Sim•TwentyFive: An Interactive Visualization System for Data-Driven Decision Support

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Abstract

Clinicians at the bedside are increasingly overwhelmed by an inundation of information and must rely largely on pattern recognition and professional experience to comprehend complex clinical data and treat their patients in a timely manner. Traditional decision support systems are based on rules and predictive models and often fail to take advantage of increasingly large digital clinical data stores available in real-time. We propose an alternative approach to delivering data-driven decision support based on an interactive system for exploring and visualizing a context of physiologically similar patients from a database. Here we present Sim•TwentyFive, a highly flexible, responsive, intuitive prototype with a comprehensive set of interaction techniques that effectively reduces the cognitive burden of querying, exploring, analyzing and comparing similar past patient episodes. Quantitative performance tests and anonymous summative evaluations from PICU physicians indicated that Sim•TwentyFive is an efficient, intuitive and clinically-useful tool.

Introduction

Critical care necessitates highly time-sensitive decision making, requiring clinical staff to respond quickly to the large amounts of data produced by patients in the intensive care unit (ICU), much of it streaming continuously from sensors or entered by other clinical staff asynchronously. ICU staff must integrate and comprehend this stream of data in the context of their education and professional experience, thereby identifying similarities between the current and past remembered cases.

While electronic medical records (EMRs) are rich resources of patient data, there are no tools available for retrieving and exploring data of physiologically similar patients to complement a physician's real-world experience and prior knowledge. Currently, such querying and exploration is done using heuristic and manual searches that are based only on categorical variables.

Recently, Kale et al. at the Virtual Pediatric Intensive Care Unit at Children's Hospital Los Angeles (CHLA) have developed an unsupervised clustering model that is able to generate similarity scores between patients based only on their associated physiological time series data.

[1] Thus, there is a need for an interactive visualization system that will translate this model into actionable clinical knowledge.

The visualization of high-density, high-dimensional continuous and categorical data of many patients simultaneously is a significant challenge. EMR data is often sparse, noisy and incomplete. However, decision support tools that utilize effective visualizations of temporal patient data have shown to increase clinical efficacy[2] compared to many poorly-design native EMR tools.[3,4,5] In particular, clinical visualization systems with parsimonious feature sets and efficient interaction techniques have been shown to save time and prevent medical errors. [6,7,8] For instance, Duke et al. demonstrated that a temporal patient data visualization speeds the time it takes to review a patient's chart for adverse drug events by 60%.[9]

Here, we present Sim•TwentyFive, an interactive visualization system for PICU decision support, physician education and treatment planning. Physicians use Sim•TwentyFive to query any particular patient episode and to explore, analyze and compare similar past patient episodes using a comprehensive set of interaction techniques.

Related Work

Several previous studies have focused on visualizing temporal patient data in electronic medical records,[10] as well as their role in optimizing human-computer interaction within natural physician workflows.[11,12,13] Tufte and Powser advocated displaying lab values in small multiples with indications of normal ranges along distorted time scales.[14,15] Consumer-driven personal health record systems such as Google Health and PatientsLikeMe[16] have employed simple Cartesian coordinate line graphs. Other tools have utilized methods ranging from parallel coordinates[17] to three-dimensional parallel bar charts[18], and have employed a myriad of interaction techniques for time exploration, typified by the Midgaard project[19]. As with the project presented in this study, some past visualizations have focused solely on web-based implementations.[20]

Less research has been conducted on visualizing patient similarity between multiple patient records for decision support. Most patient similarity visualization systems leverage only categorical variables in lifeline-style displays, such as LifeLines[21] and LifeLines2,[22] which align, rank and filter patient episodes based on discrete events; Similan,[23] which is strictly EMR-agnostic; and Amalga,[24] which focuses on query specification. Other less traditional models have used semantic/ontology technologies to automatically incorporate expert domain knowledge[25] or structure patient data for processing, such as SweetINFO[26]. AALIM[27] is the only patient similarity visualization project to base patient similarity on non-categorical patient attributes, as the system leverages multi-modality data, including radiology images and EKG readings.

Methods

Data Set

In this work, we use a novel data set collected from the PICU EHR archive at the Children's Hospital of Los Angeles. This data set contains 10,598 PICU patient episodes collected over a ten year period. The data set includes demographics, outcomes, diagnostic codes, and other annotations, as well as physiologic time series of thirteen different clinical observations, including *pulse oximetric saturation* (SpO2), *heart rate* (HR), *respiratory rate* (RR), *systolic blood pressure* (sBP), *diastolic blood pressure* (dBP), *end-tidal carbon dioxide* (EtCO2), *temperature* (Temp), *total glascow coma score* (TGCS), *peripheral capillary refill rate* (CRR), *urine output* (UO), *fraction inspired oxygen* (FiO2), *glucose* (Gluc), and *pH* (pH). The data set is described in greater detail in Marlin, et al.[1]

Similarity Scores

In the past, patient similarity has often been determined by highly-abstracted, individual level indices, such as APACHE scores[28] or information theoretic scoring models[29]; difficult-to-interpret dimensionality reduction techniques, such as principal components analysis; or oversimplified, institution-dependent measures based on billing codes such as the morbidity dissimilarity index.[30]

Since we are interested in modeling patient similarity based on temporal patterns in physiology, we use a novel similarity scoring scheme based on work by Marlin, et al.[1] They propose a Gaussian mixture model with an empirical Bayesian prior for modeling and clustering PICU physiologic time series. They show that these models can be used to separate episodes into clinically relevant groups, to motivate informative visualizations, and to derive a similarity metric between the episodes. In this paper, we trained multiple cluster models and then generated pairwise similarity scores between episodes based on average cosine similarity between the cluster likelihoods assigned to episodes by the cluster models. These scores range from 0 (completely dissimilar) to 1 (identical).

Design Process

In the current study, we employed a rapid prototyping, spiral-model design process, which was heavily-informed by formative evaluations from PICU physicians and other visualization researchers, specifically, Diana MacLean, who had shadowed PICU physicians at CHLA, the SweetINFO project group in the Stanford Center for Biomedical Informatics Research, as well as Stanford CS448B: Data Visualization students.

We prioritized flexibility, consistency, responsiveness and visual parsimony in our fundamental design. To support flexible discovery and exploration, we included interaction techniques based on their perceived ability in facilitating rapid cycles of hypothesis generation and visual querying.[31] In addition, we attempted to mitigate introducing biases by providing a comprehensive suite of controls for data/object and view/scale manipulation, which were informed by Shneiderman's data type-task taxonomy[32]. To support consistency, the y-axis ranges for each physiologic variable were reset to the default ranges upon loading a patient and color encodings were kept congruent across multiple objects (e.g. the circle and lines of a selected patient) and controls (e.g. the toggle and sort buttons). We ensured responsiveness by implementing the aforementioned cached-result AJAX query scheme and by setting a heuristic display limit of 25 patients, which appeared to be an upper limit for guaranteeing smooth D3 animations, as well as producing a gestalt visual clarity. Visual parsimony was ensured through well-principled minimalistic design patterns, informed by Tufte and others.[33]

Implementation

The data set provided by CHLA includes a 10,598 x 10,598 pairwise similarity score matrix, as well as the specific data for each 24-hour episode. Each episode contained essential demographic, outcome (i.e., mortality) and high-level diagnosis information, as well as time series data for the aforementioned 13 physiologic measures. The data was de-identified, stripped of all protected health information (PHI) and was authorized for our use by a standard CHLA data use agreement.

We parsed the data into JSONs using R for integration with D3. The physiological data was incomplete and sparse, thus, we interpolated values, but did not extrapolate to ensure visually-robust and accurate line graphs. We then extracted the physiological for the 25 most similar patients (as determined by the similarity matrix) to each patient and cached each of these physiologic arrays of time series vectors in separate JSON files. Categorical variables such as diagnoses, outcomes and height were selected, decoded, reworded, concatenated for each patient (e.g., two verbose discharge classification scales were combined and simplified to factors of "died", "improved" and "unchanged") and parsed into a single JSON file. The lists of the top 25 most similar patient episodes for each episode were also parsed for lookup purposes. We then calculated the global (i.e. all 10,598 patients) mean plus/minus a single standard deviation (i.e. one z-value) for each physiological variable and parsed the results into a single JSON file. This pre-processing resulted in a database consisting of over 900 megabytes of JSON files.

The frontend of the visualization was implemented using Data-Driven Documents (D3), which is an SVG-manipulation framework, jQuery and traditional Javascript. The system is hosted on Stanford University's common gateway interface service.

When a query is run for any episode ID, the system returns the 25 most similar patient episodes to that patient episode by, first, issuing an AJAX request to retrieve the associated cached physiological time-series data subset and, second, by applying lookups to the categorical variable JSON.

Results

Design Overview

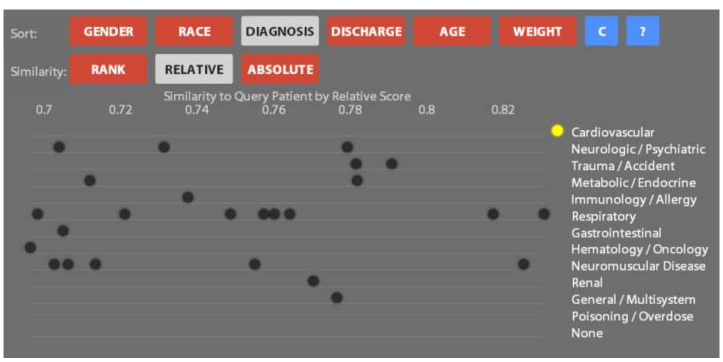
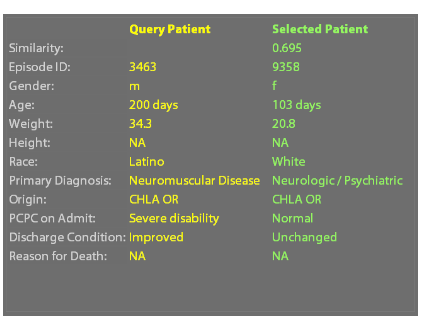


Figure 1. The patient similarity plot.



	Query Patient	Selected Patient
Similarity:		0.695
Episode ID:	3463	9358
Gender:	m	f
Age:	200 days	103 days
Weight:	34.3	20.8
Height:	NA	NA
Race:	Latino	White
Primary Diagnosis:	Neuromuscular Disease	Neurologic / Psychiatric
Origin:	CHLA OR	CHLA OR
PCPC on Admit:	Severe disability	Normal
Discharge Condition:	Improved	Unchanged
Reason for Death:	NA	NA

Figure 2. The details-on-demand table.

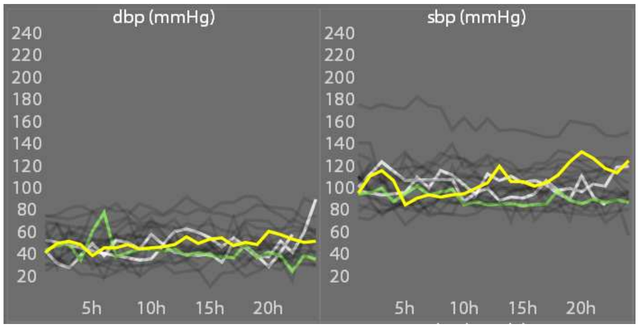


Figure 3. Two of the thirteen physiological time series charts.

The full Sim•TwentyFive visualization is contained within a single page. It is partitioned into three essential components: a details-on-demand section for direct one-to-one patient discrete attribute comparisons, an animated Cartesian coordinate plot for visualizing similarity and facilitating sorting and selection, and a collection of 13 small multiple line graphs for displaying time series physiological data.

When a user initially loads the web page, the graphics are completely obscured until all data is available and a textual indication that patient data is being retrieved is displayed. Similarly, when a query is run, a loading indication is displayed next to the input search box.

A user runs a query by typing in the episode ID of any patient-of-interest (i.e., any number 1-10,596) and pressing the *query button* or pressing enter on the keyboard. The system returns the query patient as well as the 25 most similar patients to that query patient, along with all corresponding attributes and time series physiological data.

The color encodings for the entire system are consistent between each subsection. In particular, color is used to encode the data as follows: *yellow* encodes the query patient and their associated attributes, *black* encodes unselected similar patients to the query patient and their associated attributes, *white* encodes non-query patients that have been selected by the user and clickable text, *green* encodes the most recently selected patient and is also used to reinforce and draw attention to selection actions by the user, *red* encodes toggle controls that are unselected, *light grey* encodes toggle controls that are selected and non-clickable text, *blue* encodes controls that map to a single functional execution command (such as clearing selections), and *purple* encodes population aggregates.

All subsections are linked. For instance, by selecting an individual patient's time physiological time series lines in any of the small multiple line graphs, the system automatically selects all 13 of their time series lines, as well as highlighting their associated circle in the similarity plot and displaying their essential attributes in the details-on-demand table.

The details-on-demand table always displays the query patient in the middle column. If no patient has been selected, the Selected Patient column remains empty, but the header remains and the width stays fixed. When a patient is selected, their details are displayed in the rightmost column. Likewise, when a patient is deselected, their details are removed.

The Cartesian coordinate similarity plot encodes the query patient and the 25 most similar patients to the query patient as circles. Each circle has reduced opacity and a soft, transparent edge to mitigate object occlusion effects that may occur in some instances. A circle's position along the x-axis encodes similarity to the query patient; that is, the rightmost black circle represents the most similar patient to the current query patient and so forth. The similarity axis can be set along three different scales: the default *relative* scaling positions the least similar and most similar of the 25 most similar patients at the leftmost and rightmost of the x-axis, respectively, to optimize data spread but still convey relative differences in similarity scores; *rank-ordered* scaling positions each similar patient by pure rank at equidistant intervals to optimize data spread and avoid occlusion; *absolute* scaling sets each patient on a scale from 0 to 1 to provide a gestalt sense of the overall similarity of the top-25-most-similar patient group to the query patient and provide a consistent scale between query results. When the data for a patient is initially loaded a textual header explicitly indicates that the black circles are the top-25 most similar patients and the y-axis is set as null and unlabeled (i.e., a purely one dimensional plot) to orient to the user. The query patient is always positioned at the rightmost edge of the plot. This serves as a natural and consistent marking for gauging similarity and also as an easily-referenced, explicit mark of the current query-patient attribute, as the yellow circle sits slightly off the edge of the x-axis gridlines and directly next to the y-axis labels. The y-axis can be transformed by the user to encode nominal classifications (i.e., race, gender, diagnosis category and discharge) or continuous attributes (i.e., weight and height) by vertical position. All similarity scaling and y-axis view transformations are smoothly animated and instantaneously responsive, which is critical for supporting visual and cognitive consistency.[34] When a new query is run, the user-specified similarity scaling is left unchanged and the y-axis is reset to null.

Each of the small multiples visualize time-series physiological variables for each patient's initial 24-hours in the PICU using traditional line charts. Each chart is titled with the physiological measure and the associated units (some measures, such as the Total Glascow Coma Score (TGCS) have no natural units). The query patient's hourly-discretized time series is encoded in yellow and each of the 25-most-similar patients are encoded in partially-transparent black. The initial view is set such that each line graph is scaled by the legal values (i.e., the limits in the relevant clinical practice guidelines) of a given variable along the y-axis (consistently given to no more than two decimal places). A user may choose to optimize the aspect ratios (i.e. optimally scale the y-axis) of each line chart, subsequent to the initial load. Time, in hours, is represented along each x-axis. The overlapping transparent black lines facilitate perception of both a gestalt aggregate, as well as a collection of disparate patient objects. As patient elements are selected, their physiological trend lines change to green (most recently selected) or white and their opacity is increased. In addition, aggregate polygons that representing the entire population mean ± one standard deviation may be optionally superimposed beneath the patient data lines for each measure. No key or legend is provided as the intended audience consists of professional health providers who are familiar with all chart title abbreviations and units.

The control buttons are clearly marked in bright red and blue. The user is encouraged to click the buttons by transforming the user's mouse cursor into a selection pointer when the cursor hovers over a clickable-element. In addition, when the mouse cursor hovers over clickable text (i.e., y-axis attribute labels and line chart titles), the text turns green. Upon clicking, opacity and color transitions indicate function and whether the toggle button is on or off. For instance, when the query button is clicked, it briefly turns yellow to imply a query-patient operation; when the clear or help buttons are clicked, they flash a more saturated blue, but immediately return to their previous state to indicate availability for a subsequent execution; when the toggle buttons are on, they display a distinct, constant color-palette switch until switched off; and when the chart titles are clicked to rescale the y-axis, the y-axis units flash green to call attention to the imposed shift.

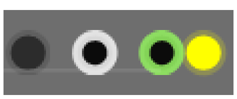


Figure 5. The encodings (from left to right) for unselected, selected, most-recently selected and query patients.

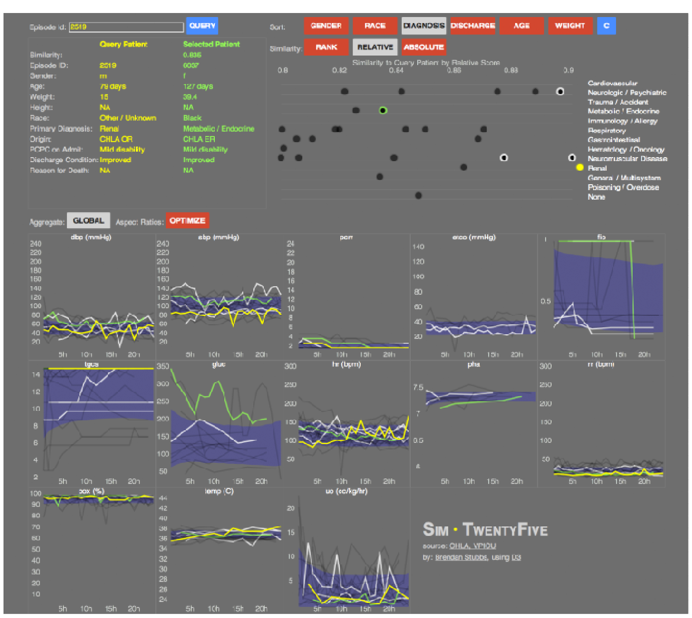


Figure 6. The entire system interface.

Interaction Techniques

The following interaction techniques are supported by Sim•TwentyFive:

- Patients may be sorted by categorical attributes: gender, race, diagnosis, discharge summary (i.e., survival or improvement); or continuous attributes: weight and age; by y-position in the similarity plot by clicking the corresponding sort button.
- Individual patients may be selected by clicking on any associated circle or line (i.e., linked patient visual objects). The associated visual objects belonging to most recently-selected patient become opaque green, the patient's attributes are displayed in the details-on-demand table and any previously-selected patients become white. These selections remain constant between view changes, such as axis-scaling and transformations.
- Individual patients may be deselected by clicking on them once (if it was the most-recently-selected patient) or twice (i.e., once to select, once to deselect).
- Groups of patients may be selected by clicking on any currently-displayed y-axis category label (e.g. "Male"). In the case of age and weight, patients within ±10 units of the clicked value are selected.
- Aspect ratios may be optimized individually by clicking on a chart title, or collectively by clicking on the "optimize" toggle button. Optimization is defined heuristically by scaling the y-axis to the currently-displayed maximum and minimum values for the given physiological variable.
- Optimized aspect ratios may be returned to the default scale by clicking the chart title or by turning the optimize toggle button off.
- Global aggregates, that is, the means ± one standard deviation for the entire population of 10,598 patients for each physiological measure may be toggled on or off (collectively) by clicking the "global" button.
- Selections can be cleared completely by clicking the "C" button and instructions are displayed by clicking the "?" button.

Evaluation

We designed and engineered Sim•TwentyFive to be a flexible, responsive and clinically-useful tool. Thus, we evaluated our system using timing and animation tests across multiple platforms, as well as anonymous open-ended summative assessments from PICU physicians.

The visualization was tested across three platforms, ranging from a low-performance 2007 Thinkpad to a high-performance 2011 desktop Mac, and four browsers: Chrome, Firefox, Safari and Internet Explorer. The results for our subjective characterizations of animation frame rates are shown in table, below.

Table 1. A summary of platform/browser testing.

Platform	Browser	Graphics load fully	Animation frame rate
2007 T60 Thinkpad (2 Ghz, 2 GB RAM)	Google Chrome 15	Yes	Excellent
	Mozilla Firefox 8	Yes	Poor
	MS Internet Explorer 9	No	N/A
2010 iPad	Safari iOS	Yes	Poor
2011 Mac (2.5 Ghz, 8 GB RAM)	Google Chrome 15	Yes	Excellent
	Mozilla Firefox 8	Yes	Good
	Safari 5	Yes	Good

Page load, reload and query timing tests (ten trials each) were run on the aforementioned 2007 Thinkpad on a standard Stanford University wireless internet connection to measure computational efficiency and responsiveness. Page loads are defined as loading the visualization with a clear browser cache in a new application instance, reloads are defined as loading the visualization in a new tab instance without clearing the cache, and queries are defined as entering a random valid patient episode ID. The results are shown in the table below.

Table 2. Timing test results.

Task	μ (s)	σ (s)
Initial page load	3.26	1.08
Page reload	7.94	0.92
Query	0.99	0.14

The summative assessment of the system included a Skype demo and feedback session with CHLA physicians, as well as an anonymous online survey. The survey was conducted using SurveyMonkey and was emailed to CHLA and Lucile Packard Children's Hospital PICU physicians along with a link to the tool and no additional directions.[35] Six PICU physicians responded to the survey and the results are shown, below.

Table 3. The summative evaluation results.

Question	Response counts				
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Information is presented in a clear and logical manner.	0	0	0	3	3
The interface is intuitive and easy to use.	0	0	0	2	4
In my experience, Sim•TwentyFive is better than current EMR patient data visualizations.	0	0	0	1	4
Sim•TwentyFive will be useful for learning about a given query patient from similar patients.	0	0	1	2	3
Sim•TwentyFive will be useful for physician education and treatment planning.	0	0	1	2	2

Discussion

Sim•TwentyFive presents a strong proof-of-concept for rapidly translating novel computational methods into a web-based interactive visualization system to support clinical decision making. Sim•TwentyFive is the first interactive tool to visualize patient similarity, as determined solely by time-series physiological data. It presents high-dimensional time series clinical data through a principled visualization design and provides well-integrated interaction techniques to facilitate effective clinical exploration, education and planning.

Our system greatly reduces the cost structure of the task of exploring physiologically-similar patients. By providing automatic retrieval of patients based on previously-computed similarity scores, our system reduces search times associated with manual or categorical-variable-based searches. By including sort and selection manipulation techniques that may be used in innumerable combinations, we enable efficient exploration and searching. By allowing for aspect ratios to be optimized, we enhance patterns[36] without sacrificing consistency. By providing integrated views with clear and consist visual encodings and robust linking and brushing, global aggregates, we enable perceptual interference.

Our results from timing tests indicate that our AJAX/JSON query framework is highly efficient. However, our frontend has widely-varying performance and Google Chrome is clearly the preferred browser. The CHLA staff members have indicated that this should not be a significant problem going forward, but we may want to implement a lighter-weight (less animation) version in the final release. This is especially pertinent if other form factors such as tablet PCs and mobile smart phones are used by the PICU physicians.

The physician evaluations show that the essential visualization design and interface is robust, flexible and intuitive; however, the use-cases for the tool may need to be more clearly defined in moving forward with a final release, such as diagnosis-specific views. We will still focus on providing a wide range of tools and view manipulations, as to not unintentionally introduce biases.[37]

By providing open-ended, exploration-focused, data manipulation mechanisms, the system mitigates introducing biases to the user's findings and conclusions.

Overall, the user comments in the survey and feedback session lauded the system. The criticisms we received were nearly all calls for additional features. We paraphrase some physician suggestions for improvements, below:

- Order nominal variables on the y-axis by frequency of inclusion in the current patient subset.
- Arrange the physiological variables in a more traditional or clinically-informed layout and allow users to drag, drop and hide the physiological charts to build a custom arrangement.
- Add events such as "surgery", "CPR" to the temporal charts.
- Add the ability to zoom in a particular graph.
- Add an explicit definition of the similarity scoring procedure.

Future Work

The current heuristic limit of displaying 25 similar patients was chosen to ensure smooth frontend responsiveness in low-performance platforms, to allow for search results to be fully cached and to adhere to a design principle of visual parsimony, as to avoid cognitive overload. However, this limitation will need to be removed in future implementations.

Similarily, while the AJAX/JSON query model is highly-efficient, it is not scalable and does not allow for customized queries of patient subsets. In the future, we will need to build a fully-robust normalized relational database backend and support multi-constraint queries.

Sim•TwentyFive relies on the fidelity and quality of the similarity scoring model. Currently, this model is still being refined, however, our tool allows researchers to explore and evaluate their model's results. In addition, we hope to provide a real time similarity scoring function such that previous similar patients to a newly-admitted PICU patient with less than 24 hours of physiological readings may be dynamically retrieved. Ideally, such a dynamic scoring system with be able to generate similarity scores per a user's preferences, such as scoring patients based on a subset of physiological measures.

Another limitation of the system is the inability to display (and sort/select/query) on detailed protected health information, such as highly-specific diagnoses. If the final implementation is deployed on a secure, private server within CHLA, we should be able to incorporate this information.

Currently, normal ranges and abnormalities for physiological readings are not indicated. This is for two reasons. First, these normal ranges are not defined in the clinical literature/guidelines for many of the measures. Second, normal ranges in pediatric care are largely dependent on age, gender, height and weight, thus, when displaying heterogeneous patient data, it is challenging to clarify to a user which normal ranges are shown. Currently, we have used a global aggregate as a proxy for this. In the future, we hope to add options to superimpose additional aggregates of patient population subsets, as defined by various combinations of age, gender, etc.

Per our physician feedback, we hope to add greater flexibility in manipulating the physiological time series charts, such as custom arrangements and zoom, as well as creating a more clinically-meaningful layout.

Our color scheme is complex and distinct; however, we may need to provide alternate color schemes, such as a traditional black on white scheme. The design of these schemes will largely be determined by the environmental lighting and the type of devices the visualization will be viewed on within the PICU (e.g., a high-gloss tablet viewed under fluorescent lighting). This would be fairly simple to implement via a swap of CSS stylesheets, once an onsite study has been conducted.

We may also implement a social WebSocket-based feature, in which multiple physicians may view and manipulate the same data, cooperatively, from disparate locations.[38] Such a feature may also employ annotations capabilities, such as those pioneered by the sense.us project.[39]

Ultimately, we will need to prove clinical efficacy as defined by improved pediatric patient health outcomes. For this end, we will need to perform a carefully-constructed, long term case study in close collaboration with domain experts.

References

1. Marlin B, Kale D, Khemani R, Wetzel R. Unsupervised pattern discovery in electronic health care data using probabilistic clustering models. Proceedings of ACM International Health Informatics Conference 2012.
2. Saleem J, Patterson E, et al. Using human factors methods to design a new interface for an electronic medical record. AMIA Annual Symp Proc. 2007; 2007: 640-644.
3. Ash JS, Berg M, Coiera E. Some unintended consequences of information technology in health care: the nature of patient care information system-related errors. J Am Med Inform Assoc. 2004 Mar-Apr;11(2):104-12. Epub 2003 Nov 21.
4. Koppel R, Metlay JP, Cohen A, Abaluck B, Localio AR, Kimmel SE, Strom BL. Role of computerized physician order entry systems in facilitating medication errors. JAMA. 2005 Mar 9;293(10):1197-203.
5. Jeffrey L. Schnipper, Jeffrey A. Linder et al. “Smart Forms” in an electronic medical record: documentation-based clinical decision support to improve disease management. J Am Med Inform Assoc. 2008;15:513-523.
6. Ludwick DA, Doucette J. Primary care physicians' experience with electronic medical records: barriers to implementation in a fee-for-service environment. International Journal of Telemedicine and Applications. 2009.
7. Miller R, Sim I. Physicians’ Use Of Electronic Medical Records: Barriers And Solutions. Health Affairs, 23, no. 2(2004): 116-126.
8. Albert Boonstra, Manda Broekhuis. Barriers to the acceptance of electronic medical records by physicians from systematic review to taxonomy and interventions. BMC Health Serv Res. 2010; 10:231.
9. Duke JD, Li X, Grannis SJ. Data visualization speeds review of potential adverse drug events in patients on multiple medications. J Biomed Inform. 2010;43(2):326–31.
10. Rind, A., Aigner, W., Miksch, S., Wang, T.D., Wongsuphasawat, K., Plaisant, C., and Shneiderman, B. Interactive information visualization for exploring and querying electronic health records: a systematic review. Technical Report, University of Maryland, 2010.
11. Zheng K, Guo M, Hanauer DA. Using the time and motion method to study clinical work processes and workflow: methodological inconsistencies and a call for standardized research. Journal of the American Medical Informatics Association. 2011;18(5):704–10.
12. Zhou, X., Ackerman, M.S., and Zheng, K. (2010) Doctors and psychosocial information: records and reuse in inpatient care. Proceedings of ACM on Human Factors in Computing Systems (SIGCHI '10. ACM Press, 1767-1776.
13. Lauren Wilcox, Jie Lu, Jennifer Lai, Steven Feiner, and Desmond Jordan. 2010. Physician-driven management of patient progress notes in an intensive care unit. In Proceedings of the 28th international conference on Human factors in computing systems (CHI '10). ACM, New York, NY, USA, 1879-1888.
14. Powsner, S. M. and Tufte, E. R. (1994). Graphical summary of patient status. The Lancet, 344(8919):386-389.
15. Powsner, S. M. and Tufte, E. R. (1997). Summarizing clinical psychiatric data. Psychiatric Services, 48:1458-1461.
16. Frost JH, Massagli MP. Social uses of personal health information within PatientsLikeMe, an online patient community: what can happen when patients have access to one another's data. J Med Internet Res. 2008 May 27;10(3):e15.
17. Mane, K. K. and Borner, K. (2007). Computational diagnostics: A novel approach to viewing medical data. In Proceedings of the 5th International Conference on Coordinated and Multiple Views in Exploratory Visualization (CMV '07), pages 27-34,Zurich, Switzerland. IEEE.
18. L. Chittaro, C. Combi, and G. Trapasso. Data minding on temporal data: a visual approach and its clinical application to hemodialysis. Journal of visualLanguages and Computing, 14:591-620, 2003.
19. Ragnar Bade, Stefan Schlechtweg, and Silvia Miksch. 2004. Connecting time-oriented data and information to a coherent interactive visualization. In Proceedings of the SIGCHI conference on Human factors in computing systems (CHI '04). ACM, New York, NY, USA, 105-112.

20. Carlo Combi, Luisa Portoni, and Francesco Pinciroli. 1999. Visualizing temporal clinical data on the WWW. In Proceedings of the Joint European Conference on Artificial Intelligence in Medicine and Medical Decision Making (AIMDM '99).
21. Plaisant, C., Mushlin, R., Snyder, A., Li, J., Heller, D., Shneiderman, B. LifeLines: using visualization to enhance navigation and analysis of patient records 1998 American Medical Informatic Association Annual Fall Symposium (Orlando, Nov. 9-11, 1998) AMIA, Bethesda MD, pp. 76-80.
22. Taowei David Wang, Krist Wongsuphasawat, Catherine Plaisant, and Ben Shneiderman, visual information seeking in multiple electronic health records: design recommendations and a process model, submitted for conference review, 2010.
23. Wongsuphasawat, K.; Shneiderman, B.; , "Finding comparable temporal categorical records: A similarity measure with an interactive visualization," Visual Analytics Science and Technology, 2009. VAST 2009. IEEE vol., no., pp.27-34, 12-13 Oct. 2009.
24. Plaisant, C., Lam, S., Shneiderman, B., Smith, M. S., Roseman, D., Marchand, G.,Gillam, M., Feied, C., Handler, J., and Rappaport, H. (2008). Searching electronic health records for temporal patterns in patient histories: A case study with Microsoft Amalga. Technical Report HCIL-2008-13, University of Maryland, College Park, MD.
25. Zillner, S.; Hauer, T.; Rogulin, D.; Tsymbal, A.; Huber, M.; Solomonides, T.; , "Semantic visualization of patient information," computer-based medical systems, 2008. CBMS '08. 21st IEEE International Symposium on , vol., no., pp.296-301, 17-19 June 2008.
26. A. Richards, M. J. O'Connor, S. B. Martins, M. Bingen, S. W. Tu, A. K. Das. SWEETInfo. 13th Conference on Artificial Intelligence in Medicine (AIME), Bled, Solvenia, Springer Verlag, LNAI 6747, 260-264. Published in 2011
27. Amir, A., Beymer, D., Grace, J., Greenspan, H., Gruhl, D., Hobbs, A., Pohl, K., et al. (2010). AALIM: a cardiac clinical decision support system powered by advanced multi-modal analytics. Studies In Health Technology And Informatics, 160(Pt 2), 846-850.
28. Knaus WA, Zimmerman JE, Wagner DP, Draper EA, Lawrence DE. APACHE acute physiology and chronic health evaluation: a physiologically based classification system. Crit Care Med 1981;9(8):591–7.
29. Cao H, Melton GB, Markatou M, Hripcsak G. Use abstracted patient-specific features to assist an information-theoretic measurement to assess similarity between medical cases. J Biomed Inform 2008 Dec;41(6):882–8
30. Schildcrout JS, Basford MA, Pulley JM, Masys DR, Roden DM, Wang D, Chute CG, Kullo IJ, Carrell D, Peissig P, Kho A, Denny JC.An analytical approach to characterize morbidity profile dissimilarity between distinct cohorts using electronic medical records. J Biomed Inform. 2010 Dec;43(6):914-23.
31. Card SK, Mackinlay JD, Shneiderman B, Readings in information visualization: using vision to think. Morgan Kaufmann, 1999.
32. Shneiderman, B. (1996). The eyes have it: A task by data type taxonomy for information visualizations. In Visual Languages, 1996. Proceedings., IEEE Symposium on, pages 336-343
33. Edward R. Tufte. 1986. *The Visual Display of Quantitative Information*. Graphics Press, Cheshire, CT, USA.
34. Heer J, Robertson G. Animated transitions in statistical data graphics. IEEE Information Visualization (InfoVis) 2007.
35. http://www.surveymonkey.com/s/T3VCD8W
36. Talbot J, Gerth J, Hanrahan P. Arc length-based aspect ratio selection.IEEE Trans Vis Comput Graph. 2011 Dec;17(12):2276-82.
37. Foo J, Winer E. Interactive multi-modal visualization environment for complex system decision making. ASME Conf. Proc. 2008, 1661 (2008).
38. http://websocket.org/
39. Jeffrey Heer, Fernanda B. Viégas, and Martin Wattenberg. 2007. Voyagers and voyeurs: supporting asynchronous collaborative information visualization. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (CHI '07). ACM, New York, NY, USA, 1029-1038.