# 1 Introduction

According to IDC (www.idc.com) – a global provider of market intelligence, advisory services, and events for the information technology, telecommunications and consumer technology markets – the worldwide shipment of smart connected devices will surpass 2.5 billion units in 2017. The decreasing trends of cost, size, and power requirements of the various devices, were accompanied by an increase in embedded computing capabilities. In addition – every device can be connected with other devices, each of which: (1) is capable of sensing/computing, communicating and actuating; (2) depends on values and state-descriptions of other devices, not necessarily within geo-spatial proximity nor with homogeneous physical characteristics, to steer the course of its own activities. Such heterogeneous device range from computers, tablets and smartphones, through embedded systems in cars and traffic lights, precision agriculture sensors and actuators, to various home appliances, bodily sensors, etc. [5, 11, 81, 102]. According to recent a study by Goldman & Sachs, over 12 billion devices are already connected to the Internet of Thing (IoT) and by 2020 that number should become 20 billion [1].

Recent works have already attempted to capitalize on the results from social networks research [4, 44, 87, 125] – namely [10, 49] have specifically pointed how the experiences from social networks of users equipped with smart devices could be generalized to *social networks of devices* in the IoT realm. In a similar spirit, attempts have been made to demonstrate the benefits of *virtual objects* as a good abstraction for tackling IoT-related problems [91]. Studies regarding integration of heterogeneous devices in various contexts abound – e.g., from smart homes in a manner that would balance the Quality of Experience (QoE) and Energy consumption [40]; to better use of smart grid [75] and enabling smart cities [143].

One of the core motivations for the proposed project is based on the observation that current practices related to the design of IoT systems are still rather compartmentalized, and the dynamics-aware fusion of data collection, analytics processing and actuation across a variety of heterogeneous IoTs has limited support. As a simple example, consider a scenario where one has a (collection of) smart bed(s), such as, e.g., RestBed (https://www.restperformance.com/) with a surface equipped with multiple sensors to improve sleeping experience. A smart home may, in addition to a RestBed, also have smart refrigerators such as, e.g., Family Hub from Samsung (http://www.samsung.com/us/explore/family-hub-refrigerator/). While the QoE estimate can be obtained based on customers survey (or, even from bodily sensors), and it can even be balanced with the energy-efficiency (cf. [40]) "in-concert" with such devices, there are some important functionalities that are lacking, and could yet significantly improve the overall experience and efficient use of the available devices/technology:

- The quality/satisfaction of sleeping is not correlated with the nutritional habits (i.e., the content of the food in the smart refrigerator and consumption patterns). This, in turn, prevents the respective manufacturers from improving their products/devices in a collaborative and context-aware manner.
- There is no formal methodology of *where* the data assembling (as well as data aggregation and decision/recommendation as well as actuation) should take place. For instance, should all the nutrition-relevant data from an ensemble of smart refrigerators be sent at the local grocery store to optimize deliveries, or should it be aggregated at some geo-social level of hierarchy. Moreover, this raises the question of how the aspects of privacy and security should be handled.

Extending the above scenario, one may consider an evolution along spatio-temporal dimension. For instance, during a lunch-break, coffee break at the Jack decides to lower by 5F the set temperature of his home heating system to activate when he is less than 1 mile from his home and in any case no later than 6PM. However, if the outside temperature drops below 55F, the home temperature must go up by 5 degrees. A colleague gives Jack a list of instructions corresponding to a new method for washing wool sweaters; he sends the file directly to his home through the social network where a service will adapt the instructions to his washing machines particular technical features and his personal preferences (e.g., extra soft cloths). At home a tip from the network tells Jack to turn off all TVs to avoid getting further depressed. During the night the washing machine starts the cycle at the time the electric company informs it to be the most favorable.

The above describes a single user interacting seamlessly with multiple devices. We observe that one could attempt to generalize the existing approaches for Social Network of Things [49,91] that can be generated/organized and dissolved on-the-fly, and enable scalability. However, even in the context of "Jack" scenario, there are certain aspects that span accross heterogeneous domains/types and at different levels of certain (e.g., hierarchical) relationships. For instance, collaboratively regulating the temperature with other units in Jaacks building has one kind of spatial, temporal, and devices extent, whereas collaboratively deciding about the cycle of the washing machine may go beyond the building – i.e., optimizng grid-demand within a city-block.

[1] http://www.goldmansachs.com/our-thinking/pages/iot-meets-everything.html

By establishing a dynamic instantiations of various components/devices comprising Internet of Things (IoT) structures, we aim to provide an automatic resource optimization and other intelligence into these evolving collections of smart connected objects, going beyond the social networks of things. Rather than endowing them with autonomously cognitive chips, we aim to enable manufacturers, retailers and users/owners, to elaborate finely tuned dispatches to be distributed toward the smart objects through *middleware fogs* located various units (e.g., homes). As part of the proposed research we plan to provide novel data analytics methodologies that will: (a) incorporate the fact that some users may not be cooperative in terms of suggested regime of use for certain devices/task; (b) provide a specific behavioral insights to be used by various manufacturers when planning the design of certain devices so that they can be better adapted to changing conditions of use. A high-level description of the architecture we target to develop for supporting such scenarios is depicted in Figure 4, providing methodologies and tools for two basic modes:

(I) The first setup consists of a set of middleware fogs, located in each smart box/gateway of a smart home or public area, grouped together in an evolving (social-like) network along with profiles of manufacturers, retailers and users/owners. The lower layer is formed by all the real devices/objects (things), such as a fridge, a washing machine, a heater, a TV, a Hi-Fi, etc., where each one is abstracted by what we refer to as WiThing (WiT) for Wireless Thing. The WiT is the first level of the device abstraction and its role is to (1) uniquely identify an object/device (2) represent the object in terms of its properties/functionalities through an MIB (Management Information Base), and (3) constitute a bidirectional interface for all communications between the object and the middleware fog located in the smart box/gateway. The intermediate layer contains the smart box/gateway where the middleware fog is implemented. The latter is composed of an ensemble of interconnected modules that will govern all the requests issued by the user through a proper front-end application. To this end, this smart box must interface with any object/device it meets in the surroundings, i.e., any virtual device communicated by the real objects/devices. The upper layer illustrates the complexity of the different couplings to form ensembles of (networks of) manufacturers, retailers and users/owners with the generic representations of their objects/devices.

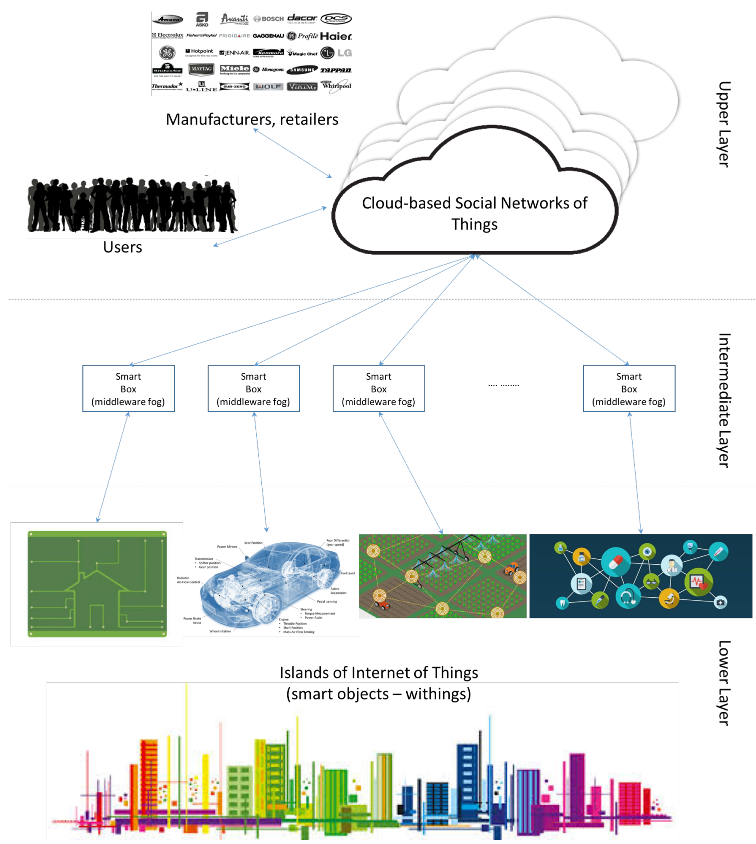


Fig. 1: Depiction of the proposed system

(II) The second setup complements the previous one in terms of inter-contexts couplings and dynamic formations (and dissolution) of corresponding instances of ensembles with heterogeneous participants. In terms of notation in Figure 1. this can be explained by the following consideration: (a) If we have an instance of a "network" of particular devices (e.g., a washers) from a collection of residential units, depending on the geographical context we may want to compose instances of collections corresponding a group of same devices but operating in a group of buildings in a near-downtown area. (b) Complementary to this, we may need to couple the "entity" corresponding to the ensemble of washers in different units in an apartment complex, with the one of entertainment devices in the same and/or neighboring buildings.

One could readily generalize this in multiple contexts – e.g., the instances representing the traffic-density in different geographical regions may be tied with the crime-rate in those and/or near-by regions and with the ones corresponding to activities of electronic devices in the police cars.

To enable such situational awareness that is flexible enough to incorporate the dynamic formation of instances that can span not only from networks of users to network of heterogeneous devices, but also through the existence of ensembles comprised of different contextual impacts (space, time, objective to be optimized, etc.) we propose the concept of

Heterogeneity And Context Aware Dynamic Avatars (HACADA) illustrated in Figure 2. We note that, in addition to the scenario-oriented discussions above, the HACADA's may be created, updated/modified and ceased based on different criteria: (a) particular cyber-properties: e.g., status of network infrastructure, privacy constraints, etc.; (b) Logical or semantical properties which may entail dynamically forming (and dissolving) hierarchies of HACADAs; (c) "expiration" of certain criteria (e.g., pat 10PM) enabling the leftover descriptors in two different HACADA-instances to be merged into one.

**Intellectual Merits:**

Throughout this complex environment, and in order to automate the deployment and control, as well as optimize the use of such ensembles of HACADAs comprising multiple instances of operational Internet of Things, a plethora of issues in data collection and processing (storage/retrieval, querying and information fusion), knowledge discovery, and security and privacy need to be investigated in unified framework. We assert that such integrated large scale effort, involving researchers from diverse backgrounds, is necessary to enable exploiting the full potential of the Internet of Things technology and make it ubiquitous of use. The proposed project has the following list of collaborative research activities as its main Intellectual Merits:

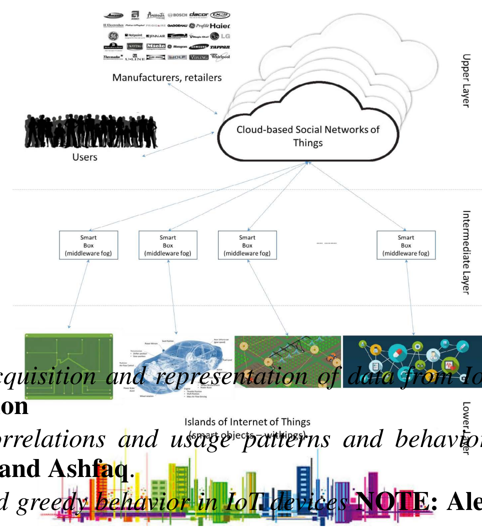


Fig. 2: Representation of Smart Objects as Avatars and Meta-avatars in the Cloud.

*Design and development of novel techniques and abstractions for acquisition and representation of data from IoT devices and users* **NOTE: mention HACADA + Mubbasir's discussion**

*Development of privacy-preserving analytics to discover hidden correlations and usage patterns and behaviors* **NOTE: mention a summary from the section written by Vladimir and Ashfaq**.

*Design and development of network protocols to mitigate the DoS and greedy behavior in IoT devices* **NOTE: Alek and Farid section-summary**

*Development of simulation platform as well as real-world testbed of heterogeneous IoTs (devices and users).* **NOTE: mention a realization of application scencario(s)**.

**Broader Impacts**: The salient broader impacts of the proposed project are:

**NOTE: need to expand**

This research effort aims to contribute to the rapid development of national and local capacity to respond to critical events and to develop technology to advance the ability and scope of Internet of Things to detect and monitor events in applications of high priority, such as surveillance and habitat monitoring. The proposed research activity is a multidisciplinary effort involving researchers with expertise in distributed databases, security, and data management and analytics. This work will also contribute to, and complement efforts under way for, the design and management of reliable smart facilities. Leveraging on the existing cooperation between Illinois Institute of Technology, Northwestern University and Rutgers University. The PIs have a long record of working on collaborative research projects and have extensively involved undergraduate students, minority students and women in their research.

The proposed collaborative project will be executed by a team of six highly accomplished researchers and their students from three different institutions, who have expertise in all the complimentary areas relevant to the research activities proposed in this project, including: Human Computer Interface, Machine Learning, Information Systems and Data Sciences, Sensor and Sensor Networking, Security, and Privacy. The PI and Co-PIs have a long and well established record of collaborating on different federal government and industry funded research projects. In the following we provide a brief introduction of the PIs and their relevant expertise.

- Ashfaq Khokhar, Illinois Institute of Technology: Wireless Sensor Networks, Data Mining, Cloud Computing
- Farid Nait-Abdesselam, Illinois Institute of Technology: Network Security, Wireless Sensor Networks
- Mubbasir Kapadia, Rutgers University: Human Computer Interface, Virtual Human Systems
- Vladimir Pavlovic, Rutgers University: Machine Learning, Dynamic System Modeling, Computer Vision
- Aleksander Kuzmanovic, Northwestern University: Networks Security, Denial-of-service Resiliency, Content Distribution
- Goce Trajcevski, Northwestern University: Moving Objects Databases,Data Management in Sensor Networks

## 2 State of the art

We now present an overview of the state of the art, both from the perspective of the current properties of devices and networking technology features, as well as from the perspective of related works in several fields that, in one way or another, may be used to achieve our objectives however, the fall short of several important aspects.

## 2.1 Whatever Proper title of this sub-section

The vast majority of devices are endowed with electronic interfaces, made of buttons and the like, inviting users to operate selections from among a limited set of options pre-featured by the manufacturers. They may concern options, such as, ventilation on/off button in an oven, a selection of delicate option in a washing machine, air-condition on/off button in a car, and so on. While these older devices are considered somehow efficient and simple, the trend is towards more technological and ubiquitous devices. The operational innovation of our approach is to make a move of the interface a step ahead and a step farther so as to realize a deep, remote and smart control. In this case, the manufacturer makes all/most of the operational parameters, such as spin speed and duration, totally manageable and configurable by the user. In turn, the user drives these parameters via software, hence makes them obeying to automatic procedures/instructions that have been elaborated and optimized in advance, with the help of the manufacturer, other contributors, and/or the networked intelligence. Thus, we need to have this new hardware/software interface managing signals/data back and forth between actuators/sensors and a logic unit with the result of detaching the user from any physical contact with the device (thing). To this end, in the project we will use open source electronic boards, such as Arduino boards (https://www.arduino.cc/), Parallella boards (https://www.parallella.org/) and/or Raspberry-Pi boards (https://www.raspberrypi.org/). They are powerful prototyping boards based on flexible, open and easy-to-use hardware and software. These devices are wirily and/or wirelessly connected to the Internet from which they can be easily visible and accessible. We foresee that their exploitation will lead microelectronic companies to develop specific chips for a massive diffusion of this new technology in a near future. In order to realize the vision of an Ambient Intelligence in a future network and service environment, heterogeneous wireless sensor and actuator networks have to be integrated into a common framework of global scale and made available to services and applications via universal service interfaces [76]. The goal is to reach a distributed open architecture with interoperability of heterogeneous systems, neutral and easy access, clear layering and resilience. It should provide the necessary network and information management services to enable reliable, secure and accurate interactions with the physical environment. The idea is to provide an integrated platform that offers unified data access, processing and services on top of existing ubiquitous services of the Internet of Things to integrate heterogeneous sensors/actuators in a uniform way. From an application perspective, a set of basic services encapsulates sensor/actuator network infrastructures hiding the underlying layers with the network communication details and heterogeneous sensor hardware and lower level protocols.

A heterogeneous networking environment indeed calls for means to hide the complexity from the end-user, as well as applications, by providing intelligent and adaptable connectivity services, thus providing an efficient application development framework. To face the coexistence of many heterogeneous set of things, a common trend in Internet of Things applications is the adoption of an abstraction layer capable of harmonizing the access to different devices with a common language and procedures [36]. Standard interfaces and data models ensure a high degree of interoperability among multiple systems. However, typical drawbacks of misconfigurations and traffic congestions are normally exasperated by the node heterogeneity. These drawbacks will be overcome in the project through the adoption of islands architecture. On the one hand, smart gateways in their locations will hide all the complexities of the underlying standards. Hence, wireless connections of the devices/machines to the web/Internet, using communication technologies like Zigbee [8], Z-wave [131], Wi-Fi [132], plus the mapping of every device to a unique ID, will provide full, intelligent and secure control over it. With these smart boxes/gateways, technological limitations will completely disappear and the devices will become identifiable only through their functionalities with clear and consistent APIs. On the other hand, the middleware fog constitutes an abstraction level where all the devices, viewed as entities sharing their functionalities (avatars), are transparently managed and used. The goal is to manage the collaboration between heterogeneous devices through a simple API level in conjunction with the mentioned communication protocol able to reach the peer within the location singularly.

Most existing solutions for middleware adopt in general a service-oriented design tailored mainly to support a network topology of sensors that is both unknown and dynamic. But while some projects focus on abstracting the sensors in the network as services (such as in HYDRA [37, 145, 146], SENSEI [95], SOCRADES [43], and COBIS [96]), other projects devote more attention to data/information abstractions and their integrations with services (among which are SOFIA [47], SATware [79], and Global Sensor Networks GSN [3]). A common thread throughout all of these solutions, however, is that they handle the challenge of an unknown topology through the use of discovery methods that are largely based on the well-known traditional service/resource discovery approaches of the existing Internet, ubiquitous environments and wireless sensor and actuator networks [6, 82, 149]. For instance, SOCRADES provides discovery on two levels, the sensor level and the service level, which can employ either standard web-service discovery or a RESTful discovery mechanism (for RESTful services). COBIS, on the other hand, uses its own service description language COBIL 2 (Collaborative Business Item Language), where service functions and keywords are annotated with a verbal description. Another point of agreement in the state-of-the-art of middleware solutions is in the widespread use of semantics and metadata to overcome heterogeneity challenges. Indeed, it is standard practice to use ontologies to model sensors, their domains, and sensor data repositories [35,37,74]. Some projects even go a step further and also include context information [95], or service descriptions [37, 145, 146]. And as a type of service composition, many projects support the concept of virtual/semantic sensors (for instance, in HYDRA, GSN and SATware), i.e. entities that abstract several aggregated physical devices under a single service. A different implementation of a similar idea, though, is provided in the SATware project, where virtual sensors actually correspond to transformations applied to a set of raw sensor streams to produce another semantically meaningful stream.

Regarding scalability, most projects address this challenge by pursuing modifications in the underlying sensor/actuator network topology. Sometimes, this is done by adopting fully-distributed infrastructures (such as in COBIS and SOFIA), and sometimes through an architecture of peer-to-peer clusters (e.g., GSN). In our view, however, while these approaches work well for the existing Internet, where traffic is made up of a relatively small amount of service interactions, they will not fit for the complex weave of interactions that will be commonplace in the Internet of Things. In the Internet of Things, a large number of requests will involve intricate coordination among millions of things and services, whereas on today's Internet most requests are largely point-to-point. Therefore, the number of packets transmitted in the network will grow strongly and nonlinearly as the number of available services increases. In such an environment, performing even a simple service discovery may exceed acceptable time, processing, and memory constraints. //NOTE: the last paragraph needs to be tied (cf. (2)/Fig.2 in the intro with the problems related to "Possible Worlds Semantics" and the efficient pruning the needs to be performed

### 2.2 Data and Process Integration

Heterogeneous data integration is a topic which, in addition to the database community broadly [28, 45], has also been investigated by more specialized research foci: – bioinformatics [60, 88]; information management and text retrieval [29, 46, 119]; sensing/actuation and tracking [12, 25, 102] (to name but a few). While the role and the impact of the semantics have been recognized and addressed [22, 24], the existing results still have limited cross-contextual support. For instance, the works investigating the benefits of semantics for resource discovery (cf. [24]) do not take into consideration the role of different devices that may enter and/or leave a particular "geo-social" network dynamically, as well as their impact on real-time adjustments (as well as the impact of their cessation). To-Do – Goce: Overview of:

a. Data integration + distributed query processing; workflows [72, 92, 94]; Wireless Actuator Networks

b. Analytics and platforms in-context (Cloud/Hadoop; NoSQL; Warehousing) [118]

## 3 Proposed research overview

We now proceed with identifying the main challenges that the proposed project will address, with a brief overview of the proposed research tasks (research challenges), followed by an introduction of the team and their expertise.

Research Challenge 1 (RC-1): Data collection and processing

Research Challenge 2 (RC-2): Knowledge discovery

Research Challenge 3 (RC-3): Security, privacy (anonymity) and trust

The Internet of Things is foreseen to bring a multitude of services with a vision of creating a smart self-configuring and interconnected world for the benefit of end users. With the extensive research and development of computer, communication and control technologies, it is possible to connect all things to the Internet such that the so-called Internet of Things (IoT) can be formed. These things may be equipped with devices such as sensors, actuators, and tags, in order to allow people and things to be connected anytime and anywhere, with anything and anyone. IoT will enable collaborations and communications among people and things, and among things themselves, which expand the current Internet and will radically change our personal, corporate, and community environments. However, a plethora of security, privacy, and trust challenges need to be addressed in order to fully realize this vision [20, 21, 22, 23]. When more and more things connect to the Internet, security and privacy issues become more serious, especially in the case that these things are equipped with actuators and can support control. For better protection of secure communication and user privacy, including location, identity and behavior habits, it is necessary to develop anonymous communication theories, methods and key technologies of anonymous communication systems in all varieties of application environments. Anonymous communication is used to hide communication participants or communication relations to achieve effective protection for network nodes and user identities. Anonymous communication can address potential network security issues, and becomes one of the hot topics in the field of network and information security. With reference to security, data anonymity, confidentiality, and integrity need to be guaranteed, along with providing authentication and authorization mechanisms in order to prevent unauthorized users (i.e., humans and devices) to access any system. Concerning privacy requirement, both data and user personal information have to be confidentially manipulated since devices may manage sensitive information (e.g., user habits, locations, etc). Finally, trust is also a fundamental issue since the IoT environment is characterized by multiple devices that have to process and handle the data in compliance with user needs and rights.

To realize a trusted, secure, and privacy preserving social network of things, we plan to address in this proposal the following security, privacy, and trust management related tasks:

T-3.1: Define a new scheme of anonymizing things and representing them as avatars in the social network of things.

T-3.2: Authentication of data collected in fogs in the presence of malicious attackers, despite the attack surface being very broad, ranging from PHY layer to application layer.

T-3.3: Achieving end-to-end secure and privacy-preserving information flow monitoring between users and things, covering all sort of things and access networks using physiological and physical layer propertie.

T-4.3: Design of secure, fast and friendly authentication schemes to allow users of the social network of things to access the data of interest through diverse mobile devices such as smartphones and tablets.

# 4 Research tasks

We now proceed with a detailed presentation of the main research of the proposed project.

## 4.1 Data collection and processing

(Goce + Mubbasir)
Data cleaning, data collection, sharing, processing, analytics
How can we secure the collected data and how to make it available?
APIs and libraries for building applications

**Knowledge Representation and Reasoning** The processed data from above will be represented as a set of discrete time series, or *fluents* which encode the states and properties of different avatar which change over time. give example. To facilitate efficient reasoning and knowledge discovery in a dynamic smart and inter-connected system of avatars, we will consider a level of abstraction, termed as *events* . Events constitute meaningful interactions between two or more avatar and serve as the basis for identifying relationships between them towards creating social networks of avatars. give example. We define the specific terms and concepts we will use for event-centric knowledge representation and reasoning below.

**Smart Avatars** The notion of smart objects [**?**] has been popularly used in the graphics and animation community to embed intelligence and semantics in virtual objects. We extend this formalism to represent both IoT objects as well as IoT users. This unified formalism allows us to seamless consider sensors, controllers, actuators, and human users within the same social community. We define a smart avatar $w \in \mathcal{W}$ as $w = \langle \mathbf{F}, s \rangle$ with a set of advertised affordances $\mathbf{F}$ and a state $s$. An affordance $f(w_o, w_u) \in \mathbf{F}$ is an advertised capability offered by a smart avatar that manipulates the states of the owner of an affordance $w_o$ and a smart avatar user $w_u$.

**State.** The state $s = \langle \theta, R \rangle$ of a smart object $w$ comprises a set of attribute mappings $\theta$ (fluents), and a collection of pairwise relationships $R$ with other avatars. With this representation, we can make logical inferences between objects using a declarative PROLOG-like knowledge reasoning engine.

**Events.** Events are used to encode context-specific interactions between two or more smart avatars, and provide an appropriate level of abstraction for knowledge discovery An event is formally defined as $e = \langle t, \Phi, \Omega \rangle$. A precondition $\Phi : \mathbf{s_w} \leftarrow \{\texttt{TRUE}, \texttt{FALSE}\}$ is a logical expression on the compound state $\mathbf{s_w}$ of a particular set of smart avatars $\mathbf{w} : \{w_1, w_2, \ldots w_{|\mathbf{r}|}\}$ that checks the validity of the states of each smart object. $\Phi$ is represented as a conjunction of clauses $\phi \in \Phi$ where each clause $\phi$ is a literal that specifies the desired attributes of smart objects, and relationships between pairs of participants. A precondition is fulfilled by $\mathbf{w} \subseteq \mathcal{W}$ if $\Phi_e(\mathbf{w}) = \texttt{TRUE}$. The event postcondition

$\Omega : \mathbf{s} \to \mathbf{s}'$ transforms the current state of all event participants $\mathbf{s}$ to $\mathbf{s}'$ by executing the effects of the event. We can extend this definition to model non-deterministic, fuzzy events with a probabilistic notion of success or failure. Events may optionally have a controller which defines the series of affordance activations within the smart avatars to produce its desired outcome. We represent this control logic using an extended version of Behavior Trees that facilitate parameterization. Parameterized Behavior Tree (PBT) [110] are an effective model for representing coordinated control logic between multiple smart avatars.

PI Kapadia has extensive prior experience in developing event-centric knowledge bases for inference and reasoning in virtual worlds [52–54, 111] which will be extended to represent the IoT domain.

This symbolic representation of avatars and theiry dynamic states in terms of key events will facilitate the development of an event calculus ? allowing us make inferences about the relationships and properties of these avatars using first and second-order logic. This reasoning will be used as the basis for knowledge discovery described in Section XX. Knowledge discovery will entail the identification of relationships between the properties of different avatars, clustering of avatar to create compound entities, and the discovery of salient events.

### 4.2 Knowledge discovery: social network of avatars (virtual world)

(Ashfaq + Vladimir)
Tasks:

- Build spatio-temporal avatar profiles
- Group avatars into groups according to similar profiles. I.e., construct social network of profiles and do graph clustering.
- Predict avatar behavior from group profiles

We will use Gaussian Process dynamic models (GPDM) as profiles. GPDMs can be used for both modeling isolated avatars and interactions between avatars. We can use a framework similar to [107–109]. Then extend using our trajectory refinement and optimization approaches [141].

However, we need to consider the fact that this system is heterogeneous, i.e., things and humans. So should have a hierarchical model, one level for things, one for humans, then merge on higher level.

Modeling the state of the cyber-human IoT avatar world is a critical component necessary for optimal IoT behavior prediction and, subsequently, decision making. This research task focuses on novel data-driven computational models and algorithms that will enable efficient, scalable and accurate estimation of the IoT world state from a (social) network of individual IoT avatars. In particular, we aim to solve this task by exploiting the parallel between data-driven modeling in IoT avatar worlds and modeling of complex heterogeneous crowd behaviors.

**Prior Art**. Consider the context of crowds, where the goal is not only to estimate the location of individuals in a group but also to predict group behavior, short (immediate flow) and long-term movement (e.g., crowd moving toward exit A), as well as the interaction of the crowd with the environment (e.g., residents entering of leaving an apartment). This problem is similar to the one we are facing. However, in the IoT context, the state will not only be represented by physical spatio-temporal locations of entities but also by their general "characteristics", such as the power usage or temperature time course, etc. Crowd state estimation may focus on macroscopic modeling (coarse flow), mesoscopic (blobs, groups of individuals), or microscopic level (individuals within a group) [144]. Models such as the Discrete Choice [9] and the social force (SF) [30, 93] model were primarily designed in the context of analytics and simulation. Combining simple person sensing (tracking) with crowd modeling is essential to address the interaction of entities. Those approaches, e.g., [19–21], use crowd simulators to constrain the dynamics of measured individuals' locations by taking into account collisions. Recent data-driven approaches [126, 148] aim to produce more realistic estimates of behaviors but are limited to simple environments and motion patterns and relatively short-term predictions. Broad environments such as large residential areas, necessitate distributed models to enable sufficient coverage and efficient computation. However, no work to-date considers the detailed aspect of the joint crowd-environment state estimation in long-term planning scenarios, particularly when the states of each entity become truly multidimensional and the crowd is heterogeneous, as is the case in our social networks of IoTs.

**Proposed Research**. This research focuses on the key questions of how to estimate, and subsequently predict, the joint state of the social network of IoT system. We assume that the sporadic, potentially interrupted, measurements of IoT profiles, called tracklets, can be obtained from multiple sensors using existing acquisition algorithms. However, the observed tracklets will include noise and significant amount of missing information. State of the environment will be similarly measured using other static or dynamic sensors. The state estimation will then be formulated as: **Task 1: Fusion**. Fuse and link the local measurements from multiple distributed sensors to identify correspondences between measurements of the same target process. **Task 2: IoT Crowd State Estimation**. Using the fused/linked

Table 1: Multiple objective terms for global crowd-environment state estimation.

| Measurement Compatibility $E_{gt}(\mathbf{t}_i^t)$ | Kinetic energy $E_{kn}(\mathbf{t}_i^t, \mathbf{t}_i^{t+1})$ | Physical constraint $E_{mv}(\mathbf{t}_i^t, \mathbf{t}_i^{t+1})$ | Social constraint $C_s(\mathbf{t}_i^t, \mathbf{t}_j^t, \mathbf{t}_i^{t+1}, \mathbf{t}_j^{t+1}, r_i, r_j)$ | Environmental constraint $C_e(\mathbf{t}_i^t, \mathbf{t}_i^{t+1}, r_i, \mathbf{z}_{k_1}^t, \mathbf{z}_{k_2}^t)$ |
|---|---|---|---|---|
| $u_i^t \Vert\mathbf{t}_i^t - \mathbf{o}_i^t\Vert^2$ | $c_{kn}\Vert\mathbf{t}_i^{t+1} - \mathbf{t}_i^t\Vert^2$ | $\begin{cases} 0 & \text{if } \Vert\mathbf{t}_i^{t+1} - \mathbf{t}_i^t\Vert \leq c_{mv}, \\ \infty & \text{otherwise.} \end{cases}$ | $\begin{cases} 0 & \text{if } \Vert\alpha(\mathbf{t}_i^{t+1} - \mathbf{t}_j^{t+1}) + (1-\alpha)(\mathbf{t}_i^t - \mathbf{t}_j^t)\Vert \\ & \geq (r_i + r_j), \quad \forall\alpha \in [0,1] \\ \infty & \text{otherwise} \end{cases}$ | $\begin{cases} 0 & \text{if } \Vert(\alpha\mathbf{t}_i^{t+1} + (1-\alpha)\mathbf{t}_i^t) - (\beta\mathbf{z}_{k_1}^t + (1-\beta)\mathbf{z}_{k_2}^t) \\ & \geq r_i, \quad \forall\alpha,\beta \in [0,1] \\ \infty & \text{otherwise} \end{cases}$ |

measurements estimate the state of the IoT crowd and the environment, taking into account their social or physical interactions. **Task 3: Data-driven Estimation**. Include historical and/or simulation data to constrain and improve local and global state estimation. To solve these Tasks we propose a global optimization framework that builds upon our preliminary work in [141]. We consider the following setup of the problem.

Consider the crowd-environment state space $\mathcal{X} = \{(\mathbf{T}_i, l_i), \mathbf{Z}\}$, $\forall i \in (1, J)$ defined as the union of the set of $J$ IoT agent "trajectories" $\mathbf{T}_i$ and the environmental configuration $\mathbf{Z}$. The trajectories have the associated agent ID $l_i \in \{1, ..., J\}$ and temporally ordered agent states $\mathbf{T}_i = \{\mathbf{t}_i^t = (x_i^t, y_i^t)\}, \quad \forall t \in (1, N_i), \quad x_i^t, y_i^t \in \mathbb{R}$, where $N_i$ denotes the number of track points available for the trajectory $i$. The environment is modeled as a set of 2D linear segments, with state $\mathbf{Z} = \{(z_{k,x_1}^t, z_{k,x_2}^t, z_{k,y_1}^t, z_{k,y_2}^t)\}, \quad \forall k = (1, N_k)$, where e.g., $z_{k,x_1}^t, z_{k,x_2}^t$ denote the horizontal minimum and maximum bound of the $k$-th linear obstacle at time $t$. For example, a rectangular wall is a set of four linear obstacles. Our goal will be to reconstruct $\mathbf{T}_i$ and $\mathbf{Z}$ from the measurements collected by distributed IoT crowd sensors, tracklets $\mathcal{O} = \{\mathbf{O}_i\}, i = 1, \ldots, M$, and the environment sensors $\mathcal{E} = \{\mathbf{E}_i\}, i = 1, \ldots, N$. Associated with each measurement will be a quantifier of uncertainty, the measurement noise precision $u_i^t$ (e.g., supposing a Gaussian noise model).

**Task A.1 -** We will assume that the association problem,associating each tracklet $\mathbf{O}_i$ with an agent $j \in \{1, ..., J\}$, need only be solved for the agents while the associations of measurements with the environment states are known and remain constant. Typically, local sensor can produce tracklets of reasonable duration along with the profile features $\mathbf{f}_i$ describing this agent (e.g., device model, personal social profile). The linking process amounts to solving a combinatorial min-flow problem on the graph defined by tracklet compatibility costs such as the tracklet profile feature differences (e.g., $\Vert\mathbf{f}_i - \mathbf{f}_j\Vert$), spatio-temporal proximity of tracklets, etc. This is a challenging task, with approaches spanning the spectrum of exact solutions based on e.g., the Hungarian algorithm, to more tractable approximations c.f., [7,80,124,126] or stochastic solutions such as JPDAF and its extensions, c.f., [41,103]. In this project we will first investigate solutions based on the min-flow problem formulation, which have shown reasonable performance based on our preliminary studies [141]. We will also compare these solutions to stochastic approximations of the JPDAF type, given their ability to handle online and distributed settings [51].

**Task A.2 -** Given the estimated associations from Task 1, the goal here is to reconstruct $\mathbf{T}_i$ and $\mathbf{Z}$ from the now associated measurements $\mathbf{O}_i, i = 1, \ldots, J$, and the environment sensors $\mathbf{E}_i, i = 1, \ldots, N$. To illustrate our proposed approach we will focus on the specific case when the environmental configuration is known and static. We will then first define the agent state estimation as a global multiobjective energy minimization problem. The choice of the multiple objectives will be driven by specific and unique problem (crowd/environment) considerations. For example, we will initially consider the following key sub-objectives, summarized in Tab. 1:

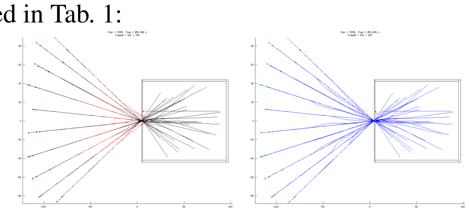

Fig. 3: Preliminary results [141] of global microscopic trajectory refinement when 20% of the tracklets are missing. Black are the trajectories of 40 agents in a bottleneck benchmark simulated using the SF model, red indicate missing data, blue are refined trajectories after optimization.

*Compatibility with Associated Measurements*: dependency of the estimate agent trajectory on the measured tracklets; *Kinetic energy*: the agents whose objective is to reach the goal position following the minimum travelled distance; *Physical constraint*: the human body set limits on the maximum walking speed $c_{mv}$ of an agent. Depending on the context, these constraints may also include the minimum speed and other biomechanical limitations, c.f., [17]; *Social constraint*: Avoidance of collisions with other agents encoded through pairwise constraint functions that depend on the size of agens $r_i$; *Environmental constraint*: Collisions between agents and the environment.

Combining the multiple objectives, our global objective will determine each track point of each $i$-th agent by solving the optimization problem $\arg\min_{\mathbf{t}_i^t} \sum_i \sum_{t=1}^{N_i} E_{gt} + \sum_{t=1}^{N_i-1} E_{kn}$ $+ \sum_{t=1}^{N_i-1} E_{mv} + \sum_{t=1}^{N_i} \sum_{i \neq j} + \sum_{t=1}^{N_i} \sum_{(i,k)} C_e$. However, direct minimization of this global objective is infeasible. In particular, collision constraints are non-convex and we desire to solve this task in a distributed manner, enabling local data processing. Additive objectives of this type are amenable to general distributed optimization using the alternating direction method of multipliers (ADMM). A particular version of that approach, investigated in [17, 18, 141], focuses on a message-passing solution to ADMM, specifically suitable for networked sensor settings. Here the global objective can be considered as a consensus optimization problem, where the consensus constraints stem from the need to satisfy pairwise agent-agent and agent-environment interaction "rules." In Fig. 3 we illustrate the effectiveness of this approach from our preliminary studies in [141]. Our method is able to effectively reconstruct large portions of the missing information, while ensuring the reconstructed trajectories are without collisions and discontinuities, and still preserve the original essence of the crowd. While this approach is appealing, its convergence may be slow (typically on order of minutes). We will consider recent ADMM acceleration approaches particularly suitable for this setting, including our own distributed adaptive penalty Fast ADMM [112]. Another challenge will be to extend this point-based estimation approach to a fully probabilistic setting, with quantifiers of posterior uncertainty. We propose to tackle this task using our recent work on ADMM for probabilistic models [13, 142], which can also be used to construct online versions of the global optimization approach. We will compare these approaches to state-of-the-art distributed dynamical system methods, including [31, 51] and the recent generative-based models of [148].

**Task A.3 -** One of the main limitations of the global optimization approaches in the limited physical and social constraints (e.g., kinetic, repulsion, etc.) that may not be fully representative of the actual IoT entity behavior. While one can overcome these drawbacks when the tracklets are accurate and densely measured, sensor failures, etc. can result in poor state estimates. We propose to use data-driven IoT profile priors to improve the state estimation approach. To construct such priors we propose to use both the data from actual IoTs as well as the data simulated in our simulators. However, such "raw" sources of data typically produce dense measurements that do not capture the "essence" of the behaviors, a desideratum for good generalization. We thus propose to first construct summaries of behavior patterns from the raw data using methods such as dynamic trajectory clustering [23, 50, 86, 136, 147]. These summaries $\tilde{\mathcal{D}} = \{\tilde{\mathbf{T}}_m, \mathbf{Z}\}$ will be specific to environment configurations $\mathbf{Z}$. Given the summaries, we will define an additional energy term $E_{av}(\mathbf{t}_i^{t-1}, \mathbf{t}_i^t, \mathbf{t}_i^{t+1}, \tilde{\mathbf{t}}_m^{t-1}, \tilde{\mathbf{t}}_m^t, \tilde{\mathbf{t}}_m^{t+1}) = \sum_m s_{m,i}^t \|\theta_i^t - \tilde{\theta}_m^t\|^2$ that models the compatibility of $\mathbf{t}$ with the cluster centers $\tilde{\mathbf{t}}$, where $s_{m,i}^t$ are the compatibility weights. This energy term will be added as another subobjective to the global optimization in Task 2. Compatibility weights can be either set apriori to estimated in the optimization process (e.g., in an EM-type of recursive estimation). We will contrast these approaches to other learning-based crowd sensing models, including [148] and [20].

Note that all three Task possess clear dependencies. Therefore, we will also investigate the utility of a closed-loop estimation system where the results of Task 2 and Task 3 can be used to improve the associations in Task 1.

## 4.3 Security, privacy and anonymity

Security poses a great challenge for IoT. In addition to security threats common for networked systems in general, IoT systems are further confronted by the fact that they necessarily rely on wireless signals for communication. We propose to address challenges stemming from the *physical layer* attacks on IoT systems. In particular, while Multi-User Multiple Input Multiple Output (MU-MIMO) systems are considered the ultimate next step in the wireless bandwidth race (because they leverage spatial multiplexing to send independent data streams to multiple terminals simultaneously, effectively improving spatial reuse), they could be utilized as an effective and sophisticated *denial-of-service* tool. Indeed, by creating controlled signals in an area, it can selectively disrupt performance of Wi-Fi networks and sensors in an area, while still making it hard to detect or classify such behavior (precisely due to uneven signal properties at different locations). Such an attack is relevant in many scenarios. Consider a location densely populated with wireless APs. Can one of the APs turn itself into a rogue mode to disrupt the other APs, i.e., clear the air, and thus improve performance for itself, while staying largely invisible to the other APs? Another example is Wi-Fi backscatter, *i.e.*, scenarios where a device backscatters Wi-Fi signals to communicate. In presence of the attack, such communication might be severely degraded, while at the same time it becomes hard to know that the attack is taking place. Given that Wi-Fi backscatter was recently proposed as a solution to communication with implanted medical devices, this scenario significantly raises the bar for addressing this emerging problem. Below, we first outline our current results in this domain, and the outline a research agenda.

**Background and Current Work**

A fundamental requirement in MU-MIMO systems is that up-to-date Channel State Information (CSI), as perceived by the clients, must be obtained by the AP over short time scales. We show that both explicit and implicit *client-fed* CSI feedback open the door to a fundamental vulnerability of MU-MIMO systems. We demonstrate that a single attacker (a Neo) can mount strategic attack, called Matrix-bending, that can dramatically reduce the throughput of an MU-MIMO system. Moreover, we show that a small number of Neos (or a single Sybil-enabled Neo) can reduce the throughput of an MU-MIMO system to a level *below* that of a corresponding single-user (SU-MIMO) system. Such a degradation translates to a significantly impaired user experience, *e.g.*, increasing the number of perceivable freeze periods while video-streaming by a factor of 10 and their total duration by a factor of 20, spending 34% of the streaming duration frozen, in comparison to merely 1.7% when using MU-MIMO under the same conditions [1, 61].

The key behind Matrix-bending is a strategically disruptive behavior in which a Neo reports its CSI with the goal of deliberately "populating" the clients' signal space as seen by the AP. By doing so, the Neo confuses the AP, which in turn fails to create "good" user clusters. In particular, by becoming a desired member of most client groups, and by driving the system towards generating extremely sub-optimal groups, the Neo effectively breaks client selection algorithms, leading to substantial throughput degradation

We demonstrate the following important features of the Matrix-bending attack: $(i)$ Matrix-bending is *a low-profile* attack. A Neo does not apply any jamming, and transmits data using only a single antenna. Moreover, it generates CSI that is statistically indistinguishable from the CSI generated by regular clients, and is capable of achieving its full impact while generating traffic at volumes that are more than an order of magnitude smaller than those generated by a regular client. $(ii)$ A single Neo has the capacity to considerably decrease MU-MIMO's throughput gains, *i.e*, by up to one third, even in the presence of $100$ legitimate clients. To bring an MU-MIMO system performance to the level of a corresponding single-user system, the number of Neos in the system need not be large, and does not depend on the number of regular clients in the system. Instead, the required number of Neos corresponds to the number of clients in a beamforming group, which is theoretically upper bounded by the number of antennas at an AP, and in practice often bounded by a smaller number, *e.g.*, $4$ in 802.11ac [48].

We design and implement a real-time 802.11ac beamforming system on a software-defined radio platform that allows us to evaluate Matrix-bending on over-the-air 5 GHz channels with complete access to CSI [2]. We evaluate MU-MIMO client selection algorithms and policies in the presence of Neos. We show that falsifying the CSI, *i.e.*, the V-matrix, of a single Neo is sufficient to reduce a substantial portion of MU-MIMO's throughput gain, *i.e.*, approximately by one third. Using 3 Neos, the throughput degrades by approximately $3\times$, often experiencing performance below the corresponding SU-MIMO system. We find that Matrix-bending's effect is most dominant over APs that attempt to maximize throughput, while it is expectedly less pronounced for the schemes that do not focus on throughput.

We further study the potential defenses against Matrix-bending. First, we evaluate random user selection algorithms. While they are less vulnerable to Matrix-bending attacks than other algorithms, such a feature comes with a significant cost: the throughput of such systems decreases below the levels achieved in SU-MIMO systems, even in the absence of a Matrix-bending attack. Second, we evaluate client CSI encryption. We find that Matrix-bending is quite effective in such scenarios when it has *no knowledge about the CSI from other clients.* The key reason is that as long as the Neos' responses are near-orthogonal to each other, they will affect other users as well. Third, we find Matrix-bending to be equally effective when it has no knowledge about its own CSI. In particular, we evaluate a method that utilizes unknown sounding preambles which aim to prevent CSI manipulation. However, we show that all realistic preamble transformations still preserve the *relative signal properties* such that the attack is still effective.

**Research Agenda**

We propose to address challenges stemming from the *physical layer* attacks on IoT systems. We will evaluate the attacks, and defenses, enabled by MU-MIMO systems. In particular, we propose research in the following directions:

*Silent DoS.* In this scenario, the attacker can jam all communication between clients and an AP in both directions, while *quiet-bubbling* the APs antennas, therefore preventing it from sensing the disturbance. The key research questions are how to effectively use *implicit* CSI in order to quiet bubble the APs and to understand the impact on the APs performance.

*Silent scrambler.* In this scenario, we consider Wi-Fi-enabled backscatter communication, where signals generated by a Wi-Fi source are backscattered by a client device. In this case, the attacker node (an 8-antenna 802.11ac AP) transmits a time-varying signal while quiet-bubbling the Wi-Fi source. The backscatter client-device responds to the scrambled signal it receives, thus disrupting the communication. *Power-killer attack.* In this scenario, we again assume the above Wi-Fi-enabled backscatter communication. The goal of this attack would be to null the signal at the backscatter device, such that the energy harvested by the backscatter client is insufficient to enable transmissions. The key research question is to determine critical time-scales and its impact on the effectiveness of the attack.

*Countermeasures.* We propose to analyze countermeasures to the above attacks. The most promising approach for the silent DoS attack is to equip APs with an additional, passive antenna, that would collect the information from the environment. Then, we would further conduct statistical analysis to find critical time scales that enable the attack detection with appropriate confidence guarantees. For the silent-scrambler and power-killer attacks, we will pursue solutions that do not require additional hardware. In all cases, we will conduct experiments on a real-time 802.11ac beamforming system on a software-defined radio platform on over-the-air 5 GHz channels [2].

(Farid + Alex)

Data security
System level security
Privacy, anonymity

Greedy behavior (?)
Key sharing problem

Privacy, trust and anonymity

## 4.4 Implementation and validation

(All)

Letters of Collaboration)
Campus wide implementation
Letters of Commitment
Shall we rely on KAA?
APIs: flexibility of formats/schemas

Given the interdisciplinary nature of the tasks in the proposed project, it is necessary to have well-defined mechanisms for assessing the validity and benefits of our findings. We will base our demonstration on variations of the two methodologically interdependent scenarios used in the introductory section. We now discuss both the broad categories of evaluation environments, and the details of the particular evaluation methodologies. We will adopt a three-fold analysis of the different aspects of our system: (1) agent-based computer simulations, (2) experiments with real humans controlling avatars in shared virtual worlds, and (3) experiments with real humans in actual real-life environments. Each of these experimental paradigms allow us stress our system along a combination of the following three axes: (1) human stress, (2) replicating the noise inherent in using humans as sensors, and (3) scalability ? i.e., the number of participants (humans or agents). Agent-based simulations harness computation to simulate high-stress events in arbitrarily large crowds of computer agents, but are unable to accurately model humans. Shared online virtual worlds provide a unique opportunity to conduct experiments with real humans in controlled settings. While experiments with human subjects in the real world offer the closest possible parallel to reality, these experiments are limited in number of subjects and the extent of stress that we can induce on the participants. However, by leveraging combinations of all 3 paradigms, we are uniquely positioned to evaluate our models and technologies in a rigorous manner.

### 4.4.1 Simulation-based Evaluations: Agents.

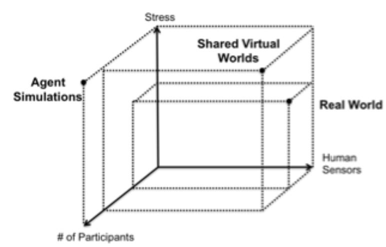


Fig. 4: Evaluation using Agent simulations, Shared Online Virtual Worlds, and Real World Experiments.

The first part of our efforts will focus on developing simulator for the two demonstration settings. Throughout the different phases of the project we will be capitalizing upon ? as well as augmenting the current capabilities of ? the SIDnet SWANS simulator [195] and SteerSuite: The Human Movement and Crowd Simulator [196], being developed at Northwestern and Rutgers respectively. SIDnet is used to evaluate various routing and tracking protocols, shapes detection, and even to evaluate the benefits of high-level programming constructs for WSN-users [113, 160, 187, 191]. SteerSuite is an open-source framework for simulating human movement, deliberation, and is especially geared towards dense crowd situations. We will integrate the functionality of these two systems and further augment them with the capability of having heterogeneous nodes and capturing various mobility models and communications between subsets of such nodes. In addition, we will augment its visualization component as well as introduce a new class of nodes with the proper interfaces to encode the following important features: (1) camera/video/audio based sensing and (2) human and human-operated sensors. For the multimodal mashup scenario, we will simulate a simplified version of the ?Gold Miner? using computer imagery, with virtual objects and sensors. The main use of the simulator in the initial stages of the proposal will be to test the various impacts of uncertainty (sensors, network structure/communication) on the quality of detecting the novel categories of spatio-temporal predicates (cf. Section 3.4) and the impact of different policies for local state-estimation and information extraction (cf. Section 3.1 and 3.3). We will employ a large variety of crowd datasets to train and validate our computational models, and in particular leverage our collaboration with Prof. Dirk Helbing who has significant expertise in crowd data collection, analysis, and modeling [197]. In particular, we will integrate our simulation infrastructure with the NervousNet platform [198] that is being actively developed by Prof. Helbing and his colleagues as part of the larger effort on the Planetary Nervous System project [199], which provides a large-scale distributed research platform for real-time mining of social activities using heterogeneous sensor networks.

### 4.4.2 Task E-2. Game Playing Evaluation: Avatars.

Agent-based simulations, such as those described above provide an efficient way to test and evaluate the different aspects of our system in an automated fashion. However, in an effort to come closer to actual human experimentation, we will conduct experiments using real human users in shared online virtual environments. The Rutgers team is uniquely positioned to conduct these experiments ? Co-PI Kapadia has developed HeapCraft [200, 2001]: a modular, extensible, and open framework for studying human behavior in shared virtual worlds such as Minecraft. HeapCraft has already been successfully demonstrated to study player behavior and incentivize cooperation in online societies [202, 203]. Additionally, Kapadia and his collaborators have also conducted lab experiments to study crowd evacuations using serious games. We will augment the existing HeapCraft framework to design the two scenarios described in Task E-3 below. HeapCraft?s modular and extensible nature allows us to easily develop emulators for the technologies being developed here, which can be rigorously and robustly tested in shared virtual worlds using real human users. In addition, we will augment the knowledge-base for emulating behavioral aspects of the avatars using large datasets of preferences and semantic relations from real social networks obtained from 4C Insights Inc. (Letter of Commitment is available in the Supplementary Documents). Our experiments will be conducted in two phases: (I) laboratory studies where up to 40 participants will be recruited to participate in a controlled experiment; (II) online server with our tools released to setup a virtual world with hundreds of human-users expected to participate.

#### 4.4.3 Task E-3. Real-World Environment Evaluations.

The system we intend to develop is intrinsically oriented to be open source. It will need obviously the contribution of community members to feed, more or less automatically, the database of avatars in the social network of things. It also relies on a proactive contribution of users to improve the rules generator services. Rules generator, indeed, should not be a static repository of rules. Rather, it is a module which dynamically generates and improves rules at runtime. The way to accomplish these tasks, i.e., the software to do it, is based on well assessed algorithms. Nevertheless, it should be also open to improvements by the users. As common practice in open source communities, a third party serves as the booster of the software and the filter of contributions from users. We expect also that manufacturers and retailers will be highly motivated to foster this software so as to maintain the performance of their apparatuses at the high end of the market, with economic consequences. Users, meanwhile, are naturally inclined to communicate their best practices and analysis. They can do so at two levels: (1) just by issuing rules/instructions in a highly simplified script language involving both experience and their logical capabilities of formalizing it in a few well-formed expressions, and (2) by more sophisticated interventions on the open source codes, profiting their high level software experience and their knowledge of cognitive disciplines.
The primers of this community will be represented by two kinds of experiments respectively realizing small scale and large scale assets of our system.

**Small scale:** A mock-up of the system will be physically realized in the lab of one of the partners (IIT?) with virtual extension to the other partners labs. Namely the former will consist of:

- a set of 4 to 6 household appliances/IoTs connected to a middleware fog.
- a middleware fog hosted by a gateway that is connected to Internet.
- a social network instance hosted by a local server.

Equally relevant features validating the system will be:
(1) its reliability and recovery procedures w.r.t. any kind of inconvenience, ranging from power breakdown to loss of the Internet connection, or even hostile attack from an insider/outsider. The mock-up will also constitute a ground truth reference for the second class of experiments.
(2) its manageability on the part of the ordinary people, both in terms of realizing a middleware fog and connecting IoTs/appliances to it, and in terms of efficiently ruling the appliances/IoTs.

As for the last aspect, the cognitive capabilities of the networked intelligence will be dynamically improved as the entire project evolves.

This mock-up will constitute a continual ground truth reference for the second type of experiments.

**Large scale:** Due to the great computational effort and massive statistics database required, this social community can survive only if attracts a huge number of members. Therefore, a main task of this project is to promote the functionalities of our infrastructure within the research community. In particular we plan to implement a cluster grouping from 1,000 to 10,000 domestic gateways (middleware fogs). Basing our dimensioning on the lower bound, the cluster should manage a total of 1,000,000 nodes. Many of the middleware functionalities are implemented locally on gateways (fogs). However, most of them needs frequent connections to the social networks of things, for instance to consult catalogues, reference instructions, tuning parameters, etc. We plan to attribute 2 GB of memory mass to each middleware which is comparable with normal memory supply of smartphones and other smart personal appliances for a total of 2 Terabytes. Moreover, given the scarce criticality of the ruled functions, we assume the clock stroke to be of the order of 1 second, and we prepare our software to manage a flow of 5,000 requests per second. These requests should be handled through 50 parallel processes entailing 25 GB RAM. As for the social network we plan to use 10 servers with 50GB RAM and 1TB memory for managing their operations in a modular and scalable way.

# 5 Broader Impact

From Rutgers:

The proposed highly interdisciplinary project combines computer vision, human modelling and simulation, optimization, robotics and autonomy, and control theory, and has the potential to impact several research areas. The proposed sensing, simulation, and optimization framework will have wide applicability in various scientific areas involving decision-making in heterogeneous and dynamic networks comprising human-operated, and autonomous sensors, with concepts that could easily generalize to event understanding in complex social, economical or cyber-biological systems, thus impacting multiple societal applications including urban infrastructure, emergency response, safety, and quality of life.

**Datasets.** We will release the reconstructed time-stamped behaviors that are collected as part of our real-world experiments in the classroom and the dining hall. This real-world dataset will include both the original, unprocessed, noisy, incomplete trajectories, as well as the processed trajectories for researchers to use and compare, when developing their own algorithms. We will also release synthetic datasets from our simulation experiments using the data-driven crowd simulator that will be developed as part of this research. All crowd datasets (both real and synthetic) will be captured for both the original, un-optimized environments, as well as the optimized layouts. We will also release extended designs actuated of environmental elements such as mobile queue separators and mobile furniture.

**Open-Source Software.** The PIs have an established record of releasing software packages related to crowd modeling and simulation [**?**, **?**]. We will build on top of these foundations and extend our existing open-source platforms to include software solutions for: (1) crowd trajectory reconstruction, (2) data-driven crowd simulation, (3) static and dynamic analysis of environments, (4) crowd-aware environment optimization, and (5) environment reconfiguration planning.

**Kaggle Competitions**. We plan to organize 2 public data analytics competitions using the collected data, hosted on kaggle.com. Kaggle is a platform for predictive modelling and analytics competitions, which is often used in academia to incentivize students to tackle challenging problems through a combination of research, system building, and peer-competitions. The goals will include trajectory estimation and reconstruction, data-driven crowd modelling, and computer-assisted designs of environments.

**Curriculum Development and Outreach.** The PIs will generate educational material on the autonomy, hardware design, sensing and simulation aspects. PI Kapadia will design a graduate seminar on *Crowd-Aware Smart Environments* that will introduce students to concepts in crowd simulation, and environment optimization. Advanced undergraduate students will also be permitted to enroll. PI Pavlovic will introduce an assignment in the machine learning course where students will learn generative models of crowd movement. The PI's will collectively organize a workshop on crowd-aware cyber-physical environments during CPS week (tentatively April 2017), which will bring together researchers from various disciplines including computer vision, machine learning, simulation, robotics, and potential adopters of the technology. Our research environment will provide interdisciplinary training ranging from distributed sensing and control, simulation and optimization, to robot motion planning.

**Under-Represented Groups and K-12 Level**. Our project can help attract a diverse group of students and broaden the diversity of students recruited into these and other STEM disciplines. Rutgers office of Enrollment Management conducts the Rutgers Future Scholars Program (RFS), which provides mentoring activities to grade 9-12 minority students from disadvantaged backgrounds and full scholarships to undergraduate programs. We will closely work with this office to participate in outreach, enrichment, and mentoring activities. We will also leverage other programs to recruit and mentor students from under-represented groups: the summer undergraduate Project RiSE (Research in Science and Engineering) for undergraduates from underrepresented populations for 8/1-week intensive summer research internships; and the Aresty Center for Rutgers Undergraduate Research- places Rutgers undergraduates in research laboratories on campus. PI Pavlovic has a multi-year track record of working with over 14 minority and female students through Aresty and RiSE, as well as multiple REUs. We will leverage the extensive diversity programs at Rutgers to recruit and support women and underrepresented minorities.

# 6 Results from current and recent prior NSF support

**Pavlovic:** The prior most closely related NSF award is IIS 1135717 RI: Small: Novel structured regression approaches to high-dimensional motion analysis, 9/1/09 - 8/31/13, \$370,292. *Intellectual Merit:* Predictive learning methods for human motion and human affective signals. Developed methods include novel dynamic ordinal regression approaches for modeling of the discrete intensity signal envelopes, and methods for inclusion of contextual information (subject-specific, event-specific) for improved event state estimation. *Broader Impacts:* Contribution to the development of human resources in science and engineering by supporting and training over ten graduate students on these grants, in addition to 14 undergraduate researchers (five of them women and minorities) supported by REUs. Products resulting from both projects are 17 publications in leading conferences (CVPR, ICCV, NIPS, ICML, ECCV) and journal publications (T-PAMI, T-KDE, IJCV) [27, 55–59, 89, 90, 97–101, 104–106, 137–140]. Two open source software were released at http://seqam.rutgers.edu.

**Aleksandar Kuzmanovic** has done extensive work in congestion control [26, 62, 63, 67, 69, 71, 85], DoS resiliency [34,42,65,68,70,77,83,84,117], measurements [32,33,64,66,73,113,114,117,121,122,127], and Web [14–16,38,39, 78,115,116,120,123,127–130,133–135]. He is currently the PI of CNS-1319086, $473,445, 8/30/13 through 8/29/17, *NetS: Small: Endpoint User Profile Control*. The **Intellectual Merit** of this proposal lies in developing auditing mechanisms on the web, and the key **Broader Impact** of this proposal is the deployment of a set of first such tools for the Web; the list of publications resulted from this project is [38, 78, 115, 116, 128–130, 135], and the list of research products from this project is available at `http://networks.cs.northwestern.edu/audit-content/`.

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# 7 Data management plan

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# 8 Project management plan including timeline

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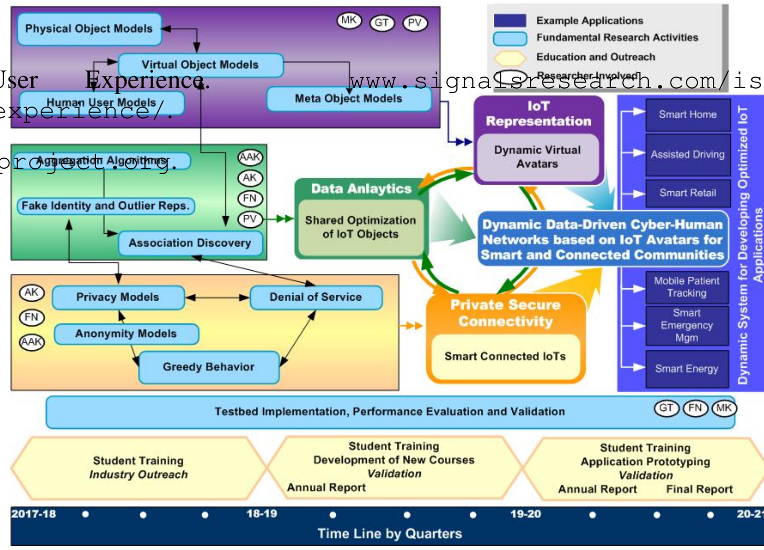


Fig. 5: Collaboration and Deliverables

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