Unit 8: Handling data with pandas

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1 Handling data with pandas

1.1 Motivation

So far, we have encountered NumPy arrays as the only way to store numerical data (we mostly ignored the built-in containers provided directly in Python).

However, while NumPy arrays are great for storing homogenous data without any particular structure, they are somewhat limited when we want to use them for high-level data analysis.

For example, we usually want to process data sets with

1. several variables;
2. multiple observations, which need not be identical across variables (some values may be missing);
3. non-homogenous data types: for examples, names need to be stored as strings, birthdays as dates and income as a floating-point number.

While NumPy can in principle handle such situations, it puts all the burden on the user. Most users would prefer to not have to deal with such low-level details.

Imagine we want to store names, birth dates and annual income for two people:

Name	Date of birth	Income
Alice	1985-01-01	30,000
Bob	1997-05-12	-

No income was reported for Bob, so it's missing. With NumPy, we could do this as follows:

[1]:
```
import numpy as np
from datetime import date

date1 = date(1985, 1, 1)            # birth date for Alice
date2 = date(1997, 5, 12)           # birth date for Bob
```

```
data = np.array([['Alice', date1, 30000.0],
                 ['Bob', date2, None]])

data
```

```
[1]: array([['Alice', datetime.date(1985, 1, 1), 30000.0],
            ['Bob', datetime.date(1997, 5, 12), None]], dtype=object)
```

```
[2]: data.dtype          # print array data type
```

```
[2]: dtype('O')
```

While we can create such arrays, they are almost useless for data analysis, in particular since everything is stored as a generic `object`.

- To be fair, NumPy offers an alternative array type called "record" or "structured" array which can handle fields of different data types.

  However, the pandas library offers much more beyond that, so there is little reason to use structured arrays.

Pandas was created to offer more versatile data structures that are straightforward to use for storing, manipulating and analysing heterogeneous data:

1. Data is clearly organised in *variables* and *observations*, similar to econometrics programs such as Stata.
2. Each variable is permitted to have a different data type.
3. We can use *labels* to select observations, instead of having to use a linear numerical index as with NumPy.

   We could, for example, index a data set using National Insurance Numbers.
4. Pandas offers many convenient data aggregation and reduction routines that can be applied to subsets of data.

   For example, we can easily group observations by city and compute average incomes.
5. Pandas also offers many convenient data import / export functions that go beyond what's in NumPy.

Should we be using pandas at all times, then? No!

- For low-level tasks where performance is essential, use NumPy.
- For homogenous data without any particular data structure, use NumPy.
- On the other hand, if data is heterogeneous, needs to be imported from an external data source and cleaned or transformed before performing computations, use pandas.

There are numerous tutorials on pandas on the internet, so we will keep this unit short and illustrate only the main concepts. Useful references to additional material include:

- The official user guide.
- The official pandas cheat sheet which nicely illustrates the most frequently used operations.
- The official API reference with details on every pandas object and function.
- There are numerous tutorials (including videos) available on the internet. See here for a list.

1.2 Creating pandas data structures

Pandas has two main data structures:

1. `Series` represents observations of a single variable.
2. `DataFrame` is a container for several variables. You can think of each individual column of a `DataFrame` as a `Series`, and each row represents one observation.

The easiest way to create a `Series` or `DataFrame` is to create them from pre-existing data.

To access pandas data structures and routines, we need to import them first. The near-universal convention is to make pandas available using the name `pd`:

[3]:
```
import pandas as pd
```

Examples:

We can create a `DataFrame` from a NumPy array:

[4]:
```
import numpy as np
import pandas as pd              # universal convention: import using pd
from numpy.random import default_rng

# Draw normally distributed data
rng = default_rng(123)
data = rng.normal(size=(10,3))

# Define variable (or column) names
varnames = ['A', 'B', 'C']

# Create pandas DataFrame
pd.DataFrame(data, columns=varnames)
```

[4]:

	A	B	C
0	-0.989121	-0.367787	1.287925
1	0.193974	0.920231	0.577104
2	-0.636464	0.541952	-0.316595
3	-0.322389	0.097167	-1.525930
4	1.192166	-0.671090	1.000269
5	0.136321	1.532033	-0.659969
6	-0.311795	0.337769	-2.207471
7	0.827921	1.541630	1.126807
8	0.754770	-0.145978	1.281902
9	1.074031	0.392621	0.005114

This code creates a `DataFrame` of three variables called `A`, `B` and `C` with 10 observations each.

Alternatively, we can create a `DataFrame` from non-homogenous data as follows:

[5]:
```
# Names (strings)
names = ['Alice', 'Bob']

# Birth dates (datetime objects)
bdates = pd.to_datetime(['1985-01-01', '1997-05-12'])

# Incomes (floats)
incomes = np.array([35000, np.nan])          # code missing income as NaN

# create DataFrame from dictionary
pd.DataFrame({'Name': names, 'Birthdate': bdates, 'Income': incomes})
```

[5]:

	Name	Birthdate	Income
0	Alice	1985-01-01	35000.0
1	Bob	1997-05-12	NaN

If data types differ across columns, as in the above example, it is often convenient to create the `DataFrame` by passing a dictionary as an argument. Each key represents a column name and each corresponding value contains the data for that variable.

1.3 Viewing data

With large data sets, you hardly ever want to print the entire `DataFrame`. Pandas by default limits the amount of data shown. You can use the `head()` and `tail()` methods to explicitly display a specific number of rows from the top or the end of a `DataFrame`.

To illustrate, we use a data set of 23 UK universities that contains the following variables:

- `Instititution`: Name of the institution
- `Country`: Country/nation within the UK (England, Scotland, ...)
- `Founded`: Year in which university (or a predecessor institution) was founded
- `Students`: Total number of students
- `Staff`: Number of academic staff
- `Admin`: Number of administrative staff
- `Budget`: Budget in million pounds
- `Russell`: Binary indicator whether university is a member of the Russell Group, an association of the UK's top research universities.

The data was compiled based on information from Wikipedia.

We read in the data stored in the file `universities.csv` (from the `data/` folder) like this:

[6]:
```
import pandas as pd

# relative path to CSV file
file = '../data/universities.csv'

# Load sample data set of UK universities
df = pd.read_csv(file, sep=';')
```

We can now display the first and last three rows:

[7]:
```
df.head(3)      # show first three rows
```

[7]:

	Institution	Country	Founded	Students	Staff	Admin	Budget	Russell
0	University of Glasgow	Scotland	1451	30805	2942.0	4003.0	626.5	1
1	University of Edinburgh	Scotland	1583	34275	4589.0	6107.0	1102.0	1
2	University of St Andrews	Scotland	1413	8984	1137.0	1576.0	251.2	0

[8]:
```
df.tail(3)      # show last three rows
```

[8]:

	Institution	Country	Founded	Students	Staff	Admin	Budget	Russell
20	University of Stirling	Scotland	1967	9548	NaN	1872.0	113.3	0
21	Queen's University Belfast	Northern Ireland	1810	18438	2414.0	1489.0	369.2	1
22	Swansea University	Wales	1920	20620	NaN	3290.0	NaN	0

To quickly compute some descriptive statistics for the *numerical* variables in the `DataFrame`, we use `describe()`:

[9]:
```
df.describe()
```

[9]:

	Founded	Students	Staff	Admin	Budget
count	23.000000	23.000000	20.000000	19.000000	22.000000
mean	1745.652174	24106.782609	3664.250000	3556.736842	768.609091

```
std     256.992149   9093.000735  2025.638038  1550.434342   608.234948
min    1096.000000   8984.000000  1086.000000  1489.000000   113.300000
25%    1589.000000  18776.500000  2294.250000  2193.500000   340.850000
50%    1826.000000  23247.000000  3307.500000  3485.000000   643.750000
75%    1941.500000  30801.500000  4439.750000  4347.500000  1023.500000
max    2004.000000  41180.000000  7913.000000  6199.000000  2450.000000

         Russell
count  23.000000
mean    0.739130
std     0.448978
min     0.000000
25%     0.500000
50%     1.000000
75%     1.000000
max     1.000000
```

Note that this automatically ignores the columns `Institution` and `Country` as they contain strings and computing the mean, etc. of a string variable does not make sense.

To see low-level information about the data type used in each column, we call `info()`:

[10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23 entries, 0 to 22
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Institution  23 non-null     object
 1   Country      23 non-null     object
 2   Founded      23 non-null     int64
 3   Students     23 non-null     int64
 4   Staff        20 non-null     float64
 5   Admin        19 non-null     float64
 6   Budget       22 non-null     float64
 7   Russell      23 non-null     int64
dtypes: float64(3), int64(3), object(2)
memory usage: 1.6+ KB
```

Pandas automatically discards missing information in computations. For example, the number of academic staff is missing for several universities, so the number of *non-null* entries reported in the table above is less than 23, the overall sample size.

1.4 Indexing

Pandas supports two types of indexing:

1. Indexing by position. This is basically identical to the indexing of other Python and NumPy containers.
2. Indexing by label, i.e. by the values assigned to the row or column index. These labels need not be integers in increasing order, as is the case for NumPy.

   We will see how to assign labels below.

Pandas indexing is performed either by using brackets `[]`, or by using `.loc[]` for label indexing, or `.iloc[]` for positional indexing.

Indexing via `[]` can be somewhat confusing:

- specifying `df['name']` returns the column `name` as a `Series` object.

- On the other hand, specifying a range such as `df[5:10]` returns the *rows* associated with the *positions* 5,...,9.

Examples:

[11]:
```
import pandas as pd

# Load sample data set of UK universities
df = pd.read_csv('../data/universities.csv', sep=';')
df['Institution']               # select a single column
```

[11]:
```
0                University of Glasgow
1              University of Edinburgh
2             University of St Andrews
3               University of Aberdeen
4            University of Strathclyde
5                                  LSE
6                                  UCL
7              University of Cambridge
8                 University of Oxford
9                University of Warwick
10             Imperial College London
11               King's College London
12            University of Manchester
13               University of Bristol
14            University of Birmingham
15    Queen Mary University of London
16                  University of York
17            University of Nottingham
18                University of Dundee
19                  Cardiff University
20              University of Stirling
21         Queen's University Belfast
22                  Swansea University
Name: Institution, dtype: object
```

[12]:
```
df[['Institution', 'Students']]     # select multiple columns using a list
```

[12]:

	Institution	Students
0	University of Glasgow	30805
1	University of Edinburgh	34275
2	University of St Andrews	8984
3	University of Aberdeen	14775
4	University of Strathclyde	22640
5	LSE	11850
6	UCL	41180
7	University of Cambridge	23247
8	University of Oxford	24515
9	University of Warwick	27278
10	Imperial College London	19115
11	King's College London	32895
12	University of Manchester	40250
13	University of Bristol	25955
14	University of Birmingham	35445
15	Queen Mary University of London	20560
16	University of York	19470
17	University of Nottingham	30798
18	University of Dundee	15915
19	Cardiff University	25898
20	University of Stirling	9548
21	Queen's University Belfast	18438
22	Swansea University	20620

To return the rows at positions 1, 2 and 3 we use

[13]:
```
df[1:4]
```

[13]:
```
                Institution   Country  Founded  Students   Staff   Admin  \
1   University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2  University of St Andrews  Scotland     1413      8984  1137.0  1576.0
3    University of Aberdeen  Scotland     1495     14775  1086.0  1489.0

   Budget  Russell
1  1102.0        1
2   251.2        0
3   219.5        0
```

Pandas follows the Python convention that indices are 0-based, and the endpoint of a slice is not included.

1.4.1 Manipulating indices

Pandas uses *labels* to index and align data. These can be integer values starting at 0 with increments of 1 for each additional element, which is the default, but they need not be. The two main methods to manipulate indices are:

- `set_index(keys=['column1', ...])`: uses the values of `column1` and optionally additional columns as indices, discarding the current index.
- `reset_index()`: resets the index to its default value, a sequence increasing integers starting at 0.

Both methods return a new `DataFrame` and leave the original `DataFrame` unchanged. If we want to change the existing `DataFrame`, we need to pass the argument `inplace=True`.

For example, we can replace the row index and use the Roman lower-case characters `a`, `b`, `c`, ... as labels instead of integers:

[14]:
```
import pandas as pd
df = pd.read_csv('../data/universities.csv', sep=';')

# Create list of lower-case letters which has same
# length as the number of observations.
index = [chr(97+i) for i in range(len(df))]     # len(df) returns number of obs.
index
```

[14]:
```
['a',
 'b',
 'c',
 'd',
 'e',
 'f',
 'g',
 'h',
 'i',
 'j',
 'k',
 'l',
 'm',
 'n',
 'o',
 'p',
 'q',
 'r',
 's',
 't',
 'u',
 'v',
 'w']
```

[15]:
```
df['index'] = index                                # create new column 'index'
df.set_index(keys=['index'], inplace=True)         # set letters as index!

# print first 3 rows using labels
df['a':'c']              # This is the same as df[:3]
```

[15]:
```
                    Institution   Country  Founded  Students   Staff   Admin  \
index
a         University of Glasgow  Scotland     1451     30805  2942.0  4003.0
b       University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
c      University of St Andrews  Scotland     1413      8984  1137.0  1576.0

       Budget  Russell
index
a       626.5        1
b      1102.0        1
c       251.2        0
```

To add to the confusion, note that when specifying a range in terms of labels, the last element *is* included! Hence the row with index `c` in the above example is shown.

We can reset the index to its default integer values using the `reset_index()` method:

[16]:
```
# Reset index labels to default value (integers 0, 1, 2, ...)
df.reset_index(drop=True).head(3)        # print first 3 rows of new DataFrame
```

[16]:
```
                Institution   Country  Founded  Students   Staff   Admin  \
0     University of Glasgow  Scotland     1451     30805  2942.0  4003.0
1   University of Edinburgh  Scotland     1583     34275  4589.0  6107.0
2  University of St Andrews  Scotland     1413      8984  1137.0  1576.0

   Budget  Russell
0   626.5        1
1  1102.0        1
2   251.2        0
```

The `drop=True` argument tells pandas to throw away the old index values instead of storing them as a column of the resulting `DataFrame`.

1.4.2 Selecting elements

To more clearly distinguish between selection by label and by position, pandas provides the `.loc[]` and `.iloc[]` methods of indexing. To make your intention obvious, you should therefore adhere to the following rules:

1. Use `df['name']` only to select *columns* and nothing else.
2. Use `.loc[]` to select by label.
3. Use `.iloc[]` to select by position.

Selection by label

To illustrate, using `.loc[]` unambiguously indexes by label:

[17]:
```
df.loc['d':'f', ['Institution', 'Students']]
```

[17]:
```
                    Institution  Students
index
d         University of Aberdeen     14775
e      University of Strathclyde     22640
f                            LSE     11850
```

With `.loc[]` we can even perform slicing on column names, which is not possible with the simpler `df[]` syntax:

[18]:
```
df.loc['d':'f', 'Institution':'Founded']
```

[18]:

index	Institution	Country	Founded
d	University of Aberdeen	Scotland	1495
e	University of Strathclyde	Scotland	1964
f	LSE	England	1895

This includes all the columns between `Institution` and `Founded`, where the latter is included since we are slicing by label.

Trying to pass in positional arguments will return an error for the given `DataFrame` since the index labels are `a`, `b`, `c`,... and not 0, 1, 2...

[19]:
```
df.loc[0:4]
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-1-11cc54301474> in <module>
----> 1 df.loc[0:4]

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexing.py in␣
 ↪__getitem__(self, key)
    877
    878             maybe_callable = com.apply_if_callable(key, self.obj)
--> 879             return self._getitem_axis(maybe_callable, axis=axis)
    880
    881     def _is_scalar_access(self, key: Tuple):

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexing.py in␣
 ↪_getitem_axis(self, key, axis)
   1086         if isinstance(key, slice):
   1087             self._validate_key(key, axis)
-> 1088             return self._get_slice_axis(key, axis=axis)
   1089         elif com.is_bool_indexer(key):
   1090             return self._getbool_axis(key, axis=axis)

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexing.py in␣
 ↪_get_slice_axis(self, slice_obj, axis)
   1120
   1121         labels = obj._get_axis(axis)
-> 1122         indexer = labels.slice_indexer(
   1123             slice_obj.start, slice_obj.stop, slice_obj.step, kind="loc"
   1124         )

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexes/base.py
 ↪in slice_indexer(self, start, end, step, kind)
   4964         slice(1, 3, None)
   4965         """
-> 4966         start_slice, end_slice = self.slice_locs(start, end, step=step,␣
 ↪kind=kind)
   4967
   4968         # return a slice

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexes/base.py
 ↪in slice_locs(self, start, end, step, kind)
   5165         start_slice = None
   5166         if start is not None:
-> 5167             start_slice = self.get_slice_bound(start, "left", kind)
   5168         if start_slice is None:
   5169             start_slice = 0
```

```
~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexes/base.py
 ↪in get_slice_bound(self, label, side, kind)
   5077         # For datetime indices label may be a string that has to be␣
 ↪converted
   5078         # to datetime boundary according to its resolution.
-> 5079         label = self._maybe_cast_slice_bound(label, side, kind)
   5080
   5081         # we need to look up the label

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexes/base.py
 ↪in _maybe_cast_slice_bound(self, label, side, kind)
   5029         # this is rejected (generally .loc gets you here)
   5030         elif is_integer(label):
-> 5031             self._invalid_indexer("slice", label)
   5032
   5033         return label

~/.conda/envs/py3-default/lib/python3.8/site-packages/pandas/core/indexes/base.py
 ↪in _invalid_indexer(self, form, key)
   3265         Consistent invalid indexer message.
   3266         """
-> 3267         raise TypeError(
   3268             f"cannot do {form} indexing on {type(self).__name__} with␣
 ↪these "
   3269             f"indexers [{key}] of type {type(key).__name__}"

TypeError: cannot do slice indexing on Index with these indexers [0] of type int
```

However, we can reset the index to its default value. Then the index labels are integers and coincide with their position, so that `.loc[]` works:

[20]:
```
df.reset_index(inplace=True, drop=True)      # reset index labels to integers,
                                             # drop original index
df.loc[0:4]
```

[20]:

	Institution	Country	Founded	Students	Staff	Admin	Budget	Russell
0	University of Glasgow	Scotland	1451	30805	2942.0	4003.0	626.5	1
1	University of Edinburgh	Scotland	1583	34275	4589.0	6107.0	1102.0	1
2	University of St Andrews	Scotland	1413	8984	1137.0	1576.0	251.2	0
3	University of Aberdeen	Scotland	1495	14775	1086.0	1489.0	219.5	0
4	University of Strathclyde	Scotland	1964	22640	NaN	3200.0	304.4	0

Again, the end point with label `4` is included because we are selecting by label.

Somewhat surprisingly, we can also pass boolean arrays to `.loc[]` even though these are clearly not labels:

[21]:
```
df.loc[df['Country'] == 'Scotland']
```

[21]:

	Institution	Country	Founded	Students	Staff	Admin
0	University of Glasgow	Scotland	1451	30805	2942.0	4003.0
1	University of Edinburgh	Scotland	1583	34275	4589.0	6107.0
2	University of St Andrews	Scotland	1413	8984	1137.0	1576.0
3	University of Aberdeen	Scotland	1495	14775	1086.0	1489.0
4	University of Strathclyde	Scotland	1964	22640	NaN	3200.0

```
18       University of Dundee  Scotland     1967     15915  1410.0  1805.0
20     University of Stirling  Scotland     1967      9548     NaN  1872.0

    Budget  Russell
0    626.5        1
1   1102.0        1
2    251.2        0
3    219.5        0
4    304.4        0
18   256.4        0
20   113.3        0
```

Indexing via `.loc[]` supports a few more types of arguments, see the official documentation for details.

Selection by position

Conversely, if we want to select items exclusively by their position and ignore their labels, we use `.iloc[]`:

[22]:
```
df.iloc[0:4, 0:2]           # select first 4 rows, first 2 columns
```

[22]:
```
                Institution   Country
0     University of Glasgow  Scotland
1   University of Edinburgh  Scotland
2  University of St Andrews  Scotland
3    University of Aberdeen  Scotland
```

Again, `.iloc[]` supports a multitude of other arguments, including boolean arrays. See the official documentation for details.

1.5 Aggregation and reduction

1.5.1 Working with entire DataFrames

The simplest way to perform data reduction is to invoke the desired routine on the entire `DataFrame`:

[23]:
```
import pandas as pd

df = pd.read_csv('../data/universities.csv', sep=';')
df.mean()
```

[23]:
```
Founded      1745.652174
Students    24106.782609
Staff        3664.250000
Admin        3556.736842
Budget        768.609091
Russell         0.739130
dtype: float64
```

Methods such as `mean()` are by default applied column-wise to each numerical column.

One big advantage over NumPy is that missing values (represented by `np.nan`) are automatically ignored:

[24]:
```
# mean() automatically drops 3 missing observations
df['Staff'].mean()
```

[24]:
```
3664.25
```

1.5.2 Splitting and grouping

Applying aggregation functions to the entire `DataFrame` is similar to what we can do with NumPy. The added flexibility of pandas becomes obvious once we want to apply these functions to subsets of data, i.e. groups, which we can define based on values or index labels.

For example, we can easily group our universities by country:

[25]:
```
import pandas as pd

df = pd.read_csv('../data/universities.csv', sep=';')

groups = df.groupby(['Country'])
```

Here `groups` is a special pandas objects which can subsequently be used to process group-specific data. To compute the group-wise averages, we can simply run

[26]:
```
groups.mean()
```

[26]:
```
                     Founded      Students        Staff        Admin  \
Country
England           1745.923077  27119.846154  4336.692308  4112.000000
Northern Ireland  1810.000000  18438.000000  2414.000000  1489.000000
Scotland          1691.428571  19563.142857  2232.800000  2864.571429
Wales             1901.500000  23259.000000  3330.000000  4514.500000

                      Budget   Russell
Country
England           1001.700000  1.000000
Northern Ireland   369.200000  1.000000
Scotland           410.471429  0.285714
Wales              644.800000  0.500000
```

Groups support column indexing: if we want to only compute the total number of students for each country in our sample, we can do this as follows:

[27]:
```
groups['Students'].sum()
```

[27]:
```
Country
England             352558
Northern Ireland     18438
Scotland            136942
Wales                46518
Name: Students, dtype: int64
```

There are numerous routines to aggregate grouped data, for example:

- `mean()`, `sum()`: averages and sums over numerical items within groups.
- `std()`, `var()`: within-group std. dev. and variances
- `size()`: group sizes
- `first()`, `last()`: first and last elements in each group
- `min()`, `max()`: minimum and maximum elements within a group

Examples:

[28]:
```
groups.size()       # return number of elements in each group
```

[28]:
```
Country
England             13
Northern Ireland     1
Scotland             7
Wales                2
dtype: int64
```

[29]:
```
groups.first()      # return first element in each group
```

[29]:
```
                                Institution  Founded  Students   Staff  \
Country
England                                 LSE     1895     11850  1725.0
Northern Ireland  Queen's University Belfast     1810     18438  2414.0
Scotland               University of Glasgow     1451     30805  2942.0
Wales                     Cardiff University     1883     25898  3330.0

                   Admin  Budget  Russell
Country
England           2515.0   415.1        1
Northern Ireland  1489.0   369.2        1
Scotland          4003.0   626.5        1
Wales             5739.0   644.8        1
```

We can create custom aggregation routines by calling `agg()` or `aggregate()` on the grouped object. To illustrate, we count the number of universities in each country that have more than 20,000 students:

[30]:
```
groups['Students'].agg(lambda x: np.sum(x >= 20000))
```

[30]:
```
Country
England             10
Northern Ireland     0
Scotland             3
Wales                2
Name: Students, dtype: int64
```

Note that we called `agg()` only on the column `Students`, otherwise the function would be applied to every column separately, which is not what we want.

The most flexible aggregation method is `apply()` which calls a given function, passing the entire group-specific subset of data (including all columns) as an argument, and glues together the results.

For example, if we want to compute the average budget per student (in pounds), we can do this as follows:

[31]:
```
# Budget is in millions of pounds, rescale by 1.0e6
groups.apply(lambda x: x['Budget'].sum() / x['Students'].sum() * 1.0e6)
```

[31]:
```
Country
England             36936.050239
Northern Ireland    20023.863760
Scotland            20981.875539
Wales               13861.301002
dtype: float64
```

We couldn't have done this with `agg()`, since `agg()` never gets to see the entire chunk of data but only one column at a time.

This section provided only a first look at pandas's "split-apply-combine" functionality implemented via `groupby`. See the official documentation for more details.

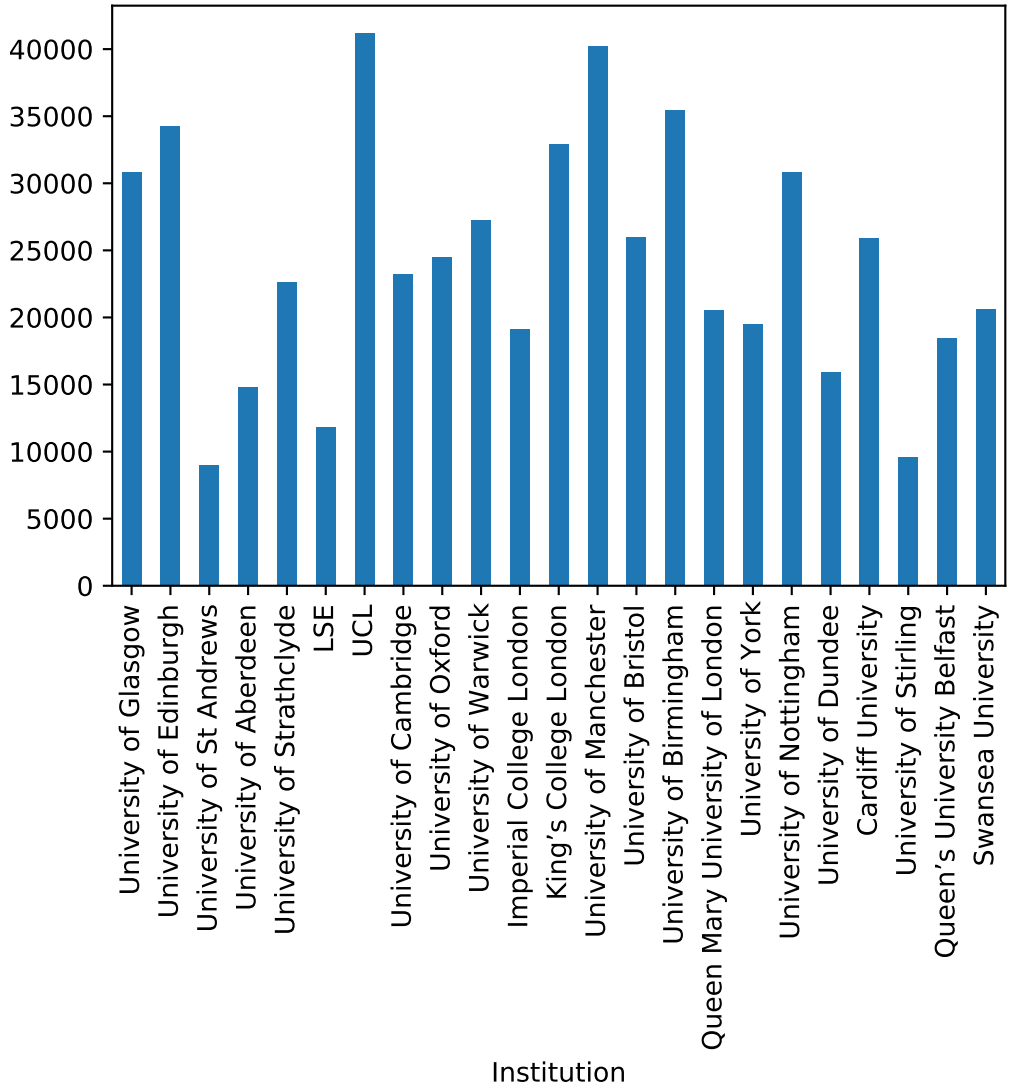
1.6 Visualisation

We covered plotting with Matplotlib in earlier units. Pandas itself implements some convenience wrappers around Matplotlib plotting routines which allow us to quickly inspect data stored in `DataFrames`. Alternatively, we can extract the numerical data and pass it to Matplotlib's routines manually.

For example, to plot student numbers as a bar chart, we can directly use pandas:

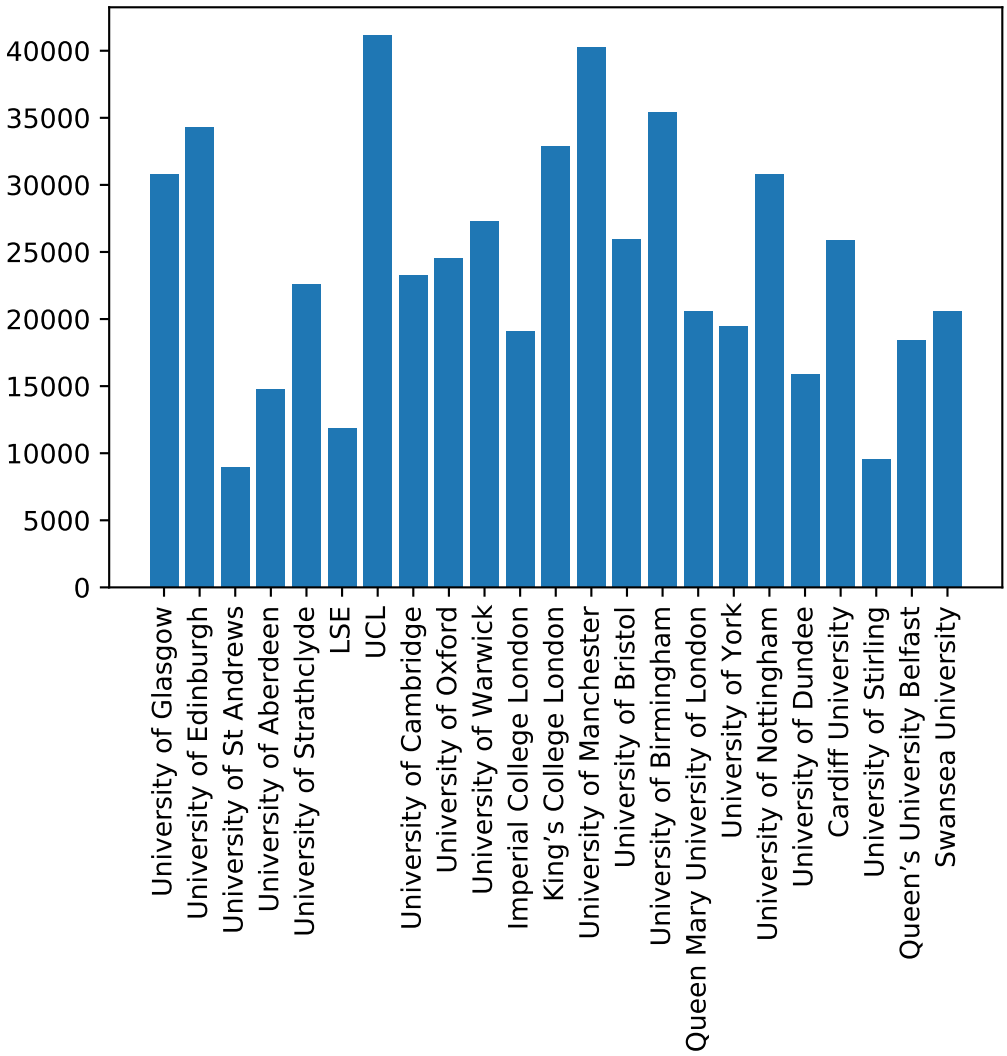
[32]:
```
import pandas as pd

df = pd.read_csv('../data/universities.csv', sep=';')

# set institution as label so they automatically show up in plot
df2 = df.set_index(keys=['Institution'])
df2['Students'].plot(kind='bar')
```

[32]: <AxesSubplot:xlabel='Institution'>



Alternatively, we can construct the graph using Matplotlib ourselves:

[33]:
```
import matplotlib.pyplot as plt

labels = df['Institution'].to_list()        # labels as list
values = df['Students'].to_numpy()          # data as NumPy array
plt.bar(labels, values)
plt.tick_params(axis='x', labelrotation=90)
```

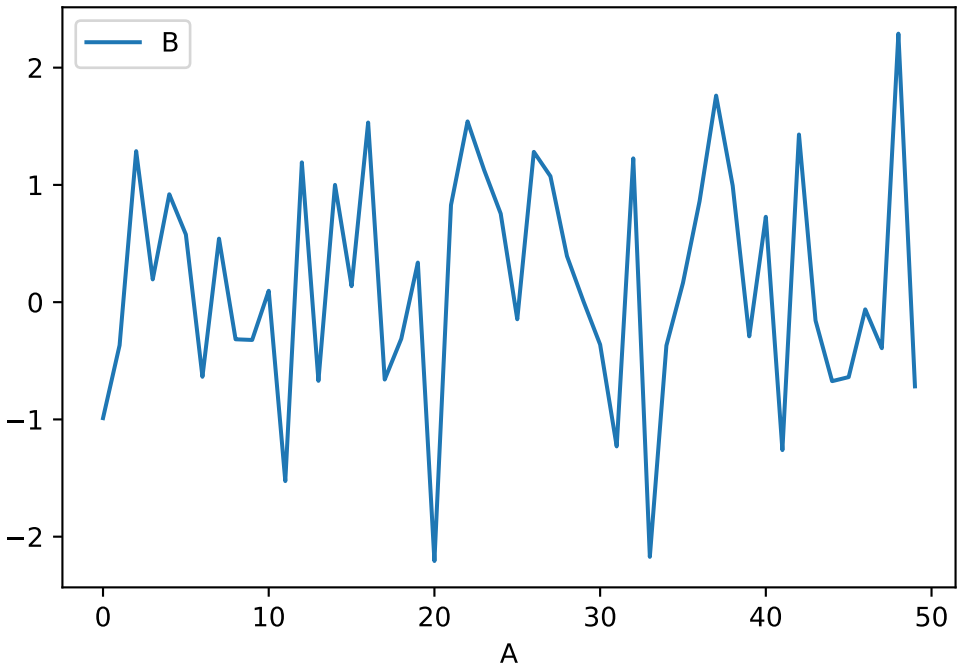


Sometimes Matplotlib's routines directly work with pandas's data structures, sometimes they don't. In cases where they don't, we can convert a `DataFrame` or `Series` object to a NumPy array using the `to_numpy()` method, and convert a `Series` to a Python list using `to_list()`, as illustrated in the example above.

To plot timeseries-like data, we can use the `plot()` method, which optionally accepts arguments to specify which columns should be used for the x-axis and which for the y-axis:

[34]:
```
import numpy as np
import pandas as pd

# Instantiate RNG
rng = np.random.default_rng(123)

# Create pandas DataFrame
nobs = 50
df = pd.DataFrame({'A': np.arange(nobs), 'B': rng.normal(size=nobs)})

df.plot(x='A', y='B')        # plot A on x-axis, B on y-axis
```

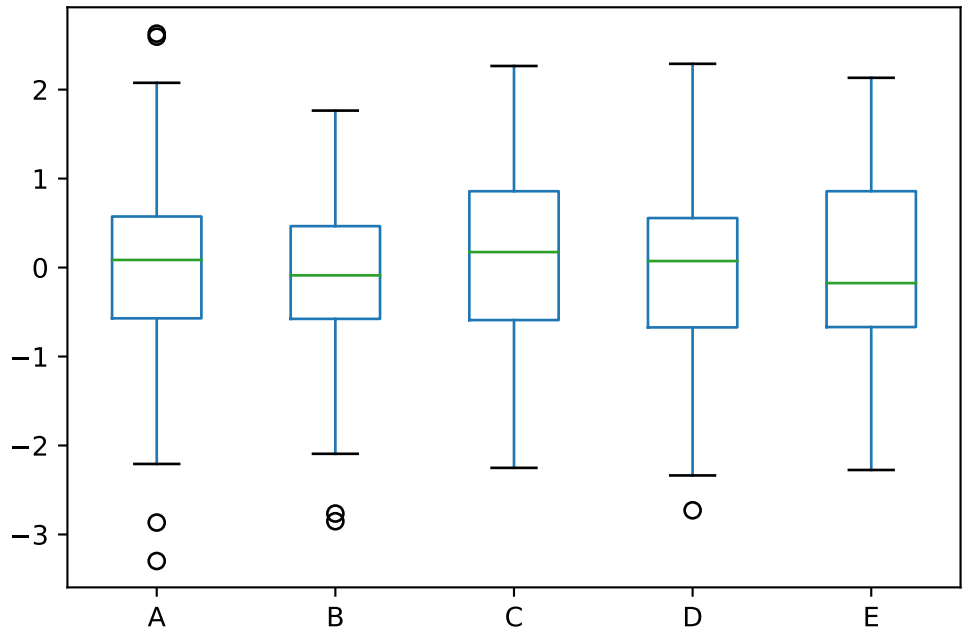
[34]:
```
<AxesSubplot:xlabel='A'>
```



To quickly generate some descriptive statistics, we can use the built-in box plot:

[35]:
```
import numpy as np
import pandas as pd

# Instantiate RNG
rng = np.random.default_rng(123)

# Create pandas DataFrame
df = pd.DataFrame(rng.normal(size=(100, 5)),
                  columns=['A', 'B', 'C', 'D', 'E'])

df.plot.box()           # same as df.plot(kind='box')
```

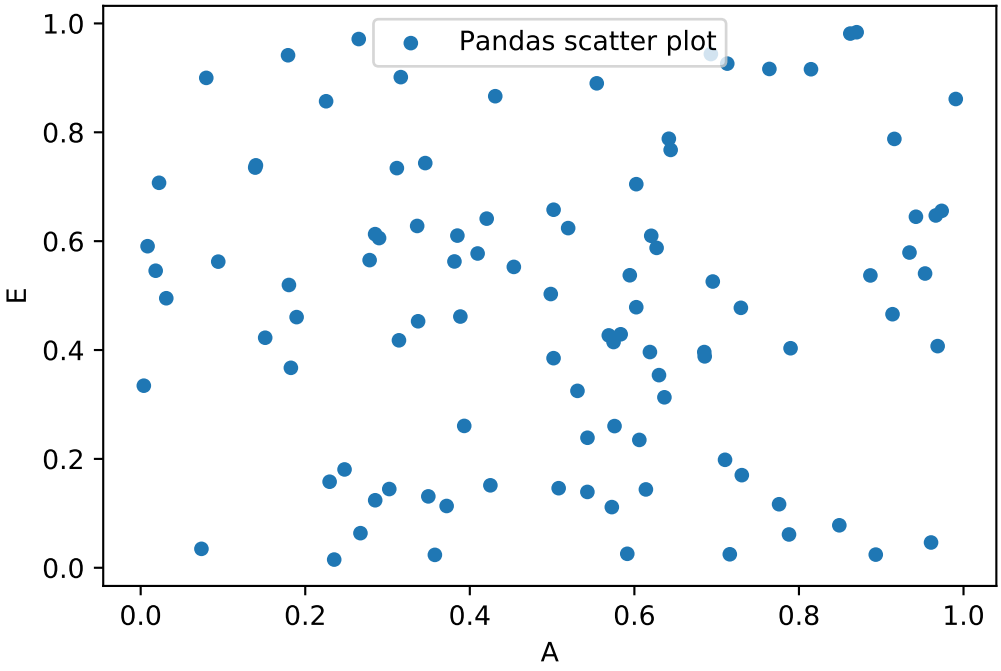
[35]:
```
<AxesSubplot:>
```



Similarly, we can generate scatter plots, plotting one column against another:

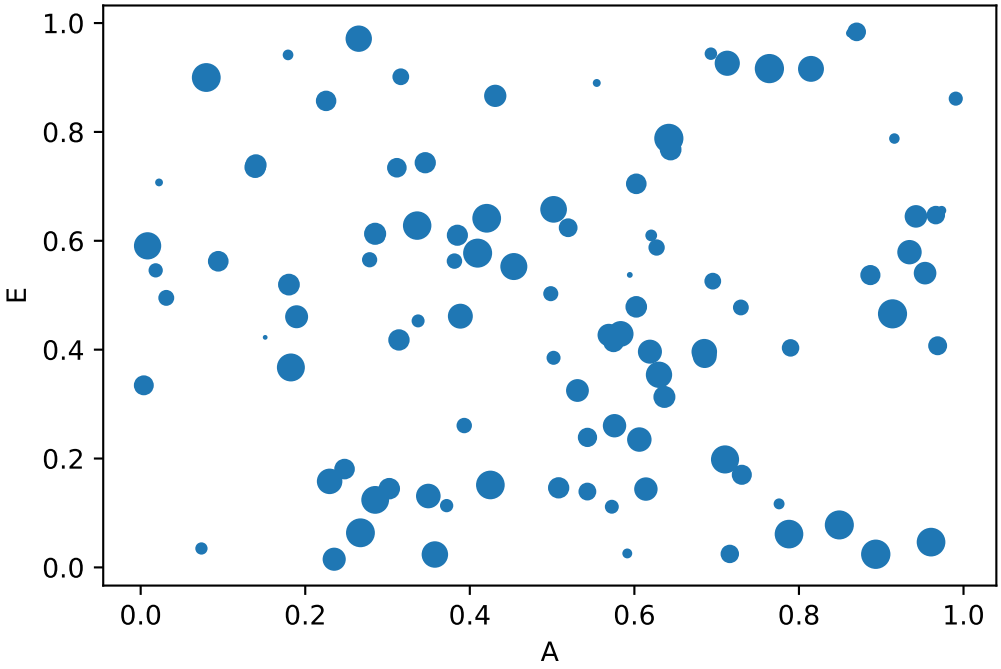
[36]:
```
# Create pandas DataFrame
df = pd.DataFrame(rng.uniform(size=(100, 5)),
                  columns=['A', 'B', 'C', 'D', 'E'])

df.plot.scatter(x='A', y='E', label='Pandas scatter plot')
```

[36]:
```
<AxesSubplot:xlabel='A', ylabel='E'>
```



[37]:
```
# We can even use a column to specify the dot size!
df.plot.scatter(x='A', y='E', s=df['B']*100.0)
```

[37]:
```
<AxesSubplot:xlabel='A', ylabel='E'>
```



In general, the wrappers implemented in pandas are useful to get an idea how the data looks like. For reusable code or more complex graphs, we'll usually want to directly use Matplotlib and pass the data converted to NumPy arrays.

2 Exercises

TBA

3 Solutions

TBA