DeepThings: Distributed Adaptive Deep Learning Inference on Resource-Constrained IoT Edge Clusters

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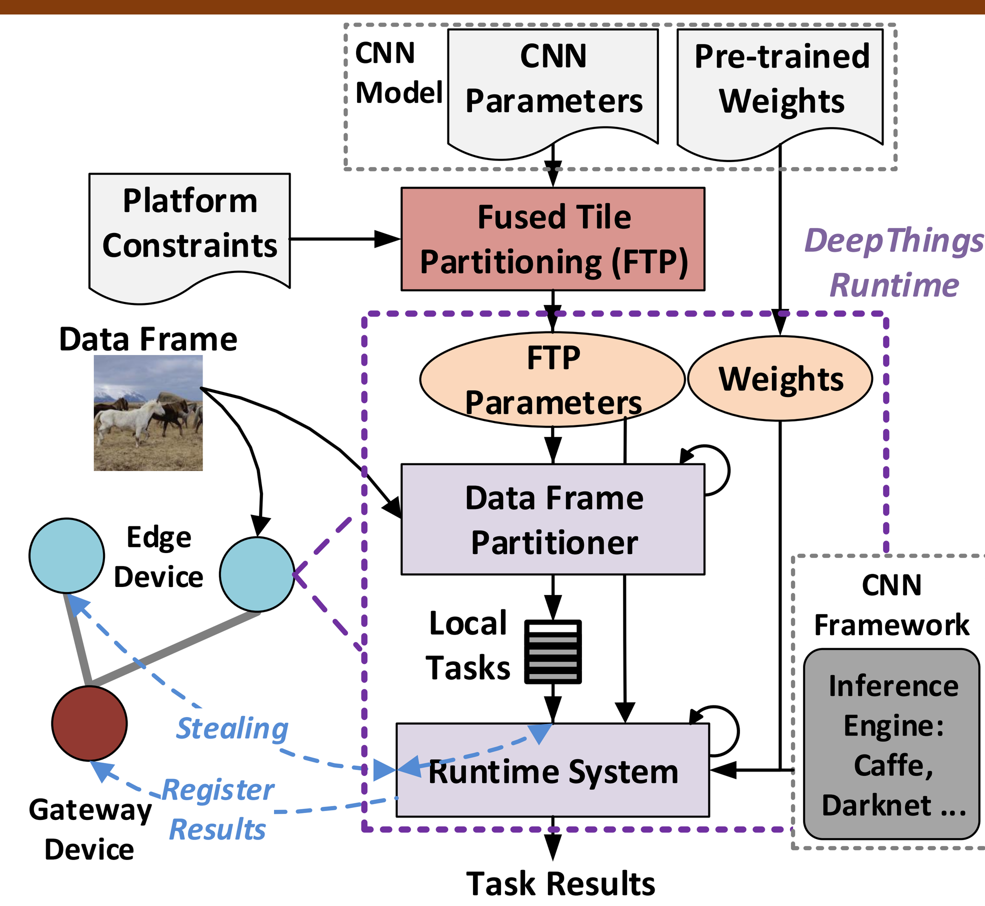
Overview

Background and Motivation

- Internet-of-Things (IoT)
  - Complicated and noisy sensing scenarios
  - Large scale data processing & analytics
  - ➢ Deep learning (DL) techniques for IoT applications
    - Computational and memory-intensive
- Cloud-based vs. fog/edge computing
  - Privacy
  - Unpredictable remote server and communication latency
  - Computational resources near the sources
    - Edge and gateway devices
- ➢ Deep learning inference in IoT edge clusters
  - ➢ Efficient deployment on resource-constrained IoT devices



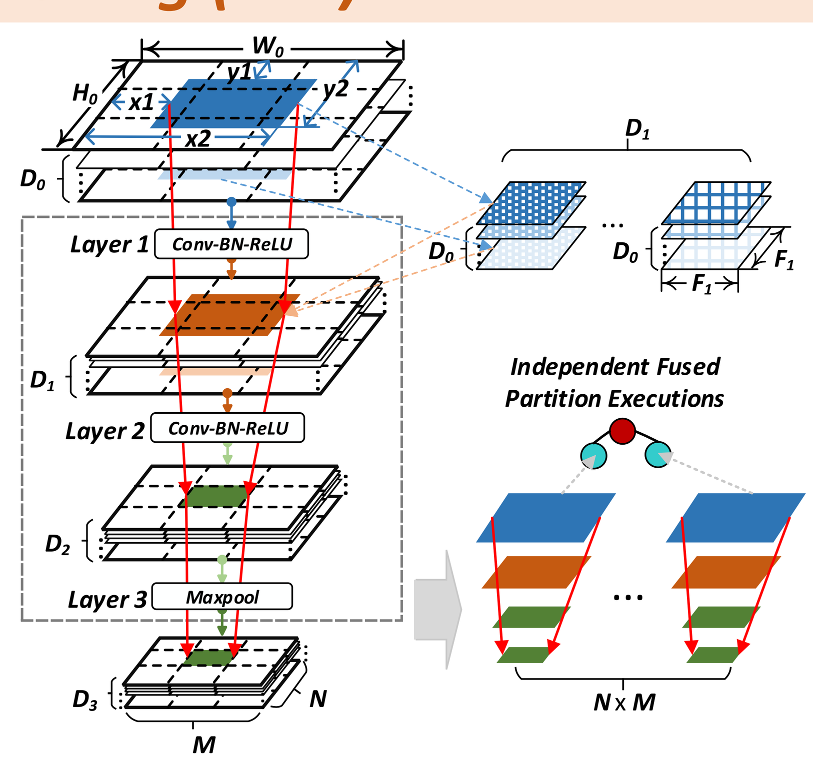
DeepThings Overview

- Fused Tile Partitioning (FTP)
  - Input data tiling
  - Layer fusion
  - ➢ Distributable tasks with lightweight data synchronization
- Distributed work stealing runtime system
  - Gateway: central coordination
  - Edge: peer-to-peer work stealing
  - ➢ Collaborative inference
- ➢ DeepThings: distributed adaptive deep learning inference on resource-constrained IoT edge clusters

DeepThings Framework

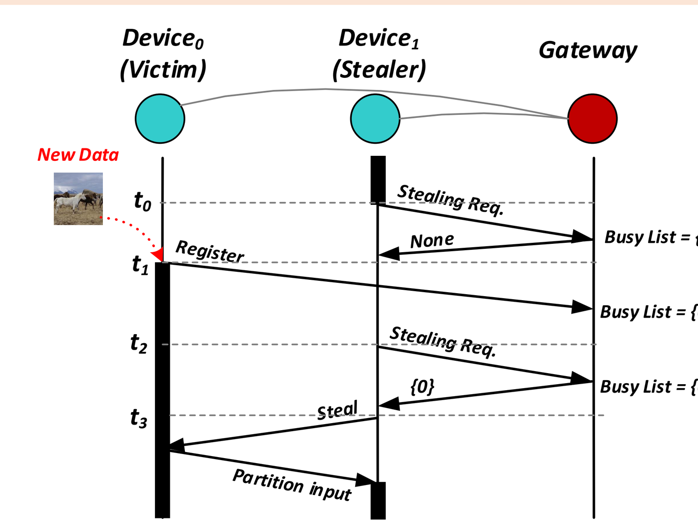
Fused Tile Partitioning (FTP)

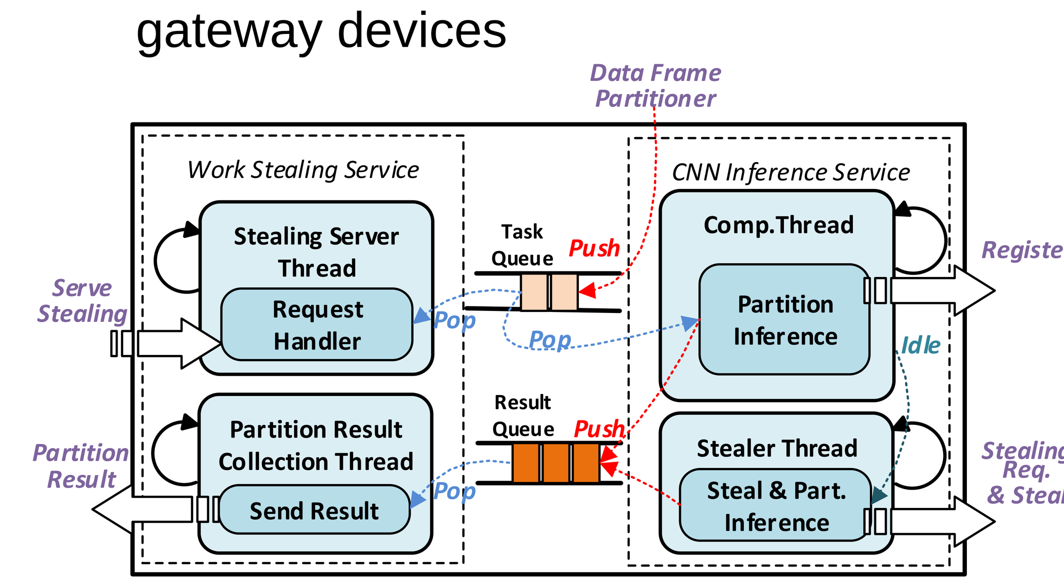
- Convolutional operation
  - Local connectivity between neurons of consecutive layers
  - ➢ Grid partitioning with boundary consideration
- Chain of multiple convolutional layers
  - Large amount of intermediate data
  - Boundary synchronization overhead per layer
  - ➢ Layer fusion
- ➢ Independent execution stacks



Distributed Work Stealing

- Distributed work stealing in local wireless area network
  - Source data partitioning & inference task generation
  - Peer-to-peer data & task migration
  - Gateway-managed load balancing
  - Local inference using external library
- Message flow between edge and gateway devices

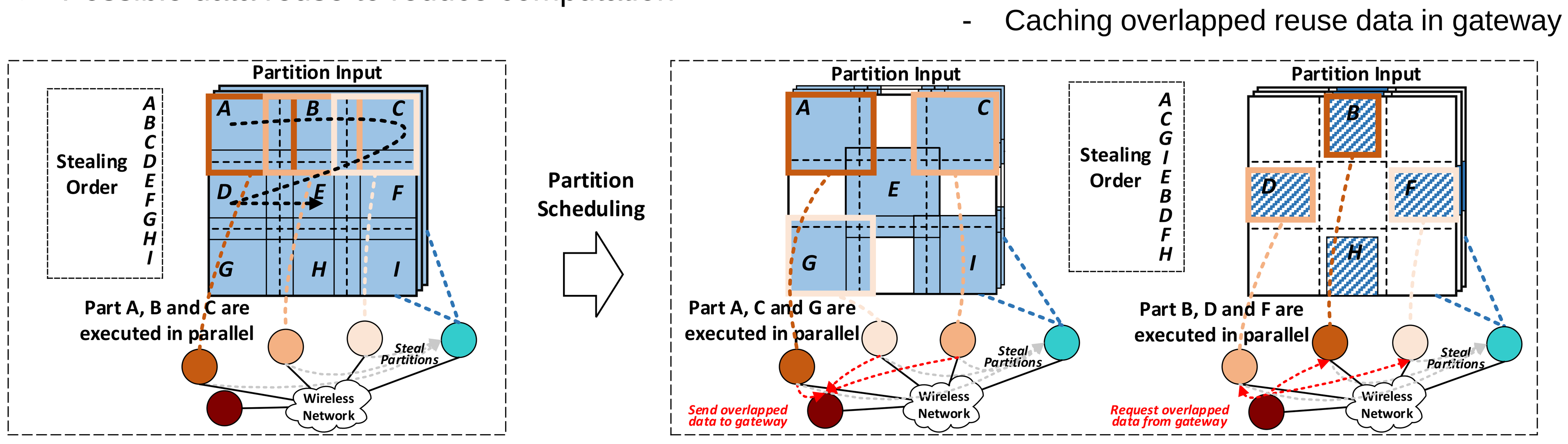




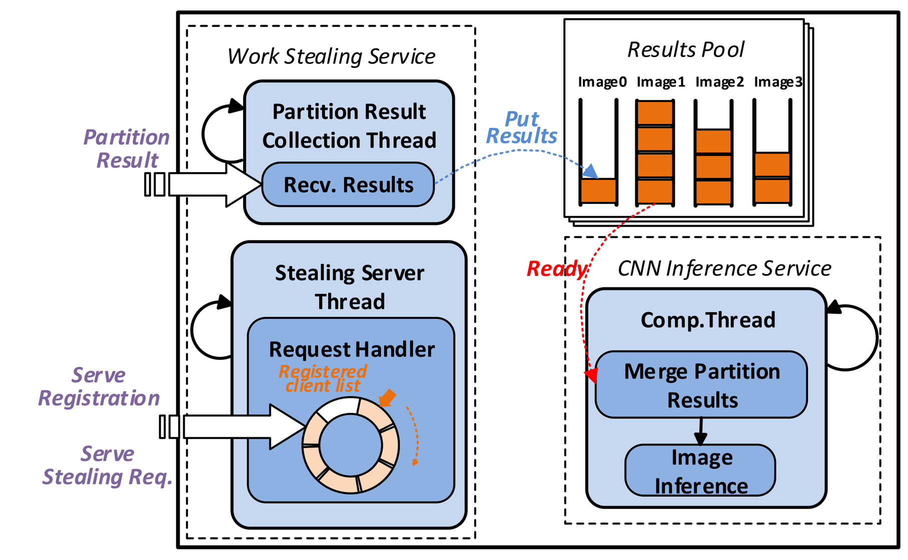
- Edge Node Runtime
  - Work stealing service
    - Serve work stealing
    - Send results to gateway
  - CNN inference service
    - Partition data frames
    - Process partitioned data
    - Perform work stealing

Data Reuse-Aware Work Scheduling

- Redundancy in Fused Tile Partitioning
  - Duplicated overlapped data for independent sub-tasks
  - Overlapped data amplified through many fused layers
  - ➢ Possible data reuse to reduce computation
- FTP partition scheduling
  - Minimize the partition dependency
    - Scheduling tasks to be stolen in dependency order
    - Caching overlapped reuse data in gateway



- Gateway Runtime
  - Work stealing service
    - Round-robin scheduling
    - Collect results from edge nodes
  - CNN inference service
    - Merge FTP partition results
    - Process remaining layers



Experimental Results

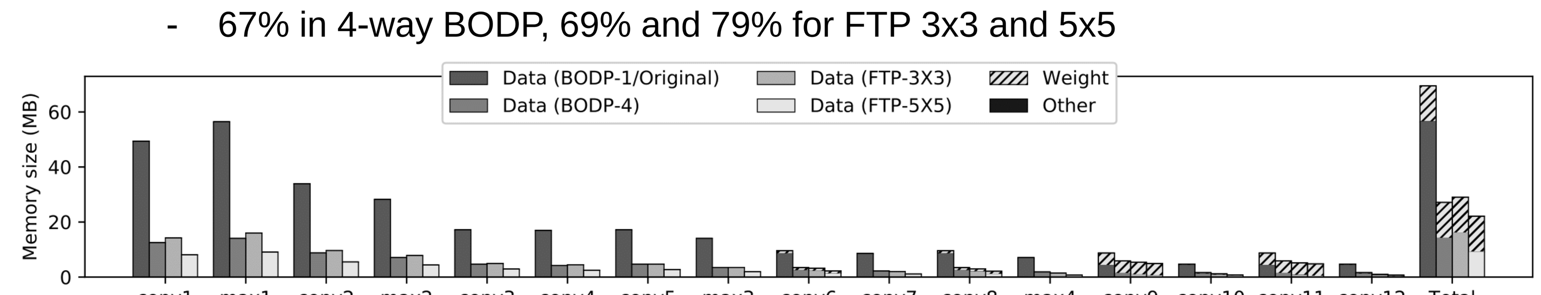
Experimental Setup

- Open-source framework
  - Retargetable implementation in C
  - TCP/IP socket APIs
  - Released in open-source form
- Experiment platform
  - Raspberry Pi 3 Model B
  - Up to 6 nodes in WLAN over WiFi
- Deep leaning application
  - You Only Look Once object detector
  - First 16 layers
  - Multiple data sources
- Experimental parameters

	DeepThings	MoDNN
Partition Method	Fused Tile Partitioning (FTP)	Biased One-Dimensional Partition (BODP)
Partition Dimensions	3x3 ~ 5x5	1x1 ~ 1x6
Distribution Method	Work Stealing (WST) Work Sharing (WSH)	Work Sharing (WSH)
Edge Node Number	1 ~ 6	

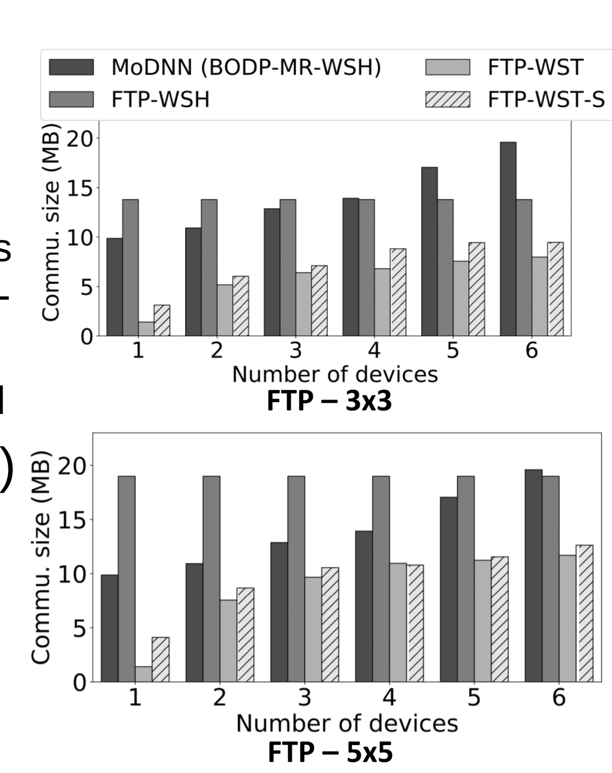
Memory Footprint

- Per device memory footprints of each layer
  - Maximum memory usage reduction
    - 61% in 4-way BODP, 58% and 68% for FTP 3x3 and 5x5
  - Average memory footprint reduction per layer
    - 67% in 4-way BODP, 69% and 79% for FTP 3x3 and 5x5



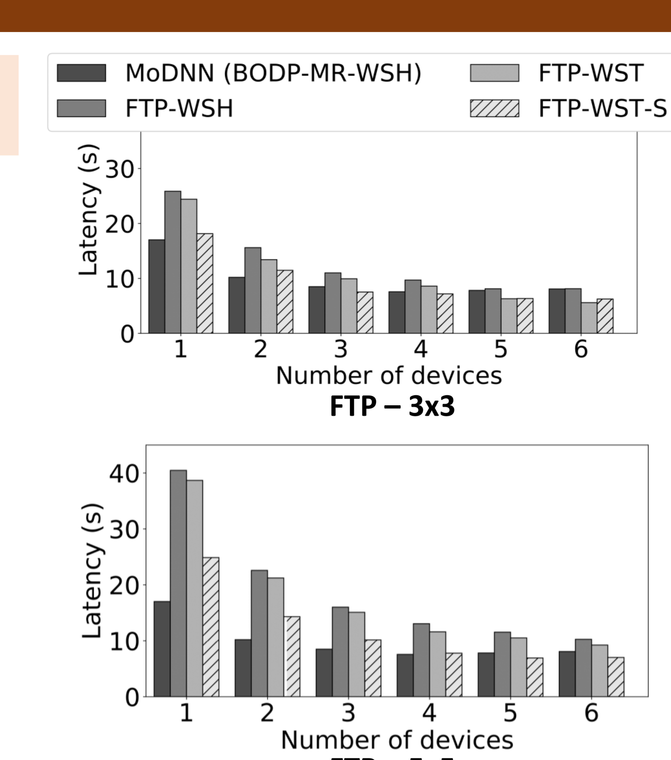
Communication Overhead

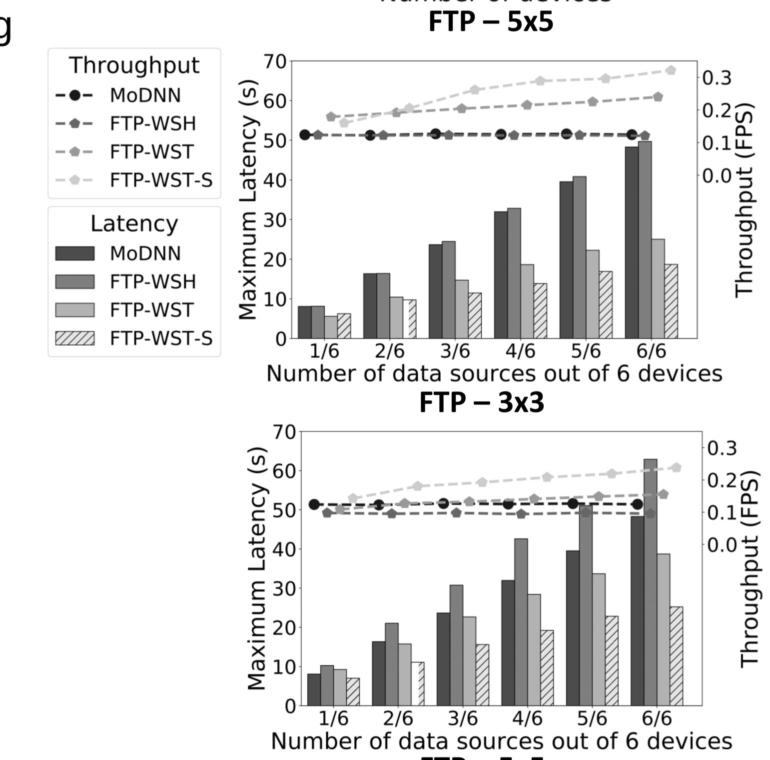
- Work sharing (WSH)
  - MoDNN: Communication overhead increases linearly with device number because of layer-based data exchange
  - FTP-WSH: Communication overhead is fixed
- Work stealing with scheduling (WST-S)
  - An average of 52% reduction comparing with WSH
  - Overhead in data reuse, amortized by smaller input data



Latency & Throughput

- Single data source
  - 6.8s with 3.5x speedup in FTP-WST-S, 6-device network
  - 8.1s with 2.1x speedup MoDNN, 6-device network
  - Scalability benefits in DeepThings
    - FTP: Avoid intensive intermediate data exchange
    - WST: Adaptively use communication bandwidth and exploit communication overhead
  - Data-reuse aware scheduling reduces 27% latency
- Multiple data sources
  - Maximum latency
    - MoDNN: proportional with number of sources
    - FTP-WST-S: 3.1x with data source(s) increasing from 1 to 6
  - Throughput
    - MoDNN: 0.12 FPS with 6 data sources
    - FTP-WST-S: 0.29 FPS with 6 data sources





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