Niagara: Scheduling DNN Inference Services on Heterogeneous Edge Processors

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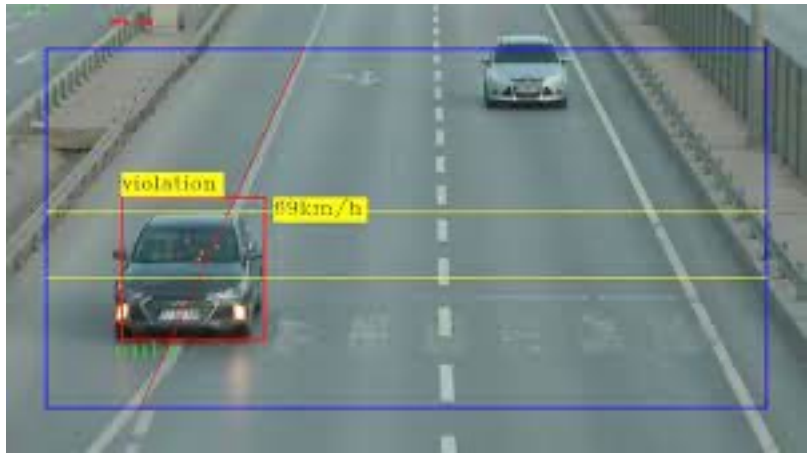
Linggui Tech Company

ICSOC 2023

Intelligent edge applications



Vehicle detection

Immersive online shopping

AR emoji

AR & VR devices

Remote healthcare devices

Smart Home Devices

Problem

Helmet/gloves wearing detection

DNN services

- Person Detection
- Pose estimation
- Gloves Detection
- Helmet Detection

- low response latency
- protect privacy
- **Low throughput problem**

Opportunities

- An edge device contains multiple **heterogeneous** processors

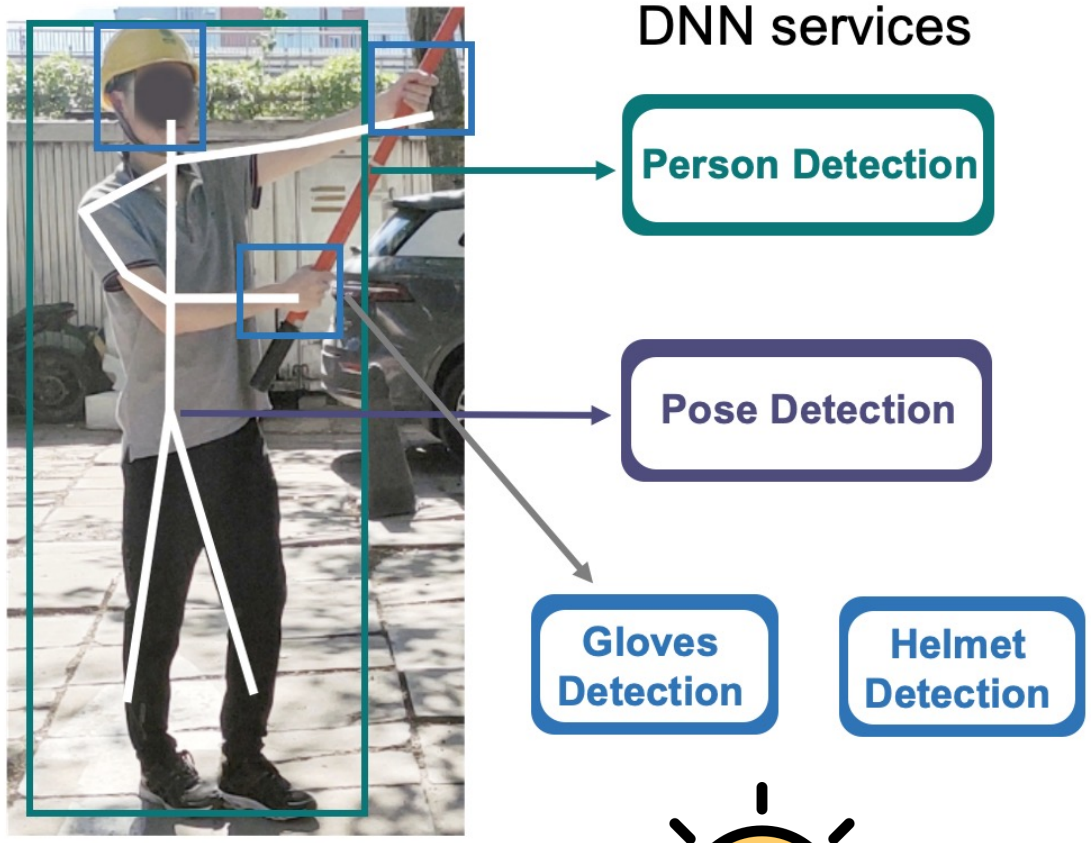
IP Cameras

Type	Processors
CPU	1- 3.0 GHz X2 + 3- 2.5 GHz Cortex A710 + 4- 1.8GHz Cortex-A510
GPU	Adreno 650
Accelerator	Hexagon 698 DSP

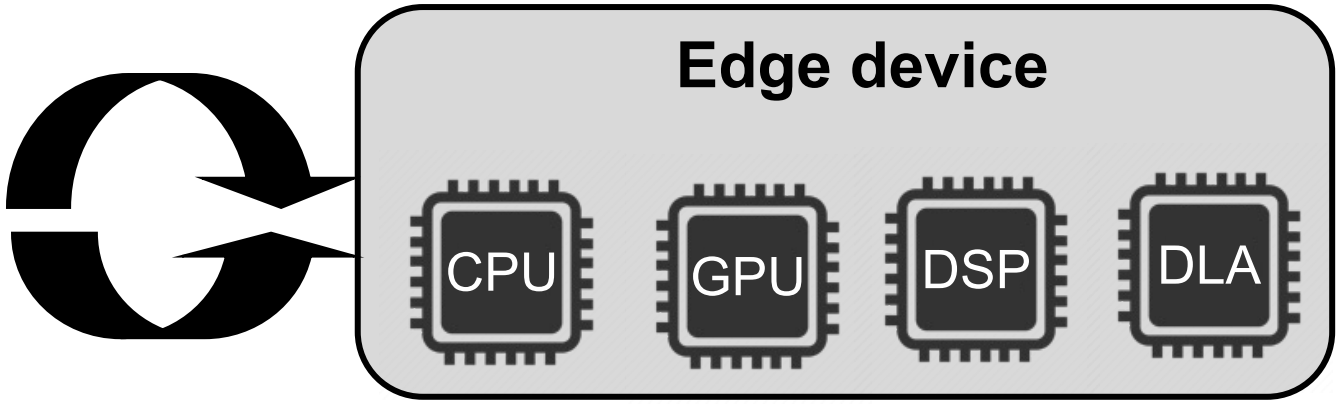
IoT devices

Type	Processors
CPU	12-core Arm Cortex-A78AE
GPU	Ampere 1024 CUDA core + 32 Tensor Cores
Accelerator	Deep learning accelerator (DLA)

Motivation



Efficient heterogeneous processors



Can we offload the DNN services to the heterogeneous processors?

Challenge#1: High complexity in scheduling design

- **DNN-inference-service-to-processor affinity and hardware support**

DNN Service	DNN Model	Latency			Utilization		
		CPU	GPU	DSP	CPU	GPU	DSP
Person detection	SSD-quant	112.1 ms	**79.9 ms**	103.1 ms	361%	56%	77%
Pose estimation	CenterNet	**22.9 ms**	31.7 ms	-	287%	30%	-
Helmet detection	SSD-Helmet-quant	25.6 ms	8.4 ms	**5.9 ms**	195%	58%	85%
Gloves detection	Pole-gloves	6.7 ms	**3.2 ms**	-	198%	34%	-
Text recognition	OCR-recognition	**30.8 ms**	38.1 ms	-	295%	35%	-

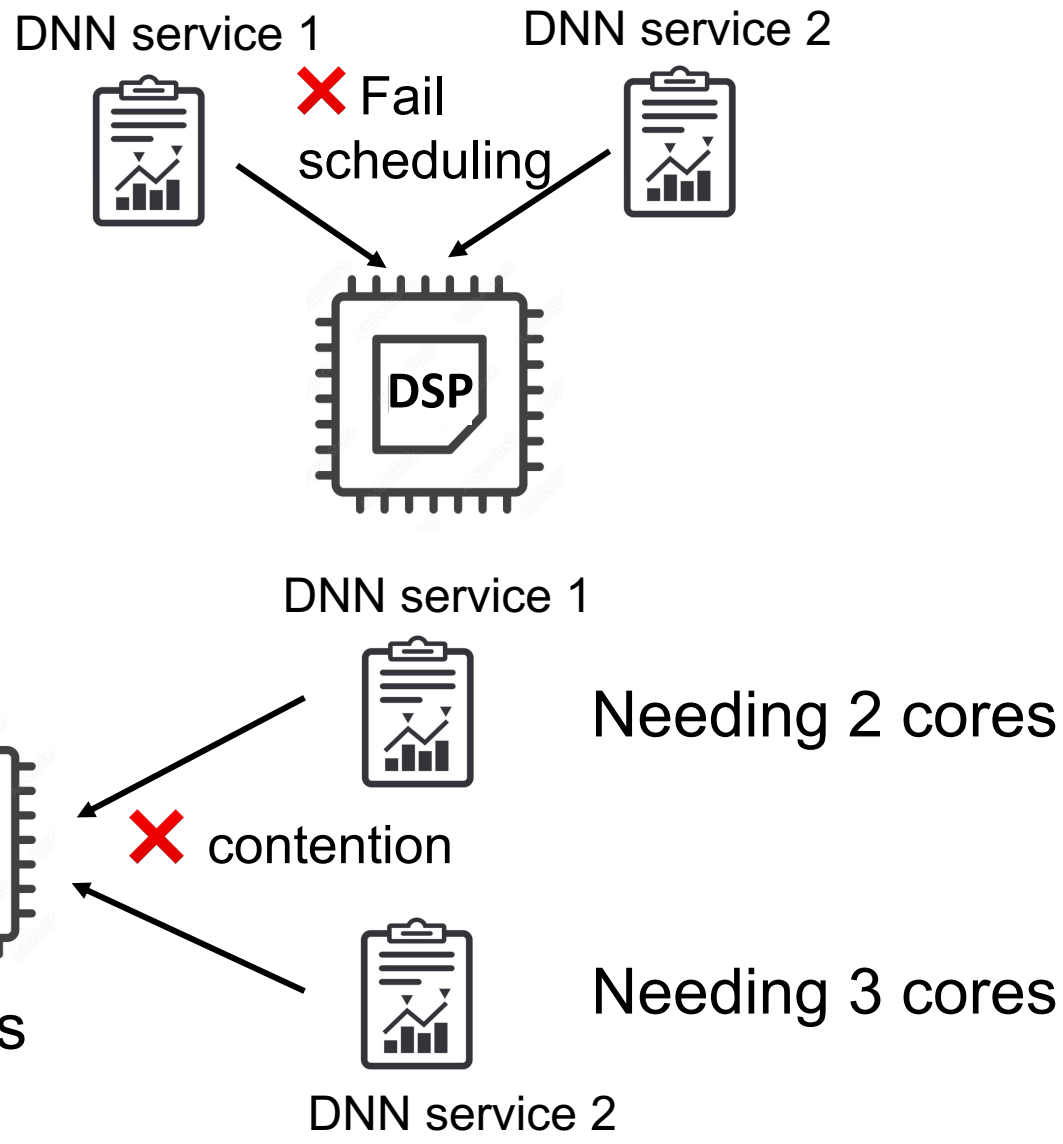
⚠ **No one-size-fits-all processor as cloud GPU.**

Challenge#1: High complexity in scheduling design

- **Parallel execution**

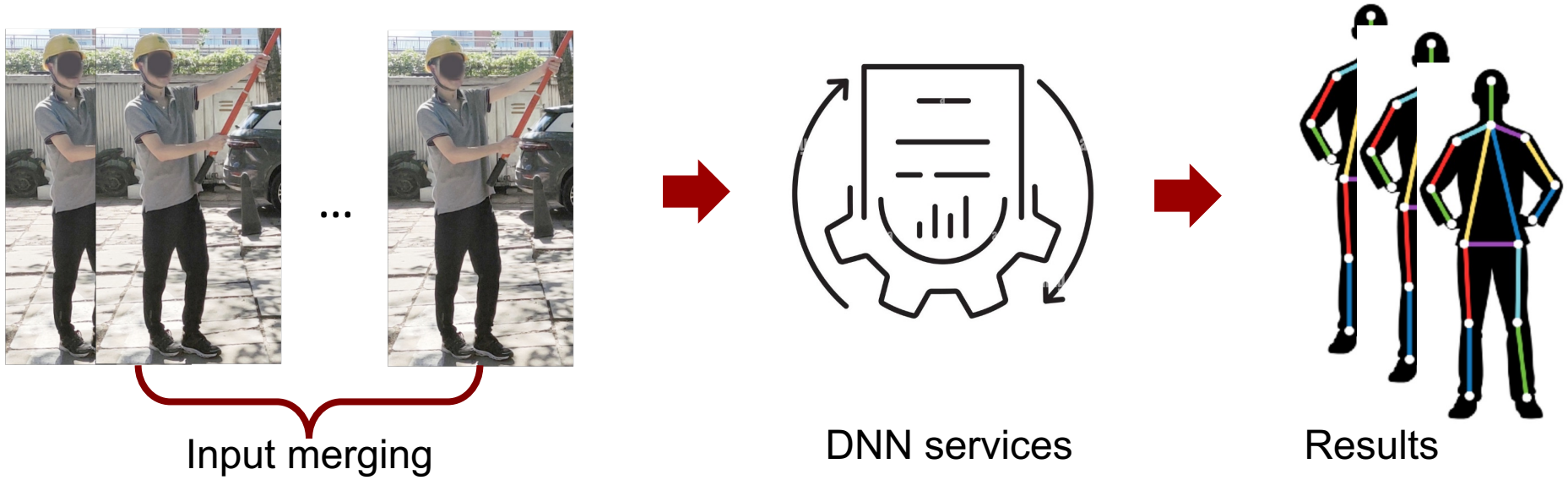
⚠ **Not all** processors support parallel execution

⚠ Optimal performance: **Not exceed** hardware capacity



Challenge#1: High complexity in scheduling design

- **Batch execution: higher throughput with longer latency**



Batch size	Latency (ms)	Throughput (DNN/s)
1	12	83.3
2	15	133.3
4	20	200.0
8	30	266.7

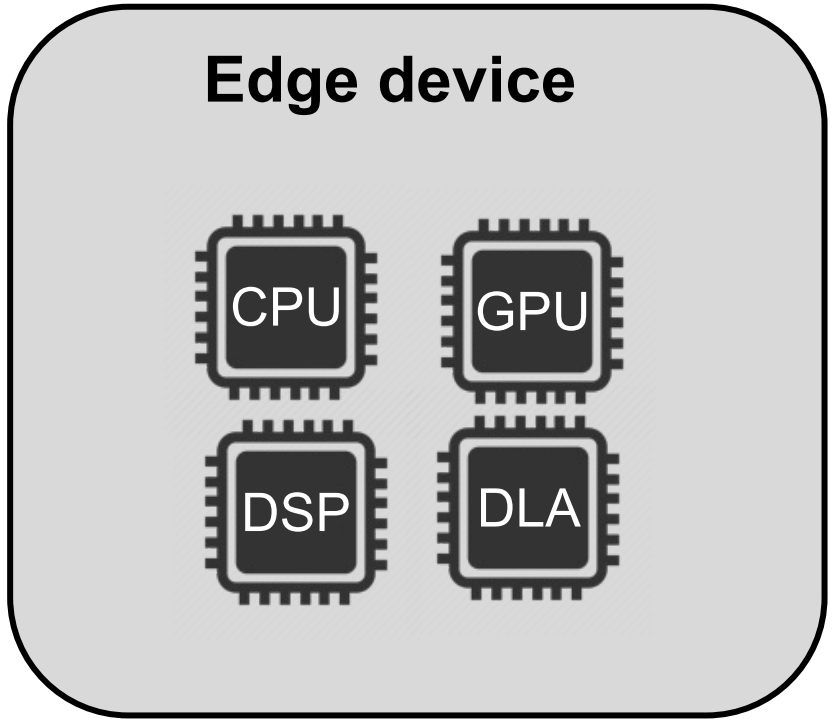
8x batch size → **2.5x latency delay** → **3.2x throughput enhancement**

Challenge#1: High complexity in scheduling design

- **Summary and implications**

Jointly considering

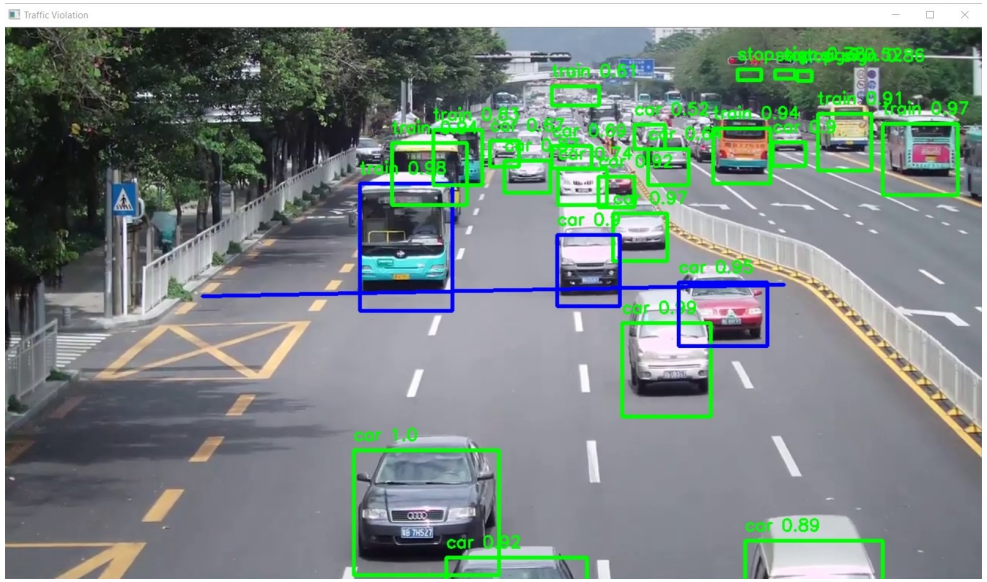
- DNN service-to-processor affinity
- Hardware support
- Parallel execution
- Batch execution

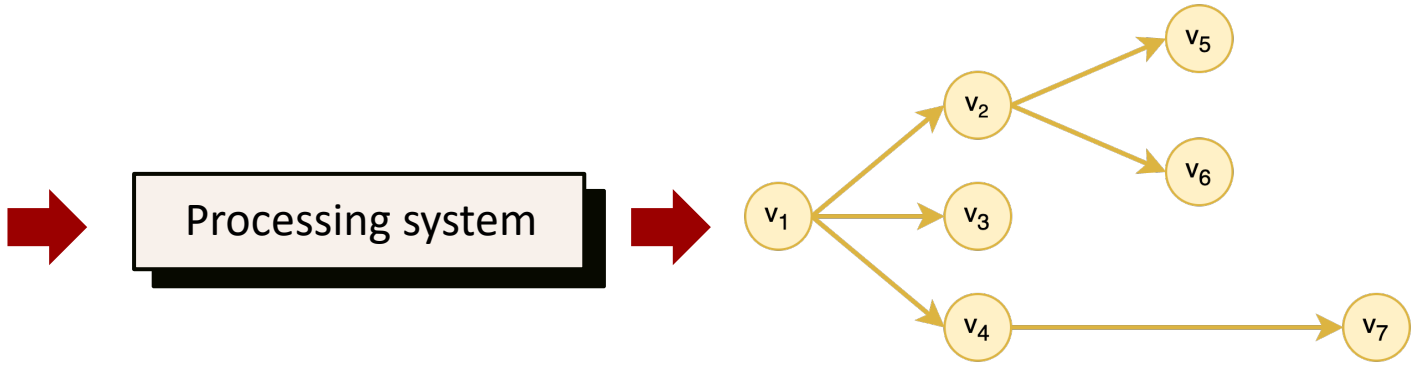


- **Existing work**
  - Online heuristic algorithm: Low performance ⚠
  - Offline algorithm: No dynamic support ⚠

Challenge#2: Unknown and mutative service workload

- **Unknown service workload limits scheduling space**





- **Existing work**
  - Lightweight methods: only one request service graph ⚠
  - Complex methods: high predicting overhead ⚠

Summary of challenges

DNN services

Person Detection

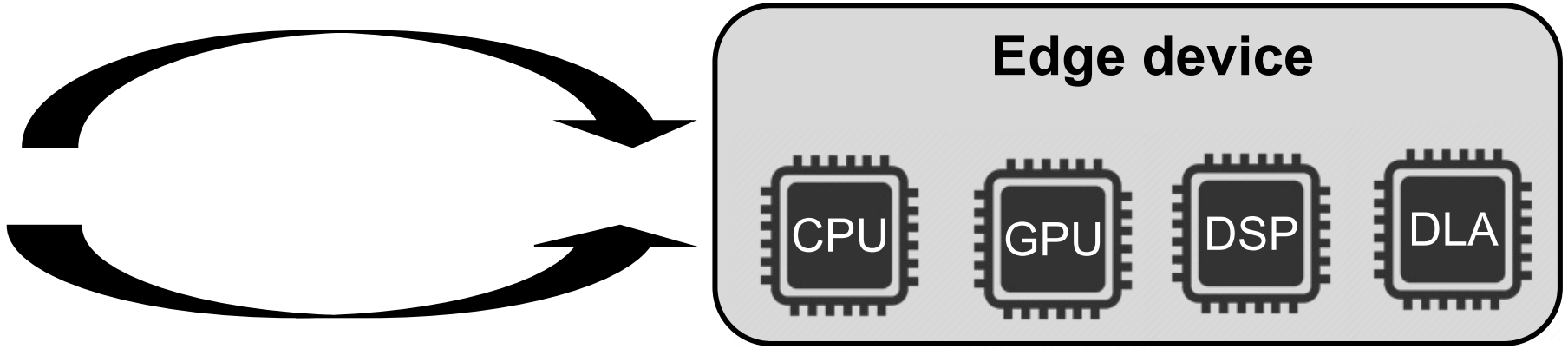
Pose Detection

Gloves Detection

Helmet Detection

#1: High complexity in scheduling design

Efficient heterogeneous processors



#2: Unknown and mutative service requests

Niagara

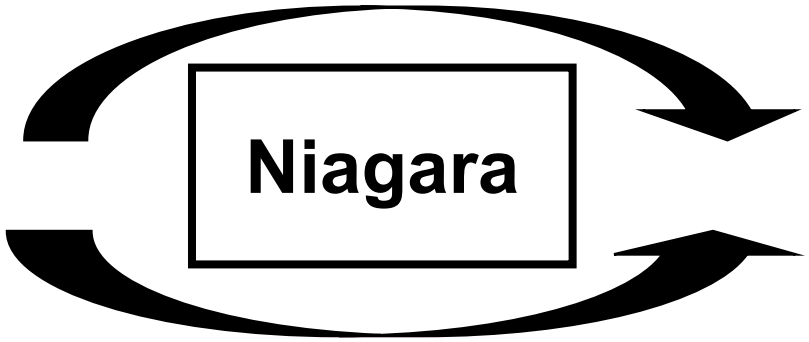
DNN services

Person Detection

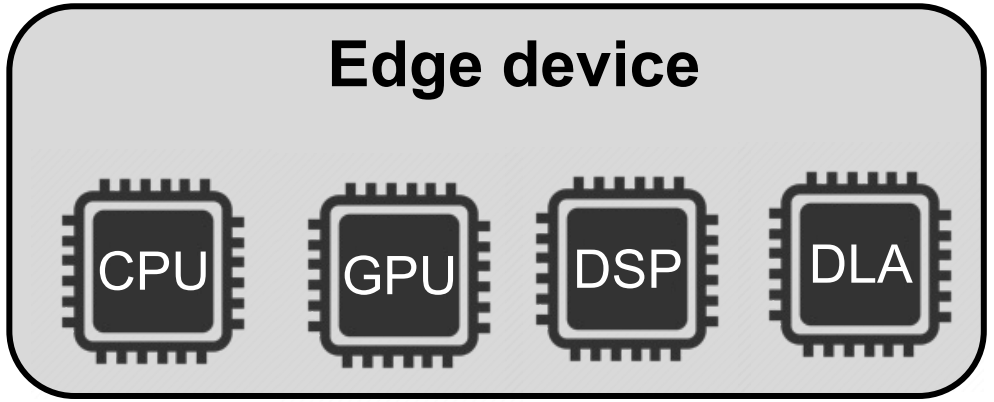
Pose Detection

Gloves Detection

Helmet Detection



Efficient heterogeneous processors



#1: offline optimization + online scheduling

#2: decouple the prediction of the service graph and coming requests

Niagara

DNN services

Person Detection

Pose Detection

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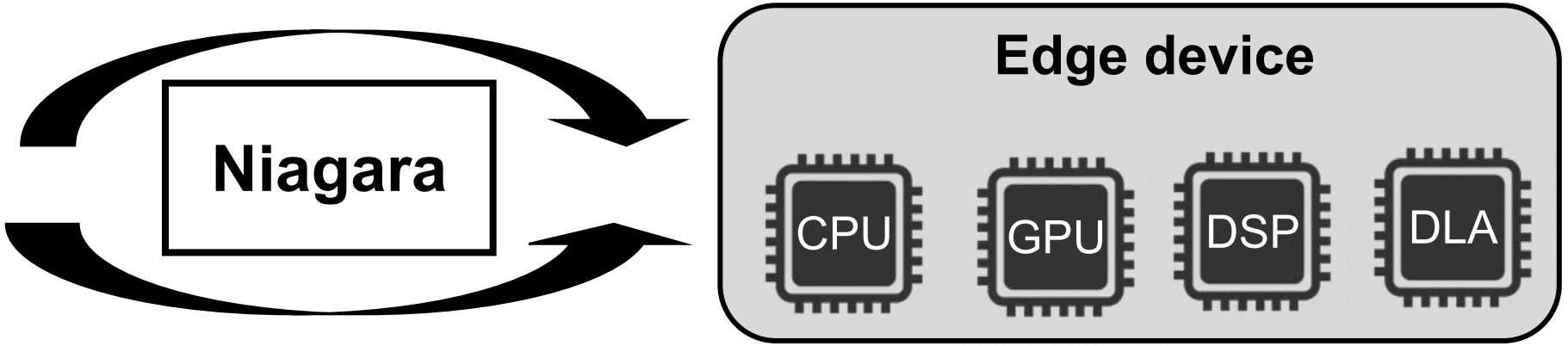
#1: offline optimization + online scheduling

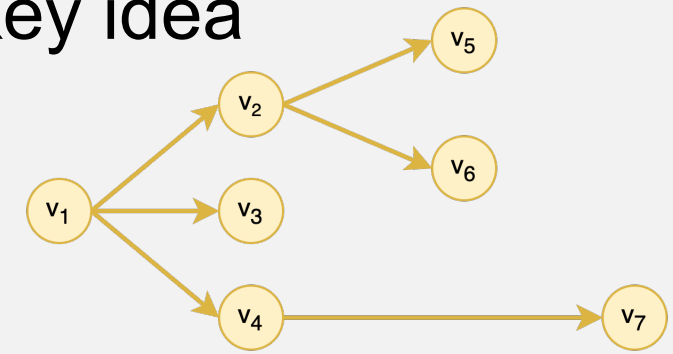
Efficient heterogeneous processors



#2: decouple the prediction of the service graph and coming requests

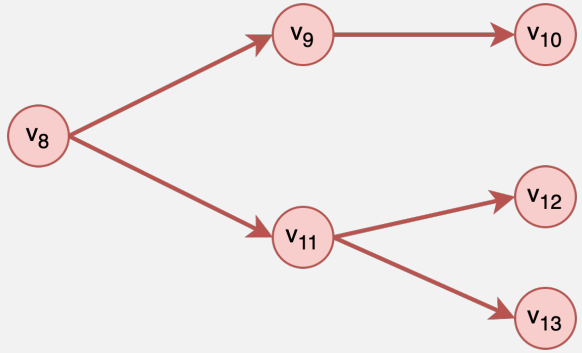
Offline optimization and online scheduling

Key idea



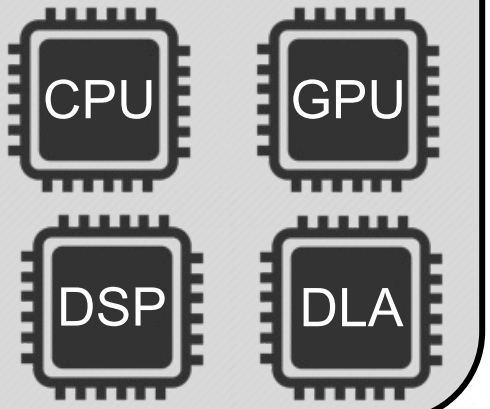
Online service graphs

Abstract



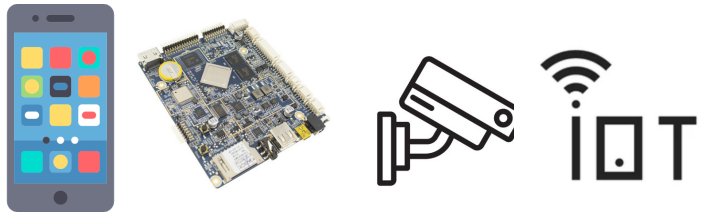
Offline service graph templates

Heterogenous processors



Template-based strategy matcher

Scheduling Problem



Deploy

Scheduling strategies

Offline optimization

- **Offline scheduling problem**
  - Decision variables

Variable	Description
Placement	Service-to-processor choice
Batch	Control batch execution
Parallel	Control parallel execution

  - Objective*: maximum throughput*
    - *max C s.t. Eq. (1)-(7)*

$$C = 1/\max\{t_i + \sum_{j=1}^{M} x_{i,j} T_{i,j}, \forall i \in N, \forall j \in M\}$$

$$\sum_{j \in \mathcal{R}_i} x_{i,j} = 1, \forall i \in N \quad (1)$$

$$t_i + \sum_{j=1}^{M} x_{i,j} T_{i,j} \leq t_k \quad (2)$$

$$\frac{t_k - t_i}{x_{i,j} x_{k,j} (1 - PL_{i,k,j})(1 - B_{i,k,j})} \geq T_{k,j} \quad (3)$$

$$x_{i,j} * x_{k,j} * PL_{i,k,j} * abs(t_k - t_i) \leq min(T_k, T_i) \quad (4)$$

$$\sum_{k=1}^{N} PL_{i,k,j} U_{k,j} + U_{i,j} \leq E_j \quad (5)$$

$$x_{i,j} * x_{k,j} * B_{i,k,j} * (t_k - t_i) \leq 0 \quad (6)$$

$$\forall v_i, v_k \in \mathcal{RQ}, t_k - t_i \leq Lat_{max}^{RQ} \quad (7)$$

Offline optimization

- **Offline scheduling problem**
  - Decision variables

Variable	Description

GUROBI solver: Less than 10% optimality loss

- *max C s.t. Eq. (1)-(7)*

$$\sum_{j \in \mathcal{R}_i} x_{i,j} = 1, \forall i \in N \quad (1)$$

$$t_i + \sum_{j=1}^{M} x_{i,j} T_{i,j} \leq t_i \quad (2)$$

$$\sum_{k=1} PL_{i,k,j} U_{k,j} + U_{i,j} \leq E_j \quad (5)$$

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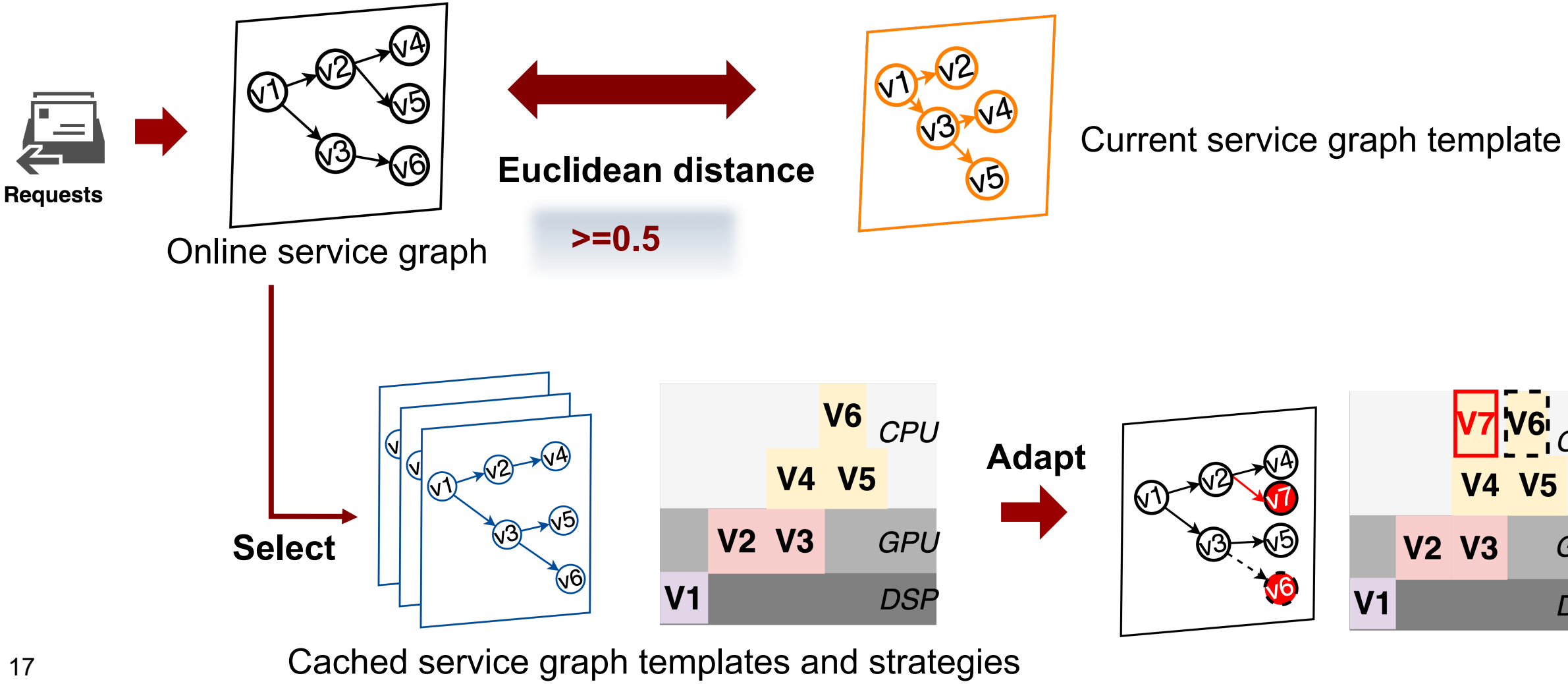
Online scheduling

- **Template-based strategy matcher**



Cached service graph templates and strategies

Niagara

DNN services

Person Detection

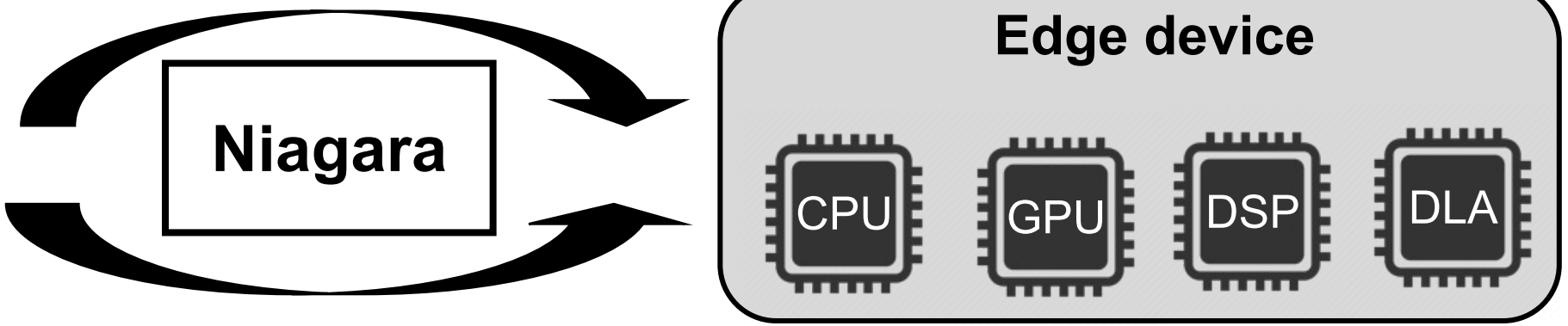
Pose Detection

Gloves Detection

Helmet Detection

#1: offline optimization + online scheduling

Efficient heterogeneous processors

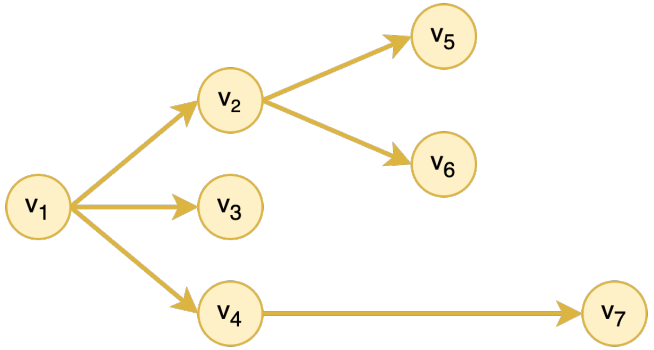


#2: decouple the prediction of the service graph and coming requests

Dynamic input predictor

- **The service graph tends to be more stable than the content.**

Different directions



Same service graph

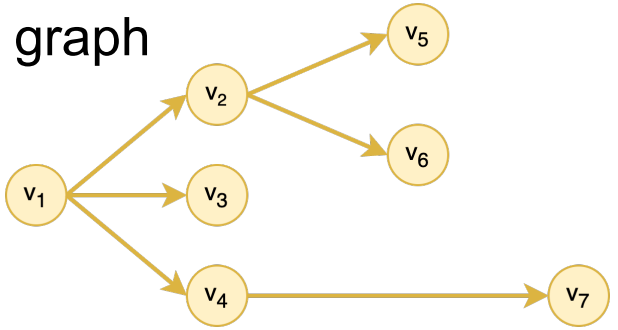
Different backgrounds

Dynamic input predictor

- **Decouple the prediction of the service graph and coming requests**

Predictor

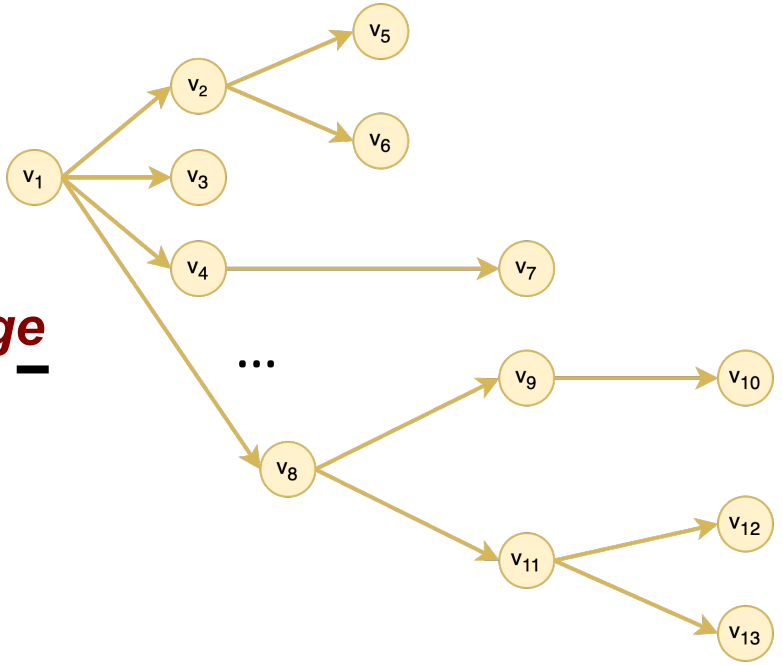
Service graph



Decouple

Merge

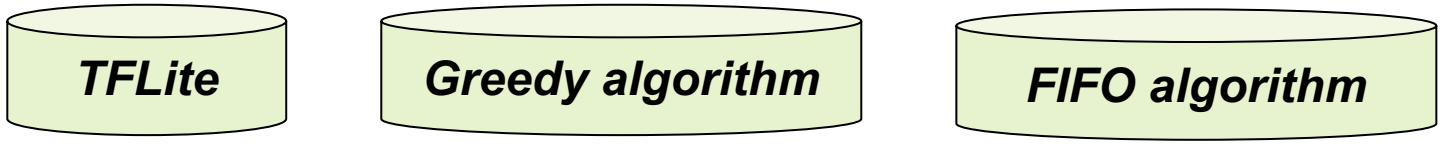
Number of the requests having the same service graph



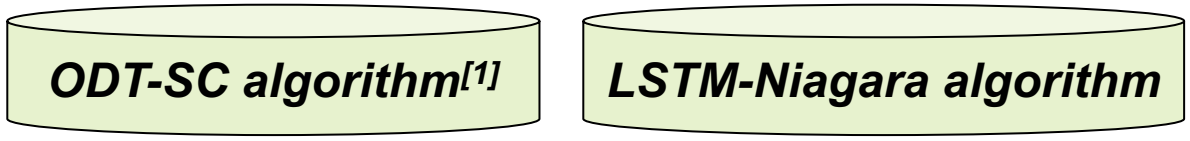
Multiple requests' service graph

Evaluation: methodology

- **Settings**
  - 8 service combinations + 11 DNN services + 3 real-world video stream
  - 3 commodity devices
  - Real-deployment
- **Baselines**
  - 3 industry baselines



  - 2 SOTA research baselines

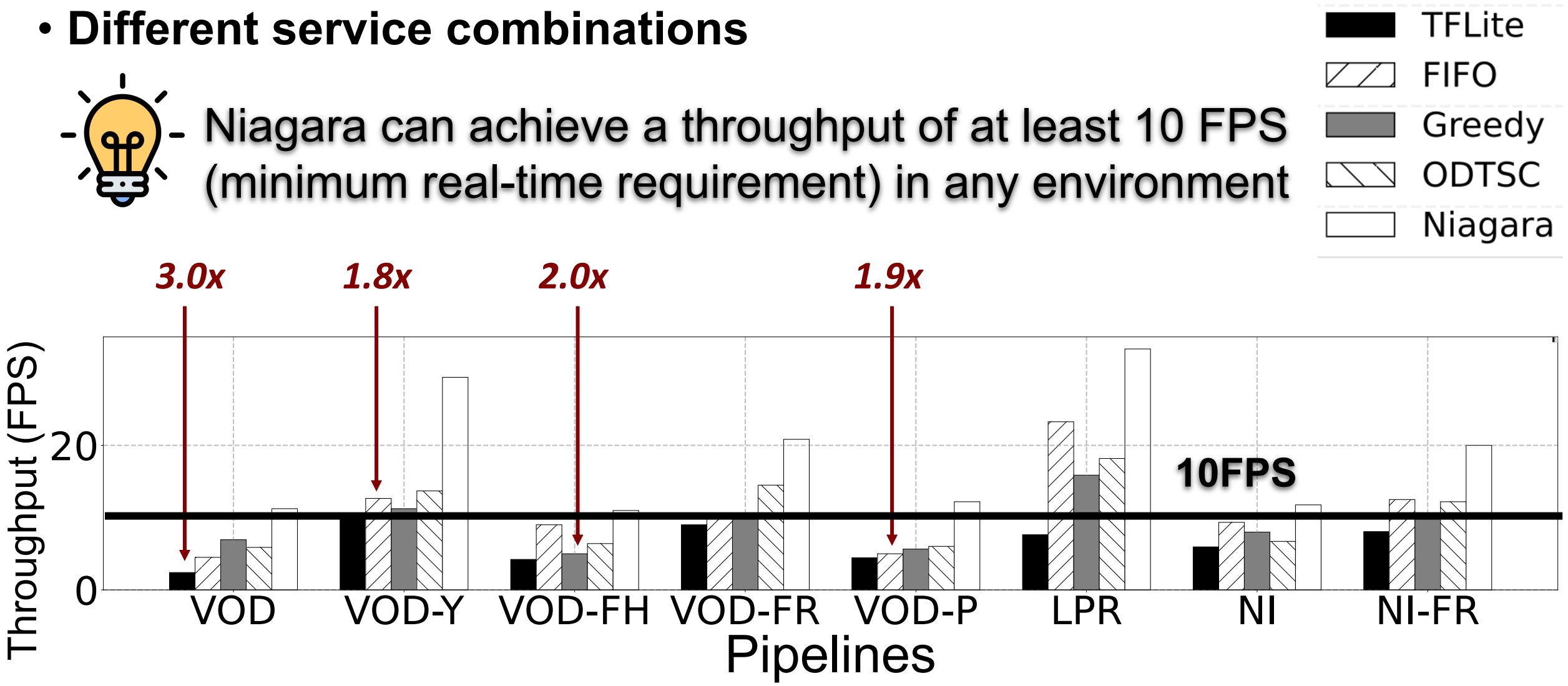


[1] Zhao G, Xu H, Zhao Y, et al. Offloading tasks with dependency and service caching in mobile edge computing[J]. IEEE Transactions on Parallel and Distributed Systems, 2021, 32(11): 2777-2792.

Evaluation: throughput

- **Different service combinations**

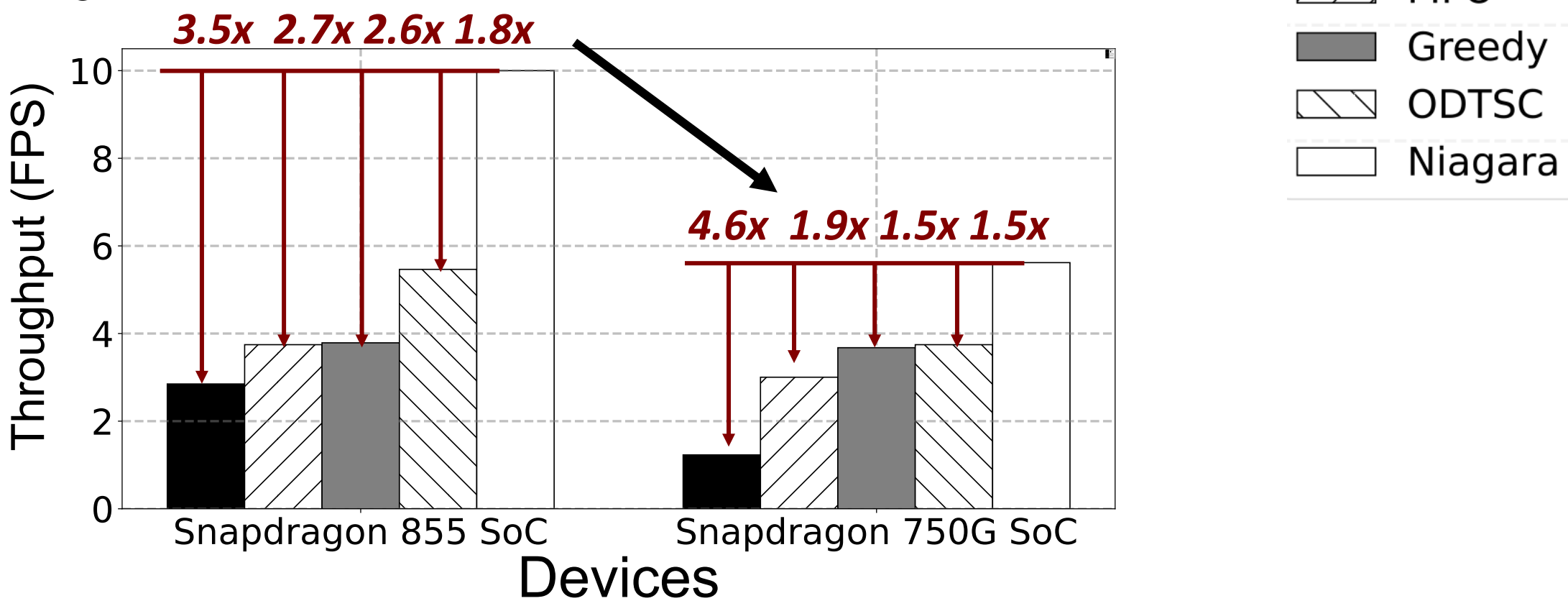
Niagara can achieve a throughput of at least 10 FPS (minimum real-time requirement) in any environment



Evaluation: throughput

- **Different devices**

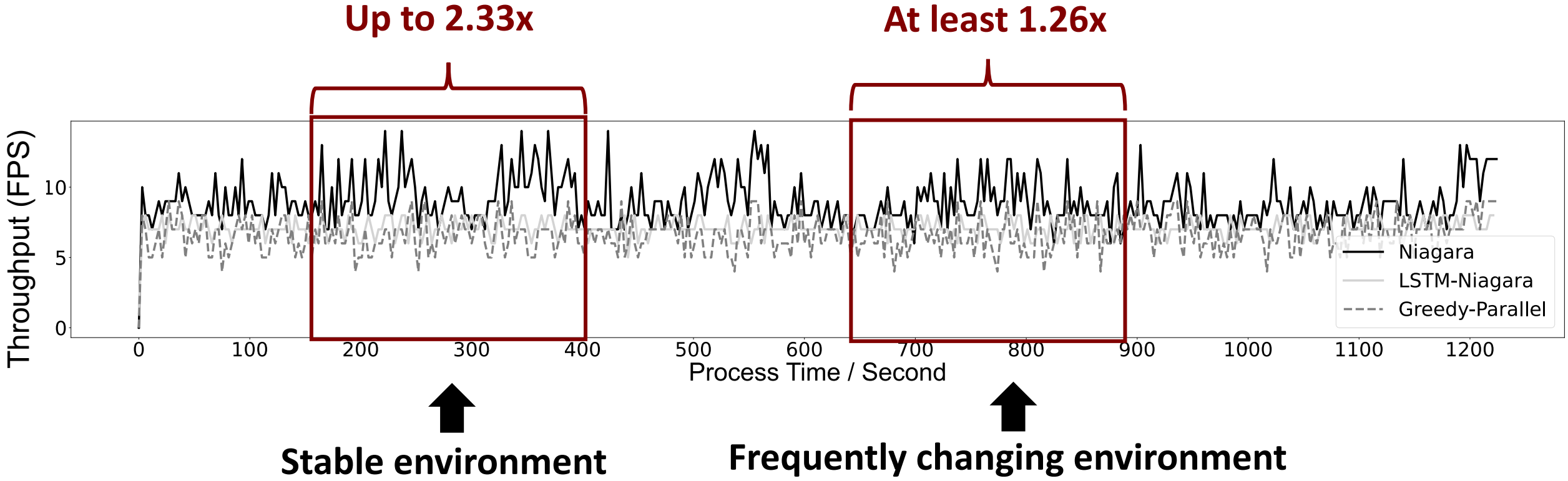
More powerful processors, more benefits



Evaluation: throughput

- **Real deployment**

Efficiently and stably improving throughput in real-world environments



Real deployment

Real execution

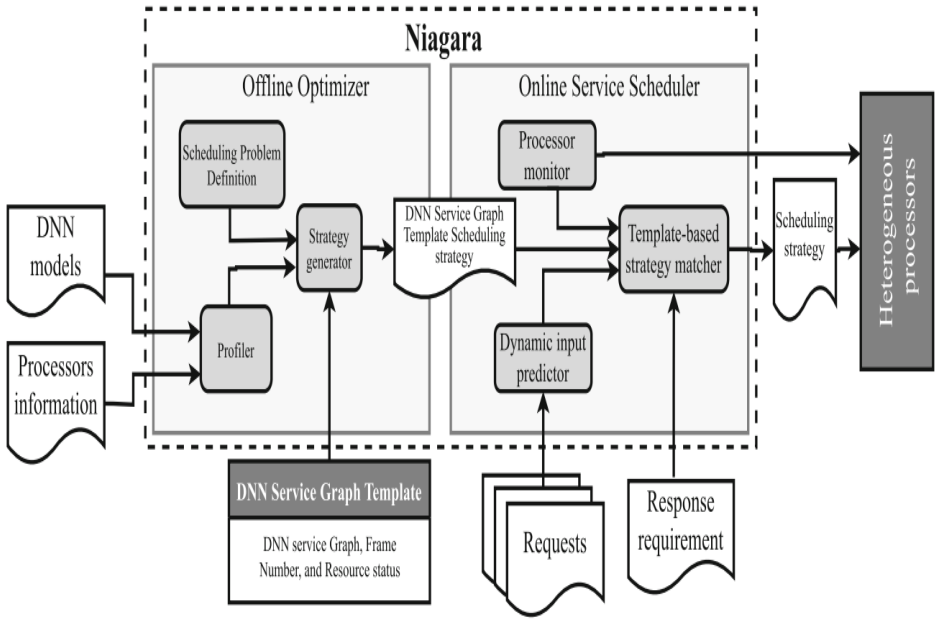
Custom-made
IP Cameras

State Grid
corporation of China

- **6-month** pilot run with **18,000** maintenance jobs
  - zero accidents
  - Save traditional human-based supervision

Thousands of substation in the future

Take-away



Niagara

- First scheduling engine for DNN services on edge heterogeneous processors
- Offline optimization + online scheduling
- Real deployment and saving traditional human-based supervision

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website https://daliangxu.github.io/

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