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A Learning Electronic Medical Record System

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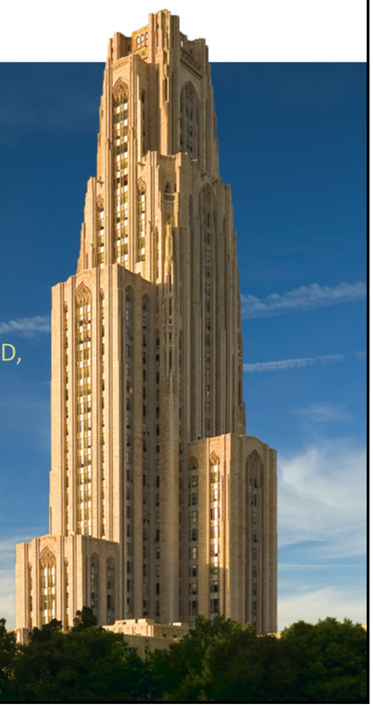
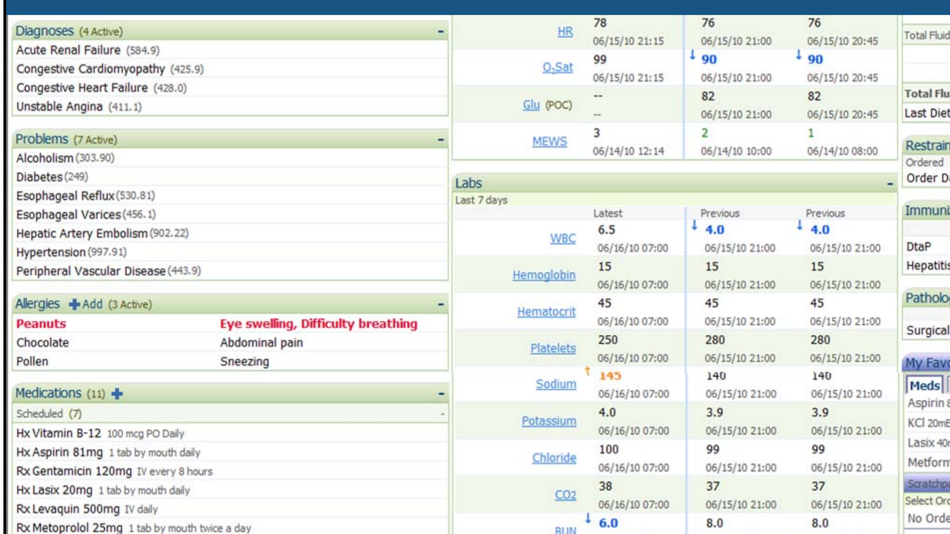


15 November 2017

Electronic Medical Record for ICU (Cerner)



[store.cerner.com/items/283]

Electronic Medical Records (EMRs)

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

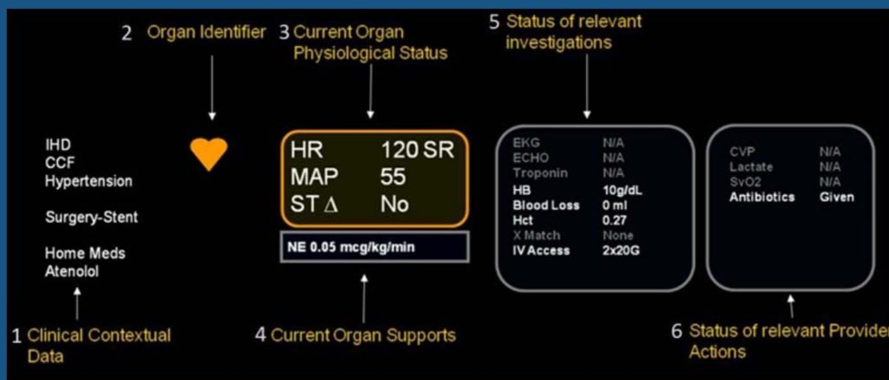
1. Manor-Shulman et al. J Crit Care 2008; 2. Hill et al. Am J Emerg Med. 2013; 3. Singh et al. Jama Intern Med. 2013; 4. American Medical Association. 2014; 5. Meeks et al. JAMIA 2014; 6. Callen et al. BMJ Qual Saf. 2011; 7. Wahls et al. BMC Fam Pract. 2007.

AMA 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

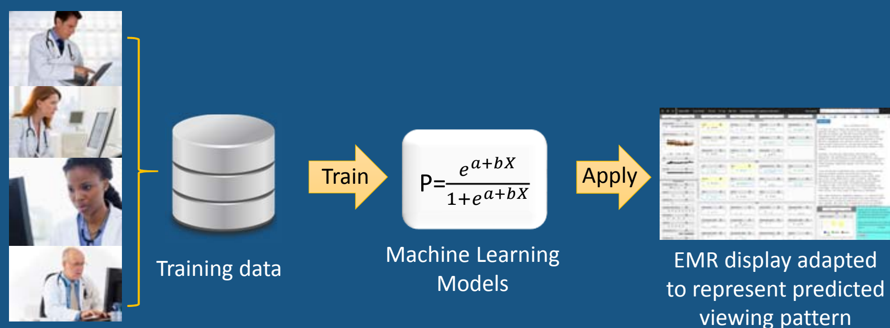
- EMR that displays the information that a physician "wants to view" for the current patient case.
- *Wants to view* is something that we can "predict."
- We make *predict*ions using machine learning "models."
- *Models* require "training data."
- The *training data* is EMR information that many "physicians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



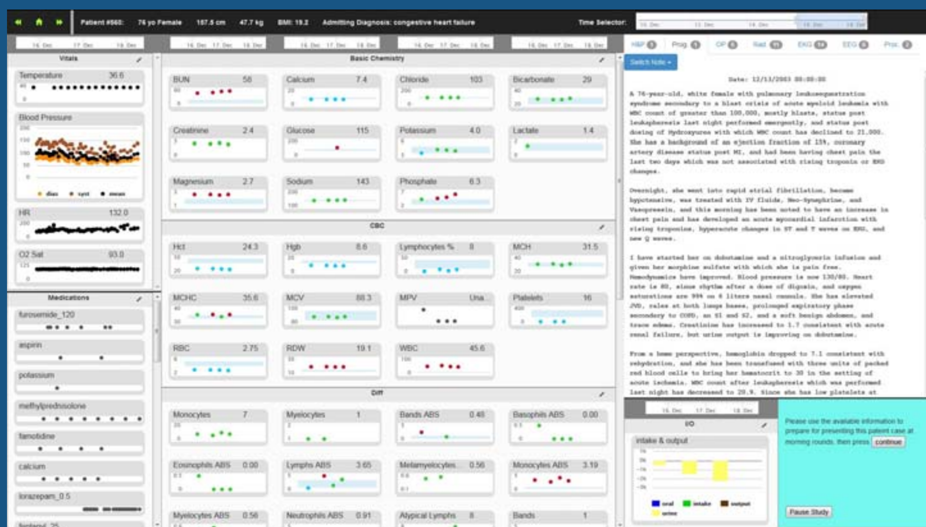
[shutterstock.com, istockphoto.com]

Patient data

- HIDENIC[10] 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

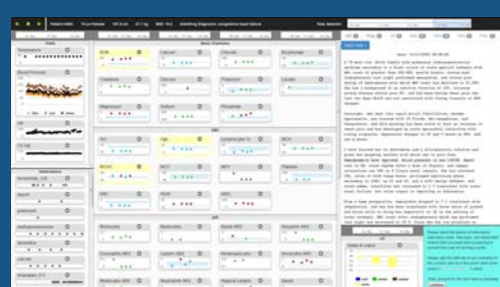


LEMR model application

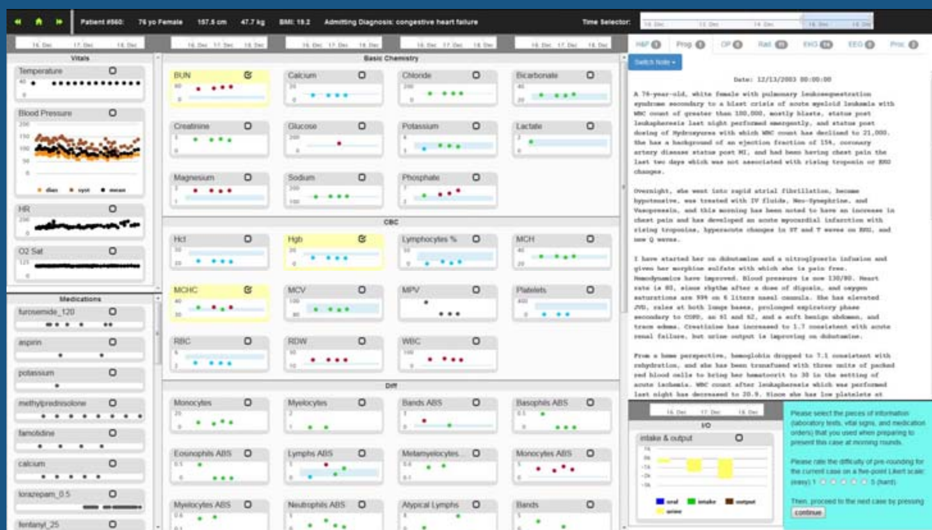
$$P = \frac{e^{a+bX}}{1+e^{a+bX}}$$

Models

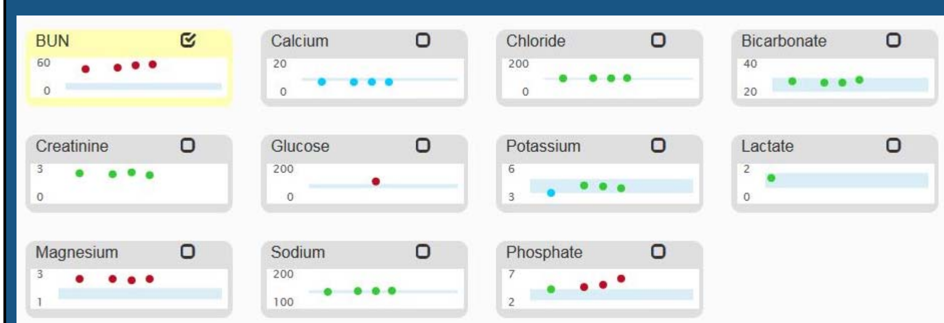
Apply models to a patient case

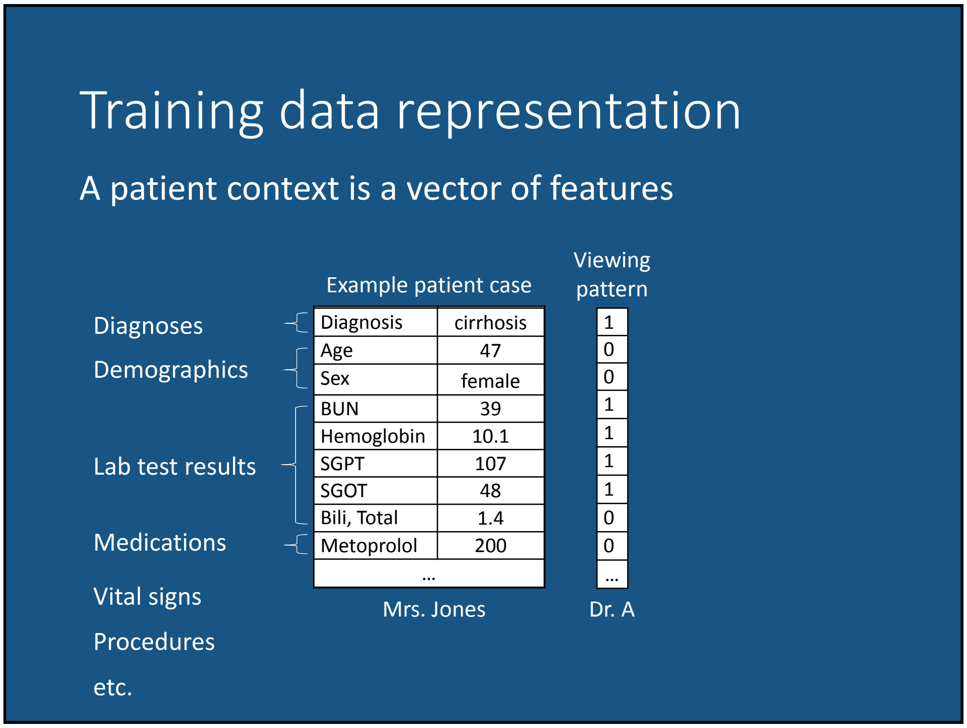


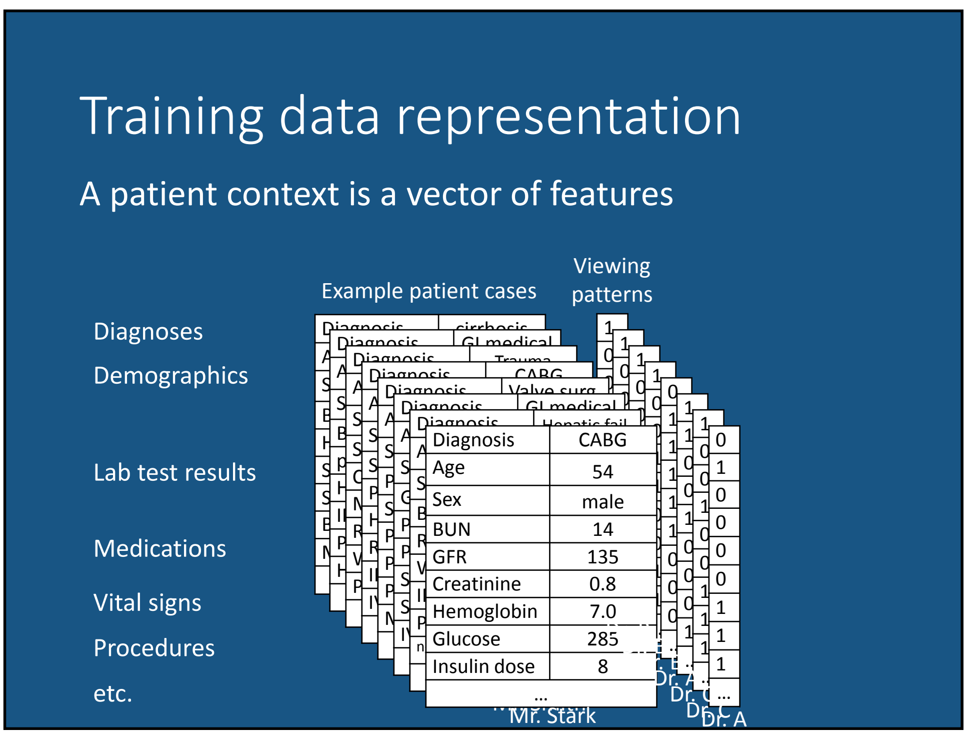
LEMR prototype



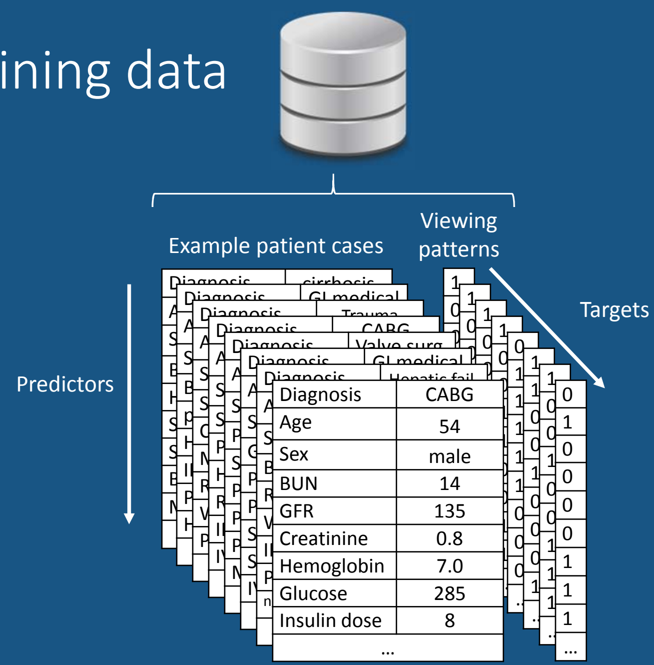
LEMR prototype




Training data representation
A patient context is a vector of features
Example patient case
Viewing pattern
Diagnoses
Demographics
Lab test results
Medications
Vital signs
Procedures
etc.
Diagnosis | cirrhosis | 1
Age | 47 | 0
Sex | female | 0
BUN | 39 | 1
Hemoglobin | 10.1 | 1
SGPT | 107 | 1
SGOT | 48 | 1
Bili, Total | 1.4 | 0
Metoprolol | 200 | 0
… | …
Mrs. Jones
Dr. A


Training data representation
A patient context is a vector of features
Example patient cases
Viewing patterns
Diagnoses
Demographics
Lab test results
Medications
Vital signs
Procedures
etc.
Diagnosis | CABG | 0
Age | 54 | 1
Sex | male | 0
BUN | 14 | 0
GFR | 135 | 0
Creatinine | 0.8 | 0
Hemoglobin | 7.0 | 1
Glucose | 285 | 1
Insulin dose | 8 | 1
… | …
Mr. Stark
Dr. A

Training data



Study 1: Build and test models

- Dataset
  - 59 patient cases from HIDENIC[10] 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.

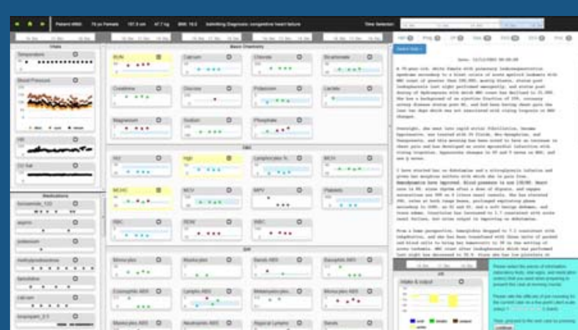
Study 1 Results

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

Highlight Laboratory Test	AUROC (95% CI)
Bilirubin Total	**0.92** (0.83, 0.97)
Liver Alanine (ALT)	**0.91** (0.72, 0.98)
Liver Aspartate (AST)	**0.91** (0.72, 0.99)
PTT Coagulation	**0.84** (0.71, 0.92)
Lactate	**0.83** (0.58, 1.00)
Phosphorus	**0.82** (0.62, 0.94)
White Blood Cell	**0.80** (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)
Average	*0.73*

Study 2: Usability study on prototype

- Four ICU clinicians
- Three to five patient cases
- Think aloud
- Interviews
- System Usability Scale[11, 12]



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 [bogging] 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

"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."

Concerns

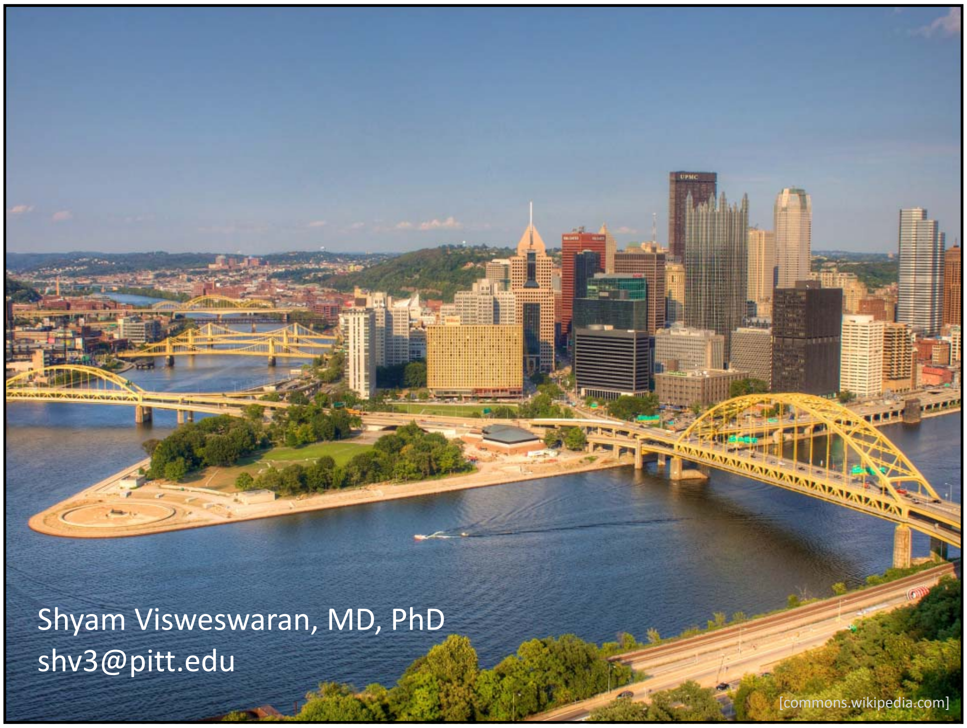
- Feasibility
- Implications of integration into workflow
- Design

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

Acknowledgements

- The many individuals in the Department of Biomedical Informatics at the University of Pittsburgh who have provided their feedback.
- The following grants:
  - NLM R01LM012095
  - NLM T15LM007059
  - NIGMS R01GM088224



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