(https://cognitiveclass.ai)

Introduction to Matplotlib and Line Plots

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* `read_excel()` method. Normally, before we can do that, we would need to download a module which *pandas* requires to read in excel files. This module is **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 **xlrd** module:

```
!conda install -c anaconda xlrd --yes
```

Now we are ready to read in our data.

In [2]:
```
df_can = pd.read_excel('https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/DV0101EN/labs/Data_Files/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 follow
s: df_can.head(10)
```

Out[3]:

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

5 rows × 43 columns

We can also veiw 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
190	Immigrants	Foreigners	Viet Nam	935	Asia	920	South-Eastern Asia	902	Developing regions
191	Immigrants	Foreigners	Western Sahara	903	Africa	912	Northern Africa	902	Developing regions
192	Immigrants	Foreigners	Yemen	935	Asia	922	Western Asia	902	Developing regions
193	Immigrants	Foreigners	Zambia	903	Africa	910	Eastern Africa	902	Developing regions
194	Immigrants	Foreigners	Zimbabwe	903	Africa	910	Eastern Africa	902	Developing regions

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.

In [11]:
```
df_can.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 43 columns):
Type        195 non-null object
Coverage    195 non-null object
OdName      195 non-null object
AREA        195 non-null int64
AreaName    195 non-null object
REG         195 non-null int64
RegName     195 non-null object
DEV         195 non-null int64
DevName     195 non-null object
1980        195 non-null int64
1981        195 non-null int64
1982        195 non-null int64
1983        195 non-null int64
1984        195 non-null int64
1985        195 non-null int64
1986        195 non-null int64
1987        195 non-null int64
1988        195 non-null int64
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2005        195 non-null int64
2006        195 non-null int64
2007        195 non-null int64
2008        195 non-null int64
2009        195 non-null int64
2010        195 non-null int64
2011        195 non-null int64
2012        195 non-null int64
2013        195 non-null int64
dtypes: int64(37), object(6)
memory usage: 65.6+ KB
```

To get the list of column headers we can call upon the dataframe's `.columns` parameter.

In [12]:
```
df_can.columns.values
```
df_can.columns: pandas.core.indexes.base.Index
df_can.columns.values: numpy.ndarray

Out[12]:
```
array(['Type', 'Coverage', 'OdName', 'AREA', 'AreaName', 'REG', 'RegN
ame',
       'DEV', 'DevName', 1980, 1981, 1982, 1983, 1984, 1985, 1986, 19
87,
       1988, 1989, 1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 19
98,
       1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 20
09,
       2010, 2011, 2012, 2013], dtype=object)
```

Similarly, to get the list of indicies we use the `.index` parameter.

In [13]:
```
df_can.index.values
```
numpy.ndarray

Out[13]:
```
array([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  1
2,
        13,  14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  2
5,
        26,  27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  3
8,
        39,  40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  5
1,
        52,  53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  6
4,
        65,  66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  7
7,
        78,  79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  9
0,
        91,  92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 10
3,
       104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 11
6,
       117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 12
9,
       130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 14
2,
       143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 15
5,
       156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 16
8,
       169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 18
1,
       182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 19
4])
```

Note: The default type of index and columns is NOT list.

In [14]:
```
print(type(df_can.columns))
print(type(df_can.index))
```

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

baseIndex or RangeIndex?

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

In [15]:
```
df_can.columns.tolist()
df_can.index.tolist()

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

df_can.columns.values
df_can.columns.tolist()

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

To view the dimensions of the dataframe, we use the `.shape` parameter.

In [16]:
```
# size of dataframe (rows, columns)
df_can.shape
```

Out[16]:
```
(195, 43)
```

Note: The main types stored in *pandas* objects are *float*, *int*, *bool*, *datetime64[ns]* and *datetime64[ns, tz] (in >= 0.17.0)*, *timedelta[ns]*, *category (in >= 0.15.0)*, 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:

drop columns

In [17]:
```
# 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[17]:

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

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:

column rename

In [18]:
```
df_can.rename(columns={'OdName':'Country', 'AreaName':'Continent', 'RegName':'Region'}, inplace=True)
df_can.columns
```

Out[18]:
```
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 [19]:
```
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 [20]:
```
df_can.isnull().sum()
```

Out[20]:
```
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 [21]:
```
df_can.describe()
```

Out[21]:

	1980	1981	1982	1983	1984	1985	
count	195.000000	195.000000	195.000000	195.000000	195.000000	195.000000	19
mean	508.394872	566.989744	534.723077	387.435897	376.497436	358.861538	4
std	1949.588546	2152.643752	1866.997511	1204.333597	1198.246371	1079.309600	12
min	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	
50%	13.000000	10.000000	11.000000	12.000000	13.000000	17.000000	1
75%	251.500000	295.500000	275.000000	173.000000	181.000000	197.000000	2
max	22045.000000	24796.000000	20620.000000	10015.000000	10170.000000	9564.000000	94

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').

df_can["Country"] same. Both are pandas.core.series.Series

In [22]:
```
df_can.Country.head()  # returns a series
```

Out[22]:
```
0         Afghanistan
1             Albania
2             Algeria
3      American Samoa
4             Andorra
Name: Country, dtype: object
```

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

In [23]:
```
df_can[['Country', 1980, 1981, 1982, 1983, 1984, 1985]].head() # retu
rns a dataframe
# notice that 'Country' is string, and the years are integers.
# for the sake of consistency, we will convert all column names to st
ring later on.
```

Out[23]:

	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

Select Row

There are main 3 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 defaul 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 corressponding index value.

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

In [24]:
```
df_can.set_index('Country', inplace=True)
# tip: The opposite of set is reset. So to reset the index, we can us
e df_can.reset_index()
```

In [25]:
```
df_can.head(3)
```

Out[25]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2(
Country												
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3‹
Albania	Europe	Southern Europe	Developed regions	1	0	0	0	0	0	1	...	1:
Algeria	Africa	Northern Africa	Developing regions	80	67	71	69	63	44	69	...	3(

3 rows × 38 columns

In [26]:
```
# 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 [32]:

```
# 1. the full row data (all columns)
print(df_can.loc['Japan'].head())
print("-------------------------")
# alternate methods
print(df_can.iloc[87].head())
print("-------------------------")
print(df_can[df_can.index == 'Japan'].T.squeeze().head())
```

```
Continent                 Asia
Region            Eastern Asia
DevName       Developed regions
1980                       701
1981                       756
Name: Japan, dtype: object
-------------------------
Continent                 Asia
Region            Eastern Asia
DevName       Developed regions
1980                       701
1981                       756
Name: Japan, dtype: object
-------------------------
Continent                 Asia
Region            Eastern Asia
DevName       Developed regions
1980                       701
1981                       756
Name: Japan, dtype: object
```

In [33]:

```
# 2. for year 2013   row      col
print(df_can.loc['Japan', 2013])

# alternate method
print(df_can.iloc[87, 36]) # year 2013 is the last column, with a pos
itional index of 36
```

```
982
982
```

In [34]:
```
# 3. for years 1980 to 1985
print(df_can.loc['Japan', [1980, 1981, 1982, 1983, 1984, 1984]])
print(df_can.iloc[87, [3, 4, 5, 6, 7, 8]])
```

```
1980    701
1981    756
1982    598
1983    309
1984    246
1984    246
Name: Japan, dtype: object
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 [35]:
```
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 [37]:
```
# useful for plotting later on
years = list(map(str, range(1980, 2014)))
years
```

Out[37]:
```
['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 [38]:
```
# 1. create the condition boolean series
condition = df_can['Continent'] == 'Asia'
print(condition.head())
```

```
Afghanistan        True
Albania           False
Algeria           False
American Samoa    False
Andorra           False
Name: Continent, dtype: bool
```

In [39]:

Filter certain rows

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

Out[39]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2(
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3
Armenia	Asia	Western Asia	Developing regions	0	0	0	0	0	0	0	...	
Azerbaijan	Asia	Western Asia	Developing regions	0	0	0	0	0	0	0	...	
Bahrain	Asia	Western Asia	Developing regions	0	2	1	1	1	3	0	...	
Bangladesh	Asia	Southern Asia	Developing regions	83	84	86	81	98	92	486	...	4

5 rows × 38 columns

In [40]:
```
# we can pass mutliple 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' 'or' operators, pandas requires we use '&' and '|' instead of 'and' and 'or'
# don't forget to enclose the two conditions in parentheses
```

Out[40]:

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

9 rows × 38 columns

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

In [41]:
```
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', '198
3',
       '1984', '1985', '1986', '1987', '1988', '1989', '1990', '199
1', '1992',
       '1993', '1994', '1995', '1996', '1997', '1998', '1999', '200
0', '2001',
       '2002', '2003', '2004', '2005', '2006', '2007', '2008', '200
9', '2010',
       '2011', '2012', '2013', 'Total'],
      dtype='object')
```

Out[41]:

	Continent	Region	DevName	1980	1981	1982	1983	1984	1985	1986	...	2(
Afghanistan	Asia	Southern Asia	Developing regions	16	39	39	47	71	340	496	...	3
Albania	Europe	Southern Europe	Developed regions	1	0	0	0	0	0	1	...	1:

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/)](http://matplotlib.org/). 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 [42]:
```
# we are using the inline backend
%matplotlib inline

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

*optional: check if Matplotlib is loaded.

In [43]:
```
print ('Matplotlib version: ', mpl.__version__) # >= 2.0.0
```

```
Matplotlib version:  3.1.0
```

*optional: apply a style to Matplotlib.

In [44]:
```
print(plt.style.available)
mpl.style.use(['ggplot']) # optional: for ggplot-like style
```

```
['seaborn-dark-palette', 'seaborn-white', 'seaborn-poster', 'seaborn-
dark', 'fast', 'dark_background', 'seaborn-colorblind', 'seaborn-tal
k', 'tableau-colorblind10', 'seaborn-deep', 'seaborn-darkgrid', 'seab
orn-paper', 'seaborn-pastel', 'seaborn-muted', 'seaborn', 'Solarize_L
ight2', 'seaborn-whitegrid', 'bmh', 'seaborn-bright', 'classic', '_cl
assic_test', 'grayscale', 'ggplot', 'fivethirtyeight', 'seaborn-noteb
ook', 'seaborn-ticks']
```

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#plotting)](http://pandas.pydata.org/pandas-docs/stable/api.html#plotting)
- [Plotting with Dataframes (http://pandas.pydata.org/pandas-docs/stable/api.html#api-dataframe-plotting)](http://pandas.pydata.org/pandas-docs/stable/api.html#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.

years = list(map(str, range(1980, 2014)))

haiti: Series

haiti.shape: (34,)

In [45]:
```
haiti = df_can.loc['Haiti', years] # passing in years 1980 - 2013 to
 exclude the 'total' column
haiti.head()
```

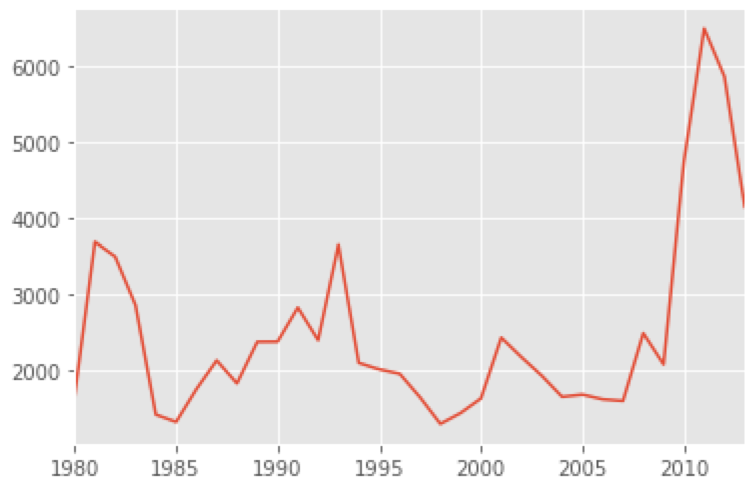
Out[45]:
```
1980    1666
1981    3692
1982    3498
1983    2860
1984    1418
Name: Haiti, dtype: object
```

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

Series.plot()

In [46]:
```
haiti.plot()
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd076bb1438>

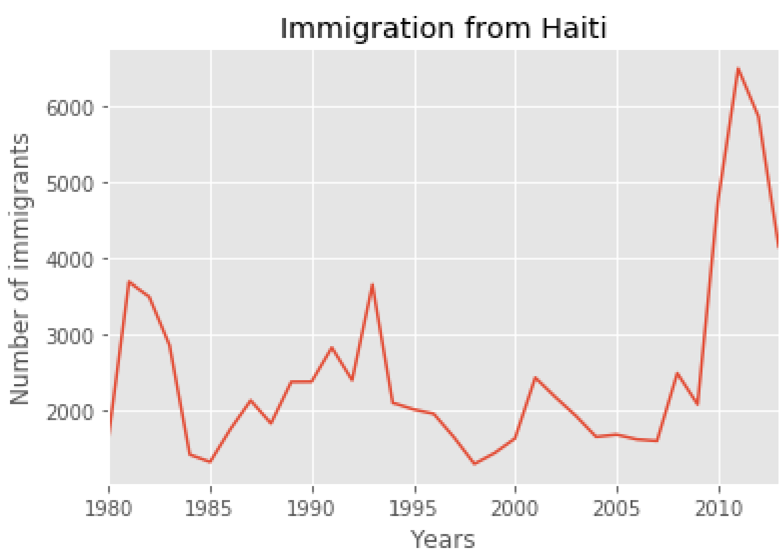


pandas automatically populated the x-axis with the index values (years), and the y-axis with the column values (population). However, notice how the years were not displayed because they are of type *string*. Therefore, let's change the type of the index values to *integer* for plotting.

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

make index int instead str

In [47]:
```
haiti.index = haiti.index.map(int) # let's change the index values of Haiti to type integer for plotting
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
```

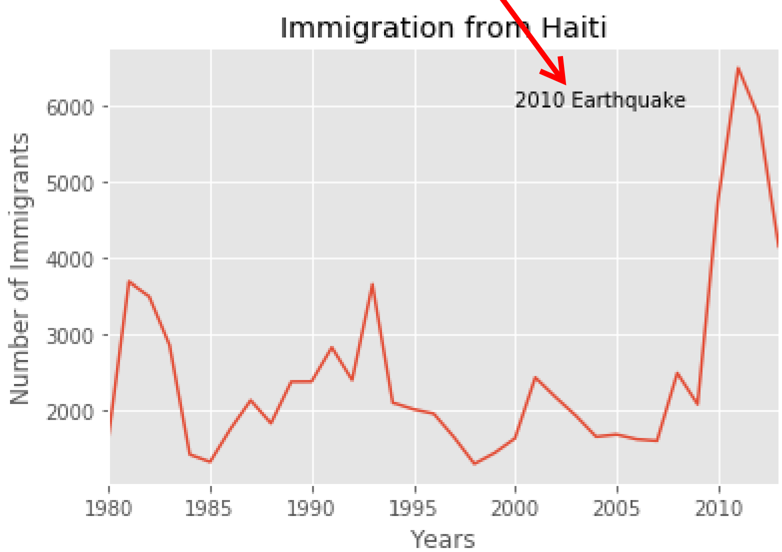


We can clearly notice how number of immigrants from Haiti spiked up from 2010 as Canada stepped up its efforts to accept refugees from Haiti. Let's annotate this spike in the plot by using the `plt.text()` method.

Series.plot(kind='line')

plt define title, xlabel ylabel

In [48]:
```
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 va
lue 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 of 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 dataframe.

Single:
haiti=df_can.loc['Haiti', years]
haiti is series

In [49]:

df_CI: DataFrame

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

Out[49]:

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	...	2004	2005	20
India	8880	8670	8147	7338	5704	4211	7150	10189	11522	10343	...	28235	36210	338
China	5123	6682	3308	1863	1527	1816	1960	2643	2758	4323	...	36619	42584	335

2 rows × 34 columns

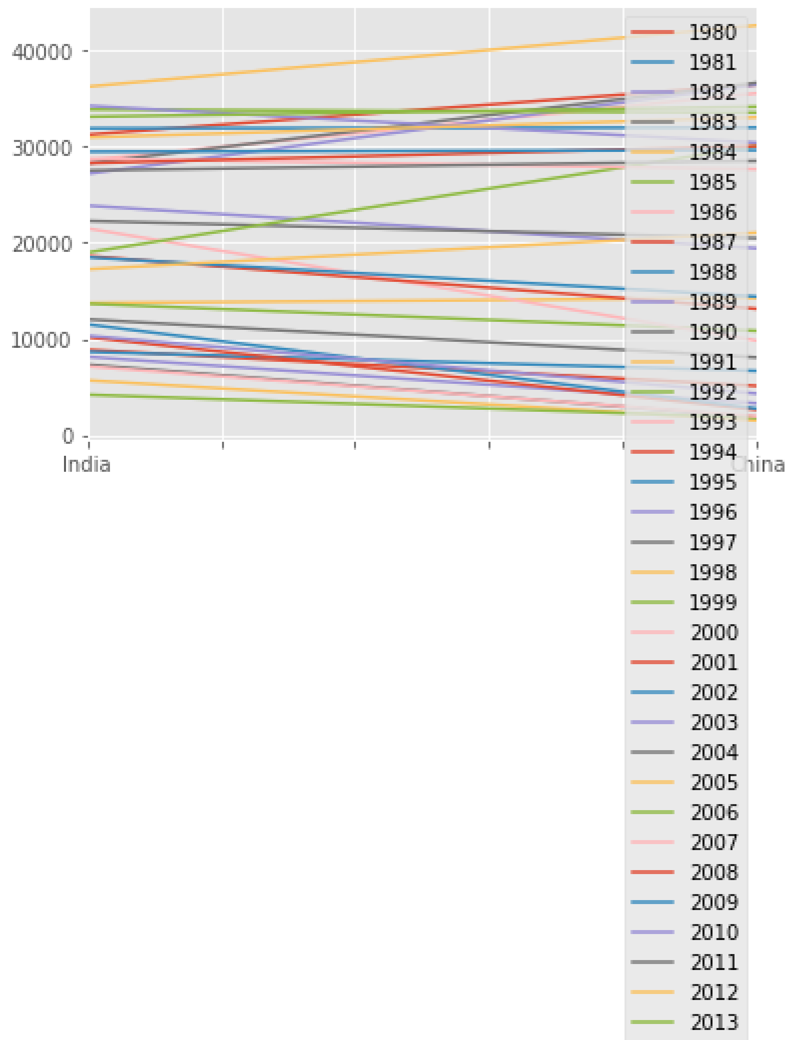
Double-click **here** for the solution.

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

In [50]:
DataFrame.plot

```
### type your answer here

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

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd075cc9710>



Double-click **here** for the solution.

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 [51]:
```
df_CI = df_CI.transpose()
df_CI.head()
```

It is different from Series

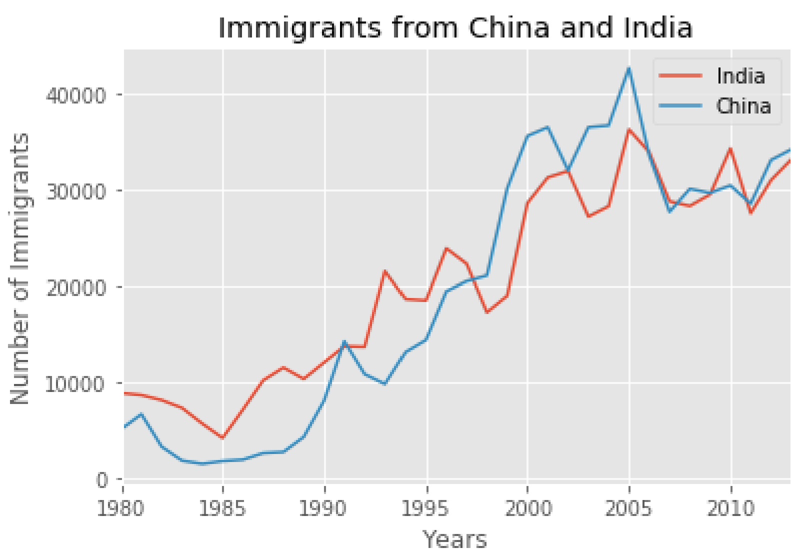
x: rows
y: columns

Out[51]:

	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 [52]:
```
### 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()
```



Double-click **here** for the solution.

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
```

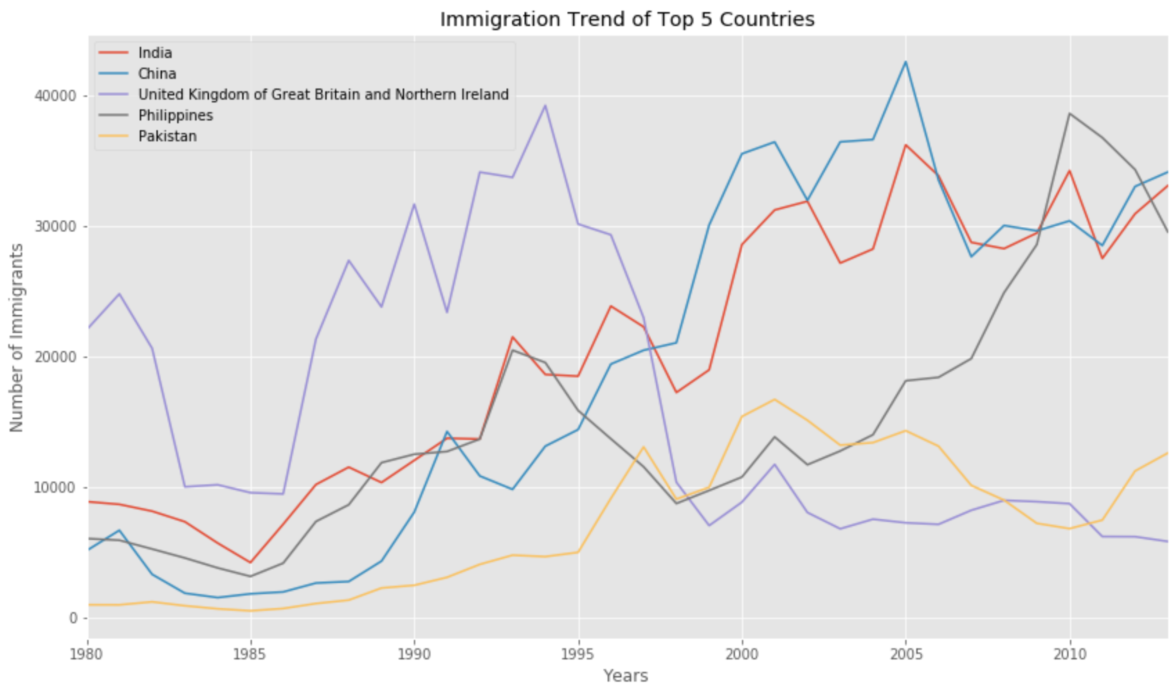
Line plot is a handy tool to display several dependent variables against one independent variable. However, it is recommended that no more than 5-10 lines on a single graph; any more than that and it becomes difficult to interpret.

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

In [53]:
```
### type your answer here

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)


df_top5.index = df_top5.index.map(int) # let's change the index value
s of df_top5 to type integer 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 Irel
and  \
1980   8880   5123                                              22045
1981   8670   6682                                              24796
1982   8147   3308                                              20620
1983   7338   1863                                              10015
1984   5704   1527                                              10170
1985   4211   1816                                               9564
1986   7150   1960                                               9470
1987  10189   2643                                              21337
1988  11522   2758                                              27359
1989  10343   4323                                              23795
1990  12041   8076                                              31668
1991  13734  14255                                              23380
1992  13673  10846                                              34123
1993  21496   9817                                              33720
1994  18620  13128                                              39231
1995  18489  14398                                              30145
1996  23859  19415                                              29322
1997  22268  20475                                              22965
1998  17241  21049                                              10367
1999  18974  30069                                               7045
2000  28572  35529                                               8840
2001  31223  36434                                              11728
2002  31889  31961                                               8046
2003  27155  36439                                               6797
2004  28235  36619                                               7533
2005  36210  42584                                               7258
2006  33848  33518                                               7140
2007  28742  27642                                               8216
2008  28261  30037                                               8979
2009  29456  29622                                               8876
2010  34235  30391                                               8724
2011  27509  28502                                               6204
2012  30933  33024                                               6195
2013  33087  34129                                               5827

      Philippines  Pakistan
1980         6051       978
1981         5921       972
1982         5249      1201
1983         4562       900
1984         3801       668
1985         3150       514
1986         4166       691
1987         7360      1072
1988         8639      1334
1989        11865      2261
1990        12509      2470
1991        12718      3079
1992        13670      4071
1993        20479      4777
1994        19532      4666
1995        15864      4994
1996        13692      9125
1997        11549     13073
1998         8735      9068
```

```
1999         9734      9979
2000        10763     15400
2001        13836     16708
2002        11707     15110
2003        12758     13205
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
```



Double-click **here** for the solution.

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!

This notebook was originally created by [Jay Rajasekharan (https://www.linkedin.com/in/jayrajasekharan)] with contributions from [Ehsan M. Kermani (https://www.linkedin.com/in/ehsanmkermani)], and [Slobodan Markovic (https://www.linkedin.com/in/slobodan-markovic)].

This notebook was recently revised by [Alex Aklson (https://www.linkedin.com/in/aklson/)]. I hope you found this lab session interesting. Feel free to contact me if you have any questions!

This notebook is part of a course on **Coursera** called *Data Visualization with Python*. If you accessed this notebook outside the course, you can take this course online by clicking [here (http://cocl.us/DV0101EN_Coursera_Week1_LAB1)].

```
In [ ]:
```