A timeline-based framework for aggregating and summarizing electronic health records

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A Timeline-based Framework for Aggregating and Summarizing Electronic Health Records

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Abstract—Electronic Health Records (EHRs) contain a significant amount of longitudinal information about a patient including pre-existing conditions, earlier diagnosis, previous treatments, active medications, base-line measurements for different clinical results, and much more. Unfortunately, data integration within an EHR and across different EHRs continue to be a limiting factor that threatens patient safety and the efficiency of healthcare providers. The disparate nature of the clinical data even within a single EHR often results in clinicians having to access and review a number of reports, modules, and tabs to access different data elements and clinical results. Due to the fragmented nature of EHR interfaces and the number of interactions that are needed to access clinical data, clinicians often spend a considerable part of their time going through the EHR of a patient in order to get a comprehensive overview and to be able to provide quality care. Data visualization and the integration of analytic models within graphical interfaces present a unique opportunity to effectively combine multiple clinical data sources and reduce the cognitive burden that disparate reports often have for end-users. With the ability of visualization techniques to summarize different data elements, we present a timeline-based framework to effectively aggregate and summarize the disparate clinical data of a patient enclosed within an EHR. The interface combines a set of visualization techniques with machine learning summarization approaches to optimize the process of understanding a patient's history through views that allow for easily skimming and jumping through time, filters for limiting the amount of information shown, and a hierarchy of summaries that provide an interface to view and compare different time frames.

1 Introduction

During the last decade, the widespread adoption of EHR systems has transformed the way clinical data is collected and reviewed. While the adoption of new health information technology continues to increase within medical centers, hospitals, and clinics; improvements in the usability of EHRs have unfortunately not kept the same pace. In general, usability problems and the inefficient navigation tools available within EHRs continue to reduce the effectiveness of electronic health records and continue to add cognitive load to providers that often results in frustration and errors.

EHR systems contain a significant amount of longitudinal information about a patient including lab results, pre-existing conditions, previous treatments, active medications, base-line measurements for different clinical results, clinical notes, and many other data elements. Unfortunately, the exiting navigation tools available within EHRs present significant challenges when providers need to perform a comprehensive review of a patient. The lack of data integration within EHRs, and the shortage of integration across different EHRs have made accessing clinical data a complicated task that threatens patient safety and the efficiency of healthcare providers.

The disparate nature of the clinical data even within a single EHR often results in clinicians having to access and review a number of reports, windows, and tabs to access different data elements, clinical modules, and objective results. Often different data elements each get their own tab and section of the EHR: lab tests, vitals, imaging, etc. are all scattered throughout the EHR system and require multiple interactions to transition between them.

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Due to the fragmented nature of EHR interfaces and the number of interactions that are needed to access clinical data, often clinicians spend a considerable part of their time going through the EHR of a patient in order to get a comprehensive overview of the patient in order to provide quality care.

Data visualization and the integration of analytic models within graphical interfaces present a unique opportunity to effectively combine multiple clinical data sources and reduce the cognitive burden that disparate reports often have for end-users. With the ability of visualization techniques to summarize different data elements, we present a timeline-based framework to effectively aggregate and summarize the disparate data of a patient contained within an EHR. The interface combines a set of visualization techniques with machine learning summarization approaches to optimize the process of understanding a patient's history through views that allow for easily skimming and jumping through time, filters for limiting the amount of information shown, and a hierarchy of summaries that provide an interface to view and compare different time frames.

In this paper, based on our interactions and consultations with clinicians, we present our framework for aggregating and summarizing EHR data through the use of two different views: *a summary view* and *a patient timeline*. In the summary view a clinician is able to gain an overview of their patient and evaluate a summary of individual time periods to be able to pinpoint a place of focus. Upon identifying a timeframe, the timeline view provides an in-depth view of the patient with data for each displayed in easy to understand visualizations and intuitive interactions for quickly moving throughout the course of time in the patient's history.

The contributions of our framework include:

- Aggregate and summarize the different data elements of an EHR
- Communicate volume and significance of contained patient data for different points in time to be able to easily identify changes that occur
- Narrow focus to specific timeframes as well as compare different moments in time
- Visualization methods for summarizing temporal information

We begin the description of our framework by first introducing the concept of a patient timeline and then showing how we can build on

Fig. 1: A longitudinal timeline of a patient's history.

this methodology to aggregate the disparate data available for each patient and optimize the process of gaining a comprehensive overview of a patient.

2 Background

Visualization is an effective tool to communicate information about the underlying data that is being represented and has been used to help make sense of the data of a patient's history. Early on Tufte introduced the concept of timelines [11] and applied them to patient histories [10]. Later LifeLines built on the work of timelines by stacking multiple records on top of one another and providing the user with the ability to simplify and manipulate the display [8, 9]. Furthermore, LifeLines2 extended on LifeLines by highlighting the summary of a collection of records [12].

Building on the work of timelines, Shneiderman et al. built EventFlow to be able to provide users with the ability to simplify temporal sequences, and showed its application to medical data [5, 13]. CareFlow utilized a similar temporal sequence interface, but embedded patient outcomes data directly into the nodes and edges of the graph [7]. CareCruiser similarly visualized event trajectories of patients and communicated the patient's condition within the visualization [3].

Moving beyond complete event analysis systems: year long medication histories have been visualized [6], a single patient's diagnoses was visualized inside a patient-centric sunburst diagram [14], and a better method to connecting time oriented data to a visualization were explored [1].

Because of the effectiveness of visualization in analyzing different aspects of information, we can also apply this methodology to build a unified approach that helps to make EHR systems more efficient. In 2015, Krause et al. identified this difficult task and built a visualization that displayed the entire course of a patient's history in a concise display [4]. Building on this existing work we have built a timeline-based framework that expands the widely accepted time-line techniques to look at longitudinal data while incorporating techniques to aggregate disparate data with the goal of simplifying the process for the clinician through the use of various visualizations.

3 Patient Timeline

Through our interactions with clinicians, we have learned that they look through the EHR of a patient in an attempt to build an overview of the patient over time up to the present moment. To accomplish this task they look at subsequent encounters through a multitude of dates, but because of the construction of current EHR systems, this becomes difficult and time consuming. Because of this limitation and the need to support a clinician's process, we present a generated timeline for a given patient in Figure 1.

Fig. 2: The summary node for a single date within a patient's EHR where a set of attribute nodes are attached on the left hand side of the node. Each attribute node encodes the significance and volume of a data element present in the EHR.

The timeline embeds the longitudinal nature of a patient by placing the different dates of their history on a vertical line. Through this timeline a clinician is able to quickly move forward or backward from the current date of focus through a simple scroll interaction.

While a basic timeline view allows for quickly jumping between different dates of a patient's EHR, clinicians would still be required to click on each individual date in order to inspect the data and build an overview of the patient. Therefore, to utilize the ability of visualization, each date in the timeline is displayed through a summary node.

3.1 Summary Nodes

Given an encounter date d_i or a date range $D = \{d_i, d_j\}$, a summary node visually encodes information about the clinical data collected during the encounter of day d_i or summarizes the information collected during a timeframe D. The size of the attribute nodes correspond to the significance and volume of information that is contained within a patient's EHR for the given timeframe of the node.

By analyzing a summary node a clinician is able to quickly understand the information that is available within the node, without requiring a click and analysis of the entire underlying data. To communicate this summary through a node, a set of attribute nodes are attached.

Each attribute node corresponds to the different data elements of the patient's EHR that are available. For example, given the following data elements in an EHR:

- Lab Test Results
- Medications
- Vitals
- Clinical Note
- Diagnosis Codes
- Procedure Codes
- Radiology Notes
- Chief Complaint

There exists eight attribute nodes, as shown in Figure 2. By altering these nodes, we can communicate both the significance and volume of the data.

First, to communicate the volume of information that is contained for a given element, the size of the attribute node is altered in order to

Fig. 3: The entire patient timeline view with a quick navigation menu on the right and the summary nodes on the left. In the middle is a visualization of the patient's lab test results. The different colored sections of each bar indicate whether the patient is in the normal range.

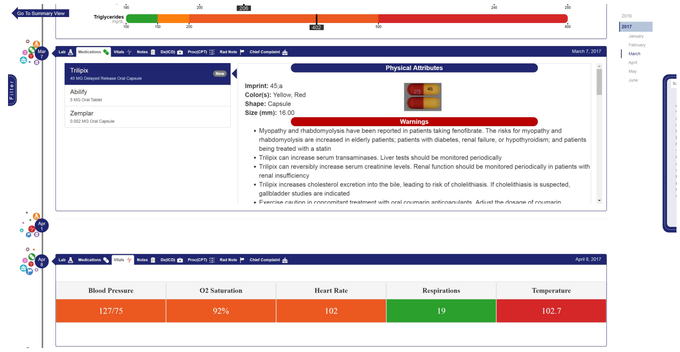


Fig. 4: A list of the patient's medications and an variety of information related to the medication. The symbol "(N)" corresponds to a newly prescribed medication.

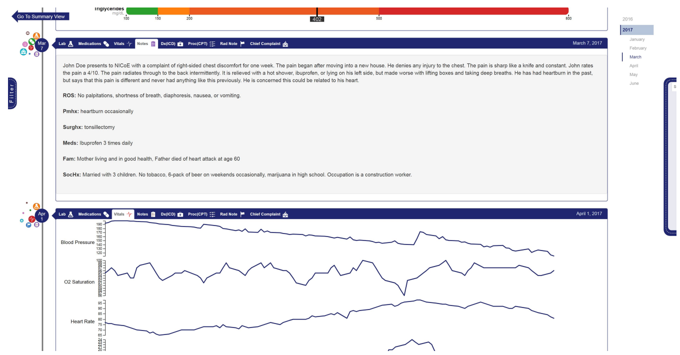


Fig. 5: The raw clinical note of the patient. Future work for this includes highlighting key areas of interest to the particular clinician.

represent the relative quantity of the data. For example, looking at the node in Figure 2, the green attribute node corresponds to the medication data element and the orange attribute node corresponds to the lab test results data element. A clinician looking at this summary node would notice the large size difference between the two attribute nodes and be able to quickly identify that this date contains a lot of lab test results and very few medications. Using this knowledge they would be able to determine whether or not this date is of interest and if they should explore it further.

Second, while varying the size of the attribute nodes is one method of highlighting the corresponding information, we can also alter the placement of the attribute nodes to communicate additional information about the clinical relevance of a particular node. For example, certain patient encounters may be routine for a given patient which may not necessarily be interesting to a clinician. However, unusual events to a patient, such as: a brand new diagnosis, a medication that they have never taken before, or an uncommon lab test could be of interest to a clinician. Therefore, by rearranging the attribute nodes such that for these scenarios the unusual events are placed above the rest the clinician would be able to quickly identify these moments to analyze.

Through the usage of a summary node and the associated attribute nodes, the current process of gaining an overview within an EHR system is simplified such that a clinician is able to gain an understanding of the data without a single click.

3.2 Data Aggregation

Due to the disparate nature of data and fragmented nature of EHR interfaces that we discussed in the introduction, we build on the timeline approach and present an aggregated view of the different data elements contained within a patient's EHR for each day. Furthermore, we utilize the ability of visualization techniques to summarize each of these elements.

Our full patient timeline view can be seen in Figure 3. This timeline is a long scrolling view that contains the entirety of the patient's history. As the clinician scrolls up or down the page, they seamlessly move between different time periods which is further enforced by looking at the navigation menu present at the top right of the screen that highlights the current timeframe that they are at. Through this navigation menu, the clinician can also jump to a different point of the timeline in a quick manner.

Moving beyond the different navigation aspects of the patient timeline, in the middle of the screen, connected to the vertical timeline on the left, exists the aggregated data from the patient's EHR. This data is aggregated and simplified into eight different tabs representing each data element available to the clinician. We highlight three of the data tabs.

The first data tab, shown in Figure 3, corresponds to the Lab Test Results of the patient. In this tab, we aggregate the lab tests of the patient on the specified date and present a visualization of the results. In a typical EHR system, the results would be displayed using plain text which compared to a visualization can be difficult to interpret. Looking at the visualization, in the third row we can see that the acceptableness of the test result goes from red to orange to green and back to orange and then red. In this test the patient is indicated by the black vertical line at about the value of 130 and because of the color coding it is easy to see that the patient is slightly out of the ideal range, something that is not easily interpretable with text.

The second data tab, shown in Figure 4, contains a list of the medications that the patient was currently taking on the specified date. In this tab, the clinician can see four medications in the list. The first two medications have a "(N)" symbol next to the name, indicating that they were newly prescribed on this date, while the subsequent medications were continued from a previous date. Compared to a typical EHR system where a clinician would be required to switch between dates and reports to identify past medications, this method of showing all of the medications that the patient is currently taking greatly simplifies the process and provides a more complete overview of the patient's medications.

In addition to not limiting the medications displayed, this tab also provides the clinician with information about when the medication was prescribed as well as general information about the medication from the NLM Pillbox API [1]. Clinicians and pharmacists alike utilize external online resources to lookup information regarding certain medications and pills, thus providing this information without requiring the user to leave the interface allows them to focus on understanding the patient rather than spending time on basic lookup tasks.

The third data tab, shown in Figure 5, contains the raw clinical note of the patient. There exist times where a clinician is interested in understanding the thought process of previous providers and thus providing this text allows for this task to still be possible. However,

[1]https://pillbox.nlm.nih.gov/developer.html

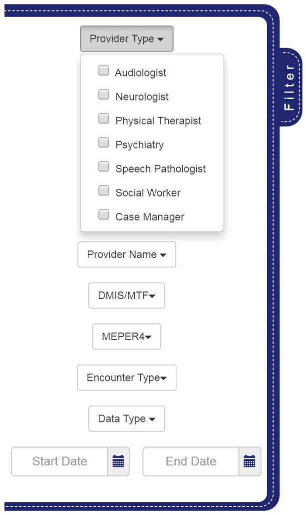
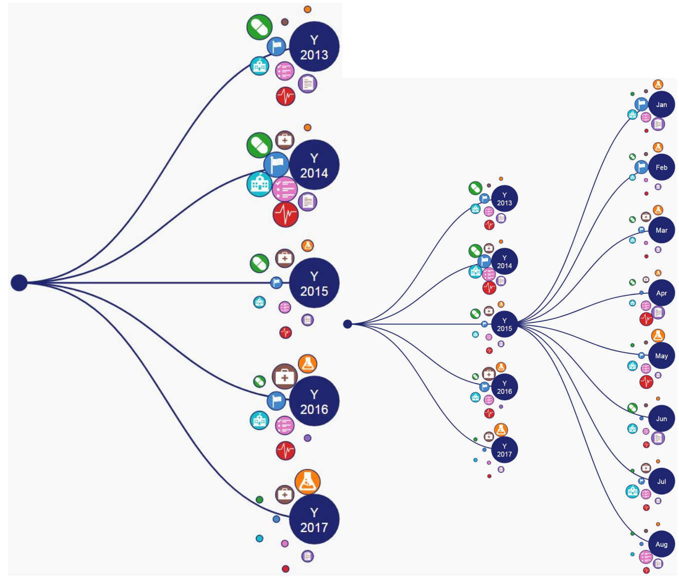


Fig. 6: The filter toolbox present in the timeline view, allowing for the clinician to remove encounters that do not fit a specific set of criteria.



(a) (b)

Fig. 7: An example of a clinician interacting with the patient tree in order to explore the patient's history: (a) the initial view of the summary tree, (b) expanded 2015 node.

through the presentation of this clinical note we identify an area of future work in highlighting keywords and important parts of the note so as to make them easily identifiable.

3.3 Filters

To further reduce the data presented to a clinician to ensure that only relevant data to them is presented, we provide a filter button on the left hand side of the timeline view that removes encounters that do not fit a specific set of criteria. Figure 6 shows the filter panel that is displayed upon clicking of the filters button and expanding the panel. Inside of this panel, we can see that the clinician is able to choose to only be presented with encounters based on:

- Provider Type: A clinician may be interested in only seeing the data for encounters that were performed by a similar type as themselves.
- Provider Name: Similarly, a clinician could look for all of the encounters for a specific provider.
- Encounter Type: A clinician may be interested in only reviewing encounters that are initial, follow-ups, acute, or T-CON.
- Data Type: a user might be interested in only showing encounters in the timeline that have data for one or multiple of the eight attributes discussed in section 3.1
- Date Filter: A provider might be interesed in reviewing encounters that happened within a given timeframe.

Using these filters, a clinician is able to view the entire history of a patient, similar to an EHR system, but they can also choose specific encounters to analyze which reduces the chance of them becoming overwhelmed with the amount of longitudinal data available.

4 Patient Summary

Through the patient timeline, we have provided clinician's with the ability to explore the EHR of a patient using a simplified interface that aggregates the various data elements. However, while these interactions have been simplified and the difficulty of clinicians' tasks have been reduced, for typical longitudinal data that spans a large amount of time there still exists a wealth of information that would need to be explored and a large amount of nodes to analyze. Thus, to complement the timeline view and build a high level overview of a patient's EHR, we present various methods of summarization.

4.1 Summary Tree

While we have utilized summary nodes for a single date in the patient's timeline, we can alter the timeframe that a node corresponds to such that it can summarize a wider span of time. Thus, rather than communicating information about a patient's EHR for a single day, the node can communicate information about an entire week, month, or year. Using these various levels, we can build a summary of the patient based on a hierarchy. We display such a summary using a tree, as shown in Figure 7a.

In this example tree, the years 2013 through 2017 are visible indicating that these are the available years of analysis for the given patient. Looking at the various nodes within the tree, it is possible to understand the change in the patient over time. For example, analyzing the lab tests attribute node (orange) it can be seen that in the span of time shown in the tree, it begins as very small and continues to grow. On the other hand, the medication attribute node (green) starts as being large and shrinks over time, indicating that the patient had both less critical medications and volume of medications. These examples showcase how it is possible to embed and learn a high level overview of the patient without needing to scroll through a long amount of time in the patient timeline.

To encourage exploration of a patient's history, we enable three interaction methods on the tree: move, zoom, and click. Users can move the tree around as well as zoom in and out to try and isolate a specific part of the tree to analyze. Clicking on a summary node in the tree causes for the timeframe of the selected node to be subdivided further. For example, starting from the tree in Figure 7a, if a user clicked on the node corresponding to the year 2015 then the tree would expand showing the summary nodes for each month of available data for the year, as shown in the expanded tree in Figure 7b. Now with the expanded tree a clinician can begin to understand the trajectory of care that the patient underwent over the course of the year. Most notably in this example the orange attribute node was large for the first five months of data, but then for the last three months of data it was almost non-existent.

Through this tree approach it can be seen how clinicians are able to analyze summaries of the patient at multiple time scales. They can drill down the history of a patient until they arrive at the point in time that they are most interested in observing, without needing to analyze the entire contents of the EHR. Furthermore, to assist clinicians

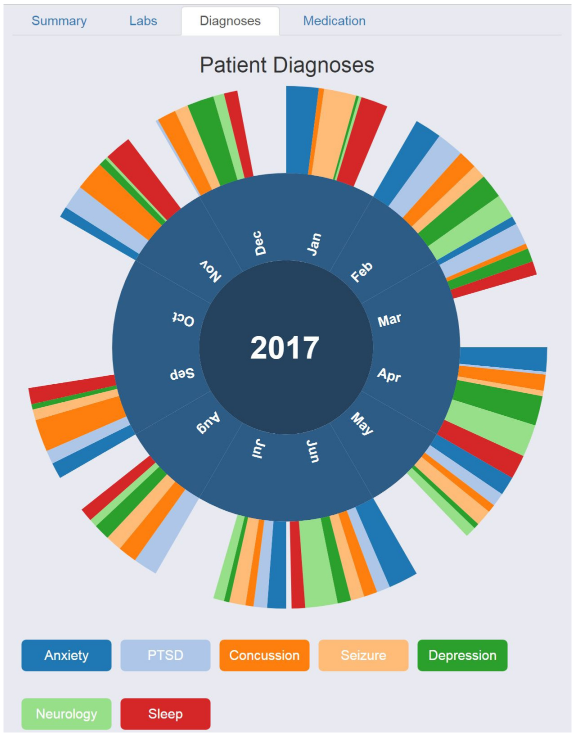


Fig. 8: A modified sunburst diagram that embeds the notion of time to visualize a patient's diagnoses for a given timeframe. Using this diagram, a clinician can develop an overview of the type of data contained and the state of the patient throughout the timeframe. (The third tab of the summary panel.)

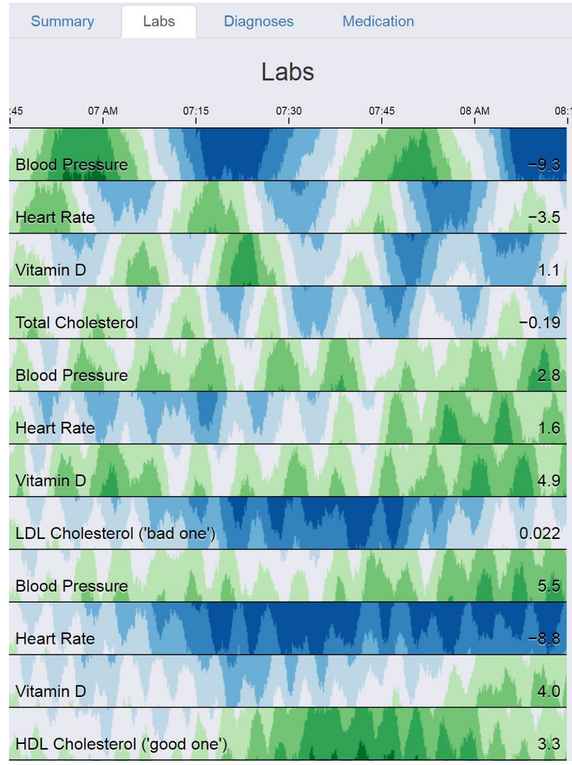


Fig. 9: Lab test results visualized as horizon charts, using D3's Cubism.js plugin [2]. This tab aggregates the data over the patient's EHR to easily be able to identify patterns and trends. (The second tab of the summary panel.)

in identifying important moments in time, it would be possible to highlight certain nodes as critical nodes where a patient was in an "unacceptable" condition as determined by the clinician.

4.2 TimeFrame Summary Panel

While the clinician interacts with the history tree through expanding and collapsing of the nodes and analyzes the attribute nodes attached to each summary node, in an effort to provide multiple levels of detail to the clinician we provide a summary panel. By double clicking on a summary node in the summary tree, the summary panel is simultaneously updated with more detailed information on the contents of the EHR for the given timeframe. Most specifically, this panel contains four different tabs of interest: Summary, Diagnoses, Lab Results, and Medications; and through these panels a clinician is able to further build an overview of the patient's history without requiring to delve deeper into the data.

The tab, "Diagnoses" (Figure 8), contains a sunburst of the diagnoses that the patient experienced. We modelled this sunburst after the patient-centric visualization developed by Klaus Mueller et al. in which they displayed the different diagnoses that patients experienced throughout their entire history [14]. Compared to the visualization by Klaus Mueller et al. where they displayed all diagnoses irrespective of time, we added an additional layer to the sunburst such that the diagnoses are aggregated based on the time period in which they occurred. Looking at the diagram we can see how the clinician is able to identify time periods where the patient experienced diagnoses compared to where they did not. For example, for January 2017 we can see that the patient had a lot of diagnoses throughout April as there is very little space left in the month, but for the month of October they did not seem to have visited a clinician at all. Through this visualization, the clinician is further able to gain an understanding of the series of encounters that the patient experienced through a given timeframe.

The tab, "Lab Results" (Figure 9), contains a series of horizon charts showing different lab test results over time. This view is similar to that of the LifeLines approach where multiple series are stacked on top of another [9]. However, in this case the view displays multiple horizon charts, using D3's Cubism.js plugin [2], for each respective lab result that the patient had received during the timeframe. With this method, a clinician is able to understand the change in a patient over time without needing to open each individual encounter and looking at the change in numbers.

The tab, "Medications" (Figure 10), contains a medication chart showcasing the medications that the patient had taken throughout the current selected node's timeframe. In the chart, clinicians are able to see points at which the patient was directed to start and stop a medication. This chart is representative of the existing research in the domain of medication histories [6]. However, we extended on this previous work by altering the thickness of each bar to indicate the prescribed dosage in order to allow clinicians to be able to see changes in the medications easier.

The tab, "Summary" (Figure 11), contains an automatically generated textual summary of the patient's clinical notes and available data. This textual summary provides a clinician with more detailed information into the current state of the patient without requiring them to read each individual clinical note contained within the EHR system, a common time consuming task. While this paper does not provide an approach to automatically summarize a patient's history into a textual summary, this tabs shows the potential for future work in the area of text summarization with the context of EHR data.

4.3 Combined View

Both the summary tree and the summary panel are most effective when placed together, and thus we built a summary view that contains coordinated panels of both. However, to support the typical clinical process of analyzing all of the patients that a clinician sees, we employed a similar technique as utilized in LifeLines [8] by stacking multiple patient summary trees on top of one another. The final summary view that we constructed is shown in Figure 12. In this summary view it is possible

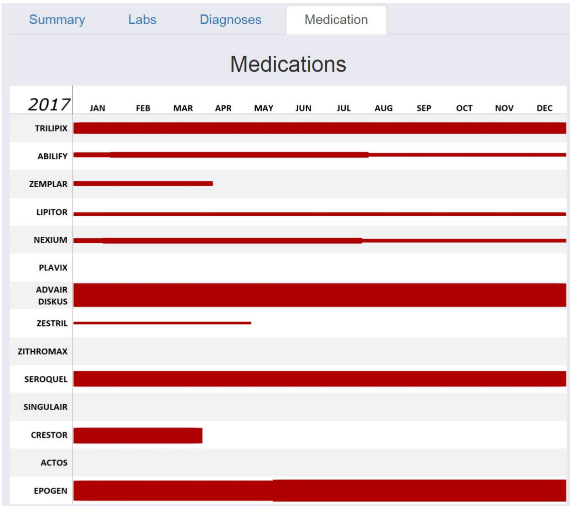


Fig. 10: The history of a patient's medications for a given timeframe, where we extend on the existing research in this domain [6] by indicating the prescribed dosage through the thickness of the horizontal bar. (The fourth tab of the summary panel.)

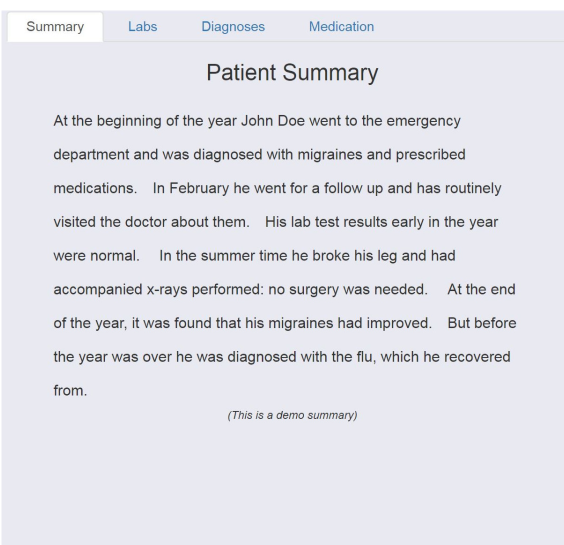


Fig. 11: An example textual summary of a patient for a given timeframe. This summary highlights the potential for future work in automatically generating a textual summary from an EHR. (The first tab of the summary panel.)

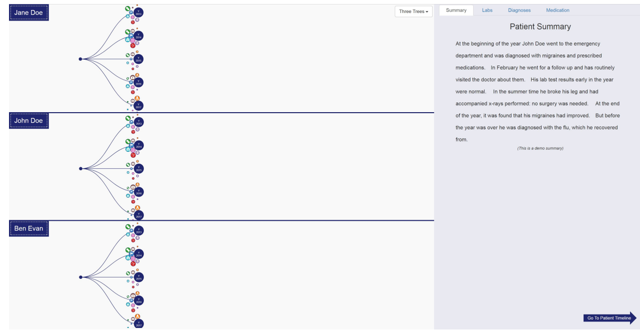


Fig. 12: The Summary View which combines both the summary tree and the summary panel in a single display to present the patient(s) that a clinician is attempting to analyze and understand. Through this view, comparison of patients at multiple and time scales and levels of detail is easily accessible.

to see that clinicians are not only able to easily switch between patients but they can also compare patients against one another, all the while they are developing an understanding of each patient.

In addition, to encourage a deeper analysis of the patients, beyond that of a summary, a button exists at the bottom of the summary panel titled "Go to Timeline", which takes the clinician to the timeline part of our framework, that we outlined in Section 3, with the page scrolled to the point that the clinician had selected in the summary tree. This ensures that the timeframe that the clinician focused on in the summary view is not lost, while still providing the capability to move forward or backward in the timeline.

5 Conclusion

Through our timeline-based framework we have presented an approach for aggregating and summarizing EHR data. We believe that this framework enables a clinician to be able to quickly skim through a patient's history over time, easily identify the changes that occur, limit the amount of information displayed, compare different timeframes and patients through a hierarchy of summaries, and focus their attention on the elements that they find most relevant. However, we identify that our current approach is limited in the fact that the tabs contained within the timeline view are not connected and require the clinician to still click between various elements of information, similar to a current EHR system. Therefore, we look forward to addressing these issues in a future case study with clinicians, integrating the framework into our current clinical environment, building more visualizations for the different elements of an EHR, and addressing the other aspects of future work discussed throughout this paper.

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