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

UCI

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.
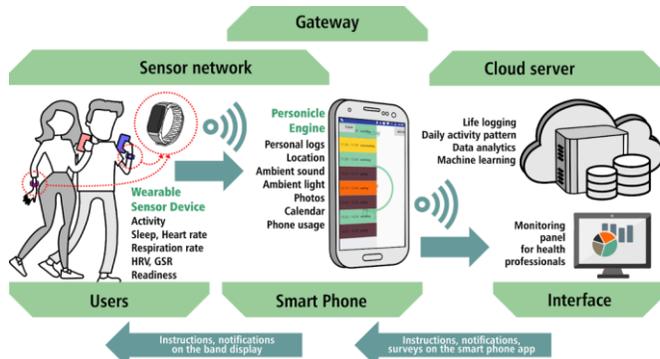
Methodology and Algorithm: Considering the fully objective and portable affect assessment in this study, we only used commercial monitoring devices (i.e., Oura ring, Samsung Watch, and Android Phones) and obtained three data modalities using the mentioned devices. We present below an overview of collectable 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.
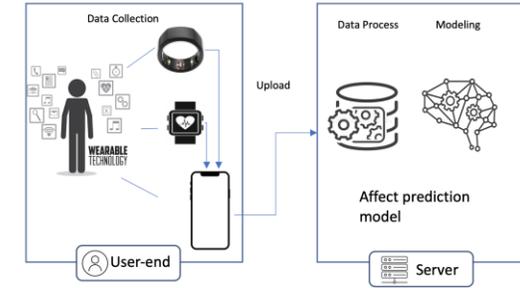
Finally, using these three modalities, we collected 52 features and trained different ML models to predict next day affect. Random forests generally showed a better performance.


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.
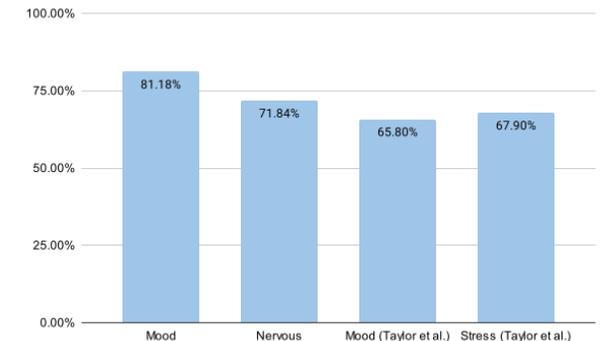
References:
[1] Sara Taylor, Natasha Jaques, Ehimwenma Nosakhare, Akane Sano, and Rosalind Picard. Personalized multitask learning for predicting tomorrow's mood, stress, and health. IEEE Transactions on Affective Computing, 11(2):200–213, 2017.
[2] Dimitris Spathis, Sandra Servia-Rodriguez, Katayoun 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.
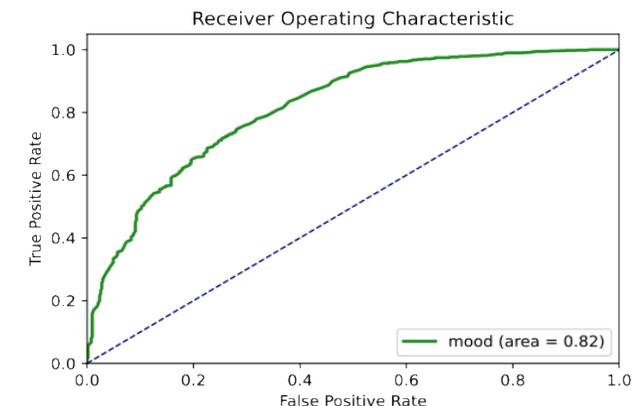
A Case for Digital Therapy: Satisfaction, Interest, and Use of Virtual Embodied Agent RITch®CBT at a hospital and shelter

RIT

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

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; SAMHSA, 2021)

- Digital mental health interventions are viable treatment options for PTSD, anxiety, etc. (Aboujaoude et all., 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
▪Patients with substance use and conflict histories	▪Exposure to VR therapy platform	▪Satisfaction ▪Interest ▪Behaviors ▪Use of VR therapist

Methodology/Algorithms

Topics
Introduction
Identifying Triggers
Awareness of Anger
Anger Management
Coping with Criticism
Communication Skills Training (non-verbal)
Communication Skills Training (verbal)
Communication Skills Training (family/children)

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

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

Thought Avatar was Genuine/Relatable	10% / 100%
Willing to Use with Therapist	80% / 90%
Enjoyed Customizing Avatar	60% / 50%
Enjoyed Interacting with Avatar	100% / 90%
Easy to Use	100% / 90%

Mean Participant Weekly Ratings on a Scale of 1-10

Cravings, Anger, Conflict, Stress/An..., Depression, COVID..., Complete..., Found...
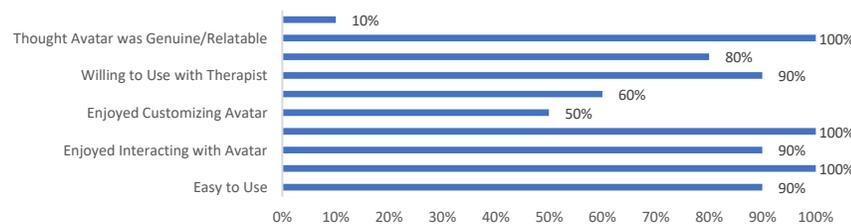
■ Week 1 ■ Week 2

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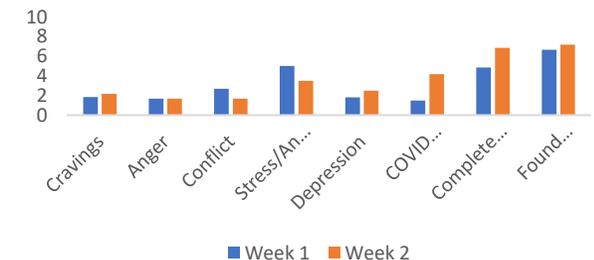
National Institute on Drug Abuse. (2017). *Trends & Statistics* [Government]. National Institute of Mental Health. https://www.drugabuse.gov/related-topics/trends-statistics

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.

Personicle

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

UCI

8% growth

Annually

$600 billion global market size in

2024

Healthcare Market Size

?

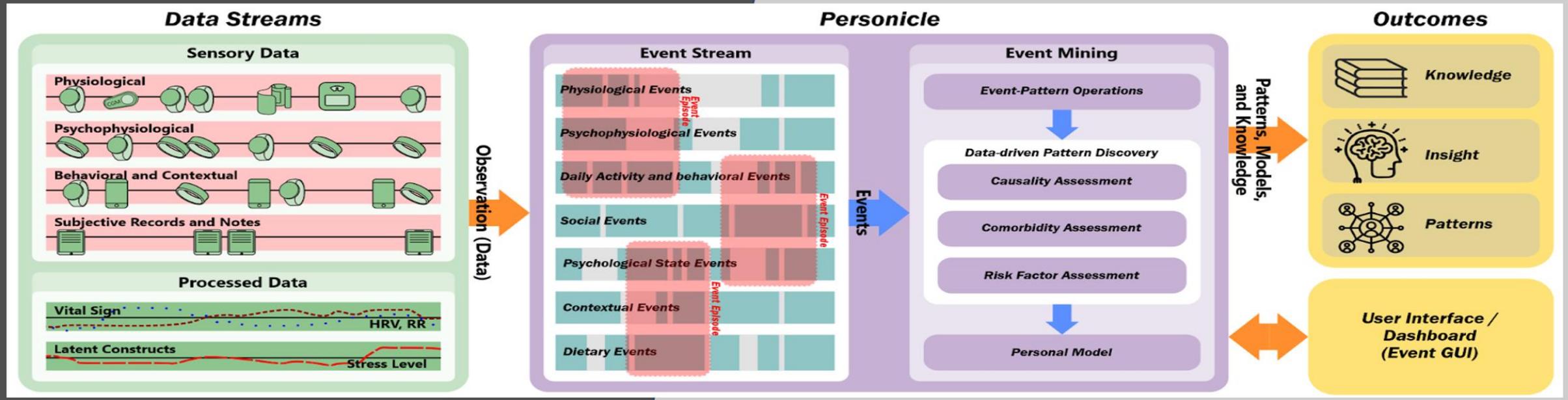Lack of necessary agility to respond rapidly to changing business and clinical drivers
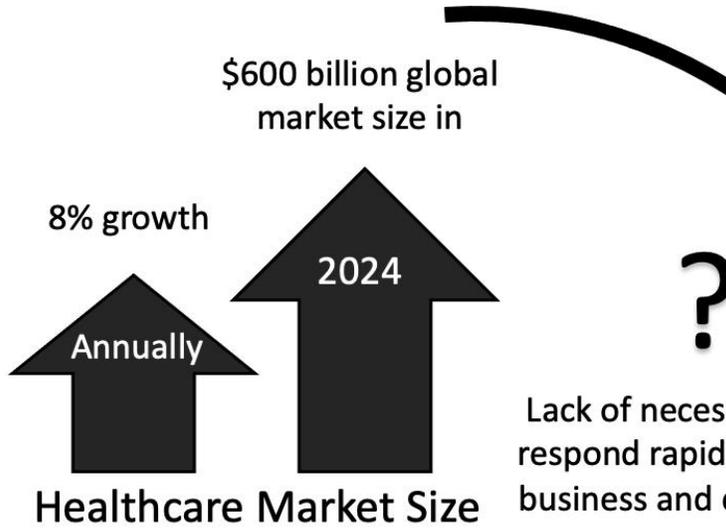
✓ The digital health platform (DHP) is an architectural approach
✓ Unlocking the value of healthcare data is a top priority

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

Data Streams | Personicle | Outcomes

Data Streams
- Sensory Data
  - Physiological
  - Psychophysiological
  - Behavioral and Contextual
  - Subjective Records and Notes
- Processed Data
  - Vital Sign — HRV, RR
  - Latent Constructs — Stress Level

Observation (Data)

Event Stream
- Physiological Events
- Psychophysiological Events
- Daily Activity and behavioral Events
- Social Events
- Psychological State Events
- Contextual Events
- Dietary Events

Event Episode

Events

Event Mining
- Event-Pattern Operations
- Data-driven Pattern Discovery
  - Causality Assessment
  - Comorbidity Assessment
  - Risk Factor Assessment
- Personal Model

Patterns, Models, and Knowledge

Outcomes
- Knowledge
- Insight
- Patterns
- User Interface / Dashboard (Event GUI)

Inconspicuous Daily Monitoring to Reduce Hospitalizations in Heart Failure Patients

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

RIT

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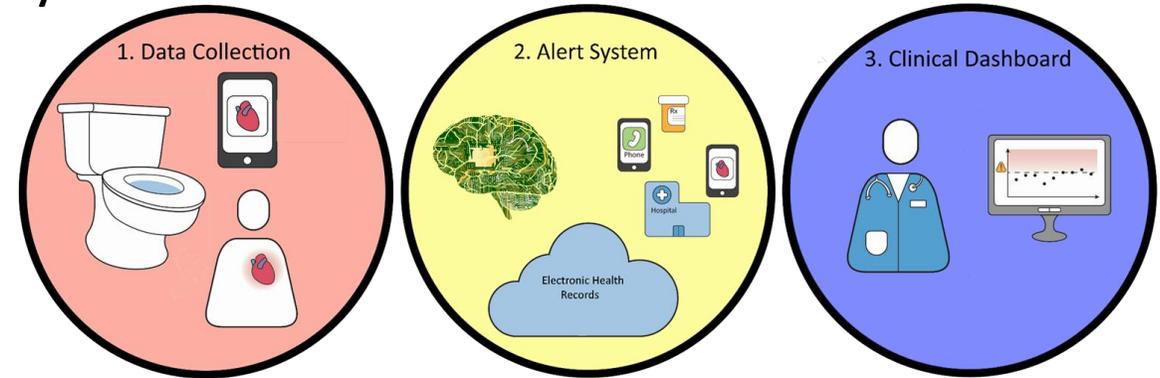
Hypothesis: Hospitalization rates and duration lengths can be reduced through the use of inconspicuous home monitoring devices and early interventions.
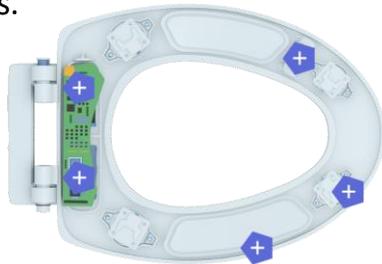
Two-Phase Study Timeline:

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.
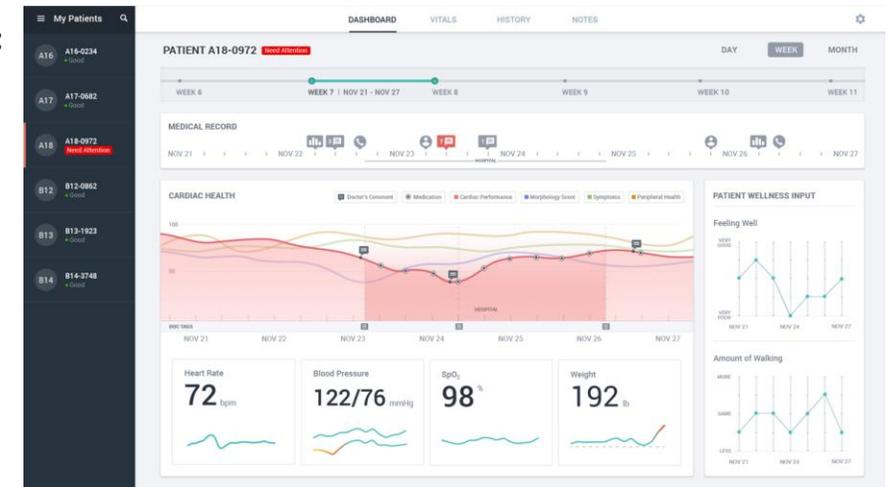
ZotCare: A Health Cybernetics Service Provider

By **Sina Labbaf** Advisors: Nikil Dutt & Amir Rahmani

UCI

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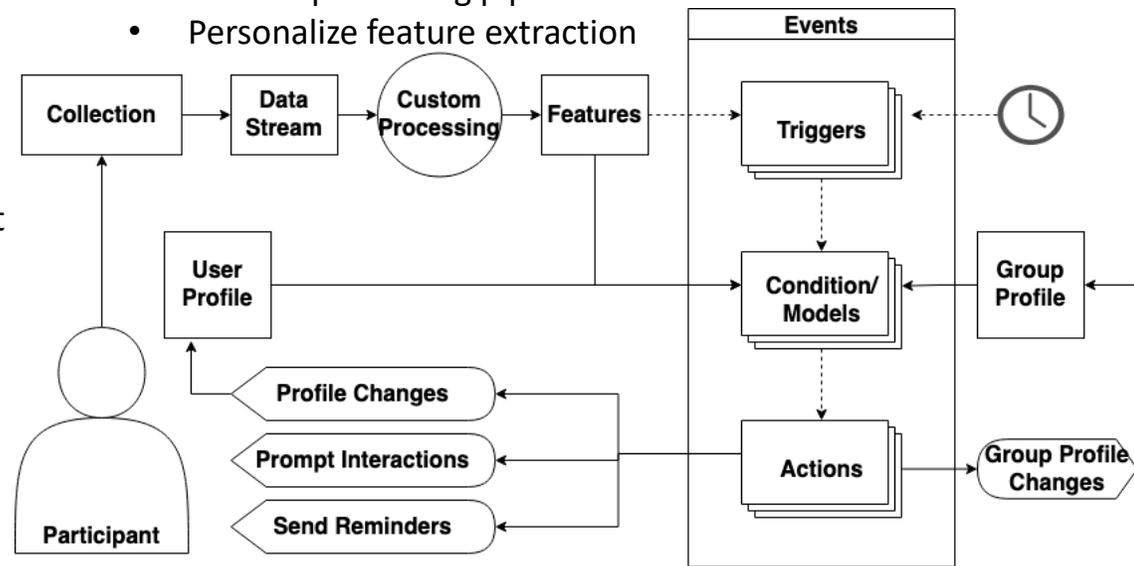
Data Flow and Control
- Using event service to create control flow
- Integrate your own logic, intervention, triage, etc.
- Using personal and progressive models to implement learning methods
  - Active learning
  - Reinforcement learning
  - Memory control system

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.

System Architecture

O/P: Fire, 98%
Exit: Exit-1
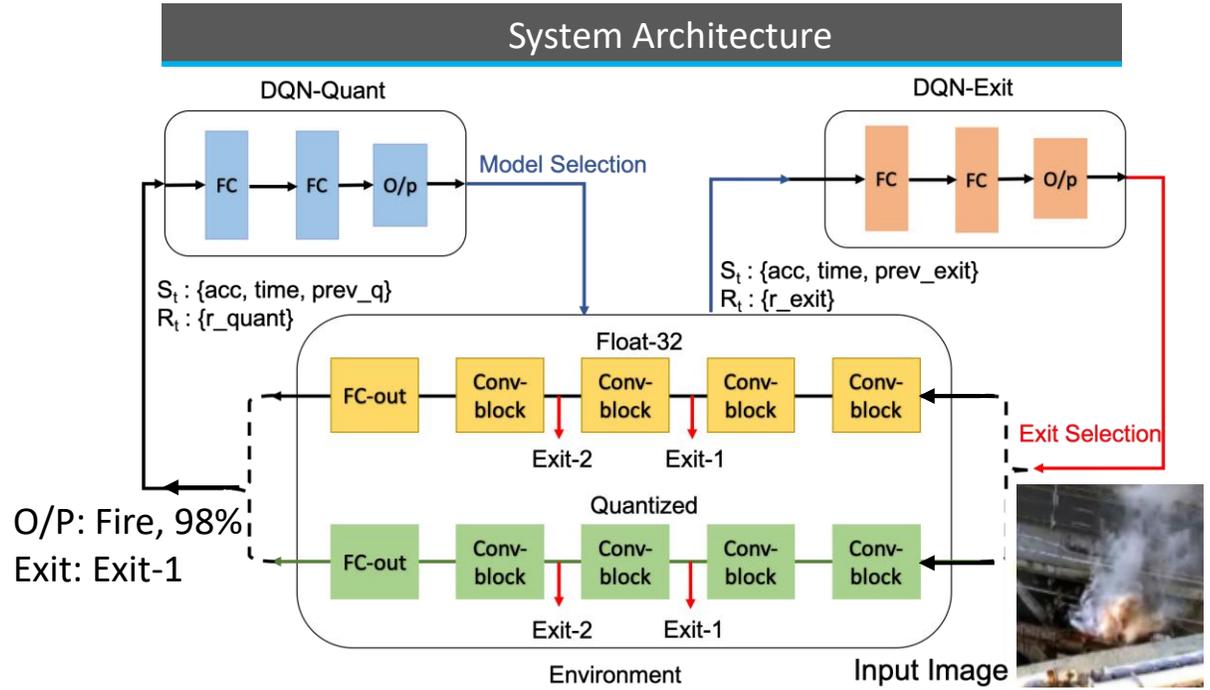
PERFORMANCE COMPARISON WITH STATE-OF-THE-ART

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),*

Sponsors: BRYX Emergency Response, Simplified.®   NSF

Drone Assisted Monitoring and Inspection in Challenged Settings

UCI

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
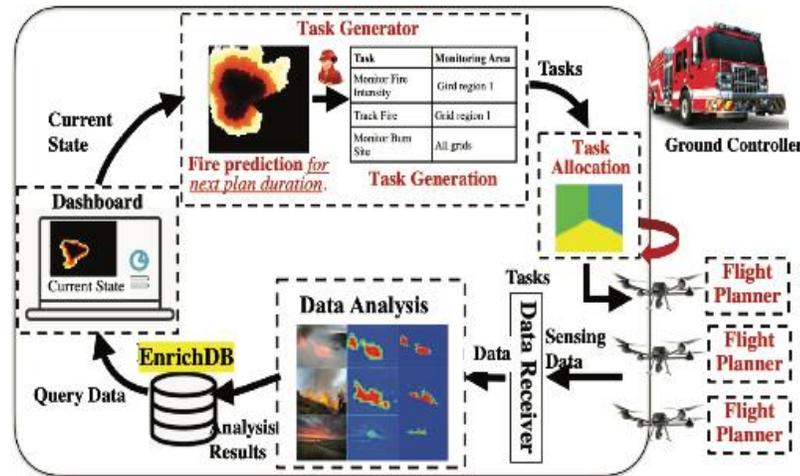
Task Generation in Prescribed Fire

Fire prediction: We use FARSITE to predict fire perimeter.
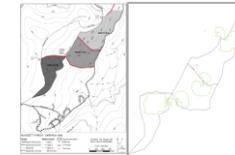
Rule-based Dynamic Task Generation: 1) Model the state of each grid → 2) Define DBF in ground controller → 3) Define the production rules.
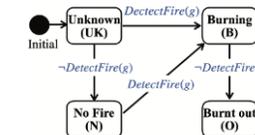
Figure: Grid State Transition

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)

$$Shift(g, \mathbf{N}, \mathbf{B}, t) \wedge (EFA(g) \geq t + \delta_{AN}) \Rightarrow UpdEFA(t)$$
$$UpdEFA(t) \wedge State(g, \mathbf{N}) \Rightarrow Add(g, FT, \max(t, EFA(g) - \delta_{ft}))$$
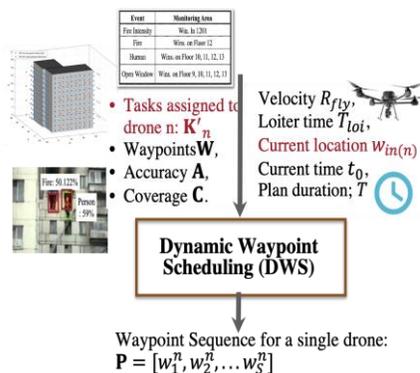
Two-Step Approach for Flight Planning

Q1: Allocation of Monitoring Tasks:

Allocate tasks by partitioning monitoring areas.

Monitoring areas $\mathbf{M}^K$
Number of drones: N

Tasks $\mathbf{K}$

Allocation of Monitoring Tasks (AMT)

Partition of monitoring areas:
$\mathbf{M}' = \{\mathbf{M}'_1, \ldots \mathbf{M}'_N\}$
Allocation of tasks:
$\mathbf{K}' = \{\mathbf{K}'_1, \ldots \mathbf{K}'_N\}$
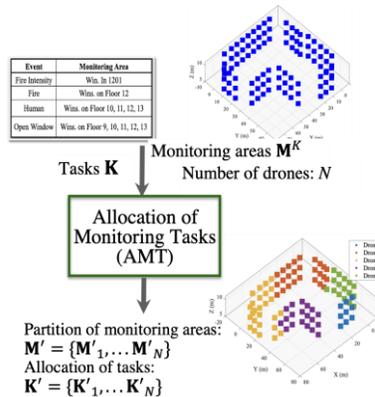
Q2: Dynamic Waypoint Scheduling:

Improve the information accuracy of tasks assigned to each drone.

- Tasks assigned to drone n: $\mathbf{K}'_n$
- Waypoints $\mathbf{W}$,
- Accuracy $\mathbf{A}$,
- Coverage $\mathbf{C}$.

Velocity R_{fly},
Loiter time T_{loi},
Current location $w_{in(n)}$
Current time t_0,
Plan duration; T

Dynamic Waypoint Scheduling (DWS)

Waypoint Sequence for a single drone:
$\mathbf{P} = [w_1^n, w_2^n, \ldots w_S^n]$

Algorithms

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

Monitoring Tasks or updates

Initial tasks → IAMT Algorithm → Task allocation

Updates → LU Algorithm → Task allocation

Return
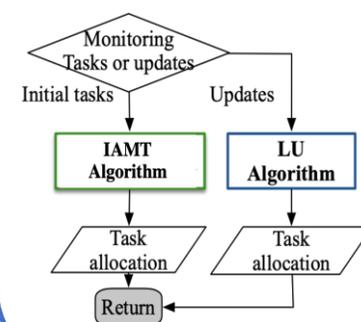
DWSF algorithm for single drone waypoint scheduling.

Monitoring tasks $\mathbf{K}'_n$, waypoints $\mathbf{W}$, Coverage matrix $\mathbf{C}$, Accuracy $\mathbf{A}_{\mathbf{D} \times \mathbf{K}}$, Observation distances $\mathbf{D}$.

Step 1 Waypoint Selection: Heuristically select waypoints $\mathbf{W}'$ from $\mathbf{W}$ to cover $\mathbf{K}'_n$ under observation distances $\mathbf{D}$.

Step 2 Fast Coverage: heuristically select waypoints $w_i \in \mathbf{W}$ to decrease the number of tasks with $AUC(k) = 0$

Step 3 Improvement of weighted AUC: heuristically select waypoint $w_i \in \mathbf{W}$ to improve the minimum weighted AUC of all tasks.

Return Waypoint Sequence P

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.
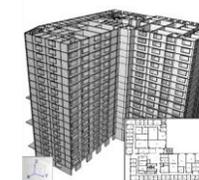
Fig. Building Structure
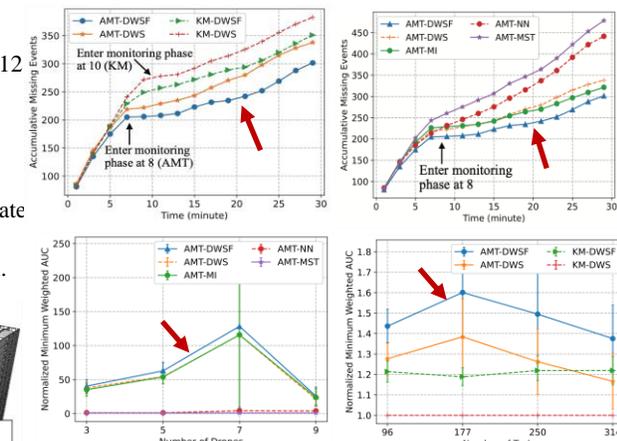
Our LU+DSWF algorithm leads to less missing events and higher information accuracy.

Reference: Fangqi Liu, Tzu-Yi Fan, Casey Grant, Cheng-Hsin Hsu, Nalini Venkatasubramanian, "DragonFly: Drone-Assisted High-Rise Monitoring for Fire Safety", SRDS, 2021.
Tzu-Yi Fan, Tun-Chi Tsai, Cheng-Hsin Hsu, Fangqi Liu, Nalini Venkatasubramanian, "WinSet: The First Multi-Modal Window Dataset for Heterogeneous Window States", BuildSys, 2021

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

UCI

"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

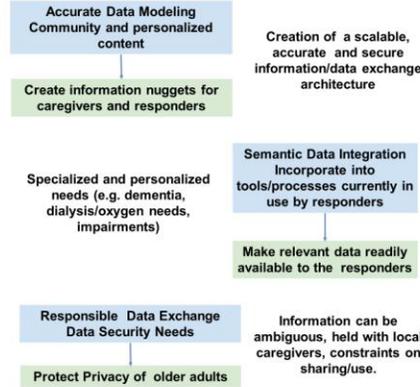*La Vita Bella Nursing Home, Dickinson, Texas Hurricane Harvey 2017*

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

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

Research and Practice Questions

- Accurate Data Modeling Community and personalized content
- Create information nuggets for caregivers and responders

- Creation of a scalable, accurate and secure information/data exchange architecture

- Specialized and personalized needs (e.g. dementia, dialysis/oxygen needs, impairments)

- Semantic Data Integration Incorporate into tools/processes currently in use by responders
- Make relevant data readily available to the responders

- Responsible Data Exchange Data Security Needs
- Protect Privacy of older adults

- Information can be ambiguous, held with local caregivers, constraints on sharing/use.

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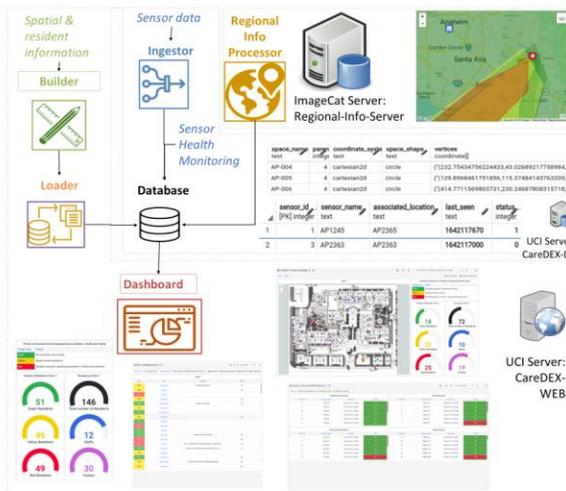
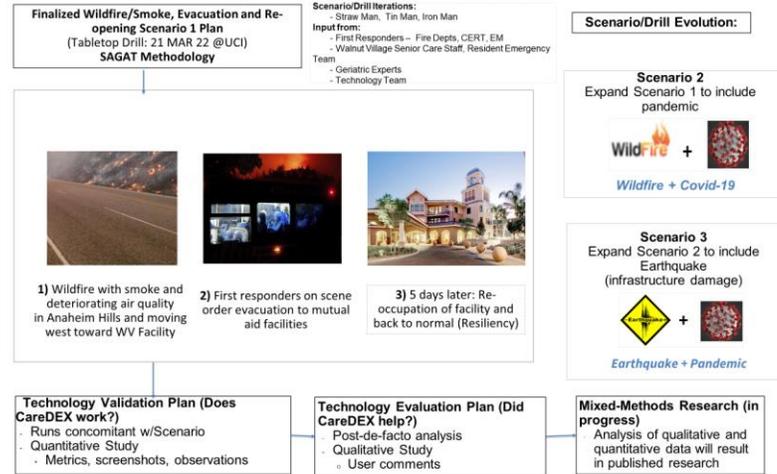Front Porch facility where the CareDEX prototype will be deployed and tested.

PROTECT YOURSELF DURING AN EARTHQUAKE! DROP, COVER, HOLD ON

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

Spatial & resident information

Sensor data

Regional Info Processor

Ingestor

Builder

ImageCat Server: Regional-Info-Server

Sensor Health Monitoring

Loader

Database

space_name text	param integer	coordinate_syste text	space_shape text	vertices coordinates
[PK] integer				
AP-004	4	cartesian2d	circle	'(232.75434756224433,43.0268921775894)'
AP-005	4	cartesian2d	circle	'(129.8968461751856,115.37484143763209)'
AP-006	4	cartesian2d	circle	'(414.7711569803731,230.2468780831571&)'

sensor_id [PK] integer	sensor_name text	associated_location text	last_seen text	status integer
1	1 AP1245	AP2365	1642117670	1
2	3 AP2363	AP2363	1642117000	0

UCI Server: CareDEX-DB

Dashboard

UCI Server: CareDEX-WEB

51   146
46   12
49   30

Technology Testing, Evaluation and Validation

Finalized Wildfire/Smoke, Evacuation and Re-opening Scenario 1 Plan
(Tabletop Drill: 21 MAR 22 @UCI)
SAGAT Methodology

Scenario/Drill Iterations:
- Straw Man, Tin Man, Iron Man
Input from:
- First Responders – Fire Depts, CERT, EM
- Walnut Village Senior Care Staff, Resident Emergency Team
- Geriatric Experts
- Technology Team

Scenario/Drill Evolution:

1) Wildfire with smoke and deteriorating air quality in Anaheim Hills and moving west toward WV Facility

2) First responders on scene order evacuation to mutual aid facilities

3) 5 days later: Re-occupation of facility and back to normal (Resiliency)

Scenario 2
Expand Scenario 1 to include pandemic
WildFire + *Wildfire + Covid-19*

Scenario 3
Expand Scenario 2 to include Earthquake (infrastructure damage)
Earthquake + *Earthquake + Pandemic*

Technology Validation Plan (Does CareDEX work?)
- Runs concomitant w/Scenario
- Quantitative Study
  - Metrics, screenshots, observations

Technology Evaluation Plan (Did CareDEX help?)
- Post-de-facto analysis
- Qualitative Study
  - User comments

Mixed-Methods Research (in progress)
Analysis of qualitative and quantitative data will result in published research

Academia Partners: UCI, UCI Health, BALL STATE UNIVERSITY, CU Boulder

Disaster Resilience Partners: RESEARCH FOUNDATION, American Red Cross, FIRE, ANAHEIM FIRE & RESCUE, Cal OES, UC DAVIS HEALTH, NATURAL HAZARDS CENTER, COUNTY OF LOS ANGELES FIRE DEPARTMENT, CAL FIRE, CITY of SAN DIEGO FIRE-RESCUE, FIRE CHIEFS ASSOCIATION

Senior Care Partners: front porch, WALNUT VILLAGE a front porch retirement community, CENTER FOR INNOVATION AND WELLBEING

Industry: ImageCat

MIT-PITT-RW Approach to Racing

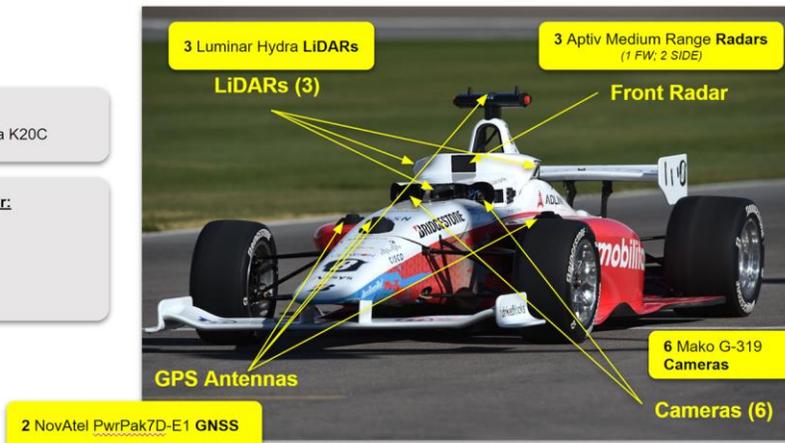Andrew Keats, BS Student, Computer Engineering

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

3 Luminar Hydra **LiDARs**
LiDARs (3)

3 Aptiv Medium Range **Radars**
(1 FW; 2 SIDE)
Front Radar

GPS Antennas

6 Mako G-319 **Cameras**

2 NovAtel PwrPak7D-E1 **GNSS**

Cameras (6)

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 use used to detect other vehicles and utilize a custom model using data collected during testing.

indy_car 0.93
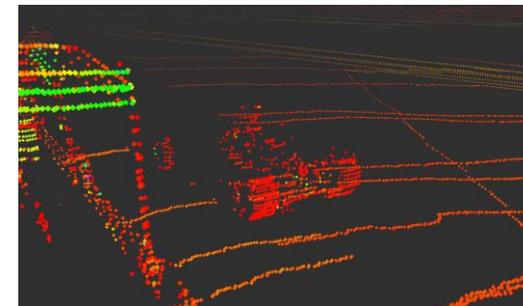
Current results show strong detection at short distances with cameras being reliable at further distances.

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 Mobilitas. Faculty advisor Amlan Ganguly.

Student Posters
Digital Twins and
Infrastructure Planning

SmartSPEC: Customizable Smart Space Datasets via Event-Driven Simulations

Andrew Chio, Daokun Jiang, Peeyush Gupta, Georgios Bouloukakis, Roberto Yus, Sharad Mehrotra, Nalini Venkatasubramanian

Exploiting semantics to generate realistic synthetic smart space datasets

UCI

TELECOM SudParis · IP PARIS · UMBC

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/dynamicity 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
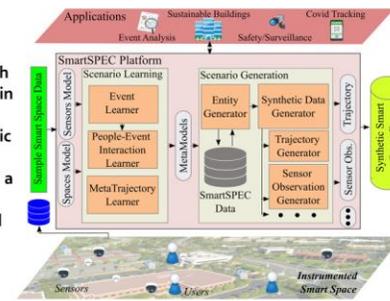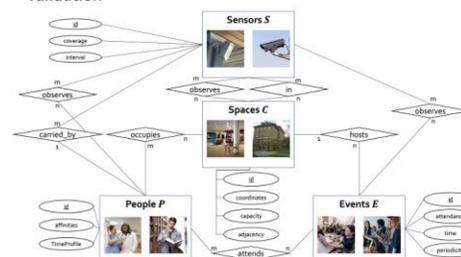
Semantic Model

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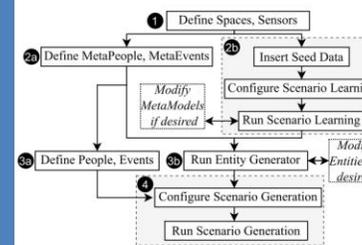
- Three modes of operation which vary in the level of user involvement/automation are provided in SmartSPEC
- In each step, models and data files used by SmartSPEC are open to be modified directly by the user for customization to a specific scenario

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

Learned Events, 2018-01-18, 3142-clwa-2051

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
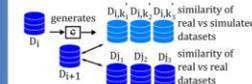- Results are recorded in a log file

2018-01-15 10:07:41

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
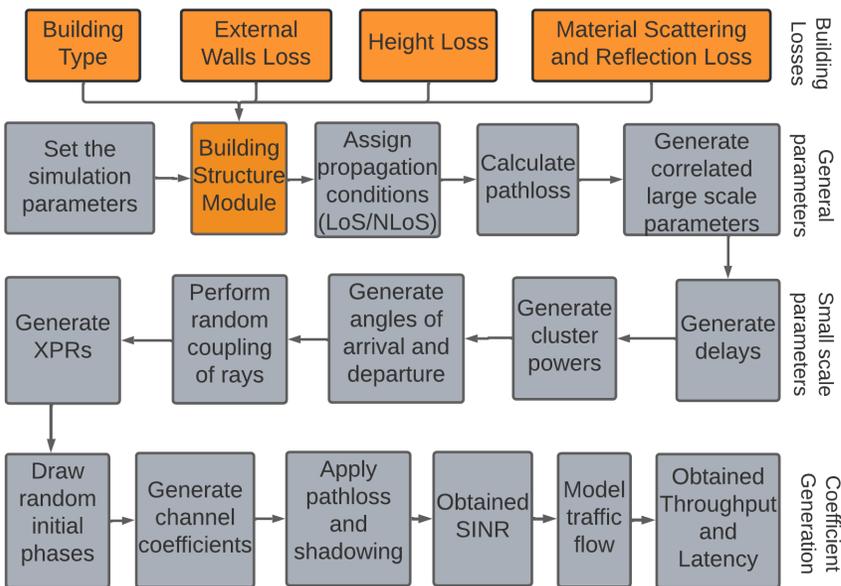- Interpret comparison between distributions based on which pairs of distributions are compared

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

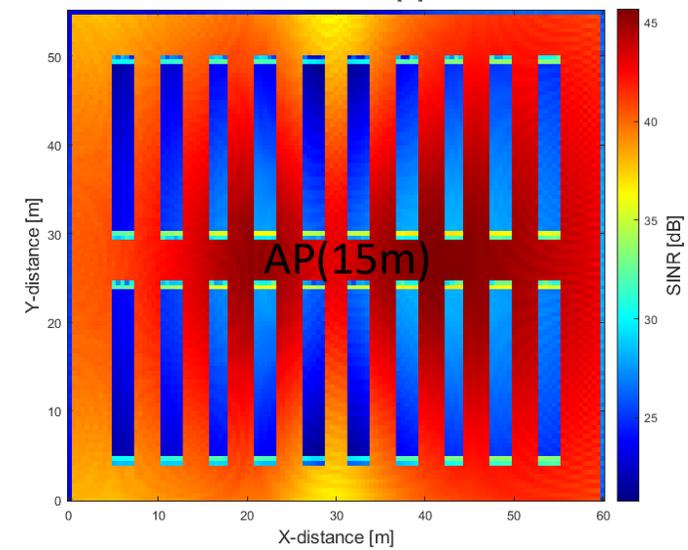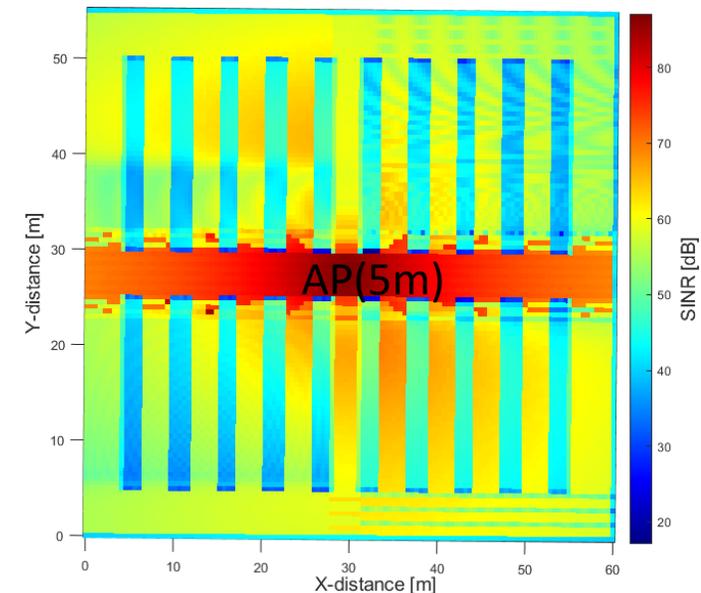- NS-3 was modified to incorporate suitable 60 GHz propagation losses in an indoor environment.

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

RAYMOND — RUN BETTER. MANAGE SMARTER.
NSF

SmartParcels: Cross-Layer IoT Planning for Smart Communities

UCI: Nalini Venkatasubramanian, Tung-Chun Chang   NTHU: Cheng-Hsin Hsu, Chia-Ying Hsieh   Télécom SudParis: Georgios Bouloukakis

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
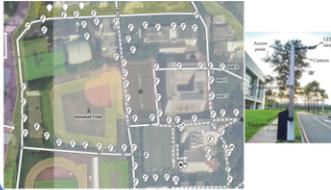
Goals

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

- 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

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

Retrofit from existing infrastructure

Reusability of the existing devices in communities
- Reduction of the deployment cost

CCTV
Free WiFi
Station monitoring AQ

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
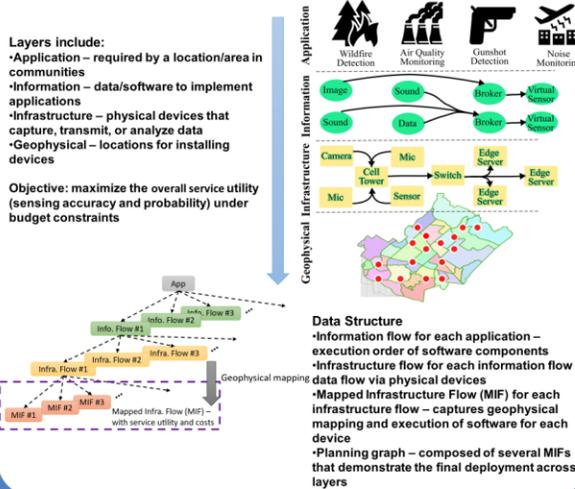
Data References and Syn
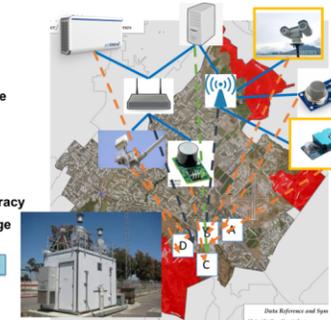
Approach

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
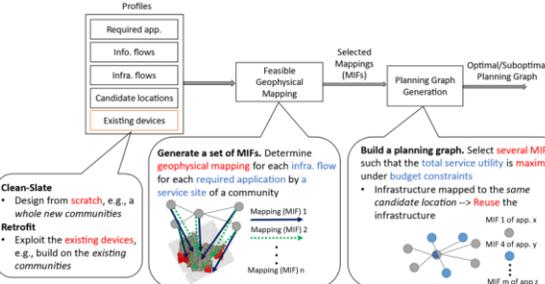
Wildfire Detection | Air Quality Monitoring | Gunshot Detection | Noise Monitoring

Application
Information
Geophysical Infrastructure Information

Geophysical mapping

Mapped Infra. Flow (MIF) – with service utility (and costs)

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

Planning Graph generation – selects and merges MIFs in order to maximize the service utility under budget constraints
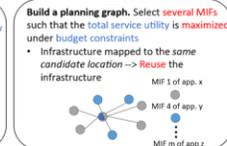
Proposed Algorithms
- Enumeration – exhaustive search for all possible mappings
- Selection – prunes out less promising mappings (utilities, communication coverage) at runtime of enumeration
- Retrofit – considers existing devices (work with enumeration and selection)

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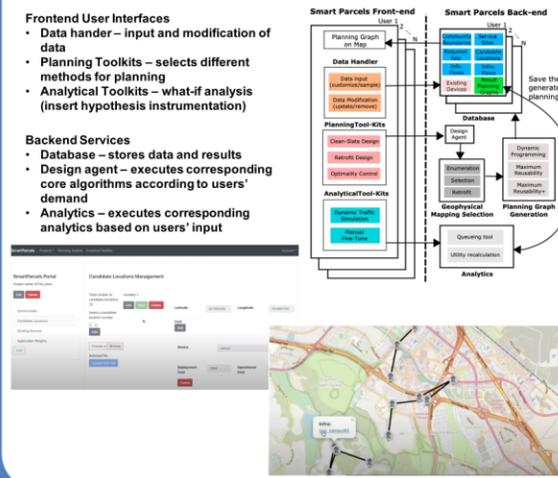- Maximum reusability plus – executes DP then MR

Profiles
- Required app.
- Info. flows
- Infra. flows
- Candidate locations
- Existing devices

Feasible Geophysical Mapping → Selected Mappings (MIFs) → Planning Graph Generation → Optimal/Suboptimal Planning Graph

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

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

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

Mapping (MIF) 1
Mapping (MIF) 2
Mapping (MIF) n

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

MIF 1 of app. x
MIF 4 of app. y
MIF m of app. z

Prototype

Web-Based User Portal with Backend Storage and Computation Services

Frontend User Interfaces
- Data handler – 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

Smart Parcels Front-end | Smart Parcels Back-end

Planning Graph on Map

Data Handler
- Data Input (customize/sample)
- Data Modification (update/remove)

Existing Devices

PlanningTool-Kits
- Clean-Slate Design
- Retrofit Design
- Optimality Control

AnalyticalTool-Kits
- Dynamic Traffic Simulation
- Manual Fine-Tune

Database

Design Agent
- Dynamic Programming
- Enumeration
- Selection
- Retrofit
- Maximum Reusability
- Maximum Reusability+

Geophysical Mapping Selection | Planning Graph Generation

Queuing tool
Utility recalculation

Analytics

SmartParcels Portal — Candidate Locations Management

Enhancing Smart Spaces with Thousands of Serverless Functions

Kevin Assogba <kta793@cs.rit.edu>, M. Mustafa Rafique <mrafique@cs.rit.edu>

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.

References

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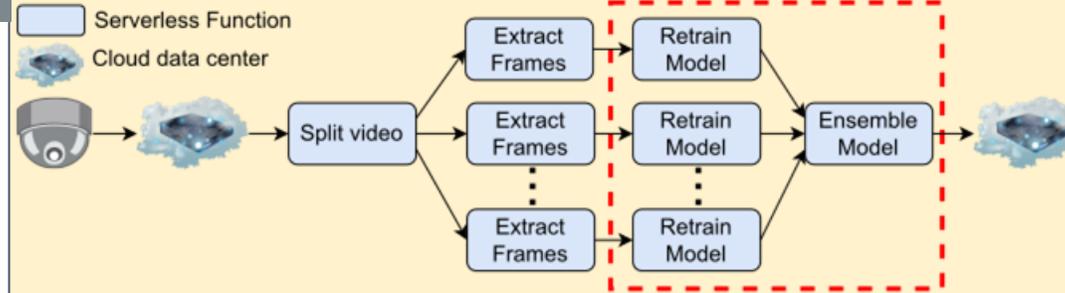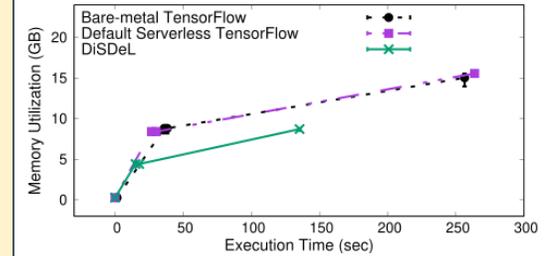
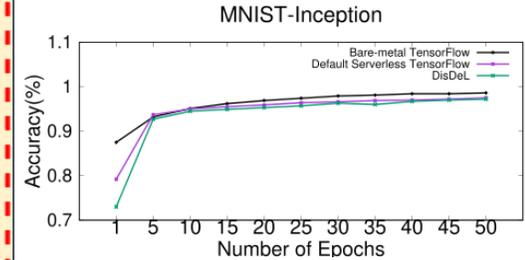*"Existing serverless platforms DO NOT support memory and time requirements of DL training workloads"*
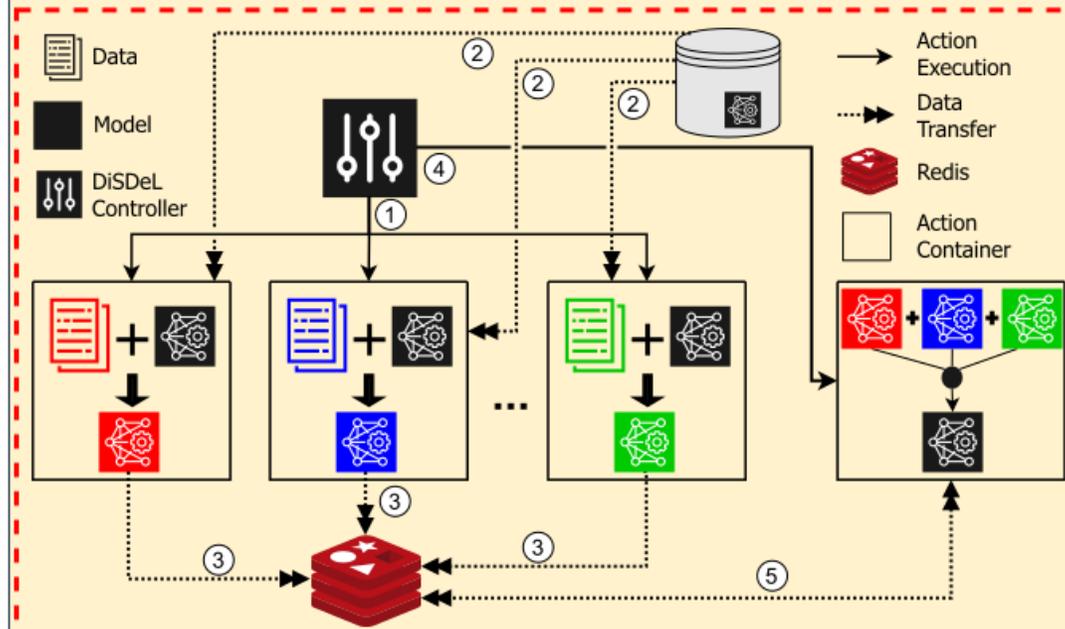
Performance Results

- 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

Service Caching at the Edge

RIT

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.
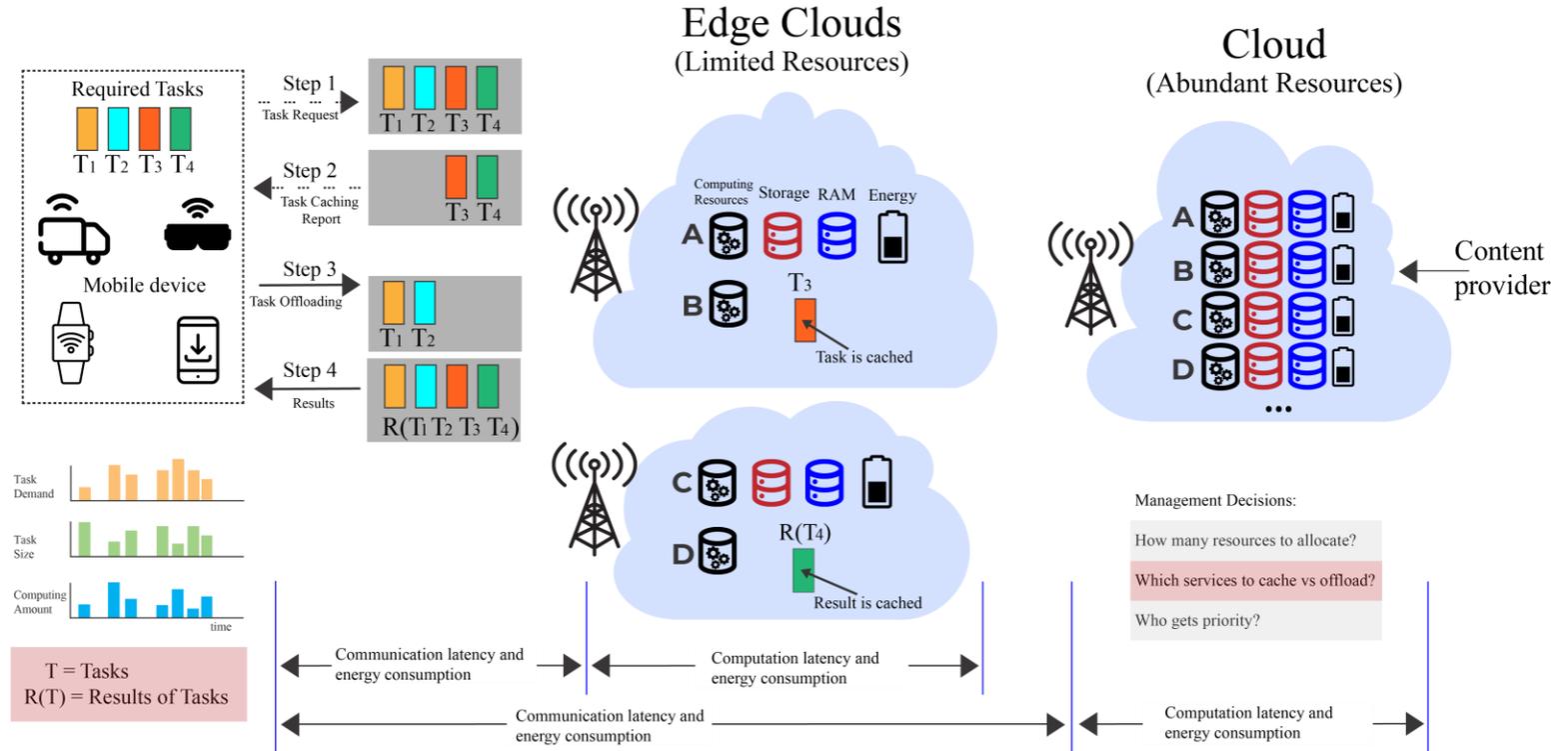
4 Milestones

- **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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