Prescribing of Opioids among Medical Professionals

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Objective

- Detect possible opioid abuse from outliers in opioid claims of health care providers.
- Data Source:
 - Drug claims to Medicare Part D from 2013.
 - https://www.cdc.gov/drugoverdose/pdf/pubs/2018-cdc-drugsurveillance-report.pdf



Source:https://www.healthline.com/health-news/opioids-problems-for-chronic-pain-patients

Background

- In 2016, approximately 63,693 Americans died from drug-overdosing.
- 42,249 (66.4%) involved at least one prescription and/or illegal opioid.
- Due to their addictive nature, opioids are treated as controlled substances in the United States.

https://www.drugabuse.gov/related-topics/trends-statistics/overdose-death-rates



Source:https://www.healthline.com/health-news/opioids-problems-for-chronic-pain-patients

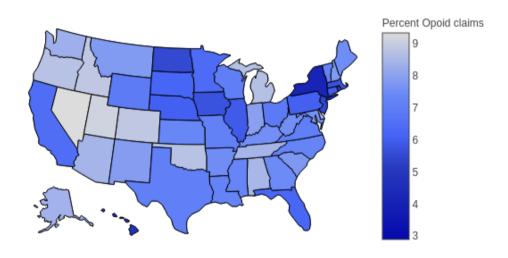
Financial Cost of Opioid Crisis

- In 2016, it was estimated that 11.5 million or 4.3% of US population over the age of twelve misused illegal or prescription opioids.[1]
- Based on 2013 data, it was estimated that the economic burden for the misuse of opioids was \$78.5 billion.[2]
- The health care costs to private insurance companies was \$14.0 thousand per patient.[2]
- It is in the interest of insurance companies to track the misuse to prescription opioids.

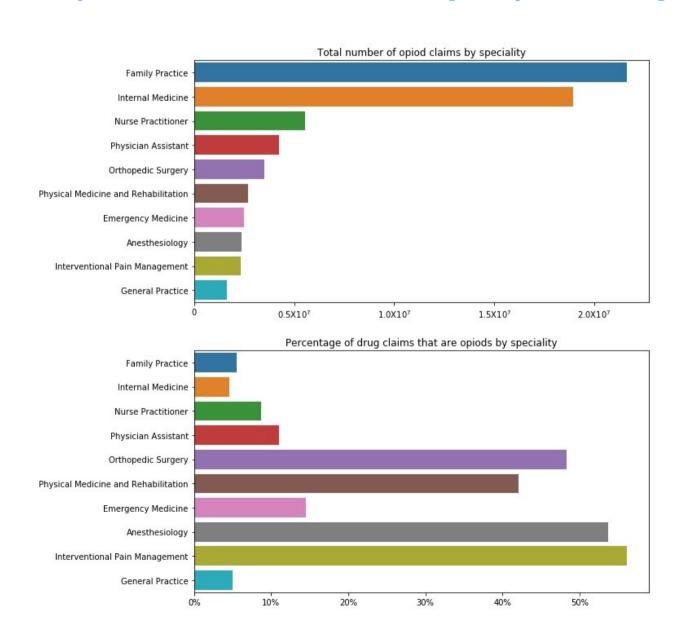
Data Set:

- 2013 dataset providers for each health care provider
 - Name
 - number of opioid and drug claim
 - percentage of claims that are opoids
 - zip code, state, and city
 - specialty
- There are 1,049,326 healthcare providers on the database,
 - 496,744 that prescribe opioids.

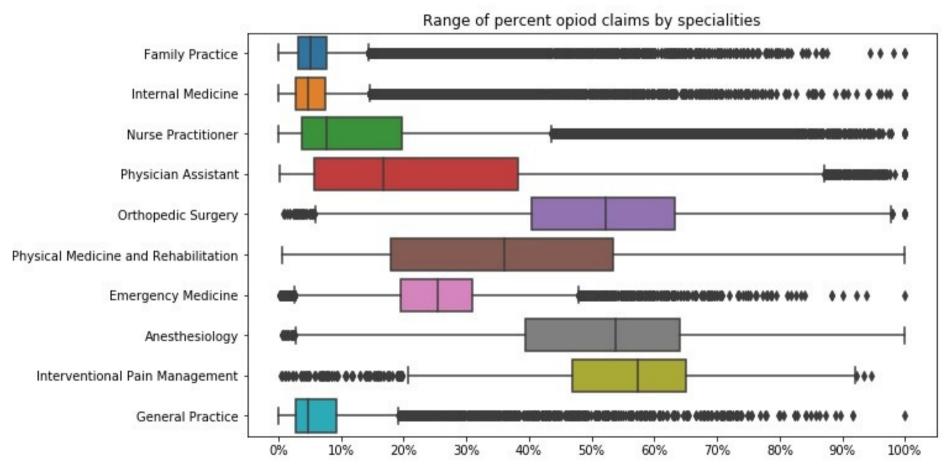
Percent Opioid Claims by State



Top Ten Opioid Prescriber by Specialty



Top Ten Opioid Prescriber Range



 Health care providers that do not prescribe opioids were excluded.

Top Ten Opioid Prescriber Range

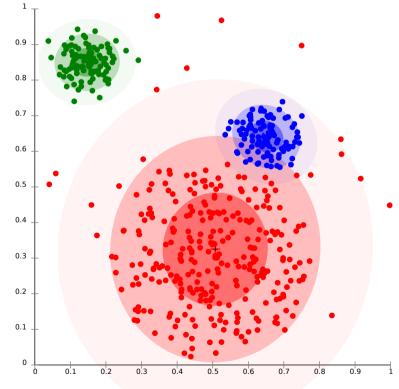
specialty description	median	1Q	3Q	top whisk	bottom whisk	# outliers	# providers	% outliers
Family Practice	5.09	3.28	7.72	14.37	0.00	5267	84070	6.27
Internal Medicine	4.74	2.85	7.55	14.60	0.00	4826	82311	5.86
Nurse Practitioner	7.68	3.77	19.72	43.66	0.00	3883	43495	8.93
Physician Assistant	16.83	5.67	38.24	87.10	0.00	204	40308	0.51
Orthopedic Surgery	52.26	40.35	63.35	97.86	5.85	52	19969	0.26
Physical Medicine and Rehabilitation	36.09	17.87	53.45	100.00	0.00	0	6164	0.00
Emergency Medicine	25.55	19.62	30.97	47.99	2.60	642	36000	1.78
Anesthesiology	53.77	39.48	64.06	100.00	2.61	24	3562	0.67
Interventional Pain Management	57.42	46.90	65.00	92.15	19.75	93	1865	4.99
General Practice	4.80	2.70	9.30	19.19	0.00	790	7143	11.06

 Health care providers that do not prescribe opioids were excluded.

Clustering

Clustering:

- Unsupervised machine learning method
- Used to assign labels to data based on attributes.
- For each specialty,
 - Clusters are created based on attributes
 - Health care provides are assigned a cluster an anomaly detection based on cluster.

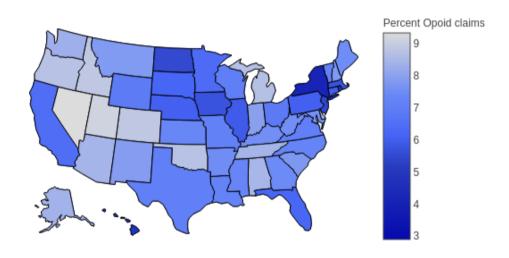


Source: https://en.wikipedia.org/wiki/Cluster_analysis

Why Cluster

- Level of opioid prescribed may be affected by other factors other than specialty.
- For example: Geography.
 Opioid use differs from one geography region to another.
- Once clusters, health care providers that were outliers by their specialty may not be within their cluster.

Percent Opioid Claims by State



Attributes

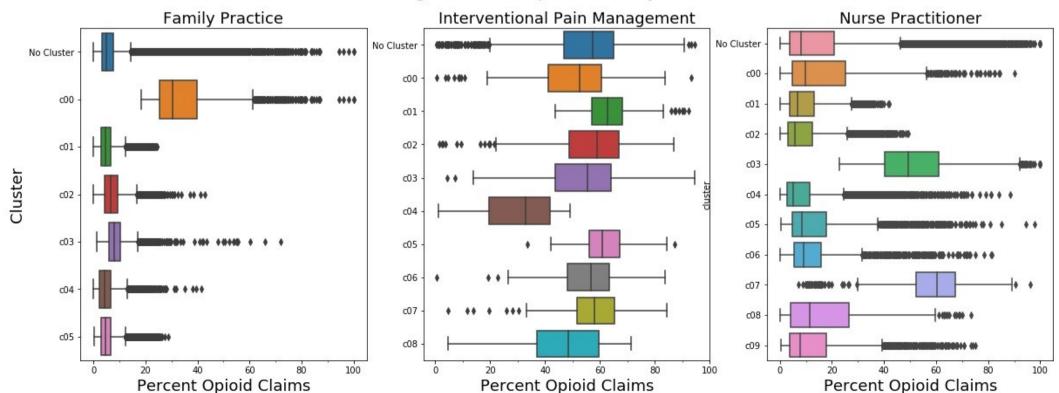
- Attributes were found in additional databases and assigned based on geography.
- Other than percent opioid claims and number of opioid claims, attributes used are:
 - Longitude and latitude
 - City population
 - Temperature (year min, max, and average)
 - City median income
- 4% of health care providers were discarded from dataset because difficult assigning one more attributes.

Source:

- https://simplemaps.com/data/us-zips
- https://www.kaggle.com/berkeleyearth/climate-change-earth-surface-temperaturedata
- https://www.kaggle.com/goldenoakresearch/us-household-income-stats-geo-locations

Clustering Pattern

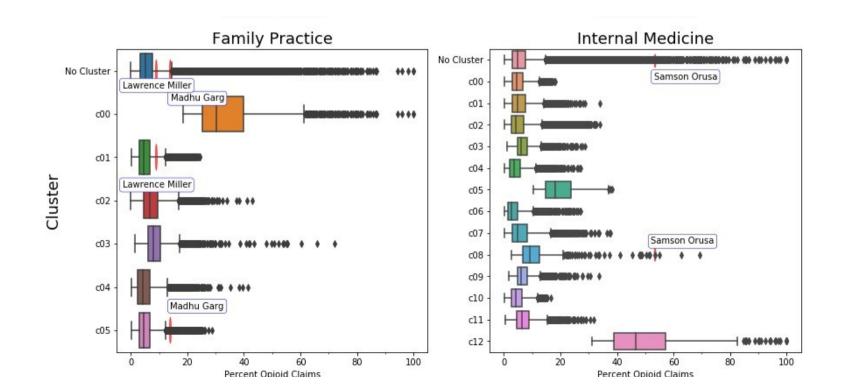
- Of the top ten specialties that proscribe opioids, three clustering patterns
 - Pattern one: family practice, internal medicine, emergency medicine and general practice
 - Pattern two: orthopedic surgery, physical medicine and rehabilitation, anesthesiology, and interventional pain management
 - Pattern three: Nurse practitioners and physician assistant
 Range of Percent Opioid claims By Cluster



Testing model against known cases of fraud

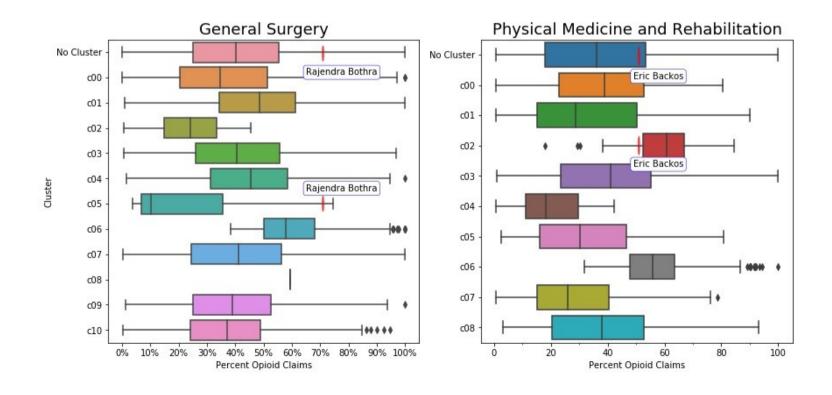
- In 2018, the United States Department of Justice had a massive crackdown on the health care opioid fraud.
 - Of these charged, 162 were prosecuted for prescribing and distributing opioid and other narcotics.
 - Checking numerous articles, four health care providers were charged as part of this investigate and in our database
- An addition doctor in the database was charged 2016 for opioid fraud
- List of doctors:
 - Bothra Rajendra (general surgery)
 - Eric Backo (physical medicine and rehabilitation)
 - Madhu Garg (family practice)
 - Lawrence Miller (family practice)
 - Samson Orusa (internal medicine)

- Madhu Garg, Lawrence Miller, and Samson Orusa
- Two cases of fraud successfully identified as outliers.
- One borderline cases.
- · For Madhu Garg clustering improved anomaly detection



Bothra Rajendra and Eric Backos

- One borderline outlier
- One failed to be detected as an outlier.



Conclusion

- Of the 5 cases of known fraud examined:
 - There were 2 clear cases clear outliers.
 - There were 2 borderline cases.
 - There was one that failed to be marked as anomalous
 - It would be desirable
- It would be desirable to have more cases of known fraud to test model.
- It would be recommended based on the outliers or borderline outliers within a cluster should be examined for possible fraud.
- Clustering help in 2 of the five cases.
- Being anomalous within the cluster is not enough for the health care provider to have opioid

Future Work

- Given the 2 borderline cases, the boundaries for outliers should be examined more closely.
- It may be beneficial to focus on the opioids that are commonly abused, such as oxycodone
- Dollar amount of claims which may be a strong indicator of fraud. This was used by considered by Gleb Esman who worked on a similar project and successfully identified fraudulent claims. [1]

[1] Desman, G. 'Building a \$60 Billion Data Model to Stop US Heathcare Fraud' https://www.splunk.com/blog/2017/09/28/building-a-60-billion-data-model-to-stop-us-healthcare-fraud-with-splunk-and-machine-learning.html.

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