

AWARD NUMBER: W81XWH-15-2-0016

TITLE: An Interactive Visualization Framework to Support
Exploration and Analysis of TBI/PTSD Clinical Data

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REPORT DATE: May 2019

TYPE OF REPORT: Annual Report

PREPARED FOR: U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

DISTRIBUTION STATEMENT: Approved for Public Release;
Distribution Unlimited

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE (DD-MM-YYYY) MAY 2019			2. REPORT TYPE ANNUAL REPORT		3. DATES COVERED (From - To) 15 Apr 2018 - 14 Apr 2019	
4. TITLE AND SUBTITLE An Interactive Visualization Framework to Support Exploration and Analysis of TBI/PTSD Clinical Data					5a. CONTRACT NUMBER	
					5b. GRANT NUMBER W81XWH-15-2-0016	
					5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Dr. Jesus Caban					5d. PROJECT NUMBER	
					5e. TASK NUMBER	
					5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) The Geneva Foundation 917 Pacific Ave, Suite 600 Tacoma, WA 98402					8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) Gay Hayden Grants Specialist US Army Medical Research Acquisition Activity Phone: 301-619-9883					10. SPONSOR/MONITOR'S ACRONYM(S) USAMRAA	
					11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution unlimited						
13. SUPPLEMENTARY NOTES						
14. ABSTRACT We propose to design, develop, and validate an interactive visualization framework that physicians assessing TBI/PTSD patients with comorbid symptoms can use to explore and analyze clinical data and that researchers can use to hypothesize new research questions. The primary aims of this project are to (1) extend our interactive visual analytic framework which combines multiple clinical measurements to allow it to be used to explore large collections of clinical data and (2) validate the effectiveness of such visualization systems among clinicians that treat service members.						
15. SUBJECT TERMS Data Visualization, Health Information Technologies, TBI/PTSD, Open Source Tools						
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON	
a. REPORT U	b. ABSTRACT U	c. THIS PAGE U			19b. TELEPHONE NUMBER (include area code)	
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INTRODUCTION: An Interactive Visualization Framework to Support Exploration and Analysis of TBI/PTSD Clinical Data

1. **KEYWORDS:** Data Visualization, Health Information Technologies, TBI/PTSD, Open Source Tools

2. **ACCOMPLISHMENTS:** The overarching goals of this project are to (1) address the gap between the acquisition of clinical measurements and the diagnosis step by providing an institutive, flexible, and customizable interactive data visualization framework and (2) validate the system among clinicians treating service members diagnosed with TBI / PTSD.

During the first year of the award, a significant amount of work was accomplished. The work accomplished during the first two years was extended to continue to reach each of the tasks and deliverables of the award. The work accomplished during the last year can be summarized as:

1. [Aims 1.7, 1.8, 2.3, 2.4, 2.5] Update system based on usability study and suggestions received from users.

Summary: Despite the growth of visual analytics and the widespread use of visualization tools, the mining and modeling of user interactions and behaviors have not kept pace despite the ability to provide critical information about the method in which users interact with the interface and visualization. Existing approaches contain substantial limitations as they rely on expertly crafted rules or for users to examine their own interactions. As part of Aim 1.8 we introduced the application of reinforcement learning onto user interactions within a visual analytic system, opening a new avenue of research for building models that can automatically learn and uncover hidden insights. We outlined three research directions that can be addressed using reinforcement learning and used to test the techniques developed under this grant: (i) providing guidance to users towards the completion of a task, (ii) personalizing guidance to match each individual user's behavior and preferences such that the guidance is "polite" and unobtrusive, and (iii) optimizing the visual analytic interface to maximize user performance. Then we present our approach focused on solving these research directions. We show how our approach builds a model that embeds knowledge about a visual analytic system and how it can automatically learn to tailor itself to a user's preferences through the application of providing guidance. Finally, we manually validate the insights embedded within our model to show how it could be further applied to optimizing an interface. Our reinforcement learning-based models can be utilized with user data or in an automatic standalone method, and ultimately allow for analysis that is not possible using standard modelling techniques.

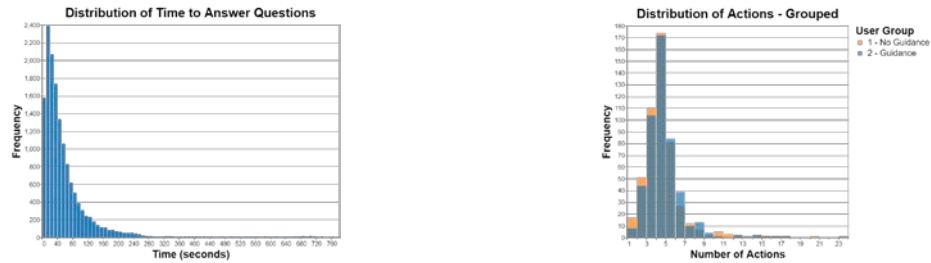


Figure 1: (left) The distribution of the time spent answering each question by all users. (right) A layered distribution graph showing the distribution of actions for both user groups.

- [Aims 1.3, 1.4] Design a modularized visual analytics framework capable of loading, filtering, and illustrating any number of clinical variables.

Summary: Automatically summarizing a collection of temporal sequences is a difficult task given the irregular and variable patterns often found in longitudinal events. Across a wide array of domains, researchers and analysts seek to determine ways to gain an overview of event datasets through the identification of the common paths as well as the trajectories that exist between individual events. While these tasks have been thoroughly researched, many approaches have not taken into account the temporal context of events and thus vital time information is commonly lost. An application has designed to visually explore temporal sequences by incorporating the context of time into event mining algorithms and then overcoming the challenges and complexities of visualizing large scale longitudinal data. The key contributions of this work are an adaptive window-based frequency sequence mining algorithm designed to identify common subsequences and build overviews of longitudinal trajectories and a novel event summary diagram to display common paths while providing multiple levels of details. The algorithm and visualization techniques have been evaluated through three case studies applied to large-scale longitudinal datasets from different domains.

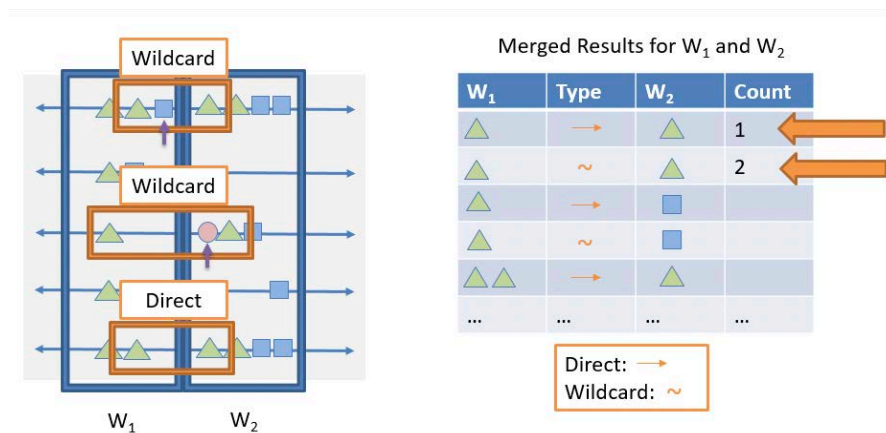


Figure 2: An example of running WindowMerge on windows W₁ and W₂. On the right the table is filled in both direct (orange arrow) and wildcard (orange ~) connections for each combination of frequent subsequences found in Figure 3. On the left, the connections for the first two rows are shown and how the counts are determined.

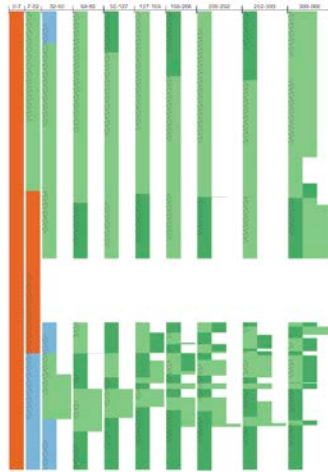


Figure 3: An event summary diagram for EHR data.

3. Performed an in-depth literature review of existing work related to temporal trajectory analysis that can be used to illustrate clinical data for TBI/PTSD patients. The visualization and analysis of temporal event data is a widely studied topic. In our literature review, we noticed two series of general studies, one that focused on lifelines and another one that was more focused on flow visualization. Table #1 summarizes our findings:

	who (tool name)	when (condition)	why (goal)	what (functionality)	how (method)
1	Care Pathway Explorer [4]	temporal event sequence data	Utilize historical EMR data to extract common sequences of medical events such as diagnoses and treatments, and investigate how these sequences correlate with patient outcome	<ol style="list-style-type: none"> 1. Show an overview of the frequent patterns 2. Examine the frequent patterns and select specific patterns of interest 3. Compute the patient subsets that match the physicians specified subtraces. 4. The Frequent Pattern Analytics mines frequent patterns and displays them in the visualization. 	<ol style="list-style-type: none"> 1. Frequent sequence mining algorithm 2. Bubble chart for overview visualization and Sankey diagram for flow visualization
2	Careflow [7]	temporal event sequence data	Help doctors devise a care plan for their patient.	<ol style="list-style-type: none"> 1. Mining care plans from data 2. Visualizing care plans 	Sankey diagram for flow visualization
3	Outflow [6], [10]	temporal event sequence data	Provide important insights into how diseases evolve over time and help clinicians understand how certain progression paths may lead to better or worse outcomes.	<ol style="list-style-type: none"> 1. Aggregate multiple event sequences 2. Display the aggregate pathways 3. Summarize the pathways corresponding outcomes 4. Allow users to explore external factors 	Sankey diagram for flow visualization
4	Decisionflow [5]	high-dimensional temporal event sequence data (e.g., thousands of event types)	Help analysts and epidemiologists to study data from groups of patients to understand what factors may influence a particular outcome	<ol style="list-style-type: none"> 1. Issue a query to retrieve subsequences of interest. 2. Aggregated to the matching data construct a DecisionFlow Graph, G. 3. G is then analyzed to extract statistics and visualized. 4. Interaction allows exploratory analysis. 	<ol style="list-style-type: none"> 1. Milestone demotion algorithm 2. Horizontal layout algorithm of milestone nodes
5	visual analytics technique [11]	temporal event sequence data	Help to understand the patterns of events observed within a population that most correlate with differences in outcome	<ol style="list-style-type: none"> 1. A visual query module to interactively specify episode definitions 2. A pattern-mining module to help discover important intermediate events within an episode 3. An interactive visualization module that help uncover event patterns that most impact outcome and how those associations change over time. 	<ol style="list-style-type: none"> 1. Visual query capabilities 2. Pattern mining techniques 3. Interactive visualization techniques
6	LifeLines [12]	personal medical history records	Design appropriate visualization and navigation techniques for presenting and exploring personal medical history records.	<ol style="list-style-type: none"> 1. Present a personal history overview on a single screen 2. Provide direct access to all detailed information from the overview with one or two clicks of the mouse 3. Make critical information or alerts visible at the overview level. 	The medical record is summarized as a set of lines and events on a zoom-able time-line
7	LifeLines2 [8]	multiple records of categorical temporal data	Find hidden patterns contained in EHRs (Electronic Health Records) and other temporal dataset		timelines with the same absolute time scale
8	PatternFinder [13]	multivariate and categorical data (over 26,000 medical events for 950 patients)	Search and discovery of temporal patterns within multivariate and categorical datasets	<ol style="list-style-type: none"> 1. Visual temporal query languages 2. Query result visualization 	<ol style="list-style-type: none"> 1. Define a temporal pattern as a sequence of events separated by time spans so that it can be queried by events and time spans components. 2. Multiple timelines for query result.
9	ActiviTree [14]	large and complex event-based temporal data	Systematic identification of sequences in social science activity diary data.	<ol style="list-style-type: none"> 1. Enable the users to create a sequence of activities 2. Show a sequence in the context of the individuals daily life 	<ol style="list-style-type: none"> 1. The sequence exploration algorithm is steered using an interactive visual interface 2. The currently explored query sequence is shown with linked view

Table 1: Summary of papers reviewed related to temporal trajectory analysis.

All scientific papers reviewed were put into specific categories. Papers #1 to #5 were designed for visualization of aggregated data. An important step in these studies was the mining or aggregating the temporal data to find patterns and then employing visualization techniques such as the Sankey diagram to illustrate the longitudinal aspects of the data. Papers #6-#8 were designed for visualization of individual data points. Lifelines was designed for personal patients clinic history visualization, although the other two methods Lifelines2 and PatternFinder are designed for multiple records, they visualize the multiple records separately. Finally, paper #9 (ActiviTree) was a method developed to allow users

to explore the event sequences rather than aggregate patterns from the multiple temporal sequences.

4. [Aims 1.3, 1.7, 1.8] Designed the *Necklace* interface. In order to help users explore the trajectory of medical claim data and compare trajectories and costs, we designed *Necklace*. The *Necklace* interface consists of three main design ideas: (1) *guided interaction*; (2) *position based global pattern finding*; (3) *multivariate comparison*. See Figures #1 and #2 for more information.

There are two kinds of rings that are part of the *Necklace* interface: root ring and branch ring. The initial display only shows a root ring, which contains the information of all the transformation and relationships in the dataset. As users interact with the interface, *Necklace* will show more and more branch rings. Each branch ring has a parent ring and a parent trajectory, and contains a parent event E and either the incoming events of E or outgoing events of E . Thus a trajectory is composed of the parent events of a series linked rings.

Each ring contains four components: nodes, groups, links and chords. Each node on the ring represents a diagnosis event, and those events on branch rings are not individual events, they present events in a trajectory. For instance, assuming there is a branch ring R which shows its parent event E_3 , and those outgoing events of E_3 , and the parent trajectory of R is $E_1 \rightarrow E_2 \rightarrow E_3$, so an event E_4 on R represents the event E_4 in the trajectory $E_1 \rightarrow E_2 \rightarrow E_3 \rightarrow E_4$. And using the ICD 9 Code, we clustered those nodes on a ring into groups. And each link inside the ring represent a transformation relationship between two events, and links from one group to another group are gathered into a chord.

The initial heights of nodes are similar and link nodes encode the incident rate of the corresponding event, which means that the more links, the higher the node will be. In addition, in each node there is a histogram for users to show more information. A ring shows abstract information when it occupies a small area, the detailed nodes information and links information will be hidden if the area is not big enough. In order to obtain detailed nodes information, users can click on outer contour of a group to expand this group to a higher level for more space, and they can also click on the inner contour of a group to shrink to a lower level. One of the advantage of ring is that it has a powerful ability to show large scaled event since a ring can show thousands of event at a time.

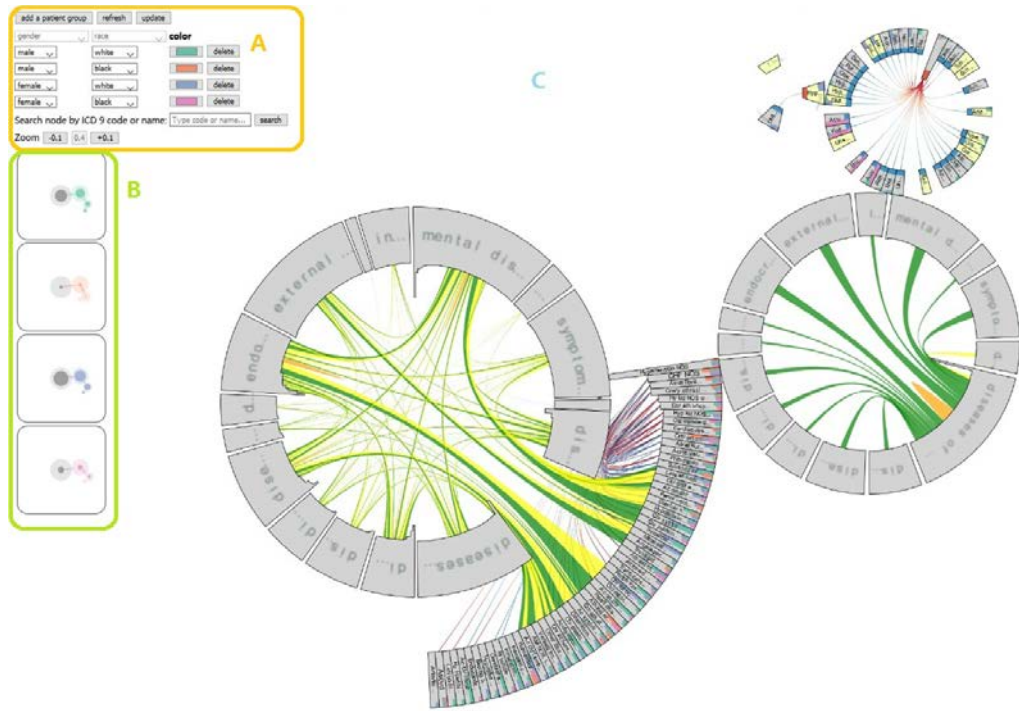


Figure 4: Screenshot of the Necklace system. Necklace visualizes temporal events trajectories, this screen shot shows CMS data, which contains 222 patients and 668 claim records. Users can explore the diagnoses trajectory by directly interacting with the visual objects shown in C, and compare trajectories of different patients cohorts with the overview graphs shown in B. And Necklace also offers a user panel, which is shown in A, for users to edit patient cohorts, search for diagnosis node and zoom the display.

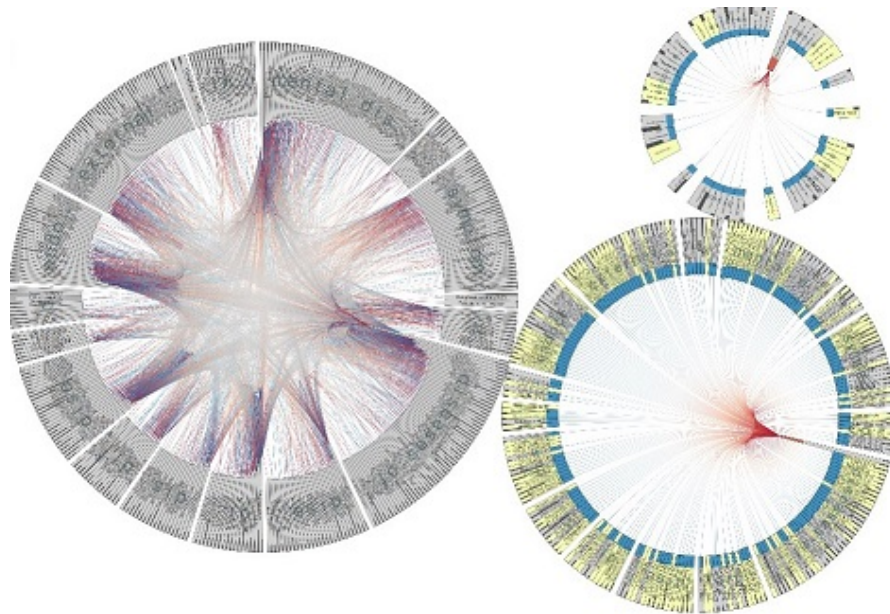


Figure 5: Screenshot of the Necklace system. Necklace visualizes temporal events trajectories, this screen shot shows CMS data, which contains 222 patients and 668 claim records.

5. [Aims 1.3, 1.7, 1.8] Developed, extended, and continued to enhance the *Patient Timeline* tool based on comments and feedback received from different clinical staff members. The *Patient Timeline tool* was developed to assist physicians explore the longitudinal medical data of a patient. In a visually appealing way, the Patient Timeline starts by displaying a tree that provides a quick glimpse of the data available for a patient. Icons and their size show if the patient has a certain type of data in their history and how much or how important that data is. The year nodes can be expanded to show another level of the tree, showing the patient's monthly data for that year. To the right of the patient's tree is a summary panel. This summary panel shows a brief text summary of the patient, their lab history, their diagnosis history and their medication history. The Labs, Diagnoses, and Medications tabs display their information in analytical models that make the data easier to digest. The Labs, Diagnoses, and Medications tabs update when a new tree node is clicked. Furthermore, three patients' tree can be seen by selecting the Three Trees display from the dropdown button at the top of the page.



Figure 6: The Patient Timeline starts by displaying a tree that provides a quick glimpse of the data available for a patient.

In the more robust portion of the Patient Timeline, the nodes are presented to us on a timeline as shown in Figure #3. Here, individual days of the patient's data can be explored in panels. Within the panels there are tabs for Labs, Medications, Vitals, Notes, Diagnoses, Procedures, Radiology Note, and Chief Complaint for a single day, assuming the patient has that type of data available for that day. To the left of the timeline, we have a filter that allows the user to filter nodes based on Provider Type, Provider Name, DMIS/MTF, MEPEP4, Encounter Type, Data Type, and/or Date. To the right we have a smaller version of the, previously presented, summary panel.

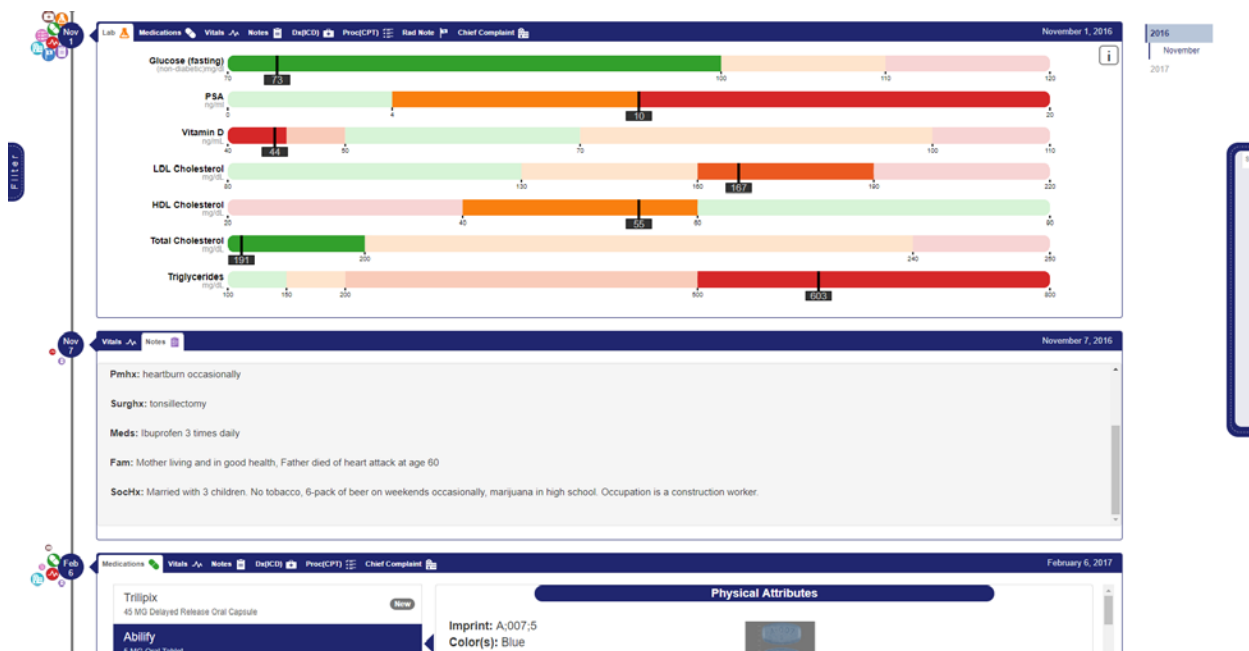


Figure 7: The nodes are presented on a timeline and individual days of the patient's data can be explored in panels.

6. [Aims 1.3, 1.7, 1.8, 1.9] In order to also satisfy the requirements from research clinicians interested in exploring clinical data but also understanding what data is available, we designed the *Database Search* tool. The *Database Search* tool was designed to facilitate the searching and exploration of databases. When the user clicks the Run Query button, the Results panel fills with statistics of their selected tables and variables. In the Results panel, they can see the Count, Missing, Mean, Standard Deviation, Zeroes, Minimum, Maximum, and Histogram for their chosen variables. Once the user has selected all the data they would like to put a request in for, they can click the Export button, followed by the 'Copy to clipboard' button to copy their selections to their computer's clipboard. This saves the user from having to individually copy and paste, or type up, the tables and variables they would like to put a request in for.

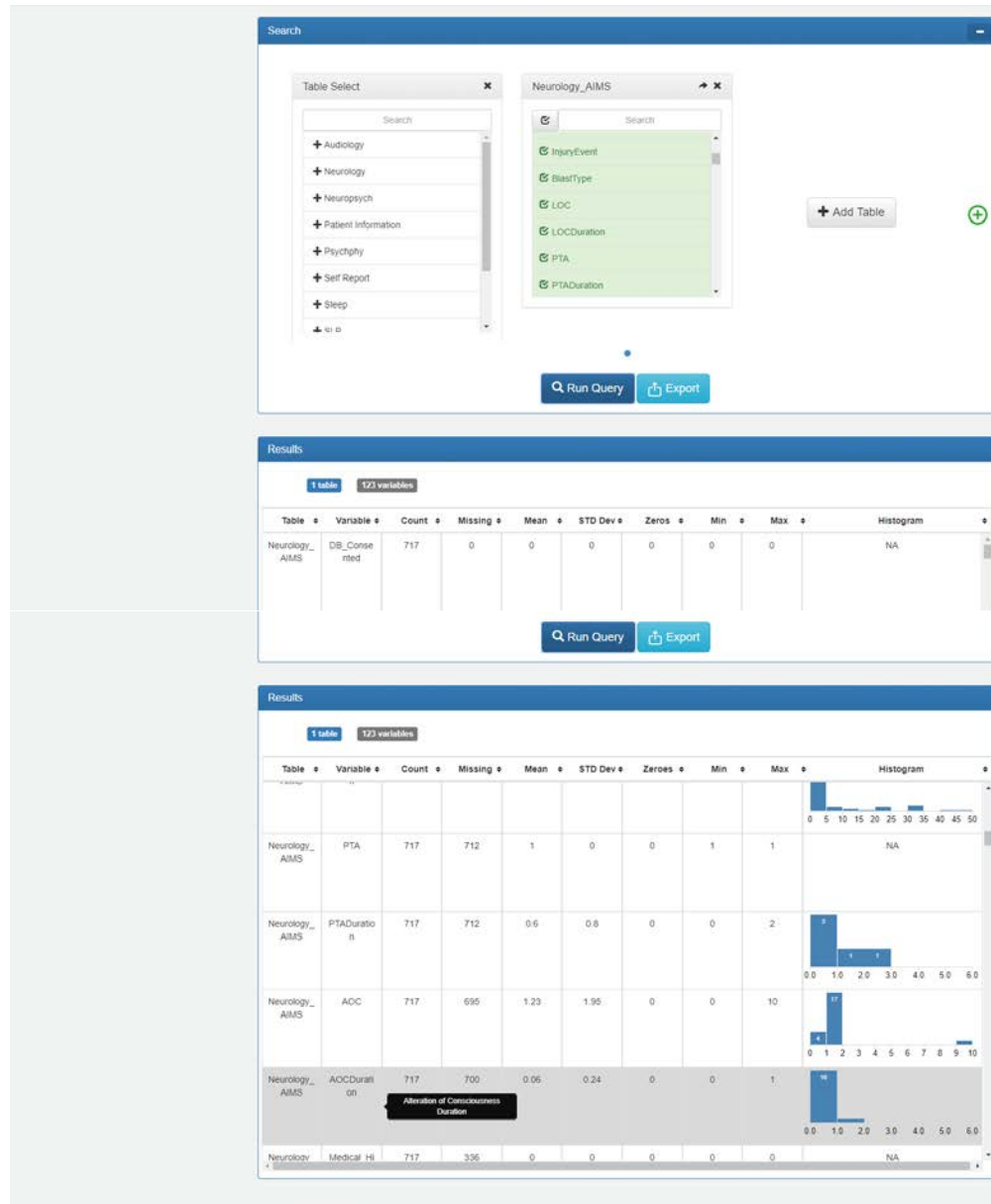


Figure 8: Screenshots of the Database Search tool designed to better explore clinical data that is available to research purposes.

7. [Aims 1.3, 1.7, 1.8, 1.9] A new module was prototyped to visually analyze clinical notes. The tool automatically highlights clinical concepts within unstructured provider notes. The new module can be used to compare clinical notes and highlight changes over time. In addition, the new module can be used to identify commonalities between different EHR notes.

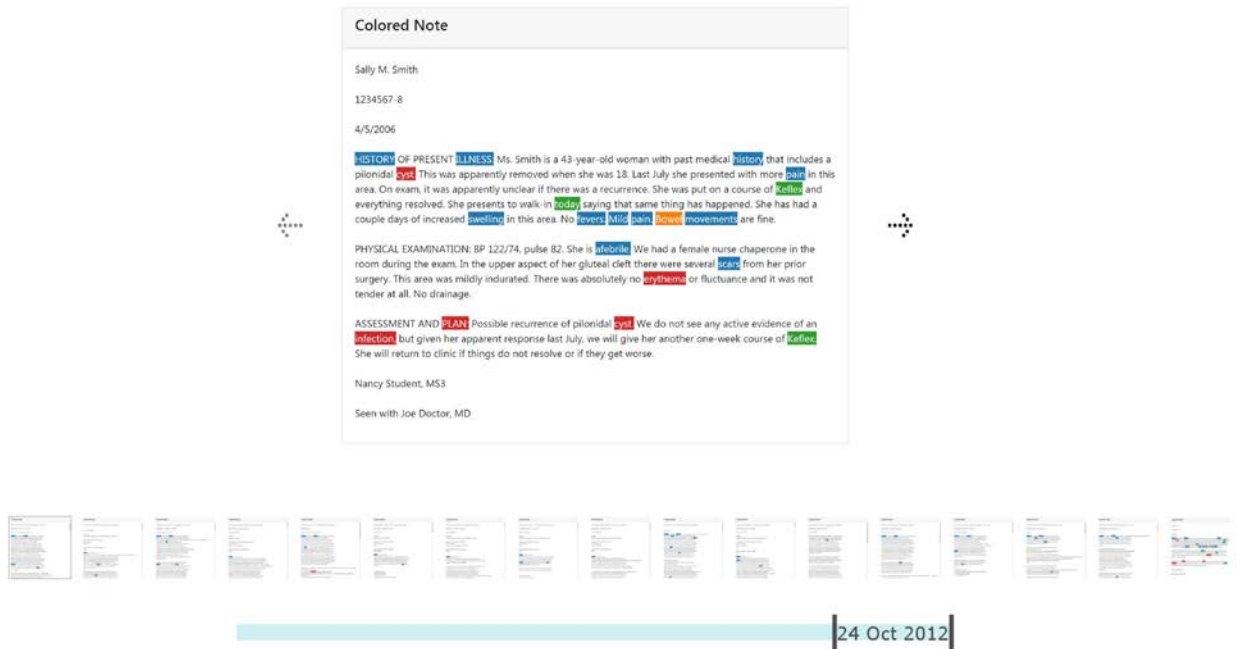


Figure 9: Screenshots of the module under development to analyze / compare clinical notes.

8. [Aims 1.3, 1.7, 1.8, 1.9] In order to better understand and validate the effectiveness of different visualization tools, we have developed a method to capture how users interact with the different systems. Given a clinical dataset and a visualization tool or dashboard, we designed an application to compare the correlations, patterns, and flows different groups follow to reach an answer for a specific clinical question.

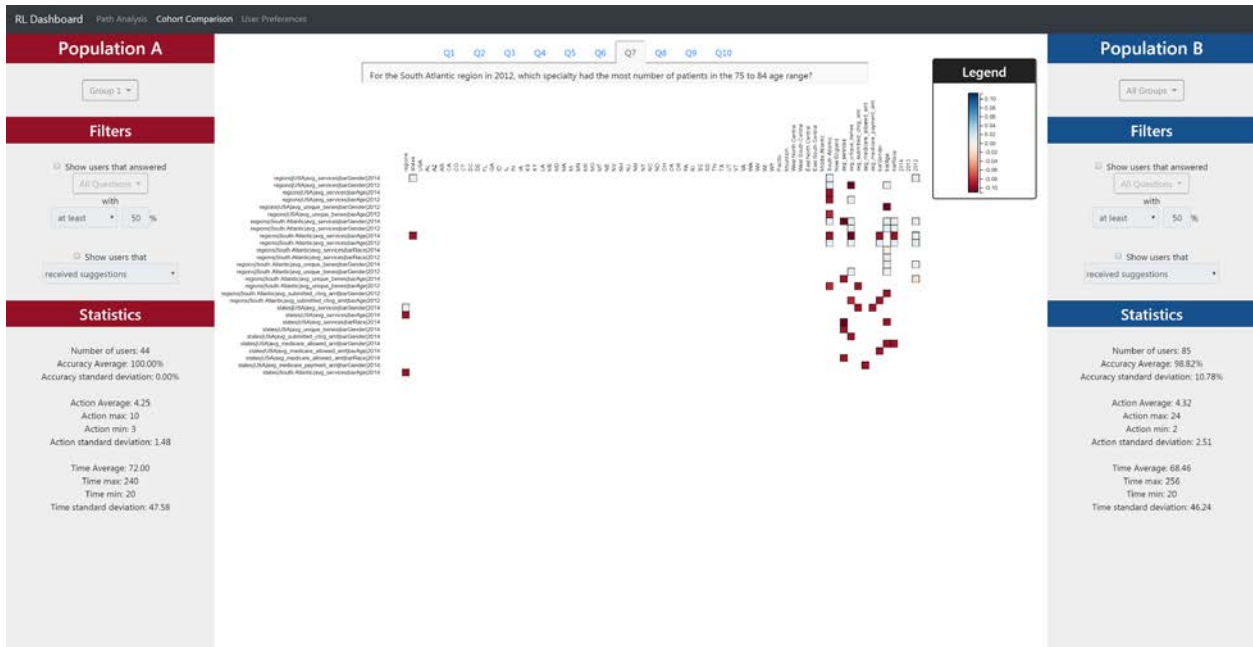


Figure 10: Screenshot of a tool designed to explore and understand how users interact with different visualization tools.

What were the major goals of the project?

The first major goal of this project was to design a visual analytic framework that combines multiple clinical measurements and allows the exploration of large collections of clinical data. In addition, the second major goal (years 2-4) was to validate the effectiveness and usability of different visualization techniques for exploring large collections of clinical variables with complex associations.

The first major goal of the second year was to iterate on our work for summarizing large, longitudinal datasets by expanding on our previous work and developing a novel visualization method for analyzing a large dataset of events. In addition, we validated the effectiveness of our visualization techniques throughout the year. The second major goal of the second year was to build a system that summarizes the various elements of a patient's EHR data. Through these two goals, we have addressed the many difficulties associated with clinical variables and data from both a big data and a singular patient-provider perspective.

The first major goal of the third year was to continue to enhance the existing tools from previous years by adding new visualization techniques, new validation approaches, and new data. That was accomplished by continuing to perform a literature review, develop the Necklace interface, continue to enhance the patient time-line framework, develop an effective interface for research clinicians to search at data, and by creating a systematic approach to analyze the patient

interaction data. During the next year the priority will be to continue to enhance those tools and make them available to other researchers, investigators, and organizations.

The first major goal of the four year was to validate the different applications using standardized techniques. During the final year the priority will be to continue to enhance make applications available to other researchers, investigators, and organizations as well as close out the project.

What was accomplished under these goals?

During the first year, four different systems were prototyped and developed to perform visualization of tabular, hierarchical, and longitudinal data. First, **VisXplore** was enhanced to become a clinical data visualization system to perform group or single-subject analysis of multivariate tabular, hierarchical, or temporal clinical data. Second, **CoFlow** was developed as an interactive multi-view and exploratory visualization tool designed to analyze longitudinal EHR data. Third, a **graph-based visualization technique** was developed to visually explore the frequency of patients going from one specific clinical diagnosis to other diagnosis. Finally, a **visual summarization approach** was created and tested with thousands of mTBI patients. Each of the tool has a corresponding draft paper describing the design and techniques. See attachments.

During the second year, two different systems were extensively prototyped and developed to effectively summarize the various data elements that are present in Electronic Health Records (EHRs). First, a novel visualization method, **event summary diagrams**, and a corresponding system were built to enable for a large dataset of events to easily be understood through a top-down interactive exploration. This visualization was evaluated with a dataset of thousands of mTBI patients and shown to reduce the visual complexity and analytical capacity required compared to existing techniques. Second, a **timeline-based framework** for aggregating and summarizing EHRs was extensively researched, designed, and developed to overcome the challenges that exist in EHR systems where data integration is lacking and the disparate nature of data creates difficulties for clinicians. Through this framework, a clinician is able to view the entire history of a patient at multiple time scales and develop an understanding of the patient state over time. Each of these tools have a corresponding draft paper describing the design and techniques. See attachments.

During the third we continued to perform a literature review, developed the Necklace interface, continued to enhance the patient time-line framework, developed an effective interface for research clinicians to search at data, and by creating a systematic approach to analyze the patient interaction data. During the next year the priority will be to continue to enhance those tools and make them available to other researchers, investigators, and organizations.

During the four year we introduced the application of reinforcement learning onto user interactions within a visual analytic system, opening a new avenue of research for building models that can automatically learn and uncover hidden insights. We outlined three research directions that can be addressed using reinforcement learning and used to test the techniques developed under this grant: (i) providing guidance to users towards the completion of a task, (ii)

personalizing guidance to match each individual user's behavior and preferences such that the guidance is "polite" and unobtrusive, and (iii) optimizing the visual analytic interface to maximize user performance. Then we present our approach focused on solving these research directions. We show how our approach builds a model that embeds knowledge about a visual analytic system and how it can automatically learn to tailor itself to a user's preferences through the application of providing guidance. Finally, we manually validate the insights embedded within our model to show how it could be further applied to optimizing an interface. Our reinforcement learning-based models can be utilized with user data or in an automatic standalone method, and ultimately allow for analysis that is not possible using standard modelling techniques.

What opportunities for training and professional development has the project provided?

"Nothing to Report."

How were the results disseminated to communities of interest?

Some of the prototype visualization tools were demonstrated during the 2018 Workshop on Visual Analytics in Healthcare and at the 2018 IEEE Visualization Conference. Three additional papers describing the other systems are currently in draft mode. See attached documents.

What do you plan to do during the next reporting period to accomplish the goals?

Continue to enhance the different system, continue the validation process, and prepare the applications for distribution.

4. IMPACT:

What was the impact on the development of the principal discipline(s) of the project?

The four prototype systems that have been designed have generated great interest among multiple providers, researchers, and administrators. Two senior individuals at the Defense Health Agency (DHA) have seen the systems and are interested in looking into how we can integrate some of those tools within the DHA enterprise enclave. In addition, widely recognized researchers from Johns Hopkins University (JHU) are interested in how to use our visualization techniques for population health.

What was the impact on other disciplines?

The impact of our work is touching multiple disciplines and research domains including clinical informatics, health IT, computer science, medicine, and population health.

What was the impact on technology transfer?

“Nothing to Report.”

What was the impact on society beyond science and technology?

“Nothing to Report.”

5. CHANGES/PROBLEMS:

Changes in approach and reasons for change

“Nothing to Report”

Actual or anticipated problems or delays and actions or plans to resolve them

The project and actions are a little bit behind schedule due to the challenges of finding qualified candidates that can obtain the credentials needed to work within a DoD facility.

Changes that had a significant impact on expenditures

No changes on expenditure.

Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents

“Nothing to Report”

6. PRODUCTS:

- **Publications, conference papers, and presentations**

Journal publications. Nothing to Report

Books or other non-periodical, one-time publications. Nothing to Report

Other publications, conference papers, and presentations

- Filip Dabek and Jesus J Caban “VisXplore: Flexible Visualization System for Analyzing Complex Clinical Datasets”, Workshop on Visual Analytics in Healthcare, ACM Digital Library, Oct. 2014
 - Filip Dabek, J. Chen, A. Garbarino, and Jesus J. Caban, “Visualization of Longitudinal Clinical Trajectories using a Graph-based Approach”, Workshop on Visual Analytics in Healthcare, ACM Digital Library, Oct. 2015
 - Dabek F., Hoover P., Caban J. (2018) Evaluating Mental Health Encounters in mTBI: Identifying Patient Subgroups and Recommending Personalized Treatments. In: Wang S. et al. (eds) Brain Informatics. BI 2018. Lecture Notes in Computer Science, vol 11309. Springer, Cham
 - Dabek F., Hoover P., Caban J. (2018) DeepDx: A Deep Learning Approach for Predicting the Likelihood and Severity of Symptoms Post Concussion. In: Wang S. et al. (eds) Brain Informatics. BI 2018. Lecture Notes in Computer Science, vol 11309. Springer, Cham
 - Filip Dabek, Jian Chen, and Jesus Caban, “Visual Summarization of a Collection of Temporal Sequences using Adaptive Frequency Mining and Graph-based Event Modeling” [Draft]
 - TrajectoryFlow: Visual Summarization of Temporal Sequences [Draft 2019]
 - A Reinforcement Learning Approach to Automatically Model and Learn from User Interactions [Draft 2019]
- **Website(s) or other Internet site(s)**

“Nothing to Report”

- **Technologies or techniques**

The design and development of our different visualization tools have produced novel techniques including:

- Novel graph-based approach to visualize clinical trajectories
- New pixel-based visualization method that works as a look-ahead tool for patients
- Novel sequence modeling algorithm to summarize longitudinal trajectories

1. Inventions, patent applications, and/or licenses

“Nothing to Report”

2. Other Products

- The four different software tools

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What individuals have worked on the project?

Name: Jesus Caban, PhD

Project Role: PI

Contribution to Project: Dr. Caban has organized meetings, tracked progress of the project, and evaluated various visualization techniques for exploring large clinical data.

Name: Elizabeth Jimenez

Project Role: Developer

Contribution to Project: Ms. Jimenez has begun implementing an interface for the visual analytics framework, in addition to developing and evaluating a visualization technique.

Name: Filip Dabek

Project Role: N/A (Data Scientist for the National Intrepid Center of Excellence)

Contribution to Project: Mr. Dabek has begun implementing an interface for the visual analytics framework, in addition to developing and evaluating a visualization technique.

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?

“Nothing to Report.”

What other organizations were involved as partners?

8. SPECIAL REPORTING REQUIREMENTS:

See attachments.

- W81XWH-15-2-0016 Year 4 Quarter Reports.pdf: copy of all the quarterly reports for year #1.
- W81XWH-15-2-0016 Year 4 Supplements.pdf: copy of all the papers and draft papers.

8. APPENDICES:

See attachment.

- W81XWH-15-2-0016 Year 4 QuadChart.ppt