Springboard—DSC Program

Capstone Project 1 Milestone Report

Determining the Likelihood and Type of Drug Abuse Visits to Emergency Departments in the US

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Background

According to The National Institute on Drug Abuse, "Addiction is a chronic disease characterized by drug seeking and use that is compulsive, or difficult to control, despite harmful consequences. The initial decision to take drugs is voluntary for most people, but repeated drug use can lead to brain changes that challenge an addicted person's self-control and interfere with their ability to resist intense urges to take drugs. These brain changes can be persistent, which is why drug addiction is considered a "relapsing" disease—people in recovery from drug use disorders are at increased risk for returning to drug use even after years of not taking the drug."[1]

Drug abuse occurs when a person takes a substance, whether illegal, prescribed or over the counter, for purposes other than those in which they are meant to be used, or when a person takes large quantities of the substance. Typically, the person is using the drug to alter his or her mood or feel better and not for a health reason.

Statistics for drug abuse include:

- Almost 21 million Americans have at least one addiction, yet only 10% of them receive treatment.[2]
- Drug overdose deaths have more than tripled since 1990.[2]
- From 1999 to 2017, more than 700,000 Americans died from overdosing on a drug.[2]
- More than 90% of people who have an addiction started to drink alcohol or use drugs before they were 18 years old.[2]
- Americans between the ages of 18 and 25 are most likely to use addictive drugs.[2]
- Alcohol and drug addiction cost the U.S. economy over $600 billion every year.[2]
- During 2008–2011, an average of 1.1 million emergency department (ED) visits were made each year for drug poisoning, with a visit rate of 35.4 per 10,000 persons.[3]

- About one-quarter (24.5%) of drug-poisoning ED visits resulted in hospital admission.[3]

Client and Problem Statement

Emergency Departments in hospitals nationwide must be prepared to accept patents that are suffering from drug abuse. They need to plan for enough staffing and supplies to handle the expected types and percentages of drug abuse related Emergency Department visits so that the departments can be prepared with enough staffing, medications, procedures, etc. to properly deal with these cases and have good outcomes.

Dataset

The Drug Abuse Warning Network (DAWN) is a public health surveillance system that monitors drug abuse related visits to emergency departments in hospitals in large metro areas across the US. According to the Substance Abuse and Mental Health Services Administration (SAMHDA),

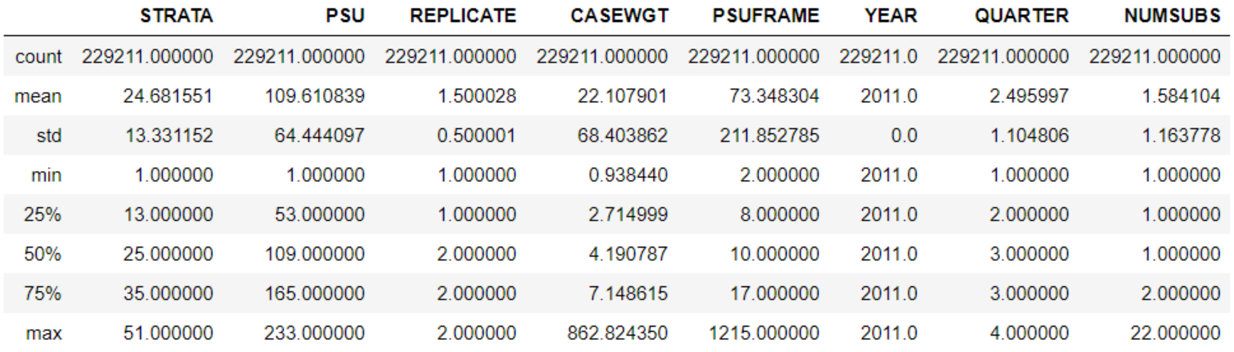
> “A DAWN case is any ED visit involving recent drug use that is implicated in the ED visit. DAWN captures both ED visits that are directly caused by drugs and those in which drugs are a contributing factor, but not the direct cause of the ED visit. Annually, DAWN produces estimates of drug-related visits to hospital EDs for the nation as a whole and for selected metropolitan areas.
>
> DAWN is used to monitor trends in drug misuse and abuse, identify the emergence of new substances and drug combinations, assess health hazards associated with drug abuse, and estimate the impact of drug misuse and abuse on the Nation’s health care system. DAWN relies on a longitudinal probability sample of hospitals located throughout the United States.
>
> To be eligible for selection into the DAWN sample, a hospital must be a non-federal, short-stay, general surgical and medical hospital located in the United States, with at least one 24-hour ED. The dataset includes demographics, drugs involved in the ED visit (up to 16 drugs from 2004 through 2008 and up to 22 drugs from 2009 through 2011), toxicology confirmation, route of administration, type of case, and disposition of the patient following the visit.
>
> Prepared DAWN Emergency Department National and Metro data tables are available on the DAWN website. The DAWN website also provides access to DAWN reports.”[4]

Data Wrangling

The initial step in the project was to 'wrangle' the data, which is the process of taking raw data and transforming it into a format that is suitable for analysis.

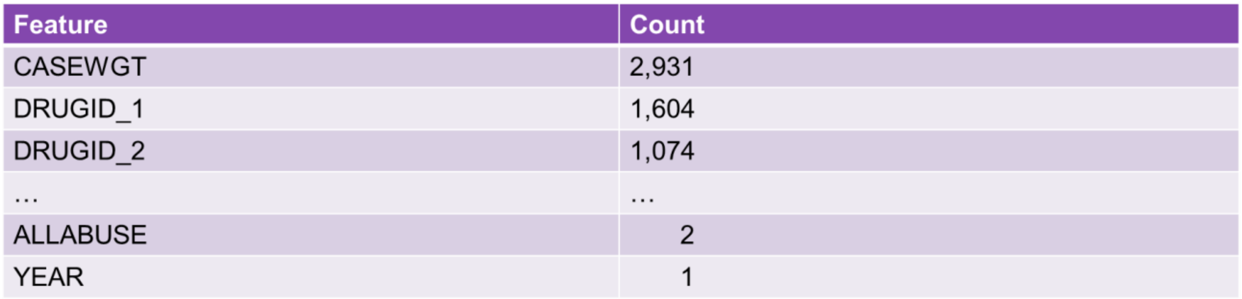
First, the DataFrame was examined to see its size and column names. It has 284 columns, and 229,221 rows. Since the DataFrame is very large and somewhat unwieldy, the decision was made to remove the 'sdled' and 'CATID' columns. These columns won't be used in the analysis because their inclusion is beyond the scope of this project. The modified DataFrame has 84 columns.

Second, summary data for all columns was obtained. Below are the results:



	STRATA	PSU	REPLICATE	CASEWGT	PSUFRAME	YEAR	QUARTER	NUMSUBS
count	229211.000000	229211.000000	229211.000000	229211.000000	229211.000000	229211.0	229211.000000	229211.000000
mean	24.681551	109.610839	1.500028	22.107901	73.348304	2011.0	2.495997	1.584104
std	13.331152	64.444097	0.500001	68.403862	211.852785	0.0	1.104806	1.163778
min	1.000000	1.000000	1.000000	0.938440	2.000000	2011.0	1.000000	1.000000
25%	13.000000	53.000000	1.000000	2.714999	8.000000	2011.0	2.000000	1.000000
50%	25.000000	109.000000	2.000000	4.190787	10.000000	2011.0	3.000000	1.000000
75%	35.000000	165.000000	2.000000	7.148615	17.000000	2011.0	3.000000	2.000000
max	51.000000	233.000000	2.000000	862.824350	1215.000000	2011.0	4.000000	22.000000

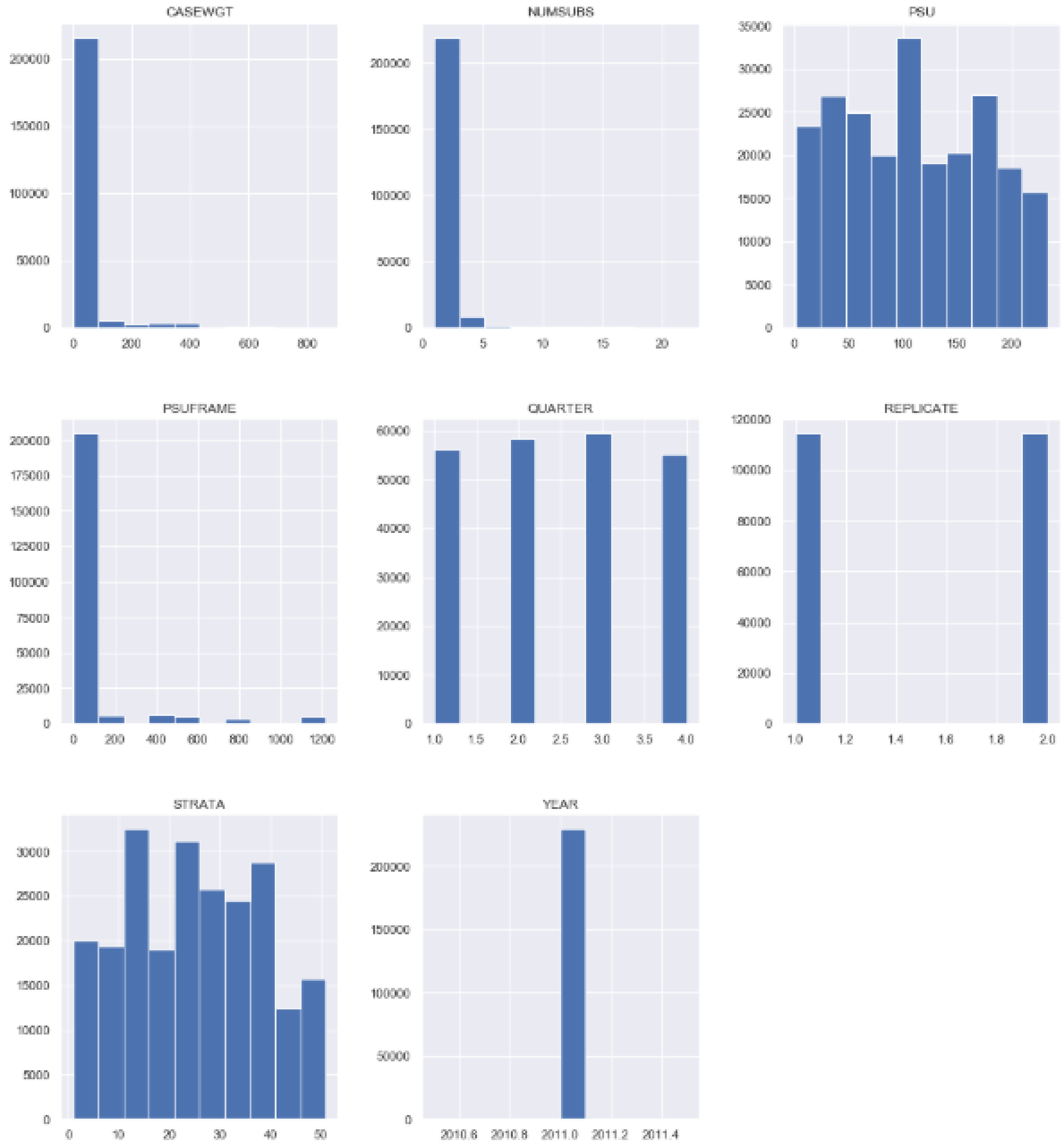
Next, the number of distinct values per column was counted. The results are below:



Feature	Count
CASEWGT	2,931
DRUGID_1	1,604
DRUGID_2	1,074
…	…
ALLABUSE	2
YEAR	1

Many of the variables in the DataFrame are categorical but are represented by numbers. In order to tell the data story better, it was decided to replace the numbers with the corresponding label. This replacement was done for all the variables including the 2600 drug names in the data glossary that was available with the dataset. Also, though there exists a shorter, cleaner way to perform the replacements than to do them one by one, due to time constraints, it was decided to use the method that is working rather than spend more time researching a more 'pythonic' method. Additionally, there were too many drug names to replace them using the same method as with the others. Therefore, it was decided to replace them by importing a dictionary and mapping the names to the numbers.

Then, subplot histograms of all quantitative variables were plotted. The resulting plots are below:

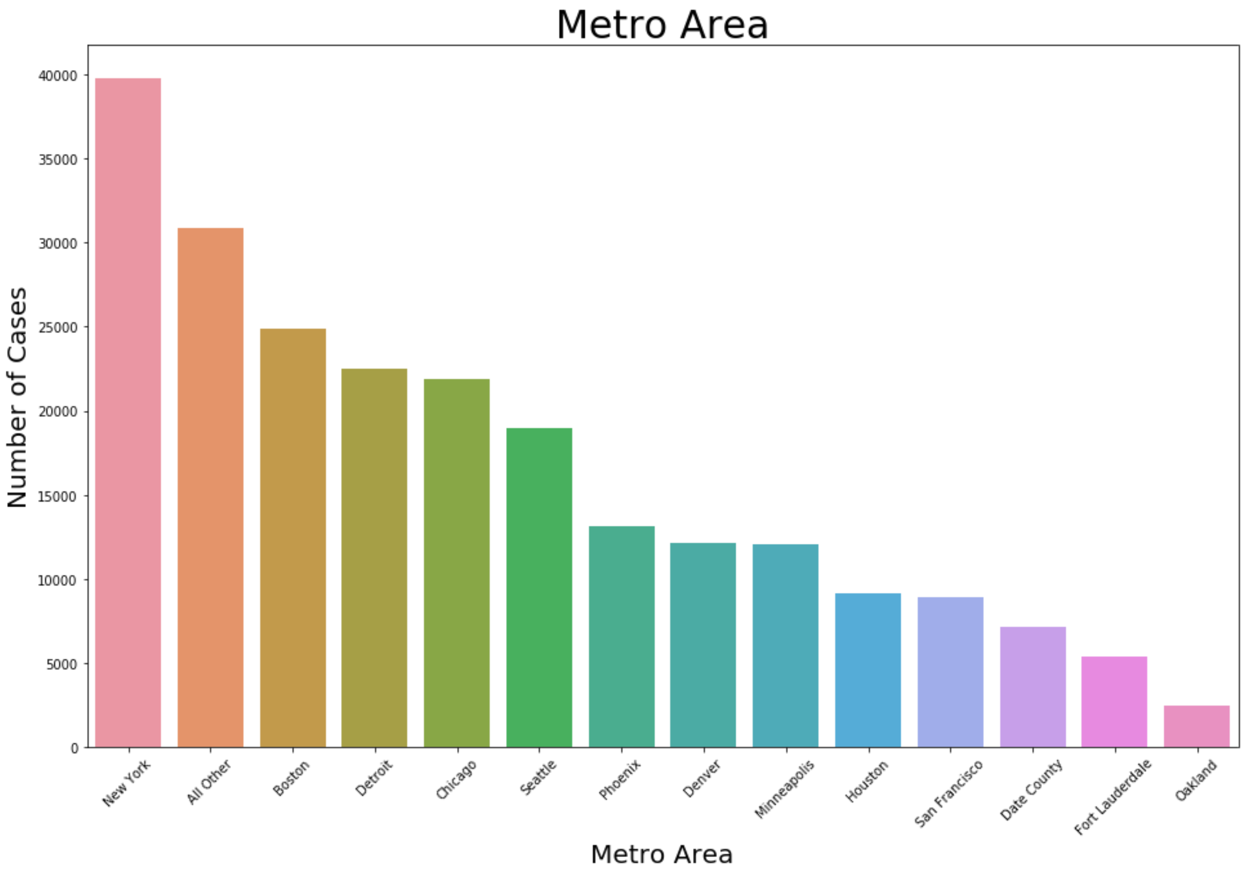


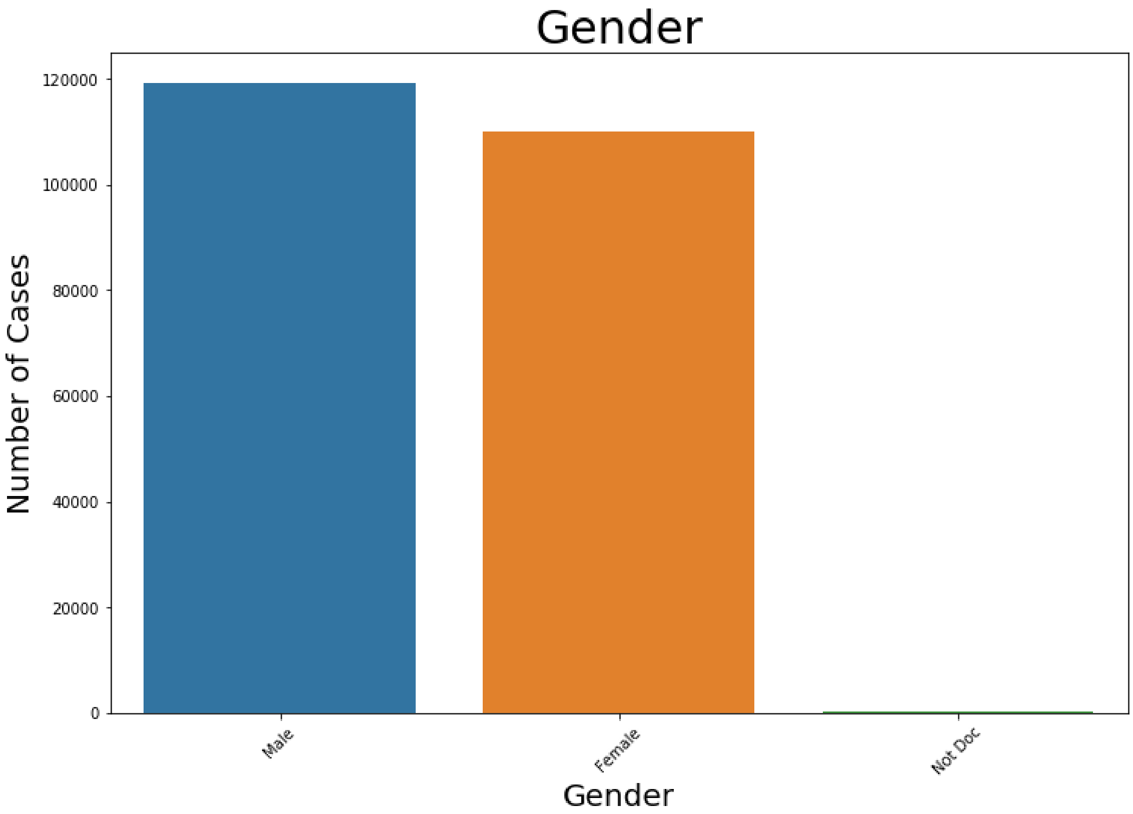
Finally, the DataFrame was checked for missing values. None were found.

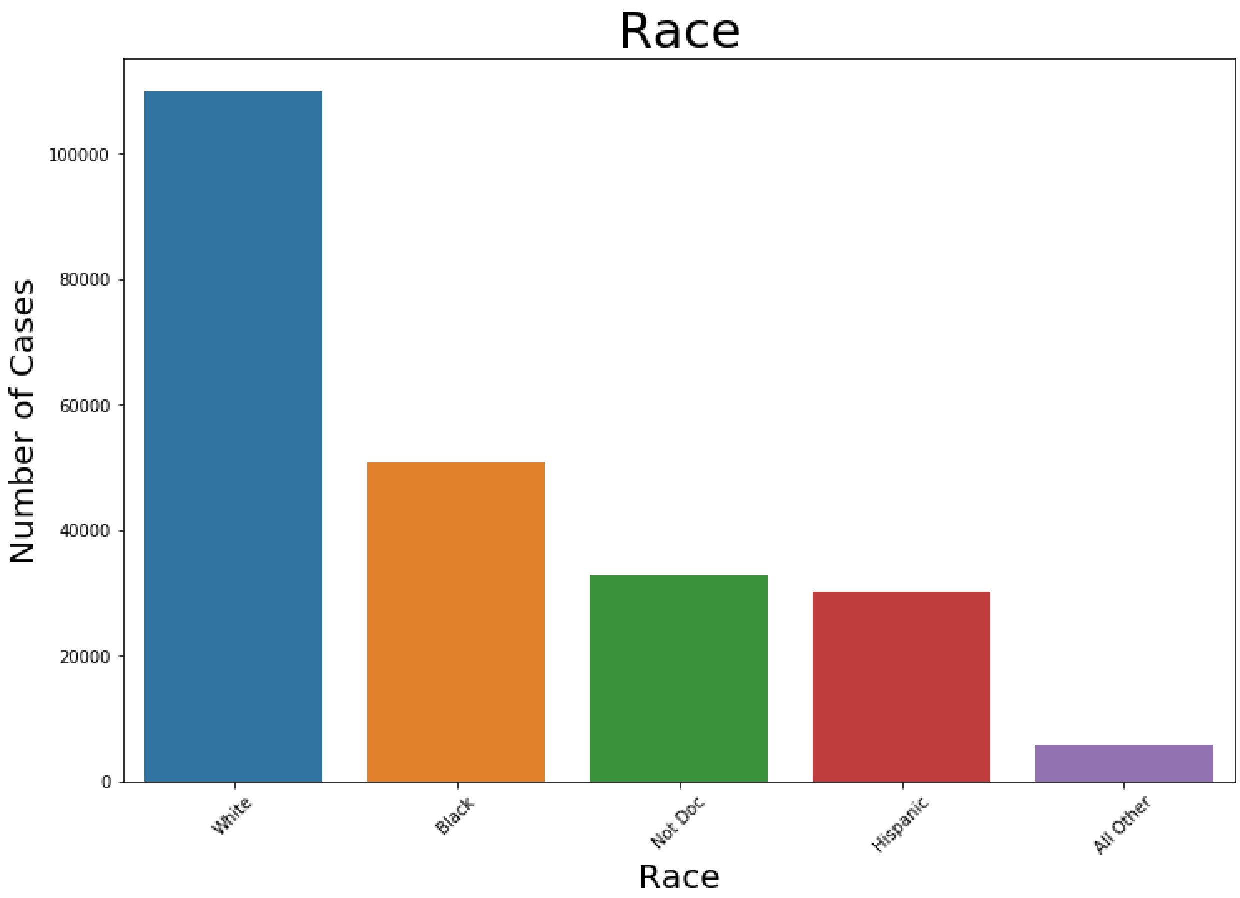
In summary, this data set has 86 columns and 229,211 rows. Most of the variables are categorical. In the original data set, the categorical variables were represented by numbers. Steps were taken to replace the numbers with their corresponding names. Since the DataFrame is very large and somewhat unwieldy the decision was made to remove the 'sdled' and 'CATID' columns. These columns won't be used in the analysis because their inclusion is beyond the scope of this project. Additionally, the number of distinct values for each variable was plotted, subplot histograms of the quantitative variables were plotted, and it was determined that the data set did not include any missing values.

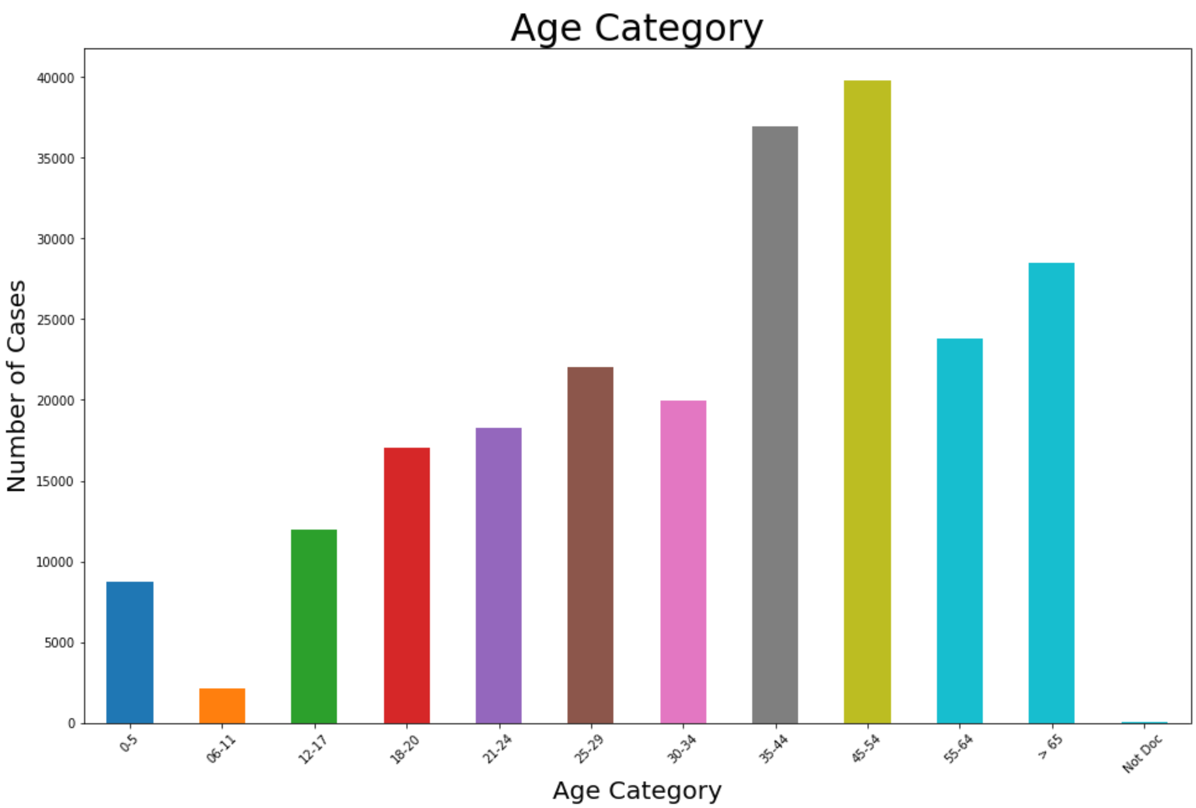
Data Story

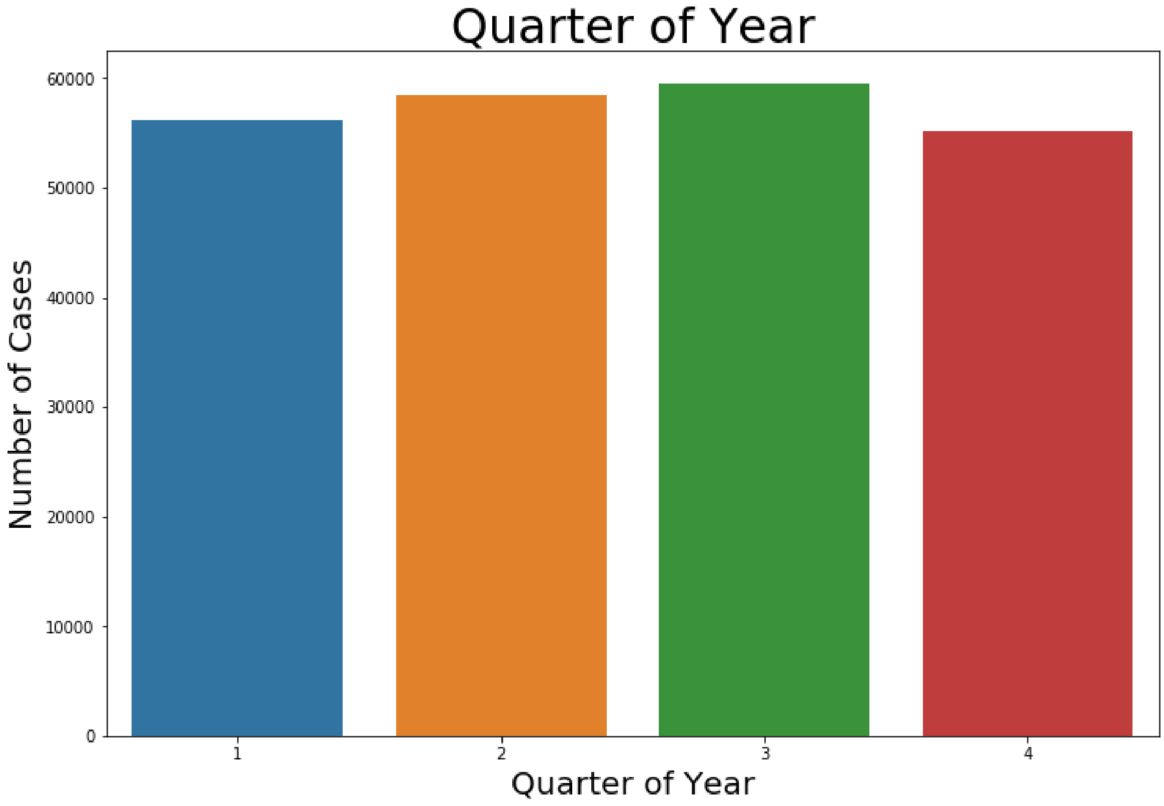
With the data wrangling done, it's time to see what story the data tells. In order to do this, all the categorical variables were plotted. The plots are below:

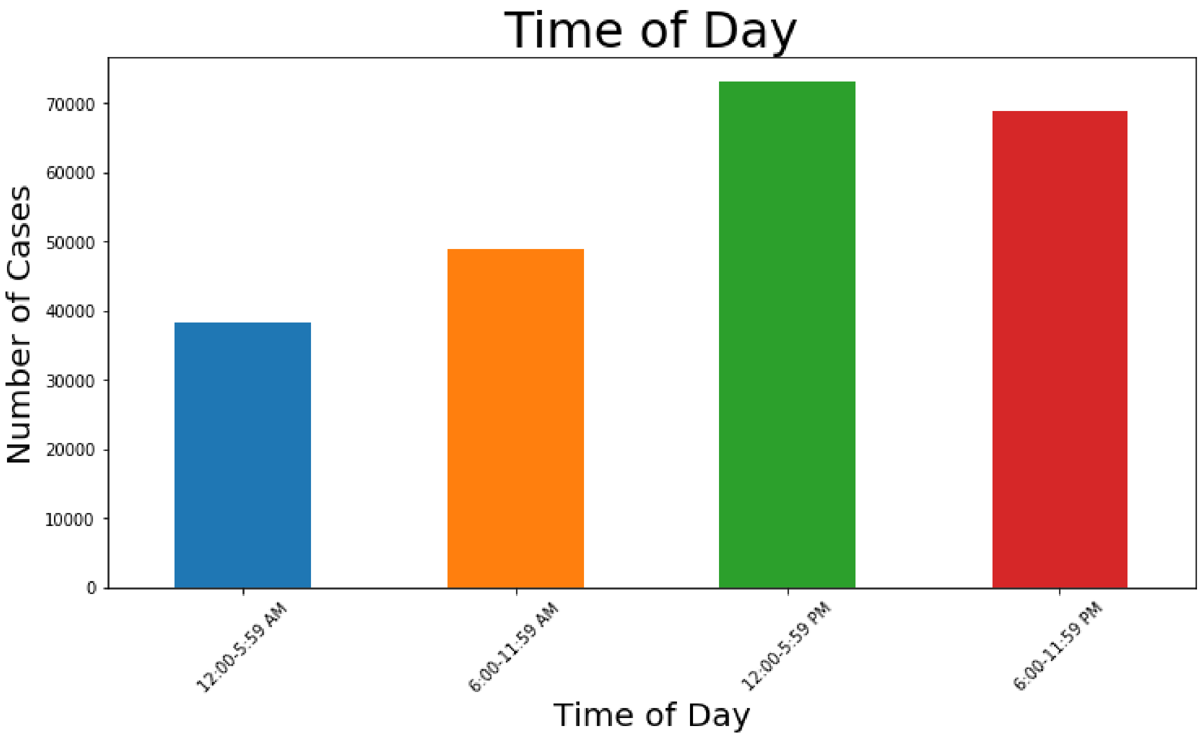



Gender
Number of Cases
120000
100000
80000
60000
40000
20000
0
Male
Female
Not Doc
Gender

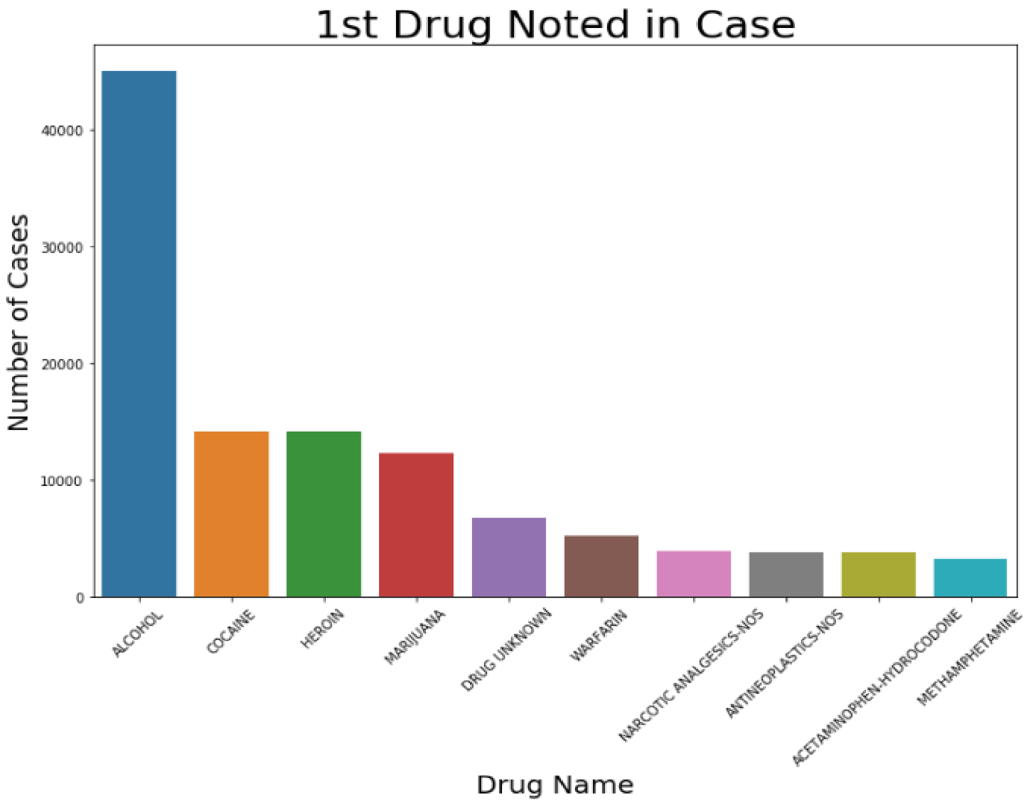

Race
Number of Cases
0
20000
40000
60000
80000
100000
White
Black
Not Doc
Hispanic
All Other
Race

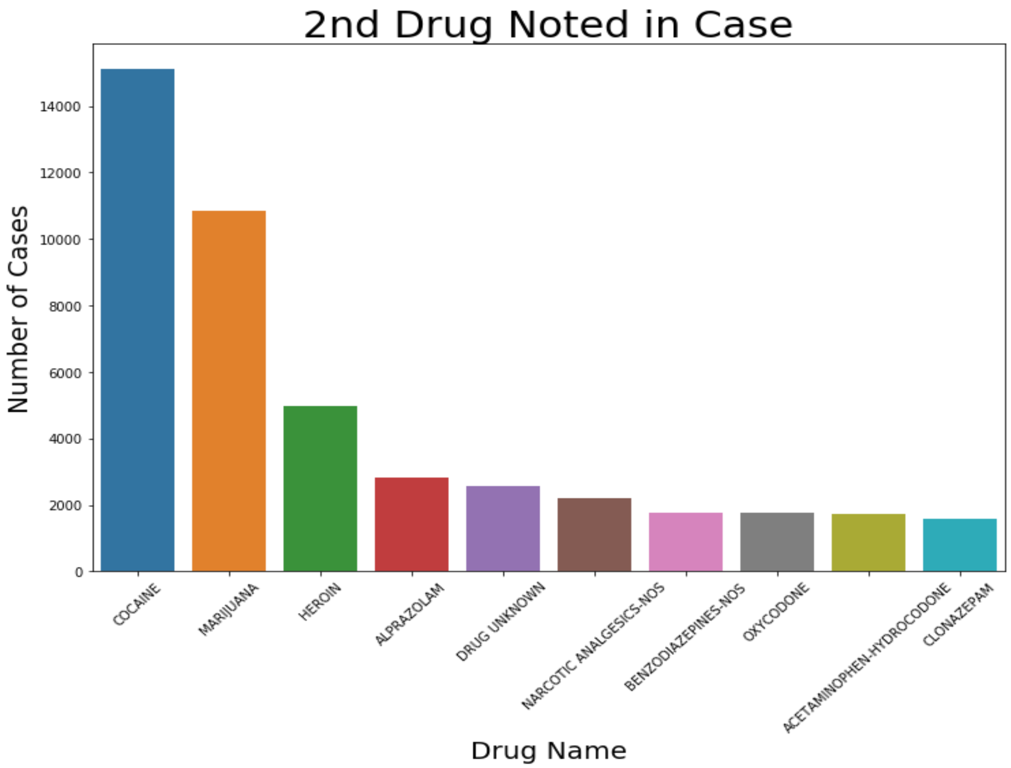

Age Category
Number of Cases
40000
35000
30000
25000
20000
15000
10000
5000
0
0-5
06-11
12-17
18-20
21-24
25-29
30-34
35-44
45-54
55-64
> 65
Not Doc
Age Category

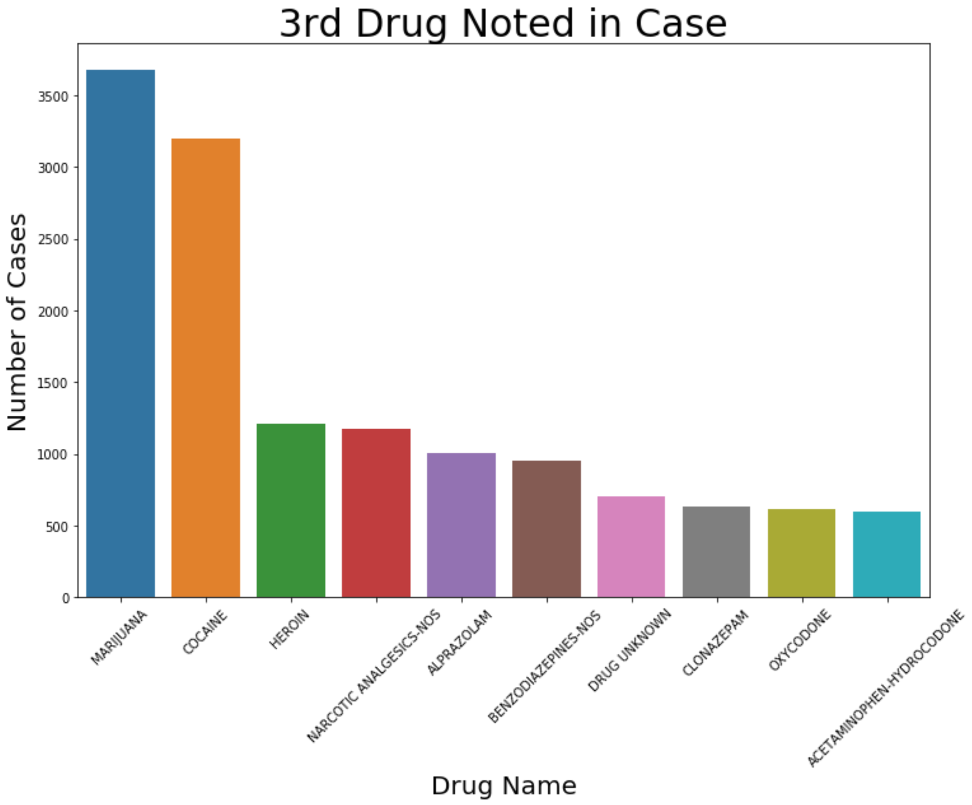

Quarter of Year
Number of Cases
60000
50000
40000
30000
20000
10000
0
1
2
3
4
Quarter of Year



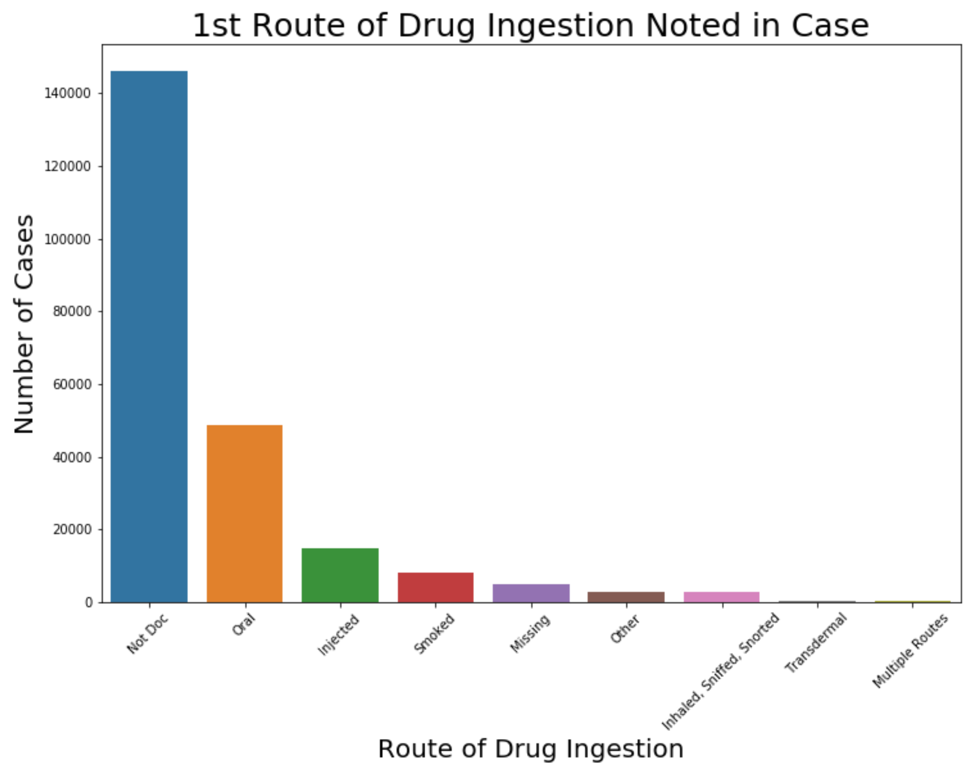
When plotting the distribution of the Drug(s) involved in the cases, it was decided to show only top 10 since there are > 2600 drugs possible. Otherwise, the graph would be too large and hard to read. Also, there were up to 22 substances involved in one case, and a plot was done for each instance. In order to be concise and deliver the main points of the content, the body of this paper does not contain all 22 of the graphs. The first few are included here, and the others are included in the appendix at the end of the document.

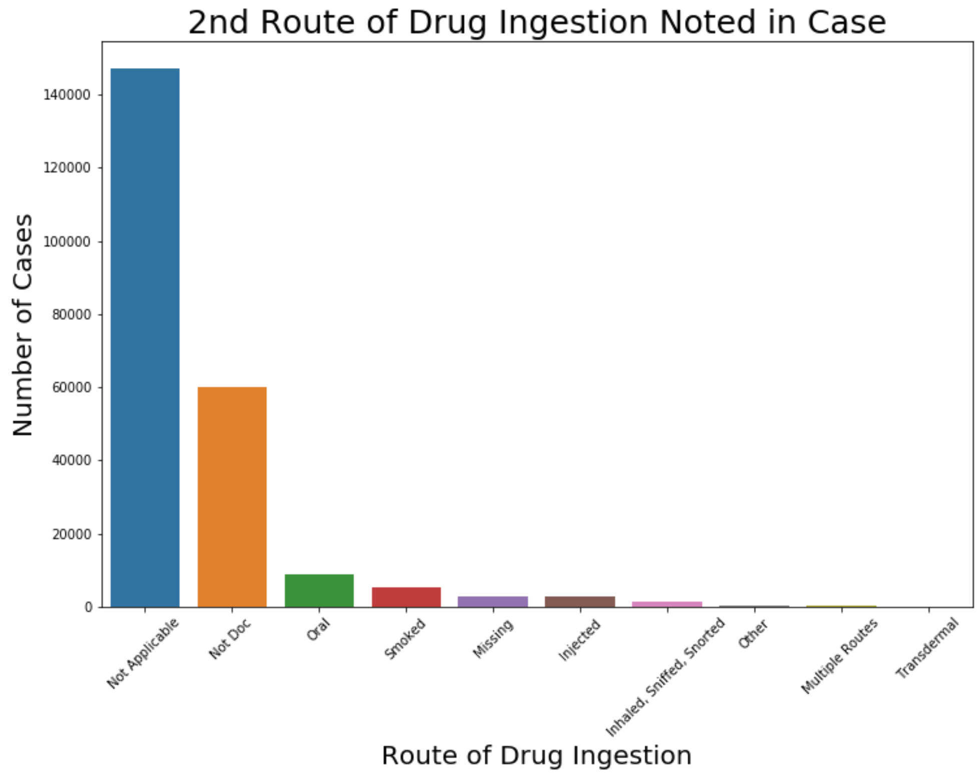

1st Drug Noted in Case
Number of Cases
0
10000
20000
30000
40000
ALCOHOL
COCAINE
HEROIN
MARIJUANA
DRUG UNKNOWN
WARFARIN
NARCOTIC ANALGESICS-NOS
ANTINEOPLASTICS-NOS
ACETAMINOPHEN-HYDROCODONE
METHAMPHETAMINE
Drug Name

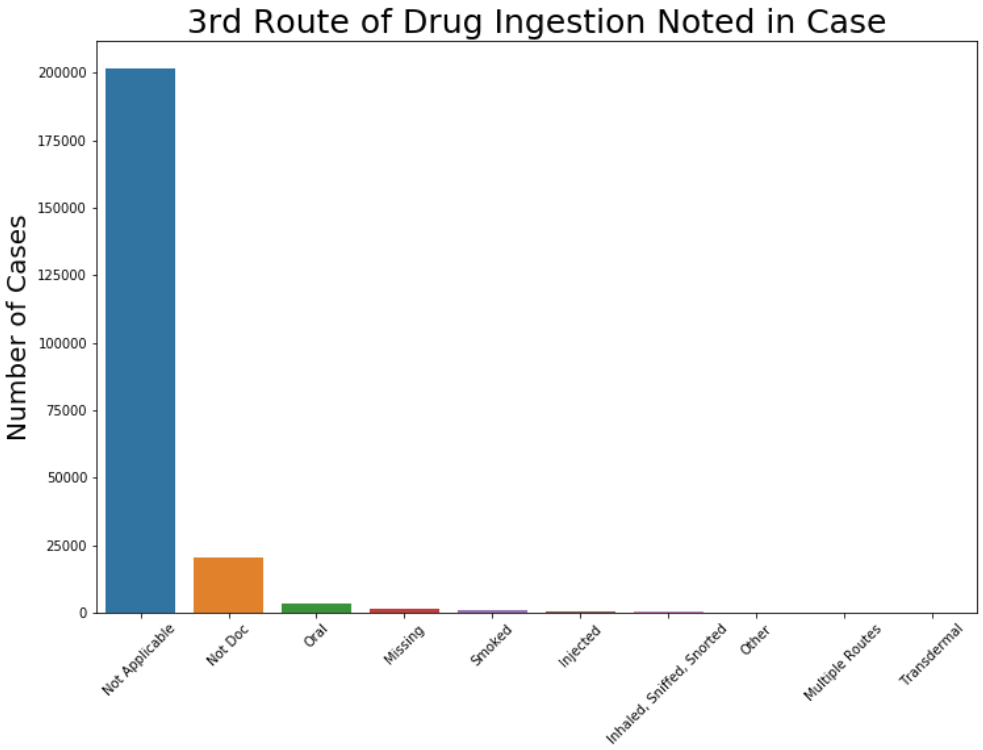

2nd Drug Noted in Case
Number of Cases
0
2000
4000
6000
8000
10000
12000
14000
COCAINE
MARIJUANA
HEROIN
ALPRAZOLAM
DRUG UNKNOWN
NARCOTIC ANALGESICS-NOS
BENZODIAZEPINES-NOS
OXYCODONE
ACETAMINOPHEN-HYDROCODONE
CLONAZEPAM
Drug Name



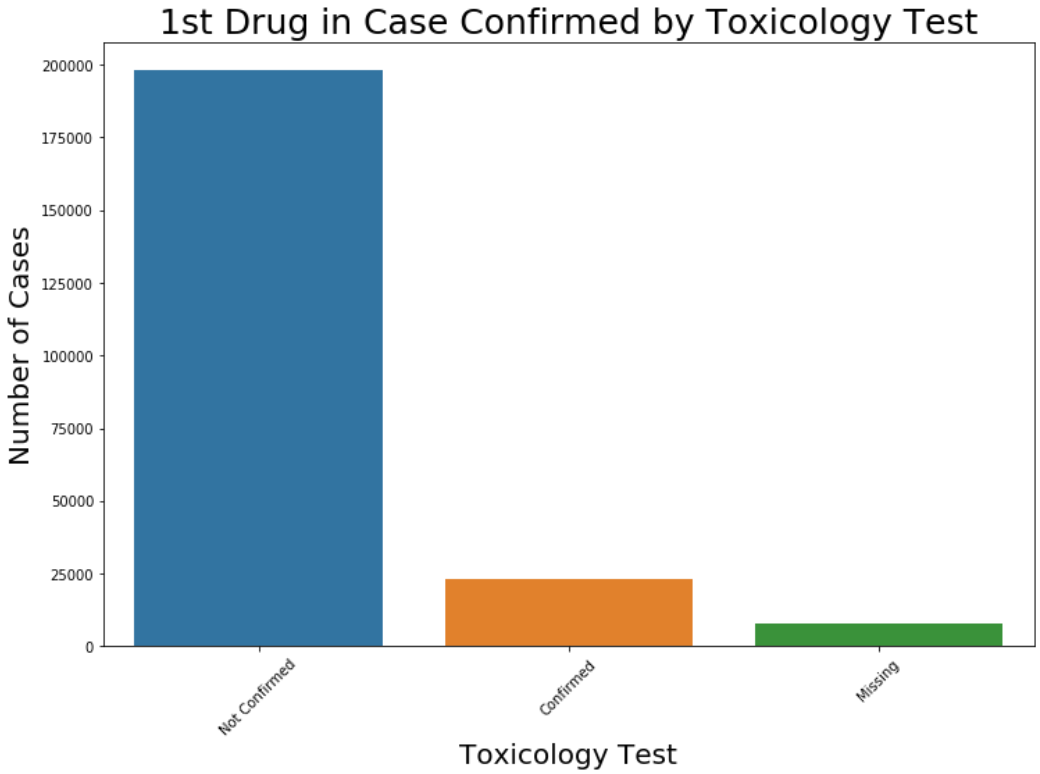
As with plotting the distribution of the Drug(s) involved in the cases, there were up to 22 routes of ingestion for substances involved in one case, and a plot was done for each instance. In order to be concise and deliver the main points of the content, the body of this paper does not contain all 22 of the graphs. The first few are included here, and the others are included in the appendix at the end of the document.

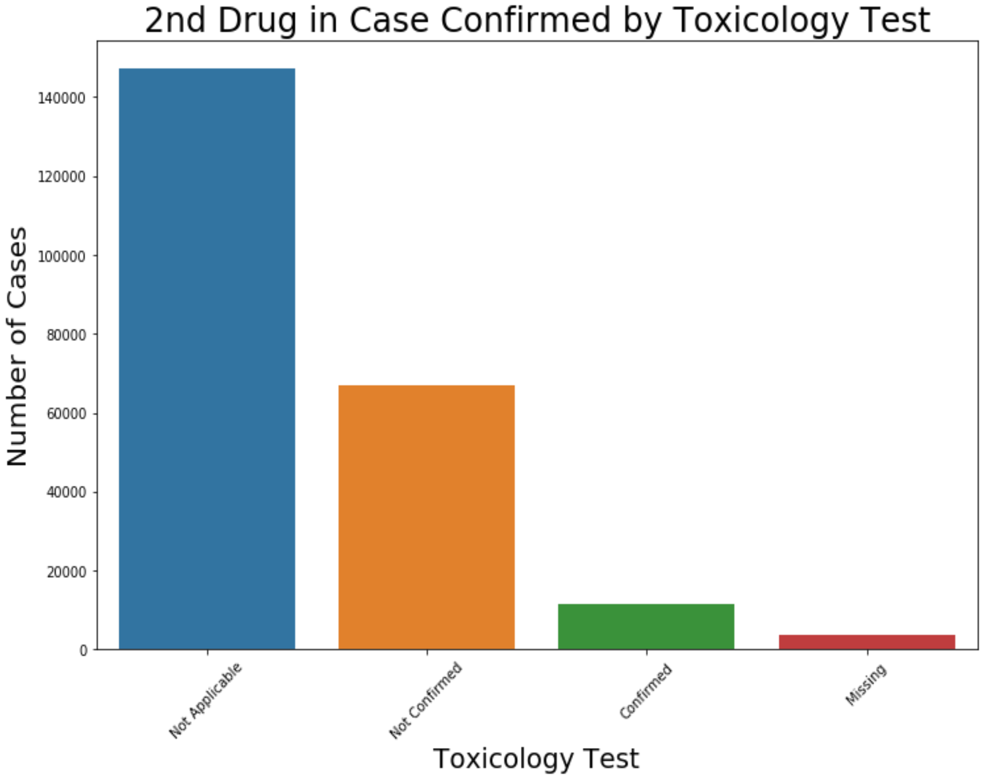

1st Route of Drug Ingestion Noted in Case
Number of Cases
140000
120000
100000
80000
60000
40000
20000
0
Not Doc
Oral
Injected
Smoked
Missing
Other
Inhaled, Sniffed, Snorted
Transdermal
Multiple Routes
Route of Drug Ingestion

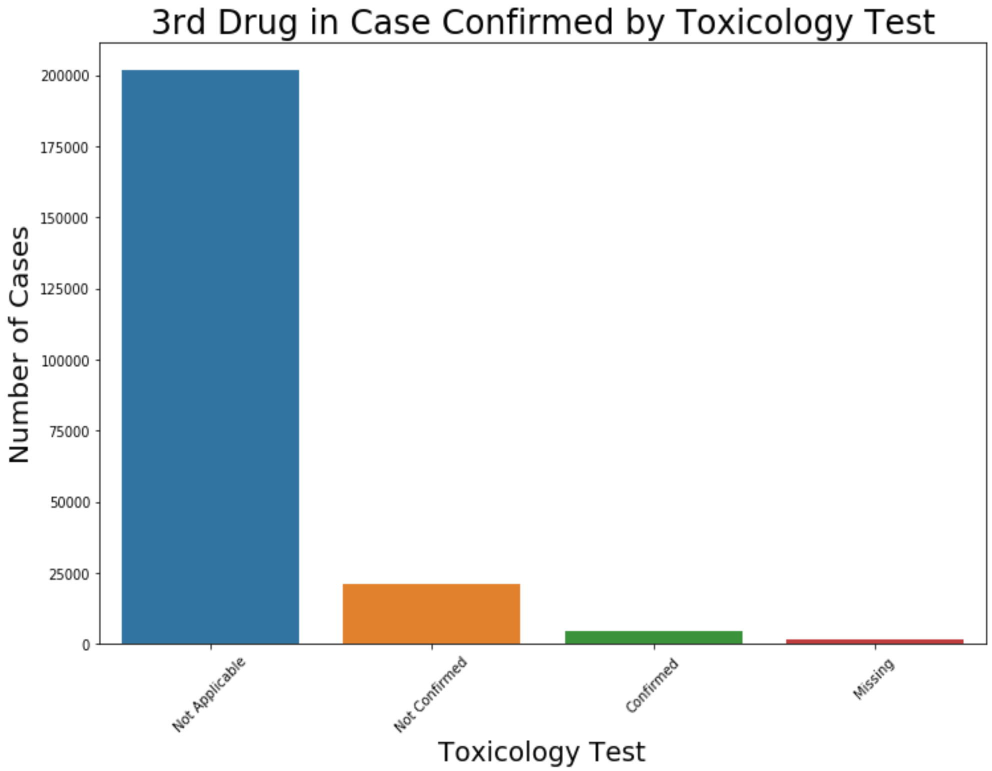

2nd Route of Drug Ingestion Noted in Case
Number of Cases
140000
120000
100000
80000
60000
40000
20000
0
Not Applicable
Not Doc
Oral
Smoked
Missing
Injected
Inhaled, Sniffed, Snorted
Other
Multiple Routes
Transdermal
Route of Drug Ingestion

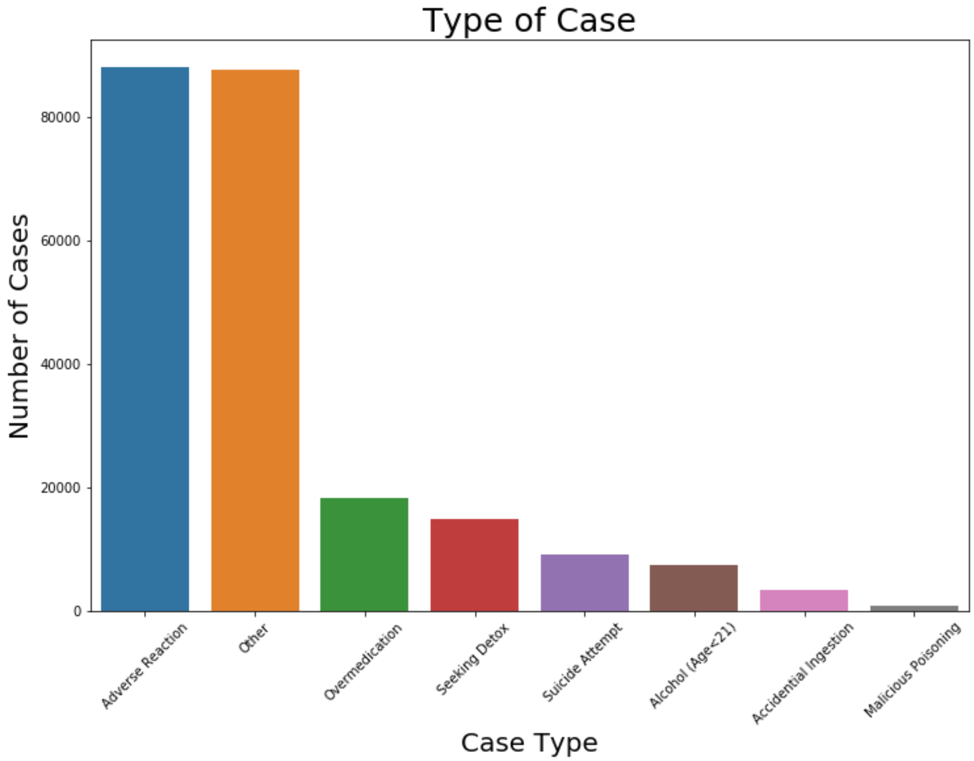


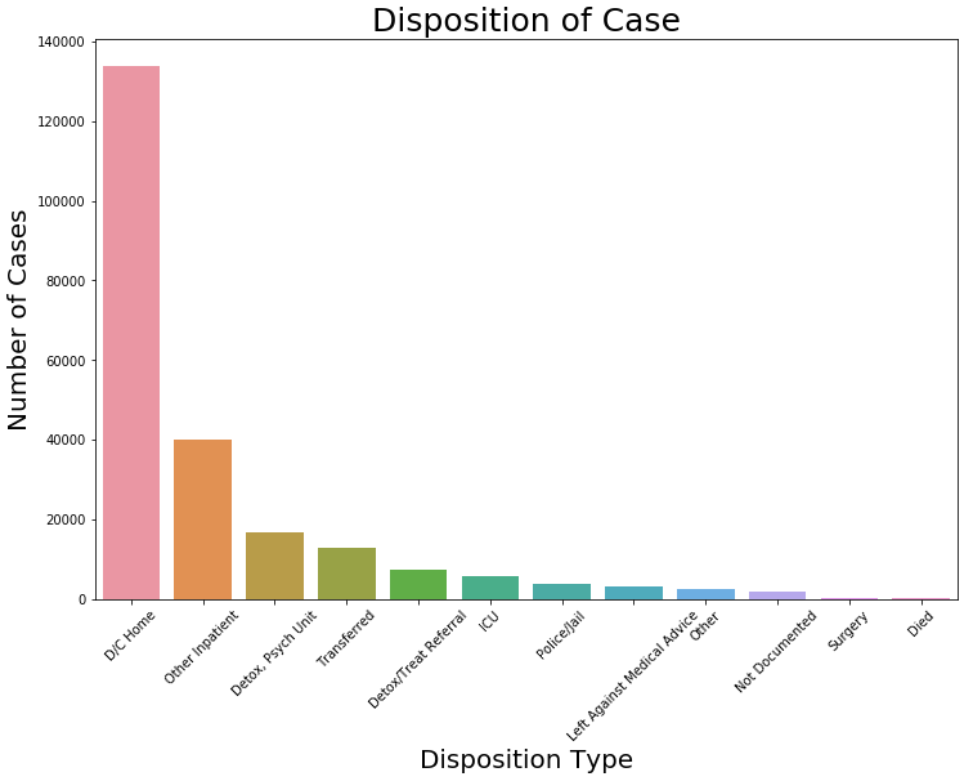
Again, as with plotting the distribution of the Drug(s) involved in the cases, whether a toxicology test was done for each of the up to 22 substances involved in one case was recorded, and a plot was done for each instance. In order to be concise and deliver the main points of the content, the body of this paper does not contain all 22 of the graphs. The first few are included here, and the others are included in the appendix at the end of the document.

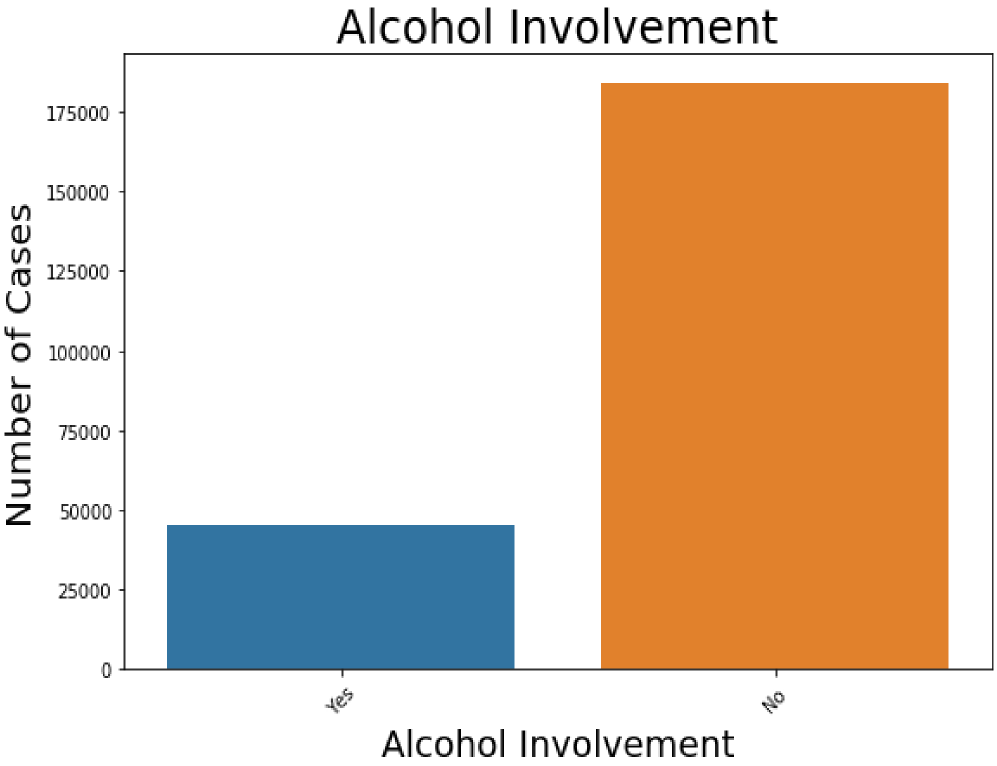

1st Drug in Case Confirmed by Toxicology Test
Number of Cases
200000
175000
150000
125000
100000
75000
50000
25000
0
Not Confirmed
Confirmed
Missing
Toxicology Test

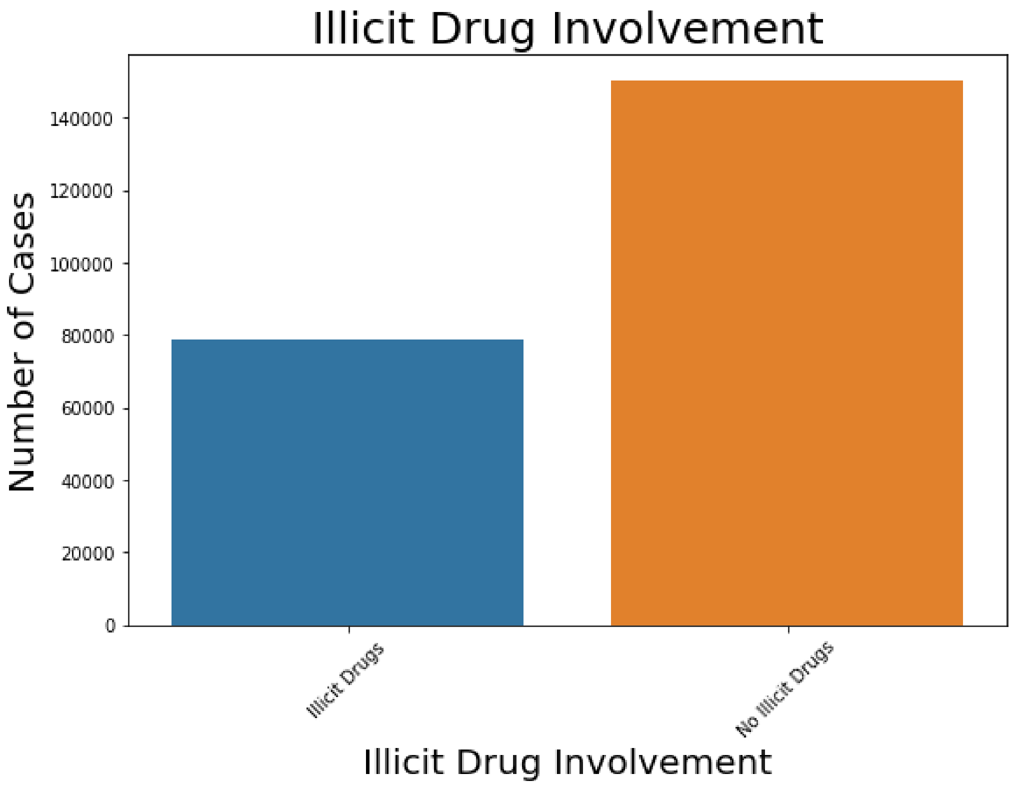

2nd Drug in Case Confirmed by Toxicology Test
Number of Cases
140000
120000
100000
80000
60000
40000
20000
0
Not Applicable
Not Confirmed
Confirmed
Missing
Toxicology Test

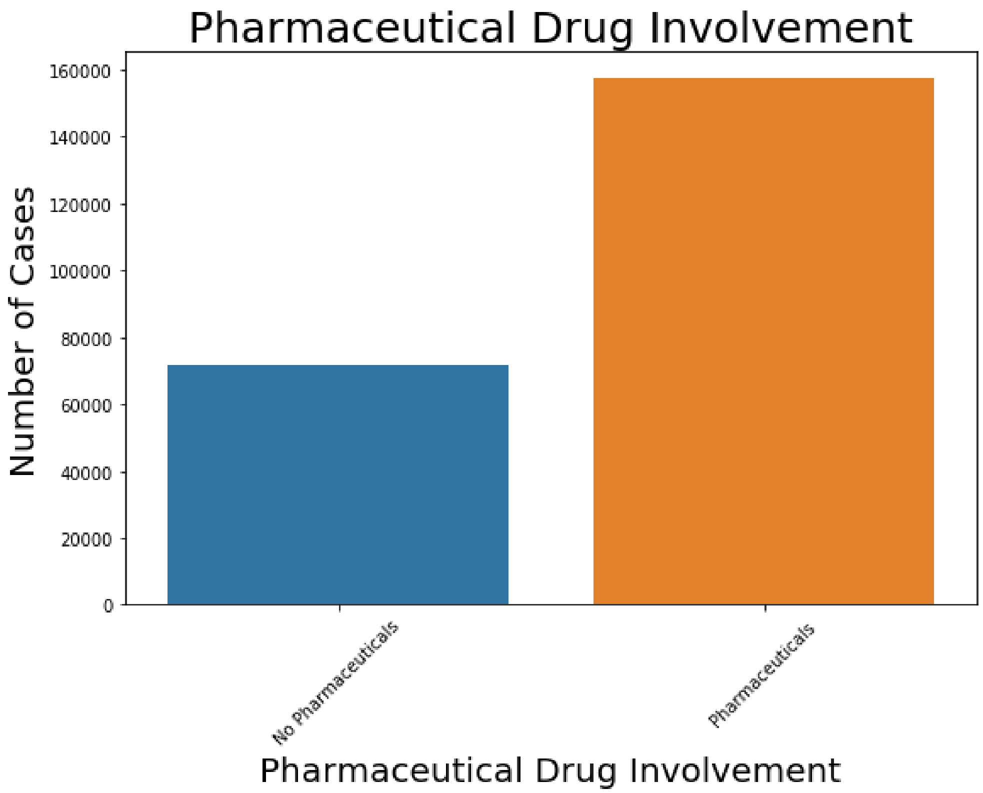

3rd Drug in Case Confirmed by Toxicology Test
Number of Cases
200000
175000
150000
125000
100000
75000
50000
25000
0
Not Applicable
Not Confirmed
Confirmed
Missing
Toxicology Test

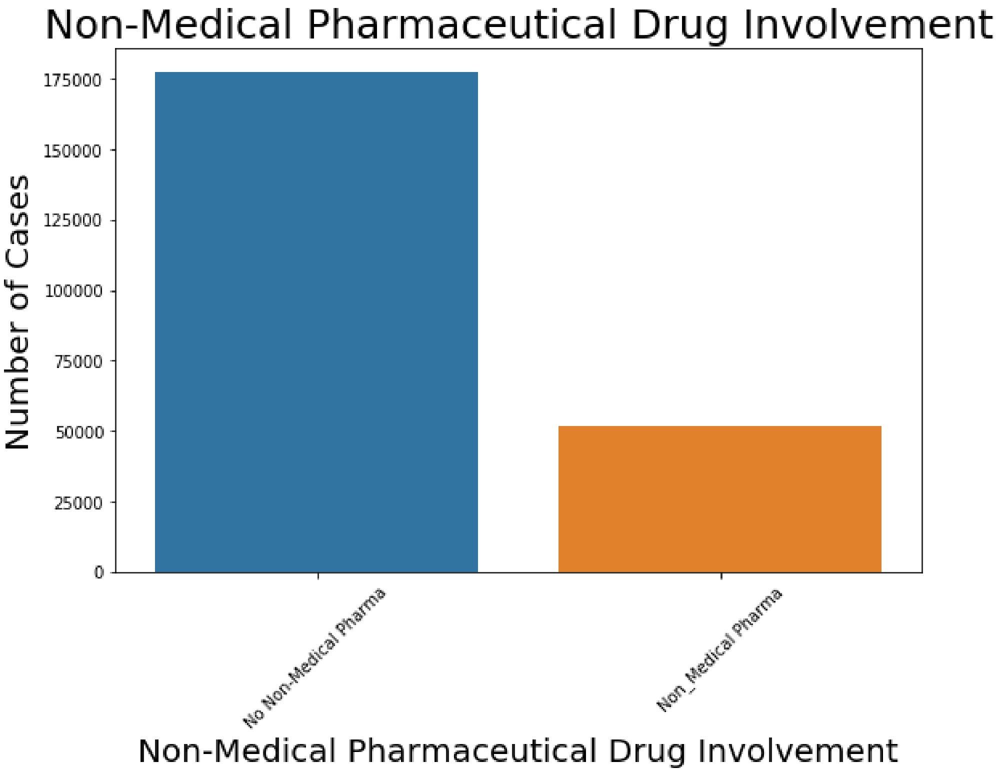

Type of Case
Number of Cases
80000
60000
40000
20000
0
Adverse Reaction
Other
Overmedication
Seeking Detox
Suicide Attempt
Alcohol (Age<21)
Accidential Ingestion
Malicious Poisoning
Case Type

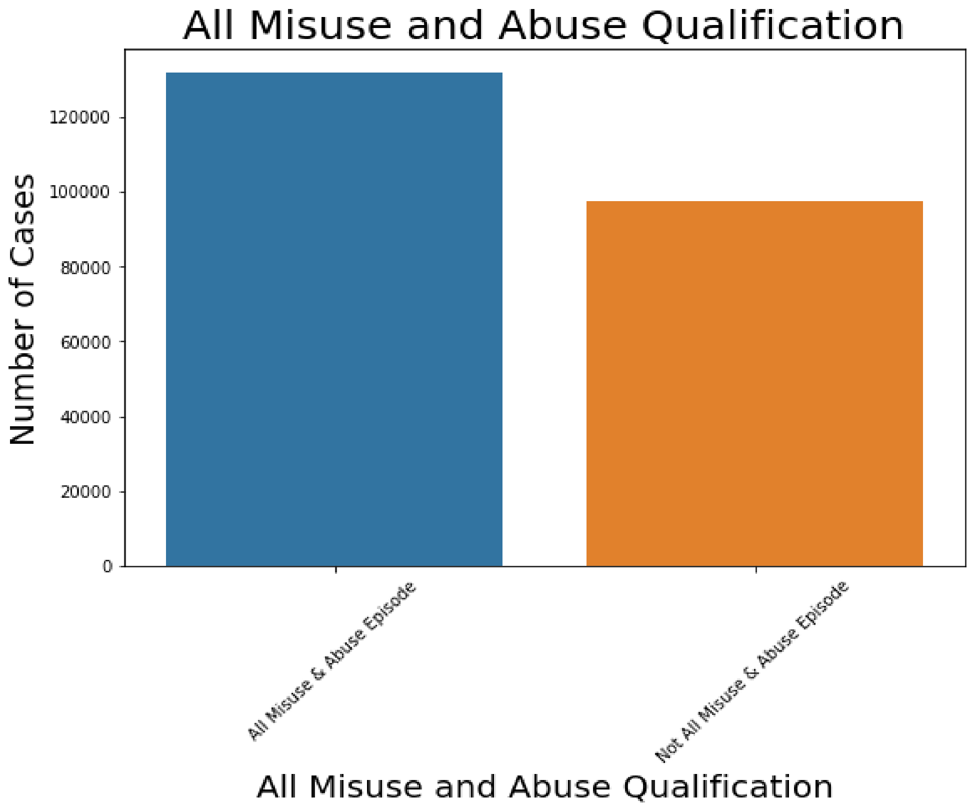

Disposition of Case
Number of Cases
140000
120000
100000
80000
60000
40000
20000
0
D/C Home
Other Inpatient
Detox, Psych Unit
Transferred
Detox/Treat Referral
ICU
Police/Jail
Left Against Medical Advice
Other
Not Documented
Surgery
Died
Disposition Type


Alcohol Involvement
Number of Cases
175000
150000
125000
100000
75000
50000
25000
0
Yes
No
Alcohol Involvement


Illicit Drug Involvement
Number of Cases
0
20000
40000
60000
80000
100000
120000
140000
Illicit Drugs
No Illicit Drugs
Illicit Drug Involvement


Pharmaceutical Drug Involvement
Number of Cases
0
20000
40000
60000
80000
100000
120000
140000
160000
No Pharmaceuticals
Pharmaceuticals
Pharmaceutical Drug Involvement


Non-Medical Pharmaceutical Drug Involvement
Number of Cases
175000
150000
125000
100000
75000
50000
25000
0
No Non-Medical Pharma
Non_Medical Pharma
Non-Medical Pharmaceutical Drug Involvement



This data set has 85 variables. Eighty of them are categorical. These variables include demographic information on each case, such as metro area, age, sex and race. They also include the name of the drug(s) ingested, the route by which the drug(s) was ingested and whether a toxicology report was done. There are up to 22 drugs involved in a case. Also included in the data are the type of case, it's disposition, whether alcohol was involved, and whether the drugs were illicit, pharmaceutical or non-medical pharmaceutical.

The following observations were seen from the plots:

- The distribution of gender was fairly even.
- The predominate race involved in the cases was white.
- Most of the cases were between the ages of 35-54.
- The time of year is evenly distributed.
- The time of day that most cases occur is between 12:00 pm and 11:59 pm.
- Alcohol, cocaine, heroin and marijuana are involved in many of the cases.
- Most of the drugs were taken orally.
- Most were not confirmed by a toxicology test.
- Most of the cases were due to adverse reactions to the drugs.
- Most cases were discharged home.
- Alcohol was not involved in many of the cases.

- Most of the drugs involved were not illicit.
- Most of the drugs involved were pharmaceutical.
- Most of the cases did not involve non-medical pharmaceutical drugs.
- Most of the cases qualified as all misuse and abuse episodes, which means that the drugs were used for purposes that is not consistent with legal or medical guidelines.

Inferential Statistics

The next step in the project was inferential statistics. Since this DataFrame has many variables, only a few were chosen for hypothesis testing. Also, since the variables are categorical, the Chi-Squared test for proportions and independence was used for the tests.

First, the locations of the cases were analyzed. Is there a significant difference in the frequency of cases in each of the cities?

- H_o: p1 = p2... = p15
- H_a: p1 != p2... != p15

The p-value was 0.0; therefore, H_o was rejected. It is reasonable to conclude that the distribution of the proportion of the location of the cases is not equal.

Second, the race of the cases was analyzed. Does the race of the patient vary significantly?

- H_o: p1 = p2... = p15
- H_a: p1 != p2... != p15

The p-value was 0.0; therefore, H_o was rejected. It is reasonable to conclude that the distribution of the proportion of race is not equal.

Next, the independence of disposition vs. case type was analyzed.

- H_o: the population frequencies are equal to the expected frequencies
- H_a: the population frequencies are not equal to the expected frequencies.

The p-value was 0.0; therefore, H_o was rejected. It is reasonable to conclude that the distribution of population frequencies are not equal to the expected frequencies.

Finally, the independence of sex vs. drugid_1 was analyzed.

- H_o: the population frequencies are equal to the expected frequencies
- H_a: the population frequencies are not equal to the expected frequencies.

The p-value was 0.0; therefore, H_o was rejected. It is reasonable to conclude that the distribution of population frequencies are not equal to the expected frequencies.

Modeling

Once the data story was completed, it was time to build the model.

Logistic Regression is the model most used for data sets that have many categorical variables. Logistic Regression is a classification technique that can be used to predict a qualitative response. In other words, these models predict the probability that a categorical variable such as gender belongs to a particular category. For example: if a person has long hair, what is the probability that he/she is female?

It was decided to use the Logistic Regression model on the full data set to determine the probably of an Emergency Department Drug Abuse visit being a particular case type. The results are in the table below:

Logistic Regression Full Data Set

Class	Precision	Recall	F1-score	Support
Accidental Ingestion	0.88	0.01	0.02	1,301
Adverse Reaction	0.92	0.99	0.95	35,239
Alcohol (Age<21)	0.99	1.00	1.00	2,968
Malicious Poisoning	0.50	0.01	0.02	317
Other	0.87	0.93	0.90	35,051
Overmedication	0.74	0.72	0.73	7,259
Seeking Detox	0.77	0.51	0.61	5,937
Suicide Attempt	0.74	0.46	0.57	3,613

Note that the table above provides values for precision, recall, f1-score and support for each class (case type). The explanation for what these values represent is below:

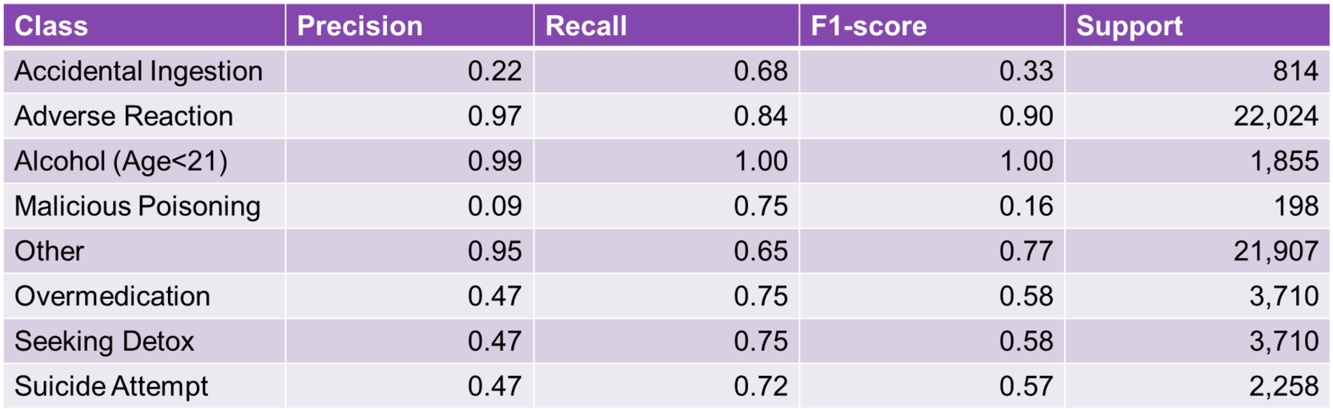
- The precision represents how many are correctly classified among that class
- The recall means how many of this class were found over the whole number of elements of this class
- The f1-score is the harmonic mean between precision & recall
- The support is the number of occurrences of the given class in the dataset (there were 35,239 instances of Adverse Reactions).

As can be seen in the table, the data set is not balanced between the case types. This classifier does not do well with classes that have lower amounts of cases.

Therefore, in the Extended Analysis notebook, other approaches were explored with the goal of improving the results obtained in this baseline modeling notebook. The approaches included combining resampling methods with Logistic Regression (LGR) and Random Forest Classifiers (RFC).

First, an attempt was made to run the full data set through SMOTE. SMOTE (synthetic minority oversampling technique) is one of the most commonly used oversampling methods to correct an imbalance problem. It aims to balance class distribution by randomly increasing minority class examples through replication. However, this operation did not work because the computer kept returning a memory error. As a result, it was decided to reduce the dataset by 50% and run the SMOTE process again. This time, the process ran successfully, and Logistic Regression was done on the more balanced reduced dataset. The results are in the table below:

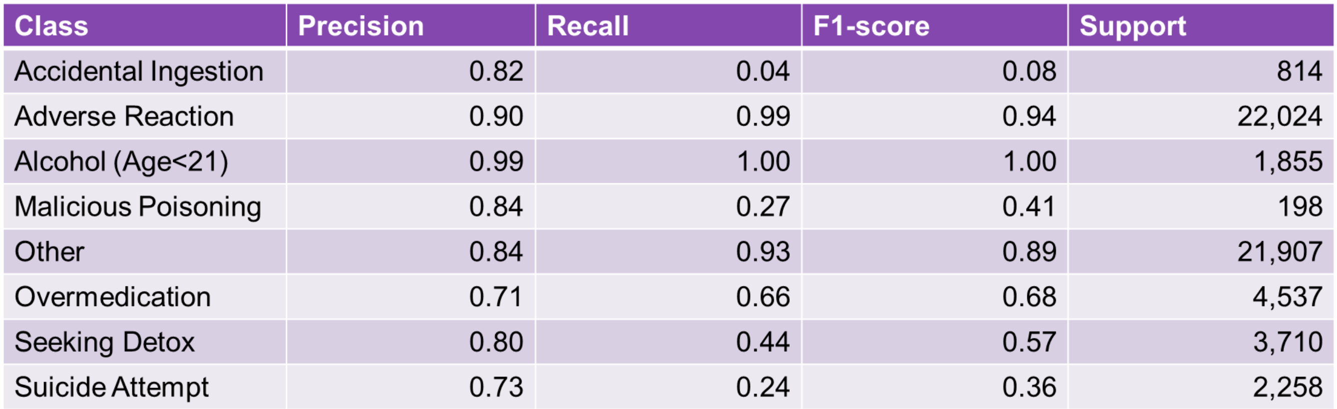
Logistic Regression Reduced Data Set



Class	Precision	Recall	F1-score	Support
Accidental Ingestion	0.22	0.68	0.33	814
Adverse Reaction	0.97	0.84	0.90	22,024
Alcohol (Age<21)	0.99	1.00	1.00	1,855
Malicious Poisoning	0.09	0.75	0.16	198
Other	0.95	0.65	0.77	21,907
Overmedication	0.47	0.75	0.58	3,710
Seeking Detox	0.47	0.75	0.58	3,710
Suicide Attempt	0.47	0.72	0.57	2,258

Since the results of the Logistic Regression on the reduced dataset were not much improved, it was decided to use the Random Forest Classifier on the reduced dataset. The results are in the table below:

Random Forest Reduced Data Set



Class	Precision	Recall	F1-score	Support
Accidental Ingestion	0.82	0.04	0.08	814
Adverse Reaction	0.90	0.99	0.94	22,024
Alcohol (Age<21)	0.99	1.00	1.00	1,855
Malicious Poisoning	0.84	0.27	0.41	198
Other	0.84	0.93	0.89	21,907
Overmedication	0.71	0.66	0.68	4,537
Seeking Detox	0.80	0.44	0.57	3,710
Suicide Attempt	0.73	0.24	0.36	2,258

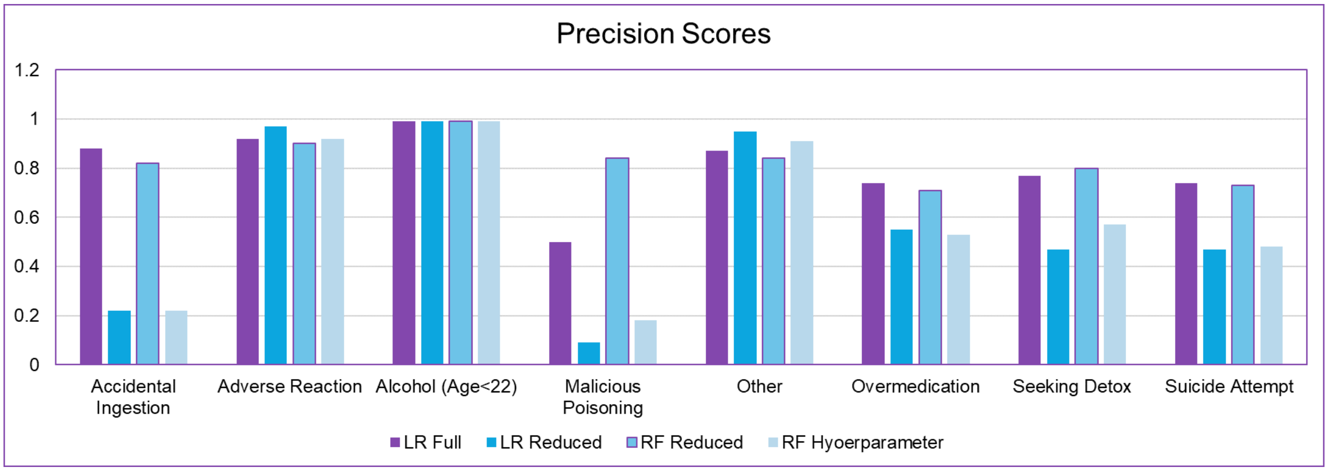
The results of the Random Forest Classifier on the reduced data set show that the model was overfitting the data. Therefore, it was decided to use the Randomized Search process to tune the hyperparameters and run the model again. The results are in the table below:

Random Forest Reduced Data Set—Hyperparameter Tuning

Class	Precision	Recall	F1-score	Support
Accidental Ingestion	0.22	0.30	0.25	814
Adverse Reaction	0.92	0.92	0.92	22,024
Alcohol (Age<21)	0.99	1.00	1.00	1,855
Malicious Poisoning	0.18	0.40	0.25	198
Other	0.91	0.75	0.82	21,907
Overmedication	0.53	0.94	0.67	4,537
Seeking Detox	0.57	0.60	0.59	3,710
Suicide Attempt	0.48	0.39	0.43	2,258

Once again, the results were not much improved. Therefore, it would be preferable to do some more fine tuning and re-run the models. However, due to time constraints, it was decided to end the project. A table comparing the precision scores for each of the models is below. It shows the overfitting in the basic models and the effect of the adjustments in the tuned models.

Precision Scores for Each Model



Conclusion and Recommendations

The purpose of this project was to help hospital Emergency Departments plan for enough staffing and supplies to handle the expected types and percentages of drug abuse related Emergency Department visits so that the departments can be prepared with enough staffing, medications, procedures, etc. to properly deal with these cases and have good outcomes.

The process used to accomplish the purpose was to prepare the data set for analysis, create plots to show the story the data told, perform inference testing and build machine learning models to predict the number and types of visits to be expected. Due to time constraints, the best model for this dataset was not determined. It is difficult to build meaningful models with this dataset because it is unbalanced.

The results did show evidence that good performing models cans be created for Adverse Reactions, Alcohol (Age < 21) and Other visit types. The precision score, or proportion of how cases that were correctly classified, of Adverse Reaction was 0.92. The recall score, or the proportion of the class that were found over the whole number of elements in the class, for Adverse Reaction was also 0.92.

The precision score, or proportion of how cases that were correctly classified, of Alcohol (Age < 21) was 0.99. The recall score, or the proportion of the class that were found over the whole number of elements in the class, for Alcohol (Age < 21) was 1.00.

The precision score, or proportion of how cases that were correctly classified, of Other cases was 0.91. The recall score, or the proportion of the class that were found over the whole number of elements in the class, for Other cases was 0.75.

Is recommended that the development of the project continue so that the case types with good results can be further explored to see which features most impact them. Also, the other case types could be further explored to see what can be done to get meaningful results from them.

Future Work

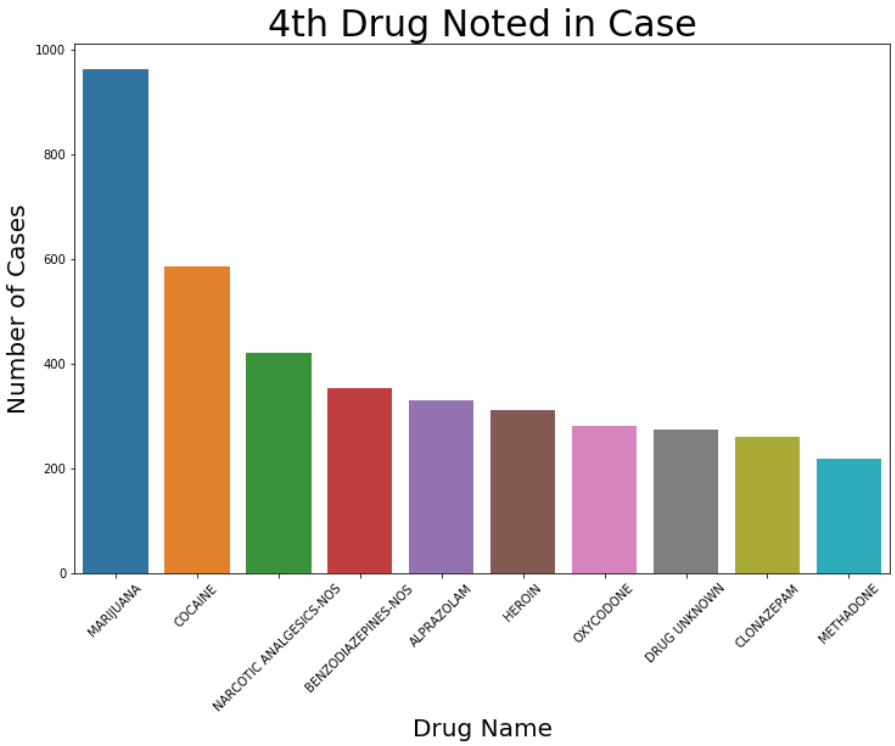
Future work for this project would include the following:

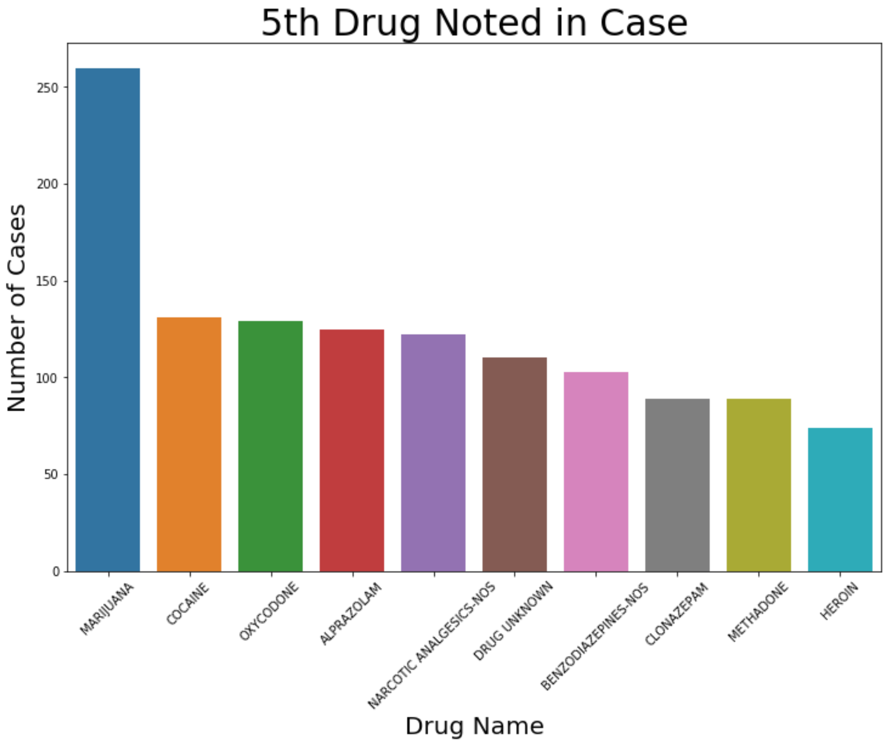
- Analyze the importance of the features to determine which ones are contributing the most to the types of cases using Random Forest
- Analyze the impact of the features by using the coefficients of the model results
- Determine the best model for the dataset by developing multiple, binary problems to further investigate it.

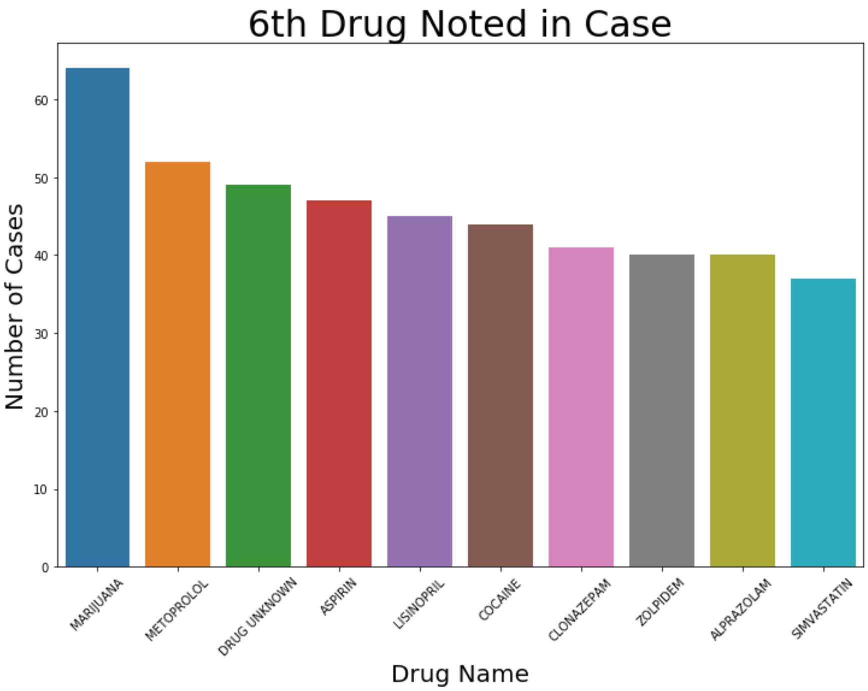
Footnotes:

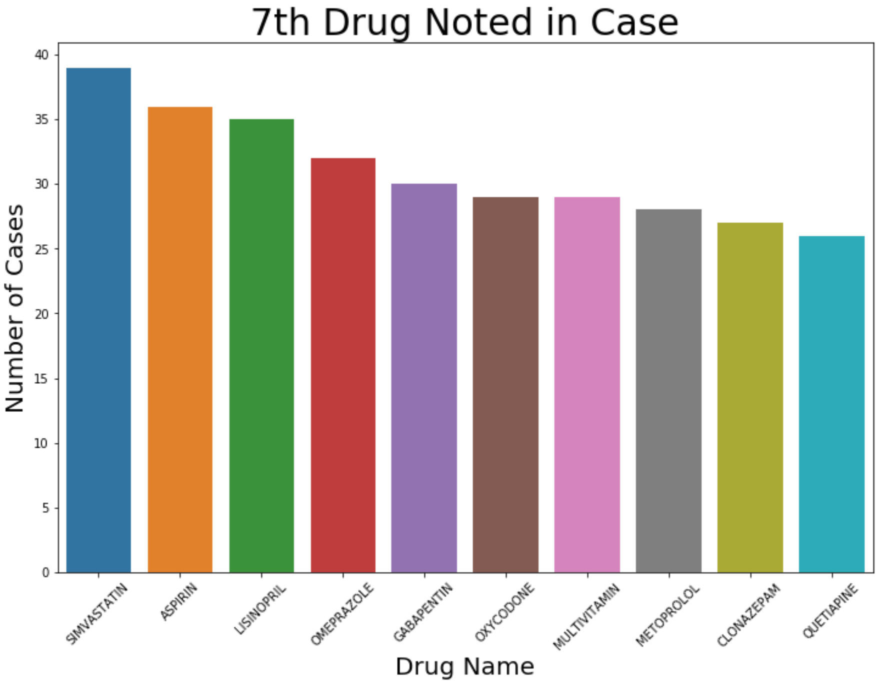
1. ‘Understanding Drug Use and Addiction’, *National Institute on Drug Abuse,* June, 2018, https://www.drugabuse.gov/publications/drugfacts/understanding-drug-use-addiction, (accessed December 14, 2019)
2. Yerby, Nathan, ‘Statistics on Addiction in America’, *Addiction Center,* December 5, 2019, https://www.addictioncenter.com/addiction/addiction-statistics/, (accessed December 14, 2019)
3. Albert, Michael, M.D., M.P.H.; McCaig, Linda F, M.P.H.; Uddin, Sayeedha, M.D., M.P.H., ‘Emergency Department Visits for Drug Poisoning: United States, 2008-2011’, *Centers for Disease Control and Prevention,* April, 2015, https://www.cdc.gov/nchs/products/databriefs/db196.htm, (accessed December 14, 2019)
4. ‘Drug Abuse Warning Network 2011 (DAWN-2011-DS0001)’, *Substance Abuse & Mental Health Services Administration,* 2011, https://www.datafiles.samhsa.gov/study-dataset/drug-abuse-warning-network-2011-dawn-2011-ds0001-nid13747, (accessed December 14, 2019)

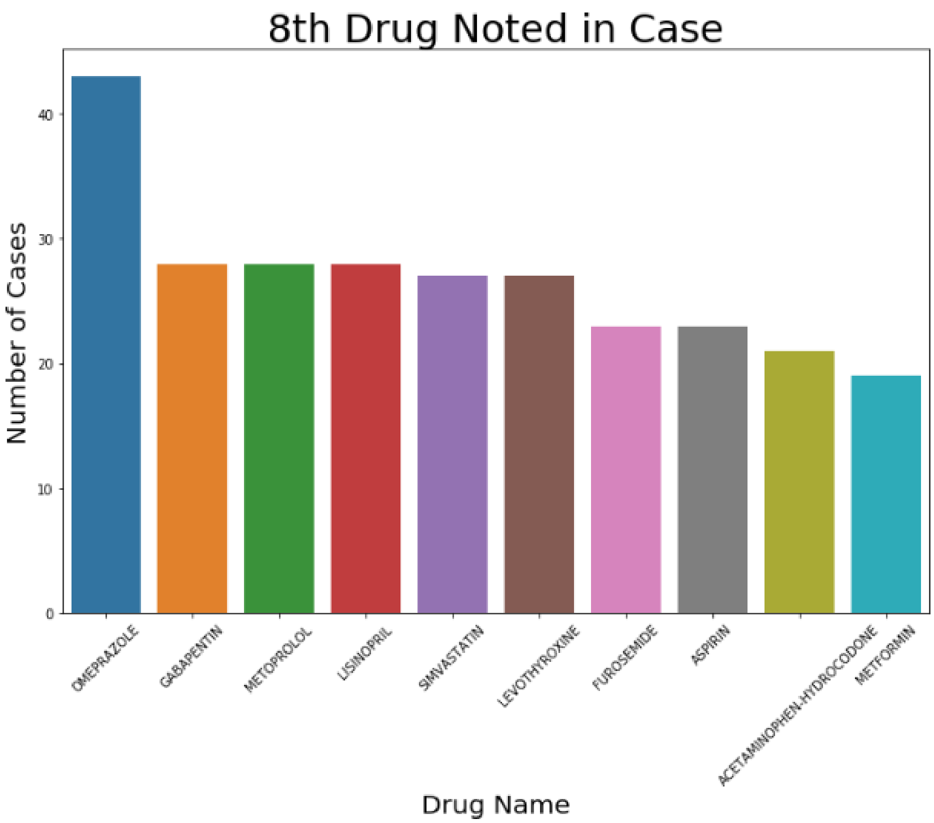
Appendix A – Graphs of Top 10 Drugs Involved in Cases

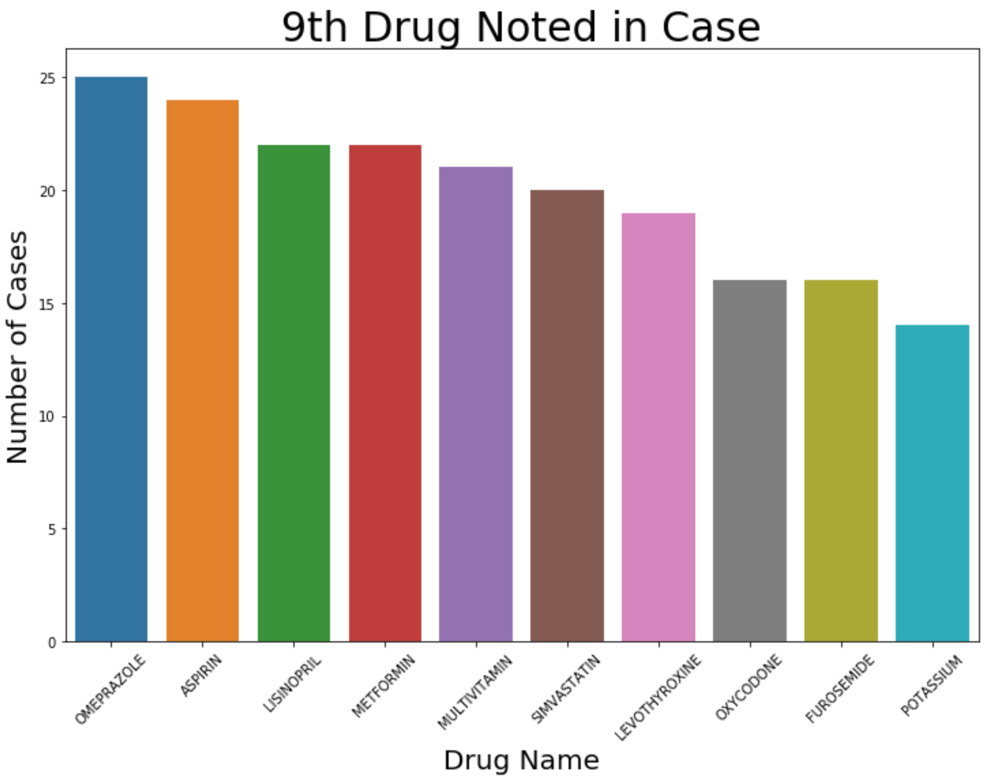


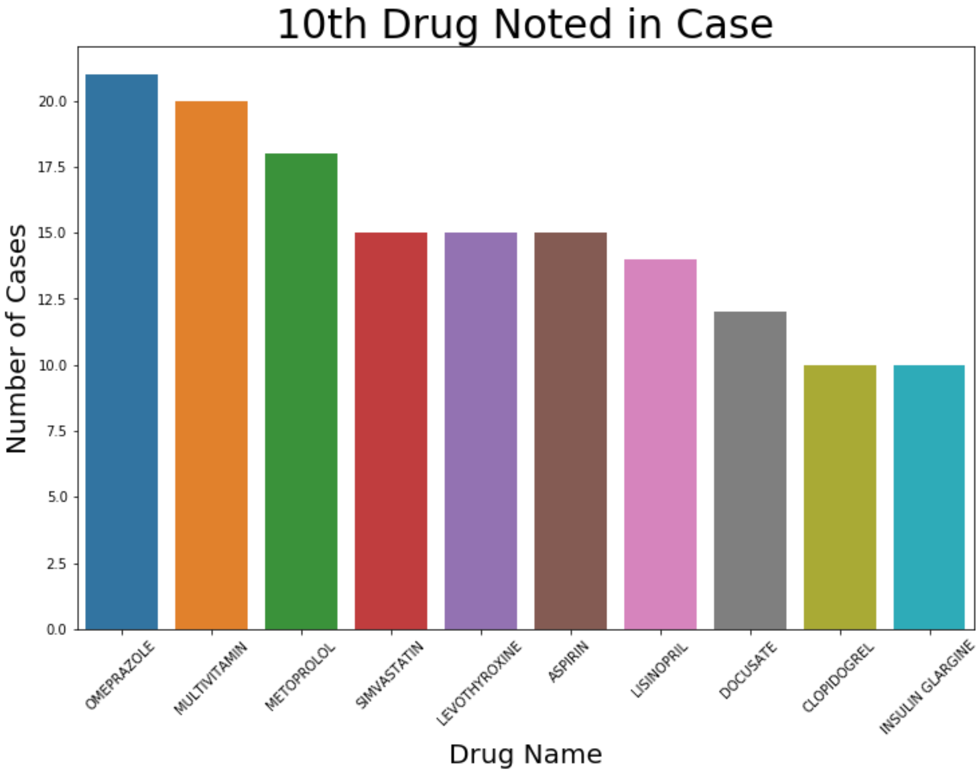


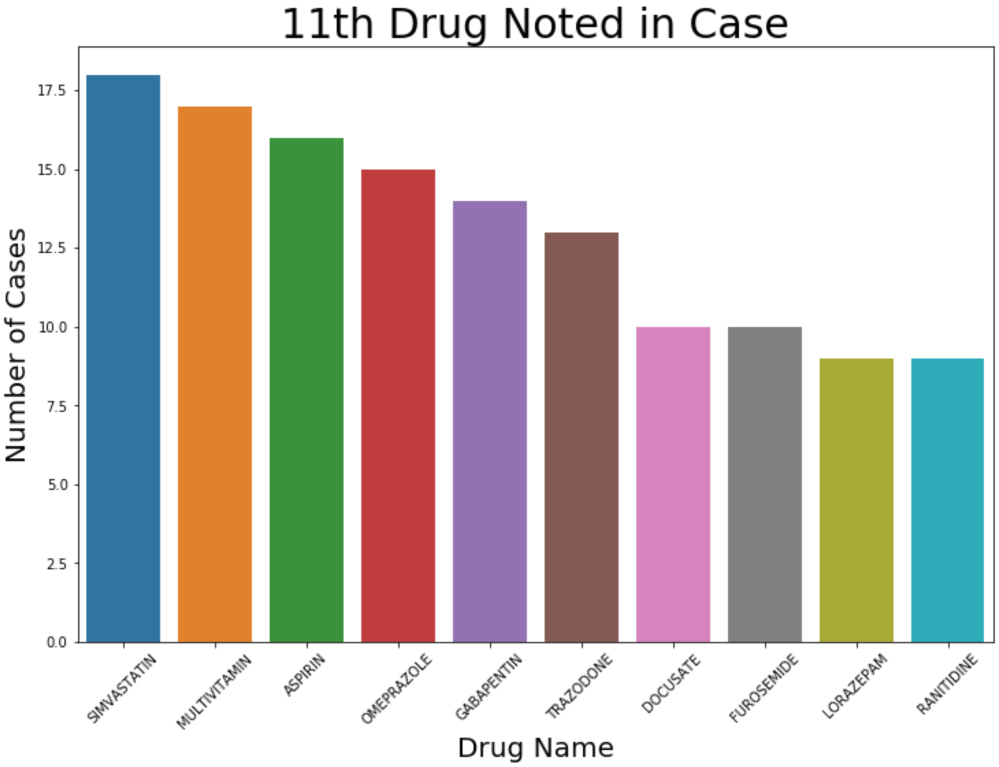

6th Drug Noted in Case
Number of Cases
0
10
20
30
40
50
60
MARIJUANA
METOPROLOL
DRUG UNKNOWN
ASPIRIN
LISINOPRIL
COCAINE
CLONAZEPAM
ZOLPIDEM
ALPRAZOLAM
SIMVASTATIN
Drug Name

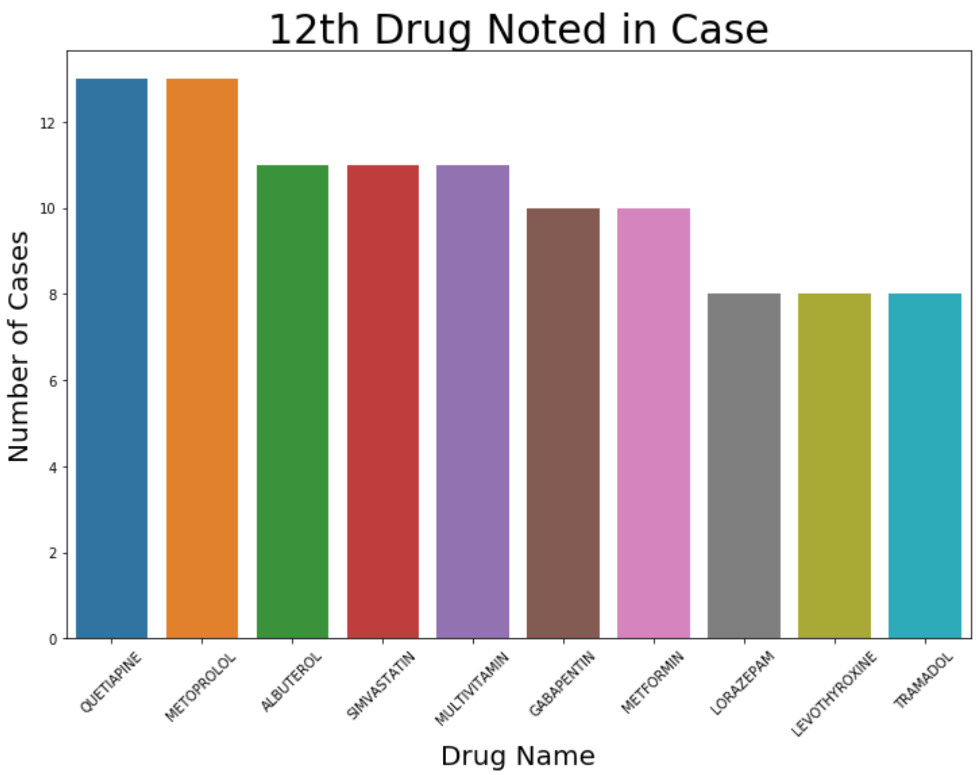

7th Drug Noted in Case
Number of Cases
0
5
10
15
20
25
30
35
40
SIMVASTATIN
ASPIRIN
LISINOPRIL
OMEPRAZOLE
GABAPENTIN
OXYCODONE
MULTIVITAMIN
METOPROLOL
CLONAZEPAM
QUETIAPINE
Drug Name

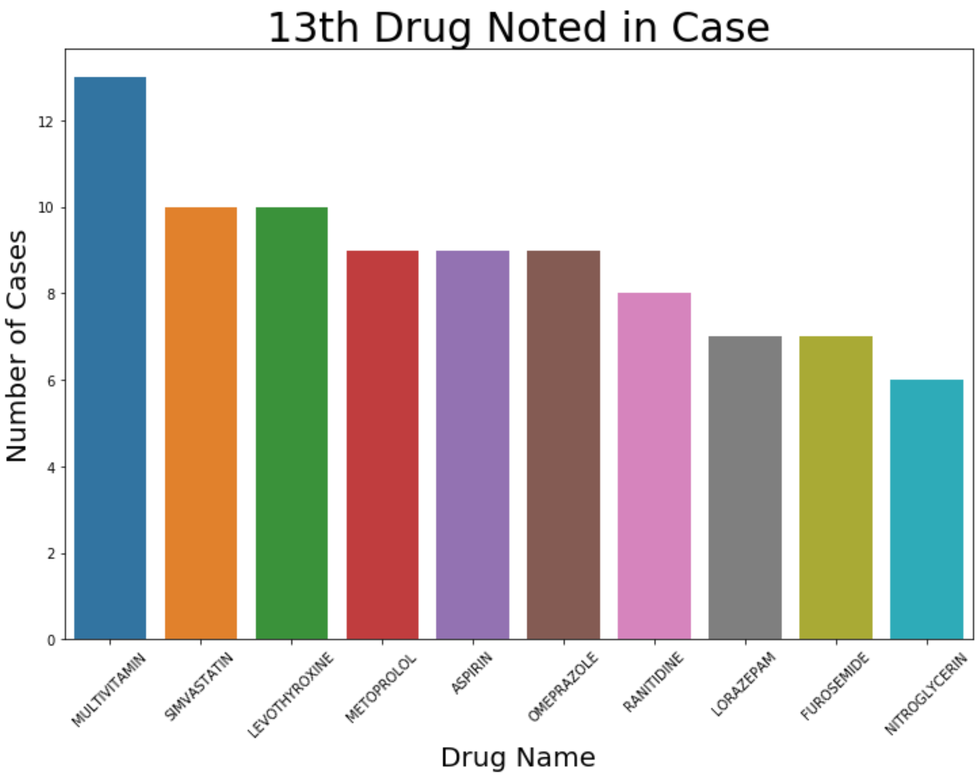

8th Drug Noted in Case
Number of Cases
0
10
20
30
40
OMEPRAZOLE
GABAPENTIN
METOPROLOL
LISINOPRIL
SIMVASTATIN
LEVOTHYROXINE
FUROSEMIDE
ASPIRIN
ACETAMINOPHEN-HYDROCODONE
METFORMIN
Drug Name

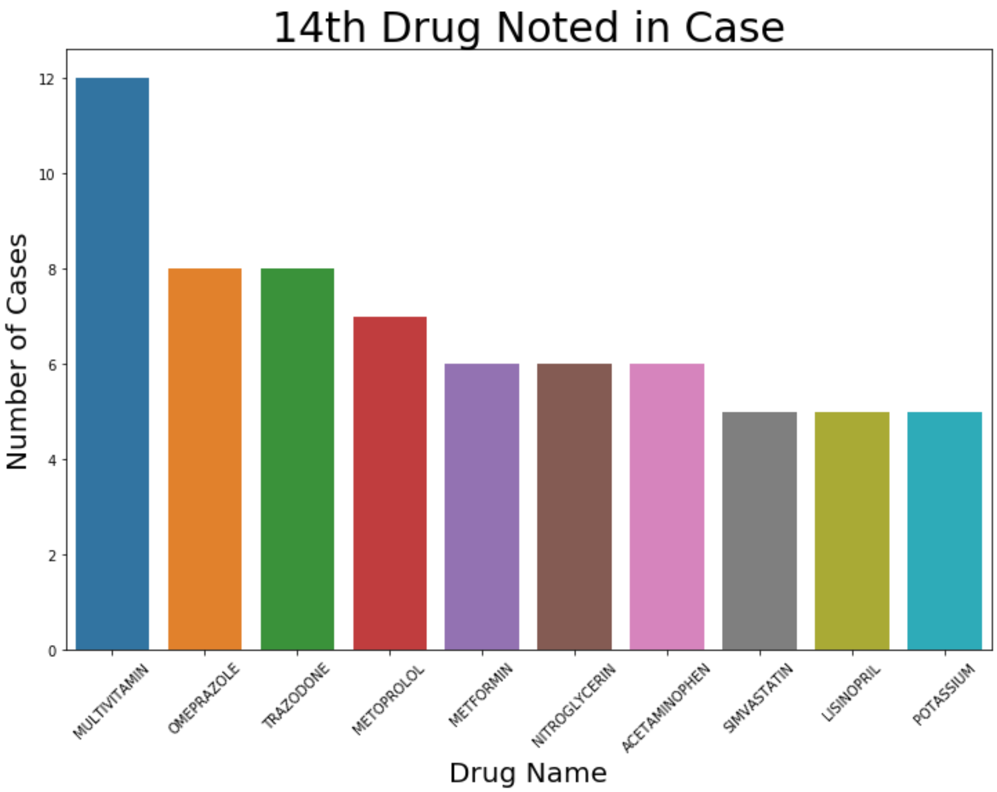

9th Drug Noted in Case
Number of Cases
0
5
10
15
20
25
OMEPRAZOLE
ASPIRIN
LISINOPRIL
METFORMIN
MULTIVITAMIN
SIMVASTATIN
LEVOTHYROXINE
OXYCODONE
FUROSEMIDE
POTASSIUM
Drug Name

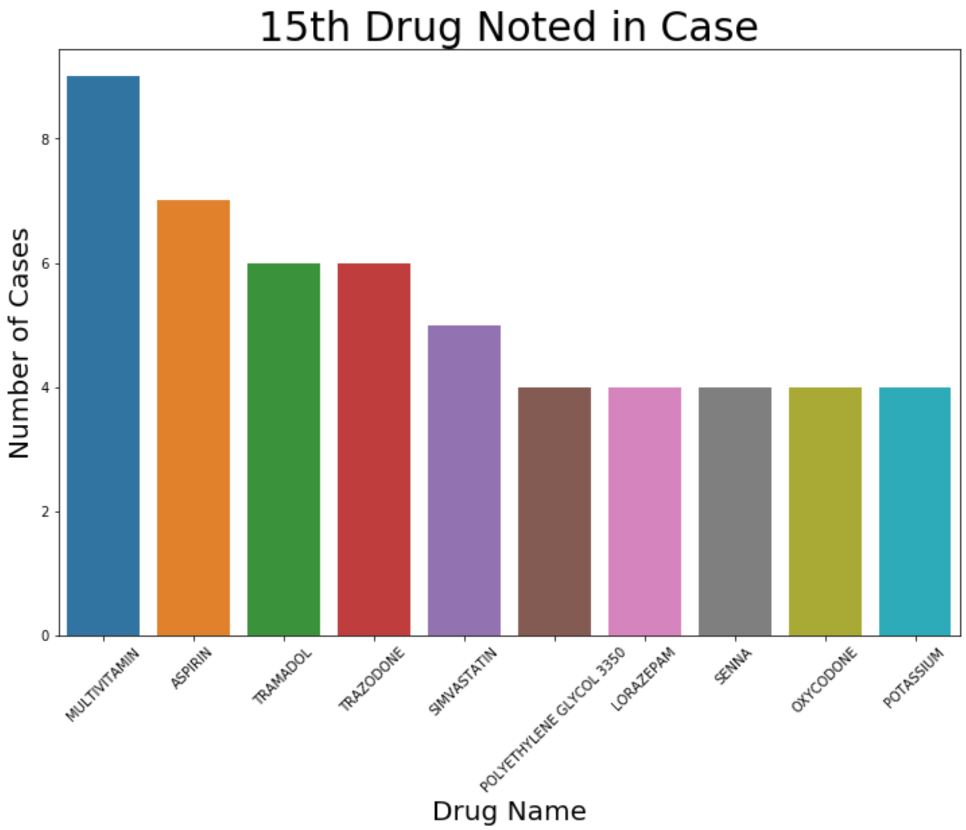

10th Drug Noted in Case
Number of Cases
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
OMEPRAZOLE
MULTIVITAMIN
METOPROLOL
SIMVASTATIN
LEVOTHYROXINE
ASPIRIN
LISINOPRIL
DOCUSATE
CLOPIDOGREL
INSULIN GLARGINE
Drug Name

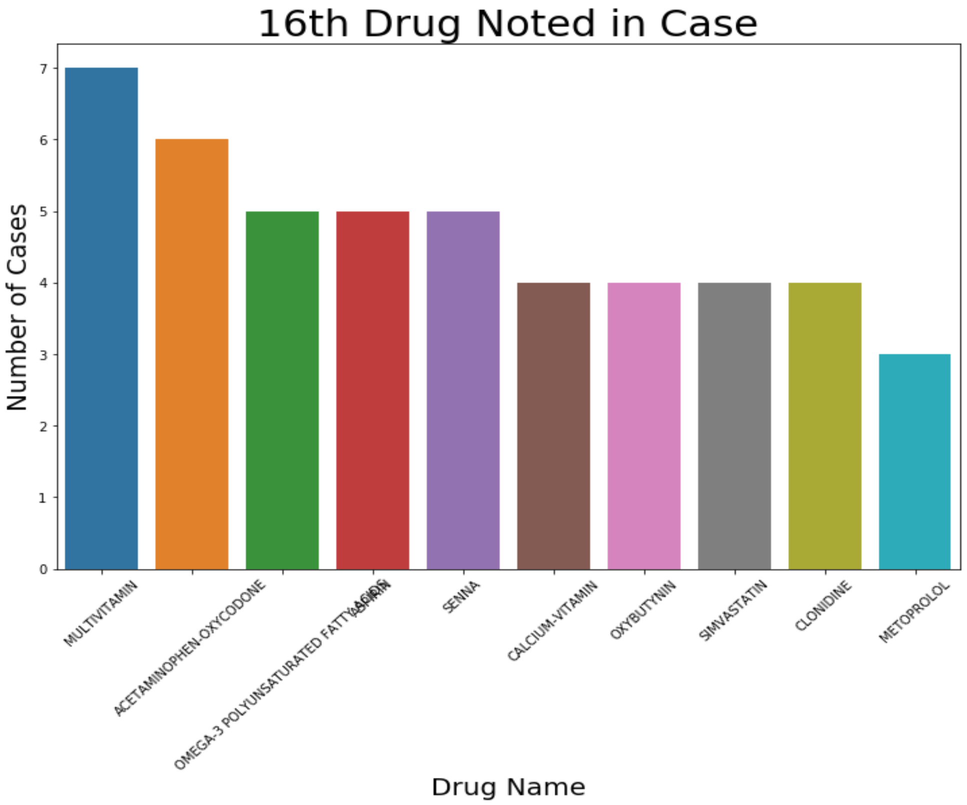

11th Drug Noted in Case
Number of Cases
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
SIMVASTATIN
MULTIVITAMIN
ASPIRIN
OMEPRAZOLE
GABAPENTIN
TRAZODONE
DOCUSATE
FUROSEMIDE
LORAZEPAM
RANITIDINE
Drug Name

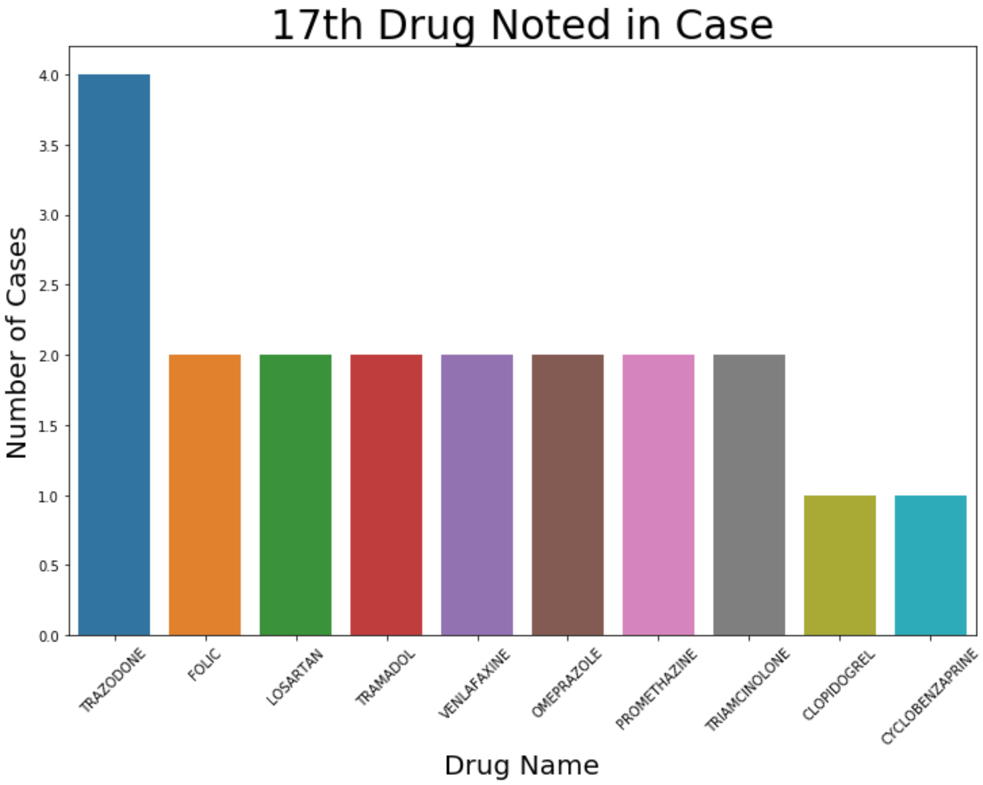

12th Drug Noted in Case
Number of Cases
0
2
4
6
8
10
12
QUETIAPINE
METOPROLOL
ALBUTEROL
SIMVASTATIN
MULTIVITAMIN
GABAPENTIN
METFORMIN
LORAZEPAM
LEVOTHYROXINE
TRAMADOL
Drug Name

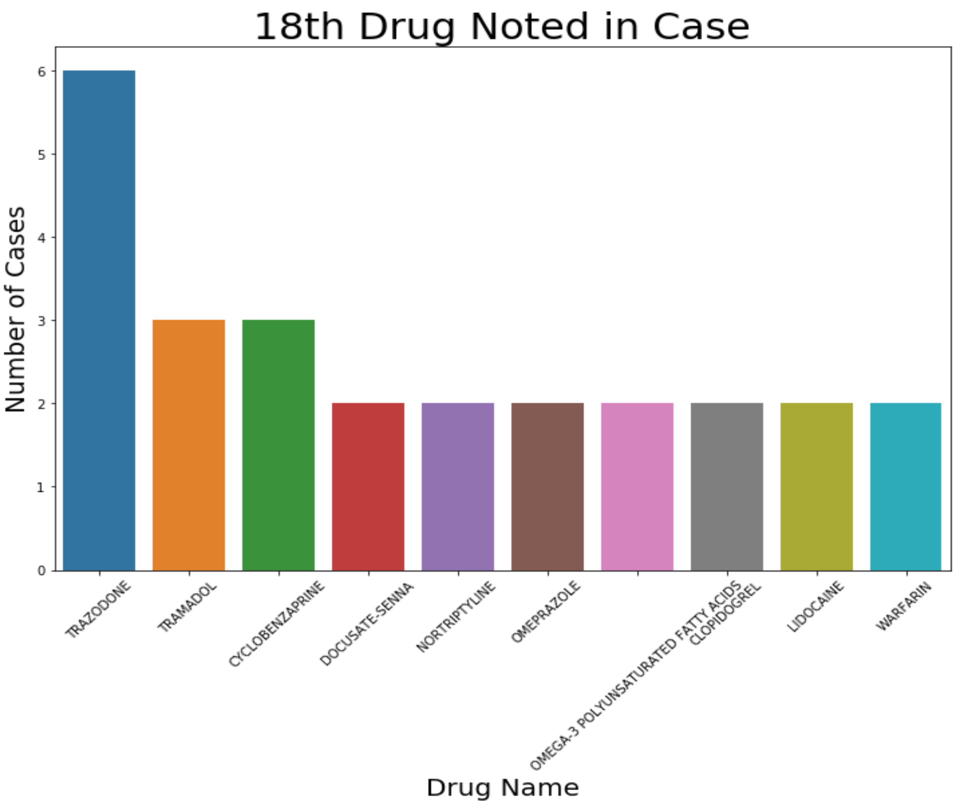

13th Drug Noted in Case
Number of Cases
0
2
4
6
8
10
12
MULTIVITAMIN
SIMVASTATIN
LEVOTHYROXINE
METOPROLOL
ASPIRIN
OMEPRAZOLE
RANITIDINE
LORAZEPAM
FUROSEMIDE
NITROGLYCERIN
Drug Name

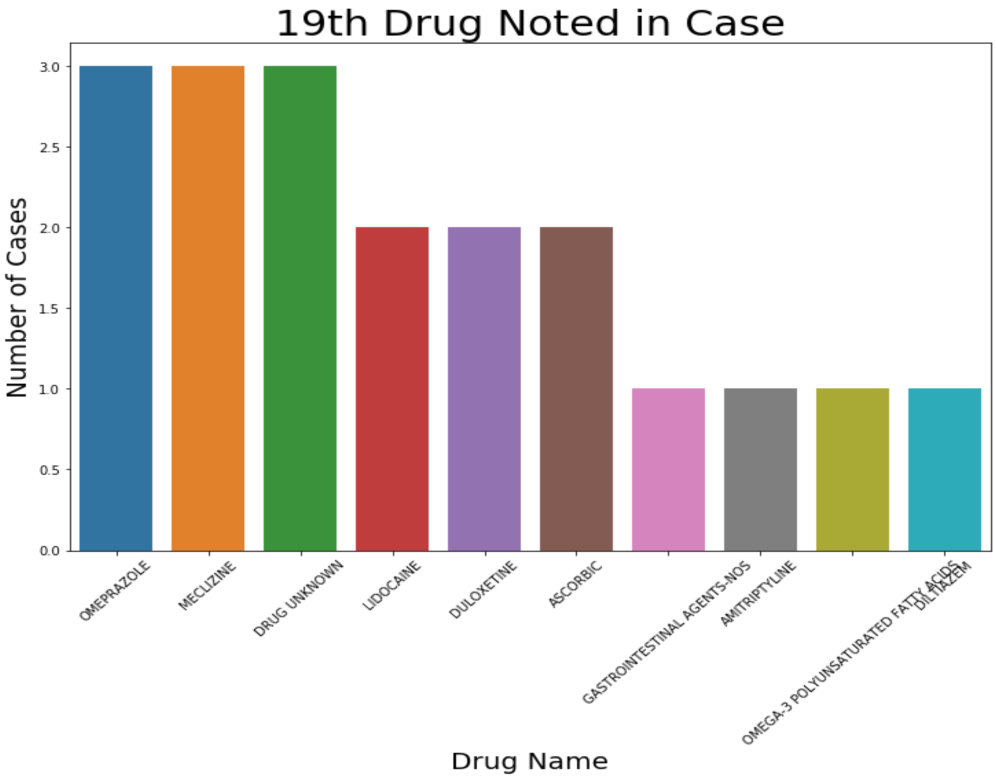

14th Drug Noted in Case
Number of Cases
0
2
4
6
8
10
12
MULTIVITAMIN
OMEPRAZOLE
TRAZODONE
METOPROLOL
METFORMIN
NITROGLYCERIN
ACETAMINOPHEN
SIMVASTATIN
LISINOPRIL
POTASSIUM
Drug Name

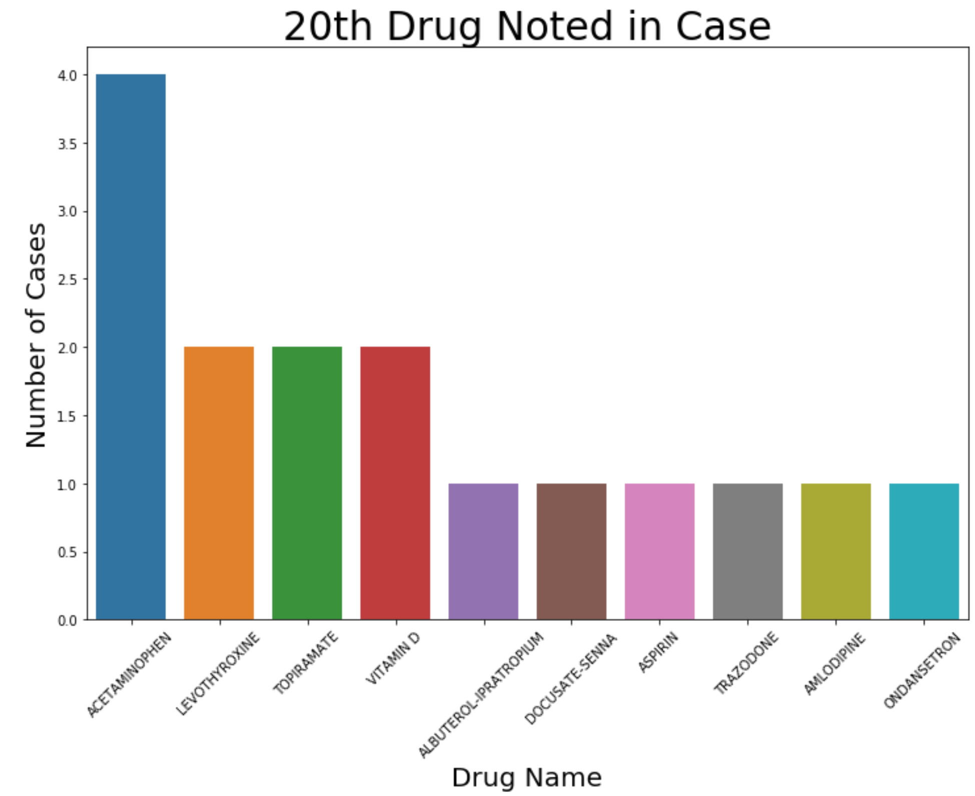

15th Drug Noted in Case
Number of Cases
0
2
4
6
8
MULTIVITAMIN
ASPIRIN
TRAMADOL
TRAZODONE
SIMVASTATIN
POLYETHYLENE GLYCOL 3350
LORAZEPAM
SENNA
OXYCODONE
POTASSIUM
Drug Name

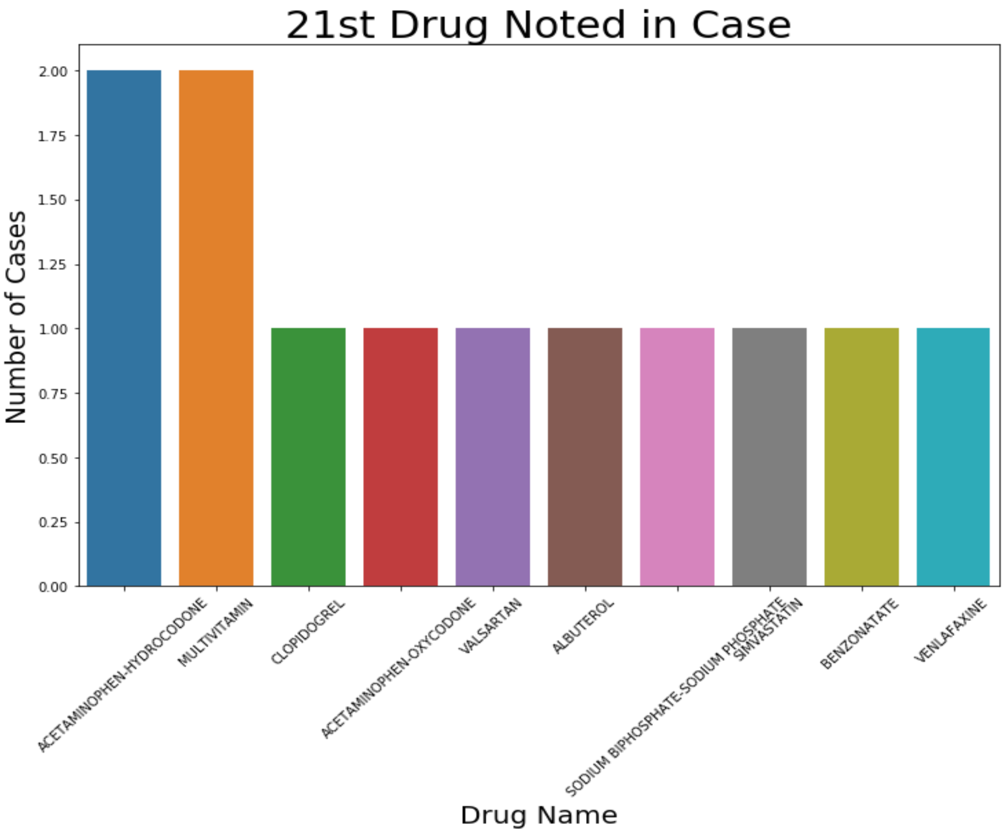

16th Drug Noted in Case
Number of Cases
0
1
2
3
4
5
6
7
MULTIVITAMIN
ACETAMINOPHEN-OXYCODONE
OMEGA-3 POLYUNSATURATED FATTY ACIDS
ASPIRIN
SENNA
CALCIUM-VITAMIN
OXYBUTYNIN
SIMVASTATIN
CLONIDINE
METOPROLOL
Drug Name

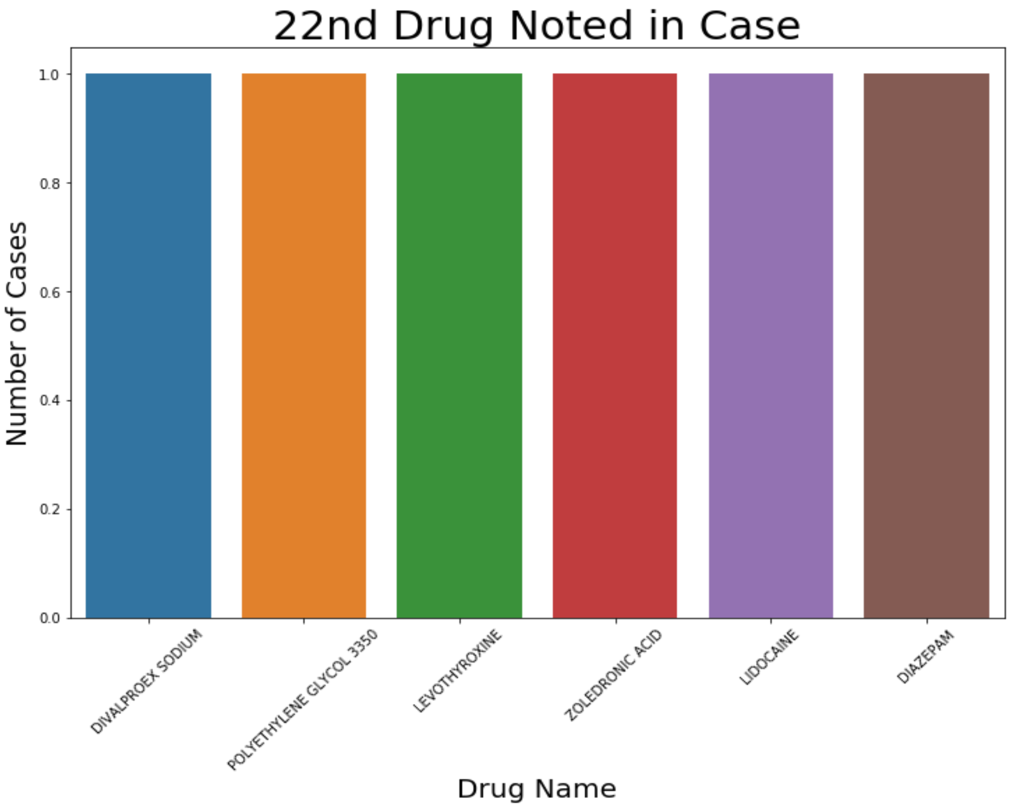

17th Drug Noted in Case
Number of Cases
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
TRAZODONE
FOLIC
LOSARTAN
TRAMADOL
VENLAFAXINE
OMEPRAZOLE
PROMETHAZINE
TRIAMCINOLONE
CLOPIDOGREL
CYCLOBENZAPRINE
Drug Name


18th Drug Noted in Case
Number of Cases
0
1
2
3
4
5
6
TRAZODONE
TRAMADOL
CYCLOBENZAPRINE
DOCUSATE-SENNA
NORTRIPTYLINE
OMEPRAZOLE
OMEGA-3 POLYUNSATURATED FATTY ACIDS
CLOPIDOGREL
LIDOCAINE
WARFARIN
Drug Name

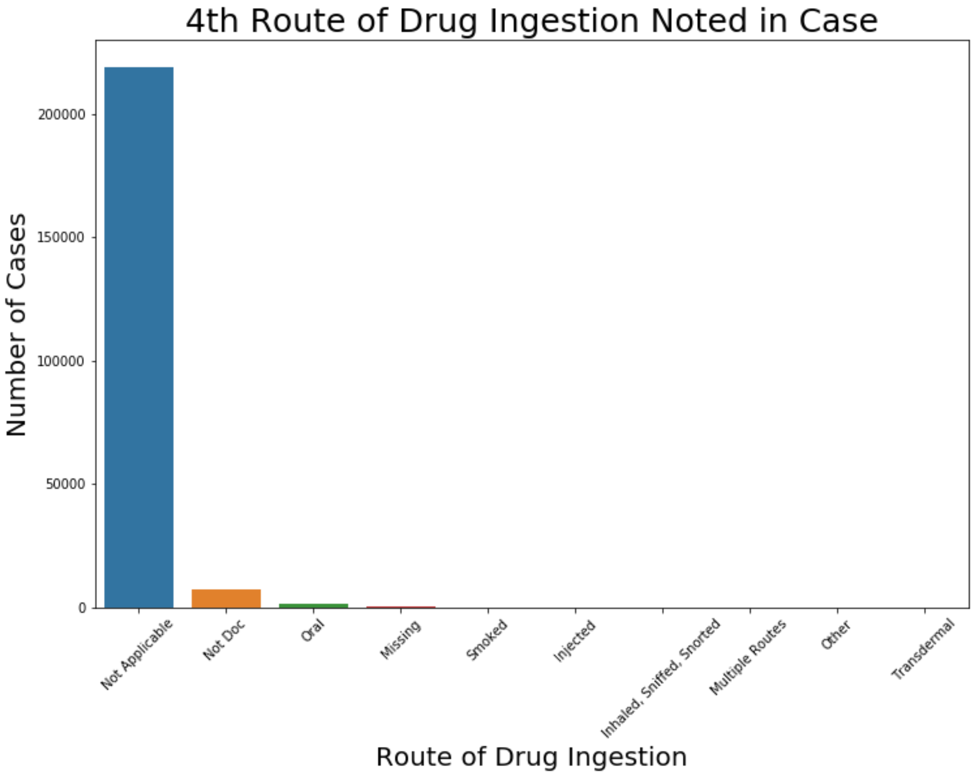

19th Drug Noted in Case
Number of Cases
0.0
0.5
1.0
1.5
2.0
2.5
3.0
OMEPRAZOLE
MECLIZINE
DRUG UNKNOWN
LIDOCAINE
DULOXETINE
ASCORBIC
GASTROINTESTINAL AGENTS-NOS
AMITRIPTYLINE
OMEGA-3 POLYUNSATURATED FATTY ACIDS
DILTIAZEM
Drug Name

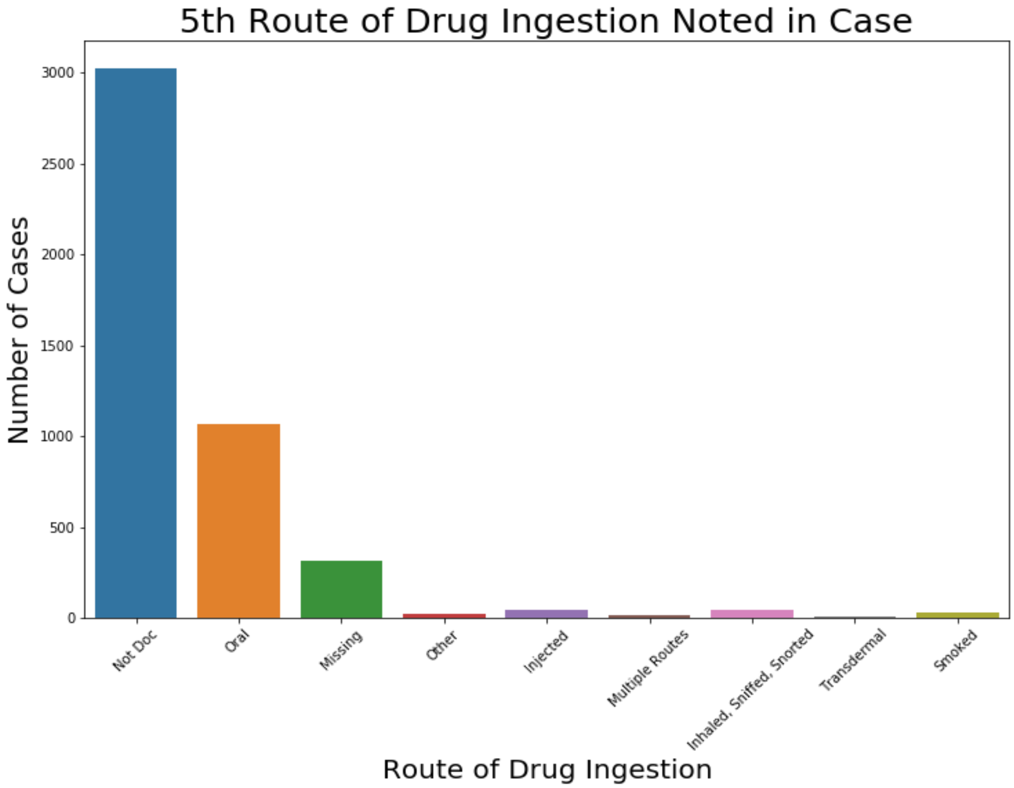

20th Drug Noted in Case
Number of Cases
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
ACETAMINOPHEN
LEVOTHYROXINE
TOPIRAMATE
VITAMIN D
ALBUTEROL-IPRATROPIUM
DOCUSATE-SENNA
ASPIRIN
TRAZODONE
AMLODIPINE
ONDANSETRON
Drug Name

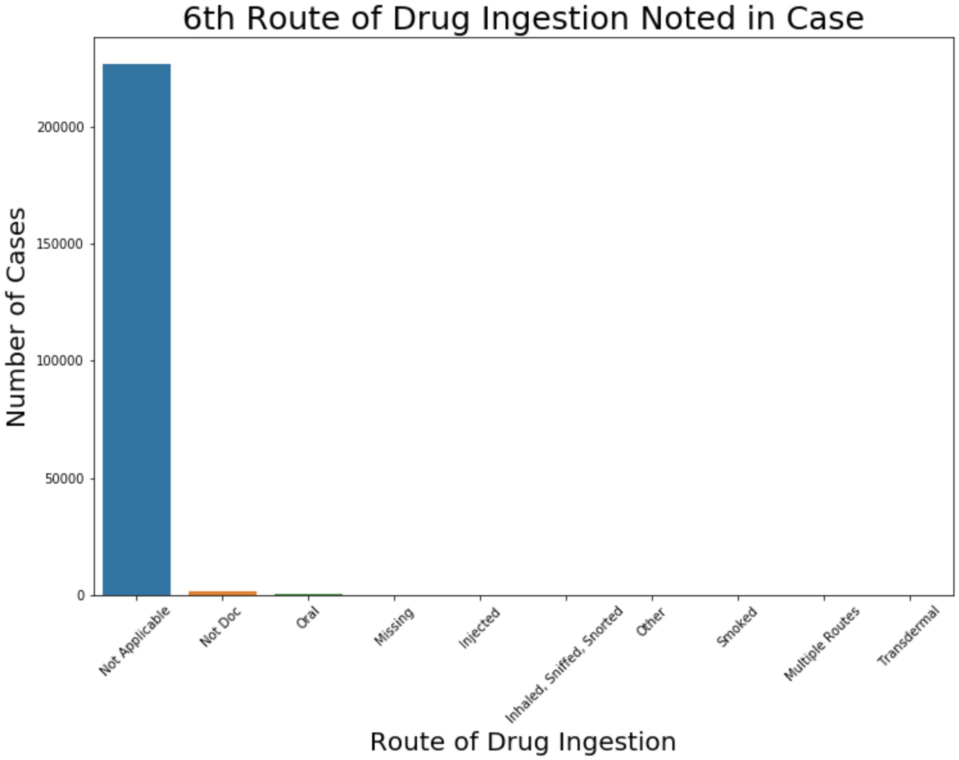

21st Drug Noted in Case
Number of Cases
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
ACETAMINOPHEN-HYDROCODONE
MULTIVITAMIN
CLOPIDOGREL
ACETAMINOPHEN-OXYCODONE
VALSARTAN
ALBUTEROL
SODIUM BIPHOSPHATE-SODIUM PHOSPHATE
SIMVASTATIN
BENZONATATE
VENLAFAXINE
Drug Name

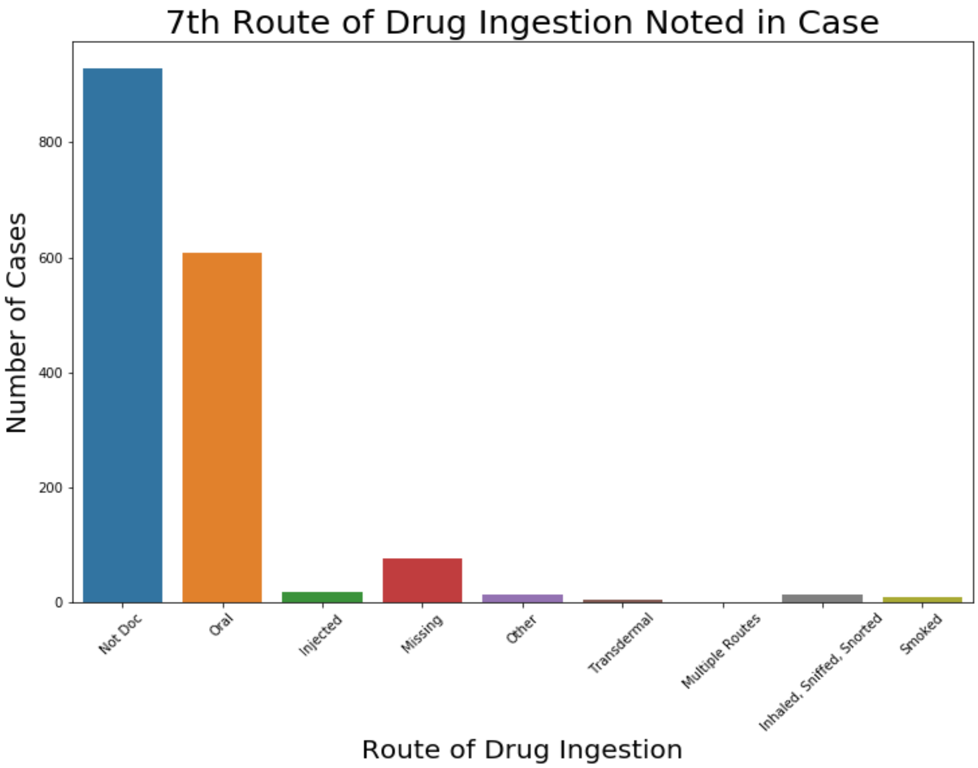

22nd Drug Noted in Case
Number of Cases
1.0
0.8
0.6
0.4
0.2
0.0
DIVALPROEX SODIUM
POLYETHYLENE GLYCOL 3350
LEVOTHYROXINE
ZOLEDRONIC ACID
LIDOCAINE
DIAZEPAM
Drug Name

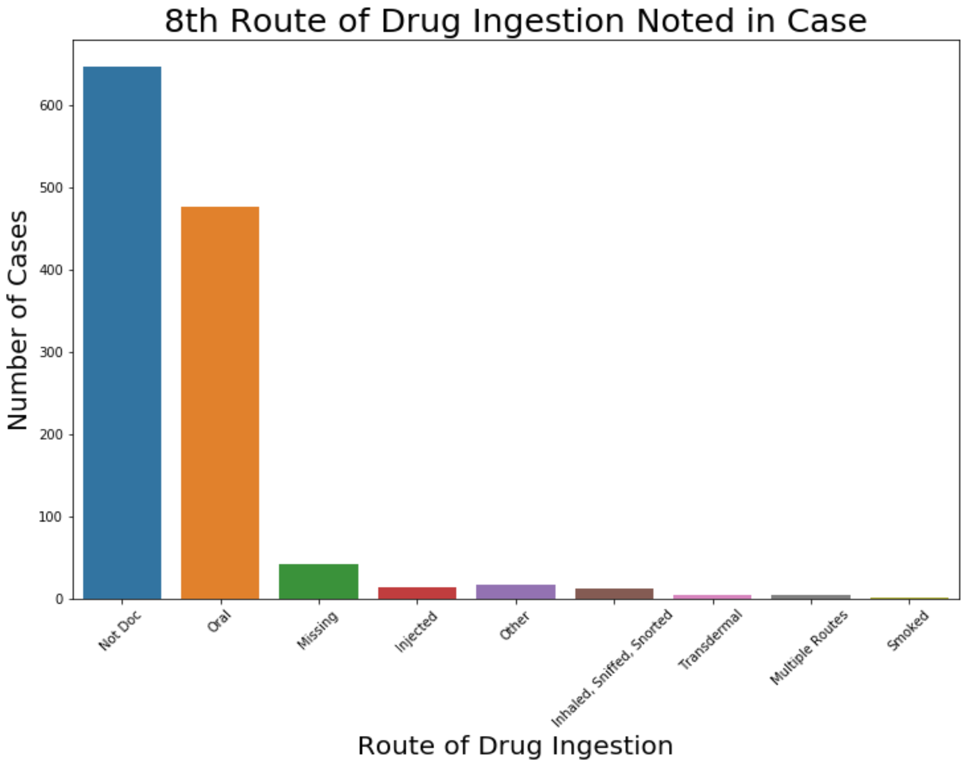
Appendix B – Graphs the Routes of Ingestion Involved in Cases

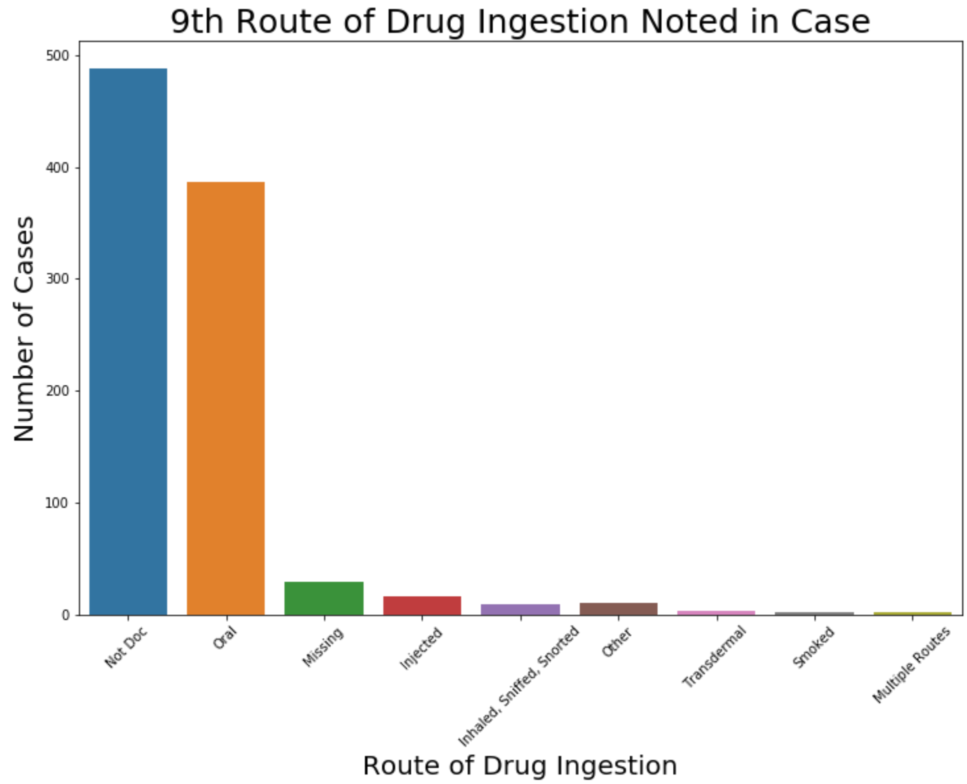


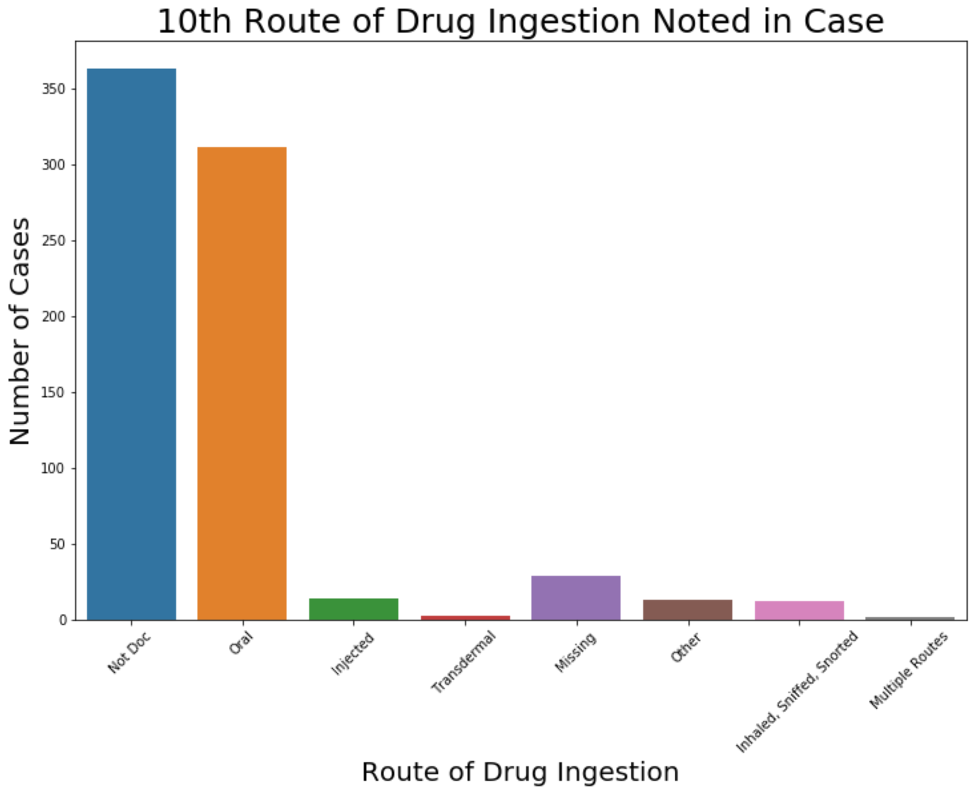

5th Route of Drug Ingestion Noted in Case
Number of Cases
3000
2500
2000
1500
1000
500
0
Not Doc
Oral
Missing
Other
Injected
Multiple Routes
Inhaled, Sniffed, Snorted
Transdermal
Smoked
Route of Drug Ingestion

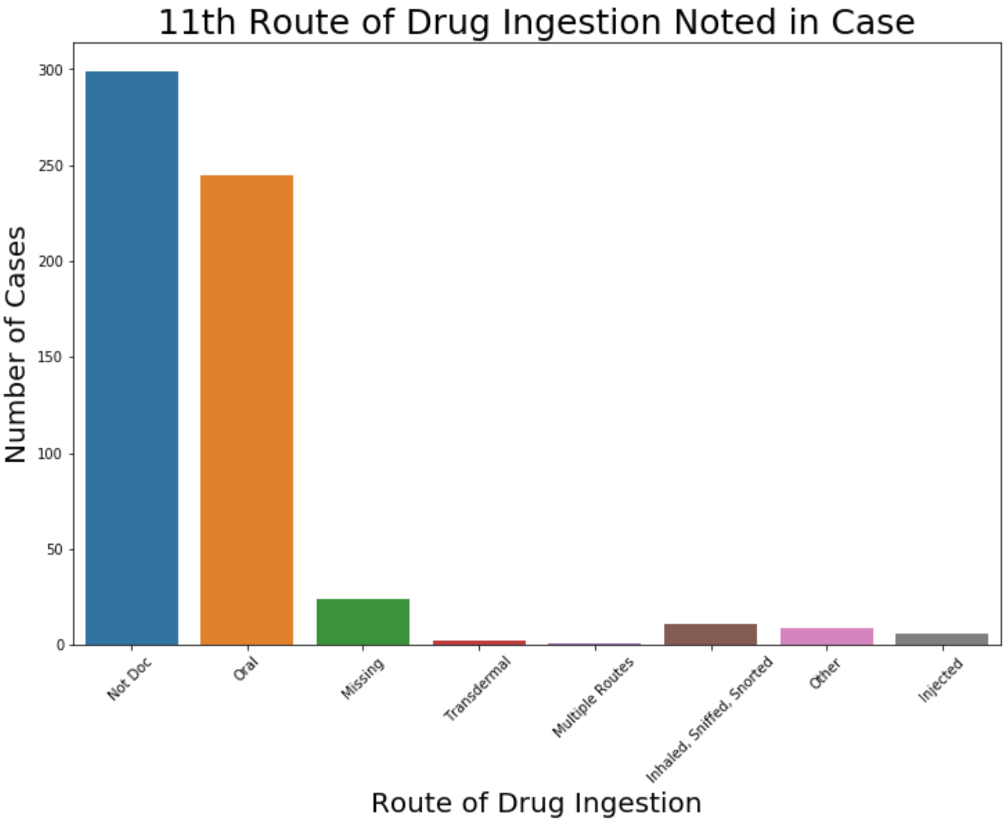

6th Route of Drug Ingestion Noted in Case
Number of Cases
200000
150000
100000
50000
0
Not Applicable
Not Doc
Oral
Missing
Injected
Inhaled, Sniffed, Snorted
Other
Smoked
Multiple Routes
Transdermal
Route of Drug Ingestion

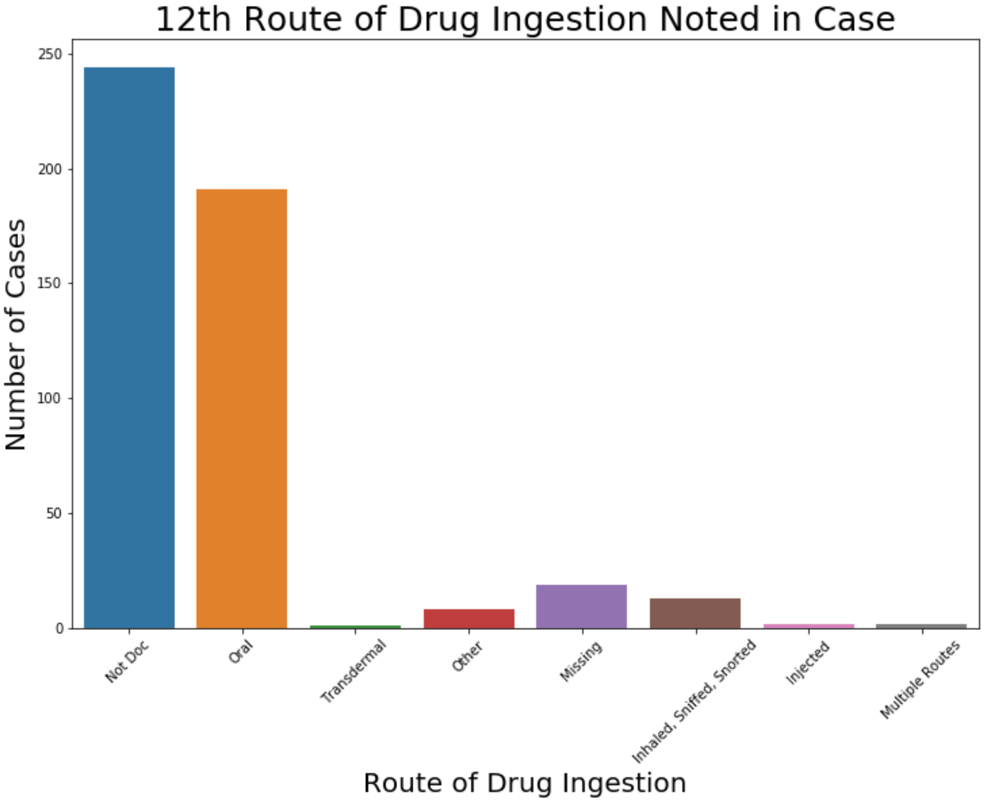

7th Route of Drug Ingestion Noted in Case
Number of Cases
0
200
400
600
800
Not Doc
Oral
Injected
Missing
Other
Transdermal
Multiple Routes
Inhaled, Sniffed, Snorted
Smoked
Route of Drug Ingestion

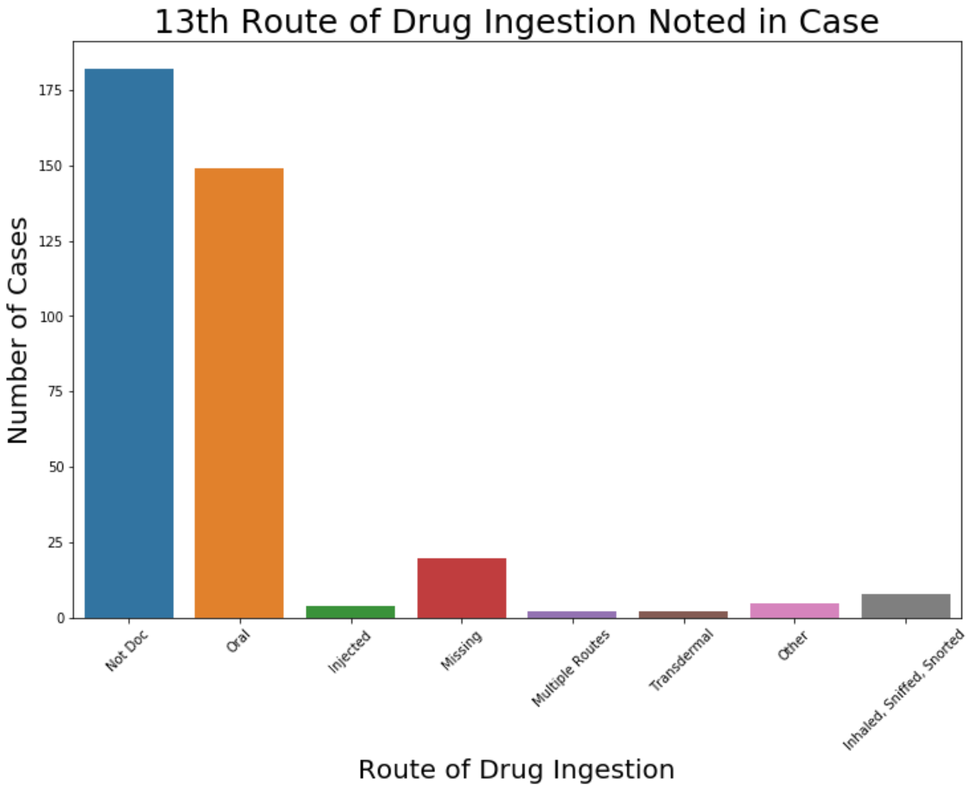

8th Route of Drug Ingestion Noted in Case
Number of Cases
0
100
200
300
400
500
600
Not Doc
Oral
Missing
Injected
Other
Inhaled, Sniffed, Snorted
Transdermal
Multiple Routes
Smoked
Route of Drug Ingestion

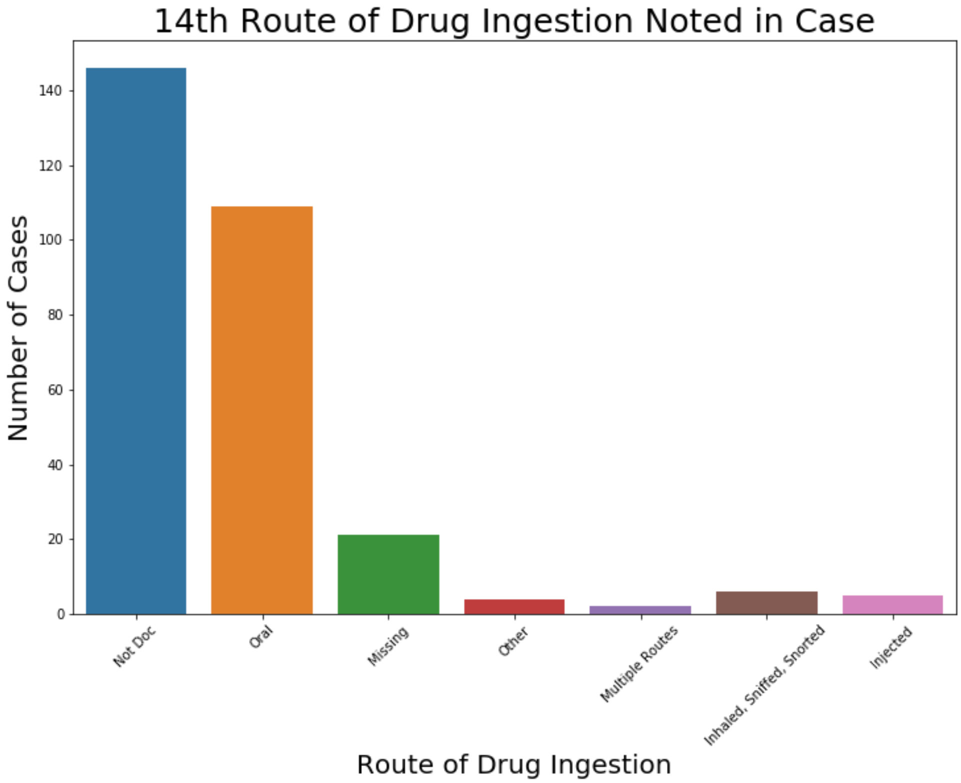

9th Route of Drug Ingestion Noted in Case
Number of Cases
500
400
300
200
100
0
Not Doc
Oral
Missing
Injected
Inhaled, Sniffed, Snorted
Other
Transdermal
Smoked
Multiple Routes
Route of Drug Ingestion

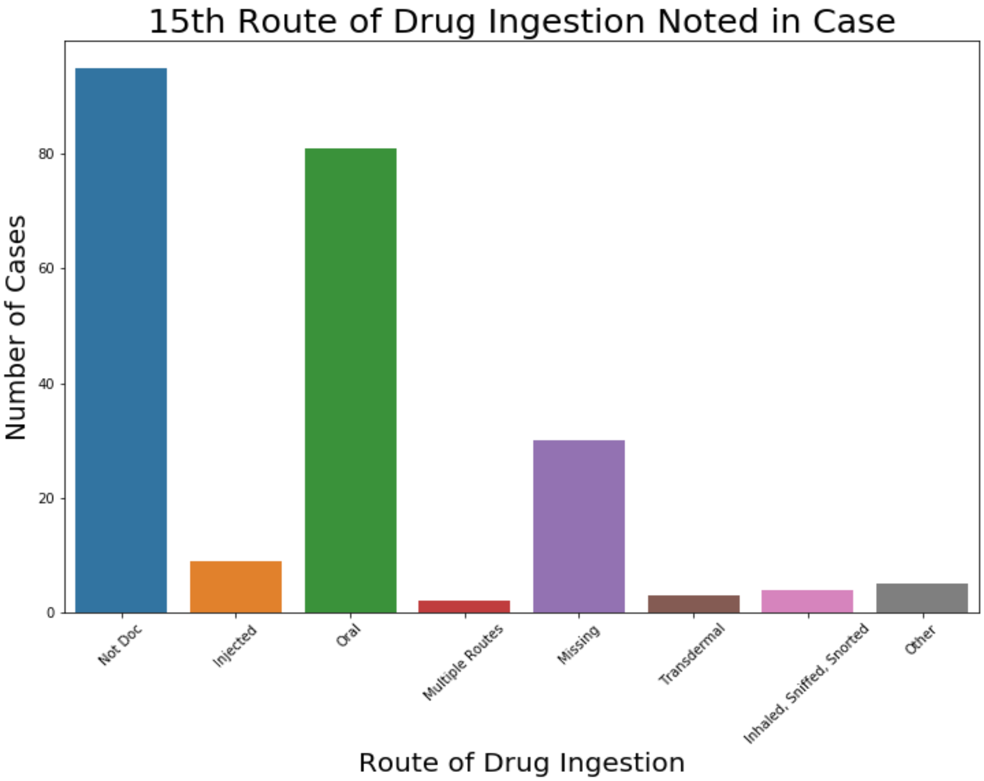

10th Route of Drug Ingestion Noted in Case
Number of Cases
350
300
250
200
150
100
50
0
Not Doc
Oral
Injected
Transdermal
Missing
Other
Inhaled, Sniffed, Snorted
Multiple Routes
Route of Drug Ingestion

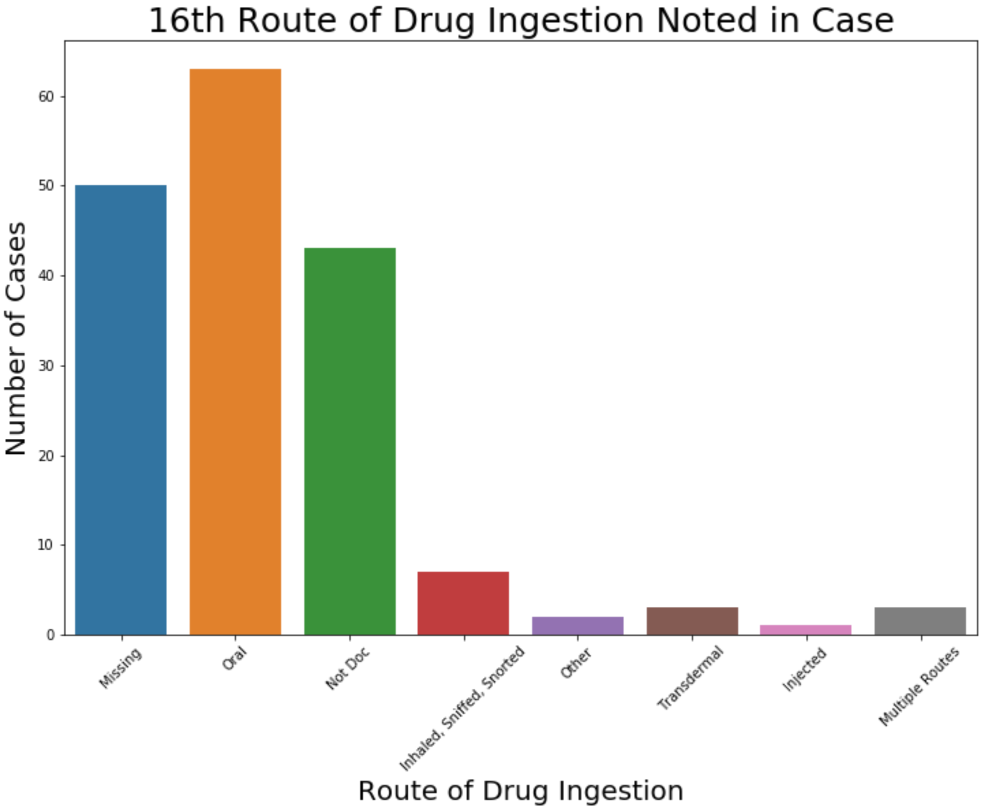

11th Route of Drug Ingestion Noted in Case
Number of Cases
300
250
200
150
100
50
0
Not Doc
Oral
Missing
Transdermal
Multiple Routes
Inhaled, Sniffed, Snorted
Other
Injected
Route of Drug Ingestion

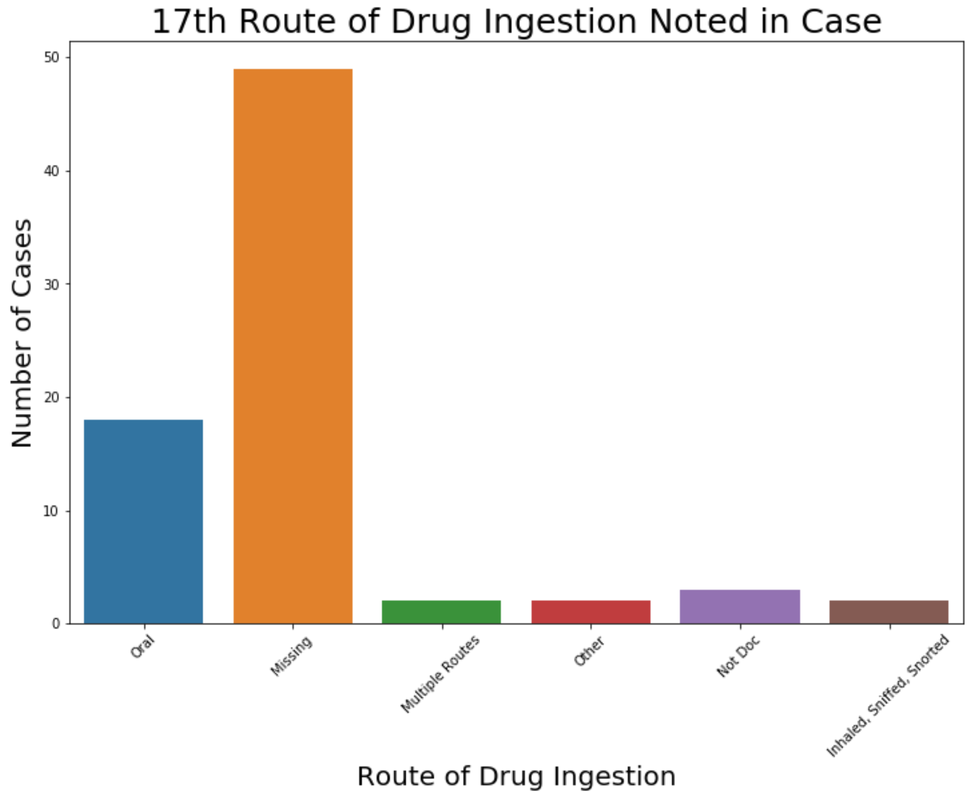

12th Route of Drug Ingestion Noted in Case
Number of Cases
250
200
150
100
50
0
Not Doc
Oral
Transdermal
Other
Missing
Inhaled, Sniffed, Snorted
Injected
Multiple Routes
Route of Drug Ingestion

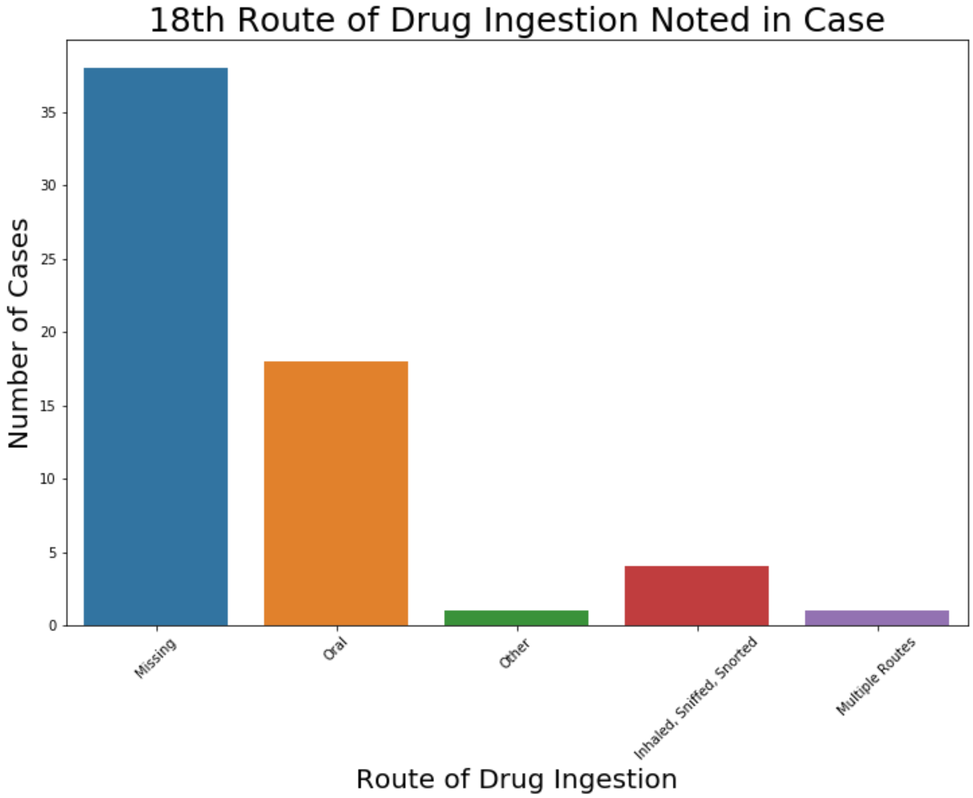

13th Route of Drug Ingestion Noted in Case
Number of Cases
0
25
50
75
100
125
150
175
Not Doc
Oral
Injected
Missing
Multiple Routes
Transdermal
Other
Inhaled, Sniffed, Snorted
Route of Drug Ingestion

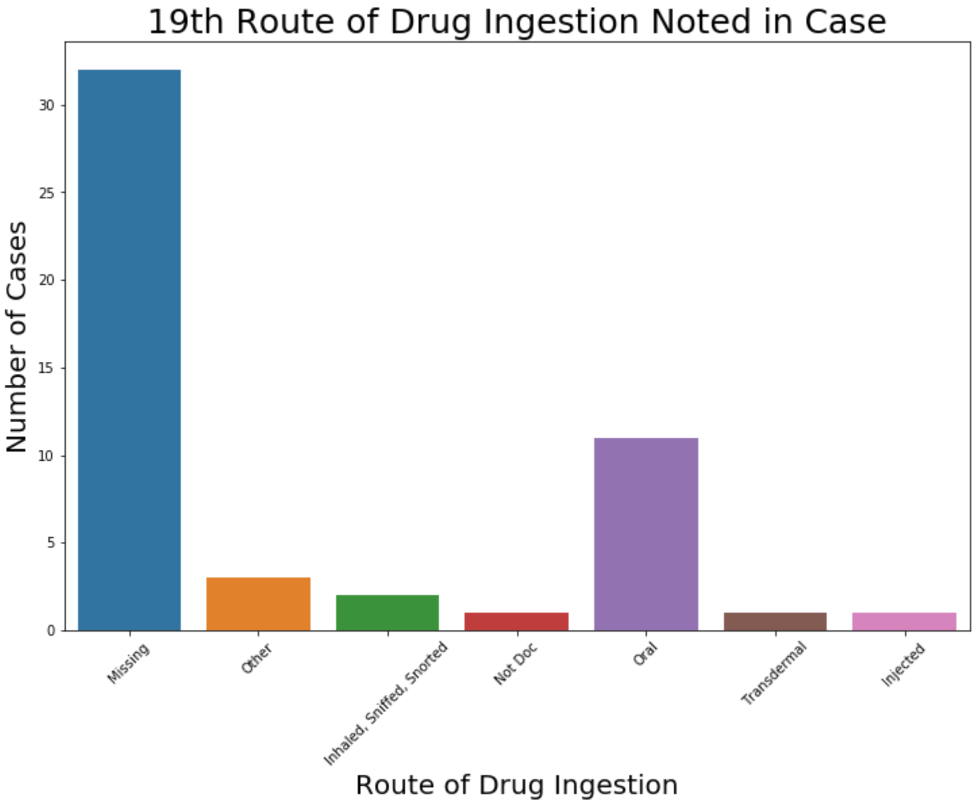

14th Route of Drug Ingestion Noted in Case
Number of Cases
0
20
40
60
80
100
120
140
Not Doc
Oral
Missing
Other
Multiple Routes
Inhaled, Sniffed, Snorted
Injected
Route of Drug Ingestion

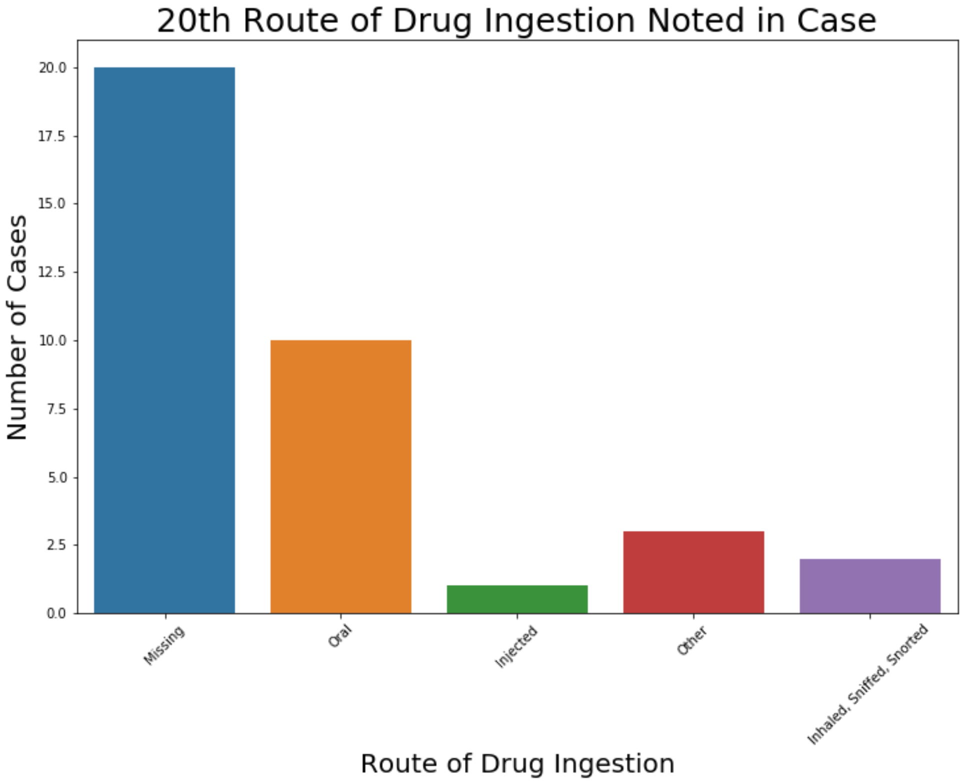

15th Route of Drug Ingestion Noted in Case
Number of Cases
0
20
40
60
80
Not Doc
Injected
Oral
Multiple Routes
Missing
Transdermal
Inhaled, Sniffed, Snorted
Other
Route of Drug Ingestion

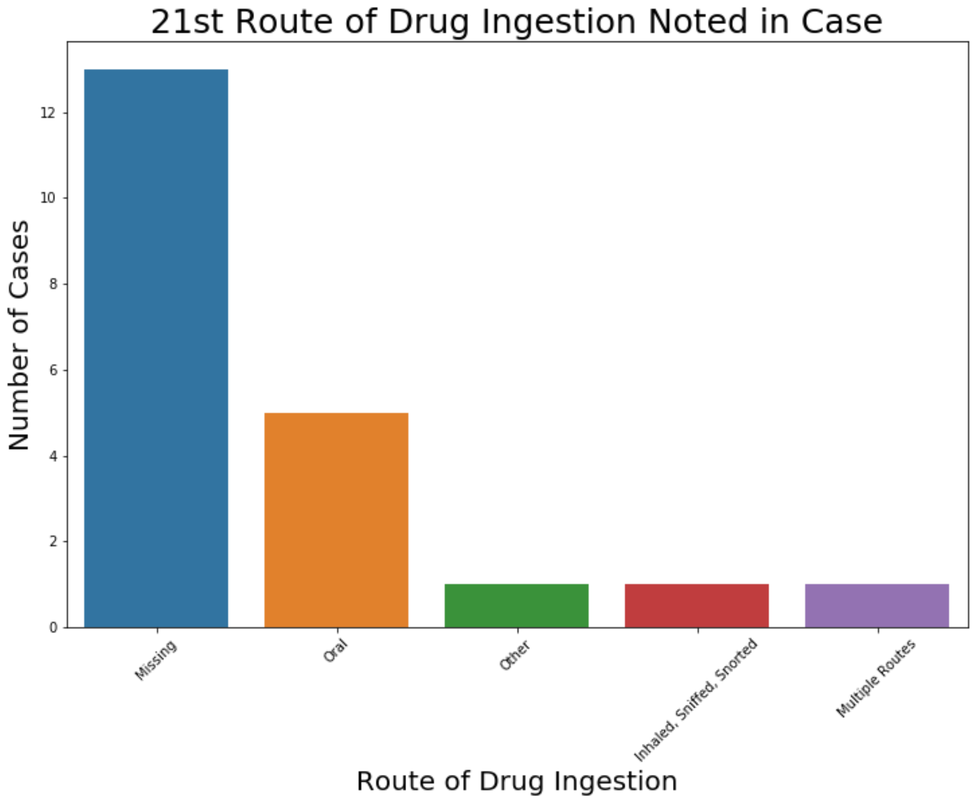

16th Route of Drug Ingestion Noted in Case
Number of Cases
0
10
20
30
40
50
60
Missing
Oral
Not Doc
Inhaled, Sniffed, Snorted
Other
Transdermal
Injected
Multiple Routes
Route of Drug Ingestion

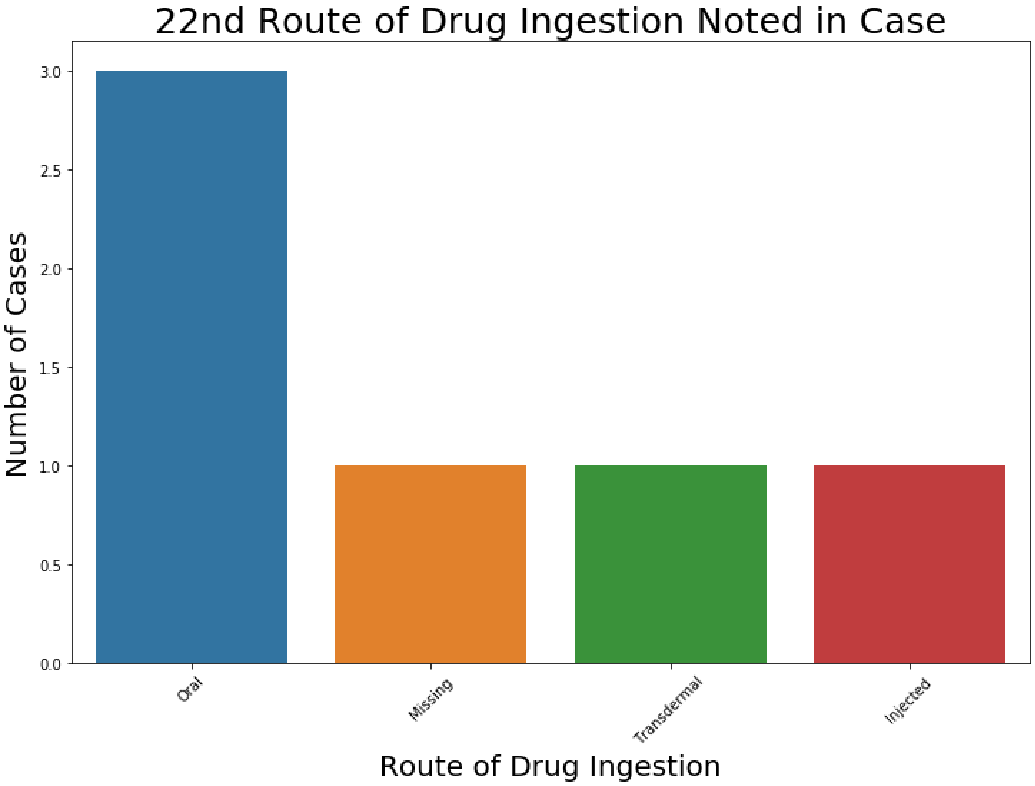

17th Route of Drug Ingestion Noted in Case
Number of Cases
0
10
20
30
40
50
Oral
Missing
Multiple Routes
Other
Not Doc
Inhaled, Sniffed, Snorted
Route of Drug Ingestion


18th Route of Drug Ingestion Noted in Case
Number of Cases
0
5
10
15
20
25
30
35
Missing
Oral
Other
Inhaled, Sniffed, Snorted
Multiple Routes
Route of Drug Ingestion

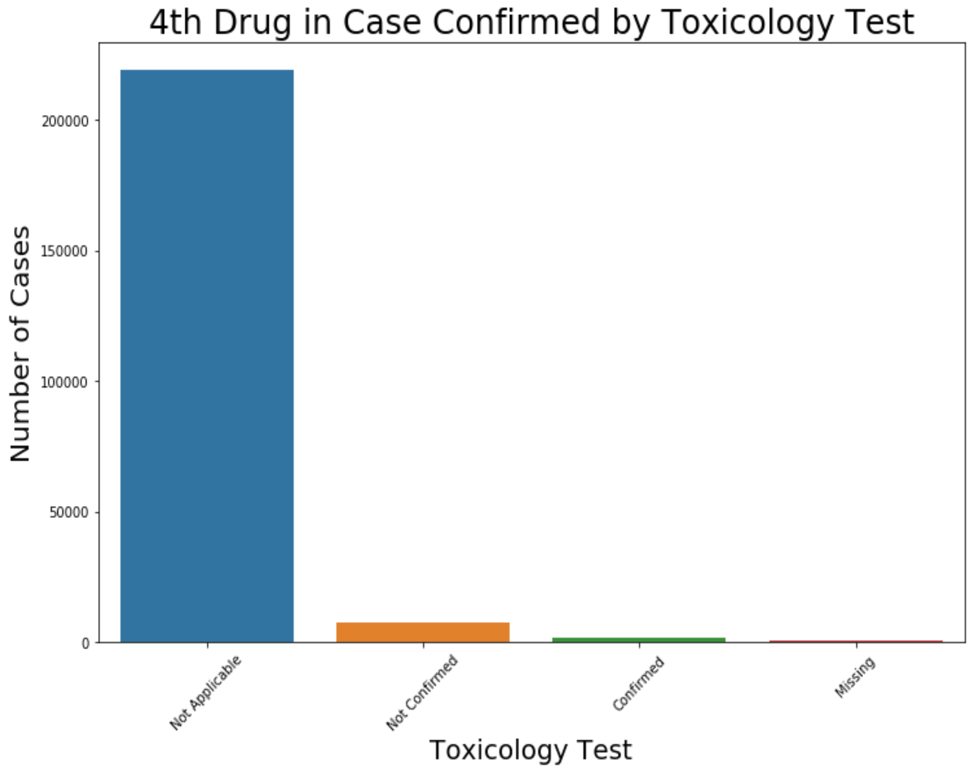

19th Route of Drug Ingestion Noted in Case
Number of Cases
0
5
10
15
20
25
30
Missing
Other
Inhaled, Sniffed, Snorted
Not Doc
Oral
Transdermal
Injected
Route of Drug Ingestion

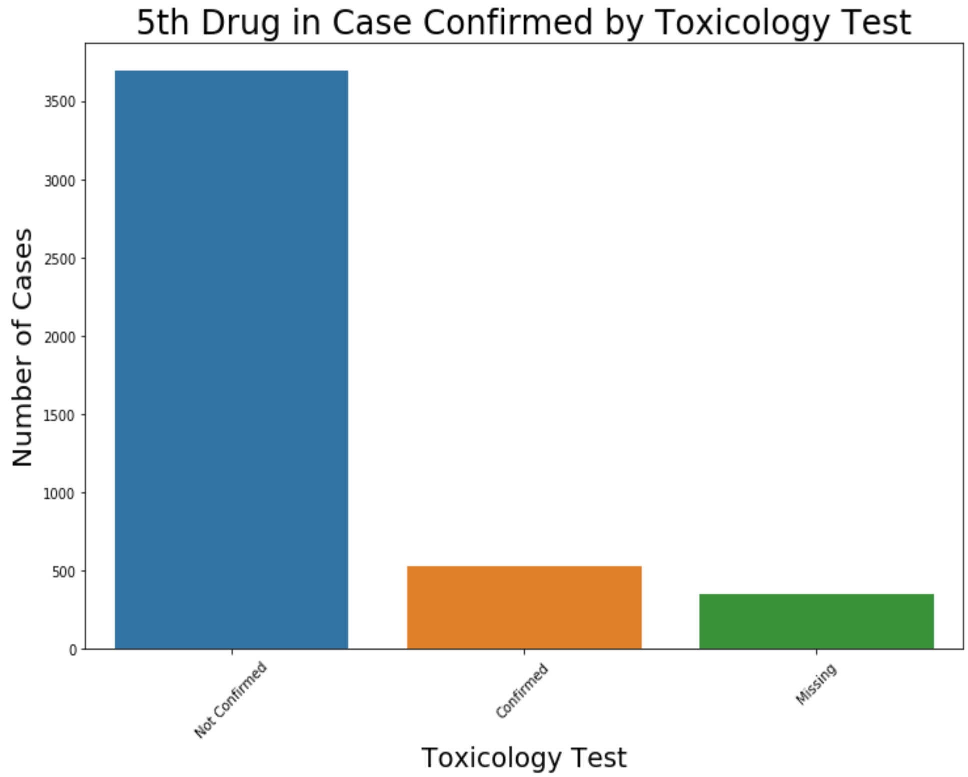

20th Route of Drug Ingestion Noted in Case
Number of Cases
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Missing
Oral
Injected
Other
Inhaled, Sniffed, Snorted
Route of Drug Ingestion

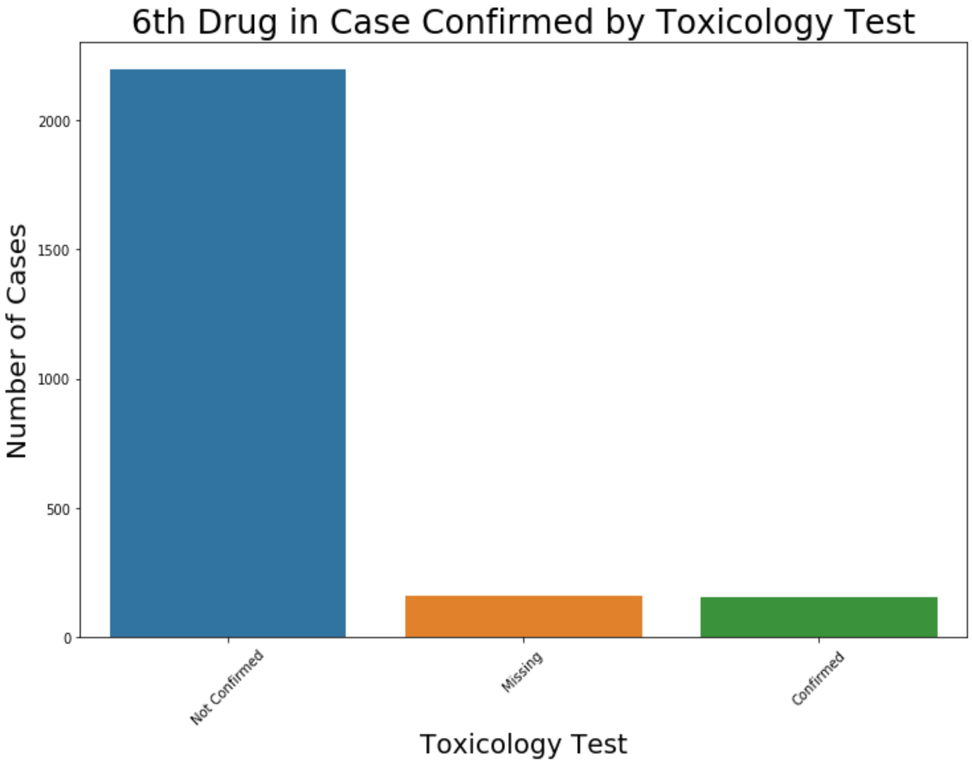

21st Route of Drug Ingestion Noted in Case
Number of Cases
0
2
4
6
8
10
12
Missing
Oral
Other
Inhaled, Sniffed, Snorted
Multiple Routes
Route of Drug Ingestion

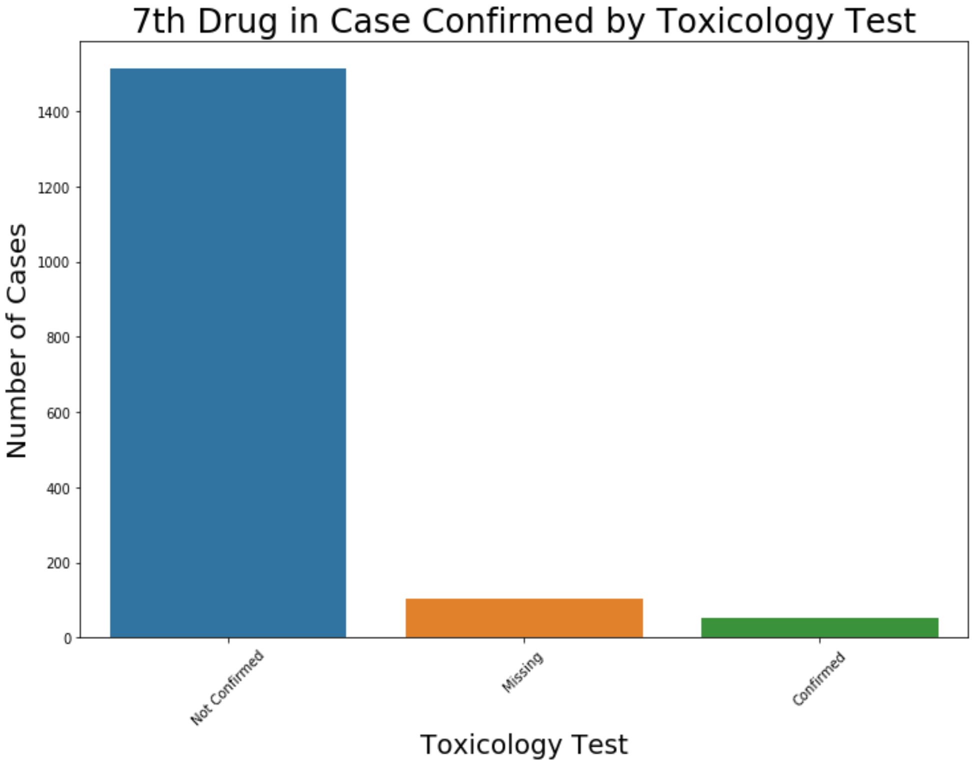

22nd Route of Drug Ingestion Noted in Case
Number of Cases
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Oral
Missing
Transdermal
Injected
Route of Drug Ingestion

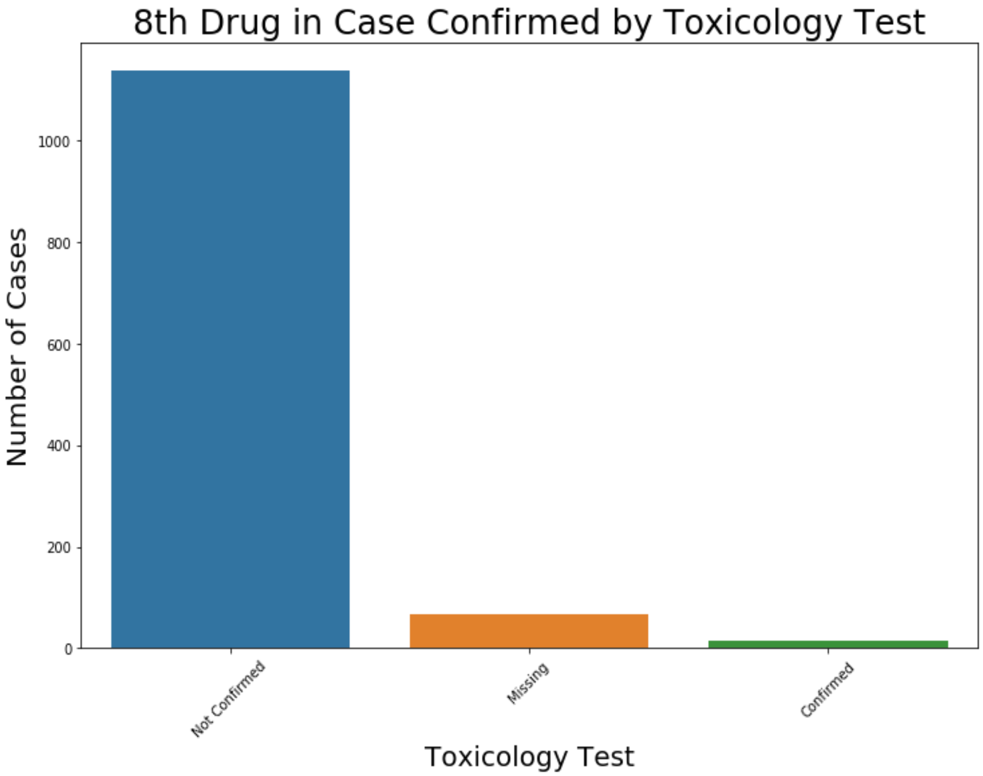
Appendix C – Graphs of Whether a Toxicology Test was Done

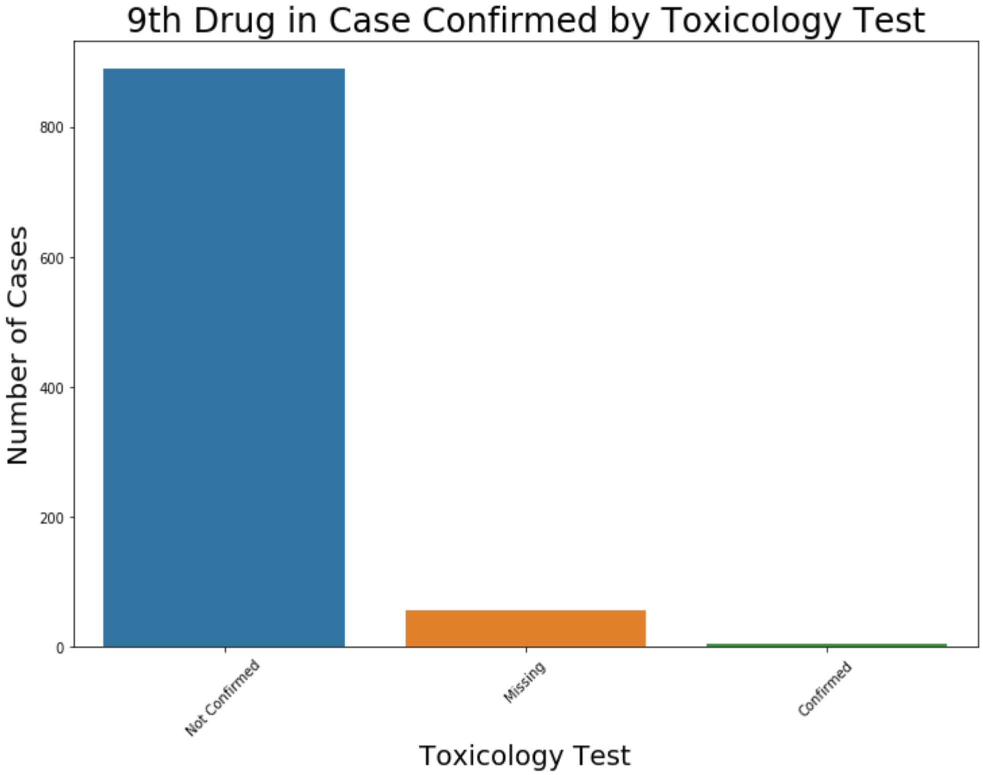


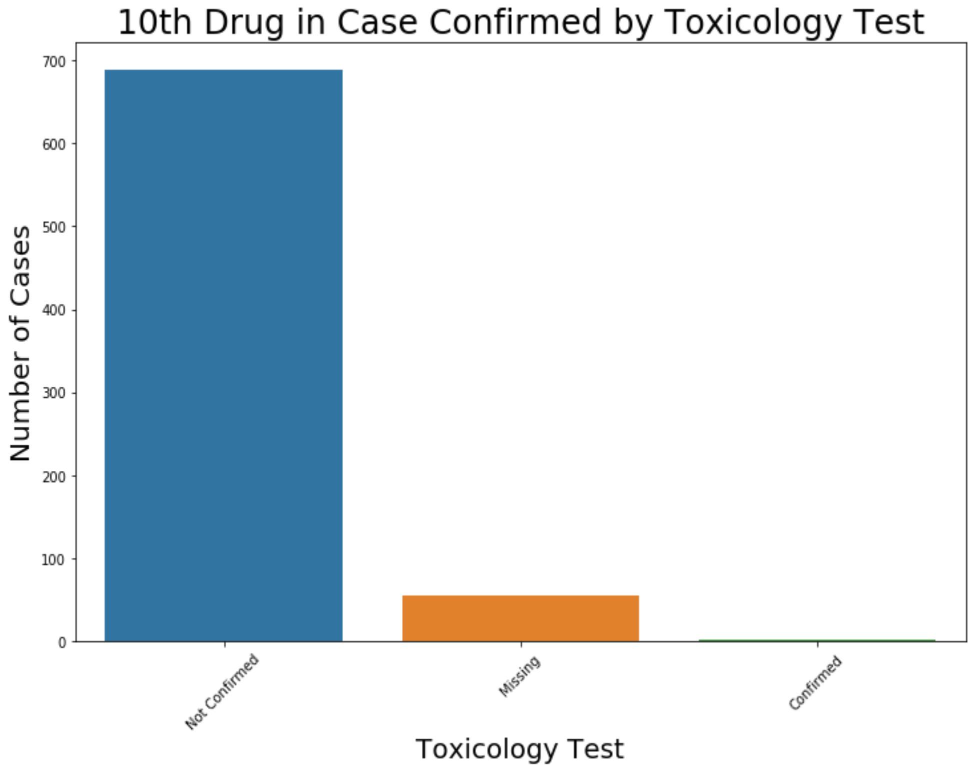


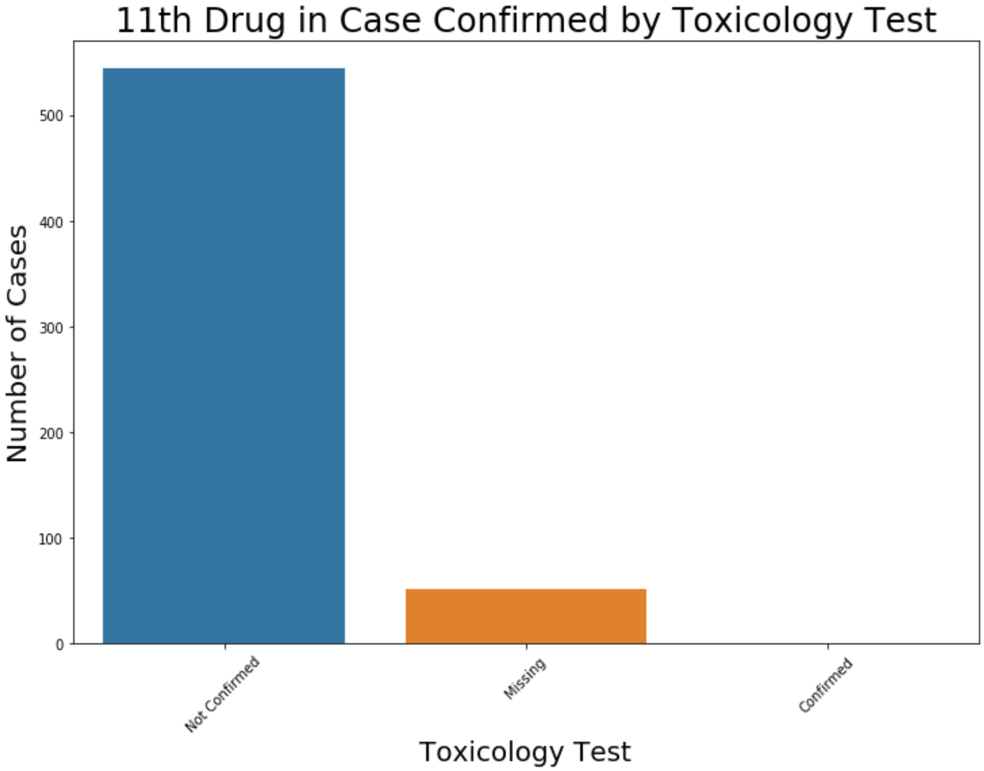

6th Drug in Case Confirmed by Toxicology Test
Number of Cases
2000
1500
1000
500
0
Not Confirmed
Missing
Confirmed
Toxicology Test

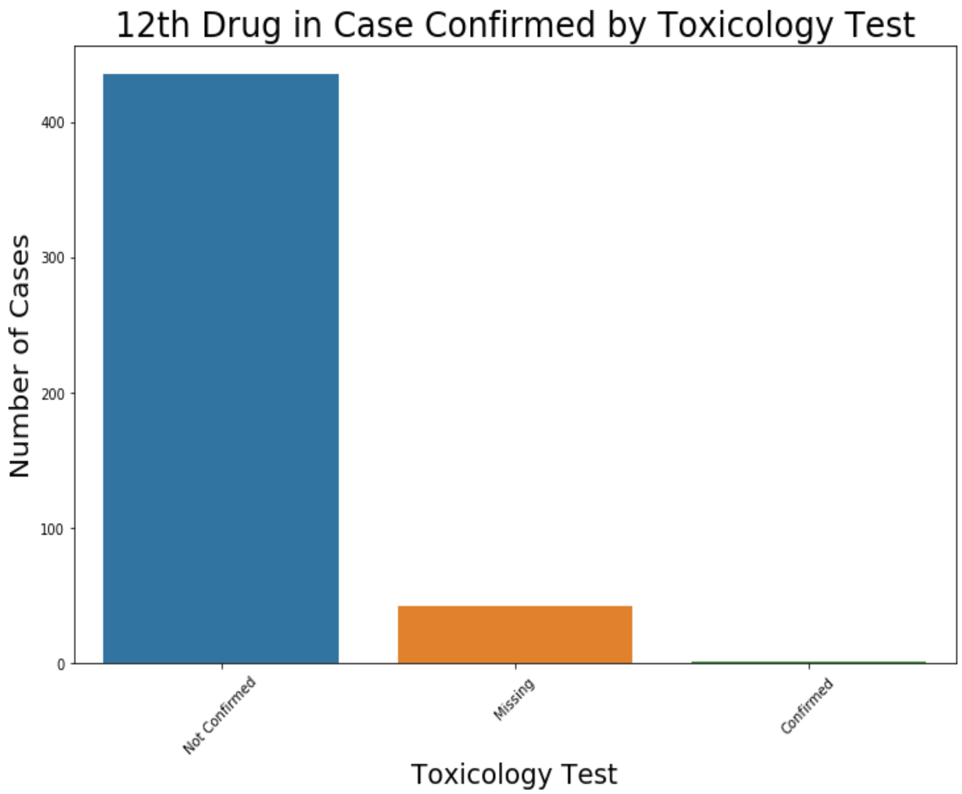

7th Drug in Case Confirmed by Toxicology Test
Number of Cases
1400
1200
1000
800
600
400
200
0
Not Confirmed
Missing
Confirmed
Toxicology Test

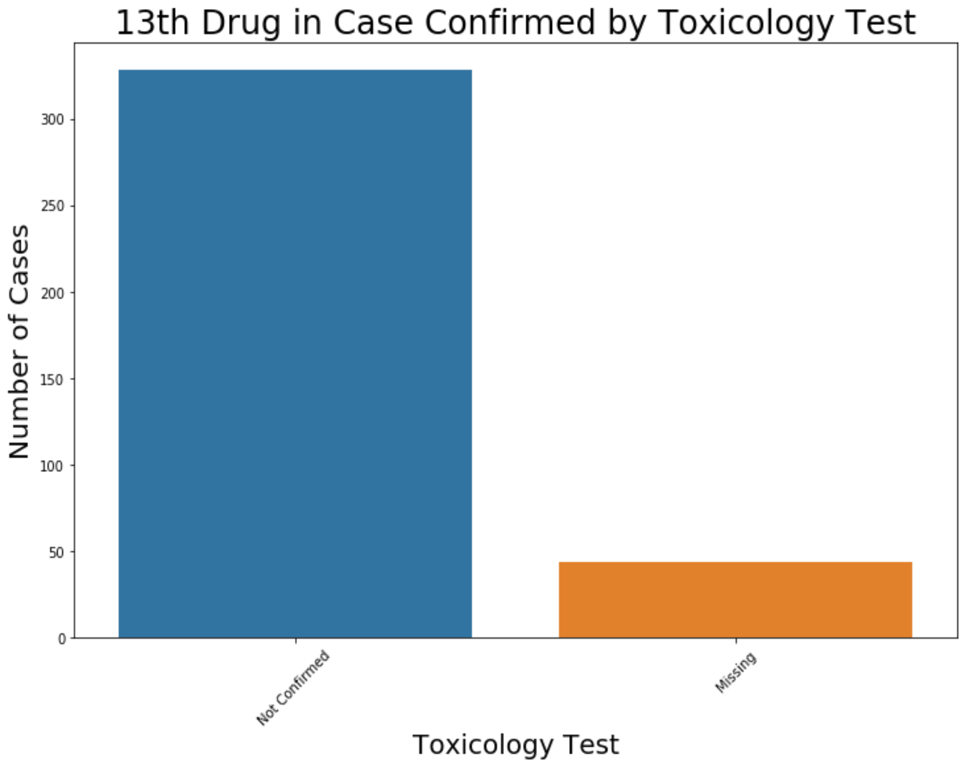

8th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
200
400
600
800
1000
Not Confirmed
Missing
Confirmed
Toxicology Test

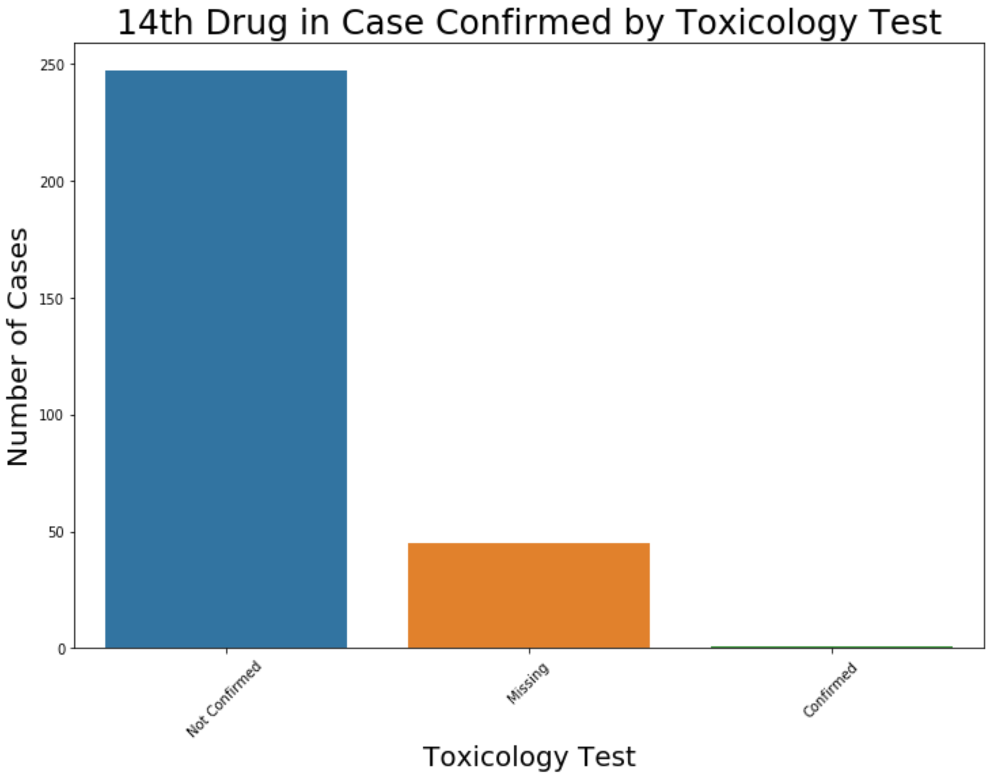

9th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
200
400
600
800
Not Confirmed
Missing
Confirmed
Toxicology Test

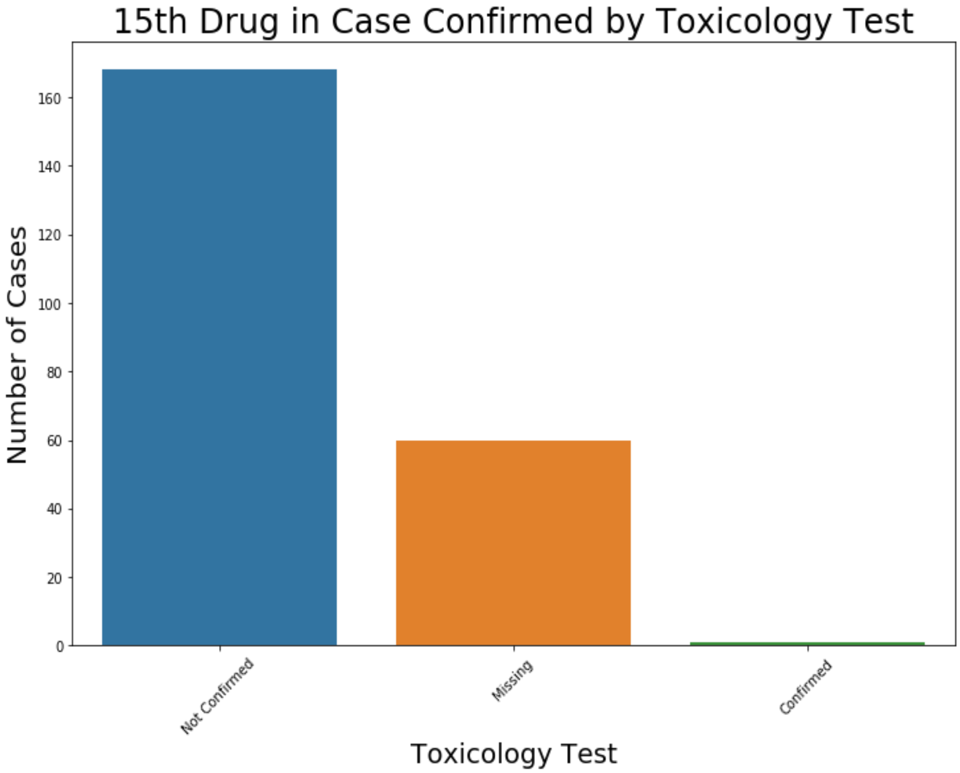

10th Drug in Case Confirmed by Toxicology Test
Number of Cases
700
600
500
400
300
200
100
0
Not Confirmed
Missing
Confirmed
Toxicology Test

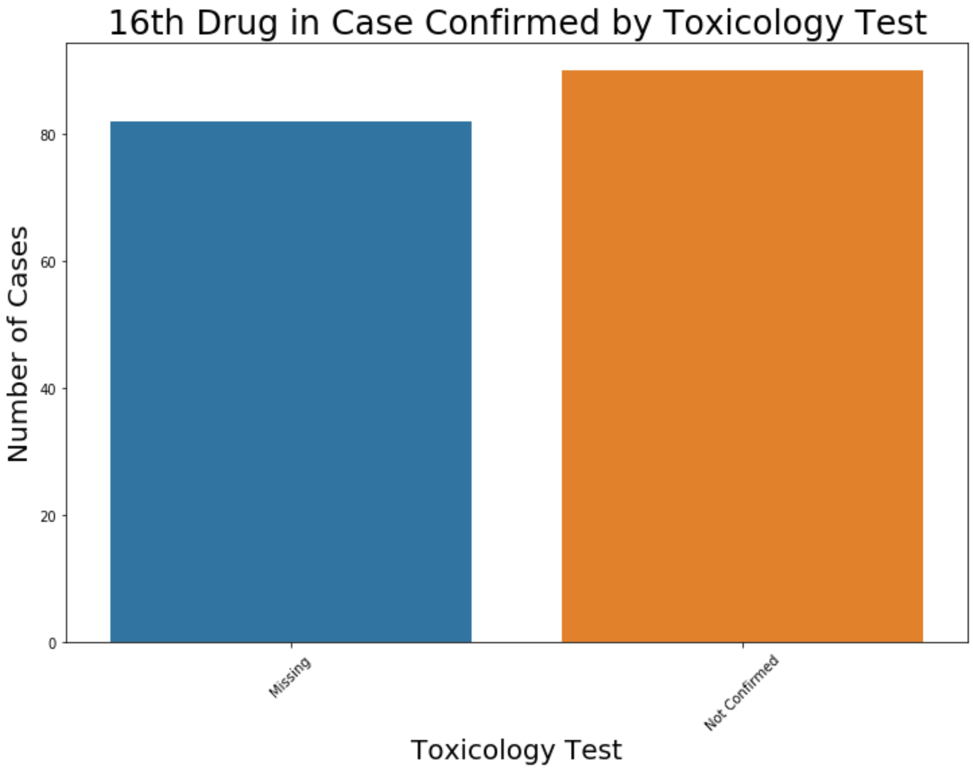

11th Drug in Case Confirmed by Toxicology Test
Number of Cases
500
400
300
200
100
0
Not Confirmed
Missing
Confirmed
Toxicology Test

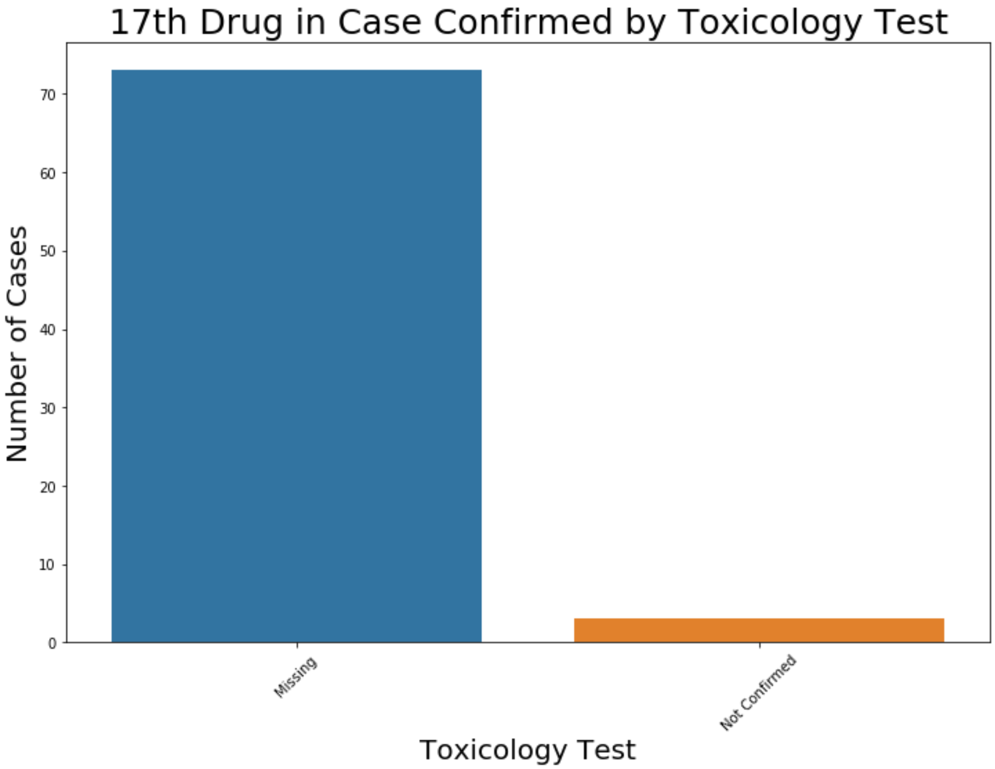

12th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
100
200
300
400
Not Confirmed
Missing
Confirmed
Toxicology Test

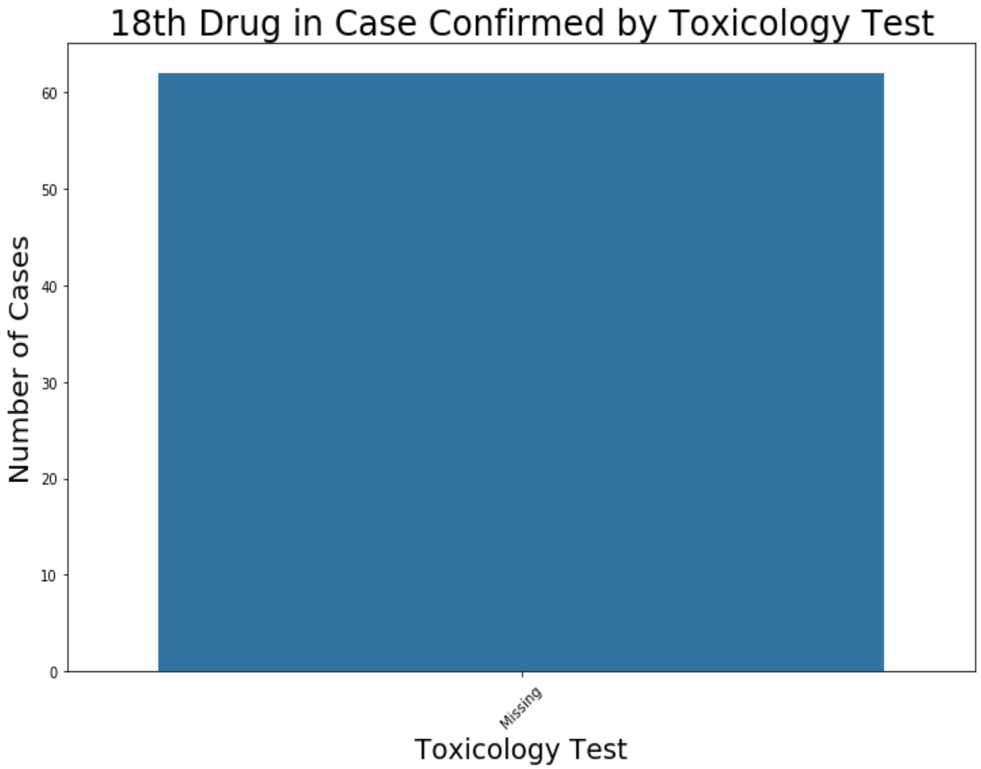

13th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
50
100
150
200
250
300
Not Confirmed
Missing
Toxicology Test

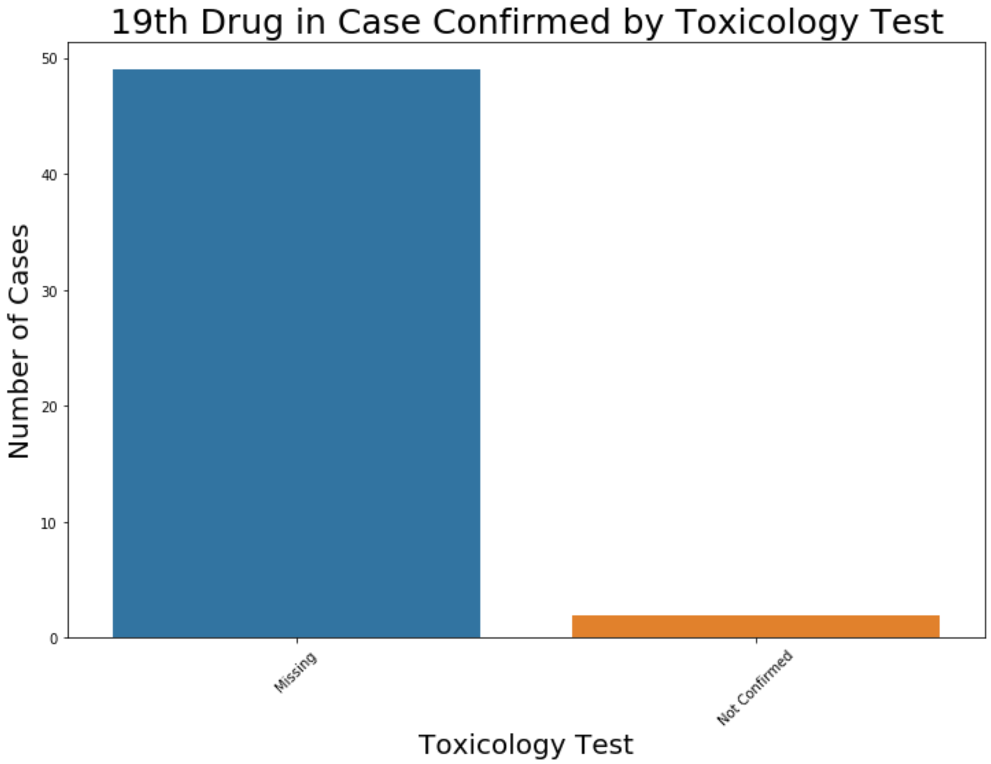

14th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
50
100
150
200
250
Not Confirmed
Missing
Confirmed
Toxicology Test

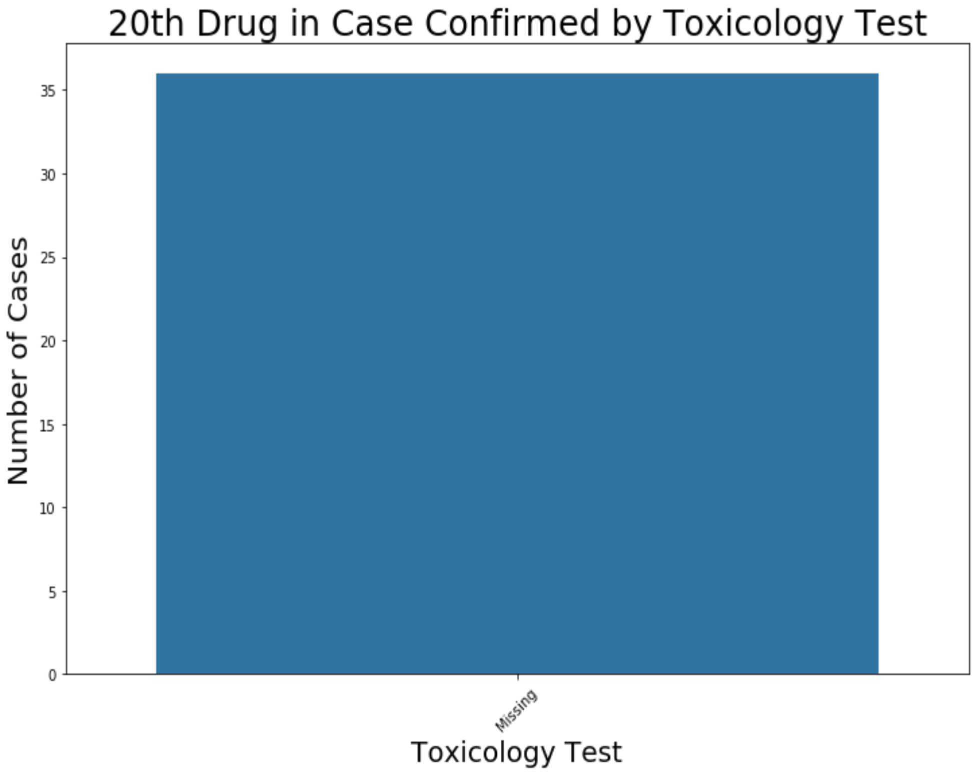

15th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
20
40
60
80
100
120
140
160
Not Confirmed
Missing
Confirmed
Toxicology Test

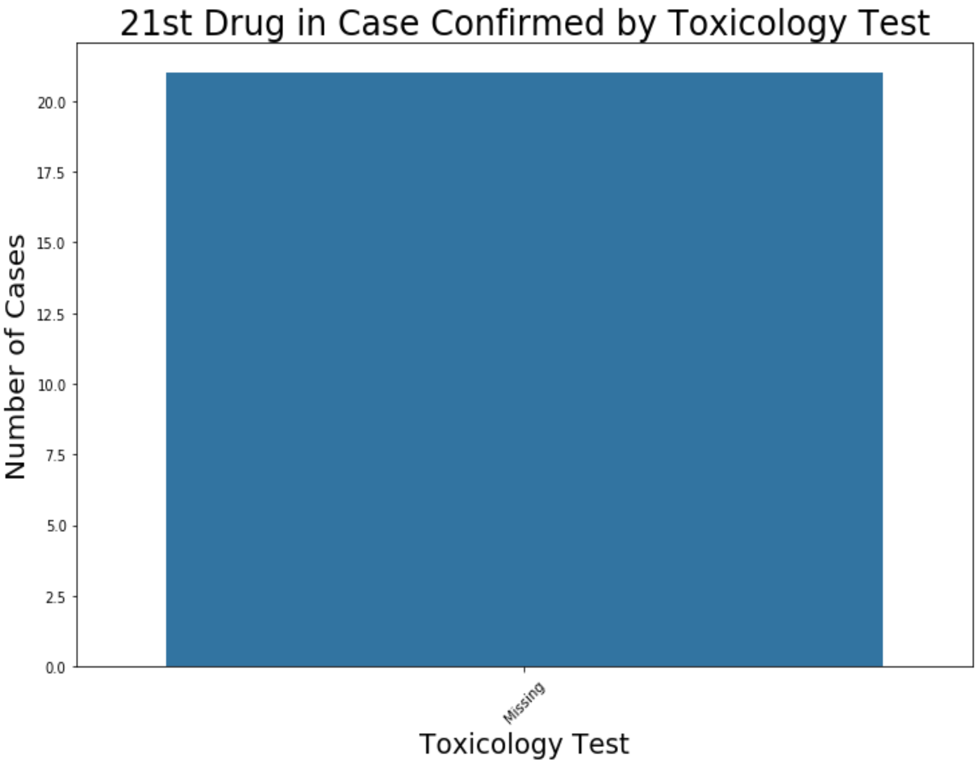

16th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
20
40
60
80
Missing
Not Confirmed
Toxicology Test

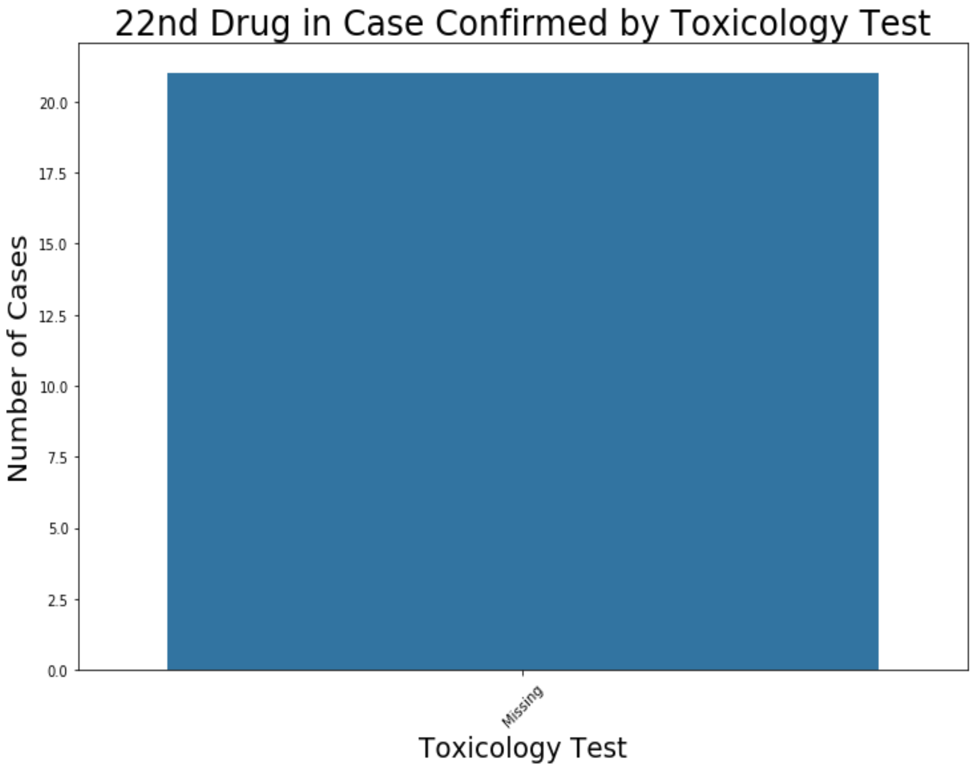

17th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
10
20
30
40
50
60
70
Missing
Not Confirmed
Toxicology Test


18th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
10
20
30
40
50
60
Missing
Toxicology Test


19th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
10
20
30
40
50
Missing
Not Confirmed
Toxicology Test


20th Drug in Case Confirmed by Toxicology Test
Number of Cases
0
5
10
15
20
25
30
35
Missing
Toxicology Test


21st Drug in Case Confirmed by Toxicology Test
Number of Cases
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Missing
Toxicology Test


22nd Drug in Case Confirmed by Toxicology Test
Number of Cases
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Missing
Toxicology Test