MAINSTREAM: DYNAMIC STEM-SHARING FOR MULTI-TENANT VIDEO PROCESSING

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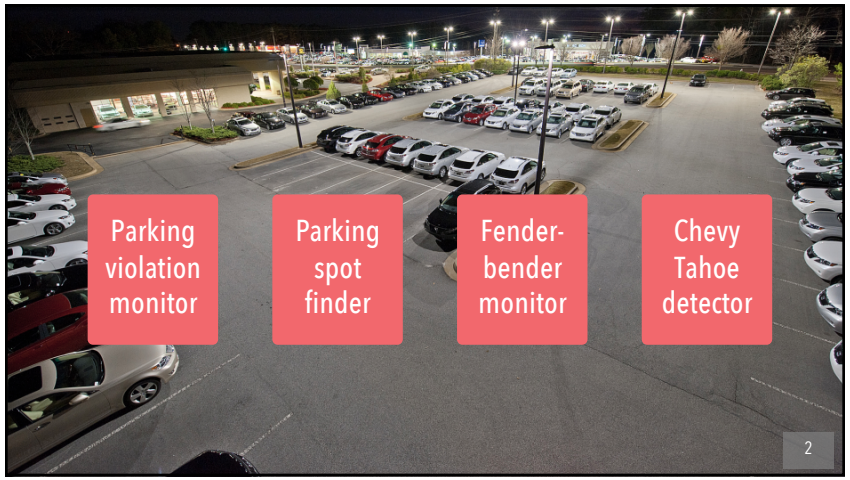

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MAINSTREAM CHALLENGES AND SOLUTIONS

❗ Concurrent DNN inference is slow

✓ Mainstream shares redundant computation

❗ Deployed apps are tuned in isolation and offline

✓ Mainstream dynamically tunes DNNs at runtime

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MAINSTREAM TAKEAWAYS

1. Enables efficient processing of set of apps
   By sharing redundant computation
2. Dynamically tune degree of specialization at runtime
3. Up to 87x improvement in F1-score
   Compared to No Sharing
4. Up to 47% improvement in F1-score
   Compared to Max Sharing

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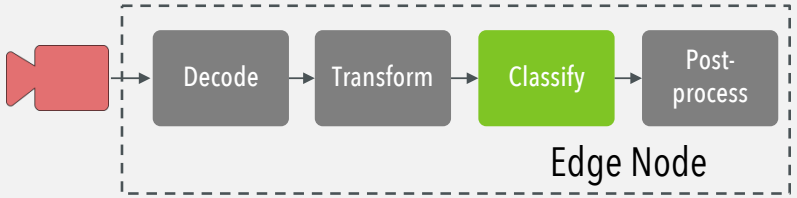
EXAMPLE VIDEO ANALYSIS PIPELINE



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DNN IS PRIMARY COST OF PIPELINE

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DNN IS PRIMARY COST OF PIPELINE

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IN MAINSTREAM: PARTIAL SHARING OF 3 DNNS

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HOW TO FIND REDUNDANCY BETWEEN DNNS?

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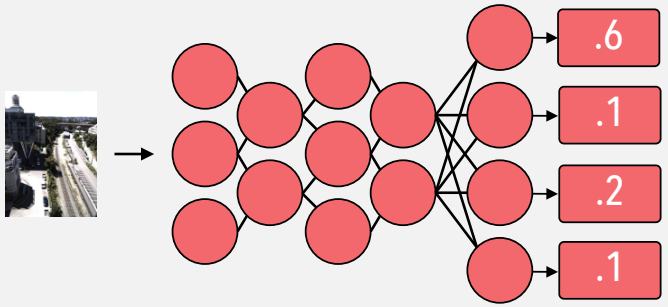
BASIC DNN



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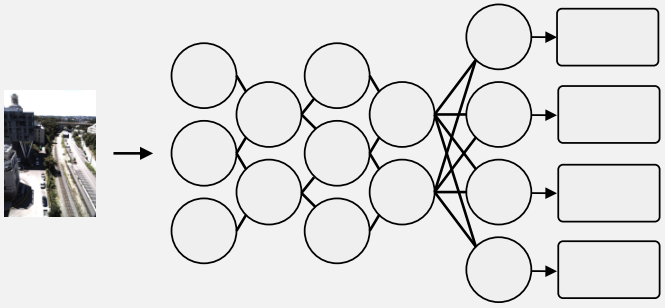
TRAINING A DNN



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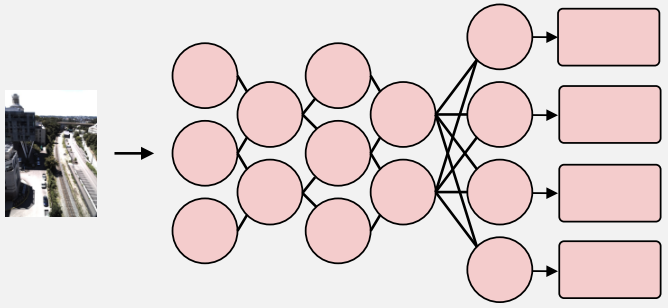
TRAINING A DNN



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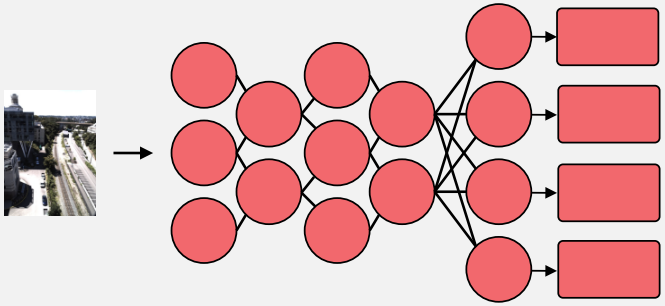
TRAINING A DNN



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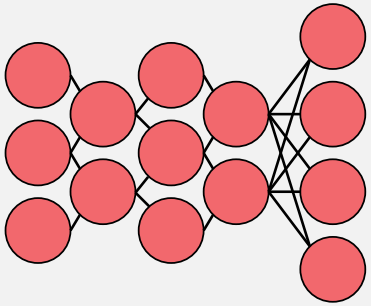
FINE-TUNING DNN #1



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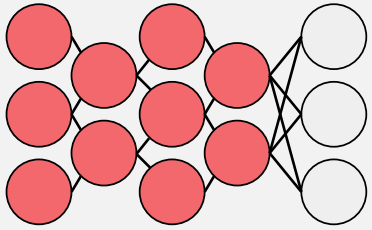

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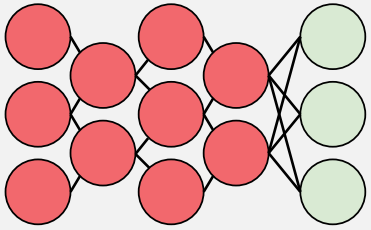
FINE-TUNING DNN #1



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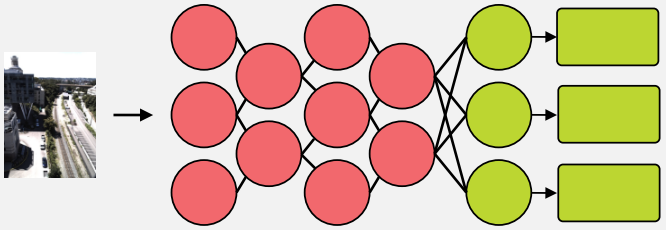
FINE-TUNING DNN #1



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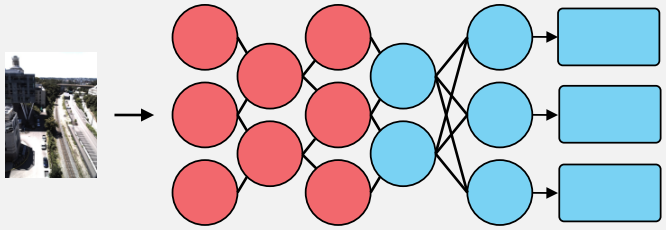
FINE-TUNING DNN #2



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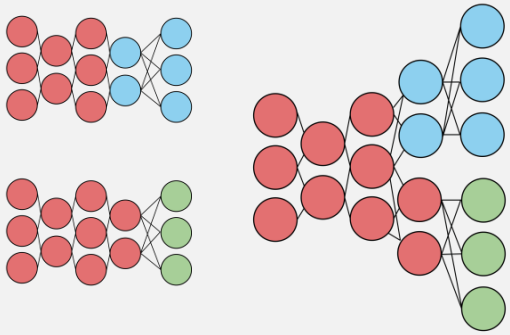
FINE-TUNING DNN #1



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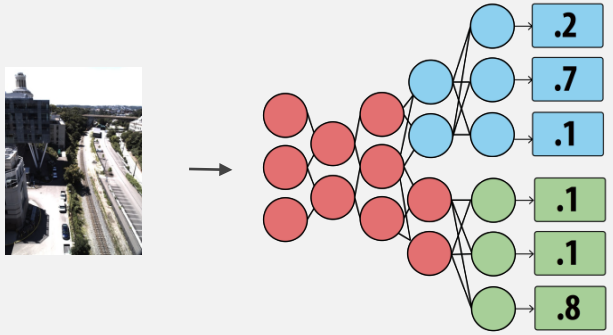
TWO DNNS AS RUN IN MAINSTREAM



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MAINSTREAM'S APPROACH

1. Merge video stream processing of concurrent apps
   By sharing redundant layers
2. Dynamically tune degree of specialization at runtime
   Based on available resources, other applications
   Maximize application effectiveness

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PERFORMANCE TRADE-OFFS FROM SPECIALIZATION

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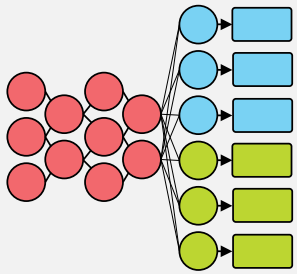
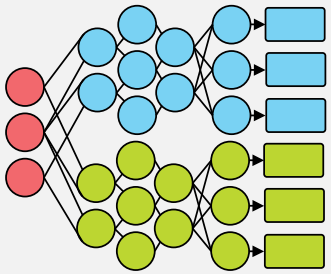


More sharing = Higher throughput



More specialization = Higher per-frame acc.

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HOW DO WE MEASURE APPLICATION PERFORMANCE?

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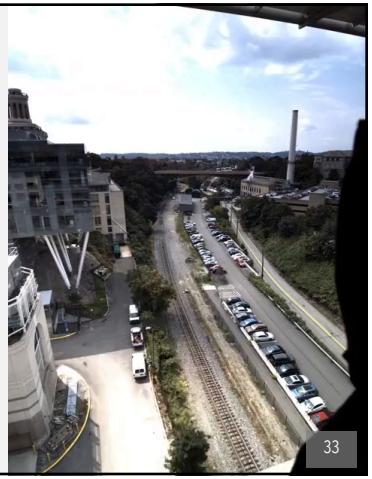
APPLICATION EXAMPLE: EVENT DETECTION



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GOAL: MAXIMIZE EVENT F1-SCORE

Event-Recall How many relevant events are detected?
Event-Precision How many detected events are relevant?
Event-F1 score Harmonic mean between precision and recall

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EFFECT OF ACCURACY AND FPS ON F1-SCORE

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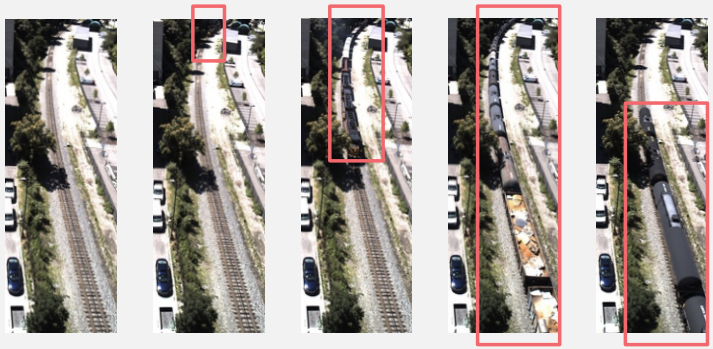

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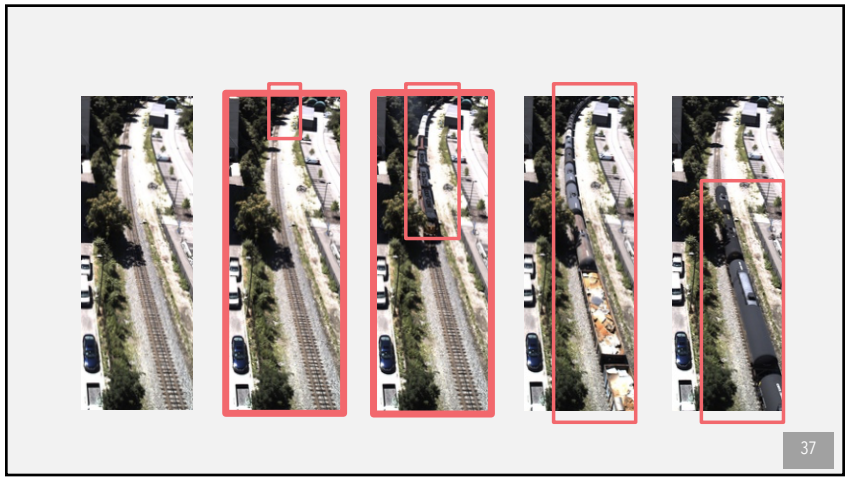
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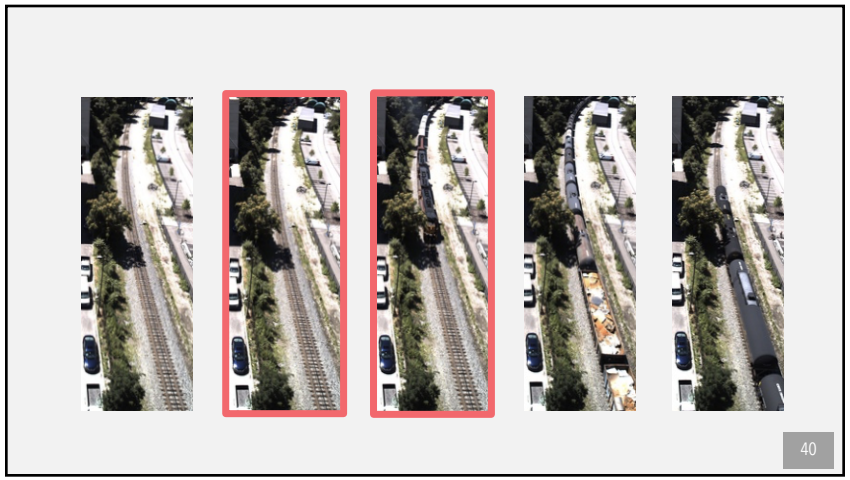
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MAINSTREAM ARCHITECTURE

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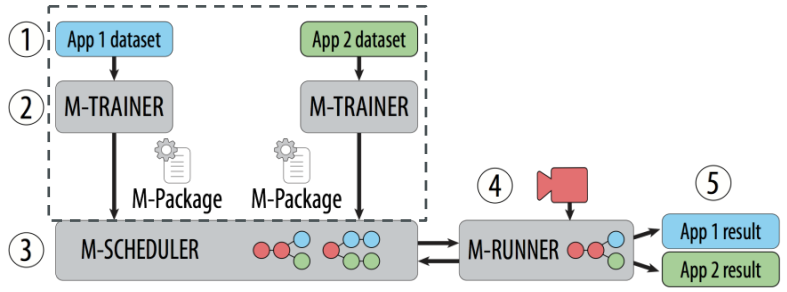

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MAINSTREAM RESULTS

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EXPERIMENTAL SETUP

Run concurrent image classification pipelines

Using MobileNets-224 DNNs

Tasks: Pedestrian, Bus, Red Car, Scramble, Schoolbus, Trains, Car

Hardware: Intel NUC

Video stream: 20FPS, 640x480

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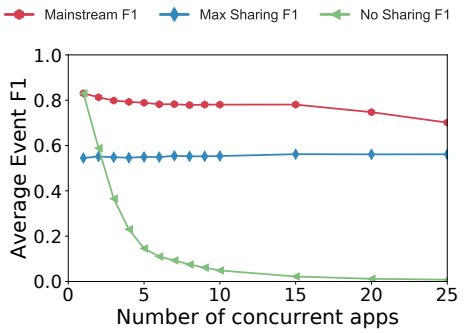
MAINSTREAM IMPROVES EVENT F1-SCORE BY 87X



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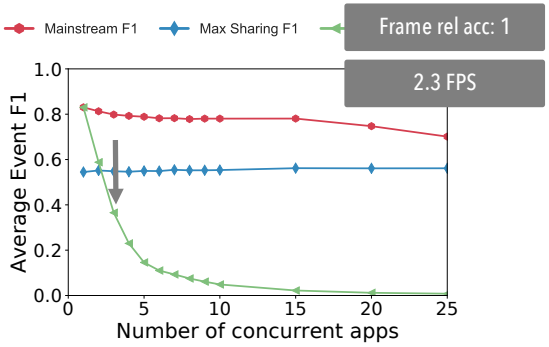

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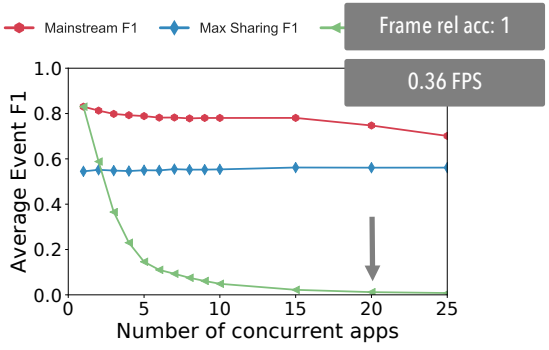

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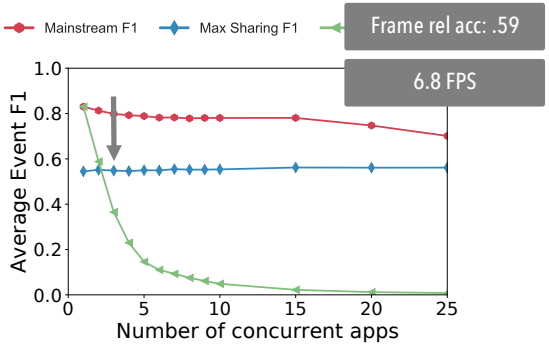

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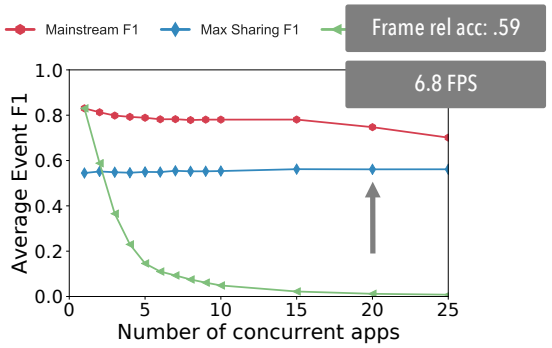

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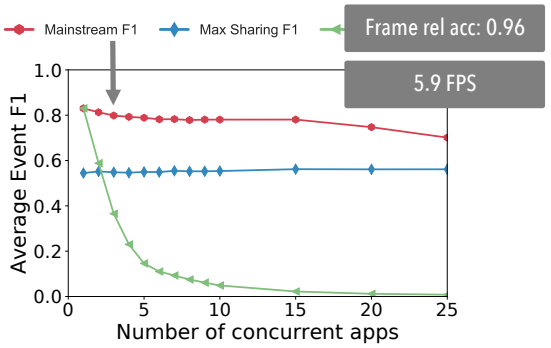

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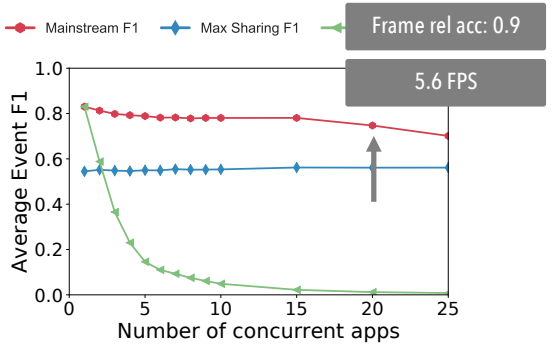

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MAINSTREAM TAKEAWAYS

1. **Enables efficient processing of set of apps**
   By sharing redundant computation
2. **Dynamically tune degree of specialization at runtime**
3. **Up to 87x improvement in F1-score**
   Compared to No Sharing
4. **Up to 47% improvement in F1-score**
   Compared to Max Sharing

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