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PandemCap: Decision Support Tool for Epidemic Management

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Abstract—Pandemics or high impact epidemics are one of the biggest threats facing humanity today. While a complete elimination of the occurrence of such threats is improbable, it is possible to contain their impact by efficient management which in turn depends on effective decision-making. In the event of a pandemic the data flows are enormous and pose severe cognitive overload to the public health decision-makers. In this context, this paper presents PandemCap, an innovative decision support tool that can be used by the public health officials for making better and well informed decisions in the event of pandemics or high impact epidemics. PandemCap provides an interactive, flexible platform to public health decision-makers by making extensive use of techniques from the domains of visual analytics and epidemic modeling. In addition, the tool also allows for the study of the impact of various interventions or control measures such as the use of vaccines, anti-virals, hospital beds, and ventilators.

I. INTRODUCTION

Highly virulent infectious diseases, such as the plague, cholera, and influenza have killed millions throughout human history. Fifty million people died as a result of the 1918 influenza pandemic and HIV/AIDS is estimated to have taken the lives of more than 35 million [1]. Epidemics, such as Severe Acute Respiratory Syndrome (SARS) in 2003, H1N1 in 2009 and the Ebola epidemic in West Africa in 2013-2016, have acted on a smaller scale but have had huge impact in terms of both social and economic disruption. Despite several advances in the domain of medical science and treatment, the rate of emergence of infectious diseases continues to increase. This could possibly be due to the growth of human population, climate change, food production pressures and greater animal-human interaction [2]. Public health emergencies, such as a pandemic outbreak, pose the task of critical decision-making to public health officials and emergency response personnel. This is a challenging task because such situations require decisions to be made on the basis of uncertain and rapidly changing information. It is in this context that this paper presents PandemCap—a visual analytics decision-support tool—for the visualization and presentation of epidemiological data. In addition, the tool also provides for the simulation of the spread/containment of the epidemic based on the implementation of control measures available to public health officials.

Specifically, PandemCap was developed as part of the EU Horizon 2020 project called PANDEM: Pandemic Risk and Emergency Management [3]. One of the key findings of the project was the lack of availability of a common and efficient visualization and resource modeling tool that could be used at EU level in the event of a pandemic outbreak. PandemCap, as presented in this paper, seeks to fulfill this gap. In addition, it is flexible enough to be extended or used in countries outside the EU as well.

This paper is structured as follows: In section II we provide the theoretical foundations of concepts such as decision-making, situational awareness, visual analytics, and epidemic models. Next, section III presents related work, where we describe some other popular visualization and simulation tools used in the domain of public health decision-making. The design architecture of our proposed tool PandemCap is described in section IV. Section V presents the implementation of PandemCap as a proof-of-concept. Subsequently, in section VI we demonstrate the use of PandemCap as a decision support tool for public health officials in an influenza outbreak scenario. Finally, we close the paper in section VII by drawing conclusions and providing an insight into future work.

II. BACKGROUND

In this section we provide background information on core concepts that are fundamental to the development of PandemCap. These include decision-making and situational awareness, visual analytics, and epidemic models, respectively.

A. Decision Making and Situational Awareness

The process of decision making involves determining the best action/choice to perform from a set of alternatives in order to arrive at a solution for a certain problem [4]. Decisions made by public health officials are based on the information provided by facts about a situation and their own suppositions. Hence, Situational Awareness (SA) is critical for the decision making process. SA provides an impression of what is taking place around a situation. Such an impression is critical to improving the decision maker’s ability to make informed decisions. Endsley [5] formally defined SA as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future”. Endsley [6] proposes a model for SA that consists of three levels of awareness that lead to decisions. These levels are as follows:
• Level 1-Perception: Perception of important elements in the environment.
• Level 2-Comprehension: Decision makers have to combine the information obtained in Level 1 with their own experience to understand the situation.
• Level 3-Projection: The ability of creating a projection of the current situation into different possibilities to anticipate their implications.

Each level in this model is built over the previous one, where projection is the most desirable. Different levels can be reached depending on the data available, the context of the situation, the expertise of the decision maker and their ability to predict future situations.

The perception level of SA requires the public health officials to collect data on various aspects of population health. This includes recording the proportion of infected people and their geographical locations as well as an account of available resources such as the number of hospital beds, mechanical ventilators, and antivirals, to name a few. Any relevant and related surveillance data is also used at this level. The comprehension and projection levels of SA require public health officials to develop an understanding of the situation and to anticipate the impact of the public health situation by assessing the impact of interventions, respectively.

Based on the information received and their own experience, public health officials evaluate interventions that can possibly reduce/contain the spread of the diseases. Such interventions include school closures, vaccinating a portion of the population, increasing or decreasing the number of resources. A comprehensive study of the effectiveness of the interventions is important because incorrect or untimely decisions can have very negative consequences such as increase in death rate, higher costs, and can even result into the progression of an outbreak into a pandemic.

In order to select the most optimal interventions to implement, decision makers need to reach the third level of SA. However, when building and comparing projections of the numerous combinations of potential choices, the decision maker can be easily overwhelmed. In this situation, information overload becomes a crucial problem that needs addressing.

In general, in the context of pandemic management the data flows are enormous. Hence, it is difficult for public health officials to process large amounts of information needed to make decisions, and even more challenging to carry out projections. In the following section we introduce visual analytics and its role in handling information overload.

B. Visual Analytics

Visual analytics is a multidisciplinary area that aims to integrate interactive visualizations with automated data analysis approaches to ease the processing of large volumes of data and support a user’s decision making process. By means of visual analytics, users can gain deeper insight about complex large-scale data and discover new knowledge as they interact with visualizations that highlight the most meaningful characteristics of the data. Originally, Thomas and Cook in define visual analytics as “the science of analytical reasoning facilitated by interactive visual interfaces.”

Figure 1 presents the visual analytics process used in the context of this project. The presented process is based on three core components: Data, Model, and Visualization; and it is founded on the definitions proposed by Keim et al. in [8]. In the Figure, it can be viewed how components interact with each other and with the user.

The data component handles the raw data, which may be structured, semi-structured, or unstructured and comes from heterogeneous sources. Usually, the data needs to be preprocessed transformed or integrated before being used by the model or visual component.

The Model component handles the mathematical models used to reflect real-world dynamics. These models can be used to simulate the behavior of a system changing over time which is initially characterized by the original data and can be controlled by the user by means of parameter refinements. Examples of models in the domain of epidemic research include [11], [12] and [13]. In brief, models drive the transformation of the data to be used for visualizations and “provide a basis for decision makers to understand their world” [14].

The Visualization component handles visual representations, which are used as the main interface between users and the data and/or models. For the user to discover useful knowledge the interaction with visualizations is needed.

In summary, visual analytic tools present themselves as solutions to handle information overload by allowing the analysis of some of the most relevant aspects of large-scale, dynamic and complex data. They achieve this by means of interactions between the data, model, and visualization components. As a result, information overload is reduced allowing users to gain a better insight and make informed decisions.

In this paper we propose PandemCap, a solution based on visual analytics that provides public health officials with insights into how the predicted impact of a pandemic changes given different types of interventions.

C. Epidemic Models

An epidemic model is a simplified representation of reality describing the transmission of an infectious disease through
a population \[15\]. Epidemic models allow us to observe the evolution of an outbreak, evaluate the impact of implementing mitigative strategies, and support emergency response and risk assessment.

The SEIR model \[16\] is one of the most commonly used epidemic models. In previous works, infectious diseases such as Ebola \[17\], Zika \[18\], and Influenza \[19\][20] have been modeled using the SEIR model. In this section we will further explain the SEIR model as it is the main foundation for the proposed model in our work (view section IV-B).

The SEIR model (view Figure 2) is a mathematical approach that describes the state of an individual over time in one of four compartments in which the population is divided in:

- Susceptible\((S)\): Individuals who can be infected with the disease.
- Exposed\((E)\): Individuals who have been infected but are still not infectious and might not exhibit signs of infection.
- Infected\((I)\): Individuals who are sick and infectious, in consequence they can spread the disease to others.
- Recovered\((R)\): Individuals who can not be infected with the disease, either because they are isolated, immune, or dead.

The model estimates the number of people in each of these four compartments by describing how people move between compartment. Thus, \(S(t)\), \(E(t)\), \(I(t)\) and \(R(t)\) are functions of time \(t\).

The total population size \(N\) is the sum of all compartments.

\[
N = S(t) + E(t) + I(t) + R(t).
\]

![Figure 2. Schema of the SEIR model.](image)

The progression from one compartment to another initiates when a susceptible individual (in compartment \(S\)) is infected at the infection rate \((IR)\), as a result the individual moves to compartment \(E\). After the latency period \((ER)\), the exposed individual becomes infectious and can spread the disease, as a result the individual moves to compartment \(I\). Finally, the infectious individual is recovered permanently at the recovery rate \((RR)\), as a result the individual moves to compartment \(R\). We can extend the SEIR model to include interventions such as mitigative strategies or resources capacity to reduce the impact of disease spread.

In the section IV-B we will explain how our solution approach extends the SEIR model.

### III. Related Work

This section describes other relevant prior works that have proposed visualization solutions for epidemic model simulations. These solutions aim to support public health workers in observing the impact of their decisions.

One example is GLEAMviz \[21\], a publicly available system that simulates realistic infectious disease spread across the world. First, the tool allows the user to design compartmental models with mitigation strategies. Next, the model created can be submitted to the GLEAMviz servers (high performance computers), which execute thousands of simulations of the possible epidemic evolutions, based on stochastic mathematical models and real-world population and mobility data. When results are ready, they can be retrieved, stored, and visualized. As outputs, GLEAMviz can produce a 3D global map, an animation, and a dynamic 2D map view of the disease evolution and spread over time, along with a related set of charts that quantitatively describe results. As well, analysis on mobility data and the structure of the airport network is provided to reflect how the notion of distance is affected. All in all, these features make GLEAMviz a convenient tool for teaching or training.

Another popular visualization and modelling tool to support decision-making in the domain of public health is PanViz \[13\]. It is an influenza simulation tool that uses spatio-temporal views to help public health officials understand the impact of decisions over the disease spread. The tool allows to set a specific day of the simulated outbreak to view statistical data about the progress of the disease and to evaluate the spread in a geospatial/map view. Specifically, the map view (based on the United States) displays the spread of the disease between different counties across a state. The tool allows to set the point of origin of the disease and choose or not the use of air travel information to influence the spread. Finally, the decision maker can, at any day of the simulation, indicate the execution of a decision (i.e., intervention) and the number of days it would take the decision to take full effect.

Afzal et al. \[22\] compared the impact of several mitigation measures at different points over time, using their proposed decision history view and spatio-temporal model view. On the one hand, in the spatio-temporal model view it is possible to adjust model parameters and explore the effect of mitigation measures over space and time. On the other hand, the decision history view allows for the user to insert decision points at any point of the time line to generate branches. As a result, the user can visualize the overall impact of lost or saved lives as a function of decisions made by comparing branches. Though the idea of presenting branches of different time lines can have many advantages, one possible disadvantage of this view is that in the presence of many branches it may be difficult to differentiate each decision line.

In this section we described visualization tools developed for supporting decision-making in the event of a public health emergency and response management. In the following sections we describe the design architecture and implementation of our proposed tool, PandemCap.

### IV. Architecture Design

In this section, we explain the PandemCap design under the components of the visual analytics process (see section II-B), which are: Data, Model and Visualization.
A. Data

With metapopulation structures such as the SEIR model, available epidemiological data can be used to map to model variables. For example, population demographic data can be accessed for a given geographic area, and these values can be assigned to stocks (e.g., the number of people in a given age cohort who are susceptible), and also to auxiliary variables (e.g., the number of hospital beds available as a resource). This is highly useful in order to build user confidence in the model, and validate the model structure by comparing model values to historical data.

B. Model

The dynamic model used for PandemCap is an extension of the SEIR model, and is based on a stock and flow structure [14], used widely in the simulation literature. It is divided into four age cohorts (00-04, 05-14, 15-64 and 65+), which is commonly known as a metapopulation model [23]-[16], although network-based models can also be implemented to simulate disease transmission [24]-[15]-[25]. In order to model the different classes of infection that can spread through the population, the infected cohort is further divided into four compartments, each reflecting a possible impact of the pathogen (asymptomatic, mild, moderate, and severe). Severe cases are hospitalized, and their flow within a hospital scenario is dictated by the availability of resources. The model can simulate the impact of the following resources in the health system: Vaccines, which can be targeted at risk groups and, depending on efficacy, would change the model flow for recipients, where they would be moved directly to the recovered stock, rather than remaining in the susceptible stock. Antivirals, which are used to treat at-risk groups at the early stage of infection, and this resource-dependent intervention can reduce the risk of acquiring a severe infection, and thereby improve overall health outcomes, as well as reducing the demand load profile on scarce hospital resources. Hospital Beds, which are the number of beds available for patients who have severe reactions to a pathogen, and these are resources that can ensure the best possible health outcomes. If a pandemic surge is overwhelming, patients will be flow into a model sector known as surge capacity, where models the impact of a lower-quality health provision scenario. Ventilators, which are resources for patients with severe respiratory problems, and the availability of these resources will improve patient outcomes. However, a lack of sufficient ventilator supply will lead to increased mortality.

The model uses a who acquires infection from whom (WAIFW) transmission structure [15], to evaluate the force of infection for a pathogen, with cohort contacts informed by a Europe-wide contact tracing survey [24]. The dynamic model also contains measures for assessing the impact of a pandemic on workforce absenteeism, and therefore it can provide an insight into business continuity challenges that arise during a prolonged pandemic. Absenteeism is calculated based on a number of factors, including: the number ill in the 15-64 cohort (factored by a ratio of how many people in that group are employed in the workforce); and the number of children that are sick (as this will mean higher number of parents would remain at home). The model also allows for school closures, and also can capture seasonality effects, where the infectivity of a pathogen can become further amplified during the winter months, as more people remain indoors, and so the probability of transmission increases.

C. Visualization

PandemCap, as mentioned previously, is specifically designed and developed for visualizing and simulating data flows and possible interventions in the event of a pandemic outbreak at EU level as part of the PANDEM project. The current design is based on the specific user needs of public health officials responsible for pandemic management at EU level.

Interactivity is one of the key user needs addressed by PandemCap. The tool allows the users to vary the intensity parameter of a pandemic scenario and select between options such as mild, moderate, and severe. In addition, various options such as save, delete, etc are also provided. The user, among other actions, can select, filter, pan or zoom views to explore the outcomes.

The impact of various interventions described in the previous section can also be visualized. Finally, the PandemCap design also allows the visualization of the distribution of cases over time, the information referring to the number of people infected, as well as the geo-spatial analysis spread of the disease.

V. PROOF-OF-CONCEPT IMPLEMENTATION

In this section we introduce the PandemCap prototype, a proof-of-concept implementation of our proposed architecture design (view section [IV]). We describe the technical aspects of the PandemCap prototype and explain the development of our solution under the components of the visual analytics process, i.e. Data, Model and Visualization (view section [II-B]).

A. Data

PandemCap gathered data from the statistical office of the European Union Eurostat [27] at the NUTS-2 level. NUTS-2 divides the EU territory into 276 territorial units for the generation of regional statistics and political interventions [27]. At this level it was possible to collect the needed geographic, population and resources data to build the epidemic model.

B. Model

The model implemented as a set of ordinary differential equations in R [28], using the deSolve library [29], which supports numerical integration algorithms including Euler’s, and also facilitates vectorization of models (which is essential to model the four different age cohorts). At a technical level, the model is implemented as an R closure, which encapsulates the model structure and data into a single object, and therefore supports running the model in parallel, as well as scaling up the model to simulate many regions within a geographic area under threat of a pathogen with pandemic potential.
PandemCap can be parameterized for each run (there are 58 parameters that can be varied), so that many of the variables can be seeded with different initial conditions, and extensive sensitivity analysis can be performed.

C. Visualization

In this section, we will present the user interface and functionalities of the PandemCap interactive web application. The front-end was developed using the web application framework Shiny version 1.0 [30] for R.

The PandemCap simulator in Figure 3 is composed by two main views:

- Panel(A) in Figure 4 is for setting the parameters and managing the control buttons to run simulations.
- Panel(B) in Figure 5 displays the visual output of the simulation.

2) Adjust the characteristics of the influenza outbreak in terms of both the *infectivity multiplier* (customizes how frequently the influenza is spread among susceptible people) and the *severity level* (customizes how severe the illness is by setting it in either mild, moderate or severe).

3) Select the interventions that the public health officer wants to analyze. These interventions can be mitigative strategies (i.e. school closure or vaccination) or adjustments over the capacity of resources (i.e. antiviral, hospital bed and mechanical ventilators).

Once the parameters for the simulation are chosen, the decision maker has the option of labeling the simulation to keep track of each run. This feature is specially useful when comparing two or more simulations side-by-side. In order to compare simulations, the user must first run and save each simulation individually.

Next, after the simulation is executed, Panel(B) in Figure 5 displays graphics that present results in a temporal and geographical way. These views are rendered every time that parameters are modified, they can be collapsed or re-opened depending of the user needs, and allow for the user to interact with them using actions such as filtering, zooming, panning.

Panel(B) is divided in seven graphics:

- Graphic(B1) includes information boxes used to show dynamic information such as mortality rates, maximum number of people infected and total number of sick people.
- Graphic(B2) presents the distribution of disease cases associated with an epidemic over time in a line chart.
- Graphic(B3) provides a geospatial analysis of the outbreak. The infected region is colored depending on the proportion of disease cases reported, using a gradient palette that generates smooth color transitions from green...
Graphic(B4) displays a bar chart that gives a quick notion of the financial impact of the simulation.

• Graphic(B5) shows the impact to the hospital system in terms of bed and mechanical ventilator capacities.

• Graphic(B6) and Graphic(B7) present the absenteeism observed between children and adults during the simulation using a line chart.

Table I

<table>
<thead>
<tr>
<th>Simulation</th>
<th>ModerateSim</th>
<th>SevereSim</th>
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<tr>
<td>Region</td>
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<td>Infectivity multiplier</td>
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<td>Yes</td>
</tr>
<tr>
<td>Vaccination</td>
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<td>No</td>
</tr>
<tr>
<td>School closure</td>
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<td>No</td>
</tr>
<tr>
<td>Antiviral</td>
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<td>Default</td>
</tr>
<tr>
<td>Bed capacity</td>
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<td>Default</td>
</tr>
<tr>
<td>Ventilator capacity</td>
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</tr>
</tbody>
</table>

(b) Comparing interventions: Evaluate in a severe outbreak the effectiveness between no interventions, closing schools and increasing the number of hospital beds.

A. Comparing outbreaks

For the first use case, we defined the following two simulations:

• ModerateSim: It is a moderate outbreak with no interventions.

• SevereSim: It is a severe outbreak with no interventions.

Moderate and severe outbreaks differ in the amount of infected people.

In order to compare between a moderate and a severe influenza epidemic, we set up the parameters in Panel A (see section V-C) on PandemCap as shown in Table I. Next, we ran the simulations to compare the outcomes. Figure 6 shows the results of the simulations in the different graphics that are displayed in Panel B (see section V-C). The decision maker can explore the visualization results to understand the magnitude of each type of outbreak. For the purpose of analysis we have labeled each Graphic in Figure 6 to use as references in this section.

In Graphic B1, the decision maker can observe that the severe simulation (SevereSim) presents a higher mortality rate compared to the moderate simulation (ModerateSim). In addition, it can be perceived in the map of Graphic B3, that SevereSim presents an intense red, which means a large amount of people are infected and the disease has spread widely. This is corroborated by the epidemic curve in Graphic B2, where the highest peak belongs to SevereSim. Graphic B5 presents the use of hospital resources between the two simulations, where it can be appreciated that the resources at hospitals are not enough to supply the demand of sick people that require hospitalization when the outbreak is severe. In brief, SevereSim shows the worst outcomes and the greatest negative impact in all aspects.

B. Comparing interventions

For the second use case, we defined the following three simulations:

• SevereSim: it is a severe outbreak with no interventions.

• SchoolCloure: it is a severe outbreak implementing school closure intervention.
In Graphic B2 the epidemic curve for IncreaseBed shows a reduction of the overall cases of infected people. This can be as a result of the increment in hospital cares.

It can be seen in Graphic B5, in relation to IncreaseBed, that there is a lack of hospital bed resources. It could be interpreted that, although there was an improvement in hospital capacity, it is still not enough to supply the entire demand for sick people in the FR22 region.

In general, we can appreciate that between the two interventions implemented, increasing hospital beds has a better impact in reducing the overall number of people infected and alleviating the health system burden in comparison with school closure.

In this section we have shown the use of PandemCap in the scenario of an influenza outbreak at the FR22 region in France. We highlight that PandemCap is a useful tool to make comparisons between different simulations and support the decision maker in contrasting projections between possible decisions. It is important to clarify that though we have presented simulation examples based on one intervention, PandemCap can also show the impact of applying a combination of interventions such as school closure, vaccination and increase the number of beds all in the same simulation.

VII. CONCLUSION AND FUTURE WORK

Countless infectious diseases continue to affect the world. Epidemic is not a new threat to human security, but globalization has changed the rules, allowing for a faster and broader spread that results in an increased risk of an epidemic turning into a pandemic [31]. The European Union has been

### Table II

**INPUT PARAMETERS FOR USE CASE “COMPARING INTERVENTIONS”**

<table>
<thead>
<tr>
<th>Simulation</th>
<th>SevereSim</th>
<th>SchoolClosure</th>
<th>IncreaseBed</th>
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<tr>
<td>Region</td>
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<td>FR22</td>
<td>FR22</td>
</tr>
<tr>
<td>Severity level</td>
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<td>Severe</td>
<td>Severe</td>
</tr>
<tr>
<td>Infectivity multiplier</td>
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<td>No</td>
<td>No</td>
</tr>
<tr>
<td>School closure</td>
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<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Antiviral</td>
<td>Default</td>
<td>Default</td>
<td>Default</td>
</tr>
<tr>
<td>Bed capacity</td>
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<td>Default</td>
<td><strong>Triple</strong></td>
</tr>
<tr>
<td>Ventilator capacity</td>
<td>Default</td>
<td>Default</td>
<td>Default</td>
</tr>
</tbody>
</table>

- IncreaseBedSim: it is a severe outbreak where the number of hospital bed resources have been tripled.

In this use case, the decision maker can employ his/her previous experience to decide which decision strategies to evaluate. In this case, the decision maker has decided to study two interventions, school closure or increase hospital beds capacity, and their effect in reducing the disease spread.

For this use case, we set the parameters in Panel A (see section V.C) on PandemCap as shown in Table II. Afterwards, we ran the simulations to compare the outcomes. Overall, the interventions are contrasted with the control case (SevereSim). The visualizations in Figure 7 show all the relevant information at a glance. For the purpose of analysis we have labeled each Graphic in Figure 7 to use as references in this section.

Examples of observations that can be made are:

- In Graphic B2 it can be observed that SchoolClosure has a minimal impact. The reason for this can be that there are still enough infected people propagating the virus.
continuously dedicated to establish strategies, identify and provide solutions in response to pandemic risk and emergency management. In order to improve and update the current mechanisms, the Pandemic Risk and Emergency Management (PANDEM) project was created. Among challenges, it has been identified that the appropriate presentation of available information to decision makers is critical in the management of a pandemic situation.

In this paper we presented PandemCap, a visual analytics decision support tool that helps public health officers understand what is happening during an outbreak and the impact of potential actions/interventions. In the context of the PANDEM project, this tool can be vital in order to decrease the response time to face an epidemic, prevent its intensification and overall its negative impact on society.

The project has extensive potential for future work. In the short term, we plan to extend the model and visualizations to include features such as human mobility patterns. As well, we plan to evaluate the usability of PandemCap using public health personnel. In the long run, we plan to add an optimization solution that is able to search within a large set of simulations to find the sequence of interventions that could help accomplish the public health officer’s objectives (e.g. decrease number of infected people) for a specific outbreak scenario.

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