Mobi-IoST: Mobility-Aware Cloud-Fog-Edge-IoT Collaborative Framework for Time-Critical Applications

Shreya Ghosh, *Student Member, IEEE*, Anwesha Mukherjee, *Student Member, IEEE*, Soumya K. Ghosh, *Senior Member, IEEE*, and Rajkumar Buyya, *Fellow, IEEE*

***Abstract*—The design of mobility-aware framework for edge/fog computing for IoT systems with back-end cloud is gaining research interest. In this paper, a mobility-driven cloud-fog-edge collaborative real-time framework, Mobi-IoST, has been proposed, which has IoT, Edge, Fog and Cloud layers and exploits the mobility dynamics of the moving agent. The IoT and edge devices are considered to be the moving agents in a 2-D space, typically over the road-network. The framework analyses the spatio-temporal mobility data (GPS logs) along with the other contextual information and employs machine learning algorithm to predict the location of the moving agents (IoT and Edge devices) in real-time. The accumulated spatio-temporal traces from the moving agents are modelled using probabilistic graphical model. The major features of the proposed framework are: (i) hierarchical processing of the information using IoT-Edge-Fog-Cloud architecture to provide better QoS in real-time applications, (ii) uses mobility information for predicting next location of the agents to deliver processed information, and (iii) efficiently handles delay and power consumption. The performance evaluations yield that the proposed Mobi-IoST framework has approximately 93% accuracy and reduced the delay and power by approximately 23–26% and 37–41% respectively than the existing mobility-aware task delegation system.**

***Index Terms*—Cloud computing, Edge computing, Fog computing, Internet of Things (IoT), Mobility analytics, Spatio-temporal data.**

I. Introduction

The advancements of Internet of Things (IoT) have manifested significant improvements on the quality of human lives in varied aspects [1]. To facilitate real-time applications, high-end processing and storage units are required. For computation and storage of these large volume of raw data generated by IoT devices, cloud computing plays a significant role. However, the cloud-only set-up is not an energy-efficient and delay-aware solution for handling such a high volume of data. To address this problem, edge and fog computing have been introduced [2]. On the other hand, seamless connectivity due to the mobility of IoT devices is a crucial factor to process the data in the remote cloud servers. For time-critical applications such as health care, connection interruption and consequently the increase in delay in delivering the processed information, result in poor Quality of Service (QoS). If the device gets disconnected due to mobility, the delivery of the processed data/ information becomes a challenge. This necessitates a hierarchical infrastructure, where each layer (IoT, edge, fog or cloud) either accumulates, stores and processes the information for reducing the delay. On the other side, movement traces, i.e., time-stamped location information of moving agents (say, mobile-users or client) are accumulated on a large scale from GPS-enabled smart phones or IoT devices. This spatio-temporal movement information opens up diverse opportunities to explore the *intent* of movement [3], [4] and thus fostering varied location based services, namely, efficient package delivery [5], traffic resource management etc. Internet of Spatial Things (IoST) brings IoT in the spatial context [6]. As discussed before, *mobility* or continuous change of locations of users is a challenging issue in task delegation or data offloading. However, analysis of these mobility information helps to explore the intent of the move and subsequently extracts the frequent movement path of a user in different contexts. If the probable location sequences of an agent in the near future can be predicted from the historical mobility information, then an effective and delay-aware solution for a time-critical application can be provided.

To address the above-mentioned challenges, we propose a Cloud-Fog-Edge based collaborative framework for the processing of IoT data and delivering the result based on mobility analysis to reduce the delay. We have considered a hierarchical mobility-based infrastructure composed of four layers: IoT layer, edge layer, fog layer, and cloud layer. Nowadays smart phone has become a popular medium for ubiquitous Internet access and varied user-specific IoT applications are accessible through smart phones. These mobile devices serve as edge devices and may frequently change the locations. The edge layer contains such edge devices i.e. mobile devices. The fog

Manuscript received April 2, 2019; revised August 9, 2019; accepted September 4, 2019. Date of publication September 16, 2019; date of current version December 30, 2020. This work was supported in part by the Department of Science and Technology, Government of India through sponsored research project to Indian Institute of Technology Kharagpur, India and in part by Melbourne-Chindia Cloud Computing (MC3) Research Network. Recommended for acceptance by Dr. A. Puliafito. *(Corresponding author: Shreya Ghosh.)*

S. Ghosh, A. Mukherjee, and S. K. Ghosh are with the Department of Computer Science and Engineering, Indian Institute of Technology Kharagpur, West Bengal 721302, India (e-mail: shreya.cst@gmail.com; anweshamukherjee2011@gmail.com; skg@cse.iitkgp.ac.in).

R. Buyya is with the CLOUDS Laboratory, School of Computing and Information Systems, The University of Melbourne, VIC 3010, Australia (e-mail: rbuyya@unimelb.edu.au).

Digital Object Identifier 10.1109/TNSE.2019.2941754

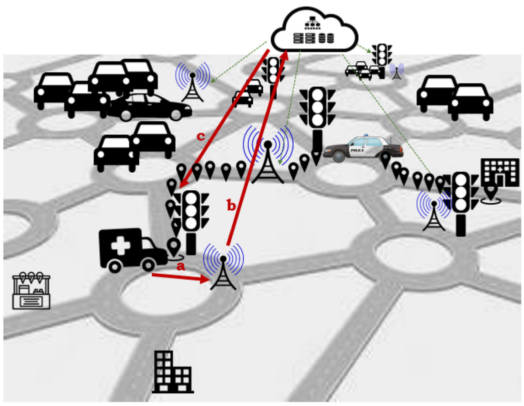

Fig. 1. Mobi-IoST for health care application (a): Ambulance sends health data from IoT devices to RSU. (b): RSU sends result with the location information to cloud. (c): Cloud predicts the nearby health care centre, shortest path and helps to actuate traffic signal.

layer contains the fog devices such as RSUs (Road Side Unit) which are large cell base stations. While the IoT and the edge devices change their locations, the RSU and the cloud data centers of the framework have static locations. The raw data generated in the IoT layer is sent to the edge layer, which is connected with the fog layer. The fog layer is connected with the cloud layer where high-end processing and mobility analysis tasks are performed.

A. Motivating Scenario

We have considered a well-known time-critical application in the domain of *health care*, where the proposed Mobi-IoST framework can be deployed. The pictorial representation of this use-case is shown in Fig. 1.

Suppose a patient, travelling in a vehicle (am), needs continuous monitoring of her/his vital health parameters such as *blood-pressure*, *pulse-rate*, *body-temperature* etc. which are collected using IoT devices and the raw data are sent to the RSU through a client application. The RSU processes the information based on functional model pre-defined by medical experts and sends the current status as normal/abnormal to the client-app. If any abnormality is detected, the RSU sends the data to the cloud to find out the nearest health centre. In the developing countries like India there is a scarcity of super-speciality hospitals at rural regions, and the ambulances are also not equipped with good medical facilities and there is a rare possibility of presence of a medical expert inside the ambulance. In such circumstances, the proposed framework can provide a preliminary support for continuous health monitoring, as well as can suggest nearby health centres in case of adverse situation. Given the current location and health-data feed from the RSU, the cloud can suggest the nearby hospital. On the other side, based on the route followed by the vehicle, the probable health centre also gets notified. Further, the mobility analysis module of cloud can help to reduce the commuting time of the vehicle by predicting less congested path in the road-network. This can be achieved when cloud analyses the traffic states (congestion, traffic breakdown etc.) of the roads and notifies the RSUs of the path. The RSU will work as a fog device. The respective RSUs can actuate the signal synchronizing mechanism such that am can reach avoiding the congested route as well as without waiting in the traffic signals. Although the scenario is motivated by the dysfunctional public health system and limited access to improved transportation and medical care in the rural areas, specifically in developing countries, such as India, *Mobi-IoST* is beneficial for any time-critical applications. For instance, in the time of emergency, a police-vehicle needs to commute with minimal delay avoiding the congested regions of a city. Mobi-IoST predicts the less congested route by analyzing the traffic states in real-time and notifies the RSUs of the route. These RSUs actuate the signal synchronizing mechanism such that the vehicle can reach the destination avoiding the congested route as well as without waiting in the traffic signals. The hierarchical placement of IoT, edge, fog devices and cloud servers in Mobi-IoST framework facilitates an effective and delay-aware solution for several time-critical applications. We believe that Mobi-IoST will act as a foundation of mobility aware network resource management for varied location-based service planning in real-time.

B. Contributions

The focus of our work is to develop a cloud-fog-edge collaborative framework which facilitates real-time IoT information processing and delivery of results based on the mobility information analytics. The key contributions can be summarized as follows:

- Mobi-IoST (Mobility-aware Internet of Spatial Things) is designed for information processing and delivering result based on the prediction of user's current location. The framework exploits the mobility knowledge of the agents to predict the probable user location and delivery of processed information at low delay and low power consumption of the user-device.
- A novel mobility modelling network has been proposed to explore the movement patterns of the user. The huge amount of spatio-temporal trajectory data is stored efficiently along with other contextual information in the cloud data centre.
- A real-time mobility prediction module has been designed to predict the location sequences of the user effectively.
- The experimental results demonstrate that the proposed system has outperformed other existing approaches in accuracy and takes much less time to learn the patterns. The simulation results also demonstrate that the proposed framework reduces the delay in delivering information and power consumption of the mobile device (user-device) compared to the existing mobility-aware task delegation approach.

To the best of our knowledge, this work is the first attempt to utilize the movement knowledge to enhance the QoS for facilitating time-critical IoT applications. The rest of the paper is structured as follows. Section II briefs the existing work in related areas. The proposed framework, *Mobi-IoST*, is discussed in Section III. The delay and power consumption models are discussed in Section IV. Section V presents the experimental and simulation results. The paper is concluded in Section VI along with future directions.

II. Related Work

The IoT refers to the connection of embedded devices within an existing Internet infrastructure where the devices are uniquely identified and the computing environment is created [1]. The raw data collected by IoT devices are processed inside the cloud servers. However, storing and processing of the raw data inside the remote cloud enhances the delay and energy consumption. To overcome this, fog computing has been introduced [2]. The raw data of IoT devices are processed inside the fog device instead of the remote cloud to reduce the delay and energy consumption. However, during data processing connection interruption becomes a challenge if the client is a mobile device. IoT has several sub-domains depending on its applications e.g. Internet of Multimedia Things (IoMT), Internet of Health Things (IoHT), Internet of Vehicles (IoV) etc [6]. IoST is a new sub-domain of IoT, which focuses on spatial data management [6]. In fog-based IoT, the switch, routers etc. work as fog devices for faster processing of the raw data collected using IoT devices. The mobile device that usually works as an edge device, is a connector between the IoT devices and the network. However, the resource hindrance is a major difficulty for these handheld devices. Therefore, the cloud servers have to be used by mobile devices to store their data [7]. The mobile devices also offload heavy computations to the cloud servers. Energy and latency in offloading have been focused on several existing approaches [8], [9]. Fog computing has also provided solutions for reducing delay and energy in the processing of IoT data [2]. In fog computing, a hierarchical architecture is followed, where the intermediate devices between the end node (or fog devices) and cloud servers participate in data processing [2]. The edge devices allow users to connect with the network and transfer data accordingly to a network which is external to the user. For transcoding massive amount of video at scale, a cloud and edge computing based collaborative system has been proposed in [10]. For balancing the traffic and computing load, a method has been discussed in [11], where the IoT devices are allocated to the base station or fog nodes to reduce the latency.

To address the task offloading issue in vehicular network, edge computing has been used in [12]. The mobile edge computing servers are deployed inside the road side access points for offloading tasks. However, the use of access points may not be energy-efficient if exhaustive computations have to be performed and there are a large number of users. Based on user mobility, an opportunistic computation offloading method has been discussed in [13]. Based on information gain, task allocation in spatial crowdsourcing has been discussed in [14]. A fog based architecture of spatial crowdsourcing has been proposed in [15], where privacy-aware task allocation and data aggregation have been focused. In [16], task offloading to cloud and delivery of result based on serialization of session information has been discussed. Further, there is a need of a mechanism where the user mobility will be predicted and result will be delivered at the optimum delay and power consumption of the mobile device.

Given the abundance of mobility/trajectory traces (GPS log) of individuals, there are several research initiatives to extract knowledge or meaningful information from the huge amount of trajectory traces. Several works are reported to model and predict next location from movement traces such as GPS log, check-in data or social network information [17]–[19]. There are challenging applications, namely, urban land-use classification from taxi-traces [20], daily activity-sequence recommendation [21] categorizing users in an academic campus [22]. It is well known that human movement traces follow spatio-temporal regularity. In this regard, Song *et al.* [23] provide a high degree of spatio-temporal uniformity by mining movement traces of 50,000 people for a period of three months. All of these studies depict that since people follow some spatio-temporal regularity in their movement history, an appropriate and effective mobility pattern modelling can help to facilitate several location-aware services.

To this end, the *Mobi-IoST* framework aims to deliver mobility-driven efficient data processing in cloud-fog-edge based IoT setup to facilitate intelligent decision making in real-time. To the best of our knowledge, none of the existing works have clearly depicted the significance of *mobility-aware* service provisioning framework in fog based IoT. In Mobi-IoST, the movement pattern modelling and location prediction approaches are novel propositions which deliver result in real-time. Moreover, the experimental observations and performance analysis show the effectiveness of *Mobi-IoST* in terms of accuracy, delay and power consumption. In summary, designing and deploying an end-to-end mobility driven framework for efficient data processing in IoT setup is a challenging issue in the present era.

III. Mobi-IoST Framework

The hierarchical structure of Mobi-IoST is represented in Fig. 2. Fig. 3 depicts the overall flow of the framework, *Mobi-IoST*. IoST or *Internet of Spatial Things* deals with IoT data along with spatial perspective. As depicted in Fig. 2, in the bottom layer several IoT sensors such as accelerometer, GPS, temperature, blood-pressure, proximity sensors capture application specific data. These IoT sensors are either present within the edge devices or connected with the edge devices, namely, mobile phone, vehicles, which change their locations. When any of these edge devices needs assistance, it contacts the current RSU (the RSU under which it currently belongs). In this work, RSU is used as *fog* device and it is capable of small scale processing. If the processing is beyond the computational capability of the RSU, then it delegates the task to the cloud. The top layer of the hierarchical structure consists of cloud servers, which store spatial data, specifically, mobility traces, location-specific information, city-structure (POI placements and other contextual information). The cloud processing unit executes the task and sends the result to the RSU,

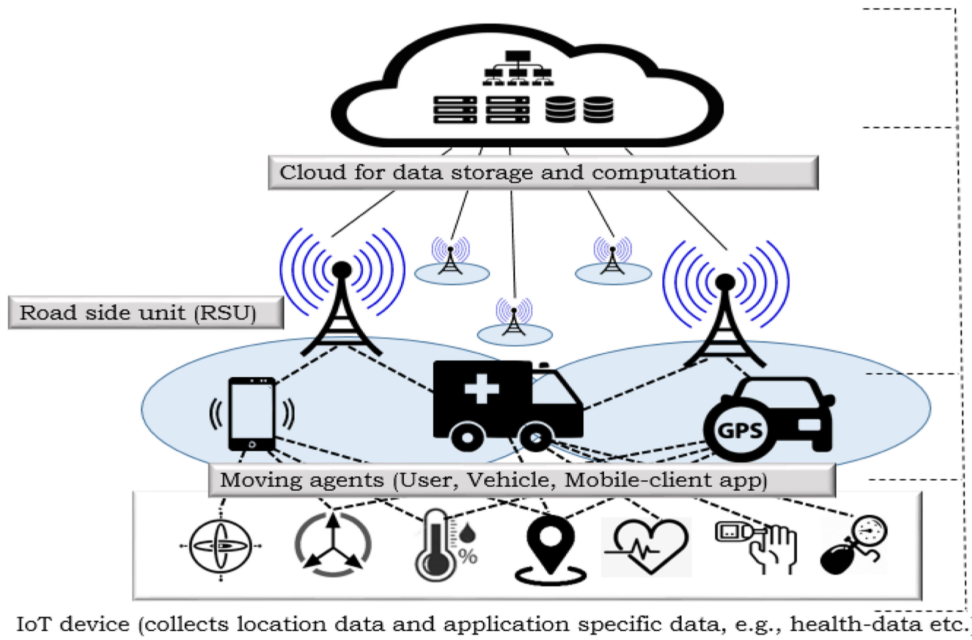

Fig. 2. Hierarchical placement of IoT, Edge, Fog devices and Cloud in *Mobi-IoST* framework.

where the tasks are application-specific such as controlling the signaling mechanism or notifying the nearest health-care center. Here, the resources can be efficiently managed by this framework: movement analysis module can predict variation of travel demand apriori and notify the RSUs accordingly, while the RSUs can decide about the dissemination of resources (traffic or network) efficiently.

The major modules of the framework are: (i) movement pattern modelling, (ii) predicting next location sequences, (iii) delivery of result after processing in a timely manner. Finally, the experimental and simulation results yield the effectiveness of the framework.

A. Exploring Movement Semantics From Trajectory Traces

This section presents the methodology to model movement patterns and predicts the next location sequences efficiently and timely manner. Location prediction of moving agents, such as, people, vehicles is a challenging task for varied location-based services [20]. Specifically, in our work, location prediction helps to locate the moving agent's locations in near future and subsequently data is sent to the appropriate RSU. Whenever a mobile device gets connected to a RSU, the GPS log of the mobile device is extracted and stored in the cloud dynamically.

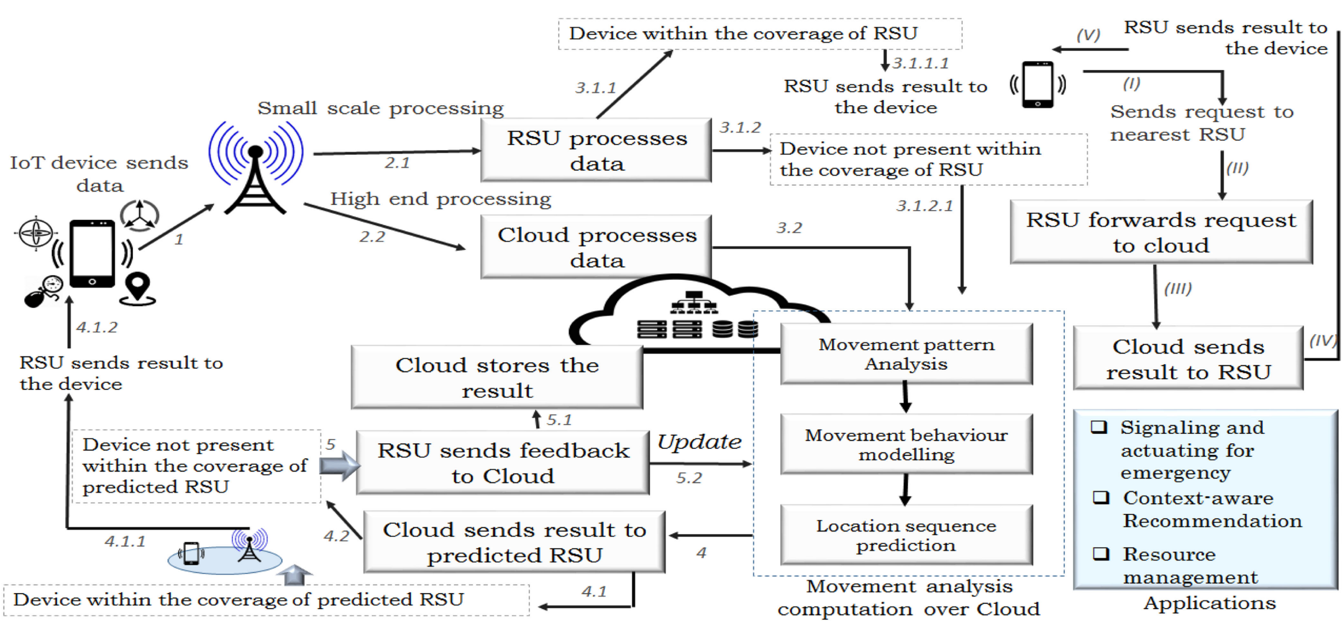

Fig. 3. Working model of the proposed framework, *Mobi-IoST*.

It may be noted that location prediction depends on several factors, namely, day of the week, time-slot of a day and road-structure. The first step of movement behaviour modelling is to find out the frequent pattern followed by the users in varied contexts. For example, the path followed by an individual differs significantly in weekends compared to his/her weekdays' trajectory signature. Moreover human movements follow some intent [3] and extracting the purpose behind any move is the fundamental step to predict next location effectively. Few preliminary concepts which are used in this paper are defined as follows:

- GPS log (G): GPS log is the collection of time-stamped latitude, longitude information. The GPS trajectory or trace is formed by connecting the location information on increasing time-ordering.
  $Traj(p_1, \ldots, p_n) : <p_1(lat_1,\ lon_1),\ t_1> \rightarrow <p_2(lat_2,\ lon_2),\ t_2> \cdots \rightarrow <p_n(lat_n,\ lon_n),\ t_n>$, where $t_1 < t_2 < \cdots < t_n$.
- Stay-Point (S): Stay-point of a trajectory is defined as a location (typically, *polygon*), where the moving agent stops for a time-value δt and $\delta t > t_{thresh}$, and all the GPS points within δt reside in the area $area_{stay}$ of the polygon, where $area_{stay} < area_r$. Here, *polygon* is a data-type which represents spatial data [24] and t_{thresh}, $area_r$ are time-threshold and coverage-area threshold for detecting stay-points from the trajectory respectively. In our analysis, we have considered the parameter values as, $t_{thresh} = 12 mins$ and $area_r = 2\ km^2$.
- POI and Geo-tagged Trajectory: *Point-of-interest (POI)* of a GPS location denotes the nearby landmark of a location, such as, residential area, supermarket etc. We have followed the $POI_{taxonomy}$[1] to extract such POI information using *Google Place API*. Geotagged trajectory is generated by appending the geo-tagged information of the stay-points within the trajectory.
- Trajectory window ($TrajW$): Trajectory window stores the location sequence information between two such stay-points in an uniform sampling rate.

Augmenting Semantic Information with GPS log: Human movement semantics can be analysed if additional information such as, POI, road-network structure and stay-point information are appended with the raw GPS traces.

– Road network of the study region is extracted from OpenStreetMap (OSM)[2]. The road network is represented by a directed graph $R = (V, E)$, where $e \subseteq |E|$ denotes the road-segments of the region and $v \subseteq |V|$ is the intersection points of such road segments. Map-matching algorithm [25] has been deployed, which considers both geometric and topological structure of the road-network to associate the road-segments along with the trajectory traces.
– Each stay-point of the trajectory is geo-tagged with the nearby POI location. Here, we have implemented the iterative *reverse geo-coding* technique to extract nearest landmark of the stay-point.

After the addition of semantic information with the raw traces, a trajectory trace takes the form:
$<p_a, t_a, Residential>, TrajW[(p_i, t_i, e_x), (p_{i+1}, t_i + \delta t, e_x), (p_{i+2}, t_i + 2 \times \delta t, e_x),], <p_b, t_b, SuperMarket>, TrajW[(p_j, t_j, e_y),\ (p_{j+1},\ t_j\ +\ \delta t,\ e_y), (p_{j+2},\ t_j + 2\ \times \delta t, e_y),], <p_c, t_c, Residential>$.

Here, p_a, p_b and p_c are three stay-points with geo-tagged information *residential building* and *supermarket*. $TrajW$ stores the route information followed by the trajectory, where e_x, e_y are the road-segments of the road-network of the study region.

Processing of Large Mobility Datasets in Cloud: With the advances in sensor technologies and the proliferation of smartphones, a huge amount of mobility traces are generated by moving agents. One of the major challenges is to analyze the vast amount of data due to computational complexity and storage limitations. To this end, we propose to migrate the computation of mobility analysis and storage of movement traces in the cloud for faster response. It may be noted that the locations and coverage areas of the RSUs need to be maintained in the cloud storage such that it can predict the next location of the moving agent to determine the appropriate RSU, which will serve the agent at that time. Here, large cell base stations [26] are the RSUs. The macrocell base station is referred to as macro RSU and microcell base station is referred to as micro RSU. The coverage area of macro RSU and micro RSU are 1–20 km and 200 m–1 km respectively [26]. The framework is implemented in Google Cloud Platform (GCP) by utilizing several storage and computational components of GCP. In our framework, cloud storage is of four types:

– *Grid based storage of the study region:* The study region is segmented into uniform hexagonal grids and information, such as, road structure or POIs, RSUs are associated with each such grids. Our proposition is to segment the spatial region into grids such that each grid encloses the coverage area of at least one micro RSU.

  The grid-segmentation process initiates with the location of one RSU. Suppose, the location of the RSU (say, RSU_i) is $p = (x, y)$ and the length of the side of the hexagon (g_i) is $a = 8\,m$. An iterative process is deployed until the complete study region is segmented with hexagonal grids. In the first iteration, center points of the 6 neighbouring grids of g_i are calculated and subsequently, the neighbouring hexagonal grids are constructed.

  In the next step, *Geohash code* of all hexagonal grids are computed. Geohash code of the grids represent the spatial location on the earth surface using unique alphanumeric strings. Cloud Spanner of GCP is used to store these information which supports horizontal scalability.
– *Road network information storage:* This module stores the road network information, namely, connections among different road-segments and road-type (highway, lane etc.). The information is stored in an *adjacency matrix* format, where each vertex maintains a list of

[1] https://developer.foursquare.com/docs/resources/categories/
[2] OpenStreetMap: https://www.openstreetmap.org

outgoing edges (outdegree of the vertex). The data-type of the list is *polyline*, which is a spatial-data type [24] and represents the road-segments on the map.

- *RSU information storage:* It stores the list of RSUs along with the unique-id, coverage area, location (latitude, longitude) and other information such as, type (micro RSU or macro RSU) etc. Cloud BigQuery of GCP is utilized to store the road network information and RSU information as well.
- *Frequent path storage:* The frequent path followed by individual moving agents are extracted and modelled in our work. Details are presented in Section III-A1. Cloud Bigtable of GCP is utilized to store the road network information.

The computational cost of the mobility traces is huge since it deals with time-series data with very high sampling rate. The key challenge is to reduce the processing time of the location prediction, and therefore, an efficient scheme is required. Here, we have deployed a *hash-based* indexing scheme, where nearby locations are stored in the subsequent buckets of the hash-table.

1) Movement Behaviour Modelling: In this section, we discuss how movement behaviour of users can be modelled to explore the frequent paths followed by them in different contexts. The process of semantic enrichment of GPS log of users has already been discussed in Section III-A. Here, we propose *User movement graph*, a multi-layer graphical model to model the users' movement patterns from the spatio-temporal context. The objective to use the multi-layer network is that human movement patterns typically depend on temporal variations (weekdays or weekends, morning or evening), road networks and stay-points. All of these information need to be encoded and interconnections of the information cannot be properly captured in a single layer.

User movement graph (MG): User movement graph is defined as $MG = (N, L, la)$, where N denotes the nodes, L denotes the links and label is represented by la. The user movement graph has four labels:

- Road network: The layer 1 consists of road network information, where nodes are intersection points of road-segments.
- RSU network: The RSU information (location and coverage area) is stored in layer 2.
- Stay-point information: The stay-point information including location and type of stay-point are stored in layer 3.
- Frequent path: The movement paths frequently followed by the user is stored in layer 4.

It may be noted that each layer is interconnected with each other. As the construction of layer 1, layer 2 and layer 3 are straight forward, we discuss the frequent pattern mining process of layer 4 in detail.

The frequent path network of layer 4 is represented by *probabilistic graphical model* or Dynamic Bayesian network $FPN(V, E, \Upsilon)$ where V is the set of stay-points, E denotes the direction of visit among different stay-points and Υ is the network quantify parameter. In this work, we have considered both *spatial location* and *temporal span* of a visit-sequence to model FPN of user movement graph. Each node (stay-points: $v \subseteq V$) of the network is conditionally independent of its non-descendants given its parent node ($Pa(v)$). Suppose, a visit-sequence is given as $V = (V_1, \ldots, V_N)$, the probability distribution is computed as follows:

$$P(V) = \prod_{i=1}^{N} P(V_i | Pa(V_i)) \tag{1}$$

FPN captures the dynamic nature of the mobility information by representing multiple copies of the spatial-information, one for each time-slice $V_t = (V_{1,t} \ldots, V_{d,t})$. Subsequently, the transition distribution from one state to other ($P(V_{t+1}|V_t)$) is computed from two time-slice Bayesian network. The spatial location information (V_t) is typically divided into two sets, namely, unobserved state variables (S_t) and the observed state variables (L_t, in our case, location information from RSUs). The joint probability distribution is calculated by unrolling two time-slice Bayesian networks:

$$\begin{aligned} P(S_0, \ldots, S_T, L_0, \ldots, L_T) = \\ P(S_0)P(L_0|S_0) \prod_{t=1}^{T} P(S_t|S_{t-1})P(L_t|S_t) \end{aligned} \tag{2}$$

It may be noted that we have represented the stay-points as grid-location and transition from one state to another state signifies that the agent is moving from one grid to another.

Next, we deploy a spatio-temporal trajectory clustering ($TrajCS$) on FPN which captures the signature or frequently visited paths of the individual. The process follows a hierarchical top-down approach, and based on the distance measure new clusters are generated and appended in the list. The trajectory clustering distance measure is computed as follows:

$$TrajCS(S_i, S_j) =$$

$$\begin{cases} 0 & if(i == 0) \\ & or(j == 0) \\ TrajCS(S_{i-1}, S_{j-1}) & if((S_i == S_j) \\ +C \times Min(T_{Score_i}, T_{Score_j}) & and(s_{i+1}) \neq (s_{j+1})) \\ MAX(TrajCS(S_{i-1}, S_j), & \\ TrajCS(S_i, S_{j-1})) & if(s_i \neq s_j) \end{cases} \tag{3}$$

where S_i represents a set of locations, s_i denotes one GPS point of the set S_i and C is the parameter to augment the probability of the path taken. T_{score} computes the temporal similarity between two different stay-points of the trajectory and $TrajCS$ method is recursively called for extracting the signature pattern. The proposed distance measure appends temporal information with the conventional *Longest Common Sub-Sequence (LCSS)* clustering method [27]. Algorithm 1 describes the basic steps of generating FPN from the trajectory traces of agents.

This section describes how users' frequent movement patterns are extracted and stored along with other contextual information. Furthermore, the trajectory clustering and multi-layer graphical model help to effectively model the movement behaviour of agents in the cloud server.

Algorithm 1: Frequent path mining - A trajectory clustering approach

Input: Set of trajectory T, stay-points S
Output: Frequent path network $<FPN(V,E,\Upsilon)>$ ▷ Frequent path network for each individual

$clus, S, V, E \leftarrow NULL$;
for *each trajectoty window* $tr \in T$ **do**
  for *each unvisited stay-point* $s \in S$ **do**
    $V.append(s)$ ▷ Create new node
    $visited \leftarrow s$
    $\Upsilon : CPT \leftarrow Create\ ConditionalProbabilityTable(s)$
    $t \leftarrow extractTemporal(s)$ ▷ Temporal information of the stay-point
    $E.append(genEdge(S,t))$ ▷ genEdge creates directed edge based on frequency of the visit and temporal information
  end for
end for
for *each path* $tr_p \in FPN$ **do** ▷ Path represents the successive sequence of stay-points
  $Ne \leftarrow ExtractTrajW(tr_p, FPN)$ ▷ Extract trajectory-windows within spatio-temporal locality
  $D \leftarrow computeLCSS(Ne, tr_p)$
  if $D > thresh$ **then**
    $Ignore\ Ne$
  end if
  if $D \leq thresh$ **then**
    $Create\ new\ cluster\ clus_t$
    $clust_t.append(Ne, tr_p)$ ▷ Appending new cluster in the list
    $visited \leftarrow Ne$
    $Modify\ CPT(clust_t)$ ▷ Modify the CPT of all nodes in $clust_t$ calculating the frequency of visit
  end if
end for

2) Next Location Sequence Prediction From Mobility Information: This helps to calculate the probable path visit by the user apriori. The location prediction task is formulated as follows: *Given the historical observations of a moving agent m and the current location L at time t, predict the agent's anticipated location sequences (S) following δ time-instances*

Typically, the task is formulated as information retrieval task considering the fact that people's movement patterns follow spatio-temporal regularity and effective movement behaviour modelling leads to accurate location prediction. Here, we have deployed *Hidden Markov model (HMM)* (say χ) based prediction technique with two kinds of stochastic variables, *state variables (hidden)* and *observable variables*. Each individual's movement is modelled as k^{th} order Markov chain and the transition from one place to another place is modelled based on MG and χ.

Algorithm 2 describes the basic steps of location prediction. The first step *map* locates the current location (grid location) of the moving agent and then the model predicts the sequences of locations based on the context and finally, *update* process updates the result based on the current input from the mobile device. It may be noted that the order (k) of the *markov chain* is dependent on the user's frequent movement pattern and extracted from FPN of user movement graph (MG).

Algorithm 2: Location prediction - map and update process

Input: User movement graph MG, Present location s, Trajectory log T
Output: $\langle s', Edge-list \rangle$ ▷sequence of next location sequences

function MAPPER(s, MG, T) :
$j \leftarrow geo-hascode(s)$ ▷ extract the grids where trajectory points placed
$E' \leftarrow extract\_pattern(MG, j)$ ▷ extract the frequent trajectory patterns within the grid
for *all* $t_i \in T$ **do**
  L $\leftarrow$ predictLoc[$\chi(t_i, s)$] ▷ HMM based prediction
  $p \leftarrow ComputeProb(s, arraylist[L, t])$ ▷ Compute transition probability for all patterns in partcular time-stamp
  $dist \leftarrow ComputeTrajCS(E', t_i)$ ▷ Compute the trajCS distance for each such pattern
  $s' \leftarrow SORT(arraylist[p], arraylist[dist])$ ▷ Predicted location with maximum probability
end for
$Print\ <s' : arraylist(E'_0)>$
function Update($s, arraylist[s']$) : ▷ If sudden change in mobility pattern observed
for *all* t_i **do**
  for *all* $e_a \in arraylist[s']$ **do**
    Append trajectory window Tr_e containing e_a in FPN
    $ModifyCPT(e_a, t_i)$ ▷ Modify CPT of all nodes with outgoing/incoming edge e_a
    $ModifyProb(e_a, t_i)$ ▷ Modify transition matrix of all sequences containing e_a
    $Mapper(s, MG, Tr_e)$
  end for
end for

$$P(s_i|s_{i-1}, s_{i-2}, \ldots, s_1) = P(s_i|s_{i-1}, \ldots, s_{i-k}) \tag{4}$$

In the next step, *forward algorithm* [28] is deployed to find out the sequences of stay-points, given as:

$$P(L^k|\chi) = \sum_{i=1}^{seq_{max}} \left[\prod_{j=1}^{k} P(L(j)|S_i(j)) * P(S_i(j)|S_i(j-1), S_i(j-2), \ldots, 1) \right] \tag{5}$$

where, seq_{max} and $S_i(j)$ represent the maximum number of hidden state sequences and hidden states. Here, model is represented as *k-order* markov chain where the next location depends on k recent observations. Next, a variant of *verterbi algorithm* using time-relationships is deployed to discover the possible sequences of states. The transition and emission probabilities of χ are computed by adjusting the model parameters. An iterative version of *forward backward algorithm* is implemented to produce the sequences effectively.

Three types of location prediction tasks have been carried out in this work: (i) location sequence prediction in a specific time-threshold, (ii) predicting appropriate POI (say, health-care center) and the path and finally, (iii) given the destination and present location of the agent predicting the path with less commuting time based on the traffic states of the road-network. The location sequence prediction in specific time-thresholds is computed directly from χ on MG. The POI and path prediction is carried out by overlapping the road-network structure (layer 1 of MG) and frequent path pattern (layer 4 of MG). Finally, given source and destination, the markov model is used along with the traffic-state of the region, where s_1 and s_n are specified. It may be noted that our algorithm (Algorithm 2) is self-adaptive, i.e., the *update* function (also, refer 'Update' arrow of Fig. 3) changes the modelling algorithm in case any of the prediction result fails.

B. *Delivery of Result After Data Processing*

The IoT devices are connected with the edge device, e.g. the sensors within the mobile device. With the increasing availability of smartphones, we have considered mobile devices as the edge devices. If the mobile device is able to process the raw data received from the IoT devices, it does the same by working as an edge device and generates the result. Otherwise, the mobile device sends the data to the RSU, which will act as a fog device. Each RSU maintains a look-up table, which holds the mobile device IDs present under its coverage. The International Mobile Equipment Identity (IMEI) number is considered as the mobile device ID. The RSU after receiving the raw data from the mobile device, checks its current load and ability to process the data. In this regard, two cases appear as follows:

- If the RSU's current load is same as the maximum load it can handle or an exhaustive computation is required to perform which is beyond the capability of the RSU, it forwards the data to the cloud along with the device ID and the request ID. After processing the data, the cloud finds the current location of the device based on the user's geo-location information (refer Section III-A). Based on the current location of the device, the cloud identifies the RSU under which the mobile device is currently located. The cloud sends the result to the RSU along with the device ID and the request ID. The RSU forwards the result to the mobile device.
- If the RSU is able to process the raw data and its current load is less than the maximum load it can handle, the RSU processes the data and sends the result to the mobile device. However, as the device is in mobility, it may be possible that the RSU finishes processing and the mobile device moves away. In such a case, the RSU sends the result to the cloud along with the request ID and the device ID. The current location of the device is predicted by the cloud based on the user's geo-location information. Based on the current location of the device, the cloud identifies the RSU under which the mobile device is currently located. The cloud sends the result to the RSU along with the device ID and the request ID. The RSU forwards the result to the mobile device.

Algorithm 3: Working Model of Mobi-IoST

Input: Raw data received from IoT devices
Output: Result after processing the raw data

1: mobile device receives raw data from the IoT devices
2: **if** mobile device is able to process the data **then**
3: mobile device works as edge device and processes the data
4: **else**
5: mobile device forwards the data to the fog device RSU under which it is currently present
6: **if** $current\ load\ of\ the\ RSU < maximum\ load\ capacity\ of\ the\ RSU$ **then**
7: go to step 11
8: **else**
9: go to step 34
10: **end if**
11: **if** RSU is able to process the data **then**
12: RSU processes the data
13: **if** the mobile device is still connected **then**
14: RSU delivers the result to the device
15: **else**
16: RSU forwards result to the cloud along with the device ID and the request ID
17: cloud predicts current location of the mobile device from the mobility information using Algorithm 1 and 2
18: cloud identifies the RSU serving the predicted location
19: cloud forwards the result to the predicted RSU along with the device ID and the request ID
20: **if** the mobile device is connected with the predicted RSU **then**
21: RSU sends the result to the mobile device
22: **else**
23: RSU sends a feedback to the cloud that the mobile device is not present in its coverage
24: cloud after receiving the feedback stores the result
25: **if** the mobile device gets connected with a RSU **then**
26: mobile device requests for the result to the RSU with the request ID
27: RSU forwards the request to the cloud
28: cloud sends the result to the RSU and updates the mobility information
29: RSU sends the result to the mobile device
30: **end if**
31: **end if**
32: **end if**
33: **else**
34: RSU sends the raw data along with the device ID and the request ID to the cloud
35: cloud processes the data
36: go to step 17
37: **end if**
38: **end if**

In our approach as the mobility information is updated dynamically, the probability of the presence of the mobile device under the predicted RSU is high. However, if the device losses connection with the network for a long duration, there is a probability that the mobile is not located under the coverage of the predicted RSU. In such cases, after receiving the result from the cloud, the predicted RSU sends feedback to the cloud that the mobile device is not present under its

TABLE I
SYMBOLS USED IN POWER AND DELAY CALCULATION

Symbol	Definition
u	Velocity of moving agent
D_c	Amount of data collected and transmitted
D_r	Amount of result data received
Up_{tmr}	Data transmission rate in uplink between mobile device and RSU
Dw_{tmr}	Data transmission rate in downlink between mobile device and RSU
Up_{trc}	Data transmission rate in uplink between RSU and cloud
Dw_{trc}	Data transmission rate in downlink between RSU and cloud
f_{mr}	Uplink data failure rate between mobile device and RSU
f_{rm}	Downlink data failure rate between mobile device and RSU
f_{rc}	Uplink data failure rate between RSU and cloud
f_{cr}	Downlink data failure rate between RSU and cloud
d_{pr}	Data amount processed per unit time by the RSU
d_{pc}	Data amount processed per unit time by the cloud
T_m	Delay to determine the current location of the device
P_a	Power consumption of mobile device in active mode
P_i	Power consumption of mobile device in idle mode

coverage. By this time, if the mobile device gets connected with a RSU, it will send a request for the result with the request ID to the RSU. The RSU then forwards it to the cloud. The cloud then sends the result to the mobile device through the RSU and updates the user mobility information accordingly. Algorithm 3 summarizes the steps of the working model of the proposed framework Mobi-IoST. As we observe in the proposed system the cloud after analysing the user mobility information, finds out the probable RSU currently serving the device and accordingly delivers the result. Hence, intelligent decision making is performed by the cloud, which makes the system efficient.

IV. DELAY AND POWER CONSUMPTION IN MOBI-IOST

The mobile device transmits the data to the RSU with which it is currently connected and requests for providing the result after processing. According to our strategy, either RSU or cloud performs data processing based on the complexity of the computation required for processing the data and the current load of the RSU. Here, two cases are considered as discussed previously:

- Information processing inside the RSU
- Information processing inside the cloud

The symbols used in the delay and power calculation of the proposed model, are defined in Table I.

A. *Delay Model for Information Processing in RSU*

The uplink data transmission delay between mobile device and RSU is given as:

$$T_{mr} = (1 + f_{mr}) * (D_c/Up_{tmr}) \tag{6}$$

The downlink data transmission delay between mobile device and RSU is given as:

$$T_{rm} = (1 + f_{rm}) * (D_r/Dw_{tmr}) \tag{7}$$

The total data transmission delay between mobile device and RSU is given as:

$$T_t = T_{mr} + T_{rm} \tag{8}$$

The data processing delay inside the RSU is given as:

$$T_{pr} = D_c/d_{pr} \tag{9}$$

The total delay for data transmission and processing is:

$$T_{tot} = T_t + T_{pr} \tag{10}$$

The mobile device while located at point i transmits the data to the RSU and requests for processing. Let the radius of the RSU's coverage area is R and the last visited point of the mobile device inside the RSU is k. The delay in movement from point i to point k is given as:

$$T_{ik} = \sum_{i=1}^{k-1}((D_{i(i+1)})/u_i) \tag{11}$$

where u_i is the velocity of the mobile device at location point i and $D_{i(i+1)}$ is the distance between two consecutive location points i and $i+1$. If $T_{ik} > T_{tot}$, the mobile device is still inside the coverage of the RSU. Hence, the RSU will deliver the result to the mobile device. Hence, the round-trip delay is given as:

$$T_{del1} = T_{tot} \tag{12}$$

The power consumption of the mobile device during this period is given as:

$$P_{del1} = T_t * P_a + T_{pr} * P_i \tag{13}$$

As the RSU performs data processing instead of the cloud, the transmission delay is reduced. Hence, the delay in delivering the result is reduced in our system. Accordingly, the power consumption of the mobile device is also reduced. Else if $T_{ik} \leq T_{tot}$, the mobile device has moved to the coverage of another RSU. Hence, the previous RSU will forward the result to the cloud along with the request ID and the mobile device ID. The cloud contains the mobility information of the mobile devices. Using the location prediction strategy described in the Section III-A2, the cloud will find out the current probable location of the mobile device. Let t is the time instant when the mobile device is at location i. The cloud finds out the location point visited by the mobile device at time instant $(t + T_{tot})$, and the RSU which is currently serving the device. The cloud delivers the result to the selected RSU, which forwards the result to the mobile device. In this case, the round-trip delay is:

$$\begin{aligned} T_{del21} = T_{tot} + (D_r/Up_{trc})(1 + f_{rc}) \\ + T_m + (D_r/Dw_{trc})(1 + f_{cr}) \end{aligned} \tag{14}$$

where T_m is the delay for determining the current location of the device and correspondingly the RSU currently serving the device, based on the mobility information of the user. The power consumption of the mobile device during this period is given as:

$$P_{del21} = T_t * P_a + (T_{pr} + (D_r/Up_{trc})(1 + f_{rc}) + T_m + (D_r/Dw_{trc})(1 + f_{cr})) * P_i \tag{15}$$

If the device is not connected with the selected RSU, the RSU will send a feedback to the cloud. If the mobile device sends request to a RSU for the result, then the cloud will deliver the result to the device through the current RSU. In this case, the round-trip delay is given as:

$$T_{del22} = T_{del21} + T_f + T_{r1} + T_{r2} + (D_r/Dw_{trc})(1 + f_{cr}) \tag{16}$$

where T_f is the delay for sending feedback from the RSU to the cloud, T_{r1} is the delay for sending request by a mobile device for result to the RSU, under which the device is present, and T_{r2} is the delay for forwarding the request by the RSU to the cloud. The power consumption of the mobile device during this period is given as:

$$P_{del22} = P_{del21} + T_{r1} * P_a + (T_f + T_{r2} + (D_r/Dw_{trc})(1 + f_{cr})) * P_i \tag{17}$$

If p_s and p_u are the probabilities of the presence and non-presence of the mobile device under the predicted RSU respectively, the round-trip delay is given as:

$$T_{del2} = p_s * T_{del21} + p_u * T_{del22} \tag{18}$$

The power consumption of the mobile device during this period is given as:

$$P_{del2} = p_s * P_{del21} + p_u * P_{del22} \tag{19}$$

However, though we have considered the case that the mobile device may not be present under the coverage of the predicted RSU, the probability of this case is very low, because the cloud is dynamically maintaining the user mobility information. As the user current location and the current RSU serving the mobile device is predicted in our system, the delay in delivering the result is reduced. Accordingly, the power consumption of the mobile device is reduced.

B. Delay Model for Information Processing in Cloud

From the previous subsection the total delay in data transmission between RSU and mobile device (T_t) has been determined using equation (10). Now, if cloud performs data processing, then the uplink data transmission delay between RSU and cloud is given as:

$$T_{rc} = (1 + f_{rc}) * (D_c/Up_{trc}) \tag{20}$$

The downlink data transmission delay between RSU and cloud is given as:

$$T_{cr} = (1 + f_{cr}) * (D_r/Dw_{trc}) \tag{21}$$

Therefore, the total data transmission delay between mobile device and cloud is given as:

$$T_{tn} = T_t + T_{rc} + T_{cr} \tag{22}$$

The data processing delay inside the cloud is given as:

$$T_c = D_c/d_{pc} \tag{23}$$

The cloud after processing the data, predicts the current location of the user by analysing the mobility information and accordingly the RSU currently serving the mobile device. After that the cloud sends the result to that RSU along with the device ID and the request ID. Hence, the round-trip delay is:

$$T_{del31} = T_{tn} + T_c + T_m \tag{24}$$

where T_m is the delay in predicting the current location and the RSU serving the device currently. The power consumption of the mobile device during this period is given as:

$$P_{del31} = T_t * P_a + (T_{rc} + T_{cr} + T_c + T_m) * P_i \tag{25}$$

If the device is not connected with the selected RSU, the RSU will send a feedback to the cloud. If the mobile device sends request to a RSU for the result, then the cloud will deliver the result to the device through the current RSU. In this case, the round-trip delay is given as:

$$T_{del32} = T_{del31} + T_f + T_{r1} + T_{r2} + (D_r/Dw_{trc})(1 + f_{cr}) \tag{26}$$

where T_f is the delay for sending feedback from the RSU to the cloud, T_{r1} is the delay for sending request by a mobile device for result to the RSU, under which the device is present, and T_{r2} is the delay for forwarding the request by the RSU to the cloud. The power consumption of the mobile device during this period is given as:

$$P_{del32} = P_{del31} + T_{r1} * P_a + (T_f + T_{r2} + (D_r/Dw_{trc})(1 + f_{cr})) * P_i \tag{27}$$

If p_s and p_u are the probabilities of the presence and non-presence of the mobile device under the predicted RSU respectively, the round-trip delay is given as:

$$T_{del3} = p_s * T_{del31} + p_u * T_{del32} \tag{28}$$

The power consumption of the mobile device during this period is given as:

$$P_{del3} = p_s * P_{del31} + p_u * P_{del32} \tag{29}$$

However, as the cloud is dynamically maintaining the user mobility information, the probability of the case that the mobile device is not present under the coverage of the predicted RSU is very low. As in the proposed model the RSU under which the user is currently present is predicted, the delay in delivering the result is faster and correspondingly the power consumption of the mobile device is reduced.

V. Performance Evaluation

The performance analysis has been carried out in following aspects: (i) movement pattern modelling, (ii) next location

TABLE II
PERFORMANCE COMPARISON OF MOVEMENT MODELLING MODULE OF MOBI-IOST WITH BASELINE METHODS

Metric	Semantic model [17]	Bayesian [29] network	LCSS [27]	Markov predictor [30]	CNN [19]	ST-RNN [18]	**Mobi-IoST**
Accuracy	84.02%	78.67%	72.95%	80.23%	86.08%	91.7%	**93.25%**
Learning (min) ($\|TrajW\| :\ 18 \times 150$)	8.4	10.2	16.8	10.6	32.4	22.8	**12.6**
Re-learning (min) ($\|TrajW\| :\ 6 \times 20$)	3.8	6.6	14.2	6.2	28.6	18.6	**4.2**

(and sequence) prediction and (iii) route prediction given the source and destination pair.

A. Mobility Dataset

The mobility dataset[3] is collected from 100 mobile users from their GPS-enabled smart phones and *Google Map timeline* for 6 months in the Kharagpur and Kolkata region of India. The dataset consists of timeseries data of GPS traces with the total time-duration of 26,8041 hours. The GPS points are logged in a high-sampling rate of 60-75 secs.

B. Experimental Setup

We aim to demonstrate the efficacy of *Mobi-IoST* with the real-life mobility dataset. Typically, *accuracy*, *recall* and *F-measure* are used to evaluate the performance of *Mobi-IoST*. Six baseline methods are implemented to compare with the proposed Mobi-IoST approach. 70% of the movement traces are used for modelling, 20% and 10% for testing and validating respectively. The location sequence prediction task is evaluated in different time-scales, from 5 mins to 60 mins. The path prediction task has been carried out in seven different time-bins (commuting time) (i) $\leq$10 mins, (ii) >10 and $\leq$15 mins, (iii) >15 and $\leq$20 mins, (iv) >20 and $\leq$30 mins, (v) >30 and $\leq$40 mins, (vi) >40 and $\leq$45 mins and (vii) >45 and $\leq$ 50 mins. The accuracy measure is represented by the path similarity between the road-segments in the predicted path and the actual query trajectory. For this purpose, the trips are divided into seven classes based on their commuting time. For each class, the tenfold cross validation policy has been deployed where all trips within the same class are randomly divided into ten folds, where nine folds are utilized for training and one fold for validation. It guarantees that any trip in the validation set will not appear in the training set. Next, the prediction accuracy for all the trips in the validation set are computed and the average value of the accuracy measure for all seven classes are reported.

C. Movement Analysis

The performance measurement of the movement analysis module have been carried out by three measurements, namely, *accuracy*, *recall* and *F-measure*. Apart from that, we evaluate the performance of the movement behaviour modelling framework by comparing with six baseline methods, *semantic trajectory modelling* [17], *Bayesian network* [29], *LCSS* [27], *Markov chain* [30], *Convolutional Neural Network (CNN) Approach* [19] and *Spatio-temporal Recurrent Neural network* (ST-RNN) [18]. It may be noted that the trajectory modelling modules of all of the cited works have been implemented with our dataset for better comparison and to depict the effectiveness of our framework.

One of the major challenge of the proposed framework is to reduce the delay in delivering the processed information, and therefore if new GPS trace comes, the system should be able to re-learn the pattern effectively. Table II shows the performance measurements (*accuracy, learning and re-learning time*) compared to six baseline methods. The cardinality (number of trajectory-windows $\times$ day) of the test data of each agent for learning and re-learning are 18×150 and 6×20 respectively. Vlachos *et al.* [27] propose non-metric similarity function *LCSS* by computing the similarity between trajectory segments. However, it only calculates the topological or geometrical similarity ignoring the semantics of the trajectories. Semantic enrichment of trajectories and modelling to predict next location has been studied in [17]. Mingqi *et al.* utilizes the *Bayesian network place classifier* [29] to categorize the semantic of stay-points. Cheng *et al.* [30] model the check-in sequences of individuals using markov chain for personalized POI recommendations. Recently researchers are devoted to deploy *neural networks* [18], [19] to predict the next location sequences accurately. Karatzoglou *et al.* [19] has utilized *CNN* for modelling semantic trajectories. However, it is observed from our experimentation that this method does not perform well for the infrequent or less-occurring locations in the trajectories and when the sequence of the stay-points are larger than 8. Since [18] is capable to model individuals' mobility pattern in different contexts by considering semantic information and spatio-temporal periodic behaviour as well, we have carried out a detailed comparison study with [18]. It is observed from Table II that our framework, *Mobi-IoST* outperforms all other baselines, except *ST-RNN* by approximately 10–18%. *Mobi-IoST* not only provides next location prediction based on some prediction technique (such as, CNN, RNN or Markov-model), rather it models individual's movement patterns over days, captures the frequent path followed in several contexts and makes the next location sequence prediction. Further, it is observed that the learning and re-learning rates of *CNN* and *ST-RNN* are significantly higher by 10–20 mins and 14–24 mins than Mobi-IoST respectively. These measurements are important for our case, since the system needs to incorporate any sudden movement pattern change of user effectively. The *neural network* based methods are costly in terms of re-learning and stability. In summary, the deep learning architectures used in the existing works are computationally intensive, and it is shown that such deep

[3] Sample dataset available: https://drive.google.com/drive/folders/1BpM-K3clH6XYpSHkFe12aGsG8n1AclI4?usp=sharing

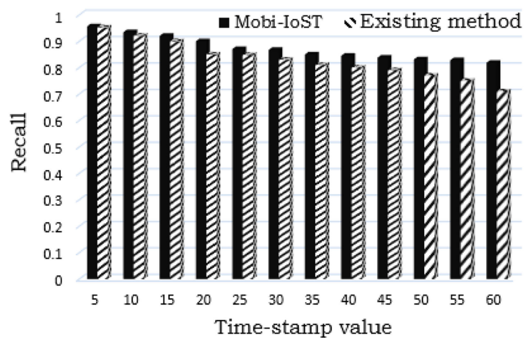

Fig. 4. Recall values for location prediction based on time-stamp value (min).

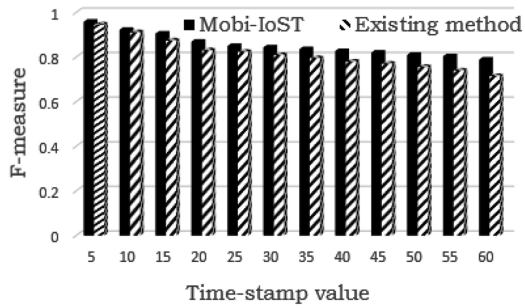

Fig. 5. F-measure values for location prediction based on time-stamp value (min).

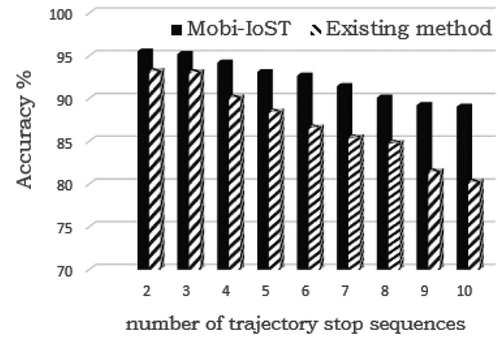

Fig. 6. Accuracy percentage for prediction trajectory sequences.

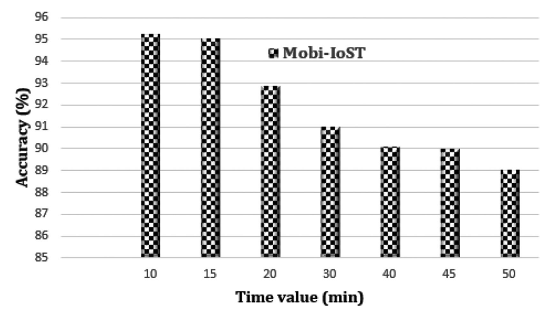

Fig. 7. Accuracy values for path prediction given source and destination.

architecture may not be beneficial for time-critical applications, where a delay-aware solution is necessary.

Figs. 4–6 show the performance metrics of *Mobi-IoST* with the existing work [18]. The accuracy to predict stay-point information is represented in Fig. 6. It may be observed that *Mobi-IoST* has accuracy of 88% to 95% for trajectory stop sequences ranging from 2 to 10. There is a significant drop of accuracy percentage from 93% to 80% of [18] in the same set-up. The key reason behind this observation is the proposed movement modelling named *User movement graph*, where user movement pattern is modelled in a multi-layer graphical model. The *frequent path network (FPN)* (layer 4 of the *User movement graph*) learns the movement paths frequently followed by the user deploying Dynamic Bayesian network. Thus, the model captures all sequences of paths visited in different spatial and temporal contexts. Next, in the proposed model, *k-order markov chain* is used to effectively model the spatio-temporal regularity of the trajectory sequences, where the next location depends on k recent observations. On the other side, the existing work [18] use deep architecture to capture the spatial and temporal contextual information, however fall short to predict long sequences of trajectory stay-point or stop points. Fig. 4 and Fig. 5 show the *recall* and *F-measure* values of location sequence prediction in different time-scale, from $5\,mins$ to $60\,mins$. Since the major aim of this work is the efficient delivery of service while the agent is on move, the experimental evaluation based on the time-stamp value is justified. We have found the recall and F-measure values in the range of 0.95 to 0.81 and 0.96 to 0.78 for twelve time-stamp values respectively. The results indicate that *Mobi-IoST* not only provides accurate predictions, but performs better than ST-RNN [18] while the time-stamp values increase as shown in Figs. 4 and 5. The reason behind the consistent prediction result with increased time-stamp value is that we have considered both spatial location and temporal span of a visit-sequence to model the proposed *FPN* of *user movement graph*. The prediction algorithm is capable to predict next location sequences based on both recent k locations and the time-duration of each stay-points. Thus, the framework is suitable to predict longer sequences of locations more effectively than existing work. Fig. 7 represents the accuracy of predicting path given source and destination, where x-axis is the commuting time. The experimental set-up is discussed in Section V-B. All of the performance measure values are computed based on the correct number of grid-id predictions. The accuracy percentage lies in the range of 89% to 95.3% for seven time-bins.

The performance evaluation is carried out to validate whether *Mobi-IoST* is suitable to deliver the processed information to the user-device based on user mobility prediction. To assist users and make intelligent decisions in time-critical applications, it is very crucial to model and predict users' next locations apriori based on varied spatio-temporal contexts. It has been observed that our framework has outperformed in all of the performance measurements compared to the baseline methods. The experimental results present that to predict user's next location Mobi-IoST takes approximately 4.23–9.02 seconds, which is used in Section V-D to determine the delay and power consumption in Mobi-IoST.

TABLE III
SIMULATION PARAMETERS

Parameter	Value
u	40-85km/hr
Up_{tmr}	50Mbps
Dw_{tmr}	70Mbps
Up_{trc}	75Mbps
Dw_{trc}	150Mbps
f_{mr}	0.008-0.25
f_{rm}	0.008-0.25
f_{rc}	0.05-0.5
f_{cr}	0.05-0.5
d_{pr}	500Mbps
d_{pc}	1Gbps
T_m	4.23-9.02s
P_a	0.11W
P_i	0.055W

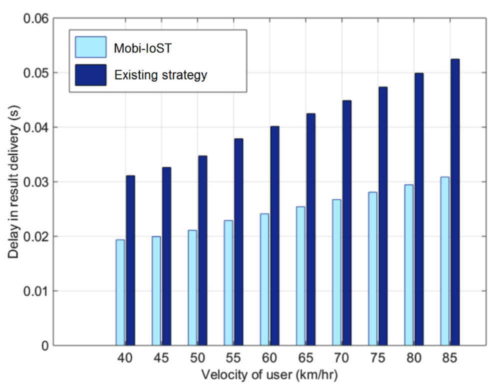

Fig. 8. Round-trip delay in proposed and existing methods (first case).

D. Delay and Power Consumption

The mobile device sends data to the RSU for processing. The RSU/cloud performs processing and sends back the result to the mobile device. The mobile device may move to the coverage of another RSU before acquiring the result. In such cases, the connection interruption period is considered 10–30 sec. MATLAB2015 is used for the simulation. The parameter values considered in this analysis are presented in Table III.

In this analysis we consider the following two cases:

- Information processing inside the RSU
- Information processing inside the cloud

In the first case, we have considered health parameter data transmitted by the mobile device. Blood pressure level (systolic and diastolic), body temperature, pulse rate and ECG data are considered. The RSU works as fog device and has functional model (pre-defined by the medical experts) to perform the processing. Based on the input (health parameter values, health profile of the user/patient and ambience parameter values) the RSU executes the functional model and predicts the health status. The RSU after processing the health data, sends back the current health status (normal/abnormal) as result to the mobile device. If abnormality is detected, then the parameters which seem to be abnormal are also notified in the result. The amount of data transmission to serve each user request is considered 70–90 KB. The round-trip delay and power consumption of the mobile device (user-device) in the proposed approach, are presented in Fig. 8 and Fig. 9. The delay and power are measured in second

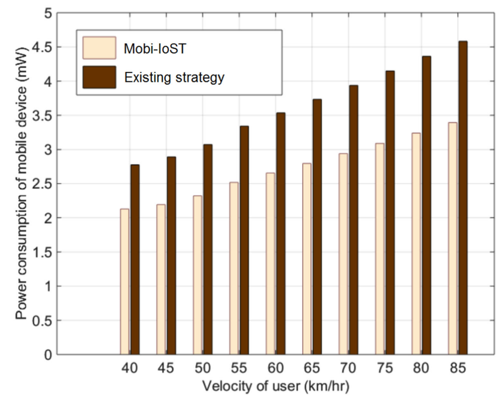

Fig. 9. Power consumption of mobile device in proposed and existing methods (first case).

(s) and watt (W) respectively. The delay and power consumption of the mobile device in case of Mobi-IoST are compared with the existing mobility-aware task delegation method [16]. This is observed that for the considered parameter values the delay in Mobi-IoST and existing method [16] are approximately 0.02–0.03s and 0.03-0.06s respectively (see Fig. 8). This is also observed that for the considered parameter values the power consumption of mobile device in Mobi-IoST and existing method [16] are approximately 2–3.5 mW and 2.5–4.5 mW respectively (see Fig. 9). In our approach the RSU works as a resourceful fog device and performs the data processing. If the device moves to the coverage of another RSU, the cloud predicts the current RSU based on user mobility information. In conventional method, the cloud performs data processing and the user receives the result through the RSU. However, if the user gets disconnected due to movement to another RSU, the user has to access the cloud to retrieve the result by serializing session information [16]. But in our approach, the cloud itself sends the result to the RSU, that is currently serving the device. The RSU then forwards the result to the mobile device. Hence, the delay and power consumption of the mobile device in the proposed system Mobi-IoST are less than the existing system [16]. This is observed that Mobi-IoST reduces the delay and power by approximately 23–26% and 37–41% respectively than the existing method [16].

In the second case, we have considered video data is transmitted by the mobile device. The RSU after processing the video data, sends back the processed data to the mobile device. The amount of transmission to serve each user request is considered 2–20 MB. The round-trip delay and power consumption of mobile device in the proposed approach, are presented in Fig. 10 and Fig. 11, and compared with the existing mobility-based task delegation method [16]. This is observed that for the considered parameter values the delay in Mobi-IoST and existing method [16] are approximately 5–20s and 10–50s respectively (see Fig. 10). This is also observed that for the considered parameter values the power consumption of mobile device in Mobi-IoST and existing method [16] are approximately ≤ 1.5 W and 0.5–3.5 W respectively (see Fig. 11). In our approach the cloud performs the data processing. After that based on user geo-location information, the cloud predicts the

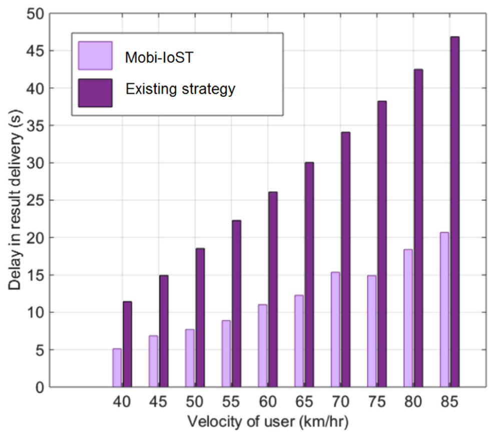

Fig. 10. Round-trip delay in proposed and existing methods (second case).

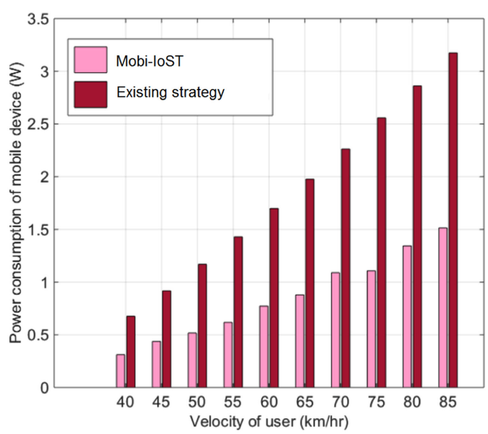

Fig. 11. Power consumption of mobile device in proposed and existing methods (second case).

current location of the user and the RSU currently serving the device. The cloud forwards the result to the RSU, which then sends back the result to the mobile device. However, in the existing method, the cloud performs data processing and the user receives the result through the RSU after accessing the cloud. Moreover, if the user gets disconnected and moves to the coverage of another RSU, the user has to access the cloud through the new RSU to retrieve the result by serializing session information. Whereas in our approach, the cloud itself sends the result to the RSU, that is currently serving the device. Hence, the delay and power consumption of the mobile device in the proposed system are less than the existing system [16]. This is observed that the proposed system reduces the delay and power by approximately 55–60% and 57–74% respectively than the existing system [16]. This is observed that for small as well as large scale processing, our Mobi-IoST reduces the delay and power consumption of the mobile device.

VI. Conclusion and Future Work

Seamless connectivity is a major challenge during data and computation offloading in any mobile network. The processing of raw data collected using IoT devices and delivery of the result to the client mobile device becomes a challenge if the client frequently changes location. In this paper, we have proposed a real-time cloud-fog-edge IoT collaborative framework, namely Mobi-IoST, for efficiently delivering the processed information to the user-device based on user mobility prediction and intelligent decision making. The mobile device acts as an edge device, and the RSU is used as fog device for processing the raw data collected by the mobile device from the IoT devices. If the user changes location and gets disconnected, the RSU forwards the result to the cloud. The cloud analyses the mobility pattern and delivers the result accordingly. The mobility prediction module primarily stores the movement traces and models the frequent path followed by the individual in different contexts and deploys a *hidden markov model* based location predictor for efficiently predicting the location sequences. The real-life data of movement traces yield approximately 10–18% improvement compared to other existing methods. Moreover, the simulation results demonstrate that the proposed fog computing framework reduces the delay and power by approximately 23–26% and 37–41% respectively than the existing mobility-aware task delegation system. The *Mobi-IoST* framework is quite generic and can be extended to capture the cellular data usage patterns from such time-series data and prediction of location sequences may help to appropriately manage the power and bandwidth related resources.

References

[1] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, “Internet of Things (IoT): A vision, architectural elements, and future directions,” *Future Gener. Comput. Syst.*, vol. 29, no. 7, pp. 1645–1660, 2013.
[2] M. Chiang and T. Zhang, “Fog and IoT: An overview of research opportunities,” *IEEE Internet Things J.*, vol. 3, no. 6, pp. 854–864, Dec. 2016.
[3] S. Ghosh and S. K. Ghosh, “Thump: Semantic analysis on trajectory traces to explore human movement pattern,” in *Proc. 25th Int. Conf. Companion World Wide Web*, 2016, pp. 35–36.
[4] S. Ghosh and S. K. Ghosh, “Exploring human movement behaviour based on mobility association rule mining of trajectory traces,” in *Proc. Int. Conf. Intell. Syst. Des. Appl.*, Springer, 2017, pp. 451–463.
[5] C. Chen *et al.*, “Crowddeliver: Planning city-wide package delivery paths leveraging the crowd of taxis,” *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 6, pp. 1478–1496, Jun. 2017.
[6] K. A. Eldrandaly, M. Abdel-Basset, and L. A. Shawky, “Internet of spatial things: A new reference model with insight analysis,” *IEEE Access*, vol. 7, pp. 19653–19669, 2019.
[7] N. Fernando, S. W. Loke, and W. Rahayu, “Mobile cloud computing: A survey,” *Future Gener. Comput. Syst.*, vol. 29, no. 1, pp. 84–106, 2013.
[8] J. Zhang *et al.*, “Energy-latency tradeoff for energy-aware offloading in mobile edge computing networks,” *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2633–2645, Aug. 2018.
[9] K. Gai, M. Qiu, H. Zhao, L. Tao, and Z. Zong, “Dynamic energy-aware cloudlet-based mobile cloud computing model for green computing,” *J. Netw. Comput. Appl.*, vol. 59, pp. 46–54, 2016.
[10] Y. Zhu, Q. He, J. Liu, B. Li, and Y. Hu, “When crowd meets big video data: Cloud-edge collaborative transcoding for personal livecast,” *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 42–53, Jan.–Mar. 2020.
[11] Q. Fan and N. Ansari, “Towards workload balancing in fog computing empowered IoT,” *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 253–262, Jan.–Mar. 2020.
[12] C. Yang, Y. Liu, X. Chen, W. Zhong, and S. Xie, “Efficient mobility-aware task offloading for vehicular edge computing networks,” *IEEE Access*, vol. 7, pp. 26652–26664, 2019.
[13] C. Wang, Y. Li, and D. Jin, “Mobility-assisted opportunistic computation offloading,” *IEEE Commun. Lett.*, vol. 18, no. 10, pp. 1779–1782, Oct. 2014.

[14] F. Tang and H. Zhang, “Spatial task assignment based on information gain in crowdsourcing,” *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 139–152, Jan.–Mar. 2020.
[15] H.-Q. Wu, L. Wang, and G. Xue, “Privacy-aware task allocation and data aggregation in fog-assisted spatial crowdsourcing,” *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 589–602, Jan.–Mar. 2020.
[16] A. Mukherjee, D. G. Roy, and D. De, “Mobility-aware task delegation model in mobile cloud computing,” *J. Supercomput.*, vol. 75, no. 1, pp. 314–339, 2019.
[17] J. J.-C. Ying, W.-C. Lee, T.-C. Weng, and V. S. Tseng, “Semantic trajectory mining for location prediction,” in *Proc. 19th ACM SIGSPATIAL Int. Conf. Adv. Geogr. Inf. Syst.*, ACM, 2011, pp. 34–43.
[18] Q. Liu, S. Wu, L. Wang, and T. Tan, “Predicting the next location: A recurrent model with spatial and temporal contexts,” in *Proc. 13th AAAI Conf. Artif. Intell.*, 2016, pp. 194–200.
[19] A. Karatzoglou, N. Schnell, and M. Beigl, “A convolutional neural network approach for modeling semantic trajectories and predicting future locations,” in *Proc. Int. Conf. Artif. Neural Netw.*, Springer, 2018, pp. 61–72.
[20] Y. Zheng, “Trajectory data mining: An overview,” *ACM Trans. Intell. Syst. Technol.*, vol. 6, no. 3, 2015, Art. no. 29.
[21] S. Ghosh, S. K. Ghosh, R. D. Das, and S. Winter, “Activity-based mobility profiling: A purely temporal modeling approach,” in *Proc. 26th Int. Conf. World Wide Web Companion*, 2018, pp. 409–416.
[22] S. Ghosh and S. K. Ghosh, “Modeling of human movement behavioral knowledge from GPS traces for categorizing mobile users,” in *Proc. 26th Int. Conf. World Wide Web Companion*, 2017, pp. 51–58.
[23] C. Song, Z. Qu, N. Blumm, and A.-L. Barabási, “Limits of predictability in human mobility,” *Science*, vol. 327, no. 5968, pp. 1018–1021, 2010.
[24] S. Shekhar and S. Chawla, *Spatial Databases: A Tour*, vol. 2003. Upper Saddle River, NJ, USA: Prentice Hall, 2003.
[25] C. E. White, D. Bernstein, and A. L. Kornhauser, “Some map matching algorithms for personal navigation assistants,” *Transp. Res. Part C: Emerg. Technol.*, vol. 8, no. 1–6, pp. 91–108, 2000.
[26] A. Mukherjee, S. Bhattacherjee, S. Pal, and D. De, “Femtocell based green power consumption methods for mobile network,” *Comput. Netw.*, vol. 57, no. 1, pp. 162–178, 2013.
[27] M. Vlachos, D. Gunopoulos, and G. Kollios, “Discovering similar multidimensional trajectories,” in *Proc. 18th Int. Conf. Data Eng.*, 2002, pp. 0673.
[28] J. Yamato, J. Ohya, and K. Ishii, “Recognizing human action in time-sequential images using hidden Markov model,” in *Proc. IEEE Comput. Soc. Conf. Comput. Vision Pattern Recognit.*, 1992, pp. 379–385.
[29] M. Lv, L. Chen, and G. Chen, “Discovering personally semantic places from GPS trajectories,” in *Proc. 21st ACM Int. Conf. Inf. Knowl. Manag.*, ACM, 2012, pp. 1552–1556.
[30] C. Cheng, H. Yang, M. R. Lyu, and I. King, “Where you like to go next: Successive point-of-interest recommendation,” in *Proc. 23rd Int. Joint Conf. Artif. Intell.*, 2013, pp. 2605–2611.

Shreya Ghosh received the B.Tech. degree from Indian Institute of Engineering Science and Technology, Shibpur, West Bengal, India, in 2015. She is currently working toward the Ph.D. degree with the Department of Computer Science and Engineering, IIT Kharagpur, Kharagpur, India. She is currently a Research Scholar with the Department of Computer Science and Engineering, IIT Kharagpur. Her current research interests include spatial informatics, trajectory data mining and cloud computing. She is the recipient of the prestigious TCS fellowship.

Anwesha Mukherjee received M.Tech. and Ph.D. degrees from the Department of Computer Science and Engineering, West Bengal University of Technology, Kolkata, India, in 2011 and 2018, respectively. She is currently working as a Research Associate with the Computer Science Department, IIT Kharagpur, West Bengal, India. Her research areas includes IoT, Fog computing, and mobile network. She was a recipient of the Young Scientist Award from International Union of Radio Science, in 2014, event held at Beijing, China.

Soumya K Ghosh is currently a currently a Professor with the Department of Computer Science and Engineering, IIT Kharagpur, West Bengal, India. He was with the Indian Space Research Organization, Bengaluru, India. He has authored or coauthored more than 200 research papers in reputed journals and conference proceedings. His current research interests include spatial data science, spatial web services, and cloud computing.

Rajkumar Buyya is currently a Redmond Barry Distinguished Professor and the Director of the Cloud Computing and Distributed Systems (CLOUDS) Laboratory, University of Melbourne, Parkville, VIC, Australia. He is currently the founding CEO of Manjrasoft, a spin-off company of the University. He has authored more than 625 publications and seven text books. He is one of the highly cited authors in computer science and software engineering worldwide (h-index = 128, g-index = 275, and more than 85 800 citations). He is recognized as a “Web of Science Highly Cited Researcher” in 2016 and 2017 by Thomson Reuters, and Scopus Researcher of the Year 2017 with Excellence in Innovative Research Award by Elsevier for his outstanding contributions to Cloud computing.