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INTERDISCIPLINARY EXPLORATIONS FOR THE SCALING OF EXPERIMENTAL INTERVENTIONS

Matías Lopez-Rosenfeld, M. Soledad Segretin, Sebastián J. Lipina

Introduction

When addressing the large amount of information available in digital form on different aspects of human development, one of the critical aspects to consider is how to organize this information in order to answer different questions from different social actors. In this context, visualizations are one of the tools available that contribute to this goal[19]. The computer applications currently

[19] In computer sciences, visualizations have generally been addressed by two communities. On the one hand, those who deal with the interaction between people and computers consider visualizations as the study of technology in itself. Many of the tools that scientists use have been developed by this community. On the other hand, there are those who are involved in developing

available for the development of visualizations allow one to quickly generate maps, charts, timelines, graphics, word clouds, and search interfaces, among others. Neighborhoods, cities, and states are settings in which different types of life events occur for different social groups, and it is precisely in such settings is where human development occurs and where social relationships are built. For example, maps have been a key instrument to identify and solve challenges in the areas of public health (Reich & Haran, 2018), economic development (Klemens et al., 2015) and psychology (Rentfrow & Jokela, 2016).

Some challenges for the design and implementation of these computational efforts in the study of human development are related to the fact that individual data do not necessarily provide information to answer questions that involve processes at different scales (e.g., inter-individual). Furthermore, since each data source contains its own set of errors and complexities, adequate statistical methods are required to integrate information from different sources (Reich & Haran, 2018). However, efforts have begun to produce promising results. For example, Osgood-Zimmerman and colleagues (2018) and Graetz and colleagues (2018) analyzed failures of child growth in different African countries and their relationship to the amount of maternal education. They collected geo-located information on growth retardation, the loss of muscle mass, and weight of children under five years of age and the mothers' years of education, all of them from different surveys carried out in tens of thousands of villages during 15 years. They

graphics, who have largely focused their efforts on hardware to create high-quality visualizations for science and other user communities. The work of both research communities has increased the capabilities of creating visualizations through different developments, such as large-scale immersive environments, high-quality three-dimensional displays, rendering software kits, and visualization libraries.

also combined this data with information on climate and local geography, and validated their statistical model by first fitting it to data from one subset of locations, and then comparing their predictions with data from other different subsets of locations. The authors used their data to identify differences and predictions of improvements over time in different regions, and from this they also managed to specify intervention priorities for early childhood policies.

In another study, researchers and educators from British Columbia (Canada) used the Early Development Instrument (EDI) to assess the emotional, cognitive, language, physical, and social development of children at their level in early childhood education, and thereby examine trends in early childhood development in different neighborhoods and school districts of the city of Vancouver. The developmental risk maps based on EDI data helped to identify vulnerability and resilience factors in child development and local needs for intervention that can help families and communities to promote the healthy development of children before they enter the first grade of primary school. The visualizations generated in this project include maps that can capture different social groups at the community, provincial, and federal levels (Hertzman & Bertrand, 2007).

Another of the instruments that have begun to be designed and implemented with large databases to address public health and human development issues are algorithms that combine different forms of machine learning. For instance, Bansak and colleagues (2018) developed a data-driven adaptive algorithm that assigns refugees to different resettlement locations to improve integration processes in the host country. The algorithm uses machine learning to discover and take advantage of synergies between the characteristics of refugees and resettlement sites. In the first instance, it was implemented with data from the historical record of two countries with different allocation policies and refugee populations (i.e., United States and Switzerland). The simulation approach improved refugee employment rates by 40% to 70% relative to commonly used allocation practices. One of the advantages of this type of approach is that it has the potential to provide different agencies with tools for implementing actions, interventions, and policies that could be quickly applied within existing institutional structures. Likewise, the development of algorithms has also begun to be used in the simulation of interventions aimed at improving aspects of human development. For example, Chittleborough and colleagues (2014) used test effect estimates and structural models from the Avon Longitudinal Study, which includes a population of 11,764 children, to examine the simulated effects of interventions aimed at improving academic skills at the beginning of primary school in educational attainments at age 16 in a context of socioeconomic inequality. The highest intensity interventions showed a 5% reduction in the effects of such types of inequalities.

On the one hand, these type of studies show the availability of theories, statistical methods, and applications that allow analyzing health, education, and development problems at different geographical scales using robust methods and open source software. On the other hand, they also illustrate the importance of combining large databases with specific conceptual and methodological approaches from relevant disciplines such as epidemiology, developmental psychology, economics, sociology, and statistics. The understanding of spatiotemporal processes from such types of interdisciplinary approaches contributes to the design of appropriate and pertinent interventions for different cultures. However, the potential of visualizations in scientific research or in efforts to transfer scientific results to interventions and policies has not yet been sufficiently addressed. This would be associated in part with the fact that visualizations frequently become a final product of scientific analysis rather than an exploration tool. Also, many of the visualization tools available to scientists cannot be updated because they are not associated with databases hosted on the internet, so once they are created they become an immutable information product. One of the reasons for this limitation is that it is difficult to collect scientific data and it depends on specific methods, so the focus of the scientific effort is usually the generation of data rather than its eventual use in applications. Furthermore, many of the scientific problems are related and interdependent and therefore involve data from multiple instruments, disciplines, and sources (Fox & Hendler, 2011).

The capacities that are being generated and used on the internet could contribute to improving these aspects. These approaches are characterized by being user-friendly - which could allow scientists to rapidly generate visualizations to explore hypotheses - and by potentially contributing to visualization scaling. Also, both aspects would permit the generation of new collection and storage approaches to develop and maintain visualizations at a low cost. At the same time, these tools can create challenges that the scientific community must anticipate. First, new approaches are required to determine the best way to visualize scientific data. For example, Lengler and Epler (2020) developed a periodic table of visualization methods that shows different techniques organized by data type and complexity of their application. There are also discussions that propose to change the general principles of effective visualization to those of greater specificity for scientific use, such as discussions concerning the best way to combine statistical methods with visualizations (e.g., Card et al., 1999). Other types of challenges are related to how to create, maintain, and analyze data for visualizations, which implies taking into account the quality of the information, as well as its potential biases and contextual relevance. While significant efforts have been made over the past two decades to address these challenges, further research is still needed to generate scalable solutions that can be dynamically and interactively adapted and updated in the context of the internet.

Visualizations and simulations in studies on child poverty

Risk calculation system

Since the late 1990s, the Unit of Applied Neurobiology[20] (UNA) has carried out research aimed at studying: (a) the associations between child poverty and self-regulatory development (cognitive and emotional); (b) the mediating factors of such associations; (c) the design, implementation, and evaluation of interventions aimed at optimizing the self-regulatory development of poor children; and (d) the transfer of technical knowledge to the design and evaluation of early childhood policies. UNA's work has generated interest in different governmental and non-governmental organizations to explore possibilities for scaling up developmental evaluation procedures, as well as the design, implementation, and impact evaluation of interventions (e.g., Segretin et al., 2014).

In 2011, a national governmental agency in charge of the health of children from 0 to 6 years old living in a contaminated river basin invited a group of UNA researchers to collaborate with the design of developmental assessments and exploration of alternative approaches to address a diversity of developmental issues. Previously, they had implemented a screening test to detect motor, cognitive and language development issues, the results of which showed that 40% of the children evaluated did not reach the

[20] http://pobrezaydesarrollocognitivo.blogspot.com/

minimum levels expected for their age. The projection of this percentage to the child population of the hydrographic basin was 36,000 children. Consequently, this degree of problems revealed the need to expand the approach such that child health referrals were not concentrated only in hospital or community health centers, which in many cases did not have the resources required by some of the issues that needed to be addressed.

Based on contemporary conceptualizations of human development[21] we developed a calculation system that articulates a set of rules and instructions arranged in such a way that their sequenced combination produces a result in terms of a specific referral for a child and her family or caretakers (Lipina et al., 2015). Specifically, given an initial state of risks (i.e., high, intermediate, absent), for different aspects of development (i.e., cognitive and/or motor), temperament[22], and home stimulation for learning, and their combination, a final state (i.e., referral or intervention) is reached that consists of an indication for the child and her parents or caretakers to access a public service that would meet the needs posed by such a specific risk profile (Figure 1).

[21] Characterized by the permanent transformation of the biological and social systems it involves, so that the directionality of the developmental trajectories varies between individuals and populations

[22] In the context of this chapter, *temperament* is defined as the individual differences in reactivity and self-regulation in the domains of emotion, activity, and attention.

DEV	TEM	HOM	INTERVENTION
0-1	0-1	0-1	1 NO INTERVENTION
0-1	0-1	1-1,5	2 HOME STIMULATION
0-1	0-1	1,5-2	3 PARENTAL PSYCHOTHERAPY
0-1	1-1,5	0-1	4 PARENTING STIMULATION
0-1	1-1,5	1-1,5	4 PARENTING STIMULATION
0-1	1-1,5	1,5-2	5 PARENTING STIMULATION + PARENTAL PSYCHOTHERAPY
0-1	1,5-2	0-1	4 PARENTING STIMULATION
0-1	1,5-2	1-1,5	6 PARENTING STIMULATION + HOME STIMULATION
0-1	1,5-2	1,5-2	4 PARENTING STIMULATION
1-1,5	0-1	0-1	7 CHILD PSYCHOTHERAPY
1-1,5	0-1	1-1,5	8 CHILD PSYCHOTHERAPY + HOME STIMULATION
1-1,5	0-1	1,5-2	8 CHILD PSYCHOTHERAPY + HOME STIMULATION
1-1,5	1-1,5	0-1	9 CHILD PSYCHOTHERAPY + PARENTING STIMULATION
1-1,5	1-1,5	1-1,5	10 CHILD PSYCHOTHERAPY + PARENTING STIMULATION + HOME STIMULATION
1-1,5	1-1,5	1,5-2	10 CHILD PSYCHOTHERAPY + PARENTING STIMULATION + HOME STIMULATION
1-1,5	1,5-2	0-1	9 CHILD PSYCHOTHERAPY + PARENTING STIMULATION
1-1,5	1,5-2	1-1,5	10 CHILD PSYCHOTHERAPY + PARENTING STIMULATION + HOME STIMULATION
1-1,5	1,5-2	1,5-2	10 CHILD PSYCHOTHERAPY + PARENTING STIMULATION + HOME STIMULATION
1,5-2	0-1	0-1	7 CHILD PSYCHOTHERAPY
1,5-2	0-1	1-1,5	8 CHILD PSYCHOTHERAPY + HOME STIMULATION
1,5-2	0-1	1,5-2	8 CHILD PSYCHOTHERAPY + HOME STIMULATION
1,5-2	1-1,5	0-1	9 CHILD PSYCHOTHERAPY + PARENTING STIMULATION
1,5-2	1-1,5	1-1,5	10 CHILD PSYCHOTHERAPY + PARENTING STIMULATION + HOME STIMULATION
1,5-2	1-1,5	1,5-2	11 CHILD PSYCHOTHERAPY + PARENTAL PSYCHOTHERAPY
1,5-2	1,5-2	0-1	9 CHILD PSYCHOTHERAPY + PARENTING STIMULATION
1,5-2	1,5-2	1-1,5	10 CHILD PSYCHOTHERAPY + PARENTING STIMULATION + HOME STIMULATION
1,5-2	1,5-2	1,5-2	11 CHILD PSYCHOTHERAPY + PARENTAL PSYCHOTHERAPY

Figure 1 - Risk combination table (green: absence; yellow: intermediate; red: high), at the level of development, temperament and household, and of the possible interventions to implement. The suggested actions are based on interdisciplinary clinical intervention criteria commonly used in pediatric services of public hospitals in the City of Buenos Aires.

This system allows the simultaneous analysis of several levels of risk and suggests a specific solution that can address such needs at the clinical (health center), social development (e.g., child development center), and/or educational (e.g., school) level. Since this system was designed based on a multidimensional conceptualization of human development, it allows the incorporation of data from different types of development assessment tools into its calculation sequence. In their original design, combinations were tested based on the following evaluation instruments, for an age range of 0 to 42 months: (a) level of developmental analysis: Bayley Scale of Child

Development (Bayley, 2015) and Weschler Preschool & Primary Scale of Intelligence (WPPSI) (Wecshler, 2014); (b) level of temperament analysis: short version of the Rothbart Child Behavior Questionnaire (Putnam & Rothbart, 2006); and (c) level of home analysis: HOME Inventory (Caldwell & Bradley, 1984). Finally, to determine the different interventions, pediatric clinical and psychopedagogical criteria commonly used in pediatric hospitals in the City of Buenos Aires were used.

Computational explorations

Once the collaboration with the governmental agency ended, we began a new stage of explorations of the calculation system together with researchers in the area of computer science. The aim of such explorations was to improve the understanding of the study of self-regulatory development and its modulating factors with and without the implementation of interventions aimed at optimizing it, based on the use of different concepts and computational tools.

Below we show some examples of visualizations developed with the aim of improving and making more complex the observation of data from research carried out at UNA, in studies with children between the ages of 4 and 8 years from different socioeconomic contexts and cities in Argentina. As in the case described in the previous section, the same indicators were used for the levels of analysis (i.e., cognition, temperament, and home stimulation), and risk levels (absent, medium, and high for the colors green, yellow, and red, respectively) defined based on comparing the value obtained for the indicators with that expected for the context of each child. It is important to clarify that such aim does not imply that visualizations replace statistical methods that allow quantifying the observed effects, but rather contribute to developing intuitions and new hypotheses that could eventually be statistically evaluated.

Sankey diagrams

A Sankey diagram is a visualization that allows representation of the development of participants of a research study with longitudinal design to be observed over time. The diagrams in Figure 2 allow the verification that the performance trajectories through the evaluation rounds have had a variable development between individuals, generating a new exploration opportunity aimed at identifying factors that could be associated with such variations.

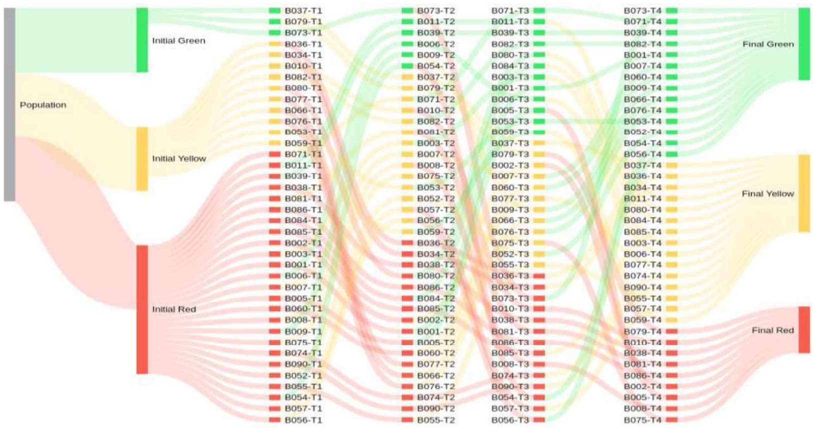

Figure 2 – Sankey diagram showing the development of cognitive performance of a group of children aged 3 to 5 years from an intervention study (longitudinal design) carried out in the city of Buenos Aires (Segretin et al., 2014). Each alphanumeric code represents an individual participant. Each column is an evaluation round. Color sets represent risk status at the start (left) and end (right) of the study.

An alternative interest for this type of visualization is the possibility of involving an interactive phase that, given the actions of a user -for example, a researcher interested in analyzing the impact of interventions aimed at optimizing children's cognitive development- can extract more specific information from a dataset. In this sense, Sankey diagrams are exploration tools that can select trajectories of particular individuals (Figure 3) or groups of individuals (Figure 4) which is achieved by placing the mouse cursor over a particular trajectory.

Although these visualizations do not contain information about the causes that explain why each individual or group has such different trajectories, it allows us to explore the occurrence of these phenomena. The causes of such diversity in the development of trajectories should continue to be explored; but individual or group development can be quickly consulted and observed with this tool.

Figure 3 - Sankey diagram showing the development of cognitive performance of the same children as in Figure 2. This case illustrates the selection of a single path that starts from a high risk level and reaches a low one at the end of the study. Identification of a single path is done by putting the mouse cursor over it.

Figure 4 - Sankey diagram showing the development of the performance trajectories of all the participants who ended up with no risk (green) and who started from different risk levels (green, yellow and red).

Risk states and simulations of interventions

Another visualization we developed allowed us to explore the makeup of the population of children who participated in the aforementioned study. In other words, we continue to consider the dimensions of cognition, temperament, and home stimulation. Each risk combination configuration of these three levels represents a state (e.g., green cognition + yellow temperament + red hearth versus yellow cognition + yellow temperament + yellow health), which permits the analysis of the distances between different states, as well as their similarities and differences based on different theoretical aspects of the combination of risks at different levels of development. One possible way to approach such analyses is by establishing relationships between possible states and defining whether two states are closer if they differ by one level, with a single adjacent color change (e.g., from red to yellow, or from yellow to green, but not from red to green). These types of definitions could contribute to the identification of a particular risk association structure for a specific population.

For example, Figure 5 shows the combination of risk states of the three levels corresponding to the population of children in the Segretin and colleagues (2014) study, represented by united circles. In this case, the opacity of each of the states was added to indicate the number of individuals in this state. In this figure it can be seen that: (a) the most frequent states are red + green + green and the variation of the household level to yellow and red; (b) there are combinations that are not observed, such as red + red + red; and (c) there are no combinations that have the temperament level in the red state.

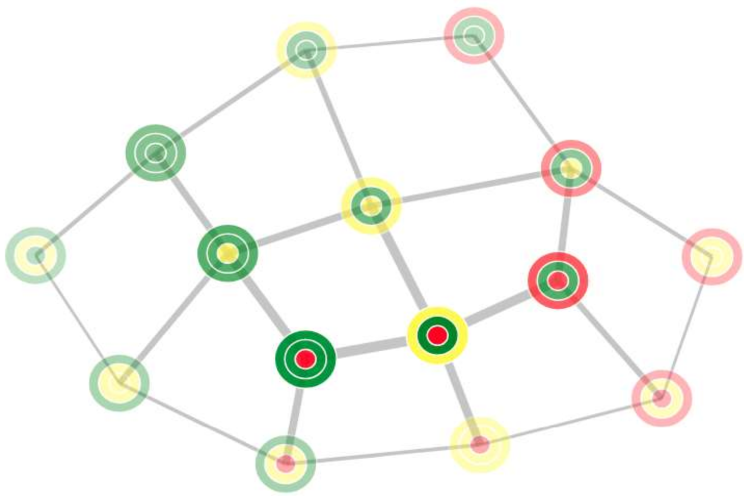

Figure 5 – Example of a network of risk states for cognition + temperament + home levels, of children from Segretin and colleagues study (2014).

Another interesting aspect of this visualization is that it can be used to simulate interventions and thereby analyze state changes. In the context of this section, we define simulations as calculations and operations that emulate what could happen under certain conditions over time. The latter requires theories of change for each level of analysis and their combination, on which we do not necessarily have evidence. In such a context we can apply assumptions based on statistical criteria, from clinical practice, or by making hypothetical assumptions based on the knowledge available in developmental science. For example, if we assume that the risk can be changed one level at a time, this would allow decisions to be made concerning at which level it would be necessary to invest intervention efforts and thereby promote the desired change of state. In an ideal scenario in which every investment is possible, the goal would be that all the states of all the children end in green for all the levels (cognition + temperament + home stimulation). However, this is not usually the case, so this type of visualization tool could contribute to identifying different subgroups of states that would have different intervention needs and priorities. For example, in a subgroup characterized by a state of green cognition + green temperament + red home stimulation, the priority could be to carry out interventions aimed at optimizing home conditions. The costs to generate changes at this level would be significantly higher and difficult to achieve compared to another characterized by green cognition + yellow temperament + green home, which could consist of working with short-term parental guidance strategies. In any case, these types of visualizations could contribute to efforts to identify subgroups with different intervention priorities. It is important to note that in the examples presented here only the cognition, temperament, and home stimulation levels were used. To the extent that researchers include other dimensions and levels, they could involve other types of tools and theories of change.

In the area of simulations there are different alternatives to explore, the choice of which must be adjusted to the research or policy objectives. One such alternative is to assume that each individual is an intelligent agent, defined as an entity that has a possible repertoire of actions that can result in profit or loss. In such a modeling process, agents need to be defined in terms of their characteristics. In the current example, an individual would be represented by the indicators of cognition, temperament, and home stimulation, each of which could take the values of green, yellow, and red. On the other hand, it is necessary to define the actions of each individual, which could eventually be defined as action 1, action 2 ... action n. However, in the current example, it is difficult to define such actions because it is not possible to anticipate the actions of each individual and the eventual gains or losses (e.g., changes in temperament or home stimulation due to interventions are not changes that depend solely on, or necessarily from, the actions of an individual). This implies that the nature of the data conditions the possibilities of implementing simulations, so in cases like this it is necessary to implement other strategies.

An alternative strategy we explored was to define probabilities of change of states. For example, taking a single level (e.g., cognition), and the criterion that there can only be a change from one level to an adjacent level, an individual or group of individuals whose current state is defined as yellow, in the future - for example, after an intervention - it would have three possible scenarios: green (improvement), yellow (remains in the same state), or red (worsens). In our exploration, we define different types of probabilities for each transition. In the example presented in Figure 6, the probability of staying in the green state is 70%, while the probability of going to the yellow state is 30%. This means that if we simulate 100 changes, an individual whose initial state is green 70 times would stay green while 30 would turn yellow. The same occurs in the yellow state, which has a 50% chance of remaining yellow, 30% going to the green state, and 20% going to the red state. With these types of rules it is possible to see the evolution of a population over time. Different types of probabilities would lead us to different patterns of development, so that some changes would be more pronounced while others slower.

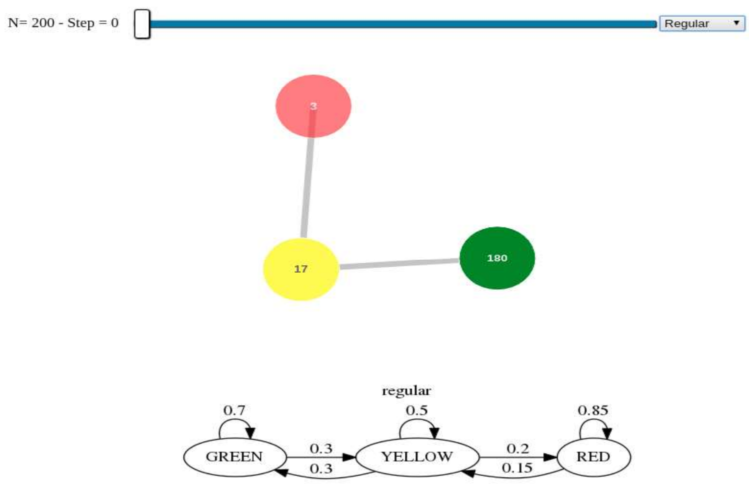

Figure 6 - Example of state change probabilities in a computer simulation context for an organization level (i.e., cognition).

The challenges for the use of this alternative are determined by several factors: what the probabilities are, how they could be modified through interventions, and what would happen in each individual or group over time. Such information is what should be considered to inform the different theories of change of the dimensions or levels to incorporate in the analysis. Likewise, this simulation tool can be used to address more complex problems involving more levels that represent different dimensions of analysis, which in turn may or may not be modified based on different types of probabilities. This poses a new challenge since it implies more definition requirements. For example, in the case illustrated in Figure 7, in which 3 levels are used, it is necessary to have the definition of 21 probabilities (3 metrics x 7 transitions), which raises the possibility of carrying out many tests, but also the difficulty of defining which values to incorporate in the model.

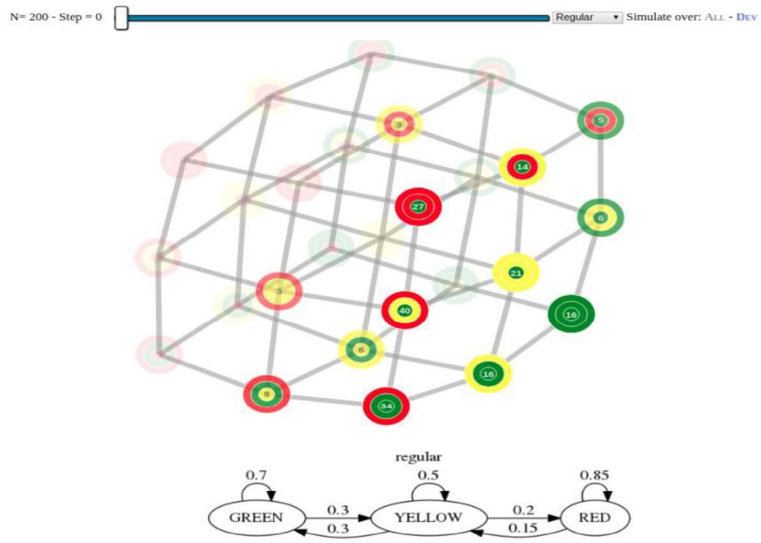

Figure 7 – Example of state change probabilities in a computer simulation context for three levels of organization (i.e., cognition, temperament, home stimulation).

In summary, the testing of different models and probabilities would contribute to the replacement of intuitive approaches by those in which it would be possible to validate hypotheses about the change of states of specific populations over time or by interventions.

Geolocation

Another type of visualization we explored was one constructed from the place of residence of children, in order to be able to observe trends and regularities in the states and changes of states over time of the levels of cognition, temperament, and home. An example of such an approach can be seen in Figure 8.

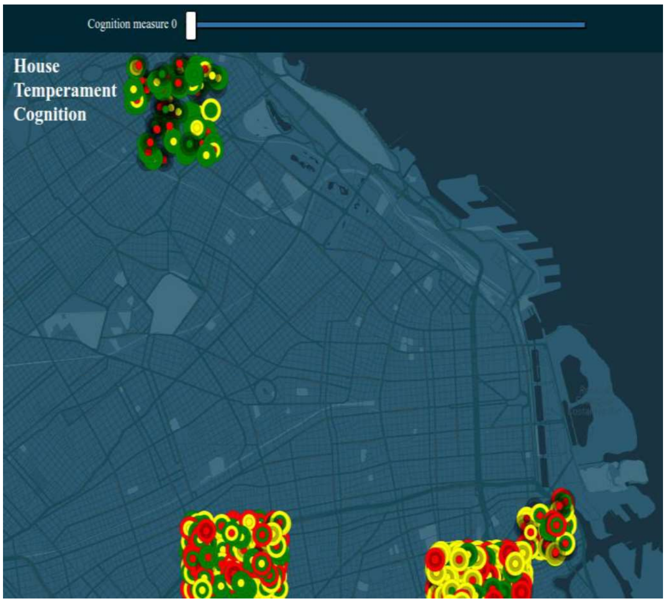

Figure 8 – Example of geolocation of risk states for levels of cognition, temperament and home stimulation ("house"). Each set of three rings represents a child and the location of their home on the map of the city of Buenos Aires. At the top can be seen a status bar that can be moved to the right to check the status of changes as a result of interventions. The data correspond to the study by Segretin and colleagues (2014).

When observing the map as a function of the three levels, some regularities are observed that would allow distinguishing subpopulations in two regions of the territory (i.e., the risk levels in the north of the city are lower than those in the south). Furthermore, by selecting one level at a time it is possible to show that: (a) the level of temperament risk does not vary in the three neighborhoods analyzed; (b) the level of house risk is lower in the north of the city, according to expectations based on the socioeconomic distribution of the population; and (c) the level of cognition risk shows more variability within each of the neighborhoods.

Conclusion

As information technologies allow researchers to develop visualizations that contribute to improving the understanding of the problems under study, they may begin to think of them less as a final product and more as a complementary tool to build knowledge. This requires researchers to use visualizations from the early stages of an investigation, documenting the relationships between them and the data. Consequently, for these purposes it is necessary to foster dialogue and collaboration between researchers from different disciplines and computational scientists to ensure that the needs of the development of new analytical methods are met and to explore generalizable forms of scalability.

In addition, frequent use of visualizations in research work could improve requirements for the design of new tools, as well as learning to share and maintain workflows and visualization products in the same way that other scientific knowledge is shared. A side effect of these efforts could be reducing costs and increasing accessibility, to generate more sophisticated visualizations of increasingly large datasets.

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