Python & ML Cheat Sheet

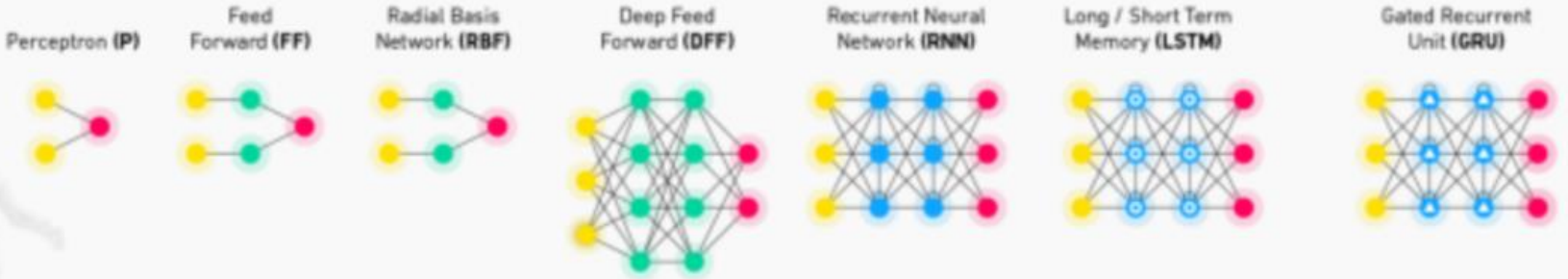
Part 1

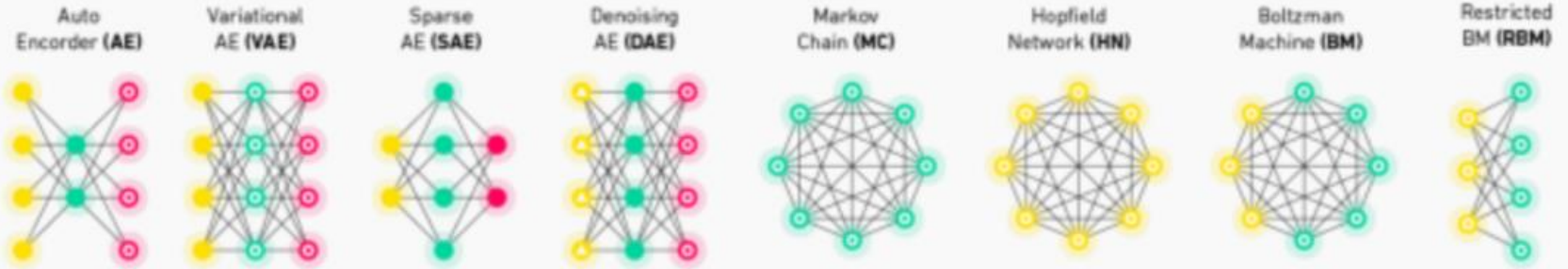
Neural Networks

Neural Networks Basic

Cheat Sheet

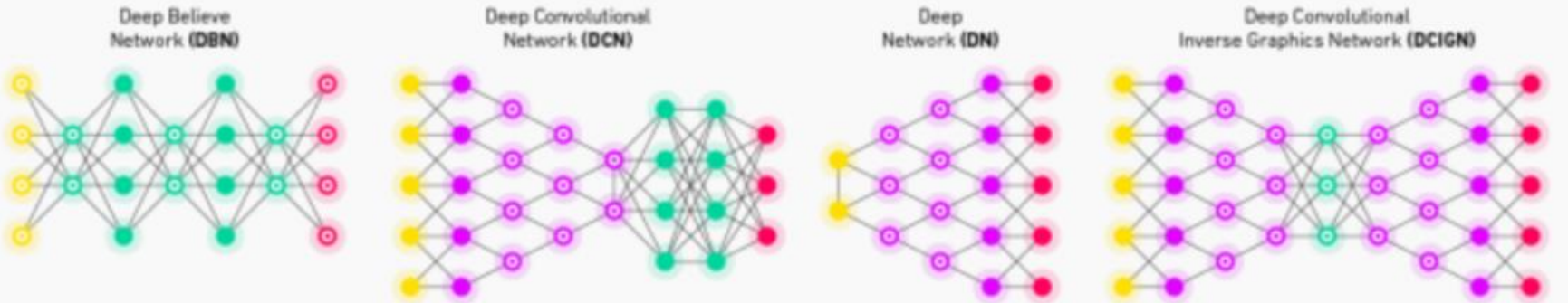
BecomingHuman.AI





Index

- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablisticc Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell



MachineLearning Overview

MACHINE LEARNING IN EMOJI

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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

CLUSTER ANALYSIS

K-MEANS
cluster.KMeans()
Similar datum into groups based on centroids

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

FEATURE REDUCTION

T-DISTRIB STOCHASTIC NEIB EMBEDDING
manifold.TSNE()
Visual 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
manifold.TSNE()

Cheat-Sheet Skicit learn

Phyton For Data Science

BecomingHuman.AI DataCamp

Skicit Learn

Skicit Learn is an open source Phyton library that implements a range if machine learning, processing, cross validation and visualization algorithm using a unified

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
>>> Xtrain, X test, y_train, y test = train_test_split (X, y, random stat33)
>>> 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)
```

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.radom((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
```

Loading the Data

Your data beeds to be nmueric and stored as NumPy arrays or SciPy sparse matric. other types that they are convertible to numeric arrays, such as Pandas Dataframe, are also

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

Imputing Missing Values

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

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test)                         Estimator score method
>>> from sklearn.metrics import accuracy_score        Metric scoring functions
>>> accuracy_score(y_test, y_pred)
```

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))
```

Model Fitting

Supervised learning

```
>>> lr.fit(X, y)                                      Fit the model to the data
>>> knn.fit(X_train, y_train)
```

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)
```

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)
```

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,
```

Skicit-learn Algorithm

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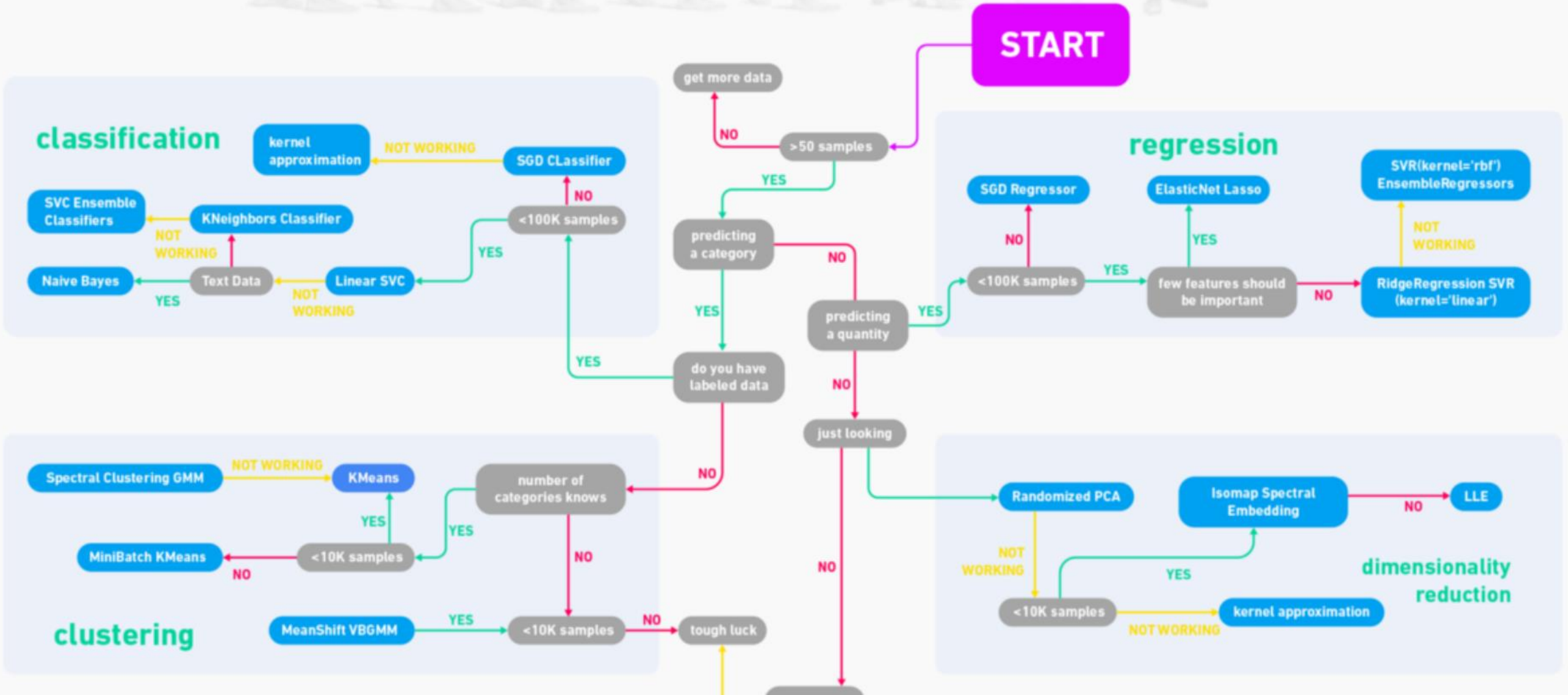

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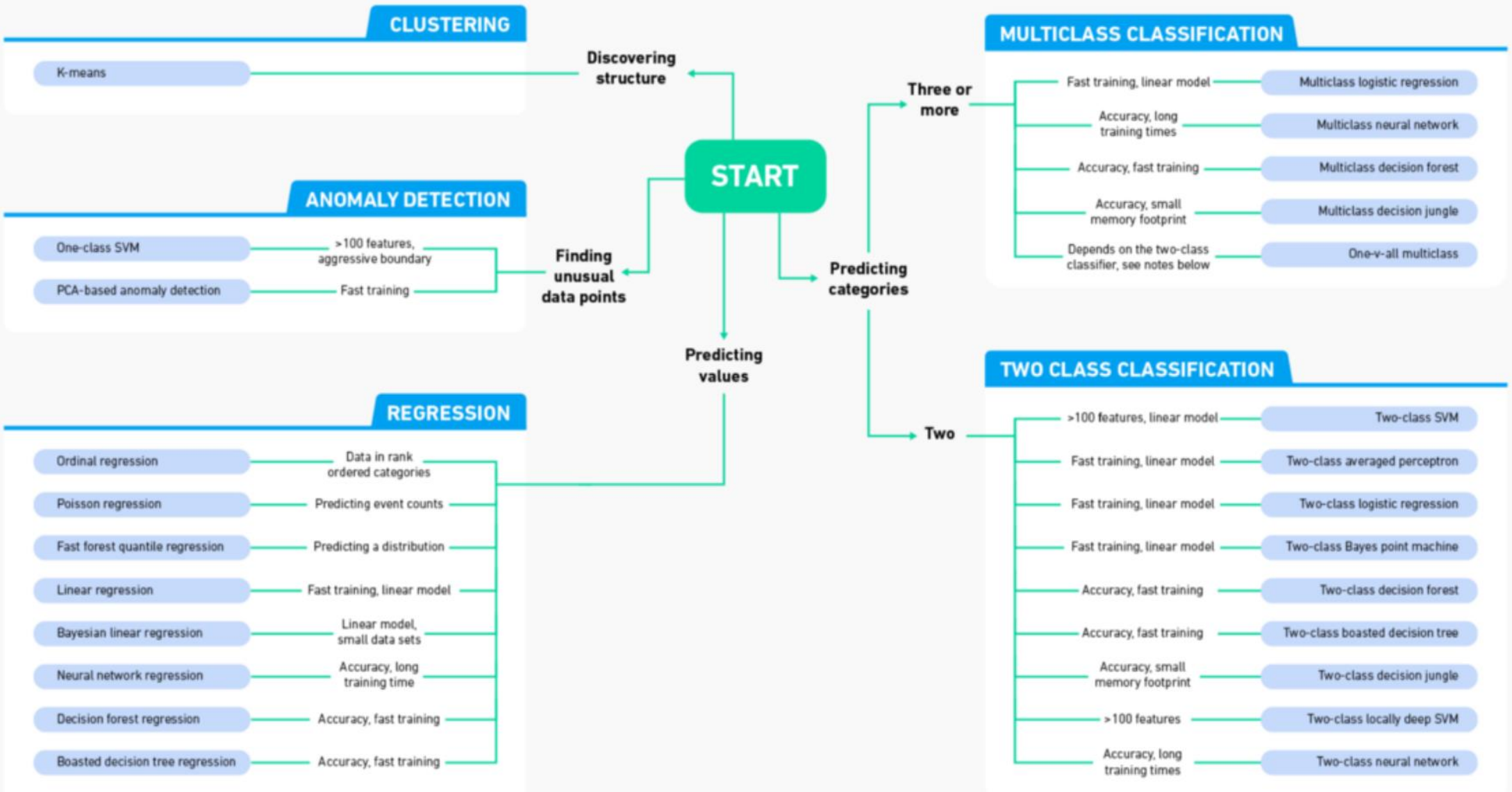
This cheat sheet helps you choose the best Azure Machine Learning Studio algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the question you're trying to answer.



Part 3

Data Science with Python

Phyton For Data Science

Cheat-Sheet Phyton Basic

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Variables and Data Types

Variable Assignment

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

Calculations With Variables

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

Calculations With Variables

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

Lists

Also see NumPy Arrays

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

Selecting List Elements

Index starts at 0

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

List Operations

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

List Methods

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

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

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 Operations

```
>>> my_array.shape          Get the dimensions of the array
>>> np.append(other_array)  Append items to an array
>>> np.insert(my_array, 1, 5)  Insert items in an array
>>> np.delete(my_array,[1])    Delete items in an array
>>> np.mean(my_array)          Mean of the array
```

Strings

Also see NumPy Arrays

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

String Operations

```
>>> my_string * 2
'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'innit'
'thisStringIsAwesomeinnit'
>>> 'm' in my_string
True
```

String Operations

Index starts at 0

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

String Methods

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

Libraries

Import libraries

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

Selective import

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

Install Python

ANACONDA — Leading open data science platform powered by Pytho

SPYDER — Free IDE that is included with Anaconda

PySpark - RDD Basics

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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]')
```

Calculations With Variables

```
>>> 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)
```

Configuration

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

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/")
```

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

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:            Apply a function to each RDD element and flatten the result
x+(x[1],x[0]))
>>> 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')]
```

Mathematical Operations

```
>>> rdd.subtract(rdd2)          Return each rdd value not contained
       .collect() in rdd2
  [('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

Reducing

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

Grouping by

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

Aggregating

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

Reshaping Data

```
>>> 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()
```

NumPy Basics Cheat Sheet

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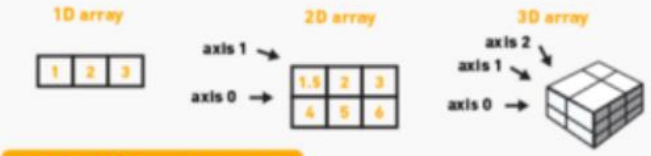
NumPy

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.



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=" ")
```

Inspecting Your Array

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
>>> np.object         Python object type values
>>> np.string_        Fixed-length string type
>>> np.unicode_       Fixed-length unicode 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
```

Copying Arrays

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

Sorting Arrays

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

Subsetting, Slicing, Indexing

Subsetting

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

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

Slicing

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

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

```
>>> b[:1]
  array([[1.5, 2., 3.]])
```
Select all items at row 0 (equivalent to b[0:1, :])

```
>>> c[1,...]
  array([[ 3., 2., 1.],
         [ 4., 5., 6.]])
```
Same as [1,:,:]

```
>>> a[ : :-1]
  array([3, 2, 1])
```
Reversed array a

Boolean Indexing

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

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]]
  array([ 4. , 2. , 6. , 1.5])
```
Select elements (1,0),(0,1),(1,2) and (0,0)

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

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
```

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. ],
```

Bokeh Cheat Sheet

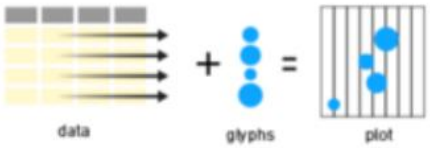
BecomingHuman.AI

DataCamp

Data Types

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]
>>> y = [6, 7, 2, 4, 5]
```

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)
```

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()
```

Glyphs

Scatter Markers

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

Line Glyphs

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

Customized Glyphs

Also see data

Selection and Non-Selection Glyphs

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

Hover Glyphs

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

Colormapping

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

Rows & Columns Layout

Rows

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

Columns

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

Nesting Rows & Columns

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

Grid Layout

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

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')
```

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])
```

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"
```

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()
```

Standalone HTML

```
>>> from bokeh.embed import file_html
```

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')
```

Cheat Sheet Pandas

BecomingHuman.AI

DataCamp

Use the following import convention: >>> import pandas as pd

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

Pandas Data Structures

Series

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

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

Data Frame

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

column / Index

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

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

a	3
b	-5
c	7
d	4

Dropping

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

Sort & Rank

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

Retrieving Series/ DataFrame Information

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

Summary

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

Selection

Also see NumPy Arrays

Getting

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

Selecting, Boolean Indexing & Setting

By Position

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

By Label

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

By Label/Position

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

Boolean Indexing

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

Setting

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

Asking For Help

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

Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f)                     Apply function
>>> df.applymap(f)                  Apply function element-wise
```

Data Alignment

Internal Data Alignment

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

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

Arithmetic Operations with Fill Methods

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

```
>>> s.add(s3, fill_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)
```

I/O

Read and Write to CSV

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

Read and Write to Excel

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

Pandas Cheat Sheet

BecomingHuman.AI

Pandas Data Structures

Pivot

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

Spread rows into columns

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

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

Pivot Table

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

Spread rows into columns

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

Unstacked

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

Stacked

Melt

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

Gather columns into rows

Advanced Indexing

Also see NumPy Arrays

Selecting

```
>>> df3.loc[:,(df3>1).any()]      Select cols with any vals >1
>>> df3.loc[:,(df3>1).all()]      Select cols with vals > 1
>>> df3.loc[:,df3.isnull().any()] Select cols with NaN
>>> df3.loc[:,df3.notnull().all()] Select cols without NaN
```

Indexing With isin

```
>>> df[(df.Country.isin(df2.Type))]  Find same elements
>>> df3.filter(items="a","b"])       Filter on values
>>> df.select(lambda x: not x%5)     Select specific elements
```

Where

```
>>> s.where(s > 0)                   Subset the data
```

Query

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

Setting/Resetting Index

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

Reindexing

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

Forward Filling

```
>>> df.reindex(range(4),
               method='ffill')
```

	Country	Capital	Population
0	Belgium	Brussels	11190846
1	India	New Delhi	1303171035
2	Brazil	Brasília	207847528
3	Brazil	Brasília	207847528

Forward Filling

```
>>> s3 = s.reindex(range(5),
                   method='bfill')
```

0	3
1	3
2	3
3	3
4	3

MultiIndexing

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

Duplicate Data

```
>>> s3.unique()                      Return unique values
>>> df2.duplicated('Type')           Check duplicates
>>> df2.drop_duplicates('Type', keep='last')  Drop duplicates
>>> df.index.duplicated()            Drop duplicates
```

Grouping Data

Aggregation

```
>>> df2.groupby(by=['Date','Type']).mean()
```

Combining Data

data1

	X1	X2
a	11.432	
b	1.303	
c	99.906	

data2

	X1	X3
a	20.784	
b	NaN	
d	20.784	

Pivot

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

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

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

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

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

	X1	X2	X3
a	11.432	20.784	
b	1.303	NaN	

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

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

Join

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

Concatenate

Vertical

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

Horizontal/Vertical

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

Dates

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

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')
)
```

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.

Tidy Data A foundation for wrangling in pandas

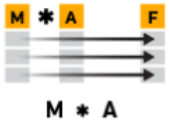
In a tidy data set:

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

&

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

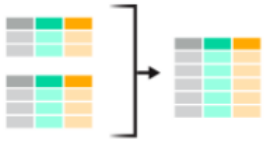
Tidy data complements pandas's vectorized operations. pandas will automatically preserve observations as you manipulate variables. No other format works as intuitively with pandas



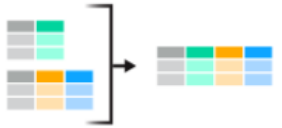
Reshaping Data Change the layout of a data set

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(columns=['Length','Height'])
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
==	Equal to	pd.isnull(obj)	Is NaN
<=	Less than or equal to	pd.notnull(obj)	Is not NaN
>=	Greater than or equal to	&,|,~,^,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.

Logic in Python (and pandas)

'\.'	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

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.

Handling Missing Data

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

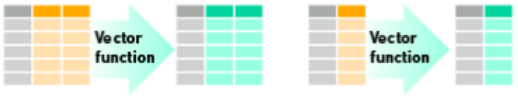
df.fillna(value)

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 allcolumns 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.

Combine Data Sets

Set Operations

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

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

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

Standard Joins

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

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

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

pd.merge(adf, bdf,

dplyr and tidyr Cheat Sheet

BecomingHuman.AI

Syntax Helpful conventions for wrangling

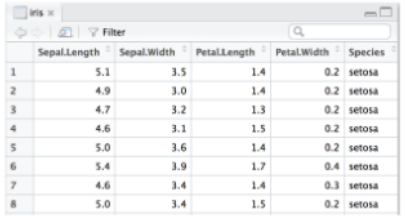
dplyr::tbl_df(iris)
Converts data to tbl class. tbl's are easier to examine than data frames. R displays only the data that fits onscreen

```
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 lef 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)
```

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

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(storms, date, c("y", "m", "d"))

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.

Group Data

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

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

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

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.

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 shifed 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

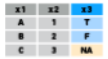
cumprod
Cumulative prod

pmax
Element-wise max

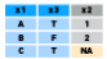
pmin
Element-wise min

Combine Data Sets

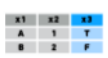
Mutating Joins



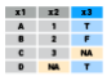
dplyr::left_join(a, b, by = "x1")
Join matching rows from b to a.



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")

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.

core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

Scipy Linear Algebra Cheat Sheet

BecomingHuman.AI

SciPy

DataCamp

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 argumen
`>>> g = np.linspace(0,np.pi,num=5)`	Create an array of evenly spaced values (number of samples)
`>>> g [3:] += np.pi`	

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`	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

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 Matrices

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

Matrix Sign Function

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

Decompositions

Eigenvalues and Eigenvectors

`>>> la, v = linalg.eig(A)`	Solve ordinary or generalized
`>>> l1, l2 = la`	eigenvalue problem for square matrix
`>>> 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

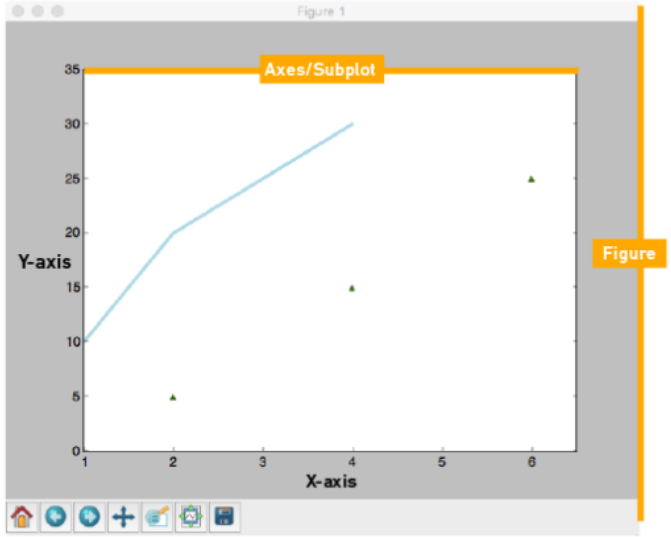
`>>> la, v = sparse.linalg.eigs(F,1)`	Eigenvalues and eigenvectors
`>>> sparse.linalg.svds(H, 2)`	SVD

interactive environments across platforms.

Matplotlib Cheat Sheet

Anatomy & Workflow

Plot Anatomy



Workflow

01 Prepare data
02 Create plot
03 Plot
04 Customize plot
05 Save plot
06 Show plot

```
>>> import matplotlib.pyplot as plt
step 1  >>> x = [1,2,3,4]
        >>> y = [10,20,25,30]
step 2  >>> fig = plt.figure()
step 3  >>> ax = fig.add_subplot(111)
step 3,4 >>> ax.plot(x, y, color='lightblue', linewidth=3)
        >>> ax.scatter([2,4,6],
                       [5,15,25],
```

Prepare The Data

Also see Lists & NumPy

Index Tricks

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

2D Data or Images

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

Create Plot

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

Figure

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

Axes

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

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

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',
           ylabel='Y-Axis',
           xlabel='X-Axis')
```
Set a title and x-and y-axis labels

```
>>> ax.legend(loc='best')
```
No overlapping plot elements

Ticks

```
>>> ax.xaxis.set(ticks=range(1,5),
                 ticklabels=[3,100,-12,"foo"])
                 direction='inout',
                 length=10)
```
Manually set x-ticks

Make y-ticks longer and go in and out

Subplot Spacing

```
>>> fig3.subplots_adjust(wspace=0.5,
                         hspace=0.3,
                         left=0.125,
                         right=0.9,
                         top=0.9,
                         bottom=0.1)
>>> fig.tight_layout()
```

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

Plotting Routines

1D Data

```
>>> lines = ax.plot(x,y)
```
Draw points with lines or markers connecting them

```
>>> ax.scatter(x,y)
```
Draw unconnected points, scaled or colored

```
>>> axes[0,0].bar([1,2,3],[3,4,5])
```
Plot vertical rectangles (constant width)

```
>>> axes[1,0].barh([0.5,1,2.5],[0,1,2])
```
Plot horiontal rectangles (constant height)

```
>>> axes[1,1].axhline(0.45)
```
Draw a horizontal line across axes

```
>>> axes[0,1].axvline(0.65)
```
Draw a vertical line across axes

```
>>> ax.fill(x,y,color='blue')
```
Draw filled polygons

```
>>> ax.fill_between(x,y,color='yellow')
```
Fill between y-values and 0

2D Data

Vector Fields

```
>>> axes[0,1].arrow(0,0,0.5,0.5)
```
Add an arrow to the axes

```
>>> axes[1,1].quiver(y,z)
```
Plot a 2D field of arrows

```
>>> axes[0,1].streamplot(X,Y,U,V)
```
Plot 2D vector fields

Data Distributions

```
>>> ax1.hist(y)
```
Plot a histogram

```
>>> ax3.boxplot(y)
```
Make a box and whisker plot

```
>>> ax3.violinplot(z)
```
Make a violin plot

Save Plot

Save figures

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

Save transparent figures

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

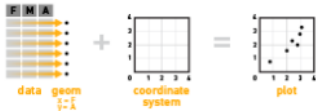
Show Plot

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

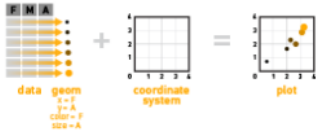
with ggplot2 Cheat Sheet

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 | add layers, elements with +

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

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.

Coordinate Systems

r <- b + geo m_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

One Variable

Continuous

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

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

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

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

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

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

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

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

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

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")
x, y, alpha, color, linetype, size, weight

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

f + geom_text(aes(label = cty))
x, y, alpha, color, fill, linetype, size, weight

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, linetype, 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)
x, y, alpha, color, fill, linetype, size,

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**))

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

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

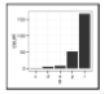
t + facet_grid(year ~ fl)
facet into both rows and columns

t + facet_wrap(~ fl)
wrap facets into a rectangular layoutof one or more discrete variables.

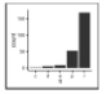
Set **scales** to let axis limits vary across facets
t + facet_grid(y ~ x, scales = "free")
x and y axis limits adjust to individual facets
- "free_x" - x axis limits adjust
- "free_y" - y axis limits adjust

Set **labeller** to adjust facet labels

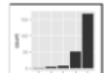
Themes

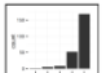


r + theme_bw()
White background with grid lines

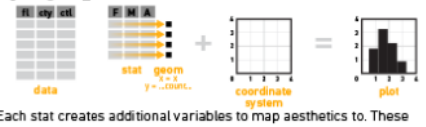


r + theme_classic()
White background no gridlines





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

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..

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..

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..

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..

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..

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..

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()

Zooming

Without clipping (preferred)

t + coord_cartesian(
xlim = c(0, 100), ylim = c(10, 20))

With clipping (removes unseen data points)

Scales

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

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

scale | aesthetic to adjust | prepackaged scale to use

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

Use with x or y aesthetics (x shown here)

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

n + scale_fill_brewer(
palette = "Blues")
For palette choices:
library(RColorBrewer)
display.brewer.all()

n + scale_fill_grey(
start = 0.2, end = 0.8,
na.value = "red")

o <- a + geom_dotplot(
aes(fill = ..x..))

o + scale_fill_gradient(
low = "red",
high = "yellow")

o + scale_fill_gradient2(
low = "red", hight = "blue",
mid = "white", midpoint = 25)

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

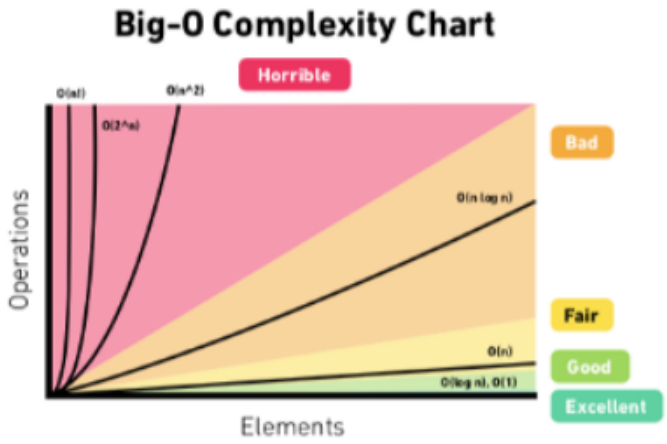
Size scales

q <- f + geom_point(
aes(size = cyl))

q + scale_size_area(max = 6)
Value mapped to area of circle (not radius)

Big-O Cheat Sheet

BecomingHuman.AI



Data Structure Operation

	Time Complexity								Space Complexity
	Average				Worst				Worst
	Access	Search	Insertion	Deletion	Access	Search	Insertion	Deletion	
Array	Θ(1)	Θ(n)	Θ(n)	Θ(n)	Θ(1)	Θ(n)	Θ(n)	Θ(n)	Θ(n)
Stack	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)
Queue	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)
Singly-Linked List	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)
Doubly-Linked List	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)	Θ(n)	Θ(1)	Θ(1)	Θ(n)
Skip List	Θ(log(n))	Θ(log(n))	Θ(log(n))	Θ(log(n))	O(n)	Θ(n)	Θ(n)	Θ(n)	O(n log(n))
Hash Table	N/A	Θ(1)	Θ(1)	Θ(1)	N/A	Θ(n)	Θ(n)	Θ(n)	Θ(n)

Array Sorting Algorithms

	Time Complexity			Space Complexity
	Best	Average	Worst	Worst
Quicksort	Ω(n log(n))	Θ(n log(n))	O(n^2)	O(n log(n))
Mergesort	Ω(n log(n))	Θ(n log(n))	O(n log(n))	O(n log(n))
Timsort	Ω(n)	Θ(n log(n))	O(n log(n))	Θ(n)
Heapsort	Ω(n log(n))	Θ(n log(n))	O(n log(n))	O(n log(n))
Bubble Sort	Ω(n)	Θ(n^2)	O(n^2)	Θ(n)
Insertion Sort	Ω(n)	Θ(n^2)	O(n^2)	Θ(n)
Selection Sort	Ω(n^2)	Θ(n^2)	O(n^2)	Ω(n^2)