Mapping Accidents in NYC - Data Bootcamp Project 2018

NYC Open Data

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1. Overview

What impacts accidents? In particular, what are the major driver-related reasons for accidents, when do they occur, and where do they occur?

Better understanding the factors that lead to accidents can help officials in two main ways. First, this can aid in the allocation of resources. This relates to both city planning - i.e. where to locate hospitals and police stations - as well as city operations - i.e. where and when to place ambulance and police teams on standby. Second, this can help officials and individuals target behaviour. Government can better inform citizens what they should be aware of as well as launch programs to incentivize targeted good behaviours and restrict targeted bad behaviours.

This project looks to leverage NYPD Motor Vehicle Collision data located on NYC Open Data (https://data.cityofnewyork.us/Public-Safety/NYPD-Motor-Vehicle-Collisions/h9gi-nx95/data). It parses collision data for the period of March 21, 2017 to March 21,2018 from the five Boroughs of NYC.

2. Data Source

2.1 Data and Module Import

NYC Open Data is a project aimed at making NYC government data freely available. It is founded thanks to a partnership between The Mayor's Office of Data Analytics (MODA), the Department of Information Technology and Telecommunications (DoITT), and Socrata. While vast amount of data are available on this site, I chose to look at NYPD Motor Vehicle Collision data.

The data was obtained through a json query via https://data.cityofnewyork.us/Public-Safety/NYPD-Motor-Vehicle-Collisions/h9gi-nx95/data)

```
In [1]:
        #Importing all required libraries
        import pandas as pd
        import matplotlib.pyplot as plt
                                             # graphics package
         import matplotlib as mpl
                                             # graphics package
         import numpy as np
         import datetime
         import matplotlib.patches as mpatches
        #Fetching Data from NYC Open Data
         url = 'https://data.cityofnewyork.us/resource/qiz3-axqb.json?$limit=500000'
        accidents = pd.read json(url)
        accidents.dtypes
Out[1]: borough
                                                   object
        contributing_factor_vehicle_1
                                                   object
        contributing factor vehicle 2
                                                   object
        contributing_factor_vehicle_3
                                                   object
        contributing factor vehicle 4
                                                   object
        contributing factor vehicle 5
                                                   object
        cross_street_name
                                                   object
        date
                                          datetime64[ns]
        latitude
                                                 float64
        location
                                                   object
        longitude
                                                  float64
        number_of_cyclist_injured
                                                    int64
        number_of_cyclist_killed
                                                    int64
        number_of_motorist_injured
                                                    int64
        number_of_motorist_killed
                                                    int64
        number_of_pedestrians_injured
                                                    int64
        number_of_pedestrians_killed
                                                    int64
        number of persons injured
                                                    int64
        number_of_persons_killed
                                                    int64
        off_street_name
                                                   object
        on street name
                                                   obiect
        time
                                                   object
                                                    int64
        unique_key
        vehicle type code1
                                                   object
        vehicle_type_code2
                                                   object
        vehicle_type_code_3
                                                   object
        vehicle type code 4
                                                   object
        vehicle type code 5
                                                   object
        zip code
                                                   object
        dtype: object
In [2]: #Getting borough data for per capita comparisons
        url2 = 'https://data.cityofnewyork.us/resource/h2bk-zmw6.json'
        boroughpop = pd.read json(url2)
        boroughpop = boroughpop.sort values(by='borough', ascending=False) #importa
        nt for later per capita calculations
        boroughpop.dtypes
```

```
http://localhost:8888/nbconvert/html/Data%20Bootcamp%20Final%20Project%20v6.ipynb?download=false
```

object

int64

Out[2]: borough

sum_population

dtype: object

2.2 Data Information

We can see here that there is a lot of information in the accidents file. The important data for the analysis are borough, date and time information, number of people killed and injured, and accident reason. We are also only interested in accidents across one full year, so as not to have overlap in analysis.

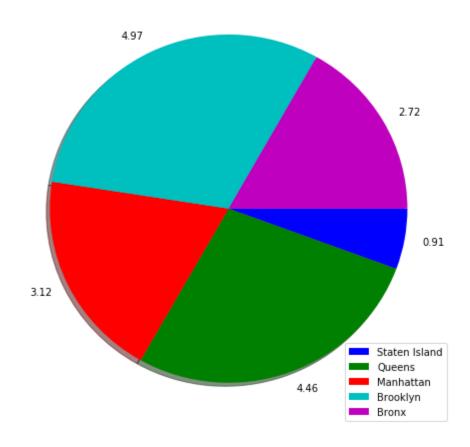
```
In [3]: | accidents.dtypes
Out[3]: borough
                                                    object
        contributing factor vehicle 1
                                                    object
         contributing_factor_vehicle_2
                                                    object
         contributing factor vehicle 3
                                                    object
         contributing_factor_vehicle_4
                                                    object
         contributing_factor_vehicle_5
                                                    object
        cross_street_name
                                                    object
         date
                                           datetime64[ns]
        latitude
                                                  float64
        location
                                                    object
        longitude
                                                   float64
        number_of_cyclist_injured
                                                     int64
         number_of_cyclist_killed
                                                     int64
         number of motorist injured
                                                     int64
         number of motorist killed
                                                     int64
        number of pedestrians injured
                                                     int64
         number_of_pedestrians_killed
                                                     int64
         number_of_persons_injured
                                                     int64
         number_of_persons_killed
                                                     int64
         off street name
                                                    object
         on street name
                                                    object
         time
                                                    object
        unique key
                                                     int64
        vehicle type code1
                                                    object
        vehicle_type_code2
                                                    object
        vehicle_type_code_3
                                                    object
         vehicle_type_code_4
                                                    object
        vehicle type code 5
                                                    object
         zip_code
                                                    object
        dtype: object
In [4]: boroughpop.dtypes
Out[4]: borough
                           object
                            int64
         sum population
         dtype: object
```

It's important to note the relative size of each borough. Staten Island is the smallest borough by far, with Queens and Brooklyn holding the lion's share of New York's population.

```
In [5]: values = round(boroughpop["sum_population"]/1000000,2)
    colors = ['b', 'g', 'r', 'c', 'm', 'y']
    labels = boroughpop['borough']

fig, ax = plt.subplots(figsize=(8, 8))
    plt.pie(values, colors=colors, labels= values,counterclock=False, shadow
=True)
    plt.title('Borough Population (In Millions)',fontsize=15)
    plt.legend(labels,loc=4)
    plt.show()
```

Borough Population (In Millions)



2.3 Data Cleaning

Below I drop the uneeded columns. I also rename the columns we will be using to make them easy to work with. I also filter out any data that doesn't fall within March 21, 2017 and March 21, 2018.

In [6]: #Understanding data columns. Dropping unneeded columns and renaming
accidents.dtypes
accidents.drop(accidents.columns[[3,4,5,6,8,9,10,17,18,19,20,22,25,26,27,28
]], axis=1, inplace=True)

rename columns
accidents.columns = ['Borough', 'Contributing_Factor_1', 'Contributing_Fact
or_2','Date','Cyclists Injured','Cyclists Killed','Motorists Injured','Moto
rists Killed','Pedestrians Injured','Pedestrians Killed','Time','Vehicle Ty
pe 1','Vehicle Type 2']

#Get one year's worth of data
accidents[(accidents['Date']>datetime.date(2017,3,21)) & (accidents['Date']
<datetime.date(2018,3,21))]</pre>

Out[6]:

	Borough	Contributing_Factor_1	Contributing_Factor_2	Date	Cyclists Injured	Су
385	MANHATTAN	Passing or Lane Usage Improper	Unspecified	2017- 03-22	0	0
576	NaN	Unspecified	Unspecified	2017- 03-30	0	0
880	NaN	Unspecified	Unspecified	2017- 03-31	0	0
1155	NaN	Unsafe Lane Changing	Unspecified	2017- 06-24	0	0
1507	NaN	Obstruction/Debris	NaN	2017- 03-22	0	0
1686	NaN	Turning Improperly	Unspecified	2017- 03-22	0	0
1687	NaN	Unspecified	Unspecified	2017- 03-22	0	0
1689	QUEENS	Backing Unsafely	Unspecified	2017- 03-22	0	0
1690	BROOKLYN	Driver Inattention/Distraction	Unspecified	2017- 03-22	0	0
1691	NaN	Reaction to Other Uninvolved Vehicle	Unspecified	2017- 03-22	0	0
1692	QUEENS	Oversized Vehicle	Unspecified	2017- 03-22	0	0
1693	BROOKLYN	Unspecified	Unspecified	2017- 03-22	0	0
	1	l	l .	L	l	<u> </u>

	Borough	Borough Contributing_Factor_1 Contributing_Fa		Date	Cyclists Injured	C
1694	QUEENS	Backing Unsafely	Unsafely Passing or Lane Usage Improper		0	0
1695	MANHATTAN	Unsafe Lane Changing	Unspecified	2017- 03-22	0	0
1697	MANHATTAN	Driver Inattention/Distraction	Unspecified	2017- 03-22	0	0
1698	MANHATTAN	Following Too Closely	Backing Unsafely	2017- 03-22	0	0
1700	NaN	Unspecified	Unspecified	2017- 03-22	0	0
1701	MANHATTAN	Driver Inattention/Distraction	Following Too Closely		0	0
1702	BROOKLYN	Unspecified	d Unspecified		0	0
1703	NaN	Unsafe Lane Changing	Unspecified	2017- 03-22	0	0
1704	NaN	Driver Inattention/Distraction	Unspecified	2017- 03-22	0	0
1705	NaN	Unsafe Lane Changing	Unspecified	2017- 03-22	0	0
1706	NaN	Driver Inexperience	Unspecified	2017- 03-22	0	0
1707	BRONX	Turning Improperly	Turning Improperly	2017- 03-22	0	0
1709	NaN	Following Too Closely	Unspecified	2017- 03-22	0	0
1710	NaN Driver Inattention/Distraction		Unspecified	2017- 03-22	0	0

	Borough	Contributing_Factor_1	Contributing_Factor_2	Date	Cyclists Injured	Су
1711	NaN	Unspecified	NaN	2017- 03-22	0	0
1712	QUEENS	Glare	NaN	2017- 03-22	0	0
1713	NaN	Unspecified	NaN	2017- 03-22	0	0
1714	MANHATTAN	Unspecified	Unspecified	2017- 03-22	0	0
307987	NaN	Unspecified	NaN	2018- 02-28	0	0
308305	QUEENS	Driver Inattention/Distraction	Unspecified	2018- 03-14	0	0
308611	NaN	Driver Inattention/Distraction	Unspecified	2018- 03-15	0	0
308648	NaN	Other Vehicular	Other Vehicular	2017- 10-24	0	0
308663	MANHATTAN	Driver Inattention/Distraction	NaN	2018- 03-06	0	0
308935	BRONX	Aggressive Driving/Road Rage	Unspecified	2018- 03-11	0	0
309332	BRONX	Other Vehicular	NaN	2018- 03-17	0	0
309338	NaN	Driver Inattention/Distraction	Unspecified	2018- 03-14	0	0
309390	BRONX	Unspecified	NaN	2018- 03-18	0	0
309638	NaN	Failure to Yield Right-of- Way	NaN	2018- 03-18	0	0

	Borough	Contributing_Factor_1	Contributing_Factor_2	Date	Cyclists Injured	Су
309672	BRONX	View Obstructed/Limited	Unspecified	2018- 03-14	0	0
309702	BRONX	Traffic Control Disregarded	Unspecified	2017- 04-10	0	0
309933	NaN	Turning Improperly	Unsafe Lane Changing	2017- 04-10	0	0
309999	MANHATTAN	Unsafe Lane Changing	Unspecified	2018- 03-15	0	0
310014	NaN	Unspecified	Unspecified	2018- 03-09	0	0
310449	QUEENS	Unsafe Speed	Unspecified	2018- 03-15	0	0
310582	MANHATTAN	Unspecified	NaN	2018- 02-15	0	0
310652	BROOKLYN	Unspecified	Unspecified	2018- 02-18	0	0
310716	NaN	Unspecified	NaN	2018- 03-15	0	0
310926	MANHATTAN	Driver Inattention/Distraction	Driver Inattention/Distraction	2018- 03-20	0	0
311251	NaN	Unspecified	Unspecified	2018- 02-27	0	0
311266	QUEENS	Failure to Yield Right-of- Way	Unspecified	2018- 03-14	0	0

	Borough	Contributing_Factor_1	Contributing_Factor_2	Date	Cyclists Injured	Су
311498	NaN	Unsafe Speed	Turning Improperly	2018- 03-10	0	0
311567	NaN	Backing Unsafely	Unspecified	2018- 03-20	0	0
311710	BROOKLYN	Unspecified	NaN	2018- 03-05	0	0
311762	MANHATTAN	Turning Improperly	Unspecified	2018- 01-10	0	0
311811	NaN	Following Too Closely	Unspecified	2017- 04-12	0	0
312000	BROOKLYN	Unsafe Speed	Unspecified	2018- 02-28	0	0
443129	NaN	Driver Inattention/Distraction	Unspecified	2018- 01-02	0	0
446262	QUEENS	Turning Improperly	Unspecified	2018- 01-18	0	0

228400 rows × 13 columns

Here I extract valuable Month and Hour information from the Date and Time columns, respectively. I also opt to add a column for "Total Killed" and "Total Injured". There seems to already be a column for this, but I prefer to do this sumation within Python.

	Danauah	Contributing Factor 1
0	Borough BROOKLYN	Contributing_Factor_1 Unspecified
1	NaN	Oversized Vehicle
2	NaN	
3		Fell Asleep
	NaN	Unsafe Speed
4	BROOKLYN	Unspecified
5	NaN	Other Vehicular
6	QUEENS	Driver Inattention/Distraction
7	NaN	Unspecified
8	NaN	Driver Inattention/Distraction
9	MANHATTAN	Turning Improperly
10	QUEENS	Alcohol Involvement
11	NaN	Driver Inattention/Distraction
12	BRONX	Driver Inattention/Distraction
13	NaN	Passing or Lane Usage Improper
14	NaN	Following Too Closely
15	QUEENS	Glare
16	NaN	Following Too Closely
17	NaN	Pavement Slippery
18	QUEENS	Unspecified
19	MANHATTAN	Driver Inattention/Distraction
20	MANHATTAN	Unsafe Lane Changing
21	BROOKLYN	Unspecified
22	MANHATTAN	Unspecified
23	NaN	Unspecified
24	QUEENS	Unsafe Speed
25	NaN	Following Too Closely
26	QUEENS	Unspecified
27	QUEENS	Unspecified
28	NaN	Driver Inexperience
29	QUEENS	Unspecified
499970	STATEN ISLAND	Unspecified
499971	STATEN ISLAND	Unspecified
499972	STATEN ISLAND	Unspecified
499973	STATEN ISLAND	Unspecified
499974	STATEN ISLAND	Unspecified
499975	MANHATTAN	Unspecified
499976	STATEN ISLAND	Unspecified
499977	STATEN ISLAND	Unspecified
499978	BRONX	Driver Inattention/Distraction
499979	STATEN ISLAND	Unspecified
499980	STATEN ISLAND	Fatigued/Drowsy
499981	STATEN ISLAND	Unspecified
499982	STATEN ISLAND	Unspecified
499983	BRONX	Unspecified
499984	STATEN ISLAND	Unspecified
499985	STATEN ISLAND	Driver Inexperience
499986	STATEN ISLAND	Driver Inexperience
499987	STATEN ISLAND	Failure to Yield Right-of-Way
499988	STATEN ISLAND	Unspecified
499989	MANHATTAN	Other Vehicular
499990	MANHATTAN	Oversized Vehicle
499991	MANHATTAN	Prescription Medication
499992	MANHATTAN	Other Vehicular
499993	MANHATTAN	Other Vehicular
499994	BRONX	Unspecified

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499995	MANHATTAN	Fatigued/Drow	sy		
499996		ger Distracti	-		
499997	MANHATTAN	Unspecifi			
499998	MANHATTAN Driver Inattent:	ion/Distracti	on		
499999	MANHATTAN Driver Inattent:	ion/Distracti	on		
	Contributing_Factor_2	Date	Cyclists	Injured	\
0		2017-03-20	,	0	
1	Unspecified			0	
2	•	2017-03-20		0	
3	Unspecified			0	
4	•	2017-03-20		0	
5	Unspecified			0	
6	•	2017-03-20		0	
7	Unspecified			0	
8	Unsafe Lane Changing			0	
9	Unspecified			0	
10	Unspecified			0	
11	Unspecified			0	
12	Driver Inattention/Distraction			0	
13	Unspecified			0	
14	Following Too Closely			0	
15	Unspecified			0	
16	Following Too Closely			0	
17	Unspecified			0	
18	•	2017-03-20		0	
19	Unspecified			0	
20	Unsafe Lane Changing			0	
21		2017-03-20		0	
22		2017-03-20		0	
23	Unspecified			0	
24	Unspecified			0	
25	Unspecified			0	
26	•	2017-03-20		0	
27	Unspecified			0	
28	Unspecified			0	
29	•	2017-03-20		0	
499970	Unspecified	2014-08-24		0	
499971	Unspecified			0	
499972	Unspecified			0	
499973	NaN	2014-08-24		0	
499974	Unspecified	2014-08-22		0	
499975	Unspecified			0	
499976	Unspecified			0	
499977	Unspecified			0	
499978	Driver Inattention/Distraction			0	
499979	Unspecified	2014-08-23		0	
499980	Traffic Control Disregarded			0	
499981	Unspecified			0	
499982	Unspecified			0	
499983	Unspecified			0	
499984	Unspecified			1	
499985	Unspecified			0	
499986	Unspecified			0	
499987	Unspecified			0	
499988	Unspecified			0	
	•				

499989 499990 499991 499992 499993 499994 499995 499997 499998 499999	Passenger Distraction 2014-08-25	
	Cyclists Killed Motorists Injured Motorists	Killed \
0	0 0	0
1	0 0	0
2	0 1 0 0	0 0
3 4	0 0	0
5	0 0	0
6	0 0	0
7	0 0	0
8	0 0	0
9	0 2	0
10	0 0	0
11 12	0 0 0 0	0 0
13	0 0	0
14	0 2	0
15	0 0	0
16	0 0	0
17	0 0	0
18	0 0	0
19	0 0	0
20 21	0 0 0	0 0
22	0 0	0
23	0 0	0
24	0 0	0
25	0 1	0
26	0 0	0
27	0 1	0
28 29	0 1 0 0	0 0
23		
499970	0 1	0
499971	0 0	0
499972	0 0	0
499973	0 0	0
499974	0 0	0
499975 499976	0 0 0 0	0 0
499976 499977	0 0	0
499978	0 0	0
499979	0 0	0
499980	0 0	0
499981	0 0	0
499982	0 0	0

499983 499984 499985 499986 499988 499990 499991 499992 499993 499994 499995 499996 499997 499998 499999	0 0 0 0 0 0 0 0 0 0			0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0	Pedestrians Injured 0		2018-04-16	Time \
1	0		2018-04-16	
2	0		2018-04-16	
3	0		2018 04 16	
4	0		2018-04-16	
5	0		2018-04-16	
6	1		2018-04-16	
7	0		2018-04-16	
8	0		2018-04-16	
9	0		2018-04-16	
10	0		2018-04-16	
10	0		2018-04-16	
12	0		2018-04-16	
13	0		2018-04-16	
14	0		2018-04-16	
1 4 15	0	6		
16	0		2018-04-16	
17	0		2018-04-16	
18	0		2018-04-16	
19	0		2018-04-16	
20	0		2018-04-16	
21	0		2018-04-16	
22	0		2018-04-16	
23	0		2018-04-16	
24	0		2018-04-16	
25	0		2018 04 16	
26	0		2018-04-16	
27	0		2018 04 16	
28	0		2018-04-16	
29	0		2018-04-16	
	ŭ	•	2010 04 10	05.05.00
 499970	0		2018-04-16	 14·15·00
499971	0		2018-04-16	
499972	0		2018-04-16	
499973	0		2018-04-16	
499974	0		2018-04-16	
499975	0		2018-04-16	
499976	0		2018-04-16	
7 22270	0	•	2010-04-10	10.71.00

499977 499978 499979 499980 499981 499982 499983 499986 499986 499987 499988 499990 499991 499991 499992 499993 499994 499995 499996 499997 499998 499998	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 2018-04-16 11:53:00 0 2018-04-16 13:47:00 0 2018-04-16 12:55:00 0 2018-04-16 18:12:00 0 2018-04-16 15:50:00 0 2018-04-16 16:08:00 0 2018-04-16 13:30:00 0 2018-04-16 13:30:00 0 2018-04-16 14:37:00 0 2018-04-16 13:30:00 0 2018-04-16 11:00:00 0 2018-04-16 11:00:00 0 2018-04-16 10:26:00 0 2018-04-16 10:26:00 0 2018-04-16 14:15:00 0 2018-04-16 15:20:00 0 2018-04-16 15:20:00 0 2018-04-16 16:45:00 0 2018-04-16 00:55:00 0 2018-04-16 01:40:00 0 2018-04-16 01:40:00 0 2018-04-16 15:48:00
\	Vehicle Type 1	Vehicle Type 2
0	PICK-UP TRUCK	NaN
1	PASSENGER VEHICLE	PASSENGER VEHICLE
2	PASSENGER VEHICLE	NaN
3	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
4	PASSENGER VEHICLE	NaN
5	PASSENGER VEHICLE	PASSENGER VEHICLE
6	SPORT UTILITY / STATION WAGON	NaN
7	SPORT UTILITY / STATION WAGON	NaN
8	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
9	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
10	PASSENGER VEHICLE	PASSENGER VEHICLE
11	SPORT UTILITY / STATION WAGON	NaN
12	SPORT UTILITY / STATION WAGON	VAN
13	PASSENGER VEHICLE	NaN
14	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
15	PASSENGER VEHICLE	NaN

16	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
17	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
18	PASSENGER VEHICLE	NaN
19	SPORT UTILITY / STATION WAGON	PASSENGER VEHICLE
20	PASSENGER VEHICLE	NaN
21	SPORT UTILITY / STATION WAGON	NaN
22	SPORT UTILITY / STATION WAGON	NaN
23	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
24	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
25	SPORT UTILITY / STATION WAGON	PICK-UP TRUCK
26	NaN	NaN
27	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
28	PASSENGER VEHICLE	SPORT UTILITY / STATION WAGON
29	PICK-UP TRUCK	NaN
•••		•••
499970	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499971	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499972	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499973	SPORT UTILITY / STATION WAGON	NaN
499974	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499975	SPORT UTILITY / STATION WAGON	UNKNOWN
499976	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499977	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499978	PASSENGER VEHICLE	PASSENGER VEHICLE
499979	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499980	SPORT UTILITY / STATION WAGON	SPORT UTILITY / STATION WAGON
499981	SPORT UTILITY / STATION WAGON	PASSENGER VEHICLE
499982	PASSENGER VEHICLE	PASSENGER VEHICLE

499983	PASSENGE	•	_E		РА	SSENGER VE	HICLE
499984	PASSENGE	R VEHICL	.E			ВІ	CYCLE
499985	PASSENGE	R VEHICL	.E		PA	SSENGER VE	HICLE
499986	M	OTORCYCL	_E				VAN
499987	PASSENGE	R VEHICL	.E		PA	SSENGER VE	HICLE
499988	SPORT UTILITY / STAT	ION WAGO	DN		PA	SSENGER VE	HICLE
499989	SPORT UTILITY / STAT	ION WAGO	DN			BI	CYCLE
499990	LARGE COM VEH(6 OR MO	RE TIRES	5)				NaN
499991		BU	JS LARGE C	OM	VEH(6	OR MORE T	IRES)
499992		Bl	JS				OTHER
499993	PASSENGE	R VEHICL	_E				OTHER
499994	PASSENGE	R VEHICL	_E				NaN
499995	SMALL COM VEH()		PA	SSENGER VE	HICLE	
499996	LIVERY VEHICLE			BICYCLE			CYCLE
499997	SPORT UTILITY / STATION WAGON					UN	KNOWN
499998	PASSENGER VEHICLE						TAXI
499999	LARGE COM VEH(6 OR MO	RE TIRES	5)		PA	SSENGER VE	HICLE
	•		,				
	Total Injured Total	Killed	MonthNumbe		Hour	Month	
0	0	0		3	0	March	
1 2	0 1	0 0		3	1 5	March March	
3	0	0		2	23	February	
4	0	0		3	1	March	
5	0	0		3	4	March	
6	1	0		3	6	March	
7	0	0		2	17	February	
8 9	0 2	0 0		3 3	4 2	March March	
10	0	0		3	3	March	
11	0	0		3	5	March	
12	0	0		3	0	March	
13	0	0		3	5	March	
14	2	0		3	8	March	
15 16	0 0	0 0		3	8 8	March March	
16 17	0	0		3	8	march March	
18	0	0		3	8	March	
19	0	0		3	6	March	
20	0	0		3	7	March	

		Data Bootcamp Final I	Project v6		
21	0	0	3	7	March
22	0	0	3	7	March
23	0	0	3	9	March
24	0	0	3	6	March
25	1	0	3	9	March
26	0	0	3	8	March
27	1	0	3	8	March
28	1	0	3	7	March
29	0	0	3	9	March
• • •		• • •			
499970	1	0	8	14	August
499971	0	0	8	15	August
499972	0	0	8	18	August
499973	0	0	8	14	August
499974	0	0	8	11	August
499975	0	0	8	20	August
499976	0	0	8	18	August
499977	0	0	8	11	August
499978	0	0	5	13	May
499979	0	0	8	12	August
499980	0	0	8	18	August
499981	0	0	8	15	August
499982	0	0	8	16	August
499983	0	0	5	13	May
499984	1	0	8	13	August
499985	0	0	8	14	August
499986	0	0	8	13	August
499987	0	0	8	11	August
499988	0	0	8	14	August
499989	1	0	8	21	August
499990	0	0	8	10	August
499991	0	0	8	10	August
499992	0	0	8	9	August
499993	0	0	8	14	August
499994	1	0	5	15	May
499995	0	0	8	16	August
499996	1	0	8	0	August
499997	0	0	8	23	August
499998	0	0	8	1	August
499999	0	0	8	15	August

[500000 rows x 18 columns]

3. Visualizing the Data

3.1 Where Accidents Occur

Accidents broken down by the five boroughs of New York City.

3.1.1 By Borough and Traveler

Injuries and deaths by borough and by type of traveler.

```
In [8]: | accidentsgrouped = accidents.groupby(['Borough']).sum()
        #sorting accidents grouped by borough so that it matches up with our boroug
        h population dataframe. This will be used later
        accidentsgrouped['boroughsort']=accidentsgrouped.index
        accidentsgrouped = accidentsgrouped.sort values(by='boroughsort', ascending
        =False)
        accidentsgrouped['Pedestrians Injured Per Cap'] = np.divide(accidentsgroupe
        d['Pedestrians Injured'],boroughpop['sum_population'])
        accidentsgrouped['Motorists Injured Per Cap'] = np.divide(accidentsgrouped[
        'Motorists Injured'],boroughpop['sum_population'])
        accidentsgrouped['Cyclists Injured Per Cap'] = np.divide(accidentsgrouped[
        'Cyclists Injured'],boroughpop['sum_population'])
        accidentsgrouped['Pedestrians Killed Per Cap'] = np.divide(accidentsgrouped
        ['Pedestrians Killed'],boroughpop['sum_population'])
        accidentsgrouped['Motorists Killed Per Cap'] = np.divide(accidentsgrouped[
        'Motorists Killed'],boroughpop['sum population'])
        accidentsgrouped['Cyclists Killed Per Cap'] = np.divide(accidentsgrouped['C
        yclists Killed'],boroughpop['sum population'])
        #Setting of dataframes around types of injuries and deaths
        pedestinjuriesbyborough = accidentsgrouped.sort values(by='Pedestrians Inju
        red', ascending=False)
        pedestdeathsbyborough = accidentsgrouped.sort values(by='Pedestrians Kille
        d', ascending=False)
        motorinjuriesbyborough = accidentsgrouped.sort values(by='Motorists Injure
        d', ascending=False)
        motordeathsbyborough = accidentsgrouped.sort values(by='Motorists Killed',
        ascending=False)
        cyclistinjuriesbyborough = accidentsgrouped.sort values(by='Cyclists Injure
        d', ascending=False)
        cyclistdeathsbyborough = accidentsgrouped.sort values(by='Cyclists Killed',
         ascending=False)
        print(accidentsgrouped)
```

	Cyclists Injured	Cyclists Kille	ed Motorist	s Injured	\		
Borough STATEN ISLAND	71	-	0	1867			
QUEENS	1119		6	12055			
MANHATTAN	1655		9	4454			
BROOKLYN	2120	:	12	13008			
BRONX	560		2	6728			
	Motorists Killed	Pedestrians In	njured Pede	estrians Kil	led		
Borough STATEN ISLAND	8		368		7		
QUEENS	19		3208		, 47		
MANHATTAN	4		2913		35		
BROOKLYN	20		4396		36		
BRONX	8		2237		18		
Danawah	Total Injured To	otal Killed Mor	nthNumber	Hour \			
Borough STATEN ISLAND	2306	15	59284 1	127464			
QUEENS	16382	72		305525			
MANHATTAN	9022	48		550439			
BROOKLYN	19524	68		919128			
BRONX	9525	28	208192 4	139047			
	boroughsort Pedestrians Injured Per Cap \						
Borough	CTATEN TOLAND		0.000403				
STATEN ISLAND QUEENS	STATEN ISLAND QUEENS		0.000403 0.000719				
MANHATTAN	MANHATTAN		0.000933				
BROOKLYN	BROOKLYN		0.000333				
BRONX	BRONX		0.000823				
	Motorists Injured Per Cap Cyclists Injured Per Cap \						
Borough							
STATEN ISLAND		0.002046		0.000078			
QUEENS		0.002703		0.000251			
MANHATTAN BROOKLYN				0.000530 0.000427			
BRONX		0.002476		0.000427			
Pedestrians Killed Per Cap Motorists Killed Per Cap \							
Borough		0.00000		0.000000			
STATEN ISLAND		0.000008		0.000009 0.000004			
QUEENS MANHATTAN		0.000011 0.000011		0.000004			
BROOKLYN		0.000011		0.000001			
BRONX		0.000007		0.000003			
	Cyclists Killed Per Cap						
Borough							
STATEN ISLAND		000e+00					
QUEENS	1.345261e-06 2.881782e-06						
MANHATTAN BROOKLYN		782e-06 174e-06					
BRONX		007e-07					

Here we see a comparison between Pedestrian, Motorists, and Cyclist injuries and deaths across Buroughs. Interestingly, the ranking between boroughs changes across types of commuters and across injuries and deaths.

Observations

- 1. Why are almost as many motorists killed on Staten Island as in the Bronx (3rd), even though Staten Island is consistently ranked lowest in all other areas?
- 2. Why does Queens take the lead for pedestrians killed, even though it is ranked 2nd and 3rd in all other types of accidents?
- 3. Why does Manhattan seem to have the highest variability amongst buroughs, being last in Motorists injured/killed, 2nd in cyclists injured/killed, and middle of the pack for pedestrian injuries?
- 4. Why does Staten Island have such low rates of Cyclist injuries and deaths?

Potential Additions

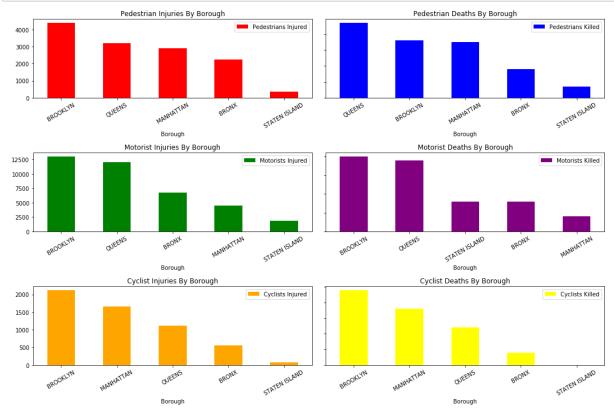
Of course, we would have to understand these numbers better in the context of per capita rates. This could be done by merging with a population dataset and dividing these rates by number of inhabitants. However, this would still not account for the fact that some areas have very high commuter rates.

Perhaps better would be to look at geographic size, or even total traffic flow. Geographic size may paint a better picture, but this still lacks information on density. In regards to total traffic flow, well, let me know if that dataset exists!

Takeaways

- 1. Do many vehicles pass through Staten Island, lending to its high motorist deaths? Or, does Staten Island have inadequate speed limits, traffic lights, stop signs, etc.? Higher speed tolerances may explain why Staten Island jumps more in deaths than in injuries. Perhaps Staten Island's motor policy needs review.
- 2. Does Queens have a higher proportion of people who walk? Or, are sidewalks inadequate, crosswalks ignored, and residents lacking general safety habits like looking both ways? In this area, perhaps Queen's outreach and development programs need review.
- 3. Does Manhattan see such high variability because it is the most diverse burough of them all? Or, does it clearly have a problem providing adequate laneways for cyclists? I know I personally see cyclists navigating erractically, crossing intersections when lights are red and even failing to look both ways when doing so. The data indicates a clear problem, supported by anecdotal evidence. Perhaps Manhattan needs to look in providing better bicycly lanes as well as fining cyclists for ignoring lights in the same way they would motorists.
- 4. Does Staten Island have few cyclists? Or does it adequately provide for them and enforce cyclist law? Perhaps Manhattan and Brooklyn could learn from them.

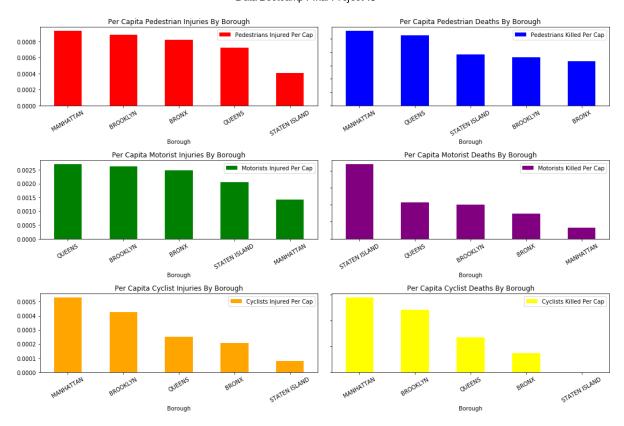
fig, ax = plt.subplots(nrows=3, ncols=2) pedestinjuriesbyborough[['Pedestrians Injured']].plot(kind='bar', ax=ax[0,0], color=['red'], width=0.5, title ="Pedestrian Injuries By Borough", figsi ze=(15, 10), legend=True, fontsize=10, rot = 30) pedestdeathsbyborough[['Pedestrians Killed']].plot(kind='bar', ax=ax[0,1], color=['blue'],width=0.5, title ="Pedestrian Deaths By Borough", figsize=(1 5, 10), legend=True, fontsize=10, sharey=ax[0,0], rot = 30) motorinjuriesbyborough[['Motorists Injured']].plot(kind='bar', ax=ax[1,0], color=['green'], width=0.5, title ="Motorist Injuries By Borough", figsize= (15, 10), legend=**True**, fontsize=10, rot = 30) motordeathsbyborough[['Motorists Killed']].plot(kind='bar', ax=ax[1,1], col or=['purple'],width=0.5, title ="Motorist Deaths By Borough", figsize=(15, 10), legend=True, fontsize=10,sharey=ax[1,0],rot = 30) cyclistinjuriesbyborough[['Cyclists Injured']].plot(kind='bar', ax=ax[2,0], color=['orange'],width=0.5, title ="Cyclist Injuries By Borough", figsize= (15, 10), legend=**True**, fontsize=10,rot = 30) cyclistdeathsbyborough[['Cyclists Killed']].plot(kind='bar', ax=ax[2,1], co lor=['yellow'],width=0.5, title ="Cyclist Deaths By Borough", figsize=(15, 10), legend=True, fontsize=10, sharey=ax[2,0], rot = 30) fig.tight layout() fig.subplots_adjust(wspace=0.05, hspace=0.7) plt.show()



Taking into account borough populations, some observations change or become clearer.

- 1. Staten Island is far ahead of the other buroughs in terms of motorists killed per capita something is clearly wrong.
- 2. Pedestrian deaths for Queens seem even more shocking now given its per capita ranking against other buroughs.
- 3. Manhattan's variability now appears largely explained. It has by far the lowest motorist deaths and injuries per capita of any borough and yet it has the highest per capita rate of injuries and deaths of cyclists and pedestrians per capita than any other burough. This is likely explained by the foot traffic density and slow traffic speed in the city. It may also indicate inadequate protection for non-motorists
- 4. The low level of cyclist injuries and deaths in Staten Island is even more impressive when looked at per capita.
- 5. Finally, a general observation is that far more drivers are killed and injured by accidents than pedestrians and cyclists (see axes). This is perhaps not surprising, though it is certainly reassuring that those who are "at fault" are those who are most affected.

```
In [10]: #setting up sorting for graphs
         pedestinjuriesbyborough = accidentsgrouped.sort values(by='Pedestrians Inju
         red Per Cap', ascending=False)
         pedestdeathsbyborough = accidentsgrouped.sort values(by='Pedestrians Killed
          Per Cap', ascending=False)
         motorinjuriesbyborough = accidentsgrouped.sort_values(by='Motorists Injured
          Per Cap', ascending=False)
         motordeathsbyborough = accidentsgrouped.sort values(by='Motorists Killed Pe
         r Cap', ascending=False)
         cyclistinjuriesbyborough = accidentsgrouped.sort_values(by='Cyclists Injure
         d Per Cap', ascending=False)
         cyclistdeathsbyborough = accidentsgrouped.sort values(by='Cyclists Killed P
         er Cap', ascending=False)
         fig, ax = plt.subplots(nrows=3, ncols=2)
         pedestinjuriesbyborough[['Pedestrians Injured Per Cap']].plot(kind='bar', a
         x=ax[0,0], color=['red'], width=0.5, title ="Per Capita Pedestrian Injuries
          By Borough", figsize=(15, 10), legend=True,fontsize=10, rot = 30,sort_colu
         mns=True)
         pedestdeathsbyborough[['Pedestrians Killed Per Cap']].plot(kind='bar', ax=a
         x[0,1], color=['blue'],width=0.5, title ="Per Capita Pedestrian Deaths By B
         orough", figsize=(15, 10), legend=True, fontsize=10, sharey=ax[0,0], rot = 30
         ,sort columns=True )
         motorinjuriesbyborough[['Motorists Injured Per Cap']].plot(kind='bar', ax=a
         x[1,0], color=['green'], width=0.5, title ="Per Capita Motorist Injuries By
          Borough", figsize=(15, 10), legend=True, fontsize=10, rot = 30, sort columns
         =True)
         motordeathsbyborough[['Motorists Killed Per Cap']].plot(kind='bar', ax=ax[1
         ,1], color=['purple'],width=0.5, title ="Per Capita Motorist Deaths By Boro
         ugh", figsize=(15, 10), legend=True, fontsize=10, sharey=ax[1,0], rot = 30, so
         rt columns=True )
         cyclistinjuriesbyborough[['Cyclists Injured Per Cap']].plot(kind='bar', ax=
         ax[2,0], color=['orange'],width=0.5, title ="Per Capita Cyclist Injuries By
          Borough", figsize=(15, 10), legend=True, fontsize=10,rot = 30,sort columns
         =True )
         cyclistdeathsbyborough[['Cyclists Killed Per Cap']].plot(kind='bar', ax=ax[
         2,1], color=['yellow'],width=0.5, title ="Per Capita Cyclist Deaths By Boro
         ugh", figsize=(15, 10), legend=True, fontsize=10,sharey=ax[2,0],rot = 30,so
         rt columns=True)
         fig.tight_layout()
         fig.subplots adjust(wspace=0.05, hspace=0.7)
         plt.show()
```



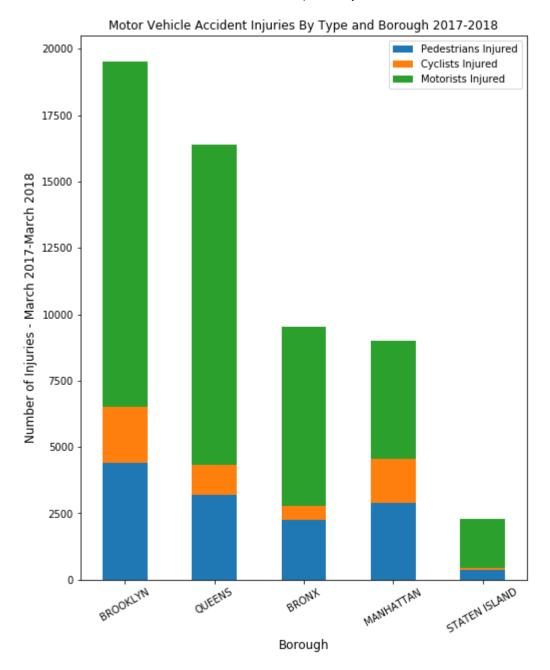
3.1.2 Borough and Traveler Summarized

Observations and Takeaways

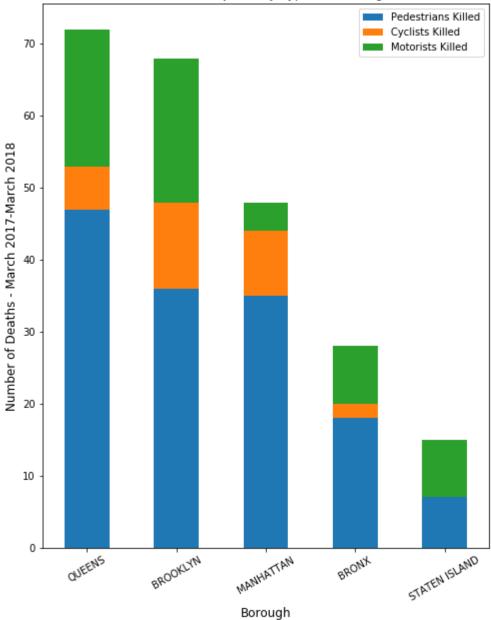
Looking at the numbers from another angle, we see that Brooklyn has the most injuries, but Queens has the most deaths. Furthermore, we see that this difference is largely due to pedestrian deaths, and this is despite the fact that Queens has fewer pedestrian injuries than Brooklyn. Does Queens have a poor hospital system that is either not getting injured pedestrians to treatment quickly enough or is losing them in the hospital themselves. Ultimately, are there more deaths that could have been just injuries?

We also see that while Manhattan and The Bronx have about the same amount of injuries, Manhattan has almost twice as many deaths as The Bronx. Again, this difference seems to be due to pedestrian deaths. This might inform us that Amblance ride windows are too long or hospital ER treatment not adequate for pedestrian type injuries.

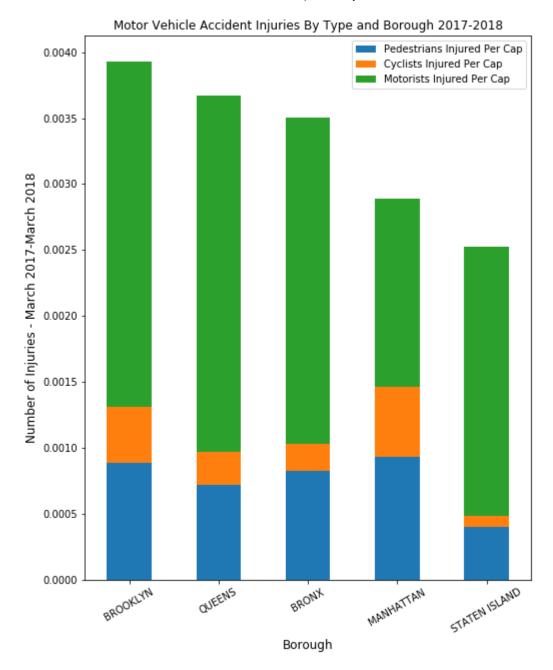
```
In [18]:
         injuriesbyborough = accidentsgrouped.sort values(by='Total Injured', ascend
         ing=False)
         deathsbyborough = accidentsgrouped.sort values(by='Total Killed', ascending
         =False)
         ax = injuriesbyborough[['Pedestrians Injured', 'Cyclists Injured', 'Motorist
         s Injured']].plot(kind='bar', stacked = True, title = "Motor Vehicle Accident
          Injuries By Type and Borough 2017-2018", figsize=(8, 10), legend=True, fon
         tsize=10, rot=30)
         ax.set_xlabel("Borough", fontsize=12)
         ax.set ylabel("Number of Injuries - March 2017-March 2018", fontsize=12)
         ax = deathsbyborough[['Pedestrians Killed','Cyclists Killed', 'Motorists Ki
         lled']].plot(kind='bar', stacked = True, title ="Motor Vehicle Accident Inju
         ries By Type and Borough 2017-2018", figsize=(8, 10), legend=True, fontsize
         =10, rot=30)
         ax.set xlabel("Borough", fontsize=12)
         ax.set ylabel("Number of Deaths - March 2017-March 2018", fontsize=12)
         plt.show()
```

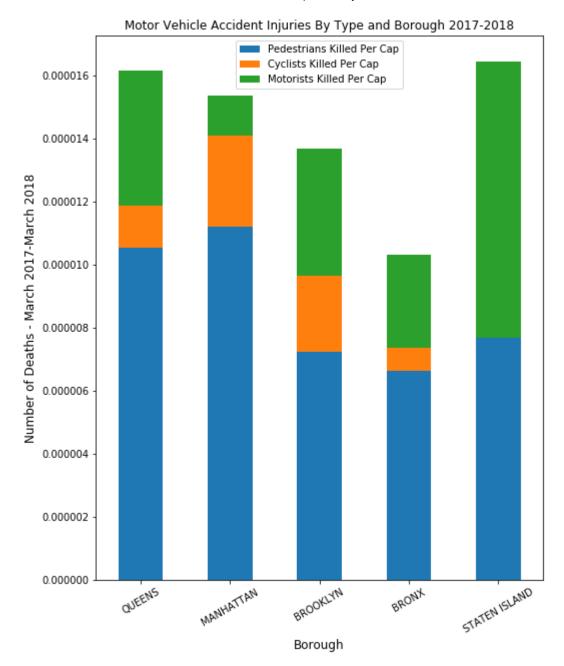






```
In [25]: injuriesbyborough['Total Injured Per Cap'] = np.divide(injuriesbyborough
         ['Total Injured'],boroughpop['sum_population'])
         deathsbyborough['Total Killed Per Cap'] = np.divide(deathsbyborough['Tot
         al Killed'],boroughpop['sum population'])
         injuriesbyborough = injuriesbyborough.sort values(by='Total Injured Per
          Cap', ascending=False)
         deathsbyborough = deathsbyborough.sort values(by='Total Killed Per Cap',
          ascending=False)
         ax = injuriesbyborough[['Pedestrians Injured Per Cap','Cyclists Injured
          Per Cap', 'Motorists Injured Per Cap']].plot(kind='bar', stacked = True
         title ="Motor Vehicle Accident Injuries By Type and Borough 2017-2018,
          figsize=(8, 10), legend=True, fontsize=10,rot=30)
         ax.set xlabel("Borough", fontsize=12)
         ax.set ylabel("Number of Injuries - March 2017-March 2018", fontsize=12)
         ax = deathsbyborough[['Pedestrians Killed Per Cap','Cyclists Killed Per
          Cap', 'Motorists Killed Per Cap']].plot(kind='bar', stacked = True,titl
         e ="Motor Vehicle Accident Injuries By Type and Borough 2017-2018", figs
         ize=(8, 10), legend=True, fontsize=10,rot=30)
         ax.set_xlabel("Borough", fontsize=12)
         ax.set_ylabel("Number of Deaths - March 2017-March 2018", fontsize=12)
         plt.show()
```





Checking the largest accidents we see that there are no major outliers contributing to this discrepency.

,	Borough	Contributing_Factor_1	. Contributing_Factor_2	Date
193648	MANHATTAN	Other Vehicular	Unspecified	2017-10-31
158552	QUEENS	Unsafe Speed	Unspecified	2017-09-18
384584	NaN	Unspecified	Unspecified	2016-06-19
230057	NaN	Unspecified	Unspecified	2016-08-31
86937	NaN	Unsafe Speed	Unspecified	2017-07-16
97738	NaN	Unspecified	l NaN	2014-10-17
66576	QUEENS	Unsafe Speed	l NaN	2017-06-17
394334	BROOKLYN	Unspecified	Unspecified	2016-08-01
383460	NaN	Unspecified	l NaN	2016-06-13
20443	NaN	Unspecified	Unspecified	2017-04-17
193648 158552 384584 230057 86937 97738 66576 394334 383460 20443 193648 158552 384584 230057 86937 97738 66576 394334 383460 20443	Cyclists	1 0 0 0 0 0 0 0	2 4 0 13 0 9 0 3 0 8 0 0 0 1 0 0 0 0 0	lled \ 8 2 0 0 0 2 0 0
158552 384584 230057 86937 97738 66576 394334	2018-04-16 2018-04-16 2018-04-16 2018-04-16 2018-04-16 2018-04-16 2018-04-16 2018-04-16	06:17:00 SPORT UTILI 13:45:00 04:17:00 06:26:00 02:04:00 00:55:00 00:08:00	Vehicle Type 1 FB TY / STATION WAGON PASSENGER VEHICLE PASSENGER VEHICLE MOTORCYCLE PASSENGER VEHICLE PASSENGER VEHICLE PASSENGER VEHICLE PASSENGER VEHICLE PASSENGER VEHICLE	

				•			
20443	2018-04-16 18:21:00			PASSENGER VEH	HICLE		
		Veh	icle Type 2	Total Injured	Total	Killed	\
193648			BU	13		10	
158552	SPORT UTILIT	Y / ST	ATION WAGON	16		3	
384584		PASSEN	GER VEHICLE	9		3	
230057		PASSEN	GER VEHICLE	3		3	
86937	SPORT UTILIT	Y / ST	ATION WAGON	8		2	
97738			NaN	0		2	
66576			NaN	1		2	
394334		PASSENGER VEHICLE				2	
383460			NaN	0		2	
20443	SPORT UTILIT	Y / ST	ATION WAGON	0		2	
	MonthNumber	Hour	Month				
193648	10	15	October				
158552	9	6	September				
384584	6	13	June				
230057	8	4	August				
86937	7	6	July				
97738	10	2	October				
66576	6	0	June				
394334	8	0	August				
383460	6	2	June				
20443	4	18	April				

3. Visualizing the Data

3.2 When Accidents Occur

Not where, but when accidents occur. Based on time of day as well as month.

3.2.1 Time of Day

Observations and Takeaways

Injuries

We see below that injuries for accidents are low in the wee hours of the night. They start rising at around 6 am, with a mini-peak at around 8 am. They fall until 10, at which point they steadily rise again before peaking at around 5pm.

It seems that accidents are low from midnights to 6 am due to few drivers on the road. Accidents spike between 6-8 am as more drivers rush to work, perhaps falling afterwards as roads get too congested for real injuries to take place.

As rushhour ends at 10pm, the rise up to 5pm can be explained by crowded, but not completely congested streets.

Interestingly, accidents occur far more at the end of the day than at the beginning. One may posit that this is due to factors such as road-rage after a stressful day at work, fatigure after a long day, or eagerness to arrive home.

In reaction, officials may determine that targeting messaging to drivers may be a good way to alert them to the risks when driving home in the evening. They may also opt to post more traffic cops and general officers throughout the city during these times.

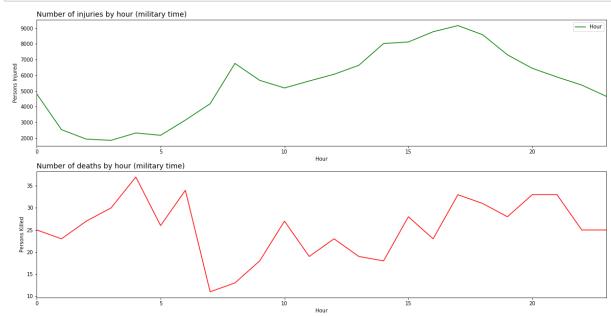
Deaths

In direct contrast with injuries, deaths occur the most in the wee hours of the night. This could be due to a number of factors including driver fatigue, drunk driving, and higher car speeds thanks to fewer drivers on the road.

Deaths plummet during the morning rush hour and interestingly rise steadily throughout the day until rush hour is over. This might be because as drivers reach the tail end of their commute home, they are more tired and more eager to get home, and, importantly, no longer in slow-moving traffic.

```
In [13]: accidentsbyhour = accidents.groupby(['Hour']).sum()

fig, ax = plt.subplots(nrows=2, ncols=1, figsize=(20, 10))
    accidentsbyhour['Total Injured'].plot(ax=ax[0], color='green')
    ax[0].set_title('Number of injuries by hour (military time)', fontsize=14,
    loc='left')
    ax[0].set_ylabel('Persons Injured')
    ax[0].legend(['Hour', 'Persons Injured'])
    accidentsbyhour['Total Killed'].plot(ax=ax[1], color='red')
    ax[1].set_title('Number of deaths by hour (military time)', fontsize=14, lo
    c='left')
    ax[1].set_ylabel('Persons Killed')
    plt.show()
```



3.2.2 Month

Observations and Takeaways

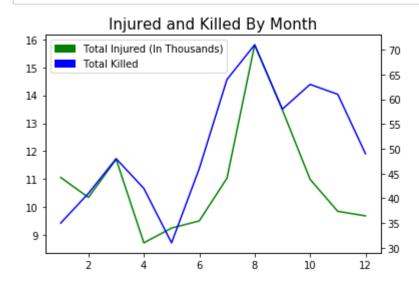
Injuries and deaths seems to show a similar seasonal trend. That being said, there is a consistently low level of deaths from January through to May.

Spring is a visibly a period of low injuries and deaths, which continues into most of summer. From August to September accidents are at their highest.

This may be weather related. More people (and tourists) might be out from August to September. It could also have to do with commuter levels - springtime is a period when many choose to take vacations. Finally, fewer deaths may occur during the cold months as weather prevents motorists from driving too quickly.

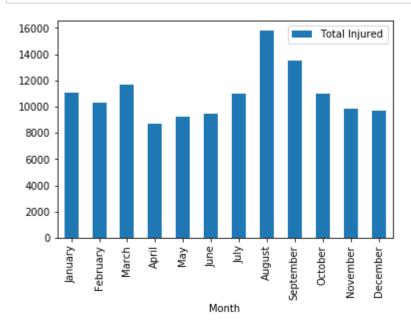
City officials could be put on "high alert," or government services increased during this fall and winter period. To balance the budget, this could be met with reduced government services during the low spring and summer months.

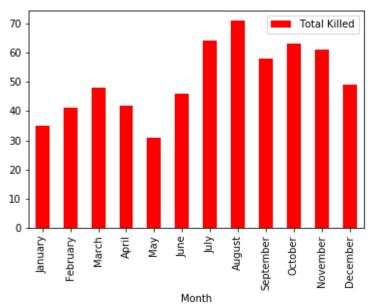
```
In [14]: injuriesbymonth = accidents.groupby(['MonthNumber']).sum()
          injuriesbymonth['Month'] = ['January', 'February', 'March', 'April', 'May',
          'June', 'July', 'August', 'September', 'October', 'November', 'December']
         fig, ax1 = plt.subplots()
         x = injuriesbymonth.index
         y1 = injuriesbymonth['Total Injured']/1000
         y2 = injuriesbymonth['Total Killed']
         ax1.set_title("Injured and Killed By Month",fontsize=15)
         ax2 = ax1.twinx()
         ax1.plot(x, y1, 'g-', label = "Total Injured")
         ax2.plot(x, y2, 'b-', label = "Total Killed")
         injured = mpatches.Patch(color='Green', label='Total Injured (In Thousan
          ds)')
         killed = mpatches.Patch(color='Blue', label='Total Killed')
         plt.legend(handles=[injured,killed])
         plt.show()
```



In [31]: injuriesbymonth.plot(y='Total Injured',kind='bar')

deathsbymonth = accidents.groupby(['MonthNumber']).sum()
 deathsbymonth['Month'] = ['January','February','March','April','May','June'
 ,'July','August','September','October','November','December']
 deathsbymonth = deathsbymonth.set_index('Month')
 deathsbymonth.plot(y='Total Killed',kind='bar', color='red')
 plt.show()

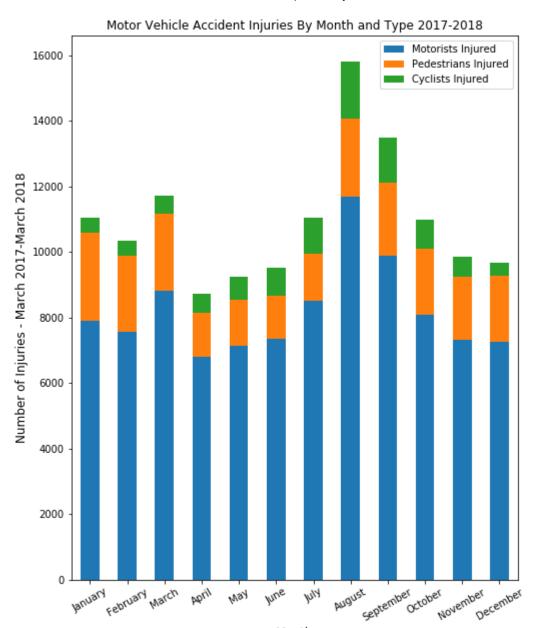




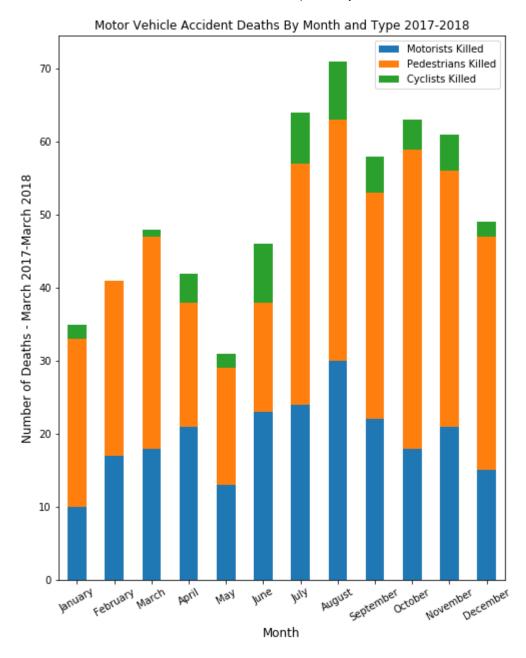
3.2.3 Month and Traveler Type

Falls and rises in injuries are driven primarily by changes in motorist injuries. This does not come as a huge surprise, given that they account for the vast majority of injuries.

However, the delta in deaths between months is caused by motorist, pedestrian, and cyclist deaths alike. Frightenenly, about half of deaths are not to the motorists, but to pedestrians and cyclists. This demonstrates the importance of protecting those on foot and bike with sidewalks, crosswalks, walking/biking lanes, etc; Motorists are protected de-facto by their cars, while those outside are extremely vulnerable.



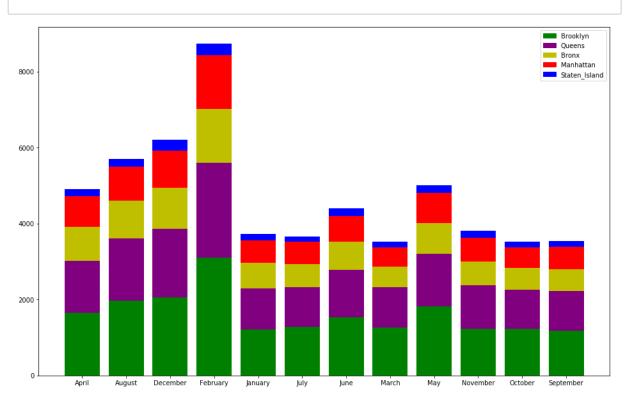
Month



3.2.4 Month and Borough

Data seems to suggest that changes in injury rates by month do not favor particular boroughs. While we observed earlier that boroughs are responsible for differening absolute amounts of accidents, their relative importance does not shift noticeably from month to month. In other words, injuries rise and fall in unison across boroughs throughout the year.

```
In [33]:
         accidentsbymonthborough = accidents.groupby(['Month', 'Borough'], as index=
         False).sum()
         fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(16, 10))
         A1 = accidentsbymonthborough.query("Borough=='BROOKLYN'")['Total Injured']
         B2 = np.add(A1,accidentsbymonthborough.query("Borough=='QUEENS'")['Total In
         jured'])
         C3= np.add(B2,accidentsbymonthborough.query("Borough=='BRONX'")['Total Inju
         red'l)
         D4 = np.add(C3,accidentsbymonthborough.query("Borough=='MANHATTAN'")['Total
          Injured'])
         E5 = np.add(D4,accidentsbymonthborough.query("Borough=='STATEN ISLAND'")['T
         otal Injured'])
         X = injuriesbymonth.index.tolist()
         plt.bar(X, E5, color = 'b')
         plt.bar(X, D4, color = 'r')
         plt.bar(X, C3, color = 'v')
         plt.bar(X, B2, color = 'purple')
         plt.bar(X, A1, color = 'g')
         Brooklyn = mpatches.Patch(color='g', label='Brooklyn')
         Queens = mpatches.Patch(color='Purple', label='Queens')
         Bronx = mpatches.Patch(color='y', label='Bronx')
         Manhattan = mpatches.Patch(color='r', label='Manhattan')
         Staten_Island= mpatches.Patch(color='b', label='Staten_Island')
         plt.legend(handles=[Brooklyn,Queens,Bronx,Manhattan,Staten Island])
         plt.show()
```



3. Visualizing the Data

3.3 Why Accidents Occur

Not where or when, but why accidents occur. The causes of accidents based on the primary car/driver at fault.

Observations and Takeaways

In the charts below I look at the top eight contributing factors to injuries and fatalities. The percentages relate to the percent that each item accounts for in the group of eight.

The biggest culprit by far for injuries is driver inattention. This is followed by a failure to yield right-of-way and following too closely.

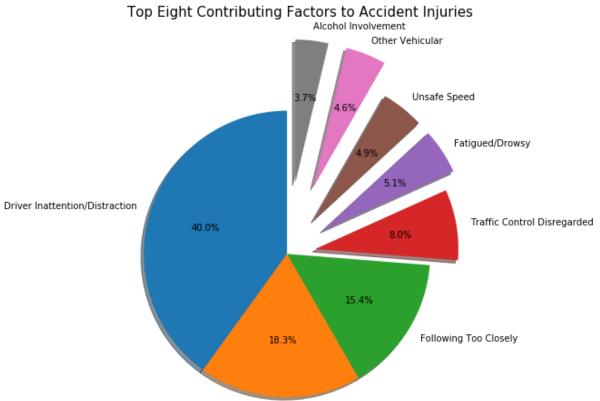
Perhaps unsurprisingly, the main causes of accident deaths are different. While the leading factor is still driver inattention, 2nd and 3rd major contributing factors are failure to yield right of way and unsafe speeds.

Surprisingly, alcohol consumption accounts for a relatively low percentage of injuries and deaths.

Officials looking to address injuries and/or fatalities can look to these results for direction in which practices to pursue and which behaviours to change.

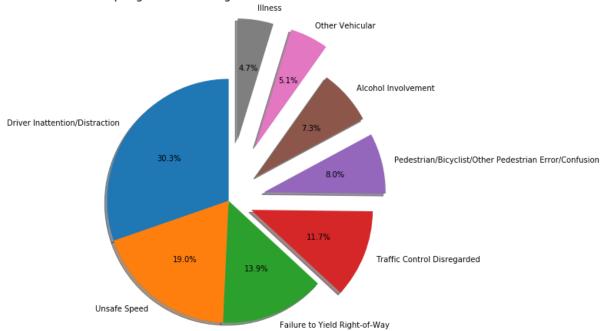
```
In [34]: #remove unspecified as an option
    accidents = accidents[accidents.Contributing_Factor_1 != 'Unspecified']
```

```
In [35]: contributing factor = accidents.groupby(['Contributing Factor 1']).sum() #qr
         oup dataset by contributing factor
         contributingfactorinjured = contributingfactor.sort_values(by='Total Injure
         d', ascending=False) #qet top 8 injuries
         contributingfactorinjured =contributingfactorinjured.head(8)
         contributingfactorkilled = contributingfactor.sort values(by='Total Killed'
         , ascending=False) #qet top 8 deaths
         contributingfactorkilled =contributingfactorkilled.head(8)
         #Plot injured pie chart
         labels = contributingfactorinjured.index
         sizes =contributingfactorinjured["Total Injured"]
         explode = (0,0,0,.2,.3,.3,.5,.5)
         fig, ax = plt.subplots(figsize=(8, 8))
         ax.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
                 shadow=True, startangle=90)
         ax.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circl
         ax.set title("Top Eight Contributing Factors to Accident Injuries", fontsize
         =15)
         #Plot deaths pie chart
         labels = contributingfactorkilled.index
         sizes =contributingfactorkilled["Total Killed"]
         explode = (0,0,0,.2,.3,.3,.5,.5)
         fig, ax = plt.subplots(figsize=(8, 8))
         ax.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
                 shadow=True, startangle=90)
         ax.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circl
         ax.set title("Top Eight Contributing Factors to Accident Deaths", fontsize=1
         5)
         plt.show()
```



Failure to Yield Right-of-Way

Top Eight Contributing Factors to Accident Deaths



4. Conclusion

If NYC government officials are not already leveraging accident data to target efforts, there are many areas in which this data can guide their efforts. Citizens of and travelers to NYC can also stand to gain from greater knowledge of when and where to be most aware in NYC. Some observations in this dataset may also be applicable across other cities and countries, as it is reasonable to suggest that many trends around time and cause of accident are ubiquitous.

Key Observations

Key accident observations for the city of New York include:

Where

- 1. Staten Island has a significantly higher per capita death rate of motorists than other boroughs.
- 2. Manhattan is the most dangerous place for cyclists and pedestrians, but the safest place for motorists.
- 3. Brooklyn has the most injuries due to accidents per capita while Staten Island has the least.
- However, Staten Island has the most deaths due to accidents per capita while the Bronx has by far the least.

When

- 1. Accidents occur the most during both morning and evening rush hour.
- Even so, the most deaths occur between 4 and 7 am, plummeting in the morning rush hour but rising again during the evening rush hour.
- 3. Spring is the period with the fewest amount of injuries and deaths due to accidents.
- 4. The late summer and fall periods see the most accidents resulting in injuries and deaths.

How/Why

- 1. While the vast majority of injuries are to the motorists themselves, half of accidents deaths are born by pedestrians and cyclists.
- 2. The top cause of both injuries and deaths in accidents is Driver Inattention/Distraction
- 3. The top three causes of death in accidents are distracted drivers, unsafe speeds, and a failure to yield the right-of-way. These causes account for almost two-thirds of all deaths in accidents.