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```


Intro to pandas

Learning Objectives:

- Gain an introduction to the `DataFrame` and `Series` data structures of the *pandas* library
- Access and manipulate data within a `DataFrame` and `Series`
- Import CSV data into a *pandas* `DataFrame`
- Reindex a `DataFrame` to shuffle data

pandas is a column-oriented data analysis API. It's a great tool for handling and analyzing input data, and many ML frameworks support *pandas* data structures as inputs. Although a comprehensive introduction to the *pandas* API would span many pages, the core concepts are fairly straightforward, and we'll present them below. For a more complete reference, the pandas docs site contains extensive documentation and many tutorials.

Basic Concepts

The following line imports the *pandas* API and prints the API version:

```
from __future__ import print_function

import pandas as pd
pd.__version__
```

```
u'0.22.0'
```

The primary data structures in *pandas* are implemented as two classes:

- **`DataFrame`**, which you can imagine as a relational data table, with rows and named columns.
- **`Series`**, which is a single column. A `DataFrame` contains one or more `Series` and a name for each `Series`.

The data frame is a commonly used abstraction for data manipulation. Similar implementations exist in Spark and R.

One way to create a `Series` is to construct a `Series` object. For example:

```
pd.Series(['San Francisco', 'San Jose', 'Sacramento'])
```

```
0    San Francisco
1         San Jose
2       Sacramento
dtype: object
```

`DataFrame` objects can be created by passing a `dict` mapping `string` column names to their respective `Series`. If the `Series` don't match in length, missing values are filled with special NA/NaN values. Example:

```
city_names = pd.Series(['San Francisco', 'San Jose', 'Sacramento'])
population = pd.Series([852469, 1015785, 485199])

pd.DataFrame({ 'City name': city_names, 'Population': population })
```

	City name	Population
0	San Francisco	852469
1	San Jose	1015785
2	Sacramento	485199

But most of the time, you load an entire file into a `DataFrame`. The following example loads a file with California housing data. Run the following cell to load the data and create feature definitions:

```
california_housing_dataframe = pd.read_csv("https://download.mlcc.google.com/mledu-datase
california_housing_dataframe.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedroom
count	17000.000000	17000.000000	17000.000000	17000.000000	17000.00000
mean	-119.562108	35.625225	28.589353	2643.664412	539.41082
std	2.005166	2.137340	12.586937	2179.947071	421.49945
min	-124.350000	32.540000	1.000000	2.000000	1.00000
25%	-121.790000	33.930000	18.000000	1462.000000	297.00000
50%	-118.490000	34.250000	29.000000	2127.000000	434.00000
75%	-118.000000	37.720000	37.000000	3151.250000	648.25000
max	-114.310000	41.950000	52.000000	37937.000000	6445.00000

The example above used `DataFrame.describe` to show interesting statistics about a `DataFrame`. Another useful function is `DataFrame.head`, which displays the first few records of a `DataFrame`:

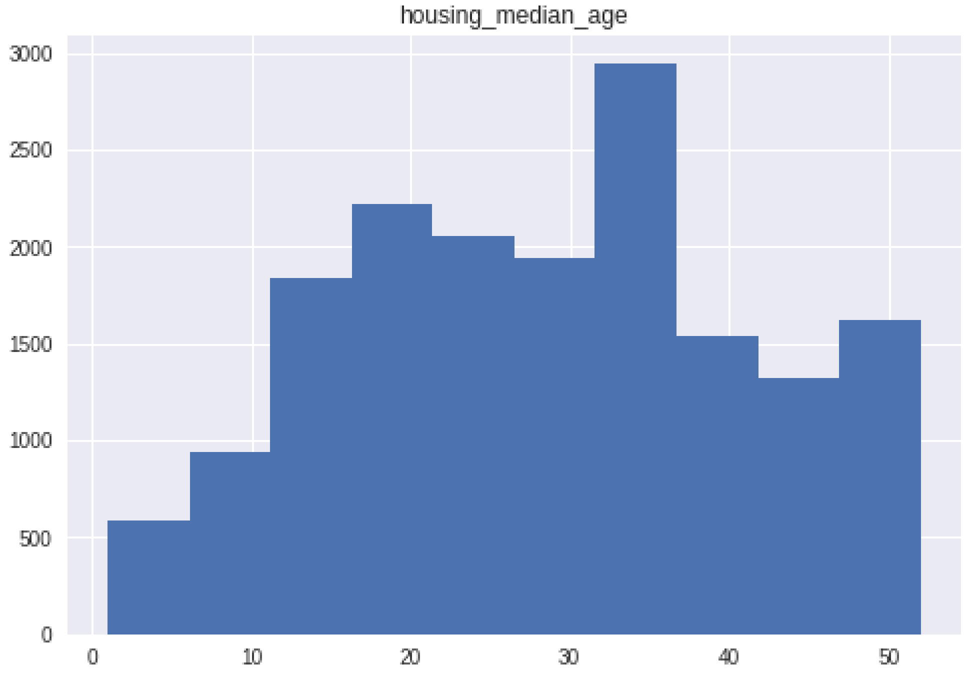
```
california_housing_dataframe.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
0	-114.31	34.19	15.0	5612.0	1283.0	1015
1	-114.47	34.40	19.0	7650.0	1901.0	1129
2	-114.56	33.69	17.0	720.0	174.0	333

Another powerful feature of *pandas* is graphing. For example, `DataFrame.hist` lets you quickly study the distribution of values in a column:

```
california_housing_dataframe.hist('housing_median_age')
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f48d19b2690>]],
      dtype=object)
```



Accessing Data

You can access `DataFrame` data using familiar Python dict/list operations:

```
cities = pd.DataFrame({ 'City name': city_names, 'Population': population })
print(type(cities['City name']))
cities['City name']
```

```
<class 'pandas.core.series.Series'>
0    San Francisco
1         San Jose
2       Sacramento
Name: City name, dtype: object
```

```
print(type(cities['City name'][1]))
cities['City name'][1]
```

```
<type 'str'>
'San Jose'
```

```
print(type(cities[0:2]))
cities[0:2]
```

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

	City name	Population
0	San Francisco	852469
1	San Jose	1015785

In addition, *pandas* provides an extremely rich API for advanced [indexing and selection](#) that is too extensive to be covered here.

Manipulating Data

You may apply Python's basic arithmetic operations to `Series`. For example:

```
population / 1000.
```

```
0     852.469
1    1015.785
2     485.199
dtype: float64
```

[NumPy](#) is a popular toolkit for scientific computing. *pandas* `Series` can be used as arguments to most NumPy functions:

```
import numpy as np

np.log(population)
```

```
0    13.655892
1    13.831172
2    13.092314
dtype: float64
```

For more complex single-column transformations, you can use `Series.apply`. Like the Python [map function](#), `Series.apply` accepts as an argument a [lambda function](#), which is applied to each value.

The example below creates a new `Series` that indicates whether `population` is over one million:

```
population.apply(lambda val: val > 1000000)
```

```
0    False
1     True
2    False
dtype: bool
```

Modifying `DataFrames` is also straightforward. For example, the following code adds two `Series` to an existing `DataFrame`:

```
cities['Area square miles'] = pd.Series([46.87, 176.53, 97.92])
cities['Population density'] = cities['Population'] / cities['Area square miles']
```

```
cities
```

	City name	Population	Area square miles	Population density
0	San Francisco	852469	46.87	18187.945381
1	San Jose	1015785	176.53	5754.177760
2	Sacramento	485199	97.92	4955.055147

Exercise #1

Modify the `cities` table by adding a new boolean column that is True if and only if *both* of the following are True:

- The city is named after a saint.
- The city has an area greater than 50 square miles.

Note: Boolean `Series` are combined using the bitwise, rather than the traditional boolean, operators. For example, when performing *logical and*, use `&` instead of `and`.

Hint: "San" in Spanish means "saint."

```
cities['Area square miles'].apply(lambda val: val > 50)&cities['City name'].apply(lambda
```

```
0    False
1     True
2    False
dtype: bool
```

Solution

Click below for a solution.

```
cities['Is wide and has saint name'] = (cities['Area square miles'] > 50) & cities['City
cities
```

	City name	Population	Area square miles	Population density	Is wide and has saint name
0	San Francisco	852469	46.87	18187.945381	False
1	San Jose	1015785	176.53	5754.177760	True

Indexes

Both `Series` and `DataFrame` objects also define an `index` property that assigns an identifier value to each `Series` item or `DataFrame` row.

By default, at construction, *pandas* assigns index values that reflect the ordering of the source data. Once created, the index values are stable; that is, they do not change when data is reordered.

```
city_names.index
```

```
RangeIndex(start=0, stop=3, step=1)
```

```
cities.index
```

```
RangeIndex(start=0, stop=3, step=1)
```

Call `DataFrame.reindex` to manually reorder the rows. For example, the following has the same effect as sorting by city name:

```
cities.reindex([2, 0, 1])
```

	City name	Population	Area square miles	Population density	Is wide and has saint name
2	Sacramento	485199	97.92	4955.055147	False
0	San Francisco	852469	46.87	18187.945381	False

Reindexing is a great way to shuffle (randomize) a `DataFrame`. In the example below, we take the index, which is array-like, and pass it to NumPy's `random.permutation` function, which shuffles its values in place. Calling `reindex` with this shuffled array causes the `DataFrame` rows to be shuffled in the same way. Try running the following cell multiple times!

```
cities.reindex(np.random.permutation(cities.index))
```

	City name	Population	Area square miles	Population density	Is wide and has saint name
1	San Jose	1015785	176.53	5754.177760	True
0	San Francisco	852469	46.87	18187.945381	False

For more information, see the [Index documentation](#).

Exercise #2

The `reindex` method allows index values that are not in the original `DataFrame`'s index values. Try it and see what happens if you use such values! Why do you think this is allowed?

```
cities.reindex([0,5,1,3,2])
```

Area square Population Is wide and has saint

Solution

Click below for the solution.

If your `reindex` input array includes values not in the original `DataFrame` index values, `reindex` will add new rows for these "missing" indices and populate all corresponding columns with `NaN` values:

```
cities.reindex([0, 4, 5, 2])
```

	City name	Population	Area square miles	Population density	Is wide and has saint name
0	San Francisco	852469.0	46.87	18187.945381	False
4	NaN	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	NaN

This behavior is desirable because indexes are often strings pulled from the actual data (see the [*pandas* reindex documentation] for an example in which the index values are browser names).

In this case, allowing "missing" indices makes it easy to reindex using an external list, as you don't have to worry about sanitizing the input.