Python Basics

Python Cheat Sheet for Beginners

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How to use this cheat sheet

Python is the most popular programming language in data science. It is easy to learn and comes with a wide array of powerful libraries for data analysis. This cheat sheet provides beginners and intermediate users a guide to starting using python. Use it to jump-start your journey with python. If you want more detailed Python cheat sheets, check out the following cheat sheets below:


Importing data in python


Data wrangling in pandas

Accessing help and getting object types

```
1 + 1 # Everything after the hash symbol is ignored by Python
help(max) # Display the documentation for the max function
type('a') # Get the type of an object — this returns str
```

Importing packages

Python packages are a collection of useful tools developed by the open-source community. They extend the capabilities of the python language. To install a new package (for example, pandas), you can go to your command prompt and type in `pip install pandas`. Once a package is installed, you can import it as follows.

```
import pandas # Import a package without an alias
import pandas as pd # Import a package with an alias
from pandas import DataFrame # Import an object from a package
```

The working directory

The working directory is the default file path that python reads or saves files into. An example of the working directory is "C://file/path". The os library is needed to set and get the working directory.

```
import os # Import the operating system package
os.getcwd() # Get the current directory
os.setcwd("new/working/directory") # Set the working directory to a new file path
```

Operators

Arithmetic operators

```
102 + 37 # Add two numbers with +
102 - 37 # Subtract a number with -
4 * 6 # Multiply two numbers with *
22 / 7 # Divide a number by another with /
22 // 7 # Integer divide a number with //
3 ** 4 # Raise to the power with **
22 % 7 # Returns 1 # Get the remainder after division with %
```

Assignment operators

```
a = 5 # Assign a value to a
x[0] = 1 # Change the value of an item in a list
```

Numeric comparison operators

```
3 == 3 # Test for equality with ==
3 != 3 # Test for inequality with !=
3 > 1  # Test greater than with >
3 >= 3 # Test greater than or equal to with >=
3 < 4  # Test less than with <
3 <= 4 # Test less than or equal to with <=
```

Logical operators

```
~(2 == 2)          # Logical NOT with ~
(1 != 1) & (1 < 1) # Logical AND with &
(1 >= 1) | (1 < 1) # Logical OR with |
(1 != 1) ^ (1 < 1) # Logical XOR with ^
```

Getting started with lists

A list is an ordered and changeable sequence of elements. It can hold integers, characters, floats, strings, and even objects.

Creating lists

```
# Create lists with [], elements separated by commas
x = [1, 3, 2]
```

List functions and methods

```
x.sorted(x) # Return a sorted copy of the list e.g., [1,2,3]
x.sort() # Sorts the list in-place (replaces x)
reversed(x) # Reverse the order of elements in x e.g., [2,3,1]
x.reversed() # Reverse the list in-place
x.count(2) # Count the number of element 2 in the list
```

Selecting list elements

Python lists are zero-indexed (the first element has index 0). For ranges, the first element is included but the last is not.

```
# Define the list
x = ['a', 'b', 'c', 'd', 'e']
x[0] # Select the 0th element in the list
x[-1] # Select the last element in the list
x[1:3] # Select 1st (inclusive) to 3rd (exclusive)
x[2:] # Select the 2nd to the end
x[:3] # Select 0th to 3rd (exclusive)
```

Concatenating lists

```
# Define the x and y lists
x = [1, 3, 6]
y = [10, 15, 21]
x + y # Returns [1, 3, 6, 10, 15, 21]
3 * x # Returns [1, 3, 6, 1, 3, 6, 1, 3, 6]
```

Getting started with dictionaries

A dictionary stores data values in key-value pairs. That is, unlike lists which are indexed by position, dictionaries are indexed by their keys, the names of which must be unique.

Creating dictionaries

```
# Create a dictionary with {}
{'a': 1, 'b': 4, 'c': 9}
```

Dictionary functions and methods

```
x = {'a': 1, 'b': 2, 'c': 3} # Define the x ditionary
x.keys() # Get the keys of a dictionary, returns dict_keys(['a', 'b', 'c'])
x.values() # Get the values of a dictionary, returns dict_values([1, 2, 3])
```

Selecting dictionary elements

```
x['a'] # 1 # Get a value from a dictionary by specifying the key
```

NumPy arrays

NumPy is a python package for scientific computing. It provides multidimensional array objects and efficient operations on them. To import NumPy, you can run this Python code `import numpy as np`

Creating arrays

```
# Convert a python list to a NumPy array
np.array([1, 2, 3]) # Returns array([1, 2, 3])
# Return a sequence from start (inclusive) to end (exclusive)
np.arange(1,5) # Returns array([1, 2, 3, 4])
# Return a stepped sequence from start (inclusive) to end (exclusive)
np.arange(1,5,2) # Returns array([1, 3])
# Repeat values n times
np.repeat([1, 3, 6], 3) # Returns array([1, 1, 1, 3, 3, 3, 6, 6, 6])
# Repeat values n times
np.tile([1, 3, 6], 3) # Returns array([1, 3, 6, 1, 3, 6, 1, 3, 6])
```

Math functions and methods

All functions take an array as the input.

```
np.log(x) # Calculate logarithm
np.exp(x) # Calculate exponential
np.max(x) # Get maximum value
np.min(x) # Get minimum value
np.sum(x) # Calculate sum
np.mean(x) # Calculate mean
np.quantile(x, q) # Calculate q-th quantile
np.round(x, n) # Round to n decimal places
np.var(x) # Calculate variance
np.std(x) # Calculate standard deviation
```

Getting started with characters and strings

```
# Create a string with double or single quotes
"DataCamp"

# Embed a quote in string with the escape character \
"He said, \"DataCamp\""

# Create multi-line strings with triple quotes
"""
A Frame of Data
Tidy, Mine, Analyze It
Now You Have Meaning
Citation: https://mdsr-book.github.io/haikus.html
"""

str[0] # Get the character at a specific position
str[0:2] # Get a substring from starting to ending index (exclusive)
```

Combining and splitting strings

```
"Data" + "Framed" # Concatenate strings with +, this returns 'DataFramed'
3 * "data " # Repeat strings with *, this returns 'data data data '
"beekeepers".split("e") # Split a string on a delimiter, returns ['b', '', 'k', '', 'p', 'rs']
```

Mutate strings

```
str = "Jack and Jill" # Define str
str.upper() # Convert a string to uppercase, returns 'JACK AND JILL'
str.lower() # Convert a string to lowercase, returns 'jack and jill'
str.title() # Convert a string to title case, returns 'Jack And Jill'
str.replace("J", "P") # Replaces matches of a substring with another, returns 'Pack and Pill'
```

Getting started with DataFrames

Pandas is a fast and powerful package for data analysis and manipulation in python. To import the package, you can use `import pandas as pd`. A pandas DataFrame is a structure that contains two-dimensional data stored as rows and columns. A pandas series is a structure that contains one-dimensional data.

Creating DataFrames

```
# Create a dataframe from a dictionary
pd.DataFrame({
 'a': [1, 2, 3],
 'b': np.array([4, 4, 6]),
 'c': ['x', 'x', 'y']
})
# Create a dataframe from a list of dictionaries
pd.DataFrame([
 {'a': 1, 'b': 4, 'c': 'x'},
 {'a': 1, 'b': 4, 'c': 'x'},
 {'a': 3, 'b': 6, 'c': 'y'}
])
```

Selecting DataFrame Elements

Select a row, column or element from a dataframe. Remember: all positions are counted from zero, not one.

```
# Select the 3rd row
df.iloc[3]
# Select one column by name
df['col']
# Select multiple columns by names
df[['col1', 'col2']]
# Select 2nd column
df.iloc[:, 2]
# Select the element in the 3rd row, 2nd column
df.iloc[3, 2]
```

Manipulating DataFrames

```
# Concatenate DataFrames vertically
pd.concat([df, df])
# Concatenate DataFrames horizontally
pd.concat([df,df],axis="columns")
# Get rows matching a condition
df.query('logical_condition')
# Drop columns by name
df.drop(columns=['col_name'])
# Rename columns
df.rename(columns={"oldname": "newname"})
# Add a new column
df.assign(temp_f=9 / 5 * df['temp_c'] + 32)
# Calculate the mean of each column
df.mean()
# Get summary statistics by column
df.agg(aggregation_function)
# Get unique rows
df.drop_duplicates()
# Sort by values in a column
df.sort_values(by='col_name')
# Get rows with largest values in a column
df.nlargest(n, 'col_name')
```

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Python For Data Science
NumPy Cheat Sheet

Learn NumPy online at www.DataCamp.com

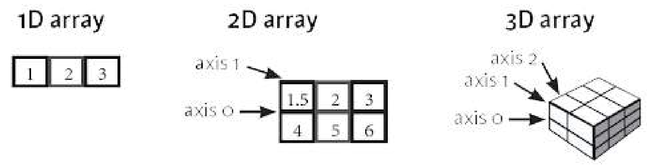
Numpy

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



> 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=" ")
```

> Asking For Help

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

> 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
```

> 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
```

> 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
>>> np.median(b) #Median
>>> np.corrcoef(a) #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

Subsetting

```
>>> a[2] #Select the element at the 2nd index
 3
>>> b[1,2] #Select the element at row 1 column 2 (equivalent to b[1][2])
 6.0
```

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 (equivalent to b[0:1, :])
 array([[1.5, 2., 3.]])
>>> 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 and columns
 array([[ 4. ,5. , 6. , 4. ],
        [ 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 index
 [array([1]),array([2]),array([3])]
>>> 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.]]])]
```

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Python For Data Science

Pandas Basics Cheat Sheet

Learn Pandas Basics online 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

Index →

a	3
b	-5
c	7
d	4

```
>>> 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

Columns →

Index →	Country	Capital	Population
0	Belgium	Brussels	11190846
1	India	New Delhi	1303171035
2	Brazil	Brasilia	207847528

```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
            'Capital': ['Brussels', 'New Delhi', 'Brasília'],
            'Population': [11190846, 1303171035, 207847528]}
>>> df = pd.DataFrame(data,
                      columns=['Country', 'Capital', 'Population'])
```

> Dropping

```
>>> s.drop(['a', 'c']) #Drop values from rows (axis=0)
>>> df.drop('Country', axis=1) #Drop values from columns(axis=1)
```

> Asking For Help

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

> Sort & Rank

```
>>> df.sort_index() #Sort by labels along an axis
>>> df.sort_values(by='Country') #Sort by the values along an axis
>>> df.rank() #Assign ranks to entries
```

> 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)
```

> Selection

Also see NumPy Arrays

Getting

```
>>> s['b'] #Get one element
 -5
>>> df[1:] #Get subset of a DataFrame
   Country Capital Population
 1 India New Delhi 1303171035
 2 Brazil Brasília 207847528
```

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]] #Select single value by row & column
 'Belgium'
>>> df.iat([0],[0])
 'Belgium'
```

By Label

```
>>> df.loc[[0], ['Country']] #Select single value by row & column labels
 'Belgium'
>>> df.at([0], ['Country'])
 'Belgium'
```

By Label/Position

```
>>> df.ix[2] #Select single row of subset of rows
 Country Brazil
 Capital Brasília
 Population 207847528
>>> df.ix[:,'Capital'] #Select a single column of subset of columns
 0 Brussels
 1 New Delhi
 2 Brasília
>>> df.ix[1,'Capital'] #Select rows and columns
 'New Delhi'
```

Boolean Indexing

```
>>> s[~(s > 1)] #Series s where value is not >1
>>> s[(s < -1) | (s > 2)] #s where value is <-1 or >2
>>> df[df['Population']>1200000000] #Use filter to adjust DataFrame
```

Setting

```
>>> s['a'] = 6 #Set index a of Series s to 6
```

> Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape #(rows,columns)
>>> df.index #Describe index
>>> df.columns #Describe DataFrame columns
>>> df.info() #Info on DataFrame
>>> df.count() #Number of non-NA values
```

Summary

```
>>> df.sum() #Sum of values
>>> df.cumsum() #Cummulative sum of values
>>> df.min()/df.max() #Minimum/maximum values
>>> df.idxmin()/df.idxmax() #Minimum/Maximum index value
>>> df.describe() #Summary statistics
>>> df.mean() #Mean of values
>>> df.median() #Median of values
```

> Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f) #Apply function
>>> df.applymap(f) #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_values=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)
```

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Working with text data in Python

Learn Python online at www.DataCamp.com

> Example data used throughout this cheat sheet

Throughout this cheat sheet, we'll be using two pandas series named `suits` and `rock_paper_scissors`.

```
import pandas as pd

suits = pd.Series(["clubs", "Diamonds", "hearts", "Spades"])
rock_paper_scissors = pd.Series(["rock ", " paper", "scissors"])
```

> String lengths and substrings

```
# Get the number of characters with .str.len()
suits.str.len() # Returns 5 8 6 6

# Get substrings by position with .str[]
suits.str[2:5] # Returns "ubs" "amo" "art" "ade"

# Get substrings by negative position with .str[]
suits.str[:-3] # "cl" "Diamo" "hea" "Spa

# Remove whitespace from the start/end with .str.strip()
rock_paper_scissors.str.strip() # "rock" "paper" "scissors"

# Pad strings to a given length with .str.pad()
suits.str.pad(8, fillchar="_") # "___clubs" "Diamonds" "__hearts" "__Spades"
```

> Changing case

```
# Convert to lowercase with .str.lower()
suits.str.lower() # "clubs" "diamonds" "hearts" "spades"

# Convert to uppercase with .str.upper()
suits.str.upper() # "CLUBS" "DIAMONDS" "HEARTS" "SPADES"

# Convert to title case with .str.title()
pd.Series("hello, world!").str.title() # "Hello, World!"

# Convert to sentence case with .str.capitalize()
pd.Series("hello, world!").str.capitalize() # "Hello, world!"
```

> Formatting settings

```
# Generate an example DataFramed named df
df = pd.DataFrame({"x": [0.123, 4.567, 8.901]})
#     x
#  0 0.123
#  1 4.567
#  2 8.901
```

```
# Visualize and format table output
df.style.format(precision = 1)
```

-	x
0	0.1
1	4.5
2	8.9

The output of `style.format` is an HTML table

> Splitting strings

```
# Split strings into list of characters with .str.split(pat="")
suits.str.split(pat="")

# [, "c" "l" "u" "b" "s", ]
# [, "D" "i" "a" "m" "o" "n" "d" "s", ]
# [, "h" "e" "a" "r" "t" "s", ]
# [, "S" "p" "a" "d" "e" "s", ]

# Split strings by a separator with .str.split()
suits.str.split(pat = "a")

# ["clubs"]
# ["Di", "monds"]
# ["he", "rts"]
# ["Sp", "des"]

# Split strings and return DataFrame with .str.split(expand=True)
suits.str.split(pat = "a", expand=True)

#        0      1
# 0  clubs   None
# 1     Di  monds
# 2     he    rts
# 3     Sp    des
```

> Joining or concatenating strings

```
# Combine two strings with +
suits + "5" # "clubs5" "Diamonds5" "hearts5" "Spades5"

# Collapse character vector to string with .str.cat()
suits.str.cat(sep=", ") # "clubs, Diamonds, hearts, Spades"

# Duplicate and concatenate strings with *
suits * 2 # "clubsclubs" "DiamondsDiamonds" "heartshearts" "SpadesSpades"
```

> Detecting Matches

```
# Detect if a regex pattern is present in strings with .str.contains()
suits.str.contains("[ae]") # False True True True

# Count the number of matches with .str.count()
suits.str.count("[ae]") # 0 1 2 2

# Locate the position of substrings with str.find()
suits.str.find("e") # -1 -1 1 4
```

> Extracting matches

```
# Extract matches from strings with str.findall()
suits.str.findall(".[ae]") # [] ["ia"] ["he"[ ["pa", "de"]

# Extract capture groups with .str.extractall()
suits.str.extractall("([ae])(.)")
#           0 1
#   match
# 1 0       a m
# 2 0       e a
# 3 0       a d
#   1       e s

# Get subset of strings that match with x[x.str.contains()]
suits[suits.str.contains("d")] # "Diamonds" "Spades"
```

> Replacing matches

```
# Replace a regex match with another string with .str.replace()
suits.str.replace("a", "4") # "clubs" "Di4monds" "he4rts" "Sp4des"

# Remove a suffix with .str.removesuffix()
suits.str.removesuffix # "club" "Diamond" "heart" "Spade"

# Replace a substring with .str.slice_replace()
rhymes = pd.Series(["vein", "gain", "deign"])
rhymes.str.slice_replace(0, 1, "r") # "rein" "rain" "reign"
```

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Python For Data Science

Matplotlib Cheat Sheet

Learn Matplotlib online 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.

> Prepare The Data

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'))
```

> 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)
```

> Save Plot

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

> Show Plot

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

> Plotting Routines

1D Data

```
>>> fig, ax = plt.subplots()
>>> 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
```

2D Data

```
>>> 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
```

Vector Fields

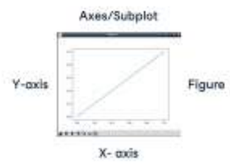
```
>>> axes[0,1].arrow(0,0,0.5,0.5) #Add an arrow to the axes
>>> axes[1,1].quiver(y,z) #Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V) #Plot a 2D field of arrows
```

Data Distributions

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

> Plot Anatomy & Workflow

Plot Anatomy



Workflow

The basic steps to creating plots with matplotlib are:

1 Prepare Data 2 Create Plot 3 Plot 4 Customized 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') #Step 5
>>> plt.show() #Step 6
```

> Close and Clear

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

> Plotting Cutomize 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 and 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
```

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datacamp plotly

Data Visualization with Plotly Express in Python

Learn Plotly online at www.DataCamp.com

> What is plotly?

Plotly Express is a high-level data visualization package that allows you to create interactive plots with very little code. It is built on top of Plotly Graph Objects, which provides a lower-level interface for developing custom visualizations.

> Interactive controls in Plotly

Plotly plots have interactive controls shown in the top-right of the plot. The controls allow you to do the following:

- **Download plot as a png:** Save your interactive plot as a static PNG.
- **Zoom:** Zoom in on a region of interest in the plot.
- **Pan:** Move around in the plot.
- **Box Select:** Select a rectangular region of the plot to be highlighted.
- **Lasso Select:** Draw a region of the plot to be highlighted.
- **Autoscale:** Zoom to a "best" scale.
- **Reset axes:** Return the plot to its original state.
- **Toggle Spike Lines:** Show or hide lines to the axes whenever you hover over data.
- **Show closest data on hover:** Show details for the nearest data point to the cursor.
- **Compare data on hover:** Show the nearest data point to the x-coordinate of the cursor.

> Plotly Express code pattern

The code pattern for creating plots is to call the plotting function, passing a data frame as the first argument. The x argument is a string naming the column to be used on the x-axis. The y argument can either be a string or a list of strings naming column(s) to be used on the y-axis.

```
px.plotting_fn(dataframe, # Dataframe being visualized
               x=["column-for-x-axis"], # Accepts a string or a list of strings
               y=["columns-for-y-axis"], # Accepts a string or a list of strings
               title="Overall plot title", # Accepts a string
               xaxis_title="X-axis title", # Accepts a string
               yaxis_title="Y-axis title", # Accepts a string
               width=width_in_pixels, # Accepts an integer
               height=height_in_pixels) # Accepts an integer
```

> Common plot types

Import plotly

```
# import plotly express as px
import plotly.express as px
```

Scatter plots

```
# Create a scatterplot on a DataFrame named clinical_data
px.scatter(clinical_data, x="experiment_1", y="experiment_2")
```

Set the `size` argument to the name of a numeric column to control the size of the points and create a bubble plot.

Line plots

```
# Create a lineplot on a DataFramed named stock_data
px.line(stock_data, x="date", y=["FB", "AMZN"])
```

Set the `line_dash` argument to the name of a categorical column to have dashes or dots for different lines.

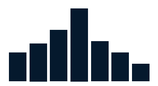
Bar plots

```
# Create a barplot on a DataFramed named commodity_data
px.bar(commodity_data, x="nation", y=["gold", "silver", "bronze"],
       color_discrete_map={"gold": "yellow",
                           "silver": "grey",
                           "bronze": "brown"})
```

Swap the `x` and `y` arguments to draw horizontal bars.

Histograms

```
# Create a histogram on a DataFramed named bill_data
px.histogram(bill_data, x="total_bill")
```



Set the `nbins` argument to control the number of bins shown in the histogram.

Heatmaps

```
# Create a heatmap on a DataFramed named iris_data
px.imshow(iris_data.corr(numeric_only=True),
          zmin=-1, zmax=1, color_continuous_scale='rdbu')
```

Set the `text_auto` argument to `True` to display text values for each cell.

> Customizing plots in plotly

The code pattern for customizing a plot is to save the figure object returned from the plotting function, call its `.update_traces()` method, then call its `.show()` method to display it.

```
# Create a plot with plotly (can be of any type)
fig = px.some_plotting_function()
# Customize and show it with .update_traces() and .show()
fig.update_traces()
fig.show()
```

Customizing markers in Plotly

When working with visualizations like scatter plots, lineplots, and more, you can customize markers according to certain properties. These include:

- `size`: set the marker size
- `color`: set the marker color
- `opacity`: set the marker transparency
- `line`: set the width and color of a border
- `symbol`: set the shape of the marker

```
# In this example, we're updating a scatter plot named fig_sct
fig_sct.update_traces(marker={"size": 24,
                              "color": "magenta",
                              "opacity": 0.5,
                              "line": {"width": 2, "color": "cyan"},
                              "symbol": "square"})
fig_sct.show()
```

Customizing lines in Plotly

When working with visualizations that contain lines, you can customize them according to certain properties. These include:

- `color`: set the line color
- `dash`: set the dash style (`"solid"`, `"dot"`, `"dash"`, `"longdash"`, `"dashdot"`, `"longdashdot"`)
- `shape`: set how values are connected (`"linear"`, `"spline"`, `"hv"`, `"vh"`, `"hvh"`,`"vhv"`)
- `width`: set the line width

```
# In this example, we're updating a scatter plot named fig_ln
fig_ln.update_traces(patch={"line": {"dash": "dot",
                                     "shape": "spline",
                                     "width": 6}})
fig_ln.show()
```

Customizing bars in Plotly

When working with barplots and histograms, you can update the bars themselves according to the following properties:

- `size`: set the marker size
- `color`: set the marker color
- `opacity`: set the marker transparency
- `line`: set the width and color of a border
- `symbol`: set the shape of the marker

```
# In this example, we're updating a scatter plot named fig_bar
fig_bar.update_traces(marker={"color": "magenta",
                              "opacity": 0.5,
                              "line": {"width": 2, "color": "cyan"}})
fig_bar.show()
```



```
# In this example, we're updating a histogram named fig_hst
fig_hst.update_traces(marker={"color": "magenta",
                              "opacity": 0.5,
                              "line": {"width": 2, "color": "cyan"}})
fig_hst.show()
```

Working with Dates and Times in Python

Learn Python Basics online at www.DataCamp.com

> Key definitions

When working with dates and times, you will encounter technical terms and jargon such as the following:

- **Date:** Handles dates without time.
- **POSIXct:** Handles date & time in calendar time.
- **POSIXlt:** Handles date & time in local time.
- **Hms:** Parses periods with hour, minute, and second
- **Timestamp:** Represents a single pandas date & time
- **Interval:** Defines an open or closed range between dates and times
- **Time delta:** Computes time difference between different datetimes

> The ISO8601 datetime format

The **ISO 8601 datetime format** specifies datetimes from the largest to the smallest unit of time **(YYYY-MM-DD HH:MM:SS TZ).** Some of the advantages of ISO 8601 are:

- It avoids ambiguities between MM/DD/YYYY and DD/MM/YYYY formats.
- The 4-digit year representation mitigates overflow problems after the year 2099.
- Using numeric month values (08 not AUG) makes it language independent, so dates make sense throughout the world.
- Python is optimized for this format since it makes comparison and sorting easier.

> Packages used in this cheat sheet

Load the packages and dataset used in this cheatsheet.

```
import datetime as dt
import time as tm
import pytz
import pandas as pd
```

In this cheat sheet, we will be using 3 pandas series — `iso, us, non_us,` and 1 pandas DataFrame `parts`

iso
1969-07-20 20:17:40
1969-11-19 06:54:35
1971-02-05 09:18:11

us
07/20/1969 20:17:40
11/19/1969 06:54:35
02/05/1971 09:18:11

non_us
20/07/1969 20:17:40
19/11/1969 06:54:35
05/02/1971 09:18:11

parts		
year	month	day
1969	7	20
1969	11	19
1971	2	5

> Getting the current date and time

```
# Get the current date
dt.date.today()

# Get the current date and time
dt.datetime.now()
```

> Reading date, datetime, and time columns in a CSV file

```
# Specify datetime column
pd.read_csv("filename.csv", parse_dates = ["col1", "col2"])

# Specify datetime column
pd.read_csv("filename.csv", parse_dates = {"col1": ["year", "month", "day"]})
```

> Parsing dates, datetimes, and times

```
# Parse dates in ISO format
pd.to_datetime(iso)

# Parse dates in US format
pd.to_datetime(us, dayfirst=False)

# Parse dates in NON US format
pd.to_datetime(non_us, dayfirst=True)

# Parse dates, guessing a single format
pd.to_datetime(iso, infer_datetime_format=True)

# Parse dates in single, specified format
pd.to_datetime(iso, format="%Y-%m-%d %H:%M:%S")

# Parse dates in single, specified format
pd.to_datetime(us, format="%m/%d/%Y %H:%M:%S")

# Make dates from components
pd.to_datetime(parts)
```

> Extracting components

```
# Parse strings to datetimes
dttm = pd.to_datetime(iso)

# Get year from datetime pandas series
dttm.dt.year

# Get day of the year from datetime pandas series
dttm.dt.day_of_year

# Get month name from datetime pandas series
dttm.dt.month_name()

# Get day name from datetime pandas series
dttm.dt.day_name()

# Get datetime.datetime format from datetime pandas series
dttm.dt.to_pydatetime()
```

> Rounding dates

```
# Rounding dates to nearest time unit
dttm.dt.round('1min')

# Flooring dates to nearest time unit
dttm.dt.floor('1min')

# Ceiling dates to nearest time unit
dttm.dt.ceil('1min')
```

> Arithmetic

```
# Create two datetimes
now = dt.datetime.now()
then = pd.Timestamp('2021-09-15 10:03:30')

# Get time elapsed as timedelta object
now - then

# Get time elapsed in seconds
(now - then).total_seconds()

# Adding a day to a datetime
dt.datetime(2022,8,5,11,13,50) + dt.timedelta(days=1)
```

> Time Zones

```
# Get current time zone
tm.localtime().tm_zone

# Get a list of all time zones
pytz.all_timezones

# Parse strings to datetimes
dttm = pd.to_datetime(iso)

# Get datetime with timezone using location
dttm.dt.tz_localize('CET', ambiguous='infer')

# Get datetime with timezone using UTC offset
dttm.dt.tz_localize('+0100')

# Convert datetime from one timezone to another
dttm.dt.tz_localize('+0100').tz_convert('US/Central')
```

> Time Intervals

```
# Create interval datetimes
start_1 = pd.Timestamp('2021-10-21 03:02:10')
finish_1 = pd.Timestamp('2022-09-15 10:03:30')
start_2 = pd.Timestamp('2022-08-21 03:02:10')
finish_2 = pd.Timestamp('2022-12-15 10:03:30')

# Specify the interval between two datetimes
pd.Interval(start_1, finish_1, closed='right')

# Get the length of an interval
pd.Interval(start_1, finish_1, closed='right').length

# Determine if two intervals are intersecting
pd.Interval(start_1, finish_1,
closed='right').overlaps(pd.Interval(start_2, finish_2, closed='right'))
```

> Time Deltas

```
# Define a timedelta in days
pd.Timedelta(7, "d")

# Convert timedelta to seconds
pd.Timedelta(7, "d").total_seconds()
```

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Python For Data Science

SciPy Cheat Sheet

Learn SciPy online at www.DataCamp.com

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(c) #Return the real part of the array elements
>>> np.imag(c) #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
>>> A.T #Tranpose matrix
>>> A.H #Conjugate transposition
>>> 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(D,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.isspmatrix_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
```

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)
```

Matrix Functions

Addition

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

Subtraction

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

Division

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

Multiplication

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

Matrix Sign Function

```
>>> np.sigm(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
```

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Python For Data Science

PySpark RDD Cheat Sheet

Learn PySpark RDD online 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

```
#Apply a function to each RDD element
 >>> rdd.map(lambda x: x+(x[1],x[0])).collect()
  [('a',7,7,'a'),('a',2,2,'a'),('b',2,2,'b')]
#Apply a function to each RDD element and flatten the result
 >>> rdd5 = rdd.flatMap(lambda x: x+(x[1],x[0]))
 >>> rdd5.collect()
  ['a',7,7,'a','a',2,2,'a','b',2,2,'b']
#Apply a flatMap function to each (key,value) pair of rdd4 without changing the keys
 >>> rdd4.flatMapValues(lambda x: x).collect()
  [('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).collect()  #Filter the RDD
 [('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).collect() #Merge the rdd values for each key
 [('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]))
#Aggregate RDD elements of each partition and then the results
>>> rdd3.aggregate((0,0),seqOp,combOp)
 (4950,100)
 #Aggregate values of each RDD key
>>> rdd.aggregateByKey((0,0),seqop,combop).collect()
 [('a',(9,2)), ('b',(2,1))]
#Aggregate the elements of each partition, and then the results
>>> rdd3.fold(0,add)
 4950
#Merge the values for each key
>>> rdd.foldByKey(0, add).collect()
 [('a',9),('b',2)]
#Create tuples of RDD elements by applying a function
>>> rdd3.keyBy(lambda x: x+x).collect()
```

> Mathematical Operations

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

> Sort

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