Data Visualization

Estimated time needed: **30** minutes

Objectives

After completing this lab you will be able to:

- Create Data Visualization with Python
- Use various Python libraries for visualization

Introduction

The aim of these labs is to introduce you to data visualization with Python as concrete and as consistent as possible. Speaking of consistency, because there is no *best* data visualization library available for Python - up to creating these labs - we have to introduce different libraries and show their benefits when we are discussing new visualization concepts. Doing so, we hope to make students well-rounded with visualization libraries and concepts so that they are able to judge and decide on the best visualization technique and tool for a given problem *and* audience.

Please make sure that you have completed the prerequisites for this course, namely **Python Basics for Data Science** (https://www.edx.org/course/python-basics-for-data-science-2?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01) and **Analyzing Data with Python** (https://www.edx.org/course/data-analysis-with-python?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01).

Note: The majority of the plots and visualizations will be generated using data stored in *pandas* dataframes. Therefore, in this lab, we provide a brief crash course on *pandas*. However, if you are interested in learning more about the *pandas* library, detailed description and explanation of how to use it and how to clean, munge, and process data stored in a *pandas* dataframe are provided in our course **Analyzing Data with Python** (https://www.edx.org/course/data-analysis-with-python?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01).

Table of Contents

Exploring Datasets with *pandas*

pandas is an essential data analysis toolkit for Python. From their website (http://pandas.pydata.org/?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01):

> *pandas* is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, **real world** data analysis in Python.

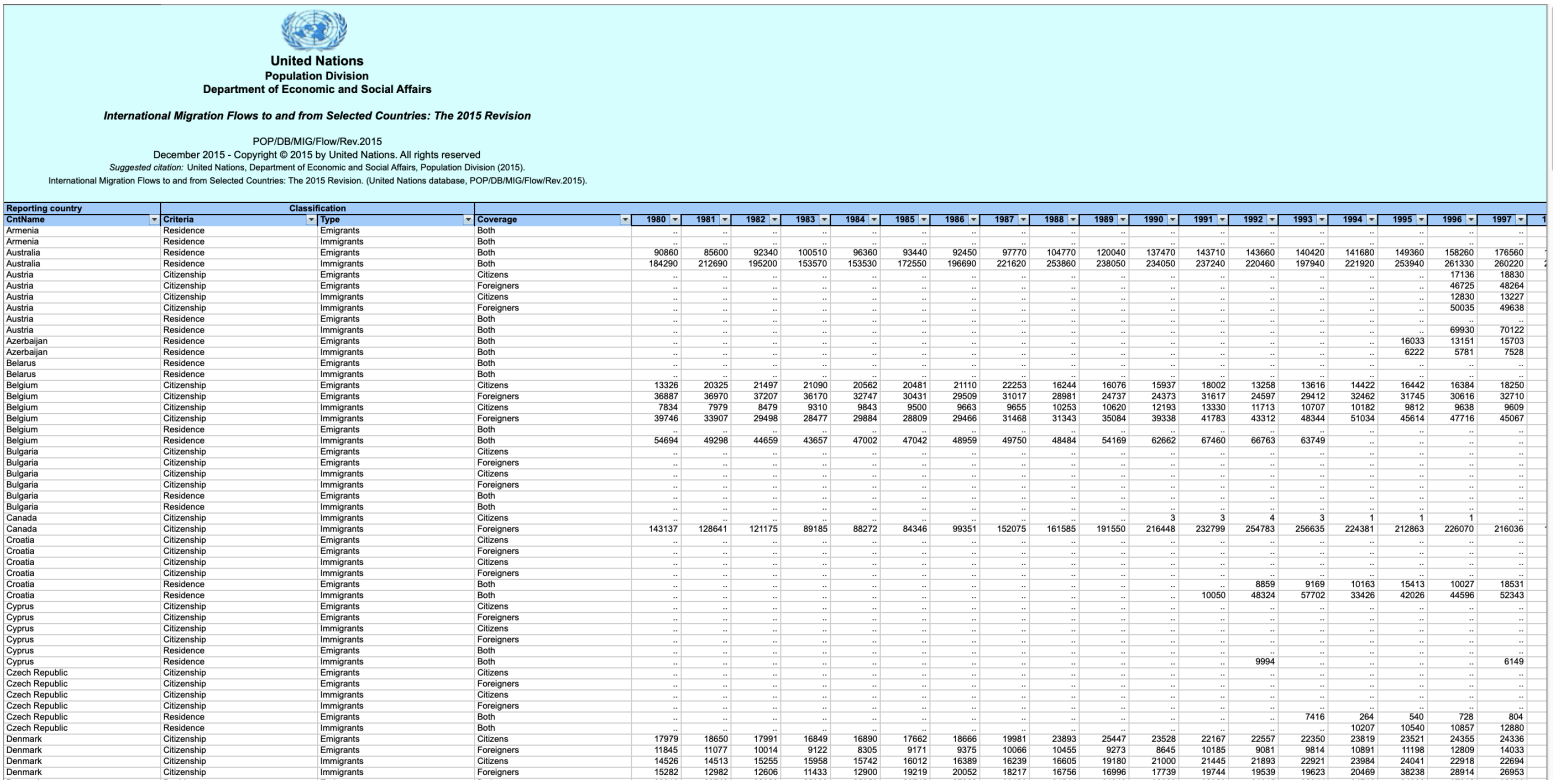
The course heavily relies on *pandas* for data wrangling, analysis, and visualization. We encourage you to spend some time and familiarize yourself with the *pandas* API Reference: http://pandas.pydata.org/pandas-docs/stable/api.html (http://pandas.pydata.org/pandas-docs/stable/api.html?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01).

The Dataset: Immigration to Canada from 1980 to 2013

Dataset Source: [International migration flows to and from selected countries - The 2015 revision (http://www.un.org/en/development/desa/population/migration/data/empirical2/migrationflows.shtml?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01)](http://www.un.org/en/development/desa/population/migration/data/empirical2/migrationflows.shtml?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01).

The dataset contains annual data on the flows of international immigrants as recorded by the countries of destination. The data presents both inflows and outflows according to the place of birth, citizenship or place of previous / next residence both for foreigners and nationals. The current version presents data pertaining to 45 countries.

In this lab, we will focus on the Canadian immigration data.



United Nations
Population Division
Department of Economic and Social Affairs

International Migration Flows to and from Selected Countries: The 2015 Revision

POP/DB/MIG/Flow/Rev.2015
December 2015 - Copyright © 2015 by United Nations. All rights reserved
Suggested citation: United Nations, Department of Economic and Social Affairs, Population Division (2015).
International Migration Flows to and from Selected Countries: The 2015 Revision. (United Nations database, POP/DB/MIG/Flow/Rev.2015).

Reporting country	Classification			1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
CntName	Criteria	Type	Coverage																		
Armenia	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Armenia	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Australia	Residence	Emigrants	Both	90860	85600	92340	100510	96360	93440	92450	97770	104770	120040	137470	143710	143660	140420	141680	149360	158260	176560
Australia	Residence	Immigrants	Both	184290	212690	195200	153570	153530	172550	196690	221620	253860	238050	234050	237240	220460	197940	221920	253940	261330	260220
Austria	Citizenship	Emigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	17136	18830
Austria	Citizenship	Emigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	46725	48264
Austria	Citizenship	Immigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	12830	13227
Austria	Citizenship	Immigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	50035	49638
Austria	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Austria	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	69930	70122
Azerbaijan	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	16033	13151	15703
Azerbaijan	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	6222	5781	7528
Belarus	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Belarus	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Belgium	Citizenship	Emigrants	Citizens	13326	20325	21497	21090	20562	20481	21110	22253	16244	16076	15937	18002	13258	13616	14422	16442	16384	18250
Belgium	Citizenship	Emigrants	Foreigners	36887	36970	37207	36170	32747	30431	29509	31017	28981	24737	24373	31617	24597	29412	32462	31745	30616	32710
Belgium	Citizenship	Immigrants	Citizens	7834	7979	8479	9310	9843	9500	9663	9655	10253	10620	12193	13330	11713	10707	10182	9812	9638	9609
Belgium	Citizenship	Immigrants	Foreigners	39746	33907	29498	28477	29884	28809	29466	31468	31343	35084	39338	41783	43312	48344	51034	45614	47716	45067
Belgium	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Belgium	Residence	Immigrants	Both	54694	49298	44659	43657	47002	47042	48959	49750	48484	54169	62662	67460	66763	63749	..	..	..	..
Bulgaria	Citizenship	Emigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Bulgaria	Citizenship	Emigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Bulgaria	Citizenship	Immigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Bulgaria	Citizenship	Immigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Bulgaria	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Bulgaria	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Canada	Citizenship	Immigrants	Citizens	..	..	..	..	..	..	..	..	..	..	3	3	4	3	1	1	1	..	..
Canada	Citizenship	Immigrants	Foreigners	143137	128641	121175	89185	88272	84346	99351	152075	161585	191550	216448	232799	254783	256635	224381	212863	226070	216036
Croatia	Citizenship	Emigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Croatia	Citizenship	Emigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Croatia	Citizenship	Immigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Croatia	Citizenship	Immigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Croatia	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	8859	9169	10163	15413	10027	18531
Croatia	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	10050	48324	57702	33426	42026	44596	52343
Cyprus	Citizenship	Emigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Cyprus	Citizenship	Emigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Cyprus	Citizenship	Immigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Cyprus	Citizenship	Immigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Cyprus	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Cyprus	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	9994	..	..	..	..	..	6149
Czech Republic	Citizenship	Emigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Czech Republic	Citizenship	Emigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Czech Republic	Citizenship	Immigrants	Citizens	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Czech Republic	Citizenship	Immigrants	Foreigners	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
Czech Republic	Residence	Emigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	7416	264	540	728	804	..
Czech Republic	Residence	Immigrants	Both	..	..	..	..	..	..	..	..	..	..	..	..	..	..	10207	10540	10857	12880	..
Denmark	Citizenship	Emigrants	Citizens	17979	18650	17991	16849	16890	17662	18666	19981	23893	25447	23528	22167	22557	22350	23819	23521	24355	24336
Denmark	Citizenship	Emigrants	Foreigners	11845	11077	10014	9122	8305	9171	9375	10066	10455	9273	8645	10185	9081	9814	10891	11198	12809	14033
Denmark	Citizenship	Immigrants	Citizens	14526	14513	15255	15958	15742	16012	16389	16239	16605	19180	21000	21445	21893	22921	23984	24041	22918	22694
Denmark	Citizenship	Immigrants	Foreigners	15282	12982	12606	11433	12900	19219	20052	18217	16756	16996	17739	19744	19539	19623	20469	38238	28914	26953

The Canada Immigration dataset can be fetched from [here (https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DV0101EN-SkillsNetwork/Data%20Files/Canada.xlsx?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01)](https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DV0101EN-SkillsNetwork/Data%20Files/Canada.xlsx?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01).

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pandas Basics

The first thing we'll do is import two key data analysis modules: *pandas* and *numpy*.

In [1]:

```
import numpy as np  # useful for many scientific computing in Python
import pandas as pd # primary data structure library
```

Let's download and import our primary Canadian Immigration dataset using *pandas*'s `read_excel()` method. Normally, before we can do that, we would need to download a module which *pandas* requires reading in Excel files. This module was **openpyxl** (formerlly **xlrd**). For your convenience, we have pre-installed this module, so you would not have to worry about that. Otherwise, you would need to run the following line of code to install the **openpyxl** module:

```
! pip3 install openpyxl
```

Now we are ready to read in our data.

In [2]:

```
df_can = pd.read_excel(
    'https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DV0101EN-SkillsNetwork/Data%20Files/Canada.xlsx',
    sheet_name='Canada by Citizenship',
    skiprows=range(20),
    skipfooter=2)

print('Data read into a pandas dataframe!')
```

```
Data read into a pandas dataframe!
```

Let's view the top 5 rows of the dataset using the `head()` function.

In [3]:

```
df_can.head()
# tip: You can specify the number of rows you'd like to see as follows: df_can.head(10)
```

Out[3]:

	Type	Coverage	OdName	AREA	AreaName	REG	RegName	DEV	DevName	1980	...	2004
0	Immigrants	Foreigners	Afghanistan	935	Asia	5501	Southern Asia	902	Developing regions	16	...	2978
1	Immigrants	Foreigners	Albania	908	Europe	925	Southern Europe	901	Developed regions	1	...	1450
2	Immigrants	Foreigners	Algeria	903	Africa	912	Northern Africa	902	Developing regions	80	...	3616
3	Immigrants	Foreigners	American Samoa	909	Oceania	957	Polynesia	902	Developing regions	0	...	0
4	Immigrants	Foreigners	Andorra	908	Europe	925	Southern Europe	901	Developed regions	0	...	0

5 rows × 43 columns

We can also view the bottom 5 rows of the dataset using the `tail()` function.

In [4]:

```
df_can.tail()
```

Out[4]:

	Type	Coverage	OdName	AREA	AreaName	REG	RegName	DEV	DevName	1980	...	2004
190	Immigrants	Foreigners	Viet Nam	935	Asia	920	South-Eastern Asia	902	Developing regions	1191	...	1816
191	Immigrants	Foreigners	Western Sahara	903	Africa	912	Northern Africa	902	Developing regions	0	...	0
192	Immigrants	Foreigners	Yemen	935	Asia	922	Western Asia	902	Developing regions	1	...	124
193	Immigrants	Foreigners	Zambia	903	Africa	910	Eastern Africa	902	Developing regions	11	...	56
194	Immigrants	Foreigners	Zimbabwe	903	Africa	910	Eastern Africa	902	Developing regions	72	...	1450

5 rows × 43 columns

When analyzing a dataset, it's always a good idea to start by getting basic information about your dataframe. We can do this by using the `info()` method.

This method can be used to get a short summary of the dataframe.

In [5]:

```
df_can.info(verbose=False)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Columns: 43 entries, Type to 2013
dtypes: int64(37), object(6)
memory usage: 65.6+ KB
```

To get the list of column headers we can call upon the data frame's `columns` instance variable.

In [6]:

```
df_can.columns
```

Out[6]:

```
Index([    'Type', 'Coverage',   'OdName',     'AREA', 'AreaName',      'REG',
        'RegName',       'DEV',  'DevName',       1980,       1981,       1982,
             1983,       1984,       1985,       1986,       1987,       1988,
             1989,       1990,       1991,       1992,       1993,       1994,
             1995,       1996,       1997,       1998,       1999,       2000,
             2001,       2002,       2003,       2004,       2005,       2006,
             2007,       2008,       2009,       2010,       2011,       2012,
             2013],
      dtype='object')
```

Similarly, to get the list of indices we use the `.index` instance variables.

In [7]:

```
df_can.index
```

Out[7]:

```
RangeIndex(start=0, stop=195, step=1)
```

Note: The default type of intance variables `index` and `columns` are **NOT** `list`.

In [8]:

```
print(type(df_can.columns))
print(type(df_can.index))
```

```
<class 'pandas.core.indexes.base.Index'>
<class 'pandas.core.indexes.range.RangeIndex'>
```

To get the index and columns as lists, we can use the `tolist()` method.

In [9]:

```
df_can.columns.tolist()
```

Out[9]:

```
['Type',
 'Coverage',
 'OdName',
 'AREA',
 'AreaName',
 'REG',
 'RegName',
 'DEV',
 'DevName',
 1980,
 1981,
 1982,
 1983,
 1984,
 1985,
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 1987,
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 1992,
 1993,
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 2003,
 2004,
 2005,
 2006,
 2007,
 2008,
 2009,
 2010,
 2011,
 2012,
 2013]
```

In [10]:

```
df_can.index.tolist()
```

Out[10]:

```
[0,
 1,
 2,
 3,
 4,
 5,
 6,
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 188,
 189,
 190,
 191,
 192,
 193,
 194]
```

In [11]:

```
print(type(df_can.columns.tolist()))
print(type(df_can.index.tolist()))
```

```
<class 'list'>
<class 'list'>
```

To view the dimensions of the dataframe, we use the `shape` instance variable of it.

In [12]:

```
# size of dataframe (rows, columns)
df_can.shape
```

Out[12]:

```
(195, 43)
```

Note: The main types stored in *pandas* objects are `float`, `int`, `bool`, `datetime64[ns]`, `datetime64[ns, tz]`, `timedelta[ns]`, `category`, and `object` (string). In addition, these dtypes have item sizes, e.g. `int64` and `int32`.

Let's clean the data set to remove a few unnecessary columns. We can use *pandas* `drop()` method as follows:

In [13]:

```
# in pandas axis=0 represents rows (default) and axis=1 represents columns.
df_can.drop(['AREA','REG','DEV','Type','Coverage'], axis=1, inplace=True)
df_can.head(2)
```

Out[13]:

	OdName	AreaName	RegName	DevName	1980	1981	1982	1983	1984	1985	...	2004	2005	2006
0	Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	...	2978	3436	3009
1	Albania	Europe	Southern Europe	Developed regions	1	0	0	0	0	0	...	1450	1223	856

2 rows × 38 columns

Let's rename the columns so that they make sense. We can use `rename()` method by passing in a dictionary of old and new names as follows:

In [14]:

```
df_can.rename(columns={'OdName':'Country', 'AreaName':'Continent', 'RegName':'Region'}, inplace=True
)
df_can.columns
```

Out[14]:

```
Index([  'Country', 'Continent',    'Region',   'DevName',        1980,
              1981,        1982,        1983,        1984,        1985,
              1986,        1987,        1988,        1989,        1990,
              1991,        1992,        1993,        1994,        1995,
              1996,        1997,        1998,        1999,        2000,
              2001,        2002,        2003,        2004,        2005,
              2006,        2007,        2008,        2009,        2010,
              2011,        2012,        2013],
      dtype='object')
```

We will also add a 'Total' column that sums up the total immigrants by country over the entire period 1980 - 2013, as follows:

In [15]:

```
df_can['Total'] = df_can.sum(axis=1)
```

We can check to see how many null objects we have in the dataset as follows:

In [16]:

```
df_can.isnull().sum()
```

Out[16]:

```
Country      0
Continent    0
Region       0
DevName      0
1980         0
1981         0
1982         0
1983         0
1984         0
1985         0
1986         0
1987         0
1988         0
1989         0
1990         0
1991         0
1992         0
1993         0
1994         0
1995         0
1996         0
1997         0
1998         0
1999         0
2000         0
2001         0
2002         0
2003         0
2004         0
2005         0
2006         0
2007         0
2008         0
2009         0
2010         0
2011         0
2012         0
2013         0
Total        0
dtype: int64
```

Finally, let's view a quick summary of each column in our dataframe using the `describe()` method.

In [17]:

```
df_can.describe()
```

Out[17]:

	1980	1981	1982	1983	1984	1985	1986	
count	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	1
mean	508.394872	566.989744	534.723077	387.435897	376.497436	358.861538	441.271795	6
std	1949.588546	2152.643752	1866.997511	1204.333597	1198.246371	1079.309600	1225.576630	21
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.500000	
50%	13.000000	10.000000	11.000000	12.000000	13.000000	17.000000	18.000000	
75%	251.500000	295.500000	275.000000	173.000000	181.000000	197.000000	254.000000	4
max	22045.000000	24796.000000	20620.000000	10015.000000	10170.000000	9564.000000	9470.000000	213

8 rows × 35 columns

---

pandas Intermediate: Indexing and Selection (slicing)

Select Column

There are two ways to filter on a column name:

Method 1: Quick and easy, but only works if the column name does NOT have spaces or special characters.

```
df.column_name              # returns series
```

Method 2: More robust, and can filter on multiple columns.

```
df['column']                 # returns series

df[['column 1', 'column 2']]  # returns dataframe
```

Example: Let's try filtering on the list of countries ('Country').

In [18]:

```
df_can.Country  # returns a series
```

Out[18]:

```
0         Afghanistan
1             Albania
2             Algeria
3      American Samoa
4             Andorra
            ...
190          Viet Nam
191    Western Sahara
192             Yemen
193            Zambia
194          Zimbabwe
Name: Country, Length: 195, dtype: object
```

Let's try filtering on the list of countries ('Country') and the data for years: 1980 - 1985.

In [19]:

```
df_can[['Country', 1980, 1981, 1982, 1983, 1984, 1985]] # returns a dataframe
# notice that 'Country' is string, and the years are integers.
# for the sake of consistency, we will convert all column names to string later on.
```

Out[19]:

	Country	1980	1981	1982	1983	1984	1985
0	Afghanistan	16	39	39	47	71	340
1	Albania	1	0	0	0	0	0
2	Algeria	80	67	71	69	63	44
3	American Samoa	0	1	0	0	0	0
4	Andorra	0	0	0	0	0	0
...	...	...	...	...	...	...	...
190	Viet Nam	1191	1829	2162	3404	7583	5907
191	Western Sahara	0	0	0	0	0	0
192	Yemen	1	2	1	6	0	18
193	Zambia	11	17	11	7	16	9
194	Zimbabwe	72	114	102	44	32	29

195 rows × 7 columns

Select Row

There are main 2 ways to select rows:

```
df.loc[label]    # filters by the labels of the index/column
    df.iloc[index]   # filters by the positions of the index/column
```

Before we proceed, notice that the default index of the dataset is a numeric range from 0 to 194. This makes it very difficult to do a query by a specific country. For example to search for data on Japan, we need to know the corresponding index value.

This can be fixed very easily by setting the 'Country' column as the index using `set_index()` method.

In [20]:

```
df_can.set_index('Country', inplace=True)
# tip: The opposite of set is reset. So to reset the index, we can use df_can.reset_index()
```

In [21]:

```
df_can.head(3)
```

Out[21]:

Country	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006	20(
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3436	3009	26
Albania	Europe	Southern Europe	Developed regions	1	0	0	0	0	0	1	...	1223	856	7(
Algeria	Africa	Northern Africa	Developing regions	80	67	71	69	63	44	69	...	3626	4807	36

3 rows × 38 columns

In [22]:

```
# optional: to remove the name of the index
df_can.index.name = None
```

Example: Let's view the number of immigrants from Japan (row 87) for the following scenarios: 1. The full row data (all columns) 2. For year 2013 3. For years 1980 to 1985

In [23]:

```
# 1. the full row data (all columns)
df_can.loc['Japan']
```

Out[23]:

```
Continent                 Asia
Region            Eastern Asia
DevName      Developed regions
1980                        701
1981                        756
1982                        598
1983                        309
1984                        246
1985                        198
1986                        248
1987                        422
1988                        324
1989                        494
1990                        379
1991                        506
1992                        605
1993                        907
1994                        956
1995                        826
1996                        994
1997                        924
1998                        897
1999                       1083
2000                       1010
2001                       1092
2002                        806
2003                        817
2004                        973
2005                       1067
2006                       1212
2007                       1250
2008                       1284
2009                       1194
2010                       1168
2011                       1265
2012                       1214
2013                        982
Total                     27707
Name: Japan, dtype: object
```

In [24]:

```
# alternate methods
df_can.iloc[87]
```

Out[24]:

```
Continent                 Asia
Region            Eastern Asia
DevName      Developed regions
1980                       701
1981                       756
1982                       598
1983                       309
1984                       246
1985                       198
1986                       248
1987                       422
1988                       324
1989                       494
1990                       379
1991                       506
1992                       605
1993                       907
1994                       956
1995                       826
1996                       994
1997                       924
1998                       897
1999                      1083
2000                      1010
2001                      1092
2002                       806
2003                       817
2004                       973
2005                      1067
2006                      1212
2007                      1250
2008                      1284
2009                      1194
2010                      1168
2011                      1265
2012                      1214
2013                       982
Total                    27707
Name: Japan, dtype: object
```

In [25]:

```
df_can[df_can.index == 'Japan']
```

Out[25]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006	2007	200
Japan	Asia	Eastern Asia	Developed regions	701	756	598	309	246	198	248	...	1067	1212	1250	128

1 rows × 38 columns

In [26]:

```
# 2. for year 2013
df_can.loc['Japan', 2013]
```

Out[26]:

```
982
```

In [27]:

```
# alternate method
# year 2013 is the last column, with a positional index of 36
df_can.iloc[87, 36]
```

Out[27]:

```
982
```

In [28]:

```
# 3. for years 1980 to 1985
df_can.loc['Japan', [1980, 1981, 1982, 1983, 1984, 1984]]
```

Out[28]:

```
1980    701
1981    756
1982    598
1983    309
1984    246
1984    246
Name: Japan, dtype: object
```

In [29]:

```
# Alternative Method
df_can.iloc[87, [3, 4, 5, 6, 7, 8]]
```

Out[29]:

```
1980    701
1981    756
1982    598
1983    309
1984    246
1985    198
Name: Japan, dtype: object
```

Column names that are integers (such as the years) might introduce some confusion. For example, when we are referencing the year 2013, one might confuse that when the 2013th positional index.

To avoid this ambuigity, let's convert the column names into strings: '1980' to '2013'.

In [30]:

```
df_can.columns = list(map(str, df_can.columns))
# [print (type(x)) for x in df_can.columns.values] #<-- uncomment to check type of column headers
```

Since we converted the years to string, let's declare a variable that will allow us to easily call upon the full range of years:

In [31]:

```
# useful for plotting later on
years = list(map(str, range(1980, 2014)))
years
```

Out[31]:

```
['1980',
 '1981',
 '1982',
 '1983',
 '1984',
 '1985',
 '1986',
 '1987',
 '1988',
 '1989',
 '1990',
 '1991',
 '1992',
 '1993',
 '1994',
 '1995',
 '1996',
 '1997',
 '1998',
 '1999',
 '2000',
 '2001',
 '2002',
 '2003',
 '2004',
 '2005',
 '2006',
 '2007',
 '2008',
 '2009',
 '2010',
 '2011',
 '2012',
 '2013']
```

Filtering based on a criteria

To filter the dataframe based on a condition, we simply pass the condition as a boolean vector.

For example, Let's filter the dataframe to show the data on Asian countries (AreaName = Asia).

In [32]:

```
# 1. create the condition boolean series
condition = df_can['Continent'] == 'Asia'
print(condition)
```

```
Afghanistan        True
Albania           False
Algeria           False
American Samoa    False
Andorra           False
                  ...
Viet Nam           True
Western Sahara    False
Yemen              True
Zambia            False
Zimbabwe          False
Name: Continent, Length: 195, dtype: bool
```

In [33]:

```
# 2. pass this condition into the dataFrame
df_can[condition]
```

Out[33]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3436	3009
Armenia	Asia	Western Asia	Developing regions	0	0	0	0	0	0	0	...	224	218
Azerbaijan	Asia	Western Asia	Developing regions	0	0	0	0	0	0	0	...	359	236
Bahrain	Asia	Western Asia	Developing regions	0	2	1	1	1	3	0	...	12	12
Bangladesh	Asia	Southern Asia	Developing regions	83	84	86	81	98	92	486	...	4171	4014
Bhutan	Asia	Southern Asia	Developing regions	0	0	0	0	1	0	0	...	5	10
Brunei Darussalam	Asia	South-Eastern Asia	Developing regions	79	6	8	2	2	4	12	...	4	5
Cambodia	Asia	South-Eastern Asia	Developing regions	12	19	26	33	10	7	8	...	370	529
China	Asia	Eastern Asia	Developing regions	5123	6682	3308	1863	1527	1816	1960	...	42584	33518
China, Hong Kong Special Administrative Region	Asia	Eastern Asia	Developing regions	0	0	0	0	0	0	0	...	729	712
China, Macao Special Administrative Region	Asia	Eastern Asia	Developing regions	0	0	0	0	0	0	0	...	21	32
Cyprus	Asia	Western Asia	Developing regions	132	128	84	46	46	43	48	...	7	9
Democratic People's Republic of Korea	Asia	Eastern Asia	Developing regions	1	1	3	1	4	3	0	...	14	10
Georgia	Asia	Western Asia	Developing regions	0	0	0	0	0	0	0	...	114	125
India	Asia	Southern Asia	Developing regions	8880	8670	8147	7338	5704	4211	7150	...	36210	33848
Indonesia	Asia	South-Eastern Asia	Developing regions	186	178	252	115	123	100	127	...	632	613
Iran (Islamic Republic of)	Asia	Southern Asia	Developing regions	1172	1429	1822	1592	1977	1648	1794	...	5837	7480
Iraq	Asia	Western Asia	Developing regions	262	245	260	380	428	231	265	...	2226	1788
Israel	Asia	Western Asia	Developing regions	1403	1711	1334	541	446	680	1212	...	2446	2625
Japan	Asia	Eastern Asia	Developed regions	701	756	598	309	246	198	248	...	1067	1212
Jordan	Asia	Western Asia	Developing regions	177	160	155	113	102	179	181	...	1940	1827

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006
Kazakhstan	Asia	Central Asia	Developing regions	0	0	0	0	0	0	0	...	506	408
Kuwait	Asia	Western Asia	Developing regions	1	0	8	2	1	4	4	...	66	35
Kyrgyzstan	Asia	Central Asia	Developing regions	0	0	0	0	0	0	0	...	173	161
Lao People's Democratic Republic	Asia	South-Eastern Asia	Developing regions	11	6	16	16	7	17	21	...	42	74
Lebanon	Asia	Western Asia	Developing regions	1409	1119	1159	789	1253	1683	2576	...	3709	3802
Malaysia	Asia	South-Eastern Asia	Developing regions	786	816	813	448	384	374	425	...	593	580
Maldives	Asia	Southern Asia	Developing regions	0	0	0	1	0	0	0	...	0	0
Mongolia	Asia	Eastern Asia	Developing regions	0	0	0	0	0	0	0	...	59	64
Myanmar	Asia	South-Eastern Asia	Developing regions	80	62	46	31	41	23	18	...	210	953
Nepal	Asia	Southern Asia	Developing regions	1	1	6	1	2	4	13	...	607	540
Oman	Asia	Western Asia	Developing regions	0	0	0	8	0	0	0	...	14	18
Pakistan	Asia	Southern Asia	Developing regions	978	972	1201	900	668	514	691	...	14314	13127
Philippines	Asia	South-Eastern Asia	Developing regions	6051	5921	5249	4562	3801	3150	4166	...	18139	18400
Qatar	Asia	Western Asia	Developing regions	0	0	0	0	0	0	1	...	11	2
Republic of Korea	Asia	Eastern Asia	Developing regions	1011	1456	1572	1081	847	962	1208	...	5832	6215
Saudi Arabia	Asia	Western Asia	Developing regions	0	0	1	4	1	2	5	...	198	252
Singapore	Asia	South-Eastern Asia	Developing regions	241	301	337	169	128	139	205	...	392	298
Sri Lanka	Asia	Southern Asia	Developing regions	185	371	290	197	1086	845	1838	...	4930	4714
State of Palestine	Asia	Western Asia	Developing regions	0	0	0	0	0	0	0	...	453	627
Syrian Arab Republic	Asia	Western Asia	Developing regions	315	419	409	269	264	385	493	...	1458	1145
Tajikistan	Asia	Central Asia	Developing regions	0	0	0	0	0	0	0	...	85	46
Thailand	Asia	South-Eastern Asia	Developing regions	56	53	113	65	82	66	78	...	575	500
Turkey	Asia	Western Asia	Developing regions	481	874	706	280	338	202	257	...	2065	1638

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006
Turkmenistan	Asia	Central Asia	Developing regions	0	0	0	0	0	0	0	...	40	26
United Arab Emirates	Asia	Western Asia	Developing regions	0	2	2	1	2	0	5	...	31	42
Uzbekistan	Asia	Central Asia	Developing regions	0	0	0	0	0	0	0	...	330	262
Viet Nam	Asia	South-Eastern Asia	Developing regions	1191	1829	2162	3404	7583	5907	2741	...	1852	3153
Yemen	Asia	Western Asia	Developing regions	1	2	1	6	0	18	7	...	161	140

49 rows × 38 columns

In [34]:

```
# we can pass multiple criteria in the same line.
# let's filter for AreaNAme = Asia and RegName = Southern Asia

df_can[(df_can['Continent']=='Asia') & (df_can['Region']=='Southern Asia')]

# note: When using 'and' and 'or' operators, pandas requires we use '&' and '|' instead of 'and' and 'or'
# don't forget to enclose the two conditions in parentheses
```

Out[34]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3436	3009
Bangladesh	Asia	Southern Asia	Developing regions	83	84	86	81	98	92	486	...	4171	4014
Bhutan	Asia	Southern Asia	Developing regions	0	0	0	0	1	0	0	...	5	10
India	Asia	Southern Asia	Developing regions	8880	8670	8147	7338	5704	4211	7150	...	36210	33848
Iran (Islamic Republic of)	Asia	Southern Asia	Developing regions	1172	1429	1822	1592	1977	1648	1794	...	5837	7480
Maldives	Asia	Southern Asia	Developing regions	0	0	0	1	0	0	0	...	0	0
Nepal	Asia	Southern Asia	Developing regions	1	1	6	1	2	4	13	...	607	540
Pakistan	Asia	Southern Asia	Developing regions	978	972	1201	900	668	514	691	...	14314	13127
Sri Lanka	Asia	Southern Asia	Developing regions	185	371	290	197	1086	845	1838	...	4930	4714

9 rows × 38 columns

Before we proceed: let's review the changes we have made to our dataframe.

In [35]:

```
print('data dimensions:', df_can.shape)
print(df_can.columns)
df_can.head(2)
```

```
data dimensions: (195, 38)
Index(['Continent', 'Region', 'DevName', '1980', '1981', '1982', '1983',
       '1984', '1985', '1986', '1987', '1988', '1989', '1990', '1991', '1992',
       '1993', '1994', '1995', '1996', '1997', '1998', '1999', '2000', '2001',
       '2002', '2003', '2004', '2005', '2006', '2007', '2008', '2009', '2010',
       '2011', '2012', '2013', 'Total'],
      dtype='object')
```

Out[35]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2005	2006	20(
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3436	3009	26:
Albania	Europe	Southern Europe	Developed regions	1	0	0	0	0	0	1	...	1223	856	7(

2 rows × 38 columns

Visualizing Data using Matplotlib

Matplotlib: Standard Python Visualization Library

The primary plotting library we will explore in the course is [Matplotlib (http://matplotlib.org/?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01)](http://matplotlib.org/?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01). As mentioned on their website:

> Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shell, the jupyter notebook, web application servers, and four graphical user interface toolkits.

If you are aspiring to create impactful visualization with python, Matplotlib is an essential tool to have at your disposal.

Matplotlib.Pyplot

One of the core aspects of Matplotlib is `matplotlib.pyplot` . It is Matplotlib's scripting layer which we studied in details in the videos about Matplotlib. Recall that it is a collection of command style functions that make Matplotlib work like MATLAB. Each `pyplot` function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc. In this lab, we will work with the scripting layer to learn how to generate line plots. In future labs, we will get to work with the Artist layer as well to experiment first hand how it differs from the scripting layer.

Let's start by importing `matplotlib` and `matplotlib.pyplot` as follows:

In [36]:

```
# we are using the inline backend
%matplotlib inline

import matplotlib as mpl
import matplotlib.pyplot as plt
```

*optional: check if Matplotlib is loaded.

In [37]:

```
print('Matplotlib version: ', mpl.__version__)  # >= 2.0.0
```

```
Matplotlib version:  3.3.4
```

*optional: apply a style to Matplotlib.

In [38]:

```
print(plt.style.available)
mpl.style.use(['ggplot']) # optional: for ggplot-like style
```

```
['Solarize_Light2', '_classic_test_patch', 'bmh', 'classic', 'dark_background', 'fast',
'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn', 'seaborn-bright', 'seaborn-colorbl
ind', 'seaborn-dark', 'seaborn-dark-palette', 'seaborn-darkgrid', 'seaborn-deep', 'seab
orn-muted', 'seaborn-notebook', 'seaborn-paper', 'seaborn-pastel', 'seaborn-poster', 's
eaborn-talk', 'seaborn-ticks', 'seaborn-white', 'seaborn-whitegrid', 'tableau-colorblin
d10']
```

Plotting in *pandas*

Fortunately, pandas has a built-in implementation of Matplotlib that we can use. Plotting in *pandas* is as simple as appending a `.plot()` method to a series or dataframe.

Documentation:

- Plotting with Series (http://pandas.pydata.org/pandas-docs/stable/api.html?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01#plotting)
- Plotting with Dataframes (http://pandas.pydata.org/pandas-docs/stable/api.html?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDV0101ENSkillsNetwork20297740-2021-01-01#api-dataframe-plotting)

Line Pots (Series/Dataframe)

What is a line plot and why use it?

A line chart or line plot is a type of plot which displays information as a series of data points called 'markers' connected by straight line segments. It is a basic type of chart common in many fields. Use line plot when you have a continuous data set. These are best suited for trend-based visualizations of data over a period of time.

Let's start with a case study:

In 2010, Haiti suffered a catastrophic magnitude 7.0 earthquake. The quake caused widespread devastation and loss of life and aout three million people were affected by this natural disaster. As part of Canada's humanitarian effort, the Government of Canada stepped up its effort in accepting refugees from Haiti. We can quickly visualize this effort using a `Line` plot:

Question: Plot a line graph of immigration from Haiti using `df.plot()`.

First, we will extract the data series for Haiti.

In [39]:

```
haiti = df_can.loc['Haiti', years] # passing in years 1980 - 2013 to exclude the 'total' column
haiti.head()
```

Out[39]:

```
1980    1666
1981    3692
1982    3498
1983    2860
1984    1418
Name: Haiti, dtype: object
```

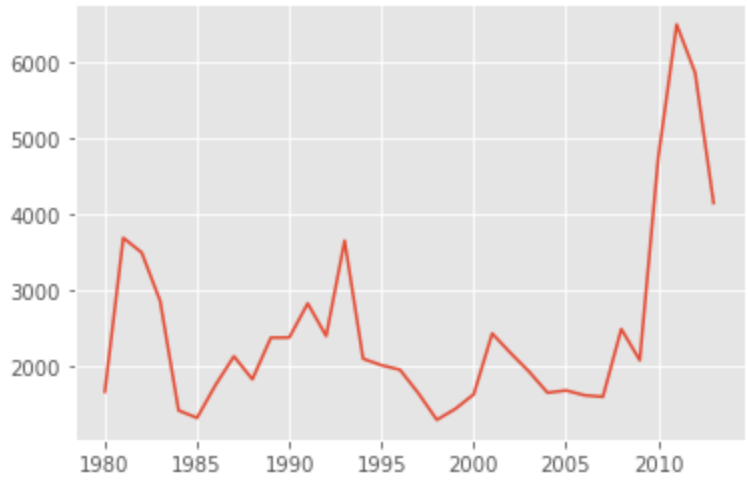
Next, we will plot a line plot by appending `.plot()` to the `haiti` dataframe.

In [40]:

```
haiti.plot()
```

Out[40]:

```
<AxesSubplot:>
```



pandas automatically populated the x-axis with the index values (years), and the y-axis with the column values (population). However, notice how the years were not displayed because they are of type *string*. Therefore, let's change the type of the index values to *integer* for plotting.

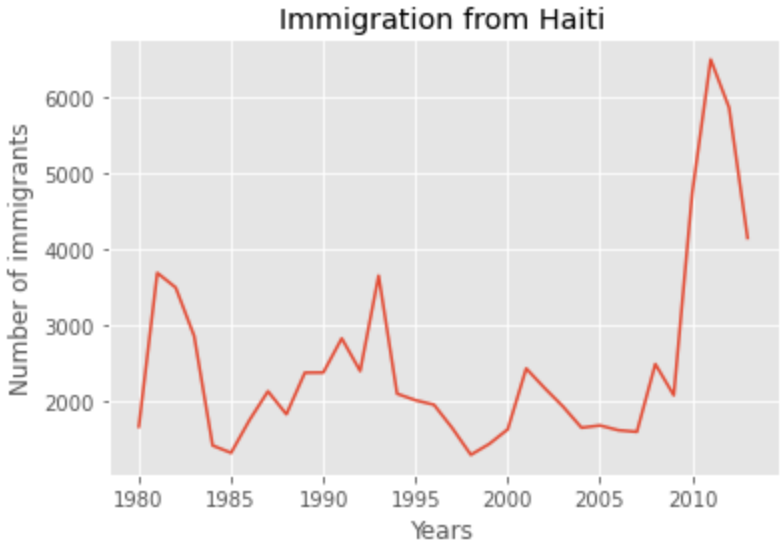
Also, let's label the x and y axis using `plt.title()`, `plt.ylabel()`, and `plt.xlabel()` as follows:

In [41]:

```
haiti.index = haiti.index.map(int) # let's change the index values of Haiti to type integer for plot
ting
haiti.plot(kind='line')

plt.title('Immigration from Haiti')
plt.ylabel('Number of immigrants')
plt.xlabel('Years')

plt.show() # need this line to show the updates made to the figure
```



We can clearly notice how number of immigrants from Haiti spiked up from 2010 as Canada stepped up its efforts to accept refugees from Haiti. Let's annotate this spike in the plot by using the `plt.text()` method.

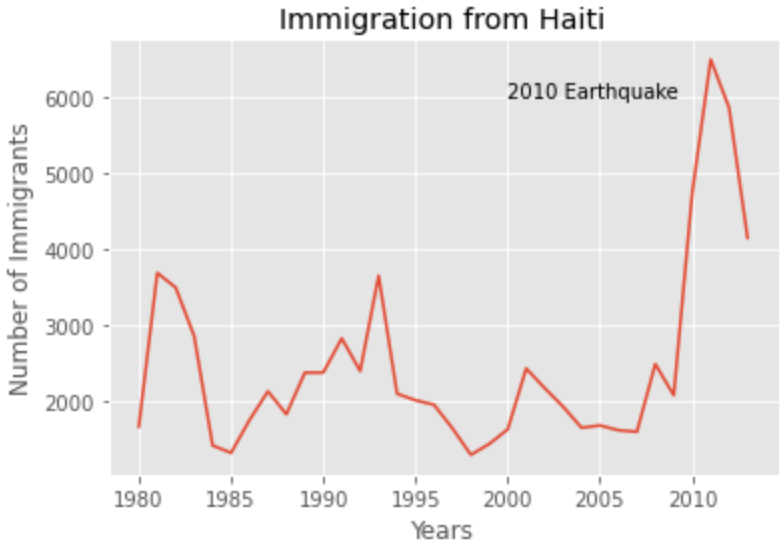
In [42]:

```
haiti.plot(kind='line')

plt.title('Immigration from Haiti')
plt.ylabel('Number of Immigrants')
plt.xlabel('Years')

# annotate the 2010 Earthquake.
# syntax: plt.text(x, y, label)
plt.text(2000, 6000, '2010 Earthquake') # see note below

plt.show()
```



With just a few lines of code, you were able to quickly identify and visualize the spike in immigration!

Quick note on x and y values in `plt.text(x, y, label)` :

```
    Since the x-axis (years) is type 'integer', we specified x as a year. The y axis (number of
    immigrants) is type 'integer', so we can just specify the value y = 6000.

plt.text(2000, 6000, '2010 Earthquake') # years stored as type int

If the years were stored as type 'string', we would need to specify x as the index position o
f the year. Eg 20th index is year 2000 since it is the 20th year with a base year of 1980.

plt.text(20, 6000, '2010 Earthquake') # years stored as type int

We will cover advanced annotation methods in later modules.
```

We can easily add more countries to line plot to make meaningful comparisons immigration from different countries.

Question: Let's compare the number of immigrants from India and China from 1980 to 2013.

Step 1: Get the data set for China and India, and display the dataframe.

In [47]:

```
### type your answer here
# df_CI = ...
# df_CI
df_CI = df_can.loc[['India', 'China'], years]
df_CI
```

Out[47]:

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	...	2004	2005	2006	2007	2
India	8880	8670	8147	7338	5704	4211	7150	10189	11522	10343	...	28235	36210	33848	28742	28
China	5123	6682	3308	1863	1527	1816	1960	2643	2758	4323	...	36619	42584	33518	27642	30

2 rows × 34 columns

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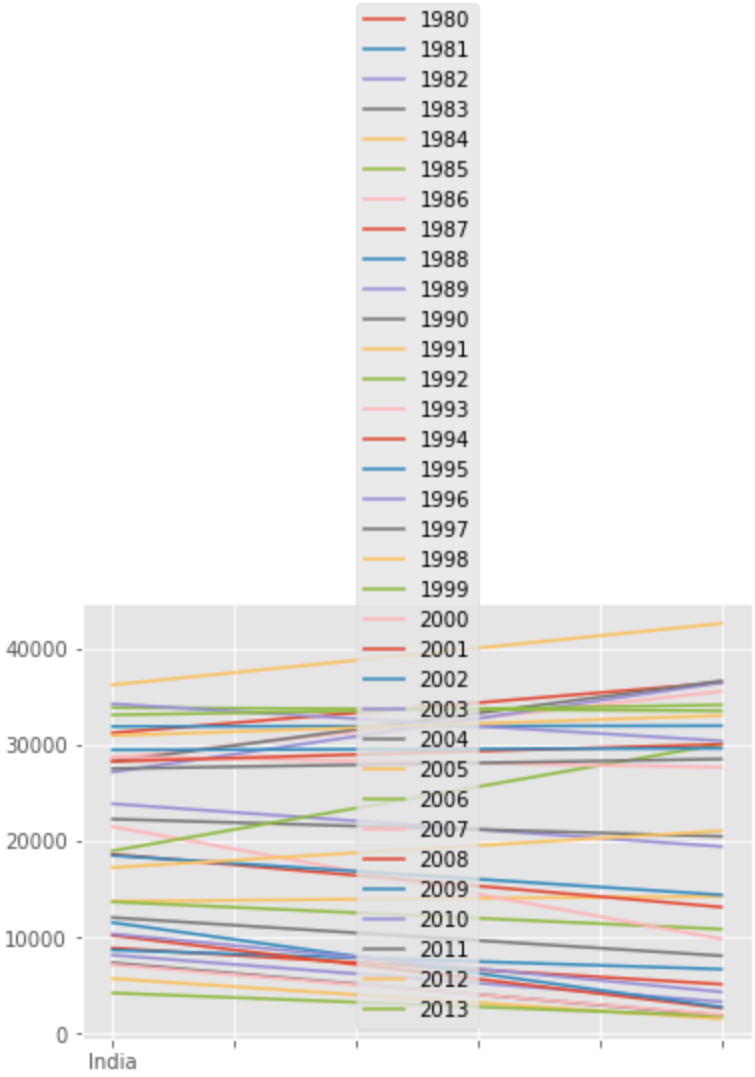
Step 2: Plot graph. We will explicitly specify line plot by passing in `kind` parameter to `plot()`.

In [48]:

```
df_CI.plot(kind='line')
```

Out[48]:

<AxesSubplot:>


1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
40000
30000
20000
10000
0
India

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That doesn't look right...

Recall that *pandas* plots the indices on the x-axis and the columns as individual lines on the y-axis. Since `df_CI` is a dataframe with the `country` as the index and `years` as the columns, we must first transpose the dataframe using `transpose()` method to swap the row and columns.

In [49]:

```
df_CI = df_CI.transpose()
df_CI.head()
```

Out[49]:

	India	China
1980	8880	5123
1981	8670	6682
1982	8147	3308
1983	7338	1863
1984	5704	1527

pandas will auomatically graph the two countries on the same graph. Go ahead and plot the new transposed dataframe. Make sure to add a title to the plot and label the axes.

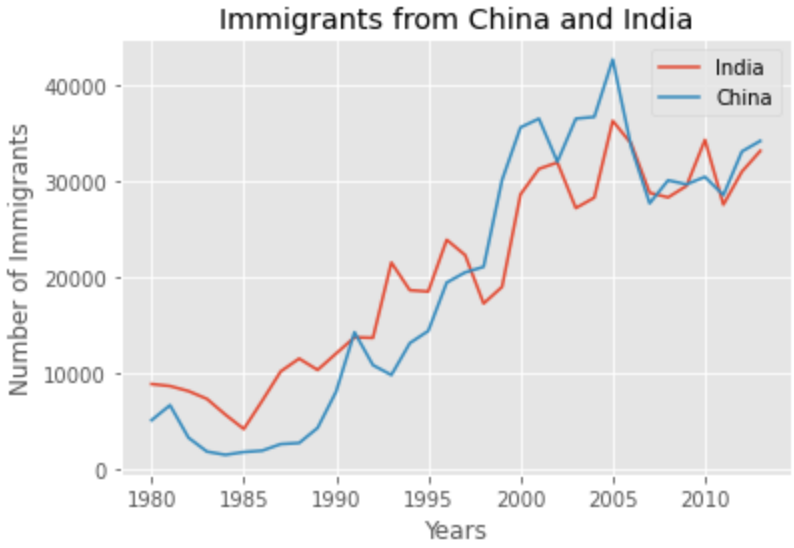
In [50]:

```
### type your answer here


    df_CI.index = df_CI.index.map(int) # let's change the index values of df_CI to type integer for
 plotting
    df_CI.plot(kind='line')

    plt.title('Immigrants from China and India')
    plt.ylabel('Number of Immigrants')
    plt.xlabel('Years')

    plt.show()
```



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From the above plot, we can observe that the China and India have very similar immigration trends through the years.

Note: How come we didn't need to transpose Haiti's dataframe before plotting (like we did for df_CI)?

That's because `haiti` is a series as opposed to a dataframe, and has the years as its indices as shown below.

```
print(type(haiti))
print(haiti.head(5))
```

```
class 'pandas.core.series.Series'
1980 1666
1981 3692
1982 3498
1983 2860
1984 1418
Name: Haiti, dtype: int64
```

Line plot is a handy tool to display several dependent variables against one independent variable. However, it is recommended that no more than 5-10 lines on a single graph; any more than that and it becomes difficult to interpret.

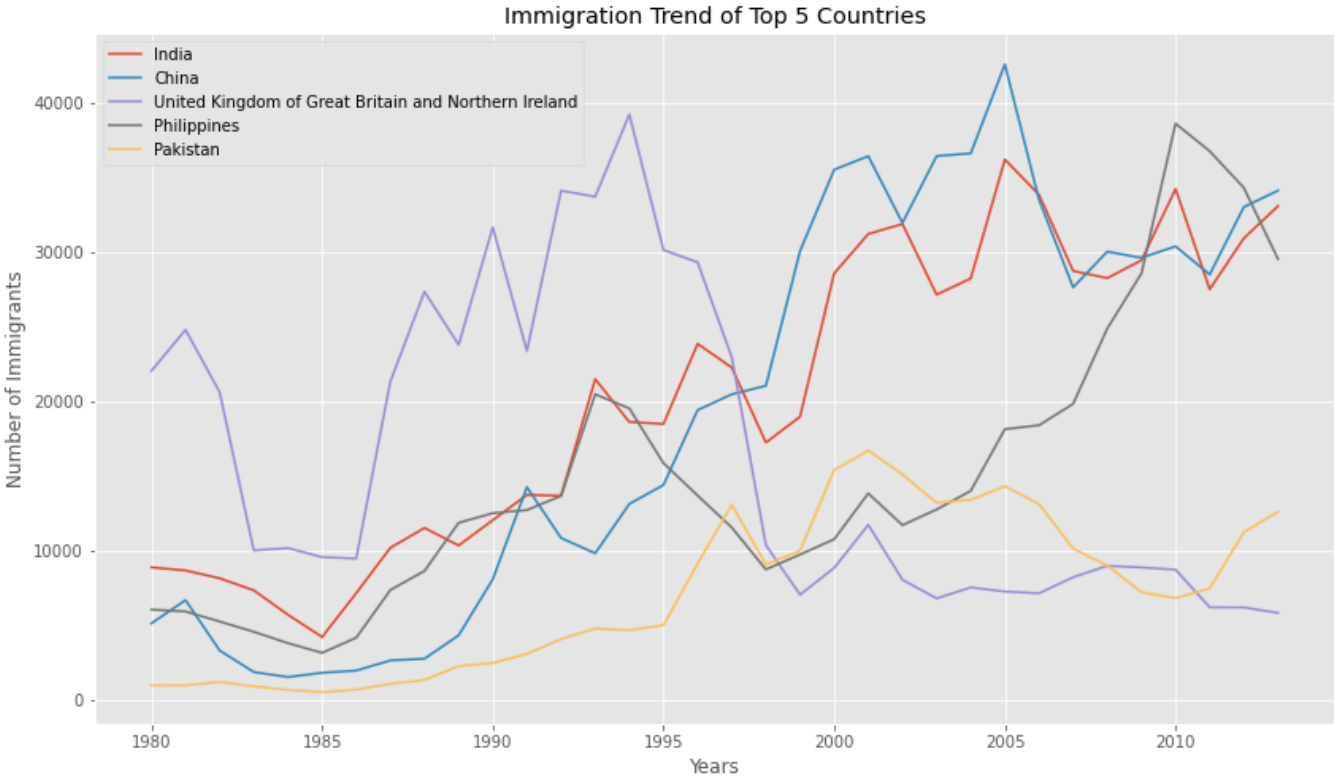
Question: Compare the trend of top 5 countries that contributed the most to immigration to Canada.

In [51]:

```
### type your answer here

  #The correct answer is:
    #Step 1: Get the dataset. Recall that we created a Total column that calculates cumulative immig
ration by country.
    #We will sort on this column to get our top 5 countries using pandas sort_values() method.

    inplace = True # paramemter saves the changes to the original df_can dataframe
    df_can.sort_values(by='Total', ascending=False, axis=0, inplace=True)

    # get the top 5 entries
    df_top5 = df_can.head(5)

    # transpose the dataframe
    df_top5 = df_top5[years].transpose()

    print(df_top5)


    #Step 2: Plot the dataframe. To make the plot more readeable, we will change the size using the
 `figsize` parameter.
    df_top5.index = df_top5.index.map(int) # let's change the index values of df_top5 to type intege
r for plotting
    df_top5.plot(kind='line', figsize=(14, 8)) # pass a tuple (x, y) size



    plt.title('Immigration Trend of Top 5 Countries')
    plt.ylabel('Number of Immigrants')
    plt.xlabel('Years')


    plt.show()
```

	India	China	United Kingdom of Great Britain and Northern Ireland	Philippines	Pakistan
1980	8880	5123	22045	6051	978
1981	8670	6682	24796	5921	972
1982	8147	3308	20620	5249	1201
1983	7338	1863	10015	4562	900
1984	5704	1527	10170	3801	668
1985	4211	1816	9564	3150	514
1986	7150	1960	9470	4166	691
1987	10189	2643	21337	7360	1072
1988	11522	2758	27359	8639	1334
1989	10343	4323	23795	11865	2261
1990	12041	8076	31668	12509	2470
1991	13734	14255	23380	12718	3079
1992	13673	10846	34123	13670	4071
1993	21496	9817	33720	20479	4777
1994	18620	13128	39231	19532	4666
1995	18489	14398	30145	15864	4994
1996	23859	19415	29322	13692	9125
1997	22268	20475	22965	11549	13073
1998	17241	21049	10367	8735	9068
1999	18974	30069	7045	9734	9979
2000	28572	35529	8840	10763	15400
2001	31223	36434	11728	13836	16708
2002	31889	31961	8046	11707	15110
2003	27155	36439	6797	12758	13205
2004	28235	36619	7533	14004	14845
2005	36210	42584	7258	11809	12381
2006	33848	33518	7140	8691	8270
2007	28742	27642	8216	7150	5291
2008	28261	30037	8979	10189	6520
2009	29456	29622	8876	10670	5026
2010	34235	30391	8724	10243	4676
2011	27509	28502	6204	7689	3802
2012	30933	33024	6195	9813	3467
2013	33087	34129	5827	11468	3977

```
2004        14004      13399
2005        18139      14314
2006        18400      13127
2007        19837      10124
2008        24887       8994
2009        28573       7217
2010        38617       6811
2011        36765       7468
2012        34315      11227
2013        29544      12603
```



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Other Plots

Congratulations! you have learned how to wrangle data with python and create a line plot with Matplotlib. There are many other plotting styles available other than the default Line plot, all of which can be accessed by passing `kind` keyword to `plot()`. The full list of available plots are as follows:

- `bar` for vertical bar plots
- `barh` for horizontal bar plots
- `hist` for histogram
- `box` for boxplot
- `kde` or `density` for density plots
- `area` for area plots
- `pie` for pie plots
- `scatter` for scatter plots
- `hexbin` for hexbin plot

Thank you for completing this lab!

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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2021-05-29	2.4	Weiqing Wang	Fixed typos and code smells.
2021-01-20	2.3	Lakshmi Holla	Changed TOC cell markdown
2020-11-20	2.2	Lakshmi Holla	Changed IBM box URL
2020-11-03	2.1	Lakshmi Holla	Changed URL and info method
2020-08-27	2.0	Lavanya	Moved Lab to course repo in GitLab

In [ ]: