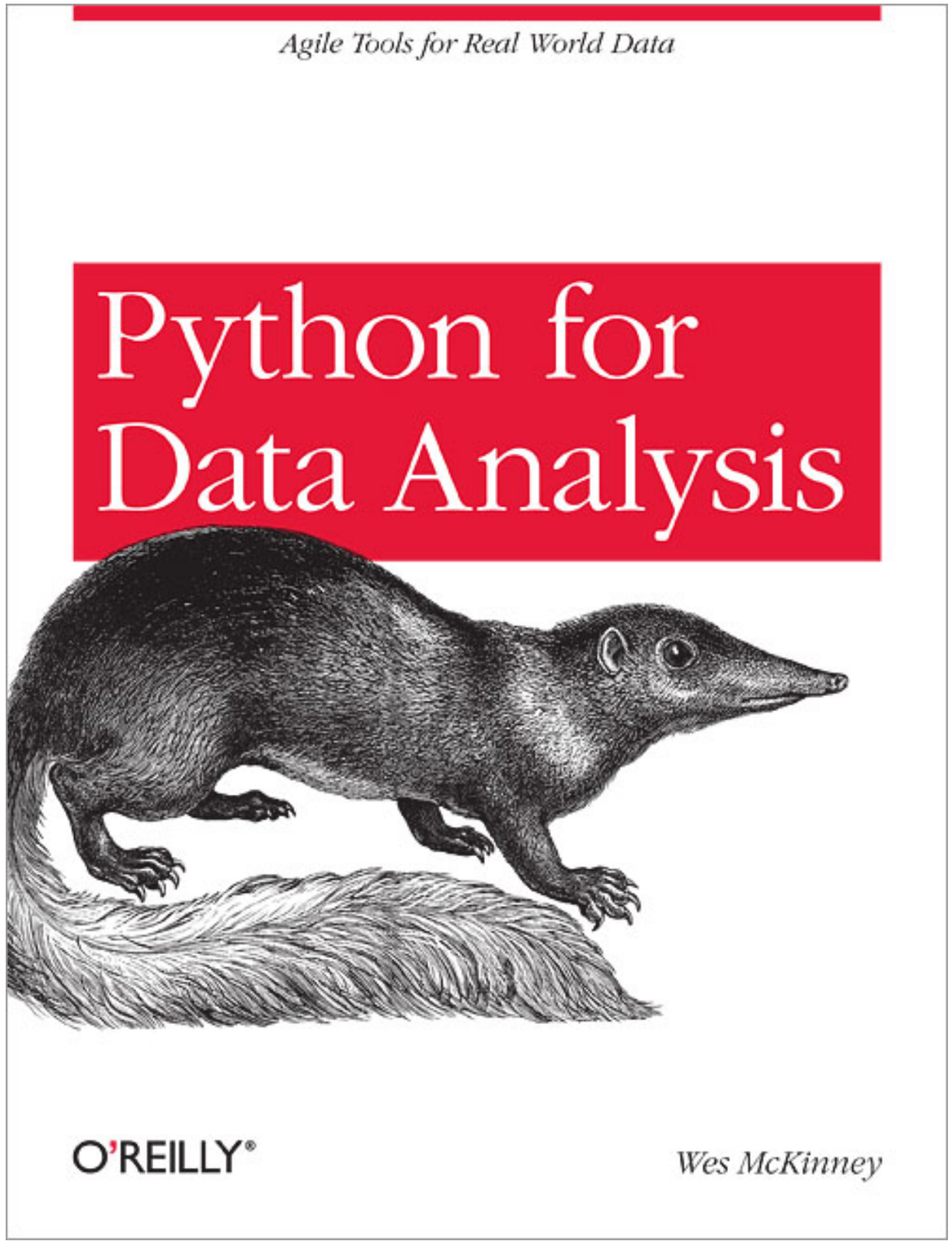
Pandas

track 2 - Pandas bases - 12nd March

Outline

1 Introduction



1 Introduction

- Pandas is a **toolkit** to manipulate data
- It based on **numpy** for computations (faster)
- **DataFrame** is the key element (like in R)
- It became quickly the data manipulation and analysis **standard** over data ecosystem in Python

1 Introduction

- You need pandas when you work with tabular or structured data

- To:

- *import* and *clean* data
- *explore* data
- *process* and *prepare* data
- and *analyse*

1 Introduction: key features

- Fast and easy API to I/O in different formats
- Working with missing records
- Merging / joining (`concat`, `join`)
- Grouping
- Reshaping
- Powerful time series manipulation

2 Data structures: import

```
import pandas as pd
import numpy as np
```

- The pandas import is always simple as this
- We import np to have access to all numpy methods

2 Data structures: Series

```
s = pd.Series([0.2, 0.4, 0.8, 1.6])

s.index
# returns: Int64Index([0, 1, 2, 3], dtype="int64")

s.values
# returns: array([ 0.2, 0.4, 0.8, 1.6 ])

s[0]  # to access data
```

```
s2 = pd.Series([0.2, 0.4, 0.8, 1.6], index=['a', 'c', 'b', 'd'])
```

- A Series is a **one-dimensional array-like** object containing an array of data
- We can access to values and indexes
- And so the data is indexed inside and can be accessible with: `s[0]`
- You can also create your own index => Series can be created from dictionaries

2 Data structures: Series

```
agedata = {“francois”: 51, “angela”: 51, “barack”: 55}

s3 = pd.Series(agedata)  # create from dict

s3[s3 > 52]  # filtering

s3 * 2  # scalar multiplication
s3.mean()

np.exp(s3)  # exponential

“angela” in s3  # boolean to find if a key is in

s3[["angela", “barack"]]  # get several values
```

- Series can be created from dictionaries (keys will be sorted)
- On Series we can do **filtering**, **scalar multiplication** or math functions applying
- Determine if an index is in the series with **in**

2 Data structures: Series

```
agedata = {“francois”: 51, “angela”: 51, “barack”: 55}
presidents = ["barack", "francois", "angela", “georges"]

s4 = pd.Series(agedata, index=presidents)

pd.isnull(s4)
s4.isnull()
pd.notnull(s4)

s3 + s4
```

```
In [20]:
s4

Out[20]:
barack      55
francois    51
angela      51
georges    NaN
dtype: float64
```

```
In [25]:
s3 + s4

Out[25]:
angela      102
barack      110
francois    102
georges     NaN
dtype: float64
```

- NaN (Not a Number) is the null element in a Series object
- isnull and notnull returns if elements are nulls
- We can add 2 Series

2 Data structures: Series

```
s4.name = “presidents_ages”
s4.index.name = “name”

s4.index = [“Lula”, “Cameron”, “Renzi”, “Putin”]
```

- An index can have a name
- Like a Series
- We can change the index afterwards

2 Data structures: DataFrame

```
data = {
    "city": ["Paris", "London", "Berlin"],
    "density": [3550, 5100, 3750],
    "area": [2723, 1623, 984],
    "population": [9645000, 8278000, 3675000],
}

df = pd.DataFrame(data)
```

```
In [55]:
df
Out[55]:
```

	area	city	density	population
0	2723	Paris	3550	9645000
1	1623	London	5100	8278000
2	984	Berlin	3750	3675000

- A dataframe is a tabular data structure, containing an ordered collection of columns,each of which can be a different value type (numeric, boolean, string, etc.)
- DataFrame has both rows and columns index

2 Data structures: DataFrame

```
columns = ["city", "area", "population", "density"]
df = pd.DataFrame(data, columns=columns)

df[“area"] or df.area
# returns a Series object of the areas in the df

df.dtypes  # to get the types of columns

df.info()
df.describe()  # give stats on the df
df.values
df.index

df = df.set_index("city")
```

- Columns can be specified
- We get a Series if we index a DataFrame

2 Data structures: DataFrame

```
df["population"] / df[“area"]

df["real_density"] = df["population"] / df[“area"]

df.ix[“Paris”]  # to get the row with index “Paris”

df[df["real_density"] < 5000]  # to fiter by density

df.sort_index(by="real_density", ascending=True)  # to sort
```

- Operations between columns are possible
- We can add new columns easily
- If we set index with `ix[]` rows are accessible

2 Data structures: DataFrame

Selecting the data

```
df[“area”]  # get the column
df.ix[“Paris”]  # get the row

# multiple columns
df[["area", “population"]]

# loc examples
df.loc["Paris", “area"]  # will return the exact value
df.loc[df["density"] < 5000, ["population", "area"]]
```

```
# iloc example
df.iloc[1, 2]
```

- Be careful when getting column or row
- For advanced indexing we have:
    - loc: selecting by label
    - iloc: selecting by position

2 Data structures: DataFrame

Assigning the data

```
df.iloc[1, 2] = 10
df.iloc[1, :] = 10

df[df["density"] == 10] = 6000
```

- After selecting (with all different ways) the data we can assign them

3 Interactions I/O

Read the data: text file

```
df = pd.read_csv("population.csv")

# with parameters
df1 = pd.read_csv(filename,
    sep=",",
    header=None,
    names=[],
    index_col=[],
    na_values=[],
)
```

read_csv	load delimited data from a file, URL, of file-like object (comma as default delimiter)
read_table	load delimited data from a file, URL, of file-like object ('\t' as default delimiter)
read_fwf	Read data in fixed-width column
read_clipboard	Read data from the clipboard

- **read_csv** is the most useful function to read the data (because the data is often used as csv format)
- we can specified a lot of parameters to read_*

3 Interactions I/O

Read the data: database

```
import sqlite3

connexion = sqlite3.connect(‘:memory:’)

df = pd.io.sql.read_frame(“SELECT * FROM table”, connexion)
```

- We can do the same with a MySQL python connector

3 Interactions I/O

Write the data

```
df = pd.to_csv(“population_out.csv”)
```

- **to_csv** is like read_csv and has the same parameters

4 DataFrame endless possibilites

```
In [71]: country = pd.read_csv("country_n_sample.csv")
```

```
In [72]: country.head()
```

Out[72]:

	isocode	countryname	rbucode	currency	order	G6	IsocodeAggregation	IsocodeAggregationName
0	AT	Austria	NCE	€	11	NO	AT	Austria
1	BE	BELUX	NWE	€	6	NO	BE	BELUX
2	CH	Switzerland	NCE	CHF	12	NO	CH	Switzerland
3	CZ	Czech Republic	NSCEE	€	15	NO	CZ	Czech Republic
4	DE	Germany	NCE	€	10	YES	DE	Germany

```
In [73]: data = pd.read_csv("daily_n_sample.csv")
```

```
In [74]: data.head()
```

Out[74]:

	Date	Isocode	ModelCode	Source	QualifiedAudience	Visits	PageViews	UniqueVisitors
0	2015-04-01 00:00:00	AT	C11A	Mobile	29.93	NaN	NaN	NaN
1	2015-04-01 00:00:00	AT	D40	Mobile	8.57	NaN	NaN	NaN
2	2015-04-01 00:00:00	AT	E28B	Mobile	21.62	NaN	NaN	NaN
3	2015-04-01 00:00:00	AT	EM20	Mobile	5.55	NaN	NaN	NaN
4	2015-04-01 00:00:00	AT	EVA	Mobile	6.00	NaN	NaN	NaN

- we defined two dataframes to illustrate the DF manipulations

4 DataFrame endless possibilites

```
data.sort_index(axis=1, ascending=False).head()  # sort on column names

data.sort_index(by="QualifiedAudience", ascending=False)

data1 = data[["Date", "Isocode", "QualifiedAudience"]].set_index(["Date", "Isocode"])
data1.rank(ascending=False, method='max')
```

- we can sort by an index or do a ranking

4 DataFrame endless possibilites

```
In [78]: pd.merge(data, country, left_on="Isocode", right_on="isocode").head()
```

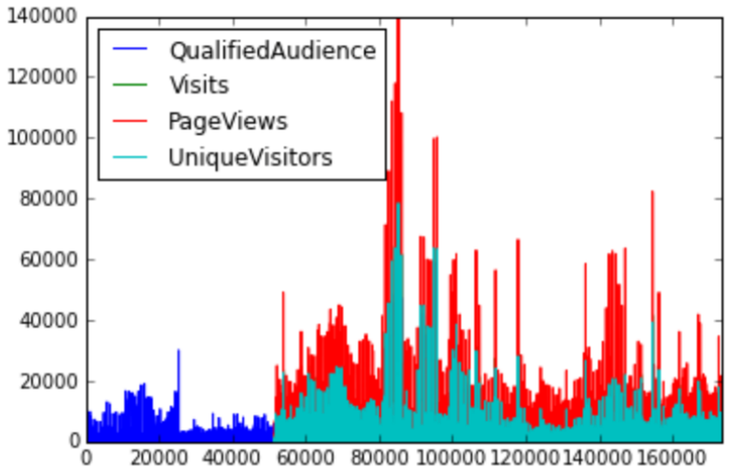
Out[78]:

	Date	Isocode	ModelCode	Source	QualifiedAudience	Visits	PageViews	UniqueVisitors	isocode	countryname	rbucode	currency	order	G
0	2015-04-01 00:00:00	AT	C11A	Mobile	29.93	NaN	NaN	NaN	AT	Austria	NCE	€	11	N
1	2015-04-01 00:00:00	AT	D40	Mobile	8.57	NaN	NaN	NaN	AT	Austria	NCE	€	11	N
2	2015-04-01 00:00:00	AT	E28B	Mobile	21.62	NaN	NaN	NaN	AT	Austria	NCE	€	11	N
3	2015-04-01 00:00:00	AT	EM20	Mobile	5.55	NaN	NaN	NaN	AT	Austria	NCE	€	11	N
4	2015-04-01 00:00:00	AT	EVA	Mobile	6.00	NaN	NaN	NaN	AT	Austria	NCE	€	11	N

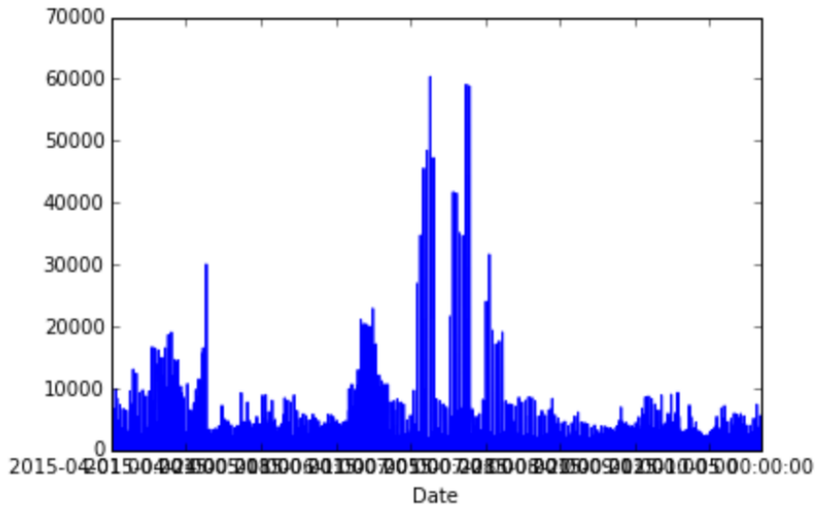
- merge is done between two dataframes on a **key** and **how**
- we can use: key, left_key and right_key
- how values are: inner (by default), left, right, outer
- after the merge you have a new dataframe to work with

4 DataFrame endless possibilites

```
In [79]: data.plot()
Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x107cda5c0>
```




```
In [92]: data["QualifiedAudience"].plot(kind="line")
Out[92]: <matplotlib.axes._subplots.AxesSubplot at 0x1117df518>
```



- you can plot the data easily in a notebook

4 DataFrame endless possibilites

```
In [110]: data[["Date", "Isocode", "QualifiedAudience"]].groupby(["Date", "Isocode"]).mean()
```

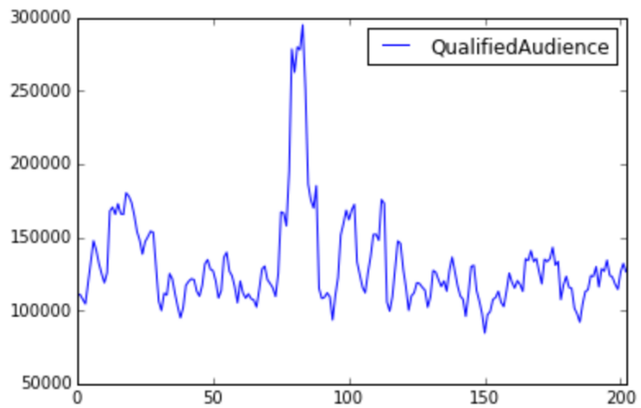
Out[110]:

		QualifiedAudience
Date	**Isocode**	
2015-04-01 00:00:00	**AT**	30.031628
	BE	52.230698
	CH	31.318182
	CZ	35.504194
	DE	212.037500
	DK	48.300000
	EE	12.826800
	ES	125.191957
	FI	36.344000
	FR	486.217073
	HU	23.504412
	IT	201.562444
	LT	12.544000
	LU	6.422000

```
data[["Date", "Isocode", "QualifiedAudience"]].groupby(["Date", "Isocode"], as_index=False).mean()
```

	Date	Isocode	QualifiedAudience
0	2015-04-01 00:00:00	AT	30.031628
1	2015-04-01 00:00:00	BE	52.230698
2	2015-04-01 00:00:00	CH	31.318182
3	2015-04-01 00:00:00	CZ	35.504194
4	2015-04-01 00:00:00	DE	212.037500
5	2015-04-01 00:00:00	DK	48.300000

```
In [124]: data[["Date", "Isocode", "QualifiedAudience"]].groupby(["Date"], as_index=False).sum().plot(kind="line")
Out[124]: <matplotlib.axes._subplots.AxesSubplot at 0x11695e860>
```



- the group_by function needs a apply (here the apply is mean)

4 DataFrame endless possibilites

- List of useful functions:
  - *df*.sort_values(by, axis, ascending)
  - *serie*.value_counts()
  - *pd*.pivot_table(data, values, index, columns, aggfunc)
  - *df*.rename(columns)
  - *df*.shape
  - *df*.unique()
  - *pd*.crosstab(serie1, serie2)
  - *df*.dropna() / *df*.fillna()
  - *pd*.concat(dataframes)
  - *df*.tail(n)