# Pandas基础 C08

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# Pandas — Panel data analysis

- 序列: indexed list
- 数据表处理
- 表间计算
- 聚合运算
- Pandas的统计功能与应用

# The Pandas Series Object —— 序列

A Pandas Series is a one-dimensional array of indexed data. It can be created from a list or array as

缺省情况类似excel的表格,自动维护标号索引



```
data = pd. Series([0.25, 0.5, 0.75, 1.0])
print(data)

data.index

0  0.25
1  0.50
2  0.75
3  1.00
1  data = pd. Series(i*i for i in [0.25, 0.5, 0.75, 1.0])
2  print(data)
3  data.index

0  0.0625
1  0.2500
2  0.75
3  1.000
```

RangeIndex(start=0, stop=4, step=1)

dtype: float64

## 与数组类似, 支持下标切片访问操作

```
data. values
array([ 0.25, 0.5, 0.75, 1. ])
The index is an array-like object of type pd. Index
     data[1]
0.5
     data[1:3]
    0.50
     0.75
dtype: float64
```

#### 也可以指定可哈希的索引项,类似dict

```
data = pd. Series([0.5, 0.25, 1.75, 1.0],
                  index=['a', 'b', 'c', 'd'])
3 | print (data)
  print(data.sort_values())
5 | data['b'] ←
   0. 50
b 0.25
c 1.75
  1.00
dtype: float64
b 0.25
a 0.50
d 1.00
c 1.75
dtype: float64
```

#### 非连续的索引项也可以, 但一般建议避免非连续数字

0.5

#### Indexers: loc, iloc, and ix

按位置索引

These slicing and indexing conventions can be a source of confusion. For example, if your Series has an explicit integer index, an indexing operation such as data[1] will use the explicit indices, while a slicing operation like data[1:3] will use the implicit Python-style index.

```
data = pd. Series(['a', 'b', 'c'], index=[1, 3, 5])
     data
     а
     b
dtype: object
                                              print (data. loc[1])
                                              print (data. iloc[1])
                                           3
     # explicit index when indexing
     data[1]
                                           а
     # implicit index when slicing
     data[1:3]
```

3 b

5 с

dtype: object

```
print(0.75 in data)
0.75 in data.values
```

False

True

```
for i in data.values: ← 迭代器, 也要指明具体字段 print(i)
```

- 0.25
- 0.5
- 0.75
- 1.0

True

for k in data.index:
 print(data[k])

- 0.5
- 0.25
- 1.75
- 1.0

```
1 a = pd. Series([2, 4, 6])
2 b = pd. Series({2:'a', 1:'b', 3:'c'})
3 print(b[1])
4 2 in b 词典数据初始化序列
```

b

#### True

```
1 for i in b:
2 print (i)
```

а

b

#### The Pandas DataFrame Object

- 视角1: 多个对齐的序列(series)的组合(record)
- 视角2: 支持多层索引的二维数据表

#### 初始化一个dataframe:字段名+数据序列

	Α	В	С	D	E	F
0	1.0	2024-01-02	1	3.0	test	流水账
1	1.0	2024-01-02	3	3.0	train	流水账
2	1.0	2024-01-02	5	3.0	test	流水账
3	1.0	2024-01-02	7	3.0	train	流水账
4	1.0	2024-01-02	9	3.0	break	流水账

# A float64 B datetime64[s] C int64 D float64 E category F object dtype: object

表5-1:可以输入给DataFrame构造器的数据

类型	说明
二维ndarray	数据矩阵, 还可以传入行标和列标
由数组、列表或元组组成的字典	每个序列会变成DataFrame的一列。所有序列的长度 必须相同
NumPy的结构化/记录数组	类似于"由数组组成的字典"
由Series组成的字典	每个Series会成为一列。如果没有显式指定索引,则 各Series的索引会被合并成结果的行索引
由字典组成的字典	各内层字典会成为一列。键会被合并成结果的行索引,跟"由Series组成的字典"的情况一样
字典或Series的列表	各项将会成为DataFrame的一行。字典键或Series索引的并集将会成为DataFrame的列标
由列表或元组组成的列表	类似于"二维ndarray"
另一个DataFrame	该DataFrame的索引将会被沿用,除非显式指定了其 他索引
NumPy的MaskedArray	类似于"二维ndarray"的情况,只是掩码值在结果 DataFrame会变成NA/缺失值

#### 词典的列表生成dataframe:

If some keys in the dictionary are missing, Pandas will fill them in with NaN (i.e., "not a number") values:

```
data = [{'a': i, 'b': 2 * i} for i in range(3)] 索引key + 列表生成式

print(data) pd. DataFrame(data)

[{'a': 0, 'b': 0}, {'a': 1, 'b': 2}, {'a': 2, 'b': 4}]

a b

0 0 0
```

#### From a two-dimensional NumPy array

Given a two-dimensional array of data, we can create a DataFrame with any specified column and index names. If omitted, an integer index will be used for each:

	foo	bar
a	0.865257	0.213169
b	0.442759	0.108267
С	0.047110	0.905718

#### 时间序列索引

	Α	В	С	D
2024-01-01	-0.420908	0.561723	1.029381	-0.547718
2024-01-02	1.107427	1.996233	-0.542999	0.532342
2024-01-03	-0.570062	0.150368	-0.121603	0.224366
2024-01-04	0.338397	0.019086	-0.236876	-1.211000
2024-01-05	0.458176	0.488300	0.099074	-2.192264
2024-01-06	0.463506	0.348168	0.154023	0.393635

df.sort\_values(by="B")

排序:

	Α	В	С	D
2024-01-04	1.181177	-1.011614	0.082741	0.277036
2024-01-01	1.272659	0.160868	-0.955028	0.111053
2024-01-02	-0.580428	0.381052	0.043766	1.561938
2024-01-06	-0.698205	0.604560	-0.960241	0.732983
2024-01-03	-0.655237	0.841888	-0.331852	1.454877
2024-01-05	-0.735982	2.021000	1.199130	-0.332525

df. sort\_index(ascending=False)

	Α	В	С	D
2024-01-06	-0.698205	0.604560	-0.960241	0.732983
2024-01-05	-0.735982	2.021000	1.199130	-0.332525
2024-01-04	1.181177	-1.011614	0.082741	0.277036
2024-01-03	-0.655237	0.841888	-0.331852	1.454877
2024-01-02	-0.580428	0.381052	0.043766	1.561938
2024-01-01	1.272659	0.160868	-0.955028	0.111053

#### df["A"]

# 下标访问:

```
      2024-01-01
      -0. 420908

      2024-01-02
      1. 107427

      2024-01-03
      -0. 570062

      2024-01-04
      0. 338397

      2024-01-05
      0. 458176

      2024-01-06
      0. 463506
```

Freq: D, Name: A, dtype: float64

#### df[0:3]

	Α	В	С	D
2024-01-01	-0.420908	0.561723	1.029381	-0.547718
2024-01-02	1.107427	1.996233	-0.542999	0.532342
2024-01-03	-0.570062	0.150368	-0.121603	0.224366

#### df.loc[dates[1]]

```
A 1. 107427
B 1. 996233
C -0. 542999
D 0. 532342
```

Name: 2024-01-02 00:00:00, dtype: float64

```
df.loc[:, ["A", "B"]]
```

# 下标切片:

```
      2024-01-01
      1.272659
      0.160868

      2024-01-02
      -0.580428
      0.381052

      2024-01-03
      -0.655237
      0.841888

      2024-01-04
      1.181177
      -1.011614

      2024-01-05
      -0.735982
      2.021000

      2024-01-06
      -0.698205
      0.604560
```

```
df. loc["20240102":"20240104", ["A", "B"]]
```

```
A B

2024-01-02 -0.580428 0.381052

2024-01-03 -0.655237 0.841888

2024-01-04 1.181177 -1.011614
```

```
a = df.loc[dates[0], "A"]
b = df.at[dates[0], "A"]
a == b
```

#### 生成视图副本:

```
df2 = df.iloc[1:4, :2].copy()
df2
```

```
AB2024-01-02-0.5804280.3810522024-01-03-0.6552370.8418882024-01-041.181177-1.011614
```

df[df["B"] > 0] # 生成布尔下标

	Α	В	С	D
2024-01-01	1.272659	0.160868	-0.955028	0.111053
2024-01-02	-0.580428	0.381052	0.043766	1.561938
2024-01-03	-0.655237	0.841888	-0.331852	1.454877
2024-01-05	-0.735982	2.021000	1.199130	-0.332525
2024-01-06	-0.698205	0.604560	-0.960241	0.732983

## 新加列:

2024-01-07 6 Freq: D, dtype: int64

2024-01-06

```
df["F"] = new_col
df
```

	Α	В	С	D	F
2024-01-01	1.272659	0.160868	-0.955028	0.111053	NaN
2024-01-02	-0.580428	0.381052	0.043766	1.561938	1.0
2024-01-03	-0.655237	0.841888	-0.331852	1.454877	2.0
2024-01-04	1.181177	-1.011614	0.082741	0.277036	3.0
2024-01-05	-0.735982	2.021000	1.199130	-0.332525	4.0
2024-01-06	-0.698205	0.604560	-0.960241	0.732983	5.0

# 算术运算-广播:

```
df["D"] = 3 # 广播机制
df
```

	Α	В	С	D	F
2024-01-01	1.272659	0.160868	-0.955028	3	NaN
2024-01-02	-0.580428	0.381052	0.043766	3	1.0
2024-01-03	-0.655237	0.841888	-0.331852	3	2.0
2024-01-04	1.181177	-1.011614	0.082741	3	3.0
2024-01-05	-0.735982	2.021000	1.199130	3	4.0
2024-01-06	-0.698205	0.604560	-0.960241	3	5.0

```
df2 = df.copy()
df2[df2 > 0] = df2*2
df2
```

	Α	В	С	D	F
2024-01-01	2.545319	0.321737	-0.955028	6	NaN
2024-01-02	-0.580428	0.762104	0.087531	6	2.0
2024-01-03	-0.655237	1.683777	-0.331852	6	4.0
2024-01-04	2.362354	-1.011614	0.165483	6	6.0
2024-01-05	-0.735982	4.042000	2.398260	6	8.0
2024-01-06	-0.698205	1.209119	-0.960241	6	10.0

## Working with NumPy ufunc

```
1 df = pd. DataFrame(rng. randint(0, 10, (3, 4)),
2 columns=['A', 'B', 'C', 'D'])
3 df
```

```
A B C D
0 9 2 6 7
1 4 3 7 7
2 2 5 4 1
```

采用Numpy的广播机制,逐元素计算

```
1 np. sin(df * np. pi / 4)
```

```
        A
        B
        C
        D

        0
        7.071068e-01
        1.000000
        -1.000000e+00
        -0.707107

        1
        1.224647e-16
        0.707107
        -7.071068e-01
        -0.707107

        2
        1.000000e+00
        -0.707107
        1.224647e-16
        0.707107
```

# 算术运算-赋值:

```
df["D"] = 3 # 广播机制
df
```

	Α	В	С	D	F
2024-01-01	1.272659	0.160868	-0.955028	3	NaN
2024-01-02	-0.580428	0.381052	0.043766	3	1.0
2024-01-03	-0.655237	0.841888	-0.331852	3	2.0
2024-01-04	1.181177	-1.011614	0.082741	3	3.0
2024-01-05	-0.735982	2.021000	1.199130	3	4.0
2024-01-06	-0.698205	0.604560	-0.960241	3	5.0

```
df2 = df.copy()
df2[df2 > 0] = df2*2
df2
```

	Α	В	С	D	F
2024-01-01	2.545319	0.321737	-0.955028	6	NaN
2024-01-02	-0.580428	0.762104	0.087531	6	2.0
2024-01-03	-0.655237	1.683777	-0.331852	6	4.0
2024-01-04	2.362354	-1.011614	0.165483	6	6.0
2024-01-05	-0.735982	4.042000	2.398260	6	8.0
2024-01-06	-0.698205	1.209119	-0.960241	6	10.0

#### 筛选+赋值:

```
data.loc[data.density > 100, ['pop', 'density']]
```

	pop	density
Florida	19552860	114.806121
New York	19651127	139.076746

Any of these indexing conventions may also be used to set or modify values; this is done in the standard way that you might be accustomed to from working with NumPy:

```
1 data. iloc[0, 2] = 90 lloc支持多重索引
2 data
```

	area	pop	density
California	423967	38332521	90.000000
Texas	695662	26448193	38.018740
New York	141297	19651127	139.076746
Florida	170312	19552860	114.806121
Illinois	149995	12882135	85.883763

#### Dataframe列间的运算自动进行索引键对齐/补缺

```
Out[22]:
                A B
            1 18 6
▶ In [23]:
                 B = pd. DataFrame (rng. randint (0, 10, (3, 3)),
                                  columns=list('BAC'))
                 В
  Out[23]:
               BAC
▶ In [24]:
                A + B
  Out[24]:
               10.0
                     8.0 NaN
                     7.0 NaN
               21.0
```

2 NaN NaN NaN

## 行列对象间支持的运算符:

The following table lists Python operators and their equivalent Pandas object methods:

Python Operator	Pandas Method(s)
+	add()
_	<pre>sub() , subtract()</pre>
*	<pre>mul() , multiply()</pre>
/	<pre>truediv() , div() , divide()</pre>
//	floordiv()
%	mod()
**	pow()

## Frame, 按行broadcasting

```
1 A = rng. randint(10, size=(3, 4))
: array([[9, 4, 1, 3],
         [6, 7, 2, 0],
         [3, 1, 7, 3]])
   1 | df = pd. DataFrame(A, columns=list('QRST'))
    2 | df - df. iloc[0]
                                             1 df. subtract(df['R'], axis=0)
     QRST
                                              QRST
   1 -3 3 1 -3
```

## 运算过程中类型自适应转换

The following table lists the upcasting conventions in Pandas when NA values are introduced:

Typeclass	Conversion When Storing NAs	NA Sentinel Value
floating	No change	np. nan
object	No change	None <b>or</b> np. nan
integer	Cast to float64	np. nan
boolean	Cast to object	None <b>or</b> np. nan

Keep in mind that in Pandas, string data is always stored with an object dtype.

#### **Detecting null values**

Pandas data structures have two useful methods for detecting null data: isnull() and notnull(). Either one will return a Boolean mask over the data. For example:

```
data = pd. Series([1, np.nan, 'hello', None])

data.isnull()

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

As mentioned in <u>Data Indexing and Selection</u>, Boolean masks can be used directly as a Series or DataFrame index:

```
data[data.notnull()]
```

2 hello dtype: object We can fill NA entries with a single value, such as zero:

dtype: float64

```
data.fillna(0)

a 1.0
b 0.0
c 2.0
d 0.0
e 3.0
dtype: float64
```

We can specify a forward-fill to propagate the previous value forward:

```
# forward-fill
data.fillna(method='ffill')

a 1.0
b 1.0
c 2.0
d 2.0
e 3.0
```

#### 例子

```
df3 = df.reindex(index=dates[0:4], columns=list(df.columns) + ["E"])
df3.loc[dates[0] : dates[2], "E"] = 1
df3
```

```
ABCDFE2024-01-01-0.554219-0.405164-0.2779793NaN1.02024-01-02-2.216250-0.1394900.16497931.01.02024-01-03-1.134139-1.3304541.13218932.01.02024-01-041.1223010.386015-0.94235433.0NaN
```

```
print(df3.fillna(value=0)) # df3.dropna() # 去掉包含na的数据行
#df3
```

```
population_dict = {'California': 38332521,
                      'Texas': 26448193,
                      'New York': 19651127,
                      'Florida': 19552860,
4
                      'Illinois': 12882135}
   population = pd. Series(population_dict)
   area_dict = {'California': 423967, 'Texas': 695662, 'New York': 141297,
                'Florida': 170312, 'Illinois': 149995}
   area = pd. Series(area_dict)
   states = pd. DataFrame({'population': population, 'area': area})
   states
```

	population	area
California	38332521	423967
Texas	26448193	695662
New York	19651127	141297
Florida	19552860	170312
Illinois	12882135	149995

Step 1、词典到序列数据 Step 2、多序列合并生成dataframe

	population	area
California	38332521.0	423967.0
Florida	NaN	170312.0
Illinois	NaN	149995.0
New York	19651127.0	141297.0
Texas	26448193.0	695662.0
W.DC	11000000.0	NaN

索引-数据与索引合并(非对齐情况):索引扩展,数据用NaN填充

```
print(states.index)
  print(states.columns) ← 行列的表头都是索引
  for i in states, columns:
      print(states[i])
Index(['California', 'Florida', 'Illinois', 'New York', 'Texas', 'W.DC'], dtype='ob
ject')
Index(['population', 'area'], dtype='object') = 都是索引对象,逻辑上对等(可互换)
California
             38332521. 0
Florida
                   NaN
Illinois
                   NaN
New York
            19651127. 0
Texas
            26448193. 0
W. DC
            11000000.0
Name: population, dtype: float64
California
           423967.0
Florida 170312.0
Illinois
            149995.0
New York
        141297. 0
            695662.0
Texas
W. DC
                 NaN
Name: area, dtype: float64
```

## 行列互换操作

```
s = data. T
     print(s)
     s['California']
                                                                     Illinois
             California
                                                         Florida
                               Texas
                                          New York
           4. 239670e+05 6. 956620e+05
                                     1. 412970e+05 1. 703120e+05 1. 499950e+05
  area
           3.833252e+07 2.644819e+07 1.965113e+07 1.955286e+07 1.288214e+07
  pop
  density 9.041393e+01
                        3.801874e+01 1.390767e+02 1.148061e+02 8.588376e+01
          4. 239670e+05
area
          3.833252e+07
pop
density
          9. 041393e+01
Name: California, dtvpe: float64
```

# 计算生成新列:

```
data['density'] = data['pop'] / data['area']
data
```

	area	pop	density
California	423967	38332521	90.413926
Florida	170312	19552860	114.806121
Illinois	149995	12882135	85.883763
New York	141297	19651127	139.076746
Texas	695662	26448193	38.018740

## 多维表操作

• 本质上是多重索引支持的2维数表

	Haine	DOD	•	DODZ		Pons	
	type		HD	WR	HD	WR	HD
year	season						
2013	1	55	29	27	74	75	48
	2	9	86	54	5	11	14
	3	18	22	79	42	39	73
	4	77	77	52	77	65	17
2014	1	45	30	9	43	16	18

Roh1

Roh2

Roh3

多维索引表操作

## 直接定位行列的索引:

```
wh_data.iloc[:3,:3] # 可以按二维表的iloc直接切片
```

	name	Bob		Guido	
	type	WR	HD	WR	
year	season				
2013	1	39	14	2	
	2	46	20	21	
	3	50	1	74	

## .loc可以实现最外层索引的切片:

```
wh_data.loc[2014:,:'Bob2'] # 右面也是闭区间
# wh_data[2014:,:'Bob2'] # TypeError: unhashable type: 'slice'
```

	name	Bob'	Bob1		2	
	type	WR	HD	WR	HD	
year	season					
2014	1	27	85	69	78	
	2	2	26	27	16	
	3	17	9	42	41	
	4		33	43	66	

## 使用indexSlice对象 (了解)

```
# wh_data.loc[2014:,(:'WR')] # invalid syntax
idx = pd.IndexSlice
wh_data.loc[idx[2014:],idx[:,'WR']] # 加入index切片对象辅助实现
```

	name	Bob1	Bob2	Bob3
	type	WR	WR	WR
year	season			
2014	1	27	69	50
	2	2	27	56
	3	17	42	82
	4	71	43	59

# 层次-组合索引(Hierarchical-Indexing)

```
      (California, 2000)
      33871648

      (California, 2010)
      37253956

      (New York, 2000)
      18976457

      (New York, 2010)
      19378102

      (Texas, 2000)
      20851820

      (Texas, 2010)
      25145561

      dtype: int64
```

```
1 pop[:, 2010]

California 37253956

New York 19378102

Texas 25145561

dtype: int64
```

#### 多键值词典索引初始化: 自动识别为多层索引

Similarly, if you pass a dictionary with appropriate tuples as keys, Pandas will automatically recognize this and use a MultiIndex by default:

```
      California
      2000
      33871648

      2010
      37253956

      New York
      2000
      18976457

      2010
      19378102

      Texas
      2000
      20851820

      2010
      25145561
```

dtwne: int64

#### MultiIndex VS extra dimension

dtype: int64

```
#unstack() method will quickly convert a multiply indexed Series
    #into a conventionally indexed DataFrame:
     pop_df = pop. unstack()
    pop_df
              2000
                       2010
 California 33871648 37253956
 New York 18976457 19378102
    Texas 20851820 25145561
     #unstack() method will quickly convert a multiply indexed Series into a conventi
    pop_df.stack()
California
           2000
                    33871648
            2010
                    37253956
            2000
New York
                    18976457
            2010
                   19378102
Texas
            2000
                    20851820
            2010
                    25145561
```

#### total under18

California	2000	33871648	9267089
California	2010	37253956	9284094
New York	2000	18976457	4687374
New Tork	2010	19378102	4318033
Texas	2000	20851820	5906301
iexas	2010	25145561	6879014

```
1  f_u18 = pop_df['under18'] / pop_df['total']
2  f_u18. unstack()
```

	2000	2010
California	0.273594	0.249211
New York	0.247010	0.222831
Texas	0.283251	0.273568

#### 多层索引的生成方案:

You can construct it from a list of tuples giving the multiple index values of each point:

You can even construct it from a Cartesian product of single indices:

```
pd. MultiIndex. from_product([['a', 'b'], [1, 2]])
```

### 多个键值直接组合为多层索引:

#### **Methods of Multilndex Creation**

The most straightforward way to construct a multiply indexed Series or DataFrame is to simply pass a list of two or more index arrays to the constructor. For example:

]:			data1	data2
	а	1	0.554233	0.356072
		2	0.925244	0.219474
	b	1	0.441759	0.610054
-		2	0.171495	0.886688

#### Data Aggregations

#### Group by certain Key:

- Splitting the data into groups based on some criteria.
- Applying a function to each group independently.
- Pandas has built-in data aggregation methods,
- such as mean(), sum(), and max().

```
Α
        BCD
0 bob
       one 3 1
1 john
       one 1 2
2 bob
       two 4 3
  jeff three 1 4
4 bob
      two 5 5
       two 9 6
  jeff
6 bob one 2 7
7 john three 6 8
```

## 按属性分组求均值:

1 health_data									
	subject	Bob		Guid	0	Sue			
	type		Temp	HR	Temp	HR	Temp		
year	visit								
2013	1	31.0	38.7	32.0	36.7	35.0	37.2		
	2	44.0	37.7	50.0	35.0	29.0	36.7		
2014	1	30.0	37.4	39.0	37.8	61.0	36.9		
	2	47.0	37.8	48.0	37.3	51.0	36.5		

```
      1 data_mean
      = health_data.mean(level='year')

      subject Bob Guido Sue

      type HR Temp HR Temp HR Temp year

      2013 37.5 38.2 41.0 35.85 32.0 36.95

      2014 38.5 37.6 43.5 37.55 56.0 36.70
```

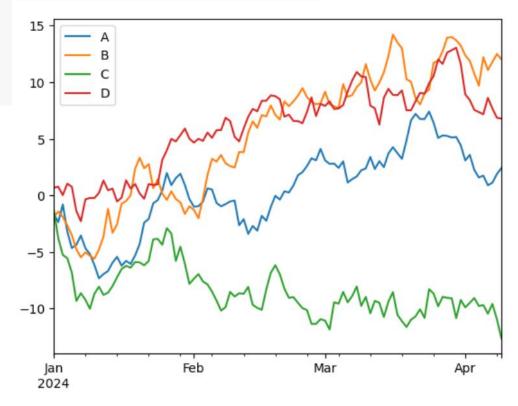
#### 数据分析应用示例: 序列可视化

```
import matplotlib.pyplot as plt
ts = pd. Series (np. random. randn (100), index=pd. date_range ("1/1/2024",
                                                                periods=100))
ts.plot()
ts = ts. cumsum()
ts.plot()
plt.legend('rs')
                                                                            Feb
                                                                                        Mar
                                                                                                    Apr
                                                               2024
```

```
dfr = pd. DataFrame(
    np. random. randn(100, 4), index=ts.index, columns=["A", "B", "C", "D"]
)

dfr2 = dfr. cumsum()
```

```
plt.figure()
dfr2.plot()
plt.legend(loc = best')
```



Neither the University of Minnesota nor any of the researchers involved can guarantee the correctness of the data, its suitability for any particular purpose, or the validity of results based on the use of the data set. The data set may be used for any research purposes under the following conditions:

- \* The user may not state or imply any endorsement from the University of Minnesota or the GroupLens Research Group.
- \* The user must acknowledge the use of the data set in publications resulting from the use of the data set (see below for citation information).
- \* The user may not redistribute the data without separate permission.
- \* The user may not use this information for any commercial or revenue-bearing purposes without first obtaining permission from a faculty member of the GroupLens Research Project at the University of Minnesota.

If you have any further questions or comments, please contact GroupLens <grouplens-info@cs.umn.edu>.

#### CITATION

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To acknowledge use of the dataset in publications, please cite the following paper:

F. Maxwell Harper and Joseph A. Konstan. 2015. The MovieLens Datasets: History and Context. ACM Transactions on Interactive Intelligent Systems (TiiS) 5, 4, Article 19 (December 2015), 19 pages. DOI=http://dx.doi.org/10.1145/2827872

# 数据分析实例: The MovieLens Dataset 电影评分数据集

名称	修改日期	类型
movies	2018/7/10 20:01	DAT
ratings	2018/7/10 20:01	DAT
README	2018/7/10 20:01	MD 文件
<ul><li>users</li></ul>	2018/7/10 20:01	DAT

```
# Read the Ratings File
ratings = pd. read_csv(os. path. join(MOVIELENS_DIR, RATING_DATA_FILE),
sep='::',
engine='python',
encoding='latin=1',
names=['user_id', 'movie_id', 'rating', 'timestamp'])

print(len(ratings), 'ratings loaded')
ratings. head() # by default显示前5条
```

1000209 ratings loaded

	user_id	movie_id	rating	timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

#### pandas.read\_csv

```
pandas.read_csv(filepath_or_buffer, *, sep=_NoDefault.no_default, delimiter=None,
header='infer', names=_NoDefault.no_default, index_col=None, usecols=None, squeeze=None,
```

#### Parameters: filepath\_or\_buffer : str, path object or file-like object

Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.

If you want to pass in a path object, pandas accepts any os.PathLike.

By file-like object, we refer to objects with a read() method, such as a file handle (e.g. via builtin open function) or StringIO.

#### sep: str, default ','

Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python's builtin sniffer tool, <code>csv.Sniffer</code>. In addition, separators longer than 1 character and different from <code>'\s+'</code> will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: <code>'\r\t'</code>.

**delimiter**: str, default None
Alias for sep.

header: int, list of int, None, default 'infer'

#### 写出数据表文件

ratings2 - Excel

運動

Acrobat



Saved to ratings2.csv

	А	В	С	D	Е	F	G	Н	1	
1	user_id	movie_id	rating	timestamp						
2	1	1193	5	978300760						
3	1	661	3	978302109						
4	1	914	3	978301968						
5	1	3408	4	978300275						
6	1	2355	5	978824291						
7	1	1197	3	978302268						
8	1	1287	5	978302039						
9	1	2804	5	978300719						
10	1	594	4	978302268						
11	1	919	4	978301368						
12	1	595	5	978824268						
13	1	938	4	978301752						
14	1	2398	4	978302281						
15	1	2918	4	978302124						
16	1	1035	5	978301753						
17	1	2791	4	978302188						
18	1	2687	3	978824268						
19	1	2018	4	978301777						

### 连续值属性量化

```
# Specify User's Age and Occupation Column

AGES = { 1: "Under 18", 18: "18-24", 25: "25-34", 35: "35-44", 45: "45-49", 50: "50-55", 56: "56+" }

OCCUPATIONS = { 0: "other or not specified", 1: "academic/educator", 2: "artist", 3: "clerical/admin",

4: "college/grad student", 5: "customer service", 6: "doctor/health care",

7: "executive/managerial", 8: "farmer", 9: "homemaker", 10: "K-12 student", 11: "lawyer",

12: "programmer", 13: "retired", 14: "sales/marketing", 15: "scientist", 16: "self-employed",

17: "technician/engineer", 18: "tradesman/craftsman", 19: "unemployed", 20: "writer" }
```

```
# Read the Users File
users = pd.read_csv(os.path.join(MOVIELENS_DIR, USER_DATA_FILE),
sep='::',
engine='python',
encoding='latin-1',
names=['user_id', 'gender', 'age', 'occupation', 'zipcode'])

users['age_desc'] = users['age'].apply(lambda x: AGES[x]) # 变换成年龄段

users['occ_desc'] = users['occupation'].apply(lambda x: OCCUPATIONS[x]) # 奶业词典
print(len(users), 'descriptions of', max_userid, 'users loaded.')
```

6040 descriptions of 6040 users loaded.

# 加工后的数据表:

	+ ( <sup>3</sup> + ∓					ers - Excel		🛕 Junfeng Hu
文件	开始 插入 绘图	の の の の の の の の の の の の の の の の の の の	审阅 视图 帮助	Acrobat 🔾 告诉我你	想要做什么			
A1	A A	В	С	D	Е	F	G	Н
1	7.		gender	age	occupation	zipcode	age_desc	occ_desc
2	0	1	F	1	10	48067	Under 18	K-12 student
3	1	2	М	56	16	70072	56+	self-employed
4	2	3	М	25	15	55117	25-34	scientist
5	3	4	Μ	45	7	2460	45-49	executive/managerial
6	4	5	Μ	25	20	55455	25-34	writer
7	5	6	F	50	9	55117	50-55	homemaker
8	6	7	М	35	1	6810	35-44	academic/educator
9	7	8	М	25	12	11413	25-34	programmer
10	8	9	М	25	17	61614	25-34	technician/engineer
11	9	10	F	35	1	95370	35-44	academic/educator
12	10	11	F	25	1	4093	25-34	academic/educator
13	11	12	M	25	12	32793	25-34	programmer

### 电影信息表:

```
print(len(movies), 'descriptions of', max_movieid, 'movies loaded.')
movies.head()
```

3883 descriptions of 3952 movies loaded.

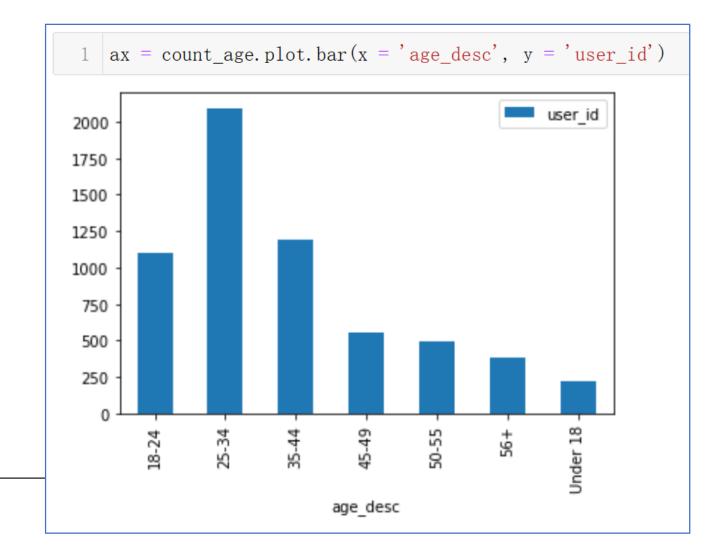
	movie_id	title	genres
0	1	Toy Story (1995)	Animation Children's Comedy
1	2	Jumanji (1995)	Adventure Children's Fantasy
2	3	Grumpier Old Men (1995)	Comedy Romance
3	4	Waiting to Exhale (1995)	Comedy Drama
4	5	Father of the Bride Part II (1995)	Comedy

1 count\_age = users.groupby(['age\_desc']).count() # 按年龄段统计 2 count\_age

	user_id	gender	zipcode	occ_desc
age_desc				
18-24	1103	1103	1103	1103
25-34	2096	2096	2096	2096
35-44	1193	1193	1193	1193
45-49	550	550	550	550
50-55	496	496	496	496
56+	380	380	380	380
Under 18	222	222	222	222

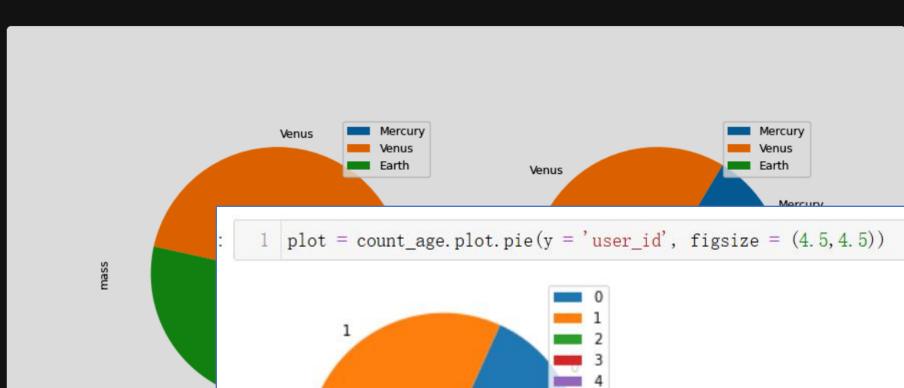
```
count_age = users.groupby(by = ['age_desc']) ['user_id'].count().reset_index()
count_age
```

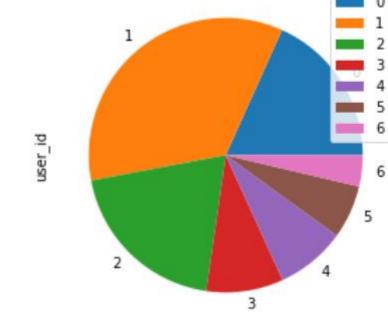
	age_desc	user_id
0	18-24	1103
1	25-34	2096
2	35-44	1193
3	45-49	550
4	50-55	496
5	56+	380
6	Under 18	222



>>> plot = df.plot.pie(subplots=True, figsize=(11, 6))







```
count_age_gender = users.groupby(by = ['age_desc', 'gender'])['user_id'].count().reset_index()
count_age_gender
```

	age_desc	gender	user_id
0	18-24	F	298
1	18-24	M	805
2	25-34	F	558
3	25-34	M	1538
4	35-44	F	338
5	35-44	M	855
6	45-49	F	189
7	45-49	М	361
8	50-55	F	146
9	50-55	M	350
10	56+	F	102
11	56+	М	278
12	Under 18	F	78
13	Under 18	М	144

1 p	<pre>1 print(count_age_gender.describe())</pre>		
	user_id		
count	14. 000000		
mean	431. 428571		
std	399. 754100		
min	78. 000000		
25%	156. 750000		
50%	318. 000000		
75%	508. 750000		
max	1538. 000000		

