IOS: Inter-Operator Scheduler for CNN Acceleration

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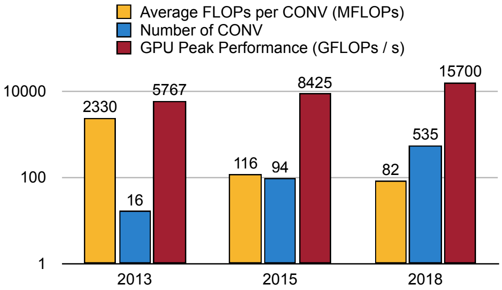
Introduction

GPU Under-utilization in CNN

A recent trend in CNN design is to replace a single branch of convolutions with multiple branches of convolutions. As a result, the number of convolutions grows while the computation FLOPs in each convolution becomes smaller.



Existing Approaches

- **Intra-operator parallelism** (TVM) executes arithmetic operations within a single operator in parallel. However, the degree of parallelism within an operator is limited, especially when the `Conv` operations are becoming smaller.
- **Graph transformation** (MetaFlow, TASO) explores merging and substituting operators to enable more parallelism. However, the possible merging are limited to same type of operators.
- **Inter-operator scheduling** (Graphi, Rammer, Nimble) schedules some operators to run concurrently. However, they use simple heuristics and don't lead to global optimal.

IOS: Inter-Operator Scheduler

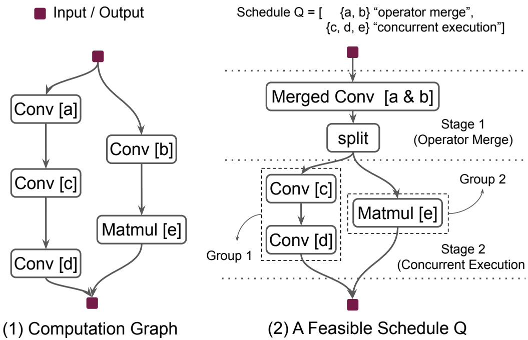
This paper introduces **IOS**, a novel **dynamic programming** algorithm to find a highly optimized schedule for **inter-operator parallelization**.

Problem Definition

Graph and Stage

A CNN is defined as a DAG $G = (V, E)$, where V is the set of operators, and E is the edge set representing dependencies.

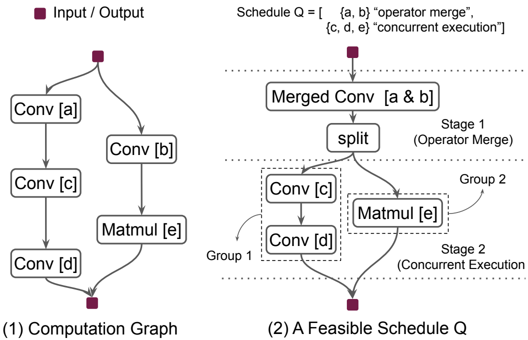
The computation graph is partitioned into multiple **stages**. Stages are executed sequentially and the operators in the same stage are executed according to a certain **parallelization strategy**.



Parallelization Strategy

Operator merge merges multiple operators of the **same type** together. For example, an 3x3 `Conv` can be merged with a 5x5 `Conv`, by padding and concatenating the kernels.

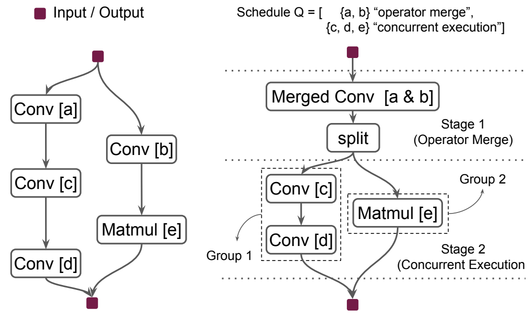
Under **concurrent execution**, the operators in the stage that have no dependencies are executed concurrently with multiple CUDA streams.



Schedule

A Schedule $Q = \{(S_1, T_1), (S_2, T_2), \dots\}$ is an assignment of operators S_i to the i-th stage and the parallelization strategy T_i of the i-th stage.

IOS finds a schedule Q^* that minimizes a cost function c for a given graph G, i.e., $Q^* = \text{argmin}_Q c(G, Q)$. In this work, c is defined as the latency of running G following schedule Q.



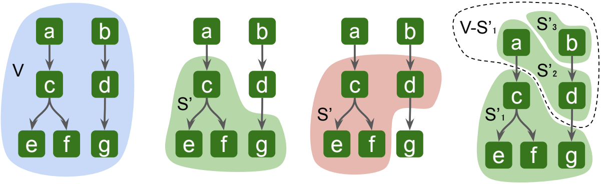
(1) Computation Graph (2) A Feasible Schedule Q

Methods

Main Idea

For an **ending** S' of S, we have:

$$\text{cost}[S] = \min_{S'}(\text{cost}[S - S'] + \text{stage\_latency}[S'])$$



(1) Operators V

(2) S' is an ending of V

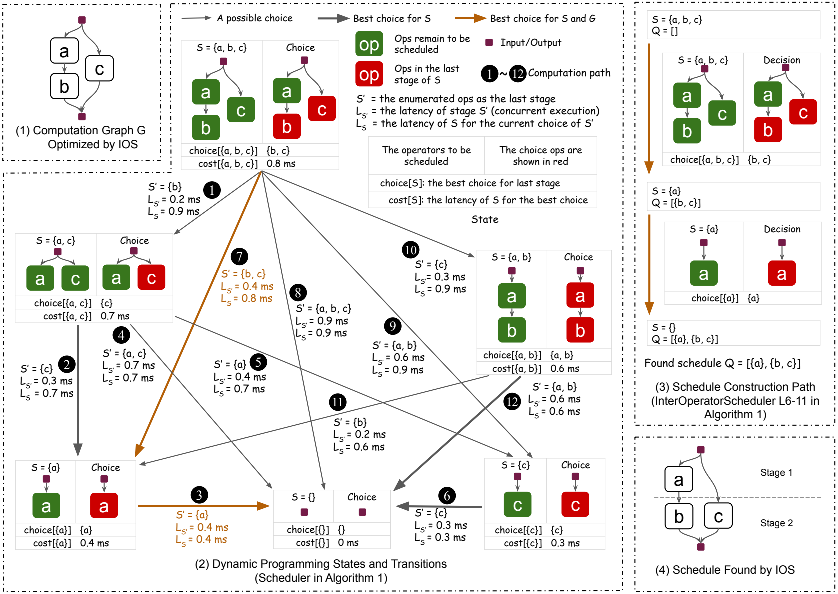
(3) S' is **not** an ending of V

(4) Partition graph by endings recursively

Core Function

function $\textsc{Scheduler}(S)$
    if $\text{cost}[S] \neq \infty$ **then**
        return $\text{cost}[S]$
    for all ending S' of S satisfying pruning strategy P **do**
        $L_{S'}, T_{S'} = \textsc{GenerateStage}(S')$
        $L_S = \textsc{Scheduler}(S - S') + L_{S'}$
        if $L_S < \text{cost}[S]$ **then**
            $\text{cost}[S] = L_S$
            $\text{choice}[S] = (S', T_{S'})$
    return $\text{cost}[S]$

Example



(1) Computation Graph G Optimized by IOS

(2) Dynamic Programming States and Transitions (Scheduler in Algorithm 1)

(3) Schedule Construction Path (InterOperatorScheduler L6-11 in Algorithm 1)

(4) Schedule Found by IOS

Time Complexity

Definition: d is the width of G, if we can find at most d operators in G such that there is no path connecting any two of them.

Theorem: The time complexity of IOS is $\mathcal{O}(\binom{n/d+2}{2}^d)$, which can be relaxed to $\mathcal{O}((n/d+1)^{2d})$, where n is the number of operators in G and d is its width.

Model	n	d	$\binom{n/d+2}{2}^d$	$\#(S, S')$	#Schedules
Inception V3	11	6	2.6×10^4	4.9×10^3	3.8×10^6
Randwire	33	8	3.7×10^9	1.2×10^6	9.2×10^{22}
NasNet	18	8	5.2×10^6	3.1×10^5	7.2×10^{12}
SqueezeNet	6	3	2.2×10^2	51	1.3×10^2

Pruning

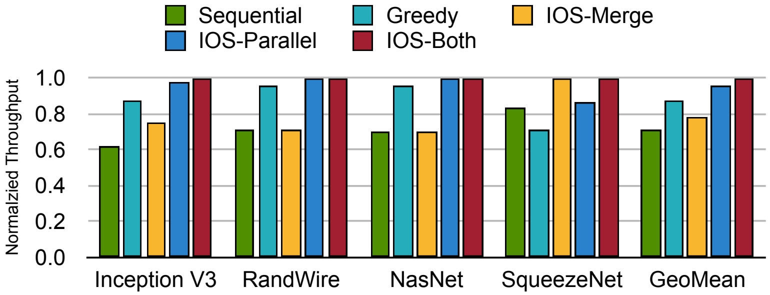
IOS without pruning can find the optimal strategy for the benchmarked graphs in 4 hours. To further reduce the search time, IOS introduces two parameters r and s. $P_{r,s}(S, S') =$ True if and only if S' has at most s groups and each group has at most r operators.

Evaluation

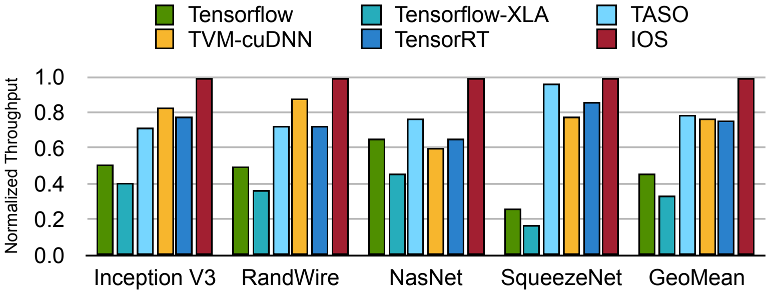
Experiments Setup

- Hardware: NVIDIA Tesla V100
- Execution Engine: A cuDNN-based C++ execution engine.
- Models: Inception V3, RandWire, NasNet-A, and SqueezeNet
- Baselines: TensorRT and TVM
- Pruning Parameters: $r = 3$ and $s = 8$

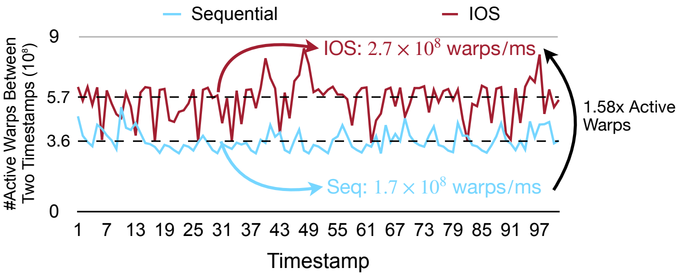
Comparison of Different Schedules



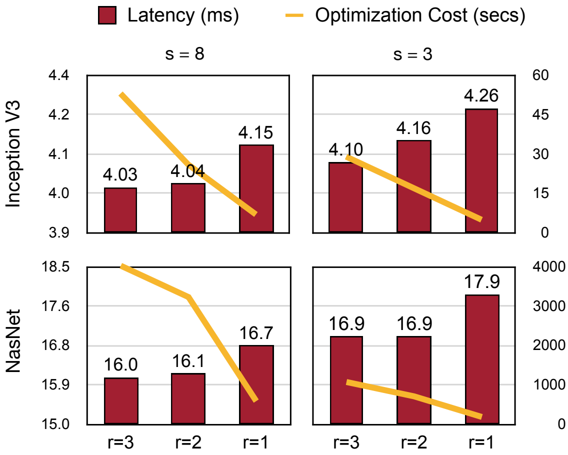
Comparison of cuDNN-based Frameworks



More Active Warps Improve Utilization



Schedule Pruning Reduces Search Time



Specialized Scheduling is Beneficial

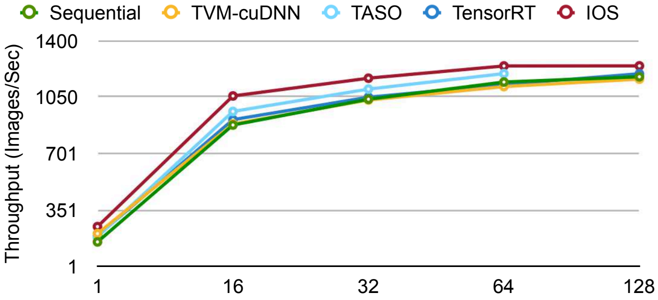
Specialization for Different Batch Sizes		Optimized for		
		1	32	128
Execute on	1	**4.03**	4.50	4.63
	32	29.21	**27.44**	27.93
	128	105.98	103.74	**103.29**

(1) Specialization for Batch Sizes

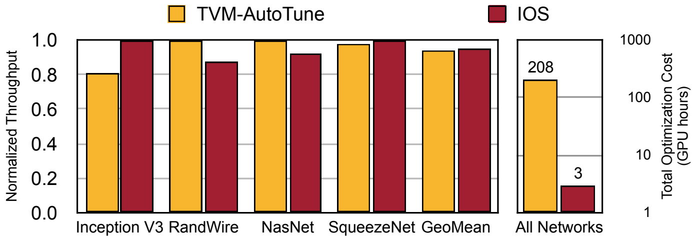
Specialization for Different Devices		Optimized for	
		K80	V100
Execute on	K80	**13.87**	14.65
	V100	4.49	**4.03**

(2) Specialization for Devices

Consistent Improvement for Different Batch Sizes



Intra- and Inter-Operator Parallelism



Summary

Conclusion

Strength

- IOS introduces the concept of **stage**, which enables dynamic programming.
- The algorithm description is detailed and the open-sourced code is clean.

Limitation

- The paper omits the detail about the profiler. IOS needs the cost of running multiple operators concurrently, which is not easy to simulate.
- The strategy space is very limited (compared with related works).
- They do not compare with similar works (Rammer etc.) in experiments.

Takeaways

- Dynamic programming works well with the DAG structure of neural networks. Other works have explored using dynamic programming for saving memory, distributed training, etc.
- We can design a reduced search space and use an efficient algorithm to find the global optimal.

Thank you!