Stony Brook University

Stony Brook Medicine

BIOMEDICAL INFORMATICS GRAND ROUNDS:

Towards Human-Centered and Interpretable Machine Learning for Early Disease Prediction Using Electronic Health Records: Bridging the Gap Between AI Models and Clinical Decision-Makers

Fusheng Wang, PhD

Richard N Rosenthal, MD

November 15, 2023

Disclosure Statement

- Dr. Wang is founder and CEO of EyeCanDo, LLC.
- Dr. Rosenthal and the planners have no relevant financial relationship with ineligible companies, whose primary business is producing, marketing, selling, reselling, or distributing health care products used by or on patients.

Stakeholder in the Loop

Stony Brook University

- Advanced machine learning models such as deep learning have shown significant promise in early disease risk prediction through electronic health records (EHR)
- However, a significant challenge remains in understanding these complex models, and building trust among critical stakeholders, including clinicians and patients, for the adoption of such tools.
- In this talk, we will present our perspective on bridging the gap between advanced AI models and practical clinical decision-making by not only building accurate models but also by explaining how they work, with iterative engagement of clinicians and patients in model development, optimization and interpretability.

Stakeholder in the Loop

Learning Objectives:

1. Understand predictive modeling for early disease risk prediction using electronic health records.
2. Recognize the major challenges of adoption of machine learning based tools in clinical practice.
3. Understand the need for human-centered explanations of AI models in healthcare.

What is the Utility of AI in Healthcare?

Advances in the ML paradigm with DL methods using large datasets have produced models with excellent performance characteristics.

Current: AI is used to improve various aspects:

- analyze medical images (e.g., X-ray, MRI) to increase accuracy of disease state detection.
- assist clinicians in diagnosing illnesses by analyzing symptoms and medical records.

Potential: AI can have even more significant healthcare benefits:

- develop new treatments and medicines (drug discovery), predict diseases for 1° and 2° prevention, and personalize healthcare for patients.
- help manage vast medical data, reducing burden for doctors to access and use important information.

What are the Drawbacks and Liabilities of AI in Healthcare?

1) Predictive validity: are the models accurate?
    a. Advances in the ML paradigm have produced models with excellent performance characteristics using large datasets.
    b. However, models based on big data may not be sensitive to regional, cultural or ethnic differences in populations
    c. This raises concerns of ecological validity: Clinical data is typically generated in a clinical environment or laboratory and may diverge from information about a person in their home or community.

2) Do the models perform better than individual clinical judgment based solely on traditional H&P, laboratory/imaging results, and clinician experience?
    a. The bottom line is that, in partnership with the patient, *the treating clinician must make the treatment recommendation.*

What are the Drawbacks and Liabilities of AI in Healthcare?

Stony Brook University

3) Uncurated models can incorporate stigma or other sources of bias.
   a. Given the need to support *beneficence* in the healthcare system, and to identify sources of bias and stigma, attention is given to the use of AI

4) When models are introduced into EHR systems in clinical practice, they are usually done as a *fait accompli* with little or no interaction with developers.
   a. Frequently leads to lack of trust among clinicians, as AI-generated models often have features that are not intuitively recognizable as clinically significant.
   b. Sometimes this is due to the labels that the developers are using for the features in the model that are stigmatizing.
   c. The bottom line: an algorithm product that a clinician doesn't understand and can't explain to a patient is unlikely to be trusted by either party.

Nelson CA, et al. JAMA Dermatol. 2020;156(5):501-512; Richardson JP et al. npj Digit. Med. 2021;4:140.; Sandhu S, et al. J Med Internet Res. 2020;22(11):e22421. Henry KE, et al., NPJ digital medicine 2022;5:1-6.; Henry KE, et al. Nat Med 2022;28:1447–1454.

Stakeholder In The Loop

Our Stakeholder-in-the-Loop (SITL) process addresses these problems in developing prediction models in healthcare:

a. Clinician and community stakeholders are involved in the model development and production cycle from the start

b. Our SITL method for technology development directly builds trust from clinician and patient stakeholders as it transforms the traditional 'deficit model' of science communication from unidirectional information delivery to *bidirectional communication* between stakeholders and the model developers[1]

c. The involved stakeholders meet regularly with the model development team and provide feedback about understandability, as well as curating feature labels that may be a source of bias or stigma.

[1] Pidgeon N. & Rogers-Hayden T. Health, Risk & Society, 2007;9:191-210.

Stakeholder In The Loop

Stony Brook University

d. This process transforms the model development ecology, creating new information flows for stakeholder input at all development stages.

e. The feedback is iterative, meaning that the feedback loop continues to shape and refine the model development over time.

f. The process addresses *ecological validity*: community-based feedback is likely to bring more local real-world information (language, culture, identity, lived experience, etc.) into the model-development process (i.e., fit) and increase both utility and acceptability.

g. The process also offers a platform for convergence in concept and language that will increase the ecological validity for both researchers and communities.

SITL: Promoting Transparency into Model Development

Stony Brook University

- Distinct cycles of stakeholder involvement:
  1. Algorithm Development
  2. Interpretability of Algorithm Outputs
  3. Clinical Translation

SITL: Promoting Transparency into Model Development

1. Algorithm Development
   a) choosing and visualizing information (Example model explanations)
   b) represents clinically relevant data
   c) allows end users to be able to rapidly assess external validity and provide feedback to the development group.

SITL: Promoting Transparency: Algorithm Development

Stony Brook University

a) The primary deliverable: model cards co-developed with stakeholders highlighting key elements of model development and include information important to the model's applicability:

b) data sources, demographic information, data elements, major pre-processing decisions, algorithm performance, intended use, potential harms of inappropriate use and ethical considerations.

c) Visualization Figure (Including Model Card)

SITL: Promoting Transparency: Algorithm Development

Stony Brook University

Model Explanations and Visualizations

Model Overview

Details

- This model, [LSTM-based-OUD-prediction](), is a LSTM based prediction model based on history of electronic health records, to predict if a patient will have risk of opioid use disorder in the future, and the corresponding risk score.
- Input: past electronic health records (diagnoses, medications, lab tests and demography)
- Output: The model has two prediction labels, TRUE or FALSE, and a risk score of LOW, MEDIUM or HIGH.
- ....more

Intended Use

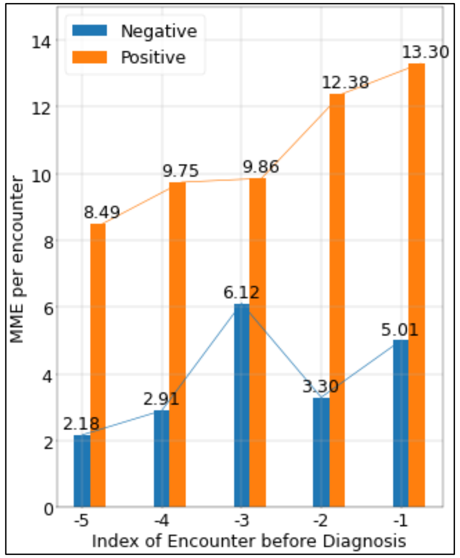
- This model is primarily aimed at providing early risk prediction of opioid use disorder for patients who have a past opioid medication history, with age between 18-66.

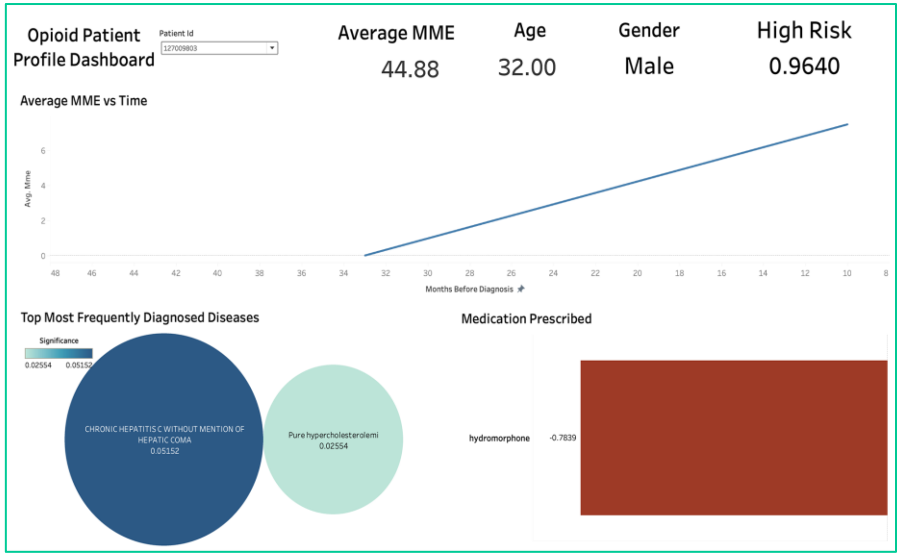
Data

- This model was trained using Cerner HealthFacts database [1], with a total of 5,231,614 patients between 2008-2017. Patients with a cancer related diagnosis were excluded from the dataset. ....more

Limitations

- The following factors may degrade the model's performance: ....more





(**a**) Model card (**b**) Ranked features (**c**) MME trends (positive vs negative) (**d**) Example screenshot of opioid risk dashboard

Example model explanations

SITL: Promoting Transparency: Algorithm Development

Stony Brook University

2. Interpretability of Algorithm Outputs
   a) Focus on evaluating individual-level explainability
   b) Iterative process of adding or deleting features of significant importance based on stakeholder perspectives

SITL: Interpretability of Algorithm Outputs

c) Patient-level interpretation techniques

1) Top Feature Summary with different interpretability methods, e.g., LIME, Shapley value.
   - Weighted word clusters using Bayesian-based probabilistic model for text data, to provide contextual information from notes or languages that are predictive

2) Summary of history contributing to the prediction.
   - For example, for OUD, relevant histories such as alcohol-related disorder, chronic pain, postoperative pain, tobacco use, and psychiatric conditions would be presented

3) Visualization of temporal trends of critical features e.g., MME for opioid-related events and diagnoses

4) Most frequent co-occurring diagnoses and medications.

SITL: CLINICAL TRANSLATION

3. Clinical translation

- The primary use case for algorithm development:
  - facilitate predicting disease-state risk in clinical settings for medical decision making

SITL: Stakeholder Engagement

1) Essential in evaluating interpretability, utility and level of trust in AI models for CDS.[1,2]

2) Must *effectively* incorporate stakeholder feedback at key points in model development:

- Conduct joint sessions with both stakeholders and model developers
- Research team members facilitate discussions
- Session outcomes measured as the number and content of stakeholder-generated topics, questions and recommendations, e.g.,
    - decisions for feature inclusion or exclusion
    - data pre-processing changes
    - features displayed for interpretability

[1] Tucci V, et al., Journal of Medical Artificial Intelligence. 2022;5:4-4. doi:10.21037/jmai-21-25

[2] Fan W, et al., Annals of Operations Research. 2020;294(1-2):567-592. doi:10.1007/s10479-018-2818-y

Stakeholder Engagement: Elicit End User Perspectives and Feedback

Stony Brook University

Develop structured protocols for separate sessions on key topic areas.
<u>Phase 1: Algorithm Development</u> *(3 60′ sessions)*:

a) Review primary data sources
b) Inclusion criteria for patients whose data used for model training (e.g.. patients with a prior opioid prescription/administration)
c) Data elements and representation (e.g., labs normalized by decile)
d) Major pre-processing decisions (e.g., representation of lab values and longitudinal data).
e) Feedback on potential bias in data sources or pre-processing.
f) Appropriate level of detail from data sources and outputs regarding generalizability and clinical utility sufficient to provide face validity to patients.
g) Co-develop a model card highlighting key elements of model development

Stakeholder Engagement: Elicit End User Perspectives and Feedback

Stony Brook University

Develop structured protocols for separate sessions on key topic areas.
Phase 2: Interpretability of Algorithm Outputs *(3 60′ sessions)*:

a) Review performance metrics for each data source and the outputs from applying different interpretability methods.
b) Iterative feedback sessions conducted with subject matter experts, stakeholders and end users
c) Evaluate features for representations of clinical and psychosocial concepts and develop appropriate labels for explainability and meaningfulness for clinical decision making
d) Separate tracks for data sources: Structured EHR, chart notes, social media data
e) Deliverable: curated features important to the predictive models that are face-valid for clinical interpretability and for display to end users

Stakeholder Engagement: Elicit End User Perspectives and Feedback

Stony Brook University

Develop structured protocols for separate sessions on key topic areas. Phase 3: Clinical Translation *(3 60′ sessions/track)*:

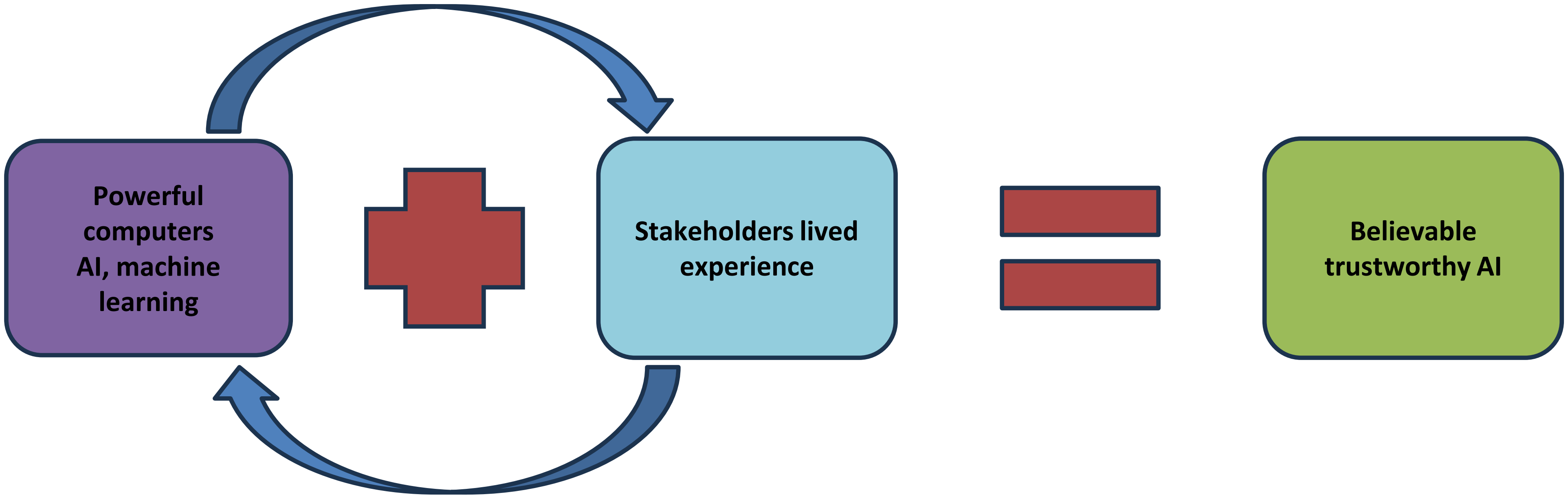
a) Work with end users and stakeholders to identify key components for algorithm usability in bedside decision-making

b) Topics include:

1. appropriate risk thresholds to display (e.g., low/medium/high categories vs. predicted probability),
2. evaluation metrics
3. determining the level of information and detail on the selected features with clinical validity and importance for prediction

STAKEHOLDER IN THE LOOP AI SOLUTION
real people drive real results

- Using AI as a tool to obtain usable, tailored answers to real problems drawing on large and diverse data providing information never before available, vetted by people to serve people

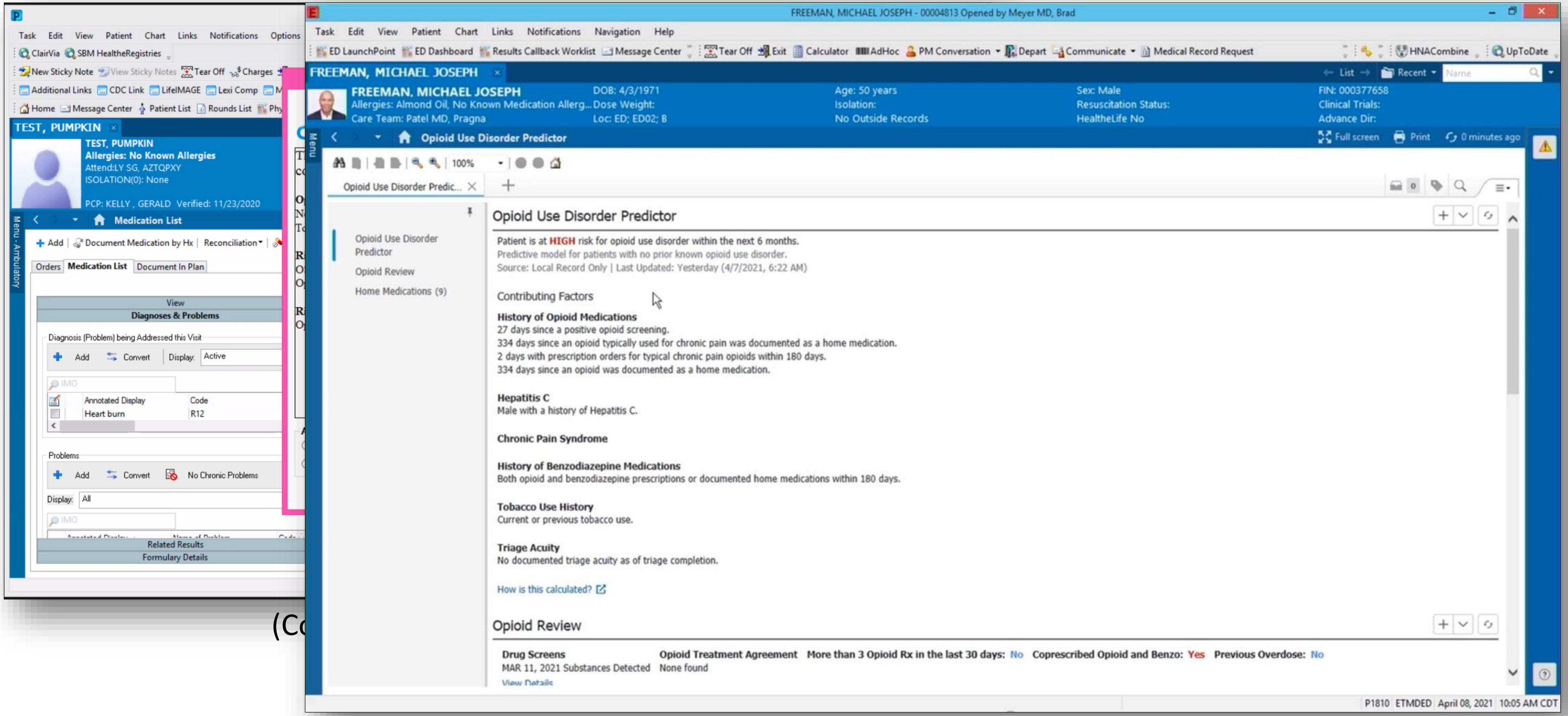


SITL: Interpretation Techniques:
Use Case: Prediction of Opioid Risks

- Opioid overdose has become a leading cause of accidental death in the U.S., and reached a record high during COVID-19
  - ~645,000 people died from opioid related OD from 1999-2021
  - 1.6M people had opioid use disorder in last year
  - Opioid use disorder (OUD): problematic pattern of opioid use leading to clinically significant impairment or distress
  - Opioid overdose (OD): high doses of opioids can lead to the slowing or stopping of breathing or even death
- Most of those at high OD risk are clinically under-identified
- A sensitive and valid approach is critically needed to identify those individuals who are at risk for using opioids




Traditional EHR Tools for Opioid Risks in EHR



(Courtesy of Cerner)

- Cerner's Opioid Use Disorder Predictor is based on a regression-based machine learning model with about 60 features
- Predictions are recorded in *Cerner Millennium* as clinical events

Our Model: Integrated Temporal and Graph Deep Learning

Traditional methods use a limited set of features or lack the modeling of temporal progression or complex EHR relationships

- We propose an integrated temporal and graph deep learning model LIGHTED
- It predicts both OD risk and OUD risk (separate tasks)
- Use large scale EHR database
- Take advantage of a large number of EHR features
- Provide multi-level interpretations: global level and patient level

[AMIA19Dong, JAMIA21Dong, JBI21Dong, AIIM22Dong]

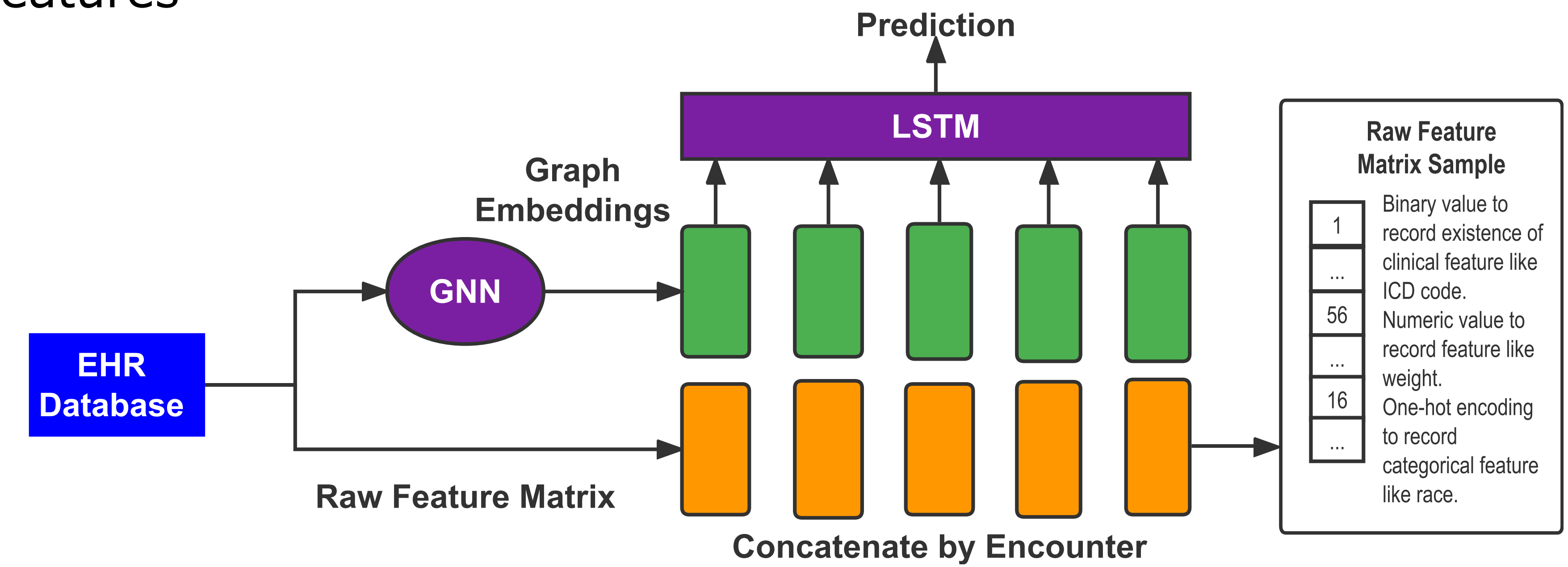
Data Sets and Features

- Data source: Cerner Health Facts: de-identified EHR data from over 600 participating hospitals
  - Extracted patients who had at least one opioid medication
  - Select up to 5 encounters per patient
  - Features: diagnoses, procedures, lab tests, medications and clinical events
  - Feature normalization: e.g., ICD-9/ICD-10; NDC to ATC
  - Aggregated features, e.g., MME (Morphine Milligram Equivalents)

Datasets	Positive	Negative	Period	Age	Number of Features
OD	44,774	5,186,840	2008 to 2017	16-66	**1,468**
Opioid Use Disorder (OUD)	111,456	5,120,158	2008 to 2017	18-66	1,185

LIGHTED: Integrate Graph Neural Network with LSTM

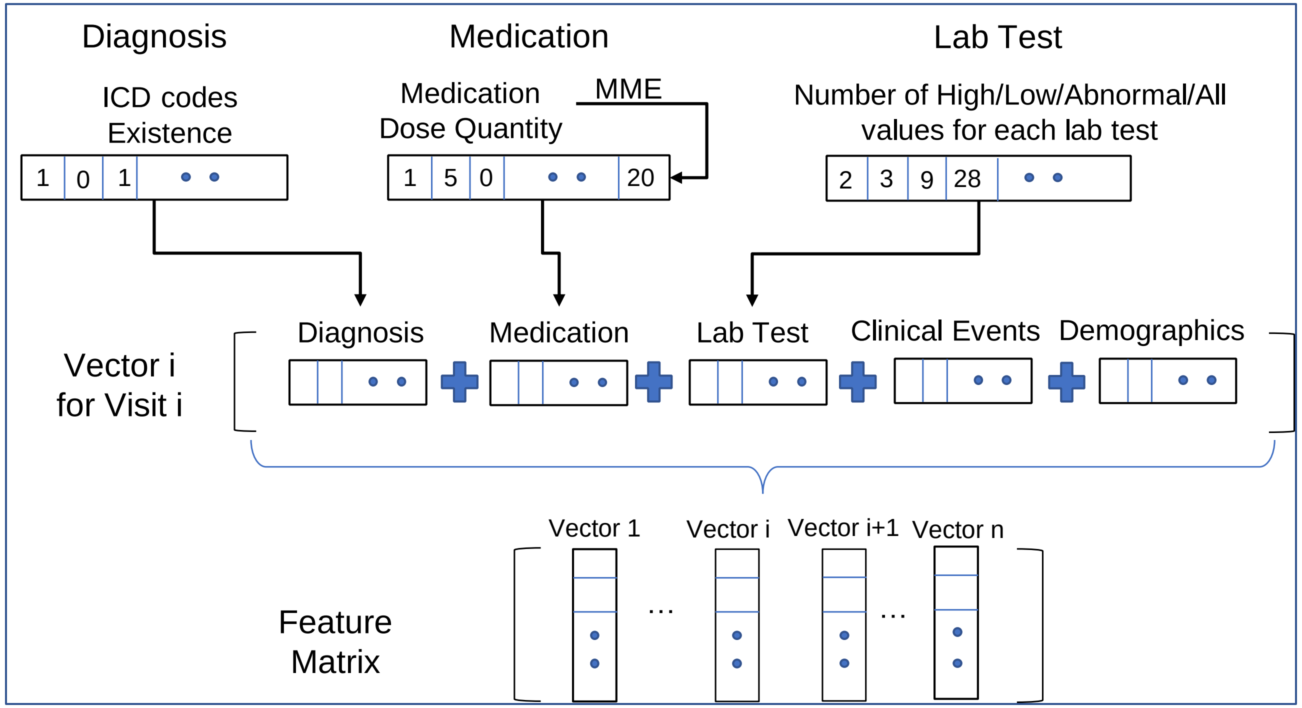
- Long short-term memory (LSTM) learns long-term dependencies by maintaining an internal state
  - Ideal on modeling temporal disease progression using multiple encounters
- Graph Neural Network(GNN) can capture the dependence of graphs with message passing between the nodes of graphs
  - Ideal for capturing complex relationships among EHR data: patients, encounters and features



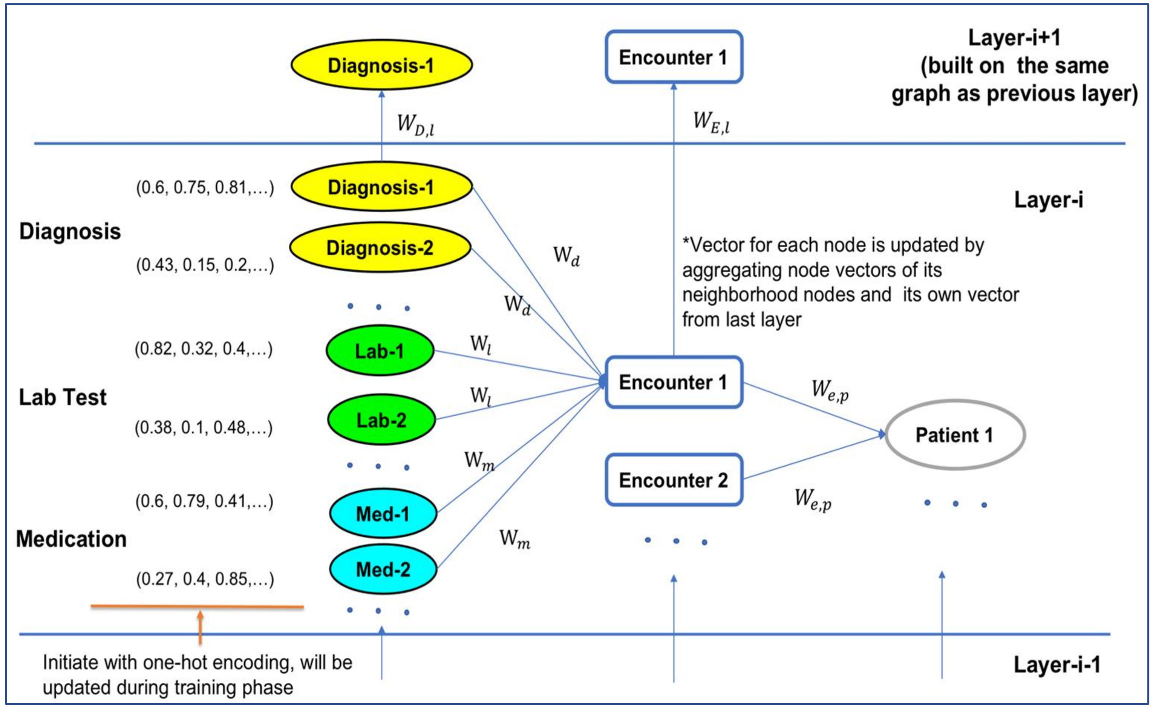
Example of Feature Representation

Stony Brook University

Original feature matrix



Example representation of features in a heterogeneous graph



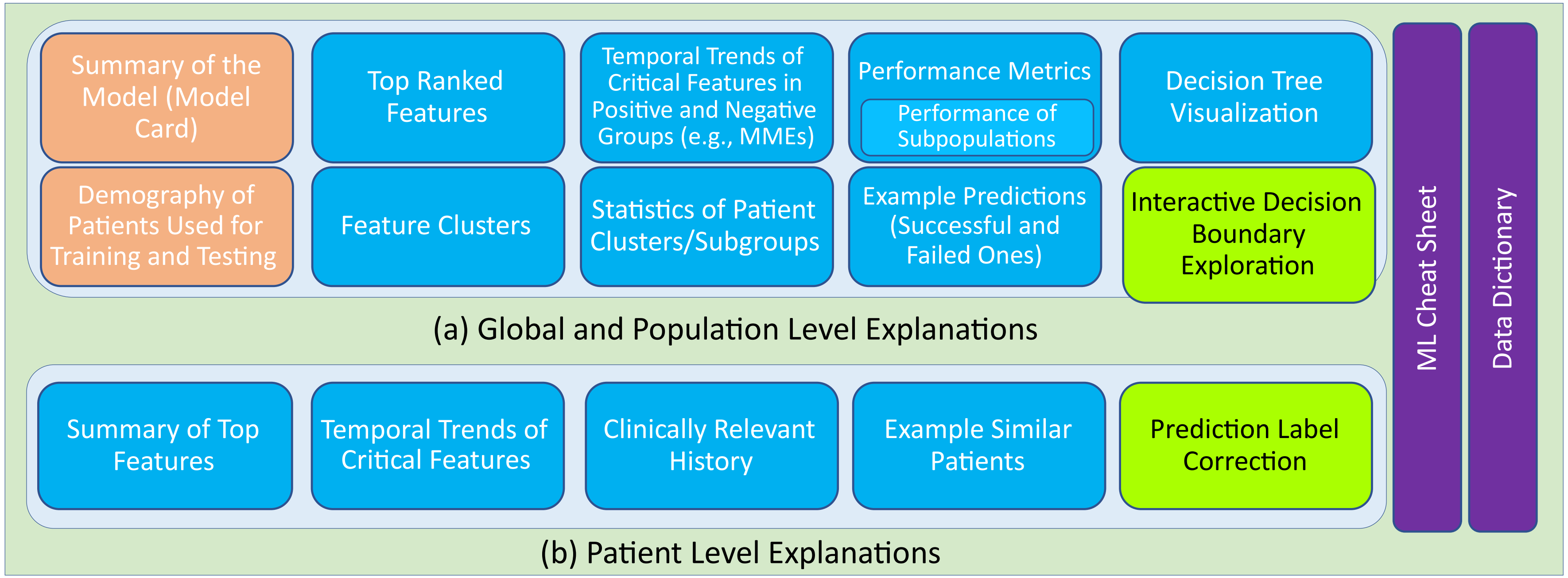
Vector of a node is updated by aggregating node vectors of its neigbhors and its own vector from last layer

OD Prediction Performance

Model	Precision	Recall	F-1	AUROC	p-value (F-1)	p-value (AUROC)
Traditional Methods (on raw feature input matrix)						
DNN	0.8006±0.0052	0.7329±0.0046	0.7683±0.0027	0.8414±0.0028	<0.01	<0.01
Sequential Models (on raw feature input matrix)						
LSTM	0.7884±0.0054	0.7616±0.0027	0.7798±0.0060	0.8618±0.0051	<0.01	<0.01
Transformer	0.8124±0.0086	0.7654±0.0109	0.7911±0.0019	0.8766±0.0060	0.117	<0.01
Graph Models (on graph embeddings)						
GCN	0.7867±0.0089	0.7533±0.0056	0.7696±0.0020	0.8395±0.0082	0.046	<0.01
HeteroRGCN	0.8003±0.0060	0.7679±0.0021	0.7750±0.0017	0.8429±0.0046	<0.01	<0.01
Sequential Graph Combined Models (on both raw input and graph embeddings)						
LSTM-GCN	0.7991±0.0093	0.7767±0.0088	0.7877±0.0052	0.8608±0.0085	<0.01	<0.01
Proposed Model (combined features)						
LIGHTED (LSTM-HeteroRGNN)	0.8182±0.0072	0.7856 ± 0.0103	**0.8006** ± 0.073	**0.8969** ± 0.0115	*	*

Multi-Level Interpretability

- Population-level: describe how the overall ML model works, including the underlying data, critical features, decision process and performance
- Patient-level: describe the individual patient risk score and the reasons behind the prediction
  - Risks of individual patients, trends of critical features such as MME, clinically relevant histories such as Tobacco use, reason for initiation of opioid medication (e.g., accident, surgery, acute pain, chronic pain, mental illness), …

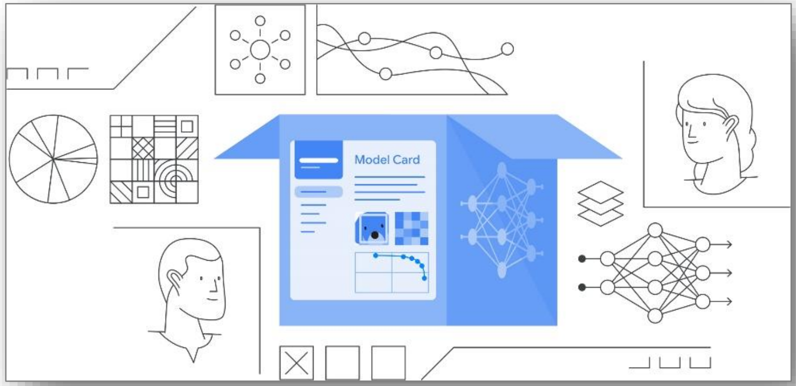


Example Model Card

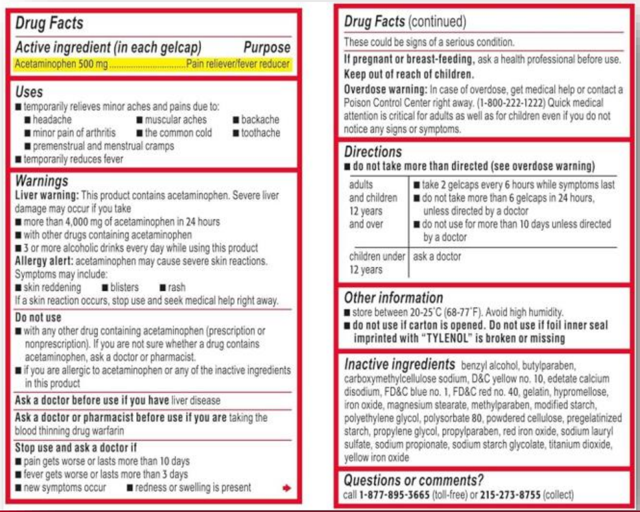
A model card documents information about a ML model, to communicate its capabilities, limitations, and potential risks to users and stakeholders

- Enhance transparency, accountability, and trust in the deployment of machine learning models
- Widely used, e.g., Hugging Face

ML Model Card



Drug Label



Drug Facts

Active ingredient (in each gelcap) — *Purpose*
Acetaminophen 500 mg .... Pain reliever/fever reducer

Uses
- temporarily relieves minor aches and pains due to:
  - headache
  - muscular aches
  - backache
  - minor pain of arthritis
  - the common cold
  - toothache
  - premenstrual and menstrual cramps
- temporarily reduces fever

Warnings
Liver warning: This product contains acetaminophen. Severe liver damage may occur if you take
- more than 4,000 mg of acetaminophen in 24 hours
- with other drugs containing acetaminophen
- 3 or more alcoholic drinks every day while using this product

Allergy alert: acetaminophen may cause severe skin reactions. Symptoms may include:
- skin reddening
- blisters
- rash

If a skin reaction occurs, stop use and seek medical help right away.

Do not use
- with any other drug containing acetaminophen (prescription or nonprescription). If you are not sure whether a drug contains acetaminophen, ask a doctor or pharmacist.
- if you are allergic to acetaminophen or any of the inactive ingredients in this product

Ask a doctor before use if you have liver disease

Ask a doctor or pharmacist before use if you are taking the blood thinning drug warfarin

Stop use and ask a doctor if
- pain gets worse or lasts more than 10 days
- fever gets worse or lasts more than 3 days
- new symptoms occur
- redness or swelling is present

Drug Facts (continued)

These could be signs of a serious condition.

If pregnant or breast-feeding, ask a health professional before use.

Keep out of reach of children.

Overdose warning: In case of overdose, get medical help or contact a Poison Control Center right away. (1-800-222-1222) Quick medical attention is critical for adults as well as for children even if you do not notice any signs or symptoms.

Directions
- **do not take more than directed (see overdose warning)**

adults and children 12 years and over	take 2 gelcaps every 6 hours while symptoms last; do not take more than 6 gelcaps in 24 hours, unless directed by a doctor; do not use for more than 10 days unless directed by a doctor
children under 12 years	ask a doctor

Other information
- store between 20-25˚C (68-77˚F). Avoid high humidity.
- **do not use if carton is opened. Do not use if foil inner seal imprinted with "TYLENOL" is broken or missing**

Inactive ingredients benzyl alcohol, butylparaben, carboxymethylcellulose sodium, D&C yellow no. 10, edetate calcium disodium, FD&C blue no. 1, FD&C red no. 40, gelatin, hypromellose, iron oxide, magnesium stearate, methylparaben, modified starch, polyethylene glycol, polysorbate 80, powdered cellulose, pregelatinized starch, propylene glycol, propylparaben, red iron oxide, sodium lauryl sulfate, sodium propionate, sodium starch glycolate, titanium dioxide, yellow iron oxide

Questions or comments?
call **1-877-895-3665** (toll-free) or **215-273-8755** (collect)

LIGHTED Model Card

Details

- This model, LIGHTED, is a hybrid LSTM and heterogenous relational graph-based prediction model based on history of electronic health records, to predict if a patient will have risk of opioid order in the future, and the corresponding risk score.
- **Input:** past electronic health records (diagnoses, medications, lab tests and demography) in up to 5 past encounters.
- **Output:** The model has two prediction labels, TRUE or FALSE, and a risk score of LOW, MEDIUM or HIGH.
- ....more

Intended Use

- This model is primarily aimed at providing early risk prediction of opioid overdose for patients who have a past opioid medication history, with age between 16-66.

Data

- This model was trained using Cerner HealthFacts database, with a total of 5,186,840 patients between 2008-2017. Patients with a cancer related diagnosis were excluded from the dataset.

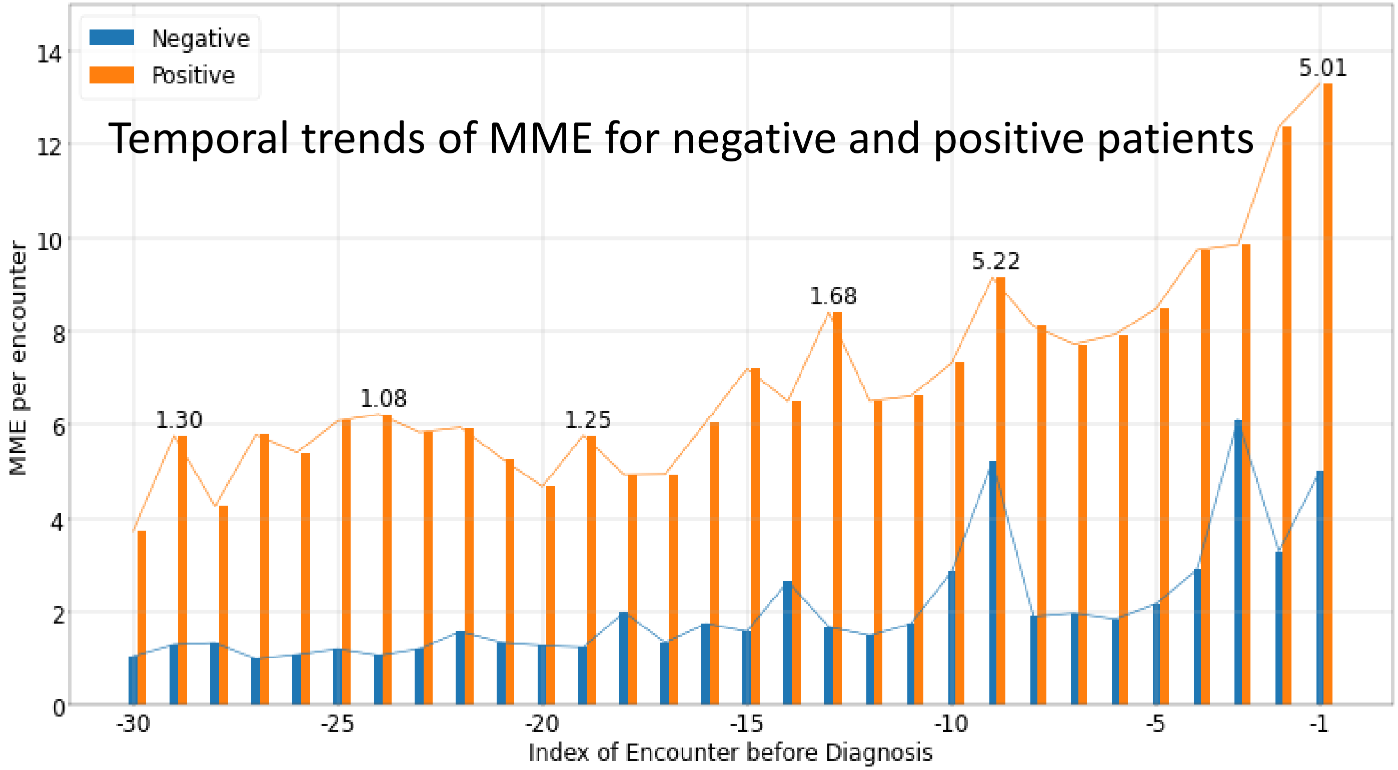
  ....more

Limitations

- The following factors may degrade the model's performance: ....more

Example Trend of Critical Feature: MME

- Morphine milligram equivalents (MME) is an opioid dosage's equivalency to morphine
- The MME/day (aggregated) metric is often used as a gauge of the overdose potential of the amount of opioid given at a particular time



Interpretability Methods for Critical Features

Common methods to explain features:

- Shapley
  - Assume each feature value has a contribution to the prediction. The contribution is measured by the difference of adding and removing a feature value
- LIME (Local Interpretable Model-agnostic Explanations)
  - LIME tries to understand how the predictions change when we perturb the data samples
- Agnostic Model
  - Use an interpretable ML model (e.g., decision tree) to approximate a "black box" DL model (like DNN), then use the interpretable model to give interpretation
- Permutation importance: randomize the value of a feature and measure the difference on prediction measurement, e.g., F1 score, and rank them
- Others: GNNExplainer for GNN, Attention Mechanism for sequence, Saliency Map for CNN

Feature Ranking - Shapley

Category	Description	Rank	Category	Description	Rank
Medication	N02A: Opioids	1	Lab Test	Respiratory Rate	11
Diagnosis	Other and unspecified disorders of back	2	Diagnosis	Diabetes mellitus	12
Diagnosis	Nondependent abuse of drugs	3	Medication	Other analgesics and antipyretics	13
Medication	MME	4	Diagnosis	Other disorders of soft tissues	14
Clinical Event	Weight	5	Lab Test	Creatinine, Serum Quantitative	15
Lab Test	Carbon dioxide	6	Lab Test	Blood Urea Nitrogen	16
Diagnosis	Essential hypertension	7	Lab Test	Glucose, Serum/Plasma Quantitative	17
Lab	BSA, Body Surface Area	8	Clinical Event	Occupant of pick-up truck or van injured in noncollision transport accident	18
Lab	Aspartate Aminotransferase / SGOT	9	Lab Test	Red Blood Cell Distribution Width (RDW)	19
Diagnosis	General symptoms	10	Medication	Antiemetics and antinauseants	20

Ranking methods: Shapley Value, Model-Agnostic Method (Decision Tree), Permutation Importance

Pain/opioids/drug misuse Accidental injury Respiratory system related

Statistics on Example Top Features between OUD and non-OUD Patients

Stony Brook University

Category	Feature	OUD patients	Non-OUD patients
Diagnosis	Pain, not elsewhere classified (prevalence)	33.77%	8.70%
Diagnosis	Nicotine dependence	65.36%	17.67%
Medication	MME (morphine milligram equivalent) (mean)	12.06 per encounter	2.35 per encounter
Medication	Essential (primary) hypertension	27.43%	24.92%
Medication	N05B: Anxiolytics	18.96%	2.40%
Medication	N02B: Other analgesics and antipyretics	31.51%	9.50%
Medication	A04A: Antiemetics and antinauseants	28.70%	9.02%
Diagnosis	Type 2 diabetes mellitus	15.51%	5.30%
Diagnosis	Cystic fibrosis	5.28%	1.44%
Diagnosis	Cellulitis and acute lymphangitis	17.68%	7.00%

Summarizing a Patient's History with Large Language Model (LLM)

- Can we provide a concise and precise summary of a patient's history that is relevant to the risk based on past encounters (demography, diagnoses, labs, clinical events, and medications) using LLM?
- Models considered for the experiment:
  - OpenAI's GPT-3.5 ,Meta's Llama2, Microsoft's Godel, Meta's BlenderBot, Google's T5, and Bloom
  - Can the model recognize ICD codes?
  - Can the model process the history effectively?
  - Generate output in organized structures
- OpenAI GPT-3.5 is the top of choice

LLM Summary Example

Stony Brook University

```
"""Give a quick summary of a 30-year-old male patient and what is wrong with them
with the following health parameters: Blood Pressure 120/80 mmHg, Cholesterol 200
mg/dl, blood sugar 90 mg/dl, and a history of the following specific ICD-10
diagnosis codes: \n

    Patient ID  Encounter ID  Admitted Date & Time  ICD-10 Diagnosis Code

    130940934 408703834 10/13/2012 10:09  786.09

    130940934 408703834 10/13/2012 10:09  786.2

    130940934 408703834 10/13/2012 10:09  493.92

    130940934 408703834 10/13/2012 10:09  478.19


Please offer guidance on managing the patient's healthcare based on these specific
ICD-10 diagnosis codes change it into there name, considering diet, exercise,
medication, and any additional tests or precautions that should be taken into
account.
```

Follow the following sequence: **History of Present Illness, Problem List, Medications, Allergies, Social History, Family History, Review of Systems, Physical Exam, Assessment.** please answer as if you are as a physician"""

LLM Summary Example

Writing a SOAP note

The patient is a 30-year-old male with the following health parameters: blood pressure 120/80 mmhg, cholesterol 200 mg/dl, blood sugar 90 mg/dl, and a history of the following specific ICD-10 diagnosis codes: 786.09, 786.2, 493.92, and 478.19.

Based on these specific icd-10 diagnosis codes, the patient's healthcare should be managed with diet, exercise, medication, and additional tests or precautions as follows:

History of present illness:

The patient has a history of shortness of breath (786.09), chest pain (786.2), asthma (493.92), and allergic rhinitis (478.19).

Problem list:

The patient's problem list includes shortness of breath, chest pain, asthma, and allergic rhinitis.

Medications:

The patient should be prescribed medications for shortness of breath, chest pain, asthma, and allergic rhinitis.

Allergies:

The patient has no known allergies.

Social history:

The patient's social history is unremarkable.

Family history:

The patient's family history is unremarkable.

Review of systems:

The patient's review of systems is negative for any other significant symptoms.

Physical exam:

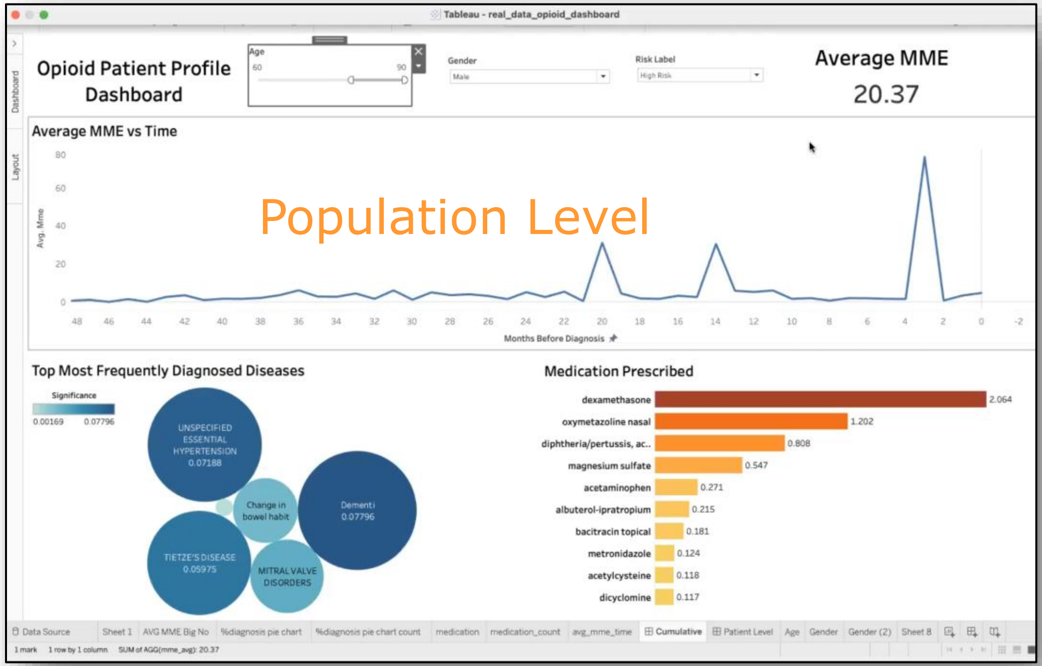
The patient's physical exam is negative for any other significant findings.

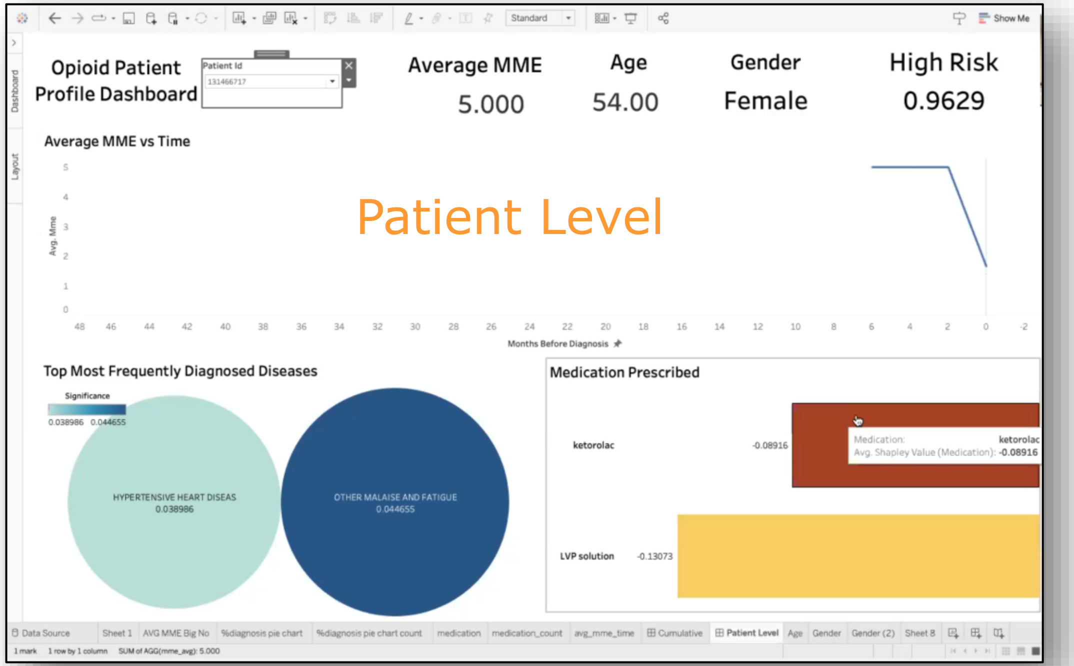
Assessment:

Based on the patient's history, problem list, and physical exam, the patient's healthcare should be managed with diet, exercise, medication, and additional tests or precautions as necessary for shortness of breath, chest pain, asthma, and allergic rhinitis.

Interpretability Dashboard

- Interactive interpretability dashboard as a bridge between models and stakeholders, incorporating all explanations
  - Work in progress
- Developed with Tableau
  - Model relevant information is stored and managed by a SQL database



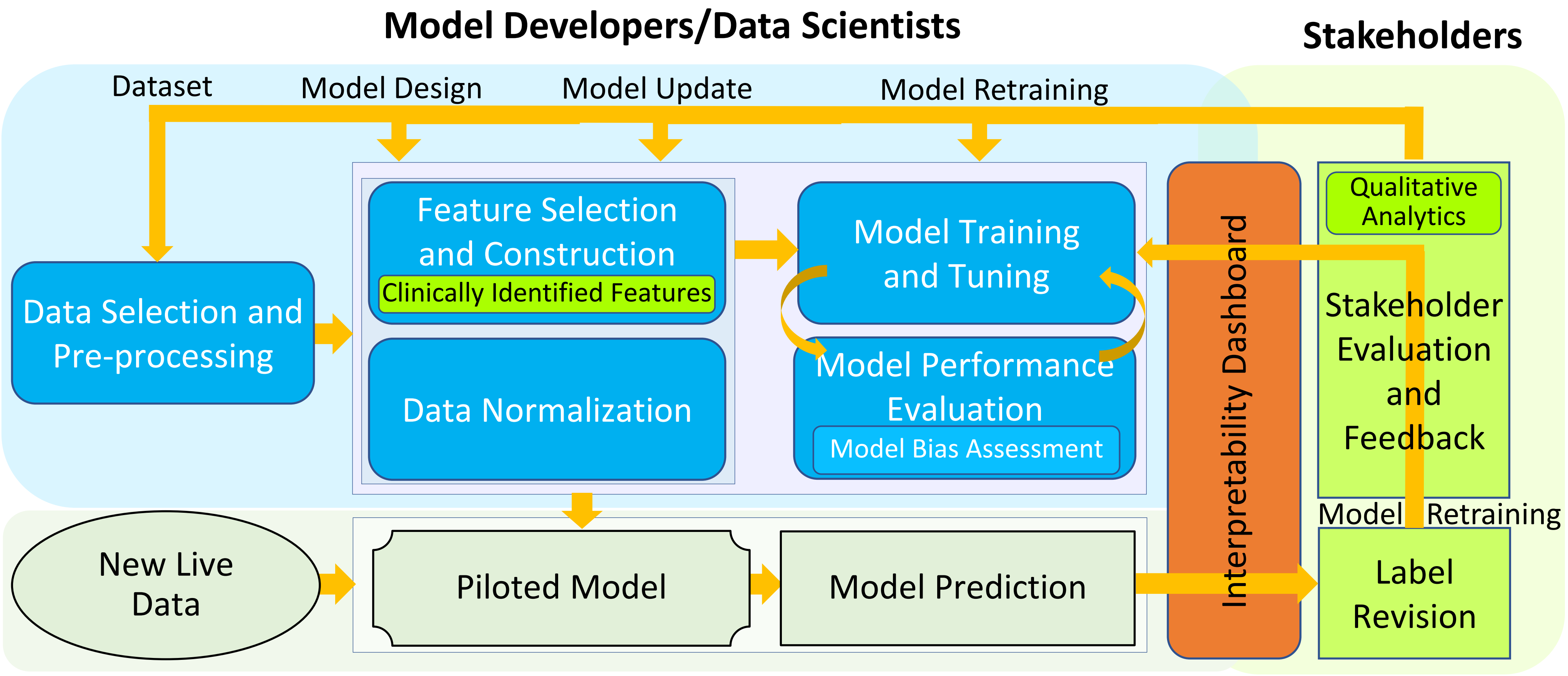


Interpretability Dashboard Demo

Stony Brook University

by Arjun Omampuliyur Balakrishnan

Stakeholder-in-the-loop Machine Learning Framework



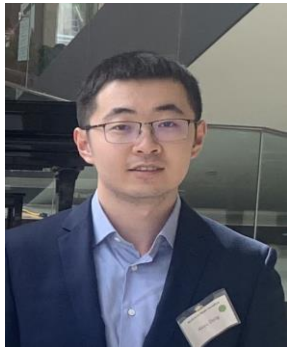
Summary of Stakeholder In The Loop ML Framework

- The SITL process involves clinicians and community stakeholders from the beginning of model development. This helps build trust and allows feedback on the model's understandability and potential biases.
- The process promotes two-way communication between stakeholders and model developers, transforming the traditional model of information delivery.
- Regular meetings and feedback ensure that the model development is shaped and refined over time, addressing concerns like bias and stigma.
- This process also increases the relevance and acceptability of the model by incorporating real-world information from the community, such as language, culture, and lived experiences.
- It provides a platform for researchers and communities to come together and improve the AI models for everyone's benefit.

Stony Brook University

Acknowledgement

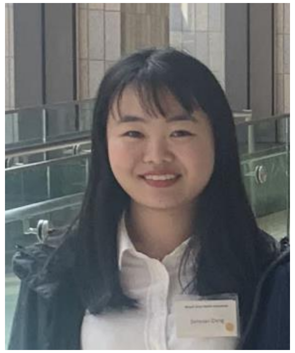
Students:

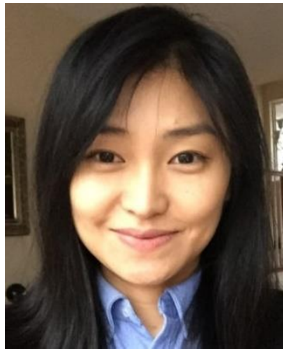

Xinyu Dong


Arjun Omampuliyur


Mitesh Jalan

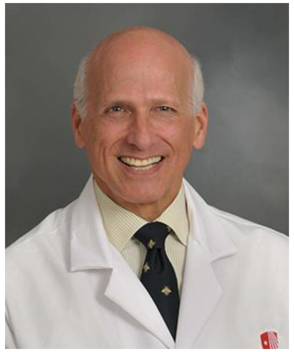

Yinan Liu


Jianyuan Deng


Xia Zhao

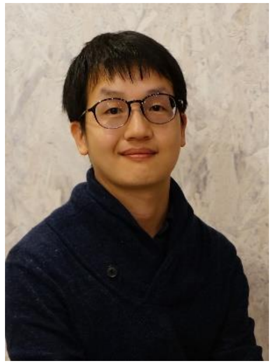
Faculty:


Fusheng Wang


Richard Rosenthal


Rachel Wong


Chao Chen


Tengfei Ma


George Leibowitz

OVPR Seed Grant Program

NSF

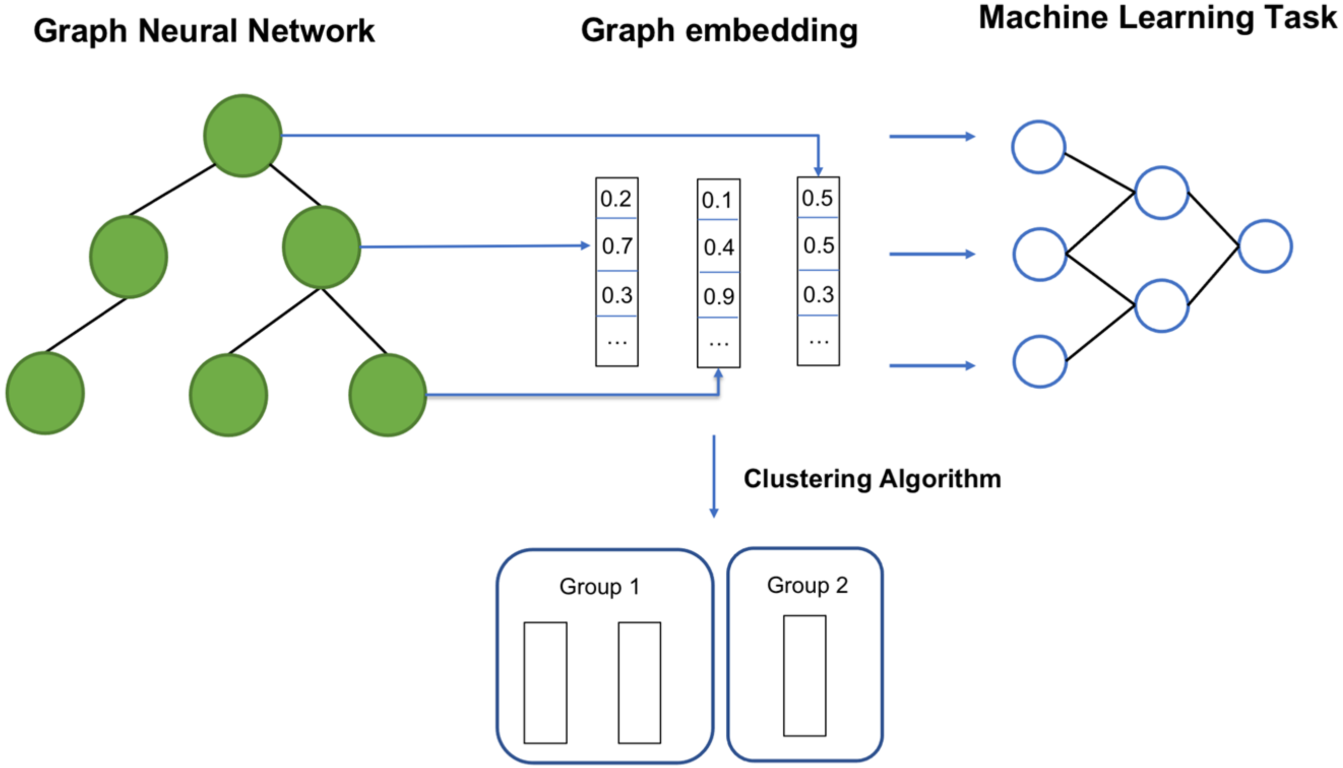
Questions?

Feature Ranking

Rank	Shapley Value	Model-Agnostic Method (Decision Tree)	Permutation Importance
1	N02A: Opioids	N02A: Opioids	N02A: Opioids
2	Other and unspecified disorders of back	Blood Pressure Diastolic	Pain Scale Score
3	Nondependent abuse of drugs	MME	Antipropulsives
4	MME	Anesthetics, general	Anesthetics, general
5	Weight	Antipropulsives	Alcohol Use
6	Carbon dioxide	Respiratory Rate	Other analgesics and antipyretics
7	Essential hypertension	Other analgesics and antipyretics	Blood Pressure Diastolic
8	BSA, Body Surface Area	Height	Blood Pressure Systolic
9	Aspartate Aminotransferase / SGOT	Heart Rate	Hypnotics and sedatives
10	General symptoms	BMI, Body Mass Index	Mean Corpuscular Hemoglobin
11	Respiratory Rate	Weight	Red Blood Cell Distribution Width
12	Diabetes mellitus	Pulse	MME
13	Other analgesics and antipyretics	Mean Arterial Pressure	Smoke, Exposure to Tobacco Smoke
14	Other disorders of soft tissues	Temperature Oral	Uterotonics
15	Creatinine, Serum Quantitative	O2 Saturation (SO2)	Blood Urea Nitrogen

Clustering on Graph Embedding

- Apply clustering algorithm to group features into feature subsets with clinical meaning, can provide a potential simplified representation of high dimensional EHR features.



Result of Clustering on Graph Embeddings

Cluster A. Accidental Injury (High*)	Cluster B. Substance/Medication Use or Toxicity (High*)	Cluster C. Reno-Pulmonary Features (Intermediate*)
Other slipping, tripping and stumbling and falls Occupant of pick-up truck or van injured in collision with fixed or stationary object Occupant of pick-up truck or van injured in noncollision transport accident Occupant of pick-up truck or van injured in collision with heavy transport vehicle or bus Other complications of procedures not elsewhere classified Motor vehicle traffic accidents Accidents caused by submersion, suffocation, and foreign bodies Other disorders of bone and cartilage Contusion of trunk Other personal history presenting hazards to health Pain, not elsewhere classified Pain associated with micturition Episodic mood disorders …….	Acetaminophen, serum quantitative Alcohol and/or drug, substance use Alcohol last use Tobacco frequency other Tobacco last use Smoking, attempt to quit in Past Smoking, willing to quit Smoking, readiness to quit Smoke, lives with someone who smokes Smoking packs/day Smoke, exposure to tobacco smoke Smoking history Tobacco type Pain scale score Drugs for constipation Barbiturate, urine Poisoning by psychotropic agents Antipsychotics Personal history of mental disorder …….	Essential (primary) hypertension Blood pressure diastolic sitting Blood pressure systolic sitting Glomerular filtration rate/1.73 sq M predicted among blacks creatinine based formula (MDRD) UA bacteria Protein, urine Protein total, urine random Potassium, whole blood Calcium, serum HCO3 Other diseases of lung Other diseases of respiratory system Drugs for treatment of tuberculosis Symptoms involving respiratory system and other chest symptoms Pain in throat and chest PIP (Peak inspiratory pressure) ……

LLM Summary Based on Notes

Please summarize the patients into following segments: History of Present Illness, Problem List, Medications, Allergies, Social History, Family History, Review of Systems, Physical Exam, Assessment. please answer as if you are as a physician:

discharge summary:

Admission Date: [**2118-6-2**] Discharge Date: [**2118-6-14**]Date of Birth: Sex: FService: MICU and then to [**Doctor Last Name **] MedicineHISTORY OF PRESENT ILLNESS: This is an 81-year-old femalewith a history of emphysema (not on home O2), who presentswith three days of shortness of breath thought by her primarycare doctor to be a COPD flare. Two days prior to admission,she was started on a prednisone taper and one day prior toadmission she required oxygen at home in order to maintainoxygen saturation greater than 90%. She has also been onlevofloxacin and nebulizers, and was not getting better, andpresented to the [**Hospital1 18**] Emergency Room.In the [**Hospital3 **] Emergency Room, her oxygen saturation was100% on CPAP. She was not able to be weaned off of thisdespite nebulizer treatment and Solu-Medrol 125 mg IV x2.Review of systems is negative for the following: Fevers,chills, nausea, vomiting, night sweats, change in weight,gastrointestinal complaints, neurologic changes, rashes,palpitations, orthopnea. Is positive for the following:Chest pressure occasionally with shortness of breath withexertion, some shortness of breath that is positionallyrelated, but is improved with nebulizer treatment.PAST MEDICAL HISTORY:1. COPD. Last pulmonary function tests in [**2117-11-3**]demonstrated a FVC of 52% of predicted, a FEV1 of 54% ofpredicted, a MMF of 23% of predicted, and a FEV1:FVC ratio of67% of predicted, that does not improve with bronchodilatortreatment. The FVC, however, does significantly improve withbronchodilator treatment consistent with her known reversibleair flow obstruction in addition to an underlying restrictiveventilatory defect. The patient has never been on homeoxygen prior to this recent episode. She has never been onsteroid taper or been intubated in the past.2. Lacunar CVA. MRI of the head in [**2114-11-4**]demonstrates "mild degree of multiple small foci of high T2.

LLM Summary Based on Notes

Stony Brook University

History of Present Illness:
An 81-year-old female with a history of emphysema presented with three days of worsening shortness of breath, initially treated as a COPD flare. Despite a prednisone taper, home oxygen, levofloxacin, and nebulizers, she did not improve. In the [**Hospital3**] ER, she had 100% oxygen saturation on CPAP but couldn't be weaned off. Positive symptoms include chest pressure and positional shortness of breath, improved with nebulizer treatment.

Problem List:

1. COPD
2. Lacunar CVA

Medications:

1. Prednisone taper
2. Levofloxacin
3. Nebulizers
4. Solu-Medrol 125 mg IV x2 (given in the ER)

Allergies:

- No information provided.

Social History:

- No detailed information provided.

Family History:

- No information provided.

Review of Systems:

- Positive for chest pressure occasionally with exertion, positional shortness of breath. Negative for fevers, chills, nausea, vomiting, night sweats, weight change, gastrointestinal complaints, neurologic changes, rashes, palpitations, orthopnea.

Physical Exam:

- Details about the physical exam are not provided.

Assessment:

1. Exacerbation of COPD
2. Respiratory distress requiring CPAP