IOSR Journal of Engineering (IOSRJEN) **www.iosrjen.org**
ISSN (e): 2250-3021, ISSN (p): 2278-8719
Volume 5, PP 62-69

A Review on Trajectory Data Mining

Komal Gothwal[1], Varsha Salunkhe[2], Ashmita Shetty[3],
Dimple Bafna[4]

[1](Assistant Professor, Information Technology, Atharva College of Engineering, Mumbai University , India)
[2](Assistant Professor, Information Technology, Atharva College of Engineering, Mumbai University , India)
[3](Assistant Professor, Information Technology, Atharva College of Engineering, Mumbai University , India)
[4](Assistant Professor, Information Technology, Atharva College of Engineering, Mumbai University , India)

Abstract: *Fast progress of area procurement innovations supports the age of trajectory information, which track the hints of moving articles. A trajectory is ordinarily spoken to by a succession of timestamped geological areas. A wide range of utilizations can profit by the trajectory information mining.*
Bringing remarkable openings, vast scale trajectory information likewise posture incredible difficulties. In this paper, we overview different uses of trajectory information mining, e.g., way disclosure, area expectation, development conduct examination, et cetera. Besides, this paper surveys a broad accumulation of existing trajectory information mining methods and talks about them in a system of trajectory information mining. This structure and the overview can be utilized as a rule for planning future trajectory information mining arrangements.

Keywords: *Big data applications, Data mining techniques, Trajectory data mining.*

I. Introduction

These days, there have been numerous advances which give positioning administrations e.g., Global Position Systems (GPS), Radio Frequency Identification (RFID), area estimation of 802.11, advanced cell sensors, GSM reference points, infrared or ultrasonic systems et cetera [1]. As an outcome, it is getting to be less demanding to produce vast scale trajectory information of following hints of moving articles.

A hint of a moving article in topographical space is nonstop while a trajectory is just an example of area focuses that the moving article goes as appeared in Fig. 1. Ordinarily, a spatial trajectory, as a least difficult instance of trajectory information, is spoken to by an arrangement of time stamped areas, e.g., (p 0, t 0), (p 1 , t 1), ..., (p 7 , t 7) in Fig. 1.1 Span and examining rate of a trajectory rely upon applications. Trajectory information are gathered from different sources. One of the most widely recognized composes is created by GPS-prepared vehicles. In addition, different sorts of directions likely originate from advanced cells, online registration information, geo-labeled messages or media in informal organizations, RFID perusers, et cetera. Subsequently, moving articles can be human creatures, creatures, vehicles, and even characteristic wonders (e.g., storms).))The contents of each section may be provided to understand easily about the paper.

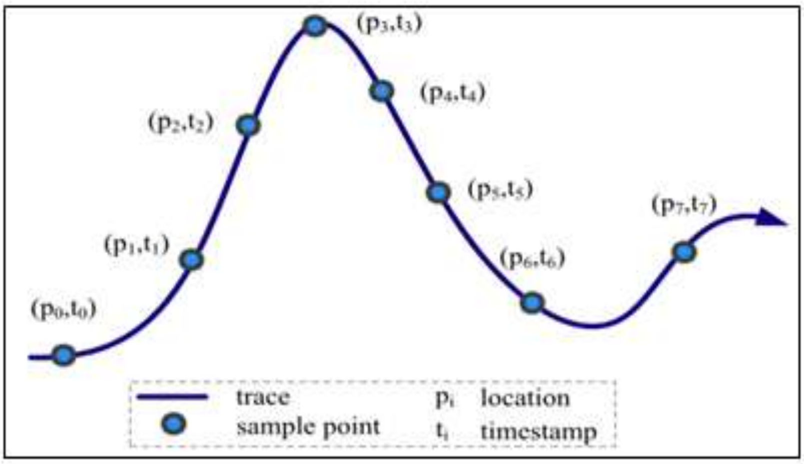

Fig. 1.1 A trajectory is generated by sampling from a continuous trace.

There exist a wide range of uses driven and enhanced by trajectory data mining, for example, way disclosure, area/goal expectation, development conduct investigation for individual or a gathering of moving items, seeming well and good of directions and different uses of urban administration.

These applications altogether advantage the average folks, business associations and government organizations.

Be that as it may, it is trying to oversee, process and mine trajectory data [2], [3]. We take a few difficulties as illustration. Right off the bat, it is a nontrivial undertaking to store a colossal volume of trajectory data which are quickly amassed.

Furthermore, it is unmanageable to characterize a likeness metric for looking at directions (which is a basic usefulness in trajectory data mining) since directions are most likely produced with various examining systems or at various inspecting rates. Thirdly, handling inquiries on the huge measure of trajectory data is exceedingly troublesome regarding space or then again time multifaceted nature.

To address these issues, a broad accumulation of approaches have been proposed and we characterize them as indicated by the primary method of trajectory data mining. Besides, we propose a structure that revamps these methodologies and after that give a thorough overview on trajectory data mining. Generally, there are three layers in the system, i.e., data gathering, trajectory data mining systems, applications.

In particular, the layer of trajectory data mining systems contains five segments recorded as follows:

Preprocessing: In the preprocessing phase, trajectories are usually cleaned, segmented, calibrated, sampled for representatives, or inferred from uncertain trajectories.

Data management: Sometimes, trajectories are compressed or simplified before being stored. In addition, proficient or adaptable capacity systems should be constructed. Besides, appropriate index structures are also necessary to support query processing.

Query processing: There are various queries that have to be processed to retrieve data, e.g., location-based queries, range queries, nearest neighbor queries,top-k queries, pattern queries, aggregate queries and other application-specific queries. These queries are processed based on an underlying storage system andindex structure.

Trajectory data mining tasks: Trajectory data mining tasks are summarized and classified into several categories, i.e., pattern mining, clustering, classification and knowledge discovery.

Privacy protection: Privacy-preserving is a crucial problem in every procedure of trajectory data mining. Several examples are provided to illustrate how to process trajectory data as well as to protect sensitive information of users. The rest of the paper is structured as follows.
Section II offers some definitions. A framework characterizing the whole procedure of trajectory data mining is presented in Section III. The next section, Section IV, cover the applications of trajectory data mining. Section V discusses a few open issues. Finally, the paper is concluded in Section VI.

II. Definitions

In the section, we define some primary terminologies, e.g., trajectory, semantic trajectory, road network, path.

Definition 1 (Trajectory): A trajectory of a moving question is a discrete follow that the moving article ventures in geological space. By and large, it is a succession of geo-areas with comparing timestamps in spatio-transient space, i.e., $T = \{< p_1 , t_1 >, < p_2 , t_2 >, \cdot , < p_n , t_n >\}$, where every component $< p_I , t_I >$ shows a moving protest is at area p_I at timestamp t_I.Further, components are arranged by timestamps, i.e., $t_j < t_k$ if $1 \leq j < k \leq n$.

A moving item can be a man, a creature, a vehicle, a cell phone, or even a marvel. A trajectory of a individual records one's follow for a time frame. For instance, a trajectory of a man in a daytime may record his way to work early in the day and his way to home around evening time.

A trajectory of a creature portrays its follow produced by every day exercises, for example, running. A trajectory of a vehicle is recorded by a GPS gadget introduced in the vehicle and for the most part reports areas of the vehicle at a settled rate, e.g., each second or consistently.

An area is normally communicated by a tuple of longitude, latitude which is recorded by a GPS gadget. Each tuple of longitude, latitude relates to an exceptional point in topographical space. An exceptional sort of trajectory data is RFID data. There are two sorts of gadgets in RFID innovation, i.e., labels (which emanate radio signs with identification data) and perusers (which recognize signals from labels). By and large, a moving article is a label gadget, i.e., a great in a distribution center. An area is communicated by identification of a peruser which identifies motion from that tag. Basically, areas of a moving item are recorded by relating topographical territories of perusers that identify its signs. Inspecting rates of trajectory data change incredibly from data source to data source. Because of vitality and capacity impediment, trajectories of various types of moving articles are tested at various rates. Trajectory data of vehicles normally have higher testing rates than those of cell phones since vehicles can give sufficient battery and capacity.

In particular, a trajectory presented above can likewise be called a topographical trajectory or a crude trajectory.

At that point, we present an exceptional sort of trajectory data that coordinate topographical positions with semantic importance. Definition 2 (semantic trajectory): Semantic trajectories are frequently produced by labeling a area point with a significant place in genuine separated from numerical directions, for example, registration data. In addition, at the point when a geological trajectory is related with portrayal content which communicates one's inclination and feeling, it is additionally a sort of semantic trajectory data. While considering trajectories created by vehicles, we regularly allude to a street system and ways in the street organize. Their definitions are given as takes after. Definition 3 (Road Network): A road network is a directed graph, G = (V , E), where V and E are a vertex set and an edge set, respectively. A vertex, v j ∈ V , is a road junction or road end. An edge, e k = v p v q ∈ E, denotes a directed road segment, on which travel direction of moving objects is from v p to v q . Definition 4 (Path): A path, P = e 1 , e 2 , · · · , e | P | ,represents a sequence of edges in a road network, where e i ∈ E and e i = e j if i = j. Specifically, consecutive edges e.g., e i and e i+1 , must share a vertex which is end vertex of ei and source vertex of e i+1 .

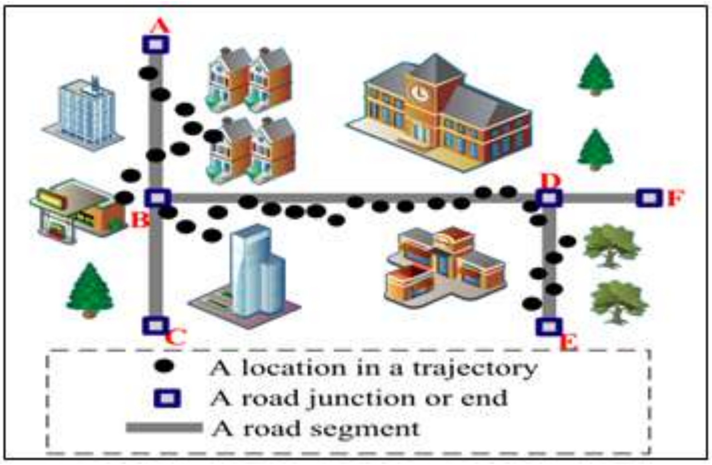

Fig. 2.1 An example of a road network and paths. All location points in a trajectory are matched to edges in a road network and as a result paths are generated. Suppose a road network is denoted by G = (V, E), where its set of vertices is V = {A, B, C , D, E , F } and its set of directed edges is E = {AB, BA, BC , CB, BD, DB, DE , ED, DF , FD}. The generated path after map-matching is AB, BD, DE.

III. A Framework Of Trajectory Data Mining

In the area, we propose a framework that condenses an entire strategy of trajectory data mining as appeared in Fig. 3.1 It is significant that only one out of every odd advance in the layer of trajectory data mining systems is fundamental and it depends on prerequisite of uses and gathered data. Initially, trajectory data are created by different moving questions and gathered from various data sources. In the paper, we preclude points of interest in data gathering. At that point, fundamental some portion of trajectory mining procedures are given five segments, i.e., preprocessing, data administration, inquiry handling, trajectory data mining errands, and protection security. At last, in the layer of uses, we survey an broad of uses from six classes.

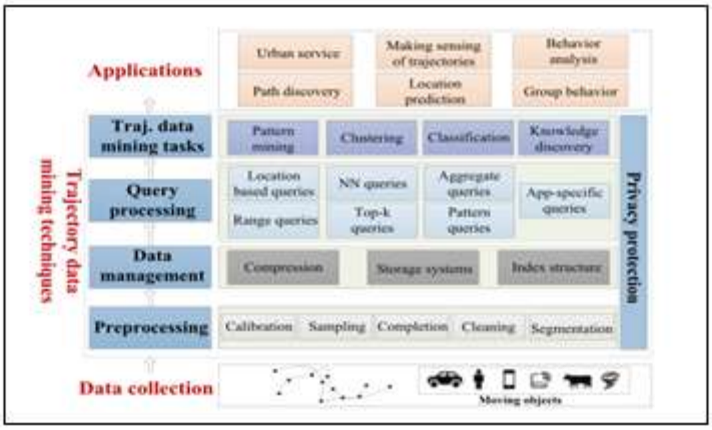

Fig 3.1 A framework of trajectory data mining.

The layer of trajectory data mining methods is composed as takes after. Preprocessing endeavors to move forward nature of trajectory data and to parcel trajectories into sub-trajectories for additionally preparing. Data administration takes care of the issue of putting away an enormous measure of trajectory data in a productive and adaptable way. Inquiry handling means to recover proper data from the basic capacity framework productively. The part of trajectory data mining errands condenses a few essential sorts of mining errands. Securing protection of clients with protection safeguarding procedures is a fundamental issue all through these four segments above and in this manner it can be joined with any segment.
All segments of trajectory data mining strategies and the layer of utilizations will be talked about progressively in following areas.

IV. Applications Of Trajectory Data Mining

A wide range of uses are driven by trajectory data mining. In the segment, we characterize these applications into following six composes. We at that point present every sort of applications through a couple of cases.

4.1. Path Discovery

Path discovery is a standout amongst the most widely recognized uses of trajectory data mining. It is critical to discover the most appropriate path in numerous application situations. Correct importance of the word "reasonable" relies upon applications. It can be the quickest, the briefest, the most prominent, thus on. A great deal of research papers [10]–[15] in the field have been distributed.

Path discovery, additionally called route discovery, is to discover at minimum one path that fulfill a predefined target given a source and a goal. Courses must be determined in light of a particular road network. Besides, geological areas in numerical style in trajectories ought to be coordinated to a guide keeping in mind the end goal to infer applicant paths or path portions. Authentic trajectories on the road network give profitable insight to gauge, look at and even build applicant courses.

The fastest path problem is an alteration of the shortest path problem. It can be settled by setting edge expenses to be time-related elements, e.g., travel time, rather than road separations. Be that as it may, in some cases the issue is summed up to various goals [10]. The goal is to limit the cost of a mix of goals.

When arranging an excursion in a new region, individuals generally attempt to locate the most continuous path between two areas [11]. Moreover, in a more sensible situation [13], an issue is conceivable to locate the most incessant path in a certain day and age, i.e., given a day and age T , a source v s what's more, a goal v d , looking through the most regular path amid T . Aside from day and age requirements, Wei et al. [12] additionally think about a circumstance of unverifiable trajectories, where trajectories are produced at a low inspecting rate due to numerous reasons, i.e., equipment restrictions, protection concerns, vitality limitations. In Fig. 5, a trajectory is produced by examining at a low frequency with just S, A, B, D as test focuses. The development amongst An and B are dubious and there are different courses, e.g., hued lines in Fig. 4.1

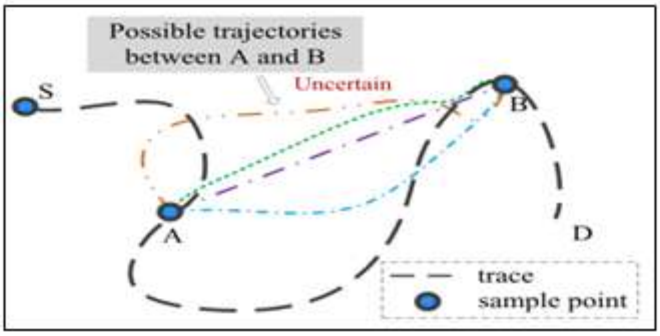

Fig. 4.1 An example of uncertain trajectories. A trajectory from S to D is generated at a relatively low sampling rate and only two points A and B are sampled. Movement between A and B is uncertain.

As a rule, the most incessant paths outflank the speediest paths or the most limited paths since the incessant ones reflect normal steering inclinations of past explorers. It additionally lessens the danger of fizzled paths which are conceivably unpaved, risky or hindered by a current road work. Regarding open transportation, individuals' genuine interest for open transportation are utilized to recognize and advance existing defective transport courses, in this manner enhancing use productivity of open transportation [14].

To consider different driving inclinations, Dai et al. [15] propose a suggestion framework that picks distinctive courses for drivers with various driving inclinations. This sort of customized course proposal keeps away from blemishes of past remarkable suggestion and enhances nature of client fulfillment.

4.2. Location/Destination Prediction

Location based services (LBSs), also called location-aware services, are highly advantageous to people in urban areas.It has been revealed that human versatility is unprecedented normal and along these lines unsurprising. Numerous area based applications require area forecast or goal forecast to send commercials to targeted purchasers, to prescribe vacationer spots or eateries, or to set goals in route systems. Goal forecast is firmly identified with path discovery. In the event that a continuous outing matches some portion of an incessant course in a dataset of historical trajectories, the goal of the continuous course is potentially the goal of the continuous trek. In any case, there exist a couple of limitations in real world situations. Research illustrations are expressed as takes after. Xue et al. [16], [17] call attention to a data sparsity issue, which shows that accessible trajectories are excessively few, making it impossible to cover all conceivable trajectories. To handle the data sparsity issue, all trajectories are decayed into sub-trajectories, and at that point blended trajectories are produced by interfacing sub-trajectories together. An extended set of trajectories thatcan bolster goal expectation is exponentially expanded by this method. In this paper, security insurance is also considered to secure touchy area data of clients. Noulas et al. [18] center around an issue of anticipating the next place that a client will visit, by investigating human versatility designs. A lot of registration data are used to think about human development with a qualitative portrayal. At that point a set of highlights which are relating to potential factors that may drive development of clients are removed. Aside from portability examples of individual clients, another consider [19] additionally ponders social congruity of clients, i.e., one's development is impacted by others'. Both normality also, similarity are considered to enhance the prescient control. Besides, heterogeneous versatility datasets e.g., GPS trajectories, cell tower data, WiFi signals, keen card exchanges, registration areas from online social networks rather than a solitary sort of trajectories are acquainted with support expectation execution.

4.3. Movement Behavior Analysis

Trajectory data give a great deal of chances to analyze development conduct of moving articles [20]–[25]. Discovery of development designs is crucial for understanding human conduct. One critical challenge in this theme is to extricate abnormal state semantics of conduct, i.e., surmising fundamental purposes or parts of moving items. Renso et al. [20] propose a way to deal with get it conduct of individuals who move in a geographical setting by extricating versatility behavioral examples. At that point, human conduct is derived from these examples which are mined from trajectory data. Anticipating human conduct precisely under crisis is a crucial issue for calamity alarming, debacle administration, calamity help and societal remaking after debacles.

Song et al. [21] analyze crisis conduct of people what's more, their versatility designs after a major atomic mishap in Japan, utilizing a substantial human versatility database. It is demonstrated that crisis conduct after calamities sometimes connects with their normal versatility designs. Moreover, several affecting variables, e.g., social relationship, power of a calamity, harm level, new detailing, and populace stream, are examined and in this way a prescient model is determined.

Another examination [22] addresses an issue of detecting parts of moving articles from trajectory data. It is expected that the natural structure, i.e., the dispersion of conduct, describes every part. Thusly, the part of a moving question can be recognized by investigating structures of trajectories. Human versatility conduct can be considered from spatial, temporal and social viewpoints.

Gao et al. [23] exhibit a thorough analysis of temporal impacts in demonstrating portability conduct. It has been contemplated that human versatility displays solid temporal cyclic examples in the time of hour, day or week. Liu et al. [24] propose a method to demonstrate trajectories in terms of client choice on going to a state of intrigue (POI) what's more, lead rationality analysis upon trajectory conduct. Rationality of trajectory conduct is investigated through several affecting variables.

4.4. Group Behavior Analysis

Moving articles, especially individuals and animals, sometimes tend to shape gatherings or groups because of their social conduct. For example, development of a man is influenced by not just personal exercises, yet in addition social ties with that of the bunches he has a place with. In addition, a get-together example, as a novel demonstrating of trajectory designs, portrays development design of a gathering of moving items. Cases incorporate festivals, parades, activity clog, substantial scale business advancements, dissents, etc. The subject of mining gathering examples or gathering designs has pulled in a great deal of research consideration [5]– [7], [26], [27]. Informally, a social occasion in reality shows an unusual or critical occasion.

Zheng et al. [5] present a social occasion design produced by a thick and proceeding with gathering of moving articles. Social occasion evacuates prerequisite for sound participation in traditional bunch designs (e.g., rush, guard and swarm), prompting a general participation that allows moving items to enter or leave its gathering whenever. An augmentation [6] infers a proficient online discovery approach, i.e., in an incremental way to consolidating recently produced trajectory data.

Another investigation [7] also goes for productively finding moving items which move together. A gathering is characterized as a group that at any rate m moving items being thickly associated for no less than a specific term of time. It is extremely not quite the same as social occasion meaning previously mentioned. Additionally, an inspecting free approach is proposed to stay away from imperfections of testing subordinate ones, e.g., caravan, swarm.

Gupta et al. [26] first address an issue of effectively demonstrating individual and gathering conduct and after that present a reproduction framework that recreates individuals' development conduct keeping in mind the end goal to create spatio-temporal development data. The reproduction is of extraordinary criticalness since a lot of development data in broad daylight space are constrained and inaccessible in reality.

A current report [27] is to detect and analyze moving dynamic spatio-temporal locales and their portability in vast sensor datasets. This sort of area regularly infers locally extreme zones of precipitation, anomalous ocean surface temperature readings, and locally abnormal amounts of water contamination, etc. It can also be viewed as mining bunch designs of a marvel.

4.5. Urban Service

Information found with trajectory data mining strategies enhances quality of life in urban regions from several angles [8], [9], [28]–[31]. Through analyzing an extensive scale of trajectory data gathered from electronic vehicles, Li et al. [28] fathom a challenging question of how to strategically convey charging stations and charging focuses, in this manner limiting normal time to the closest charging station and normal sitting tight time for an accessible charging point. Inducing road maps from substantial scale GPS follows are exceptionally encouraging and appealing, since building maps from geographical reviews are costly and occasional.

Liu et al. [29] address an issue of guide deduction in a practical setting, i.e., GPS follows has low determination and sampling frequency. Several procedures for outline from meager data are explored and widely evaluated. Movement volume estimation is an essential errand in numerous applications, for example, chance analysis, quality of administration, area positioning. A current report [30] intends to gauge activity volume for people on foot inside shut situations.

Learning on individuals' essence gives a valuable chance to enhancing framework, e.g., areas of data work areas, shops or toilets, path-widths of hallways in a stadium. Stopping administration is of incredible significance to natives in urban regions. Stopping places (especially on-street stopping) are usually inaccessible in existing electronic maps.

iPark [31] intends to empower stopping seek applications and to give complete stopping data, i.e., clarifying a current delineate stopping zones in view of trajectory data of vehicles. A created city naturally has diverse functional areas, e.g., residential territories, business locale, and educational territories. The learning is exceedingly valuable to the two residents and urban organizers.

Individuals living a city require the learning to help their choice on purchasing or leasing a house, picking a work. Then, the learning encourages urban organizers to make choices on future improvement of the city and to evaluate impacts of past policies. Yuan et al. [8], [9] address a issue of finding locales of various capacities in a city in view of a substantial scale of trajectory data. A point show based approach has been proposed to bunch portioned areas into functional zones, where an area is viewed as an archive what's more, a capacity as a point.

4.6. Making Sense of Trajectories

Crude trajectory data which are as arrangement of geographical areas and timestamps neglect to bode well to individuals without semantic portrayal. There exist an incredible numerous investigations [4], [32]–[35] to facilitate interpretation of crude trajectory data. Unlike semantic trajectory that can't express development properties of moving articles, e.g., overspeed, stopover,

Su et al. [4] propose a segment and-summarization approach that automatically produces a short intelligible content to depict a trajectory. The approach not just expands expressivity of traditional semantic trajectories yet in addition maintains a strategic distance from a challenging issue of capacity, preparing and transmission of expansive volume of semantic trajectories.

A crude trajectory data is first sectioned by conduct of a moving item, and afterward qualities of every trajectory division are summarized by short textual portrayal. Moreover, a proto framework named STMaker [32] in light of this thought is actualized.

It is positively important that semantic significance of areas and short textual messages gathered by social media administrations give an extraordinary opportunity to interpret crude trajectory data. TOPTRAC [33] points to detect dormant subject in trajectory data. Specifically, the approach not just finds semantic districts with a sound theme yet in addition extricates mobility examples of human creatures between semantic locales.

Essentially, Lu et al. [35] utilize a bunching based way to deal with find semantic locales. A great deal of developing area mindful applications require a semantic documentation of an area point, e.g., "home", ''work", rather than latitude and longitude facilitates. Lv et al. [34] propose a method of automatically finding personal semantic spots (i.e., both a physical area and semantic importance of the area).

V. Open Issues

Regardless of its different applications, trajectory data mining systems must be enhanced from numerous angles. We offer a couple of open issues in the accompanying. In the first place, albeit current trajectory data mining methods help to break down conduct of moving articles, we have constrained comprehension of main drivers of such fascinating conduct by any means.

Second, current security protecting techniques are a long way from enough. Protection safeguarding is of incredible significance to trajectory data sharing and distribution. Third, it is conceivable to extricate considerably more esteem if trajectory data are joined with other Well springs of data, e.g., human services data. For example, breaking down connection between's one's authentic trajectories and his or her sickness may give signs to reasons for the ailment.

VI. Conclusion

Trajectory data mining is gainful to singular subjects. One can comprehend his or her development conduct better through investigating authentic trajectories. Moreover, trajectory data mining gives a lot of comfort to people in general, e.g., course proposal, continuous activity data distribution by transport organizations. Be that as it may, individuals endure from protection ruptures if their trajectories are gathered also, used improperly. Also, individuals are for the most part bothered by business commercials which are potentially pushed for the sake of customized administrations. For the legislature and a few associations, trajectory data mining diminishes cost of supervision and administration. In urban regions, trajectory data mining from vehicle trajectories gives an effective and adaptable strategy to screen activity state of the entire city. Another illustration is to record unlawful or sporadic conduct which is most likely important to discover obligations later.

For illustration, overspeed can be induced from trajectories. This confirm is important particularly in roads without roadside cameras. Correspondingly, business associations hope to cut down their expenses in temperance of trajectory data mining. For case, RFID data, as an exceptional sort of trajectories, for sure help to oversee product stocks. Area procurement advances produce tremendous measure of trajectory data. Trajectory data which track hints of moving objects is normally spoken to by an arrangement of time stamped topographical areas. A lot of utilizations are made after mining trajectory data. The overview audits a broad gathering of existing examinations in the proposed framework of trajectory data mining.

References

[1] H. Jeung, H. Lu, S. Sathe, and M. L. Yiu, ''Managing evolving uncertainty in trajectory databases,'' IEEE Trans. Knowl. Data Eng., vol. 26, no. 7, pp. 1692–1705, Jul. 2014.

[2] R. G. Baraniuk, ''More is less: Signal processing and the data deluge,'' Science, vol. 331, no. 6018, pp. 717–719, Feb. 2011.

[3] S. Liu, J. Pu, Q. Luo, H. Qu, L. M. Ni, and R. Krishnan, ''VAIT: A visual analytics system for metropolitan transportation,'' IEEE Trans. Intell. Transp. Syst., vol. 14, no. 4, pp. 1586–1596, Dec. 2013.

[4] H. Su et al., ''Making sense of trajectory data: A partition-and-summarization approach,'' in Proc. 31St IEEE Int. Conf. Data Eng. (ICDE), Seoul, South Korea, Apr. 2015, pp. 963–974.

[5] K. Zheng, Y. Zheng, N. J. Yuan, and S. Shang, ''On discovery of gathering patterns from trajectories,'' in Proc. 29th IEEE Int. Conf. Data Eng. (ICDE), Brisbane, QLD, Australia, Apr. 2013, pp. 242–253.

[6] K. Zheng, Y. Zheng, N. J. Yuan, S. Shang, and X. Zhou, ''Online discovery of gathering patterns over trajectories,'' IEEE Trans. Knowl. Data Eng., vol. 26, no. 8, pp. 1974–1988, Aug. 2014.

[7] X. Li, V. Ceikute, C. S. Jensen, and K. Tan, ''Effective online group discovery in trajectory databases,'' IEEE Trans. Knowl. Data Eng., vol. 25, no. 12, pp. 2752–2766, Dec. 2013.

[8] N. J. Yuan, Y. Zheng, X. Xie, Y. Wang, K. Zheng, and H. Xiong, ''Discovering urban functional zones using latent activity trajectories,'' IEEE Trans. Knowl. Data Eng., vol. 27, no. 3, pp. 712–725, Mar. 2015.

[9] J. Yuan, Y. Zheng, and X. Xie, ''Discovering regions of different functions in a city using human mobility and POIs,'' in Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD), Beijing, China, Aug. 2012, pp. 186–194.

[10] E. H.-C. Lu, W.-C. Lee, and V. S. Tseng, ''Mining fastest path from trajectories with multiple destinations in road networks,'' Knowl. Inf. Syst., vol. 29, no. 1, pp. 25–53, Oct. 2011.

[11] Z. Chen, H. T. Shen, and X. Zhou, ''Discovering popular routes from trajectories,'' in Proc. 27th Int. Conf. Data Eng. (ICDE), Hanover, Germany, Apr. 2011, pp. 900–911.

[12] L.-Y. Wei, Y. Zheng, and W.-C. Peng, ''Constructing popular routes from uncertain trajectories,'' in Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD), Beijing, China, Aug. 2012, pp. 195–203.

[13] W. Luo, H. Tan, L. Chen, and L. M. Ni, ''Finding time period-based most frequent path in big trajectory data,'' in Proc. ACM SIGMOD Int. Conf. Manage. Data (SIGMOD), New York, NY, USA, Jun. 2013, pp. 713–724.

[14] Y. Liu et al., ''Exploiting heterogeneous human mobility patterns for intelligent bus routing,'' in Proc. IEEE Int. Conf. Data Mining (ICDM), Shenzhen, China, Dec. 2014, pp. 360–369.

[15] J. Dai, B. Yang, C. Guo, and Z. Ding, ''Personalized route recommendation using big trajectory data,'' in Proc. 31st IEEE Int. Conf. Data Eng. (ICDE), Seoul, South Korea, Apr. 2015, pp. 543–554.

[16] A. Y. Xue, R. Zhang, Y. Zheng, X. Xie, J. Huang, and Z. Xu, ''Destination prediction by sub-trajectory synthesis and privacy protection against such prediction,'' in Proc. 29th IEEE Int. Conf. Data Eng. (ICDE), Brisbane, QLD, Australia, Apr. 2013, pp. 254–265.

[17] A. Y. Xue, R. Zhang, Y. Zheng, X. Xie, J. Yu, and Y. Tang, ''DesTeller: A system for destination prediction based on trajectories with privacy protection,'' in Proc. PVLDB, 2013, vol. 6. no. 12, pp. 1198–1201.

[18] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo, ''Mining user mobility features for next place prediction in location-based services,'' in Proc. 12th IEEE Int. Conf. Data Mining (ICDM), City of Brussels, Belgium, Dec. 2012, pp. 1038–1043.

[19] Y. Wang et al., ''Regularity and conformity: Location prediction using heterogeneous mobility data,'' in Proc. 21st ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Sydney, NSW, Australia, Aug. 2015, pp. 1275–1284.

[20] C. Renso, M. Baglioni, J. A. F. de Macêdo, R. Trasarti, and M. Wachowicz, ''How you move reveals who you are: Understanding human behavior by analyzing trajectory data,'' Knowl. Inf. Syst., vol. 37, no. 2, pp. 331–362, Nov. 2013.

[21] X. Song, Q. Zhang, Y. Sekimoto, and R. Shibasaki, ''Prediction of human emergency behavior and their mobility following large-scale disaster,'' in Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD), New York, NY, USA, Aug. 2014, pp. 5–14.

[22] S. Ando and E. Suzuki, ''Role-behavior analysis from trajectory data by cross-domain learning,'' in Proc. 11th IEEE Int. Conf. Data Mining (ICDM), Vancouver, BC, Canada, Dec. 2011, pp. 21–30.

[23] H. Gao, J. Tang, X. Hu, and H. Liu, ''Modeling temporal effects of human mobile behavior on location-based social networks,'' in Proc. 22nd ACM Int. Conf. Inf. Knowl. Manage. (CIKM), San Francisco, CA, USA, Oct./Nov. 2013, pp. 1673–1678.

[24] S. Liu, Q. Qu, and S. Wang, ''Rationality analytics from trajectories,'' ACM Trans. Knowl. Discovery Data, vol. 10, no. 1, p. 10, Jul. 2015.

[25] M. C. González, C. A. Hidalgo, and A.-L. Barabási, ''Understanding individual human mobility patterns,'' Nature, vol. 453, pp. 779–782, Jun. 2008. [Online]. Available: http://dx.doi.org/10.1038/nature06958

[26] A. Gupta et al., ''A mobility simulation framework of humans with group behavior modeling,'' in Proc. IEEE 13th Int. Conf. Data Mining, Dallas, TX, USA, Dec. 2013, pp. 1067–1072.

[27] M. P. McGuire, V. P. Janeja, and A. Gangopadhyay, ''Mining trajectories of moving dynamic spatio-temporal regions in sensor datasets,'' Data Mining Knowl. Discovery, vol. 28, no. 4, pp. 961–1003, Jul. 2014.

[28] Y. Li, J. Luo, C. Y. Chow, K. L. Chan, Y. Ding, and F. Zhang, ''Growing the charging station network for electric vehicles with trajectory data analytics,'' in Proc. 31st IEEE Int. Conf. Data Eng. (ICDE), Seoul, South Korea, Apr. 2015, pp. 1376–1387.

[29] X. Liu, J. Biagioni, J. Eriksson, Y. Wang, G. Forman, and Y. Zhu, ''Mining large-scale, sparse GPS traces for map inference: Comparison of approaches,'' in Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD), Beijing, China, Aug. 2012, pp. 669–677.

[30] T. Liebig, Z. Xu, M. May, and S. Wrobel, ''Pedestrian quantity estimation with trajectory patterns,'' in Proc. Eur. Conf. Mach. Learn. Knowl. Discovery Databases (ECML PKDD), Bristol, U.K., Sep. 2012. pp. 629–643.

[31] B. Yang, N. Fantini, and C. S. Jensen, ''iPark: Identifying parking spaces from trajectories,'' in Proc. 16th Int. Conf. Extending Database Technol. (EDBT), Genoa, Italy, Mar. 2013, pp. 705–708.

[32] H. Su, K. Zheng, K. Zheng, J. Huang, and X. Zhou, ''STMaker: A system to make sense of trajectory data,'' in Proc. PVLDB, 2014, vol. 7. no. 13, pp. 1701–1704.

[33] Y. Kim, J. Han, and C. Yuan, ''TOPTRAC: Topical trajectory pattern mining,'' in Proc. 21st ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Sydney, NSW, Australia, Aug. 2015, pp. 587–596.

[34] M. Lv, L. Chen, and G. Chen, ''Discovering personally semantic places from GPS trajectories,'' in Proc. 21st ACM Int. Conf. Inf. Knowl. Manage. (CIKM), Maui, HI, USA, Oct./Nov. 2012, pp. 1552–1556.

[35] C. Lu, P.-R. Lei, W.-C. Peng, and I.-J. Su, ''A framework of mining semantic regions from trajectories,'' in Proc. 16th Int. Conf. Database Syst. Adv. Appl. (DASFAA), Hong Kong, Apr. 2011, pp. 193–207.