

Introduction

In this tutorial, we will learn how to create maps for different objectives. To do that, we will part ways with Matplotlib and work with another Python visualization library, namely **Folium**. What is nice about **Folium** is that it was developed for the sole purpose of visualizing geospatial data. While other libraries are available to visualize geospatial data, such as **plotly**, they might have a cap on how many API calls you can make within a defined time frame. **Folium**, on the other hand, is completely free.

Importing required libraries

```
In [15]: import pandas as pd
import numpy as np
```

Introduction to Folium

Folium is a powerful Python library that helps you create several types of Leaflet maps. The fact that the Folium results are interactive makes this library very useful for dashboard building.

From the official Folium documentation page:

Folium builds on the data wrangling strengths of the Python ecosystem and the mapping strengths of the Leaflet.js library. Manipulate your data in Python, then visualize it in on a Leaflet map via Folium.

Folium makes it easy to visualize data that's been manipulated in Python on an interactive Leaflet map. It enables both the binding of data to a map for choropleth visualizations as well as passing Vincent/Vega visualizations as markers on the map.

The library has a number of built-in tilesets from OpenStreetMap, Mapbox, and Stamen, and supports custom tilesets with Mapbox or Cloudmade API keys. Folium supports both GeoJSON and TopoJSON overlays, as well as the binding of data to those overlays to create choropleth maps with color-brewer color schemes.

Let's install Folium

Folium is not available by default. So, we first need to install it before we are able to import it.

```
In [1]: # Run this command on your anaconda prompt
#Command:!pip3 install folium
import folium

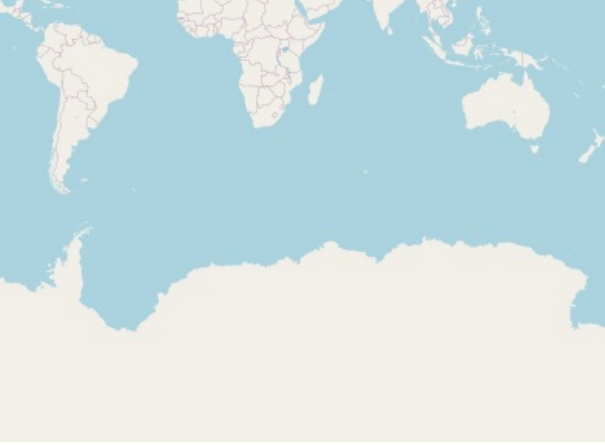
print('Folium installed and imported!')
```

Folium installed and imported!

Generating the world map is straightforward in **Folium**. You simply create a **Folium Map** object, and then you display it. What is attractive about **Folium** maps is that they are interactive, so you can zoom into any region of interest despite the initial zoom level.

```
In [2]: # define the world map
world_map = folium.Map()

# display world map
world_map
```



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Go ahead. Try zooming in and out of the rendered map above.

You can customize this default definition of the world map by specifying the centre of your map, and the initial zoom level.

All locations on a map are defined by their respective *Latitude* and *Longitude* values. So you can create a map and pass in a center of *Latitude* and *Longitude* values of **[0, 0]**.

For a defined center, you can also define the initial zoom level into that location when the map is rendered. **The higher the zoom level the more the map is zoomed into the center.**



stan and play with the zoom level to see how it affects the rendered map.

```
around Pakistan with a low zoom level  
[30.3753, 69.3451], zoom_start=4)
```

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Let's create the map again with a higher zoom level.

```
In [4]: # define the world map centered around Pakistan with a higher zoom level
world_map = folium.Map(location=[30.3753, 69.3451], zoom_start=8)
```



Load map: File -> Trust Notebook

Looks Pretty!!!!

As you can see, the higher the zoom level the more the map is zoomed into the given center.

Question: Create a map of China with a zoom level of 4.

```
In [8]: ### type your answer here
```

► [Click here for a sample python solution](#)

Another cool feature of **Folium** is that you can generate different map styles.

A. Stamen Toner Maps

These are high-contrast B+W (black and white) maps. They are perfect for data mashups and exploring river meanders and coastal zones.

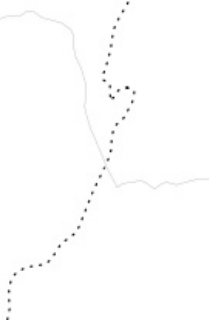
Let's create a Stamen Toner map of Pakistan with a zoom level of 4.

```
In [45]: # define the world map centered around Pakistan with a higher zoom level
world_map = folium.Map(location=[30.3753, 69.3451], zoom_start=8, tiles='Stamen Toner')

# display world map
world_map
```

Out

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Feel free to zoom in and out to see how this style compares to the default one.

B. Stamen Terrain Maps

These are maps that feature hill shading and natural vegetation colors. They showcase advanced labeling and linework generalization of dual-carriageway roads.

Let's create a Stamen Terrain map of Pakistan with zoom level 4.

In [11]:

```
# define the world map centered around Pakistan with a higher zoom level
world_map = folium.Map(location=[30.3753, 69.3451], zoom_start=8, tiles='Stamen Terrain')
```

Out

Load map: File -> Trust Notebook



Zoom in and notice how the borders start showing as you zoom in, and the displayed country names are in English.

Question: Create a map of China to visualize its hill shading and natural vegetation. Use a zoom level of 6.

```
In [12]: ### type your answer here
```

► Click here for a sample python solution

Maps with Markers

Let's download and import the data on police department incidents using `pandas read_csv()` method.

[Download Dataset](#)

```
In [18]: df_incidents = pd.read_csv('Police_Department_Incidents_2016_data.csv')
print('Dataset downloaded and read into a pandas dataframe!')
```

Dataset downloaded and read into a pandas dataframe!

```
In [19]: df_incidents.head()
```

```
Out[19]:
```

	IncidentNum	Category	Descript	DayOfWeek	Date	Time	PdDistrict	Resolution	Address	X	Y	
0	120058272	WEAPON LAWS	POSS OF PROHIBITED WEAPON	Friday	01/29/2016 12:00:00 AM	11:00	SOUTHERN	ARREST, BOOKED	800 Block of BRYANT ST	-122.403405	37.775421	(37.775421, -122.403405)
1	120058272	WEAPON LAWS	FIREARM, LOADED, IN VEHICLE, POSSESSION OR USE	Friday	01/29/2016 12:00:00 AM	11:00	SOUTHERN	ARREST, BOOKED	800 Block of BRYANT ST	-122.403405	37.775421	(37.775421, -122.403405)
2	141059263	WARRANTS	WARRANT ARREST	Monday	04/25/2016 12:00:00 AM	14:59	BAYVIEW	ARREST, BOOKED	KEITH ST / SHAFTER AV	-122.388856	37.729981	(37.729981, -122.388856)
3	160013662	NON-CRIMINAL	LOST PROPERTY	Tuesday	01/05/2016 12:00:00 AM	23:50	TENDERLOIN	NONE	JONES ST / OFARRELL ST	-122.412971	37.785788	(37.785788, -122.412971)
4	160002740	NON-CRIMINAL	LOST PROPERTY	Friday	01/01/2016 12:00:00 AM	00:30	MISSION	NONE	16TH ST / MISSION ST	-122.419672	37.765050	(37.765050, -122.419672)

So each row consists of 13 features:

1. **IncidentNum**: Incident Number
2. **Category**: Category of crime or incident
3. **Descript**: Description of the crime or incident
4. **DayOfWeek**: The day of week on which the incident occurred
5. **Date**: The Date on which the incident occurred
6. **Time**: The time of day on which the incident occurred
7. **PdDistrict**: The police department district
8. **Resolution**: The resolution of the crime in terms whether the perpetrator was arrested or not
9. **Address**: The closest address to where the incident took place
10. **X**: The longitude value of the crime location
11. **Y**: The latitude value of the crime location
12. **Location**: A tuple of the latitude and the longitude values
13. **PdId**: The police department ID

Let's find out how many entries there are in our dataset.

```
In [20]: df_incidents.shape
```

```
Out[20]: (119999, 13)
```

So the dataframe consists of 119999 crimes, which took place in the year 2016. In order to reduce computational cost, let's just work with the first 100 incidents in this dataset.

```
In [21]: # get the first 100 crimes in the df_incidents dataframe
limit = 100
df_incidents = df_incidents.iloc[0:limit, :]
```

Let's confirm that our dataframe now consists only of 100 crimes.

```
In [22]: df_incidents.shape
```

```
Out[22]: (100, 13)
```

Now that we reduced the data a little, let's visualize where these crimes took place in the city of San Francisco. We will use the default style, and we will initialize the zoom level to 12.

```
In [23]: # San Francisco latitude and longitude values
latitude = 37.77
longitude = -122.42
```

```
In [24]: # create map and display it
sanfran_map = folium.Map(location=[latitude, longitude], zoom_start=12)
```

```
Out[24]: 
p: File -> Trust Notebook
```

Now let's superimpose the locations of the crimes onto the map. The way to do that in **Folium** is to create a *feature group* with its own features and style and then add it to the `sanfran_map`.

```
In [25]: # instantiate a feature group for the incidents in the dataframe
incidents = folium.map.FeatureGroup()

# loop through the 100 crimes and add each to the incidents feature group
for lat, lng, in zip(df_incidents.Y, df_incidents.X):
    incidents.add_child(
        folium.features.CircleMarker(
            [lat, lng],
            radius=5, # define how big you want the circle markers to be
            color='yellow',
            fill=True,
            fill_color='blue',
            fill_opacity=0.6
        )
    )

# add incidents to map
sanfran_map.add_child(incidents)
```

Out [25]



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You can also add some pop-up text that would get displayed when you hover over a marker. Let's make each marker display the category of the crime when hovered over.

```
In [28]: # instantiate a feature group for the incidents in the dataframe
incidents = folium.map.FeatureGroup()

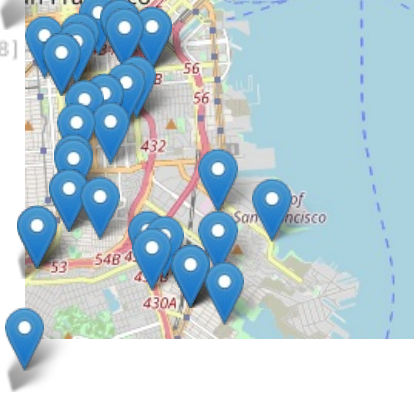
# loop through the 100 crimes and add each to the incidents feature group
for lat, lng, in zip(df_incidents.Y, df_incidents.X):
    incidents.add_child(
        folium.features.CircleMarker(
            [lat, lng],
            radius=5, # define how big you want the circle markers to be
            color='yellow',
            fill=True,
            fill_color='blue',
            fill_opacity=0.6
        )
    )

# add pop-up text to each marker on the map
latitudes = list(df_incidents.Y)
longitudes = list(df_incidents.X)
labels = list(df_incidents.Category)

for lat, lng, label in zip(latitudes, longitudes, labels):
    folium.Marker([lat, lng], popup=label).add_to(sanfran_map)

# add incidents to map
sanfran_map.add_child(incidents)
```

Out [28]



p: File -> Trust Notebook

Isn't this really cool? Now you are able to know what crime category occurred at each marker.

If you find the map to be so congested with all these markers, there are two remedies to this problem. The simpler solution is to remove these location markers and just add the text to the circle markers themselves as follows:

```
In [30]: # create map and display it
sanfran_map = folium.Map(location=[latitude, longitude], zoom_start=12)

# loop through the 100 crimes and add each to the map
for lat, lng, label in zip(df_incidents.Y, df_incidents.X, df_incidents.Category):
    folium.features.CircleMarker(
        [lat, lng],
        radius=5, # define how big you want the circle markers to be
        color='yellow',
        fill=True,
        popup=label,
        fill_color='blue',
        fill_opacity=0.6
    ).add_to(sanfran_map)

# show map
sanfran_map
```


Out [30]



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The other proper remedy is to group the markers into different clusters. Each cluster is then represented by the number of crimes in each neighborhood. These clusters can be thought of as pockets of San Francisco which you can then analyze separately.

To implement this, we start off by instantiating a *MarkerCluster* object and adding all the data points in the dataframe to this object.

```
In [31]: from folium import plugins

# let's start again with a clean copy of the map of San Francisco
sanfran_map = folium.Map(location = [latitude, longitude], zoom_start = 12)

# instantiate a mark cluster object for the incidents in the dataframe
incidents = plugins.MarkerCluster().add_to(sanfran_map)

# loop through the dataframe and add each data point to the mark cluster
for lat, lng, label, in zip(df_incidents.Y, df_incidents.X, df_incidents.Category):
    folium.Marker(
        location=[lat, lng],
        icon=None,
        popup=label,
    ).add_to(incidents)

# display map
sanfran_map
```

Out [31]

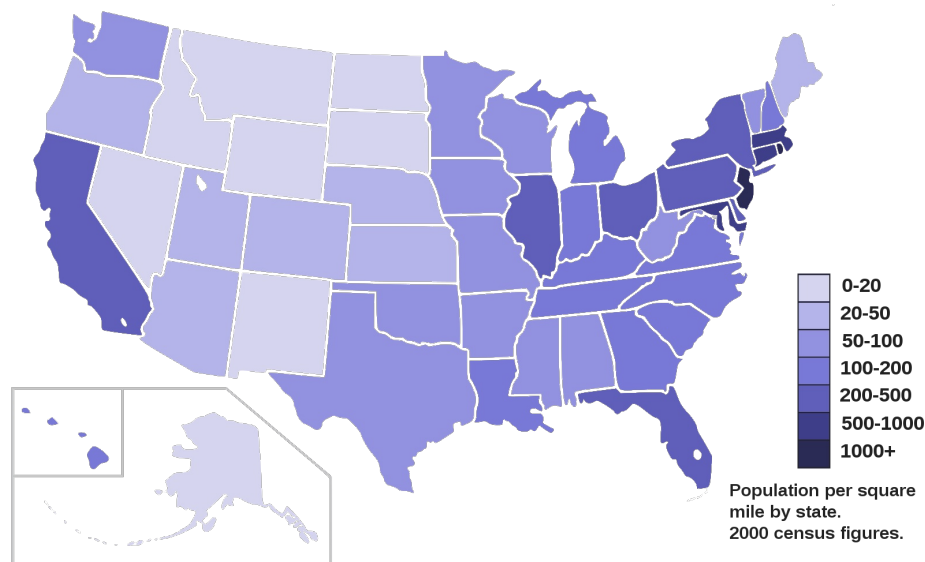


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Notice how when you zoom out all the way, all markers are grouped into one cluster, *the global cluster*, of 100 markers or crimes, which is the total number of crimes in our dataframe. Once you start zooming in, the *global cluster* will start breaking up into smaller clusters. Zooming in all the way will result in individual markers.

Choropleth Maps

A **Choropleth** map is a thematic map in which areas are shaded or patterned in proportion to the measurement of the statistical variable being displayed on the map, such as population density or per-capita income. The choropleth map provides an easy way to visualize how a measurement varies across a geographic area, or it shows the level of variability within a region. Below is a **Choropleth** map of the US depicting the population by square mile per state.



Now, let's create our own **Choropleth** map of the world depicting immigration from various countries to Canada.

Download the Canadian Immigration dataset and read it into a *pandas* dataframe.

[Download Dataset](#)

```
In [33]: df = pd.read_excel('Canada.xlsx',
    sheet_name='Canada by Citizenship',
    skiprows=range(20),
    skipfooter=2)

print('Data downloaded and read into a dataframe!')
```

Data downloaded and read into a dataframe!

Let's take a look at the first five items in our dataset.

```
In [34]: df.head()
```

```
Out[34]:
```

	Type	Coverage	OdName	AREA	AreaName	REG	RegName	DEV	DevName	1980	...	2004	2005	2006	2007	2008	2009	2010
0	Immigrants	Foreigners	Afghanistan	935	Asia	5501	Southern Asia	902	Developing regions	16	...	2978	3436	3009	2652	2111	1746	17
1	Immigrants	Foreigners	Albania	908	Europe	925	Southern Europe	901	Developed regions	1	...	1450	1223	856	702	560	716	5
2	Immigrants	Foreigners	Algeria	903	Africa	912	Northern Africa	902	Developing regions	80	...	3616	3626	4807	3623	4005	5393	47
3	Immigrants	Foreigners	American Samoa	909	Oceania	957	Polynesia	902	Developing regions	0	...	0	0	1	0	0	0	
4	Immigrants	Foreigners	Andorra	908	Europe	925	Southern Europe	901	Developed regions	0	...	0	0	1	1	0	0	

5 rows × 43 columns

Let's find out how many entries there are in our dataset.

```
In [36]: # print the dimensions of the dataframe
print(df_can.shape)
```

```
(195, 43)
```

Clean up data. We will make some modifications to the original dataset to make it easier to create our visualizations. Refer to *Introduction to Matplotlib and Line Plots* and *Area Plots, Histograms, and Bar Plots* notebooks for a detailed description of this preprocessing.

```
In [38]: # clean up the dataset to remove unnecessary columns (eg. REG)
df.drop(['AREA', 'REG', 'DEV', 'Type', 'Coverage'], axis=1, inplace=True)

# let's rename the columns so that they make sense
df.rename(columns={'OdName': 'Country', 'AreaName': 'Continent', 'RegName': 'Region'}, inplace=True)

# for sake of consistency, let's also make all column labels of type string
df.columns = list(map(str, df.columns))

# add total column
df['Total'] = df.sum(axis=1)

# years that we will be using in this lesson - useful for plotting later on
years = list(map(str, range(1980, 2014)))
print('data dimensions:', df.shape)
```

```
data dimensions: (195, 39)
```

```
C:\Users\Meer Moazzam\AppData\Local\Temp\ipykernel_10336\4025872728.py:11: FutureWarning: Dropping of nuisance
columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise T
ypeError. Select only valid columns before calling the reduction.
  df['Total'] = df.sum(axis=1)
```

```
In [39]: df.head()
```

```
Out[39]:
```

	Country	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	...	2005	2006	2007	2008	2009	2010	2011	2012	2013
0	Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	...	3436	3009	2652	2111	1746	1758	2203	2635	2014
1	Albania	Europe	Southern Europe	Developed regions	1	0	0	0	0	0	...	1223	856	702	560	716	561	539	620	0
2	Algeria	Africa	Northern Africa	Developing regions	80	67	71	69	63	44	...	3626	4807	3623	4005	5393	4752	4325	3774	4
3	American Samoa	Oceania	Polynesia	Developing regions	0	1	0	0	0	0	...	0	1	0	0	0	0	0	0	
4	Andorra	Europe	Southern Europe	Developed regions	0	0	0	0	0	0	...	0	1	1	0	0	0	0	1	

5 rows × 39 columns

In order to create a **Choropleth** map, we need a GeoJSON file that defines the areas/boundaries of the state, county, or country that we are interested in. In our case, since we are endeavoring to create a world map, we want a GeoJSON that defines the boundaries of all world countries. For your convenience, we will be providing you with this file, so let's go ahead and download it. Let's name it **world_countries.json**.

[Download file](#)

Now that we have the GeoJSON file, let's create a world map, centered around **[0, 0]** *latitude* and *longitude* values, with an initial zoom

level of 2.

```
In [41]: world_geo = r'world_countries.json' # geojson file

# create a plain world map
world_map = folium.Map(location=[0, 0], zoom_start=2)
```

And now to create a `Choropleth` map, we will use the `choropleth` method with the following main parameters:

1. `geo_data` , which is the GeoJSON file.
2. `data` , which is the dataframe containing the data.
3. `columns` , which represents the columns in the dataframe that will be used to create the `Choropleth` map.
4. `key_on` , which is the key or variable in the GeoJSON file that contains the name of the variable of interest. To determine that, you will need to open the GeoJSON file using any text editor and note the name of the key or variable that contains the name of the countries, since the countries are our variable of interest. In this case, **name** is the key in the GeoJSON file that contains the name of the countries. Note that this key is case_sensitive, so you need to pass exactly as it exists in the GeoJSON file.

```
In [42]: # generate choropleth map using the total immigration of each country to Canada from 1980 to 2013
world_map.choropleth(
    geo_data=world_geo,
    data=df_can,
```



\\site-packages\\folium\\folium.py:409: FutureWarning: The choropleth method has been replaced by the new Choropleth class, which has the same arguments. See the example notebook to do this.

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As per our `Choropleth` map legend, the darker the color of a country and the closer the color to red, the higher the number of immigrants from that country. Accordingly, the highest immigration over the course of 33 years (from 1980 to 2013) was from China, India, and the Philippines, followed by Poland, Pakistan, and interestingly, the US.

Notice how the legend is displaying a negative boundary or threshold. Let's fix that by defining our own thresholds and starting with 0 instead of -6,918!

```
In [43]: world_geo = r'world_countries.json'

# create a numpy array of length 6 and has linear spacing from the minimum total immigration to the maximum total
threshold_scale = np.linspace(df_can['Total'].min(),
                              df_can['Total'].max(),
                              6, dtype=int)
```

```
threshold_scale = threshold_scale.tolist() # change the numpy array to a list
threshold_scale[-1] = threshold_scale[-1] + 1 # make sure that the last value of the list is greater than the m
# let Folium determine the scale
```

```
0], zoom_start=2)
```

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Much better now! Feel free to play around with the data and perhaps create **Choropleth** maps for individuals years, or perhaps decades, and see how they compare with the entire period from 1980 to 2013.

Thank you

Author

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