Abstract: The goal of spatial data mining is to discover potentially useful, interesting, and non-trivial patterns from spatial data-sets (e.g., GPS trajectory of smartphones). Spatial data mining is societally important having applications in public health, public safety, climate science, etc. For example, in epidemiology, spatial data mining helps to find areas with a high concentration of disease incidents to manage disease outbreaks. Computational methods are needed to discover spatial patterns since the volume and velocity of spatial data exceed the ability of human experts to analyze it. Spatial data has unique characteristics like spatial autocorrelation and spatial heterogeneity which violate the i.i.d (Independent and Identically Distributed) assumption of traditional statistic and data mining methods. Therefore, using traditional methods may miss patterns or may yield spurious patterns, which are costly in societal applications. Further, there are additional challenges such as MAUP (Modifiable Areal Unit Problem) as illustrated by a recent court case debating gerrymandering in elections. In this article, we discuss tools and computational methods of spatial data mining, focusing on the primary spatial pattern families: hotspot detection, colocation detection, spatial prediction, and spatial outlier detection. Hotspot detection methods use domain information to accurately model more active and high-density areas. Colocation detection methods find objects whose instances are in proximity to each other in a location. Spatial prediction approaches explicitly model the neighborhood relationship of locations to predict target variables from input features. Finally, spatial outlier detection methods find data that differ from their neighbors. Lastly, we describe future research and trends in spatial data mining.

KeyWords: Spatial Data Mining, Spatial Statistics, Spatial Patterns, Hotspot Detection, Colocation Detection, Spatial Prediction, Spatial Outlier Detection, Spatial Autocorrelation, MAUP.

Definitions

- **Spatial data:** Any data that includes location information such as street address, or longitude and latitude.

- **Independent and Identically Distributed (i.i.d) assumption:** A classical assumption in statistics that presumes data samples to be independent of each other and are distributed identically.
• **Spatial autocorrelation**: It is defined as a measure of dependency among points in a spatial neighborhood. The dependency of spatial data rejects the independence assumption of classical statistics.

• **Spatial heterogeneity (or spatial non-stationarity)**: It refers to the variation in events, features and relationships across a region. It violates identical distribution assumption.

• **Spatial continuity**: It refers to the presence of spatial dependency or spatial correlation in input data over a space.

• **Spatial statistics**: A generalization of traditional statistics for spatial data that makes it possible to model spatial dependency and heterogeneity.

• **Spatial data mining**: A generalization of traditional data mining that explores the trade-offs between computational scalability and mathematical rigor, for spatial data.

1 Introduction

The remarkable growth in location-aware data (e.g., GPS tracks of smart phones, remotely sensed satellite imagery) and recent advances in computer infrastructure highlight the need for automated systems to discover spatial patterns in the data. Spatial data mining (SDM) is the process of discovering non-trivial, interesting and previously unknown, but potentially useful patterns from large spatial and spatio-temporal databases [12, 14, 18, 6]. Given a geospatial dataset, the three key steps for detecting spatial patterns are as follows: (1) pre-processing data to correct noise, error, and missing information along with space-time analysis to identify underlying spatial or spatio-temporal distribution, (2) applying a relevant SDM algorithm to the pre-processed data to produce an output pattern, (3) post-processing the output pattern, and then having domain experts analyze the output to identify novel insights. Further refinement of the SDM algorithm may be needed based on the interpretation of results in the last step.

SDM techniques are crucial to large organizations that make decisions and policies based on large spatial data sets. Table 1 lists some of the domains and relevant SDM applications. For example in ecology and environmental management, scientists classify remote sensing images to classes (e.g., vegetation, wetland, etc.) on a land-cover map. In public safety, the discovery of crime hotspots events may help police departments to allocate resources effectively. Also, in climate science, finding the effects of distant locations on the temperature of a given location can lead to a more accurate temperature estimates.

The data inputs of SDM include spatial attributes such as latitude, longitude, and elevation, which are used to define the spatial location and extent of spatial objects. Spatial objects include extended objects such as points, lines, and polygons. The spatial relationships among objects are a vital and rich source of information that can enhance feature selection for improving the performance of traditional methods.

Further, traditional data mining and machine learning techniques may miss patterns or may yield spurious patterns that have a high-cost (e.g., stigmatization). This is due to the nature of spatial data (e.g., spatial autocorrelation and spatial heterogeneity) that violates classical assumption in statistics, which is common
Table 1: Examples of application domains of spatial data mining.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Spatial data mining application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public safety</td>
<td>Discovery of hotspot patterns from crime event maps.</td>
</tr>
<tr>
<td>Epidemiology</td>
<td>Detection of disease outbreak</td>
</tr>
<tr>
<td>Business</td>
<td>Market allocation to maximize stores profits</td>
</tr>
<tr>
<td>Neuroscience</td>
<td>Discovering patterns of human brain activity from neuroimages</td>
</tr>
<tr>
<td>Climate Science</td>
<td>Finding positive or negative correlations between temperatures of distant places</td>
</tr>
</tbody>
</table>

in data mining and machine learning techniques. The sensitivity of statistical methods to space partitioning and non-stationarity of spatial data along time and space are other key characteristics and challenges of spatial data [9].

Spatial statistics and spatial data mining are overlapping fields which support each other in many aspects. Spatial statistics have explored many test statistics that can inform the design of interest measure in spatial data mining. Statistical techniques possess a high mathematical rigor however, computational scalability is not a primary consideration. In contrast, SDM techniques explicitly address a trade-off between mathematical rigor and computational scalability to analysis spatial big data. Figure 1 illustrates the trade-off between spatial statistics, data mining, and spatial data mining. We will detail it further in section 4.

Scope: This article aims to highlight the difference between spatial data mining, traditional data mining, and spatial pattern families. However, we do not discuss spatial statistics and related mathematics in detail. Further, the detailed description of traditional data mining techniques falls outside the scope of this article interested audience can refer to [15] as a comprehensive guide in those topics. Another key sub-field in spatial data mining is trajectory data mining, and the detailed description of trajectory data mining techniques falls outside the scope of this article. Interested readers can refer to [20], which provides a comprehensive survey on trajectory data mining. Finally, spatial data mining is widely applied to many disciplines (e.g., remote sensing, geography) and related domains (e.g., public health, landscape architecture, urban studies,) describing which is beyond the scope of this article.

Organization: The article is organized as follows. Section 2 provides a brief background on spatial statistics. Section 3 explains four important pattern families, its related applications, and statistical methods. In Section 4 a short highlight of the difference between spatial statistics and spatial data mining followed by future research and trends are provided. Learning objectives and instructional assessment questions are in Section 5 and Section 6 respectively. We provide resources for further reading in Section 7.

2 Spatial Statistics

Spatial statistics [3, 4] adheres to the properties spatial auto-correlation and heterogeneity. This differs from traditional statistics which presumes independent and identical distribution (i.i.d) of sample data for their calculations. The i.i.d assumption is the foundation of majority of data mining methods and statistics
Figure 1: An illustrative example of the trade-off between spatial statistics, spatial data mining, and traditional data mining techniques.

Spatial statistics is sensitive to space partitioning and the values depend on the shape and scale of the partitions. This concept is formally referred to as themodifiable areal unit problem (MAUP). It is also referred to as the multi-scale effect. For example, results can differ when aggregated on states versus household level. Gerrymandering of election districts is another prominent example of MAUP where political parties redraw the boundaries of districts to improve their possibility of winning. Figure 2 shows an example of gerrymandering where a population of 15 that supports candidate A and a population of 10 that supports candidate B are to be partitioned into 5 congressional districts. Only one partition scheme is fair (Figure 2c). In the other schemes gerrymandering gives an unfair advantages to majority of the party (Figure 2b) or the minority party (Figure 2d).

Following example shows that choosing a proper spatial model is critically important in SDM. In Figure 3a, there are three types of points, squares (□), circles (○) and triangles (△). Each point type has two instances. For calculating the spatial correlation between the different points, we partition the space, as shown in Figure 3b and 3c. The spatial distribution of each point type is a feature vector that corresponds to its count in each partition. As shown in Table 2a, based on region partitioning (e.g., Figure 3b and Figure 3c), Pearson’s correlations and support between (○, △) and (○, □) are varied. The correlation between triangles and circles in Figure 3a is negative, but...
Figure 2: Example of gerrymandering. (a) Base data; (b) Horizontal partitioning, A takes all seats, 5A - 0B; (c) Vertical partitioning, 3A - 2B; (d) Partitioning helping minority B get majority of seats, 2A - 3B.

Figure 3: Example of spatial statistics.

(a) Distribution of different points
(b) Region partitioning A
(c) Region partitioning B
(d) Neighborhood relationship based on the neighborhood graph

the correlation between triangles and circles in Figure 3b is positive. On the other hand, region partitioning in Figure 3c indicates the opposite results in comparison with Figure 3b. Therefore, the results and spatial relationships are varied based on how the study area is partitioned. The spatial relationship between circles and triangles and circles and squares are lost due to different partitioning, as shown in Figure 3b and 3c respectively. By contrast, Figure 3d shows that a participation index (Table 2b) is able to accurately capture the adjacency.

Table 2: Pearson’s correlation coefficient for region partitioning and a participation index for a neighborhood graph. Results show that the partitioning breaks spatial relationships, whereas the neighborhood graph preserves the relationship.

<table>
<thead>
<tr>
<th></th>
<th>Partition A</th>
<th>Pairs</th>
<th>Partition B</th>
<th>Pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson’s Correlation</td>
<td>0.9</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>Support</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

(a) Association Rules – Gerrymandering Risks

<table>
<thead>
<tr>
<th>Pairs</th>
<th>Ripley’s Cross K</th>
<th>Participation Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>□□</td>
<td>0.33</td>
<td>0.67</td>
</tr>
<tr>
<td>□□</td>
<td>0.5</td>
<td>1</td>
</tr>
</tbody>
</table>

(b) Neighborhood relationship based on neighborhood graph

Methods in spatial statistics can be categorized based on the type of input data as follows: (1) geostatistics for point referenced data, (2) lattice statistics for areal data, (3) spatial point processes for spatial point patterns.

Geostatistics: Geostatistics analyzes spatial continuity and weak stationarity, which are inherent features of spatial data sets. Geostatistical techniques rely on statistical models that use random variables to model the uncertainty. Geostatistics offers a range of statistical tools, such as kriging, for interpolating the value of a random field at the unsampled locations.
3 Spatial Pattern Families

Spatial data mining methods are designed to detect spatial patterns [13]. We focus on four important pattern families, namely, hotspots, colocations, spatial predictions, and spatial outliers. These pattern families are widely applied in many societally relevant domains such as epidemiology, criminology, traffic safety, ecology, environmental science, climate science, urban planning, etc.

3.1 Hotspot Detection

Given a set of geospatial points which are related to an activity in a spatial domain, hotspots are the regions that are more active and have higher density of points compared to other regions. John Snow’s work in 1854 was an early path breaking example of spatial hotspot detection, where he successfully identified the source of a cholera outbreak. He found that the highest incidence of disease was in proximity to the Broad street water pump (see Figure 5a). This is an illustrative example that shows the importance of hotspot detection in epidemiology domain. However, it must be noted that the notion of a hotspot is domain specific and hotspot detection techniques should consider domain knowledge to model hotspot regions correctly and effectively. For example, hotspots are typically modeled as circular areas in epidemiology or as paths in traffic engineering [16], etc.

Given widespread applications of hotspot detection, software suites have been developed to detect hotspots in spatial and spatio-temporal data sets. SatScan [10] is one of the most prominent free software used for hotspot detection. It relies on hypothesis testing for candidate hotspots which are discovered by a cylindrical scanning of the space. The null hypothesis is based on complete spatial randomness (CSR). The alternative hypothesis states that events are
Figure 5: Analysis of water pump sites and deaths from cholera in London in 1854.

more dense inside the cylinder than outside. A candidate is considered statistically significant, if it has the highest log-likelihood ratio amongst all the candidate hotspots (see figure [5]).

### 3.2 Colocation Detection

Spatial colocation patterns [11] represent subsets of features whose instances are located near one another. For example, the symbiotic relationship between the Nile crocodile and Egyptian plover bird exhibits a colocation pattern. Many biological dependencies exhibit colocation patterns. Figure 6a illustrates the spatial distribution detected via a colocation algorithm of instances of five features, namely, plover, crocodile, green trees, dry trees, and wildfire. Similar analysis on crime datasets has shown the colocation of bars with street fights.

To measure the degree of clustering in a point distribution, we can use Ripley’s K function (section 3). It is based on an average number of points whose distance is smaller than a predefined threshold from any chosen point. The null hypothesis of Ripley’s K also relies on CSR. The cross-K function extends Ripley’s K function to cases when there are multiple features. It is a spatial statistical method to detect collocation patterns between features of point events. The cross-K function $K(h)$ for binary spatial features is defined as:

$$K_{ij}(h) = \lambda_j^{-1} \mathbb{E} \left[ \text{number of type } j \text{ instances within distance } h \text{ of a randomly chosen type } i \text{ instance} \right],$$

where $\lambda_i$ is the density (number per unit area) of type $i$ instances and $h$ is the distance. Figure [6b] shows the cross-K function results for the input represented in Figure [6a]. As can be seen, crocodile and plover have high cross-K values which means they are more likely to be located near each other. The low value between green tree and wildfire means that these two are usually located far from each other.

Participation index is an upper bound of the cross-K function. It is a popular measure of colocation due to its computational properties [7]. The index uses a participation ratio, which is another measure for colocation detection. The
participation ratio of feature $f_1$ in a colocation pattern $CP$, $pr(CP, f_1)$ is the portion of feature $f_1$ engaging in the pattern $CP$. Participation index is defined as $pi(CP) = \min_{f_i \in CP} pr(CP, f_i)$. In the other words, it is the minimum participation ratio of all features engaging in the colocation pattern. Table 2b shows the participation index values for the colocation pattern in Figure 3a. One pattern is ($\odot$, $\triangle$). The $pr((\odot, \triangle), \odot)$ is 1 because all circles are participating in colocation pattern ($\odot, \triangle$). Also, two triangles are engaging in colocation pattern ($\odot, \triangle$) which means $pr((\odot, \triangle), \triangle) = \frac{2}{3} \approx 0.67$. So, $pi(\odot, \triangle) = 0.67$, which is the minimum value of the participation ratio of engaged features in the colocation pattern.

### 3.3 Spatial Prediction

Spatial prediction, also known as spatial classification and regression, is used to identify the relationship between variables in different datasets. These variables are of two types: explanatory variables (i.e., explanatory attributes or features), and a target variable (also known as, dependent variable). If the target variable is discrete, the problem is known as spatial classification. However, when target variables are continuous, the problem is termed as spatial regression. The goal of spatial prediction is to predict the value of target variables from explanatory variables using training samples of data and the neighborhood relationships among the locations.

Traditional data mining and machine learning techniques do not generalize well to spatial prediction and often perform poorly [8]. For example, in Figure 7b, a decision tree is used to classify wetland and dry land using spectral features from a satellite image shown in Figure 7a. Compared to the ground truth in Figure 7c the output of the decision tree contains a large amount of “salt-and-pepper” error. Spatial prediction requires the methods that can handle spatial autocorrelation and heterogeneity [8, 1].

The spatial auto-regressive (SAR) model is a supervised learning technique that belongs to the family of spatial regression models. It uses the spatial relationship between explanatory features to predict target variables. A neighborhood relationship is necessary for modeling the spatial relationship of explanatory features and it is usually an additional input to SAR. The SAR model is defined as follows:

$$y = \rho Wy + X\beta + \epsilon,$$

(2)
where, \( W \) is an adjacency matrix, and \( W_y \) models the effect of neighborhood in addition to the effects of selected features \( X \) on the target variable \( y \). Parameters \( \rho \) and \( \beta \) can be learned using Equation 2. Notice that linear regression, which follows the i.i.d assumption, is a special case of the SAR model when \( \rho \) is zero. Therefore, SAR model is more general compared to linear regression model.

For modeling the spatial heterogeneity, we can use a non-parametric technique known as Geographically Weighted Regression (GWR). GWR does not perform regression on all data samples. Instead, it relies on kernel size configuration where it calculates a local weighted average using neighborhood samples that are within the same bandwidth (e.g., search window) as the current data location (focal point). Samples that are closer to the current location in the search window will get more weights.

To address spatial autocorrelation in aerial imagery, we can use Convolutional Neural Networks (CNN) [2], which perform convolutions using neighborhood data. However, they may not address spatial variability. Thus, spatial variability aware neural networks (SVANN) have been proposed which take distance into account while training neural networks [5]. In SVANN each parameter is a map, i.e., a function of a location. SVANN has two alternatives for prediction. Zone-based prediction uses the local neural networks for the zone at hand for prediction. The second approach is to combine the predictions from all local neural networks, and favoring the nearby models using distance weighting.

### 3.4 Spatial Outlier Detection

Outliers may be global or spatial. Global outliers are data samples that are inconsistent with the rest of the data samples, such as credit card fraud. In contrast, spatial outliers differ from other data only in their neighborhood [13]. For example, a new house surrounded by older houses in a developed city can be considered as a spatial outlier, but it may not be a global outlier based on the overall age of houses in the city. In another example, Figure 8 shows the 1992 United States presidential election results (grey vs. black) for all 50 states. Indiana is the spatial outlier in this example. Spatial outlier detection is vital for applications that need to find an unusual or suspicious activity or objects compared to their neighborhoods.

There are two classes of statistical tests for detecting spatial outliers, graphical tests, and quantitative tests. Graphical tests detect outliers via analyzing visualized patterns from data. Examples include Variogram clouds and Moran scatter plots. Quantitative tests calculate the difference between non-spatial
attributes of inspected points and their spatial neighbors. When the difference is larger than a predefined threshold, an outlier is detected. Neighborhood spatial statistics and scatterplots are quantitative tests.

4 Discussion and Future Directions

Discussion: Spatial statistics and spatial data mining overlap as shown in Figure 9. Spatial statistical techniques (e.g., Spatial Scan Statistic [10] and Ripley’s K function) are mathematically rigorous which can eliminate chance patterns and evaluates the robustness of an output from a spatial pattern mining algorithm. However, a key challenge in such techniques is computational scalability when using spatial big data that contains thousands of point features that grow exponentially. This highlights the limitations of spatial statistics which are potentially addressed in spatial data mining (SDM). For example, in colocation detection, participation index [7] is introduced that defines an upper-bound on the cross-K function such that index decreases monotonically as the size of the colocation pattern increases [18]. The upper bound allows to limit the colocation search space providing a computationally feasible algorithms to detect colocation patterns.

Future directions: Most research in spatial data mining assumes 1) that space is Euclidean and isometric (i.e., it has the same statistical properties along different directions), and 2) that neighborhoods are symmetric. However, in many applications, space is a network space. For example, road networks and river networks can be modeled by network space more effectively. Considering network structure is one of the challenges of using network space, but research in this area promises to provide more accurate insights.

In addition to the space dimension, the temporal dimension is another crucial aspect of spatial data. Useful information and patterns can often be identified
by adding a temporal dimension to SDM techniques. Detection of the time point that impacts some phenomenon is a key problem, which is called change detection. For example, change detection helps to detect when climate change occurred in a region such that appropriate protective action can be taken in that region. In teleconnection discovery problem, we have collection of spatial time series of different locations. Teleconnection discovery aims to find pairs of positively or negatively correlated points of time series at great distance. Teleconnection discovery is used in climate science to more accurately predict temperatures of different places in the world. Adding the time dimension to SDM problems will likely open new and more complex statistical, mathematical, and computational models that can address grand societal challenges.

Finally, domain experts provide a rich source of information to enhance data-driven spatial models. Simulation models usually integrate physical rules and related domain knowledge into the data mining models to gain new and useful insights [9]. Simulation models are usually complicated from a computational perspective. Consequently, new data science approaches are needed that implement fast approximate solutions of simulation models. Due to potentially high cost of spurious patterns in societal applications (e.g., crime pattern analysis, disease outbreaks), it is important that new techniques are statistically robust.

5 Learning Objectives

After reading this article, you will be able to do the following:

1. Explain the i.i.d assumption and illustrate why it is not valid for spatial data.

2. Describe the following two key concepts in spatial statistics:
   - spatial autocorrelation
   - spatial heterogeneity

3. Define MAUP and explain gerrymandering as an example of MAUP.
4. List three areas of spatial statistics and briefly explain them.

5. Name five spatial patterns and illustrate them.

6 **Instructional Assessment Questions**

1. Which statement(s) violate the independence assumption?
   
   (a) “Mohamed Lee” is a rare name, even though “Mohamed” is the most frequent first name and “Lee” is the most frequent last name.
   
   (b) Near things are more related than distant things.
   
   (c) Nearby video frames often show common people and objects.
   
   (d) All of the above

2. Which of the three images in Figure 8 exhibits the highest spatial autocorrelation?
   
   (a) image 10a
   
   (b) image 10b
   
   (c) image 10c

3. Which statement(s) violate the identical distribution assumption underlying traditional statistical methods?
   
   (a) Cancer cell heterogeneity makes treatment of cancer difficult.
   
   (b) No two places on Earth are exactly alike.
   
   (c) All politics is local.
   
   (d) All of the above

4. Which of the following are properties of spatial data?
   
   (a) Autocorrelation
   
   (b) Heterogeneity
   
   (c) Implicit relationships (e.g., neighbor)
5. Which of the following is not attributed to spatial auto-correlation?
   (a) Nearby cities have similar climate.
   (b) Neighboring areas tend to plant similar farm crops.
   (c) Near things are more related than distant things.
   (d) Spatial data mining results are less reliable near the edges of a study area.

6. Which of the following is correct about gerrymandering:
   (a) It is about redrawing boundaries of districts.
   (b) It can help a party or group to take a political advantage.
   (c) It can change the result of an election in a way which contradicts the popular vote.
   (d) All of the above

7. Spatial pattern families include hotspots, colocations, location predictions, and spatial outliers. Which pattern does each question below correspond to?
   (a) Which countries are very different from their neighbors?
   (b) Which highway-segments have abnormally high accident rates?
   (c) Where will a hurricane that’s brewing over the ocean make landfall?
   (d) Which retail-store-types often co-locate in shopping malls?

8. Which does not illustrate a spatial-hotspot pattern family?
   (a) Roads with an unusually high rate of traffic accidents.
   (b) Areas with an unusually high concentration of museums.
   (c) Cities with unusually high numbers of students enrolled in a particular massive open online course (MOOC).
   (d) A neighborhood with an unusually high rate of an infectious disease (or crime).

9. Which does not illustrate colocation?
   (a) A loud sound temporally follows a bright flash of lightning.
   (b) Nuclear power plants are usually located near water.
   (c) Egyptian plover birds live close to Nile crocodiles.
   (d) College campuses often have bookstores nearby.

10. Which of the following is false about spatial outliers?
    (a) An oasis (isolated area of vegetation) is a spatial outlier area in a desert.
    (b) A spatial outlier may reveal discontinuities and abrupt changes.
    (c) A spatial outlier is significantly different from their spatial neighbors.
    (d) A spatial outlier is significantly different from the population as a whole.

(d) All of the above
7 Additional Resources

- A sequence of 8 short presentations: [https://www.youtube.com/playlist?list=PLN5UPhU05nn8WE4ZbzUwUhzq_p2XChK6r](https://www.youtube.com/playlist?list=PLN5UPhU05nn8WE4ZbzUwUhzq_p2XChK6r)
- Encyclopedia of GIS [19]: This publication has many articles about the topics in this article. The book is available in thousands of institutions around the world that subscribe to Springer. Many of articles are also available on Google Books. Topics covered include:
  1. Change detection.
  2. Colocation patterns
  3. Colocation mining
  4. Crime mapping
  5. Data mining
  6. Evolving spatial patterns
  7. Facility location problem
  8. Geostatistics
  9. Hotspots
  10. Hotspot detection and prioritization
  11. The modifiable areal unit problem (MAUP)
  12. Outlier detection, spatial
  13. Partitioning
  14. Remote sensing
  15. Spatial anomaly detection
  16. Spatial big data
  17. Spatial data mining
  18. Spatial decision trees
  19. Spatial networks
  20. Spatial prediction
  21. Spatial statistical analysis
- Commercially popular software on analysing geospatial data sets: ArcGIS software: [https://www.arcgis.com/](https://www.arcgis.com/)

8 Acknowledgements

This article is supported by National Science Foundation under Grant No.1541876, 1029711, 1737633, IIS-1320580, IIS-0940818, and IIS-1218168, the USDOD under Grants No.HM1582-08-1-0017 and HM0210-13-1-0005, the Advanced Research ProjectsAgency-Energy (ARPA-E), U.S. Department of Energy under Award
No.DE-AR0000795, the NIH under Grant No. UL1 TR002494, KL2TR002492, and TL1 TR002493, the USDA under Grant No.2017-51181-27222, and the OVPR Infrastructure Investment Initiative, Minnesota Supercomputing Institute (MSI), and Provost’s Grand Challenges Exploratory Research and International Enhancements Grants at the University of Minnesota. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof. Also, we appreciate Kim Koffolt’s helpful comments and feedbacks for enhancing readability of the paper.

References

[6] Jiawei Han and Harvey J Miller. Geographic data mining and knowledge discovery. CRC Press, 2009.


