Importing City of Buffalo 311 Calls

```
import pandas as pd

df = pd.read_csv("https://data.buffalony.gov/resource/whkc-e5vr.csv")
pd.set_option('display.max_columns', None)
df.head()
```

| | case_reference | open_date | closed_date | status | subject | reason | type | object_type | address_number | address_line_1 | address_line_2 | city | state | zip_code | property_id | location | latitude | longitude | council_distri |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 514722 | 2010-07-19T12:06:00.000 | 2010-07-19T14:15:00.000 | Closed | Dept of Public Works | Streets | Sweeper (Req_Serv) | Street | NaN | RAMONA | NaN | Buffalo | NY | UNKNOWN | NaN | NaN | NaN | NaN | UNKNOW |
| **1** | 1000802971 | 2018-02-12T06:47:00.000 | 2018-02-12T10:33:00.000 | Closed | Buffalo Police Department | Police | Police Issue (Req_Serv) | Street | NaN | Brinkman Ave | NaN | Buffalo | NY | UNKNOWN | NaN | NaN | NaN | NaN | UNKNOW |
| **2** | 541218 | 2011-01-11T09:12:00.000 | 2011-01-26T10:01:00.000 | Closed | Utilities | National Grid | Streetlights (Req_Serv) | Street | NaN | CLIFF | NaN | Buffalo | NY | UNKNOWN | NaN | NaN | NaN | NaN | UNKNOW |
| **3** | 1000708750 | 2017-07-10T11:36:00.000 | 2017-07-10T14:27:00.000 | Closed | Dept of Public Works | Streets | Sweeper (Req_Serv) | Street | NaN | SPRING | NaN | Buffalo | NY | UNKNOWN | NaN | NaN | NaN | NaN | UNKNOW |
| **4** | 1000892866 | 2018-08-18T15:44:00.000 | 2018-08-20T22:00:00.000 | Closed | Dept of Public Works | Forestry | Tree Planting Request (Req_Serv) | Property | NaN | NaN | NaN | Buffalo | NY | UNKNOWN | NaN | NaN | NaN | NaN | UNKNOW |

```
df['open_date'] = pd.to_datetime(df['open_date'])
df['closed_date'] = pd.to_datetime(df['closed_date'])
df.dtypes
```

```
case_reference                    int64
open_date                datetime64[ns]
closed_date              datetime64[ns]
status                           object
subject                          object
reason                           object
type                             object
object_type                      object
address_number                  float64
address_line_1                   object
address_line_2                  float64
city                             object
state                            object
zip_code                         object
property_id                      object
location                         object
latitude                        float64
longitude                       float64
council_district                 object
council_district_2011            object
police_district                  object
census_tract                     object
census_block_group               object
census_block                     object
neighborhood                     object
x_coordinate                    float64
y_coordinate                    float64
census_tract_2010                object
census_block_group_2010          object
census_block_2010                object
tractce20                        object
geoid20_tract                    object
geoid20_blockgroup               object
geoid20_block                    object
dtype: object
```

## Question:

It looks like status, subject, reason, type and object type might be interesting categorical variables

- Which of these can be described by a limited number of categories?
- Which are not described easily as a limited number of outcomes?

```
object_columns = df.select_dtypes(include=['object']).columns
df[object_columns].describe().T
```

| | count | unique | top | freq |
|---|---|---|---|---|
| **status** | 1000 | 2 | Closed | 997 |
| **subject** | 1000 | 9 | DPIS | 631 |
| **reason** | 1000 | 17 | Housing | 631 |
| **type** | 1000 | 51 | Housing Violations (Req_Serv) | 608 |
| **object_type** | 1000 | 3 | Property | 777 |
| **address_line_1** | 952 | 470 | HOPKINS | 26 |
| **city** | 1000 | 1 | Buffalo | 1000 |
| **state** | 1000 | 2 | NY | 984 |
| **zip_code** | 1000 | 19 | UNKNOWN | 233 |
| **property_id** | 764 | 726 | 112.50-2-17 | 3 |
| **location** | 767 | 719 | 42 856463120634494\n, | 9 |
| **council_district** | 1000 | 1 | UNKNOWN | 1000 |
| **council_district_2011** | 1000 | 10 | UNKNOWN | 233 |
| **police_district** | 1000 | 6 | District A | 280 |
| **census_tract** | 1000 | 78 | UNKNOWN | 233 |
| **census_block_group** | 1000 | 7 | UNKNOWN | 233 |
| **census_block** | 1000 | 93 | UNKNOWN | 233 |
| **neighborhood** | 1000 | 35 | UNKNOWN | 233 |
| **census_tract_2010** | 1000 | 70 | UNKNOWN | 233 |
| **census_block_group_2010** | 1000 | 7 | UNKNOWN | 233 |
| **census_block_2010** | 1000 | 105 | UNKNOWN | 233 |
| **tractce20** | 1000 | 77 | UNKNOWN | 353 |
| **geoid20_tract** | 1000 | 77 | UNKNOWN | 353 |
| **geoid20_blockgroup** | 1000 | 197 | UNKNOWN | 353 |
| **geoid20_block** | 1000 | 451 | UNKNOWN | 353 |

Answer:

- The best limited number categories to work with is status, subject, reason, and object
- Type made it difficult to work with its 51 unique values

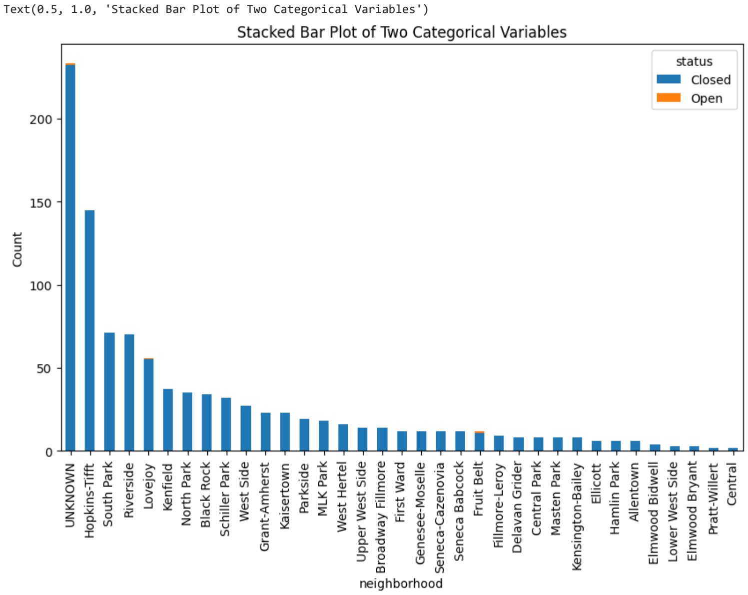
## Task:

Figure out which of the outcomes fit into a limited number of categories, and then produce some graphs explaining how they are related to council district, police district, neighborhood.

This graph did appear more detailed with more values data in the open status. However they updated api at the end of the day and a lot of the open status where changed to closed.

```
import matplotlib.pyplot as plt

grouped_data = df.groupby(['neighborhood', 'status']).size().unstack(fill_value=0)
grouped_data = grouped_data.loc[grouped_data.sum(axis=1).sort_values(ascending=False).index]
grouped_data.plot(kind='bar', stacked=True, figsize=(10, 6))

plt.xlabel('neighborhood')
plt.ylabel('Count')
plt.title('Stacked Bar Plot')
```

```
Text(0.5, 1.0, 'Stacked Bar Plot of Two Categorical Variables')
```

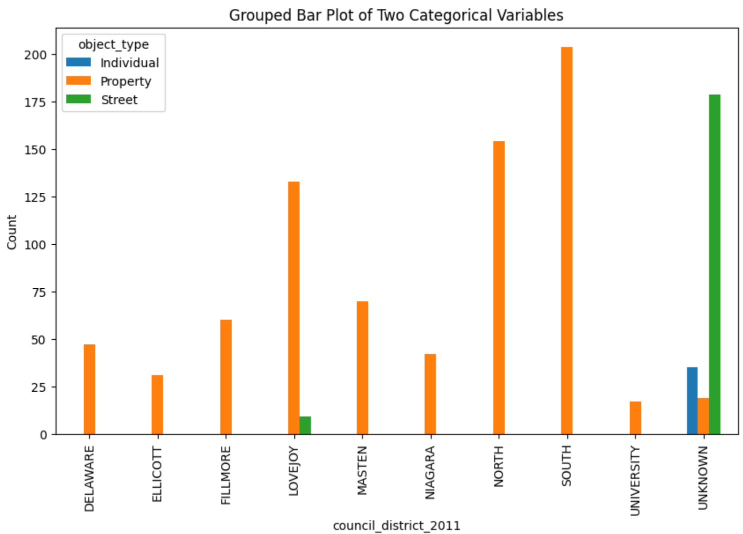



The graph displays the reputation of each neighborhood, depicting the total number of 311 phone calls aggregated as a stacked data plot, showing the status of closed and open cases. From this graph, we can infer that Hopkins-Tiff, South Park, and Riverside are the top three neighborhoods with the highest number of 311 calls.

```
import seaborn as sns

cross_tab = pd.crosstab(df['subject'], df['police_district'])

# Create a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(cross_tab, annot=True, cmap='viridis', fmt='d')
plt.title('Heatmap')
plt.xlabel('police_district')
plt.ylabel('subject')
plt.show()
```

This heat map indicates that among the police districts, District A and District D receive the highest number of 311 calls. Specifically, it highlights that the highest subject type and district combination is DPIS in District A, followed by DPIS in District D.

```
grouped_data = df.groupby(['council_district_2011', 'object_type']).size().unstack(fill_value=0)

grouped_data.plot(kind='bar', figsize=(10, 6))

plt.xlabel('council_district_2011')
plt.ylabel('Count')
plt.title('Grouped Bar Plot')
plt.legend(title='object_type')
plt.show()
```



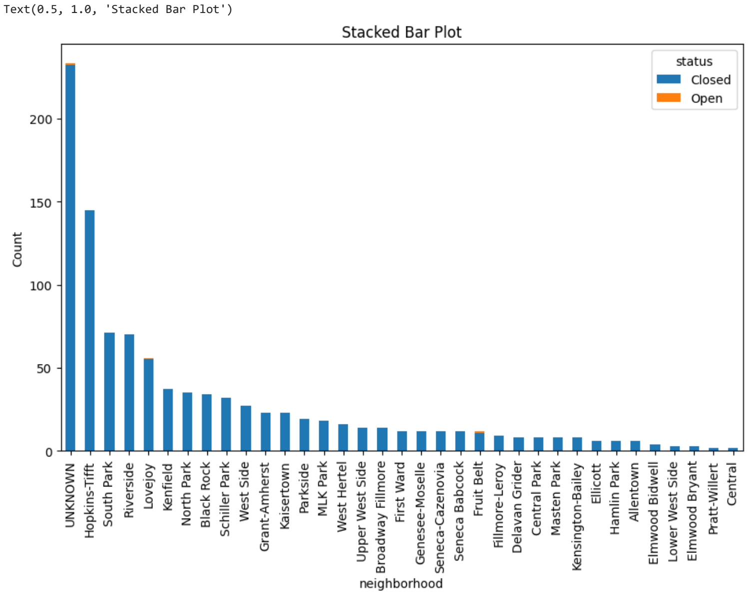

This grouped bar plot illustrates that most 311 phone calls with object types "individual" or "property" are categorized in the council district as "unknown", except for some values in Lovejoy. Additionally, the object type "properties" barely constitute the majority of the council districts, with very few of them classified as "unknown". In conclusion, this indicates that the majority of calls regarding are "individual" and "street" object types are labeled as unknown, while "property" object types are asummed to be correctly classified within the council district.

## Question:

- Do different districts and/or neighborhoods tend to different numbers of 311 calls?

```
grouped_data = df.groupby(['neighborhood', 'status']).size().unstack(fill_value=0)
grouped_data = grouped_data.loc[grouped_data.sum(axis=1).sort_values(ascending=False).index]
grouped_data.plot(kind='bar', stacked=True, figsize=(10, 6))

plt.xlabel('neighborhood')
plt.ylabel('Count')
plt.title('Stacked Bar Plot')
```

```
Text(0.5, 1.0, 'Stacked Bar Plot')
```




## Answer:

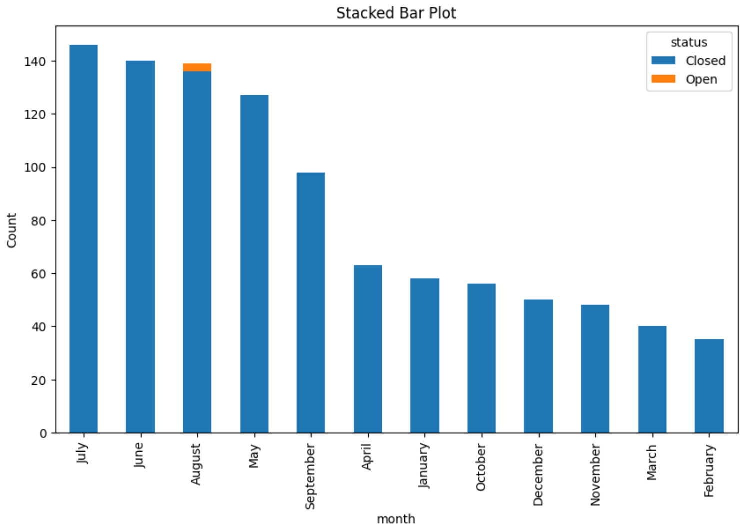
- It appears that Hopkins-Tifft, South Park, and Riverside have the highest number of 311 calls on aggerate

## Question:

- Do different months have different number of 311 reports?
- What about different years?

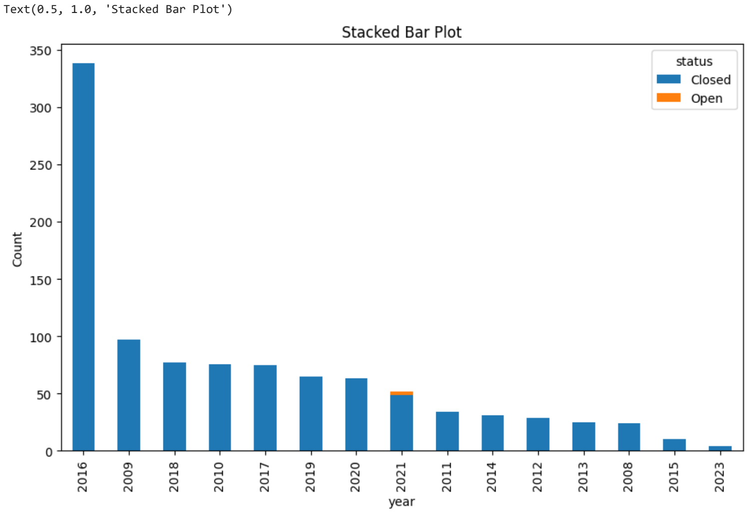
```python
df['month'] = df['open_date'].dt.month_name()

grouped_data = df.groupby(['month', 'status']).size().unstack(fill_value=0)
grouped_data = grouped_data.loc[grouped_data.sum(axis=1).sort_values(ascending=False).index]
grouped_data.plot(kind='bar', stacked=True, figsize=(10, 6))

plt.xlabel('month')
plt.ylabel('Count')
plt.title('Stacked Bar Plot')
```

```
Text(0.5, 1.0, 'Stacked Bar Plot')
```




```python
df['year'] = df['open_date'].dt.year

grouped_data = df.groupby(['year', 'status']).size().unstack(fill_value=0)
grouped_data = grouped_data.loc[grouped_data.sum(axis=1).sort_values(ascending=False).index]
grouped_data.plot(kind='bar', stacked=True, figsize=(10, 6))

plt.xlabel('year')
plt.ylabel('Count')
plt.title('Stacked Bar Plot')
```

```
Text(0.5, 1.0, 'Stacked Bar Plot')
```




Answer:

- It appears that the busiest months for 311 calls are July, followed by June, August, and May.
- It appears that the busiest years for 311 calls were 2016, 2009