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

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Introduction

Electronic medical records (EMRs) should present patient data in a way that enhances a clinician's ability to understand the overall state of a patient and detect significant clinical changes, while decreasing the clinician's cognitive workload. Our goal is to create a **Learning EMR (LEMR) system** that (1) analyzes past data access patterns, to (2) predict, and then (3) highlight current data needs.

A Prediction Experiment

Training data

A physician (author SV) reviewed 59 randomly chosen ICU patient cases and identified the relevant laboratory tests (RLTs) of interest for each case.

Predictive model

The RLTs were treated as targets to be predicted. Clinical features were extracted from each case as potential predictors. We applied logistic regression to learn 21 predictive models. The average AUROC was 0.73.

Modeling summary

Features – demographics, test results, vital signs
Targets – relevant laboratory tests (RLTs)
Model – penalized logistic regression
Evaluation – leave-one-out cross-fold

Table 1. AUROC for patient-specific prediction of relevant laboratory tests (RLTs) of interest.

Laboratory Test	AUROC	95% CI		# +
		Lower	Upper	
Bilirubin Total	0.92	0.83	0.97	5
Liver ALT	0.91	0.72	0.98	4
Liver AST	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	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
Platelets	0.70	0.53	0.82	28
Lymphocytes Absolute	0.64	0.26	0.95	2
Neutrophils Absolute	0.64	0.27	0.95	2
Red Blood Cell	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**			

Limitations

Data were sufficient to evaluate only 21 laboratory tests. Also, the identification of RLTs for training were based on manual coding by a clinician. In a mature LEMR, this training data would be available automatically from EMR usage data.

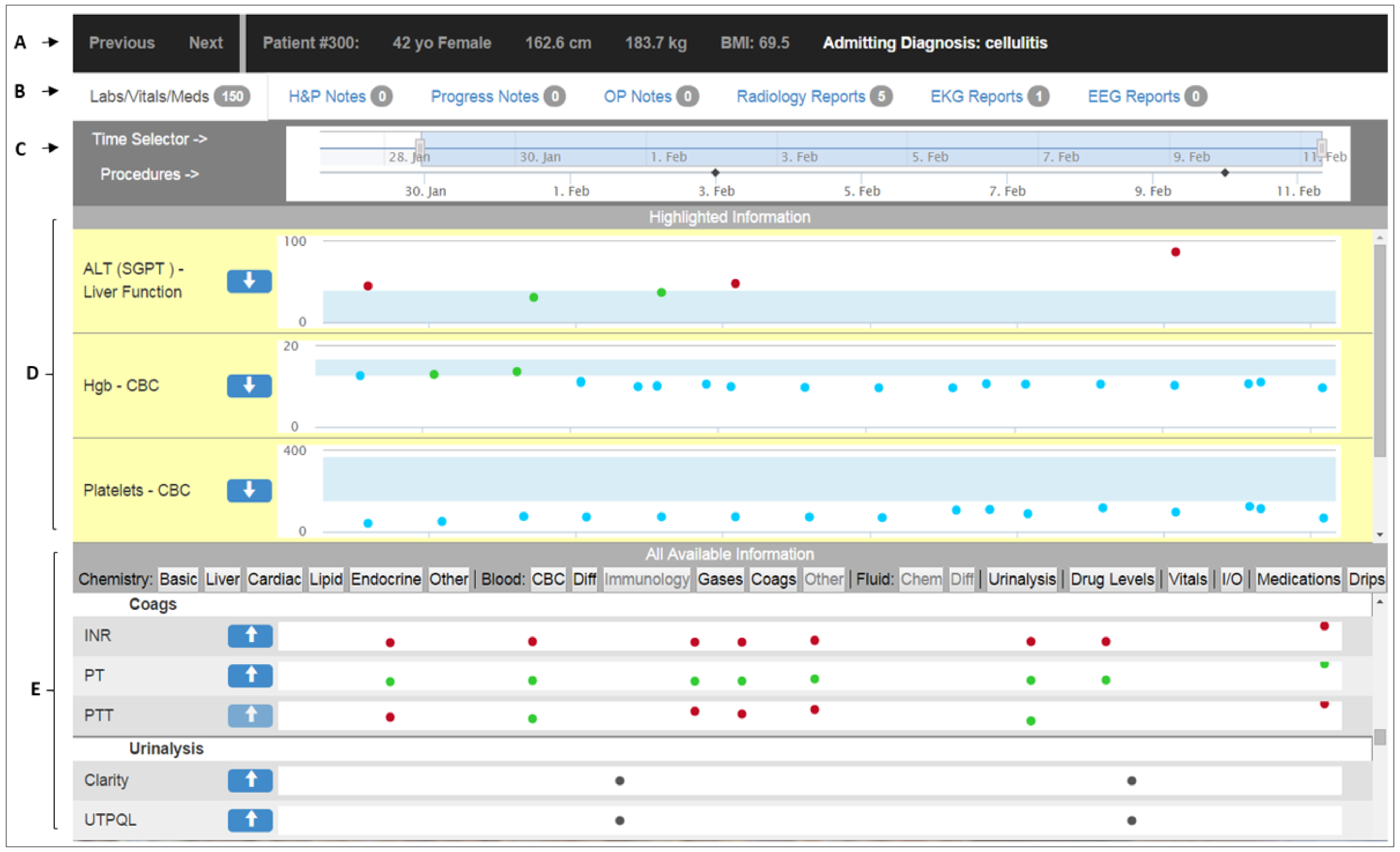

Figure 1. Screenshot of the LEMR prototype. A) demographics toolbar for switching between patients, a brief summary of current patient's demographic information, and admitting diagnosis; B) quick access tabs for navigating among the various types of patient data; C) time range selector for choosing the time range of data to display; D) Highlighted Information Display (HID) where high value data are collated and displayed; E) all data display shows all of the available data from each category.

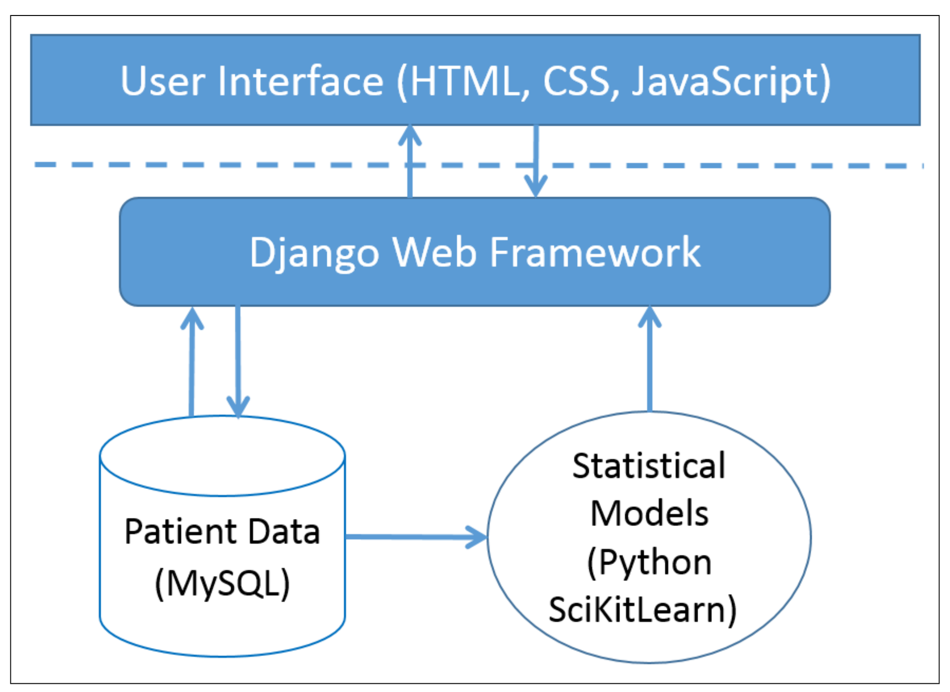

Figure 2. Components of the LEMR system.

Construction of a Prototype

A prototype LEMR was developed to investigate possible approaches to highlighting relevant data. The prototype components are shown in Figure 2 and a screenshot is shown in Figure 1. The Highlighted Information Display or HID (Figure 1 label D) is where the high-valued (relevant) patient data are collated and displayed. The HID can be populated in both of the following ways:

- *Manual modification* where a clinician user adds or removes items using the blue arrow buttons
- *Automatic modification* where predictive models determine the information that is being displayed

A Usability Study

Methods

Four Critical Care Medicine fellows used the prototype to review 3 to 5 selected patent cases both with and without data highlighting.

Results

- Fellows had general enthusiasm for the LEMR approach
- System Usability Scale composite score for the four users was 79 out of 100[1]
- Identified *advantages*: Automatic adaption to different specialists and a potential for time savings
- Identified *concerns*: feasibility of the implementation and 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.
- 3 of 4 fellows liked the timeline approach to displaying data but wanted to see exact values without hovering over data points.

Reference

1. Brooke J. SUS-A quick and dirty usability scale. Usability evaluation in industry. 1996;189(194):4-7.

Conclusion & Future Work

The above results provide initial support for the feasibility and usefulness of a LEMR. In future work we plan to:

1. Extend existing models using larger and more comprehensive training datasets
2. Train models that predict and then highlight medications, procedures, and laboratory results that are likely to be of interest (relevant)
3. Make further refinements to the interface
4. Conduct additional evaluation studies
5. Investigate ways of automatically training the models, such as by using cursor or eye movement tracking

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