5.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 using the category 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
```

5.1 Grouping

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

In [2]:
```
composers = pd.read_excel('Datasets/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

In [4]:
```
# MZ
# you don't have to explicitly go through the table and groupe elements
# simply use the 'groupby' function
```

5.1.1 Single level

What if we want now to count how many composers we have in each category? 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
# MZ: create new type of object from Pandas
```

Out[5]: <pandas.core.groupby.generic.DataFrameGroupBy object at 0x7f5ff3cfbf60>

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. As for the Dataframe, let's look at a summary of the object:

In [6]:
```
composer_grouped.describe()
# MZ: get all the statistics by the groups created

# MZ: for example to see the different levels
composers.country.unique()
```

Out[6]:
```
array(['Austria', 'Germany', 'Italy', 'Russia', 'Czechia', 'Finland',
       'France', 'RUssia', 'England', 'Belgium', 'Spain', 'USA'],
      dtype=object)
```

So we have a dataframe with a statistical summary of the the contents. The "names" of the groups are here the indices of the Dataframe. These names are simply all the different categories that were present in the column we used for grouping. Now we can recover a single group:

In [7]:
```
composer_grouped.get_group('baroque')
```

Out[7]:

	composer	birth	death	period	country
14	Haendel	1685	1759.0	baroque	Germany
16	Purcell	1659	1695.0	baroque	England
17	Charpentier	1643	1704.0	baroque	France
20	Couperin	1626	1661.0	baroque	France
21	Rameau	1683	1764.0	baroque	France
28	Caldara	1670	1736.0	baroque	Italy
29	Pergolesi	1710	1736.0	baroque	Italy
30	Scarlatti	1685	1757.0	baroque	Italy
31	Caccini	1587	1640.0	baroque	Italy
47	Bach	1685	1750.0	baroque	Germany

In [8]:
```
composer_grouped.get_group('post-romantic')
```

Out[8]:

	composer	birth	death	period	country
0	Mahler	1860	1911.0	post-romantic	Austria
2	Puccini	1858	1924.0	post-romantic	Italy
8	Sibelius	1865	1957.0	post-romantic	Finland
18	Bruckner	1824	1896.0	post-romantic	Austria
49	Strauss	1864	1949.0	post-romantic	Germany

5.2.2 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 [9]:
```
# MZ: groupping can be done on multiple columns
composer_grouped = composers.groupby(['period','country'])
composer_grouped.describe()
```

Out[9]:

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

In [10]:
```
composer_grouped.get_group(('baroque','Germany'))
```

Out[10]:

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

5.2 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 output).

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 [11]:
```
composer_grouped.mean()
# MZ: often you can directly apply the functions on the Pandas object
```

Out[11]:

		birth	death
period	country		
baroque	England	1659.000000	1695.000000
	France	1650.666667	1709.666667
	Germany	1685.000000	1754.500000
	Italy	1663.000000	1717.250000
classic	Austria	1744.000000	1800.000000
	Czechia	1731.000000	1799.000000
	Italy	1749.000000	1801.000000
	Spain	1754.000000	1806.000000
modern	Austria	1885.000000	1935.000000
	Czechia	1854.000000	1928.000000
	England	1936.500000	1983.000000
	France	1916.500000	2004.000000
	Germany	1895.000000	1982.000000
	RUssia	1891.000000	1953.000000
	Russia	1894.000000	1973.000000
	USA	1918.333333	1990.000000
post-romantic	Austria	1842.000000	1903.500000
	Finland	1865.000000	1957.000000
	Germany	1864.000000	1949.000000
	Italy	1858.000000	1924.000000
renaissance	Belgium	1464.500000	1534.000000
	England	1551.500000	1624.500000
	Italy	1552.666667	1616.666667
romantic	Czechia	1832.500000	1894.000000
	France	1821.000000	1891.333333
	Germany	1806.500000	1865.750000
	Italy	1817.250000	1875.750000
	Russia	1836.000000	1884.000000
	Spain	1863.500000	1912.500000

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

Out[12]:

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

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

In [13]:
```
def mult(ser):
    return ser.max() * 3
```

In [14]:
```
composer_grouped.apply(mult)
# MZ: most functions can be applied irrespectively of the object (DataFr
ame, group, Series, etc.)
```

```
/usr/local/lib/python3.5/dist-packages/pandas/core/computation/check.py:1
9: UserWarning: The installed version of numexpr 2.4.3 is not supported i
n pandas and will be not be used
The minimum supported version is 2.6.1

  ver=ver, min_ver=_MIN_NUMEXPR_VERSION), UserWarning)
```

Out[14]:

		composer	birth	death	period
period	**country**				
baroque	**England**	PurcellPurcellPurcell	4977	5085.0	baroquebaroquebaroq
	France	RameauRameauRameau	5049	5292.0	baroquebaroquebaroq
	Germany	HaendelHaendelHaendel	5055	5277.0	baroquebaroquebaroq
	Italy	ScarlattiScarlattiScarlatti	5130	5271.0	baroquebaroquebaroq
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	modernmodernmoderr
	Czechia	JanacekJanacekJanacek	5562	5784.0	modernmodernmoderr
	England	WaltonWaltonWalton	5913	5949.0	modernmodernmoderr
	France	MessiaenMessiaenMessiaen	5775	6048.0	modernmodernmoderr
	Germany	OrffOrffOrff	5685	5946.0	modernmodernmoderr
	RUssia	ProkofievProkofievProkofiev	5673	5859.0	modernmodernmoderr
	Russia	StravinskyStravinskyStravinsky	5718	5925.0	modernmodernmoderr
	USA	GlassGlassGlass	5811	5970.0	modernmodernmoderr
post-romantic	**Austria**	MahlerMahlerMahler	5580	5733.0	post-romanticpost-rom romantic
	Finland	SibeliusSibeliusSibelius	5595	5871.0	post-romanticpost-rom romantic
	Germany	StraussStraussStrauss	5592	5847.0	post-romanticpost-rom romantic
	Italy	PucciniPucciniPuccini	5574	5772.0	post-romanticpost-rom romantic
renaissance	**Belgium**	LassusLassusLassus	4596	4782.0	renaissancerenaissanc
	England	DowlandDowlandDowland	4689	4878.0	renaissancerenaissanc
	Italy	PalestrinaPalestrinaPalestrina	4701	4929.0	renaissancerenaissanc
romantic	**Czechia**	SmetanaSmetanaSmetana	5523	5712.0	romanticromanticroma
	France	MassenetMassenetMassenet	5526	5736.0	romanticromanticroma
	Germany	WagnerWagnerWagner	5499	5691.0	romanticromanticroma
	Italy	VerdiVerdiVerdi	5574	5757.0	romanticromanticroma
	Russia	MussorsgskyMussorsgskyMussorsgsky	5517	5661.0	romanticromanticroma
	Spain	GranadosGranadosGranados	5601	5748.0	romanticromanticroma

5.3 Unstacking

Let's have a look again at one of our grouped Dataframe on which we applied some summary function like a mean on the age column:

In [15]:
```
composers['age']= composers['death']-composers['birth']
```

In [16]:
```
composers.groupby(['country','period']).age.mean()
```

Out[16]:
```
country  period
Austria  classic          56.000000
         modern           50.000000
         post-romantic    61.500000
Belgium  renaissance      69.500000
Czechia  classic          68.000000
         modern           74.000000
         romantic         61.500000
England  baroque          36.000000
         modern           81.000000
         renaissance      73.000000
Finland  post-romantic    92.000000
France   baroque          59.000000
         modern           87.500000
         romantic         70.333333
Germany  baroque          69.500000
         modern           87.000000
         post-romantic    85.000000
         romantic         59.250000
Italy    baroque          54.250000
         classic          52.000000
         post-romantic    66.000000
         renaissance      64.000000
         romantic         58.500000
RUssia   modern           62.000000
Russia   modern           79.000000
         romantic         48.000000
Spain    classic          52.000000
         romantic         49.000000
USA      modern           81.000000
Name: age, dtype: float64
```

Here we have two level of indices, with the main one being the country which contains all periods. Often for plotting we however need to have the information in another format. In particular we would like each of these values to be one observation in a regular table. For example we could have a country vs period table where all elements are the mean age. To do that we need to **unstack** our multi-level Dataframe:

In [17]:
```
# MZ: to obtain regular 2dim object
composer_unstacked = composers.groupby(['country','period']).age.mean().
unstack()
```

In [18]:
```
composer_unstacked
```

Out[18]:

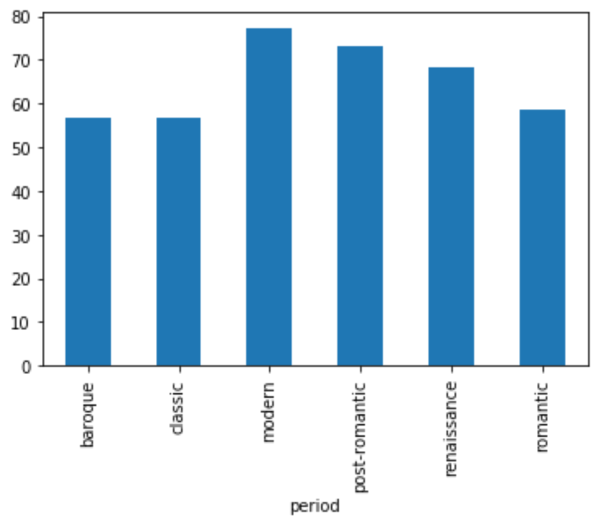
period	baroque	classic	modern	post-romantic	renaissance	romantic
country						
Austria	NaN	56.0	50.0	61.5	NaN	NaN
Belgium	NaN	NaN	NaN	NaN	69.5	NaN
Czechia	NaN	68.0	74.0	NaN	NaN	61.500000
England	36.00	NaN	81.0	NaN	73.0	NaN
Finland	NaN	NaN	NaN	92.0	NaN	NaN
France	59.00	NaN	87.5	NaN	NaN	70.333333
Germany	69.50	NaN	87.0	85.0	NaN	59.250000
Italy	54.25	52.0	NaN	66.0	64.0	58.500000
RUssia	NaN	NaN	62.0	NaN	NaN	NaN
Russia	NaN	NaN	79.0	NaN	NaN	48.000000
Spain	NaN	52.0	NaN	NaN	NaN	49.000000
USA	NaN	NaN	81.0	NaN	NaN	NaN

5.4 Plotting groups

The possibility to create groups gives us also the opportunity to easily create interesting plots without writing too much code. For example we can caluclate the average age of composers in each period and plot it as a bar plot:

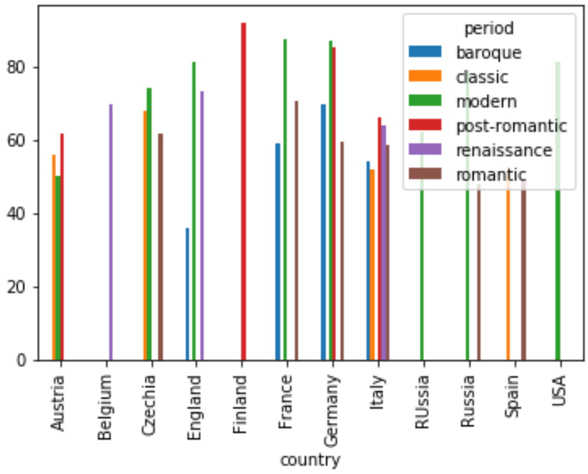
In [19]:
```
composers.groupby('period')['age'].mean().plot(kind = 'bar')
# MZ: group by period and plot the mean of the ages
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6024431278>



We can also use our unstacked table of country vs. period to automatically plot all average ages split by country and period:

In [20]:
```
composer_unstacked.plot(kind = 'bar');
# average age for each country and each period
```



There are much more powerful ways of using grouping-like features for plotting using the ggplot type grammar of graphics where objects can be grouped within an "aeasthetic". In the example above the "colour aesthetic" would e.g. be assigned to the period variable. Such an approach removes the need to do explicit groupings as done here.