



# **Python Tips for Data Scientist**

***Release 1.00***

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Welcome to my **Python Tips for Data Scientist** notes! In those notes, you will learn some useful tips for Data Scientist daily work. The PDF version can be downloaded from [HERE](#).



## PREFACE

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### Chinese proverb

The palest ink is better than the best memory. – old Chinese proverb

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## 1.1 About

### 1.1.1 About this tutorial

This document is a summary of my valueable experiences in using Python for Data Scientist daily work. The PDF version can be downloaded from [HERE](#). **You may download and distribute it. Please be aware, however, that the note contains typos as well as inaccurate or incorrect description.**

In this repository, I try to use the detailed Data Scientist related demo code and examples to share some useful python tips for Data Scientist work. If you find your work wasn't cited in this note, please feel free to let me know.

Although I am by no means a python programming and Data Scientist expert, I decided that it would be useful for me to share what I learned about Python in the form of easy tutorials with detailed example. I hope those tutorials will be a valuable tool for your studies.

The tutorials assume that the reader has a preliminary knowledge of python programing, LaTeX and Linux. And this document is generated automatically by using [sphinx](#).

### 1.1.2 About the authors

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- **Biography**

Wenqiang Feng is Data Scientist within DST's Applied Analytics Group. Dr. Feng's responsibilities include providing DST clients with access to cutting-edge skills and technologies, including Big Data analytic solutions, advanced analytic and data enhancement techniques and modeling.

Dr. Feng has deep analytic expertise in data mining, analytic systems, machine learning algorithms, business intelligence, and applying Big Data tools to strategically solve industry problems in a cross-functional business. Before joining DST, Dr. Feng was an IMA Data Science Fellow at The Institute for Mathematics and its Applications (IMA) at the University of Minnesota. While there, he helped startup companies make marketing decisions based on deep predictive analytics.

Dr. Feng graduated from University of Tennessee, Knoxville, with Ph.D. in Computational Mathematics and Master's degree in Statistics. He also holds Master's degree in Computational Mathematics from Missouri University of Science and Technology (MST) and Master's degree in Applied Mathematics from the University of Science and Technology of China (USTC).

- **Declaration**

The work of Wenqiang Feng was supported by the IMA, while working at IMA. However, any opinion, finding, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the IMA, UTK and DST.

## 1.2 Motivation for this tutorial

No matter you like it or not, Python has been one of the most popular programming languages. I have been using Python for almost 4 years. Frankly speaking, I wasn't impressed and attracted by Python at the first using. After starting working in industry, I have to use Python. Gradually I recognize the elegance of Python and use it as one of my main programming language. But I found that:

- Most of the Python books or tutorials which emphasize on programming will overwhelm the green hand.
- While most of the Python books or tutorials Data Scientist or Data Analysis didn't cover some essential skills from the engineer side.

So I want to keep some of my valuable tips which are heavily applied in my daily work.



## 1.3 Feedback and suggestions

Your comments and suggestions are highly appreciated. I am more than happy to receive corrections, suggestions or feedbacks through email (Wenqiang Feng: [von198@gmail.com](mailto:von198@gmail.com)) for improvements.



## PYTHON INSTALLATION

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**Note:** This Chapter *Python Installation* is for beginner. If you have some Python programming experience, you may skip this chapter.

---

No matter what operator system is, I will strongly recommend you to install Anaconda which contains Python, Jupyter, spyder, Numpy, Scipy, Numba, pandas, DASK, Bokeh, HoloViews, Datashader, matplotlib, scikit-learn, H2O.ai, TensorFlow, CONDA and more.

Download link: <https://www.anaconda.com/distribution/>



## NOTEBOOKS

---

**Note:** This Chapter *Notebooks* is for beginner. If you have some Python programming experience, you may skip this chapter.

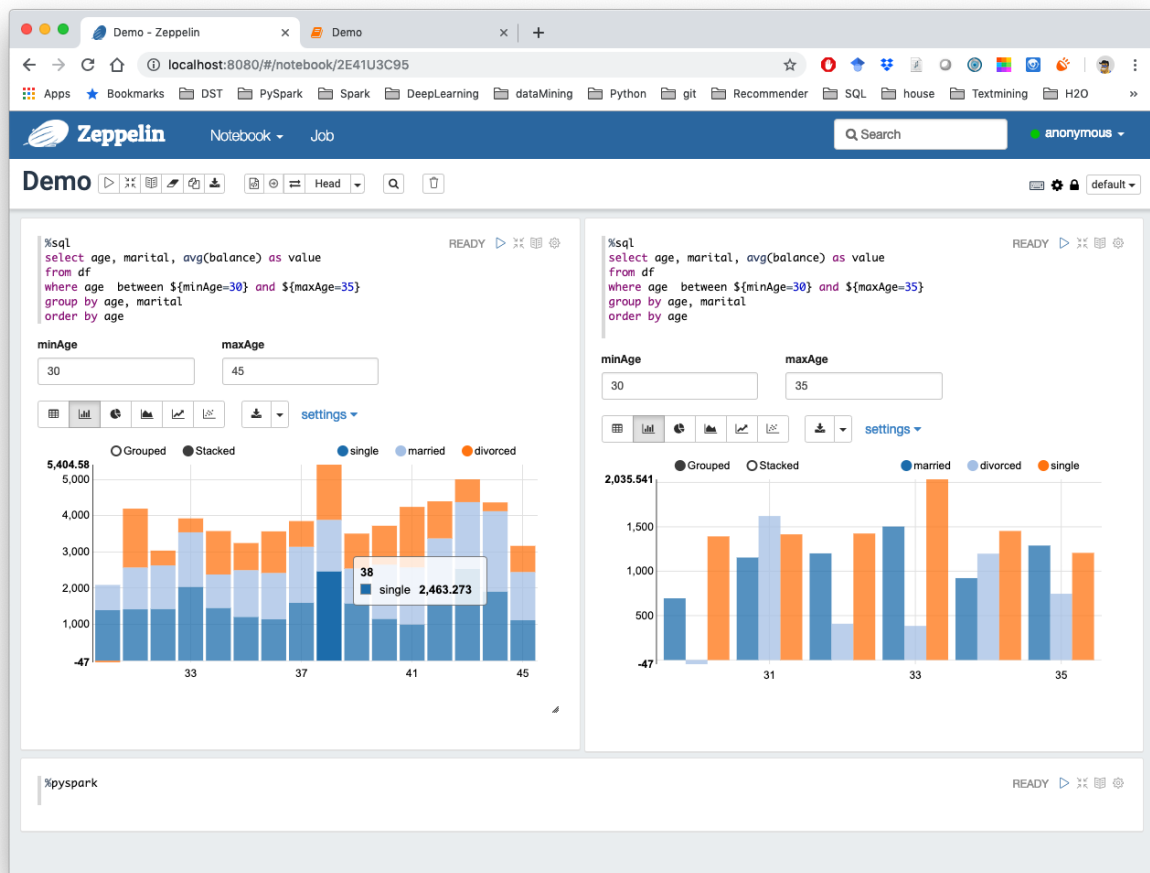
---

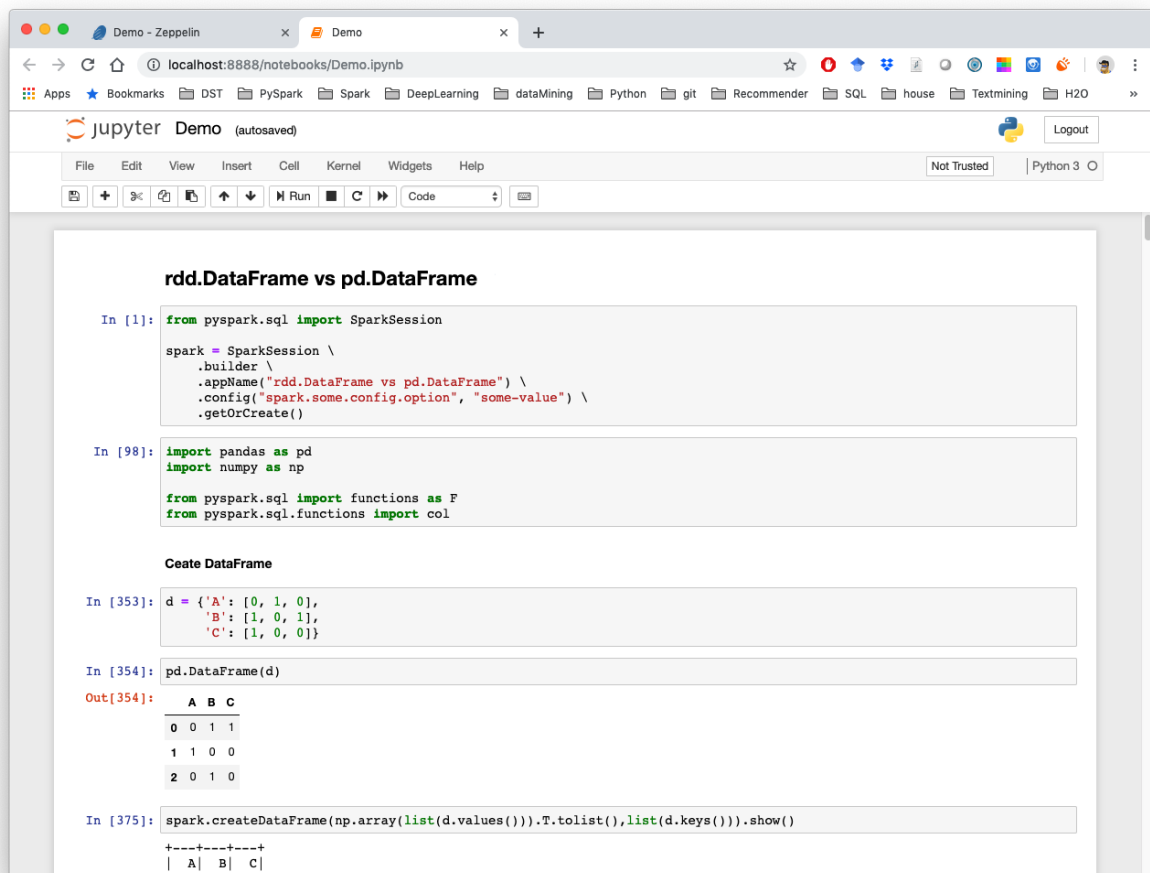
### 3.1 Apache Zeppelin

The Zeppelin (Apache Zeppelin) is an open-source Web-based notebook that enables data-driven, interactive data analytics and collaborative documents with Python, PySpark, SQL, Scala and more.

### 3.2 Jupyter Notebook

The Jupyter Notebook (Ipython Notebook) is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.





The screenshot shows a Jupyter Notebook titled "Demo" running on a local host. The notebook contains several code cells for comparing RDD and Pandas DataFrames.

**rdd.DataFrame vs pd.DataFrame**

```
In [1]: from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("rdd.DataFrame vs pd.DataFrame") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

```
In [98]: import pandas as pd
import numpy as np

from pyspark.sql import functions as F
from pyspark.sql.functions import col
```

**Create DataFrame**

```
In [353]: d = {'A': [0, 1, 0],
              'B': [1, 0, 1],
              'C': [1, 0, 0]}
```

```
In [354]: pd.DataFrame(d)
```

```
Out[354]:
```

	A	B	C
0	0	1	1
1	1	0	0
2	0	1	0

```
In [375]: spark.createDataFrame(np.array(list(d.values())).T.tolist(), list(d.keys())).show()
```

A	B	C
0	1	1
1	0	0
0	1	0





## PRIMER FUNCTIONS

---

**Note:** This Chapter *Primer Functions* is for beginner. If you have some Python programming experience, you may skip this chapter.

---

The following functions have been heavily used in my daily Data Scientist work.

### 4.1 \*

Single asterisk as used in function declaration allows variable number of arguments passed from calling environment. Inside the function it behaves as a tuple.

:: Python Code:

```
my_list = [1,2,3]
print(my_list)
print(*my_list)
```

:: Output:

```
[1, 2, 3]
1 2 3
```

### 4.2 range

:: Python Code:

```
print(range(5))
print(*range(5))
print(*range(3,8))
```

:: Ouput:

```
range(0, 5)
0 1 2 3 4
3 4 5 6 7
```

## 4.3 random

More details can be found at:

- random: <https://docs.python.org/3/library/random.html#random.randint>
- np.random: <https://docs.scipy.org/doc/numpy/reference/routines.random.html>

### 4.3.1 random.random

:: Python Code:

```
import random
random.random()

# (b - a) * random() + a
random.uniform(3, 8)
```

:: Ouput:

```
0.33844051243073625
7.772024014335885
```

### 4.3.2 np.random

:: Python Code:

```
np.random.random_sample()
np.random.random_sample(4)
np.random.random_sample([2, 4])

# (b - a) * random_sample() + a
a = 3; b = 8
(b-a)*np.random.random_sample([2, 4])+a
```

:: Ouput:

```
0.11919402208670005
array([0.07384755, 0.9005251 , 0.30030561, 0.38221819])
array([[0.76851156, 0.56973309, 0.47074505, 0.7814957 ],
       [0.5778028 , 0.94653057, 0.51193493, 0.48693931]])

array([[4.65799262, 6.32702018, 6.55545234, 5.45877784],
       [7.69941994, 4.68709357, 5.49790728, 4.60913966]])
```

## 4.4 round

Sometimes, we really do not need the scientific decimals for `output` results. So you can use this function to round an array to the given number of decimals.

:: Python Code:

```
np.round(np.random.random_sample([2,4]),2)
```

:: Ouput:

```
array([[0.76, 0.06, 0.41, 0.4 ],
       [0.07, 0.51, 0.84, 0.76]])
```

## 4.5 TODO..

:: Python Code:

:: Ouput:

:: Python Code:

:: Ouput:

:: Python Code:

:: Ouput:

:: Python Code:

:: Ouput:

## DATA STRUCTURES

---

**Note:** This Chapter *Data Structures* is for beginner. If you have some Python programming experience, you may skip this chapter.

---

### 5.1 List

List is one of data structures which is heavily using in my daily work.

#### 5.1.1 Create list

##### 1. Create empty list

The empty list is used to initialize a list.

:: Python Code:

```
my_list = []  
type(my_list)
```

:: Output:

```
list
```

I applied the empty list to initialize my `silhouette score` list when I try to find the optimal number of the clusters.

:: Example:

```
min_cluster = 3  
max_cluster = 8
```

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```
# silhouette_score
scores = []

for i in range(min_cluster, max_cluster):
    score = np.round(np.random.random_sample(), 2)
    scores.append(score)

print(scores)
```

:: Output:

```
[0.16, 0.2, 0.3, 0.87, 0.59]
```

### 5.1.2 Unpack list

## 5.2 Tuple

A tuple is an assortment of data, separated by commas, which makes it similar to the Python list, but a tuple is fundamentally different in that a tuple is “immutable.” This means that it cannot be changed, modified, or manipulated.

[VanderPlas2016] [McKinney2013] [Georg2018]

## PD . DATAFRAME MANIPULATION

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**Note:** This Chapter *Notebooks* is for beginner. If you have some Python programming experience, you may skip this chapter.

---

### 6.1 TODO..





## RDD . DATAFRAME MANIPULATION

---

**Note:** This Chapter *Notebooks* is for beginner. If you have some Python programming experience, you may skip this chapter.

---

### 7.1 TODO..



## PD.DATAFRAME VS PD.DATAFRAME

### 8.1 Create DataFrame

#### 8.1.1 From DataBase

login.txt:

```
runawayhorse001
PythonTips
```

```
#User Information
try:
    login = pd.read_csv(r'login.txt', header=None)
    user = login[0][0]
    pw = login[0][1]
    print('User information is ready!')
except:
    print('Login information is not available!!!')

#Database information
host = '##.###.###.##'
db_name = 'db_name'
table_name = 'table_name'
```

:: Comparison:

```
conn = psycopg2.connect(host=host, database=db_name, user=user,
    ↪password=pw)
cur = conn.cursor()

sql = """
    select *
    from {table_name}
```

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```
"".format(table_name=table_name)
dp = pd.read_sql(sql, conn)
```

```
# connect to database
url = 'jdbc:postgresql://' + host + ':5432/' + db_name + '?user=' + user + '&
    ↳ password=' + pw
properties = {'driver': 'org.postgresql.Driver', 'password': pw, 'user':
    ↳ user}
ds = spark.read.jdbc(url=url, table=table_name, properties=properties)
```

## 8.1.2 From List

```
my_list = [['a', 1, 2], ['b', 2, 3], ['c', 3, 4]]
col_name = ['A', 'B', 'C']
```

:: Python Code:

```
# caution for the columns=
pd.DataFrame(my_list, columns= col_name)
#
spark.createDataFrame(my_list, col_name).show()
```

:: Comparison:

	A	B	C
0	a	1	2
1	b	2	3
2	c	3	4

**Attention:** Pay attention to the parameter `columns=` in `pd.DataFrame`. Since the default value will make the list as rows.

:: Python Code:

```
# caution for the columns=
pd.DataFrame(my_list, columns= col_name)
#
pd.DataFrame(my_list, col_name)
```

:: Comparison:

	A	B	C		0	1	2
0	a	1	2	A	a	1	2
1	b	2	3	B	b	2	3
2	c	3	4	C	c	3	4

### 8.1.3 From Dict

```
d = {'A': [0, 1, 0],
      'B': [1, 0, 1],
      'C': [1, 0, 0]}
```

:: Python Code:

```
pd.DataFrame(d) for
# Tedious for PySpark
spark.createDataFrame(np.array(list(d.values())) .T.tolist(), list(d.
→keys())) .show()
```

:: Comparison:

	A	B	C
0	0	1	1
1	1	0	0
2	0	1	0

## 8.2 Load DataFrame

### 8.2.1 From .csv

### 8.2.2 From .json

Data from: <http://api.luftdaten.info/static/v1/data.json>

8.2.3 From DataBase

```
dp = pd.read_json("data/data.json")
ds = spark.read.json('data/data.json')
```

:: Python Code:

```
dp[['id','timestamp']].head(4)
#
ds[['id','timestamp']].show(4)
```

:: Comparison:

↪-----+				+-----+-----			
↪timestamp					id		↪
id timestamp				+-----+-----			
↪-----+							
0	2994551481	2019-02-28	17:23:52		2994551481	2019-02-28	↪
↪17:23:52							
1	2994551482	2019-02-28	17:23:52		2994551482	2019-02-28	↪
↪17:23:52							
2	2994551483	2019-02-28	17:23:52		2994551483	2019-02-28	↪
↪17:23:52							
3	2994551484	2019-02-28	17:23:52		2994551484	2019-02-28	↪
↪17:23:52							
↪-----+				+-----+-----			
				only showing top 4 rows			

8.3 First n Rows

:: Python Code:

```
dp.head(4)
#
ds.show(4)
```

:: Comparison:

				+-----+-----+-----+-----+			
					TV Radio Newspaper Sales		
TV	Radio	Newspaper	Sales	+-----+-----+-----+-----+			

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0	230.1	37.8	69.2	22.1	230.1   37.8	69.2   22.1
1	44.5	39.3	45.1	10.4	44.5   39.3	45.1   10.4
2	17.2	45.9	69.3	9.3	17.2   45.9	69.3   9.3
3	151.5	41.3	58.5	18.5	151.5   41.3	58.5   18.5
						+-----+-----+-----+-----+
only showing top 4 rows						

## 8.4 Column Names

:: Python Code:

```
dp.columns
#
ds.columns
```

:: Comparison:

```
Index(['TV', 'Radio', 'Newspaper', 'Sales'], dtype='object')
['TV', 'Radio', 'Newspaper', 'Sales']
```

## 8.5 Data types

:: Python Code:

```
dp.dtypes
#
ds.dtypes
```

:: Comparison:

```
TV          float64      [('TV', 'double'),
Radio        float64      ('Radio', 'double'),
Newspaper    float64      ('Newspaper', 'double'),
Sales        float64      ('Sales', 'double')]
dtype: object
```

## 8.6 Fill Null

```
my_list = [['a', 1, None], ['b', 2, 3], ['c', 3, 4]]
dp = pd.DataFrame(my_list, columns=['A', 'B', 'C'])
ds = spark.createDataFrame(my_list, ['A', 'B', 'C'])
#
dp.head()
ds.show()
```

:: Comparison:

	A	B	C
0	male	1	NaN
1	female	2	3.0
2	male	3	4.0

	A	B	C
0	male	1	null
1	female	2	3
2	male	3	4

:: Python Code:

```
dp.fillna(-99)
#
ds.fillna(-99).show()
```

:: Comparison:

	A	B	C
0	male	1	-99
1	female	2	3.0
2	male	3	4.0

	A	B	C
0	male	1	-99
1	female	2	3
2	male	3	4

## 8.7 Replace Values

:: Python Code:

```
# caution: you need to chose specific col
dp.A.replace(['male', 'female'], [1, 0], inplace=True)
dp
#caution: Mixed type replacements are not supported
ds.na.replace(['male', 'female'], ['1', '0']).show()
```



:: Comparison:

	A	B	C
0	1	1	NaN
1	0	2	3.0
2	1	3	4.0

	A	B	C
0	1	1	null
1	0	2	3
2	1	3	4

## 8.8 Rename Columns

### 8.8.1 Rename all columns

:: Python Code:

```
dp.columns = ['a', 'b', 'c', 'd']
dp.head(4)
#
ds.toDF('a', 'b', 'c', 'd').show(4)
```

:: Comparison:

	a	b	c	d
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5

	a	b	c	d
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5

only showing top 4 rows

### 8.8.2 Rename one or more columns

```
mapping = {'Newspaper': 'C', 'Sales': 'D'}
```

:: Python Code:

```
dp.rename(columns=mapping).head(4)
#
new_names = [mapping.get(col, col) for col in ds.columns]
ds.toDF(*new_names).show(4)
```

:: Comparison:

	TV	Radio	C	D
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5

+-----+-----+-----+-----+  
| TV|Radio| C| D|  
+-----+-----+-----+-----+  
230.1	37.8	69.2	22.1
44.5	39.3	45.1	10.4
17.2	45.9	69.3	9.3
151.5	41.3	58.5	18.5
+-----+-----+-----+-----+  
only showing top 4 rows

---

**Note:** You can also use `withColumnRenamed` to rename one column in PySpark.

:: Python Code:

```
ds.withColumnRenamed('Newspaper', 'Paper').show(4)
```

:: Comparison:

	TV	Radio	Paper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5

+-----+-----+-----+-----+  
| TV|Radio|Paper|Sales|  
+-----+-----+-----+-----+  
230.1	37.8	69.2	22.1
44.5	39.3	45.1	10.4
17.2	45.9	69.3	9.3
151.5	41.3	58.5	18.5
+-----+-----+-----+-----+  
only showing top 4 rows

---

## 8.9 Drop Columns

```
drop_name = ['Newspaper', 'Sales']
```

:: Python Code:

```
dp.drop(drop_name,axis=1).head(4)  
#  
ds.drop(*drop_name).show(4)
```

:: Comparison:

	TV	Radio
0	230.1	37.8
1	44.5	39.3
2	17.2	45.9
3	151.5	41.3

only showing top 4 rows

## 8.10 Filter

```
dp = pd.read_csv('Advertising.csv')
#
ds = spark.read.csv(path='Advertising.csv',
                    header=True,
                    inferSchema=True)
```

:: Python Code:

```
dp[dp.Newspaper<20].head(4)
#
ds[ds.Newspaper<20].show(4)
```

:: Comparison:

	TV	Radio	Newspaper	Sales
7	120.2	19.6	11.6	13.2
6	13.2			
8	8.6	2.1	1.0	4.8
0	4.8			
11	214.7	24.0	4.0	17.4
0	17.4			
13	97.5	7.6	7.2	9.7
2	9.7			

only showing top 4 rows

:: Python Code:

```
dp[ (dp.Newspaper<20) & (dp.TV>100) ].head(4)
#
ds[ (ds.Newspaper<20) & (ds.TV>100) ].show(4)
```

:: Comparison:

```
→+-----+
→TV|Radio|Newspaper|Sales|
   TV  Radio  Newspaper  Sales
→+-----+
7  120.2   19.6        11.6   13.2
→6| 13.2|
11 214.7   24.0         4.0   17.4
→0| 17.4|
19 147.3   23.9        19.1   14.6
→1| 14.6|
25 262.9    3.5        19.5   12.0
→5| 12.0|
→+-----+
only showing top 4 rows
```

## 8.11 With New Column

:: Python Code:

```
dp['tv_norm'] = dp.TV/sum(dp.TV)
dp.head(4)
#
ds.withColumn('tv_norm', ds.TV/ds.groupBy().agg(F.sum("TV"))).
→collect()[0][0]).show(4)
```

:: Comparison:

```
→+-----+-----+-----+
→TV|Radio|Newspaper|Sales|          tv_norm|
   TV  Radio  Newspaper  Sales  tv_norm
→+-----+-----+-----+
0  230.1   37.8        69.2   22.1  0.007824
→2| 22.1|0.007824268493802813|
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```

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```

1  44.5  39.3      45.1  10.4  0.001513 | 44.5| 39.3|      45.
→1| 10.4|0.001513167961643...|
2  17.2  45.9      69.3   9.3  0.000585 | 17.2| 45.9|      69.
→3|  9.3|5.848649200061207E-4|
3 151.5  41.3      58.5  18.5  0.005152 |151.5| 41.3|      58.
→5| 18.5|0.005151571824472517|

+-----+-----+-----+
→+-----+-----+-----+
only showing top 4 rows

```

:: Python Code:

```

dp['cond'] = dp.apply(lambda c: 1 if ((c.TV>100)&(c.Radio<40)) else 2,
→if c.Sales> 10 else 3,axis=1)
#
ds.withColumn('cond',F.when((ds.TV>100)&(ds.Radio<40),1)\
    .when(ds.Sales>10, 2)\
    .otherwise(3)).show(4)

```

:: Comparison:

```

→+-----+-----+-----+
→TV|Radio|Newspaper|Sales|cond|
   TV  Radio  Newspaper  Sales  cond
→+-----+-----+-----+
0  230.1  37.8      69.2  22.1    1 | 230.1| 37.8|      69.
→2| 22.1|    1|
1  44.5  39.3      45.1  10.4    2 | 44.5| 39.3|      45.
→1| 10.4|    2|
2  17.2  45.9      69.3   9.3    3 | 17.2| 45.9|      69.
→3|  9.3|    3|
3 151.5  41.3      58.5  18.5    2 |151.5| 41.3|      58.
→5| 18.5|    2|

+-----+-----+-----+
→+-----+-----+-----+
only showing top 4 rows

```

:: Python Code:

```

dp['log_tv'] = np.log(dp.TV)
dp.head(4)
#
ds.withColumn('log_tv',F.log(ds.TV)).show(4)

```

:: Comparison:

	TV	Radio	Newspaper	Sales	log_tv	
	TV	Radio	Newspaper	Sales	log_tv	
0	230.1	37.8	69.2	22.1	5.438514	230.1   37.8   69.
1	44.5	39.3	45.1	10.4	3.795489	44.5   39.3   45.
2	17.2	45.9	69.3	9.3	2.844909	17.2   45.9   69.
3	151.5	41.3	58.5	18.5	5.020586	151.5   41.3   58.

only showing top 4 rows

:: Python Code:

```
dp['tv+10'] = dp.TV.apply(lambda x: x+10)
dp.head(4)
#
ds.withColumn('tv+10', ds.TV+10).show(4)
```

:: Comparison:

	TV	Radio	Newspaper	Sales	tv+10	
	TV	Radio	Newspaper	Sales	tv+10	
0	230.1	37.8	69.2	22.1	240.1	230.1   37.8   69.
1	44.5	39.3	45.1	10.4	54.5	44.5   39.3   45.
2	17.2	45.9	69.3	9.3	27.2	17.2   45.9   69.
3	151.5	41.3	58.5	18.5	161.5	151.5   41.3   58.

only showing top 4 rows

## 8.12 Join

```

leftp = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                      'B': ['B0', 'B1', 'B2', 'B3'],
                      'C': ['C0', 'C1', 'C2', 'C3'],
                      'D': ['D0', 'D1', 'D2', 'D3']},
                      index=[0, 1, 2, 3])

rightp = pd.DataFrame({'A': ['A0', 'A1', 'A6', 'A7'],
                       'F': ['B4', 'B5', 'B6', 'B7'],
                       'G': ['C4', 'C5', 'C6', 'C7'],
                       'H': ['D4', 'D5', 'D6', 'D7']},
                       index=[4, 5, 6, 7])

lefts = spark.createDataFrame(leftp)
rights = spark.createDataFrame(rightp)

```

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

	A	F	G	H
4	A0	B4	C4	D4
5	A1	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

### 8.12.1 Left Join

:: Python Code:

```

leftp.merge(rightp,on='A',how='left')
#
lefts.join(rights,on='A',how='left')
      .orderBy('A',ascending=True).show()

```

:: Comparison:

	A	B	C	D	F	G	H
0	A0	B0	C0	D0	B4	C4	D4
1	A1	B1	C1	D1	B5	C5	D5

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```

2  A2  B2  C2  D2  NaN  NaN  NaN      | A2| B2| C2|_
  ↳D2|null|null|null|
3  A3  B3  C3  D3  NaN  NaN  NaN      | A3| B3| C3|_
  ↳D3|null|null|null|

+---+---+---+---+---+---+---+
  ↳+

```

## 8.12.2 Right Join

:: Python Code:

```

leftp.merge(rightp,on='A',how='right')
#
lefts.join(rights,on='A',how='right')
      .orderBy('A',ascending=True).show()

```

:: Comparison:

```

  ↳+
                                     +---+---+---+---+---+---+---+
                                     |  A|  B|  C|  D|  F|  G|  _
  ↳H|
      A      B      C      D      F      G      H      +---+---+---+---+---+---+---+
  ↳+
0  A0      B0      C0      D0      B4      C4      D4      | A0| B0| C0| D0| B4| C4|_
  ↳D4|
1  A1      B1      C1      D1      B5      C5      D5      | A1| B1| C1| D1| B5| C5|_
  ↳D5|
2  A6      NaN      NaN      NaN      B6      C6      D6      | A6|null|null|null| B6| C6|_
  ↳D6|
3  A7      NaN      NaN      NaN      B7      C7      D7      | A7|null|null|null| B7| C7|_
  ↳D7|

+---+---+---+---+---+---+---+
  ↳+

```

## 8.12.3 Inner Join

:: Python Code:

```

leftp.merge(rightp,on='A',how='inner')
#
lefts.join(rights,on='A',how='inner')
      .orderBy('A',ascending=True).show()

```



:: Comparison:

	A	B	C	D	F	G	H
0	A0	B0	C0	D0	B4	C4	D4
1	A1	B1	C1	D1	B5	C5	D5

## 8.12.4 Full Join

:: Python Code:

```
leftp.merge(rightp,on='A',how='full')
#
lefts.join(rights,on='A',how='full')
        .orderBy('A',ascending=True).show()
```

:: Comparison:

	A	B	C	D	F	G	H
0	A0	B0	C0	D0	B4	C4	D4
1	A1	B1	C1	D1	B5	C5	D5
2	A2	B2	C2	D2	NaN	NaN	NaN
3	A3	B3	C3	D3	NaN	NaN	NaN
4	A6	NaN	NaN	NaN	B6	C6	D6
5	A7	NaN	NaN	NaN	B7	C7	D7

## 8.13 Concat Columns

```
my_list = [('a', 2, 3),
           ('b', 5, 6),
           ('c', 8, 9),
           ('a', 2, 3),
           ('b', 5, 6),
           ('c', 8, 9)]
col_name = ['col1', 'col2', 'col3']
#
dp = pd.DataFrame(my_list, columns=col_name)
ds = spark.createDataFrame(my_list, schema=col_name)
```

	col1	col2	col3
0	a	2	3
1	b	5	6
2	c	8	9
3	a	2	3
4	b	5	6
5	c	8	9

:: Python Code:

```
dp['concat'] = dp.apply(lambda x: '%s%s'%(x['col1'],x['col2']),axis=1)
dp
#
ds.withColumn('concat',F.concat('col1','col2')).show()
```

:: Comparison:

	col1	col2	col3	concat
0	a	2	3	a2
1	b	5	6	b5
2	c	8	9	c8
3	a	2	3	a2
4	b	5	6	b5
5	c	8	9	c8

	col1	col2	col3	concat
0	a	2	3	a2
1	b	5	6	b5
2	c	8	9	c8
3	a	2	3	a2
4	b	5	6	b5
5	c	8	9	c8

## 8.14 GroupBy

:: Python Code:

```
dp.groupby(['col1']).agg({'col2':'min','col3':'mean'})
#
ds.groupBy(['col1']).agg({'col2': 'min', 'col3': 'avg'}).show()
```

:: Comparison:

	col2	col3	
col1			
a	2	3	
b	5	6	
c	8	9	

## 8.15 Pivot

:: Python Code:

```
pd.pivot_table(dp, values='col3', index='col1', columns='col2',
→aggfunc=np.sum)
#
ds.groupBy(['col1']).pivot('col2').sum('col3').show()
```

:: Comparison:

col2	2	5	8	
col1				
a	6.0	NaN	NaN	
b	NaN	12.0	NaN	
c	NaN	NaN	18.0	



## PACKAGE WRAPPER

It's super easy to wrap your own package in Python. I packed some functions which I frequently used in my daily work. You can download and install it from [My PySpark Package](#). The hierarchical structure and the directory structure of this package are as follows.

### 9.1 Hierarchical Structure

```
PySparkTools/  
├── __init__.py  
├── PySparkTools  
│   ├── __init__.py  
│   ├── Manipulation  
│   │   ├── DataManipulation.py  
│   │   └── __init__.py  
│   └── Visualization  
│       ├── __init__.py  
│       ├── PyPlots.py  
│       └── PyPlots.pyc  
├── README.md  
├── requirements.txt  
├── setup.py  
└── test  
    ├── spark-warehouse  
    ├── test1.py  
    └── test2.py
```

From the above hierarchical structure, you will find that you have to have `__init__.py` in each directory. I will explain the `__init__.py` file with the example below:

## 9.2 Set Up

```
from setuptools import setup, find_packages

try:
    with open("README.md") as f:
        long_description = f.read()
except IOError:
    long_description = ""

try:
    with open("requirements.txt") as f:
        requirements = [x.strip() for x in f.read().splitlines() if x.
→strip()]
except IOError:
    requirements = []

setup(name='PySparkTools',
      install_requires=requirements,
      version='1.0',
      description='Python Spark Tools',
      author='Wenqiang Feng',
      author_email='von198@gmail.com',
      url='https://github.com/runawayhorse001/PySparkTools',
      packages=find_packages(),
      long_description=long_description
    )
```

## 9.3 ReadMe

```
# PySparkTools

This is my PySpark Tools. If you want to colne and install it, you can_
→use

- clone

```{bash}
git clone git@github.com:runawayhorse001/PySparkTools.git
```

- install

```{bash}
```

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```
cd PySparkTools
pip install -r requirements.txt
python setup.py install
```

- test

```{bash}
cd PySparkTools/test
python test1.py
```
```





---

CHAPTER

**TEN**

---

**MAIN REFERENCE**



## BIBLIOGRAPHY

- [VanderPlas2016] Jake VanderPlas. [Python Data Science Handbook: Essential Tools for Working with Data](#), 2016.
- [McKinney2013] Wes McKinney. [Python for Data Analysis](#), 2013.
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