Final project, Data 601, Spring 2019 - Analysis of New York State Fire Department Fallen Heroes Data

- Dataset 1: New York State Fallen Firefighters Memorial Roll of Honor data
- Dataset 2: Fire Department Directory for New York State
- Merging column: Fire Department Name

About the data:

- My final project combines two different datasets. The datasets cover different aspects of New York State Fire Departments.
- The first dataset; "New York State Fallen Firefighters Memorial Roll of Honor", contains the names, ranks department names, dates of death and locations on Memorial Wall of Firefighters who have sacrificed their lives in order to save others.
- The second dataset; "Fire Department Directory for New York State", contains an annually update list of names, location, phone numbers and Division of Homeland Security and Emergency Services (DHSES) ID for Fire Departments in New York State. The data is collected and maintained by the Office of Fire Prevention & Control (OFPC) within DHSES.
- I found this data through the suggestions for project data ideas on Blackboard.

My story:

- Firefighters are one of the most amazing and selfless people in the world. I beleive that most humans, given a choice, would always save themselves. Firefighters on the other hand are the brave few people in the world who would jump into a fire to save another person.
- There have been many tragedies in this world. However, only a handful of them have had an impact as big as the attack on September 11th, 2001.

- When I saw these two datasets, I thought I could combine the data to identify patterns about such incidents from temporal data of fatalities in fire departments of New York State. I think this data analysis will help me see the impact of that one incident in comparison to others.
- While exploring patterns in the combined dataset, following questions came to my mind:
  - Everyone knows about September 11th, 2001 and that people died but can it be determined from the combined data, which county most of the firefighters came from?
    - Key Observation - **Combining the two datasets** I am able to infer that on **September 11, 2001, New York County** happened to face a severe crisis, in which hundreds of firefighters gave their lives.
    - The firefighters that sacrificed their lives on 9/11 came from **New York County**.
    - **Story time** - 9/11 was one of the biggest terrorist attacks in American History on American soil killing thousands of people.
    - This link specifies that on that day:
    - "Of the 2,977 victims killed in the September 11 attacks, 412 were emergency workers in New York City who responded to the World Trade Center."
    - "This included: **343 firefighters** (including a chaplain and two paramedics) of the New York City Fire Department (FDNY)".
    - My dataframe - top_date_of_death_county_df shows that on 9/11, 2001 New York County had in-fact had 343 fatalities.
  - During 9/11 was there a fire department where most of the fatalities occurred?
    - During 9/11 the fire department located at "9 metrotech center", Brooklyn, New York seems to be the station from which most of the firefighters operated.
    - Intuitively this looks reasonable as the World Trade Center is in lower Manhattan that is very close to Brooklyn by waterways.
  - It is understandable that there will be few high ranking officials directly involved in rescue operations. Does the combined data tell us the ranks of the firefighters that sacrificed their lives?
    - I was able to determine that most fatalities on 9/11 happened for the "Firefighter" rank.
    - The second highest fatalities were for "Lieutenant" rank followed by "Captain" and "Battallion Chief".
  - Is there any incident comparable to 9/11 in terms of fire fighter fatalities? Where did such an incident occur?
    - Using my analysis I was also able to determine that there is no incident, as per the datasets, that can compare to 9/11, in terms of fatalities. However, it looks like on August 2nd, 1978 there was an incident that might have caused some fatalities. After googling around, I found that the Waldbaum Fire of August 2, 1978 had killed six firefighters.
  - Which fire departments across the state of New York have had the most fatalities? Can the top ten fatal locations be represented visually with information about the most fatal incident for that location?
    - I was also able to visualize using a map of New York State, the dates of the most fatal incident, alongwith count of fatalities. I was able to visualize the most fatal incident ranked by top ten most fatal locations across the state of New York.

Data properties and access information:

Data properties and access information:

- Data available through Fire Department Directory Data from NYS Open Data site and New York State Fallen Firefighters Memorial Roll of Honor.
- Download Link 1 and Link 2 for data source.
- Downloaded file named: "New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv" and "Fire_Department_Directory_for_New_York_State.csv".
- These two data sources can be merged based on the Fire Department's name column that can be found in both files.
- There is no cost to accessing this data.
- Accessing this data does not require creation of an account.
- Accessing this data does not violate any laws.
- This data do not appear to have been previously analyzed based on a Google search.
- A preliminary survey of the data in New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv indicates there are 2549 rows, 5 columns, and the file is 196 KB. The Fire_Department_Directory_for_New_York_State.csv has 1773 rows, 12 columns, and the file is 245 KB.

In [1]:

```
!pip install folium
!pip install nltk

import numpy as np
import pandas as pd
import time
import datetime
from datetime import datetime
import calendar
import chardet
import missingno as msno
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import os
import random
import re
import folium

import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
nltk.download('punkt')
from nltk.tokenize import word_tokenize
import string

import warnings
warnings.filterwarnings("ignore")

start_time = time.time()
print('\n\nPandas',pd.__version__)
print('Matplotlib',matplotlib.__version__)
print('Seaborn',sns.__version__)
print('File Size In KB for New_York_State_Fallen_Firefighters_Memorial CSV: ',(os.path.getsize('Ne
w_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv')/1000),' KB')
print('File Size In KB for Fire_Department CSV : ',
(os.path.getsize('Fire_Department_Directory_for_New_York_State.csv')/1000),' KB')
NY = 'New York State'
```

```
Requirement already satisfied: folium in /opt/conda/lib/python3.6/site-packages (0.9.0)
Requirement already satisfied: requests in /opt/conda/lib/python3.6/site-packages (from folium)
(2.20.1)
Requirement already satisfied: branca>=0.3.0 in /opt/conda/lib/python3.6/site-packages (from
folium) (0.3.1)
Requirement already satisfied: jinja2>=2.9 in /opt/conda/lib/python3.6/site-packages (from folium)
(2.10)
Requirement already satisfied: numpy in /opt/conda/lib/python3.6/site-packages (from folium)
(1.13.3)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.6/site-packages (from
requests->folium) (2018.11.29)
Requirement already satisfied: urllib3<1.25,>=1.21.1 in /opt/conda/lib/python3.6/site-packages
(from requests->folium) (1.23)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /opt/conda/lib/python3.6/site-packages
(from requests->folium) (3.0.4)
Requirement already satisfied: idna<2.8,>=2.5 in /opt/conda/lib/python3.6/site-packages (from
requests->folium) (2.7)
```

```
Requirement already satisfied: six in /opt/conda/lib/python3.6/site-packages (from branca>=0.3.0->
folium) (1.11.0)
Requirement already satisfied: MarkupSafe>=0.23 in /opt/conda/lib/python3.6/site-packages (from
jinja2>=2.9->folium) (1.1.0)
Requirement already satisfied: nltk in /opt/conda/lib/python3.6/site-packages (3.4.1)
Requirement already satisfied: six in /opt/conda/lib/python3.6/site-packages (from nltk) (1.11.0)


Pandas 0.23.4
Matplotlib 2.2.2
Seaborn 0.9.0
File Size In KB for New_York_State_Fallen_Firefighters_Memorial CSV:  195.981  KB
File Size In KB for Fire_Department CSV :  244.968  KB
```

```
[nltk_data] Downloading package stopwords to /home/jovyan/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /home/jovyan/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Exploring data

Encoding check for the input CSV files to ensure data is in right format

In [2]:

```
with open('New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv','rb') as fraw:
    file_content = fraw.read()
```

In [3]:

```
chardet.detect(file_content)
```

Out[3]:

```
{'encoding': 'utf-8', 'confidence': 0.99, 'language': ''}
```

Character encoding of the CSV file is utf-8 and confidence level is 0.99(99%). Hence I will provide encoding='utf-8' while loading the file into Pandas DataFrame using read_csv()

In [4]:

```
with open('Fire_Department_Directory_for_New_York_State.csv','rb') as fraw:
    file_content = fraw.read()
```

In [5]:

```
chardet.detect(file_content)
```

Out[5]:

```
{'encoding': 'ascii', 'confidence': 1.0, 'language': ''}
```

Character encoding of the CSV file is ascii and confidence level is 1(100%).

Exploring file contents from the CSVs:

In [6]:

```
!head -n 3 New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv
```

```
Name,Rank,Fire Department,Date of Death,Location on Memorial
Abe Dias,Firefighter,Haverstraw Fire Department,01/08/1906,20 Bottom
Abraham Price,Captain,Rochester Fire Department,04/26/1924,  5 Top
```

In [7]:

```
!head -n 3 Fire_Department_Directory_for_New_York_State.csv
```

```
Fire Department Name,Fire Department Code,Address,City,State,Zip Code,County Code,County
Name,Phone Number,Latitude,Longitude,Location 1
ALBANY FIRE DEPARTMENT,01001,26 BROAD STREET,ALBANY,NY,12202-0000,01,Albany,5184477879,42.662577,-
73.759898,"(42.662577, -73.759898)"
ALTAMONT FIRE DEPARTMENT,01002,115 MAIN STREET PO BOX
642,ALTAMONT,NY,12009,01,Albany,5188618171,42.702865,-74.02531,"(42.702865, -74.02531)"
```

Next, I will extract the data from CSV files and insert into dataframes for processing

In [8]:

```
pd.options.display.max_rows = 40

start_time_before_load_file1 = time.time()
fire_fighters_df = pd.read_csv("New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv",enc
oding ='utf-8')
print('Time taken to load fire fighters data : ',time.time() - start_time_before_load_file1,'secon
ds')
print('Before Shape of fire_fighters_df : ',fire_fighters_df.shape)
print('Dropping rows with duplicate data from fire_fighters_df.')
fire_fighters_df.drop_duplicates()
print('After Shape of fire_fighters_df : ',fire_fighters_df.shape)

start_time_before_load_file2 = time.time()
fire_department_df = pd.read_csv("Fire_Department_Directory_for_New_York_State.csv")
print('\n\nTime taken to load fire department data : ',time.time() - start_time_before_load_file2,
'seconds')
print('Before Shape of fire_department_df : ',fire_department_df.shape)
print('Dropping rows with duplicate data from fire_department_df.')
fire_department_df.drop_duplicates()
print('After Shape of fire_department_df : ',fire_department_df.shape)
```

```
Time taken to load fire fighters data :  0.07521891593933105 seconds
Before Shape of fire_fighters_df :  (2549, 5)
Dropping rows with duplicate data from fire_fighters_df.
After Shape of fire_fighters_df :  (2549, 5)


Time taken to load fire department data :  0.027831077575683594 seconds
Before Shape of fire_department_df :  (1773, 12)
Dropping rows with duplicate data from fire_department_df.
After Shape of fire_department_df :  (1773, 12)
```

- The dataframes do not have any duplicate data.

The New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor.csv/fire_fighters_df dataframe contains 2549 rows and 5 columns.

The Fire_Department_Directory_for_New_York_State.csv/fire_department_df dataframe contains 1773 rows and 12 columns.

Let us explore the data a bit using head(), tail(), info(), describe() for both dataframes

In [9]:

```
fire_fighters_df.head()
```

Out[9]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial
0	Abe Dias	Firefighter	Haverstraw Fire Department	01/08/1906	20 Bottom
1	Abraham Price	Captain	Rochester Fire Department	04/26/1924	5 Top
2	Adam Damm	Firefighter	New York City Fire Department	02/27/1907	6 Bottom
3	Adam D. Rand	Firefighter	New York City Fire Department	09/11/2001	16 Top

	Name	Rank	Fire Department	Date of Death	Location on Memorial
4	Adam Fisher	Captain	Buffalo Fire Department	01/2[illegible]/189[illegible]	14 Bottom

In [10]:

```
fire_fighters_df.tail()
```

Out[10]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial
2544	Willliam E. Bennett	Chief	Kennedy Fire Department	09/04/2001	4 Bottom
2545	Winfield A. Walsh	Firefighter	New York City Fire Department	01/04/1947	15 Top
2546	Winifred Knapp	Fire Police	Owego Fire Department	11/06/1965	8 Top
2547	W. John Eckerson	Firefighter	Beukendaal Volunteer Fire Department	08/19/1956	20 Bottom
2548	Zigmund Klemowski	Firefighter	Buffalo Fire Department	07/21/1976	8 Top

In [11]:

```
fire_fighters_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2549 entries, 0 to 2548
Data columns (total 5 columns):
Name                    2549 non-null object
Rank                    2549 non-null object
Fire Department         2549 non-null object
Date of Death           2548 non-null object
Location on Memorial    2549 non-null object
dtypes: object(5)
memory usage: 99.6+ KB
```

In [12]:

```
fire_fighters_df.describe()
```

Out[12]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial
count	2549	2549	2549	2548	2549
unique	2535	91	551	1878	70
top	Michael O'Brien	Firefighter	New York City Fire Department	09/11/2001	11 Top
freq	2	1619	1222	349	95

In [13]:

```
fire_department_df.head()
```

Out[13]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Location 1
0	ALBANY FIRE DEPARTMENT	1001	26 BROAD STREET	ALBANY	NY	12202-0000	1	Albany	5.184478e+09	42.662577	-73.759898	(42.662577, -73.759898)
1	ALTAMONT FIRE DEPARTMENT	1002	115 MAIN STREET PO BOX 642	ALTAMONT	NY	12009	1	Albany	5.188618e+09	42.702865	-74.025310	(42.702865, -74.02531)

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Location 1
2	BERNE FIRE DEPARTMENT	1003	CANADAY ROAD	BERNE	NY	12023	1	Albany	5.18872[illegible]e+09	42.612842	-74.070082	(42.612842, -74.070082)
3	BOGHT COMMUNITY FIRE DEPARTMENT	1004	1095 LOUDON ROAD	COHOES	NY	12047	1	Albany	5.187850e+09	42.783571	-73.743969	(42.783571, -73.743969)
4	COEYMANS FIRE DEPARTMENT	1005	67 CHURCH STREET	COEYMANS	NY	12045	1	Albany	5.187562e+09	42.474106	-73.798832	(42.474106, -73.798832)

In [14]:

```
fire_department_df.tail()
```

Out[14]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Location
1768	HIMROD FIRE DEPARTMENT	62006	3530 HIMROD ROAD	HIMROD	NY	14842	62	Yates	6.072438e+09	42.592109	-76.955867	(42.59210 76.95586
1769	MIDDLESEX HOSE COMPANY	62008	5537 WATER STREET	MIDDLESEX	NY	14507	62	Yates	5.853930e+09	42.705097	-77.272390	(42.70509 -77.2723
1770	PENN YAN FIRE DEPARTMENT	62009	125 ELM STREET	PENN YAN	NY	14527	62	Yates	3.155366e+09	42.660786	-77.055047	(42.66078 77.05504
1771	POTTER FIRE DEPARTMENT	62010	1255 PHELPS ROAD	MIDDLESEX	NY	14507	62	Yates	7.165543e+09	42.704203	-77.210211	(42.70420 77.21021
1772	RUSHVILLE HOSE COMPANY	62011	5 SOUTH MAIN ST PO BOX 636	RUSHVILLE	NY	14544	62	Yates	7.165546e+09	42.739010	-77.290900	(42.7390 -77.290

In [15]:

```
fire_department_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1773 entries, 0 to 1772
Data columns (total 12 columns):
Fire Department Name    1773 non-null object
Fire Department Code    1773 non-null int64
Address                 1773 non-null object
City                    1773 non-null object
State                   1773 non-null object
Zip Code                1773 non-null object
County Code             1773 non-null int64
County Name             1773 non-null object
Phone Number            1723 non-null float64
Latitude                1754 non-null float64
Longitude               1754 non-null float64
Location 1              1754 non-null object
dtypes: float64(3), int64(2), object(7)
memory usage: 166.3+ KB
```

In [16]:

```
fire_department_df.describe()
```

Out[16]:

	Fire Department Code	County Code	Phone Number	Latitude	Longitude
count	1773.000000	1773.000000	1.723000e+03	1754.000000	1754.000000
mean	32142.637338	32.106599	5.836917e+09	42.504047	-75.475262

	Fire Department Code	County Code	Phone Number	Latitude	Longitude
std	18076.796358	18.080252	1.780322e+09	0.971825	1.871169
min	1001.000000	0.000000	8.319430e+06	40.589435	-79.741600
25%	15069.000000	15.000000	5.182395e+09	41.986486	-76.889797
50%	33025.000000	33.000000	6.072255e+09	42.624451	-75.010532
75%	50008.000000	50.000000	7.165328e+09	43.062057	-73.854090
max	62011.000000	62.000000	9.177389e+09	44.995546	-71.952388

In [17]:

```
fire_department_df.describe(include='all')
```

Out[17]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longituc
count	1773	1773.000000	1773	1773	1773	1773	1773.000000	1773	1.723000e+03	1754.000000	1754.0000
unique	1755	NaN	1714	1335	1	1337	NaN	59	NaN	NaN	Na
top	GREENVILLE FIRE DEPARTMENT	NaN	PO BOX 158	ROCHESTER	NY	12401	NaN	Suffolk	NaN	NaN	Na
freq	3	NaN	4	14	1773	9	NaN	108	NaN	NaN	Na
mean	NaN	32142.637338	NaN	NaN	NaN	NaN	32.106599	NaN	5.836917e+09	42.504047	-75.47526
std	NaN	18076.796358	NaN	NaN	NaN	NaN	18.080252	NaN	1.780322e+09	0.971825	1.87116
min	NaN	1001.000000	NaN	NaN	NaN	NaN	0.000000	NaN	8.319430e+06	40.589435	-79.74160
25%	NaN	15069.000000	NaN	NaN	NaN	NaN	15.000000	NaN	5.182395e+09	41.986486	-76.88979
50%	NaN	33025.000000	NaN	NaN	NaN	NaN	33.000000	NaN	6.072255e+09	42.624451	-75.01053
75%	NaN	50008.000000	NaN	NaN	NaN	NaN	50.000000	NaN	7.165328e+09	43.062057	-73.85409
max	NaN	62011.000000	NaN	NaN	NaN	NaN	62.000000	NaN	9.177389e+09	44.995546	-71.95238

In [18]:

```
fire_department_df.describe(include='object')
```

Out[18]:

	Fire Department Name	Address	City	State	Zip Code	County Name	Location 1
count	1773	1773	1773	1773	1773	1773	1754
unique	1755	1714	1335	1	1337	59	1710
top	GREENVILLE FIRE DEPARTMENT	PO BOX 158	ROCHESTER	NY	12401	Suffolk	(42.86943, -77.29118)
freq	3	4	14	1773	9	108	3

Data Cleanup and Pre-processing before joining the dataframes

In [19]:

```
print('Number of firefighter names in fire_fighters_df : ',fire_fighters_df['Name'].count())
print('Number of unique firefighter names in fire_fighters_df : ',fire_fighters_df['Name'].nunique
())
print('\n')
print('Number of unique Fire Department Names in fire_department_df : ',fire_department_df['Fire D
epartment Name'].nunique())
print('Number of unique Fire Department Codes in fire_department_df : ',fire_department_df['Fire D
epartment Code'].nunique())
print('Number of rows in fire_department_df : ',fire_department_df.shape[0])
```

```
Number of firefighter names in fire_fighters_df :  2549
Number of unique firefighter names in fire_fighters_df :  2535


Number of unique Fire Department Names in fire_department_df :  1755
Number of unique Fire Department Codes in fire_department_df :  1772
Number of rows in fire_department_df :  1773
```

Obsevation 1

- In fire_fighters_df 14 people have same name which is fine.

Obsevation 2

- Number of unique Fire Department Names are lesser than Fire Department Codes in fire_department_df.
  - This indicates that there are some Fire Department Names with different Fire Department Codes in fire_deparment_df. This will cause duplicate row entries in merged dataframe after joining.
  - Hence, I need to drop data from fire_deparment_df that have the same department name but different department codes. From these multiple entries I can only keep one entry. As the fire_fighters_df does not specify a code or address for department, I can simply match by name and choose to keep one. I will fix this in step 1 below.

Observation 3

- Number of rows in fire_department_df is 1773 but unique Fire Department Codes in fire_department_df is 1772.
  - This indicates that there are at least two rows with same Fire Department Code. This will create duplicate entries in merged dataframe.
  - Hence, I need to check whether the department with same department code exist in fire_fighters_df. If it does not exist then removing those department codes will not affect the analysis.
  - Thus I will remove this **data discrepancy in fire_department_df** without any effect on anything else. I will fix this in step 2 below.

Step 1

In [20]:

```
'''
Dropping data to keep one entry for fire departments that have same department names but different
department codes from fire_deparment_df.
'''
print('Index with same department name but different department code in fire_deparment_df:')
for department in list(fire_department_df['Fire Department Name'].value_counts().index):
    if fire_department_df[fire_department_df['Fire Department Name']==department]['Fire Department
Name'].value_counts().values > 1:
        index_list_of_same_department_name=list(fire_department_df[fire_department_df['Fire Departm
ent Name']==department].index)
        print(index_list_of_same_department_name)
        for indx in index_list_of_same_department_name[:-1]:
            fire_department_df.drop(index=indx,inplace=True)
```

```
Index with same department name but different department code in fire_deparment_df:
[559, 1007, 1703]
[284, 1421]
[32, 300]
[209, 763]
[352, 1701]
[371, 815]
[499, 1136]
[754, 1004]
[515, 1529]
[1580, 1687]
[607, 832]
[114, 930]
[1637, 1766]
[80, 1255]
[393, 709]
[10, 750]
[427, 725]
```

Step 2

In [21]:

```
fire_department_df['Fire Department Code'].value_counts().head()
```

Out[21]:

```
42004    2
22007    1
52083    1
30060    1
28013    1
Name: Fire Department Code, dtype: int64
```

In [22]:

```
'''
Looking for the rows with same department code
'''
fire_department_df[fire_department_df['Fire Department Code']==42004]
```

Out[22]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Locat
1135	BRUNSWICK NO 1 FIRE DEPARTMENT	42004	566 HOOSICK ROAD	TROY	NY	12180	42	Rensselaer	5.182729e+09	42.740294	-73.656569	(42.74 73.65
1136	BRUSHTON FIRE DEPARTMENT	42004	816 COUNTY RD 7 PO BOX 607	BRUSHTON	NY	12916	17	Franklin	5.185296e+09	42.740294	-73.656569	(42.74 73.65

In [23]:

```
'''
Checking whether the department name with duplicate deparment code exists in fire_fighters_df
'''
fighters_department_list=list(fire_fighters_df['Fire Department'].apply(lambda x : x.split(' ')[0].
lower()))
exits='N'
for fighters_department in fighters_department_list:
    if (fighters_department == 'brunswick') or (fighters_department =='brushton') :
        exits = 'Y'
        break

if  exits=='Y' :
    print('Yes, the department name with duplicate deparment code exists in fire_fighters_df.')
else:
    print('No, the department name with duplicate deparment code does not exists in
fire_fighters_df.')
```

```
No, the department name with duplicate deparment code does not exists in fire_fighters_df.
```

In [24]:

```
'''
As, the department name with duplicate deparment code does not exist in fire_fighters_df, dropping
this data from fire_deparment_df will not
affect the analysis. Therefore, I am dropping it.
'''
for department_code in list(fire_department_df['Fire Department Code'].value_counts().index):
    if fire_department_df[fire_department_df['Fire Department Code']==department_code]['Fire
Department Code'].value_counts().values > 1:
        index_list_of_same_department_code=list(fire_department_df[fire_department_df['Fire Departm
ent Code']==department_code].index)
        print('Index list of same department code : ',index_list_of_same_department_code)
        for indx in index_list_of_same_department_code:
            fire_department_df.drop(index=indx,inplace=True)
            print('Dropped index : ',indx)
```

```
Index list of same department code :  [1135, 1136]
Dropped index :  1135
Dropped index :  1136
```

In [25]:

```
print('After cleanup shape of fire_department_df : ',fire_department_df.shape)
print('Number of unique Fire Department Name in fire_department_df : ',fire_department_df['Fire De
partment Name'].nunique())
print('Number of unique Fire Department Code in fire_department_df : ',fire_department_df['Fire De
partment Code'].nunique())
```

```
After cleanup shape of fire_department_df :  (1753, 12)
Number of unique Fire Department Name in fire_department_df :  1753
Number of unique Fire Department Code in fire_department_df :  1753
```

Now, the fire_department_df dataframe contains 1753 rows and 12 columns.

Pre-processing Messy Deparment Names

In [26]:

```
def department_preprocess(department):
    """
    Takes in a string of department name, then performs the following:
    1. Convert department name to lowercase
    2. Split department name in words
    3. Remove all punctuations
    4. Remove empty strings from department name
    5. Remove all stopwords
    6. Remove repetitive filler words from department name
       Replace words that can cause issues while join is performed based on department name.
    7. Join cleaned department name tokens back to a phrase
    8. Complete spelling corrections of department name
    9. Return clean department name
    """
    en_stops = set(stopwords.words('english'))

    """
    Convert department name to lowercase
    """
    department_lowercase = department.lower()

    """
    Split department name in words
    """
    list_of_words = word_tokenize(department_lowercase)

    """
    Remove all punctuations
    Check characters to see if they are in punctuation
    """
    list_of_words_without_punctuation=[''.join(this_char for this_char in this_string if
(this_char not in string.punctuation))for this_string in list_of_words]

    """
    Remove empty strings from department name
    """
    list_of_words_without_punctuation = list(filter(None, list_of_words_without_punctuation))

    """
    Remove any stopwords
    """
    filtered_word_list = [w for w in list_of_words_without_punctuation if w not in en_stops]

    """
    Remove repetitive filler words from department name
    """
    ignore_lst=['fire','department','city','vol','volunteer','no','district',
                'dept','deparment','company','co','engine']
    filtered_word_list = [w for w in filtered_word_list if w not in ignore_lst]

    """
    Join cleaned department name tokens back to a phrase
    """
    clean_department=' '.join(filtered_word_list)

    """
    Complete spelling corrections of department name
    """
    clean_department = clean_department.replace('centre','center')
    clean_department = clean_department.replace('ctr','center')
    clean_department = clean_department.replace('cliff','clift')
    clean_department = clean_department.replace('springs','spring')
    clean_department = clean_department.replace('sq','square')
    clean_department = clean_department.replace('tact','tract')

    """
    Return clean department name
    """
    return clean_department
```

In [27]:

```
'''
For fire_fighters_df :
Convert column data to lowercase
Create new column with 'Department' as column name
'''
fire_fighters_df = fire_fighters_df.applymap(lambda s:s.lower() if type(s) == str else s)
fire_fighters_df['Department']=fire_fighters_df['Fire Department']
fire_fighters_df.head()
```

Out[27]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department
0	abe dias	firefighter	haverstraw fire department	01/08/1906	20 bottom	haverstraw fire department
1	abraham price	captain	rochester fire department	04/26/1924	5 top	rochester fire department
2	adam damm	firefighter	new york city fire department	02/27/1907	6 bottom	new york city fire department
3	adam d. rand	firefighter	new york city fire department	09/11/2001	16 top	new york city fire department
4	adam fisher	captain	buffalo fire department	01/23/1891	14 bottom	buffalo fire department

In [28]:

```
'''
Applying department_preprocess() to the new key column of fire_fighters_df
'''
fire_fighters_df['Department']=fire_fighters_df['Department'].apply(department_preprocess)
fire_fighters_df.head()
```

Out[28]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department
0	abe dias	firefighter	haverstraw fire department	01/08/1906	20 bottom	haverstraw
1	abraham price	captain	rochester fire department	04/26/1924	5 top	rochester
2	adam damm	firefighter	new york city fire department	02/27/1907	6 bottom	new york
3	adam d. rand	firefighter	new york city fire department	09/11/2001	16 top	new york
4	adam fisher	captain	buffalo fire department	01/23/1891	14 bottom	buffalo

In [29]:

```
'''
For fire_department_df :
Convert column data to lowercase
Create new column with 'Department' as column name
'''
fire_department_df = fire_department_df.applymap(lambda s:s.lower() if type(s) == str else s)
fire_department_df['Department']=fire_department_df['Fire Department Name']
```

```
fire_department_df.head()
```

Out[29]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Location 1	Dep
0	albany fire department	1001	26 broad street	albany	ny	12202-0000	1	albany	5.184478e+09	42.662577	- 73.759898	(42.662577, - 73.759898)	al de
1	altamont fire department	1002	115 main street po box 642	altamont	ny	12009	1	albany	5.188618e+09	42.702865	- 74.025310	(42.702865, -74.02531)	alta de
2	berne fire department	1003	canaday road	berne	ny	12023	1	albany	5.188720e+09	42.612842	- 74.070082	(42.612842, - 74.070082)	b de
3	boght community fire department	1004	1095 loudon road	cohoes	ny	12047	1	albany	5.187850e+09	42.783571	- 73.743969	(42.783571, - 73.743969)	co de
4	coeymans fire department	1005	67 church street	coeymans	ny	12045	1	albany	5.187562e+09	42.474106	- 73.798832	(42.474106, - 73.798832)	c de

In [30]:

```
'''
Applying department_preprocess() to the new key column of fire_department_df
'''
fire_department_df['Department']=fire_department_df['Department'].apply(department_preprocess)
fire_department_df.head()
```

Out[30]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Location 1	Dep
0	albany fire department	1001	26 broad street	albany	ny	12202-0000	1	albany	5.184478e+09	42.662577	- 73.759898	(42.662577, - 73.759898)	
1	altamont fire department	1002	115 main street po box 642	altamont	ny	12009	1	albany	5.188618e+09	42.702865	- 74.025310	(42.702865, -74.02531)	
2	berne fire department	1003	canaday road	berne	ny	12023	1	albany	5.188720e+09	42.612842	- 74.070082	(42.612842, - 74.070082)	
3	boght community fire department	1004	1095 loudon road	cohoes	ny	12047	1	albany	5.187850e+09	42.783571	- 73.743969	(42.783571, - 73.743969)	co
4	coeymans fire department	1005	67 church street	coeymans	ny	12045	1	albany	5.187562e+09	42.474106	- 73.798832	(42.474106, - 73.798832)	c

In [31]:

```
'''
Check after creation and key column preprocess for fire_department_df if there are departments tha
t have same key.
'''
for department in list(fire_department_df['Department'].value_counts().index):
    if fire_department_df[fire_department_df['Department']==department]['Department'].value_counts
().values > 1:
        print(department)
```

```
johnson
lakeside
lincoln
```

In [32]:

```
'''
Viewing rows of fire_department_df with same Department key
'''
fire_department_df[fire_department_df['Department'].isin(['lincoln','johnson','lakeside'])]
```

Out[32]:

	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	County Code	County Name	Phone Number	Latitude	Longitude	Location 1
81	johnson city fire department	4018	320 harry l drive	johnson city	ny	13790	4	broome	6.077300e+09	42.122658	-75.961976	(42.122658, -75.961976)
698	lincoln fire department	27014	po box 60	clockville	ny	13043	27	madison	3.156980e+09	43.041530	-75.744760	(43.04153, -75.74476)
936	lakeside fire department	34024	1002 state fair blvd pob 69	syracuse	ny	13209	34	onondaga	3.154877e+09	43.099219	-76.247604	(43.099219, -76.247604)
1013	johnson fire department	36022	creamery road po box 85	johnson	ny	10933	36	orange	9.143557e+09	41.366001	-74.505299	(41.366001, -74.505299)
1014	lakeside fire company	36023	po box 779	monroe	ny	10950	36	orange	9.147834e+09	41.278719	-74.215037	(41.278719, -74.215037)
1664	lincoln volunteer fire dept	59006	719 plank road	ontario	ny	14519	59	wayne	7.165248e+09	43.183402	-77.344196	(43.183402, -77.344196)

After joining if the above departments creates duplicate rows in merge df I will need to take care of that.

Merging the two dataframes into one dataframe

In [33]:

```
merge_df = pd.merge(fire_fighters_df,fire_department_df,how='inner',on='Department')
print('Shape of merge_df : ',merge_df.shape)
print('Number of unique name in merge_df : ',merge_df['Name'].nunique())
print('Number of unique Fire Department Name in merge_df : ',merge_df['Fire Department Name'].nuni
que())
print('Percentage of records lost in merge_df after processing data from fire_fighters_df : ',
      ((fire_fighters_df.shape[0]-merge_df.shape[0])/fire_fighters_df.shape[0])*100)
print('\n\n')
merge_df.head()
```

```
Shape of merge_df :  (2462, 18)
Number of unique name in merge_df :  2447
Number of unique Fire Department Name in merge_df :  450
Percentage of records lost in merge_df after processing data from fire_fighters_df :
3.4131031777167515
```

Out[33]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department	Fire Department Name	Fire Department Code	Address	City	State	Zip Code
0	abe dias	firefighter	haverstraw fire department	01/08/1906	20 bottom	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927
1	benjamin nelson	firefighter	haverstraw fire department	01/08/1906	16 top	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927
2	joseph albert	firefighter	haverstraw fire	01/08/1906	20 top	haverstraw	haverstraw fire	44004	25 fairmount	haverstraw	ny	10927

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department	Fire Department Name	Fire Department Code	Address	City	State	Zip Code
	albert		department				department		avenue			
3	william e. hughes	firefighter	haverstraw fire department	01/08/1906	10 top	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927
4	abraham price	captain	rochester fire department	04/26/1924	5 top	rochester	rochester fire dept (city)	28008	185 exchange blvd suite 660	rochester	ny	14614

- Earlier I observed that in fire_fighters_df 14 people have same name. Here I see 2462 - 2447 = 15 people have same name. So there is one duplicate record.

Next I will be checking for duplicate records in merge_df and removing it in meaningfull way

In [34]:

```
'''
Function to concatenate of values passed as parameters
'''
def new_col(cols):
    return cols[0]+cols[1]+cols[2]+str(cols[3])+cols[4]
```

In [35]:

```
'''
Applying new_col function on those columns of the merge_df which are from fire_fighter_df
'''
merge_df['firefighter']=merge_df[['Name','Rank','Fire Department','Date of Death','Location on
Memorial']].apply(new_col,axis=1)
```

In [36]:

```
"""
Checking whether any duplicate entries from fire_fighter_df exists or not in merge_df after mergin
g.
If it exists I will delete the duplicate after matching with original Fire Department and Fire Dep
artment Name column
"""
for this_firefighter in list(merge_df['firefighter'].value_counts().index):
    if merge_df[merge_df['firefighter']==this_firefighter]['firefighter'].value_counts().values > 1
:
        index_list_of_repeated_firefighter=list(merge_df[merge_df['firefighter']==this_firefighter]
.index)
        print('Index list of repeated fire fighter data in merge_df :
',index_list_of_repeated_firefighter)

        remove_index=merge_df[(merge_df['firefighter']==this_firefighter)
                                       & (merge_df['Fire Department']!=merge_df['Fire Department Name'])].in
ex
        print('Index to remove : ',remove_index.values)

        merge_df.drop(index=remove_index.values,inplace=True)
```

```
Index list of repeated fire fighter data in merge_df :  [2199, 2200]
Index to remove :  [2200]
```

Reseting Index of merge_df

In [37]:

```
'''
Reseting Index of merge_df after droping indexes
'''
merge_df=merge_df.reset_index(drop=True)
'''
The firefighter column is no longer needed so, I am dropping the column.
'''
merge_df.drop(['firefighter'], axis=1,inplace=True)
print('After cleanup the shape of merge_df is : ',merge_df.shape)
```

```
After cleanup the shape of merge_df is :  (2461, 18)
```

After cleanup the merge_df has 2461 rows and 18 columns

I have my final data analysis dataframe now.

Let's explore the data a bit using head(), tail(), info(), describe() on merge_df

In [38]:

```
merge_df.head()
```

Out[38]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department	Fire Department Name	Fire Department Code	Address	City	State	Zip Code	(
0	abe dias	firefighter	haverstraw fire department	01/08/1906	20 bottom	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927	
1	benjamin nelson	firefighter	haverstraw fire department	01/08/1906	16 top	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927	
2	joseph albert	firefighter	haverstraw fire department	01/08/1906	20 top	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927	
3	william e. hughes	firefighter	haverstraw fire department	01/08/1906	15 top	haverstraw	haverstraw fire department	44004	25 fairmount avenue	haverstraw	ny	10927	
4	abraham price	captain	rochester fire department	04/26/1924	5 top	rochester	rochester fire dept (city)	28008	185 exchange blvd suite 660	rochester	ny	14614	

In [39]:

```
merge_df.tail()
```

Out[39]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department	Fire Department Name	Fire Department Code	Address	City	State	Z Coc
2456	william h. smith	firefighter	la grange fire department	02/27/1988	11 top	la grange	la grange fire department	14015	504 freedom plains road	poughkeepsie	ny	1260
2457	william j. tripp, jr.	firefighter	richford fire department	04/13/2002	6 top	richford	richford fire department	54009	14 bowery lane po box 70	richford	ny	1383
2458	william mellon	firefighter	bay ridge fire company	06/19/1997	10 top	bay ridge	bay ridge volunteer fire company	57002	1080 bay road	lake george	ny	12845 461
2459	william mohan	firefighter	somers fire department	01/01/1983	18 bottom	somers	somers volunteer fire dept	60049	119 primrose st po box b	lincolndale	ny	1054
2460	william v. lattrell	fire chief	keeseville volunteer fire department	08/25/1953	5 top	keeseville	keeseville fire department	10014	8 pleasant street	keeseville	ny	1294

In [40]:

```
merge_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2461 entries, 0 to 2460
Data columns (total 18 columns):
Name                      2461 non-null object
Rank                      2461 non-null object
Fire Department           2461 non-null object
Date of Death             2460 non-null object
Location on Memorial      2461 non-null object
Department                2461 non-null object
Fire Department Name      2461 non-null object
Fire Department Code      2461 non-null int64
Address                   2461 non-null object
City                      2461 non-null object
State                     2461 non-null object
Zip Code                  2461 non-null object
County Code               2461 non-null int64
County Name               2461 non-null object
Phone Number              2454 non-null float64
Latitude                  2435 non-null float64
Longitude                 2435 non-null float64
Location 1                2435 non-null object
dtypes: float64(3), int64(2), object(13)
memory usage: 346.2+ KB
```

In [41]:

```
merge_df.describe()
```

Out[41]:

	Fire Department Code	County Code	Phone Number	Latitude	Longitude
count	2461.000000	2461.000000	2.454000e+03	2435.000000	2435.000000
mean	26986.032101	30.806176	6.674294e+09	41.394062	-74.678477
std	12259.308288	11.810849	1.264497e+09	1.023542	1.612965
min	1001.000000	1.000000	3.152451e+09	40.589435	-79.577671
25%	24001.000000	31.000000	6.078493e+09	40.693840	-73.997017
50%	24001.000000	31.000000	7.189992e+09	40.693840	-73.987100
75%	30009.000000	31.000000	7.189992e+09	42.555045	-73.987100
max	62005.000000	62.000000	9.149863e+09	44.942971	-72.300746

In [42]:

```
merge_df.describe(include='all')
```

Out[42]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department	Fire Department Name	Fire Department Code	Address	City	State	Z Co
count	2461	2461	2461	2460	2461	2461	2461	2461.000000	2461	2461	2461	24
unique	2447	84	485	1811	68	449	449	NaN	447	408	1	4
top	thomas f. carrigan	firefighter	new york city fire department	09/11/2001	13 top	new york	new york city fire department	NaN	9 metrotech center	brooklyn	ny	1120 58
freq	2	1569	1222	345	90	1349	1349	NaN	1349	1349	2461	13
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	26986.032101	NaN	NaN	NaN	N
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	12259.308288	NaN	NaN	NaN	N
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1001.000000	NaN	NaN	NaN	N
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	24001.000000	NaN	NaN	NaN	N
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	24001.000000	NaN	NaN	NaN	N
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	30009.000000	NaN	NaN	NaN	N
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	62005.000000	NaN	NaN	NaN	N

In [43]:

```
merge_df.describe(include='object')
```

Out[43]:

	Name	Rank	Fire Department	Date of Death	Location on Memorial	Department	Fire Department Name	Address	City	State	Zip Code	County Name	I
count	2461	2461	2461	2460	2461	2461	2461	2461	2461	2461	2461	2461	
unique	2447	84	485	1811	68	449	449	447	408	1	414	58	
top	thomas f. carrigan	firefighter	new york city fire department	09/11/2001	13 top	new york	new york city fire department	9 metrotech center	brooklyn	ny	11201-5884	new york	(4 -
freq	2	1569	1222	345	90	1349	1349	1349	1349	2461	1349	1349	

Next, I will explore the column metadata...

- What are the data types for the columns in our data?
- How many unique entries are there in each column where type is object?
- Below I will exlpore the first five rows of each column where type is object?
- Why am I exploring unique entries for objects?
  - Because there could possibly be categorical data or datetime data in an object column.
- After finishing the data exploration I will transform these object type columns with categorical data into 'category' type and object type columns with datetime data into 'datetime' type

In [44]:

```
first_n_entries=5
print('Total rows in the dataframe:', merge_df.shape[0])
for col, col_type in merge_df.dtypes.iteritems():
    if(col_type=='object'):
        print(col, 'has', merge_df[col].nunique(), 'unique entries')
        print('First', first_n_entries, 'entries are')
        print(merge_df[col][0:first_n_entries])
        print('')
```

```
Total rows in the dataframe: 2461
Name has 2447 unique entries
First 5 entries are
0              abe dias
1       benjamin nelson
2         joseph albert
3     william e. hughes
4         abraham price
Name: Name, dtype: object

Rank has 84 unique entries
First 5 entries are
0    firefighter
1    firefighter
2    firefighter
3    firefighter
4        captain
Name: Rank, dtype: object

Fire Department has 485 unique entries
First 5 entries are
0    haverstraw fire department
1    haverstraw fire department
2    haverstraw fire department
3    haverstraw fire department
4     rochester fire department
Name: Fire Department, dtype: object

Date of Death has 1811 unique entries
First 5 entries are
0    01/08/1906
```

```
1    01/08/1906
2    01/08/1906
3    01/08/1906
4    04/26/1924
Name: Date of Death, dtype: object

Location on Memorial has 68 unique entries
First 5 entries are
0    20 bottom
1       16 top
2       20 top
3       15 top
4        5 top
Name: Location on Memorial, dtype: object

Department has 449 unique entries
First 5 entries are
0    haverstraw
1    haverstraw
2    haverstraw
3    haverstraw
4     rochester
Name: Department, dtype: object

Fire Department Name has 449 unique entries
First 5 entries are
0    haverstraw fire department
1    haverstraw fire department
2    haverstraw fire department
3    haverstraw fire department
4    rochester fire dept (city)
Name: Fire Department Name, dtype: object

Address has 447 unique entries
First 5 entries are
0            25 fairmount avenue
1            25 fairmount avenue
2            25 fairmount avenue
3            25 fairmount avenue
4    185 exchange blvd suite 660
Name: Address, dtype: object

City has 408 unique entries
First 5 entries are
0    haverstraw
1    haverstraw
2    haverstraw
3    haverstraw
4     rochester
Name: City, dtype: object

State has 1 unique entries
First 5 entries are
0    ny
1    ny
2    ny
3    ny
4    ny
Name: State, dtype: object

Zip Code has 414 unique entries
First 5 entries are
0    10927
1    10927
2    10927
3    10927
4    14614
Name: Zip Code, dtype: object

County Name has 58 unique entries
First 5 entries are
0    rockland
1    rockland
2    rockland
3    rockland
4      monroe
Name: County Name, dtype: object
```

```
Location 1 has 442 unique entries
First 5 entries are
0    (41.196363, -73.966849)
1    (41.196363, -73.966849)
2    (41.196363, -73.966849)
3    (41.196363, -73.966849)
4    (43.151658, -77.611092)
Name: Location 1, dtype: object
```

- In the data set, there are thirteen object type columns: Name, Rank, Fire Department, Date of Death, Location on Memorial, Department, Fire Department Name, Address, City, State, Zip Code, County Name, Location 1

Data Type Transformation

- Now, I will count the frequency of these unique values per column and print frequency of top five most frequent elements.
- I will check if a column with object data type has categorical data or not?
- I will check if a column with object data type has datetime data or not?
- If and when necessary, I will perform some transformations on the data.

In [45]:

```python
for this_column in merge_df.columns:
    print('====', this_column, 'has', merge_df[this_column].nunique(), 'unique entries ====')
    print(merge_df[this_column].value_counts().head(5))
    print('')
```

```
==== Name has 2447 unique entries ====
thomas f. carrigan    2
john clarke           2
michael o’brien       2
james j. hughes       2
george brown          2
Name: Name, dtype: int64

==== Rank has 84 unique entries ====
firefighter        1569
lieutenant          222
captain             141
firefighter         106
battalion chief      59
Name: Rank, dtype: int64

==== Fire Department has 485 unique entries ====
new york city fire department     1222
buffalo fire department            123
new york city fire department      122
rochester fire department           52
albany fire department              51
Name: Fire Department, dtype: int64

==== Date of Death has 1811 unique entries ====
09/11/2001    345
10/17/1966     12
04/24/1854     11
01/01/1978     10
08/01/1932      8
Name: Date of Death, dtype: int64

==== Location on Memorial has 68 unique entries ====
13 top    90
12 top    87
10 top    86
14 top    86
11 top    85
Name: Location on Memorial, dtype: int64

==== Department has 449 unique entries ====
new york     1349
buffalo       125
rochester      52
```

```
albany         51
syracuse       45
Name: Department, dtype: int64

==== Fire Department Name has 449 unique entries ====
new york city fire department      1349
buffalo fire department             125
rochester fire dept (city)           52
albany fire department               51
syracuse fire department (city)      45
Name: Fire Department Name, dtype: int64

==== Fire Department Code has 449 unique entries ====
24001    1349
15100     125
28008      52
1001       51
34051      45
Name: Fire Department Code, dtype: int64

==== Address has 447 unique entries ====
9 metrotech center             1349
195 court street                125
185 exchange blvd suite 660      52
26 broad street                  51
511 south state street           45
Name: Address, dtype: int64

==== City has 408 unique entries ====
brooklyn     1349
buffalo       125
rochester      59
albany         52
syracuse       46
Name: City, dtype: int64

==== State has 1 unique entries ====
ny    2461
Name: State, dtype: int64

==== Zip Code has 414 unique entries ====
11201-5884    1349
14202          125
14614           52
12202-0000      51
13202           45
Name: Zip Code, dtype: int64

==== County Code has 58 unique entries ====
31    1349
15     161
30     109
52      96
60      74
Name: County Code, dtype: int64

==== County Name has 58 unique entries ====
new york       1349
erie            161
nassau          109
suffolk          96
westchester      74
Name: County Name, dtype: int64

==== Phone Number has 444 unique entries ====
7.189992e+09    1349
7.168515e+09     125
5.854287e+09      52
5.184478e+09      51
3.154736e+09      45
Name: Phone Number, dtype: int64

==== Latitude has 442 unique entries ====
40.693840    1349
42.887005     125
43.151658      52
42.662577      51
```

```
43.046921      45
Name: Latitude, dtype: int64

==== Longitude has 442 unique entries ====
-73.987100    1349
-78.881198     125
-77.611092      52
-73.759898      51
-76.147406      45
Name: Longitude, dtype: int64

==== Location 1 has 442 unique entries ====
(40.69384, -73.9871)       1349
(42.887005, -78.881198)     125
(43.151658, -77.611092)      52
(42.662577, -73.759898)      51
(43.046921, -76.147406)      45
Name: Location 1, dtype: int64
```

- After exploring the data I observed that Rank, Fire Department, Location on Memorial, Department, Fire Department Name, City, State, Zip Code, County Name columns contain categorical data.
- I will transform these columns into 'category' data type.
- Also Date of Death column contain datetime data.
- I will transform the above column into 'datetime' data type.

In [46]:

```
"""
Next, I transform the object data type for Rank to 'category' data type
"""
merge_df['Rank'] = merge_df['Rank'].astype('category')
merge_df['Rank'].dtype
```

Out[46]:

```
CategoricalDtype(categories=['1st assistant chief', '1st deputy commissioner',
                  '2nd assistant chief', '2nd assistant foreman',
                  '2nd lieutenant', 'acting district chief',
                  'acting lieutenant', 'assistant chief', 'assistant chief ',
                  'assistant chief    ', 'assistant engineer',
                  'assistant foreman', 'battalion chief', 'battalion chief ',
                  'captain', 'captain ', 'captain    ', 'captain/juniors',
                  'captain` ', 'chaplain', 'chief', 'chief ', 'chief   ',
                  'chief    ', 'chief’s aide', 'commissioner', 'deputy chief',
                  'deputy chief ', 'deputy commissioner', 'deputy coordinator',
                  'deputy coordinator ', 'division chief', 'driver',
                  'engineer', 'ex-assistant chief ', 'ex-captain', 'ex-chief',
                  'ex-chief ', 'ex-lieutenant', 'fdny paramedic',
                  'fire chief ', 'fire marshal', 'fire marshal ',
                  'fire police', 'fire police capt. ', 'fire police captain',
                  'fire police captain    ', 'fire police lieutenant',
                  'firefigher', 'firefighter', 'firefighter ',
                  'firefighter    ', 'firefighter, ex-captain',
                  'firefighter/commissioner', 'firefighter/emt ',
                  'firefighter/fire police', 'firefighter/past chief',
                  'firefighter’s aide', 'foreman', 'honorary assistant chief',
                  'hoseman', 'inspector', 'ladderman', 'lieutenant',
                  'lieutenant ', 'lieutenant fire police',
                  'lieutenant/fire police', 'lineman', 'marine engineer',
                  'marine engineer ', 'master mechanic', 'paramedic',
                  'past chief', 'past foreman', 'patrolman, fire patrol',
                  'pilot', 'president', 'probationary firefighter',
                  'protective', 'relief driver', 'supervising fire marshal ',
                  'tillerman', 'training instructor', 'truckman'],
                 ordered=False)
```

In [47]:

```
"""
Next, I transform the object data type for Fire Department to 'category' data type
"""
merge_df['Fire Department'] = merge_df['Fire Department'].astype('category')
```

```
merge_df['Fire Department'] = merge_df['Fire Department'].astype('category')
merge_df['Fire Department'].dtype
```

Out[47]:

```
CategoricalDtype(categories=['adams center fire department', 'akron fire department',
                  'alabama fire department', 'albany fire department',
                  'albion fire department', 'alplaus fire department',
                  'amityville fire department', 'amsterdam fire department',
                  'ancram fire department', 'angola fire department',
                  ...
                  'wilmington fire department', 'woodgate fire department',
                  'woodmere fire department', 'wyandanch fire department',
                  'yaphank fire department', 'yonkers fire department',
                  'yonkers fire department ', 'york fire department',
                  'youngstown volunteer fire company',
                  'youngsville fire department'],
                 ordered=False)
```

In [48]:

```
"""
Next, I transform the object data type for Location on Memorial to 'category' data type
"""
merge_df['Location on Memorial'] = merge_df['Location on Memorial'].astype('category')
merge_df['Location on Memorial'].dtype
```

Out[48]:

```
CategoricalDtype(categories=['   1 bottom', '   1 bottom ', '   1 top', '   2 top',
                  '   3 bottom', '   4 bottom', '   4 top', '   5 bottom',
                  '   6 bottom', '   8 top', '  1 bottom', '  1 bottom  ',
                  '  1 top', '  2 bottom', '  2 bottom  ', '  2 top',
                  '  3  bottom', '  3  top', '  3 bottom', '  3 top',
                  '  4 bottom', '  4 top', '  5 bottom', '  5 top',
                  '  6 bottom', '  6 bottom  ', '  6 top', '  7 bottom',
                  '  7 top', '  8 bottom', '  8 top', '  9 bottom', '  9 top',
                  '  9 top  ', ' 6 bottom', ' 8 top', ' 9 bottom', '10 bottom',
                  '10 top', '11 bottom', '11 bottom ', '11 top', '12 bottom',
                  '12 top', '12 top ', '13 bottom', '13 top', '14 bottom',
                  '14 top', '15 bottom', '15 top', '16 bottom', '16 top',
                  '17 bottom', '17 top', '18 bottom', '18 top', '19 bottom',
                  '19 top', '19 top ', '2 top', '20 bottom', '20 top',
                  '20 top ', '21 bottom', '21 top', '6 top', '8 top'],
                 ordered=False)
```

In [49]:

```
"""
Next, I transform the object data type for Department to 'category' data type
"""
merge_df['Department'] = merge_df['Department'].astype('category')
merge_df['Department'].dtype
```

Out[49]:

```
CategoricalDtype(categories=['adams center', 'akron', 'alabama', 'albany', 'albion',
                  'alplaus', 'amityville', 'amsterdam', 'ancram', 'angola',
                  ...
                  'williston park', 'wilmington', 'woodgate', 'woodmere',
                  'wyandanch', 'yaphank', 'yonkers', 'york', 'youngstown',
                  'youngsville'],
                 ordered=False)
```

In [50]:

```
"""
Next, I transform the object data type for Fire Department Name to 'category' data type
"""
merge_df['Fire Department Name'] = merge_df['Fire Department Name'].astype('category')
merge_df['Fire Department Name'].dtype
```

Out[50]:

```
CategoricalDtype(categories=['adams center fire department', 'akron fire department',
                  'alabama fire department', 'albany fire department',
                  'albion fire department', 'alplaus fire department',
                  'amityville fire department', 'amsterdam fire department',
                  'ancram fire department', 'angola fire department',
                  ...
                  'williston park fire department',
                  'wilmington fire department', 'woodgate vol fire department',
                  'woodmere fire department',
                  'wyandanch volunteer fire company',
                  'yaphank fire department', 'yonkers fire department',
                  'york fire department', 'youngstown fire department',
                  'youngsville fire company'],
                 ordered=False)
```

In [51]:

```
"""
Next, I transform the object data type for City to 'category' data type
"""
merge_df['City'] = merge_df['City'].astype('category')
merge_df['City'].dtype
```

Out[51]:

```
CategoricalDtype(categories=['adams center', 'akron', 'albany', 'albion', 'alplaus',
                  'amherst', 'amityville', 'amsterdam', 'ancram', 'angola',
                  ...
                  'wilmington', 'wilson', 'woodgate', 'woodmere', 'wyandanch',
                  'yaphank', 'yonkers', 'york', 'youngstown', 'youngsville'],
                 ordered=False)
```

In [52]:

```
"""
Next, I transform the object data type for State to 'category' data type
"""
merge_df['State'] = merge_df['State'].astype('category')
merge_df['State'].dtype
```

Out[52]:

```
CategoricalDtype(categories=['ny'], ordered=False)
```

In [53]:

```
"""
Next, I transform the object data type for Zip Code to 'category' data type
"""
merge_df['Zip Code'] = merge_df['Zip Code'].astype('category')
merge_df['Zip Code'].dtype
```

Out[53]:

```
CategoricalDtype(categories=['10023', '10509', '10510', '10522', '10528', '10533',
                  '10536', '10540', '10547', '10552',
                  ...
                  '14845', '14850', '14865', '14870', '14871', '14886',
                  '14887', '14895', '14901', '14903'],
                 ordered=False)
```

In [54]:

```
"""
Next, I transform the object data type for County Name to 'category' data type
"""
merge_df['County Name'] = merge_df['County Name'].astype('category')
merge_df['County Name'].dtype
```

Out[54]:

```
CategoricalDtype(categories=['albany', 'allegany', 'broome', 'cattaraugus', 'cayuga',
                   'cortland', 'delaware', 'dutchess', 'erie', 'essex',
                   'franklin', 'fulton', 'genesee', 'greene', 'hamilton',
                   'herkimer', 'jefferson', 'lewis', 'livingston', 'madison',
                   'monroe', 'montgomery', 'nassau', 'new york', 'niagara',
                   'oneida', 'onondaga', 'ontario', 'orange', 'orleans',
                   'oswego', 'otsego', 'putnam', 'rensselaer', 'rockland',
                   'saratoga', 'schenectady', 'schoharie', 'schuyler', 'seneca',
                   'st. lawrence', 'steuben', 'suffolk', 'sullivan', 'tioga',
                   'tompkins', 'ulster', 'warren', 'washington', 'wayne',
                   'westchester', 'wyoming', 'yates'],
                  ordered=False)
```

In [55]:

```
"""
Next, I transform the object data type for Date of Death to 'datetime' data type
"""
merge_df['Date of Death']=pd.to_datetime(
                                  merge_df['Date of Death'],
                                  format='%m/%d/%Y')
```

Let us look at the data types of columns after transformation

In [56]:

```
merge_df.dtypes
```

Out[56]:

```
Name                              object
Rank                            category
Fire Department                 category
Date of Death             datetime64[ns]
Location on Memorial            category
Department                      category
Fire Department Name            category
Fire Department Code               int64
Address                           object
City                            category
State                           category
Zip Code                        category
County Code                        int64
County Name                     category
Phone Number                     float64
Latitude                         float64
Longitude                        float64
Location 1                        object
dtype: object
```

Now the dataframe has...

- Three object type columns: Name, Address and Location 1
- One datetime Type columns: Date of Death
- Nine categorical columns: Rank, Fire Department, Location on Memorial, Department, Fire Department Name, City, State, Zip Code, County Name
- Five numerical columns: Fire Department Code, County Code with data type int64,Phone Number, Latitude, Longitude with data type float64

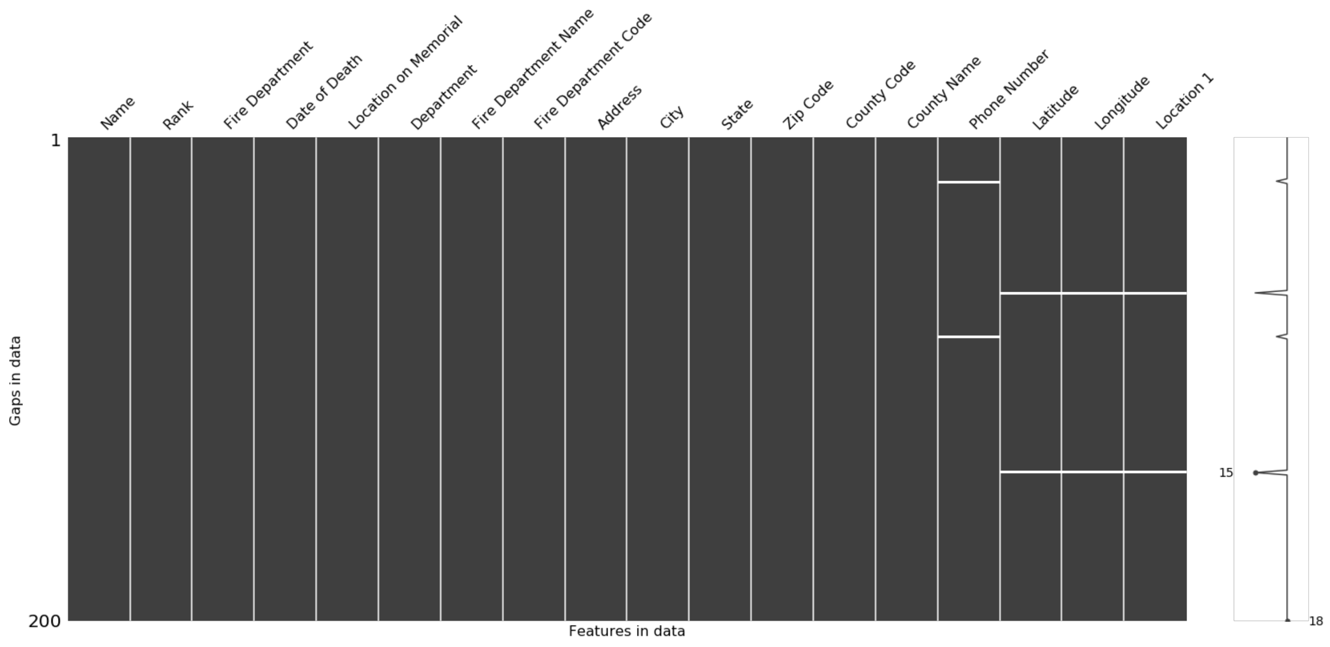
Data clean up, Missing data detection and Fill up

Black = filled; white = empty

In [57]:

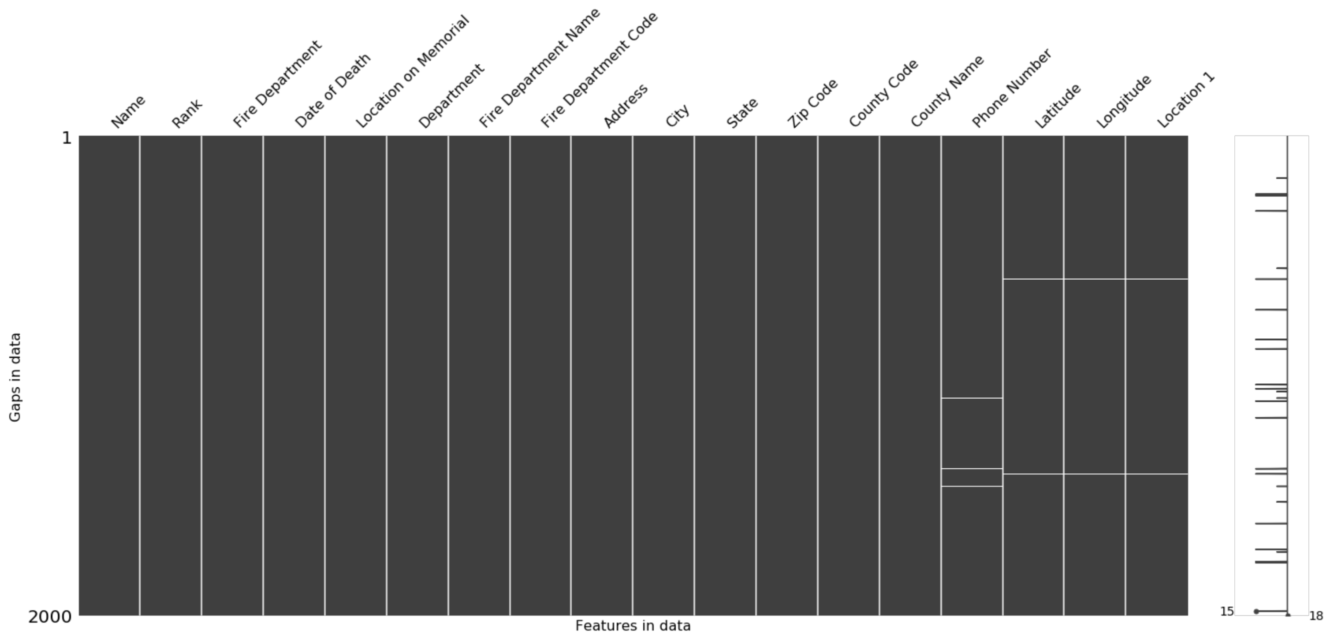
```
"""
Searching for missing data in sample set of 200 randomly selected data points
"""
```

```
_=msno.matrix(merge_df.sample(200))
plt.xlabel('Features in data',fontsize=16)
plt.ylabel('Gaps in data',fontsize=16)
plt.show()
```



In [58]:

```
"""
Searching for missing data in sample set of 2000 randomly selected data points
"""
_=msno.matrix(merge_df.sample(2000))
plt.xlabel('Features in data',fontsize=16)
plt.ylabel('Gaps in data',fontsize=16)
plt.show()
```



From the graphs one can see the data has some missing values for few columns like Date of Death, Phone Number, Latitude, Longitude, Location 1.

Data Clean up

I will perform the following tasks:

- Drop all rows and columns where entire row or column is NaN.
- Drop columns with duplicate data or with 50% missing value.

- Drop columns where all rows have the same value.
  - Such columns have no data variety and nothing useful to contribute to my data analysis.

In [59]:

```
print('Shape of data frame before Cleanup :',merge_df.shape)

print('Drop all rows and columns where entire row or column is NaN.')
merge_df.dropna(how='all',axis=0,inplace=True) # rows
merge_df.dropna(how='all',axis=1,inplace=True) # columns

print('Drop columns with duplicate data or with 50% missing value.')
half_count = len(merge_df)*.5
merge_df = merge_df.dropna(thresh=half_count, axis=1)
merge_df = merge_df.drop_duplicates()

print('Drop columns where all rows have the same value.')
for this_column in merge_df.columns:
    if (merge_df[this_column].nunique()==1):
        unique_entry=merge_df.iloc[0][this_column]
        print('Drop column ',this_column,' where all rows have the same value : ', unique_entry)
        merge_df.drop([this_column],axis=1,inplace=True)

print('Shape of data frame after cleanup :',merge_df.shape)
```

```
Shape of data frame before Cleanup : (2461, 18)
Drop all rows and columns where entire row or column is NaN.
Drop columns with duplicate data or with 50% missing value.
Drop columns where all rows have the same value.
Drop column  State  where all rows have the same value :  ny
Shape of data frame after cleanup : (2461, 17)
```

Through the above process I was able to conclude that in my dataset...

- There are no rows and columns where entire row or column is NaN.
- There are no columns with duplicate data and with 50% missing value.
- There is one column, State where all rows have the same value.
  - Hence, I will be dropping the column State as it has no data variety and nothing useful to contribute to my data analysis.

Missing data detection and fill up using random sampling in a meaningful way

That is get data from the same County Name

In [60]:

```
merge_df.head().T
```

Out[60]:

	0	1	2	3	4
Name	abe dias	benjamin nelson	joseph albert	william e. hughes	abraham price
Rank	firefighter	firefighter	firefighter	firefighter	captain
Fire Department	haverstraw fire department	haverstraw fire department	haverstraw fire department	haverstraw fire department	rochester fire department
Date of Death	1906-01-08 00:00:00	1906-01-08 00:00:00	1906-01-08 00:00:00	1906-01-08 00:00:00	1924-04-26 00:00:00
Location on Memorial	20 bottom	16 top	20 top	15 top	5 top
Department	haverstraw	haverstraw	haverstraw	haverstraw	rochester
Fire Department Name	haverstraw fire department	haverstraw fire department	haverstraw fire department	haverstraw fire department	rochester fire dept (city)
Fire Department Code	44004	44004	44004	44004	28008
Address	25 fairmount avenue	25 fairmount avenue	25 fairmount avenue	25 fairmount avenue	185 exchange blvd suite 660
City	haverstraw	haverstraw	haverstraw	haverstraw	rochester

	0	1	2	3	4
City	haverstraw	haverstraw	haverstraw	haverstraw	rochester
Zip Code	10927	10927	10927	10927	14614
County Code	44	44	44	44	28
County Name	rockland	rockland	rockland	rockland	monroe
Phone Number	8.45429e+09	8.45429e+09	8.45429e+09	8.45429e+09	5.85429e+09
Latitude	41.1964	41.1964	41.1964	41.1964	43.1517
Longitude	-73.9668	-73.9668	-73.9668	-73.9668	-77.6111
Location 1	(41.196363, -73.966849)	(41.196363, -73.966849)	(41.196363, -73.966849)	(41.196363, -73.966849)	(43.151658, -77.611092)

In [61]:

```
"""
Counting null data per column
"""
merge_df.isnull().sum()
```

Out[61]:

```
Name                        0
Rank                        0
Fire Department             0
Date of Death               1
Location on Memorial        0
Department                  0
Fire Department Name        0
Fire Department Code        0
Address                     0
City                        0
Zip Code                    0
County Code                 0
County Name                 0
Phone Number                7
Latitude                   26
Longitude                  26
Location 1                 26
dtype: int64
```

In [62]:

```
"""
Percentage of missing data per column
"""
(merge_df.isnull().sum()/len(merge_df)).sort_values(ascending=False)
```

Out[62]:

```
Location 1               0.010565
Latitude                 0.010565
Longitude                0.010565
Phone Number             0.002844
Date of Death            0.000406
Fire Department Name     0.000000
Rank                     0.000000
Fire Department          0.000000
Location on Memorial     0.000000
Department               0.000000
Address                  0.000000
Fire Department Code     0.000000
City                     0.000000
Zip Code                 0.000000
County Code              0.000000
County Name              0.000000
Name                     0.000000
dtype: float64
```

I was able to find that Location 1, Latitude, Longitude, Phone Number, Date of Death columns have some missing data

Filling up missing data of Location 1, Latitude and Longitude through sampling of data in same County Name

In [63]:

```
print("Data index for missing Location 1 : ",list(merge_df[merge_df['Location 1'].isnull()].index)
)
print("Data index for missing Latitude : ",list(merge_df[merge_df['Latitude'].isnull()].index))
print("Data index for missing Longitude : ",list(merge_df[merge_df['Longitude'].isnull()].index))
```

```
Data index for missing Location 1 :  [1715, 1716, 1717, 1718, 1719, 1720, 1721, 1722, 1723, 1724,
1725, 1726, 1727, 1728, 1729, 1730, 1731, 1732, 1733, 1734, 1735, 1736, 1737, 1752, 2351, 2445]
Data index for missing Latitude :  [1715, 1716, 1717, 1718, 1719, 1720, 1721, 1722, 1723, 1724,
1725, 1726, 1727, 1728, 1729, 1730, 1731, 1732, 1733, 1734, 1735, 1736, 1737, 1752, 2351, 2445]
Data index for missing Longitude :  [1715, 1716, 1717, 1718, 1719, 1720, 1721, 1722, 1723, 1724, 17
25, 1726, 1727, 1728, 1729, 1730, 1731, 1732, 1733, 1734, 1735, 1736, 1737, 1752, 2351, 2445]
```

In [64]:

```
'''
County Name based sampling for Location 1, Latitude and Longitude data
'''
location1_smapling_dict={}
latitude_smapling_dict={}
longitude_smapling_dict={}
null_index=list(merge_df[merge_df['Location 1'].isnull()].index)
print(null_index)

for indx in null_index:
    print('index :',indx)
    this_county=merge_df.iloc[indx]['County Name']
    print(this_county)
    sample_location1=random.choice(list(merge_df[(merge_df['County Name']==this_county)
                                                 & (merge_df['Location 1'].notnull())]['Location 1
))

    sample_latitude=float(sample_location1.split(',')[0][1:])
    sample_longitude=float(sample_location1.split(',')[1][:-1].strip())

    location1_smapling_dict[indx]=sample_location1
    latitude_smapling_dict[indx]=sample_latitude
    longitude_smapling_dict[indx]=sample_longitude

print(location1_smapling_dict)
print(latitude_smapling_dict)
print(longitude_smapling_dict)
```

```
[1715, 1716, 1717, 1718, 1719, 1720, 1721, 1722, 1723, 1724, 1725, 1726, 1727, 1728, 1729, 1730, 17
31, 1732, 1733, 1734, 1735, 1736, 1737, 1752, 2351, 2445]
index : 1715
broome
index : 1716
broome
index : 1717
broome
index : 1718
broome
index : 1719
broome
index : 1720
broome
index : 1721
broome
index : 1722
broome
index : 1723
broome
index : 1724
broome
index : 1725
broome
index : 1726
broome
index : 1727
broome
```

```
index : 1728
broome
index : 1729
broome
index : 1730
broome
index : 1731
broome
index : 1732
broome
index : 1733
broome
index : 1734
broome
index : 1735
broome
index : 1736
broome
index : 1737
broome
index : 1752
nassau
index : 2351
nassau
index : 2445
columbia
{1715: '(42.111249, -76.073003)', 1716: '(42.162783, -75.894162)', 1717: '(42.06305, -75.42649)',
1718: '(42.111249, -76.073003)', 1719: '(42.06305, -75.42649)', 1720: '(42.23717, -76.05457)', 172
1: '(42.162783, -75.894162)', 1722: '(42.098898, -76.049109)', 1723: '(42.162783, -75.894162)', 17
24: '(42.083166, -76.065433)', 1725: '(42.328955, -75.967353)', 1726: '(42.098898, -76.049109)', 1
727: '(42.162783, -75.894162)', 1728: '(42.111249, -76.073003)', 1729: '(42.083166, -76.065433)',
1730: '(42.06305, -75.42649)', 1731: '(42.06305, -75.42649)', 1732: '(42.098898, -76.049109)', 173
3: '(42.122658, -75.961976)', 1734: '(42.098898, -76.049109)', 1735: '(42.111249, -76.073003)', 17
36: '(42.06305, -75.42649)', 1737: '(42.06305, -75.42649)', 1752: '(40.83546, -73.69373)', 2351: '
(40.720178, -73.564111)', 2445: '(42.21772, -73.70847)'}
{1715: 42.111249, 1716: 42.162783, 1717: 42.06305, 1718: 42.111249, 1719: 42.06305, 1720: 42.23717,
1721: 42.162783, 1722: 42.098898, 1723: 42.162783, 1724: 42.083166, 1725: 42.328955, 1726: 42.09889
8, 1727: 42.162783, 1728: 42.111249, 1729: 42.083166, 1730: 42.06305, 1731: 42.06305, 1732: 42.0988
98, 1733: 42.122658, 1734: 42.098898, 1735: 42.111249, 1736: 42.06305, 1737: 42.06305, 1752: 40.835
46, 2351: 40.720178, 2445: 42.21772}
{1715: -76.073003, 1716: -75.894162, 1717: -75.42649, 1718: -76.073003, 1719: -75.42649, 1720: -76
.05457, 1721: -75.894162, 1722: -76.049109, 1723: -75.894162, 1724: -76.065433, 1725: -75.967353,
1726: -76.049109, 1727: -75.894162, 1728: -76.073003, 1729: -76.065433, 1730: -75.42649, 1731: -75
.42649, 1732: -76.049109, 1733: -75.961976, 1734: -76.049109, 1735: -76.073003, 1736: -75.42649, 1
737: -75.42649, 1752: -73.69373, 2351: -73.564111, 2445: -73.70847}
```

In [65]:

```
'''
Filling up the missing values of Location 1, Latitude and Longitude with sampled data
'''
merge_df['Location 1'].fillna(location1_smapling_dict,inplace=True)
merge_df['Latitude'].fillna(latitude_smapling_dict,inplace=True)
merge_df['Longitude'].fillna(longitude_smapling_dict,inplace=True)
```

Filling up missing data of Phone Number through sampling of data in same County Name

In [66]:

```
print("Data index for missing Phone Number : ",list(merge_df[merge_df['Phone
Number'].isnull()].index))
```

```
Data index for missing Phone Number :  [1839, 1840, 1889, 2002, 2003, 2294, 2375]
```

In [67]:

```
'''
County Name based sampling for Phone Number data
'''
phone_number_smapling_dict={}
null_phone_number_index=list(merge_df[merge_df['Phone Number'].isnull()].index)
print(null_phone_number_index)
```

```
for indx in null_phone_number_index:
    print('index :',indx)
    this_county=merge_df.iloc[indx]['County Name']
    print(this_county)
    sample_phone_number=random.choice(list(merge_df[(merge_df['County Name']==this_county)
                                                    & (merge_df['Phone Number'].notnull())]['Phone
umber']))


    phone_number_smapling_dict[indx]=sample_phone_number

print(phone_number_smapling_dict)
```

```
[1839, 1840, 1889, 2002, 2003, 2294, 2375]
index : 1839
oneida
index : 1840
oneida
index : 1889
ulster
index : 2002
broome
index : 2003
broome
index : 2294
ulster
index : 2375
ulster
{1839: 3158536884.0, 1840: 3157245151.0, 1889: 8453311959.0, 2002: 6077727016.0, 2003: 6077727016.0
, 2294: 8453311959.0, 2375: 8453388422.0}
```

In [68]:

```
'''
Filling up the missing values of Phone Number with sampled data
'''
merge_df['Phone Number'].fillna(phone_number_smapling_dict,inplace=True)
```

Filling up missing data of Date of Death through sampling of data in same County Name

In [69]:

```
print("Data index for missing Date of Death : ",list(merge_df[merge_df['Date of Death'].isnull()].
index))
```

```
Data index for missing Date of Death :  [2059]
```

In [70]:

```
'''
County Name based sampling for Date of Death data
'''
null_date_of_death_index=list(merge_df[merge_df['Date of Death'].isnull()].index)
print('null_date_of_death_index : ',null_date_of_death_index)

this_county=merge_df.iloc[null_date_of_death_index]['County Name'].values
print('this_county : ',this_county)

sample_date_of_death=datetime.strftime(random.choice(list(merge_df[(merge_df['County
Name']==this_county) &
                                                                   (merge_df['Date of Death'].notnu
()))]['Date of Death'])),'%m/%d/%Y')
print('sample_date_of_death : ',sample_date_of_death)

sample_date_of_death_in_datetime=datetime.strptime(sample_date_of_death,'%m/%d/%Y')
print('sample_date_of_death_in_datetime : ',sample_date_of_death_in_datetime)
```

```
null_date_of_death_index :  [2059]
this_county :  [orange]
Categories (58, object): [albany, allegany, broome, cattaraugus, ..., wayne, westchester, wyoming,
yates]
sample_date_of_death :  02/03/2015
```

```
sample_date_of_death_in_datetime :  2015-02-03 00:00:00
```

In [71]:

```
'''
Filling up the missing values of Date of Death with sampled data
'''
merge_df['Date of Death'].fillna(sample_date_of_death_in_datetime,inplace=True)
```

In [72]:

```
merge_df.isnull().sum()
```

Out[72]:

```
Name                    0
Rank                    0
Fire Department         0
Date of Death           0
Location on Memorial    0
Department              0
Fire Department Name    0
Fire Department Code    0
Address                 0
City                    0
Zip Code                0
County Code             0
County Name             0
Phone Number            0
Latitude                0
Longitude               0
Location 1              0
dtype: int64
```

Missing data have been filled up successfully for Location 1, Latitude, Longitude, Phone Number and Date of Death columns

Start of data analysis - Visualization and Exploratory Data Analysis

... for merged data of New_York_State_Fallen_Firefighters_Memorial_Roll_of_Honor, Fire_Department_Directory_for_New_York_State in New York State

Let's ask our data some questions about fire fighter fatalities in New York State.

- Let's start with some basic questions that combines the fatality count from one dataset with the county/city data from another.
- Which county and/or city had a high fatality count?
- **Top ten fatality count by county for New York State fire departments**

In [73]:

```
merge_df['County Name']=merge_df['County Name'].apply(lambda x : x.strip())
merge_df.groupby('County Name')['Name'].count().sort_values(ascending=False).head(10)
```

Out[73]:

```
County Name
new york       1349
erie            161
nassau          109
suffolk          96
westchester      74
monroe           71
onondaga         70
albany           63
rensselaer       34
broome           34
Name: Name, dtype: int64
```

- **Top ten fatality count by city for fire departments in New York State**

In [74]:

```
merge_df['City']=merge_df['City'].apply(lambda x : x.strip())
merge_df.groupby('City')['Name'].count().sort_values(ascending=False).head(10)
```

Out[74]:

```
City
brooklyn       1349
buffalo         125
rochester        59
albany           52
syracuse         46
troy             27
binghamton       25
yonkers          18
schenectady      13
auburn           12
Name: Name, dtype: int64
```

The answer to the question is Brooklyn, New York County, New York has had some very high fatality counts. I will now dive deeper into the data to find more about patterns in fatalities in New York State's fire departments.

Method defined to compute normalized value for a column of dataframe

Formula for normalization used is as follows:

$$\mathbf{X_{new}} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

In [75]:

```
'''
This method will return the value normalized between 0 and 1, given a number, maximum value and mi
nimum value of the column in the dataframe
'''
def compute_norm(number, max_val, min_val):
    return (number - min_val)/(max_val - min_val)
```

In [76]:

```
'''
This method will take a dataframe and return a dataframe with one extra column of normalized value
s for the colum of dataframe that
needs to be normalized. Created as I will reuse this a number of times.
'''
def get_normalized_value_df(df_to_process, name_of_column_to_normalize):
    norm_df = df_to_process

    normalized_value_list = []
    for num in np.array(norm_df[name_of_column_to_normalize]):
        normalized_value_list.append(compute_norm(number=float(num),
                                                   max_val=float(norm_df[name_of_column_to_normalize
.nlargest(1)),
                                                   min_val=float(norm_df[name_of_column_to_normalize
.nsmallest(1))
                                                  )
                                     )
    norm_df['normalized_'+name_of_column_to_normalize] = normalized_value_list
    return norm_df
```

Processing date time to extract year, month of death

In [77]:

```
'''
Counting the number of fatalities in each of the top five fatal years
'''
```

```
merge_df['Year'] = merge_df['Date of Death'].apply(lambda time: time.year)
merge_df['Year'].value_counts().head()
```

Out[77]:

```
2001    356
1978     35
1945     31
1959     30
1956     30
Name: Year, dtype: int64
```

In [78]:

```
'''
Counting the number of fatalities by month
'''
merge_df['Month'] = (merge_df['Date of Death'].dt.month).apply(lambda x : calendar.month_abbr[int(x
)])
months=['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
merge_df['Month'] = pd.Categorical(merge_df['Month'],
                                   categories=months,
                                   ordered=True)
merge_df['Month'].value_counts()
```

Out[78]:

```
Sep    467
Jan    350
Feb    202
Dec    177
Apr    176
Nov    171
Jul    170
Mar    161
Aug    160
May    158
Oct    142
Jun    127
Name: Month, dtype: int64
```

Above two analysis indicates that there was some significant incident that happened in the month of September. It also indicates that 2001 was a dangerous year for firefighters

- As I have two different datasets, one with records of dates of an incident and the other has relevant location information, if I combine the two datasets I can infer **when** and **where** such an incident occurred!
- Hence, I am trying to visualize dates by fatality count for top five fatal years and top five fatal counties combination.

Exploring fatalities by date of death for a county in New York State

- **Extracting the top five fatal counties by fatality count for processing**

In [79]:

```
top_counties_of_fire_fighter_death = merge_df.groupby(['County Name'])['Name'].count().sort_values
(ascending=False).head().index.values
top_counties_of_fire_fighter_death
```

Out[79]:

```
[new york, erie, nassau, suffolk, westchester]
Categories (58, object): [albany, allegany, broome, cattaraugus, ..., wayne, westchester, wyoming,
yates]
```

In [80]:

```
top_counties_of_fire_fighter_death_df = merge_df[merge_df['County
Name'].isin(top_counties_of_fire_fighter_death)]
```

- **Extracting the top five years by fatality count for processing**

In [81]:

```
top_five_year_of_fire_fighter_death = merge_df.groupby(['Year'])
['Name'].count().sort_values(ascending=False).head().index.values
top_five_year_of_fire_fighter_death
```

Out[81]:

```
array([2001, 1978, 1945, 1959, 1974])
```

- **Extracting the top five years from top five fatal counties by fatality count for processing**

In [82]:

```
top_death_county_year_df = top_counties_of_fire_fighter_death_df[

top_counties_of_fire_fighter_death_df['Year'].isin(top_five_year_of_fire_fighter_death)]
```

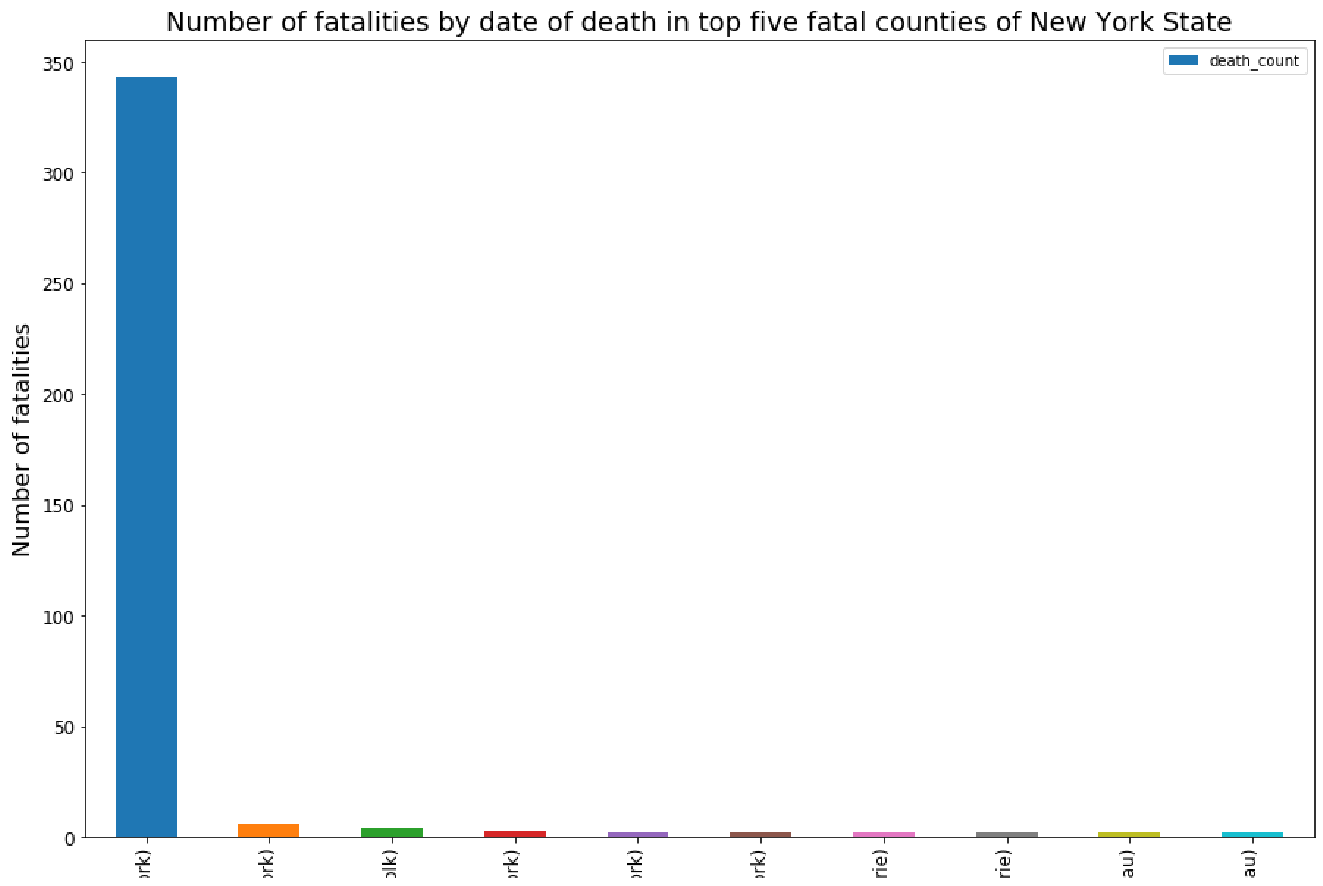
In [83]:

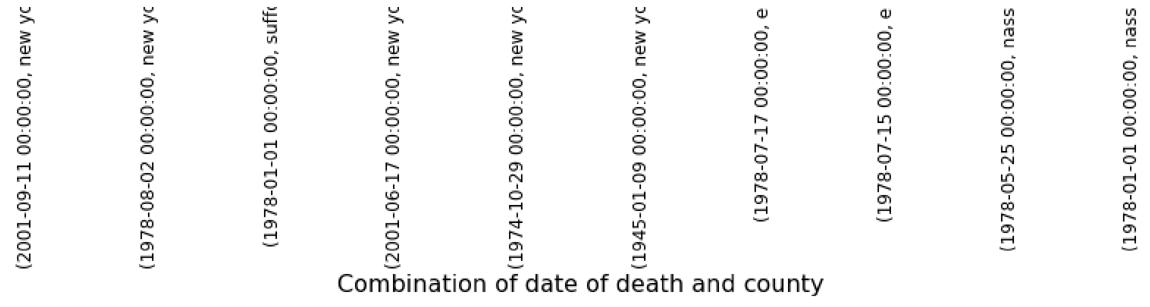
```
top_date_of_death_county_df=pd.DataFrame(list(top_death_county_year_df.groupby(['Date of Death','C
ounty Name'])['Name']

.count().sort_values(ascending=False).head(10).items()),
                                           columns=['date_of_death_county_combo','death_count'])
```

In [84]:

```
top_date_of_death_county_df.plot.bar(x='date_of_death_county_combo',y='death_count',figsize=(15,10
))
plt.title('Number of fatalities by date of death in top five fatal counties of '+ NY,fontsize=18)
plt.setp(plt.gca().get_xticklabels(), rotation=90, fontsize=12)
plt.setp(plt.gca().get_yticklabels(), fontsize=12)
plt.xlabel('Combination of date of death and county',fontsize=16)
plt.ylabel('Number of fatalities',fontsize=16)
plt.show()
```





In [85]:

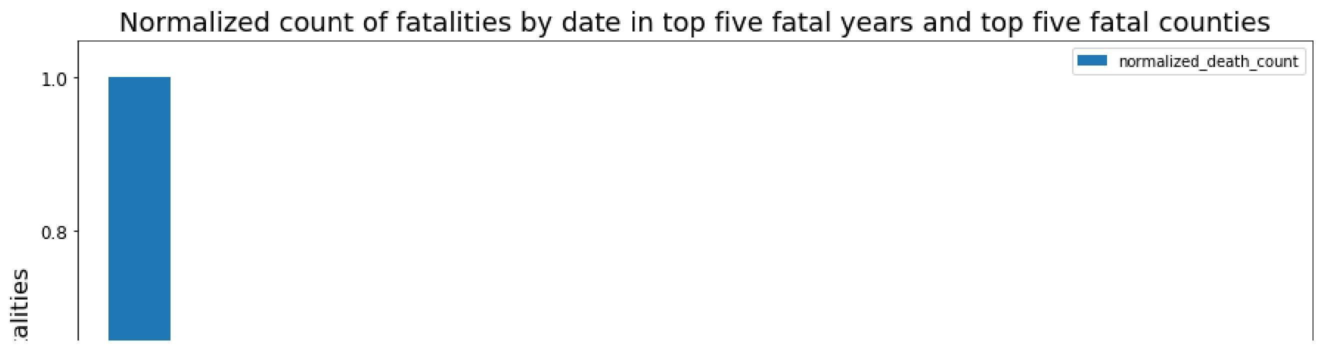
```
'''
Computing the normalized count of fatalities by date of death for top five fatal years in top five
fatal counties
I am computing normalized count to detect if 2001-09-11 combined with New York County is an outlie
r in terms of number of fatalities.
'''
top_date_of_death_county_norm_df =
get_normalized_value_df(df_to_process=top_date_of_death_county_df,
                                                                 name_of_column_to_normalize='death_count
top_date_of_death_county_norm_df
```

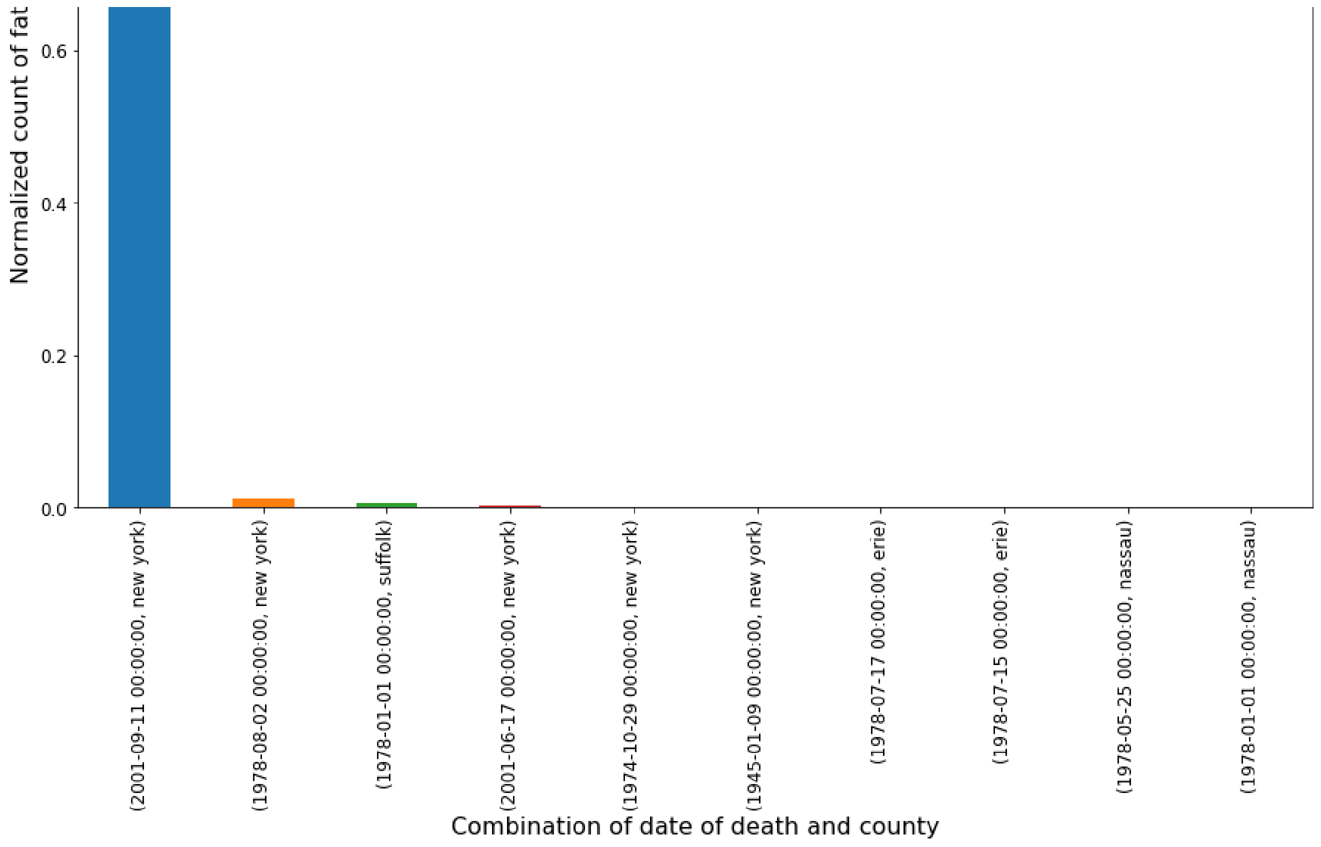
Out[85]:

	date_of_death_county_combo	death_count	normalized_death_count
0	(2001-09-11 00:00:00, new york)	343	1.000000
1	(1978-08-02 00:00:00, new york)	6	0.011730
2	(1978-01-01 00:00:00, suffolk)	4	0.005865
3	(2001-06-17 00:00:00, new york)	3	0.002933
4	(1974-10-29 00:00:00, new york)	2	0.000000
5	(1945-01-09 00:00:00, new york)	2	0.000000
6	(1978-07-17 00:00:00, erie)	2	0.000000
7	(1978-07-15 00:00:00, erie)	2	0.000000
8	(1978-05-25 00:00:00, nassau)	2	0.000000
9	(1978-01-01 00:00:00, nassau)	2	0.000000

In [86]:

```
top_date_of_death_county_norm_df.plot.bar(x='date_of_death_county_combo',
y='normalized_death_count', figsize=(15,10))
plt.setp(plt.gca().get_xticklabels(), rotation=90, fontsize=12)
plt.setp(plt.gca().get_yticklabels(), fontsize=12)
plt.xlabel('Combination of date of death and county',fontsize=16)
plt.ylabel('Normalized count of fatalities',fontsize=16)
plt.title('Normalized count of fatalities by date in top five fatal years and top five fatal
counties',fontsize=18)
plt.show()
```





Key observation:

Combining the two datasets I am able to infer that on **September 11, 2001, New York County** happened to face a severe crisis, in which hundreds of firefighters gave their lives.

Answering our question 1 - Everyone knows about September 11th, 2001 and that people died but can it be determined from the combined data, which county most of the firefighters came from?

- The firefighters that sacrificed their lives on 9/11 they came from **New York County**.

Story time

9/11 was one of the biggest terrorist attacks in American History on American soil killing thousands of people.

- This link specifies that on that day:
  - "Of the 2,977 victims killed in the September 11 attacks, 412 were emergency workers in New York City who responded to the World Trade Center."
  - "This included: **343 firefighters** (including a chaplain and two paramedics) of the New York City Fire Department (FDNY)".
  - The top_date_of_death_county_df shows that on 9/11, 2001 New York County had 343 fatalities.
- **Thus by combining two datasets I am able to prove that using the power of data analysis one may make fairly accurate inferences about real-life incidents.**

Next, I will try to find the answer to my second question - During 9/11 was there a fire department where most of the fatalities occurred?

- For that purpose I will try and extract the location data for the department address and combine that with fatality count. Both these pieces of data are present in my merged dataframe and will help me determine the exact department.

Top ten fire department location for incident

In [87]:

```
top_death_year_df=merge_df[merge_df['Year'].isin(top_five_year_of_fire_fighter_death)]
top_death_date_address_wise_df=top_death_year_df.groupby(['Date of Death','Address'])['Name'].coun
t().sort_values(ascending=False).head(21)
```

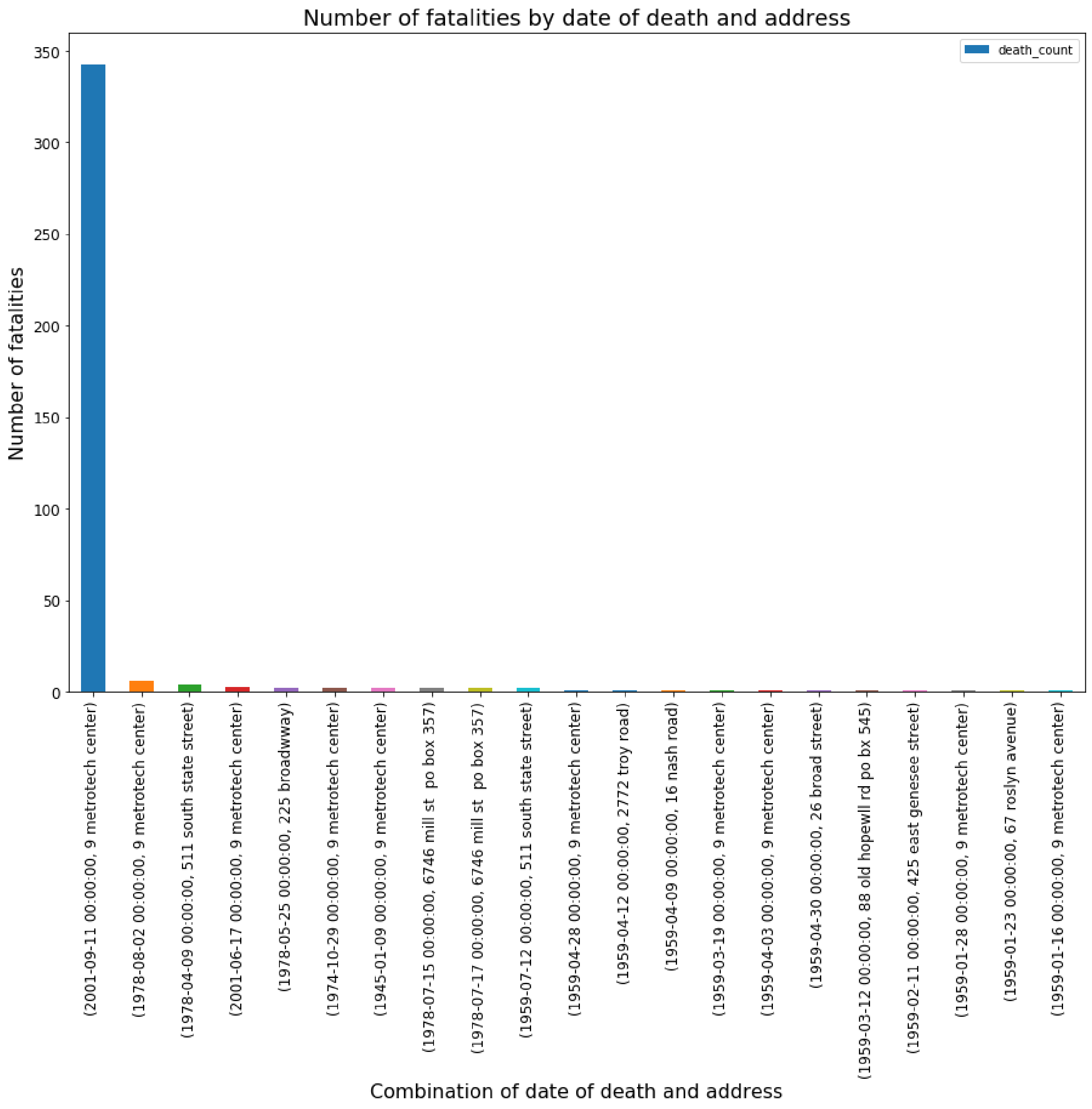
In [88]:

```
top_death_date_address_df=pd.DataFrame(list(top_death_date_address_wise_df.items()),
                                                    columns=['date_of_death_address_combo','death_count'])
```

In [89]:

```
top_death_date_address_df.plot.bar(x='date_of_death_address_combo',y='death_count',figsize=(15,10))

plt.setp(plt.gca().get_xticklabels(), rotation=90, fontsize=12)
plt.setp(plt.gca().get_yticklabels(), fontsize=12)
plt.xlabel('Combination of date of death and address',fontsize=16)
plt.ylabel('Number of fatalities',fontsize=16)
plt.title('Number of fatalities by date of death and address',fontsize=18)
plt.show()
```

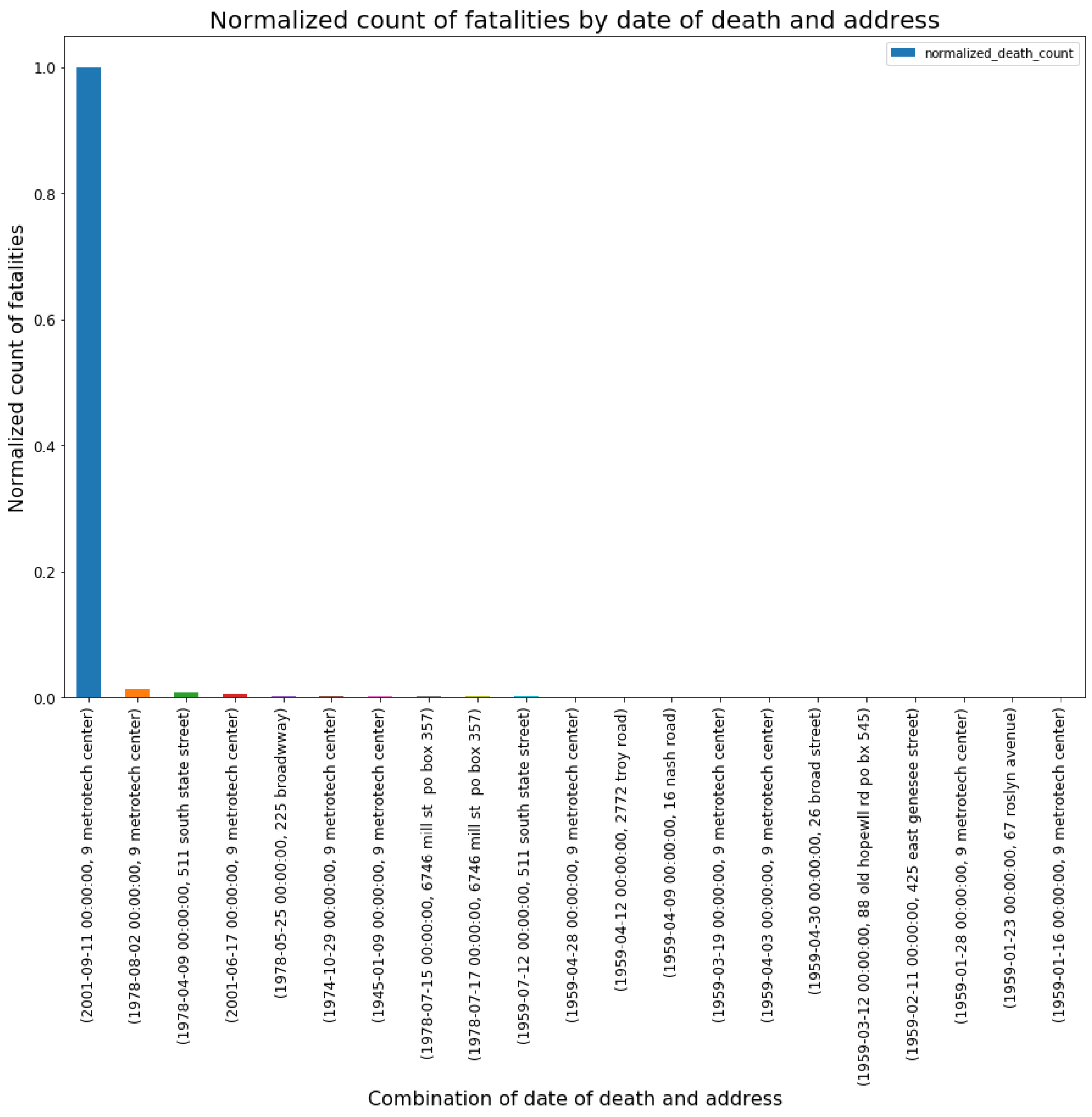


In [90]:

```
'''
Computing the normalized count of fatalities for addresses
I am computing normalized counts to detect if address and 2001-09-01 has outliers for number of fa
talities.
'''
top_death_date_address_norm_df = get_normalized_value_df(df_to_process=top_death_date_address_df,
                                                         name_of_column_to_normalize='death_count')
```

In [91]:

```
top_death_date_address_norm_df.plot.bar(x='date_of_death_address_combo',
y='normalized_death_count', figsize=(15,10))
plt.setp(plt.gca().get_xticklabels(), rotation=90, fontsize=12)
plt.setp(plt.gca().get_yticklabels(), fontsize=12)
plt.xlabel('Combination of date of death and address',fontsize=16)
plt.ylabel('Normalized count of fatalities',fontsize=16)
plt.title('Normalized count of fatalities by date of death and address',fontsize=20)
plt.show()
```



- From the chart above I was able to determine that "9 metrotech center" of Brooklyn New York is the station from which most of the firefighters operated.
- Intuitively this looks reasonable as the World Trade Center is in lower Manhattan that is very close to Brooklyn by waterways.
- Thus, I have answered the **second** question.

Our **third** question is about ranks of firefighters who passed away on 9/11 - It is understandable that there will be few high ranking officials directly involved in rescue operations. Does the combined data tell us the ranks of the firefighters that sacrificed their lives?

- I do have rank information in the firefighter dataset. I can combine the date of deaths with county of fire department in the other dataset to determine the ranks of the firefighters that died on 9/11.

Analyzing fatalities by county and firefighter ranks

Analyzing fatalities by county and firefighter ranks

In [92]:

```
top_five_rank_of_fire_fighter_death = merge_df.groupby(['Rank'])
['Name'].count().sort_values(ascending=False).head().index.values
top_five_rank_of_fire_fighter_death
```

Out[92]:

```
[firefighter, lieutenant, captain, firefighter, battalion chief]
Categories (84, object): [1st assistant chief, 1st deputy commissioner, 2nd assistant chief, 2nd a
ssistant foreman, ..., supervising fire marshal, tillerman, training instructor, truckman]
```

In [93]:

```
top_death_county_year_rank_df = top_death_county_year_df[

top_death_county_year_df['Rank'].isin(top_five_rank_of_fire_fighter_death)]
```

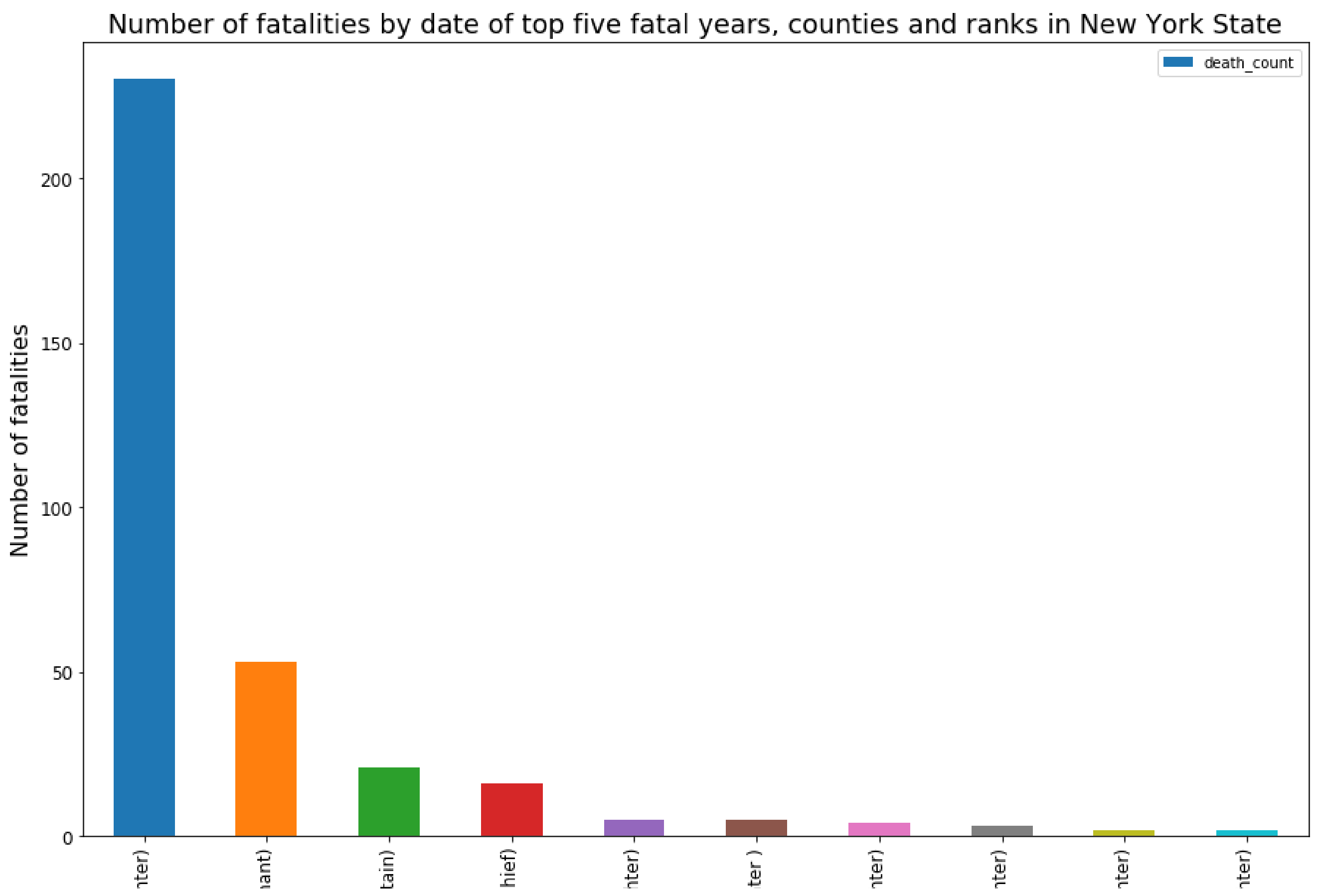
In [94]:

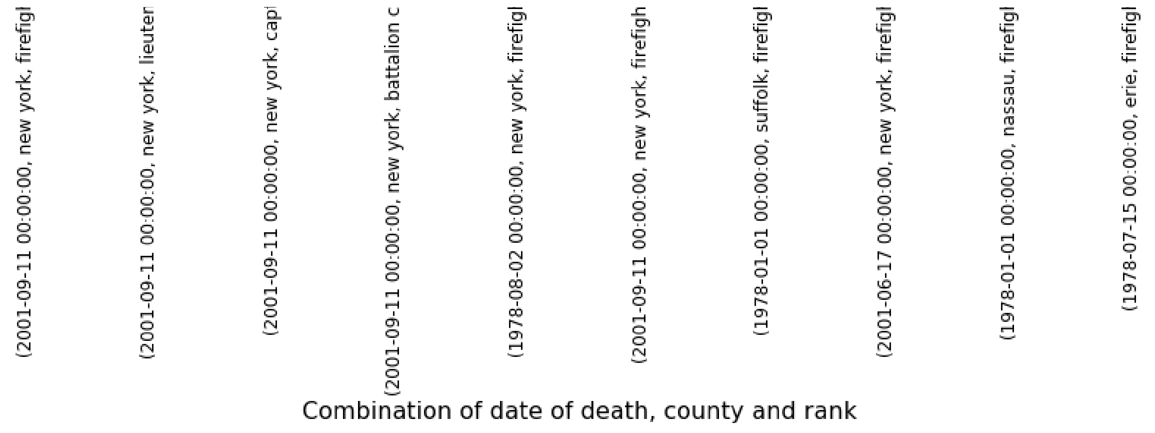
```
top_death_date_of_death_county_rank_df=pd.DataFrame(list(top_death_county_year_rank_df.groupby(['D
ate of Death','County Name','Rank'])['Name']
                                                    .count().sort_values(ascending=False).head(10).
ems()),

columns=['date_of_death_county_rank_combo','death_count'])
```

In [95]:

```
top_death_date_of_death_county_rank_df.plot.bar(x='date_of_death_county_rank_combo',y='death_count'
,figsize=(15,10))
plt.title('Number of fatalities by date of top five fatal years, counties and ranks in ' + NY,font
size=18)
plt.setp(plt.gca().get_xticklabels(), rotation=90, fontsize=12)
plt.setp(plt.gca().get_yticklabels(), fontsize=12)
plt.xlabel('Combination of date of death, county and rank',fontsize=16)
plt.ylabel('Number of fatalities',fontsize=16)
plt.show()
```



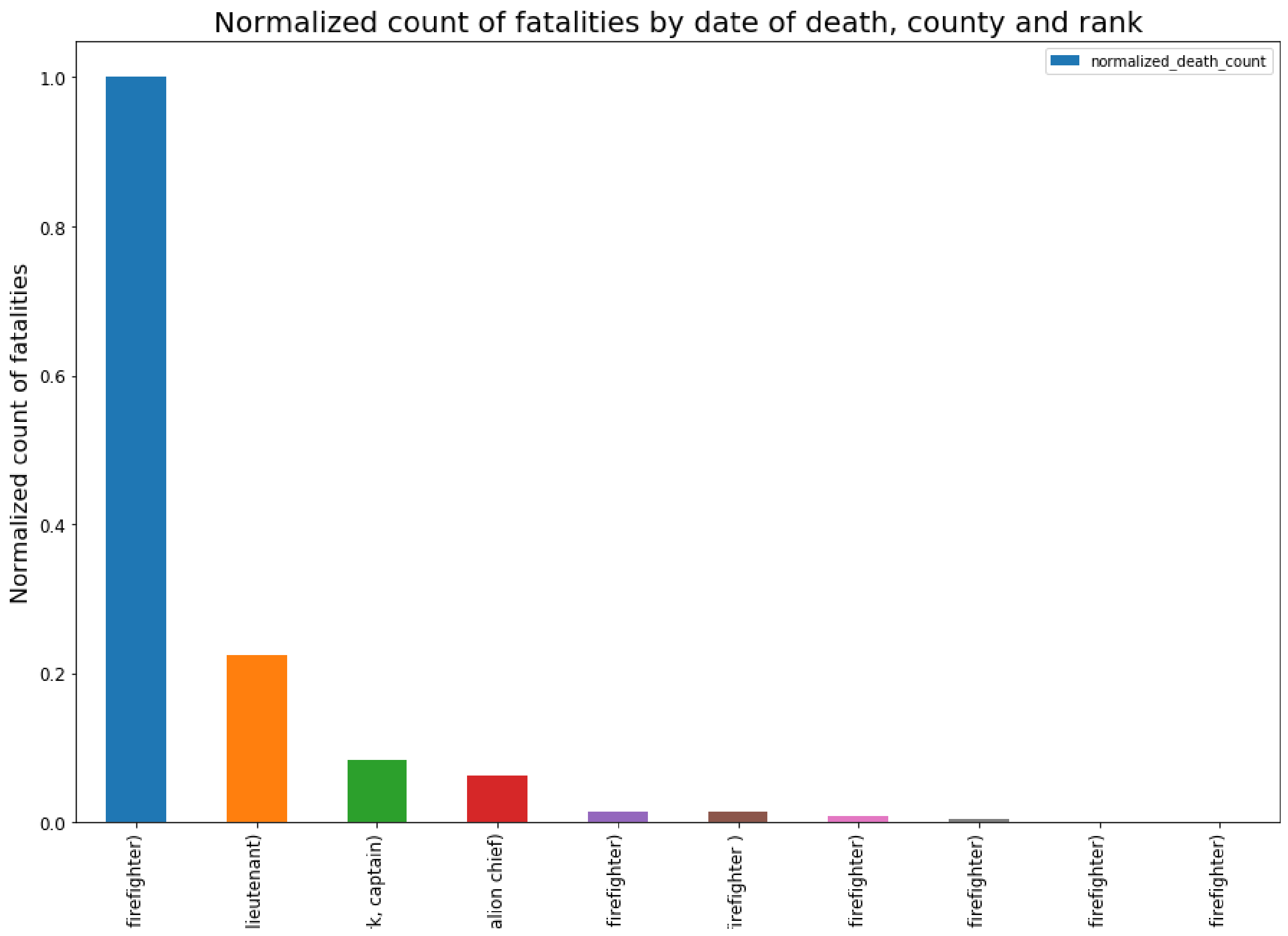


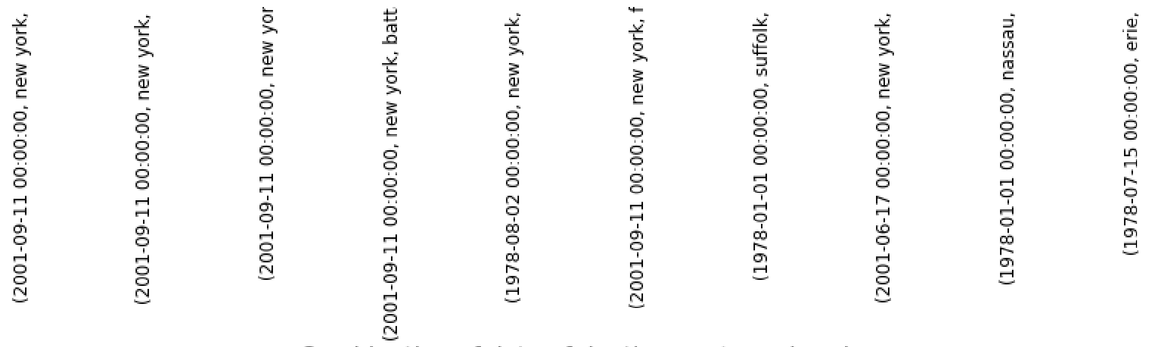
In [96]:

```
'''
Computing the normalized count of fatalities for top five fatal counties and rank
I am computing normalized counts to detect if new york, 2001-09-11, firefighter has outliers for n
umber of fatalities.
'''
top_death_date_of_death_county_rank_norm_df =
get_normalized_value_df(df_to_process=top_death_date_of_death_county_rank_df,
                                                                       name_of_column_to_normalize='
ath_count')
```

In [97]:

```
top_death_date_of_death_county_rank_norm_df.plot.bar(x='date_of_death_county_rank_combo',
y='normalized_death_count', figsize=(15,10))
plt.setp(plt.gca().get_xticklabels(), rotation=90, fontsize=12)
plt.setp(plt.gca().get_yticklabels(), fontsize=12)
plt.xlabel('Combination of date of death, county and rank',fontsize=16)
plt.ylabel('Normalized count of fatalities',fontsize=16)
plt.title('Normalized count of fatalities by date of death, county and rank',fontsize=20)
plt.show()
```





- From the chart above I was able to determine that most fatalities on 9/11 happened for the "Firefighter" rank.
- The second highest fatalities were for "Lieutenant" rank followed by "Captain" and "Battallion Chief".
- This link shows that a "Firefighter" is in-fact the lowest ranked official in the Fire Department of New York(FDNY).
- This answers my **third** question.
- The chart above can also help answer the **fourth** question I had - Is there any incident comparable to 9/11 in terms of fire fighter fatalities? Where did such an incident occur?
    - No, there is no incident, as per the datasets that can compare to 9/11, in terms of fatalities. However, it looks like on August 2nd, 1978 there was an incident that might have caused some fatalities. After googling around, I found that the Waldbaum Fire on August 2, 1978 had killed six firefighters.

- My **fifth** and final question was about trying to visualize fatalities across the whole state of New York - Which fire departments across the state of New York have had the most fatalities? Can the top ten fatal locations be represented visually with information about the most fatal incident for that location?
    - I will try to visualize that now.
    - I have not normalized the data because I want to show the count of fatalities.

In [98]:

```
'''
For this visualizaton I am using previously created dataframe for top ten fatal location to get th
e address, date_of_death and death_counts
value in different columns.I am breaking up the tuple in column date_of_death_address_combo to obt
ain the individual columns mentioned.
'''
top_death_count_date_address_list=[]
for date_address_tuple in list(top_death_date_address_df['date_of_death_address_combo']):
    death_count_date_address_dict ={}
    death_count_date_address_dict['death_count']
=top_death_date_address_df[top_death_date_address_df['date_of_death_address_combo']==date_address_t
uple].iloc[0]['death_count']
    death_count_date_address_dict['date_of_death'] =date_address_tuple[0]
    death_count_date_address_dict['address'] =date_address_tuple[1]
    top_death_count_date_address_list.append(death_count_date_address_dict)
top_death_count_date_address_df=pd.DataFrame(top_death_count_date_address_list)
top_death_count_date_address_df
```

Out[98]:

	address	date_of_death	death_count
0	9 metrotech center	2001-09-11	343
1	9 metrotech center	1978-08-02	6
2	511 south state street	1978-04-09	4
3	9 metrotech center	2001-06-17	3
4	225 broadwway	1978-05-25	2
5	9 metrotech center	1974-10-29	2
6	9 metrotech center	1945-01-09	2
7	6746 mill st po box 357	1978-07-15	2
8	6746 mill st po box 357	1978-07-17	2
9	511 south state street	1959-07-12	2
10	9 metrotech center	1959-04-28	1

	address	date_of_death	death_count
11	2772 troy road	1959-04-12	1
12	16 nash road	1959-04-09	1
13	9 metrotech center	1959-03-19	1
14	9 metrotech center	1959-04-03	1
15	26 broad street	1959-04-30	1
16	88 old hopewll rd po bx 545	1959-03-12	1
17	425 east genesee street	1959-02-11	1
18	9 metrotech center	1959-01-28	1
19	67 roslyn avenue	1959-01-23	1
20	9 metrotech center	1959-01-16	1

In [99]:

```
location_list=[]
all_loc_dict = {}
indx = 0
for address in list(top_death_count_date_address_df['address']):

    county=merge_df[merge_df['Address']==address].iloc[0]['County Name']
    city=merge_df[merge_df['Address']==address].iloc[0]['City']
    zip_code=merge_df[merge_df['Address']==address].iloc[0]['Zip Code']
    full_address=address + ", " + county + " county, " + city + " city, " + NY + ", " + zip_code
    latitude=merge_df[merge_df['Address']==address].iloc[0]['Latitude']
    longitude=merge_df[merge_df['Address']==address].iloc[0]['Longitude']
    location1=merge_df[merge_df['Address']==address].iloc[0]['Location 1']
    date_of_death=top_death_count_date_address_df.iloc[indx]['date_of_death']
    death_count=top_death_count_date_address_df.iloc[indx]['death_count']

    '''
    Ignoring a location if it is repeating in the list.
    As top_death_count_date_address_df is sorted by count of fatalities I will get the highest fat
ality count for an address
    '''
    if address not in list(all_loc_dict.keys()):
        location_dict={}
        location_dict['latitude']=latitude
        location_dict['longitude']=longitude
        location_dict['location']=location1
        location_dict['lat_long']=[latitude,longitude]
        location_dict['full_address']=full_address
        location_dict['date_of_death']=date_of_death
        location_dict['death_count']=death_count
        all_loc_dict[address] = location_dict
    indx += 1

for address_key, location_value in all_loc_dict.items():
    location_list.append(location_value)

location_df = pd.DataFrame(location_list)
location_df
```

Out[99]:

	date_of_death	death_count	full_address	lat_long	latitude	location	longitude
0	2001-09-11	343	9 metrotech center, new york county, brooklyn ...	[40.69384, -73.9871]	40.693840	(40.69384, -73.9871)	-73.987100
1	1978-04-09	4	511 south state street, onondaga county, syrac...	[43.046921, -76.147406]	43.046921	(43.046921, -76.147406)	-76.147406
2	1978-05-25	2	225 broadwway, nassau county, bethpage city, N...	[40.738833, -73.479646]	40.738833	(40.738833, -73.479646)	-73.479646
3	1978-07-15	2	6746 mill st po box 357, erie county, boston ...	[42.628713, -78.738227]	42.628713	(42.628713, -78.738227)	-78.738227
4	1959-04-12	1	2772 troy road, schenectady county, schenectad...	[42.804901, -73.893102]	42.804901	(42.804901, -73.893102)	-73.893102
5	1959-04-09	1	16 nash road, erie county, kenmore city, New Y...	[42.965344, -78.869445]	42.965344	(42.965344, -78.869445)	-78.869445

	date_of_death	death_count	full_address	lat_long	latitude	location	longitude
6	1959-04-30	1	26 broad street, albany county, albany city, N...	[42.662577, -73.759898]	42.662577	(42.662577, -73.759898)	-73.759898
7	1959-03-12	1	88 old hopewll rd po bx 545, dutchess county, ...	[41.57888, -73.91097]	41.578880	(41.57888, -73.91097)	-73.910970
8	1959-02-11	1	425 east genesee street, onondaga county, faye...	[43.02976, -76.005992]	43.029760	(43.02976, -76.005992)	-76.005992
9	1959-01-23	1	67 roslyn avenue, nassau county, sea cliff cit...	[40.84858, -73.644801]	40.848580	(40.84858, -73.644801)	-73.644801

In [100]:

```python
def regioncolors(num_of_death):
    if num_of_death > 100:
        return 'red'
    else:
        return 'darkgreen'
location_df["color"] = location_df['death_count'].apply(regioncolors)
location_df
```

Out[100]:

	date_of_death	death_count	full_address	lat_long	latitude	location	longitude	color
0	2001-09-11	343	9 metrotech center, new york county, brooklyn ...	[40.69384, -73.9871]	40.693840	(40.69384, -73.9871)	-73.987100	red
1	1978-04-09	4	511 south state street, onondaga county, syrac...	[43.046921, -76.147406]	43.046921	(43.046921, -76.147406)	-76.147406	darkgreen
2	1978-05-25	2	225 broadwway, nassau county, bethpage city, N...	[40.738833, -73.479646]	40.738833	(40.738833, -73.479646)	-73.479646	darkgreen
3	1978-07-15	2	6746 mill st po box 357, erie county, boston ...	[42.628713, -78.738227]	42.628713	(42.628713, -78.738227)	-78.738227	darkgreen
4	1959-04-12	1	2772 troy road, schenectady county, schenectad...	[42.804901, -73.893102]	42.804901	(42.804901, -73.893102)	-73.893102	darkgreen
5	1959-04-09	1	16 nash road, erie county, kenmore city, New Y...	[42.965344, -78.869445]	42.965344	(42.965344, -78.869445)	-78.869445	darkgreen
6	1959-04-30	1	26 broad street, albany county, albany city, N...	[42.662577, -73.759898]	42.662577	(42.662577, -73.759898)	-73.759898	darkgreen
7	1959-03-12	1	88 old hopewll rd po bx 545, dutchess county, ...	[41.57888, -73.91097]	41.578880	(41.57888, -73.91097)	-73.910970	darkgreen
8	1959-02-11	1	425 east genesee street, onondaga county, faye...	[43.02976, -76.005992]	43.029760	(43.02976, -76.005992)	-76.005992	darkgreen
9	1959-01-23	1	67 roslyn avenue, nassau county, sea cliff cit...	[40.84858, -73.644801]	40.848580	(40.84858, -73.644801)	-73.644801	darkgreen

Using the Folium library and Link let's take a look at where the incident locations are in New York State!

In [101]:

```python
folium_map = folium.Map(location=location_df.iloc[0]['lat_long'],
                        zoom_start=7,
                        tiles='Stamen Terrain')
for curr_loc in list(location_df.index):
    folium.Marker(location=location_df.iloc[curr_loc]['lat_long'],
                  popup="Date of most fatal incident : "+
                  datetime.strftime(location_df.iloc[curr_loc]['date_of_death'],'%B,%d,%Y')+
                  " Number of deaths on that date : "+
                  str(location_df.iloc[curr_loc]['death_count'])+
                  " Location : "+
                  location_df.iloc[curr_loc]['full_address'],
                  icon=folium.Icon(color=location_df.iloc[curr_loc]['color'],
                                   icon_color='white',
                                   icon='male',
                                   angle=0,
                                   prefix='fa')
                 ).add_to(folium_map)
folium_map
```

Out[101]:

- If you click on each of the markers you can see the dates of the most fatal incident, alongwith number of fatalities.
- The visualization above shows the data for the most fatal incident ranked by top ten most fatal locations across the state of New York.

In [102]:

```
print('Total Time taken:',time.time() - start_time,'seconds')
```

```
Total Time taken: 57.42645597457886 seconds
```

Conclusions from Analysis of New York State Fire Department Fallen Heroes Data

- **Key Observation** - **Combining the two datasets** I am able to infer that on **September 11, 2001, New York County** happened to face a severe crisis, in which hundreds of firefighters gave their lives.
  - The firefighters that sacrificed their lives on 9/11 they came from **New York County**.
  - **Story time** - 9/11 was one of the biggest terrorist attacks in American History on American soil killing thousands of people.
  - This link specifies that on that day:
  - "Of the 2,977 victims killed in the September 11 attacks, 412 were emergency workers in New York City who responded to the World Trade Center."
  - "This included: **343 firefighters** (including a chaplain and two paramedics) of the New York City Fire Department (FDNY)".
  - My dataframe - top_date_of_death_county_df shows that on 9/11, 2001 New York County had in-fact had 343 fatalities.
- During 9/11 the fire department located at "9 metrotech center", Brooklyn, New York seems to be the station from which most of the firefighters operated.
  - Intuitively this looks reasonable as the World Trade Center is in lower Manhattan that is very close to Brooklyn by waterways.
- I was able to determine that most fatalities on 9/11 happened for the "Firefighter" rank.
  - The second highest fatalities were for "Lieutenant" rank followed by "Captain" and "Battallion Chief".
- Using my analysis I was also able to determine that there is no incident, as per the datasets, that can compare to 9/11, in terms of fatalities. However, it looks like on August 2nd, 1978 there was an incident that might have caused some fatalities. After googling around, I found that the Waldbaum Fire of August 2, 1978 had killed six firefighters.
- I was also able to visualize using a map of New York State, the dates of the most fatal incident, alongwith count of fatalities. I was able to visualize the most fatal incident ranked by top ten most fatal locations across the state of New York.

Learnings from Final Project for Data 601

- I learnt about how to merge data from two different datasets and perform meaningful analysis from it.
- I learnt how to deal with messy data and carry out pre-processing in order to find proper key of joining.
- I used my knowledge from project two where I learnt about Folium library that allowed me to visualize data about fatalities from

"Fire Department" locations on an actual map and infer occurrences of significant incidents.
- I was able to visualize the impact of an incident like 9/11 and compare that to smaller incidents like the Waldbaum Fire of August 2, 1978.