# Mainstream: Adaptive compute sharing for video analysis

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### Overview

#### Goal:

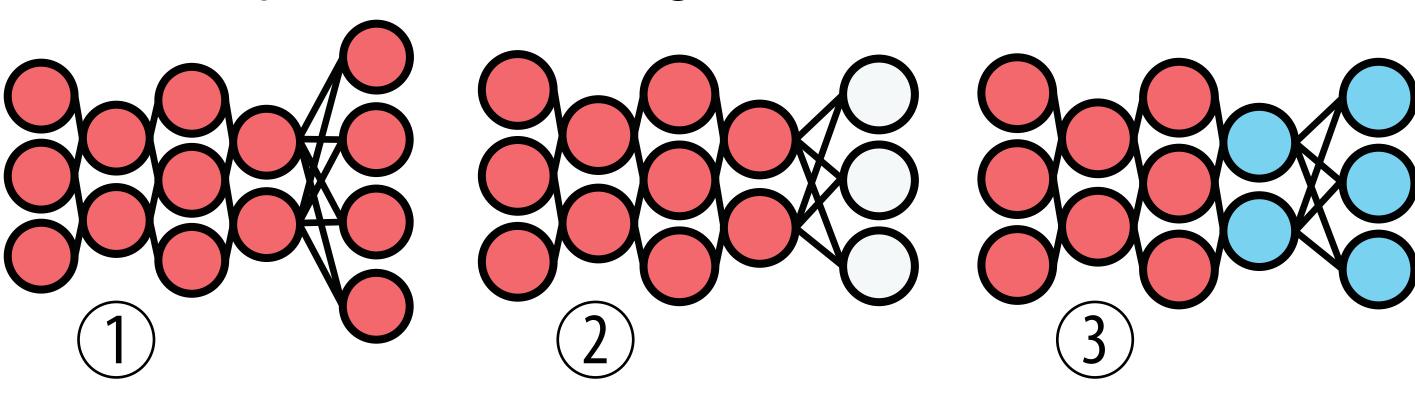
- Efficiently run concurrent streaming video analysis apps **Problem:** 
  - Most video analysis apps perform DNN inference
  - Running several full DNNs becomes very slow

#### **Mainstream:**

- Identifies and shares redundant DNN computation
- By exploiting nature of fine-tuned DNNs
- Decides at runtime how much to share
  - Balances specialization vs. sharing trade-off
  - Optimizes when hardware and set of apps is known

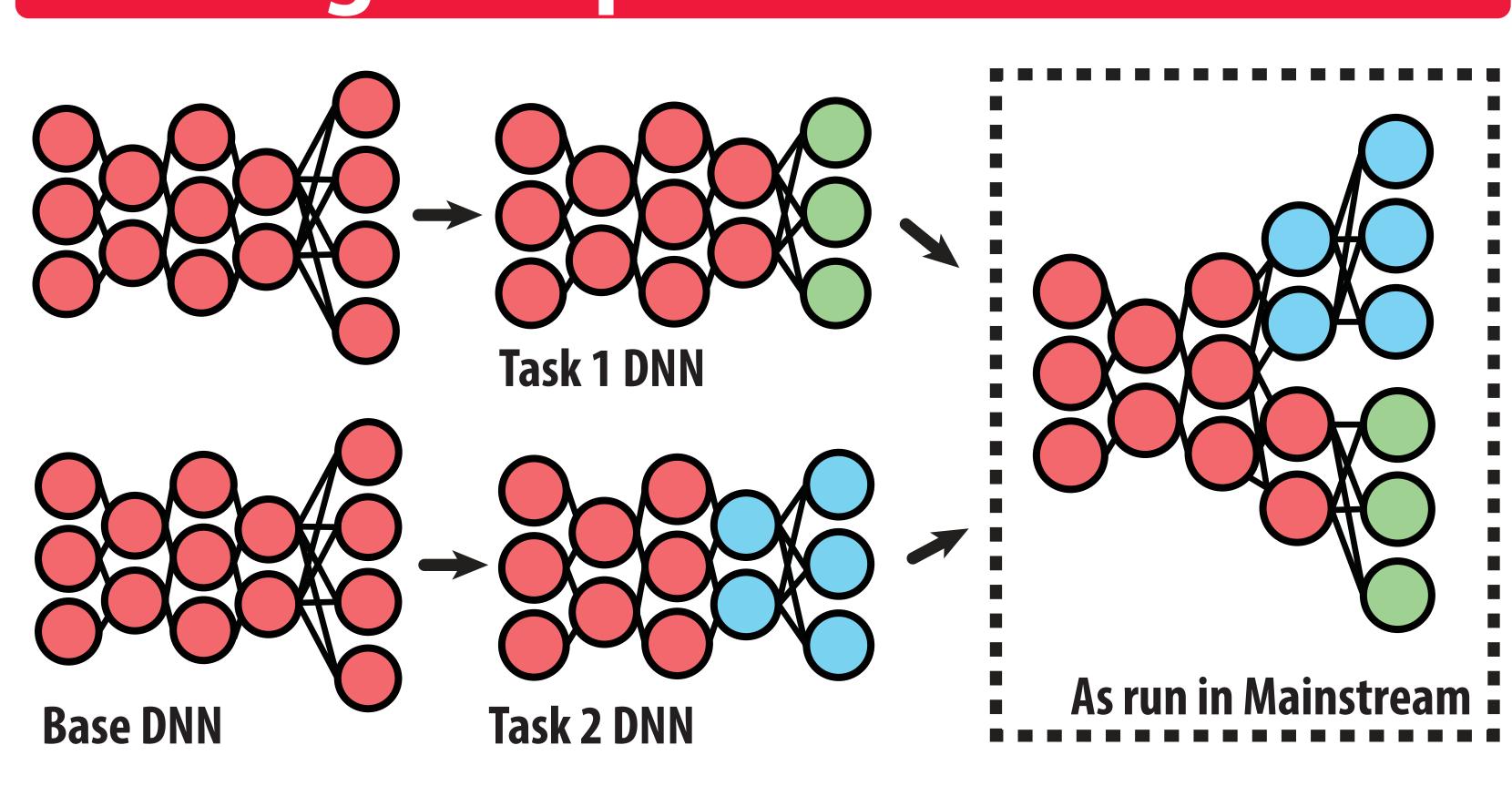
# Transfer Learning

- When training task B, use DNN pre-trained for task A
  - Common practice for training networks

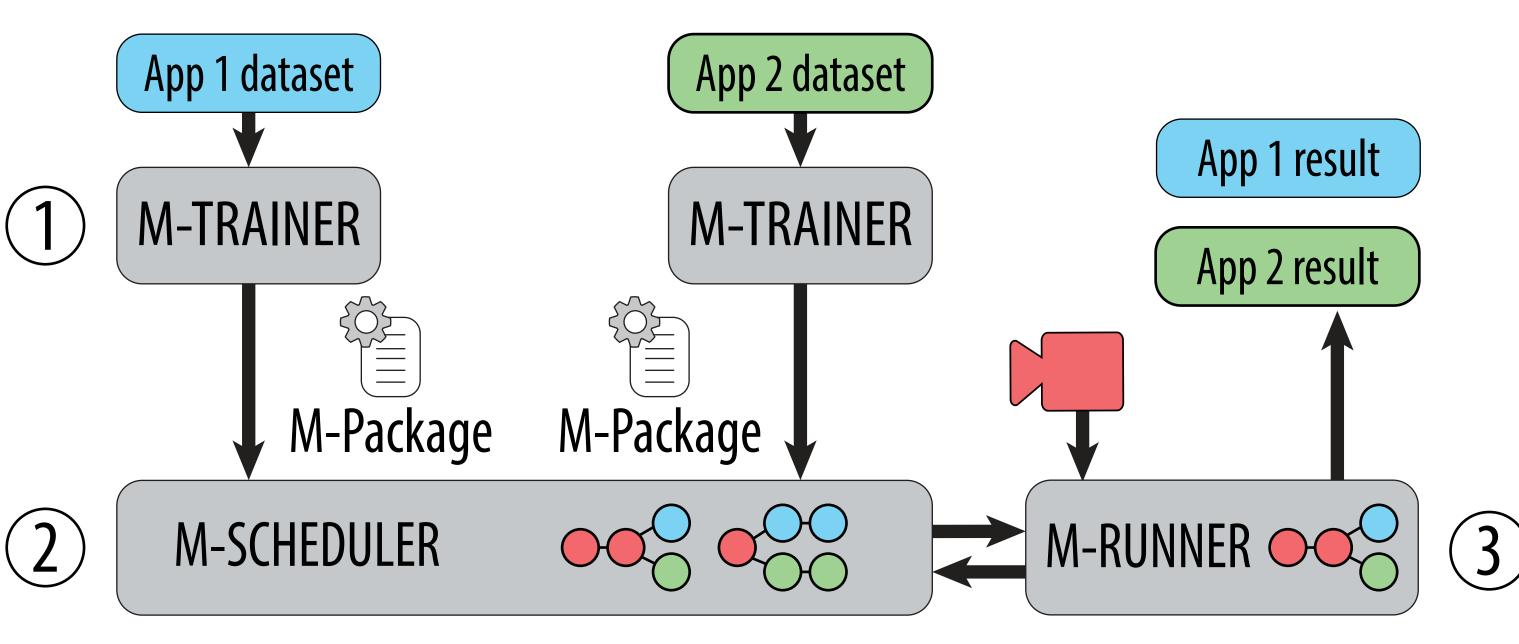


- 1. Network is trained from scratch for task A (e.g., ImageNet)
- 2. Replace A-specific final layer with B-specific final layer
- 3. Fine-tune part of network for task B, other layers held frozen

# **Sharing Computation**



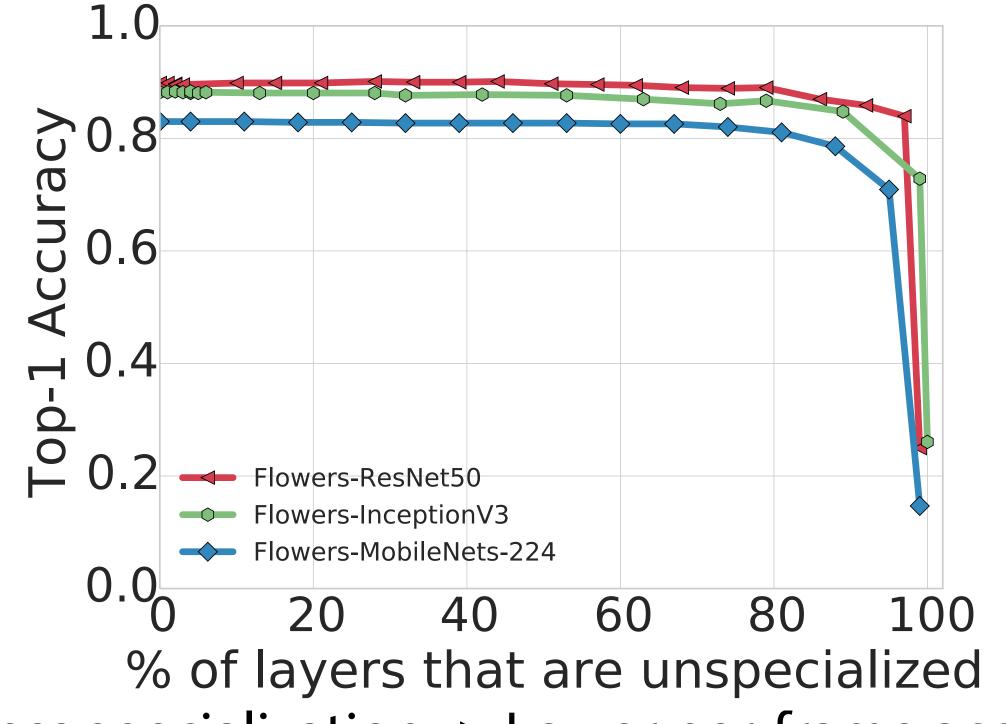
### Mainstream Architecture



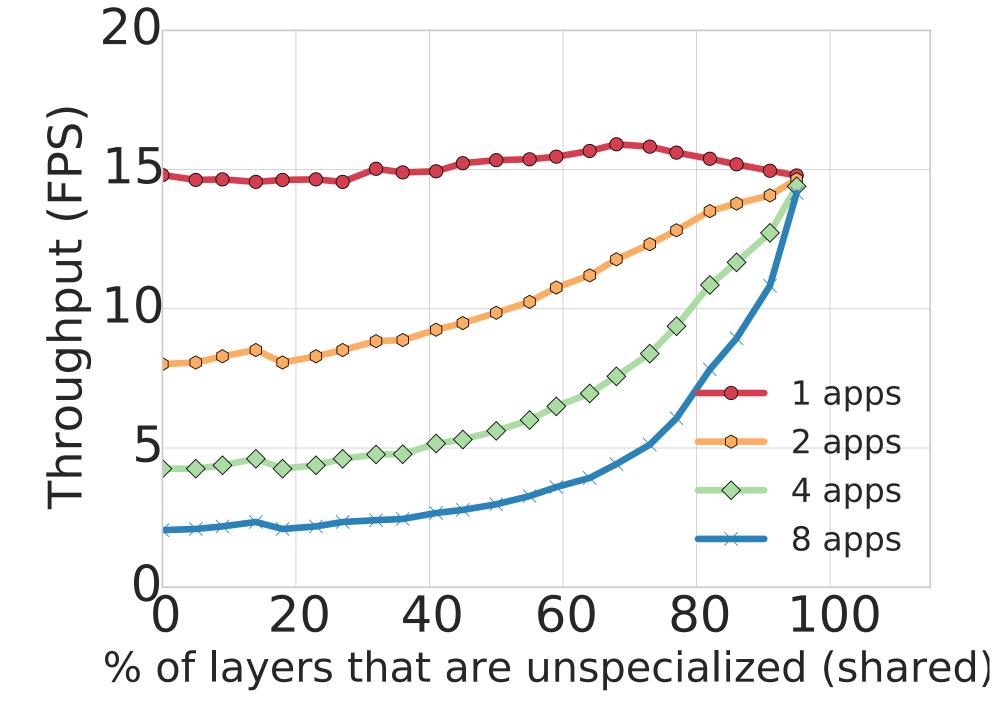
- 1. M-trainer trains DNNs with varying % of network held frozen
- 2. M-Scheduler determines amount of DNN to share for each app
- 3. M-Runner processes video stream using deployed DNNs

## Specialization vs. Sharing Trade-off

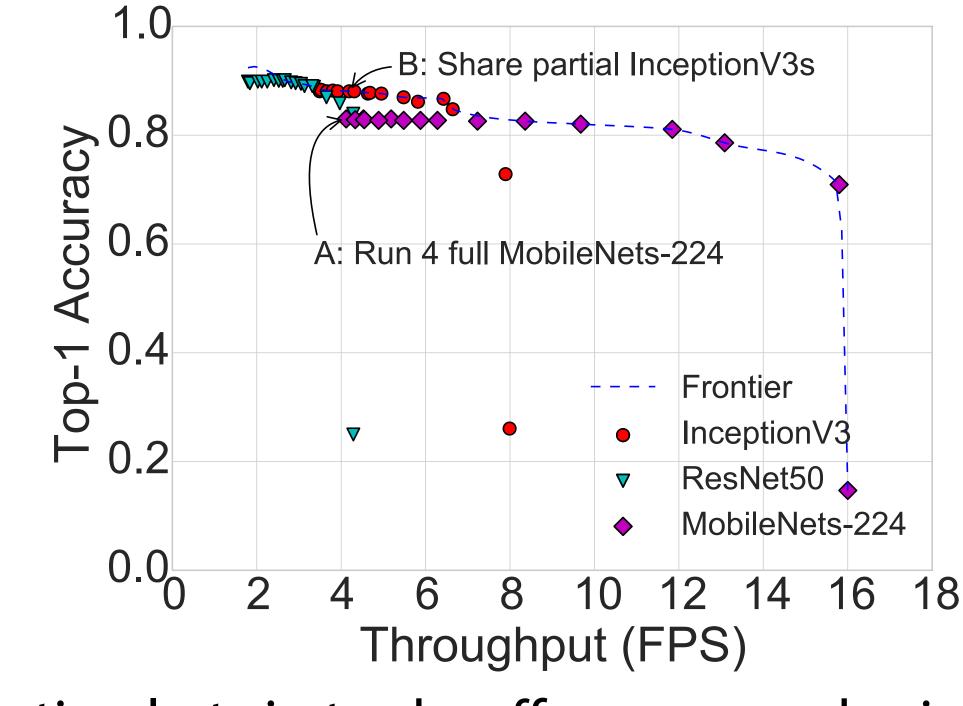
Experimental setup: Train image classifiers to recognize flowers. Run simulatenous classification pipelines on an Intel NUC.



Less specialization -> Lower per-frame acc.



Less specialization -> Higher throughput



Optimal pts in trade-off space use sharing

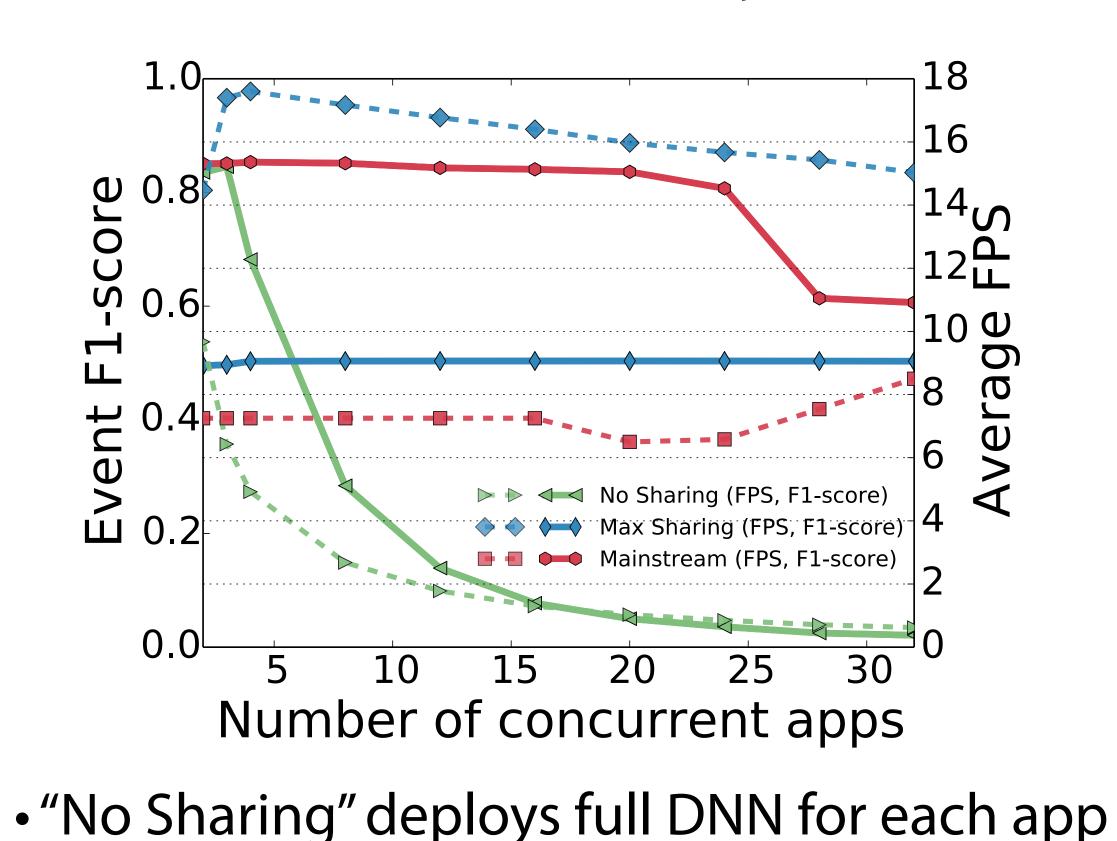
## **Application Performance**

Recall: % of events detected;

**Precision:** % of detected events that are correct;

recision

F1 score: Harmonic mean of precision and



- Recall Event 0.0 Number of concurrent apps
- "No Sharing" (NS) has low FPS, high acc.
- "Max Sharing" has high FPS, low acc.
- Mainstream gives up to 28X higher F1

" Max Sharing"shares all but final layer

