

Machine Learning to Detect Opioid Misuse from Primary Care Notes

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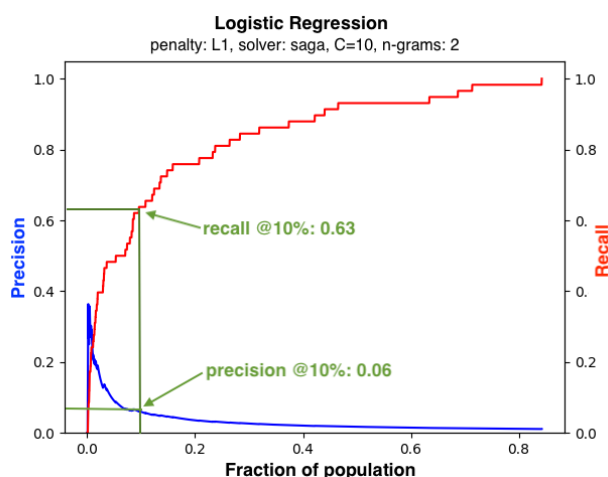
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Introduction

Prescription opioid misuse is prevalent among patients prescribed long term opioid therapy (LTOT), which is defined as daily opioid use for at least three months¹. Misuse includes behaviors such as taking too much medication, taking another person's medication, taking it incorrectly, or using opioid for reasons other than pain². Opioid misuse may result in a diagnosis of opioid use disorder (OUD), which is the chronic use of opioids that causes clinically significant distress, impairment, or harm². Interventions to address opioid misuse are being developed, however, there is no current approach to detect opioid misuse in the electronic health record (EHR). Opioid misuse behaviors preceding OUD diagnosis are often documented in clinical notes but is difficult to detect. We investigated the ability of machine learning to identify patients with opioid misuse from primary care physician (PCP) notes prior to OUD diagnosis. We chose OUD as the label for supervised machine learning as a reasonable first step, even though not all patients with opioid misuse will develop OUD.

Methods

We identified 31,356 LTOT patients in 315 UPMC primary care practices who had received at least three opioid prescriptions over a three-month period between 2016 and 2021, and we extracted 1,837,522 deidentified PCP notes for these patients. Of these LTOT patients 283 (~1%) were later diagnosed with OUD (ICD-10-CM F11.20). These patients were labeled as positive and notes occurring after the OUD diagnosis were excluded. We trained and evaluated supervised machine learning models, including random forest, logistic regression, and decision trees, on n-grams of PCP notes to predict the occurrence of OUD using the sci-kit learn Python package. All notes for an individual patient were concatenated, and patients were split into 80%/20% train-test groups. For the training set, non-OUD patients were under sampled to 50%. Models were evaluated on the area under the ROC curve (AUROC), recall and precision at the top 10% of predicted scores.



Logistic regression (with parameters: saga solver, L1 penalty, C=10, 2-word n-gram) performed the best with an AUROC of 0.86, and 63% recall/sensitivity and 6% precision/positive predictive value for the top 10% of scores (Figure 1). Feature importance (i.e., coefficient for logistic regression) of top ten features are listed in Table 1.

Results

Logistic regression (with parameters: saga solver, L1 penalty, C=10, 2-word n-gram) performed the best with an AUROC of 0.86, and 63% recall/sensitivity and 6% precision/positive predictive value for the top 10% of scores (Figure 1). Feature importance (i.e., coefficient for logistic regression) of top ten features are listed in Table 1.

Discussion

The model was effective in that it included most patients (63%) who went on to receive an OUD diagnosis within the top 10% of scores. Top ranked features reflected opioid misuse concepts (e.g., opioid abuse, heroin) and opioid addiction treatment (e.g., suboxone, withdrawal) that are related to OUD. As patients may exhibit misuse behaviors (and may even meet criteria for OUD) without receiving an OUD diagnosis, further review is needed to determine if patients receiving high scores have PCP notes that describe misuse behaviors, indicating a higher precision than the 6% for OUD diagnosed patients. However, given that <1% of patients receive an OUD diagnosis, these results indicate a great improvement in efficiency over manually labeling all or a random sample of clinical notes. Future plans include manually reviewing a sample of notes for misuse behaviors and evaluating the model on these individual notes rather than at the patient level.

Table 1. Feature importance

word/phrase	weight
opiod abuse	75.5
suboxone	49.9
narcotics	47.2
withdrawal	33.6
heroin	32.9
abuse	31.4
lithium	31.3
opiod use	30.1
inhale puffs	29.8
drug screen	28.6

References

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2. Strain E, Saxon AJ, Hermann R. Opioid use disorder: epidemiology, pharmacology, clinical manifestations, course, screening, assessment, and diagnosis. *UpToDate.* Waltham (MA): UpToDate. 2018 Jul 13.