

# Computation Offloading Scheduling for Deep Neural Network Inference in Mobile Computing

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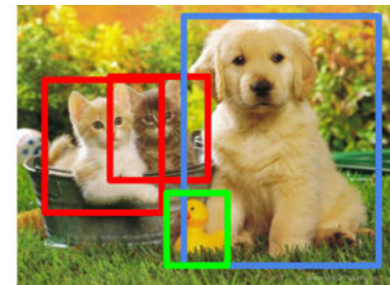
# Outline

1. Introduction
2. Model
3. Tree-structure DNN Scheduling
  - Path-wise scheduling
  - Layer-wise scheduling
4. Scheduling for DAG-Style DNNs
5. Experiment
6. Conclusions

# 1. Introduction

- DNN inference in mobile applications

- Image classification
- Object detection



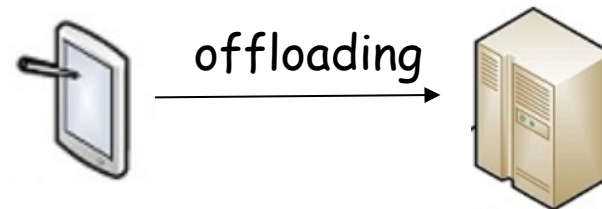
CAT, DOG, DUCK

- QoS measurement

- Inference latency

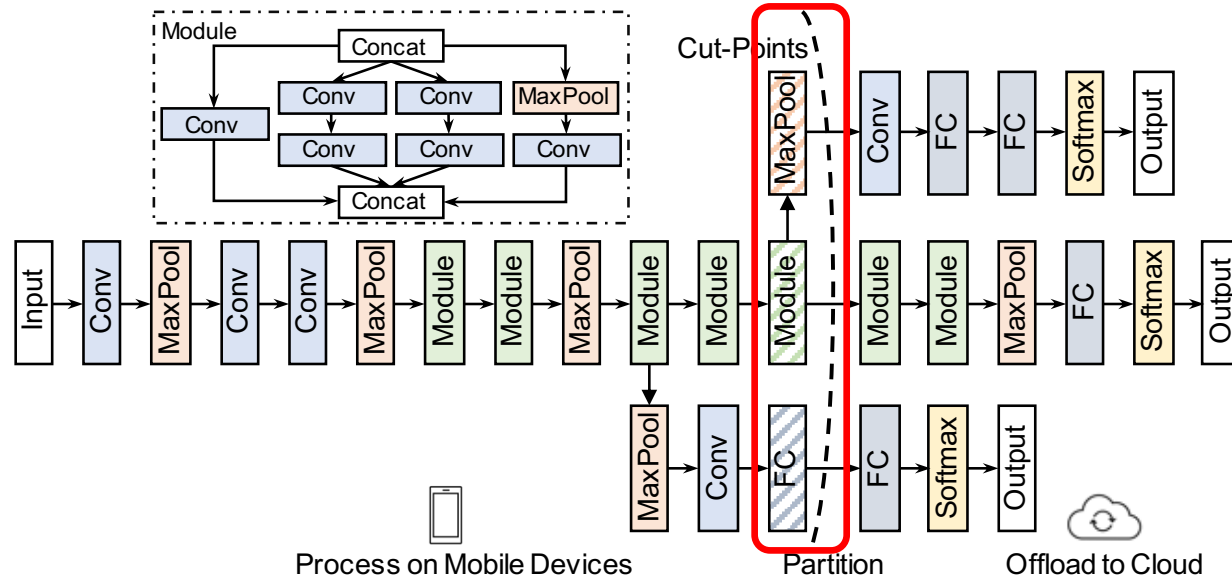
- Cooperative DNN inference

- Computation offloading



# Motivation

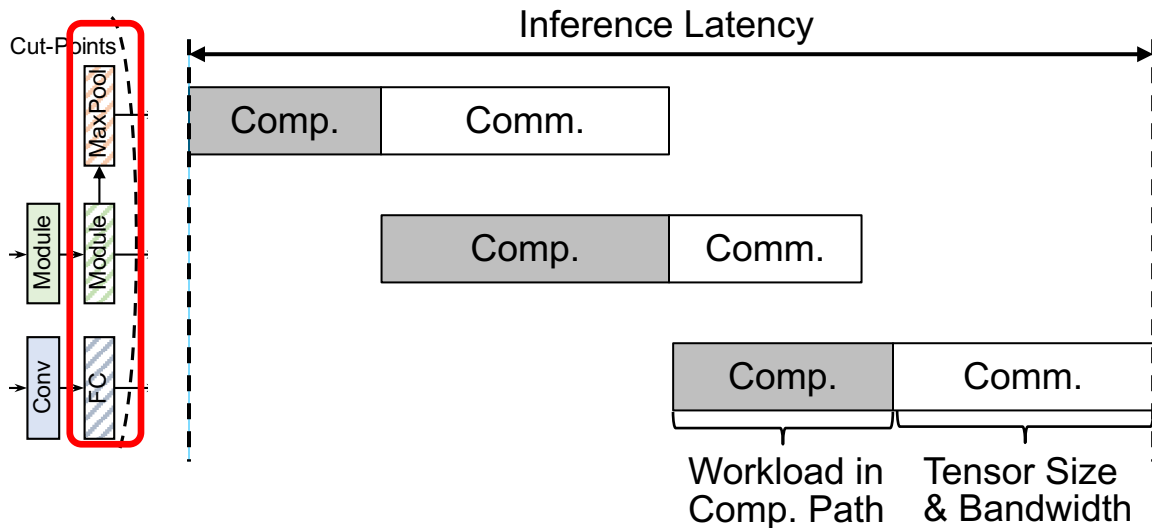
- Offloading pipeline
  - May have multiple offloading subtasks



- Scheduling problem
  - Computation and communication priorities

# 2. Model

- Two-stage offloading pipeline



- Comp.: process DNN layers from input to cut-points
- Comm.: upload intermediate results to cloud servers
- Cloud processing time is negligible

# Problem Formulation

- Objective

- Minimize inference latency for a given DNN

$$\min_{\sigma} \tau = t_{|S|} - t_0$$

- Recursive calculation of the completion time

$$t_i = \max\{t_0 + \sum_{k=1}^i f(x_k), t_{i-1}\} + g(x_i), \forall x_i \in \sigma$$

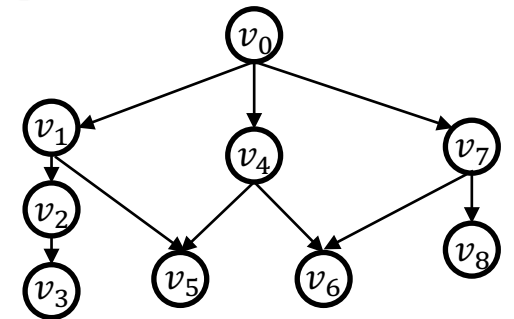
- Constraints

- Precedence constraint

$$i \leq j, \forall x_i \prec x_j, \forall x_j \in \sigma$$

- Permutation constraint

$$\cup_{x_i \in \sigma} x_i = S, |\sigma| = |S|$$



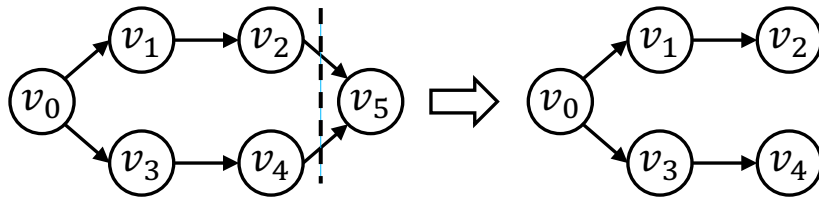
↓ Schedule

$$\sigma = [x_0, x_1, \dots, x_8]$$

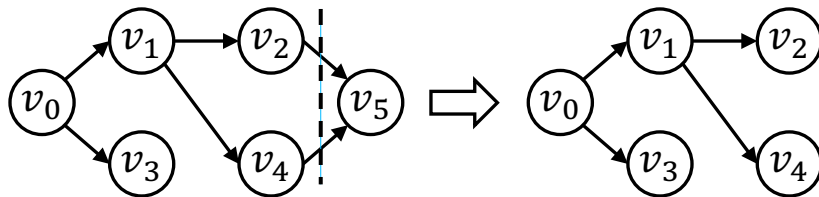
A permutation of  $\{v_0, \dots, v_8\}$

# DNN Structures after Partition

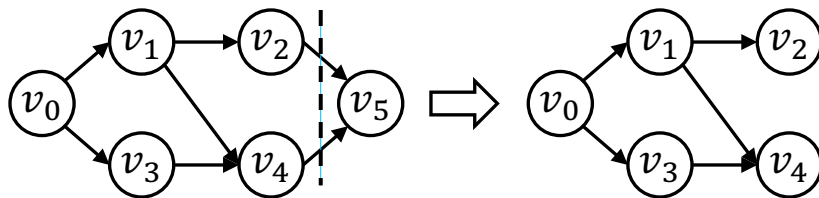
- Tree-structure
  - Multi-path tree



- General tree



- DAG

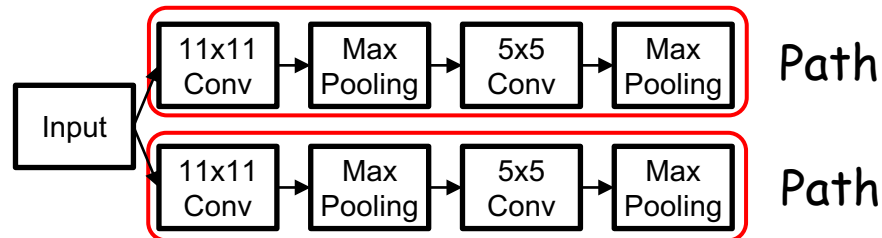


# 3. Tree-structure DNN Scheduling

- Scheduling granularities

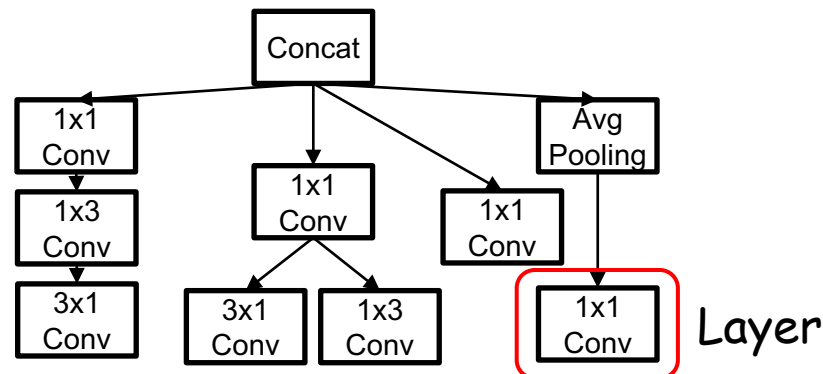
- Path-wise scheduling

- Can be optimally solve by applying Johnson's rule



- Layer-wise scheduling

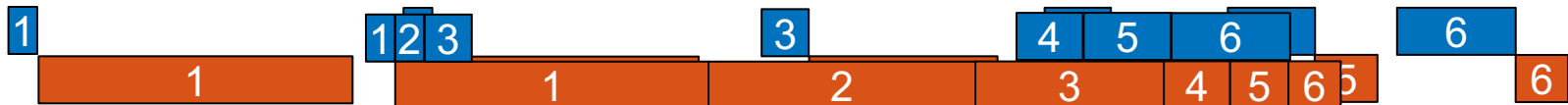
- Extend Johnson's rule for the optimal solution





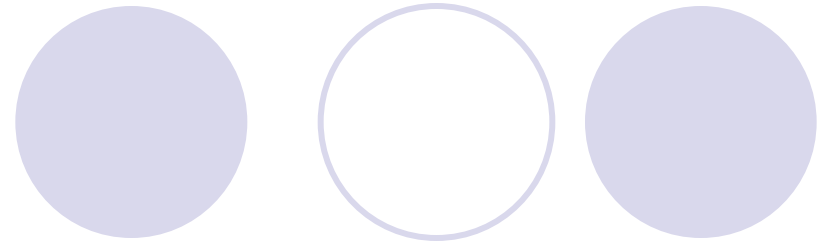
# Path-wise Scheduling

- Optimal scheduling with Johnson's rule
  - Each path is a task with two operations
  - Split tasks into comm./comp.-domination groups
  - $H = \{1, 2, 3\}$ , increasing order of **comp.**
  - $L = \{4, 5, 6\}$ , decreasing order of **comm.**

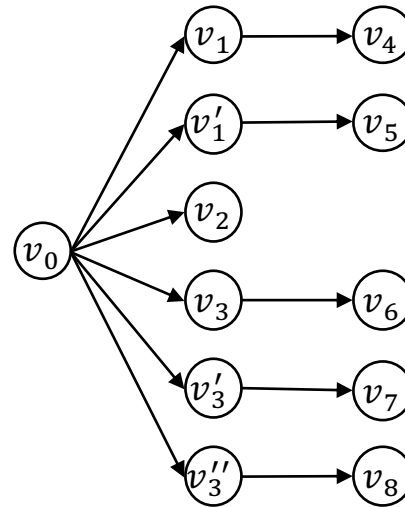
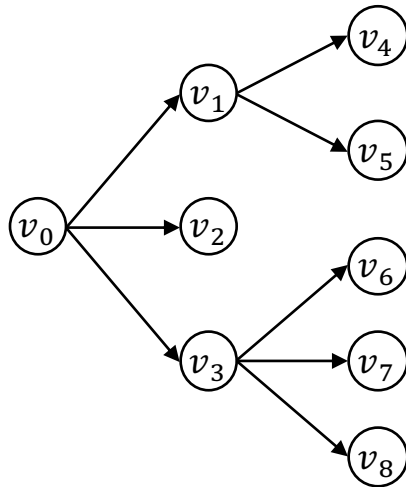


- Can extend to any structures with conversion

# DAG Conversion

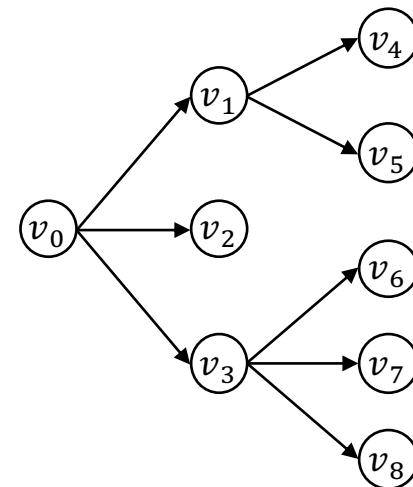


- Apply path-wise scheduling on arbitrary DNNs
  - Breadth-first search on graph
  - Duplicate each internal nodes
  - Avoid re-processing duplicated layers in inference



# Layer-wise Scheduling

- For arbitrary tree-structure DNNs
  - Johnson's rule + conversion is suboptimal
  - Challenge: precedence constraints
- Recursively merge schedules of subtrees
  - Schedule of a subtree:
    - **list** covering all its node
  - At internal nodes:
    - **Merge** lists of children nodes
    - **Group** it with head of the merged list
  - Johnson's rule for comparisons



# Layer-wise Scheduling



- Property

Theorem 1: The schedule generated by the recursive merging approach is optimal for tree-structure DAGs.

- Proof

- Sketch : mathematical induction

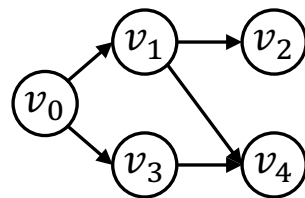
- Merging and grouping will not lose optimal schedule

- Insights:

- Merging preserve the precedence constraints
- For nodes without precedence constraints, Johnson's rule finds their optimal schedule

# 4. Scheduling for DAG-Style DNNs

- More complex precedence constraints
  - DAG scheduling is NP-hard
  - Inspired by **topological sort**
    - Iteratively sort nodes with no successors with Johnson's rule
    - Scheduled nodes are removed from the DAG



↓ Schedule

$$\sigma = [v_0, v_1, v_3, v_4, v_2]$$

# 5. Experiment



- Prototype implemented with PyTorch
  - gRPC is used for offloading
  - PyTorch Profiler is used to measure comp. time
- DNNs used in evaluation
  - Alex-Parallel<sup>[1]</sup>: multi-path tree
  - GoogleNet<sup>[2]</sup>: tree
  - Multi-Stream Network<sup>[3]</sup>: tree
  - RandWire<sup>[4]</sup>: DAG

[1].K. He et. al., "Deep residual learning for image recognition," in IEEE CVPR, 2016, pp. 770-778

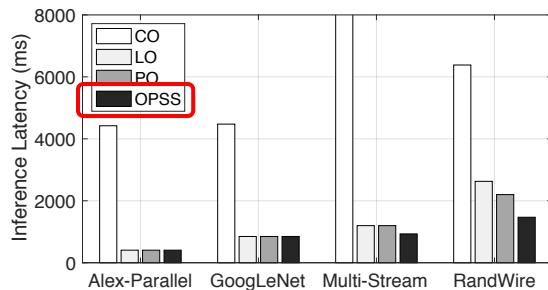
[2].C. Szegedy et. al., "Going deeper with convolutions," in IEEE CVPR, 2015, pp. 1-9.

[3].Y.-W. Chao, et. al., "Learning to detect human-object interactions," in IEEE WACV, 2018, pp. 381-389.

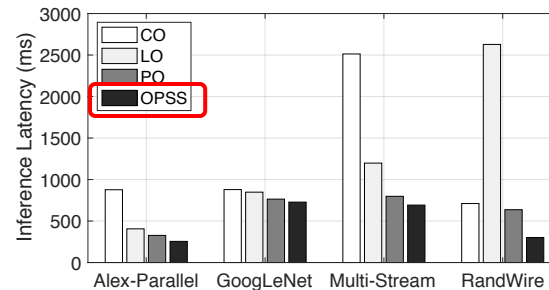
[4].S. Xie, et. al., "Exploring randomly wired neural networks for image recognition," in IEEE ICCV, 2019, pp. 1284-1293.

# Experiment Results

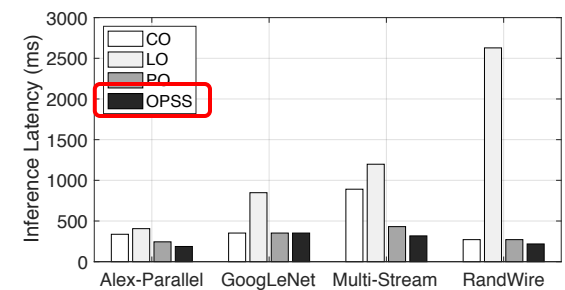
- Latency on different network environment  
(CO: Cloud-Only, LO: Local-Only, PO: Partition-Only)



3G

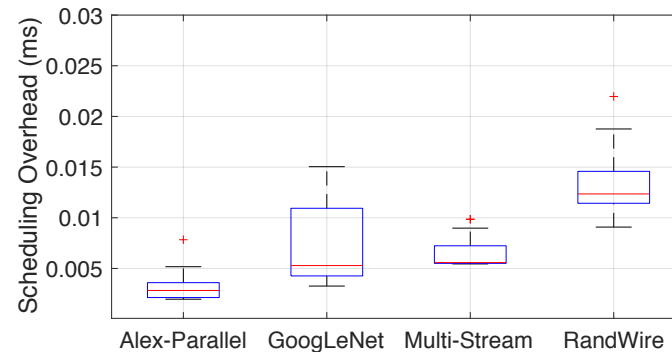


4G



Wi-Fi

- Scheduling overhead



# 6. Conclusion



- Proposed an **offloading pipeline**
  - Hide comm. time behind comp.
- Optimal **path-wise** scheduling
  - Intend for trees with **multi-paths**
  - Can apply to arbitrary DNNs with **conversion**
- Optimal **layer-wise** scheduling
  - Can apply to arbitrary **tree-structure** DNNs
  - Recursively merge schedule lists
- Evaluation on a **prototype** system



# Questions



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