JAMIA Journal Club

# Identifying risk of opioid use disorder for patients taking opioid medications with deep learning

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# The US Opioid Overdose Epidemic

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

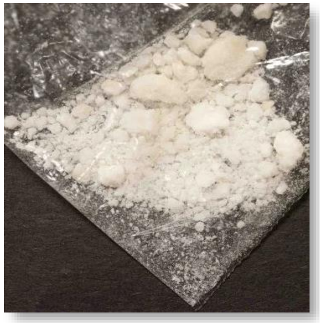
**130+**
Overdose (OD) death per day

**10.3 m**
misused opioid prescriptions per year

**47,600**
OD death per year

**2.0 million**
had opioid use disorder (OUD)






# The Op emic

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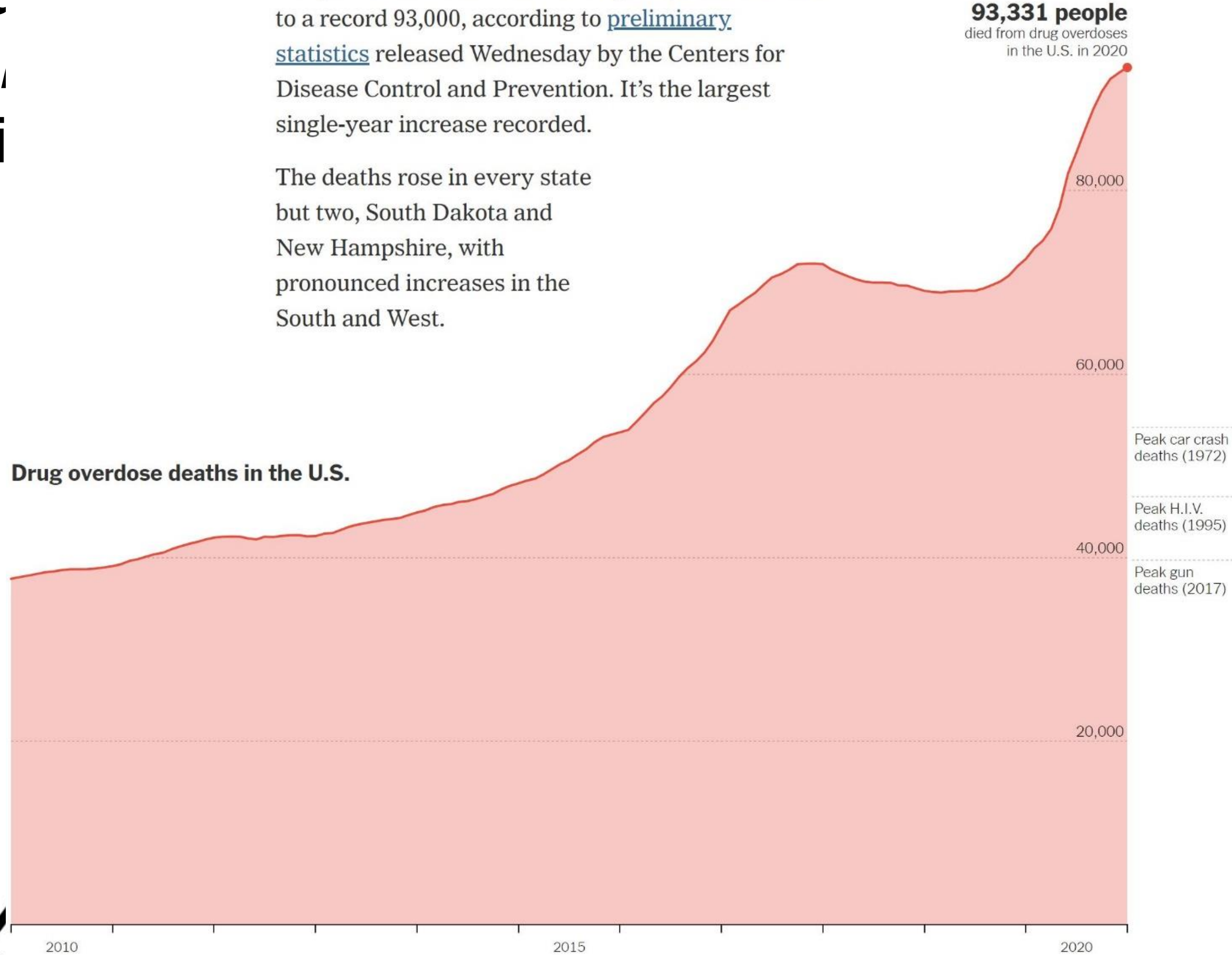
The New York Times

# ‘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.




Source: Centers for Disease Control and Prevention

# The Impact of the Opioid Epidemic

- CDC estimates that the total "economic burden" of prescription opioid misuse in US is $78.5B per 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]

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

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.

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

# Opioid Use Disorder (OUD)

- OUD: 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

1. Opioids are often taken in larger amounts or over a longer period than was intended.
2. There is a persistent desire or unsuccessful efforts to cut down or control opioid use.
3. A great deal of time is spent in activities necessary to obtain the opioid, use the opioid, or recover from its effects.
4. Craving, or a strong desire or urge to use opioids.
5. Recurrent opioid use resulting in a failure to fulfill major role obligations at work, school, or home.
6. Continued opioid use despite having persistent or recurrent social or interpersonal problems caused or exacerbated by the effects of opioids.
7. Important social, occupational, or recreational activities are given up or reduced because of opioid use.
8. Recurrent opioid use in situations in which it is physically hazardous.
9. Continued opioid use despite knowledge of having a persistent or recurrent physical or psychological problem that is likely to have been caused or exacerbated by the substance.
10. Exhibits tolerance.
11. Exhibits withdrawal.

- Overdose: Opioids affect the part of the brain that regulates breathing; High doses of opioids can lead to the slowing or stopping of breathing
  - When one deliberately misuses a prescription, uses an illicit opioid such as heroin, or uses high potent opioids such as fentanyl

# Combating the Opioid Epidemic: the Questions

- Can we predict 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)

# AI Driven Prediction of Opioid Risks

- 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% cases, and < 2 years for 54%
  - 18-25: 1.3% were diagnosed with OUD after first opioid exposure (mean: ~674 days)

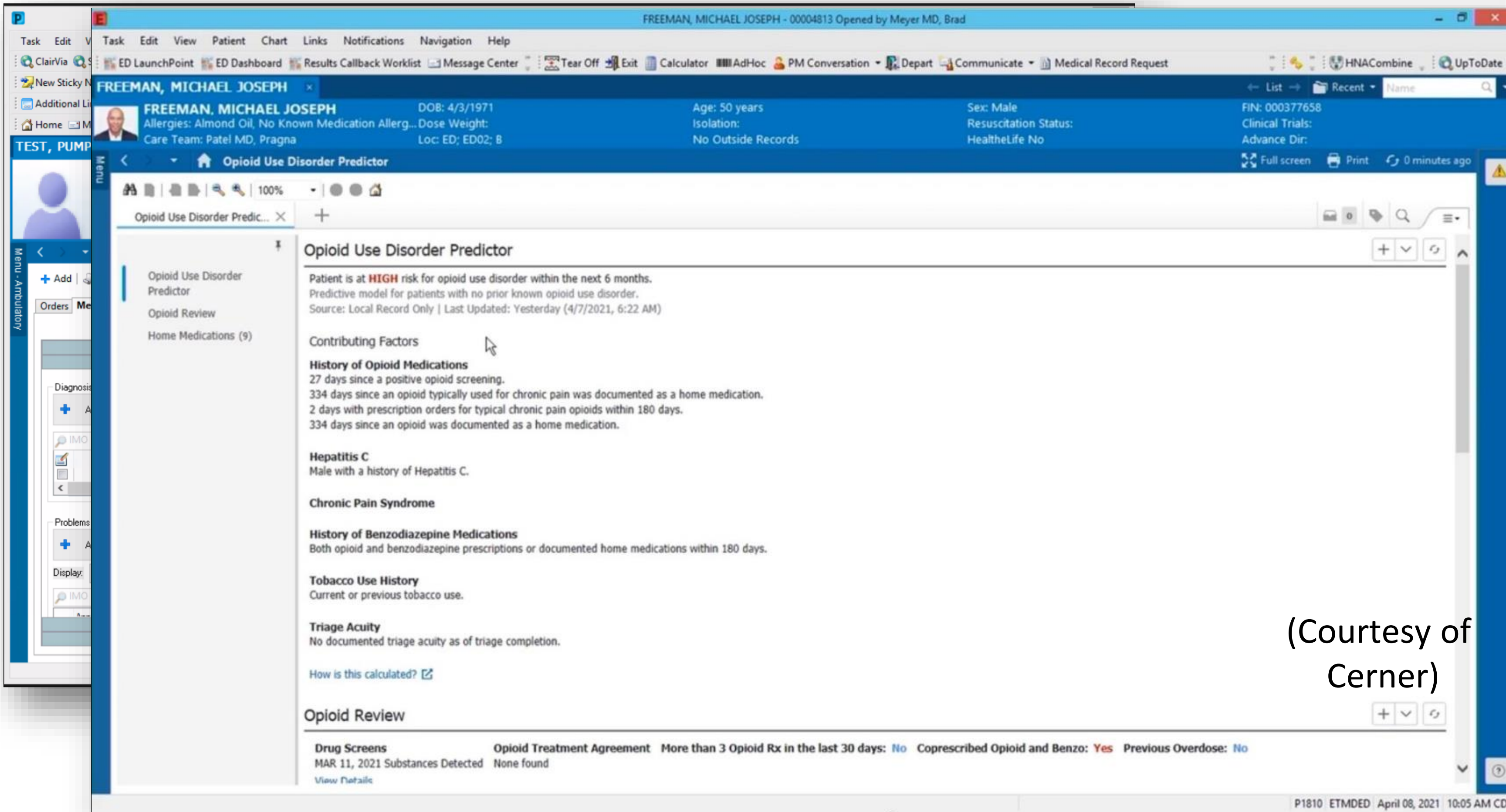
(based on Health Facts: 278,847 patients with opioid medication, 2010-2017)

A 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 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 have the potential to provide clinicians with critical information to help inform decisions about opioid prescribing and treatment in order to reduce opioid related harms, if integrated into clinical workflow
- Opioid risk predictive models:
  - Customized rules based approach
  - Machine learning based approach
  - Integrated rules and machine learning based approach

# EHR Tools for Opioid Risks in EHR




(Courtesy of Cerner)

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

| Related Work | Data Sources | Features | 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

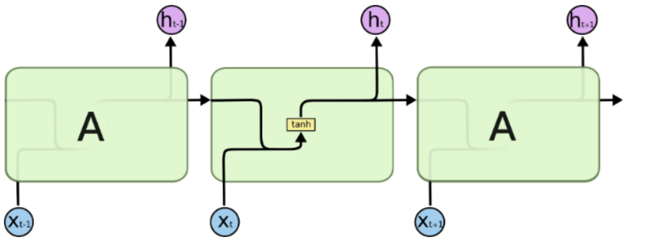
# Our Approach: Building Opioid Risk Prediction Models Using Temporal Deep Learning with Big EHR Data

- Predicting opioid use disorder in the future
- Using large scale EHR datasets – Cerner's Health Facts
- Take advantage of large number of EHR features
- 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

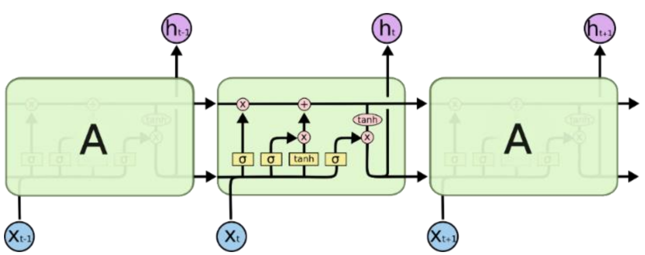
| | Data Sources | Feature Set | No. of Features | Methods | Prediction Target |
|---|---|---|---|---|---|
| **Our models** | Cerner Health Facts | Diagnosis, lab, clinical events, medications, demographics | 1,468 | LSTM and variations | Opioid use disorder |

# 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



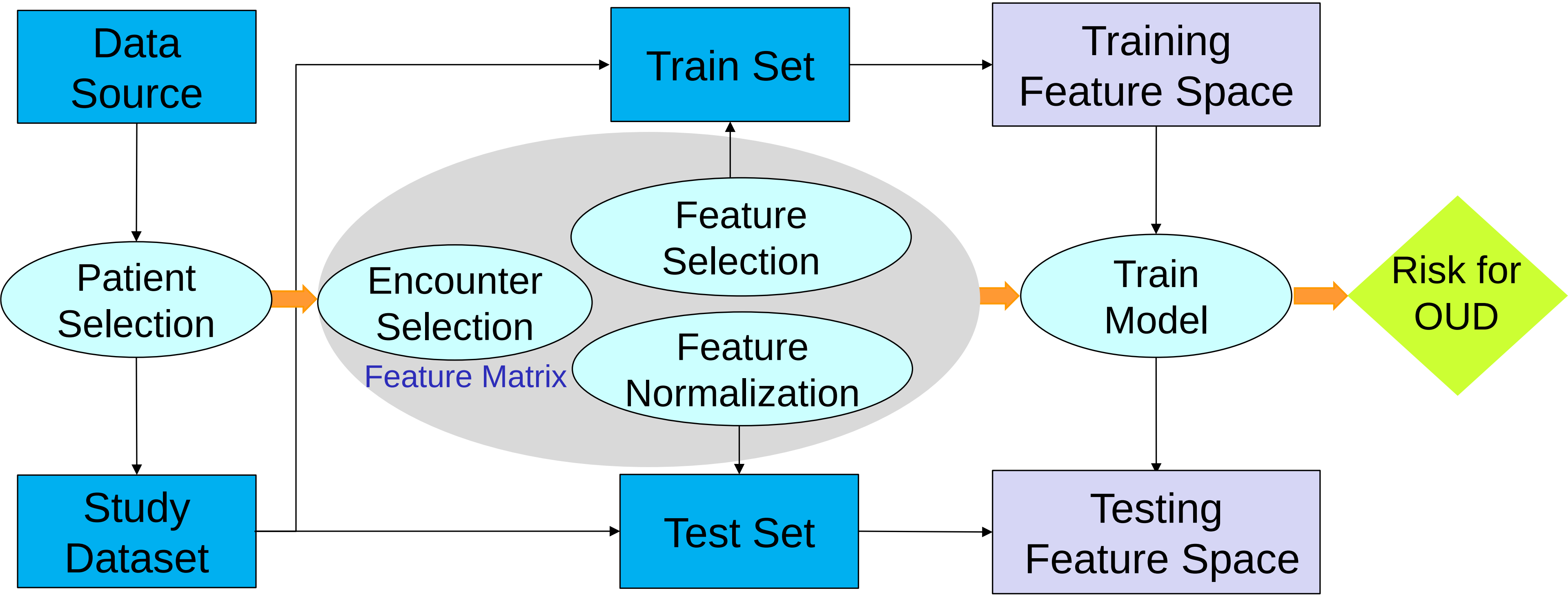

LSTM

# Data Source – Cerner Health Facts

- 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 - Cohort Selection

All Patients

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

Remove 1,540,227 patients with cancer

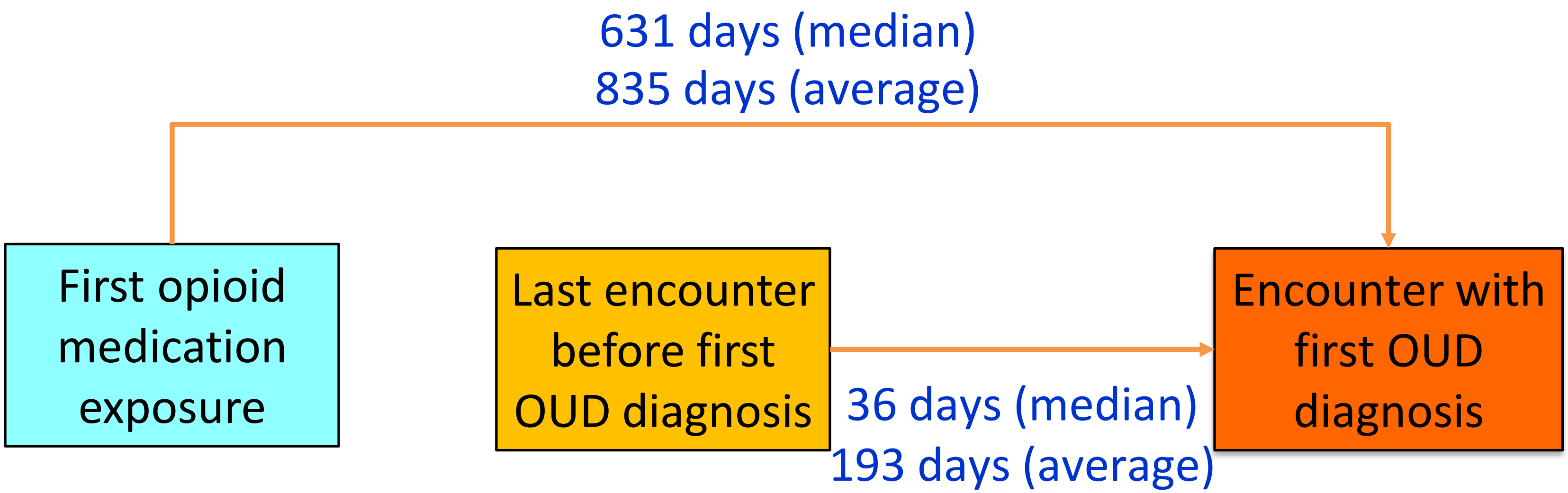
Aged between 18 and 66
when first exposed to opioid medications
(2,161,469 are removed)

Identifying positive patients by OUD ICD codes

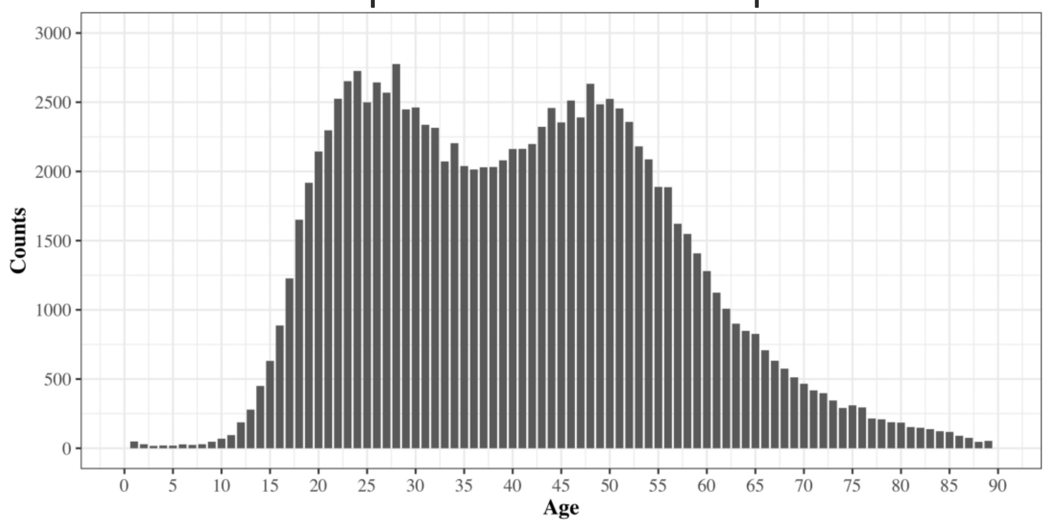
OUD “Positive” Patients
(111,456)

OUD “Negative” Patients
(5,120,158)

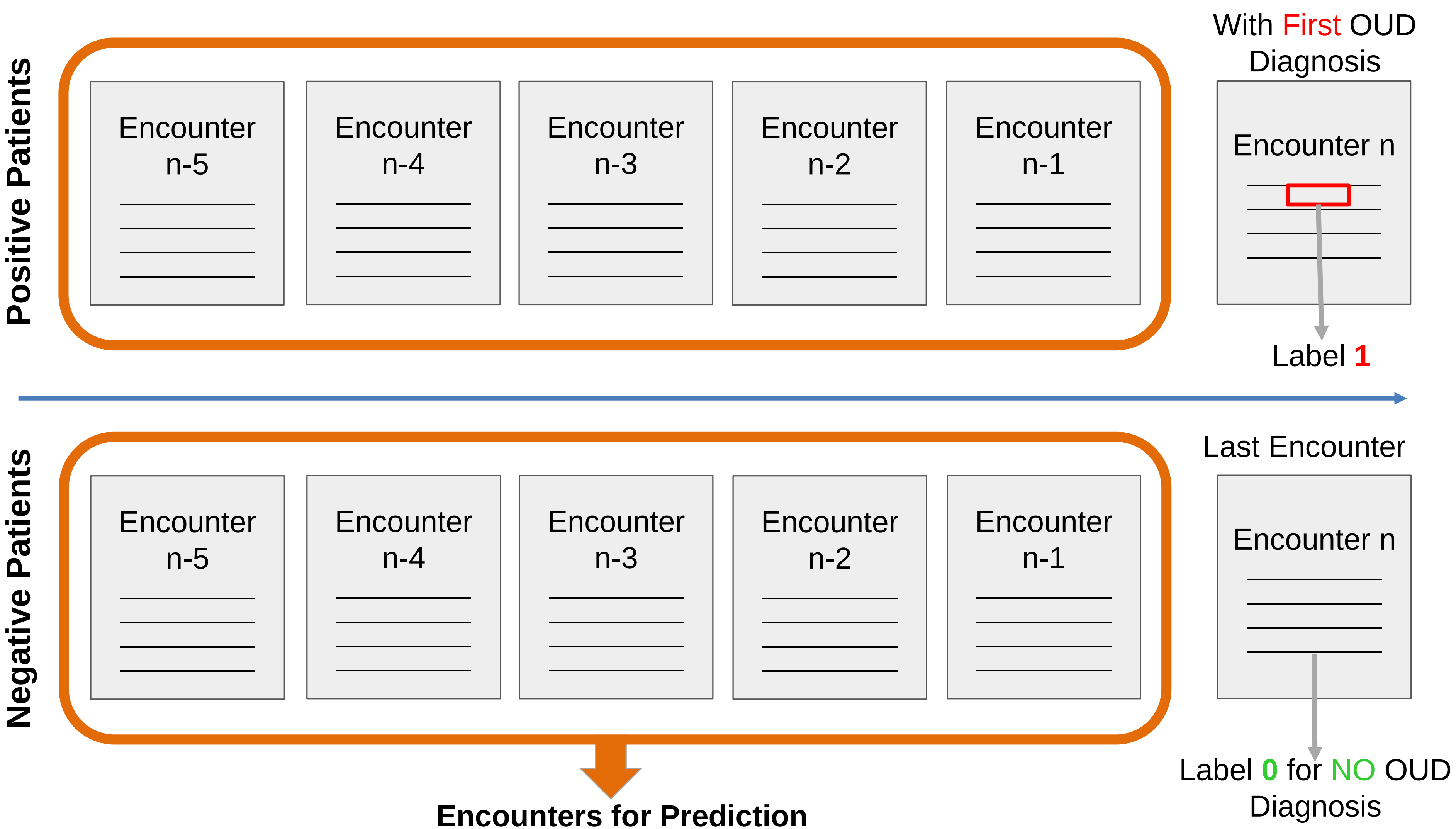
# Opioid Use Order Trajectory Statistics



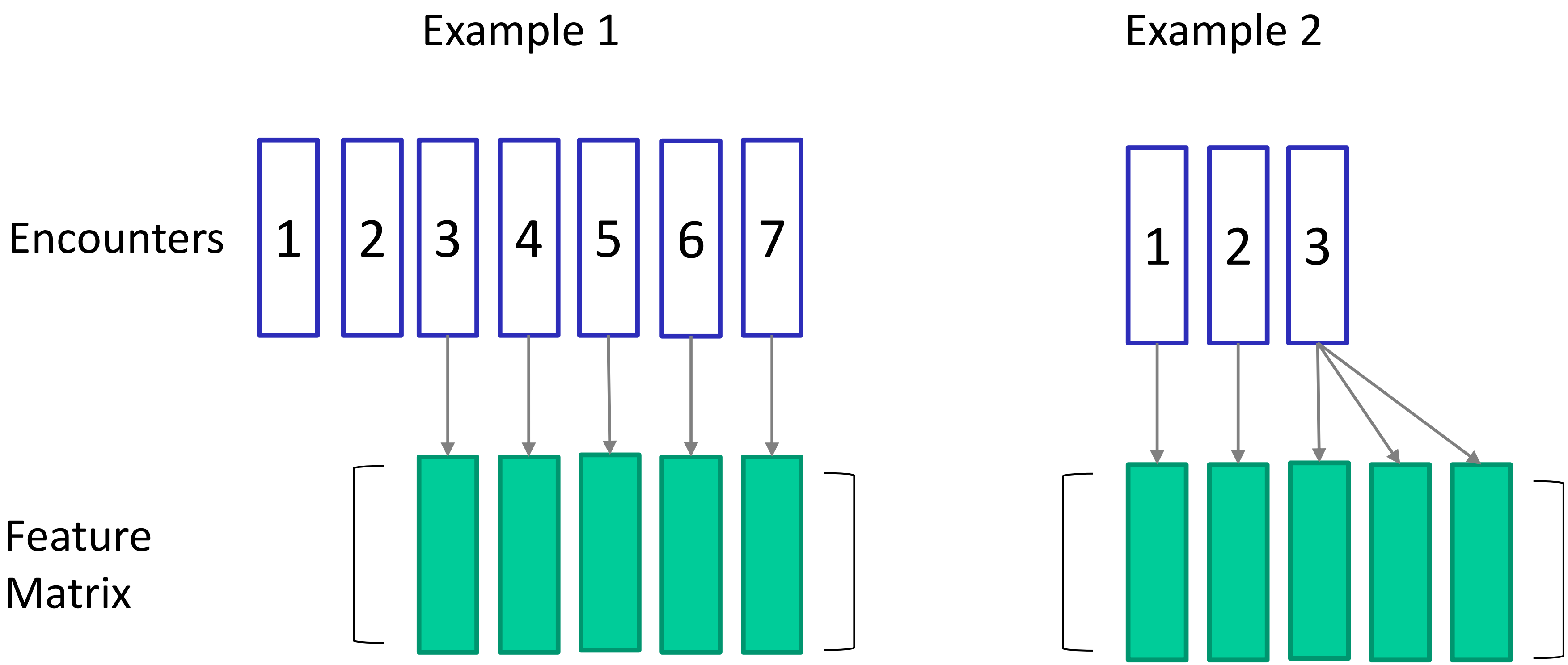

Age distribution of first opioid medication exposure for OUD patients



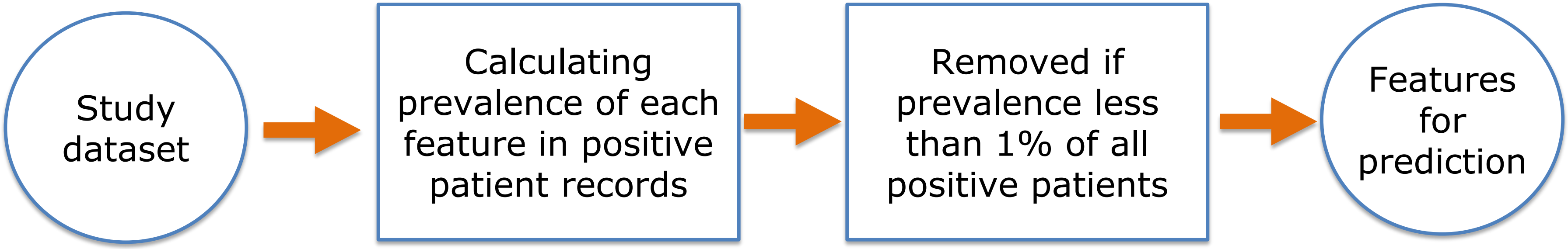
# Encounters for Building the Models



# Encounters for Building the Models (cont'd)



# Feature Selection




| Dataset | Category | Number of Features |
|---|---|---|
| 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 characters)
- For medications, convert NDC codes to ATC codes (level 3), which is more meaningful for predication

| NDC code | Generic name | DrugBank → | ATC code | |
|---|---|---|---|---|
| 0641-6125-01 | Morphine sulfate | | N02AA01 | 1st level **N**: nervous system<br>2nd level **N02**: analgesics<br>3rd level **N02A**: opioids<br>4th level **N02AA**: natural opium alkaloids<br>5th level **N02AA01**: morphine |

- 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 clinical events with multiple occurrences in one encounter, we will use the last value
- For features with multiple numeric values in one encounter, we will record the highest, median and lowest values

# MME (Morphine Milligram Equivalents)

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

| Opioid (doses in mg/day except where noted) | Conversion Factor |
|---|---|
| Codeine | 0.15 |
| Fentanyl transdermal (in mcg/hr) | 2.4 |
| Hydrocodone | 1 |
| Hydromorphone | 4 |
| Methadone: | |
| 1-20 mg/day | 4 |
| 21-40 mg/day | 8 |
| 41-60 mg/day | 10 |
| >=61-80 mg/day | 12 |
| Morphine | 1 |
| Oxycodone | 1.5 |
| Oxymorphone | 3 |

# Missing Values

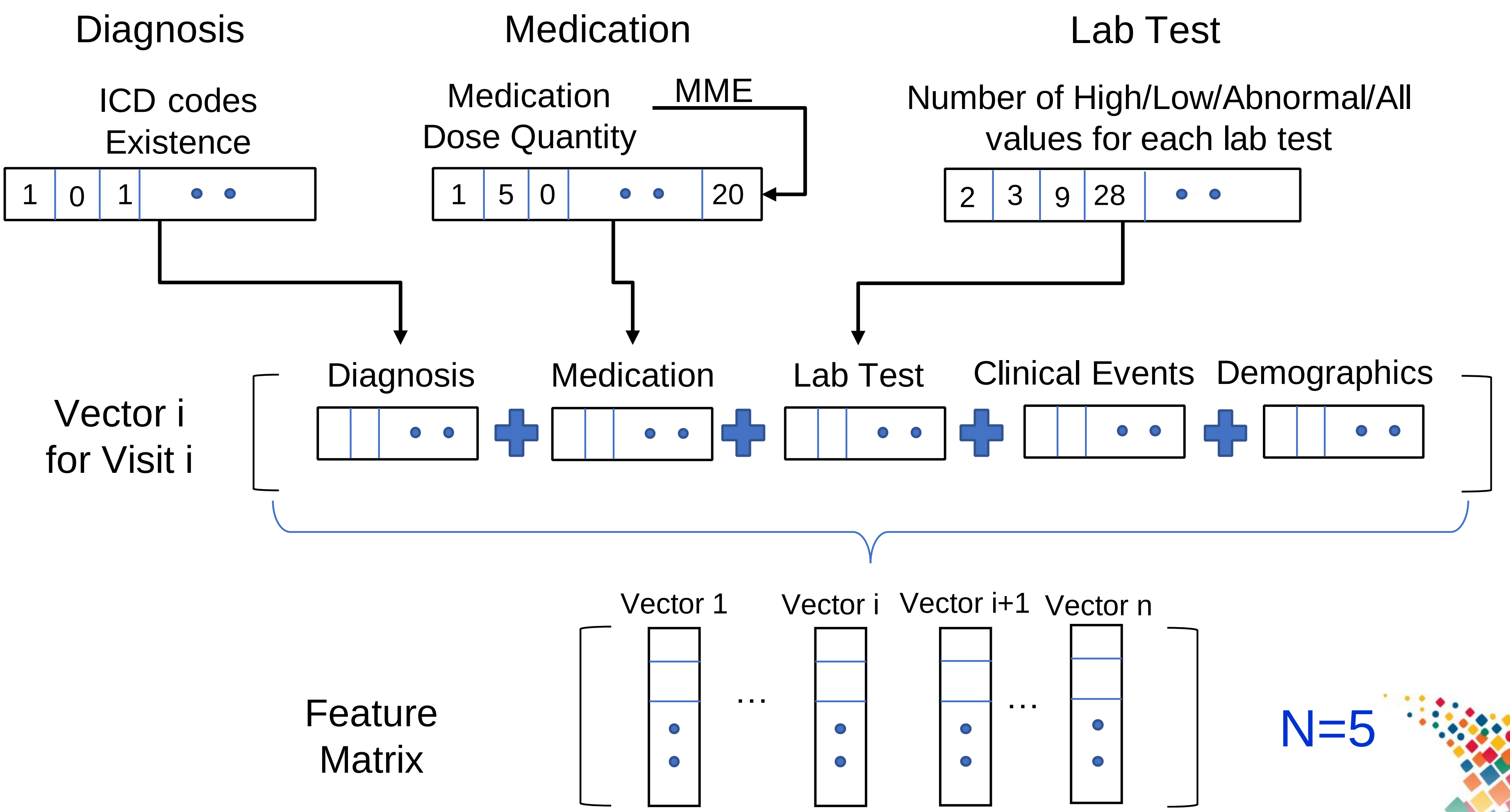
| | Non-OUD patients | OUD patients |
|---|---|---|
| **Total number of patients** | 5 072 110 | 111 456 |
| **Clinical events** | | |
| Average number of clinical events per patient | 335.46 | 539.28 |
| Portion of clinical events with missing values | 37.89 (11.30%) | 71.27 (13.21%) |
| **Laboratory tests** | | |
| Average number of laboratory tests per patient | 184.02 | 356.65 |
| Portion of laboratory tests with missing values | 40.57 (22.05%) | 85.37 (23.94%) |

# Imputation for Missing Values

- Imputation methods
  - Median: Use the median value of all input patients
  - Mean: Use the mean value of all input patients
  - MICE: Assume regression relation among features, iteratively impute one feature on other features
  - KNN: Use the majority value of the patient's most similar k neighbor patients
- Difference in prediction results is minimal, we conclude that the imputation methods did not make a tangible difference

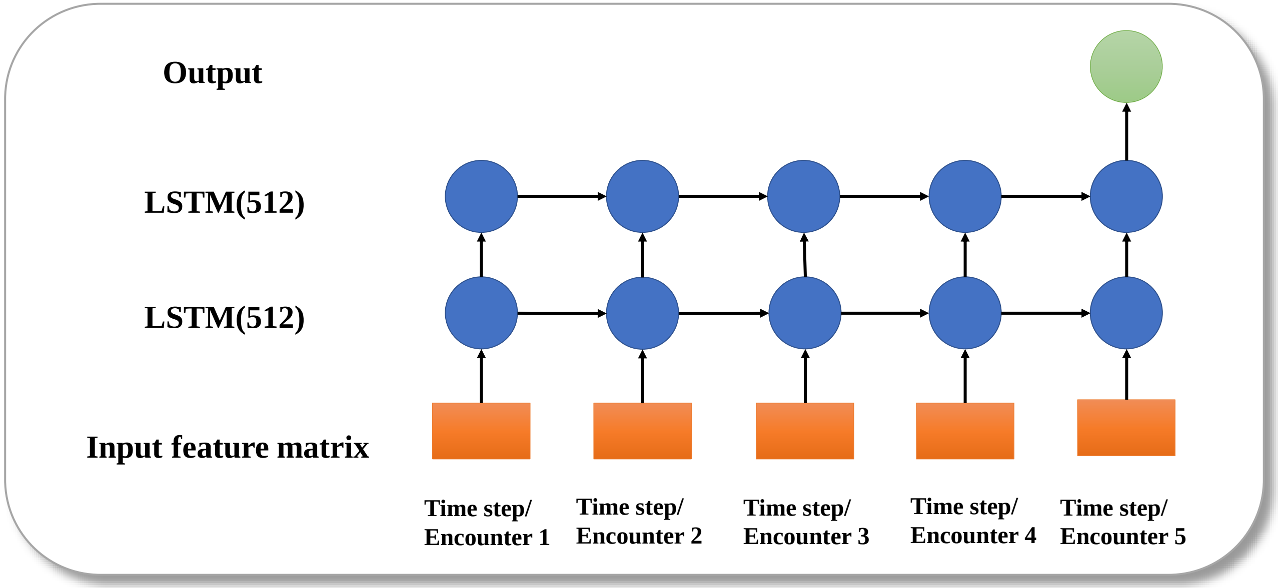
| Method | Precision | Recall | F1 Score | AUCROC |
|---|---|---|---|---|
| **Median** | **0.8184** | 0.7865 | 0.8023 | **0.9369** |
| Mean | 0.8183 | 0.7851 | 0.8014 | 0.8977 |
| MICE | 0.8128 | 0.8017 | **0.8072** | 0.9002 |
| KNN | 0.7984 | **0.8034** | 0.8009 | 0.8854 |

# Feature Matrix Construction



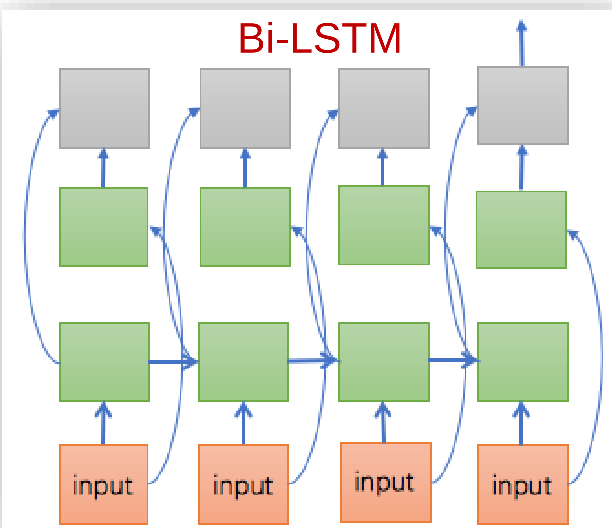
# Predictive Models

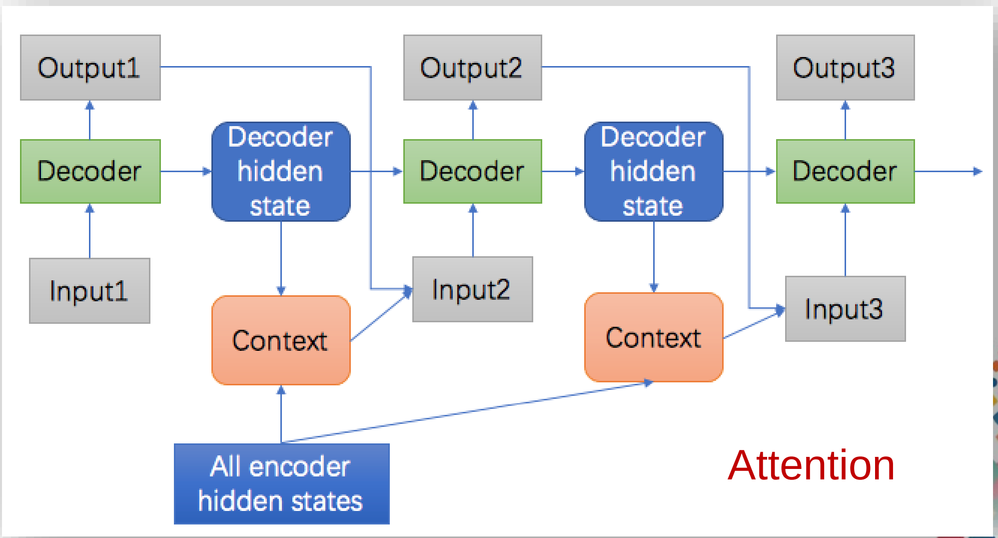
- Traditional Machine Learning
  - Random Forest, Logistic Regression, Decision Tree
- Deep Learning
  - Dense Neural Network
  - **LSTM (Long short-term memory)**
  - Variants of LSTM



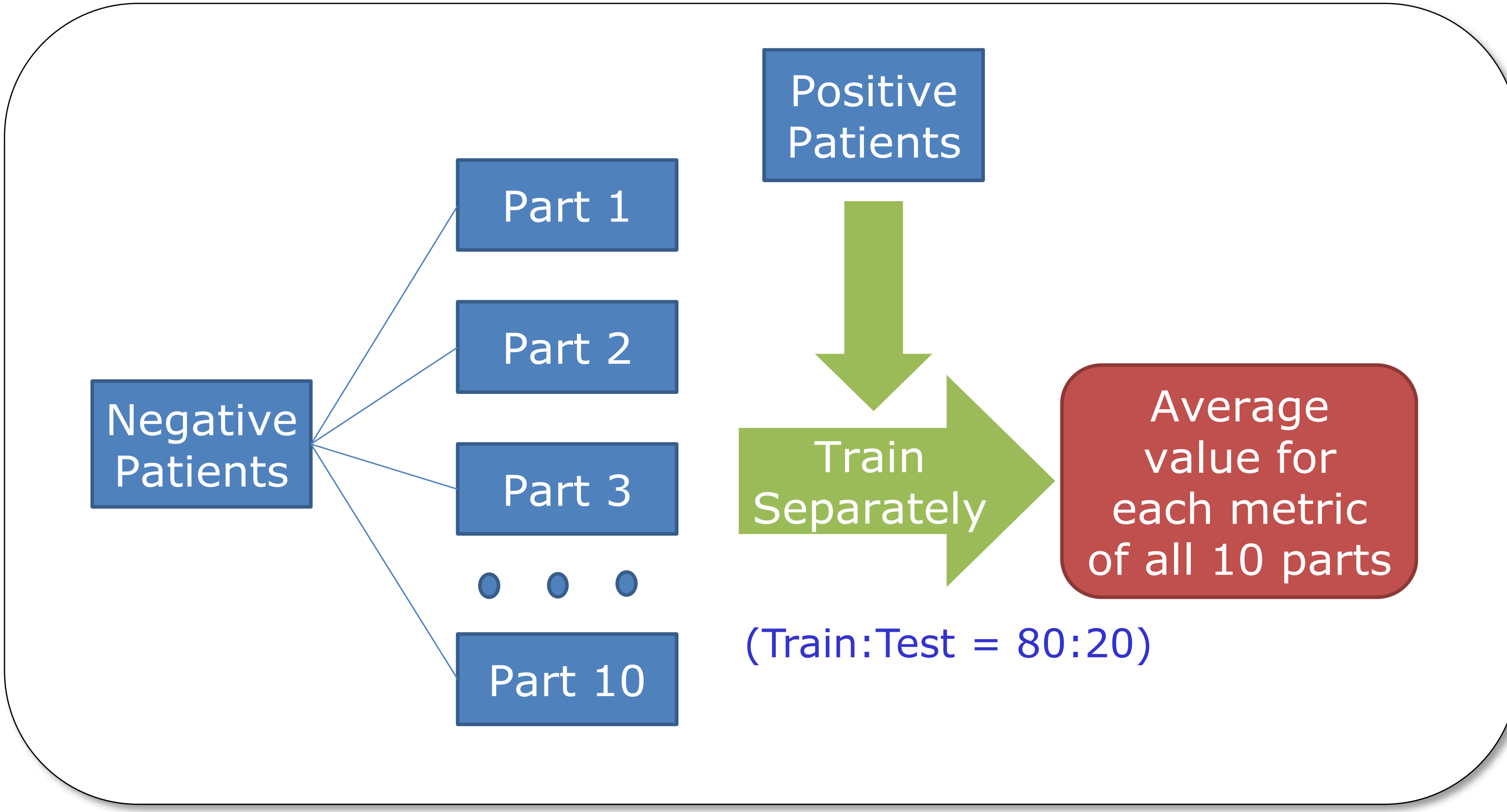
# Variants of LSTMs

- 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: 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



# Performance Evaluation Experiment Setup



# OUD Prediction Performance

| 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)

| 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 |

# Comparison of LSTM Performance with Different Number of Encounters

| No. of encounters | Precision | Recall | F1 | ROC AUC |
|---|---|---|---|---|
| 3 | 0.6281 | 0.7487 | 0.7326 | 0.9206 |
| 4 | 0.7468 | 0.7635 | 0.7610 | 0.9267 |
| 5 | **0.8184** | **0.7865** | **0.8023** | **0.9369** |
| 6 | 0.7732 | 0.7722 | 0.7769 | 0.9304 |
| 7 | 0.7812 | 0.7737 | 0.7796 | 0.9311 |
| 8 | 0.6935 | 0.7549 | 0.7447 | 0.9231 |
| 9 | 0.6242 | 0.7500 | 0.7352 | 0.9211 |
| 10 | 0.6310 | 0.7498 | 0.7349 | 0.9210 |

# Performance Comparison without Race Information

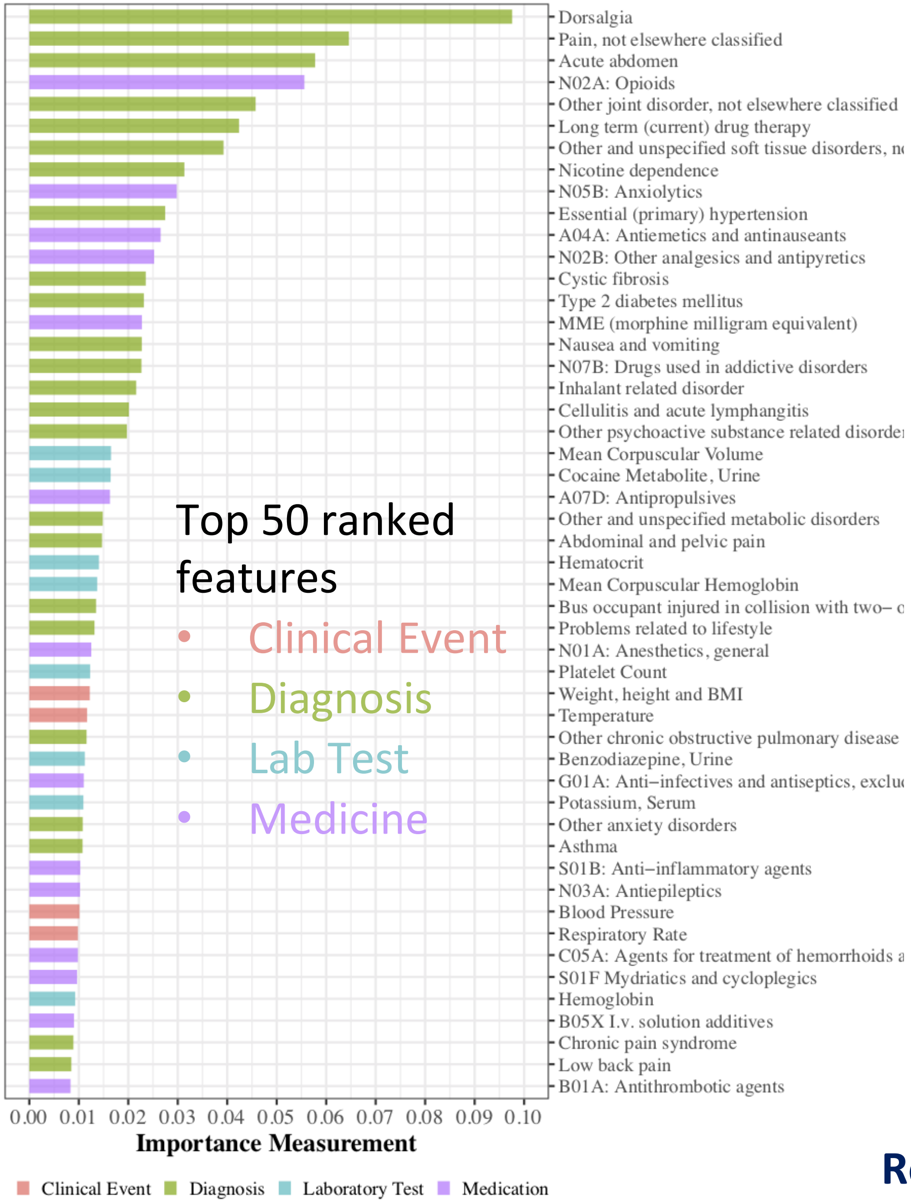
| LSTM | With Race/ Ethnicity | Without Race/ Ethnicity | P-value |
|---|---|---|---|
| Precision | 0.8184 | 0.8183 | 0.9621 |
| Recall | 0.7865 | 0.7865 | 1.0000 |
| F1 | 0.8023 | 0.8022 | 0.8924 |
| ROC_AUC | 0.9369 | 0.9368 | 0.9262 |

No significant difference between using race/ethnicity or without race/ethnicity

# 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

# Top 50 Ranked Features




- 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)

**Results**

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# Top 20 Ranked Features 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

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

| Category | Feature | OUD patients | Non-OUD patients |
|---|---|---|---|
| Diagnosis | Dorsalgia (back or spine pain) | 37.71%<br>(patients diagnosed with the code) | 20.27% |
| Diagnosis | Pain, not elsewhere classified | 33.77% | 8.7% |
| Diagnosis | Nicotine dependence | 65.36% | 17.67% |
| Medication | Acute abdomen | 32.91% | 28.29% |
| Medication | Essential (primary) hypertension | 27.43% | 24.92% |
| Medication | MME (morphine milligram equivalent) | 12.06 per encounter | 2.35 per encounter |
| Medication | N05B: Anxiolytics | 18.96%<br>(patients took the medicine) | 2.4% |
| Medication | N02B: Other analgesics and antipyretics | 31.51% | 9.5% |
| Medication | A04A: Antiemetics and antinauseants | 28.7% | 9.02% |

# Statistics on Example Top Features between OUD and non-OUD Patients (cont'd)

| Category | Feature | OUD patients | Non OUD patients |
|---|---|---|---|
| Diagnosis | Other joint disorder, not elsewhere classified | 13.2% | 8.98% |
| Diagnosis | Long term (current) drug therapy | 34.2% | 23.96% |
| Diagnosis | Other and unspecified soft tissue disorders, not elsewhere classified | 30.80% | 18.72% |
| Diagnosis | Cystic fibrosis | 5.28% | 1.44% |
| Diagnosis | Type 2 diabetes mellitus | 15.51% | 5.30% |
| Diagnosis | Nausea and vomiting | 28.02% | 19.39% |
| Diagnosis | Inhalant related disorder | 1.04% | 0.03% |
| Diagnosis | Cellulitis and acute lymphangitis | 17.68% | 7% |
| Diagnosis | Other psychoactive substance related disorders | 25.68% | 0.79% |
| Diagnosis | Essential (primary) hypertension | 27.43% | 24.92% |

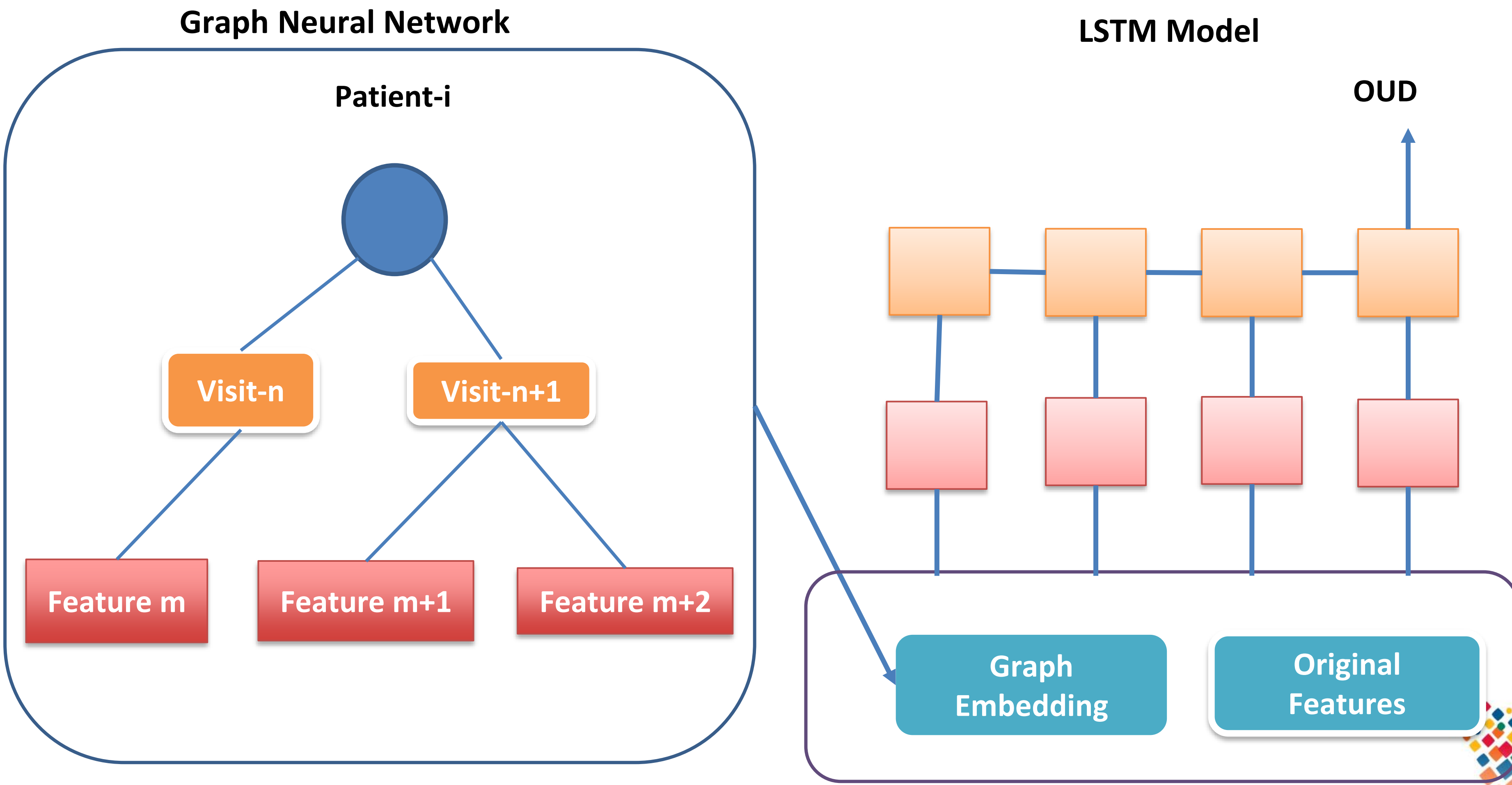
# Top 20 Ranked Features by Different Methods

| Rank | LSTM | DNN | Random Forest | Decision Tree |
|---|---|---|---|---|
| 1 | Dorsalgia | Pain, not elsewhere classified | N02A: Opioids | N02B: Other analgesics and antipyretics |
| 2 | Pain, not elsewhere classified | N02A: Opioids | Essential hypertension | Pain Scale Score |
| 3 | Acute abdomen | Pain Scale Score | Nondependent abuse of drugs | N02A: Opioids |
| 4 | N02A: Opioids | Pregnancy Status | Pain, not elsewhere classified | Alcohol Use |
| 5 | Other joint disorder, not elsewhere classified | N01A: Anesthetics, general | Pain Scale Score | A04A: Antiemetics and antinauseants |
| 6 | Long term (current) drug therapy | A07D: Antipropulsives | Blood Pressure | Blood Pressure |
| 7 | Other and unspecified soft tissue disorders, not elsewhere classified | Alcohol Last Use | General symptoms | Pregnancy Status |
| 8 | Nicotine dependence | Tobacco Frequency | Alcohol Use | A07D: Antipropulsives |
| 9 | N05B: Anxiolytics | R05D: Cough suppressants, excluding combinations with expectorants | Pregnancy Status | N01A: Anesthetics, general |
| 10 | Essential (primary) hypertension | Creatinine, Serum Quant | Potassium, Serum | Alcohol Frequency |
| 11 | A04A: Antiemetics and antinauseants | Red Blood Cell Distribution Width (RDW) | N06A: Antidepressants | Tobacco Frequency |
| 12 | N02B: Other analgesics and antipyretics | Heart Rate Post Treatment | Osteoarthrosis and allied disorders | Nondependent abuse of drugs |
| 13 | Cystic fibrosis | Comfort Measures for Pain | Special investigations and examinations | Essential hypertension |
| 14 | Type 2 diabetes mellitus | N05C: Hypnotics and sedatives | Drug dependence | Demographics, race/ethnicity |
| 15 | MME (morphine milligram equivalent) | Blood Pressure | A07D: Antipropulsives | Other and unspecified disorders of back |
| 16 | Nausea and vomiting | N02B: Other analgesics and antipyretics | Other symptoms involving abdomen and pelvis | Pain, not elsewhere classified |
| 17 | N07B: Drugs used in addictive disorders | Alcohol Use | N01A: Anesthetics, general | General symptoms |
| 18 | Inhalant related disorder | Alcohol Frequency | Demographics, race/ethnicity | D04A: Antipruritics, including antihistamines, anesthetics,etc |
| 19 | Cellulitis and acute lymphangitis | Smoke, Lives with Someone Who Smokes | Cystic fibrosis | N01B: Anesthetics, local |
| 20 | Other psychoactive substance related disorders | A04A: Antiemetics and antinauseants | Tobacco Frequency Other | Heart Rate |
| Method | **Permutation** | **Permutation** | **Gini impurity importance** | **Gini impurity importance** |

# 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

# Ongoing: Proposed Structure of LSTM+GNN model

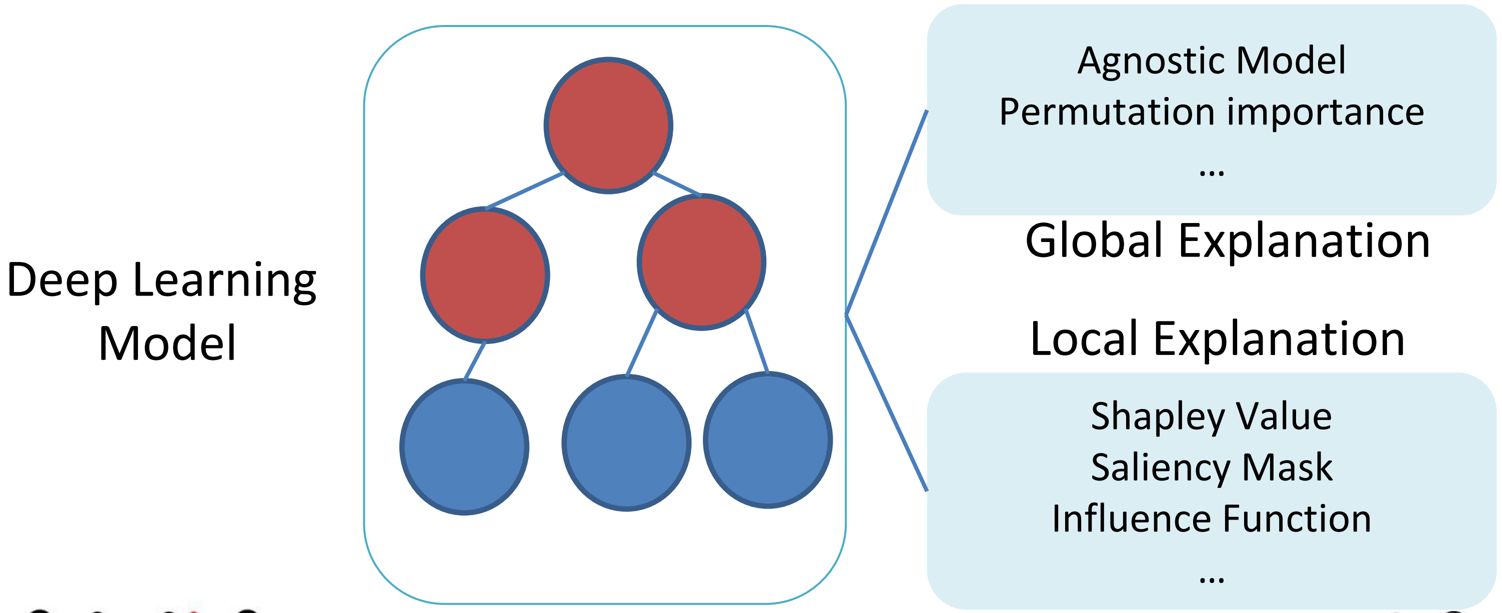


# Preliminary Results with GNN+LSTM

| Model | Precision | Recall | F-1 | 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+GNN | 0.831 | **0.7923** | **0.8139** | **0.9441** |

# Ongoing: Human-centric Interpretability OUD Prediction

- 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



# Conclusion

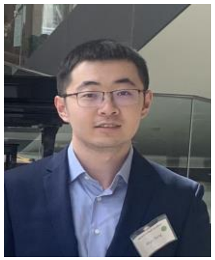
- Predicting risk of OUD for patients can provide targeted, focused early interventions for smarter and safer clinical decision support
- LSTM based predictive model for OUD risk using EHR history demonstrates promising performance
- The sequential deep learning model is capable of identifying patients who will develop OUD in the future and can provide critical insight on risk factors

# Source Codes

https://github.com/StonyBrookDB/oudprediction

# Acknowledgement

## Students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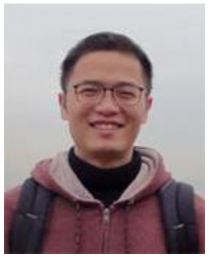
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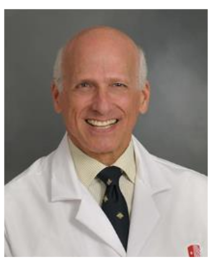
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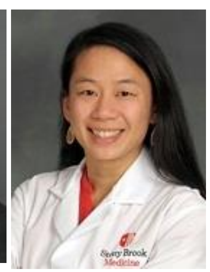
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Questions?
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# Patient Demographics

| | All patients | OUD patients |
|---|---|---|
| Total Number | 7,288,835 | 129,057 |
| **Sex** | | |
| Male | 3,086,693 (42.35%) | 62750 (48.63%) |
| Female | 4,200,098 (57.62%) | 66282 (51.36%) |
| Other/Missing | 2,044 (0.02%) | 25 (0.02%) |
| **Age** (first medical exposure to opioid medication) | | |
| 0-15 | 816,243 (11.20%) | 2,424 (1.88%) |
| 16-25 | 1,014,798 (13.92%) | 23,509 (18.22%) |
| 26-35 | 1,103,246 (15.14%) | 28,572 (22.14%) |
| 36-45 | 966,276 (13.2%6) | 24,610 (19.07%) |
| 46-55 | 1,122,720 (15.40%) | 26,978 (20.90%) |
| 56-65 | 809,234 (11.10%) | 13,069 (10.12%) |
| >66 | 1,442,641 (19.79%) | 9,804 (7.60%) |
| Missing | 13,677 (0.2%) | 91 (0.07%) |
| **Race** | | |
| Caucasian | 5,187,681 (71.17%) | 97,834 (75.81%) |
| African | 1,137,289 (15.60%) | 19,872 (15.40%) |
| Asian | 112,933 (1.55%) | 418 (0.32%) |
| Hispanic | 123,135 (1.69%) | 979 (0.76%) |
| Other | 527,313 (7.23%) | 7,112 (5.51%) |
| Missing | 200,484 (2.75%) | 2,842 (2.2%) |

# ICD Codes for OUD

| Version | Condition | Code | Code Description |
|---|---|---|---|
| ICD-9 | opioid dependence | 304.01 | Opioid type dependence, continuous use |
| ICD-9 | opioid dependence | 304.02 | Opioid type dependence, episodic use |
| ICD-9 | opioid dependence | 304.72 | Combinations of opioid type drug with any other drug dependence, episodic use |
| ICD-9 | opioid abuse | 305.50 | Opioid abuse, unspecified use |
| ICD-9 | opioid dependence | 304.03 | Opioid type dependence, in remission |
| ICD-9 | opioid dependence | 304.00 | Opioid type dependence, unspecified use |
| ICD-9 | opioid abuse | 305.51 | Opioid abuse, continuous use |
| ICD-9 | opioid dependence | 304.71 | Combinations of opioid type drug with any other drug dependence, continuous use |
| ICD-9 | opioid dependence | 304.73 | Combinations of opioid type drug with any other drug dependence, in remission |
| ICD-10 | opioid abuse | F11.1 | Opioid abuse |
| ICD-10 | opioid abuse | F11.120 | Opioid abuse with intoxication, uncomplicated |
| ICD-10 | opioid abuse | F11.121 | Opioid abuse with intoxication delirium |
| ICD-10 | opioid abuse | F11.129 | Opioid abuse with intoxication, unspecified |
| ICD-10 | opioid abuse | F11.15 | Opioid abuse with opioid-induced psychotic disorder |
| ICD-10 | opioid abuse | F11.150 | Opioid abuse with opioid-induced psychotic disorder with delusions |
| ICD-10 | opioid abuse | F11.188 | Opioid abuse with other opioid-induced disorder |
| ICD-10 | opioid dependence | F11.21 | Opioid dependence, in remission |
| ICD-10 | opioid dependence | F11.22 | Opioid dependence with intoxication |
| ICD-10 | opioid dependence | F11.222 | Opioid dependence with intoxication with perceptual disturbance |
| ICD-10 | opioid dependence | F11.229 | Opioid dependence with intoxication, unspecified |
| ICD-10 | opioid dependence | F11.24 | Opioid dependence with opioid-induced mood disorder |
| ICD-10 | opioid dependence | F11.259 | Opioid dependence with opioid-induced psychotic disorder, unspecified |
| ICD-10 | opioid dependence | F11.29 | Opioid dependence with unspecified opioid-induced disorder |
| ICD-10 | opioid misuse | F11.94 | Opioid use, unspecified with opioid-induced mood disorder |
| ICD-10 | opioid misuse | F11.950 | Opioid use, unspecified with opioid-induced psychotic disorder with delusions |
| ICD-10 | opioid misuse | F11.951 | Opioid use, unspecified with opioid-induced psychotic disorder with hallucinations |
| ICD-10 | opioid misuse | F11.99 | Opioid use, unspecified with unspecified opioid-induced disorder |
| ICD-10 | opioid abuse | F11.122 | Opioid abuse with intoxication with perceptual disturbance |
| ICD-10 | opioid abuse | F11.19 | Opioid abuse with unspecified opioid-induced disorder |
| ICD-10 | opioid dependence | F11.220 | Opioid dependence with intoxication, uncomplicated |
| ICD-10 | opioid dependence | F11.23 | Opioid dependence with withdrawal |
| ICD-10 | opioid dependence | F11.251 | Opioid dependence with opioid-induced psychotic disorder with hallucinations |
| ICD-10 | opioid dependence | F11.281 | Opioid dependence with opioid-induced sexual dysfunction |
| ICD-10 | opioid dependence | F11.288 | Opioid dependence with other opioid-induced disorder |
| ICD-10 | opioid misuse | F11.93 | Opioid use, unspecified with withdrawal |
| ICD-10 | opioid abuse | F11.12 | Opioid abuse with intoxication |
| ICD-10 | opioid abuse | F11.14 | Opioid abuse with opioid-induced mood disorder |
| ICD-10 | opioid abuse | F11.151 | Opioid abuse with opioid-induced psychotic disorder with hallucinations |
| ICD-10 | opioid abuse | F11.159 | Opioid abuse with opioid-induced psychotic disorder, unspecified |
| ICD-10 | opioid abuse | F11.182 | Opioid abuse with opioid-induced sleep disorder |
| ICD-10 | opioid dependence | F11.2 | Opioid dependence |
| ICD-10 | opioid dependence | F11.20 | Opioid dependence, uncomplicated |
| ICD-10 | opioid dependence | F11.221 | Opioid dependence with intoxication delirium |
| ICD-10 | opioid dependence | F11.25 | Opioid dependence with opioid-induced psychotic disorder |
| ICD-10 | opioid dependence | F11.250 | Opioid dependence with opioid-induced psychotic disorder with delusions |
| ICD-10 | opioid dependence | F11.28 | Opioid dependence with other opioid-induced disorder |
| ICD-10 | opioid poisoning | F11.959 | opioid use, unspecified with opioid-induced psychotic disorder, unspecified |