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Original Research

Visual analytics of COVID-19 dissemination in São Paulo state, Brazil

Wilson E. Marcilio-Jr *, Danilo M. Eler, Rogério E. Garcia, Ronaldo C.M. Correia, Rafael M. B. Rodrigues

Department of Mathematics and Computer Science, São Paulo State University (UNESP), Presidente Prudente, SP, Brazil

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ABSTRACT

Visual analytics techniques are useful tools to support decision-making and cope with increasing data, particularly to monitor natural or artificial phenomena. When monitoring disease progression, visual analytics approaches help decision-makers to understand or even prevent dissemination paths. In this paper, we propose a new visual analytics tool for monitoring COVID-19 dissemination. We use k-nearest neighbors of cities to mimic neighboring cities and analyze COVID-19 dissemination based on comparing a city under consideration and its neighborhood. Moreover, such analysis is performed within periods, which facilitates the assessment of isolation policies. We validate our tool by analyzing the progression of COVID-19 in neighboring cities of São Paulo state, Brazil.

1. Introduction

The novel coronavirus (SARS-CoV-2), or simply COVID-19, has already infected more than 116 million people worldwide and caused over one million deaths by March 2021. While understanding the biological aspects of such a virus is essential [1–3], it is necessary to monitor the evolution in the number of cases in cities and their neighborhoods to provide information to decision-makers to think about strategies isolation policies according to the risk of dissemination. Moreover, citizens must be aware of how the isolation policies affect the disease dissemination patterns that usually follow a hierarchy spreading from bigger cities to neighborhoods. So, besides presenting the number of city confirmed cases, we also present the number of cases in its neighborhood. Comparing a city and its neighborhood allows verifying if a neighborhood has the main focus of COVID-19 dissemination or various dissemination points. For example, if a city under consideration has a bigger number of cases than its neighborhood, it stands out in the influence of the neighborhood; on the other hand, if the neighborhood stands out over the city under consideration, the neighborhood can have one or more cities that could influence cities with fewer confirmed cases. Finally, if both the city in analysis and its neighborhood have a high number of confirmed cases, such a neighborhood has high COVID-19 dissemination.

To validate our methodology, we provide several case studies by analyzing cities in the Sao Paulo state, Brazil. Besides highlighting the cities on the map, our tool also summarizes the risk of dissemination using a radial visualization. We use the slope of the number of cases to interpret the risk of dissemination. Note that we are focusing on the dissemination risk rather than the number of cases itself. In the radial visualization, the circle encodes the city in the analysis, while a donut chart maps the neighboring cities. We use color saturation to indicate the risk of dissemination. That is, darker colors will represent cities with a higher risk of dissemination.

This paper is organized as follows: in Section 2, we briefly delineate some related works; Section 3 presents the hierarchical spreading of COVID-19, from which our methodology is based; Section 4 shows the proposed visual analytics tool; analyses using the tool are presented in Section 5; in Section 6, we discuss some aspects of the technique; we conclude our work in Section 7.

* Corresponding author.
E-mail address: wilson.marcilio@unesp.br (W.E. Marcilio-Jr).

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2. Related works

Using data to detect and quantify health events is a useful strategy to understand disease outbreaks. Usually, the strategies use data mining or visualization techniques to monitor events related to a disease of interest.

Visualization-based strategies for monitoring the dissemination of diseases account for the fact that graphical representations can enhance the ability to identify data patterns and tendencies. In this case, it is better to look at visual variables, such as position, color, or area, than tables or reports to identify tendencies of growth and many other patterns. The literature presents many examples of systems using visualization techniques to enhance the analysis of disease dissemination, such as the work of Hafen et al. [4], where they delineate a strategy to detect outbreaks based on monitoring pre-diagnostic data of emergency department chief complaints. Although using simple line curves, the visualization components helped at identifying patterns in the data. HealthMap [5], on the other hand, uses geolocation of media reports to integrate outbreak textual data in a single resource. The system helps extract useful information and summarize unstructured data of disease reports, facilitating decision-maker’s analysis. Another interesting approach is to use what-if strategies and visualize the outcomes depending on the decision alternatives applied when dealing with disease outbreaks [6]. Other strategies employing visualization tools are using heatmaps to analyze patterns of hand-foot-mouth disease [7], employing intelligent graph visualizations and reordered matrices to understand influenza dissemination paths [8], or visualizing the effect of decision measures implemented during a simulated pandemic influenza scenario [9].

From the data mining perspective, it is usually interesting to contrast social network posts related to diseases with officially reported cases. These approaches are based on the strength of the relationship between officially reported cases and the searches on the web or posts on social media using words related to the diseases [10–13]. For instance, most of the works use the web and social media to detect Influenza-like Illness events [10,14,15]. An excellent example of using data-mining techniques to detect disease outbreaks in the Dutch system Coosto [16], which uses Google Trends and social media data to detect outbreaks using a cut-off criterion. Other works also have shown that Twitter data is highly correlated to disease activity [17,18], such as predicting Dengue cases [19] or using Twitter-based data to automatically monitor avian influenza outbreaks, showing that one-third of outbreak notifications were reported on Twitter earlier than official reports [20].

In this work, we provide a visual analytics approach to monitor the evolution of dissemination of COVID-19 to facilitate analysis of dissemination during and post isolation. We use visualization techniques and analysis based on time windows to help analysts monitor how neighboring cities’ situation affects the dissemination of COVID-19 to a city in the analysis.

3. Background

This section explains the hierarchical spreading behavior of COVID-19, which we use to define each city’s neighborhoods.

The basic idea of the hierarchical spreading of COVID-19 is that cities with confirmed cases disseminate infection to their neighboring cities. In this case, the neighboring cities are the cities with confirmed cases inside the k nearest cities to the city in the analysis. Note that regional cities (bigger cities) are most likely to disseminate COVID-19 to their neighborhoods due to the bigger number of inhabitants, more job opportunities, more cultural access, and other social aspects that could attract people from neighboring cities. Fig. 1 illustrates the hierarchical spreading, where an orange circle represents a city with a confirmed case, and the arrows indicate potential dissemination paths due to location proximity.

To formalize the definition of a neighborhood for city A, Algorithm 1 shows the computation of each city’s k nearest cities in the Sao Paulo state based on the latitude and longitude coordinates.

**Algorithm 1.** Computing k nearest cities.

1: Procedure k_nearest_cities(cities, k)  
2: latlong_coords ← get_latlong(cities);  
3: knn_sets ← KNN(latlong_coords, k);  
4: Return knn_sets;

To augment the city A’s neighborhood, besides the k nearest cities of A, we also add to the neighborhood the cities with A in their k nearest cities set. In this way, we simulate better the interaction between a city and its neighborhood. Finally, it is essential to mention that a few cities may not present confirmed cases. Thus, these cities do not appear in the visualization tool (see Section 4).

4. Visualization design

Our visual analytics approach has the main objective of helping decision-makers analyze a city’s situation based on disease dissemination. Besides information of a city in interest, our tool provides information about the situation of its neighborhood. We delineate the following requirements for our visual analytics approach to monitor the dissemination curves and help analysis based on the number of infections by COVID-19:

- **R1:** facilitate comparison of the situation between a city and its neighborhood;  
- **R2:** visualize the evolution of the number of cases as users change a time window, as well as contrasting it with the accumulated number of cases since the notification of the first confirmed case;  
- **R3:** visualize the dissemination curve to check if it is increasing or if it is flattening;  
- **R4:** quickly understand the situation of a neighborhood in the analysis.

First, it is necessary to define the neighborhood of a city. Our strategy follows the hierarchical spreading scheme of COVID-19, as explained in Section 3, which states that a city with confirmed cases influence (i.e., can disseminate) its neighboring cities. These neighboring cities are retrieved using the k nearest neighbors algorithm. In our case, city A’s neighborhood consists of its the k nearest cities and the cities with A in their k nearest cities set. Given that, we can analyze a city based on its dissemination as well as its neighborhood. In the following, we present how we accomplish each requirement.

Fig. 2 shows the tool used to monitor the evolution of COVID-19 in the Sao Paulo state, Brazil, and the dissemination risk based on city neighborhoods. The tool has a few components. First, the evolution of the number of cases for the whole period starting from February 27th (2020) locates at the top left (a). Second, we provide a visual representation of the dissemination risk by summarizing the neighborhood of
the analyzed city at the top center of the visualization (b). The color saturation depicts the dissemination risk – darker colors represent cities with more critical situations – mapped from the angle formed by the slope of COVID-19 cases. That is, color saturation maps the angle below the line segment formed by the point \((a, n_a)\) and \((b, n_b)\), where \(n_a\) is the number of cases in the first day of the time window \((a)\) and \(n_b\) is the accumulated number of cases in the period \((a, b)\). Third, we provide the curves of the number of cases in the central area of the component. The first line of curves indicates the number of cases for the whole period since the first notification of confirmed cases ((c) and (d)). The second line of curves indicates the number of cases only inside the time window ((e) and (f)), which could be useful to assess how isolation policies are affecting the dissemination in a period – note that the graph is generated based on the number of cases in the first day of the period \((a)\) and the accumulated number of cases for the period \((a, b)\). Finally, the representation of the time window (period of analysis) is shown at the bottom of the visualization. We also provide a map of the São Paulo state (g) to visualize the neighborhood in the analysis.

**R1: Facilitate comparison between city and its neighborhood**

To facilitate a comparison between a city and its neighborhood, users can use the infection curves for the city itself and the neighborhood. With such visualization, it is possible to understand if the city is being influenced by its neighborhood when the number of confirmed cases is greater for the neighborhood or if the city influences the neighborhood when the number of confirmed cases is greater for the city. Fig. 3 illustrates a city influencing its neighborhood in the time window and the total number of cases. Note that the number of cases in Presidente Prudente is by far bigger than in its neighborhood.

**R2: Visualize the evolution of the number of cases in a time window**

Using a time window, i.e., focusing analysis in a specified number of days, helps monitor the evolution of dissemination in chunks of time and facilitates the comparison among cities. In this case, questions such as which city responds better to isolation policies and how the isolation policy in a certain period affected the dissemination of a posterior period can be answered. Fig. 4 illustrates how using the time window for analyzing only the confirmed cases inside the period helps us visualize flattening the Birigui city’s curve.

**R3: Visualize the increasing and flattening of the curves**

Fig. 2. Visual analytics of COVID-19 confirmed cases. (A) The number of cases for the whole period. (B) The visual representation of the analyzed neighborhood with color saturation encoding a high slope of new cases. The accumulated number of cases for a period in the neighborhood (C) and the analyzed city is based on the total number of cases (D). The accumulated number of cases for a period in the neighborhood (E) and in the city (F) based only on the number of cases inside the time window. (G) São Paulo state map showing the selected city and its neighborhood. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
To monitor confirmed cases’ evolution, we use the São Paulo government’s data at SEADE.\(^1\) The data consists of daily updated cases in each city with a confirmed case. To create the visualization tool, we only use the city name, daily confirmed cases, and the date attributes – the latitude and longitude coordinates of each city are retrieved using the geopy\(^2\) library. Further, the isolation index is also provided by the São Paulo government\(^3\) for only a few cities. The isolation index consists of the percentage of inhabitants in isolation.

Given the daily updated data, we can use a time window to investigate the progression and dissemination of COVID-19 since the first notification in São Paulo’s state capital, São Paulo. Notice that, while using a time window of seven days (without loss of generalization), we could investigate disease progression in the next few days in São Paulo’s neighborhood. So, it is not our tool’s concern to select cities hypothesizing that they will disseminate the virus. Instead, investigators select a city of interest and then use the time window to visualize and understand the first notification and confirmed cases’ progression compared to its neighbors.

5. Results

In this section, we inspect the dissemination evolution of various cities in the Sao Paulo state, Brazil. We used a time window of 20 days to assess the following periods: from April 19th to May 9th, from April 21st to May 11th, and from April 26th to May 16th.

5.1. Regional city presents risk of dissemination to its neighbors

Presidente Prudente. Fig. 6 shows the evolution of the confirmed cases of Presidente Prudente. Up to May 16th, Presidente Prudente has 89 confirmed cases, as shown on the figure’s left. However, it is interesting to note how was the acceleration of confirmed new cases in the city in the period of April 19th to May 9th, from April 21st to May 11th, and from April 26th to May 16th. This city, in particular, has been giving the lowest isolation indices in the Sao Paulo state – we highlight in red the mean of the isolation indices in the period.

It is worth noticing that besides presenting a critical situation in the city itself, Presidente Prudente greatly influences its neighborhood. Fig. 7 shows how the number of cases in the city grows as the time window moves (observe the circle in the center of the donut chart), besides the number of different cities presenting confirmed cases. For instance, the increasing number of neighborhood cases can be seen by looking at the period’s curves. Finally, see how Caiabu maintains the risk of dissemination lower than the other cities through the days.

Martinópolis. After inspecting Presidente Prudente, we could notice that such a regional city greatly influences its neighborhood according to the risk of dissemination. In this case, given the low isolation index of Presidente Prudente, it could be useful to understand how neighboring cities can respond to such risk. Taking the city of Martinópolis as an example, we can see from Fig. 7 in the radial representation that social distancing policies might help the city maintain the number of cases. See how in the first period (from April 19th to May 9th), the city was the second in the risk of dissemination, while in the last period of analysis

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1. https://www.seade.gov.br/coronavirus/.
2. https://geopy.readthedocs.io/
3. https://www.saopaulo.sp.gov.br/coronavirus/isolamento/
5.3. The effect of the isolation index

This section analyzes the number of cases and the risk of dissemination by comparing two neighboring cities, Araraquara and Birigui. Here, we also use these cities’ isolation indices to hypothesize about their relation to the number of cases, although we would need statistical analysis to make hard conclusions.

Fig. 10 shows the curves for the city of Birigui. From contrasting the curves in the bottom with the isolation index, we can see how it affects the dissemination of the COVID-19. From the second to the third period, the curve of cases starts to present a plateau.

Fig. 11 shows the dissemination curves and the isolation indices for Araraquara. In this case, low isolation indices might be the reason for the increase in the number of cases. Araraquara has a more critical dissemination curve, which could be explained – together with other reasons – by the low isolation index, which was 44% ±/− 0.05 from April 17th to May 7th. Finally, due to the augment to 48% ±/− 0.055 from April 19th to May 9th, it is possible to see a little flattening in the curve from April 21st to May 11th.

5.3. The effect of the isolation index

This section aims to analyze cities in neighborhoods with a rapidly increasing number of cases, besides making relations to isolation indices for hypothesis generation. For this purpose, we analyze three periods: from March 23th to April 12th, from April 13th to May 3rd, and from May 1st to May 21st.

Fig. 12 shows how the situation was from March 23th to April 12th. We can see that only five cities presented confirmed cases – 16 confirmed cases in total among all neighboring cities. The figure also shows the neighborhood on the bottom.

The neighborhoods’ situation takes a real change from April 13th to May 3rd, as seen in Fig. 13. There are many cities presenting confirmed cases, led by Americana and Limeira’s cities. The city of Americana, for example, was only the penultimate city with the highest risk of dissemination from March 23th to April 12th (see Fig. 12). For instance, this period was responsible for increasing 122 (of 140) by May 3rd.

To understand why Americana and Limeira’s cities present such an increasing number of confirmed cases, Fig. 14 shows their curves for the period in the analysis together with the isolation index of an earlier period, i.e., from March 23th to April 12th. In this case, we see that although the isolation index of Americana was greater than Limeira’s, the city presented more cases in the period, even with a lower population – Americana has approximately 230 hundred inhabitants while Limeira has approximately 300 hundred inhabitants. The answer to this question can be found by analyzing the neighborhoods of both Limeira and Americana.

Fig. 15 explains why Americana shows more cases from April 13th to May 3rd. Firstly, the accumulated number of cases in the neighborhood is bigger for Americana. Second, the donut chart shows that Americana is part of a riskier neighborhood, i.e., the number of cities influencing Americana is bigger, and the darker colors stress the risk of contamination of these cities.

Backing to the Santa Gertrudes’s neighborhood, we finish by analyzing the last period, from May 1st to May 21st. Fig. 16 shows the situation of the neighborhood up to May 21st. The first thing to notice is the curve inclination of the cases in the period, where it is possible to see the exponential pattern of COVID-19. Then, we can see that two other cities (Araras and Cordenopolis) notified almost the total number of cases in this period. The influence that the risk of the neighborhood plays in these cities can explain such a pattern.

Finally, the higher isolation index for both earlier periods of analysis for Americana made it possible to present a lower number of infections in this critical period, as shown in Fig. 17.

5.4. Analysis of bigger and regional cities

This section aims to analyze cities closer to the São Paulo state capital (Sã0 Paulo) and other regional cities. For earlier periods, readers will see that the curves seem flattened. However, this is due to the scale used to convey the number of cases. Earlier periods are influenced by the number of cases reported by the analyzed neighborhoods in this section. For instance, analysts can recall the donut charts to visually investigate the evolution of the number of cases.

Santos. By March 29th, Santos’s city did not present any confirmed cases. Besides that, its neighborhood was not presenting a critical situation if we look at the number of confirmed cases in Fig. 18.

Although the situation was not critical at such a moment, the isolation indices in Table 1 could indicate difficult periods ahead according to these cities’ geolocation, the low isolation indices are even more severe, which are very close to the capital, São Paulo.

Moving the time window seven days further, i.e., analyzing the period from March 16th to April 5th, we can note much change in the reported number of cases. First, 191 of the 194 cases were reported in this period, in which the city of Santos reported 72 cases only in six days, as indicated in Fig. 19, in contrast to a greater period for Santo André.

Fig. 20 shows the situation of Santos’ neighborhood through the days. The donut chart and the color code reveal that the number of cases reported in the periods of analysis (20 days) shows an increasing pattern, configuring that such neighborhood does not reach the curve maxima. This vital information could guide decision-makers on isolation policies since it seems that the applied isolation policy up to now is not effective enough.

Ribeirão Preto. Fig. 21 shows the number of case curves and the donut chart to assess the evolution of confirmed cases in the neighborhood of Presidente Prudente. Presidente Prudente is the most influential city (a higher number of cases).
chart encoding the increase of Ribeirao Preto’s neighborhood for neighborhood from March 23rd to April 12th. The visual analytics tool shows an example where the city in the analysis influences its neighborhood, i.e., while Ribeirao Preto presents 43 cases in the period, each of the other cities presents only two confirmed cases.

The situation was different by May 3rd, in which the neighboring cities with confirmed cases jumped from four to eight. However, even with many neighboring cities with confirmed cases, Rio Preto still
presents a higher number of infections than the cities in its neighborhood combined. Additionally, the increase in the number of cases seems to have a slow pace until May 3rd, which cannot be said for further periods, as we will see in the following. (see Fig. 22).

Fig. 23 shows the situation in the neighborhood by May 23rd. Notice a big step in the number of cases reported on May 7th and an apparent increase in the number of cases reported both for the city of Ribeirao Preto and its neighborhood. Such a pattern can also be noticed by darkening the donut chart of the map’s boundaries.

Finally, Fig. 24 shows that the COVID-19 dissemination for Ribeirao Preto has not presented a decrease. Instead, the number of cases seems to be increasing rapidly, which can be dangerous due to low isolation indices presented by the cities with more critical curves – see Table 2 the isolation indices for Ribeirao Preto and Sertãozinho.

São José do Rio Preto. Fig. 25 shows how the number of cases’ overall curve is similar between Ribeirao Preto (discussed in the previous section) and Sáo José do Rio Preto are similar. In both situations, we can see a sudden increase in the number of cases indicated by a red line segment.

As for Ribeirao Preto, the city of São José do Rio Preto is the most influential in its neighborhood, as shown in Fig. 26 for the period from April 16th to May 5th. The image shows that the cases in São Josè do Rio Preto are three times greater than the accumulated cases for all the cities presenting confirmed cases.

Advancing the time window, Fig. 27 shows the situation from May 5th to May 22nd. Here, besides the rapid increase in the number of cases in the following days from May 5th in São José do Rio Preto, we can note...
a rapid increase in the neighborhood number. While such a pattern can be explained by the interaction between the cities and consequently the dissemination of COVID-19 from São José do Rio Preto to its neighborhood – see how the increase in the neighborhood occurs later São José do Rio Preto –, other explanations could be accumulated the number of COVID-19 tests that were delayed and reported in such period. Fig. 27 also suggests that the neighborhood would maintain the contamination low. However, it is not what happens in the following days.

Fig. 28 shows our last period of analysis, from May 22nd to June 10th. The curves suggest an increase in the number of cases for the city and its neighborhood, and we cannot realize any plateau in the aggregated number of cases in the neighborhood. However, it is important to emphasize how the city of Jaci went from presenting the most critical curve in the neighborhood (see the donut chart in Fig. 27)) to only four cases in this period such a pattern could be the result of isolation policies, but unfortunately, we do not have data to confirm.

São Paulo. Finally, we analyze the evolution in the number of São Paulo cases (capital) and its neighborhood. By June 10th, São Paulo has already reported 80,457 cases of COVID-19, which is the most critical situation in the whole state (even in the whole country of Brazil). Here, we summarize the evolution of the number of cases for São Paulo and its neighborhood for various periods. Firstly, Fig. 29 shows São Paulo’s situation and its neighborhood from February 26th to March 16th. Note that only five cities in the neighborhood presented confirmed cases, with one case notified for each one. Advancing for the period from March 14th to April 2nd, a few more cities in the neighborhood start to present confirmed cases with the rapid increase (see Table 3), as shown in the donut chart.
From this period until June 10th, São Paulo’s and its neighborhood do not change in the increase in the number of reported cases. Fig. 30a and 30b show how the dissemination of COVID-19 continues at a rapid pace in São Paulo’s neighborhood.

The cities in the donut chart of Fig. 30a are very populous, besides interacting with themselves. On top of that, the isolation indexes are not useful, as seen in Fig. 31, which could aggregate even more.

6. Discussion

Throughout the results section, we could demonstrate the usefulness of our visual analytics tool to understand the dissemination of COVID-19 in cities of interest by analyzing cities’ influence on their neighborhood and vice versa. It is important to emphasize that our tool helps analyze the evolution while it is not mainly focused on the number of cases a city or a neighborhood may present. In this case, our tool draws attention to cities or neighborhoods that present an increasing number of confirmed cases.

Table 2

| City              | Isolation index |
|-------------------|-----------------|
| Ribeirão Preto    | 47% ± 0.026     |
| Sertãozinho      | 47% ± 0.017     |

Fig. 20. The situation of Santos’ neighborhood on different days. There is an increasing pattern in the number of confirmed cases by inspecting the neighborhood using the color scale and donut chart representation.

Fig. 21. The situation of Ribeirão Preto’s neighborhood from March 13th to April 12th. Ribeirão Preto, being the most influential city in the neighborhood, dominates the number of cases.

Fig. 22. The situation of Ribeirão Preto’s neighborhood from April 13th to May 3rd. The neighboring cities start to show an increase in the number of cases.

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Fig. 23. The situation of Ribeirão Preto’s neighborhood from May 3rd to May 23rd. Besides more cities presenting confirmed cases, an increase in the number of cases can be noticed.

Fig. 24. The situation of Ribeirão Preto’s neighborhood from May 20th to June 8th. Rio Preto dominates the number of cases while other cities also show an increased pattern for their curves.

Fig. 25. Although many confirmed cases, Rio Preto and São José do Rio Preto show the same rapid increase pattern, as indicated by a dashed red line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
cases so that we believe that it could be employed even after infection by COVID-19 is controlled and employed to monitor the dissemination of other diseases.

While we defined the neighborhood of a city as cities with spatial proximity, it is important to stress that this may not reflect the reality in some cases. For example, for a regional city, a neighborhood may be defined as the set of cities influenced by or influence cities according to some aspects, such as citizens that commute from smaller cities to greater ones to work.

Other indicators. Although we use the absolute number of confirmed cases to monitor the progression of COVID-19 dissemination, other indicators could be employed, such as a relation between the number of confirmed cases and the number of performed tests or total population. We choose the absolute number of cases in this work since it is the most straightforward approach to visualize the progression and be a well-known metric and more comfortable to understand. Notice that a more accurate picture of the epidemiological status would need a relationship between the number of tests and the neighborhood population. However, our tool offers easy interpretability and the capacity to reach a broader audience. Finally, different types of indicators (that would be useful to monitor even other diseases) can be easily incorporated in future works.

Visualization tool. The visualization tool is available at RADAR⁴.

7. Conclusions

Visual analytics techniques help discover patterns that would be difficult to perceive by looking only at raw data. In this work, we

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⁴ https://covid19.fct.unesp.br/analise-regional/en/
employed visualization metaphors to analyze the evolution of the number of cases of COVID-19 in the São Paulo state, Brazil. Our methodology consists of visualizing the dissemination based on time windows and contrasting the number of cases in the periods of analyses with the cities’ isolation indices. Throughout several analyses, we show how our visualization design helps analyze a city’s situation according to the number of cases in a time window and neighborhood situation. We show that our methodology emphasizes how the isolation index benefit cities regarding the dissemination, even when these cities are part of critical neighborhoods in the sense of the number of cases.

We hope that decision-makers can use our methodology to monitor the evaluation of the number of cases in cities and neighborhoods to respond to dissemination risks quickly.

CRediT authorship contribution statement

Wilson E. Marcílio-Jr: Conceptualization, Methodology, Software, Data curation, Visualization, Writing - original draft, Writing - review & editing. Danilo M. Eler: Conceptualization, Methodology, Software, Data curation, Visualization, Writing - original draft, Supervision, Writing - review & editing. Rogério E. Garcia: Data curation, Writing - original draft, Supervision, Writing - review & editing. Ronaldo C.M. Correia: Data curation, Writing - original draft, Supervision, Writing - review & editing. Rafael M.B. Rodrigues: Data curation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan, J. Xu, X. Gu, Z. Cheng, T. Yu, J. Xia, Y. Wei, W. Wu, X. Xie, W. Yin, H. Li, M. Liu, Y. Xiao, H. Gao, L. Guo, J. Xie, G. Wang, R. Jiang, Z. Gao, Q. Jin, J. Wang, B. Cao, Clinical features
of patients infected with 2019 novel coronavirus in wuhan, china, Lancet 395 (10223) (2020) 497–506, https://doi.org/10.1016/S0140-6736(20)30183-5.

[2] F. Qi, S. Qian, S. Zhang, Z. Zhang, Single cell rna sequencing of 13 human tissues identify cell types and receptors of human coronaviruses, Biochem. Biophys. Res. Commun. doi:https://doi.org/10.1016/j.bbrc.2020.03.044. http://www.sciencedirect.com/science/article/pii/S0006291X20305284.

[3] H. Xu, L. Zhong, J. Deng, J. Peng, H. Dan, X. Zeng, T. Li, Q. Chen, High expression of ace2 receptor of 2019-ncov on the epithelial cells of oral mucosa, Int. J. Oral Sci. doi:10.1038/s41368-020-0074-x.

[4] R. Hafen, D. Anderson, W. Cleveland, R. Maciejewski, D. Ebert, A. Abusalah, M. Yakout, M. Ouzzani, S. Grannis, Syndromic surveillance: Stl for modeling, visualizing, and monitoring disease counts, BMC Med. Informatics Decis. Making 9 (1). doi:10.1186/1472-6947-9-21.

[5] C.C. Freifeld, K.D. Mandl, B.Y. Reis, J.S. Brownstein, HealthMap: global infectious disease monitoring through automated classification and visualization of internet media reports, J. Am. Med. Informatics Assoc. 15 (2) (2008) 150–157. arXiv:https://academic.oup.com/jamia/article-pdf/15/2/150/2086063/15-2-150.pdf, doi: 10.1197/jamia.M2544. doi: 10.1197/jamia.M2544.

[6] R. Brigantic, D. Ebert, C. Corley, R. Maciejewski, G. Muller, A. Taylor, Development of a quick look pandemic influenza modeling and visualization tool, in: ISCRAM 2010–7th International Conference on Information Systems for Crisis Response and Management: Defining Crisis Management 3.0, Proceedings, Information Systems for Crisis Response and Management, ISCRAM, 2010, 7th International Conference on Information Systems for Crisis Response and Management, ISCRAM 2010; Conference date: 02-05-2010 Through 05-05-2010.

[7] J.-X. Huang, J.-F. Wang, Z.-J. Li, Y. Wang, S.-J. Lai, W.-Z. Yang, Visualized exploratory spatiotemporal analysis of hand-foot-mouth disease in southern China, PloS One 10 (11) (2015) e014341, https://doi.org/10.1371/journal.pone.0143411, https://www.frontiersin.org/article/10.3389/fvets.2018.00263.

[8] G.E. Coelho, P.L. Leal, M. de Paula Cerroni, A.C.R. Simplicio, J.B. de Siqueira, Dengue surveillance based on a computational model of spatio-temporal locality of twitter, in: Proceedings of the 3rd International Web Science Conference, WebSci ’11, Association for Computing Machinery, New York, NY, USA, 2011. doi: 10.1145/2527031.2527049.

[9] J. Gomide, A. Veloso, W. Meira, V. Almeida, F. Benevenuto, F. Ferraz, M. Teixeira, Dengue disease in poultry with the implementation of new technologies and big data: A focus on avian influenza virus, Front. Vet. Sci. 5 (2018) 263, https://doi.org/10.3389/fvets.2018.00263 , https://www.frontiersin.org/article/10.3389/fvets.2018.00263.

[10] A. Culotta, Towards detecting influenza epidemics by analyzing twitter messages, in: SOMA 10, 2010.

[11] A. Culotta, Towards detecting influenza epidemics by analyzing twitter messages, in: IEEE Conf. on Computer Communications Workshops (INFOCOM WKSHIPS), 2011.

[12] D.A. Broniatowski, M.J. Paul, M. Dredze, National and local influenza surveillance through twitter: an analysis of the 2012–2013 influenza epidemic, PLoS ONE (2013).

[13] M. Santillana, A.T. Nguyen, M. Dredze, M.J. Paul, E.O. Nsoesie, J.S. Brownstein, Combining search, social media, and traditional data sources to improve influenza surveillance, PLoS Comput. Biol. doi:10.1371/journal.pcbi.1004513.

[14] J. Astill, R.A. Dara, E.D.G. Fraser, S. Sharif, Detecting and predicting emerging disease in poultry with the implementation of new technologies and big data: A focus on avian influenza virus, Front. Vet. Sci. 5 (2018) 263, https://doi.org/10.3389/fvets.2018.00263.

[15] J.H. van de Belt, P.T. van Stockum, L.J. Engelken, J. Lancee, R.S. Schrijver, J. Rodriguez-Batio, E. Tacconelli, K. Saris, M.M.H.J. van Gelder, A. Voss, Social media posts and online search behaviour as early-warning system for mrsa outbreaks, in: Antimicrobial Resistance & Infection Control, 2018.

[16] J. Astill, R.A. Dara, E.D.G. Fraser, S. Sharif, Detecting and predicting emerging disease in poultry with the implementation of new technologies and big data: A focus on avian influenza virus, Front. Vet. Sci. 5 (2018) 263, https://doi.org/10.3389/fvets.2018.00263.

[17] J. Gomide, A. Veloso, W. Meira, V. Almeida, F. Benevenuto, F. Ferraz, M. Teixeira, Dengue disease monitoring through automated classification and visualization of internet media reports, in: Proceedings of the 3rd International Web Science Conference, WebSci ’11, Association for Computing Machinery, New York, NY, USA, 2011. doi: 10.1145/2527031.2527049.

[18] G.E. Coelho, P.L. Leal, M. de Paula Cerroni, A.C.R. Simplicio, J.B. de Siqueira, Sensitivity of the dengue surveillance system in brazil for detecting hospitalized cases, PLoS Neglected Trop. Dis. 10 (2016).

[19] C. Marques-Toledo, C.M. Degener, L.C. Vinhal, G.E. Coelho, W. Meira, C.T. Cdeço, M.M. Teixeira, Dengue prediction by the web: Tweets are a useful tool for estimating and forecasting dengue at country and city level, PLoS Neglected Trop. Dis. 11 (2017) 1747–1757.

[20] S. Yousefinaghani, R. Dara, Z. Poljak, T.M. Bernardo, S. Sharif, The assessment of twitter’s potential for outbreak detection: Avian influenza case study, Sci. Rep. (2019).

[21] A. Somarakis, V. van Unen, F. Koning, B. Lelieveldt, T. Hoff, Imacyte: Visual exploration of cellular microenvironments for imaging mass cytometry data, IEEE Trans. Visual Comput. Graphics (1) (2021) 98–110, https://doi.org/10.1109/TVCG.2019.2931299.