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Mobile crowd sensing

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Abstract - With the development of mobile sensing and mobile social networking techniques, Mobile Crowd Sensing and Computing (MCSC), which leverages heterogeneous crowd sourced data for large-scale sensing, has become a leading paradigm. Built on top of the participatory sensing vision, MCSC has two characteristic features: it leverages heterogeneous crowd sourced data from two data sources: participatory sensing and participatory social media; and it presents the fusion of human and machine intelligence in both the sensing and computing processes. This article characterizes the unique features and challenges of MCSC. We further present early efforts on MCSC to demonstrate the benefits of aggregating heterogeneous crowd sourced data.

I.INTRODUCTION

The effective use of the incredible and contin-uous production of data coming from different sources (e.g.,enterprises, the Internet of Things, online systems) will transform our life and work. Within this context, people are not only data consumers, but participate in different ways (e.g., smartphone sensing, online posting) in the data production process. In this article, we discuss the opportunities that heterogeneous human participation offer to systems and services that rely on large-scale sensing.It is essential to first clarify the motivation of taking the human in the loop for large- scale sensing. In the past few years, researchers have studied the benefits of understanding urban community dynamics . However, traditional stationary wireless sensor network deployments often fail to capture such dynamics because they either do not have enough sensing capabilities or are limited in terms of scalability (e.g., high deployment and maintenance cost). Mobile crowd sensing and computing (MCSC) offers a new method of large- scale sensing and computing. On one hand, the sheer number of mobile devices (e.g., smart phones, tablets, wear-able devices) and their inherent mobility provide the ability to sense and infer people’s context (e.g., ambient noise) in an unprecedented manner. On the other hand, highly scalable sensing with mobile devices in combination with cloud computing support gives MCSC systems the scalability and versatility properties that are often lacking in static deployments. Although it is quite difficult to attempt a formal definition of the MCSC paradigm, we could state that MCSC is a new sensing paradigm that empowers ordinary people to contribute data sensed or generated from their mobile devices, and aggregates and processes heterogeneous crowd sourced data in the cloud for intelligent service provision.

From the Artificial Intelligence (AI) perspective, MCSC is founded on a distributed problem solving model where crowds are engaged in complex problem solving procedures through open calls. The concept of crowd-powered problem solving has been explored in several research areas. The term “crowd sourcing” was coined in 2005 by Wired. The definition of the term crowd sourcing is as follows: the practice of obtaining needed services or content by solic-iting contributions from a large group of peo-ple, and especially from an online community. Wikipedia, where thousands of contributors from across the globe have collectively created the world’s largest encyclopedia, is a typical example. MCSC extends this concept by going beyond the boundaries of online communities and reaching out to the mobile device user population for sensing participation. With participa-tory sensing, first proposed by Burke et al. we see for the first time solutions that require explicit human involvement in accomplishing sensing tasks. MCSC broadens the concept of participatory sensing from two aspects. First, it takes advantage of various forms of human participation in the mobile Internet era. Generally speaking, MCSC sensing modalities can be obtained from specific hardware sensors (e.g., accelerometers, cameras) available on mobile devices and from the information trail (e.g., social media posts) directly generated by users. Second, MCSC presents the fusion of human and machine intelligence in both the sensing and computing processes. The usage of heterogeneous crowd sourced data as well as the integration of human and machine intelligence opens up new and unexpected opportunities. We use the following trip planning scenario to showcase the characteristics of MCSC. Trip planning is a typical MCSC application. With participatory sensing, we can collect GPS trajectory data from vehicles and compute the optimal route when answering a query with departure and destination points. However, for a more complex query, that is, to generate an itinerary for a visitor to a city given the time budget (start time, end time), it is not possible to leverage a single trajectory dataset. Further information such as points of interest (POIs) in the city, the best time to visit the POIs, and user preferences for different POIs, are further needed. The information can be obtained, however, by reusing the user-generated data from location-based social networks (LBSNs). The above scenario demonstrates the aggregated power of participatory sensing and social networks for intelligent service provision. The key contributions of this article can be summarized as follows:

Characterizing the main features of MCSC by combining participatory sensing and participatory social media. Exploring the fusion of human and machine intelligence in MCSC, and discussing the key research challenges such as cross-space data mining and data quality maintenance. Presenting several representative studies to demonstrate the power and usage of MCSC, including two of our recent works and ones from other research groups.

II.EXISTING SYSTEM

Grid users usually demand a combination of different resources as a bundle in order to perform their tasks. The available resources include computational power, disk space, memory space, and network bandwidth. For instance consider a grid user that can demand a bundle consisting of a computation service and a storage service: The computing service should have two processors

DRAWBACKS OF EXISTING SYSTEM

Because of the complexity of utility functions in repeated auctions, previous works presented recursive formulas for equilibrium strategies in sequential auctions.

Accordingly, learning in repeated auctions is harder compared to finite games.

Calculation of the equilibrium strategies is impractical, and as a consequence, previous works studied users bidding according to random strategies.

III.PROPOSED SYSTEM

The proposed system models the allocation problem as a market where suppliers auction off similar bundles of their resources among active grid users, while users have budget constraints for discovering the available resources (via brokers) and for describing their jobs. It uses general terms to describe the task requirements and the features of the available resources, so that a wide range of user/supplier objectives can be obtained by appropriate definition of the system parameters.

It presents a dynamic market-based model for allocation of grid resources where users obtain their required resources by updating their bids in a repeated-auction setting. It showed that users with budget constraints are better off submitting their bids based on their success rates and presented an efficient bidding algorithm that can be easily implemented in grid systems.

ADVANTAGES

- The new system presents a bidding algorithm that maximizes every user’s profit and hence constitutes equilibrium of the resource-allocation game.
- The proposed resource-allocation protocol based on repeatedly auctioning shares of the grid resources supports the dynamic nature of the grid environment.
- The model can handle variable number of users entering each auction, users demanding multiple shares of the auctioned resources.

Fusion of Human and Machine Intelligence

The primary feature of MCSC is having varying human participation (e.g., locating sensing objects, capturing pictures, posting in MSNs) in the large - scale problem solving process. The coexistence of human and machine power, how-ever, needs to be orchestrated in an optimal manner to enhance them both. An important reason to combine human and machine intelligence is that they often show distinct strengths and weaknesses, as illustrated in Fig. 2. We refer to the fusion of human intelligence (HI) and machine intelligence (MI) as HMI, which characterizes the complementary roles of HI and MI in problem solving and integrates them for MCSC service provision.

As there are three import-ant layers in a generic MCSC framework, and HI and MI work collaboratively over all these layers. For example, in the crowd sensing layer, machines can allocate tasks to proper participants according to the task needs and human behavior patterns, and the selected workers can execute the assigned tasks using their cognition/ perception abilities. In the data transmission layer, human mobility patterns and social inter-actions facilitate the development of optimized networking methods . In the data processing layer, the integrated power of HMI can attain higher performance (e.g., accuracy of classification) than either one.

Key Research Challenges

The combination of two participatory data generation modes in MCSC also raises new research challenges and issues, some of which are discussed below.

Heterogeneous, Cross-Space Data Mining

The strength of MCSC relies on the usage of crowd sourced data from both physical and virtual societies. The same sensing object (e.g., a social gathering on a street corner) will interact with both spaces and leave fragmented data in each space, making the information obtained from different communities (online or offline) different. For instance, we can learn social relationships from online social networks, and infer group activities using smart phone sensing in the real world. Obviously, the complementary nature of heterogeneous communities will bring new opportunities to develop new human-centric services. Therefore, we should integrate and fuse the information from heterogeneous, cross-space data sources we refer to it as cross-space data mining to attain a comprehensive picture of the sensing object. Potential research issues include how data in crowd sensing. Smart Photo quantified the utility of crowd sourced photos based on the associated contextual information, such as the smart phone's orientation, position, and location.

MCSC on the Road

The study of MCSC brings new potential in many application areas. This section first makes a summary of two of our ongoing works. The first work is a trip planning application that demonstrates the power of using a combination of participatory sensing and social media data. The second work illustrates our efforts on HMI in MCSC. We also use more examples from other research groups to demonstrate the power of MCSC.

Trip Planning with Heterogeneous Crowd Data

In the introduction, we described the trip planning scenario. A detailed analysis of the problem as well as our solution is presented below. As shown in order to plan a trip for visiting a popular tourist city, one needs to select a number of user-preferred POIs among hundreds of available venues (V1 to V5 in Fig. 3).Figure out the order in which they are visited, ensure the total time it takes to visit them (the stay time), transit from one venue to the next(the transit time), and meet the user's time budget. In order to address the trip planning problem, information about the POIs and links among POIs needs to be acquired to build a POI net-work model. Two types of crowd sourced data sources can be exploited:GPS trajectories of people and taxis, which can indicate the stay time in each place and the transit time between two places Previous studies rely on one of the We have evaluated the performance of Trip-Planner over the datasets collected from San Francisco. 15,759 POIs of the city were obtained from FourSquare. We ranked all POIs in descending order based on their total check-in times. The top 1000 POIs were finally used in our work, considering that tourists would seldom visit POIs with few check-INS. The taxi GPS data of San Francisco was obtained from the CRAW-DAD[4] data sharing website. Two similar queries with the same time budget (8.5 h) but different trip starting times were predefined. The start time of the two queries was set to 7:00 a.m. and 10:00 a.m., respectively. As shown on the right of Fig. 3, given the time budget, the user can have seven preferred venues for the first query and eight for the second one. This is because for the first query, the planned route starts around the morning rush hour and thus needs more transit time. We also find that the route for the two queries are different. These results indicate that Trip Planner is traffic-aware with the usage of taxi GPS data. Moreover, with LBSN data in use, our method is more venue-aware. For example, it is suggested that the user go to an Italian restaurant for lunch just after leaving the airport, since it is almost lunch time, and many people visit that venue during that time period.

HMI in Crowd-Powered Data Transmission

The success of MCSC relies on the effective transmission of data from individual mobile devices to the destination nodes (e.g., data requesters, backend servers). The mobility of mobile devices and their carriers not only pro-vides nice coverage for sensing tasks but also brings challenges to data transmission. For instance, network topology, device connectivity, and communication interfaces evolve over time, which makes it hard to find stable routes for crowd sensed data transmission. We refer to it as the "transient" networking issue in MCSC.To address this issue, people often form opportunistic social networks (OPSNs) . Since the source node and destination nodes may never meet in OPSNs, forwarding data packets from their sender to the nodes of interest is often based on a broker-based solution. In this solution, a selected broker node first stores the data from its sender, carries it while in motion, and then forwards it to intermediate or destination nodes. The assumption is that all users are will-ing to act as brokers. However, this assumption does not always hold: according to sociological theories, socially selfishness is a basic attribute of human beings, and thus the selected brokers may deny requests from other nodes to save their own resources (e.g., storage, power). Therefore, how to motivate people to participate in opportunistic data transmission becomes a crucial challenge of MCSC. We have developed two HMI-enhanced approaches to promote user participation in broker-based data dissemination. In the first approach people are inspired by social/ethical reasons, while in the second one a solid economic model is leveraged. We illustrate them in Fig. 4 and describe them in detail below.

The Hybrid Social Networking (HSN) Model: The HSN model is inspired by the multi-community involvement and cross-com-munity traversing nature of modern people. For example, at one moment, Bob is staying at a place with Internet connection and can communicate with his online friends; later, he may travel by train with merely opportunistic connection to nearby passengers. We use HSN to indicate the smooth switching and collaboration between online and opportunistic communities.

One of the key issues addressed by HSN is social selfishness. According to people are willing to help their friends. Following this finding, HSN allows the data sender to choose brokers online from their social connections to avoid the selfishness problem. The online approach also reduces the cost of popular node selection (to shorten transmission latency, the ones with high probability to meet more people are selected as brokers), which does not require direct contact in the real world. The selected brokers will disseminate the information and do matchmaking with potential interested nodes in opportunistic communities. We compared the performance of HSN with single-community-dependent methods (e.g., the pure opportunistic networking method). Experiment results indicate that great performance improvement is obtained when using HSN . This is because that the integration of online communities shortens the broker selection process, and increases the opportunity to select popular brokers.

HSN is a typical HMI-powered approach, where HI and MI are fused in a hybrid manner via two units. The prior unit is sequential, where social relation and user popularity (HI) are derived first and then used for broker selection (MI); the latter is parallel, where user movement (HI) and matchmaking (MI) work simultaneously to fulfill the data transmission task.

The Market Model with Intermediaries: Inspired by how buyers and sellers interact in traditional markets, we introduce the model of markets with intermediaries as an incentive mechanism to stimulate node cooperation in MCSC. In many markets (e.g., stock markets, agricultural markets in developing countries), individual buyers and sellers do not interact directly with each other, but trade via intermediaries instead . These intermediaries, also called traders, often set the prices of trans-actions. The similarities between markets with intermediaries and data dissemination in opportunistic social networks drive us to use the former as an incentive mechanism in the latter. A data sender is like a seller in a market, and a data receiver is like a buyer: she “buys” a unit of goods if she receives the data from traders. As shown in Fig. 4 (bottom), the connections (built based on direct contacts) among traders, sellers, and buyers will form a trading network.

For simplicity, each seller i initially holds one unit of the good, which she values at v_i; she is willing to sell it at any price that is at least v_i (sell value). Each buyer j values one copy of the good at v_j (buy value) and will try to obtain a copy of the good if she can do it by paying no more than v_j. Each trader t offers a bid price b_{ti} to each sell-er i with which she connects, and an ask price a_{tj} to each connected buyer j. After receiving offered prices by traders, each seller and buyer can only choose at most one trader with which to deal. A flow of goods from sellers through traders to buyers is finally generated. Figure 4 gives an example of such a trading model, including the bid price, ask price, and flow of goods (indicated by the solid lines).

In this approach, transactions are made based on a game process. In the game, a trader’s strat-egy is a choice of bid and ask prices to propose to each neighboring seller and buyer; a seller or buyer’s strategy is a choice of a neighboring trad-er to deal with, or the decision not to take part in a transaction. The participants (sellers, traders, and buyers) are motivated to get their payoffs.

Note that in traditional markets, currency is gen-erally used as a medium for buying and selling. In our model, we further expand this concept by allowing virtual currency to be used. That is to say, services can pay “virtual coins” to the partici-pants, and participants need to spend some coins in service usage. In our case, both data senders and brokers can receive their payoffs in “virtual coins.” Experiments indicate that our approach can enhance user participation in MCSC data transmission. HMI is also embedded in a hybrid way in this case. In association with social interactions and price settings (HI), the trading network model (MI) is formed (a parallel unit); afterward, the stakeholders bargain and make decisions (HI) to fulfill the data transmission task (a sequential unit).

Other Efforts on MCSC

Beyond our recent works, MCSC has also been found useful in several other studies. Zheng et al. proposed a model to infer fine-grained air quality information throughout a city. The learn-ing model leveraged the air quality data report-ed by existing monitor stations and a variety of crowd-contributed data in the city, such as traffic flow (offline space) and POIs in LBSNs (online space). Du et al. leveraged a combination of social media and historical physical activity data to predict activity attendance and facilitate social interaction in the real world.

IV.CONCLUSION

MCSC shows its difference in the literature by leveraging varying levels of user participation in data contribution and aggregating heterogeneous crowd sourced data for novel service pro-vision. We have characterized the key features of MCSC, such as explicit/implicit sensing, and heterogeneous cross-space data mining. To fully leverage the power of crowd participation, MCSC needs deep fusion of human and machine intelligence. Three HMI patterns are thus identified. We further present the early efforts on MCSC.

As an emerging paradigm for large-scale sensing, numerous challenges and research opportunities remain to be investigated. First, MCSC is an instance that bridges the gap between cyber space and physical space. The problems to solve in such a hyperspace are much more complex, and need to integrate various HI and MI units as interdependent parameters in a unique solution. Second, in hyperspace, we should exploit cross-space fea-tures for aggregated sensing and data under-standing. Third, as community-enabled sensing, the generic features of a community, such as sensing scale (ranging from a group to an urban scale), community structure, and user collabora-tion should be further studied [5, 13], which are paid little attention in existing studies.

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