11. Splitting data

Often one has tables that mix regular variables (e.g. the size of cells in microscopy images) with categorical variables (e.g. the type of cell to which they belong). In that case, it is quite usual to split the data by categories or *groups* to do computations. Pandas allows to do this very easily.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

11.1 Grouping

Let's import some data and have a look at them:

In [2]:
```
composers = pd.read_excel('Data/composers.xlsx', sheet_name='Sheet5')
```

In [3]:
```
composers.head()
```

Out[3]:

	composer	birth	death	period	country
0	Mahler	1860	1911.0	post-romantic	Austria
1	Beethoven	1770	1827.0	romantic	Germany
2	Puccini	1858	1924.0	post-romantic	Italy
3	Shostakovich	1906	1975.0	modern	Russia
4	Verdi	1813	1901.0	romantic	Italy

We also add a column here to calculate the composers' age:

In [4]:
```
composers['age'] = composers.death - composers.birth
```

11.1.1 Single level

What if we want now to count how many composers we have in a certain category like the period or country? In classical computing we would maybe do a for loop to count occurrences. Pandas simplifies this with the `groupby()` function, which actually groups elements by a certain criteria, e.g. a categorical variable like the period:

In [5]:
```
composer_grouped = composers.groupby('period')
composer_grouped
```

Out[5]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x11d2fc850>
```

The output is a bit cryptic. What we actually have is a new object called a group which has a lot of handy properties. First let's see what the groups actually are. We can find all groups with `groups` :

In [6]:
```
composer_grouped.groups
```

Out[6]:
```
{'baroque': Int64Index([14, 16, 17, 20, 21, 28, 29, 30, 31, 47], dtype='int64
'),
 'classic': Int64Index([9, 10, 32, 40, 51], dtype='int64'),
 'modern': Int64Index([3, 7, 11, 12, 19, 25, 45, 46, 50, 53, 54, 55, 56], dty
pe='int64'),
 'post-romantic': Int64Index([0, 2, 8, 18, 49], dtype='int64'),
 'renaissance': Int64Index([13, 26, 27, 36, 37, 43, 44], dtype='int64'),
 'romantic': Int64Index([1, 4, 5, 6, 15, 22, 23, 24, 33, 34, 35, 38, 39, 41,
42, 48, 52], dtype='int64')}
```

We have a dictionary, where each *period* that appears in the Dataframe is a key and each key contains a list of dataframe *indices* of rows with those periods. We will rarely directly use those indices, as most operations on groups only use those "behind the scene".

For example we can use `describe()` on a group object, just like we did it before for a Dataframe:

In [7]:
```
composer_grouped.describe()#.loc['Austria','birth']
```

Out[7]:

	birth								death		.
	count	mean	std	min	25%	50%	75%	max	count	mean	.
period											
baroque	10.0	1663.300000	36.009412	1587.0	1647.0	1676.5	1685.0	1710.0	10.0	1720.200000	.
classic	5.0	1744.400000	12.054045	1731.0	1732.0	1749.0	1754.0	1756.0	5.0	1801.200000	.
modern	13.0	1905.692308	28.595992	1854.0	1891.0	1902.0	1918.0	1971.0	11.0	1974.090909	.
post-romantic	5.0	1854.200000	17.123084	1824.0	1858.0	1860.0	1864.0	1865.0	5.0	1927.400000	.
renaissance	7.0	1527.142857	59.881629	1397.0	1528.5	1540.0	1564.5	1567.0	7.0	1595.285714	.
romantic	17.0	1824.823529	25.468695	1770.0	1810.0	1824.0	1841.0	1867.0	17.0	1883.588235	.

6 rows × 24 columns

We see here that the statistical analysis has been done for each group, the index of each row being the group name (or key in the dictionary). If we are interested in a specific group we can also easily recover it:

In [8]:
```
composer_grouped.get_group('classic')
```

Out[8]:

	composer	birth	death	period	country	age
9	Haydn	1732	1809.0	classic	Austria	77.0
10	Mozart	1756	1791.0	classic	Austria	35.0
32	Cimarosa	1749	1801.0	classic	Italy	52.0
40	Soler	1754	1806.0	classic	Spain	52.0
51	Dusek	1731	1799.0	classic	Czechia	68.0

We see that this returns a sub-group from the original table. Effectively it is almost equivalent to:

In [9]:
```
composers[composers.period == 'classic']
```

Out[9]:

	composer	birth	death	period	country	age
9	Haydn	1732	1809.0	classic	Austria	77.0
10	Mozart	1756	1791.0	classic	Austria	35.0
32	Cimarosa	1749	1801.0	classic	Italy	52.0
40	Soler	1754	1806.0	classic	Spain	52.0
51	Dusek	1731	1799.0	classic	Czechia	68.0

11.1.2 Multi-level

If one has multiple categorical variables, one can also do a grouping on several levels. For example here we want to classify composers both by period and country. For this we just give two column names to the `groupby()` function:

In [10]:
```python
composer_grouped = composers.groupby(['period','country'])
composer_grouped.describe()
```

Out[10]:

		birth								death	
		count	mean	std	min	25%	50%	75%	max	count	m
period	country										
baroque	England	1.0	1659.000000	NaN	1659.0	1659.00	1659.0	1659.00	1659.0	1.0	16
	France	3.0	1650.666667	29.263174	1626.0	1634.50	1643.0	1663.00	1683.0	3.0	17
	Germany	2.0	1685.000000	0.000000	1685.0	1685.00	1685.0	1685.00	1685.0	2.0	17
	Italy	4.0	1663.000000	53.285395	1587.0	1649.25	1677.5	1691.25	1710.0	4.0	17
classic	Austria	2.0	1744.000000	16.970563	1732.0	1738.00	1744.0	1750.00	1756.0	2.0	18
	Czechia	1.0	1731.000000	NaN	1731.0	1731.00	1731.0	1731.00	1731.0	1.0	17
	Italy	1.0	1749.000000	NaN	1749.0	1749.00	1749.0	1749.00	1749.0	1.0	18
	Spain	1.0	1754.000000	NaN	1754.0	1754.00	1754.0	1754.00	1754.0	1.0	18
modern	Austria	1.0	1885.000000	NaN	1885.0	1885.00	1885.0	1885.00	1885.0	1.0	19
	Czechia	1.0	1854.000000	NaN	1854.0	1854.00	1854.0	1854.00	1854.0	1.0	19
	England	2.0	1936.500000	48.790368	1902.0	1919.25	1936.5	1953.75	1971.0	1.0	19
	France	2.0	1916.500000	12.020815	1908.0	1912.25	1916.5	1920.75	1925.0	2.0	20
	Germany	1.0	1895.000000	NaN	1895.0	1895.00	1895.0	1895.00	1895.0	1.0	19
	RUssia	1.0	1891.000000	NaN	1891.0	1891.00	1891.0	1891.00	1891.0	1.0	19
	Russia	2.0	1894.000000	16.970563	1882.0	1888.00	1894.0	1900.00	1906.0	2.0	19
	USA	3.0	1918.333333	18.502252	1900.0	1909.00	1918.0	1927.50	1937.0	2.0	19
post-romantic	Austria	2.0	1842.000000	25.455844	1824.0	1833.00	1842.0	1851.00	1860.0	2.0	19
	Finland	1.0	1865.000000	NaN	1865.0	1865.00	1865.0	1865.00	1865.0	1.0	19
	Germany	1.0	1864.000000	NaN	1864.0	1864.00	1864.0	1864.00	1864.0	1.0	19
	Italy	1.0	1858.000000	NaN	1858.0	1858.00	1858.0	1858.00	1858.0	1.0	19
renaissance	Belgium	2.0	1464.500000	95.459415	1397.0	1430.75	1464.5	1498.25	1532.0	2.0	15
	England	2.0	1551.500000	16.263456	1540.0	1545.75	1551.5	1557.25	1563.0	2.0	16
	Italy	3.0	1552.666667	23.965253	1525.0	1545.50	1566.0	1566.50	1567.0	3.0	16
romantic	Czechia	2.0	1832.500000	12.020815	1824.0	1828.25	1832.5	1836.75	1841.0	2.0	18
	France	3.0	1821.000000	19.672316	1803.0	1810.50	1818.0	1830.00	1842.0	3.0	18
	Germany	4.0	1806.500000	26.388129	1770.0	1800.00	1811.5	1818.00	1833.0	4.0	18
	Italy	4.0	1817.250000	28.004464	1797.0	1800.00	1807.0	1824.25	1858.0	4.0	18
	Russia	2.0	1836.000000	4.242641	1833.0	1834.50	1836.0	1837.50	1839.0	2.0	18
	Spain	2.0	1863.500000	4.949747	1860.0	1861.75	1863.5	1865.25	1867.0	2.0	19

29 rows × 24 columns

In [11]:
```python
composer_grouped.get_group(('baroque','Germany'))
```

Out[11]:

	composer	birth	death	period	country	age
14	Haendel	1685	1759.0	baroque	Germany	74.0
47	Bach	1685	1750.0	baroque	Germany	65.0

11.2 Operations on groups

The main advantage of this Group object is that it allows us to do very quickly both computations and plotting without having to loop through different categories. Indeed Pandas makes all the work for us: it applies functions on each group and then reassembles the results into a Dataframe (or Series depending on the operation).

For example we can apply most functions we used for Dataframes (mean, sum etc.) on groups as well and Pandas seamlessly does the work for us:

In [12]:
```
composer_grouped.mean()
```

Out[12]:

		birth	death	age
period	**country**			
baroque	**England**	1659.000000	1695.000000	36.000000
	France	1650.666667	1709.666667	59.000000
	Germany	1685.000000	1754.500000	69.500000
	Italy	1663.000000	1717.250000	54.250000
classic	**Austria**	1744.000000	1800.000000	56.000000
	Czechia	1731.000000	1799.000000	68.000000
	Italy	1749.000000	1801.000000	52.000000
	Spain	1754.000000	1806.000000	52.000000
modern	**Austria**	1885.000000	1935.000000	50.000000
	Czechia	1854.000000	1928.000000	74.000000
	England	1936.500000	1983.000000	81.000000
	France	1916.500000	2004.000000	87.500000
	Germany	1895.000000	1982.000000	87.000000
	RUssia	1891.000000	1953.000000	62.000000
	Russia	1894.000000	1973.000000	79.000000
	USA	1918.333333	1990.000000	81.000000
post-romantic	**Austria**	1842.000000	1903.500000	61.500000
	Finland	1865.000000	1957.000000	92.000000
	Germany	1864.000000	1949.000000	85.000000
	Italy	1858.000000	1924.000000	66.000000
renaissance	**Belgium**	1464.500000	1534.000000	69.500000
	England	1551.500000	1624.500000	73.000000
	Italy	1552.666667	1616.666667	64.000000
romantic	**Czechia**	1832.500000	1894.000000	61.500000
	France	1821.000000	1891.333333	70.333333
	Germany	1806.500000	1865.750000	59.250000
	Italy	1817.250000	1875.750000	58.500000
	Russia	1836.000000	1884.000000	48.000000
	Spain	1863.500000	1912.500000	49.000000

In [13]:
```
composer_grouped.count()
```

Out[13]:

period	country	composer	birth	death	age
baroque	England	1	1	1	1
	France	3	3	3	3
	Germany	2	2	2	2
	Italy	4	4	4	4
classic	Austria	2	2	2	2
	Czechia	1	1	1	1
	Italy	1	1	1	1
	Spain	1	1	1	1
modern	Austria	1	1	1	1
	Czechia	1	1	1	1
	England	2	2	1	1
	France	2	2	2	2
	Germany	1	1	1	1
	RUssia	1	1	1	1
	Russia	2	2	2	2
	USA	3	3	2	2
post-romantic	Austria	2	2	2	2
	Finland	1	1	1	1
	Germany	1	1	1	1
	Italy	1	1	1	1
renaissance	Belgium	2	2	2	2
	England	2	2	2	2
	Italy	3	3	3	3
romantic	Czechia	2	2	2	2
	France	3	3	3	3
	Germany	4	4	4	4
	Italy	4	4	4	4
	Russia	2	2	2	2
	Spain	2	2	2	2

We can also design specific functions (again, like in the case of Dataframes) and apply them on groups:

In [14]:
```
def mult(myseries):
    return myseries.max() * 3
```

In [15]:
```
composer_grouped.apply(mult)
```

Out[15]:

period	country	composer	birth	death	period
baroque	England	PurcellPurcellPurcell	4977	5085.0	baroquebaroquebaroque
	France	RameauRameauRameau	5049	5292.0	baroquebaroquebaroque
	Germany	HaendelHaendelHaendel	5055	5277.0	baroquebaroquebaroque
	Italy	ScarlattiScarlattiScarlatti	5130	5271.0	baroquebaroquebaroque
classic	Austria	MozartMozartMozart	5268	5427.0	classicclassicclassic
	Czechia	DusekDusekDusek	5193	5397.0	classicclassicclassic
	Italy	CimarosaCimarosaCimarosa	5247	5403.0	classicclassicclassic
	Spain	SolerSolerSoler	5262	5418.0	classicclassicclassic
modern	Austria	BergBergBerg	5655	5805.0	modernmodernmodern
	Czechia	JanacekJanacekJanacek	5562	5784.0	modernmodernmodern
	England	WaltonWaltonWalton	5913	5949.0	modernmodernmodern
	France	MessiaenMessiaenMessiaen	5775	6048.0	modernmodernmodern
	Germany	OrffOrffOrff	5685	5946.0	modernmodernmodern
	RUssia	ProkofievProkofievProkofiev	5673	5859.0	modernmodernmodern
	Russia	StravinskyStravinskyStravinsky	5718	5925.0	modernmodernmodern
	USA	GlassGlassGlass	5811	5970.0	modernmodernmodern
post-romantic	Austria	MahlerMahlerMahler	5580	5733.0	post-romanticpost-romanticpost-romantic
	Finland	SibeliusSibeliusSibelius	5595	5871.0	post-romanticpost-romanticpost-romantic
	Germany	StraussStraussStrauss	5592	5847.0	post-romanticpost-romanticpost-romantic
	Italy	PucciniPucciniPuccini	5574	5772.0	post-romanticpost-romanticpost-romantic
renaissance	Belgium	LassusLassusLassus	4596	4782.0	renaissancerenaissancerenaissance
	England	DowlandDowlandDowland	4689	4878.0	renaissancerenaissancerenaissance
	Italy	PalestrinaPalestrinaPalestrina	4701	4929.0	renaissancerenaissancerenaissance
romantic	Czechia	SmetanaSmetanaSmetana	5523	5712.0	romanticromanticromantic
	France	MassenetMassenetMassenet	5526	5736.0	romanticromanticromantic
	Germany	WagnerWagnerWagner	5499	5691.0	romanticromanticromantic
	Italy	VerdiVerdiVerdi	5574	5757.0	romanticromanticromantic
	Russia	MussorsgskyMussorsgskyMussorsgsky	5517	5661.0	romanticromanticromantic
	Spain	GranadosGranadosGranados	5601	5748.0	romanticromanticromantic

11.3 Reshaping dataframes

As we see above, grouping operations can create more or less complex dataframes by adding one or multiple indexing levels. There are multiple ways to "reshape" such dataframes in order to make thm usable e.g. for plotting. Typically, plotting software based on a grammar of graphics expect a simple 2D dataframe where each line is an observation with several properties.

11.3.1 re-indexing, unstacking

One of the most common "reshaping" is to reset the index. In its simplest form, it will create a new dataframe, where each row corresponds to one observation. For example in the case of a dataframe with multi-indices, it will re-cast these indices as columns:

In [16]:
```
composer_grouped = composers.groupby(['period','country']).mean()
composer_grouped.head(10)
```

Out[16]:

		birth	death	age
period	**country**			
baroque	**England**	1659.000000	1695.000000	36.00
	France	1650.666667	1709.666667	59.00
	Germany	1685.000000	1754.500000	69.50
	Italy	1663.000000	1717.250000	54.25
classic	**Austria**	1744.000000	1800.000000	56.00
	Czechia	1731.000000	1799.000000	68.00
	Italy	1749.000000	1801.000000	52.00
	Spain	1754.000000	1806.000000	52.00
modern	**Austria**	1885.000000	1935.000000	50.00
	Czechia	1854.000000	1928.000000	74.00

In [17]:
```
composer_grouped.reset_index().head(5)
```

Out[17]:

	period	country	birth	death	age
0	baroque	England	1659.000000	1695.000000	36.00
1	baroque	France	1650.666667	1709.666667	59.00
2	baroque	Germany	1685.000000	1754.500000	69.50
3	baroque	Italy	1663.000000	1717.250000	54.25
4	classic	Austria	1744.000000	1800.000000	56.00

One can of course be more specific and reset only specific indices e.g. by level:

In [18]:
```
composer_grouped.reset_index(level=1).head(5)
```

Out[18]:

	country	birth	death	age
period				
baroque	England	1659.000000	1695.000000	36.00
baroque	France	1650.666667	1709.666667	59.00
baroque	Germany	1685.000000	1754.500000	69.50
baroque	Italy	1663.000000	1717.250000	54.25
classic	Austria	1744.000000	1800.000000	56.00

11.3.2 unstacking

Another way to move indices to columns is to *unstack* a dataframe, in other words pivot some indices to columns:

In [19]:
```
composer_grouped.unstack()
```

Out[19]:

	birth									
country	**Austria**	**Belgium**	**Czechia**	**England**	**Finland**	**France**	**Germany**	**Italy**	**RUssia**	**F**
period										
baroque	NaN	NaN	NaN	1659.0	NaN	1650.666667	1685.0	1663.000000	NaN	
classic	1744.0	NaN	1731.0	NaN	NaN	NaN	NaN	1749.000000	NaN	
modern	1885.0	NaN	1854.0	1936.5	NaN	1916.500000	1895.0	NaN	1891.0	
post-romantic	1842.0	NaN	NaN	NaN	1865.0	NaN	1864.0	1858.000000	NaN	
renaissance	NaN	1464.5	NaN	1551.5	NaN	NaN	NaN	1552.666667	NaN	
romantic	NaN	NaN	1832.5	NaN	NaN	1821.000000	1806.5	1817.250000	NaN	

6 rows × 36 columns

This creates a multi-level column indexing.

11.3.3 Wide to long: melt

A very common operation when handling tables is to switch from wide to long format and vice versa. In our composer example, let's for example imagine that you want both `birth` and `death` dates to be grouped in a single column called `dates` . But you still need to know if that data is a birth or date, so you need a new column that indicates that. To achieve that, we need to specify `id_vars` a list of columns to be used as *identifiers* e.g. the composer name, and `value_vars` , a list of columns that should become rows:

In [20]:
```
composers.head(5)
```

Out[20]:

	composer	birth	death	period	country	age
0	Mahler	1860	1911.0	post-romantic	Austria	51.0
1	Beethoven	1770	1827.0	romantic	Germany	57.0
2	Puccini	1858	1924.0	post-romantic	Italy	66.0
3	Shostakovich	1906	1975.0	modern	Russia	69.0
4	Verdi	1813	1901.0	romantic	Italy	88.0

In [21]:
```
pd.melt(composers, id_vars=['composer'], value_vars=['birth', 'death'])
```

Out[21]:

	composer	variable	value
0	Mahler	birth	1860.0
1	Beethoven	birth	1770.0
2	Puccini	birth	1858.0
3	Shostakovich	birth	1906.0
4	Verdi	birth	1813.0
...	...	...	...
109	Smetana	death	1884.0
110	Janacek	death	1928.0
111	Copland	death	1990.0
112	Bernstein	death	1990.0
113	Glass	death	NaN

114 rows × 3 columns

We can keep more of the original columns as *identifiers* and also specify names for the *variable* and *value* columns:

In [22]:
```
melted = pd.melt(composers, id_vars=['composer','period','age','country'], v
alue_vars=['birth', 'death'],
                var_name = 'date_type', value_name='dates')
melted
```

Out[22]:

	composer	period	age	country	date_type	dates
0	Mahler	post-romantic	51.0	Austria	birth	1860.0
1	Beethoven	romantic	57.0	Germany	birth	1770.0
2	Puccini	post-romantic	66.0	Italy	birth	1858.0
3	Shostakovich	modern	69.0	Russia	birth	1906.0
4	Verdi	romantic	88.0	Italy	birth	1813.0
...	...	...	...	...	...	...
109	Smetana	romantic	60.0	Czechia	death	1884.0
110	Janacek	modern	74.0	Czechia	death	1928.0
111	Copland	modern	90.0	USA	death	1990.0
112	Bernstein	modern	72.0	USA	death	1990.0
113	Glass	modern	NaN	USA	death	NaN

114 rows × 6 columns

11.4 Plotting

We have seen above that we can create groups and apply functions to them to get some summary of them as new dataframes or series that could then also be reshaped. The final result of these operations is then ideally suited to be plotted in a very efficient way.

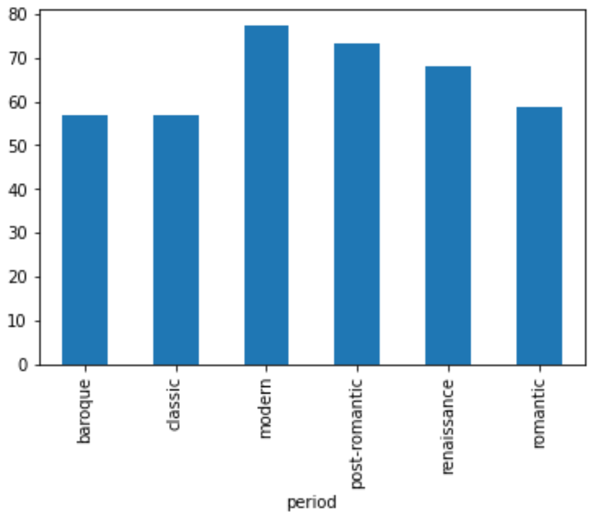
Here's a simple example: we group composers by periods and then calculate the mean age, resulting in a series where periods are indices:

In [23]:
```
composers.groupby('period')['age'].mean()
```

Out[23]:
```
period
baroque          56.900000
classic          56.800000
modern           77.181818
post-romantic    73.200000
renaissance      68.142857
romantic         58.764706
Name: age, dtype: float64
```

We can just add one more operation to that line to create a bar plot illustrating this:

In [24]:
```
composers.groupby('period')['age'].mean().plot(kind = 'bar');
```



The built-in plotting capabilities of Pandas automatically used the indices to label the bars, and also used the series name as a general label.

Using more advanced libraries, we can go further than that and use multiple columns to create complex plots. This will be shown in the next chapter.