Towards Elasticity in Heterogeneous Edge-dense Environments

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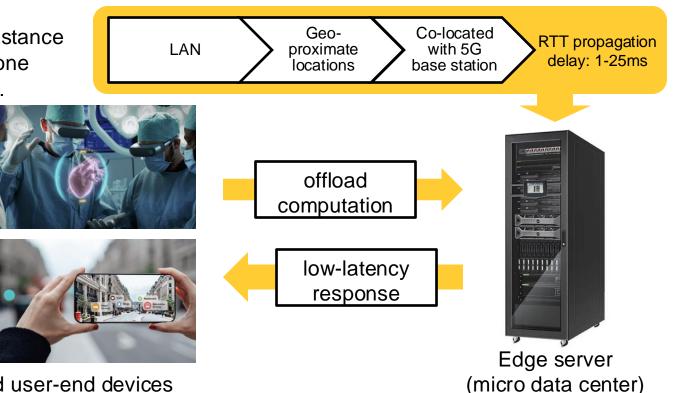
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Emerging applications enabled by edge

AR/VR

Wearable cognitive assistance Autonomous vehicle/drone Interactive gaming

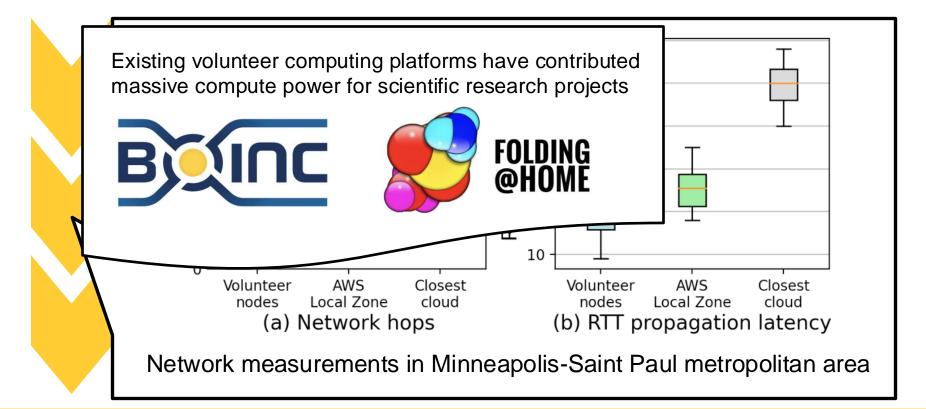


Resource-constrained user-end devices

Existing edge infrastructures					
	Are existing edge resources sufficient to support scalable latency-sensitive computation offloading?				
a	mazon AWS Local Zones		Azure Stack		
aw	Answer: No . They are limited by geo-distribution, sub-optimal performance, high expanses, and scaling capacity.				
Wavelength 5G Azure Edge Zones Google Cloud Anthos Outposts					
Public edge cloud	Only available at major metropolitan areas (limited point-of-presence)	On- premise solution	Expensive to maintain private infrastructures/hardware		
	Delivered latency performance is less satisfactory (shown later)		Lack of scaling capacity		



Can volunteer resources come into play?



Can volunteer resources come into play?

They are widely/densely distributed with unlimited potential to scale cost-efficiently under appropriate incentive models

Volunteer resources are **greener complements** of existing edge infrastructures to enable **elastic edge computing** everywhere

They are powerful: personal PCs/laptops/devices are equipped with faster cpu/gpu/storage hardware



Now challenges...

Heterogeneous clientto-edge networks

Heterogeneous edge nodes

Dense and geodistributed resource distribution

Unreliable edge node

Heterogeneous edgedense environments



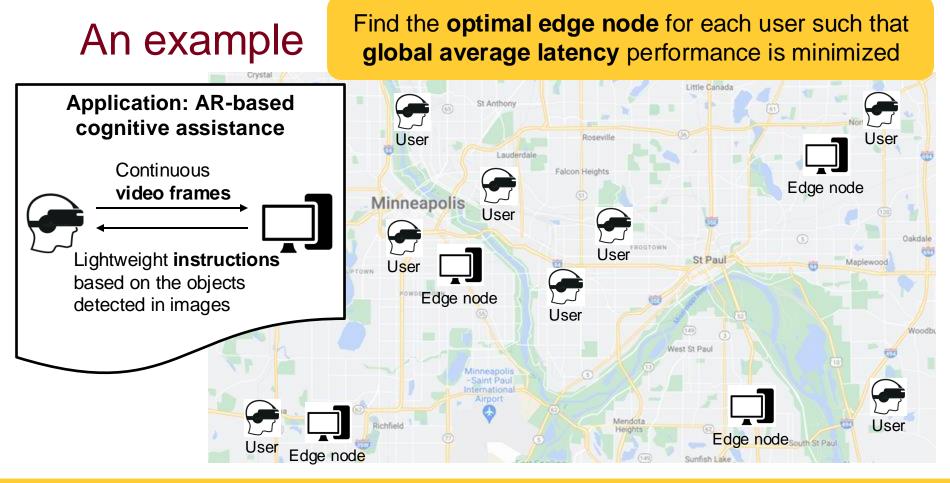
Our objective

Achieve edge elasticity in Heterogeneous edge-dense environments

Specifically...

In a system with *n* users and *m* edge nodes, how to minimize the average end-to-end latency perceived by all users in *Heterogeneous edge-dense environments*







Problem formulation

Consider a *heterogeneous edge-dense environment* with <u>n users</u> and <u>m edge</u> nodes in a specified area.

Edge Assignment (EA): A <u>users-to-edge match</u> that assigns each user u_i ($1 \le i \le n$) an edge node e_j ($1 \le j \le m$) to offload computation.

$$EA = \{ < u_1, e_{j_1} >, < u_2, e_{j_2} >, \dots, < u_n, e_{j_n} > \} \xrightarrow{\text{equivalent}} EA = \{S_1, S_2, \dots, S_m\}$$

Objective function: End-to-end latency $P(EA) = \frac{1}{n} \sum_{i=1}^{n} (D_{prop_{i}}^{j_{i}} + D_{trans_{i}}^{j_{i}} + D_{proc}(e_{j_{i}}, S_{j_{i}}))$ From edge node's view: S_{j} denotes the set of users attached to edge node e_{j} Building the property of the property of the property of the processing delay: determined by i) node capacity $e_{j_{i}}$ and ii) existing workload $S_{j_{i}}$ on this node

Problem formulation

$${}_{EA\in\Phi}^{Min} P(EA) = \frac{1}{n} \sum_{i=1}^{n} (D_{prop_{i}}^{j_{i}} + D_{trans_{i}}^{j_{i}} + D_{proc}(e_{j_{i}}, S_{j_{i}}))$$

 D_{prop} and D_{trans} are only subject to client-centric views

Client-centric (distributed) edge selection approach

 D_{proc} is varying under different hardware and resource contention levels

Lightweight and accurate performance profiling process

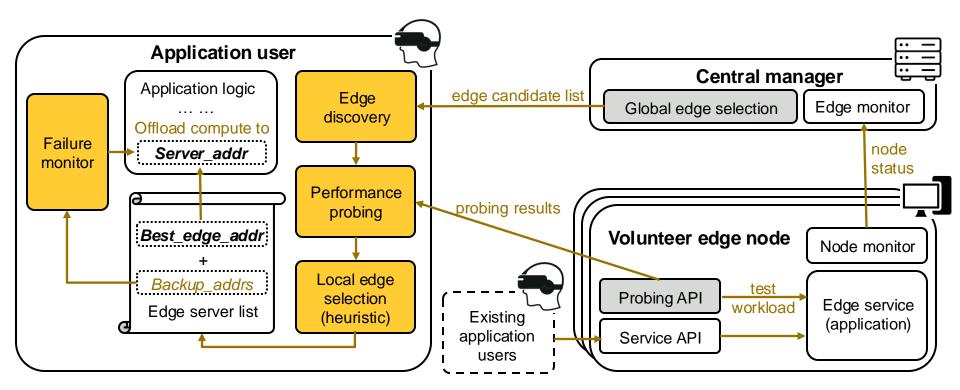
Both users and edge nodes are dynamic with high node churn

Adapt to system dynamics in real-time

Fault tolerance mechanisms to guarantee continuous services



System design





1. Edge discovery

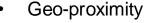
For each user who wants to discover nearby edge resources, we employ a **2-step approach**: (1) **Global edge selection** followed by a (2) **Local edge selection**.

Global edge selection: Central manager examines present edge nodes on certain factors to generate a coarse-grained Candidate edge list.

Candidate edge list: A subset of edge nodes that are **expected** to provide low latency responses for specific users

TopN: size of the Candidate edge list

- **TopN** is an important configurable system parameter in our design
- Larger *TopN* value brings higher accuracy and flexibility to the edge selection process, but also introduce higher overhead



- Resource utilization
- Network affiliation
- Customized tags

2. Performance probing

After the user obtains the *Candidate edge list* (with *TopN* candidates in the list), it applies a **probing approach** to predict edge performance during runtime.

Performance probing: Initiated by end-users directly to *TopN* candidate edge nodes to collect (1) end-to-end networking metrics, and (2) "what-if" processing performance.

• *D_{prop}*: **RTT propagation delay** from the user to the testing candidate edge node

Easy to test by Ping

D_{trans}: Data transfer delay limited by the available bandwidth between the user and the testing candidate edge node

Consume currently available bandwidth and **compete** existing networking traffic



2. Performance probing

After the user obtains the *Candidate edge list* (with *TopN* candidates in the list), it applies a **probing approach** to predict edge performance during runtime.



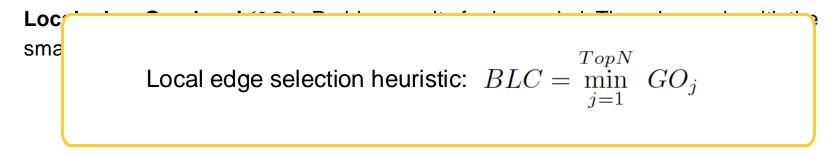
"what-in performance. the processing time measured by invoking a *test symmetic* workload to simulate "new-user-join" scenarios.

Test workload: Synthetic workload (compute offload request) based on the same application logic and compute requirements as the real offloading task



3. Local edge selection

After the user has the probing results of all edge candidates, local edge selection policy is used to sort the *Candidate edge list* to identify the best candidate.



Global-view Overhead (GO_j) : considering the interference to existing workload on edge node j.

$$GO_{j} = n_{j} \times (\underline{D_proc_{probing} - D_proc_{current}}) + LO_{j}$$

#existing users on node j Performance degradation



Evaluation

Real-world experiments setup:

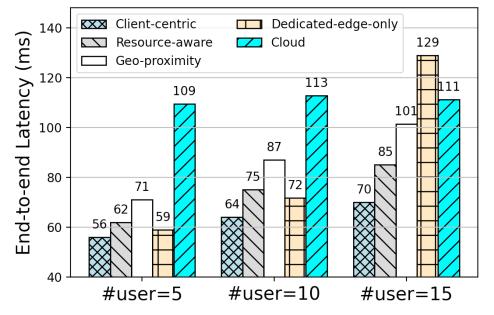
- 20 participants in 10-mile radius, Minneapolis-Saint Paul metro area
- 15 users, 5 volunteer edge nodes, 4 AWS Local Zone

Node	Processor	Processing time – single video frame (ms)
V1	IntelR Core™ i7-9700, 8 cores	24
V2	IntelR Core [™] i7-2720, 6 cores	32
V3	IntelR Core [™] i9-8950HK, 6 cores	31
V4	IntelR Core™ i5-8250U, 4 cores	45
V5	IntelR Core [™] i5-5250U, 2 cores	49
D6-D9	AWS Local Zone t3.xlarge	30
Cloud	AWS ec2 t3.xlarge	30



Edge Elasticity

Baselines: Geo-proximity, resource-aware weighted round-robin, dedicated-edgeonly, closest cloud



✓ Client-centric approach scales with load



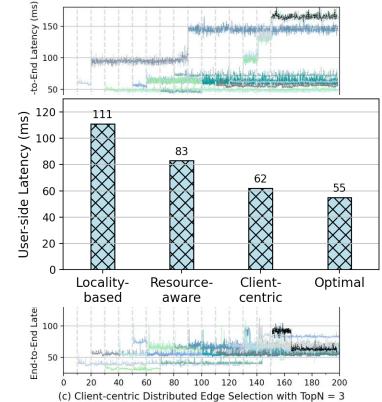
Static edge with increasing #users

- 9 volunteer nodes (4 x t2.medium, 4 x t2.xlarge, 1 x t2.2xlarge), 15 application users (15 x t2.micro)
- Within 50 miles, RTT ε [8, 55] ms

(a) Resource contention leads to overloading of local nodes

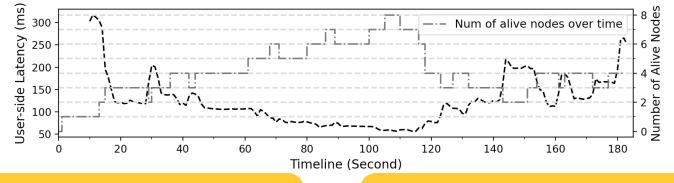
(b) Inability to identify network heterogeneity

(c) Performance probing and multinode connection lead to low latency



Static users with high edge churn

- Edge node arrivals Poisson distribution
- Edge node lifetime Weibull distribution
- 18 edge nodes (8 x t2.medium, 8 x t2.xlarge, 2 x t2.2large)



Correlation between average performance and edge resource availability Effective load balancing leads to low latency when new edge nodes join

Conclusion

- Existing edge deployments are not sufficient to support elastic edge computing everywhere. **Volunteer resources** can be greener compliments to existing edge infrastructures.
- We present the notion of *Heterogeneous edge-dense environments*, and formulate a latency optimization problem towards edge elasticity.
- We design and implement a **client-centric edge selection approach** to achieve a near-optimal performance in dynamic environments.





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