In [1]: # importing libraries import pandas as pd import numpy as np import seaborn as sns import matplotlib.pyplot as plt %matplotlib inline Import dataset df = pd.read csv('311 dataset.csv', low memory=False) df.head() **Bridge** Bri Complaint Incident Incident Unique Created Closed Agency **Agency Descriptor** Location Type High Highway **Address Date Date** Name Zip Key Type Name Direct 12/31/2015 01-01-71 New York Noise -Loud 11:59:45 NYPD **0** 32310363 16 City Police Street/Sidewalk 10034.0 VERMILYEA NaN Street/Sidewalk Music/Party Department PM 0:55 **AVENUE** 12/31/2015 01-01-New York Blocked 27-07 23 **1** 32309934 11:59:44 NYPD City Police 16 No Access Street/Sidewalk 11105.0 NaN Driveway **AVENUE** 1:26 PM Department 01-01-New York 12/31/2015 2897 Blocked 11:59:29 NYPD 10458.0 VALENTINE **2** 32309159 City Police No Access Street/Sidewalk NaN 16 Driveway **AVENUE** 4:51 Department 12/31/2015 01-01-2940 New York Commercial **BAISLEY** 3 32305098 11:57:46 NYPD 16 City Police Illegal Parking Overnight Street/Sidewalk 10461.0 NaN 7:43 **AVENUE** Department Parking 12/31/2015 01-01-New York 87-14 57 Blocked NYPD 11373.0 32306529 11:56:58 City Police Illegal Parking Street/Sidewalk 16 NaN Sidewalk **ROAD** Department 3:24 5 rows × 53 columns # shape of the dataframe df.shape (300698, 53)Out[4]: # columns in df df.columns Out[5]: Index(['Unique Key', 'Created Date', 'Closed Date', 'Agency', 'Agency Name', 'Complaint Type', 'Descriptor', 'Location Type', 'Incident Zip', 'Incident Address', 'Street Name', 'Cross Street 1', 'Cross Street 2', 'Intersection Street 1', 'Intersection Street 2', 'Address Type', 'City', 'Landmark', 'Facility Type', 'Status', 'Due Date', 'Resolution Description', 'Resolution Action Updated Date', 'Community Board', 'Borough', 'X Coordinate (State Plane)', 'Y Coordinate (State Plane)', 'Park Facility Name', 'Park Borough', 'School Name', 'School Number', 'School Region', 'School Code', 'School Phone Number', 'School Address', 'School City', 'School State', 'School Zip', 'School Not Found', 'School or Citywide Complaint', 'Vehicle Type', 'Taxi Company Borough', 'Taxi Pick Up Location', 'Bridge Highway Name', 'Bridge Highway Direction', 'Road Ramp', 'Bridge Highway Segment', 'Garage Lot Name', 'Ferry Direction', 'Ferry Terminal Name', 'Latitude', 'Longitude', 'Location'], dtype='object') # converting the columns into lower case and replacing the space with '_'. df.columns = df.columns.str.lower().str.replace(' ',' ') # checking for NaN or null values in df df.isna().sum() Out[7]: unique_key 0 0 created_date closed_date 2164 agency 0 agency_name 0 0 complaint_type 5914 descriptor location_type 131 incident_zip 2615 incident_address 44410 44410 street_name 49279 cross_street_1 49779 cross_street_2 intersection street 1 256840 intersection_street_2 257336 address_type 2614 landmark 300349 facility_type 2171 status due date 3 resolution_description 0 resolution_action_updated_date 2187 community_board 0 x_coordinate_(state_plane) 3540 y_coordinate_(state_plane) 3540 park_facility_name park_borough 0 school_name 0 school_number school region school_code school_phone_number 0 school_address 0 school_city 0 school_state 0 school_zip 1 school_not_found school_or_citywide_complaint 300698 vehicle_type taxi_company_borough 300698 300698 taxi_pick_up_location
bridge_highway_name 300698 300455 300455 bridge_highway_direction 300485 road_ramp 300485 bridge_highway_segment garage_lot_name ferry_direction 300698 300697 ferry_terminal_name 300696 latitude 3540 longitude 3540 location 3540 dtype: int64 In [8]: df.nunique() 300698 Out[8]: unique_key created date 259493 237165 closed date agency 1 3 agency_name 24 complaint_type 45 descriptor location_type 18 incident zip 201 107652 incident_address street name cross street 1 5982 cross street 2 5823 4413 intersection_street_1 intersection street 2 4172 address type 5 city 53 116 landmark facility_type 1 4 due date 259851 ${\tt resolution_description}$ 18 resolution action updated date 237895 community board 75 borough 6 x_coordinate_(state_plane) 63226 y coordinate (state plane) 73694 park facility name 2 park borough 6 school name 2 $\verb|school_number|$ school region 1 school code 1 school_phone_number 2 school address school city school state 1 school_zip school_not_found school or citywide complaint vehicle type 0 0 taxi_company_borough taxi_pick_up_location bridge highway name 29 bridge_highway_direction 34 2 road ramp bridge_highway_segment 160 garage lot name 0 ferry_direction 1 ferry_terminal_name 2 latitude 125122 longitude 125216 126048 location dtype: int64 Read or convert the columns 'Created Date' and Closed Date' to datetime datatype create a new column 'Request_Closing_Time' as the time elapsed between request creation and request closing df['closed date'] = pd.to datetime(df['closed date']) df['created date'] = pd.to datetime(df['created date']) requested closing time = df['closed date'] - df['created date'] df['requested_closing_time'] = requested_closing_time # converting the date difference into minutes requested_closing_time_min = df['requested_closing_time']/np.timedelta64(1,'m') In [14]: df['requested closing time min'] = requested closing time min df.head() unique_key created_date closed_date agency agency_name complaint_type descriptor location_type incident_zip incident_address New York City 2015-12-31 2016-01-01 71 VERMILYEA Noise -Loud 32310363 **NYPD** Street/Sidewalk 10034.0 Police 23:59:45 00:55:00 Street/Sidewalk Music/Party **AVENUE** Department New York City 2015-12-31 2016-01-01 Blocked 32309934 **NYPD** No Access Street/Sidewalk 11105.0 27-07 23 AVENUE Police 23:59:44 01:26:00 Driveway Department New York City 2015-12-31 2016-01-01 2897 VALENTINE Blocked 32309159 Police No Access Street/Sidewalk 10458.0 23:59:29 04:51:00 Driveway **AVENUE** Department New York City Commercial 2015-12-31 2016-01-01 2940 BAISLEY 32305098 NYPD Police Illegal Parking Overnight Street/Sidewalk 10461.0 23:57:46 07:43:00 **AVENUE** Parking Department New York City 2015-12-31 2016-01-01 Blocked 32306529 **NYPD** Illegal Parking Street/Sidewalk 11373.0 87-14 57 ROAD Police 23:56:58 03:24:00 Sidewalk Department 5 rows × 55 columns # creating new dataframe new df = df[['unique_key','created_date','closed_date','agency', 'agency_name','complaint_type', 'descriptor 'address_type','city','facility_type', 'status', 'due_date','borough', 'location', 'requested_closing_time', 'requested_closing_time_min']] new_df.head() Out[17]: unique_key created_date closed_date agency agency_name complaint_type descriptor location_type address_type city facil New York City 2015-12-31 2016-01-01 Noise -Loud 32310363 NYPD Police Street/Sidewalk ADDRESS NEW YORK 23:59:45 00:55:00 Street/Sidewalk Music/Party Department New York City 2015-12-31 2016-01-01 Blocked 32309934 NYPD Police No Access Street/Sidewalk **ADDRESS ASTORIA** 23:59:44 01:26:00 Driveway Department New York City 2015-12-31 2016-01-01 Blocked 32309159 NYPD Police No Access Street/Sidewalk **ADDRESS BRONX** 23:59:29 04:51:00 Driveway Department New York City Commercial 2015-12-31 2016-01-01 32305098 NYPD Police Illegal Parking Overnight Street/Sidewalk **ADDRESS BRONX** 23:57:46 07:43:00 Department Parking New York City 2015-12-31 2016-01-01 Blocked 32306529 NYPD Police Illegal Parking Street/Sidewalk ADDRESS ELMHURST 23:56:58 03:24:00 Sidewalk Department Converting the series city and borough into lower case to avoid redudancies new df['city'] = new df['city'].str.lower() In [18]: pd.options.mode.chained_assignment = None C:\Users\Naveen\anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html# returning-a-view-versus-a-copy """Entry point for launching an IPython kernel. new df['borough'] = new df['borough'].str.lower() pd.options.mode.chained_assignment = None new df.head() new_df.shape Out[20]: (300698, 17) new df.duplicated().sum() Out[21]: 0 new_df.isnull().sum() Out[22]: unique_key 0 created_date 0 closed date 2164 0 agency agency_name 0 ${\tt complaint_type}$ 0 5914 descriptor location type 131 2815 address_type 2614 city facility_type 2171 status 3 due date 0 borough 3540 location requested closing_time 2164 requested closing time min 2164 dtype: int64 pd.set_option('mode.chained_assignment', None) new_df.dropna(inplace=True) new df.isnull().sum() In [24]: Out[24]: unique key created date 0 0 closed_date 0 agency agency_name 0 complaint_type 0 descriptor 0 0 location_type address_type city 0 facility_type 0 status 0 due date borough location 0 requested closing time 0 requested_closing_time_min dtype: int64 new df.dtypes Out[25]: unique_key created date datetime64[ns] closed date datetime64[ns] object agency agency_name object complaint type object descriptor object location_type object address_type object city object facility type object object status due date object borough object location object requested_closing_time timedelta64[ns] requested closing time min float64 dtype: object Provide major insights/patterns that you can offer in a visual format; at least 4 major conclusions that you can come up with after generic data mining. 1) In [26]: | df['location type'].value counts() plot=sns.countplot(df['location type']) plot.set xticklabels(plot.get xticklabels(),rotation=90) plt.show() C:\Users\Naveen\AppData\Roaming\Python\Python37\site-packages\seaborn\ decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `d ata', and passing other arguments without an explicit keyword will result in an error or misinterpretation. FutureWarning 250000 200000 150000 100000 50000 Residential Building/House Street/Sidewalk House of Worship Residential Building Park/Playground Vacant Lot House and Store Commercial Roadway Tunnel Bridge Club/Bar/Restaurant Store/Commercial Subway Station Parking Lot Erminal Highway location_type Insight: - Street/ SideWalk is the most used Location Type by New York people. From the plot, we can see it out-counts most other types 2) plt.figure(figsize=(12,4)) plot2=sns.countplot(df['descriptor']) plt.title('Counts based on the Descriptor') plot2.set_xticklabels(plot2.get_xticklabels(),rotation=90) plt.show() C:\Users\Naveen\AppData\Roaming\Python\Python37\site-packages\seaborn_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be ata', and passing other arguments without an explicit keyword will result in an error or misinterpretation. Counts based on the Descriptor 60000 50000 40000 30000 20000 10000 Unauthorized Bus Layover Double Parked Blocking Vehicle Double Parked Blocking Traffic Loud Music/Party Commercial Overnight Parking Blocked Sidewalk Posted Parking Sign Violation Blocked Hydrant With License Plate Loud Talking Car/Truck Music Drtured In Prohibited Area Congestion/Gridlock Car/Truck Horn Other (complaint details) No Shelter Overnight Commercial Storage Engine Idling Underage - Licensed Est Chronic Stoplight Violation Chronic Speeding Playing in Unsuitable Place Banging/Pounding Police Report Requested Police Report Not Requested Disruptive Passenger **Truck Route Violation** After Hours - Licensed Est Detached Trailer Language Access Complaint descriptor Insights: - "Descriptor" variable plotted here is based on the Complaint type - From the above, it is seen that Loud Music/Party is highest registered count by the people against - It comes under the "Noise" Complaint type. 3) plt.figure(figsize=(10,6)) sns.countplot(df.loc[df['location_type'].isin(['Street/Sidewalk','Store/Commercial','Club/Bar/Restaurant'])] ['location_type'], data=df, hue='borough') plt.show() the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `d ata', and passing other arguments without an explicit keyword will result in an error or misinterpretation. FutureWarning borough 80000 MANHATTAN OUEENS BRONX 70000 BROOKLYN Unspecified 60000 STATEN ISLAND 50000 40000 30000 20000 10000 0 Street/Sidewalk Club/Bar/Restaurant Store/Commercial location_type Conclusion: - The plot is used to measure of usage count of location type's in the Cities of Newyork - From above, we can infer that, Street/SideWalks of BROOKLYN is most used by the people of Newyork - Footfall in Sidewalks is higher than anyother compared in overall Borough. 4) plt.figure(figsize=(10,4)) series=df['complaint_type'].value_counts() series.nlargest().index plot4=sns.barplot(x=series.nlargest().index,y=series.nlargest().values) plot4.set_xticklabels(plot4.get_xticklabels(),rotation =90) plt.show() 80000 70000 60000 50000 40000 30000 20000 10000 Blocked Driveway Noise - Street/Sidewalk Derelict Vehicle **Illegal Parking** Noise - Commercial Insights: - The above graph is used to find out which complaint type has been registered high in count. - As visualised, since Driveway Block is has high count, it is the problem faced most, by the people around. Order the complaint types based 'Request_Closing_Time', grouping them for different locations. df.pivot table(index = 'complaint type', values= 'requested closing time min', aggfunc= lambda x : x.mean(), fill value='-') CAMBRIA CENTRAL **SAINT BAYSIDE BELLEROSE BRONX BROOKLYN** city ARVERNE ASTORIA Astoria OZ **HEIGHTS PARK ALBANS** complaint_type **Animal Abuse** 129.218 300.01 196.471 763.481 156.808 440.13 289.95 681.35 442.305 20 **Animal in a Park** Bike/Roller/Skate 104.359 294 207.538 300.282 Chronic **Blocked** 294.878 153.784 79.6611 375.706 264.647 461.759 281.207 265 151.558 288.967 605.965 **Driveway** 354.03 623 **Derelict Vehicle** 178.093 581.355 374.169 201.587 1030.09 428.711 553.654 356.849 966.647 **Disorderly Youth** 215.475 174.156 249.031 178.383 111 254.304 105.55 160 **Drinking** 283.345 235.083 347.615 57.6833 292 14.3167 114 158 212.434 Graffiti 92 273.094 533.943 494.592 845.704 **Homeless** 108.888 295.055 172.533 2348 446.514 281.689 1367.37 454.242 110 **Encampment Illegal Fireworks** 166.408 336.492 140.375 91.8333 138.982 251.058 **Illegal Parking** 290.003 282.677 153.76 492.188 236.533 394.851 275.658 28 256.334 674.606 Noise -187.982 212.513 152.371 281.841 137.233 134.02 404.446 179.166 228.601 186.015 Commercial Noise - House of 93.7318 121.333 212.092 131.817 273.573 158.458 278.75 184.192 129 Worship Noise - Park 77 179.707 196.354 84.85 281.912 189.032 49.2167 342 Noise -119.544 207.07 222.794 91.86 544.094 313.579 197.76 276.483 196.016 201.971 219 Street/Sidewalk Noise - Vehicle 111.593 210.551 102.505 154.99 79.4667 333.648 197.007 415.026 207.515 227 **Panhandling** 62 69 449 852.824 258.989 **Posting** 352.2 207.72 201.657 77.1 135.6 **Advertisement** Squeegee 186.776 **Traffic** 324.611 91.6167 345.531 295.421 512.803 237.906 213 Urinating in 41.5167 277.543 452.483 233.959 390.8 323.406 Public 296.125 112.675 409.542 271.686 143.308 211 Vending 22 rows × 53 columns Provide a statistical test to accept or reject the Null Hypothesis along with the corresponding 'p-value'. Whether the average response time across complaint types is similar or not (overall) \$H_0\$: Overall ComplaintType and Average Response Time doesn't have any significant difference \$H_a\$: Atleast one of the ComplaintType's and Avg. Response Time has significant difference import scipy.stats as stats top = new_df['complaint_type'].value_counts().index top Out[32]: Index(['Blocked Driveway', 'Illegal Parking', 'Noise - Street/Sidewalk', 'Noise - Commercial', 'Derelict Vehicle', 'Noise - Vehicle', 'Animal Abuse', 'Traffic', 'Noise - Park', 'Vending', 'Drinking', 'Noise - House of Worship', 'Posting Advertisement', 'Disorderly Youth', 'Graffiti'], dtype='object') from statsmodels.formula.api import ols import statsmodels.api as sm In [34]: sample = new_df[new_df['complaint_type'].isin(top)] mod = ols('requested_closing_time_min ~ complaint_type', data = sample).fit() sm.stats.anova_lm(mod) F PR(>F) Out[34]: df sum_sq mean_sq 14.0 1.043265e+09 7.451890e+07 578.768616 complaint_type 0.0 **Residual** 290869.0 3.745061e+10 1.287542e+05 NaN NaN F-stat Conclusion: - From the F-stat, the p_value < 0.05 - Hence, we reject null hypothesis Are the type of complaint or service requested and location related? Hypothesis: \$H_0\$: The complaint or service requested and location are not related/independent • \$H_0\$: They are related/ dependent topall = df['complaint type'].value counts().index sample = df[df['complaint type'].isin(topall)] ct = pd.crosstab(sample['complaint_type'], sample.location) Out[35]: (40.500049 location -74.24348482977875) -74.2379063249761) -74.23740031497493) -74.23801175120917) -74.23802262609722) -74.2380 complaint_type **Animal Abuse** 0 0 0 0 0 Bike/Roller/Skate 0 0 0 0 0 Chronic **Blocked** 0 0 0 0 0 Driveway **Derelict Vehicle** 0 0 0 0 **Disorderly Youth** 0 0 0 0 0 **Drinking** 0 0 0 0 Graffiti 0 0 0 0 0 **Homeless** 0 0 0 0 **Encampment Illegal Fireworks** 0 0 0 0 0 **Illegal Parking** Noise -0 0 0 0 0 Commercial Noise - House of 0 0 0 0 0 Worship 0 0 0 Noise - Park 0 Noise -0 0 0 0 Street/Sidewalk Noise - Vehicle 0 0 0 0 0 0 **Panhandling** 0 0 **Posting** 0 0 0 0 0 **Advertisement** 0 0 Squeegee 0 Traffic 0 0 0 0 0 Urinating in 0 0 **Public** 0 0 0 0 0 Vending 21 rows × 126048 columns chisquare , p , df, et = stats.chi2 contingency(ct) print('Results : statistic={:.4f}, pvalue={}'.format(chisquare,p)) Results: statistic=4161473.2250, pvalue=0.0 Conclusion: • Here, p_value < 0.05 • Thus " we reject null hypothesis"