HUMANA-MAYS HEALTHCARE ANALYTICS 2019 CASE COMPETITION

Long-term Opioid Therapy Prediction Project

I. The Business Problem

The use of long-term opioid therapy (LTOT) has increased in the treatment of chronic non-cancer pain. Studies have shown a series of adverse effects including respiratory, gastrointestinal, musculoskeletal, cardiovascular, immune, endocrine, central nervous systems, and overdose[1]. Some states such as New York have passed regulations and guidelines to prevent overuse or unintended use of opioids. For example, a new legislation was enacted to limit initial opioid prescribing to a 7 day supply for acute pain and Medicaid has implemented rules to lock a member with one provider and one pharmacy to prevent unintended use [2]. However, a lot of factors that might cause LTOT are not studied systematically and there are potentially other important factors that are not discovered yet. In addition, sharing information can be a challenge due to HIPPA regulations, thus machine learning systems leveraging existing data are desirable.

The goal of this project is to build a machine learning model that intakes claims and other available information and outputs a ranked list of members by their likelihood to become LTOT based on information learned on and before the opioid naive fill, which is defined by a prescription fill of an opioid after a 90 days with no opioid use.

II. Data Understanding and Preparation

1. Data source

Raw training data and a holdout set are provided by Humana. Data comes from various sources documenting members' medical related behaviors, including:

1. Medical claims
2. Diagnosis, surgery
3. New providers
4. Pharmacy claims
5. Rejected pharmacy claims
6. Calls to the payer

Training data has 6,086,969 records for 14,000 members and holdout set has 1,480,394 records for 6,000 members.

2. **Software and Tools**

Data processing and modeling are performed with python 3.7. Modeling is done with scikit-learn and xgboost.

3. **Target Variable**

The target variable is LTOT, which is defined as continuous use of an opioid medication with 90% of days covered over a 6 month period after the first opioid naive claim. The data is provided since Jan. 2016. The target variable is derived from the *RX_Claim - Paid* category of *event_descr* (event type). In order to ensure quality and accuracy of the target variable, several steps are taken before calculating opioid use days:

1. Select out members that have a Day 0 and have opioid claims on Day 0. 21 members are dropped.
2. Select Day 0 - Day 180 for all members.
3. Check whether *MME* (indicator of opioid use) is missing for any opioid prescription. 403 members are identified with missing values in this step and are dropped from training data since missing MME affects LTOT calculation.
4. Only keep prescriptions with MME > 0.

RX_Claim - Paid data ends up with 13,576 members, whose data will be used in the training process instead of the original 14,000 members. After summing up *PAY_DAY_SUPPLY_CNT* (number of days of opioid prescription) and subtracting the extra days, 8,555 members are classified as LTOT (labeled as 1), 5,021 are not (labeled as 0). Figure 1 shows the distribution of the target variable (named *label*).

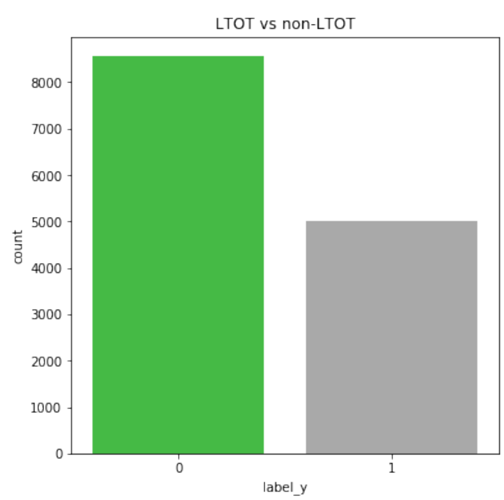

Figure 1 The distribution of target variable, *label* (1: LTOT, 0: non-LTOT)

4. **Feature Selection**

All training data after Day 0 is deleted to avoid data leakage. Original features are kept as much as possible to detect any patterns potentially contributing to LTOT. Some additional features are generated based on domain knowledge. An overview of features broken down by event type:

A. Fully paid medical claims
    a. Diagnosis. Several medical conditions are known as associated with opioid use, including low back pain, joint disease/arthritis, and headache/migraine [3]. Psychological conditions also affect opioid use, such as bipolar, depression, anxiety, and Schizophrenia [4]. These diagnoses are coded as categorical features with all other diagnoses coded as *other*.
    b. Place of Treatment. Places apparent for more than 100 times across all training data are kept as categorical features. Places with counts smaller than 100 are coded as *other*.
    c. *Charge_amount*, *Net_Paid_Amount*, and *Member_Responsible_Amount* are kept as numeric features.
    d. *Charge_amount*, *Net_Paid_Amount*, and *Member_Responsible_Amount* of medical conditions mentioned above are added as new numeric features.
B. New diagnosis
    a. Five types of new diagnosis (CAD, diabetes, Hypertension, CPD, and CHF) plus *new diagnosis - top 5* are kept as categorical features.
C. Surgery
    a. *Surgery* is treated as an event type category.
D. New provider
    a. *New Provider* is treated as an event type category.
E. Paid Rx claims
    a. Opioid only claims are selected out from all the Rx claims by conditioning on *MME > 0*. Features on opioid claims are generated on the subset:
        i. Opioid drug brand are kept as categorical feature. Brand of all other drugs are coded as *other*.
        ii. MME are grouped into four categories: MME < 50; 50 <= MME < 90; 90 <= MME < 120; and MME >= 120.
        iii. *Rx_cost*, *Net_Paid_Amount*, and *Member_Responsible_Amount* are kept as numeric features.
        iv. *PAY_DAY_SUPPLY_CNT* is kept as numeric feature.
    b. All Rx claims
        i. *Net_Paid_Amount*, *Member_Responsible_Amount, PAY_DAY_SUPPLY_CNT,* and *PAYABLE_QTY* are kept as numeric features.

ii. Specialty, GPI_Drug_Class_Description, and Drug_Group_Description are categorical features.

F. Rejected Rx claims
   a. *Brand_Name* is processed using opioid drug brand in paid Rx claims, i.e., opioid brands are kept as categorical features and all other rejected brands are coded as *other*.
   b. *Member_Responsible_Amount* and *PAY_DAY_SUPPLY_CNT* are calculated for opioid brands.
   c. *Member_Responsible_Amount* and *PAY_DAY_SUPPLY_CNT* of all rejected Rx claims are also kept as numeric features.

G. Calls
   a. Call types (inbound calls by provider, member, and other) are kept as categorical features.

5. Feature Engineering

In order to capture the impacts of historical behaviors on the occurrence of a current event, LTOT, features are aggregated by various time frames on the person level. Counting back from Day 0, data is broken into different time frames based on *Days*: previous 3 days (Day -3 to Day 0), 7 days (Day -7 to Day 0), 31 days (Day -31 to Day 0), 100 days (Day -100 to Day 0), 300 days (Day -300 to Day 0), and 800 days (Day -800 to Day 0). In each time frame:

A. Distributional statistics are generated for numeric features, including minimum, maximum, mean, median, standard deviation, and sum.
B. Counts are calculated for all categorical features. Missing counts are replaced with 0 indicating 0 occurrence.

Transforming features to time series enables the model to account for the impact of features based on how far back the information goes. All features are numeric after feature engineering and are ready for training.

6. Feature Description

The final dataset has 13,576 rows and 5,273 features. For model selection purposes, the data is then split into training and validation sets at a 8:2 ratio.

III. Models

1. Model Evaluation Plan

The goal is to find the best model to predict LTOT in the future after a naive opioid drug fill. We think the best measures for a good model in this case are precision and AUC, when recall is decent. That's because eventually our positive predictions will generate a member list for the clinical and administrative team to act on. Member interventions will likely require clinical or subject matter experts, whose time is limited and costly.In order to build credibility of the models and also work with limited resources, we would prefer our positive predictions to have more true positives, which is measured by precision. AUC is another good measure given that this is a slightly imbalanced dataset.

2. Baseline Model

Logistic Regression model was deployed to show initial performance. Hyperparameters were default in scikit-learn *LogistcRegression* function. The model reached 0.78 precision and 0.76 recall. AUC of baseline model is 0.859.

3. Model Selection, Tuning, & Evaluation

a. Model Selection

Random Forest, Gradient Boosting, and Extreme Gradient Boosting were also trained and evaluated on validation set. Extreme Gradient Boosting exhibit the best performance, thus is selected for fine tuning.

b. Hyperparameter Tuning

Hyperparameter tuning was performed with random search via three-fold cross validation. Evaluation score is the built-in '*roc_auc*' method. Parameters tuned were:

1. max_depth: 3, 4, 5, 6, 7, 10, 20, 30, 50
2. gamma: 0. 0.1, 0.2
3. min_child_weight: 1, 2, 3, 4, 5, 6
4. subsample: 0.6, 0.7, 0.8, 0.9, 1
5. colsample_bytree: 0.6, 0.7, 0.8, 0.9, 1
6. reg_alpha: 0. 0.00001, 0.0001, 0.001, 0.005, 0.05, 0.08, 0.1
7. reg_lambda: 0. 0.00001, 0.0001, 0.001, 0.005, 0.01
8. n_estimator: 100, 200, 300, 500, 700, 1000
9. scale_pos_weight = 1.5
10. learning_rate: 0.001, 0.01, 0.1

The best performing set of hyperparameters are: max_depth = 4, gamma = 0.1, min_child_weight = 3, subsample = 1, colsample_bytree = 1, reg_alpha = 0.005, reg_lamba = 0.0001, n_estimator = 200, scale_pos_weight = 1.5, learning_rate = 0.1.

c. Model performance

The best performing model was able to reach AUC score of 0.920 on validation set. Precision is 0.83, and recall is 0.85. **Figure 2** shows the ROC curve on validation set.

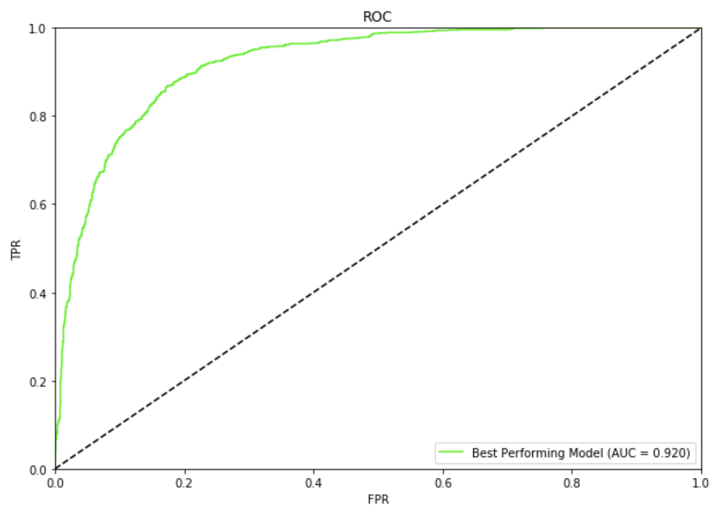

Figure 2 ROC Plot of Best Performing Model(XGBoosting)

d. Model Understanding

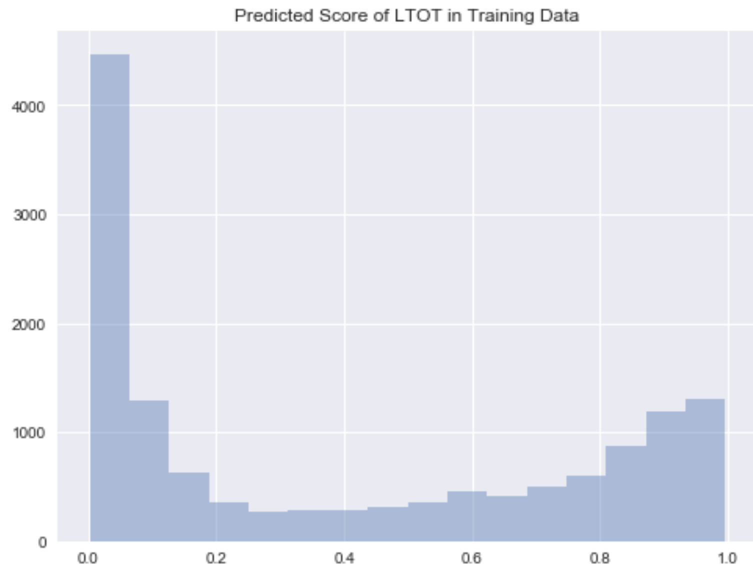

Figure 3 Distribution of Predicted Score of LTOT in Training Data

Using the best performing model we were able to get a score for likelihood of LTOT for the 13,576 member in the provided set (training and validation set). This step completely overfits the data and was only done for exploration and demonstration. The distribution of the score is shown above. Most (5,237, 39%) of them have low scores (<0.1), and 26% (3,482) of them have a score greater than 0.8, and 7% (961) have a score greater than 0.95.

e. Feature Importance & Insights

Feature importance is extracted from the best performing model. Plots of feature importance in *gain* and the predictability of top 20 features are shown in figures in Appendix. There are three types of features proved to have the most predictive importance (information gain or gain) to predict future LTOT:

1. Opioid history and current use
2. Rx history and current use
3. Medical history and current use

In particular, the top impactful features are: Maximum of opioid days per fill in the past 300 days, Number of opioid days filled on day 0, Max of opioid days per fill in the past 800 days, Total opioid days in the past 100 days.

The most important features are listed by the look back period in the table below. As mentioned in the feature engineering section, all of the features are examined by six time look back time periods. These time periods are current (day -3 to day 0), 7 days (a week), 31 days (a month), 100 days (about 3 months), 300 days (about a year), and 800 days look back. This method will enable analysis on the impact of the features based on how far back the information goes. In reality, because not all members have the same length of claims history, it is convenient to look at the impactful features by look back period.

For detailed feature names and importance ranking, please see the appendix.

Table. Most important features by look back time period in the best model

Look back time period	Important features
Current (day 0)	Opioid fill day supply and MME
	Opioid fill insurance paid amount
	Fentanyl use, Oxycodone HCL, INF-Antibiotics use
	Admitted to inpatient
	Member paid amount for new drug
	New provider count in the past 3 days
	Rejected supply count in the past 3 days
7 days (week)	Surgeries
31 days (month)	Nursing facility or surgeries
	Neuro drugs
100 days (~3 months)	Opioid fill day supply, quantity and insurance paid amount
	Rejected supply count and non opioid brand fills
	Use of nursing facility and ambulance
300 days (~ 1 year)	Opioid fill day supply and MME
	Prescriber specialty: Physical Medicine & Rehab Pain Medicine
800 days (~ 2 years)	Opioid fill day supply, quantity, MME and paid amount
	Psych-anx drug use
	Prescriber specialty: Anesthesiology Pain Medicine
	Rejected $ amount for any drug

IV. Recommendation and Actionability

1. Recommendation

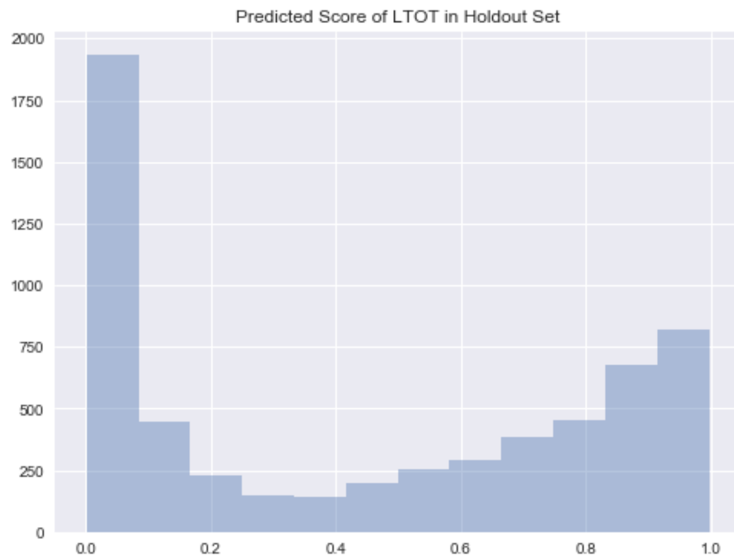

Figure 4 Distribution of Predicted Score of LTOT in Holdout Set

Scores of 5,976 members in the holdout set are predicted using the best performing model. 2,043 of them (34%) of them have scores lower than 0.1, which means they are very low risk for LTOT, and about 25% of them have scores higher than 0.75. 466 (8%) are very high risk, with scores higher than 0.95.

Preventing LTOT is a complex issue which requires multiple intervention points to effectively address. The main agents to focus on would be the member's pharmacy, prescriber, and primary care provider as well as the member's insurance company. These agents have an impact on how the member can access opioids and can also provide supportive services in cases of LTOT, as detailed below. One recommendation on model utilization is that on day 0 of the naive opioid event fill date, the member's medical claims and call histories are sent to the model to generate a score ranged from 0 to 1, representing the likelihood of LTOT after this prescription fill. Various actions can be taken based on the score.

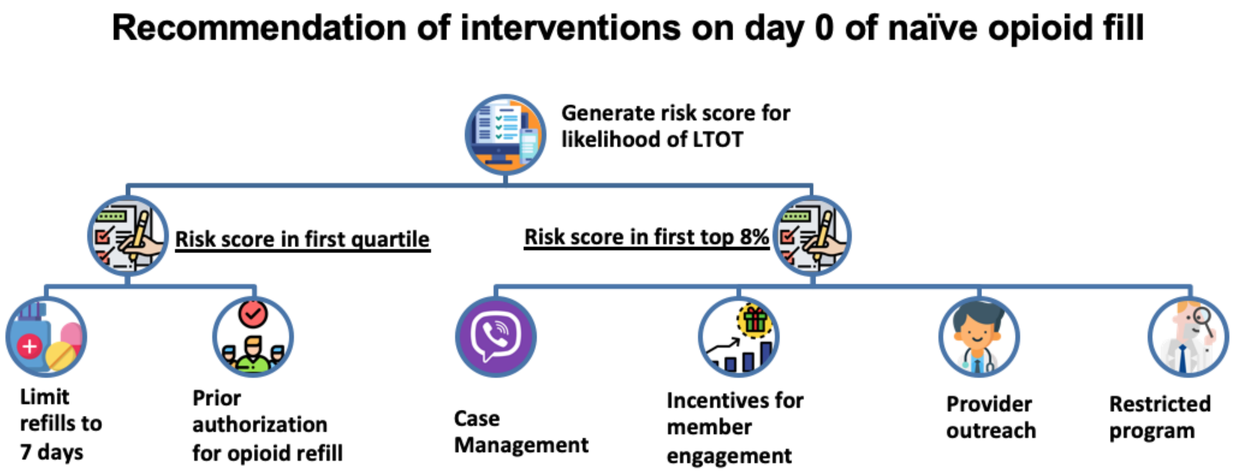

Figure 5. Recommendations of Interventions on Day 0 of Naive Opioid Fill

Since resources are usually limited, it is recommended to put members in two high risk brackets and use different interventions tailored to those brackets.

A. The first group includes members in the highest quartile. In the training set, this approximately corresponds to a score of 0.75 and higher. Proactive interventions can be implemented on them as listed below:
   a. Only allow up to seven days of refills for the naive opioid fill.
   b. Partner with the member's prescriber and pharmacy to implement prior authorization for any opioid refill after a naive opioid event. This means that after a member's first pharmacy fill, the prescriber needs to request prior authorization from the payer with justification and these requests will be reviewed and triaged by a pain specialist representing the payer. Only when a request is approved, the pharmacy can be allowed to fill the next opioid prescription.

B. The second group includes members in the top 8% of the ranking. This represents 466 members in the holdout data whose scores are 0.95 and higher. In addition to the interventions recommended from above, further actions are recommended here:
   a. Focused case management on members. Deploy a care team consisting of psychologists, social workers, nurses, pharmacists, and other trained staff to telephonically engage and screen members for risk of substance abuse. The intervention would follow the SBIRT model [5] (Screening, Brief Intervention, and Referral to Treatment). SBIRT provides a standardized way to screen members for risk substance use behaviors, and as appropriate, conduct motivational interviewing and refer to treatment.
   b. Members identified with substance use disorders are referred to a specialist for substance abuse treatment. Members who opt out of this treatment require prior authorization for any opioid prescription and are restricted to one prescriber and

one pharmacy. Members identified as high risk for substance abuse disorder are referred to supportive programs such as peer counselors, central call center help line, and alternative pain relief treatments.

c. Since the interventions above depends on the members to agree to engage (opt in), small incentives should be offered to encourage compliance.
d. Provide continuity of care by contacting the member's opioid prescriber and primary care doctor. Send them alerts regarding member's risk of LTOT and educate them on the guidelines of strict opioid prescriptions.
e. Enroll members in a more restricted program for a year. During this time members can only get opioid from one provider and one pharmacy.

C. Create an app to establish a community for high risk patients to ask questions and find peer support, guided by pain specialists and psychologists. High risk here can be defined by any threshold at the predictive score at the health plan's discretion.

2. Actionability

There are a few challenges to consider when implementing the interventions:

A. Medical history availability. Not all the members got covered by Humana for the same length of time on a naive opioid event. The longer the patient is covered by Humana, the better the score can predict LTOT.
B. Member opt-in. For example, in the recommendation for case management, member opt-in rate will be a challenge. That's why another recommendation was made to offer incentive in various forms, if possible.
C. Regulatory compliance.
D. Members who are opioid addictive and also in pain. It is always challenging to care for patients who are opioid addictive and also in pain due to chronic conditions. It is important to balance the restriction rules to prevent overdose and the availability of treatment. In this case, a referral to a pain specialist is crucial.
E. Exclusions. The interventions should exclude patients who are in hospice or in active cancer treatment.

3. Future steps

The following steps are suggested to improve the model:

A. Define LTOT. We only identified LTOT from day 0 to 179. However, if a member had a LTOT episode after day 179, it should be treated as another training record. This will increase trainable sample size and might also increase model accuracy to capture member's outcome of interest.

B. LTOT in the history. Although our model took most of the available historical records into account, LTOT in the history should be a great addition to predict future LTOT.

Reference:

1. Baldini, A., Von Korff, M., & Lin, E. H. (2012). A Review of Potential Adverse Effects of Long-Term Opioid Therapy: A Practitioner's Guide. *The primary care companion for CNS disorders*, *14*(3), PCC.11m01326. doi:10.4088/PCC.11m01326
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4. Rollin M. Gallagher, Lisa J. Rosenthal (2008), Chronic Pain and Opiates: Balancing Pain Control and Risks in Long-Term Opioid Treatment, Archives of Physical Medicine and Rehabilitation, Volume 89, Issue 3, Supplement 1, ISSN 0003-9993, https://doi.org/10.1016/j.apmr.2007.12.003.
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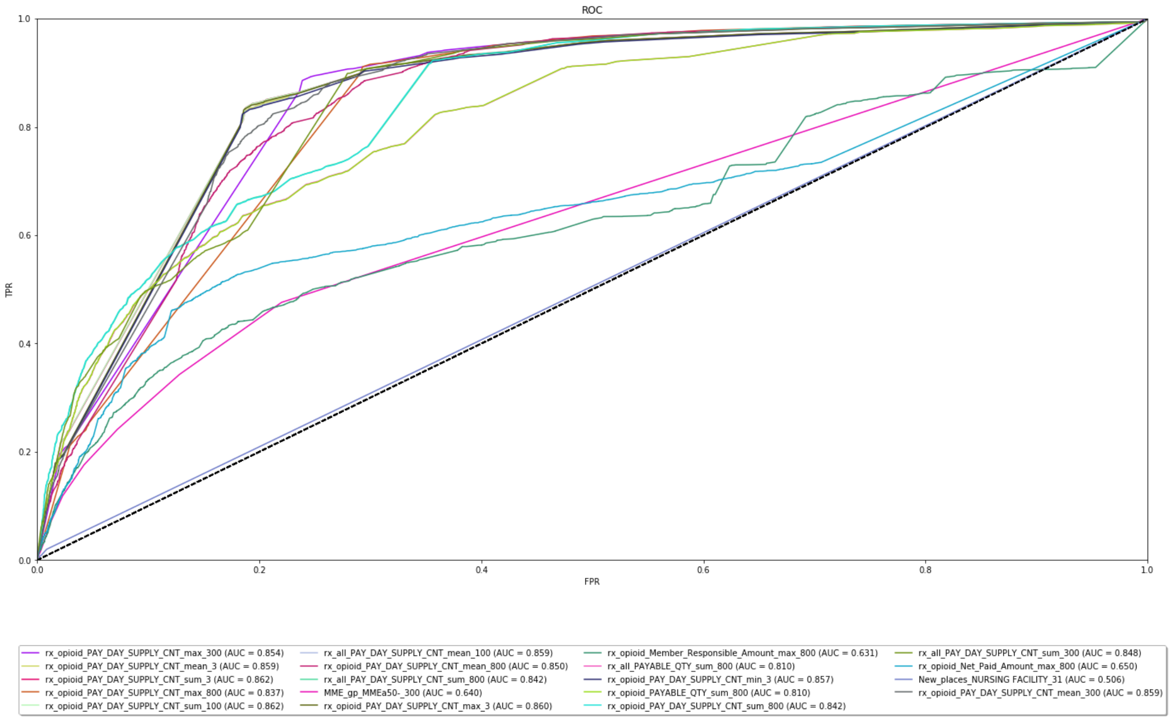
Appendix

AUC of selected features



List of top 50 ranked important features

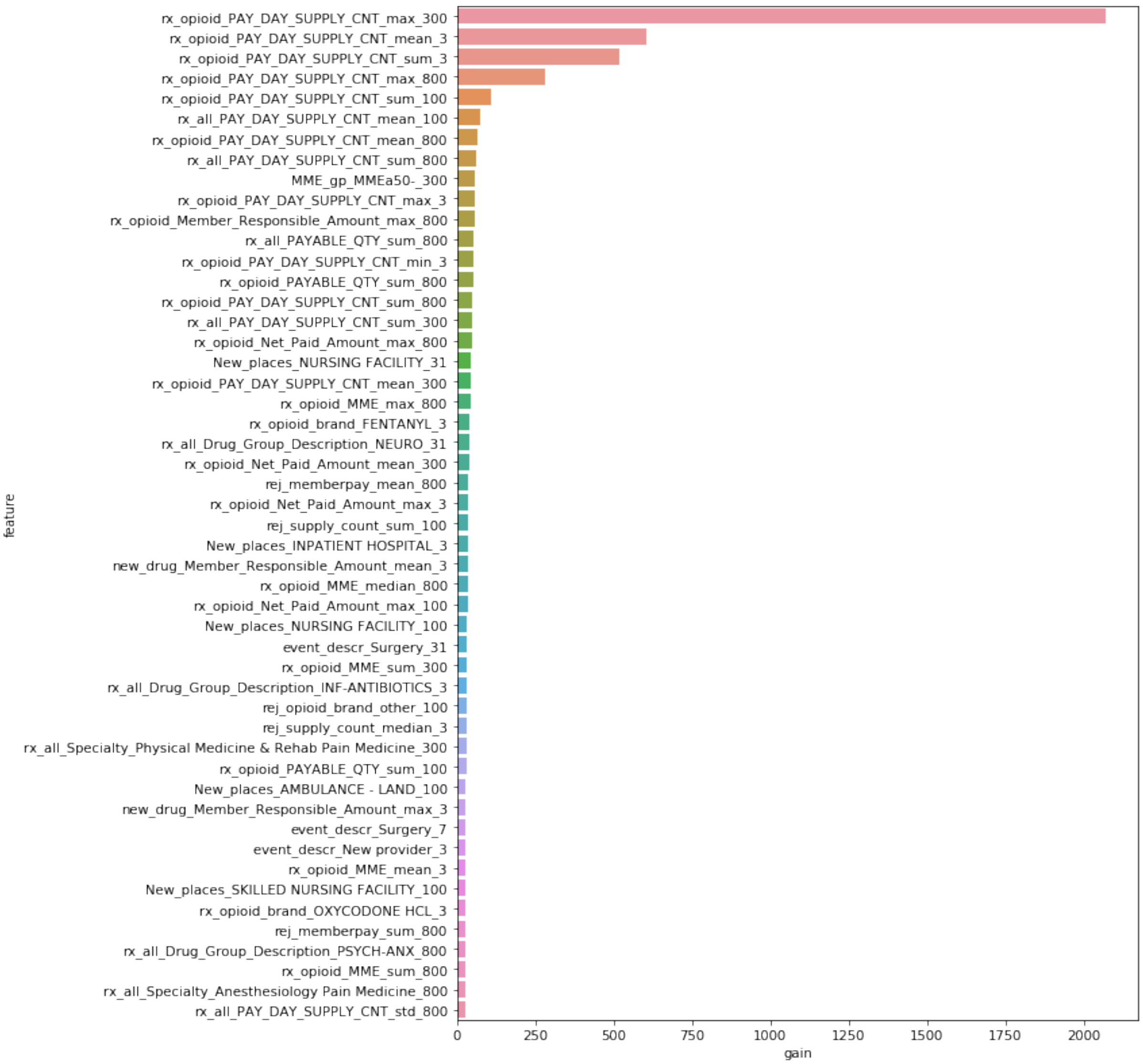


Table. List of top 50 ranked important features

Rank	Category	Subcategory	Business Name	Stats	Feature	Gain
1	2. Opioid history	Opioid pay day supply count	Maximum of opioid days per fill in the past 300 days	max	rx_opioid_PAY_DAY_SUPPLY_CNT_max_300	2,072
2	1. Opioid current	Opioid pay day supply count	Number of opioid days filled on day 0	mean	rx_opioid_PAY_DAY_SUPPLY_CNT_mean_3	604
3	1. Opioid current	Opioid pay day supply count	Number of opioid days filled on day 0	sum	rx_opioid_PAY_DAY_SUPPLY_CNT_sum_3	520
4	2. Opioid history	Opioid pay day supply count	Max of opioid days per fill in the past 800 days	max	rx_opioid_PAY_DAY_SUPPLY_CNT_max_800	281
5	2. Opioid history	Opioid pay day supply count	Total opioid days in the past 100 days	sum	rx_opioid_PAY_DAY_SUPPLY_CNT_sum_100	109
6	2. Opioid history	Opioid pay day supply count	Average opioid days per fill in the past 100 days	mean	rx_all_PAY_DAY_SUPPLY_CNT_mean_100	73
7	2. Opioid history	Opioid pay day supply count	Average opioid days per fill in the past 100 days	mean	rx_opioid_PAY_DAY_SUPPLY_CNT_mean_800	65
8	2. Opioid history	Opioid pay day supply count	Total opioid days in the past 800 days	sum	rx_all_PAY_DAY_SUPPLY_CNT_sum_800	61
9	2. Opioid history	MME less than 50	Count of prescriptions with MME<50 in the past 300 days	count	MME_gp_MMEa50-_300	58
10	1. Opioid current	Opioid pay day supply count	Number of opioid days filled on day 0	max	rx_opioid_PAY_DAY_SUPPLY_CNT_max_3	57
11	2. Opioid history	Opioid member paid amount	Total member paid $ amount on opioid in the past 800 days	max	rx_opioid_Member_Responsible_Amount_max_800	56

12	2. Opioid history	Opioid payable quantity	Total quantity of opioid in the past 800 days	sum	rx_all_PAYABLE_QTY_sum_800	53
13	1. Opioid current	Opioid pay day supply count	Number of opioid days filled on day 0	min	rx_opioid_PAY_DAY_SUPPLY_CNT_min_3	52
14	2. Opioid history	Opioid payable quantity	Total quantity of opioid in the past 800 days	sum	rx_opioid_PAYABLE_QTY_sum_800	51
15	2. Opioid history	Opioid pay day supply count	Total opioid days in the past 800 days	sum	rx_opioid_PAY_DAY_SUPPLY_CNT_sum_800	50
16	2. Opioid history	Opioid pay day supply count	Total opioid days in the past 300 days	sum	rx_all_PAY_DAY_SUPPLY_CNT_sum_300	47
17	2. Opioid history	Opioid net paid amount	Max of insurance paid $ amount in the past 800 days	max	rx_opioid_Net_Paid_Amount_max_800	47
18	6. Medical service history	Nursing facility services	Count of nursing facility services(claims) in the past 31 days	count	New_places_NURSING FACILITY_31	46
19	2. Opioid history	Opioid pay day supply count	Average opioid days per prescription in the past 300 days	mean	rx_opioid_PAY_DAY_SUPPLY_CNT_mean_300	44
20	2. Opioid history	MME	Max MME taken in the past 800 days	max	rx_opioid_MME_max_800	43
21	1. Opioid current	Fentanyl use	Use of Fentanyl on day 0	count	rx_opioid_brand_FENTANYL_3	41
22	4. Rx history	Neuro drug count	Count of Neuro drug fills in the past 31 days	count	rx_all_Drug_Group_Description_NEURO_31	40
23	2. Opioid history	Opioid net paid amount	Average insurance paid $ amount for opioid in the past 300 days	mean	rx_opioid_Net_Paid_Amount_mean_300	38
24	4. Rx history	Rejected member payment	Average rejected member paid $ amount for any drug in the past 800 days	mean	rej_memberpay_mean_800	37

25	1. Opioid current	Opioid net paid amount	Cost of opioid drug filled on day 0	max	rx_opioid_Net_Paid_Amount_max_3	36
26	4. Rx history	Rejected supply count	Total supply of rejected fills in the past 100 days	sum	rej_supply_count_sum_100	36
27	5. Medical service current use	Inpatient services	Admitted in inpatient on day 0	count	New_places_INPATIENT HOSPITAL_3	35
28	3. Rx current	Member paid amount for new drug	Member paid $ amount for new drugs on day 0	mean	new_drug_Member_Responsible_Amount_mean_3	34
29	2. Opioid history	MME	Median of MME taken in the past 800 days	Median	rx_opioid_MME_median_800	33
30	2. Opioid history	Opioid net paid amount	Max of insurance paid $ amount in the past 100 days	max	rx_opioid_Net_Paid_Amount_max_100	33
31	6. Medical service history	Nursing facility services	Count of nursing facility services(claims) in the past 100 days	count	New_places_NURSING FACILITY_100	33
32	6. Medical service history	Surgery services	Count of surgery services(claims) in the past 31 days	count	event_descr_Surgery_31	33
33	2. Opioid history	MME	Sum of MME per fill in the past 300 days	sum	rx_opioid_MME_sum_300	32
34	3. Rx current	INF-Antibiotics drug count	INF-Antibiotics use on day 0	count	rx_all_Drug_Group_Description_INF-ANTIBIOTICS_3	31
35	4. Rx history	Rejected non opioid brand	Rejected non opioid brand fills in the past 100 days	count	rej_opioid_brand_other_100	30
36	4. Rx history	Rejected supply count	Median of rejected supply count in the past 3 days	median	rej_supply_count_median_3	30
37	4. Rx history	Prescriber specialty: Physical Medicine &	Count of all rx fills with prescriber specialty: Physical Medicine & Rehab Pain Medicine in	count	rx_all_Specialty_Physical Medicine & Rehab Pain Medicine_300	30

		Rehab Pain Medicine	the past 300 days			
38	2. Opioid history	Opioid payable quantity	Total quantity of opioid in the past 100 days	sum	rx_opioid_PAYABLE_QTY_sum_100	30
39	6. Medical service history	Ambulance - land services	Count of ambulance services(claims) in the past 100 days	count	New_places_AMBULANCE - LAND_100	28
40	3. Rx current	Member paid amount for new drug	Member paid $ amount for new drug on day 0	max	new_drug_Member_Responsible_Amount_max_3	28
41	6. Medical service history	Surgery services	Count of surgery services(claims) in the past 7days	count	event_descr_Surgery_7	28
42	6. Medical service history	New provider count	Count of new providers in the past 3 days	count	event_descr_New provider_3	28
43	1. Opioid current	MME	MME member got on day 0	mean	rx_opioid_MME_mean_3	28
44	6. Medical service history	Skilled nursing facility services	Count of Skilled nursing facility services(claims) in the past 100 days	count	New_places_SKILLED NURSING FACILITY_100	27
45	1. Opioid current	Oxycodone HCL	Oxycodone HCL member got on day 0	count	rx_opioid_brand_OXYCODONE HCL_3	27
46	4. Rx history	Rejected member payment	Total member rejected $ amount for any drug in the past 800 days	sum	rej_memberpay_sum_800	27
47	4. Rx history	Psych-anx drug use	Use of Pysch-anx drug in the past 800 days	count	rx_all_Drug_Group_Description_PSYCH-ANX_800	27
48	2. Opioid history	MME	Sum of MME per fill in the past 800 days	sum	rx_opioid_MME_sum_800	27
49	4. Rx history	Prescriber specialty: Anesthesiology	Count of all rx filles with prescriber specialty:	count	rx_all_Specialty_Anesthesiology Pain Medicine_800	26

		Pain Medicine	Anesthesiology Pain Medicine in the past 800 days			
50	2. Opioid history	Opioid pay day supply count	Variation of opioid fill days in the past 800 days	std	rx_all_PAY_DAY_SUPPLY_CNT_std_800	25