Python For Data Science *Cheat Sheet*

Python Basics

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Variables and Data Types

Variable Assignment

```
>>> x=5
>>> x
 5
```

Calculations With Variables

`>>> x+2` `7`	Sum of two variables
`>>> x-2` `3`	Subtraction of two variables
`>>> x*2` `10`	Multiplication of two variables
`>>> x**2` `25`	Exponentiation of a variable
`>>> x%2` `1`	Remainder of a variable
`>>> x/float(2)` `2.5`	Division of a variable

Types and Type Conversion

`str()`	`'5', '3.45', 'True'`	Variables to strings
`int()`	`5, 3, 1`	Variables to integers
`float()`	`5.0, 1.0`	Variables to floats
`bool()`	`True, True, True`	Variables to booleans

Asking For Help

```
>>> help(str)
```

Lists

Also see NumPy Arrays

```
>>> a = 'is'
>>> b = 'nice'
>>> my_list = ['my', 'list', a, b]
>>> my_list2 = [[4,5,6,7], [3,4,5,6]]
```

Selecting List Elements

Index starts at 0

Subset	
`>>> my_list[1]`	Select item at index 1
`>>> my_list[-3]`	Select 3rd last item
Slice	
`>>> my_list[1:3]`	Select items at index 1 and 2
`>>> my_list[1:]`	Select items after index 0
`>>> my_list[:3]`	Select items before index 3
`>>> my_list[:]`	Copy my_list
Subset Lists of Lists	
`>>> my_list2[1][0]`	my_list[list][itemOfList]
`>>> my_list2[1][:2]`	

List Operations

```
>>> my_list + my_list
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list * 2
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list2 > 4
True
```

List Methods

`>>> my_list.index(a)`	Get the index of an item
`>>> my_list.count(a)`	Count an item
`>>> my_list.append('!')`	Append an item at a time
`>>> my_list.remove('!')`	Remove an item
`>>> del(my_list[0:1])`	Remove an item
`>>> my_list.reverse()`	Reverse the list
`>>> my_list.extend('!')`	Append an item
`>>> my_list.pop(-1)`	Remove an item
`>>> my_list.insert(0,'!')`	Insert an item
`>>> my_list.sort()`	Sort the list

Strings

```
>>> my_string = 'thisStringIsAwesome'
>>> my_string
'thisStringIsAwesome'
```

String Operations

```
>>> my_string * 2
'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'Innit'
'thisStringIsAwesomeInnit'
>>> 'm' in my_string
True
```

String Operations

Index starts at 0

```
>>> my_string[3]
>>> my_string[4:9]
```

String Methods

`>>> my_string.upper()`	String to uppercase
`>>> my_string.lower()`	String to lowercase
`>>> my_string.count('w')`	Count String elements
`>>> my_string.replace('e', 'i')`	Replace String elements
`>>> my_string.strip()`	Strip whitespaces

Libraries

Import libraries

```
>>> import numpy
>>> import numpy as np
```

Selective import

```
>>> from math import pi
```

pandas — Data analysis

learn — Machine learning

NumPy — Scientific computing

matplotlib — 2D plotting

Install Python

ANACONDA — Leading open data science platform powered by Python

spyder — Free IDE that is included with Anaconda

jupyter — Create and share documents with live code, visualizations, text, ...

Numpy Arrays

Also see Lists

```
>>> my_list = [1, 2, 3, 4]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[4,5,6]])
```

Selecting Numpy Array Elements

Index starts at 0

Subset	
`>>> my_array[1]` `2`	Select item at index 1
Slice	
`>>> my_array[0:2]` `array([1, 2])`	Select items at index 0 and 1
Subset 2D Numpy arrays	
`>>> my_2darray[:,0]` `array([1, 4])`	my_2darray[rows, columns]

Numpy Array Operations

```
>>> my_array > 3
array([False, False, False,  True], dtype=bool)
>>> my_array * 2
array([2, 4, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
array([6, 8, 10, 12])
```

Numpy Array Functions

`>>> my_array.shape`	Get the dimensions of the array
`>>> np.append(other_array)`	Append items to an array
`>>> np.insert(my_array, 1, 5)`	Insert items in an array
`>>> np.delete(my_array,[1])`	Delete items in an array
`>>> np.mean(my_array)`	Mean of the array
`>>> np.median(my_array)`	Median of the array
`>>> my_array.corrcoef()`	Correlation coefficient
`>>> np.std(my_array)`	Standard deviation

Python For Data Science *Cheat Sheet*

SciPy - Linear Algebra

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SciPy

The **SciPy** library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

Interacting With NumPy

Also see NumPy

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]])
```

Index Tricks

```
>>> np.mgrid[0:5,0:5]          Create a dense meshgrid
>>> np.ogrid[0:2,0:2]          Create an open meshgrid
>>> np.r_[3,[0]*5,-1:1:10j]    Stack arrays vertically (row-wise)
>>> np.c_[b,c]                 Create stacked column-wise arrays
```

Shape Manipulation

```
>>> np.transpose(b)            Permute array dimensions
>>> b.flatten()                Flatten the array
>>> np.hstack((b,c))           Stack arrays horizontally (column-wise)
>>> np.vstack((a,b))           Stack arrays vertically (row-wise)
>>> np.hsplit(c,2)             Split the array horizontally at the 2nd index
>>> np.vpslit(d,2)             Split the array vertically at the 2nd index
```

Polynomials

```
>>> from numpy import poly1d
>>> p = poly1d([3,4,5])        Create a polynomial object
```

Vectorizing Functions

```
>>> def myfunc(a):
        if a < 0:
          return a*2
        else:
          return a/2
>>> np.vectorize(myfunc)       Vectorize functions
```

Type Handling

```
>>> np.real(b)                 Return the real part of the array elements
>>> np.imag(b)                 Return the imaginary part of the array elements
>>> np.real_if_close(c,tol=1000)  Return a real array if complex parts close to 0
>>> np.cast['f'](np.pi)        Cast object to a data type
```

Other Useful Functions

```
>>> np.angle(b,deg=True)       Return the angle of the complex argument
>>> g = np.linspace(0,np.pi,num=5)  Create an array of evenly spaced values
                                    (number of samples)
>>> g [3:] += np.pi
>>> np.unwrap(g)               Unwrap
>>> np.logspace(0,10,3)        Create an array of evenly spaced values (log scale)
>>> np.select([c<4],[c*2])     Return values from a list of arrays depending on
                               conditions
>>> misc.factorial(a)          Factorial
>>> misc.comb(10,3,exact=True)  Combine N things taken at k time
>>> misc.central_diff_weights(3)  Weights for Np-point central derivative
>>> misc.derivative(myfunc,1.0)   Find the n-th derivative of a function at a point
```

Linear Algebra

Also see NumPy

You'll use the `linalg` and `sparse` modules. Note that `scipy.linalg` contains and expands on `numpy.linalg`.

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(b)
>>> C = np.mat(np.random.random((10,5)))
>>> D = np.mat([[3,4], [5,6]])
```

Basic Matrix Routines

Inverse

```
>>> A.I                        Inverse
>>> linalg.inv(A)              Inverse
```

Transposition

```
>>> A.T                        Tranpose matrix
>>> A.H                        Conjugate transposition
```

Trace

```
>>> np.trace(A)                Trace
```

Norm

```
>>> linalg.norm(A)             Frobenius norm
>>> linalg.norm(A,1)           L1 norm (max column sum)
>>> linalg.norm(A,np.inf)      L inf norm (max row sum)
```

Rank

```
>>> np.linalg.matrix_rank(C)   Matrix rank
```

Determinant

```
>>> linalg.det(A)              Determinant
```

Solving linear problems

```
>>> linalg.solve(A,b)          Solver for dense matrices
>>> E = np.mat(a).T            Solver for dense matrices
>>> linalg.lstsq(F,E)          Least-squares solution to linear matrix
                               equation
```

Generalized inverse

```
>>> linalg.pinv(C)             Compute the pseudo-inverse of a matrix
                               (least-squares solver)
>>> linalg.pinv2(C)            Compute the pseudo-inverse of a matrix
                               (SVD)
```

Creating Sparse Matrices

```
>>> F = np.eye(3, k=1)         Create a 2X2 Identity matrix
>>> G = np.mat(np.identity(2)) Create a 2x2 Identity matrix
>>> C[C > 0.5] = 0
>>> H = sparse.csr_matrix(C)   Compressed Sparse Row matrix
>>> I = sparse.csc_matrix(D)   Compressed Sparse Column matrix
>>> J = sparse.dok_matrix(A)   Dictionary Of Keys matrix
>>> E.todense()                Sparse matrix to full matrix
>>> sparse.issparse(csc(A))    Identify sparse matrix
```

Sparse Matrix Routines

Inverse

```
>>> sparse.linalg.inv(I)       Inverse
```

Norm

```
>>> sparse.linalg.norm(I)      Norm
```

Solving linear problems

```
>>> sparse.linalg.spsolve(H,I) Solver for sparse matrices
```

Sparse Matrix Functions

```
>>> sparse.linalg.expm(I)      Sparse matrix exponential
```

Matrix Functions

Addition

```
>>> np.add(A,D)                Addition
```

Subtraction

```
>>> np.subtract(A,D)           Subtraction
```

Division

```
>>> np.divide(A,D)             Division
```

Multiplication

```
>>> A @ D                      Multiplication operator (Python 3)
>>> np.multiply(D,A)           Multiplication
>>> np.dot(A,D)                Dot product
>>> np.vdot(A,D)               Vector dot product
>>> np.inner(A,D)              Inner product
>>> np.outer(A,D)              Outer product
>>> np.tensordot(A,D)          Tensor dot product
>>> np.kron(A,D)               Kronecker product
```

Exponential Functions

```
>>> linalg.expm(A)             Matrix exponential
>>> linalg.expm2(A)            Matrix exponential (Taylor Series)
>>> linalg.expm3(D)            Matrix exponential (eigenvalue decomposition)
```

Logarithm Function

```
>>> linalg.logm(A)             Matrix logarithm
```

Trigonometric Functions

```
>>> linalg.sinm(D)             Matrix sine
>>> linalg.cosm(D)             Matrix cosine
>>> linalg.tanm(A)             Matrix tangent
```

Hyperbolic Trigonometric Functions

```
>>> linalg.sinhm(D)            Hyperbolic matrix sine
>>> linalg.coshm(D)            Hyperbolic matrix cosine
>>> linalg.tanhm(A)            Hyperbolic matrix tangent
```

Matrix Sign Function

```
>>> np.signm(A)                Matrix sign function
```

Matrix Square Root

```
>>> linalg.sqrtm(A)            Matrix square root
```

Arbitrary Functions

```
>>> linalg.funm(A, lambda x: x*x)  Evaluate matrix function
```

Decompositions

Eigenvalues and Eigenvectors

```
>>> la, v = linalg.eig(A)      Solve ordinary or generalized
                               eigenvalue problem for square matrix
>>> l1, l2 = la                Unpack eigenvalues
>>> v[:,0]                     First eigenvector
>>> v[:,1]                     Second eigenvector
>>> linalg.eigvals(A)          Unpack eigenvalues
```

Singular Value Decomposition

```
>>> U,s,Vh = linalg.svd(B)     Singular Value Decomposition (SVD)
>>> M,N = B.shape
>>> Sig = linalg.diagsvd(s,M,N)  Construct sigma matrix in SVD
```

LU Decomposition

```
>>> P,L,U = linalg.lu(C)       LU Decomposition
```

Sparse Matrix Decompositions

```
>>> la, v = sparse.linalg.eigs(F,1)  Eigenvalues and eigenvectors
>>> sparse.linalg.svds(H, 2)         SVD
```

Asking For Help

```
>>> help(scipy.linalg.diagsvd)
>>> np.info(np.matrix)
```

Python For Data Science *Cheat Sheet*

NumPy Basics

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NumPy

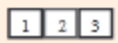
The **NumPy** library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Use the following import convention:

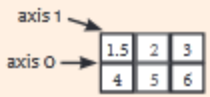
```
>>> import numpy as np
```

NumPy Arrays

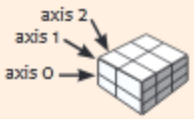
1D array



2D array



3D array



Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]],
                 dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4))                  Create an array of zeros
>>> np.ones((2,3,4),dtype=np.int16)  Create an array of ones
>>> d = np.arange(10,25,5)           Create an array of evenly
                                     spaced values (step value)
>>> np.linspace(0,2,9)               Create an array of evenly
                                     spaced values (number of samples)
>>> e = np.full((2,2),7)             Create a constant array
>>> f = np.eye(2)                    Create a 2X2 identity matrix
>>> np.random.random((2,2))          Create an array with random values
>>> np.empty((3,2))                  Create an empty array
```

I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv", delimiter=',')
>>> np.savetxt("myarray.txt", a, delimiter=" ")
```

Data Types

```
>>> np.int64       Signed 64-bit integer types
>>> np.float32     Standard double-precision floating point
>>> np.complex     Complex numbers represented by 128 floats
>>> np.bool        Boolean type storing TRUE and FALSE values
>>> np.object      Python object type
>>> np.string_     Fixed-length string type
>>> np.unicode_    Fixed-length unicode type
```

Inspecting Your Array

```
>>> a.shape             Array dimensions
>>> len(a)              Length of array
>>> b.ndim              Number of array dimensions
>>> e.size              Number of array elements
>>> b.dtype             Data type of array elements
>>> b.dtype.name        Name of data type
>>> b.astype(int)       Convert an array to a different type
```

Asking For Help

```
>>> np.info(np.ndarray.dtype)
```

Array Mathematics

Arithmetic Operations

```
>>> g = a - b                        Subtraction
  array([[-0.5,  0. ,  0. ],
         [-3. , -3. , -3. ]])
>>> np.subtract(a,b)                 Subtraction
>>> b + a                            Addition
  array([[ 2.5,  4. ,  6. ],
         [ 5. ,  7. ,  9. ]])
>>> np.add(b,a)                      Addition
>>> a / b                            Division
  array([[ 0.66666667,  1.        ,  1.        ],
         [ 0.25      ,  0.4       ,  0.5       ]])
>>> np.divide(a,b)                   Division
>>> a * b                            Multiplication
  array([[  1.5,   4. ,   9. ],
         [  4. ,  10. ,  18. ]])
>>> np.multiply(a,b)                 Multiplication
>>> np.exp(b)                        Exponentiation
>>> np.sqrt(b)                       Square root
>>> np.sin(a)                        Print sines of an array
>>> np.cos(b)                        Element-wise cosine
>>> np.log(a)                        Element-wise natural logarithm
>>> e.dot(f)                         Dot product
  array([[ 7.,  7.],
         [ 7.,  7.]])
```

Comparison

```
>>> a == b                           Element-wise comparison
  array([[False,  True,  True],
         [False, False, False]], dtype=bool)
>>> a < 2                            Element-wise comparison
  array([True, False, False], dtype=bool)
>>> np.array_equal(a, b)             Array-wise comparison
```

Aggregate Functions

```
>>> a.sum()                          Array-wise sum
>>> a.min()                          Array-wise minimum value
>>> b.max(axis=0)                    Maximum value of an array row
>>> b.cumsum(axis=1)                 Cumulative sum of the elements
>>> a.mean()                         Mean
>>> b.median()                       Median
>>> a.corrcoef()                     Correlation coefficient
>>> np.std(b)                        Standard deviation
```

Copying Arrays

```
>>> h = a.view()          Create a view of the array with the same data
>>> np.copy(a)            Create a copy of the array
>>> h = a.copy()          Create a deep copy of the array
```

Sorting Arrays

```
>>> a.sort()              Sort an array
>>> c.sort(axis=0)        Sort the elements of an array's axis
```

Subsetting, Slicing, Indexing

Also see Lists

Subsetting

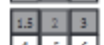

```
>>> a[2]                  Select the element at the 2nd index
  3
```


```
>>> b[1,2]                Select the element at row 1 column 2
  6.0                    (equivalent to b[1][2])
```

Slicing


```
>>> a[0:2]                Select items at index 0 and 1
  array([1, 2])
```


```
>>> b[0:2,1]              Select items at rows 0 and 1 in column 1
  array([ 2.,  5.])
```




```
>>> b[:1]                 Select all items at row 0
  array([[1.5, 2., 3.]])  (equivalent to b[0:1, :])
>>> c[1,...]              Same as [1,:,:]
  array([[[ 3.,  2.,  1.],
          [ 4.,  5.,  6.]]])
>>> a[ : :-1]             Reversed array a
  array([3, 2, 1])
```

Boolean Indexing


```
>>> a[a<2]                Select elements from a less than 2
  array([1])
```

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]]  Select elements (1,0),(0,1),(1,2) and (0,0)
  array([ 4. , 2. , 6. , 1.5])
>>> b[[1, 0, 1, 0]][:,[0,1,2,0]]  Select a subset of the matrix's rows
  array([[ 4. ,  5. ,  6. ,  4. ],   and columns
         [ 1.5,  2. ,  3. ,  1.5],
         [ 4. ,  5. ,  6. ,  4. ],
         [ 1.5,  2. ,  3. ,  1.5]])
```

Array Manipulation

Transposing Array

```
>>> i = np.transpose(b)      Permute array dimensions
>>> i.T                      Permute array dimensions
```

Changing Array Shape

```
>>> b.ravel()                Flatten the array
>>> g.reshape(3,-2)          Reshape, but don't change data
```

Adding/Removing Elements

```
>>> h.resize((2,6))          Return a new array with shape (2,6)
>>> np.append(h,g)           Append items to an array
>>> np.insert(a, 1, 5)       Insert items in an array
>>> np.delete(a,[1])         Delete items from an array
```

Combining Arrays

```
>>> np.concatenate((a,d),axis=0)  Concatenate arrays
  array([ 1,  2,  3, 10, 15, 20])
>>> np.vstack((a,b))              Stack arrays vertically (row-wise)
  array([[ 1. ,  2. ,  3. ],
         [ 1.5,  2. ,  3. ],
         [ 4. ,  5. ,  6. ]])
>>> np.r_[e,f]                    Stack arrays vertically (row-wise)
>>> np.hstack((e,f))              Stack arrays horizontally (column-wise)
  array([[ 7.,  7.,  1.,  0.],
         [ 7.,  7.,  0.,  1.]])
>>> np.column_stack((a,d))        Create stacked column-wise arrays
  array([[ 1, 10],
         [ 2, 15],
         [ 3, 20]])
>>> np.c_[a,d]                    Create stacked column-wise arrays
```

Splitting Arrays

```
>>> np.hsplit(a,3)           Split the array horizontally at the 3rd
  [array([1]),array([2]),array([3])]  index
>>> np.vsplit(c,2)           Split the array vertically at the 2nd index
[array([[[ 1.5,  2. ,  1. ],
         [ 4. ,  5. ,  6. ]]]),
 array([[[ 3.,  2.,  3.],
         [ 4.,  5.,  6.]]])]
```

Python For Data Science *Cheat Sheet*

Pandas Basics

Learn Python for Data Science Interactively at www.DataCamp.com

Pandas

The **Pandas** library is built on NumPy and provides easy-to-use **data structures** and **data analysis** tools for the Python programming language.

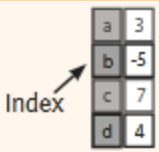
Use the following import convention:

```
>>> import pandas as pd
```

Pandas Data Structures

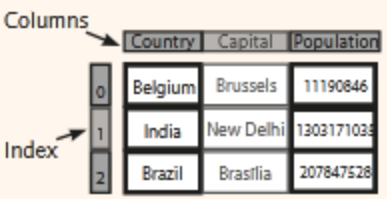
Series

A **one-dimensional** labeled array capable of holding any data type




```
>>> s = pd.Series([3, -5, 7, 4], index=['a', 'b', 'c', 'd'])
```

DataFrame



A **two-dimensional** labeled data structure with columns of potentially different types

```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
            'Capital': ['Brussels', 'New Delhi', 'Brasília'],
            'Population': [11190846, 1303171035, 207847528]}

>>> df = pd.DataFrame(data,
                      columns=['Country', 'Capital', 'Population'])
```

Asking For Help

```
>>> help(pd.Series.loc)
```

Selection

Also see NumPy Arrays

Getting

```
>>> s['b']
-5

>>> df[1:]
   Country     Capital  Population
1   India   New Delhi  1303171035
2  Brazil    Brasília   207847528
```

Get one element

Get subset of a DataFrame

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]]
'Belgium'
>>> df.iat([0],[0])
'Belgium'
```

Select single value by row & column

By Label

```
>>> df.loc[[0], ['Country']]
'Belgium'
>>> df.at([0], ['Country'])
'Belgium'
```

Select single value by row & column labels

By Label/Position

```
>>> df.ix[2]
Country      Brazil
Capital    Brasília
Population  207847528
```

Select single row of subset of rows

```
>>> df.ix[:,'Capital']
0     Brussels
1    New Delhi
2     Brasília
```

Select a single column of subset of columns

```
>>> df.ix[1,'Capital']
'New Delhi'
```

Select rows and columns

Boolean Indexing

```
>>> s[~(s > 1)]
>>> s[(s < -1) | (s > 2)]
>>> df[df['Population']>1200000000]
```

Series `s` where value is not >1
`s` where value is <-1 or >2
Use filter to adjust DataFrame

Setting

```
>>> s['a'] = 6
```

Set index `a` of Series `s` to 6

Dropping

```
>>> s.drop(['a', 'c'])
>>> df.drop('Country', axis=1)
```

Drop values from rows (axis=0)
Drop values from columns(axis=1)

Sort & Rank

```
>>> df.sort_index()
>>> df.sort_values(by='Country')
>>> df.rank()
```

Sort by labels along an axis
Sort by the values along an axis
Assign ranks to entries

Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape
>>> df.index
>>> df.columns
>>> df.info()
>>> df.count()
```

(rows,columns)
Describe index
Describe DataFrame columns
Info on DataFrame
Number of non-NA values

Summary

```
>>> df.sum()
>>> df.cumsum()
>>> df.min()/df.max()
>>> df.idxmin()/df.idxmax()
>>> df.describe()
>>> df.mean()
>>> df.median()
```

Sum of values
Cummulative sum of values
Minimum/maximum values
Minimum/Maximum index value
Summary statistics
Mean of values
Median of values

Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f)
>>> df.applymap(f)
```

Apply function
Apply function element-wise

Data Alignment

Internal Data Alignment

NA values are introduced in the indices that don't overlap:

```
>>> s3 = pd.Series([7, -2, 3], index=['a', 'c', 'd'])
>>> s + s3
a    10.0
b     NaN
c     5.0
d     7.0
```

Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_value=0)
a    10.0
b    -5.0
c     5.0
d     7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

I/O

Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> df.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')
```

Read multiple sheets from the same file

```
>>> xlsx = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite:///:memory:')
>>> pd.read_sql("SELECT * FROM my_table;", engine)
>>> pd.read_sql_table('my_table', engine)
>>> pd.read_sql_query("SELECT * FROM my_table;", engine)
```

`read_sql()` is a convenience wrapper around `read_sql_table()` and `read_sql_query()`

```
>>> df.to_sql('myDf', engine)
```

Python For Data Science *Cheat Sheet*

Pandas

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Reshaping Data

Pivot

```
>>> df3= df2.pivot(index='Date',
                   columns='Type',
                   values='Value')
```

Spread rows into columns

	Date	Type	Value
0	2016-03-01	a	11.432
1	2016-03-02	b	13.031
2	2016-03-01	c	20.784
3	2016-03-03	a	99.906
4	2016-03-02	a	1.303
5	2016-03-03	c	20.784

Type	a	b	c
Date			
2016-03-01	11.432	NaN	20.784
2016-03-02	1.303	13.031	NaN
2016-03-03	99.906	NaN	20.784

Pivot Table

```
>>> df4 = pd.pivot_table(df2,
                         values='Value',
                         index='Date',
                         columns='Type'])
```

Spread rows into columns

Stack / Unstack

```
>>> stacked = df5.stack()
>>> stacked.unstack()
```

Pivot a level of column labels
Pivot a level of index labels

		0	1
1	5	0.233482	0.390959
2	4	0.184713	0.237102
3	3	0.433522	0.429401

Unstacked

1	5	0	0.233482
		1	0.390959
2	4	0	0.184713
		1	0.237102
3	3	0	0.433522
		1	0.429401

Stacked

Melt

```
>>> pd.melt(df2,
            id_vars=["Date"],
            value_vars=["Type", "Value"],
            value_name="Observations")
```

Gather columns into rows

	Date	Type	Value
0	2016-03-01	a	11.432
1	2016-03-02	b	13.031
2	2016-03-01	c	20.784
3	2016-03-03	a	99.906
4	2016-03-02	a	1.303
5	2016-03-03	c	20.784

	Date	Variable	Observations
0	2016-03-01	Type	a
1	2016-03-02	Type	b
2	2016-03-01	Type	c
3	2016-03-03	Type	a
4	2016-03-02	Type	a
5	2016-03-03	Type	c
6	2016-03-01	Value	11.432
7	2016-03-02	Value	13.031
8	2016-03-01	Value	20.784
9	2016-03-03	Value	99.906
10	2016-03-02	Value	1.303
11	2016-03-03	Value	20.784

Iteration

```
>>> df.iteritems()
>>> df.iterrows()
```

(Column-index, Series) pairs
(Row-index, Series) pairs

Advanced Indexing

Also see NumPy Arrays

Selecting

```
>>> df3.loc[:,(df3>1).any()]
>>> df3.loc[:,(df3>1).all()]
>>> df3.loc[:,df3.isnull().any()]
>>> df3.loc[:,df3.notnull().all()]
```

Select cols with any vals >1
Select cols with vals > 1
Select cols with NaN
Select cols without NaN

Indexing With isin

```
>>> df[(df.Country.isin(df2.Type))]
>>> df3.filter(items="a","b"])
>>> df.select(lambda x: not x%5)
```

Find same elements
Filter on values
Select specific elements

Where

```
>>> s.where(s > 0)
```

Subset the data

Query

```
>>> df6.query('second > first')
```

Query DataFrame

Setting/Resetting Index

```
>>> df.set_index('Country')
>>> df4 = df.reset_index()
>>> df = df.rename(index=str,
                   columns={"Country":"cntry",
                            "Capital":"cptl",
                            "Population":"ppltn"})
```

Set the Index
Reset the Index
Rename DataFrame

Reindexing

```
>>> s2 = s.reindex(['a','c','d','e','b'])
```

Forward Filling

```
>>> df.reindex(range(4),
               method='ffill')
   Country     Capital   Population
0  Belgium    Brussels     11190846
1    India   New Delhi   1303171035
2   Brazil    Brasília    207847528
3   Brazil    Brasília    207847528
```

Backward Filling

```
>>> s3 = s.reindex(range(5),
                   method='bfill')
0  3
1  3
2  3
3  3
4  3
```

MultiIndexing

```
>>> arrays = [np.array([1,2,3]),
              np.array([5,4,3])]
>>> df5 = pd.DataFrame(np.random.rand(3, 2), index=arrays)
>>> tuples = list(zip(*arrays))
>>> index = pd.MultiIndex.from_tuples(tuples,
                                      names=['first', 'second'])
>>> df6 = pd.DataFrame(np.random.rand(3, 2), index=index)
>>> df2.set_index(["Date", "Type"])
```

Duplicate Data

```
>>> s3.unique()
>>> df2.duplicated('Type')
>>> df2.drop_duplicates('Type', keep='last')
>>> df.index.duplicated()
```

Return unique values
Check duplicates
Drop duplicates
Check index duplicates

Grouping Data

Aggregation

```
>>> df2.groupby(by=['Date','Type']).mean()
>>> df4.groupby(level=0).sum()
>>> df4.groupby(level=0).agg({'a':lambda x:sum(x)/len(x),
                              'b': np.sum})
```

Transformation

```
>>> customSum = lambda x: (x+x%2)
>>> df4.groupby(level=0).transform(customSum)
```

Missing Data

```
>>> df.dropna()
>>> df3.fillna(df3.mean())
>>> df2.replace("a", "f")
```

Drop NaN values
Fill NaN values with a predetermined value
Replace values with others

Combining Data

data1

	X1	X2
a	11.432
b	1.303
c	99.906

data2

	X1	X3
a	20.784
b	NaN
d	20.784

Merge

```
>>> pd.merge(data1,
             data2,
             how='left',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN

```
>>> pd.merge(data1,
             data2,
             how='right',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN
d	NaN	20.784

```
>>> pd.merge(data1,
             data2,
             how='inner',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN

```
>>> pd.merge(data1,
             data2,
             how='outer',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN
d	NaN	20.784

Join

```
>>> data1.join(data2, how='right')
```

Concatenate

Vertical

```
>>> s.append(s2)
```

Horizontal/Vertical

```
>>> pd.concat([s,s2],axis=1, keys=['One','Two'])
>>> pd.concat([data1, data2], axis=1, join='inner')
```

Dates

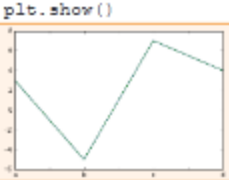
```
>>> df2['Date']= pd.to_datetime(df2['Date'])
>>> df2['Date']= pd.date_range('2000-1-1',
                               periods=6,
                               freq='M')
>>> dates = [datetime(2012,5,1), datetime(2012,5,2)]
>>> index = pd.DatetimeIndex(dates)
>>> index = pd.date_range(datetime(2012,2,1), end, freq='BM')
```

Visualization

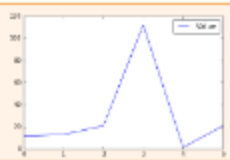
Also see Matplotlib

```
>>> import matplotlib.pyplot as plt
```

```
>>> s.plot()
>>> plt.show()
```



```
>>> df2.plot()
>>> plt.show()
```



R For Data Science *Cheat Sheet*

data.table

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data.table

data.table is an R package that provides a high-performance version of base R's `data.frame` with syntax and feature enhancements for ease of use, convenience and programming speed.

Load the package:

```
> library(data.table)
```

Creating A `data.table`

```
> set.seed(45L)
> DT <- data.table(V1=c(1L,2L),
                   V2=LETTERS[1:3],
                   V3=round(rnorm(4),4),
                   V4=1:12)
```

Create a `data.table` and call it `DT`

Subsetting Rows Using `i`

```
> DT[3:5,]
> DT[3:5]
> DT[V2=="A"]
> DT[V2 %in% c("A","C")]
```

Select 3rd to 5th row
Select 3rd to 5th row
Select all rows that have value `A` in column `V2`
Select all rows that have value `A` or `C` in column `V2`

Manipulating on Columns in `j`

```
> DT[,V2]
 [1] "A" "B" "C" "A" "B" "C" ...
> DT[,.(V2,V3)]
> DT[,sum(V1)]
[1] 18
> DT[,.(sum(V1),sd(V3))]
   V1        V2
1: 18 0.4546055
> DT[,.(Aggregate=sum(V1),
        Sd.V3=sd(V3))]
   Aggregate     Sd.V3
1:        18 0.4546055
> DT[,.(V1,Sd.V3=sd(V3))]

> DT[,.(print(V2),
        plot(V3),
        NULL)]
```

Return `V2` as a vector

Return `V2` and `V3` as a `data.table`
Return the sum of all elements of `V1` in a vector
Return the sum of all elements of `V1` and the std. dev. of `V3` in a `data.table`

The same as the above, with new names

Select column `V2` and compute std. dev. of `V3`, which returns a single value and gets recycled
Print column `V2` and plot `V3`

Doing `j` by Group

```
> DT[,.(V4.Sum=sum(V4)),by=V1]
   V1 V4.Sum
1:  1     26
2:  2     42
> DT[,.(V4.Sum=sum(V4)),
     by=.(V1,V2)]
> DT[,.(V4.Sum=sum(V4)),
     by=sign(V1-1)]
  sign V4.Sum
1:    0     26
2:    1     42
> DT[,.(V4.Sum=sum(V4)),
     by=.(V1.01=sign(V1-1))]
> DT[1:5,.(V4.Sum=sum(V4)),
       by=V1]
> DT[,.N,by=V1]
```

Calculate sum of `V4` for every group in `V1`

Calculate sum of `V4` for every group in `V1` and `V2`
Calculate sum of `V4` for every group in `sign(V1-1)`

The same as the above, with new name for the variable you're grouping by
Calculate sum of `V4` for every group in `V1` after subsetting on the first 5 rows
Count number of rows for every group in `V1`

General form: `DT[i, j, by]`

"Take `DT`, subset rows using `i`, then calculate `j` grouped by `by`"

Adding/Updating Columns By Reference in `j` Using `:=`

```
> DT[,V1:=round(exp(V1),2)]
> DT
     V1 V2       V3 V4
1: 2.72  A -0.1207  1
2: 7.39  B -0.1427  2
3: 2.72  C -1.0993  3
4: 7.39  A -0.3571  4
...
> DT[,c("V1","V2"):=list(round(exp(V1),2),
                         LETTERS[4:6])]
> DT[,':='(V1=round(exp(V1),2),
           V2=LETTERS[4:6])][]
      V1 V2       V3 V4
1:  15.15  D -0.1207  1
2: 1619.71  E -0.1427  2
3:  15.15  F -1.0993  3
4: 1619.71  D -0.3571  4
> DT[,V1:=NULL]
> DT[,c("V1","V2"):=NULL]
> Cols.chosen=c("A","B")
> DT[,Cols.Chosen:=NULL]

> DT[,(Cols.Chosen):=NULL]
```

`V1` is updated by what is after `:=`
Return the result by calling `DT`

Columns `V1` and `V2` are updated by what is after `:=`
Alternative to the above one. With `[]`, you print the result to the screen

Remove `V1`
Remove columns `V1` and `V2`

Delete the column with column name `Cols.chosen`

Delete the columns specified in the variable `Cols.chosen`

Indexing And Keys

```
> setkey(DT,V2)
> DT["A"]
   V1 V2       V3 V4
1:  1  A -0.2382  1
2:  2  A -1.6142  4
3:  1  A  1.0492  7
4:  2  A  0.3262 10
> DT[c("A","C")]
> DT["A",mult="first"]

> DT["A",mult="last"]

> DT[c("A","D")]
   V1 V2       V3 V4
1:  1  A -0.2382  1
2:  2  A -1.6142  4
3:  1  A  1.0492  7
4:  2  A  0.3262 10
5: NA  D       NA NA
> DT[c("A","D"),nomatch=0]
   V1 V2       V3 V4
1:  1  A -0.2382  1
2:  2  A -1.6142  4
3:  1  A  1.0492  7
4:  2  A  0.3262 10
> DT[c("A","C"),sum(V4)]

> DT[c("A","C"),
     sum(V4),
     by=.EACHI]
   V2 V1
1:  A 22
2:  C 30
> setkey(DT,V1,V2)
> DT[.(2,"C")]
   V1 V2       V3 V4
1:  2  C  0.3262  6
2:  2  C -1.6142 12
> DT[.(2,c("A","C"))]
   V1 V2       V3 V4
1:  2  A -1.6142  4
2:  2  A  0.3262 10
3:  2  C  0.3262  6
4:  2  C -1.6142 12
```

A key is set on `V2`; output is returned invisibly
Return all rows where the key column (set to `V2`) has the value `A`

Return all rows where key column (`V2`) has value `A` or `C`
Return first row of all rows that match value `A` in key column `V2`
Return last row of all rows that match value `A` in key column `V2`
Return all rows where key column `V2` has value `A` or `D`

Return all rows where key column `V2` has value `A` or `D`

Return total sum of `V4`, for rows of key column `V2` that have values `A` or `C`
Return sum of column `V4` for rows of `V2` that have value `A`, and another sum for rows of `V2` that have value `C`

Sort by `V1` and then by `V2` within each group of `V1` (invisible)
Select rows that have value 2 for the first key (`V1`) and the value `C` for the second key (`V2`)

Select rows that have value 2 for the first key (`V1`) and within those rows the value `A` or `C` for the second key (`V2`)

Advanced Data Table Operations

```
> DT[.N-1]
> DT[,.N]
> DT[,.(V2,V3)]
> DT[,list(V2,V3)]
> DT[,mean(V3),by=.(V1,V2)]
   V1 V2          V1
1:  1  A  0.4053
2:  1  B  0.4053
3:  1  C  0.4053
4:  2  A -0.6443
5:  2  B -0.6443
6:  2  C -0.6443
```

Return the penultimate row of the `DT`
Return the number of rows
Return `V2` and `V3` as a `data.table`
Return `V2` and `V3` as a `data.table`
Return the result of `j`, grouped by all possible combinations of groups specified in `by`

.SD & .SDcols

```
> DT[,print(.SD),by=V2]
> DT[,.SD[c(1,.N)],by=V2]
> DT[,lapply(.SD,sum),by=V2]

> DT[,lapply(.SD,sum),by=V2,
     .SDcols=c("V3","V4")]
   V2       V3 V4
1:  A -0.4764 22
2:  B -0.4764 26
3:  C -0.4764 30
> DT[,lapply(.SD,sum),by=V2,
     .SDcols=paste0("V",3:4)]
```

Look at what `.SD` contains
Select the first and last row grouped by `V2`
Calculate sum of columns in `.SD` grouped by `V2`

Calculate sum of `V3` and `V4` in `.SD` grouped by `V2`

Calculate sum of `V3` and `V4` in `.SD` grouped by `V2`

Chaining

```
> DT <- DT[,.(V4.Sum=sum(V4)),
           by=V1]
   V1 V4.Sum
1:  1     26
2:  2     42
> DT[V4.Sum>40]
> DT[,.(V4.Sum=sum(V4)),
     by=V1][V4.Sum>40]
   V1 V4.Sum
1:  2     42
> DT[,.(V4.Sum=sum(V4)),
     by=V1][order(-V1)]
   V1 V4.Sum
1:  2     42
2:  1     26
```

Calculate sum of `V4`, grouped by `V1`

Select that group of which the sum is >40
Select that group of which the sum is >40 (chaining)

Calculate sum of `V4`, grouped by `V1`, ordered on `V1`

set()-Family

set()

Syntax: `for (i in from:to) set(DT, row, column, new value)`

```
> rows <- list(3:4,5:6)
> cols <- 1:2
> for(i in seq_along(rows))
    {set(DT,
         i=rows[[i]],
         j=cols[i],
         value=NA)}
```

Sequence along the values of `rows`, and for the values of `cols`, set the values of those elements equal to `NA` (invisible)

setnames()

Syntax: `setnames(DT,"old","new")[]`

```
> setnames(DT,"V2","Rating")
> setnames(DT,
           c("V2","V3"),
           c("V2.rating","V3.DC"))
```

Set name of `V2` to `Rating` (invisible)
Change 2 column names (invisible)

setnames()

Syntax: `setcolorder(DT,"neworder")`

```
> setcolorder(DT,
              c("V2","V1","V4","V3"))
```

Change column ordering to contents of the specified vector (invisible)

R For Data Science *Cheat Sheet*

Tidyverse for Beginners

Learn More R for Data Science Interactively at www.datacamp.com

Tidyverse

The **tidyverse** is a powerful collection of R packages that are actually data tools for transforming and visualizing data. All packages of the tidyverse share an underlying philosophy and common APIs.

The core packages are:

- **ggplot2**, which implements the grammar of graphics. You can use it to visualize your data.
- **dplyr** is a grammar of data manipulation. You can use it to solve the most common data manipulation challenges.
- **tidyr** helps you to create tidy data or data where each variable is in a column, each observation is a row end each value is a cell.
- **readr** is a fast and friendly way to read rectangular data.
- **purrr** enhances R's functional programming (FP) toolkit by providing a complete and consistent set of tools for working with functions and vectors.
- **tibble** is a modern re-imaginging of the data frame.
- **stringr** provides a cohesive set of functions designed to make working with strings as easy as posssible
- **forcats** provide a suite of useful tools that solve common problems with factors.

You can install the complete tidyverse with:

```
> install.packages("tidyverse")
```

Then, load the core tidyverse and make it available in your current R session by running:

```
> library(tidyverse)
```

Note: there are many other tidyverse packages with more specialised usage. They are not loaded automatically with library(tidyverse), so you'll need to load each one with its own call to `library()`.

Useful Functions

`> tidyverse_conflicts()`	Conflicts between tidyverse and other packages
`> tidyverse_deps()`	List all tidyverse dependencies
`> tidyverse_logo()`	Get tidyverse logo, using ASCII or unicode characters
`> tidyverse_packages()`	List all tidyverse packages
`> tidyverse_update()`	Update tidyverse packages

Loading in the data

`> library(datasets)`	Load the datasets package
`> library(gapminder)`	Load the gapminder package
`> attach(iris)`	Attach iris data to the R search path

dplyr

Filter

`filter()` allows you to select a subset of rows in a data frame.

`> iris %>% filter(Species=="virginica")`	Select iris data of species "virginica"
`> iris %>% filter(Species=="virginica", Sepal.Length > 6)`	Select iris data of species "virginica" and sepal length greater than 6.

Arrange

`arrange()` sorts the observations in a dataset in ascending or descending order based on one of its variables.

`> iris %>% arrange(Sepal.Length)`	Sort in ascending order of sepal length
`> iris %>% arrange(desc(Sepal.Length))`	Sort in descending order of sepal length

Combine multiple `dplyr` verbs in a row with the pipe operator `%>%`:

`> iris %>% filter(Species=="virginica") %>% arrange(desc(Sepal.Length))`	Filter for species "virginica" then arrange in descending order of sepal length

Mutate

`mutate()` allows you to update or create new columns of a data frame.

`> iris %>% mutate(Sepal.Length=Sepal.Length*10)`	Change Sepal.Length to be in millimeters
`> iris %>% mutate(SLMm=Sepal.Length*10)`	Create a new column called SLMm

Combine the verbs `filter()`, `arrange()`, and `mutate()`:

```
> iris %>%
    filter(Species=="Virginica") %>%
    mutate(SLMm=Sepal.Length*10) %>%
    arrange(desc(SLMm))
```

Summarize

`summarize()` allows you to turn many observations into a single data point.

`> iris %>% summarize(medianSL=median(Sepal.Length))`	Summarize to find the median sepal length
`> iris %>% filter(Species=="virginica") %>% summarize(medianSL=median(Sepal.Length))`	Filter for virginica then summarize the median sepal length

You can also summarize multiple variables at once:

```
> iris %>%
    filter(Species=="virginica") %>%
    summarize(medianSL=median(Sepal.Length),
              maxSL=max(Sepal.Length))
```

`group_by()` allows you to summarize within groups instead of summarizing the entire dataset:

`> iris %>% group_by(Species) %>% summarize(medianSL=median(Sepal.Length), maxSL=max(Sepal.Length))`	Find median and max sepal length of each species
`> iris %>% filter(Sepal.Length>6) %>% group_by(Species) %>% summarize(medianPL=median(Petal.Length), maxPL=max(Petal.Length))`	Find median and max petal length of each species with sepal length > 6

ggplot2

Scatter plot

Scatter plots allow you to compare two variables within your data. To do this with ggplot2, you use `geom_point()`

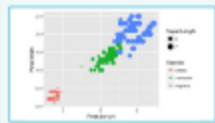
`> iris_small <- iris %>% filter(Sepal.Length > 5)` `> ggplot(iris_small, aes(x=Petal.Length, y=Petal.Width)) + geom_point()`	Compare petal width and length

Additional Aesthetics

- Color

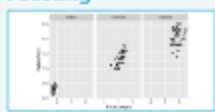
```
> ggplot(iris_small, aes(x=Petal.Length,
                         y=Petal.Width,
                         color=Species)) +
    geom_point()
```

- Size



```
> ggplot(iris_small, aes(x=Petal.Length,
                         y=Petal.Width,
                         color=Species,
                         size=Sepal.Length)) +
    geom_point()
```

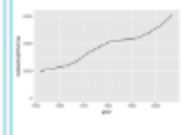
Faceting



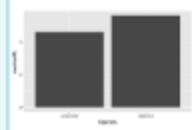
```
> ggplot(iris_small, aes(x=Petal.Length,
                         y=Petal.Width)) +
    geom_point()+
    facet_wrap(~Species)
```

Line Plots

```
> by_year <- gapminder %>%
    group_by(year) %>%
    summarize(medianGdpPerCap=median(gdpPercap))
> ggplot(by_year, aes(x=year,
                      y=medianGdpPerCap))+
    geom_line()+
    expand_limits(y=0)
```



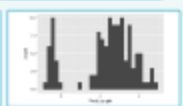
Bar Plots



```
> by_species <- iris %>%
    filter(Sepal.Length>6) %>%
    group_by(Species) %>%
    summarize(medianPL=median(Petal.Length))
> ggplot(by_species, aes(x=Species,
                         y=medianPL)) +
    geom_col()
```

Histograms

```
> ggplot(iris_small, aes(x=Petal.Length))+
    geom_histogram()
```



Box Plots

```
> ggplot(iris_small, aes(x=Species,
                         y=Sepal.Width))+
    geom_boxplot()
```

DataCamp
Learn R for Data Science Interactively

Python For Data Science *Cheat Sheet*

Scikit-Learn

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Scikit-learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.

A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>> iris = datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y_test, y_pred)
```

Loading The Data

Also see NumPy & Pandas

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable.

```
>>> import numpy as np
>>> X = np.random.random((10,5))
>>> y = np.array(['M','M','F','F','M','F','M','M','F','F','F'])
>>> X[X < 0.7] = 0
```

Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        random_state=0)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>> svc = SVC(kernel='linear')
```

Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>> pca = PCA(n_components=0.95)
```

K Means

```
>>> from sklearn.cluster import KMeans
>>> k_means = KMeans(n_clusters=3, random_state=0)
```

Model Fitting

Supervised learning	
`>>> lr.fit(X, y)`	Fit the model to the data
`>>> knn.fit(X_train, y_train)`	
`>>> svc.fit(X_train, y_train)`	
Unsupervised Learning	
`>>> k_means.fit(X_train)`	Fit the model to the data
`>>> pca_model = pca.fit_transform(X_train)`	Fit to data, then transform it

Prediction

Supervised Estimators	
`>>> y_pred = svc.predict(np.random.random((2,5)))`	Predict labels
`>>> y_pred = lr.predict(X_test)`	Predict labels
`>>> y_pred = knn.predict_proba(X_test)`	Estimate probability of a label
Unsupervised Estimators	
`>>> y_pred = k_means.predict(X_test)`	Predict labels in clustering algos

Preprocessing The Data

Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test = scaler.transform(X_test)
```

Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>> scaler = Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X_train)
>>> normalized_X_test = scaler.transform(X_test)
```

Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>> enc = LabelEncoder()
>>> y = enc.fit_transform(y)
```

Imputing Missing Values

```
>>> from sklearn.preprocessing import Imputer
>>> imp = Imputer(missing_values=0, strategy='mean', axis=0)
>>> imp.fit_transform(X_train)
```

Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>> poly = PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test)
```
Estimator score method

```
>>> from sklearn.metrics import accuracy_score
>>> accuracy_score(y_test, y_pred)
```
Metric scoring functions

Classification Report

```
>>> from sklearn.metrics import classification_report
>>> print(classification_report(y_test, y_pred))
```
Precision, recall, f1-score and support

Confusion Matrix

```
>>> from sklearn.metrics import confusion_matrix
>>> print(confusion_matrix(y_test, y_pred))
```

Regression Metrics

Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5, 2]
>>> mean_absolute_error(y_true, y_pred)
```

Mean Squared Error

```
>>> from sklearn.metrics import mean_squared_error
>>> mean_squared_error(y_test, y_pred)
```

R^2 Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_pred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(y_true, y_pred)
```

Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

Tune Your Model

Grid Search

```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {"n_neighbors": np.arange(1,3),
              "metric": ["euclidean", "cityblock"]}
>>> grid = GridSearchCV(estimator=knn,
                        param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)
```

Randomized Parameter Optimization

```
>>> from sklearn.grid_search import RandomizedSearchCV
>>> params = {"n_neighbors": range(1,5),
              "weights": ["uniform", "distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn,
                                 param_distributions=params,
                                 cv=4,
                                 n_iter=8,
                                 random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```

Python For Data Science *Cheat Sheet*

Keras

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Keras

Keras is a powerful and easy-to-use deep learning library for Theano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

A Basic Example

```
>>> import numpy as np
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>> data = np.random.random((1000,100))
>>> labels = np.random.randint(2,size=(1000,1))
>>> model = Sequential()
>>> model.add(Dense(32,
                    activation='relu',
                    input_dim=100))
>>> model.add(Dense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

Data

Also see NumPy, Pandas & Scikit-Learn

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the `train_test_split` module of `sklearn.cross_validation`.

Keras Data Sets

```
>>> from keras.datasets import boston_housing,
                               mnist,
                               cifar10,
                               imdb
>>> (x_train,y_train),(x_test,y_test) = mnist.load_data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

Other

```
>>> from urllib.request import urlopen
>>> data = np.loadtxt(urlopen("http://archive.ics.uci.edu/
ml/machine-learning-databases/pima-indians-diabetes/
pima-indians-diabetes.data"),delimiter=",")
>>> X = data[:,0:8]
>>> y = data [:,8]
```

Model Architecture

Sequential Model

```
>>> from keras.models import Sequential
>>> model = Sequential()
>>> model2 = Sequential()
>>> model3 = Sequential()
```

Multilayer Perceptron (MLP)

Binary Classification

```
>>> from keras.layers import Dense
>>> model.add(Dense(12,
                    input_dim=8,
                    kernel_initializer='uniform',
                    activation='relu'))
>>> model.add(Dense(8,kernel_initializer='uniform',activation='relu'))
>>> model.add(Dense(1,kernel_initializer='uniform',activation='sigmoid'))
```

Multi-Class Classification

```
>>> from keras.layers import Dropout
>>> model.add(Dense(512,activation='relu',input_shape=(784,)))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(512,activation='relu'))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(10,activation='softmax'))
```

Regression

```
>>> model.add(Dense(64,activation='relu',input_dim=train_data.shape[1]))
>>> model.add(Dense(1))
```

Convolutional Neural Network (CNN)

```
>>> from keras.layers import Activation,Conv2D,MaxPooling2D,Flatten
>>> model2.add(Conv2D(32,(3,3),padding='same',input_shape=x_train.shape[1:]))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(32,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))

>>> model2.add(Conv2D(64,(3,3), padding='same'))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(64,(3, 3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))

>>> model2.add(Flatten())
>>> model2.add(Dense(512))
>>> model2.add(Activation('relu'))
>>> model2.add(Dropout(0.5))
>>> model2.add(Dense(num_classes))
>>> model2.add(Activation('softmax'))
```

Recurrent Neural Network (RNN)

```
>>> from keras.klayers import Embedding,LSTM
>>> model3.add(Embedding(20000,128))
>>> model3.add(LSTM(128,dropout=0.2,recurrent_dropout=0.2))
>>> model3.add(Dense(1,activation='sigmoid'))
```

Inspect Model

```
>>> model.output_shape          Model output shape
>>> model.summary()             Model summary representation
>>> model.get_config()          Model configuration
>>> model.get_weights()         List all weight tensors in the model
```

Compile Model

MLP: Binary Classification

```
>>> model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
```

MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
```

MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
                  loss='mse',
                  metrics=['mae'])
```

Recurrent Neural Network

```
>>> model3.compile(loss='binary_crossentropy',
                   optimizer='adam',
                   metrics=['accuracy'])
```

Model Training

```
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               verbose=1,
               validation_data=(x_test4,y_test4))
```

Evaluate Your Model's Performance

```
>>> score = model3.evaluate(x_test,
                            y_test,
                            batch_size=32)
```

Prediction

```
>>> model3.predict(x_test4, batch_size=32)
>>> model3.predict_classes(x_test4,batch_size=32)
```

Save/ Reload Models

```
>>> from keras.models import load_model
>>> model3.save('model_file.h5')
>>> my_model = load_model('my_model.h5')
```

Model Fine-tuning

Optimization Parameters

```
>>> from keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss='categorical_crossentropy',
                   optimizer=opt,
                   metrics=['accuracy'])
```

Early Stopping

```
>>> from keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               validation_data=(x_test4,y_test4),
               callbacks=[early_stopping_monitor])
```

Preprocessing

Also see NumPy & Scikit-Learn

Sequence Padding

```
>>> from keras.preprocessing import sequence
>>> x_train4 = sequence.pad_sequences(x_train4,maxlen=80)
>>> x_test4 = sequence.pad_sequences(x_test4,maxlen=80)
```

One-Hot Encoding

```
>>> from keras.utils import to_categorical
>>> Y_train = to_categorical(y_train, num_classes)
>>> Y_test = to_categorical(y_test, num_classes)
>>> Y_train3 = to_categorical(y_train3, num_classes)
>>> Y_test3 = to_categorical(y_test3, num_classes)
```

Train and Test Sets

```
>>> from sklearn.model_selection import train_test_split
>>> X_train5,X_test5,y_train5,y_test5 = train_test_split(X,
                                                         y,
                                                         test_size=0.33,
                                                         random_state=42)
```

Standardization/Normalization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(x_train2)
>>> standardized_X = scaler.transform(x_train2)
>>> standardized_X_test = scaler.transform(x_test2)
```

Python For Data Science *Cheat Sheet*

PySpark - RDD Basics

Learn Python for data science Interactively at www.DataCamp.com

Spark

PySpark is the Spark Python API that exposes the Spark programming model to Python.

Initializing Spark

SparkContext

```
>>> from pyspark import SparkContext
>>> sc = SparkContext(master = 'local[2]')
```

Inspect SparkContext

```
>>> sc.version                  Retrieve SparkContext version
>>> sc.pythonVer                Retrieve Python version
>>> sc.master                   Master URL to connect to
>>> str(sc.sparkHome)           Path where Spark is installed on worker nodes
>>> str(sc.sparkUser())         Retrieve name of the Spark User running SparkContext
>>> sc.appName                  Return application name
>>> sc.applicationId            Retrieve application ID
>>> sc.defaultParallelism       Return default level of parallelism
>>> sc.defaultMinPartitions     Default minimum number of partitions for RDDs
```

Configuration

```
>>> from pyspark import SparkConf, SparkContext
>>> conf = (SparkConf()
            .setMaster("local")
            .setAppName("My app")
            .set("spark.executor.memory", "1g"))
>>> sc = SparkContext(conf = conf)
```

Using The Shell

In the PySpark shell, a special interpreter-aware SparkContext is already created in the variable called `sc`.

```
$ ./bin/spark-shell --master local[2]
$ ./bin/pyspark --master local[4] --py-files code.py
```

Set which master the context connects to with the `--master` argument, and add Python .zip, .egg or .py files to the runtime path by passing a comma-separated list to `--py-files`.

Loading Data

Parallelized Collections

```
>>> rdd = sc.parallelize([('a',7),('a',2),('b',2)])
>>> rdd2 = sc.parallelize([('a',2),('d',1),('b',1)])
>>> rdd3 = sc.parallelize(range(100))
>>> rdd4 = sc.parallelize([("a",["x","y","z"]),
                           ("b",["p", "r"])])
```

External Data

Read either one text file from HDFS, a local file system or or any Hadoop-supported file system URI with `textFile()`, or read in a directory of text files with `wholeTextFiles()`.

```
>>> textFile = sc.textFile("/my/directory/*.txt")
>>> textFile2 = sc.wholeTextFiles("/my/directory/")
```

Retrieving RDD Information

Basic Information

```
>>> rdd.getNumPartitions()          List the number of partitions
>>> rdd.count()                     Count RDD instances
 3
>>> rdd.countByKey()                Count RDD instances by key
 defaultdict(<type 'int'>,{'a':2,'b':1})
>>> rdd.countByValue()              Count RDD instances by value
 defaultdict(<type 'int'>,{('b',2):1,('a',2):1,('a',7):1})
>>> rdd.collectAsMap()              Return (key,value) pairs as a dictionary
 {'a': 2,'b': 2}
>>> rdd3.sum()                      Sum of RDD elements
 4950
>>> sc.parallelize([]).isEmpty()    Check whether RDD is empty
  True
```

Summary

```
>>> rdd3.max()                      Maximum value of RDD elements
  99
>>> rdd3.min()                      Minimum value of RDD elements
  0
>>> rdd3.mean()                     Mean value of RDD elements
  49.5
>>> rdd3.stdev()                    Standard deviation of RDD elements
  28.866070047722118
>>> rdd3.variance()                 Compute variance of RDD elements
  833.25
>>> rdd3.histogram(3)               Compute histogram by bins
  ([0,33,66,99],[33,33,34])
>>> rdd3.stats()                    Summary statistics (count, mean, stdev, max & min)
```

Applying Functions

```
>>> rdd.map(lambda x: x+(x[1],x[0]))          Apply a function to each RDD element
       .collect()
  [('a',7,7,'a'),('a',2,2,'a'),('b',2,2,'b')]
>>> rdd5 = rdd.flatMap(lambda x: x+(x[1],x[0]))   Apply a function to each RDD element and flatten the result
>>> rdd5.collect()
  ['a',7,7,'a','a',2,2,'a','b',2,2,'b']
>>> rdd4.flatMapValues(lambda x: x)           Apply a flatMap function to each (key,value)
       .collect()                            pair of rdd4 without changing the keys
  [('a','x'),('a','y'),('a','z'),('b','p'),('b','r')]
```

Selecting Data

Getting

```
>>> rdd.collect()                   Return a list with all RDD elements
  [('a', 7), ('a', 2), ('b', 2)]
>>> rdd.take(2)                     Take first 2 RDD elements
  [('a', 7), ('a', 2)]
>>> rdd.first()                     Take first RDD element
  ('a', 7)
>>> rdd.top(2)                      Take top 2 RDD elements
  [('b', 2), ('a', 7)]
```

Sampling

```
>>> rdd3.sample(False, 0.15, 81).collect()   Return sampled subset of rdd3
  [3,4,27,31,40,41,42,43,60,76,79,80,86,97]
```

Filtering

```
>>> rdd.filter(lambda x: "a" in x)  Filter the RDD
       .collect()
  [('a',7),('a',2)]
>>> rdd5.distinct().collect()       Return distinct RDD values
  ['a',2,'b',7]
>>> rdd.keys().collect()            Return (key,value) RDD's keys
  ['a', 'a', 'b']
```

Iterating

```
>>> def g(x): print(x)
>>> rdd.foreach(g)                  Apply a function to all RDD elements
  ('a', 7)
  ('b', 2)
  ('a', 2)
```

Reshaping Data

Reducing

```
>>> rdd.reduceByKey(lambda x,y : x+y)     Merge the rdd values for each key
       .collect()
  [('a',9),('b',2)]
>>> rdd.reduce(lambda a, b: a + b)        Merge the rdd values
  ('a',7,'a',2,'b',2)
```

Grouping by

```
>>> rdd3.groupBy(lambda x: x % 2)         Return RDD of grouped values
        .mapValues(list)
        .collect()
>>> rdd.groupByKey()                      Group rdd by key
       .mapValues(list)
       .collect()
  [('a',[7,2]),('b',[2])]
```

Aggregating

```
>>> seqOp = (lambda x,y: (x[0]+y,x[1]+1))
>>> combOp = (lambda x,y:(x[0]+y[0],x[1]+y[1]))
>>> rdd3.aggregate((0,0),seqOp,combOp)    Aggregate RDD elements of each partition and then the results
  (4950,100)
>>> rdd.aggregateByKey((0,0),seqop,combop)   Aggregate values of each RDD key
       .collect()
  [('a',(9,2)), ('b',(2,1))]
>>> rdd3.fold(0,add)                      Aggregate the elements of each partition, and then the results
  4950
>>> rdd.foldByKey(0, add)                 Merge the values for each key
       .collect()
  [('a',9),('b',2)]
>>> rdd3.keyBy(lambda x: x+x)             Create tuples of RDD elements by applying a function
       .collect()
```

Mathematical Operations

```
>>> rdd.subtract(rdd2)                    Return each rdd value not contained in rdd2
       .collect()
  [('b',2),('a',7)]
>>> rdd2.subtractByKey(rdd)               Return each (key,value) pair of rdd2 with no matching key in rdd
       .collect()
  [('d', 1)]
>>> rdd.cartesian(rdd2).collect()         Return the Cartesian product of rdd and rdd2
```

Sort

```
>>> rdd2.sortBy(lambda x: x[1])           Sort RDD by given function
       .collect()
  [('d',1),('b',1),('a',2)]
>>> rdd2.sortByKey()                      Sort (key, value) RDD by key
       .collect()
  [('a',2),('b',1),('d',1)]
```

Repartitioning

```
>>> rdd.repartition(4)                    New RDD with 4 partitions
>>> rdd.coalesce(1)                       Decrease the number of partitions in the RDD to 1
```

Saving

```
>>> rdd.saveAsTextFile("rdd.txt")
>>> rdd.saveAsHadoopFile("hdfs://namenodehost/parent/child",
                         'org.apache.hadoop.mapred.TextOutputFormat')
```

Stopping SparkContext

```
>>> sc.stop()
```

Execution

```
$ ./bin/spark-submit examples/src/main/python/pi.py
```

Python For Data Science *Cheat Sheet*

PySpark - SQL Basics

Learn Python for data science Interactively at www.DataCamp.com

PySpark & Spark SQL

Spark SQL is Apache Spark's module for working with structured data.

Initializing SparkSession

A SparkSession can be used create DataFrame, register DataFrame as tables, execute SQL over tables, cache tables, and read parquet files.

```
>>> from pyspark.sql import SparkSession
>>> spark = SparkSession \
        .builder \
        .appName("Python Spark SQL basic example") \
        .config("spark.some.config.option", "some-value") \
        .getOrCreate()
```

Creating DataFrames

From RDDs

```
>>> from pyspark.sql.types import *
```

Infer Schema

```
>>> sc = spark.sparkContext
>>> lines = sc.textFile("people.txt")
>>> parts = lines.map(lambda l: l.split(","))
>>> people = parts.map(lambda p: Row(name=p[0],age=int(p[1])))
>>> peopledf = spark.createDataFrame(people)
```

Specify Schema

```
>>> people = parts.map(lambda p: Row(name=p[0],
                                     age=int(p[1].strip())))
>>> schemaString = "name age"
>>> fields = [StructField(field_name, StringType(), True) for
field_name in schemaString.split()]
>>> schema = StructType(fields)
>>> spark.createDataFrame(people, schema).show()
  +--------+---+
  |    name|age|
  +--------+---+
  |    Mine| 28|
  |   Filip| 29|
  |Jonathan| 30|
  +--------+---+
```

From Spark Data Sources

JSON

```
>>> df = spark.read.json("customer.json")
>>> df.show()
+--------------------+---+---------+--------+--------------------+
|             address|age|firstName |lastName|         phoneNumber|
+--------------------+---+---------+--------+--------------------+
|[New York,10021,N...| 25|     John|   Smith|[[212 555-1234,ho...|
|[New York,10021,N...| 21|     Jane|     Doe|[[322 888-1234,ho...|
+--------------------+---+---------+--------+--------------------+
>>> df2 = spark.read.load("people.json", format="json")
```

Parquet files

```
>>> df3 = spark.read.load("users.parquet")
```

TXT files

```
>>> df4 = spark.read.text("people.txt")
```

Duplicate Values

```
>>> df = df.dropDuplicates()
```

Queries

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

Select

```
>>> df.select("firstName").show()
>>> df.select("firstName","lastName") \
      .show()
>>> df.select("firstName",
              "age",
              explode("phoneNumber") \
             .alias("contactInfo")) \
      .select("contactInfo.type",
              "firstName",
              "age") \
      .show()
>>> df.select(df["firstName"],df["age"]+ 1)
      .show()
>>> df.select(df['age'] > 24).show()
```

When

```
>>> df.select("firstName",
              F.when(df.age > 30, 1) \
             .otherwise(0)) \
      .show()
>>> df[df.firstName.isin("Jane","Boris")]
              .collect()
```

Like

```
>>> df.select("firstName",
              df.lastName.like("Smith")) \
      .show()
```

Startswith - Endswith

```
>>> df.select("firstName",
              df.lastName \
                .startswith("Sm")) \
      .show()
>>> df.select(df.lastName.endswith("th"))\
      .show()
```

Substring

```
>>> df.select(df.firstName.substr(1, 3) \
                             .alias("name")) \
      .collect()
```

Between

```
>>> df.select(df.age.between(22, 24)) \
      .show()
```

Show all entries in `firstName` column

Show all entries in `firstName`, `age` and `type`

Show all entries in `firstName` and `age`, add 1 to the entries of `age`

Show all entries where `age` >24

Show `firstName` and 0 or 1 depending on `age` >30

Show `firstName` if in the given options

Show `firstName`, and `lastName` is `TRUE` if `lastName` is like `Smith`

Show `firstName`, and `TRUE` if `lastName` starts with `Sm`

Show last names ending in `th`

Return substrings of `firstName`

Show `age`: values are `TRUE` if between 22 and 24

Add, Update & Remove Columns

Adding Columns

```
>>> df = df.withColumn('city',df.address.city) \
           .withColumn('postalCode',df.address.postalCode) \
           .withColumn('state',df.address.state) \
           .withColumn('streetAddress',df.address.streetAddress) \
           .withColumn('telePhoneNumber',
                       explode(df.phoneNumber.number)) \
           .withColumn('telePhoneType',
                       explode(df.phoneNumber.type))
```

Updating Columns

```
>>> df = df.withColumnRenamed('telePhoneNumber', 'phoneNumber')
```

Removing Columns

```
>>> df = df.drop("address", "phoneNumber")
>>> df = df.drop(df.address).drop(df.phoneNumber)
```

GroupBy

```
>>> df.groupBy("age")\
      .count() \
      .show()
```

Group by `age`, count the members in the groups

Filter

```
>>> df.filter(df["age"]>24).show()
```

Filter entries of `age`, only keep those records of which the values are >24

Sort

```
>>> peopledf.sort(peopledf.age.desc()).collect()
>>> df.sort("age", ascending=False).collect()
>>> df.orderBy(["age","city"],ascending=[0,1])\
      .collect()
```

Missing & Replacing Values

```
>>> df.na.fill(50).show()
>>> df.na.drop().show()
>>> df.na \
      .replace(10, 20) \
      .show()
```

Replace null values
Return new `df` omitting rows with null values
Return new `df` replacing one value with another

Repartitioning

```
>>> df.repartition(10)\
      .rdd \
      .getNumPartitions()
>>> df.coalesce(1).rdd.getNumPartitions()
```

`df` with 10 partitions

`df` with 1 partition

Running SQL Queries Programmatically

Registering DataFrames as Views

```
>>> peopledf.createGlobalTempView("people")
>>> df.createTempView("customer")
>>> df.createOrReplaceTempView("customer")
```

Query Views

```
>>> df5 = spark.sql("SELECT * FROM customer").show()
>>> peopledf2 = spark.sql("SELECT * FROM global_temp.people")\
                 .show()
```

Output

Data Structures

```
>>> rdd1 = df.rdd
>>> df.toJSON().first()
>>> df.toPandas()
```

Convert `df` into an RDD
Convert `df` into a RDD of string
Return the contents of `df` as Pandas `DataFrame`

Write & Save to Files

```
>>> df.select("firstName", "city")\
      .write \
      .save("nameAndCity.parquet")
>>> df.select("firstName", "age") \
      .write \
      .save("namesAndAges.json",format="json")
```

Stopping SparkSession

```
>>> spark.stop()
```

Inspect Data

```
>>> df.dtypes
>>> df.show()
>>> df.head()
>>> df.first()
>>> df.take(2)
>>> df.schema
```

Return `df` column names and data types
Display the content of `df`
Return first `n` rows
Return first row
Return the first `n` rows
Return the schema of `df`

```
>>> df.describe().show()
>>> df.columns
>>> df.count()
>>> df.distinct().count()
>>> df.printSchema()
>>> df.explain()
```

Compute summary statistics
Return the columns of `df`
Count the number of rows in `df`
Count the number of distinct rows in `df`
Print the schema of `df`
Print the (logical and physical) plans

Python For Data Science *Cheat Sheet*

Matplotlib

Learn Python Interactively at www.DataCamp.com

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

matplotlib

1 Prepare The Data

Also see Lists & NumPy

1D Data

```
>>> import numpy as np
>>> x = np.linspace(0, 10, 100)
>>> y = np.cos(x)
>>> z = np.sin(x)
```

2D Data or Images

```
>>> data = 2 * np.random.random((10, 10))
>>> data2 = 3 * np.random.random((10, 10))
>>> Y, X = np.mgrid[-3:3:100j, -3:3:100j]
>>> U = -1 - X**2 + Y
>>> V = 1 + X - Y**2
>>> from matplotlib.cbook import get_sample_data
>>> img = np.load(get_sample_data('axes_grid/bivariate_normal.npy'))
```

2 Create Plot

```
>>> import matplotlib.pyplot as plt
```

Figure

```
>>> fig = plt.figure()
>>> fig2 = plt.figure(figsize=plt.figaspect(2.0))
```

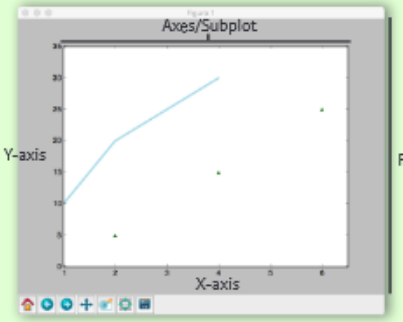
Axes

All plotting is done with respect to an `Axes`. In most cases, a subplot will fit your needs. A subplot is an axes on a grid system.

```
>>> fig.add_axes()
>>> ax1 = fig.add_subplot(221) # row-col-num
>>> ax3 = fig.add_subplot(212)
>>> fig3, axes = plt.subplots(nrows=2,ncols=2)
>>> fig4, axes2 = plt.subplots(ncols=3)
```

Plot Anatomy & Workflow

Plot Anatomy



Figure

Workflow

The basic steps to creating plots with matplotlib are:

1 Prepare data 2 Create plot 3 Plot 4 Customize plot 5 Save plot 6 Show plot

```
>>> import matplotlib.pyplot as plt
>>> x = [1,2,3,4]                          Step 1
>>> y = [10,20,25,30]
>>> fig = plt.figure()                     Step 2
>>> ax = fig.add_subplot(111)              Step 3
>>> ax.plot(x, y, color='lightblue', linewidth=3)   Step 3, 4
>>> ax.scatter([2,4,6],
               [5,15,25],
               color='darkgreen',
               marker='^')
>>> ax.set_xlim(1, 6.5)
>>> plt.savefig('foo.png')
>>> plt.show()                             Step 6
```

4 Customize Plot

Colors, Color Bars & Color Maps

```
>>> plt.plot(x, x, x, x**2, x, x**3)
>>> ax.plot(x, y, alpha = 0.4)
>>> ax.plot(x, y, c='k')
>>> fig.colorbar(im, orientation='horizontal')
>>> im = ax.imshow(img,
                   cmap='seismic')
```

Markers

```
>>> fig, ax = plt.subplots()
>>> ax.scatter(x,y,marker=".")
>>> ax.plot(x,y,marker="o")
```

Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--')
>>> plt.plot(x,y,'--',x**2,y**2,'-.')
>>> plt.setp(lines,color='r',linewidth=4.0)
```

Text & Annotations

```
>>> ax.text(1,
            -2.1,
            'Example Graph',
            style='italic')
>>> ax.annotate("Sine",
                xy=(8, 0),
                xycoords='data',
                xytext=(10.5, 0),
                textcoords='data',
                arrowprops=dict(arrowstyle="->",
                                connectionstyle="arc3"),)
```

Mathtext

```
>>> plt.title(r'$sigma_i=15$', fontsize=20)
```

Limits, Legends & Layouts

Limits & Autoscaling

```
>>> ax.margins(x=0.0,y=0.1)                  Add padding to a plot
>>> ax.axis('equal')                         Set the aspect ratio of the plot to 1
>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5])    Set limits for x-and y-axis
>>> ax.set_xlim(0,10.5)                      Set limits for x-axis
```

Legends

```
>>> ax.set(title='An Example Axes',          Set a title and x-and y-axis labels
           ylabel='Y-Axis',
           xlabel='X-Axis')
>>> ax.legend(loc='best')                    No overlapping plot elements
```

Ticks

```
>>> ax.xaxis.set(ticks=range(1,5),           Manually set x-ticks
                 ticklabels=[3,100,-12,"foo"])
>>> ax.tick_params(axis='y',                 Make y-ticks longer and go in and out
                   direction='inout',
                   length=10)
```

Subplot Spacing

```
>>> fig3.subplots_adjust(wspace=0.5,         Adjust the spacing between subplots
                         hspace=0.3,
                         left=0.125,
                         right=0.9,
                         top=0.9,
                         bottom=0.1)
>>> fig.tight_layout()                       Fit subplot(s) in to the figure area
```

Axis Spines

```
>>> ax1.spines['top'].set_visible(False)     Make the top axis line for a plot invisible
>>> ax1.spines['bottom'].set_position(('outward',10))   Move the bottom axis line outward
```

3 Plotting Routines

1D Data

```
>>> lines = ax.plot(x,y)                     Draw points with lines or markers connecting them
>>> ax.scatter(x,y)                          Draw unconnected points, scaled or colored
>>> axes[0,0].bar([1,2,3],[3,4,5])           Plot vertical rectangles (constant width)
>>> axes[1,0].barh([0.5,1,2.5],[0,1,2])      Plot horiontal rectangles (constant height)
>>> axes[1,1].axhline(0.45)                  Draw a horizontal line across axes
>>> axes[0,1].axvline(0.65)                  Draw a vertical line across axes
>>> ax.fill(x,y,color='blue')                Draw filled polygons
>>> ax.fill_between(x,y,color='yellow')      Fill between y-values and 0
```

Vector Fields

```
>>> axes[0,1].arrow(0,0,0.5,0.5)             Add an arrow to the axes
>>> axes[1,1].quiver(y,z)                    Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V)            Plot 2D vector fields
```

Data Distributions

```
>>> ax1.hist(y)                              Plot a histogram
>>> ax3.boxplot(y)                           Make a box and whisker plot
>>> ax3.violinplot(z)                        Make a violin plot
```

2D Data or Images

```
>>> fig, ax = plt.subplots()
>>> im = ax.imshow(img,                      Colormapped or RGB arrays
                   cmap='gist_earth',
                   interpolation='nearest',
                   vmin=-2,
                   vmax=2)
```

```
>>> axes2[0].pcolor(data2)                   Pseudocolor plot of 2D array
>>> axes2[0].pcolormesh(data)                Pseudocolor plot of 2D array
>>> CS = plt.contour(Y,X,U)                  Plot contours
>>> axes2[2].contourf(data1)                 Plot filled contours
>>> axes2[2]= ax.clabel(CS)                  Label a contour plot
```

5 Save Plot

Save figures

```
>>> plt.savefig('foo.png')
```

Save transparent figures

```
>>> plt.savefig('foo.png', transparent=True)
```

6 Show Plot

```
>>> plt.show()
```

Close & Clear

```
>>> plt.cla()                                Clear an axis
>>> plt.clf()                                Clear the entire figure
>>> plt.close()                              Close a window
```

Python For Data Science *Cheat Sheet*

Seaborn

Learn Data Science Interactively at www.DataCamp.com

Statistical Data Visualization With Seaborn

The Python visualization library **Seaborn** is based on matplotlib and provides a high-level interface for drawing attractive statistical graphics.

Make use of the following aliases to import the libraries:

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
```

The basic steps to creating plots with Seaborn are:

1. Prepare some data
2. Control figure aesthetics
3. Plot with Seaborn
4. Further customize your plot

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
>>> tips = sns.load_dataset("tips")                    Step 1
>>> sns.set_style("whitegrid")                         Step 2
>>> g = sns.lmplot(x="tip",                            Step 3
                   y="total_bill",
                   data=tips,
                   aspect=2)
>>> g = (g.set_axis_labels("Tip","Total bill(USD)").
set(xlim=(0,10),ylim=(0,100)))                         Step 4
>>> plt.title("title")
>>> plt.show(g)                                        Step 5
```

1 Data

Also see Lists, NumPy & Pandas

```
>>> import pandas as pd
>>> import numpy as np
>>> uniform_data = np.random.rand(10, 12)
>>> data = pd.DataFrame({'x':np.arange(1,101),
                         'y':np.random.normal(0,4,100)})
```

Seaborn also offers built-in data sets:

```
>>> titanic = sns.load_dataset("titanic")
>>> iris = sns.load_dataset("iris")
```

2 Figure Aesthetics

Also see Matplotlib

`>>> f, ax = plt.subplots(figsize=(5,6))`	Create a figure and one subplot

Seaborn styles

`>>> sns.set()`	(Re)set the seaborn default
`>>> sns.set_style("whitegrid")`	Set the matplotlib parameters
`>>> sns.set_style("ticks", {"xtick.major.size":8, "ytick.major.size":8})`	Set the matplotlib parameters
`>>> sns.axes_style("whitegrid")`	Return a dict of params or use with `with` to temporarily set the style

Context Functions

`>>> sns.set_context("talk")`	Set context to `"talk"`
`>>> sns.set_context("notebook", font_scale=1.5, rc={"lines.linewidth":2.5})`	Set context to `"notebook"`, scale font elements and override param mapping

Color Palette

`>>> sns.set_palette("husl",3)`	Define the color palette
`>>> sns.color_palette("husl")`	Use with `with` to temporarily set palette
`>>> flatui = ["#9b59b6","#3498db","#95a5a6","#e74c3c","#34495e","#2ecc71"]`	
`>>> sns.set_palette(flatui)`	Set your own color palette

3 Plotting With Seaborn

Axis Grids

`>>> g = sns.FacetGrid(titanic, col="survived", row="sex")`	Subplot grid for plotting conditional relationships
`>>> g = g.map(plt.hist,"age")`	
`>>> sns.factorplot(x="pclass", y="survived", hue="sex", data=titanic)`	Draw a categorical plot onto a Facetgrid
`>>> sns.lmplot(x="sepal_width", y="sepal_length", hue="species", data=iris)`	Plot data and regression model fits across a FacetGrid

`>>> h = sns.PairGrid(iris)`	Subplot grid for plotting pairwise relationships
`>>> h = h.map(plt.scatter)`	
`>>> sns.pairplot(iris)`	Plot pairwise bivariate distributions
`>>> i = sns.JointGrid(x="x", y="y", data=data)`	Grid for bivariate plot with marginal univariate plots
`>>> i = i.plot(sns.regplot, sns.distplot)`	
`>>> sns.jointplot("sepal_length", "sepal_width", data=iris, kind='kde')`	Plot bivariate distribution

Categorical Plots

Scatterplot

`>>> sns.stripplot(x="species", y="petal_length", data=iris)`	Scatterplot with one categorical variable
`>>> sns.swarmplot(x="species", y="petal_length", data=iris)`	Categorical scatterplot with non-overlapping points

Bar Chart

`>>> sns.barplot(x="sex", y="survived", hue="class", data=titanic)`	Show point estimates and confidence intervals with scatterplot glyphs

Count Plot

`>>> sns.countplot(x="deck", data=titanic, palette="Greens_d")`	Show count of observations

Point Plot

`>>> sns.pointplot(x="class", y="survived", hue="sex", data=titanic, palette={"male":"g", "female":"m"}, markers=["^","o"], linestyles=["-","--"])`	Show point estimates and confidence intervals as rectangular bars

Boxplot

`>>> sns.boxplot(x="alive", y="age", hue="adult_male", data=titanic)`	Boxplot
`>>> sns.boxplot(data=iris,orient="h")`	Boxplot with wide-form data

Violinplot

`>>> sns.violinplot(x="age", y="sex", hue="survived", data=titanic)`	Violin plot

Regression Plots

`>>> sns.regplot(x="sepal_width", y="sepal_length", data=iris, ax=ax)`	Plot data and a linear regression model fit

Distribution Plots

`>>> plot = sns.distplot(data.y, kde=False, color="b")`	Plot univariate distribution

Matrix Plots

`>>> sns.heatmap(uniform_data,vmin=0,vmax=1)`	Heatmap

4 Further Customizations

Also see Matplotlib

Axisgrid Objects

`>>> g.despine(left=True)`	Remove left spine
`>>> g.set_ylabels("Survived")`	Set the labels of the y-axis
`>>> g.set_xticklabels(rotation=45)`	Set the tick labels for x
`>>> g.set_axis_labels("Survived", "Sex")`	Set the axis labels
`>>> h.set(xlim=(0,5), ylim=(0,5), xticks=[0,2.5,5], yticks=[0,2.5,5])`	Set the limit and ticks of the x-and y-axis

Plot

`>>> plt.title("A Title")`	Add plot title
`>>> plt.ylabel("Survived")`	Adjust the label of the y-axis
`>>> plt.xlabel("Sex")`	Adjust the label of the x-axis
`>>> plt.ylim(0,100)`	Adjust the limits of the y-axis
`>>> plt.xlim(0,10)`	Adjust the limits of the x-axis
`>>> plt.setp(ax,yticks=[0,5])`	Adjust a plot property
`>>> plt.tight_layout()`	Adjust subplot params

5 Show or Save Plot

Also see Matplotlib

`>>> plt.show()`	Show the plot
`>>> plt.savefig("foo.png")`	Save the plot as a figure
`>>> plt.savefig("foo.png", transparent=True)`	Save transparent figure

Close & Clear

Also see Matplotlib

`>>> plt.cla()`	Clear an axis
`>>> plt.clf()`	Clear an entire figure
`>>> plt.close()`	Close a window

Python For Data Science *Cheat Sheet*

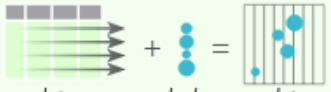
Bokeh

Learn Bokeh Interactively at www.DataCamp.com, taught by Bryan Van de Ven, core contributor

Plotting With Bokeh

The Python Interactive Visualization library **Bokeh** enables high-performance visual presentation of large datasets in modern web browsers.

Bokeh's mid-level general purpose `bokeh.plotting` interface is centered around two main components: data and glyphs.



The basic steps to creating plots with the `bokeh.plotting` interface are:

1. Prepare some data:

Python lists, NumPy arrays, Pandas DataFrames and other sequences of values

2. Create a new plot
3. Add renderers for your data, with visual customizations
4. Specify where to generate the output
5. Show or save the results

```
>>> from bokeh.plotting import figure
>>> from bokeh.io import output_file, show
>>> x = [1, 2, 3, 4, 5]                                  Step 1
>>> y = [6, 7, 2, 4, 5]
>>> p = figure(title="simple line example",               Step 2
              x_axis_label='x',
              y_axis_label='y')
>>> p.line(x, y, legend="Temp.", line_width=2)           Step 3
>>> output_file("lines.html")                            Step 4
>>> show(p)                                              Step 5
```

1 Data

Also see Lists, NumPy & Pandas

Under the hood, your data is converted to Column Data Sources. You can also do this manually:

```
>>> import numpy as np
>>> import pandas as pd
>>> df = pd.DataFrame(np.array([[33.9,4,65, 'US'],
                                [32.4,4,66, 'Asia'],
                                [21.4,4,109, 'Europe']]),
                      columns=['mpg','cyl', 'hp', 'origin'],
                      index=['Toyota', 'Fiat', 'Volvo'])
```

```
>>> from bokeh.models import ColumnDataSource
>>> cds_df = ColumnDataSource(df)
```

2 Plotting

```
>>> from bokeh.plotting import figure
>>> p1 = figure(plot_width=300, tools='pan,box_zoom')
>>> p2 = figure(plot_width=300, plot_height=300,
                x_range=(0, 8), y_range=(0, 8))
>>> p3 = figure()
```

3 Renderers & Visual Customizations

Glyphs

Scatter Markers

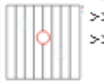
```
>>> p1.circle(np.array([1,2,3]), np.array([3,2,1]),
              fill_color='white')
>>> p2.square(np.array([1.5,3.5,5.5]), [1,4,3],
              color='blue', size=1)
```

Line Glyphs

```
>>> p1.line([1,2,3,4], [3,4,5,6], line_width=2)
>>> p2.multi_line(pd.DataFrame([[1,2,3],[5,6,7]]),
                  pd.DataFrame([[3,4,5],[3,2,1]]),
                  color="blue")
```

Customized Glyphs

Also see Data



Selection and Non-Selection Glyphs

```
>>> p = figure(tools='box_select')
>>> p.circle('mpg', 'cyl', source=cds_df,
             selection_color='red',
             nonselection_alpha=0.1)
```

Hover Glyphs

```
>>> hover = HoverTool(tooltips=None, mode='vline')
>>> p3.add_tools(hover)
```

Colormapping

```
>>> color_mapper = CategoricalColorMapper(
                   factors=['US', 'Asia', 'Europe'],
                   palette=['blue', 'red', 'green'])
>>> p3.circle('mpg', 'cyl', source=cds_df,
              color=dict(field='origin',
                         transform=color_mapper),
                         legend='Origin'))
```

Rows & Columns Layout

Rows

```
>>> from bokeh.layouts import row
>>> layout = row(p1,p2,p3)
```

Columns

```
>>> from bokeh.layouts import columns
>>> layout = column(p1,p2,p3)
```

Nesting Rows & Columns

```
>>>layout = row(column(p1,p2), p3)
```

Grid Layout

```
>>> from bokeh.layouts import gridplot
>>> row1 = [p1,p2]
>>> row2 = [p3]
>>> layout = gridplot([[p1,p2],[p3]])
```

Tabbed Layout

```
>>> from bokeh.models.widgets import Panel, Tabs
>>> tab1 = Panel(child=p1, title="tab1")
>>> tab2 = Panel(child=p2, title="tab2")
>>> layout = Tabs(tabs=[tab1, tab2])
```

Linked Plots

Also see Data

Linked Axes

```
>>> p2.x_range = p1.x_range
>>> p2.y_range = p1.y_range
```

Linked Brushing

```
>>> p4 = figure(plot_width = 100, tools='box_select,lasso_select')
>>> p4.circle('mpg', 'cyl', source=cds_df)
>>> p5 = figure(plot_width = 200, tools='box_select,lasso_select')
>>> p5.circle('mpg', 'hp', source=cds_df)
>>> layout = row(p4,p5)
```

Legends

Legend Location

Inside Plot Area

```
>>> p.legend.location = 'bottom_left'
```

Outside Plot Area

```
>>> r1 = p2.asterisk(np.array([1,2,3]), np.array([3,2,1])
>>> r2 = p2.line([1,2,3,4], [3,4,5,6])
>>> legend = Legend(items=[("One" , [p1, r1]),("Two" , [r2])], location=(0, -30))
>>> p.add_layout(legend, 'right')
```

Legend Orientation

```
>>> p.legend.orientation = "horizontal"
>>> p.legend.orientation = "vertical"
```

Legend Background & Border

```
>>> p.legend.border_line_color = "navy"
>>> p.legend.background_fill_color = "white"
```

4 Output

Output to HTML File

```
>>> from bokeh.io import output_file, show
>>> output_file('my_bar_chart.html', mode='cdn')
```

Notebook Output

```
>>> from bokeh.io import output_notebook, show
>>> output_notebook()
```

Embedding

Standalone HTML

```
>>> from bokeh.embed import file_html
>>> html = file_html(p, CDN, "my_plot")
```

Components

```
>>> from bokeh.embed import components
>>> script, div = components(p)
```

5 Show or Save Your Plots

```
>>> show(p1)
>>> show(layout)
```

```
>>> save(p1)
>>> save(layout)
```

Statistical Charts With Bokeh

Also see Data

Bokeh's high-level `bokeh.charts` interface is ideal for quickly creating statistical charts

Bar Chart

```
>>> from bokeh.charts import Bar
>>> p = Bar(df, stacked=True, palette=['red','blue'])
```

Box Plot

```
>>> from bokeh.charts import BoxPlot
>>> p = BoxPlot(df, values='vals', label='cyl',
                legend='bottom_right')
```

Histogram

```
>>> from bokeh.charts import Histogram
>>> p = Histogram(df, title='Histogram')
```

Scatter Plot

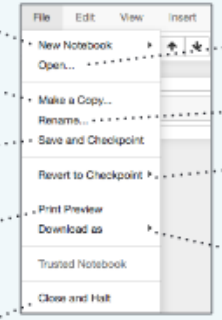
```
>>> from bokeh.charts import Scatter
>>> p = Scatter(df, x='mpg', y ='hp', marker='square',
                xlabel='Miles Per Gallon',
                ylabel='Horsepower')
```

Python For Data Science *Cheat Sheet*

Jupyter Notebook

Learn More Python for Data Science Interactively at www.DataCamp.com

Saving/Loading Notebooks

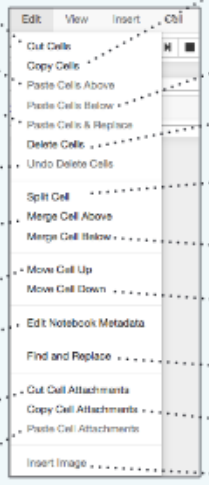


- Create new notebook
- Open an existing notebook
- Make a copy of the current notebook
- Rename notebook
- Save current notebook and record checkpoint
- Revert notebook to a previous checkpoint
- Preview of the printed notebook
- Download notebook as
  - IPython notebook
  - Python
  - HTML
  - Markdown
  - reST
  - LaTeX
  - PDF
- Close notebook & stop running any scripts

Writing Code And Text

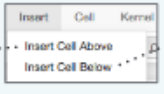
Code and text are encapsulated by 3 basic cell types: markdown cells, code cells, and raw NBConvert cells.

Edit Cells



- Cut currently selected cells to clipboard
- Copy cells from clipboard to current cursor position
- Paste cells from clipboard above current cell
- Paste cells from clipboard below current cell
- Paste cells from clipboard on top of current cel
- Delete current cells
- Revert "*Delete Cells*" invocation
- Split up a cell from current cursor position
- Merge current cell with the one above
- Merge current cell with the one below
- Move current cell up
- Move current cell down
- Adjust metadata underlying the current notebook
- Find and replace in selected cells
- Remove cell attachments
- Copy attachments of current cell
- Paste attachments of current cell
- Insert image in selected cells

Insert Cells



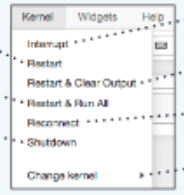
- Add new cell above the current one
- Add new cell below the current one

Working with Different Programming Languages

Kernels provide computation and communication with front-end interfaces like the notebooks. There are three main kernels:

IPython | IRkernel | IJulia

Installing Jupyter Notebook will automatically install the IPython kernel.

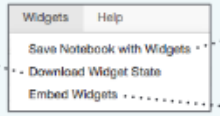


- Restart kernel
- Interrupt kernel
- Restart kernel & run all cells
- Interrupt kernel & clear all output
- Restart kernel & run all cells
- Connect back to a remote notebook
- Run other installed kernels

Widgets

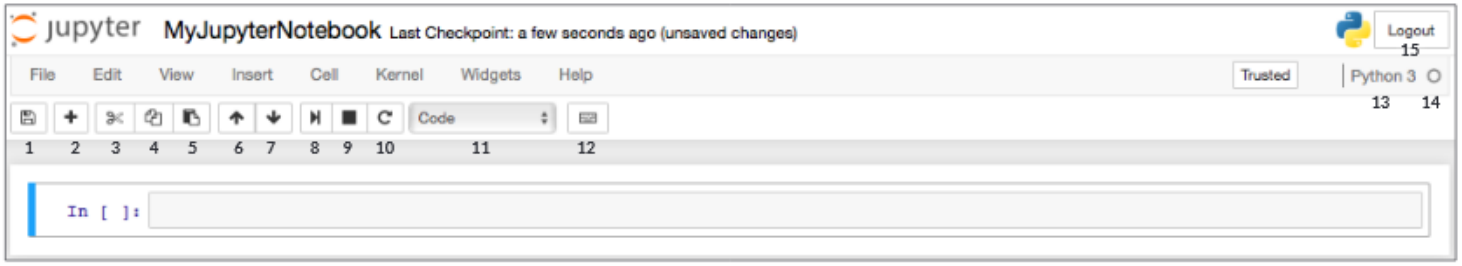
Notebook widgets provide the ability to visualize and control changes in your data, often as a control like a slider, textbox, etc.

You can use them to build interactive GUIs for your notebooks or to synchronize stateful and stateless information between Python and JavaScript.



- Download serialized state of all widget models in use
- Save notebook with interactive widgets
- Embed current widgets

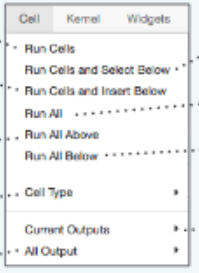
Command Mode:



Edit Mode:

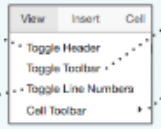
1. Save and checkpoint
2. Insert cell below
3. Cut cell
4. Copy cell(s)
5. Paste cell(s) below
6. Move cell up
7. Move cell down
8. Run current cell
9. Interrupt kernel
10. Restart kernel
11. Display characteristics
12. Open command palette
13. Current kernel
14. Kernel status
15. Log out from notebook server

Executing Cells



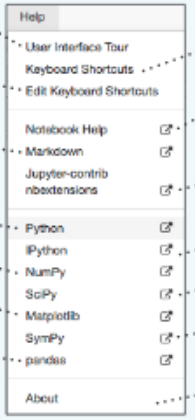
- Run selected cell(s)
- Run current cells down and create a new one below
- Run current cells down and create a new one above
- Run all cells
- Run all cells above the current cell
- Run all cells below the current cell
- Change the cell type of current cell
- toggle, toggle scrolling and clear current outputs
- toggle, toggle scrolling and clear all output

View Cells



- Toggle display of Jupyter logo and filename
- Toggle display of toolbar
- Toggle display of cell action icons:
  - None
  - Edit metadata
  - Raw cell format
  - Slideshow
  - Attachments
  - Tags
- Toggle line numbers in cells

Asking For Help



- Walk through a UI tour
- List of built-in keyboard shortcuts
- Edit the built-in keyboard shortcuts
- Notebook help topics
- Description of markdown available in notebook
- Information on unofficial Jupyter Notebook extensions
- Python help topics
- IPython help topics
- NumPy help topics
- SciPy help topics
- Matplotlib help topics
- SymPy help topics
- Pandas help topics
- About Jupyter Notebook