MSIN00143 Programming for Business Analytics - Group D2 - The Economic Loss from Fire Incidents - A Machine Learning Approach

December 12, 2022

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1 Introduction

Fire incidents are becoming one of the most urgent global issues. According to recent studies, the cost of fires in developed countries is estimated to reach 1% of the GDP amounting to around \$76bn worldwide (Universitas21, no date). Looking at specific countries, the estimated economic lost due to fire incidents in UK between 2017 and 2018 was between £5.73bn and £11.46bn (NFCC, 2019), while in 2016, the economic loss in Canada on cost of fires were up to $7.6 billion (Douglas, 2016). This project is to focus on the estimated economic loss on fire of Canada's largest city, Toronto, due to the recent news that the city is facing an understaffed and tight budget for fire issues, especially during periods of COVID restrictions when residents were encouraged to spend more time at home (Boisvert, 2021). There were 10% of fire trucks unavailable due to insufficient firefighters; according to the Toronto Professional Fire Fighters Association (TPFFA). Our target is to know the estimated economic loss on fire as a reference for the government's budgeting.

By considering how much money the government should budget for the fire department, we believe it is significant to know the loss of economic cost fire incidents can cause. Therefore, we will answer the following question: **What is the estimated economic loss of a fire incident?**

2 Data Preparation

We use data on fire incidents provided by the City of Toronto (https://ckan0.cf.opendata.inter.prod-toronto.ca/tl/dataset/fire-incidents/resource/fa5c7de5-10f8-41cf-883a-9b30a67c7b56). It was last updated on 15/11/2022 on ckan open resources platform. The dataset provides fire incident information from the Ontario Fire Marshal. It should be noted that the data set excluded personal information and the exact address was excluded due to privacy purposes (Ckan, 2022).

[237]:
```
import pandas as pd
df = pd.read_csv('fire-incidents-data.csv')
df.shape
```

[237]:
```
(17536, 43)
```

This dataset contains 43 columns and 17536 rows. The data preparation will consist of four steps.

2.1 Import packages

[238]:
```
# Import packages.
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import sklearn.model_selection as model_selection
import statsmodels.api as sm
import seaborn as sns
import xgboost as xgb
import json
from sklearn.cluster import KMeans
from sklearn.linear_model import LogisticRegression, LinearRegression
```

```
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score, f1_score, mean_squared_error
from sklearn import svm, datasets
from sklearn.multiclass import OneVsRestClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MultiLabelBinarizer
from IPython.core.interactiveshell import InteractiveShell
from IPython import display
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVR
pd.options.mode.chained_assignment = None
InteractiveShell.ast_node_interactivity = "all"
```

2.2 Identify rows with the missing dependent variable values

[239]:
```
# Print number of rows with Estimated_Dollar_Loss missing values.
print("There are " + str(df.Estimated_Dollar_Loss.isna().sum()) + " rows with␣
↪missing Estimated_Dollar_Loss")
```

```
There are 1909 rows with missing Estimated_Dollar_Loss
```

As the economic loss is our dependent variable, we drop the rows that have missing values.

[240]:
```
# New data frame with rows that have an Estimated Dollar Loss.
df1 = df[df.Estimated_Dollar_Loss.notnull()]

# Check number of rows with Estimated_Dollar_Loss missing values.
print("There are " + str(df1.Estimated_Dollar_Loss.isna().sum()) + " rows with␣
↪missing Estimated_Dollar_Loss")
```

```
There are 0 rows with missing Estimated_Dollar_Loss
```

2.3 Data transformation to create new variables

Our dataset contains two time variables, "TFS_Alarm_Time" and "TFS_Arrival_Time", indicating the time at which the alarm first appeared at the local station, and the time at which the firefighters arrived at the fire incident location respecitvely. We are interested in including a variable with the difference between these two times.

[241]:
```
# Create two new variables of time without the "T".
df1 = df1.assign(Alarm_Time = df1.TFS_Alarm_Time.str.replace("T", " "),␣
↪Arrival_Time = df1.TFS_Arrival_Time.str.replace("T", " "))

# Create new variable of time difference and use numpy and pandas to format␣
↪into datetime.
df1 = df1.assign(Time_Difference = (pd.to_datetime(df1["Arrival_Time"],␣
↪format='%Y-%m-%d %H:%M:%S') - pd.to_datetime(df1["Alarm_Time"],␣
↪format='%Y-%m-%d %H:%M:%S'))/np.timedelta64(1, 'h'))
```

```
# Drop the redundant variables.
df2 = df1.drop(columns = ['TFS_Alarm_Time', 'TFS_Arrival_Time', 'Alarm_Time',␣
↪'Arrival_Time'])
```

2.4 Identify rows with missing independent variable values

[242]:
```
# Print columns with respective missing values.
for i in dict(zip(df2.isna().sum().index, df2.isna().sum())):
    print("There are " + str(dict(zip(df2.isna().sum().index, df2.isna().
↪sum()))[i]) + " rows with missing " + str(i))
```

```
There are 0 rows with missing _id
There are 7 rows with missing Area_of_Origin
There are 4411 rows with missing Building_Status
There are 4413 rows with missing Business_Impact
There are 0 rows with missing Civilian_Casualties
There are 0 rows with missing Count_of_Persons_Rescued
There are 0 rows with missing Estimated_Dollar_Loss
There are 4412 rows with missing Estimated_Number_Of_Persons_Displaced
There are 15294 rows with missing Exposures
There are 7 rows with missing Ext_agent_app_or_defer_time
There are 4413 rows with missing Extent_Of_Fire
There are 0 rows with missing Final_Incident_Type
There are 4413 rows with missing Fire_Alarm_System_Impact_on_Evacuation
There are 4413 rows with missing Fire_Alarm_System_Operation
There are 4413 rows with missing Fire_Alarm_System_Presence
There are 0 rows with missing Fire_Under_Control_Time
There are 7 rows with missing Ignition_Source
There are 0 rows with missing Incident_Number
There are 0 rows with missing Incident_Station_Area
There are 80 rows with missing Incident_Ward
There are 0 rows with missing Initial_CAD_Event_Type
There are 1 rows with missing Intersection
There are 0 rows with missing Last_TFS_Unit_Clear_Time
There are 1 rows with missing Latitude
There are 4413 rows with missing Level_Of_Origin
There are 1 rows with missing Longitude
There are 7 rows with missing Material_First_Ignited
There are 7 rows with missing Method_Of_Fire_Control
There are 0 rows with missing Number_of_responding_apparatus
There are 0 rows with missing Number_of_responding_personnel
There are 7 rows with missing Possible_Cause
There are 0 rows with missing Property_Use
There are 4413 rows with missing Smoke_Alarm_at_Fire_Origin
There are 4413 rows with missing Smoke_Alarm_at_Fire_Origin_Alarm_Failure
There are 4413 rows with missing Smoke_Alarm_at_Fire_Origin_Alarm_Type
```

```
There are 4413 rows with missing
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation
There are 4413 rows with missing Smoke_Spread
There are 4413 rows with missing Sprinkler_System_Operation
There are 4413 rows with missing Sprinkler_System_Presence
There are 7 rows with missing Status_of_Fire_On_Arrival
There are 0 rows with missing TFS_Firefighter_Casualties
There are 0 rows with missing Time_Difference
```

All independent variabes have been checked for missing values. The missing values for each variable have been replaced with an exisitng category uder 'undetermined' or 'missing'. The number of persons displaced by the fire incident has been categorised into 5 categories. Variables that have a siginifcant amount of missing values have been dropped from the dataset.

[243]:
```python
# Drop the 7 rows with missing Area_of_Origin.
df3 = df2[df2.Area_of_Origin.notnull()]

# Fill the missing values with respective 'undetermined' or 'missing' category.
df3[['Building_Status']] = df3[['Building_Status']].fillna("10 - Missing␣
↪Entries")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df3[['Business_Impact']] = df3[['Business_Impact']].fillna("10 - Missing")

# Categorise Estimated_Number_Of_Persons_Displaced into 5 categories.
df3['Estimated_Number_Of_Persons_Displaced'] =␣
↪df3['Estimated_Number_Of_Persons_Displaced'].astype('Int64')
df3['Estimated_Number_Of_Persons_Displaced'] = pd.
↪cut(df3['Estimated_Number_Of_Persons_Displaced'], bins = [0, 10, 50, 100,␣
↪500, 1000], include_lowest = True, labels = ["0 - 10", "11 - 50", "51 -␣
↪100", "101 - 500", "500+"])
df3['Estimated_Number_Of_Persons_Displaced'] =␣
↪df3['Estimated_Number_Of_Persons_Displaced'].astype('category')
df3['Estimated_Number_Of_Persons_Displaced'] =␣
↪df3['Estimated_Number_Of_Persons_Displaced'].cat.
↪add_categories("Undetermined").fillna("Undetermined")

# Drop the 7 rows with missing Ext_agent_app_or_defer_time.
df4 = df3[df3.Ext_agent_app_or_defer_time.notnull()]

# Fill the missing values with respective 'undetermined' or 'missing' category.
df4[['Extent_Of_Fire']] = df4[['Extent_Of_Fire']].fillna("99 - Undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df4[['Fire_Alarm_System_Impact_on_Evacuation']] =␣
↪df4[['Fire_Alarm_System_Impact_on_Evacuation']].fillna("9 - Undetermined")
```

```python
# Fill the missing values with respective 'undetermined' or 'missing' category.
df4[['Fire_Alarm_System_Operation']] = df4[['Fire_Alarm_System_Operation']].
    ↪fillna("9 - Fire alarm system operation ndertermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df4[['Fire_Alarm_System_Presence']] = df4[['Fire_Alarm_System_Presence']].
    ↪fillna("9 - Undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df4[['Ignition_Source']] = df4[['Ignition_Source']].fillna("999 - Undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df4[['Incident_Ward']] = df4[['Incident_Ward']].fillna("999. Missing")

# Drop the row with missing Intersection.
df5 = df4[df4.Intersection.notnull()]

# Drop the row with missing Latitude.
df6 = df5[df5.Latitude.notnull()]

# Drop columns Level_Of_Origin and Exposures.
df7 = df6.drop(columns = ['Level_Of_Origin', 'Exposures'])

# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Smoke_Alarm_at_Fire_Origin']] = df7[['Smoke_Alarm_at_Fire_Origin']].
    ↪fillna("9 - Floor/suite space of fire origin: Smoke alarm presence␣
    ↪undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Smoke_Alarm_at_Fire_Origin_Alarm_Failure']] =␣
    ↪df7[['Smoke_Alarm_at_Fire_Origin_Alarm_Failure']].fillna("98 - Not␣
    ↪applicable: Alarm operated OR presence/operation undertermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Smoke_Alarm_at_Fire_Origin_Alarm_Type']] =␣
    ↪df7[['Smoke_Alarm_at_Fire_Origin_Alarm_Type']].fillna("9 - Type␣
    ↪undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation']] =␣
    ↪df7[['Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation']].
    ↪fillna("9 - Undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Smoke_Spread']] = df7[['Smoke_Spread']].fillna("10 - Missing Entries")
```

```python
# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Sprinkler_System_Operation']] = df7[['Sprinkler_System_Operation']].
 ↪fillna("9 - Activation/operation undetermined")

# Fill the missing values with respective 'undetermined' or 'missing' category.
df7[['Sprinkler_System_Presence']] = df7[['Sprinkler_System_Presence']].
 ↪fillna("9 - Undetermined")
```

[244]:
```python
# Print columns with respective missing values.
for i in dict(zip(df7.isna().sum().index, df7.isna().sum())):
    print("There are " + str(dict(zip(df7.isna().sum().index, df7.isna().
 ↪sum()))[i]) + " rows with missing " + str(i))
```

```
There are 0 rows with missing _id
There are 0 rows with missing Area_of_Origin
There are 0 rows with missing Building_Status
There are 0 rows with missing Business_Impact
There are 0 rows with missing Civilian_Casualties
There are 0 rows with missing Count_of_Persons_Rescued
There are 0 rows with missing Estimated_Dollar_Loss
There are 0 rows with missing Estimated_Number_Of_Persons_Displaced
There are 0 rows with missing Ext_agent_app_or_defer_time
There are 0 rows with missing Extent_Of_Fire
There are 0 rows with missing Final_Incident_Type
There are 0 rows with missing Fire_Alarm_System_Impact_on_Evacuation
There are 0 rows with missing Fire_Alarm_System_Operation
There are 0 rows with missing Fire_Alarm_System_Presence
There are 0 rows with missing Fire_Under_Control_Time
There are 0 rows with missing Ignition_Source
There are 0 rows with missing Incident_Number
There are 0 rows with missing Incident_Station_Area
There are 0 rows with missing Incident_Ward
There are 0 rows with missing Initial_CAD_Event_Type
There are 0 rows with missing Intersection
There are 0 rows with missing Last_TFS_Unit_Clear_Time
There are 0 rows with missing Latitude
There are 0 rows with missing Longitude
There are 0 rows with missing Material_First_Ignited
There are 0 rows with missing Method_Of_Fire_Control
There are 0 rows with missing Number_of_responding_apparatus
There are 0 rows with missing Number_of_responding_personnel
There are 0 rows with missing Possible_Cause
There are 0 rows with missing Property_Use
There are 0 rows with missing Smoke_Alarm_at_Fire_Origin
There are 0 rows with missing Smoke_Alarm_at_Fire_Origin_Alarm_Failure
There are 0 rows with missing Smoke_Alarm_at_Fire_Origin_Alarm_Type
There are 0 rows with missing
```

```
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation
There are 0 rows with missing Smoke_Spread
There are 0 rows with missing Sprinkler_System_Operation
There are 0 rows with missing Sprinkler_System_Presence
There are 0 rows with missing Status_of_Fire_On_Arrival
There are 0 rows with missing TFS_Firefighter_Casualties
There are 0 rows with missing Time_Difference
```

2.5 Categorise the dependent variable

For visualisation purposes, we will categorise the economic loss from fire incidents into 7 categories, with logarithmic increases.

[245]:
```
df7['Estimated_Dollar_Loss'] = df7['Estimated_Dollar_Loss'].astype('Int64')
df7['Estimated_Dollar_Loss_Categorised'] = pd.cut(df7['Estimated_Dollar_Loss'],␣
  ↪bins = [0, 100, 1000, 10000, 100000, 1000000, 10000000, 100000000],␣
  ↪include_lowest = True, labels = ["0 - 100", "101 - 1000", "1001 - 10000",␣
  ↪"10001 - 100000", "100001 - 1000000", "1000001-10000000",␣
  ↪"10000001-100000000"])
```

2.6 Convert variables to their respective data type

The columns that have object data type are now considered to be categorical.

[246]:
```
# Identify columns with object data type and convert to categories.
object_cols_obj = df7.columns[df7.dtypes == "object"].tolist()
for col_obj in object_cols_obj:
    df7[col_obj] = df7[col_obj].astype("category")

# Identify columns with int64 data type and convert to int64.
object_cols_int64 = df7.columns[df7.dtypes == "Int64"].tolist()
for col_int64 in object_cols_int64:
    df7[col_int64] = df7[col_int64].astype("int64")
```

3 Exploratory and Descriptive Analysis

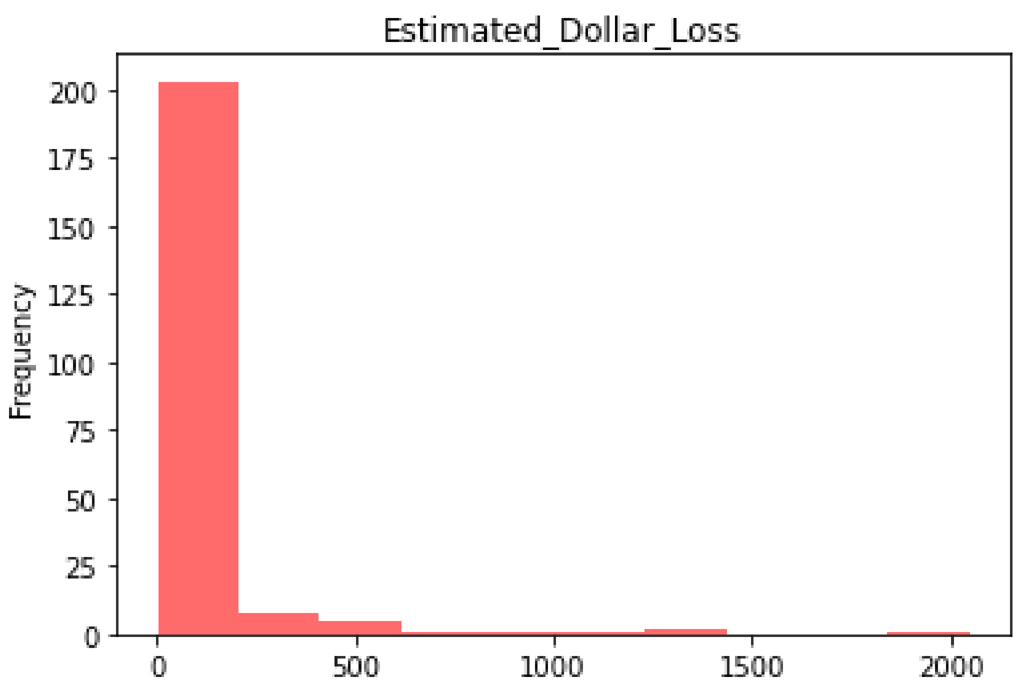
The Exploratory and Descriptive Analysis consists of three sections.

3.1 Data Visualisations

[247]:
```
Estimated_Loss = pd.crosstab(index = df7["Estimated_Dollar_Loss_Categorised"],␣
  ↪columns = "count")
Estimated_Loss

df7["Estimated_Dollar_Loss"].value_counts().plot(kind = "hist", color =␣
  ↪"#FF6A6A", title = "Estimated_Dollar_Loss", xlabel="Loss (in USD)",␣
  ↪ylabel="Count of Fires")
```

[247]: col_0   count
Estimated_Dollar_Loss_Categorised
0 - 100   3293
101 - 1000   3172
1001 - 10000   5042
10001 - 100000   3402
100001 - 1000000   675
1000001-10000000   33
10000001-100000000   2

[247]: <AxesSubplot:title={'center':'Estimated_Dollar_Loss'}, ylabel='Frequency'>

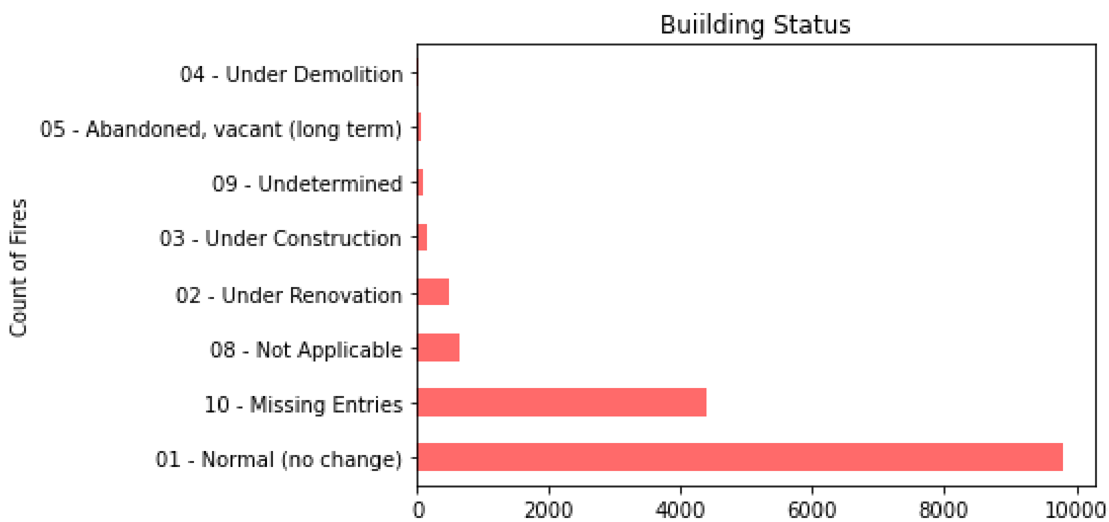


[248]:
```python
# Frequency table for Building_Status.
Building_Status = pd.crosstab(index = df7["Building_Status"], columns = "count")
Building_Status

# Bar chart for Building Status.
df7["Building_Status"].value_counts().plot(kind = "barh", color = "#FF6A6A",
 ↪title = "Buiilding Status", xlabel = "Count of Fires", ylabel = "Building
 ↪Status Type")
```

[248]: col_0   count
Building_Status
01 - Normal (no change)   9797
02 - Under Renovation   482

```
03 - Under Construction              152
04 - Under Demolition                 16
05 - Abandoned, vacant (long term)    55
08 - Not Applicable                  631
09 - Undetermined                     83
10 - Missing Entries                4403
```

[248]: <AxesSubplot:title={'center':'Buiilding Status'}, ylabel='Count of Fires'>

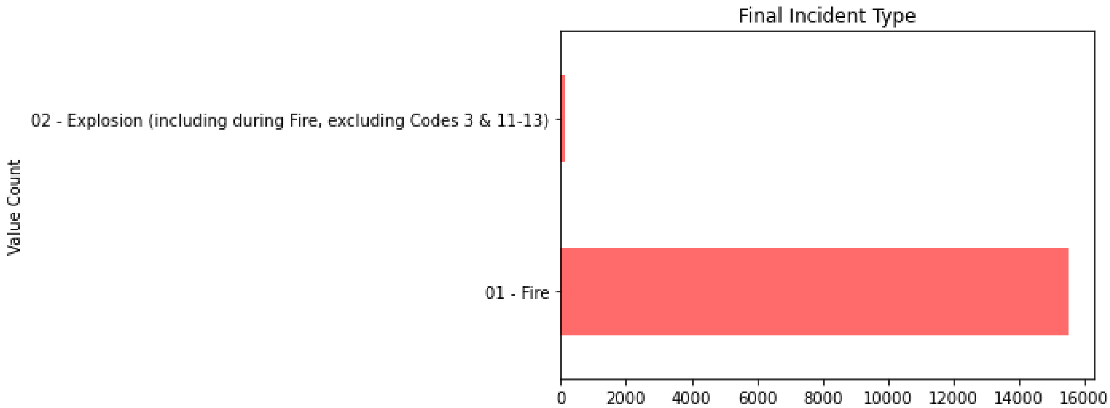


[249]:
```python
# Frequency table for Final_Incident_Type.
Incident_Type = pd.crosstab(index = df7["Final_Incident_Type"], columns =␣
↪"count", )
Incident_Type

# Bar chart for Final_Incident_Type.
df7["Final_Incident_Type"].value_counts().plot(kind = "barh", color =␣
↪"#FF6A6A", title = "Final Incident Type", xlabel = "Value Count", ylabel =␣
↪"Incident Type")
```

[249]:

col_0	count
Final_Incident_Type	
01 - Fire	15513
02 - Explosion (including during Fire, excludin…	106

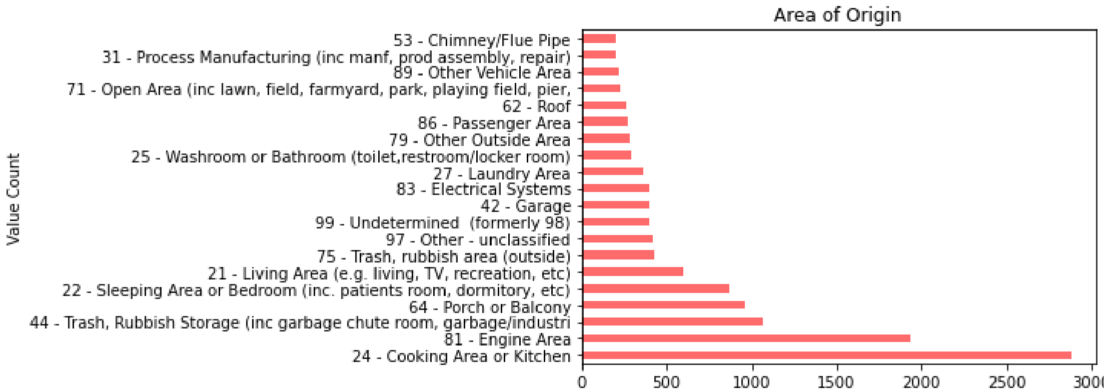
[249]: <AxesSubplot:title={'center':'Final Incident Type'}, ylabel='Value Count'>



[250]:
```python
# Frequency table for Area_of_Origin.
Area_of_Fire_Origin = pd.crosstab(index = df7["Area_of_Origin"], columns =␣
↪"count")
Area_of_Fire_Origin

# Bar chart for top 20 Area_of_Origin.
df7["Area_of_Origin"].value_counts(sort = True).head(20).plot(kind = "barh",␣
↪color = "#FF6A6A", title = "Area of Origin", xlabel = "Value Count", ylabel␣
↪= "Area of Origin")
```

[250]:
```
col_0                                              count
Area_of_Origin
11 - Lobby, Entranceway                               87
12 - Hallway, Corridor                               150
13 - Stairway, Escalator                              88
18 - Covered Court, Atrium, mall concourse             7
19 - Other Means of Egress                            14
…                                                  …
92 - Residential/Business: Restaurant area            10
93 - Residential/Business: Other busines area         12
97 - Other - unclassified                            418
99 - Undetermined  (formerly 98)                     402
990 - Under Investigation                              6

[73 rows x 1 columns]
```

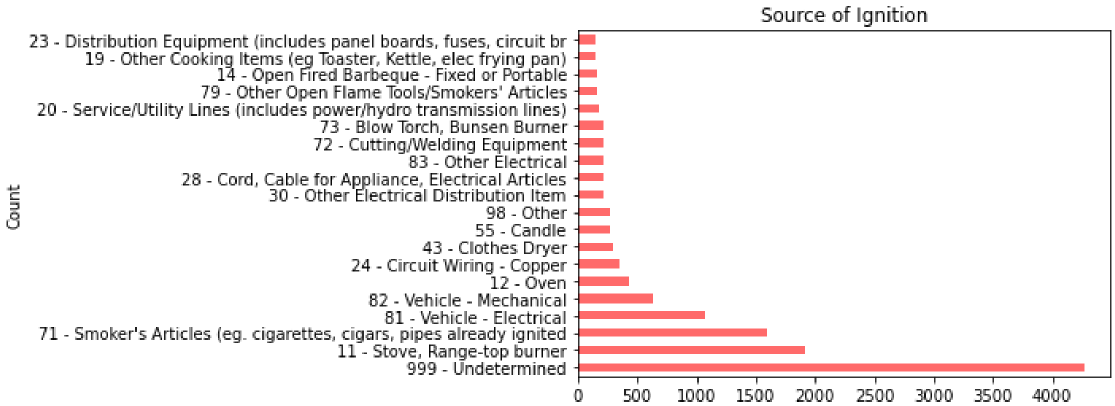
[250]:
```
<AxesSubplot:title={'center':'Area of Origin'}, ylabel='Value Count'>
```



[251]:
```
# Frequency table for Ignition_Source.
Source_of_Ignition = pd.crosstab(index = df7["Ignition_Source"], columns =␣
↪"count")
Source_of_Ignition

# Bar chart for top 20 Ignition_Source.
df7["Ignition_Source"].value_counts(sort = True).head(20).plot(kind = "barh",␣
↪color = "#FF6A6A", title = "Source of Ignition", ylabel= "Ignition Source␣
↪Type", xlabel = "Count")
```

[251]:
```
col_0                                            count
Ignition_Source
100 - Outdoor fireplace/heater                      13
101 - Exposure, source structure detached            5
102 - Exposure, source structure semi-detached …     4
103 - Exposure, source outside storage containe…     4
104 - Exposure, source open fire (inc campfire,…    20
…                                                  …
96 - Chemical Reaction (eg. spontaneous combust…   112
97 - Rekindle                                       11
98 - Other                                         267
999 - Undetermined                                4267
9990 - Under Investigation                          16

[84 rows x 1 columns]
```

[251]:
```
<AxesSubplot:title={'center':'Source of Ignition'}, ylabel='Count'>
```

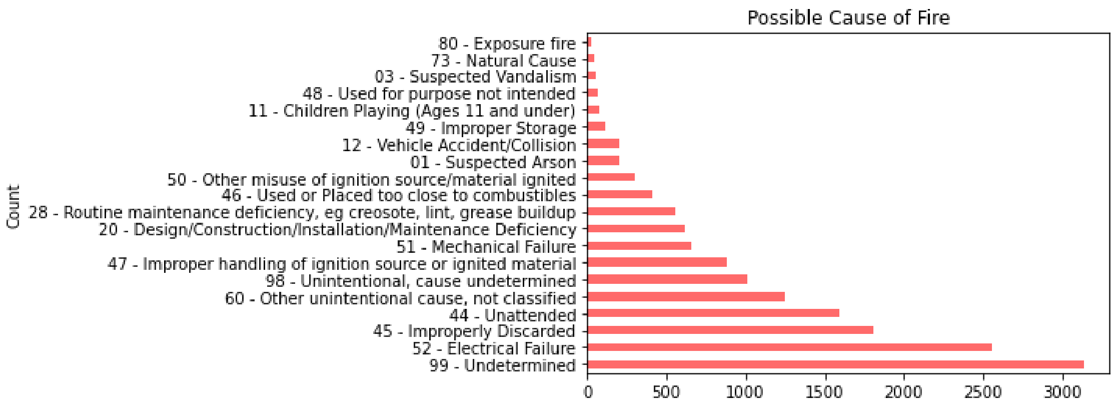


[252]:
```python
# Frequency table for Possible_Cause.
PossibleCause = pd.crosstab(index = df7["Possible_Cause"], columns = "count")
PossibleCause

# Bar chart for top 20 Possible_Cause.
df7["Possible_Cause"].value_counts(sort = True).head(20).plot(kind = "barh",␣
 ↪color = "#FF6A6A", title = "Possible Cause of Fire", xlabel = "Count",␣
 ↪ylabel= "Possible Cause")
```

[252]:
```
col_0                                                  count
Possible_Cause
01 - Suspected Arson                                     205
02 - Riot/Civil Commotion                                  1
03 - Suspected Vandalism                                  60
04 - Suspected Youth Vandalism (Ages 12 to 17)            17
11 - Children Playing (Ages 11 and under)                 79
12 - Vehicle Accident/Collision                          202
20 - Design/Construction/Installation/Maintenan…     620
28 - Routine maintenance deficiency, eg creosot…     557
44 - Unattended                                         1594
45 - Improperly Discarded                               1811
46 - Used or Placed too close to combustibles            406
47 - Improper handling of ignition source or ig…     882
48 - Used for purpose not intended                        65
49 - Improper Storage                                    117
50 - Other misuse of ignition source/material i…     307
51 - Mechanical Failure                                  654
52 - Electrical Failure                                 2555
60 - Other unintentional cause, not classified          1243
72 - Rekindle                                             15
73 - Natural Cause                                        44
80 - Exposure fire                                        22
```

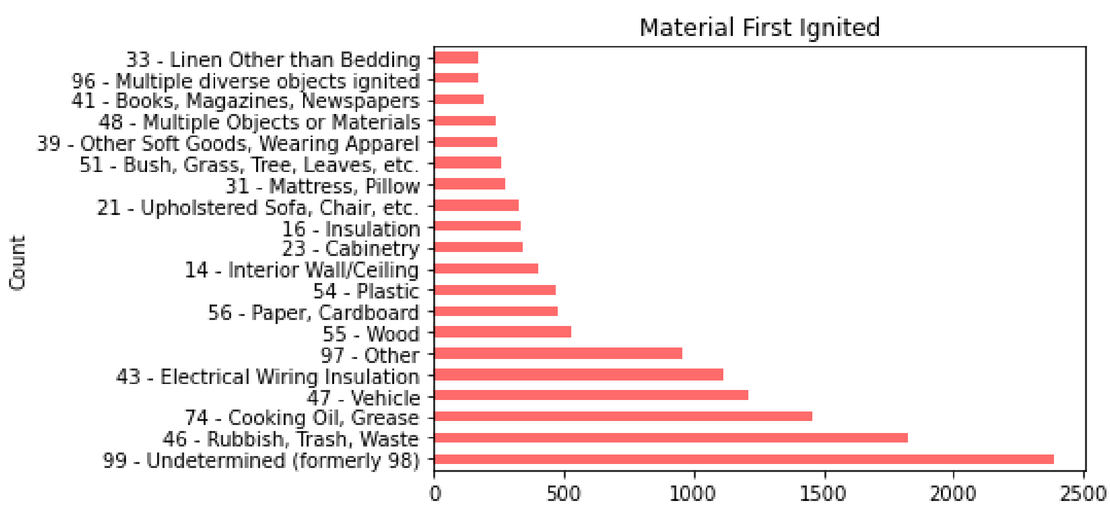
```
98 - Unintentional, cause undetermined            1011
99 - Undetermined                                 3141
990 - Under Investigation                           11
```

[252]: <AxesSubplot:title={'center':'Possible Cause of Fire'}, ylabel='Count'>



[253]:
```
# Bar chart for top 20 Material_First_Ignited.
df7["Material_First_Ignited"].value_counts(sort = True).head(20).plot(kind =␣
↪"barh", color = "#FF6A6A", title = "Material First Ignited", xlabel =␣
↪"Count", ylabel= "Material First Ignited Type")
```

[253]: <AxesSubplot:title={'center':'Material First Ignited'}, ylabel='Count'>



[254]:
```
# Frequency table for Method_Of_Fire_Control.
```

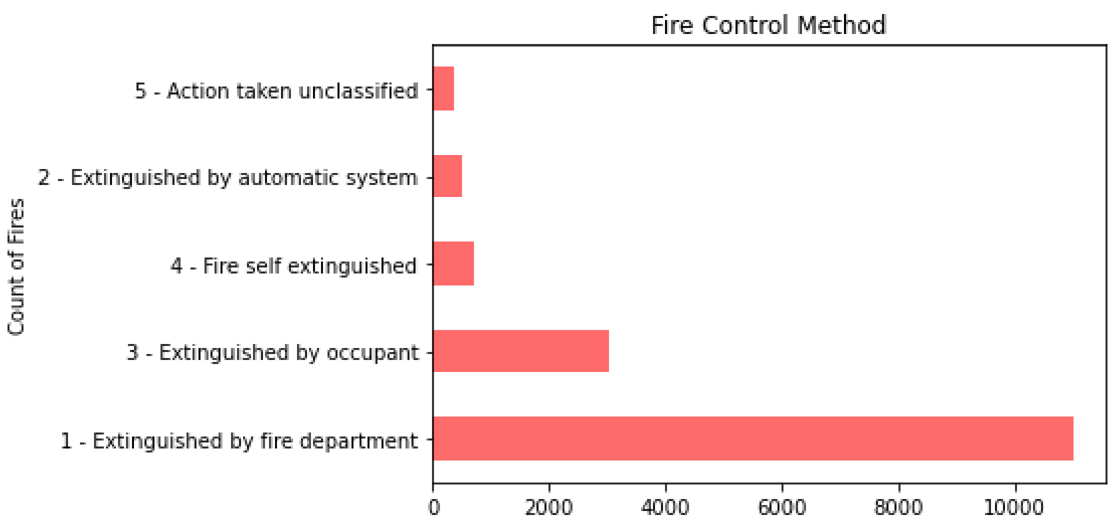
```
Fire_Control_Method = pd.crosstab(index = df7["Method_Of_Fire_Control"],␣
↪columns = "count")
Fire_Control_Method

# Bar chart for top 20 Material_First_Ignited.
df7["Method_Of_Fire_Control"].value_counts(sort = True).head(20).plot(kind =␣
↪"barh", color = "#FF6A6A", title = "Fire Control Method", xlabel = "Count of␣
↪Fires", ylabel = "Action Type")
```

[254]:

```
col_0                                  count
Method_Of_Fire_Control
1 - Extinguished by fire department    11012
2 - Extinguished by automatic system     505
3 - Extinguished by occupant            3036
4 - Fire self extinguished               704
5 - Action taken unclassified            362
```

[254]:

```
<AxesSubplot:title={'center':'Fire Control Method'}, ylabel='Count of Fires'>
```

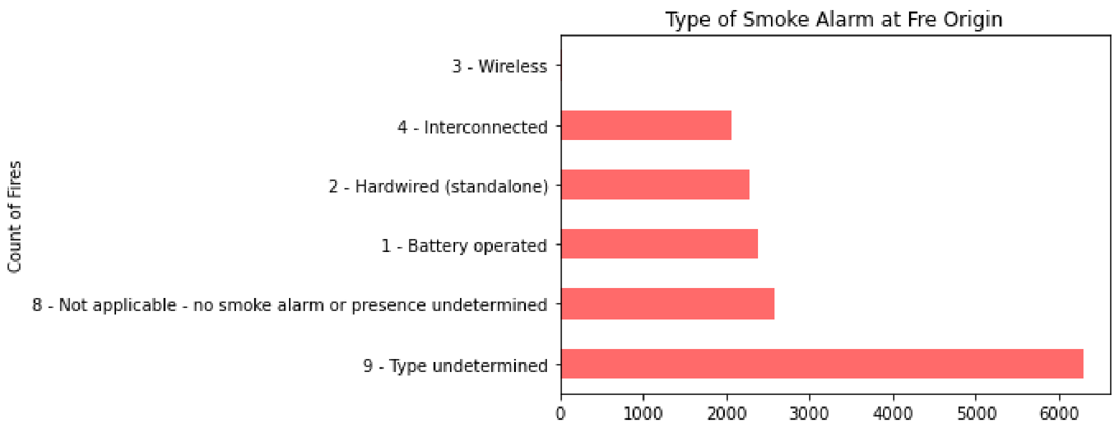


[255]:

```
# Frequency table for Smoke_Alarm_at_Fire_Origin_Alarm_Type.
Fire_Alarm_Type = pd.crosstab(index =␣
↪df7["Smoke_Alarm_at_Fire_Origin_Alarm_Type"], columns = "count")
Fire_Alarm_Type

# Bar chart for top 20 Smoke_Alarm_at_Fire_Origin_Alarm_Type.
df7["Smoke_Alarm_at_Fire_Origin_Alarm_Type"].value_counts(sort = True).head(30).
↪plot(kind = "barh", color = "#FF6A6A", title = "Type of Smoke Alarm at Fire␣
↪Origin", xlabel = "Count of Fires", ylabel = "Fire Alarm Type")
```

[255]: col_0   count
Smoke_Alarm_at_Fire_Origin_Alarm_Type
1 - Battery operated   2380
2 - Hardwired (standalone)   2276
3 - Wireless   24
4 - Interconnected   2066
8 - Not applicable - no smoke alarm or presence…   2569
9 - Type undetermined   6304

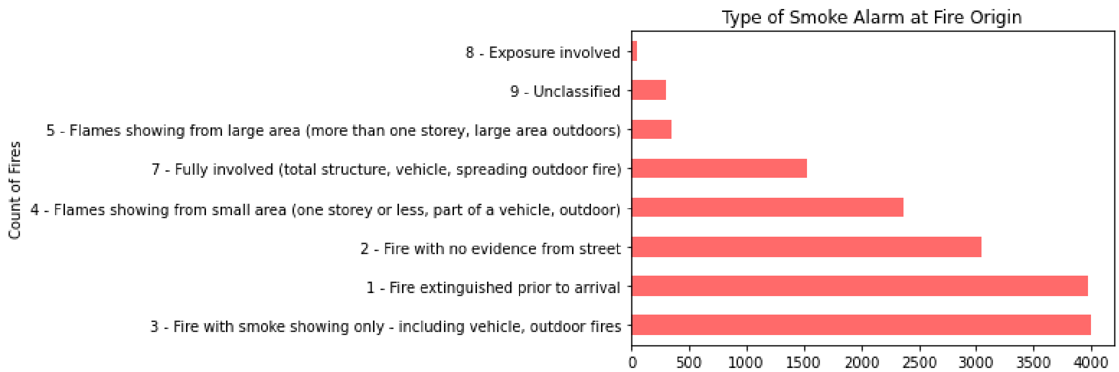
[255]: <AxesSubplot:title={'center':'Type of Smoke Alarm at Fre Origin'}, ylabel='Count of Fires'>



[256]:
```
# Frequency table for Status_of_Fire_On_Arrival.
Status_of_Fire = pd.crosstab(index = df7["Status_of_Fire_On_Arrival"], columns
↪= "count")
Status_of_Fire

# Bar chart for top 20 Status_of_Fire_On_Arrival.
df7["Status_of_Fire_On_Arrival"].value_counts(sort = True).head(20).plot(kind =
↪"barh", color = "#FF6A6A", title = "Type of Smoke Alarm at Fire Origin",
↪xlabel = "Count of Fires", ylabel = "Status of Fire")
```

[256]: col_0   count
Status_of_Fire_On_Arrival
1 - Fire extinguished prior to arrival   3978
2 - Fire with no evidence from street   3041
3 - Fire with smoke showing only - including ve…   3997
4 - Flames showing from small area (one storey …   2368
5 - Flames showing from large area (more than o…   355
7 - Fully involved (total structure, vehicle, s…   1531
8 - Exposure involved   52
9 - Unclassified   297

[256]: <AxesSubplot:title={'center':'Type of Smoke Alarm at Fire Origin'}, ylabel='Count of Fires'>



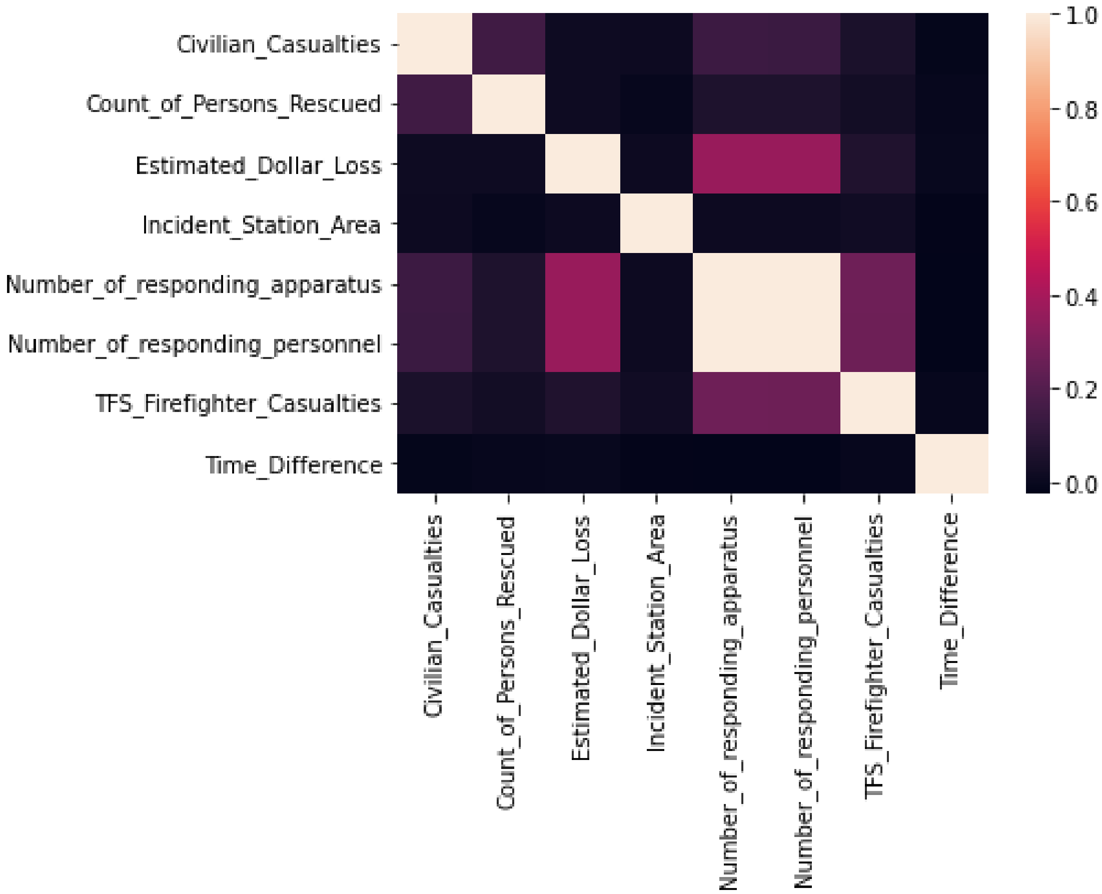
From the bar charts, we can observe that after the data preparation, many categorical variables are highly skewed, with some variables such as Final_Incident_Type, which have most of the observations under one category. These instances will need to be considered when developing the models.

3.2 Correlation Visualisation

A correlation heatmap is useful to check the correlation between variables. Unappropriate variables such as "_id" and GPS coordinates have been dropped from the heatmap.

[257]:
```python
# New sub dataframe without _id and coordinates.
df7_2 = df7.drop(["_id", "Latitude", "Longitude"], axis = 1)

# Plotting heatmap.
correlation = df7_2.corr()
sns.heatmap(correlation)
plt.show()
```

[257]: <AxesSubplot:>



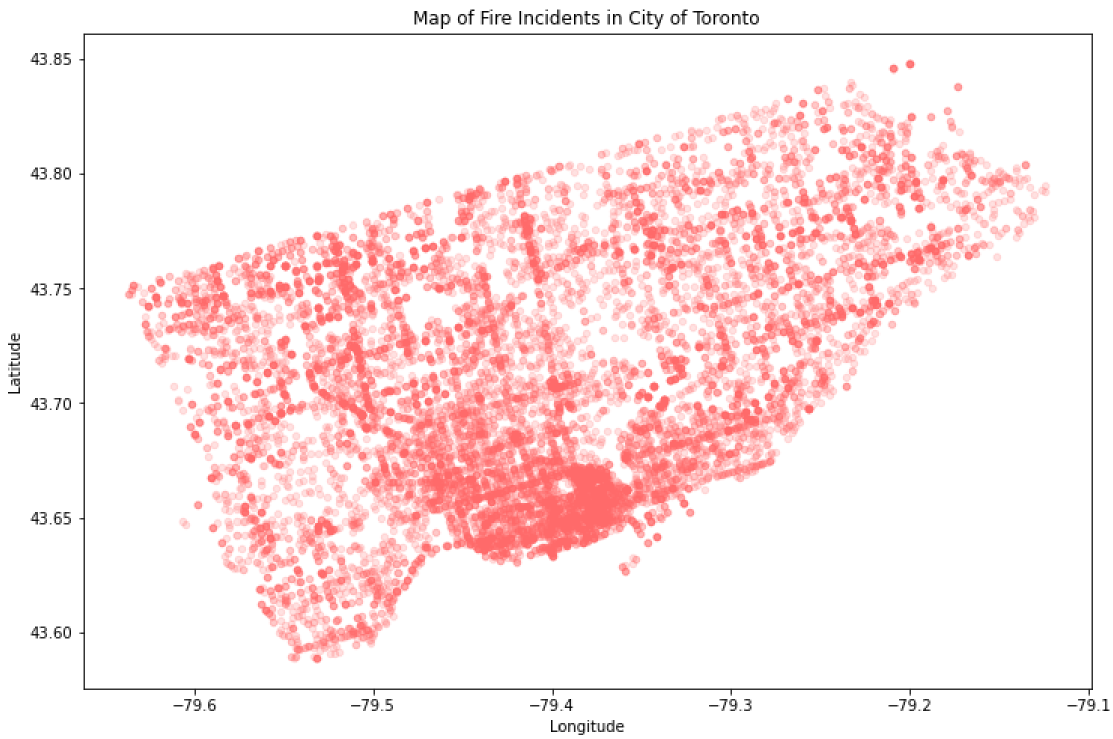
As observed from the heatmap, the dependent variable "Estimated_Dollar_Loss" has moderate positive correlation with "Number_of_responding_apparatus" and "Number_of_responding_personnel". Intuitevely, as the need for firefighters and resourced to keep a fire incident under control increases, we can infer the extent of the fire incident increases too, leading to a higher loss in economic terms. Moreover, there seems to be a perfect correlation between "Number_of_responding_apparatus" and "Number_of_responding_personnel", which should be considered when running models.

3.3 GPS Coordinates

Our dataset contains GPS Coordinates for each incident. Although these variables cannot be used directly in the predictive model run in this project, location might be an important predictor for the economic loss due to fire incidents. Firstly, we can visualise these coordinates in a scatter plot which resembles the outline of City of Toronto.

[258]:
```
# Scatter plot for GPS coordinates.
df7.plot(kind = "scatter", x = "Longitude", y = "Latitude", alpha = 0.2,␣
 ↪figsize = (12,8), color = "#FF6A6A", title = "Map of Fire Incidents in City␣
 ↪of Toronto")
```

[258]: <AxesSubplot:title={'center':'Map of Fire Incidents in City of Toronto'}, xlabel='Longitude', ylabel='Latitude'>



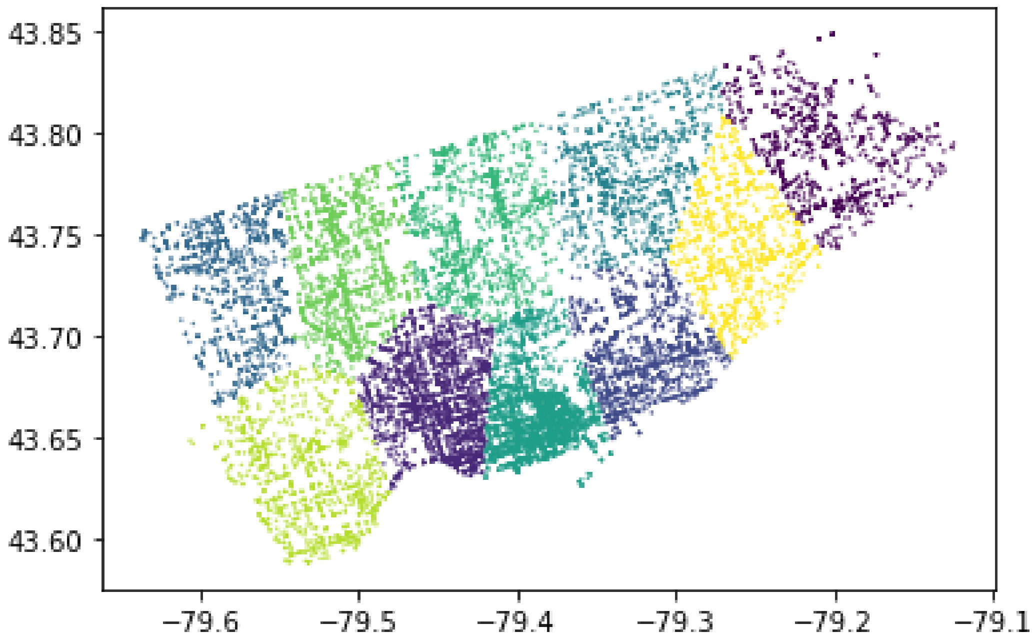
To use location as a indepedent variable in our models, we can use clustering. K-Means clustering has been employed to identify 10 clusters of GPS coordinates, which will be then used as categorical independent variables in our predictive models.

[259]:
```python
# Create a sub data frame with only GPS Coordinates.
df7_3 = df7.loc[:, "Latitude":"Longitude"]

# Use KMeans to create 10 geographical clusters.
KM = KMeans(10)
KM.fit(df7_3)

# Predict clusters and assign to clusters.
clusters = KM.fit_predict(df7_3)

# Create a new column in our dataset with each cluster.
df8 = df7.copy()
df8['GPS_Cluster'] = clusters

# Visualise the clusters created by KMeans.
plt.scatter(df7['Longitude'], df7['Latitude'], c = df8['GPS_Cluster'], s = 0.2)
plt.show()
```

```
# Convert type to category.
df8['GPS_Cluster'] = df8['GPS_Cluster'].astype('category')
```

[259]: KMeans(n_clusters=10)

[259]: <matplotlib.collections.PathCollection at 0x7fa0dfbbaaf0>



4 Linear Regression

A linear regression model can be used to estimate a regression with estimated economic loss from fire incidents as the dependent variable, and the other variables as the predictors. Many of the independent variables have to be dropped from the dataset, such as the GPS Coordinates and the ID number. As the dataset contains categorical independent variables, dummies have to be created in order to run the regression model.

4.1 First Linear Regression

[260]:
```
df9 = df8.drop(['Latitude', 'Longitude', 'Incident_Number',
 ↪'Final_Incident_Type', 'Estimated_Dollar_Loss_Categorised',
 ↪'Ext_agent_app_or_defer_time', 'Fire_Under_Control_Time', 'Intersection',
 ↪'Last_TFS_Unit_Clear_Time'], axis = 1)

# Creating a dummy variable for the variable 'Area_of_Origin' and dropping the
 ↪first one.
```

```
Area_of_Origin = pd.get_dummies(df9['Area_of_Origin'], prefix =␣
↪'Area_of_Origin', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Area_of_Origin],axis=1)

# Creating a dummy variable for the variable 'Building_Status' and dropping the␣
↪first one.
Building_Status = pd.get_dummies(df9['Building_Status'], prefix =␣
↪'Building_Status', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Building_Status],axis=1)

# Creating a dummy variable for the variable 'Business_Impact' and dropping the␣
↪first one.
Business_Impact = pd.get_dummies(df9['Business_Impact'], prefix =␣
↪'Business_Impact', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Business_Impact],axis=1)

# Creating a dummy variable for the variable␣
↪'Estimated_Number_Of_Persons_Displaced' and dropping the first one.
Estimated_Number_Of_Persons_Displaced = pd.
↪get_dummies(df9['Estimated_Number_Of_Persons_Displaced'], prefix =␣
↪'Estimated_Number_Of_Persons_Displaced', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Estimated_Number_Of_Persons_Displaced],axis=1)

# Creating a dummy variable for the variable 'Extent_Of_Fire' and dropping the␣
↪first one.
Extent_Of_Fire = pd.get_dummies(df9['Extent_Of_Fire'] ,prefix =␣
↪'Extent_Of_Fire', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Extent_Of_Fire],axis=1)

# Creating a dummy variable for the variable␣
↪'Fire_Alarm_System_Impact_on_Evacuation' and dropping the first one.
Fire_Alarm_System_Impact_on_Evacuation = pd.
↪get_dummies(df9['Fire_Alarm_System_Impact_on_Evacuation'], prefix =␣
↪'Fire_Alarm_System_Impact_on_Evacuation', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Fire_Alarm_System_Impact_on_Evacuation],axis=1)

# Creating a dummy variable for the variable 'Fire_Alarm_System_Operation' and␣
↪dropping the first one.
```

```
Fire_Alarm_System_Operation = pd.
 ↪get_dummies(df9['Fire_Alarm_System_Operation'], prefix =␣
 ↪'Fire_Alarm_System_Operation', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Fire_Alarm_System_Operation],axis=1)

# Creating a dummy variable for the variable 'Fire_Alarm_System_Presence' and␣
 ↪dropping the first one.
Fire_Alarm_System_Presence = pd.get_dummies(df9['Fire_Alarm_System_Presence'],␣
 ↪prefix = 'Fire_Alarm_System_Presence', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Fire_Alarm_System_Presence],axis=1)

# Creating a dummy variable for the variable 'Ignition_Source' and dropping the␣
 ↪first one.
Ignition_Source = pd.get_dummies(df9['Ignition_Source'], prefix =␣
 ↪'Ignition_Source', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Ignition_Source],axis=1)

# Creating a dummy variable for the variable 'Incident_Station_Area' and␣
 ↪dropping the first one.
Incident_Station_Area = pd.get_dummies(df9['Incident_Station_Area'], prefix =␣
 ↪'Incident_Station_Area', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Incident_Station_Area],axis=1)

# Creating a dummy variable for the variable 'Incident_Ward' and dropping the␣
 ↪first one.
Incident_Ward = pd.get_dummies(df9['Incident_Ward'], prefix = 'Incident_Ward',␣
 ↪drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Incident_Ward],axis=1)

# Creating a dummy variable for the variable 'Initial_CAD_Event_Type' and␣
 ↪dropping the first one.
Initial_CAD_Event_Type = pd.get_dummies(df9['Initial_CAD_Event_Type'], prefix =␣
 ↪'Initial_CAD_Event_Type', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Initial_CAD_Event_Type],axis=1)

# Creating a dummy variable for the variable 'Material_First_Ignited' and␣
 ↪dropping the first one.
Material_First_Ignited = pd.get_dummies(df9['Material_First_Ignited'], prefix =␣
 ↪'Material_First_Ignited', drop_first = True)
#Adding the results to the master dataframe
```

```
df9 = pd.concat([df9,Material_First_Ignited],axis=1)

# Creating a dummy variable for the variable 'Method_Of_Fire_Control' and␣
 ↪dropping the first one.
Method_Of_Fire_Control = pd.get_dummies(df9['Method_Of_Fire_Control'], prefix =␣
 ↪'Method_Of_Fire_Control', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Method_Of_Fire_Control],axis=1)

# Creating a dummy variable for the variable 'Possible_Cause' and dropping the␣
 ↪first one.
Possible_Cause = pd.get_dummies(df9['Possible_Cause'], prefix =␣
 ↪'Possible_Cause', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Possible_Cause],axis=1)

# Creating a dummy variable for the variable 'Property_Use' and dropping the␣
 ↪first one.
Property_Use = pd.get_dummies(df9['Property_Use'], prefix = 'Property_Use',␣
 ↪drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Property_Use],axis=1)

# Creating a dummy variable for the variable 'Smoke_Alarm_at_Fire_Origin' and␣
 ↪dropping the first one.
Smoke_Alarm_at_Fire_Origin = pd.get_dummies(df9['Smoke_Alarm_at_Fire_Origin'],␣
 ↪prefix = 'Smoke_Alarm_at_Fire_Origin', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Smoke_Alarm_at_Fire_Origin],axis=1)

# Creating a dummy variable for the variable␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Failure' and dropping the first one.
Smoke_Alarm_at_Fire_Origin_Alarm_Failure = pd.
 ↪get_dummies(df9['Smoke_Alarm_at_Fire_Origin_Alarm_Failure'], prefix =␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Failure', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Smoke_Alarm_at_Fire_Origin_Alarm_Failure],axis=1)

# Creating a dummy variable for the variable␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Type' and dropping the first one.
Smoke_Alarm_at_Fire_Origin_Alarm_Type = pd.
 ↪get_dummies(df9['Smoke_Alarm_at_Fire_Origin_Alarm_Type'], prefix =␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Type', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Smoke_Alarm_at_Fire_Origin_Alarm_Type],axis=1)
```

```python
# Creating a dummy variable for the variable␣
↪'Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation' and dropping␣
↪the first one.
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation = pd.
↪get_dummies(df9['Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation'],␣
↪prefix = 'Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation',␣
↪drop_first = True)
#Adding the results to the master dataframe
df9 = pd.
↪concat([df9,Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation],axis=1)

# Creating a dummy variable for the variable 'Smoke_Spread' and dropping the␣
↪first one.
Smoke_Spread = pd.get_dummies(df9['Smoke_Spread'], prefix = 'Smoke_Spread',␣
↪drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Smoke_Spread],axis=1)

# Creating a dummy variable for the variable 'Sprinkler_System_Operation' and␣
↪dropping the first one.
Sprinkler_System_Operation = pd.get_dummies(df9['Sprinkler_System_Operation'],␣
↪prefix = 'Sprinkler_System_Operation', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Sprinkler_System_Operation],axis=1)

# Creating a dummy variable for the variable 'Sprinkler_System_Presence' and␣
↪dropping the first one.
Sprinkler_System_Presence = pd.get_dummies(df9['Sprinkler_System_Presence'],␣
↪prefix = 'Sprinkler_System_Presence', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Sprinkler_System_Presence],axis=1)

# Creating a dummy variable for the variable 'Status_of_Fire_On_Arrival' and␣
↪dropping the first one.
Status_of_Fire_On_Arrival = pd.get_dummies(df9['Status_of_Fire_On_Arrival'],␣
↪prefix='Status_of_Fire_On_Arrival', drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,Status_of_Fire_On_Arrival],axis=1)

# Creating a dummy variable for the variable 'GPS_Cluster' and dropping the␣
↪first one.
GPS_Cluster = pd.get_dummies(df9['GPS_Cluster'], prefix = 'GPS_Cluster',␣
↪drop_first = True)
#Adding the results to the master dataframe
df9 = pd.concat([df9,GPS_Cluster],axis=1)
```

```python
# Drop the original variables.
df10 = df9.drop(['_id', 'Area_of_Origin', 'Building_Status', 'Business_Impact',␣
 ↪ 'Estimated_Number_Of_Persons_Displaced', 'Extent_Of_Fire',␣
 ↪'Fire_Alarm_System_Impact_on_Evacuation', 'Fire_Alarm_System_Operation',␣
 ↪'Fire_Alarm_System_Presence', 'Ignition_Source', 'Incident_Station_Area',␣
 ↪'Incident_Ward','Initial_CAD_Event_Type','Material_First_Ignited',␣
 ↪'Method_Of_Fire_Control', 'Possible_Cause', 'Property_Use',␣
 ↪'Smoke_Alarm_at_Fire_Origin','Smoke_Alarm_at_Fire_Origin_Alarm_Failure',␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Type',␣
 ↪'Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation',␣
 ↪'Smoke_Spread', 'Sprinkler_System_Operation', 'Sprinkler_System_Presence',␣
 ↪'Status_of_Fire_On_Arrival'], axis = 1)
```

[261]:
```python
# Splitting training and testing sets.
X = df10.drop('Estimated_Dollar_Loss', axis = 1).values
y = df10['Estimated_Dollar_Loss'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.8,␣
 ↪test_size = 0.2, shuffle = True)
```

[262]:
```python
# Fit linear regression model.
lr1 = sm.OLS(y_train, X_train).fit()

# Create a list with coefficient names.
coefficient_names = df10.columns.tolist()
coefficient_names.remove("Estimated_Dollar_Loss")

# Use predict.
lr1_y_pred = lr1.predict(X_test)
```

[263]:
```python
# Print the accuracy.
print("First linear regression model accuracy: {:.2f}".format(lr1.rsquared))
```

```
First linear regression model accuracy: 0.34
```

The first linear regression model return an R^2 of 0.34, which means 34% of the variability is explained by the model. In order to improve the accuracy of the model, we can look at the assumptions made for this first regression.

Firstly, we have assumed there is a lin-lin relationship between the predictors and the dependent variable. Using skewness, we can check the asymmetry of the variables.

Secondly, we have included both “Number_of_responding_personnel” and “Number_of_responding_apparatus” in our regression. From the variable heatmap shown previously in the EDA, we can observe how the these two variables have a strong positive correlation. Inclusing these two variables violate the assumption of no perfect multicollinearity between independent variables. Hence, we expect that by not including one of these variables, the degree of multicollinearity in our regression should decrease.

Therefore, a second linear regression model will be run with these observations taken into consideration.

4.2 Second Linear Regression

We can test for skewness.

[264]:
```
# Testing the skewness of the continuous variables.
df8.drop(["_id", "Incident_Station_Area", "Latitude", "Longitude"], axis = 1).
↪skew(numeric_only = True)
```

[264]:
```
Civilian_Casualties                  9.691473
Count_of_Persons_Rescued            74.007854
Estimated_Dollar_Loss               88.439465
Number_of_responding_apparatus      14.665865
Number_of_responding_personnel      13.525164
TFS_Firefighter_Casualties          12.112583
Time_Difference                     92.991034
dtype: float64
```

As observed, all of the continuous variables have high skewness, to mitigate this problem, we can take the logs of these variables to run a log-log regression.

[265]:
```
# New data frame to not override the original dataset.
df11 = df8.copy()

# Use Numpy's log1p to log(x+1), where x is the variable.
df11["Estimated_Dollar_Loss"] = np.log1p(df11["Estimated_Dollar_Loss"])
df11["Civilian_Casualties"] = np.log1p(df11["Civilian_Casualties"])
df11["Count_of_Persons_Rescued"] = np.log1p(df11["Count_of_Persons_Rescued"])
df11["Number_of_responding_apparatus"] = np.
↪log1p(df11["Number_of_responding_apparatus"])
df11["Number_of_responding_personnel"] = np.
↪log(df11["Number_of_responding_personnel"])
df11["Time_Difference"] = np.log1p(df11["Time_Difference"])
df11["TFS_Firefighter_Casualties"] = np.
↪log1p(df11["TFS_Firefighter_Casualties"])

# Testing the skewness of the continuous variables after taking logs.
df11.drop(["_id", "Incident_Station_Area", "Latitude", "Longitude"], axis = 1).
↪skew(numeric_only = True)
```

[265]:
```
Civilian_Casualties                  4.448073
Count_of_Persons_Rescued            10.461469
Estimated_Dollar_Loss               -0.804670
Number_of_responding_apparatus      -0.082444
Number_of_responding_personnel      -0.447439
TFS_Firefighter_Casualties           9.761605
Time_Difference                     30.162486
```

```
dtype: float64
```

As observed, the skewness of the variables is reduced significantly. Then, we drop "Number_of_responding_apparatus" to reduce multicollinearity, and all the other indepedent variables that are redundant when running the regression. We create new dummies as df12, which contains the logged continuous variables, does not include the dummies for the categorical variables.

[266]:
```
df12 = df11.drop(['Latitude', 'Longitude', 'Incident_Number',␣
 ↪'Final_Incident_Type', 'Estimated_Dollar_Loss_Categorised',␣
 ↪'Ext_agent_app_or_defer_time', 'Fire_Under_Control_Time', 'Intersection',␣
 ↪'Last_TFS_Unit_Clear_Time'], axis = 1)

# Creating a dummy variable for the variable 'Area_of_Origin' and dropping the␣
 ↪first one.
Area_of_Origin = pd.get_dummies(df12['Area_of_Origin'],prefix =␣
 ↪'Area_of_Origin', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Area_of_Origin],axis=1)

# Creating a dummy variable for the variable 'Building_Status' and dropping the␣
 ↪first one.
Building_Status = pd.get_dummies(df12['Building_Status'], prefix =␣
 ↪'Building_Status', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Building_Status],axis=1)

# Creating a dummy variable for the variable 'Business_Impact' and dropping the␣
 ↪first one.
Business_Impact = pd.get_dummies(df12['Business_Impact'], prefix =␣
 ↪'Business_Impact', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Business_Impact],axis=1)

# Creating a dummy variable for the variable␣
 ↪'Estimated_Number_Of_Persons_Displaced' and dropping the first one.
Estimated_Number_Of_Persons_Displaced = pd.
 ↪get_dummies(df12['Estimated_Number_Of_Persons_Displaced'], prefix =␣
 ↪'Estimated_Number_Of_Persons_Displaced', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Estimated_Number_Of_Persons_Displaced],axis=1)

# Creating a dummy variable for the variable 'Extent_Of_Fire' and dropping the␣
 ↪first one.
Extent_Of_Fire = pd.get_dummies(df12['Extent_Of_Fire'], prefix =␣
 ↪'Extent_Of_Fire', drop_first = True)
#Adding the results to the master dataframe
```

```
df12 = pd.concat([df12,Extent_Of_Fire],axis=1)

# Creating a dummy variable for the variable 'Fire_Alarm_System_Impact_on_Evacuation' and dropping the first one.
Fire_Alarm_System_Impact_on_Evacuation = pd.get_dummies(df12['Fire_Alarm_System_Impact_on_Evacuation'], prefix = 'Fire_Alarm_System_Impact_on_Evacuation', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Fire_Alarm_System_Impact_on_Evacuation],axis=1)

# Creating a dummy variable for the variable 'Fire_Alarm_System_Operation' and dropping the first one.
Fire_Alarm_System_Operation = pd.get_dummies(df12['Fire_Alarm_System_Operation'], prefix = 'Fire_Alarm_System_Operation', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Fire_Alarm_System_Operation],axis=1)

# Creating a dummy variable for the variable 'Fire_Alarm_System_Presence' and dropping the first one.
Fire_Alarm_System_Presence = pd.get_dummies(df12['Fire_Alarm_System_Presence'], prefix = 'Fire_Alarm_System_Presence', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Fire_Alarm_System_Presence],axis=1)

# Creating a dummy variable for the variable 'Ignition_Source' and dropping the first one.
Ignition_Source = pd.get_dummies(df12['Ignition_Source'], prefix = 'Ignition_Source', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Ignition_Source],axis=1)

# Creating a dummy variable for the variable 'Incident_Station_Area' and dropping the first one.
Incident_Station_Area = pd.get_dummies(df12['Incident_Station_Area'], prefix = 'Incident_Station_Area', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Incident_Station_Area],axis=1)

# Creating a dummy variable for the variable 'Incident_Ward' and dropping the first one.
Incident_Ward = pd.get_dummies(df12['Incident_Ward'], prefix = 'Incident_Ward', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Incident_Ward],axis=1)
```

```
# Creating a dummy variable for the variable 'Initial_CAD_Event_Type' and␣
↪dropping the first one.
Initial_CAD_Event_Type = pd.get_dummies(df12['Initial_CAD_Event_Type'], prefix␣
↪= 'Initial_CAD_Event_Type', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Initial_CAD_Event_Type],axis=1)

# Creating a dummy variable for the variable 'Material_First_Ignited' and␣
↪dropping the first one.
Material_First_Ignited = pd.get_dummies(df12['Material_First_Ignited'], prefix␣
↪= 'Material_First_Ignited', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Material_First_Ignited],axis=1)

# Creating a dummy variable for the variable 'Method_Of_Fire_Control' and␣
↪dropping the first one.
Method_Of_Fire_Control = pd.get_dummies(df12['Method_Of_Fire_Control'], prefix␣
↪= 'Method_Of_Fire_Control', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Method_Of_Fire_Control],axis=1)

# Creating a dummy variable for the variable 'Possible_Cause' and dropping the␣
↪first one.
Possible_Cause = pd.get_dummies(df12['Possible_Cause'], prefix =␣
↪'Possible_Cause', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Possible_Cause],axis=1)

# Creating a dummy variable for the variable 'Property_Use' and dropping the␣
↪first one.
Property_Use = pd.get_dummies(df12['Property_Use'], prefix = 'Property_Use',␣
↪drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Property_Use],axis=1)

# Creating a dummy variable for the variable 'Smoke_Alarm_at_Fire_Origin' and␣
↪dropping the first one.
Smoke_Alarm_at_Fire_Origin = pd.get_dummies(df12['Smoke_Alarm_at_Fire_Origin'],␣
↪prefix = 'Smoke_Alarm_at_Fire_Origin', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Smoke_Alarm_at_Fire_Origin],axis=1)

# Creating a dummy variable for the variable␣
↪'Smoke_Alarm_at_Fire_Origin_Alarm_Failure' and dropping the first one.
```

```python
Smoke_Alarm_at_Fire_Origin_Alarm_Failure = pd.
 ↪get_dummies(df12['Smoke_Alarm_at_Fire_Origin_Alarm_Failure'], prefix =␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Failure', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Smoke_Alarm_at_Fire_Origin_Alarm_Failure],axis=1)

# Creating a dummy variable for the variable␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Type' and dropping the first one.
Smoke_Alarm_at_Fire_Origin_Alarm_Type = pd.
 ↪get_dummies(df12['Smoke_Alarm_at_Fire_Origin_Alarm_Type'], prefix =␣
 ↪'Smoke_Alarm_at_Fire_Origin_Alarm_Type', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Smoke_Alarm_at_Fire_Origin_Alarm_Type],axis=1)

# Creating a dummy variable for the variable␣
 ↪'Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation' and dropping␣
 ↪the first one.
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation = pd.
 ↪get_dummies(df12['Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation'],␣
 ↪prefix =  'Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation',␣
 ↪drop_first = True)
#Adding the results to the master dataframe
df12 = pd.
 ↪concat([df12,Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation],axis=1)

# Creating a dummy variable for the variable 'Smoke_Spread' and dropping the␣
 ↪first one.
Smoke_Spread = pd.get_dummies(df12['Smoke_Spread'], prefix = 'Smoke_Spread',␣
 ↪drop_first = True)
#Adding the results to the master dataframe
df12= pd.concat([df9,Smoke_Spread],axis=1)

# Creating a dummy variable for the variable 'Sprinkler_System_Operation' and␣
 ↪dropping the first one.
Sprinkler_System_Operation = pd.get_dummies(df12['Sprinkler_System_Operation'],␣
 ↪prefix = 'Sprinkler_System_Operation', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Sprinkler_System_Operation],axis=1)

# Creating a dummy variable for the variable 'Sprinkler_System_Presence' and␣
 ↪dropping the first one.
Sprinkler_System_Presence = pd.get_dummies(df12['Sprinkler_System_Presence'],␣
 ↪prefix = 'Sprinkler_System_Presence', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Sprinkler_System_Presence],axis=1)
```

```
# Creating a dummy variable for the variable 'Status_of_Fire_On_Arrival' and␣
↪dropping the first one.
Status_of_Fire_On_Arrival = pd.get_dummies(df12['Status_of_Fire_On_Arrival'],␣
↪prefix = 'Status_of_Fire_On_Arrival', drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,Status_of_Fire_On_Arrival],axis=1)

# Creating a dummy variable for the variable 'GPS_Cluster' and dropping the␣
↪first one.
GPS_Cluster = pd.get_dummies(df12['GPS_Cluster'], prefix='GPS_Cluster',␣
↪drop_first = True)
#Adding the results to the master dataframe
df12 = pd.concat([df12,GPS_Cluster],axis=1)

# Drop the original variables.
df13 = df12.drop(['_id','Area_of_Origin', 'Number_of_responding_apparatus',␣
↪'Building_Status', 'Business_Impact',␣
↪'Estimated_Number_Of_Persons_Displaced', 'Extent_Of_Fire',␣
↪'Fire_Alarm_System_Impact_on_Evacuation', 'Fire_Alarm_System_Operation',␣
↪'Fire_Alarm_System_Presence', 'Ignition_Source', 'Incident_Station_Area',␣
↪'Incident_Ward', 'Initial_CAD_Event_Type', 'Material_First_Ignited',␣
↪'Method_Of_Fire_Control', 'Possible_Cause', 'Property_Use',␣
↪'Smoke_Alarm_at_Fire_Origin', 'Smoke_Alarm_at_Fire_Origin_Alarm_Failure',␣
↪'Smoke_Alarm_at_Fire_Origin_Alarm_Type',␣
↪'Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation',␣
↪'Smoke_Spread', 'Sprinkler_System_Operation', 'Sprinkler_System_Presence',␣
↪'Status_of_Fire_On_Arrival'], axis = 1)
```

[273]:
```
# Splitting training and testing sets.
X_2 = df13.drop('Estimated_Dollar_Loss', axis = 1).values
y_2 = df13['Estimated_Dollar_Loss'].values
X_train_2, X_test_2, y_train_2, y_test_2 = train_test_split(X_2, y_2,␣
↪train_size = 0.8, test_size = 0.2, shuffle = True)

# Fit linear regression model.
lr2 = sm.OLS(y_train_2, X_train_2).fit()

# Create a list with coefficient names.
coefficient_names_2 = df13.columns.tolist()
coefficient_names_2.remove("Estimated_Dollar_Loss")

# Use predict.
lr2_y_pred = lr2.predict(X_test_2)

# Print model summary.
print(lr2.summary(xname = coefficient_names_2))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.469
Model:                            OLS   Adj. R-squared:                  0.431
Method:                 Least Squares   F-statistic:                     12.26
Date:                Mon, 12 Dec 2022   Prob (F-statistic):               0.00
Time:                        10:19:17   Log-Likelihood:            -1.7765e+05
No. Observations:               12495   AIC:                         3.570e+05
Df Residuals:                   11654   BIC:                         3.632e+05
Df Model:                         840
Covariance Type:            nonrobust
================================================================================
================================================================================
========================================
                                                           coef    std err
t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----------------------------------------
Civilian_Casualties
-1.036e+04   9257.366     -1.119      0.263   -2.85e+04    7784.098
Count_of_Persons_Rescued
-1.676e+04   8378.845     -2.001      0.045   -3.32e+04    -338.942
Number_of_responding_personnel
1.033e+04    235.584     43.840      0.000    9866.194    1.08e+04
TFS_Firefighter_Casualties
-1.931e+05   2.34e+04     -8.240      0.000   -2.39e+05   -1.47e+05
Time_Difference
4150.8250   3.05e+04      0.136      0.892   -5.56e+04    6.39e+04
GPS_Cluster
-1560.3932   8066.424     -0.193      0.847   -1.74e+04    1.43e+04
Area_of_Origin_12 - Hallway, Corridor
-6.403e+04   5.86e+04     -1.092      0.275   -1.79e+05    5.09e+04
Area_of_Origin_13 - Stairway, Escalator
-7.238e+04    6.4e+04     -1.131      0.258   -1.98e+05     5.3e+04
Area_of_Origin_18 - Covered Court, Atrium, mall concourse
982.6104   1.85e+05      0.005      0.996   -3.62e+05    3.64e+05
Area_of_Origin_19 - Other Means of Egress
-1.27e+04    1.2e+05     -0.106      0.916   -2.49e+05    2.23e+05
Area_of_Origin_21 - Living Area (e.g. living, TV, recreation, etc)
-8.213e+04   5.02e+04     -1.635      0.102   -1.81e+05    1.63e+04
Area_of_Origin_22 - Sleeping Area or Bedroom (inc. patients room, dormitory,
etc)                                                     -9.519e+04   4.99e+04
-1.908      0.056   -1.93e+05    2615.910
Area_of_Origin_23 - Dining or Beverage Area (inc mess, canteen, lunchroom,
cafeteria                                                  -5.904e+04   6.69e+04
-0.883      0.377    -1.9e+05    7.21e+04
Area_of_Origin_24 - Cooking Area or Kitchen
```

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-5.797e+04   5.08e+04     -1.141      0.254   -1.58e+05    4.16e+04
Area_of_Origin_25 - Washroom or Bathroom (toilet,restroom/locker room)
-5.22e+04   5.27e+04     -0.990      0.322   -1.56e+05    5.11e+04
Area_of_Origin_26 - Sauna
-8.596e+04   1.08e+05     -0.797      0.426   -2.97e+05    1.26e+05
Area_of_Origin_27 - Laundry Area
-5.861e+04   6.09e+04     -0.963      0.336   -1.78e+05    6.07e+04
Area_of_Origin_28 - Office
-7.001e+04   7.62e+04     -0.919      0.358   -2.19e+05    7.94e+04
Area_of_Origin_29 - Electronic Equipment
-1.301e+04   6.47e+04     -0.201      0.840    -1.4e+05    1.14e+05
Area_of_Origin_30 - Sales, Showroom Area
-4.758e+04   9.42e+04     -0.505      0.613   -2.32e+05    1.37e+05
Area_of_Origin_31 - Process Manufacturing (inc manf, prod assembly, repair)
-1.324e+05   6.36e+04     -2.081      0.037   -2.57e+05   -7697.098
Area_of_Origin_32 - Assembly Area (inc school room,spectator area, church, etc)
-1.846e+04   1.21e+05     -0.153      0.878   -2.55e+05    2.18e+05
Area_of_Origin_33 - Laboratory
-1.965e+05   1.33e+05     -1.474      0.140   -4.58e+05    6.47e+04
Area_of_Origin_34 - Operating Room, Treatment or Examination Area
1.438e+05   2.06e+05      0.700      0.484   -2.59e+05    5.47e+05
Area_of_Origin_35 - Performance Area (inc stage, rink, boxing ring, gym floor,
altar                                                  2.579e+04   2.27e+05
0.114      0.909   -4.18e+05     4.7e+05
Area_of_Origin_39 - Other Functional Area
-6.439e+04   8.43e+04     -0.764      0.445    -2.3e+05    1.01e+05
Area_of_Origin_41 - Closet (eg. clothes, broom, linen closet, etc.)
-7.402e+04   7.08e+04     -1.046      0.296   -2.13e+05    6.47e+04
Area_of_Origin_42 - Garage
-1.761e+04   5.26e+04     -0.335      0.738   -1.21e+05    8.54e+04
Area_of_Origin_43 - Locker (apartment storage)
-6.95e+04    1.1e+05     -0.634      0.526   -2.84e+05    1.45e+05
Area_of_Origin_44 - Trash, Rubbish Storage (inc garbage chute room,
garbage/industri                                                 -5.794e+04
5.01e+04     -1.157      0.247   -1.56e+05    4.03e+04
Area_of_Origin_45 - Supply Storage Room (inc maintenance/office/document
storage, et                                                 -4.689e+04
8.84e+04     -0.530      0.596    -2.2e+05    1.26e+05
Area_of_Origin_46 - Product Storage (inc products or materials awaiting manuf,
assembly)                                              -1.712e+05   8.53e+04
-2.007      0.045   -3.38e+05   -4021.646
Area_of_Origin_47 - Shipping/Receiving/Loading Platform
-1.62e+05   8.64e+04     -1.874      0.061   -3.31e+05    7415.777
Area_of_Origin_48 - Records storage area (inc vaults)
-5.858e+04   2.89e+05     -0.203      0.839   -6.24e+05    5.07e+05
Area_of_Origin_49 - Other Storage Area
-1.037e+05   6.38e+04     -1.626      0.104   -2.29e+05    2.13e+04
Area_of_Origin_50 - Basement/cellar (not partitioned)
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-4.792e+04   5.84e+04   -0.821   0.412   -1.62e+05   6.65e+04
Area_of_Origin_51 - Elevator (includes shaft)
-1.309e+05   1.02e+05   -1.279   0.201   -3.31e+05   6.97e+04
Area_of_Origin_52 - HVAC Equipment Room (furnace room, water heater closet, boiler)   -3.245e+04   6.86e+04
-0.473   0.636   -1.67e+05   1.02e+05
Area_of_Origin_53 - Chimney/Flue Pipe
-9.485e+04   7.01e+04   -1.353   0.176   -2.32e+05   4.26e+04
Area_of_Origin_54 - Incinerator Room
1.641e+04   3.85e+05   0.043   0.966   -7.37e+05   7.7e+05
Area_of_Origin_55 - Mechanical/Electrical Services Room
-6.626e+04   6.01e+04   -1.103   0.270   -1.84e+05   5.15e+04
Area_of_Origin_56 - Conveyor Shaft or Chute (inc dumbwaiter, laundry chute, garbage   7.088e+04   1.1e+05
0.647   0.518   -1.44e+05   2.86e+05
Area_of_Origin_57 - Ducting - Heating, Air Conditioning
-6873.4788   1.07e+05   -0.064   0.949   -2.16e+05   2.02e+05
Area_of_Origin_58 - Ducting - Exhaust (inc cooking, fumes, etc.)
-2.08e+05   7.74e+04   -2.688   0.007   -3.6e+05   -5.63e+04
Area_of_Origin_59 - Utility Shaft (eg. electrical wiring/phone, etc.)
1978.8329   1.01e+05   0.020   0.984   -1.96e+05   2e+05
Area_of_Origin_60 - Other Building Services/Support Facilities
-3.087e+05   1.12e+05   -2.749   0.006   -5.29e+05   -8.86e+04
Area_of_Origin_61 - Exterior Wall
-3.266e+04   5.97e+04   -0.547   0.584   -1.5e+05   8.44e+04
Area_of_Origin_62 - Roof
-1.276e+05   5.96e+04   -2.141   0.032   -2.44e+05   -1.08e+04
Area_of_Origin_63 - Awning or Canopy
-5.267e+04   1.02e+05   -0.514   0.607   -2.53e+05   1.48e+05
Area_of_Origin_64 - Porch or Balcony
-8.233e+04   4.94e+04   -1.667   0.095   -1.79e+05   1.45e+04
Area_of_Origin_65 - Crawl Space (includes sub-structure)
-8.226e+04   1.31e+05   -0.629   0.529   -3.39e+05   1.74e+05
Area_of_Origin_66 - Concealed Ceiling Area
-1.92e+05   7.74e+04   -2.481   0.013   -3.44e+05   -4.03e+04
Area_of_Origin_67 - Concealed Floor Area
-1.219e+05   1.12e+05   -1.087   0.277   -3.42e+05   9.78e+04
Area_of_Origin_68 - Concealed Wall Area
5.842e+04   9.31e+04   0.628   0.530   -1.24e+05   2.41e+05
Area_of_Origin_69 - Attic Area
-6.284e+04   7.52e+04   -0.836   0.403   -2.1e+05   8.45e+04
Area_of_Origin_70 - Other Structural Area
-1.182e+05   7.56e+04   -1.563   0.118   -2.66e+05   3.01e+04
Area_of_Origin_71 - Open Area (inc lawn, field, farmyard, park, playing field, pier,   -6.612e+04   5.86e+04
-1.128   0.259   -1.81e+05   4.87e+04
Area_of_Origin_72 - Court, Patio, Terrace
-8.882e+04   6.19e+04   -1.434   0.152   -2.1e+05   3.26e+04

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Area_of_Origin_73 - Parking Area, Parking Lot
-6.939e+04   5.97e+04     -1.163      0.245   -1.86e+05    4.76e+04
Area_of_Origin_74 - Storage Area (outside)
-6.869e+04   6.44e+04     -1.066      0.286   -1.95e+05    5.76e+04
Area_of_Origin_75 - Trash, rubbish area (outside)
-6.97e+04   5.32e+04     -1.311      0.190   -1.74e+05    3.45e+04
Area_of_Origin_76 - Fuel Dispensing Area (outside)
6.828e+04   4.04e+05     0.169      0.866   -7.24e+05     8.6e+05
Area_of_Origin_78 - Attached Deck
-7.615e+04   6.48e+04     -1.176      0.240   -2.03e+05    5.08e+04
Area_of_Origin_79 - Other Outside Area
-1.093e+05   5.45e+04     -2.005      0.045   -2.16e+05   -2433.632
Area_of_Origin_81 - Engine Area
-8.122e+04   5.19e+04     -1.564      0.118   -1.83e+05    2.06e+04
Area_of_Origin_82 - Running Gear (inc wheels and braking systems, transmission
syste                                                -8.375e+04   7.46e+04
-1.123      0.261    -2.3e+05    6.24e+04
Area_of_Origin_83 - Electrical Systems
-7.953e+04   5.41e+04     -1.470      0.142   -1.86e+05    2.65e+04
Area_of_Origin_84 - Fuel Systems (eg. fuel tank, etc.)
-4.148e+04   8.07e+04     -0.514      0.607      -2e+05    1.17e+05
Area_of_Origin_85 - Operator/Control Area
-1.437e+05   6.93e+04     -2.074      0.038    -2.8e+05   -7883.786
Area_of_Origin_86 - Passenger Area
-9.29e+04   5.65e+04     -1.643      0.100   -2.04e+05    1.79e+04
Area_of_Origin_87 - Trunk/Cargo Area
-8.102e+04   6.07e+04     -1.334      0.182      -2e+05     3.8e+04
Area_of_Origin_89 - Other Vehicle Area
-9.495e+04   5.79e+04     -1.640      0.101   -2.08e+05    1.85e+04
Area_of_Origin_91 - Multiple Areas of Origin
-1.681e+04    1.3e+05     -0.129      0.897   -2.71e+05    2.38e+05
Area_of_Origin_92 - Residential/Business: Restaurant area
3.416e+04   1.57e+05      0.218      0.828   -2.73e+05    3.42e+05
Area_of_Origin_93 - Residential/Business: Other busines area
-2.021e+05   1.29e+05     -1.561      0.119   -4.56e+05    5.17e+04
Area_of_Origin_97 - Other - unclassified
-1.177e+05   5.29e+04     -2.223      0.026   -2.21e+05   -1.39e+04
Area_of_Origin_99 - Undetermined  (formerly 98)
-1.278e+05   5.34e+04     -2.396      0.017   -2.32e+05   -2.33e+04
Area_of_Origin_990 - Under Investigation
4.155e+06   2.27e+05     18.293      0.000    3.71e+06     4.6e+06
Building_Status_02 - Under Renovation
-2.896e+04   2.25e+04     -1.284      0.199   -7.32e+04    1.52e+04
Building_Status_03 - Under Construction
-5.008e+04   3.62e+04     -1.383      0.167   -1.21e+05    2.09e+04
Building_Status_04 - Under Demolition
-409.1540   1.13e+05     -0.004      0.997   -2.22e+05    2.21e+05
Building_Status_05 - Abandoned, vacant (long term)
```

```
-6.159e+04    6.3e+04     -0.978      0.328   -1.85e+05    6.18e+04
Building_Status_08 - Not Applicable
2.783e+04   2.16e+04      1.289      0.197   -1.45e+04    7.01e+04
Building_Status_09 - Undetermined
-1.421e+05   5.03e+04     -2.826      0.005   -2.41e+05   -4.35e+04
Building_Status_10 - Missing Entries
-2.587e+04    3.8e+05     -0.068      0.946   -7.71e+05    7.19e+05
Business_Impact_10 - Missing
-1.188e+05   1.23e+05     -0.963      0.335    -3.6e+05    1.23e+05
Business_Impact_2 - May resume operations within a week
-9515.9796   2.19e+04     -0.435      0.664   -5.24e+04    3.34e+04
Business_Impact_3 - May resume operations within a month
-4.301e+04   4.29e+04     -1.003      0.316   -1.27e+05     4.1e+04
Business_Impact_4 - May resume operations within a year
-9.868e+04   8.09e+04     -1.220      0.223   -2.57e+05    5.99e+04
Business_Impact_5 - May not resume operations
6.403e+05   6.21e+04     10.318      0.000    5.19e+05    7.62e+05
Business_Impact_8 - Not applicable (not a business)
-3928.3822   9825.062     -0.400      0.689   -2.32e+04    1.53e+04
Business_Impact_9 - Undetermined
3961.6465   1.89e+04      0.209      0.834   -3.31e+04    4.11e+04
Estimated_Number_Of_Persons_Displaced_11 - 50
-5.17e+04   2.83e+04     -1.824      0.068   -1.07e+05    3862.606
Estimated_Number_Of_Persons_Displaced_51 - 100
-5.178e+04   5.18e+04     -0.999      0.318   -1.53e+05    4.98e+04
Estimated_Number_Of_Persons_Displaced_101 - 500
-1.098e+05   7.02e+04     -1.563      0.118   -2.47e+05    2.79e+04
Estimated_Number_Of_Persons_Displaced_500+
1.883e+05   3.77e+04      4.992      0.000    1.14e+05    2.62e+05
Estimated_Number_Of_Persons_Displaced_Undetermined
8.657e+04   5.37e+05      0.161      0.872   -9.66e+05    1.14e+06
Extent_Of_Fire_10 - Spread beyond building of origin
-5.161e+04   5.96e+04     -0.866      0.386   -1.68e+05    6.52e+04
Extent_Of_Fire_11 - Spread beyond building of origin, resulted in exposure
fire(s)                                                  -1.439e+05   4.83e+04
-2.980      0.003   -2.38e+05   -4.92e+04
Extent_Of_Fire_2 - Confined to part of room/area of origin
-3.94e+04   1.06e+04     -3.715      0.000   -6.02e+04   -1.86e+04
Extent_Of_Fire_3 - Spread to entire room of origin
-9.46e+04   2.27e+04     -4.174      0.000   -1.39e+05   -5.02e+04
Extent_Of_Fire_4 - Spread beyond room of origin, same floor
-1.104e+05   2.37e+04     -4.653      0.000   -1.57e+05   -6.39e+04
Extent_Of_Fire_5 - Multi unit bldg: spread beyond suite of origin but not to
separated suite(s)                                     -1.615e+05   6.72e+04
-2.406      0.016   -2.93e+05   -2.99e+04
Extent_Of_Fire_6 - Multi unit bldg: spread to separate suite(s)
-1.667e+05   7.74e+04     -2.153      0.031   -3.18e+05    -1.5e+04
Extent_Of_Fire_7 - Spread to other floors, confined to building
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-1.109e+05   3.11e+04     -3.566      0.000   -1.72e+05      -5e+04
Extent_Of_Fire_8 - Entire Structure
3.184e+05    5.2e+04      6.127      0.000    2.17e+05     4.2e+05
Extent_Of_Fire_9 - Confined to roof/exterior structure
-6.347e+04   2.75e+04     -2.308      0.021   -1.17e+05   -9574.832
Extent_Of_Fire_99 - Undetermined
-6.878e+04   4.96e+04     -1.387      0.165   -1.66e+05    2.84e+04
Fire_Alarm_System_Impact_on_Evacuation_2 - Some persons (at risk) evacuated as a
result of hearing fire alarm system                  1.207e+04   2.08e+04
0.579      0.562   -2.88e+04    5.29e+04
Fire_Alarm_System_Impact_on_Evacuation_3 - No one (at risk) evacuated as a
result of hearing fire alarm system                        3.381e+04   2.37e+04
1.429      0.153   -1.26e+04    8.02e+04
Fire_Alarm_System_Impact_on_Evacuation_4 - Fire Alarm system operated but failed
to alert occupant(s)                                 -2.466e+04   7.66e+04
-0.322      0.748   -1.75e+05    1.26e+05
Fire_Alarm_System_Impact_on_Evacuation_7 - Not applicable: Occupant(s) first
alerted by other means                                   -2527.5085   1.98e+04
-0.128      0.899   -4.14e+04    3.63e+04
Fire_Alarm_System_Impact_on_Evacuation_8 - Not applicable: No fire alarm system,
no persons present                                   -1.162e+04   2.14e+04
-0.544      0.586   -5.35e+04    3.02e+04
Fire_Alarm_System_Impact_on_Evacuation_9 - Undetermined
2.048e+04   2.08e+04      0.982      0.326   -2.04e+04    6.13e+04
Fire_Alarm_System_Operation_2 - Fire alarm system did not operate
2.705e+04   1.95e+04      1.385      0.166   -1.12e+04    6.53e+04
Fire_Alarm_System_Operation_8 - Not applicable (no system)
4.315e+04    2.7e+04      1.598      0.110   -9777.862    9.61e+04
Fire_Alarm_System_Operation_9 - Fire alarm system operation ndertermined
-1.188e+05   1.23e+05     -0.963      0.335    -3.6e+05    1.23e+05
Fire_Alarm_System_Operation_9 - Fire alarm system operation undetermined
4.424e+04   2.18e+04      2.028      0.043    1472.461     8.7e+04
Fire_Alarm_System_Presence_2 - No Fire alarm system
-5.405e+04   2.55e+04     -2.120      0.034   -1.04e+05   -4067.671
Fire_Alarm_System_Presence_8 - Not applicable (bldg not classified by OBC OR
detached/semi/town home)                                  -1.25e+04   2.49e+04
-0.502      0.616   -6.13e+04    3.63e+04
Fire_Alarm_System_Presence_9 - Undetermined
-5.64e+04   2.07e+04     -2.722      0.007    -9.7e+04   -1.58e+04
Ignition_Source_101 - Exposure, source structure detached
-1.475e+04   2.18e+05     -0.068      0.946   -4.43e+05    4.13e+05
Ignition_Source_102 - Exposure, source structure semi-detached or attached
-2.091e+05   2.49e+05     -0.839      0.401   -6.98e+05    2.79e+05
Ignition_Source_103 - Exposure, source outside storage container, tank
-1448.1444   2.49e+05     -0.006      0.995    -4.9e+05    4.88e+05
Ignition_Source_104 - Exposure, source open fire (inc campfire, rubbish fire)
4747.1522   1.52e+05      0.031      0.975   -2.94e+05    3.04e+05
Ignition_Source_105 - Exposure, source forest, trees, wildland
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-2476.2830   3.98e+05     -0.006      0.995   -7.82e+05    7.77e+05
Ignition_Source_106 - Exposure, source grass, shrubs, trees
7379.7307   1.89e+05      0.039      0.969   -3.64e+05    3.79e+05
Ignition_Source_107 - Exposure, source vehicle (outside structure)
4.297e+04   1.75e+05      0.246      0.806      -3e+05    3.86e+05
Ignition_Source_108 - Exposure, source other
1.065e+05   1.54e+05      0.690      0.490   -1.96e+05    4.09e+05
Ignition_Source_11 - Stove, Range-top burner
7752.0010    1.2e+05      0.065      0.949   -2.28e+05    2.43e+05
Ignition_Source_12 - Oven
-8727.0046   1.21e+05     -0.072      0.943   -2.46e+05    2.29e+05
Ignition_Source_13 - Microwave
1682.2102   1.35e+05      0.012      0.990   -2.64e+05    2.67e+05
Ignition_Source_14 - Open Fired Barbeque - Fixed or Portable
444.0159   1.23e+05      0.004      0.997    -2.4e+05    2.41e+05
Ignition_Source_15 - Range Hood
3.713e+04   1.33e+05      0.279      0.780   -2.24e+05    2.98e+05
Ignition_Source_16 - Deep Fat Fryer
-2082.2318   1.27e+05     -0.016      0.987   -2.52e+05    2.48e+05
Ignition_Source_17 - Wood burning stove
8384.9423    1.3e+05      0.065      0.948   -2.46e+05    2.62e+05
Ignition_Source_19 - Other Cooking Items (eg Toaster, Kettle, elec frying pan)
2047.2671   1.24e+05      0.017      0.987    -2.4e+05    2.44e+05
Ignition_Source_20 - Service/Utility Lines (includes power/hydro transmission
lines)                                                    2.557e+04   1.24e+05
0.206      0.837   -2.18e+05    2.69e+05
Ignition_Source_21 - Transformer
1.167e+05    1.3e+05      0.897      0.370   -1.38e+05    3.72e+05
Ignition_Source_22 - Meter
-1.31e+05   1.82e+05     -0.719      0.472   -4.88e+05    2.26e+05
Ignition_Source_23 - Distribution Equipment (includes panel boards, fuses,
circuit br                                                  -2.906e+04   1.25e+05
-0.233      0.815   -2.73e+05    2.15e+05
Ignition_Source_24 - Circuit Wiring - Copper
1.457e+04   1.21e+05      0.121      0.904   -2.22e+05    2.51e+05
Ignition_Source_25 - Circuit Wiring - Aluminum
1.618e+04   1.97e+05      0.082      0.934   -3.69e+05    4.02e+05
Ignition_Source_26 - Terminations-Copper (incl receptacles, switches, lights)
3266.7120   1.26e+05      0.026      0.979   -2.44e+05    2.51e+05
Ignition_Source_27 - Terminations-Aluminum (incl receptables, switches, lights)
5.659e+04   2.09e+05      0.271      0.787   -3.53e+05    4.67e+05
Ignition_Source_28 - Cord, Cable for Appliance, Electrical Articles
5166.5945   1.22e+05      0.042      0.966   -2.34e+05    2.45e+05
Ignition_Source_29 - Extension Cord, Temporary Wiring
-1.812e+04   1.26e+05     -0.143      0.886   -2.66e+05     2.3e+05
Ignition_Source_30 - Other Electrical Distribution Item
9174.6786   1.22e+05      0.075      0.940    -2.3e+05    2.49e+05
Ignition_Source_31 - Central Heating/Cooling Unit
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-7.037e+04   1.31e+05     -0.537      0.592   -3.27e+05    1.87e+05
Ignition_Source_32 - Water Heater
-3.562e+04   1.52e+05     -0.234      0.815   -3.34e+05    2.63e+05
Ignition_Source_33 - Space Heater - Fixed
2.578e+04   1.36e+05      0.189      0.850   -2.42e+05    2.93e+05
Ignition_Source_34 - Space Heater - Portable
1.202e+04   1.29e+05      0.093      0.926   -2.42e+05    2.66e+05
Ignition_Source_35 - Fireplace - Factory Built
5.604e+04   1.65e+05      0.339      0.735   -2.68e+05     3.8e+05
Ignition_Source_36 - Fireplace - Masonry
6.081e+04    1.3e+05      0.469      0.639   -1.93e+05    3.15e+05
Ignition_Source_37 - Fireplace Insert
1.414e+04   1.57e+05      0.090      0.928   -2.94e+05    3.22e+05
Ignition_Source_38 - Chimney - Factory Built
7.848e+04   2.01e+05      0.390      0.696   -3.16e+05    4.73e+05
Ignition_Source_39 - Chimney - Masonry
4.341e+04   1.76e+05      0.246      0.806   -3.02e+05    3.89e+05
Ignition_Source_40 - Flue Pipe
2.576e+04   1.42e+05      0.181      0.856   -2.53e+05    3.04e+05
Ignition_Source_41 - Other Heating Equipment
1.7e+04    1.3e+05      0.131      0.896   -2.37e+05    2.71e+05
Ignition_Source_42 - Television, Radio, Stereo, Tape Recorder, etc.
-1.46e+04   1.37e+05     -0.106      0.915   -2.84e+05    2.55e+05
Ignition_Source_43 - Clothes Dryer
5638.1075   1.26e+05      0.045      0.964   -2.41e+05    2.52e+05
Ignition_Source_44 - Iron, Pressing Machine
-4.216e+04   2.11e+05     -0.200      0.842   -4.56e+05    3.72e+05
Ignition_Source_45 - Washing Machine
9160.8464    1.6e+05      0.057      0.954   -3.04e+05    3.22e+05
Ignition_Source_46 - Electric Blanket, Heating Pad
6.596e-09   3.44e-09      1.916      0.055   -1.51e-10    1.33e-08
Ignition_Source_47 - Refrigerator, Freezer (includes vending machine)
3.625e+04   1.39e+05      0.261      0.794   -2.36e+05    3.08e+05
Ignition_Source_48 - Air Conditioner - Window or Room Unit
-1.941e+04   1.57e+05     -0.124      0.902   -3.27e+05    2.88e+05
Ignition_Source_49 - Other Appliances
-222.8416   1.26e+05     -0.002      0.999   -2.47e+05    2.46e+05
Ignition_Source_51 - Incandescent Lamp - Light Bulb, Spotlight
6526.3086   1.26e+05      0.052      0.959   -2.41e+05    2.54e+05
Ignition_Source_52 - Florescent Lamp (includes ballast)
1.122e+05   1.39e+05      0.808      0.419    -1.6e+05    3.84e+05
Ignition_Source_53 - Christmas Lights, Decorative Lighting
4372.7131   2.16e+05      0.020      0.984    -4.2e+05    4.28e+05
Ignition_Source_54 - Lamp (eg. coal, oil, naphtha, etc.)
1.085e+04   2.08e+05      0.052      0.958   -3.97e+05    4.18e+05
Ignition_Source_55 - Candle
-135.7195   1.21e+05     -0.001      0.999   -2.37e+05    2.37e+05
Ignition_Source_56 - Halogen Lamp or light
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1.33e+04   1.46e+05      0.091      0.927   -2.73e+05       3e+05
Ignition_Source_59 - Other Lighting Equipment
1.024e+04   1.36e+05      0.075      0.940   -2.56e+05    2.77e+05
Ignition_Source_61 - Incinerator
-1.328e+05   2.93e+05     -0.453      0.650   -7.07e+05    4.42e+05
Ignition_Source_62 - Heat Treatment Equipment (eg. furnace, oven, kiln, quench
tanks,                                                  6.544e+04   1.34e+05
0.489      0.625   -1.97e+05    3.28e+05
Ignition_Source_63 - Painting Equipment
-8.026e+04   1.69e+05     -0.476      0.634   -4.11e+05     2.5e+05
Ignition_Source_64 - Chemical Processing Equipment (eg. reactors, distilling
units, e                                                  1.914e+05   2.52e+05
0.760      0.447   -3.02e+05    6.85e+05
Ignition_Source_69 - Other Processing Equipment
3.744e+04   1.35e+05      0.278      0.781   -2.26e+05    3.01e+05
Ignition_Source_71 - Smoker's Articles (eg. cigarettes, cigars, pipes already
ignited                                                 -1355.4682   1.18e+05
-0.011      0.991   -2.34e+05    2.31e+05
Ignition_Source_72 - Cutting/Welding Equipment
354.2165   1.22e+05      0.003      0.998   -2.39e+05     2.4e+05
Ignition_Source_73 - Blow Torch, Bunsen Burner
1.89e+04   1.23e+05      0.154      0.877   -2.21e+05    2.59e+05
Ignition_Source_74 - Salamander
1.781e+04   1.99e+05      0.089      0.929   -3.73e+05    4.09e+05
Ignition_Source_75 - Matches (open flame)
2003.8115   1.35e+05      0.015      0.988   -2.63e+05    2.67e+05
Ignition_Source_76 - Lighters (open flame)
805.5353   1.29e+05      0.006      0.995   -2.52e+05    2.54e+05
Ignition_Source_77 - Matches or Lighters (unable to distinguish)
3420.2437   1.27e+05      0.027      0.978   -2.45e+05    2.52e+05
Ignition_Source_79 - Other Open Flame Tools/Smokers' Articles
-1.297e+04   1.23e+05     -0.106      0.916   -2.54e+05    2.28e+05
Ignition_Source_80 - Portable generator
-552.1682   1.78e+05     -0.003      0.998   -3.49e+05    3.48e+05
Ignition_Source_81 - Vehicle - Electrical
7286.2115   1.19e+05      0.061      0.951   -2.27e+05    2.41e+05
Ignition_Source_82 - Vehicle - Mechanical
-8144.0641    1.2e+05     -0.068      0.946   -2.44e+05    2.28e+05
Ignition_Source_83 - Other Electrical
3062.5388   1.22e+05      0.025      0.980   -2.36e+05    2.42e+05
Ignition_Source_84 - Other Mechanical
-3.297e+04   1.24e+05     -0.265      0.791   -2.77e+05    2.11e+05
Ignition_Source_85 - Vehicle collision
4.595e+04   1.33e+05      0.346      0.729   -2.14e+05    3.06e+05
Ignition_Source_88 - Multiple Ignition Source or Igniting Equipment (suspected
arson)                                                  1.136e+05   1.77e+05
0.643      0.520   -2.33e+05     4.6e+05
Ignition_Source_91 - Fireworks
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-9570.1068   1.44e+05     -0.066      0.947   -2.92e+05    2.73e+05
Ignition_Source_92 - Open Fire (eg. camp fire, rubbish fire, etc.)
-7.146e+04    1.3e+05     -0.552      0.581   -3.25e+05    1.82e+05
Ignition_Source_93 - Hot Ashes, Embers, Spark
-3051.2203   1.24e+05     -0.025      0.980   -2.45e+05    2.39e+05
Ignition_Source_94 - Static Electricity (spark)
7413.5623   1.72e+05      0.043      0.966   -3.29e+05    3.44e+05
Ignition_Source_95 - Lightning
-3.715e+05   1.96e+05     -1.896      0.058   -7.56e+05    1.26e+04
Ignition_Source_96 - Chemical Reaction (eg. spontaneous combustion, etc.)
-1.928e+04   1.28e+05     -0.151      0.880   -2.69e+05    2.31e+05
Ignition_Source_97 - Rekindle
1.464e+04   1.94e+05      0.076      0.940   -3.66e+05    3.95e+05
Ignition_Source_98 - Other
-2.7e+04   1.21e+05     -0.224      0.823   -2.64e+05     2.1e+05
Ignition_Source_999 - Undetermined
-1.192e+04   1.18e+05     -0.101      0.920   -2.44e+05     2.2e+05
Ignition_Source_9990 - Under Investigation
4.203e+05   1.71e+05      2.457      0.014     8.5e+04    7.56e+05
Incident_Station_Area_112
-6.714e+04   6.74e+04     -0.996      0.319   -1.99e+05    6.49e+04
Incident_Station_Area_113
-2.661e+04   7.32e+04     -0.364      0.716    -1.7e+05    1.17e+05
Incident_Station_Area_114
-3.668e+04   6.49e+04     -0.565      0.572   -1.64e+05    9.05e+04
Incident_Station_Area_115
3166.2305   7.78e+04      0.041      0.968   -1.49e+05    1.56e+05
Incident_Station_Area_116
-2.175e+04   6.79e+04     -0.320      0.749   -1.55e+05    1.11e+05
Incident_Station_Area_121
-7.424e+04   7.07e+04     -1.050      0.294   -2.13e+05    6.43e+04
Incident_Station_Area_122
2.013e+04   7.47e+04      0.269      0.788   -1.26e+05    1.67e+05
Incident_Station_Area_123
-2.236e+04   8.13e+04     -0.275      0.783   -1.82e+05    1.37e+05
Incident_Station_Area_125
2931.8459   9.05e+04      0.032      0.974   -1.75e+05     1.8e+05
Incident_Station_Area_131
-1.024e+05   7.66e+04     -1.336      0.182   -2.53e+05    4.79e+04
Incident_Station_Area_132
-6.327e+04    6.6e+04     -0.958      0.338   -1.93e+05    6.62e+04
Incident_Station_Area_133
2459.6896   7.45e+04      0.033      0.974   -1.43e+05    1.48e+05
Incident_Station_Area_134
-2.56e+04    7.7e+04    -0.333      0.739   -1.77e+05    1.25e+05
Incident_Station_Area_135
-6.045e+04   7.95e+04     -0.761      0.447   -2.16e+05    9.53e+04
Incident_Station_Area_141
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-9.485e+04	7.43e+04	-1.276	0.202	-2.41e+05	5.09e+04
Incident_Station_Area_142					
-6.251e+04	7.47e+04	-0.837	0.402	-2.09e+05	8.38e+04
Incident_Station_Area_143					
-5.726e+04	6.83e+04	-0.838	0.402	-1.91e+05	7.67e+04
Incident_Station_Area_145					
-7.719e+04	6.91e+04	-1.117	0.264	-2.13e+05	5.83e+04
Incident_Station_Area_146					
-2.857e+04	7.46e+04	-0.383	0.702	-1.75e+05	1.18e+05
Incident_Station_Area_211					
-7287.8253	9.29e+04	-0.078	0.937	-1.89e+05	1.75e+05
Incident_Station_Area_212					
-5428.9337	9.11e+04	-0.060	0.952	-1.84e+05	1.73e+05
Incident_Station_Area_213					
2.852e+04	8.78e+04	0.325	0.745	-1.44e+05	2.01e+05
Incident_Station_Area_214					
-2.499e+04	9.51e+04	-0.263	0.793	-2.11e+05	1.61e+05
Incident_Station_Area_215					
-4.052e+04	1.04e+05	-0.390	0.696	-2.44e+05	1.63e+05
Incident_Station_Area_221					
2.936e+04	8.68e+04	0.338	0.735	-1.41e+05	2e+05
Incident_Station_Area_222					
7912.5911	8.47e+04	0.093	0.926	-1.58e+05	1.74e+05
Incident_Station_Area_223					
9566.4418	8.63e+04	0.111	0.912	-1.6e+05	1.79e+05
Incident_Station_Area_224					
1.479e+04	8.96e+04	0.165	0.869	-1.61e+05	1.91e+05
Incident_Station_Area_225					
2.197e+04	8.26e+04	0.266	0.790	-1.4e+05	1.84e+05
Incident_Station_Area_226					
2.019e+04	8.83e+04	0.229	0.819	-1.53e+05	1.93e+05
Incident_Station_Area_227					
1.298e+04	9.56e+04	0.136	0.892	-1.74e+05	2e+05
Incident_Station_Area_231					
-1.937e+04	8.24e+04	-0.235	0.814	-1.81e+05	1.42e+05
Incident_Station_Area_232					
-6.039e+04	8.49e+04	-0.712	0.477	-2.27e+05	1.06e+05
Incident_Station_Area_233					
-4.152e+04	8.09e+04	-0.513	0.608	-2e+05	1.17e+05
Incident_Station_Area_234					
-2.057e+04	8.9e+04	-0.231	0.817	-1.95e+05	1.54e+05
Incident_Station_Area_235					
6363.3874	8.37e+04	0.076	0.939	-1.58e+05	1.7e+05
Incident_Station_Area_241					
-5435.5024	9.86e+04	-0.055	0.956	-1.99e+05	1.88e+05
Incident_Station_Area_242					
4.227e+04	8.68e+04	0.487	0.626	-1.28e+05	2.12e+05
Incident_Station_Area_243					

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2.97e+04   8.51e+04      0.349      0.727   -1.37e+05    1.97e+05
Incident_Station_Area_244
-2.563e+04   8.22e+04     -0.312      0.755   -1.87e+05    1.36e+05
Incident_Station_Area_245
-1.655e+04    8.3e+04     -0.199      0.842   -1.79e+05    1.46e+05
Incident_Station_Area_311
2.158e+04    8.2e+04      0.263      0.792   -1.39e+05    1.82e+05
Incident_Station_Area_312
1.736e+04   8.34e+04      0.208      0.835   -1.46e+05    1.81e+05
Incident_Station_Area_313
-3174.4139   7.87e+04     -0.040      0.968   -1.58e+05    1.51e+05
Incident_Station_Area_314
6267.0495   8.06e+04      0.078      0.938   -1.52e+05    1.64e+05
Incident_Station_Area_315
-3.264e+04   7.82e+04     -0.417      0.676   -1.86e+05    1.21e+05
Incident_Station_Area_321
-4.239e+04   8.82e+04     -0.480      0.631   -2.15e+05    1.31e+05
Incident_Station_Area_322
-6013.9993   8.37e+04     -0.072      0.943    -1.7e+05    1.58e+05
Incident_Station_Area_323
-1415.2367   8.59e+04     -0.016      0.987    -1.7e+05    1.67e+05
Incident_Station_Area_324
3359.0119   8.64e+04      0.039      0.969   -1.66e+05    1.73e+05
Incident_Station_Area_325
1.049e+04   7.92e+04      0.132      0.895   -1.45e+05    1.66e+05
Incident_Station_Area_326
3.764e+04   9.03e+04      0.417      0.677   -1.39e+05    2.15e+05
Incident_Station_Area_331
-3.624e+04   7.99e+04     -0.454      0.650   -1.93e+05     1.2e+05
Incident_Station_Area_332
-3.049e+04   7.85e+04     -0.388      0.698   -1.84e+05    1.23e+05
Incident_Station_Area_333
-1.299e+04   8.14e+04     -0.159      0.873   -1.73e+05    1.47e+05
Incident_Station_Area_334
-4.692e+04   7.97e+04     -0.589      0.556   -2.03e+05    1.09e+05
Incident_Station_Area_335
-241.8757   1.89e+05     -0.001      0.999    -3.7e+05     3.7e+05
Incident_Station_Area_341
-1.885e+05   7.61e+04     -2.478      0.013   -3.38e+05   -3.94e+04
Incident_Station_Area_342
-4.985e+04   8.05e+04     -0.619      0.536   -2.08e+05    1.08e+05
Incident_Station_Area_343
-1.469e+04   7.89e+04     -0.186      0.852   -1.69e+05     1.4e+05
Incident_Station_Area_344
1.397e+04   7.74e+04      0.180      0.857   -1.38e+05    1.66e+05
Incident_Station_Area_345
-7.83e+04   7.42e+04     -1.056      0.291   -2.24e+05    6.71e+04
Incident_Station_Area_346
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-4.686e+04   1.63e+05     -0.288      0.774   -3.66e+05    2.72e+05
Incident_Station_Area_411
2664.6231   7.97e+04      0.033      0.973   -1.54e+05    1.59e+05
Incident_Station_Area_412
-1.092e+05   9.43e+04     -1.157      0.247   -2.94e+05    7.57e+04
Incident_Station_Area_413
-1.464e+05   9.74e+04     -1.502      0.133   -3.37e+05    4.46e+04
Incident_Station_Area_415
-1.296e+05   8.99e+04     -1.441      0.150   -3.06e+05    4.67e+04
Incident_Station_Area_421
1.017e+05   7.65e+04      1.329      0.184   -4.82e+04    2.52e+05
Incident_Station_Area_422
-6.924e+04   8.11e+04     -0.854      0.393   -2.28e+05    8.97e+04
Incident_Station_Area_423
-9.052e+04    7.5e+04     -1.207      0.228   -2.38e+05    5.65e+04
Incident_Station_Area_424
-5.143e+04   1.15e+05     -0.448      0.654   -2.77e+05    1.74e+05
Incident_Station_Area_425
-1.061e+05   8.73e+04     -1.215      0.224   -2.77e+05    6.51e+04
Incident_Station_Area_426
-9.862e+04    7.4e+04     -1.332      0.183   -2.44e+05    4.65e+04
Incident_Station_Area_431
-1.721e+05    9.9e+04     -1.738      0.082   -3.66e+05     2.2e+04
Incident_Station_Area_432
-1.805e+05   9.06e+04     -1.991      0.046   -3.58e+05   -2806.966
Incident_Station_Area_433
-1.925e+05    8.7e+04     -2.213      0.027   -3.63e+05    -2.2e+04
Incident_Station_Area_434
-1.211e+05   9.34e+04     -1.296      0.195   -3.04e+05     6.2e+04
Incident_Station_Area_435
-1.52e+05   9.09e+04     -1.671      0.095    -3.3e+05    2.63e+04
Incident_Station_Area_441
-5.471e+04   8.61e+04     -0.635      0.525   -2.23e+05    1.14e+05
Incident_Station_Area_442
-2.702e+04   7.54e+04     -0.358      0.720   -1.75e+05    1.21e+05
Incident_Station_Area_443
-7.796e+04   8.52e+04     -0.915      0.360   -2.45e+05    8.91e+04
Incident_Station_Area_444
-1.911e+05   9.42e+04     -2.029      0.042   -3.76e+05   -6490.024
Incident_Station_Area_445
-1.796e+05   8.77e+04     -2.048      0.041   -3.52e+05   -7712.143
Incident_Ward_2.0
5950.2447   4.52e+04      0.132      0.895   -8.27e+04    9.46e+04
Incident_Ward_3.0
7.033e+04   5.98e+04      1.176      0.240   -4.69e+04    1.88e+05
Incident_Ward_4.0
-6.715e+04   5.39e+04     -1.245      0.213   -1.73e+05    3.86e+04
Incident_Ward_5.0
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7.004e+04   5.83e+04      1.201      0.230   -4.43e+04    1.84e+05
Incident_Ward_6.0
126.4274   6.19e+04      0.002      0.998   -1.21e+05    1.22e+05
Incident_Ward_7.0
-1.348e+05   6.49e+04     -2.075      0.038   -2.62e+05   -7463.203
Incident_Ward_8.0
-4.663e+04   6.57e+04     -0.710      0.478   -1.75e+05    8.21e+04
Incident_Ward_9.0
-2.891e+04   6.42e+04     -0.450      0.652   -1.55e+05    9.69e+04
Incident_Ward_10.0
-7.294e+04   6.73e+04     -1.085      0.278   -2.05e+05    5.89e+04
Incident_Ward_11.0
-1.34e+05   6.24e+04     -2.149      0.032   -2.56e+05   -1.18e+04
Incident_Ward_12.0
-2.332e+05   6.52e+04     -3.577      0.000   -3.61e+05   -1.05e+05
Incident_Ward_13.0
-8.881e+04    6.6e+04     -1.346      0.178   -2.18e+05    4.05e+04
Incident_Ward_14.0
-8.528e+04   6.67e+04     -1.278      0.201   -2.16e+05    4.55e+04
Incident_Ward_15.0
-6.615e+04   6.86e+04     -0.964      0.335   -2.01e+05    6.83e+04
Incident_Ward_16.0
-8.197e+04   7.35e+04     -1.115      0.265   -2.26e+05    6.22e+04
Incident_Ward_17.0
-1.062e+05       7e+04     -1.516      0.130   -2.43e+05    3.11e+04
Incident_Ward_18.0
-7.292e+04   6.74e+04     -1.082      0.279   -2.05e+05    5.92e+04
Incident_Ward_19.0
-1.018e+05   7.25e+04     -1.403      0.160   -2.44e+05    4.04e+04
Incident_Ward_20.0
-1.093e+05   7.21e+04     -1.516      0.130   -2.51e+05    3.21e+04
Incident_Ward_21.0
-1.745e+05   7.39e+04     -2.362      0.018   -3.19e+05   -2.97e+04
Incident_Ward_22.0
-1.038e+05   7.73e+04     -1.342      0.180   -2.55e+05    4.78e+04
Incident_Ward_23.0
-1.031e+05    7.6e+04     -1.357      0.175   -2.52e+05    4.58e+04
Incident_Ward_24.0
-1.109e+05   7.81e+04     -1.419      0.156   -2.64e+05    4.23e+04
Incident_Ward_25.0
-8.284e+04    7.7e+04     -1.076      0.282   -2.34e+05    6.81e+04
Incident_Ward_26.0
-1.748e+05   8.53e+04     -2.049      0.040   -3.42e+05   -7566.934
Incident_Ward_27.0
-1.466e+05   7.53e+04     -1.948      0.051   -2.94e+05     899.885
Incident_Ward_28.0
-1.224e+05   7.55e+04     -1.622      0.105    -2.7e+05    2.55e+04
Incident_Ward_29.0
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-1.191e+05   8.28e+04     -1.439      0.150   -2.81e+05    4.31e+04
Incident_Ward_30.0
-1.624e+05   8.12e+04     -1.998      0.046   -3.22e+05   -3090.083
Incident_Ward_31.0
-1.809e+05   8.94e+04     -2.023      0.043   -3.56e+05   -5627.962
Incident_Ward_32.0
-1.651e+05   8.93e+04     -1.849      0.065    -3.4e+05    9964.612
Incident_Ward_33.0
-1.594e+05   8.61e+04     -1.852      0.064   -3.28e+05    9281.619
Incident_Ward_34.0
-1.13e+05   8.38e+04     -1.348      0.178   -2.77e+05    5.13e+04
Incident_Ward_35.0
-1.535e+05   8.72e+04     -1.760      0.078   -3.24e+05    1.74e+04
Incident_Ward_36.0
-1.568e+05   8.92e+04     -1.758      0.079   -3.32e+05    1.81e+04
Incident_Ward_37.0
-8.722e+04   8.55e+04     -1.021      0.307   -2.55e+05    8.03e+04
Incident_Ward_38.0
-1.407e+05   8.72e+04     -1.615      0.106   -3.12e+05    3.01e+04
Incident_Ward_39.0
-1.592e+05   1.01e+05     -1.575      0.115   -3.57e+05    3.89e+04
Incident_Ward_40.0
-1.277e+05   9.09e+04     -1.406      0.160   -3.06e+05    5.04e+04
Incident_Ward_41.0
-1.624e+05    9.3e+04     -1.746      0.081   -3.45e+05    1.99e+04
Incident_Ward_42.0
-1.621e+05   9.01e+04     -1.799      0.072   -3.39e+05    1.45e+04
Incident_Ward_43.0
-1.343e+05   9.09e+04     -1.478      0.139   -3.12e+05    4.38e+04
Incident_Ward_44.0
-1.137e+05   9.34e+04     -1.217      0.224   -2.97e+05    6.94e+04
Incident_Ward_999. Missing
-7.823e+04   7.03e+04     -1.113      0.266   -2.16e+05    5.95e+04
Initial_CAD_Event_Type_Alarm Commercial/Industrial
3.08e+05   1.38e+05      2.232      0.026    3.75e+04    5.79e+05
Initial_CAD_Event_Type_Alarm Highrise - Commercial - Downtown
3.726e+05   1.98e+05      1.883      0.060   -1.53e+04     7.6e+05
Initial_CAD_Event_Type_Alarm Highrise Commercial
4.489e+05   4.14e+05      1.084      0.279   -3.63e+05    1.26e+06
Initial_CAD_Event_Type_Alarm Highrise Residential
2.445e+05   1.31e+05      1.870      0.062   -1.18e+04    5.01e+05
Initial_CAD_Event_Type_Alarm Highrise Residential Downtown
3.137e+05    1.4e+05      2.246      0.025    3.99e+04    5.87e+05
Initial_CAD_Event_Type_Alarm Institution
1.67e+05   1.84e+05      0.908      0.364   -1.93e+05    5.27e+05
Initial_CAD_Event_Type_Alarm Institution Downtown
2.906e+05   2.18e+05      1.336      0.182   -1.36e+05    7.17e+05
Initial_CAD_Event_Type_Alarm Residential
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2.705e+05   1.41e+05      1.920      0.055   -5683.757    5.47e+05
Initial_CAD_Event_Type_Alarm Waterfront Marina/Industrial
2.715e+05   4.52e+05      0.600      0.548   -6.15e+05    1.16e+06
Initial_CAD_Event_Type_CC
4.169e+05   1.37e+05      3.032      0.002    1.47e+05    6.86e+05
Initial_CAD_Event_Type_CCA
5.149e+05   3.02e+05      1.707      0.088   -7.64e+04    1.11e+06
Initial_CAD_Event_Type_COM
2.237e+05   4.04e+05      0.554      0.579   -5.67e+05    1.01e+06
Initial_CAD_Event_Type_CONM
4.054e+05   2.31e+05      1.751      0.080   -4.84e+04    8.59e+05
Initial_CAD_Event_Type_Carbon Monoxide - Non Medical
4.536e+05   3.03e+05      1.497      0.135   -1.41e+05    1.05e+06
Initial_CAD_Event_Type_Check Call
3.384e+05   1.71e+05      1.982      0.047    3772.173    6.73e+05
Initial_CAD_Event_Type_FACC
1.822e+05   2.02e+05      0.903      0.366   -2.13e+05    5.78e+05
Initial_CAD_Event_Type_FACI
3.558e+05   1.31e+05      2.708      0.007    9.83e+04    6.13e+05
Initial_CAD_Event_Type_FAHC
2.706e+05   1.77e+05      1.526      0.127   -7.71e+04    6.18e+05
Initial_CAD_Event_Type_FAHCD
3.656e+05   1.46e+05      2.509      0.012    7.99e+04    6.51e+05
Initial_CAD_Event_Type_FAHR
3.108e+05    1.3e+05      2.399      0.016    5.68e+04    5.65e+05
Initial_CAD_Event_Type_FAHRD
3.426e+05   1.34e+05      2.563      0.010    8.06e+04    6.05e+05
Initial_CAD_Event_Type_FAI
3.534e+05   1.39e+05      2.542      0.011    8.09e+04    6.26e+05
Initial_CAD_Event_Type_FAID
2.141e+05   1.61e+05      1.333      0.183   -1.01e+05    5.29e+05
Initial_CAD_Event_Type_FAIS
3.662e+05   1.54e+05      2.380      0.017    6.46e+04    6.68e+05
Initial_CAD_Event_Type_FAR
3.466e+05   1.33e+05      2.611      0.009    8.64e+04    6.07e+05
Initial_CAD_Event_Type_FAS
1.138e-09   1.06e-09      1.078      0.281   -9.32e-10    3.21e-09
Initial_CAD_Event_Type_FAWMI
4.845e+05   3.24e+05      1.497      0.134    -1.5e+05    1.12e+06
Initial_CAD_Event_Type_FICI
3.528e+05   1.29e+05      2.730      0.006    9.95e+04    6.06e+05
Initial_CAD_Event_Type_FIG
4.497e+05    1.3e+05      3.472      0.001    1.96e+05    7.04e+05
Initial_CAD_Event_Type_FIHC
3.017e+05   1.77e+05      1.700      0.089   -4.61e+04    6.49e+05
Initial_CAD_Event_Type_FIHCD
3.1e+05   1.47e+05      2.115      0.034    2.27e+04    5.97e+05
Initial_CAD_Event_Type_FIHR
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2.928e+05   1.29e+05      2.267      0.023    3.97e+04    5.46e+05
Initial_CAD_Event_Type_FIHRD
3.345e+05   1.33e+05      2.518      0.012    7.41e+04    5.95e+05
Initial_CAD_Event_Type_FIHV
1.669e+05   1.46e+05      1.146      0.252   -1.19e+05    4.52e+05
Initial_CAD_Event_Type_FII
2.453e+05   1.38e+05      1.774      0.076   -2.58e+04    5.16e+05
Initial_CAD_Event_Type_FIID
3.001e+05   1.77e+05      1.693      0.090   -4.74e+04    6.48e+05
Initial_CAD_Event_Type_FIIS
-9.257e+04   1.56e+05     -0.593      0.553   -3.98e+05    2.13e+05
Initial_CAD_Event_Type_FIO
3.007e+05   1.39e+05      2.162      0.031    2.81e+04    5.73e+05
Initial_CAD_Event_Type_FIOS
3.25e+05   1.47e+05      2.207      0.027    3.64e+04    6.14e+05
Initial_CAD_Event_Type_FIR
3.195e+05   1.29e+05      2.479      0.013    6.69e+04    5.72e+05
Initial_CAD_Event_Type_FIS
3.012e+05   1.58e+05      1.912      0.056   -7659.993     6.1e+05
Initial_CAD_Event_Type_FISD
3.305e+05   1.88e+05      1.760      0.078   -3.75e+04    6.99e+05
Initial_CAD_Event_Type_FITP
4.274e+05   1.42e+05      3.000      0.003    1.48e+05    7.07e+05
Initial_CAD_Event_Type_FIW
1.762e+05   3.57e+05      0.493      0.622   -5.24e+05    8.76e+05
Initial_CAD_Event_Type_FIWMI
2.614e+05   4.67e+05      0.559      0.576   -6.55e+05    1.18e+06
Initial_CAD_Event_Type_Fire -  Highrise Residential
2.147e+05    1.3e+05      1.651      0.099   -4.02e+04     4.7e+05
Initial_CAD_Event_Type_Fire - Alarm Waterfront Highrise
2.086e+05   3.13e+05      0.666      0.506   -4.06e+05    8.23e+05
Initial_CAD_Event_Type_Fire - Commercial/Industrial
2.751e+05    1.3e+05      2.115      0.034    2.01e+04     5.3e+05
Initial_CAD_Event_Type_Fire - Grass/Rubbish
4.475e+05   1.31e+05      3.414      0.001    1.91e+05    7.04e+05
Initial_CAD_Event_Type_Fire - Highrise Commercial
3.385e+05   2.58e+05      1.311      0.190   -1.68e+05    8.45e+05
Initial_CAD_Event_Type_Fire - Highrise Commercial - Downtown
2.731e+05   2.18e+05      1.256      0.209   -1.53e+05       7e+05
Initial_CAD_Event_Type_Fire - Highrise Residential - Downtown
2.369e+05    1.5e+05      1.578      0.115   -5.73e+04    5.31e+05
Initial_CAD_Event_Type_Fire - Hydro Vault
1.495e+04   1.85e+05      0.081      0.935   -3.47e+05    3.77e+05
Initial_CAD_Event_Type_Fire - Institution
1.569e+05   1.64e+05      0.958      0.338   -1.64e+05    4.78e+05
Initial_CAD_Event_Type_Fire - Institution - Downtown
3.35e+05   3.12e+05      1.072      0.284   -2.77e+05    9.47e+05
Initial_CAD_Event_Type_Fire - Institution - School
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3.004e+06   1.67e+05     17.988      0.000    2.68e+06    3.33e+06
Initial_CAD_Event_Type_Fire - Other
6.353e+04   1.61e+05      0.395      0.693   -2.52e+05    3.79e+05
Initial_CAD_Event_Type_Fire - Outside Storage
2.602e+05   1.68e+05      1.548      0.122   -6.93e+04     5.9e+05
Initial_CAD_Event_Type_Fire - Residential
2.386e+05   1.29e+05      1.857      0.063   -1.33e+04    4.91e+05
Initial_CAD_Event_Type_Fire - Subway
3.79e+05   1.84e+05      2.063      0.039    1.89e+04    7.39e+05
Initial_CAD_Event_Type_Fire - Subway - Downtown
-5.206e-10   7.56e-10     -0.689      0.491      -2e-09    9.61e-10
Initial_CAD_Event_Type_Fire - Transformer/Pole
4.758e+05   1.73e+05      2.756      0.006    1.37e+05    8.14e+05
Initial_CAD_Event_Type_Fire Alarm - Check Call
3.09e+05   4.11e+05      0.752      0.452   -4.97e+05    1.11e+06
Initial_CAD_Event_Type_Fire Waterfront Marina/Industrial
3.669e+05   4.52e+05      0.812      0.417   -5.19e+05    1.25e+06
Initial_CAD_Event_Type_HAZ1
3.969e+05   1.95e+05      2.031      0.042    1.39e+04     7.8e+05
Initial_CAD_Event_Type_HAZ2
2.263e+05   2.26e+05      1.002      0.316   -2.16e+05    6.69e+05
Initial_CAD_Event_Type_Hazmat Level 1
4.21e+05   3.03e+05      1.390      0.165   -1.73e+05    1.01e+06
Initial_CAD_Event_Type_Hazmat Level 2
2.496e+05      4e+05      0.625      0.532   -5.34e+05    1.03e+06
Initial_CAD_Event_Type_ISFA
-4.878e-12   8.62e-10     -0.006      0.995   -1.69e-09    1.68e-09
Initial_CAD_Event_Type_ISFI
2.348e+05   2.54e+05      0.924      0.355   -2.63e+05    7.33e+05
Initial_CAD_Event_Type_Island Fire Alarm Response
7.658e+04    4.4e+05      0.174      0.862   -7.85e+05    9.38e+05
Initial_CAD_Event_Type_LKFI
3.601e+05   4.66e+05      0.773      0.439   -5.53e+05    1.27e+06
Initial_CAD_Event_Type_MECC
4.591e+05   4.15e+05      1.106      0.269   -3.55e+05    1.27e+06
Initial_CAD_Event_Type_MECR
4.84e+05      4e+05      1.209      0.227      -3e+05    1.27e+06
Initial_CAD_Event_Type_MEO
3.84e+05   1.89e+05      2.030      0.042    1.31e+04    7.55e+05
Initial_CAD_Event_Type_MEPI
-6.756e+05   5.06e+05     -1.336      0.181   -1.67e+06    3.15e+05
Initial_CAD_Event_Type_MESC
4.086e+05   4.03e+05      1.013      0.311   -3.82e+05     1.2e+06
Initial_CAD_Event_Type_METB
5.501e+05   4.02e+05      1.370      0.171   -2.37e+05    1.34e+06
Initial_CAD_Event_Type_MEU
3.533e+05   2.99e+05      1.180      0.238   -2.34e+05     9.4e+05
Initial_CAD_Event_Type_Medical - Other
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5.492e+05   2.68e+05      2.048      0.041    2.35e+04    1.07e+06
Initial_CAD_Event_Type_Medical - Trouble Breathing
2.923e+05   3.23e+05      0.905      0.366   -3.41e+05    9.26e+05
Initial_CAD_Event_Type_Medical - Unconscious
-2.072e-10   7.88e-10     -0.263      0.793   -1.75e-09    1.34e-09
Initial_CAD_Event_Type_NGASFI
3.199e+05   1.89e+05      1.693      0.091   -5.05e+04     6.9e+05
Initial_CAD_Event_Type_NGASLK
3.966e+05   2.34e+05      1.698      0.089   -6.12e+04    8.54e+05
Initial_CAD_Event_Type_Natural Gas Fire
1.551e+05   2.56e+05      0.606      0.545   -3.47e+05    6.57e+05
Initial_CAD_Event_Type_Natural Gas Leak
3.394e+05   4.13e+05      0.822      0.411    -4.7e+05    1.15e+06
Initial_CAD_Event_Type_PA
6.359e+05   4.01e+05      1.584      0.113   -1.51e+05    1.42e+06
Initial_CAD_Event_Type_PUB
4.387e+05   4.01e+05      1.094      0.274   -3.47e+05    1.22e+06
Initial_CAD_Event_Type_REHL
-7.028e+04   4.13e+05     -0.170      0.865    -8.8e+05     7.4e+05
Initial_CAD_Event_Type_VEAF
4.574e+05   1.46e+05      3.129      0.002    1.71e+05    7.44e+05
Initial_CAD_Event_Type_VEAT
4.212e+05   1.73e+05      2.436      0.015    8.22e+04     7.6e+05
Initial_CAD_Event_Type_VEATH
3.569e+05   1.81e+05      1.968      0.049    1438.462    7.12e+05
Initial_CAD_Event_Type_VEF
5.261e+05    1.3e+05      4.039      0.000    2.71e+05    7.81e+05
Initial_CAD_Event_Type_VEFH
4.704e+05   1.31e+05      3.579      0.000    2.13e+05    7.28e+05
Initial_CAD_Event_Type_VEFHE
3.47e+05   2.14e+05      1.620      0.105   -7.27e+04    7.67e+05
Initial_CAD_Event_Type_VEFU
2.798e+05    1.4e+05      2.002      0.045    5778.152    5.54e+05
Initial_CAD_Event_Type_VEPI
4.488e+05   2.99e+05      1.502      0.133   -1.37e+05    1.03e+06
Initial_CAD_Event_Type_VEPIH
3.836e+05   1.68e+05      2.288      0.022     5.5e+04    7.12e+05
Initial_CAD_Event_Type_Vehicle - Personal Injury
4.662e+05   3.99e+05      1.168      0.243   -3.16e+05    1.25e+06
Initial_CAD_Event_Type_Vehicle - Personal Injury Highway
4.989e+05   2.56e+05      1.953      0.051   -1939.535       1e+06
Initial_CAD_Event_Type_Vehicle Accident - Trapped
-2.048e+05   2.17e+05     -0.945      0.345   -6.29e+05     2.2e+05
Initial_CAD_Event_Type_Vehicle Accident - Trapped - Highway
5.096e+05   4.08e+05      1.248      0.212   -2.91e+05    1.31e+06
Initial_CAD_Event_Type_Vehicle Accident with Fire
4.303e+05    1.8e+05      2.396      0.017    7.82e+04    7.82e+05
Initial_CAD_Event_Type_Vehicle Fire
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4.956e+05    1.3e+05      3.798      0.000     2.4e+05    7.51e+05
Initial_CAD_Event_Type_Vehicle Fire - Highway
4.414e+05   1.34e+05      3.300      0.001    1.79e+05    7.04e+05
Initial_CAD_Event_Type_Vehicle Fire - Highway Elevated
4.272e+05      4e+05      1.068      0.285   -3.57e+05    1.21e+06
Initial_CAD_Event_Type_Vehicle Fire - Underground
2.08e+05   1.94e+05      1.072      0.284   -1.72e+05    5.88e+05
Initial_CAD_Event_Type_WAT
3.48e+05   2.35e+05      1.482      0.138   -1.12e+05    8.08e+05
Initial_CAD_Event_Type_WDH
4.288e+05   1.78e+05      2.408      0.016    7.97e+04    7.78e+05
Initial_CAD_Event_Type_Water Problem
5.678e+05   2.07e+05      2.739      0.006    1.61e+05    9.74e+05
Initial_CAD_Event_Type_Wires Down - Hydro
5.693e+05   3.22e+05      1.771      0.077    -6.1e+04     1.2e+06
Material_First_Ignited_12 - Exterior Cladding
2998.7908   5.98e+04      0.050      0.960   -1.14e+05     1.2e+05
Material_First_Ignited_13 - Floor
7.867e+04   6.29e+04      1.251      0.211   -4.46e+04    2.02e+05
Material_First_Ignited_14 - Interior Wall/Ceiling
5.944e+04   5.16e+04      1.151      0.250   -4.18e+04    1.61e+05
Material_First_Ignited_15 - Structural Member
-2.031e+04   6.03e+04     -0.337      0.736   -1.38e+05    9.78e+04
Material_First_Ignited_16 - Insulation
5495.5632   5.18e+04      0.106      0.916   -9.61e+04    1.07e+05
Material_First_Ignited_19 - Other Building Component
5.001e+04   5.86e+04      0.853      0.393   -6.49e+04    1.65e+05
Material_First_Ignited_21 - Upholstered Sofa, Chair, etc.
6.042e+04   5.36e+04      1.128      0.259   -4.46e+04    1.65e+05
Material_First_Ignited_22 - Non-upholstered Chair, etc.
5.5e+04   7.89e+04      0.697      0.486   -9.96e+04     2.1e+05
Material_First_Ignited_23 - Cabinetry
5.548e+04   5.36e+04      1.035      0.301   -4.96e+04    1.61e+05
Material_First_Ignited_29 - Other Furniture
5.456e+04   6.26e+04      0.872      0.383   -6.81e+04    1.77e+05
Material_First_Ignited_31 - Mattress, Pillow
5.202e+04    5.6e+04      0.929      0.353   -5.77e+04    1.62e+05
Material_First_Ignited_32 - Bedding
4.467e+04   6.12e+04      0.730      0.465   -7.52e+04    1.65e+05
Material_First_Ignited_33 - Linen Other than Bedding
5.39e+04   5.89e+04      0.915      0.360   -6.15e+04    1.69e+05
Material_First_Ignited_34 - Wearing Apparel on a Person
5.475e+04   8.72e+04      0.628      0.530   -1.16e+05    2.26e+05
Material_First_Ignited_35 - Curtain, Drapery
6.278e+04   7.09e+04      0.886      0.376   -7.62e+04    2.02e+05
Material_First_Ignited_36 - Rug, Carpet
5.045e+04   6.83e+04      0.738      0.460   -8.35e+04    1.84e+05
Material_First_Ignited_39 - Other Soft Goods, Wearing Apparel
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3.231e+04   5.57e+04   0.580   0.562   -7.69e+04   1.42e+05
Material_First_Ignited_40 - Christmas Tree
1.43e+05   1.53e+05   0.934   0.350   -1.57e+05   4.43e+05
Material_First_Ignited_41 - Books, Magazines, Newspapers
5.887e+04   5.68e+04   1.036   0.300   -5.25e+04   1.7e+05
Material_First_Ignited_42 - Cleaning Supplies
8.938e+04   8.69e+04   1.029   0.304   -8.09e+04   2.6e+05
Material_First_Ignited_43 - Electrical Wiring Insulation
3.988e+04   4.94e+04   0.807   0.420   -5.7e+04   1.37e+05
Material_First_Ignited_44 - Creosote (chimney, flue pipe)
3.784e+04   6.93e+04   0.546   0.585   -9.79e+04   1.74e+05
Material_First_Ignited_45 - Nest
1.601e+05   1.12e+05   1.431   0.152   -5.92e+04   3.79e+05
Material_First_Ignited_46 - Rubbish, Trash, Waste
5.861e+04   4.91e+04   1.194   0.232   -3.76e+04   1.55e+05
Material_First_Ignited_47 - Vehicle
2.536e+04   4.97e+04   0.511   0.610   -7.2e+04   1.23e+05
Material_First_Ignited_48 - Multiple Objects or Materials
4.551e+04   5.53e+04   0.822   0.411   -6.3e+04   1.54e+05
Material_First_Ignited_51 - Bush, Grass, Tree, Leaves, etc.
6.122e+04   5.68e+04   1.078   0.281   -5.01e+04   1.73e+05
Material_First_Ignited_52 - Agricultural Product - Grown (eg. straw, seeds, etc.)   7.655e+04   7.92e+04
0.967   0.334   -7.87e+04   2.32e+05
Material_First_Ignited_53 - Agricultural Product - Other (eg pesticide, fertilizer)   5.239e+04
1.98e+05   0.265   0.791   -3.35e+05   4.4e+05
Material_First_Ignited_54 - Plastic
5.411e+04   5.09e+04   1.062   0.288   -4.57e+04   1.54e+05
Material_First_Ignited_55 - Wood
5.095e+04   5e+04   1.019   0.308   -4.71e+04   1.49e+05
Material_First_Ignited_56 - Paper, Cardboard
5.107e+04   5.13e+04   0.994   0.320   -4.96e+04   1.52e+05
Material_First_Ignited_57 - Fabric - Natural (eg. cotton, wool, etc.)
4.354e+04   6.51e+04   0.669   0.504   -8.41e+04   1.71e+05
Material_First_Ignited_58 - Fabric - Synthetic, Combination
3.36e+04   6.17e+04   0.545   0.586   -8.73e+04   1.54e+05
Material_First_Ignited_59 - Asphalt, Tar Product
-3.772e+04   7.88e+04   -0.479   0.632   -1.92e+05   1.17e+05
Material_First_Ignited_61 - Propane
4.395e+04   7.62e+04   0.577   0.564   -1.05e+05   1.93e+05
Material_First_Ignited_62 - Natural Gas
9.106e+04   8.04e+04   1.133   0.257   -6.65e+04   2.49e+05
Material_First_Ignited_69 - Other Gases
3.325e+04   9.85e+04   0.338   0.736   -1.6e+05   2.26e+05
Material_First_Ignited_71 - Gasoline
1.426e+04   6.14e+04   0.232   0.816   -1.06e+05   1.35e+05
Material_First_Ignited_72 - Diesel Fuel/Fuel Oil

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1.147e+05   8.66e+04      1.325      0.185    -5.5e+04    2.84e+05
Material_First_Ignited_73 - Alcohol (methanol)
1.386e+05   1.71e+05      0.810      0.418   -1.97e+05    4.74e+05
Material_First_Ignited_74 - Cooking Oil, Grease
5.357e+04   5.05e+04      1.061      0.289   -4.54e+04    1.53e+05
Material_First_Ignited_75 - Paint, varnish stored in container
6.477e+04   1.34e+05      0.483      0.629   -1.98e+05    3.28e+05
Material_First_Ignited_79 - Other Flammable, Combustible Liquid
2.955e+05   7.28e+04      4.057      0.000    1.53e+05    4.38e+05
Material_First_Ignited_81 - Rubber, not classified above
1692.8309   7.79e+04      0.022      0.983   -1.51e+05    1.54e+05
Material_First_Ignited_82 - Oxidizing material (inc bleach, peroxide)
6.767e+04   1.87e+05      0.363      0.717   -2.98e+05    4.33e+05
Material_First_Ignited_83 - Oily rags (inc. paint rags, etc)
3.705e+04   8.26e+04      0.449      0.654   -1.25e+05    1.99e+05
Material_First_Ignited_86 - Pyrophoric metals
1.767e+05   2.99e+05      0.591      0.554   -4.09e+05    7.62e+05
Material_First_Ignited_87 - Other chemicals, materials not classified above
7.365e+04   7.44e+04      0.990      0.322   -7.21e+04    2.19e+05
Material_First_Ignited_96 - Multiple diverse objects ignited
1.984e+04   5.67e+04      0.350      0.726   -9.14e+04    1.31e+05
Material_First_Ignited_97 - Other
4.246e+04   4.89e+04      0.869      0.385   -5.34e+04    1.38e+05
Material_First_Ignited_99 - Undetermined (formerly 98)
4.112e+04   4.82e+04      0.854      0.393   -5.33e+04    1.36e+05
Material_First_Ignited_990 - Under Investigation
4.69e+06   2.27e+05     20.620      0.000    4.24e+06    5.14e+06
Method_Of_Fire_Control_2 - Extinguished by automatic system
2.849e+04   3.02e+04      0.944      0.345   -3.07e+04    8.76e+04
Method_Of_Fire_Control_3 - Extinguished by occupant
3.106e+04   1.97e+04      1.581      0.114   -7459.872    6.96e+04
Method_Of_Fire_Control_4 - Fire self extinguished
3400.8059   2.25e+04      0.151      0.880   -4.06e+04    4.74e+04
Method_Of_Fire_Control_5 - Action taken unclassified
1.351e+04   2.66e+04      0.507      0.612   -3.87e+04    6.57e+04
Possible_Cause_02 - Riot/Civil Commotion
-6.934e-10   7.44e-10     -0.932      0.351   -2.15e-09    7.65e-10
Possible_Cause_03 - Suspected Vandalism
7.86e+04   6.47e+04      1.215      0.224   -4.82e+04    2.05e+05
Possible_Cause_04 - Suspected Youth Vandalism (Ages 12 to 17)
-5.326e+04   1.39e+05     -0.383      0.702   -3.26e+05    2.19e+05
Possible_Cause_11 - Children Playing (Ages 11 and under)
8.42e+04   6.15e+04      1.369      0.171   -3.64e+04    2.05e+05
Possible_Cause_12 - Vehicle Accident/Collision
9.671e+04   6.02e+04      1.607      0.108   -2.12e+04    2.15e+05
Possible_Cause_20 - Design/Construction/Installation/Maintenance Deficiency
7.538e+04   4.01e+04      1.879      0.060   -3252.298    1.54e+05
Possible_Cause_28 - Routine maintenance deficiency, eg creosote, lint, grease
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buildup                                                      7.796e+04   4.22e+04
1.846      0.065   -4809.564    1.61e+05
Possible_Cause_44 - Unattended
9.104e+04   3.87e+04      2.354      0.019    1.52e+04    1.67e+05
Possible_Cause_45 - Improperly Discarded
9.027e+04   3.74e+04      2.412      0.016    1.69e+04    1.64e+05
Possible_Cause_46 - Used or Placed too close to combustibles
7.267e+04   4.25e+04      1.710      0.087   -1.06e+04    1.56e+05
Possible_Cause_47 - Improper handling of ignition source or ignited material
6.949e+04   3.83e+04      1.814      0.070   -5596.791    1.45e+05
Possible_Cause_48 - Used for purpose not intended
7.11e+04    6.5e+04      1.093      0.274   -5.64e+04    1.99e+05
Possible_Cause_49 - Improper Storage
8.398e+04   5.56e+04      1.512      0.131   -2.49e+04    1.93e+05
Possible_Cause_50 - Other misuse of ignition source/material ignited
9.768e+04   4.29e+04      2.279      0.023    1.37e+04    1.82e+05
Possible_Cause_51 - Mechanical Failure
6.961e+04    4.1e+04      1.698      0.090   -1.08e+04     1.5e+05
Possible_Cause_52 - Electrical Failure
6.364e+04    3.8e+04      1.673      0.094   -1.09e+04    1.38e+05
Possible_Cause_60 - Other unintentional cause, not classified
6.848e+04   3.76e+04      1.819      0.069   -5310.378    1.42e+05
Possible_Cause_72 - Rekindle
6.136e+04    1.4e+05      0.438      0.661   -2.13e+05    3.36e+05
Possible_Cause_73 - Natural Cause
1.109e+05   9.34e+04      1.188      0.235   -7.21e+04    2.94e+05
Possible_Cause_80 - Exposure fire
1.264e+05   9.67e+04      1.307      0.191   -6.32e+04    3.16e+05
Possible_Cause_98 - Unintentional, cause undetermined
9.311e+04   3.73e+04      2.494      0.013    1.99e+04    1.66e+05
Possible_Cause_99 - Undetermined
7.867e+04   3.55e+04      2.215      0.027    9062.426    1.48e+05
Possible_Cause_990 - Under Investigation
2.662e+06   1.46e+05     18.179      0.000    2.37e+06    2.95e+06
Property_Use_102 - Theatre - Concert Hall, Live
2.625e+04   1.84e+05      0.142      0.887   -3.35e+05    3.87e+05
Property_Use_103 - TV, radio, motion picture studio
7.905e+04   1.71e+05      0.463      0.643   -2.55e+05    4.13e+05
Property_Use_111 - Museum
-3.457e+04   1.97e+05     -0.175      0.861   -4.21e+05    3.52e+05
Property_Use_112 - Art Gallery
8.126e+04   2.92e+05      0.279      0.781   -4.91e+05    6.53e+05
Property_Use_113 - Library
-3.476e+04   1.95e+05     -0.178      0.859   -4.18e+05    3.48e+05
Property_Use_114 - Auditorium
6.444e+04   2.24e+05      0.288      0.773   -3.74e+05    5.03e+05
Property_Use_115 - Lecture Hall
-2.64e+04   3.96e+05     -0.067      0.947   -8.02e+05    7.49e+05
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Property_Use_121 - Bowling Alley, Billiard Centre, pool hall
-8058.4568   2.12e+05     -0.038      0.970   -4.23e+05    4.07e+05
Property_Use_122 - Dance Studio
-5.967e-10   5.72e-10     -1.043      0.297   -1.72e-09    5.25e-10
Property_Use_123 - Community/Exhibition/Dance Hall
5.534e+04   1.54e+05      0.360      0.719   -2.46e+05    3.57e+05
Property_Use_124 - Sports/Country/Social/Yacht Club
1.542e+04   1.37e+05      0.113      0.910   -2.53e+05    2.84e+05
Property_Use_125 - Gymnasium
1.33e+05   1.97e+05      0.676      0.499   -2.53e+05    5.19e+05
Property_Use_126 - Non Residential Club
2.839e+04   2.91e+05      0.098      0.922   -5.41e+05    5.98e+05
Property_Use_127 - Casino
-4.252e+04   2.84e+05     -0.150      0.881   -5.99e+05    5.14e+05
Property_Use_128 - Bingo Hall
4.386e+04   3.88e+05      0.113      0.910   -7.16e+05    8.04e+05
Property_Use_131 - School - Pre-Elementary
7.094e+04   3.91e+05      0.181      0.856   -6.96e+05    8.38e+05
Property_Use_132 - School - Elementary
-1.038e+04   1.11e+05     -0.093      0.926   -2.28e+05    2.07e+05
Property_Use_133 - School - Secondary Junior High (Gr. 7 & 8)
-2.418e+05    1.8e+05     -1.343      0.179   -5.95e+05    1.11e+05
Property_Use_134 - School - Secondary/Senior High (Gr. 9+)
1.109e+06   1.26e+05      8.816      0.000    8.62e+05    1.36e+06
Property_Use_135 - School - Technical, Industrial Trade
-5.458e+05   2.46e+05     -2.218      0.027   -1.03e+06   -6.34e+04
Property_Use_136 - School - Business, Commerce, Secretarial
-4.643e+04   4.11e+05     -0.113      0.910   -8.52e+05    7.59e+05
Property_Use_137 - School - Post Secondary (University)
2.802e+04   1.16e+05      0.241      0.810      -2e+05    2.56e+05
Property_Use_138 - School - Post Secondary (College)
1.842e+05   1.83e+05      1.007      0.314   -1.74e+05    5.43e+05
Property_Use_142 - Bus Terminal
4.029e+04   1.96e+05      0.206      0.837   -3.44e+05    4.25e+05
Property_Use_143 - Railway Station
1.041e+05   1.68e+05      0.621      0.535   -2.25e+05    4.33e+05
Property_Use_144 - Subway Station
-1.267e+04   1.25e+05     -0.102      0.919   -2.57e+05    2.32e+05
Property_Use_145 - Marine Terminal
-6.62e+04   2.15e+05     -0.308      0.758   -4.88e+05    3.55e+05
Property_Use_151 - Restaurants (occupant load greater than 30 persons, licensed)
1.551e+04   9.42e+04      0.165      0.869   -1.69e+05       2e+05
Property_Use_152 - Bar, Tavern, Night Club
-3.912e+04   1.08e+05     -0.362      0.718   -2.51e+05    1.73e+05
Property_Use_153 - Church, Other Similar Place of Worship
8.152e+04   1.25e+05      0.653      0.514   -1.63e+05    3.26e+05
Property_Use_154 - Funeral Facility
1.389e-09    5.9e-10      2.354      0.019    2.32e-10    2.55e-09
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Property_Use_155 - Legislative Facility/Building
5.937e+04   2.89e+05      0.206      0.837   -5.06e+05    6.25e+05
Property_Use_156 - Court Facility
5.252e+04   1.96e+05      0.268      0.789   -3.32e+05    4.37e+05
Property_Use_157 - Day Care Centre
2.054e+05   1.81e+05      1.135      0.256   -1.49e+05     5.6e+05
Property_Use_158 - Church Hall
-5.595e+04   2.24e+05     -0.249      0.803   -4.96e+05    3.84e+05
Property_Use_161 - Arena
-9.001e+05   2.45e+05     -3.679      0.000   -1.38e+06   -4.21e+05
Property_Use_162 - Ice Rink
1.676e+05   2.53e+05      0.662      0.508   -3.29e+05    6.64e+05
Property_Use_163 - Indoor Swimming Facility
-7.988e+04   2.59e+05     -0.308      0.758   -5.88e+05    4.28e+05
Property_Use_172 - Stadium
1.242e+05   2.86e+05      0.434      0.664   -4.37e+05    6.85e+05
Property_Use_173 - Exhibition, Fair Stand, Amusement Park Structure
2.992e+04   2.07e+05      0.144      0.885   -3.76e+05    4.36e+05
Property_Use_174 - Bleacher, Grandstand, Reviewing Stand
8.336e-10   5.89e-10      1.415      0.157   -3.21e-10    1.99e-09
Property_Use_175 - Tent or temporary structure for assembly activity
5.987e+04   3.97e+05      0.151      0.880   -7.19e+05    8.39e+05
Property_Use_199 - Other Assembly
9.505e+04   1.63e+05      0.581      0.561   -2.25e+05    4.15e+05
Property_Use_201 - Jail, Prison, Penitentiary
1.192e+05   1.85e+05      0.643      0.520   -2.44e+05    4.82e+05
Property_Use_202 - Reformatory (with detention quarters)
-7584.1354   3.94e+05     -0.019      0.985   -7.79e+05    7.64e+05
Property_Use_203 - Adult Detention Camp (minimum security)
-4.458e+04   3.93e+05     -0.114      0.910   -8.15e+05    7.25e+05
Property_Use_204 - Police Station (with detention quarters)
7.569e+04   2.84e+05      0.267      0.790    -4.8e+05    6.32e+05
Property_Use_206 - Psychiatric Hospital (with detention quarters)
8.376e+04   1.67e+05      0.500      0.617   -2.44e+05    4.12e+05
Property_Use_211 - Psychiatric Hospital (without detention quarters)
1.12e+05   3.89e+05      0.288      0.773    -6.5e+05    8.74e+05
Property_Use_212 - Public/Private Hospital
7.841e+04   1.26e+05      0.622      0.534   -1.69e+05    3.26e+05
Property_Use_216 - Convalescent Home or long term care (excluding senior care)
5.122e+04   2.89e+05      0.177      0.859   -5.16e+05    6.18e+05
Property_Use_217 - Infirmary
1.171e-09   5.43e-10      2.156      0.031    1.06e-10    2.24e-09
Property_Use_218 - Hospice
-3.109e+05   3.93e+05     -0.790      0.429   -1.08e+06     4.6e+05
Property_Use_222 - Institute for the blind, deaf
2.73e+04   2.84e+05      0.096      0.923    -5.3e+05    5.84e+05
Property_Use_223 - Seniors long term care facility, licensed
-3.255e+04   1.31e+05     -0.248      0.804    -2.9e+05    2.24e+05
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Property_Use_229 - Other care facility
1.441e+05   1.83e+05      0.787      0.431   -2.15e+05    5.03e+05
Property_Use_231 - Shelter for displaced/abused persons
7.274e+04   1.13e+05      0.644      0.520   -1.49e+05    2.94e+05
Property_Use_232 - Halfway/Transitional House
4.565e+04   1.35e+05      0.337      0.736    -2.2e+05    3.11e+05
Property_Use_233 - Group Home
6.446e+04   1.49e+05      0.433      0.665   -2.27e+05    3.56e+05
Property_Use_234 - Retirement Home
-1.136e+05   1.23e+05     -0.925      0.355   -3.54e+05    1.27e+05
Property_Use_299 - Other Care & Detention Not Classified
-7.803e+04   2.86e+05     -0.273      0.785   -6.38e+05    4.82e+05
Property_Use_301 - Detached Dwelling
4.222e+04   8.92e+04      0.473      0.636   -1.33e+05    2.17e+05
Property_Use_302 - Semi-Detached Dwelling
3.35e+04   9.03e+04      0.371      0.711   -1.43e+05     2.1e+05
Property_Use_303 - Attached Dwelling (eg. rowhouse, townhouse, etc.)
2.781e+04   9.04e+04      0.308      0.758   -1.49e+05    2.05e+05
Property_Use_311 - Rooming/Boarding/Lodging House
1.329e+04   9.67e+04      0.137      0.891   -1.76e+05    2.03e+05
Property_Use_321 - Multi-Unit Dwelling - 2 to 6 Units
5.545e+04   9.23e+04      0.601      0.548   -1.25e+05    2.36e+05
Property_Use_322 - Multi-Unit Dwelling - 7 to 12 Units
-5.104e+04    9.5e+04     -0.538      0.591   -2.37e+05    1.35e+05
Property_Use_323 - Multi-Unit Dwelling - Over 12 Units
1.429e+04   8.89e+04      0.161      0.872    -1.6e+05    1.88e+05
Property_Use_331 - Apartment, Flat, Tenement with Business
1.522e+04   9.21e+04      0.165      0.869   -1.65e+05    1.96e+05
Property_Use_332 - Detached Dwelling with Business
4.443e+04   1.74e+05      0.255      0.798   -2.96e+05    3.85e+05
Property_Use_333 - Semi-Detached Dwelling with Business
-1.558e+04   1.61e+05     -0.097      0.923   -3.32e+05       3e+05
Property_Use_334 - Attached Dwelling with Business
3.372e+04   1.03e+05      0.328      0.743   -1.68e+05    2.35e+05
Property_Use_335 - Detached/Semi/Attached with Accessory Apartment Above Grade
-3.953e+05   1.15e+05     -3.446      0.001    -6.2e+05    -1.7e+05
Property_Use_336 - Detached/Semi/Attached with Accessory Apartment Below Grade
1.054e+05    1.5e+05      0.702      0.483   -1.89e+05       4e+05
Property_Use_341 - Motor Home, Camper, Trailer
8.559e+04   1.81e+05      0.473      0.636   -2.69e+05     4.4e+05
Property_Use_342 - Mobile Home
1.835e+05   3.96e+05      0.463      0.644   -5.94e+05    9.61e+05
Property_Use_343 - Tent
1.44e+05   4.25e+05      0.339      0.735   -6.89e+05    9.77e+05
Property_Use_344 - Houseboat
-2.246e+05   3.43e+05     -0.654      0.513   -8.98e+05    4.49e+05
Property_Use_355 - Hotel, Motel, Lodging - 4 or more guests or suites
-9483.7661   1.06e+05     -0.089      0.929   -2.18e+05    1.99e+05
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Property_Use_356 - Hotel, Motel, Lodging - Less than 4 guests or suites (inc
B&B)                                                    -1.788e+04   3.97e+05
-0.045      0.964   -7.95e+05    7.59e+05
Property_Use_361 - School/College Dormitory (detached from educational facility)
-9388.8782    1.8e+05     -0.052      0.958   -3.62e+05    3.44e+05
Property_Use_365 - Detached Garage
2.509e+04   9.91e+04      0.253      0.800   -1.69e+05    2.19e+05
Property_Use_366 - Residential Club (inc sorority, fraternity)
1.666e+04   1.94e+05      0.086      0.932   -3.64e+05    3.97e+05
Property_Use_367 - Hostel
-1.711e+04   1.44e+05     -0.118      0.906      -3e+05    2.66e+05
Property_Use_369 - Convent, Monastery
6.337e+04   3.89e+05      0.163      0.871      -7e+05    8.27e+05
Property_Use_399 - Other Residential
-3465.0063   1.57e+05     -0.022      0.982   -3.11e+05    3.04e+05
Property_Use_401 - Bank
1.927e+04   1.44e+05      0.134      0.893   -2.62e+05    3.01e+05
Property_Use_402 - Post Office
-3.086e+04   2.87e+05     -0.107      0.915   -5.94e+05    5.33e+05
Property_Use_403 - Barber Shop, Hairdresser, Beauty Parlor, tanning salon
2.82e+04   1.34e+05      0.211      0.833   -2.34e+05     2.9e+05
Property_Use_404 - Laundry, Dry Cleaner (includes self-service)
3.643e+04   1.13e+05      0.322      0.748   -1.85e+05    2.58e+05
Property_Use_405 - General Business Office
3025.2455   9.79e+04      0.031      0.975   -1.89e+05    1.95e+05
Property_Use_406 - Police Station (without detention quarters)
-3.784e+04   3.94e+05     -0.096      0.924   -8.11e+05    7.35e+05
Property_Use_407 - Dental/Medical Office
5.431e+04   1.41e+05      0.386      0.699   -2.21e+05     3.3e+05
Property_Use_410 - Small Tool/Appliance Rental/Service Establishment
-8.125e+04   3.96e+05     -0.205      0.837   -8.58e+05    6.95e+05
Property_Use_411 - Fire Station
1.449e+05   2.83e+05      0.512      0.608   -4.09e+05    6.99e+05
Property_Use_412 - Engineering, Architect or Tech office
-2.532e+04   3.96e+05     -0.064      0.949   -8.02e+05    7.51e+05
Property_Use_413 - Mailing, photocopying office
-8.809e-10    6.1e-10     -1.445      0.148   -2.08e-09    3.14e-10
Property_Use_414 - Document centre, record repository (inc archives)
-1.041e+05   4.04e+05     -0.257      0.797   -8.96e+05    6.88e+05
Property_Use_415 - Computer, electronic data processing, records storage
2.551e+04   2.38e+05      0.107      0.915   -4.41e+05    4.92e+05
Property_Use_416 - Furniture, upholstery repair without sales
1.576e+05   2.85e+05      0.553      0.580   -4.01e+05    7.16e+05
Property_Use_418 - Tent or temporary structure for business or personal service
activity                                             -1.193e+04   2.46e+05
-0.048      0.961   -4.95e+05    4.71e+05
Property_Use_498 - Garage:  General Auto Parking - Structure
3.097e+04   1.05e+05      0.294      0.769   -1.75e+05    2.37e+05
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Property_Use_499 - Other Business or Personal Services
617.9500 9.98e+04 0.006 0.995 -1.95e+05 1.96e+05
Property_Use_501 - Restaurant (occupant load less than 30 persons)
-3744.6844 9.52e+04 -0.039 0.969 -1.9e+05 1.83e+05
Property_Use_502 - Supermarket, Grocery Store
-1.947e+04 1.13e+05 -0.172 0.864 -2.42e+05 2.03e+05
Property_Use_503 - Specialty Food Store (eg. butcher, delicatessen, etc.)
1.999e+04 1.15e+05 0.174 0.862 -2.06e+05 2.46e+05
Property_Use_504 - Convenience/Variety Store
5.257e+04 1.37e+05 0.385 0.700 -2.15e+05 3.2e+05
Property_Use_505 - Liquor/Wine/Beer Store
1.388e+05 2.4e+05 0.579 0.563 -3.31e+05 6.09e+05
Property_Use_506 - Market - Outdoors (flowers, fruit, vegetable sales)
3.307e+04 3.91e+05 0.085 0.933 -7.34e+05 8e+05
Property_Use_507 - Market - Indoors (flowers, fruit, vegetable sales)
-5.488e+04 2.82e+05 -0.194 0.846 -6.08e+05 4.98e+05
Property_Use_510 - Mall - public area common to multi store facility
1.959e+04 1.07e+05 0.183 0.854 -1.9e+05 2.29e+05
Property_Use_511 - Department Store
-9074.5437 1.43e+05 -0.063 0.949 -2.9e+05 2.72e+05
Property_Use_512 - Catalogue/Mail Order Outlet
2.472e+05 3.96e+05 0.625 0.532 -5.29e+05 1.02e+06
Property_Use_521 - Clothing Store, Accessories, fur
-2.086e+05 1.43e+05 -1.458 0.145 -4.89e+05 7.18e+04
Property_Use_522 - Fabric Store
-1.621e+06 3.95e+05 -4.099 0.000 -2.4e+06 -8.46e+05
Property_Use_523 - Furniture/Appliance Store
-2.014e+05 1.47e+05 -1.372 0.170 -4.89e+05 8.63e+04
Property_Use_524 - Paint/Wallpaper Store
9.434e-10 4.71e-10 2.002 0.045 1.98e-11 1.87e-09
Property_Use_525 - Hardware Store
3.596e+04 2.4e+05 0.150 0.881 -4.35e+05 5.07e+05
Property_Use_526 - Building Supply Store
1.739e+05 2.13e+05 0.816 0.415 -2.44e+05 5.92e+05
Property_Use_527 - Lumber Yard
-2.725e+05 2.86e+05 -0.952 0.341 -8.34e+05 2.89e+05
Property_Use_528 - Garden Supply
1.003e+05 2.86e+05 0.351 0.726 -4.6e+05 6.61e+05
Property_Use_529 - Book/Stationary/Art Supply Store
-4.859e+04 2.84e+05 -0.171 0.864 -6.05e+05 5.08e+05
Property_Use_530 - Pharmacy
-1.055e+04 1.64e+05 -0.064 0.949 -3.33e+05 3.12e+05
Property_Use_531 - Florist
-2.203e+05 2.9e+05 -0.759 0.448 -7.89e+05 3.49e+05
Property_Use_534 - Video Rental Shop
-5.816e+04 3.9e+05 -0.149 0.882 -8.23e+05 7.07e+05
Property_Use_535 - Computer/electronics store, service or repair
1.199e+06 2.42e+05 4.947 0.000 7.24e+05 1.67e+06

Property_Use_537 - Rug, floor covering store
-3.676e+05 2.9e+05 -1.269 0.204 -9.35e+05 2e+05
Property_Use_539 - Gifts, jewellery, leather goods, mixed goods
-2.795e+05 1.76e+05 -1.584 0.113 -6.25e+05 6.63e+04
Property_Use_541 - Tent or temporary structure for Mercantile activity
1.72e+05 3.08e+05 0.559 0.576 -4.31e+05 7.75e+05
Property_Use_543 - Big Box Store
-5926.9854 2.37e+05 -0.025 0.980 -4.71e+05 4.6e+05
Property_Use_599 - Other Mercantile
-6.252e+04 1.14e+05 -0.550 0.582 -2.85e+05 1.6e+05
Property_Use_601 - Motor Vehicle Sales
-7462.4714 1.2e+05 -0.062 0.950 -2.42e+05 2.27e+05
Property_Use_602 - Service Station
1.263e+04 1.46e+05 0.086 0.931 -2.74e+05 2.99e+05
Property_Use_603 - Motor Vehicle Repair Garage
7562.7838 9.89e+04 0.076 0.939 -1.86e+05 2.01e+05
Property_Use_604 - Motor Vehicle Parts, Accessory Sales
5.581e+04 2.38e+05 0.234 0.815 -4.11e+05 5.23e+05
Property_Use_607 - Marina, Marine Service Station
2.49e+05 2.56e+05 0.973 0.330 -2.52e+05 7.5e+05
Property_Use_609 - Other Vehicle Sales/Service
-1.899e+04 1.7e+05 -0.112 0.911 -3.52e+05 3.14e+05
Property_Use_612 - Hydro Distribution Facility
3.886e+05 1.19e+05 3.276 0.001 1.56e+05 6.21e+05
Property_Use_614 - Gas Distribution Facility
6.838e+04 2.13e+05 0.321 0.749 -3.5e+05 4.86e+05
Property_Use_615 - Water Works
4.781e+04 2.91e+05 0.164 0.870 -5.23e+05 6.19e+05
Property_Use_617 - Sanitary Services (includes plant)
4.733e+04 1.65e+05 0.287 0.774 -2.76e+05 3.7e+05
Property_Use_619 - Other Utilities
4.198e+04 1.47e+05 0.286 0.775 -2.45e+05 3.29e+05
Property_Use_620 - Heating Plant - central/district heating plant, steam, etc
7.501e+05 4.35e+05 1.724 0.085 -1.03e+05 1.6e+06
Property_Use_621 - Mfg: Petroleum Products
3.972e+04 2.92e+05 0.136 0.892 -5.32e+05 6.12e+05
Property_Use_622 - Mfg: Chemicals, inc hazardous chemicals
-3.381e+04 1.6e+05 -0.212 0.832 -3.47e+05 2.79e+05
Property_Use_623 - Mfg: Plastics
4.371e+04 1.37e+05 0.320 0.749 -2.24e+05 3.12e+05
Property_Use_624 - Mfg: Paint, Varnishes, Lacquers
-9369.1032 3.93e+05 -0.024 0.981 -7.79e+05 7.6e+05
Property_Use_625 - Mfg: Drugs, Cosmetics, Pharmaceutical
-1.014e+05 1.81e+05 -0.560 0.576 -4.56e+05 2.54e+05
Property_Use_626 - Mfg: Rubber Goods
5.483e+04 1.45e+05 0.379 0.705 -2.29e+05 3.38e+05
Property_Use_627 - Mfg: Asphalt Products
-3.839e+04 2.41e+05 -0.159 0.874 -5.11e+05 4.34e+05

Property_Use_629 - Mfg: Other Chemical/Petroleum/Paint/Plastic Products
2651.2512 1.4e+05 0.019 0.985 -2.72e+05 2.77e+05
Property_Use_631 - Mfg: Meat/Poultry/Fish Products
1.274e+05 2.14e+05 0.597 0.551 -2.91e+05 5.46e+05
Property_Use_633 - Mfg: Grain Products, Bakery Goods
3.436e+04 1.21e+05 0.284 0.776 -2.03e+05 2.71e+05
Property_Use_634 - Mfg: Alcoholic Beverages
4.339e+04 3.03e+05 0.143 0.886 -5.51e+05 6.38e+05
Property_Use_637 - Mfg: Vegetable/Animal Oil Products
-1.735e+05 3.97e+05 -0.437 0.662 -9.51e+05 6.04e+05
Property_Use_638 - Mfg: Sugar Refining, Sugar Products
1.931e+04 2.25e+05 0.086 0.931 -4.21e+05 4.6e+05
Property_Use_639 - Mfg: Other Agr/Food, Beverage, Tabac products
-1.789e+04 1.37e+05 -0.130 0.896 -2.87e+05 2.51e+05
Property_Use_640 - Mfg: Canning, preserving, processing fruits, vegetables
-6.211e+04 3.93e+05 -0.158 0.875 -8.33e+05 7.09e+05
Property_Use_641 - Mfg: Textile Manufacturing (e.g. preparing fibers, spinning, weaving) -1.665e+04 2.85e+05
-0.058 0.953 -5.75e+05 5.42e+05
Property_Use_644 - Mfg: Wearing Apparal Manufacturing
-6901.9103 2.39e+05 -0.029 0.977 -4.76e+05 4.62e+05
Property_Use_645 - Mfg: Dry Cleaning Plant
2.592e+06 2.4e+05 10.802 0.000 2.12e+06 3.06e+06
Property_Use_646 - Mfg: Floor covering and coated fabrics (exc rubber, ceramic)
-1.316e+05 2.87e+05 -0.459 0.646 -6.93e+05 4.3e+05
Property_Use_649 - Mfg: Other Textiles, Clothing, Leather goods
2.295e+05 1.83e+05 1.253 0.210 -1.3e+05 5.88e+05
Property_Use_651 - Mfg: Pulp, Paper Processing
1.061e+04 1.16e+05 0.092 0.927 -2.17e+05 2.38e+05
Property_Use_652 - Mfg: Primary Processing (eg sawmill, plywood manufacturer, etc) 3.512e+06 3.96e+05
8.869 0.000 2.74e+06 4.29e+06
Property_Use_653 - Mfg: Secondary Processing (eg finished goods, furniture, etc)
3.513e+04 1.14e+05 0.309 0.757 -1.88e+05 2.58e+05
Property_Use_654 - Mfg: Printing, Publishing (eg newspapers, magazines, books)
3.234e+05 1.58e+05 2.042 0.041 1.3e+04 6.34e+05
Property_Use_655 - Mfg: Job Printing (eg forms, greeting cards, etc)
6.152e+04 1.96e+05 0.314 0.753 -3.22e+05 4.45e+05
Property_Use_659 - Mfg: Other Wood, Furniture, Paper Products, Printing
-7575.4969 1.13e+05 -0.067 0.947 -2.3e+05 2.15e+05
Property_Use_661 - Mfg: Road Vehicles, Parts
1.03e+04 1.43e+05 0.072 0.942 -2.69e+05 2.9e+05
Property_Use_663 - Mfg: Watercraft, Parts
5.327e+04 3.94e+05 0.135 0.892 -7.19e+05 8.25e+05
Property_Use_664 - Mfg: Aircraft, Parts
5.166e+04 2.84e+05 0.182 0.855 -5.04e+05 6.07e+05
Property_Use_665 - Specialty Vehicles, Parts
8.422e+04 2.88e+05 0.292 0.770 -4.81e+05 6.49e+05

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Property_Use_669 - Mfg: Other Vehicles, Parts
-7.726e+04   2.42e+05     -0.319      0.750   -5.53e+05    3.98e+05
Property_Use_671 - Mfg: Primary Metal Processing (eg refining, melting, etc)
1.645e+05   1.95e+05      0.842      0.400   -2.18e+05    5.47e+05
Property_Use_672 - Mfg: Secondary Metal Processing (eg rolling, drawing,
polishing)                                                  -3.33e+04
1.37e+05     -0.242      0.809   -3.03e+05    2.36e+05
Property_Use_673 - Mfg: Prec.Goods/Instruments (eg surgical instr, cameras, etc)
2.776e+05   2.88e+05      0.964      0.335   -2.87e+05    8.42e+05
Property_Use_674 - Mfg: Precious Metals, Jewellery
-9.347e+04    3.9e+05     -0.240      0.811   -8.58e+05    6.71e+05
Property_Use_678 - Mfg:Glass & glass products, china, pottery
-2287.1999   3.92e+05     -0.006      0.995   -7.71e+05    7.66e+05
Property_Use_679 - Mfg: Other Metal/Eletctrical/Miscellaneous Products
7.129e+04   1.18e+05      0.602      0.547   -1.61e+05    3.03e+05
Property_Use_682 - Sto: Chemicals, inc hazardous chemicals
4.754e+04   2.87e+05      0.166      0.868   -5.15e+05     6.1e+05
Property_Use_683 - Sto: Plastics
-1.874e+05   3.06e+05     -0.612      0.541   -7.88e+05    4.13e+05
Property_Use_691 - Sto: Tank, Tank Farm, Other Liquids
-1.593e+05   4.12e+05     -0.387      0.699   -9.66e+05    6.47e+05
Property_Use_699 - Sto: Other Chem/Petroleum/Paint/Plastic Products
5.403e+04   3.96e+05      0.137      0.891   -7.21e+05    8.29e+05
Property_Use_701 - Sto: Meat/Poultry/Fish products
6.009e+04   2.14e+05      0.281      0.779   -3.59e+05    4.79e+05
Property_Use_702 - Sto: Dairy Goods, Produce
2.203e+05   3.98e+05      0.554      0.580   -5.59e+05       1e+06
Property_Use_703 - Sto: Grain Products, Bakery Goods
2.099e+04   2.85e+05      0.074      0.941   -5.38e+05     5.8e+05
Property_Use_705 - Sto: Soft Drinks
-3.418e+05   3.98e+05     -0.858      0.391   -1.12e+06    4.39e+05
Property_Use_707 - Sto: Vegetable/Animal Oil Products
1.666e+05   4.02e+05      0.415      0.678    -6.2e+05    9.54e+05
Property_Use_708 - Sto: Sugar Refining, Sugar Products
-1.074e+05   3.89e+05     -0.276      0.783    -8.7e+05    6.55e+05
Property_Use_709 - Sto: Cold Storage - Processed Food
-5.996e+05   2.44e+05     -2.458      0.014   -1.08e+06   -1.22e+05
Property_Use_716 - Sto: Packed food stuffs (not classified by other codes)
-1.63e+05   2.42e+05     -0.675      0.500   -6.36e+05     3.1e+05
Property_Use_719 - Sto: Other Agri Products, Food, Beverages, Tobacco, etc
1.979e+04   3.93e+05      0.050      0.960   -7.51e+05    7.91e+05
Property_Use_721 - Sto: Textiles
1.058e+05   3.99e+05      0.265      0.791   -6.76e+05    8.88e+05
Property_Use_723 - Sto: Wearing Apparal
-3.158e+05   3.89e+05     -0.812      0.417   -1.08e+06    4.47e+05
Property_Use_724 - Sto: Dry Cleaning Plant
-9.506e+04   2.86e+05     -0.332      0.740   -6.56e+05    4.66e+05
Property_Use_729 - Sto: Other Textile Goods
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-1.693e-10   4.98e-10     -0.340      0.734   -1.15e-09    8.07e-10
Property_Use_731 - Sto: Pulp, Paper
1.618e+05   2.41e+05      0.672      0.501    -3.1e+05    6.34e+05
Property_Use_733 - Secondary Products (eg. finished goods, furniture, etc.)
2.78e+05   3.94e+05      0.705      0.481   -4.95e+05    1.05e+06
Property_Use_739 - Sto: Other Wood, Furniture, Paper Products, Printing
9.033e+04    2.4e+05      0.376      0.707   -3.81e+05    5.61e+05
Property_Use_741 - Sto: Road Vehicles, Parts
-2.088e+05   1.81e+05     -1.152      0.249   -5.64e+05    1.46e+05
Property_Use_742 - Sto: Rail Vehicles, Parts
1.603e+05   3.96e+05      0.404      0.686   -6.17e+05    9.37e+05
Property_Use_745 - Sto: Specialty Vehicles, Parts
7.749e-10   4.18e-10      1.853      0.064   -4.49e-11    1.59e-09
Property_Use_749 - Sto: Other Vehicles, Parts
-4.646e+04   2.83e+05     -0.164      0.870   -6.02e+05    5.09e+05
Property_Use_753 - Sto: Precision Goods/Instruments
1.351e+05   3.94e+05      0.343      0.731   -6.36e+05    9.07e+05
Property_Use_759 - Sto: Other Metal/Electrical/Misc Parts
-1.443e+05   2.92e+05     -0.495      0.621   -7.16e+05    4.27e+05
Property_Use_760 - Sto: Warehouse, variety of items, not classified by codes
-6.764e+04   1.21e+05     -0.560      0.576   -3.04e+05    1.69e+05
Property_Use_761 - Sto: Glass & Glass Products, pottery, chinaware
2.159e+05   3.92e+05      0.551      0.582   -5.53e+05    9.85e+05
Property_Use_769 - Sto: Tent or temporary structure for industrial storage
1.41e+05   3.05e+05      0.462      0.644   -4.57e+05    7.39e+05
Property_Use_791 - Recycling Facility
-4.454e+04   1.16e+05     -0.384      0.701   -2.72e+05    1.83e+05
Property_Use_792 - Waste Transfer Station
-7.522e+04    1.2e+05     -0.626      0.531   -3.11e+05     1.6e+05
Property_Use_793 - Laboratory
2.638e+04      2e+05      0.132      0.895   -3.65e+05    4.17e+05
Property_Use_799 - Other Industrial
3.196e+04   1.14e+05      0.281      0.779   -1.91e+05    2.55e+05
Property_Use_801 - Mine
1.096e+04   3.07e+05      0.036      0.972   -5.91e+05    6.13e+05
Property_Use_803 - Quarry
1.24e+05   4.42e+05      0.280      0.779   -7.43e+05    9.91e+05
Property_Use_812 - Bridge, Overpass, Trestle, Tunnel, Underpass
1.445e+05    2.3e+05      0.627      0.530   -3.07e+05    5.96e+05
Property_Use_821 - Radio Transmission Site, Microwave Tower
2.567e+05   4.49e+05      0.572      0.568   -6.24e+05    1.14e+06
Property_Use_822 - Telephone Exchange
2.209e+05   3.45e+05      0.640      0.522   -4.55e+05    8.97e+05
Property_Use_831 - Agricultural Products
-2.018e+04   3.44e+05     -0.059      0.953   -6.94e+05    6.53e+05
Property_Use_832 - Processed Food Beverages
-4.779e+05   3.09e+05     -1.549      0.121   -1.08e+06    1.27e+05
Property_Use_833 - Flammable/Combustible Liquids, Gases
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-5.801e+04   4.86e+05   -0.119   0.905   -1.01e+06   8.94e+05
Property_Use_834 - Chemicals, Plastics, Rubber Products
-4.713e+05   3.44e+05   -1.370   0.171   -1.15e+06   2.03e+05
Property_Use_835 - Textiles, Fibres, Clothing
-1.32e-09   4.52e-10   -2.919   0.004   -2.21e-09   -4.33e-10
Property_Use_836 - Metal Products, Machinery, Appliances
-1.014e+05   2.77e+05   -0.366   0.714   -6.44e+05   4.41e+05
Property_Use_837 - Vehicles or Vehicle Parts
6.854e+04   2.18e+05   0.314   0.753   -3.59e+05   4.96e+05
Property_Use_838 - General Goods
1.468e+05   3.11e+05   0.471   0.637   -4.64e+05   7.57e+05
Property_Use_839 - Tent or temporary structure not classified under other occupancy 1.913e+05   2.78e+05
0.689   0.491   -3.53e+05   7.35e+05
Property_Use_841 - Mailbox
1.393e+05   3.43e+05   0.406   0.685   -5.34e+05   8.12e+05
Property_Use_842 - Fence
1.02e+05   2.22e+05   0.460   0.645   -3.33e+05   5.37e+05
Property_Use_843 - Shed, Children's Playhouse
8.67e+04   2.24e+05   0.387   0.699   -3.53e+05   5.26e+05
Property_Use_844 - Privy
1.894e+05   2.46e+05   0.769   0.442   -2.93e+05   6.72e+05
Property_Use_845 - Telephone Booth
-8.763e-10   3.44e-10   -2.545   0.011   -1.55e-09   -2.01e-10
Property_Use_846 - Hydro/Telephone Pole
1.398e+05   2.24e+05   0.624   0.532   -2.99e+05   5.79e+05
Property_Use_847 - Toll Station, Weather/Bus Shelter
1.848e+05   3.06e+05   0.604   0.546   -4.15e+05   7.85e+05
Property_Use_848 - Trash/Rubbish/Garbage Container or Dumpster
1.086e+05   2.15e+05   0.506   0.613   -3.12e+05   5.29e+05
Property_Use_849 - Tarpot
1.43e+05   2.57e+05   0.556   0.578   -3.61e+05   6.47e+05
Property_Use_850 - Parking Lot Kiosk
1.1e+05   2.44e+05   0.452   0.651   -3.67e+05   5.87e+05
Property_Use_852 - Clothing Drop Box, etc.
2.219e+05   3.12e+05   0.712   0.477   -3.89e+05   8.33e+05
Property_Use_853 - Gazebo
2.247e+05   2.89e+05   0.777   0.437   -3.42e+05   7.92e+05
Property_Use_854 - Sauna - Outdoors
-9.31e+04   3.59e+05   -0.260   0.795   -7.96e+05   6.1e+05
Property_Use_855 - Outbuildings - structure not classified elsewhere
1.223e+05   2.31e+05   0.530   0.596   -3.3e+05   5.75e+05
Property_Use_856 - Freestanding deck
-6.904e+04   2.59e+05   -0.267   0.790   -5.77e+05   4.39e+05
Property_Use_860 - Lawn around structure
1.088e+05   2.42e+05   0.449   0.653   -3.66e+05   5.84e+05
Property_Use_861 - Open Land (eg. light ground cover, bush, grass, etc.)
1.138e+05   2.19e+05   0.520   0.603   -3.15e+05   5.43e+05

Property_Use_862 - Forest, Standing Timber
1.681e+05 2.5e+05 0.672 0.502 -3.23e+05 6.59e+05
Property_Use_863 - Tree, Hedge
9.902e+04 2.39e+05 0.414 0.679 -3.7e+05 5.68e+05
Property_Use_864 - Dump, Land Fill Site
-2.059e+04 3.44e+05 -0.060 0.952 -6.94e+05 6.53e+05
Property_Use_866 - Silo, Storage Facility
2.466e+04 3.06e+05 0.081 0.936 -5.76e+05 6.25e+05
Property_Use_868 - Greenhouse
-2.711e+05 4.37e+05 -0.620 0.535 -1.13e+06 5.86e+05
Property_Use_869 - Other farm building (e.g. curing shed, growing facility)
4.298e-10 4.06e-10 1.058 0.290 -3.66e-10 1.23e-09
Property_Use_870 - Barn - containing equipment or produce only
8484.9563 4.37e+05 0.019 0.985 -8.48e+05 8.65e+05
Property_Use_871 - Barn - housing animals
1.186e-10 3.99e-10 0.297 0.766 -6.64e-10 9.01e-10
Property_Use_872 - Animal shelter, excluding farm structures
2.696e+04 4.42e+05 0.061 0.951 -8.39e+05 8.93e+05
Property_Use_890 - Composting site (large scale, eg municipal)
1.207e+05 4.35e+05 0.277 0.782 -7.33e+05 9.74e+05
Property_Use_891 - Outdoor general auto parking
9.902e+04 2.18e+05 0.455 0.649 -3.27e+05 5.25e+05
Property_Use_893 - Cemetery
6.844e+04 2.86e+05 0.239 0.811 -4.93e+05 6.3e+05
Property_Use_896 - Sidewalk, street, roadway, highway, hwy (do not use for fire incidents) 1.04e+05 2.15e+05
0.483 0.629 -3.18e+05 5.26e+05
Property_Use_897 - Structure under 10 sq. metres not classified
1.206e+05 2.25e+05 0.536 0.592 -3.2e+05 5.62e+05
Property_Use_898 - Other property non structure not classified
1.262e+05 2.18e+05 0.580 0.562 -3.01e+05 5.53e+05
Property_Use_901 - Automobile
9.012e+04 2.15e+05 0.419 0.675 -3.31e+05 5.11e+05
Property_Use_902 - Small Truck (eg. pick-up, van, etc.)
7.576e+04 2.16e+05 0.351 0.726 -3.48e+05 4.99e+05
Property_Use_903 - Large Truck (Excluding Truck Trailer)
5.806e+04 2.17e+05 0.267 0.789 -3.68e+05 4.84e+05
Property_Use_904 - Trailer Combin. (e.g. auto trailer, small t&t, t&t, etc)
4.269e+04 2.23e+05 0.191 0.848 -3.95e+05 4.8e+05
Property_Use_905 - Motorcycle
8.495e+04 2.34e+05 0.364 0.716 -3.73e+05 5.43e+05
Property_Use_906 - Bus, Trackless Trolley
9.809e+04 2.22e+05 0.443 0.658 -3.36e+05 5.32e+05
Property_Use_907 - Emergency Vehicle
4.604e+04 2.58e+05 0.178 0.858 -4.6e+05 5.52e+05
Property_Use_909 - Multiple Road Vehicles
1.051e+05 2.36e+05 0.446 0.656 -3.57e+05 5.67e+05
Property_Use_911 - Railway Train

7813.7011   3.47e+05   0.023   0.982   -6.72e+05   6.87e+05
Property_Use_912 - Subway Train
-739.3967   3e+05   -0.002   0.998   -5.89e+05   5.88e+05
Property_Use_914 - Multiple Rail Vehicles
1.132e+05   3.43e+05   0.330   0.741   -5.59e+05   7.85e+05
Property_Use_921 - Private or Business Watercraft
4.26e+04   2.63e+05   0.162   0.872   -4.74e+05   5.59e+05
Property_Use_941 - Construction Vehicles
1.79e+05   2.28e+05   0.784   0.433   -2.68e+05   6.26e+05
Property_Use_942 - Industrial Vehicles
1.568e+05   2.65e+05   0.591   0.554   -3.63e+05   6.77e+05
Property_Use_943 - Agricultural Vehicles
7.555e+04   3.43e+05   0.220   0.826   -5.97e+05   7.48e+05
Property_Use_944 - Multiple Specialty Vehicles
9.679e+04   3.42e+05   0.283   0.777   -5.74e+05   7.68e+05
Property_Use_945 - Tank truck - Compressed or LP Gas, flammable liquid, chemicals 1607.0844
4.37e+05   0.004   0.997   -8.56e+05   8.59e+05
Property_Use_946 - Other specialty vehicle
7.144e+04   2.26e+05   0.316   0.752   -3.72e+05   5.15e+05
Property_Use_994 - Multiple Vehicles - combination of types
8.601e+04   2.54e+05   0.339   0.735   -4.12e+05   5.84e+05
Property_Use_999 - Other Vehicle
9.136e+04   2.19e+05   0.417   0.677   -3.38e+05   5.21e+05
Smoke_Alarm_at_Fire_Origin_2 - Floor/suite of fire origin: Smoke alarm present and operated 4832.5975   1.87e+04
0.258   0.796   -3.19e+04   4.15e+04
Smoke_Alarm_at_Fire_Origin_3 - Floor/suite of fire origin: Smoke alarm present did not operate -1.049e+04   1.92e+04
-0.546   0.585   -4.81e+04   2.72e+04
Smoke_Alarm_at_Fire_Origin_4 - Floor/suite of fire origin: Smoke alarm present, operation undetermined -6777.4860   2.11e+04
-0.321   0.748   -4.82e+04   3.46e+04
Smoke_Alarm_at_Fire_Origin_9 - Floor/suite of fire origin: Smoke alarm presence undetermined 3.308e+04   1.66e+04
1.988   0.047   463.832   6.57e+04
Smoke_Alarm_at_Fire_Origin_9 - Floor/suite space of fire origin: Smoke alarm presence undetermined -1.188e+05   1.23e+05
-0.963   0.335   -3.6e+05   1.23e+05
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_2 - Dead battery
-2.111e+04   4.65e+04   -0.454   0.650   -1.12e+05   7.01e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_3 - Electrical line or battery not connected 2.273e+04   5.06e+04
0.449   0.653   -7.64e+04   1.22e+05
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_4 - Remote from fire - smoke did not reach alarm -1.065e+04   3.54e+04
-0.301   0.764   -8e+04   5.87e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_5 - Separated from fire (e.g. wall,

etc) -3.025e+04 4.02e+04
-0.752 0.452 -1.09e+05 4.86e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_6 - Improper installation of unit
-3.07e+04 7.16e+04 -0.429 0.668 -1.71e+05 1.1e+05
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_7 - Unit failure
-4.597e+04 4.61e+04 -0.998 0.318 -1.36e+05 4.43e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_8 - Tampered with (vandalism)
-3.783e+04 8.23e+04 -0.460 0.646 -1.99e+05 1.23e+05
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_9 - Other reason
-1.524e+04 3.76e+04 -0.406 0.685 -8.89e+04 5.84e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_98 - Not applicable: Alarm operated OR presence/operation undertermined -1.188e+05 1.23e+05
-0.963 0.335 -3.6e+05 1.23e+05
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_98 - Not applicable: Alarm operated OR presence/operation undetermined -2.307e+04 3.48e+04
-0.663 0.507 -9.13e+04 4.51e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Failure_99 - Reason for inoperation undetermined -6708.7412
3.7e+04 -0.181 0.856 -7.93e+04 6.58e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Type_2 - Hardwired (standalone)
-1188.3074 1.43e+04 -0.083 0.934 -2.93e+04 2.69e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Type_3 - Wireless
3.757e+04 9.49e+04 0.396 0.692 -1.49e+05 2.24e+05
Smoke_Alarm_at_Fire_Origin_Alarm_Type_4 - Interconnected
2678.7482 1.56e+04 0.171 0.864 -2.8e+04 3.34e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Type_8 - Not applicable - no smoke alarm or presence undetermined -1.796e+04 1.93e+04
-0.931 0.352 -5.58e+04 1.99e+04
Smoke_Alarm_at_Fire_Origin_Alarm_Type_9 - Type undetermined
842.9717 1.6e+04 0.053 0.958 -3.05e+04 3.22e+04
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation_2 - Some persons (at risk) self evacuated as a result of hearing alarm -2.664e+04 2.07e+04
-1.285 0.199 -6.73e+04 1.4e+04
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation_3 - No one (at risk) evacuated as a result of hearing alarm -681.9311 2.07e+04
-0.033 0.974 -4.12e+04 3.98e+04
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation_4 - Alarm operated but failed to alert occupant(s) (at risk) 3.696e+04 8.07e+04
0.458 0.647 -1.21e+05 1.95e+05
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation_7 - Not applicable: Occupant(s) first alerted by other means -5098.1089
1.49e+04 -0.341 0.733 -3.44e+04 2.42e+04
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation_8 - Not applicable: No alarm, no persons present -1.047e+04
1.66e+04 -0.632 0.527 -4.3e+04 2.2e+04
Smoke_Alarm_Impact_on_Persons_Evacuating_Impact_on_Evacuation_9 - Undetermined
-503.0840 1.73e+04 -0.029 0.977 -3.44e+04 3.34e+04
Smoke_Spread_10 - Spread beyond building of origin

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-2.922e+05   1.19e+05     -2.455      0.014   -5.25e+05   -5.89e+04
Smoke_Spread_2 - Confined to part of room/area of origin
-2.309e+05   1.18e+05     -1.958      0.050   -4.62e+05     294.637
Smoke_Spread_3 - Spread to entire room of origin
-2.379e+05   1.18e+05     -2.015      0.044   -4.69e+05   -6501.035
Smoke_Spread_4 - Spread beyond room of origin, same floor
-2.439e+05   1.18e+05     -2.068      0.039   -4.75e+05   -1.27e+04
Smoke_Spread_5 - Multi unit bldg: spread beyond suite of origin but not to
separated suite(s)                                           -2.533e+05   1.18e+05
-2.140      0.032   -4.85e+05   -2.13e+04
Smoke_Spread_6 - Multi unit bldg: spread to separate suite(s)
-2.441e+05   1.19e+05     -2.056      0.040   -4.77e+05   -1.14e+04
Smoke_Spread_7 - Spread to other floors, confined to building
-2.594e+05   1.18e+05     -2.198      0.028   -4.91e+05    -2.8e+04
Smoke_Spread_8 - Entire Structure
-2.666e+05   1.18e+05     -2.254      0.024   -4.98e+05   -3.48e+04
Smoke_Spread_9 - Confined to roof/exterior structure
-2.21e+05   1.18e+05     -1.866      0.062   -4.53e+05    1.12e+04
Smoke_Spread_99 - Undetermined
-2.062e+05   1.18e+05     -1.740      0.082   -4.38e+05     2.6e+04
Sprinkler_System_Operation_2 - Did not activate: remote from fire
-9363.6523   1.28e+04     -0.734      0.463   -3.44e+04    1.56e+04
Sprinkler_System_Operation_3 - Did not activate: fire too small to trigger
system                                                        1812.8749   1.34e+04
0.135      0.893   -2.45e+04    2.82e+04
Sprinkler_System_Operation_4 - Other reason for non activation/operation
-1.797e+04   2.38e+04     -0.755      0.450   -6.46e+04    2.87e+04
Sprinkler_System_Operation_5 - Did not activate: reason unknown
1.035e+04   2.46e+04      0.421      0.674   -3.79e+04    5.86e+04
Sprinkler_System_Operation_8 - Not applicable - no sprinkler system present
-1.231e+04   1.64e+04     -0.752      0.452   -4.44e+04    1.98e+04
Sprinkler_System_Operation_9 - Activation/operation undetermined
-9262.3543   1.61e+04     -0.576      0.565   -4.08e+04    2.23e+04
Sprinkler_System_Presence_2 - Partial sprinkler system present
1.293e+04   9369.019      1.380      0.168   -5432.533    3.13e+04
Sprinkler_System_Presence_3 - No sprinkler system
1.81e+04   1.36e+04      1.331      0.183   -8560.759    4.48e+04
Sprinkler_System_Presence_9 - Undetermined
5477.7350   1.08e+04      0.507      0.612   -1.57e+04    2.67e+04
Status_of_Fire_On_Arrival_2 - Fire with no evidence from street
-9637.8850   9675.206     -0.996      0.319   -2.86e+04    9327.140
Status_of_Fire_On_Arrival_3 - Fire with smoke showing only - including vehicle,
outdoor fires                                            -5327.7971   9832.189
-0.542      0.588   -2.46e+04    1.39e+04
Status_of_Fire_On_Arrival_4 - Flames showing from small area (one storey or
less, part of a vehicle, outdoor)                           -1.238e+04   1.05e+04
-1.173      0.241    -3.3e+04    8297.853
Status_of_Fire_On_Arrival_5 - Flames showing from large area (more than one
```

storey, large area outdoors) -1.203e+04 1.57e+04
-0.766 0.444 -4.28e+04 1.88e+04
Status_of_Fire_On_Arrival_7 - Fully involved (total structure, vehicle, spreading outdoor fire) -1.706e+04
1.18e+04 -1.449 0.147 -4.01e+04 6013.192
Status_of_Fire_On_Arrival_8 - Exposure involved
-1.358e+04 3.33e+04 -0.408 0.683 -7.88e+04 5.16e+04
Status_of_Fire_On_Arrival_9 - Unclassified
1.969e+04 1.5e+04 1.313 0.189 -9710.831 4.91e+04
GPS_Cluster_1
2.292e+04 2.98e+04 0.769 0.442 -3.55e+04 8.13e+04
GPS_Cluster_2
5929.5298 2.15e+04 0.275 0.783 -3.63e+04 4.81e+04
GPS_Cluster_3
-3388.4453 2.79e+04 -0.121 0.903 -5.81e+04 5.14e+04
GPS_Cluster_4
3118.7991 1.77e+04 0.176 0.860 -3.16e+04 3.78e+04
GPS_Cluster_5
5616.1242 1.8e+04 0.312 0.755 -2.96e+04 4.09e+04
GPS_Cluster_6
-5290.0944 1.46e+04 -0.361 0.718 -3.4e+04 2.34e+04
GPS_Cluster_7
-1098.0858 1.3e+04 -0.084 0.933 -2.66e+04 2.44e+04
GPS_Cluster_8
-1005.0040 1.73e+04 -0.058 0.954 -3.48e+04 3.28e+04
GPS_Cluster_9
-2139.7577 2.81e+04 -0.076 0.939 -5.73e+04 5.3e+04
Smoke_Spread_10 - Spread beyond building of origin
-2.922e+05 1.19e+05 -2.455 0.014 -5.25e+05 -5.89e+04
Smoke_Spread_2 - Confined to part of room/area of origin
-2.309e+05 1.18e+05 -1.958 0.050 -4.62e+05 294.637
Smoke_Spread_3 - Spread to entire room of origin
-2.379e+05 1.18e+05 -2.015 0.044 -4.69e+05 -6501.035
Smoke_Spread_4 - Spread beyond room of origin, same floor
-2.439e+05 1.18e+05 -2.068 0.039 -4.75e+05 -1.27e+04
Smoke_Spread_5 - Multi unit bldg: spread beyond suite of origin but not to separated suite(s) -2.533e+05 1.18e+05
-2.140 0.032 -4.85e+05 -2.13e+04
Smoke_Spread_6 - Multi unit bldg: spread to separate suite(s)
-2.441e+05 1.19e+05 -2.056 0.040 -4.77e+05 -1.14e+04
Smoke_Spread_7 - Spread to other floors, confined to building
-2.594e+05 1.18e+05 -2.198 0.028 -4.91e+05 -2.8e+04
Smoke_Spread_8 - Entire Structure
-2.666e+05 1.18e+05 -2.254 0.024 -4.98e+05 -3.48e+04
Smoke_Spread_9 - Confined to roof/exterior structure
-2.21e+05 1.18e+05 -1.866 0.062 -4.53e+05 1.12e+04
Smoke_Spread_99 - Undetermined
-2.062e+05 1.18e+05 -1.740 0.082 -4.38e+05 2.6e+04

```
Sprinkler_System_Operation_2 - Did not activate: remote from fire
-9363.6523   1.28e+04     -0.734      0.463   -3.44e+04    1.56e+04
Sprinkler_System_Operation_3 - Did not activate: fire too small to trigger
system                                                    1812.8749   1.34e+04
0.135      0.893   -2.45e+04    2.82e+04
Sprinkler_System_Operation_4 - Other reason for non activation/operation
-1.797e+04   2.38e+04     -0.755      0.450   -6.46e+04    2.87e+04
Sprinkler_System_Operation_5 - Did not activate: reason unknown
1.035e+04   2.46e+04      0.421      0.674   -3.79e+04    5.86e+04
Sprinkler_System_Operation_8 - Not applicable - no sprinkler system present
-1.231e+04   1.64e+04     -0.752      0.452   -4.44e+04    1.98e+04
Sprinkler_System_Operation_9 - Activation/operation undetermined
-9262.3543   1.61e+04     -0.576      0.565   -4.08e+04    2.23e+04
Sprinkler_System_Presence_2 - Partial sprinkler system present
1.293e+04   9369.019      1.380      0.168   -5432.533    3.13e+04
Sprinkler_System_Presence_3 - No sprinkler system
1.81e+04   1.36e+04      1.331      0.183   -8560.759    4.48e+04
Sprinkler_System_Presence_9 - Undetermined
5477.7350   1.08e+04      0.507      0.612   -1.57e+04    2.67e+04
Status_of_Fire_On_Arrival_2 - Fire with no evidence from street
-9637.8850   9675.206     -0.996      0.319   -2.86e+04    9327.140
Status_of_Fire_On_Arrival_3 - Fire with smoke showing only - including vehicle,
outdoor fires                                        -5327.7971   9832.189
-0.542      0.588   -2.46e+04    1.39e+04
Status_of_Fire_On_Arrival_4 - Flames showing from small area (one storey or
less, part of a vehicle, outdoor)                        -1.238e+04   1.05e+04
-1.173      0.241    -3.3e+04    8297.853
Status_of_Fire_On_Arrival_5 - Flames showing from large area (more than one
storey, large area outdoors)                             -1.203e+04   1.57e+04
-0.766      0.444   -4.28e+04    1.88e+04
Status_of_Fire_On_Arrival_7 - Fully involved (total structure, vehicle,
spreading outdoor fire)                                      -1.706e+04
1.18e+04     -1.449      0.147   -4.01e+04    6013.192
Status_of_Fire_On_Arrival_8 - Exposure involved
-1.358e+04   3.33e+04     -0.408      0.683   -7.88e+04    5.16e+04
Status_of_Fire_On_Arrival_9 - Unclassified
1.969e+04    1.5e+04      1.313      0.189   -9710.831    4.91e+04
GPS_Cluster_1
2.292e+04   2.98e+04      0.769      0.442   -3.55e+04    8.13e+04
GPS_Cluster_2
5929.5298   2.15e+04      0.275      0.783   -3.63e+04    4.81e+04
GPS_Cluster_3
-3388.4453   2.79e+04     -0.121      0.903   -5.81e+04    5.14e+04
GPS_Cluster_4
3118.7991   1.77e+04      0.176      0.860   -3.16e+04    3.78e+04
GPS_Cluster_5
5616.1242    1.8e+04      0.312      0.755   -2.96e+04    4.09e+04
GPS_Cluster_6
```

```
-5290.0944   1.46e+04     -0.361      0.718    -3.4e+04    2.34e+04
GPS_Cluster_7
-1098.0858    1.3e+04     -0.084      0.933   -2.66e+04    2.44e+04
GPS_Cluster_8
-1005.0040   1.73e+04     -0.058      0.954   -3.48e+04    3.28e+04
GPS_Cluster_9
-2139.7577   2.81e+04     -0.076      0.939   -5.73e+04     5.3e+04
==============================================================================
Omnibus:                    34190.424   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):       4375137335.350
Skew:                          33.530   Prob(JB):                         0.00
Kurtosis:                    2901.125   Cond. No.                     1.16e+18
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.02e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

[274]:
```
# Print the R squared.
print("First linear regression R squared: {:.2f}".format(lr1.rsquared))
print("Second linear regression R squared: {:.2f}".format(lr2.rsquared))
```

```
First linear regression R squared: 0.34
Second linear regression R squared: 0.47
```

In the second linear regression model, where we have used logs to mitigate the skewness problem of the continuous variables, and an independent variable that had high correlation with another variable has been dropped, the R^2 improves by 13%.

[275]:
```
# Print the RMSE for the linear regressions.
print("The RMSE for the linear regression model using original data is: {:.2f}".
 ↪format(np.sqrt(mean_squared_error(y_test, lr1_y_pred))))
print("The RMSE for the linear regression model using log transformed data is:␣
 ↪{:.2f}".format(np.sqrt(mean_squared_error(y_test_2, lr2_y_pred))))
```

```
The RMSE for the linear regression model using original data is: 891363.36
The RMSE for the linear regression model using log transformed data is:
364707.94
```

The RMSE for the second linear regression model improves significantly, but it's still very high. To improve the accuracy of our predictions, we could look at other types of regression models. XGBoost dominates structured datasets on regression predictive modeling problems, increasing efficiency (Brownlee, 2021).

5 Additional Regression Models

Apart from linear regression, two additional regression models have been employed in this project.

5.1 Support Vector Machine

Rather than attempting to minimize the discrepancy between the actual and predicted values like linear regression models, Support Vector Machine (SVM) regression seeks to fit the best line within a given margin of error (Raj, 2020). We can compare the RMSE of two SVM regressions. Firstly, the original dataset will be used with no log tranformation. In the second regression, we will use the continuous variables with log transformed data.

[282]:
```
# Run SVM regression using data used for the first regression.
regressor = SVR(kernel = 'rbf')
regressor.fit(X_train, y_train)
y_pred_svr = regressor.predict(X_test)
score_train = np.sqrt(mean_squared_error(y_test, y_pred_svr))
```

[282]:
```
SVR()
```

[283]:
```
# Run SVM regression using data used for the second regression (logged␣
↪continuous variables).
regressor_2 = SVR(kernel = 'rbf')
regressor_2.fit(X_train_2, y_train_2)
y_pred_svr_2 = regressor_2.predict(X_test_2)
score_train_2 = np.sqrt(mean_squared_error(y_test_2, y_pred_svr_2))
```

[283]:
```
SVR()
```

[284]:
```
# Print the RMSE for the SVM regressions.
print("The RMSE for the SVM regression model using original data is: {:.2f}".
↪format(score_train))
print("The RMSE for the SVM regression model using log transformed data is: {:.
↪2f}".format(score_train_2))
```

```
The RMSE for the SVM regression model using original data is: 938951.04
The RMSE for the SVM regression model using log transformed data is: 221518.85
```

5.2 Extreme Gradient Boosting

XGBoost is a relatively new algorithm which performs well on medium-sized data with subgroups and structured datasets (Hachcham, 2022). We can compare the RMSE of two XGBoost regressions. Firstly, the original dataset will be used with no log tranformation. In the second regression, we will use the continuous variables with log transformed data.

[276]:
```
# Run XGBoost using data used for the first regression.
data_dmatrix = xgb.DMatrix(data = X_train, label = y_train)
xg_reg = xgb.XGBRegressor(objective ='reg:linear', eval_metric = "rmsle")
xg_reg.fit(X_train,y_train)
preds = xg_reg.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, preds))
```

```
[10:19:49] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp
.macosx-10.9-x86_64-cpython-38/xgboost/src/objective/regression_obj.cu:213:
reg:linear is now deprecated in favor of reg:squarederror.
```

[276]:
```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric='rmsle', feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.300000012, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=0,
             num_parallel_tree=1, objective='reg:linear', predictor='auto', …)
```

[279]:
```
# Run XGBoost using data used for the second regression (logged continuous␣
 ↪variables).
data_dmatrix_2 = xgb.DMatrix(data = X_train_2, label = y_train_2)
xg_reg_2 = xgb.XGBRegressor(objective = 'reg:linear', eval_metric = "rmsle")
xg_reg_2.fit(X_train_2,y_train_2)
preds_2 = xg_reg_2.predict(X_test_2)
rmse_2 = np.sqrt(mean_squared_error(y_test_2, preds_2))
```

```
[10:20:27] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp
.macosx-10.9-x86_64-cpython-38/xgboost/src/objective/regression_obj.cu:213:
reg:linear is now deprecated in favor of reg:squarederror.
```

[279]:
```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric='rmsle', feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.300000012, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=0,
             num_parallel_tree=1, objective='reg:linear', predictor='auto', …)
```

[280]:
```
# Print the RMSE for the XGBoost regressions.
print("The RMSE for the XGBoost using original data is: {:.2f}".format(rmse))
print("The RMSE for the XGBoost using log transformed data is: {:.2f}".
 ↪format(rmse_2))
```

```
The RMSE for the XGBoost using original data is: 808767.20
The RMSE for the XGBoost using log transformed data is: 1125976.56
```

The RMSE for both models is high, however, the RMSE for the XGBoost regression using the log transformed data is higher.

```
[285]: # Print the RMSE for the regressions.
print("The RMSE for the linear regression model using original data is: {:.2f}".
 ↪format(np.sqrt(mean_squared_error(y_test, lr1_y_pred))))
print("The RMSE for the linear regression model using log transformed data is:␣
 ↪{:.2f}".format(np.sqrt(mean_squared_error(y_test_2, lr2_y_pred))))
print("The RMSE for the SVM regression model using original data is: {:.2f}".
 ↪format(score_train))
print("The RMSE for the SVM regression model using log transformed data is: {:.
 ↪2f}".format(score_train_2))
print("The RMSE for the XGBoost using original data is: {:.2f}".format(rmse))
print("The RMSE for the XGBoost using log transformed data is: {:.2f}".
 ↪format(rmse_2))
```

```
The RMSE for the linear regression model using original data is: 891363.36
The RMSE for the linear regression model using log transformed data is:
364707.94
The RMSE for the SVM regression model using original data is: 938951.04
The RMSE for the SVM regression model using log transformed data is: 221518.85
The RMSE for the XGBoost using original data is: 808767.20
The RMSE for the XGBoost using log transformed data is: 1125976.56
```

The RMSE generally decreases when: 1. "Number_of_responding_apparatus" is removed to decrease multicollinearity. 2. Continuous variables including the dependent variable are log transformed. This emphasises the importance of fitting the right data and checking for multicollinearity and skewness in our dataset before running models. However, looking at the RMSE's from our models, we would expect the accuracy of the XGBoost to be higher than the accuracy of the SVM regression. A possible reason for the low accuracy could be that XGBoost is more likely than SVM regression to overfit. Moroever, XGBoost is sensitive to hyperparameter adjustment, therefore if the parameters are not tuned properly, the accuracy decreases.

6 Conclusions

To find the most important predictors for economic losses from fire incidents from our dataset, we will use the model summary from the second linear regression model. Firstly, we can create a table with the lowest 50 p-values from our regression.

```
[289]: # Assign the summary from the second linear regression.
lr2_summary = lr2.summary(xname = coefficient_names_2)

# Create a table from the summary.
lr2_table = pd.DataFrame(lr2_summary.tables[1].data[1:], columns=lr2_summary.
 ↪tables[1].data[0])

# Sort the table by descending p-values.
lr2_table_sortedp = lr2_table.sort_values(by ='P>|t|', ascending = True).
 ↪head(50)
```

```python
lr2_table_sortedp = lr2_table_sortedp.drop(["std err", "t", "[0.025", "0.
↪975]"], axis = 1)
lr2_table_sortedp
```

[289]:

		coef	P>|t|
104	Extent_Of_Fire_7 - Spread to other floors, con…	-1.109e+05	0.000
89	Business_Impact_5 - May not resume operations	6.403e+05	0.000
424	Initial_CAD_Event_Type_VEFH	4.704e+05	0.000
557	Property_Use_161 - Arena	-9.001e+05	0.000
636	Property_Use_522 - Fabric Store	-1.621e+06	0.000
647	Property_Use_535 - Computer/electronics store,…	1.199e+06	0.000
494	Material_First_Ignited_990 - Under Investigation	4.69e+06	0.000
95	Estimated_Number_Of_Persons_Displaced_500+	1.883e+05	0.000
105	Extent_Of_Fire_8 - Entire Structure	3.184e+05	0.000
540	Property_Use_134 - School - Secondary/Senior H…	1.109e+06	0.000
485	Material_First_Ignited_79 - Other Flammable, C…	2.955e+05	0.000
434	Initial_CAD_Event_Type_Vehicle Fire	4.956e+05	0.000
423	Initial_CAD_Event_Type_VEF	5.261e+05	0.000
386	Initial_CAD_Event_Type_Fire - Institution - Sc…	3.004e+06	0.000
686	Property_Use_652 - Mfg: Primary Processing (eg…	3.512e+06	0.000
297	Incident_Ward_12.0	-2.332e+05	0.000
682	Property_Use_645 - Mfg: Dry Cleaning Plant	2.592e+06	0.000
99	Extent_Of_Fire_2 - Confined to part of room/ar…	-3.94e+04	0.000
100	Extent_Of_Fire_3 - Spread to entire room of or…	-9.46e+04	0.000
101	Extent_Of_Fire_4 - Spread beyond room of origi…	-1.104e+05	0.000
3	TFS_Firefighter_Casualties	-1.931e+05	0.000
2	Number_of_responding_personnel	1.033e+04	0.000
77	Area_of_Origin_990 - Under Investigation	4.155e+06	0.000
521	Possible_Cause_990 - Under Investigation	2.662e+06	0.000
659	Property_Use_612 - Hydro Distribution Facility	3.886e+05	0.001
379	Initial_CAD_Event_Type_Fire - Grass/Rubbish	4.475e+05	0.001
359	Initial_CAD_Event_Type_FIG	4.497e+05	0.001
435	Initial_CAD_Event_Type_Vehicle Fire - Highway	4.414e+05	0.001
594	Property_Use_335 - Detached/Semi/Attached with…	-3.953e+05	0.001
340	Initial_CAD_Event_Type_CC	4.169e+05	0.002
420	Initial_CAD_Event_Type_VEAF	4.574e+05	0.002
98	Extent_Of_Fire_11 - Spread beyond building of …	-1.439e+05	0.003
373	Initial_CAD_Event_Type_FITP	4.274e+05	0.003
744	Property_Use_835 - Textiles, Fibres, Clothing	-1.32e-09	0.004
83	Building_Status_09 - Undetermined	-1.421e+05	0.005
45	Area_of_Origin_60 - Other Building Services/Su…	-3.087e+05	0.006
392	Initial_CAD_Event_Type_Fire - Transformer/Pole	4.758e+05	0.006
440	Initial_CAD_Event_Type_Water Problem	5.678e+05	0.006
358	Initial_CAD_Event_Type_FICI	3.528e+05	0.006
347	Initial_CAD_Event_Type_FACI	3.558e+05	0.007
43	Area_of_Origin_58 - Ducting - Exhaust (inc coo…	-2.08e+05	0.007
120	Fire_Alarm_System_Presence_9 - Undetermined	-5.64e+04	0.007

```
355                         Initial_CAD_Event_Type_FAR   3.466e+05   0.009
351                       Initial_CAD_Event_Type_FAHRD   3.426e+05   0.010
352                         Initial_CAD_Event_Type_FAI   3.534e+05   0.011
753                 Property_Use_845 - Telephone Booth  -8.763e-10   0.011
349                       Initial_CAD_Event_Type_FAHCD   3.656e+05   0.012
363                       Initial_CAD_Event_Type_FIHRD   3.345e+05   0.012
370                         Initial_CAD_Event_Type_FIR   3.195e+05   0.013
51          Area_of_Origin_66 - Concealed Ceiling Area   -1.92e+05   0.013
```

We can observe from the results of there are a number of predictors that have a very small p-value, and have a relatively coefficient in size. The following table shows the interpretation of some interesting coefficients.

[308]:
```python
# Create table with 5 intepretations.
interpretation = pd.DataFrame({
    "If": ["The business will not resume operations",
                    "The business was a computer/electronic store",
                    ">500 people had to be displaced",
                    "Number of responding personnel increases by 1%",
                    "Incident occured because of a water problem"],
    "Economic loss increases by": [("6,403,000%"),
                        ("1,199,000%"),
                        ("1,883,000%"),
                        ("10,330%"),
                        ("567,800%")]})

# Display the interpretations.
interpretation
```

[308]:

	If	Economic loss increases by
0	The business will not resume operations	6,403,000%
1	The business was a computer/electronic store	1,199,000%
2	>500 people had to be displaced	1,883,000%
3	Number of responding personnel increases by 1%	10,330%
4	Incident occured because of a water problem	567,800%

Several implications can be drawn from this report. Firstly, the type of operations a business does influences the total economic loss it can incurr if it suffers a fire incident. Moreover, the cause of the incident is one of the most important predictor. For instance, incidents due to water problem cause significant increases in economic losses. Hence, local governemnt should heavily invest in the maintainance and improvement of water systems in cities to avoid massive losses in the case of a fire incident. However, it is important to note that reverse causality might be an issue in this regression, as the number of people displaced and the number of responding personnel may be correlated with an additional unobserved variable.

7 Limitations

The study at hand is not short of certain limitations that should be accounted for when interpreting the results. Firstly, the data utilized is limited to incidents in Toronto, which may not be representative of fire incidents in other places. Secondly, the data used in this project is limited to economic losses, which may not be representative of other types of losses associated with fire incidents. Thirdly, the models used in this project are limited to regressions, which have not yielded high accuracies which enable future predictions. Further analysis should be conducted to identify additional factors that may influence economic losses associated with fire incidents in order to reduce the MSE of the models. This could include investigating the effects of weather, building characteristics, and other environmental factors. Furthermore, more sophisticated machine learning techniques such as neural networks and decision trees should be investigated to improve model accuracy. Moreover, data from other cities should be included in the analysis to ensure that the findings are transferable to other locations. To reduce the problem of reverse causality, instrumental variables could be assessed to identify the direction of causality by introducing a third variable that is correlated with the independent variable, but not with the dependent variable. In this case, a third variable could be used that is correlated with the number of personnel, but not with the economic loss of a fire incident, such as the budget of fire stations.

Overall, this project provides a useful starting point for understanding the economic losses associated with fire incidents. However, further research is needed to improve the accuracy of the models and to better understand the factors that influence economic losses associated with fire incidents.

8 References

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9 Appendix

9.1 Attribution Statement and Project Management

9.1.1 Attribution Statement

The connection starts long before the group work starts; special thanks to our TA Saraansh Arya who pulled us together with regular weekly meetings from the beginning of the term. We had 11 group meetups and 4 meetings with TA (excluding meetings during class and TA drop-off hours). Starting from dataset research, all group members contributed more than three different datasets, and considering the cleanliness, data sufficiency, data updated degree, and the interesting level of the prediction topic, the Toronto Fire Incidents Data provided by Ching-Yu was selected. Afterwards, Viren took the responsibility of data cleaning, Rachel took on the regression, Bhakti was in charge of the exploratory data analysis, and Ching-Yu for managing Trello. Viren, Rachel, and Bhakti finished the model running of linear regression, SVM regressor, and XGBoost, including the model selection and troubleshooting. Ching-Yu and Viren structured and finalised the final report with all merging and markdowns. Finally, this report will not be done without the advice and suggestions from David and Saraansh.

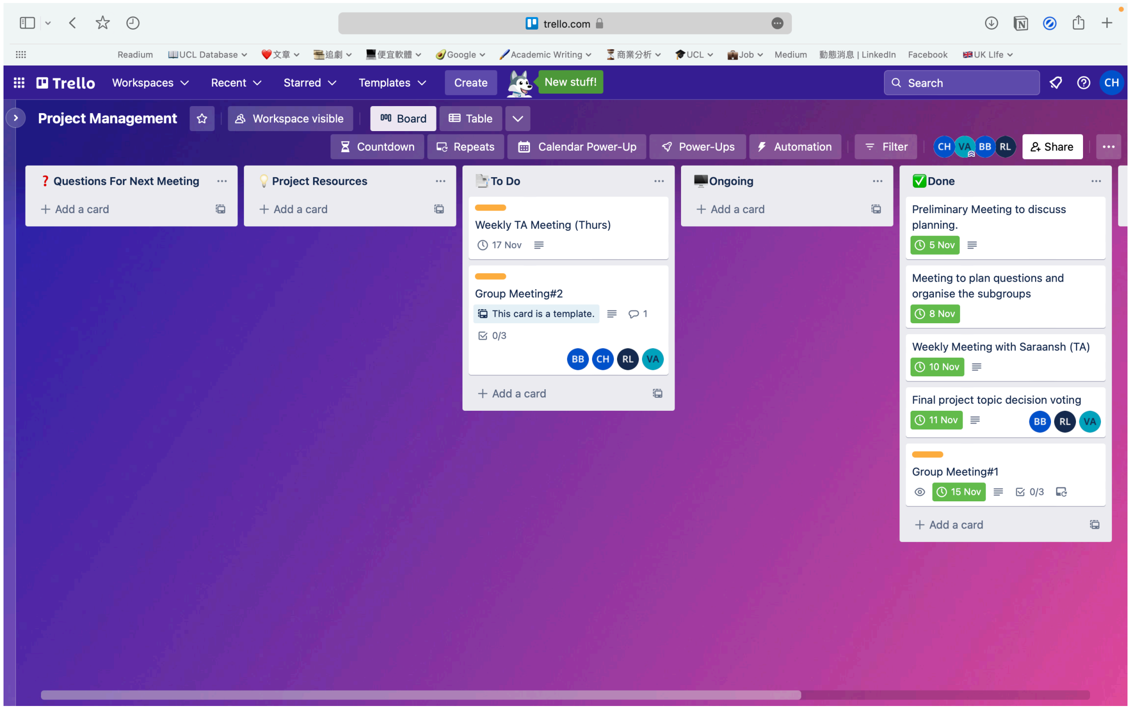
9.1.2 Project Management

Trello was used as a project management tool. Please find attached four screenshots of the Trello board corresponding to four different weeks, and two calendar screenshots.

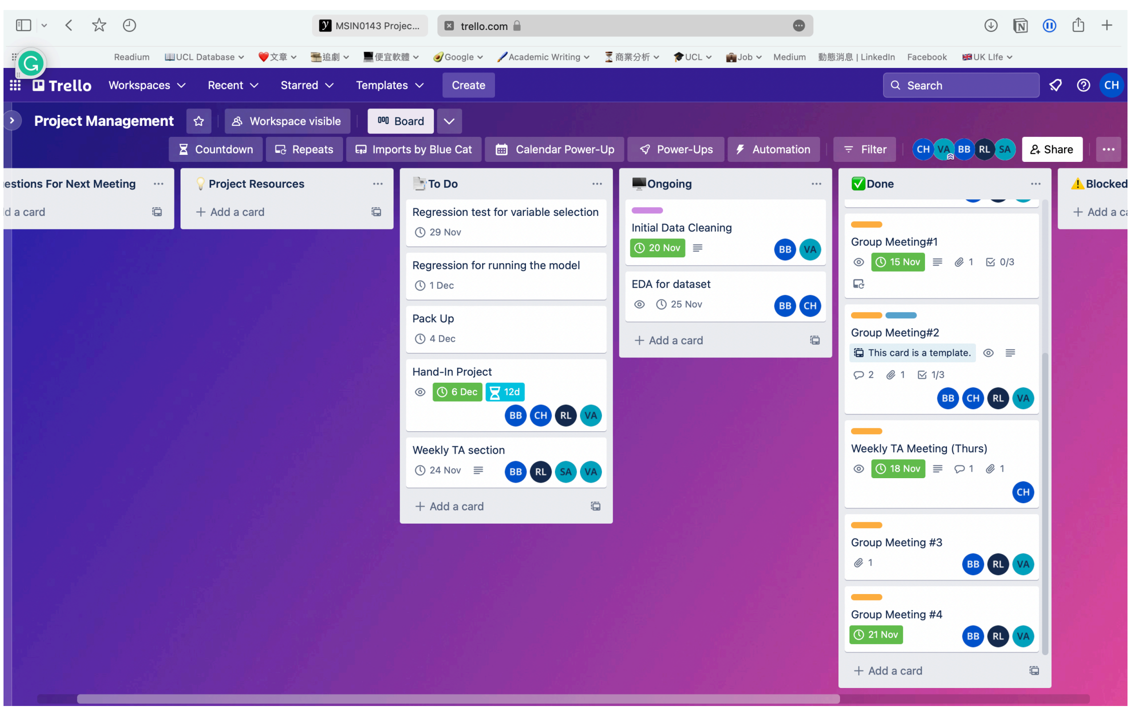
Weekly Trello Boards

[43]:
```
display.Image("Trello Screenshot 1.png")
display.Image("Trello Screenshot 2.png")
display.Image("Trello Screenshot 3.png")
display.Image("Trello Screenshot 4.png")
```

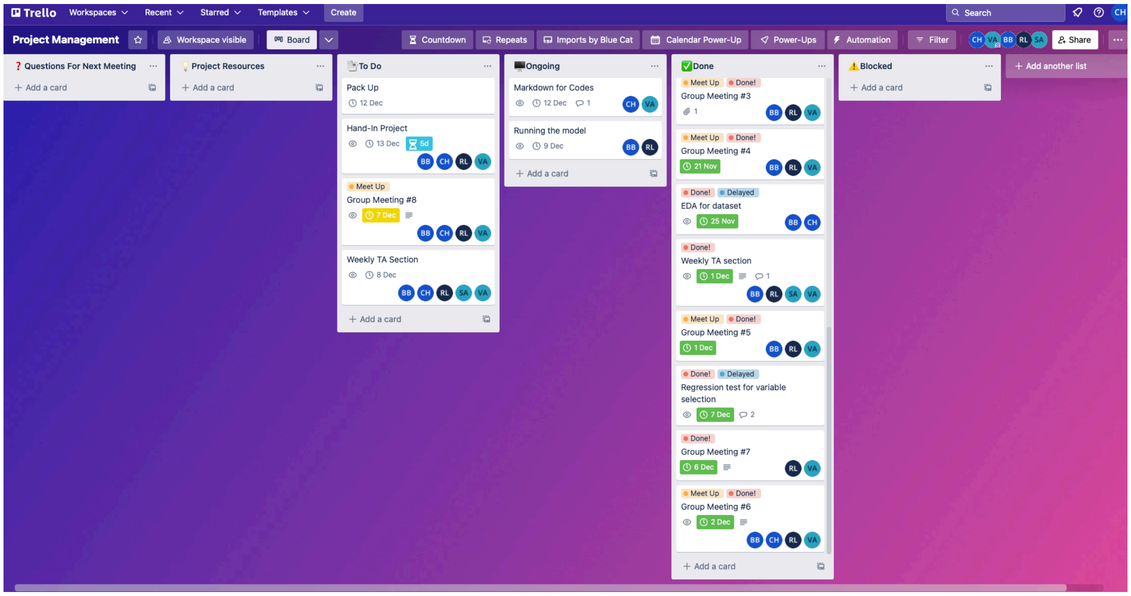
[43]:


trello.com
Trello
Workspaces
Recent
Starred
Templates
Create
New stuff!
Search
Project Management
Workspace visible
Board
Table
Countdown
Repeats
Calendar Power-Up
Power-Ups
Automation
Filter
Share
Questions For Next Meeting
Add a card
Project Resources
Add a card
To Do
Weekly TA Meeting (Thurs)
17 Nov
Group Meeting#2
This card is a template.
0/3
Add a card
Ongoing
Add a card
Done
Preliminary Meeting to discuss planning.
5 Nov
Meeting to plan questions and organise the subgroups
8 Nov
Weekly Meeting with Saraansh (TA)
10 Nov
Final project topic decision voting
11 Nov
Group Meeting#1
15 Nov
0/3
Add a card

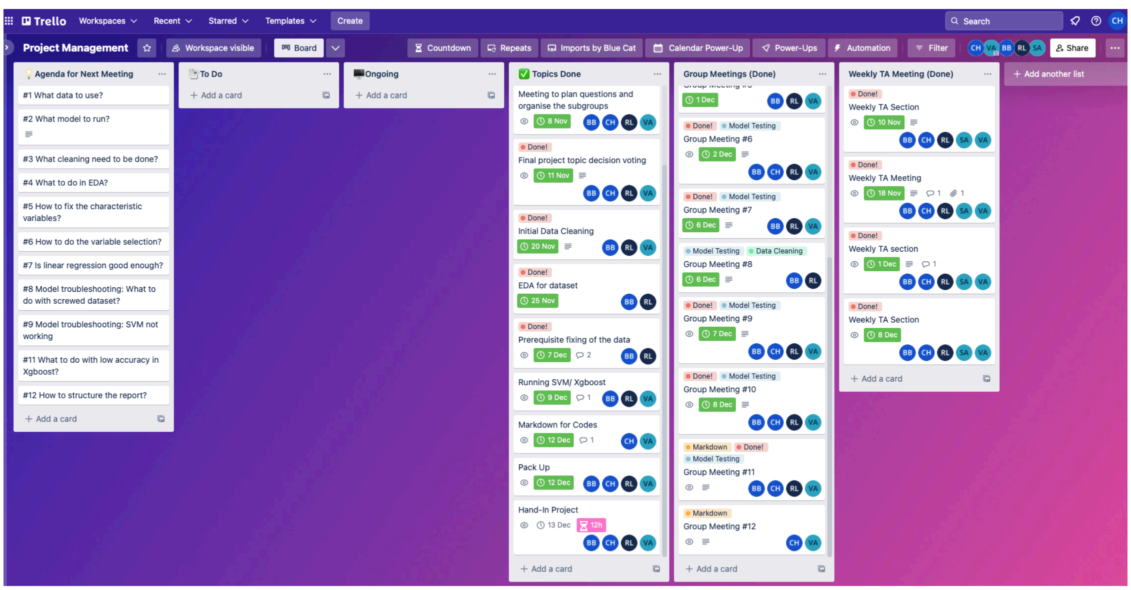
[43]:


MSIN0143 Projec...
trello.com
Trello
Workspaces
Recent
Starred
Templates
Create
Search
Project Management
Workspace visible
Board
Countdown
Repeats
Imports by Blue Cat
Calendar Power-Up
Power-Ups
Automation
Filter
Share
estions For Next Meeting
d a card
Project Resources
Add a card
To Do
Regression test for variable selection
29 Nov
Regression for running the model
1 Dec
Pack Up
4 Dec
Hand-In Project
6 Dec
12d
Weekly TA section
24 Nov
Add a card
Ongoing
Initial Data Cleaning
20 Nov
EDA for dataset
25 Nov
Add a card
Done
Group Meeting#1
15 Nov
0/3
Group Meeting#2
This card is a template.
1/3
Weekly TA Meeting (Thurs)
18 Nov
Group Meeting #3
Group Meeting #4
21 Nov
Add a card
Blocked
Add a ca

[43]:



[43]:



Trello Calendars

[44]:
```
display.Image("Trello Screenshot 5.png")
display.Image("Trello Screenshot 6.png")
```

[44]:

[44]:

Remark: All members participated in their relative meetings (attendance is recorded in Trello Screenshot 4)

9.2 Word Count

[306]:

```python
# The wordcount was printed before references and appendix.

def wordcount(nb_filename):
    with open(nb_filename) as json_file:
            data = json.load(json_file)
    wordCount = 0
```

```
    for each in data['cells']:
        cellType = each['cell_type']
        if cellType == "markdown":
            content = each['source']
            for line in content:
                temp = [word for word in line.split()]
                wordCount = wordCount + len(temp)
    return wordCount

wordcount("MSIN00143 Group D2 - The Economic Loss from Fire Incidents - A␣
 ↪Machine Learning Approach.ipynb")
```

[306]: 1998