Opioid Rx ML Model Proposal

Machine Learning to Reduce Opioid Addiction

Introduction

With Machine Learning (ML), we can reduce surplus prescription opioids and positively impact opioid addiction in the United States

The *Opioid Rx ML Model* is a proposed project that will

1. Gather and label new, innovative data
2. Train a ML model to accurately predict post-op opioid usage
3. Provide an access point to physicians to use the model

About the author: Casey Whorton is an experienced Data Scientist and analytics professional who has worked in the healthcare, automotive and manufacturing industries.

> 232,000 Deaths

"From 1999 to 2018, more than 232,000 people died in the United States from overdoses involving to prescription opioids." - Centers of Disease Control

https://www.cdc.gov/drugoverdose/data/prescribing/overview.html

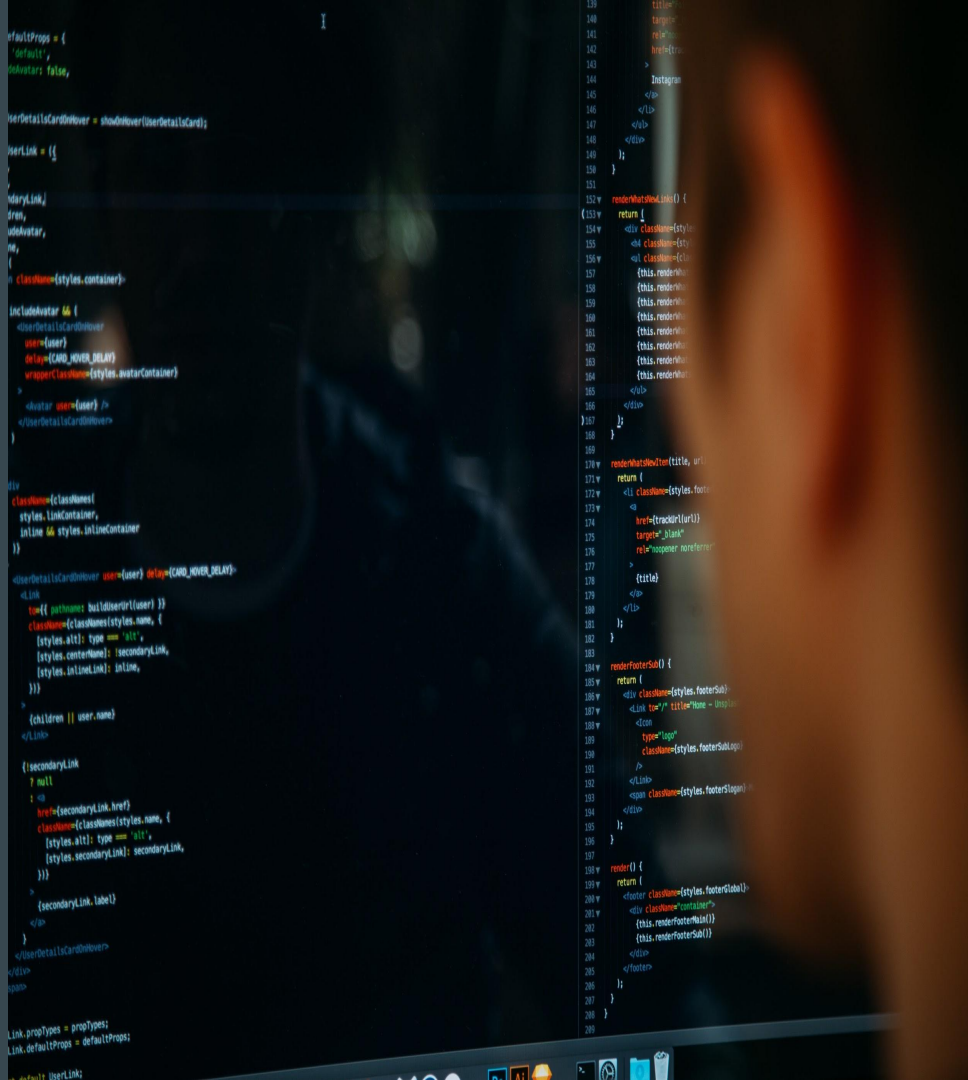
Business Case

- Opioid addiction is considered an epidemic in the United States
  - Sometimes those addicted to opioids move on to even more dangerous substances, such as heroin
- There are many factors that have led to this epidemic, but one could be the over-prescribing of opioids to patients, causing a surplus that can be used for recreational use or black market sale

- *Reducing the number of prescribed opioid medications in circulation is one way to reduce the number of deaths in the future*
- *Cost to the patient can be reduced if the number of pills are reduced.*
- *The cost of treating addicted people can also be reduced nationwide*

Why Machine Learning?

- Manually recording the opioids taken by patients post-op would be time consuming
- Making a tailored forecast for a single patient's opioid usage based on patient records is difficult
- Machine Learning learns the patterns and trends of historic data
- A ML algorithm can tell us, for similar patients, the expected opioid usage
- Machine learning can give unbiased predictions, when trained properly



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Minimal Viable Product (MVP)

Deliverables

Rx Forecast Prediction Model: Trained model that uses patient information, such as demographics, average usage across populations, and other risk factors to forecast the usage of opioids for post-op pain management.

Managed portal to access model: A secure portal where physicians can access the trained model and obtain predictions for new patients.

Defining Success

MAPE (Mean Average Percentage Error): An average error from actual usage of opioids, in percent. Targeting <=10%

Total reduction of prescribed medication (count): A reduction in the annual amount of opioids entering the population.

Total cost reduction ($): A reduction in the annual cost of prescribed medication, in dollars, is required to consider the project a success

MVP Development

From start to launch

Data

People

Model Building

Platform

Timeline

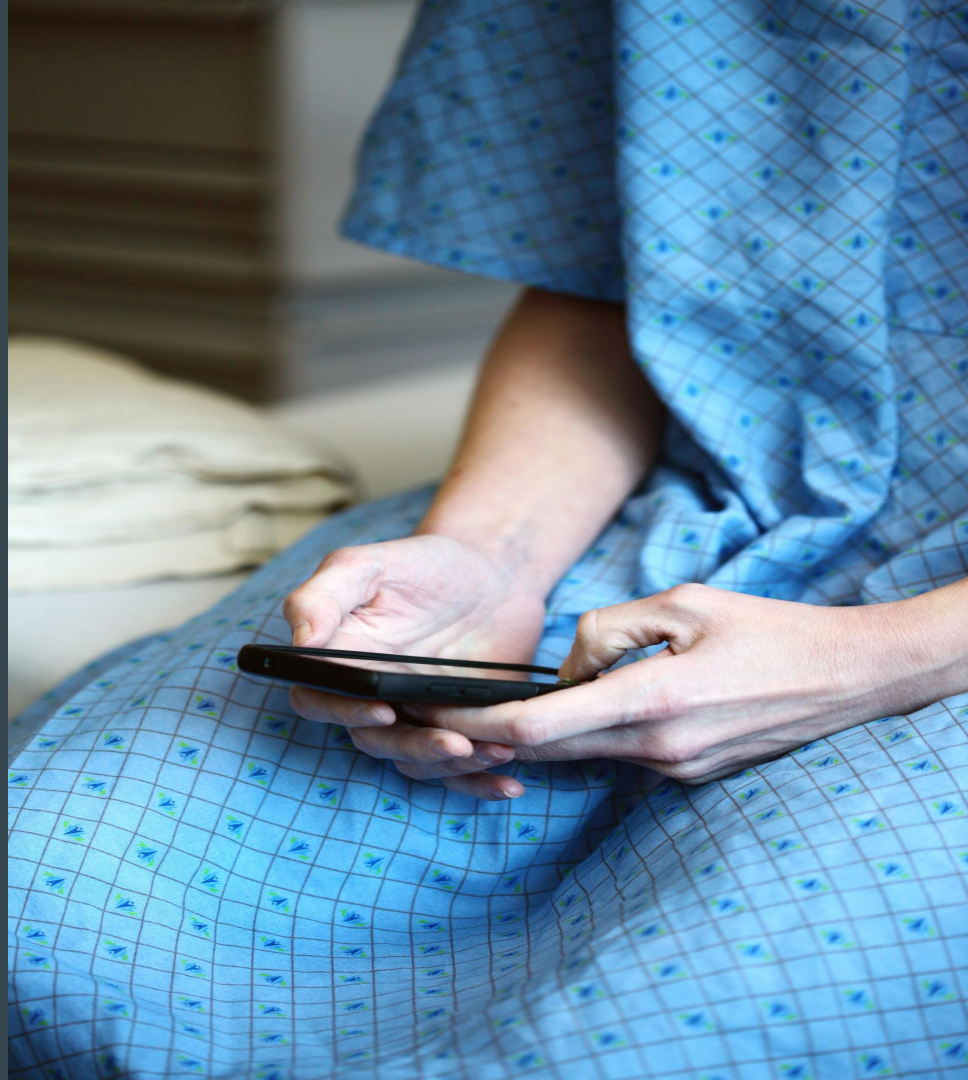
Patient Data

Crucial data for an effective ML model:

1. Who is taking the Opioids after surgery
2. How are they taking opioids after surgery
3. How do patients feel while taking opioids after surgery
4. When do patients no longer need opioids to manage pain

Data gathering & labeling:

- Launch a text messaging system to survey post-op patients
    - Partner with vendor for this service



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People

- MVP Team
  - Prescribing Physician - Subject Matter Expert(s) (SME)
  - AI Product Manager
  - Machine Learning Engineer
  - Data Scientist
  - Data Engineer
  - Web Developers
  - Cloud Architect
- Vendor relationships
  - IT security
  - Phone messaging & survey service
- Onboarding
  - ~ 2 weeks for onboarding with SMEs and on-premises database

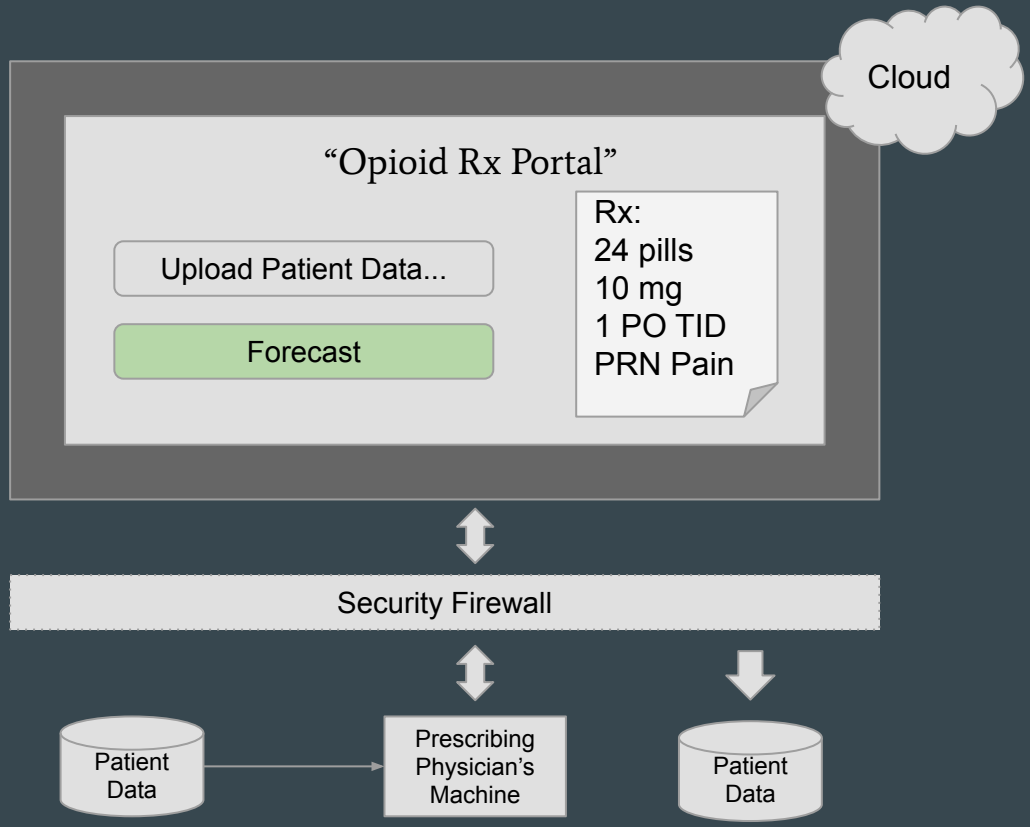
Photo by Nick Fewings on Unsplash

Model Building

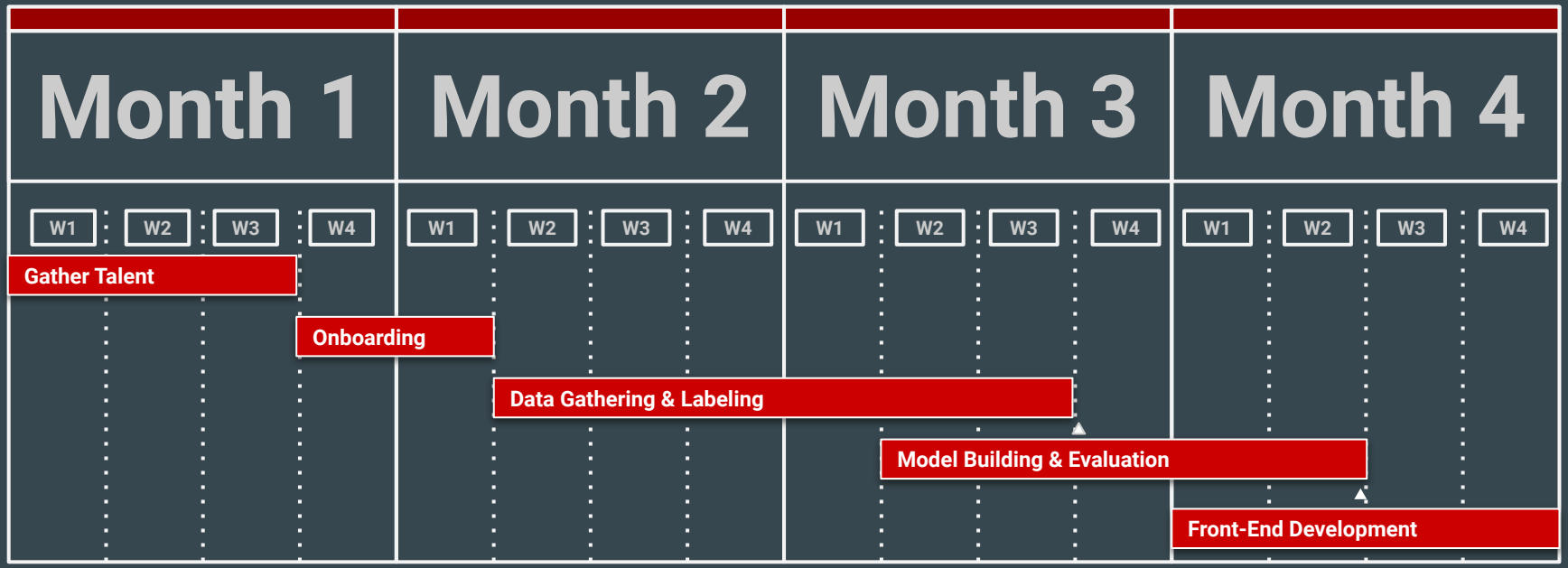
Prerequisite: Acquire Data	Step 1: Data Exploration	Step 2: Train Models	Step 3: Evaluate Best Model on Test Data	Step 4: Launch Decision
Patient data needs to be gathered *before* model building begins.	Explore data for consistency and completeness. Handle missing data and outliers. Look for any bias the data can present to the model.	Using available open-source machine learning toolset, train parameterized models with acquired data.	A test dataset is data never seen by the model during training. Its purpose is to evaluate the model's performance on unseen data.	If model evaluation metrics on test data pass the test, move to launch. If model evaluation metrics do not pass then repeats step 2 and 3 with different technique/data, or halt project.

Managed Platform

- Purpose: where physicians and physician staff get forecast of opioids necessary to cover a patient's post-of pain
- Platform and accessing model API is cloud managed
- Patient data means higher security standards
  - Partner with IT security expert
- Historical predictions will be saved, so security is still important (PHI)
- Using patient data can be either:
  - Entered into platform before prediction, or
  - Uploaded into platform from patient database
- Currently aiming to support single patient prediction



Timeline to MVP Launch



MVP: 3 - 4 Months

Broad talent and quickly launching data gathering and labeling will be key to success

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Phases for Adoption

Phase 1: Proof-of-concept or pilot phase with a single practice that conducts routine wisdom teeth extractions

- Initial model evaluation metrics will be measured and evaluated for accuracy (MAPE, MAE)
- Initial business metrics will be measured and evaluated for a high, medium, or low return on investment (ROI)

Phase 2: Larger representative sample of practices will be signed onto the platform

- Continue model evaluation metrics
- A/B testing with new practices
- Move improved model into production, new version number
- Business metric evaluation
- With a good ROI, move to phase 3

Phase 3: Payed access the portal and model API,

- Gain support from third party hosting the model
- “Go-to-Market”

Go-to-Market Strategy

Product attributes and proof points:

- Trained on data for the most common dental surgery procedures
- Secure, managed platform for predictions
- Reduces cost by <enter phase 1 amount> ($)
- Reduces opioids in population <enter phase 1 amount> (count)

Audience:

- Dental surgery practices & Endodontists
- General surgery practices

Marketing:

- Healthcare conventions
- Email blast-marketing

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Conclusion

With Machine Learning (ML), we can reduce surplus prescription opioids and positively impact opioid addiction in the United States

This plan gives 3 - 4 months to know the viability of this product in the market

Broad talent and quickly launching data gathering and labeling will be key to success

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Appendix

Timeline - Details

- Obtain talent ~ 3 weeks
  - Data gathering and labeling: Data Engineer & Software Engineer
  - Web and front-end (On hold until prototype model is evaluated): Web designer & Cloud architect
  - Model training and evaluation: Machine Learning Engineer
  - Product management: Product Manager
- Onboarding ~ 2 weeks
  - Give team a chance to meet with SMEs, learn about problem, ask questions about data
- Data Gathering and Labeling ~ 6 weeks
  - Software Engineer will prepare text messaging system to gather data
  - Launch text messaging system to patients leaving the practice after wisdom tooth extraction surgery
  - Data Engineer will save data and prepare for training and consumption during serving
- Model training and evaluation ~ 4 weeks
  - ML engineer can prepare concurrently with data gathering
  - Will train model and evaluate against our metrics we require for success
  - Given satisfactory model, go to step 5
- Develop front-end prototype and provision on the cloud ~ 2 weeks
  - Develop user interface (UI) with physician to understand features needed for UI
  - Provision cloud compute, hosting, and security resources for portal and model to be hosted
- Launch