

Scientific Programming

Practical 8

Introduction

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Announcements

Two announcements:

Gabriele Masina is the new tutor for this course

Please specify your time-slot preference at <https://doodle.com/poll/2cs4qs5cztvdfpn5>

Midterm: on Wednesday, November 4th - 11.30 - 13.30 online

(simulation of the midterm on Monday, November 2nd - 14.30 - 16.30 online)



Exercise 1

```
biancol@bludell:~/work/courses/QCBsciprolab2020$ python3 exercises/filterFasta.py --help
usage: filterFasta.py [-h] inputFasta inputIDS outputFasta

Filters a fasta file

positional arguments:
  inputFasta  The input fasta file
  inputIDS    The IDS to keep
  outputFasta The output fasta file with filtered entries

optional arguments:
  -h, --help  show this help message and exit
biancol@bludell:~/work/courses/QCBsciprolab2020$ python3 exercises/filterFasta.py file_samples/contigs82.fasta file_samples/contig_ids.txt file_samples/filtered_contigs.fasta
Writing contig MDC001115.177
Writing contig MDC013284.379
Writing contig MDC018185.243
Writing contig MDC018185.241
Writing contig MDC004527.213
Writing contig MDC012176.157
Writing contig MDC001204.810
Writing contig MDC004389.256
Writing contig MDC018297.229
Writing contig MDC001802.364
```

```
biancol@bludell:~/work/courses/QCBsciprolab2020$ cat file_samples/filtered_contigs.fasta | grep ">"
>MDC001115.177
>MDC013284.379
>MDC018185.243
>MDC018185.241
>MDC004527.213
>MDC012176.157
>MDC001204.810
>MDC004389.256
>MDC018297.229
>MDC001802.364
>MDC014057.243
>MDC021015.302
>MDC017187.314
>MDC012865.410
```

Pandas

Pandas (**panel-data**) is a very efficient library to deal with **numerical tables** and time series

```
import pandas as pd
```

Two data structures:

Series: 1D tables

DataFrames: 2D tables

<https://pandas.pydata.org/>

Series

Series are 1-dimensional structures (like lists) containing data. Series are characterized by two types of information: the **values** and the **index** (a list of labels associated to the data). A bit like **list** and a bit like **dictionary**!

```
Values and index explicitly defined
A    15
B     7
C    20
D     3
E    15
F     1
G     5
H    17
I    15
L    17
dtype: int64
The index: Index(['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'L'], dtype='object')
The values: [15  7 20  3 15  1  5 17 15 17]
-----

From dictionary
forty    40
four     4
one      1
ten     10
three    3
two      2
dtype: int64
Index(['forty', 'four', 'one', 'ten', 'three', 'two'], dtype='object')
[40  4  1 10  3  2]
```

```
import pandas as pd
import random

print("Values and index explicitly defined")
#values and index explicitly defined
S = pd.Series([random.randint(0,20) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print(S)
print("The index:", S.index)
print("The values:", S.values)

print("-----\n")
print("From dictionary")
#from a dictionary
S1 = pd.Series({"one" : 1, "two" : 2, "ten": 10,
               "three" : 3, "four": 4, "forty" : 40})

print(S1)
print(S1.index)
print(S1.values)
```

Series

Series are 1-dimensional structures (like lists) containing data. Series are characterized by two types of information: the **values** and the **index** (a list of labels associated to the data). A bit like **list** and a bit like **dictionary**!

If not specified, the index is added by default

```
Default index
0      8
1      2
2      8
3     10
4      1
5      5
6      3
7      8
8      9
9      5
dtype: int64
RangeIndex(start=0, stop=10, step=1)
[ 8  2  8 10  1  5  3  8  9  5]
```

```
Same value repeated
0      1.27
1      1.27
2      1.27
3      1.27
4      1.27
5      1.27
6      1.27
7      1.27
8      1.27
9      1.27
dtype: float64
RangeIndex(start=0, stop=10, step=1)
[1.27 1.27 1.27 1.27 1.27 1.27 1.27 1.27 1.27 1.27]
```

```
print("Default index")
#index added by default
myData = [random.randint(0,10) for x in range(10)]
S2 = pd.Series(myData)

print(S2)
print(S2.index)
print(S2.values)

print("-----\n")
print("Same value repeated")
S3 = pd.Series(1.27, range(10))
print(S3)
print(S3.index)
print(S3.values)
```

Series

Data in a series can be accessed by using the **label** (i.e. the index) as in a dictionary or through its **position** as in a list. Slicing is also allowed both by **position** and **index**.

In the latter case, `Series[S:E]` with **S** and **E** **indexes**, both **S** and **E** are included.

```
import pandas as pd
import random

#values and index explicitly defined
S = pd.Series([random.randint(0,20) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print(S)
print("")

print("Value at label \"A\":", S["A"])
print("Value at index 1:", S[1])
print("")

print("Slicing from 1 to 3:") #note 3 excluded
print(S[1:3])
print("")
print("Slicing from C to H:") #note H included!
print(S["C":"H"])
print("")

print("Retrieving from list:")
print(S[[1,3,5,7,9]])
print(S[["A", "C", "E", "G"]])
print("")

print("Top 3")
print(S.head(3))
print("")
print("Bottom 3")
print(S.tail(3))
```

```
A    15
B    11
C     4
D     7
E     1
F     4
G    15
H    14
I    14
L    17
dtype: int64
```

```
Value at label "A": 15
Value at index 1: 11
```

```
Slicing from 1 to 3:
B    11
C     4
dtype: int64
```

```
Slicing from C to H:
C     4
D     7
E     1
F     4
G    15
H    14
dtype: int64
```


Series

Data in a series can be accessed by using the **label** (i.e. the index) as in a dictionary or through its **position** as in a list. Slicing is also allowed both by **position** and **index**.

In the latter case, `Series[S:E]` with **S and E labels**, both **S and E** are included.

```
import pandas as pd
import random

#values and index explicitly defined
S = pd.Series([random.randint(0,20) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print(S)
print("")

print("Value at label \"A\":", S["A"])
print("Value at index 1:", S[1])
print("")

print("Slicing from 1 to 3:") #note 3 excluded
print(S[1:3])
print("")
print("Slicing from C to H:") #note H included!
print(S["C":"H"])
print("")

print("Retrieving from list:")
print(S[[1,3,5,7,9]])
print(S[["A", "C", "E", "G"]])
print("")

print("Top 3")
print(S.head(3))
print("")
print("Bottom 3")
print(S.tail(3))
```

Retrieving from list:

```
B    11
D     7
F     4
H    14
L    17
dtype: int64
A    15
C     4
E     1
G    15
dtype: int64
```

Top 3

```
A    15
B    11
C     4
dtype: int64
```

Bottom 3

```
H    14
I    14
L    17
dtype: int64
```

Series

Example: Given a list of 10 integers, we want to divide them by 2.

Important operations on series:

Operator broadcasting

Operations can automatically be broadcast to the entire Series. This is a quite cool feature and **saves us from looping through the elements of the Series.**

Without pandas:

```
import random

listS = [random.randint(0,20) for x in range(0,10)]

print(listS)

for el in range(0,len(listS)):
    listS[el] /=2 #compact of X = X / 2

print(listS)
```

[6, 4, 5, 19, 14, 16, 9, 3, 13, 11]
[3.0, 2.0, 2.5, 9.5, 7.0, 8.0, 4.5, 1.5, 6.5, 5.5]

Series

Example: Given a list of 10 integers, we want to divide them by 2.

Important operations on series:

Operator broadcasting

Operations can automatically be broadcast to the entire Series. This is a quite cool feature and **saves us from looping through the elements of the Series.**

```
A    4
B   13
C   14
D    6
E   13
F    2
G   13
H   19
I   20
L    7
dtype: int64
```

```
A    2.0
B    6.5
C    7.0
D    3.0
E    6.5
F    1.0
G    6.5
H    9.5
I   10.0
L    3.5
dtype: float64
```

With pandas (operator broadcasting):

```
import pandas as pd
import random

S = pd.Series([random.randint(0,20) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print(S)
print("")
S1 = S / 2
print(S1)
```

Series

Important operations on series:

Operator broadcasting

Filtering

We can also apply boolean operators to obtain only the **sub-Series** with all the values satisfying a specific condition. This allows us to **filter** the Series.

```
import pandas as pd
import random

S = pd.Series([random.randint(0,20) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print(S)
print("")
S1 = S>10
print(S1)
print("")
S2 = S[S > 10]
print(S2)
```

```
A    3
B    3
C   18
D    1
E   12
F   11
G    4
H   11
I    5
L   14
dtype: int64
```

```
A    False
B    False
C     True
D    False
E     True
F     True
G    False
H     True
I    False
L     True
dtype: bool
```

```
C    18
E    12
F    11
H    11
L    14
dtype: int64
```



series of True and False where condition is/is not met

Series

Important operations on series:

Operator broadcasting

Filtering

Computing stats

```
import pandas as pd
import random

S = pd.Series([random.randint(0,10) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print("The data:")
print(S)
print("")
print("Its description")
print(S.describe())
print("")
print("Specifying different quantiles:")
print(S.quantile([0.1,0.2,0.8,0.9]))
print("")
print("Histogram:")
print(S.value_counts())
print("")
print("The type is a Series:")
print(type(S.value_counts()))
print("Summing the values:")
print(S.sum())
print("")
print("The cumulative sum:")
print(S.cumsum())
```

```
The data:
A      5
B      4
C     10
D      3
E      4
F      1
G      4
H      8
I      7
L      5
dtype: int64
```

```
Its description
count    10.000000
mean      5.100000
std       2.601282
min       1.000000
25%       4.000000
50%       4.500000
75%       6.500000
max      10.000000
dtype: float64
```

```
Specifying different quantiles:
0.1    2.8
0.2    3.8
0.8    7.2
0.9    8.2
dtype: float64
```

```
Histogram:
4      3
5      2
10     1
8      1
7      1
3      1
1      1
dtype: int64
```

Series

Important operations on series:

Operator broadcasting

Filtering

Computing stats

```
import pandas as pd
import random

S = pd.Series([random.randint(0,10) for x in range(0,10)],
              index = list("ABCDEFGHIL"))

print("The data:")
print(S)
print("")
print("Its description")
print(S.describe())
print("")
print("Specifying different quantiles:")
print(S.quantile([0.1,0.2,0.8,0.9]))
print("")
print("Histogram:")
print(S.value_counts())
print("")
print("The type is a Series:")
print(type(S.value_counts()))
print("Summing the values:")
print(S.sum())
print("")
print("The cumulative sum:")
print(S.cumsum())
```

```
The data:
A    5
B    4
C   10
D    3
E    4
F    1
G    4
H    8
I    7
L    5
dtype: int64
```

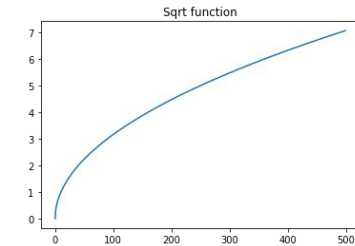
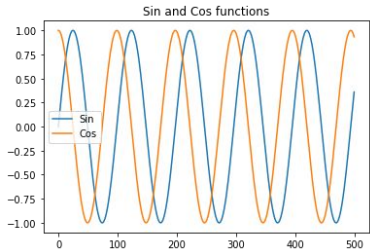
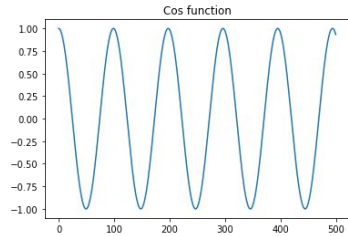
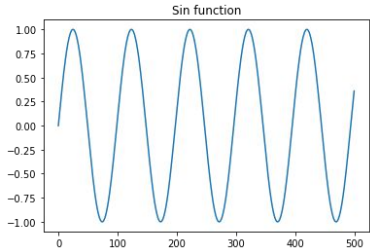
```
The type is a Series:
<class 'pandas.core.series.Series'>
Summing the values:
51
```

```
The cumulative sum:
A    5
B    9
C   19
D   22
E   26
F   27
G   31
H   39
I   46
L   51
dtype: int64
```

see notes for the complete results and other features like `Series.fillna(values)`

Plotting data

It is quite easy to plot data in Series and DataFrames thanks to matplotlib



```
import math
import matplotlib.pyplot as plt
import pandas as pd
```

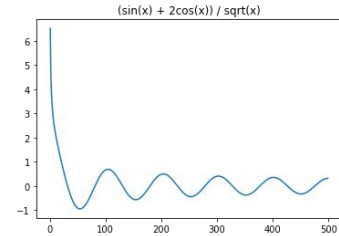
```
x = [i/10 for i in range(0,500)]
```

```
y = [math.sin(2*i/3.14 ) for i in x]
y1 = [math.cos(2*i/3.14 ) for i in x]
y2 = [math.sqrt(i) for i in x]
#print(x)
```

```
ySeries = pd.Series(y)
ySeries1 = pd.Series(y1)
ySeries2 = pd.Series(y2)
```

```
ySeries.plot()
plt.title("Sin function")
plt.show()
plt.close()
ySeries1.plot()
plt.title("Cos function")
plt.show()
plt.close()
plt.title("Sin and Cos functions")
ySeries.plot()
ySeries1.plot()
plt.legend(["Sin", "Cos"])
plt.show()
plt.close()
```

```
ySeries2.plot()
plt.title("Sqrt function")
plt.show()
plt.close()
ySeries2 = (ySeries + 2*ySeries1)/ySeries2
ySeries2.plot()
plt.title("(sin(x) + 2cos(x)) / sqrt(x)")
plt.show()
```



two series and legend



DataFrames

2D analogous of Series.

They have an **index** and several **columns**.

Data can be dishomogeneous.

Most of the the things seen for Series apply to DataFrames

```
   dayLength  temperature
Jan         9.7           1
Feb        10.9           3
Mar        12.5           8
Apr        14.1          13
May        15.6          17
Jun        16.3          20
Jul         15.9          22
Aug         14.6          22
Sep         13.0          18
Oct         11.4          13
Nov         10.0           6
Dec          9.3           2
```

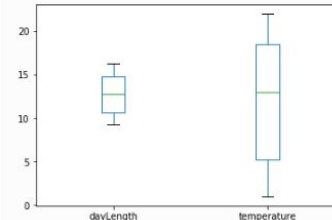
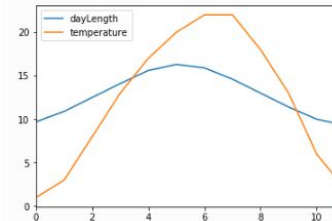
```
Index(['dayLength', 'temperature'], dtype='object')
Index(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct',
       'Nov', 'Dec'],
      dtype='object')
```

```
import pandas as pd
```

```
myData = {
    "temperature" : pd.Series([1, 3, 8, 13, 17, 20, 22, 22,18 ,13,6,2],
                              index = ["Jan", "Feb", "Mar", "Apr", "May", "Jun",
                                         "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
                              ),
    "dayLength" : pd.Series([9.7, 10.9, 12.5, 14.1, 15.6, 16.3, 15.9,
                             14.6,13,11.4,10,9.3],
                             index = ["Jan", "Feb", "Mar", "Apr", "May", "Jun",
                                        "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]
                             )
}
```

```
DF = pd.DataFrame(myData)
print(DF)
```

```
print(DF.columns)
print(DF.index)
```



DataFrames

We can **load external files**, extract info and apply operators, broadcasting and filtering...

Load from file



1. Select by column `DataFrame[col]` returns a Series
2. Select by row label `DataFrame.loc[row_label]` returns a Series
3. Select row by integer location `DataFrame.iloc[row_position]` returns a Series
4. Slice rows `DataFrame[S:E]` (S and E are labels, both included) returns a DataFrame
5. Select rows by boolean vector `DataFrame[bool_vect]` returns a DataFrame

Row ID	Sales	Profit	Product	Category
1	261.5400	-213.25	Office Supplies	
49	10123.0200	457.81	Office Supplies	
50	244.5700	46.71	Office Supplies	
80	4965.7595	1198.97	Technology	
85	394.2700	30.94	Office Supplies	
86	146.6900	4.43	Furniture	
97	93.5400	-54.04	Office Supplies	

```
import pandas as pd
```

```
orders = pd.read_csv("file_samples/sampled_data_orders.csv", sep=";",  
index_col=0, header=0)
```

```
print("The Order Quantity column (top 5)")
```

```
print(orders["Order Quantity"].head(5))
```

```
print("")
```

```
print("The Sales column (top 10)")
```

```
print(orders.Sales.head(10))
```

```
print("")
```

```
print("The row with ID:50")
```

```
r50 = orders.loc[50]
```

```
print(r50)
```

```
print("")
```

```
print("The third row:")
```

```
print(orders.iloc[3])
```

```
print("The Order Quantity, Sales, Discount and Profit of the 2nd,  
4th, 6th and 8th row:")
```

```
print(orders[1:8:2][["Order Quantity", "Sales", "Discount", "Profit"]])
```

```
print("The Order Quantity, Sales, Discount and Profit of orders with  
discount > 10%:")
```

```
print(orders[orders["Discount"] > 0.1][["Order Quantity", "Sales",  
"Discount", "Profit"]])
```

see notes for results

Merging DataFrames

```
pandas.merge(DataFrame1, DataFrame2, on="col_name", how="inner/outer/left/right")
```

1. how = inner : non-matching entries are discarded;
2. how = left : ids are taken from the first DataFrame;
3. how = right : ids are taken from the second DataFrame;
4. how = outer : ids from both are retained.

```
inJ = pd.merge(DFs1,DFs2, on = "id", how = "inner")  
print(inJ)
```

```
leftJ = pd.merge(DFs1,DFs2, on = "id", how = "left")  
print(leftJ)
```

DFs1

		id	type
0	SNP_FB_0411211	SNP	
1	SNP_FB_0412425	SNP	
2	SNP_FB_0942385	SNP	
3	CH01f09	SSR	
4	Hi05f12x	SSR	
5	SNP_FB_0942712	SNP	

DFs2

	chr	id
0	1	SNP_FB_0411211
1	15	SNP_FB_0412425
2	7	SNP_FB_0942385
3	9	CH01f09
4	1	SNP_FB_0428218

Inner merge (only common in both)

	id	type	chr
0	SNP_FB_0411211	SNP	1
1	SNP_FB_0412425	SNP	15
2	SNP_FB_0942385	SNP	7
3	CH01f09	SSR	9

Left merge (IDS from DFs1)

	id	type	chr
0	SNP_FB_0411211	SNP	1
1	SNP_FB_0412425	SNP	15
2	SNP_FB_0942385	SNP	7
3	CH01f09	SSR	9
4	Hi05f12x	SSR	NaN
5	SNP_FB_0942712	SNP	NaN

Right merge (IDS from DFs2)

	id	type	chr
0	SNP_FB_0411211	SNP	1
1	SNP_FB_0412425	SNP	15
2	SNP_FB_0942385	SNP	7
3	CH01f09	SSR	9
4	SNP_FB_0428218	NaN	1

Outer merge (IDS from both)

	id	type	chr
0	SNP_FB_0411211	SNP	1
1	SNP_FB_0412425	SNP	15
2	SNP_FB_0942385	SNP	7
3	CH01f09	SSR	9
4	Hi05f12x	SSR	NaN
5	SNP_FB_0942712	SNP	NaN
6	SNP_FB_0428218	NaN	1

Merging DataFrames

The columns we merge on do not necessarily need to be the same, we can specify a correspondence between the row of the first dataframe (the one on the left) and the second dataframe (the one on the right) specifying which columns must have the same values to perform the merge.

This can be done by using the parameters `right_on = column_name` and `left_on = column_name`

```
import pandas as pd
```

```
d = dict({"A" : [1,2,3,4], "B" : [3,4,73,13]})  
d2 = dict({"E" : [1,4,3,13], "F" : [3,1,71,1]})
```

```
DF = pd.DataFrame(d)  
DF2 = pd.DataFrame(d2)
```

```
merged_onBE = DF.merge(DF2, left_on = 'B', right_on = 'E', how = "inner")  
merged_onAF = DF.merge(DF2, right_on = "F", left_on = "A", how = "outer")  
print("DF:")  
print(DF)  
print("DF2:")  
print(DF2)  
print("\ninner merge on BE")  
print(merged_onBE)  
print("\nouter merge on AF:")  
print(merged_onAF)
```

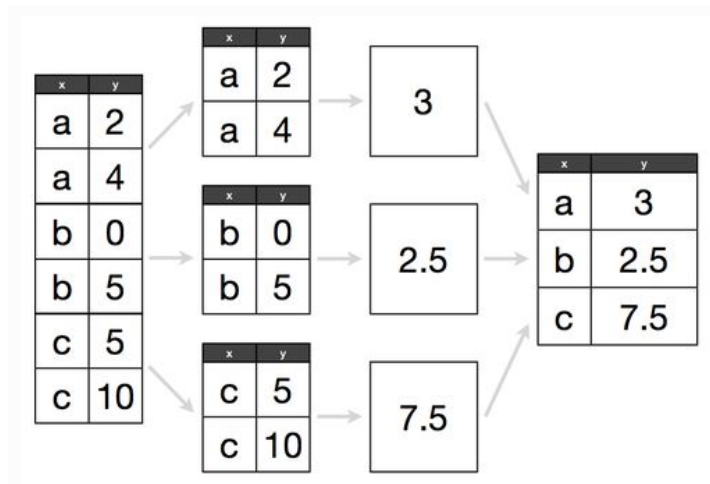
```
DF:  
   A  B  
0  1  3  
1  2  4  
2  3 73  
3  4 13  
DF2:  
   E  F  
0  1  3  
1  4  1  
2  3 71  
3 13  1
```

```
inner merge on BE  
   A  B  E  F  
0  1  3  3 71  
1  2  4  4  1  
2  4 13 13  1
```

```
outer merge on AF:  
   A  B  E  F  
0  1.0  3.0  4.0  1.0  
1  1.0  3.0 13.0  1.0  
2  2.0  4.0  NaN  NaN  
3  3.0 73.0  1.0  3.0  
4  4.0 13.0  NaN  NaN  
5  NaN  NaN  3.0 71.0
```

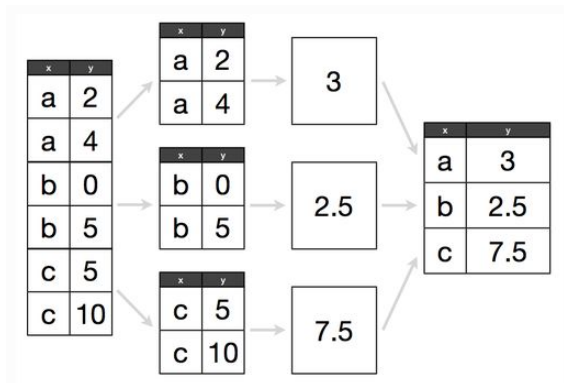
Grouping DataFrames

The split-apply-aggregate paradigm



Grouping DataFrames

The split-apply-aggregate paradigm



```
import pandas as pd
```

```
test = {"x": ["a","a", "b", "b", "c", "c"],  
        "y": [2,4,0,5,5,10]}
```

```
DF = pd.DataFrame(test)
```

```
print(DF)
```

```
print("")
```

```
gDF = DF.groupby("x")
```

```
for i,g in gDF:
```

```
    print("Group: ", i)
```

```
    print(g)
```

```
    print(type(g))
```

```
aggDF = gDF.aggregate(pd.DataFrame.mean)
```

```
print(aggDF)
```

```
x y  
0 a 2  
1 a 4  
2 b 0  
3 b 5  
4 c 5  
5 c 10
```

```
Group: a
```

```
x y  
0 a 2  
1 a 4
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Group: b
```

```
x y  
2 b 0  
3 b 5
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Group: c
```

```
x y  
4 c 5  
5 c 10
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
y
```

```
x  
a 3.0  
b 2.5  
c 7.5
```

Grouping DataFrames

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```
import pandas as pd

test = {"x": ["a","a", "b", "b", "c", "c" ],
        "y": [2,4,0,5,5,10]
       }

DF = pd.DataFrame(test)
print(DF)
print("")
gDF = DF.groupby("x")
for i,g in gDF:
    print("Group: ", i)
    print(g)
    print(type(g))

aggDF = gDF.aggregate(pd.DataFrame.mean)
print(aggDF)
```

```
#without looping through the groups...
print("\nThe 'a' group:")
print(gDF.get_group('a'))
print("\nThe 'c' group:")
print(gDF.get_group('c'))
```

The 'a' group:

	x	y
0	a	2
1	a	4

The 'c' group:

	x	y
4	c	5
5	c	10

Grouping DataFrames

Row ID	Sales	Profit	Product Category
1	261.5400	-213.25	Office Supplies
49	10123.0200	457.81	Office Supplies
50	244.5700	46.71	Office Supplies
80	4965.7595	1198.97	Technology
85	394.2700	30.94	Office Supplies

Group: Furniture
Group: Office Supplies
Group: Technology

Count elements per category:

Office Supplies	4610
Technology	2065
Furniture	1724

Name: Product Category, dtype: int64

Total values:

Product Category	Sales	Profit
Furniture	5178590.542	117433.03
Office Supplies	3752762.100	518021.42
Technology	5984248.182	886313.52

Mean values (sorted by profit):

Product Category	Sales	Profit
Furniture	3003.822820	68.116607
Office Supplies	814.048178	112.369072
Technology	2897.941008	429.207516

The most profitable is Technology

Questions:

How many Product categories?

Total sales and profits per category?

What is the most profitable category?

```
import pandas as pd
import matplotlib.pyplot as plt

orders = pd.read_csv("file_samples/sampledata_orders.csv", sep=";",
                    index_col =0, header=0)

SPC = orders[["Sales", "Profit", "Product Category"]]
print(SPC.head())

SPC.plot(kind = "hist", bins = 10)
plt.show()

print("")
grouped = SPC.groupby("Product Category")
for i,g in grouped:
    print("Group: ", i)

print("")
print("Count elements per category:") #get the series corresponding to the column
                                     #and apply the value_counts() method
print(orders["Product Category"].value_counts())
print("")
print("Total values:")
print(grouped.aggregate(pd.DataFrame.sum))

print("Mean values (sorted by profit):")
mv_sorted = grouped.aggregate(pd.DataFrame.mean).sort_values(by="Profit")
print(mv_sorted)
print("")
print("The most profitable is {}".format(mv_sorted.index[-1]))
```

Q Search the docs ...

Input/output

General functions

Series

DataFrame

pandas arrays

Panel

Index objects

Date offsets

Window

GroupBy

Resampling

Style

Plotting

General utility functions

Extensions

API reference

This page gives an overview of all public pandas objects, functions and methods. All classes and functions exposed in `pandas.*` namespace are public.

Some subpackages are public which include `pandas.errors`, `pandas.plotting`, and `pandas.testing`. Public functions in `pandas.io` and `pandas.tseries` submodules are mentioned in the documentation. `pandas.api.types` subpackage holds some public functions related to data types in pandas.

Warning

The `pandas.core`, `pandas.compat`, and `pandas.util` top-level modules are PRIVATE. Stable functionality in such modules is not guaranteed.

- Input/output
 - Pickling
 - Flat file
 - Clipboard
 - Excel
 - JSON
 - HTML
 - HDFStore: PyTables (HDF5)
 - Feather
 - Parquet
 - ORC
 - SAS
 - SPSS
 - SQL
 - Google BigQuery
 - STATA
- General functions
 - Data manipulations
 - Top-level missing data
 - Top-level conversions
 - Top-level dealing with datetimelike
 - Top-level dealing with intervals

<https://pandas.pydata.org/pandas-docs/stable/reference/series.html>

<https://pandas.pydata.org/pandas-docs/stable/reference/frame.html>

Series

Constructor

`Series([data, index, dtype, name, copy, ...])` One-dimensional ndarray with axis labels (including time series).

Attributes

Axes

<code>Series.index</code>	The index (axis labels) of the Series.
<code>Series.array</code>	The ExtensionArray of the data backing this Series or Index.
<code>Series.values</code>	Return Series as ndarray or ndarray-like depending on the dtype.
<code>Series.dtype</code>	Return the dtype object of the underlying data.
<code>Series.shape</code>	Return a tuple of the shape of the underlying data.
<code>Series.nbytes</code>	Return the number of bytes in the underlying data.
<code>Series.ndim</code>	Number of dimensions of the underlying data, by definition 1.
<code>Series.size</code>	Return the number of elements in the underlying data.
<code>Series.T</code>	Return the transpose, which is by definition self.
<code>Series.memory_usage([index, deep])</code>	Return the memory usage of the Series.
<code>Series.hasnans</code>	Return if I have any nans; enables various perf speedups.
<code>Series.empty</code>	Indicator whether DataFrame is empty.
<code>Series.dtypes</code>	Return the dtype object of the underlying data.
<code>Series.name</code>	Return the name of the Series.

Conversion

<code>Series.astype(dtype[, copy, errors])</code>	Cast a pandas object to a specified dtype <code>dtype</code> .
<code>Series.convert_dtypes([infer_objects, ...])</code>	Convert columns to best possible dtypes using dtypes supporting <code>pd.NA</code> .
<code>Series.infer_objects()</code>	Attempt to infer better dtypes for object columns.
<code>Series.copy([deep])</code>	Make a copy of this object's indices and data.
<code>Series.bool()</code>	Return the bool of a single element Series or DataFrame.
<code>Series.to_numpy([dtype, copy, na_value])</code>	A NumPy ndarray representing the values in this Series or Index.

Binary operators

<code>Series.ne([other[, level, fill_value, axis]])</code>	Return Not equal to of series and other, element-wise (binary operator <code>ne</code>).
<code>Series.eq([other[, level, fill_value, axis]])</code>	Return Equal to of series and other, element-wise (binary operator <code>eq</code>).
<code>Series.product([axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>Series.dot([other])</code>	Compute the dot product between the Series and the columns of other.

Function application, GroupBy & window

<code>Series.apply(func[, convert_dtype, args])</code>	Invoke function on values of Series.
<code>Series.agg([func, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>Series.aggregate([func, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>Series.transform(func[, axis])</code>	Call <code>func</code> on self producing a Series with transformed values.
<code>Series.map(arg[, na_action])</code>	Map values of Series according to input correspondence.
<code>Series.groupby([by, axis, level, as_index, ...])</code>	Group Series using a mapper or by a Series of columns.
<code>Series.rolling(window[, min_periods, ...])</code>	Provide rolling window calculations.
<code>Series.expanding([min_periods, center, axis])</code>	Provide expanding transformations.
<code>Series.ewm([com, span, halflife, alpha, ...])</code>	Provide exponential weighted (EW) functions.
<code>Series.pipe(func, *args, **kwargs)</code>	Apply <code>func</code> (self, *args, **kwargs).

Computations / descriptive stats

First things first

We are going to need some libraries

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In **Linux** you can install the libraries by typing in a terminal `sudo pip3 install matplotlib`, `sudo pip3 install pandas` and `sudo pip3 install numpy` (or `sudo python3.X -m pip install matplotlib`, `sudo python3.X -m pip install pandas` and `sudo python3.6 -m pip install numpy`), where X is your python version.

In **Windows** you can install the libraries by typing in the command prompt (to open it type `cmd` in the search) `pip3 install matplotlib`, `pip3 install pandas` and `pip3 install numpy`.

Exercises

1. The file `top_3000_words.txt` is a one-column file representing the top 3000 English words. Read the file and for each letter, count how many words start with that letter. Store this information in a dictionary. Create a pandas series from the dictionary and plot an histogram of all initials counting more than 100 words starting with them.

Show/Hide Solution

2. The file `filt_aligns.tsv` is a tab separated value file representing alignments of paired-end reads on some apple chromosomes. Paired end reads have the property of being X bases apart from each other as they have been sequenced from the two ends of some size-selected DNA molecules.



Each line of the file has the following information

`readID\tChrPE1\tAlignmentPosition1\tChrPE2\tAlignmentPosition2`. The two ends of the same pair have the same readID. Load the read pairs aligning on the same chromosome into two dictionaries. The first (`inserts`) having readID as keys and the insert size (i.e. the absolute value of `AlignmentPosition1 - AlignmentPosition2`) as value. The second dictionary (`chrs`) will have readID as key and chromosome ID as value. Example:

```
readID Chr11 31120 Chr11 31472
readID1 Chr7 12000 Chr11 11680
```

will result in:

```
inserts = {"readID" : 352, "readID1" : 320}
chrs = {"readID" : "Chr11", "readID1" : "Chr7"}
```