

Time Methods

Python Datetime Review

Basic Python outside of Pandas contains a datetime library:

In [1]:

```
import numpy as np
import pandas as pd
from datetime import datetime
```

In [4]:

```
# To illustrate the order of arguments
my_year = 2017
my_month = 1
my_day = 2
my_hour = 13
my_minute = 30
my_second = 15
```

In [5]:

```
# January 2nd, 2017
my_date = datetime(my_year, my_month, my_day)
```

In [6]:

```
# Defaults to 0:00
my_date
```

Out[6]:

```
datetime.datetime(2017, 1, 2, 0, 0)
```

In [8]:

```
# January 2nd, 2017 at 13:30:15
my_date_time = datetime(my_year, my_month, my_day, my_hour, my_minute, my_second)
my_date_time
```

Out[8]:

```
datetime.datetime(2017, 1, 2, 13, 30, 15)
```

You can grab any part of the datetime object you want

In [9]:

```
my_date.year
```

Out[9]:

```
2017
```

In [12]:

```
my_date_time.hour
```

Out[12]:

```
13
```

Pandas

Pandas

Converting to datetime

Often when data sets are stored, the time component may be a string. Pandas easily converts strings to datetime objects.

In [13]:

```
myser = pd.Series(['Nov 3, 2000', '2000-01-01', None])
```

In [14]:

```
myser
```

Out[14]:

```
0    Nov 3, 2000
1    2000-01-01
2             None
dtype: object
```

In [16]:

```
myser[0]
```

Out[16]:

```
'Nov 3, 2000'
```

pd.to_datetime()

https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#converting-to-timestamps

In [18]:

```
pd.to_datetime(myser)
```

Out[18]:

```
0    2000-11-03
1    2000-01-01
2             NaT
dtype: datetime64[ns]
```

In [19]:

```
pd.to_datetime(myser)[0]
```

Out[19]:

```
Timestamp('2000-11-03 00:00:00')
```

In [20]:

```
# Here we mention time that have 31 as date so python can easily understand which one is date and which one is month
obvi_euro_date = '31-12-2000'
```

In [21]:

```
pd.to_datetime(obvi_euro_date)
```

```
C:\Users\Chromsy\AppData\Local\Temp\ipykernel_2436\163700324.py:1: UserWarning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the default) was specified. This may lead to inconsistently parsed dates! Specify a format to ensure consistent parsing.
  pd.to_datetime(obvi_euro_date)
```

Out[21]:

```
Timestamp('2000-12-31 00:00:00')
```

In [22]:

```
# 10th of Dec OR 12th of October?  
# We may need to tell pandas  
euro_date = '10-12-2000'
```

In [24]:

```
pd.to_datetime(euro_date) # Here python made a guess but we can fix that if not correct
```

Out[24]:

```
Timestamp('2000-10-12 00:00:00')
```

In [26]:

```
pd.to_datetime(euro_date, dayfirst=True) # Here we set day is first
```

Out[26]:

```
Timestamp('2000-12-10 00:00:00')
```

Custom Time String Formatting

Sometimes dates can have a non standard format, luckily you can always specify to pandas the format. You should also note this could speed up the conversion, so it may be worth doing even if pandas can parse on its own.

A full table of codes can be found here: <https://docs.python.org/3/library/datetime.html#strptime-and-strptime-format-codes>

In [28]:

```
style_date = '12--Dec--2000' # Here date in random style
```

In [29]:

```
pd.to_datetime(style_date, format='%d--%b--%Y') # check above link to know these codes
```

Out[29]:

```
Timestamp('2000-12-12 00:00:00')
```

In [30]:

```
strange_date = '12th of Dec 2000'
```

In [32]:

```
pd.to_datetime(strange_date) # It can understand by its own
```

Out[32]:

```
Timestamp('2000-12-12 00:00:00')
```

Data

Retail Sales: Beer, Wine, and Liquor Stores

Units: Millions of Dollars, Not Seasonally Adjusted

Frequency: Monthly

U.S. Census Bureau, Retail Sales: Beer, Wine, and Liquor Stores [MRTSSM4453USN], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/MRTSSM4453USN>, July 2, 2020.

```
In [34]:
```

```
sales = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Com] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\RetailSales_BeerWineLiquor.csv")
```

```
In [35]:
```

```
sales
```

```
Out[35]:
```

| | DATE | MRTSSM4453USN |
|-----|------------|---------------|
| 0 | 1992-01-01 | 1509 |
| 1 | 1992-02-01 | 1541 |
| 2 | 1992-03-01 | 1597 |
| 3 | 1992-04-01 | 1675 |
| 4 | 1992-05-01 | 1822 |
| ... | ... | ... |
| 335 | 2019-12-01 | 6630 |
| 336 | 2020-01-01 | 4388 |
| 337 | 2020-02-01 | 4533 |
| 338 | 2020-03-01 | 5562 |
| 339 | 2020-04-01 | 5207 |

340 rows × 2 columns

```
In [36]:
```

```
sales.iloc[0]['DATE']
```

```
Out[36]:
```

```
'1992-01-01'
```

```
In [39]:
```

```
type(sales.iloc[0]['DATE']) # Here we see that dates are in strings
```

```
Out[39]:
```

```
str
```

```
In [40]:
```

```
sales['DATE'] = pd.to_datetime(sales['DATE'])
```

```
In [41]:
```

```
sales
```

```
Out[41]:
```

| | DATE | MRTSSM4453USN |
|-----|------------|---------------|
| 0 | 1992-01-01 | 1509 |
| 1 | 1992-02-01 | 1541 |
| 2 | 1992-03-01 | 1597 |
| 3 | 1992-04-01 | 1675 |
| 4 | 1992-05-01 | 1822 |
| ... | ... | ... |
| 335 | 2019-12-01 | 6630 |

| | DATE | MRTSSM4453USN |
|-----|------------|---------------|
| 336 | 2020-01-01 | 4388 |
| 337 | 2020-02-01 | 4533 |
| 338 | 2020-03-01 | 5562 |
| 339 | 2020-04-01 | 5207 |

340 rows x 2 columns

In [42]:

```
sales.iloc[0]['DATE']
```

Out[42]:

```
Timestamp('1992-01-01 00:00:00')
```

In [43]:

```
type(sales.iloc[0]['DATE'])
```

Out[43]:

```
pandas._libs.tslibs.timestamps.Timestamp
```

Attempt to Parse Dates Automatically

parse_dates - bool or list of int or names or list of lists or dict, default False The behavior is as follows:

boolean. If True -> try parsing the index.

list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.

list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.

dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index cannot be represented as an array of datetimes, say because of an unparseable value or a mixture of timezones, the column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`. To parse an index or column with a mixture of timezones, specify `date_parser` to be a partially-applied `pandas.to_datetime()` with `utc=True`. See Parsing a CSV with mixed timezones for more.

In [45]:

```
# Parse Column at Index 0 as Datetime
sales = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Com] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\RetailSales_BeerWineLiquor.csv", parse_dates=[0])
```

In [46]:

```
sales
```

Out[46]:

| | DATE | MRTSSM4453USN |
|---|------------|---------------|
| 0 | 1992-01-01 | 1509 |
| 1 | 1992-02-01 | 1541 |
| 2 | 1992-03-01 | 1597 |

| | DATE | MRTSSM4453USN |
|-----|------------|---------------|
| 3 | 1992-04-01 | 1675 |
| 4 | 1992-05-01 | 1822 |
| ... | ... | ... |
| 335 | 2019-12-01 | 6630 |
| 336 | 2020-01-01 | 4388 |
| 337 | 2020-02-01 | 4533 |
| 338 | 2020-03-01 | 5562 |
| 339 | 2020-04-01 | 5207 |

340 rows × 2 columns

In [47]:

```
type(sales.iloc[0]['DATE'])
```

Out[47]:

```
pandas._libs.tslibs.timestamps.Timestamp
```

Resample

A common operation with time series data is resampling based on the time series index. Let's see how to use the `resample()` method. [\[reference\]](#)

In [49]:

```
# Our index
sales.index
```

Out[49]:

```
RangeIndex(start=0, stop=340, step=1)
```

In [50]:

```
# Reset DATE to index
sales = sales.set_index('DATE')
```

In [51]:

```
sales
```

Out[51]:

| | MRTSSM4453USN |
|------------|---------------|
| DATE | |
| 1992-01-01 | 1509 |
| 1992-02-01 | 1541 |
| 1992-03-01 | 1597 |
| 1992-04-01 | 1675 |
| 1992-05-01 | 1822 |
| ... | ... |
| 2019-12-01 | 6630 |
| 2020-01-01 | 4388 |
| 2020-02-01 | 4533 |
| 2020-03-01 | 5562 |
| 2020-04-01 | 5207 |

When calling `.resample()` you first need to pass in a **rule** parameter, then you need to call some sort of aggregation function.

The **rule** parameter describes the frequency with which to apply the aggregation function (daily, monthly, yearly, etc.)

It is passed in using an "offset alias" - refer to the table below. [\[reference\]](#)

The aggregation function is needed because, due to resampling, we need some sort of mathematical rule to join the rows (mean, sum, count, etc.)

| TIME SERIES OFFSET ALIASES | | | |
|----------------------------|--|--|--|
| ALIAS | | DESCRIPTION | |
| B | | business day frequency | |
| C | | custom business day frequency (experimental) | |
| D | | calendar day frequency | |
| W | | weekly frequency | |
| M | | month end frequency | |
| SM | | semi-month end frequency (15th and end of month) | |
| BM | | business month end frequency | |
| CBM | | custom business month end frequency | |
| MS | | month start frequency | |
| SMS | | semi-month start frequency (1st and 15th) | |
| BMS | | business month start frequency | |
| CBMS | | custom business month start frequency | |
| Q | | quarter end frequency | |
| | | intentionally left blank | |
| ALIAS | | DESCRIPTION | |
| BQ | | business quarter endfrequency | |
| QS | | quarter start frequency | |
| BQS | | business quarter start frequency | |
| A | | year end frequency | |
| BA | | business year end frequency | |
| AS | | year start frequency | |
| BAS | | business year start frequency | |
| BH | | business hour frequency | |
| H | | hourly frequency | |
| T, min | | minutely frequency | |
| S | | secondly frequency | |
| L, ms | | milliseconds | |
| U, us | | microseconds | |
| N | | nanoseconds | |

In [53]:

```
# Yearly Means # Here ruel A can see in above list
sales.resample(rule='A').mean()
```

Out[53]:

| MRTSSM4453USN | |
|---------------|-------------|
| DATE | |
| 1992-12-31 | 1807.250000 |
| 1993-12-31 | 1794.833333 |
| 1994-12-31 | 1841.750000 |
| 1995-12-31 | 1833.916667 |
| 1996-12-31 | 1929.750000 |
| 1997-12-31 | 2006.750000 |
| 1998-12-31 | 2115.166667 |
| 1999-12-31 | 2206.333333 |
| 2000-12-31 | 2375.583333 |
| 2001-12-31 | 2468.416667 |
| 2002-12-31 | 2491.166667 |
| 2003-12-31 | 2539.083333 |

| DATE | MRTSSM4453USN |
|------------|---------------|
| 2004-12-31 | 2682.416667 |
| 2005-12-31 | 2797.250000 |
| 2006-12-31 | 3001.333333 |
| 2007-12-31 | 3177.333333 |
| 2008-12-31 | 3292.000000 |
| 2009-12-31 | 3353.750000 |
| 2010-12-31 | 3450.083333 |
| 2011-12-31 | 3532.666667 |
| 2012-12-31 | 3697.083333 |
| 2013-12-31 | 3839.666667 |
| 2014-12-31 | 4023.833333 |
| 2015-12-31 | 4212.500000 |
| 2016-12-31 | 4434.416667 |
| 2017-12-31 | 4602.666667 |
| 2018-12-31 | 4830.666667 |
| 2019-12-31 | 4972.750000 |
| 2020-12-31 | 4922.500000 |

Resampling rule 'A' takes all of the data points in a given year, applies the aggregation function (in this case we calculate the mean), and reports the result as the last day of that year. Note 2020 in this data set was not complete.

.dt Method Calls

Once a column or index is in a datetime format, you can call a variety of methods off of the .dt library inside pandas:

<https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.dt.html>

In [55]:

```
sales = sales.reset_index()
sales
```

Out[55]:

| | index | DATE | MRTSSM4453USN |
|-----|-------|------------|---------------|
| 0 | 0 | 1992-01-01 | 1509 |
| 1 | 1 | 1992-02-01 | 1541 |
| 2 | 2 | 1992-03-01 | 1597 |
| 3 | 3 | 1992-04-01 | 1675 |
| 4 | 4 | 1992-05-01 | 1822 |
| ... | ... | ... | ... |
| 335 | 335 | 2019-12-01 | 6630 |
| 336 | 336 | 2020-01-01 | 4388 |
| 337 | 337 | 2020-02-01 | 4533 |
| 338 | 338 | 2020-03-01 | 5562 |
| 339 | 339 | 2020-04-01 | 5207 |

340 rows x 3 columns

In [56]:

```
help(sales['DATE'].dt)
```

In [57]:

```
sales['DATE'].dt.month
```

Out[57]:

```
0      1
1      2
2      3
3      4
4      5
..
335    12
336     1
337     2
338     3
339     4
Name: DATE, Length: 340, dtype: int64
```

In [58]:

```
sales['DATE'].dt.is_leap_year
```

Out[58]:

```
0      True
1      True
2      True
3      True
4      True
...
335  False
336   True
337   True
338   True
339   True
Name: DATE, Length: 340, dtype: bool
```

Inputs and Outputs

NOTE: Typically we will just be either reading csv files directly or using pandas-datareader to pull data from the web. Consider this lecture just a quick overview of what is possible with pandas (we won't be working with SQL or Excel files in this course)

Data Input and Output

This notebook is the reference code for getting input and output, pandas can read a variety of file types using its `pd.read_` methods. Let's take a look at the most common data types:

Check out the references here!

This is the best online resource for how to read/write to a variety of data sources!

https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html

| Format Type | Data Description | Reader | Writer |
|-------------|--------------------------------------|--------------------------------|------------------------------|
| text | CSV | read_csv | to_csv |
| text | JSON | read_json | to_json |
| text | HTML | read_html | to_html |
| text | Local clipboard | read_clipboard | to_clipboard |
| binary | MS Excel | read_excel | to_excel |
| binary | OpenDocument | read_excel | |
| binary | HDF5 Format | read_hdf | to_hdf |
| binary | Feather Format | read_feather | to_feather |
| binary | Parquet Format | read_parquet | to_parquet |
| binary | Msgpack | read_msgpack | to_msgpack |
| binary | Stata | read_stata | to_stata |
| binary | SAS | read_sas | |
| binary | Python Pickle Format | read_pickle | to_pickle |
| SQL | SQL | read_sql | to_sql |
| SQL | Google Big Query | read_gbq | to_gbq |

Reading in a CSV

Comma Separated Values files are text files that use commas as field delimiters.

Unless you're running the virtual environment included with the course, you may need to install `xlrd` and `openpyxl`.

In your terminal/command prompt run:

```
conda install xlrd
conda install openpyxl
```

Then restart Jupyter Notebook. (or use `pip install` if you aren't using the Anaconda Distribution)

Understanding File Paths

You have two options when reading a file with pandas:

1. If your `.py` file or `.ipynb` notebook is located in the **exact** same folder location as the `.csv` file you want to read, simply pass in the file name as a string, for example:

```
df = pd.read_csv('some_file.csv')
```

2. Pass in the entire file path if you are located in a different directory. The file path must be 100% correct in order for this to work. For example:

```
df = pd.read_csv("C:\\Users\\myself\\files\\some_file.csv")
```

Print your current directory file path with `pwd`

In [60]:

```
pwd
```

```
Out[60]:
```

```
'C:\\Users\\Chromsy'
```

List the files in your current directory with ls

```
In [61]:
```

```
ls
```

```
Volume in drive C has no label.  
Volume Serial Number is 246B-60C4
```

```
Directory of C:\\Users\\Chromsy
```

```
24-12-2022  01:08    <DIR>          .  
24-12-2022  01:08    <DIR>          ..  
24-12-2022  01:09    <DIR>          .conda  
11-12-2022  12:41                25 .condarc  
11-12-2022  12:41    <DIR>          .continuum  
23-12-2022  23:22    <DIR>          .ipynb_checkpoints  
11-12-2022  20:21    <DIR>          .ipython  
11-12-2022  12:40    <DIR>          .jupyter  
28-11-2022  20:19    <DIR>          .skiko  
30-04-2022  21:57                6,881 -1.14-windows.xml  
30-04-2022  14:42    <DIR>          3D Objects  
30-04-2022  14:42    <DIR>          Contacts  
12-12-2022  20:50    <DIR>          Desktop  
04-12-2022  02:23    <DIR>          Documents  
24-12-2022  01:06    <DIR>          Downloads  
13-12-2022  13:30                29,705 Downloads.ipynb  
30-04-2022  14:42    <DIR>          Favorites  
30-04-2022  14:42    <DIR>          Links  
30-04-2022  14:42    <DIR>          Music  
14-12-2022  17:09                43,279 NumPy.ipynb  
30-04-2022  14:46    <DIR>          OneDrive  
24-12-2022  01:08                52,082 Pandas Input and Output.ipynb  
22-12-2022  00:44                72,444 Pandas Combining DataFrames , Text Methods.ipynb  
19-12-2022  02:04                252,099 Pandas Conditional Formatting ,Useful methods.ipynb  
21-12-2022  01:09                249,801 Pandas Missing values, Groupby Operations and Multi-l  
evel Index.ipynb  
16-12-2022  19:03                169,112 Pandas Series and dataframe.ipynb  
20-12-2022  18:47    <DIR>          Pictures  
30-04-2022  14:42    <DIR>          Saved Games  
30-04-2022  14:44    <DIR>          Searches  
13-12-2022  01:16                18,752 tips.csv  
29-05-2022  16:20    <DIR>          Tracing  
13-12-2022  01:17                29,705 U Basics.ipynb  
09-05-2022  11:55    <DIR>          Videos  
                11 File(s)          923,885 bytes  
                22 Dir(s)    1,960,468,480 bytes free
```

NOTE! Common confusion point! Take note that all read input methods are called directly from pandas with `pd.read` , all output methods are called directly off the dataframe with `df.to`

CSV Input

```
In [63]:
```

```
df= pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Com]  
] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction  
to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\example.csv")  
df
```

Out [63]:

| | a | b | c | d |
|---|----|----|----|----|
| 0 | 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 | 7 |
| 2 | 8 | 9 | 10 | 11 |
| 3 | 12 | 13 | 14 | 15 |

In [68]:

```
df = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Co  
m] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction  
to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\example.csv"  
,header=None)  
df # Here we remove as a b c d as headers now this Dataframe donr have any header
```

Out [68]:

| | 0 | 1 | 2 | 3 |
|---|----|----|----|----|
| 0 | a | b | c | d |
| 1 | 0 | 1 | 2 | 3 |
| 2 | 4 | 5 | 6 | 7 |
| 3 | 8 | 9 | 10 | 11 |
| 4 | 12 | 13 | 14 | 15 |

In [69]:

```
df = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Co  
m] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction  
to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\example.csv"  
,index_col=0)  
df # Here we set index as 0 column we cansue it by set by set_index(df['a'])
```

Out [69]:

| | b | c | d |
|----|----|----|----|
| a | | | |
| 0 | 1 | 2 | 3 |
| 4 | 5 | 6 | 7 |
| 8 | 9 | 10 | 11 |
| 12 | 13 | 14 | 15 |

CSV Output

Set index=False if you do not want to save the index , otherwise it will add a new columnn to the .csv file that includes your index and call it "Unnamed: 0" if your index did not have a name. If you do want to save your index, simply set it to True (the default value).

In [71]:

```
df.to_csv('D:\\Study\\new_file.csv') # Here we have write file as well with formate
```

In [72]:

```
df.to_csv('D:\\Study\\new_file.csv',index=False) # Here we have write file as well with f  
ormate , Here index is false means  
# it would not take any extra columns f  
or index
```

HTML

Pandas can read table tabs off of HTML. This only works if your firewall isn't blocking pandas from accessing the internet!

Unless you're running the virtual environment included with the course, you may need to install `lxml`, `html5lib`, and `BeautifulSoup4`.

In your terminal/command prompt run:

```
conda install lxml
```

or

```
pip install lxml
```

Then restart Jupyter Notebook (you may need to restart your computer). (or use `pip install` if you aren't using the Anaconda Distribution)

In [2]:

```
url = "https://en.wikipedia.org/wiki/World_population"
```

In [5]:

```
tables = pd.read_html(url) # here it shows all tables from the page
tables
```

Out[5]:

```
[      Population      1      2      3      4      5      6      7      8      9  \
0      Year      1804      1930      1960      1974      1987      1999      2011      2022      2037
1  Years elapsed  200,000+      126      30      14      13      12      12      11      15
```

```
      10
0  2057
1  20 ,
```

```
      #  \
0      1
1      2
2      3
3      4
4      5
5      6
6      7
7      8
8      9
9     10
10    NaN
11  Notes: .mw-parser-output .reflist{font-size:90...
```

```
      Most populous countries  \
0      China[B]
1      India
2      United States
3      Indonesia
4      Pakistan
5      Brazil
6      Nigeria
7      Bangladesh
8      Russia
9      Mexico
10     World total
11  Notes: .mw-parser-output .reflist{font-size:90...
```

```
      2000  \
0     1270
1     1053
~     ~~~
```

```

2      283
3      212
4      136
5      176
6      123
7      131
8      146
9      103
10     6127
11 Notes: .mw-parser-output .reflist{font-size:90...

```

```

2015 \
0      1376
1      1311
2      322
3      258
4      208
5      206
6      182
7      161
8      146
9      127
10     7349
11 Notes: .mw-parser-output .reflist{font-size:90...

```

```

2030[A]
0      1416
1      1528
2      356
3      295
4      245
5      228
6      263
7      186
8      149
9      148
10     8501
11 Notes: .mw-parser-output .reflist{font-size:90... ,

```

| | Region | Density(inhabitants/km2) | Population(millions) | \ |
|---|-----------------------------------|--------------------------|----------------------|---|
| 0 | Asia | 104.1 | 4641 | |
| 1 | Africa | 44.4 | 1340 | |
| 2 | Europe | 73.4 | 747 | |
| 3 | Latin America | 24.1 | 653 | |
| 4 | Northern America[<i>note 2</i>] | 14.9 | 368 | |
| 5 | Oceania | 5 | 42 | |
| 6 | Antarctica | ~0 | 0.004[<i>91</i>] | |

```

Most populous country \
0      1,411,778,000 - China[note 1]
1      0,211,401,000 - Nigeria
2      0,146,171,000 - Russia, approx. 110 million in...
3      0,214,103,000 - Brazil
4      0,332,909,000 - United States
5      0,025,917,000 - Australia
6      N/A[note 3]

```

```

Most populous city (metropolitan area)
0      13,515,000 - Tokyo Metropolis(37,400,000 - Gre...
1      09,500,000 - Cairo(20,076,000 - Greater Cairo)
2      13,200,000 - Moscow(20,004,000 - Moscow metrop...
3      12,252,000 - São Paulo City(21,650,000 - São P...
4      08,804,000 - New York City(23,582,649 - New Yo...
5      05,367,000 - Sydney
6      00,001,258 - McMurdo Station ,

```

| | Rank | Country / Dependency | Population | Percentage of the world | \ |
|---|------|----------------------|------------|-------------------------|---|
| 0 | 1 | China | 1412600000 | NaN | |
| 1 | 2 | India | 1373761000 | NaN | |
| 2 | 3 | United States | 333472984 | NaN | |
| 3 | 4 | Indonesia | 275773800 | NaN | |
| 4 | 5 | Pakistan | 229488994 | NaN | |
| 5 | 6 | Nigeria | 216746934 | NaN | |
| 6 | 7 | Brazil | 215552699 | NaN | |

| | | | | |
|---|----|------------|-----------|-----|
| 7 | 8 | Bangladesh | 168220000 | NaN |
| 8 | 9 | Russia | 147190000 | NaN |
| 9 | 10 | Mexico | 128271248 | NaN |

| | | |
|---|-------------|---|
| | | Date Source (official or from the United Nations) |
| 0 | 31 Dec 2021 | National annual estimate[93] |
| 1 | 1 Mar 2022 | Annual national estimate[94] |
| 2 | 23 Dec 2022 | National population clock[95] |
| 3 | 1 Jul 2022 | National annual estimate[96] |
| 4 | 1 Jul 2022 | UN projection[97] |
| 5 | 1 Jul 2022 | UN projection[97] |
| 6 | 23 Dec 2022 | National population clock[98] |
| 7 | 1 Jul 2020 | Annual Population Estimate[99] |
| 8 | 1 Oct 2021 | 2021 preliminary census results[100] |
| 9 | 31 Mar 2022 | National quarterly estimate[101] |

| | Rank | Country | Population | Area (km2) | Density (pop/km2) |
|---|------|----------------|------------|------------|-------------------|
| 0 | 1 | Singapore | 5921231 | 719 | 8235 |
| 1 | 2 | Bangladesh | 165650475 | 148460 | 1116 |
| 2 | 3 | Palestine[103] | 5223000 | 6025 | 867 |
| 3 | 4 | Lebanon | 5296814 | 10400 | 509 |
| 4 | 5 | Taiwan | 23580712 | 35980 | 655 |
| 5 | 6 | South Korea | 51844834 | 99720 | 520 |
| 6 | 7 | Rwanda | 13173730 | 26338 | 500 |
| 7 | 8 | Israel | 8914885 | 21937 | 406 |
| 8 | 9 | Haiti | 11334637 | 27750 | 408 |
| 9 | 10 | Netherlands | 17400824 | 41543 | 419, |

| | Rank | Country | Population | Area (km2) | Density (pop/km2) | \ |
|---|------|----------------|------------|------------|-------------------|---|
| 0 | 1 | India | 1389637446 | 3287263 | 423 | |
| 1 | 2 | Pakistan | 242923845 | 796095 | 305 | |
| 2 | 3 | Bangladesh | 165650475 | 148460 | 1116 | |
| 3 | 4 | Japan | 124214766 | 377915 | 329 | |
| 4 | 5 | Philippines | 114597229 | 300000 | 382 | |
| 5 | 6 | Vietnam | 103808319 | 331210 | 313 | |
| 6 | 7 | United Kingdom | 67791400 | 243610 | 278 | |
| 7 | 8 | South Korea | 51844834 | 99720 | 520 | |
| 8 | 9 | Taiwan | 23580712 | 35980 | 655 | |
| 9 | 10 | Sri Lanka | 23187516 | 65610 | 353 | |

| | |
|---|-----------------------------------|
| | Population trend[citation needed] |
| 0 | Growing |
| 1 | Rapidly growing |
| 2 | Rapidly growing |
| 3 | Declining[104] |
| 4 | Growing |
| 5 | Growing |
| 6 | Growing |
| 7 | Steady |
| 8 | Steady |
| 9 | Growing , |

| | Year | Population | Yearly growth | Density (pop/km2) | \ |
|----|------|------------|---------------|-------------------|-------------------|
| | Year | Population | % | Number | Density (pop/km2) |
| 0 | 1951 | 2584034261 | 1.88% | 47603112 | 17 |
| 1 | 1952 | 2630861562 | 1.81% | 46827301 | 18 |
| 2 | 1953 | 2677608960 | 1.78% | 46747398 | 18 |
| 3 | 1954 | 2724846741 | 1.76% | 47237781 | 18 |
| 4 | 1955 | 2773019936 | 1.77% | 48173195 | 19 |
| .. | ... | ... | ... | ... | ... |
| 65 | 2016 | 7464022000 | 1.14% | 84225000 | 50 |
| 66 | 2017 | 7547859000 | 1.12% | 83837000 | 51 |
| 67 | 2018 | 7631091000 | 1.10% | 83232000 | 51 |
| 68 | 2019 | 7713468000 | 1.08% | 82377000 | 52 |
| 69 | 2020 | 7795000000 | 1.05% | 81331000 | 52 |

| | |
|----|------------------|
| | Urban population |
| | Number % |
| 0 | 775067697 30% |
| 1 | 799282533 30% |
| 2 | 824289989 31% |
| 3 | 850179106 31% |
| 4 | 877008842 32% |
| .. | ... |
| 65 | 4060653000 54% |
| 66 | 4140100000 55% |

```

66      4140189000 55%
67      4219817000 55%
68      4299439000 56%
69      4378900000 56%

```

```
[70 rows x 7 columns],
```

| | Region | 1500 | 1600 | 1700 | 1750 | 1800 | 1850 | 1900 | 1950 | \ |
|---|--------------------------|------|------|------|------|------|------|------|------|---|
| 0 | World | 585 | 660 | 710 | 791 | 978 | 1262 | 1650 | 2521 | |
| 1 | Africa | 86 | 114 | 106 | 106 | 107 | 111 | 133 | 221 | |
| 2 | Asia | 282 | 350 | 411 | 502 | 635 | 809 | 947 | 1402 | |
| 3 | Europe | 168 | 170 | 178 | 190 | 203 | 276 | 408 | 547 | |
| 4 | Latin America[Note 1] | 40 | 20 | 10 | 16 | 24 | 38 | 74 | 167 | |
| 5 | Northern America[Note 1] | 6 | 3 | 2 | 2 | 7 | 26 | 82 | 172 | |
| 6 | Oceania | 3 | 3 | 3 | 2 | 2 | 2 | 6 | 13 | |

| | 1999 | 2008 | 2010 | 2012 | 2050 | 2150 |
|---|------|------|------|------|------|------|
| 0 | 6008 | 6707 | 6896 | 7052 | 9725 | 9746 |
| 1 | 783 | 973 | 1022 | 1052 | 2478 | 2308 |
| 2 | 3700 | 4054 | 4164 | 4250 | 5267 | 5561 |
| 3 | 675 | 732 | 738 | 740 | 734 | 517 |
| 4 | 508 | 577 | 590 | 603 | 784 | 912 |
| 5 | 312 | 337 | 345 | 351 | 433 | 398 |
| 6 | 30 | 34 | 37 | 38 | 57 | 51 |

| | Region | 1500 | 1600 | 1700 | 1750 | 1800 | 1850 | 1900 | 1950 | \ |
|---|--------------------------|------|------|------|------|------|------|------|------|---|
| 0 | Africa | 14.7 | 17.3 | 14.9 | 13.4 | 10.9 | 8.8 | 8.1 | 8.8 | |
| 1 | Asia | 48.2 | 53.0 | 57.9 | 63.5 | 64.9 | 64.1 | 57.4 | 55.6 | |
| 2 | Europe | 28.7 | 25.8 | 25.1 | 20.6 | 20.8 | 21.9 | 24.7 | 21.7 | |
| 3 | Latin America[Note 1] | 6.8 | 3.0 | 1.4 | 2.0 | 2.5 | 3.0 | 4.5 | 6.6 | |
| 4 | Northern America[Note 1] | 1.0 | 0.5 | 0.3 | 0.3 | 0.7 | 2.1 | 5.0 | 6.8 | |
| 5 | Oceania | 0.5 | 0.5 | 0.4 | 0.3 | 0.2 | 0.2 | 0.4 | 0.5 | |

| | 1999 | 2008 | 2010 | 2012 | 2050 | 2150 |
|---|------|------|------|------|------|------|
| 0 | 13.0 | 14.5 | 14.8 | 15.2 | 25.5 | 23.7 |
| 1 | 61.6 | 60.4 | 60.4 | 60.3 | 54.2 | 57.1 |
| 2 | 11.2 | 10.9 | 10.7 | 10.5 | 7.6 | 5.3 |
| 3 | 8.5 | 8.6 | 8.6 | 8.6 | 8.1 | 9.4 |
| 4 | 5.2 | 5.0 | 5.0 | 5.0 | 4.5 | 4.1 |
| 5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.6 | 0.5 |

| | Year | World | Africa | Asia | Europe | Latin America& Carib.[Note 1] | \ |
|----|-----------|---------|--------|--------|--------|-------------------------------|-------|
| 0 | 70,000 BC | < 0.015 | NaN | NaN | NaN | | 0.0 |
| 1 | 10,000 BC | 4 | NaN | NaN | NaN | | NaN |
| 2 | 8000 BC | 5 | NaN | NaN | NaN | | NaN |
| 3 | 6500 BC | 5 | NaN | NaN | NaN | | NaN |
| 4 | 5000 BC | 5 | NaN | NaN | NaN | | NaN |
| 5 | 4000 BC | 7 | NaN | NaN | NaN | | NaN |
| 6 | 3000 BC | 14 | NaN | NaN | NaN | | NaN |
| 7 | 2000 BC | 27 | NaN | NaN | NaN | | NaN |
| 8 | 1000 BC | 50 | 7.0 | 33.0 | 9.0 | | NaN |
| 9 | 500 BC | 100 | 14.0 | 66.0 | 16.0 | | NaN |
| 10 | AD 1 | 200 | 23.0 | 141.0 | 28.0 | | NaN |
| 11 | 1000 | 400 | 70.0 | 269.0 | 50.0 | | 8.0 |
| 12 | 1500 | 458 | 86.0 | 243.0 | 84.0 | | 39.0 |
| 13 | 1600 | 580 | 114.0 | 339.0 | 111.0 | | 10.0 |
| 14 | 1700 | 682 | 106.0 | 436.0 | 125.0 | | 10.0 |
| 15 | 1750 | 791 | 106.0 | 502.0 | 163.0 | | 16.0 |
| 16 | 1800 | 1000 | 107.0 | 656.0 | 203.0 | | 24.0 |
| 17 | 1850 | 1262 | 111.0 | 809.0 | 276.0 | | 38.0 |
| 18 | 1900 | 1650 | 133.0 | 947.0 | 408.0 | | 74.0 |
| 19 | 1950 | 2525 | 229.0 | 1394.0 | 549.0 | | 169.0 |
| 20 | 1955 | 2758 | 254.0 | 1534.0 | 577.0 | | 193.0 |
| 21 | 1960 | 3018 | 285.0 | 1687.0 | 606.0 | | 221.0 |
| 22 | 1965 | 3322 | 322.0 | 1875.0 | 635.0 | | 254.0 |
| 23 | 1970 | 3682 | 366.0 | 2120.0 | 657.0 | | 288.0 |
| 24 | 1975 | 4061 | 416.0 | 2378.0 | 677.0 | | 326.0 |
| 25 | 1980 | 4440 | 478.0 | 2626.0 | 694.0 | | 365.0 |
| 26 | 1985 | 4853 | 550.0 | 2897.0 | 708.0 | | 406.0 |
| 27 | 1990 | 5310 | 632.0 | 3202.0 | 721.0 | | 447.0 |
| 28 | 1995 | 5735 | 720.0 | 3475.0 | 728.0 | | 487.0 |
| 29 | 2000 | 6127 | 814.0 | 3714.0 | 726.0 | | 527.0 |
| 30 | 2005 | 6520 | 920.0 | 3945.0 | 729.0 | | 564.0 |
| 31 | 2010 | 6930 | 1044.0 | 4170.0 | 735.0 | | 600.0 |
| 32 | 2015 | 7349 | 1186.0 | 4393.0 | 738.0 | | 634.0 |

| | North America[Note 1] | Oceania | Notes |
|----|-----------------------|---------|-------------------|
| 0 | 0.0 | NaN | [121] |
| 1 | NaN | NaN | [122] |
| 2 | NaN | NaN | NaN |
| 3 | NaN | NaN | NaN |
| 4 | NaN | NaN | NaN |
| 5 | NaN | NaN | NaN |
| 6 | NaN | NaN | NaN |
| 7 | NaN | NaN | NaN |
| 8 | NaN | NaN | [citation needed] |
| 9 | NaN | NaN | NaN |
| 10 | NaN | NaN | NaN |
| 11 | 1.0 | 2.0 | NaN |
| 12 | 3.0 | 3.0 | NaN |
| 13 | 3.0 | 3.0 | NaN |
| 14 | 2.0 | 3.0 | NaN |
| 15 | 2.0 | 2.0 | NaN |
| 16 | 7.0 | 3.0 | NaN |
| 17 | 26.0 | 2.0 | NaN |
| 18 | 82.0 | 6.0 | NaN |
| 19 | 172.0 | 12.7 | [123] |
| 20 | 187.0 | 14.2 | NaN |
| 21 | 204.0 | 15.8 | NaN |
| 22 | 219.0 | 17.5 | NaN |
| 23 | 231.0 | 19.7 | NaN |
| 24 | 242.0 | 21.5 | NaN |
| 25 | 254.0 | 23.0 | NaN |
| 26 | 267.0 | 24.9 | NaN |
| 27 | 281.0 | 27.0 | NaN |
| 28 | 296.0 | 29.1 | NaN |
| 29 | 314.0 | 31.1 | NaN |
| 30 | 329.0 | 33.4 | NaN |
| 31 | 344.0 | 36.4 | NaN |
| 32 | 358.0 | 39.3 | NaN , |

| 0 | NaN | This section needs additional citations for ve... | | | |
|---|------|---|------------|---------------------|--------------|
| | Year | UN est.(millions) | Difference | USCB est.(millions) | Difference.1 |
| 0 | 2005 | 6542 | - | 6473 | - |
| 1 | 2010 | 6957 | 415 | 6866 | 393 |
| 2 | 2015 | 7380 | 423 | 7256 | 390 |
| 3 | 2020 | 7795 | 415 | 7643 | 380 |
| 4 | 2025 | 8184 | 390 | 8007 | 363 |
| 5 | 2030 | 8549 | 364 | 8341 | 334 |
| 6 | 2035 | 8888 | 339 | 8646 | 306 |
| 7 | 2040 | 9199 | 311 | 8926 | 280 |
| 8 | 2045 | 9482 | 283 | 9180 | 254 |
| 9 | 2050 | 9735 | 253 | 9408 | 228, |

| | Year | World | Asia | Africa | Europe \ |
|----|------|-------|---------------|---------------|-------------|
| 0 | 2000 | 6144 | 3,741 (60.9%) | 811 (13.2%) | 726 (11.8%) |
| 1 | 2005 | 6542 | 3,978 (60.8%) | 916 (14.0%) | 729 (11.2%) |
| 2 | 2010 | 6957 | 4,210 (60.5%) | 1,039 (14.9%) | 736 (10.6%) |
| 3 | 2015 | 7380 | 4,434 (60.1%) | 1,182 (16.0%) | 743 (10.1%) |
| 4 | 2020 | 7795 | 4,641 (59.5%) | 1,341 (17.2%) | 748 (9.6%) |
| 5 | 2025 | 8184 | 4,823 (58.9%) | 1,509 (18.4%) | 746 (9.1%) |
| 6 | 2030 | 8549 | 4,974 (58.2%) | 1,688 (19.8%) | 741 (8.7%) |
| 7 | 2035 | 8888 | 5,096 (57.3%) | 1,878 (21.1%) | 735 (8.3%) |
| 8 | 2040 | 9199 | 5,189 (56.4%) | 2,077 (22.6%) | 728 (7.9%) |
| 9 | 2045 | 9482 | 5,253 (55.4%) | 2,282 (24.1%) | 720 (7.6%) |
| 10 | 2050 | 9735 | 5,290 (54.3%) | 2,489 (25.6%) | 711 (7.3%) |
| 11 | 2055 | 9958 | 5,302 (53.2%) | 2,698 (27.1%) | 700 (7.0%) |
| 12 | 2060 | 10152 | 5,289 (52.1%) | 2,905 (28.6%) | 689 (6.8%) |
| 13 | 2065 | 10318 | 5,256 (51.0%) | 3,109 (30.1%) | 677 (6.6%) |
| 14 | 2070 | 10459 | 5,207 (49.8%) | 3,308 (31.6%) | 667 (6.4%) |
| 15 | 2075 | 10577 | 5,143 (48.6%) | 3,499 (33.1%) | 657 (6.2%) |
| 16 | 2080 | 10674 | 5,068 (47.5%) | 3,681 (34.5%) | 650 (6.1%) |
| 17 | 2085 | 10750 | 4,987 (46.4%) | 3,851 (35.8%) | 643 (6.0%) |
| 18 | 2090 | 10810 | 4,901 (45.3%) | 4,008 (37.1%) | 638 (5.9%) |
| 19 | 2095 | 10852 | 4,812 (44.3%) | 4,152 (38.3%) | 634 (5.8%) |
| 20 | 2100 | 10875 | 4,719 (43.4%) | 4,280 (39.4%) | 630 (5.8%) |

Latin America/Caribbean Northern America Oceania

| | | | |
|----|------------|------------|-----------|
| 0 | 522 (8.5%) | 312 (5.1%) | 31 (0.5%) |
| 1 | 558 (8.5%) | 327 (5.0%) | 34 (0.5%) |
| 2 | 591 (8.5%) | 343 (4.9%) | 37 (0.5%) |
| 3 | 624 (8.5%) | 357 (4.8%) | 40 (0.5%) |
| 4 | 654 (8.4%) | 369 (4.7%) | 43 (0.6%) |
| 5 | 682 (8.3%) | 380 (4.6%) | 45 (0.6%) |
| 6 | 706 (8.3%) | 391 (4.6%) | 48 (0.6%) |
| 7 | 726 (8.2%) | 401 (4.5%) | 50 (0.6%) |
| 8 | 742 (8.1%) | 410 (4.5%) | 53 (0.6%) |
| 9 | 754 (8.0%) | 418 (4.4%) | 55 (0.6%) |
| 10 | 762 (7.8%) | 425 (4.4%) | 57 (0.6%) |
| 11 | 767 (7.7%) | 432 (4.3%) | 60 (0.6%) |
| 12 | 768 (7.6%) | 439 (4.3%) | 62 (0.6%) |
| 13 | 765 (7.4%) | 447 (4.3%) | 64 (0.6%) |
| 14 | 759 (7.3%) | 454 (4.3%) | 66 (0.6%) |
| 15 | 750 (7.1%) | 461 (4.4%) | 67 (0.6%) |
| 16 | 739 (6.9%) | 468 (4.4%) | 69 (0.7%) |
| 17 | 726 (6.8%) | 474 (4.4%) | 71 (0.7%) |
| 18 | 711 (6.6%) | 479 (4.4%) | 72 (0.7%) |
| 19 | 696 (6.4%) | 485 (4.5%) | 74 (0.7%) |
| 20 | 680 (6.3%) | 491 (4.5%) | 75 (0.7%) |

| | | | | | | | | | |
|-------------------------|---------------|-------|------|------|------|------|------|------|------|
| Population(in billions) | 0.5 | 0.5.1 | 1 | 1.1 | 2 | 2.1 | 4 | 4.1 | \ |
| 0 | Year | 1500 | 1500 | 1804 | 1804 | 1927 | 1927 | 1974 | 1974 |
| 1 | Years elapsed | — | 304 | 304 | 123 | 123 | 47 | 47 | 48 |

| | | | |
|---|------|------|---|
| 8 | 8.1 | 16 | \ |
| 0 | 2022 | 2022 | .mw-parser-output .tooltip-dotted{border-botto... |
| 1 | 48 | 48 | — |

| | | | | | | | | | |
|---|-------------------------|---------------------------------|---------|------|--------|------|-------|------|---|
| | | | | | 16.1 | | | | |
| 0 | .mw-parser-output | .tooltip-dotted{border-botto... | | | | | | | |
| 1 | | | | | NaN | , | | | |
| | Population(in billions) | 0.375 | 0.375.1 | 0.75 | 0.75.1 | 1.5 | 1.5.1 | 3 | \ |
| 0 | Year | 1171 | 1171 | 1715 | 1715 | 1881 | 1881 | 1960 | |
| 1 | Years elapsed | — | 544 | 544 | 166 | 166 | 79 | 79 | |

| | | | | | |
|---|------|------|------|--------------|--------------|
| | 3.1 | 6 | 6.1 | 12 | 12.1 |
| 0 | 1960 | 1999 | 1999 | c. 2100[146] | c. 2100[146] |
| 1 | 39 | 39 | 39 | c. 100+ | c. 100+ |

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tput .navbar-collapse{float:left;text-align:left}.mw-parser-output .navbar-boxtext{word-
spacing:0}.mw-parser-output .navbar ul{display:inline-block;white-space:nowrap;line-heigh
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put .navbar li{word-spacing:-0.125em}.mw-parser-output .navbar a>span,.mw-parser-output .
navbar a>abbr{text-decoration:inherit}.mw-parser-output .navbar-mini abbr{font-variant:sm
all-caps;border-bottom:none;text-decoration:none;cursor:inherit}.mw-parser-output .navbar
-ct-full{font-size:114%;margin:0 7em}.mw-parser-output .navbar-ct-mini{font-size:114%;mar
gin:0 4em}vteGlobal human population \

| | |
|---|------------------------------|
| 0 | Major topics |
| 1 | Biological andrelated topics |
| 2 | Populationecology |
| 3 | Society and population |
| 4 | Literature |
| 5 | Publications |
| 6 | Lists |
| 7 | Events andorganizations |
| 8 | Related topics |
| 9 | Commons Human overpopulation |

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tput .navbar-collapse{float:left;text-align:left}.mw-parser-output .navbar-boxtext{word-

spacing:0}).mw-parser-output .navbar ul{display:inline-block;white-space:nowrap;line-height:1.2em}.mw-parser-output .navbar-brackets::before{margin-right:-0.125em;content:"["}.mw-parser-output .navbar-brackets::after{margin-left:-0.125em;content:"]"}.mw-parser-output .navbar li{word-spacing:-0.125em}.mw-parser-output .navbar a>span,.mw-parser-output .navbar a>abbr{text-decoration:inherit}.mw-parser-output .navbar-mini abbr{font-variant:small-caps;border-bottom:none;text-decoration:none;cursor:inherit}.mw-parser-output .navbar-ct-full{font-size:114%;margin:0 7em}.mw-parser-output .navbar-ct-mini{font-size:114%;margin:0 4em}vteGlobal human population.1

0 Demographics of the world Demographic transiti...

1 Population biology Population decline Populati...

2 Earth's energy budget $I = P \times A \times T$ Kaya ident...

3 Biocapacity Human overpopulation Malthusian ca...

4 A Modest Proposal Observations Concerning the ...

5 Population and Environment Population and Deve...

6 Population and housing censuses by country Lar...

7 7 Billion Actions International Conference on ...

8 Deep ecology Fertility and intelligence Green ...

9 Commons Human overpopulation

Articles related to the world's population \

0 vteHuman impact on the environmentGeneral Anth...

1 vteHuman impact on the environment

2 General

3 Causes

4 Effects

5 Mitigation

6 Commons Category by country assessment mitiga...

7 vteLists of countries by population statistics

8 Global

9 Continents/subregions

10 Intercontinental

11 Cities/urban areas

12 Past and future

13 Population density

14 Growth indicators

15 Other demographics

16 Health

17 Education and innovation

18 Economic

19 List of international rankings Lists by country

20 vteHierarchy of life

21 Biosphere > Biome > Ecosystem > Biocenosis > P...

22 vteGlobalization

23 Journals Outline Studies

24 Aspects

25 Issues

26 Global

27 Other

28 Theories

29 Notablescholars

30 Economics

31 Political economy

32 Politics / sociology

33 Non-academic

34 Category Business portal

Articles related to the world's population.1

0 vteHuman impact on the environmentGeneral Anth...

1 vteHuman impact on the environment

2 Anthropocene Environmental issues list of issu...

3 Agriculture cannabis cultivation irrigation me...

4 Biodiversity threats biodiversity loss decline...

5 Alternative fuel vehicle propulsion Birth cont...

```

6 Commons Category by country assessment mitiga...
7 vteLists of countries by population statistics
8 Current population United Nations Demographics...
9 Africa Antarctica Asia Europe North America Ca...
10 Americas Arab world Commonwealth of Nations Eu...
11 World cities National capitals Megacities Mega...
12 Past and future population World population es...
13 Current density Past and future population den...
14 Population growth rate Natural increase Net re...
15 Age at childbearing Age at first marriage Age ...
16 Antidepressant consumption Antiviral medicatio...
17 Bloomberg Innovation Index Education Index Int...
18 Access to financial services Development aid d...
19 List of international rankings Lists by country
20 vteHierarchy of life
21 Biosphere > Biome > Ecosystem > Biocenosis > P...
22 vteGlobalization
23 Journals Outline Studies
24 Alter-globalization Anti-globalization Cultura...
25 Global Climate change Climate justice Disease ...
26 Climate change Climate justice Disease COVID-1...
27 Brain drain reverse Care drain Development aid...
28 Capital accumulation Dependency Development Ea...
29 Economics David Autor Richard Baldwin Ravi Bat...
30 David Autor Richard Baldwin Ravi Batra Jagdish...
31 Samir Amin Giovanni Arrighi Robert W. Cox Andr...
32 Arjun Appadurai Daniele Archibugi K. Anthony A...
33 Noam Chomsky Thomas Friedman Naomi Klein John ...
34 Category Business portal ,
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2 Effects
3 Mitigation
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2 Biodiversity threats biodiversity loss decline...
3 Alternative fuel vehicle propulsion Birth cont...
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    vteLists of countries by population statistics \
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1 Continents/subregions
2 Intercontinental
3 Cities/urban areas
4 Past and future
5 Population density
6 Growth indicators
7 Other demographics
8 Health
9 Education and innovation
10 Economic
11 List of international rankings Lists by country

    vteLists of countries by population statistics.1
0 Current population United Nations Demographics...
1 Africa Antarctica Asia Europe North America Ca...
2 Americas Arab world Commonwealth of Nations Eu...
3 World cities National capitals Megacities Mega...
4 Past and future population World population es...
5 Current density Past and future population den...
6 Population growth rate Natural increase Net re...
7 Age at childbearing Age at first marriage Age ...
8 Antidepressant consumption Antiviral medicatio...
9 Bloomberg Innovation Index Education Index Int...
10 Access to financial services Development aid d...
11 List of international rankings Lists by country ,
    vteHierarchy of life \
0 Biosphere > Biome > Ecosystem > Biocenosis > P...

```

```

vteHierarchy of life.1
0 Biosphere > Biome > Ecosystem > Biocenosis > P... ,
  vteGlobalization \
0 Journals Outline Studies
1 Aspects
2 Issues
3 Global
4 Other
5 Theories
6 Notablescholars
7 Economics
8 Political economy
9 Politics / sociology
10 Non-academic
11 Category Business portal

vteGlobalization.1
0 Journals Outline Studies
1 Alter-globalization Anti-globalization Cultura...
2 Global Climate change Climate justice Disease ...
3 Climate change Climate justice Disease COVID-1...
4 Brain drain reverse Care drain Development aid...
5 Capital accumulation Dependency Development Ea...
6 Economics David Autor Richard Baldwin Ravi Bat...
7 David Autor Richard Baldwin Ravi Batra Jagdish...
8 Samir Amin Giovanni Arrighi Robert W. Cox Andr...
9 Arjun Appadurai Daniele Archibugi K. Anthony A...
10 Noam Chomsky Thomas Friedman Naomi Klein John ...
11 Category Business portal , 1
0
0 Global Climate change Climate justice Disease COVID-1...
1 Other Brain drain reverse Care drain Development aid...,
0 1
0 Economics David Autor Richard Baldwin Ravi Batra Jagdish...
1 Political economy Samir Amin Giovanni Arrighi Robert W. Cox Andr...
2 Politics / sociology Arjun Appadurai Daniele Archibugi K. Anthony A...
3 Non-academic Noam Chomsky Thomas Friedman Naomi Klein John ...,
0 1
0 Authority control: National libraries Germany]

```

Not Useful Tables

Pandas found 24 tables on that page. Some are not useful:

In [8]:

```
len(tables) #Here total number of tables
```

Out[8]:

24

Tables that need formatting

Some will be misaligned, meaning you need to do extra work to fix the columns and rows:

In [9]:

```
tables[0] # Here first table from page
```

Out[9]:

| | Population | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---------------|----------|------|------|------|------|------|------|------|------|------|
| 0 | Year | 1804 | 1930 | 1960 | 1974 | 1987 | 1999 | 2011 | 2022 | 2037 | 2057 |
| 1 | Years elapsed | 200,000+ | 126 | 30 | 14 | 13 | 12 | 12 | 11 | 15 | 20 |

In [18]:

```
world_topten = tables[1]
world_topten
```

Out[18]:

| # | Most populous countries | | 2000 | 2015 | 2030[A] |
|----|---|---------------|---|---|---|
| 0 | 1 | China[B] | 1270 | 1376 | 1416 |
| 1 | 2 | India | 1053 | 1311 | 1528 |
| 2 | 3 | United States | 283 | 322 | 356 |
| 3 | 4 | Indonesia | 212 | 258 | 295 |
| 4 | 5 | Pakistan | 136 | 208 | 245 |
| 5 | 6 | Brazil | 176 | 206 | 228 |
| 6 | 7 | Nigeria | 123 | 182 | 263 |
| 7 | 8 | Bangladesh | 131 | 161 | 186 |
| 8 | 9 | Russia | 146 | 146 | 149 |
| 9 | 10 | Mexico | 103 | 127 | 148 |
| 10 | NaN | World total | 6127 | 7349 | 8501 |
| 11 | Notes: .mw-parser-output .reflist{font-size:90... | | Notes: .mw-parser-output .reflist{font-size:90... | Notes: .mw-parser-output .reflist{font-size:90... | Notes: .mw-parser-output .reflist{font-size:90... |

In [19]:

```
#Here we are going to remove 11 row
world_topten = world_topten.drop(11,axis=0)
world_topten
```

Out[19]:

| # | Most populous countries | | 2000 | 2015 | 2030[A] |
|----|-------------------------|---------------|------|------|---------|
| 0 | 1 | China[B] | 1270 | 1376 | 1416 |
| 1 | 2 | India | 1053 | 1311 | 1528 |
| 2 | 3 | United States | 283 | 322 | 356 |
| 3 | 4 | Indonesia | 212 | 258 | 295 |
| 4 | 5 | Pakistan | 136 | 208 | 245 |
| 5 | 6 | Brazil | 176 | 206 | 228 |
| 6 | 7 | Nigeria | 123 | 182 | 263 |
| 7 | 8 | Bangladesh | 131 | 161 | 186 |
| 8 | 9 | Russia | 146 | 146 | 149 |
| 9 | 10 | Mexico | 103 | 127 | 148 |
| 10 | NaN | World total | 6127 | 7349 | 8501 |

In [20]:

```
# Here we are going to drop # column
world_topten = world_topten.drop('#',axis=1)
world_topten
```

Out[20]:

| Most populous countries | | 2000 | 2015 | 2030[A] |
|-------------------------|----------|------|------|---------|
| 0 | China[B] | 1270 | 1376 | 1416 |
| 1 | India | 1053 | 1311 | 1528 |

| 2 | Most populous countries | 2000 | 2015 | 2030 Est. |
|----|-------------------------|------|------|-----------|
| 1 | China | 1270 | 1376 | 1416 |
| 3 | Indonesia | 212 | 258 | 295 |
| 4 | Pakistan | 136 | 208 | 245 |
| 5 | Brazil | 176 | 206 | 228 |
| 6 | Nigeria | 123 | 182 | 263 |
| 7 | Bangladesh | 131 | 161 | 186 |
| 8 | Russia | 146 | 146 | 149 |
| 9 | Mexico | 103 | 127 | 148 |
| 10 | World total | 6127 | 7349 | 8501 |

In [22]:

```
# Renaming columns by own
world_topten.columns = ['Country', '2000', '2015', '2030 Est.']
world_topten
```

Out[22]:

| | Country | 2000 | 2015 | 2030 Est. |
|----|---------------|------|------|-----------|
| 0 | China[B] | 1270 | 1376 | 1416 |
| 1 | India | 1053 | 1311 | 1528 |
| 2 | United States | 283 | 322 | 356 |
| 3 | Indonesia | 212 | 258 | 295 |
| 4 | Pakistan | 136 | 208 | 245 |
| 5 | Brazil | 176 | 206 | 228 |
| 6 | Nigeria | 123 | 182 | 263 |
| 7 | Bangladesh | 131 | 161 | 186 |
| 8 | Russia | 146 | 146 | 149 |
| 9 | Mexico | 103 | 127 | 148 |
| 10 | World total | 6127 | 7349 | 8501 |

In [23]:

```
tables[6]
```

Out[23]:

| | Year | Population | Yearly growth | | Density(pop/km2) | Urban population | |
|-----|------|------------|---------------|----------|------------------|------------------|-----|
| | Year | Population | % | Number | Density(pop/km2) | Number | % |
| 0 | 1951 | 2584034261 | 1.88% | 47603112 | 17 | 775067697 | 30% |
| 1 | 1952 | 2630861562 | 1.81% | 46827301 | 18 | 799282533 | 30% |
| 2 | 1953 | 2677608960 | 1.78% | 46747398 | 18 | 824289989 | 31% |
| 3 | 1954 | 2724846741 | 1.76% | 47237781 | 18 | 850179106 | 31% |
| 4 | 1955 | 2773019936 | 1.77% | 48173195 | 19 | 877008842 | 32% |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 65 | 2016 | 7464022000 | 1.14% | 84225000 | 50 | 4060653000 | 54% |
| 66 | 2017 | 7547859000 | 1.12% | 83837000 | 51 | 4140189000 | 55% |
| 67 | 2018 | 7631091000 | 1.10% | 83232000 | 51 | 4219817000 | 55% |
| 68 | 2019 | 7713468000 | 1.08% | 82377000 | 52 | 4299439000 | 56% |
| 69 | 2020 | 7795000000 | 1.05% | 81331000 | 52 | 4378900000 | 56% |

Write to html Output

If you are working on a website and want to quickly output the .html file, you can use `to_html`

In [41]:

```
# Saving table this to html
world_topten.to_html('D:\Study\sample.html', index= False)
```

`read_html` is not perfect, but its quite powerful for such a simple method call!

In []:

Excel Files

Pandas can read in basic excel files (it will get errors if there are macros or extensive formulas relying on outside excel files), in general, pandas can only grab the raw information from an .excel file.

NOTE: Requires the openpyxl and xlrd library! Its provided for you in our environment, or simply install with:

```
pip install openpyxl
pip install xlrd
```

Heavy excel users may want to check out this website: <https://www.python-excel.org/>

You can think of an excel file as a Workbook containin sheets, which for pandas means each sheet can be a `DataFrame`.

Excel file input with `read_excel()`

In [47]:

```
df = pd.read_excel("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCours
e.Com] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduc
tion to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\my_excel_file.xlsx"
                , sheet_name='First_Sheet')
df # Here we can give sheet name if there are more than one sheets , for single sheet we
can skip that
```

Out[47]:

| | a | b | c | d |
|---|----|----|----|----|
| 0 | 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 | 7 |
| 2 | 8 | 9 | 10 | 11 |
| 3 | 12 | 13 | 14 | 15 |

What if you don't know the sheet name? Or want to run a for loop for certain sheet names? Or want every sheet?

Several ways to do this: <https://stackoverflow.com/questions/17977540/pandas-looking-up-the-list-of-sheets-in-an-excel-file>

In [50]:

```
# Suppose there were many sheet in excel file and we want name of all sheet so we can try that
wb = pd.ExcelFile("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Com] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\my_excel_file.xlsx")
wb.sheet_names
```

Out[50]:

```
['First_Sheet']
```

In [55]:

```
# or see end
pd.ExcelFile("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Com] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\my_excel_file.xlsx").sheet_names
```

Out[55]:

```
['First_Sheet']
```

Grab all sheets

In [58]:

```
excel_sheets = pd.read_excel("D:\\Study\\Programming\\python\\Python course from udemy\\[GigaCourse.Com] Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\01 - Introduction to Course\\1UNZIP-FOR-NOTEBOOKS-FINAL\\03-Pandas\\my_excel_file.xlsx", sheet_name=None)
```

In [59]:

```
type(excel_sheets) # it has store all sheet name as in form of dict
```

Out[59]:

```
dict
```

In [61]:

```
excel_sheets.keys() # Here we can call those sheet name
```

Out[61]:

```
dict_keys(['First_Sheet'])
```

In [63]:

```
df=excel_sheets['First_Sheet']
df
```

Out[63]:

| | a | b | c | d |
|---|----|----|----|----|
| 0 | 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 | 7 |
| 2 | 8 | 9 | 10 | 11 |
| 3 | 12 | 13 | 14 | 15 |

Saving Excel file

In [65]:

```
df.to_excel('D:\\Study\\sample_excel.xlsx', sheet_name='First_Sheet', index=False)
```

SQL Connections

NOTE: Highly recommend you explore specific libraries for your specific SQL Engine. Simple search for your database+python in Google and the top results should hopefully include an API.

- [MySQL](#)
- [PostgreSQL](#)
- [MS SQL Server](#)
- [Oracle](#)
- [MongoDB](#)

Let's review pandas capabilities by using SQLite, which comes built in with Python.

Example SQL Database (temporary in your RAM)

You will need to install sqlalchemy with:

```
pip install sqlalchemy
```

to follow along. To understand how to make a connection to your own database, make sure to review: <https://docs.sqlalchemy.org/en/13/core/connections.html>

In [66]:

```
from sqlalchemy import create_engine
```

In [70]:

```
temp_db = create_engine('sqlite:///memory:')
```

Write to Database

In [76]:

```
tables[5]
```

Out[76]:

| | Rank | Country | Population | Area(km2) | Density(pop/km2) | Population trend[citation needed] |
|---|------|----------------|------------|-----------|------------------|-----------------------------------|
| 0 | 1 | India | 1389637446 | 3287263 | 423 | Growing |
| 1 | 2 | Pakistan | 242923845 | 796095 | 305 | Rapidly growing |
| 2 | 3 | Bangladesh | 165650475 | 148460 | 1116 | Rapidly growing |
| 3 | 4 | Japan | 124214766 | 377915 | 329 | Declining[104] |
| 4 | 5 | Philippines | 114597229 | 300000 | 382 | Growing |
| 5 | 6 | Vietnam | 103808319 | 331210 | 313 | Growing |
| 6 | 7 | United Kingdom | 67791400 | 243610 | 278 | Growing |
| 7 | 8 | South Korea | 51844834 | 99720 | 520 | Steady |
| 8 | 9 | Taiwan | 23580712 | 35980 | 655 | Steady |
| 9 | 10 | Sri Lanka | 23187516 | 65610 | 353 | Growing |

In [80]:

```
pop = tables[5]
```

In [83]:

```
pop.to_sql(name='populations1',con=temp_db)
```

```
Out[83]:
```

10

Read from SQL Database

```
In [84]:
```

```
# Read in an entire table
pd.read_sql(sql='populations1',con=temp_db)
```

```
Out[84]:
```

| | index | Rank | Country | Population | Area(km2) | Density(pop/km2) | Population trend[citation needed] |
|---|-------|------|----------------|------------|-----------|------------------|-----------------------------------|
| 0 | 0 | 1 | India | 1389637446 | 3287263 | 423 | Growing |
| 1 | 1 | 2 | Pakistan | 242923845 | 796095 | 305 | Rapidly growing |
| 2 | 2 | 3 | Bangladesh | 165650475 | 148460 | 1116 | Rapidly growing |
| 3 | 3 | 4 | Japan | 124214766 | 377915 | 329 | Declining[104] |
| 4 | 4 | 5 | Philippines | 114597229 | 300000 | 382 | Growing |
| 5 | 5 | 6 | Vietnam | 103808319 | 331210 | 313 | Growing |
| 6 | 6 | 7 | United Kingdom | 67791400 | 243610 | 278 | Growing |
| 7 | 7 | 8 | South Korea | 51844834 | 99720 | 520 | Steady |
| 8 | 8 | 9 | Taiwan | 23580712 | 35980 | 655 | Steady |
| 9 | 9 | 10 | Sri Lanka | 23187516 | 65610 | 353 | Growing |

```
In [85]:
```

```
# Read in with a SQL Query
pd.read_sql_query(sql="SELECT Country FROM populations1",con=temp_db)
```

```
Out[85]:
```

| Country | |
|---------|----------------|
| 0 | India |
| 1 | Pakistan |
| 2 | Bangladesh |
| 3 | Japan |
| 4 | Philippines |
| 5 | Vietnam |
| 6 | United Kingdom |
| 7 | South Korea |
| 8 | Taiwan |
| 9 | Sri Lanka |

It is difficult to generalize pandas and SQL, due to a wide array of issues, including permissions,security, online access, varying SQL engines, etc... Use these ideas as a starting off point, and you will most likely need to do your own research for your own situation.

```
In [ ]:
```