Project Introudction

In this project, we used code violations dataset from Syracuse open data portal and asked several questions to answer.

This dataset records every housing code violation in Syracuse, as well as where it occurred, when it occurred, what the violation was, as well as the name and location of who is responsible for the violation.

Questions we answered:

1. Is there any correlation between neighborhood/location and type of violation?
2. Are the building owners generally local? Are any of them repeat offenders?
3. How did COVID impact the number of housing violations (if at all)?
4. Have the kinds of violations given out changed over time?
5. Will we see a relationship between demographic and the types/amount of violations?

Major steps in the process:

1. Data cleaning and transformation

We read the dataset and did data cleaning and transformation on several columns. This step included converting column types (string to datetime), checking date range and filtering bad records (date recorded as back to year 1900), merging our data with API-sourced census data, and doing some string cleaning in the violation column (a shorter version of violation name is created excluding redundant information).
2. Descriptive analysis and plotting
We worked on some descriptive analysis regarding several attributes in the data table using seaborn and also by grouping the data.
3. Answering addressed questions
We answered the questions listed
4. Conclusion and Discussion
Listing our results and discussion for this project

Code begins below:

Group member who is in charge of producing code and analyzing is mentioned as in "()" after minor titles.

In [ ]:
```
# import needed modules
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
# read in dataset and merge dataset
df1 = pd.read_csv('Datasets/Code_Violations.csv')
df2 = pd.read_csv('Datasets/Code_Violations-1.csv')
code_violations = pd.concat([df1, df2], ignore_index=True)
print(code_violations.shape)
```

```
(98420, 24)
```

Step 1. Data cleaning and transformation

1. Glimpse the dataset (Hang)

In [ ]:
```
code_violations.dtypes
# Many of these columns are chracters
```

Out[ ]:
```
X                        float64
Y                        float64
violation_number          object
complaint_address         object
complaint_zip              int64
SBL                       object
violation                 object
violation_date            object
comply_by_date            object
status_type_name          object
complaint_number          object
complaint_type_name       object
open_date                 object
owner_name                object
inspector_id               int64
Neighborhood              object
Vacant                    object
owner_address             object
owner_city                object
owner_state               object
owner_zip_code            object
Latitude                 float64
Longitude                float64
ObjectId                   int64
dtype: object
```

In [ ]:
```
code_violations.head()
```

Out[ ]:

	X	Y	violation_number	complaint_address	complaint_zip	SBL	violation	violation_date	cor
0	-8.480408e+06	5.317057e+06	2021-14216	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2021/08/27 14:20:05.683+00	
1	-8.480408e+06	5.317057e+06	2021-07690	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2021/05/20 15:28:46.050+00	
2	-8.480408e+06	5.317057e+06	2020-03502	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC 27-43 (e) (1)(2)(3)(4) Certification	2020/09/29 08:47:31.553+00	
3	-8.480408e+06	5.317057e+06	2020-02530	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2020/08/31 12:09:43+00	
4	-8.480408e+06	5.317057e+06	98169	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2020/05/26 11:13:15+00	

5 rows × 24 columns

2. convert date string to datetime type (Hang)

In [ ]:

```
# remove redundant part
code_violations['violation_date']=code_violations['violation_date'].str[0:19]
code_violations['comply_by_date']=code_violations['comply_by_date'].str[0:19]
# convert to datetime format
code_violations['violation_date']=pd.to_datetime(code_violations['violation_date'])
code_violations['comply_by_date']=pd.to_datetime(code_violations['comply_by_date'])
# Should be datetime here, time zone by default is UTC, I think it should be EDT or EST since it's in Syra
print(code_violations[['comply_by_date','violation_date']].dtypes)

# Find the date range
print('violation date range: '+str(code_violations['violation_date'].dt.date.min()) + ' to ' +str(code_vio
print('violation complied date range: '+str(code_violations['comply_by_date'].dt.date.min()) + ' to ' +str
```

```
# It's about 5 years
# Some of the comply_by_date seems not right by showing 1900-01-01
```

```
comply_by_date    datetime64[ns]
violation_date    datetime64[ns]
dtype: object
violation date range: 2018-12-26 to 2023-10-27
violation complied date range: 1900-01-01 to 2023-12-28
```

Findings by far:

1. This dataset provides records from December 2018 to October 2023
2. Some of the comply_by_date seems not right by showing 1900-01-01

3. mark the potential bad records/values (Hang)

In [ ]:
```
# check if the original character just read 1900/01/01
index_bad_comply_by_date=code_violations[code_violations['comply_by_date']=='1900-01-01'].index
temp_table=pd.concat([df1, df2], ignore_index=True)
print(temp_table.iloc[index_bad_comply_by_date,].shape[0])
# There are 119 rows having comply_by_date of 1900/01/01
print(temp_table.iloc[index_bad_comply_by_date,8].head())
del temp_table
# Threr are 2 possible reason this happens: 1. bad records.
# 2. (I don't know what exactly this comply_by_date means), if it is a designated date the owner should cor
# However, if the date violation is actually complied, then we can calculate the date duration

# index_bad_comply_by_date is kept, if we want do some calculations involved with two type of dates, we cou
```

```
119
690     1900/01/01 00:00:00+00
720     1900/01/01 00:00:00+00
1018    1900/01/01 00:00:00+00
1020    1900/01/01 00:00:00+00
2188    1900/01/01 00:00:00+00
Name: comply_by_date, dtype: object
```

In [ ]:
```
# Now check the dataset
code_violations.head()
```

Out[ ]:

	X	Y	violation_number	complaint_address	complaint_zip	SBL	violation	violation_date	comp
0	-8.480408e+06	5.317057e+06	2021-14216	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2021-08-27 14:20:05	
1	-8.480408e+06	5.317057e+06	2021-07690	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2021-05-20 15:28:46	
2	-8.480408e+06	5.317057e+06	2020-03502	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC 27-43 (e) (1)(2)(3)(4) Certification	2020-09-29 08:47:31	
3	-8.480408e+06	5.317057e+06	2020-02530	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2020-08-31 12:09:43	
4	-8.480408e+06	5.317057e+06	98169	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2020-05-26 11:13:15	

5 rows × 24 columns

4. combine with demographic data (from US census) (Andrea)

In [ ]:

```
import requests

# getting our zipcodes of interest
unique_zipcodes = code_violations['complaint_zip'].unique()
zipcodes_str = ','.join(map(str, unique_zipcodes))
state = '36'

api_url = 'https://api.census.gov/data/2019/acs/acs5/profile'
params = {
    # total population, median household income, est white population
    'get': 'NAME,DP05_0001E,DP03_0062E,DP05_0014E',
    'for': f'zip code tabulation area:{zipcodes_str}',
    'in': f'state:{state}',
```

```
    'key': '766b906ae7f8eaf962beff4b707574f968d40e3b'
}

response = requests.get(api_url, params=params)
if response.status_code == 200:
    data = response.json()

else:
    # Print an error message if the request was not successful
    print(f"Error: {response.status_code}, {response.text}")
```

In [ ]:
```
# converting JSON to dataframe and cleaning
zip_data = df = pd.DataFrame(data[1:], columns=data[0])

# filtering columns
selected_columns = ['DP05_0001E', 'DP03_0062E', 'DP05_0014E', 'zip code tabulation area']
zip_data = zip_data[selected_columns]
zip_data

# rename remaining columns
zip_data = zip_data.rename(columns={
    'DP05_0001E': 'Total Population',
    'DP03_0062E': 'Median Household Income',
    'DP05_0014E': 'White Population',
    'zip code tabulation area': 'zipcode'
})
zip_data
```

Out[ ]:

	Total Population	Median Household Income	White Population	zipcode
0	16513	38018	1044	13203
1	14952	92575	1139	13215
2	6787	20196	159	13202
3	18741	34856	923	13204
4	12597	53012	807	13207
5	16723	43674	1207	13206
6	17212	32579	1161	13205
7	27916	31319	840	13210
8	8369	62485	661	13224
9	22833	38475	1163	13208
10	15107	66866	1452	13219
11	8439	74098	520	13214

In [ ]:

```
# converting zipcodes to int64 to match complaint_zip type
zip_data['zipcode'] = zip_data['zipcode'].astype('int64')

# merging with code violations data
code_violations = pd.merge(code_violations, zip_data, left_on='complaint_zip', right_on='zipcode', how='le

# deleting extra zip column
code_violations = code_violations.drop(columns=['zipcode'])
code_violations.sample(5)
```

Out[ ]:

	X	Y	violation_number	complaint_address	complaint_zip	SBL	violation	violation_date
57623	-8.477970e+06	5.323577e+06	2023-15502	835 Lemoyne Ave	13208	003.-12-11.0	2020 PMCNYS - Section 604.3 - Electrical syste...	2023-08-28 15:36:21
87964	-8.478515e+06	5.316829e+06	2022-00998	246-48 Coolidge Ave	13205	086.-01-13.0	2020 PMCNYS - Section 304.13 - Window, skyligh...	2022-01-21 08:17:52
2452	-8.475365e+06	5.315352e+06	2021-03709	420 Jamesville Ave & Smith La	13210	058.-09-22.0	2020 PMCNYS - Section 305.3 - interior surfaces	2021-03-11 07:45:03
24889	-8.472682e+06	5.319357e+06	2021-13858	2301 Fayette St E & Bruce St	13224	036.-06-20.1	SPCC - Section 27-72 (f) - Overgrowth	2021-08-23 16:16:45
49960	-8.479606e+06	5.322617e+06	2022-07611	1 Carousel Center Dr	13204	114.-02-05.6	SPCC - Section 27-57 (a) (17) - Improper Exten...	2022-05-09 09:47:01

5 rows × 27 columns

Now, we have access to the total population, median household income, and white population for each zipcode in our data.

5. altering violation column (Andrea)

In [ ]:

```
violation_names = code_violations['violation'].unique()
#print(violation_names)
```

```
# the majority of violations contain the info we really want after the last hyphen
code_violations['violation name'] = code_violations['violation']
# adding a space before the hyphen prevents us from splitting on a range (ex: 27-15)
code_violations['violation name'] = code_violations['violation name'].apply(lambda x: x.rsplit(' -', 1)[-1]
code_violations
```

Out[ ]:

	X	Y	violation_number	complaint_address	complaint_zip	SBL	violation	violation_date
0	-8.480408e+06	5.317057e+06	2021-14216	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2021-08-27 14:20:05
1	-8.480408e+06	5.317057e+06	2021-07690	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2021-05-20 15:28:46
2	-8.480408e+06	5.317057e+06	2020-03502	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC 27-43 (e) (1)(2)(3)(4) Certification	2020-09-29 08:47:31
3	-8.480408e+06	5.317057e+06	2020-02530	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2020-08-31 12:09:43
4	-8.480408e+06	5.317057e+06	98169	1631-33 Onondaga St W	13204	091.-14-10.0	SPCC - Section 27-72 (f) - Overgrowth	2020-05-26 11:13:15
...	...	...	...	...	...	...	...	...
98415	-8.476467e+06	5.322191e+06	2021-17327	501 John St & Gilbert Ave	13208	009.-12-16.0	SPCC - Section 27-72 (e) - Trash & Debris	2021-10-20 15:48:06
98416	-8.475855e+06	5.321612e+06	2021-17282	402 Park St	13203	015.-08-07.0	SPCC SEC. 27-15	2021-10-20 10:33:49
98417	-8.475599e+06	5.324050e+06	2021-16959	627 Darlington Rd	13208	005.-16-09.0	2020 PMCNYS - Section 305.3 - interior surfaces	2021-10-13 14:43:47
98418	-8.475599e+06	5.324050e+06	2021-16953	627 Darlington Rd	13208	005.-16-09.0	2020 PMCNYS -	2021-10-13 14:27:49

	X	Y	violation_number	complaint_address	complaint_zip	SBL	violation	violation_date
							Section 505.1 - General	
98419	-8.475599e+06	5.324050e+06	2021-16952	627 Darlington Rd	13208	005.-16-09.0	2020 PMCNYS - Section 305.3 - interior surfaces	2021-10-13 14:25:40

98420 rows × 28 columns

Summarization:

In this part, our team discovered the dataset, did cleaning and transformation on several columns.

Step 2. Descriptive analysis and plotting

1. How many unique values are there in each column? (Hang)

In [ ]:
```
for column in code_violations:
    print(str(code_violations[column].unique().shape[0])+'/98420'+f' unique {column}')
print('unique 12 complaint_zip shown in the list: '+str(code_violations['complaint_zip'].unique()))
print('unique 3 status types shown in the list: '+str(code_violations['status_type_name'].unique()))
print('unique 3 Vacant types shown in the list: '+str(code_violations['Vacant'].unique()))
# violation_number are smaller than row counts, this might means there are many rows mentioning the same vi
# There are only about 10k out of 100k unique complaint address
# unique complaint_address and SBL have almost the same number, I think these two columns might be highly a
# unique complaint_number are just 1/3 of the total rows, this might means many rows have the same complai

# About X and Y, I believe it's the coordinate in a projected coordinate system, however, if we cannot find
# If we want to project the data from a geographic coordinate system, we can just use long/lats
```

```
1125/98420 unique X
925/98420 unique Y
81363/98420 unique violation_number
13565/98420 unique complaint_address
12/98420 unique complaint_zip
13564/98420 unique SBL
793/98420 unique violation
74872/98420 unique violation_date
54986/98420 unique comply_by_date
3/98420 unique status_type_name
34483/98420 unique complaint_number
43/98420 unique complaint_type_name
28580/98420 unique open_date
9924/98420 unique owner_name
59/98420 unique inspector_id
35/98420 unique Neighborhood
3/98420 unique Vacant
9337/98420 unique owner_address
874/98420 unique owner_city
53/98420 unique owner_state
1127/98420 unique owner_zip_code
925/98420 unique Latitude
1125/98420 unique Longitude
98420/98420 unique ObjectId
12/98420 unique Total Population
12/98420 unique Median Household Income
12/98420 unique White Population
620/98420 unique violation name
unique 12 complaint_zip shown in the list: [13204 13202 13206 13208 13205 13203 13207 13210 13214 13224 13
215 13219]
unique 3 status types shown in the list: ['Closed' 'Open' 'Void']
unique 3 Vacant types shown in the list: [nan 'Residential' 'Commercial']
```

2. What are the violation types and how frequent each type is? (Hang)

In [ ]:

```
violation_counts=code_violations.groupby('violation name')['X'].count().to_frame().sort_values(by=['X'],as
violation_counts=violation_counts.reset_index()
violation_counts.describe(percentiles=[.25,.75,.90])
```

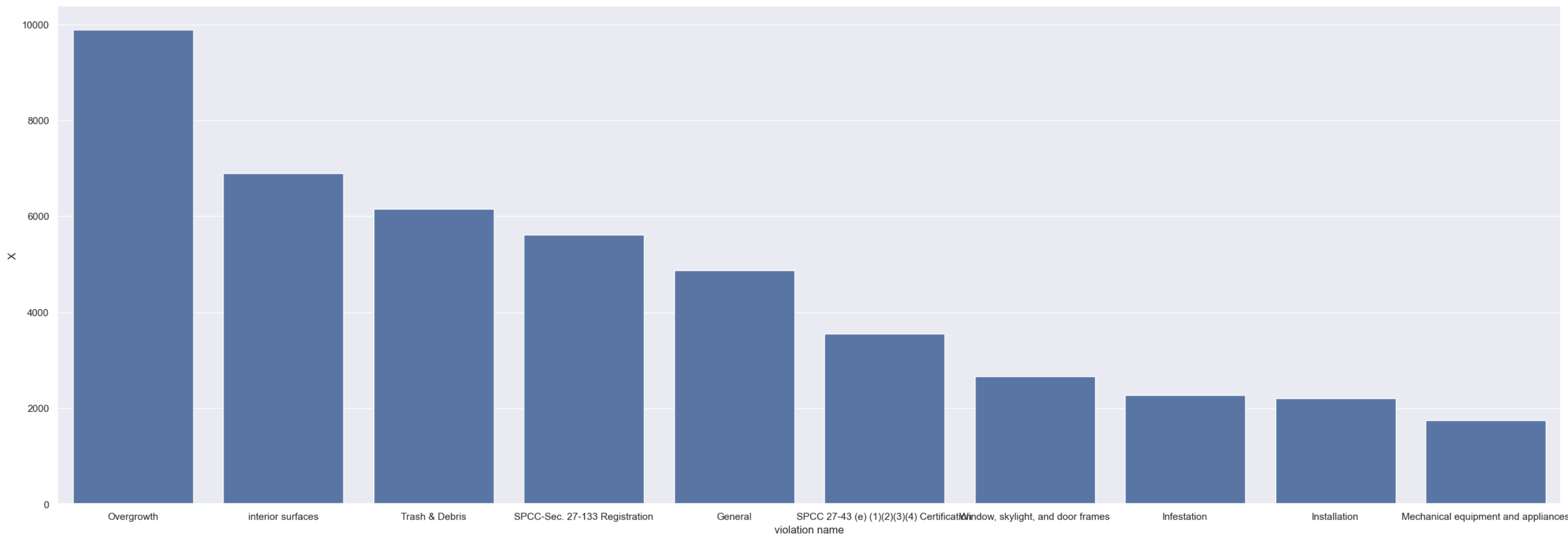
Out[ ]:

	X
count	620.000000
mean	158.711290
std	687.962217
min	1.000000
25%	2.000000
50%	7.000000
75%	49.000000
90%	304.300000
max	9887.000000

In [ ]:

```
# 90% of the counts of violations are under 200 cases through about 5 years, what about the most frequent c
top10_frequent_violations=violation_counts[violation_counts['X']>200].head(10)
sns.set(rc={'figure.figsize':(30, 10)})
sns.barplot(x='violation name',y='X',data=top10_frequent_violations)
# we could generate a simple version of this 'violation' column, excluding information not so useful like
```

Out[ ]: <AxesSubplot:xlabel='violation name', ylabel='X'>



3. What are the complaint types and how frequent is each type? (Hang)

In [ ]:

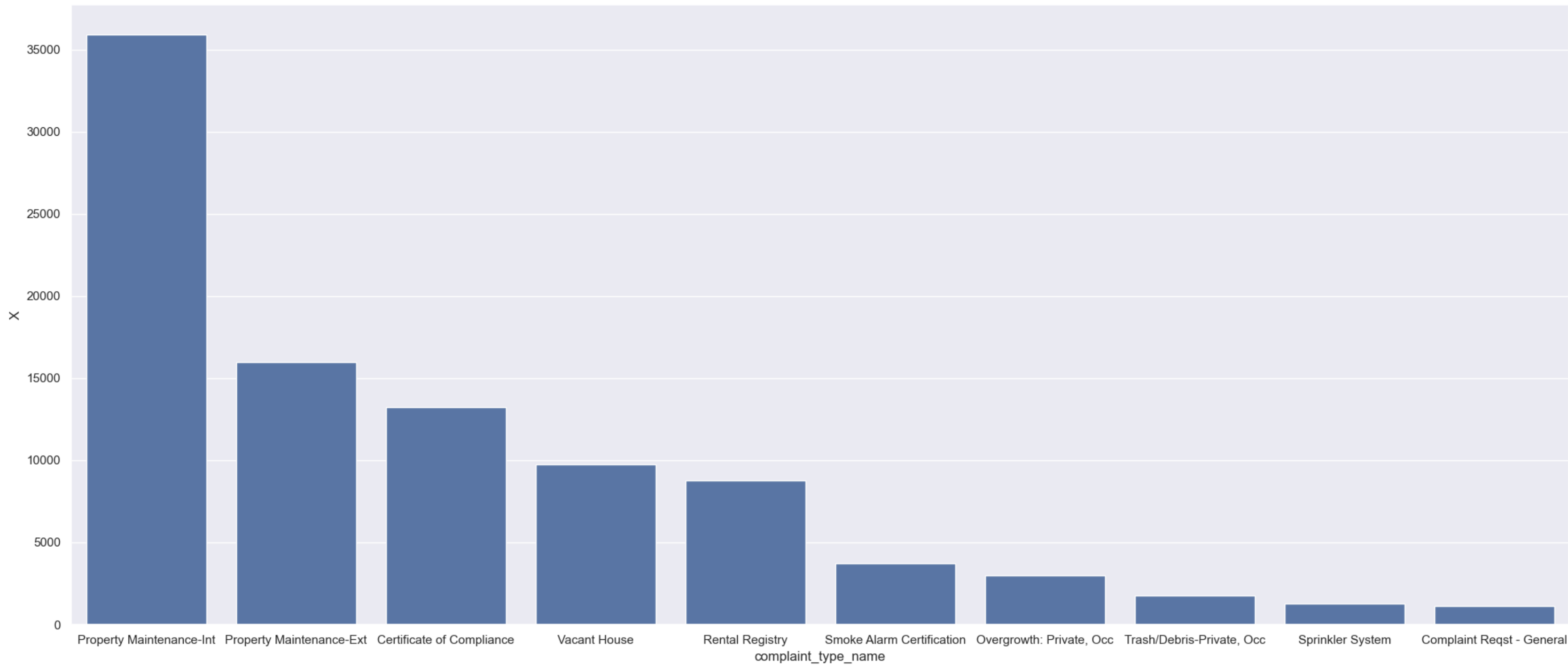
```
complaint_counts=code_violations.groupby('complaint_type_name')['X'].count().to_frame().sort_values(by=['X
complaint_counts=complaint_counts.reset_index()
complaint_counts.describe(percentiles=[.25,.75,.90])
```

Out[ ]:

	X
count	43.000000
mean	2288.395349
std	6358.091905
min	1.000000
25%	7.500000
50%	95.000000
75%	637.500000
90%	7745.400000
max	35927.000000

In [ ]:
```
# what about the most frequent complaints?
top10_frequent_complaints=complaint_counts[complaint_counts['X']>200].head(10)
sns.set(rc={'figure.figsize':(24, 10)})
sns.barplot(x='complaint_type_name',y='X',data=top10_frequent_complaints)
```

Out[ ]: <AxesSubplot:xlabel='complaint_type_name', ylabel='X'>



Step 3. Answering addressed questions

Question 1. Is there any correlation between neighborhood/location and type of violation? (Hang)

1.1. Case numbers within each neighborhood

In [ ]:
```
# 1. Total case number within each neighborhood
total_case_neighborhood=code_violations.groupby('Neighborhood')['violation'].count().to_frame().sort_values
total_case_neighborhood.columns=['total_case_count']
```

```
# 2. Total violation type within each neighborhood
unique_violation_neighborhood=code_violations.groupby('Neighborhood')['violation'].nunique().to_frame().so
unique_violation_neighborhood.columns=['unique_violation_count']
# 3. Total complaint type within each neighborhood
unique_complaint_neighborhood=code_violations.groupby('Neighborhood')['complaint_type_name'].nunique().to_
unique_complaint_neighborhood.columns=['unique_complaint_count']
compare_table=pd.concat([total_case_neighborhood,unique_violation_neighborhood,unique_complaint_neighborho
compare_table
```

Out[ ]:

Neighborhood	total_case_count	unique_violation_count	unique_complaint_count
Northside	15467	406	30
Near Westside	7859	322	29
Brighton	7423	281	21
Washington Square	5503	305	26
Eastwood	5428	314	24
Park Ave	4535	263	19
Elmwood	4513	221	22
Southside	4368	236	20
Southwest	3818	241	21
Skunk City	3544	211	20
North Valley	3346	239	21
Lincoln Hill	2751	249	18
Strathmore	2701	190	19
Salt Springs	2440	229	17
Prospect Hill	2410	246	26
Court-Woodlawn	2396	219	21
Westcott	2177	234	19
Hawley Green	2131	216	19
Far Westside	2018	207	19
Tipp Hill	1952	199	21
Near Eastside	1895	191	17
Downtown	1740	227	20
Sedgwick	1585	193	13
Outer Comstock	1442	176	16

	total_case_count	unique_violation_count	unique_complaint_count
Neighborhood			
University Neighborhood	1188	135	13
University Hill	993	185	20
South Valley	952	123	14
Meadowbrook	484	116	16
Lakefront	248	92	20
Franklin Square	173	55	11
Winkworth	163	45	11
Hawley-Green	131	51	9
South Campus	14	6	4
Park Ave.	2	2	2

1.2. The most frequent violation type for each neighborhoods

In [ ]:

```
violation_neighborhood=code_violations.groupby(['Neighborhood','violation name'])['violation'].count().to_
violation_neighborhood.reset_index(inplace=True)
violation_neighborhood_top1=violation_neighborhood.iloc[violation_neighborhood.groupby('Neighborhood')['vio
violation_neighborhood_top1
```

Out[ ]:

	Neighborhood	violation name
0	Brighton	Overgrowth
1	Court-Woodlawn	Overgrowth
2	Downtown	Maintenance of required safeguards
3	Eastwood	Overgrowth
4	Elmwood	Overgrowth
5	Far Westside	SPCC-Sec. 27-133 Registration
6	Franklin Square	SPCC 27-43 (e) (1)(2)(3)(4) Certification
7	Hawley Green	interior surfaces
8	Hawley-Green	General
9	Lakefront	Maintained System
10	Lincoln Hill	Overgrowth
11	Meadowbrook	Overgrowth
12	Near Eastside	interior surfaces
13	Near Westside	Overgrowth
14	North Valley	Overgrowth
15	Northside	Overgrowth
16	Outer Comstock	interior surfaces
17	Park Ave	interior surfaces
18	Park Ave.	SPCC 27-43 (e) (1)(2)(3)(4) Certification
19	Prospect Hill	interior surfaces
20	Salt Springs	interior surfaces
21	Sedgwick	General
22	Skunk City	Overgrowth
23	South Campus	SPCC 27-43 (e) (1)(2)(3)(4) Certification
24	South Valley	Overgrowth

	Neighborhood	violation name
25	Southside	Overgrowth
26	Southwest	Overgrowth
27	Strathmore	Overgrowth
28	Tipp Hill	Overgrowth
29	University Hill	SPCC 27-43 (e) (1)(2)(3)(4) Certification
30	University Neighborhood	SPCC-Sec. 27-133 Registration
31	Washington Square	interior surfaces
32	Westcott	SPCC-Sec. 27-133 Registration
33	Winkworth	Overgrowth

Methods used:

In this part of analysis, group-by functions and summary statistics are mainly used to answer frequency-related questions among neighborhoods.

Findings:

1. The violation case counts for the neighborhoods are different. "Northside" has the most total violation cases associated (15k), which is about 200% of the following neighborhood "near westside".
2. Fot the majority of neighborhoods, the most frequent violation type is "overgrowth", while for some neighborhoods, they have issues concerning "certification", "registration" and "interior surfaces". Not like others, that for downtown neighborhood is "Maintenance of required safeguards".

Question 2. Are the building owners generally local? Are any of them repeat offenders? (Hang)

2.1. Violation counts of owners

In [ ]:
```
owner_zip=code_violations.groupby(['owner_name','owner_zip_code']).size().reset_index()
owner_zip.columns=['owner_name','owner_zip_code','violation_case_count']
```

```
owner_zip.sort_values('violation_case_count',inplace=True,ascending=False)
owner_zip['violation_case_count'].describe(percentiles=[.25,.75,.90,.99])
```

Out[ ]:
```
count    10272.000000
mean         9.511001
std         28.396806
min          1.000000
25%          1.000000
50%          3.000000
75%          9.000000
90%         21.000000
99%         93.290000
max       1597.000000
Name: violation_case_count, dtype: float64
```

In [ ]:
```
# create a list of zip codes in Syracuse
Syracuse_zip_list=range(13201,13226)
remove_list=[13213,13216,13222,13223]
Syracuse_zip_list=np.delete(Syracuse_zip_list, [Syracuse_zip_list.index(x) for x in remove_list])
addition=np.array([13235,13244,13250,13251,13252,13261,13290])
Syracuse_zip_list=np.append(Syracuse_zip_list,addition)
Syracuse_zip_list=Syracuse_zip_list.astype(str)
Syracuse_zip_list
```

Out[ ]:
```
array(['13201', '13202', '13203', '13204', '13205', '13206', '13207',
       '13208', '13209', '13210', '13211', '13212', '13214', '13215',
       '13217', '13218', '13219', '13220', '13221', '13224', '13225',
       '13235', '13244', '13250', '13251', '13252', '13261', '13290'],
      dtype='<U21')
```

In [ ]:
```
owner_top10_counts=owner_zip.head(10)
local_top10=owner_top10_counts.loc[owner_top10_counts['owner_zip_code'].isin(Syracuse_zip_list),:]
alien_top10=owner_top10_counts.loc[owner_top10_counts['owner_zip_code'].isin(Syracuse_zip_list)==0,:]
owner_top10_counts
```

Out[ ]:

	owner_name	owner_zip_code	violation_case_count
3571	GSPDC	13202	1597
10085	William D'Angelo	13088	616
7319	Otto Apartments LLC	60602	544
4214	Infisium Property Management	13120	515
1231	Ballantyne Garden Apt Syr LLC	11219	489
1232	Ballantyne Gardens Apts/Jackie	13205	489
4202	Infisium Properties	13206	444
9147	Syr Model Nbhrd Corp	13205	438
7274	Onondaga Hilltop Homes Inc	10022	394
4767	Jerry Murphy	13104	352

In [ ]:

```
print([local_top10.shape[0],local_top10['violation_case_count'].sum()])
print([alien_top10.shape[0],alien_top10['violation_case_count'].sum()])
```

```
[4, 2968]
[6, 2910]
```

2.2. Local vs. alien owners

In [ ]:

```
local_owner=owner_zip.loc[owner_zip['owner_zip_code'].isin(Syracuse_zip_list),:]
[local_owner.shape[0],local_owner['violation_case_count'].sum()]
```

Out[ ]: [7007, 51506]

In [ ]:

```
alien_owner=owner_zip.loc[owner_zip['owner_zip_code'].isin(Syracuse_zip_list)==0,:]
[alien_owner.shape[0],alien_owner['violation_case_count'].sum()]
```

Out[ ]: [3265, 46191]

Methods used:

In this part of analysis, data frame filtering using pandas and summary statistics with group-by function are mainly used.

Findings:

1. The majority (99%) of owners listed in the violation records are associated with less than about 93 records. Among the top 10 most frequent seen owners, most of them are companies while there are two owners that might be individuals.
2. Among the unique owners list, about 70% of them are local owners, which contribute about 50k violation records, while the left 30% of owners are aliens but contribute about 46k violation records. Based on the information, local owners are less likely to offend the regulations.

Question 3. How did COVID impact the number of housing violations (if at all)? (Hang)

3.1. Covid outbreak

Timeline information source: https://www.cdc.gov/museum/timeline/covid19.html

Based on the information provided by CDC (Centers for Disease Control and Prevention) in US, "After more than 118,000 cases in 114 countries and 4,291 deaths,the WHO declares COVID-19 a pandemic" on March 11, 2020

Soon on March 13, 2020, "The Trump Administration declares a nationwide emergency and issues an additional travel ban on non-U.S. citizens traveling from 26 European countries due to COVID-19."

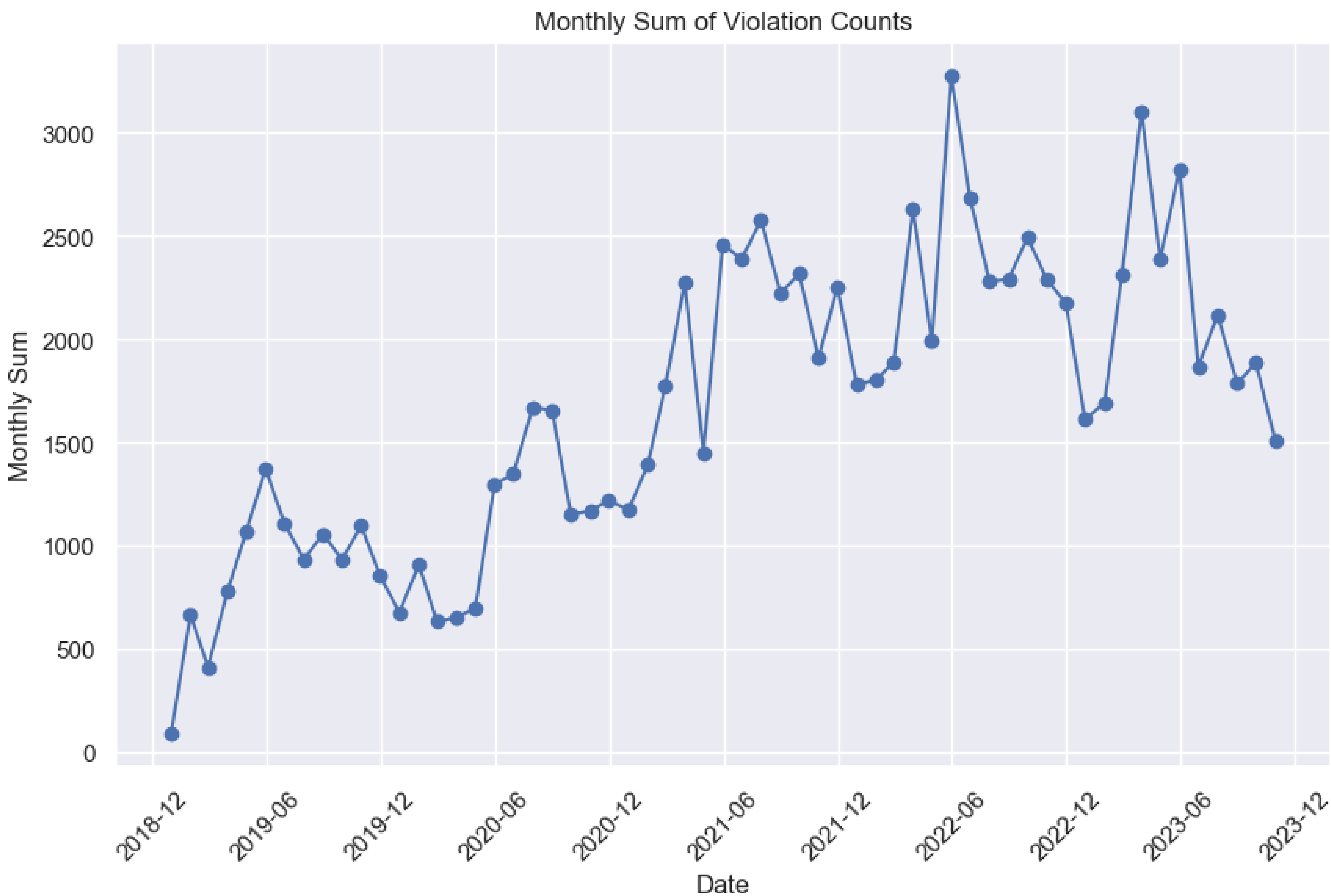
Based on these information and experience, let's assume the Covid affects U.S. mostly from 2020 to early 2022.

In [ ]:
```
monthly_sum=code_violations.resample('M',on='violation_date')['violation'].count().to_frame().reset_index(
monthly_sum.head()
```

Out[ ]:

	violation_date	violation
0	2018-12-31	95
1	2019-01-31	668
2	2019-02-28	415
3	2019-03-31	781
4	2019-04-30	1070

In [ ]:
```
import matplotlib.dates as mdates
fig, ax = plt.subplots(figsize=(10, 6))
plt.plot(monthly_sum['violation_date'], monthly_sum['violation'], marker='o', linestyle='-', color='b')
plt.title('Monthly Sum of Violation Counts')
plt.xlabel('Date')
plt.xticks(rotation=45)
plt.ylabel('Monthly Sum')
ax.xaxis.set_major_locator(mdates.MonthLocator(interval=6))
plt.grid(True)
plt.show()
```



Methods used:

In this part of analysis, plotting with matplotlib is mainly used.

Findings:

Based on the plot, I cannot conclude there are influences on violation counts from Covid due to the lack of information before

2019.

Question 4. Have the types of violations given out changed over time? (Andrea)

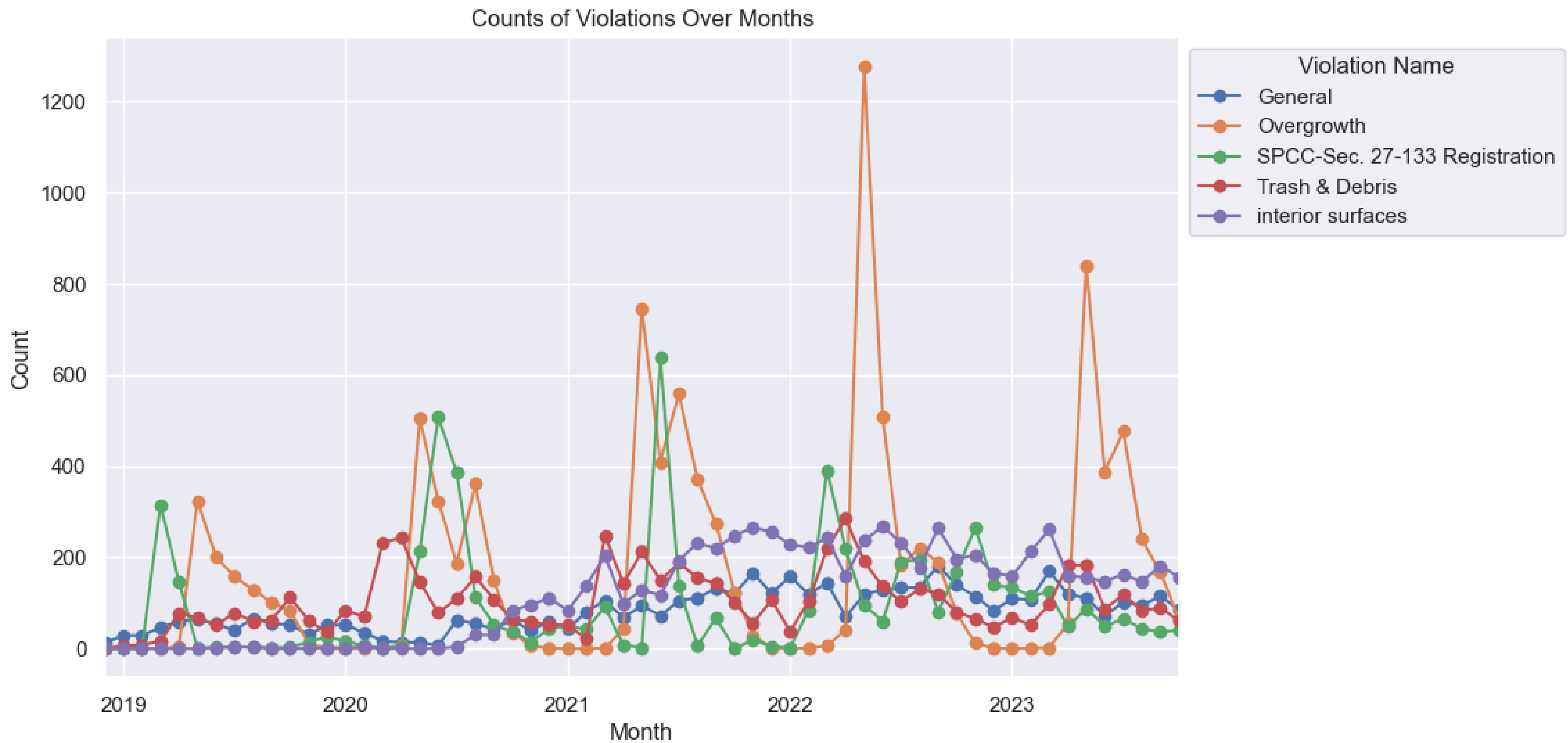
In [ ]:
```
# there are 620 unique code violations, too many to track all of them
len(code_violations['violation name'].unique())
violation_counts = code_violations['violation name'].value_counts()

# Get the top 10 violations and filter data
top_5_violations = violation_counts.head(5).index
top_violations = code_violations[code_violations['violation name'].isin(top_5_violations)]

# there are 33427 instances, around one third of our data contained in the top 5 violations
len(top_violations)
```

Out[ ]: 33427

Now let's look at the presence of these top violations over time:

In [ ]:
```
# grouping data by month
top_violations['month'] = top_violations['violation_date'].dt.to_period('M')
by_violation = top_violations.groupby(['violation name','month']).size().reset_index(name='count')
```

In [ ]:
```
# pivot the table for better visualization
pivot_table = by_violation.pivot(index='month', columns='violation name', values='count').fillna(0)

# Plotting
pivot_table.plot(kind='line', marker='o', figsize=(10, 6))
plt.title('Counts of Violations Over Months')
plt.xlabel('Month')
plt.ylabel('Count')
plt.legend(title='Violation Name', bbox_to_anchor=(1, 1), loc='upper left')
plt.show()
```



Overgrowth, trash, and registration all seem to have some irregularities. Some background information on registration:

SPCC-Sec. 27-133 Registration Source: https://library.municode.com/ny/syracuse/codes/code_of_ordinances?nodeId=REGEOR_CH27PRCOCOSY_ART9RERE_S27-133RE

Owners need to complete an application form, disclose necessary information, pay fees, and comply with specific eligibility criteria, including having no open cases, being current on taxes, and passing inspections. The application form and compliance affidavit must be signed by the property owner or a registered property manager. Filing periods for applications depend on the property's location within the city's quadrants, and certificates are issued by specific deadlines.

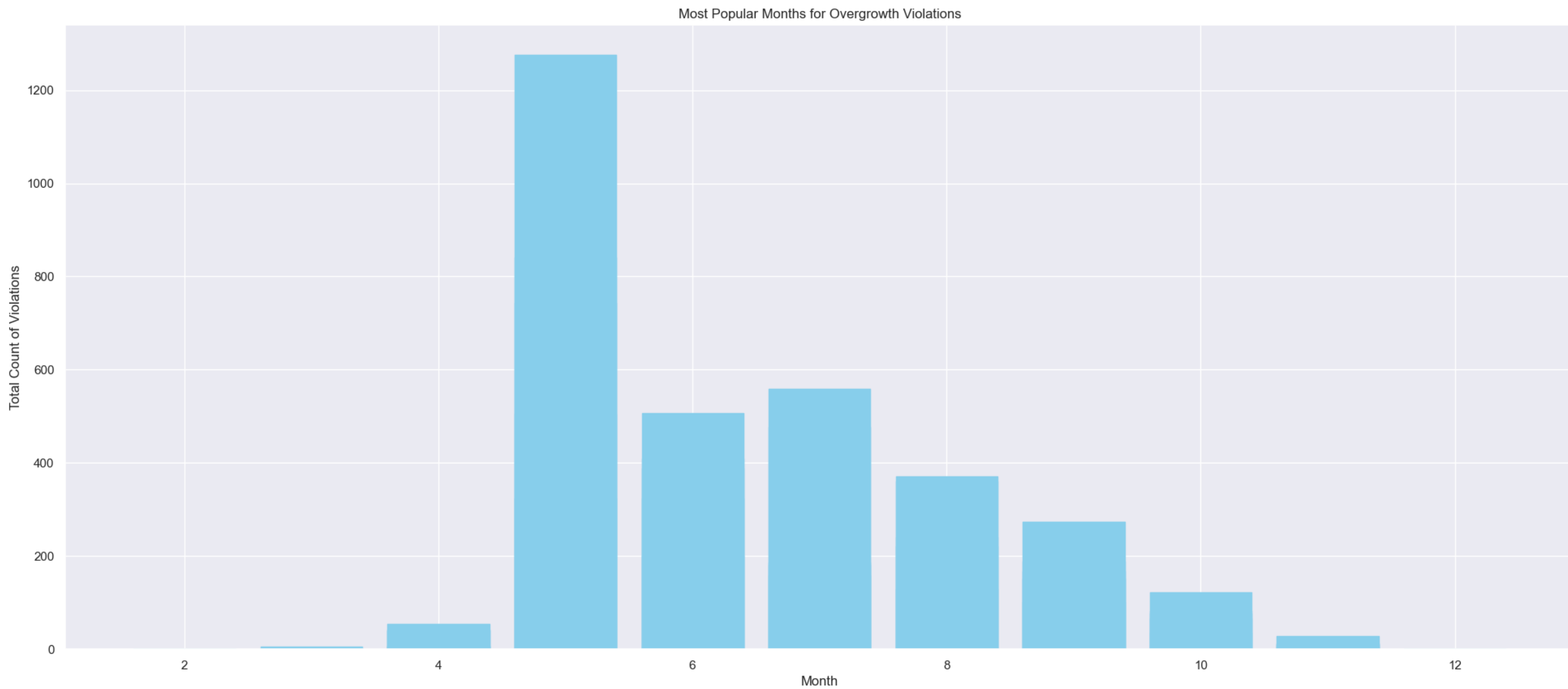
There is a specific location-dependent deadline for the registration application, which would explain the roughly annual spikes in the data. It also applies specifically to rental properties, which would explain its prevalance in a more urban town with a large college population like Syracuse. Now let's explore the other two violations, starting with overgrowth:

In [ ]:
```
overgrowth = by_violation[by_violation['violation name']=='Overgrowth']
overgrowth['month'] = overgrowth['month'].dt.to_timestamp()
overgrowth['month'] = overgrowth['month'].dt.month
overgrowth.groupby('month').sum()
```

Out[ ]:

month	violation name	count
2	OvergrowthOvergrowthOvergrowth	3
3	OvergrowthOvergrowthOvergrowthOvergrowth	11
4	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	149
5	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	3689
6	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	1829
7	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	1563
8	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	1322
9	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	881
10	OvergrowthOvergrowthOvergrowthOvergrowthOvergr...	384
11	OvergrowthOvergrowthOvergrowthOvergrowth	58
12	OvergrowthOvergrowthOvergrowth	3

In [ ]:
```
plt.bar(overgrowth['month'], overgrowth['count'], color='skyblue',edgecolor='skyblue')
plt.title('Most Popular Months for Overgrowth Violations')
plt.xlabel('Month')
plt.ylabel('Total Count of Violations')
plt.show()
```



So generally, these violations are occurring in the warmer months, which we would expect in a climate like Syracuse. Now, let's look into our other violation showing some irregularity, trash and debris:

In [ ]:
```
trash = by_violation[by_violation['violation name']=='Trash & Debris'].sort_values(by='count', ascending=Fa
trash.head(10)
```

Out[ ]:

	violation name	month	count
203	Trash & Debris	2022-04	285
190	Trash & Debris	2021-03	248
179	Trash & Debris	2020-04	243
178	Trash & Debris	2020-03	233
202	Trash & Debris	2022-03	220
192	Trash & Debris	2021-05	212
204	Trash & Debris	2022-05	191
194	Trash & Debris	2021-07	188
216	Trash & Debris	2023-05	184
215	Trash & Debris	2023-04	183

It looks like there was a spike right around the beginning of COVID, but the top months are all in the spring or summer. Let's see if this is indicative of a larger pattern:

In [ ]:

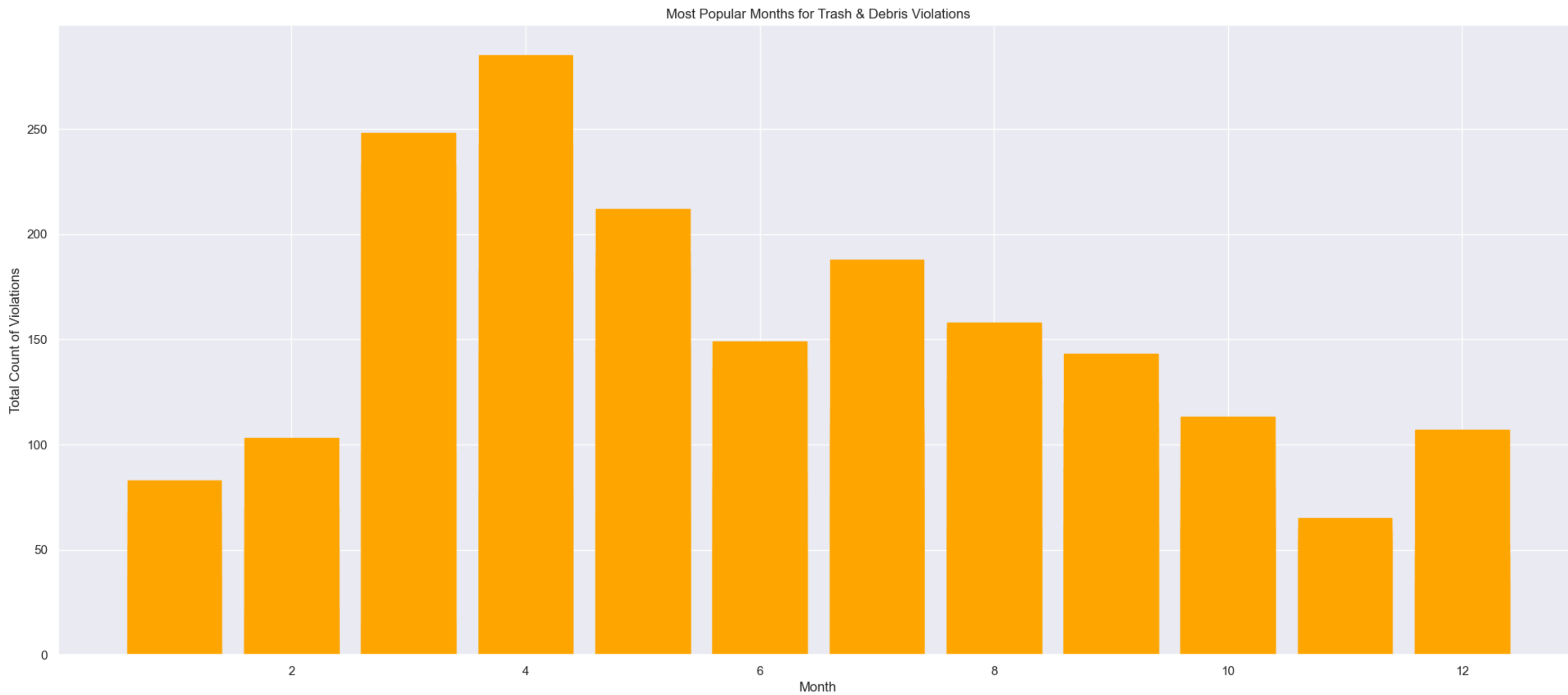
```
trash['month'] = trash['month'].dt.to_timestamp()
trash['month'] = trash['month'].dt.month
trash.groupby('month').sum()
```

Out[ ]:

month	violation name	count
1	Trash & DebrisTrash & DebrisTrash & DebrisTras...	247
2	Trash & DebrisTrash & DebrisTrash & DebrisTras...	253
3	Trash & DebrisTrash & DebrisTrash & DebrisTras...	814
4	Trash & DebrisTrash & DebrisTrash & DebrisTras...	932
5	Trash & DebrisTrash & DebrisTrash & DebrisTras...	800
6	Trash & DebrisTrash & DebrisTrash & DebrisTras...	502
7	Trash & DebrisTrash & DebrisTrash & DebrisTras...	596
8	Trash & DebrisTrash & DebrisTrash & DebrisTras...	588
9	Trash & DebrisTrash & DebrisTrash & DebrisTras...	522
10	Trash & DebrisTrash & DebrisTrash & DebrisTras...	419
11	Trash & DebrisTrash & DebrisTrash & DebrisTras...	240
12	Trash & DebrisTrash & DebrisTrash & DebrisTras...	243

In [ ]:

```
plt.bar(trash['month'], trash['count'], color='orange',edgecolor='orange')
plt.title('Most Popular Months for Trash & Debris Violations')
plt.xlabel('Month')
plt.ylabel('Total Count of Violations')
plt.show()
```



Although there does seem to be some relation between trash violations and month, it is not as obvious as overgrowth.

Question 5. Is there a relationship between demographic and types/amounts of violations? (Andrea)

First, let's look at the relationship between demographics and amounts of violations:

In [ ]:
```
# get violation counts for each zip
by_zip = code_violations.groupby('complaint_zip').size().reset_index(name='count')

# merge the grouped data with the demographics
by_zip_all = pd.merge(by_zip, zip_data, left_on='complaint_zip', right_on='zipcode', how='left')

# converting all columns to numeric
by_zip_all = by_zip_all.apply(pd.to_numeric)
by_zip_all.sort_values(by="count", ascending=False)
```

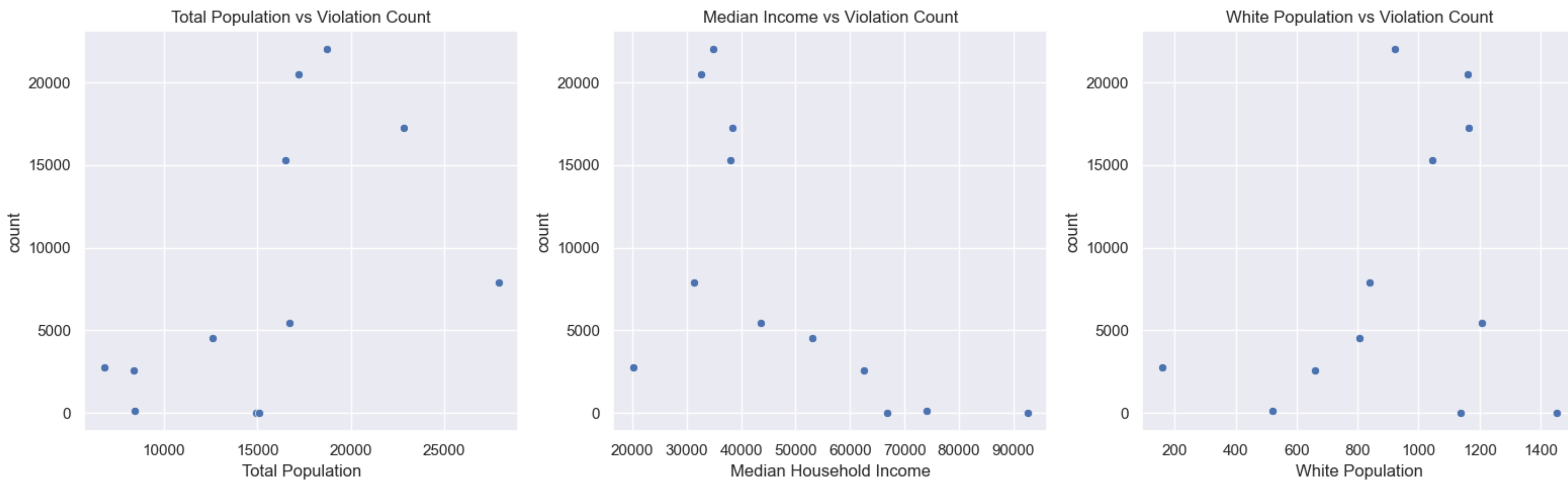
Out[ ]:

	complaint_zip	count	Total Population	Median Household Income	White Population	zipcode
2	13204	22004	18741	34856	923	13204
3	13205	20474	17212	32579	1161	13205
6	13208	17235	22833	38475	1163	13208
1	13203	15308	16513	38018	1044	13203
7	13210	7927	27916	31319	840	13210
4	13206	5434	16723	43674	1207	13206
5	13207	4550	12597	53012	807	13207
0	13202	2742	6787	20196	159	13202
11	13224	2595	8369	62485	661	13224
8	13214	125	8439	74098	520	13214
9	13215	25	14952	92575	1139	13215
10	13219	1	15107	66866	1452	13219

Now let's examine the relationship between number of violations and each demographic variable:

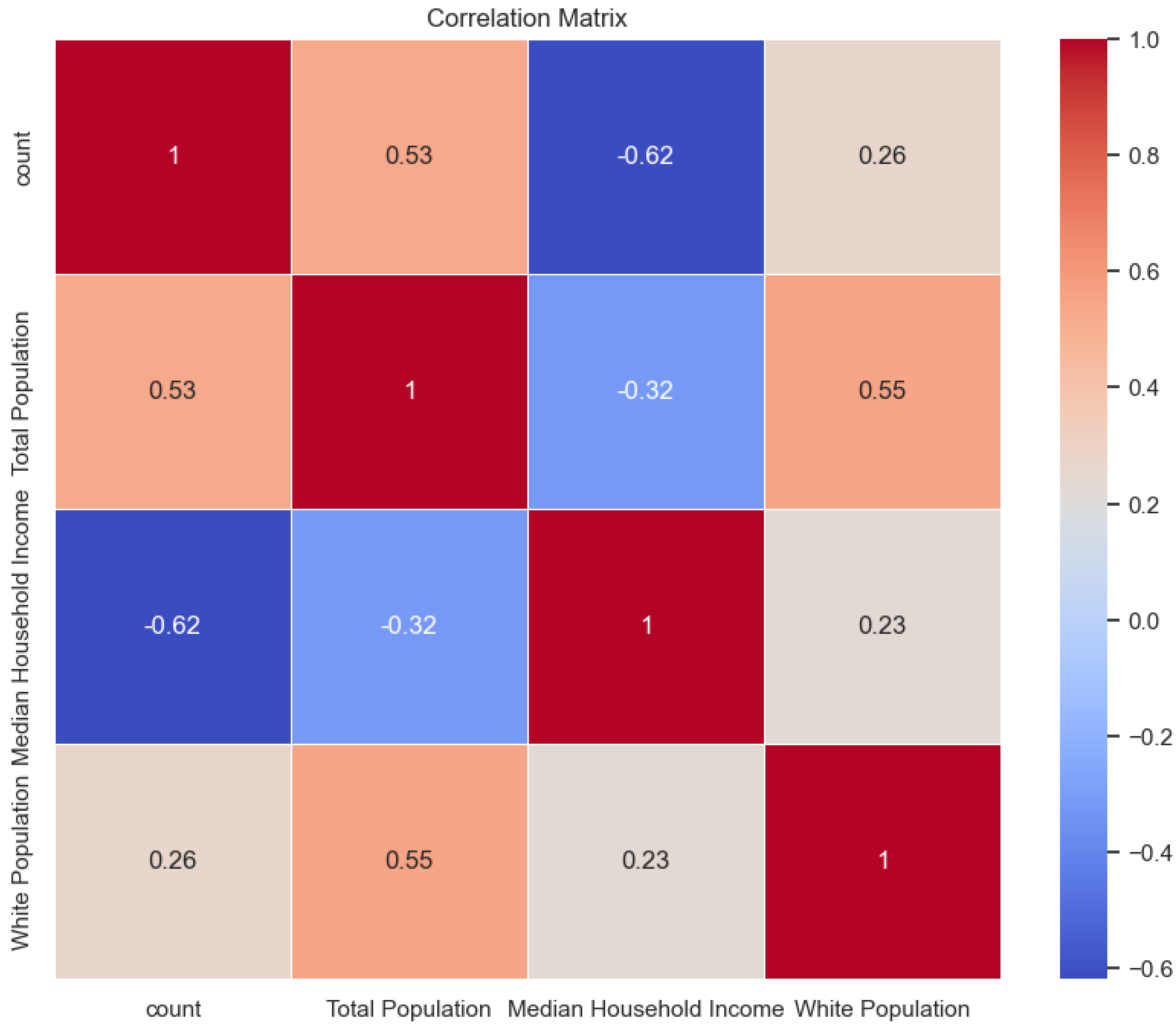
In [ ]:

```
# Scatter plots for individual relationships
plt.figure(figsize=(16, 5))

plt.subplot(1, 3, 1)
sns.scatterplot(data=by_zip_all, x='Total Population', y='count')
plt.title('Total Population vs Violation Count')

plt.subplot(1, 3, 2)
sns.scatterplot(data=by_zip_all, x='Median Household Income', y='count')
plt.title('Median Income vs Violation Count')

plt.subplot(1, 3, 3)
sns.scatterplot(data=by_zip_all, x='White Population', y='count')
plt.title('White Population vs Violation Count')

plt.tight_layout()
plt.show()
```



Looking further, we can obtain the correlation between all variables:

In [ ]:
```
correlation_matrix = by_zip_all[['count', 'Total Population', \
                                  'Median Household Income', 'White Population']].corr()

# heatmap of the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
count
Total Population
Median Household Income
White Population
1
0.53
-0.62
0.26
0.53
1
-0.32
0.55
-0.62
-0.32
1
0.23
0.26
0.55
0.23
1
count
Total Population
Median Household Income
White Population
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

Most notably, there is a decent negative correlation between median income and code violations. Otherwise, our demographic variables prove to have week realtionships to the amount of code violations. Now, let's look at the most common violation type for each zipcode.

In [ ]:
```
by_zip_type_income = code_violations.groupby(['complaint_zip', \
    'Median Household Income', 'violation name']).size().reset_index(name='count')

# Find the most common violation for each combination of 'zipcode' and 'median_income'
most_common_violations = by_zip_type_income.sort_values('count', \
    ascending=False).drop_duplicates(['complaint_zip', 'Median Household Income'])
most_common_violations
```

Out[ ]:

	complaint_zip	Median Household Income	violation name	count
1211	13205	32579	Overgrowth	2610
856	13204	34856	Overgrowth	2037
1999	13208	38475	Overgrowth	1457
464	13203	38018	Overgrowth	1248
2371	13210	31319	SPCC-Sec. 27-133 Registration	778
1496	13206	43674	Overgrowth	715
1709	13207	53012	Overgrowth	710
2648	13224	62485	Overgrowth	260
128	13202	20196	Maintenance of required safeguards	181
2485	13214	74098	Overgrowth	19
2509	13215	92575	Overgrowth	11
2518	13219	66866	SPCC-Sec. 27-133 Registration	1

Overwhelmingly, the top violation among all zipcodes is overgrowth. However, maintenance of required safeguards is a standout -- it was not in our top violations overall, and it is only the top violation for 13202. Here are the specifics of the violation:

Source: https://up.codes/s/maintenance-of-required-safeguards

"Where any device, equipment, system, condition, arrangement, level of protection, or any other feature is required for compliance with the provisions of the Fire Code, or otherwise installed, such device, equipment, system, condition, arrangement, level of protection, or other feature shall thereafter be continuously maintained in accordance with the 2015 IFC, the 2015 IPMC, and applicable referenced standards."

This also happens to be the zipcode with the smallest median household income by far, indicating that there is a potential that the popularity of this violation may be related to the affordability (or lack thereof) of maintiaining their systems in accordance with the Fire Code.

Additionally, Syracuse University is located within 13210, so it is interesting that it is one of the two zipcodes with registration issues. As discussed earlier, the violation specfically deals with rental properties, so it actually makes a lot of sense that the zipcode mostly containing college students has a rental-related violation as its most popular.

Step 4. Conclusions and Discussion

Here are the key takeaways from our analysis:

- Total violation records among neighborhoods are different, but most frequent seen violation types are similar
- "Owners" associated with the highest count of violation records are mostly companies. Local owners have lower per capita violation counts compared with non-local owners
- Constraint by the date range of this dataset, the influence of Covid-19 on code violations is hard to tell
- Changes in violations over time are primarily influenced by time of year
- There appears to be some connection between income and type/amount of violations