

Management of Scientific Data

Exam Project: 311 Service Requests in New York City

Exam Project

Structure

1. Data Management Plan
2. The Dataset: 311 Service Requests in New York City
3. Socrata Open Data API (SODA)
4. Data Quality Control
5. Data Analysis
6. Preserving and publishing

Data Management Plan

Creation of the Data Management plan

- The wizard by CLARIN-D (<https://www.clarin-d.net/de/aufbereiten/datenmanagementplan-entwickeln>) was used as a guide for which fields should be included
 - Not all fields were applicable since this is a small project
 - Some fields were added or re-ordered to better accomodate this project

Data Management Plan

Structure

- Project Information
- Research Data Information
- Documentation
- Storage and Backup
- Data sharing
- Licensing

Project Information

Project Supervisor

John Wigg

Institution

Friedrich Schiller University Jena

Context

Exam project for the course Management of Scientific Data

Research Question

"What is the influence of national holidays on 311 Service Requests?"

Research Data Information

Produced data

Description

- Python Jupyter Notebook (.ipynb) used for this DMP as well as to access, analyze and visualise data
- PDF version of the notebook (.pdf)

Data formats

- `.ipynb` - Python Jupyter Notebooks
- `.pdf` - Portable Document Format

Pre-existing data

Sources

- *311 Service Requests from 2010 to Present*
- provided by the City of New York Department of Technology and Telecommunications (DoITT)
- accessible at the NYC OpenData portal:
<https://data.cityofnewyork.us/Social-Services/311-Service-Requests-from-2010-to-Present/erm2-nwe9>
- the data was accessed via the Socrata Open Data API (SODA)

Reusability for other researchers

- data will stay freely available at <https://data.cityofnewyork.us/Social-Services/311-Service-Requests-from-2010-to-Present/erm2-nwe9>

Creation of derived works

- FAQ states that there are no restrictions on how the data can be used: <https://opendata.cityofnewyork.us/faq/>
- terms of use are not clear about this

Relationship between produced and pre-existing data

- generated data are filtering, analysis and visualization scripts applied to the pre-existing data.

Documentation

- use Jupyter (<https://jupyter.org>) or any other compatible software to access notebooks
- Python 3.7.4
- in the notebooks, the following Python libraries were used:
 - matplotlib 3.2.1, pandas 1.0.1, numpy 1.18.1, sodapy 2.1.0

Storage and Backup

- generated data is kept in a public GitHub repository:
<https://github.com/john-wigg/mosd-exam>
- data can be read by everyone, write access is restricted by GitHub's internal access management

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Data Sharing

- the complete generated project data is freely available at
<https://github.com/john-wigg/mosd-exam>

Licensing

- produced data is licensed under the MIT license, a very permissive license

The Dataset

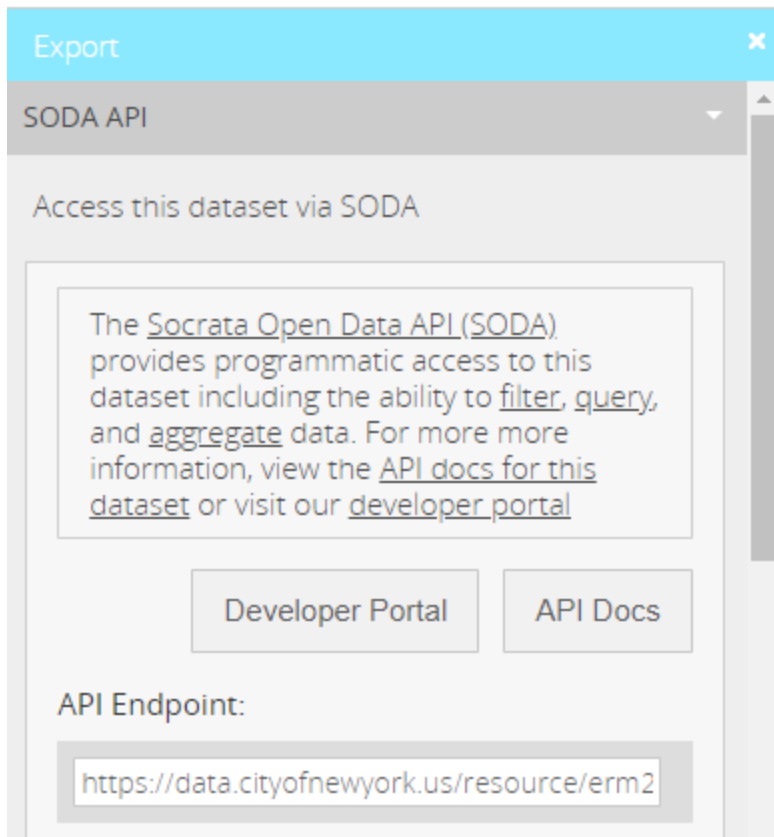
311 Service Requests in New York City from 2010 to present

Problem: Size of the Dataset

- the dataset is *very* large
 - ~ 12 GB as .csv download
 - data is updated daily
- loading whole dataset at once not a good idea
- Is there a way to filter relevant data without downloading the whole set?
 - **Socrata Open Data API (SODA)**

Socrata Open Data API (SODA)

The Socrata Open Data API (SODA) provides programmatic access to this dataset including the ability to filter, query, and aggregate data.



sodapy

- `sodapy` provides Python bindings of the API.

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```
In [1]: from sodapy import Socrata
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```
In [1]: from sodapy import Socrata
```

Each Socrata dataset is hosted on a domain and has an identifier:

```
In [2]: socrata_domain = 'data.cityofnewyork.us'  
socrata_dataset_identifier = 'erm2-nwe9'
```

Optionally, an application token can be generated by registering at <https://opendata.socrata.com/>.

This removes data limits:

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This removes data limits:

```
In [3]: with open("application.token", "r") as f:
        socrata_token = f.read()
```

Create a `client` that can be used to access the data:

Create a `client` that can be used to access the data:

```
In [4]: client = Socrata(socrata_domain, socrata_token)
print("Domain: {domain:}\nSession: {session:}\nURI Prefix: {uri_prefix:}".format(**
```

```
Domain: data.cityofnewyork.us
```

```
Session: <requests.sessions.Session object at 0x00000202C6C8AF08>
```

```
URI Prefix: https://
```

We can now use SoQL clauses (<https://dev.socrata.com/docs/queries/>) to query and filter the data "over the air".

Example: Calls that were created on January 10th 2015 between 12 AM and 2 PM:

We can now use SoQL clauses (<https://dev.socrata.com/docs/queries/>) to query and filter the data "over the air".

Example: Calls that were created on January 10th 2015 between 12 AM and 2 PM:

```
In [5]: import pandas as pd
```

We can now use SoQL clauses (<https://dev.socrata.com/docs/queries/>) to query and filter the data "over the air".

Example: Calls that were created on January 10th 2015 between 12 AM and 2 PM:

```
In [5]: import pandas as pd
```

```
In [6]: results = client.get(socrata_dataset_identifier, where = "created_date between '2015-01-10T12:00:00' and '2015-01-10T14:00:00'")
df = pd.DataFrame.from_dict(results)
```

In [7]: `df.head()`

Out [7]:

	unique_key	created_date	closed_date	agency	agency_name	complaint_type	descriptor	location
0	29690137	2015-01-10T12:00:00.000	2015-01-10T12:00:00.000	DSNY	BCC - Brooklyn South	Derelict Vehicles	14 Derelict Vehicles	Street
1	29689451	2015-01-10T12:00:00.000	2015-01-12T10:13:00.000	DOT	Department of Transportation	Street Light Condition	Street Light Out	NaN
2	29691167	2015-01-10T12:00:03.000	2015-01-16T05:27:49.000	DOT	Department of Transportation	Broken Muni Meter	Coin or Card Did Not Register	Street
3	29686604	2015-01-10T12:00:06.000	2015-01-10T15:50:40.000	NYPD	New York City Police Department	Noise - Residential	Banging/Pounding	Residential Building
4	29685180	2015-01-10T12:00:30.000	2015-02-20T19:33:19.000	DOT	Department of Transportation	Highway Condition	Graffiti - Highway	Highway

5 rows × 38 columns

Retreive metadata and data properties with SODA

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Socrata also allows access to metadata:

Retreive metadata and data properties with SODA

Socrata also allows access to metadata:

```
In [8]: md = client.get_metadata(socrata_dataset_identifier)
md.keys()
```

```
Out[8]: dict_keys(['id', 'name', 'attribution', 'averageRating', 'category', 'createdA
t', 'description', 'displayType', 'downloadCount', 'hideFromCatalog', 'hideFrom
DataJson', 'indexUpdatedAt', 'newBackend', 'numberOfComments', 'oid', 'provenan
ce', 'publicationAppendEnabled', 'publicationDate', 'publicationGroup', 'public
ationStage', 'rowClass', 'rowIdentifierColumnId', 'rowsUpdatedAt', 'rowsUpdated
By', 'tableId', 'totalTimesRated', 'viewCount', 'viewLastModified', 'viewType',
'approvals', 'columns', 'grants', 'metadata', 'owner', 'query', 'rights', 'tabl
eAuthor', 'tags', 'flags'])
```


The metadata contains e.g. information about the columns:

The metadata contains e.g. information about the columns:

```
In [9]: print("Number of columns: ", len(md["columns"]))
print("-----")
for d in md["columns"][:5]:
    print(d["fieldName"], end="")
    if ("description" in d):
        print(": " + d["description"], end="")
    else:
        print(": NO DESCRIPTION")
```

Number of columns: 46

unique_key: Unique identifier of a Service Request (SR) in the open data set

created_date: Date SR was created

closed_date: Date SR was closed by responding agency

agency: Acronym of responding City Government Agency

agency_name: Full Agency name of responding City Government Agency

We can also use SODA to count the rows of the dataset without downloading it:

We can also use SODA to count the rows of the dataset without downloading it:

```
In [10]: client.get(socrata_dataset_identifier, select="count(*)")
```

```
Out[10]: [{'count': '23501686'}]
```

Data Quality Control

Data Quality Control

NOTE: This data does not present a full picture of 311 calls or service requests, in part because of operational and system complexities associated with remote call taking necessitated by the unprecedented volume 311 is handling during the Covid-19 crisis. The City is working to address this issue. (Source: <https://data.cityofnewyork.us/Social-Services/311-Service-Requests-from-2010-to-Present/erm2-nwe9>)

→ we should avoid data from 2020

Quality Control using SODA

Quality Control using SODA

- use the metadata to start with quality control
- e.g. find columns with missing descriptions

```
In [11]: print("Columns with missing descriptions:")
         for d in md["columns"]:
             if ("description" not in d):
                 print("{} ({{}}) with data type {}".format(d["fieldName"], d["name"], d["data"])
```

```
Columns with missing descriptions:
:@computed_region_efsh_h5xi (Zip Codes) with data type number.
:@computed_region_f5dn_yrer (Community Districts) with data type number.
:@computed_region_yeji_bk3q (Borough Boundaries) with data type number.
:@computed_region_92fq_4b7q (City Council Districts) with data type number.
:@computed_region_sbqj_enih (Police Precincts) with data type number.
```


- we can still retrieve the fields `name` and `dataTypeName` to get a better idea
 - field name seems to indicate special or computed fields
- Looking at specific entries may give more clues.

→ **Fields do not seem relevant to the research question.**

Since the data set should contain only records since 2010, we can also check for invalid or missing creation dates:

Since the data set should contain only records since 2010, we can also check for invalid or missing creation dates:

```
In [12]: results = client.get(socrata_dataset_identifier, where = "created_date < '2010-01-01'")
         results
```

```
Out[12]: []
```

Since the data set should contain only records since 2010, we can also check for invalid or missing creation dates:

```
In [12]: results = client.get(socrata_dataset_identifier, where = "created_date < '2010-01-01'")
         results
```

```
Out[12]: []
```

In this case, all entries seem to have a valid date associated.

Retreiving the relevant Data using SODA

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- download only the interesting part of the data

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What is the influence of national holidays on 311 Service Requests?

Example: Independence Day 2019

Retreiving the relevant Data using SODA

- download only the interesting part of the data

What is the influence of national holidays on 311 Service Requests?

Example: Independence Day 2019

- retrieve data around July 4th 2019.

```
In [13]: results = client.get(socrata_dataset_idenfier, limit=500000, where = "created_date >= '2019-07-01'")
df = pd.DataFrame.from_dict(results)
```



```
In [14]: df.head()
```

```
Out[14]:
```

	unique_key	created_date	closed_date	agency	agency_name	complaint_type	descriptor	cross_street_1
0	43022702	2019-06-20T00:00:00.000	2019-06-24T11:20:00.000	DOT	Department of Transportation	Traffic Signal Condition	LED Lense	LINDEN BLVD
1	43032740	2019-06-20T00:00:00.000	2019-07-15T00:00:00.000	DOHMH	Department of Health and Mental Hygiene	Standing Water	Sewer or Drain	PRINCE STREET
2	43021298	2019-06-20T00:00:00.000	2019-06-20T00:48:00.000	DOT	Department of Transportation	Traffic Signal Condition	Controller	NaN
3	43024836	2019-06-20T00:00:00.000	2019-07-09T00:00:00.000	DOHMH	Department of Health and Mental Hygiene	Standing Water	Other - Explain Below	FOSTER AVENUE
4	43024837	2019-06-20T00:00:00.000	2019-07-11T00:00:00.000	DOHMH	Department of Health and Mental Hygiene	Standing Water	Other - Explain Below	37 AVENUE

5 rows × 41 columns

```
In [15]: df.shape
```

```
Out[15]: (192190, 41)
```

```
In [15]: df.shape
```

```
Out[15]: (192190, 41)
```

The dataset is still very large, but manageable!

Quality Control using Pandas

Quality Control using Pandas

- do "local" quality control on the smaller dataset

Plot a matrix highlighting all missing values (yellow are missing):

Quality Control using Pandas

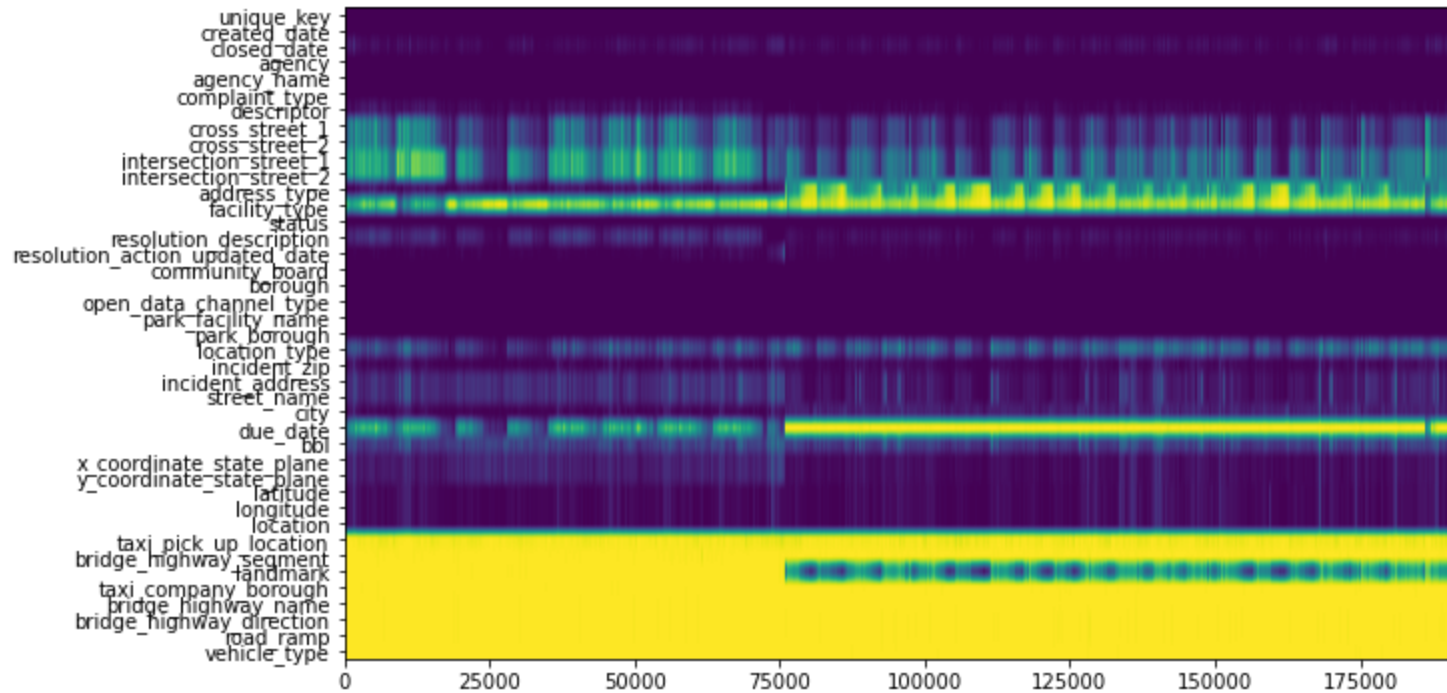
- do "local" quality control on the smaller dataset

Plot a matrix highlighting all missing values (yellow are missing):

```
In [16]: %%capture
import numpy as np
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(10, 6));
ax = plt.gca();
ax.imshow(np.array(df.isna()).transpose(), aspect='auto');
ax.set_yticks((range(0, len(df.columns))));
ax.set_yticklabels(df.columns);
```

```
In [17]: fig
```

```
Out[17]:
```



- some `closed_date` seem to be missing
- it is hard to see but `descriptor` also has some missing values
- other fields may be specific to certain complaint types

- use pandas to gather which types of complaints were made
how often

- use pandas to gather which types of complaints where made how often

```
In [18]: values = df["complaint_type"].value_counts()  
         len(values.keys())
```

```
Out[18]: 196
```

- use pandas to gather which types of complaints where made how often

```
In [18]: values = df["complaint_type"].value_counts()  
         len(values.keys())
```

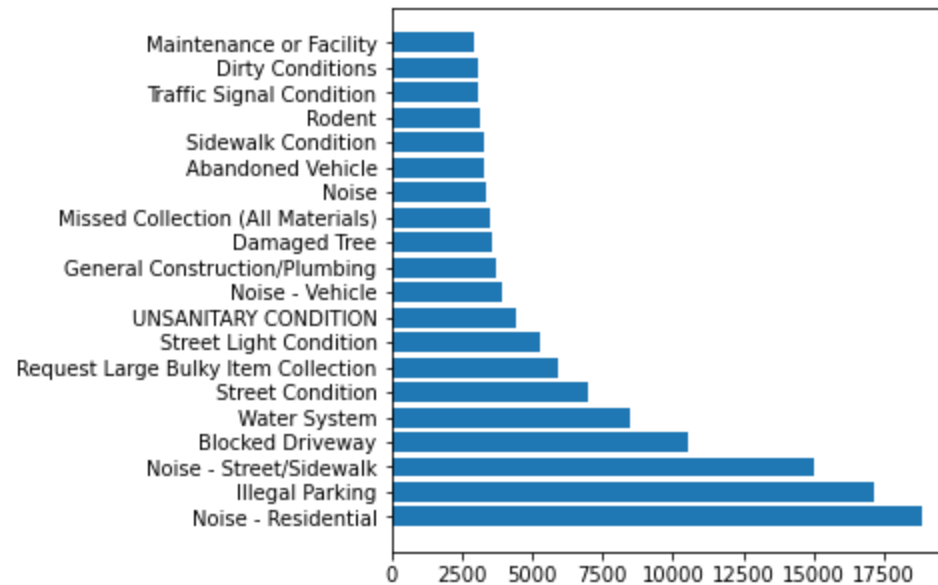
```
Out[18]: 196
```

We can see that there are 196 types of complaints hat occurred in the time period.

- list the 20 most common complaint types:

- list the 20 most common complaint types:

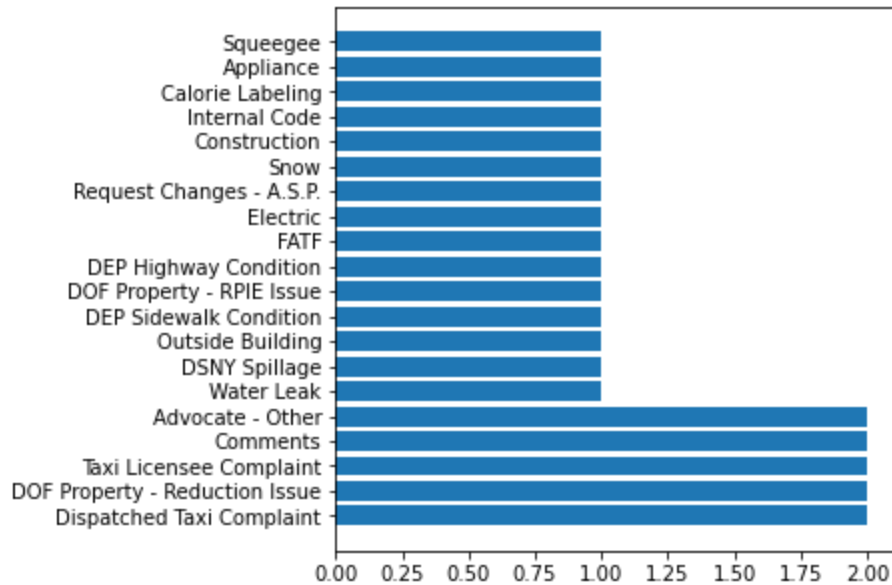
```
In [19]: plt.figure(figsize=(5, 5))  
plt.barh(values.keys()[:20], values[:20]);
```



- rare complaint types may reveal erroneous entries

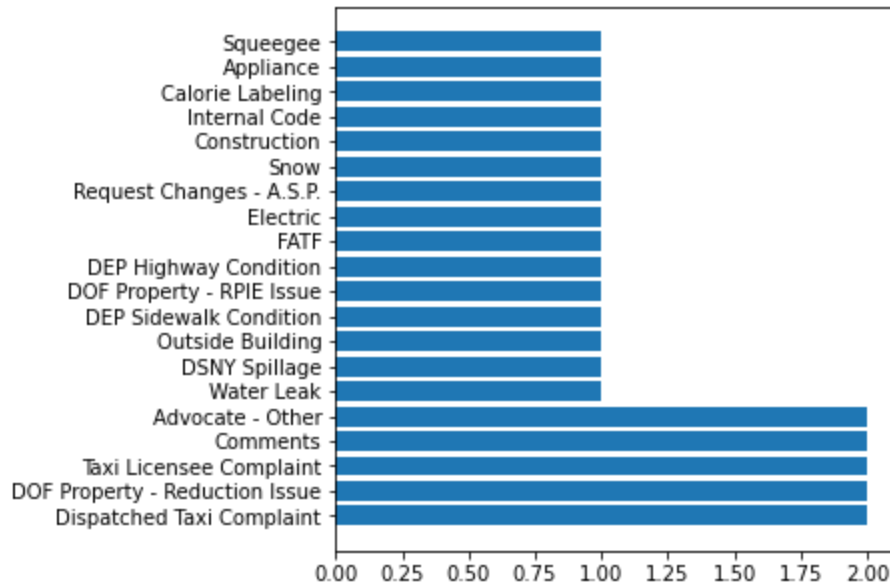
- rare complaint types may reveal erroneous entries

```
In [20]: plt.figure(figsize=(5, 5))  
plt.barh(values.keys()[-20:], values[-20:]);
```



- rare complaint types may reveal erroneous entries

```
In [20]: plt.figure(figsize=(5, 5))  
plt.barh(values.keys()[-20:], values[-20:]);
```



- in this case, all entries seem to be reasonable
- clustering is the proper way to do this

Data Analysis

Data Analysis

What is the influence of national holidays on 311 Service Requests?

Example: Independence Day 2019

- Is there a spike in overall complaints?

- Is there a spike in overall complaints?
- convert the `created_date` column to pandas dates first

```
In [21]: df["created_date_format"] = pd.to_datetime(df["created_date"])
```

- Is there a spike in overall complaints?
- convert the `created_date` column to pandas dates first

```
In [21]: df["created_date_format"] = pd.to_datetime(df["created_date"])
```

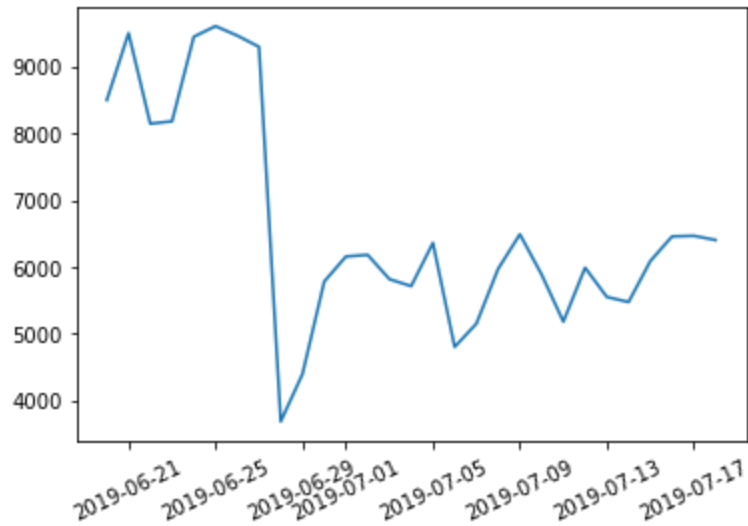
- resample and count the complaints per day

```
In [22]: df_grouped = df.resample('D', on='created_date_format').count()
```

- plot the total number of complaints per day

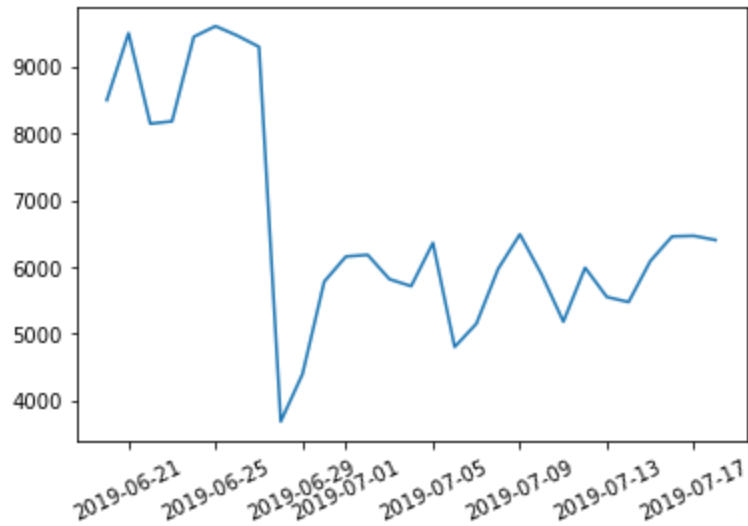
- plot the total number of complaints per day

```
In [23]: plt.plot(df_grouped.index, df_grouped["unique_key"]);  
plt.xticks(rotation=25);
```



- plot the total number of complaints per day

```
In [23]: plt.plot(df_grouped.index, df_grouped["unique_key"]);  
plt.xticks(rotation=25);
```



- look at more specific complaint types
- noise complaints might be interesting

```
In [24]: import re
df["complaint_type"].value_counts()[df["complaint_type"].value_counts().keys().str.
```

```
Out[24]: Noise - Residential      18874
Noise - Street/Sidewalk      14985
Noise - Vehicle              3947
Noise                        3375
Noise - Commercial          2736
Noise - Park                 659
Noise - Helicopter           146
Noise - House of Worship      64
Name: complaint_type, dtype: int64
```


- There is also a complaint type especially for illegal fireworks

- There is also a complaint type especially for illegal fireworks

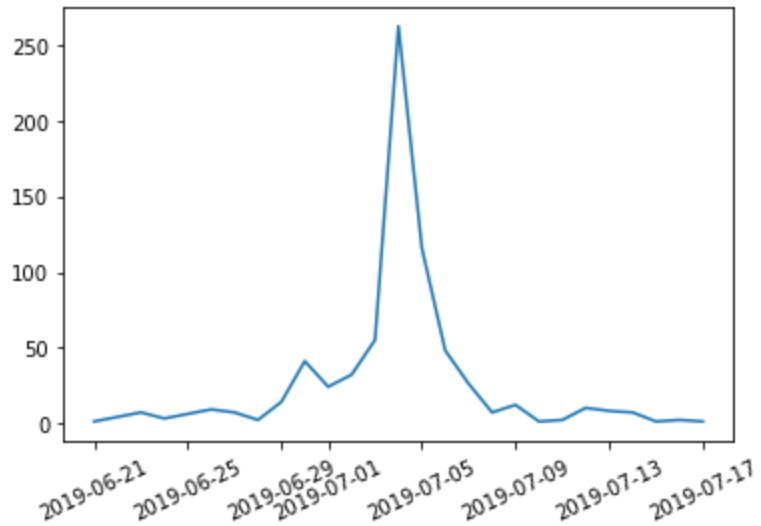
```
In [25]: df["complaint_type"].value_counts()[df["complaint_type"].value_counts().keys().str.
```

```
Out[25]: Illegal Fireworks      709  
         Name: complaint_type, dtype: int64
```

- plot the number of illegal firework complaints per day

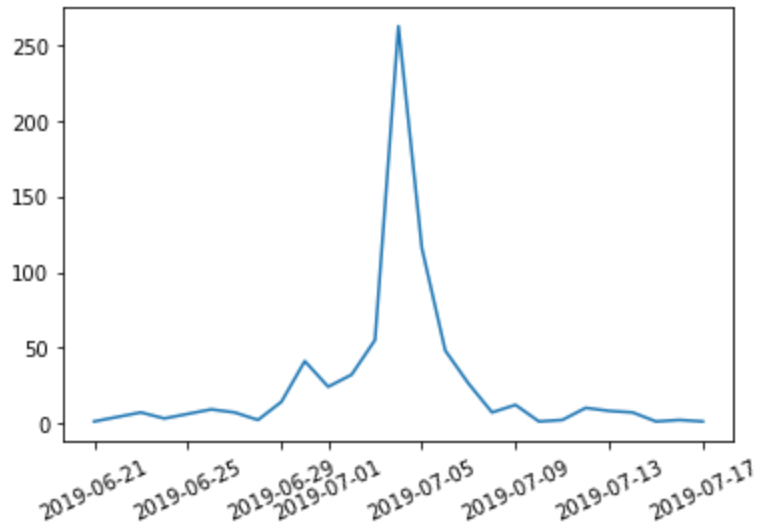
- plot the number of illegal firework complaints per day

```
In [26]: df_fireworks_grouped = df[df["complaint_type"] == "Illegal Fireworks"].resample('D')  
plt.plot(df_fireworks_grouped.index, df_fireworks_grouped["unique_key"]);  
plt.xticks(rotation=25);
```



- plot the number of illegal firework complaints per day

```
In [26]: df_fireworks_grouped = df[df["complaint_type"] == "Illegal Fireworks"].resample('D')  
plt.plot(df_fireworks_grouped.index, df_fireworks_grouped["unique_key"]);  
plt.xticks(rotation=25);
```



- large uptick on July 4th
- almost no complaints otherwise

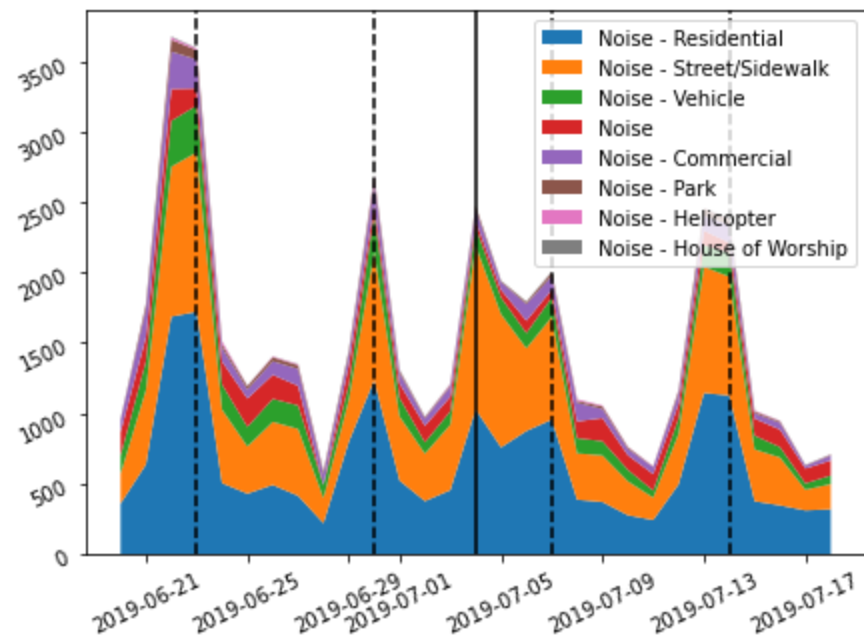
- stackplot of all noise complaints by type

- stackplot of all noise complaints by type

```
In [27]: %%capture
keys = df["complaint_type"].value_counts()[df["complaint_type"].value_counts().keys
s = pd.Series(index=df_grouped.index, dtype='int')
noise_counts = []
for key in keys:
    noise_counts.append(s.add(df[df["complaint_type"] == key].resample('D', on='cre
fig = plt.figure(figsize=(7, 5))
ax = plt.gca()
ax.stackplot(df_grouped.index, noise_counts);
ax.tick_params(rotation=25);
ax.legend(keys);
ax.axvline(pd.to_datetime('2019-06-23'), color='black', linestyle='dashed');
ax.axvline(pd.to_datetime('2019-06-30'), color='black', linestyle='dashed');
ax.axvline(pd.to_datetime('2019-07-07'), color='black', linestyle='dashed');
ax.axvline(pd.to_datetime('2019-07-14'), color='black', linestyle='dashed');
ax.axvline(pd.to_datetime('2019-07-04'), color='black');
```

```
In [28]: fig
```

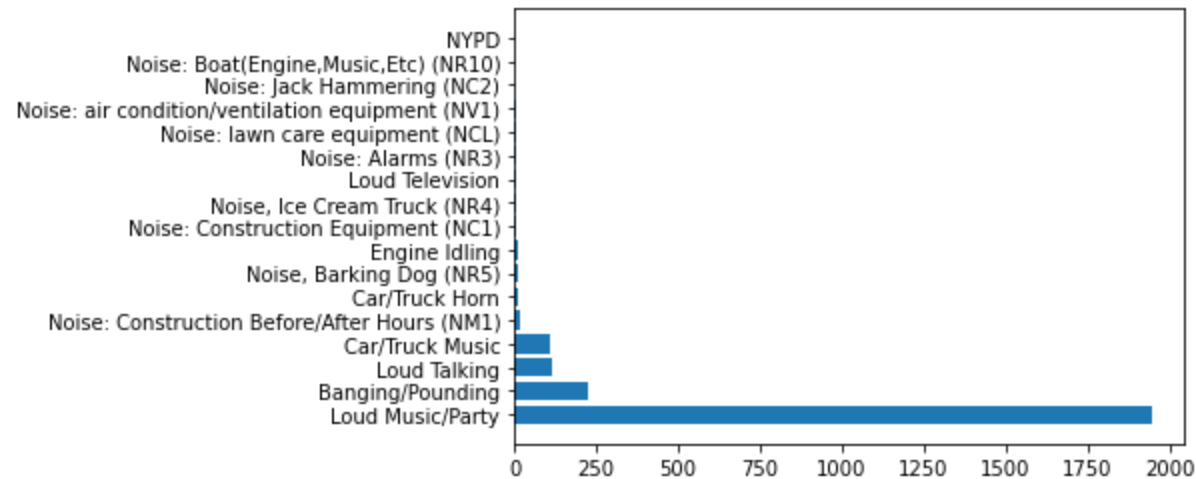
Out[28]:



- decode noise complaints by type

- decode noise complaints by type

```
In [29]: date_selector = (df["created_date_format"] > pd.to_datetime('2019-07-04T00:00:00'))
counts = df[df["complaint_type"].str.contains("Noise") & date_selector]["descriptor"]
plt.barh(counts.keys(), counts);
```



Preserving and publishing

GitHub repo: <https://github.com/john-wigg/mosd-exam>

- the GitHub repository preserves past versions
- the data is decentralized
- the data can be accessed by everyone
- MIT License allows data to be freely used by other researchers
- for larger projects, publishing the results in a journal may lead to better visibility