Pandas

Big Data
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Objectives

1. Introduce Series and DataFrame data structures
2. Understand Pandas features
3. Fluent data manipulation with Pandas
4. Data exploration

Bibliography

Jake VanderPlas. *Python Data Science Handbook*. Chapter 3. O'Reilly. (Link).

Table of Contents

Introduction

A DS/ML workflow needs more features

- Missing data
- Data input
- Operations on groups
- Label columns and rows

Pandas provides all those features, and more

- Pandas = **PAN**el **DA**ta **S**ystem
- Built on NumPy's ndarray
- Provides dataframes

Pandas provides two main objects

- `Series` and `DataFrame`

Convention

```
^^I^^I^^Iimport numpy as
    np
^^I^^I^^Iimport pandas as
    pd
^^I^^I^^I
```

The Pandas `Series` object (I)

A `Series` is a one-dimensional array of indexed data

- NumPy arrays indices are implicit (i.e. its position)
- Series indices are explicit, and can be any type

Two attributes

- `values`: ndarray
- `index`: `pd.Index` object

Two indices

- Implicit: Regular index
- Explicit: Custom index

Index	Values
'a'	0.25
'b'	0.5
'c'	0.75
'd'	0.99

```
^^I^^I^^Idata = pd.Series
    ([0.25, 0.5, 0.75,
    1.0])
^^I^^I^^Idata.values
^^I^^I^^Idata.index
^^I^^I^^Idata[1:3]
^^I^^I^^I
```

The Pandas `Series` object (II)

Custom indices

```
^^I^^I^^IIn[1] : data = pd.Series([0.25, 0.5, 0.75,
    1.0],
^^I^^I^^I                    index=['a', 'b', 'c', '
   d'])
^^I^^I^^IIn [2]: data
^^I^^I^^IOut[1]:
^^I^^I^^Ia     0.25
^^I^^I^^Ib     0.50
^^I^^I^^Ic     0.75
^^I^^I^^Id     1.00
^^I^^I^^Idtype: float64

^^I^^I^^IIn [3]: data['a']
^^I^^I^^IOut[2]: 0.25
^^I^^I^^IIn [4]: data[0]
^^I^^I^^IOut[3]: 0.25
^^I^^I^^I
```

The Pandas `DataFrame` object

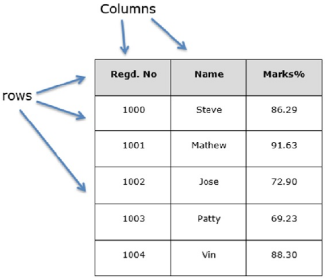
Dataframe concept (I)

A `DataFrame` is a 2-D tabular data structure

- Similar to a spreadsheet
- Homogeneous columns
- Heterogeneous rows

Two read-only attributes, both `pd.Index`

- `index`: Rows
- `columns`: Columns



(Source)

The Pandas DataFrame object

Dataframe concept (II)

DataFrame example

```
In [1]:  import seaborn as sns

In [2]:  iris = sns.load_dataset('iris')
In [3]:  iris.head()

Out[1]:
sepal_length   sepal_width   petal_length   petal_width  species
0             5.1           3.5            1.4           0.2   setosa
1             4.9           3.0            1.4           0.2   setosa
2             4.7           3.2            1.3           0.2   setosa
3             4.6           3.1            1.5           0.2   setosa
4             5.0           3.6            1.4           0.2   setosa
In [246]: iris.columns
Out[246]:
Index(['sepal_length', 'sepal_width', 'petal_length',
       'petal_width', 'species'], dtype='object')
^^I^^I
```

The Pandas DataFrame object

Constructing DataFrame objects (I)

Manual initialization

- From a single Series object
  `pd.DataFrame(population, columns=['population'])`
- From several Series objects
  `pd.DataFrame('population': population, 'area': area)`
- From a dictionary
  `pd.DataFrame([{'a': 0, 'b': 0}, {'a': 1, 'b': 2}])`
- From a NumPy 2-D array
  ```
  pd.DataFrame(np.random.rand(3, 2),
  columns=['foo', 'bar'], index=['a', 'b', 'c'])
  ```

The Pandas `DataFrame` object

Constructing `DataFrame` objects (II)

Read from a file

- CSV (very common!!!): `pd.read_csv('filename.csv')`
- Excel:
  `pd.read_excel('filename.xlsx', sheetname='mysheet')`

CSV example

```
# This CSV file contains data about weights and heights
"id", "weight","height","sex",  "race"
1,    143.5,   81.6,    "Female","White"
2,    109.1,   83.7,    "Female","Black"
4,    104.8,   54.6,    "Female","Hisp"
7,    130.2,   81.7,    "Male",  "White"
```

CVS can be exported from MS Excel or programatically

Data indexing and selection

Series

Dictionary-like syntax

```
^^I^^I^^I>>> data = pd.Series
    ([0.25, 0.5, 0.75, 1.0],
    index=['a', 'b', 'c', 'd'])

^^I^^I^^I>>> 'a' in data
^^I^^I^^ITrue

^^I^^I^^I>>> data.keys()
^^I^^I^^IIndex(['a', 'b', 'c'],
    dtype='object')

^^I^^I^^I>>> list(data.items())
^^I^^I^^I[('a', 0.25), ('b',
    0.5), ('c', 0.75)]
```

Array-like syntax

```
^^I^^I^^I>> data['a':'c'] #
    Explicit index
^^I^^I^^Ia      0.25
^^I^^I^^Ib      0.50
^^I^^I^^Ic      0.75
^^I^^I^^Idtype: float64
^^I^^I^^I>> data[0:2] # Implicit
    index
^^I^^I^^Ia      0.25
^^I^^I^^Ib      0.50
^^I^^I^^Idtype: float64
^^I^^I^^I>> data[data>0.5] #
    Masking
^^I^^I^^Ic      0.75
^^I^^I^^Id      1.00
^^I^^I^^Idtype: float64
^^I^^I^^I>> data[['b','c']] #
    Fancy index
```

Data indexing and selection

DataFrame

Dictionary-like syntax

```
^^I^^I^^I>>> data['area']
^^I^^I^^I>>> data.area
^^I^^I^^I>>> data.area is data['area']
^^I^^I^^ITrue
^^I^^I^^I>>> data['density'] = data['pop']/data['area']
^^I^^I^^I
```

Array-like syntax

```
^^I^^I^^I>>> data.values # Get values array
^^I^^I^^I>>> data.T # Transpose
^^I^^I^^I>>> data[0] # First row
^^I^^I^^I>>> data['area'] # Area column
^^I^^I^^I
```

Remember indexing conventions

- Indexing refers to columns (`data['area']`)
- Slicing refers to rows (`data['Florida':'Illinois']`)
- Masking refers to rows (`data[data.density > 100]`)

Data indexing and selection

loc, iloc and ix

Two types of indices in Pandas

- Explicit and implicit
- Indexing (`data[0]`) is explit
- Slicing (`data[:2]`) is implicit (Python-like)
- Source of troubles!

Pandas makes explicit the used scheme

- `loc`: Explicit index
- `iloc`: Implicit index
- `ix`: Hybrid

```
^^I^^I^^I# Series
^^I^^I^^I>>> serie.loc[1]
^^I^^I^^I>>> serie.loc[1:3]
^^I^^I^^I>>> serie.iloc[1]
^^I^^I^^I>>> serie.iloc[1:3]

^^I^^I^^I# Dataframes
^^I^^I^^I>>> df.iloc[:3, :2]
^^I^^I^^I>>> df.loc[:'illinois',
    :'pop']
^^I^^I^^I>>> df.ix[:3, :'pop']
^^I^^I^^I>>> df.loc[df.data>100,
    ['pop', 'density']]
^^I^^I^^I>>> df.iloc[0, 2] = 90
^^I^^I^^I
```

Operating on data

Overview (I)

Pandas fully supports NumPy's ufuncs

- Efficient computations

Additional Pandas features

- Index and column name preservation
- Index aligning
- Easy data combination

```
^^I^^I^^I>>> rng = np.random.
    RandomState(42)
^^I^^I^^I>>> df = pd.DataFrame(rng.
    randint(0, 10, (3,4)))
^^I^^I^^I>>> df = pd.DataFrame(rng.
    randint(0, 10, (3,4)), columns=['A
    ', 'B', 'C', 'D'])
^^I^^I^^I>>> print(df)
^^I^^I^^I   A  B  C  D
^^I^^I^^I0  7  2  5  4
^^I^^I^^I1  1  7  5  1
^^I^^I^^I2  4  0  9  5
^^I^^I^^I>>> np.sin(df * np.pi / 4)
^^I^^I         A        B     C     D
^^I^^I^^I 0  -7.07e-01  1.0  -0.7  1.22e
    -16
^^I^^I^^I 1   7.07e-01  -0.7  -0.7  7.07e
    -01
^^I^^I^^I 2   1.22e-16  0.0  0.7  -7.07e
```

Operating on data

Overview (II)

Index preservation

```
^^I^^I^^I>>> A = pd.Series([2, 4, 6], index=[0, 1,
    2])
^^I^^I^^I>>> B = pd.Series([1, 3, 5], index=[1, 2,
    3])
^^I^^I^^I>>> A + B
^^I^^I^^I0     NaN
^^I^^I^^I1     5.0
^^I^^I^^I2     9.0
^^I^^I^^I3     NaN
^^I^^I^^Idtype: float64
^^I^^I^^I>>> A.add(B, fill_value=0)
^^I^^I^^I0     2.0
^^I^^I^^I1     5.0
^^I^^I^^I2     9.0
^^I^^I^^I3     5.0
^^I^^I^^Idtype: float64
^^I^^I^^I
```

Operating on data

Missing data (I)

NumPy supports missing data in floating-point data

- Specific value defined by IEEE
- Available as `np.nan`

Pandas supports missing data through two mechanisms

- `None` object, interpreted as NaN (`Not a Number`)
- `np.nan`: for floating-point data
- Almost automatic NaN handling (types upcast)

```
^^I^^I^^I>>> pd.Series([1, np.nan,
    2, None])
^^I^^I^^I0      1.0
^^I^^I^^I1      NaN
^^I^^I^^I2      2.0
^^I^^I^^I3      NaN
^^I^^I^^Idtype: float64
^^I^^I^^I
```

Pandas

Missing data (II)

Useful functions for missing data

- `isnull()`: Boolean mask with missing data
- `notnull()`: Opposite of isnull()
- `dropna()`: Filtered data
- `fillna()`: NaNs filled

```
^^I^^I^^I>>> data = pd.Series
    ([1, np.nan, 'hello', None
    ])
^^I^^I^^I>>> data[data.notnull()
    ]
^^I^^I^^I0        1
^^I^^I^^I2    hello
^^I^^I^^Idtype: object

^^I^^I^^I>>> data.dropna()
^^I^^I^^I0        1
^^I^^I^^I2    hello
^^I^^I^^Idtype: object

^^I^^I^^I>>> data.fillna(0)
^^I^^I^^I0        1
^^I^^I^^I1        0
^^I^^I^^I2    hello
^^I^^I^^I3        0
```

Combining datasets
`pd.concat()` (I)

Many times we need to combine two or more datasets

- Pandas provides `pd.concat()`, `append()` and `pd.merge()`

pd.concat() signature

```
^^I^^Ipd.concat(objs, axis=0, join='outer',
    join_axes=None, ignore_index=False, keys
    =None, levels=None, names=None,
    verify_integrity=False, copy=True)
^^I^^I
```

By default, `pd.concat()` joins rows preserving index

- `axis`: Join columns (`axis=1`)
- `verify_integrity`: Raise error if duplicates (`verify_integrity=True`)
- `ignore_index`: Create new index (`ignore_index=True`)
- `join`: Can be 'outer' (union) or 'inner' (intersection)

Combining datasets

pd.concat() (II)

```
>> df1 = pd.DataFrame([{'A': 'A0', 'B': 'B0'}, {'A': 'A1', 'B': 'B1'
    }])
>> df2 = pd.DataFrame([{'A': 'A2', 'B': 'B2'}, {'A': 'A3', 'B': 'B3'
    }])

>> print(df1), print(df2); print(pd.concat([df1, df2]))
   A   B          A   B         A   B
0  A0  B0      0  A2  B2     0  A0  B0
1  A1  B1      1  A3  B3     1  A1  B1
                             0  A2  B2
                             1  A3  B3
>> pd.concat([df1, df2], axis=1)
   A   B   A   B
0  A0  B0  A2  B2
1  A1  B1  A3  B3
>> df1.append(df2)
^^I^^I^^I
```

Combining datasets

`pd.merge()` (I)

Merging based on relational algebra

- Similar to databases tables joins
- Pretty intelligent figuring out the desired output
- By default, join dataframes using shared columns names

Combining datasets

pd.merge() (II)

One-to-one

```
>> print(df1); print(df2)
  employee        group
0      Bob   Accounting
1     Jake  Engineering
2     Lisa  Engineering
3      Sue           HR
  employee  hire_date
0     Lisa       2004
1      Bob       2008
2     Jake       2012
3      Sue       2014
>> print(pd.merge(df1, df2))
  employee group   hire_date
0      Bob Accounting   2008
1     Jake Engineering  2012
2     Lisa Engineering  2004
3      Sue HR           2014
^^I^^I
```

Many-to-one

```
>>> print(df3); print(df4)
  employee  group  hire_date
0      Bob   Accounting   2008
1     Jake  Engineering   2012
2     Lisa  Engineering   2004
3      Sue           HR   2014
        group  supervisor
0  Accounting  Carly
1 Engineering  Guido
2          HR  Steve
>> print(pd.merge(df3, df4))
employee  group  hire_date  supervisor
0  Bob   Accounting   2008   Carly
1 Jake  Engineering   2012   Guido
2 Lisa  Engineering   2004   Guido
3  Sue           HR   2014   Steve
^^I^^I
```

Combining datasets

pd.merge() (III)

Many-to-many

```
>>> print(df1); print(df5)
  employee        group               group        skills
0      Bob   Accounting     0    Accounting          math
1     Jake  Engineering     1    Accounting  spreadsheets
2     Lisa  Engineering     2   Engineering        coding
3      Sue           HR     3   Engineering         linux
                            4            HR  spreadsheets
                            5            HR  organization

>>> pd.merge(df1, df5)
  employee        group        skills
0      Bob   Accounting          math
1      Bob   Accounting  spreadsheets
2     Jake  Engineering        coding
3     Jake  Engineering         linux
4     Lisa  Engineering        coding
5     Lisa  Engineering         linux
6      Sue           HR  spreadsheets
7      Sue           HR  organization
^^I^^I
```

Combining datasets

pd.merge() (IV)

pd.merge() signature

```
^^I^^Ipd.merge(left, right, how='inner', on=
    None, left_on=None, right_on=None,
    left_index=False, right_index=False,
    sort=False, suffixes=('_x', '_y'), copy=
    True, indicator=False, validate=None)
^^I^^I
```

Arguments:

- `on`: Key column name
- `left_on`: Left table key column name
- `right_on`: Right table key column name
- `how`: Set arithmetic, `'inner'` (default, intersection), `'outer'` (union, fills missings with NaNs), `'left'` (left entries), `'right'` (right entries)

Combining datasets

pd.merge() (V)

```
>>> A                    >>> B
    lkey  value              rkey  value
0   foo   1              0   foo   5
1   bar   2              1   bar   6
2   baz   3              2   qux   7
3   foo   4              3   bar   8

>>> A.merge(B, left_on='lkey', right_on='rkey', how='outer')
    lkey   value_x   rkey   value_y
0   foo    1         foo    5
1   foo    4         foo    5
2   bar    2         bar    6
3   bar    2         bar    8
4   baz    3         NaN    NaN
5   NaN    NaN       qux    7
^^I^^I
```

Aggregation in Pandas (I)

The first step in data analysis is summarization

- First contact with data
- Insight to the dataset

Aggregation methods

- Applied to columns

Aggregation	Description
`count()`	Total number of items
`first()`, `last()`	First and last item
`mean()`, `median()`	Mean and median
`min()`, `max()`	Minimum and maximum
`std()`, `var()`	Standard dev. and variance
`mad()`	Mean absolute deviation
`prod()`	Product of all items
`sum()`	Sum of all items
`describe()`	Data summary

```
>>> import seaborn as sns
>>> planets = sns.load_dataset('planets')
>>> planets.head()
            method  number  orbital_period  mass  distance  year
0  Radial Velocity  1       269.300         7.10     77.40  2006
1  Radial Velocity  1       874.774         2.21     56.95  2008
2  Radial Velocity  1       763.000         2.60     19.84  2011
3  Radial Velocity  1       326.030        19.40    110.62  2007
4  Radial Velocity  1       516.220        10.50    119.47  2009
>>> planets.dropna().describe()
       number  orbital_period    mass  distance       year
count  498.00      498.000000  498.00  498.0000    498.000
mean     1.73      835.778671    2.50   52.0682   2007.377
std      1.17     1469.128259    3.63   46.5960      4.167
min      1.00        1.328300    0.00    1.3500   1989.000
25%      1.00       38.272250    0.21   24.4975   2005.000
50%      1.00      357.000000    1.24   39.9400   2009.000
75%      2.00      999.600000    2.86   59.3325   2011.000
max      6.00    17337.500000   25.00  354.0000   2014.000
>>> planets.mean()
number               1.785507
orbital_period    2002.917596
mass                 2.638161
distance           264.069282
year              2009.070531
dtype: float64
^^I^^I^^I
```

Grouping in Pandas (I)

Aggregation is generally used ...

- ... good to operate with the whole dataset ...
- ... but also is is usually insufficient

We need conditional aggregations

- Aggregate conditionally on some label

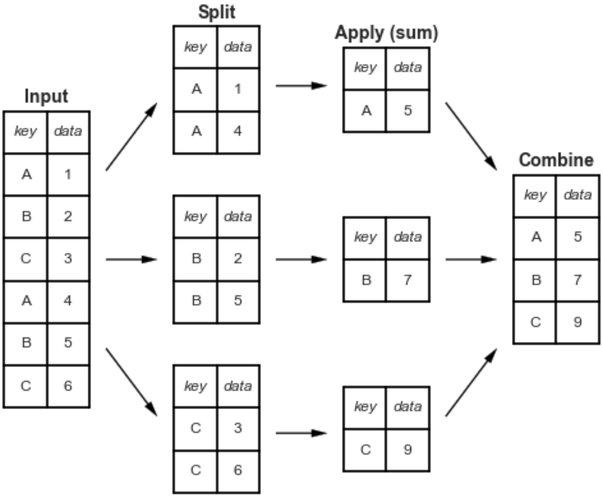
This is done with the operation `groupby` (yes, that name comes from SQL)

- Example: `df.groupby("key")`

Three tasks in one step

1. *Split*: Break up dependening on a key
2. *Apply*: Compute some function
3. *Combine*: Merge results into an output

Grouping in Pandas (II)



Grouping in Pandas (III)

```
>>> df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                       'data': range(6)})
>>> print(df)
  key  data
0   A     0
1   B     1
2   C     2
3   A     3
4   B     4
5   C     5
>>> df.groupby('key')
<pandas.core.groupby.groupby.DataFrameGroupBy object at 0
    x102685438>
>>> df.groupby('key').sum()
     data
key
A       3
B       5
C       7
^^I^^I^^I
```

Grouping in Pandas (IV)

Several mapping methods available

- List
  `df.groupby([2,3,4,1]).sum()`
- Dictionary
  `df.groupby('A': 'vowel', 'B': 'consonant', 'C': 'vowel')`
- Python function
  `df.groupby(str.lower)`
- Multiple keys
  `planets.groupby(['method', 'year'])`
- Mixed keys
  `df.groupby(['key1', 'key2', str.lower])`

Grouping in Pandas (V)

The method `groupby()` returns an object `groupby`

- Basicly, it is a collection of dataframes
  `planets.groupby('method').get_group('Transit')`
- Column selection as dataframe
  `planets.groupby('method')['year']`

Interesting groupby attribute, `groups`

- Dictionary with groups
  `planets.groupby('method').groups`
- Compatible with the `len()` method
  `len(planets.groupby('method'))`

Grouping in Pandas (VI)

Usual operations with groupings

- Aggregation:
  `df.groupby('key').aggregate(['min', np.median, max])`
  `df.groupby('key').aggregate('data1': 'min', 'data2': 'max')`
- Filtering:
  `planets.groupby('method').filter(lambda x: x['distance'].mean() > 50.)`
- Transformation:
  `df.groupby('key').transform(lambda x: x - x.mean())`

Apply(): Apply arbitrary function and combine results

- Takes a function as argument that takes a DataFrame

```
planets.groupby("method").apply(lambda x: x / x.sum())
```

Grouping in Pandas (VII)

Grouping by decade

```
^^I^^Idecade = 10 * (planets['year'] // 10)
^^I^^Idecade = decade.astype(str) + 's'
^^I^^Idecade.name = 'decade'
^^I^^Iplanets.groupby(['method', decade])['number'
    ].sum().unstack().fillna(0)
^^I^^I
```