

# Edge AI: On-Demand Accelerating Deep Neural Network Inference via Edge Computing

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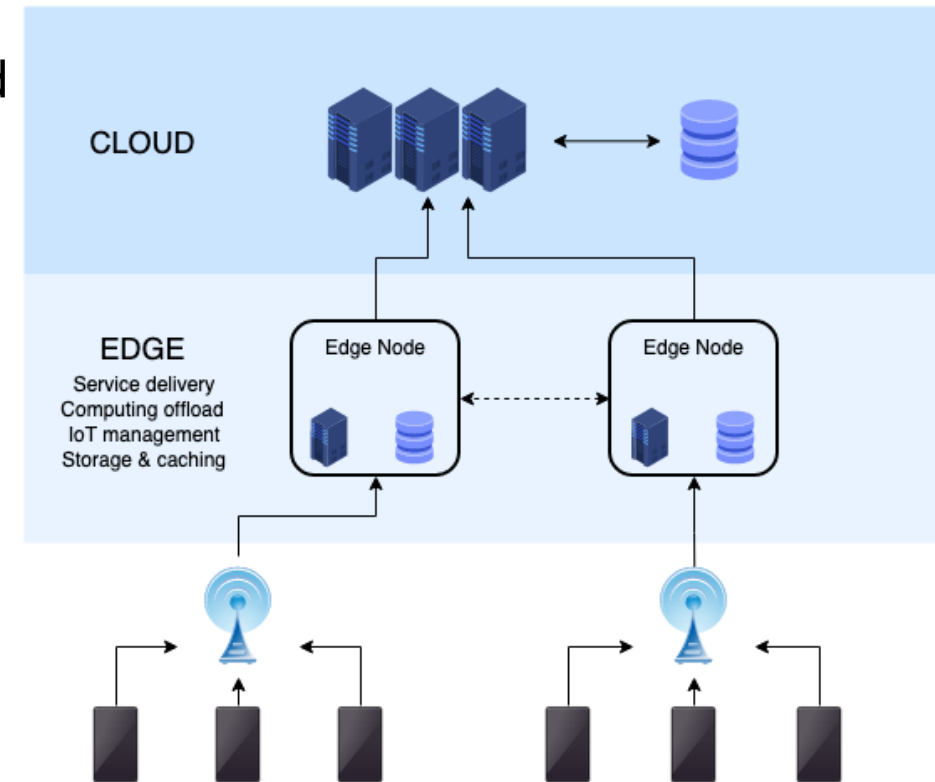
Neural Network Acceleration Study Season #2

# Contents of presentation

- Introduction and Background
- Key contribution: Edgent Framework
  - DNN partitioning
  - DNN right-sizing
- Performance Evaluation
- Conclusion and Discussion

# Introduction: Deep Neural Networks (1)

- **Mobile devices fail**
  - To the tremendous amount of computation required
- **Resort to cloud datacenter for intensive DNN computation**
  - Input data : generated mobile devices
  - Sent to remote cloud data center (computations)
  - Devices receive the execution results
- **Problems**
  - Intolerable latency
  - Extravagant energy



# Introduction: Deep Neural Networks (2)

- **Network bandwidth issue**

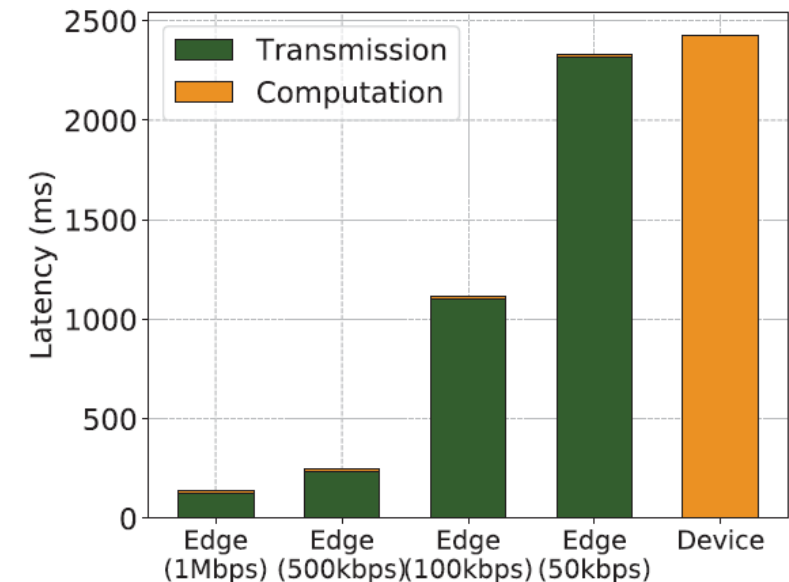
- network bandwidth drop : from 1Mbps to 50kbps
- Inference latency : from 0.123s to 2.317s

- **Mission-critical DNN-based applications**

- Intelligent security
- Industrial robotics

- **To solve this problems**

- Propose *Edgent* framework
  1. DNN partitioning : some layers process edge, some layers process device
  2. DNN right-sizing : branchyNet framework (early-exit mechanism)



# DNN Partitioning

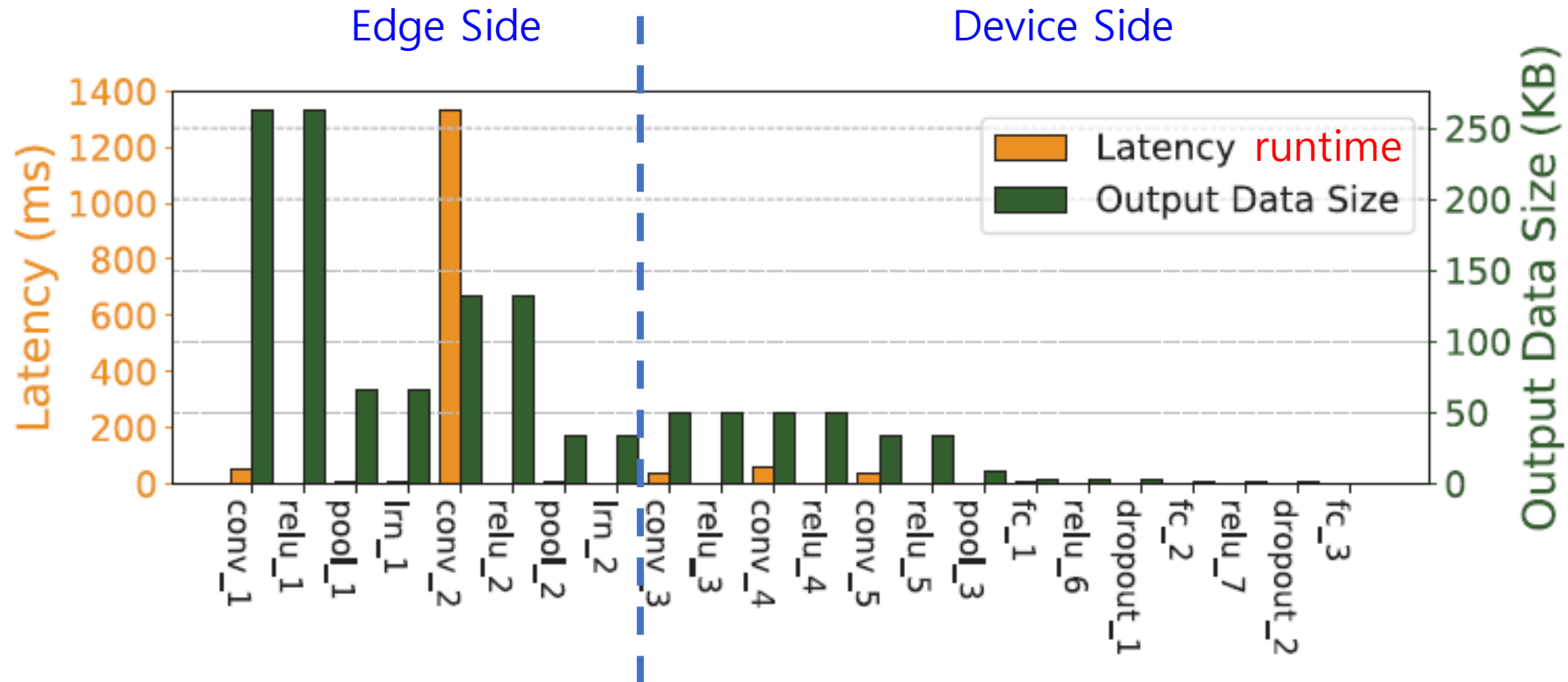


Fig. 3. AlexNet layer-wise runtime and output data size on Raspberry Pi.

# DNN Right-Sizing

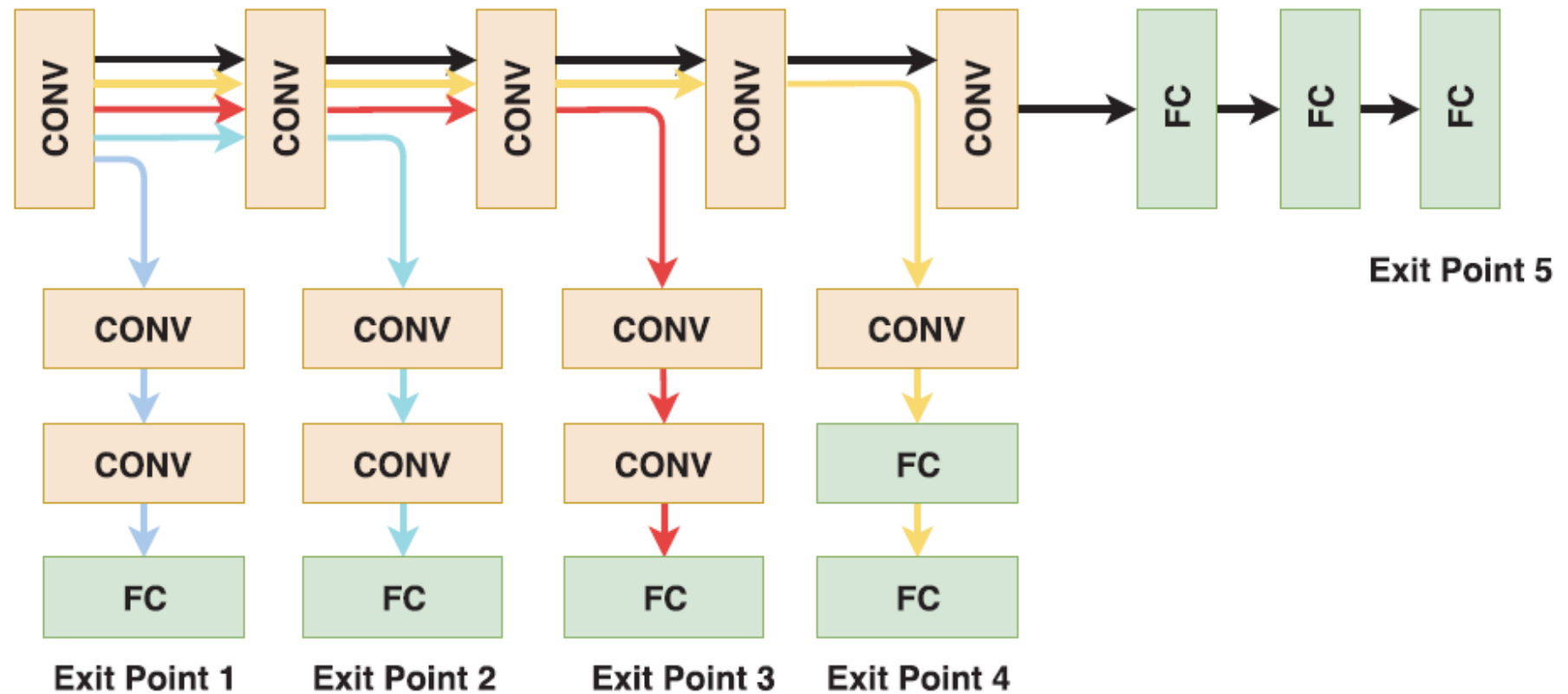
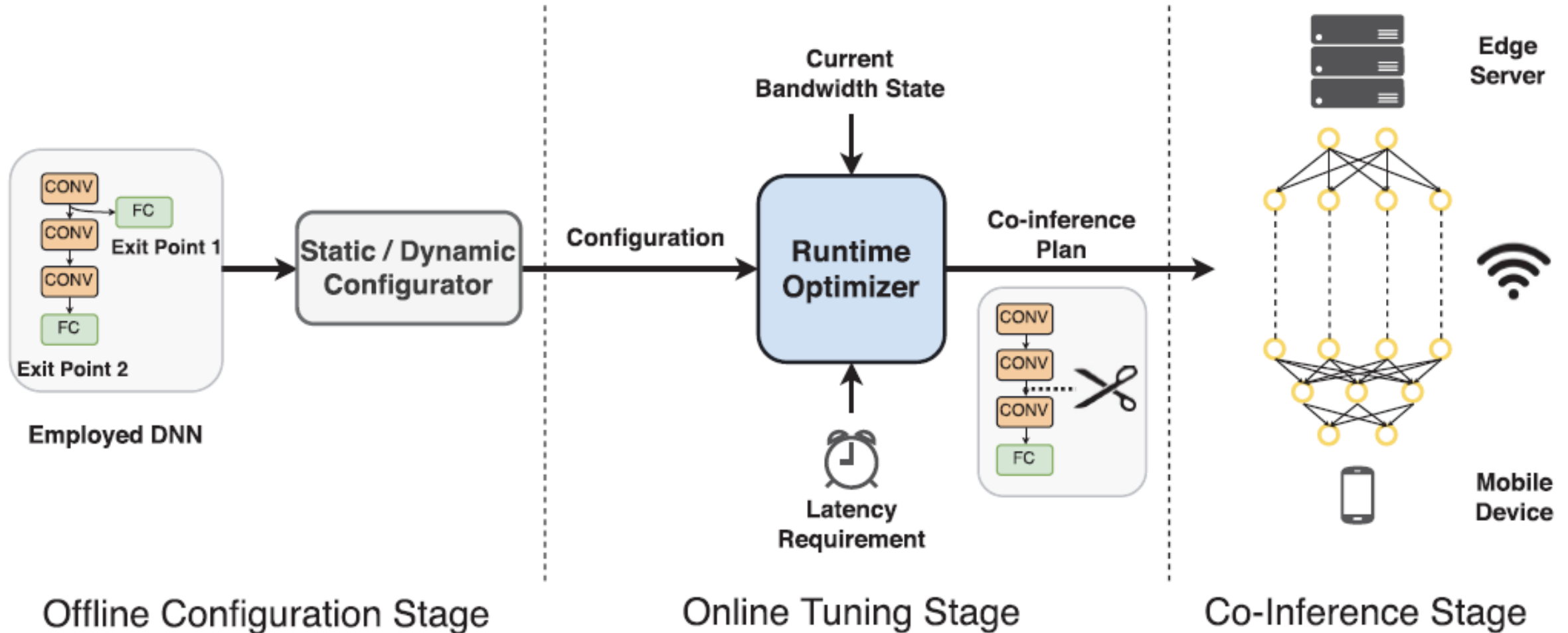


Fig. 4. A branchy AlexNet model with five exit points.

# Edgent Framework



# Edgent Framework

- **Offline configuration stage**

- Pre-defined Static/Dynamic configurator
- Composed of the **trained branchy DNN** and **optimal selection** for different bandwidth states

- **Online tuning stage**

- Current bandwidth state, latency requirement
- Runtime optimizer → Co-inference Plan

- **Co-inference stage**

- Selected exit point and partition point
- Execute server side and device side



# Edgent for Static Environment

- **Offline configuration stage**

- Profile layer-wise inference latency on the mobile device and edge server
- Train the DNN model with multiple exit points via BranchyNet framework

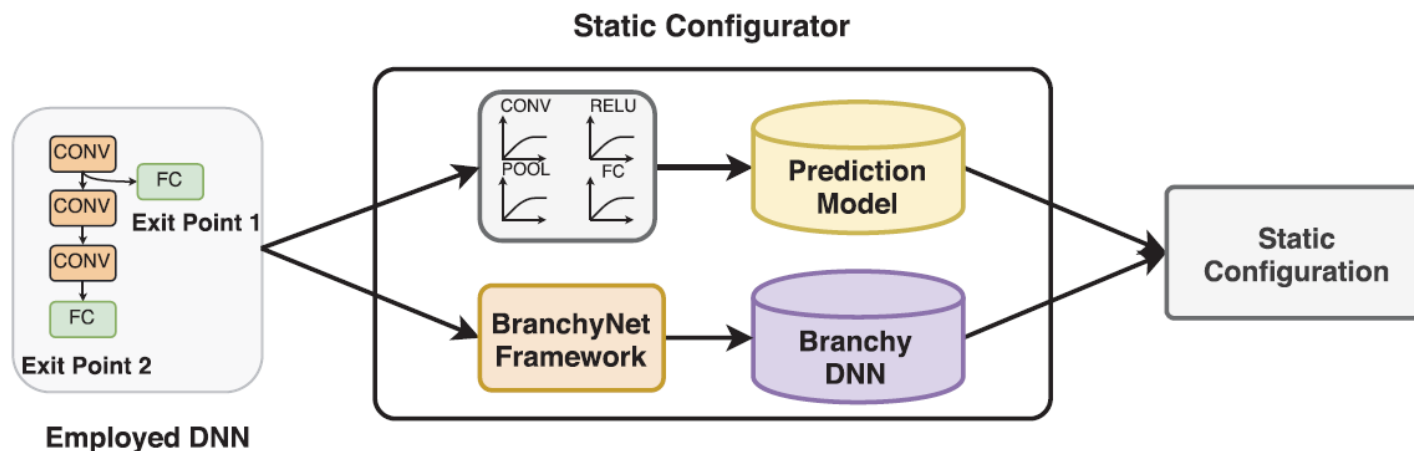
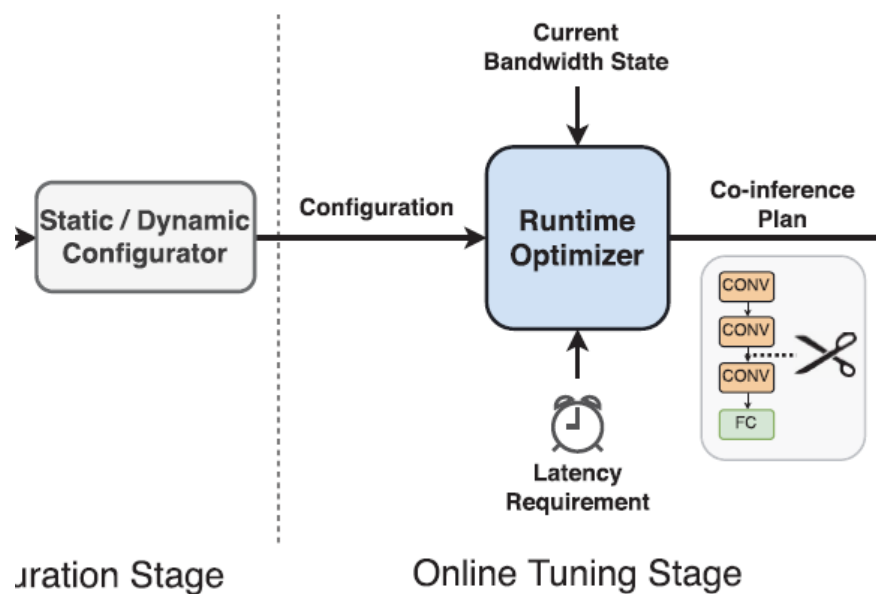


Fig. 6. The static configurator of Edgent.

# Edgent for Static Environment

- **Online tuning stage**

- Runtime optimizer component : search optimal exit point and partition point



# Edgent for Static Environment

- Online tuning stage

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**Algorithm 1** Runtime Optimizer for Static Environment

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**Input:**

$M$ : the number of exit points in the DNN model

$\{N_i | i = 1, \dots, M\}$ : the number of layers in the branch of exit point  $i$

$\{L_j | j = 1, \dots, N_i\}$ : the layers in the branch of exit point  $i$

$\{D_j | j = 1, \dots, N_i\}$ : layer-wise output data size in the branch of exit point  $i$

$f(L_j)$ : the prediction model that returns the  $j$ -th layer's latency

$B$ : current available bandwidth

$Input$ : input data size

$Latency$ : latency requirement

**Output:**

Selection of exit point and partition point

**1: Procedure**

**2: for**  $i = M, \dots, 1$  **do**

3:   Select the branch of  $i$ -th exit point

4:   **for**  $j = 1, \dots, N_i$  **do**

5:      $ES_j \leftarrow f_{edge}(L_j)$

6:      $ED_j \leftarrow f_{device}(L_j)$

7:   **end for**

8:    $A_{i,p} = \underset{p=1, \dots, N_i}{\operatorname{argmin}} (\sum_{j=1}^{p-1} ES_j + \sum_{k=p}^{N_i} ED_k + Input/B + D_{p-1}/B)$

9:   **if**  $A_{i,p} \leq Latency$  **then**

10:     **return** Exit point  $i$  and partition point  $p$

11:   **end if**

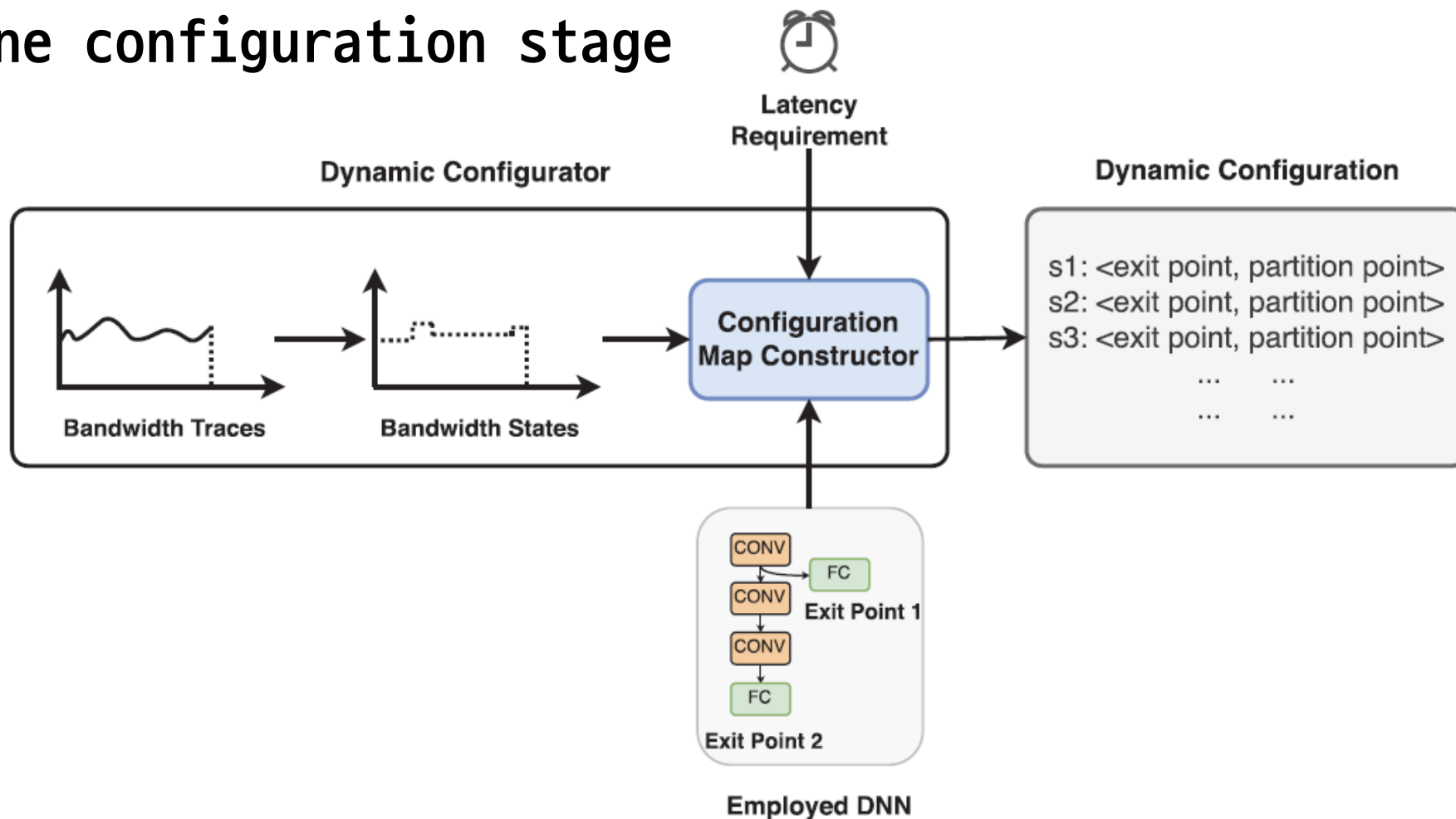
12: **end for**

13: **return** NULL   ▷ can not meet the latency requirement

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# Edgent for Dynamic Environment

- Offline configuration stage



# Edgent for Dynamic Environment

- Offline configuration stage

$$reward_{step} = \begin{cases} \exp(acc) + throughput, & t_{step} \leq t_{req}, \\ 0, & \text{else,} \end{cases}$$

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**Algorithm 2** Configuration Map Construction

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**Input:**

$\{s_i | i = 1, \dots, N\}$ : the bandwidth states

$\{C_j | j = 1, \dots, M\}$ : the co-inference strategy

$R(C_j)$ : the reward of co-inference strategy  $C_j$

**Output:**

Configuration Map

1: **Procedure**

2: **for**  $i = 1, \dots, N$  **do**

3:   Select the bandwidth state  $s_i$

4:    $reward_{max} = 0, C_{optimal} = 0$

5:   **for**  $j = 1, \dots, M$  **do**

6:      $reward_{c_j} \leftarrow R(C_j)$

7:     **if**  $reward_{max} \leq reward_{c_j}$  **then**

8:        $reward_{max} = reward_{c_j}, C_{optimal} = C_j$

9:     **end if**

10:   **end for**

11:   Get the corresponding *exit point* and *partition point* of  $C_{optimal}$

12:   Add  $S_i :< exit point, partition point >$  to the Configuration Map

13: **end for**

14: **return** Configuration Map

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# Edgent for Dynamic Environment

- Online tuning stage

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**Algorithm 3** Runtime Optimizer for Dynamic Environment

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**Input:**

$\{B_{1,\dots,t}\}$ : the accumulated bandwidth measurements until the current moment  $t$

$\{C_j | j = 1, \dots, t\}$ : the co-inference strategy

$\{s_i | i = 1, \dots, t\}$ : the bandwidth states

$D(B_{1,\dots,t})$ : the bandwidth state detection function that returns the current bandwidth state

$find(s)$ : find the co-inference strategy corresponds to the given state  $s$

**Output:**

Co-inference strategy

1: **Procedure**

2:  $C_t = C_{t-1}$

3:  $s_t = D(B_{1,\dots,t})$

4: **if**  $s_t \neq s_{t-1}$  **then**

5:    $C_t \leftarrow find(s_t)$

6: **end if**

7:  $s_{t-1} = s_t$

8:  $C_{t-1} = C_t$

9: **return**  $C_t$

# Experimental Setup

- **Raspberry Pi and desktop PC**

- Static bandwidth env. : WonderShaper tool [45]
- Dynamic bandwidth env. : Belgium 4G/LTE bandwidth logs [46] emulation
- Use BraychNet framework : AlexNet as the toy model
- AlexNet model : 5 exit point, cifar-10 dataset

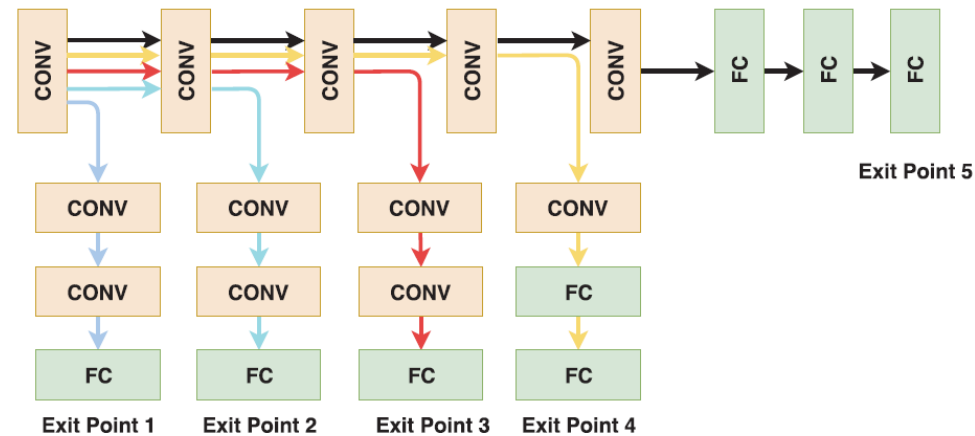
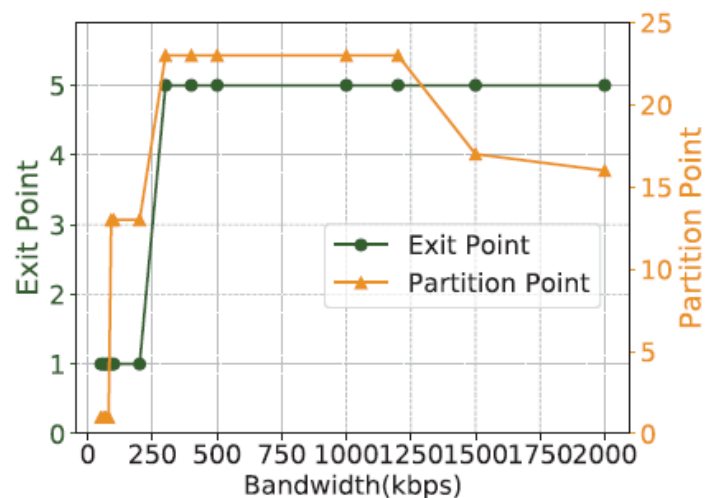


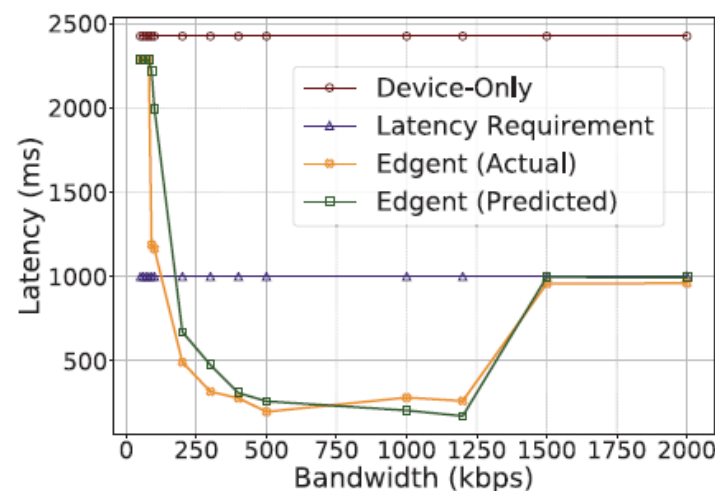
Fig. 4. A branchy AlexNet model with five exit points.

# Experimental Results

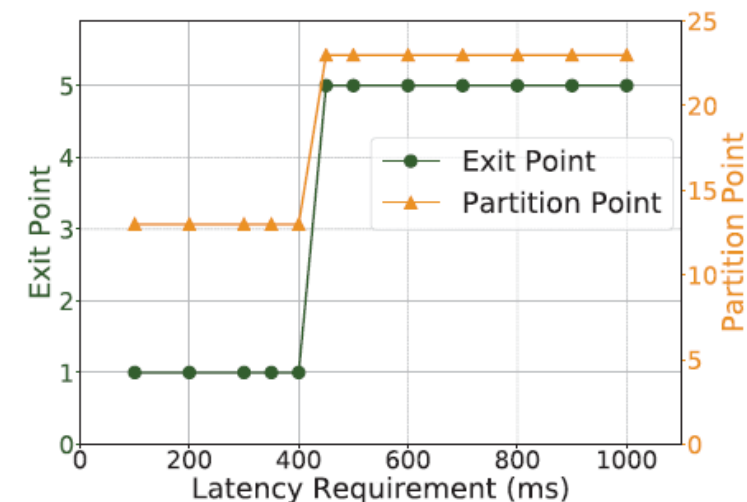
- Static Bandwidth Environment



(a) Selection under different bandwidths



(b) Model runtime under different bandwidths



(c) Selection under different latency requirements



# Experimental Results

- Static Bandwidth Environment

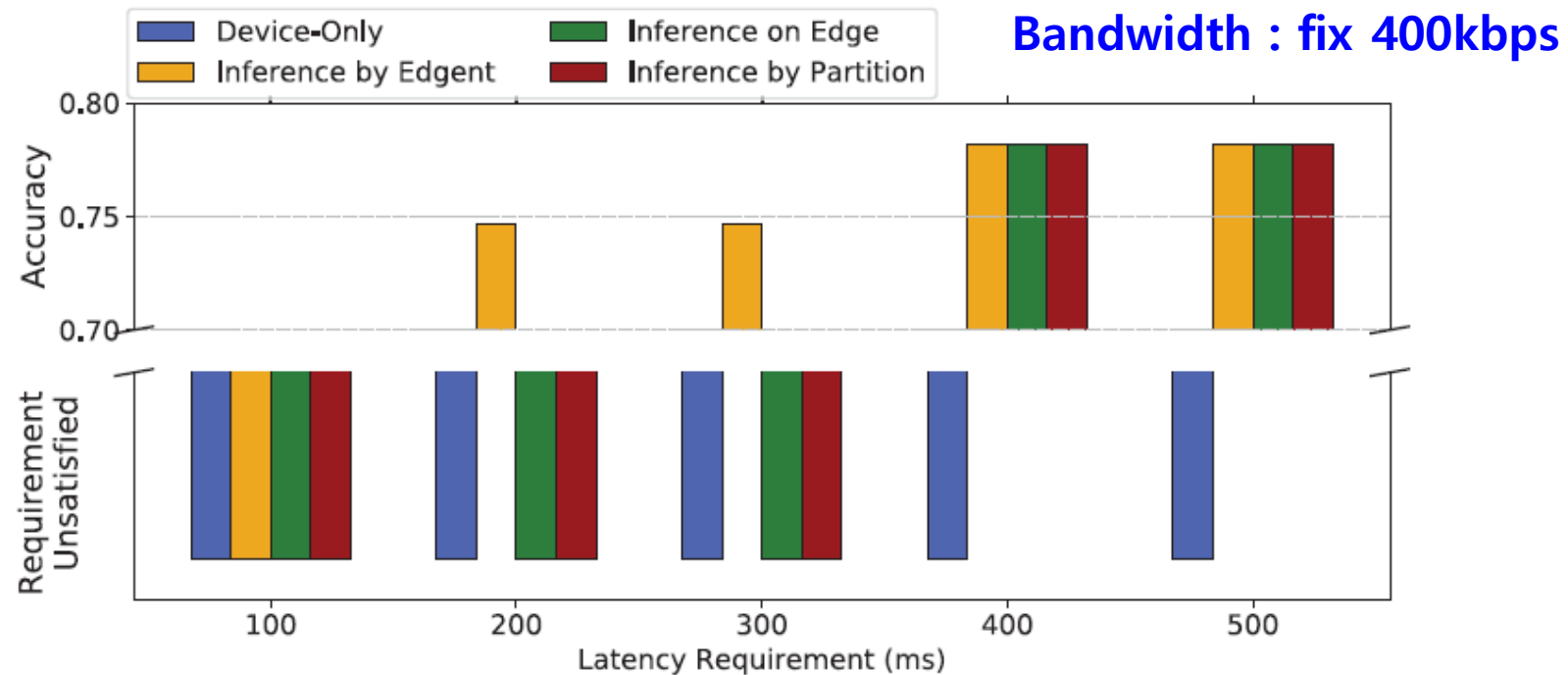
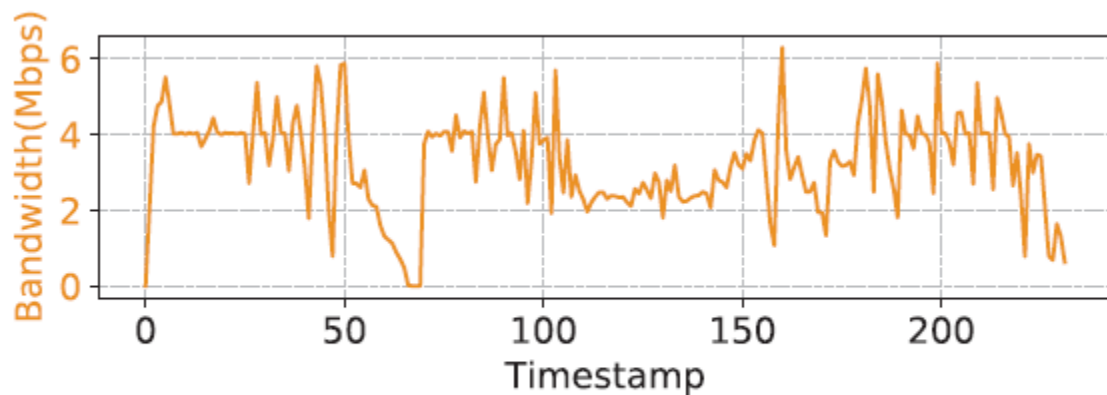


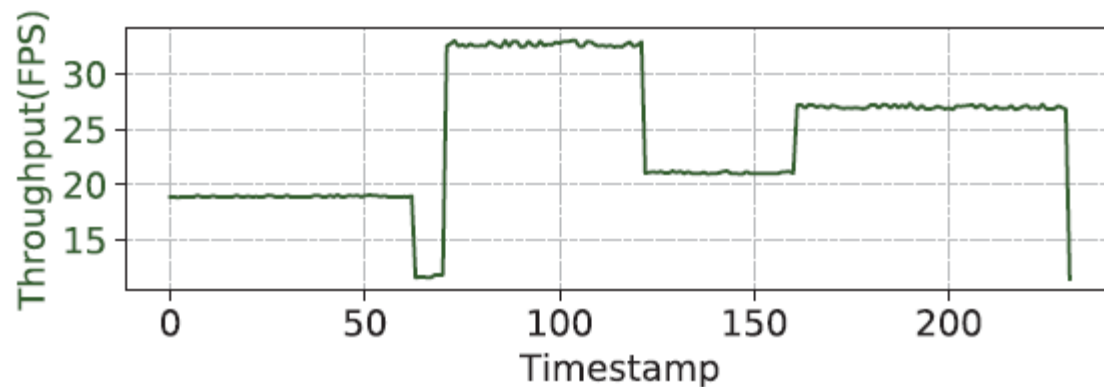
Fig. 9. The accuracy comparison under various latency requirement.

# Experimental Results

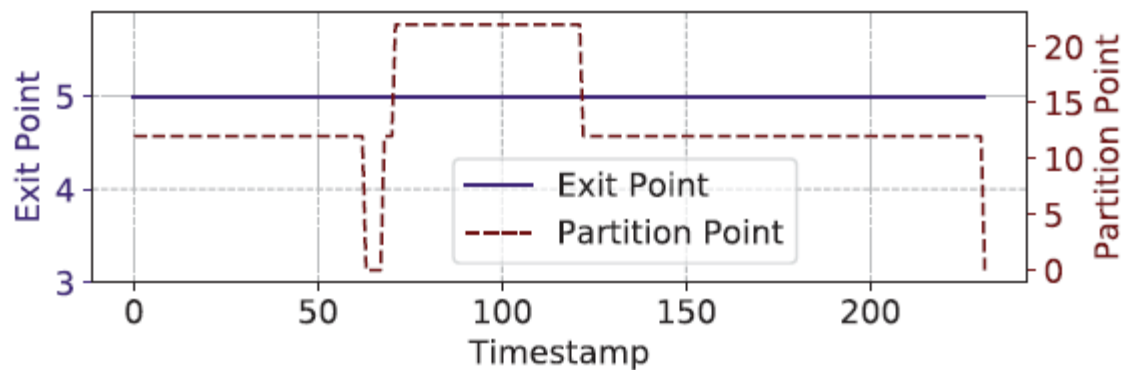
- Dynamic Bandwidth Environment



(a) A example bandwidth trace on Belgium 4G/LTE dataset [46]



(b) The throughput of DNN model inference



# Conclusion

- **Propose Edgent Framework**
  - Two design knobs to optimize DNN inference latency
    1. DNN partitioning : profiling layer-wise runtime
    2. DNN right-sizing : branchy network → early-exit mechanism
    3. Optimizing → low-latency edge intelligence
- **Proposed prototype implementation : Raspberry Pi & PC**
  - show feasibility and effectiveness

# Thank you