Development and Preliminary Evaluation of a Prototype of a Learning Electronic Medical Record System

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Abstract

Electronic medical records (EMRs) are capturing increasing amounts of data per patient. For clinicians to efficiently and accurately understand a *patient's clinical state, better way*s are needed to determine when and how to display EMR data. We built a prototype system that records how physicians view EMR data, which we used to train models that predict which EMR data will be relevant in a given patient. We call this approach a Learning EMR (LEMR). A physician used the prototype to review 59 intensive care unit (ICU) patient cases. We used the data-access patterns from these cases to train logistic regression models that, when evaluated, had AUROC values as high as 0.92 and that averaged 0.73, supporting that the approach is promising. A preliminary usability study identified advantages of the system and a few concerns about implementation. Overall, 3 of 4 ICU physicians were enthusiastic about features of the prototype.

Introduction

According to the American Medical Association, reducing cognitive burden is one of the top eight priorities for improving electronic medical record (EMR) usability[1]. One instance of high cognitive burden is information overload where an "individual's efficiency in using information is hampered by the amount of relevant, and potentially useful, information available to them"[2]. The display of patient data in current EMRs is not specific to the clinical context and burdens the physician who must search through the data to compile a clinically relevant narrative of the patient.

As EMRs capture increasing amounts of data per patient, compiling a clinical narrative becomes cognitively more demanding. This information overload is particularly challenging in settings such as the intensive care unit (ICU) where large amounts of data per patient are collected. A study in a Canadian hospital estimated that the average ICU patient generates a median of 1,348 data points per day[3]. This equates to a new data point being added to a patient's record almost every minute. An EMR that focuses the physician's attention on relevant patient data could help reduce the time needed to assess the patient's condition and improve the quality of the resulting judgments[1], enabling improved decision making, reduced medical errors, and greater efficiency.

Research efforts in the display of patient data have progressed in various directions including graphical summaries[4], methods to summarize and display temporal data[5], and the context specific integration of data using either systems[6] or disease[7-9] based approaches. Integrated data displays aggregate information from different sources and display it in one location (e.g., a cardiovascular system view, or a diabetes management view). These displays can improve performance and efficiency of physicians. For example, Pickering et al. developed an interface called AWARE that dynamically presented highly valued data to the physician at the ICU bedside in an integrated fashion[10]. When evaluated, AWARE reduced time to task completion and medical error in the assessment of ICU patients with a hypothesized acute bleed[10, 11].

AWARE and other existing integrated systems use rules to identify which of the thousands of available data points are relevant for specific patient contexts[12]. Rules are usually manually constructed from disease models, ontologies, and expert opinion. Such rule-based systems have several advantages. They are likely to be clinically informative, since they are based on clinical knowledge, and they can be readily programmed and applied to patient data that are available in electronic form. However, construction of rules is tedious and time-consuming. Moreover, rules have

limited coverage of the large space of clinical conditions, and a rule-based display may not adequately portray the context of a patient whose condition presents in an unusual way or a patient who has multiple maladies[13].

An alternative to a rule-based approach is to identify data that are relevant in assessing a patient's current clinical condition using a data-driven approach. Such an approach identifies patterns of useful patient data from data-access activities of physicians on past patient cases, and these patterns are applied to a patient case to highlight data relevant for that patient. Such an approach has several advantages. It does not require expert input to develop patterns, the patterns are derived using a large set of past patient cases, and the patterns can cover a wide range of clinical conditions. Moreover, such a system can continually update the patterns by learning from each interaction a physician has with it and can adapt to the specific environment in which it was being used. In other words, it would be a Learning EMR (LEMR).

Appropriate user-interface design will be vital to the success of a LEMR. Displays that adapt to suit the context of use have the potential to optimize the use of scarce resources, including user attention and screen-display real estate[14]. To be successful, these designs must provide dynamic displays that inform without disorienting. Recent efforts have explored novel designs for displays of laboratory data[10], for configuration of multiple components in an EMR display[15-17], and for knowledge-based adaptations of order entry menus[18]. A successful LEMR would build upon these results, using a combination of appropriate interface design techniques[19-21] and arrangements with context-sensitive adaptations based on patterns of system use.

We built a prototype LEMR that uses a data-driven approach to predict and highlight the data that are most relevant to a patient case. A physician reviewed patient cases and identified the relevant data for each case. The identified data became the dataset for training and evaluating classification models that predict if a data item is important to understanding the current patient's state. The results are used to determine if the data-driven approach is promising. Four more physicians used the prototype LEMR in a usability study. We describe the physician reactions to both the LEMR concept and the prototype. The results of the usability study provide an initial assessment of the desirability of such a system and an evaluation of the prototype design.

Methods

1. LEMR prototype

For this study the LEMR prototype required (1) screens to display patient data, (2) a dynamic region of the screen that could be filled with the clinically relevant data items, (3) the ability to record which data items a physician found clinically relevant, and (4) a framework to connect all of the components.

Highlighted Information Display (HID)

The LEMR prototype needed a clear and intuitive way to indicate which items were clinically relevant for a patient case. For this purpose, we allocated a region of the screen to be dynamically populated with the clinically relevant items. We called this region the Highlighted Information Display (HID) because the items found in it are the items that should stand out to the physician user.

Recording data-access patterns

We relied on physicians manually selecting the items they found most clinically useful for the most recent day of each patient case they reviewed. To indicate an item as useful, the prototype had a means for the user to move it into and out of the HID. Every time that a user modified the contents of the HID, the prototype recorded the changes in a database.

Components of the prototype LEMR

The prototype LEMR consists of four main components: a user interface, a web framework, a patient database, and a module with statistical models. These components are shown in Figure 1. The user interface is implemented using HTML, CSS, and JavaScript, and is powered by Django, an open source Python Web framework[22]. Patient data are stored in a MySQL patient database, which is queried to provide data shown in the user interface. This database also stores data viewing activities that are captured during EMR use. These data are used to train statistical models that predict data items (e.g., laboratory results) that are typically viewed in given a clinical context. These models are then applied to a current patient case in the database to predict the data items that are likely to be viewed and thus should populate the HID for that case.

Before enough training data are collected, the prototype relies on users viewing real patient cases and manually populating the HID with the data items in those cases that they think are most relevant. After some manual training data are collected, models start to automatically highlight the items that they predict to be of interest. When the HID is automatically populated from the models' predictions, the user retains the ability to manually modify its contents. Any manual modifications then feed back into the statistical models to further improve them.

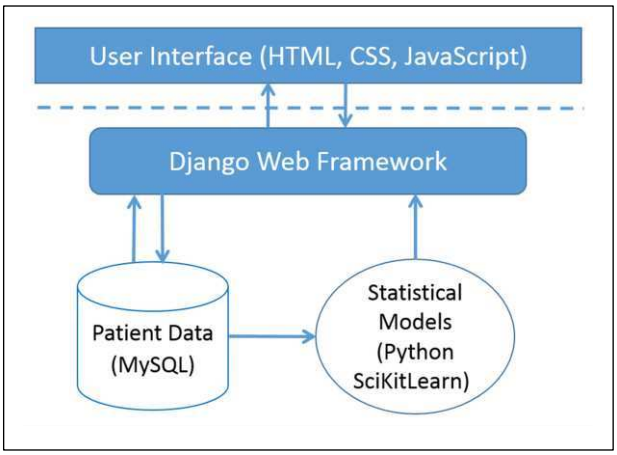

Figure 1. Components of the LEMR system.

2. Predictive modeling

We developed and evaluated logistic regression models to predict laboratory test results that are relevant to understanding a patient's current condition. We used de-identified data on 58 ICU patient cases that were randomly selected from a large ICU dataset that is described below. In this early study, we focused on predicting only laboratory test results using demographics and all laboratory test results as features.

ICU patient data

The patient data come from the High DENsity Intensive Care (HIDENIC) dataset, containing fully de-identified and HIPAA-compliant EMR data on 12,000 patients who were hospitalized in ICUs at the University of Pittsburgh Medical Center (UPMC) from July 2000 through December 2001[23]. HIDENIC contains structured data including demographics, physiological measurements collected at the bedside (including vital signs), laboratory values, medication and fluid administration records, and unstructured data in the form of a variety of clinical text reports (history and physical, progress, and operative procedure notes; radiology, EKG, and EEG reports).

The HIDENIC dataset contains patient information from ICU admission until ICU discharge. Because we were interested in physician behaviors during the review of an average day of an ICU patient, we defined the data for a patient case to be from admission to a random day during the patent's ICU hospitalization. Using this dataset, we were able to show a patient case to a physician and have them act as if the case was a current patient of theirs.

Extracting the features

The features used for predicting the clinical relevance of each laboratory test were extracted from each patient case and included both temporal and non-temporal items. Temporal features included the most recent value of each laboratory test and a Boolean value for whether that test result had appeared within the last 24 hours of available patient data. There were 190 distinct laboratory tests in the dataset, so the temporal test features totaled 380 (= 190 * the two features extracted from each test). There were five non-temporal demographic features (age, sex, weight, height, and body mass index) and one additional temporal feature of days since ICU admission. Therefore, in total there was a set of 386 predictive features for every patient case.

Collecting the training cases

Each of the 190 laboratory tests defines a binary target (dependent) variable that indicates whether that test is clinically relevant in a given patient case, and therefore should be placed in the HID. To collect this target data, 59 patient cases were randomly selected from the HIDENIC dataset. The cases were loaded into the LEMR prototype and a single physician reviewer (author SV) used the prototype to identify the tests that are relevant for each patient case within a given clinical context. In particular, the reviewer imagined that he was the attending who was taking care of the patient. He read the clinical reports and examined the test results to determine the clinical course since admission to the ICU. Then, for the last day for which patient data were displayed, he identified which tests were relevant in providing evidence about (1) changes in the clinical condition of the patient, or (2) the emergence of a new clinical problem. Any test that the reviewer moved into the HID for a patient case was considered clinically relevant for that case and was combined with that patient's feature set to create a positive training example for that test. Any test that the reviewer did not move into the HID for a patient case was considered not clinically relevant for that case and was combined with that patient's feature set to create a negative training example for that test.

Modeling and evaluation

Each laboratory test had a training dataset constructed from the 59 patient cases that were reviewed. We used each test's training dataset to train a penalized logistic regression model that predicts if that test is relevant to the current patient case. The models were build using the scikit-learn Python package[24] and evaluated using leave-one-out cross-fold validation. We measured performance using the Area Under the Receiver Operating Characteristic curve (AUROC).

3. Usability study

A usability study was conducted to gauge physician assessment of the LEMR concept. Four fellows in UPMC's Department of Critical Care Medicine participated in the study. This study was approved by the University of Pittsburgh Institutional Review Board (ID PRO14020588). Each physician used the prototype to review three to five selected patient cases. For each case, the physicians were shown a patient's data from ICU admission to a random day during that patients ICU hospitalization. The physicians were asked to familiarize themselves with the case as if they were the attending physicians. No data were highlighted in the HID for the initial look at each patient case. Next, the physicians were shown an additional day of data that was meant to simulate rounding on the subsequent day. For the additional day, items had been manually highlighted, based on relevant items identified by a physician on the research team (SV). The physicians were asked to use the features of the prototype to highlight/unhighlight items until the highlighted items represented the data that they thought another physician who was looking at the same case would want to see when assessing the most recent 24 hours, given that they had been following the patient case during the current ICU admission.

During the review of each patient case, screen tracking software recorded all of the on screen actions and an audio recording captured each physician's think-aloud comments. After a physician reviewed the allotted patient cases, additional time was allocated for a semi-structured interview of him or her. We asked about their perceptions regarding the LEMR concept in general and the prototype specifically. The interviews were coded independently by two researchers (AK and HH) before meeting to create a consensus. The coding was used to identify general themes in the responses. Each physician also filled out the System Usability Scale[25] based on their interactions with the prototype.

Results

1. Prototype

A screen shot of the user interface of the LEMR prototype is shown in Figure 2. Panel A, the patient demographics toolbar, allows the user to move between patients and gives a brief summary of the current patient's demographic information and admitting diagnosis. Panel B contains quick access tabs for navigating among the various types of patient data, including laboratory test results, medication orders, and clinical text reports (e.g., history & physical (H&P) reports, progress notes, and operative procedure notes). Currently the "Labs/Vitals/Meds" tab is selected. This prototype uses times-series plots to display these non-text based clinical items (laboratory test results, vital signs, medication orders, and intake and output data). Panel C, the time range selector, is used to define time ranges of data to display. Below the time-range selector is the procedures axis, which is labeled with the defined times. Black diamonds on this axis represent procedures (surgeries, biopsies, etc.) that the current patient has had. Hovering over a diamond gives more details on that procedure. Panel D, the HID, shows high detail plots of selected clinical items. These plots have a labeled y-axis and blue bands to indicate the normal range. Panel E displays all available results, including those found in the HID, using plots with condensed y-axes. These plots give a notion of trends over time and are arranged by group type (chemistry, lipids, cardiac, etc.). The buttons across the top of this panel list all of the different group types and can be used to jump to a specific type. For both Panel D and Panel E, different colors are used to indicate when a value is within or outside of normal range (blue = below; green = within; red = above; black = no defined normal range).

For any given patient, the items highlighted in the HID are meant to be the ones that are most clinically relevant for that patient at the current time. The HID can be populated with items by both automatic and manual means. For automatic population, the LEMR uses stored statistical models to predict the probability that each item is relevant given the current patient state. The items that have a predicted probability above a set threshold are displayed. To make manual changes to the contents of the HID, a user clicks on the arrow buttons next to each clinical item's name. There are buttons to move items into the HID and buttons to remove items from there.

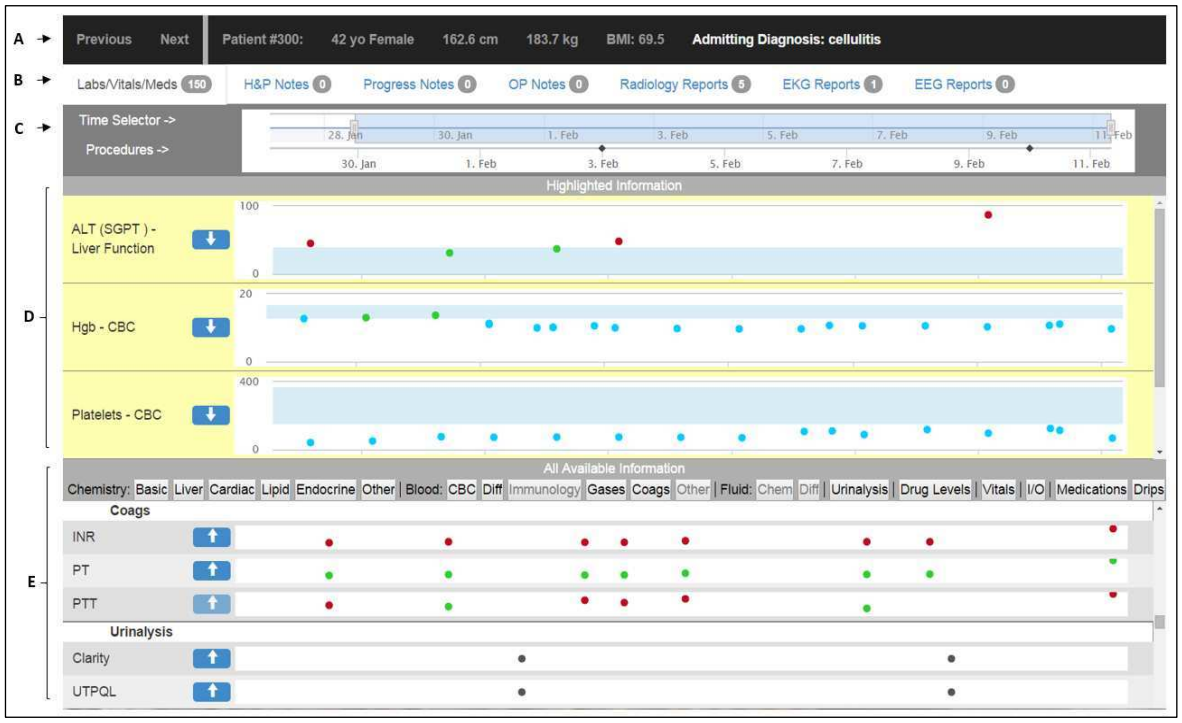

Figure 2. Screenshot of the LEMR prototype. A) demographics toolbar; B) quick access tabs; C) time range selector; D) Highlighted Information Display (HID); E) all data display. Both D and E are scrollable.

2. Predictive models

We derived penalized logistic regression models for the 21 distinct laboratory tests that were identified as clinically relevant (accessed) for at least two patient cases in the dataset. The AUROC values for those models and the number of positive (# +) training cases in their datasets are shown in Table 1. The average AUROC is 0.73. The top seven tests shown in the table have an average AUROC greater than 0.80.

3. Usability study

The physicians were generally enthusiastic about the LEMR approach. They identified advantages, such as adaptation to different specialists and the potential for time savings. Concerns included the feasibility of the implementation and the possible implications of integration into workflow. For instance, some participants worried that over-reliance on highlighted items might cause physicians to miss important details in the remainder of the record.

Three of the physicians liked the timeline approach to displaying the data but would like to see the exact value of each result without needing to hover over a data point with the mouse. Two of the physicians discussed other information resources such as the summary sheet that they currently print out for each patient before rounding. One physician discussed a desire for the EMR to include a checklist of all the things that must be checked for each patient every day.

The System Usability Scale composite score for the four users was 78.75. The scale ranges from 0 to 100 and any score above 68 is generally considered to be above average usability[26].

Table 1. AUROC for patient-specific prediction of the clinical relevance of each laboratory test				
		95% CI		
Laboratory Test	**AUROC**	**Lower**	**Upper**	**# +**
Bilirubin Total	0.92	0.83	0.97	5
Liver Alanine Aminotransferase	0.91	0.72	0.98	4
Liver Aspartate Transaminase	0.91	0.72	0.99	4
PTT Coagulation	0.84	0.71	0.92	9
Lactate	0.83	0.58	1.00	2
Phosphorus	0.82	0.62	0.94	11
White Blood Cell Count	0.80	0.67	0.91	8
INR Coagulation	0.79	0.63	0.89	11
Hematocrit	0.77	0.59	0.89	37
Sodium	0.75	0.61	0.86	18
Glucose	0.73	0.55	0.87	12
Chloride	0.73	0.59	0.82	2
Blood Urea Nitrogen	0.73	0.56	0.85	22
Hemoglobin	0.71	0.54	0.83	33
Platelet Count	0.70	0.53	0.82	28
Lymphocytes Absolute Count	0.64	0.26	0.95	2
Neutrophils Absolute Count	0.64	0.27	0.95	2
Red Blood Cell Count	0.57	0.25	0.97	3
Magnesium	0.56	0.27	0.89	5
Potassium	0.52	0.37	0.68	11
Calcium	0.47	0.28	0.83	5
Average	0.73			

Discussion

We developed and evaluated a prototype LEMR system that uses a data-driven approach to adapt its display to highlight the data items that are most relevant in a patient case. Our preliminary results show varying performance for the predictive models that identify when 21 laboratory tests are relevant, but one-third of them had an AUROC of 0.80 or greater, supporting that this approach is promising. Moreover, in a usability study ICU physicians were generally supportive of the LEMR approach, and identified advantages and concerns with the prototype.

With the accumulation of data in the EMRs, physicians are at increased risk of making errors due to information overload[27, 28]. The LEMR system we are developing may help to reduce this risk by identifying and highlighting the small subset of the available information[29] that is relevant when making medical decisions for a patient. Similar data display techniques, such as Microsoft Word's split menu font selection list, have resulted in faster selections and higher user performance ratings[19]. Split menus combine the convenience of frequency ordered menus with the consistency of alphabetically ordered menus. The LEMR prototype has a similar structure where the HID provides convenience and the rest of the prototype provides consistency.

The LEMR also has similarities to other tools[18, 30] that have explored mining interaction patterns from previous users to inform the presentation of information/choices/etc. These other tools have benefited from crowd wisdom[31], where

the collective knowledge of many people can be better than the knowledge of any individual in the population. In terms of a LEMR, a physician who is inexperienced with a certain patient type could benefit from seeing items highlighted based on the information that a more experienced physician would access. This would bring the inexperienced physician's attention to an important item that they may have otherwise overlooked. Highly experienced physicians could perform the initial training of the system to further capitalize on this effect.

The AUROC performance of the models developed during this study ranged from ~0.50 to 0.92. The higher scores are a promising sign for the approach because we used a small number of training cases and a limited set of possible features. A dataset of only 59 cases leaves only 58 training cases for each fold of the validation. If a LEMR were implemented in a hospital setting, it would learn every time a physician interacts with it. That would mean additional training cases extracted for each patient every day. Using this approach, the size of the training set would quickly grow to a huge number of samples. The feature set used in this study was purposely restricted to very basic predictors. Many more temporal features, such as the slope between the last two values of a laboratory test, could prove to be very useful when predicting if a test is relevant to a patient context. Numerous other data types, such as vital signs and medication orders, were not considered but could be included as well. With an increase in the training set size and an expanded feature set, the predictive accuracy of each model would likely improve.

Our usability study provided preliminary support for the feasibility of the LEMR idea. Participants' concerns regarding feasibility and integration into existing workflows are valid practical points that we hope to explore after modeling and interface design issues are more mature. The possibility of over-reliance on highlighted items is a key concern—EMR displays that encourage overly narrow readings of patient information may cause important data to be missed. Design lessons from prior work in personalized interfaces[20] and related areas will inform the development of prototypes exploring alternative displays, with continued usability studies providing vital physician feedback.

The continual extraction of training data is the biggest advantage a LEMR has over rule-based context sensitive EMR systems. Rule-based systems do not generalize well and their display of data may not be optimal for any patient who does not fit into a planned context[13]. For example, a patient can have both diabetes mellitus and chronic kidney disease. A display that was designed specifically for a patient with diabetes may not adequately represent the complexities of the case. The LEMR, which learns from every interaction a user has with it, could represent some of the important complexity of any case and could learn to meet information needs as they change overtime.

The data-driven approach we are taking also allows for the same LEMR system to be implemented in almost any healthcare setting. For example, if the LEMR were implemented in a particular unit at a hospital, the combined interactions from all of the physicians in that unit would aid the system in adapting to how patients are handled in that environment. The system would not be limited to one set of models either; it could use hierarchical learning to have a different set of models for each class of users, such as physicians of different specialties. The same theory would apply when implementing the LEMR in a hospital wide setting. The models could customize to the different groups of users in the different units.

Limitations

Our study has several limitations. The training of the predictive models was limited by the small training dataset. It contained enough data to evaluate the prediction of 21 laboratory tests. This limitation will be addressed in a future study where more patient cases are reviewed and other types of clinical data are included in the items whose access is tracked. Moreover, we plan to develop predictive models for data items beyond laboratory test results.

The usability study was limited to four participants. In the future we plan to conduct usability studies with a larger number of participants, potentially including side-by-side empirical comparisons aimed at understanding the impact of alternative design strategies on physician interactions with the EMR, in terms of both accuracy and efficiency

We obtained data-access information from a physician user who manually highlighted data items that were relevant to a patient case. This manual acquisition of data-access information is a limitation of the current study. In a mature LEMR that is deployed, such data-access information would be inferred automatically from computer mouse activity, eye movement tracking, and from clinical notes (e.g., progress notes) in which pertinent data items are recorded.

Conclusion

EMRs should synthesize and present patient data in such a way that it enhances the physician's ability to understand the overall state of the patient and detect significant changes in the clinical course while decreasing the physician's cognitive workload. We proposed a data-driven approach to displaying EMR data in a context specific manner. We built a prototype, trained and evaluated predictive models, and conducted a usability study as first steps in the development of a LEMR. This study supports the feasibility of the approach and provides insight on development concerns and opportunities. We plan to use the lessons learned from this study to extend the models using larger and more comprehensive datasets, to further refine the interface, and to conduct additional evaluation studies of the LEMR.

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