NYC Complaints DataSet Analysis

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Abstract: *Launched on March 9, 2003, NYC311 provides services to New York residents - 24 hours a day, 7 days a week in nearly 180 languages. On an average, it receives more than 50,000 calls, texts and emails combined daily. This study explores the relationship amongst different columns, such as complaint types, time to close a complaint, etc and how they are related with borough, time and agency. This study also aims to analyze the 311 complaints dataset and find causations of different anomalies found in data. It has been found that there are a few attributes which are highly correlated (either positively or negatively) with other attributes from supporting datasets.*
A copy of the report is available at:
https://docs.google.com/a/nyu.edu/document/d/1CZEp-McMnW7ZK9JqylFL_TwXBL46ZXatwkkljy86KBY/edit?usp=sharing
The code, results and plots are available on github at:
https://github.com/aparajita2930/NYC_Complaints_Analysis

1. Introduction

Since its launch, NYC311 has received more than 158 million calls and has been a clearinghouse for all things New York City government, providing information on more than 4,000 topics, routing details to the appropriate City agencies and providing customers with service request numbers for use in tracking the progress of their inquiry.

In doing so, vast amount of data is collected, which can be used to drive valuable insights. In this project we summarize the data across all columns. We also work on finding spatio-temporal and temporal relations in the data. With over 15M rows, the distributed framework that Big Data technologies provide prove to be beneficial to analyze the data. We have use the NYU Hadoop cluster to perform all the processing, analysis and aggregating our dataset.

Part - I

2. Data Summary and Quality

The first step that has been performed to set up the data environment for the project was to join the two files - one for the year 2009 and the other for the year 2010-2017 into a single file using the script https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/src/join_csvs.py (Spark). This script saves the single merged file into HDFS.

After going through the 311 dataset for 2009 to 2017 and assigning a base, a semantic, and a validity type we derived a summary of the data. A few of the things that we noted are:

- No Invalid or Null values in two columns: “Created Date” and “Agency”
- Two invalid values in “Unique Key” column - two of the keys could be tagged as invalid as they are duplicates and hence violate the functional dependency requirement
- The column “Resolution Action Updated Date” has the highest number of invalid records with dates lying outside of the range or even dates that are before the created date or after the closed date for the complaint
- Data referring to the same place or thing represented in slightly different ways from each other - eg: lowercase and uppercase, punctuations, etc. - To deal with this issue, the the data in each column has been standardized and dictionaries and lists of the domain of the particular columns have been maintained wherever possible to perform lookups
- A few of the zips are invalid meaning that they are outside of the areas of NYC

The details of each of the 52 columns in the dataset is as below. It shows the number of Valid, Invalid and Null elements in the particular column as well as the number of elements having a particular base data type. The semantic type column below shows the count of each semantic type of elements in a column, separated by ‘|’. Obtaining the below information has been a two step process:

- First, the scripts whose names begin with 1 to 52 in the github repository folder: https://github.com/aparajita2930/NYC_Complaints_Analysis/tree/master/src/column_summary were executed to generate output.
- These outputs were fed to the script https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/src/column_summary/0_column_summary.py to generate the summary.

No.	Column Name	Validity			Datatype				Semantic Type
		VALID	INVALID	NULL	INT	DECIMAL	DATETIME	TEXT	
1	Unique Key	15405235	2	0	15405237	0	0	0	Key:15405237
2	Created Date	15405239	0	0	0	0	15405239	0	Created_Date:15405239
3	Closed Date	9659702	5201708	543829	0	0	14867225	538014	Text:5745537 | Closed_Date:9659702
4	Agency	15405239	0	0	0	0	0	15405239	Agency:15405239
5	Agency Name	15388894	16345	0	0	0	0	15405239	None:16345 | Agency_Name:15388894
6	Complaint Type	15404536	702	1	0	0	0	15405239	None:702 | Complaint_Type:15404537
7	Descriptor	15043169	219044	143026	0	0	0	15405239	Descriptor:15186195 | None:219044
8	Location Type	11310491	29468	4065280	0	0	0	15405239	None:29468 | Loc_Type:15375771
9	Incident Zip	14222212	90824	1092203	14311176	0	0	1094063	Incident_Zip:15403800 |None:1439
10	Incident Address	11744922	235008	3425309	164	0	0	15405075	Address:15170231 | None:235008
11	Street Name	11147745	831105	3426389	989	1	0	15404249	Street:14574134 | None:831105
12	Cross Street 1	9522359	1361938	4520942	50	0	0	15405189	Street:14043301 | None:1361938
13	Cross Street 2	9507944	1312925	4584370	40	0	0	15405199	Street:14092314 | None:1312925
14	Intersection Street 1	1871099	573071	12961069	322	0	0	15404917	Street:14832168 | None:573071
15	Intersection Street 2	1963690	477528	12964021	53	0	0	15405186	Street:14927711 | None:477528
16	Address Type	14687020	0	718219	0	0	0	15405239	Address_Type:15405239
17	City	3134816	11183846	1086577	25	0	0	15405214	City:4221393 | None:11183846
18	Landmark	8490	0	15396749	0	0	0	15405239	None:15396749 | Landmark:8490
19	Facility Type	3606883	0	11798356	0	0	0	15405239	Facility_Type:15405239
20	Status	15405131	0	108	0	0	0	15405239	Status:15405239
21	Due Date	6065893	10381	9328965	0	0	6076274	9328965	Text:9339346 | Due_Date:6065893
22	Resolution Action Updated Date	379163	14709076	317000	0	0	15088239	317000	Text:15026076 | Res_Date:379163
23	Community Board	12754172	16458	2634609	0	0	0	15405239	None:16458 | Community_Board:15388781
24	Borough	13886183	0	1519056	0	0	0	15405239	Borough:15405239
25	X Coordinate (State Plane)	13766562	0	1638677	13766562	0	0	1638677	State_Plane_Cord:13766559 | Text:1638680
26	Y Coordinate (State Plane)	13766562	0	1638677	13766562	0	0	1638677	State_Plane_Cord:13766559 | Text:1638680
27	Park Facility Name	24101	69387	15311751	0	0	0	15405239	None:69387 | Park:15335852
28	Park Borough	13886183	0	1519056	0	0	0	15405239	Park_Borough:15405239
29	School Name	15083	78405	15311751	0	0	0	15405239	School:15326834 | None:78405
30	School Number	15221	75080	15314938	15229	0	0	15390010	None:75080 | School_Number:15330159
31	School Region	15215	6	15390018	0	0	0	15405239	School_Region:15405233 | None:6
32	School Code	15083	146	15390010	0	0	0	15405239	None:146 | School_Code:15405093
33	School Phone Number	76200	0	15329039	76200	0	0	15329039	School_Phone_Number:15405239
34	School Address	90944	2536	15311759	0	0	0	15405239	Address:15402703 | None:2536
35	School City	19311	74177	15311751	0	0	0	15405239	None:74177 | School_City:15331062
36	School State	93488	0	15311751	0	0	0	15405239	School_State:15405239
37	School Zip	93387	101	15311751	93487	0	0	15311752	School_Zip:15405238 | None:1
38	School Not Found	5921449	0	9483790	0	0	0	15405239	School_Not_Found_Indicator:15405239
39	School or Citywide Complaint	3992	0	15401247	0	0	0	15405239	School_Or_Citywide_Complaint_Indicator:15405239
40	Vehicle Type	7974	0	15397265	0	0	0	15405239	Vehicle_Type:15405239
41	Taxi Company Borough	13350	0	15391889	0	0	0	15405239	Taxi_Company_Borough:15405239
42	Taxi Pick Up Location	123079	0	15282160	0	0	0	15405239	Taxi_Pickup_Loc:15405239
43	Bridge Highway Name	42651	0	15362588	0	0	0	15405239	Bridge_Highway_Name:15405239
44	Bridge Highway Direction	42589	0	15362650	0	0	0	15405239	Bridge_Highway_Direction:15405239
45	Road Ramp	42245	0	15362994	0	0	0	15405239	Road_Map:15405239
46	Bridge Highway Segment	18716	29880	15356643	0	0	0	15405239	None:29880 | Bridge_Highway_Segment:15375359
47	Garage Lot Name	5086	0	15400153	0	0	0	15405239	Garage_Name:15405239
48	Ferry Direction	3562	0	15401677	0	0	0	15405239	Ferry_Direction:15405239
49	Ferry Terminal Name	37	10227	15394975	7	0	0	15405232	None:10227 | Ferry_Terminal_Name:15395012
50	Latitude	13766559	3	1638677	0	13766562	0	1638677	None:15405239
51	Longitude	13766499	63	1638677	60	13766502	0	1638677	None:15405239
52	Location	13766559	3	1638677	0	0	0	15405239	Geo_Code:13766562 | Text:1638677

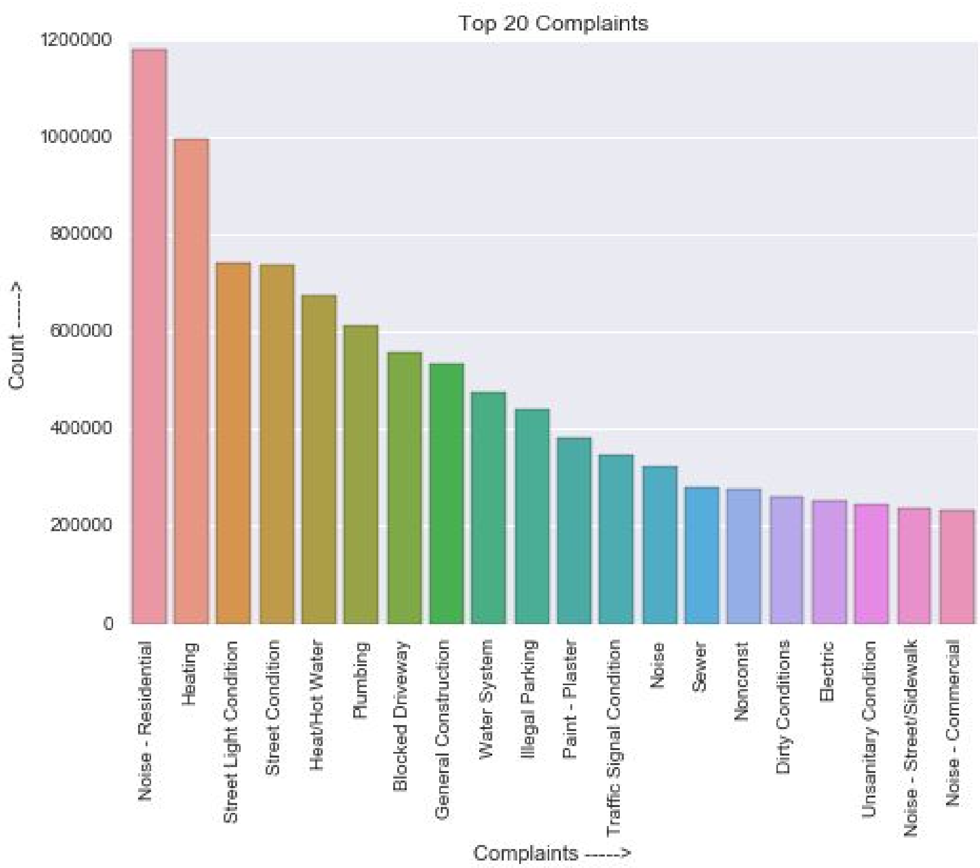
3. Complaint Trends

(All the graphs in this section have been created using the script: https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/plots/visualizations.ipynb)
In this section, the data has been summarized along various dimensions - like hour of the day, year or day of week as well as by location, city or borough.

The data to plot the graphs in section 3.1 to 3.6 have been generated using the script: https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/use_cases/complaint_type_distribution.py.

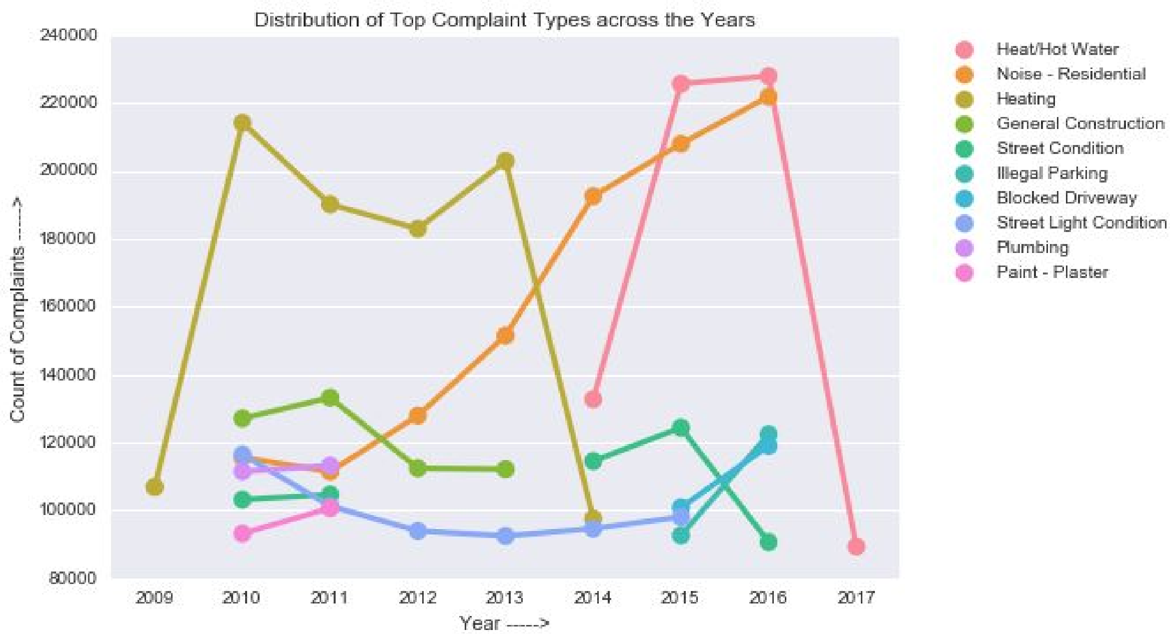
3.1. Distribution of Top 20 Complaints

Though 311 records complaints for more than 4000 categories, Noise –Residential (7.66%), Heating (6.46%), Street Light Conditions (4.8%) and Street Conditions (4.8%) are the most complained about.



3.2. Distribution of Top Complaint Types across the Years

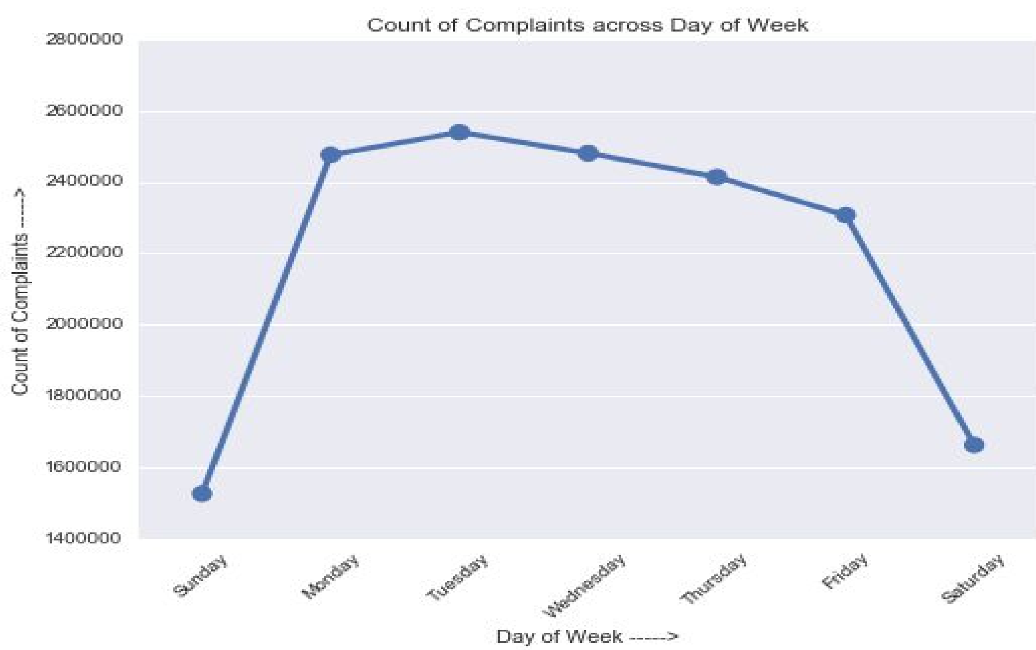
Over the years, some trends can be observed. Each year, Noise and Heating were most complained about.



It is also observed from data, that label ‘Heating’ was changed to ‘Heat/Hot Water’ in 2014.

3.3. Distribution of Complaints across Day of Week

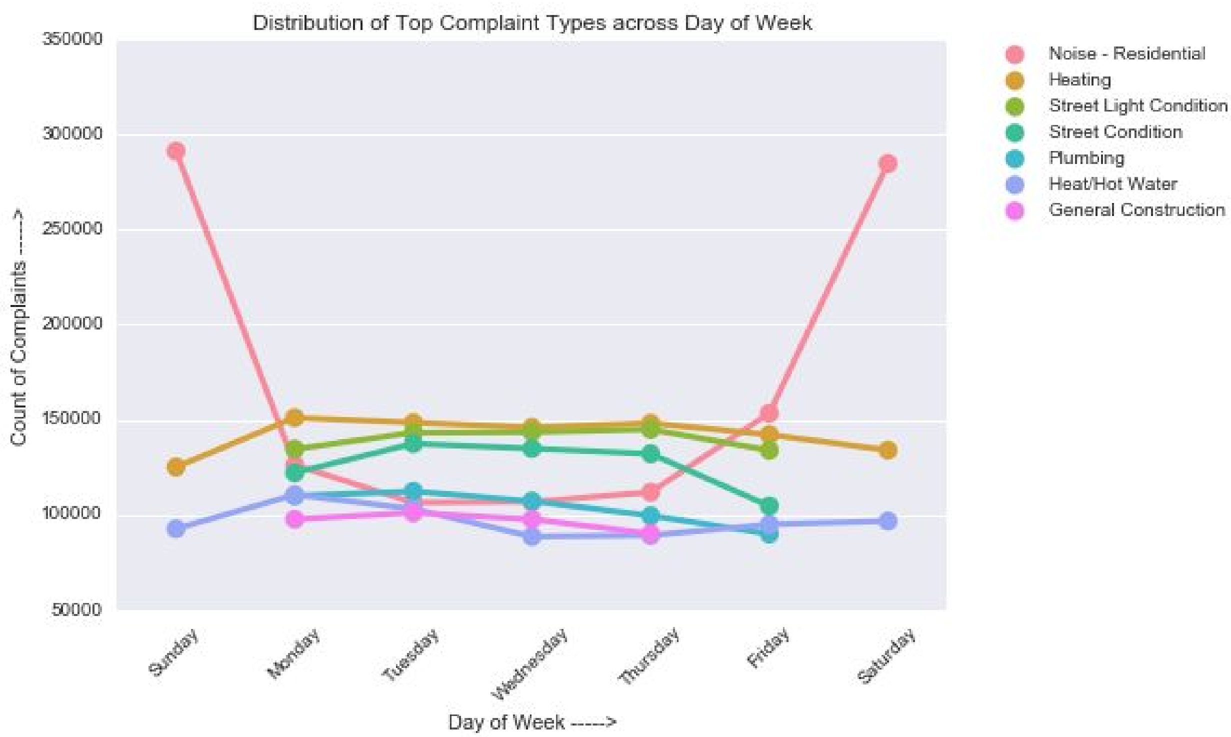
Maximum number of complaints, 16.48% of the total complaints, were registered on a Tuesday. Least number of complaints were registered on Saturday (10.79%) and Sunday (9.90 %).



3.4. Distribution of Top Complaint Types across Day of Week

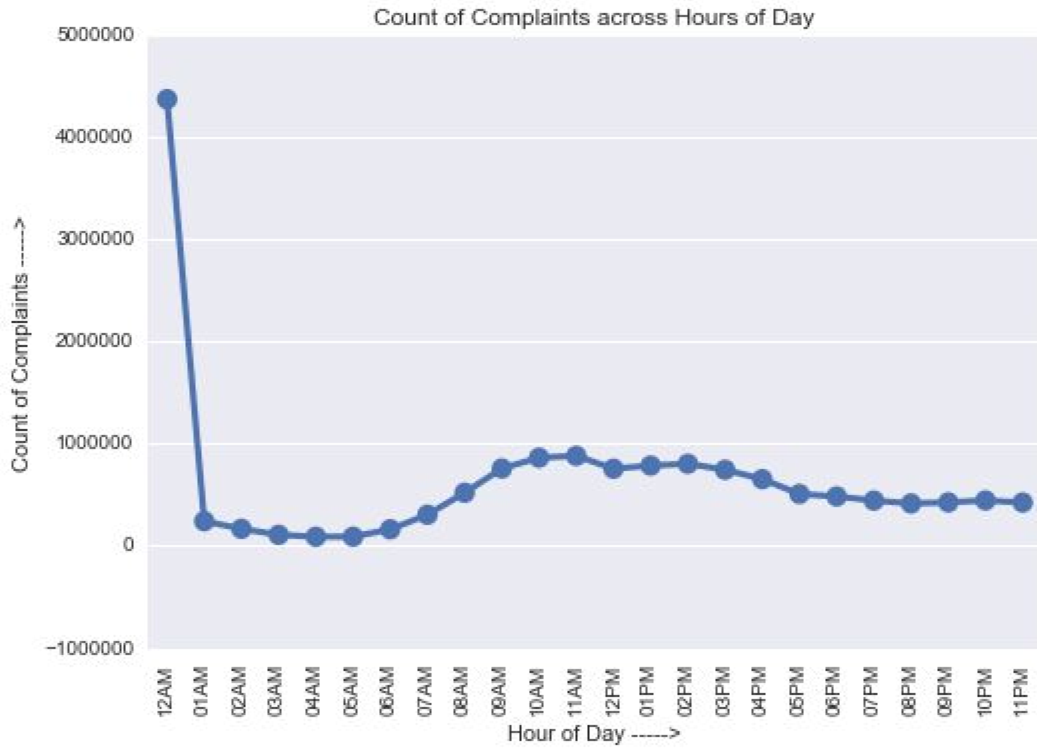
As expected, Noise from Residential buildings consists of maximum number of 311 complaints on Friday and the weekend as people often party over the weekend. Noise complaints are followed by Heating and Hot Water complaints.

On the weekdays, Heating issues form the maximum number of 311 complaints. Street Light Conditions and Street Conditions are 2nd and 3rd most complained about on the weekdays. This might be due to the fact that residents drive to their work over the weekdays and might observe bad street conditions.

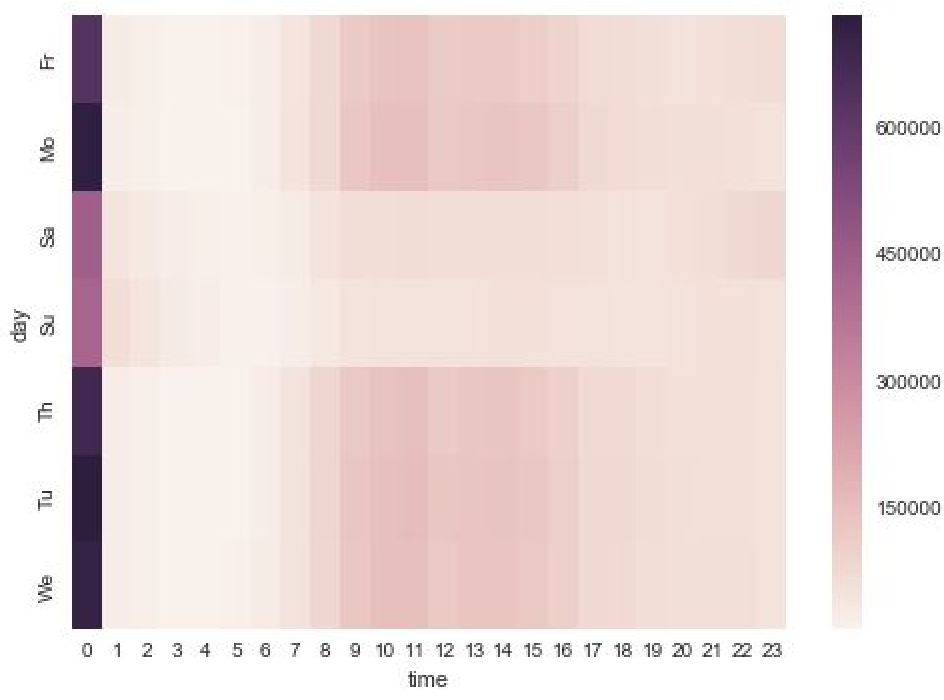


3.5. Distribution of Complaints across Hour of Day

Maximum number of complaints, about 28.34% of total, were registered at midnight. A marginal increase in 311 Complaints is also observed from 7AM to 6PM.

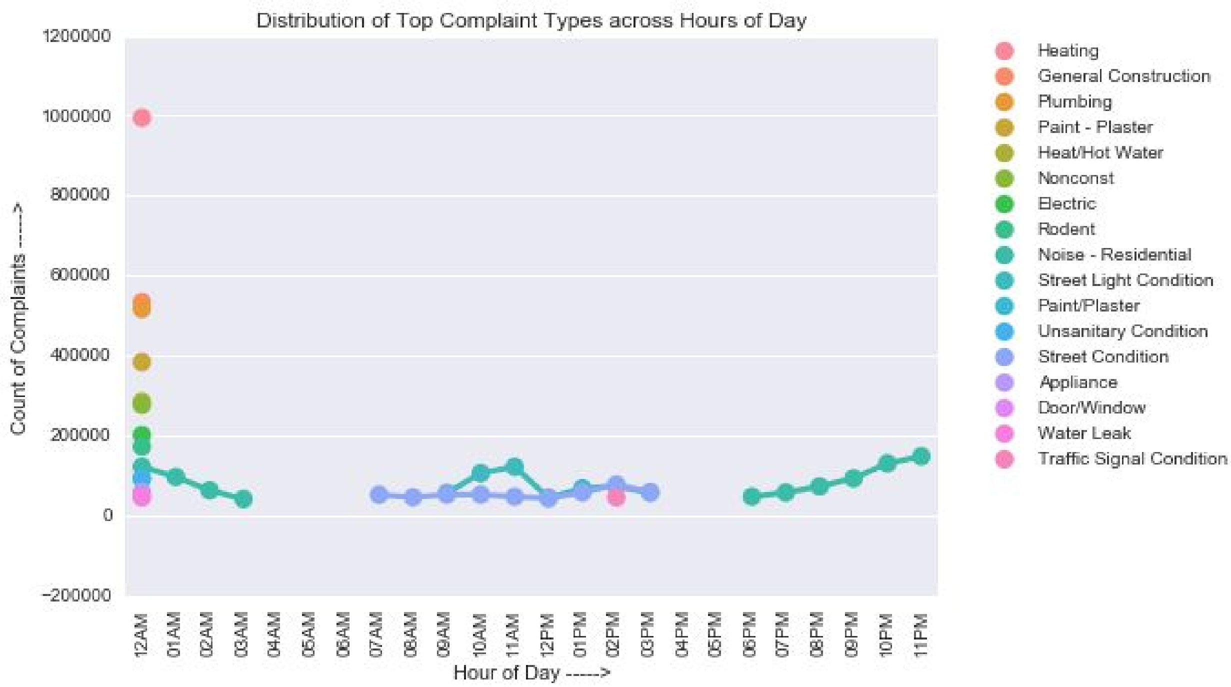


Below is a heat map showing the Distribution of Number of Complaints Across Time and Day of Week:



3.6. Distribution of Top Complaint Types across Hours of Day

Though we expected Noise complaints to be the dominant complaints at midnight, we observed that heating and plumbing complaints were the most reported.

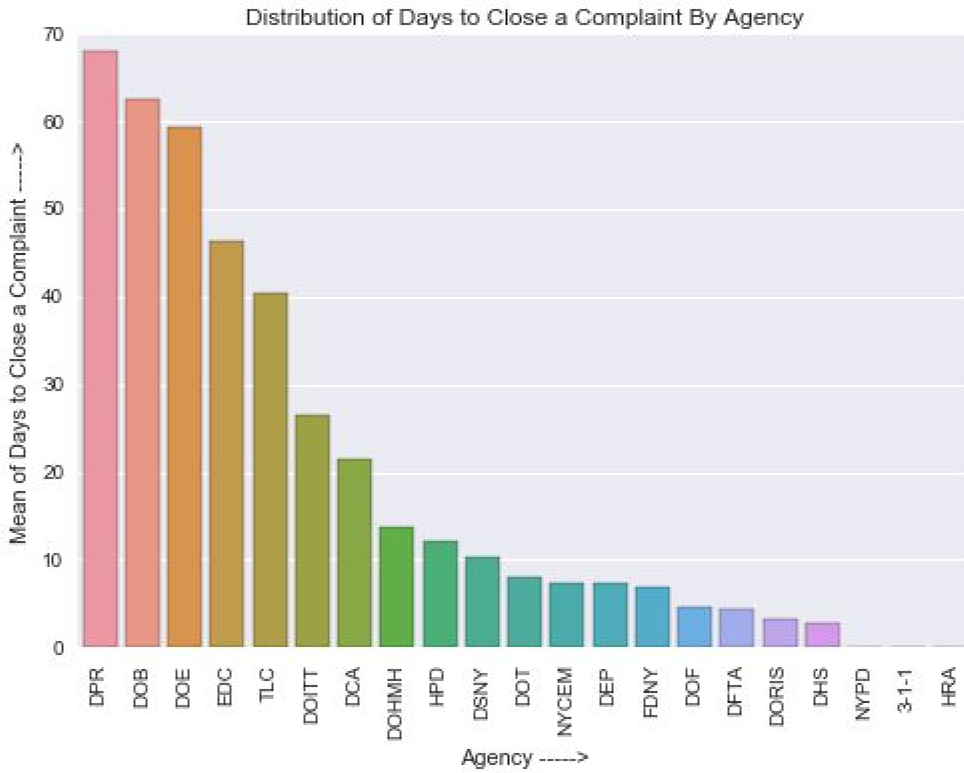


We can also see an increase in 311 complaints for street conditions during the day as observed previously.

3.7. Distribution of Mean Days to Close a Complaint by Agency

The data to plot the graph has been generated using the script:
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/use_cases/closing_time_distribution.py.

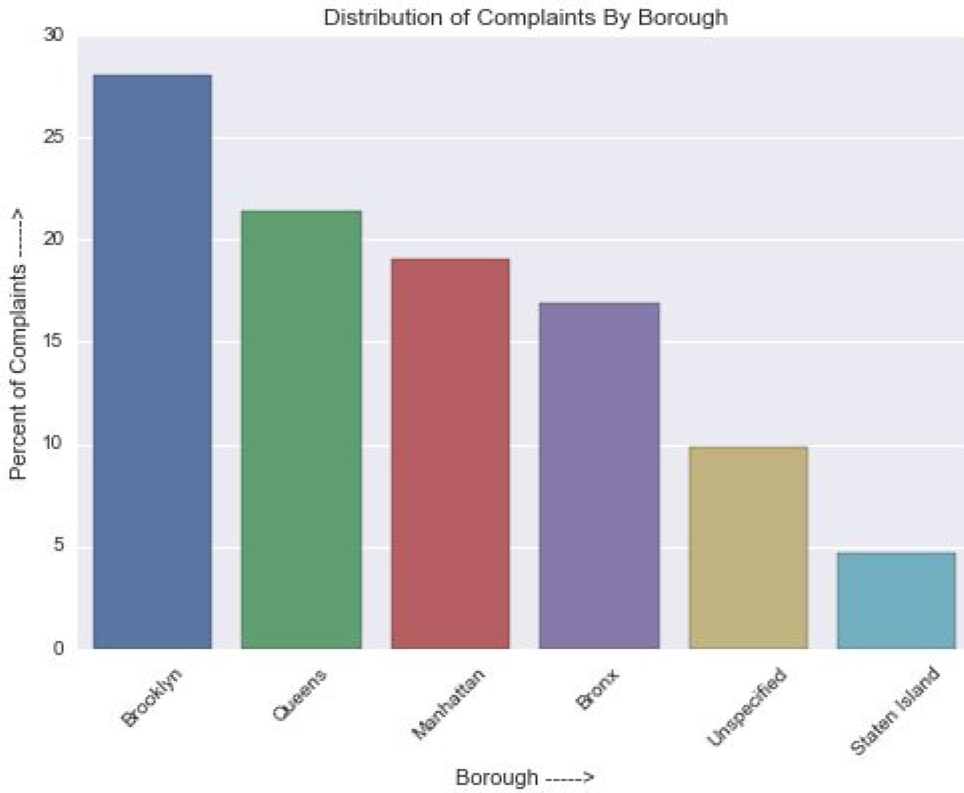
We observe that the average number of days to close a complaint varies highly across the different agencies with agency DPR taking the longest amount of time to close a complaint and with HRA taking the shortest time.



However, the short time to close complaints by NYPD, 3-1-1 or HRA as observed above can also be due to the effect of lack of valid closing times on many records.

3.8. Distribution of Complaints by Borough

The data to plot the graph has been generated using the script: https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/use_cases/comp_count.py. We observe that Brooklyn has the highest number of complaints and Staten Island the lowest. This can be due to the fact that Brooklyn is the highest populated borough in NYC and Staten Island, the least populated one [6].



We also see that about 10% of the complaints do not have the borough information associated with them.

Part - II

4. Experimental Setup

Cluster Configuration

We used NYU Cluster ‘Dumbo’ for this project. NYU Dumbo is 48-node Hadoop cluster, running Cloudera CDH 5.9.0 (Hadoop 2.6.0 with Yarn).

Master Nodes	2 Master Nodes 2x12-core Intel "Haswell" (c 2014) CPUs 128GB memory 8TB RAID1 disk
Computer Nodes	44 compute nodes

	2x8-core Intel "Haswell" (c 2014) CPUs 128GB memory 16x2 TB disk for HDFS
Network	10 Gb Ethernet
Operating System	Linux (Centos 6.5)

Tools

Following tools were used in this assignment:

- Spark - To perform analysis on data
- SparkSQL - To perform analysis on data
- Jupyter Notebooks - To display output data
- Matplotlib - To create plots for output data
- SeaBorn - To create plots for output data

5. Hypothesis being Investigated

- Hypothesis 1:

  We noticed that the number of heating/hot water complaints much higher than expected on certain days. We hypothesize that this might be related to abrupt drop in temperatures.

- Hypothesis 2:

  We noticed that the number of vehicular noise complaints are quite a bit higher for certain ZIP codes and dates. We posit that this might be related to vehicle collisions in that area.

- Hypothesis 3:

  We noticed that the number of homeless complains are higher in some boroughs. We hypothesize that this might be due to certain socio-economics factors.

5.1 Hypothesis 1

The results and visualizations provided in this section can be generated by the scripts:

https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/use_cases/heating_complaint_distribution.py
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/plots/Part%202%20Visualizations.ipynb

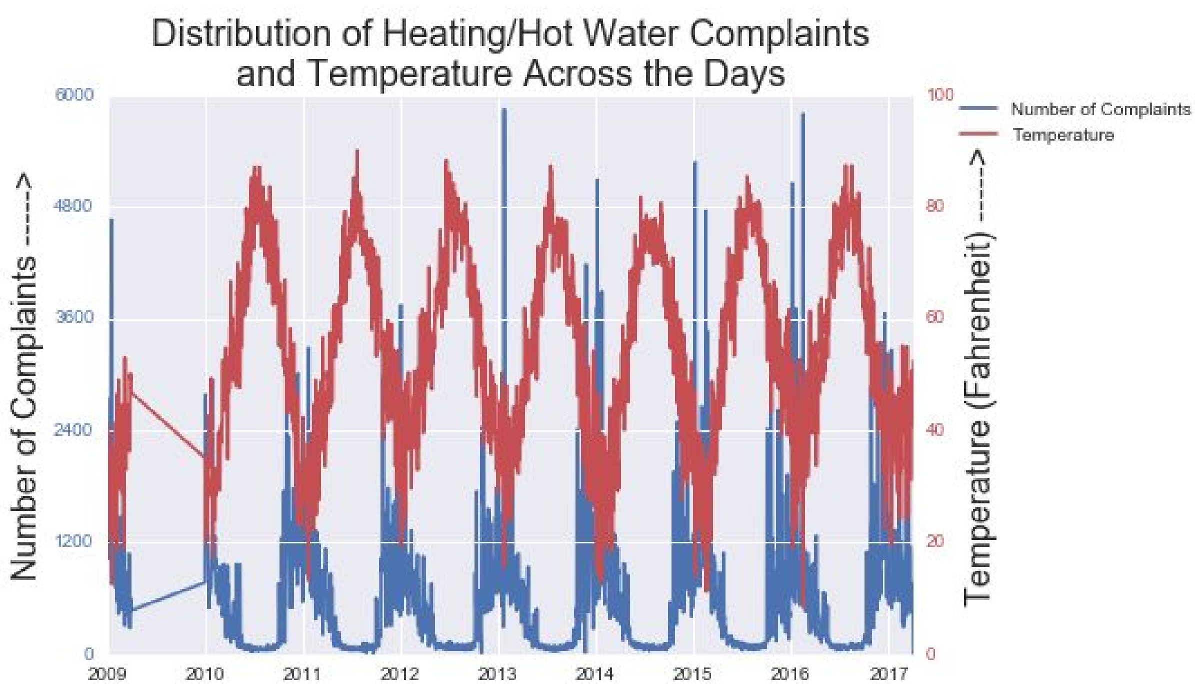
Description of analysis to prove or disprove the hypothesis:

To test our hypothesis that there is an increase in the number of heating/hot water complaints with abrupt drop in temperatures, we integrate our existing dataset with the weather data (only "John F Kennedy International Airport" station) from [7].

We begin our analysis by counting the number of heating/hot water complaints grouped by the date part of the “created date” column in our original dataset. There is no cleaning of the data required since in Part - I we had observed that the “created date” column does not have any invalid or Null entries. We then join this data with the weather data that we obtained from [7].
Once the count for each date is obtained, to check whether the count is out of the usual, we try to detect outliers (very high/very low number of complaints) by the quartile method. To obtain the quartiles, we convert our RDD to a Spark DataFrame and apply the SparkSQL function “percentile”. Once the quartile information is obtained, we apply the following:
Let’s say, Quartile 1 is Q1 and Quartile 3 in Q3;
The Inter-Quartile Range can be found by, IQR = Q3 - Q1
Outliers/Unexpected Number of Complaints lie in the range of : < (Q1 - 1.5IQR) and > (Q3 + 1.5IQR)

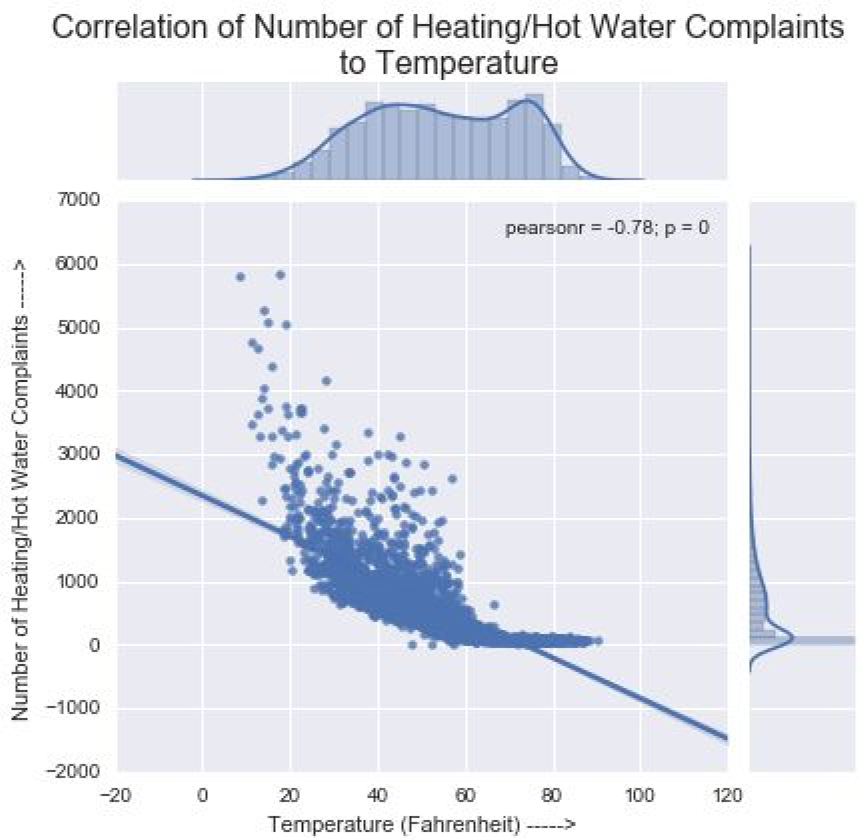
We observe that there are no data points below the above mentioned lower bound. However, there are quite a few data points that are above the prior mentioned upper bound. Also, we notice that these data points are associated with drop in temperatures. This can be seen by the plots below.

Visualization:



As can also be seen from the above plot, the temperature and number of heating/hot water complaints are inversely related. A spike in the number of complaints is usually always accompanied by a drop in temperature.

Correlation plot between the Number of Complaints and Temperature:



Relationship/correlated attributes for this hypothesis with an associated score:

Using the script mentioned at the beginning of this section, we generate a summary of the data as follows: (Results file: https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/res_use_cases/heating_complaints_temp_summary.out)

min_num_complaints	0
quartile_1_num_complaints	86
median_num_complaints	399
quartile_3_num_complaints	909.5
max_num_complaints	5847
correlation_score_num_complaints_temp	-0.78

From the above, we see that the correlation score between the number of heating/hot water complaints and temperature is -0.78 which implies that these two attributes are highly negatively correlated. That is, when one increases, the other decreases. The correlation score here is the Pearson's coefficient.

Why is the hypothesis true or false?:

From the above analysis, plots and correlation score, it can be deduced that our hypothesis is true. There is indeed a relation between the increase in number of heating/hot water complaints and a drop in temperature.

5.2 Hypothesis 2

The results and visualizations provided in this section can be generated by the scripts:

https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/use_cases/noise_collisions_distribution.py
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/plots/Part%202%20Visualizations.ipynb

Description of analysis to prove or disprove the hypothesis:

To test our hypothesis of whether or not there is a correlation between the number of vehicular noise complaints and the number of vehicle collisions we first had to extract the necessary information from the data set provide by the NYPD on vehicle collisions [8].

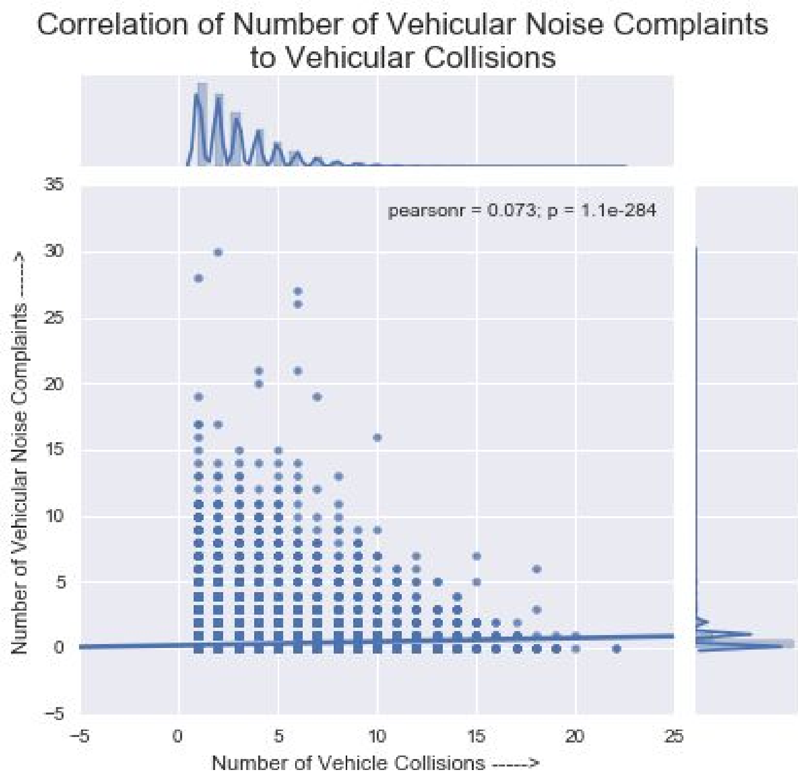
We start by counting the number of vehicular noise complaints and group them by the "created date" column and the "ZIP" column in the 311 data set. Then we counted the number of vehicle collisions and grouped them by the "DATE" and "ZIP" column in the NYPD vehicle collisions. The we proceeded to combine the two counts we extracted by date. For all ZIP columns, we checked if it is a valid ZIP, that is, if it is within the bounds of NYC.

Once the counts were combined we implemented the same method as we did in Hypothesis 1 to find bounds where outliers/unexpected values should be.

We found that few data points fell above the upper bound we created based off of the quartiles. We also notice that there is no correlation between the number of vehicular noise complaints and the number of vehicle collisions as the associated score between them is 0.07. We also checked the correlation of the vehicular noise complaints and vehicle collisions at the extremities. Even at the extremities, the correlation coefficient is much less (0.01). Due to huge amount of spatio-temporal data we could not visualize the data using Python plots. However, we could plot the correlation plot between the number of vehicular noise complaints and the number of vehicle collisions as shown below.

Visualization:

Correlation plot between the Number of Vehicular Noise Complaints and Vehicle Collisions:



Relationship/correlated attributes for this hypothesis with an associated score: eg: (taxi_income, precipitation, 0.7):

Using the script mentioned at the beginning of this section, we generate a summary of the data as follows: (Results file: https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/res_use_cases/noise_complaint_dist_summary.out)

	Statistics	**Value**
0	min_num_complaints	0.00
1	quartile_1_num_complaints	0.00
2	median_num_complaints	0.00
3	quartile_3_num_complaints	0.00
4	max_num_complaints	30.00
5	correlation_score_num_noise_collisions	0.07
6	correlation_score_fringe_num_noise_collisions	0.01

From the above, we see that the correlation score between the number of vehicular noise complaints and vehicle collisions is 0.07 and 0.01 at the extremities which implies that these two attributes are not correlated. The correlation score here is the Pearson's coefficient.

Why is the hypothesis true or false?:

From the above analysis, plots and correlation score, it can be deduced that our hypothesis is false. There is no relation between the number of vehicular noise complaints and the number of vehicle collisions.

5.3 Hypothesis 3

The results and visualizations provided in this section can be generated by the scripts:

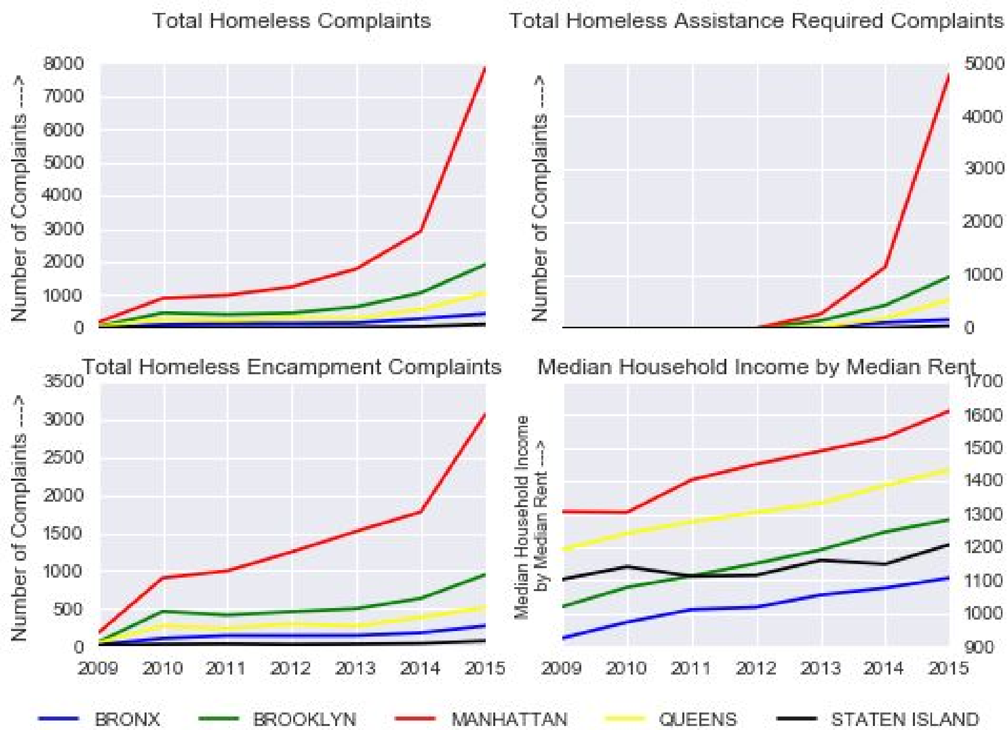
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/use_cases/homeless_income_distribution.py

Description of analysis to prove or disprove the hypothesis:

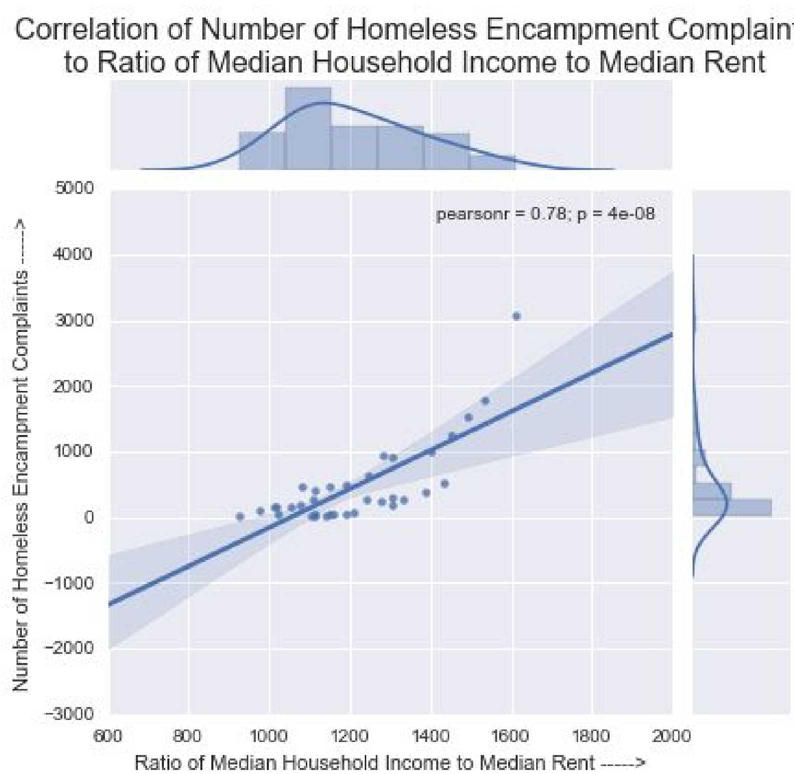
To test our hypothesis we integrate our existing dataset with the American Community Survey's (ACS) Economic Data from [9]

We started our hypothesis by calculating with ratio of median household income with median rent, henceforth known as Income Gap for each borough from years 2009 - 2015.
In our existing dataset, there are two categories of complaints related to homeless people - namely Homeless Person Assistance and Homeless Encampment. We proceeded by counting the number of homeless complaints for both these complaints and also individually per borough per year. We filtered out the boroughs which were not specified.We then joined these datasets with ACS dataset.

Visualization:



Correlation plot between the Number of Homeless Encampment Complaints and Income Gap:



Using the script mentioned at the beginning of this section, we generate a summary of the data as follows:

Total Homeless Complaints
(Results file:
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/res_use_cases/combined_homeless_complaint_dist_summary.out)

min_num_complaints	0
quartile_1_num_complaints	33.25
median_num_complaints	254.5
quartile_3_num_complaints	841
max_num_complaints	42744
correlation_score_num_homeless_income	0.67

Total Homeless Encampment Complaints
(Results file:
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/res_use_cases/homeless_encampment_complaint_dist_summary.out)

min_num_complaints	0
quartile_1_num_complaints	28.75
median_num_complaints	146.5
quartile_3_num_complaints	464
max_num_complaints	3379
correlation_score_num_homeless_income	0.78

Total Homeless Assistance Complaints
(Results file:
https://github.com/aparajita2930/NYC_Complaints_Analysis/blob/master/results/res_use_cases/homeless_assistance_complaint_dist_summary.out)

min_num_complaints	0
quartile_1_num_complaints	0
median_num_complaints	0
quartile_3_num_complaints	204.75
max_num_complaints	39365
correlation_score_num_homeless_income	0.54

From the above, we see that the correlation is highest between the number of Homeless Encampment complaints and the ratio of the median household income to median rent, with the correlation score being 0.78 which implies that these two attributes highly positively correlated. That is, when the Income Gap increases, the number of homeless encampment complaints also increase. The correlation score here is the Pearson's coefficient.

Why is the hypothesis true or false?:

From the above analysis, plots and correlation score, it can be deduced that our hypothesis is true. There is indeed a relation between the increase in number of homeless encampment complaints and income gap in borough.

6. Individual Contributions

Each of the us in the team have worked on brainstorming the use cases that would give us valuable insights from the data. We divided the task amongst ourselves with each of us responsible for a number of scripts in Part 1. In Part 2, each of us was responsible for at least one hypothesis and other analysis.

7. Summary

In Part 1, we observed various data quality issues - like missing data, same data represented in various forms, invalid data, etc. With over 15M rows, Big Data technologies proved to be beneficial in analyzing and aggregating the data over various dimensions. Also, we could identify various trends in the complaints, the way people complaint and how complaints are dealt with.

In Part 2, we found the following:

List of relationships/correlated attributes with an associated score:

Attribute 1	Attribute 2	Association Score (Pearson Correlation Coefficient)
Heating/Hot Water Complaints	Temperature	-0.78
Vehicular Noise	Vehicle Collisions	0.07
Vehicular Noise (at the extremities)	Vehicle Collisions	0.01
All Homeless Complaints	Ratio of Median Household Income to Median Rent	0.67
Homeless Encampment Complaints	Ratio of Median Household Income to Median Rent	0.78
Homeless Assistance Complaints	Ratio of Median Household Income to Median Rent	0.54

Discussion of key findings of all the previous hypothesis:

To summarize the findings of all the above hypothesis, we see that:

- Heating/Hot Water Complaints is highly negatively correlated - With abrupt drop in temperatures, the number of Heating/Hot Water Complaints increase significantly.
- Vehicular Noise and Vehicle Collisions are not at all related - There is no relation between the Noise complaints and Vehicle/Traffic Collisions.

- Homeless Encampment Complaints have the highest correlation with the Income Gap as compared to other forms of Homeless related Complaints - Socio-Economic factors play a major role in the number of homeless related complaints.

Discussion of Issues and Challenges faced and how they have been addressed:

- Our data had unicode characters as well as quoted commas. Quoted commas implied we had to use Python CSV reader module. However, the Python CSV reader module cannot deal with unicode characters. To address this, we supplied the argument "use_unicode = False" to Spark's textFile function. This ensured that we could use the CSV reader module to read in the data as well as handle quoted commas.
- In Hypothesis 2, given the large number of ZIPs and dates, plotting a trend of the number of vehicular noise complaints and the number of vehicle collisions proved to be cumbersome. We looked at many other packages but could not get to use them for our specific use-case. Thus, to visualize the data, we plotted the correlation plot between the vehicular noise complaints and vehicle collisions using Python Seaborn.

8. References

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