Kasthuri Jayarajah | Research Statement

As cities worldwide invest heavily in smart city infrastructure, it invites opportunities for a next wave of cyber-physical systems (CPS) and applications. Unlike its predecessors, they can now be ***real-time, predictive and proactive*** – in my work, I (a) optimize sensing pipelines of networked sensor deployments to achieve improved machine intelligence with cheap hardware, (b) leverage smartphones and infrastructural sensors and social sensing to capture various physical contexts, (c) use analytical and behavioral insights to both proactively optimize urban operations and promote smarter policy decisions, and (d) intervene at real-time to actuate human behavioural change. My work explores solutions to real-world urban problems cutting across **applied machine/deep learning, edge computing, indoor/outdoor mobility modelling, network science, urban science and marketing science**.

My work has featured at top-tier conferences and journals (over 10 publications at **UbiComp/IMWUT, MobiSys, SenSys, CIKM, ACM TOIT**). Recently, I was named one of 5 finalists worldwide for the **Gaetano Borriello Outstanding Student Award at UbiComp 2019**, and I'm a recipient of the **Google Women Techmakers Scholarship** (APAC, 2017) and the SMU Multidisciplinary Doctoral Fellowship (2018). My PhD has been supported by the A*STAR Graduate Scholarship and the SMU-CMU LARC Exchange Fellowship. I have forged fruitful collaborations with academic (e.g., Cambridge University w/Cecilia Mascolo, UIUC w/Tarek Abdelzaher, Carnegie Mellon University w/Bei Bei Li) and government organizations (e.g., Urban Redevelopment Authority, Singapore).

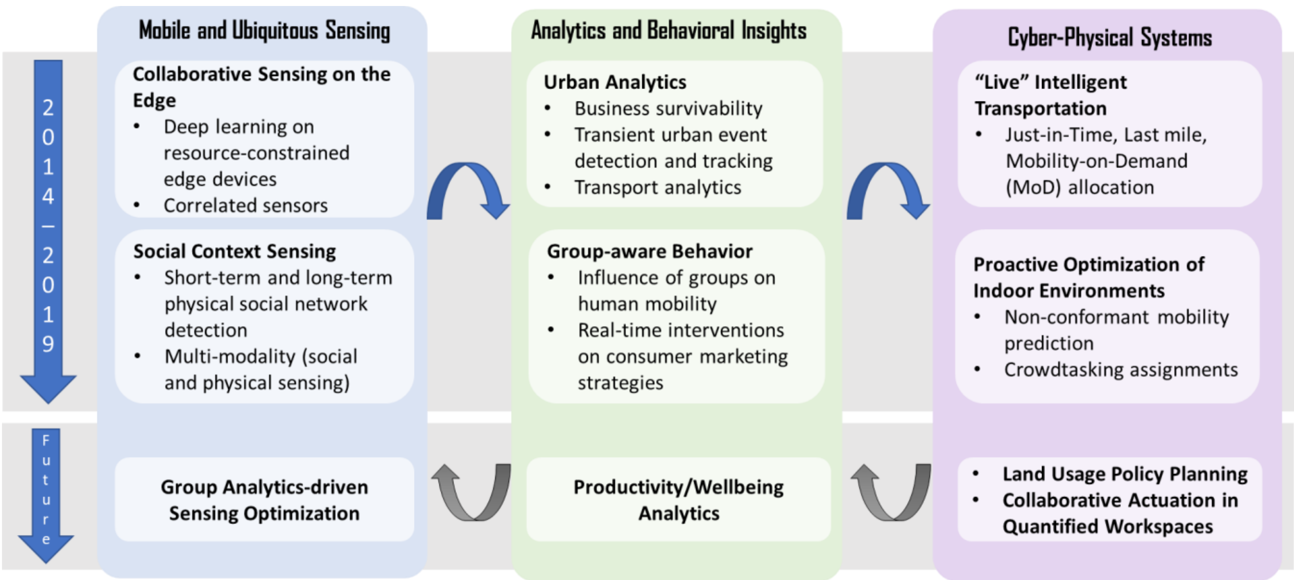

Figure 1: Research Overview

In my dissertation titled "Exploiting Mobility for Predictive Urban Applications and Operations", I have specifically focused on exploiting individual and collective mobility, at various scales (e.g., within buildings, city-scale, etc.) to enable a range of novel cyber physical systems. Within this broader theme, my current research interests and accomplishments can be organized around three technical themes, as I illustrate in Figure 1.

(1) Mobile and ubiquitous sensing: This research focuses on the astute use of smartphones and infrastructural sensors for capturing novel physical contexts such as the social groups of occupants in smart environments. More recently, to support the vision of a billion tiny IoT devices operating at the edge and processing rich sensory inputs (e.g., video/audio) for real-time applications, my focus extends to optimizing sensing pipelines through the concept of Collaborative Sensing.

(2) Deriving analytics and behavioral insights: This line of research focuses on characterizing individual and collective human behavior (movement behavior, in particular), at campus and city scales, for generating analytical insights cutting across domains such as retail (e.g., longevity of businesses), transportation (e.g., urban event detection) and consumer marketing (e.g., customer attitudes towards promotional campaigns).

(3) Enabling cyber-physical systems that are *real-time, predictive and proactive*: This research focuses on enabling novel applications such as "live", intelligent transportation systems. For example, the BuScope system [4] ingests public transportation transactions at *real-time*, generates *predictions* of disembarkation of its thousands of commuters, and *proactively* allocates mobility-on-demand, shared vehicles for last-mile mobility that dramatically reduces wait times of commuters.

My research interests further extend to explore the **interconnections between these themes**. In past work, I've investigated the forward path (signified by the blue arrows in Fig 1) where I explored the use of **WiFi-based campus-scale indoor mobility** data to (1) **sense** social contexts of individuals (both short-term groups and enduring, longer-term relationships), (2) studied **behavioural variations** in individuals under the influence of such social groups, and (3) exploited insights on such variations for **proactive optimization** of smart building applications (e.g., predicting deviations from routines to optimize worker allocation in a crowd-tasking platform [3]).

As part of future plans, in addition to deeper investigations within these themes and their forward connections, I'm keen to explore, as signified by the grey arrows in Fig 1, (1) how analytical insights can in turn inform optimization strategies for sensing/inferencing infrastructure (e.g., use probabilistic estimates of stay times of groups to subsample vision sensing for energy benefits), and (2) in deriving behavioral insights from the sustained use of novel cyber-physical systems (e.g., employee acceptance and improvements in wellness/productivity through behavioural interventions in quantified workplaces) – essentially, closing the loop between the three themes.

1 Sensing and Optimization

1.1 Collaborative Vision Sensing on the Edge

A variety of physical environments, including smart cities and tactical battlefield networks are increasingly being instrumented with large numbers of resource-constrained sensors and IoT devices (e.g., cameras, microphone arrays and environmental sensors). A rising recent trend involves executing inferencing pipelines (to perform increasingly complex tasks, such as object recognition or target localization), ***in-situ*** and in ***real time***, at such edge nodes. There are two salient features associated with these trends: (1) Sensors are often deployed with varying degrees of redundant coverage--e.g., cameras in buildings often have partially overlapping fields of view, implying that their sensed data are implicitly spatiotemporally correlated, and (2) inferencing increasingly involves the execution of computationally prohibitive machine learning (ML) pipelines (e.g., CNNs for image-based object detection). Executing such deep neural networks (DNNs) gives rise to well-known throughput bottlenecks and prohibitive energy consumption.

We introduce and explore the paradigm of **Collaborative Deep Intelligence** that exploits **sensor multiplicity** (e.g., a group of networked cameras with overlapping views) for performance benefits such as improved accuracy with minimal overhead of latency. We explore alternate designs for collaboration for the illustrative task of person detection on video sequences [1, 2]: (1) probabilistic fusion of independent deep inferences at the output stage (CNMS) [2], (2) augmentation of the image channels of a reference camera (i.e., the typical RGB) with additional input from collaborator views' past inferences (CSSD) [2], and, more recently, (3) by **adapting the ML pipeline on-the-fly. For the latter,** we do so by (a) first employing a light-weight scene summarization technique that extracts knowledge from collaborators' views, from early hidden layers of the deep pipeline that is shared over the network and (b) injecting the digest back into the later layers of the reference camera's processing pipeline for improved accuracy. Compared to the former alternatives, this design incurs zero re-training of the deep networks, adds minimal overhead to the processing pipeline and the bandwidth required for sharing digests over the network and seamlessly rolls back to the default, non-collaborative operational mode when collaborators are not available or deemed unreliable.

This work is thus motivated by a fundamental research question: ***to enable execution on mobile/embedded devices, is it possible to rely on collaboration to replicate the accuracy of very-deep, but high accuracy neural networks while incurring the computational expense only of shallower, older DNNs (with concomitant latency and energy benefits)?*** On benchmark datasets, we observe an improvement of 10% recall (20% gain) with as little as a single collaborator.

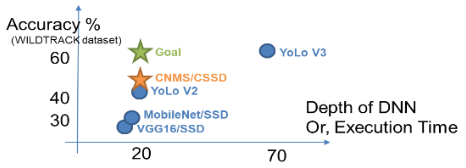

Figure 2: The trade-off between detection accuracy and depth/complexity of state-of-the-art DNNs. As the complexity increases it is possible to obtain improved accuracy. In this work, we exploit collaborative intelligence to bridge the accuracy gap between shallow and deep DNNs for vision sensing.

In ongoing work, I explore additional performance benefits by virtue of collaboration – for instance, we explore a range of operational modes including (a) hybrid execution of shallow/deep processing across nodes, and (b) early discard of deep pipelines based on reliability estimates at early layers of the pipeline, for potential savings in energy of battery-powered devices.

1.2 Social Context Sensing [9, 10]

A large part of my PhD research has focused on understanding collective and individual mobility behaviour of humans, both indoors and outdoors. To understand collective behaviour, it is key to extract the social relationships amongst co-located individuals. To passively detect organic social groups, we rely on correlated movement (exhibited via WiFi-based mobility and inertial sensors on-board the smartphone carried by individuals) [10]. Through the use of continuous and longitudinal mobility observations made available via a server-side, WiFi-based indoor positioning system, and by adopting measures from network science, I developed a set of features, based on their collective spatiotemporal co-location characteristics, to quantify the strength-of-ties between different students [9]. As I explain next, such passively extracted "physical – social" relationships have been demonstrated to reveal key insights into human mobility (sections 2.2 and 2.3) which has then been exploited to enable novel, proactive applications in indoor environments (section 3.2).

2 Mobility-driven Analytics and Behavioral Insights

2.1 Analytics for Urban Policy Decisions [5, 8]

Retail Analytics for Land Use Governance [5]: A key question that urban planners grapple with is in allocating the land resources of a city for different uses such as residential, commercial and recreational. In this work, I investigate how aggregate mobility data from heterogeneous sources such as public transportation and social media, can aid in quantifying urban constructs (e.g., customer visitation patterns, mobility dynamics of neighborhoods) and then demonstrate their use, as an example, in predicting the survival chances of individual retailers, a key performance measure of land use decisions of a city. Intuitively, check-in volumes and comments on such social networks provide a sampling of the visitor interactions at individual venues and reveal the competitive distribution of retail outlets across different neighbourhoods. By combining such venue-oriented information with neighbourhood-scale traffic flows, derived from taxi data, the likelihood of individual retail businesses (especially restaurants) failing, over the next 6 months, can be predicted with over 80% accuracy, across 10 different major cities. With retail being a notoriously competitive business, our techniques open up the possibility for urban planners to obtain fine-grained predictions of the vibrancy of retail businesses in different sectors and neighbourhoods, and thereby perform policy-level interventions (such as rental rebates) to alleviate such economic weaknesses. This work is important as it demonstrates how urban mobility & social media data can be collectively combined to characterize the performance of individual businesses, going beyond the commonplace use case of optimizing transportation operations.

2.2 Empirical Insights on Indoor Mobility and the Influence of Social Ties [3, 8]

As humans spend a significant portion of their daily lives interacting with others, understanding how the presence of social groups (e.g., friends, families, etc.) affects human behaviour is an area of enduring and practical interest. My work focuses on discerning the differences in the behavior of individuals in public spaces (e.g., campuses, shopping malls), when they are alone vs. when they amongst groups [8]. In particular, I focus on three aspects of behavior: (1) people's mobility patterns (stay times at places and next place transitions) for over 6000 students on SMU campus, (2) level of interruptability (responsiveness to calls/SMSs), and (3) app usage. The analyses revealed interesting findings that can ultimately impact design decisions of smartphone-based systems and applications. For example, the individuals in larger groups tend to dwell at places for longer amounts of time, but they are also less likely to move together from place to place, when compared to individuals who are alone or are in small groups. Information such as this is useful in applications such as context-based advertising (if the advertiser estimates that the best time to send a targeted promotion is when a person is about to transit to a particular store) and as I elaborate in future plans, possibly open up opportunities to optimize the sensing infrastructure. Further, by studying mobility and social ties at multiple scales (i.e., indoor and outdoor), I demonstrate that human mobility is predictable and that feathers of a bird indeed flock together with social ties exhibiting high similarity in their routineness [3].

2.3 Real-Time Interventions in Marketing and Social Science Settings [6, 7]

The LiveLabs ecosystem [11], deployed on our SMU campus, allows for the study of human behaviour through the capture of hyper-contexts such as location and group, at real-time. It consists of (a) a passive, server-side system for monitoring indoor mobility of thousands of users who connect to the university's WiFi infrastructure, (b) a suite of mobile applications running on opt-in participants' phones that capture interactions of its participants with their respective phones, and (3) a behavioural intervention engine that allows experimenters to use such contexts to send interventions, in the form of mobile notifications, to the participants' mobile phones, to actuate behavioural change or theorize new hypotheses. The eco-system was validated to allow for in-the-field, randomized behavioral experimentation [7].

In an effort to enable a **novel class of social experimentation** driven by the situation context of participants [6], we measured the cohesiveness of organic, social groups on-campus, at real time, and demonstrated its role in consumers' attitude towards mobile promotions. Prior literature in consumer marketing research have found that several key contextual variables (e.g., time, location and crowdedness at which a consumer receives the promotion) influence consumer attitudes towards promotions. In this research, we theorized and investigated the joint influence of temporal proximity (to the promotion validity period) and the strength of the social group a consumer is in, at the time of receiving a promotion, on the consumer's response to promotions. We theorized that a consumer belonging to a cohesive group (characterized by a low weighted ego-network diameter) will prefer a promotion offer that is temporally proximal (vs. distal)—i.e.., one that can be redeemed fairly soon. On the other hand, an individual belonging to a diffusive group (characterized by a high weighted ego-network diameter) will prefer a promotional message with a longer lead time.

3. Predictive Cyber Physical Systems

3.1 Enabling ``Live" Smart City Services [4]

Thus far, while urban commuting data has been used extensively in providing useful insights into human mobility behavior, such analysis have been performed largely in offline fashion and to aid medium-to-long term urban planning. One key contribution of my research has been in advocating for **near real-time and**

predictive mobility-driven urban applications. In [8], we demonstrate the power of applying predictive analytics on real-time mobility data, specifically the smart-card generated trip data of millions of public bus commuters in Singapore, to create novel and **"live" smart city services**. We base this work on the observation that a vast majority of public bus trips are predictable and driven by routine commuting patterns which manifests in two aspects: (a) individual-level regularity and (b) aggregate-level conformity.

We propose and evaluate **BuScope**, a live mobility analytics platform, which enables making operational decisions or generating neighborhood-level insights on streaming mobility data, with **O(mins) responsiveness**. The platform is flexible enough to recompute the analytical insights, at both individual and bus-level specificity, very frequently for peak city-scale workloads—e.g., it incurs 17.33 msecs average latency to process each of ~270,000 boarding and alighting transactions generated by 221,217 commuters on 3777 buses, during a typical weekday, 30-minute peak period. Using realistic neighbourhood-scale simulation models, we show that look-ahead prediction of the number of disembarking passengers allows us to dynamically pre-position shared, last-mile vehicles at different bus stops—this can reduce the waiting time experienced by a disembarking customer by 75%, to about 30 secs for single capacity vehicles.

3.2 Proactive Optimization of Indoor Environments: Non-Conformant Mobility Prediction [3]

In the past, studies have relied on the predictability of mobility to generate various urban insights. In a complementary effort, this work demonstrates **the ability to even predict instances of *unpredictability***, sufficiently in advance – i.e., to predict moments when individuals will default from their routine behavior. This work describes a framework to detect episodes of future anomalous mobility using an individual's current deviation from his/her routine mobility together with the anomalous behaviour of his/her social ties, with over 90% accuracy even at reasonably long look-ahead times of 4 hours. Such social tie-aware prediction of unexpected movement behaviour is not just of academic interest; we show how proactive optimization of urban operations is possible through the exemplar use case of task assignment to crowd-workers on a smart campus. We demonstrate that, in comparison to workers with a likely anomalous mobility behaviour, others achieve higher task completion rates.

4. Future Research Plans

In the coming future, I intend to broadly investigate the possibilities around ***dramatically increasing the operational efficiency of future urban environments through a combination of applied ML advances and human behavior-driven optimizations***. I am excited to explore opportunities for optimizations in the following key problem areas that I believe are central to future cities:

(1) Sensing at the Edge: With a paradigm shift towards edge-centric smart city applications where low-powered IoT devices store, process and analyse data at real time[1], there's an increasing need for optimizing sensing and inference pipelines. While my present work explores re-configurations of the ML pipeline, I believe that human behavior-driven strategies have largely been unexplored, thus far. Such optimizations should also cater for heterogeneous deployments – for e.g., sensors that are multi-modal and offer varying fidelity (resolutions, sampling rates, etc.). Enabling such low-latency and energy-efficient sense-making will be desirable for future scenarios involving, for e.g., human-robot interactions as part of Industry 4.0 and autonomous vehicles.

(2) Future Work Environments: While the success of smart environment deployments has traditionally been measured through hard metrics (e.g., wait time reduction of transportation systems), increasingly, there has been interest in softer metrics such as the quality of life of its residents, and productivity[2] as a sign of the health of the economy. With an anticipated boom of personal wearables

[1] https://www.computerworld.com/article/3509960/internet-of-things-trends-for-2020.html
[2] https://newsroom.intel.com/wp-content/uploads/sites/11/2018/03/smart-cities-whats-in-it-for-citizens.pdf

and IoT devices at workplaces[3], unobtrusive, continuous and privacy-preserving quantification of productivity and employee wellbeing, I believe, will be of critical interest for future cities. In addition to offering behavioral insights, a key application of technology would be in enabling in-situ interventions for promoting positive behavioural change.

(3) Policy Planning of Traditional Urban Resources: I am excited by the possibilities of data-driven planning and policymaking related to traditional urban resources such as real estate. For instance, driven by the careful analysis of large-scale human behaviour and choice data (through a combination of physical and social sensing), in future, key policies on the optimal blend of trades a local neighborhood that maximizes both the utility for its residents as well as the business units, could be achieved.

I elaborate on the individual work products I intend to explore in detail, below.

Behavioral Insights-Driven Sensing Optimizations: In my work so far, I have considered optimizing deep learning-based inference pipelines by exploiting sensor multiplicity -- i.e., improving the inference accuracy by sharing perspectives across a group of sensors. However, I envision that significant additional optimizations are possible through the inclusion of mobility-driven behavioral insights (for e.g., on mobility) back in to the sensing pipelines. As I described earlier, human mobility, in the presence of social ties, varies from individual mobility (e.g., dwell times at restaurants). Such dwell time and transition-related heuristics, I envision, can open up exciting avenues to optimize the vision-sensing logic of cameras in future. Given that a group is detected within a region of a camera's perspective, using the a-priori knowledge that the group would stay at the same location for the next 15 minutes (with high probability), the camera can thus refrain from processing that specific area within its view resulting in overall savings on processing effort. In future work, I would like to explore a range of such individual and collective mobility-driven aspects in the optimization of the mobility sensing infrastructure.

Multi-Modal Collaborative Sensing: Whilst my current research focus has been limited to optimizing vision sensing on embedded platforms, the concept of collaborative sensing per se is not limited to the vision processing alone. More generally, the possibility to collaborate and share sensed perspectives, should and is applicable across other sensing modalities and inference pipelines, both deep (e.g., keyword spotting across voice-based personal assistants such as Alexa) and shallow (e.g., gesture/activity recognition across a set of body-worn smart devices). In addition to the exploration of improving performance metrics such as accuracy, latency and throughput at inference time, there's also opportunities to investigate whether and if the training process can too benefit from sensor multiplicity. I'm also excited about opportunities to extend collaborative intelligence to cross-modal sensors (e.g., audio and inertial sensors on a group of Earable devices) and am currently brainstorming novel use cases in such settings.

The above two lines of enquiry, I believe, would be of interest to researchers from embedded systems and ubiquitous computing groups, with special focus on enabling energy efficiency and low latency in low-resource environments.

Quantified Workplaces, Insights-Driven Collaborative Actuation and Behavioral Interventions: While my PhD work has primarily focused on sensing, analytics and applications based on human mobility, as part of future work, I plan to venture into other aspects of daily life – productivity and wellbeing in workplaces (specifically, open plan offices). Despite the early welcome of such open work spaces touted to improve collaboration and innovation, there has been growing concern that such spaces can actually hinder productivity due to a variety of reasons[4]. As a first step, I plan to instrument a working lab with multi-modal sensors (head-worn EEG sensing to passively detecting bursts of productivity vs. distractions, ambient sensing including noise levels, light levels and temperature, and social/proximity sensing to measure the impact of people presence) to curate longitudinal analytics and insights related to human productivity and wellbeing (both, physical and emotional)

[3] https://iiot-world.com/smart-buildings/smart-workplace-and-the-internet-of-things/

[4] https://hbr.org/2019/11/the-truth-about-open-offices

in open spaces. Using such insights, I'm excited to explore the feasibility of collaborative actuation of the workplace infrastructure (e.g., adjust lux levels, AC vent openings) and behavioural interventions (e.g., ambient reminders to sedentary workers requesting to take breaks) on improving worker wellness and performance. I believe that this line of research would be of interest across multiple disciplines including ubiquitous computing, organizational behaviour and preventive medicine.

Land Use Policy Planning: As a natural extension to the retail survivability analytics line of work, with collaboration from government agency partners, I am exploring ways in which the analytical insights can be used for future policy planning of the city. A key direction currently pursued is in understanding aggregate trade viability (as opposed to individual businesses) across different parts of the city to then devise the optimal mix of land use (e.g., 50% F&B, 10% parking facilities, 30% other retail, 10% public transportation infrastructure) for both existing and greenfield land parcels that maximizes the potential use of the limited land resource to benefit both the public and vendors. Additional questions also include the exploration of how the opening (or closure) of individual business of differing nature can in turn affect the footfall or mobility to a neighborhood, and related disamenities (e.g., noise, congestion, illegal parking). I believe that this continued line of research would interest researchers from the ubiquitous computing, urban computing and ISM groups along with government agencies.

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