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# A Learning Electronic Medical Record System

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## Electronic Medical Record for ICU (Cerner)

Diagnoses (4 Active)	HR	78	76	76	Total Fluid
Acute Renal Failure (584.9)	06/15/10 21:15		06/15/10 21:00	06/15/10 20:45	
Congestive Cardiomyopathy (425.9)					
Congestive Heart Failure (428.0)					
Unstable Angina (411.1)					
<b>Problems (7 Active)</b>					
Alcoholism (303.90)					
Diabetes (249)					
Esophageal Reflux (530.81)					
Esophageal Varices (456.1)					
Hepatic Artery Embolism (902.22)					
Hypertension (997.91)					
Peripheral Vascular Disease (443.9)					
<b>Allergies + Add (3 Active)</b>					
<b>Peanuts</b>	<b>Eye swelling, Difficulty breathing</b>				
Chocolate	Abdominal pain				
Pollen	Sneezing				
<b>Medications (11) +</b>					
Scheduled (7)					
Hx Vitamin B-12 100 mcg PO Daily					
Hx Aspirin 81mg 1 tab by mouth daily					
Rx Gentamicin 120mg IV every 8 hours					
Hx Lasix 20mg 1 tab by mouth daily					
Rx Levaquin 500mg IV daily					
Rx Metoprolol 25mg 1 tab by mouth twice a day					
	<b>O<sub>2</sub>Sat</b>	<b>99</b>	<b>90</b>	<b>90</b>	
	06/15/10 21:15	06/15/10 21:00	06/15/10 20:45		
	<b>Glu (POC)</b>	--	<b>82</b>	<b>82</b>	Total Fluid
	06/15/10 21:15	06/15/10 21:00	06/15/10 20:45		Last Diet
	<b>MEWS</b>	<b>3</b>	<b>2</b>	<b>1</b>	Restraint
	06/14/10 12:14	06/14/10 10:00	06/14/10 08:00		Ordered
					Order De
<b>Labs</b>					
Last 7 days					
	<b>WBC</b>	<b>6.5</b>	<b>4.0</b>	<b>4.0</b>	Immuniz
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		DtaP
	<b>Hemoglobin</b>	<b>15</b>	<b>15</b>	<b>15</b>	Hepatitis
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		Patholog
	<b>Hematocrit</b>	<b>45</b>	<b>45</b>	<b>45</b>	Surgical I
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		My Favo
	<b>Platelets</b>	<b>250</b>	<b>280</b>	<b>280</b>	Medis   L
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		Aspirin 8
	<b>Sodium</b>	<b>145</b>	<b>140</b>	<b>140</b>	KCl 20mEq
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		Lasix 40m
	<b>Potassium</b>	<b>4.0</b>	<b>3.9</b>	<b>3.9</b>	Metformi
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		Scratcho
	<b>Chloride</b>	<b>100</b>	<b>99</b>	<b>99</b>	Select Ord
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		No Order
	<b>CO<sub>2</sub></b>	<b>38</b>	<b>37</b>	<b>37</b>	
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		
	<b>BUN</b>	<b>6.0</b>	<b>8.0</b>	<b>8.0</b>	
	06/16/10 07:00	06/15/10 21:00	06/15/10 21:00		

[store.cerner.com/items/283]

## Electronic Medical Records (EMRs)

- Contain massive amounts of healthcare data
  - 1,400 new data points per patient per day<sup>1</sup>
  - 4,000 mouse clicks in a 10-hour shift<sup>2</sup>
- Can result in information overload<sup>3</sup> and increase cognitive workload on physicians<sup>4</sup>
- Can lead to patient safety concerns<sup>5</sup>
  - Missed test results<sup>3,6</sup>
  - Treatment delays<sup>7</sup>

1. Manor-Shulman et al. J Crit Care 2008; 2. Hill et al. Am J Emerg Med. 2013; 3. Singh et al. Jama Intern Med. 2013; 4. American Medical Association. 2014; 5. Meeks et al. JAMIA 2014; 6. Callen et al. BMJ Qual Saf. 2011; 7. Wahls et al. BMC Fam Pract. 2007.

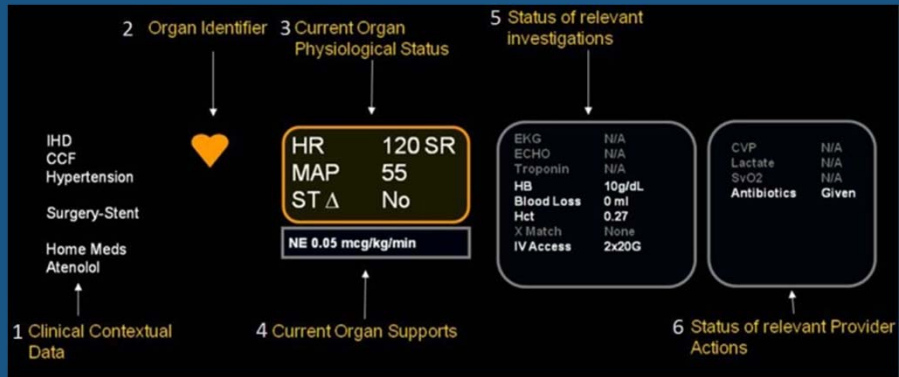


## The American Medical Association

- Reducing cognitive workload is a top priority in improving EMRs
- EMRs should:
  - Support medical-decision making
  - Provide context sensitive data
  - Adjust for environment and user preferences

4. Improving care: Priorities to improve electronic health record usability. 2014.

## Redesigned EMR system: AWARE



[8. Pickering et al. Appl Clin Inform. 2010.]

- Uses rules
- Context sensitive

## Unfortunately...

- Construction of rule bases is difficult and time consuming
- It is **not scalable** to build EMRs that rely on rule bases

Can we find a data-driven alternative?

## Data-driven alternative

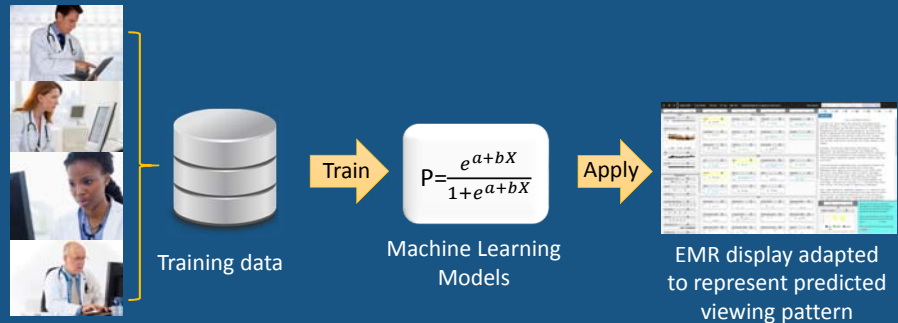
- EMR that displays the information that a physician “wants to view” for the current patient case.
- *Wants to view* is something that we can “predict.”
- We make *predictions* using machine learning “models.”
- *Models* require “training data.”
- The *training data* is EMR information that many “physicians viewed” for many different patient cases.

## What is a Learning Electronic Medical Record?

- A medical record that learns from its users, in order to improve the display of information for those users.

# How do we build a LEMR?

We can use **physician viewing patterns**



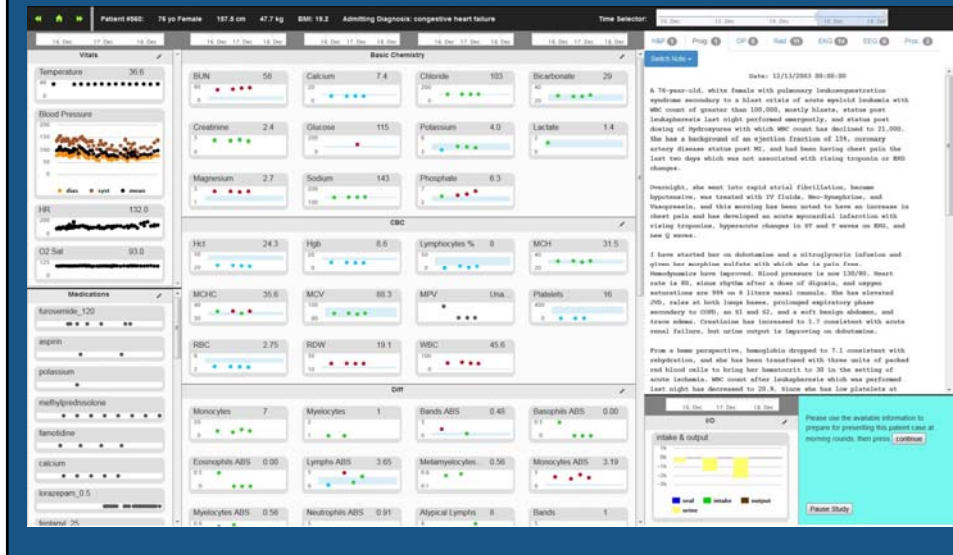
[shutterstock.com, istockphoto.com]

## Patient data

- HIDENIC<sup>10</sup> dataset
  - 1000s of de-identified electronic records
  - Patients admitted to University of Pittsburgh Medical Center (UPMC) Intensive Care Units (ICUs)

10. Visweswaran et al. AMIA. 2010.

# LEMR prototype



# LEMR model application

$$P = \frac{e^{a+bX}}{1+e^{a+bX}}$$

Models

Apply models to a patient case



# LEMR prototype

The screenshot displays a comprehensive patient dashboard. On the left, there are sections for Vitals (Temperature, Blood Pressure, HR, O2 Sat), Medications (Lorazepam, Aspirin, Potassium, Methylprednisolone, Fentanyl, Calcium, Intracranial Pressure, Fentanyl), and a Time Selector. The main area is divided into Basic Chemistry (BUN, Creatinine, Magnesium, Calcium, Glucose, Sodium, Chloride, Potassium, Phosphate, Bicarbonate, Lactate) and CBC (Hct, Hgb, Lymphocytes %, MCH, MCHC, MCV, MPV, Platelets, RBC, RDW, WBC, Monocytes, Myelocytes, Bands ABS, Bicytosis ABS, Eosinophils ABS, Lymphs ABS, Metamyelocytes, Monocytes ABS, Neutrophils ABS, Atypical Lymphs, Bands). A clinical note on the right provides a detailed history of the patient's condition, including symptoms like chest pain and rapid atrial fibrillation, and treatments such as aspirin, nitroglycerin, and IV fluids. A 'Print & Output' section is also visible at the bottom right.

# LEMR prototype

This view shows a grid of individual lab test cards. Each card displays the test name, a numerical scale, and a series of colored dots representing data points. The BUN card is highlighted in yellow and has a checkmark icon. The tests shown are: BUN (scale 0-60), Calcium (0-20), Chloride (0-200), Bicarbonate (0-40), Creatinine (0-3), Glucose (0-200), Potassium (0-6), Lactate (0-2), Magnesium (0-3), Sodium (0-200), and Phosphate (0-7).

# Training data representation

A patient context is a vector of features

	Example patient case		Viewing pattern
Diagnoses	Diagnosis	cirrhosis	1
Demographics	Age	47	0
	Sex	female	0
Lab test results	BUN	39	1
	Hemoglobin	10.1	1
	SGPT	107	1
	SGOT	48	1
	Bili, Total	1.4	0
Medications	Metoprolol	200	0
	...		...
Vital signs			
Procedures			
etc.			

Mrs. Jones                      Dr. A

# Training data representation

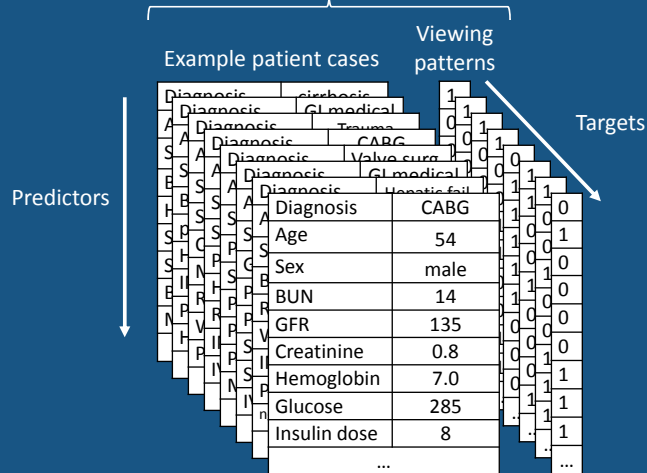
A patient context is a vector of features

	Example patient cases		Viewing patterns
Diagnoses	Diagnosis	cirrhosis	1
Demographics	Diagnosis	GI medical	1
	Diagnosis	Trauma	0
Lab test results	Diagnosis	CABG	1
	Diagnosis	Valve cura	0
	Diagnosis	GI medical	1
	Diagnosis	Hepatic fail	1
	Diagnosis	CABG	1
Medications	Age	54	1
	Sex	male	0
Vital signs	BUN	14	1
	GFR	135	0
	Creatinine	0.8	0
	Hemoglobin	7.0	1
	Glucose	285	1
Procedures	Insulin dose	8	1
	...		...

Mr. Stärk                      Dr. A



## Training data



## Study 1: Build and test models

- Dataset
  - 59 patient cases from HIDENIC<sup>10</sup> dataset
  - Physician identified lab tests that he or she would want to view based on earlier data
- Models
  - Penalized logistic regression
  - Predictors: lab test values, time since test, & demographics
  - Targets: the lab tests that the physician identified as wanting to view (Boolean)
- Evaluation
  - Leave-one-out cross fold
  - AUROC

10. Visweswaran et al. AMIA. 2010.

## Study 1 Results

- AUROC scores are promising
- Top seven models have AUROCs  $\geq 0.8$
- Despite small training sets and limited feature set

Highlight Laboratory Test	AUROC (95% CI)
Bilirubin Total	<b>0.92</b> (0.83, 0.97)
Liver Alanine (ALT)	<b>0.91</b> (0.72, 0.98)
Liver Aspartate (AST)	<b>0.91</b> (0.72, 0.99)
PTT Coagulation	<b>0.84</b> (0.71, 0.92)
Lactate	<b>0.83</b> (0.58, 1.00)
Phosphorus	<b>0.82</b> (0.62, 0.94)
White Blood Cell	<b>0.80</b> (0.67, 0.91)
INR Coagulation	0.79 (0.63, 0.89)
Hematocrit	0.77 (0.59, 0.89)
Sodium	0.75 (0.61, 0.86)
Glucose	0.73 (0.55, 0.87)
Chloride	0.73 (0.59, 0.82)
Blood Urea Nitrogen	0.73 (0.56, 0.85)
Hemoglobin	0.71 (0.54, 0.83)
Platelets	0.70 (0.53, 0.82)
Lymphocytes Absolute	0.64 (0.26, 0.95)
Neutrophils Absolute	0.64 (0.27, 0.95)
Red Blood Cell	0.57 (0.25, 0.97)
Magnesium	0.56 (0.27, 0.89)
Potassium	0.52 (0.37, 0.68)
Calcium	0.47 (0.28, 0.83)
<i>Average</i>	<i>0.73</i>

## Study 2: Usability study on prototype

- Four ICU clinicians
- Three to five patient cases
- Think aloud
- Interviews
- System Usability Scale<sup>11, 12</sup>



11. Brooke. Usability Evaluation in Industry. 1996.  
 12. Sauro. Measuring Usability LLC. 2011.

## Study 2 Results

### Positives

- Important
- Improve quality of care
- Adaptable
- Reduction in information burden
- Design
- System Usability Scale composite score: 79

"To design something that utilizes current behaviors, optimize it, is certainly something that is important."

"I think it would probably improve quality of care overall."

"Definitely applicable because not all [types of] physicians look at the same type of data."

"Anything that is willing and able to highlight the most relevant information without [boggling] down my day with information I do not need would be great."

"I like the concept because everything is graphically shown instead of tables of numbers."

## Study 2 Results

### Concerns

"I just don't know how to make it feasible in the ICU setting where we have to address every organ system and almost every single abnormality."

"If you focus too much on what is standard...then you miss out on the rare things that happen."

"I don't like the idea of blue. Red means stop, so whether it is high or low it should be red."

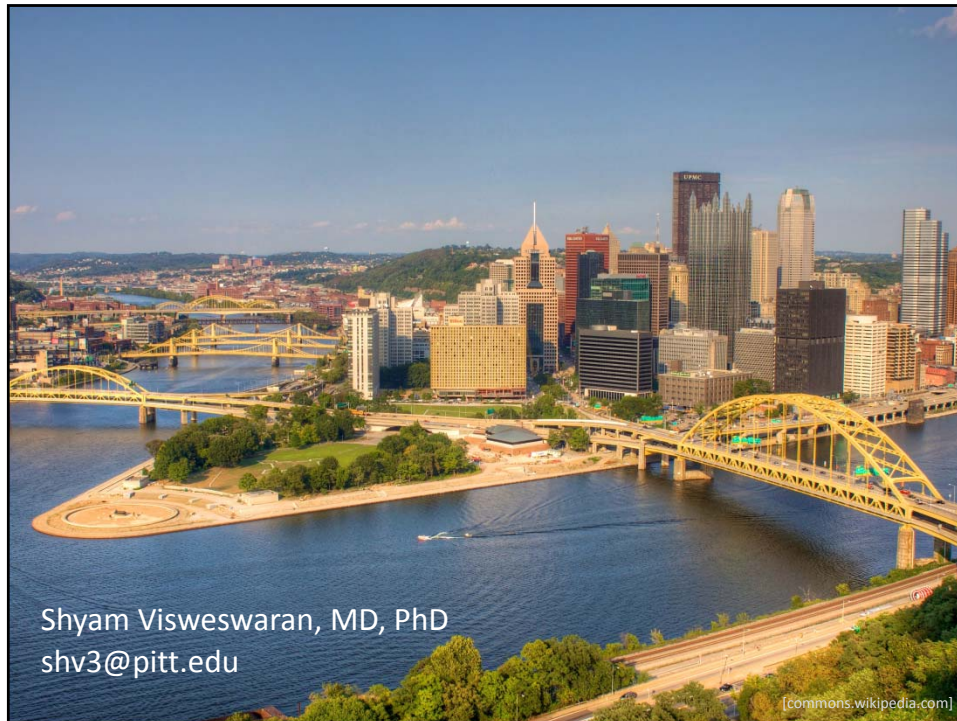
- Feasibility
- Implications of integration into workflow
- Design

## Conclusions

- We developed a prototype of a LEMR system that learns how to predict and highlight data that a physician is likely to view
- Our preliminary results provide support for often being able to predict accurately the EMR data that a physician is likely to view
- A usability study provides insights about the strengths and concerns of clinicians regarding the LEMR prototype in particular and LEMR systems in general

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[commons.wikipedia.com]

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