

Uncovering Weaknesses in Health Care Systems

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Abstract

This paper describes a method to uncover weaknesses in health care systems which is particularly important in these days due to the increasing number of chronic diseases affecting the entire population and not only the older age groups. Moreover, pandemic situations, for example caused by COVID-19, create an additional burden for health care systems impacting the equitable supply of medical resources, the availability of medical staff, and the economy. Our data exploration and visualization tool based on time-series data focuses on such weaknesses in health care systems. In this paper we experiment with typical data scenarios that can be exploited to find patterns and insights. To reach this goal we transform and analyze the relevant data first, to finally provide an interactive geographic regional-based representation in which the users can navigate and find useful hints to confirm, reject, or refine their hypotheses about the data. We illustrate the usefulness of our work by applying it to data containing information about age groups, number of hospitalizations, intensive care unit bed occupations, and regional aspects in Switzerland over time. We conclude the paper by discussing limitations and scalability issues.

Keywords: exploratory data analysis, small multiples, multivariate analysis, health care systems, geographic maps, information visualization

1 Introduction

An increasing number of chronic diseases and aging population will put more and more pressure on health care in the future [27]. This, in the context of a pandemic, like the one caused by the COVID-19 virus, makes the situation even more dramatic. The bottleneck in health care systems is caused by two factors: materials and resources on one side and financial resources on the other one [38]. Both sides have impacts on each other and it is of great importance to understand what has to be done for providing possible solutions.

The aim of this paper is to analyze, explore, and visualize the utilization of the health care system capacities caused by the COVID-19 virus and to find weaknesses in the system. Hereby, we define a **weakness in a health care system** as one or several issues that are actually not taken into account to get the best out of patients' medical treatments to improve their health situations.

To reach our goal and to get hints about such weaknesses, we combine data visualization with multivariate temporal data analysis on open data (see Fig. 1), that is, we exploit several concepts from information science to tackle this challenging problem. Our work focuses on supporting experts in the field of medicine to understand the current situation in order to improve the treatments for the patients. The novelty of our approach is that we can integrate multivariate time-series data in a geographic context while allowing interaction techniques in all involved data dimensions, that are the multivariate, the time-series, as well as the geographic one.

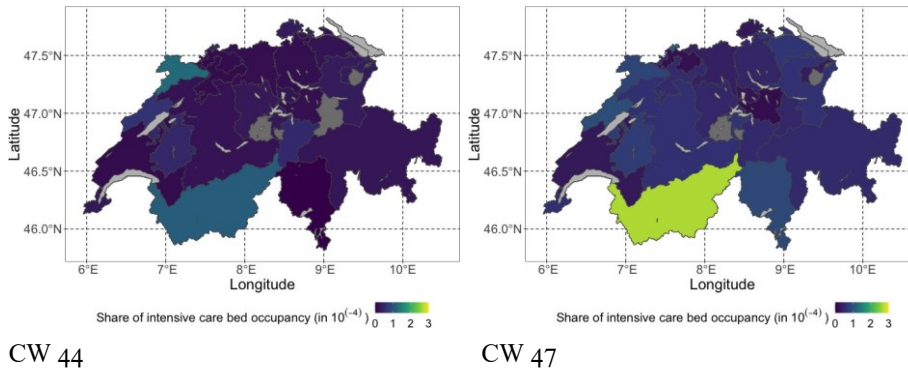


Fig. 1 The occupation of the intensive beds per calendar week (CW) in Switzerland: The geographic maps show that the COVID-19 wave did not hit the intensive station occupancy equally in Switzerland. A quite large effect is recognized in the canton of Valais in which the intensive care bed occupancy has changed drastically from calendar week 44 to calendar week 47.

To illustrate our method we present an application case taking into account data from Switzerland. The used data is published by the office of federal statistics in Switzerland and includes information on the hospital admission by age class and the intensive care unit bed occupations over time. In the application, we show the impact of COVID-19 hospitalizations on the occupations of intensive beds per age class and region.

The remainder of the paper is organized as follows: In Section 2 we compare our approach with existing research in this domain before we start describing the data in use (Section 3). The visualizations are introduced in Section 4 while we discuss the application case in Section 5. We explain limitations in Section 6 before the paper is concluded in Section 7.

2 Related Work

COVID-19 had a major impact on the world economy and the new virus could not be foreseen for individual countries. Hence, it brought a huge uncertainty in the resources planning [14]. Social and community factors affect weaknesses and shortfalls in current health care systems. For the moment, resource planning is often done top-down at the federal level and research priorities are determined [41]. As shown during the COVID-19 pandemic, such top-down decisions may not allow enough flexibility to meet the needs of physically, socially, and culturally diverse communities.

The population-resource-environment system is guaranteed in a sustainable way through geo-spatial planning [34] which is defining clusters and summarizing geographic density of businesses, suppliers, and associated institutions in a particular region [28]. The obtained clusters allow determining places with underuse or overuse [13, 23].

Staudt et al. [31] propose small multiples in combination with multivariate models to execute geo-spatial planning. Already in the middle nineties Tukey [36] used visualization techniques in combination with statistical values to analyze data. Exploratory data analysis (EDA) combines the ideas of Tukey by bringing together visualization and transformation of the data [39].

The obtained data presents a high granularity, which allows a lot of possibilities to compare the caseload of COVID-19 positive cases as well as the occupancy of the intensive care unit over time. For such a comparison, the

literature proposes to use small multiples [8] to allow comparisons in one view.

Time-series allows to model and to forecast the future on seen events and hence might explain weaknesses in a health care system. This method was applied recently to forecast the number of COVID-19 cases in India [35]. However, the application of time-series has a longer history in use. For example, time-series were used to determine health care quality [26] and determinants of health care [29].

Several researchers analyzed weaknesses in health care systems based on the results from different countries [6, 18, 40]. However, the researchers only apply data analysis with a limited number of features. For example, Morr and Ali- Hassan [22] try to integrate data analysis and visualization more and more into the control and application of disease management.

Visualization is mostly used in health care for different purposes as for example ambulance service planning [15], decision making in anesthesia [30], disease surveillance [2], and several more [1, 3, 4, 7].

In particular, taking into account the COVID-19 pandemic, the occupation of the beds for a hospital in France was modeled with the help of a simulation [17]. This model got developed to hold track on the situation and to maintain a high level of care quality. Health care systems must be prepared for special events that might have impacts by causing immense costs in several sectors.

To help explain the impacts, several applications of time-series analysis in health care were developed. Especially, time-series are used for determining the health care quality [26] and determinants of health care expenditures [29]. More recently, the method is applied for associating infections, respiratory [5], or care-associated ones [21] with treatments. However, there is not much work on evaluating the weaknesses on health care systems themselves, apart from applying simulation [17], time-series approaches [26] on health care quality, and COVID-19 dashboards [16, 24, 25, 37] that monitor typical pandemic-related attributes, also partially taking into account the situations in hospitals. But such dashboards alone are not able to give insights in several data aspects combining patients' data, medical resources, as well as regional aspects.

Health care is a quite complex application domain covering a range of data aspects, hence there have already been attempts to combine typical data dimensions in a visualization or visual analytics system [9]. To reach this goal, several visualization techniques have been used like traditional bar

charts, scatter plots, or histograms, but even more complex ones making use of geographic maps [1, 3, 4, 7], typically displayed in the form of small multiples [19, 24, 37], but more in some kind of stand-alone fashion.

However, in our approach we are combining health care data from the perspective of the patients, enrich it with financial aspects as well as typical resources required, and explore region-based impacts as well as temporal events such as the COVID-19 pandemic. Although there are lots of dashboards for visually exploring COVID-19 data [16, 24, 25, 37], our work is, to the best of our knowledge, the first attempt to combine health care system data from several perspectives under the shadow of the COVID-19 pandemic. Additionally, we apply a multivariate data analysis to the data, to consider interactions and to predict solutions for the system.

3 Data Model

The health care data enriched with patient and financial aspects can be modeled as a list L_{jt} of $l \in \mathbb{N}$ quantities. All the lists create a set L of $n \in \mathbb{N}$ observations, whereas $L = \bigcup_j$. Each list L_{jt} consists of three subgroups, namely the health care elements h_{jit} , demographic/financial elements of the population d_{jrt} , and geographic information g_j . Mathematically, the list will be written as $L_{jt} = \{h_{jit}, d_{jrt}, g_j\}$. The geographic information will be described by a list of geometries, given in a shape format. Several health care and demographic/financial elements can be considered for each list. The same number of variables needs to be considered for the whole data set. At least each subgroup contains one element. Mathematically, the three subgroups will be written as

$$h_{jit}, \quad 1 \leq i \leq l_1 \text{ and } l_1 \leq l \quad (1)$$

$$d_{jrt}, \quad l_1 \leq r \leq l_2 \text{ and } l_2 \leq l \quad (2)$$

$$g_j, \quad (3)$$

where $l = l_1 + l_2 + 1$ represents the number of quantities in a list. t represents the time stamp and j the considered observation from the set L . The time level can be given in days, weeks, months, or years. Each list L_{jt} is representative for one region g_j , with h_{jit} representing the i^{th} health care variable and d_{jrt} the j^{th} demographic/financial variable for time stamp t . Depending on the available data, the list L_{jt} can be considered on a more detailed level of

g_j . For example, oftentimes geographic regions are considered in a raster with a dimension of 100 by 100 square meters, the less detailed geographic representation is on the country level. In Switzerland for example, we mostly have data on the cantonal or even on the longitude or latitude level.

However, the list L_{jt} cannot be used as such, as most of the data cannot be compared over regions like this. For this purpose, health care variables h_{jit} are being scaled by a key performance indicator kpi_t bringing all the regions on a comparable level. Traditional scaling variables cannot be used, as the scale is executed by looking at each variable separately and will have a huge impact on the interpretation of the multivariate model. The choice of a relevant key performance indicator is hence of major importance for the use of the multivariate analysis. The key performance indicator can change with the time stamp. By scaling the data with the key performance indicator, we obtain the modified list

$$\tilde{L}_{jt} = \{h_{jit} / kpi_t, d_{jrt}, g_j\}. \quad (4)$$

The objective of this paper is to represent selected health care information along demographic/financial parameters for a selected time stamp on a geographic map. For each visualization a set \dot{L}_{irt} of lists \tilde{L}_{jt} for given health care and demographic/financial variables will be considered. The set \dot{L}_{irt} is a subset of \tilde{L} . Mathematically, the selection of observations \tilde{L}_{jt} will be written as

$$\dot{L}_{irt} = \bigcup_j \{h_{jit} / kpi_t, d_{jrt}, g_j\}, \quad (5)$$

where i , r , and t are fixed values. The subset \dot{L}_{irt} contains the selected health care and demographic/financial information for all regions only once. As the health care information is represented along the categories of the selected demographic/financial element, it results in small multiple graphs. This will allow the comparison of changes over the characteristics of the demographic/financial along the geographical information. Mostly, the demographic/financial data are categorical variables with at least two classes. If the demographic or financial data are numerical variables, we will apply discretization to the numerical variables. Different methods of discretization exist [20, 32, 33].

The multivariate statistics, namely correlation or time-series clustering, are applied to consider the changes over time and to reveal weaknesses in the overall setup by considering a specified number of health care variables along demographic/financial and regional information. Hence, the multi-

variate statistics allows to look for interactions along the variables, which is not given through the small multiples visualizations. For this purpose, we select from the set of lists $\dot{L}_{ir,t}$ (see Equation 5) a fixed number of health care and demographic/financial variables over time and for all considered regions g_j . In the case of a correlation, we only consider two health care variables x and y along one demographic/financial variable over time for all considered regions. In the case of a multivariate clustering analysis a combination of health care and demographic/financial variables can be considered. Multivariate clustering gives sense for a selection of more than three health care variables and at least two demographic/financial information.

Mathematically, the subset will be written as

$$\bar{L}_{ir} = \bigcup_t \dot{L}_{ir,t}, \quad (6)$$

where i represents the selected health care variables and r the respective demographic/financial variables.

A multivariate analysis is applied on the subset L_{ir} for the chosen health care and demographic/financial variables by considering the regional separations and the time evolution to measure interactions and relations among the regions. Mathematically, this can be written as

$$f_{jt}(\bar{L}_{ir}), \quad (7)$$

with j and t taking into account the regional separations and the time evolution.

In the following case, a correlation is calculated for two selected health care variables i_1 and i_2 along one selected demographic/financial r_1 information. Mathematically, the set from Equation 6 can be simplified to the case

$$\bar{L}_{i_1 i_2 r_1} = \bigcup_{j,t} \{h_{ji_1 t}/kpi_t, h_{ji_2 t}/kpi_t, d_{jr_1 t}, g_j\}. \quad (8)$$

The correlation is calculated as follows

$$f_{jt}(\bar{L}_{i_1 i_2 r_1}) = \text{Cor}(h_{ji_1 t}/kpi_t, h_{ji_2 t}/kpi_t) \quad \forall \text{ categories} \in r_1 \quad (9)$$

In this case the correlation (see Equation 9) will be calculated for the selected variables i_1 and i_2 for the considered timestamp along the categories of r_1 .

The objective is then to visualize the multivariate results on a geographic map for comparing them. For this purpose the results obtained for each region need to be summarized in a set.

Mathematically, this can be written as

$$\check{L}_x = \bigcup_{jt} f_{jt}(\bar{L}_{xy}). \quad (10)$$

With the obtained set, a multivariate data analysis can be represented on a geographic map and allows to show interactions and relationships along the considered health care and demographic/financial elements.

4 Design Decisions and Visualization

In this section, we describe the general framework to uncover weaknesses in health care systems. We found our design decisions based on the studied literature in Section 2 and come up with easy-to-use visualizations that are appropriate to show the data under investigation.

4.1 Visualization Techniques

The combination of all three sorts of variables, namely health, demographic/financial, and geographical information, over time, allows to represent the health care information along with the demographic/financial and geographic information in small multiples representations. The small multiples are plotted for all selected time stamps and then allow to show the evolution of the health care variables along the considered demographic variable. We consider these visualizations as useful since they are easy to understand and since they allow to find hints to the solutions of our tasks-at-hand. The fact that there is not much knowledge and experience needed to interpret the visualizations makes them in particular useful for health care professionals, people working in health care administration, epidemiologists, even politicians.

4.2 Interaction Techniques

To consider the interaction and the impact of one phenomenon on the short-fall of another phenomenon, we apply a multivariate analysis. The most simple case exists, when we only consider two variables. In this case, a correlation measure is the most simple one. Indeed, this method can be extended by considering time-series clustering which also allows to compare the interaction of several variables. The analysis is executed over the whole consi-

dered time period, however separately for each demographic and geographical information.

Consequently, with the first univariate small multiples, demographic/financial and geographic changes over time can be represented. Combining these results with one of the multivariate analyses allows to point out the weaknesses in the health care system. The weaknesses can be observed visually in the geographic maps by detecting visual patterns and anomalies that might hint at a situation that did not occur in all of the regions in the same way, hence one region might suffer from such a weakness while the others do not.

5 Application Case: Switzerland

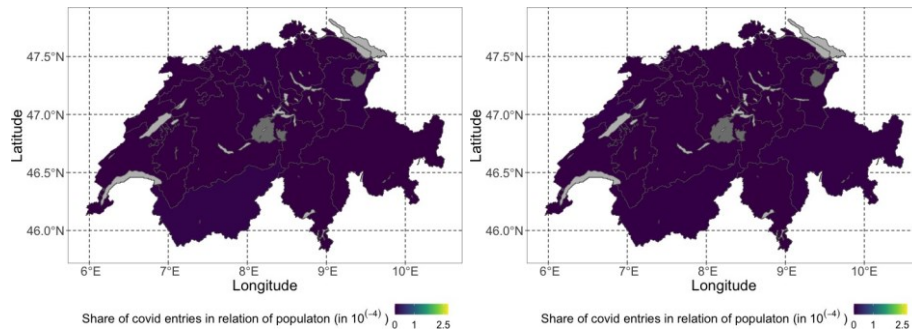
For our application case, we gathered data from the federal statistic office. We analyze the impact of the COVID-19 hospitalization on the intensive care unit, however, many more variables could be integrated like the number of COVID-19 infections, patients' genders, smoking habits, or number of vaccinations, just to mention a few. Our research question is: Is the intensive unit care having a shortfall due to the COVID-19 hospitalizations? In the data set [10], we have the hospitalization from the start of the COVID-19 pandemic from March 2020 to the end of 2021. The hospitalizations are registered accordingly to nine age classes, namely 0 to 9, 10 to 19, 20 to 29, 30 to 39, 40 to 49, 50 to 59, 60 to 69, 70 to 79, and older than 80 years. The intensive care units are also gathered from the federal statistic office from Switzerland, however in a different table and not according to the age classes [11]. To make both tables comparable, we scaled our data with population accordingly to the geographical information [12]. The scaling by the population for each geographic information allows to compare the results for Switzerland, as not each canton represents the same population. If no scale had been performed, cantons with higher population as Zurich would have been overestimated. For the representation case, we choose two calendar weeks, namely the week 44 and 47. The calendar week 44 represents the week where the highest number of bed occupations for all cantons over the total period in Switzerland was registered. The highest number of bed occupations is obtained for the canton Valais, whereas the calendar week 47 represents the week where the Ticino, the canton with the first COVID-19 registration has the highest number.

In Figure 2, the number of hospitalizations is represented according to the age classes and the cantons. No hospitalizations are registered for patients with ages younger than 49 years. The first hospitalizations are registered for ages from 50 on. The number is still very low, especially for ages from 50 to 59, the Ticino, Valais, Fribourg, Neuchâtel, and Glarus show such cases. From the 60 years on, the canton Solothurn is also showing some cases. For older people the same situation remains. Valais seems to be the most impacted canton as can be observed in all of the diagrams.

In Figure 3, the same information as in Figure 2 is represented. However, in this case another time stamp was chosen and we represent the calendar week 47. As in the calendar week 44, no hospitalizations are registered for patients younger than 39. This time a few hospitalizations are registered for the ones from 40 to 49. However, this time the Valais is not the canton with the most cases, this time the Ticino has the highest number of hospitalizations. This is no surprise as the calendar week 47 was chosen accordingly for representing this case. The same cantons as in the calendar week 44 seem to be concerned.

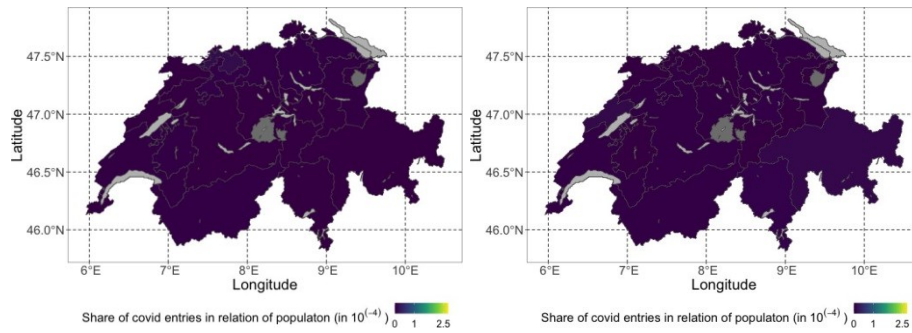
In 2020, all operations were stopped as the federals feared that the intensive unit could not have enough beds. So how does the number of hospitalizations is impacting the intensive care unit? For both considered weeks, the share of intensive care bed occupancy is not the highest. The maximum share registered in Switzerland, namely 0.003 represented by the color yellow, can be two times higher than the one represented here. However, in both cases the Valais shows the highest intensive bed occupation. Ticino, which has its highest number of hospitalization in calendar week 47, has not such a big occupation of intensive bed occupancy in this week. The case for Valais looks much more difficult.

From Figures 2, 3, and 4, we would make the claim that especially the canton of Valais has weaknesses in the intensive care unit. To confirm this result, we performed a correlation calculation over the entire time series by age group and canton. The results are represented in Figure 4. The figures reflect that there is also a relationship between young patients and the intensive station. Indeed, the Valais is a canton which has some difficulties with intensive unit care through the hospitalizations of COVID-19. However, this canton is not the one with highest weaknesses. The Ticino is the canton over all age classes with the most difficulties, followed by Bern and Zurich. The canton Jura is the one where the impact of the hospitalizations on the intensive station occupancy is the lowest.



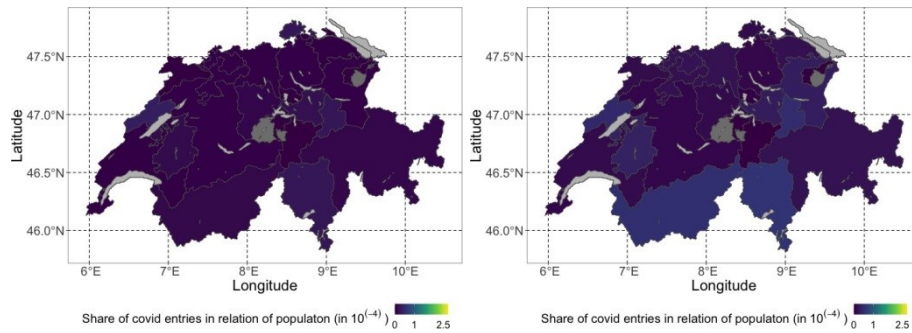
0-9

10-19



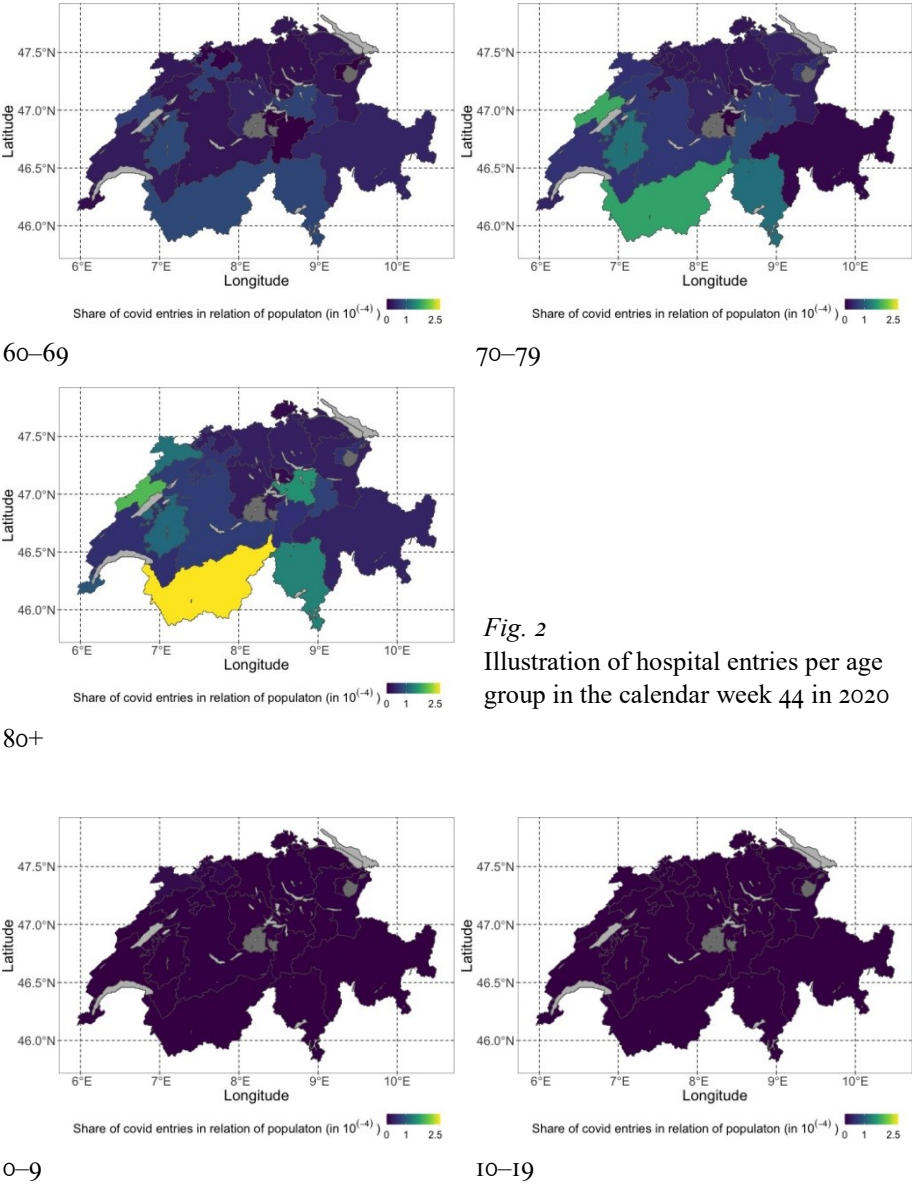
20-29

30-39



40-49

50-59



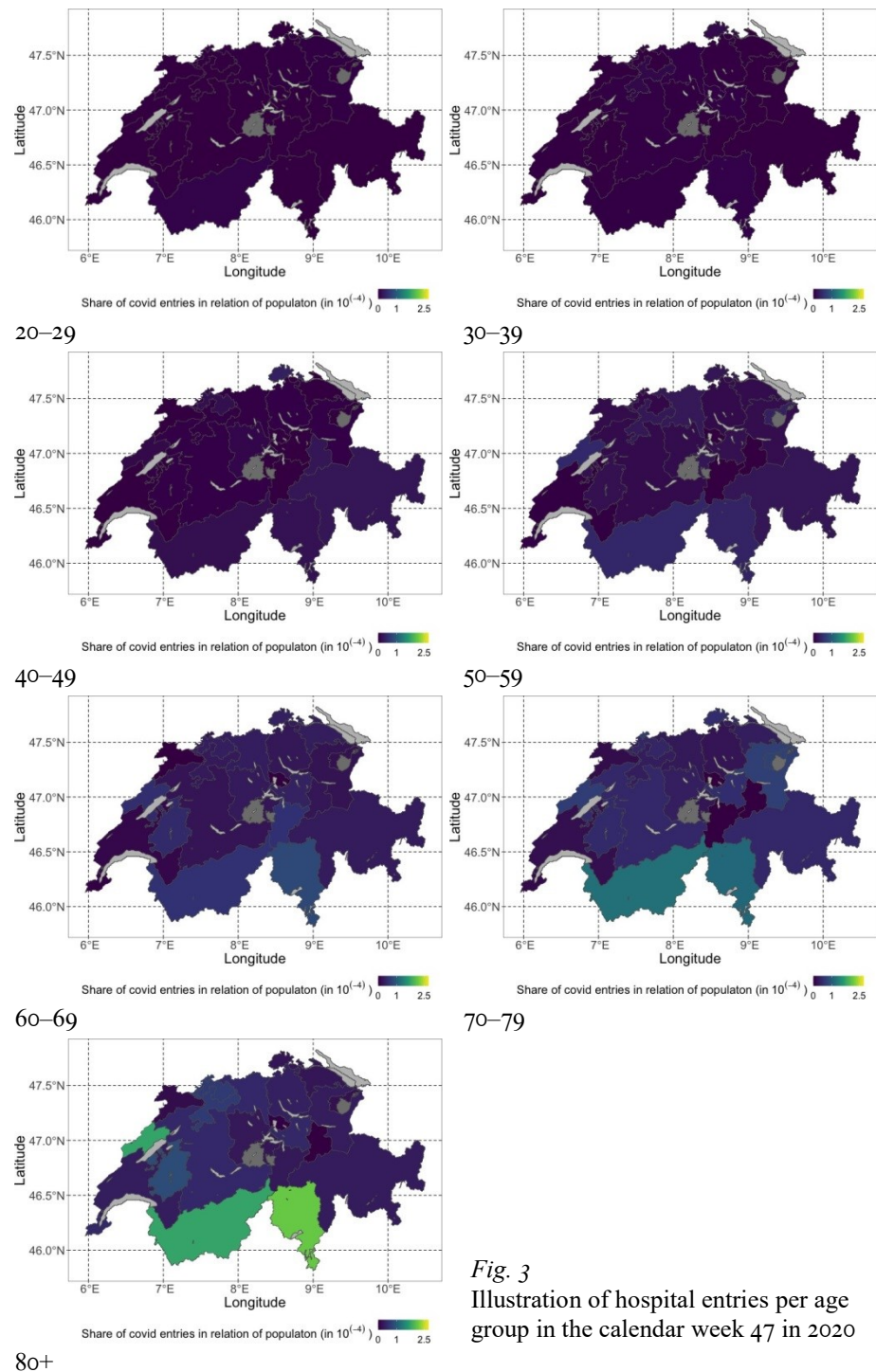
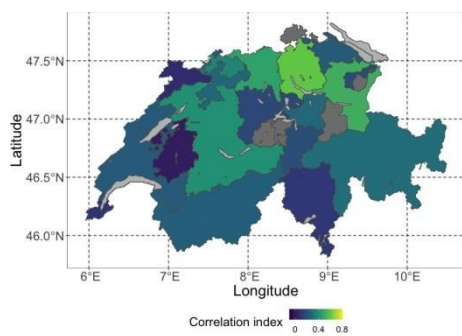
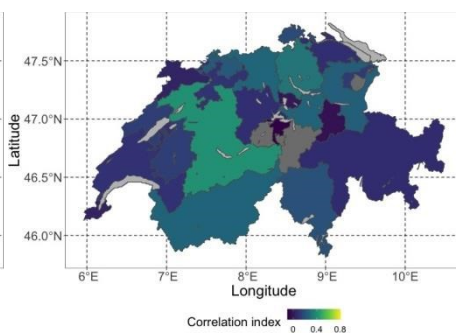


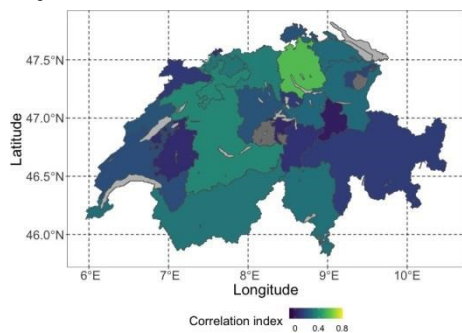
Fig. 3
Illustration of hospital entries per age group in the calendar week 47 in 2020



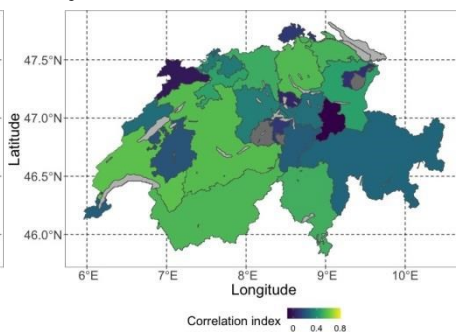
0-9



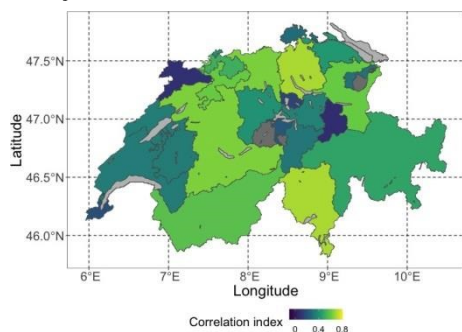
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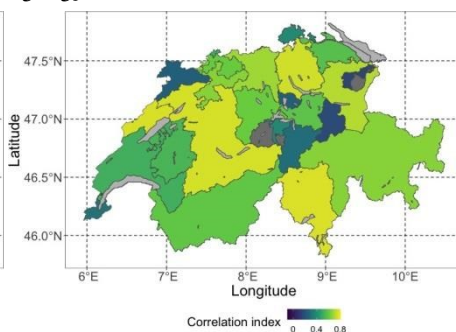
20-29



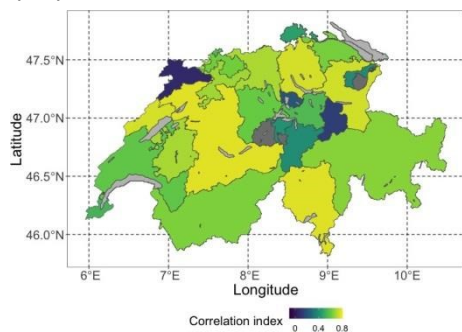
30-39



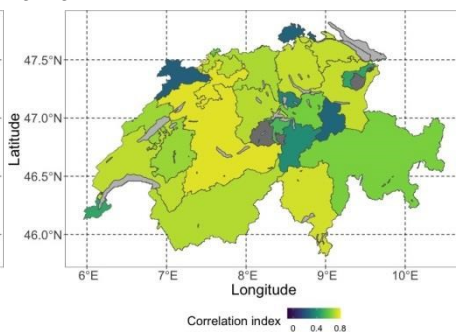
40-49



50-59



60-69



70-79

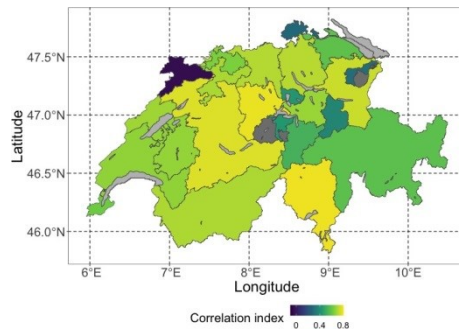
*Fig. 4*

Illustration of the correlation between the entries in hospital and the intensive bed occupation per age group in Switzerland

80+

6 Limitations and Scalability

The major limitation is coming from the open data. For the moment, not all data is published in high granularity (time and variables) or cannot be associated with a regional information. Secondly, the data from the federal statistical office is all published in one excel sheet, prepared for human use and not for a programming language as Python or R which requires some knowledge about data formats and libraries first, before starting to analyze this kind of data.

Our application case is limited to a handful of variables. However, this can be extended to more variables which will allow more comparisons. By including more variables and obtaining more comparisons, our visualizations need to be programmed in an interactive dashboard, whereas each user can search for the desired case.

With the extension, we get a larger variable space and hence the multivariate analysis will be more complicated. Hence, the extension is not straightforward and needs to be considered.

Additionally, each multivariate data analysis is executed for a chosen demographic/finance variable alone. A multivariate analysis of the health care variables along with the demographic/finance variables and geography is missing. To extend the consideration of the multivariate analysis of the health care variables to the demographic/finance variables at a two-level-method could be considered, as already researched in stacking in machine learning. That means, on a first level the relationships between the health care variables will be analyzed for each demographic variables with their given category.

ries. On a second level the obtained results will be analyzed along the demographic variables.

In our application case, we only considered the health care services and the actual situation of a pandemic situation. An extension would be to consider the evolution of the health status of a population. This would help to better plan the health care services.

7 Conclusion and Future Work

Visualizations have been applied for a long time in health care. Their importance level is increasing year by year. In this paper, we propose a visualization technique with algorithmic approaches combining health care data from the perspective of the patients with financial data with a fixed time stamp. Additionally, the combined data is analyzed along a multivariate statistic model to conjecture and hypothesize about weaknesses in the health care system. The small multiples allow to get a good overview on the hospitalizations over the age classes and the geography as well. However, it is impossible to conclude from the resulting graphical outputs what the impact on the intensive care unit actually is. Only through a multivariate analysis, some flaws could be determined. The main result is that the first canton having a COVID-19 case, namely Ticino, represents the biggest shortfalls on the intensive care unit. The Valais, which is the canton with a large number of hospitalizations does not seem to be that much impacted by the shortfall of the intensive unit care. However, the intensive care represented a big occupation. For future work we plan to create an advanced visual analytics system for this kind of data equipped with a multitude of interactive visualizations and algorithms. Moreover, user evaluation with and without eye tracking is of particular interest to detect design flaws and to improve our tool. We will also investigate more advanced statistical methods, also Monte Carlo simulations or agent-based simulations as well as more advanced multivariate analyses might yield better results.

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