Spatial Big-Data Challenges Intersecting Mobility and Cloud Computing

Invited Paper*

Shashi Shekhar
University of Minnesota
Minneapolis, MN, USA
shekhar@cs.umn.edu

Michael R. Evans
University of Minnesota
Minneapolis, MN, USA
mevans@cs.umn.edu

Viswanath Gunturi
University of Minnesota
Minneapolis, MN, USA
gunturi@cs.umn.edu

KwangSoo Yang
University of Minnesota
Minneapolis, MN, USA
ksyang@cs.umn.edu

ABSTRACT

Increasingly, location-aware datasets are of a size, variety, and update rate that exceeds the capability of spatial computing technologies. This paper addresses the emerging challenges posed by such datasets, which we call Spatial Big Data (SBD). SBD examples include trajectories of cellphones and GPS devices, vehicle engine measurements, temporally detailed road maps, etc. SBD has the potential to transform society via next-generation routing services such as eco-routing. However, the envisaged SBD-based next-generation routing services pose several significant challenges for current routing techniques. SBD magnifies the impact of partial information and ambiguity of traditional routing queries specified by a start location and an end location. In addition, SBD challenges the assumption that a single algorithm utilizing a specific dataset is appropriate for all situations. The tremendous diversity of SBD sources substantially increases the diversity of solution methods. Newer algorithms may emerge as new SBD becomes available, creating the need for a flexible architecture to rapidly integrate new datasets and associated algorithms.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications

General Terms

Algorithms

*Previously seen at the 2012 NSF Workshop on Social Networks and Mobility in the Cloud.

MobiDE '12, May 20, 2012 Scottsdale, Arizona, USA

Keywords

Spatial Big Data, Mobility Services, Data Mining

1. INTRODUCTION

Mobility services, e.g., routing and navigation, are a set of ideas and technologies that transform lives by understanding the geo-physical world, knowing and communicating relations to places in that world, and navigating through those places. Mobility in this context can be defined as efficient, safe and affordable travel in our cities and towns. The transformational potential of mobility services is already evident. From Google Maps [22] to consumer Global Positioning System (GPS) devices, society has benefited immensely from routing services and technology. Scientists use GPS to track endangered species to better understand behavior, and farmers use GPS for precision agriculture to increase crop yields while reducing costs. We've reached the point where a hiker in Yellowstone, a biker in Minneapolis, and a taxi driver in Manhattan know precisely where they are, their nearby points of interest, and how to reach their destinations.

Increasingly, however, the size, variety, and update rate of datasets exceed the capacity of commonly used spatial computing and spatial database technologies to learn, manage, and process the data with reasonable effort. We believe that harnessing Spatial Big Data (SBD) represents the next generation of routing services. Examples of emerging SBD datasets include temporally detailed (TD) roadmaps that provide speeds every minute for every road-segment, GPS trace data from cell-phones, and engine measurements of fuel consumption, greenhouse gas (GHG) emissions, etc. SBD has transformative potential. A 2011 McKinsey Global Institute report estimates savings of "about $600 billion annually by 2020" in terms of fuel and time saved [34] by helping vehicles avoid congestion and reduce idling at red lights or left turns. Preliminary evidence for the transformative potential includes the experience of UPS, which saves millions of gallons of fuel by simply avoiding left turns (Figure 1(a)) and associated engine-idling when selecting routes [31]. Immense savings in fuel-cost and GHG emission are possible in the future if other fleet owners and consumers avoided left-turns and other hot spots of idling, low fuel-efficiency, and congestion. Ideas advanced in this proposal are likely to facilitate 'eco-routing' to help identify routes which reduce fuel consumption and GHG emissions, as compared to traditional route services reducing distance traveled or travel-time. Eco-routing has the potential to significantly reduce US consumption of petroleum, the dominant source of energy for transportation (Figure 1(b)). It may even reduce the gap between domestic petroleum consumption and production (Figure 1(c)), helping bring the nation closer to the goal of energy independence [54].

However, SBD raises many new challenges for the state of the art in spatial computing for routing services. In this paper, we describe the mergence of SBD in the context of today's mobility services. We then describe in detail six main challenge areas that we believe must be addressed before using Spatial Big Data.

2. TRADITIONAL MOBILITY SERVICES

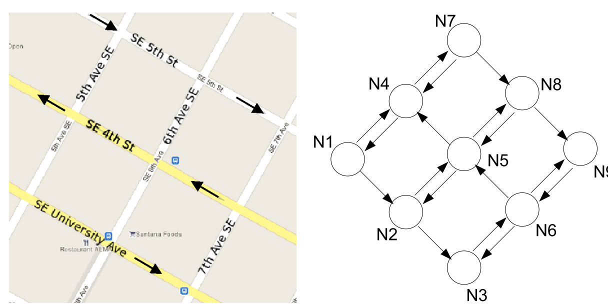
Traditional routing systems utilize digital road maps [23, 36, 38, 47]. Figure 2(a) shows a physical road map and Figure 2(b) shows its digital, i.e., graph-based, representation. Road intersections are often modeled as vertices and the road segments connecting adjacent intersections are represented as edges in the graph. For example, the intersection of 'SE 5th Ave' and 'SE University Ave' is modeled as node N1. The segment of 'SE 5th Ave' between 'SE University Ave' and 'SE 4th Street' is represented by the edge N1-N4. The directions on the edges indicate the permitted traffic directions on the road segments. Digital roadmaps also include additional attributes for road-intersections (e.g., turn restrictions) and road-segments (e.g., center-lines, road-classification, speed-limit, historic speed, historic travel time, address-ranges, etc.) Figure 2(c) shows a tabular representation of the digital road map. Additional attributes are shown in the node and edge tables respectively. For example, the entry for edge E1 (N1-N2) in the edges table shows its speed and distance. Such datasets include roughly 100 million (10^8) edges for the roads in the U.S.A. [36]

Route determination services [33,49], abbreviated as routing services, include the following two services [45]. The first deals with determination of a best route given a start location, end location, optional waypoints, and a preference function. Here, choice of preference function could be: fastest, shortest, easiest, pedestrian, public transportation, avoid locations/areas, avoid highways, avoid tollways, avoid U-turns, and avoid ferries. Route finding is often based on classic shortest path algorithms such as Dijktra's [28], A* [11], hierarchical [24, 25, 46, 48], materialization [42, 44, 46], and other algorithms for static graphs [4,6–10,17–19,39, 43]. Shortest path finding is often of interest to tourists as well as drivers in unfamiliar areas. In contrast, commuters often know a set of alternative routes between their home and work. They often use an alternate service to compare their favorite routes using real-time traffic information, e.g., scheduled maintenance and current congestion. Both services return route summary information along with auxiliary details such as route maneuver and advisory information, route geometry, route maps, and turn-by-turn instructions in an audio-visual presentation media.

3. EMERGING SPATIAL BIG DATA

SBD are significantly more detailed than traditional digital roadmaps in terms of attributes and time-resolution. In this subsection we describe three representative sources of SDB that may be harnessed in next generation routing services.

Spatio-Temporal Engine Measurement Data: Many modern fleet vehicles include rich instrumentation such as GPS receivers, sensors to periodically measure sub-system properties [26, 27, 32, 35, 51, 52], and auxiliary computing, storage and communication devices to log and transfer accumulated datasets. Engine measurement datasets may be used to study the impacts of the environment (e.g., elevation changes, weather), vehicles (e.g., weight, engine size, energy-source), traffic management systems (e.g., traffic light timing policies), and driver behaviors (e.g., gentle acceleration or braking) on fuel savings and GHG emissions. These datasets may include a time-series of attributes such as vehicle location, fuel levels, vehicle speed, odometer values, engine speed in revolutions per minute (RPM), engine load, emissions of greenhouse gases (e.g., CO2 and NOX), etc. Fuel efficiency can be estimated from fuel levels and distance traveled as well as engine idling from engine RPM. These attributes may be compared with geographic contexts such as elevation changes and traffic signal patterns to improve understanding of fuel efficiency and GHG emission. For example, Figure 3 shows heavy truck fuel consumption as a function of elevation from a recent study at Oak Ridge National Laboratory [5]. Notice how fuel consumption changes drastically with elevation slope changes. Fleet owners have studied such datasets to fine-tune routes to reduce unnecessary idling [1, 2]. It is tantalizing to explore the potential of this dataset to help consumers gain similar fuel savings and GHG emission reduction. However, these datasets can grow big. For example, measurements of 10 engine variables, once a minute, over the 100 million US vehicles in existence [16, 50], may have 10^{14} data-items per year.



(a) A Road Map [22] (b) Graph Representation

Nodes

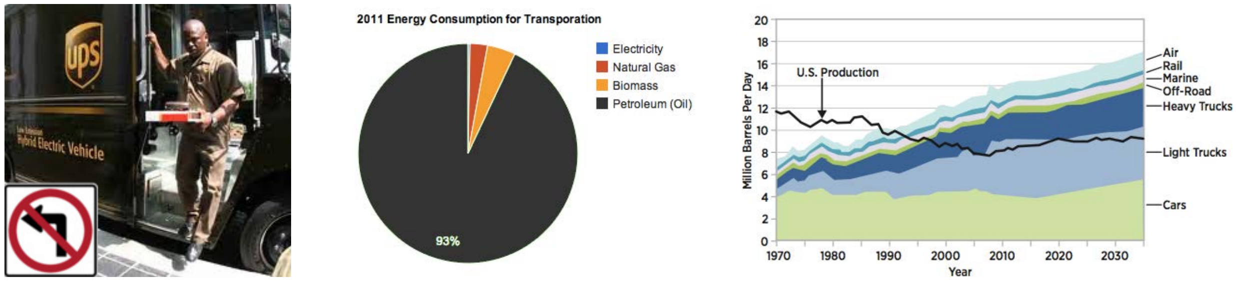
NID
N1
N2
N3
N4
N5
N6
N7
N8
N9

Edges

EID	From	To	Speed	Distance
E1	N1	N2	35mph	0.075mi
E2	N1	N4	30mph	0.075mi
E3	N2	N3	35mph	0.078mi
E4	N2	N5	30mph	0.078mi
E5	N3	N6	30mph	0.077mi
E6	N4	N1	30mph	0.075mi
E7	N4	N7	30mph	0.078mi
E8	N5	N2	30mph	0.078mi
...	...	...	...	...

(c) Tabular Representation of digital road maps

Figure 2: Current representation of road maps as directed graphs with scalar travel time values.



(a) UPS avoids left-turns to save fuel [31].

(b) Petroleum is dominant energy source for US Transportation [55].

(c) Gap between US petroleum consumption and production is large and growing [3, 12].

Figure 1: Eco-routing supports sustainability and energy independence. (Best in color)

GPS Trace Data: A different type of data, GPS trajectories, is becoming available for a larger collection of vehicles due to rapid proliferation of cell-phones, in-vehicle navigation devices, and other GPS data-logging devices [20] such as those distributed by insurance companies [57]. Such GPS traces allow indirect estimation of fuel efficiency and GHG emissions via estimation of vehicle-speed, idling and congestion. They also make it possible to provide personalized route suggestions to users to reduce fuel consumption and GHG emissions. For example, Figure 4 shows 3 months of GPS trace data from a commuter with each point representing a GPS record taken at 1 minute intervals, 24 hours a day, 7 days a week. As can be seen, 3 alternative commute routes are identified between home and work from this dataset. These routes may be compared for engine idling which are represented by darker (red) circles. Assuming the availability of a model to estimate fuel consumption from speed profiles, one may even rank alternative routes for fuel efficiency. In recent years, consumer GPS products [20, 53] are evaluating the potential of this approach. Again, a key hurdle is the dataset size, which can reach 10^{13} items per year given constant minute-resolution measurements for all 100 million US vehicles.

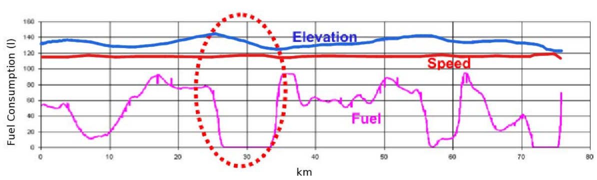


Figure 3: Engine measurement data improve understanding of fuel consumption [5]. (Best in color)

Historical Speed Profiles: Traditionally, digital road maps consisted of center lines and topologies of the road networks [21, 47]. These maps are used by navigation devices and web applications such as Google Maps [22] to suggest routes to users. New datasets from companies such as NAVTEQ [36], use probe vehicles and highway sensors (e.g., loop detectors) to compile travel time information across road segments for all times of the day and week at fine temporal resolutions (seconds or minutes). This data is applied to a profile model, and patterns in the road speeds are identified throughout the day. The profiles have data for every five minutes, which can then be applied to the road segment, building up an accurate picture of speeds based on historical data. Such TD roadmaps contain much more speed information than traditional roadmaps. While traditional roadmaps (Figure 2(a)) have only one scalar value of speed for a given road segment (e.g., EID 1), TD roadmaps may potentially list speed/travel time for a road segment (e.g., EID 1) for thousands of time points (Figure 5(a)) in a typical week. This allows a commuter to compare alternate start-times in addition to alternative routes. It may even allow comparison of (start-time, route) combinations to select distinct preferred routes and distinct start-times. For example, route ranking may differ across rush hour and non-rush hour and in general across different start times. However, TD roadmaps are big and their size may exceed 10^{13} items per year for the 100 million road-segments in the US when associated with per-minute values for speed or travel-time. Thus, industry is using speed-profiles, a lossy compression based on the idea of a typical day of a week, as illustrated in Figure 5(b), where each (road-segment, day of the week) pair is associated with a time-series of speed values for each hour of the day.

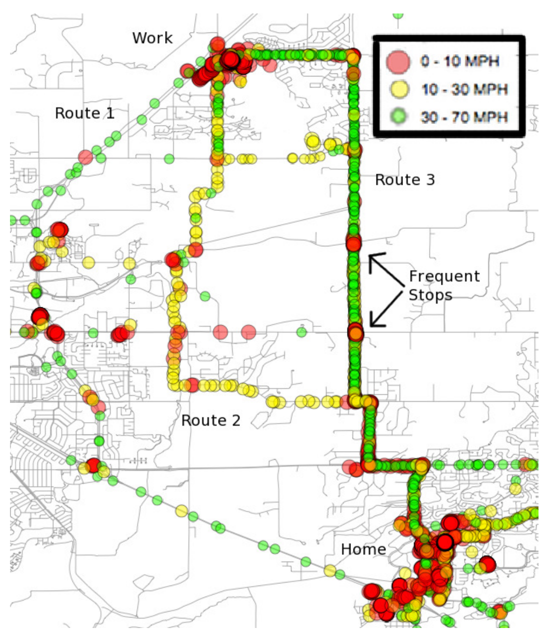
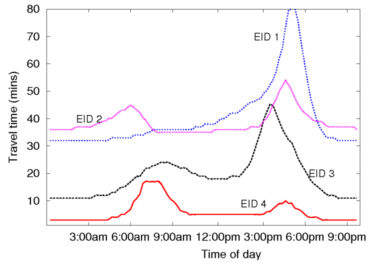
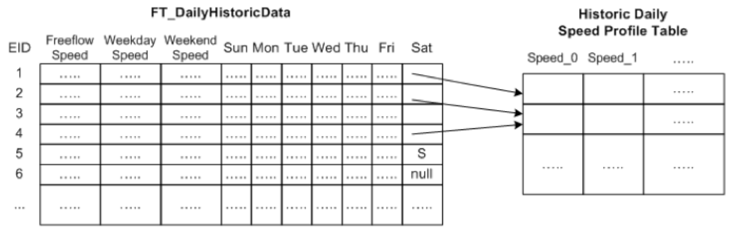


Figure 4: A commuter's GPS tracks over three months reveal preferred routes. (Best viewed in color)

In the near future, values for the travel time of a given edge and start time will be a distribution instead of scalar. For example, analysis of GPS tracks may show that travel-time



(a) Travel time along four road segments over a day.



(b) Schema for Daily Historic Speed Data.

Figure 5: Spatial Big Data on Historical Speed Profiles. (Best viewed in color)

for a road-segment is not unique, even for a given start-time of a typical week. Instead, it may consist of different values (e.g., 1, 2, 3 units), with associated frequencies (e.g., 10, 30, 20). The availability of such SBD may allow comparison of routes, start-times and (route, start-time) combinations for statistical distribution criteria such as mean and variance. We also envision richer temporal detail on many preference functions such as fuel cost. Other emerging datasets include those related to pot-holes [40], crime reports [41], and social media reports of events on road networks [56].

4. NEW CHALLENGES

The challenges posed by SBD for state of the art spatial computing are significant. First, it requires a change in frame of reference from a snapshot perspective to the perspective of the individual traveling through a transportation network [14]. For instance, consider the new temporally detailed (TD) roadmaps providing historical travel-time (or speed) for each road-segment for every distinct minute of a week. Consider a person sitting in a vehicle and moving along a chosen path in a TD roadmap. She would experience a different road-segment and its historical speed as well as traversal-time at different time-intervals, which may be distinct from the start-time.

Second, the growing diversity of SBD significantly increases computational cost because it magnifies the impact of the partial nature and ambiguity of traditional routing query specification. Typically, a routing query is specified by a starting location and a destination. Traditional routing services would identify a small set of routes based on limited route properties (e.g., travel-distance, travel-time (historical and current)) available in traditional digital roadmap datasets. In contrast, SBD face orders of magnitude richer information, more preference functions (e.g., fuel efficiency, GHG emission, safety, etc.) and correspondingly larger sets of choices.

New questions thus arise in the context of eco-routing: What is the computational structure of determining routes that minimize fuel consumption and GHG emissions? Does this problem satisfy the assumptions behind traditional shortest path algorithms (e.g., stationary ranking of alternative routes assumed by a dynamic programming principle)? For example, temporally detailed roadmaps can potentially provide a distinct route for every possible start-time, even when we just consider travel-time. This raises an optimality challenge of correctly determining the fastest route corresponding to each start-time, since ranking of candidate routes might vary with time of day (rush hour vs. non-rush hour). It also raises a representation challenge to summarize potentially large sets of routes in the result. In addition, the computational challenge of efficiently determining a large collection of routes (e.g., one for each start time and preference function) could perhaps be done by identifying and reducing unnecessary computations via leveraging current cloud computing paradigm (e.g., map reduce) or via novel custom cloud computing paradigms, tentatively called spatial cloud computing.

Third, the tremendous diversity of SBD sources substantially increases the need for diverse solution methods. For example, methods for determining fuel efficient routes that leverage engine measurement and GPS track datasets may be quite different from algorithms to identify minimal travel-time routes for a given start-time exploiting TD roadmaps. In addition, SBD data (e.g., TD roadmaps, GPS-tracks and engine-measurement datasets) differ in coverage, roadmap attributes and statistical details. For example, TD roadmaps cover an entire country, but provide mean travel-time for a road-segment for a given start-time in a week. In contrast, GPS-track and engine-measurements have smaller coverage to well-travelled routes and time-periods, but may provide a richer statistical distribution of travel-time for each road-segment, perhaps revealing newer patterns such as seasonality. New algorithms are likely to emerge as new SBD become available and as a result, a new, flexible, architecture will be needed to rapidly integrate new datasets and associated algorithms.

A fourth challenge area concerns the use of geospatial reasoning in sensing and inference across space and time. Multiple tradeoffs (including those arising in privacy considerations) can come to the fore with attempts to sense and draw inferences from stable or mobile sensors. New challenges arise from crowd-sourced sensors. For example, the ubiquity of mobile phones presents an incredible opportunity for gathering information about all aspects of our world and the people living in it [29]. Already research has shown the potential for mobile phones with built-in motion detectors carried by everyday users to detect earthquakes mere seconds after they begin [15]. Navigation companies frequently utilize mobile phone records to estimate traffic levels on busy highways [56]. How can computers efficiently utilize this prevalent sensing power of mobile phones without drastically impacting battery life or personal privacy concerns? This raises many computer science questions related to sensor placement, configuration, etc.

Fifth, we must deal with the many privacy issues surrounding geographic information. While location information (GPS in phones and cars) can provide great value to users and industry, streams of such data also introduce "spooky" privacy concerns of stalking and "geo-slavery" [13]. Computer science efforts at obfuscating location information to date have largely yielded negative results. Thus, many individuals hesitate to engage in mobile commerce due to concerns about privacy of their locations, trajectories and other spatio-temporal personal information [30]. Spatio-temporal computing research is needed to address many questions such as: "[should] people reasonably expect that their movements will be recorded and aggregated..."? [37]. How do we quantify location privacy in relation to its spatio-temporal precision of measurement? How can users easily understand and set privacy constraints on location information? How does quality of location-based service change with variations in obfuscation level?

Finally, we anticipate that geospatial information will one day be used to make predictions about a broad range of issues including the next location of a car driver, the risk of forthcoming famine or cholera, or the future path of a hurricane. Models may also predict the location of probable tumor growth in a human body or the spread of cracks in silicon wafers, aircraft wings, and highway bridges. Such predictions would challenge the best of machine learning and reasoning algorithms, including directions with geospatial time series data. Many current techniques assume independence between observations and stationarity of phenomena. Novel techniques accounting for spatial auto-correlation and non-stationarity may enable more accurate predictions. The challenge will be ensuring that such techniques retain computational efficiency.

5. ACKNOWLEDGEMENTS

We would like to thank Eric Horvitz (Microsoft), the Computing Community Consortium (CCC), Hillol Kargupta (UMBC), Erik Hoel (ESRI), Oak Ridge National Labs (ORNL), Joe Newell and the US-DoD for their helpful comments and support.

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