A Scalable Framework for Spatiotemporal Analysis of Location-based Social Media Data

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Abstract

In the past several years, social media (e.g., Twitter and Facebook) has been experiencing a spectacular rise and popularity, and becoming a ubiquitous discourse for content sharing and social networking. With the widespread of mobile devices and location-based services, social media typically allows users to share whereabouts of daily activities (e.g., check-ins and taking photos), and thus strengthens the roles of social media as a proxy to understand human behaviors and complex social dynamics in geographic spaces. Unlike conventional spatiotemporal data, this new modality of data is dynamic, massive, and typically represented in stream of unstructured media (e.g., texts and photos), which pose fundamental representation, modeling and computational challenges to conventional spatiotemporal analysis and geographic information science. In this paper, we describe a scalable computational framework to harness massive location-based social media data for efficient and systematic spatiotemporal data analysis. Within this framework, the concept of space-time trajectories (or paths) is applied to represent activity profiles of social media users. A hierarchical spatiotemporal data model, namely a spatiotemporal data cube model, is developed based on collections of space-time trajectories to represent the collective dynamics of social media users across aggregation boundaries at multiple spatiotemporal scales. The framework is implemented based upon a public data stream of *Twitter* feeds posted on the continent of North America. To demonstrate the advantages and performance of this framework, an interactive flow mapping interface (including both single-source and multiple-source flow mapping) is developed to allow real-time, and interactive visual exploration of movement dynamics in massive location-based social media at multiple scales.

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1. Introduction

Social media represents "a group of Internet-based applications that are built on the ideological and technological foundations of web 2.0, and that allow the creation and exchange of user generated content" [21]. Typical examples include Twitter, Facebook, Foursquare, Flickr. In recent years, these on-line applications have been attracting hundreds of millions of users for everyday social networking and content sharing, and at the same time collecting a huge amount of user-generated social media data (e.g., text messages, photos, videos, and structure of social relationship). Twitter, for example, has grown at an exponential rate since its founding. As of December of 2013, monthly active Twitter users have reached more than 3.9 percent of global population and 17.9 percent of the United States, and have sent more than 300 billion of so-called tweets (individual user posts)¹. On another front, with widespread of smart mobile devices and location-based services, location-aware mobile devices have become prevalent access points to social media services. Accordingly, location has become a crucial aspect of social media data. Hundreds of millions of smartphone users carry their location-enabled smartphones virtually every day, record and share their whereabouts and experiences via social media. From a perspective of geographic information science (GIScience), these users could be viewed as ubiquitous "citizen sensors" that move in geographic spaces, sense and share the surrounding environment using social media contents of various kinds. The inclusion of location or spatial dimension blurs the interface between the cyberspace of social media and geographic space of the real world [40], and together with the temporal dimension, makes social media as promising proxies to understand the social dynamics in geographic spaces.

With accesses to fine-grained social media footprints at individual levels, location-based social media data provide a set of new lens to examine complex social dynamics. By taking advantage of this new modality of data source, extensive studies with significant societal impacts have been recently reported. In behavioral sciences, for example, massive individual geo-tagged social media records can be used to study human activity (e.g., travel) patterns and the effects on human life [7]. By further leveraging friendship networking information, one can quantitatively model the patterns of human activities and then make predictions for the future [e.g., 2, 34]. At an aggregate level, a careful aggregation of social media footprints for a subpopulation (e.g., a geographic region) could lead to a better understanding of this subpopulation [5, 23] and the connections with others [e.g., 45]. In public health surveillance, studies have shown that, for certain diseases (e.g., influenza), a careful analysis of geo-located Twitter messages could provide surveillance capabilities comparable with the official

¹Source: http://www.sec.gov

CDC (US Centers for Disease Control and Prevention) reports, but in a much more timely manner [e.g., 36, 27].

The initial successes in exploiting location-based social media data, demonstrate great potentials and provide tremendous opportunities to gain new scientific insights. Distinct characteristics of location-based social media data. however, pose fundamental representation, modeling and computational challenges to GIScience, spatiotemporal databases and spatiotemporal analysis. As described in [43], location-based social media data generated by a massive number of social media users are often big and produced continuously at an ever fast rate. Millions of social media users frequently update or change their status and locations. Consider the aforementioned case of daily new tweets and even extend the desirable time window to months or years. Evidently, location-based social media data and other user-generated geospatial contents are becoming an important contribution source of big data [25]. Gray [12] suggests a fourth paradigm, namely data-intensive inquiries or eScience, for scientific discoveries to survive the deluge of big data. While GIScience is shifting rapidly to embrace the fourth paradigm [44, 42], the big data nature of location-based social media is well beyond the capability of mainstream geographic information systems (GIS). Furthermore, the dynamic and real-time characteristics of social media data hinder direct applications of conventional GIS, which tends to represent the real world as static forms instead of dynamic processes [11]. In addition, social media contents are usually produced in unstructured forms of media (e.g., texts, photos and videos) in contrast to the typical well-structured, ready-to-use geospatial data sources. Extra efforts, such as data retrieving and data mining processes, are often necessary to obtain the data and then make the data meaningful and sensible.

To address these challenges, this paper presents a scalable computational framework to harness the massive location-based social media data to support systematic and efficient analysis of spatiotemporal dynamics. In the presented framework, location-based social media data are firstly regularized in terms of space-time trajectories or paths to represent the activity profile of each social medial individual. To exploit the unstructured contents of social media, specific data mining methods can be plugged into the described framework to gain valuable information of interests. As a particular example, this paper examines the chance of influenza like illness (ILI) infection by monitoring text messages in Twitter posts. Within the context of data warehouse and on-line analytical processing (OLAP) [19], a data cube model for space-time trajectories is designed, constructed and regularly maintained to support systematic and efficient spatiotemporal analysis of massive location-based social media data. Specifically, this data cube frames the spatiotemporal dynamics of location-based social media in a multidimensional space (or a cube) of location, time and social media users, and decomposes this multidimensional space (cube) into a multi-scale, hierarchical structure of *cuboids*. A set of measures that characterize the spatiotemporal dynamics of location-based social media are specifically defined for each cuboid (e.g., number of social media users and activities) and each pair of cuboids (e.g., number of travels from one cuboid to another) of the data cube. The measures of cuboids can be flexibly merged or split according to the dimensional intervals of interest (e.g., administrative boundaries). Aggregation functions associated with these measures are also defined to support data cube operations (e.g., merge and split measures of cuboids). With the data cube model decomposed into arrays of cuboids, one can exploit the collective spatiotemporal dynamics in particular regions of interest at multiple levels of spatiotemporal scales (scale effects) and different aggregation boundaries (zoning effects) in a very efficient manner. The presented framework thus transforms the massive, dynamic and unstructured location-based social media data into flexible geospatial datasets that could be easily compatible with the high performance analytical environment of cyberGIS [42] and the typical work-flows of conventional GIS analysis. Implementation details of the framework are described based on an open access of Twitter post stream. An on-line visual analytical interface, including single-source and multiple-source flow mapping, is developed to allow near real-time, interactive visual exploration of multiple scales of distribution and movement dynamics in massive location-based social media data.

In the remainder of this paper, key concepts of data representation, particularly space-time trajectories, are first introduced in the Section 2. Section 3 introduces the spatiotemporal data cube model for efficient analysis of locationbased social media data. Based on a public data stream of *Twitter* feeds posted on the continent of North America, the implementation details of presented framework are discussed in Section 4. In Section 5 the on-line flow mapping interface is introduced and demonstrated to showcase the advantages and effectiveness of the proposed framework. Section 6 summarizes the paper and discusses future work.

2. Space-time trajectories

Consider a set of N individuals frequently sharing their activities (e.g., message posts and check-ins) through a location-based social media platform, which exhaustively collects activities of users. To ease the privacy and security concerns of individual users, we suppose that the location-based social media platform is designed to collect these data anonymously, that is, the social media platform is unaware of the identities of individual users and no names or other personal identifiers are shared. Each individual is assumed to move continuously in geographic spaces, either freely in a Euclidean space, or restrictively in a regularized network space, e.g., roads, railways, or airways, and frequently share messages via social media channels.

The concept of space-time paths or trajectories has long been used as a simple and effective means for representing and characterizing human mobility pattern [16] and spatial trajectory analysis [46]. In this paper, we assume that each user $u_{id}(id \in [1, N])$ corresponds to a continuously moving, lifetime space-time trajectory T_{id} in a geographic space. This "true" trajectory T_{id} is measured and approximated by TS_{id} , a series of footprints tuples of location (s_{id}) , timestamp (t_{id}) and message content (m_{id}) of in social media, i.e.: $TS_{id} = \{(s_{id}^0, t_{id}^0, m_{id}^0), (s_{id}^1, t_{id}^1, m_{id}^1), \ldots, (s_{id}^i, t_{id}^i, m_{id}^i), \ldots\}$, where $t_{id}^0 \leq t_{id}^1 \leq \ldots t_{id}^i \leq \ldots$ Different from conventional trajectories of moving objects [46] where measurements are often abundant and sampled at regular time intervals, measurements for trajectory of location-based social media TS_{id} (i.e., user activities) are often very temporally sparse and irregular [8]. Inactive social media users could have long time of sedative period before next social media activities, and yet due to privacy concerns, users have choice to disable location options when posting activities. Consequently, the intermediate positions between measurements on TS_{id} cannot be reliably reconstructed by commonly used methods (e.g., interpolation and map-matching) in spatial trajectory analysis. [1] referred to this particular type of trajectories as "episodic movement data". In the following analysis, we assume that T_{id} is a step function of time \mathcal{T} defined by trajectory samples TS_{id} , i.e., a social media user u_{id} stays at the same location during $[t_i, t_{i+1}]$ as at t_i until a new activity is posted at t_{i+1} when u_{id} moves from s_i to s_{i+1} .

To characterize the massive number of space-time trajectories associated with social media users, several geometric measures of trajectories are particularly of interest. Individuals typically return to the same location frequently, and the locations are ranked based on the number of visited times in each trajectory. We refer the most frequently visited location area as the *home* of the individual. To represent the mobility of an individual, radius of gyration [10] is maintained based on an individual's spatial footprint. Compared with GPS logs or mobile phone records, location-based social media data provide access to the contents of messages or activities (m). Despite of being unstructured, these contents carry important clues to latent attributes of social media users. Specific data mining methods could be applied to derive desirable attributes about social media users, such as health statuses [36], socio-demographic information [4, 33], and opinions on specific subjects [28]. As a specific example to illustrate the proposed framework, this paper focuses on infection spread of ILI; a previously developed text mining method [43] is applied to text messages to diagnose the chance that a social media user is ILI affected during a time period of space-time trajectories.

3. A data cube model for location-based social media data analytics

A space-time trajectory provides a representation of individual activity footprint in the cyberspace of social media. Oftentimes, researchers are interested in collective characteristics of a subpopulation, e.g., distribution of activities of a certain group of social media users at specific regions during specific time periods. As mentioned in the previous section, the data characteristics of locationbased social media (e.g., massive and dynamic) hinder the application of conventional database and analysis methods in these aggregated analysis. In the remainder of this section, a spatiotemporal data cube model is described to support efficient spatiotemporal analytics of aggregated statistics of massive amount of space-time trajectories.

Data warehouse and on-line analytical processing (OLAP) were originally designed for effective analytics of massive business transactions. In OLAP, data are typically represented as a data cube [13], defined by a set of *fact* tables associated with a set of *dimension* tables, and *hierarchies*. According to the specification of dimension tables, a data cube discretizes a multidimensional space into a lattice of hierarchical *cuboids*, with *base cuboids* representing primitive compartments in the multidimensional space at the finest level. Base cuboids are filled with values of measures specified in the fact tables against all the dimensions. Data cube operations, such as *roll-up* (merging cuboids) and *drill-down* (splitting cuboids) could be applied for different levels of aggregations. The concepts of data warehousing and data cube have been adapted to spatial data [17]. Since then, an amount of efforts have been reported to exploit the power of spatial data cube in traditional GIS and spatial analysis [e.g., 35, 3], visual analytics of spatiotemporal processes [24], analysis of massive moving objects [e.g., 30, 22], and closely related, analysis of mobile cyber-physical systems [e.g., 32.37].

In this paper, we extend the concept of data cube for spatiotemporal analysis of location-based social media data. Based on the space-time trajectories introduced previously, we are particularly interested in investigating the human population distribution and mobility patterns represented in location-based social media. Due to the effect of population heterogeneity or the well known modifiable areal unit problem (MAUP) [29], conclusion drawn from a group of individuals (a subpopulation) would probably not be applicable to another group or aggregation of groups (population). Data cubes provide an effective tool to examine the collective spatiotemporal dynamics of massive social media users (space-time trajectories) at multiple levels of spatiotemporal scales (scale effects) and different aggregation rules (zoning effects). In the spatiotemporal data cube, we specify the dimension tables with *spatial*, *temporal* and *human* (social media users) dimension. Cuboids in the data cube are indexed by intervals at these three dimensions. To facilitate the spatiotemporal analysis of location-based social media data, we consider two different kinds of facts, facts for a single cuboid and facts for interactions between pairs of cuboids. Similar as in Leonardi et al. [22], a graphical conceptual model for data warehouses, namely a Dimensional Fact Model [9], is adopted to represent the fact schema within a single cuboid (Figure 1), and the fact schema between pair of cuboids (Figure 2). For each fact schema, we introduce a list of measures that are common and significant for characterizing population distribution and movement dynamics represented in location-based social media data, which will be specifically defined later in this section. Depending on application scenarios, this data cube model is extensible for additional appropriate measures.

Each of the three dimensions is organized at hierarchical levels of granularities, and details of the hierarchical structures are depicted in Figure 1 and Figure 2. For the spatial dimension, we consider a spatial grid with high resolution in the finest granularity. In the following discussion, we choose the cell size as $1km \times 1km$ to be compatible with the commonly used global population grid datasets, such as LandScan Global Population Database [6] and the Global

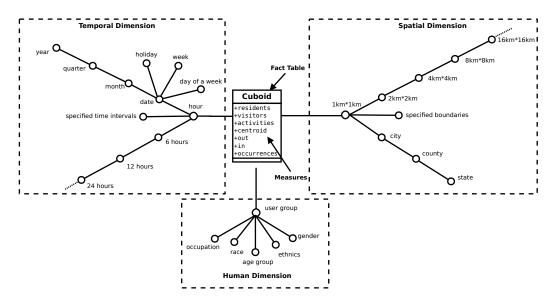


Figure 1: Fact schema of a spatiotemporal data cube (cuboid)

Rural-Urbana Mapping Project (GRUMP) [20]. Different resolution could be applied depending on application scenarios. Two different kinds of spatial hierarchies are considered based on the primitive spatial grid. The size of spatial grid cells keeps increasing by merging adjacent cells in the first spatial hierarchy, and in the other hierarchy, base grid cells aggregated by administrative boundaries such as cities, then cities by counties, counties by states and so on. Similarly for the temporal dimension, we choose fine temporal intervals as base intervals. Empirically, we choose the base temporal intervals as 1 hour in the following discussion. The base temporal intervals either keep merging with adjacent intervals or aggregated by days, days aggregated by weeks or months and so on. For the dimension of human (social media users), we start from individuals, which can be further organized according to the health status (e.g., ILI affected or not) or socio-demographic characteristics (e.g. age groups). It should be noted that, based on base cuboids, flexible hierarchy structures at each dimension could be defined. In the spatial dimension, for example, base cuboids could be aggregated according to arbitrarily specified spatial regions.

3.1. Measures

For a fixed group of social media users, a cuboid in the data cube corresponds to a contiguous spatial region and a temporal interval. Given a cuboid c in the data cube, the measures listed in Figure 1 can be defined for a group of users u. For notation simplicity, u is dropped in the denotation.

1. R(c) (residents): the number of distinct social media users in u whose homes locate within spatial boundary of c;

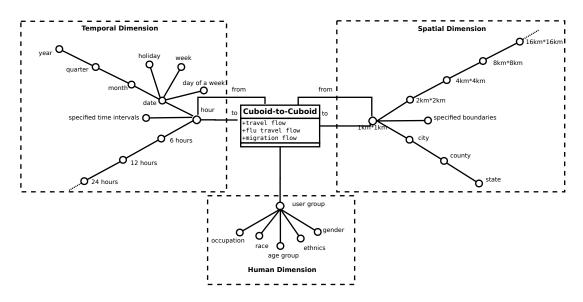


Figure 2: Fact schema of a spatiotemporal data cube (cuboid-to-cuboid)

- 2. V(c) (visitors): the number of distinct social media users in u who has posted activities in c (one user could post multiple activities);
- 3. A(c) (activities): the number of social media activities by individuals in u occurring in c;
- 4. $O(\mathbf{c})$ (out): the number of moves made by \mathbf{u} from \mathbf{c} to other cells;
- 5. I(c) (in): the number of moves made by u into c from other cells;
- 6. S(c) (centroid): the expected location of social media activities by individuals in u occurring in c;
- 7. $V_{flu}(c)$ (occurrences): the number of distinct social media users in u that post activities in c diagnosed as ILI affected occurrences;

Apparently, $O(\mathbf{c}) \leq V(\mathbf{c})$, $I(\mathbf{c}) \leq V(\mathbf{c})$, $V_{flu}(\mathbf{c}) \leq V(\mathbf{c})$ and $V(\mathbf{c}) \leq A(\mathbf{c})$. Figure 2 defines a list of measures quantifying the interactions between pairs of cuboids \mathbf{c}_i and \mathbf{c}_j :

- 1. $F(c_i, c_j)$ (travel flows): the number of *moves* made by social media users u starting from cuboid c_i and ending in cuboid c_j ;
- 2. $F_{flu}(c_i, c_j)$ (flu travel flows): the number of *moves* made by social media users u starting from cuboid c_i and ending in cuboid c_j made by ILI occurrences;
- 3. $F_{migration}(c_i, c_j)$ (migration flows): the number of social media users in u migrating home location from cuboid c_i to cuboid c_j ;

A move will be flagged as a ILI-related one if either the starting or ending social media activity is diagnosed as an ILI activity by the text mining method [43]. Apparently, $F_{flu}(\mathbf{c}_i, \mathbf{c}_j) \leq F(\mathbf{c}_i, \mathbf{c}_j)$ and $F_{migration}(\mathbf{c}_i, \mathbf{c}_j) \leq F(\mathbf{c}_i, \mathbf{c}_j)$. All of these three flow measures are asymmetry, i.e., $F(\mathbf{c}_i, \mathbf{c}_j) \neq F(\mathbf{c}_j, \mathbf{c}_i)$, $F_{flu}(\mathbf{c}_i, \mathbf{c}_j) \neq F_{flu}(\mathbf{c}_j, \mathbf{c}_i)$, $F_{migration}(\mathbf{c}_i, \mathbf{c}_j) \neq F_{migration}(\mathbf{c}_j, \mathbf{c}_i)$. We assume that $F(\mathbf{c}_i, \mathbf{c}_j) = 0$, $F_{flu}(\mathbf{c}_i, \mathbf{c}_j) = 0$ and $F_{migration}(\mathbf{c}_i, \mathbf{c}_j) = 0$ when *i* equals *j*. As mentioned in the previous section, a space-time trajectory is essentially a collection of step functions. Therefore, flow is an aggregation of space-time trajectories based on points of trajectories instead of the segments in-between.

3.2. Aggregation functions

Aggregation functions of measures are critical for the construction and query operations of date cubes [13]. It allows for aggregating measures at higher levels of the hierarchy (super-aggregates) based on those of lower levels (subaggregates). Let \mathcal{H} denote a spatiotemporal hierarchy corresponding to a group of social media users \boldsymbol{u} , and without losing generality, let \boldsymbol{c}_1 and \boldsymbol{c}_2 be two disjoint cuboids in \mathcal{H} which can be further decomposed into K disjoint subcuboids $\{\boldsymbol{c}_{1,i}, i = 1, \ldots, K\}$ with $\boldsymbol{c}_1 = \bigcup_{i=1}^K \boldsymbol{c}_{1,i}$, and $\{\boldsymbol{c}_{2,i}, j = 1, \ldots, K\}$ with $\boldsymbol{c}_2 = \bigcup_{j}^K \boldsymbol{c}_{2,j}$. Suppose we already have the measures for sub-cuboids $(\boldsymbol{c}_{1,i} \text{ and } \boldsymbol{c}_{2,j})$, aggregation functions define how to get measures for cuboids \boldsymbol{c}_1 and \boldsymbol{c}_2 . For measures A of \boldsymbol{c}_1 , and flow measures F and F_{flu} between \boldsymbol{c}_1 and \boldsymbol{c}_2 , superaggregates can be written as recursive functions of sub-aggregates:

$$A(\boldsymbol{c}_1) = \sum_{i=1}^{K} A(\boldsymbol{c}_{1,i})$$
(1)

$$F(c_1, c_2) = \sum_{i,j=1}^{i,j=K} F(c_{1,i}, c_{2,j})$$
(2)

$$F_{flu}(\boldsymbol{c}_1, \boldsymbol{c}_2) = \sum_{i,j=1}^{i,j=K} F_{flu}(\boldsymbol{c}_{1,i}, \boldsymbol{c}_{2,j})$$
(3)

$$F_{migration}(\boldsymbol{c}_1, \boldsymbol{c}_2) = \sum_{i,j=1}^{i,j=K} F_{migration}(\boldsymbol{c}_{1,i}, \boldsymbol{c}_{2,j})$$
(4)

For measure S, I and O, the super-aggregates c_1 needs the support of other measures. Specifically for S:

$$S(c_1) = \frac{1}{A(c_1)} \sum_{i=1}^{K} A(c_{1,i}) S(c_{1,i}) = \frac{\sum_{i=1}^{K} A(c_{1,i}) S(c_{1,i})}{\sum_{i=1}^{K} A(c_{1,i})}$$
(5)

For measures I and O on c_1 , we need to remove the space-time trajectories that occurred within the boundaries of c_1 according to the definition of I and O. Hence, we have:

$$O(\mathbf{c}_{1}) = \sum_{i=1}^{K} O(\mathbf{c}_{1,i}) - \sum_{i=1}^{K} \sum_{j=1}^{K} F(\mathbf{c}_{1,i}, \mathbf{c}_{1,j})$$
(6)

$$I(\mathbf{c}_{1}) = \sum_{i=1}^{K} I(\mathbf{c}_{1,i}) - \sum_{i=1}^{K} \sum_{j=1}^{K} F(\mathbf{c}_{1,i}, \mathbf{c}_{1,j})$$
(7)

The super-aggregates of A, F, F_{flu} , and $F_{migration}$ can be computed directly from the sub-aggregates. Gray et al. [13] categorize aggregation functions of such measures as *distributive* functions. For S, I and O, the computation of super-aggregates needs help from other auxiliary variables, such as A, F, and thus S, thus aggregation functions of I and O are *algebraic* functions according to [13].

Compared to Eqs. 1-7, the super-aggregates of R, V and V_{flu} , i.e., the distinct number of residents, social media users and social media users diagnosed as flu occurrences in a cuboid, cannot be obtained as a recursive function of subaggregates. The aggregation function of R, V and V_{flu} are holistic function [13], since the raw space-time trajectories are needed to compute the aggregation at all levels of scales. It is computationally impractical, particularly considering the location-based social media data are massive and increasing continuously. It amounts to the distinct counting problem in spatiotemporal database, and considerable attention has been paid to approximate the number of distinct objects in a database with auxiliary measures. [31] simply represented the superaggregates of such measures as the sums of sub-cells. Tao et al. [38] applied a probabilistic counting approach, namely Flajolet and Martin algorithm, to aggregate the count of distinct objects. By following [22], this paper approximates the distinct number of social media users and those diagnosed as flu occurrences as:

$$V(\boldsymbol{c}_{1}) = \sum_{i=1}^{K} V(\boldsymbol{c}_{1,i}) - \sum_{i=1}^{K} \sum_{j=1}^{K} F(\boldsymbol{c}_{1,i}, \boldsymbol{c}_{1,j})$$
(8)

$$V_{flu}(\boldsymbol{c}_1) = \sum_{i=1}^{K} V_{flu}(\boldsymbol{c}_{1,i}) - \sum_{i=1}^{K} \sum_{j=1}^{K} F_{flu}(\boldsymbol{c}_{1,i}, \boldsymbol{c}_{1,j})$$
(9)

$$R(\boldsymbol{c}_{1}) = \sum_{i=1}^{K} R(\boldsymbol{c}_{1,i}) - \sum_{i=1}^{K} \sum_{j=1}^{K} F_{migration}(\boldsymbol{c}_{1,i}, \boldsymbol{c}_{1,j})$$
(10)

As a simple illustration of this approximation in a special case, suppose cuboids c_1 and c_2 share the same spatial boundaries, and correspond to two adjacent temporal intervals \mathcal{T}_1 and \mathcal{T}_2 . There are N active social media users within the spatial boundaries posting activities both at \mathcal{T}_1 and \mathcal{T}_2 . Therefore, $V(c_1) = V(c_2) = F(c_1, c_2) = N$. According to Equation (8), the superaggregates for $c_1 \cup c_2$, $V(c_1 \cup c_2) = N + N - N = N$, which is obviously the case.

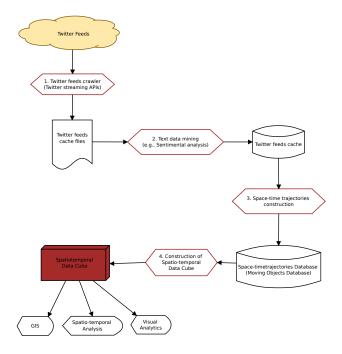


Figure 3: Framework architecture

4. Implementation

In this section, we discuss the implementation of the data model introduced in the previous sections based on a public data stream of Twitter feeds. Figure 3 shows the system architecture of the framework and the data flow through different components.

The first step is to retrieve data from Twitter. While it is millions of social media users that are generating massive social media contents, social media service, as hosts of these data, usually limit direct or full access to these contents. Twitter, in particular, provides multiple levels of interfaces to access the corpse of Twitter feeds collection. Twitter streaming API (application programming interface), particularly, allows anyone to near real-timely retrieve a 1% sample of all the data by specifying a set of filters, such as geographic boundaries of interests. Despite the 1% limit of sampling, it has been reported recently that the streaming API returns almost the complete set of the geo-tagged tweets that are of interest of this paper [26]. A tweets crawler was developed based on the Twitter streaming API to collect tweets posted in the continent of North America. The returning tweets were organized as a set of tuples (u, s, t, m). In the second step, a text mining method was applied to unstructured text messages m [43] to diagnose the chance that a twitter user infected by ILI by monitoring a dictionary of keywords related to the ILI symptoms, such as "flu", "cough", "sneeze" and "fever". It should be noted that, depending on

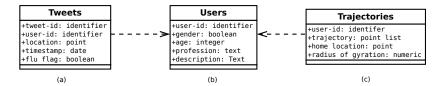


Figure 4: Schema of a space-time trajectories database

application scenarios, other data mining methods could be plugged in this step to gain interested information of each tweet.

The resulted tweets are then organized into space-time trajectories and loaded into a moving objects database [15] developed in-house based on Mon $goDB^2$ - a NoSQL database. As discussed previously, we assume that each social media user corresponds to a continuously evolving space-time trajectory to continuously record activities. The schema of the moving objects database is shown in Figure 4. Specifically, the *Users* profile table (Figure 4 (b)) describes the socio-demographic and related information (e.g., age, gender, profession) of Tweeters indexed by user-id. Similar with the detection of ILI infection cases, some demographic information of Twitter users could be learned based on the contents of tweets (e.g. [4, 33]). Figure 4 (a) describes the schema of resulted tweets of the preceded data mining process, where tweet-id and user-id respectively identify a tweet and the Twitter user (described in the Users table) that posted this tweet, *flu-flaq* indicates whether a tweet was diagnosed as ILI infection case, *location* and *time-stamp* represent the spatiotemporal information that the tweet was posted. Compared to the detection of ILI infection cases, it is usually difficult to tell based on the social media contents when the infected case would recover from the infection. Empirically, we use an average recovery period of seven days and flag a Twitter user, once diagnosed, as an infected case for a week. The table of *Trajectories* (Figure 4 (c)) describes the lifelong space-time trajectories associated with user profiles described in the Users table. In addition to the spatiotemporal footprints forming space-time trajectories, the geometric measures characterizing a space-time trajectory discussed in the previous section, including *home location* and *radius of qyration*, are also computed and updated. Empirically, the initial *home location* of a space-time trajectory corresponds to the most frequently visited place of the first 50 geolocated tweets activities, and keep updated afterwards. Algorithm 1 describes the basic procedures in the construction of space-time trajectories.

Based on the space-time trajectories database (a moving object database) of a group of social media users U, the fourth step is generating and regularly maintaining the spatiotemporal data cube, which is known as extract-transformation-load (ETL) process in the context of data warehouse [19]. We consider tweets posted in the area of North America (longitude ranging from

²http://www.mongodb.org

Algorithm 1 Construction of space-time trajectories

Input: p: a list of Twitter posts p_1, p_2, \ldots **Output:** T: a set of space-time trajectories T_{id} , $id \in [1, N]$ 1: for each $p_i \in p$ do $id \leftarrow p_i.user-id$ 2: if $T_{id} \in T$ then 3: T_{id} .append (p_i) 4: 5:else $T_{id} \leftarrow new \ trajectory$ 6: 7: T_{id} .append (p_i) $T.insert(T_{id})$ 8: end if 9: 10:update-home-location (T_{id}) \triangleright update home location of T_{id} update-gyration-radius (T_{id}) 11: \triangleright update gyration radius of T_{id} 12: end for

 -167.276413° to -56.347517° and latitude from 5.499550° to 82.296478° in WGS84 datum), which was divided into a lattice of cuboids with spatial cell size as 0.008333° , or approximately 1km, and temporal resolution as 1 hour in the finest granularity (level 1), corresponding to a 13312×9216 spatial grid evolving over time. The cell size of the spatial grid doubles as the level (scale) increases (see Figure 6(a) for an illustration), and on the top level (level 10), the PPS area is decomposed into a 26×18 spatial grid. Based on the configuration of spatiotemporal data cube, Algorithm 2 can be used to compute measures for each cuboid and it has been implemented in MongoDB. It is worth noting that function update-measures at line 4 of Algorithm 2 is a recursive function based on Eqs. 1-10. Corresponding to the conceptual models in Figure 1 and Figure 2, Figure 5 shows the detail table schema for the facts of a single cuboid (Figure 5 (a)) and flows between cuboids (Figure 5 (b)). The fields of *level* and *geometry* in the spatial dimensional table specify the structures of spatial hierarchy, and the equivalent for the table of temporal dimension are the fields of *level* and *interval.* With the temporal interval fixed (e.g., level = 1, interval = 1), Figure 6 gives an illustrative example for the schema of a single cuboid. Figure 6 (a) demonstrates two levels of spatial hierarchies, and Figure 6 (b) shows the joining result of three associated tables of spatial dimension, temporal dimension and cuboid fact tables. In addition to the uniform spatial grids and temporal intervals, conventional concepts of spatiotemporal databases, such as spatial join and spatial queries, could be applied to such tables as Figure 6 (b), for further aggregating the measures according to arbitrary spatiotemporal regions.

5. An on-line mapping interface for exploration of movement dynamics in location-based social media

The analytical framework based on the spatiotemporal data cube model frames the massive, dynamic and unstructured location-based social media data

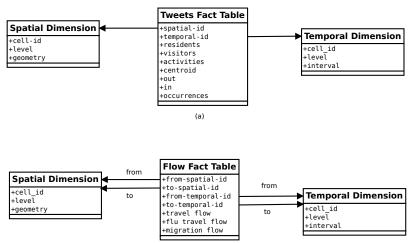
Algorithm 2 Construction of a spatiotemporal data cube

Input: T: a set of space-time trajectories $T_{id}, id \in [1, N]$

Output: C: a spatiotemporal data cube, or a lattice of cuboids c_i

- 1: for each $T_i \in T$ do 2: $mbb \leftarrow \text{get-mbb}(T_i)$
 - $mbb \leftarrow get-mbb(T_i)$ $\triangleright mbb$: the minimum bounding box of T_i
- 3: for each c_i overlaps with mbb do
- 4: update-measures $(c_i, T_i) \triangleright$ recursively update measures according to Eqs.1-10 5: end for

6: end for



(b)

Figure 5: Schema of a spatiotemporal data cube for Twitter feeds. There are two fact tables, one is for the facts of a single cuboid (a), and the other for facts of flows between cuboids (b).

| | spatial: | spatial: | temporal: | temporal: | visitors | activities | residents | |
|--|----------|----------|-----------|-----------|----------|------------|-----------|--|
| nort 1 contrar 2 Harry Park 5 67 | level | cell-id | level | cell-id | | | | |
| And | 1 | 1 | 1 | 1 | 5 | 10 | 8 | |
| 0 - V Albertay Are 8 B Barray Are B | 1 | 2 | 1 | 1 | 3 | 5 | 6 | |
| a subjective 3 subjective S 4 togenistic 7 Ubau S 10 million 1 | 1 | 3 | 1 | 1 | 2 | 4 | 3 | |
| 12 Processor | 1 | 4 | 1 | 1 | 5 | 8 | 7 | |
| 9 10 13 14 | 2 | 1 | 1 | 1 | 10 | 22 | 24 | |
| 9 10 0 13 14 | 1 | 5 | 1 | 1 | 5 | 6 | 5 | |
| 1 | 1 | 6 | 1 | 1 | 4 | 9 | 7 | |
| 11 12 15 16 ® | | | 1 | 1 | | | | |
| | 2 | 2 | 1 | 1 | 12 | 20 | 18 | |
| (a) | | | | (b) | | | | |

Figure 6: An example table of a data cube with two levels of hierarchy on spatial dimension. (a) shows an example map and the boundaries of two levels of spatial hierarchy. Black dashed lines indicate the spatial boundaries of the cuboids at (fine) level 1, and red solid lines indicate the spatial boundaries of cuboids at (coarse) level 2; (b) is the fact table associated with each cuboid defined in (a).

into a structured data model to support systematic and efficient spatiotemporal analysis of location-based social media data. To illustrate the previously introduced concepts and showcase the advantages of the framework, we developed an on-line interactive visual analytical interface for the spatiotemporal data cube. Due to the limitation of space, not all of the concepts introduced above could be illustrated. In this section, a flow mapping service is specifically presented based on the spatiotemporal data cube for visual exploration of movement dynamics at multiple spatiotemporal scales. Readers are referred to http://www.flumapper.org for further demonstrations of the presented framework.

Flow mapping is a widely used visual analytical method to depict and represent geographical dynamics of movement, in which each edge represents a movement (flow) between pair-wise interacting geographical regions. Locationbased social media data provide individual-level moving trajectories at real-time or near real-time, and thus an appealing opportunity to investigate geographical movements, people migration in particular, across multiple spatiotemporal scales, from macro migration trends across the globe to characteristics of individual daily activity. Based on the spatiotemporal data cube built for the continent of North America, an interactive, near real-time flow mapping service for location-based Twitter data is developed to explore the multiple scales of flow information derived from the data cube.

5.1. Single-source flow mapping

Since Tobler [39] introduced a generic method to produce flow maps with the assistance of computers, considerable efforts have been put to improve the lavout of flow maps. To remove the possible visual clutters (e.g., edge crossings), a recent method was presented for single-source flow mapping [41] by taking advantage of unique features of spiral trees. To facilitate the multi-scale visual analytics of the flow information in the spatiotemporal data cube, this spiral tree-based flow mapping method was adopted and implemented within an interactive environment of cyberGIS [42]. Based on the spatiotemporal data cube model, the number of travels (i.e., flow) made by hundreds of millions of Twitter users between pairs of specified areas during a specified time window could be efficiently retrieved. This flow mapping service, back-boned by the spatiotemporal data cube model, thus allows users to interactively explore the movement dynamics of hundreds of millions of Twitter users implied in massive location-based Twitter feeds collection. As mentioned previously, the flu status of each Twitter users was also learned from the contents of tweets, and it thus makes possible that one can monitor the movement patterns of potentially flu-affected Twitter users. In this context, this flow mapping service with support of spatiotemporal data cube provides a promising tool for public health researchers and practitioners.

As discussed in the previous section, the spatiotemporal data cube organizes the collective dynamics of social media as hierarchical levels of scales. Depending on the granularity of study, one could select appropriate levels of details in the data cube. To investigate the movement dynamics in location-based social media at a city level, for example, lower levels with finer cell size could be more useful and for dynamics at national level, upper levels with large cell size might be more appropriate. In the city of Los Angeles, Figure 7 maps seven days (16:00 January 29th, 2014 to 15:59 February 05th, 2014) of flows (number of travels in location-based social media) that traveled out from the neighborhood of Los Angels International airport (LAX) at the 2nd level (cell size as 2km) of the data cube to the other areas of the city. The solid dots represent the centroid of each cell and the edges represents the movements (flows) between different cells with thicker edges means more number of flows. Users can query the exact number of flow associated with a segment by hovering the mouse over that segment as the green segment show in Figure (7 - 9). This map with cell size of 2km might contain much trivial details for investigating the movement dynamics at continental levels, in which case one could increase the aggregation size. At the 9th granularity level of the data cube (cell size as 256km), Figure 8 shows a map of flow that traveled from the same origin and during the same period as in Figure 7 to the other areas of the North America.

For the same origins, Figure 9 demonstrates a flow map of flu-affected Twitter users who traveled during the same time period as the previous two Figures (Figure 7 and 8). One can easily check to where the potential flu-affected Twitter users of LAX neighborhood travel. There are totally 73 potential flu-acted Twitter users who made travels out of the area of Los Angels during the specified time period. As indicated in the highlighted segment in Figure 9, 41 of 73 potential flu-affected Twitter users made travels to the northeastern area of the United States. The background map in Figure 9 shows a risk map generated from the occurrences of flu-affected tweets by kernel density estimation [43]. By rendering the areas with higher potential flu risk redder and areas with lower risk greener, the background map demonstrates near real-time distribution of flu risk across the United States. Combined with the flow maps of travels, this mapping service could be a promising alternative tool for the surveillance and management of flu risk at multiple levels of spatiotemporal scales.

5.2. Multiple-source flow mapping

The single-source flow maps provide valuable insights into how social media users move in and out of a particular region during a time period. With the source location fixed, the single-source flow maps usually lead to clean and less clutter maps. It might be difficult, however, to glean a comprehensive view of overall move patterns of the area of interest by considering one source at each time. The multi-source flow mapping approach attempts to address this challenge by visualizing all the significant movements of an area [14]. As we increase the spatial granularity level (e.g. from level 2 to level 1 in Figure 6), the number of cuboids and associated movement flows increases exponentially, which tends to lead to maps with dramatic visual clutters. To address this issue, we developed an interactive scalable level-of-detail approach to visualize all-to-all movements of a specific area based on the spatiotemporal data cube model.



Figure 7: A flow map of number of travels during seven days (January 29th to February 5th, 2014) from the LAX neighborhood to the rest area of Los Angeles.



Figure 8: A flow map of number of travels during seven days (January 29th to February 5th, 2014) from the Los Angeles to the other areas of North America.



Figure 9: A flow map of number of travels made by potential flu-affected Twitter users during seven days (January 29th to February 5th, 2013) from the Los Angeles to the other areas of North America.

The core part of this approach is to adaptively select the locations or nodes (i.e., centroids of cuboids) that are critical to represent the movement flow patterns at each level of spatial granularity. A node is considered as critical if its score, which amounts to sum of incoming and outgoing degree, is ranked high enough both global (among all the nodes) and locally (among its neighbor cells). To address the scalability issue for massive number of nodes, we implemented this filtering process using an Apache Hadoop³ cluster to take advantage of the distributed computation resources across multiple computing cores. The commonly used flow mapping algorithms, namely Force Directed Edge Bundling [18], is then applied to visualize the flows between the selected critical nodes. This algorithm bundles the close movements together to further reduce the clutter.

As an example, Figure 10 shows a result of multi-source flow map for the movement flows at a regional scale between major cities in the southwest of the United States (e.g., Los Angeles, San Francisco, Las Vegas, Phoenix, Denver and Salt Lake city) during the time period between 22:00 of January 31st, 2014 and 21:59 of February 7th, 2014. The resulting flow maps are presented according to a coloring schema with color of red for larger number of movement flows and color of blue for smaller number of movement flows. It should be noted here that only the movement flows within the extent of display window are visualized, although the data cube is built for the entire North America. In Figure 10, travels between selected pairs of cities are listed along the connecting edges. From Los Angels to Phoenix, for example, the listed label 'Flow#: (118, 158)' means there were 118 number of travels made from Los Angels to Phoenix and

³http://hadoop.apache.org/

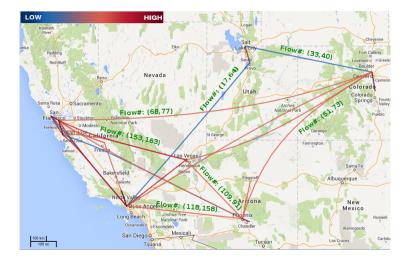


Figure 10: Multiple-source flow maps of the travel flows between major cities in the southwest of the United States during the 22:00 of January 31st, 2014 to the 21:59 of February 7th, 2014.

158 for the opposite direction. In Figure 10, one can clearly see the travel patterns among the listed cities captured in the cyberspace of Twitter. During the specified time period, it is apparent that most travels happen between the listed cities and the associated suburb areas, and more travels between Denver and western cities (e.g., Las Vegas, Los Angels and Phoenix) than Denver and Salt Lake city, although Salt Lake city is significantly closer to Denver than the western cities. Figure 11 shows a resulting flow map that covers the entire area of the North America during the same time period as in Figure 10. Similarly, the number of travel between cities are labeled. One can clearly see the overall travel patterns at a continental scale between major cities in the North America through the multiple-source flow mapping.

6. Conclusion and future work

In this paper, we presented a general framework to harness the massive location-based social media data for scalable and efficient spatiotemporal analysis of massive location-based social media data. In the presented framework, we first adopted the concept of space-time trajectories (or path) to represent the activities of social media users. An individual social media user corresponds to a continuously evolving space-time trajectory. By representing the potential path space as a lattice of primitive cuboids, a hierarchical multi-scale model, namely a data cube model, is designed, constructed and regularly maintained to support systematic spatiotemporal analysis of location-based social media data. Based on the data cube, one can easily query and summarize the spatiotemporal distribution and dynamics in location-based social media by specified aggregation boundaries, such as spatial regions, time duration and population group

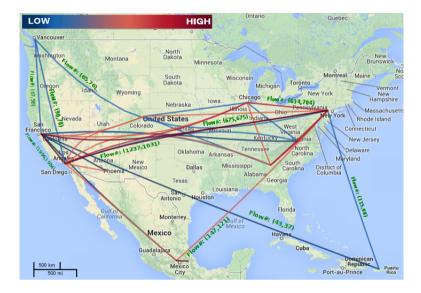


Figure 11: Multiple-source flow maps of the travel flows of the major cities in North America during the 22:00 of January 31st, 2014 to the 21:59 of February 7th, 2014.

at multiple scales. The system architectures and implementation details based on an public Twitter feeds collection of the Untied States were discussed. To showcase the effectiveness of the presented framework, we developed an on-line interactive flow mapping service based on the spatiotemporal data cube model to effectively represent the movement dynamics of groups of social media users (e.g., ILI affected users) from a continent scale to a fine blocks level of scale.

The findings of this paper lay solid foundations for the future research in spatiotemporal analysis of location-based social media data. On the application side, the data cube model provides a novel structured spatiotemporal data source that can be easily integrated with conventional GIS and spatiotemporal analysis tools for mapping, modeling, and analyzing large-scale complex spatiotemporal dynamics at different scales. In this paper, we did not explicitly consider the structure of social network of social media users, which conveys important interaction information between social media users. People do things together with friends on a daily basis, and interact with and get influenced by them. Valuable information could be discovered for social media users by accounting for the activities of their friends and their interaction with them. For example, social media users identified as infected cases of ILI also put their frequently interacted friends at high risks to get infected. Social medial data provide access to the social interactions between friends, and thus make it possible to investigate the spread of infection in a very fine individual level. Another example is that we assumed the space-time trajectories are step functions consisting of a sequence of moves between time-stamps and locations. It is apparently not the case in reality. With the help of the locations of close friends', we could estimate locations of social media users at un-sampled time-stamps. The proposed data model is rather general and flexible. In addition to the Twitter streams, data from other forms of social media could also be incorporated. We are particularly interested in the integration with the Foursquare data, which make senses of the geographic coordinates with names and attributes of locations (e.g., restaurants, hospitals) and thus provide more detail information about daily activities. How to deal with uncertainty of the location-based social media data in the proposed data model is another topic that warrants further investigation. In location-based social media data and the data model, all of the spatiotemporal information, social media contents, and the data mining results of contents are uncertain in reality. Characterization of such uncertainties is desirable for effective use of such data sources and the data model.

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