Pandas

Inteligencia Artificial en los Sistemas de Control Autónomo
Máster Universitario en Ingeniería Industrial

Departamento de Automática

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

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

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

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

The Pandas `Series` object (II)

Custom indices

```
In [1] : data = pd.Series([0.25, 0.5, 0.75, 1.0],
                          index=['a', 'b', 'c', 'd'])
In [2]: data
Out[1]:
a       0.25
b       0.50
c       0.75
d       1.00
dtype: float64

In [3]: data['a']
Out[2]: 0.25
In [4]: data[0]
Out[3]: 0.25
```

The Pandas `DataFrame` object

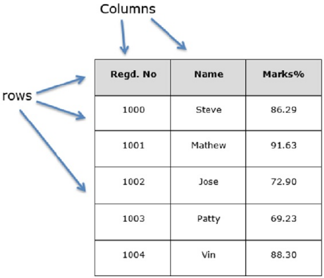
Dataframe concept (I)

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')
```

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

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

>>> 'a' in data
True

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

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

>>> data['e'] = 1.25
```

Array-like syntax

```
>> data['a':'c'] #Explicit index
a      0.25
b      0.50
c      0.75
dtype: float64
>> data[0:2] # Implicit index
a      0.25
b      0.50
dtype: float64
>> data[data>0.5] # Masking
c      0.75
d      1.00
dtype: float64
>> data[['b','c']] # Fancy index
b      0.50
c      0.75
dtype: float64
```

Data indexing and selection

DataFrame

Dictionary-like syntax

```
>>> data['area']
>>> data.area
>>> data.area is data['area']
True
>>> data['density'] = data['pop'
    ]/data['area']
```

Array-like syntax

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

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

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

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

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

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

Operating on data

Overview (II)

Index preservation

```
>>> A = pd.Series([2, 4, 6], index=[0, 1, 2])
>>> B = pd.Series([1, 3, 5], index=[1, 2, 3])
>>> A + B
0    NaN
1    5.0
2    9.0
3    NaN
dtype: float64
>>> A.add(B, fill_value=0)
0    2.0
1    5.0
2    9.0
3    5.0
dtype: float64
```

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)

```
>>> pd.Series([1, np.nan, 2, None])
0    1.0
1    NaN
2    2.0
3    NaN
dtype: float64
```

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

```
>>> data = pd.Series([1, np.nan,
      'hello', None])
>>> data[data.notnull()]
0         1
2     hello
dtype: object

>>> data.dropna()
0         1
2     hello
dtype: object

>>> data.fillna(0)
0         1
1         0
2     hello
3         0
dtype: object
```

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

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

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)
```

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
```

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
```

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
```

Combining datasets
pd.merge() (IV)

pd.merge() signature

```
pd.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)
```

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
```

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
```

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

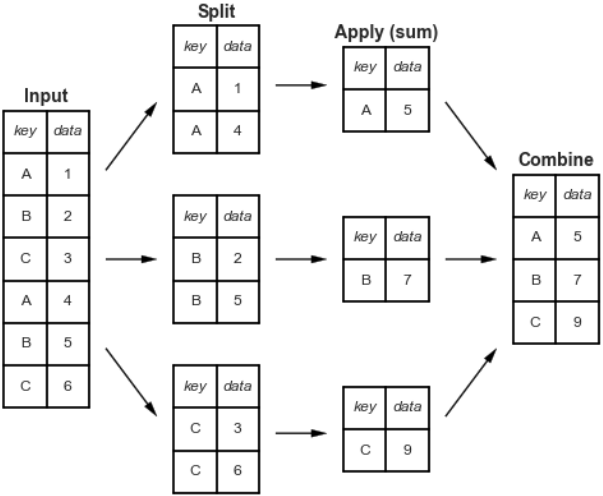
This is done with the operation `groupby` (yes, that name comes from SQL)

- 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
```

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

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