Visual Analytics for Bettering the Evaluation and Care of Health

Literature Review

Erica Hu (430220535)
Supervisor: Dr. Simon Poon

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1 Introduction

The field of data science and informatics in healthcare and medicine is a rapidly growing area especially with increasing availability and adoption of electronic health records (EHRs) [1]. With immense amounts of data being recorded daily, this presents an opportunity to analyse this information in the form of interactive web-based visualisations. Over the years, the availability and demand of data visualisation tools have also increased with expansion of web development. With this rising importance of information retrieval and representation, the growth of areas like HCI (Human-Computer Interaction) is seen.

As technologies and research areas in data visualisation expands, an opportunity arises to apply these skills and methodologies on the abundant digital data in healthcare and medicine. With the digitisation of medical data, there has been a rapid emergence of architectures that manage national electronic health records internationally [2]. Whilst digitisation of health records come with many advantages such as consistency and lower error rates, there is a lack of work in representing this information graphically, especially in Australia.

Graphical representations of data more effectively communicates information to human readers, which is a concept that has been researched widely in the HCI and psychology community. This extensive field dedicated to researching how humans interpret abstracted data and make decisions is known as 'sense-making'. There have been numerous studies conducted surrounding sense-making, where the effect of graphically represented data is measured against the effects of traditional statistical representations. These measured effects are often used to evaluate decision-making processes of scientists in a laboratory environment or policy-makers in a governing body.

The gap exists where the two fields, medical informatics and sense-making, overlap. This is especially prevalent in the context of Australia. There have been research projects, namely the BEACH (Bettering the Evaluation and Care of Health) program, where cross-sectional data is collected over an extended time-period with the aim of improving the quality of health and care in the field of general practice. If policy-makers, researchers and the general public are able to access rich and high-quality data in easily-understood visual representations, an opportunity arises where weaknesses and problems within the healthcare system are more quickly recognised and remedied.

While visual analytics provides an opportunity to improve the state of healthcare, the potential biases and misrepresentations in data must be measured, which is where sense-making experiments and practices may aid in identifying when and where visualisations are appropriate in generating correct insight.

2 Uses of Visualisation in Health Informatics

This section of the review will focus mostly on the use of electronic health records - its introduction and its strengths and weaknesses at representing and retrieving data. The existing use of visualisation tools for EHR will also be discussed from literature.

Electronic Health Records

National electronic health record architectures have been emerging and presenting challenges to the existing healthcare systems, practitioners and policy-makers. *Gunter & Terry* [2] have presented a discussion and critical analysis of these challenges and looks at the different methods of EHR implementations in the United States and Australia.

The introduction of electronic health records has delivered many advantages to the medical system, especially in regards to efficiency and error-handling. As the input fields of electronic records are restrictive and decrease errors due to handwriting problems, the data collected in general is cleaner and superior to traditional paper records. Another advantage is the ease of physical storage, back-up and transportation. *Gunter & Terry* further discusses the role of information technology as the forefront of medical backends, especially in providing comprehensive longitudinal data. Longitudinal data is especially useful for tracking all medical interactions across the population, and is the method used predominantly in the United States. This described system aims to amass a collection of health information on each individual to feed into national 'knowledge and decision support systems' [3].

The implementation of large-scale electronic health record systems is also highly expensive [2], and though the aim is to better the care of health, there is still much debate surrounding the safety and feasibility of sharing medical information across multiple institutions and regulating bodies. However, the growth of these EHR systems will continue to grow, as third parties, hospital administrators and physician advocacy groups continue to push for centralised intelligence.

Gunter & Terry's work was focussed heavily on the costs and risks surrounding litigation and privacy of patients and did not analyse the level of participation from uses on both ends. In particular, though the implementation of EHRs will eventually become compulsory in many states internationally, the quality and accuracy of data input was not analysed, especially in the context of older practitioners who may not be computer literate. The article lacked in quantitative analysis on the efficacy of EHR systems, where metrics such as latency and accuracy of users may be indicative of the gaps in the system implementation that could be addressed in the future.

The lack of investigation into user participation is addressed by *Tsai & Starren* [4], which focusses on the role of patients' interaction within the digital system. The use of EHRs allows for better analysis of all health histories, especially when in the form of time series. An issue that arises is how this data is analysed and interpreted, given that the patient should have access rights their their own information. As a patient user, the large amount of personal clinical data may be overwhelming, and the knowledge's effect (if any) on interaction with their general practitioners including the decision making process during treatment is yet to be measured in depth. Representing traditional clinical information digitally or graphically could poise as a litigation risk based on information being misconveyed. Representing information differently could stimulate different questions to be asked, and it is still being questioned whether having interactive data results will help end-to-end users make better decisions and find trouble spots for allocation of resources.

Though different representations of medical data could lead to biased treatment and policy decisions, *Walsh* argues from a clinicians point of view that medicine is far from factual science [5]. Patient management is a process that requires initial tentative decisions and diagnoses, which continually evolves based on re-analysing and reinterpreting historical data given new information per encounter. Again, this process is dependent on the participation of patients aiding practitioners in making the most appropriate medical decision. The incorporation of EHRs provides a better platform for information retrieval that reduces duplication while also improving comprehension. Having a centralised source of data also provides a holistic view of the system's efficiency and weaknesses, which signals to administrators the areas in need of improvement of management or resources/subsidies.

Visualising Electronic Health Data

While electronic health record systems are continually producing burgeoning amounts of data, the challenge becomes visualising this high-dimensional time-series data in innovative and creative ways. *West et al.* [6] have identified some of the challenges discovered by previous research (between 1996 and 2013) and provided a systematic review of new design techniques seeking to improve the effectiveness of visualisations.

Firstly, we introduce the most widely recognised visualisations, which are the common two-dimensional graphs often in linear or bar chart form. While these charts are easily interpreted by a wide audience, the issue arises when multiple dimensions and measurement axes are introduced, as is usually the case with medical data. A solution that is effective up to a point may be stacking the bars and lines, or changing the colour scale to represent a third dimension. However, these additions on top of the traditional line and bar graphs are only effective up to a certain point before the chart becomes too crowded and inhibits the reader from understanding and retaining the information.

One of the most effective methods of representing medical data for knowledge generation was the **coxcomb chart**, intoduced by Florence Nightingale in 1858, which implements a polar-area graph. Nightingale used this type of graph to represent the causes of death in each month of the year during war, which made the graph's radial style highly effective for cyclical time series data. Another graph used widely in scientific laboratory diagnoses is the **fishbone diagram** where problems and potential causes with worst case scenarios are plotted along the fishbone 'spines', much like a tree. The advantage of using a standardised graph like this ensures comprehension from scientists and medical practitioners in the field. This style of graph is widely used as an indicator for the need of intervention, and the effectiveness of intervention.

Clinical data by nature is longitudinal and information changes over time is most easily modelled with time as the horizontal axis. This is also the layout that's most easily intepreted, and provides the clearest insight into changes in trends [7], associations and comparisons between features. The existing LifeLines and LifeLines2 project[1] run by the University of Maryland is focussed on *West et al.*. Though existing tools are available and in development for representing medical data, there has still been little application of it on large scale. Though *West et al.* argues that because health records are such large and complex datasets, a completely new set of visualisation techniques should be invented and explored. Though this may be in part true, the more traditional types of graphs should not be completely discounted, as they are still most widely understood. The need for large scale comprehension is important if information is to be shared with administrators, institutions and governing bodies to identify trouble spots and make decisions. Further, because there is little application on the large scale as forementioned, it is difficult to assess how generalisable these visualisations are, and so the experiments mentioned in this paper are tightly bound to a small group of experimental subjects.

Research conducted by the LifeLines team found that users wanted to see both numerical and categorical data as well as the ability to dig deeper from overarching trends into the finer details. These features were introduced in LifeLines2, which converged with similar features of another system, LifeFlow[2], also run at the University of Maryland. The advantage of LifeFlow was that it allowed new users to explore the data at a high level and understand general trends and patterns.

To further understand how patterns and trends change over time, *Hripcsak* [8] introduced a method of using simplified linear graphs to represent the correlation between abstract concepts with laboratory values. *West et al.* recognised *Hripcsak*'s idea as a useful method of showing how temporal patterns can be found visually in EHR data using pattern matching, but was discounted due to its lack of new and innovative attributes. However, this research may be useful in correlating multidimensional laboratory values with time as a method of

[1] http://www.cs.umd.edu/hcil/lifelines/
[2] http://www.cs.umd.edu/hcil/lifeflow/

dimension reduction through the aggregation of multiple similar records.

Recalling Nightingale's polar-area graph, a similar concept was proposed by *Joshi & Szolovits* [9], where a radial starburst is used to represent data over a 100-dimensional space. Due to the data's dimensional complexity, machine learning was used to cluster similar groups of patients based on eight features. This clustering step allowed analysts to look at patients, their condition and severity with a simplified profile (based on the cluster attributes) to provide context. This is a classic example of how 'big data' methodologies have aided in simplifying the analysis of high-dimensional clinical data. Reducing the number of dimensions also greatly reduces variance in the statistics, which potentially provides an interesting foundation for decision making tools. A drawback is that *Joshi & Szolovit*'s tool is static, lacking in interactive features like LifeLines and LifeFlow that allow users to look beneath the top layer graphs. However, *West et al.* still deems it a useful tool as it is customisable with filters and switch-on/off features.

Finally, some of the most important considerations when visualising medical data is how to convey information effectively and correctly without overwhelming the viewer with a cluttered graph. This paper has collated many worthy researchers' experiments with styles and methods of visualising complex data, and features such as colour, normalising, scaling and resizing data (clustering to address dimensionality) all have their purposes depending on the intended information to be conveyed.

3 Visualisation Methods

While this review so far has predominantly focussed on specified visualisations of medical records and health data, there is a plethora of external visualisation methods that have yet to be explored in the medical informatics field. This section will look at some general recommendations for creating effective graphs and the insights that can be gained from them.

Visual Perception

Contemporary data visualisation tools often look at all possible mappings between data and visualisation elements, with the aim of choosing the best combination between the two. Given the large set of possible mappings between data and type of visualisation, the best mapping should fulfill the user's information needs be best. *Gulden*'s paper [10] looks to optimise this process through the use of **Gestalt Patterns**. Gestalt Patterns in this paper refer to a psychological phenomena when "The [perceived] whole is other than the sum of the parts", occurring during the cognitive processes of humans understanding visuals. The features emphasised in human visual perception are broken down into shape, colour, orientation and alignment. Noticing one feature out of a crowd as differently coloured is an example of human pattern-matching, which is highly important when considering the types and styles of visualsation to be used best to communicate information.

To break down the optimisation model, visual variables are used as features that compare efficacy of certain graphics. The seven visual variables chosen are: **shape, colour, size, orientation, size, value** (lightness/darkness) and **texture**. Next, the type of data of interest is defined as either quanitative, ordinal or nominal, and the most effective types of visual variables are linked together.

Though this model of variable selection was interesting in choosing the appropriate visual tools for types of data, the degree to which the author's tool improves efficiency in finding the optimal mapping has yet to be examined. Further, the model prototype was based on previous literature, but was not fully tested. While an interesting concept incorporating human visual perception into data analytics, *Ceneda et al.*'s paper [11] better defines the variables in human perceptron and bridging the gap of knowledge retrieval.

Human perception is biased and users are more likely to notice features that are greatly different from the others. *Ceneda et al.* builds on a conceptual model of 'guidance', where the knowledge gap of the user is identified first. This gap may be either known or unknown (i.e. the user is actively seeking an answer, or the user is scanning for general knowledge). The next step is what the paper calls a guidance function, which takes the user's knowledge gap and additional input, where input is a combination of domain knowledge, data, visualisations and images. The output of this guidance function should be the knowledge that the user is seeking.

The aim of this paper was to optimise the 'guidance function' so that the user will always gain the relevant information to bridge their knowledge gap. Though both papers bring interesting methods of modelling the decision making process of selecting the best visualisation features, neither provided an extensive concrete mapping of features to types of variables, which would be useful knowledge for the visualisation community.

Time Series Data

As discussed in multiple articles, the effective representation of time series data is highly important in generating insights in clinical data, which is temporal by nature. The advantages of implementing visualisations on large time series data is outlined by *Lin et al.* [12] where visualisations are used to discover patterns in large databases.

One of the greatest advantages of visualisation is fast anomaly detection by human eye. For example, in time series data mining and systems monitoring, the problem of detecting anomalies, faults and interesting patterns has received a lot of attention in research areas. This advantage is extendible to medical data in combination with the fishbone diagram introduced by *West et al.* [6] to identify abnormalities that should receive attention and treatment.

Lin et al. also introduces a calendar and cluster-based visualisation, where insights can be gained from following the progress of a particular cluster, or the changes within a given cluster. This is a technique that is apparently widely used, as was already introduced by *Joshi & Szolovits* [9] to aggregate similar groups of patients. However, here the author's incorporation of a calendar allows for an interactive perusal of the data, rather than implementing the timescale as the horizontal axis.

Further, in cyclical time series data, a spiral graph is reintroduced by *Weber et al.* [13] and mentioned by *Lin et al.*. A tool was developed where each periodic section of the time series is mapped into a 'ring', and attributes (such as colour texture, line thickness) are used to represent the multiple dimensions in data values. This method aimed to identify periodic and cyclical structures and patterns, however a core weakness of this method was its dependence on choosing the correct period so that cyclical effects are not averaged out. Further, this method is strictly bound to data that do exhibit cyclical patterns, and provides very little insight to those that do not.

4 Evidence-Based Decision Making

Sense-Making

Found from numerous literatures and experiments, the brain finds it easier to recognise and process visual patterns and trends over numbers and statistical values. This means that to provide meaning from large datasets to human audiences, the data needs to be extrapolated into visual patterns and trends. A research field known as **sense-making** was introduced earlier in this review, and *Lee et al.* [14] extends on this through the use of digital visualisations.

The paper centres around an experiment that analyses how people make sense of unfamiliar visualisations, based on an existing model, NOVIS (NOvice's information VIsualisation Sensemaking). Historically, NOVIS has been very theoretical without a distinct and concrete implementation, and this paper has developed and proposed their own implementation that tests the quality and rate of information retrieval in users, and aims to investigate how people make sense of unfamiliar visualisations.

When looking at how graphs a comprehended, the primary factors that influence comprehension are: (1) graph formats, (2) visual characteristics, (3) knowledge about graphs, and (4) knowledge about the content described by the graph. The method included both quantitative and qualitative assessments that followed the NOVIS model, which consists of the five steps (plus miscellaneous):

1. **Encountering visualisation**: Users are presented with the visualisation, but are not expected to do anything. Feedback is collected, such as initial impressions of the image.

2. **Constructing a frame**: Users broadly interpret the visualisation. What does it represent? What do the features (numbers, colours, etc) mean?

3. **Exploring visualisation**: The users understand the visualisation more deeply. They *retrieve information* by comparing and contrasting graphs and numbers, and noticed patterns. The users also *recall domain knowledge*. How does their existing knowledge affect their interpretation?

4. **Questioning the frame**: This is when the user starts doubting their assumptions and interpretation of the unknown visualisation, and start linking to their unknown knowledge.

5. **Floundering on visualisation**: This is when the user does not know what to do with the information visualisation as none of their 'frames' seem appropriate.

6. Miscellaneous

The greatest limitation of this experiment, also identified by the author, was the use of the **think aloud method**, where not all thought processes are captured as participants will be thinking a lot faster than they can verbalise. Despite this limitation, this paper does contribute to the visualisation community to help understand how novice users' function cognitively when viewing unseen visualisations. This helps designers and developers to pinpoint the techniques and features that should be emphasised to aid the novices' visualisation literacy.

Improving Healthcare

Clinical research is currently heavily reliant on clinical trials, however there is now an observed transition towards using existing clinical data as exploratory and discovery research. This transition has shown a shift of researchers paying more attention to large datasets of patient history. Visualisations are able to quickly reveal problems in data quality and data appropriateness, which is a prominent issue when existing clinical data is repurposed for a secondary experiment. *Shneiderman et al.* [15] explores some of the ways that interactive visualisations can help improve the quality of healthcare.

This paper again emphasises the importance of temporal patterns, and how clinically relevant patterns are often hidden in the data and inaccessible without visual analysis. Additionally, national health data is inherently geospatial, which means that the data will vary from individuals, to households, and even entire states in the country. The issue of multi-dimensionality is reintroduced, making it difficult to find patterns and interaction terms that help to define statistical relationships (including clusters, outliers/anomalies and gaps in data). Due to the nature of the data, the use of interactive visualisations can greatly enrich and simplify the knowledge gathering process.

If knowledge gathering is available to a wide range of viewers, including clinicians and regulators, the insights generated can greatly simplify the data-driven policy-making and decision-making process. Firstly, the benefit of visualisations to clinicians is the ability to more effectively identify cohorts of patients that fit the requirements for a particular clinical trial, as patient selection has historically been an expensive process.

Secondly, having available mass health data represented intuitively can greatly improve the public's understanding of the medical health system and its drawbacks by demystifying the encoded data. This generates public awareness, which is often the driver for regulatory and policy changes. With improvements in tools and methods of analysing multivariate data, generated insights can help decision-makers gauge the health and treatment of the population. For example, recognising gaps in populations' access to healthcare, nutritional standards and prevalent ailments can aid in policy-making.

Further, recalling visualisations' potential to identify anomalies, this potential may also be extended to model epidemics and evaluate responses [16]. Epidemics (such as obesity) are known to follow particular trends and patterns, and being able to identify them earlier on may aid in monitoring, predictive analytics and treatment. However, one of the most difficult issues is the correlation between multiple variables and insights, as interactions and comorbidity are rarely transparent relationships.

5 Evaluating Performance and Contributions of Visualisations

While visualisations presents the opportunity of improving many processes and generating new insights, the effectiveness of these tools must also be analysed. The following are two main experiments that have looked at the testing visualisation perception extensively.

Accuracy and Latency of Decision Making

Clinical decision support systems (CDSS) are health information technology systems that help with clinical decision-making for health professionals and physicians. These systems aim to link observations and symptoms during health encounters with historical knowledge to influence clinicians by providing insight and information to improve healthcare. These systems have now evolved beyond relational databases and have started including smart templates, data visualisations and improvements in graphics. With CDSS's now encompassing graphics and visualisations, there is an increasing need for evaluating the speed and efficacy of certain data representations given the appropriate task.

To evaluate a visualisation model, *Pieczkiewicz & Finkelstein* [17] have devised a testing model based on four dominant measures proposed by *Starren & Johnson* [18] as defined below:

- **Accuracy** is the overall correctness of the answer or the overall quality and appropriateness of the decision made based on information presented in a visualisation.
- **Latency** is the amount of time the user takes to make a decision based on the visualisation.
- **User preference** is the degree to which a user chooses one visualisation over another, and though this may not impact performance, it may be indicative of types of visualisations that are more likely to be ignored in reporting.
- **Compactness** is the size of the visualisation on a display medium.

This experiment utilised a multi-reader multi-case (MRMC) design, where multiple readers examine all the cases under all the different modes of interest. This method is commonly used for assessing accuracy, but is also extendible to measuring latency. The advantage of using MRMC is that it provides control over potential unpredictable factors that may arise in a clinical setting. Because each individual is assessing the same set of different test cases, the results may be averaged out reliably without needing to account for individual tendencies and biases given a certain dataset.

Of course the reliability of the results are still dependent on selecting good representative cases and readers, in which case MRMC boasts generalisable and reproducible evaluations. However, a drawback of MRMC recognised by the author is that it's not 'naturalistic'. This refers to the fact that it is not clinically realistic in reality for readers to assess that many cases sequentially, meaning the conclusions may be taken out of context.

The design of this experiment was comprehensive and took into account the needed sample sizes, as well as the user characteristics such as backgrounds and levels of experience as a method of normalising the variation in results. A difficulty that was mentioned but not well addressed was how the 'gold standard' was established for each test case (as in the most correct decisions given a clinical visualisation). In reality, it is difficult to define the 'truth' and best decision given medical records of a patient. However, a definition of some of the qualitative and quantitative measures in defining the optimal solution(s) would have greatly strengthened the experiment proposal.

Comparing Visual Analytics with Conventional Analysis Methods

While *Pieczkiewicz & Finkelstein*'s work focussed on comparing decisions made based on visualisations against the 'gold standard' or optimal solutions, an alternative method of analysis involves comparison between two communication mediums. A comparative study of domain scientists' trust in visual analytics and conventional analysis methods is introduced by *Dasgupta et al.* as the second alternative [19].

This study addresses the lack of empirical research in the investigation of the impact that visual analytics have on domain experts' trust in the data and their insight generation process. The interaction between **familiarity** and **type of medium** on the perceived confidence in the analysis outcome. The two gaps in research that are filled by this paper are: (1) determining the type of visual analytics design that ensure high trust in domain experts, and (2) determining whether a transparent visual analytics general process induce a greater level of trust in domain experts than more traditional data representations.

Conventional tools employed were results and data from Excel and R, and for each output there was a corresponding graphical representation. The three different types of graphs used were: (1) a **heatmap** showing an overview of the dataset of quantitative measurements, (2) a **pathway** which is a logical group of proteins (or attributes) that work together, and (3) a **canvas** which is an interactive 'board' that allows the user to pin data and hypotheses on cards. Scientists (biologists) were broken into two groups: experienced and novice. Given both versions of the data, these scientists were assessed while conducting tasks that fall into one of two categories: retrieval and interpretation.

The final analysis looked at two hypotheses: (1) the level of trust vs. experience in the field, and (2) the level of trust vs. complexity of the task. The final results concluded that with complex tasks, subjects were more likely to look at hte heatmaps, as they were easier to interpret when large amounts of numerical data was involved. Secondly, experience did not appear to affect the results, which surprised the authors. Even biologists with limited statistical knowledge were able to investigate the large and complex datasets with the aid of visualisation tools. The only difference found was that more experienced scientists tended to be more sceptical of the data backend. They preferred the opportunity to access the data and statistical tests. Though they trusted the visualisations, they believed that there may be better ways of priming the data for presentation.

This experimental design is both relevant and extendible to testing the performance of medical data visualisations. This is due to the fact that both datasets are rich in details and parameters, where there often isn't one optimal solution or decision to be made, but rather an optimal *range*.

6 Conclusion

With the growing adoption of electronic health data collection, there is an increasing need for interpreting this data in more effective and innovative ways to aid decision and policy making. While there are medical record visualisation tools being developed and explored, they have not yet matured to be generalisable on the national scale to generate insight and knowledge. Additionally, research in data visualisations have been around for decades, but never truly expanded as it has recently with the inundation of medical and meta data. This presents an opportunity for the two fields to work complementarily. However, a gap in research has yet to be filled where the effectiveness of cross-sectional medical data represented in visual form is analysed on its efficacy of knowledge delivery and insight generation.

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