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An Spatial-Temporal Model to Explore Interesting Dense Regions over Time

Felipe Mateus Freire Pontes

Natal-RN
Mês (por extenso) e ano

Felipe Mateus Freire Pontes

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Trabalho de conclusão de curso de graduação do curso de Tecnologia e Análise em Desenvolvimento de Sistemas da Diretoria de Gestão e Tecnologia de Informação do Instituto Federal do Rio Grande do Norte como requisito parcial para a obtenção do grau de Tecnologo em Análise e Desenvolvimento de Sistemas.

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Citação

Autor

An Spatial-Temporal Model to Explore Interesting Dense Regions over Time

Author: Felipe Mateus Freire Pontes
Supervisor: Dr. Plácido Antônio de Souza Neto

Abstract

O resumo em língua estrangeira (em inglês *Abstract*, em espanhol *Resumen*, em francês *Résumé*) é uma versão do resumo escrito na língua vernícula para idioma de divulgação internacional. Ele deve apresentar as mesmas características do anterior (incluindo as mesmas palavras, isto é, seu conteúdo não deve diferir do resumo anterior), bem como ser seguido das palavras representativas do conteúdo do trabalho, isto é, palavras-chave e/ou descritores, na língua estrangeira. Embora a especificação abaixo considere o inglês como língua estrangeira (o mais comum), não fica impedido a adoção de outras linguas (a exemplo de espanhol ou francês) para redação do resumo em língua estrangeira.

Keywords: Keyword 1, Keyword 2, Keyword 3.

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Sumário

1 Introduction

More than ever we are overwhelmed by an amount of data which is created every day. When we compare how data has been created over the past years, we realize that is already increasing significantly. Besides this evolution, nowadays we have the most diverse kinds of data (e.g., documents, tweets, pictures, videos, GIFs, check-ins).

This phenomenon has been called *Big Data* and represents an increasing field of study for the time being. Therefore researchers are analyzing and learning with these information we create. However the increasing amount of data make analyses hard to perform. So, people are investing in techniques and tools to tackle challenges such as data mining, data cleaning, data visualization, data classification, data exploration and so on.

One common kind of data is what we called *spatial data*, which are data the comes with geographical attributes like latitude and longitude (e.g., tweets, restaurants reviews, place check-ins). Spatial data can be very insightful, for instance, a check-in at the airport by your sister in the morning of your birthday, probably it means you will have a surprise.

As each record in spatial data represents an activity in a precise geographical location, analyzing such data enables discoveries grounded on facts. Analysts are often interested to observe spatial patterns and trends to improve their decision making process. Spatial data analysis has various applications such as smart city management, disaster management and autonomous transport (RODDICK et al., 2004; TELANG; PADMANABHAN; DESHPANDE, 2012).

1.1 Problem Definition

Spatial data analysis is often performed in *exploratory context*: the analyst does not have a precise query in mind and she explores data in iterative steps in order to find potentially interesting results. Traditionally, an exploratory analysis scenario on spatial data is described as follows: the analyst visualizes a subset of data using a query in an vi-

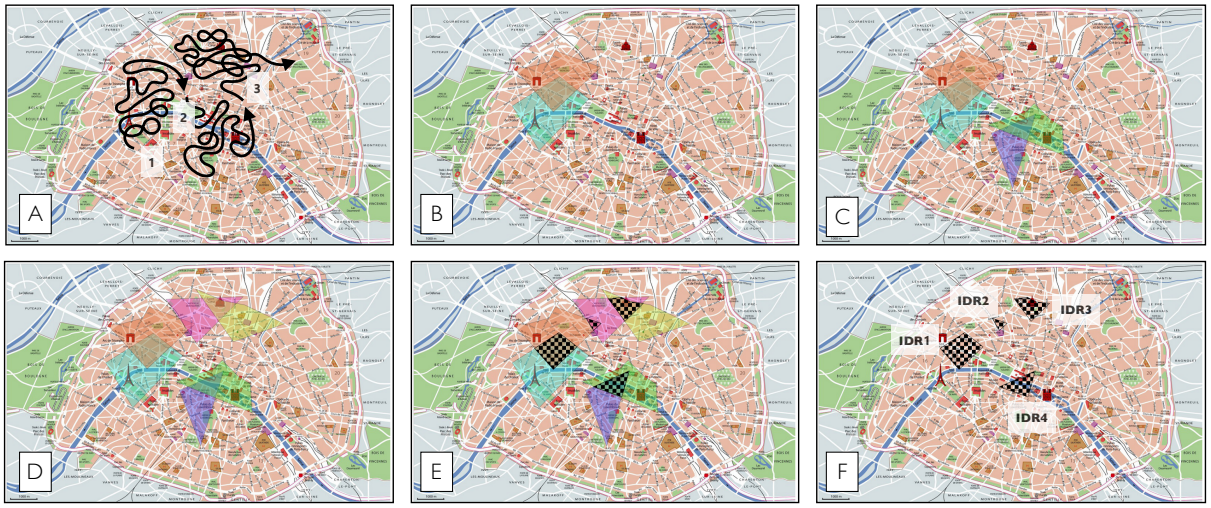

Figura 1: The process of exploring Paris home-stays.

sualization environment (e.g., Tableau[1], Exhibit[2], Spotfire[3]). The result will be illustrated on a geographical map. Then she investigates on different parts of the data by zooming in/out and panning the map in order to discover patterns and trends of interest. The analyst may iterate on this process several times by issuing different queries and focusing on different aspects of data.

The large size of spatial data make the analyst feel lost during the exploration. There could be thousands of points in each neighborhood of a city, for example. Analysts require to obtain only few options (so-called "highlights") to act as a direction and be able to focus on. In the perfect scenario, these options are not randomly chosen and represent what they showed to be interested in the previous iterations.

In this work, we formulate a solution for "information highlighting using feedback collected over time", i.e., highlight few geographical points based on interests of the analyst in order to guide the her towards what she should concentrate on in consecutive iterations of the analysis process.

1.1.1 Case Study

Now, we will present a case study in order to show the functionality of our approach in practice.

[1] *http://www.tableau.com*
[2] *http://www.simile-widgets.org/exhibit/*
[3] *http://spotfire.tibco.com*

Example. *Lucas is planning to spend few days in Paris, France. His appreciation of French culture makes him interested in new experiences in the city. He decides to rent a home-stay from Airbnb website*[4]*. He likes to discover the city, hence he is open to any type of lodging in any region with an interest to stay in the city center. The website returns* 4000 *different locations. As he has no other preferences, an exhaustive investigation needs scanning each location independently which is nearly infeasible. While he is scanning few first options, he shows interest in the region of "Champ de Mars" (near Eiffel Tower), but he forgets or doesn't feel necessary to click a point there. By collecting feedback on his mouse moves over the home-stays in Paris, our system can quickly detect his interest in the region and short-list a small subset of locations (i.e., highlights) accordingly to be recommended to Lucas.*

We follow the above example to describe how implicit feedback is collected in action. Figure 1 shows Lucas' steps to explore home-stays in Paris. Figure 1.A shows his mouse movements in different time stages. In this example, we consider $g = 3$ and capture Lucas' feedback in three different time segments (progressing from Figures 1.B to 1.D). It shows that Lucas started his search around Eiffel Tower and Arc de Triomphe (Figure 1.B) and gradually showed interest in south (Figure 1.C) and north (Figure 1.D) as well. All intersections between those regions are discovered (hatching regions in Figure 1.E) which will constitute the set of *Interesting Dense Regions* (Figure 1.F), i.e., IDR1 to IDR4.

What if Lucas wanted to come back to Paris, France next year? He will have to repeat the same exploratory analyse, unless he remember the exact location of home-stays he showed interest last year. Using our system, he won't need to remember, because his preferences were collected and can be used to highlight a subset of similar home-stays.

In the context of exploratory analysis, the analyst may change his preferences between session (e.g., in the winter, Lucas may want to be close to the Eiffel Tower, but in the summer, he may not). In order to tackle this challenge we also apply a temporal analyse to identify patterns in how the analyst preferences change between sessions which allow our highlighting method to be more precise and consistent to the analyst interest.

1.2 Objectives

In this section, we define the general and specific objectives of our work.

[4] *http://www.airbnb.com*

1.2.1 General Objectives

- Introduce a time-aware guidance approach for spatial data exploration;
- Elaborate how temporal analyses can be effectively applied in data exploration;

1.2.2 Specific Objectives

- Describe our data model used for temporal analyses;
- Describe our concept of *Interesting Dense Regions* used for collecting feedback;
- Present the results of our guidance approach.

1.3 Organization

The next chapters is as follow: in the Chapter 2 we discuss the background of this work. Chapter 3 defines the data model. Chapter 4 presents how the feedback is collected during exploration. Chapter 5 presents how temporal analysis is applied. Chapter 6 presents how highlight interesting points in order to guide the user using collected feedback and results from temporal analysis. Chapter 7 shows experiments and its results. Chapter 8 presents some conclusions and future directions.

2 Background

This chapter gives an overview of related work in literature about feedback exploitation, information-highlighting methods and temporal analysis applications. We also present the system we are extending.

2.1 Related Work

The literature in spatial data analysis has a focus on *efficiency* of exploratory interactions. The common approach is to design pre-computed index which enable efficient retrieval of spatial data (LINS; KLOSOWSKI; SCHEIDEGGER, 2013). However, we should also put attention in the *value* of spatial data, because is very common to see an analyst getting lost in the huge amount of geographical points. In order to overcome this challenge, visualization environments (e.g., Tableau[1], Exhibit[2], Spotfire[3]) offer features to manipulate data (e.g., filters, aggregate queries, etc).

2.1.1 Feedback exploitation

Our proposed spatial-temporal model leverage the spatial data analysis by exploiting collected feedback during the analyst exploration to highlight subsets of geographical points. In the literature, are several instances of feedback exploitation to guide the analysts in further analysis steps (e.g., Boley et al. (2013)). The common approach is a top-k processing methodology in order to prune the search space based on the explicit feedback and recommend a small subset of interesting results of size k. A clear distinction of our work is that it doesn't aim for pruning, but leveraging the actual data with potential interesting results that the analyst may miss due to the huge volume of spatial data. While in top-k processing algorithms, analyst choices are limited to k, we offer the freedom of

[1] *http://www.tableau.com*
[2] *http://www.simile-widgets.org/exhibit/*
[3] *http://spotfire.tibco.com*

choice where highlights get seamlessly updated with new analyst choices.

2.1.2 Information-highlighting methods

There exist few instances of information-highlighting methods in the literature: Liang e Huang (2010), Robinson (2011), Wongsuphasawat et al. (2016), Willett, Heer e Agrawala (2007). All these methods are *objective* and do not apply to the context of spatial guidance where user feedback is involved. In terms of recommendation, few approaches focus on spatial dimension (BAO et al., 2015; LEVANDOSKI et al., 2012) while the context and result diversification are missing.

2.1.3 Temporal analysis applications

There are currently several instances which combine temporal analysis with spatial data in the literature (e.g., Baculo et al. (2017), Balahadia e Trillanes (2017), Chidean et al. (2018), Ghahramani, Zhou e Hon (2018), Kamath e Caverlee (2013), Lopes-Teixeira, Batista e Ribeiro (2018), Ma et al. (2017), Mijović et al. (2016), Tomoki e Keiji (2010), Nara e Torrens (2007), Zhan et al. (2017), Zheng et al. (2018)). Those are applications of temporal analysis in specific context, which does not involve user feedback, but represent how temporal analysis could be insightful.

Baculo et al. (2017) and Balahadia e Trillanes (2017) make use of public data of Manila, the most densely populated city in the Philippines, to combine spatial data, temporal analysis and prediction model to allow decision makers to prepare an effective public management plan. Ma et al. (2017) and Zheng et al. (2018) also perform real-world analyses of how events (e.g., protests) impact the taxi trajectories which results could provide helpful insights for traffic control and transit service plans for city administrators. Both perform insightful analyses which we will use as inspiration.

Chidean et al. (2018) present how to detect spatial-temporal patterns in the context of wind power resource in the Iberian Peninsula using Second-Order Data-Coupled Clustering algorithm. Despite the detailed study, it does not work in a exploratory context.

Ghahramani, Zhou e Hon (2018), Lopes-Teixeira, Batista e Ribeiro (2018) and Zhan et al. (2017) demostrate how temporal analyses can be applied in the geographical context. Zhan et al. (2017) goes deeper generating a hierarchical cluster tree. Regardless of insights and methods, it does not contribute to the subject in question.

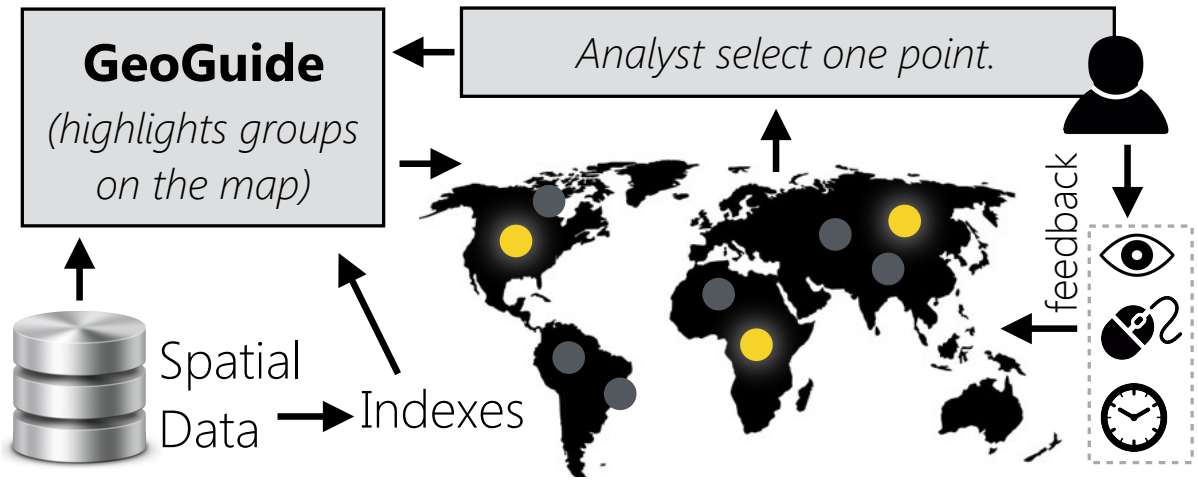

Figura 2: GeoGuide Framework

Kamath e Caverlee (2013) propose a novel reinforcement learning approach to predict events (i.e., online meme) in the spatial-temporal context.

Nara e Torrens (2007) introduce a 3D visualization of space-time which helps to qualitatively and quantitatively analyze the spatiotemporal patterns and tendencies. We will make use of this visualization approach to display our collected data in chapter 4.

2.2 GeoGuide

GeoGuide (OMIDVAR-TEHRANI et al., 2017) is a spatial data visualization environment which keep track of user preferences during exploration in order to use collected feedback to highlight subsets of geographical points that may be interesting to the analyst. Figure 2 illustrates the main components of GeoGuide architecture which we will present in the next subsections.

2.2.1 Preprocessing

GeoGuide requires a preprocessing step in order to create a index which will be used during highlighting. The index is a comparative table between every points with two quality metrics, i.e., relevance and diversity.

2.2.1.1 Relevance

Relevance represent how a point a is similar to a point b in the current dataset. GeoGuide use the relevance to highlight points in the same line with the analyst feedback.

2.2.1.2 Diversity

Diversity represent how distant is the region where a point a is to the region where point b is located. It allows the analyst to explore different regions, but still work with relevant points to his interest.

2.2.2 Tracking User Preferences

In order to keep track of user preferences, GeoGuide use both explicit and implicit feedback. Explicit feedback is when the user is analyzing the attributes of a point (e.g., the house description in a Airbnb context) and explicitly ask to explore similar points to the current selected one. Implicit feedback is tracked using the mouse movements, gaze tracking and metrics like "how long the user was analyzing the profile of a point".

2.2.3 Highlighting Spatial Data

GeoGuide combine both preprocessed index and collected feedback to highlight a subset of spatial data according to the analyst preferences. GeoGuide highlighting feature prove to be efficient in terms of "how many steps the analyst takes until complete a task of finding a point in a request location". Using GeoGuide the analysts were able to complete the task using in average 10.7 steps, while using Tableau, they took about 43 steps.

In this work, we will leverage GeoGuide into two new concepts: i. interesting dense regions and ii. understanding how the user preferences change over time.

3 Data Model Definition

3.1 Spatial layer

Each point in a dataset ($p \in \mathcal{P}$) is described using its coordinates (latitude and longitude) and also associated with a set of attributes ($dom(p)$). For instance, TODO

3.2 Interesting Dense Regions

TODO

We have IDRs per iteration/session where implicit feedback is captured such mouse moves (or eye gaze). In the beginning, each IDRs is a group of raw points described using its coordinates (latitude and longitude) and a timestamp (the unix timestamp it was captured). These raw points once captured will enter the clustering (for now, ST-DBSCAN) phase to generate the IDR itself with a profile. The profile is built based on the spatial layer and it should represent a summary of its contained points from the spatial layer.

- A profile has summary of its spatial points number attributes. For each number attribute in $dom(p)$, we calculate the average, median and standard deviation based on the points contained in the IDR.
- A profile has a word rank R of the terms in the text attributes of its spatial points. For each text attribute in $dom(p)$, we evaluate the most used terms in order to create a word rank (KUMAR; KAUR, 2017).
- A profile has a map M between the $< name, value >$ of categoricals attributes and its relevance in $dom(p)$.
- TODO: datetime attributes
- A profile has a meta property with values such the count of points in the IDR.

3.3 Highlighting

TODO

4 Collecting feedback

TODO

5 Applying temporal analysis

TODO

6 Guiding the user

TODO

7 Experiments

TODO

7.1 Results

TODO

8 Conclusion

To our knowledge...

8.1 Contributions

TODO

8.2 Restrictions

TODO

8.3 Future work

TODO

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