Battle of the Neighborhoods

An Exploratory Study on Air Pollution in Urban Areas

By

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1. Introduction

1.1 Background
Air Pollution is a burning problem nowadays, especially in urban areas. So It is necessary to examine what is responsible for poor air quality. A good way to do that is to determine what differentiates the cities with Least polluted air from those with Most polluted air. In this project we've used population data and the internal surroundings of 16 such cities to determine what the difference is between the two groups.

1.2 Target Audience
This study pretty much concerns every one, Because of the fact that everyone consumes air and is affected by it. **But the primary audience of this study is the City authorities and Urban Planners who are responsible for designing and Planning the structure of a city**, so that they have an insight on what could possibly lead to a City which is Pollution free.

2. Problem Statement

The core question that we want to answer is **What is responsible for poor air quality in many Cities in the World?** But in this study, we will attempt to address 2 more specific Problems. These are:

1. **Do the internal structure and surroundings of these cities have a significant impact on Air Pollution? If it does, what kind of structures in a city correlates to the city being more polluted?**
2. **What role does population have in case of Pollution? Does Higher Population Density mean More Pollution?**

3. Data

To understand and explore the following Open Data were used:

1. List of most-polluted cities by particulate matter concentration: https://en.wikipedia.org/wiki/List_of_most-polluted_cities_by_particulate_matter_concentration
2. A Comparative list of the Most and Least Polluted Cities in the World: https://www.rd.com/list/most-and-the-least-polluted-cities/
3. *Foursquare* Developers Access to venue data: https://foursquare.com/
4. Population Data from *Wikipedia*: https://en.wikipedia.org/wiki/List_of_cities_proper_by_population_density
5. Latitude & Longitude of Cities using *geopy* library: https://github.com/geopy/geopy

Using this data will allow exploration and examination to answer the questions. The venue data will be used to properly determine the common internal surroundings of each city and determine if there is some kind of correlation to pollution. The Population data will be used to compare the population density to examine if cities with higher pollution are also more densely populated. The lists of most polluted and least polluted cities will be used as reference. From these, we will use the 8 most polluted and 8 least polluted cities to compare the common venues within the cities retrieved from Foursquare location data and the population densities of the cities got from Wikipedia and other sources. The *geopy* library was used to extract the latitude & longitude values of the cities.

4. Methodology

4.1 Analytic Approach

There are 2 different stages in our Analysis. In the 1st stage we compare the common venues within the most polluted and least polluted cities and determine if these surroundings have any effect on pollution. In the 2nd stage we compare the population densities of those cities to determine if a higher population density results in more pollution.

***First Stage**:*

1. Gathering all resources & importing necessary libraries.
2. Creating a list each for most & least polluted cities in the world using relevant data sources.
3. Getting the Latitude & Longitude values of the cities using Python geocoder library an putting all the data in a dataframe.
4. Finding out all the nearby venues within a certain radius in each city, categorizing them & putting all the results in a dataframe.
5. Finding out the most common venues from each city using Python pandas toolkit.
6. Comparing the common venues to find out if there is any pattern of differences between the most & least polluted cities.

***Second Stage**:*

1. Gathering the population densities of all the listed cities and creating a dataframe using this data.
2. Creating a visualization of the population data using the dataframe, separating most polluted & least polluted cities.
3. Using the visualization, finding out if higher population density in cities corresponds to more pollution.

4.2 Exploratory Data Analysis

1. Importing Necessary Libraries¶

In [1]:
```
import pandas as pd # library for data analysis
import requests # library to handle requests
from bs4 import BeautifulSoup # library to parse HTML documents
import numpy as np
import json # library to handle JSON files

#!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim # convert an address into latitude and longitude values

import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# import k-means from clustering stage
from sklearn.cluster import KMeans

#!conda install -c conda-forge folium=0.5.0 --yes
import folium # map rendering library

print('Libraries imported.')
```

```
Libraries imported.
```

2. Creating Dataframe

In [30]:
```
Polluted_Cities = ['Delhi, India','Faisalabad, Pakistan','Hotan, China','Dhaka, Bangladesh','Manama, Bahrain','Kabul, Afghanistar
Least_Polluted_Cities = ['Honolulu, Hawaii','Zurich, Switzerland','Adelaide, Australia','Calgary, Canada','Helsinki, Finland','Re
```

In [31]:
```
mp_latitude = []
mp_longitude = []
lp_latitude = []
lp_longitude = []

for address in Polluted_Cities:
    geolocator = Nominatim(user_agent="pollution_explorer")
    location = geolocator.geocode(address)
    mp_latitude.append(location.latitude)
    mp_longitude.append(location.longitude)

for address in Least_Polluted_Cities:
    geolocator = Nominatim(user_agent="pollution_explorer")
    location = geolocator.geocode(address)
    lp_latitude.append(location.latitude)
    lp_longitude.append(location.longitude)
```

Most Polluted Cities

In [32]:
```
Polluted_df = pd.DataFrame(Polluted_Cities,columns =['Cities'])
Polluted_df['Latitude'] = mp_latitude
Polluted_df['Longitude'] = mp_longitude
Polluted_df
```

Out[32]:

	Cities	Latitude	Longitude
0	Delhi, India	28.651718	77.221939
1	Faisalabad, Pakistan	31.422056	73.092325
2	Hotan, China	37.114464	79.919681
3	Dhaka, Bangladesh	23.810651	90.412647
4	Manama, Bahrain	26.223504	50.582244
5	Kabul, Afghanistan	34.526011	69.177684
6	Ulaanbaatar, Mongolia	47.918468	106.917702
7	Kuwait City, Kuwait	29.379709	47.973563

Least Polluted Cities

In [33]:
```
Least_Polluted_df = pd.DataFrame(Least_Polluted_Cities,columns =['Cities'])
Least_Polluted_df['Latitude'] = lp_latitude
Least_Polluted_df['Longitude'] = lp_longitude
Least_Polluted_df
```

Out[33]:

	Cities	Latitude	Longitude
0	Honolulu, Hawaii	21.304547	-157.855676
1	Zurich, Switzerland	47.374449	8.541042
2	Adelaide, Australia	-34.928181	138.599931
3	Calgary, Canada	51.053423	-114.062589
4	Helsinki, Finland	60.167488	24.942747
5	Reykjavík, Iceland	64.145981	-21.942237
6	Hamburg, Germany	53.550341	10.000654
7	Wellington, New Zealand	-41.288795	174.777211

3. Explore all Cities

Most Polluted Cities

In [36]:
```
polluted_venues = getNearbyVenues(names=Polluted_df['Cities'],
                                  latitudes=Polluted_df['Latitude'],
                                  longitudes=Polluted_df['Longitude']
                                 )
```

```
Delhi, India
Faisalabad, Pakistan
Hotan, China
Dhaka, Bangladesh
Manama, Bahrain
Kabul, Afghanistan
Ulaanbaatar, Mongolia
Kuwait City, Kuwait
```

In [37]:
```
polluted_venues
```

Out[37]:

	City	City Latitude	City Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Delhi, India	28.651718	77.221939	Amritsari Lassi Wala	28.657325	77.224138	Snack Place
1	Delhi, India	28.651718	77.221939	Jolly Creations Designer Boutique	28.662689	77.226300	Boutique
2	Delhi, India	28.651718	77.221939	Haveli Dharampura	28.653247	77.232309	Hotel
3	Delhi, India	28.651718	77.221939	Naturals Ice Cream	28.634455	77.222139	Ice Cream Shop
4	Delhi, India	28.651718	77.221939	Spice Market	28.657287	77.222595	Food & Drink Shop
...	...	...	...	...	...	...	...
504	Kuwait City, Kuwait	29.379709	47.973563	His Majesty The Coffee	29.381494	47.993029	Café
505	Kuwait City, Kuwait	29.379709	47.973563	Savage Coffee Bar	29.374179	47.984571	Café
506	Kuwait City, Kuwait	29.379709	47.973563	Courtyard Marriott	29.377580	47.990664	Hotel
507	Kuwait City, Kuwait	29.379709	47.973563	Soul Coffee House	29.380683	47.992802	Coffee Shop
508	Kuwait City, Kuwait	29.379709	47.973563	Salhia Complex (مجمع الصالحية)	29.363111	47.966551	Shopping Mall

509 rows × 7 columns

Least Polluted Cities

In [38]:
```
Least_polluted_venues = getNearbyVenues(names=Least_Polluted_df['Cities'],
                                        latitudes=Least_Polluted_df['Latitude'],
                                        longitudes=Least_Polluted_df['Longitude']
                                       )
```

```
Honolulu, Hawaii
Zurich, Switzerland
Adelaide, Australia
Calgary, Canada
Helsinki, Finland
Reykjavík, Iceland
Hamburg, Germany
Wellington, New Zealand
```

In [39]:
```
Least_polluted_venues
```

Out[39]:

	City	City Latitude	City Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Honolulu, Hawaii	21.304547	-157.855676	Honolulu Museum of Art	21.303687	-157.848598	Art Museum
1	Honolulu, Hawaii	21.304547	-157.855676	'Iolani Palace	21.306702	-157.859083	Monument / Landmark
2	Honolulu, Hawaii	21.304547	-157.855676	Yanagi Sushi	21.300900	-157.853968	Japanese Restaurant
3	Honolulu, Hawaii	21.304547	-157.855676	Arvo	21.298634	-157.861077	Coffee Shop
4	Honolulu, Hawaii	21.304547	-157.855676	Bar Leather Apron	21.308298	-157.863644	Cocktail Bar
...	...	...	...	...	...	...	...
795	Wellington, New Zealand	-41.288795	174.777211	Bethel Woods	-41.281243	174.775058	BBQ Joint
796	Wellington, New Zealand	-41.288795	174.777211	Victoria Street Farmers' Market	-41.293560	174.772766	Farmers Market
797	Wellington, New Zealand	-41.288795	174.777211	Deluxe Espresso Bar	-41.294124	174.783600	Coffee Shop
798	Wellington, New Zealand	-41.288795	174.777211	Cable Car Museum	-41.285307	174.767741	Museum
799	Wellington, New Zealand	-41.288795	174.777211	Wellington Zoo	-41.319530	174.784495	Zoo

800 rows × 7 columns

4. Analyzing Each City

Most Polluted Cities

In [42]:
```
# one hot encoding
polluted_onehot = pd.get_dummies(polluted_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
polluted_onehot['City'] = polluted_venues['City']

# move neighborhood column to the first column
#fixed_columns = [toronto_onehot.columns[-1]] + list(toronto_onehot.columns[:-1])
#toronto_onehot = toronto_onehot[fixed_columns]

polluted_onehot.head()
```

Out[42]:

	Afghan Restaurant	Airport Lounge	Airport Terminal	American Restaurant	Antique Shop	Arcade	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	...	Tech Startup	Thai Restaurant	Theater	Tibetan Restaurant	Trail	Tu Resta
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	

Least Polluted Cities

In [43]:
```
# one hot encoding
Least_polluted_onehot = pd.get_dummies(Least_polluted_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
Least_polluted_onehot['City'] = Least_polluted_venues['City']

# move neighborhood column to the first column
#fixed_columns = [toronto_onehot.columns[-1]] + list(toronto_onehot.columns[:-1])
#toronto_onehot = toronto_onehot[fixed_columns]

Least_polluted_onehot.head()
```

Out[43]:

	Afghan Restaurant	American Restaurant	Antique Shop	Argentinian Restaurant	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Australian Restaurant	BBQ Joint	...	Vegetarian / Vegan Restaurant	Vietnamese Restaurant	Watch Shop	Waterfront	Wine Bar
0	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0

5. Grouping rows by City and by taking the mean of the frequency of occurrence of each category

Most Polluted Cities

In [44]:
```
polluted_grouped = polluted_onehot.groupby('City').mean().reset_index()
polluted_grouped
```

Out[44]:

	City	Afghan Restaurant	Airport Lounge	Airport Terminal	American Restaurant	Antique Shop	Arcade	Art Gallery	Art Museum	Arts & Crafts Store	...	Tapas Restaurant	Tech Startup	Thai Restaurant	Theater	T Resta
0	Delhi, India	0.000000	0.000000	0.000000	0.00	0.00	0.01	0.02	0.01	0.000000	...	0.00	0.000000	0.000000	0.01	
1	Dhaka, Bangladesh	0.000000	0.000000	0.000000	0.00	0.00	0.00	0.00	0.00	0.018182	...	0.00	0.018182	0.018182	0.00	
2	Faisalabad, Pakistan	0.000000	0.000000	0.000000	0.00	0.00	0.00	0.00	0.00	0.000000	...	0.00	0.000000	0.000000	0.00	
3	Hotan, China	0.000000	0.000000	0.000000	0.00	0.00	0.00	0.00	0.00	0.000000	...	0.00	0.000000	0.000000	0.00	
4	Kabul, Afghanistan	0.090909	0.045455	0.090909	0.00	0.00	0.00	0.00	0.00	0.000000	...	0.00	0.000000	0.000000	0.00	
5	Kuwait City, Kuwait	0.000000	0.000000	0.000000	0.04	0.01	0.00	0.00	0.00	0.000000	...	0.01	0.000000	0.010000	0.00	
6	Manama, Bahrain	0.000000	0.000000	0.000000	0.03	0.00	0.00	0.00	0.00	0.000000	...	0.00	0.000000	0.020000	0.00	
7	Ulaanbaatar, Mongolia	0.000000	0.000000	0.000000	0.01	0.00	0.00	0.00	0.00	0.000000	...	0.00	0.000000	0.000000	0.01	

8 rows × 138 columns

Least Polluted Cities

In [45]:
```
Least_polluted_grouped = Least_polluted_onehot.groupby('City').mean().reset_index()
Least_polluted_grouped
```

Out[45]:

	City	Afghan Restaurant	American Restaurant	Antique Shop	Argentinian Restaurant	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Australian Restaurant	...	Tunnel	Vegetarian / Vegan Restaurant	Vietnamese Restaurant	Watch Shop	Wa
0	Adelaide, Australia	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.03	...	0.00	0.00	0.01	0.00	
1	Calgary, Canada	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	...	0.00	0.02	0.01	0.00	
2	Hamburg, Germany	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	...	0.01	0.00	0.01	0.00	
3	Helsinki, Finland	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	...	0.00	0.01	0.00	0.00	
4	Honolulu, Hawaii	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00	...	0.00	0.00	0.02	0.00	
5	Reykjavík, Iceland	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	...	0.00	0.00	0.00	0.00	
6	Wellington, New Zealand	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	...	0.00	0.00	0.01	0.00	
7	Zurich, Switzerland	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.00	...	0.00	0.05	0.00	0.01	

6. Printing each City along with the top 10 most common venues

Most Polluted Cities

In [47]:
```
num_top_venues = 10

for hood in polluted_grouped['City']:
    print("----"+hood+"----")
    temp = polluted_grouped[polluted_grouped['City'] == hood].T.reset_index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).reset_index(drop=True).head(num_top_venues))
    print('\n')
```

Least Polluted Cities

In [46]:
```
num_top_venues = 10

for hood in Least_polluted_grouped['City']:
    print("----"+hood+"----")
    temp = Least_polluted_grouped[Least_polluted_grouped['City'] == hood].T.reset_index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).reset_index(drop=True).head(num_top_venues))
    print('\n')
```

7. Checking Population Density of each City from www.wikipedia.com & creating a DataFrame

In [51]:
```
Pop_density_Cities = pd.DataFrame(Polluted_Cities + Least_Polluted_Cities, columns = ['City'])
# Filling up the Population Density column by manually searching through Wikipedia and other public sources.
Pop_density_Cities['Population Density'] = [29259.12,2500,850,75290,21000,16100,350,20500,5664,4700,412.84,1501.1,3070,480,2400,
Pop_density_Cities
```

Out[51]:

	City	Population Density
0	Delhi, India	29259.12
1	Faisalabad, Pakistan	2500.00
2	Hotan, China	850.00
3	Dhaka, Bangladesh	75290.00
4	Manama, Bahrain	21000.00
5	Kabul, Afghanistan	16100.00
6	Ulaanbaatar, Mongolia	350.00
7	Kuwait City, Kuwait	20500.00
8	Honolulu, Hawaii	5664.00
9	Zurich, Switzerland	4700.00
10	Adelaide, Australia	412.84
11	Calgary, Canada	1501.10
12	Helsinki, Finland	3070.00
13	Reykjavík, Iceland	480.00
14	Hamburg, Germany	2400.00

5. Results

Each City along with the top 10 most common venues

Most Polluted

----Delhi, India----

	venue	freq
0	Indian Restaurant	0.18
1	Hotel	0.07
2	Café	0.06
3	Lounge	0.04
4	Food & Drink Shop	0.03
5	Snack Place	0.03
6	Coffee Shop	0.03
7	Fast Food Restaurant	0.02
8	Bakery	0.02
9	Chinese Restaurant	0.02

----Dhaka, Bangladesh----

	venue	freq
0	Café	0.13
1	Coffee Shop	0.11
2	Hotel	0.07
3	Clothing Store	0.05
4	Indian Restaurant	0.05
5	Nightclub	0.04
6	Ice Cream Shop	0.04
7	Seafood Restaurant	0.02
8	Italian Restaurant	0.02
9	Hotel Bar	0.02

----Faisalabad, Pakistan----

	venue	freq
0	Fast Food Restaurant	0.13
1	Pizza Place	0.13
2	Café	0.13
3	Shopping Mall	0.09
4	Restaurant	0.09
5	Ice Cream Shop	0.09
6	Hotel	0.04
7	Burger Joint	0.04
8	Park	0.04
9	Sandwich Place	0.04

Least Polluted

----Adelaide, Australia----

	venue	freq
0	Hotel	0.07
1	Café	0.06
2	Pub	0.06
3	Coffee Shop	0.05
4	Bar	0.04
5	Park	0.04
6	Cocktail Bar	0.03
7	Australian Restaurant	0.03
8	Garden	0.03
9	Pizza Place	0.02

----Calgary, Canada----

	venue	freq
0	Restaurant	0.08
1	Coffee Shop	0.05
2	Steakhouse	0.04
3	Pizza Place	0.03
4	Deli / Bodega	0.03
5	Pub	0.03
6	Italian Restaurant	0.03
7	Park	0.03
8	Bakery	0.03
9	Diner	0.03

----Hamburg, Germany----

	venue	freq
0	Café	0.09
1	Park	0.08
2	Coffee Shop	0.07
3	Plaza	0.04
4	Cocktail Bar	0.04
5	Supermarket	0.03
6	Hotel	0.03
7	Bakery	0.03
8	Theater	0.03
9	Farmers Market	0.02

----Hotan, China----

	venue	freq
0	Xinjiang Restaurant	0.22
1	Park	0.11
2	Bus Station	0.11
3	Café	0.11
4	Middle Eastern Restaurant	0.11
5	River	0.11
6	Shopping Mall	0.11
7	Hotel	0.11
8	North Indian Restaurant	0.00
9	Opera House	0.00

----Helsinki, Finland----

	venue	freq
0	Scandinavian Restaurant	0.06
1	Café	0.05
2	Coffee Shop	0.05
3	Hotel	0.05
4	Park	0.05
5	Beer Bar	0.04
6	French Restaurant	0.03
7	Wine Bar	0.03
8	Pizza Place	0.03
9	Sushi Restaurant	0.03

----Kabul, Afghanistan----

	venue	freq
0	Hotel	0.23
1	Café	0.14
2	Afghan Restaurant	0.09
3	Airport Terminal	0.09
4	Shopping Mall	0.09
5	Restaurant	0.05
6	French Restaurant	0.05
7	Fried Chicken Joint	0.05
8	Soccer Field	0.05
9	Gym	0.05

----Honolulu, Hawaii----

	venue	freq
0	Japanese Restaurant	0.10
1	Bakery	0.05
2	Coffee Shop	0.04
3	Café	0.04
4	Seafood Restaurant	0.04
5	Grocery Store	0.03
6	Pizza Place	0.03
7	Chinese Restaurant	0.03
8	American Restaurant	0.03
9	Noodle House	0.03

----Kuwait City, Kuwait----

	venue	freq
0	Café	0.25
1	Coffee Shop	0.14
2	Restaurant	0.06
3	American Restaurant	0.04
4	Shopping Mall	0.04
5	Middle Eastern Restaurant	0.04
6	Burger Joint	0.03
7	Breakfast Spot	0.03
8	Ice Cream Shop	0.02
9	Japanese Restaurant	0.02

----Reykjavík, Iceland----

	venue	freq
0	Seafood Restaurant	0.08
1	Bar	0.08
2	Café	0.06
3	Restaurant	0.05
4	Scandinavian Restaurant	0.04
5	Coffee Shop	0.04
6	Hotel	0.04
7	Park	0.03
8	Concert Hall	0.03
9	Hostel	0.02

----Manama, Bahrain----

	venue	freq
0	Coffee Shop	0.09
1	Café	0.08
2	Hotel	0.08
3	Restaurant	0.05
4	American Restaurant	0.03
5	Spa	0.03
6	Asian Restaurant	0.03
7	Lounge	0.03
8	Italian Restaurant	0.03
9	Ice Cream Shop	0.03

----Wellington, New Zealand----

	venue	freq
0	Café	0.08
1	Coffee Shop	0.06
2	Restaurant	0.06
3	Bar	0.04
4	Brewery	0.04
5	Seafood Restaurant	0.03
6	Hotel	0.03
7	Park	0.03
8	Beer Bar	0.02
9	Gym	0.02

----Ulaanbaatar, Mongolia----

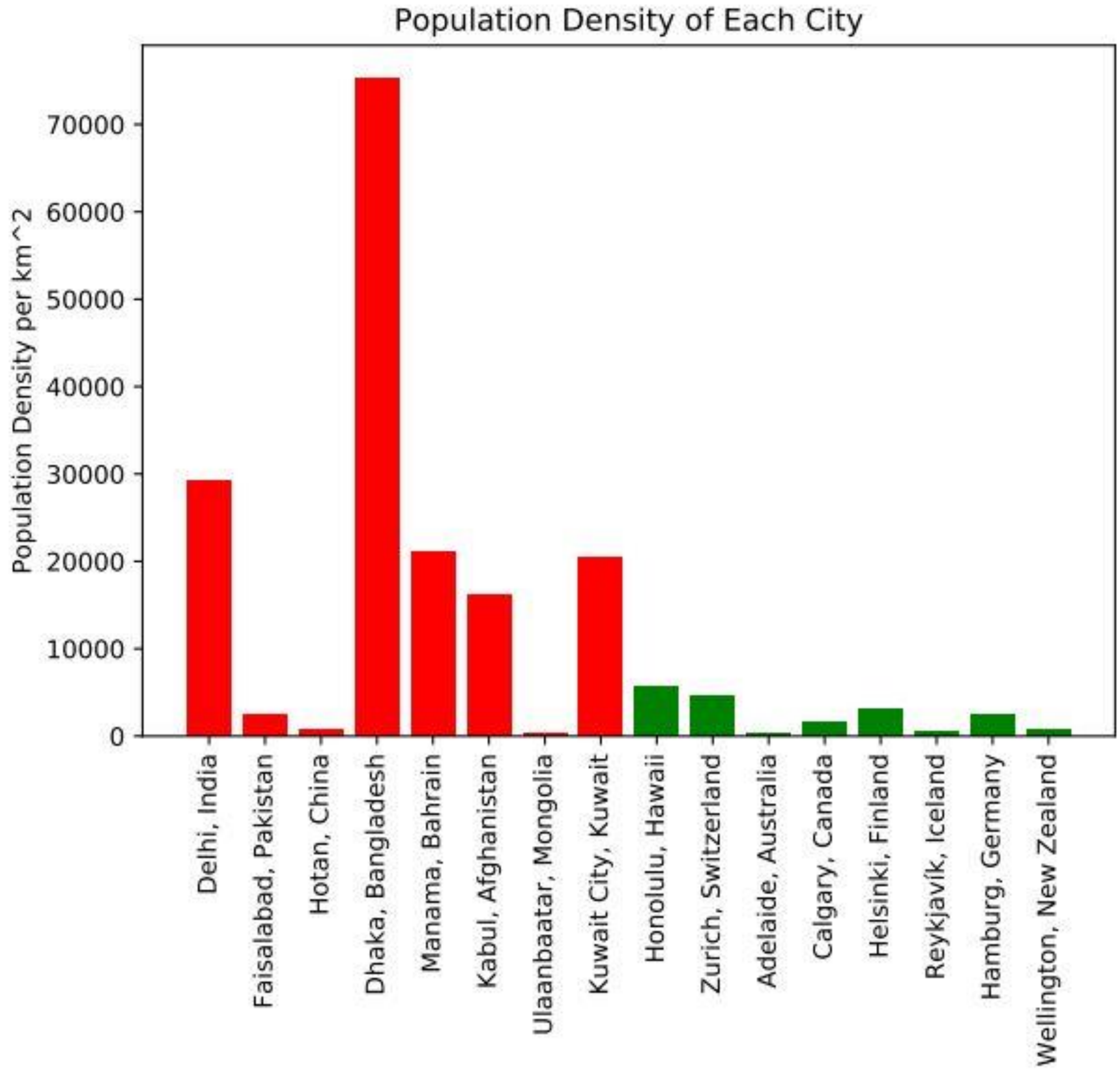
	venue	freq
0	Coffee Shop	0.17
1	Restaurant	0.06
2	Hotel	0.04
3	Italian Restaurant	0.03
4	Clothing Store	0.03
5	Café	0.03
6	Fast Food Restaurant	0.03
7	Japanese Restaurant	0.03
8	Lounge	0.03
9	Movie Theater	0.03

----Zurich, Switzerland----

	venue	freq
0	Plaza	0.07
1	Café	0.07
2	Bar	0.07
3	Swiss Restaurant	0.06
4	Hotel	0.06
5	Bakery	0.05
6	Vegetarian / Vegan Restaurant	0.05
7	Cocktail Bar	0.04
8	Pedestrian Plaza	0.03
9	Gym / Fitness Center	0.02

As we can see, despite being far apart in terms of Pollution, all 16 cities have pretty much same types of venues consisting of Restaurants, Hotels, Coffee Shops etc. So, it can be concluded that Pollution must correlated to something other than the internal surroundings of a City.

Plotting the Population Density of each City



Here, Red bars represent Most Polluted Cities & Green ones represent Least Polluted Cities. As we can see, Cities with higher Population Density tend to be more polluted. This is one of the reasons of pollution and it correlates much more than the internal surroundings of a City to Pollution.

6. Discussions

In this study, the following issues were worth discussing:

1. One important drawback of analyzing with common location data is that **it doesn't account for relative weights of the venues**. For example it gives equal weight to a tannery and a coffee shop. But clearly a tannery is a way more significant venue than a coffee shop,specially in our case. **So it is recommended to address this issue in future studies and if possible come up with a way to single out important venues like tanneries or factories.**
2. The radius limitation gives rise to a problem too. In many cases the entities responsible for air pollution are situated at the edge of the cities. So our analysis can't properly include them. **It is recommended to address this issue in future studies too.**
3. In case of population density, even though in most cases a higher population density means more pollution, there are some pretty significant outliers too. For example Honolulu has a way higher population density than Hotan despite being much less polluted. So clearly population density alone can't explain pollution. Other factors, like Waste Management systems should be considered as pointed out in our data sources. **It is recommended to study what other factors in a city leads to more pollution in future works.**

7. Conclusion

In this study, a comprehensive approach was taken to study what factors are behind air pollution in many cities. Analyzing location,common venues and population data of **8 Most Polluted** & **8 Least Polluted** cities, we can share at least 2 concluding remarks:

1. **The most common structures and venues within a city are pretty much the same in most of them and they have little effect in making a city a polluted one. Some significant venues might seem to be exceptions but the regular surroundings have little to no impact in this case, hence uncorrelated to pollution.**
2. **Even though there can be many other factors, Densely populated cities tend to be more polluted than less densely populated cities. So, there is a positive correlation between population density & pollution.**

City authorities and Urban planners should take note of these remarks,plan accordingly and there should be further study in order to solve the problem of air pollution in big cities.

8. Appendix

For further information on this study, check the *Github* repository :
https://github.com/Saiful185/Data_Science_Capstone