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
>>> x-2
3
>>> x*2
10
>>> x**2
25
>>> x%2
1
>>> x/float(2)
2.5
```

Sum of two variables
Subtraction of two variables
Multiplication of two variables
Exponentiation of a variable
Remainder of a variable
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]
>>> my_list[-3]
```

Select item at index 1
Select 3rd last item

Slice

```
>>> my_list[1:3]
>>> my_list[1:]
>>> my_list[:3]
>>> my_list[:]
```

Select items at index 1 and 2
Select items after index 0
Select items before index 3
Copy my_list

Subset Lists of Lists

```
>>> my_list2[1][0]
>>> my_list2[1][:2]
```

my_list[list][itemOfList]

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)
>>> my_list.count(a)
>>> my_list.append('!')
>>> my_list.remove('!')
>>> del(my_list[0:1])
>>> my_list.reverse()
>>> my_list.extend('!')
>>> my_list.pop(-1)
>>> my_list.insert(0,'!')
>>> my_list.sort()
```

Get the index of an item
Count an item
Append an item at a time
Remove an item
Remove an item
Reverse the list
Append an item
Remove an item
Insert an item
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()
>>> my_string.lower()
>>> my_string.count('w')
>>> my_string.replace('e', 'i')
>>> my_string.strip()
```

String to uppercase
String to lowercase
Count String elements
Replace String elements
Strip whitespace from ends

Libraries

Import libraries

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

Selective import

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

pandas — Data analysis
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
>>> np.append(other_array)
>>> np.insert(my_array, 1, 5)
>>> np.delete(my_array,[1])
>>> np.mean(my_array)
>>> np.median(my_array)
>>> my_array.corrcoef()
>>> np.std(my_array)
```

Get the dimensions of the array
Append items to an array
Insert items in an array
Delete items in an array
Mean of the array
Median of the array
Correlation coefficient
Standard deviation

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NumPy Basics

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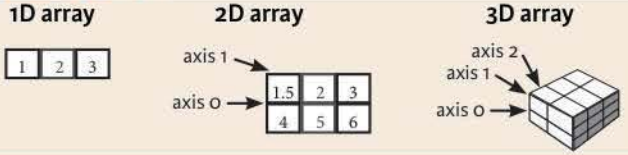
NumPy

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



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 0 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.]]])]
```

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Pandas Basics

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Pandas

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

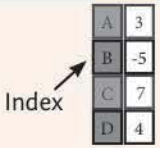
Use the following import convention:

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

Pandas Data Structures

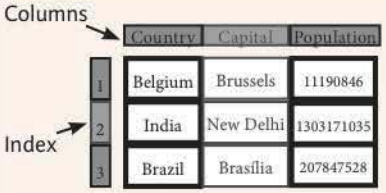
Series

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', 'Brasilia'],
            '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(by='Country')
>>> s.order()
>>> df.rank()
```

Sort by row or column index
Sort a series by its values
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.idmin()/df.idmax()
>>> 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)
>>> pd.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> pd.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()`

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

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.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
```

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*

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))
```

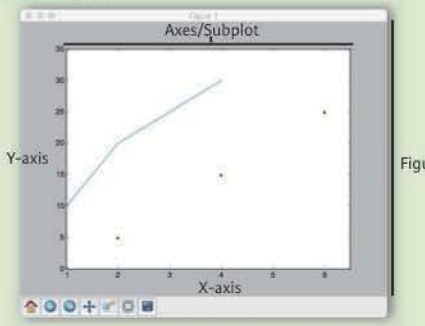
Axes

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

```
>>> 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 o
```

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
```

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

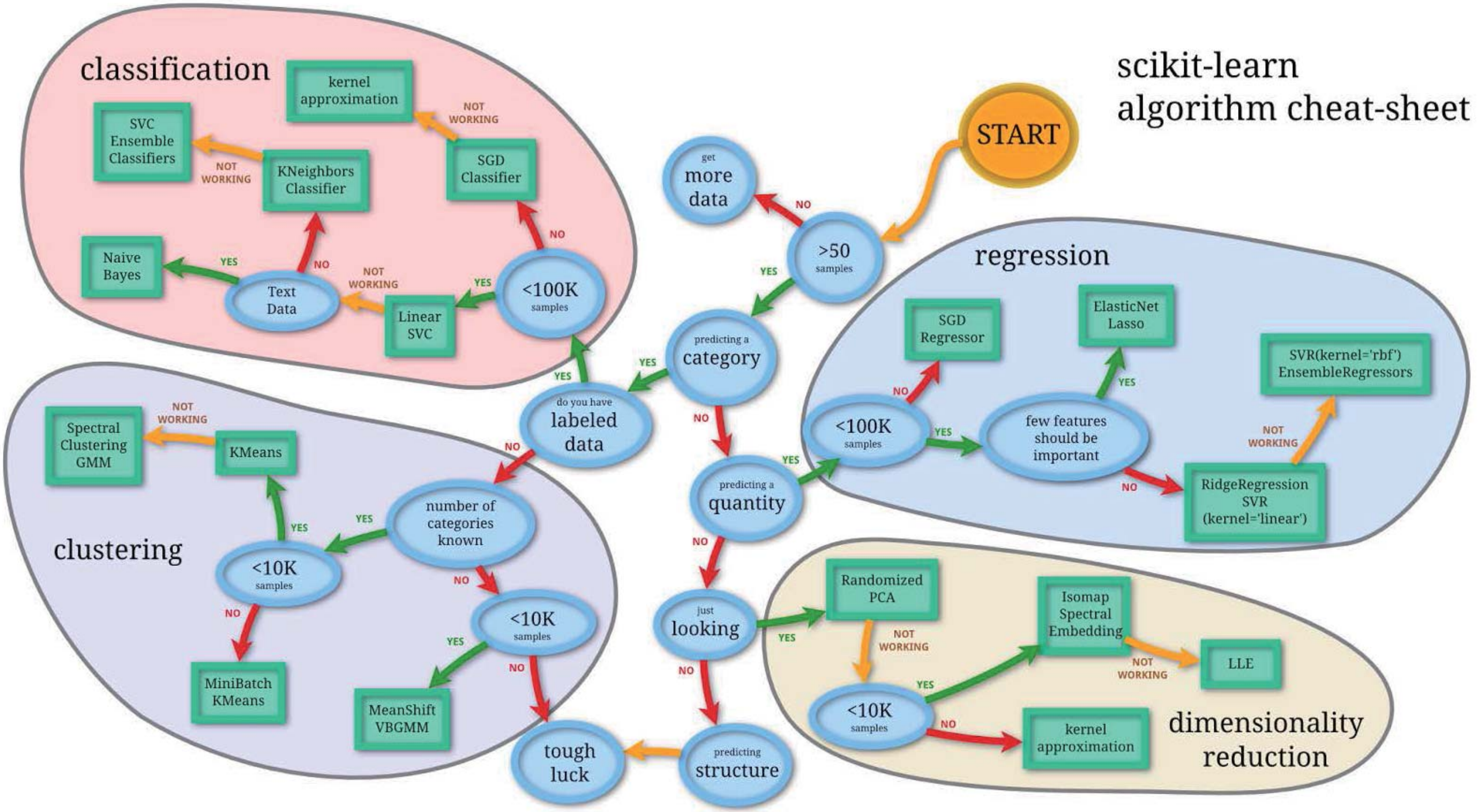
```
>>> plt.savefig('foo.png', transparent=True)
```

6 Show Plot

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

Close & Clear

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


scikit-learn
algorithm cheat-sheet
START
>50 samples
get more data
predicting a category
do you have labeled data
predicting a quantity
just looking
predicting structure
tough luck
classification
<100K samples
SGD Classifier
kernel approximation
Linear SVC
Text Data
Naive Bayes
KNeighbors Classifier
SVC Ensemble Classifiers
clustering
number of categories known
<10K samples
KMeans
Spectral Clustering GMM
MiniBatch KMeans
<10K samples
MeanShift VBGMM
regression
<100K samples
SGD Regressor
few features should be important
ElasticNet Lasso
RidgeRegression SVR (kernel='linear')
SVR(kernel='rbf') EnsembleRegressors
dimensionality reduction
Randomized PCA
<10K samples
Isomap Spectral Embedding
LLE
kernel approximation
YES
NO
NOT WORKING

Python For Data Science *Cheat Sheet*

Scikit-Learn

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

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.cross_validation 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.cross_validation 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*

PySpark 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) pair of rdd4 without changing the keys
       .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)   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*

Keras

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

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*

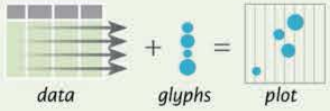
Bokeh

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'])
```

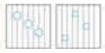
```
>>> from bokeh.models import ColumnDataSource
>>> cds_df = ColumnDataSource(df)
```

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.circle('mpg', 'cyl', source=cds_df,
             selection_color='red',
             nonselection_alpha=0.1)
```

Hover Glyphs

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

Colormapping

```
>>> color_mapper = CategoricalColorMapper(
                   factors=['Europe', 'Asia', 'US'],
                   palette=['red', 'green', 'blue'])
>>> p.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('npg', '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')
```

Summarize Data

`df['w'].value_counts()`
Count number of rows with each unique value of variable

`len(df)`
# of rows in DataFrame.

`df['w'].nunique()`
# of distinct values in a column.

`df.describe()`
Basic descriptive statistics for each column (or GroupBy)

pandas provides a large set of **summary functions** that operate on different kinds of pandas objects (DataFrame columns, Series, GroupBy, Expanding and Rolling (see below)) and produce single values for each of the groups. When applied to a DataFrame, the result is returned as a pandas Series for each column. Examples:

`sum()`
Sum values of each object.

`count()`
Count non-NA/null values of each object.

`median()`
Median value of each object.

`quantile([0.25,0.75])`
Quantiles of each object.

`apply(function)`
Apply function to each object.

`min()`
Minimum value in each object.

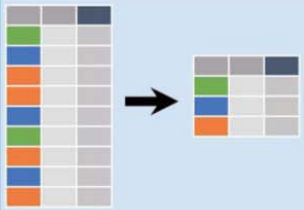
`max()`
Maximum value in each object.

`mean()`
Mean value of each object.

`var()`
Variance of each object.

`std()`
Standard deviation of each object.

Group Data



`df.groupby(by="col")`
Return a GroupBy object, grouped by values in column named "col".

`df.groupby(level="ind")`
Return a GroupBy object, grouped by values in index level named "ind".

All of the summary functions listed above can be applied to a group. Additional GroupBy functions:

`size()`
Size of each group.

`agg(function)`
Aggregate group using function.

The examples below can also be applied to groups. In this case, the function is applied on a per-group basis, and the returned vectors are of the length of the original DataFrame.

`shift(1)`
Copy with values shifted by 1.

`rank(method='dense')`
Ranks with no gaps.

`rank(method='min')`
Ranks. Ties get min rank.

`rank(pct=True)`
Ranks rescaled to interval [0, 1].

`rank(method='first')`
Ranks. Ties go to first value.

`shift(-1)`
Copy with values lagged by 1.

`cumsum()`
Cumulative sum.

`cummax()`
Cumulative max.

`cummin()`
Cumulative min.

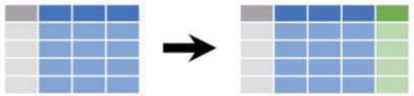
`cumprod()`
Cumulative product.

Handling Missing Data

`df.dropna()`
Drop rows with any column having NA/null data.

`df.fillna(value)`
Replace all NA/null data with value.

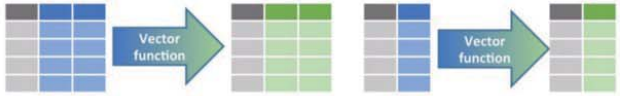
Make New Columns



`df.assign(Area=lambda df: df.Length*df.Height)`
Compute and append one or more new columns.

`df['Volume'] = df.Length*df.Height*df.Depth`
Add single column.

`pd.qcut(df.col, n, labels=False)`
Bin column into n buckets.



pandas provides a large set of **vector functions** that operate on all columns of a DataFrame or a single selected column (a pandas Series). These functions produce vectors of values for each of the columns, or a single Series for the individual Series. Examples:

`max(axis=1)`
Element-wise max.

`clip(lower=-10,upper=10)`
Trim values at input thresholds

`min(axis=1)`
Element-wise min.

`abs()`
Absolute value.

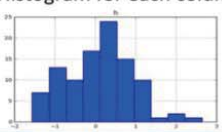
Windows

`df.expanding()`
Return an Expanding object allowing summary functions to be applied cumulatively.

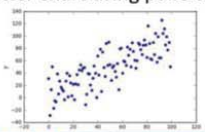
`df.rolling(n)`
Return a Rolling object allowing summary functions to be applied to windows of length n.

Plotting

`df.plot.hist()`
Histogram for each column



`df.plot.scatter(x='w',y='h')`
Scatter chart using pairs of points



Combine Data Sets

adf

x1	x2
A	1
B	2
C	3

+

bdf

x1	x3
A	T
B	F
D	T

=

Standard Joins

x1	x2	x3
A	1	T
B	2	F
C	3	NaN

`pd.merge(adf, bdf, how='left', on='x1')`
Join matching rows from bdf to adf.

x1	x2	x3
A	1.0	T
B	2.0	F
D	NaN	T

`pd.merge(adf, bdf, how='right', on='x1')`
Join matching rows from adf to bdf.

x1	x2	x3
A	1	T
B	2	F

`pd.merge(adf, bdf, how='inner', on='x1')`
Join data. Retain only rows in both sets.

x1	x2	x3
A	1	T
B	2	F
C	3	NaN
D	NaN	T

`pd.merge(adf, bdf, how='outer', on='x1')`
Join data. Retain all values, all rows.

Filtering Joins

x1	x2
A	1
B	2

`adf[adf.x1.isin(bdf.x1)]`
All rows in adf that have a match in bdf.

x1	x2
C	3

`adf[~adf.x1.isin(bdf.x1)]`
All rows in adf that do not have a match in bdf.

ydf

x1	x2
A	1
B	2
C	3

+

zdf

x1	x2
B	2
C	3
D	4

=

Set-like Operations

x1	x2
B	2
C	3

`pd.merge(ydf, zdf)`
Rows that appear in both ydf and zdf (Intersection).

x1	x2
A	1
B	2
C	3
D	4

`pd.merge(ydf, zdf, how='outer')`
Rows that appear in either or both ydf and zdf (Union).

x1	x2
A	1

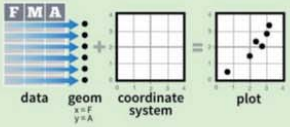
```
pd.merge(ydf, zdf, how='outer',
         indicator=True)
.query('_merge == "left_only"')
.drop(['_merge'],axis=1)
```
Rows that appear in ydf but not zdf (Setdiff).

Data Visualization with ggplot2 Cheat Sheet

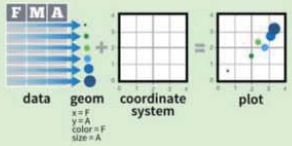
RStudio

Basics

ggplot2 is based on the **grammar of graphics**, the idea that you can build every graph from the same few components: a **data** set, a set of **geoms**—visual marks that represent data points, and a **coordinate system.**



To display data values, map variables in the data set to aesthetic properties of the geom like **size**, **color**, and **x** and **y** locations.



Build a graph with **qplot()** or **ggplot()**

aesthetic mappings · data · geom

qplot(x = cty, y = hwy, color = cyl, data = mpg, geom = "point"**)**

Creates a complete plot with given data, geom, and mappings. Supplies many useful defaults.

ggplot(data = mpg, **aes(**x = cty, y = hwy**))**

Begins a plot that you finish by adding layers to. No defaults, but provides more control than qplot().

data

```
ggplot(mpg, aes(hwy, cty)) +
 geom_point(aes(color = cyl)) +
 geom_smooth(method ="lm") +
 coord_cartesian() +
 scale_color_gradient() +
 theme_bw()
```

add layers, elements with +

layer = geom + default stat + layer specific mappings

additional elements

Add a new layer to a plot with a **geom_*()** or **stat_*()** function. Each provides a geom, a set of aesthetic mappings, and a default stat and position adjustment.

last_plot()

Returns the last plot

ggsave("plot.png", width = 5, height = 5)

Saves last plot as 5' x 5' file named "plot.png" in working directory. Matches file type to file extension.

Geoms - Use a geom to represent data points, use the geom's aesthetic properties to represent variables. Each function returns a layer.

One Variable

Continuous

```
a <- ggplot(mpg, aes(hwy))
```

a + geom_area(stat = "bin")
x, y, alpha, color, fill, linetype, size
b + geom_area(aes(y = ..density..), stat = "bin")

a + geom_density(kernel = "gaussian"**)**
x, y, alpha, color, fill, linetype, size, weight
b + geom_density(aes(y = ..county..))

a + geom_dotplot()
x, y, alpha, color, fill

a + geom_freqpoly()
x, y, alpha, color, linetype, size
b + geom_freqpoly(aes(y = ..density..))

a + geom_histogram(binwidth = 5**)**
x, y, alpha, color, fill, linetype, size, weight
b + geom_histogram(aes(y = ..density..))

Discrete

```
b <- ggplot(mpg, aes(fl))
```

b + geom_bar()
x, alpha, color, fill, linetype, size, weight

Graphical Primitives

```
c <- ggplot(map, aes(long, lat))
```

c + geom_polygon(aes(group = group)**)**
x, y, alpha, color, fill, linetype, size

```
d <- ggplot(economics, aes(date, unemploy))
```

d + geom_path(lineend="butt", linejoin="round', linemitre=1**)**
x, y, alpha, color, linetype, size

d + geom_ribbon(aes(ymin=unemploy - 900, ymax=unemploy + 900)**)**
x, ymax, ymin, alpha, color, fill, linetype, size

```
e <- ggplot(seals, aes(x = long, y = lat))
```

e + geom_segment(aes(
xend = long + delta_long,
yend = lat + delta_lat)**)**
x, xend, y, yend, alpha, color, linetype, size

e + geom_rect(aes(xmin = long, ymin = lat, xmax= long + delta_long, ymax = lat + delta_lat)**)**
xmax, xmin, ymax, ymin, alpha, color, fill, linetype, size

Two Variables

Continuous X, Continuous Y

```
f <- ggplot(mpg, aes(cty, hwy))
```

f + geom_blank()

f + geom_jitter()
x, y, alpha, color, fill, shape, size

f + geom_point()
x, y, alpha, color, fill, shape, size

f + geom_quantile()
x, y, alpha, color, linetype, size, weight

f + geom_rug(sides = "bl"**)**
alpha, color, linetype, size

f + geom_smooth(model = lm**)**
x, y, alpha, color, fill, linetype, size, weight

f + geom_text(aes(label = cty)**)**
x, y, label, alpha, angle, color, family, fontface, hjust, lineheight, size, vjust

Discrete X, Continuous Y

```
g <- ggplot(mpg, aes(class, hwy))
```

g + geom_bar(stat = "identity")
x, y, alpha, color, fill, linetype, size, weight

g + geom_boxplot()
lower, middle, upper, x, ymax, ymin, alpha, color, fill, linetype, shape, size, weight

g + geom_dotplot(binaxis = "y", stackdir = "center"**)**
x, y, alpha, color, fill

g + geom_violin(scale = "area"**)**
x, y, alpha, color, fill, linetype, size, weight

Discrete X, Discrete Y

```
h <- ggplot(diamonds, aes(cut, color))
```

h + geom_jitter()
x, y, alpha, color, fill, shape, size

Continuous Bivariate Distribution

```
i <- ggplot(movies, aes(year, rating))
```

i + geom_bin2d(binwidth = c(5, 0.5)**)**
xmax, xmin, ymax, ymin, alpha, color, fill, linetype, size, weight

i + geom_density2d()
x, y, alpha, colour, linetype, size

i + geom_hex()
x, y, alpha, colour, fill size

Continuous Function

```
j <- ggplot(economics, aes(date, unemploy))
```

j + geom_area()
x, y, alpha, color, fill, linetype, size

j + geom_line()
x, y, alpha, color, linetype, size

j + geom_step(direction = "hv"**)**
x, y, alpha, color, linetype, size

Visualizing error

```
df <- data.frame(grp = c("A", "B"), fit = 4:5, se = 1:2)
k <- ggplot(df, aes(grp, fit, ymin = fit-se, ymax = fit+se))
```

k + geom_crossbar(fatten = 2**)**
x, y, ymax, ymin, alpha, color, fill, linetype, size

k + geom_errorbar()
x, ymax, ymin, alpha, color, linetype, size, width (also **geom_errorbarh()**)

k + geom_linerange()
x, ymin, ymax, alpha, color, linetype, size

k + geom_pointrange()
x, y, ymin, ymax, alpha, color, fill, linetype, shape, size

Maps

```
data <- data.frame(murder = USArrests$Murder,
  state = tolower(rownames(USArrests)))
map <- map_data("state")
l <- ggplot(data, aes(fill = murder))
```

l + geom_map(aes(map_id = state), map = map**) +**
expand_limits(x = map$long, y = map$lat**)**
map_id, alpha, color, fill, linetype, size

Three Variables

```
seals$z <- with(seals, sqrt(delta_long^2 + delta_lat^2))
m <- ggplot(seals, aes(long, lat))
```

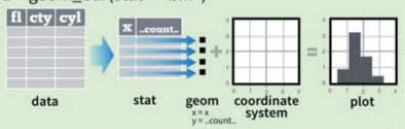
m + geom_contour(aes(z = z)**)**
x, y, z, alpha, colour, linetype, size, weight

m + geom_raster(aes(fill = z), hjust=0.5, vjust=0.5, interpolate=FALSE**)**
x, y, alpha, fill

m + geom_tile(aes(fill = z)**)**
x, y, alpha, color, fill, linetype, size

Stats - An alternative way to build a layer

Some plots visualize a **transformation** of the original data set. Use a **stat** to choose a common transformation to visualize, e.g. a + geom_bar(stat = "bin")



Each stat creates additional variables to map aesthetics to. These variables use a common **..name..** syntax.

stat functions and geom functions both combine a stat with a geom to make a layer, i.e. stat_bin(geom="bar") does the same as geom_bar(stat="bin")

stat function | layer specific mappings | variable created by transformation

i + **stat_density2d**(aes(fill = ..level..), geom = "polygon", n = 100)

geom for layer | parameters for stat

1D distributions

a + **stat_bin**(binwidth = 1, origin = 10)
x, y | ..count.., ..ncount.., ..density.., ..ndensity..
a + **stat_bindot**(binwidth = 1, binaxis = "x")
x, y, | ..count.., ..ncount..
a + **stat_density**(adjust = 1, kernel = "gaussian")
x, y, | ..count.., ..density.., ..scaled..

2D distributions

f + **stat_bin2d**(bins = 30, drop = TRUE)
x, y, fill | ..count.., ..density..
f + **stat_binhex**(bins = 30)
x, y, fill | ..count.., ..density..
f + **stat_density2d**(contour = TRUE, n = 100)
x, y, color, size | ..level..

3 Variables

m + **stat_contour**(aes(z = z))
x, y, z, order | ..level..
m+ **stat_spoke**(aes(radius= z, angle = z))
angle, radius, x, xend, y, yend | ..x.., ..xend.., ..y.., ..yend..
m + **stat_summary_hex**(aes(z = z), bins = 30, fun = mean)
x, y, z, fill | ..value..
m + **stat_summary2d**(aes(z = z), bins = 30, fun = mean)
x, y, z, fill | ..value..

Comparisons

g + **stat_boxplot**(coef = 1.5)
x, y | ..lower.., ..middle.., ..upper.., ..outliers..
g + **stat_ydensity**(adjust = 1, kernel = "gaussian", scale = "area")
x, y | ..density.., ..scaled.., ..count.., ..n.., ..violinwidth.., ..width..

Functions

f + **stat_ecdf**(n = 40)
x, y | ..x.., ..y..
f + **stat_quantile**(quantiles = c(0.25, 0.5, 0.75), formula = y ~ log(x), method = "rq")
x, y | ..quantile.., ..x.., ..y..
f + **stat_smooth**(method = "auto", formula = y ~ x, se = TRUE, n = 80, fullrange = FALSE, level = 0.95)
x, y | ..se.., ..x.., ..y.., ..ymin.., ..ymax..

General Purpose

ggplot() + **stat_function**(aes(x = -3:3), fun = dnorm, n = 101, args = list(sd=0.5))
x | ..y..
f + **stat_identity**()
ggplot() + **stat_qq**(aes(sample=1:100), distribution = qt, dparams = list(df=5))
sample, x, y | ..x.., ..y..
f + **stat_sum**()
x, y, size | ..size..
f + **stat_summary**(fun.data = "mean_cl_boot")
f + **stat_unique**()

Scales

Scales control how a plot maps data values to the visual values of an aesthetic. To change the mapping, add a custom scale.


n <- b + **geom_bar**(aes(fill = fl))
n

scale_ | aesthetic to adjust | prepackaged scale to use | scale specific arguments

n + **scale_fill_manual**(
values = c("skyblue", "royalblue", "blue", "navy"),
limits = c("d", "e", "p", "r"), breaks =c("d", "e", "p", "r"),
name = "fuel", labels = c("D", "E", "P", "R"))

range of values to include in mapping | title to use in legend/axis | labels to use in legend/axis | breaks to use in legend/axis

General Purpose scales

Use with any aesthetic:
alpha, color, fill, linetype, shape, size

scale_*_continuous() - map cont' values to visual values
scale_*_discrete() - map discrete values to visual values
scale_*_identity() - use data values **as** visual values
scale_*_manual(values = c()) - map discrete values to manually chosen visual values

X and Y location scales

Use with x or y aesthetics (x shown here)

scale_x_date(labels = date_format("%m/%d"), breaks = date_breaks("2 weeks")) - treat x values as dates. See ?strptime for label formats.
scale_x_datetime() - treat x values as date times. Use same arguments as scale_x_date().
scale_x_log10() - Plot x on log10 scale
scale_x_reverse() - Reverse direction of x axis
scale_x_sqrt() - Plot x on square root scale

Color and fill scales

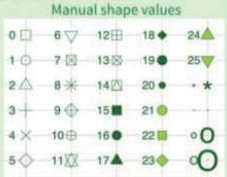
Discrete	Continuous
n <- b + **geom_bar**(aes(fill = fl))	o <- a + **geom_dotplot**(aes(fill = ..x..))
n + **scale_fill_brewer**(palette = "Blues") For palette choices: library(RColorBrewer) display.brewer.all()	o + **scale_fill_gradient**(low = "red", high = "yellow")
	o + **scale_fill_gradient2**(low = "red", hight = "blue", mid = "white", midpoint = 25)
n + **scale_fill_grey**(start = 0.2, end = 0.8, na.value = "red")	o + **scale_fill_gradientn**(colours = terrain.colors(6)) Also: rainbow(), heat.colors(), topo.colors(), cm.colors(), RColorBrewer::brewer.pal()

Shape scales



p <- f + **geom_point**(aes(shape = fl))
p + **scale_shape**(solid = FALSE)
p + **scale_shape_manual**(values = c(3:7)) Shape values shown in chart on right

Manual shape values



Size scales


q <- f + **geom_point**(aes(size = cyl))
q + **scale_size_area**(max = 6) Value mapped to area of circle (not radius)

Coordinate Systems

r <- b + geom_bar()

r + **coord_cartesian**(xlim = c(0, 5))
xlim, ylim
The default cartesian coordinate system

r + **coord_fixed**(ratio = 1/2)
ratio, xlim, ylim
Cartesian coordinates with fixed aspect ratio between x and y units

r + **coord_flip**()
xlim, ylim
Flipped Cartesian coordinates

r + **coord_polar**(theta = "x", direction=1)
theta, start, direction
Polar coordinates

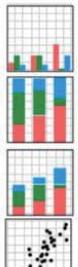
r + **coord_trans**(ytrans = "sqrt")
xtrans, ytrans, limx, limy
Transformed cartesian coordinates. Set extras and strains to the name of a window function.

z + **coord_map**(projection = "ortho", orientation=c(41, -74, 0))
projection, orientation, xlim, ylim
Map projections from the mapproj package (mercator (default), azequalarea, lagrange, etc.)

Position Adjustments

Position adjustments determine how to arrange geoms that would otherwise occupy the same space.

s <- ggplot(mpg, aes(fl, fill = drv))



s + **geom_bar**(**position = "dodge"**)
Arrange elements side by side

s + **geom_bar**(**position = "fill"**)
Stack elements on top of one another, normalize height

s + **geom_bar**(**position = "stack"**)
Stack elements on top of one another

f + **geom_point**(**position = "jitter"**)
Add random noise to X and Y position of each element to avoid overplotting

Each position adjustment can be recast as a function with manual **width** and **height** arguments

s + **geom_bar**(**position = position_dodge(width = 1)**)

Themes

r + **theme_bw**()
White background with grid lines

r + **theme_grey**()
Grey background (default theme)

r + **theme_classic**()
White background no gridlines

r + **theme_minimal**()
Minimal theme

ggthemes - Package with additional ggplot2 themes

Faceting

Facets divide a plot into subplots based on the values of one or more discrete variables.

t <- ggplot(mpg, aes(cty, hwy)) + geom_point()

t + **facet_grid**(. ~ fl)
facet into columns based on fl

t + **facet_grid**(year ~ .)
facet into rows based on year

t + **facet_grid**(year ~ fl)
facet into both rows and columns

t + **facet_wrap**(~ fl)
wrap facets into a rectangular layout

Set **scales** to let axis limits vary across facets

t + **facet_grid**(y ~ x, **scales = "free"**)
x and y axis limits adjust to individual facets
- **"free_x"** - x axis limits adjust
- **"free_y"** - y axis limits adjust

Set **labeller** to adjust facet labels

t + facet_grid(. ~ fl, **labeller = label_both**)

fl: c	fl: d	fl: e	fl: p	fl: r

t + facet_grid(. ~ fl, **labeller = label_bquote**(alpha ^ .(x)))

α^c	α^d	α^e	α^p	α^r

t + facet_grid(. ~ fl, **labeller = label_parsed**)

c	d	e	p	r

Labels

t + **ggtitle**("New Plot Title")
Add a main title above the plot
t + **xlab**("New X label")
Change the label on the X axis
t + **ylab**("New Y label")
Change the label on the Y axis
t + **labs**(title =" New title", x = "New x", y = "New y")
All of the above

Use scale functions to update legend labels

Legends

t + **theme**(legend.position = "bottom")
Place legend at "bottom", "top", "left", or "right"
t + **guides**(color = "none")
Set legend type for each aesthetic: colorbar, legend, or none (no legend)
t + **scale_fill_discrete**(name = "Title", labels = c("A", "B", "C"))
Set legend title and labels with a scale function.

Zooming

Without clipping (preferred)
t + **coord_cartesian**(xlim = c(0, 100), ylim = c(10, 20))

With clipping (removes unseen data points)

t + **xlim**(0, 100) + **ylim**(10, 20)
t + **scale_x_continuous**(limits = c(0, 100)) + **scale_y_continuous**(limits = c(0, 100))

Data Wrangling with dplyr and tidyr Cheat Sheet

RStudio

Tidy Data - A foundation for wrangling in R

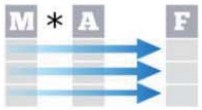
In a tidy data set:

Each **variable** is saved in its own **column**

&

Each **observation** is saved in its own **row**

Tidy data complements R's **vectorized operations**. R will automatically preserve observations as you manipulate variables. No other format works as intuitively with R.



Syntax - Helpful conventions for wrangling

dplyr::**tbl_df(iris)**

Converts data to tbl class. tbl's are easier to examine than data frames. R displays only the data that fits onscreen:

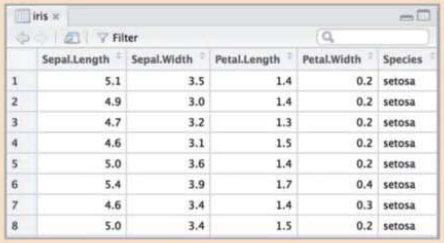
```
Source: local data frame [150 x 5]

   Sepal.Length Sepal.Width Petal.Length
1           5.1         3.5          1.4
2           4.9         3.0          1.4
3           4.7         3.2          1.3
4           4.6         3.1          1.5
5           5.0         3.6          1.4
..          ...         ...          ...
Variables not shown: Petal.Width (dbl),
  Species (fctr)
```

dplyr::**glimpse(iris)**

Information dense summary of tbl data.

utils::**View(iris)**

View data set in spreadsheet-like display (note capital V).



	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa
7	4.6	3.4	1.4	0.3	setosa
8	5.0	3.4	1.5	0.2	setosa

dplyr::**%>%**

Passes object on left hand side as first argument (or . argument) of function on righthand side.

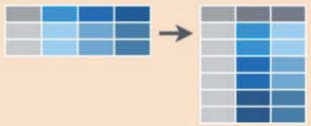
`x %>% f(y)` *is the same as* `f(x, y)`

`y %>% f(x, ., z)` *is the same as* `f(x, y, z )`

"Piping" with %>% makes code more readable, e.g.

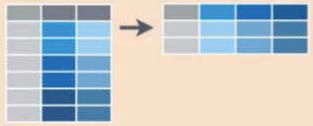
```
iris %>%
  group_by(Species) %>%
  summarise(avg = mean(Sepal.Width)) %>%
  arrange(avg)
```

Reshaping Data - Change the layout of a data set



tidyr::**gather(cases, "year", "n", 2:4)**

Gather columns into rows.



tidyr::**spread(pollution, size, amount)**

Spread rows into columns.

tidyr::**separate(storms, date, c("y", "m", "d"))**

Separate one column into several.

tidyr::**unite(data, col, ..., sep)**

Unite several columns into one.

dplyr::**data_frame(a = 1:3, b = 4:6)**

Combine vectors into data frame (optimized).

dplyr::**arrange(mtcars, mpg)**

Order rows by values of a column (low to high).

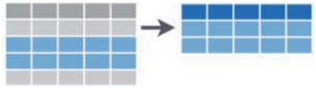
dplyr::**arrange(mtcars, desc(mpg))**

Order rows by values of a column (high to low).

dplyr::**rename(tb, y = year)**

Rename the columns of a data frame.

Subset Observations (Rows)



dplyr::**filter(iris, Sepal.Length > 7)**

Extract rows that meet logical criteria.

dplyr::**distinct(iris)**

Remove duplicate rows.

dplyr::**sample_frac(iris, 0.5, replace = TRUE)**

Randomly select fraction of rows.

dplyr::**sample_n(iris, 10, replace = TRUE)**

Randomly select n rows.

dplyr::**slice(iris, 10:15)**

Select rows by position.

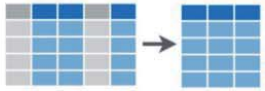
dplyr::**top_n(storms, 2, date)**

Select and order top n entries (by group if grouped data).

Logic in R - ?Comparison, ?base::Logic

<	Less than	!=	Not equal to
>	Greater than	%in%	Group membership
==	Equal to	is.na	Is NA
<=	Less than or equal to	!is.na	Is not NA
>=	Greater than or equal to	&, |, !, xor, any, all	Boolean operators

Subset Variables (Columns)



dplyr::**select(iris, Sepal.Width, Petal.Length, Species)**

Select columns by name or helper function.

Helper functions for select - ?select

select(iris, contains("."))
Select columns whose name contains a character string.

select(iris, ends_with("Length"))
Select columns whose name ends with a character string.

select(iris, everything())
Select every column.

select(iris, matches(".t."))
Select columns whose name matches a regular expression.

select(iris, num_range("x", 1:5))
Select columns named x1, x2, x3, x4, x5.

select(iris, one_of(c("Species", "Genus")))
Select columns whose names are in a group of names.

select(iris, starts_with("Sepal"))
Select columns whose name starts with a character string.

select(iris, Sepal.Length:Petal.Width)
Select all columns between Sepal.Length and Petal.Width (inclusive).

select(iris, -Species)
Select all columns except Species.

devtools::**install_github("rstudio/EDAWR")** for data sets

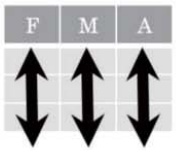
Learn more with **browseVignettes(package = c("dplyr", "tidyr"))** • dplyr 0.4.0• tidyr 0.2.0 • Updated: 1/15

Data Wrangling with pandas Cheat Sheet

http://pandas.pydata.org

Tidy Data – A foundation for wrangling in pandas

In a tidy data set:



&

Each **variable** is saved in its own **column**

Each **observation** is saved in its own **row**

Tidy data complements pandas's **vectorized operations**. pandas will automatically preserve observations as you manipulate variables. No other format works as intuitively with pandas.

M * A

Syntax – Creating DataFrames

	a	b	c
1	4	7	10
2	5	8	11
3	6	9	12

```
df = pd.DataFrame(
        {"a" : [4 ,5, 6],
         "b" : [7, 8, 9],
         "c" : [10, 11, 12]},
       index = [1, 2, 3])
```

Specify values for each column.

```
df = pd.DataFrame(
    [[4, 7, 10],
     [5, 8, 11],
     [6, 9, 12]],
    index=[1, 2, 3],
    columns=['a', 'b', 'c'])
```

Specify values for each row.

		a	b	c
n	v			
d	1	4	7	10
	2	5	8	11
e	2	6	9	12

```
df = pd.DataFrame(
        {"a" : [4 ,5, 6],
         "b" : [7, 8, 9],
         "c" : [10, 11, 12]},
index = pd.MultiIndex.from_tuples(
        [('d',1),('d',2),('e',2)],
          names=['n','v'])))
```

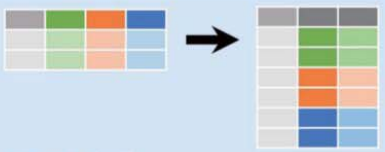
Create DataFrame with a MultiIndex

Method Chaining

Most pandas methods return a DataFrame so that another pandas method can be applied to the result. This improves readability of code.

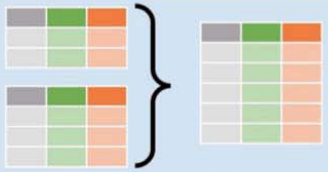
```
df = (pd.melt(df)
        .rename(columns={
                'variable' : 'var',
                'value' : 'val'})
        .query('val >= 200')
    )
```

Reshaping Data – Change the layout of a data set



pd.melt(df)
Gather columns into rows.

df.pivot(columns='var', values='val')
Spread rows into columns.



pd.concat([df1,df2])
Append rows of DataFrames

pd.concat([df1,df2], axis=1)
Append columns of DataFrames

df.sort_values('mpg')
Order rows by values of a column (low to high).

df.sort_values('mpg',ascending=False)
Order rows by values of a column (high to low).

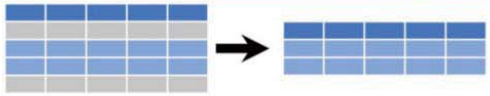
df.rename(columns = {'y':'year'})
Rename the columns of a DataFrame

df.sort_index()
Sort the index of a DataFrame

df.reset_index()
Reset index of DataFrame to row numbers, moving index to columns.

df.drop(['Length','Height'], axis=1)
Drop columns from DataFrame

Subset Observations (Rows)



df[df.Length > 7]
Extract rows that meet logical criteria.

df.drop_duplicates()
Remove duplicate rows (only considers columns).

df.head(n)
Select first n rows.

df.tail(n)
Select last n rows.

df.sample(frac=0.5)
Randomly select fraction of rows.

df.sample(n=10)
Randomly select n rows.

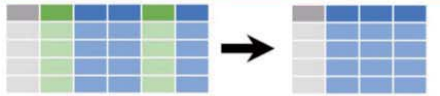
df.iloc[10:20]
Select rows by position.

df.nlargest(n, 'value')
Select and order top n entries.

df.nsmallest(n, 'value')
Select and order bottom n entries.

Logic in Python (and pandas)			
<	Less than	!=	Not equal to
>	Greater than	df.column.isin(*values*)	Group membership
==	Equals	pd.isnull(*obj*)	Is NaN
<=	Less than or equals	pd.notnull(*obj*)	Is not NaN
>=	Greater than or equals	&,|,~,^,df.any(),df.all()	Logical and, or, not, xor, any, all

Subset Variables (Columns)



df[['width','length','species']]
Select multiple columns with specific names.

df['width'] *or* **df.width**
Select single column with specific name.

df.filter(regex='*regex*')
Select columns whose name matches regular expression *regex*.

regex (Regular Expressions) Examples	
'\.'	Matches strings containing a period '.'
'Length$'	Matches strings ending with word 'Length'
'^Sepal'	Matches strings beginning with the word 'Sepal'
'^x[1-5]$'	Matches strings beginning with 'x' and ending with 1,2,3,4,5
''^(?!Species$).*'	Matches strings except the string 'Species'

df.loc[:,'x2':'x4']
Select all columns between x2 and x4 (inclusive).

df.iloc[:,[1,2,5]]
Select columns in positions 1, 2 and 5 (first column is 0).

df.loc[df['a'] > 10, ['a','c']]
Select rows meeting logical condition, and only the specific columns .

Summarise Data

dplyr::**summarise(iris, avg = mean(Sepal.Length))**
Summarise data into single row of values.

dplyr::**summarise_each(iris, funs(mean))**
Apply summary function to each column.

dplyr::**count(iris, Species, wt = Sepal.Length)**
Count number of rows with each unique value of variable (with or without weights).

Summarise uses **summary functions**, functions that take a vector of values and return a single value, such as:

dplyr::**first**
First value of a vector.

dplyr::**last**
Last value of a vector.

dplyr::**nth**
Nth value of a vector.

dplyr::**n**
# of values in a vector.

dplyr::**n_distinct**
# of distinct values in a vector.

IQR
IQR of a vector.

min
Minimum value in a vector.

max
Maximum value in a vector.

mean
Mean value of a vector.

median
Median value of a vector.

var
Variance of a vector.

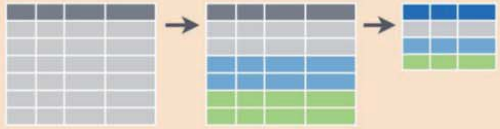
sd
Standard deviation of a vector.

Group Data

dplyr::**group_by(iris, Species)**
Group data into rows with the same value of Species.

dplyr::**ungroup(iris)**
Remove grouping information from data frame.

iris %>% group_by(Species) %>% summarise(…)
Compute separate summary row for each group.



Make New Variables

dplyr::**mutate(iris, sepal = Sepal.Length + Sepal. Width)**
Compute and append one or more new columns.

dplyr::**mutate_each(iris, funs(min_rank))**
Apply window function to each column.

dplyr::**transmute(iris, sepal = Sepal.Length + Sepal. Width)**
Compute one or more new columns. Drop original columns.

Mutate uses **window functions**, functions that take a vector of values and return another vector of values, such as:

dplyr::**lead**
Copy with values shifted by 1.

dplyr::**lag**
Copy with values lagged by 1.

dplyr::**dense_rank**
Ranks with no gaps.

dplyr::**min_rank**
Ranks. Ties get min rank.

dplyr::**percent_rank**
Ranks rescaled to [0, 1].

dplyr::**row_number**
Ranks. Ties got to first value.

dplyr::**ntile**
Bin vector into n buckets.

dplyr::**between**
Are values between a and b?

dplyr::**cume_dist**
Cumulative distribution.

dplyr::**cumall**
Cumulative `all`

dplyr::**cumany**
Cumulative `any`

dplyr::**cummean**
Cumulative `mean`

cumsum
Cumulative `sum`

cummax
Cumulative `max`

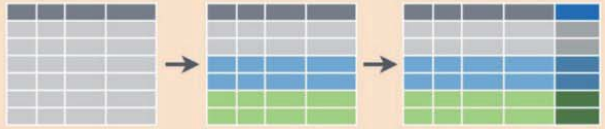
cummin
Cumulative `min`

cumprod
Cumulative `prod`

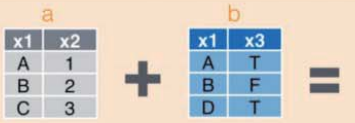
pmax
Element-wise `max`

pmin
Element-wise `min`

iris %>% group_by(Species) %>% mutate(…)
Compute new variables by group.



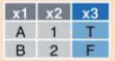
Combine Data Sets



Mutating Joins

dplyr::**left_join(a, b, by = "x1")**
Join matching rows from b to a.

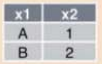
dplyr::**right_join(a, b, by = "x1")**
Join matching rows from a to b.



dplyr::**inner_join(a, b, by = "x1")**
Join data. Retain only rows in both sets.

dplyr::**full_join(a, b, by = "x1")**
Join data. Retain all values, all rows.

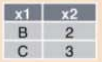
Filtering Joins



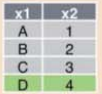
dplyr::**semi_join(a, b, by = "x1")**
All rows in a that have a match in b.

dplyr::**anti_join(a, b, by = "x1")**
All rows in a that do not have a match in b.

Set Operations



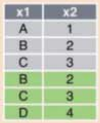
dplyr::**intersect(y, z)**
Rows that appear in both y and z.



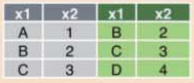
dplyr::**union(y, z)**
Rows that appear in either or both y and z.

dplyr::**setdiff(y, z)**
Rows that appear in y but not z.

Binding



dplyr::**bind_rows(y, z)**
Append z to y as new rows.



dplyr::**bind_cols(y, z)**
Append z to y as new columns.
Caution: matches rows by position.

devtools::**install_github("rstudio/EDAWR")** for data sets

Learn more with **browseVignettes(package = c("dplyr", "tidyr"))** • dplyr 0.4.0• tidyr 0.2.0 • Updated: 1/15

General Minimization Algorithm:

$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k$ *or* $\Delta\mathbf{x}_k = (\mathbf{x}_{k+1} - \mathbf{x}_k) = \alpha_k \mathbf{p}_k$

Steepest Descent Algorithm:

$\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha_k \mathbf{g}_k$ **where,** $\mathbf{g}_k = \nabla F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}_k}$

Stable Learning Rate: ($\alpha_k = \alpha$, constant) $\alpha < \frac{2}{\lambda_{max}}$

$\{\lambda_1\ \lambda_2, \ldots, \lambda_n\}$ Eigenvalues of Hessian matrix A

Learning Rate to Minimize Along the Line:

$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k \overset{is}{\Rightarrow} \alpha_k = -\frac{\mathbf{g}_k^T \mathbf{p}_k}{\mathbf{p}_k^T \mathbf{A} \mathbf{p}_k}$ (For quadratic fn.)

After Minimization Along the Line:

$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k \Rightarrow \mathbf{g}_{k+1}^T \mathbf{p}_k = 0$

ADALINE: $\mathbf{a} = purelin(\mathbf{W}\mathbf{p} + \mathbf{b})$

Mean Square Error: *(for ADALINE it is a quadratic fn.)*

$F(\mathbf{x}) = E[e^2] = E[(t - a)^2] = E[(t - \mathbf{x}^T\mathbf{z})^2]$

$F(\mathbf{x}) = c - 2\mathbf{x}^T\mathbf{h} + \mathbf{x}^T\mathbf{R}\mathbf{x}$,

$c = E[t^2]$, $\mathbf{h} = E[t\mathbf{z}]$ *and* $\mathbf{R} = E[\mathbf{z}\mathbf{z}^T] \Rightarrow \mathbf{A} = 2\mathbf{R}, \mathbf{d} = -2\mathbf{h}$

Unique minimum, if it exists, is $\mathbf{x}^* = \mathbf{R}^{-1}\mathbf{h}$,

where $\mathbf{x} = \begin{bmatrix} {}_1\mathbf{w} \\ b \end{bmatrix}$ and $\mathbf{z} = \begin{bmatrix} \mathbf{p} \\ 1 \end{bmatrix}$

LMS Algorithm: $\mathbf{W}(k+1) = \mathbf{W}(k) + 2\alpha\, \mathbf{e}(k)\, \mathbf{p}^T(k)$

$\mathbf{b}(k+1) = \mathbf{b}(k) + 2\alpha\, \mathbf{e}(k)$

Convergence Point: $\mathbf{x}^* = \mathbf{R}^{-1}\mathbf{h}$

Stable Learning Rate: $0 < \alpha < 1/\lambda_{max}$ where λ_{max} is the maximum eigenvalue of R

Adaptive Filter ADALINE:

$$a(k) = purelin(\mathbf{W}\mathbf{p}(k) + b) = \sum_{i=1}^{R} \mathbf{w}_{1,i}\, y(k - i + 1) + b$$

Backpropagation Algorithm:

Performance Index:

Mean Square error: $F(\mathbf{x}) = E[\mathbf{e}^T\mathbf{e}] = E[(\mathbf{t} - \mathbf{a})^T(\mathbf{t} - \mathbf{a})]$

Approximate Performance Index: (single sample)

$\hat{F}(x) = \mathbf{e}^T(k)\mathbf{e}(k) = (\mathbf{t}(k) - \mathbf{a}(k))^T(\mathbf{t}(k) - \mathbf{a}(k))$

Sensitivity: $\mathbf{s}^m = \frac{\partial \hat{F}}{\partial \mathbf{n}^m} = \left[\frac{\partial \hat{F}}{\partial n_1^m} \quad \frac{\partial \hat{F}}{\partial n_2^m} \quad \cdots \quad \frac{\partial \hat{F}}{\partial n_{s^m}^m}\right]^T$

Forward Propagation: $\mathbf{a}^0 = \mathbf{p}$,

$\mathbf{a}^{m+1} = \mathbf{f}^{m+1}(\mathbf{W}^{m+1}\mathbf{a}^m + \mathbf{b}^{m+1})$ *for* $m = 0, 1, \ldots, M-1$

$\mathbf{a} = \mathbf{a}^M$

Backward Propagation: $\mathbf{s}^M = -2\dot{\mathbf{F}}^M(\mathbf{n}^M)(\mathbf{t} - \mathbf{a})$,

$\mathbf{s}^m = \dot{\mathbf{F}}^m(\mathbf{n}^m)(\mathbf{W}^{m+1})^T\mathbf{s}^{m+1}$ *for* $m = M-1, \ldots, 2, 1$, where

$\dot{\mathbf{F}}^m(\mathbf{n}^m) = \text{diag}\left(\left[\dot{f}^m(n_1^m) \quad \dot{f}^m(n_2^m) \quad \ldots \quad \dot{f}^m(n_{s^m}^m)\right]\right)$

$$\dot{f}^m(n_j^m) = \frac{\partial f^m(n_j^m)}{\partial n_j^m}$$

Weight Update (Approximate Steepest Descent):

$\mathbf{W}^m(k+1) = \mathbf{W}^m(k) - \alpha \mathbf{s}^m(\mathbf{a}^{m-1})^T$

$\mathbf{b}^m(k+1) = \mathbf{b}^m(k) - \alpha \mathbf{s}^m$

*Heuristic Variations of Backpropagation:

Batching: The parameters are updated only after the entire training set has been presented. The gradients calculated for each training example are averaged together to produce a more accurate estimate of the gradient.(If the training set is complete, i.e., covers all possible input/output pairs, then the gradient estimate will be exact.)

Backpropagation with Momentum (MOBP):

$\Delta\mathbf{W}^m(k) = \gamma\Delta\mathbf{W}^m(k-1) - (1-\gamma)\alpha\, \mathbf{s}^m(\mathbf{a}^{m-1})^T$

$\Delta\mathbf{b}^m(k) = \gamma\Delta\mathbf{b}^m(k-1) - (1-\gamma)\alpha\, \mathbf{s}^m$

Variable Learning Rate Backpropagation (VLBP)

1. If the squared error (over the entire training set) increases by more than some set percentage ζ (typically one to five percent) after a weight update, then the weight update is discarded, the learning rate is multiplied by some factor $\rho < 1$, and the momentum coefficient γ (if it is used) is set to zero.
2. If the squared error decreases after a weight update, then the weight update is accepted and the learning rate is multiplied by some factor $\eta > 1$. If γ has been previously set to zero, it is reset to its original value.
3. If the squared error increases by less than ζ, then the weight update is accepted but the learning rate and the momentum coefficient are unchanged.

Association: $\mathbf{a} = hardlim(\mathrm{W}^0\mathrm{P}^0 + \mathbf{W}\mathbf{p} + b)$

An association is a link between the inputs and outputs of a network so that when a stimulus A is presented to the network, it will output a response B.

Associative Learning Rules:

Unsupervised Hebb Rule:

$\mathbf{W}(q) = \mathbf{W}(q-1) + \alpha\, \mathbf{a}(q)\mathbf{p}^T(q)$

Hebb with Decay:

$\mathbf{W}(q) = (1-\gamma)\mathbf{W}(q-1) + \alpha\, \mathbf{a}(q)\mathbf{p}^T(q)$

Instar: $\mathbf{a} = hardlim(\mathbf{W}\mathbf{p} + b)$, $\mathbf{a} = hardlim({}_1\mathbf{w}^T\mathbf{p} + b)$

The instar is activated for ${}_1\mathbf{w}^T\mathbf{p} = \|{}_1\mathbf{w}\|\|\mathbf{p}\| cos\theta \geq -b$

where θ is the angle between $\mathbf{p}$ and ${}_1\mathbf{w}$.

Instar Rule:

${}_i\mathbf{w}(q) = {}_i\mathbf{w}(q-1) + \alpha\, a_i(q)(\mathbf{p}(q) - {}_i\mathbf{w}(q-1))$

${}_i\mathbf{w}(q) = (1-\alpha)\, {}_i\mathbf{w}(q-1) + \alpha\, \mathbf{p}(q)$, *if* $(a_i(q) = 1)$

Kohonen Rule:

${}_i\mathbf{w}(q) = {}_i\mathbf{w}(q-1) + \alpha\,(\mathbf{p}(q) - {}_i\mathbf{w}(q-1))$ *for* $i \in X(q)$

Outstar Rule: $\mathbf{a} = satlins(\mathbf{W}p)$

$\mathbf{w}_j(q) = \mathbf{w}_j(q-1) + \alpha\left(\mathbf{a}(q) - \mathbf{w}_j(q-1)\right)\mathrm{p}_j(q)$

Competitive Layer: $\mathbf{a} = compet(\mathbf{W}\mathbf{p}) = compet(\mathbf{n})$

Competitive Learning with the Kohonen Rule:

${}_{i^*}\mathbf{w}(q) = {}_{i^*}\mathbf{w}(q-1) + \alpha\left(\mathbf{p}(q) - {}_{i^*}\mathbf{w}(q-1)\right)$

$= (1-\alpha)\, {}_{i^*}\mathbf{w}(q-1) + \alpha\, \mathbf{p}(q)$

${}_{i^*}\mathbf{w}(q) = {}_{i^*}\mathbf{w}(q-1)$, $i \neq i^*$ where i^* is the winning neuron.

Self-Organizing with the Kohonen Rule:

${}_i\mathbf{w}(q) = {}_i\mathbf{w}(q-1) + \alpha\left(\mathbf{p}(q) - {}_i\mathbf{w}(q-1)\right)$

$= (1-\alpha)\, {}_i\mathbf{w}(q-1) + \alpha\, \mathbf{p}(q)$, $i \in N_{i^*}(d)$

$N_i(d) = \{j, d_{i,j} \leq d\}$

LVQ Network: $(w_{k,i}^2 = 1) \Rightarrow$ subclass i is a part of class k

$n_i^1 = -\left\| {}_i\mathbf{w}^1 - \mathbf{p} \right\|$, $\mathbf{a}^1 = compet(\mathbf{n}^1)$, $\mathbf{a}^2 = \mathbf{W}^2\mathbf{a}^1$

LVQ Network Learning with the Kohonen Rule:

${}_{i^*}\mathbf{w}^1(q) = {}_{i^*}\mathbf{w}^1(q-1) + \alpha\left(\mathbf{p}(q) - {}_{i^*}\mathbf{w}^1(q-1)\right)$,

if $a_{k^*}^2 = t_{k^*} = 1$

${}_{i^*}\mathbf{w}^1(q) = {}_{i^*}\mathbf{w}^1(q-1) - \alpha\left(\mathbf{p}(q) - {}_{i^*}\mathbf{w}^1(q-1)\right)$,

if $a_{k^*}^2 = 1 \neq t_{k^*} = 0$

---

hardlim: $a = \begin{cases} 0 & n < 0 \\ 1 & n \geq 0 \end{cases}$, ***hardlims***: $a = \begin{cases} -1 & n < 0 \\ +1 & n \geq 0 \end{cases}$, ***purelin***: $a = n$, ***Logsig***: $a = \frac{1}{1+e^{-n}}$, ***tansig***: $a = \frac{e^n - e^{-n}}{e^n + e^{-n}}$, ***poslin***: $a = \begin{cases} 0 & n < 0 \\ n & n \geq 0 \end{cases}$,

compet: $a = \begin{cases} 1 & \text{neuron with max } n \\ 0 & \text{all other neurons} \end{cases}$, ***satlin***: $a = \begin{cases} 0 & n < 0 \\ n & -1 \leq n \leq 1 \\ 1 & n > 1 \end{cases}$, ***satlins***: $a = \begin{cases} -1 & n < 0 \\ n & -1 \leq n \leq 1 \\ 1 & n > 1 \end{cases}$,

Delay: $a(t) = u(t-1)$, ***Integrator***: $a(t) = \int_0^t u(\tau)d\tau + a(0)$

****HINT:**

$diag([1\ 2\ 3]) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}$

Linear Vector Spaces:

Definition: A linear vector space, X, is a set of elements (vectors) defined over a scalar field, F, that satisfies the following conditions:

1) if $x \in X$ and $y \in X$ then $x+y \in X$. **2)** $x+y=y+x$ **3)** $(x+y)+z=x+(y+z)$
4) There is a unique vector $0 \in X$, such that $x+0=x$ for all $x \in X$.
5) For each vector $x \in X$ there is a unique vector in X, to be called $(-x)$, such that $x+(-x)=0$. **6)** multiplication, for all scalars $a \in F$, and all vectors $x \in X$,
7) For any $x \in X$, $1x=x$ (for scalar 1).
8) For any two scalars $a \in F$ and $b \in F$ and any $x \in X$, $a(bx)=(ab)x$.
9) $(a+b)x=ax+bx$. **10)** $a(x+y)=ax+ay$.

Linear Independence: Consider n vectors $\{x_1, x_2, .., x_n\}$. If there exists n scalars $a_1, a_2, \ldots, a_n$, at least one of which is nonzero, such that $a_1x_1 + a_2x_2 + \ldots + a_nx_n = 0$, then the $\{x_i\}$ are linearly dependent.

Spanning a Space:
Let X be a linear vector space and let $\{u_1, u_2, \ldots, u_n\}$ be a subset of vectors in X. This subset spans X if and only if for every vector $x \in X$ there exist scalars $x_1, x_2, \ldots, x_n$ such that $x = x_1u_1+x_2u_2+\ldots+x_nu_n$.

Inner Product: (x, y) for any scalar function of x and y.
1. $(x,y) = (y,x)$ 2. $(x, ay_1 + by_2) = a(x,y_1) + b(x,y_2)$
3. $(x,x) \geq 0$, where equality holds iff x is the zero vector.

Norm: Ascalar function $\|x\|$ is called a norm if it satisfies:
1. $\|x\| \geq 0$ 2. $\|x\| = 0$ if and only if $x = 0$.
3. $\|ax\| = |a|\|x\|$ 4. $\|x + y\| \leq \|x\| + \|y\|$

Angle: The angle θ bet. 2 vectors x and y is defined by $\cos\theta = \frac{(x,y)}{\|x\|\,\|y\|}$

Orthogonality: 2 vectors $x, y \in X$ are said to be orthogonal if $(x,y) = 0$.

Gram Schmidt Orthogonalization:
Assume that we have n independent vectors $y_1, y_2, \ldots, y_n$. From these vectors we will obtain n orthogonal vectors $v_1, v_2, \ldots, v_n$.

$$v_1 = y_1, \quad v_k = y_k - \sum_{i=1}^{k-1} \frac{(v_i, y_k)}{(v_i, v_i)} v_i,$$

$$where\ \frac{(v_i, y_k)}{(v_i, v_i)} v_i\ is\ the\ projection\ of\ y_k\ on\ v_i$$

Vector Expansions:

$$x = \sum_{i=1}^{n} x_i v_i = x_1v_1 + x_2v_2 + \cdots + x_nv_n,$$

$$for\ orthogonal\ vectors, x_j = \frac{(v_j, x)}{(v_j, v_j)}$$

Reciprocal Basis Vectors:

$$(r_i, v_j) = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases}, \quad x_j = (r_j, x)$$

To compute the reciprocal basis vectors: set $\mathbf{B} = [v_1\ v_2\ \ldots\ v_n]$,
$\mathbf{R} = [r_1\ r_2\ \ldots\ r_n]$, $\mathbf{R}^T = \mathbf{B}^{-1}$ In matrix form: $\mathbf{x}^v = \mathbf{B}^{-1}\mathbf{x}^s$

Transformations:
A *transformation* consists of three parts:
domain: $X = \{x_i\}$, range: $Y = \{y_i\}$, and a rule relating each $x_i \in X$ to an element $y_i \in Y$.

Linear Transformations: transformation A is *linear* if:
1. for all $x_1, x_2 \in X$, $A(x_1+x_2) = A(x_1) + A(x_2)$
2. for all $x \in X, a \in R$, $A(ax) = aA(x)$

Matrix Representations:
Let $\{v_1, v_2, \ldots, v_n\}$ be a basis for vector space X, and let $\{u_1, u_2, \ldots, u_n\}$ be a basis for vector space Y. Let A be a linear transformation with domain X and range Y: $A(x) = y$
The coefficients of the matrix representation are obtained from

$$A(v_j) = \sum_{i=1}^{m} a_{ij}u_i$$

Change of Basis: $\mathbf{B}_t = [\mathbf{t}_1\ \mathbf{t}_2\ \ldots \mathbf{t}_n]$, $\mathbf{B}_w = [\mathbf{w}_1\ \mathbf{w}_2\ \ldots \mathbf{w}_n]$
$\mathbf{A}' = [\mathbf{B}_w^{-1}\mathbf{A}\mathbf{B}_t]$

Eigenvalues & Eigenvectors: $\mathbf{Az} = \lambda\mathbf{z}$, $|[\mathbf{A} - \lambda\mathbf{I}]| = 0$

Diagonalization: $\mathbf{B} = [\mathbf{z}_1\ \mathbf{z}_2\ \ldots \mathbf{z}_n]$,
where $\{\mathbf{z}, \mathbf{z}_2, \ldots, \mathbf{z}_n\}$ are the eigenvectors of a square matrix A,
$[\mathbf{B}^{-1}\mathbf{A}\mathbf{B}] = \mathrm{diag}([\lambda_1\ \lambda_2\ \ldots \lambda_n])$

Perceptron Architecture:

$\mathbf{a} = hardlim(\mathbf{Wp} + \mathbf{b})$, $\mathbf{W} = [{}_1\mathbf{w}^T\ {}_2\mathbf{w}^T\ \ldots\ {}_S\mathbf{w}^T]^T$,
$a_i = hardlim(n_i) = hardlim({}_i\mathbf{w}^T\,\mathrm{p} + b_i)$

Decision Boundary: ${}_i\mathbf{w}^T\,\mathrm{p} + b_i = 0$
The decision boundary is always orthogonal to the weight vector.
Single-layer perceptrons can only classify linearly separable vectors.

Perceptron Learning Rule

$$\mathbf{W}^{new} = \mathbf{W}^{old} + \mathbf{ep}^T, \mathbf{b}^{new} = \mathbf{b}^{old} + \mathbf{e},$$
$$where\ \ \mathbf{e} = \mathbf{t} - \mathbf{a}$$

Hebb's Postulate: "When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

Linear Associator: $\mathbf{a} = purelin(\mathbf{Wp})$

The Hebb Rule: *Supervised Form:* $w_{ij}^{new} = w_{ij}^{old} + t_{qi}P_{qi}$

$$\mathbf{W} = \boldsymbol{t}_1\boldsymbol{P}_1^T + \boldsymbol{t}_2\boldsymbol{P}_2^T + \cdots + \boldsymbol{t}_Q\boldsymbol{P}_Q^T$$

$$\mathbf{W} = [\mathbf{t}_1\ \mathbf{t}_2 \ldots \mathbf{t}_Q]\begin{bmatrix}\mathbf{p}_1^T \\ \mathbf{p}_2^T \\ \vdots \\ \mathbf{p}_Q^T\end{bmatrix} = \mathbf{TP}^T$$

Pseudoinverse Rule: $\mathbf{W} = \mathbf{TP}^+$
When the number, R, of rows of $\mathbf{P}$ is greater than the num ber of columns, Q, of $\mathbf{P}$ and the columns of $\mathbf{P}$ are independent, then the pseudoinverse can be computed by $\mathbf{P}^+ = (\mathbf{P}^T\mathrm{P})^{-1}\mathbf{P}^T$

Variations of Hebbian Learning:

Filtered Learning (Ch.14): $\mathbf{W}^{new} = (1-\gamma)\mathbf{W}^{old} + \alpha\mathbf{t}_q\mathbf{p}_q^T$

Delta Rule (Ch.10): $\mathbf{W}^{new} = \mathbf{W}^{old} + \alpha(\mathbf{t}_q - \mathbf{a}_q)\mathbf{p}_q^T$

Unsupervised Hebb (Ch.13): $\mathbf{W}^{new} = \mathbf{W}^{old} + \alpha\mathbf{a}_q\mathbf{p}_q^T$

Taylor: $F(\mathbf{x}) = F(\mathbf{x}^*) + \nabla F(\mathbf{x})^T|_{\mathbf{x}=\mathbf{x}^*}(\mathbf{x}-\mathbf{x}^*) + \frac{1}{2}(\mathbf{x}-\mathbf{x}^*)\nabla^2 F(\mathbf{x})^T|_{\mathbf{x}=\mathbf{x}^*}(\mathbf{x}-\mathbf{x}^*) + \cdots$

Grad $\nabla F(\mathbf{x}) = \left[\frac{\partial}{\partial x_1}F(\mathbf{x})\ \ \frac{\partial}{\partial x_2}F(\mathbf{x})\ \ \ldots \frac{\partial}{\partial x_n}F(\mathbf{x})\right]^T$

Hessian: $\nabla^2 F(\mathbf{x}) =$

$$\begin{bmatrix} \frac{\partial}{\partial x_1^2}F(\mathbf{x}) & \frac{\partial}{\partial x_1 \partial x_2}F(\mathbf{x}) \ldots & \frac{\partial}{\partial x_1 \partial x_n}F(\mathbf{x}) \\ \frac{\partial}{\partial x_2 \partial x_1}F(\mathbf{x}) & \frac{\partial}{\partial x_2^2}F(\mathbf{x}) \ldots & \frac{\partial}{\partial x_2 \partial x_n}F(\mathbf{x}) \\ \vdots & \vdots & \vdots \\ \frac{\partial}{\partial x_n \partial x_1}F(\mathbf{x}) & \frac{\partial}{\partial x_n \partial x_2}F(\mathbf{x}) \ldots & \frac{\partial}{\partial x_n^2}F(\mathbf{x}) \end{bmatrix}$$

Directional Derivatives:

1st Dir.Der.: $\frac{\mathbf{p}^T\nabla F(\mathbf{x})}{\|\mathbf{p}\|}$, **2nd Dir.Der.:** $\frac{\mathbf{p}^T\nabla^2 F(\mathbf{x})\mathbf{p}}{\|\mathbf{p}\|^2}$

Minima:
Strong Minimum: if a scalar $\delta > 0$ exists, such that $F(x) < F(x+\Delta x)$ for all Δx such that $\delta > \|\Delta x\| > 0$.
Global Minimum: if $F(x) < F(x+\Delta x)$ for all $\Delta x \neq 0$
Weak Minimum: if it is not a strong minimum, and a scalar $\delta > 0$ exists, such that $F(x) \leq F(x+\Delta x)$ for all Δx such that $\delta > \|\Delta x\| > 0$.

Necessary Conditions for Optimality:
1st-Order Condition: $\nabla F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}^*} = 0$ (Stationary Points)
2nd-Order Condition: $\nabla^2 F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}^*} \geq 0$ (Positive Semi-definite Hessian Matrix).

Quadratic fn.: $F(\mathrm{x}) = \frac{1}{2}\mathbf{x}^T\mathbf{A}\,\mathbf{x} + \mathbf{d}^T\mathbf{x} + \mathrm{c}$

$\nabla F(\mathrm{x}) = \mathbf{Ax} + \mathbf{d}$, $\nabla^2 F(\mathrm{x}) = \mathbf{A}$, $\boldsymbol{\lambda_{min}} \leq \frac{\mathbf{p}^T\mathbf{A}\,\mathbf{p}}{\|\mathbf{p}\|^2} \leq \boldsymbol{\lambda_{max}}$

About

TensorFlow

TensorFlow™ is an open source software library for numerical computation using data flow graphs. TensorFlow was originally developed for the purposes of conducting machine learning and deep neural networks research, but the system is general enough to be applicable in a wide variety of other domains as well.

Skflow

Scikit Flow provides a set of high level model classes that you can use to easily integrate with your existing Scikit-learn pipeline code. Scikit Flow is a simplified interface for TensorFlow, to get people started on predictive analytics and data mining. Scikit Flow has been merged into TensorFlow since version 0.8 and now called TensorFlow Learn.

Keras

Keras is a minimalist, highly modular neural networks library, written in Python and capable of running on top of either TensorFlow or Theano

Installation

How to install new package in Python:

`pip install <package-name>`

Example: `pip install requests`

How to install tensorflow?

device = **cpu/gpu**

python_version = **cp27/cp34**

```
sudo pip install
https://storage.googleapis.com/
tensorflow/linux/$device/tensorflow-
0.8.0-$python_version-none-linux_x86
_64.whl
```

How to install Skflow

`pip install sklearn`

How to install Keras

`pip install keras`

update ~/.keras/keras.json - replace "theano" by "tensorflow"

Helpers

Python helper

Important functions

`type(object)`
Get object type

`help(object)`
Get help for object (list of available methods, attributes, signatures and so on)

`dir(object)`
Get list of object attributes (fields, functions)

`str(object)`
Transform an object to string

`object?`
Shows documentations about the object

`globals()`
Return the dictionary containing the current scope's global variables.

`locals()`
Update and return a dictionary containing the current scope's local variables.

`id(object)`
Return the identity of an object. This is guaranteed to be unique among simultaneously existing objects.

```
import __builtin__
dir(__builtin__)
```

Other built-in functions

TensorFlow

Main classes

`tf.Graph()`
`tf.Operation()`
`tf.Tensor()`
`tf.Session()`

Some useful functions

`tf.get_default_session()`
`tf.get_default_graph()`
`tf.reset_default_graph()`
`ops.reset_default_graph()`
`tf.device("/cpu:0")`
`tf.name_scope(value)`
`tf.convert_to_tensor(value)`

TensorFlow Optimizers

`GradientDescentOptimizer`
`AdadeltaOptimizer`
`AdagradOptimizer`
`MomentumOptimizer`
`AdamOptimizer`
`FtrlOptimizer`
`RMSPropOptimizer`

Reduction

`reduce_sum`
`reduce_prod`
`reduce_min`
`reduce_max`
`reduce_mean`
`reduce_all`
`reduce_any`
`accumulate_n`

Activation functions

`tf.nn?`
relu
relu6
elu
softplus
softsign
dropout
bias_add
sigmoid
tanh
sigmoid_cross_entropy_with_logits
softmax
log_softmax
softmax_cross_entropy_with_logits
sparse_softmax_cross_entropy_with_logits
weighted_cross_entropy_with_logits
etc.

Skflow

Main classes

TensorFlowClassifier
TensorFlowRegressor
TensorFlowDNNClassifier
TensorFlowDNNRegressor
TensorFlowLinearClassifier
TensorFlowLinearRegressor
TensorFlowRNNClassifier
TensorFlowRNNRegressor
TensorFlowEstimator

Each classifier and regressor have following fields

n_classes=0 (Regressor), n_classes are expected to be input (Classifiers)

batch_size=32,
steps=200, // except TensorFlowRNNClassifier - there is 50
optimizer='Adagrad',
learning_rate=0.1,

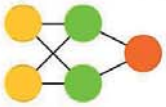
A mostly complete chart of

Neural Networks

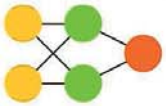
- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablistic Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolution or Pool

Perceptron (P)

Feed Forward (FF)

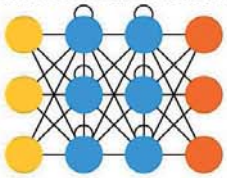


Radial Basis Network (RBF)

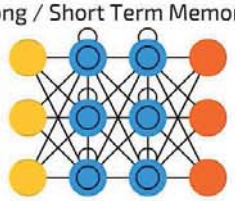


Deep Feed Forward (DFF)

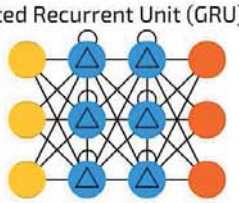
Recurrent Neural Network (RNN)



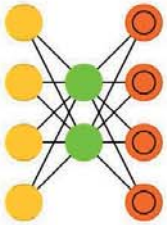
Long / Short Term Memory (LSTM)



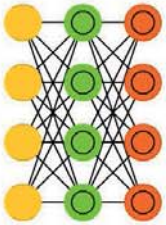
Gated Recurrent Unit (GRU)



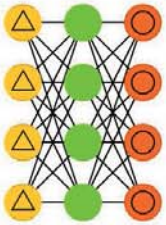
Auto Encoder (AE)



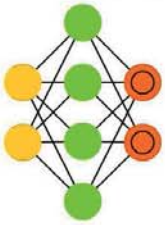
Variational AE (VAE)



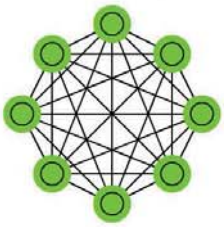
Denoising AE (DAE)



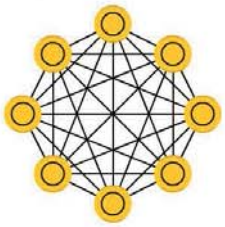
Sparse AE (SAE)



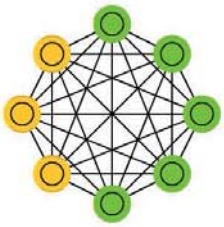
Markov Chain (MC)



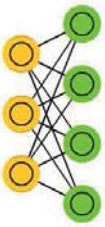
Hopfield Network (HN)



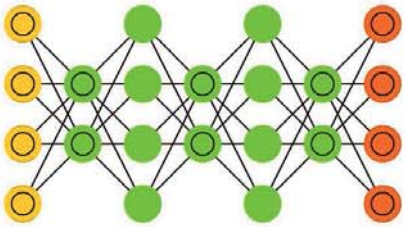
Boltzmann Machine (BM)



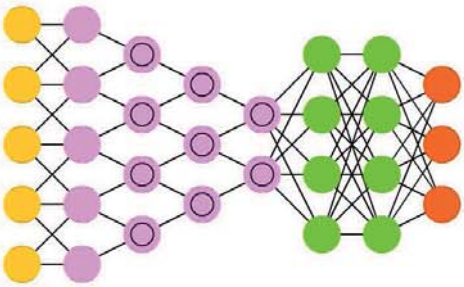
Restricted BM (RBM)



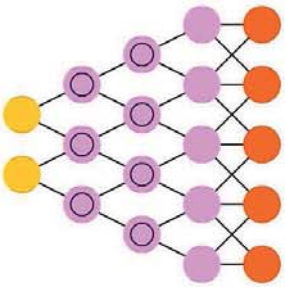
Deep Belief Network (DBN)



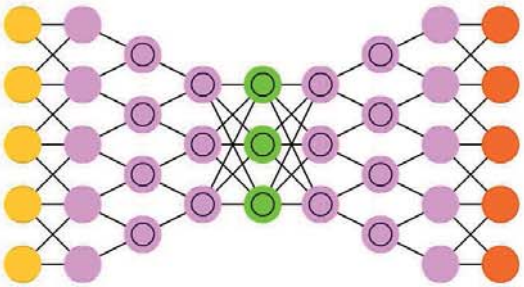
Deep Convolutional Network (DCN)



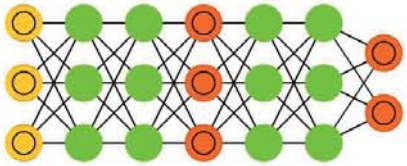
Deconvolutional Network (DN)



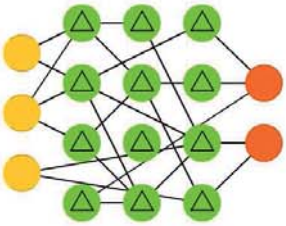
Deep Convolutional Inverse Graphics Network (DCIGN)



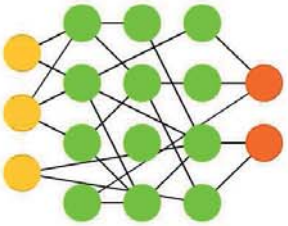
Generative Adversarial Network (GAN)



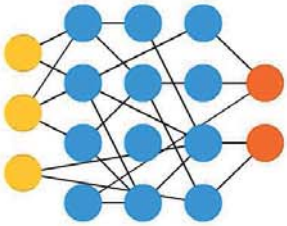
Liquid State Machine (LSM)



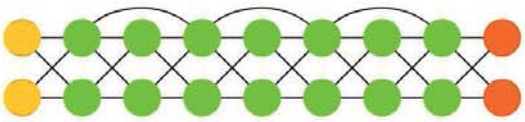
Extreme Learning Machine (ELM)



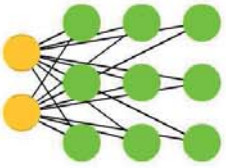
Echo State Network (ESN)



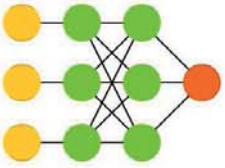
Deep Residual Network (DRN)



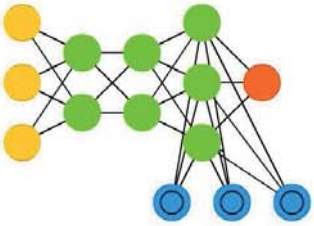
Kohonen Network (KN)



Support Vector Machine (SVM)

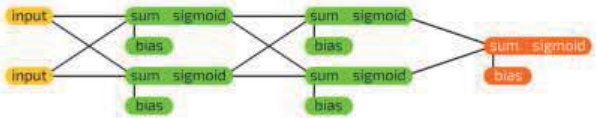


Neural Turing Machine (NTM)

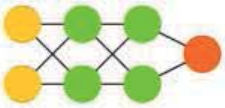


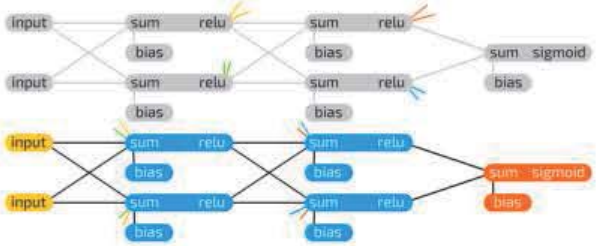
An informative chart to build

Neural Network Graphs

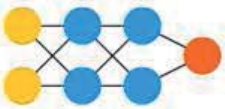


Deep Feed Forward Example

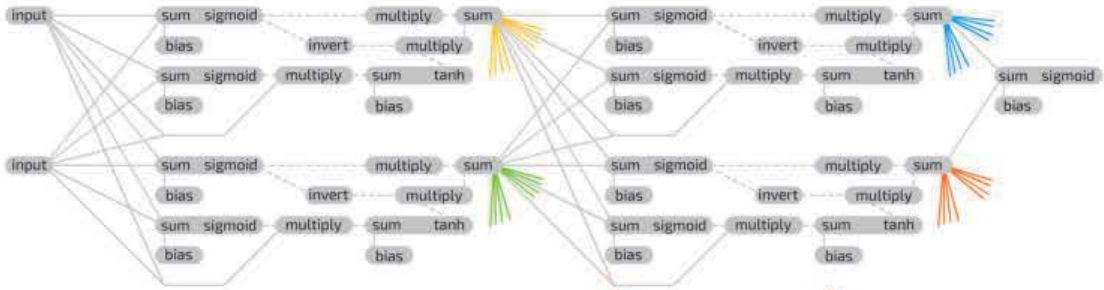




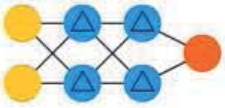
Deep Recurrent Example
(previous iteration)

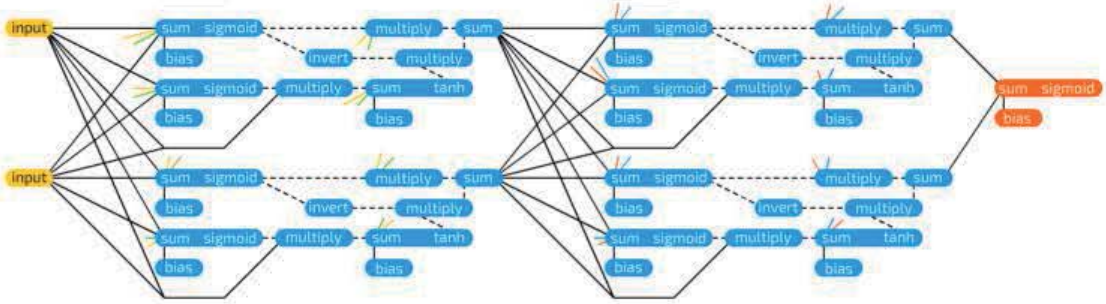


Deep Recurrent Example

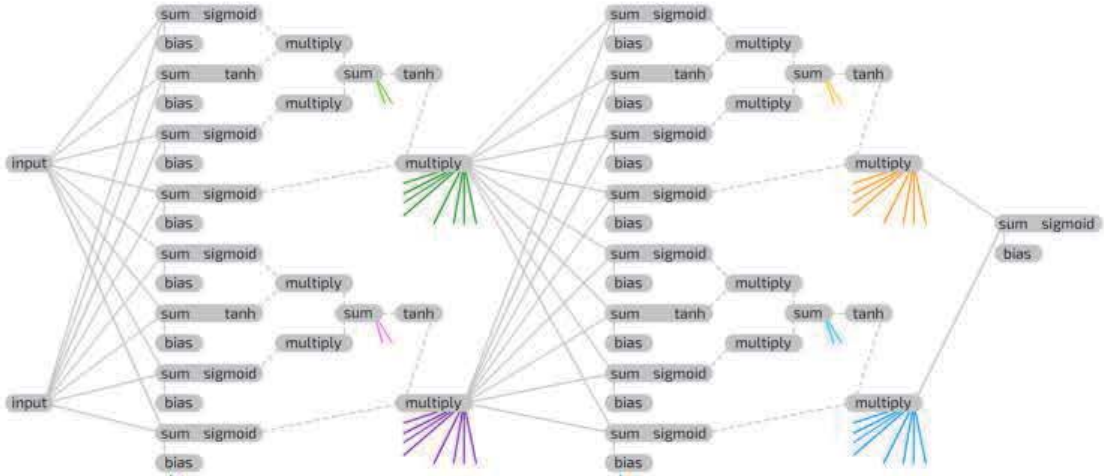


Deep GRU Example
(previous iteration)

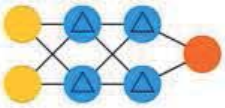


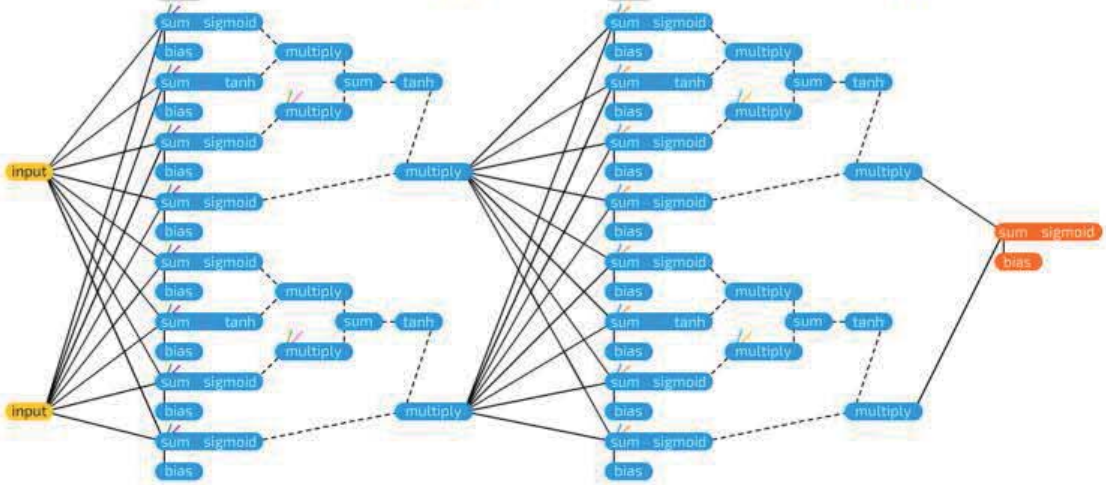


Deep GRU Example



Deep LSTM Example
(previous iteration)





Deep LSTM Example

MACHINE LEARNING IN EMOJI

SUPERVISED UNSUPERVISED REINFORCEMENT

SUPERVISED human builds model based on input / output

UNSUPERVISED human input, machine output
human utilizes if satisfactory

REINFORCEMENT human input, machine output
human reward/punish, cycle continues

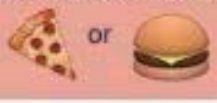
BASIC REGRESSION

LINEAR linear_model.LinearRegression()

Lots of numerical data

LOGISTIC linear_model.LogisticRegression()

Target variable is categorical



CLASSIFICATION

NEURAL NET neural_network.MLPClassifier()

Complex relationships. Prone to overfitting
Basically magic.

K-NN neighbors.KNeighborsClassifier()

Group membership based on proximity

DECISION TREE tree.DecisionTreeClassifier()

If/then/else. Non-contiguous data
Can also be regression

RANDOM FOREST ensemble.RandomForestClassifier()

Find best split randomly
Can also be regression

SVM svm.SVC() svm.LinearSVC()

Maximum margin classifier. Fundamental
Data Science algorithm

NAIVE BAYES GaussianNB() MultinomialNB() BernoulliNB()

Updating knowledge step by step with new info

CLUSTER ANALYSIS

K-MEANS cluster.KMeans()

Similar datum into groups
based on centroids

ANOMALY DETECTION covariance.EllipticalEnvelope()

Finding outliers
through grouping

FEATURE REDUCTION

T-DISTRIB STOCHASTIC NEIB EMBEDDING manifold.TSNE()

Visualize high dimensional data. Convert
similarity to joint probabilities

PRINCIPLE COMPONENT ANALYSIS decomposition.PCA()

Distill feature space into components that
describe greatest variance

CANONICAL CORRELATION ANALYSIS decomposition.CCA()

Making sense of cross-correlation
matrices

LINEAR DISCRIMINANT ANALYSIS lda.LDA()

Linear combination of features that
separates classes

OTHER IMPORTANT CONCEPTS

BIAS VARIANCE TRADEOFF

UNDERFITTING / OVERFITTING

INERTIA

ACCURACY FUNCTION $(TP + TN) / (P + N)$

PRECISION FUNCTION $TP / (TP + FP)$

SPECIFICITY FUNCTION $TN / (FP + TN)$

SENSITIVITY FUNCTION $TP / (TP + FN)$

@emilyinamillion made this

Array Sorting Algorithms

Algorithm	Time Complexity			Space Complexity
	Best	Average	Worst	Worst
Quicksort	Ω(n log(n))	θ(n log(n))	O(n^2)	O(log(n))
Mergesort	Ω(n log(n))	θ(n log(n))	O(n log(n))	O(n)
Timsort	Ω(n)	θ(n log(n))	O(n log(n))	O(n)
Heapsort	Ω(n log(n))	θ(n log(n))	O(n log(n))	O(1)
Bubble Sort	Ω(n)	θ(n^2)	O(n^2)	O(1)
Insertion Sort	Ω(n)	θ(n^2)	O(n^2)	O(1)
Selection Sort	Ω(n^2)	θ(n^2)	O(n^2)	O(1)
Tree Sort	Ω(n log(n))	θ(n log(n))	O(n^2)	O(n)
Shell Sort	Ω(n log(n))	θ(n(log(n))^2)	O(n(log(n))^2)	O(1)
Bucket Sort	Ω(n+k)	θ(n+k)	O(n^2)	O(n)
Radix Sort	Ω(nk)	θ(nk)	O(nk)	O(n+k)
Counting Sort	Ω(n+k)	θ(n+k)	O(n+k)	O(k)
Cubesort	Ω(n)	θ(n log(n))	O(n log(n))	O(n)

Common Data Structure Operations

Data Structure	Time Complexity								Space Complexity
	Average				Worst				Worst
	Access	Search	Insertion	Deletion	Access	Search	Insertion	Deletion	
Array	Θ(1)	Θ(n)	Θ(n)	Θ(n)	O(1)	O(n)	O(n)	O(n)	O(n)
Stack	Θ(n)	Θ(n)	Θ(1)	Θ(1)	O(n)	O(n)	O(1)	O(1)	O(n)
Queue	Θ(n)	Θ(n)	Θ(1)	Θ(1)	O(n)	O(n)	O(1)	O(1)	O(n)
Singly-Linked List	Θ(n)	Θ(n)	Θ(1)	Θ(1)	O(n)	O(n)	O(1)	O(1)	O(n)
Doubly-Linked List	Θ(n)	Θ(n)	Θ(1)	Θ(1)	O(n)	O(n)	O(1)	O(1)	O(n)
Skip List	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(n)	O(n)	O(n)	O(n)	O(n log(n))
Hash Table	N/A	Θ(1)	Θ(1)	Θ(1)	N/A	O(n)	O(n)	O(n)	O(n)
Binary Search Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(n)	O(n)	O(n)	O(n)	O(n)
Cartesian Tree	N/A	Θ(log(n))	Θ(log(n))	Θ(log(n))	N/A	O(n)	O(n)	O(n)	O(n)
B-Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(n)
Red-Black Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(n)
Splay Tree	N/A	Θ(log(n))	Θ(log(n))	Θ(log(n))	N/A	O(log(n))	O(log(n))	O(log(n))	O(n)
AVL Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(n)
KD Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(n)	O(n)	O(n)	O(n)	O(n)

<BIG-O-CHEATSHEET>

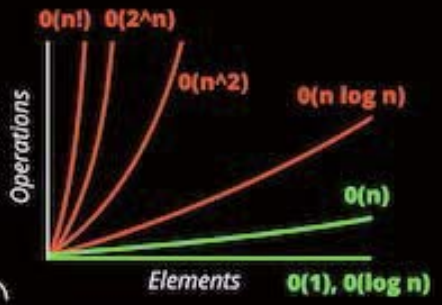
www.bigocheatsheet.com

LEGEND

TIME Complexity vs. **SPACE** Complexity

Good Fair Bad

Good Fair Bad



DATA STRUCTURE Operations

DATA Structure

TIME Complexity

Average

	Access	Search	Insertion	Deletion
Array	Θ(1)	Θ(n)	Θ(n)	Θ(n)
Stack	Θ(n)	Θ(n)	Θ(1)	Θ(1)
Queue	Θ(n)	Θ(n)	Θ(1)	Θ(1)
Singly-Linked List	Θ(n)	Θ(n)	Θ(1)	Θ(1)
Doubly-Linked List	Θ(n)	Θ(n)	Θ(1)	Θ(1)
Skip List	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))
Hash Table	N/A	Θ(1)	Θ(1)	Θ(1)
Binary Search Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))
Cartesian Tree	N/A	Θ(log(n))	Θ(log(n))	Θ(log(n))
B-Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))
Red-Black Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))
Splay Tree	N/A	Θ(log(n))	Θ(log(n))	Θ(log(n))
AVL Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))
KD Tree	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))

Worst

	Access	Search	Insertion	Deletion
Array	O(1)	O(n)	O(n)	O(n)
Stack	O(n)	O(n)	O(1)	O(1)
Queue	O(n)	O(n)	O(1)	O(1)
Singly-Linked List	O(n)	O(n)	O(1)	O(1)
Doubly-Linked List	O(n)	O(n)	O(1)	O(1)
Skip List	O(n)	O(n)	O(n)	O(n)
Hash Table	N/A	O(n)	O(n)	O(n)
Binary Search Tree	O(n)	O(n)	O(n)	O(n)
Cartesian Tree	N/A	O(n)	O(n)	O(n)
B-Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))
Red-Black Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))
Splay Tree	N/A	O(log(n))	O(log(n))	O(log(n))
AVL Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))
KD Tree	O(n)	O(n)	O(n)	O(n)

SPACE Complexity

	Worst
Array	O(n)
Stack	O(n)
Queue	O(n)
Singly-Linked List	O(n)
Doubly-Linked List	O(n)
Skip List	O(n log(n))
Hash Table	O(n)
Binary Search Tree	O(n)
Cartesian Tree	O(n)
B-Tree	O(n)
Red-Black Tree	O(n)
Splay Tree	O(n)
AVL Tree	O(n)
KD Tree	O(n)

ARRAY SORTING Algorithms

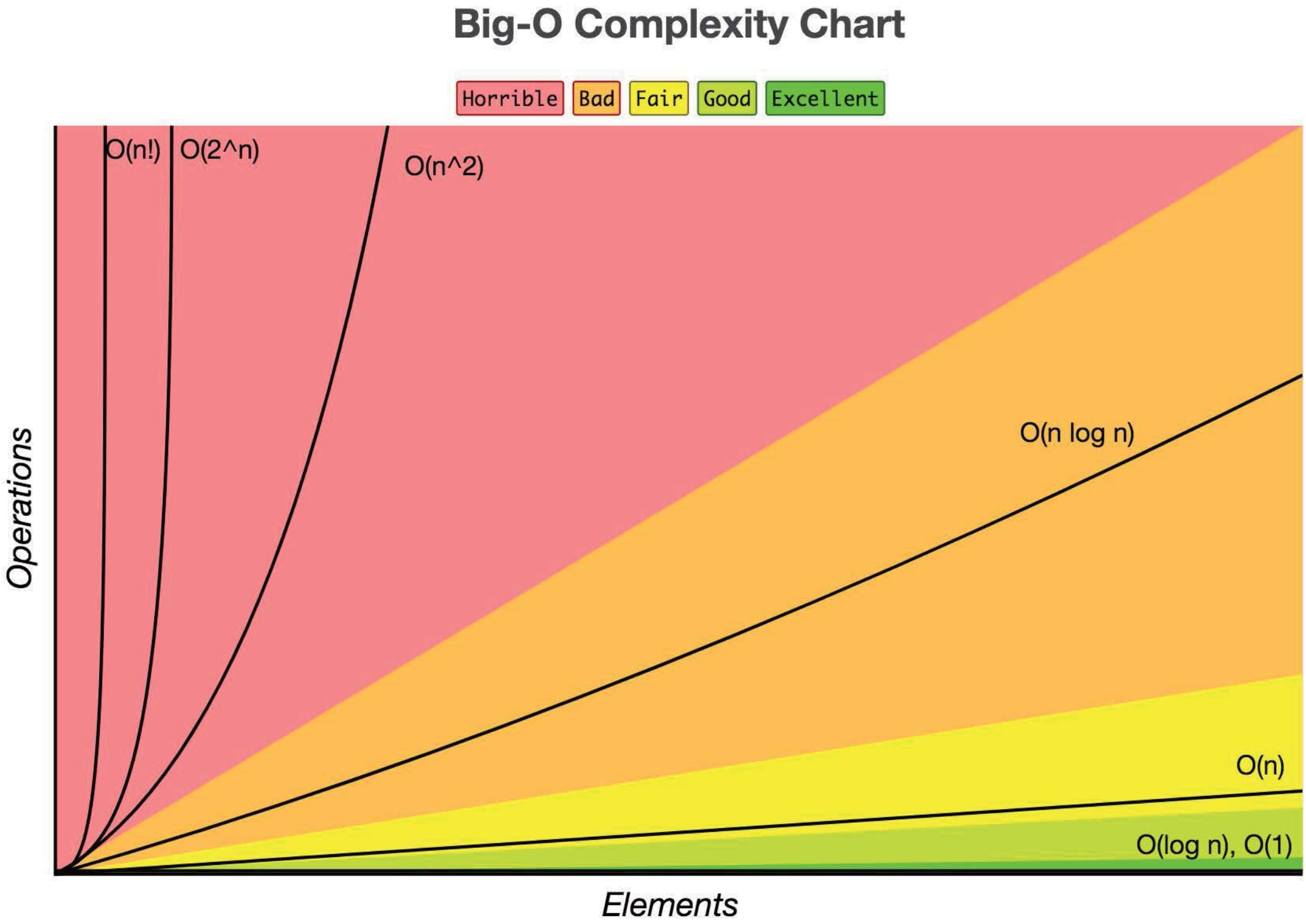
ARRAY Algorithms

TIME Complexity

	Best	Average	Worst
Quicksort	Ω(n log(n))	Θ(n log(n))	O(n^2)
Mergesort	Ω(n log(n))	Θ(n log(n))	O(n log(n))
Timsort	Ω(n)	Θ(n log(n))	O(n log(n))
Heapsort	Ω(n log(n))	Θ(n log(n))	O(n log(n))
Bubble Sort	Ω(n)	Θ(n^2)	O(n^2)
Insertion Sort	Ω(n)	Θ(n^2)	O(n^2)
Selection Sort	Ω(n^2)	Θ(n^2)	O(n^2)
Tree Sort	Ω(n log(n))	Θ(n log(n))	O(n^2)t
Shell Sort	Ω(n log(n))	Θ(n(log(n))^2)	O(n(log(n))^2)
Bucket Sort	Ω(n+k)	Θ(n+k)	O(n^2)
Radix Sort	Ω(nk)	Θ(nk)	O(nk)
Counting Sort	Ω(n+k)	Θ(n+k)	O(n+k)
Cubesort	Ω(n)	Θ(n log(n))	O(n log(n))

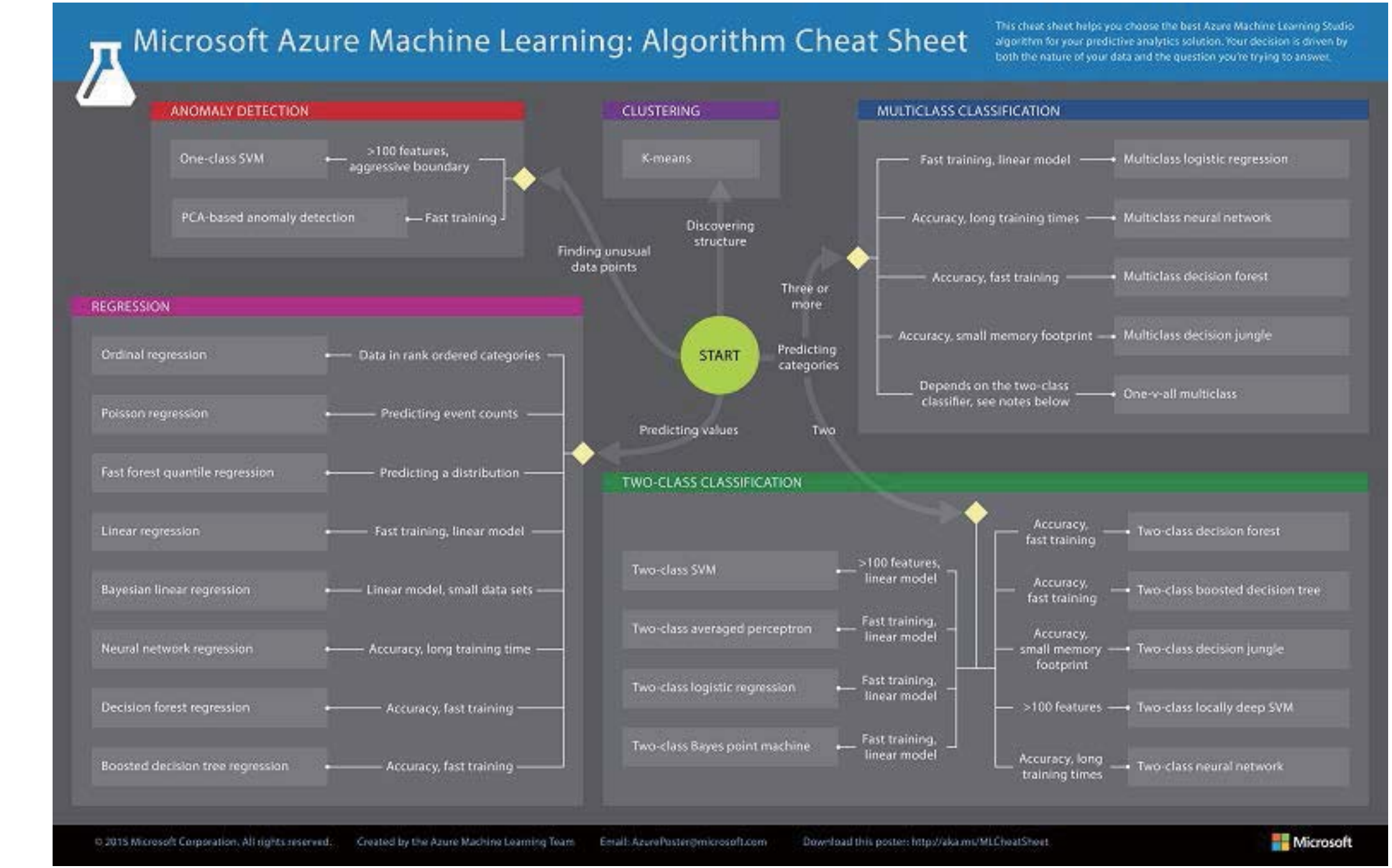
SPACE Complexity

	Worst
Quicksort	O(log(n))
Mergesort	O(n)
Timsort	O(1)
Heapsort	O(1)
Bubble Sort	O(1)
Insertion Sort	O(1)
Selection Sort	O(1)
Tree Sort	O(n)
Shell Sort	O(1)
Bucket Sort	O(n)
Radix Sort	O(n+k)
Counting Sort	O(k)
Cubesort	O(n)


Big-O Complexity Chart
Horrible
Bad
Fair
Good
Excellent
O(n!)
O(2^n)
O(n^2)
O(n log n)
O(n)
O(log n), O(1)
Operations
Elements

Microsoft Azure Machine Learning: Algorithm Cheat Sheet

This cheat sheet helps you choose the best Azure Machine Learning Studio algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the question you're trying to answer.



Created by the Azure Machine Learning Team Email: AzurePoster@microsoft.com
Download this poster: http://aka.ms/MLCheatSheet

Microsoft