Distributed Inference with Deep Learning Models across Heterogeneous Edge Devices

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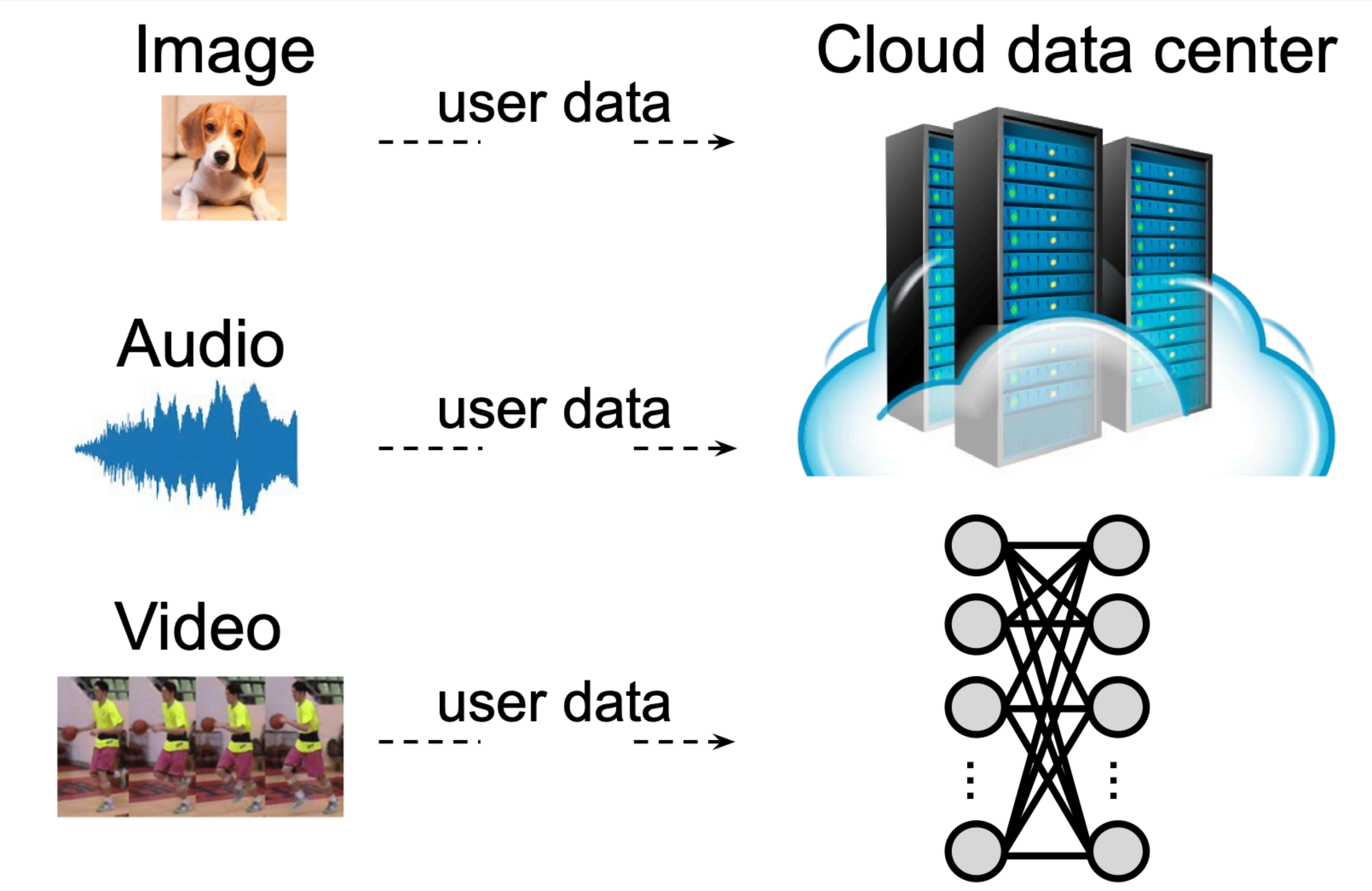
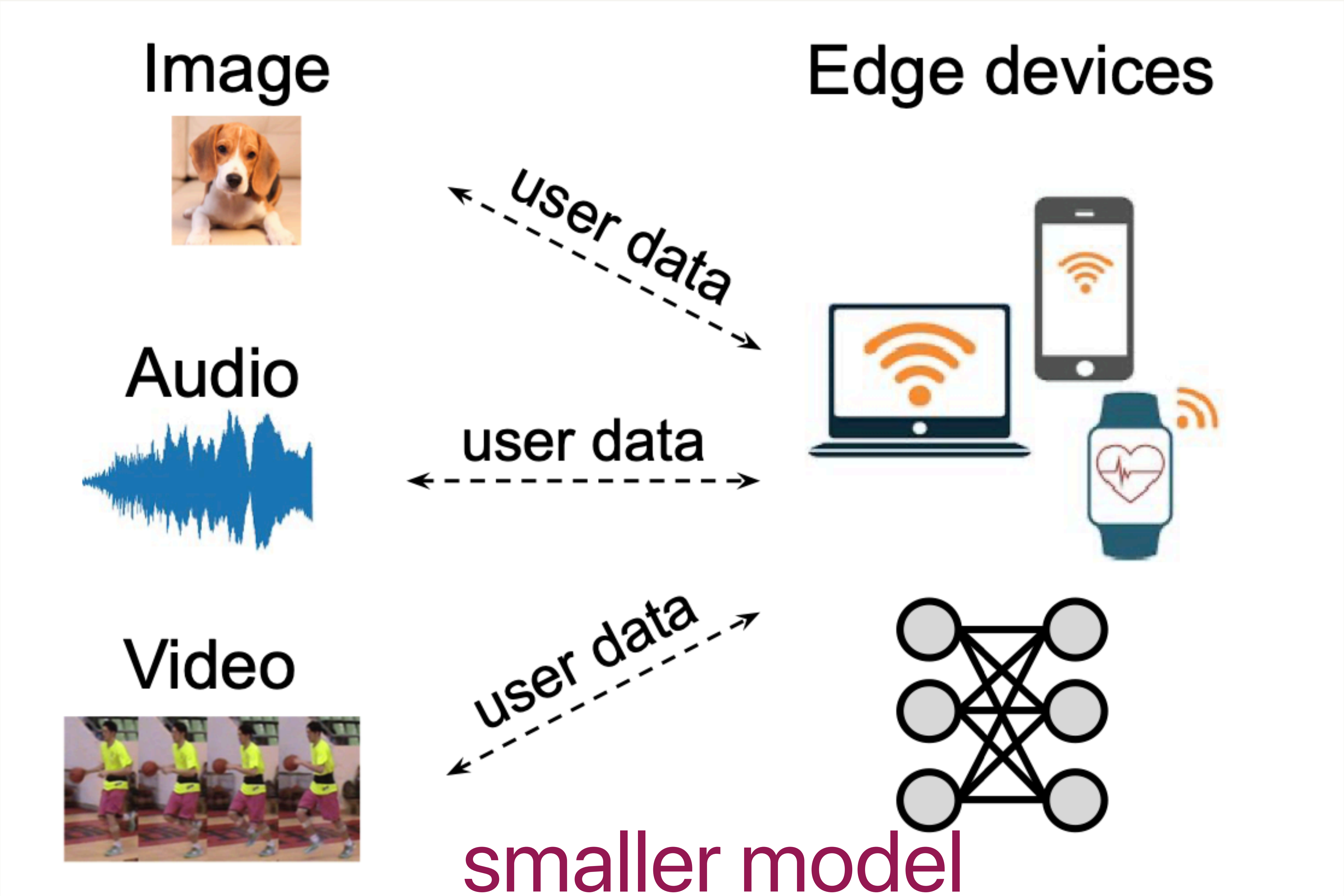
Model Deployment: Cloud or Edge?

Cloud -> transmission overhead and privacy issue



Model Deployment: Cloud or Edge?

Edge -> Limited computation capacity leads to high latency

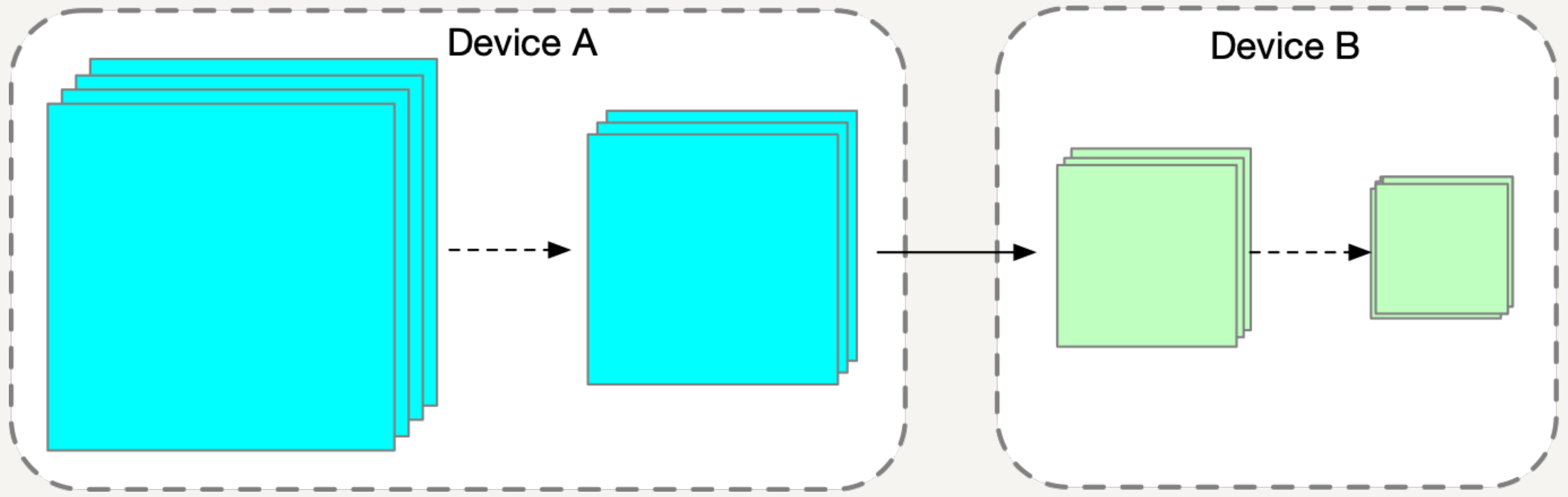


smaller model

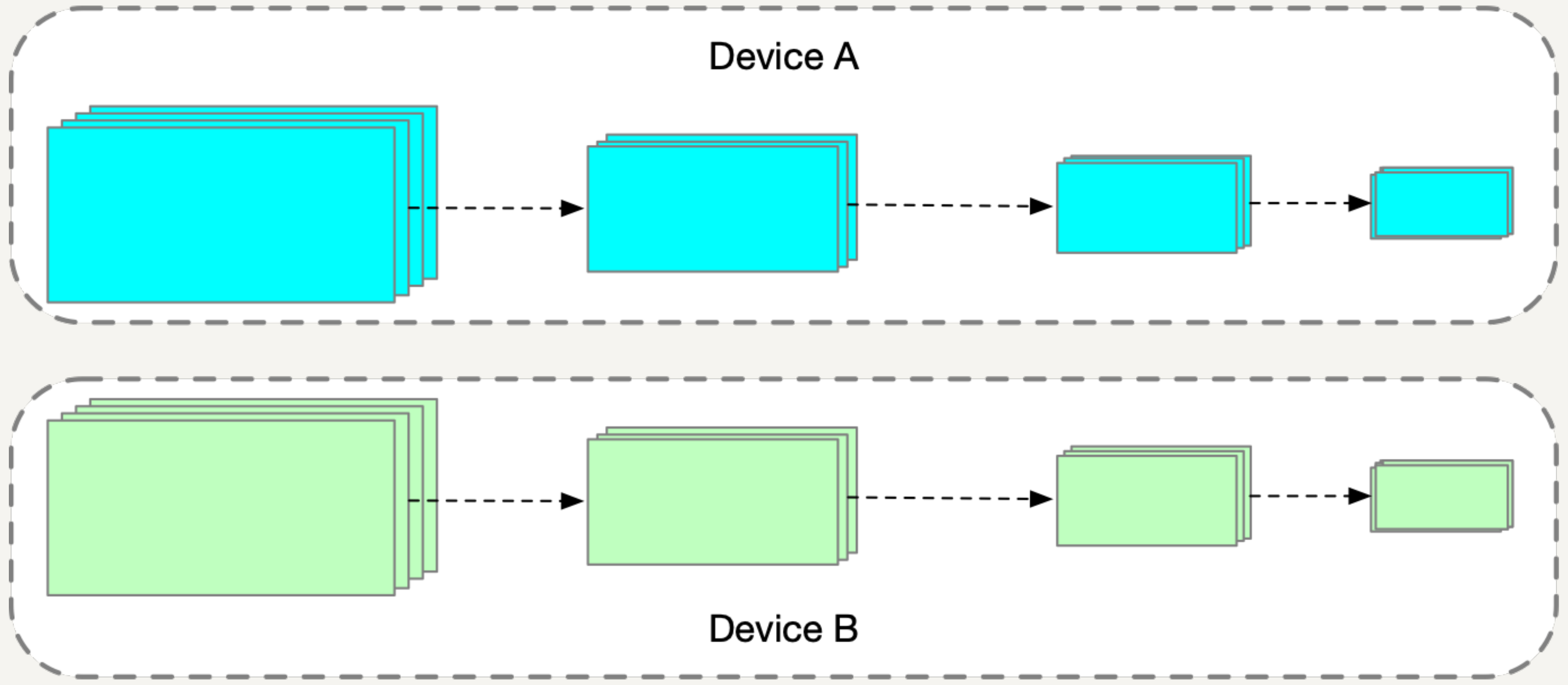
Another idea: distribute the inference workload for acceleration

How to partition the inference workload

- Sequential partition
  - Partition the model ***layer-wise***
  - The computation resources are underutilized

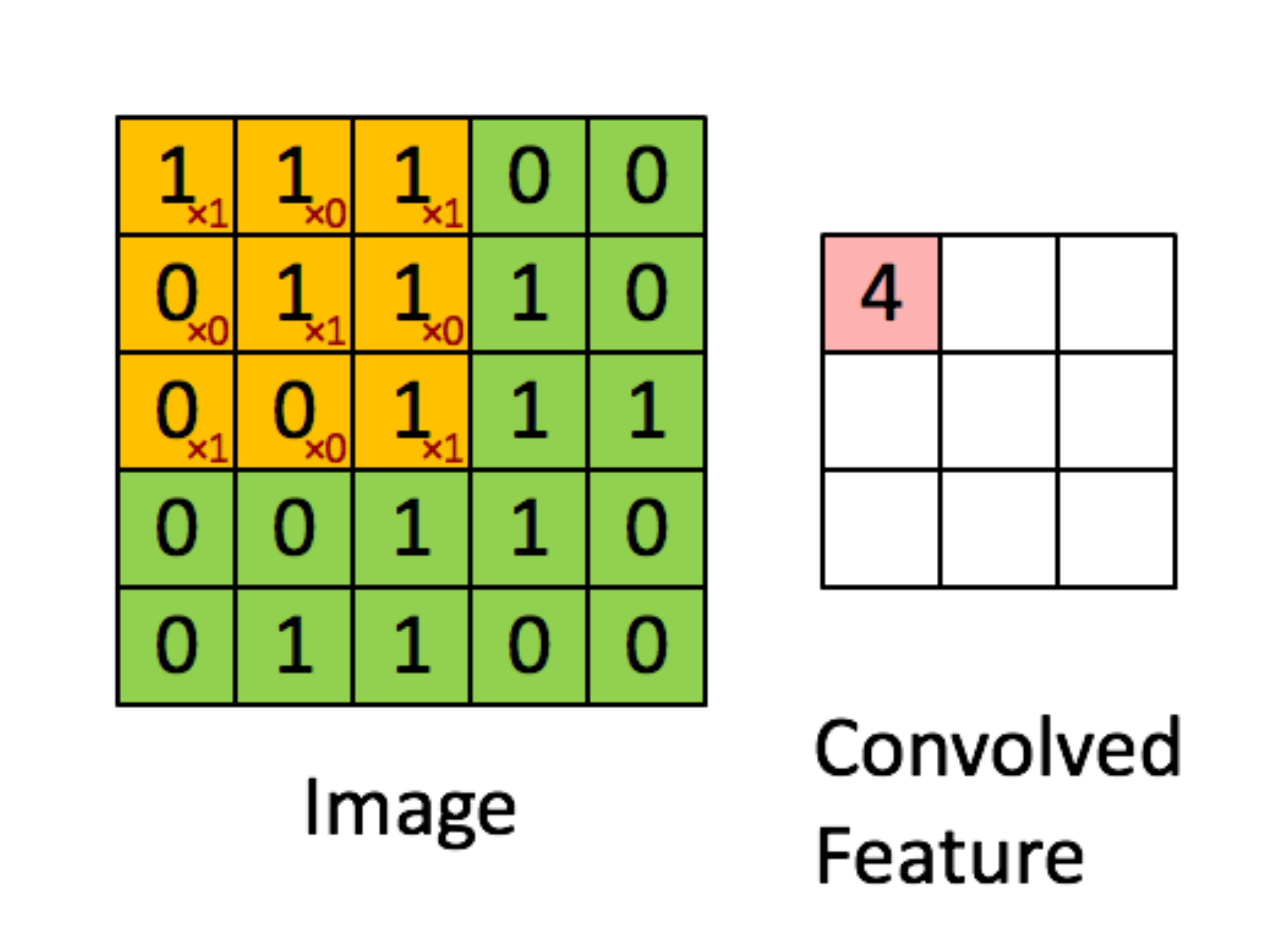


- Parallel partition
  - Parallel paths executed simultaneously



Convolution Operation

"Sliding window" applied on the image step by step

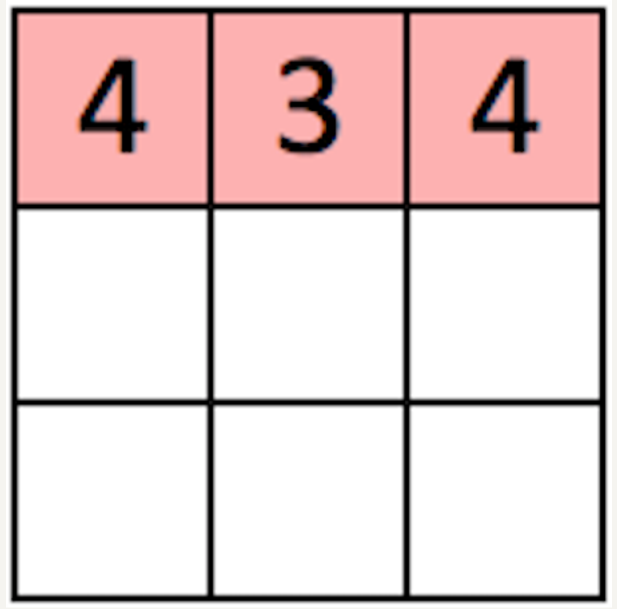


Model Partition - Single Conv Layer

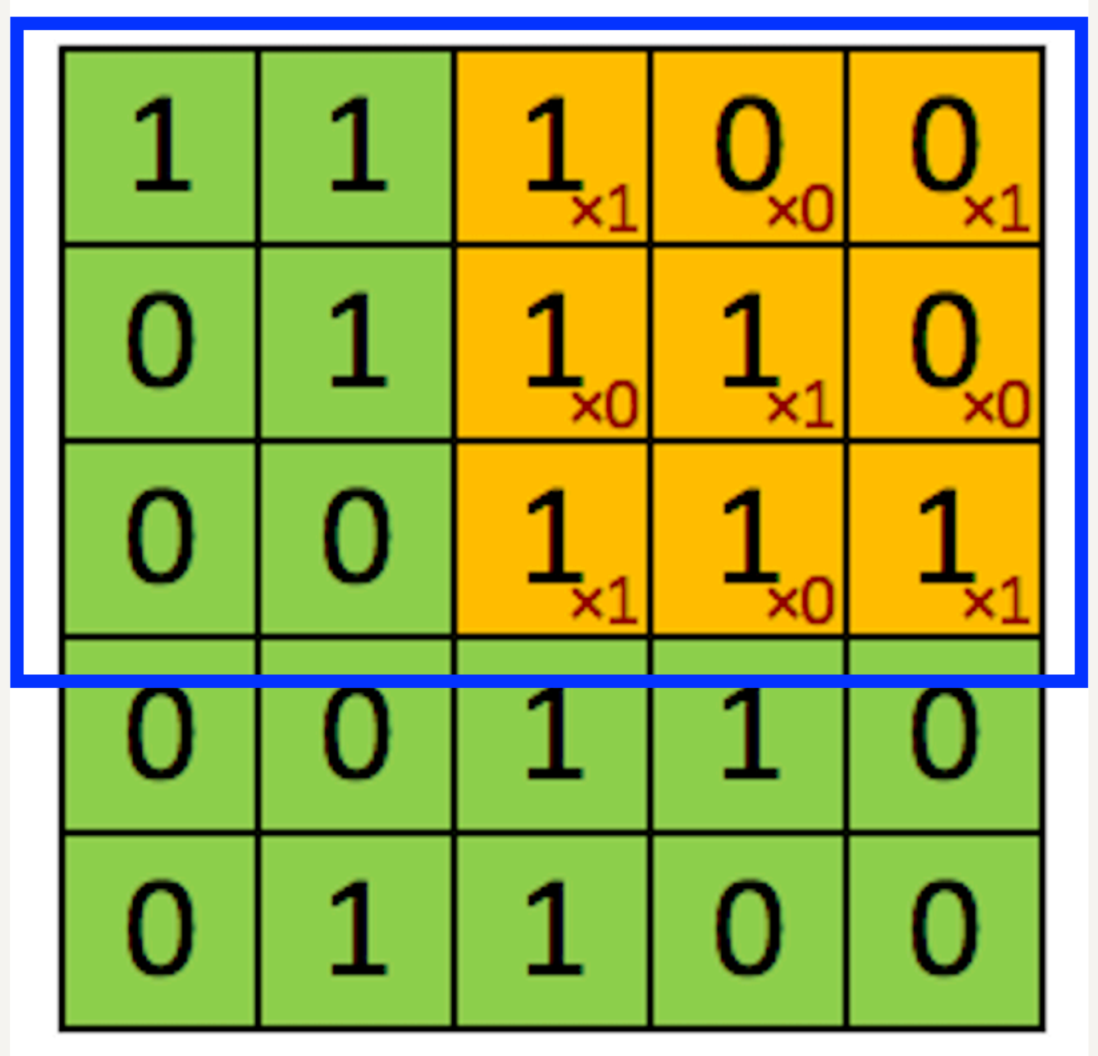
Step 1: decide the range of output partition

Step 2: calculate the range of the required input

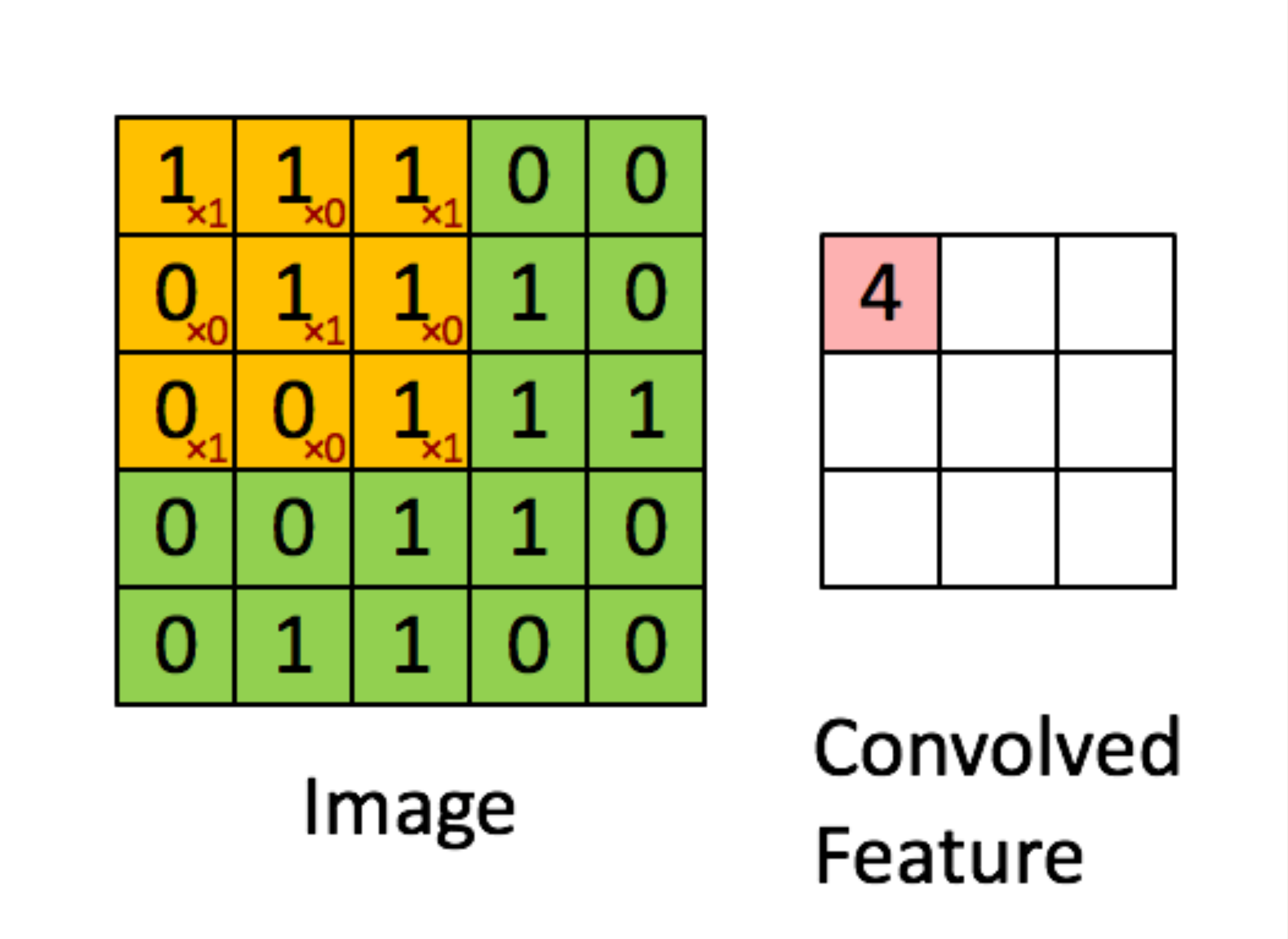
Step 3: feed the input partition to the convolution layer



Output Range



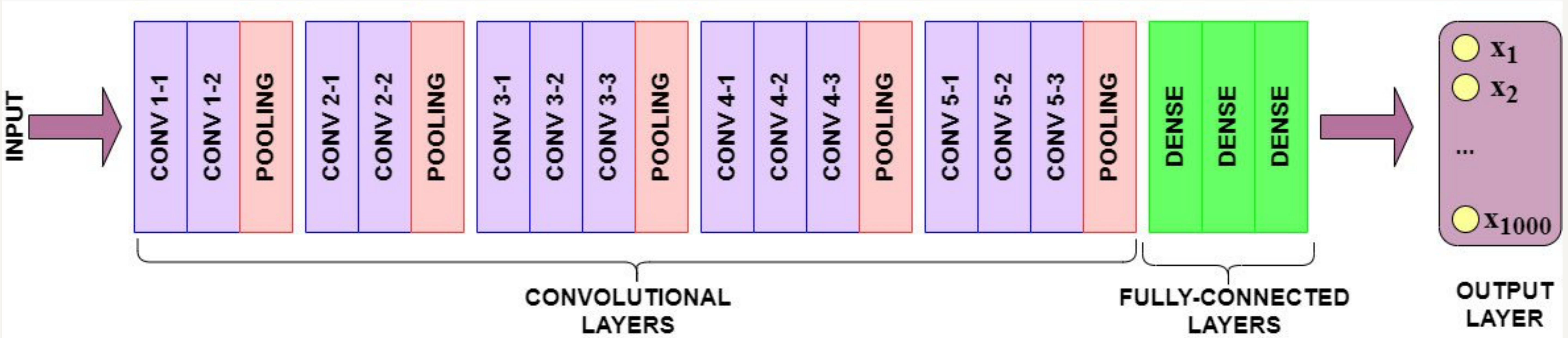
Required Input Range



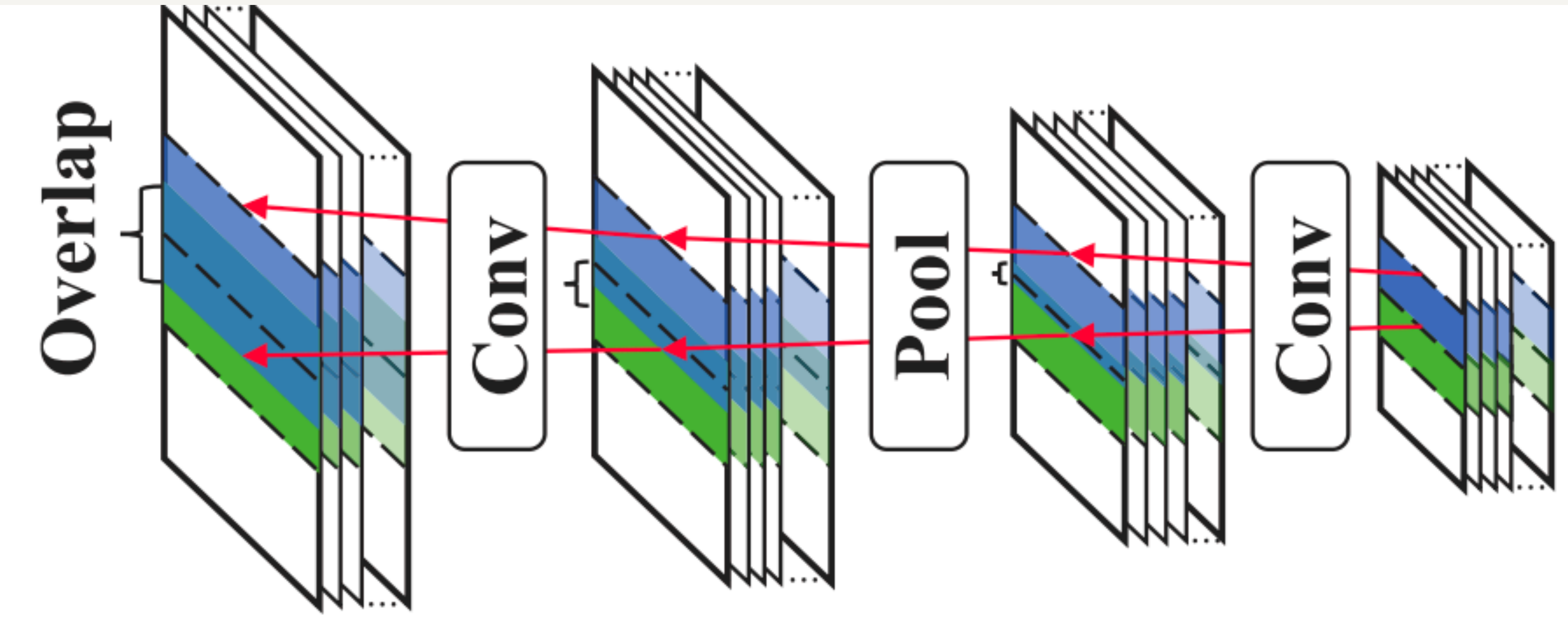
Partitioned Computation

Model Partition - Chained Layers

Chain structured model, *e.g.*, VGG-16



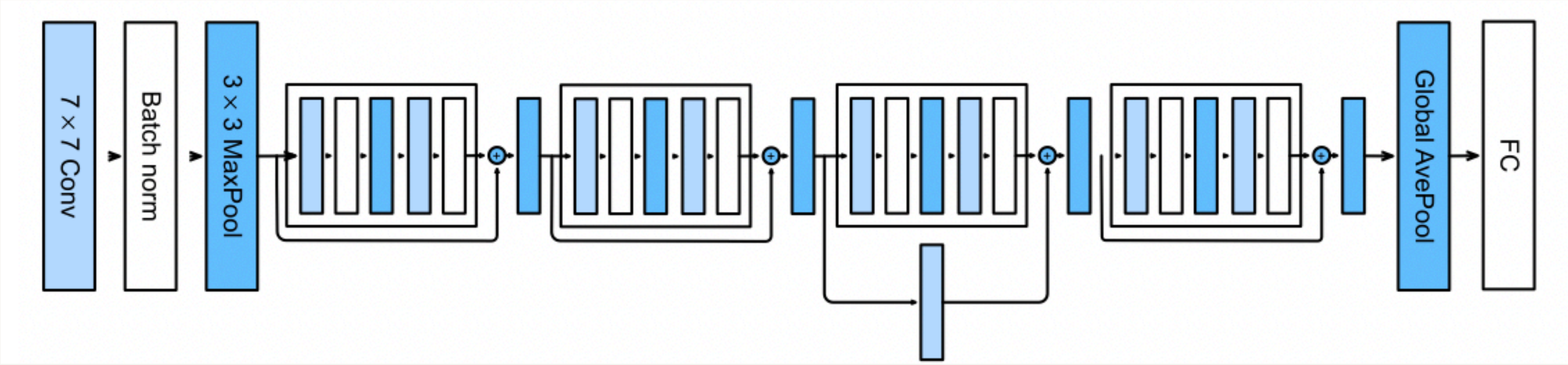
Trace all the way back to the first layer



Existing Solution: DeepThings

Model Partition - Computation Graph

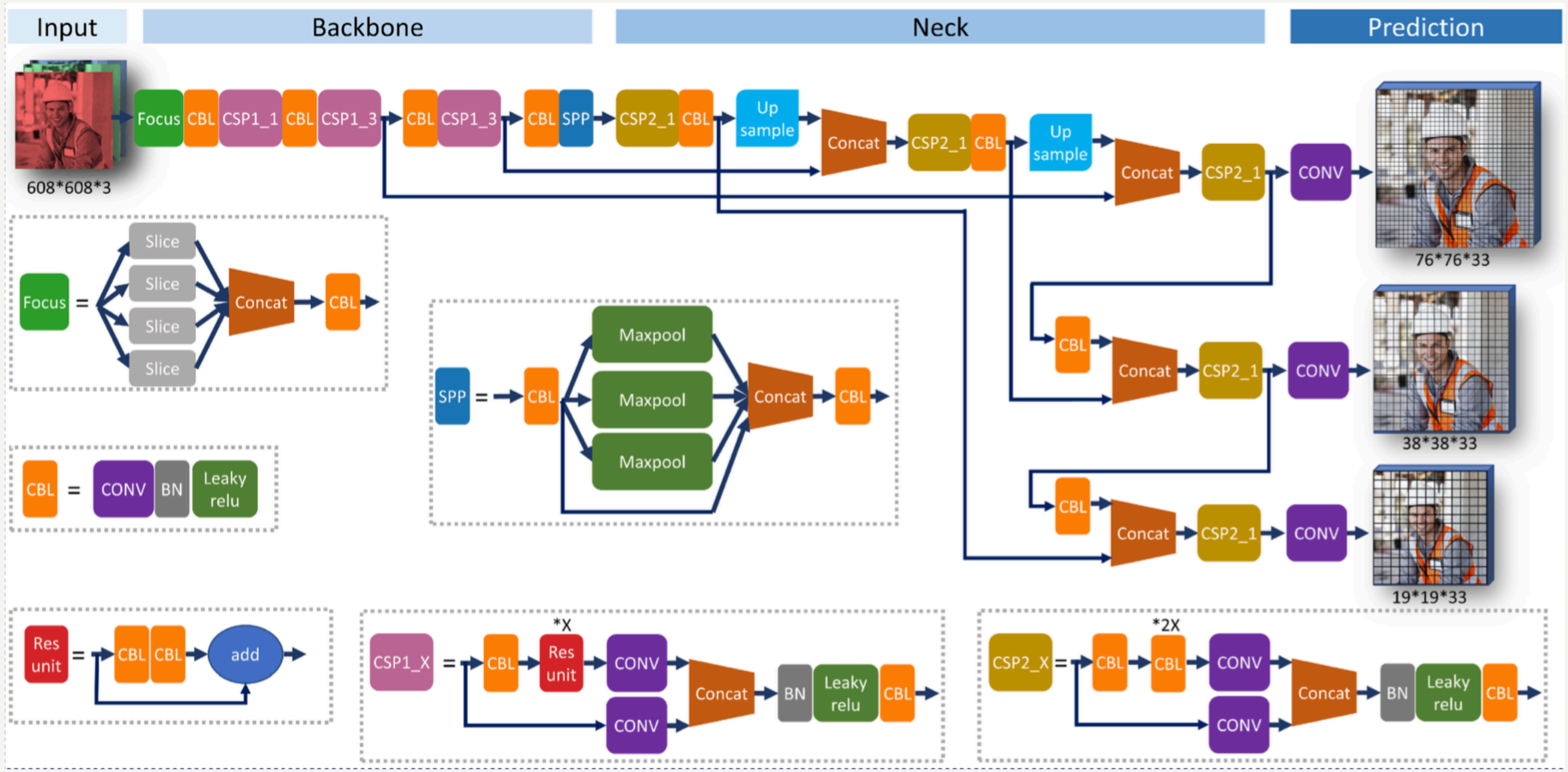
Directed Acyclic Graph (DAG) structured model, *e.g.*, ResNet



Some computation graphs can be easily turned into a chain, and manually fix the layer dependency.

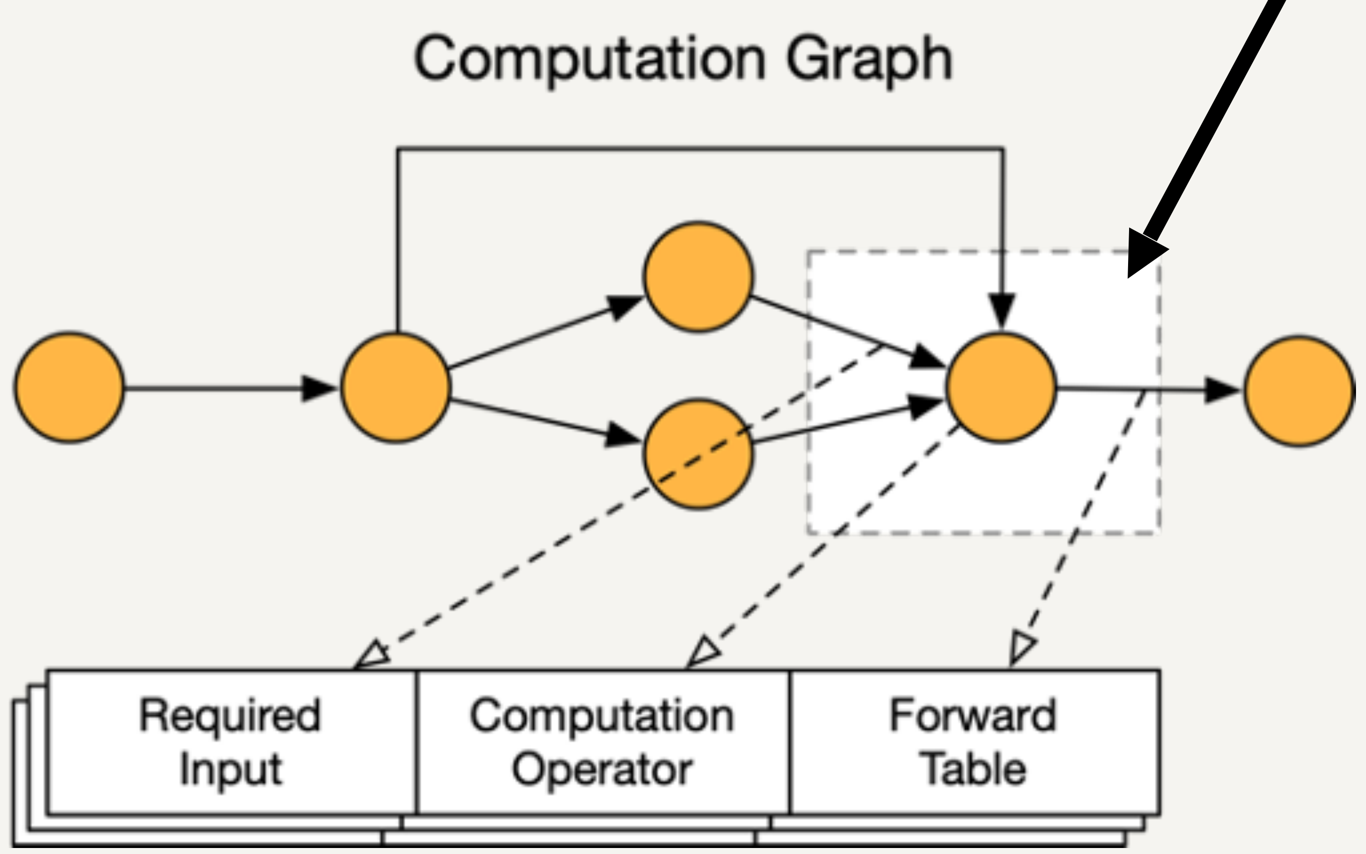
Model Partition - Computation Graph

Some not... like YoloV5



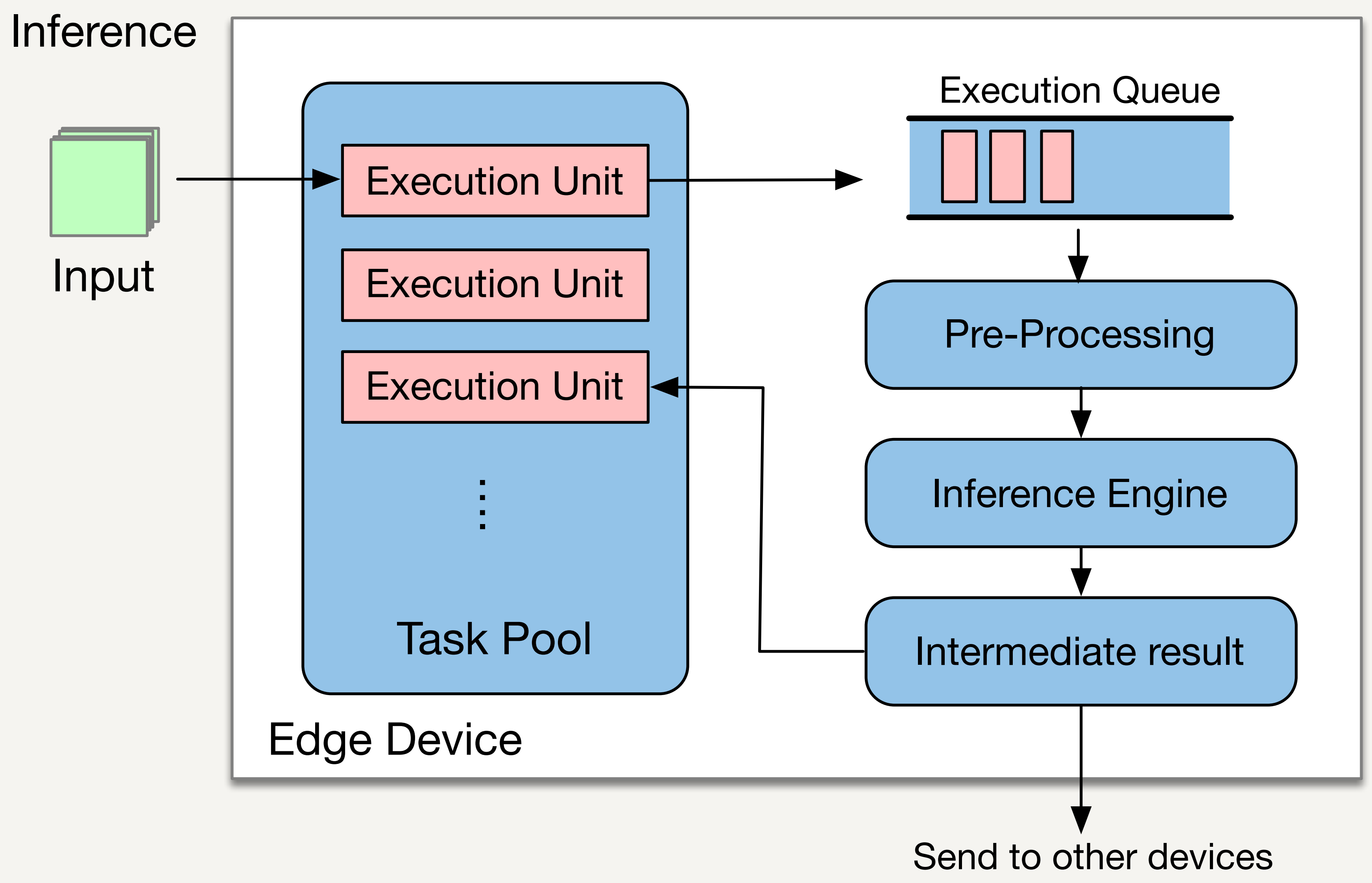
Our Design - EdgeFlow Overview

- Setup Phase
  - partition the computation graph into ***execution units***
  - The **layer dependency is maintained** by the communication between execution units



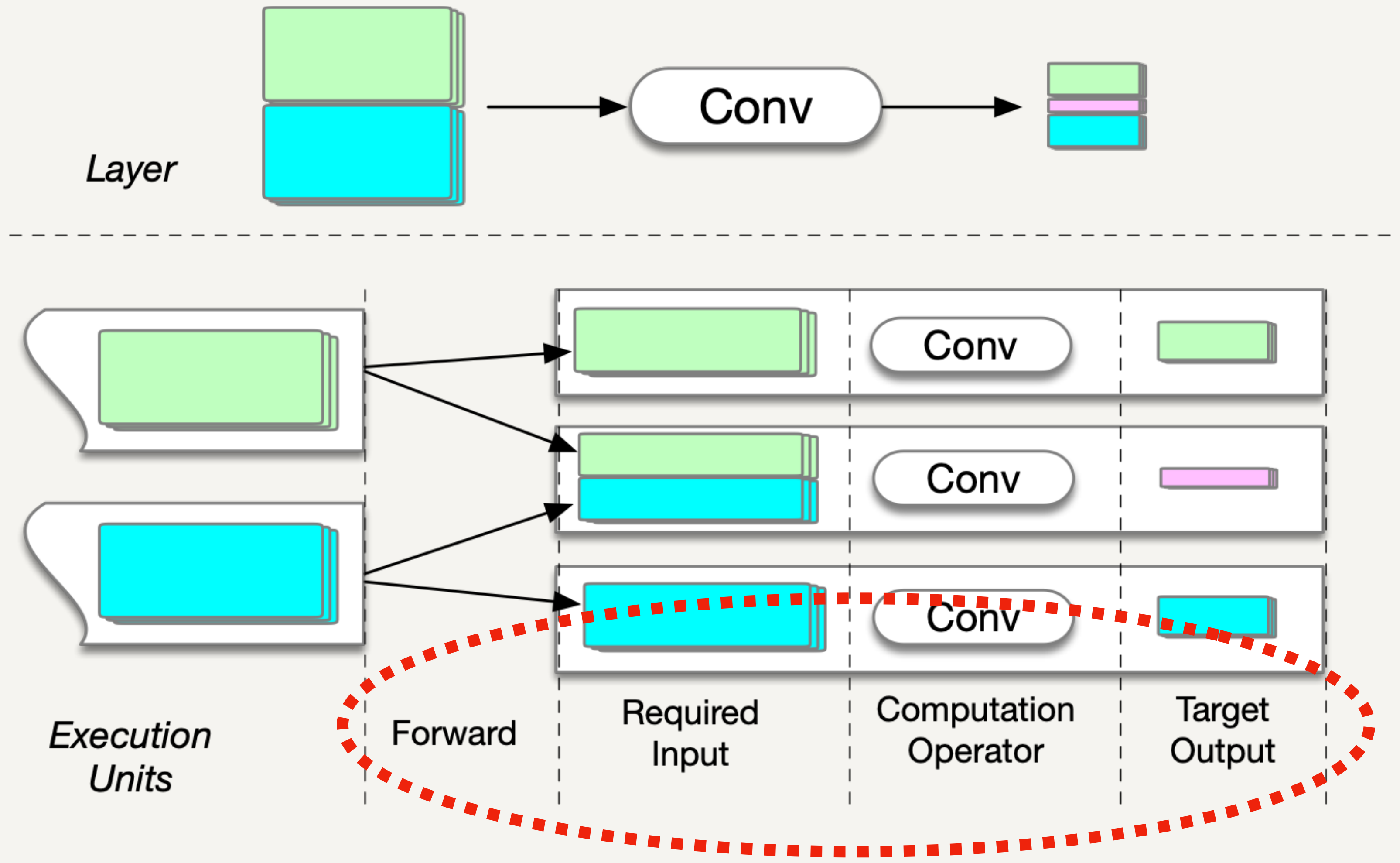
Our Design - EdgeFlow Overview

- Inference Phase
  - Execution units collaboratively finish the inference
  - ***Equivalent*** result as computed on a single device



Model Partitioning

- Layer partitioning
  - Each execution unit computes ***part*** of the output of this layer
  - Calculate the ***required part*** of the input needed to complete the computation task
  - Update the forward table of preceding execution units



Problem: how to find the optimum partition scheme?

Problem Formulation

- Assume n available devices, output features of current layer ranges from row 0 to row H
- The partition decision variables can be expressed as an integer vector $\mathbf{x} = (x_0, x_1, \ldots, x_n)$
  - device i computes output ranges from row $x_{i-1} + 1$ to row x_i

$$x_i \in \mathbf{Z}^+, i = 0, 1, \ldots, n$$

$$x_0 = 0, x_n = H$$

$$x_0 \leq x_1 \leq \cdots \leq x_n$$

Problem Formulation

- Objective: finish time of the current layer l
  - $T_{l,i}$ denote the time that device i finish its partition of layer l
- The optimization problem can expressed as

$$
\begin{aligned}
\min_{x} \quad & \max(T_{l,1}, T_{l,2}, \ldots, T_{l,n}) \\
s.t. \quad & x_i \in \mathbf{Z}^+, i = 0, 1, \ldots, n \\
& x_0 = 0, x_n = H \\
& x_0 \leq x_1 \leq \cdots \leq x_n
\end{aligned}
$$

Problem Formulation

- $T_{l,i}$ estimation: transmission time + computation time

$$T_{l,i} = t_{\text{trans}}(i;l) + t_{\text{comp}}(i;l)$$

- Computation time can be estimated with a pre-trained linear regression model

number of rows to compute

$$t_{comp}(i) = Y_i(x_i - x_{i-1}; l).$$

layer settings

- Transmission time can be estimated by

finish time of layer m at device j

wait all the transmission done

$$t_{\text{trans}}(i;l) = \max_{j\in\{1,\ldots,n\}, m\in M} 1_{\{p_{m,i,j}>0\}}(T_{m,j} + \frac{p_{m,i,j}}{B_{i,j}})$$

valid when the transmission is positive

The layers required by current layer

Transmission from j to i

Problem Transformation

- Original problem

$$\begin{aligned} \min_{x} \quad & \max(T_{l,1}, T_{l,2}, \ldots, T_{l,n}) \\ s.t. \quad & x_i \in \mathbf{Z}^+, i = 0, 1, \ldots, n \\ & x_0 = 0, x_n = H \\ & x_0 \leq x_1 \leq \cdots \leq x_n \end{aligned}$$

- Step 1: introducing auxiliary variable and relax the integer constraint

$$\begin{aligned} \min_{x,\lambda} \quad & \lambda \\ s.t. \quad & T_{l,i} \leq \lambda, i \in \{1, \ldots, n\} \\ & x_i \in \mathbf{Z}^+, i = 0, 1, \ldots, n \\ & x_0 = 0, x_n = H \\ & x_0 \leq x_1 \leq \cdots \leq x_n \end{aligned}$$

Problem Transformation

- Step 2: removing the indicator function

$$1_{\{p_{m,i,j}>0\}}(T_{m,j} + \frac{p_{m,i,j}}{B_{i,j}}) + Y_i(x_i - x_{i-1}; l) \leq \lambda$$

The finish time of layer m at different device should be roughly the same

As long as $T_{m,\mathrm{j}}$ is not greater than other required devices, the constraint is loose, and won't affect the result.

Problem Transformation

- Step 3: re-express the transmission size

$p_{m,i,j}$ is the overlapping area between the **required input range** (s_i, e_i)

and the **output range** $(x_{m,j-1}, x_{m,j})$ of layer m at device j

$$\begin{aligned} p_{m,i,j} &= \min(e_i, x_{m,j}) - \max(s_i, x_{m,j-1}) \\ &= \min(e_i - s_i, e_i - x_{m,j-1}, x_{m,j} - s_i, x_{m,j} - x_{m,j-1}) \end{aligned}$$

$$\begin{aligned} \min_{p_{m,i,j}} \quad & -p_{m,i,j} \\ s.t. \quad & p_{m,i,j} \leq e_i - s_i, \quad p_{m,i,j} \leq e_i - x_{m,j-1}, \\ & p_{m,i,j} \leq x_{m,j} - s_i, \quad p_{m,i,j} \leq x_{m,j} - x_{m,j-1}. \end{aligned}$$

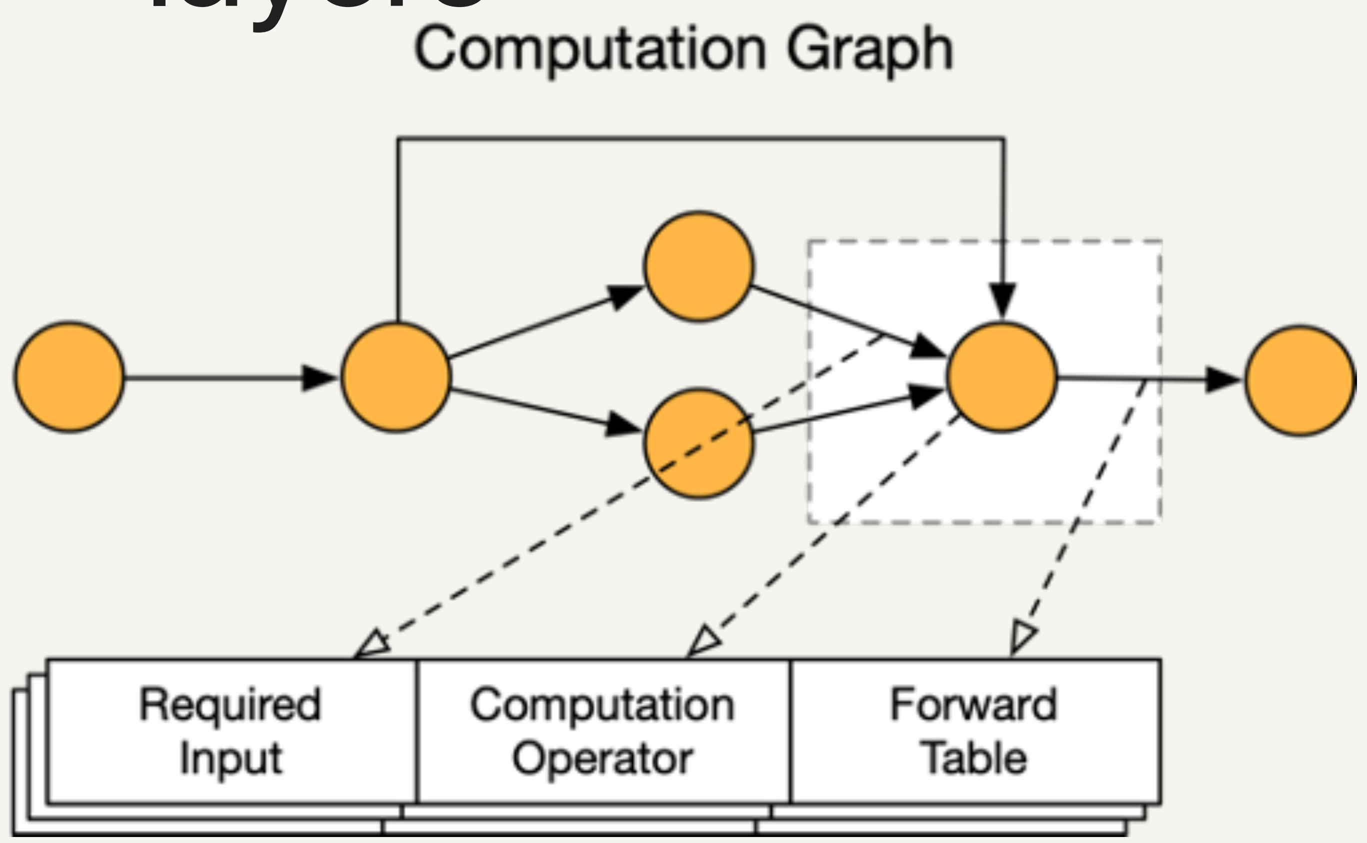
Problem Transformation

- Linear Programming Approximation

$$
\begin{aligned}
\min_{x,\lambda,p} \quad & \lambda - \sum_{m,i,j} p_{m,i,j} \\
s.t. \quad & x_0 = 0, x_n = H \\
& x_0 \le x_1 \le \cdots \le x_n \\
& T_{m,j} + \frac{p_{m,i,j}}{B_{i,j}} + Y_i(x_i - x_{i-1}; l) \le \lambda \\
& p_{m,i,j} \le e_i - s_i, \quad p_{m,i,j} \le e_i - x_{m,j-1}, \\
& p_{m,i,j} \le x_{m,j} - s_i, \quad p_{m,i,j} \le x_{m,j} - x_{m,j-1}.
\end{aligned}
$$

Model Partition

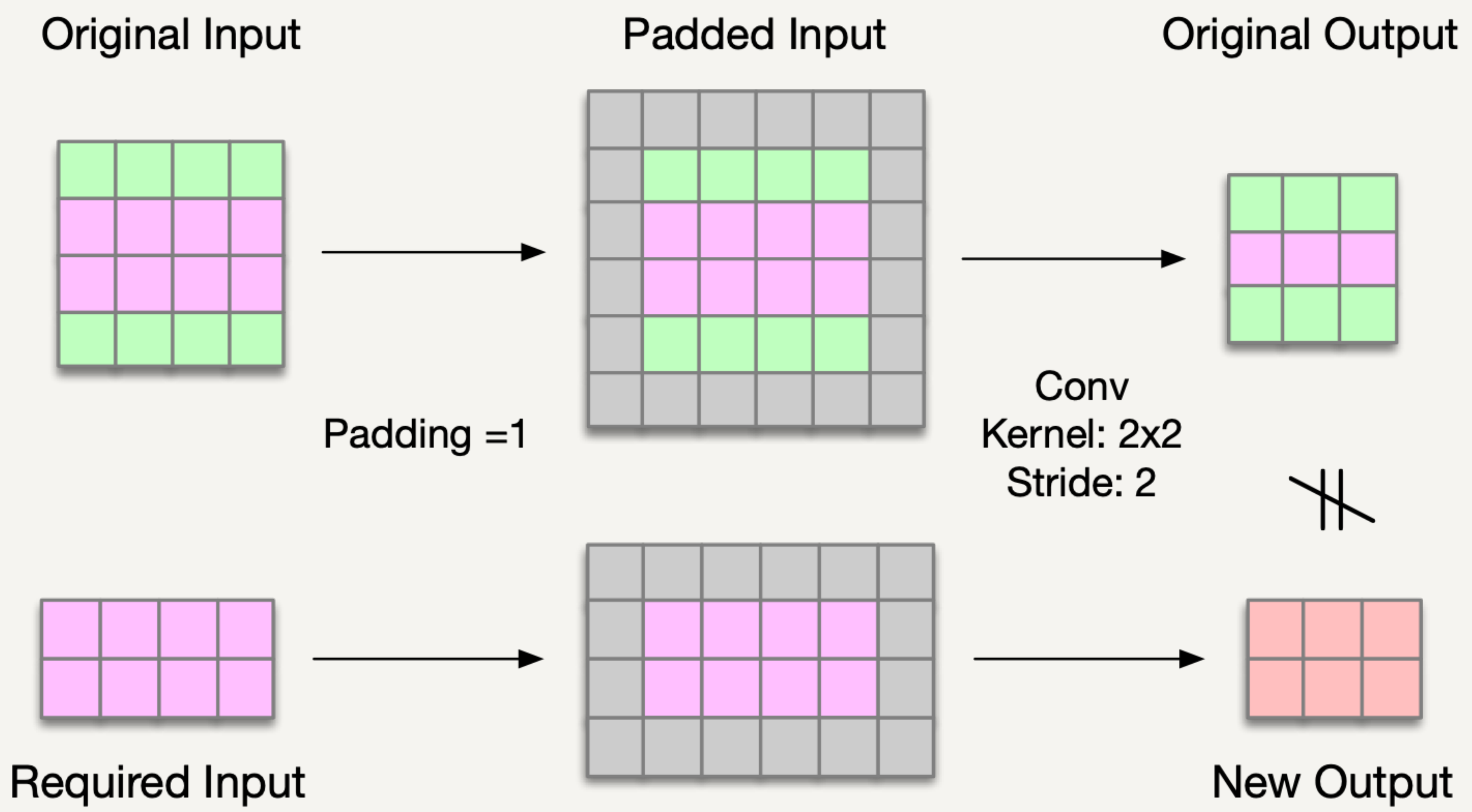
- Partition the model layer by layer in topological order
- Solve the LP problem for each layer to obtain the partition scheme
- The finish time estimation of previous layer becomes a parameter of the optimization problem of the following layers



$$T_{m,j} + \frac{p_{m,i,j}}{B_{i,j}} + Y_i(x_i - x_{i-1}; l) \leq \lambda$$

Padding Issue

- Directly feeding the input partition to the conv/pool layer may not yield the correct output



Padding Issue

- Solution: pre-padding mechanism
  - Set the padding parameter of conv/pool layer to 0
  - Manually add paddings when necessary

$$i_s = o_s \times \text{stride} - \text{padding},$$
$$i_e = (o_e - 1) \times \text{stride} + \text{kernel\_size} - \text{padding},$$

$$\text{upper\_padding} = \begin{cases} -i_s, & i_s < 0 \\ 0, & \text{otherwise} \end{cases},$$

$$\text{bottom\_padding} = \begin{cases} i_e - H_i, & i_e > H_i \\ 0, & \text{otherwise} \end{cases}.$$

Inference Phase

- The units will be executed when the input requirements are satisfied
- The output will be forwarded to fulfill the requirement of next execution unit
- Intermediate results ***flow*** through execution units to finish the inference

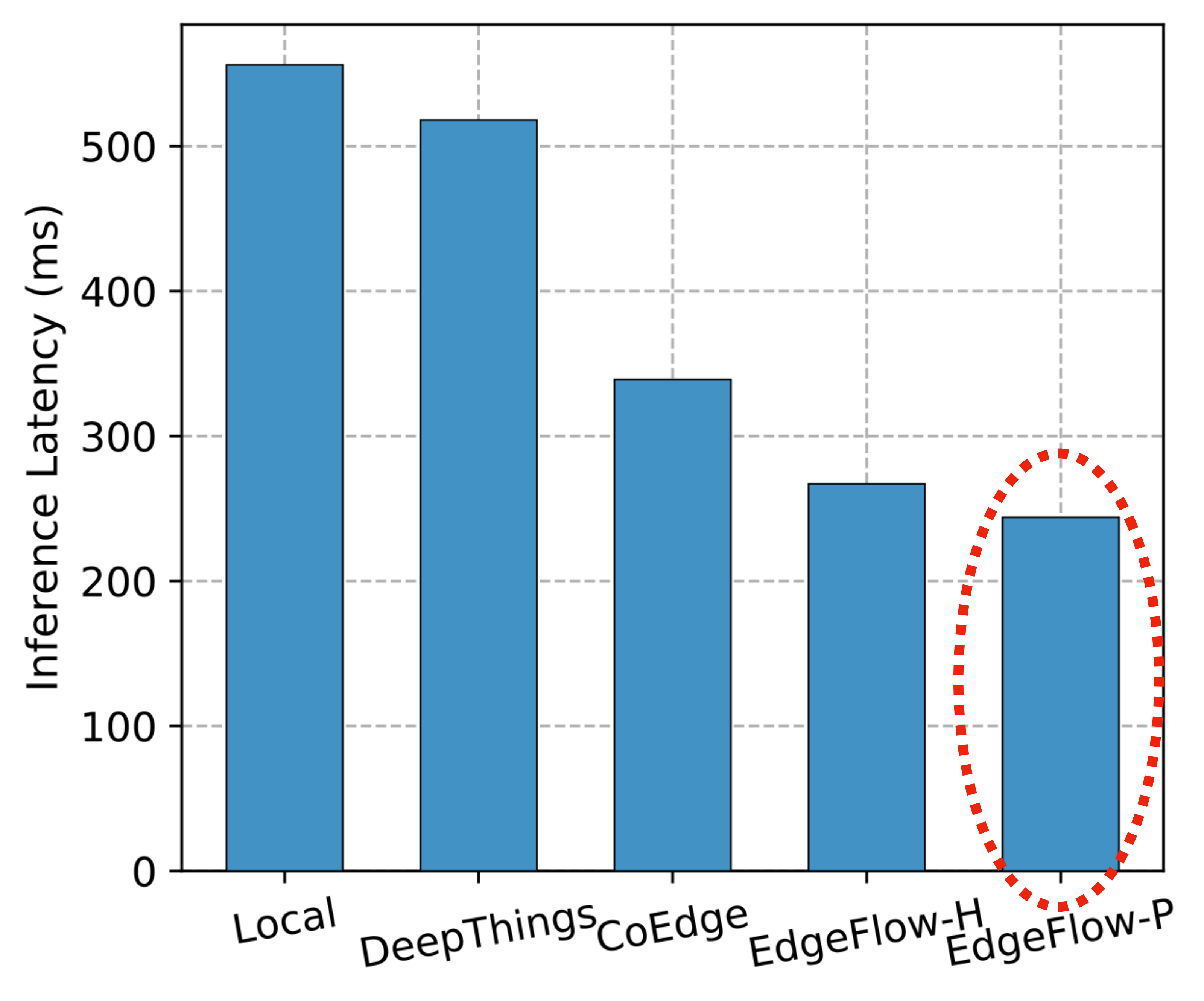
System name : ***EdgeFlow***

Evaluation

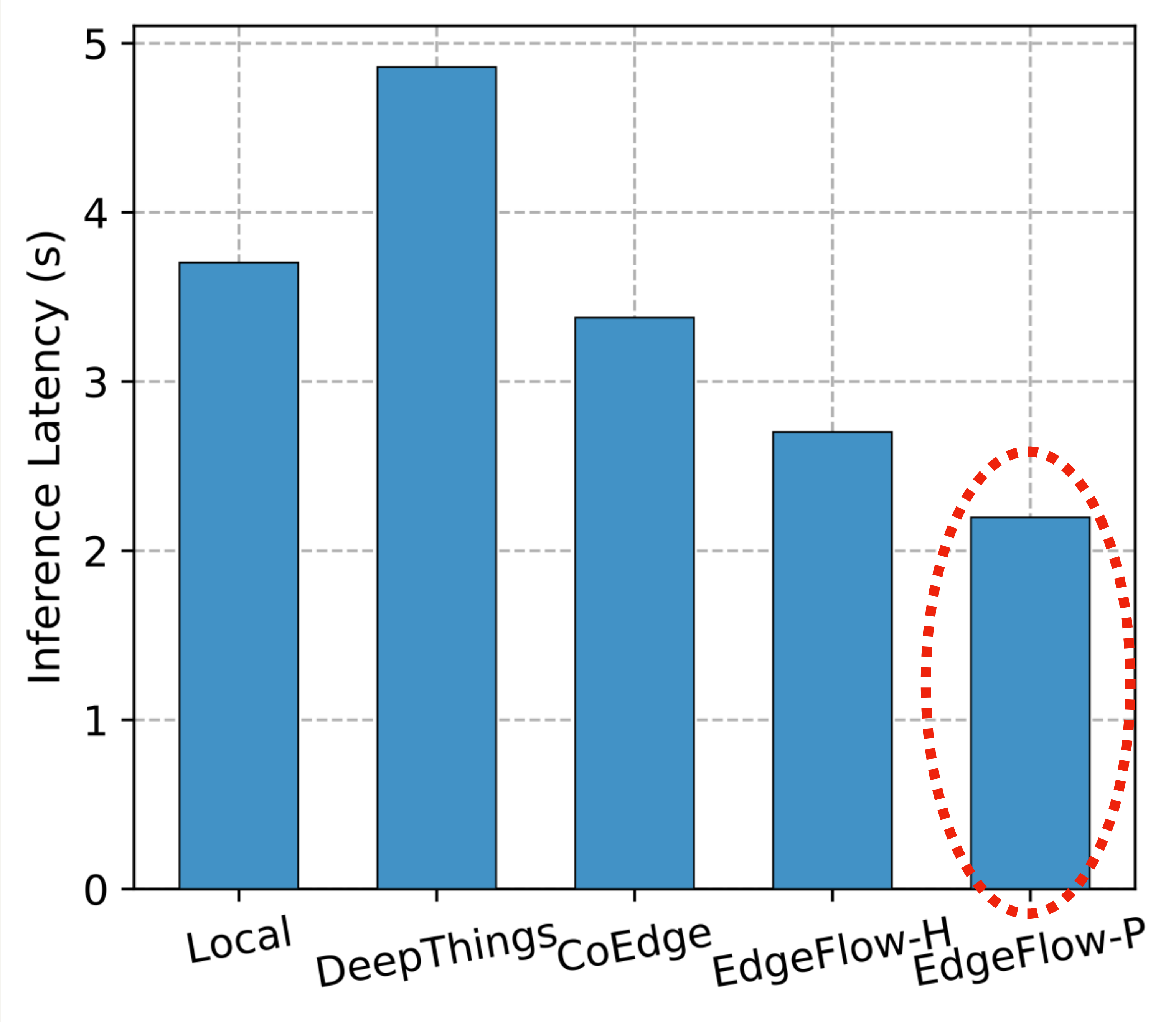
- 2 deep learning models
  - VGG-16: Classic image classification model in chain structure
  - YoloV5X: Latest object detection model with complicated structure
- 6 heterogeneous virtual machines
- Baselines
  - Local: deploy the model on a single device
  - Existing methods: DeepThings and CoEdge

Evaluation

Proposed method (EdgeFlow-P) achieves lowest inference latency with both models



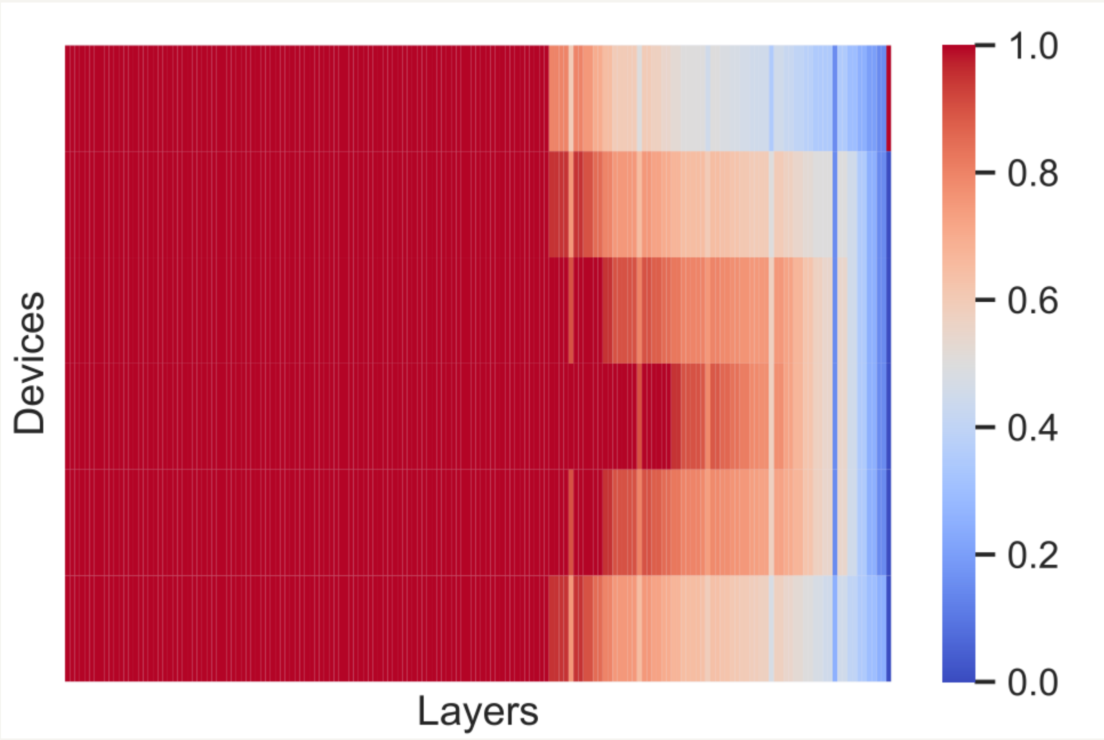
VGG-16



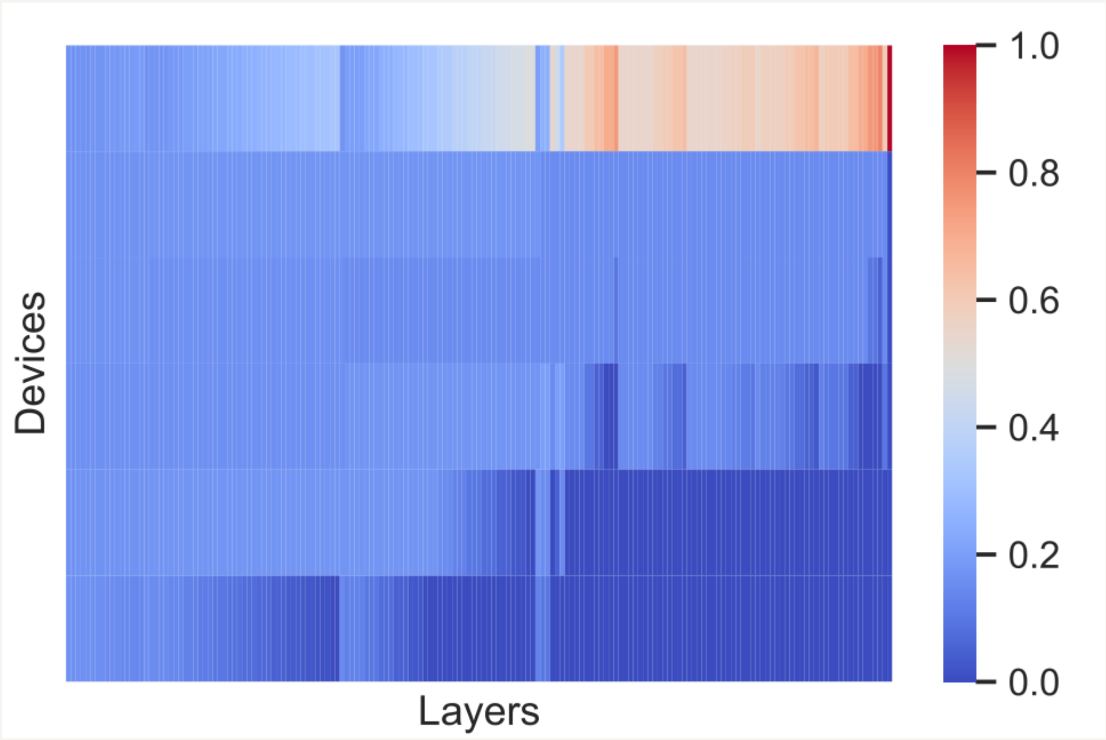
YoloV5X

Evaluation

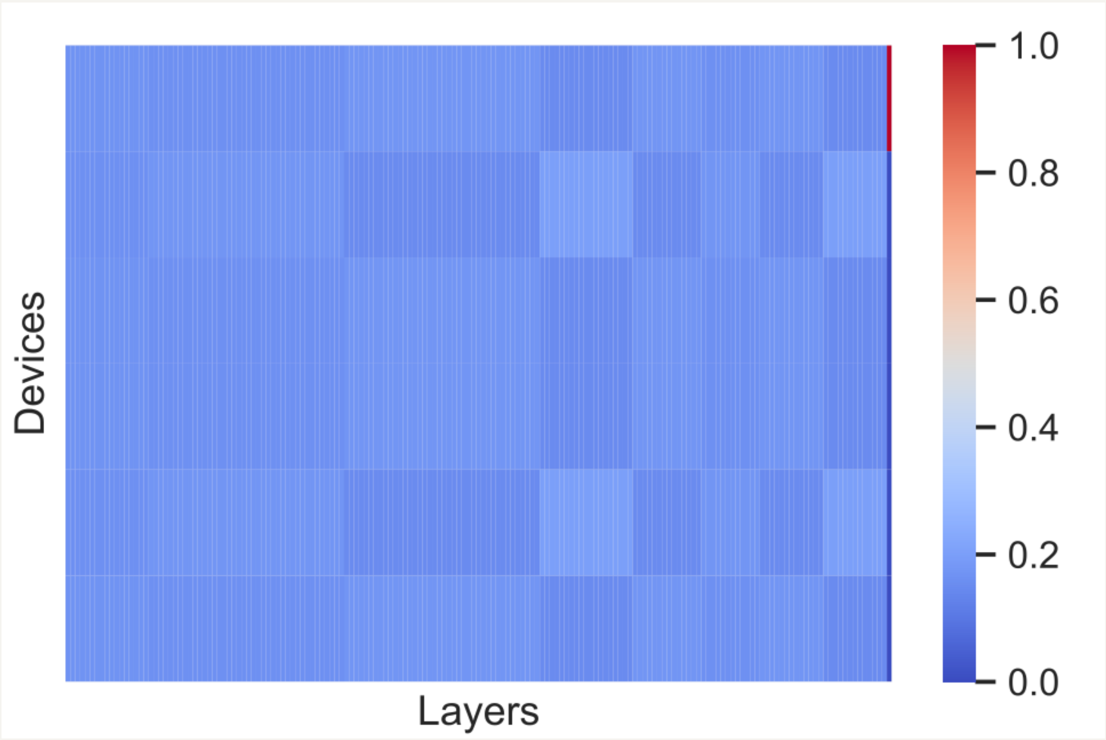
- Partition scheme of YoloV5
  - DeepThings: redundant computation in the early layers
  - CoEdge: workload gradually concentrates on a single device
  - EdgeFlow: relatively even distribution among devices



DeepThings



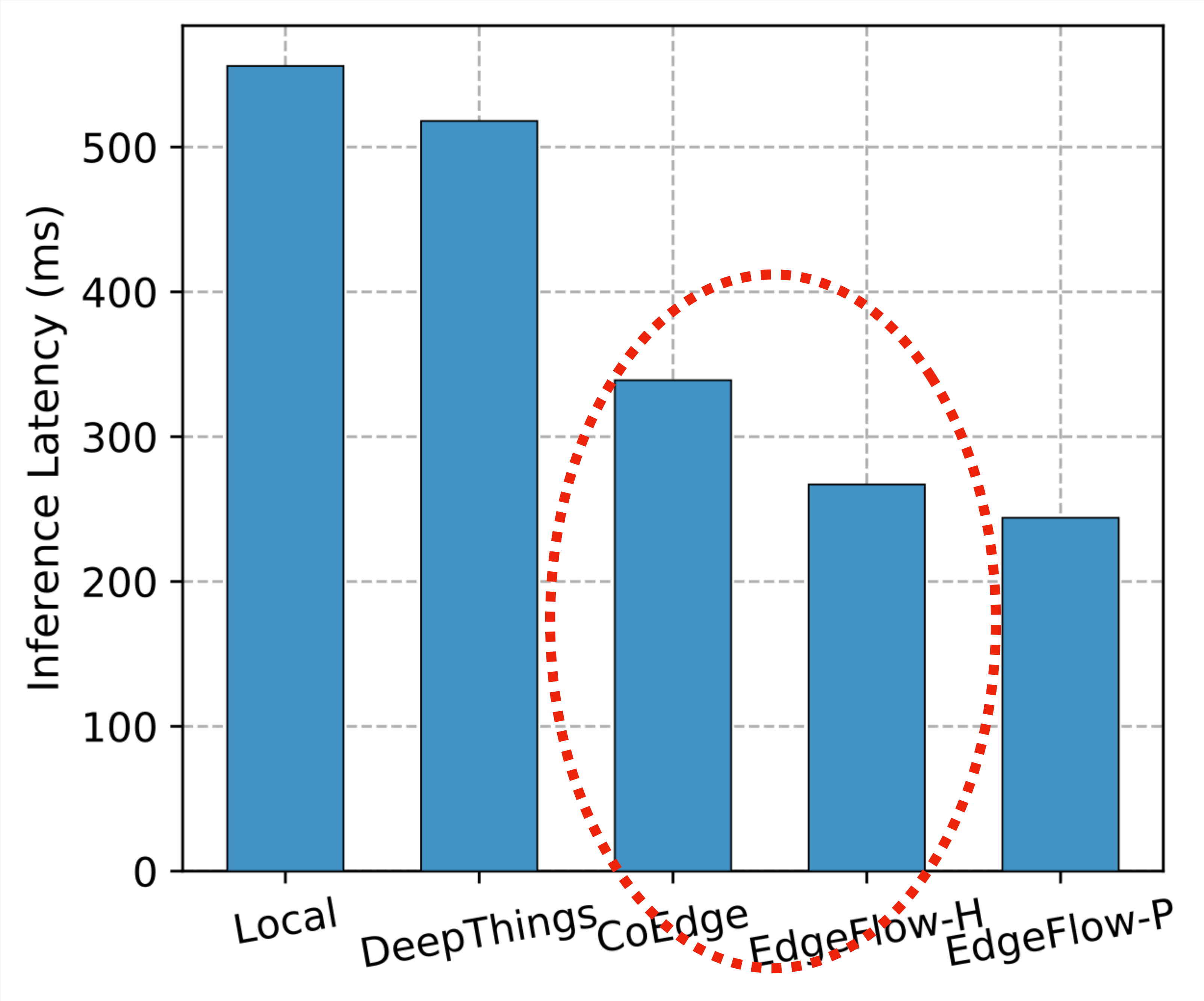
CoEdge



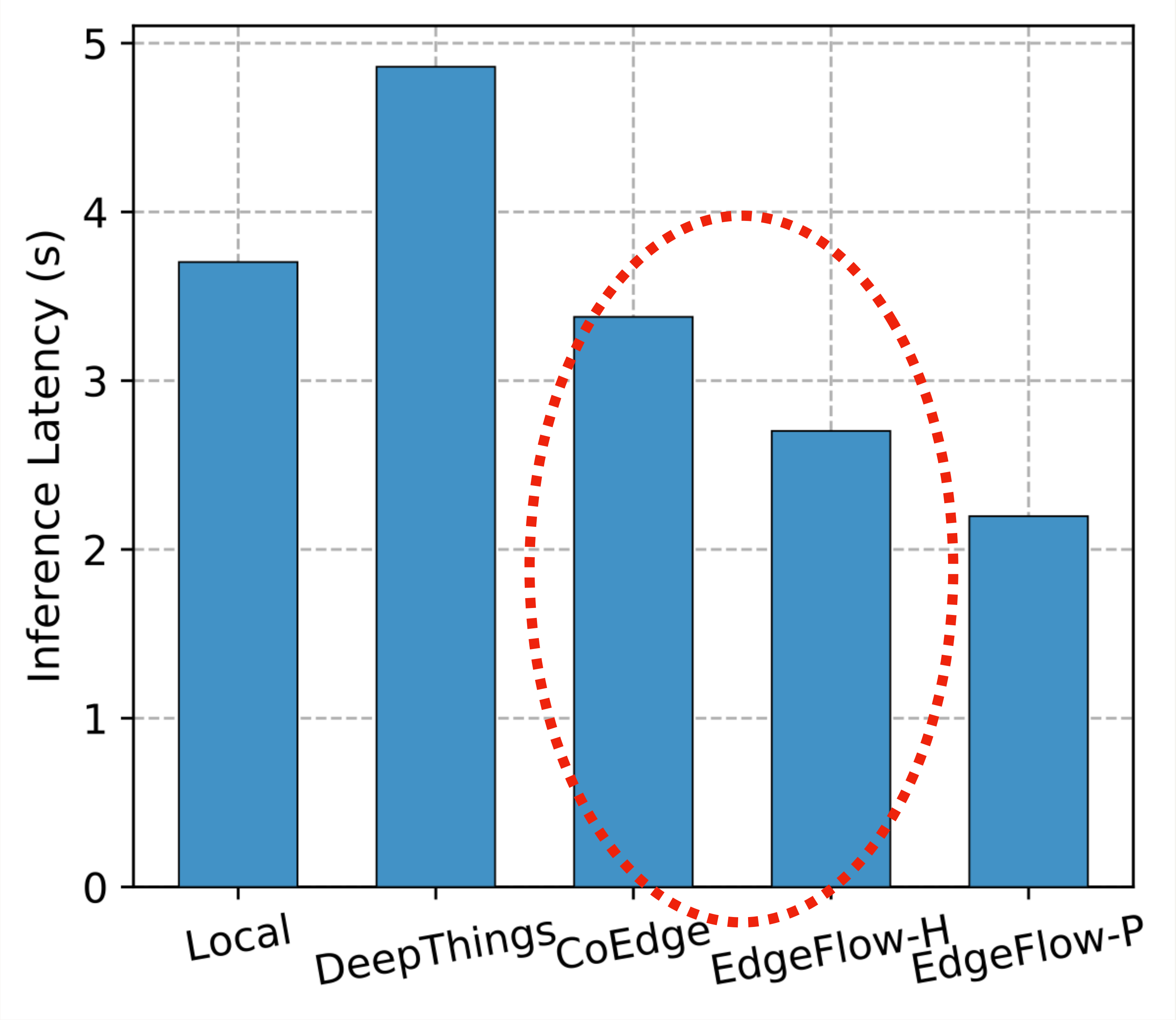
EdgeFlow

Evaluation

EdgeFlow-H and CoEdge share the same partition scheme, yet still faster than CoEdge



VGG-16



YoloV5X

Conclusion

- The model structure significantly affects the performance of existing distributed inference systems.
- *EdgeFlow* breaks the layer into execution units, and maintain the complicated layer dependencies by controlling the flow of intermediate results.
- Evaluation results show *EdgeFlow* has a distinct advantage, especially with complicated DAG-structured model

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