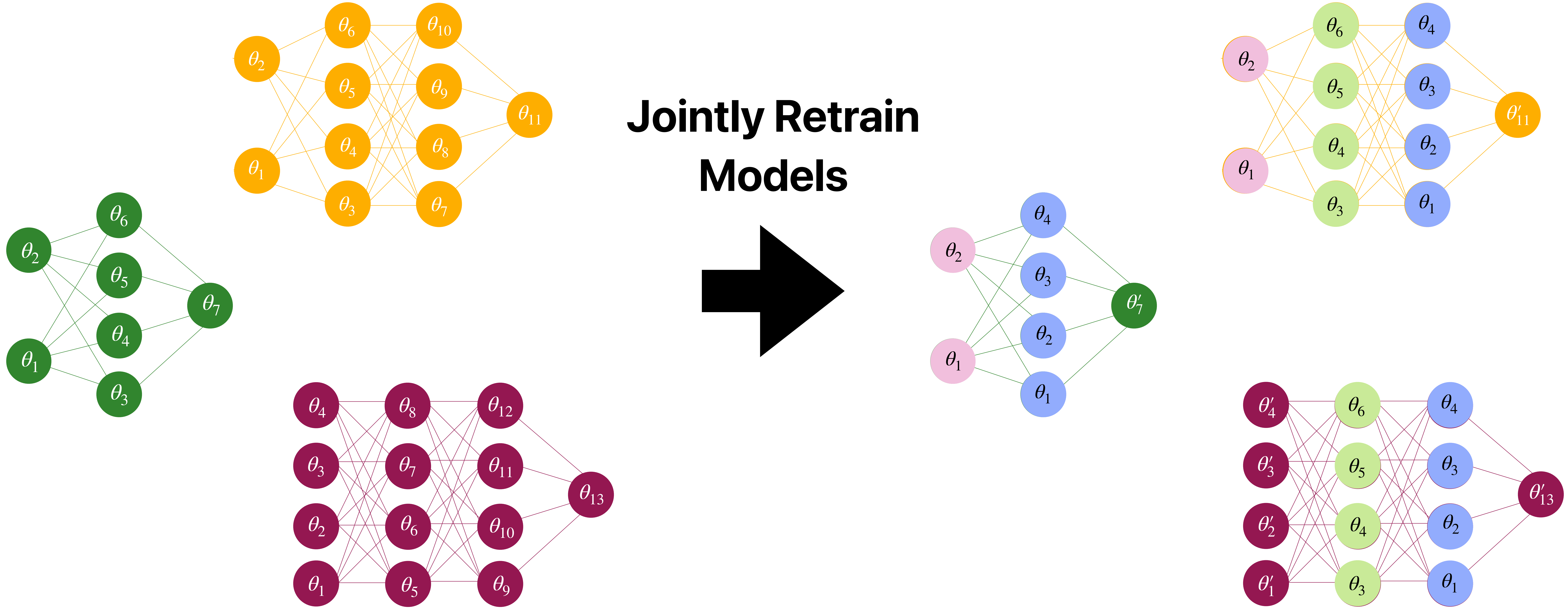

Model Merging Challenges

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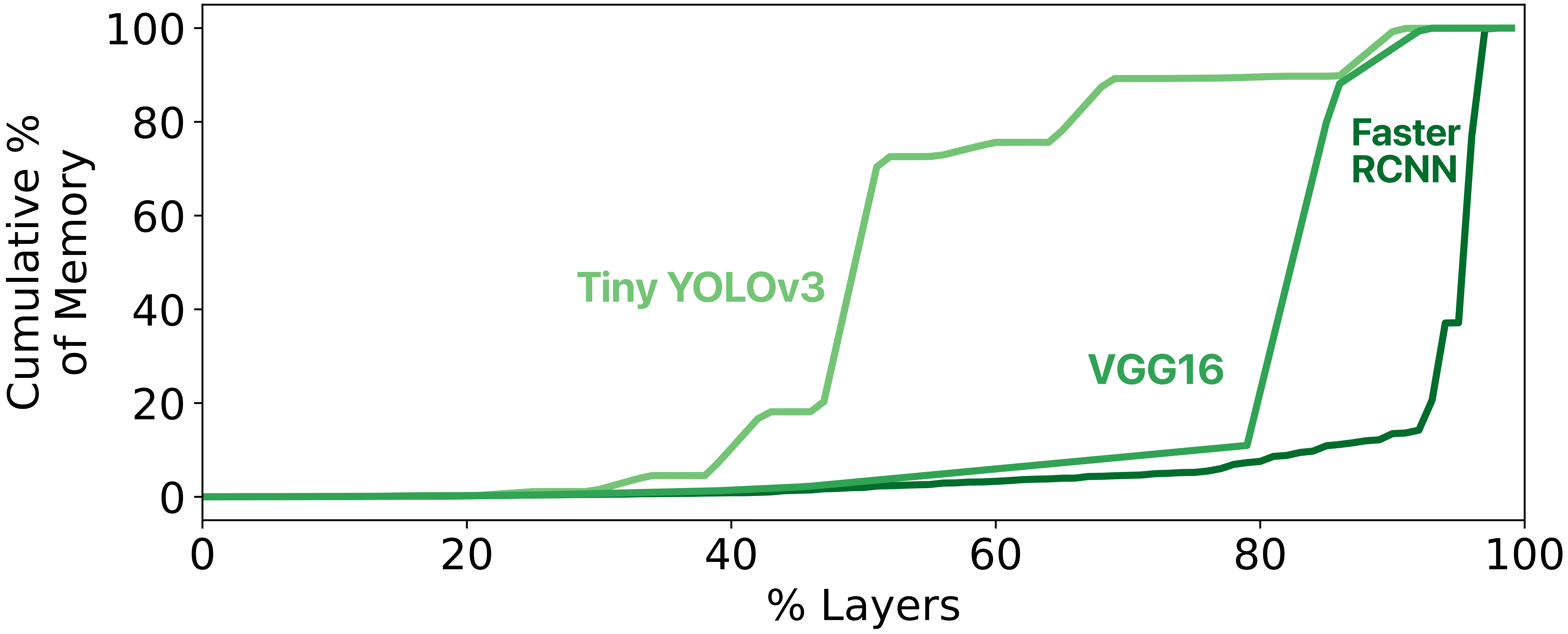
- The more layers you merge, the lower the accuracy achieved during retraining
- Difficult to predict precisely how many layers will be mergeable before accuracy violations occur
- Each instance of retraining is costly

Observation 1: Presence of “Heavy-Hitter” Layers



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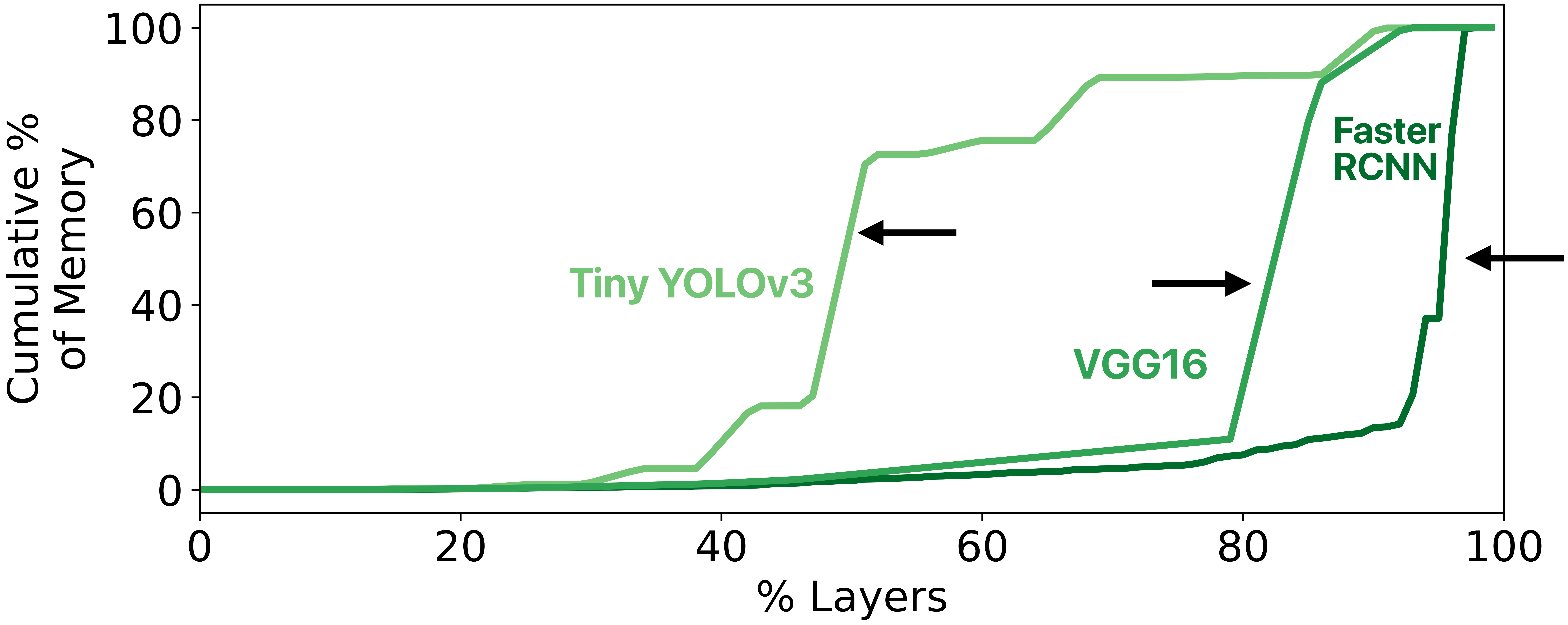

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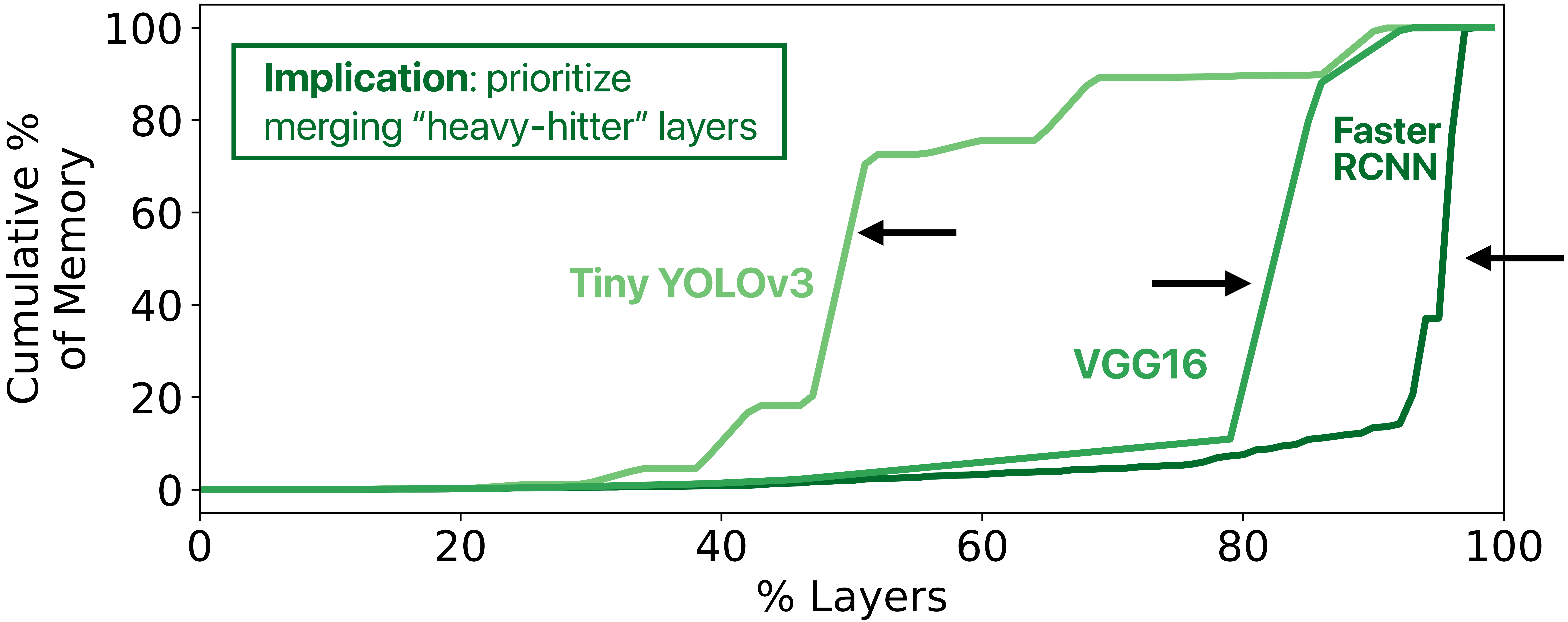

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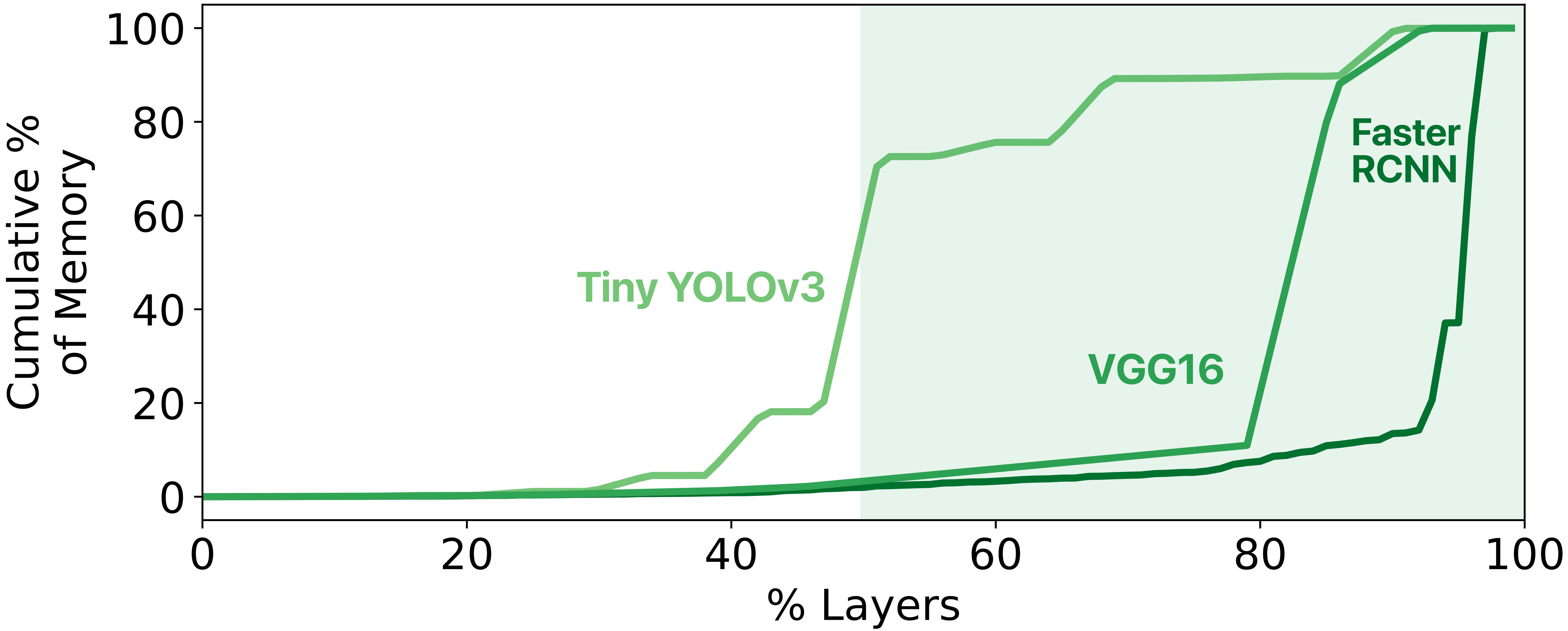

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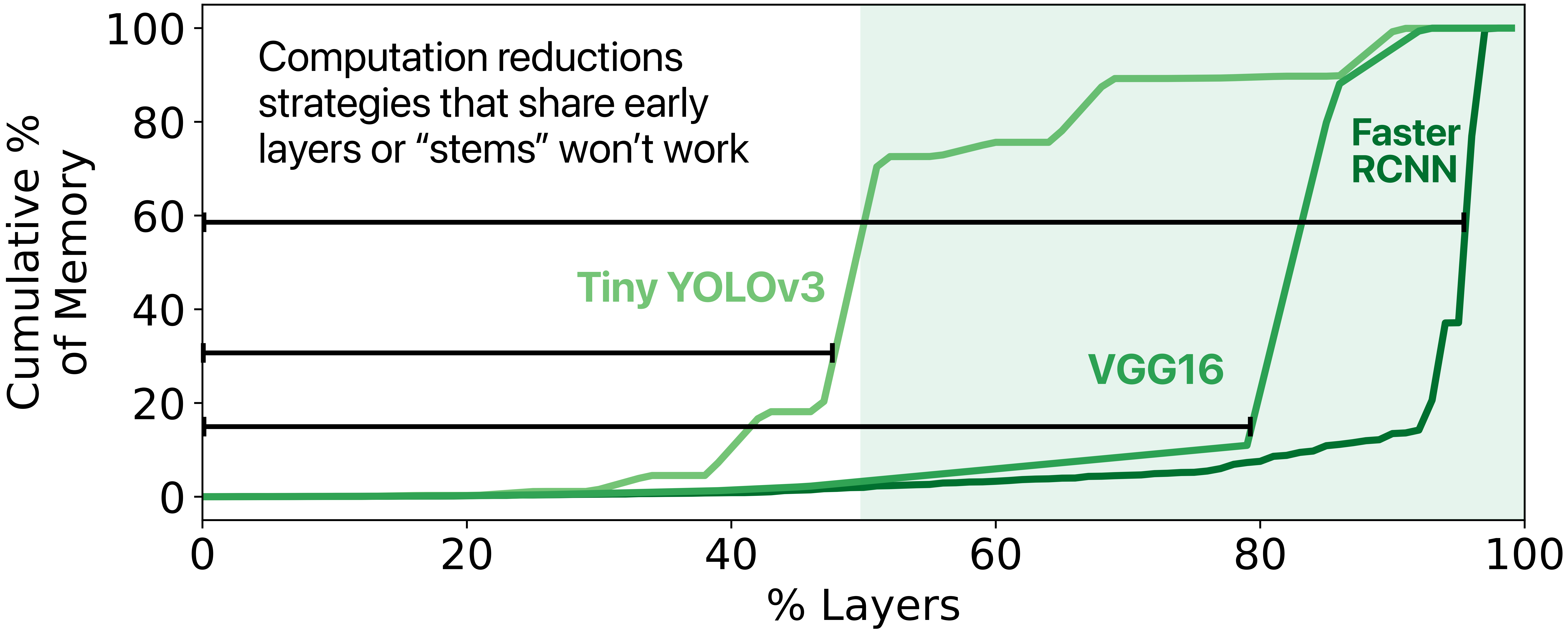
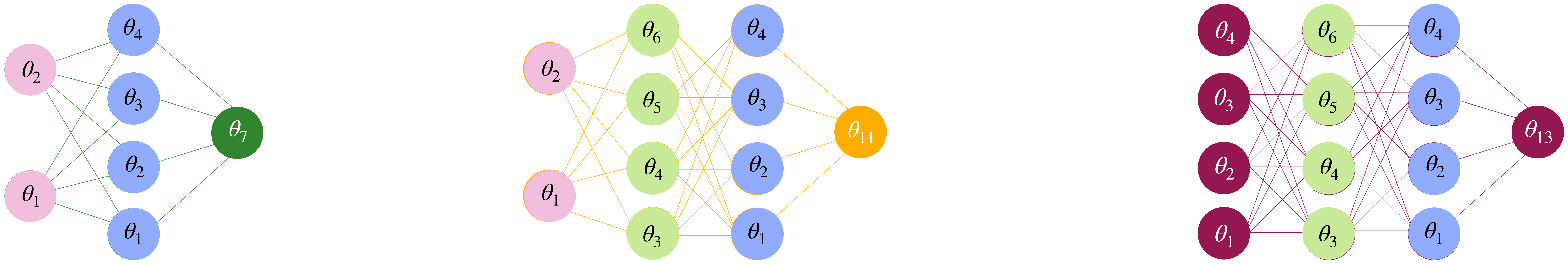
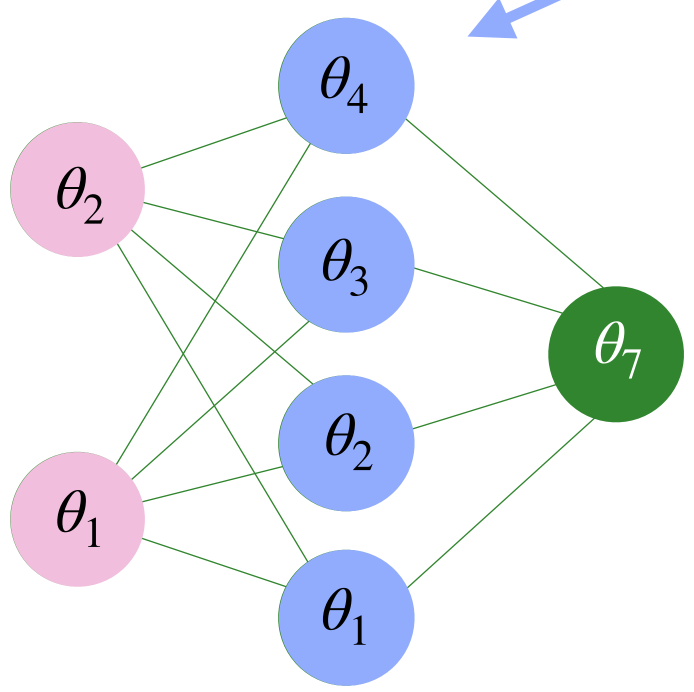


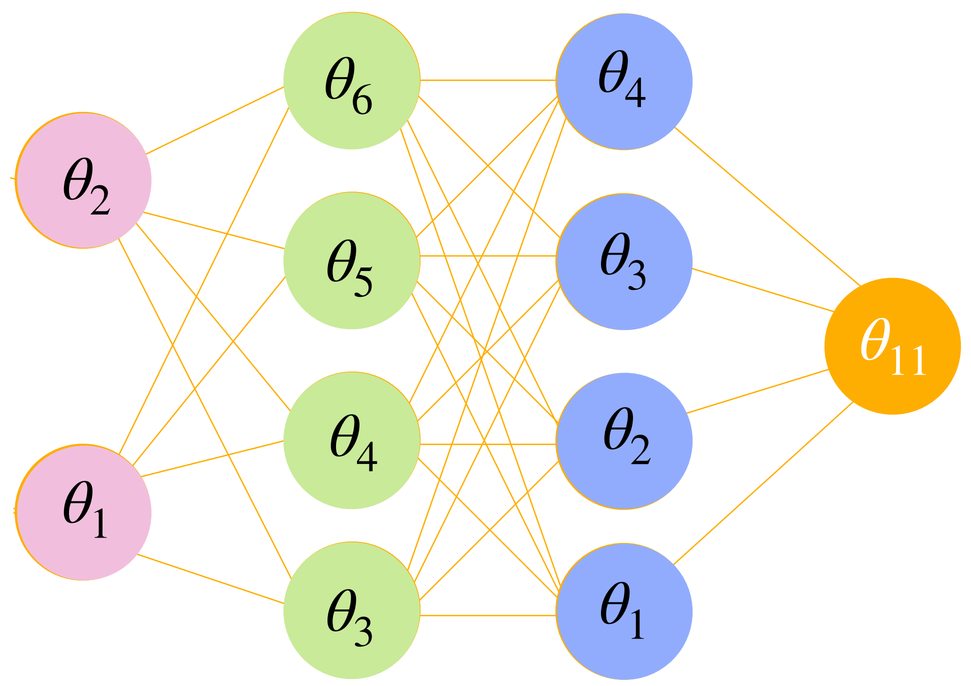
Observation 2: Per-layer merging decisions can be made in isolation

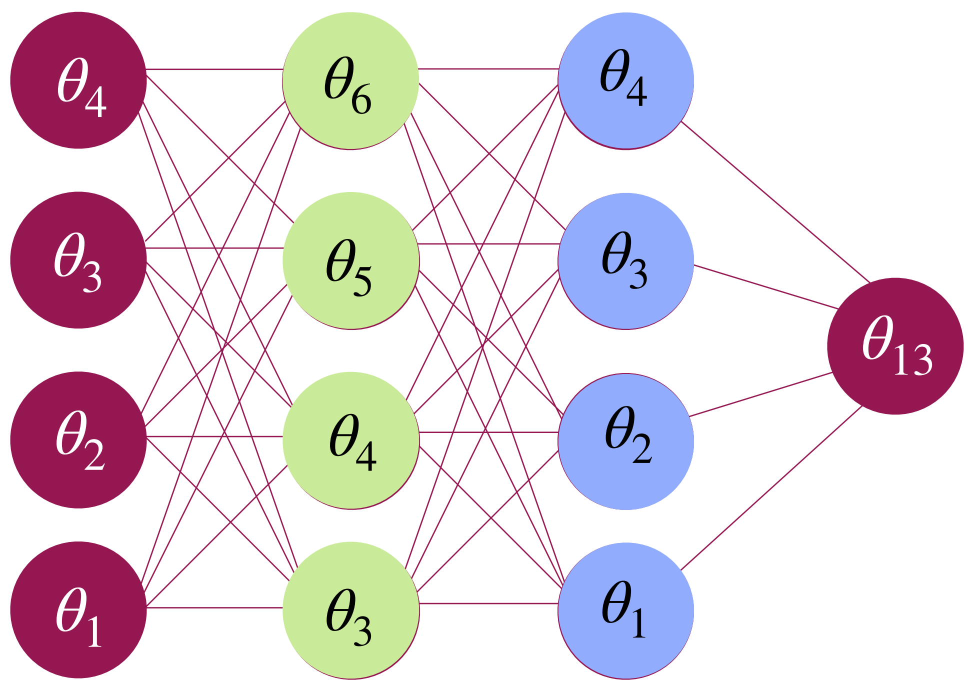


Observation 2: Per-layer merging decisions can be made in isolation

Ability to successfully retrain (i.e., preserve accuracy) when merging these layers...







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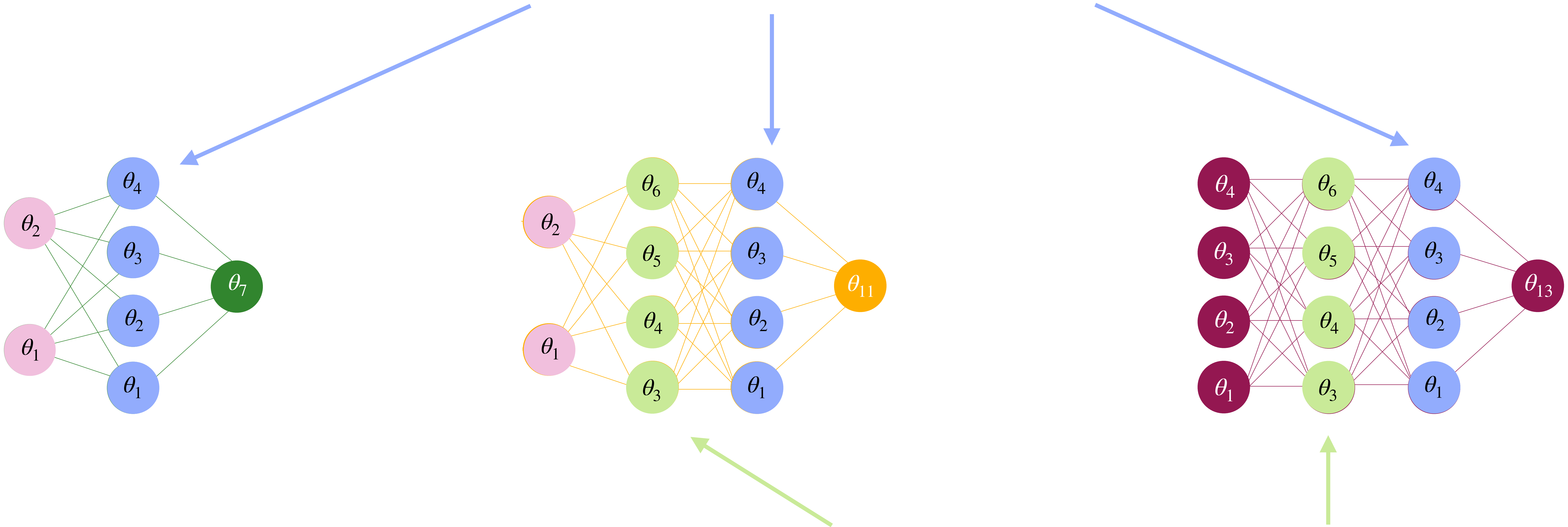

…does not depend on also merging these layers.

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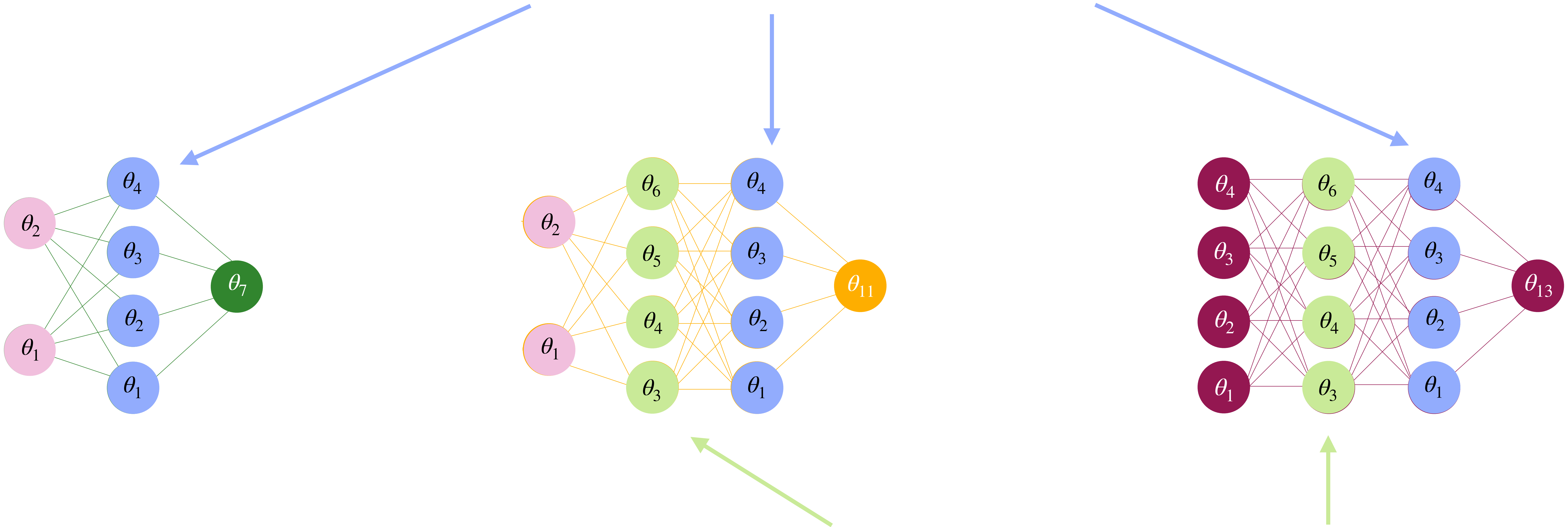


…does not depend on also merging these layers.

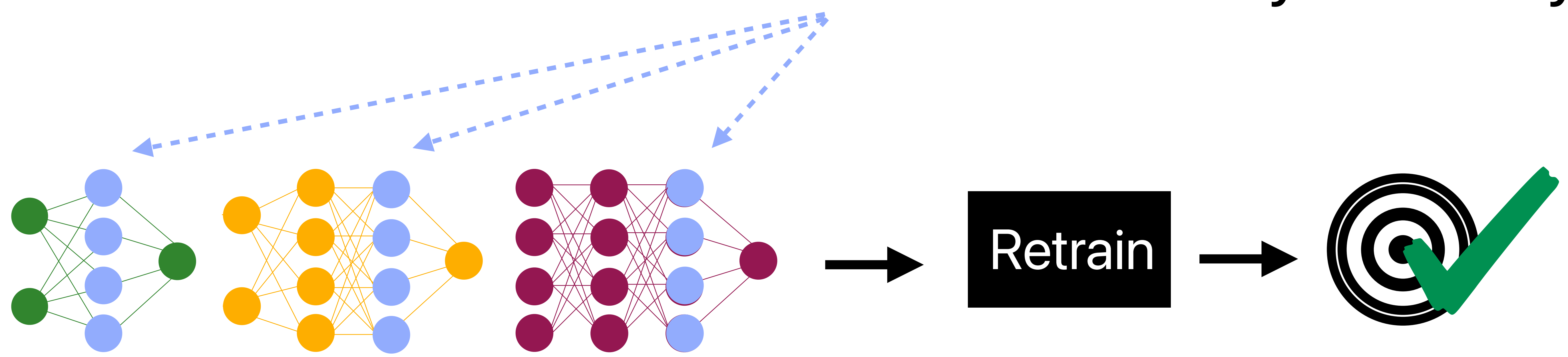
Implication: we can try merging layers independently one at at time

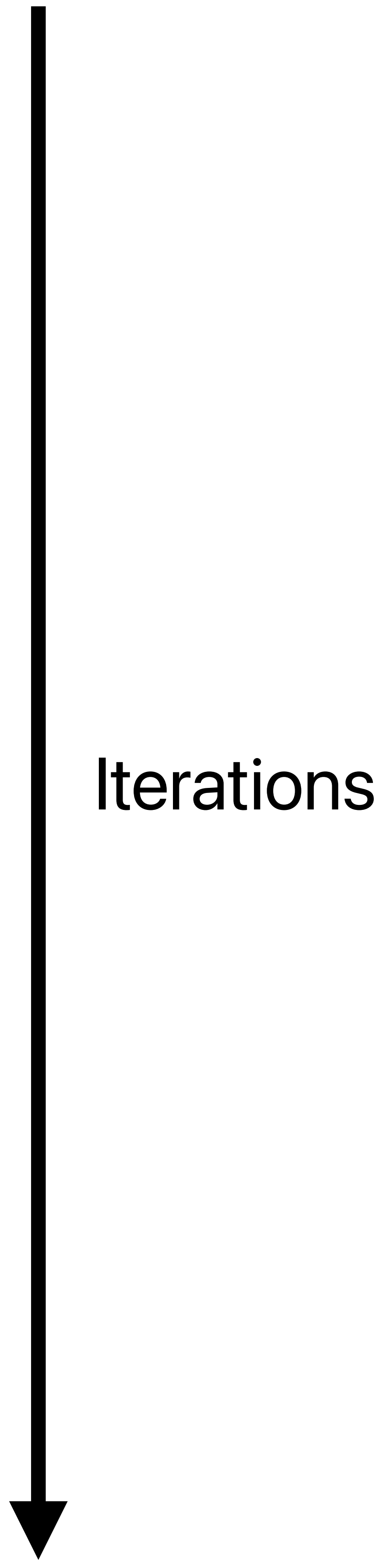
Model Merging Strategy

Model Merging Strategy

Start with heavy-hitter layers

Merge one
additional layer
per iteration





Model Merging Strategy

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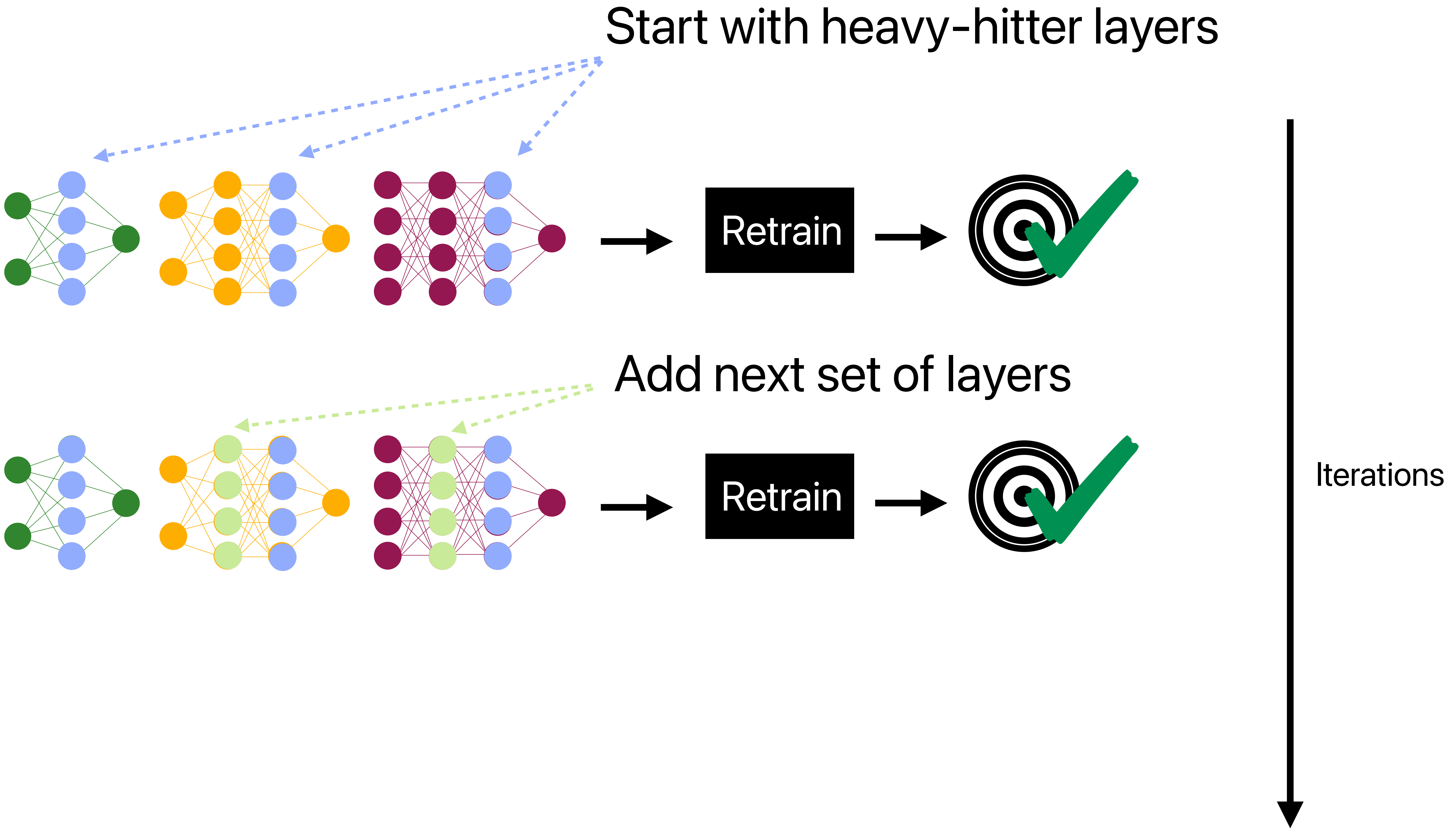

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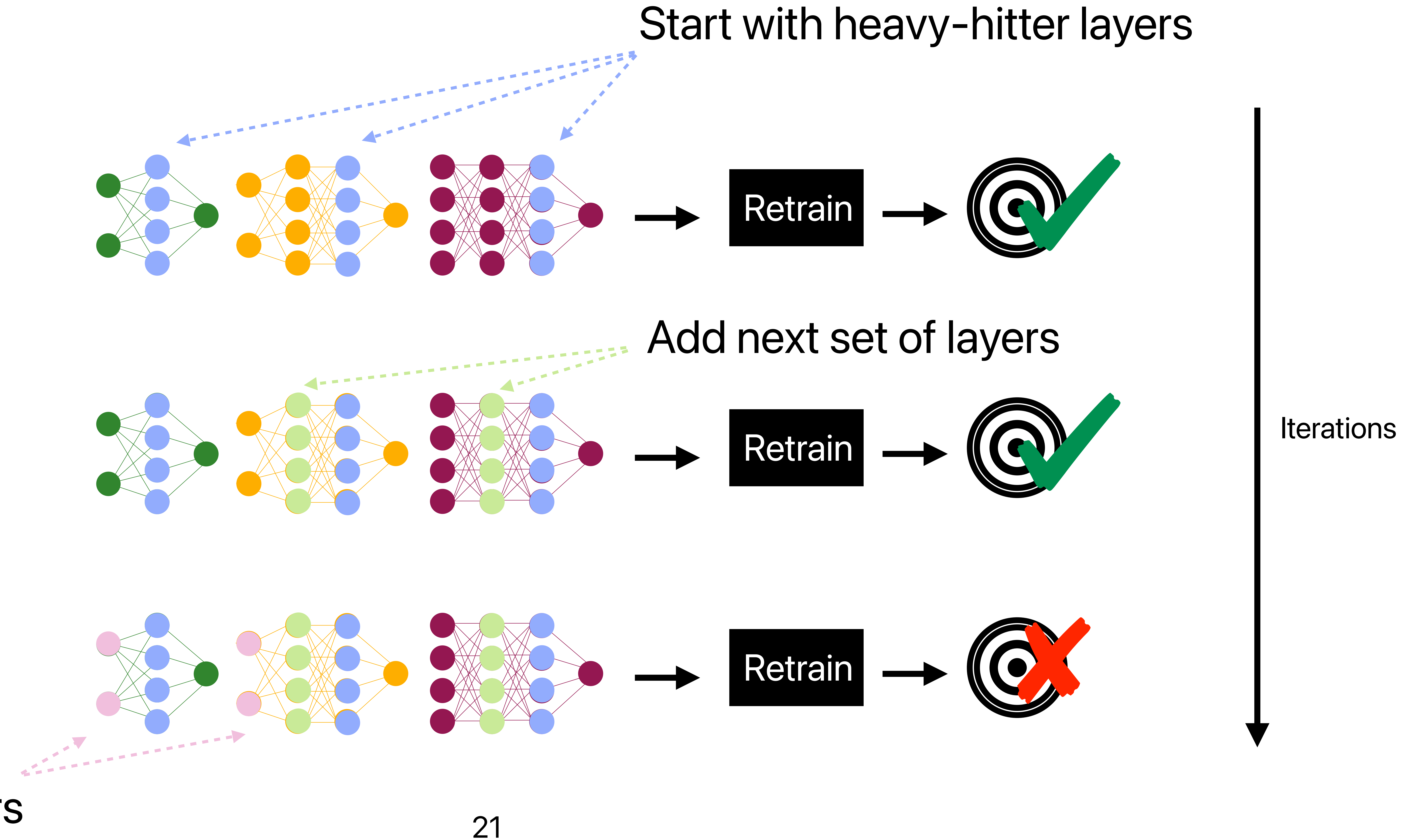

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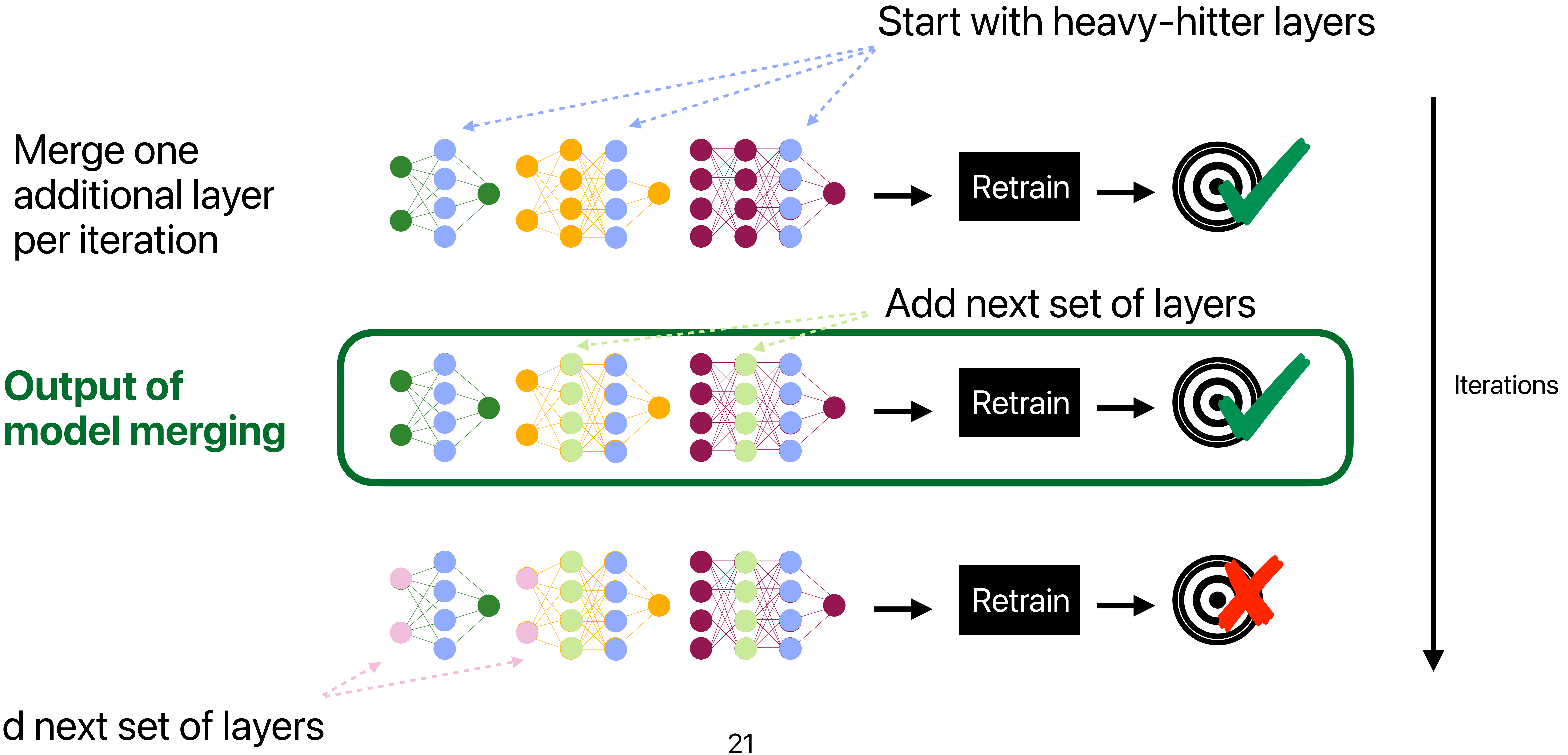
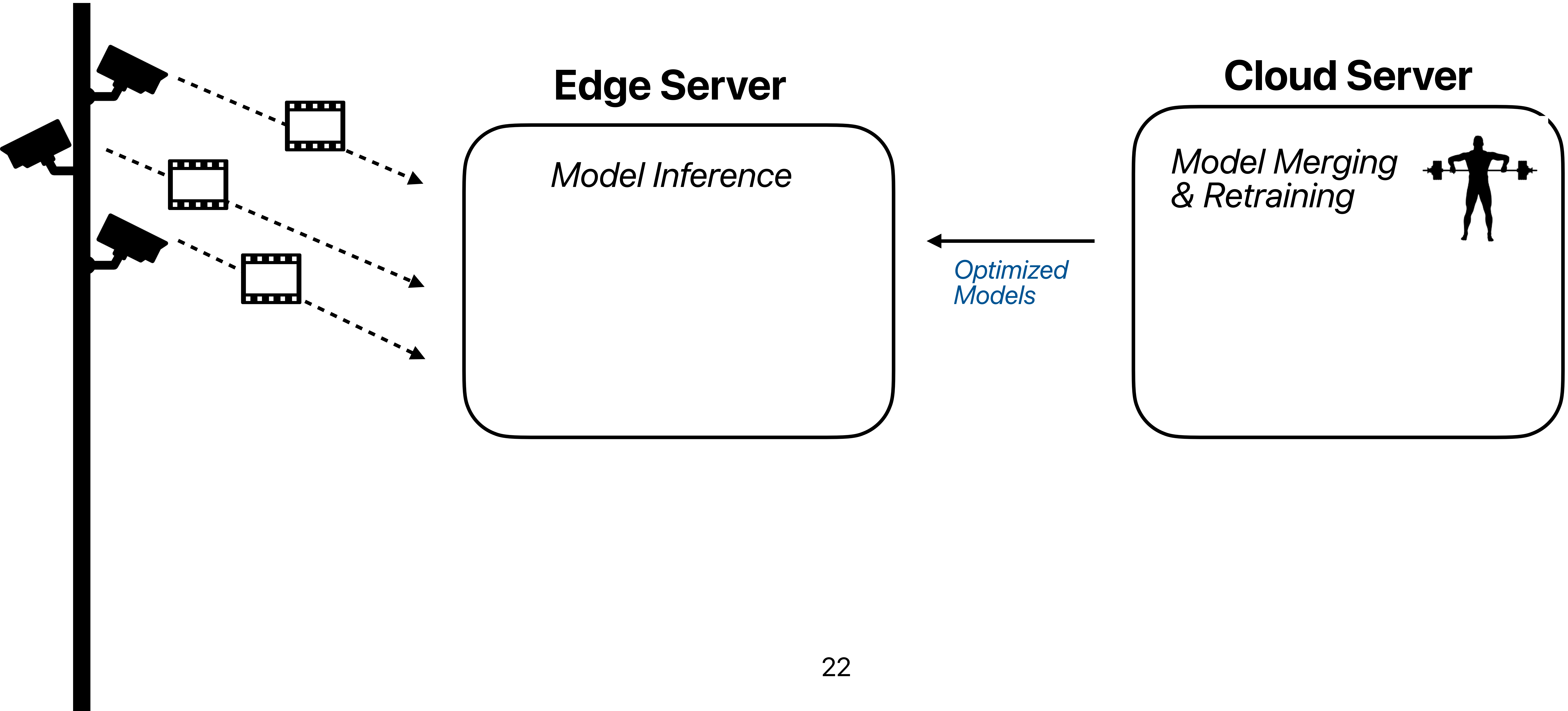


System Design



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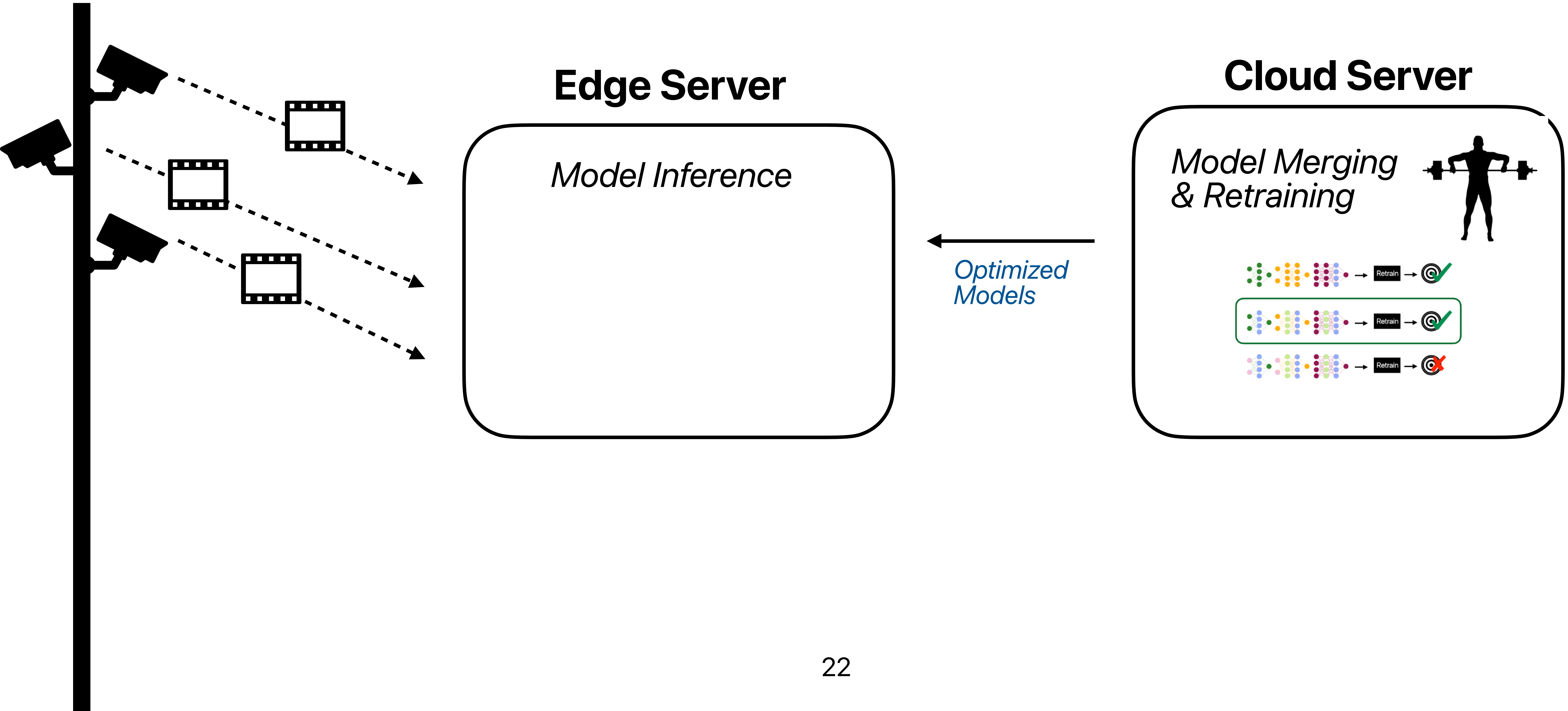

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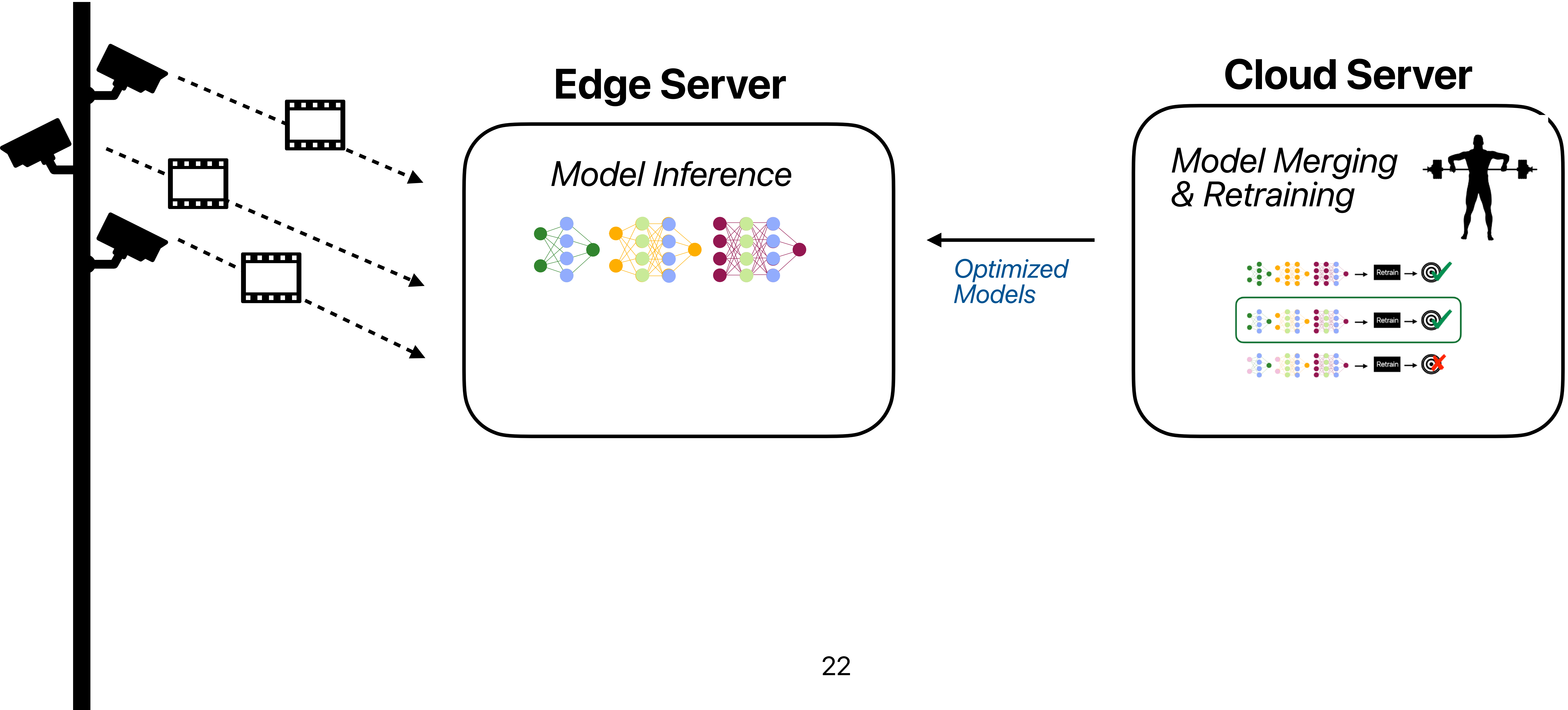

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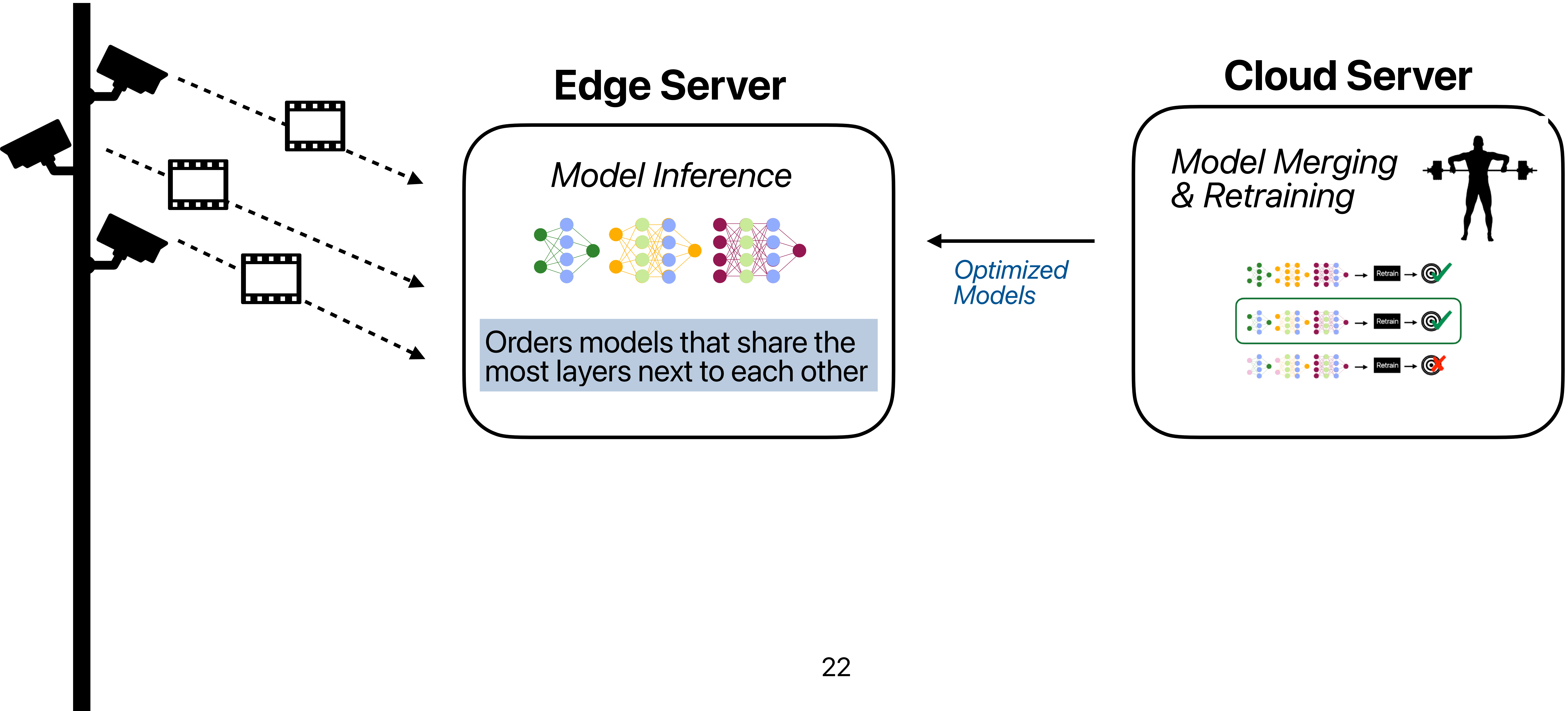

Gemel Evaluation

- Accuracy Improvements
- GPU Memory Savings
- Varying FPS, Accuracy, SLA
- Comparison to Stem-Sharing Approach
- Incremental Memory Savings
- Merging Heuristic Ablation
- Microbenchmarks
- Generalizability

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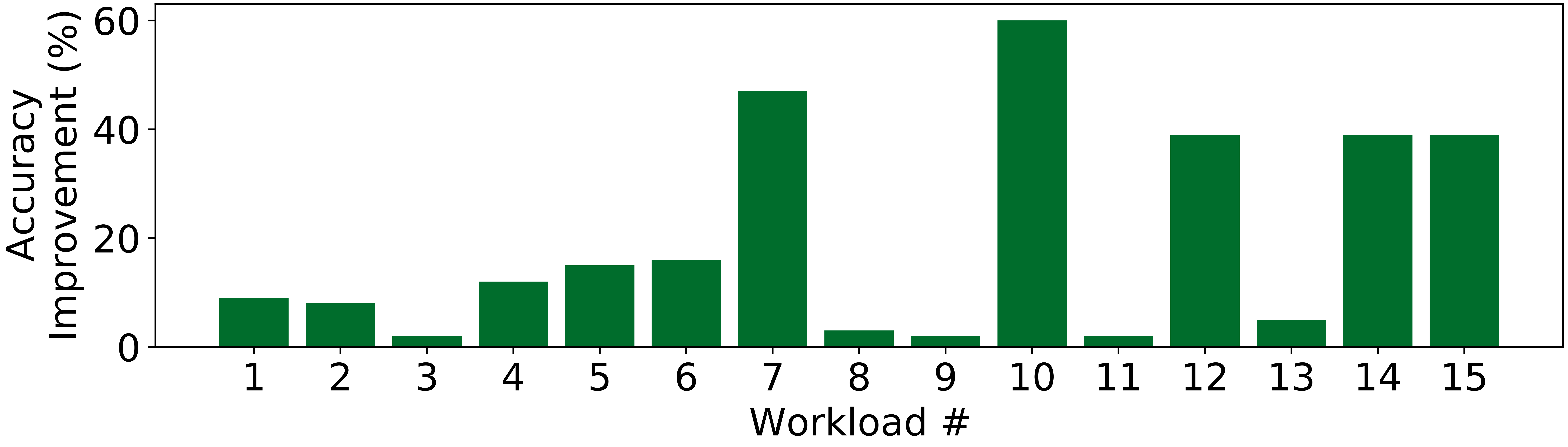
Improvement in Query Accuracy



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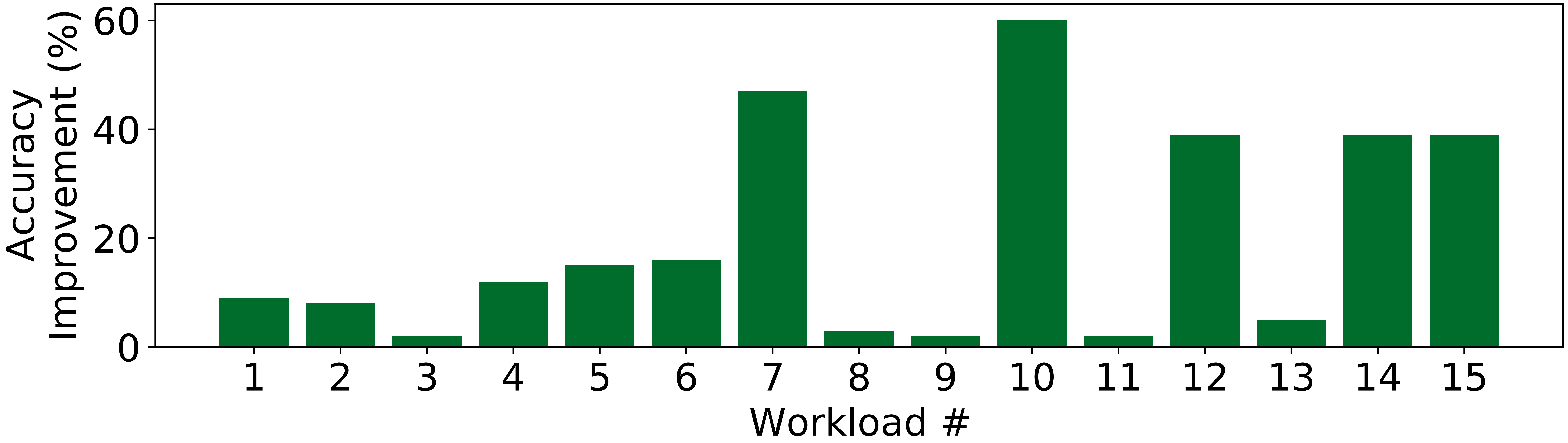
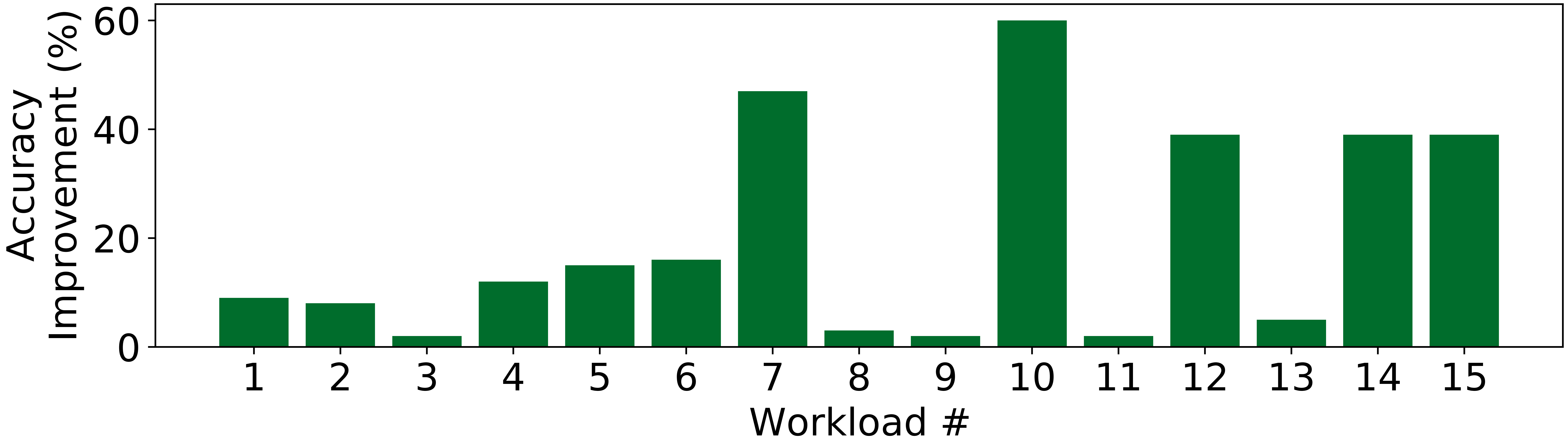


Gemel improves per-workload query accuracy by 2-60%.

Improvement in Query Accuracy



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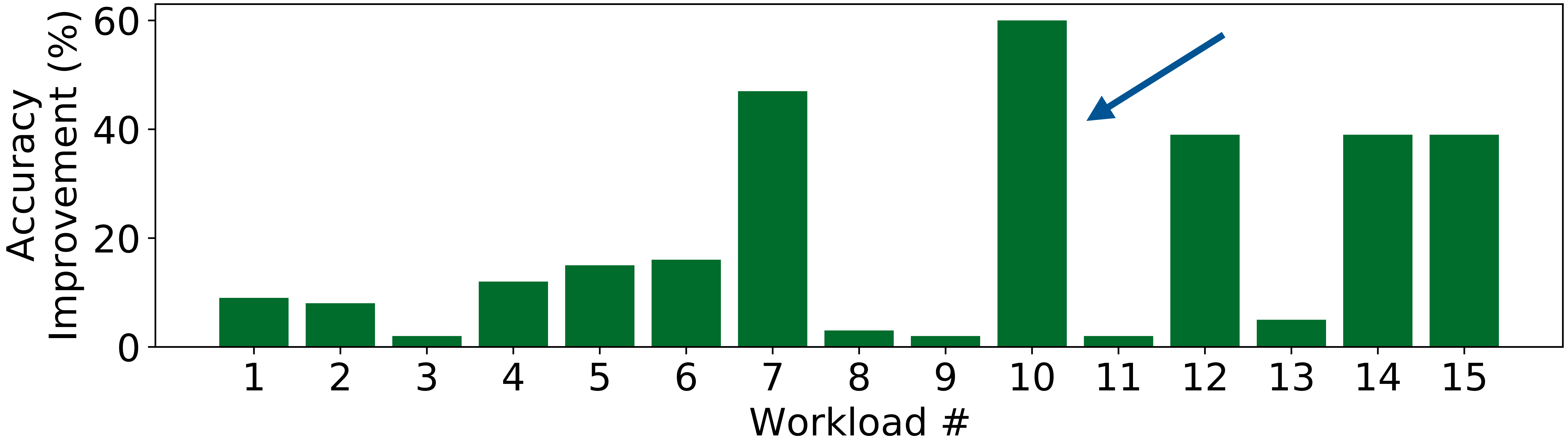

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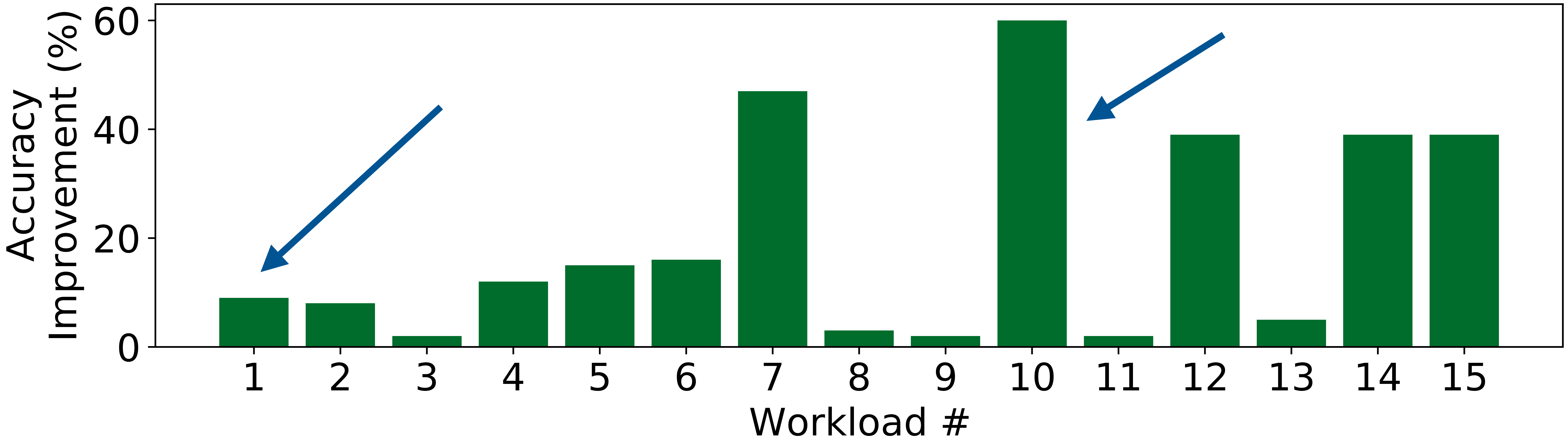

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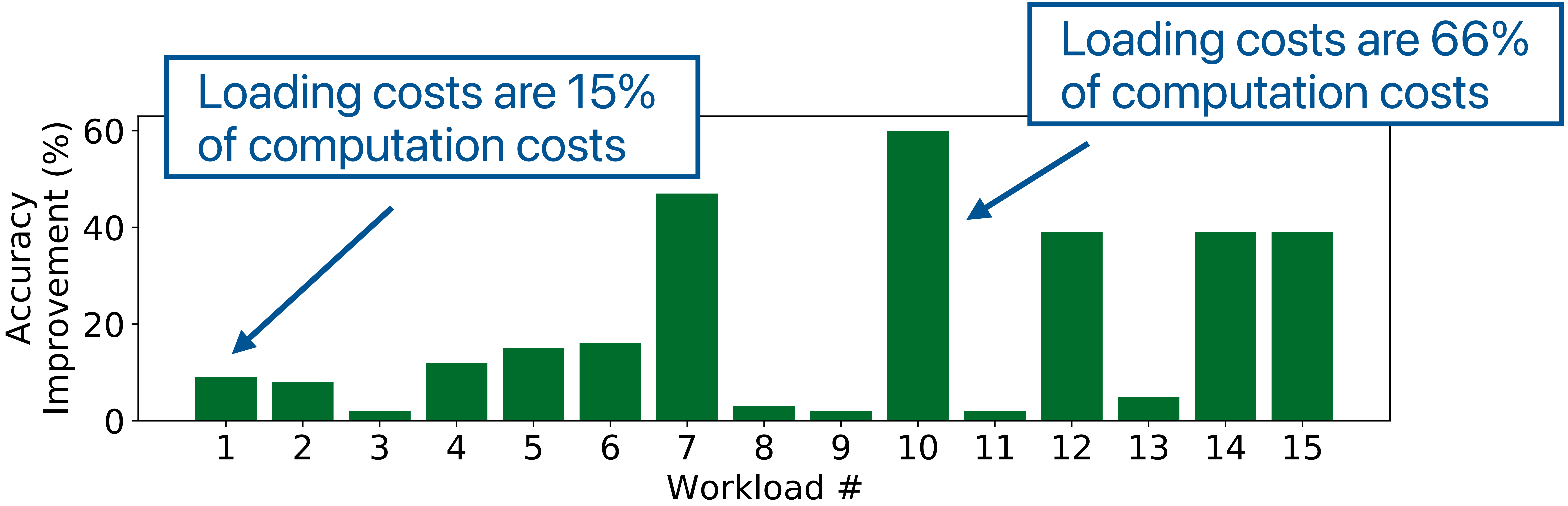

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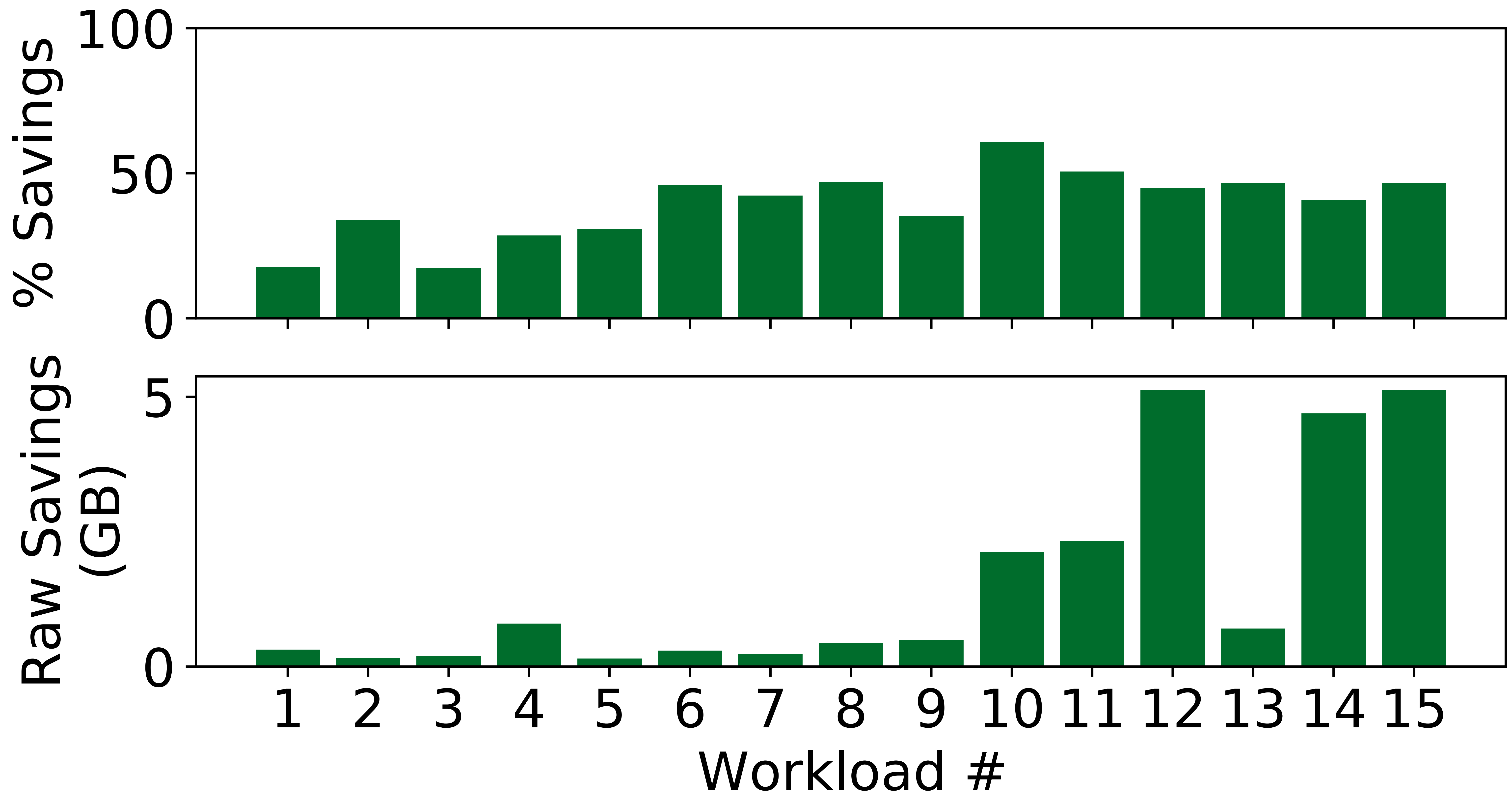
Memory Savings Achieved



Gemel reduces per-workload memory usage by 18-61%.

Which translates to 150MB to 5.12 GB in raw savings

Varying FPS, Accuracy Target, SLA

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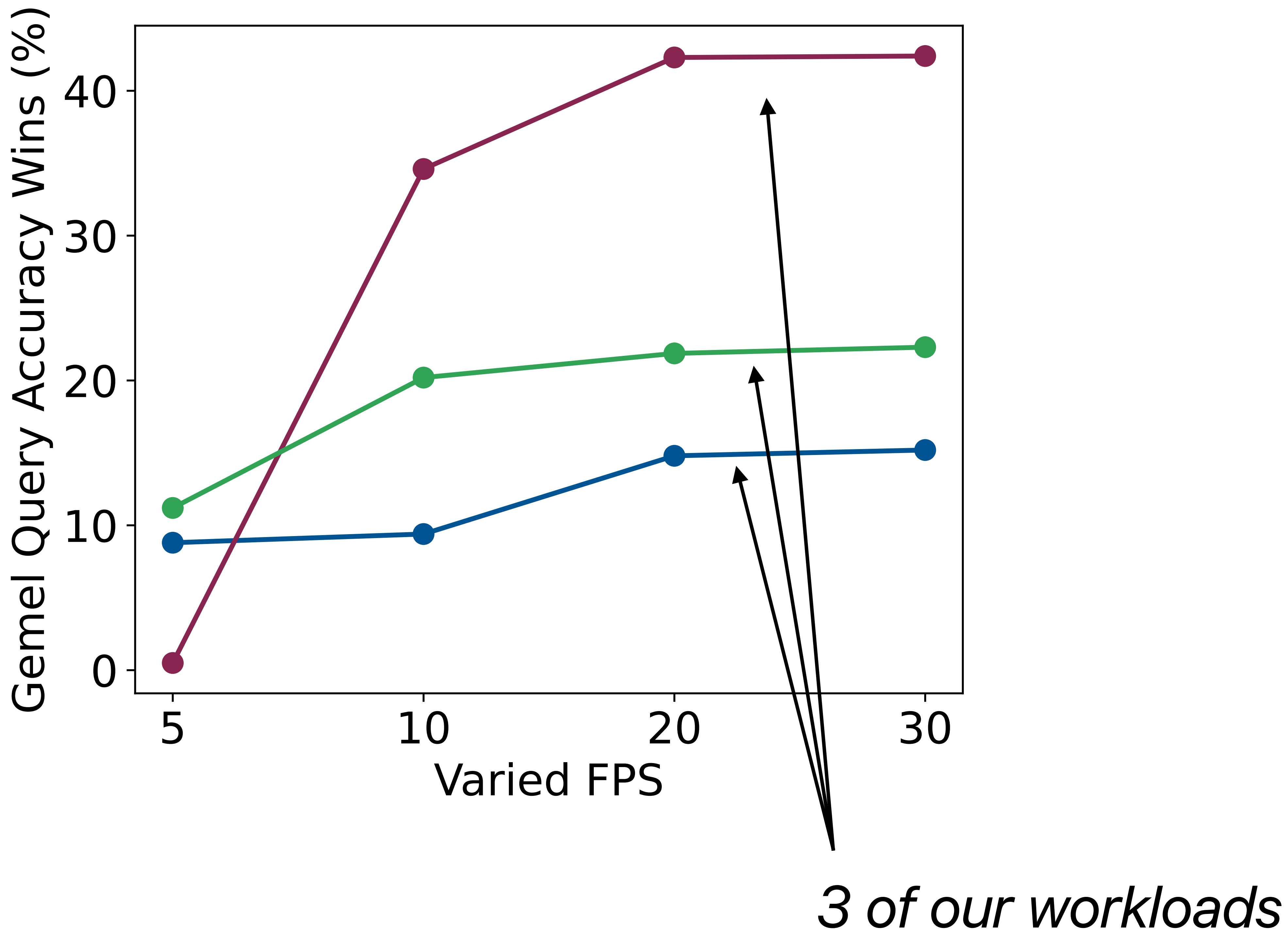
↑ FPS, Gemel's wins ↑



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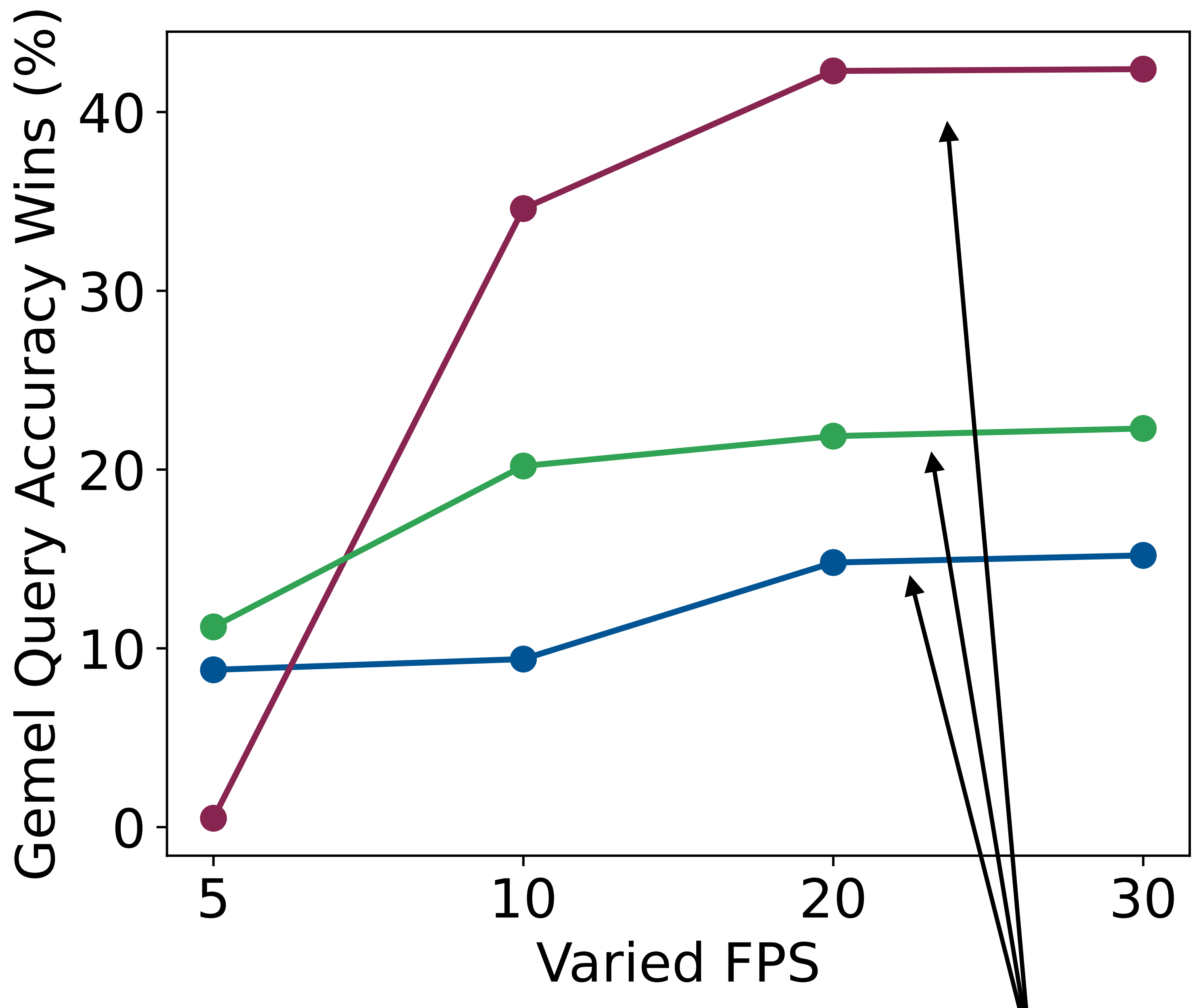
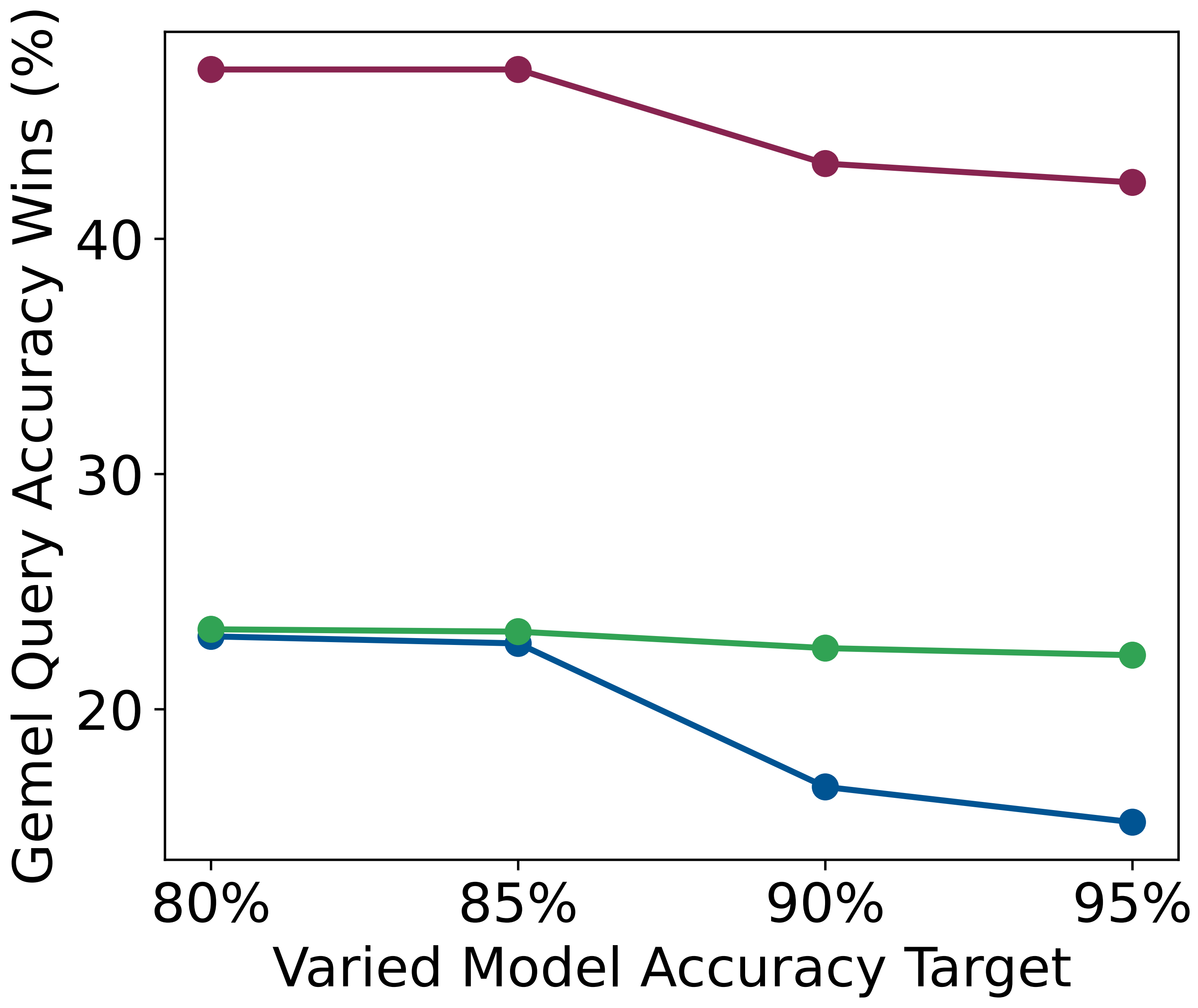


↓ Model Acc. Target, Gemel's wins ↑



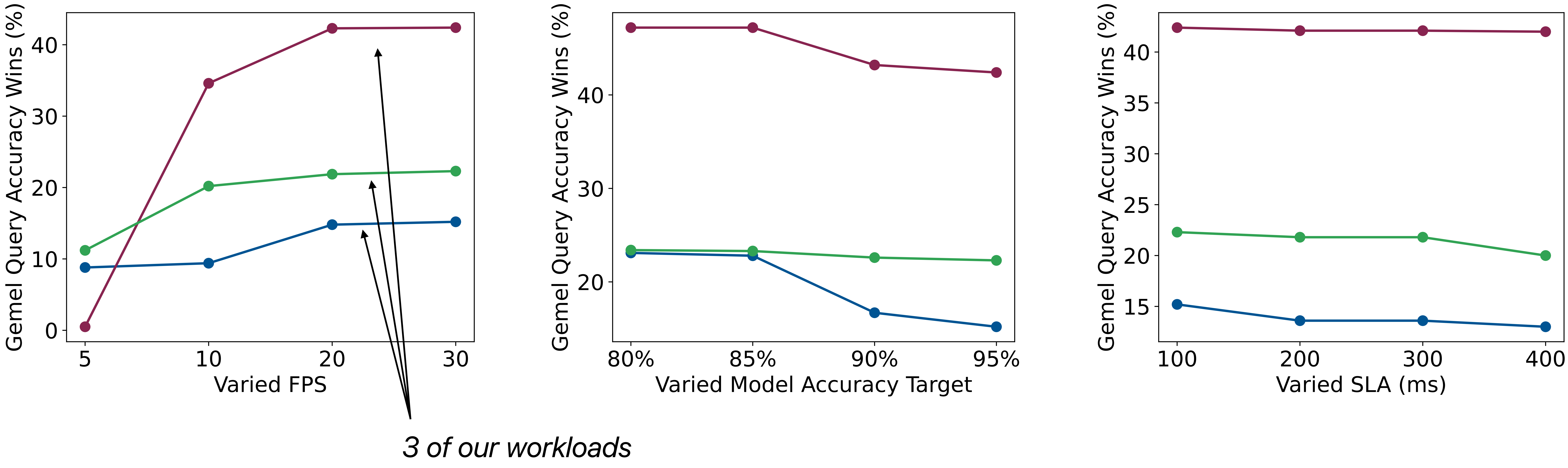
3 of our workloads

Varying FPS, Accuracy Target, SLA

↑ FPS, Gemel's wins ↑

↓ Model Acc. Target, Gemel's wins ↑

More stringent SLAs, Gemel's wins ↑



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Gemel

- Tackles GPU memory bottlenecks for real-time video analytics at the edge
- Exploits redundancies across models to find unified weights for layers with shared definitions
- Achieves considerable memory savings and application accuracy improvements

Source code available at github.com/artpad6/gemel_nsdi23