

Center for Smart Spaces Research (CSSR) NSF IUCRC Initiative

Planning Meeting
April 11-12, 2022

Slide Deck Day 1 – April 11, 2022

NSF: The National Science Foundation; IUCRC: Industry University Cooperative Research Center



Industry introductions



Abbott



Clearsense



HERITAGE
CHRISTIAN SERVICES

IBM Research

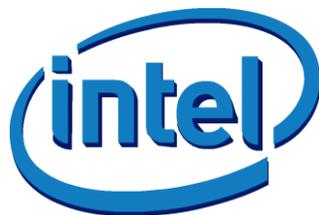


IBM Watson Health™



ImageCat

INGRAM MICRO



NAVWAR



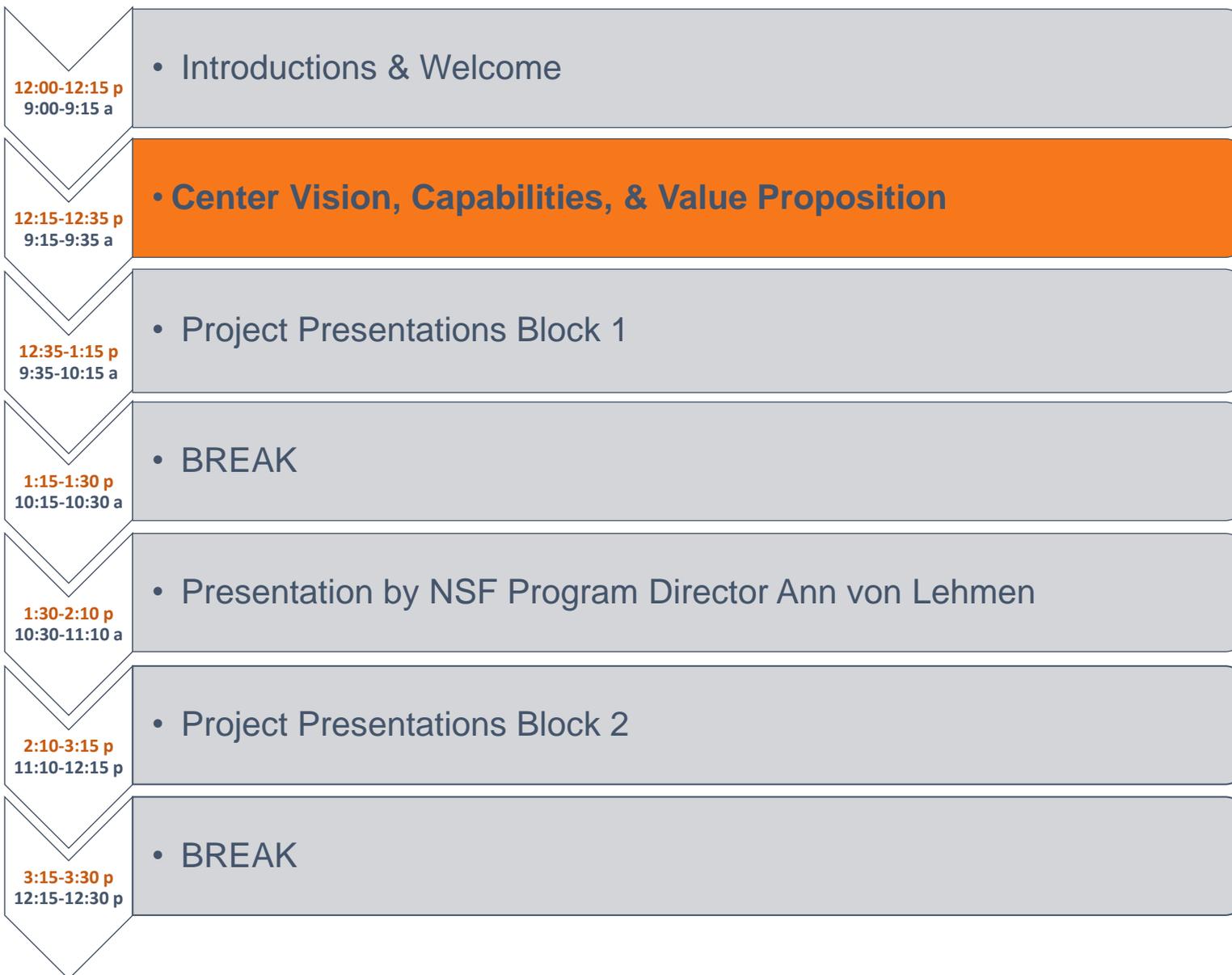
NLST orolia

PIKE

QUALITROL®

RAYMOND





Center for Smart Spaces Research (CSSR) NSF IUCRC Initiative

*Planning Meeting
April 11-12, 2022*

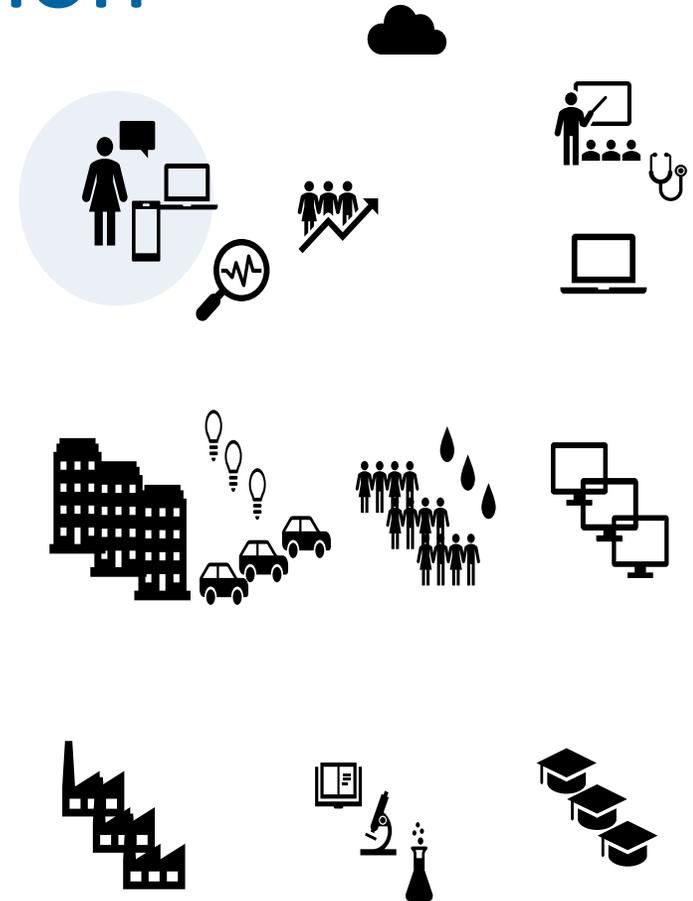
CENTER VISION

*Mohan Kumar, Center Director, CSSR
Rochester Institute of Technology*

NSF: The National Science Foundation; IUCRC: Industry University Cooperative Research Center

Smart Spaces: Vision

- **Humans** – well-being, health, food, safety, privacy, education, resources, connectivity, data, ...
- **Physical and Virtual Spaces** – smart, energy conserving, reactive and proactive
- **Society** - inclusive, safe, resilient, and sustainable
- **Cities** - smart transportation, water and power distribution, waste management ...
- **Industry** - workforce that is ready, diverse and inclusive
- **Products** - Commercialization of ideas



CSSR initiatives will create smart spaces that can be employed effectively, efficiently, and reliably for multiple applications, with close collaborations with Industry.

Mission

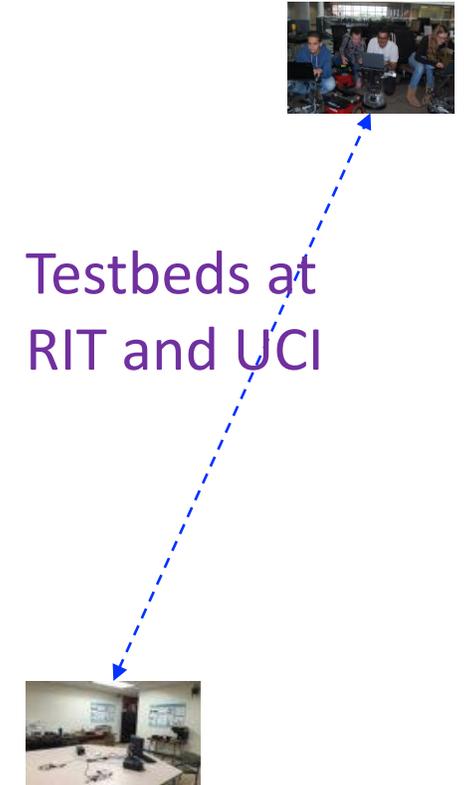
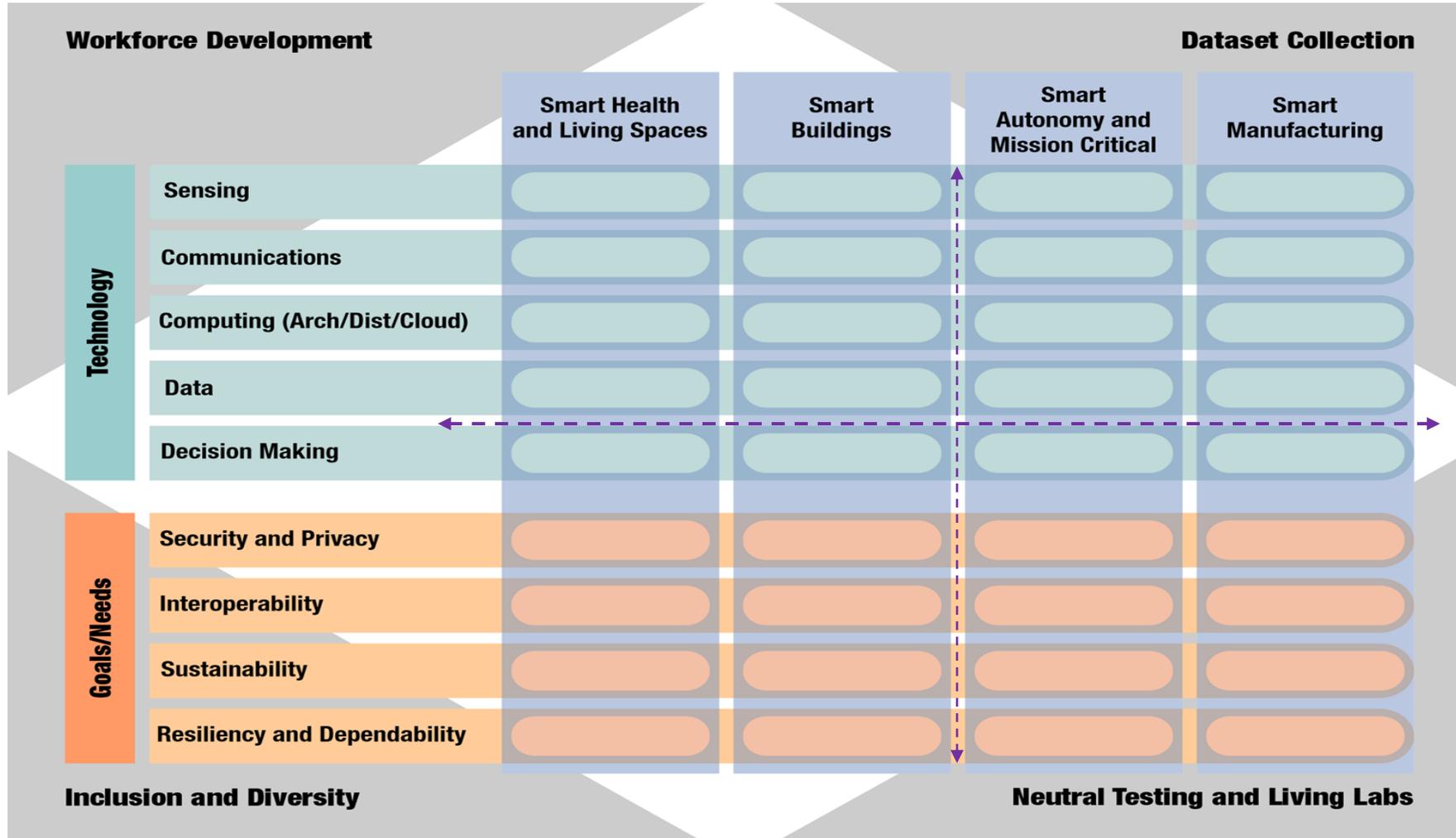
CSSR will be a Multi-Institutional, Multidisciplinary Center for industry and university to come together

Research at CSSR will be aligned with industry needs in 'smart spaces'

Industry partners will have access to precompetitive research outcomes, data, and testbeds at CSSR sites

New courses and research & developmental opportunities will be created for students at all levels

Smart Spaces – Technological Challenges and Verticals



Testbeds at RIT and UCI

Smart Spaces and IUCRC Goals

Talent discovery and
workforce development

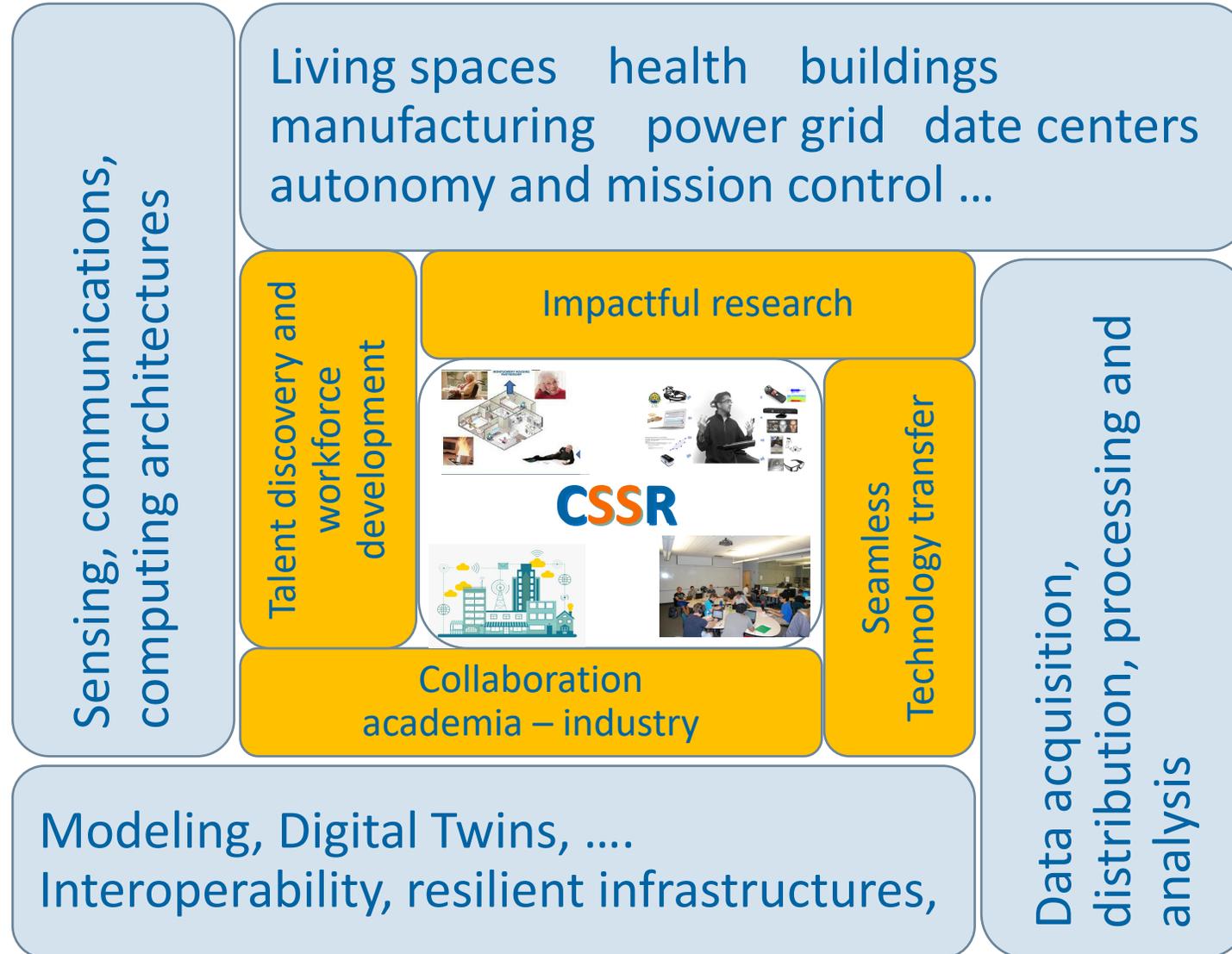
Impactful research



Seamless Technology
transfer

Collaboration
academia – industry

Research and Application Areas



Meetings with Industry Colleagues

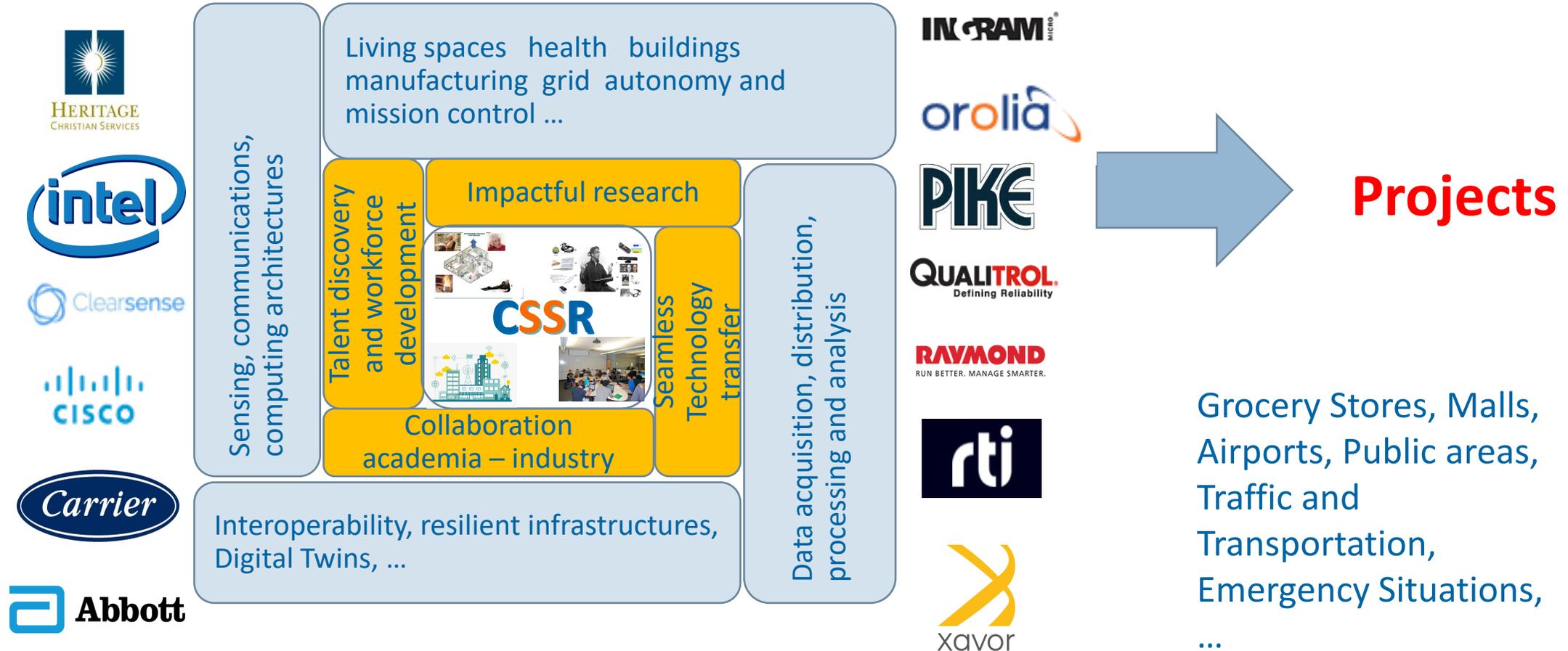
IBM Research  IBM Watson Health®  ImageCat



Not for Profit Federal Agencies

Results of Meetings

IBM Research  IBM Watson Health  ImageCat



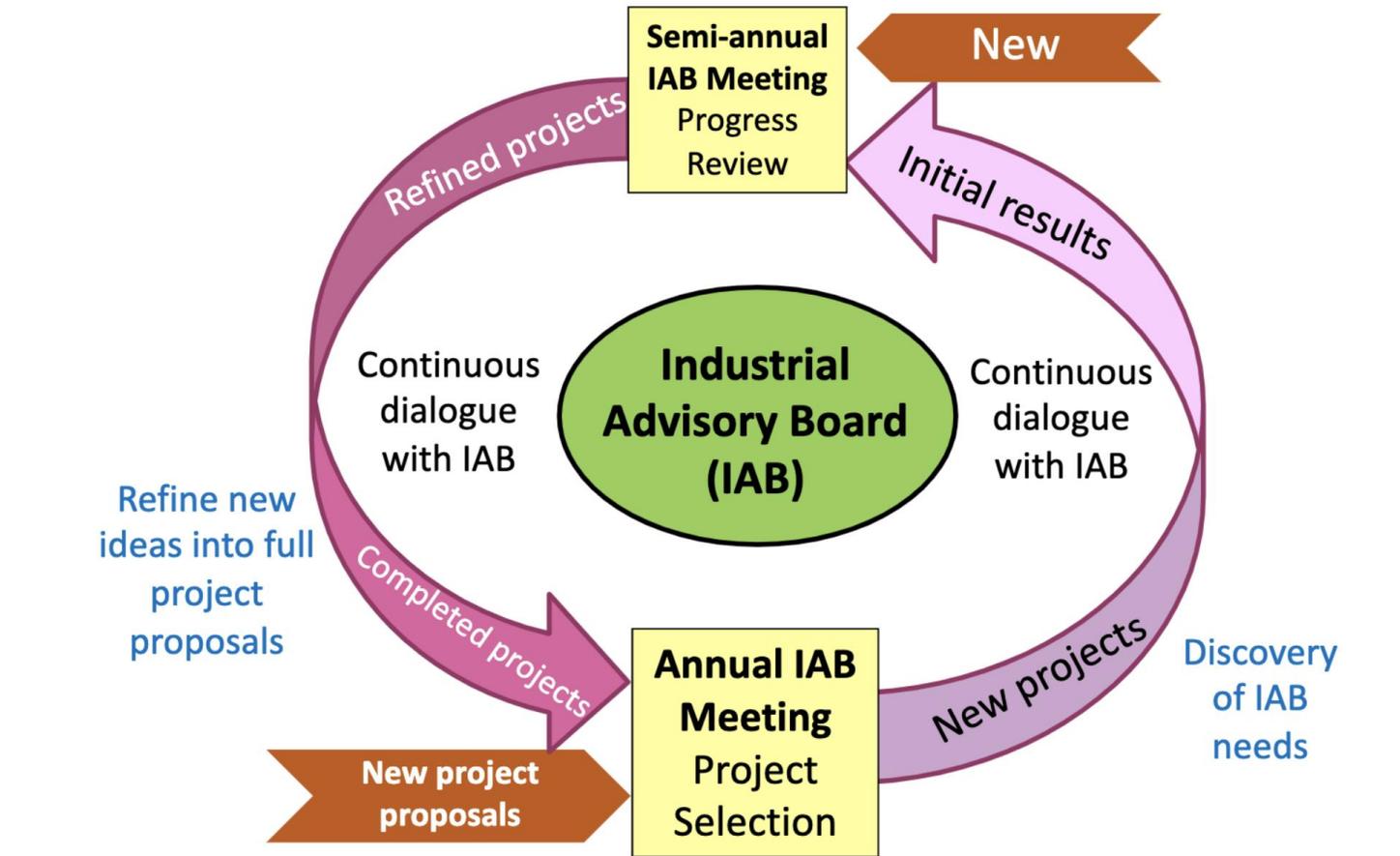
Not for Profit Federal

Role of Industry Board



Enhance participation

- Industry
- University
- Research and application areas
- Students, Faculty, DEI



RIT and UCI

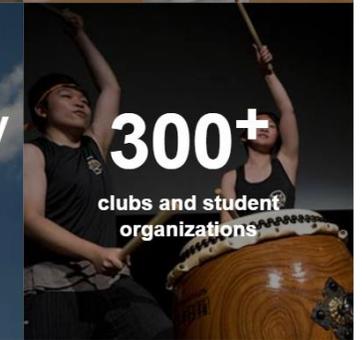
- World class researchers
 - Competitive projects, publications, recognition
- Outstanding students
 - Quality, Quantity, Diversity
- Excellent Facilities
 - Centers, Institutes, Labs
- Strong Support from University Leaderships
- Strong record of collaborations with Industry
 - Funded projects, coops, capstones, internships, alumni, ..



Scope to add more universities

REUs
RETs
GREPs
International

Thank you!



Our Mission

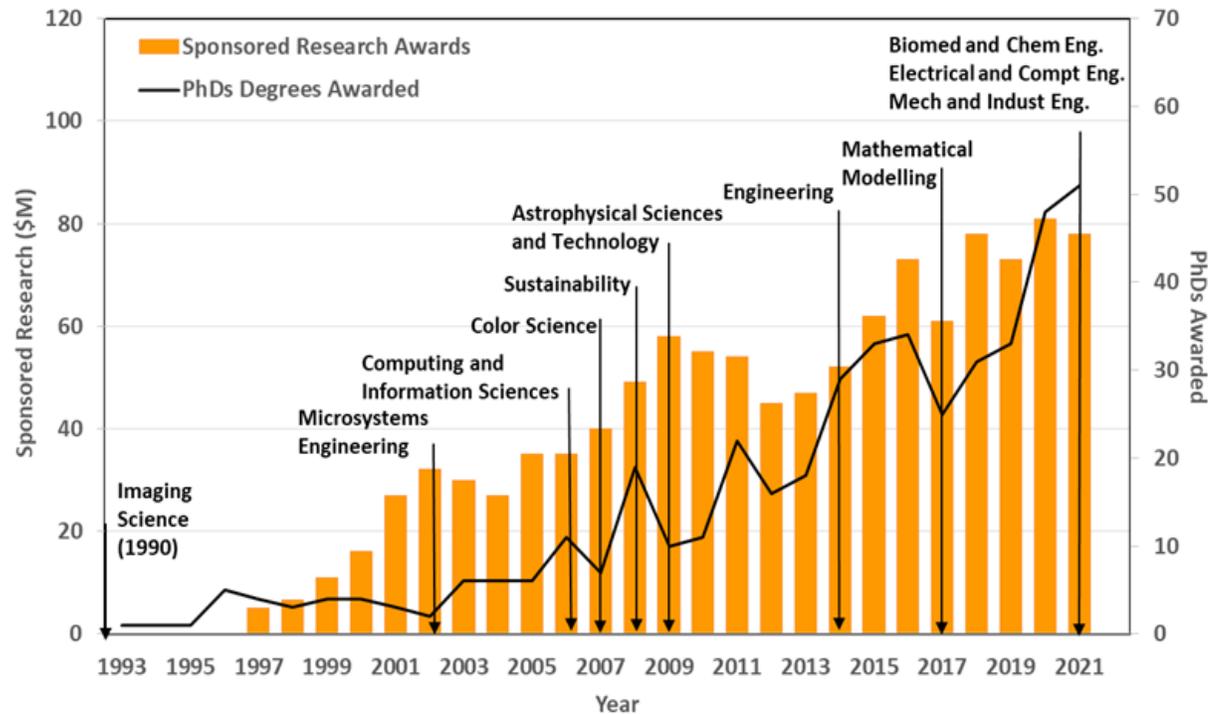
At Rochester Institute of Technology, we shape the future and improve the world through creativity and innovation. As an engaged, intellectually curious, and socially conscious community, we leverage the power of technology, the arts, and design for the greater good.

Rochester Institute of Technology

Site Director: Amlan Ganguly

Accelerating Trajectory in Research, Doctoral Education, and National Prominence

Growth in Research @ RIT



Degrees Awarded

Doctorate	51
Master's	1,296
Advanced Certificates	130
Bachelor's	3,008
Associate, Diploma, Certificate	109
Academic Year 2020-2021 Total	4,594

RIT Academic Resources

■ Faculty

- Distinguished research portfolio
- Experienced in conducting sponsored research with govt. and industry sponsors
- Advising student researchers

■ Students

- UG and Grad researchers
- Diversity

■ World class research space

- Labs
- Design centers
- Research Centers



Degree Programs by the Numbers

11

Ph.D. Programs

73

Master's Degrees

78

Bachelor's Degrees

49

Accelerated Dual-Degree Programs

Center Faculty Members - Investigators

■ Networks and Distributed Systems

- **Mohan Kumar, CS**
- Minseok Kwon, CS
- M. Mustafa Rafique, CS
- Xumin Liu, CS
- **Amlan Ganguly, Deptt Head CE, GCI**

■ Wireless and 5G

- Andres Kwasinski, CE
- Hanif Rahbari, CSEC, GCI

■ Robotics

- **Ferat Sahin, Deptt Head EE**
- Daniel Kaputa, ECET
- **Zachary Butler, Inter. Chair CS**

■ Access Technologies

- **Peter Hauser, Interim. Assoc. Dean, NTID**
- Wendy Daniels, NTID
- Spencer Monton, NTID

■ Machine Learning & Data Science

- **Andreas Savakis, CE, Dir. CHAI**
- Dongfang Liu, CE
- Alex Loui, CE

■ Healthcare

- **Linwei Wang, CS, Dir. PHT**
- Caroline Easton, BH
- Chris Homan, CS

■ Smart Manufacturing

- Michael Kuhl, ISE
- Rui Liu, ME

■ Security and Privacy

- Mehdi Mirakhorli, SE, GCI
- Ivan De Oliveira Nunes, CSEC, GCI

Signature Interdisciplinary Research Centers



**Future Photon Institute and
Photonics for Quantum (PfQ)**



**ESL Global Cybersecurity Institute and
The Center for Human Aware AI (CHAI)**



Personalized Healthcare Technology (PHT180)



Center for Computational Relativity and Gravitation

NY State Research Centers



NYS Center for Advance Technology - AMPRint



NYS Center of Excellence in Sustainable Manufacturing & NYS Pollution Prevention Institute

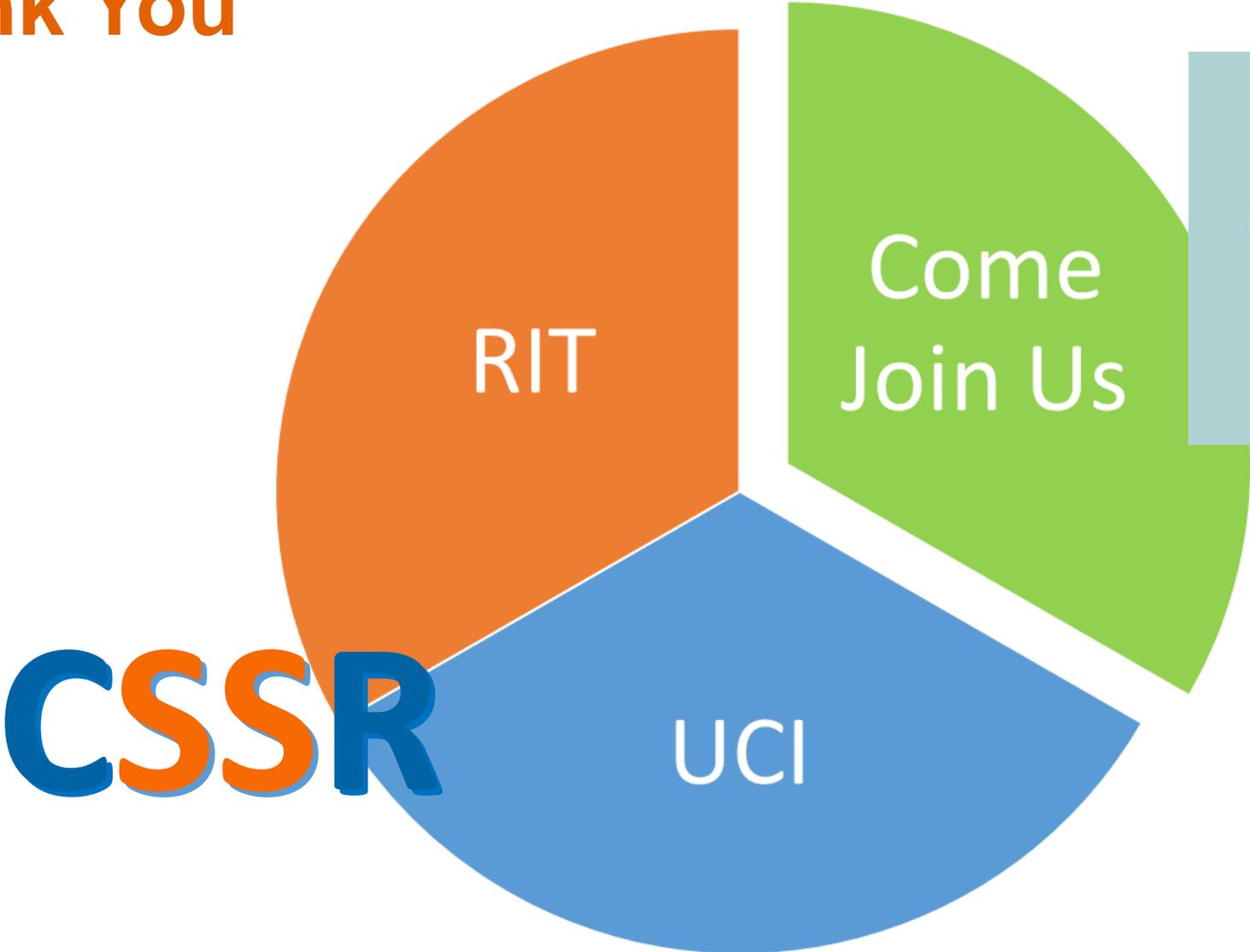


RIT/NYBEST Battery Prototyping Center



NYS Center of Excellence - Digital Games Hub

Thank You



The image features the UCI logo in a dark blue, bold, sans-serif font. The logo is centered within a light blue, circular, multi-lobed decorative shape that resembles a stylized flower or a gear. The background is a solid, medium blue color.

UCI

**Bright Past.
Brilliant Future.**

Site Director: Nalini Venkatasubramanian

37,243

Total Students

Fall 2021

9,886

Degrees

Awarded in 2021

\$8B

Annual Economic Impact

UC Economic Impact Analysis, 2021

25,634

Total Workforce

Fall 2021



TOP 10
Public University
in the U.S.

— U.S. News & World Report

48
GRADUATE
programs/specialties ranked among
nation's top 50

— U.S. News & World Report

TOP 10
Cool School
For Sustainability
— Sierra magazine



1 of 66

leading research universities elected into the prestigious Association of American Universities

170+
UCI Health Doctors
named as "Physicians of Excellence"

— Orange County Medical Association

#2
Public University
for upward
social mobility
— U.S. News & World Report

#3 in the nation for
Diversity

— The Wall Street Journal/Times Higher Education 2022 College Rankings

One of America's
Best Hospitals
for 21 consecutive years

— U.S. News & World Report



Chao Family
Comprehensive Cancer Center
O.C.'s only National Cancer
Institute-designated
comprehensive cancer center

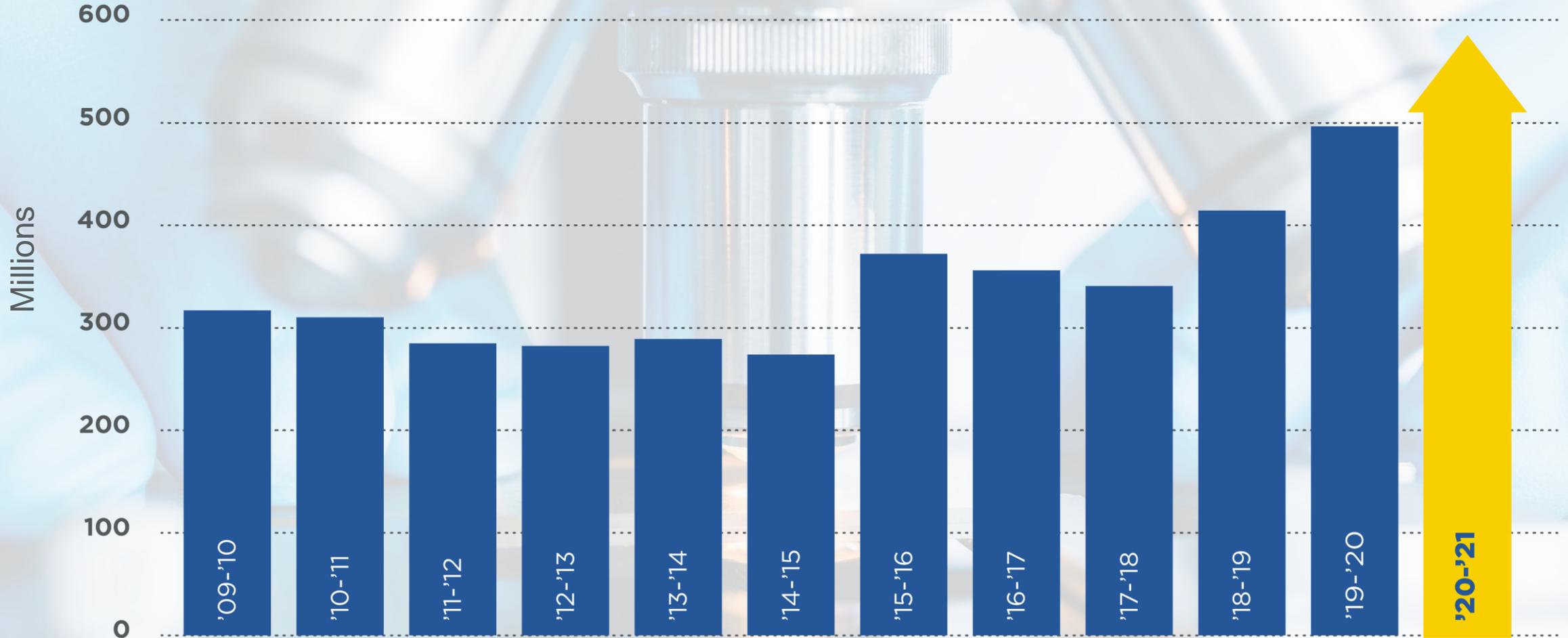
— National Institutes of Health



5 NOBEL
PRIZES

Four in chemistry, one in physics

External Research Grants and Contracts



Reshaping Computing

120

**Research &
Teaching
Faculty**

3,500

**Undergrad
Students**

500

**Master's
Students**

350

**Doctoral
Students**

\$30M

**New
Research
Awards
Annually**

○ Focus, scale, and diversity

- Only computing School on West Coast, one of the largest in the nation
- ~3% of annual US computing degrees
- 35% first-gen, 25% female, 15% URM students

○ Computer Science, Informatics, and Statistics under a single roof

- From statistical methods, machine learning, and cloud computing to privacy, accessibility, and data justice
- Reshaping all aspects of computing, from education and core technologies to ethical and socially-responsible applications

Major Research Centers & Initiatives

UCI Office of Data and Information Technology

 **INSTITUTE for SOFTWARE RESEARCH**
UNIVERSITY of CALIFORNIA • IRVINE

 **Connected Learning Lab**

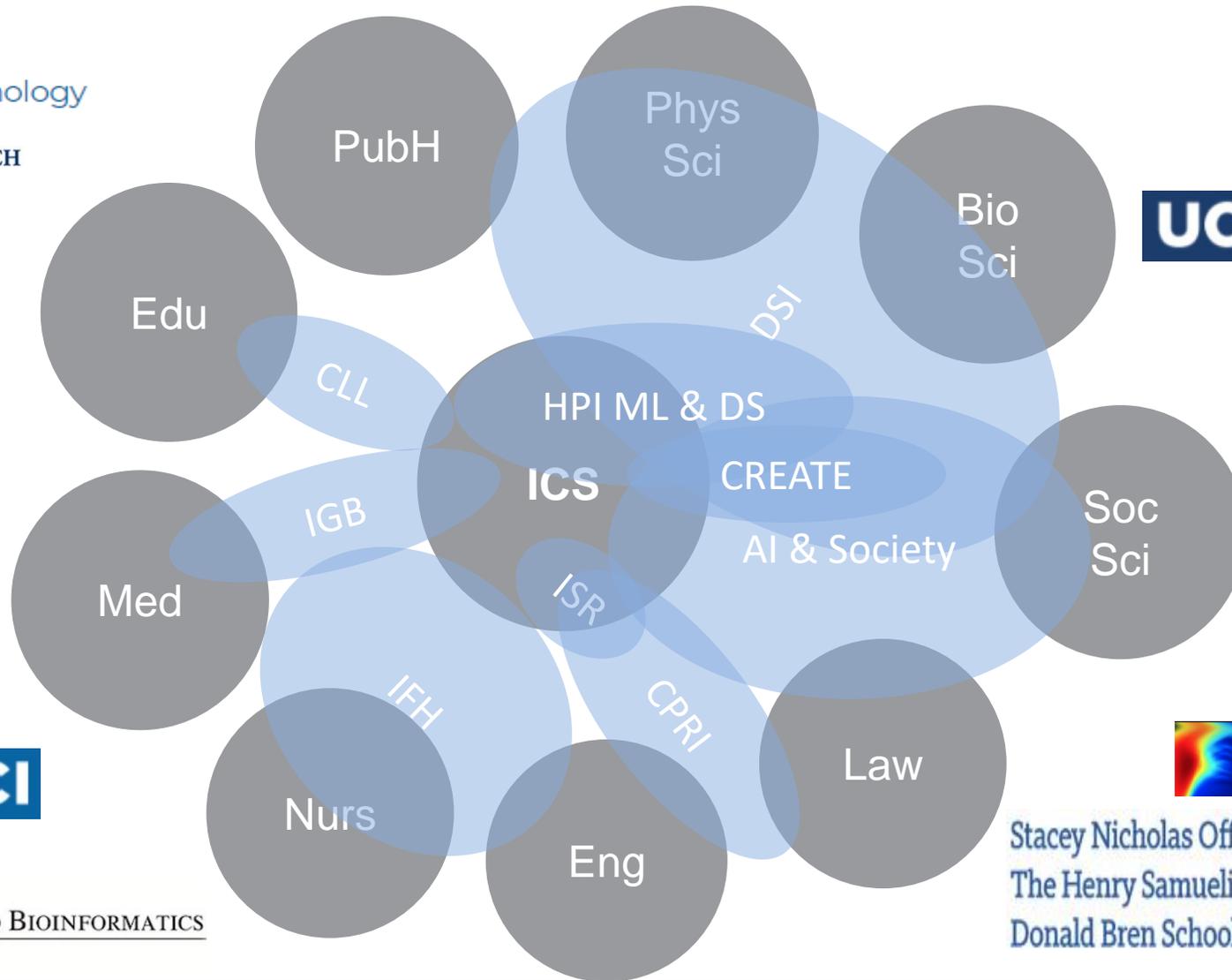
 **IFH**
Institute for Future Health

 **ERT**
Center for Emergency Response Technologies

 **CHRS**
UCIrvine

Water UCI

 **INSTITUTE FOR GENOMICS AND BIOINFORMATICS**
University of California, Irvine



UCI Data Science Initiative

UCI Steckler Center for Responsible, Ethical, and Accessible Technology

UCI Cybersecurity Policy & Research Institute

 **HPI** Hasso Plattner Institut
Digital Engineering • Universität Potsdam

UCI CALIT2

 **Center for Machine Learning and Intelligent Systems**
Bren School of Information and Computer Science
University of California, Irvine

Stacey Nicholas Office of Access & Inclusion
The Henry Samueli School of Engineering
Donald Bren School of Information and Computer Sciences

UCI Donald Bren School of Information & Computer Sciences

Research Strengths

- Artificial Intelligence / Machine Learning / Data Science
 - 15+ core faculty, 100+ PhD students
 - Center for Machine Learning and Intelligent Systems
 - Institute for Genomics and Bioinformatics
 - HPI Center on ML and Data Science
 - Data Science Initiative
 - Center for Responsible, Ethical, and Accessible Technology
- Database Systems
 - 6 core faculty, 20+ PhD students
- Cybersecurity
 - 6 core faculty, 25 PhD students
 - Cybersecurity Policy and Research Institute
- Software Engineering
 - 7 faculty, 20 PhD students
 - Institute for Software Research
- Embedded Systems
 - 7 core faculty, 20+ PhD students
 - Center for Embedded and Cyberphysical Systems
- Networked Systems
 - 5 core faculty, 20+ PhD students
- Graphics and Visualization
 - 3 core faculty, 10 PhD students
- Human-Computer Interaction
 - 5 core faculty, 20 PhD students
- Digital Media and Learning / Games
 - 7 core faculty, 25 PhD students
 - Connected Learning Lab

IoT-Enabled Smart Communities - Sample Projects

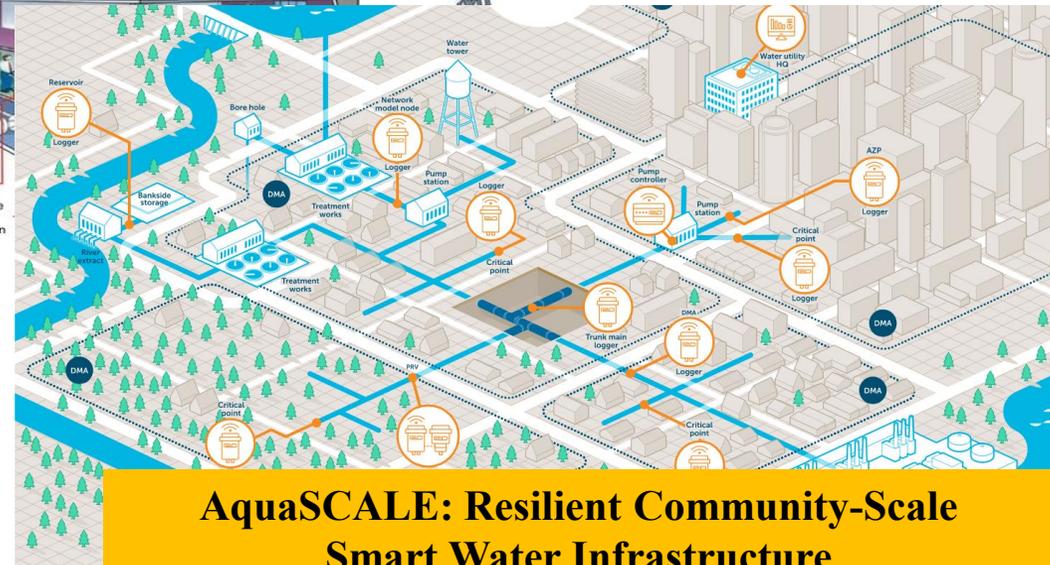
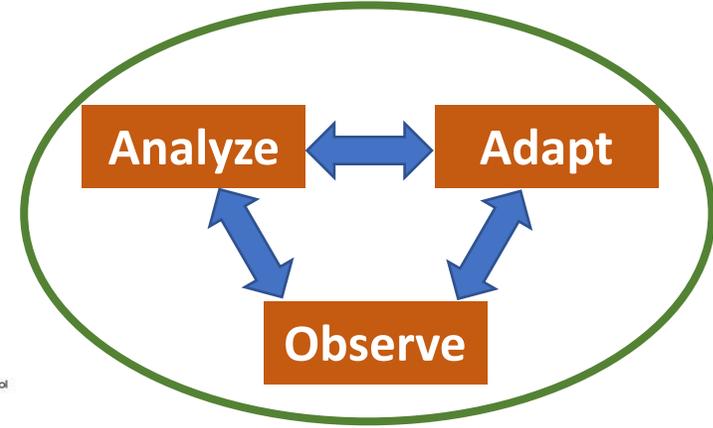
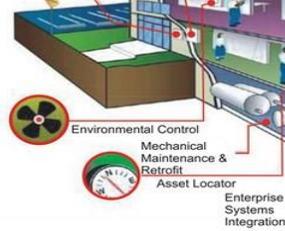
SCALE: Personal and home health Awareness and Alerting



Cloud-based public safety awareness and alert system



TIPPERS: Privacy & Awareness in SmartSpaces



AquaSCALE: Resilient Community-Scale Smart Water Infrastructure

Sample SmartSpaces Built - UCI

Responsphere - A Campus-wide infrastructure to instrument, monitor, disaster drills & technology validation



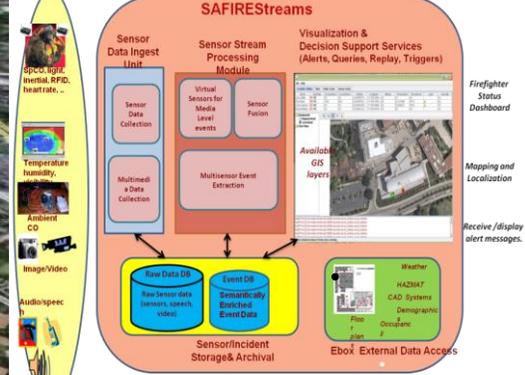
SCALE - A smart community awareness and alerting testbed @ Montgomery County, MD. A NIST/Whitehouse SmartAmerica Project extended to Global Cities Challenge.

Extending the Internet of Things to Everyone: Residents of an affordable housing complex who cannot otherwise afford broadband are given smart community sensors. A resident, possibly elderly, is in distress and the sensor sends a signal to the nearest base station.



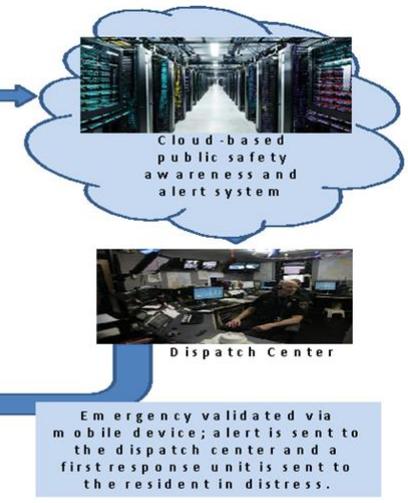
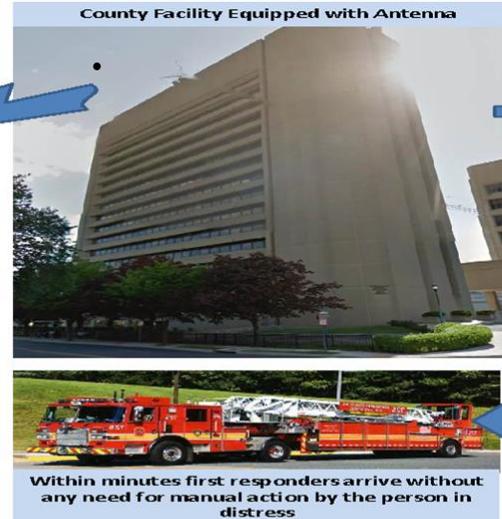
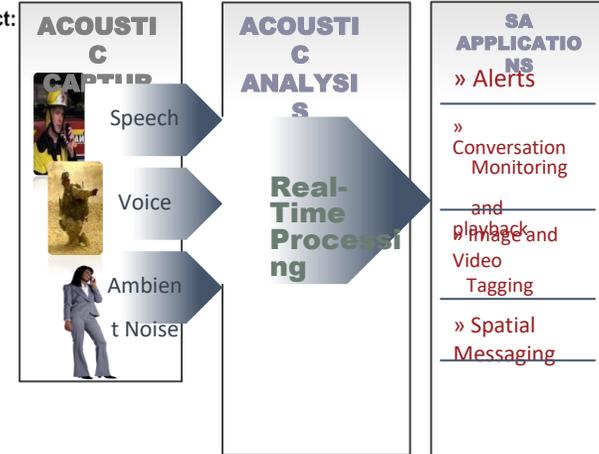
SAFIRE - Situational awareness for fire incident command

The SAFIRE (Situational awareness for Firefighters) Project: Sensing -> Sensemaking for the Fire Practice

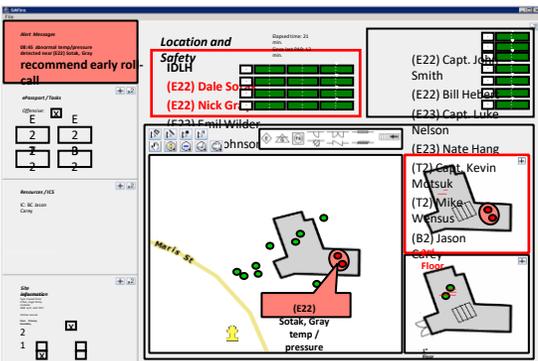


Goal: Reliable Timely SA over Unpredictable Infrastructure

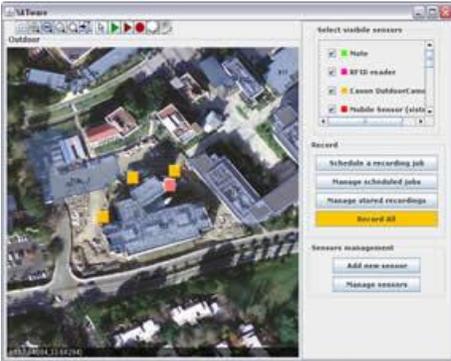
OpsTalk - Speech based awareness & alerting system for soldiers on the field



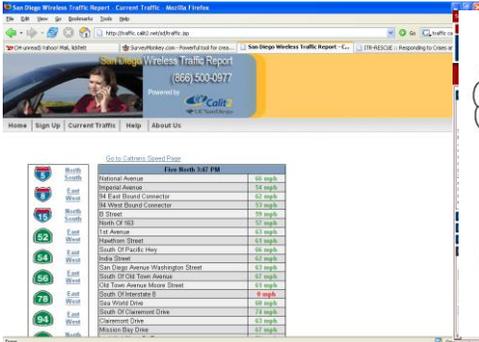
Derivative Software Artifacts



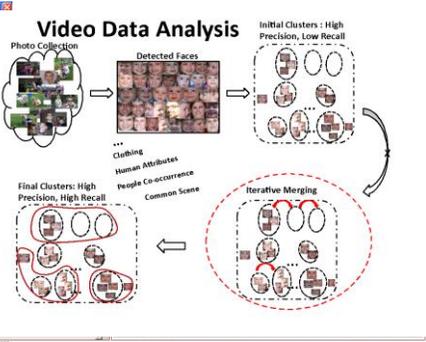
Fire Incident Command Board: real-time SA for ICs @ fire sites



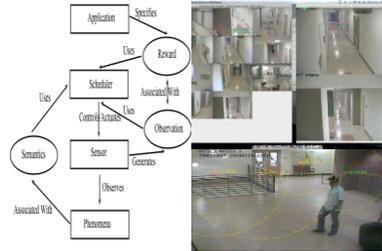
SATWARE: Semantic sensor processing middleware



P2P speech-based traffic information collection system



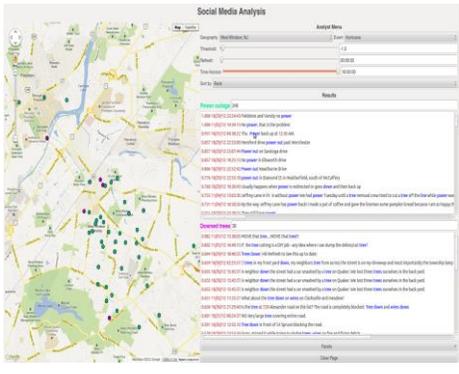
Adaptive Video Data Collection



Disaster Portal for multi-level situational awareness



Crisis Alert Warning System



Smart-C: Social Media Analysis for Disasters

SCALE (Smart Community Awareness and Alerting)

A SmartAmerica Project – Democratizing IoT

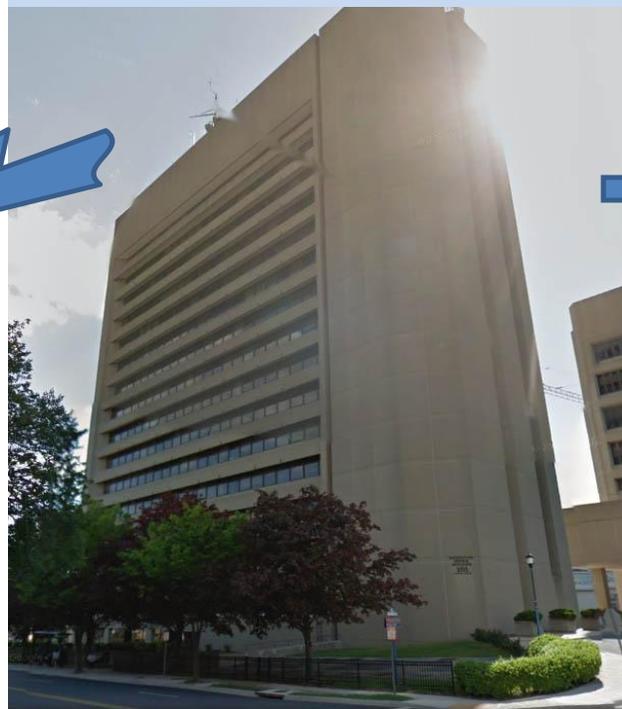
Extending the Internet of Things to Everyone: Residents of an affordable housing complex who cannot otherwise afford broadband are given smart community sensors. A resident, possibly elderly, is in distress and the sensor sends a signal to the nearest base station.



MONTGOMERY HOUSING PARTNERSHIP



County Facility Equipped with Antenna



Cloud-based public safety awareness and alert system



Dispatch Center

Emergency validated via mobile device; alert is sent to the dispatch center and a first response unit is sent to the resident in distress.



Within minutes first responders arrive without any need for manual action by the person in distress



SigFox WIRELESS
REINVENT RADIO COMMUNICATION



UCIrvine
University of California, Irvine



InnovativeIntegration
Global Solutions for Technology Visionaries

TIPPERS@UCI: A Testbed for IoT-Based Privacy Preserving Smartspaces



Diverse set of sensors installed

- 6 Story Building
- 90,000 sq. ft classroom
- 125 Faculty Offices
- 90 Research Labs
- Lecture Halls
- Departmental Offices



TIPPERS Hackathons

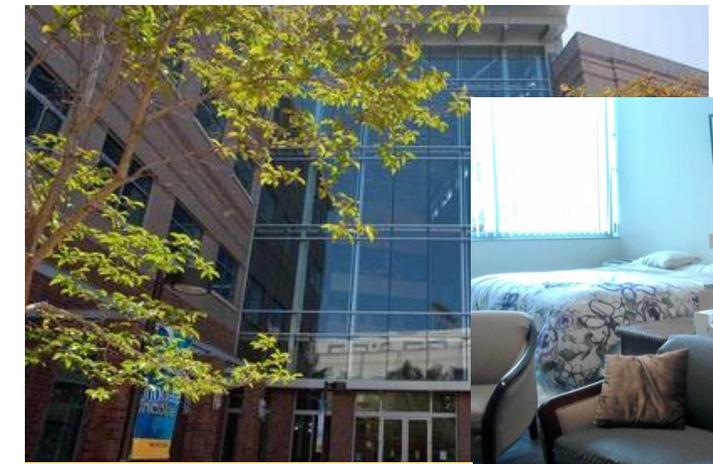


1st TIPPERS IoT

Smart Accessible Classrooms for Students with Special Needs, RIT



TIPPERS Privacy-Enabled Resilient Smart Buildings/Campuses, UCI



SimHome Smart Home Testbed@Calit2



AI AND ROBOTICS



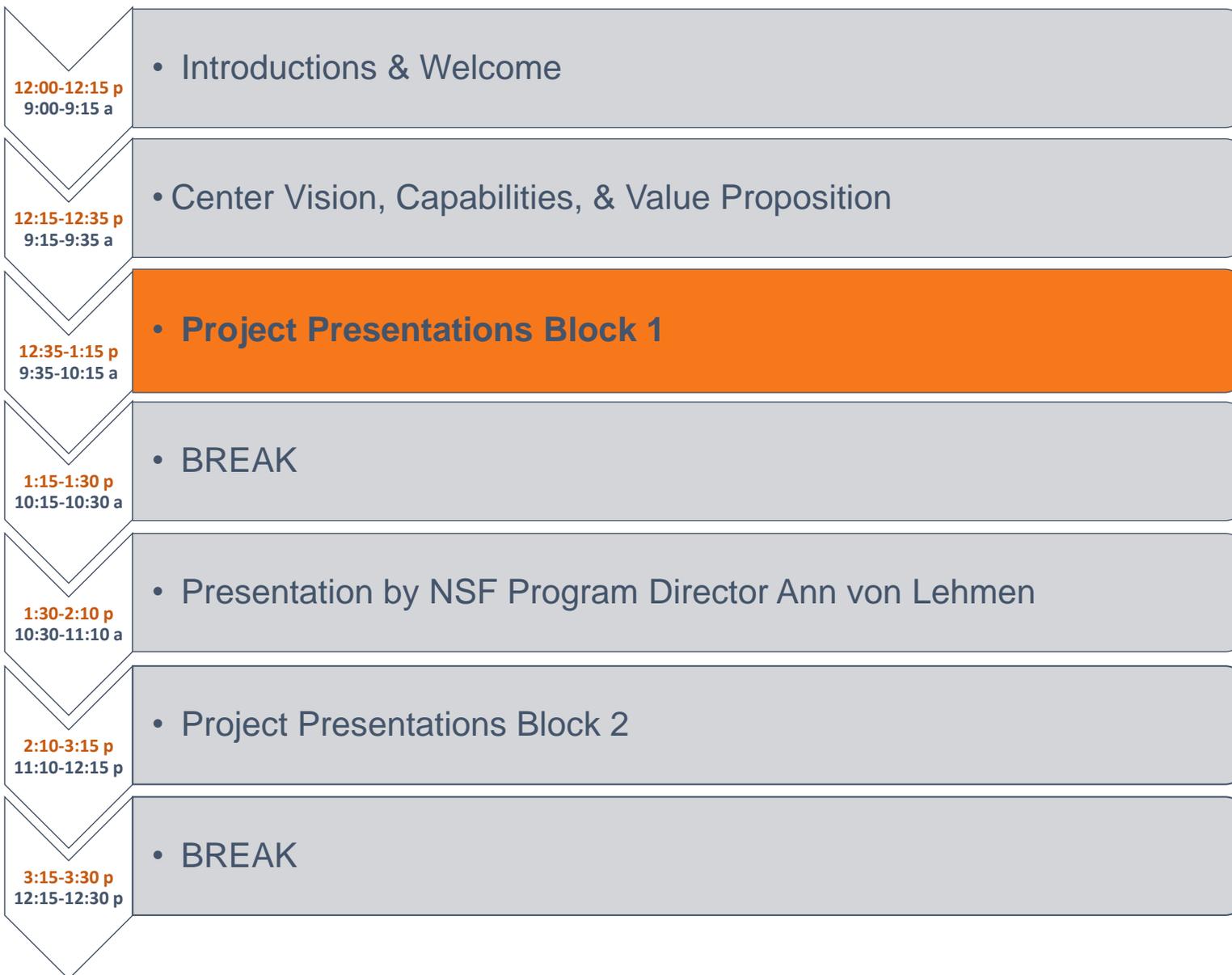
SMART HOME TECHNOLOGIES



MOBILE DIGITAL HEALTH CENTER



Digital Health Exploratory UCI Senior health Center

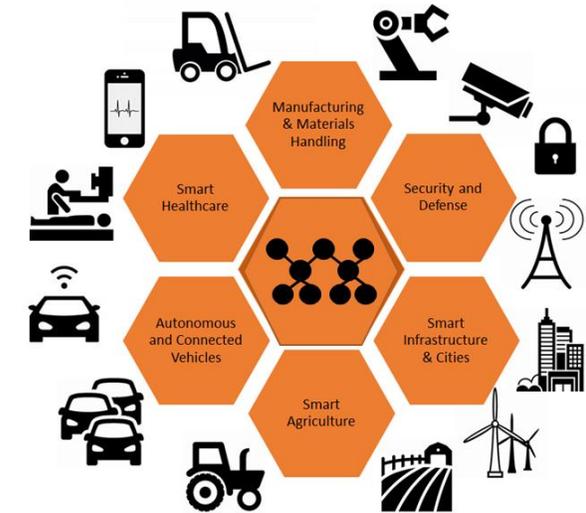


Infrastructure-Informed, Tiered Edge-Computing Architectures for Smart Spaces

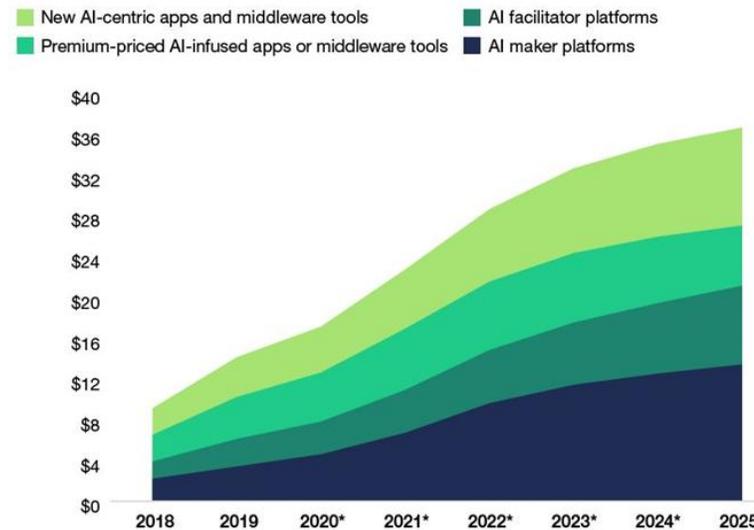
PIs: Amlan Ganguly (RIT), Marco Levorato (UCI),
Andres Kwasinski (RIT), Michael Kuhl (RIT),
Nalini Venkatasubramanian (UCI) and Amir Rahmani (UCI)

Industry Needs and Relevance

- Data-driven decision making
- Higher automation
- Big-Data storage
- Data communication
- Tiered, distributed, elastic processing/storage capacity - mobile/edge to cloud



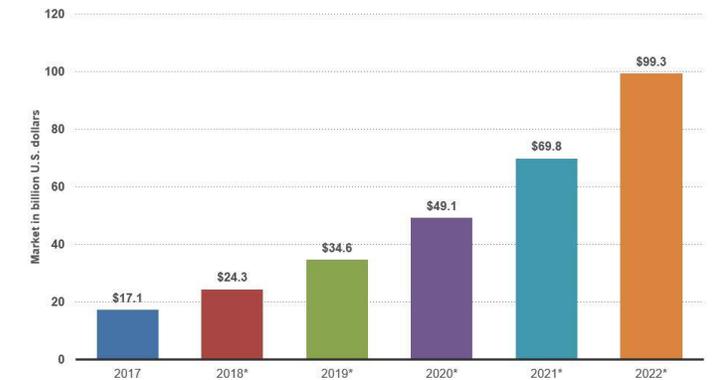
Global AI software market by segment (US\$ billions)



*Forrester forecast

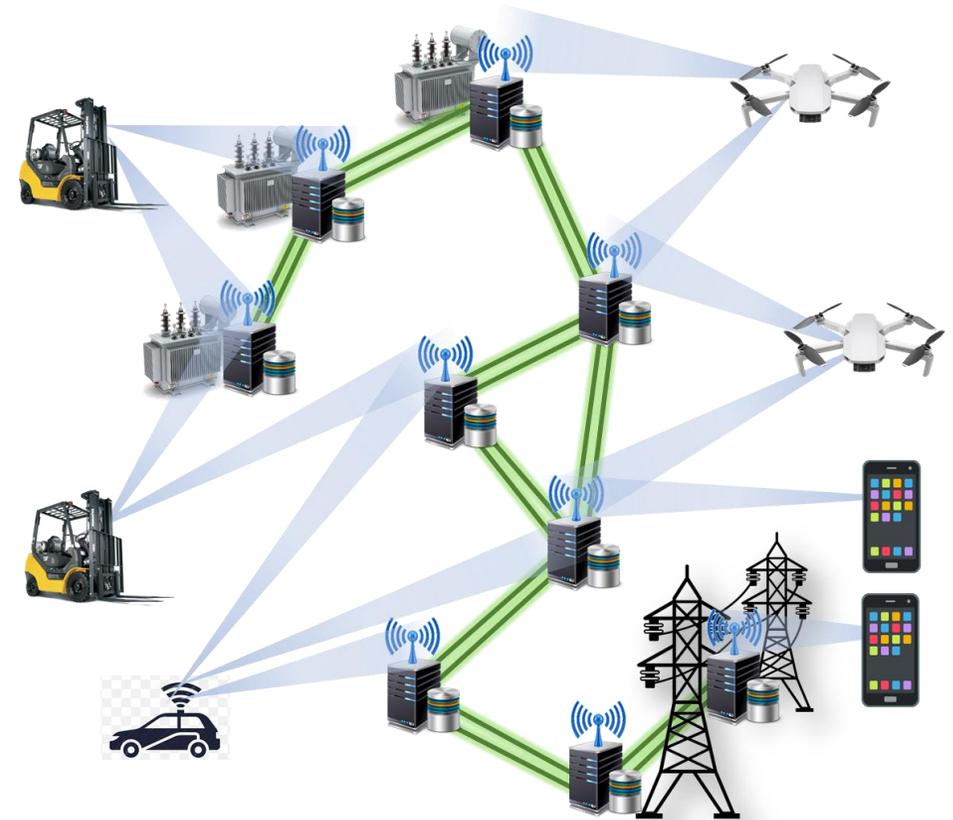
Big Data and Hadoop Market Size Forecast Worldwide 2017-2022

Size of Hadoop and Big Data Market Worldwide From 2017 To 2022 (in billion U.S. dollars)



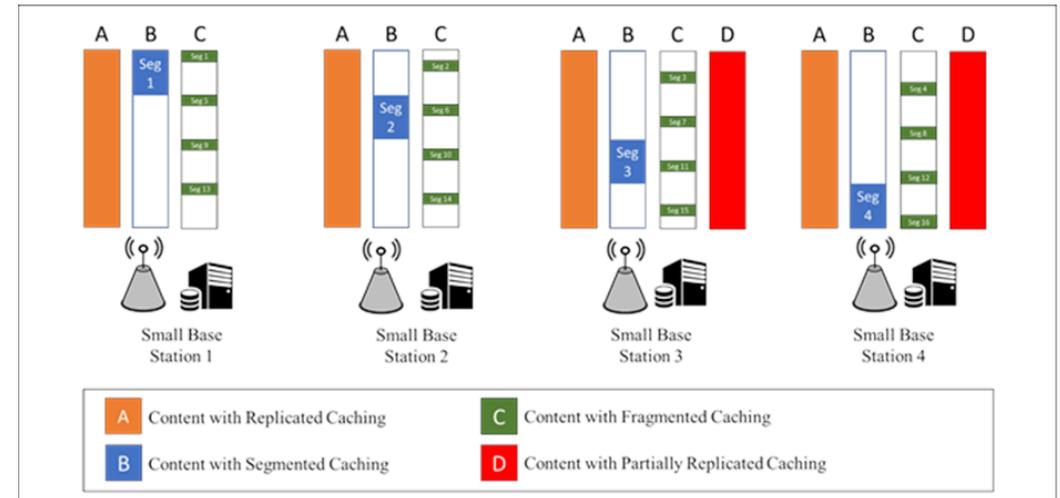
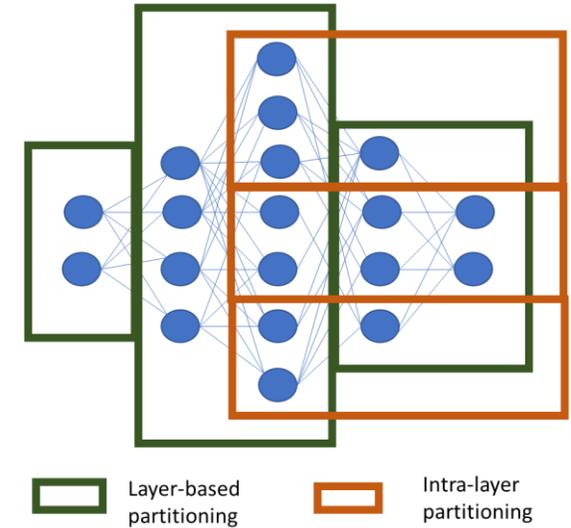
Project Goals

- Physical **Infrastructure-dependent** computing infrastructure design
- **Automated design methodology** for tiered interconnected computing architecture
- **Partition context (data and applications)** among tiered nodes and mobile/user node
- Model partitioning approaches to optimize
 - **Performance, synchronization**
 - **Resource utilization**
 - **Redundancy, flexibility & robustness of applications**
 - **Security and privacy**



Approach

- Develop **simulation framework** to evaluate design metrics
 - **Inputs:** infrastructure definition (**common language**), context definition (**data and apps – DL/DNN**),
 - Tiered Architecture
 - DL/DNN model partitioning
 - Data partitioning for **caching context data**
 - **Outputs:**
 - **metrics**
 - Validate with the **UCI-HYDRA test-bed**
- Use **heuristics with the simulator** to **create design methodologies**
 - Define comprehensive performance **metric**
 - **Classical methods:** Linear/Nonlinear Programming
 - **Genetic Algorithms**
 - **Machine Learning**
- Develop solutions across **prominent verticals**
 - Autonomous vehicles
 - Smart grid/power delivery
 - Healthcare



Deliverables and Impact

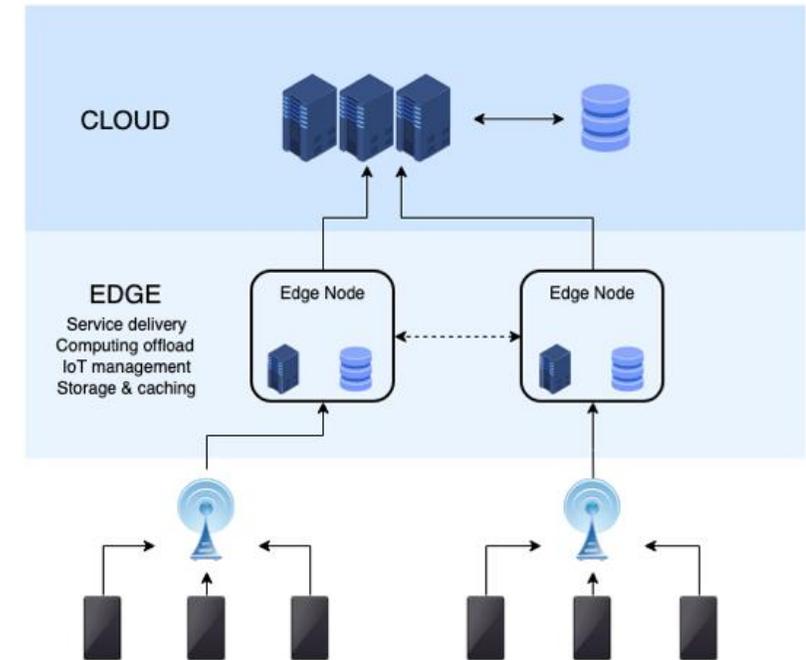
- Year 1:
 - Define smart space/infrastructure specifications – **common language**
 - Define design goals measurement **metrics**
 - Edge computing **architecture design methodology** using the simulator
 - Validate the simulation tool with the **HYDRA** test-bed.
- Years 2-5:
 - Evaluate **application (DNN)** and **data partitioning** algorithms
 - **Validate solutions** using the test-bed for known applications.
- These emerging applications will require **significant computational capacity.**
- **Not possible at the mobile node alone**
- Complex edge architecture design need to be **automated – not hand-crafted**
- **Multiple verticals** will be impacted

Dynamic Neural Pipelines for Real-Time IoT Systems

PIs: Marco Levorato (UCI), Amlan Ganguly (RIT)

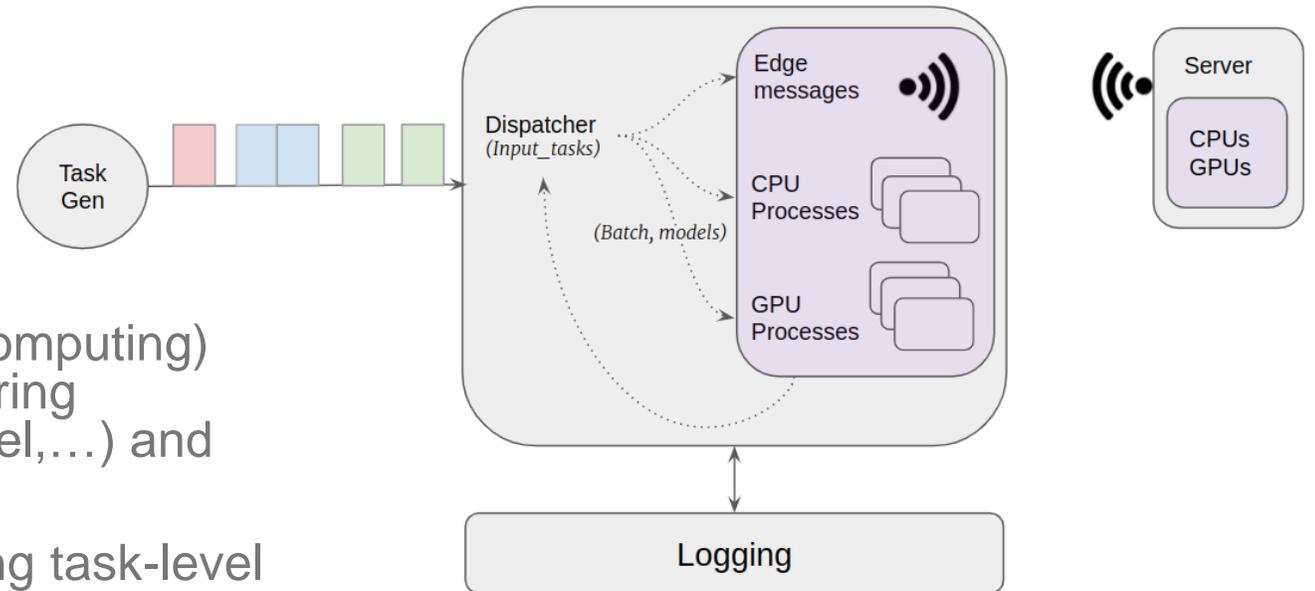
Industry Needs and Relevance

- IoT/vehicular systems need to operate in a broad range of environments, technological context and resource availability
- Current systems use centralized computing solutions that may be inefficient in many operating conditions and settings



Project Goals

- Develop flexible distributed (local vs edge computing) data analysis pipelines capable of reconfiguring computing based on context (energy, channel,...) and sample/data (complexity).
- Lightweight ML (e.g., DRL) models controlling task-level routing.
- Build and evaluate application specific deployments: (1) autonomous cars/UAVs; (2) healthcare; (3) augmented reality.
- Connection with Capstone projects



Approach

Milestone 1

- Development of frameworks enabling AI-empowered task routing across internal resources (CPU, GPU) and external resources (edge servers).
- Control of the neural model to be executed.
- Lightweight DRL models trained on heterogeneous input features across layers.

Milestone 2

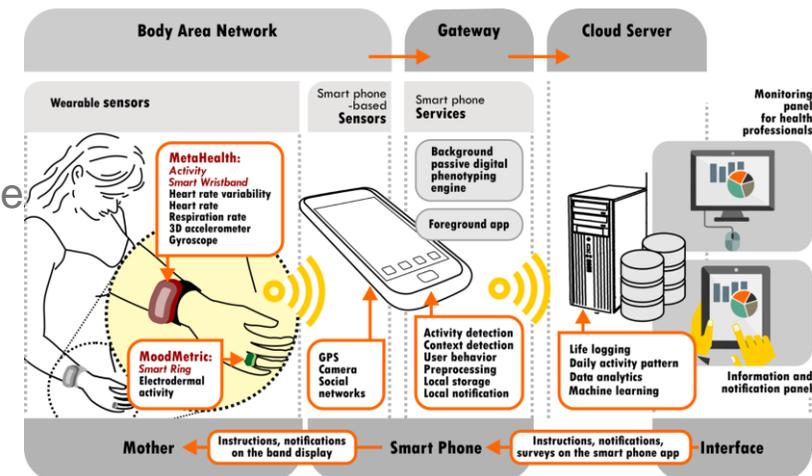
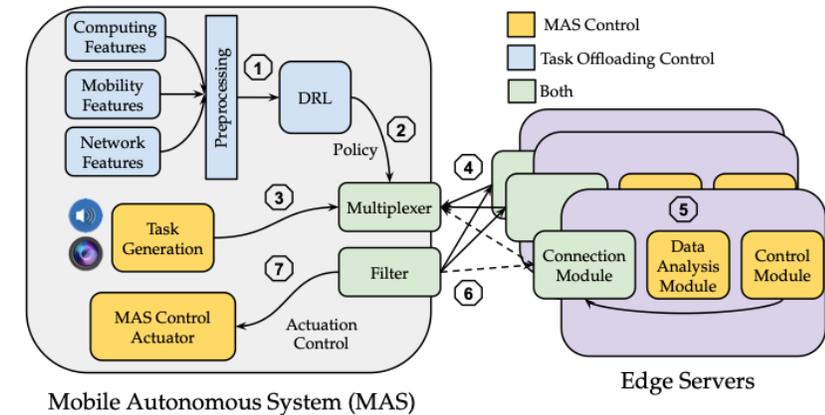
- Extension of the Hydra platform to include internal resource and modules update
- Expansion of the Hydra testbed to include MU-MIMO communications and LiDAR sensing/analysis

Milestone 3

- Integration of the framework in the UNITE healthcare platform
- Real-time acquisition and joint processing of biophysical signals, phone usage and user input
- Task: mental state detection, real-time decision making to control interaction with the user (active learning)

Milestone 4

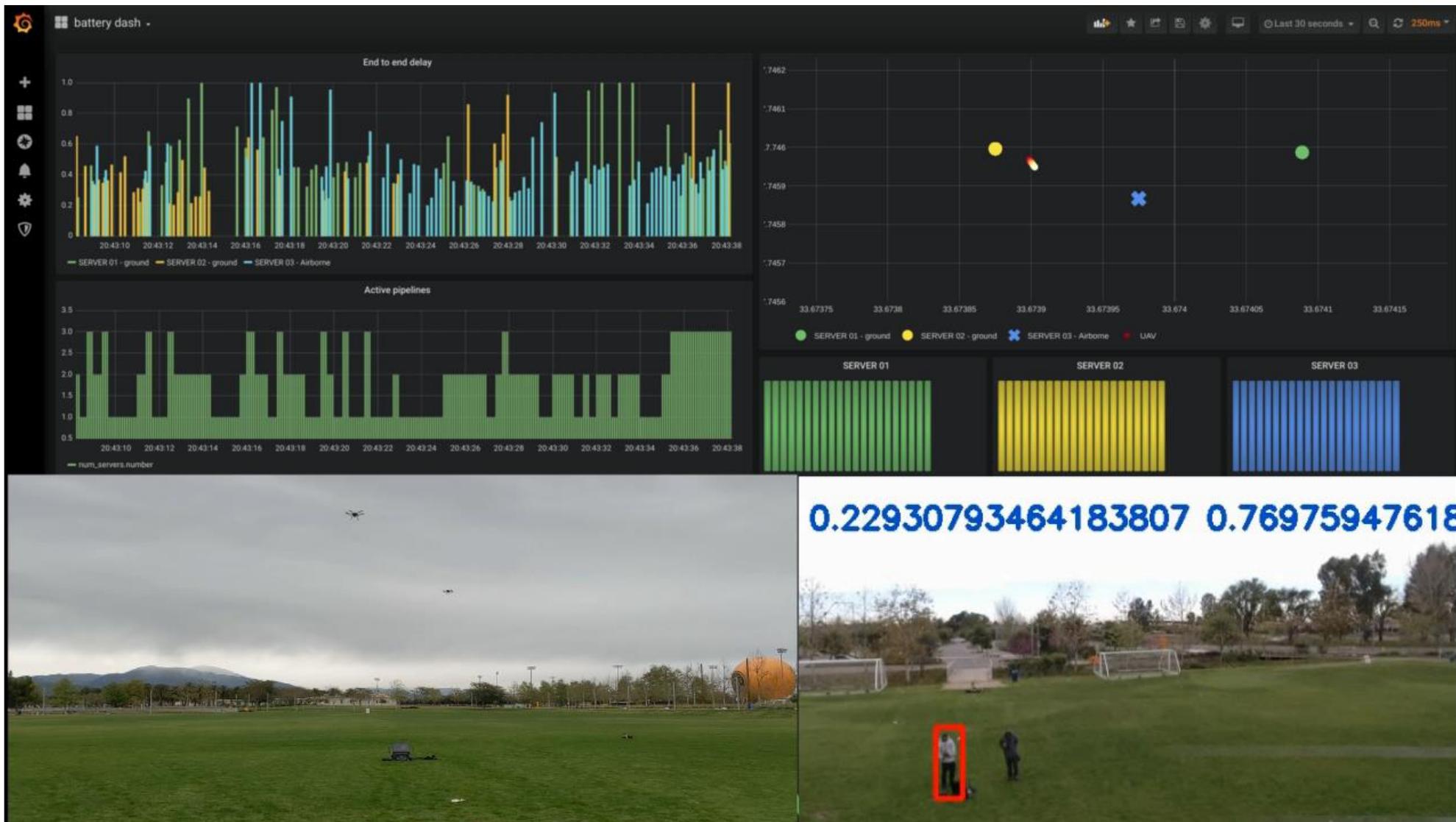
- Adaptation of the logic to specific Augmented Reality settings. Support to object detection/image analysis under computing/communication constraints

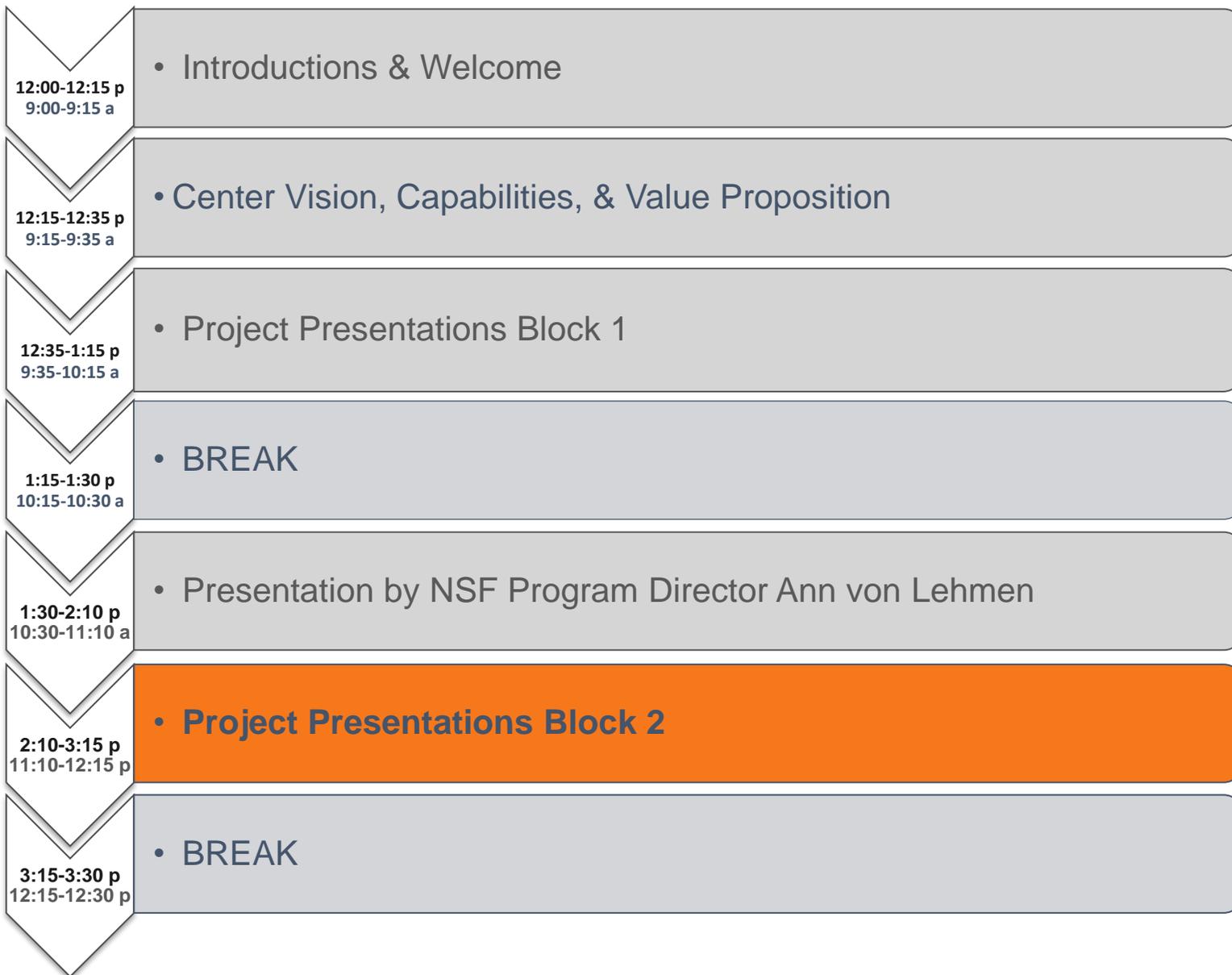


Deliverables and Scope

- Year 1 - Deliverables
 - Middleware platform for the dynamic routing of tasks (CPU, GPU, Edge)
 - Complete demo on CV for vehicles (extended to MU-MIMO)
 - Proof of concept for healthcare using the Unite platform
 - Characterization of AR platform
 - Two demos in the first year
- Our solutions will optimize how resources are used in response to changes in
 - Input data
 - Available resources (energy, channel, computing)
- Innovative neural models to facilitate flexible computing
- Middleware (based on our Hydra platform) shared with partners
- Proof of concept for key verticals
- Data collection for different applications
- **Long-term vision**
 - Multimodal sensing, support to DNN partitioning (vertical and horizontal)
 - Automated adaptation to systems/applications

Starting point - Hydra (DARPA)



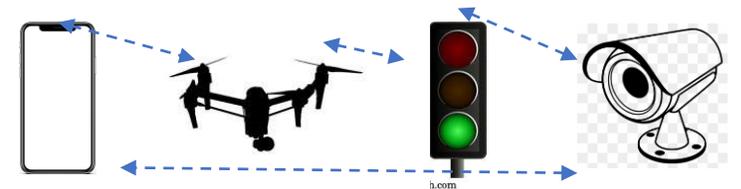


Interoperability in Heterogeneous Smart Spaces

PIs: Mohan Kumar (RIT), Nalini Venkatasubramanian (UCI),
Ivan D. Nunes (RIT)

Industry Needs and Relevance

- Devices by different manufacturers have different protocols, architectures
 - Devices are heterogeneous – CPU/GPU, Communication protocols, memory, sensing
- Making disparate devices to talk to each other is a complex time-consuming process
- Device identification is a challenge
- It should be possible to utilize and combine services by disparate devices, seamlessly
- Domain experts should focus on task at hand



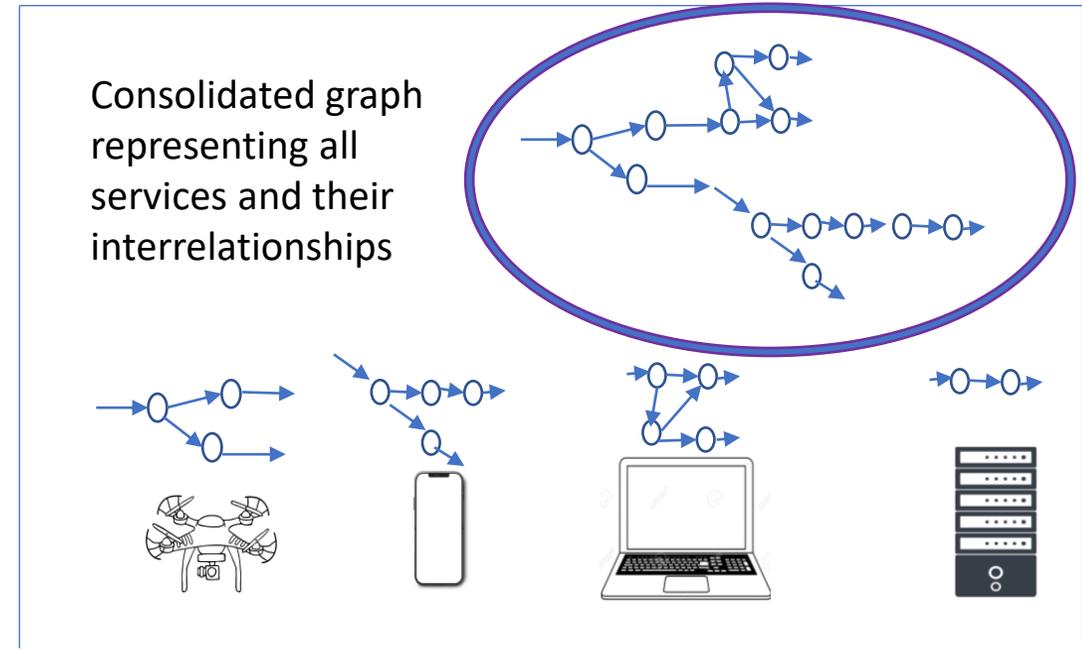
Time and effort

Project Goals

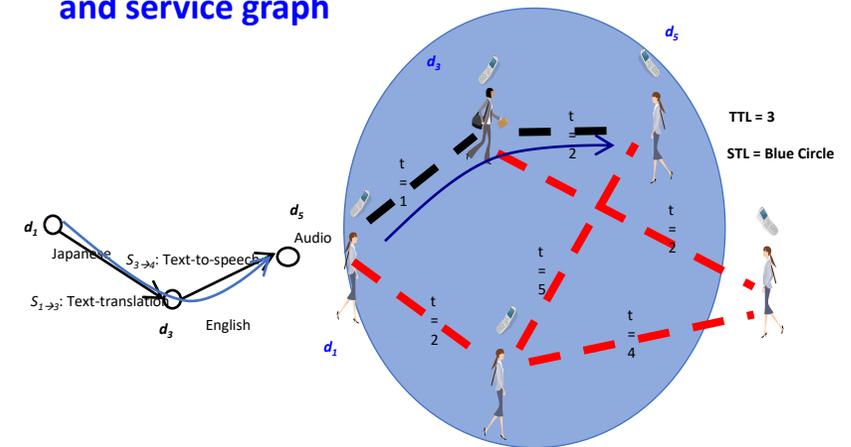
- Enhance interoperability in various verticals
 - Smart Grids
 - Manufacturing floor
 - Construction site
 - Emergency situations
 - Homes and Hospitals
- Efficient utilization of time and resources
 - Find services and resources to execute on time
- Enable proactive services
 - Preparedness for emergency services
 - Meet application/user needs

Approach

- Manifest device resources as services
 - Abstract services as graphs
- Combine services using graphs
- DL to make services context-aware
- Language tools for service composition
- Location and time; delay tolerance
 - Spatio-temporal reachability graphs
- Proactive services to address situations
- Investigate placement of mediators at the edge

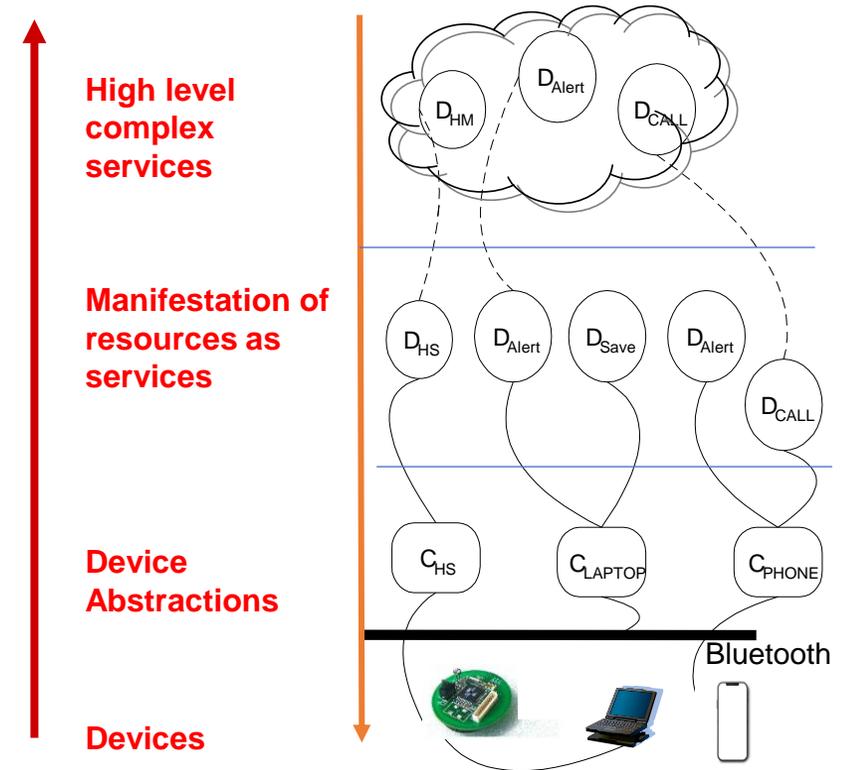


Combining STRG and service graph



Deliverables and Scope

- Device identification in
 - e.g., homes, smart grids, and hospitals
- Service composition in
 - e.g., UAV networks, smart grid, and hospitals
- Attestation techniques for secure services
- Long term research/developments
 - Opportunistic and delay-tolerant networks
 - Adaptive mechanisms to mask heterogeneity
 - Deploy services proactively
 - Privacy preserving features into the framework
 - High integrity PNT
 - Mediator location



Robust Infrastructure for Activity Recognition and Awareness

PIs: Nalini Venkatasubramanian (UCI), Amir Rahmani (UCI), Mohan Kumar (RIT), Linwei Wang (RIT)

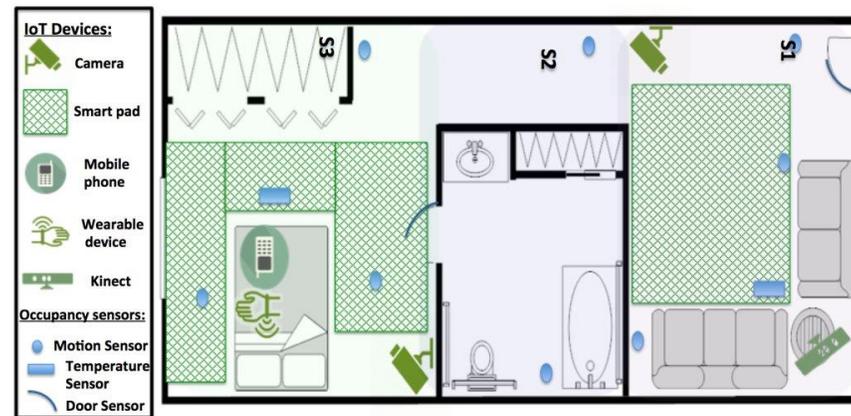
Industry Needs and Relevance

Perpetual Sensing and Awareness Systems

- Activity Recognition: Continuous monitoring of spaces, people and events
- Heterogeneous devices generate data, communicate using diverse network interfaces
- Data processed locally onsite or remotely at server/cloud --> actionable awareness



Activity Monitoring of Critical Health Events: Assisted Living

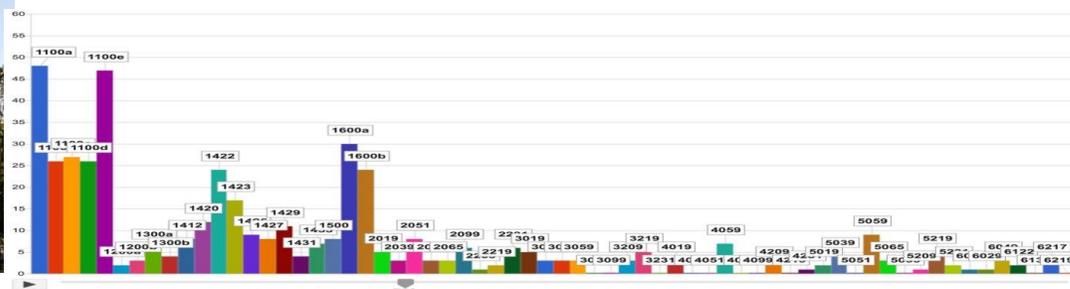


2011-06-11	22:12:51.392546	M002	ON
2011-06-11	22:12:53.136226	M002	OFF
2011-06-11	22:13:35.127237	M002	ON
2011-06-11	22:13:37.374172	M002	OFF
2011-06-11	22:13:52.962109	M002	ON
2011-06-11	22:13:54.921775	M002	OFF
2011-06-11	22:14:19.029588	M003	ON
2011-06-11	22:14:24.463032	M003	OFF
2011-06-11	22:16:23.882752	M002	ON
2011-06-11	22:16:27.38464	M002	OFF
2011-06-11	22:16:35.393099	M002	ON
2011-06-11	22:16:37.395173	M002	OFF
2011-06-11	22:18:46.632368	M002	ON
2011-06-11	22:18:49.060381	M002	OFF
2011-06-11	22:22:16.492332	M002	ON
2011-06-11	22:22:20.107873	M002	OFF
2011-06-11	22:25:46.975955	M002	ON
2011-06-11	22:25:48.704359	M002	OFF
2011-06-11	22:32:09.329972	T002	25.5

- Perpetual Operation
 - **Resource limitations** in IoT awareness systems
 - Impacts energy **efficiency**, service **availability**, **quality** of service, **privacy**.

Need Robust infrastructure that is accurate, cost-effective & non-intrusive.

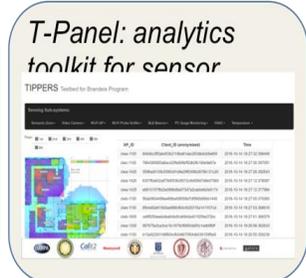
Activity Recognition in a Smart Campus



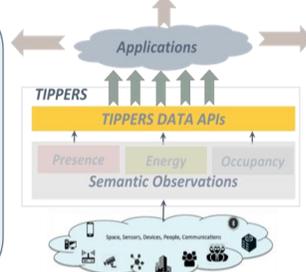
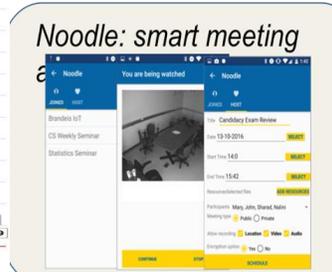
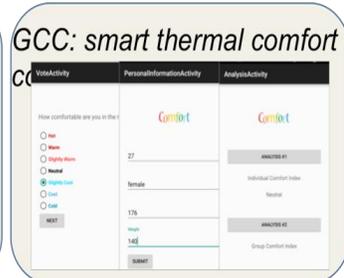
Presence-Based Applications



Analytics Applications



Energy-Based Applications



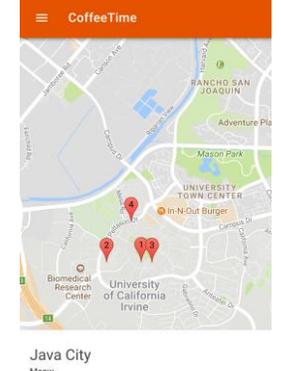
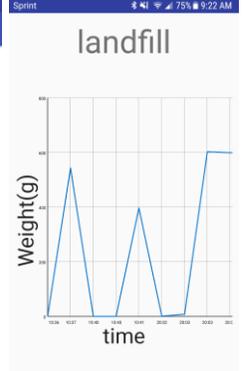
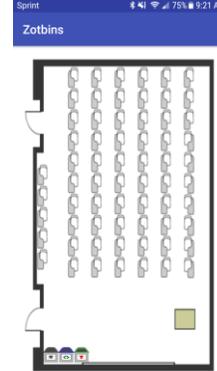
Open APIs will lead to more applications.



Student developed apps Self-Awareness app (SAPP)



Hackathon apps: ZotBins and CoffeeTime



Project Goals

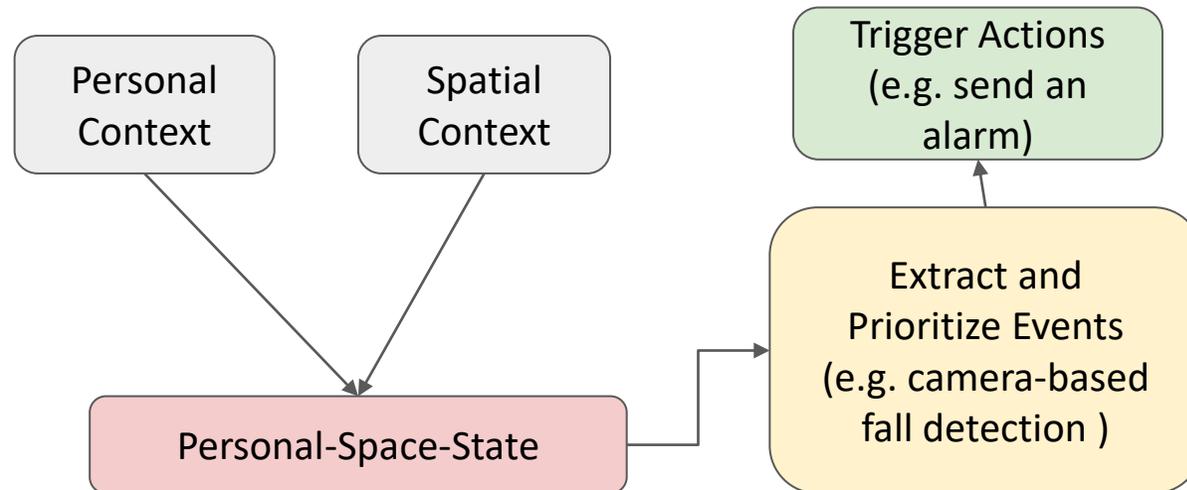
Challenges for robust operation

- Heterogeneous sensors and networks – varying data quality and coverage
 - BLE Beacons, motion sensors – coarse-grained view of events/activities
 - Vision-based – improved accuracy, but might have occlusions or a narrow field of view.
 - BLE, WiFi, LPWAN, 5G
- Broad range of AI and analytics methods
 - ML and deep learning algorithms for activity detection – from limited training to robust inference
 - Multiple combinations - different computational complexity, resource/memory needs
 - Vision processing – more accuracy, more computational cost
- Failures and overloads
 - Low battery capacity, congested networks, overloaded servers
 - Big data processing and big-small data processing
 - Missing data and delayed data
- Privacy and Security Risks



Approach: Personal-Space-State Semantics

- Use semantics: application, individual, and space to extract events and trigger actions.
 - Leveraging dynamic and changing “personal-space-state”
 - AI-based approach for sensor activations, messaging, and compute processing
 - Enhance system performance and lifetime without loss of application quality/accuracy.
- Develop Cross-layer Redundancy Techniques for dependable operation
 - Support integration of information from multiple sensors
 - Exploit multiple paths and multiple access networks for robust communication



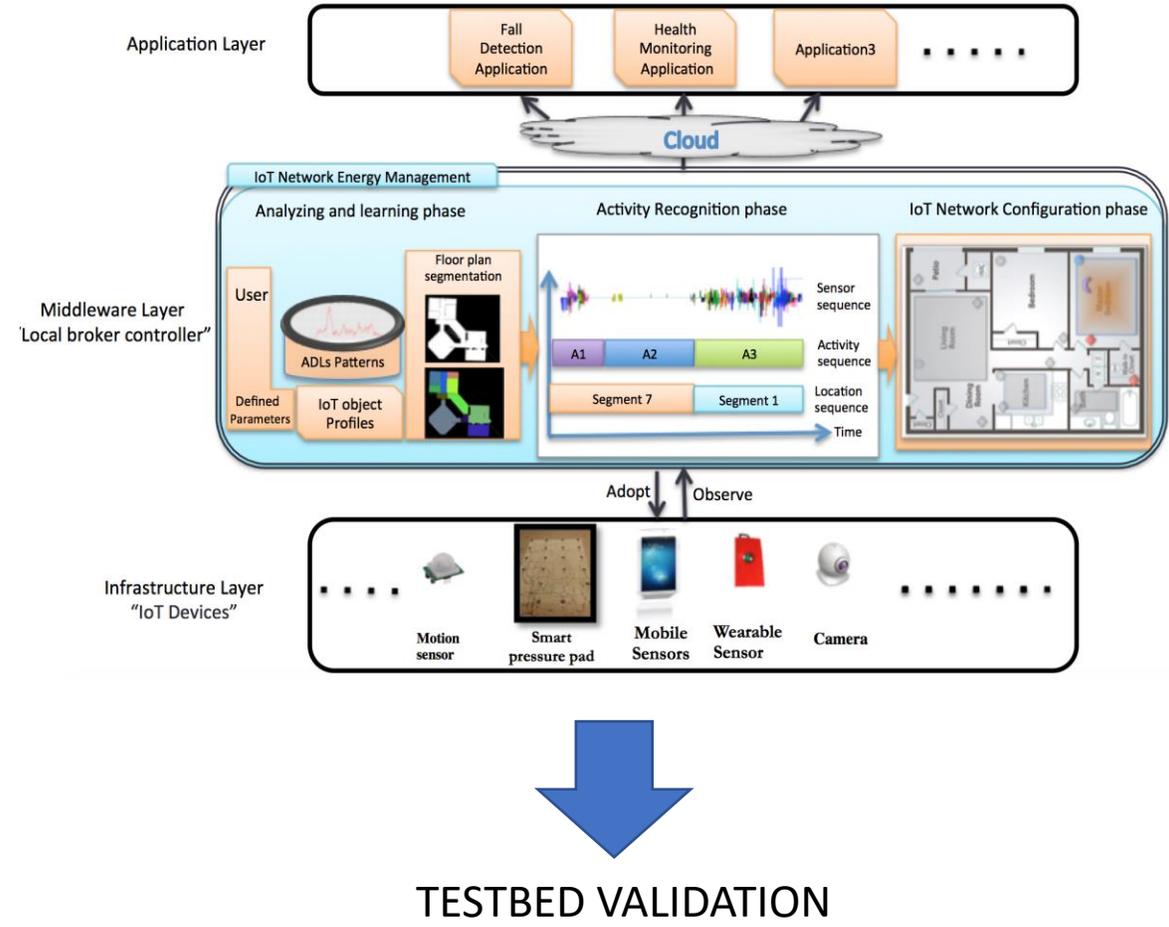
Deliverables and Scope

Short-term activities

- Gather/analyze health datasets (UCI collaboratory)
- Develop personal space-state models and and design activity recognition algorithms for selected tasks
- Prototype middleware platform
- Determine points-of-failure in testbeds with use cases from smart home/building testbeds with multiple personal and in-situ devices for focused services, e.g elderly fall detection.

Longer -term vision

- Deployment and operation challenges in complex scaled up scenarios – dependability at scale.
- Robust resource provisioning and system configuration to handle device, systems and network failures.
- Novel settings – accessibility-aware classrooms in K-12 schools, smart waiting rooms in clinics/hospitals

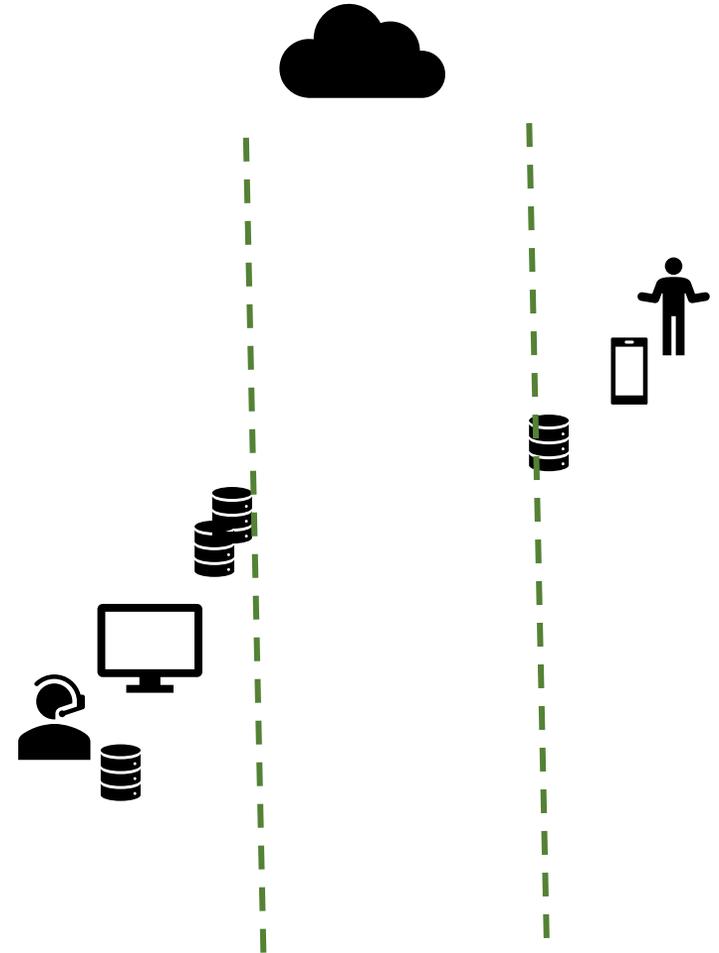


Data Staging in Smart Environments

PIs: Mohan Kumar (RIT), Nalini Venkatasubramanian (UCI),
Minseok Kwon (RIT), Sergio Gago-Masague (UCI)

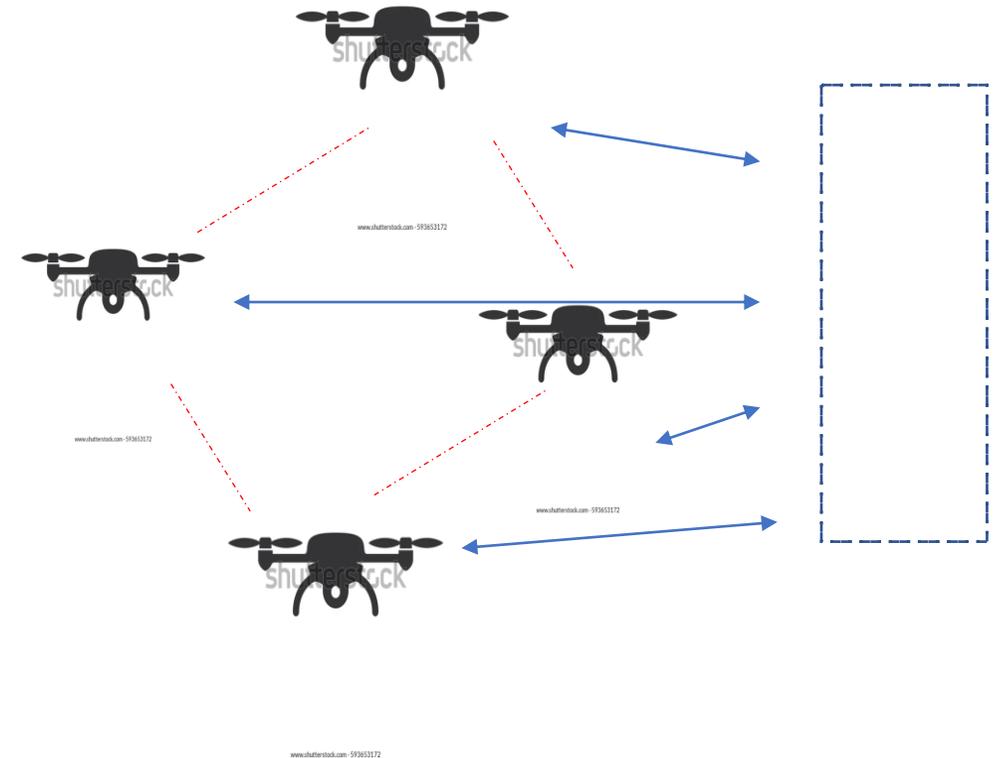
Industry Needs and Relevance

- **Telepresence is an essential part of smart spaces**
 - Remote experts connect with users to interact seamlessly
 - E.g., Hospital at home, inspection of building under construction
 - Working from home situations
- **Data distribution tradeoffs - horizontal and vertical**
 - Device, peer, edge and cloud
- **Time-/location-sensitive multi-modal information**
 - Spatio-temporal locality of sensed data, data needs, users
 - Cloud introduces latency and privacy leakages
 - Keep data closer to user
- **Data accessible to low resource user devices**
- **Delay tolerant data availability**
 - Application context
 - When BW, Energy, are available and at low cost...



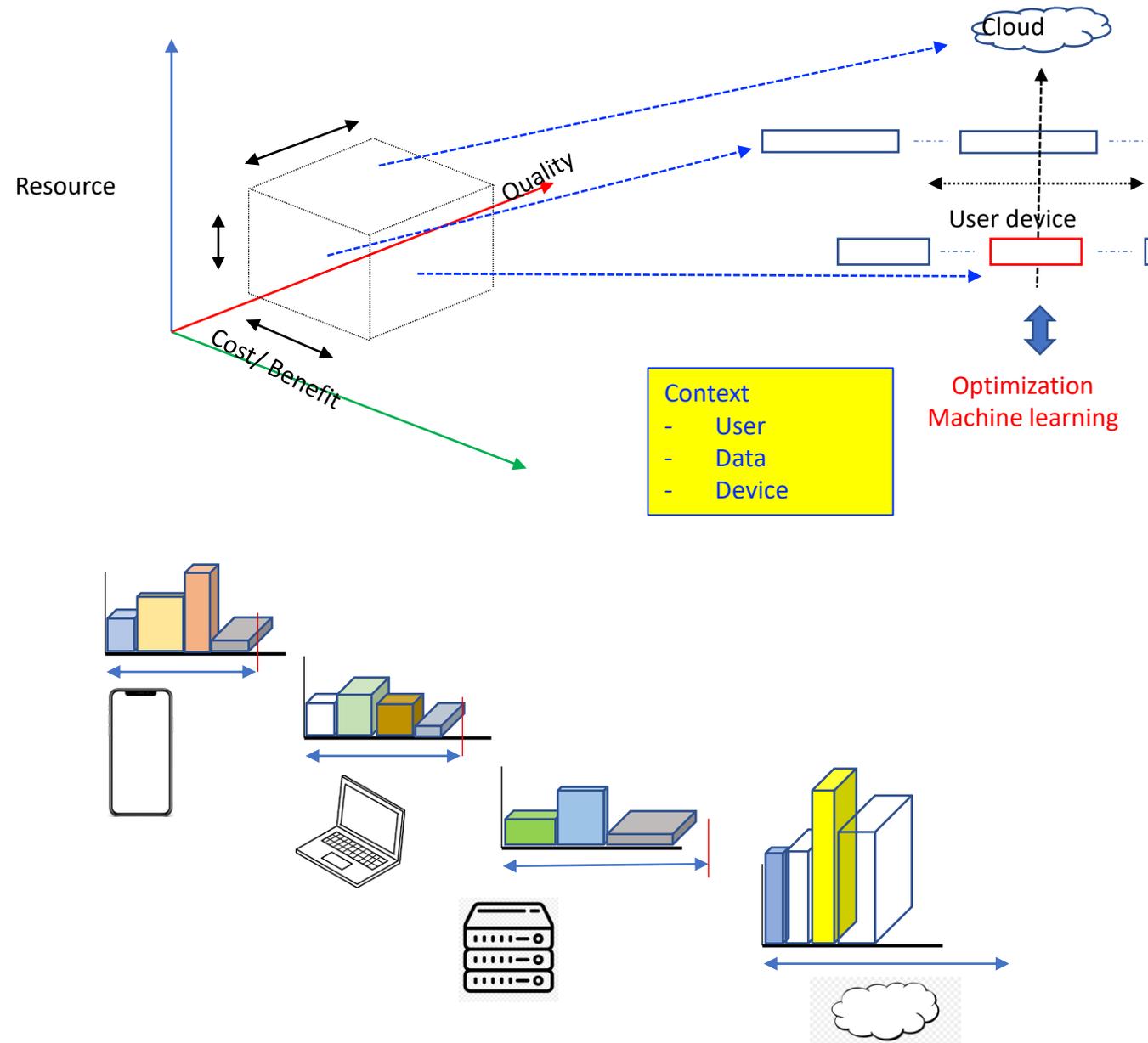
Project Goals

- Data – where, when, anyhow
 - Context-aware
- Just-in time access to data
- Mobile, dynamic environments
- Upload planning
- Privacy-preserving
- Solutions applicable to different domains
 - Telepresence
 - Dynamic network of UAVs
 - Remote consultations, participation
 - Time-/location aware



Approach

- **Multiparameter Optimization**
 - Resources, quality, benefits
 - Context information – elasticity
 - Location, time, user preferences,
 - M/L to learn context and context change
- Hierarchical caches
- Inter-relationship between users
- Security and privacy - quality
- Dependence between contents
 - enables proactive techniques
- RDMA techniques to move content among edge devices



Deliverables and Scope

- Multi-parameter optimization algorithms
- Prototype testing with synthetic/data
 - e.g., smart hospital, forest fire situations
- Long term developments
 - Privacy-preserving data staging optimization
 - M/L to determine contexts and relationships
 - RDMA techniques for efficient data transfers
 - Prototype testing for specific application cases
 - Building construction
 - Manufacturing
 - Smart grid
 - Data Rendering

Creating Digital Twin Toolkits for Smart Spaces

PI: Nalini Venkatasubramanian (UCI), Sharad Mehrotra (UCI),
Mohan Kumar (RIT), Amlan Ganguly (RIT)

Industry Needs and Relevance

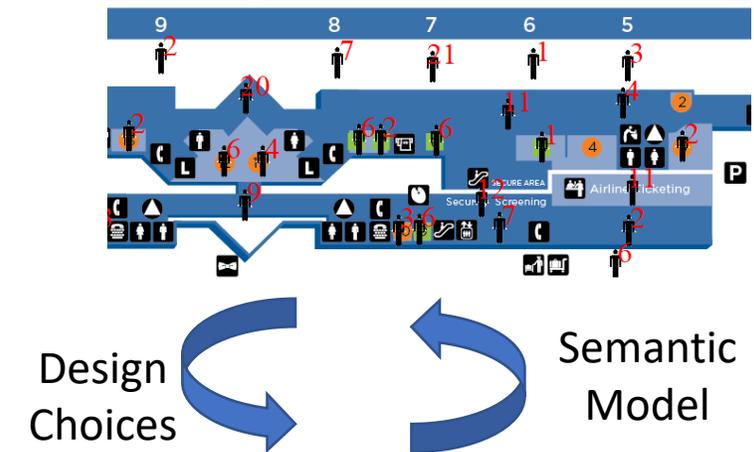
Digital Twin: A Digital Representation of Smart Spaces and its Evolution

Why?

- Explore possibilities from **design to operation**
 - Cost-effectiveness, design, instrumentation, retrofit
- Conduct **long-term analysis of resilience and sustainability** at different **granularities** (a smart building to smart city/community)

How?

- **Learn accurate models of smartspaces** by capturing geo-spatial attributes of smart space entities and evolution of events/activities over time
- **Generate synthetic scenarios** and associated datasets for system assessment and evaluation



Digital Twins for Communities (Relevance)

Current issues: citizen safety, quality of life, wellness, environmental sustainability



- 9 out of 10 people worldwide breath polluted air

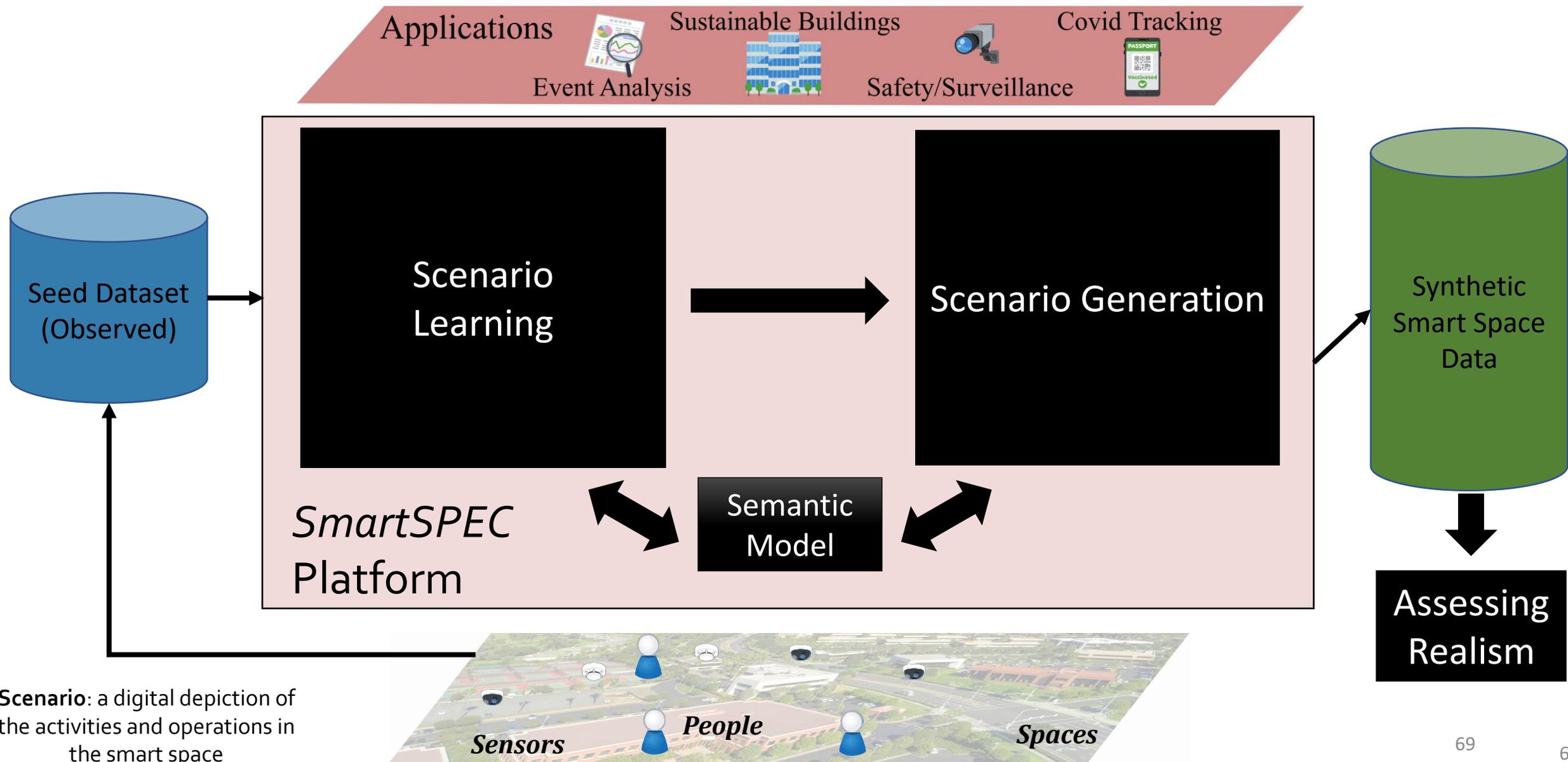
California wildfires (2011 – 2020): Consumed wildland areas:
 ~14.5 Yosemite National Parks, Impacted WUI communities



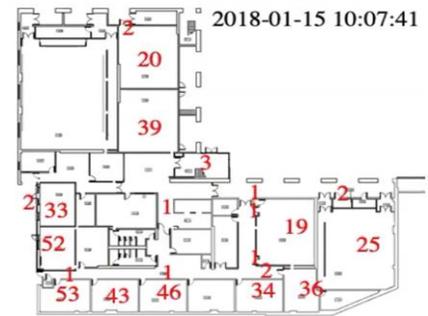
	Community	Applications
A	Irvine Spectrum	Gunshot detection
B	Quail hill (near highway)	Air quality & noise monitoring
C	Shady Canyon Preserve (wildland)	Wildfire detection
D	Shady Canyon (WUI)	Wildfire detection & air quality monitoring

Approach: Create Digital Twin Tools and Synthetic Datasets

Exploit semantics to generate realistic synthetic smart space datasets



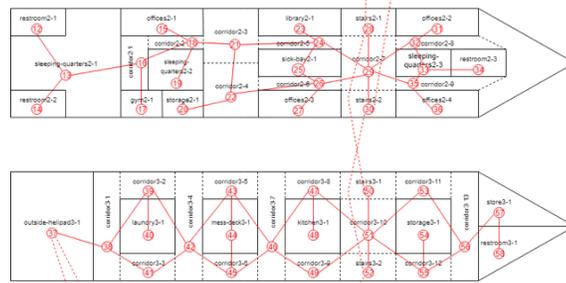
Modeling real and synthetic smartspaces and events



Simulated Donald Bren Hall



Bren Hall, UC Irvine



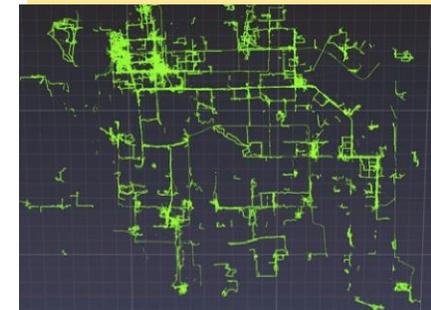
Credit: Navy Media Content Services

Trident Warrior, US Navy exercise



Beijing, China

City-scale
Mobility Modeling

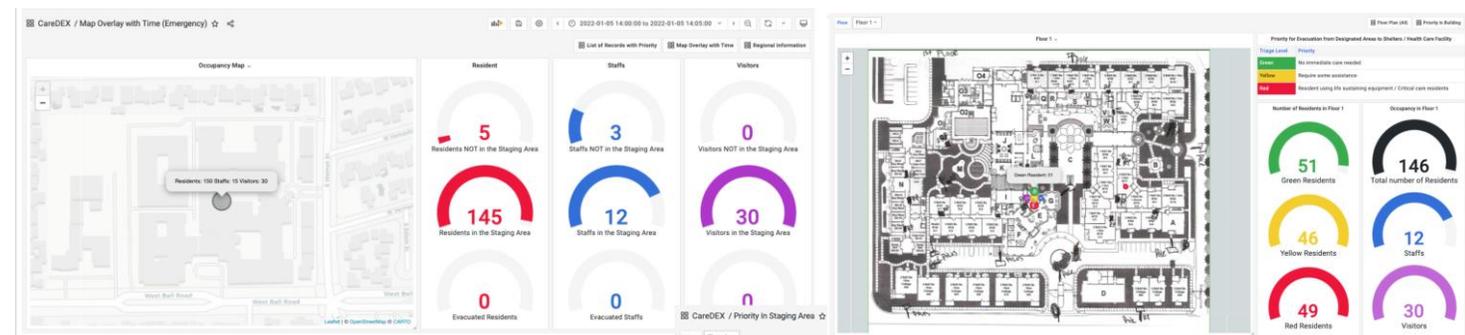


GeoLife GPS Trajectories

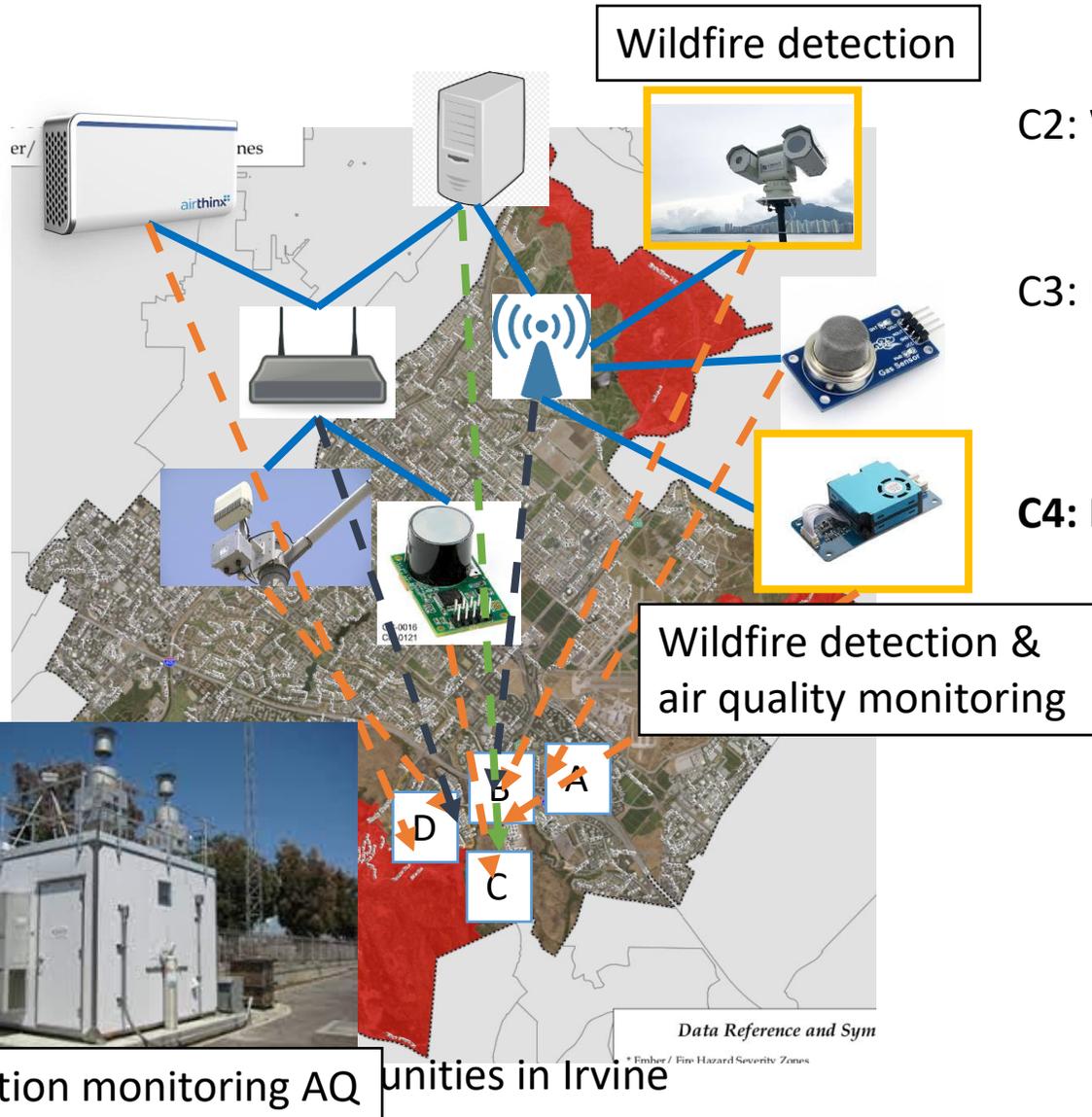
A Senior Care Facility
Modeling Occupancy and Evacuation in a Fire Event



Occupancy -
Simulated Shopping Mall



Digital Twins: Planning Smart Spaces



C1: What - devices to use

- Sensing (different accuracy & range), networking (different range), and computing

C2: Where - to put them

- Sensing device – **sensing coverage**
- Networking devices – **communication coverage**

C3: How - to use/multiplex for different needs

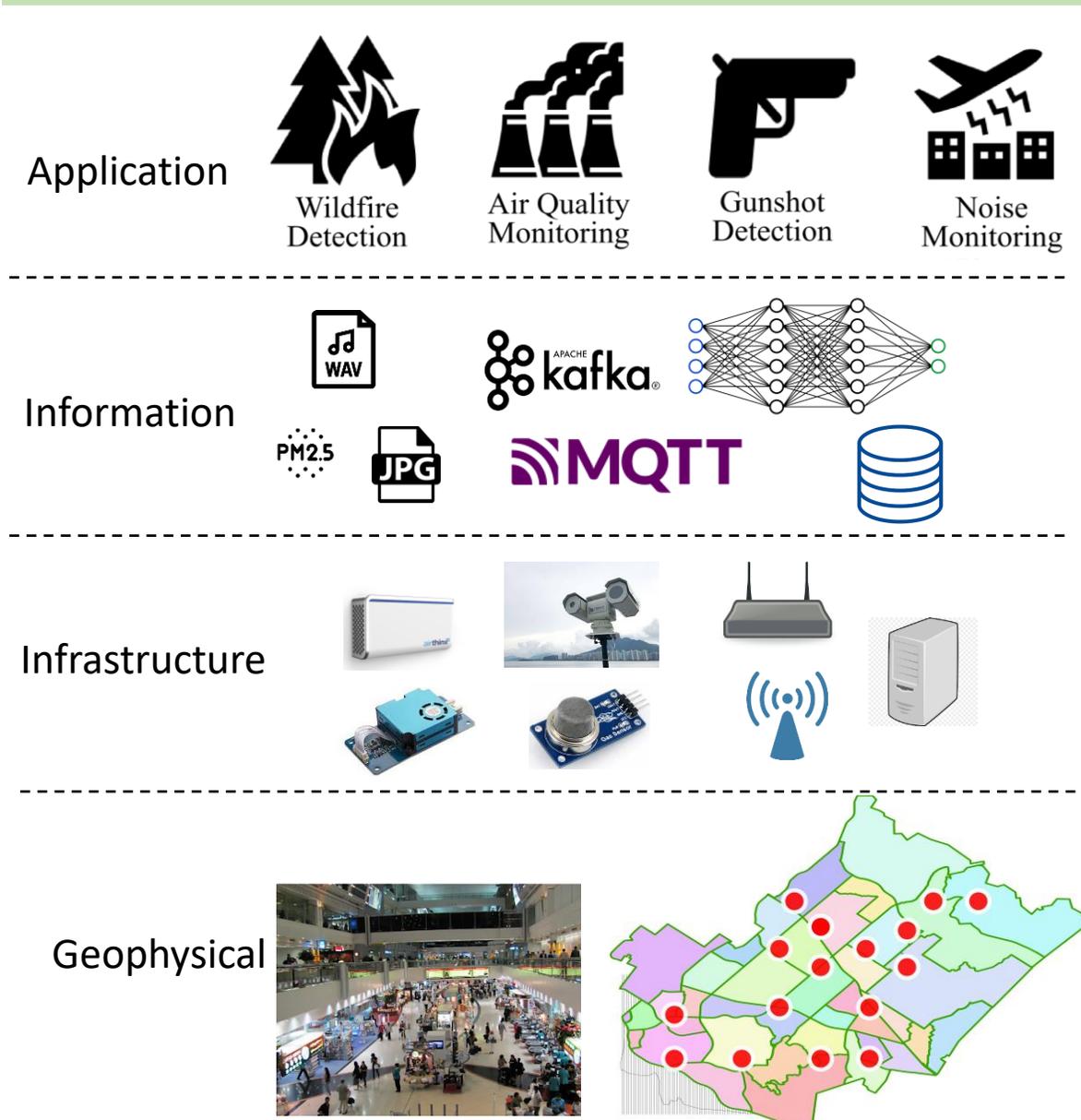
- Trade-off between *accuracy* and *deployment efficiency*
 - Expensive devices usually have a higher accuracy
 - More cheap devices can have a higher coverage

C4: How - to exploit pre-deployed infrastructure

- Reuse existing (already deployed) devices to reduce the cost

	Community	Applications
A	Irvine Spectrum	Gunshot detection
B	Quail hill (near highway)	Air quality & noise monitoring
C	Shady Canyon Preserve (wildland)	Wildfire detection
D	Shady Canyon (WUI)	Wildfire detection & air quality monitoring

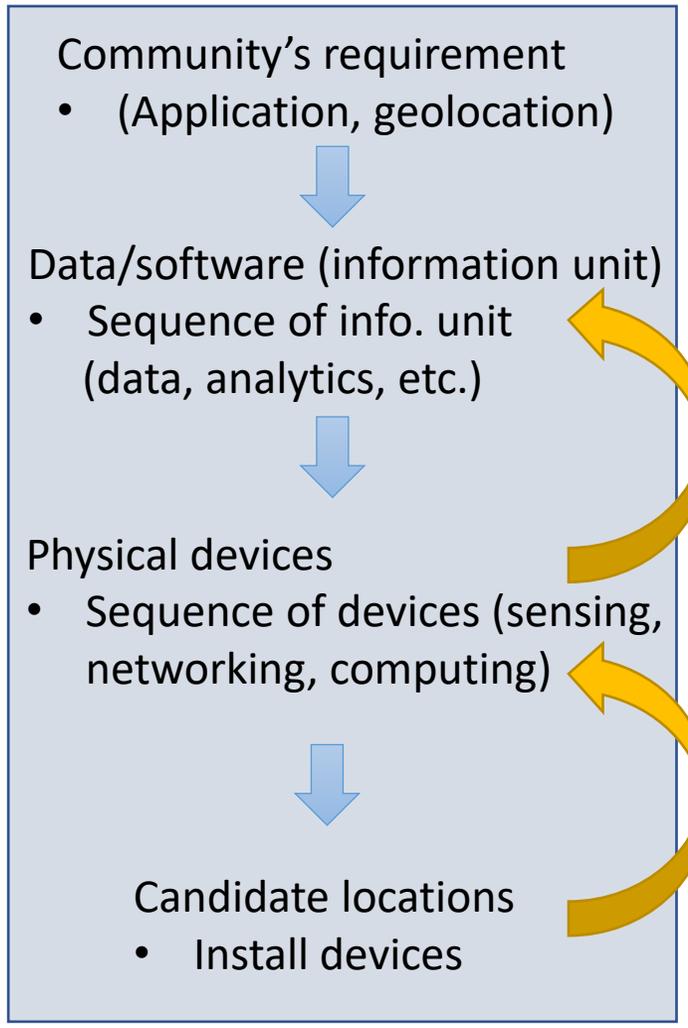
SmartParcels: IoT Planning For Communities



Goal: for required applications, find ideal

- Data/software
- Physical devices
- Candidate locations to maximize overall **sensing probability** and **accuracy**

Constraint: fixed budgets



Approach:

- Geophysical mapping** – select feasible mappings
- Planning generation** – maximize utility by exploiting reusability

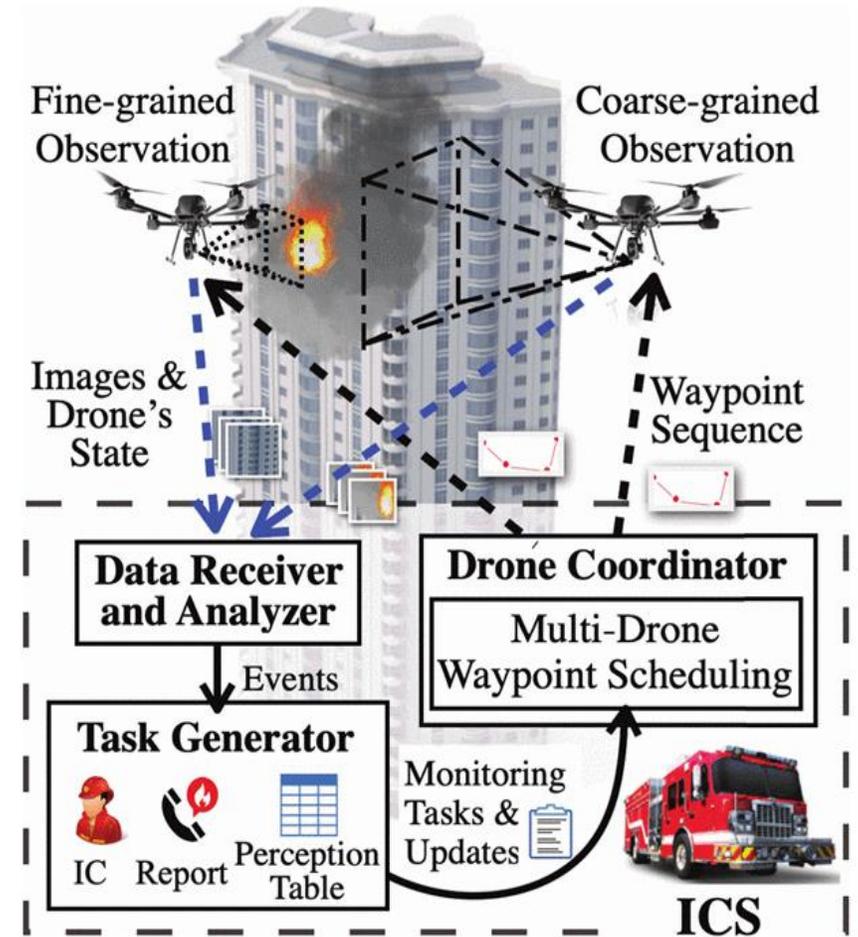
Two designs:
Clean-slate, retrofit

Automated Drone Infrastructure Inspection

PIs: Marco Levorato (UCI), Nalini Venkatasubramanian (UCI)
and Amlan Ganguly (RIT)

Project Goals

- Develop and test systems capable of automatically inspecting hardly accessible infrastructures with or without human assistance using autonomous aerial or ground vehicles.
- Proof of concept for 2 use-cases: (i) roof inspection; (ii) powerlines inspection
- Definition of feasible computing pipelines (sensing-to-control) based on neural networks matching the capabilities of resource constrained drones



Industry Needs and Relevance

- Reliable computing pipelines controlling jointly controlling information acquisition and navigation of the drones
- Optimization of the acquired information with no (or limited) human intervention
- Automated evaluation of coverage as well as anomaly detection
- Visual interaction with human operator



Approach

Milestone 1

- Taskable autonomous navigation interface

Milestone 2

- Sensing-to-control pipeline jointly controlling navigation and coverage

Milestone 3

- Integration of interaction with the user

Milestone 4

- Evaluation of mission performance metrics



Deliverables and Scope

Year 1 - Deliverables

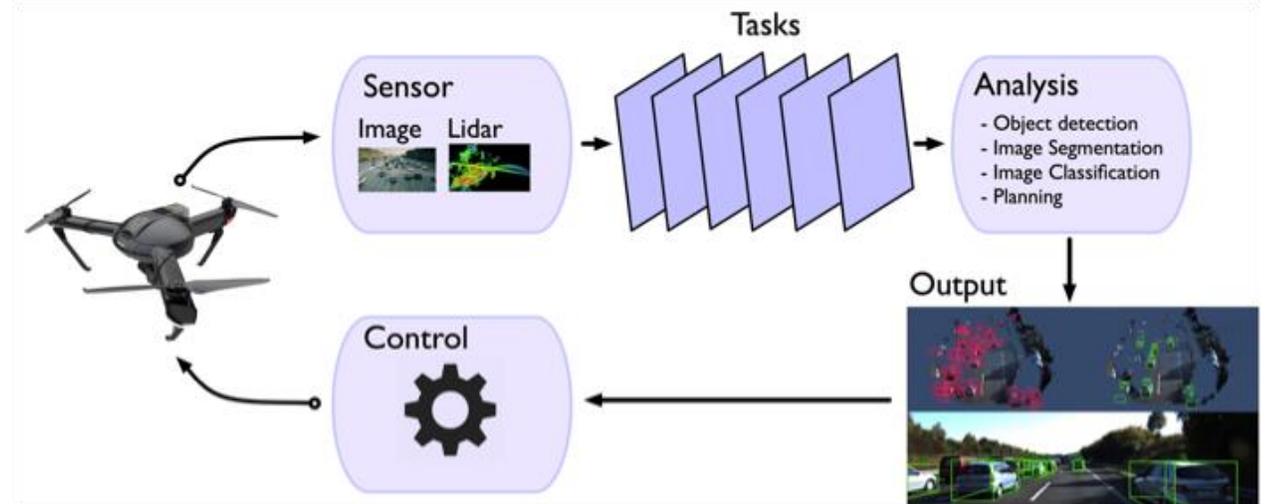
- Software for the joint navigation and mission control of the drone
- Pipeline for the optimization of coverage and anomaly detection
- Proof of concept for roof inspection application
- Environment for the design of powerline inspection application

Demos

- 1 yearly

Long-term vision

- Composable pipelines for flexible mission
- Advanced interaction with the user



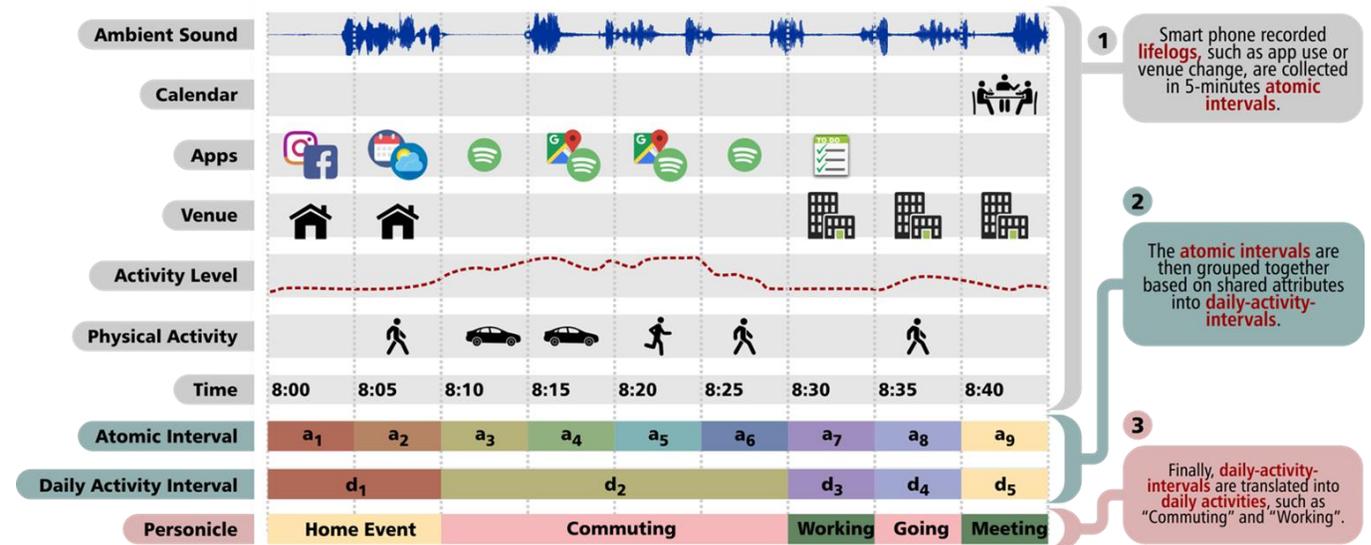
- New sensing to control algorithms for the evaluation of captured information
- Middleware platform realizing the sensing-to-control pipeline
- (long term vision) taskable/composable pipelines for flexible missions with lifetime estimation
- 2 proof of concept applications

The Personicle: Personal Chronicle Platform

PIs: Amir Rahmani (UCI), Ramesh Jain (UCI), Nikil Dutt (UCI), Christopher Homan (RIT)

Industry Needs and Relevance

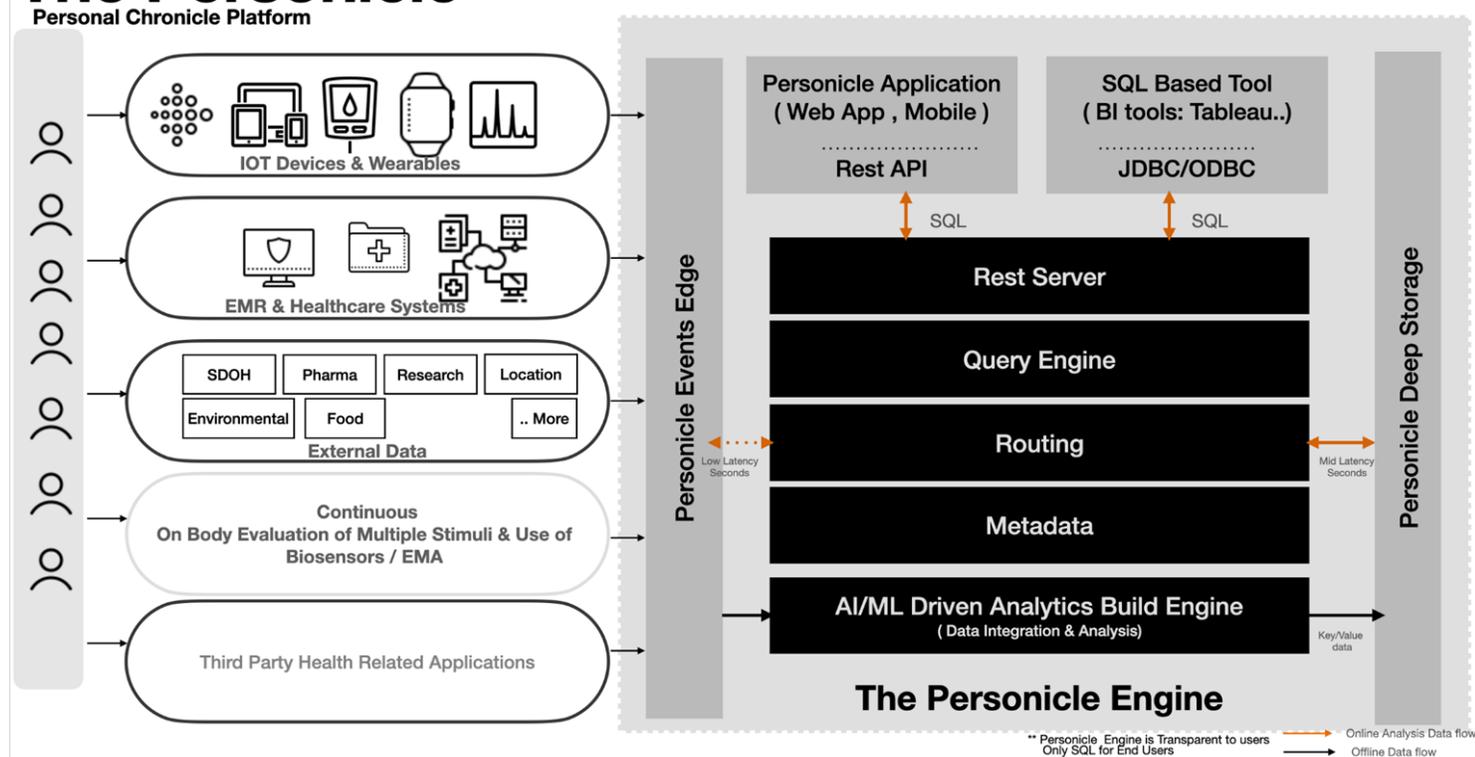
- **Holistic personal models** of individuals for developing personalized, predictive, precise, and participatory (P4) approaches.
- Continuously capture individual events of **lifestyle, health, social, environmental** in everyday settings
- Health data heterogeneity and diversity
- Transforming raw data to meaningful **events** and actionable **insights**
- **Scalable sensing and sensemaking**
- **Privacy and security** for personal health applications
- **Standardization**



Project Goals

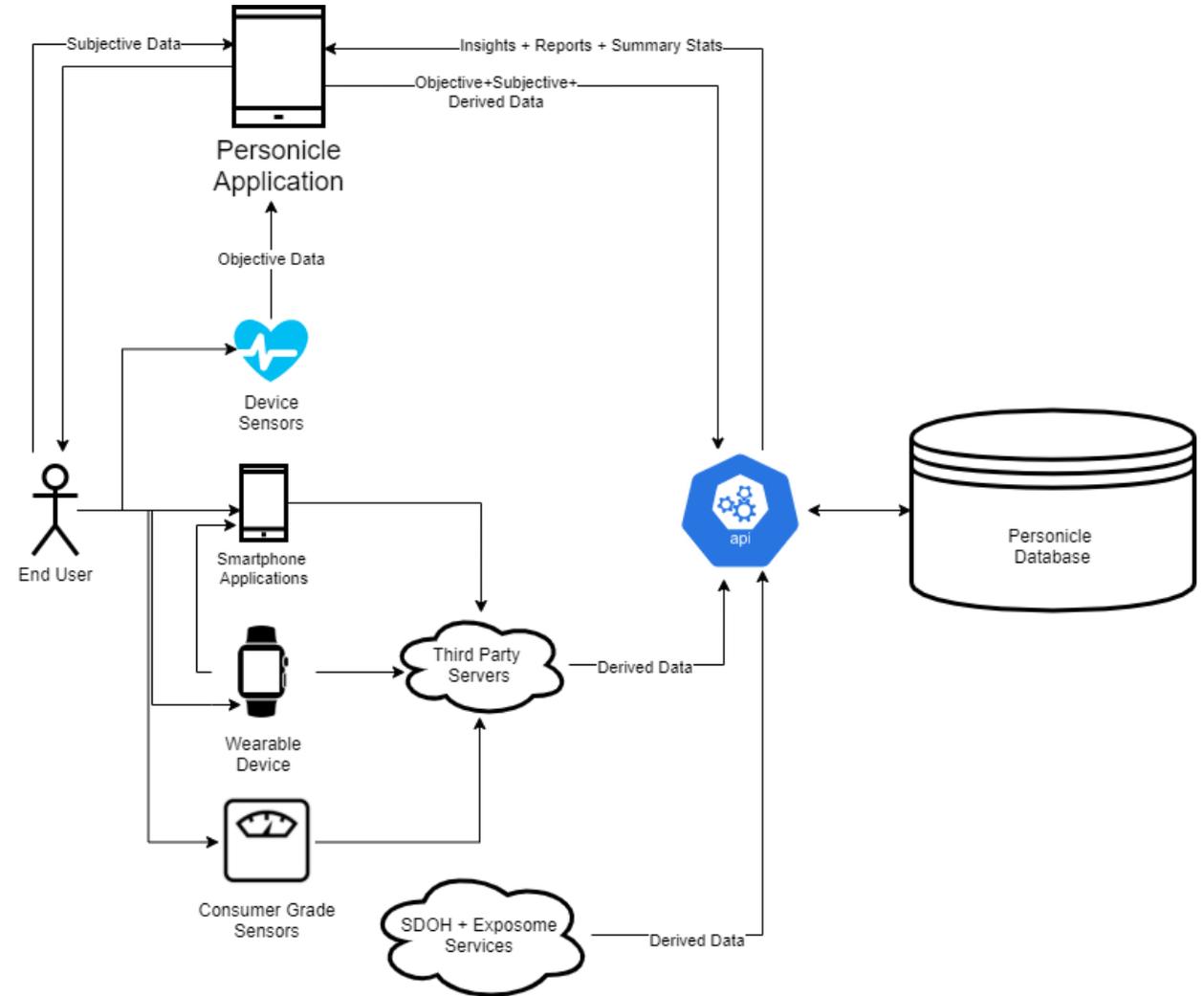
- An open-source platform to continuously capture, store, process, and manage heterogeneous data in everyday setting.
- Building Personicle: A chronicle of all events for a person.
- Enabling interactive event mining
- Offering a scalable and agile event repository and processing
- Automated lifelogging and activity recognition for behavioral studies
- Data visualization and dashboards for different stakeholders

The Personicle



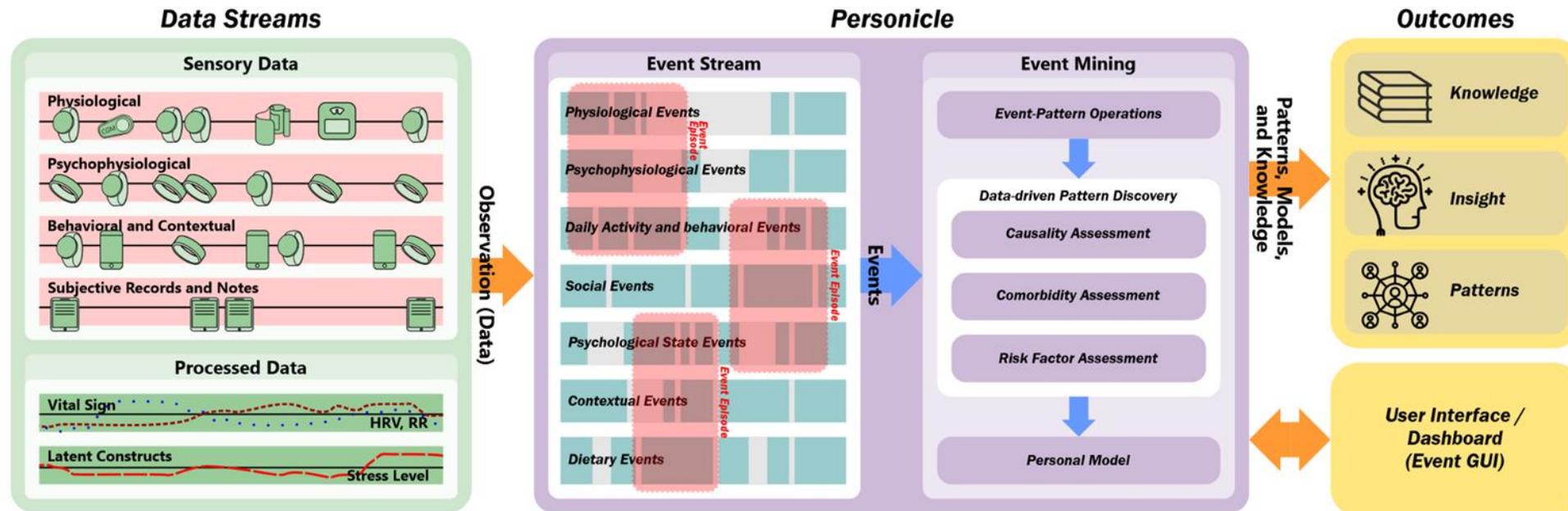
Approach

- Existing collaboration among the PIs and industrial partners
 - ClearSense & Xavor
- Support data integration from a **more diverse set of devices** to better capture the **contextual** and **environmental** factors
 - e.g., home robots, environmental sensors
- Provide interoperability to interface with clinical EHR systems by implementing **FHIR standard APIs**
- Address **security** and **privacy** challenges involved in this process
- Integrate **event mining** capabilities to build personal models (digital twins)
- **Test** the platform in the other related projects in the center for iterative enhancements



Deliverables and scope

- Short-term (Year 1):
 - The first demo of the open-source platform for academia and industry with the ability to
 - ingest data from home robots and other sensors in smart spaces
 - integrate FHIR interfaces for data export and import
 - Workforce training (undergrad and grad)
 - A standard reference architecture with the collaboration of the ISO WG11
- Long-term
 - Holistic data integration (e.g., exposome, food, genomics, etc.)
 - Offering robust and secure services while offering interoperability and privacy
 - Full integration of event mining and personal model building services



Integrated At-Home Health

PIs: Linwei Wang (RIT), Caroline Easton (RIT), Chris Homan (RIT), Amir Rahmani (UCI), Nalini Venkatasubramanian (UCI)

Industrial Needs and Relevance

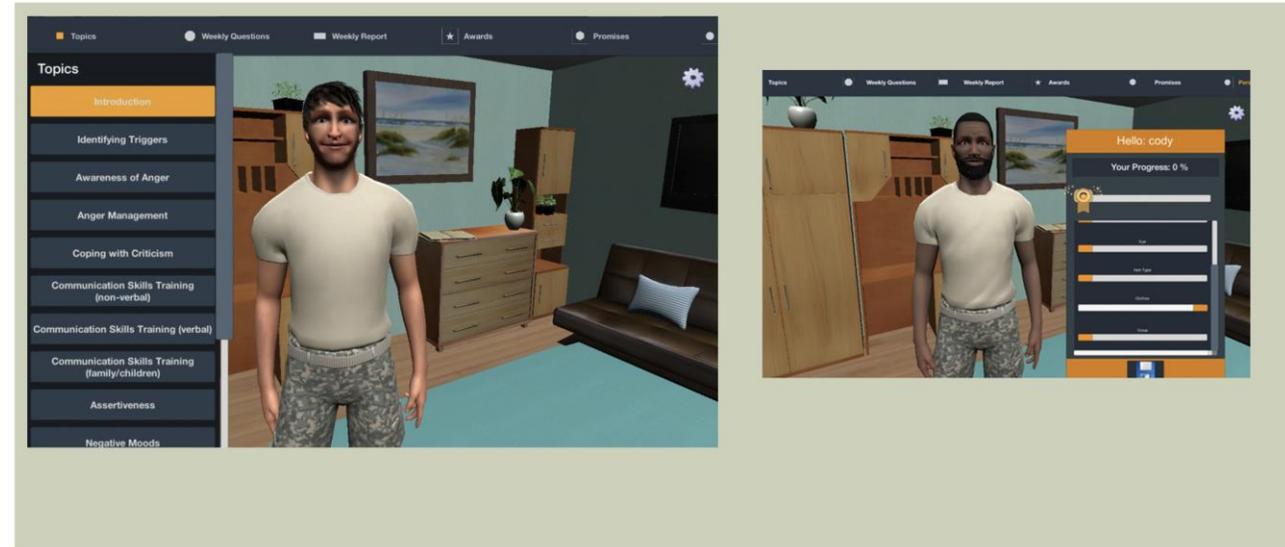
- Chronic illness management constitutes ~75% of total health expenditures in the US
- ~1/3 of people living with chronic illness also experience mental-health disorders
- Visit-based care does NOT meet the demand
 - limited & disparate access to care
 - Isolated care approach to interconnected mental-physical health
- At-home monitoring & intervention is the future

Project Goals

- Goals: **At-home digital intervention system** for individuals living with chronic conditions
 - Triggering & delivering
 - Mental health & behavioral interventions
- Objectives:
 - **Triggering & personalizing** intervention
 - In collaboration with remote physicians
 - In synergy with data collection platform from other IUCRC teams & projects
 - **Delivering** intervention at home
 - Including mental health intervention & behavioral interventions

Approach

- Foundation/prototype:
 - RITch®CBT
 - Interactive platform
 - Avatar coach
 - Evidence-based CBT
- Research plan:
 - Expand platform for affective data (voice, facial, etc) data collection
 - Integration with smart space data collection from other IUCRC projects
 - AI methodology for triggering & **personalizing** intervention (doze, content, etc)
 - Extend intervention modules to meet mental health and behavioral needs
 - Feasibility study



Deliverables and Scope

- Expected Outcomes: Intelligent at-home intervention systems
 - **Personalized on-demand intervention at home → address barrier to and disparity of access to care**
 - Behavioral and mental health intervention for individuals living with chronic conditions → **integrated** care of mental and physical health
- Deliverables
 - **Year 1:** Enhanced RITch®CBT with data collection and other smart-space systems
 - **Year 2-3:** Enhanced RITch®CBT with AI-backed intervention delivery & expanded capacity of intervention modules
 - **Year 4-5:** Feasibility study with IUCRC partners (Hillside, URMCM, RRH)

Smart Spaces for Behavioral Health

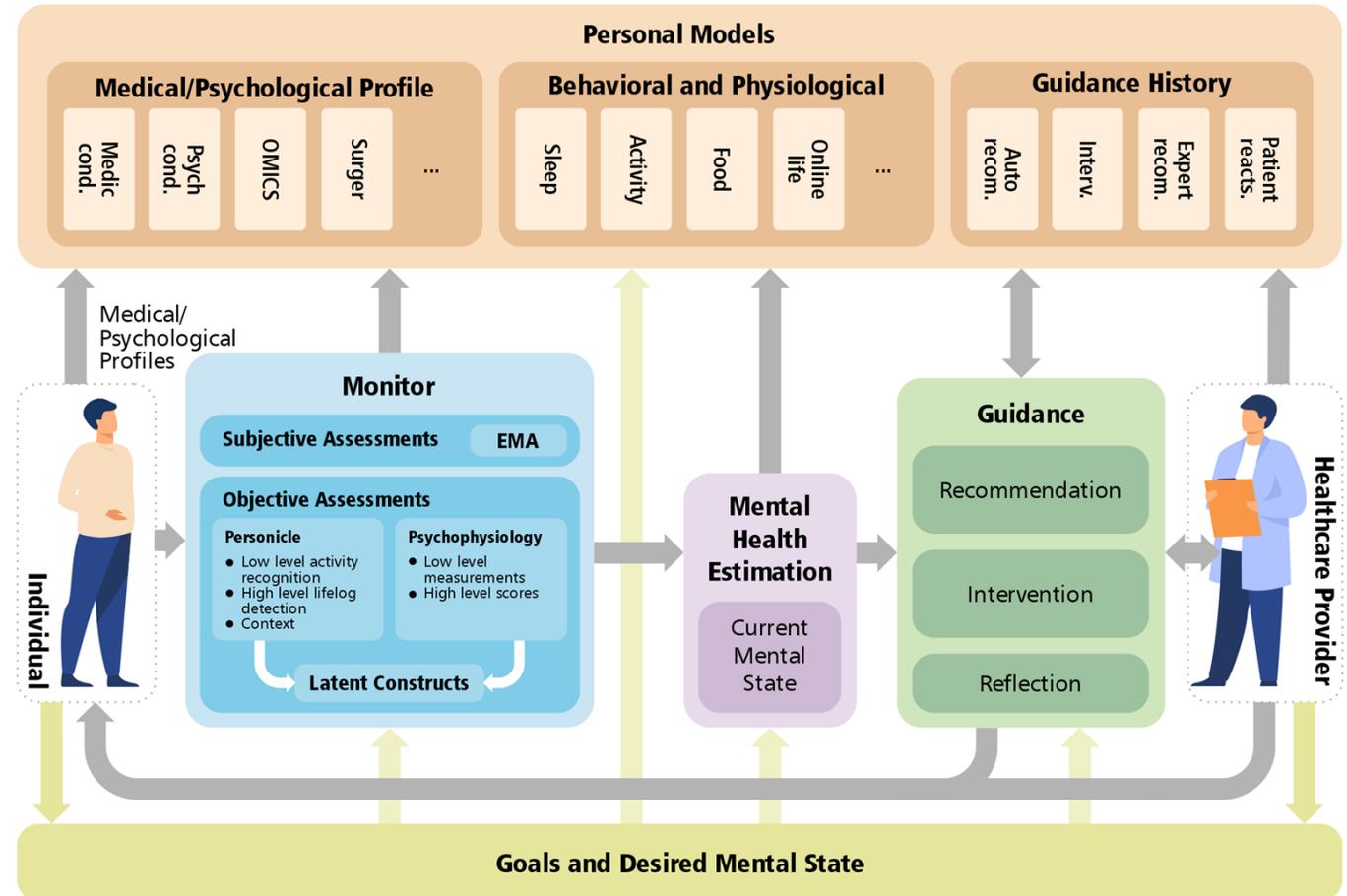
PIs: Amir Rahmani (UCI), Nikil Dutt (UCI), Jessica Borelli (UCI), Melissa Pinto (UCI), Ramesh Jain (UCI), Caroline Easton (RIT), Linwei Wang (RIT)

Industry Needs and Relevance

- Existing digital behavioral and mental healthcare solutions commonly take on a **reactive approach**.
 - Individuals need to self-monitor and document symptoms.
- The need for more **comprehensive and objective monitoring** of mental and behavioral health.
 - Each individual may benefit from personally tailored treatment.
- The need for **living labs** to capture behavior and mental health in **everyday settings**.
- Making sense of high-dimensional multimodal sensory data from the body area networks as well as smart spaces.
 - For monitoring, assessment, and guidance

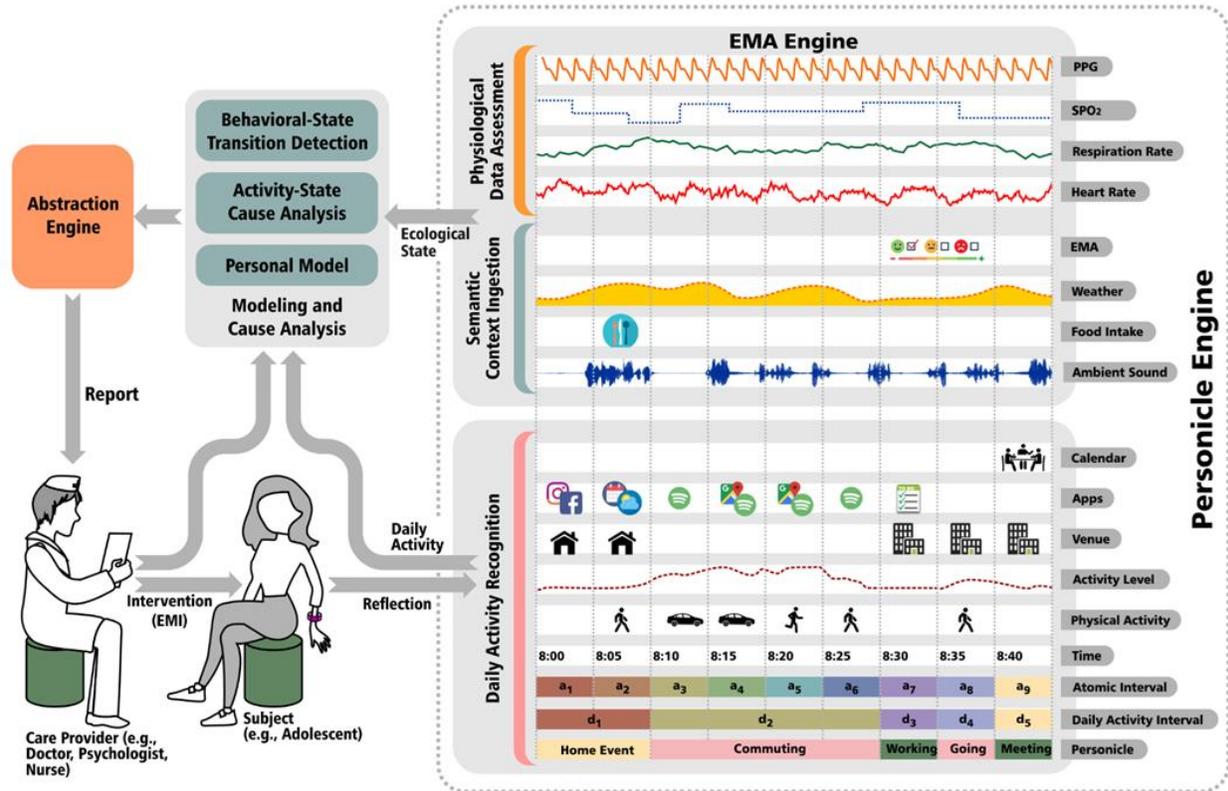
Project Goals

- Develop different components required for realizing the notion of **Personalized Mental Health Navigation (MHN)**
 - A cybernetic goal-based system that deploys a continuous cyclic loop of **monitoring**, **estimation**, and **guidance** to steer the individual towards mental flourishing.
- Living labs



Approach

- Building upon existing collaboration with two behavioral health organizations
- Multi-modal data collection to objectively and subjectively monitor mental health and behavior
 - Psychophysiology through wearables
 - e.g., HR, HR variability, GSR, RR, etc.
 - Sleep and physical activity
 - EMA and self-reports
 - Lifelogs via mobile and ambient sensing
 - e.g., location, sound, smartphone logs, facial expression, etc.
 - ML-models to capture latent constructs
 - e.g., stress, emotion, loneliness, etc.
- Using Personicle as the backend
- Existing data and data analytics pipelines



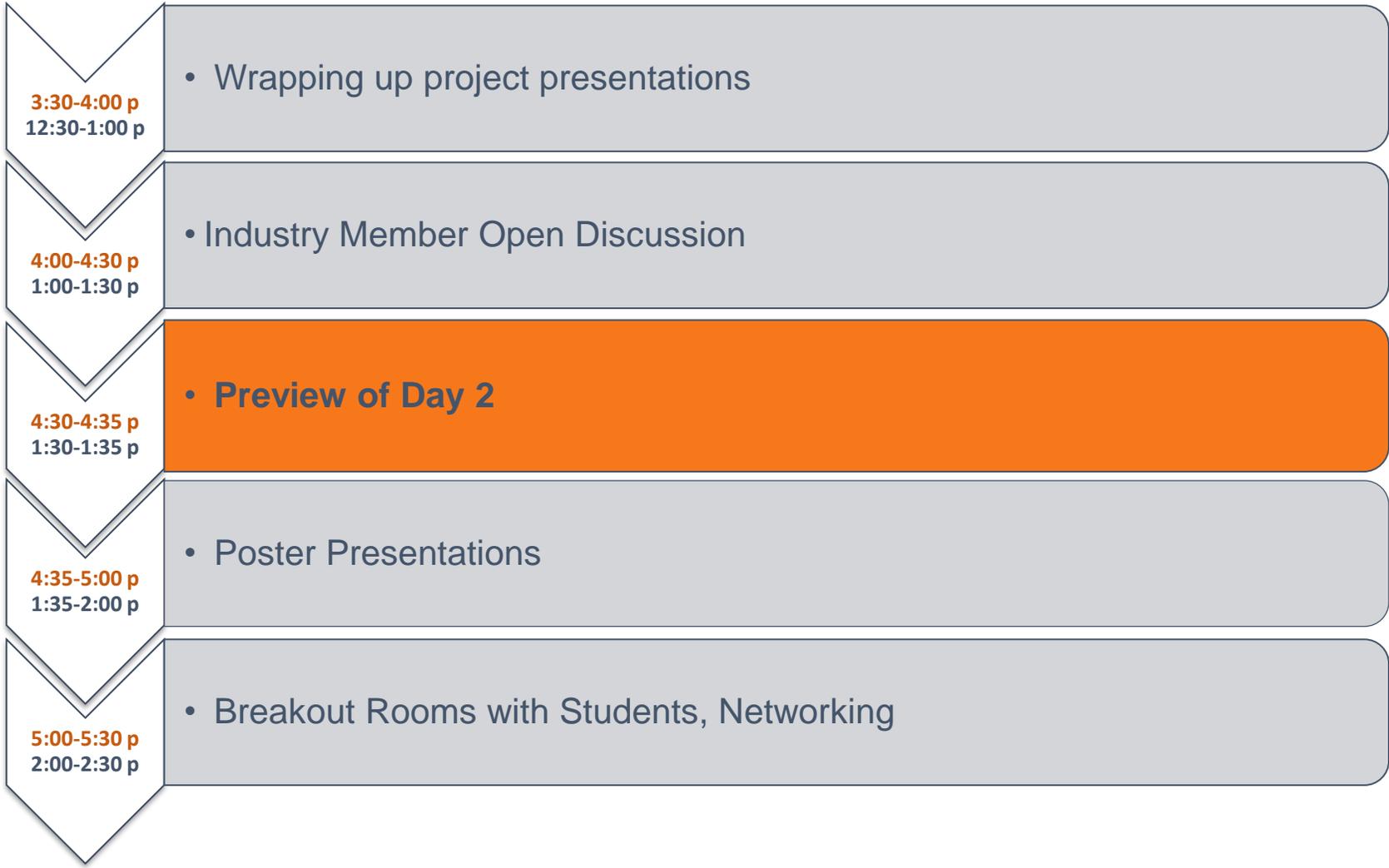
Settings and Use Cases

- HillSide behavioral health facility, Atlanta, GA
 - Supporting adolescents struggling with emotional regulation
 - Dialectical Behavior Therapy (DBT), Recreational Therapy, etc.
 - Both outpatient and inpatient
 - Full access to their comprehensive and local EHR
 - Comprehensive daily assessment
 - An ongoing IRB-approved study
 - Access to camera and mic at cottages
- River Stones Residential Treatment Services, San Bernardino, CA
 - More like home settings
 - Treating adolescents
 - Youth development specialists
 - Depression, Anxiety, PTSD, Trauma, etc.

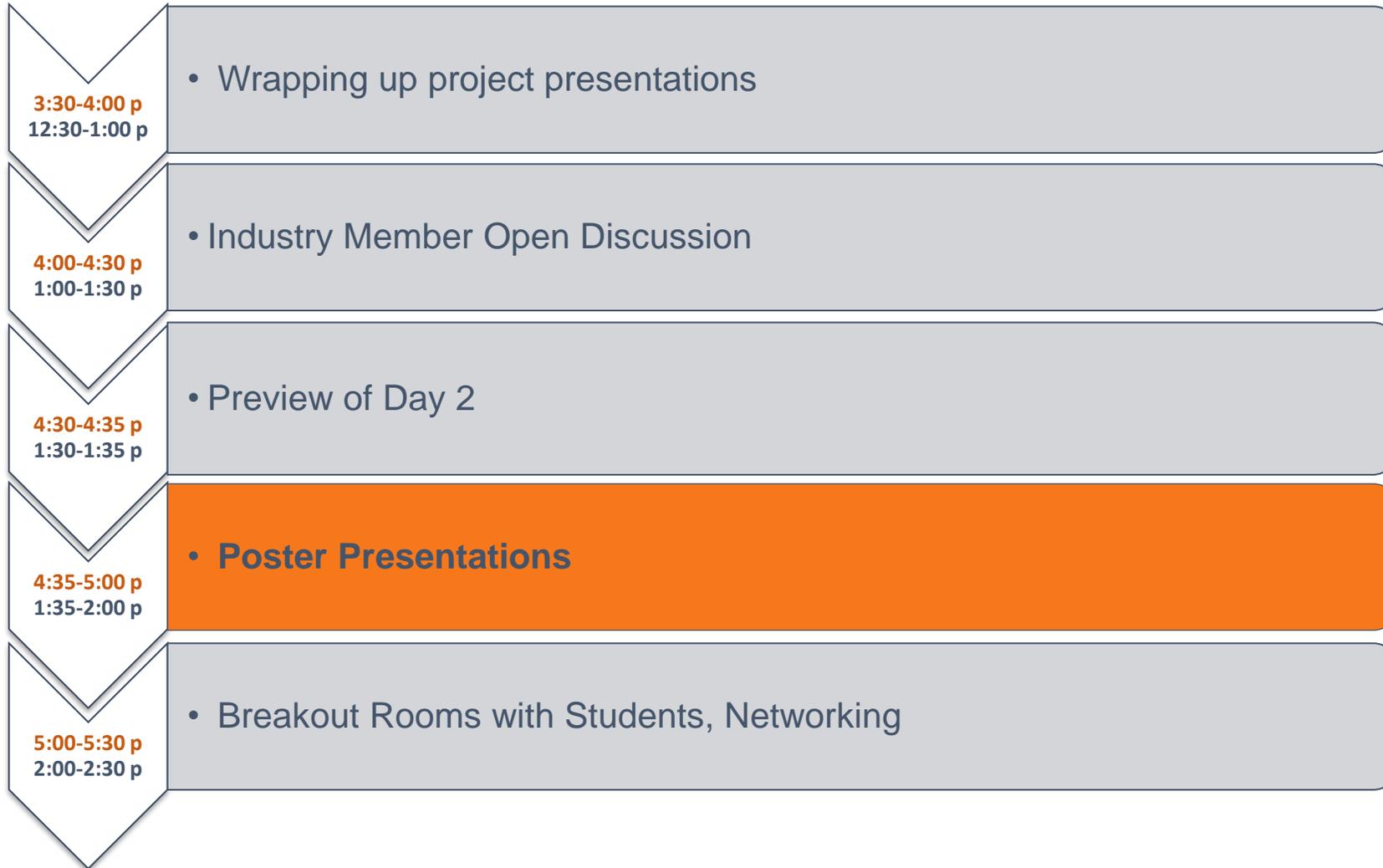


Deliverables and Scope

- Short-term (Year 1):
 - The first demo of the Monitor module for objective mental health assessment.
 - A de-identified multi-modal dataset of mental health-related measurements.
 - A data processing and machine learning pipeline for objective mental health assessment.
 - Workforce training (undergrad and grad).
 - Building two Living labs for behavioral studies.
- Long-term
 - The complete realization of the MHN as a goal-based closed-loop guidance system.
 - Addressing privacy and security aspects of the MHN system.







Student Posters

Smart Spaces and Healthcare

Objective Prediction of Tomorrow's Affect Using Multi-Modal Physiological Data and Personal Chronicles: A Study of Monitoring College Student Well-being in 2020

Salar Jafarlou, PhD student in Computer Science

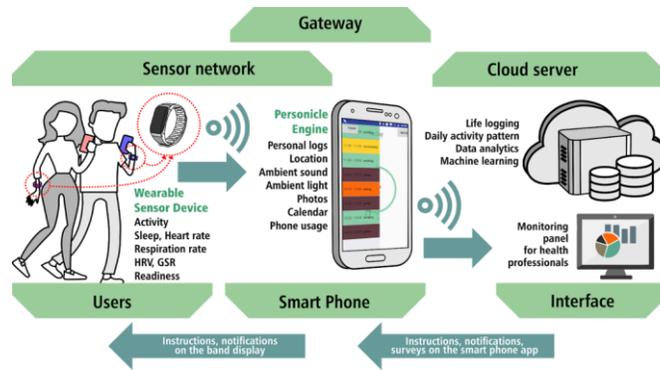
Abstract: Recent advancements of ubiquitous wearable technologies have increased the reliability of such tools in detecting and accurately estimating mental states (e.g., mood, stress, etc.), offering comprehensive and continuous monitoring of individuals over time. The goal of our study was:

1. to investigate the capacity to more accurately predict affect through a fully automatic
2. objective approach using multiple commercial devices.

Background: Affective disturbances and dysregulation or instability in experienced affect are core facets of many types of psychopathology. Monitoring and increased understanding of one's affect contributes to the regulation of affect and as such is a key component of many forms of intervention or approaches to manage affective disturbances. Previous attempts to model an individual's mental state were limited to subjective approaches or the inclusion of only a few modalities

Approach: Thus, the goal of this study is to address the limitations of previous studies (e.g., time span and partial reliance on subjective assessment), by both expanding the time length of data collection to about 12-months during the eventful year of 2020 and also by limiting to exclusively use objective measurements to model users' next day affect. Using only objective measures by commercial devices to predict an individual's affect:

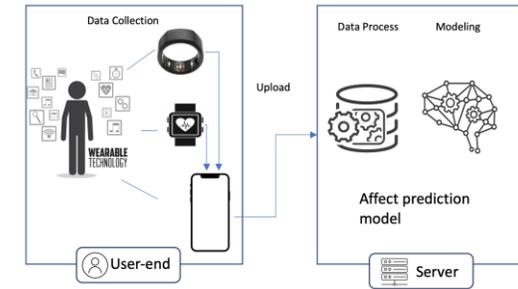
- enable us to monitor mental health in a more continuous and convenient way
- makes mental health monitoring service accessible to more people.



Methodology and Algorithm: Considering the fully objective and portable affect assessment in this study, we only used commercial monitoring devices (i.e., Oura ring, Samsung Watch, and Android Phones) and obtained three data modalities using the mentioned devices. We present below an overview of collectable features from these modalities.

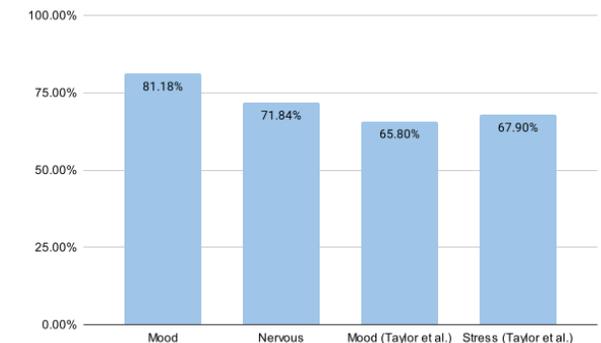
- **Smart Ring:** sleep (e.g., length of awake, deep and REM sleep stages), physiology (e.g., heart rate, heart rate variability), and activity of users (e.g., daily movement and rest time, etc.)
- **Smart Watch:** Accelerometer (ACC) and photoplethysmography (PPG)
- **Smart Phone:** major physical (e.g., in vehicle, still, on bicycle) and behavioral activities (e.g., working, commuting, relaxing) throughout the day.

Finally, using these three modalities, we collected 52 features and trained different ML models to predict next day affect. Random forests generally showed a better performance.



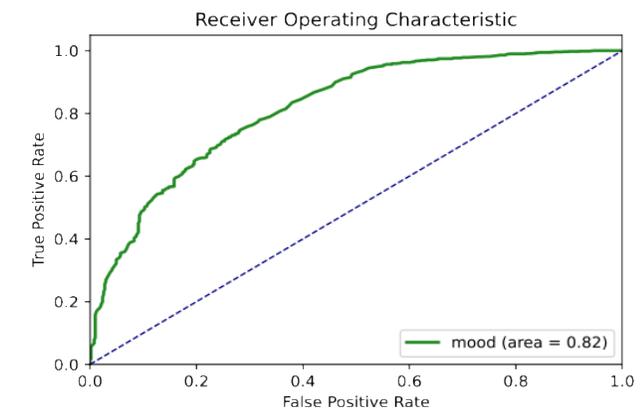
Results:

1. Prediction accuracy of mood and nervousness affect to Taylor et al [1] showing about **16%** and **4%** improvement in accuracy for mood and stress (i.e., nervousness) prediction,
2. The receiver operating characteristic (ROC) of the mood prediction model yielding **0.82** area under curve (AUC) that has **8.1%** improvement compared to the best values reported by Spathis et. Al [2] for mood prediction.



References:

- [1] Sara Taylor, Natasha Jaques, Ehimwenma Nosakhare, Akane Sano, and Rosalind Picard. Personalized multitask learning for predicting tomorrow's mood, stress, and health. *IEEE Transactions on Affective Computing*, 11(2):200–213, 2017.
- [2] Dimitris Spathis, Sandra Servia-Rodriguez, Katayoun Farrahi, Cecilia Mascolo, and Jason Rentfrow. Passive mobile sensing and psychological traits for large scale mood prediction. In *Proceedings of the 13th EAI International Conference on Pervasive Computing Technologies for Healthcare*, pages 272–281, 2019.



A Case for Digital Therapy: Satisfaction, Interest, and Use of Virtual Embodied Agent RITch® CBT at a hospital and shelter

Celeste Sangiorgio, PhD., Cassandra Berbary, PhD., Caroline Easton, PhD., Cory Crane, PhD.

Funding: CBT Therapy Content & Trial, NIH RO1 DA018284-01 A1 | Office of the Vice President of Research-Avatar Development, PHT180 Pilot - Platform Development | Digital Therapy Development & Deployment- HRSA Rural OUD/SUD Grant

Abstract

The present study examined satisfaction, interest, and use of virtual avatar assisted CBT, RITch® CBT, a 12-session virtual therapy platform developed to mirror evidence-based treatment for co-occurring substance use, conflict, and negative mood (SADV). Pilot testing occurred at two sites: an inpatient chemical dependency hospitalization program (n = 10; 20% female) and a homeless shelter (n = 3; 100% male).

Background

- Substance Use Disorders continue to increase across the US, >\$700 billion annually (SAMSHA, 2021)
- High co-occurring rates of mental health, medical problems, & Intimate Partner Violence (NIDA, 2017; SAMSHA, 2021)
- Digital mental health interventions are viable treatment options for PTSD, anxiety, etc. (Aboujaoude et al., 2020; Easton et al., 2018)

Approach:

In both sites, participants were briefed on RITch® CBT, logged into the program, and completed a module digital avatar assisted CBT treatment. Following use of RITch® CBT, participants were asked to rate their interest in the avatar and their satisfaction with the platform.

Controlled variables	Independent variable	Dependent variable
<ul style="list-style-type: none"> ▪ Patients with substance use and conflict histories 	<ul style="list-style-type: none"> ▪ Exposure to VR therapy platform 	<ul style="list-style-type: none"> ▪ Satisfaction ▪ Interest ▪ Behaviors ▪ Use of VR therapist

Methodology/Algorithms



Measure	Construct
Questionnaire	Satisfaction
Questionnaire	Interest
Performance	Use
Performance	Effectiveness

Results

- Hospital site had greater success in identifying and administering treatment (10 participants) compared to shelter site (3 participants)
- Barriers at shelter site included: untreated severe and persistent mental illness, dysregulated behavior, inability to engage with materials
- Hospital participants had brief, structured contact with platform
- Shelter staff struggled to structure and implement platform
- Hospital participants and shelter participants that engaged with the application reported high levels of satisfaction with the platform and interest in continued engagement

References

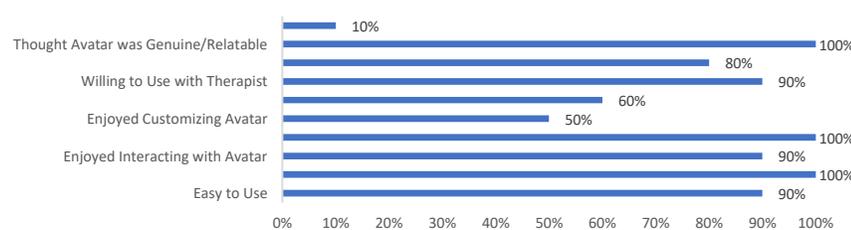
Aboujaoude, E., Gega, L., Parish, M. B., & Hilty, D. M. (2020). Editorial: Digital Interventions in Mental Health: Current Status and Future Directions. *Frontiers in Psychiatry, 11*. <https://www.frontiersin.org/article/10.3389/fpsy.2020.00111>

Easton, C. J., Berbary, C. M., & Crane, C. A. (2018). Avatar and technology assisted platforms in the treatment of co-occurring addiction and IPV among male offenders. *Advances in Dual Diagnosis, 11*(3), 126–134. <https://doi.org/10.1108/ADD-03-2018-0003>

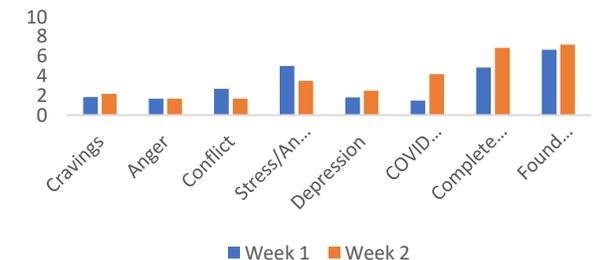
National Institute on Drug Abuse. (2017). *Trends & Statistics* [Government]. National Institute of Mental Health. <https://www.drugabuse.gov/related-topics/trends-statistics>

Substance Abuse and Mental Health Services Administration. (2021). *Key Substance Use and Mental Health Indicators in the United States: Results from the 2020 National Survey on Drug Use and Health*. 156.

Percentage of Participants Endorsing "Agree" or "Strongly Agree"

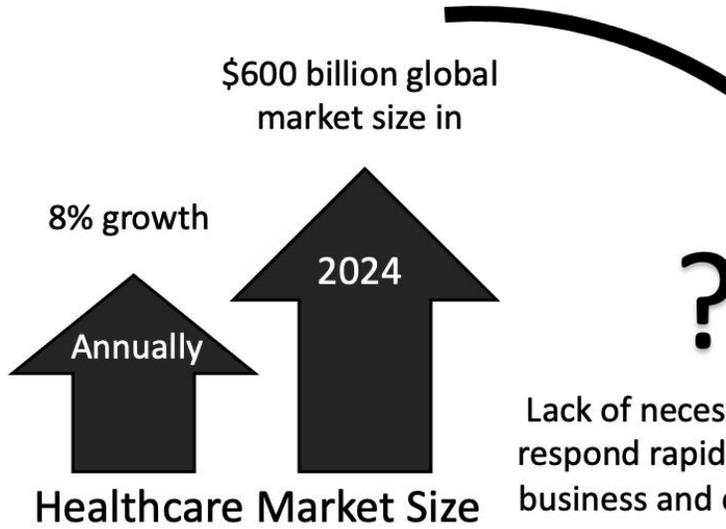


Mean Participant Weekly Ratings on a Scale of 1-10



Personicle

Mahyar Abbasian (ICS PHD), Vaibhav Pandey (Clearsense)



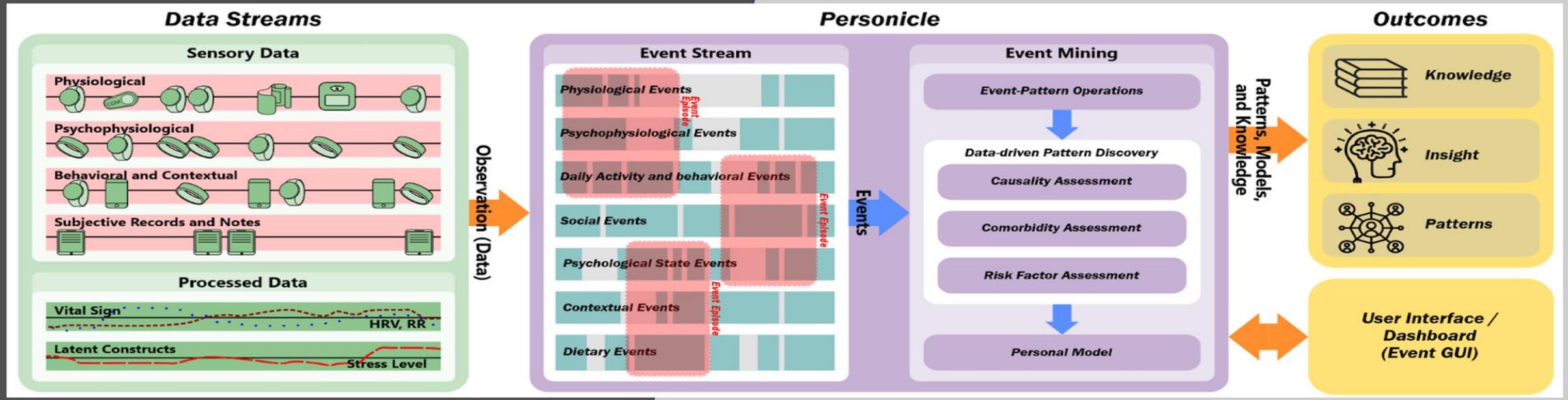
- ✓ The digital health platform (DHP) is an architectural approach
- ✓ Unlocking the value of healthcare data is a top priority

?

Lack of necessary agility to respond rapidly to changing business and clinical drivers

Providing an infrastructure to help healthcare providers build their applications on top of Personicle

- Focusing on Data Management (providing tools)
- Especially on PHN and model building
- Build and manage individuals' health state
- Provide interoperability

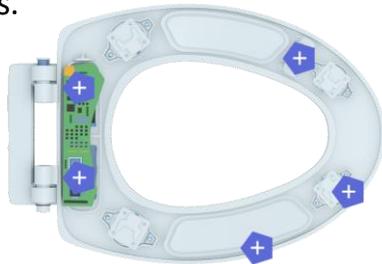


Inconspicuous Daily Monitoring to Reduce Hospitalizations in Heart Failure Patients

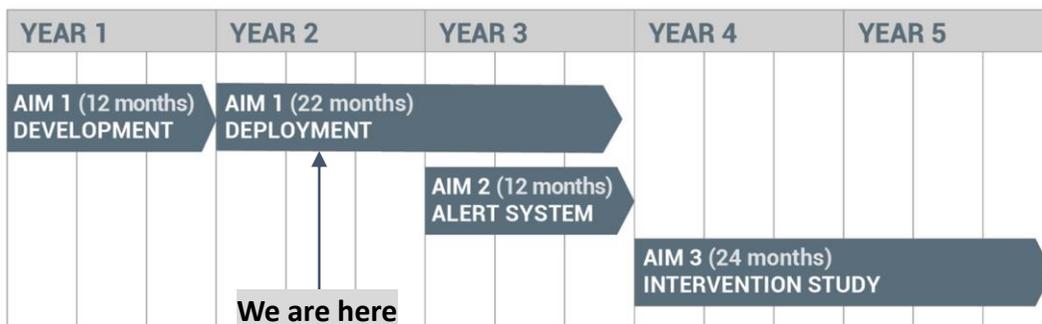
By: Computational Biomedicine Lab @ RIT, Ryan Missel, PhD Student in Computing and Information Sciences

Abstract: Cardiovascular disease is the leading cause of deaths worldwide and there is much interest in at-home daily monitoring for early interventions. The Heart Seat aims to be a non-invasive method to collect health data daily without change to patient behavior. From this, an automated risk prediction system will be deployed to provide health care providers with adverse event prediction and signs of early deterioration via a clinical dashboard.

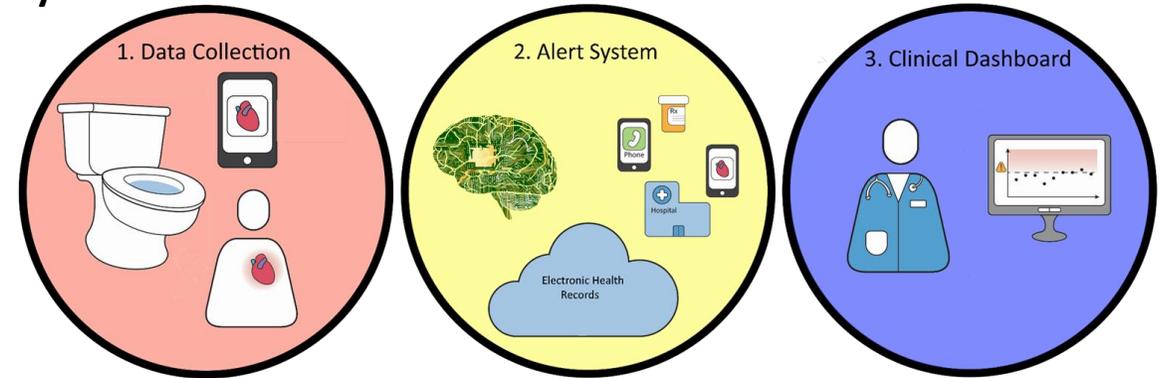
Hypothesis: Hospitalization rates and duration lengths can be reduced through the use of inconspicuous home monitoring devices and early interventions.



Two-Phase Study Timeline:



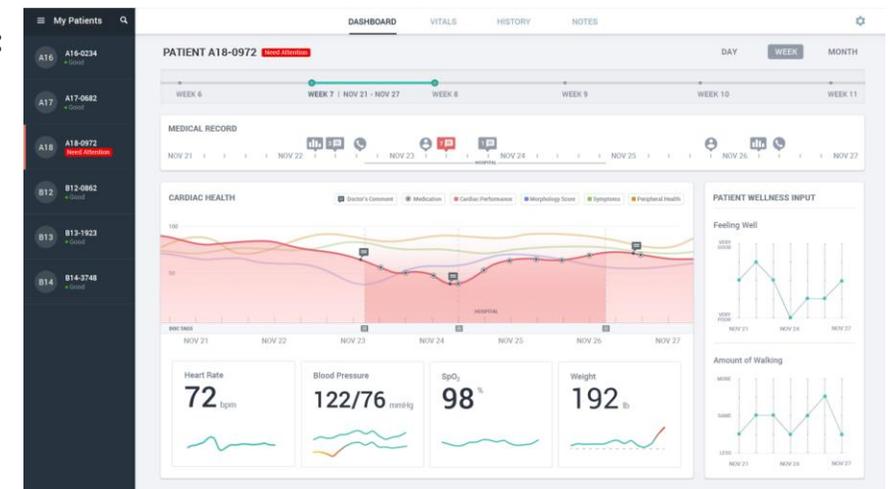
Study Aims:



Aim 1 (Data Collection): Build a dataset of electronic health records, daily wellness inputs, and seat recordings via the Heart Seat, a Wellness App, and hospitalizations.

Aim 2 (Alert System): Train time-dependent machine learning models that predict daily hospitalization risk and forecast adverse events.

Aim 3 (Clinical Dashboard): Deploy the system on a facing dashboard monitoring and prediction.



Supported by: Award NO: R01NR018301, by the National Institutes of Health (NIH) / National Institute of Nursing Research (NINR)

ZotCare: A Health Cybernetics Service Provider

By Sina Labbaf Advisors: Nikil Dutt & Amir Rahmani



What is ZotCare?

- ZotCare is a BAAS for health cybernetics
- Making complex mHealth application simple

- Covers very component and service you will need
- Easy to use for non-CS researchers
- Advance mode for CS researchers to focus on problems

Data Collection

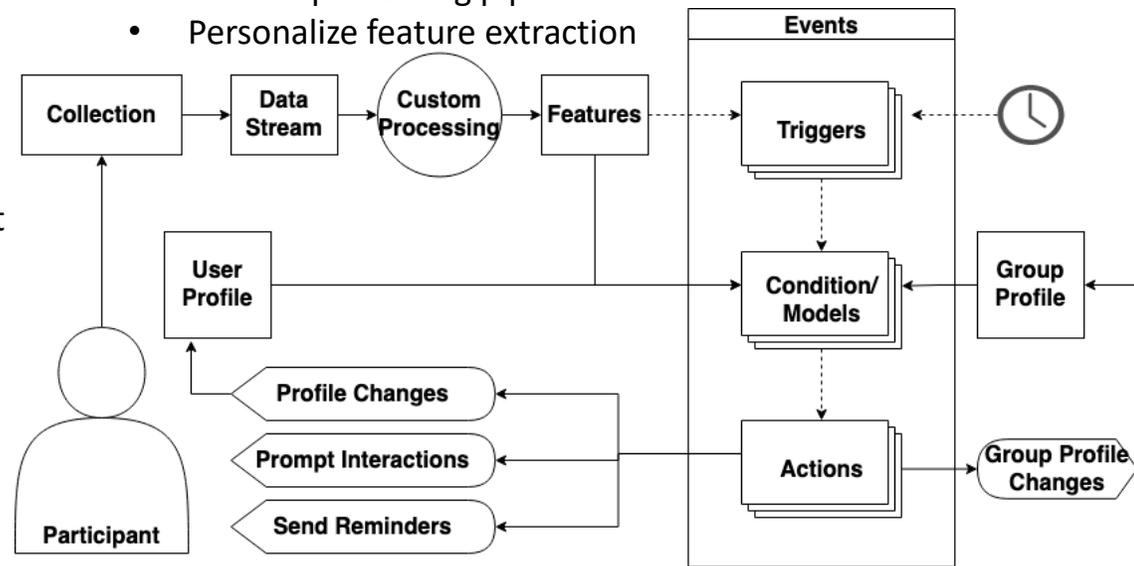
- Objective sensor data
 - Bio signals (ZotCare wearable)
 - Behavioral
 - Contextual
- Subjective data
 - ZotCare Mobile component

Models and Profiles

- User and group profiles
- Personalize or progress over data
- Create local or personal customization

Data Processing

- Custom processing pipeline
- Personalize feature extraction



Data Flow and Control

- Using event service to create control flow
- Integrate your own logic, intervention, triage, etc.
- Using personal and progressive models to implement learning methods
 - Active learning
 - Reinforcement learning
 - Memory control system

Components

ZotCare Mobile app

- Interactions (programmable by researchers)
- Device sync and stats
- Local profiles

Researchers dashboard

- Tweaking the services

- Hooking into the APIs

- Data analysis

- 3rd party hooks

SDK

- For local and 3rd party processing

Wearable app

- Smart data collection

Use cases

- Mental Health Navigation study

- 30 college students / 2 phases

- Smart interventions

- NSF UNITE

- 10-40 pregnant moms / 5 phases

- Active learning

- Smart intervention

- Profile personalization

- Other studies

- SLIM (with Turk, Finland)

- Hillside study

- DCCC

- SleepIn

- Etc.

Student Posters Autonomy and Mission-Critical Applications

Dynamic Exit Selection in Multi-Exit Deep Neural Networks using Deep Reinforcement Learning

Abhishek Vashist, PhD Candidate, RIT

Motivation

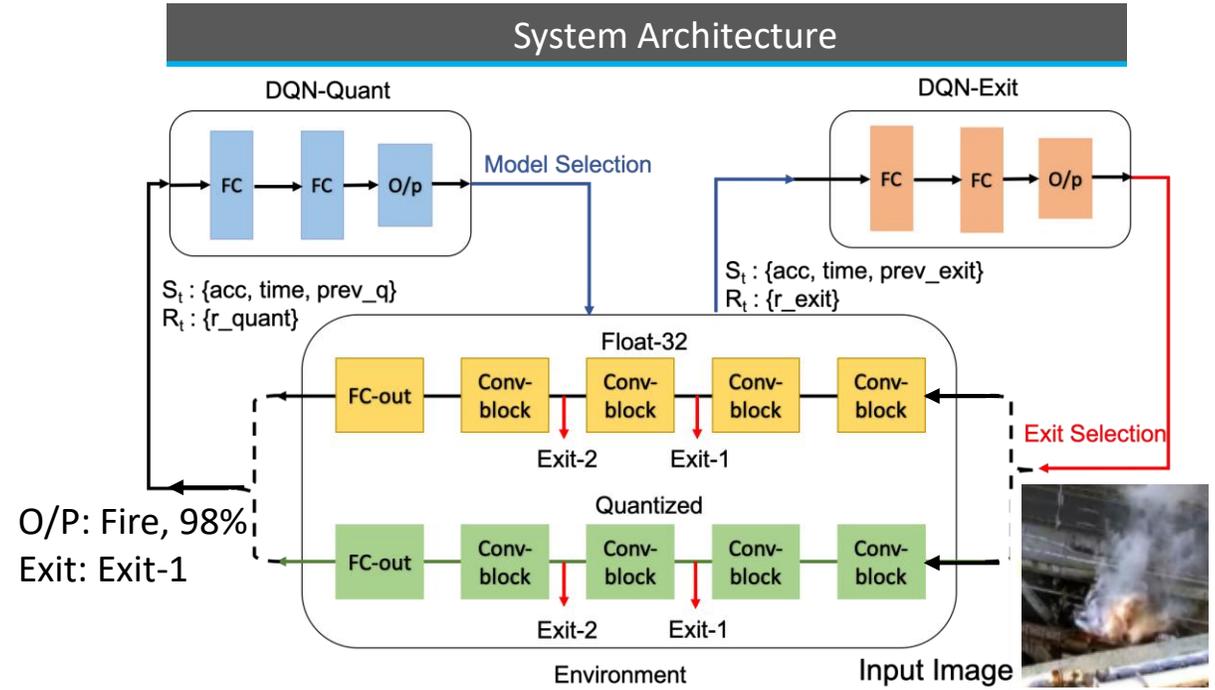
- Situation awareness for first responders in smart environments enables intelligent and faster response.
- Such applications requires an edge/mobile device to process information.
- Multi-exit DNNs are used to reduce computational load and faster inference with static sub-optimal exit selection strategy.
- We propose using Deep Q Network (DQN) based technique for dynamic exit selection in multi-exit DNNs.

Approach

- DQN is trained to learn exit-selection strategy
- Utilizes various hardware and network state information:
 - Accuracy, inf. Time, exits, and battery-SoC
- A separate DQN is implemented for adaptive quantization.
- At run-time, exit selection and model selection is performed for input images

Results

- 63.5% decrease in inference latency.
- 33% reduction in computation energy.
- Classifies 2.2X more inputs compared to static exit selection.



PERFORMANCE COMPARISON WITH STATE-OF-THE-ART

Approach	Network	Accuracy (%)	Threshold
-	AlexNet [6]	83.4	-
Threshold [3]	B-AlexNet [3]	79.19	0.0001, 0.05
-	Exit-AlexNet [4]	80	0.5,0.5
DQN based	DQN-ExitAlexNet	81.5	Dynamic
-	ResNet18 [1]	90	-
Threshold [3]	B-ResNet110 [3]	79.17	0.3, 0.2
-	Exit-ResNet [4]	88.5	0.5,0.5
DQN based	DQN-ExitResNet	85.1	Dynamic

* A. Vashist, S. V. Vidya Shanmugham, A. Ganguly and S. M. P D, "DQN Based Exit Selection in Multi-Exit Deep Neural Networks for Applications Targeting Situation Awareness," 2022 IEEE International Conference on Consumer Electronics (ICCE),

Drone Assisted Monitoring and Inspection in Challenged Settings

Goals and Overview

We propose a **DragonFly** system, a drone-based sensor data collection platform for improving situational awareness in different fire settings.

- 1) We design a rule-based system for generating drone monitoring tasks based on the firefighter's interest and the fire prediction.
- 2) Design the multiple-drone flight planning approach to optimize the motions of drones to fulfill multiple tasks with diverse monitoring requirements.

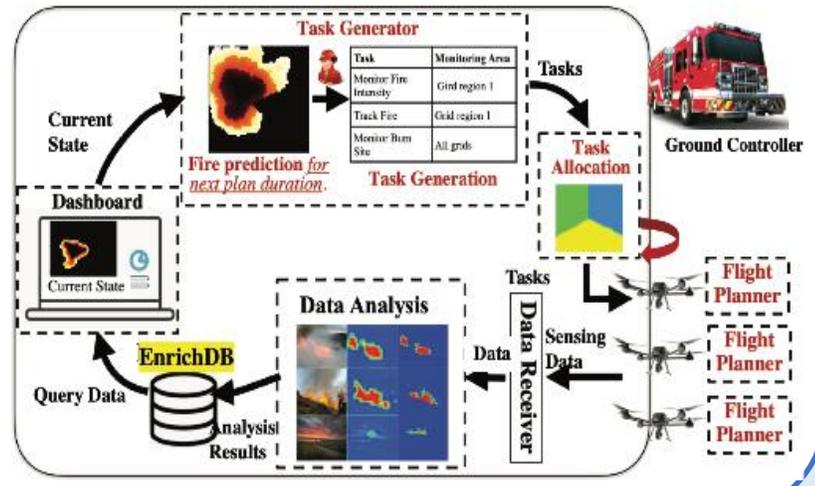
Missions in high-rise fires (HF) & prescribed fires (RF)

- 1) Fire detection (HF & RF)
- 2) Human detection (HF & RF)
- 3) Open window detection (HF)
- 4) Fire tracking (HF & RF)
- 5) Fire intensity monitoring (RF)

Challenges in high-rise fires (HF) & prescribed fires (RF)

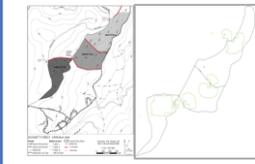
- 1) 3D space motion planning and coverage (HF)
- 2) Repetitive monitoring tasks (HF & RF)
- 3) Coverage vs data quality (HF & RF)
- 4) Heterogenous drones (RF)
- 5) Imperfect network condition (RF)

System Architecture



Task Generation in Prescribed Fire

Fire prediction: We use FARSITE to predict fire perimeter.



Rule-based Dynamic Task Generation: 1) Model the state of each grid → 2) Define DBF in ground controller → 3) Define the production rules.

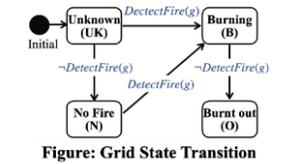


Table: DBF in the GC

Grid	State	EFA	Mission
(0, 0)	N	10	FT
(0, 1)	B	2	IM
(0, 2)	N	5	BS
(0, 3)	B	1	IM

Production Rules: (exemplary rules for detect abnormal fire)

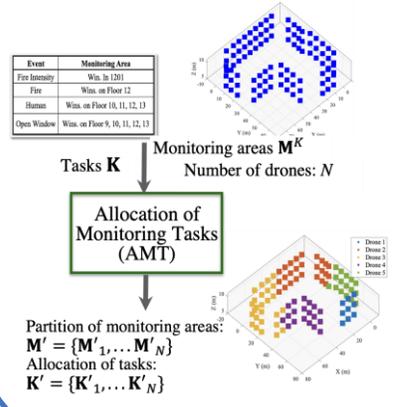
$$\text{Shift}(g, N, B, t) \wedge (EFA(g) \geq t + \delta_{AN}) \Rightarrow \text{UpdEFA}(t)$$

$$\text{UpdEFA}(t) \wedge \text{State}(g, N) \Rightarrow \text{Add}(g, FT, \max(t, EFA(g) - \delta_{ft}))$$

Two-Step Approach for Flight Planning

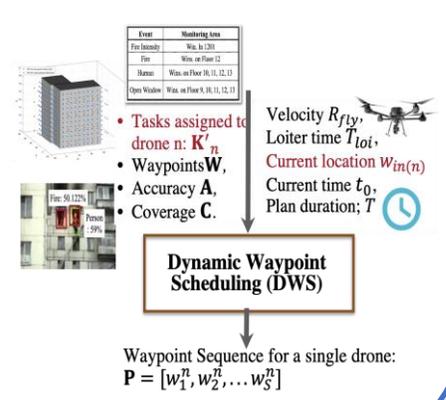
Q1: Allocation of Monitoring Tasks:

Allocate tasks by partitioning monitoring areas.



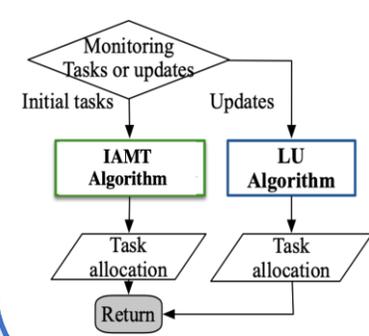
Q2: Dynamic Waypoint Scheduling:

Improve the information accuracy of tasks assigned to each drone.

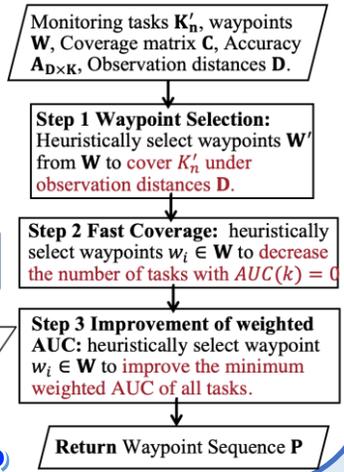


Algorithms

IAMT+ LU algorithm: allocate initial monitoring tasks and locally updating allocations to manage updates tasks or drones during execution.



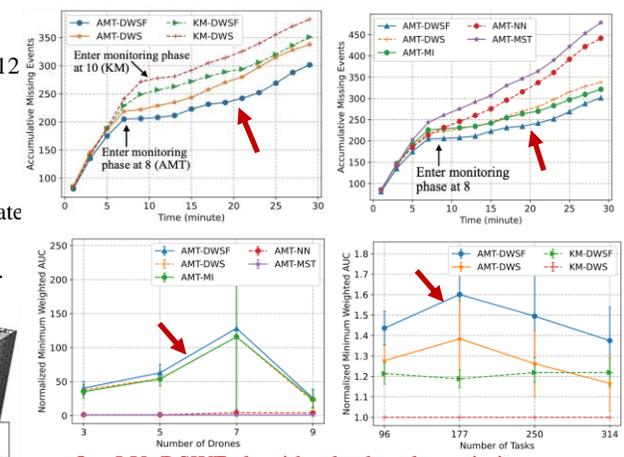
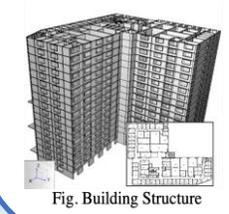
DWSF algorithm for single drone waypoint scheduling.



Results in High-rise Fire

Simulation Setup:

We use DBH in UCI with 12 floors and 384 windows. We simulate the fire spread in building structure and generate tasks based on firefighting manual.



Our LU+DWSF algorithm leads to less missing events and higher information accuracy.



CareDEX: Enabling Disaster Resilience in Aging Communities via a Secure Data Exchange

N Venkatasubramanian (PI), S Mehrotra (Co-PI), N Dutt (Co-PI), R Bhope, M Kenne, E Khatbi, M Bazargani, G Wang, N Lahjouji, UC Irvine School of Information and Computer Science
L Gibbs, J Rousseau, UC Irvine School of Medicine C Davison, Ball State University N Campbell, CU Boulder R Eguchi, Z Hu, ImageCat Inc. A Kimball, V Hutchison, Fire Protection Research Foundation



"Proactively co-produce information about the needs of SHFs, responders, and individuals for information preparedness during a disaster."

Goals and Overview

- Many older adults live in age-friendly communities and senior health facilities (SHFs) that promote independent living.
- Due to a variety of physical illnesses (need for life-sustaining equipment, limited mobility) and cognitive afflictions (e.g., dementia, Alzheimer's), older persons are frequently unable to shelter safely in place or escape on their own during a crisis.
- Empower first responders to improve response outcomes during disasters by having seamless access to information about the living facilities (e.g., floor plans, operational status, number of residents), the residents (e.g., health conditions such as the need for dialysis, oxygen, and personal objects to reduce anxiety) and regional impact of a disaster event along with support for evacuation decision-making.
- Evaluate the situational awareness information offered by the CareDEX technology for disaster response, as well as a qualitative analysis (by participants/users) of feedback on the CareDEX technology

La Via Bella Nursing Home, Dickinson, Texas Hurricane Harvey 2017



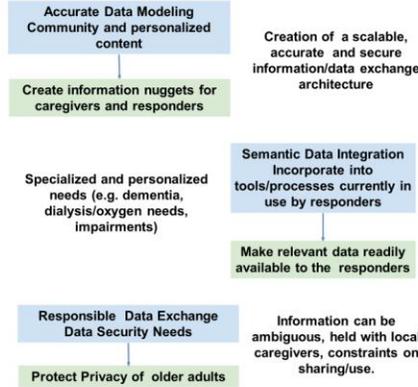
Hurricane Katrina - 75% of deaths were 60+ yrs.



Arkansas nursing home aides shielded residents from falling debris with their bodies



Research and Practice Questions



Future Work

- Create data models and databases to ingest and store data about facilities and individuals. Provide Cloud-based solutions for online access and enable real-time linkages with local, regional agencies.
- Create ontology for interoperable, pipelined data ingestion. Design protocols to query/access external systems on forecasted or ongoing disasters.
- Provide flexibility to accommodate a variety of SHFs to record emergency plans and track resources.
- Create different tabs for data or information access into the CareDEX platform for the different stakeholders.
- Allow regional data on disasters to be collected, archived and used in updating emergency and evacuation plans.
- Develop links with regional organizations to maintain data consistency.
- Design protocols that protect personal information on each resident must be embedded in the platform.
- Plan engagement with SHFs and rollout technology through drills and get feedback from stakeholders.



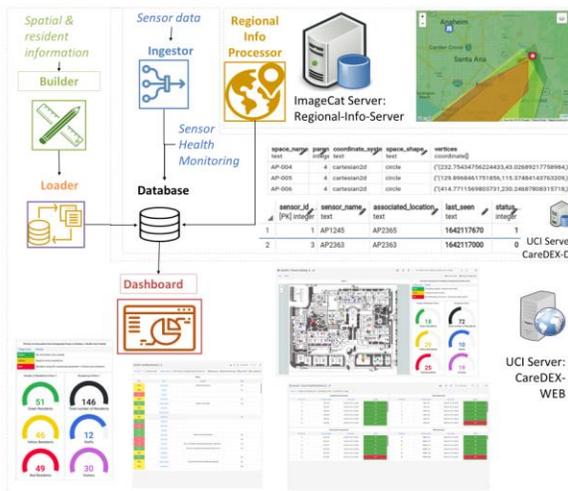
Front Porch facility where the CareDEX prototype will be deployed and tested.



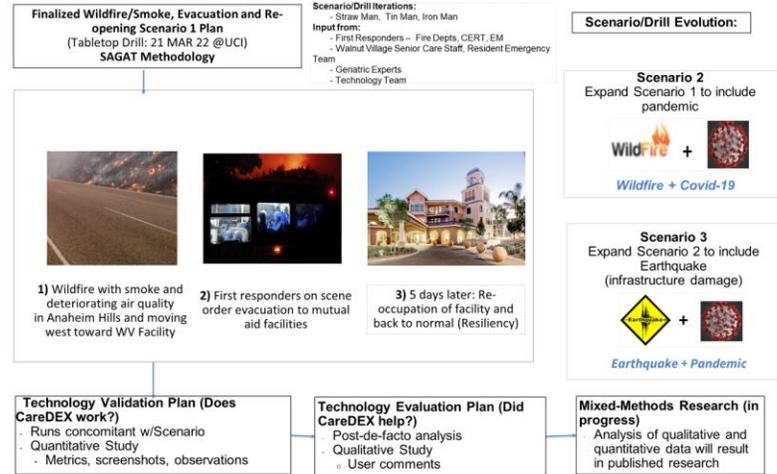
Validate CareDEX at the October 2022 Great CA Annual ShakeOut

System Design

Component	Function
Builder	Provides a tool to create representation of spatial data and resident information
Loader	Creates and populate space, resident and sensor info table with info that Builder generates
Ingestor	Receives heterogeneous sensor readings and ingest to database
Regional Information Processor	Provides regional impact of a disaster event and support evacuation decision-making
Dashboard	Provides on-demand access of critical information need for responders in various scenarios



Technology Testing, Evaluation and Validation



MIT-PITT-RW Approach to Racing

Andrew Keats, BS Student, Computer Engineering

Background:

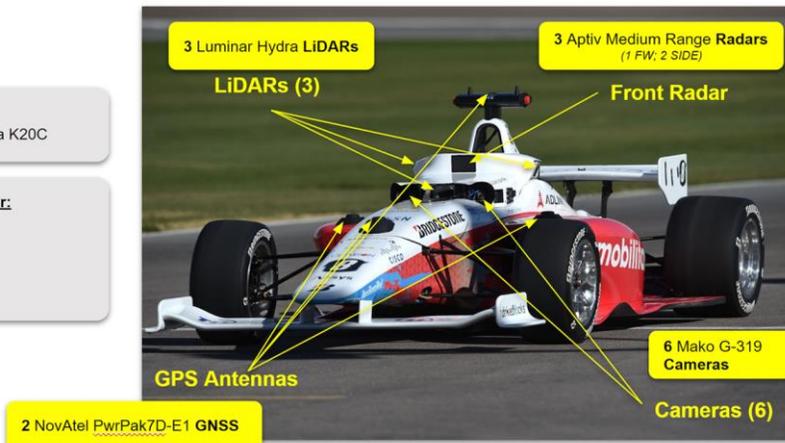
MIT-PITT-RW is a team that competes in the Indy Autonomous Challenge (IAC). The team comprises of students from the Massachusetts Institute of Technology, University of Pittsburgh, Rochester Institute of Technology and the University of Waterloo. The platform used for the competition is a Dallara AV-21 race car. Work has been focused on modeling and controls for use at speeds above 140MPH.

Engine:

4 Piston Racing-built Honda K20C

Adlink Onboard Computer:

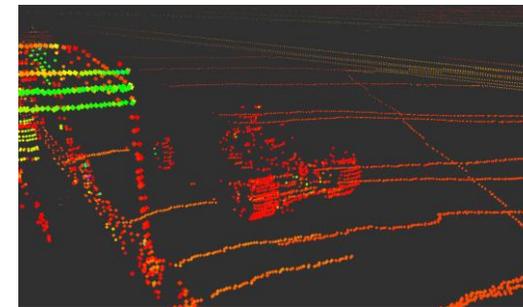
64 GB RAM
Intel® Xeon® 9th Gen
NVIDIA Quadro RTX 8000



Work is also currently being done to perception and track to locate other vehicles on the track.

Methodology/Algorithms:

The current method for perception utilizes LiDAR, radar and cameras to detect the other vehicles. With respect to LiDAR a clustering approach is being used to detect the other cars. The figure below shows a LiDAR scan from the Luminar LiDAR of another AV-21. The cameras on the car are used to detect other vehicles and utilize a custom model using data collected during testing.



Current results show strong detection at short distances with cameras being reliable at further distances.

Major Results:

137 MPH lap average at Las Vegas Motor Speedway. Live car detections on track using camera and LiDAR

Acknowledgment:

Team sponsors Oracle and Mobilias. Faculty advisor Amlan Ganguly.

Student Posters

Digital Twins and

Infrastructure Planning

Motivation

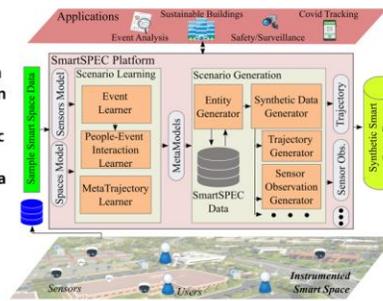
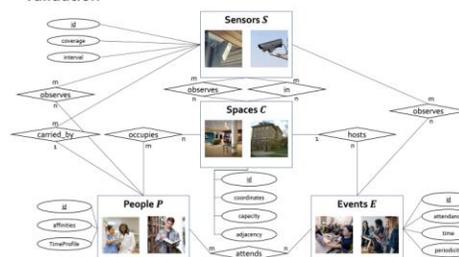
- Realistic data is necessary to test and validate smart space approaches with respect to the robustness of algorithms, failure testing, scalability testing, and operation in extreme scenarios
- Challenges in obtaining real data include the deployment of sensors, the recruitment of participants, and the preservation of participant privacy
- Generating realistic synthetic data using offline modeling and simulators is equally challenging: semantics of smart space components must be properly modeled and faithful to reality, which can be difficult due to the variability/dynamics of activities of people and their activities



System Overview

SmartSPEC Overview and Architecture

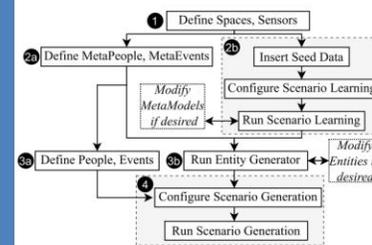
- SmartSPEC starts with a smart space that is instrumented with some limited number of sensors, which produce observations in a smart space seed dataset
- The seed dataset is used to learn and extract different semantic patterns of people and their activities (Scenario Learning)
- Extracted patterns are used to generate new synthetic data in a semantic manner (Scenario Generation)
- Applications can use the new synthetic dataset for testing and validation



Semantic Model

- A smart space is characterized using spaces (the underlying geographical layout), people (the inhabitants of spaces), events (the activities of people), and sensors (devices observing phenomena in the smart space)
- These concepts are highly interrelated with each other

Modes of Operation



- Three modes of operation which vary in the level of user involvement/automation are provided in SmartSPEC
- In each step, models and data files used by SmartSPEC are open to be modified directly by the user for customization to a specific scenario

Scenario Learning

Extracting semantic patterns from seed data

Learning Events through Occupancy

- Events are learned through occupancy, an intermediate concept to estimate when one event ends, and another starts
- Define occupancy by counting the number of unique people in the dataset that were in a space over a time period
- Use the *Change Point Detection* algorithm to learn *breakpoints* between events: the times for which there are large changes in occupancy
- Apply the *Agglomerative Clustering* ML clustering technique to group similar types of events, based on set of attendees, time of event, and space



Breakpoints occur when there are large changes in occupancy

Occupancy stays roughly consistent during an event

Learning People-Event Interactions

- Characterize people based on their set of attended events
- Apply the *Agglomerative Clustering* ML clustering technique to group similar profiles of people, based on set of attended events

Scenario Generation

Creating new synthetic datasets with semantics

Entity Generator: Generating Events

- Select the type of event to create based on cluster group size
- Determine *time profile* of event: When will the event occur?
- Determine *location* of event: Where does the event occur?
- Determine *attendance*: how many of each profile of person are allowed to attend

Entity Generator: Generating People

- Select the profile of person to create based on cluster group size
- Determine time profile of person: when do they enter/exit the simulated space?
- Assign *event affinity*: what is the person's likelihood of attending a certain type of event

Synthetic Data Generator

- Each simulated person repeatedly selects events to attend for the duration of time they are in the simulated smart space
- Event selection and attendance must not violate semantic and physical constraints on smart space entities
- Results are recorded in a log file



Assessing Realism

Quantifying the realism of synthetically generated datasets

Assessing Realism: Space Occupancy

- Occupancy*: number of unique people in a space over a time period
- Extract occupancy time-series from real, simulated datasets
- Find mean-squared error between occupancy counts



Assessing Realism: People's Trajectory

- Trajectory: sequence of spaces visited by a person over a time period
- Extract sets of trajectories per day from real, simulated datasets
- Use *control variables* to partition trajectories into comparable bins
- Match trajectories in corresponding bins such that the total distance between pairs of trajectories are minimized

Interpreting Realism

- Obtain a distribution of distance difference between partitions of real data to quantify variance in real datasets
- Obtain a distribution of distance difference between partitions of real data and synthetic data to quantify variance in real to simulated datasets
- Compare distributions of real vs real against real vs simulated datasets
- Interpret comparison between distributions based on which pairs of distributions are compared

Evaluation of 60 GHz Wireless Connectivity for an Automated Warehouse

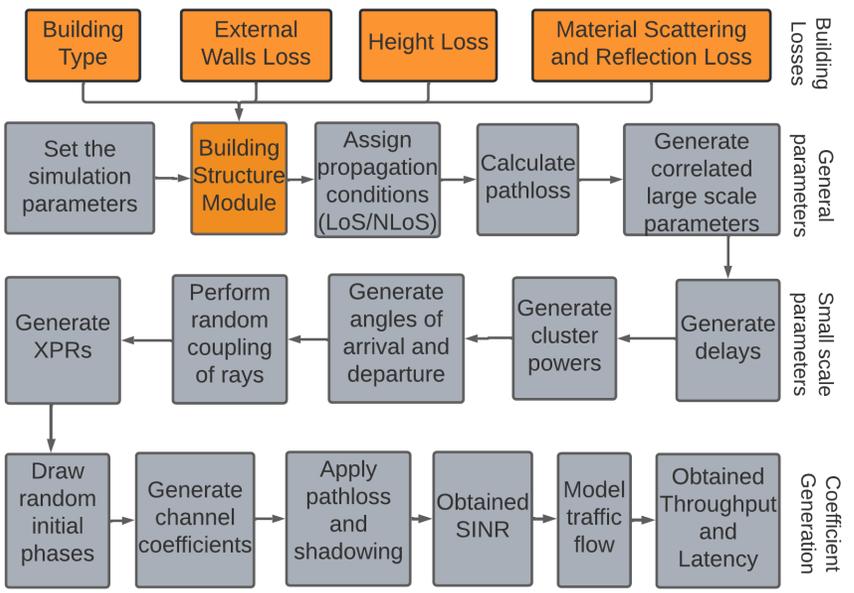
Rahul Singh Gulia, PhD Student, Rochester Institute of Technology

Abstract

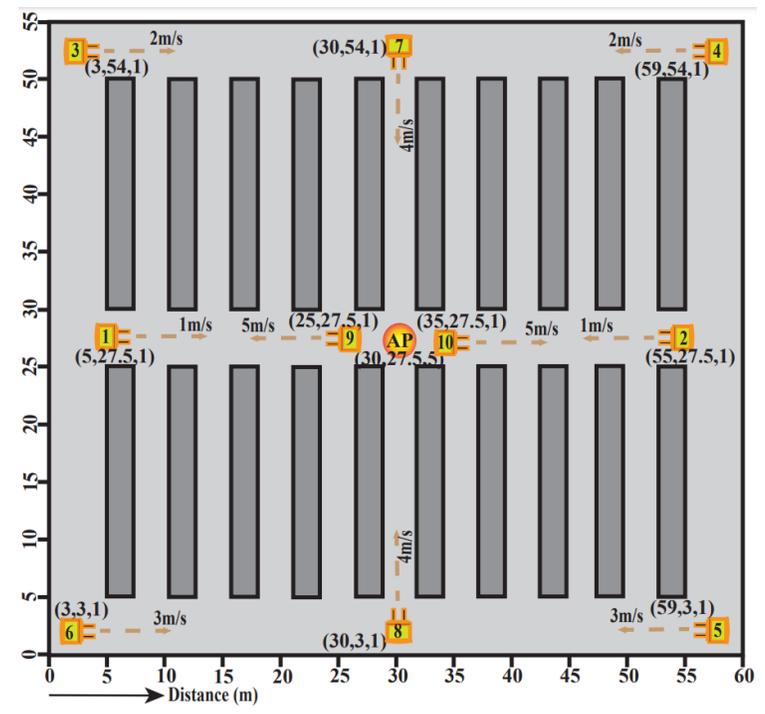
- Industry 4.0 autonomous material handling agents demand high-speed indoor network connectivity in warehouses.
- In this paper, we evaluate the performance of a 60 GHz wireless network inside a smart.
- The performance of the network depends on Line-of-sight (LOS) and Non- Line-of-sight (nLOS) path signals, reflective environment, and the number of autonomous material handling agents (AMHAs) in the warehouse.
- The SINR distribution, throughput and latency of the network was studied to understand the 60 GHz network connectivity in the smart warehouse .

Approach

- NS-3 was modified to incorporate suitable 60 GHz propagation losses in an indoor environment.

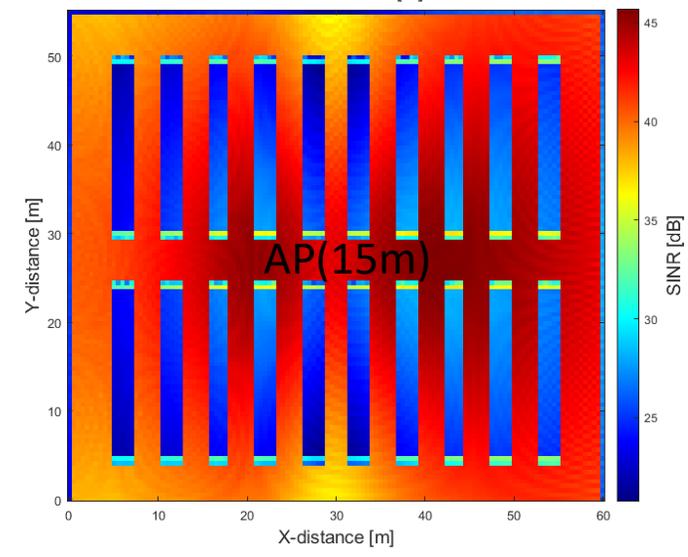
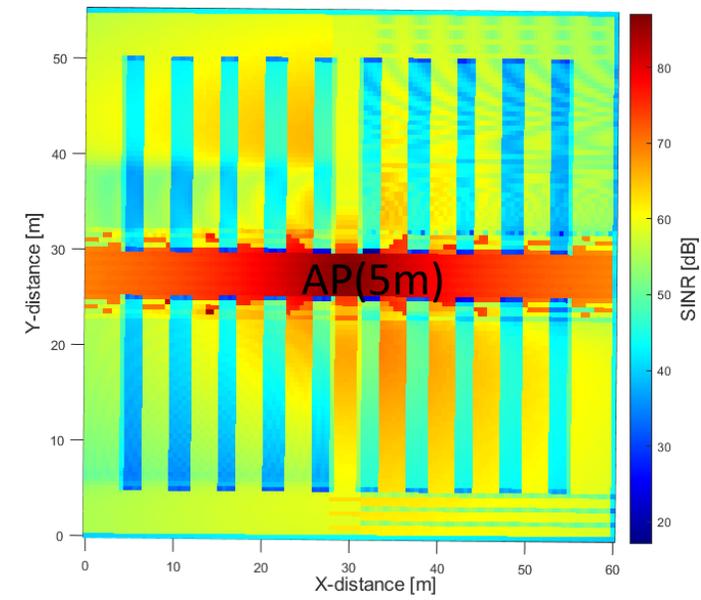


Warehouse Model



Results

- We noticed better signal reception in the case of shorter AP heights (5m) and an abrupt SINR transition from LOS to nLOS path due to the change from LOS dominated high SINR values to nLOS dominated side aisles.
- A smooth transition was observed from LOS aisles to the nLOS aisles for AP at 15m with overall lower SINR due to increase in the AP-AMHA distance and decrease in the dominance of LOS signals.



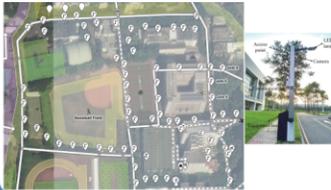
Sponsors



Creating an Urban Planning Tool for IoT Infrastructure Instrumentation in Smart Communities

Motivation

- IoT is a promising technology for implementing applications in smart communities, such as noise monitoring, air quality monitoring, auto-dimming streetlights, etc.
- Different aspects need to be determined to implement multiple applications: information (data analytics), infrastructure (sensing, networking, computing devices), and deployment of devices
- Design of such application is usually siloed within each community, which results in inefficient deployment of devices
- Urban planners need a tool to enhance smart communities with IoT by generating a comprehensive and cost-effective plan



Goals

- Implement an urban planning tool that generates a plan to implement multiple applications in communities

Reusability of sensors

- One sensor for different applications



Reusability of networking devices

- One networking device transmits data between multiple devices (sensors, computational devices)



Reusability of computational devices and analytic results

- One computational device executes as many data analytics as possible



- The plan includes ideal data/software, physical devices, and deployment locations
- Trade offs the efficiency (execution time) and optimality of the plan under budget constraints (deployment, operational)
- Provide flexible toolkits for urban planners to explore different hypotheses other than the output plan

Retrofit from existing infrastructure

Reusability of the existing devices in communities

- Reduction of the deployment cost



Challenges

C1: What - devices to use

- Sensing (different accuracy & range), networking (different range), and computing

C2: Where - to put them

- Sensing device – sensing coverage
- Networking devices – communication coverage

C3: How - to use/multiplex for different needs

- Trade-off between accuracy and deployment efficiency
- Expensive devices usually have a higher accuracy
- More cheap devices can have a higher coverage

C4: How - to exploit pre-deployed infrastructure

- Reuse existing (already deployed) devices to reduce the cost

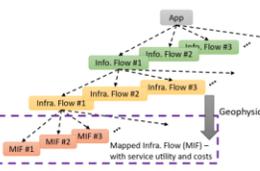
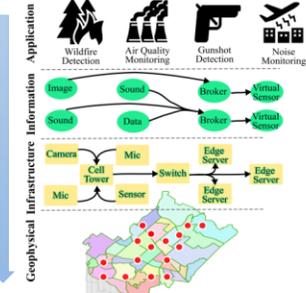


Approach

Cross-Layer IoT Planning – Divide the Problem into Several Layers

- Layers include:
- Application – required by a location/area in communities
 - Information – data/software to implement applications
 - Infrastructure – physical devices that capture, transmit, or analyze data
 - Geophysical – locations for installing devices

Objective: maximize the overall service utility (sensing accuracy and probability) under budget constraints



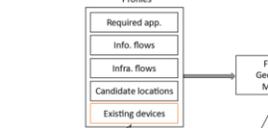
- Data Structure**
- Information flow for each application – execution order of software components
 - Infrastructure flow for each information flow – data flow via physical devices
 - Mapped infrastructure flow (MIF) for each infrastructure flow – captures geophysical mapping and execution of software for each device
 - Planning graph – composed of several MIFs that demonstrate the final deployment across layers

Algorithms

Two-Phase Computation, each Phase Provides Several Algorithms

Geophysical mapping selection – generates a set of MIFs for each infrastructure flow required by each application of a location

- Proposed Algorithms**
- Enumeration – exhaustive search for all possible mappings
 - Selection – prunes out less promising mappings (utilities, communication coverage) at runtime of enumeration
 - Retrofit – considers existing devices (work with enumeration and selection)



Clean-Slate

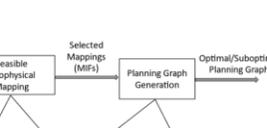
- Design from scratch, e.g., a whole new communities

Retrofit

- Exploit the existing devices, e.g., build on the existing communities

Planning Graph generation – selects and merges MIFs in order to maximize the service utility under budget constraints

- Proposed Algorithms**
- Dynamic programming – recursively includes one MIF
 - Maximum reusability – iteratively includes one MIF with the highest reusability (investment efficiency & communication coverage)
 - Maximum reusability plus – executes DP then MR



Generate a set of MIFs. Determine geophysical mapping for each infra. flow for each required application by a service site of a community

Build a planning graph. Select several MIFs such that the total service utility is maximized under budget constraints

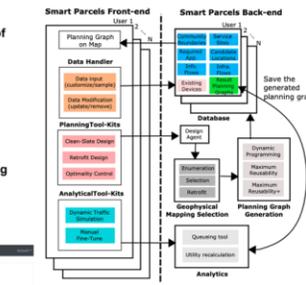
- Infrastructure mapped to the same candidate location -> Reuse the infrastructure

Prototype

Web-Based User Portal with Backend Storage and Computation Services

- Frontend User Interfaces**
- Data hander – input and modification of data
 - Planning Toolkits – selects different methods for planning
 - Analytical Toolkits – what-if analysis (insert hypothesis instrumentation)

- Backend Services**
- Database – stores data and results
 - Design agent – executes corresponding core algorithms according to users' demand
 - Analytics – executes corresponding analytics based on users' input



Background

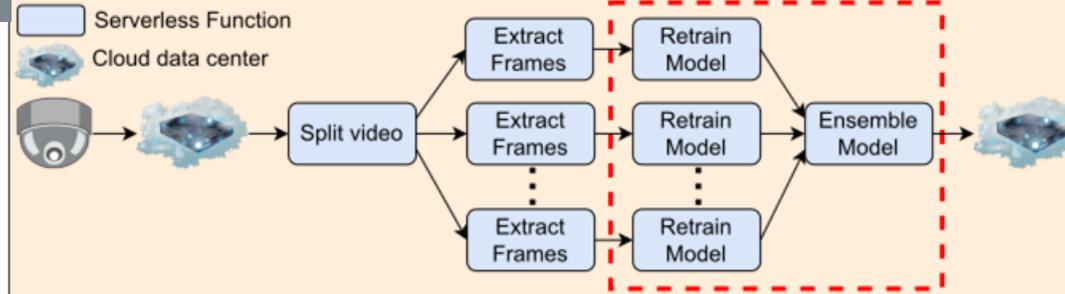
- **Adaptivity is critical for smart spaces.**
- Deep learning (DL) training **costs ~\$1 per 1K parameters.**
- Serverless computing has become the **most cost efficient** cloud computing services.

Methodology

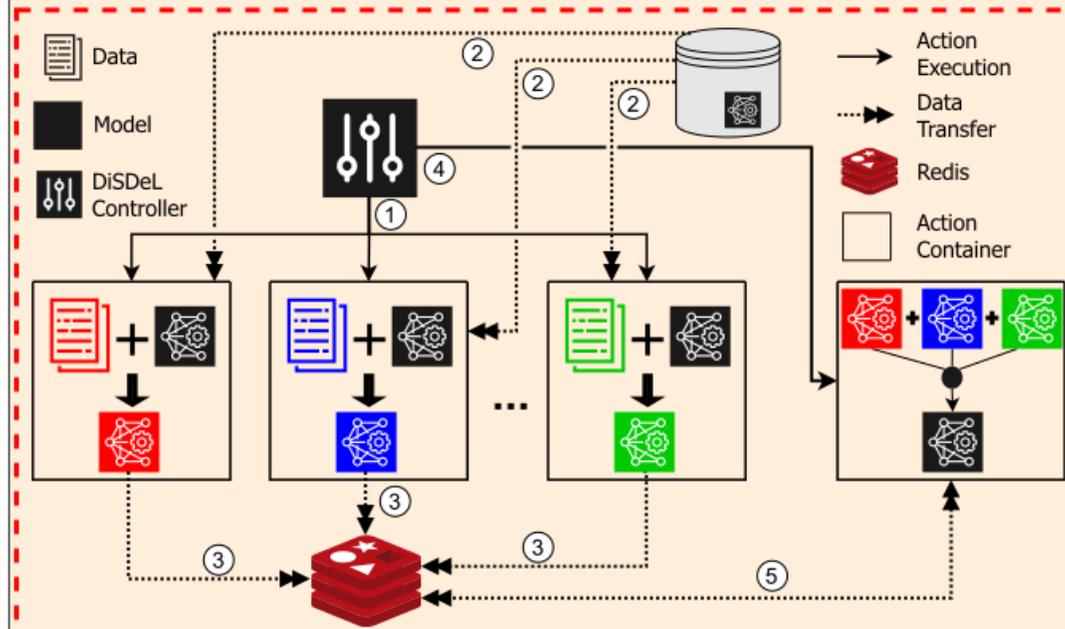
- **Estimate memory and duration** using runtime image, data and DL model sizes.
- **Concurrently train** the DL model on images from assigned video.
- **Store trained DL model parameters** on an in-memory key-value store, i.e., Redis.
- Execute **weighted aggregation of model parameters** to yield single ensemble model.
- Store **ensemble model** to database, i.e., AWS S3 bucket, for on-line inference.

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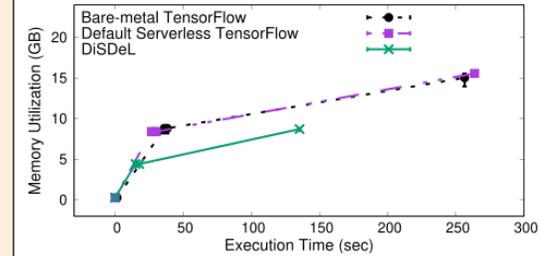


"Existing serverless platforms DO NOT support memory and time requirements of DL training workloads"

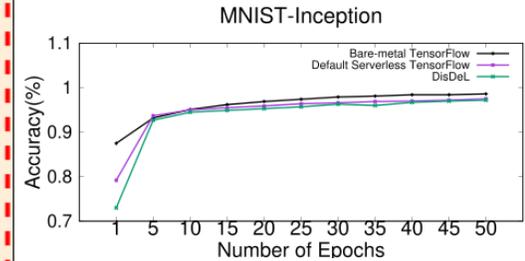


Performance Results

- DL training jobs execute as serverless functions with a **0% failure rate.**
- Thousands of concurrent serverless functions **reduce the job duration.**



Training accuracy is as high as a bare-metal environment.



Future Work

- Explore communication strategies to remove overheads of central storage.
- Accelerate DL training jobs with specialized hardware, i.e., GPUs.

Acknowledgements

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Service Caching at the Edge

Carlos Barrios (RIT), Mohan Kumar (RIT)

1 Abstract

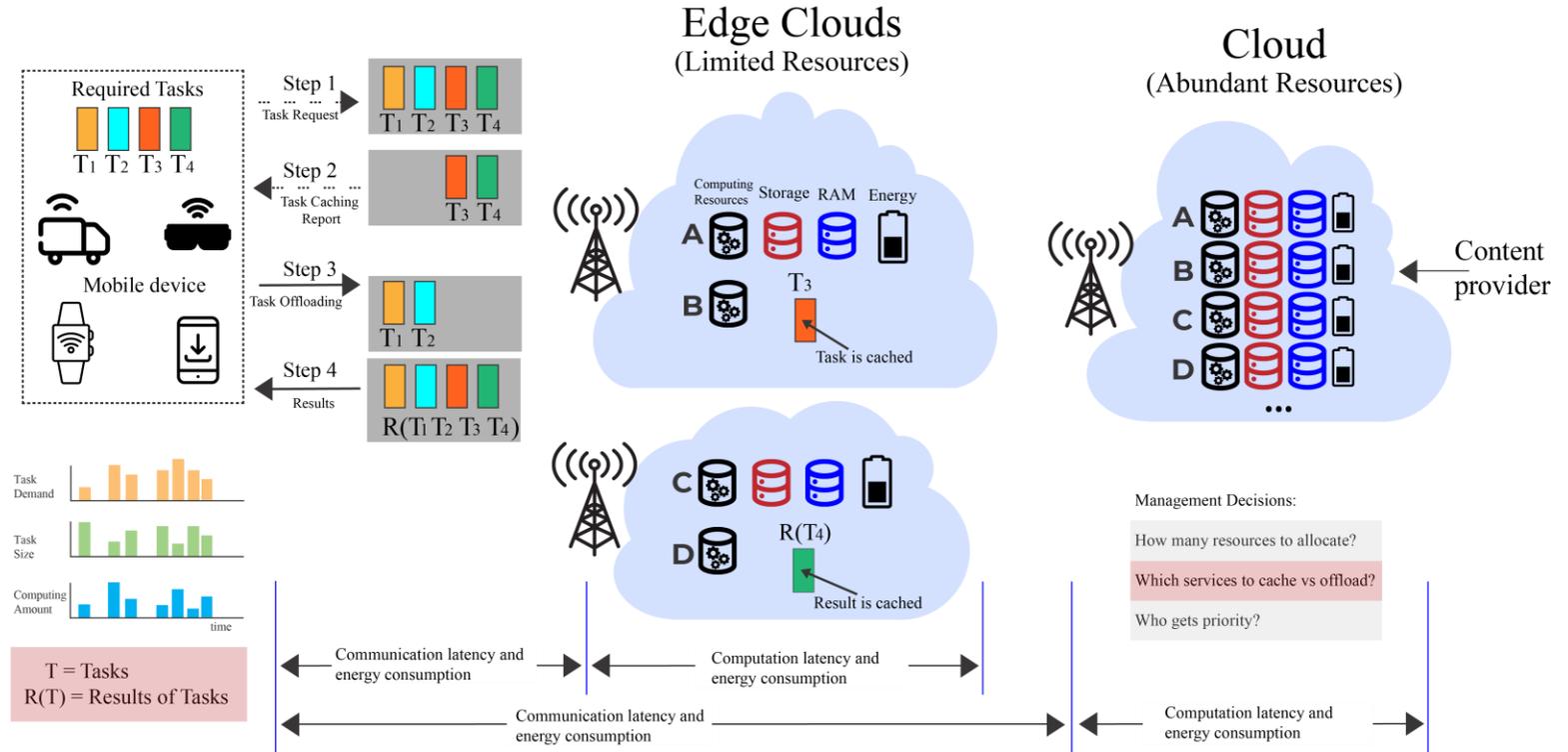
- Increasing number of connected devices require **novel techniques** to keep internet **traffic congestion low**.
- Users expect high Quality of Experience (QoE) with smartphones, wearables, smart-home devices, transportation and Industry 4.0 supporting devices.
- Service caching** and **computation reuse** can **minimize latency** when requesting services.
- Challenges** include interoperability due to device and data heterogeneity, limited storage, computation, RAM, bandwidth, and energy on edge servers, user mobility (spatial and temporal dynamics), scalability for deployment, unknown task demand and variable size, privacy and security.

2 Background

- Service **caching** involves **storing service code (or VMs)** in memory at the edge, minimizing latency and energy use when transferring programs.
- Computation **reuse** involves **storing results of service computation for given inputs**, so results can be used in similar future requests.
- Servers can cache or offload based on **popularity or context**.
- Recent efforts move away from data-centric network architecture by converting data into services.

3 Approach

- Goals:** optimize **cache hit rate**, minimize **task latency**, minimize **energy consumption** (for transmission and computation).
- Spatial and temporal considerations** of service caching (neighboring device vs local edge vs cloud, each offering different computation and storage capabilities, consider movement and demand prediction).
- Relationship between data** items (likelihood of access to related data) - context is used to make these relationships via **cognitive engines**. **Semantic task names** are used to find matches in a heterogeneous environment. QoE improved based on **priority** (medical vs gaming vs email).
- Optimization is usually NP-Hard. **Heuristics** such as Lyapunov optimization are implemented, many involve integer linear programming (ILP).
- SDN** can be leveraged to implement communication & management for these solutions within protocols with less overhead.
- Approaches should consider **privacy and security**, since user data can be sensitive.



4 Milestones

- Development of new approaches and heuristics** for service caching in application scenarios related to industry.
- Evaluation** of initial approaches (cache hit rates, task latency, and energy consumption against state of the art benchmarks).
- Refine initial approaches targeting **interoperability**.

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