Microsoft

Research Faculty Summit 2018

Systems | Fueling future disruptions

Network Decomposition

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@OpenFog #fogcomputing

Network Decomposition

- Vertical & Horizontal Decomposition:
  - Who does what, at what timescale, how to glue them together?
  - Allocation of functions, not just resources
  - Vertical: Layering as decomposition
  - Horizontal: Cloud – Edge/Fog as decomposition

- Architecture supports Applications:
  - Source-channel separation: Digital communication
  - TCP/IP: Internet applications
  - Edge/Fog: IoT / 5G / Dispersive AI

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The Princeton **EDGE** Lab

2009

Distribute functions to network edge

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2015

Decompose functions along Cloud-2-Things Continuum

Interfaces

Massive storage
Heavy duty computation
Global coordination
Wide-area connectivity

Real time processing
Rapid innovation
User-centric
Edge resource pooling

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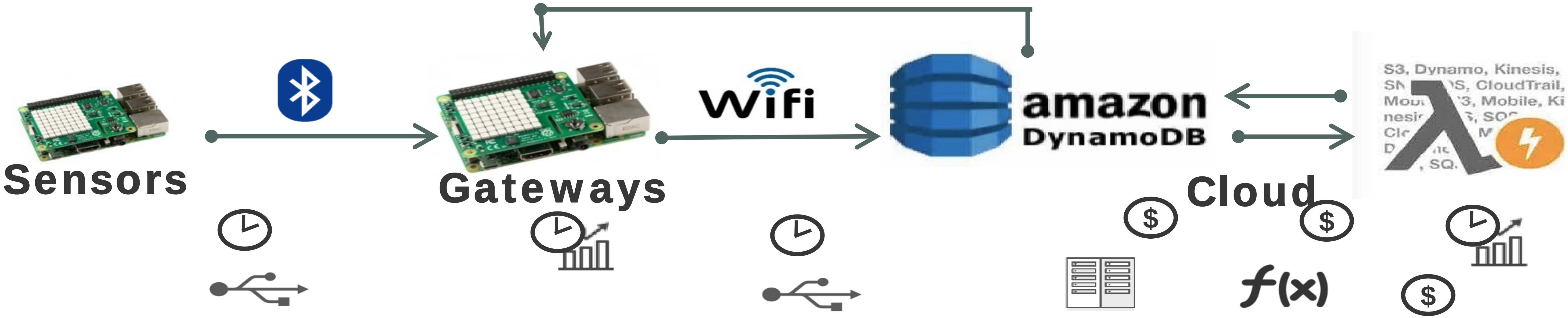
Applications to Dispersive AI

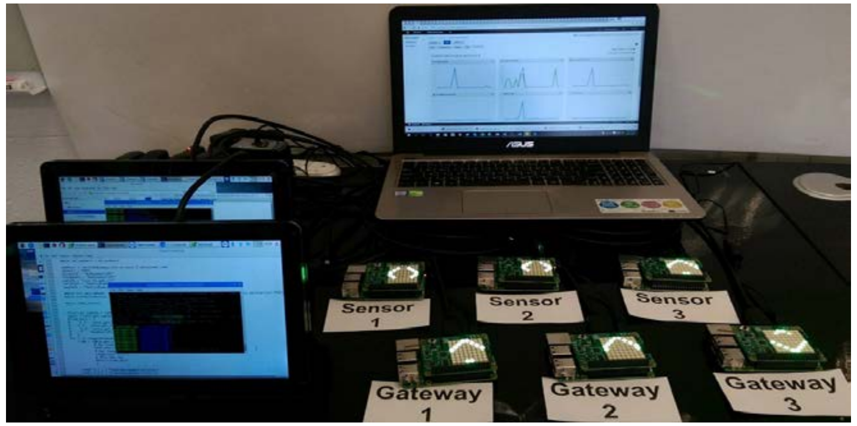
- Design machine learning algorithms that support fast responses
  - Enable IoT systems with intelligence here and now

- Decompose machine learning into multiple geographically distributed components, collectively or jointly operating
  - Optimize communication costs and centralized data processing costs
  - Make best use of local/proximal resources

- Proactively pre-position content and computing
  - Parallel successive refinement for streaming mining
  - Reduce infrastructure costs and improve quality of experience

Testing Decompositions of Machine Learning



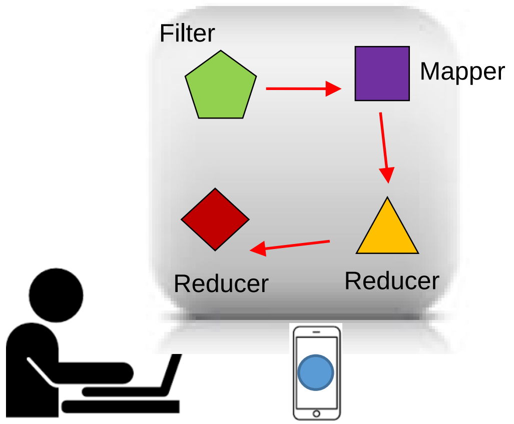


- Specialized testbed developed
- Linear regression decomposition: 70% reduction in data transmission
- Demonstrations: IEEE FWC’17, ACM SenSys’17 NYC Media Lab Summit’17.

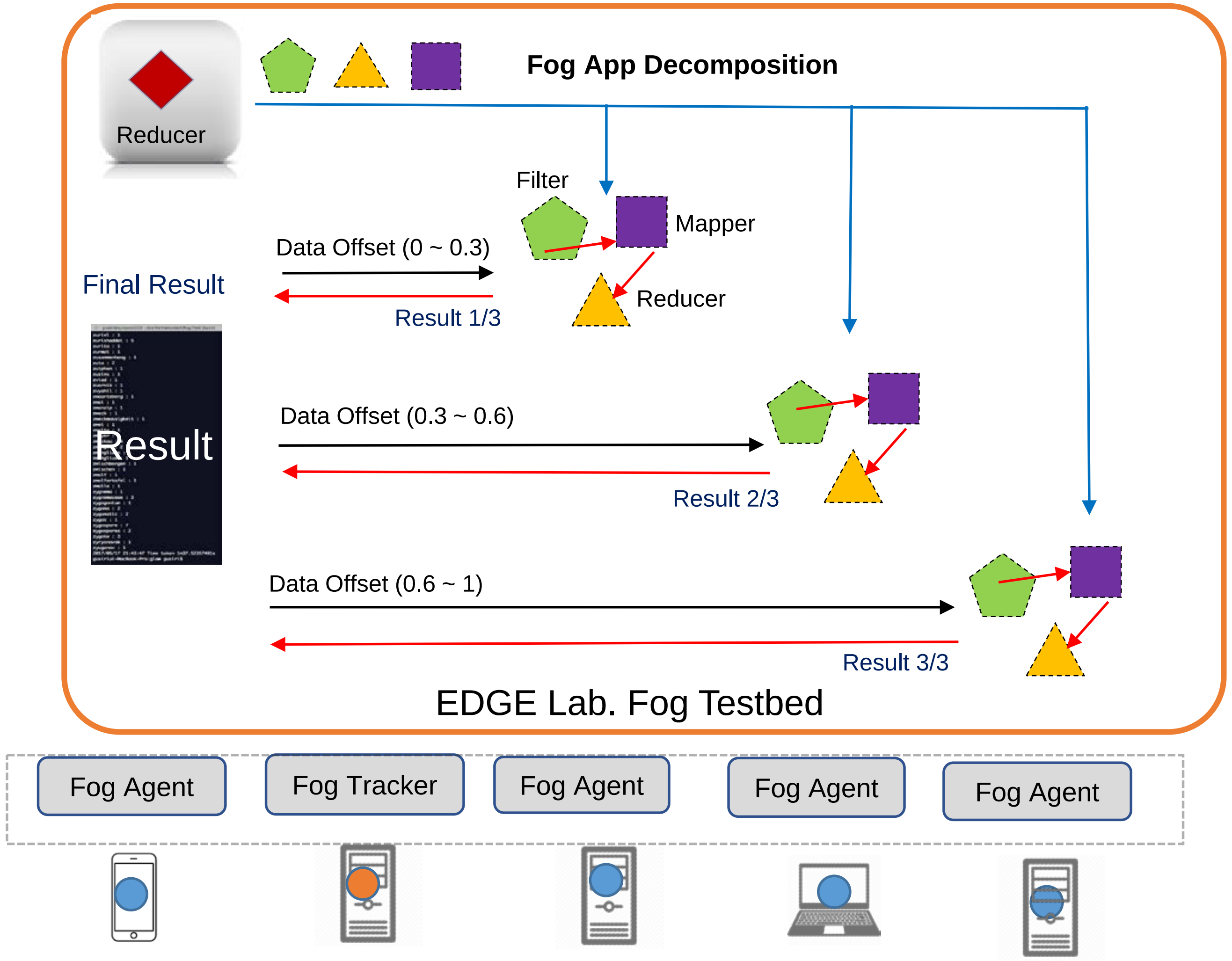
New MapReduce

- Re-visit MapReduce for Fog environment
  - Coordination & consistency
  - Robustness through redundancy
  - Computation decomposition
  - Task placement and scheduling along C2T
  - Automating deployment
- Prototype provides primary MapReduce APIs
  - Filter
  - Map
  - Reduce
  - ReduceByKey
  - MapByKey

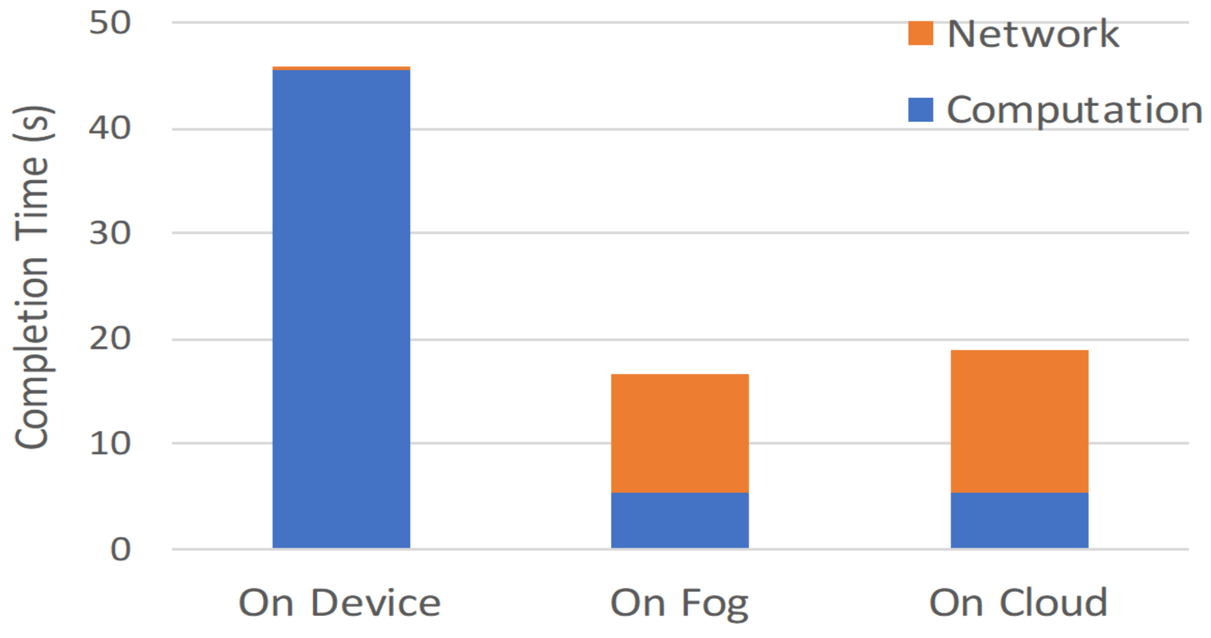
Local Fog MapReduce

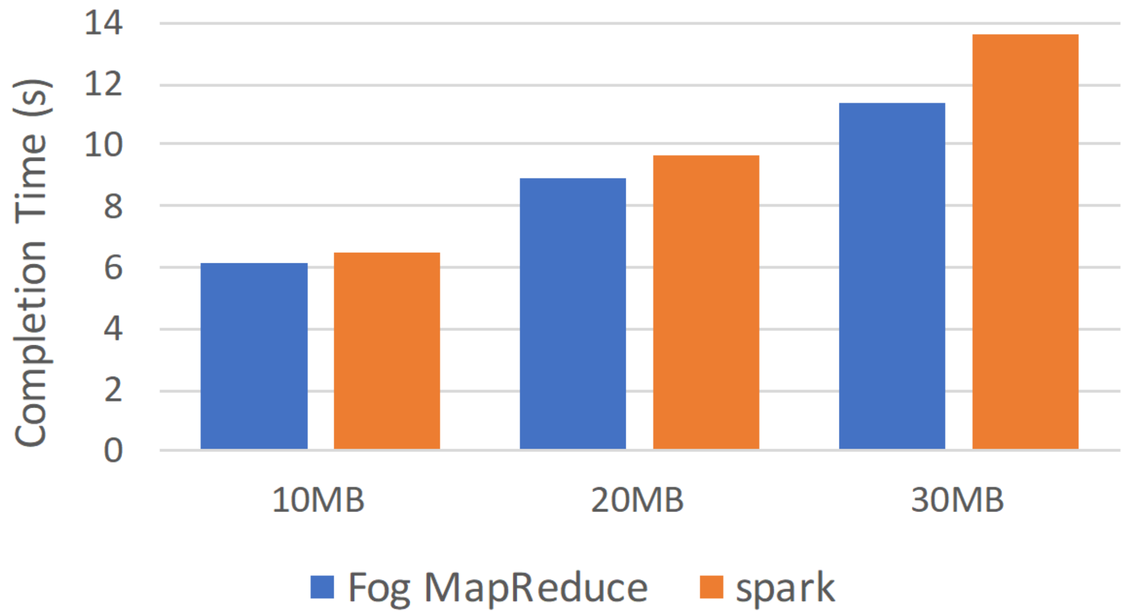


Distributed Fog MapReduce



Simple Example: Counting Words in a File





Unique Features in Edge/Fog

- Heterogeneity/Under-organization of resources/devices
- Variability/Volatility in availability/mobility
- Bandwidth/Battery constraints
- Proximity to sensors/actuators

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Two Toy Examples

- Drone Camera Network
  - Aakanksha Chowdhery, Shirley Wang

- Personalized Placement Learning in AR/VR
  - Surin Ahn, Maria Gorlatova, Parinaz Naghizadeh

Outdoor Live Coverage

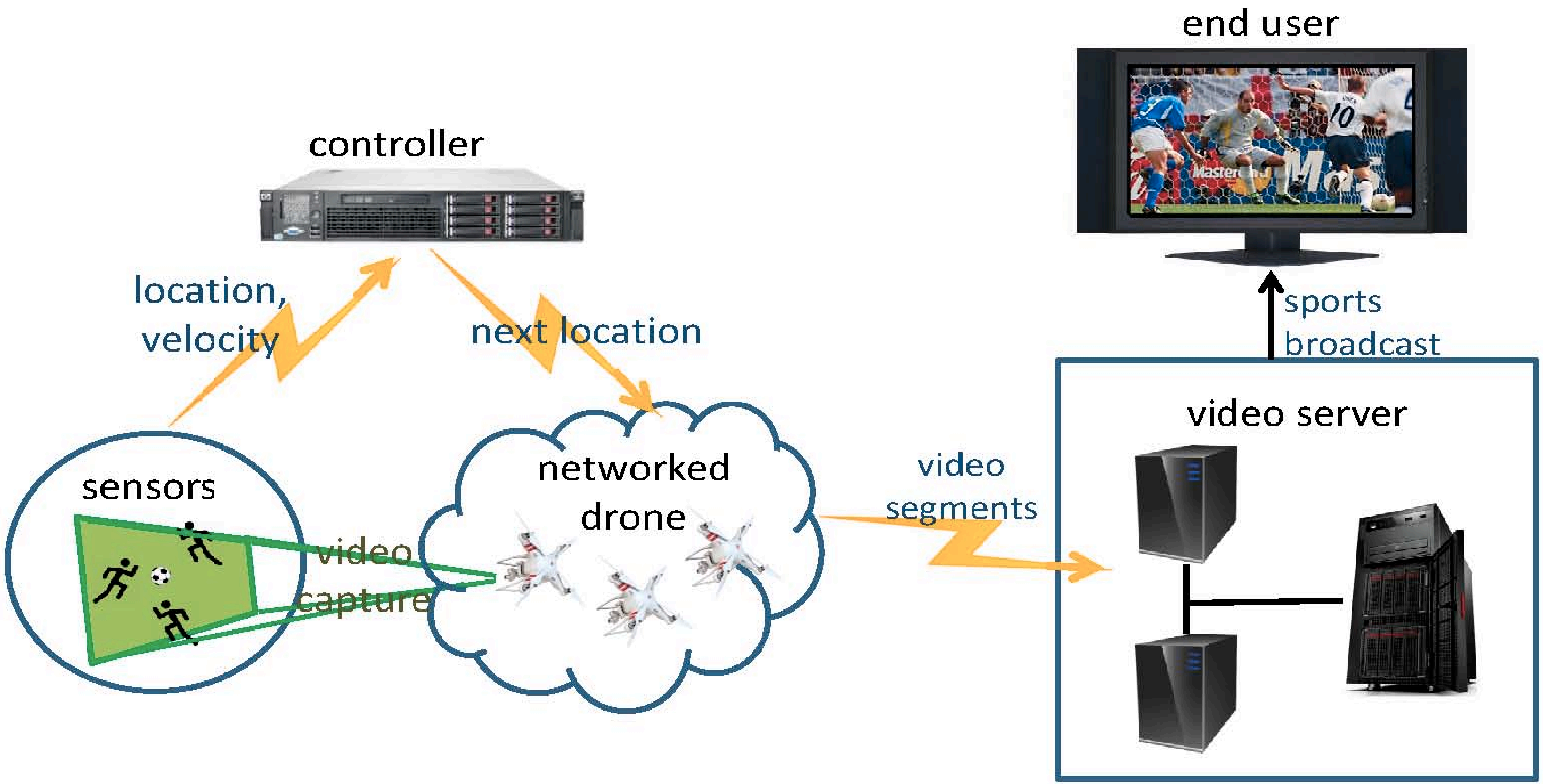
- Stadiums use 30-50 cameras to capture games nationally broadcast

- NFL recently introduced cameras over crosswires: SkyCam, SpiderCam

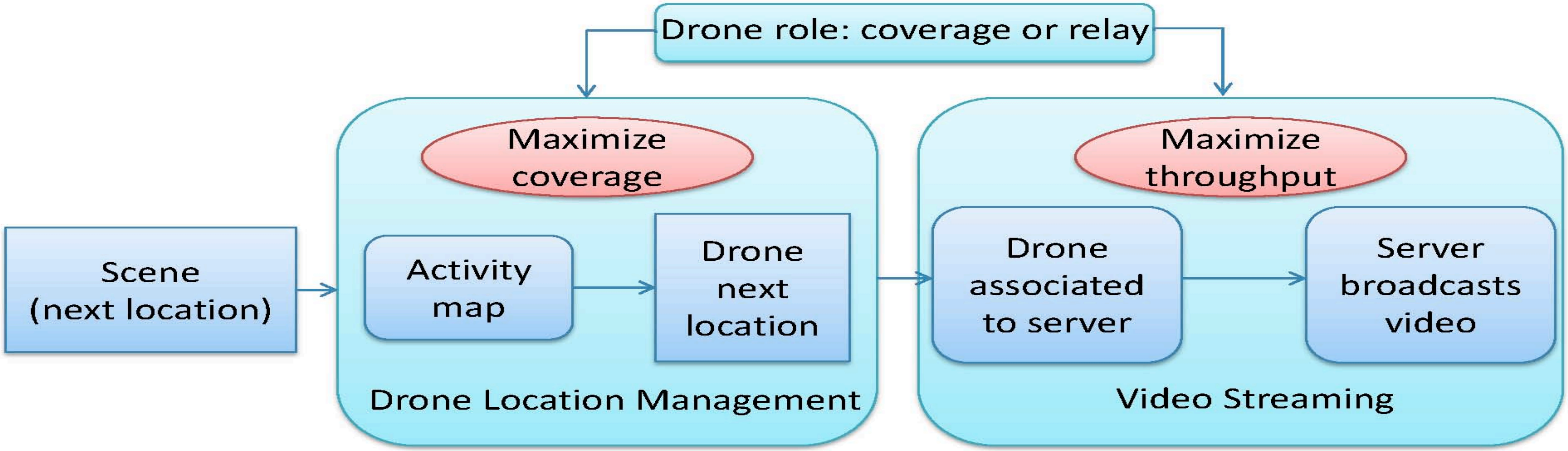
Network Decomposition

- Distributed
  - Make decision locally; low latency
  - Suboptimal: all drones prioritize covering the most important scene
- Centralized
  - Cloud makes decisions, cost benefits and efficiency
  - Round-trip time limits drone trajectory coordination rate, response to game dynamics
- One decomposition:
  - Drones form a fog network: trajectory planning, collision avoidance
  - Centralized coordination for next target location, drone function

One Choice of Decomposition



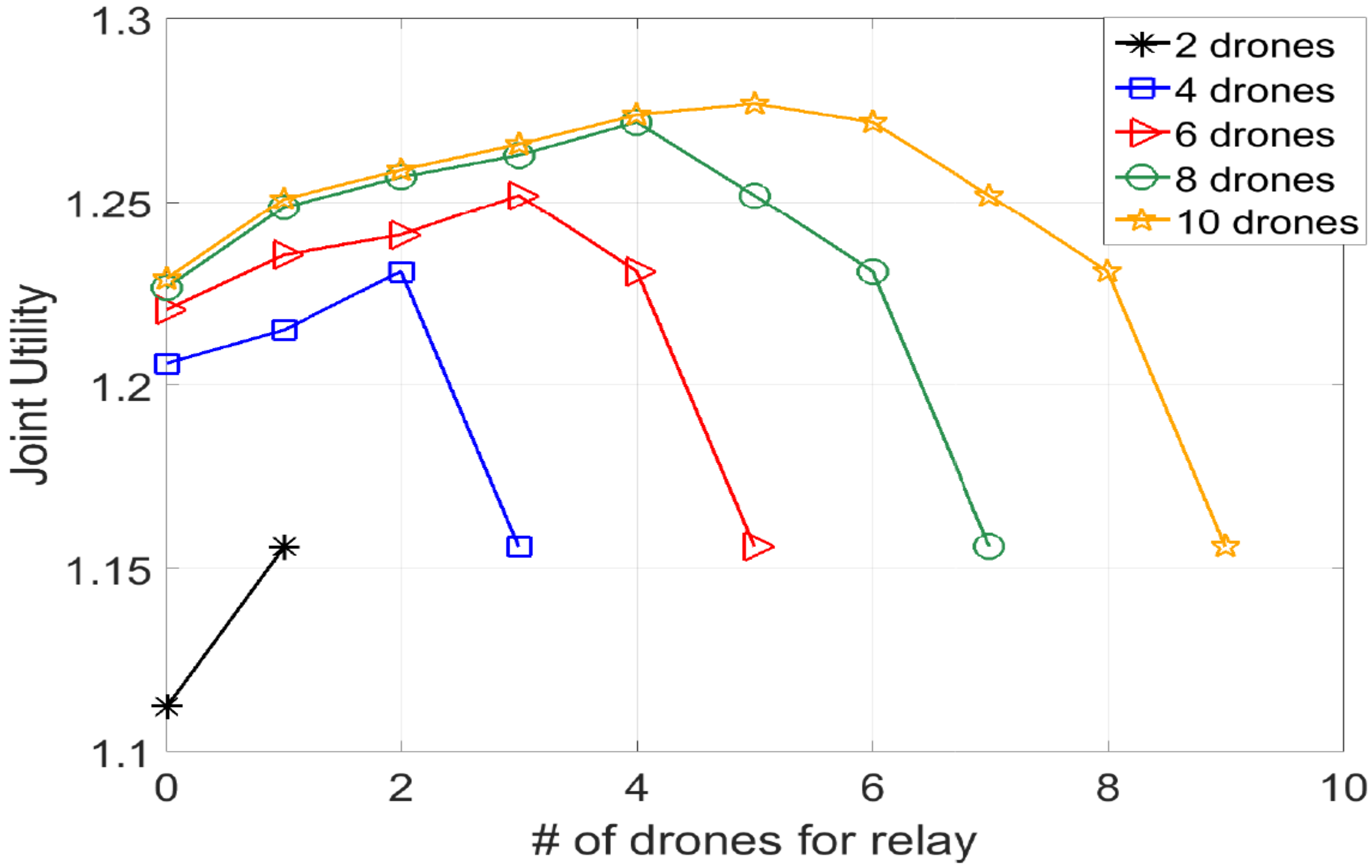
Coverage vs. Throughput



- Sensors on players/ball (location, speed)
- Predict locations of next importance scenes
- Match drones to each important scene

- Max throughput: drone selects the best server
- Throughput boosting: drone as relay

Joint Optimization and drone allocation



Optimal allocation of drones as relay

Observations

- A system to coordinate a network of drones to capture and broadcast a sports game from drone cameras over a wireless channel

- Joint Optimization
  - **Maximize the coverage of interesting scenes**: drone location assignment algorithm.
  - **Maximize video quality**: drone-server association scheme, drone as relay.

- Evaluation: optimal 4 drones for coverage, 4 as relay
  - achieve 94% coverage
  - support 2K video streaming at 20Mbps

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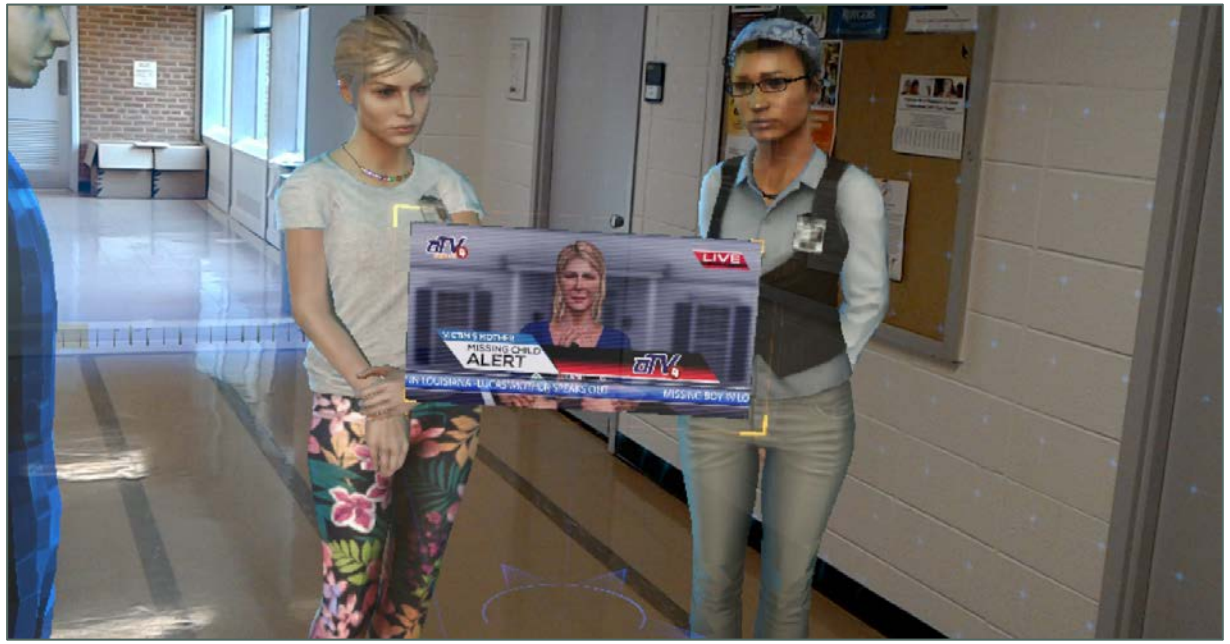
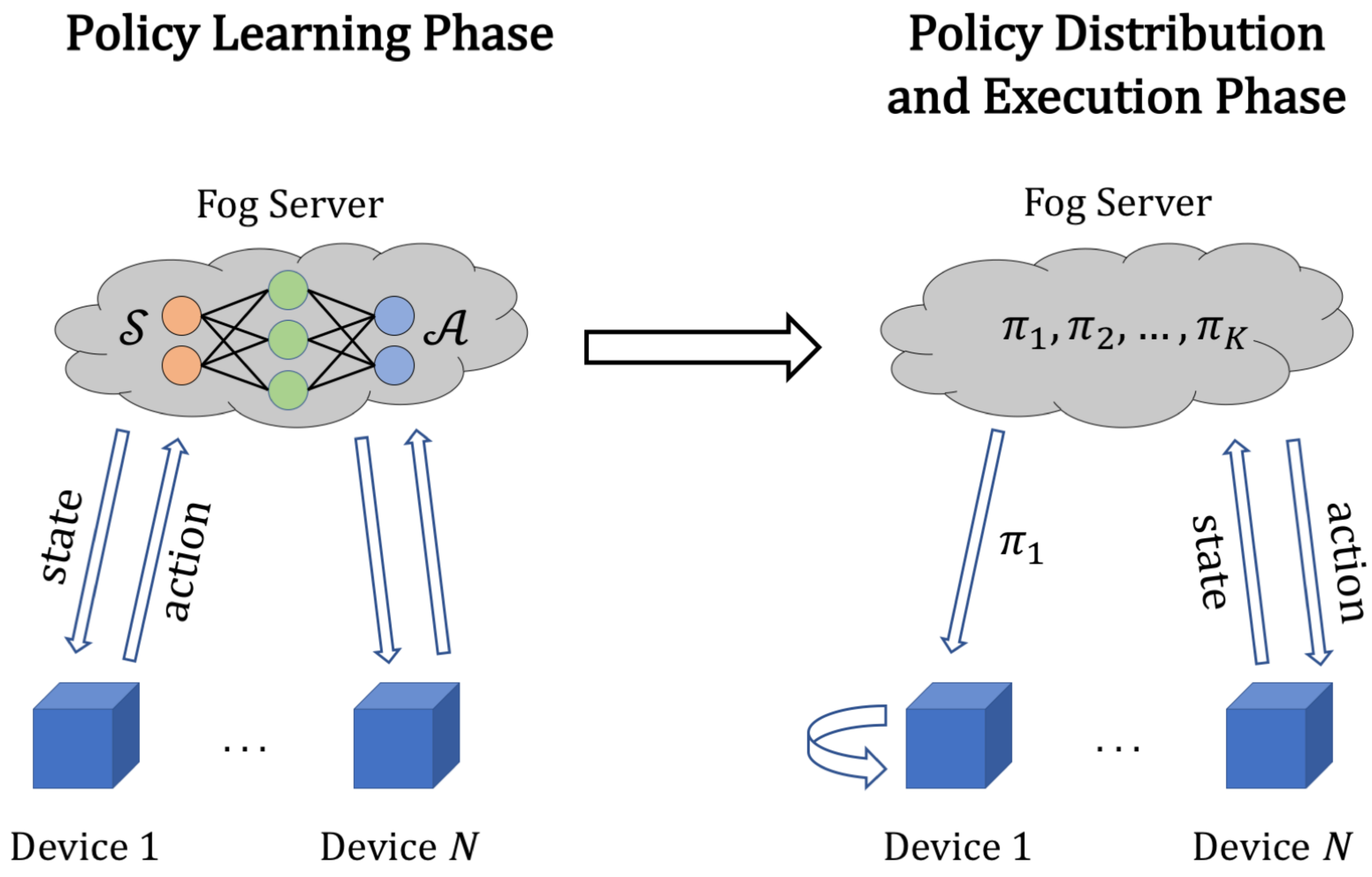


Personalized AR Object Placement:

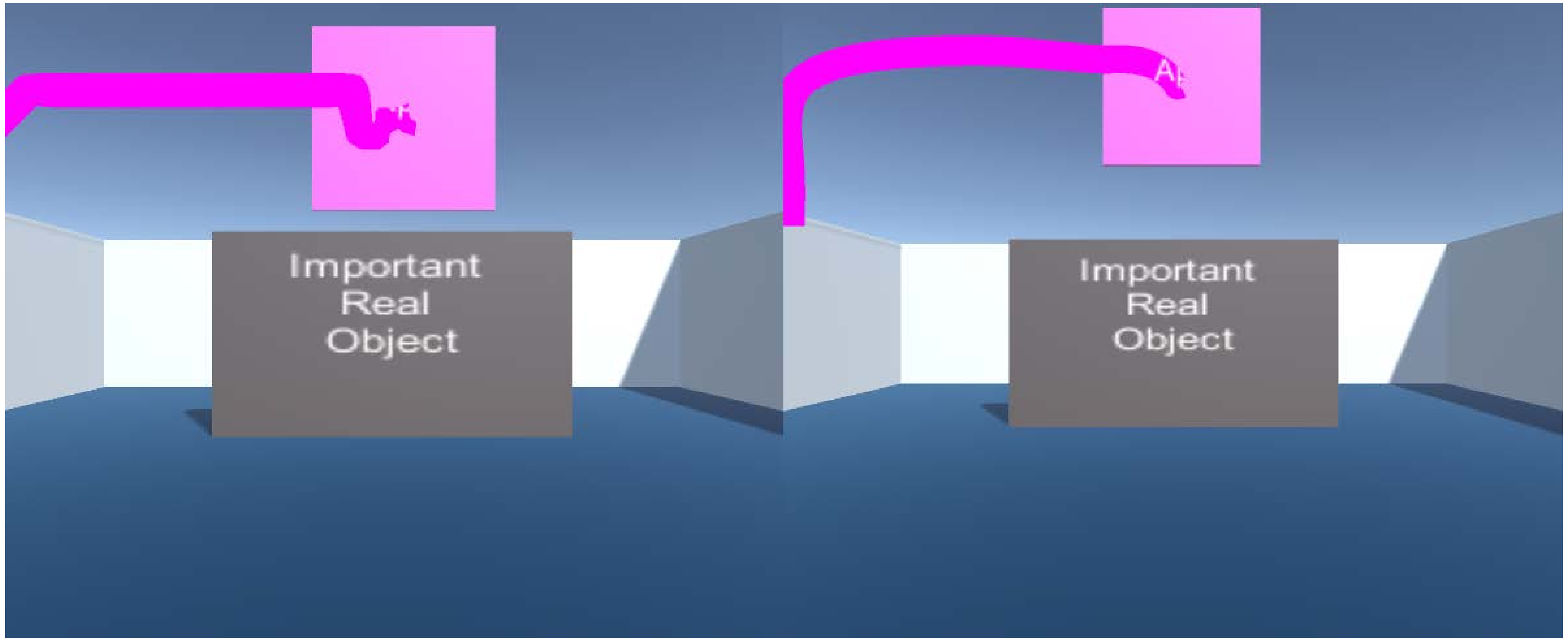
Where Does Learning Happen?

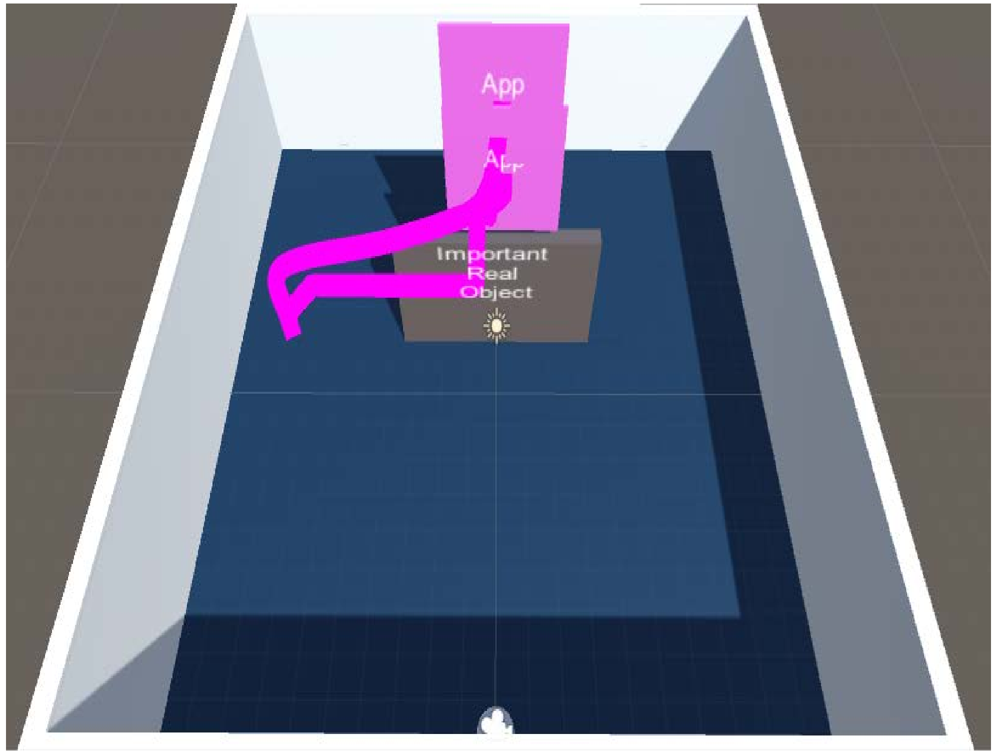
Network Decomposition

- **Policy learning phase:**
  - Present users with simulated environments; collect their actions
  - Use imitation learning to learn personalized hologram placements
- **Policy execution phase:**
  - Send to powerful devices
  - Run on behalf of resource-constrained devices



Personalized Placement Learning

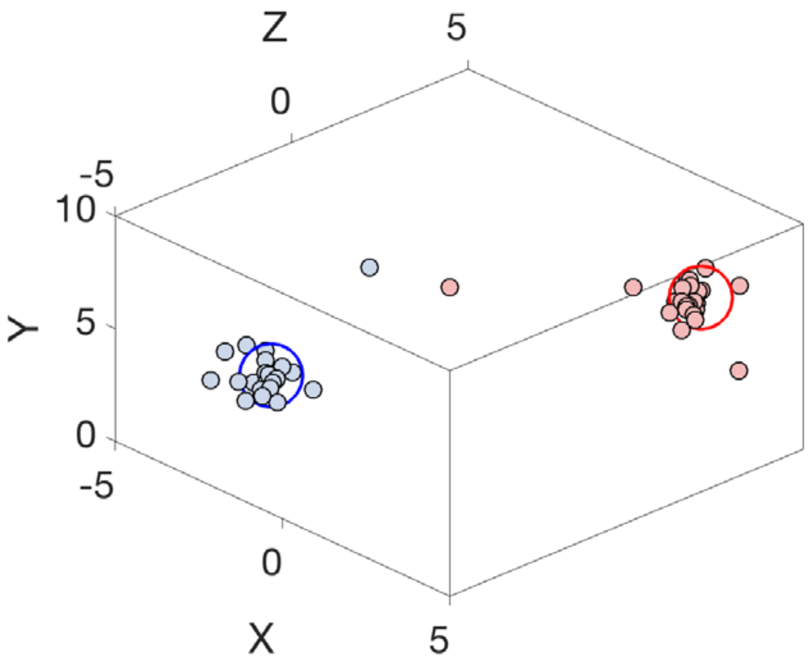




User-controlled hologram Agent-controlled hologram

Birds-eye view shows matching trajectories in addition to placements

Learning A User’s Preference Fast



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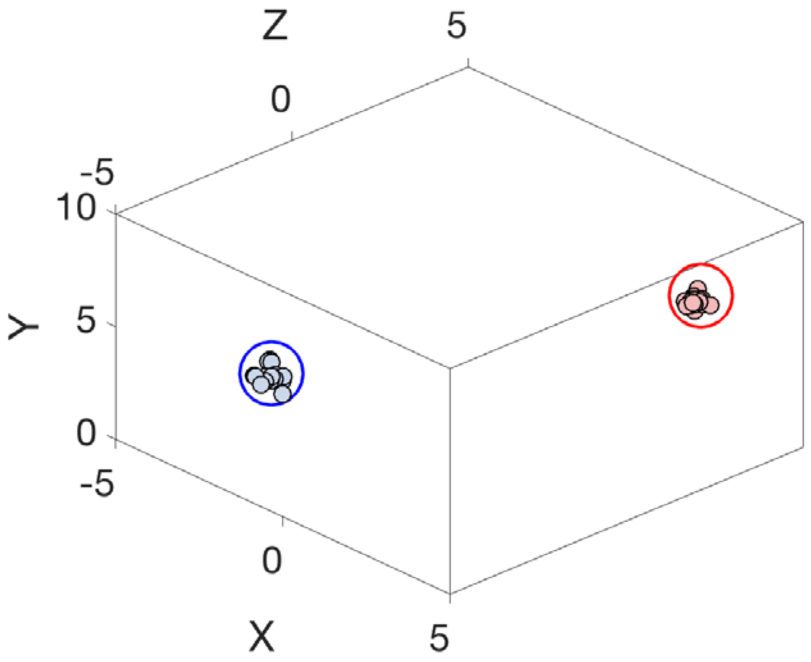
Demos



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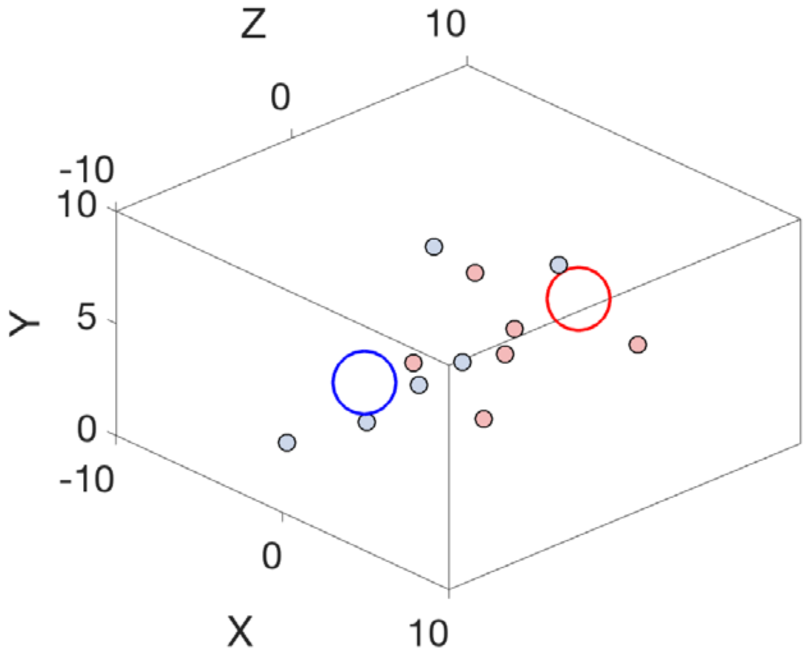
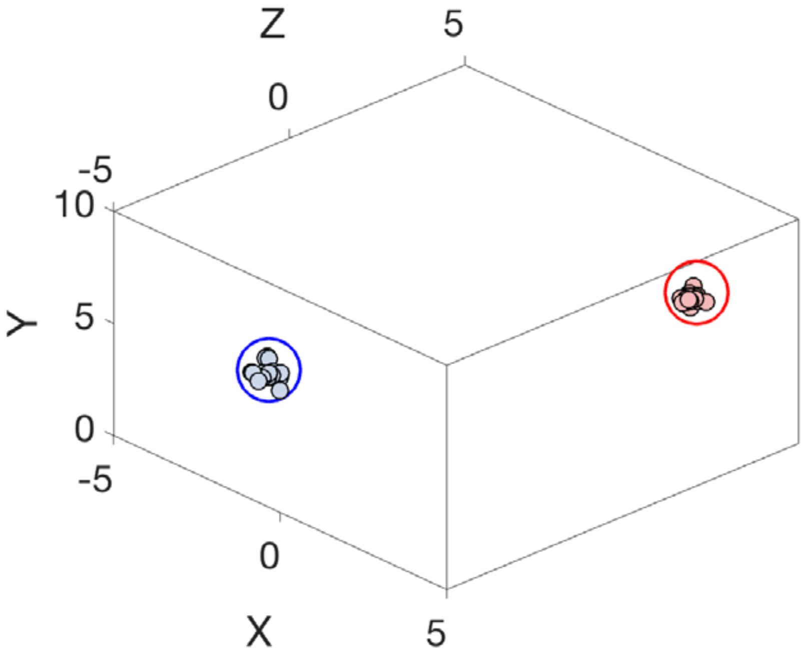
Demos

Each circle represents the users’ desired destination. Dots represent algorithm’s action. As early as 13 demos, agent achieves accuracy.

State Space Reduction Helps



Full image as state



Reduced state-space

Hologram destinations after 12 trials when using the full AR image as the state. Compared with the reduced state-space there is degradation in accuracy.

Overarching Questions

- Where to place a function/data set?
- What is the interface among modules?

The Edge/Fog Advantage: SCALE

- Security
- Cognition
- Agility
- Latency
- Efficiency

Thank you!

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