Unlocking Climate Solutions

CDP Competition Starter Notebook

Example data mapping, EDA and data wrangling pipeline to relate CDP Corporate response data to CDP Cities data and external data sets containing social equity data.

Parameters

Input

CDP Corporate Questionnaire response data sets

- **2019_Full_Climate_Change_Dataset.csv** = 2019 Climate Change publically disclosed questionnaire responses for North America
- **2019_Full_Water_Security_Dataset.csv** = 2019 Water Security publically disclosed questionnaire responses for North America

CDP Cities Questionnaire response data sets

- **2020_-_Full_Cities_Dataset.csv** = Full 2020 Cities Questionnaire response data set

CDP Cities Meta data sets

- **NA_HQ_public_data.csv** = CDP curated Organisations metadata, mapping publically disclosed North American organisations to HQ city and state

External Non-CDP data sets

- **SVI2018_US.csv** = US Centers for Disease Control and Prevention (CDC) Social Vulnerability Index (SVI) Data for 2018 (Census tract level) - available publicly bat https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html
- **SVI2018_US_COUNTY.csv** = US Centers for Disease Control and Prevention (CDC) Social Vulnerability Index (SVI) Data for 2018 (County level) - available publicly at https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html
- **uscities.csv** = metadata for United States cities and towns, with information such as populations size, median age and lat,lng location coordinates - available publicly at https://simplemaps.com/data/us-cities.

SVI 2018 Documentation and Data Dictionary
https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2018.html

Output

EDA and Visualisations to begin investigating the CDP competition data sets, environmental performance indicators and social-equity KPIs.

Imports

I

```
# standard libs
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
import json

# plotting libs
import seaborn as sns

# geospatial libs
from mpl_toolkits.basemap import Basemap
from shapely.geometry import Polygon
import geopandas as gpd
import folium
import plotly.graph_objects as go
import plotly_express as px

# set in line plotly
from plotly.offline import init_notebook_mode;
init_notebook_mode(connected=True)

print(os.getcwd())
```

```
/kaggle/working
```

Data

Import Data

```
# import corporate response data
cc_df = pd.read_csv('../input/cdp-unlocking-climate-solutions/Corporations/Corporations Responses/Climate Change/2019_Full_Climate_Change_Dataset.csv')
```

```
ws_df = pd.read_csv('../input/cdp-unlocking-climate-solutions/Corporations/Corporations Responses/Water Security/2019_Full_Water_Security_Dataset.csv')
```

```
/opt/conda/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3063: DtypeWarning:

Columns (19) have mixed types.Specify dtype option on import or set low_memory=False.
```

```
# import cities response df
cities_df = pd.read_csv("../input/cdp-unlocking-climate-solutions/Cities/Cities Responses/2020_Full_Cities_Dataset.csv")
```

```
# external data - import CDC social vulnerability index data - census tract level
svi_df = pd.read_csv("../input/cdp-unlocking-climate-solutions/Supplementary Data/CDC Social Vulnerability Index 2018/SVI2018_US.csv")
```

```
# cities metadata - lat,lon locations for US cities
cities_meta_df = pd.read_csv("../input/cdp-unlocking-climate-solutions/Supplementary Data/Simple Maps US Cities Data/uscities.csv")

# cities metadata - CDP metadata on organisation HQ cities
cities_cdpmeta_df = pd.read_csv("../input/cdp-unlocking-climate-solutions/Supplementary Data/Locations of Corporations/NA_HQ_public_data.csv")
```

Helpers

```
def list_dedupe(x):
    """
    Convert list to dict and back to list to dedupe

    Parameters
    ----------
    x: list
        Python list object
```

```
    Returns
    -------
    dictionary:
        dictionary object with duplicates removed

    """
    return list(dict.fromkeys(x))
```

Set up and Parameters

Calculations

Data Cleaning & EDA

Extract City Questionnaire Response and map Cities to Organisations

- Extract city response data for question 6.2 Does your city collaborate in partnership with businesses in your city on sustainability projects?
- Map cities to organisations who are headquartered within that city, using the NA_HQ_public_data.csv meta data file

(see CDP Cities questionnaire guidance)

```
cities_6_2 = cities_df[cities_df['Question Number'] == '6.2']\
    .rename(columns={'Organization': 'City'})

cities_6_2['Response Answer'] = cities_6_2['Response Answer'].fillna('No Response')

cities_6_2.head()
```

	Questionnaire	Year Reported to CDP	Account Number	City	Country	CDP Region	Parent Section	Section	Questio Numbe

2093	Cities 2020	2020	54538	Bath and North East Somerset	United Kingdom of Great Britain and Northern I...	Europe	Opportunities	Collaboration	6.2
2107	Cities 2020	2020	42120	City of Salvador	Brazil	Latin America	Opportunities	Collaboration	6.2
2112	Cities 2020	2020	826210	Junta Intermunicipal de Medio Ambiente de la C...	Mexico	Latin America	Opportunities	Collaboration	6.2
2594	Cities 2020	2020	37241	City of Berkeley	United States of America	North America	Opportunities	Collaboration	6.2
3561	Cities 2020	2020	50549	City of Fort Worth	United States of America	North America	Opportunities	Collaboration	6.2

Clean Organisation City HQ Metadata

```
# state abbreviation dictionary
us_state_abbrev = {
    'Alabama': 'AL',
    'Alaska': 'AK',
    'American Samoa': 'AS',
    'Arizona': 'AZ',
```

'Arkansas': 'AR',
'California': 'CA',
'Colorado': 'CO',
'Connecticut': 'CT',
'Delaware': 'DE',
'District of Columbia': 'DC',
'Florida': 'FL',
'Georgia': 'GA',
'Guam': 'GU',
'Hawaii': 'HI',
'Idaho': 'ID',
'Illinois': 'IL',
'Indiana': 'IN',
'Iowa': 'IA',
'Kansas': 'KS',
'Kentucky': 'KY',
'Louisiana': 'LA',
'Maine': 'ME',
'Maryland': 'MD',
'Massachusetts': 'MA',
'Michigan': 'MI',
'Minnesota': 'MN',
'Mississippi': 'MS',
'Missouri': 'MO',
'Montana': 'MT',
'Nebraska': 'NE',
'Nevada': 'NV',
'New Hampshire': 'NH',
'New Jersey': 'NJ',
'New Mexico': 'NM',
'New York': 'NY',
'North Carolina': 'NC',
'North Dakota': 'ND',
'Northern Mariana Islands':'MP',
'Ohio': 'OH',
'Oklahoma': 'OK',
'Oregon': 'OR',
'Pennsylvania': 'PA',

```
    'Puerto Rico': 'PR',
    'Rhode Island': 'RI',
    'South Carolina': 'SC',
    'South Dakota': 'SD',
    'Tennessee': 'TN',
    'Texas': 'TX',
    'Utah': 'UT',
    'Vermont': 'VT',
    'Virgin Islands': 'VI',
    'Virginia': 'VA',
    'Washington': 'WA',
    'West Virginia': 'WV',
    'Wisconsin': 'WI',
    'Wyoming': 'WY'
}

# map dict to clean full state names to abbreviations
cities_cdpmeta_df['state'] = cities_cdpmeta_df['address_state'].map(us_state_abbrev)

# infill non-matched from dict
cities_cdpmeta_df['state'] = cities_cdpmeta_df['state'].fillna(cities_cdpmeta_df['address_state'])
cities_cdpmeta_df['state'] = cities_cdpmeta_df['state'].replace({'ALBERTA':'AB'})
cities_cdpmeta_df['address_city'] = cities_cdpmeta_df['address_city'].replace({'CALGARY':'Calgary'})
cities_cdpmeta_df= cities_cdpmeta_df.drop(columns=['address_state'])

# create joint city state variable
cities_cdpmeta_df['city_state'] = cities_cdpmeta_df['address_city'].str.cat(cities_cdpmeta_df['state'],sep=",
")

cities_cdpmeta_df
```

	account_number	organization	public	invitation_status	request_status	theme	survey_year	survey_na
0	58859	Hewlett Packard Enterprise Company	public	Submitted	Submitted	Climate Change	2020	Climate Change 2

1	31831	Bausch Health Cos. Inc.	public	Submitted	Submitted	Climate Change	2020	Climate Change 2
2	40952	BWI Group	public	Submitted	Submitted	Climate Change	2020	Climate Change 2
3	30634	Guangdong Textiles	public	Submitted	Submitted	Climate Change	2020	Climate Change 2
4	19582	Johnson Controls International PLC	public	Submitted	Submitted	Climate Change	2020	Climate Change 2
...	...	...	...	...	...	...	...	...
3294	38267	American Cleaning Supply, Inc.	public	Submitted	Submitted	Water	2020	Water Se 2020
3295	848018	CANACOL ENERGY LTD.	public	Submitted	Submitted	Water	2020	Water Se 2020
3296	61423	AlmadenÂ Press	public	Submitted	Submitted	Water	2020	Water Se 2020
3297	847168	Raytheon Technologies Corporation	public	Submitted	Submitted	Water	2020	Water Se 2020
3298	38144	BWAY Corporation	public	Submitted	Submitted	Water	2020	Water Se 2020

3299 rows × 14 columns

Summarise the cities metadata to count the number organisations (HQ) per city

```
cities_count = cities_cdpmeta_df[['organization', 'address_city', 'state', 'city_state']]\
      .groupby(['address_city', 'state', 'city_state']).count().\
        sort_values(by = ['organization'],ascending = False)\
          .reset_index()\
            .rename(columns={'organization' : 'num_orgs'})
cities_count.head()
```

	address_city	state	city_state	num_orgs
0	New York	NY	New York, NY	138
1	Calgary	AB	Calgary, AB	94
2	Toronto	ON	Toronto, ON	85
3	San Jose	CA	San Jose, CA	54
4	Chicago	IL	Chicago, IL	45

City name conversion

- Align City names in CDP City questionnaire response data ('City Org') with common city names that may be present in external data sets
- e.g. 'City of Boulder' -> Boulder

Note This data quality control step can also be addressed by using the 'City' column in the 2019_Cities_Disclosing_to_CDP.csv dataset

```
# convert indexes to columns'
cities_count.reset_index(inplace=True)
cities_count = cities_count.rename(columns = {'index':'city_id'})
cities_df.reset_index(inplace=True)
cities_df = cities_df.rename(columns = {'index':'city_org_id'})

# convert id and city label columns into lists
city_id_no = list_dedupe(cities_count['city_id'].tolist())
city_name = list_dedupe(cities_count['address_city'].tolist())

city_org_id_no = list_dedupe(cities_df['city_org_id'].tolist())
city_org_name = list_dedupe(cities_df['Organization'].tolist())

# remove added index column in cities df
cities_df.drop('city_org_id', inplace=True, axis=1)
cities_count.drop('city_id', inplace=True, axis=1)

# zip to join the lists and dict function to convert into dicts
city_dict = dict(zip(city_id_no, city_name))
city_org_dict = dict(zip(city_org_id_no, city_org_name))
```

In [11]:

```
# compare dicts - matching when city name appears as a substring in the full city
org name
city_names_df = pd.DataFrame(columns=['City ID No.','address_city', 'City Org ID No.','City Org',
'Match']) # initiate empty df

for ID, seq1 in city_dict.items():
    for ID2, seq2 in city_org_dict.items():
        m = re.search(seq1, seq2) # match string with regex search
        if m:
            match = m.group()
            # Append rows in Empty Dataframe by adding dictionaries
            city_names_df = city_names_df.append({'City ID No.': ID, 'address_city': seq1, 'City Org ID No.':
ID2, 'City Org': seq2, 'Match' : match}, ignore_index=True)

# subset for city to city org name matches
city_names_df = city_names_df.loc[:,['address_city','City Org']]

city_names_df.head()
```

	address_city	City Org
0	New York	New York City
1	Calgary	City of Calgary
2	Toronto	City of Toronto
3	Chicago	City of Chicago
4	Houston	City of Houston

```
Join city_org names to city-org count table
cities_count  = pd.merge(cities_count, city_names_df, on='address_city', how='left')
cities_count.head()
```

	address_city	state	city_state	num_orgs	City Org
0	New York	NY	New York, NY	138	New York City

1	Calgary	AB	Calgary, AB	94	City of Calgary
2	Toronto	ON	Toronto, ON	85	City of Toronto
3	San Jose	CA	San Jose, CA	54	NaN
4	Chicago	IL	Chicago, IL	45	City of Chicago

Join Count of Disclosing Organisations in HQ Cities with Question 6.2 Response dataframe

- Label the response variable as a city's current Sustainability Project Collaboration

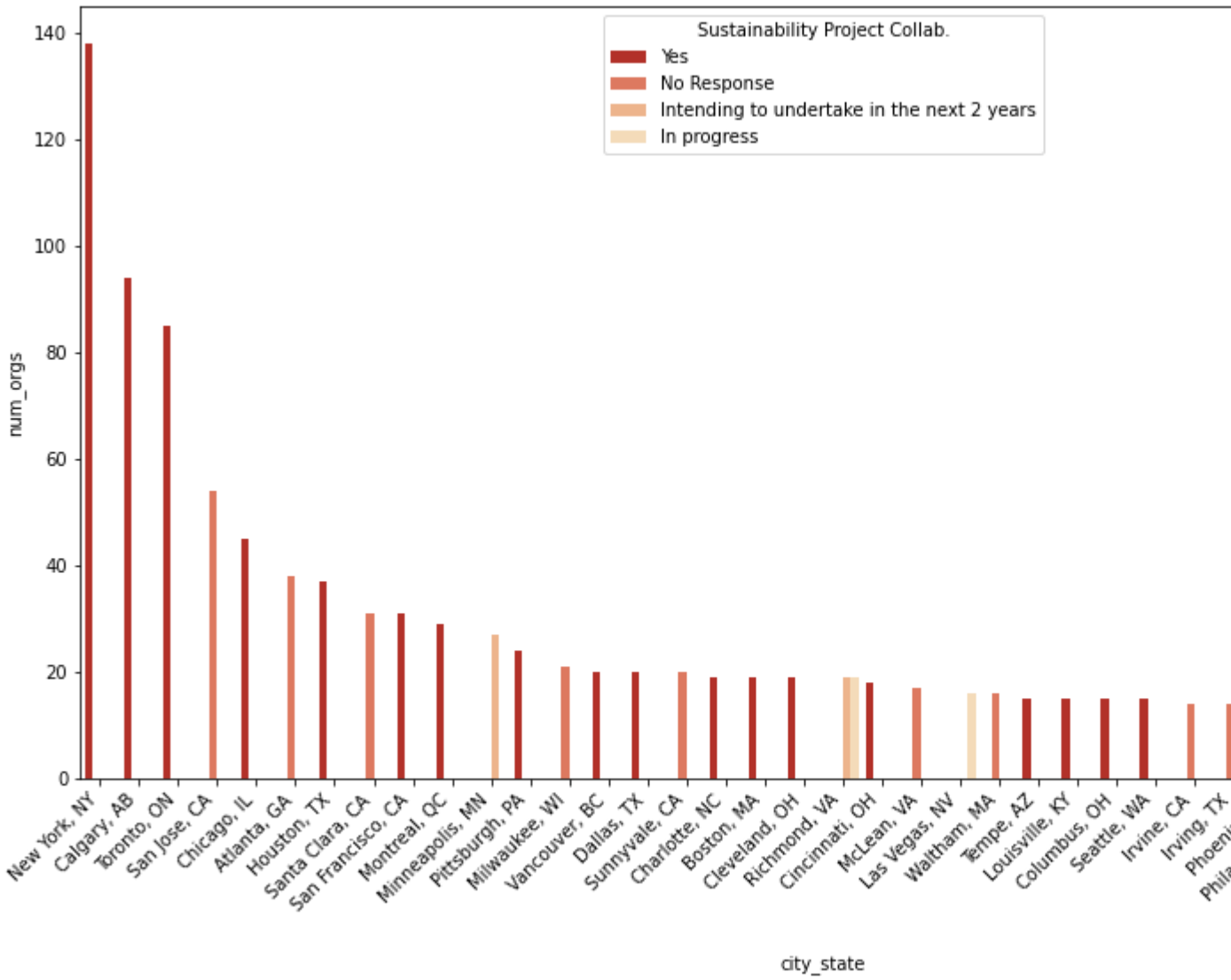
```
cities_6_2 = cities_6_2[['City', 'Response Answer']].rename(columns={'City' : 'City Org'})
cities_count = pd.merge(left=cities_count, right=cities_6_2, how='left',
                        on ='City Org').rename(columns={'Response Answer' : 'Sustainability Project Collab.'})

cities_count['Sustainability Project Collab.'] = cities_count['Sustainability Project Collab.'].fillna('No Response')
```

Plot cities containing the highest proportion of organisations disclosing to CDP

- Highlight number of disclosing orgnanisations with a HQ in the city
- Highlight the city's response to question 6.2 as bar colour

```
cities_count_50 = cities_count.iloc[0:40,:]

plt.figure(figsize=(15,8))
ax = sns.barplot(
   x="city_state", y="num_orgs",
   hue = "Sustainability Project Collab.",
   data=cities_count_50 ,
   palette="OrRd_r"
)

plt.xticks(
   rotation=45,
   horizontalalignment='right',
   fontweight='light',
   fontsize='medium'
)
```

(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37]),
<a list of 38 Text major ticklabel objects>)



Spatial plot of cities and organisation mapping

Example bubble map with plotting with plotly

```
# subset for lat, lng cities data
cities_meta_df = cities_meta_df[['city', 'state_id', 'lat','lng']].rename(columns={'city' : 'address_city',
'state_id' : 'state'})
cities_meta_df.head()
```

	address_city	state	lat	lng

0	New York	NY	40.6943	-73.9249
1	Los Angeles	CA	34.1139	-118.4068
2	Chicago	IL	41.8373	-87.6862
3	Miami	FL	25.7839	-80.2102
4	Dallas	TX	32.7936	-96.7662

In [16]:

```
# join coordinates to cities count
cities_count = pd.merge(left=cities_count, right=cities_meta_df, how='left', on=['address_city', 'state'])

# convert text response to question 6.2 to an integar encoding
resp_int_df = cities_count[["Sustainability Project Collab."]]
resp_int_df= resp_int_df.rename(columns={'Sustainability Project Collab.' : 'resp_int'})

labels = resp_int_df['resp_int'].unique().tolist()
mapping = dict( zip(labels,range(len(labels))) )
resp_int_df.replace({'resp_int': mapping},inplace=True)

resp_list = resp_int_df['resp_int'].tolist()
cities_count['resp_int'] = resp_list
cities_count.head()
```

Out[16]:

	address_city	state	city_state	num_orgs	City Org	Sustainability Project Collab.	lat	lng
0	New York	NY	New York, NY	138	New York City	Yes	40.6943	-73.9249
1	Calgary	AB	Calgary, AB	94	City of Calgary	Yes	NaN	NaN
2	Toronto	ON	Toronto, ON	85	City of Toronto	Yes	NaN	NaN
3	San Jose	CA	San Jose, CA	54	NaN	No Response	37.3019	-121.8486
4	Chicago	IL	Chicago, IL	45	City of Chicago	Yes	41.8373	-87.6862

- Highlight number of disclosing orgnanisations with a HQ in the city via bubble size
- Highlight city's response to question 6.2 as bubble colour and highlight in hover box

In [17]:

```
# plot spatial bubble map
```

```
cities_count['text'] = cities_count['address_city'] + '<br>Number of Orgs: ' +
(cities_count['num_orgs']).astype(str) +\
   '<br>Sustainability Project Colloboration: ' + (cities_count['Sustainability Project Collab.']).astype(str)
limits = [(0,20),(21,40),(41,60),(61,80),(81,100)]
cities = []
scale = 5

fig = go.Figure()

for i in range(len(limits)):
   lim = limits[i]
   fig.add_trace(go.Scattergeo(
      locationmode = 'USA-states',
      lon = cities_count['lng'],
      lat = cities_count['lat'],
      text = cities_count['text'],
      marker = dict(
         size = cities_count['num_orgs']*scale,
         color = cities_count['resp_int'],
         line_color='rgb(40,40,40)',
         line_width=0.5,
         sizemode = 'area'
      ),
      name = '{0} - {1}'.format(lim[0],lim[1])))

fig.update_layout(
      title_text = '2019 CDP Climate Change Corporate Responders (Public) by City',
      showlegend = False,
      geo = dict(
         scope = 'usa',
         landcolor = 'rgb(217, 217, 217)',
      )
   )

fig.show()
```

2019 CDP Climate Change Corporate Responders (Public) by City

Build NYC City Specific Dataset

Combine SVI dataset with CDP City Questionnaire and Organisation level 2019 Climate Change questionnaire response data

E.g. :

- Identify which organisations located within NYC see climate-related opportunities within their operations
- Match organisations with areas of the city that suffer from high unemployment rates
- Pinpoint areas of NYC that present an opportunity for corporate collobaration and therefore an uplift in social equity metrics

Subset climate change questionnaire response data for question C2.4a
C2.4a Provide details of opportunities identified with the potential to have a substantive financial or strategic impact on your business.

(see CDP Climate Change questionnaire guidance)

In [18]:

```
cc_2_4a = cc_df[cc_df['question_number'] == 'C2.4a']
```

Join 2019 corporate responses with organisation HQ metadata, matching climate change questionnaire organisations to their HQ city

In [19]:

```
cities_cdpmeta_join = cities_cdpmeta_df[["account_number", 'survey_year', 'address_city']]
cc_2_4a = pd.merge(left=cc_2_4a, right=cities_cdpmeta_join,  left_on=['account_number','survey_year'], right_on = ['account_number','survey_year'])
```

Subset for NYC HQ Cities

In [20]:

```
cc_nyc = cc_2_4a[(cc_2_4a['address_city'] =='New York')]
```

Join City Linked C2.4a response data to citys question 6.2 response data frame, matching NYC city level responses to NYC organisation level climate change questionnaire responses

In [21]:

```
cities_6_2['City Org'] = cities_6_2['City Org'].replace({'New York City':'New York'})
cc_nyc = pd.merge(left=cc_nyc, right= cities_6_2,  left_on=['address_city'], right_on = ['City Org']).rename(columns={'Response Answer' : 'sustain_collab'})
cc_nyc.head()
```

Out[21]:

	account_number	organization	survey_year	response_received_date	accounting_period_to	ors_response_id	su
0	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
1	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
2	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
3	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
4	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20

5 rows × 23 columns

Subset SVI data for NYC Counties from Federal Information Processing Standard (FIPS) codes

- The Bronx is Bronx County (ANSI / FIPS 36005)
- Brooklyn is Kings County (ANSI / FIPS 36047)
- Manhattan is New York County (ANSI / FIPS 36061)
- Queens is Queens County (ANSI / FIPS 36081)
- Staten Island is Richmond County (ANSI / FIPS 36085)

(source: https://guides.newman.baruch.cuny.edu/nyc_data)

In [22]:

```
nyc_svi_df = svi_df[svi_df['STCNTY'].isin([36005, 36047, 36061, 36081, 36085])]
nyc_svi_df['City'] = 'New York'
print(nyc_svi_df.shape)
nyc_svi_df.head()
```

(2166, 125)

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

Out[22]:

	ST	STATE	ST_ABBR	STCNTY	COUNTY	FIPS	LOCATION	AREA_SQMI	E_TOTPOP	M_TO
338	36	NEW YORK	NY	36005	Bronx	36005000100	Census Tract 1, Bronx County, New York	0.647574	7080	290
339	36	NEW YORK	NY	36005	Bronx	36005011000	Census Tract 110, Bronx County, New York	0.798960	0	12
340	36	NEW YORK	NY	36005	Bronx	36005016300	Census Tract 163, Bronx County, New York	0.226262	0	12
341	36	NEW YORK	NY	36005	Bronx	36005017100	Census Tract 171, Bronx County, New York	0.067409	0	12
342	36	NEW YORK	NY	36005	Bronx	36005024900	Census Tract 249, Bronx County, New York	0.067077	0	12

5 rows × 125 columns

Spatial Plotting

- Choropleth Map of NYC SVI Data, displaying unemployment rates across NYC

In [23]:

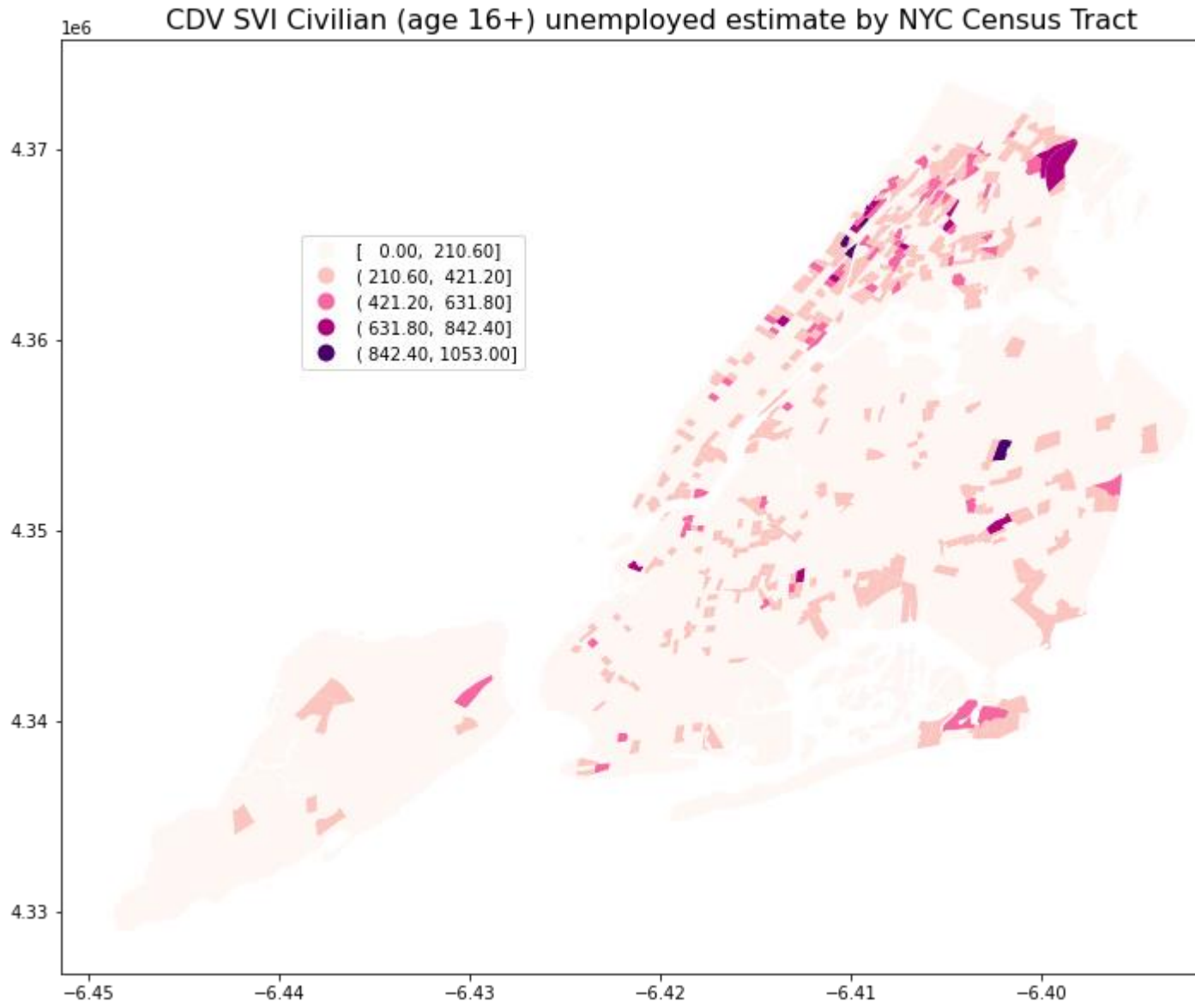
```
# import shapefile of NYC census tracts
geodf = gpd.read_file('../input/cdp-unlocking-climate-solutions/Supplementary Data/NYC CDP Census Tract Shapefiles/nyu_2451_34505.shp')

# join geospatial data to SVI unemployment rates ('E_UNEMP')
gdf_join = geodf[['tractid', 'geometry']].to_crs('+proj=robin')
nyc_join =  nyc_svi_df[['E_UNEMP', 'FIPS']]
gdf_join["tractid"] = pd.to_numeric(geodf["tractid"])
gdf_nyc = pd.merge(left=gdf_join, right=nyc_join, how='left', left_on='tractid', right_on = 'FIPS')
gdf_nyc.head()
```

Out[23]:

	tractid	geometry	E_UNEMP	FIPS
0	36005000100	POLYGON ((-6405751.163 4360116.782, -6405762.7...	0	36005000100
1	36005000200	POLYGON ((-6404380.786 4362843.462, -6404292.9...	295	36005000200
2	36005000400	MULTIPOLYGON (((-6403867.969 4362923.469, -640...	244	36005000400
3	36005001600	POLYGON ((-6403785.110 4363597.161, -6403701.0...	164	36005001600
4	36005001900	MULTIPOLYGON (((-6410358.054 4362148.858, -641...	192	36005001900

In [24]:

```
# plot unemployment rate variation across NYC
colors = 5
cmap = 'RdPu'
figsize = (16, 10)
ax = gdf_nyc.dropna().plot(column='E_UNEMP', cmap=cmap, figsize=figsize, scheme='equal_interval', k=colors, legend=True)
ax.set_title('CDV SVI Civilian (age 16+) unemployed estimate by NYC Census Tract', fontdict={'fontsize': 16}, loc='center')
ax.get_legend().set_bbox_to_anchor((.40, .8))
```



Join Neighbourhood level SVI data to Corporate and City level CDP Response Data for NYC

e.g for the Bronx

In [25]:

```
del cc_df
del cities_df
del svi_df
del cities_meta_df
del cities_cdpmeta_df
del cities_6_2
del cities_count
del cc_2_4a
```

In [26]:

```
# subset for Bronx
bb_df = nyc_svi_df[(nyc_svi_df.COUNTY =='Bronx')]

# join to city and climate change response data
print(cc_nyc.shape)
cc_nyc = cc_nyc.rename(columns={'City Org' : 'City'})
nyc_df = pd.merge(cc_nyc,bb_df,on='City',how='outer')
print(nyc_df.shape)
```

```
(2465, 23)
(835635, 147)
```

In [27]:

```
nyc_df.head()
```

Out[27]:

	account_number	organization	survey_year	response_received_date	accounting_period_to	ors_response_id	su
0	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
1	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
2	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
3	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20
4	3551	Colgate Palmolive Company	2019	2019-07-31T17:54:20Z	NaN	40142	20 20

5 rows × 147 columns

Water Responses

Identify organisations with facilities oeprating in the Hudson river basin, flagging companies who's operations may impact NYC's major fresh water resource

In [28]:

```
ws_df_4_1c = ws_df[ws_df['question_number'] == 'W4.1c']
ws_df_4_1c = ws_df_4_1c[ws_df_4_1c['response_value'].notnull()]
ws_df_4_1c.head()
```

Out[28]:

	account_number	organization	survey_year	response_received_date	accounting_period_to	ors_response_id	submis
816	32533	Integrated Device Technology, Inc.	2019	2019-07-30T16:38:01Z	NaN	58637	2019-0 03T17
933	32533	Integrated Device Technology, Inc.	2019	2019-07-30T16:38:01Z	NaN	58637	2019-0 03T17
940	32533	Integrated Device Technology, Inc.	2019	2019-07-30T16:38:01Z	NaN	58637	2019-0 03T17
1043	32533	Integrated Device Technology, Inc.	2019	2019-07-30T16:38:01Z	NaN	58637	2019-0 03T17
1091	32533	Integrated Device Technology, Inc.	2019	2019-07-30T16:38:01Z	NaN	58637	2019-0 03T17

Reshape data

- Climate change and water response datasets are often presented in long format in the CDP datasets.
- These data sets will become more useful when widened on the 'column_name' variable, enabling you to derive measurable metrics and KPIs from questionnaire response data

In [29]:

```
# pivot data
ws_df_4_1c_wide = ws_df_4_1c.pivot_table(index=['account_number', 'organization', 'row_number'],
```

```
                columns='column_name',
                values='response_value',
                aggfunc=lambda x: ' '.join(x)).reset_index()
# identify orgs with facilities within the Hudson river basin
ws_df_4_1c_wide = ws_df_4_1c_wide[ws_df_4_1c_wide['W4.1c_C2River basin'].str.contains('Hudson',
na=False)]
ws_df_4_1c_wide.head()
```

Out[29]:

column_name	account_number	organization	row_number	W4.1c_C1Country/Region	W4.1c_C2River basin	W4.1c_C3Nu of facilities ex to water risk
92	2982	Celgene Corporation	10	United States of America	Hudson River	5.0
408	34390	Momentive	1	United States of America	Hudson River	1.0
460	59905	Darling Ingredients Inc	3	United States of America	Hudson River	1.0

In [30]:

```
ws_df.head()
```

Out[30]:

	account_number	organization	survey_year	response_received_date	accounting_period_to	ors_response_id	submission
0	20111	Vander Bend	2019	2019-07-18T16:12:55Z	NaN	60218	2019-09-03T15:51:0
1	20111	Vander Bend	2019	2019-07-18T16:12:55Z	NaN	60218	2019-09-03T15:51:0
2	20111	Vander Bend	2019	2019-07-18T16:12:55Z	NaN	60218	2019-09-03T15:51:0

3	20111	Vander Bend	2019	2019-07-18T16:12:55Z	NaN	60218	2019-09-03T15:51:0
4	20111	Vander Bend	2019	2019-07-18T16:12:55Z	NaN	60218	2019-09-03T15:51:0

Modelling

What next?

Suggested analysis and modelling techniques that you can be apply as you tackle the competitions problem statement.

Suggestions below are **only** a guide. You are not limited to these approaches - use your imagination and publically available data to tackle this challenge from any angle you can dream of!

NLP principles to investigate the social-environmental overlap between Corporations and Cities Climate Change 'Readiness'

Utilise pythons NLP capabilities and tokenization approaches such as Term Frequency–inverse Document Frequency (TF-IDF) (1) to construct a Document Term Matrix (DTM) from questionnaire responses, highlighting key terms in free text answers to aid in topic identification

- e.g. summarise city 'readiness' for climate change and the hazards they anticipate (Cities Question 2.1)
- e.g outline the future adaptations cities must implement to prepare for environmental challenges (City Question 3.0)

- - e.g. find common topics in examples of colloboration between cities and business on sustainability projects (City Question 6.2a)
- Apply sentiment analysis to detect whether a city sees opportunity (positive sentiment/polarity) (Cities Question 6.0) or concern (negative sentiment/polarity) (City Question 2.2) over future climate scenarios
- Combine DTM and Sentiment analysis to build a combined KPI that incorporates measures of sentiment and susceptibility into one metric, identifying cities with high levels of percieved risk who may be open to colloboration with business as they foster climate resilience.
  - e.g. Sentiment x Susceptibility = Climate Risk Sensitivity Score

Social Accounting with Water Shadow Price Modeling

Using external datasets and water-related risks identified by Corporations (Water Security Question W4.2), build a 'Shadow Price' of water for Corporations operating in a selection of North American cities.

- A shadow price (3) can attempt to account for the total cost of a Corporations water use, estimating all internal and external costs ,as well as exposure to water stress.
- The shadow price coefficient can be combined within volumetric withdrawal data (Water Security Question W5.1a) to assign a Water Risk Cost per company, weighting corporate activties with a measure of the inersection between environmental risks and social impact.
    - e.g. Water risk cost for Company = Shadow price for Company * Water withdrawal volume for Company

References

1. Muñoz (2020). Getting started with NLP: Tokenization, Document-Term Matrix, TF-IDF. Medium. https://medium.com/analytics-vidhya/getting-started-with-nlp-tokenization-document-term-matrix-tf-idf-2ea7d01f1942
2. Reyes-Menendez A, Saura JR, Alvarez-Alonso C. Understanding #WorldEnvironmentDay User Opinions in Twitter: A Topic-Based Sentiment Analysis Approach. Int J Environ Res Public Health. 2018;15(11):2537. Published 2018 Nov 13. doi:10.3390/ijerph15112537. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6267440/
3. FIR-PRI. Portfolio Analysis Using Water Shadow Pricing: How Valuing Water Risk Can Reduce Carbon Emissions. https://www.fir-pri-awards.org/wp-content/uploads/MasterThesis_Chisem.pdf

In [ ]: