Big Data and AI Driven Opioid Epidemic Research

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The US Opioid Overdose Epidemic

- The US is experiencing opioid epidemic due to the misuse and abuse of opioids

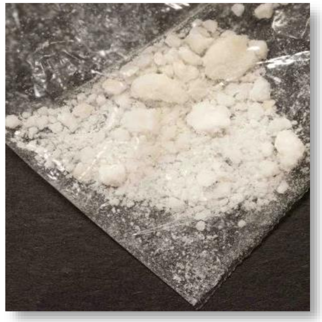
130+
Overdose (OD) death per day

10.3 m
misused opioid prescriptions per year

47,600
OD death per year

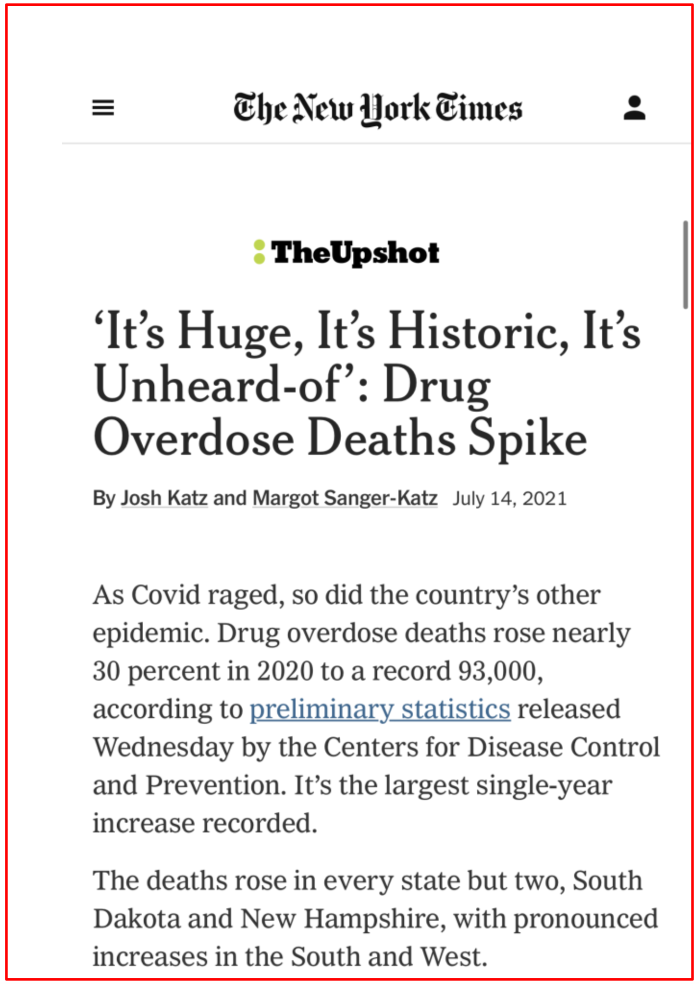
2.0 million
had opioid use disorder (OUD)






The Opioid Epidemic During the COVID-19 Pandemic

"The emergence of coronavirus disease 2019 (COVID-19) and subsequent **disruptions in health care and social safety nets** combined with **social and economic stressors** will fuel the opioid epidemic." JAMA Editorial, Sep 18, 2020



The New York Times

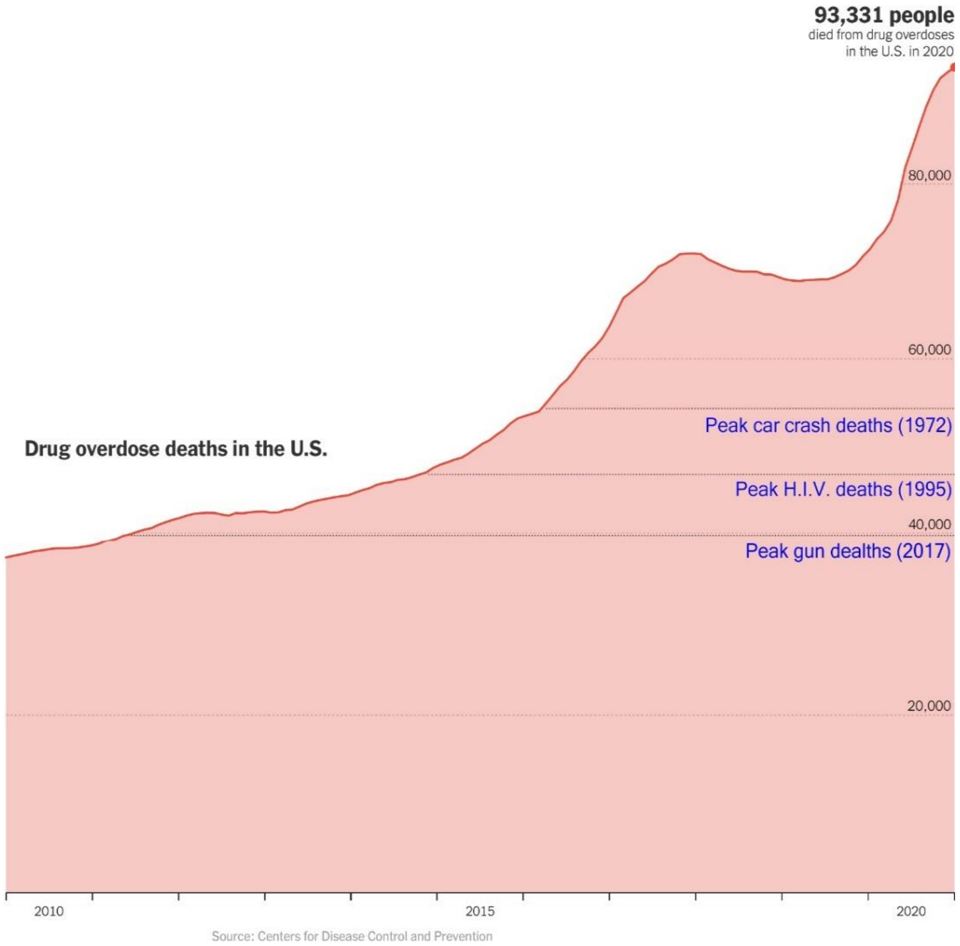
TheUpshot

'It's Huge, It's Historic, It's Unheard-of': Drug Overdose Deaths Spike

By Josh Katz and Margot Sanger-Katz July 14, 2021

As Covid raged, so did the country's other epidemic. Drug overdose deaths rose nearly 30 percent in 2020 to a record 93,000, according to preliminary statistics released Wednesday by the Centers for Disease Control and Prevention. It's the largest single-year increase recorded.

The deaths rose in every state but two, South Dakota and New Hampshire, with pronounced increases in the South and West.



The Impact of Opioid Epidemic

- CDC estimates that the total "economic burden" of prescription opioid misuse in US is $78.5B a year, including the costs of healthcare, lost productivity, addiction treatment, and criminal justice involvement
- Opioid use has a significant correlation to criminal justice involvement [JAMA18]

Opioid epidemic erupts into surge in narcotic-related crimes

District Attorney delivers a special presentation on opioid-related crimes to mayors and other officials from Suffolk County's villages at Lake Grove Village Hall.

Most criminal cases in Suffolk County, NY, the officials said, relate to opioid epidemic.

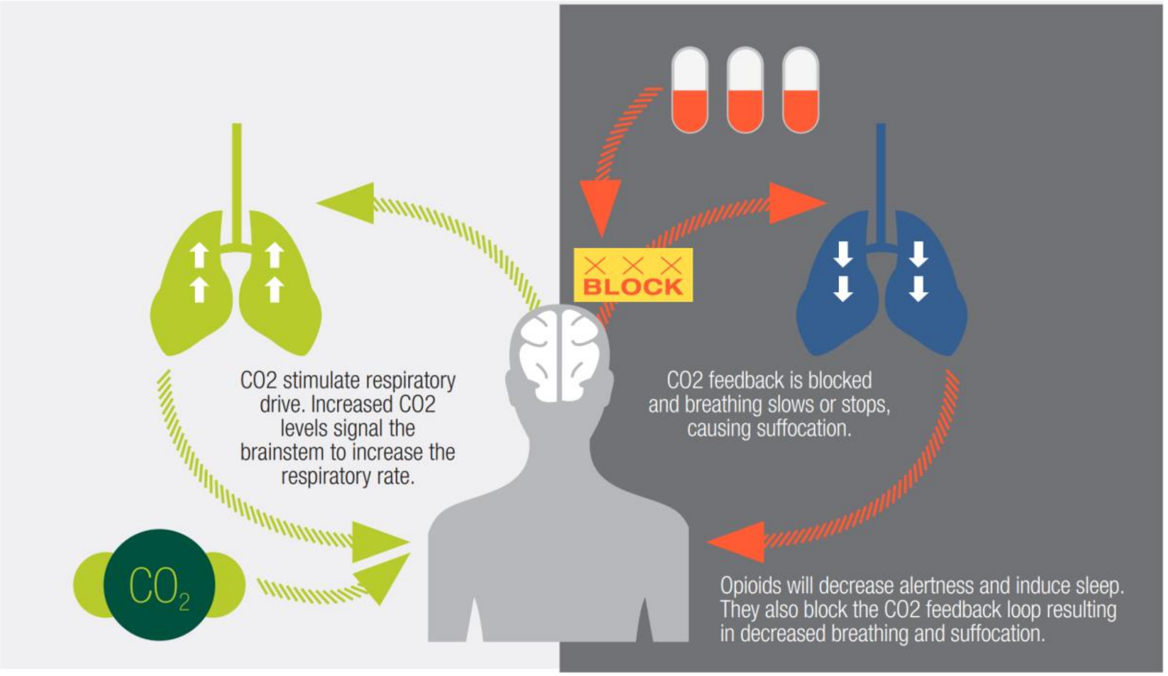
Combating opioid epidemic becomes a high priority for governments, healthcare providers and researchers.

Opioid Use Disorder (OUD) and Opioid Overdose (OD)

- Opioid use disorder: Problematic pattern of opioid use leading to clinically significant impairment or distress (at least two DSM-5 criteria)
  - Unsuccessful efforts to cut down or control use, or use resulting in social problems, a failure to fulfill obligations at work/school/home, etc

- Overdose: Opioids affect the part of the brain that regulates breathing; High doses of opioids can lead to the slowing or stopping of breathing and sometimes death
  - Occurs when a patient deliberately misuses a prescription, uses an illicit opioid (such as heroin), or uses an opioid contaminated with other even more potent opioids (such as fentanyl)

The effect of opioids on the respiratory system



Combating the Opioid Epidemic: the Questions

- Can we predict OD/OUD risks of patients in the future based on EHR history?

  ➔ Develop machine learning (including deep learning) based predictive models using patients' past EHR to predict future risk

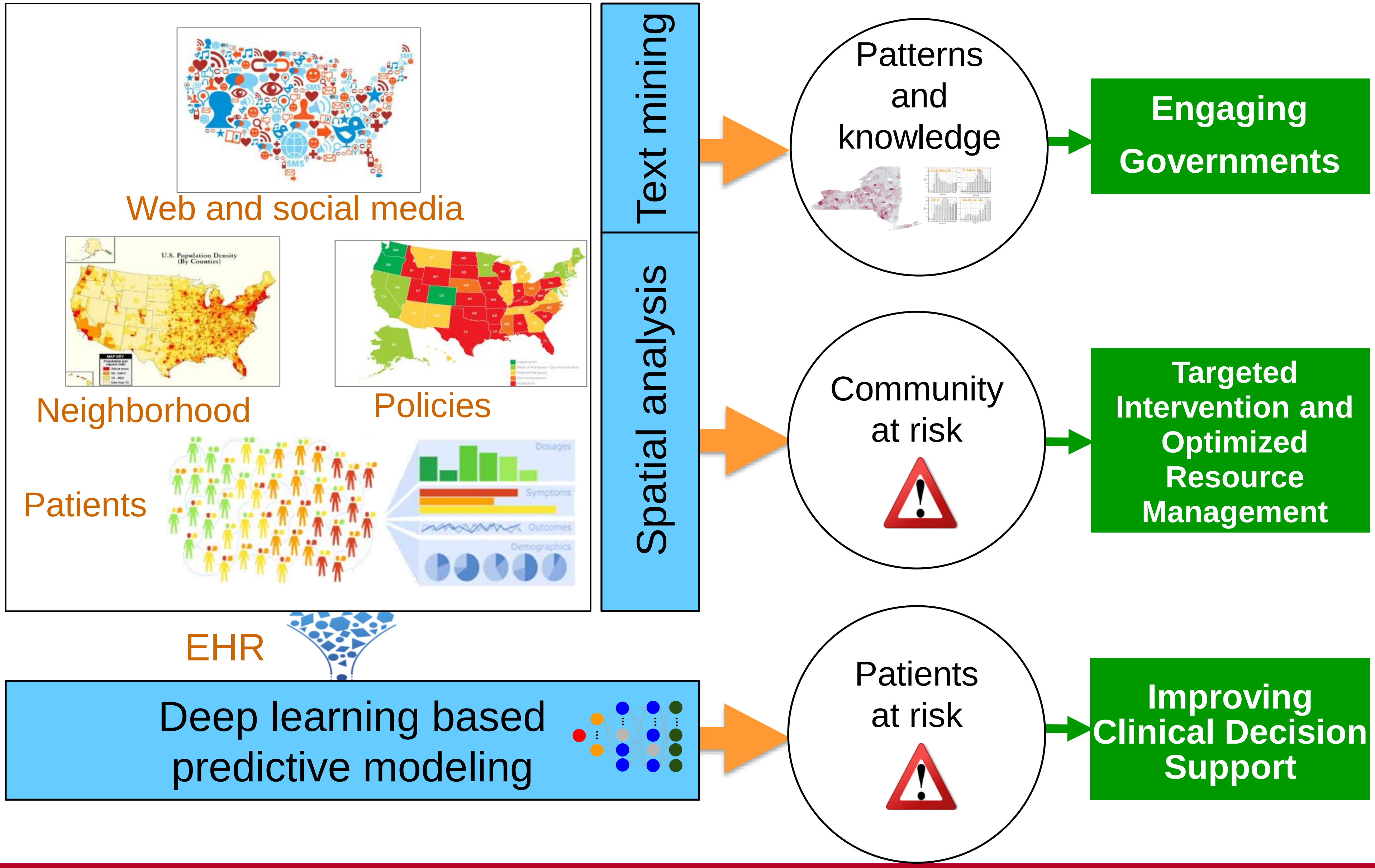
- Which regions or communities have most serious opioid problems for targeted interventions and optimized resource management?

  ➔ Fine-grain geospatial analysis to discover disparities and geospatial patterns

- What are the opinions of the public, the emotions of the opioid users and the psychological effects of opioid use?

  ➔ Text mining of social media data (Twitter/Reddit)

Big Data and AI Driven Opioid Epidemic Research



Outline

- Machine learning/deep learning based prediction of opioid risk
- Geospatial and temporal analysis of OD in NY
- Geospatial disparities on accessing resources
  - Naloxone pharmacies and Buprenorphine services
- Opioid epidemic study using social media

AI Driven Prediction of Opioid Risks

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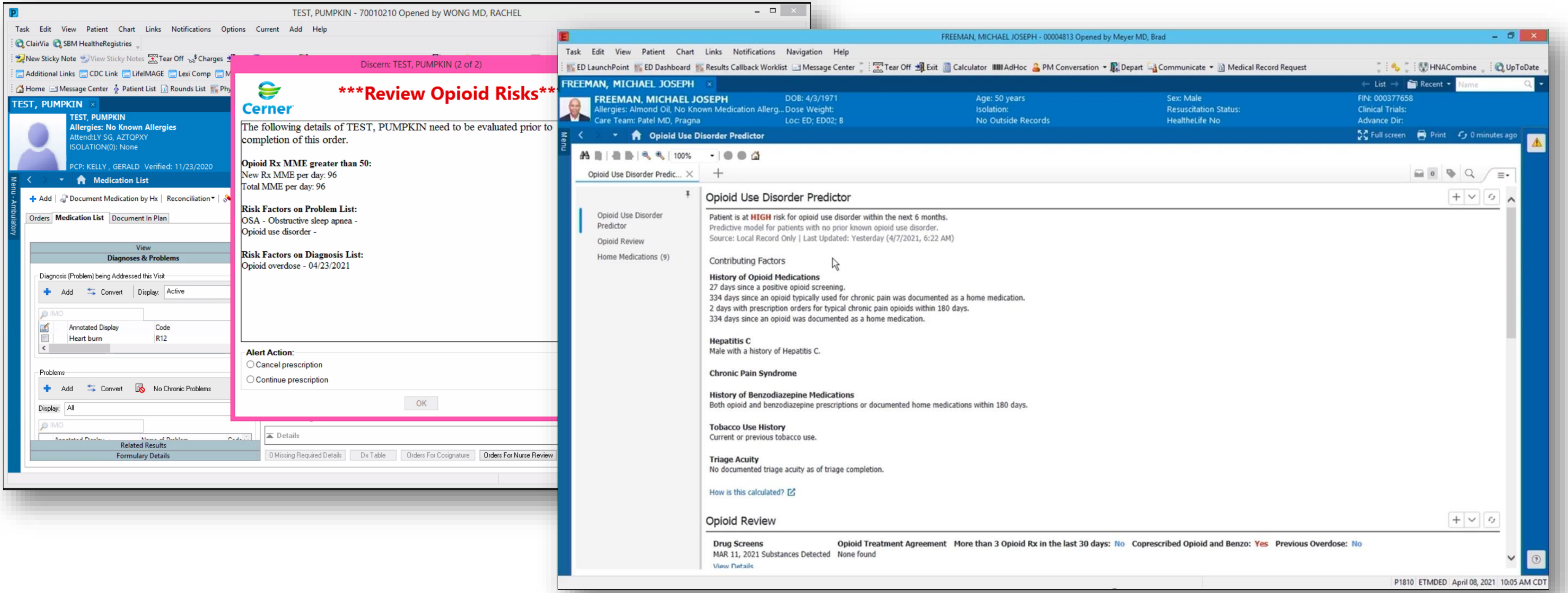
- Only ≈22% of people with OUD receive specific treatment, while most remain at high OD risk that is clinically under-identified
- The mean interval between first opioid medication and first OUD diagnosis: <1 year for 34.12% cases, and < 2 years for 54.07%
  - 18-25: 1.3% were diagnosed with OUD after first opioid exposure (~674 days)

  (based on Health Facts: 278,847 patients with opioid medication, 2010-2017)
- *Sensitive and valid approach is critically needed* to identify those individuals who are at risk for using opioids and would then be at increased risk for a trajectory of increasing use of prescription opioids, OUD severity, or opioid overdose

Predictive Modeling of Opioid Risks

- Much recent work has been on developing prediction models that assess an individuals’ risk of experiencing OD or OUD
- They are the precursors to prognostic tools that, when integrated into clinical workflow, can provide clinicians with critical information to help inform decisions about opioid prescribing and treatment in order to reduce opioid related harms
- Predictive models:
  - Customized rules based approach
  - Machine learning based approach
  - Integrated rules and machine learning based approach

EHR Tools for Opioid Risks in EHR



Cerner's Opioid Use Disorder Predictor combines discern expert rules and a machine learning based OUD predictor model, and predictions are recorded in *Cerner Millennium* as clinical events

Related Research Work on Opioid Risk Prediction

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Related Work	Data Sources	Feature Set	No. of Features	Methods	Prediction Target
Lo-Ciganic et al (2019)	Medicare	Medication, demographics	268	Gradient boosting machine(GBM), DNN	Opioid overdose
Lo-Ciganic et al (2020)	Medicare	Medication, demographics	269	Elastic net, random forests, GBM, DNN	Opioid use disorder
S. Wadekar et al (2020)	2016 NSDUH survey	Socioeconomic, demographics, physical and psychological status	18	Logistic regression, decision tree and random forest	Opioid use disorder
M. Glanz et al (2018)	KPCO EHR database	Demographics, tobacco use, metal health condition, medications	34	Cox regression	Opioid overdose
Randall et al (2019)	MSMC-EHR	Lab test, vital sign	100	Random forest	Opioid dependence risk

Traditional methods either use a limited set of features or lack the modeling of temporal progression with a state-of-the-art method, which lead to limited performance

Our Approach: Building Opioid Risk Prediction Models Using Temporal Deep Learning with Big EHR Data

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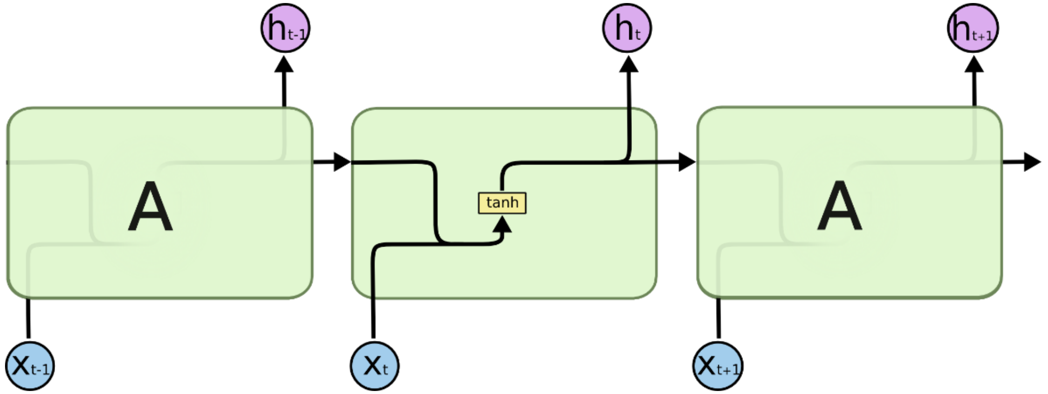
- Predicting both opioid use disorder (OUD excluding OD), and opioid overdose (OD) in the future
- Using large scale EHR datasets – Cerner's Health Facts database
- Take advantage of large number of EHR features (demographics, diagnosis, labs, medications, and clinical events)
- Use state-of-the-art sequential deep learning methods: long short-term memory (LSTM) to model the temporal aspect for the prediction
- Generate top ranked features as a reference for assisting clinical decision support

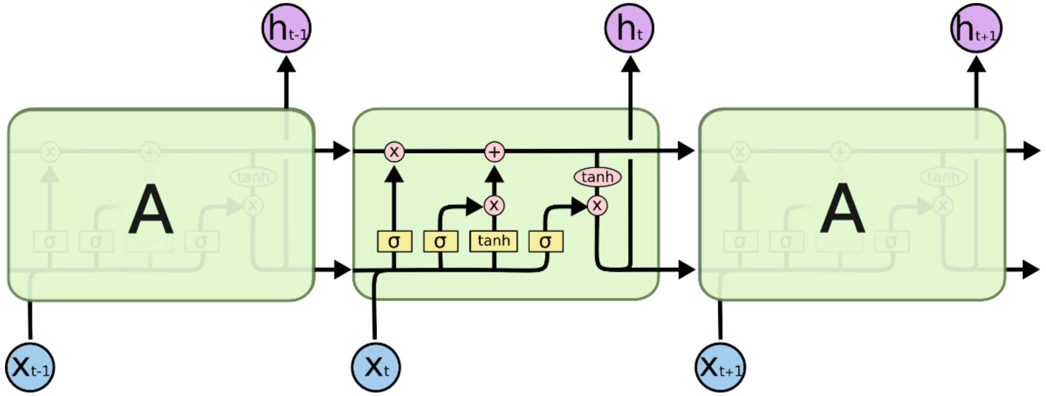
	Data Sources	Feature Set	No. of Features	Methods	Prediction Target
Our models	Cerner Health Facts database	Diagnosis, lab, clinical events, medications, demographics	1185/ 1468	LSTM + Graph Neural Networks	Opioid use disorder Opioid overdose

Long Short-Term Memory (LSTM)

- Recurrent Neural Network (RNN) captures temporal patterns and relations in a sequence of events, and overcomes the limitations of Dense Neural Network (DNN)
- LSTM is an RNN architecture to learn long-term dependencies by maintaining an internal state
  - LSTM can memorize information for a longer duration designed to learn long/short term dependency of data in a sequence
  - Ideal on modeling temporal disease progression
- LSTM also overcomes the limitation of RNN on possible vanishing and exploding gradients in back propagation



RNN



LSTM

Data Source – Cerner Health Facts

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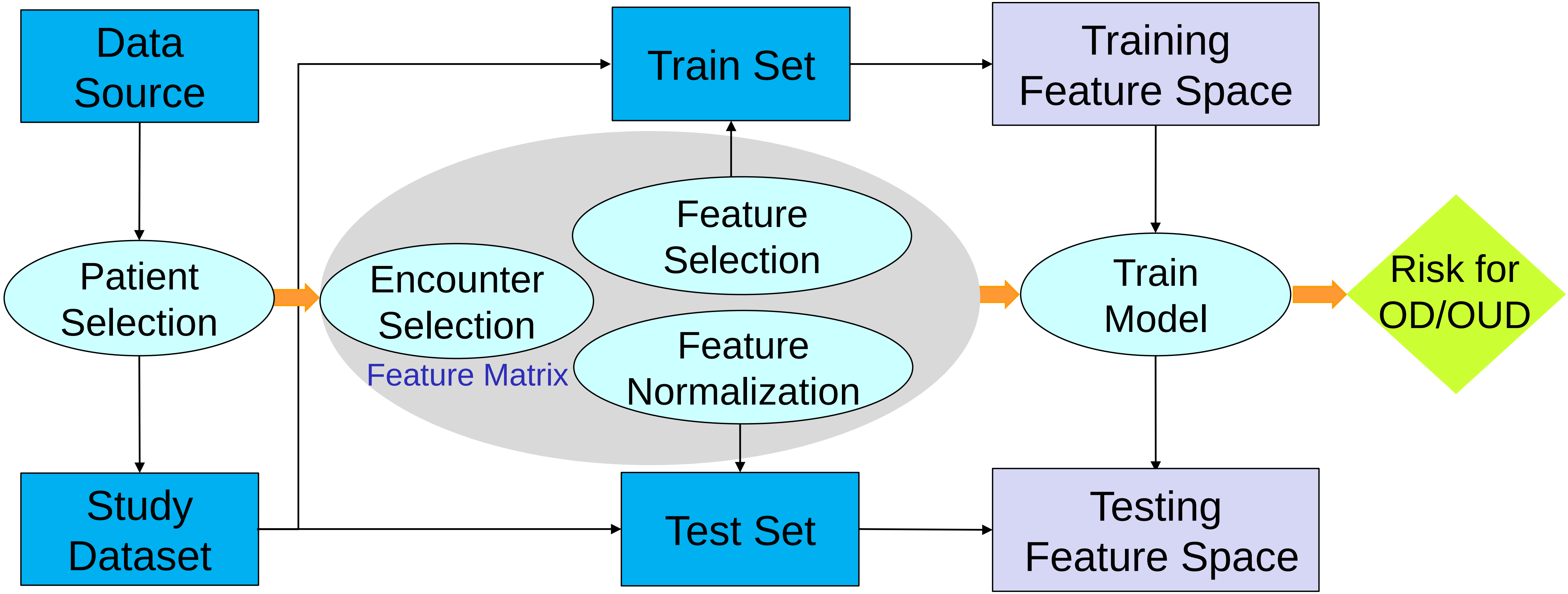
- De-identified EHR data from over 600 participating Cerner client hospitals (latest version: Real-World Data)
- ~ 69M patients (2008-2017)

Category	Description
Diagnoses	Diseases, symptoms, poisoning for patients
Procedures	Surgical, medical or diagnostic interventions received by patients
Laboratory Tests	Procedures in which a health care provider takes a sample of a patient's blood, urine, other bodily fluid or body tissue to get information about the patient's health
Medications	Dose quantity of medication taken by patients
Clinical Events	Related symptoms, personal health status (like smoking history, tobacco use, etc)
Demographics	Age, gender, race/ethnicity

Overall Pipeline



Preprocessing - Patients Selection

All Patients

With at least one prescription of opioid medication between 2008.1.1 and 2017.12.31

Remove patients with cancer

Keep patients with age between 18 and 66 when first exposed to opioid medications (2,161,469 are removed)

Identification by OD/OUD ICD codes

"Positive" Patients

"Negative" Patients

Medication with Ingredients Related to Opioid: butorphanol, diamorphine, eluxadoline, oxycodone……

ICD codes for Cancer: 225.9, 227.3, 227.4 ……

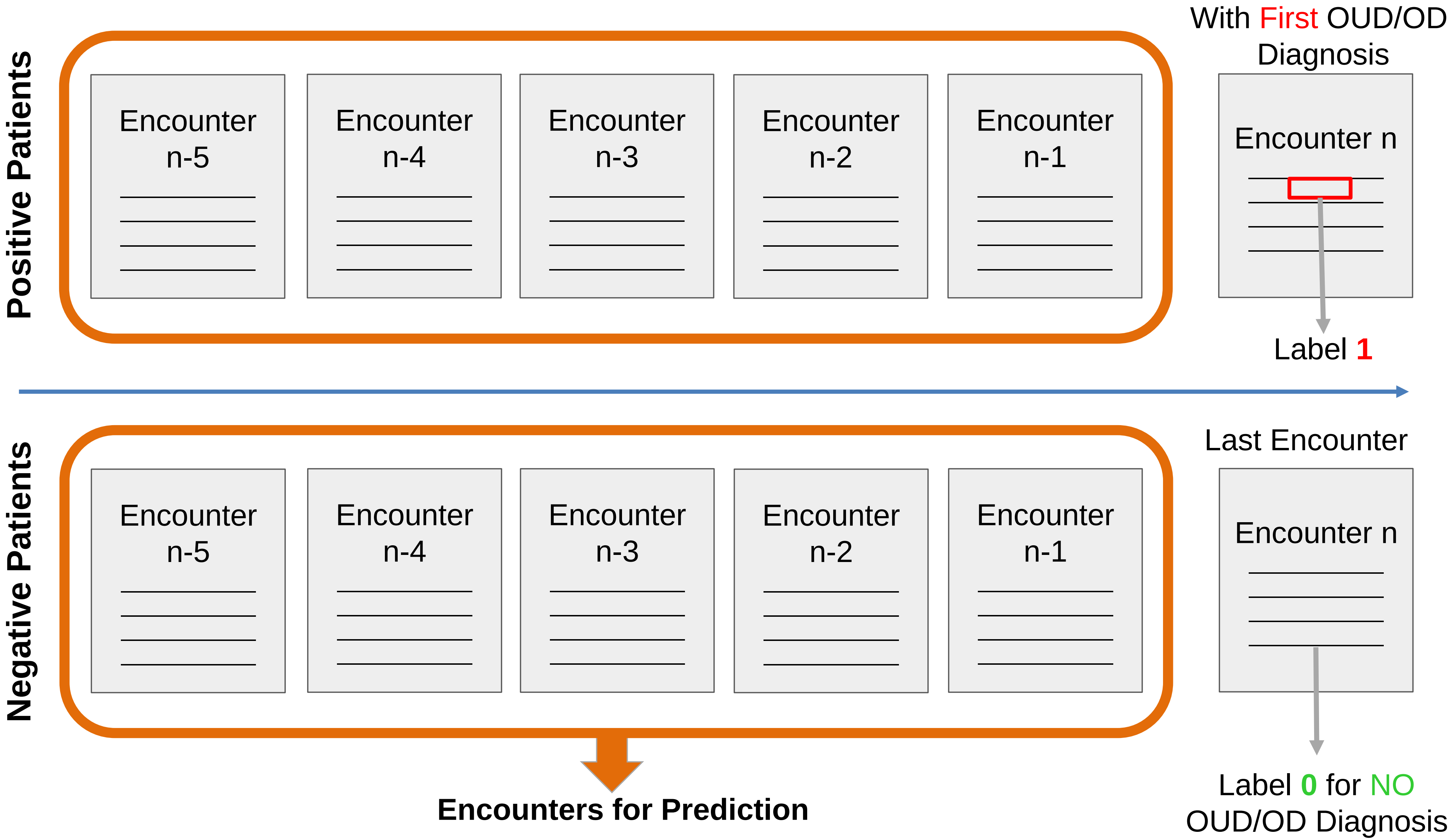
ICD codes for OD/OUD: T40.0, T40.1, T40.2 ……

Study Datasets (Positive/Negative Patients)

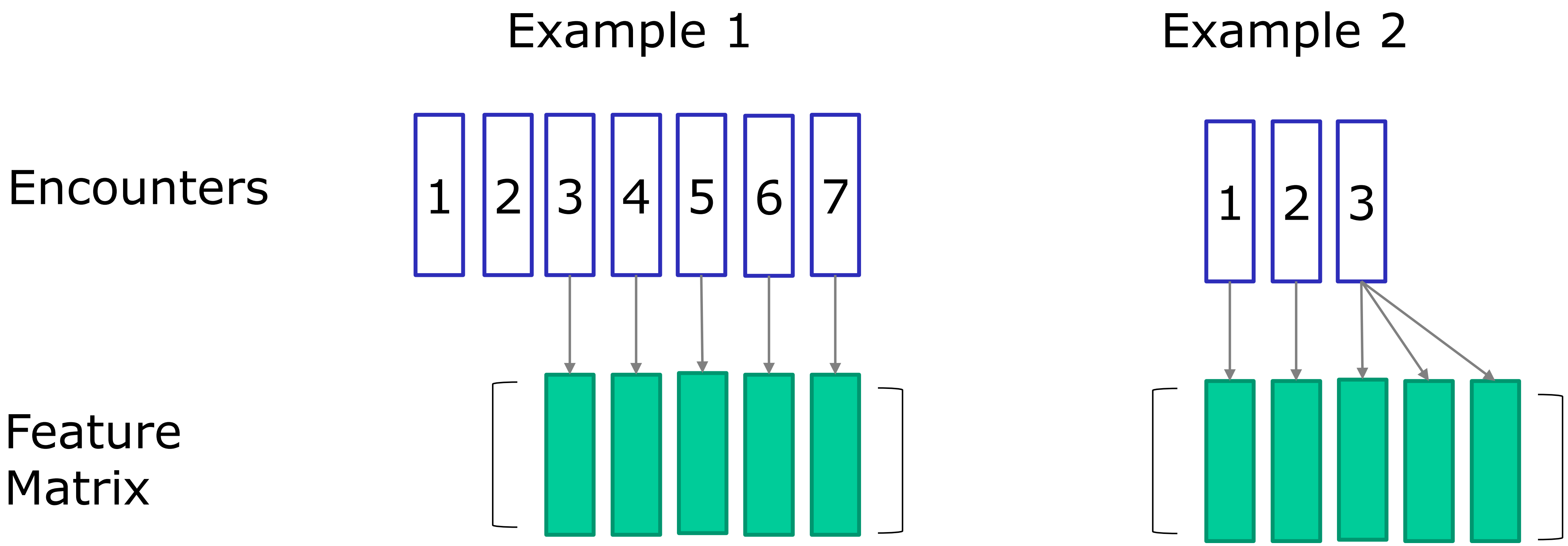
Datasets	Positive	Negative	Timespan
Opioid Overdose (OD)	44,774	5,186,840	2008 to 2017
Opioid Use Disorder (OUD)	111,456	5,120,158	2008 to 2017

Gender distribution (1.325:1 of female to male) is close between positive (OUD) and negative (non-OUD patients)

Encounters for Building the Models



Encounters for Building the Models (cont’d)



Features Selection

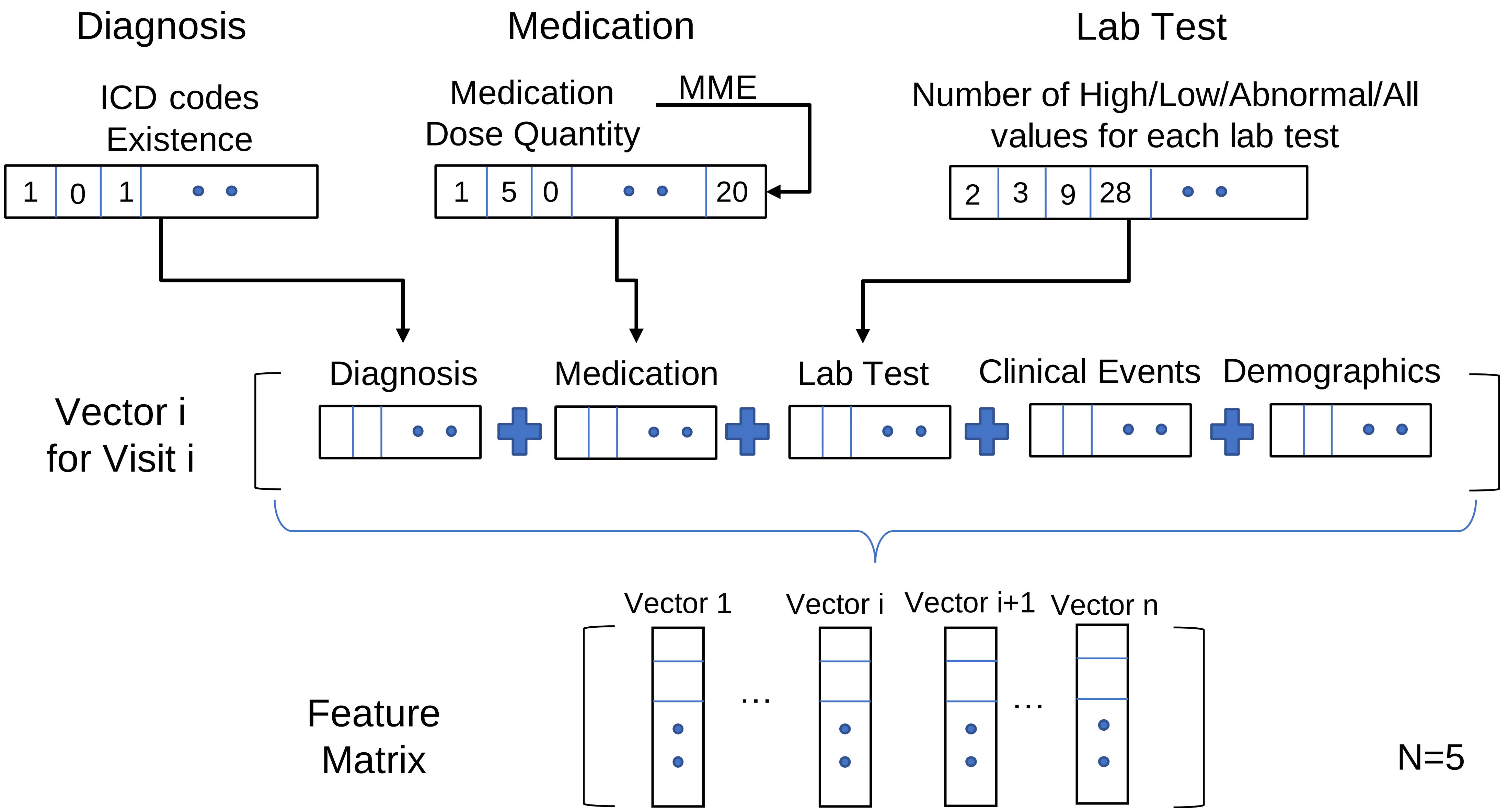
Study dataset → Calculating prevalence of each feature in positive patient records → Removed if prevalence less than 1% of all positive patients → Features for prediction

Datasets	Category	Number of Features
Opioid Overdose (Total: 1,185)	Diagnoses, Procedures	414
	Laboratory Test Result	394
	Demographics	3
	Clinical Events	227
	Medications	147
Opioid Use Disorder (Total: 1,468)	Diagnoses, Procedures	457
	Laboratory Tests	530
	Demographics	3
	Clinical Events	251
	Medications	227

Feature Normalization

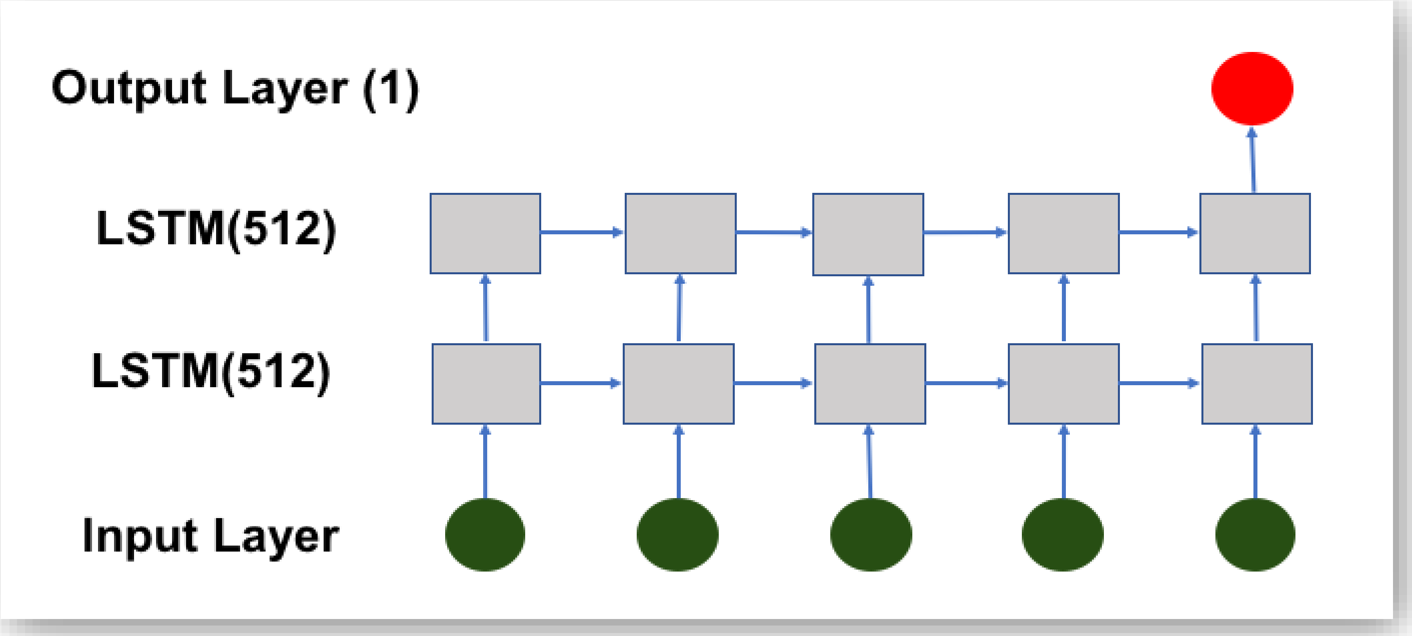
- For diagnosis codes, convert all ICD-9 codes to ICD10 codes (first 3 digits)
- For medications, convert NDC codes to ATC codes (level 3, first 4 digits), which is more meaningful for predication (NDC doesn’t record ingredients)
- MME (morphine milligram equivalents) is generated as an aggregate feature
- For lab tests in an encounter, we record the number of abnormal values, the total number of lab tests, and the ratio between the two values
- For most clinical events, we will use the last value for the patient as the value in the feature space, for feature with multiple numeric values in one visit, we will also record the highest, median and lowest values
- For missing values, we use the median imputation (other imputations such as MICE and KNN have similar results)

Feature Matrix Construction



Predictive Models

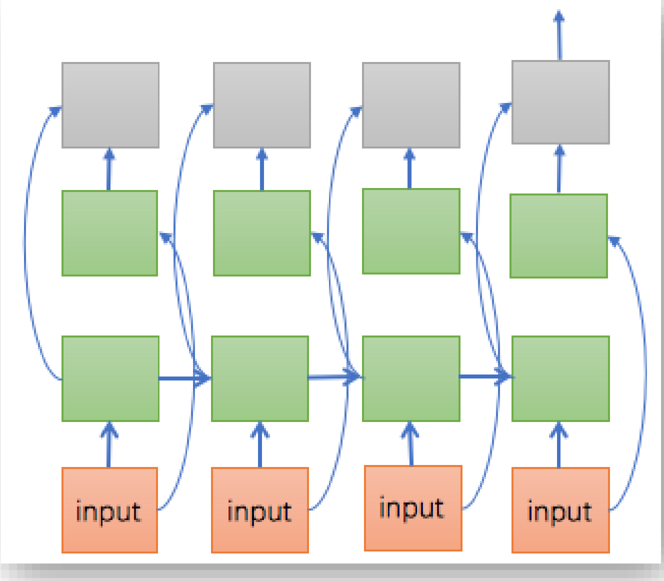
- Traditional Machine Learning
  - Random Forest, Logistic Regression, Decision Tree
- Deep Learning
  - Dense Neural Network
  - **LSTM (Long short-term memory)**
  - Variants of LSTM



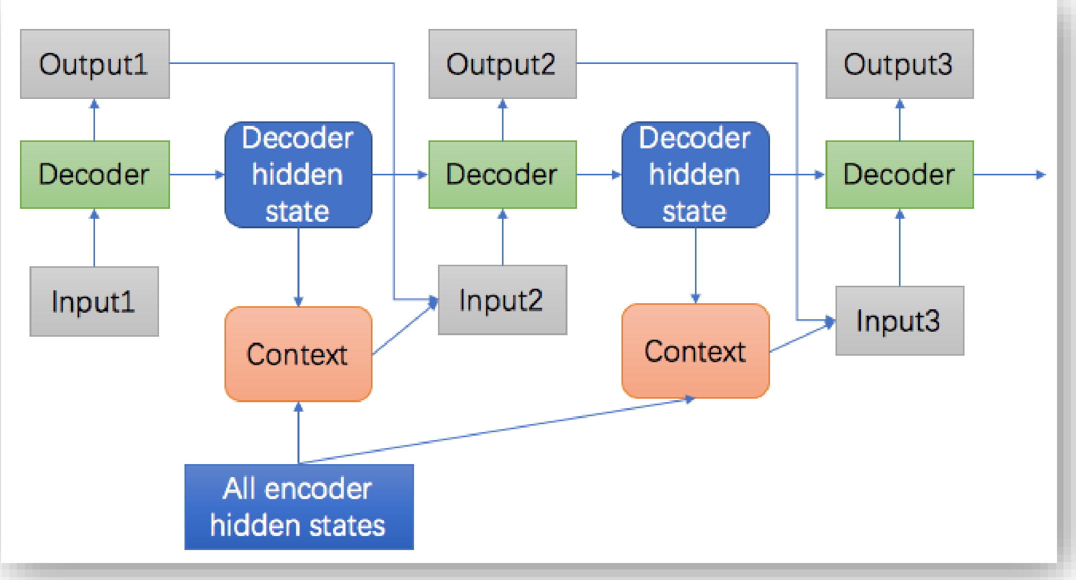
Variants of LSTMs

- Bidirectional LSTM(Bi-LSTM): with one more hidden layer trained from back to front. Has the advantage that hidden layers can preserve information from both the past and the future
- LSTM with Attention: an application of LSTM model on sequence to sequence prediction:A special encoder-decoder embedding method allows each decoder in each step access overall context. Allows the model to focus on the relevant parts of the input sequence as needed

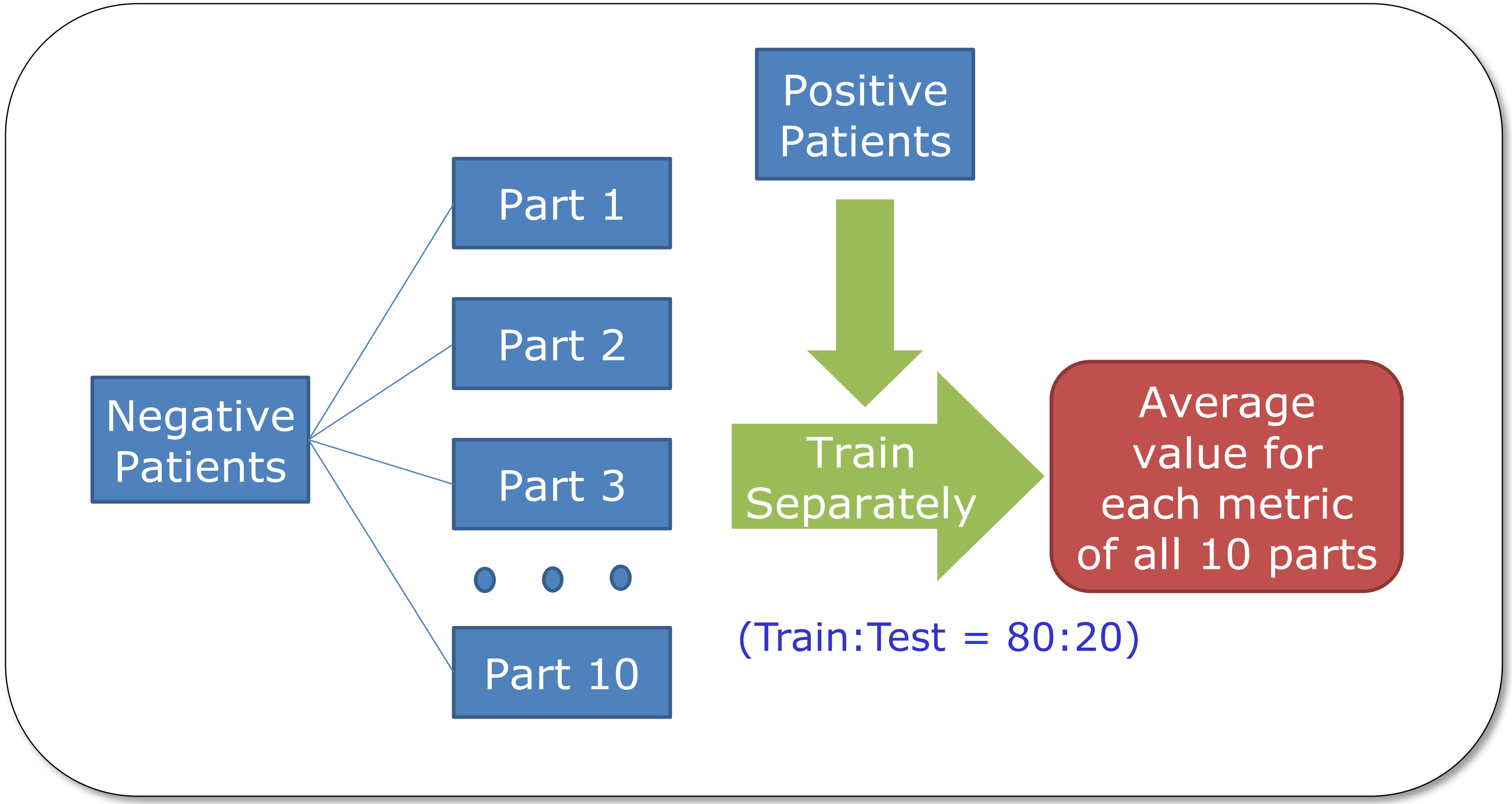
Bi-LSTM



Attention



Performance Evaluation Experiment Setup



OUD Prediction Performance

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Model	Precision	Recall	F1 score	AUCROC
Random Forest	**0.8565**	0.6871	0.7545	0.9112
Decision Tree	0.7592	0.7281	0.7453	0.8823
Logistic Regression	0.7507	0.6020	0.6722	0.7933
Dense Neural Network	0.8019	0.7694	0.7855	0.9224
LSTM	0.8184	**0.7865**	**0.8023**	0.9369
LSTM with Attention	0.8131	0.7814	0.7969	**0.9491**
Bi-LSTM	0.7710	0.7804	0.7759	0.9463

- Recall (sensitivity): fraction of identified positive patients of all positive patients
- Precision: fraction of true positive patients among all identified patients
- F1 score considers both precision and recall, we regard it as the best aggregated assessment of the overall prediction performance

OUD Prediction Performance for Young Adults (18-25)

Stony Brook University

Age	Prediction Model	Precision	Recall	F1	AUC
All (18-66)	Random Forest	**0.8565**	0.6871	0.7545	0.9112
	Decision Tree	0.7592	0.7281	0.7453	0.8823
	Logistic Regression	0.7507	0.6020	0.6722	0.7933
	DNN	0.8019	0.7694	0.7855	0.9224
	LSTM	0.8184	**0.7865**	**0.8023**	**0.9369**
Young (18-25)	Random Forest	0.9819	0.7937	0.8778	0.8584
	Decision Tree	0.8519	0.7440	0.7943	0.7449
	Logistic Regression	0.9937	0.6954	0.8201	0.6093
	Dense Neural Network	0.9619	**0.8501**	0.9026	0.9297
	LSTM	0.9756	0.8428	**0.9058**	0.9316

OD Prediction Performance

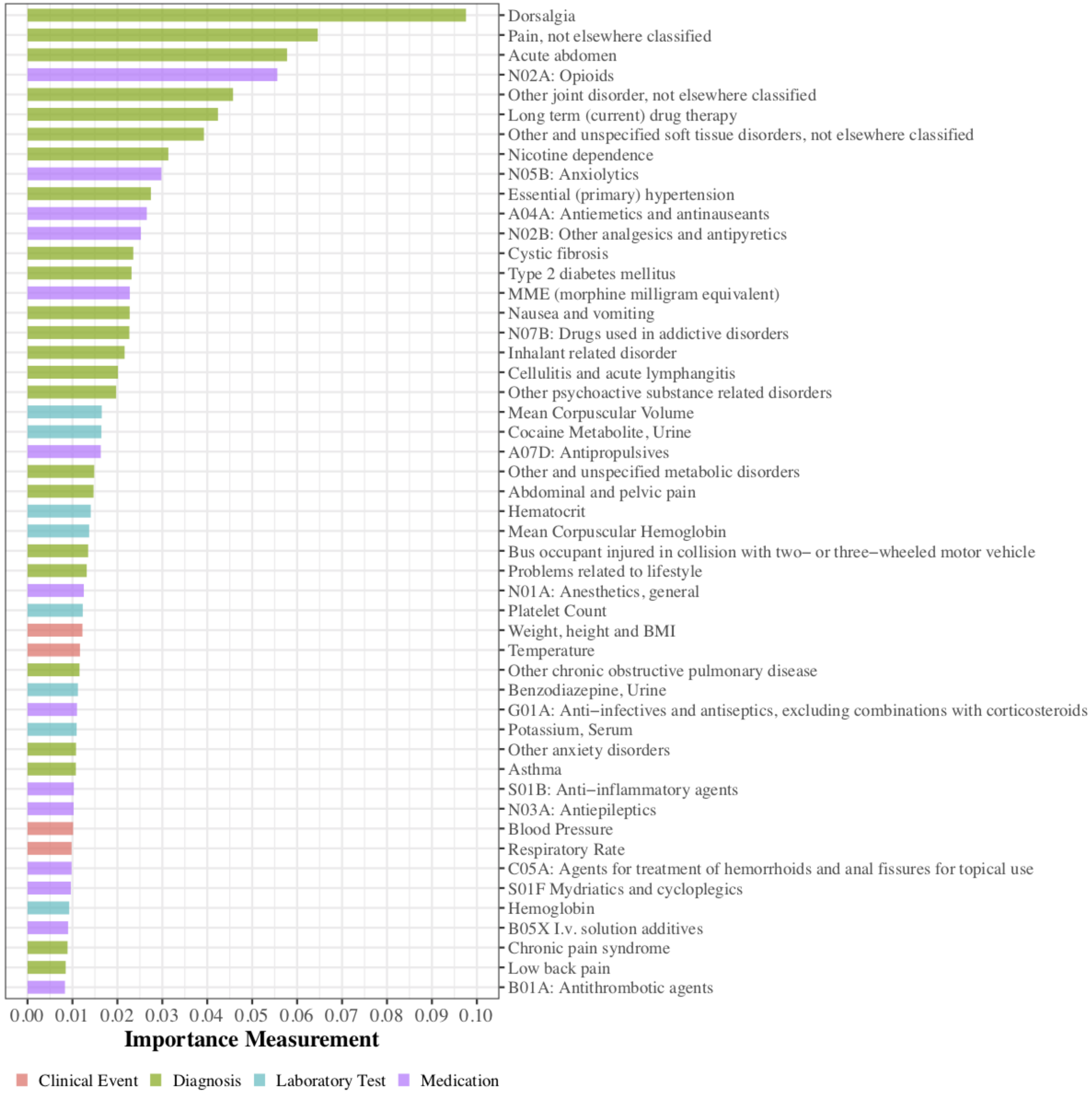
Stony Brook University

Prediction Model	Precision	Recall	F-1	AUCROC
Random Forest	0.7695	0.7055	0.7361	0.8167
Decision Tree	0.7277	0.7047	0.7160	0.7892
Logistic Regression	0.7539	0.6050	0.6647	0.7147
Dense Neural Network	0.8006	0.7329	0.7683	0.8214
LSTM Network	0.7884	**0.7616**	0.7798	0.8318
LSTM with Attention	0.8128	0.7512	**0.7815**	0.8449

Feature Importance

- Permutation Importance
  - Deep learning model is hard to interpret
  - The idea is that feature importance can be measured by looking at how much the score (e.g., F1 score) decreases when a feature is not available
- Implementation
  - Measure how much F1 score decreases by randomly shuffling the values of a feature
  - Rank the features by the decreases

Feature Importance (OUD)



- Opioid related medications had high rankings, including dose quantity of opioid medications and MME
- Other pain treatment related medications (N02B: Other analgesics and antipyretics; N01A: Anesthetics, general; N01B: Anesthetics, local) were also among the top features
- Several highly ranked diagnosis features were related to pain, such as dorsalgia, as well as pain not elsewhere classified, acute abdominal and pelvic pain, and joint or tissue disorder
- Other substances also appeared as highly ranked features, including tobacco use and alcohol use, and administration of anxiolytics (ATC code N05B)

Top 20 Features for Prediction of Opioid Use Disorder by LSTM

Category	Description	Rank	Category	Description	Rank
Diagnosis	Dorsalgia *(back or spine pain)*	1	Medication	A04A: Antiemetics and antinauseants	11
Diagnosis	Pain, not elsewhere classified	2	Medication	N02B: Other analgesics and antipyretics	12
Diagnosis	Acute abdomen	3	Diagnosis	Cystic fibrosis	13
Medication	N02A: Opioids	4	Diagnosis	Type 2 diabetes mellitus	14
Diagnosis	Other joint disorder, not elsewhere classified	5	Medication	MME (morphine milligram equivalent)	15
Diagnosis	Long term (current) drug therapy	6	Diagnosis	Nausea and vomiting	16
Diagnosis	Other and unspecified soft tissue disorders, not elsewhere classified	7	Medication	N07B: Drugs used in addictive disorders	17
Diagnosis	Nicotine dependence	8	Diagnosis	Inhalant related disorder	18
Medication	N05B: Anxiolytics	9	Diagnosis	Cellulitis and acute lymphangitis	19
Diagnosis	Essential (primary) hypertension	10	Diagnosis	Other psychoactive substance related disorders	20

Type 2 diabetes: Patients with diabetes frequently use opioids to manage diabetes-related neuropathic pain, which may put them at increased risk of OUD
Cellulitis: Heroin or opioids abused via IV injection may cause infections like cellulitis
cystic fibrosis: cystic fibrosis patients are at higher risk of developing a dangerous thinning of bones. They may experience joint pain, arthritis and muscle pain

Top 20 Features for Prediction of OD by LSTM

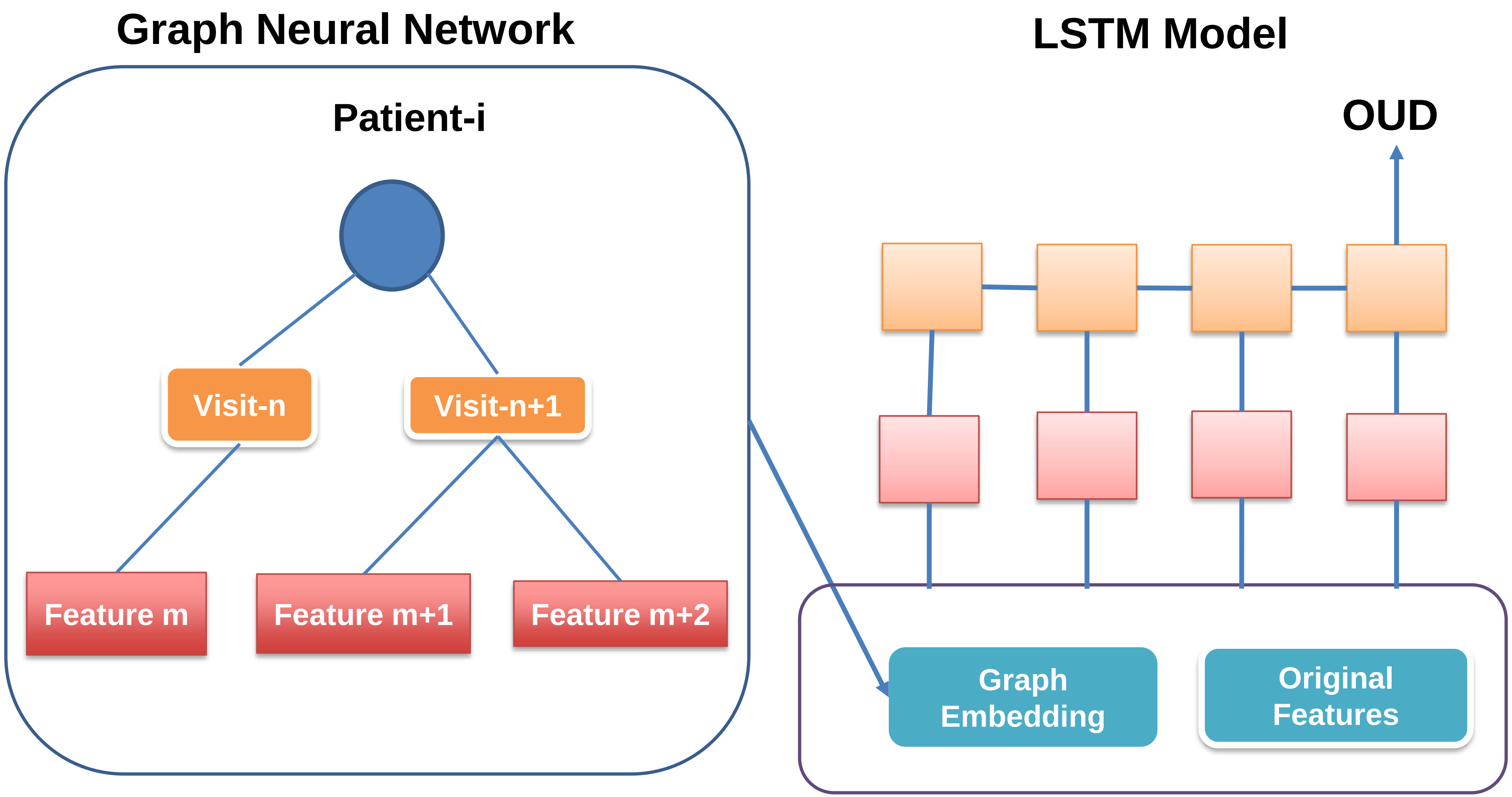
Stony Brook University

Category	Description	Rank	Category	Description	Rank
Medication	N02A: Opioids	1	Medication	MME	11
Clinical Event	Pain Scale Score	2	Clinical Event	Smoke, Exposure to Tobacco Smoke	12
Medication	A07D: Antipropulsives	3	Medication	G02A: Uterotonics	13
Medication	N01A: Anesthetics, general	4	Laboratory Test	Blood Urea Nitrogen	14
Clinical Event	Alcohol Use	5	Medication	R05D: Cough and cold preparations	15
Medication	N02B: Other analgesics and antipyretics	6	Laboratory Test	Alkaline Phosphatase, Serum	16
Clinical Event	Blood Pressure	7	Clinical Event	Heart Rate	17
Medication	N05C	8	Laboratory Test	Chloride, Serum	18
Laboratory Test	Mean Corpuscular Hemoglobin	9	Clinical Event	Height/Weight/BMI	19
Laboratory Test	Red Blood Cell Distribution Width (RDW)	10	Laboratory Test	Monocyte Count	20

Ongoing: Graph Based Neural Networks

- The graphical structure underlying EHR data has the potential to improve the performance of prediction tasks such as heart failure and Alzheimer's Disease
- Graph Neural Network(GNN) is a class of deep learning models that can work on data described by graphs. GNN can capture the dependence of graphs via message passing between the nodes of graphs
- We propose to combine GNN and LSTM to improve the prediction
  - Capture the relation among patient, visit and features
  - Differentiate different types of nodes (patient/visit/feature) and edges (between patient and visit, visit and feature)
  - Temporal effects are included in visits node embeddings

In Progress: Proposed Structure of LSTM+GNN model



Preliminary Results with GNN+LSTM

Target	Model	Precision	Recall	F-1	AUCROC
Opioid Overdose	Random Forest	0.7695	0.7055	0.7361	0.8167
	Decision Tree	0.7277	0.7047	0.7160	0.7892
	Logistic Regression	0.7539	0.6050	0.6647	0.7147
	Dense Neural Network	0.8006	0.7329	0.7683	0.8214
	LSTM	0.7884	0.7616	0.7798	0.8318
	LSTM+GNN	**0.8008**	**0.7682**	**0.7917**	**0.8802**
Opioid Use Disorder	Random Forest	**0.8565**	0.6871	0.7545	0.9112
	Decision Tree	0.7592	0.7281	0.7453	0.8823
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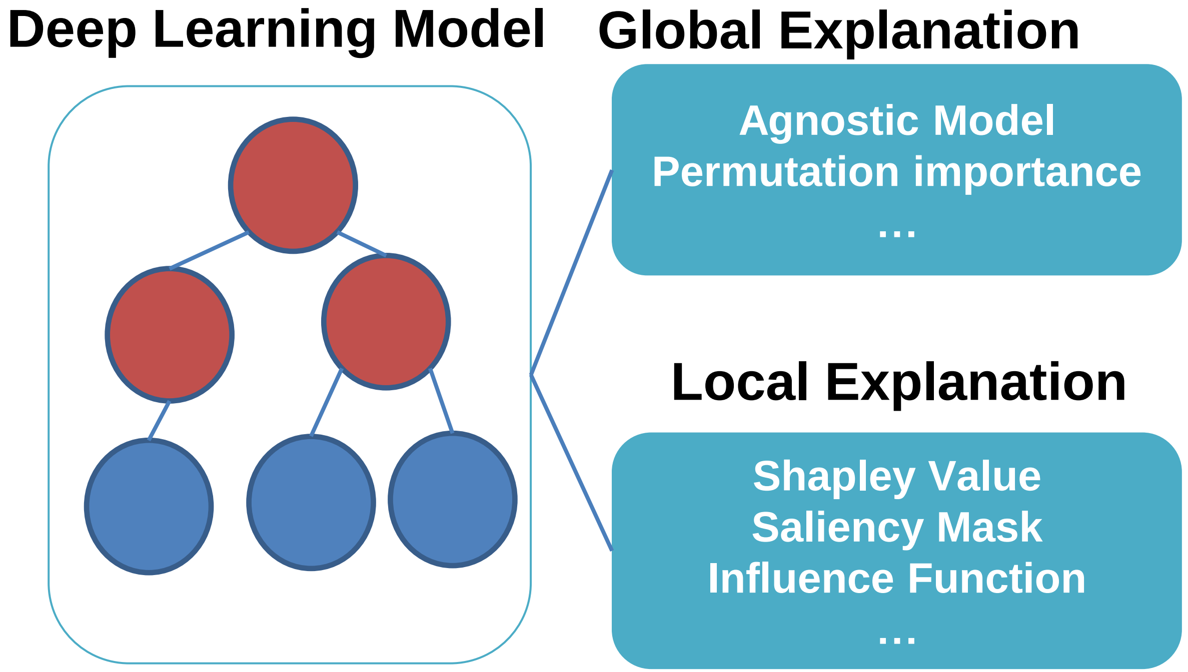
	Dense Neural Network	0.8019	0.7694	0.7855	0.9224
	LSTM	0.8184	0.7865	0.8023	0.9369
	LSTM+GNN	0.831	**0.7923**	**0.8139**	**0.9441**

In Progress: Human-centric Interpretability for Deep Learning

- To make it meaningful for clinicians to make informed decisions, we will provide both population level explanation and patient-specific explanation
  - Population level (global): provide an interpretation of the model on all patients, including feature ranking, statistics, correlation and temporal progression
  - Patient level (local): for each patient, the model will generate a risk score and the contribution of each feature for the score

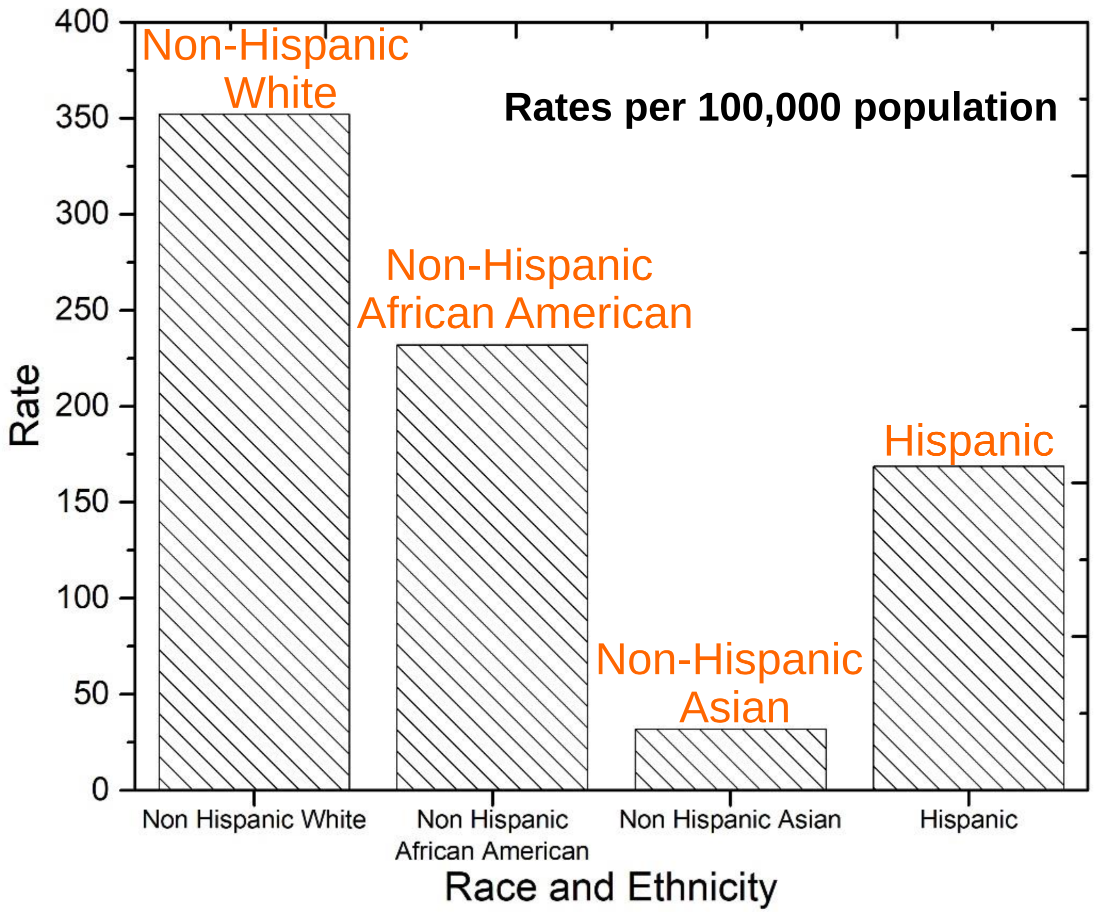


Geospatial and Temporal Analysis of Opioid Poisoning Using Claims Data – NYS SPARCS

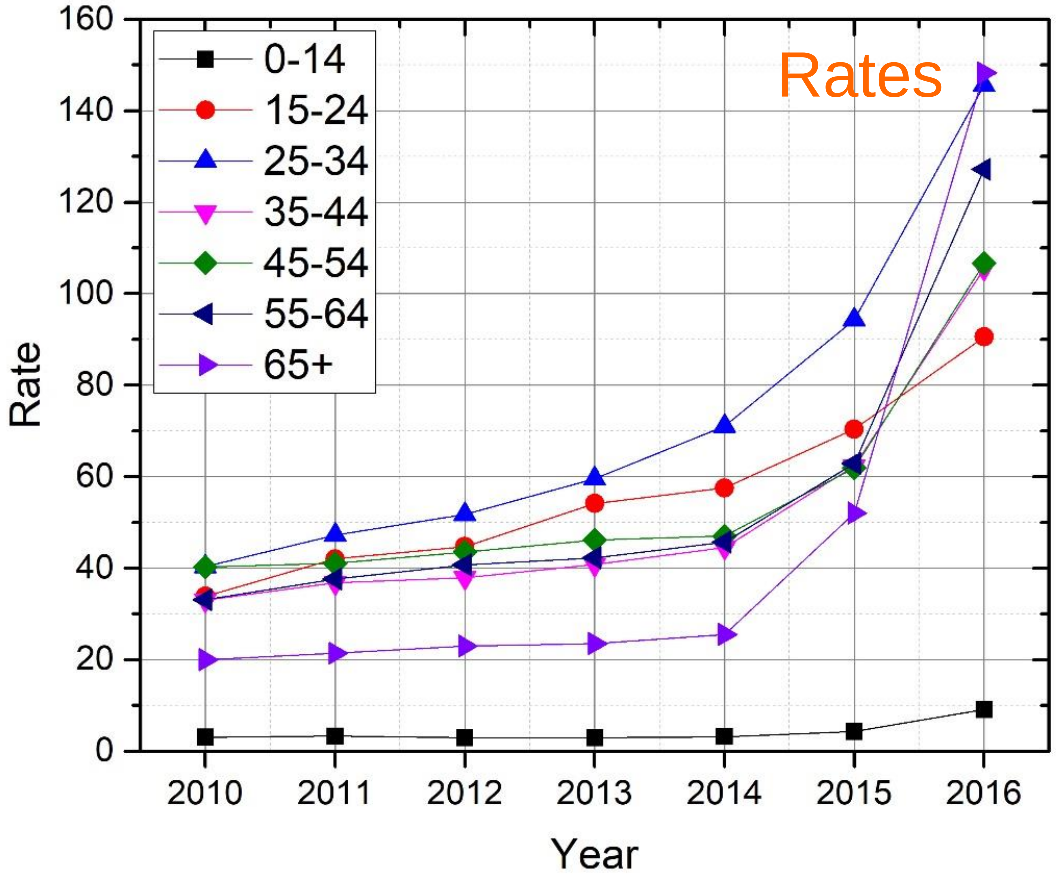
- Goal: to evaluate geographic, temporal, and sociodemographic differences of opioid poisoning
- Use NY Department of Health, Statewide Planning and Research (SPARCS) patient discharge records
  - Inpatient, outpatient, emergency room, ambulatory
  - Diagnoses and treatments, services, and charges, addresses included
- Extract all patient records with opioid poisoning related diagnosis from 2010-2019 (ongoing with annually updated data)
  - ICD-9/ICD-10 for opiates, opium, heroin, methadone, and other related narcotics
  - Use zip codes extracted from patient addresses

[AMIA2017, AJPM2019, SciRep2021]

Rate Disparity in Race and Ethnicity Groups



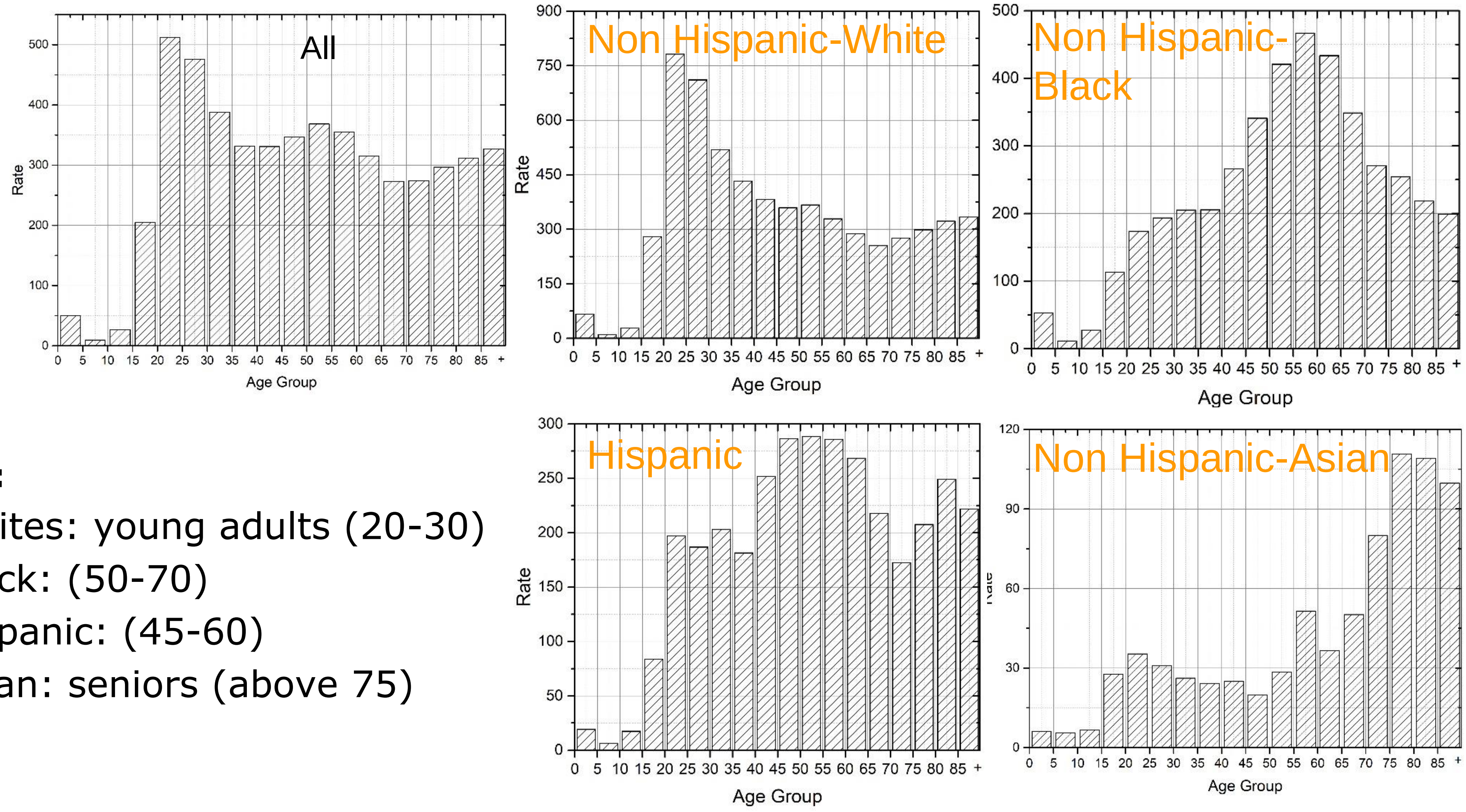
Temporal Trends for Age Groups



Rates per 100,000 population

The age group of 65+ had the most dramatic increase after 2014

Age Distribution of Rates by Race and Ethnicity

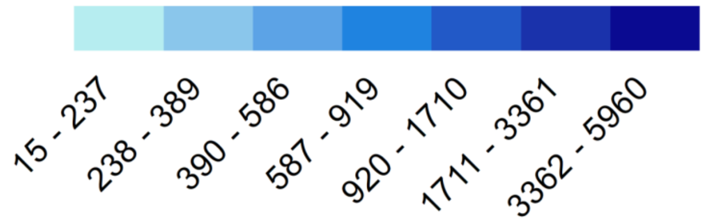


Peaks:

- Whites: young adults (20-30)
- Black: (50-70)
- Hispanic: (45-60)
- Asian: seniors (above 75)

Rates per 100,000 population

Rate of OD per 100,000 Persons at ZIP Code Level, 2017-2019



Authorities seize enough fentanyl for "1 million overdoses"

OCTOBER 28, 2017 / 10:12 PM / CBS/AP

MASTIC BEACH, N.Y. -- Authorities on Long Island announced on Saturday the seizure of 750 grams of fentanyl from a home in Mastic Beach, CBS New York reports.

OD in

Disparities of Opioid Related Resources

- Naloxone (Narcan) rapidly reverses the effects of an opioid overdose. Most studies find survival near 100% when naloxone was administered before death
- Naloxone is a prescription medication, but NYS has issued a ”standing order” prescription

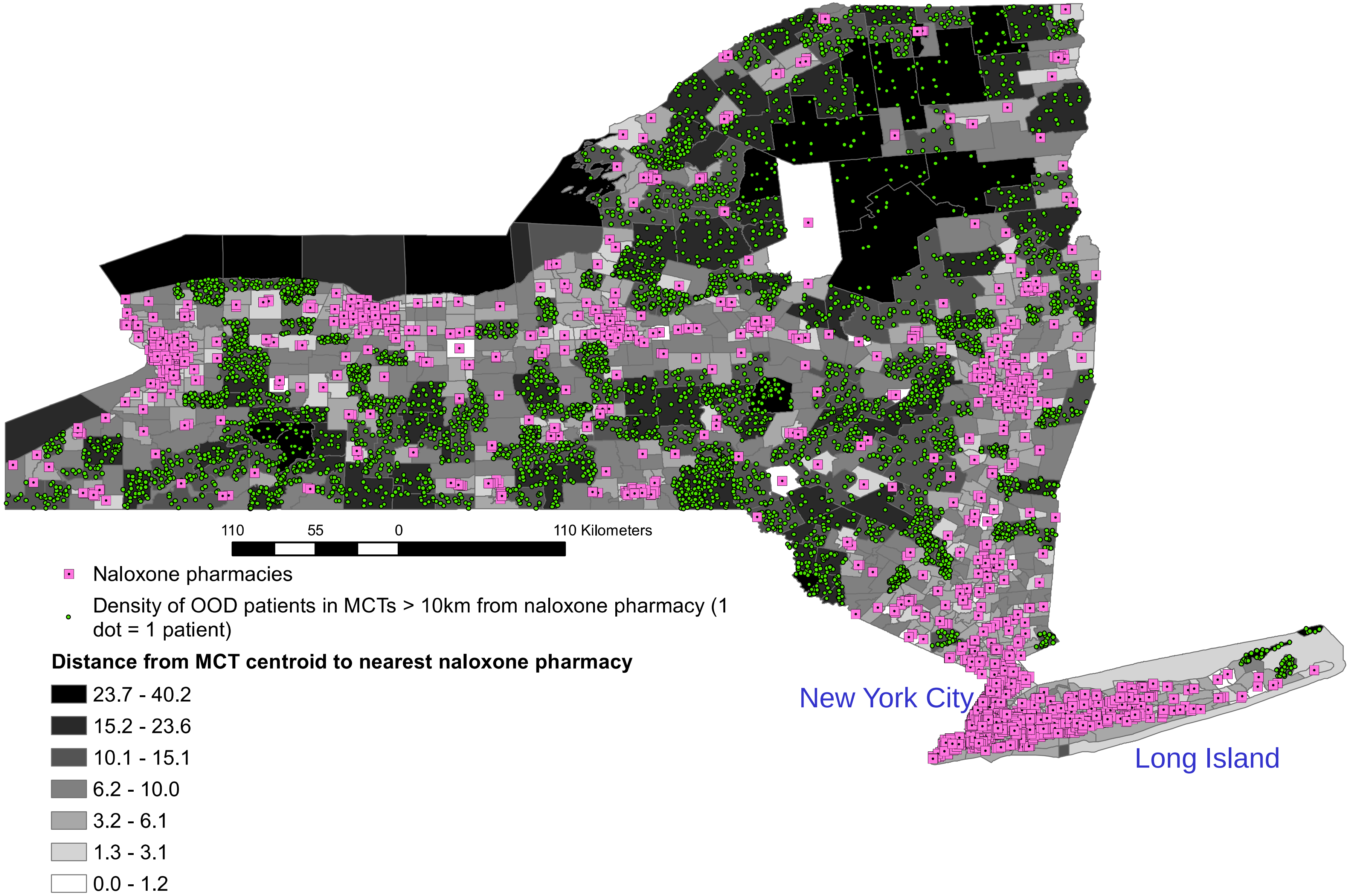
- Buprenorphine is among FDA approved Medication-assisted treatment (MAT) medications that prevent withdrawal symptoms
- Less chance of withdrawal, less abuse potential, less chance of overdose
- Buprenorphine is a schedule III controlled substance, waiver needed from SAMHSA to get licensed for prescription
- Access to buprenorphine services remains challenging in many localities, despite substantial increases in the number of waivered providers [OIG20]

Our Goal: High Resolution Geospatial Analysis on Resource Disparities at Census Tract Level

[Kayley Abell-Hart 2021, Under Review]

Density of Naloxone-Far OD Patients vs Naloxone Pharmacies

Stony Brook University

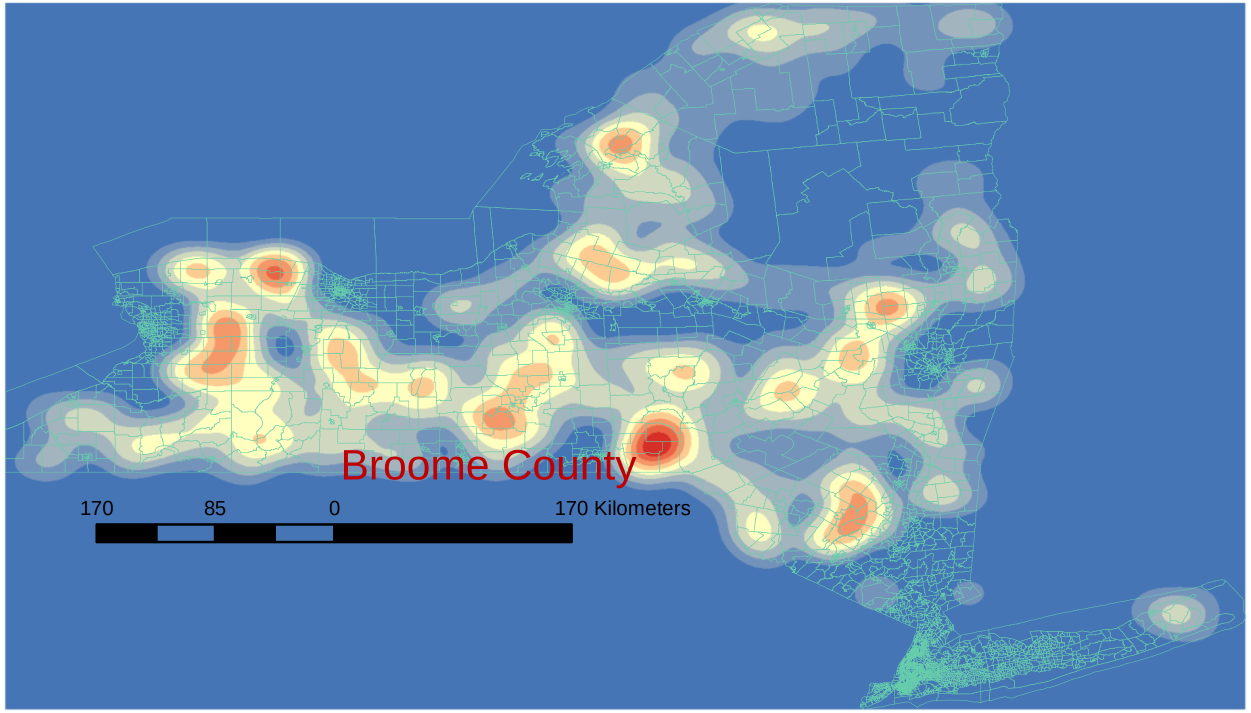


Kernel Density Estimation of Naloxone-Far Patients

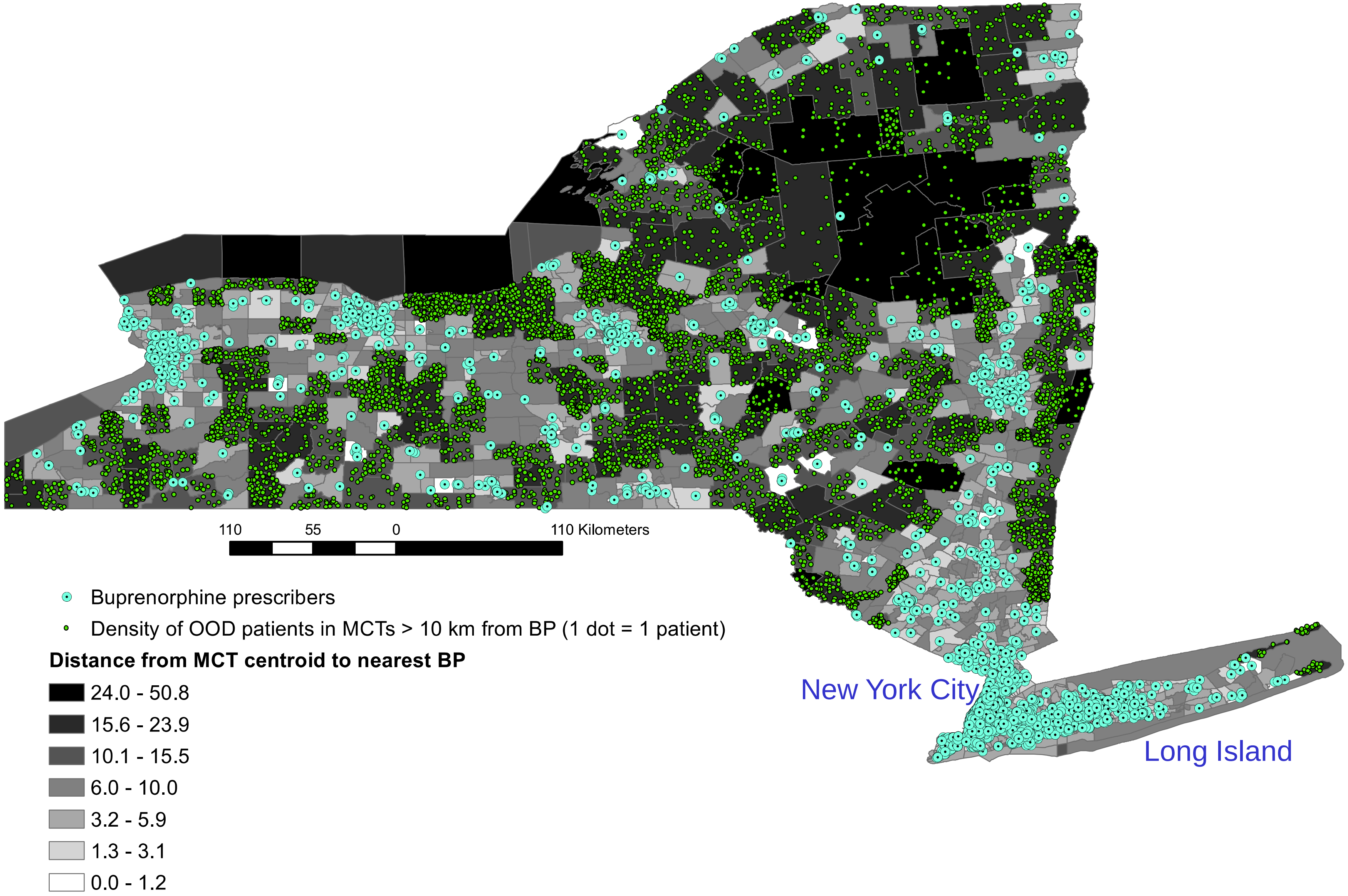
KDE of naloxone-far patients

- 0 - 0.018
- 0.019 - 0.035
- 0.036 - 0.053
- 0.054 - 0.07
- 0.071 - 0.088
- 0.089 - 0.11
- 0.12 - 0.12
- 0.13 - 0.14
- 0.15 - 0.16

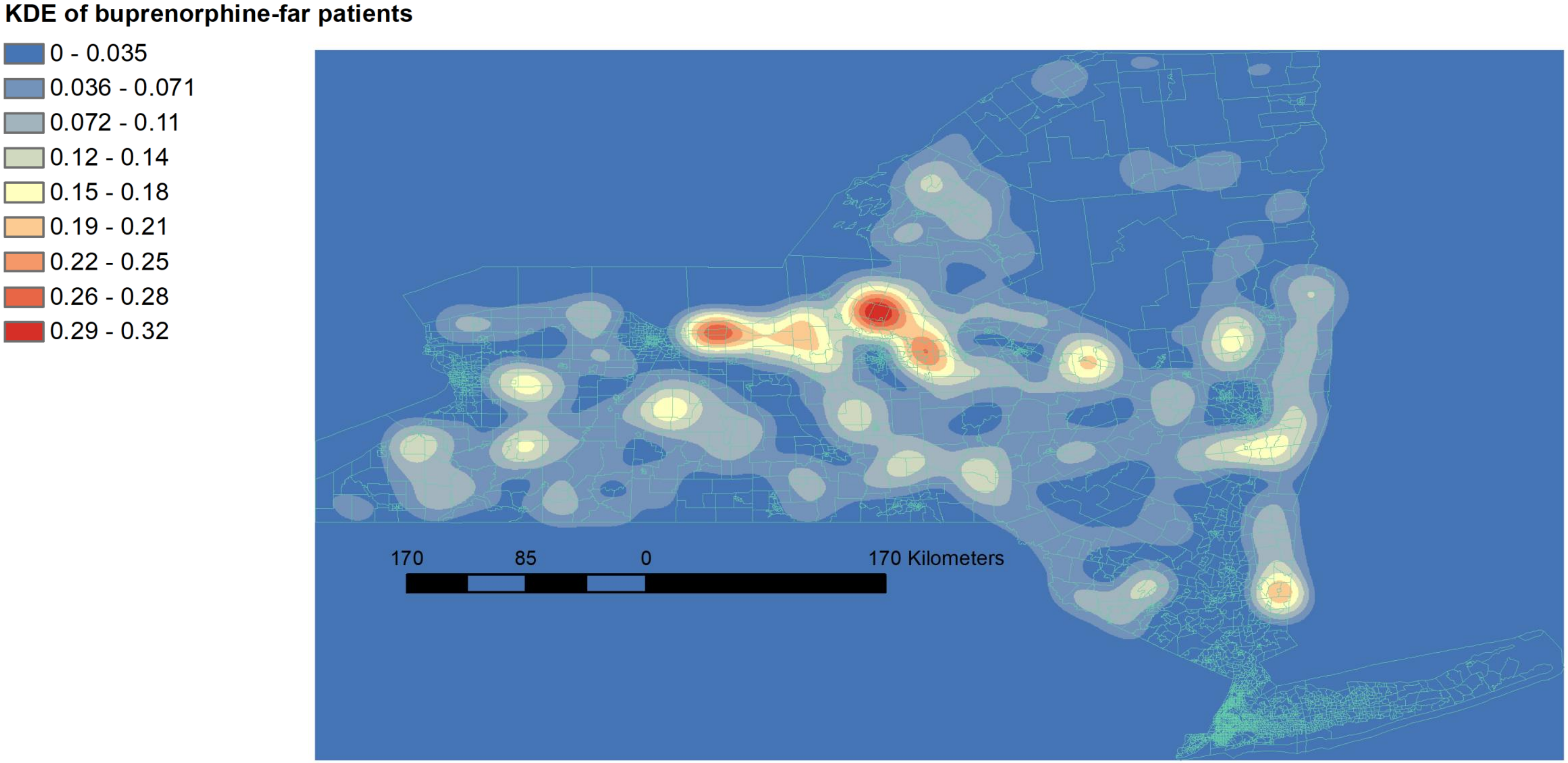
Although Broome County has several naloxone pharmacies, they are all in the western part of the county, while there are opioid overdose patients living in the eastern part.



Density of Buprenorphine-Far OD Patients vs Prescribers



Kernel Density of Buprenorphine-Far Patients

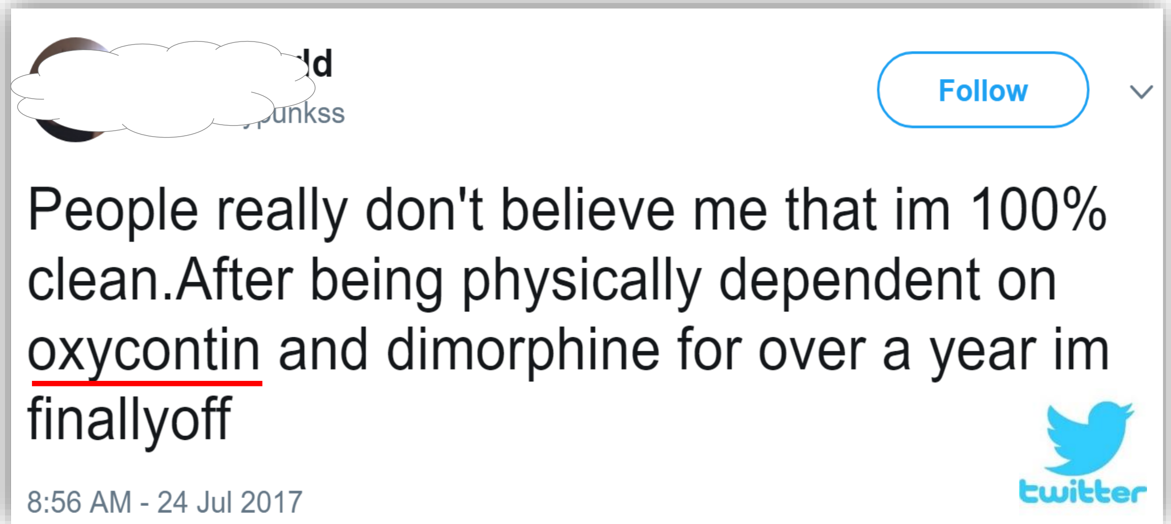


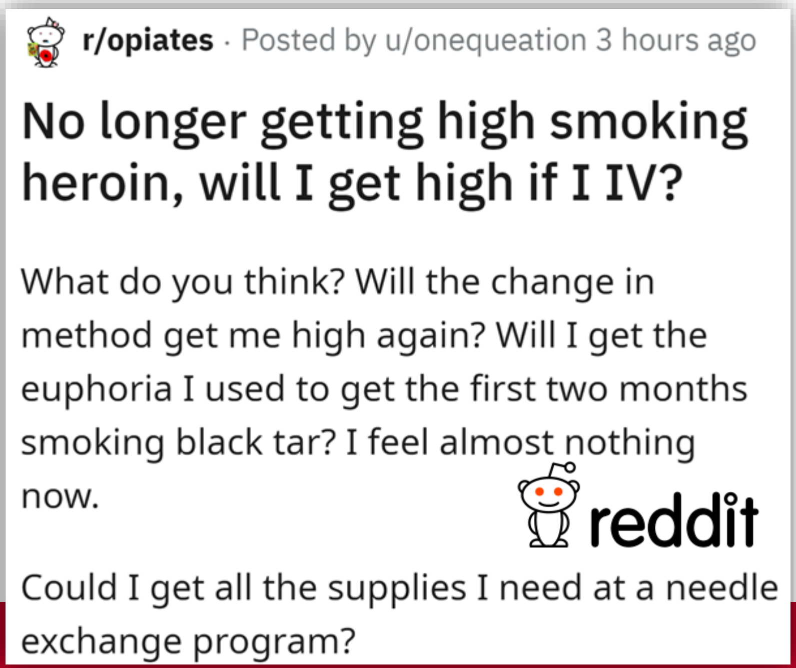
Actions?

- Target non-participating pharmacies
- Market over-the-counter naloxone
- Expand addiction psychiatry services
- Target non-waivered prescribers
- Increase telehealth options for MAT, e.g., make covid-19 expansions permanent

Opioid Epidemic Study Using Social Media

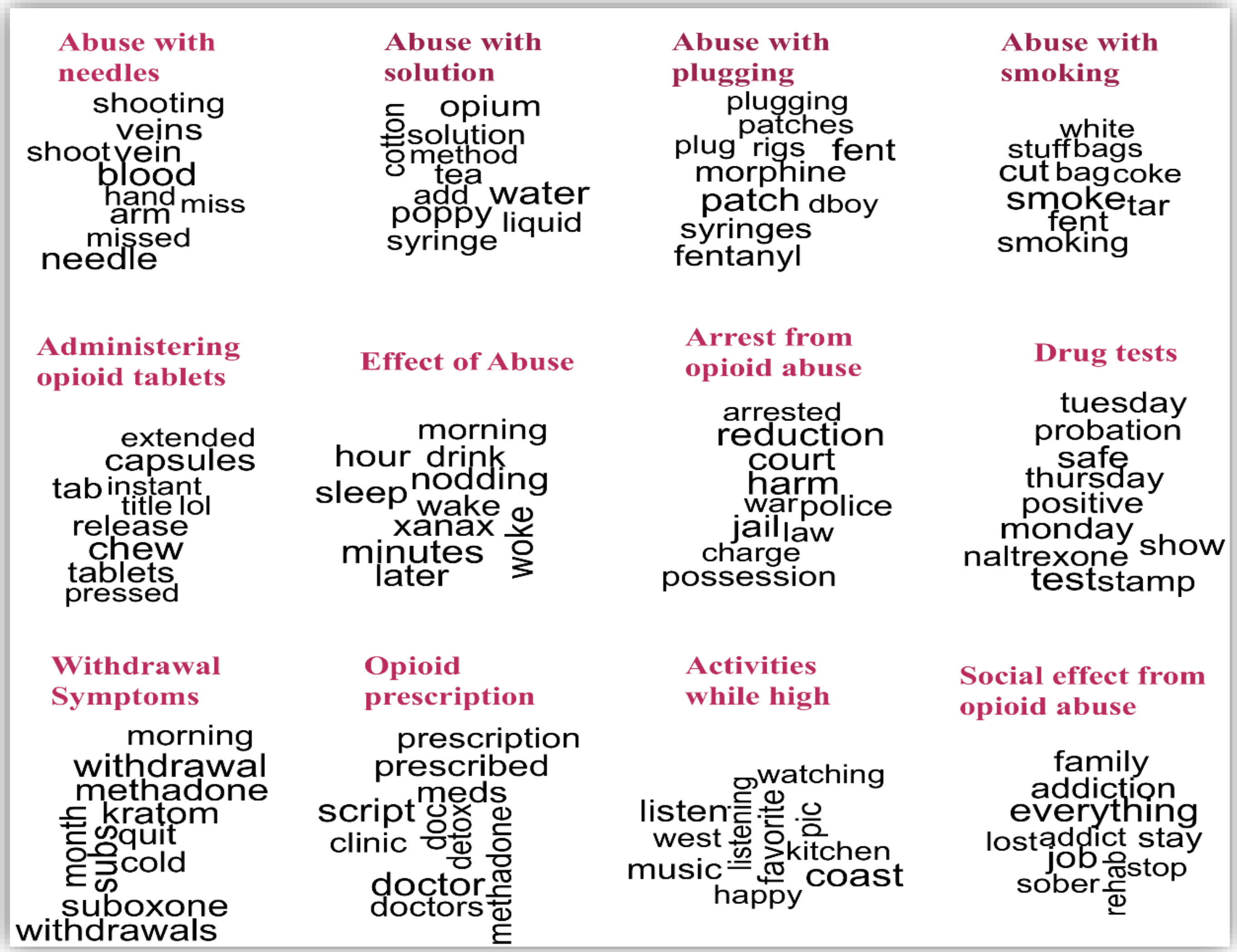
- Advantage of social media over traditional surveys is the immediate accessibility of data
- Analyzing opioid-related social media posts has the potential to reveal patterns of opioid abuse at a national scale, and understand opinions of the public and opioid users
- Spatial-temporal trends, content analysis (topic modeling), types of users and their background, suicide intention, etc.

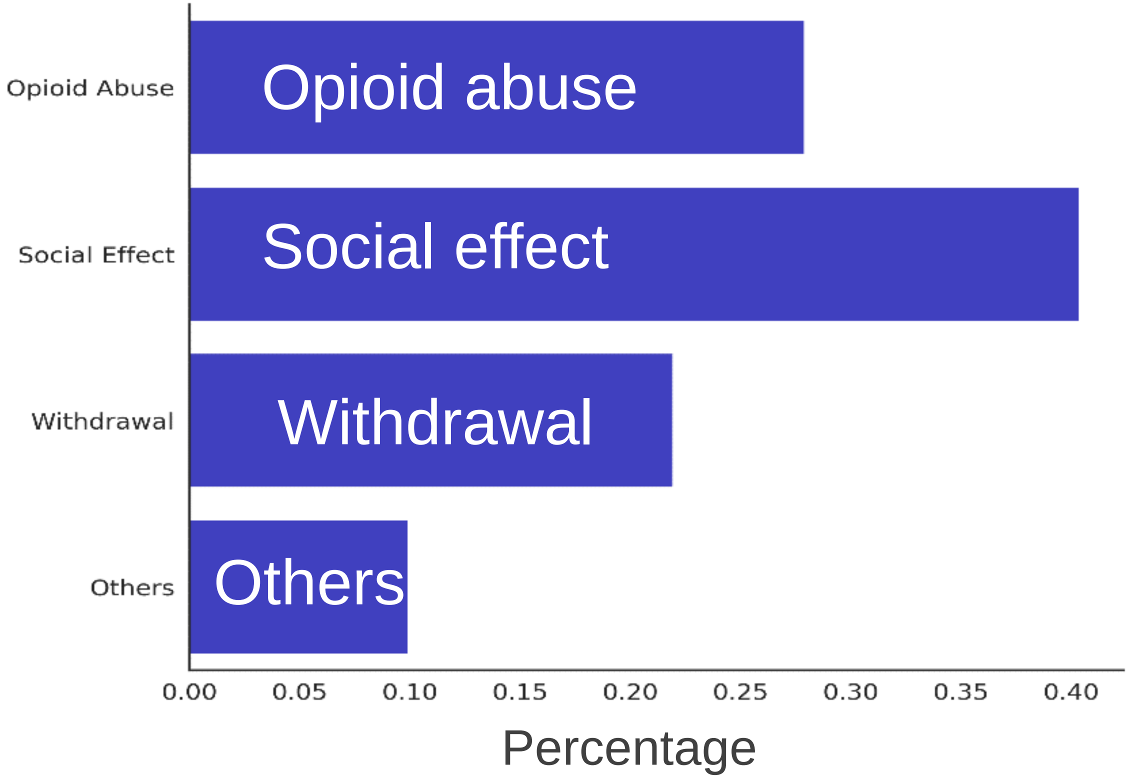




Reddit Based Opioid Discussion Analysis

- Posts on the category of "subreddit *r/opiates*" in Reddit from January of 2014 to October of 2017



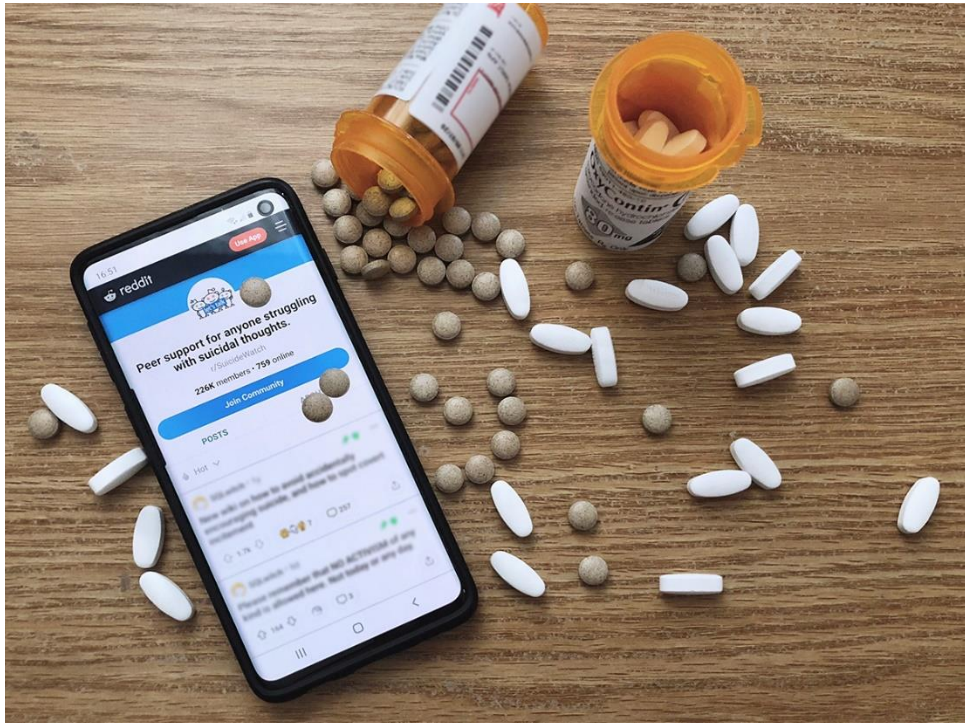


Most discussed topics are the social effects of opioid abuse followed by the different ways of abusing opioids

Detection of Suicidality among Opioid Users on Reddit Using Machine Learning

Stony Brook University

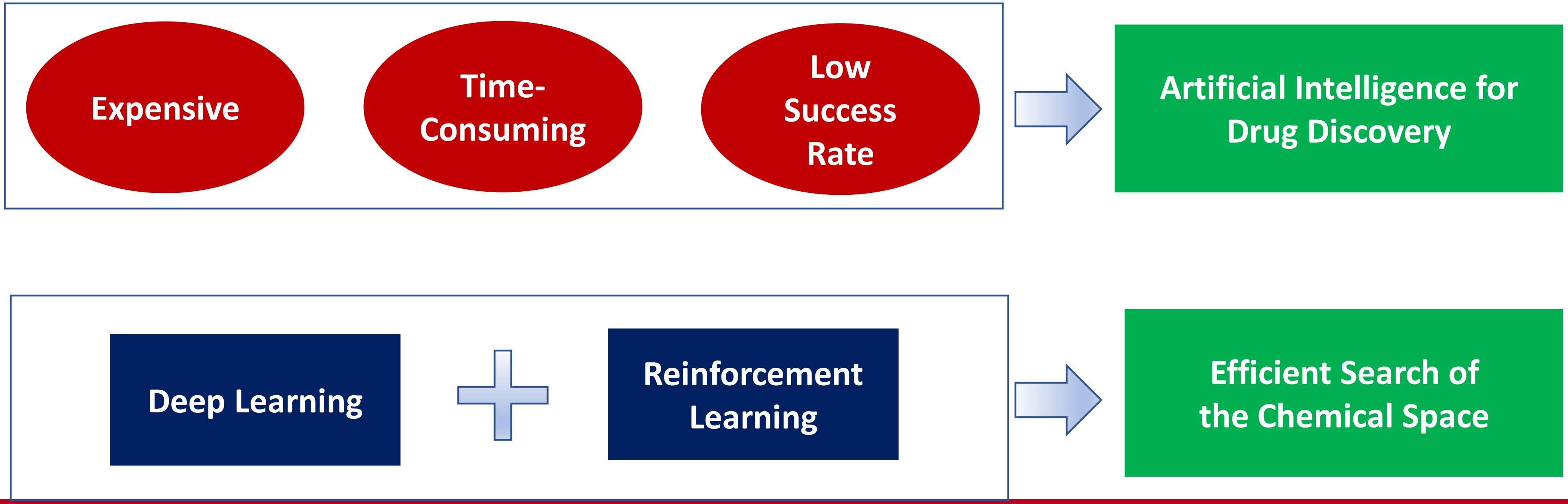
- Consequences of OUD:
  - Causes impaired judgment
  - Likely to engage in reckless and suicidal like behaviors without conscious suicidal intent
  - May also lack willpower and motivation to live making them vulnerable to impulsive dosing



- Goals:
  - To gain insight into individuals with OUD who are prone to suicide through their use of language at Reddit
  - Use deep learning to learn language subtleties between suicidal and non-suicidal individuals
  - Specifically, we predict: 1) suicidality among opioid users; and 2) opioid usage among suicidal individuals

Better Opioid Analgesics With Reduced Overdose Effects Using AI

- Opioids are still among the most prescribed medications for pain management. However, lethal respiratory depression can occur when overdosed
- Identify lead compounds for novel opioid analgesics with reduced overdose effects and seek to accelerate the discovery process
- Leverage data mining and machine learning techniques to explore the chemical space
  - Establish a robust target product profile and develop an efficient deep reinforcement learning framework to generate molecules with multiple desired properties



References

Opioid Use Disorder Prediction:

- [JAMIA2021] Xinyu Dong, et al: *Identifying risk of opioid use disorder for patients taking opioid medications with deep learning*. Journal of the American Medical Informatics Association, Volume 28, Issue 8, August 2021, Pages 1683–1693.

  Source codes: https://github.com/StonyBrookDB/oudprediction

Opioid Overdose Prediction:

- [JBI2021] Xinyu Dong, et al, *Predicting opioid overdose risk of patients with opioid prescriptions using electronic health records based on temporal deep learning*. Journal of Biomedical Informatics, Volume 116, 2021, 103725.

  Source codes: https://github.com/StonyBrookDB/odprediction

Opioid Medication Patterns:

- Jianyuan Deng, et al: *A Large-Scale Observational Study on the Temporal Trends and Risk Factors of Opioid Overdose: Real-World Evidence for Better Opioids*. Drugs - Real World Outcomes. 2021 Sep;8(3):393-406.

Opioid Poisoning Patterns in NYS:

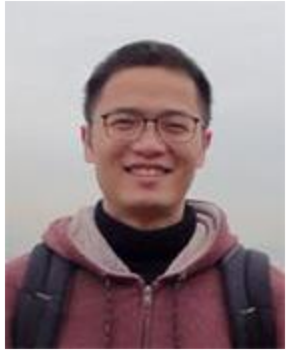
- Xin Chen, et al: *A Large-Scale Retrospective Study of Opioid Poisoning in New York State with Implications for Targeted Interventions*. Scientific Reports 11, 5152 (2021).
- Anthony Xiang, et al: *Association of Opioid Use Disorder With 2016 Presidential Voting Patterns: A Cross-Sectional Study in New York State at Census Tract Level*. JMIR Public Health Surveill 2021;7(4):e23426

Social Media:

- Hannah Yao, et al: *Detection of Suicidality Among Opioid Users on Reddit: Machine Learning–Based Approach*. Journal of Medical Internet Research. Vol 22, No 11 (2020): November.

Acknowledgement

Students:



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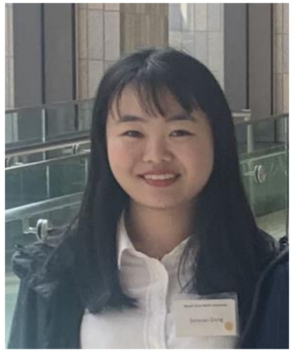

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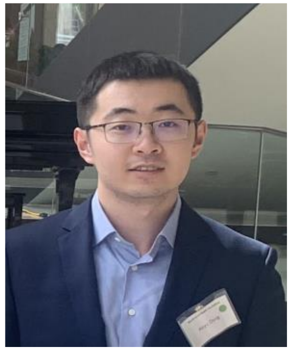
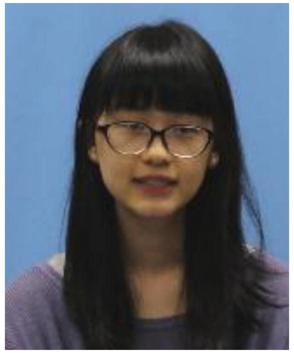


Xinyu Dong



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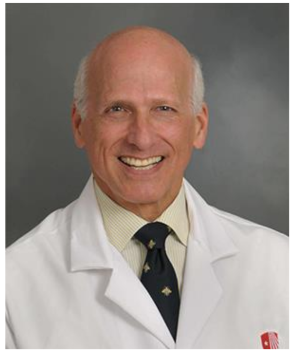
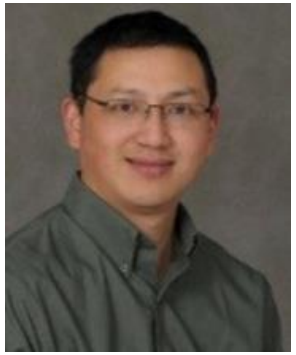


Richard Rosenthal



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