# 00-Pandas - A Quick Introduction

November 26, 2023

## 0.1 Pandas - A Quick Introduction

[1]:
```
# needed to plot correctly in jupyter notebook
import matplotlib.pyplot as plt
plt.style.use('ggplot')
%matplotlib inline
```

Pandas is a powerful open source python package used for data analysis. It's API provides functionalities that not only allows us to import or export data in various formats (ex: cvs, html, json, etc.) but also to manipulate data in ways commonly required in the preprocessing step for Machine Learning (ex: detect missing data, compute statistics, dealing with time series, hashing, indexing and much more).

The primary two components of pandas are the `Series` and `DataFrame`. A `Series` is essentially a 1-d array commonly thought of as a column vector, while `DataFrame` is a table that aggregates many different `Series`.

## 0.2 Importing

The standard way of importing pandas into python is via:

`import pandas as pd`

where `pd` is the standard convention designator for the library.

[2]:
```
import pandas as pd
```

## 0.3 Reading and Writing Data

Pandas supports many different file formats and encodings through various `read` methods built-in in its io module. For example, to read in a csv file one can use `read_csv()` function, whereas writing a csv file is accomplished through the `to_csv` method. The former returns a populated DataFrame with the contents of the file, whereas the latter writes a DataFrame in csv format to disk.

For example, we can use pandas to import an avocado prices/sales in US dataset and than save it in another location:

[3]:
```
df = pd.read_csv('./datasets/avocado.csv', index_col=0)
df.to_csv('/tmp/avocado.cvs')
```

Similar methods for importing from json, html, excel, SQL and so on, are consistently provided by the same *io* module.

Also, note that the `index_col` argument to the `read_csv` call specifies which column should be used as an index of each entry (in our case column zero). If it's not specified, then pandas will automatically create one. This is to be avoided because this index is written to the file upon calling `to_csv`. Hence, loading and saving multiple times will create many redundant columns that have no special meaning.

## 0.4 Viewing Data

We can view the data frame, i.e. `print(df)` to see how the data frame looks like. However, using `print` will output all data. More commonly is to print just a few entries via `head()` and `tail()` methods, which output the first and the last rows of the DataFrame, respectively. Both methods have a default argument of 5 rows, however you can supply any integer number of rows you would like to visualize.

[4]:
```
df.head()
```

[4]:
```
         Date  AveragePrice  Total Volume     4046       4225    4770  \
0  2015-12-27          1.33      64236.62  1036.74   54454.85   48.16
1  2015-12-20          1.35      54876.98   674.28   44638.81   58.33
2  2015-12-13          0.93     118220.22   794.70  109149.67  130.50
3  2015-12-06          1.08      78992.15  1132.00   71976.41   72.58
4  2015-11-29          1.28      51039.60   941.48   43838.39   75.78

   Total Bags  Small Bags  Large Bags  XLarge Bags          type  year  region
0     8696.87     8603.62       93.25          0.0  conventional  2015  Albany
1     9505.56     9408.07       97.49          0.0  conventional  2015  Albany
2     8145.35     8042.21      103.14          0.0  conventional  2015  Albany
3     5811.16     5677.40      133.76          0.0  conventional  2015  Albany
4     6183.95     5986.26      197.69          0.0  conventional  2015  Albany
```

[5]:
```
df.tail(3)
```

[5]:
```
          Date  AveragePrice  Total Volume     4046     4225    4770  \
9   2018-01-21          1.87      13766.76  1191.92  2452.79  727.94
10  2018-01-14          1.93      16205.22  1527.63  2981.04  727.01
11  2018-01-07          1.62      17489.58  2894.77  2356.13  224.53

    Total Bags  Small Bags  Large Bags  XLarge Bags     type  year  \
9      9394.11     9351.80       42.31          0.0  organic  2018
10    10969.54    10919.54       50.00          0.0  organic  2018
11    12014.15    11988.14       26.01          0.0  organic  2018

            region
9   WestTexNewMexico
10  WestTexNewMexico
11  WestTexNewMexico
```

### 0.4.1 DataFrame Makeup

One of the first things you may one to look at, is the makeup of a DataFrame, namely: the number of entries, the label of each column, how many objects are null, what data types are in each column and so forth. This is where the `.info()` method comes in. It prints a concise summary of the DataFrame.

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 18249 entries, 0 to 11
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Date          18249 non-null  object
 1   AveragePrice  18249 non-null  float64
 2   Total Volume  18249 non-null  float64
 3   4046          18249 non-null  float64
 4   4225          18249 non-null  float64
 5   4770          18249 non-null  float64
 6   Total Bags    18249 non-null  float64
 7   Small Bags    18249 non-null  float64
 8   Large Bags    18249 non-null  float64
 9   XLarge Bags   18249 non-null  float64
 10  type          18249 non-null  object
 11  year          18249 non-null  int64
 12  region        18249 non-null  object
dtypes: float64(9), int64(1), object(3)
memory usage: 1.9+ MB
```

Moreover, for numerical data we can easily get the summary statistics for each column of our DataFrame via the `describe()` method.

[7]:
```
df.describe()
```

[7]:

| | AveragePrice | Total Volume | 4046 | 4225 | 4770 \ |
|---|---|---|---|---|---|
| count | 18249.000000 | 1.824900e+04 | 1.824900e+04 | 1.824900e+04 | 1.824900e+04 |
| mean | 1.405978 | 8.506440e+05 | 2.930084e+05 | 2.951546e+05 | 2.283974e+04 |
| std | 0.402677 | 3.453545e+06 | 1.264989e+06 | 1.204120e+06 | 1.074641e+05 |
| min | 0.440000 | 8.456000e+01 | 0.000000e+00 | 0.000000e+00 | 0.000000e+00 |
| 25% | 1.100000 | 1.083858e+04 | 8.540700e+02 | 3.008780e+03 | 0.000000e+00 |
| 50% | 1.370000 | 1.073768e+05 | 8.645300e+03 | 2.906102e+04 | 1.849900e+02 |
| 75% | 1.660000 | 4.329623e+05 | 1.110202e+05 | 1.502069e+05 | 6.243420e+03 |
| max | 3.250000 | 6.250565e+07 | 2.274362e+07 | 2.047057e+07 | 2.546439e+06 |

| | Total Bags | Small Bags | Large Bags | XLarge Bags | year |
|---|---|---|---|---|---|
| count | 1.824900e+04 | 1.824900e+04 | 1.824900e+04 | 18249.000000 | 18249.000000 |
| mean | 2.396392e+05 | 1.821947e+05 | 5.433809e+04 | 3106.426507 | 2016.147899 |
| std | 9.862424e+05 | 7.461785e+05 | 2.439660e+05 | 17692.894652 | 0.939938 |

```
min    0.000000e+00  0.000000e+00  0.000000e+00       0.000000   2015.000000
25%    5.088640e+03  2.849420e+03  1.274700e+02       0.000000   2015.000000
50%    3.974383e+04  2.636282e+04  2.647710e+03       0.000000   2016.000000
75%    1.107834e+05  8.333767e+04  2.202925e+04     132.500000   2017.000000
max    1.937313e+07  1.338459e+07  5.719097e+06  551693.650000   2018.000000
```

## 0.5 Indexing & Slicing

DataFrame's provide dictionary like indexing support. So to reference a specific column we can use our `df` object with a key that represents the name of the column we want. For example referencing the *"AveragePrice"* column we can do the following:

[8]:
```
df['AveragePrice']
```

[8]:
```
0      1.33
1      1.35
2      0.93
3      1.08
4      1.28
       …
7      1.63
8      1.71
9      1.87
10     1.93
11     1.62
Name: AveragePrice, Length: 18249, dtype: float64
```

We can, of course, use the `head()` and `tail()` methods as before:

[9]:
```
df['AveragePrice'].head(3)
```

[9]:
```
0    1.33
1    1.35
2    0.93
Name: AveragePrice, dtype: float64
```

Actually indexes are objects themselves, namely `RangeIndex` objects. In the context of the DataFrame these objects describe how rows are formated. We can obtain or view this object for our DataFrame via the `index` attribute:

[10]:
```
df.index
```

[10]:
```
Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9,
        …
        2,  3,  4,  5,  6,  7,  8,  9, 10, 11],
      dtype='int64', length=18249)
```

Moreover, we can index a DataFrame by a hybrid approach where we first index a specific column based on the key and then an integer number corresponding to the i'th row entry we are interested in:

[11]:
```
df['AveragePrice']
```

[11]:
```
0      1.33
1      1.35
2      0.93
3      1.08
4      1.28
       …
7      1.63
8      1.71
9      1.87
10     1.93
11     1.62
Name: AveragePrice, Length: 18249, dtype: float64
```

We can also use either `loc` or `iloc` attributes of a DataFrame to reference entries in a more traditional manner. That is, loc provides referencing by label, whereas iloc provides purely integer based indexing by position. Both attributes allow slicing in the same manner as lists or numpy arrays.

[12]:
```
df.loc[0]['AveragePrice']
```

[12]:
```
0    1.33
0    0.99
0    1.17
0    0.97
0    1.13
     …
0    1.04
0    1.41
0    1.55
0    1.60
0    1.62
Name: AveragePrice, Length: 432, dtype: float64
```

Note that the *0* in the `df.loc[0]['AveragePrice']` expression is treaded as a label and not as an integer.

[13]:
```
df.iloc[0][1]
```

```
/tmp/ipykernel_136454/2309508539.py:1: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer keys will
always be treated as labels (consistent with DataFrame behavior). To access a
value by position, use `ser.iloc[pos]`
  df.iloc[0][1]
```

[13]: 1.33

While in the `df.iloc[0][1]` the indexes *0* and *1* are actual integers.

### 0.5.1 Conditional Selection

Combining indexing together with conditional expressions we can create new DataFrame's that contain only specific parts of our data. For example, we can select all data within our DataFrame that is associated with the Atlanta region.

[14]:
```
new_df = df[df['region'] == 'Atlanta']
```

Note that this is possible due to the conditional form of indexing. Reading through the creation of the new frame we: - first, reference the *region* column, - then, out of all the labels in this column we select only those that have the label *Atlanta* , - and finally, we use the result to index the original data frame such that we select all data for which the condition is true.

Printing the head of `new_df` yields:

[15]:
```
new_df.head(3)
```

[15]:
```
         Date  AveragePrice  Total Volume       4046      4225    4770  \
0  2015-12-27          0.99     386100.49  292097.36  27350.92  297.90
1  2015-12-20          1.08     331377.53  251774.15  20702.45  103.06
2  2015-12-13          0.96     417772.47  324932.28  31019.08  275.80

   Total Bags  Small Bags  Large Bags  XLarge Bags          type  year  \
0    66354.31    48605.95    17748.36         0.00  conventional  2015
1    58797.87    46930.26    11867.61         0.00  conventional  2015
2    61545.31    38903.57    22628.21        13.53  conventional  2015

    region
0  Atlanta
1  Atlanta
2  Atlanta
```

### 0.5.2 Multiple Selection / Filtering

Above, we selected parts of our data frames based on single labels of columns and conditions. However, pandas DataFrame's also support more advanced selection/filtering techniques that are based on slicing and multiple condition concatenation.

First, we can select multiple columns of our data by indexing with a list of column names. For example, we may use to select the `AveragePrice` and `Total Volume` of the avocado dataset.

[16]:
```
multiple_slection_df = df[['AveragePrice', 'Total Volume']]
multiple_slection_df.head()
```

```
[16]:    AveragePrice  Total Volume
      0           1.33      64236.62
      1           1.35      54876.98
      2           0.93     118220.22
      3           1.08      78992.15
      4           1.28      51039.60
```

Secondly, we can conditionally select multiple entries (rows) of our data by concatenating different conditions. For example, to select all the `organic` type avocados that have an average price bellow \$1.024 we can do the following:

```
[17]: multiple_slection_df = df[(df['type'] == 'organic') & (df['AveragePrice'] < 1.
       ↪02)]
      multiple_slection_df.head(3)
```

```
[17]:           Date  AveragePrice  Total Volume    4046     4225  4770  Total Bags  \
      0   2015-12-27          0.91       2272.26   15.53   508.49  0.00     1748.24
      2   2015-12-13          0.87       4054.49   26.21   738.96  2.58     3286.74
      24  2015-07-12          1.01       6269.43  409.42  2453.22  0.00     3406.79

          Small Bags  Large Bags  XLarge Bags     type  year    region
      0      1008.20      740.04          0.0  organic  2015     Boise
      2      1147.38     2139.36          0.0  organic  2015     Boise
      24       80.00     3326.79          0.0  organic  2015  Columbus
```

When dealing with multiple text based labels that we want to select, concatenating individual condition may become cumbersome. A better approach is to use the `.isin()` method. For example, to select avocados that come from Atlanta, Columbus and SouthCentral `region` we can do the following:

```
[18]: selection_condition = df['region'].isin(['Atlanta', 'Columbus', 'SouthCentral'])
      df[selection_condition]
```

```
[18]:           Date  AveragePrice  Total Volume       4046      4225    4770  \
      0   2015-12-27          0.99     386100.49  292097.36  27350.92  297.90
      1   2015-12-20          1.08     331377.53  251774.15  20702.45  103.06
      2   2015-12-13          0.96     417772.47  324932.28  31019.08  275.80
      3   2015-12-06          1.07     357636.82  283024.01  23740.85  181.92
      4   2015-11-29          0.99     333280.79  250288.65  28889.63  307.83
      ..         …           …             …          …         …       …
      7   2018-02-04          1.41     135996.73   29097.18   3815.01    0.00
      8   2018-01-28          1.42     137453.79   29301.71   4418.91    0.00
      9   2018-01-21          1.44     138349.93   22596.66   3200.09    0.00
      10  2018-01-14          1.50     146720.73   31829.24   4472.99    0.00
      11  2018-01-07          1.41     126323.33   25296.77   3848.62    3.00

          Total Bags  Small Bags  Large Bags  XLarge Bags          type  year  \
      0     66354.31    48605.95    17748.36         0.00  conventional  2015
```

```
1      58797.87    46930.26    11867.61          0.00  conventional  2015
2      61545.31    38903.57    22628.21         13.53  conventional  2015
3      50690.04    37032.67    13654.66          2.71  conventional  2015
4      53794.68    33031.72    20738.55         24.41  conventional  2015
..          …           …           …       …             …     …
7     103084.54    96116.60     6967.94          0.00       organic  2018
8     103733.17    98629.14     5104.03          0.00       organic  2018
9     112553.18   105354.48     7198.70          0.00       organic  2018
10    110418.50   102266.31     8152.19          0.00       organic  2018
11     97174.94    90151.57     7023.37          0.00       organic  2018

          region
0        Atlanta
1        Atlanta
2        Atlanta
3        Atlanta
4        Atlanta
..           …
7   SouthCentral
8   SouthCentral
9   SouthCentral
10  SouthCentral
11  SouthCentral

[1014 rows x 13 columns]
```

### 0.5.3 Setting (Re-Setting) the Index

By now you may have noticed that when we imported our data, the indexes of each entry were automatically set by pandas to increasing integer numbers displayed in bold on the left most column. However, for the avocado data the *Date* column seems a more appropriate index.

We can set the index to the appropriate column by using the `set_index` method either to create a new DataFrame object or modifying the existing DataFrame *in place*.

[19]:
```
new_df = df.set_index('Date')
```

[20]:
```
new_df.head(3)
```

[20]:
```
            AveragePrice  Total Volume     4046       4225    4770  \
Date
2015-12-27          1.33      64236.62  1036.74   54454.85   48.16
2015-12-20          1.35      54876.98   674.28   44638.81   58.33
2015-12-13          0.93     118220.22   794.70  109149.67  130.50

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
Date
2015-12-27     8696.87     8603.62       93.25          0.0  conventional
```

```
2015-12-20     9505.56     9408.07       97.49          0.0  conventional
2015-12-13     8145.35     8042.21      103.14          0.0  conventional

            year  region
Date
2015-12-27  2015  Albany
2015-12-20  2015  Albany
2015-12-13  2015  Albany
```

[21]:
```
df.set_index('Date', inplace=True)
```

[22]:
```
df.head(3)
```

[22]:
```
            AveragePrice  Total Volume     4046       4225    4770  \
Date
2015-12-27          1.33      64236.62  1036.74   54454.85   48.16
2015-12-20          1.35      54876.98   674.28   44638.81   58.33
2015-12-13          0.93     118220.22   794.70  109149.67  130.50

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
Date
2015-12-27     8696.87     8603.62       93.25          0.0  conventional
2015-12-20     9505.56     9408.07       97.49          0.0  conventional
2015-12-13     8145.35     8042.21      103.14          0.0  conventional

            year  region
Date
2015-12-27  2015  Albany
2015-12-20  2015  Albany
2015-12-13  2015  Albany
```

One thing to note here, is that the *Date* column is not directly recognized by pandas, since the cvs file does not contain any format information. However, we can easily get around this problem by using pandas `to_datetime()` method. This, of course must be done before setting the index.

[23]:
```
df = pd.read_csv('datasets/avocado.csv', index_col=0)
df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace = True)
df.head(3)
```

[23]:
```
            AveragePrice  Total Volume     4046       4225    4770  \
Date
2015-12-27          1.33      64236.62  1036.74   54454.85   48.16
2015-12-20          1.35      54876.98   674.28   44638.81   58.33
2015-12-13          0.93     118220.22   794.70  109149.67  130.50

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
```

```
Date
2015-12-27     8696.87     8603.62       93.25          0.0  conventional
2015-12-20     9505.56     9408.07       97.49          0.0  conventional
2015-12-13     8145.35     8042.21      103.14          0.0  conventional

            year  region
Date
2015-12-27  2015  Albany
2015-12-20  2015  Albany
2015-12-13  2015  Albany
```

Reverting back to the original DataFrame is straight forward via the `.reset_index()` method. When called with no arguments pandas simply attaches increasing integer indexes to the DataFrame and keeps the previous index as column of our data:

[24]:
```
df = df.reset_index()
df.head(3)
```

[24]:
```
        Date  AveragePrice  Total Volume     4046       4225    4770  \
0 2015-12-27          1.33      64236.62  1036.74   54454.85   48.16
1 2015-12-20          1.35      54876.98   674.28   44638.81   58.33
2 2015-12-13          0.93     118220.22   794.70  109149.67  130.50

   Total Bags  Small Bags  Large Bags  XLarge Bags          type  year  region
0     8696.87     8603.62       93.25          0.0  conventional  2015  Albany
1     9505.56     9408.07       97.49          0.0  conventional  2015  Albany
2     8145.35     8042.21      103.14          0.0  conventional  2015  Albany
```

However, sometimes we may wish to discard the previous index column altogether. This can be accomplished by setting the `drop` argument of `.reset_index()` method to `True`.:

[25]:
```
df.set_index('Date', inplace = True)
df = df.reset_index(drop=True)
df.head(3)
```

[25]:
```
   AveragePrice  Total Volume     4046       4225    4770  Total Bags  \
0          1.33      64236.62  1036.74   54454.85   48.16     8696.87
1          1.35      54876.98   674.28   44638.81   58.33     9505.56
2          0.93     118220.22   794.70  109149.67  130.50     8145.35

   Small Bags  Large Bags  XLarge Bags          type  year  region
0     8603.62       93.25          0.0  conventional  2015  Albany
1     9408.07       97.49          0.0  conventional  2015  Albany
2     8042.21      103.14          0.0  conventional  2015  Albany
```

### 0.6 Sorting

You may have noticed that our data frame does not contain entries in exact chronological order:

```
[26]: df = pd.read_csv('datasets/avocado.csv', index_col=0)
      df['Date'] = pd.to_datetime(df['Date'])
      df.set_index('Date', inplace = True)
      df
```

```
[26]:             AveragePrice  Total Volume     4046       4225    4770  \
      Date
      2015-12-27          1.33      64236.62  1036.74   54454.85   48.16
      2015-12-20          1.35      54876.98   674.28   44638.81   58.33
      2015-12-13          0.93     118220.22   794.70  109149.67  130.50
      2015-12-06          1.08      78992.15  1132.00   71976.41   72.58
      2015-11-29          1.28      51039.60   941.48   43838.39   75.78
      …                      …            …        …         …       …
      2018-02-04          1.63      17074.83  2046.96    1529.20    0.00
      2018-01-28          1.71      13888.04  1191.70    3431.50    0.00
      2018-01-21          1.87      13766.76  1191.92    2452.79  727.94
      2018-01-14          1.93      16205.22  1527.63    2981.04  727.01
      2018-01-07          1.62      17489.58  2894.77    2356.13  224.53

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
      Date
      2015-12-27     8696.87     8603.62       93.25          0.0  conventional
      2015-12-20     9505.56     9408.07       97.49          0.0  conventional
      2015-12-13     8145.35     8042.21      103.14          0.0  conventional
      2015-12-06     5811.16     5677.40      133.76          0.0  conventional
      2015-11-29     6183.95     5986.26      197.69          0.0  conventional
      …                  …           …           …            …           …
      2018-02-04    13498.67    13066.82      431.85          0.0       organic
      2018-01-28     9264.84     8940.04      324.80          0.0       organic
      2018-01-21     9394.11     9351.80       42.31          0.0       organic
      2018-01-14    10969.54    10919.54       50.00          0.0       organic
      2018-01-07    12014.15    11988.14       26.01          0.0       organic

                  year            region
      Date
      2015-12-27  2015            Albany
      2015-12-20  2015            Albany
      2015-12-13  2015            Albany
      2015-12-06  2015            Albany
      2015-11-29  2015            Albany
      …            …                 …
      2018-02-04  2018  WestTexNewMexico
      2018-01-28  2018  WestTexNewMexico
      2018-01-21  2018  WestTexNewMexico
      2018-01-14  2018  WestTexNewMexico
      2018-01-07  2018  WestTexNewMexico
```

```
[18249 rows x 12 columns]
```

To fix this, we can sort the `Date` indexes by calling the `.sort_index()` method:

[27]:
```
df = df.sort_index()
df
```

[27]:
```
            AveragePrice  Total Volume        4046       4225       4770  \
Date
2015-01-04          1.75      27365.89     9307.34    3844.81     615.28
2015-01-04          1.49      17723.17     1189.35   15628.27       0.00
2015-01-04          1.68       2896.72      161.68     206.96       0.00
2015-01-04          1.52      54956.80     3013.04   35456.88    1561.70
2015-01-04          1.64       1505.12        1.27    1129.50       0.00
…                    …             …           …          …          …
2018-03-25          1.36     908202.13   142681.06  463136.28  174975.75
2018-03-25          0.70    9010588.32  3999735.71  966589.50   30130.82
2018-03-25          1.42     163496.70    29253.30    5080.04       0.00
2018-03-25          1.70     190257.38    29644.09   70982.10       0.00
2018-03-25          1.34    1774776.77    63905.98  908653.71     843.45

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
Date
2015-01-04    13598.46    13061.10      537.36         0.00       organic
2015-01-04      905.55      905.55        0.00         0.00       organic
2015-01-04     2528.08     2528.08        0.00         0.00       organic
2015-01-04    14925.18    11264.80     3660.38         0.00  conventional
2015-01-04      374.35      186.67      187.68         0.00       organic
…                  …           …           …           …            …
2018-03-25   127409.04   103579.41    22467.04      1362.59  conventional
2018-03-25  4014132.29  3398569.92   546409.74     69152.63  conventional
2018-03-25   129163.36   109052.26    20111.10         0.00       organic
2018-03-25    89631.19    89424.11      207.08         0.00       organic
2018-03-25   801373.63   774634.09    23833.93      2905.61  conventional

            year              region
Date
2015-01-04  2015           Southeast
2015-01-04  2015             Chicago
2015-01-04  2015  HarrisburgScranton
2015-01-04  2015          Pittsburgh
2015-01-04  2015               Boise
…            …                 …
2018-03-25  2018             Chicago
2018-03-25  2018        SouthCentral
2018-03-25  2018        SouthCentral
2018-03-25  2018          California
```

```
2018-03-25  2018            NewYork

[18249 rows x 12 columns]
```

Now if we would like the data in descending order we can supply to `sort_index()` method the argument `ascending=Flase`:

[28]:
```python
df.sort_index(ascending=False)
```

[28]:
```
            AveragePrice  Total Volume       4046       4225     4770  \
Date
2018-03-25          1.34    1774776.77   63905.98  908653.71   843.45
2018-03-25          1.31      11125.08     533.97    1113.33     0.00
2018-03-25          1.52      15372.80    2399.71    3164.80     0.00
2018-03-25          1.21     330371.24   87782.44  137599.47   131.89
2018-03-25          1.60     271723.08   26996.28   77861.39   117.56
…                    …           …         …          …         …
2015-01-04          0.99     668086.00  117454.09  429518.41  5553.60
2015-01-04          1.70       1885.48     748.62      30.19     0.00
2015-01-04          1.46     612910.15  233286.13  216611.20  4370.99
2015-01-04          1.40     116253.44    3267.97   55693.04   109.55
2015-01-04          1.75      27365.89    9307.34    3844.81   615.28

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
Date
2018-03-25   801373.63   774634.09    23833.93      2905.61  conventional
2018-03-25     9477.78     7760.23     1717.55         0.00       organic
2018-03-25     9808.29     9789.70       18.59         0.00       organic
2018-03-25   104857.44    95210.59     7089.08      2557.77  conventional
2018-03-25   166747.85    87108.00    79495.39       144.46       organic
…                …           …           …            …             …
2015-01-04   115559.90    67894.33    47661.52         4.05  conventional
2015-01-04     1106.67     1106.67        0.00         0.00       organic
2015-01-04   158641.83   115068.71    43573.12         0.00       organic
2015-01-04    57182.88    57182.88        0.00         0.00  conventional
2015-01-04    13598.46    13061.10      537.36         0.00       organic

            year              region
Date
2018-03-25  2018             NewYork
2018-03-25  2018            Columbus
2018-03-25  2018       PhoenixTucson
2018-03-25  2018  HarrisburgScranton
2018-03-25  2018                West
…            …                   …
2015-01-04  2015              Denver
2015-01-04  2015               Tampa
```

```
2015-01-04  2015           TotalUS
2015-01-04  2015    BuffaloRochester
2015-01-04  2015          Southeast

[18249 rows x 12 columns]
```

Aside from sorting the index, pandas provides `.sort_values()` method through which we can sort one or multiple columns in both ascending and descending order. For example, sorting by the `AveragePrice` in descending order and then the `region` in ascending order can be done as follows:

[29]:
```
df.sort_values(['AveragePrice', 'region'], ascending=[False, True])
```

[29]:
```
            AveragePrice  Total Volume       4046       4225      4770  \
Date
2016-10-30          3.25      16700.94    2325.93   11142.85      0.00
2017-04-16          3.17       3018.56    1255.55      82.31      0.00
2016-11-06          3.12      19043.80    5898.49   10039.34      0.00
2017-03-12          3.05       2068.26    1043.83      77.36      0.00
2017-08-27          3.04      12656.32     419.06    4851.90    145.09
…                    …            …         …         …        …
2017-02-26          0.49      44024.03     252.79    4472.68      0.00
2015-12-27          0.49    1137707.43  738314.80  286858.37  11642.46
2017-03-05          0.48      50890.73     717.57    4138.84      0.00
2017-02-05          0.46    2200550.27 1200632.86  531226.65  18324.93
2017-03-05          0.44      64057.04     223.84    4748.88      0.00

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
Date
2016-10-30     3232.16     3232.16        0.00         0.00       organic
2017-04-16     1680.70     1542.22      138.48         0.00       organic
2016-11-06     3105.97     3079.30       26.67         0.00       organic
2017-03-12      947.07      926.67       20.40         0.00       organic
2017-08-27     7240.27     6960.97      279.30         0.00       organic
…                 …          …           …          …           …
2017-02-26    39298.56      600.00    38698.56         0.00       organic
2015-12-27   100891.80    70749.02    30142.78         0.00  conventional
2017-03-05    46034.32     1385.06    44649.26         0.00       organic
2017-02-05   450365.83   113752.17   330583.10      6030.56  conventional
2017-03-05    59084.32      638.68    58445.64         0.00       organic

            year            region
Date
2016-10-30  2016      SanFrancisco
2017-04-16  2016             Tampa
2016-11-06  2016      SanFrancisco
2017-03-12  2017  MiamiFtLauderdale
2017-08-27  2017  RaleighGreensboro
```

```
…           …                …
2017-02-26  2017   CincinnatiDayton
2015-12-27  2015       PhoenixTucson
2017-03-05  2017             Detroit
2017-02-05  2017       PhoenixTucson
2017-03-05  2017   CincinnatiDayton

[18249 rows x 12 columns]
```

### 0.7 Adding/Dropping Columns

We can create new DataFrame columns from scratch, but it is also common to derive them from other columns, i.e. by adding columns together, by changing their units and so on. For example, we might be interested in the `Total Volume` of units sold in units of thousand avocados sold. To do this, we can use any arithmetic operation applied to a column:

[30]:
```
df['Total Volume 1000 Unit'] = df['Total Volume'] / 1000
df.head(3)
```

[30]:
```
            AveragePrice  Total Volume     4046      4225    4770  Total Bags  \
Date
2015-01-04          1.75      27365.89  9307.34   3844.81  615.28    13598.46
2015-01-04          1.49      17723.17  1189.35  15628.27    0.00      905.55
2015-01-04          1.68       2896.72   161.68    206.96    0.00     2528.08

            Small Bags  Large Bags  XLarge Bags     type  year  \
Date
2015-01-04    13061.10      537.36          0.0  organic  2015
2015-01-04      905.55        0.00          0.0  organic  2015
2015-01-04     2528.08        0.00          0.0  organic  2015

                        region  Total Volume 1000 Unit
Date
2015-01-04           Southeast                27.36589
2015-01-04             Chicago                17.72317
2015-01-04  HarrisburgScranton                 2.89672
```

We can drop a column by using the `.drop()` method together with the column name (or index) we want to erase and the appropriate axis (0 - for rows, 1 - for columns).

[31]:
```
df = df.drop('Total Volume 1000 Unit', axis=1)
df.head(3)
```

[31]:
```
            AveragePrice  Total Volume     4046      4225    4770  Total Bags  \
Date
2015-01-04          1.75      27365.89  9307.34   3844.81  615.28    13598.46
2015-01-04          1.49      17723.17  1189.35  15628.27    0.00      905.55
```

```
2015-01-04          1.68       2896.72   161.68    206.96    0.00     2528.08

            Small Bags  Large Bags  XLarge Bags     type  year  \
Date
2015-01-04    13061.10      537.36          0.0  organic  2015
2015-01-04      905.55        0.00          0.0  organic  2015
2015-01-04     2528.08        0.00          0.0  organic  2015

                        region
Date
2015-01-04           Southeast
2015-01-04             Chicago
2015-01-04  HarrisburgScranton
```

## 0.8 Summary statistics

Aside from global summary statistics through `.describe()` method, pandas provides functionality to summarize specific parts of a DataFrame. Most common methods are the `.mean()`, `.median()`, `.mode()`, `.min()`, `.max()`, `.var()`, `.std()`, `.sum()` and `.quantile()`.

For example, combing slicing techniques with the `.mean()` method we can easily compute the average volume of sold avocados for the Atlanta region in 2018:

[32]:
```
atlanta_2018_df = df[(df['region'] == 'Atlanta') & (df['year'] == 2018)]
atlanta_2018_df.head(3)
```

[32]:
```
            AveragePrice  Total Volume       4046      4225     4770  \
Date
2018-01-07          1.53      15714.11     405.37   4195.19     0.00
2018-01-07          0.98     713915.80  364463.12  47869.41  1459.65
2018-01-14          1.10     670766.04  298975.97  60229.21  1604.90

            Total Bags  Small Bags  Large Bags  XLarge Bags         type  \
Date
2018-01-07    11113.55     7883.61     3229.94         0.00      organic
2018-01-07   300123.62   217644.43    78287.66      4191.53  conventional
2018-01-14   309955.96   171508.47   134436.39      4011.10  conventional

            year   region
Date
2018-01-07  2018  Atlanta
2018-01-07  2018  Atlanta
2018-01-14  2018  Atlanta
```

[33]:
```
atlanta_2018_df['Total Volume'].mean()
```

[33]:
```
342975.9354166667
```

We can also compute a summary statistic on multiple columns. The median for the `AveragePrice` and `Total Volume` can be computed as follows:

[34]:
```
atlanta_2018_df[['Total Volume', 'AveragePrice']].mean()
```

[34]:
```
Total Volume    342975.935417
AveragePrice         1.288750
dtype: float64
```

Moreover, we can compute multiple statistics via the `.agg()` method which takes as input a list of functions and applies each function on the specified columns. To illustrate we'll use functions provided by numpy with pandas `.agg()` to get the min, max and median values of the `Total Volume`:

[35]:
```
import numpy as np
atlanta_2018_df['Total Volume'].agg([np.min, np.max, np.median])
```

```
/tmp/ipykernel_136454/3661235333.py:2: FutureWarning: The provided callable
<function min at 0x7fb59c1ad670> is currently using Series.min. In a future
version of pandas, the provided callable will be used directly. To keep current
behavior pass the string "min" instead.
  atlanta_2018_df['Total Volume'].agg([np.min, np.max, np.median])
/tmp/ipykernel_136454/3661235333.py:2: FutureWarning: The provided callable
<function max at 0x7fb59c1ad550> is currently using Series.max. In a future
version of pandas, the provided callable will be used directly. To keep current
behavior pass the string "max" instead.
  atlanta_2018_df['Total Volume'].agg([np.min, np.max, np.median])
/tmp/ipykernel_136454/3661235333.py:2: FutureWarning: The provided callable
<function median at 0x7fb59c014a60> is currently using Series.median. In a
future version of pandas, the provided callable will be used directly. To keep
current behavior pass the string "median" instead.
  atlanta_2018_df['Total Volume'].agg([np.min, np.max, np.median])
```

[35]:
```
min        11165.57
max       957792.07
median    280745.50
Name: Total Volume, dtype: float64
```

And by combining slicing with `.agg()` we can get multiple statistics on multiple columns:

[36]:
```
atlanta_2018_df[['AveragePrice', 'Total Volume']].agg([np.min, np.max, np.
 ↪median, np.mean])
```

```
/tmp/ipykernel_136454/2515133910.py:1: FutureWarning: The provided callable
<function min at 0x7fb59c1ad670> is currently using Series.min. In a future
version of pandas, the provided callable will be used directly. To keep current
behavior pass the string "min" instead.
  atlanta_2018_df[['AveragePrice', 'Total Volume']].agg([np.min, np.max,
np.median, np.mean])
```

```
/tmp/ipykernel_136454/2515133910.py:1: FutureWarning: The provided callable
<function max at 0x7fb59c1ad550> is currently using Series.max. In a future
version of pandas, the provided callable will be used directly. To keep current
behavior pass the string "max" instead.
  atlanta_2018_df[['AveragePrice', 'Total Volume']].agg([np.min, np.max,
np.median, np.mean])
/tmp/ipykernel_136454/2515133910.py:1: FutureWarning: The provided callable
<function median at 0x7fb59c014a60> is currently using Series.median. In a
future version of pandas, the provided callable will be used directly. To keep
current behavior pass the string "median" instead.
  atlanta_2018_df[['AveragePrice', 'Total Volume']].agg([np.min, np.max,
np.median, np.mean])
/tmp/ipykernel_136454/2515133910.py:1: FutureWarning: The provided callable
<function mean at 0x7fb59c1ade50> is currently using Series.mean. In a future
version of pandas, the provided callable will be used directly. To keep current
behavior pass the string "mean" instead.
  atlanta_2018_df[['AveragePrice', 'Total Volume']].agg([np.min, np.max,
np.median, np.mean])
```

[36]:
```
        AveragePrice   Total Volume
min          0.86000   11165.570000
max          1.67000  957792.070000
median       1.26500  280745.500000
mean         1.28875  342975.935417
```

### 0.8.1 Cumulative Statistics

Pandas also includes counter part methods to compute cumulative statistics namely: `.cumsum()`, `.cummax()`, `cummin()` and `.cumprod()`.

Say we wanted to add a column that contains the cumulative `Total Volume` up to the current date:

[37]:
```
atlanta_2018_df = atlanta_2018_df.copy(deep=True) # needed to get rid of a␣
↪nasty warnning
atlanta_2018_df['Cumultative Total Volume'] =  atlanta_2018_df['Total Volume'].
↪cumsum()
atlanta_2018_df.head()
```

[37]:
```
            AveragePrice  Total Volume       4046      4225     4770  \
Date
2018-01-07          1.53      15714.11     405.37   4195.19     0.00
2018-01-07          0.98     713915.80  364463.12  47869.41  1459.65
2018-01-14          1.10     670766.04  298975.97  60229.21  1604.90
2018-01-14          1.56      16151.70     291.55   3583.40     0.00
2018-01-21          1.10     639421.29  288131.95  56731.74  1612.56

            Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
Date
```

```
2018-01-07    11113.55     7883.61     3229.94        0.00       organic
2018-01-07   300123.62   217644.43    78287.66     4191.53  conventional
2018-01-14   309955.96   171508.47   134436.39     4011.10  conventional
2018-01-14    12276.75     7227.80     5048.95        0.00       organic
2018-01-21   292945.04   158655.80   128969.24     5320.00  conventional

            year   region  Cumultative Total Volume
Date
2018-01-07  2018  Atlanta                  15714.11
2018-01-07  2018  Atlanta                 729629.91
2018-01-14  2018  Atlanta                1400395.95
2018-01-14  2018  Atlanta                1416547.65
2018-01-21  2018  Atlanta                2055968.94
```

### 0.8.2 Grouped Summaries

While we can slice our data any way we want, sometimes it becomes very inefficient (or even insurmountable) to write down every selection we need. For example, we may want to obtain the totals quantities for both `convetional` and `organic` type avocados for each date index. This is where the `.groupby()` method comes into play. The `.groupby()` method allows us to group our data based on any of the column labels, select specific columns and compute needed statistics, all in one go.

[38]:
```python
quatities_list = ['Total Volume', '4046', '4225', '4770', 'Total Bags', 'Small␣
 ↪Bags', 'Large Bags', 'XLarge Bags']

totals_df = df.drop(['type'], axis=1)
totals_df.groupby(['region', 'Date'])[quatities_list].sum()
```

[38]:
```
                             Total Volume       4046       4225      4770  \
region           Date
Albany           2015-01-04      42247.23    2876.92   28441.30     49.90
                 2015-01-11      42377.64    1041.85   31945.46    127.12
                 2015-01-18      45629.75     922.16   31719.10    135.77
                 2015-01-25      46263.39     956.25   33344.88    164.14
                 2015-02-01      72102.11    1387.02   60116.56    179.32
…                                     …          …          …         …
WestTexNewMexico 2018-02-25     914092.79  433191.27  174015.44  10590.75
                 2018-03-04     953327.40  456101.67  166762.14   9907.85
                 2018-03-11     919735.54  469664.22  157324.88  11389.19
                 2018-03-18     871147.55  459691.14  139096.59   8422.08
                 2018-03-25     980488.46  440851.42  201757.56  11017.42

                             Total Bags  Small Bags  Large Bags  XLarge Bags
region           Date
Albany           2015-01-04    10879.11    10349.58      529.53         0.00
                 2015-01-11     9263.21     8874.48      388.73         0.00
```

```
                 2015-01-18    12852.72    12582.76      269.96        0.00
                 2015-01-25    11798.12    11055.65      742.47        0.00
                 2015-02-01    10419.21    10266.85      152.36        0.00
…                                  …           …           …           …
WestTexNewMexico 2018-02-25   296295.33   139671.58   147306.32     9317.43
                 2018-03-04   320555.74   178367.28   138653.24     3535.22
                 2018-03-11   281357.25   168890.92   110574.41     1891.92
                 2018-03-18   263937.74   163306.66    98762.27     1868.81
                 2018-03-25   326862.06   163579.69   161235.74     2046.63

[9126 rows x 8 columns]
```

[39]:

```python
totals_df.groupby(['region', 'Date'])[quatities_list].agg([np.median, np.mean])
```

```
/tmp/ipykernel_136454/3086156435.py:1: FutureWarning: The provided callable
<function median at 0x7fb59c014a60> is currently using SeriesGroupBy.median. In
a future version of pandas, the provided callable will be used directly. To keep
current behavior pass the string "median" instead.
  totals_df.groupby(['region', 'Date'])[quatities_list].agg([np.median,
np.mean])
/tmp/ipykernel_136454/3086156435.py:1: FutureWarning: The provided callable
<function mean at 0x7fb59c1ade50> is currently using SeriesGroupBy.mean. In a
future version of pandas, the provided callable will be used directly. To keep
current behavior pass the string "mean" instead.
  totals_df.groupby(['region', 'Date'])[quatities_list].agg([np.median,
np.mean])
/tmp/ipykernel_136454/3086156435.py:1: FutureWarning: The provided callable
<function median at 0x7fb59c014a60> is currently using SeriesGroupBy.median. In
a future version of pandas, the provided callable will be used directly. To keep
current behavior pass the string "median" instead.
  totals_df.groupby(['region', 'Date'])[quatities_list].agg([np.median,
np.mean])
```

[39]:

```
                             Total Volume                    4046                \
                                   median        mean      median        mean
region           Date
Albany           2015-01-04     21123.615   21123.615    1438.460    1438.460
                 2015-01-11     21188.820   21188.820     520.925     520.925
                 2015-01-18     22814.875   22814.875     461.080     461.080
                 2015-01-25     23131.695   23131.695     478.125     478.125
                 2015-02-01     36051.055   36051.055     693.510     693.510
…                                   …           …           …           …
WestTexNewMexico 2018-02-25    457046.395  457046.395  216595.635  216595.635
                 2018-03-04    476663.700  476663.700  228050.835  228050.835
                 2018-03-11    459867.770  459867.770  234832.110  234832.110
                 2018-03-18    435573.775  435573.775  229845.570  229845.570
                 2018-03-25    490244.230  490244.230  220425.710  220425.710
```

```
                                  4225                   4770             \
                                median        mean     median       mean
region           Date
Albany           2015-01-04   14220.650   14220.650    24.950     24.950
                 2015-01-11   15972.730   15972.730    63.560     63.560
                 2015-01-18   15859.550   15859.550    67.885     67.885
                 2015-01-25   16672.440   16672.440    82.070     82.070
                 2015-02-01   30058.280   30058.280    89.660     89.660
…                                   …           …        …       …
WestTexNewMexico 2018-02-25   87007.720   87007.720  5295.375   5295.375
                 2018-03-04   83381.070   83381.070  4953.925   4953.925
                 2018-03-11   78662.440   78662.440  5694.595   5694.595
                 2018-03-18   69548.295   69548.295  4211.040   4211.040
                 2018-03-25  100878.780  100878.780  5508.710   5508.710

                             Total Bags              Small Bags              \
                                 median        mean      median        mean
region           Date
Albany           2015-01-04    5439.555    5439.555    5174.790    5174.790
                 2015-01-11    4631.605    4631.605    4437.240    4437.240
                 2015-01-18    6426.360    6426.360    6291.380    6291.380
                 2015-01-25    5899.060    5899.060    5527.825    5527.825
                 2015-02-01    5209.605    5209.605    5133.425    5133.425
…                                   …           …           …         …
WestTexNewMexico 2018-02-25  148147.665  148147.665   69835.790   69835.790
                 2018-03-04  160277.870  160277.870   89183.640   89183.640
                 2018-03-11  140678.625  140678.625   84445.460   84445.460
                 2018-03-18  131968.870  131968.870   81653.330   81653.330
                 2018-03-25  163431.030  163431.030   81789.845   81789.845

                            Large Bags             XLarge Bags
                                median        mean      median       mean
region           Date
Albany           2015-01-04    264.765     264.765       0.000      0.000
                 2015-01-11    194.365     194.365       0.000      0.000
                 2015-01-18    134.980     134.980       0.000      0.000
                 2015-01-25    371.235     371.235       0.000      0.000
                 2015-02-01     76.180      76.180       0.000      0.000
…                                 …           …          …       …
WestTexNewMexico 2018-02-25  73653.160   73653.160    4658.715   4658.715
                 2018-03-04  69326.620   69326.620    1767.610   1767.610
                 2018-03-11  55287.205   55287.205     945.960    945.960
                 2018-03-18  49381.135   49381.135     934.405    934.405
                 2018-03-25  80617.870   80617.870    1023.315   1023.315

[9126 rows x 16 columns]
```

## 0.9 Visualization

We are now ready to graph our data in order to gain some insights. Pandas nicely wraps matplotlib functionalities to support many types of data graphs, including: bar plots, line plots, scatter plots and histograms.

[40]:
```python
import matplotlib.pyplot as plt
```

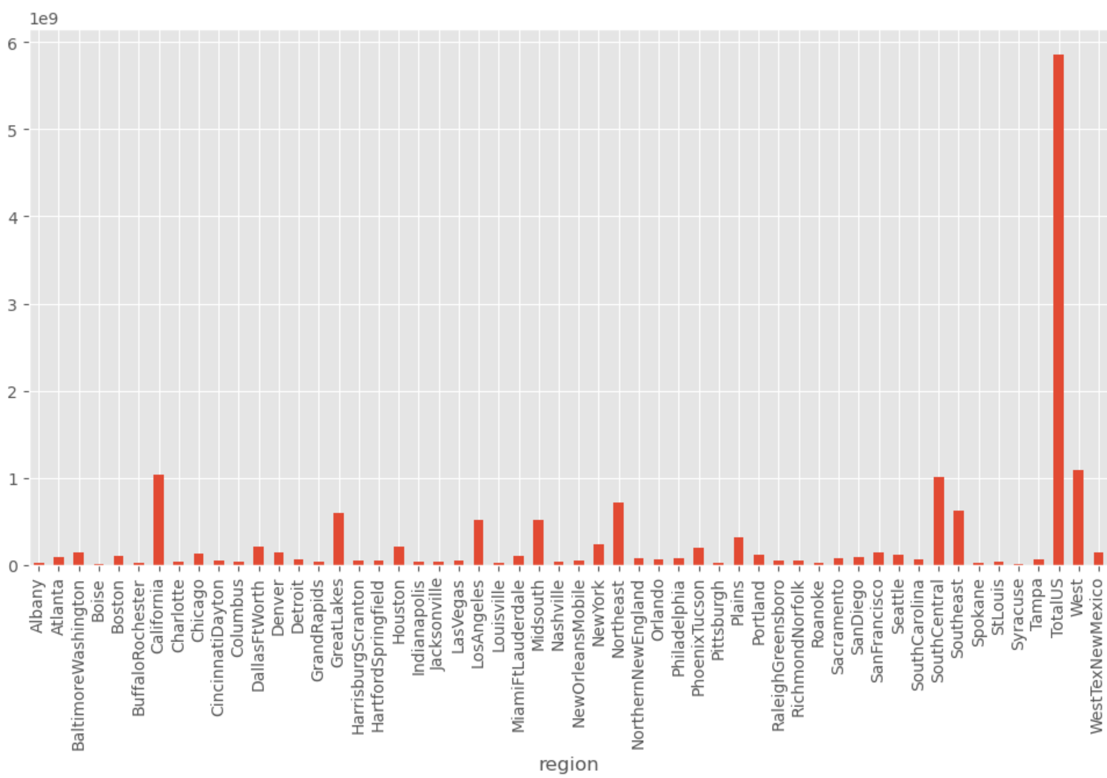
### 0.9.1 Bar plots

Bar plots are great for revealing relationships between categorical (ex: `region`) and numeric (`Total Volume` sold) variables. However, we often have to manipulate your data first in order to get the numbers you need for plotting.

For example we can get

[41]:
```python
volume_by_type_df = totals_df.groupby('region')['Total Volume'].sum()
volume_by_type_df.plot(kind='bar', figsize=(12, 6))
```

[41]: `<Axes: xlabel='region'>`

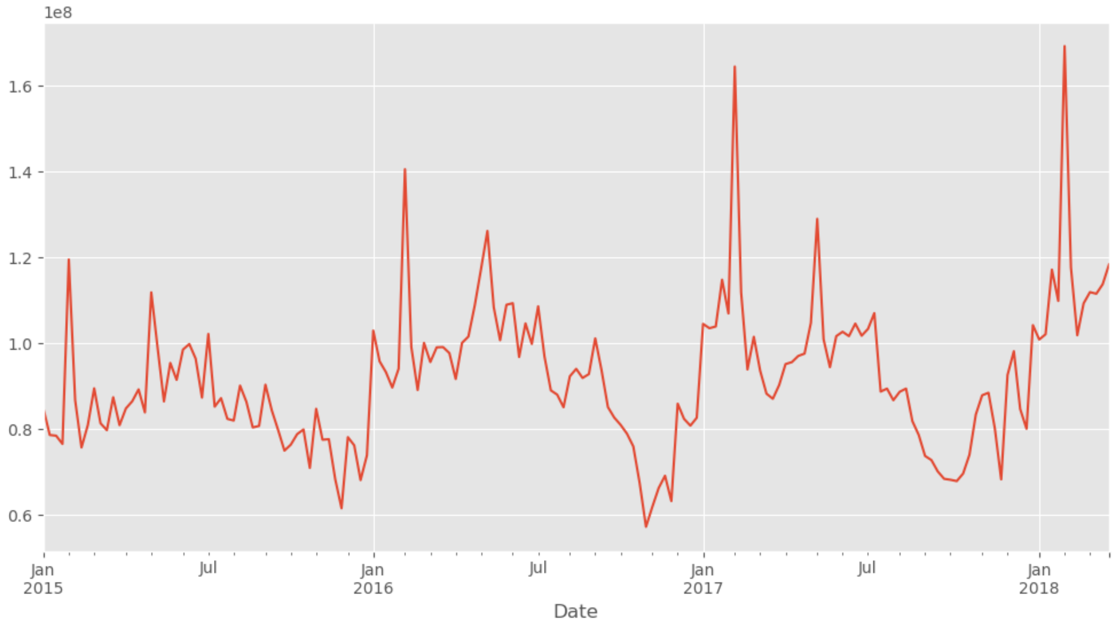


### 0.9.2 Line plots

Line plots are used to grasp the relation between numeric variables, especially in the context of a time series. For example to see how the `Total Volume` of avocados changed over time we can do the following:

[42]:
```
total_by_date = df.groupby('Date')['Total Volume'].sum()
total_by_date.plot(kind='line', figsize=(12,6))
```

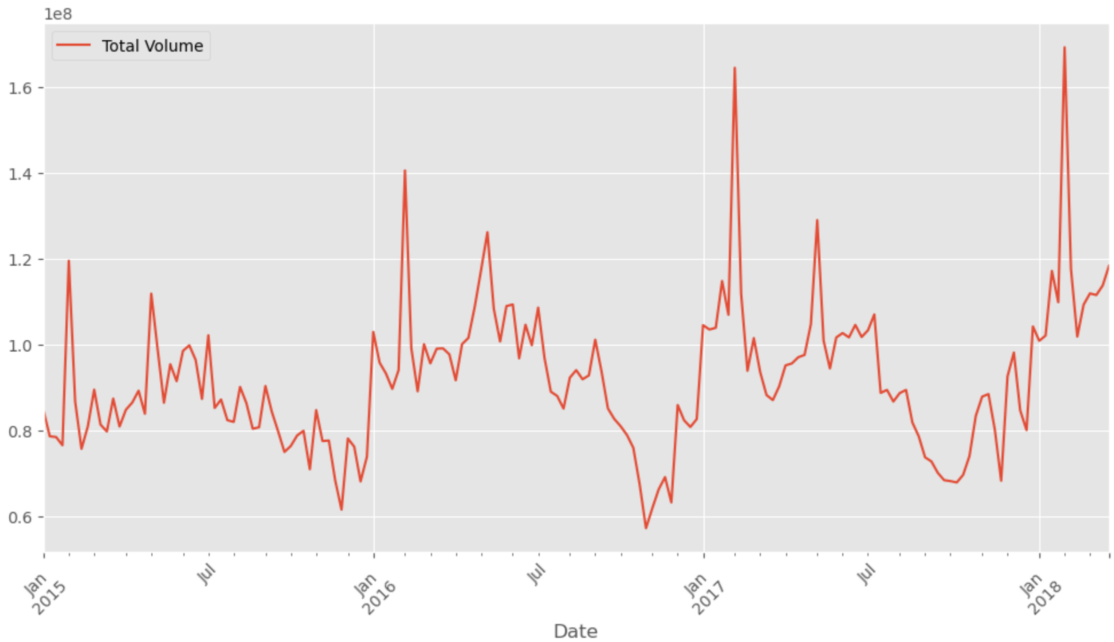
[42]: <Axes: xlabel='Date'>




We can write our own annotation for the x and y axes, provide a title, rotate the x axis labels a number of degrees and so on:

[43]:
```
total_by_date.plot(x='Date', y='Total volume', kind='line', rot=45,␣
↪figsize=(12,6), legend=True)
```

[43]: <Axes: xlabel='Date'>

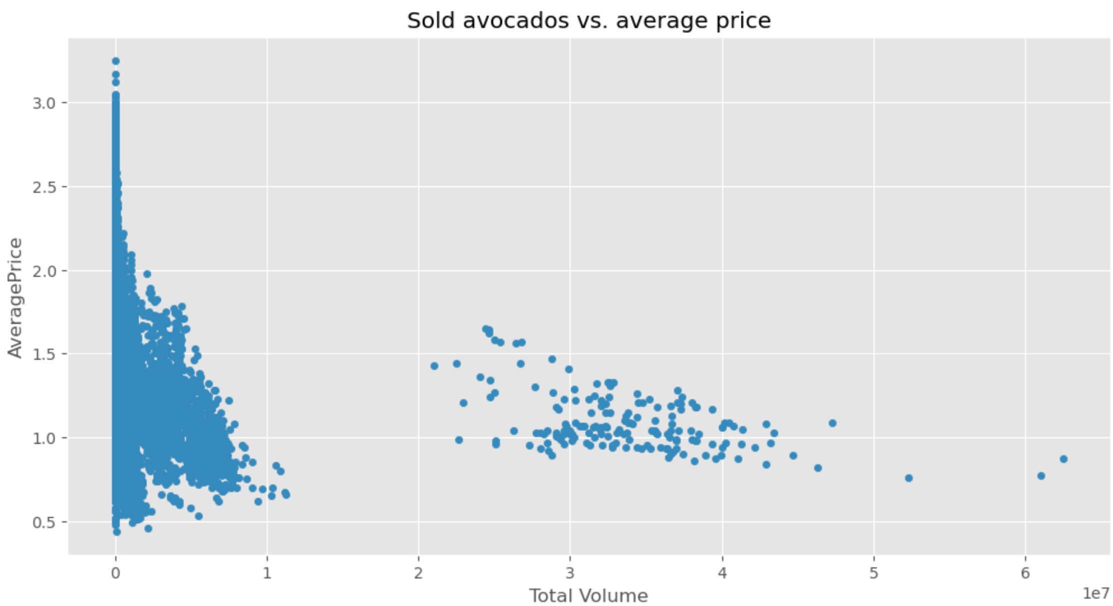



### 0.9.3 Scatter Plots

These plots are designed to visualize a more general relationship between variables (not necessarily a time series). For example, we can use scatter plot to see if there is a relationship between the `Total Volume` sold and the average price of avocados:

[44]:
```
df.plot(x='Total Volume', y='AveragePrice', kind='scatter', title='Sold␣
↪avocados vs. average price', figsize=(12,6))
```

[44]:
```
<Axes: title={'center': 'Sold avocados vs. average price'}, xlabel='Total
Volume', ylabel='AveragePrice'>
```

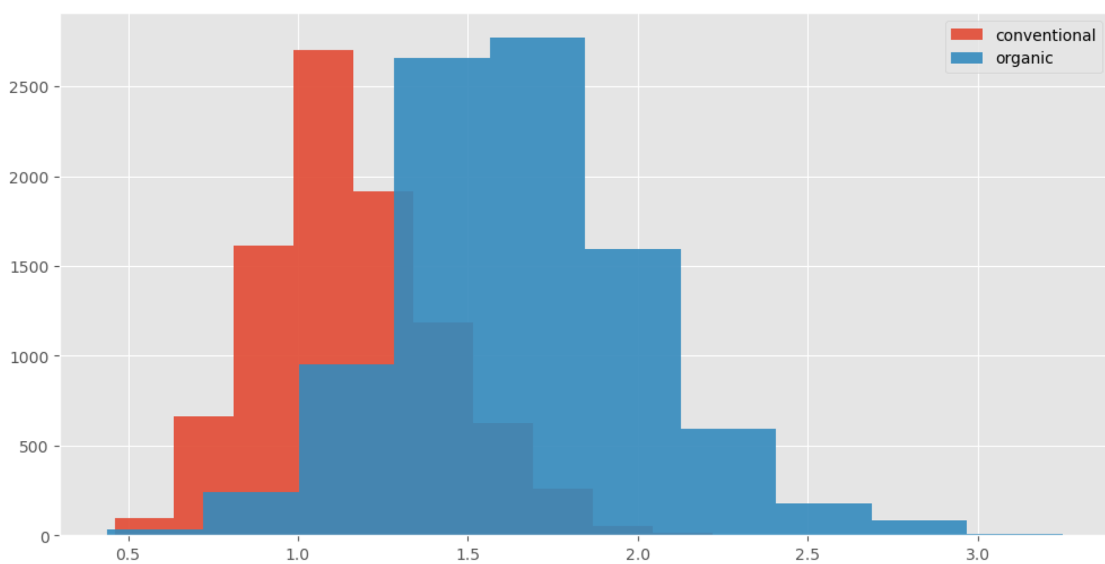



### 0.9.4 Histograms

Histograms are very useful to visualize the distribution of a variable. For example, we might be interested in the distributions of the `AveragePrice` relative to each type of avocados:

[45]:
```
plt.figure(figsize=(12,6))
df[df['type'] == 'conventional']['AveragePrice'].hist(alpha=0.9)
df[df['type'] == 'organic']['AveragePrice'].hist(alpha=0.9)
plt.legend(['conventional', 'organic'])
```

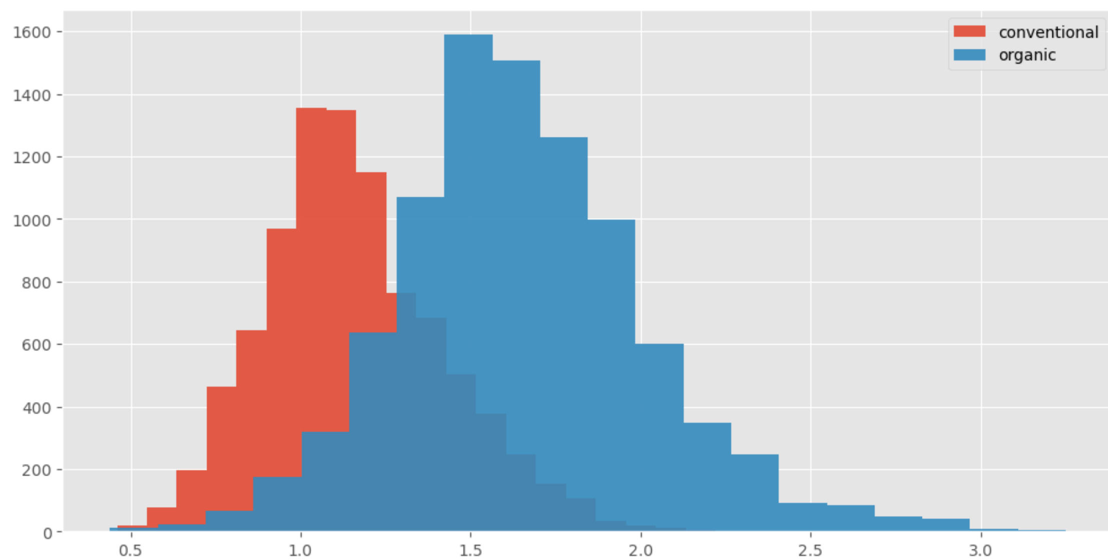
[45]: `<matplotlib.legend.Legend at 0x7fb55b70dfa0>`



Here, `alpha` is the histogram transparency parameter which ranges from zero (invisible) to one (opaque). More over we can get a more fine grained histogram by setting the number of `bins`.

[46]:
```
plt.figure(figsize=(12,6))
df[df['type'] == 'conventional']['AveragePrice'].hist(alpha=0.9, bins=20)
df[df['type'] == 'organic']['AveragePrice'].hist(alpha=0.9, bins=20)
plt.legend(['conventional', 'organic'])
```

[46]:
```
<matplotlib.legend.Legend at 0x7fb55b70d100>
```

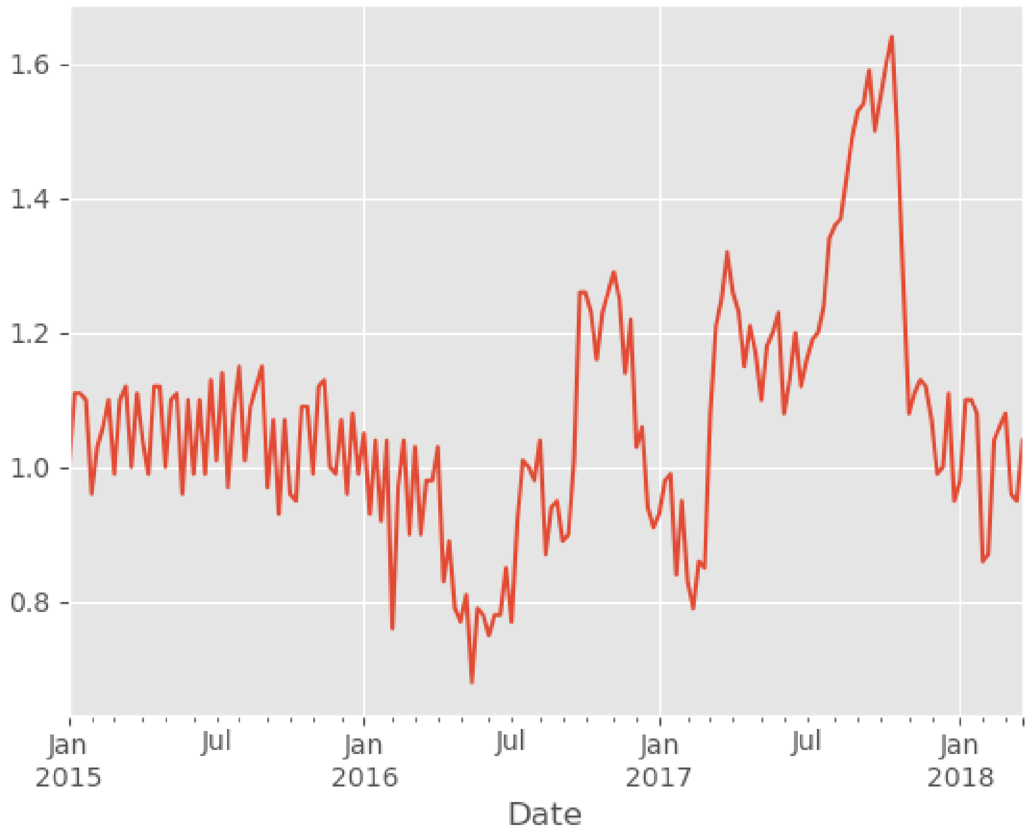



### 0.9.5 More Visualization

Now, say we wanted to visualize the evolution of the `AvaragePrice` price column for the Atlanta region for conventional type avocados. We can simply do:

[47]:
```
atlanta_df = df[(df['region'] == 'Atlanta') & (df['type'] == 'conventional')]
atlanta_df['AveragePrice'].plot()
```

[47]:
```
<Axes: xlabel='Date'>
```



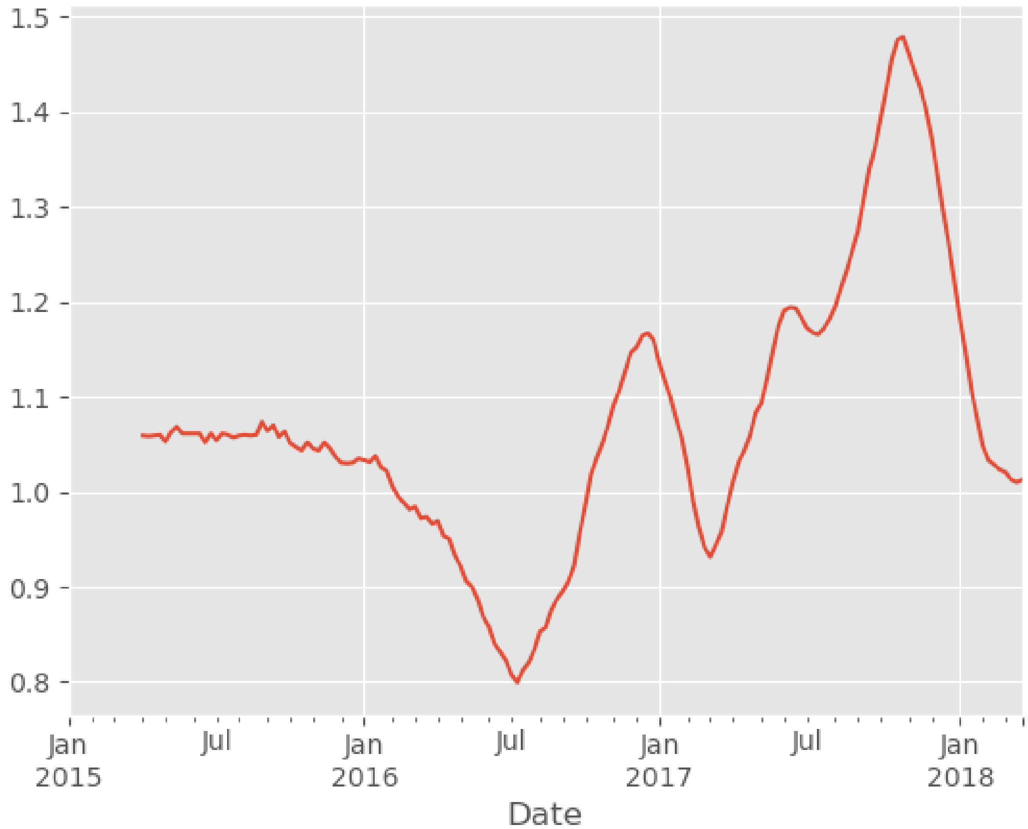

Looking at the graph, the data seems to be a little cramped up. Hence, this is where statistics like moving averages come at handy. To compute a moving average in pandas we will combine the calls to `rolling()` and `mean()` methods. The first sets the moving window size in the number of points, whereas the latter just computes the mean - in our case the mean of the provided window.

To demonstrate we'll compute the moving average over a window of 14 points and then plot the result.

[48]:
```
ma14_df = atlanta_df['AveragePrice'].rolling(14).mean()
```

[49]:
```
ma14_df.plot()
```

[49]: `<Axes: xlabel='Date'>`



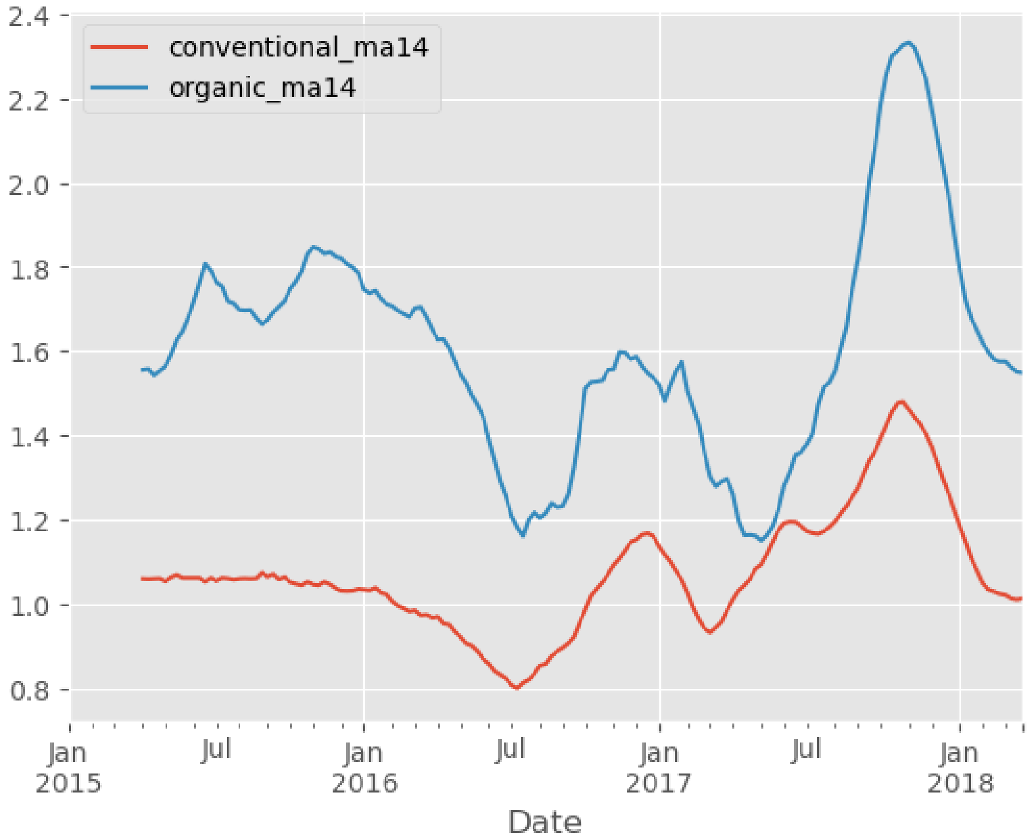

Often times we may want to view several evolutions on the same graph. Say for example we are interested in viewing both `organic` and `convetional` type avocados 14 days rolling averages over time. For this we can build a new frame which contains the rolling averages for both types of avocados and then plot the result:

[50]:
```
graph_df = pd.DataFrame() # empty data frame
tmp_df = pd.DataFrame()
atlanta_df = df[df['region'] == 'Atlanta'].copy(deep=True) # select Atlanta

# iterate through unique types, compute rolling mean averages and add them to␣
↪the graph
for avocado_type in atlanta_df['type'].unique():
    avocado_type_df = atlanta_df[atlanta_df['type'] == avocado_type]
    graph_df[f"{avocado_type}_ma14"] = avocado_type_df['AveragePrice'].
↪rolling(14).mean()

graph_df.plot()
```

[50]:
```
<Axes: xlabel='Date'>
```




Note that the `.unique()` DataFrame method was used here to create a numpy array of unique values for the type labels, such that we could iterate over each avocado type in turn.

## 0.10 Dealing with Missing Data

As one might expect, computing the a moving average for the first $n - 1$ points of the window is not possible. The way pandas deals with this problem is to fill these entries `NaN` as can be seen bellow.

[51]:
```
graph_df.head(14)
```

[51]:
```
            conventional_ma14  organic_ma14
Date
2015-01-04                NaN           NaN
2015-01-11                NaN           NaN
2015-01-18                NaN           NaN
2015-01-25                NaN           NaN
2015-02-01                NaN           NaN
2015-02-08                NaN           NaN
2015-02-15                NaN           NaN
2015-02-22                NaN           NaN
```

```
2015-03-01                 NaN           NaN
2015-03-08                 NaN           NaN
2015-03-15                 NaN           NaN
2015-03-22                 NaN           NaN
2015-03-29                 NaN           NaN
2015-04-05            1.059286         1.555
```

Given that in a general dataset missing values may occur in any given row or column, pandas has a couple of useful methods to detect, remove or fill these values.

The first method `.isna()` generates a True/False table for every value in the DataFrame, where False corresponds to non-missing values, while True correspond to `NaN`'s. In the case of our graph DataFrame example this looks like this:

[52]:
```
graph_df.isna()
```

[52]:
```
            conventional_ma14  organic_ma14
Date
2015-01-04               True          True
2015-01-11               True          True
2015-01-18               True          True
2015-01-25               True          True
2015-02-01               True          True
…                       …             …
2018-02-25              False         False
2018-03-04              False         False
2018-03-11              False         False
2018-03-18              False         False
2018-03-25              False         False

[169 rows x 2 columns]
```

Of course, by its self this method is not very helpful in determining which values are missing in the case of a real dataset. However, we can quickly find out in which column contains missing values by additionally applying the `.any()` method, which returns whether any element is True, potentially over the columns. For example:

[53]:
```
graph_df.isna().any()
```

[53]:
```
conventional_ma14    True
organic_ma14         True
dtype: bool
```

returns true for both of its columns because both contain `NaN` values. Furthermore, we can combine the output of `.isna()` with summarizing methods to count the number of missing values in each column, namely:

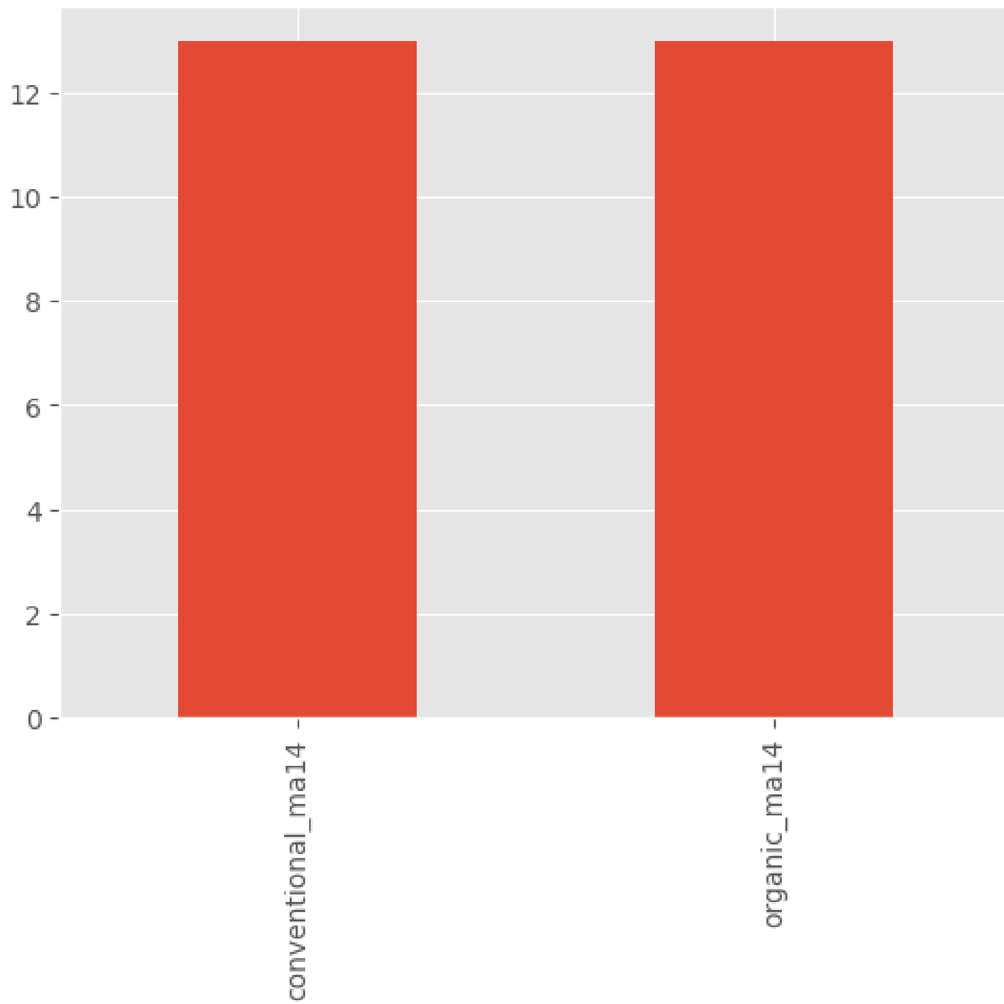
[54]:
```
graph_df.isna().sum()
```

[54]:
```
conventional_ma14    13
organic_ma14         13
dtype: int64
```

that correctly outputs 13 for both columns, since the first $n-1$ values out of 14 for our rolling 14 day window could't be computed. And since we now know the counts of missing values for each column, we can further visualize the distribution of these counts by simply doing a bar plot of the result:

[55]:
```
graph_df.isna().sum().plot(kind='bar')
```

[55]:
```
<Axes: >
```




Upon discovering these values we can either remove or replace them. Removing missing values is accomplished through the `dropna()` method:

[56]:
```
graph_df.dropna().head()
```

[56]:
```
            conventional_ma14  organic_ma14
Date
2015-04-05           1.059286      1.555000
2015-04-12           1.058571      1.557143
2015-04-19           1.059286      1.542143
2015-04-26           1.060000      1.552857
2015-05-03           1.052857      1.564286
```

Whereas replacing them is accomplished through `.fillna()` method, which replaces `NaN` with the value supplied as its argument:

[57]:
```
graph_df.fillna(0).head()
```

[57]:
```
            conventional_ma14  organic_ma14
Date
2015-01-04                0.0           0.0
2015-01-11                0.0           0.0
2015-01-18                0.0           0.0
2015-01-25                0.0           0.0
2015-02-01                0.0           0.0
```

### 0.11 Encoding Categorical Features

It is very common to see categorical features in a dataset. However, Machine Learning algorithms can only read numerical values. So, an important part of the data engineering processes is to transform these features into meaningful numeric representations. As it turns out there are two popular techniques for doing so:

- Label Encoding – which transforms the categorical data by assigning unique integers based on alphabetical ordering of the class values.
- One-Hot Encoding – which transforms the categorical data by representing it as vectors of zero values and a single one value. For each sample data point, the position of the one value in the one-hot encoded vector representation indicates the category to which it belongs.

Of the two techniques, one-hot encoding is preferred since it does not introduce an artificial ordering of the data by which an Machine Learning algorithm may by "tricked" (see here for an example).

Luckily, pandas integrates an easy to use one step method to transform our categories into their one-hot encoded counter parts, namely: `.get_dummies()`. For example, we can encode the type (organic/conventional) of avocados form the Atlanta region as:

[58]:
```
atlanta_df = df[df['region'] == 'Atlanta'].drop(columns=['region', 'year'])
atlanta_df.head()
```

[58]:
```
            AveragePrice  Total Volume       4046      4225    4770  \
Date
2015-01-04          1.00     435021.49  364302.39  23821.16   82.15
```

```
2015-01-04          1.76       3846.69    1500.15    938.35     0.00
2015-01-11          1.84       3743.82    1613.69   1207.72     0.00
2015-01-11          1.11     397542.72  330411.24  18958.22  1135.18
2015-01-18          1.86       4294.01    2138.51    989.40     0.00

            Total Bags  Small Bags  Large Bags  XLarge Bags          type
Date
2015-01-04    46815.79    16707.15    30108.64          0.0  conventional
2015-01-04     1408.19     1071.35      336.84          0.0       organic
2015-01-11      922.41      865.00       57.41          0.0       organic
2015-01-11    47038.08    21309.61    25728.47          0.0  conventional
2015-01-18     1166.10     1019.34      146.76          0.0       organic
```

Note, that we dropped the `region` column since all samples are from the same region and the `year` column since it conveys the same information as the `Date` index. And getting the the actual encoding is as simple as:

[59]:
```
atlanta_one_hot_df = pd.get_dummies(atlanta_df)
atlanta_one_hot_df.head()
```

[59]:
```
            AveragePrice  Total Volume       4046      4225     4770  \
Date
2015-01-04          1.00     435021.49  364302.39  23821.16    82.15
2015-01-04          1.76       3846.69    1500.15    938.35     0.00
2015-01-11          1.84       3743.82    1613.69   1207.72     0.00
2015-01-11          1.11     397542.72  330411.24  18958.22  1135.18
2015-01-18          1.86       4294.01    2138.51    989.40     0.00

            Total Bags  Small Bags  Large Bags  XLarge Bags  \
Date
2015-01-04    46815.79    16707.15    30108.64          0.0
2015-01-04     1408.19     1071.35      336.84          0.0
2015-01-11      922.41      865.00       57.41          0.0
2015-01-11    47038.08    21309.61    25728.47          0.0
2015-01-18     1166.10     1019.34      146.76          0.0

            type_conventional  type_organic
Date
2015-01-04               True         False
2015-01-04              False          True
2015-01-11              False          True
2015-01-11               True         False
2015-01-18              False          True
```

Also, notice that by default `.get_dummies()` appends new columns to each sample in each row which are named with the prefix of previous column name ('type' in our case) concatenated with a suffix of the specific class, where the separator is '_'. All these are user configurable, for example we may want to get something like:

[60]:
```
atlanta_one_hot_df = pd.get_dummies(atlanta_df, prefix='', prefix_sep='')
atlanta_one_hot_df.head()
```

[60]:
```
            AveragePrice  Total Volume       4046      4225     4770  \
Date
2015-01-04          1.00     435021.49  364302.39  23821.16    82.15
2015-01-04          1.76       3846.69    1500.15    938.35     0.00
2015-01-11          1.84       3743.82    1613.69   1207.72     0.00
2015-01-11          1.11     397542.72  330411.24  18958.22  1135.18
2015-01-18          1.86       4294.01    2138.51    989.40     0.00

            Total Bags  Small Bags  Large Bags  XLarge Bags  conventional  \
Date
2015-01-04    46815.79    16707.15    30108.64          0.0          True
2015-01-04     1408.19     1071.35      336.84          0.0         False
2015-01-11      922.41      865.00       57.41          0.0         False
2015-01-11    47038.08    21309.61    25728.47          0.0          True
2015-01-18     1166.10     1019.34      146.76          0.0         False

            organic
Date
2015-01-04    False
2015-01-04     True
2015-01-11     True
2015-01-11    False
2015-01-18     True
```