Humana-Mays 2019 Case Analysis Report

Background and Key Performance Indicator

According to Center for Disease Control and Prevention (CDC), more than 700,000 people have died due to drug overdose in the past decade and among those more than 68% involved the use of an opioid including prescription and illicit opioids[1]. And the growth is projected to continue in the next few years. In particular, it's been found that longer duration and higher dosage of opioids are highly associated with long term opioids therapy behavior.

To cope with the existing opioids epidemic, CDC has published regulations on safe prescriptions for chronic pain. The Center for Medicare and Medicaid (CMS) also requires Humana to alert prescribers to inappropriate opioids utilization. Yet, combating opioid addiction is not as simple as reducing the statistics - it also has a bearing on societal economics and human wellbeing. As argued by Florence in "The Economic Burden of Prescription Opioid Overdose, Abuse and Dependence in the United States, 2013"[2], the estimated incremental costs for annual health insurance after Diagnosis with Prescription Opioid Misuse Disorder is about $15K for private health insurance, $17K for Medicare and $13K for Medicaid in 2013. In addition, the total fatal costs from lost productivity and health care for the society is about $21,513.

This project aims to correctly detect Humana members' long-term opioids therapy (LTOT) behavior and explore preventive measures that could curb opioids addiction. Assume the demonstration of LTOT behavior as positive events, and non-LTOT behavior as negative events. The confusion matrix in Figure 1.1 has outlined four different combinations of predicted and actual values of the target "LTOT". While correct classification might generate streams of benefits, misclassifications usually carry costs to stakeholders. Hence essentially, the objective of this project is to increase the correct classifications (particularly True Positives) and reduce misclassifications (especially False Negatives since failure to detect true LTOT members is more fatal). This tradeoff can thus be illustrated by ROC curve as in Figure 1.2. Since classifications are based upon the threshold value determined by the best tradeoff point on ROC curve, we can set ROC and AUC as our KPIs.

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[1] Opioid Overdose | Understanding the Epidemic. (2018, December). Retrieved October 15, 2019, from https://www.cdc.gov/drugoverdose/epidemic/index.html.

[2] Florence, C. S., Zhou, C., Luo, F., & Xu, L. (2016, October). The Economic Burden of Prescription Opioid Overdose, Abuse, and Dependence in the United States, 2013. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5975355/.

		Predicted Class		
		LTOT	Non-LTOT	Total
Actual Class	LTOT	**True Positive** Predicted LTOT Actually LTOT	**False Negative** Predicted non-LTOT Actually LTOT	Total Actually Positive
	Non-LTOT	**False Positive** Predicted LTOT Actually Non-LTOT	**True Negative** Predicted Non-LTOT Actually Non-LTOT	Total Actually Negative
	Total	Total Predicted Positive	Total Predicted Negative	Grand Total

Figure 1.1 Confusion Matrix for Correct and Incorrect Classifications
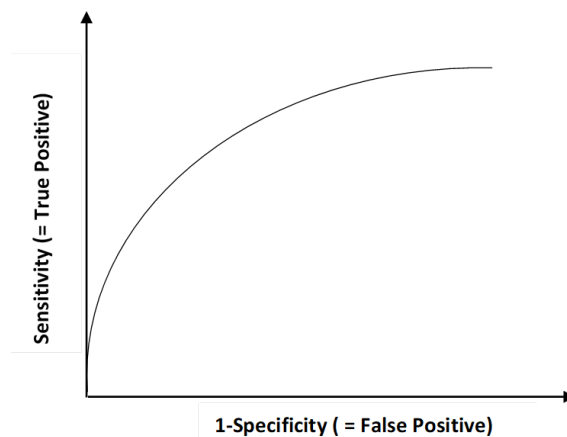

Figure 1.2 ROC Curve

Depth and Description

I. Variable Reduction

The longitudinal medical records allow us to create a holistic view of patients. Apart from 8 variables related to patients' opioid behaviors, the original dataset also records 16 types of medical events. Each event has a variety of event attributes. To consolidate data in a comprehensive and efficient way, we perform variable reduction based on extensive research on health care terminologies[4]. To start with, all events and attributes are categorized and attributes with highest relevance to business issue are identified as in Figure 2.1. This procedure meant to facilitate the choice of attributes to be kept and considered in later stages. Next, appropriate variable transformation is performed (which

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[4] USA Managed Care Organization. *Health Care Terminology Glossary* [PDF file]. Retrieved from https://www.usamco.com/pdf/glossary.pdf

will be discuss in detail in the next section) on these attributes based on their intrinsic type and characteristics.

Event Category	Event	Attributes	Attributes to be Kept
Call Category	Inbound Call by Mbr Inbound Call by Other Inbound Call by Prov	Call Category	Call Frequency Call Recency
		Inquiry Reason Description	
		Disposition Description	
		Origin	
		Location	
Diagnosis Category	Surgery Fully Paid Claim New Diagnosis - Top 5 New Diagnosis - CAD New Diagnosis - Diabetes New Diagnosis - CPD New Diagnosis - CHF New Diagnosis - Hypertension	Diagnosis	New Diagnosis Frequency Diagnosis Key Word Frequency Place of Treatment Frequency
		Place of Treatment	
		Member Responsible Amount	Member Responsible Amount
		Charge Amount	
		Net Paid Amount	
Rx Claim Category	Rx Claim - Paid Rx Claim – Reject Rx Claim - New Drug Rx Claim - FirstTimeMailOrder	Brand Name	Drug Group Description Rx Claim Frequency Rx Claim Recency Member Responsible Amount
		Drug Group Description	
		GPI Drug Group8 ID	
		GPI Drug Class Description	
		Generic Name	
	New Provider	Diagnosis	New Provider Frequency New Provider Recency
		Place of Treatment	

Figure 2.1 Categorization and Identification of Key Attributes

II. Variable Transformation

1. Preprocess - unfold event categories as new columns

In order to capture every attribute of different event type, it's necessary to preprocess attributes and restructure the data frame. As can be seen in Figure 2.1, some event categories share same group of attributes. To unfold the overlapping activities that are associated with multiple events from the same person, it is of the best practice to append all useful attributes (or events) as new columns such that longitudinal records are transformed to only one horizontal record for each patient. A simplified example of prior and after data transformation is demonstrated in the following:

Event_Descr	Attribute1	Attribute2	Attribute3	Attribute4	Attribute5	Attribute9
Inbound Call by Mbr	Call Category	Inquiry Reason	Disposition descr	Origin	Location	NaN
Fully Paid Claim	Diagnosis	Place of Treatment	Charge Amt	Net Paid Amt	Mbr Responsible Amt	NaN
RX Claim - Rejected	Status Code	Diagnosis	COB	Claim Tier	Brand Name	Mbr Responsible Amount

Figure 2.2 Pre-Processing Data Structure

ID	Event_descr	Days	Call Category	Diagnosis	Mbr Responsible Amt	MME
ID10010854159	Inbound Call by Mbr	-629	Inquiry Reason descr	NaN	NaN	NaN
ID10010854159	Fully Paid Claim	-595	NaN	UNSPECIFIED ESSENTIAL HYPERTENSIO	13.58	NaN
ID10010854159	RX Claim -Rejected	-588	NaN	SYMPTOMS, SIGNS, ILL DEFINED CONDITIONS	4.0	NaN

Figure 2.3 Post-Processing Data Structure

2. RFM Method

RFM, which stands for Recency, Frequency and Monetary, is the dominant technique applied on events to create new variables that can summarize and capture activity patterns. Take the event "RX Claim – Paid" for instance:

- Frequency – for each drug group, how frequently did the patient pay and possess the medication on hand after standardization (formula shown as below). The newly created variable will start with 'Freq_';

$$standardized\ frequency = \frac{freq\ of\ getting\ medication}{total\ number\ of\ days\ prior\ to\ anchor\ day}$$

- Recency – for each drug group, when was the most recent date (against the anchor date) the patient has paid for a medication. The variable will start with 'Rec_';
- Monetary – how much in total or on average was the patient responsible to pay. The variable will start with 'Mon_';

These new columns are then attached to the tabular data frame for patients as in Figure 2.4:

ID	Freq_paid_PAIN	Rec_paid_inf-antibiotics	Mon_paid_mean	Mon_paid_sum	Mean_MME
ID10010854159	5	601	2.17	165.66	15
ID10024447278	38	836	0.91	54.66	27.5
ID1002482139	8	432	1.16	167.41	38.03

Figure 2.4 RFM techniques on Event

3. Clinical Feature Extraction

To preserve the clinical information that could not be easily quantified, methods other than RFM are applied.

- Event Fully Paid Claim

There is massive amount of clinical information stored in the column "diagnosis" of the original dataset. However, considering the significance of all different diagnoses, we believe the activities of top 5 diseases (Hypertension, CAD, CPD, CHF and Diabetes) would be the priority on which RFM can thus be applied. Hence, we filter activities on top 5 disease and calculate the RFM of selected records in in Figure 2.5.

ID	Freq_diag_diabetes_fully_paid_claim	Freq_diag_CAD_fully_paid_claim	Freq_diag_CPD_fully_paid_claim	Freq_diag_CHF_fully_paid_claim	Freq_diag_hypertension_fully_paid_claim
ID10010854159	5	0	0	0	6
ID1002482139	0	2	1	2	3

Figure 2.5 Feature Extraction for event "Fully Paid Claim"

- Event Surgery

Same as trivial variations in diagnosis, we select top 100 most commonly mentioned surgery as the new attributes and perform RFM method on each of surgeries. These new attributes are labeled as '(Rec/Freq/Mon) + surgery_diag_+ (surgery name)', the result can be seen form Figure 2.6.

ID	Freq_surgery_diag_colon	Freq_surgery_diag_cataract	Freq_surgery_diag_screening	Freq_surgery_diag_malignant	Freq_surgery_diag_senile
ID10010854159	0	2	0	0	1
ID1002482139	1	2	1	1	0

Figure 2.6 Feature Extraction for event "Surgery"

4. LTOT Define

The target variable of the predictive model is whether a patient will exhibit Long Term Opioid Therapy (LTOT) behavior (0 = No, 1 = Yes) based on his/her medical behaviors on record. LTOT is defined as having continuous use of an opioid medication with more than 90% of days over 180 days period after anchor day. Primary interest resides in "Rx Claim

– Paid" events with non-null MME values as they imply the patient has paid for an opioid medication. The logic for defining LTOT used in this project is outlined as follows and can be seen from Figure 2.7:

- Filter out "Rx Claim – Paid" events which are cancelled out by "Rx Claim – Rejected" (i.e. the patient did not receive the opioid medication) on the same medication.
- A patient is defined as having LTOT if total MME covered days > 162 days in 180-day period after anchor day.
- Duplicated covered days are counted only once.

Event Description	Status Code = Reversal	Days	MME Payday Supply Count	MME Days Covered Running Total
RX Claim - Paid		0	5	5
		5	30	35
		32	30	62
		64	5	-
Rx Claim - Reversal	**Reversal**	**64**	-	62
RX Claim - Paid		67	30	92
		97	30	122
		127	30	152
		157	30	175
175 MME Pay Day Supply Count -- LTOT				

Figure 2.7 Identification of LTOT

III. Rationale for Model Selection

1. Tree ensemble model: XGBoost

Considering our data is in tabular structure (not image or graph data), we choose tree ensemble model to process our large dataset with 400+ features. Among all the tree ensemble models, XGBoost (Extreme Gradient Boosting) outperforms the others for the following reasons[5]:

- Parallelized Tree Building:
  Running with parallelization within each tree, XGBoost creates branches independently which speeds up calculation and higher accuracy.
- Tree Pruning Depth-First Approach:
  XGboost uses depth-first approach to specify tree depth at first and prune tree backward instead of pruning on loss criteria, leading to better computation performance.
- Regularization for Avoiding Overfitting:

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[5] Morde, V. (2019, April 8). XGBoost Algorithm: Long May She Reign! Retrieved from https://towardsdatascience.com/https-medium-com-vishalmorde-xgboost-algorithm-long-she-may-rein-edd9f99be63d.

It penalizes complexity of model to prevent overfitting.

- Efficient Handling of Missing Data:
  Being aware of missing value, XGBoost learns and handles different sparse pattern efficiently.
- In-built Cross Validation Capability:
  With this algorithm, it's not necessary to explicitly specify exact number of iterations in every single run.

2. Parameter Setting

Since our predicted variable is binary (LTOT or not), we import XGBoost classifier to train the model. Data is partitioned such that 90% of all records are kept as training set and the rest 10% as the test set. Setting the parameter "grow_policy" as 'lossguide' and "tree_method" as 'hist' can help increase calculation speed and achieve faster convergence of loss. To optimize values of parameters listed in Figure 3.1, GridSearch is applied to iterate over candidate models and returns the best performing one based on the highest AUC.

Best Parameter Selection		Explanation
User-defined Parameter	grow_policy = 'lossguide'	Splits at nodes with the highest loss change
	tree_method = 'hist'	Use a fast histogram optimized approximate greedy method. In this case, only a subset of possible split values is considered.
Gridsearch Recommended Parameter	colsample_bytree=0.6	the column subsampling rate per tree
	gamma= 1	The value of this option specifies the minimum relative improvement in squared error reduction for a split to happen
	max_depth= 4	Specify the maximum tree depth. Higher values will make the model more complex and can lead to overfitting
	min_child_weight = 5	Specify the minimum number of observations for a leaf
	subsample= 1.0	Specify the row sampling ratio of the training instance

Figure 3.1 Parameter Setting of XGBoost Model [6]

[6] XGBoost. (2019, October 2). Retrieved from http://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/xgboost.html.

3. Loss Function

In order to train the model, Logarithmic loss function is chosen to minimize the loss function and prevent overfitting. In particular, the log loss function will take higher penalty for misclassifications, and lower penalty for correct classifications. Figure 3.2 displays the log loss of the XGBoost model for each of the epochs. It has been found that the loss function of training dataset continues to decrease through 150th epochs, while the loss function of test dataset continues to increase. Since a simple and predictive model is much preferable, it's set such that the stopping of the final model occurs at around 150 epochs.
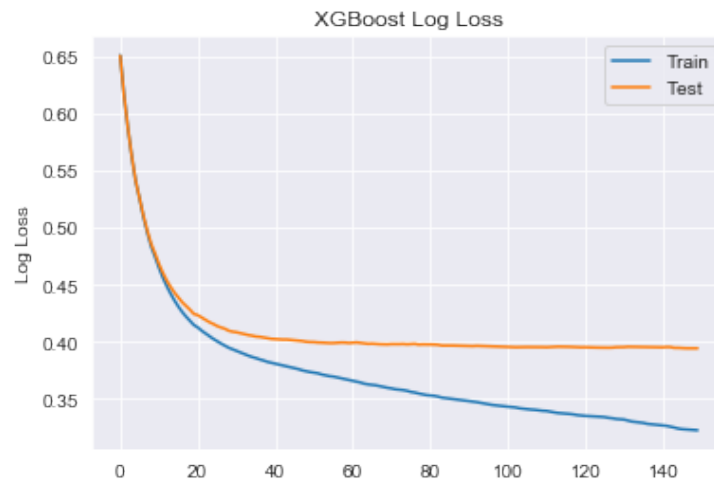
Figure 3.2 logarithmic loss of the XGBoost model

IV.   Key Drivers of Outcome

What are the features that drives LTOT outcome significantly? Are the patients with these characteristics more likely to have LTOT or less likely? XGBoost allows us to investigate feature importance and visualize with the Feature Importance Plot in Figure 4.1. A feature with a longer bar indicates it has a greater number of splits in the decision tree, and thus is considered more crucial in classifying a patient to be LTOT or not.
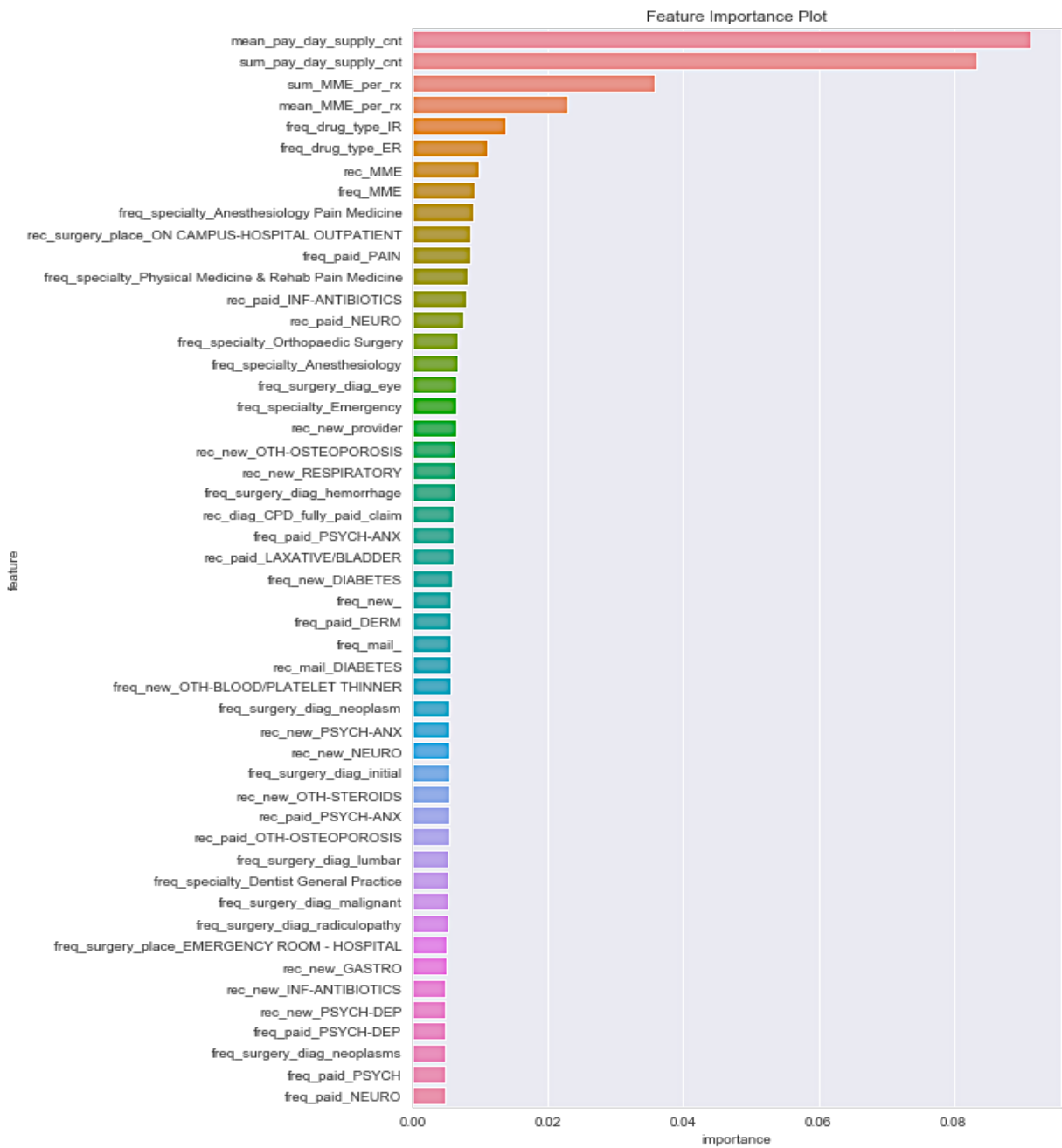

Figure 4.1 Feature Significance Plot

Whether these features are positively correlated with having LTOT or negatively is also interesting. The SHAP plots in XGBoost graphically visualize the correlation between features and target. Now combining Feature Importance Plot and SHAP plot, interpretation of important features which are significantly driving LTOT will be readily realizable:

1. **Mean_pay_day_supply_cnt**:
   The most important among all 480 features stands for the average number of days supplied by opioid medication per claim. This feature is positively correlated with probability of LTOT. The higher the average pay_day_supply_cnt per claim a patient has, the more likely the patient will have LTOT. Refer to Figure 4.2.
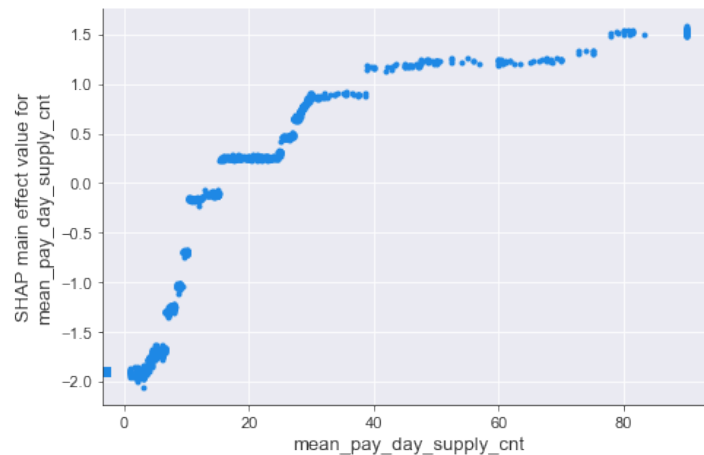
Figure 4.2 SHAP Plot for Mean_Pay_Day_Supply_Count

2. **Sum_pay_day_supply_cnt**:
   2nd most important among all 480 features stands for the total number of days supplied by opioid medication. The SHAP plot shows a positive correlation with LTOT probability, which means when a patient has in total more days covered by opioid medication, this patient will have higher chance of having LTOT. Refer to Figure 4.3.
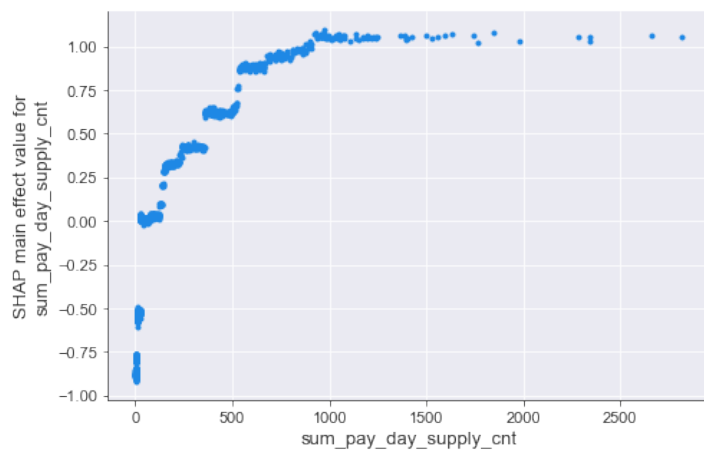

Figure 4.3 SHAP Plot for Sum_Pay_Day_Supply_Count

3. **Sum_MME_per_rx**:

The 3rd most important feature stands for the total opioid usage (pay_day_supply_count × MME) for a patient. Despite the outliers, there is positive correlation between the total opioid usage and the chance of having LTOT. Patients having more opioid usage are more likely to have LTOT behavior. Refer to Figure 4.4.
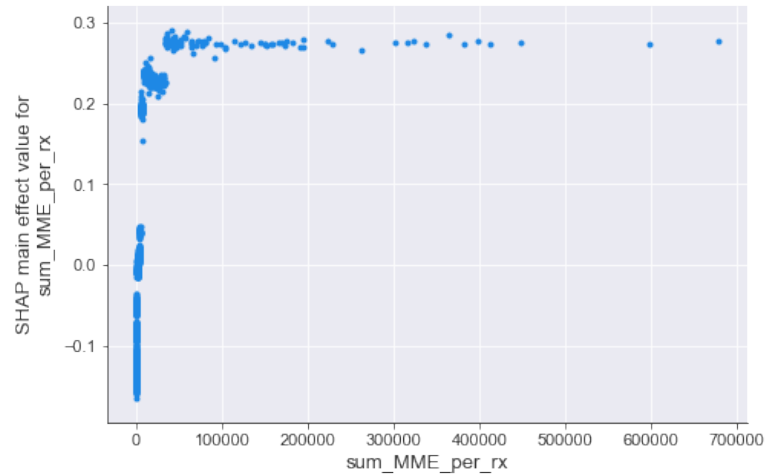

Figure 4.4 SHAP Plot for Sum_MME_Per_RX

4. **Mean_MME_per_rx**:

The 4th most important feature stands for the average opioid usage (pay_day_supply_count × MME) per Rx Claim - Paid. The SHAP plot shows positive correlation with LTOT probability, which indicates patients prescribed with more opioid on average are more likely to have LTOT. Refer to Figure 4.5.
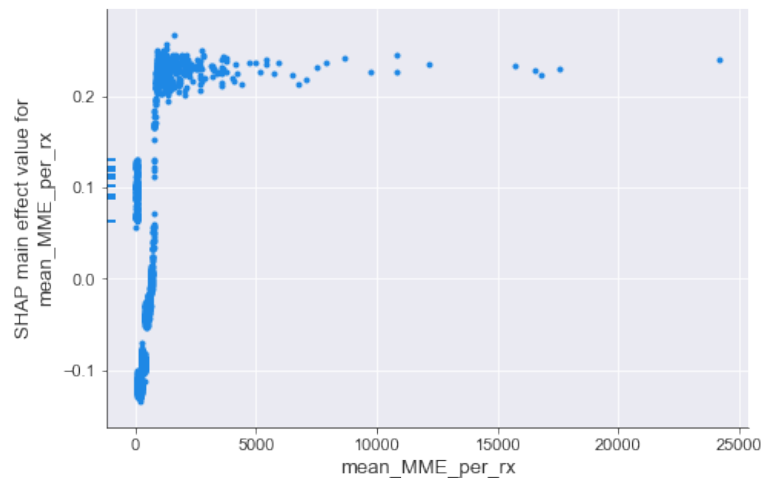

Figure 4.5 SHAP Plot for Mean_MME_Per_RX

5. **Freq_drug_type_IR**:

   The 5th most important feature stands for the frequency of a patient receiving opioid medication in immediate-release formulation (rather than extended-release/long-acting release formulation). *Note that this frequency is standardized for all patients by the number of days on record before their respective anchor day. The frequency of IR type of opioids is positively associated with LTOT once exceed 0.01/day. Refer to Figure 4.6.
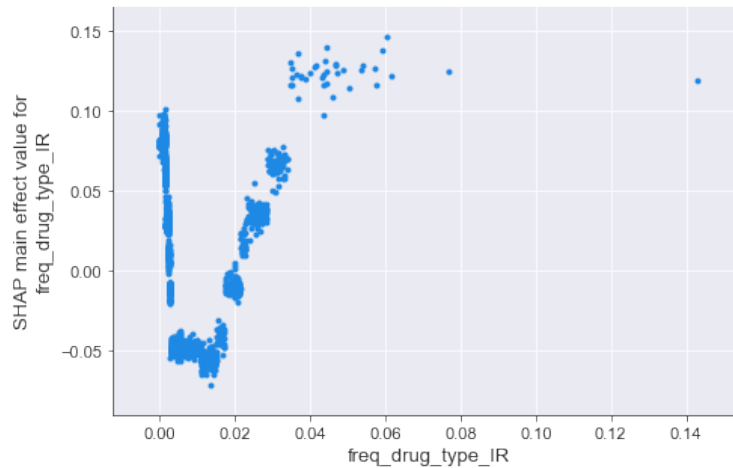

Figure 4.6 SHAP Plot for Freq_drug_type_IR

6. **Freq_MME**:

   It stands for the frequency of a patient's paid claims for an opioid medication. *Note that this frequency is standardized for all patients by the number of days on record before day 0. The SHAP plot shows a negative correlation when the frequency is less than 0.015/day, then a positive correlation when the frequency is greater than 0.015/day, holding other variables constant. Refer to Figure 4.7.
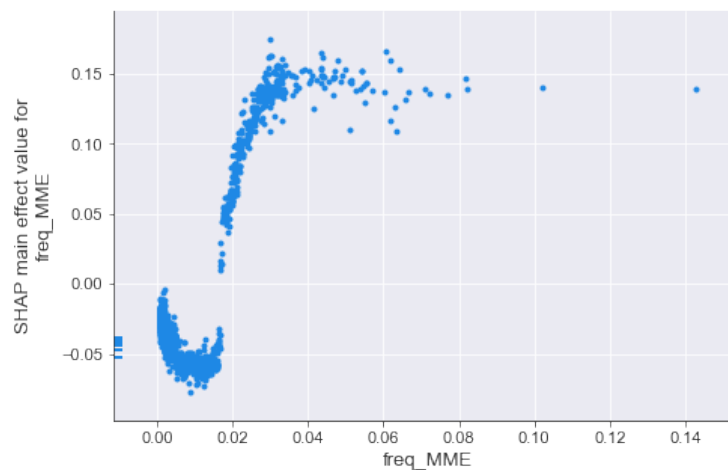

Figure 4.7 SHAP Plot for Freq_MME

7. Other important features:

While the prior features are mostly associated with opioids dosage are significant, the following few attributes also worth our attention. For instance, holding other variables constant, the frequency of a patient receiving opioids prescription from an anesthesiologist is negatively correlated with LTOT probability. Moreover, patients with more frequent claims for anxiety medication have a higher possibility of having LTOT. Refer to Figure 4.8 and 4.9.
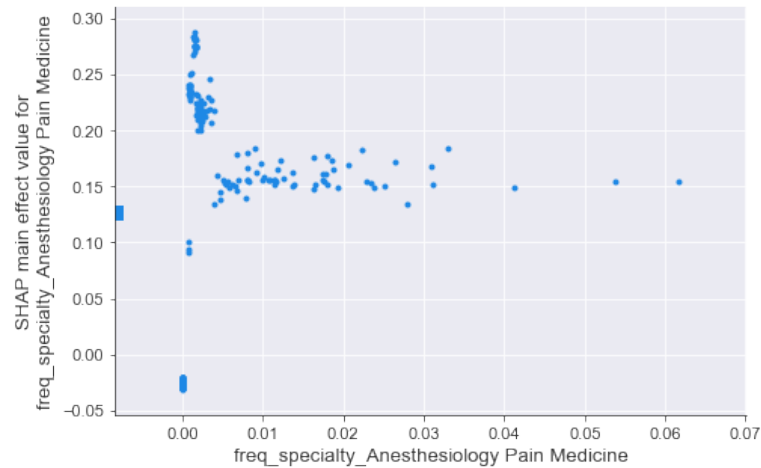

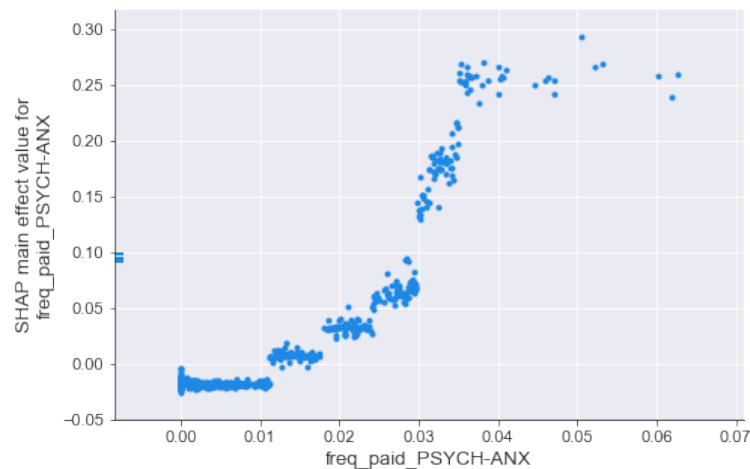*Figure 4.8 SHAP Plot for Freq_Specialty_Anesthesiology*

Figure 4.9 SHAP Plot for Freq_Paid_Psych-Anx

V.   Model Performance Evaluation

As mentioned earlier, the model is evaluated based on ROC and AUC (area under the ROC curve). Models that give curves closer to the top-left corner indicate a better performance. The dashed line along the diagonal acts as a base line, indicating the classification is done randomly (i.e. 50/50). The finalized model as shown in Figure 5.1 of this project output a

desirable AUC score as high as 0.89, implying that the model is pretty good at classifications, and that positive class can be well separated from those negative classes.
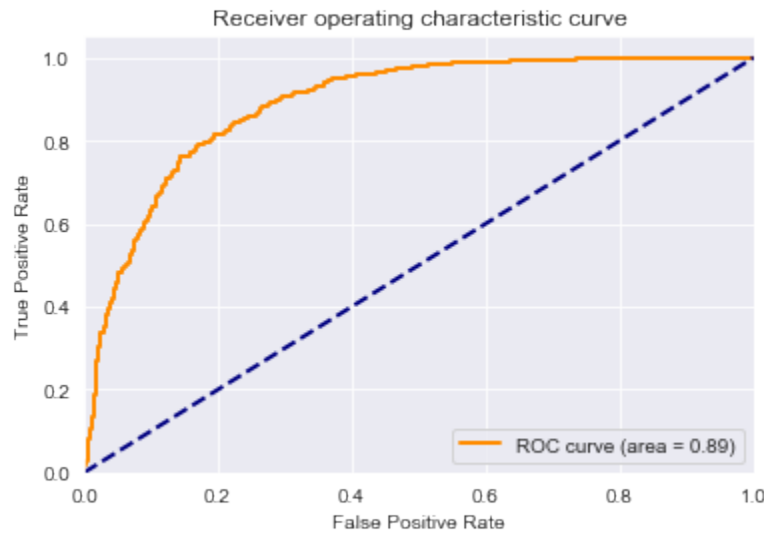

Figure 5.1 ROC and AUC for Final Model

Recommendation and Insights

I.   Suggested Patient Segmentation

To provide actionable recommendation in business context, we design a matrix based on risk of LTOT and difficulty of intervention and select top four significant features as our categorizing criteria: MME dosage, MME frequency, Pay day supply count and IR frequency. Each patient could have high values for all four features (corresponds to low difficulty level of intervention) or low values for all four features (corresponds to high difficulty level of intervention). With the addition of LTOT probability, all patients can be grouped into four types. The relationship can be represented in Figure 6.1 and 6.2.

- **Type 1 - High Risk of LTOT, Low Difficulty in Intervention:**
This group of patients generally have high MME usage, high frequency of prescribing MME, high day counts of having MME on hand high IR usage and hence becomes our top priority to implement early intervention.
- **Type 2 - High Risk of LTOT, High Difficulty in Intervention:**
This group of patients generally have low MME usage, low frequency of prescribing MME, low day counts of having MME on hand, low IR usage and hence leave not much space for improvement. Since this group could not be easily intervened but has a high risk of LTOT, we consider this group of patients as our second priority for action.
- **Type 3 - Low Risk of LTOT, Low Difficulty in Intervention:**
This group of patients generally have high MME usage, high frequency of prescribing MME, high day counts of having MME on hand, high IR usage. Though with possible access to

adjust MME, this group of patients are not with high risk of LTOT and hence becomes our second priority to implement early intervention.

- **Type 4 - Low Risk of LTOT, High Difficulty in Intervention:**

This group of patients generally have low MME usage, low frequency of prescribing MME, low day counts of having MME on hand, low IR usage and hence leave not much space for improvement. With high difficulty in intervention and low probability of LTOT, this type of patients are our last priority to action for early intervention.

	High	Low
High	Type2: High Risk of LTOT High Difficulty in Intervention	Type 4: Low Risk of LTOT High Difficulty in Intervention
Low	Type 1: High Risk of LTOT Low Difficulty in Intervention	Type3: Low Risk of LTOT Low Difficulty in Intervention

Figure 6.1 Classification Matrix on Difficulty in Intervention (x-axis) and Risks of LTOT (y-axis)

	High	Low
High	MME_dosage ($\downarrow$) MME_frequency($\downarrow$) Pay Day Supply Count ($\downarrow$) IR ($\downarrow$)	MME_dosage ($\downarrow$) MME_frequency($\downarrow$) Pay Day Supply Count ($\downarrow$) IR ($\downarrow$)
Low	MME_dosage ($\uparrow$) MME_frequency($\uparrow$) Pay Day Supply Count ($\uparrow$) IR ($\uparrow$)	MME_dosage ($\uparrow$) MME_frequency($\uparrow$) Pay Day Supply Count ($\uparrow$) IR ($\uparrow$)

Figure 6.2 Classification Matrix Based on elasticity in Intervention (x-axis) and Risks of LTOT (y-axis)
Note: $\downarrow$ represents low value, $\uparrow$ represents large value

II.   **Researched Recommendation and Action Plans**

Researched Recommendations:

1. **Opioid Prescription Guideline**
Our model result suggests opioid dosage, frequency, and pay day supply count significantly drive patients' risk of having LTOT. Evidence has also shown that long-term opioid use often begins with treatment of acute pain since higher dosage is needed for relieving the pain.
- Carefully reassess individual benefits and risks, avoiding increasing dosage to $\geq$ 90 MME/day[7].
- Prescribe the shortest effective dosage, i.e. the quantity should not be greater than needed for the expected duration of pain.

2. **Alternative medicines**
Several researches have recently suggested that opioids may not be the best medication in treating chronic non-cancer pain. Non-opioids alternatives, in comparison, have also been found effective and insalubrious in pain control without increasing the risk of opioids addiction. Non-opioid therapies can help ameliorate the severity of pain and reduce the likelihood of opioids dependence, and in some cases, may even help eliminate the need for surgery[8].
- Prescribers should opt for non-opioids medications (e.g. ibuprofen, aspirin) or non-drug therapies (e.g. acupuncture, massage) in the first place.
- Effectively communicate with patients about normalization of pain to prevent exaggerated perception of their pain level.

3. **Anesthesiologists Partnership**
"A patient's first exposure to opioids may be during the perioperative period, a time where anesthesiologists have a significant role in pain management[9]." According to our model results, having the specialty as anesthesiologists of MME prescription is negatively associated with probability of getting LTOT. Hence, we can team up with anesthesiologists during the whole surgical process.

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[7] National Center for Injury Prevention and Control, Centers for Disease Control and Prevention. "CDC Guideline for Prescribing Opioids for Chronic Pain | Drug Overdose | CDC Injury Center." Centers for Disease Control and Prevention, Centers for Disease Control and Prevention, 2019, www.cdc.gov/drugoverdose/prescribing/guideline.html.

[8] American Society of Anesthesiologists. "Non-Opioid Treatment for Chronic Pain - When Seconds Count." *Pain Management Non-Opioid Treatment*, www.asahq.org/whensecondscount/pain-management/non-opioid-treatment/.

[9] Koepke, Elena J., et al. "The Rising Tide of Opioid Use and Abuse: the Role of the Anesthesiologist." Perioperative Medicine, BioMed Central, 3 July 2018, perioperativemedicinejournal.biomedcentral.com/articles/10.1186/s13741-018-0097-4.

- In preoperative period, anesthesiologists can educate patients about anesthesia-related knowledge during anesthesia clinic visits and introduce other opioid-free anesthesia options such as multimodal analgesia to patients.
- In intraoperative and postoperative setting, anesthesiologists can advise physicians or providers outside of initial surgery encounter about appropriate opioid dosage and expected length of prescription to avoid long-term dependence of opioid.

4. **Anxiety**

While it's difficult to determine the causal effect, our model suggests patients with more frequent claims for anxiety medication have a higher possibility of having LTOT. Research has also been found to support bi-directional relationship between opioid abuse and psychological disease[10]. But it's also important to notice that "opioids become less effective if a person suffers from depression, which can lead to increased use to achieve the desired effect"[11].

- Prior to giving opioid subscription, prescribers should first screen patients for symptoms of anxiety
- If patients have dual diagnosis, prescribers should consider tailor treatments to address both conditions

Action Plans Tailored to Patient Segments:

- **Top priority – Type 1: High Risk of LTOT and Low Difficulty of Intervention**
For this group of patients, our primary focus relies on the adjustment on MME dosage and frequency. And it's highly recommended that they be prescribed effective dosage in accordance with the opioid prescription guideline or try out alternative non-opioid medications to help control the MME dosage and frequency.
- **2nd priority – Type 2: High Risk of LTOT and High Difficulty of Intervention**
Since this group of patients display low MME dosage and frequency which is difficult to reduce further, we recommend allocating additional resources to prevent other possible reasons associated with High Risk of LTOT. For instance, if a patient exhibits symptom of anxiety, timely psychological counselling might be necessary to prevent future opioids abuse.
- **2nd priority – Type 3: Low Risk of LTOT and Low Difficulty of Intervention**
For type 3 patients, cost evaluation of early intervening their clinical activities is necessary. If low, it's recommended to strengthen opioid prescription guideline and prescribe

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[10] Smith, K. (2018, November 25). Depression and Opioids: How Painkillers Affect Mental Health. Retrieved from https://www.psycom.net/depression.central.opioid.abuse.html.

11 Scherrer, J. F., Salas, J., Stock, E. M., Ahmedani, B. K., Sullivan, M. D., Burroughs, T., … Bucholz, K. K. (2016). Prescription Opioid Duration, Dose, and Increased Risk of Depression in 3 Large Patient Populations. Retrieved from http://www.annfammed.org/content/14/1/54.

alternative non-opioid medication. If high, continuant monitoring is critical before they develop LTOT.

Possible Impacts to the Business

As outlined earlier, some potential opioids overdose incidents can be early detected and thus intervened based on those influential factors. For instance, for Type 1 members who have high risks of LTOT and low difficulty in preventive measures, reducing the frequency of MME (equivalent to frequency of Prescription opioids) from 0.04/day to 0.02/day while keeping all else the same might help reduce the likelihood of LTOT by almost 67% *(*this figure needs further verification as other features also play a role in affect the LTOT probability)*. This huge reduction in probability of LTOT suggests that appropriate early preventions can save people from substance abuses and potential deaths. It's likely that this person can be successfully converted from high risk of LTOT to low risk of LTOT thus avoid the possibility of substance abuse death.

From the healthcare insurance company's perspective, higher predictive power to identify LTOT patients combined with effective early interventions could significantly save the company's effort and decrease business risk. With sixteen million members that Humana serves, our algorithm could potentially decrease the risk and uncertainty associated with 1.04% of Humana members, which amounts to about 166400 people. Meanwhile, the collaboration between physicians, anesthesiologists, pharmacists, and outside providers would facilitate cost-saving practice in the entire healthcare eco-system. In general, as one of the top crises in US society, opioid epidemic has cost over a trillion dollars since 2001 driven largely by lost earnings and productivity to employers and lost tax revenue for governments[12]. Overall, successful detection of potential LTOT behaviors could save costs of losing productivity, ensure the efficient allocation of health care resources and promise well-beings of Humana members and the public.

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Appendix

Please check out the complete python code, feature matrix, and optimum model in this link
(https://github.com/DataCruncherHumana/Humana-DataCruncher)

- *Humana.ipynb*
  The comprehensive python code we develop for this project, from feature engineering to model performance.
- *Design_matrix.parquet*
  The processed data ready for modeling.
- *Xgb.model*
  XGBoost model with the best set of parameters. This model is applied to HMAHCC_HOLDOUT for predicting and ranking.

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