# Cheat Sheets for AI

## Neural Networks, Machine Learning, DeepLearning & Big Data

**The Most Complete List of Best AI Cheat Sheets**

BecomingHuman.AI

# Table of Content

## Neural Networks



## Machine Learning



## Data Science with Python

# Part 1

# Neural Networks

# Neural Networks Basic

## Cheat Sheet

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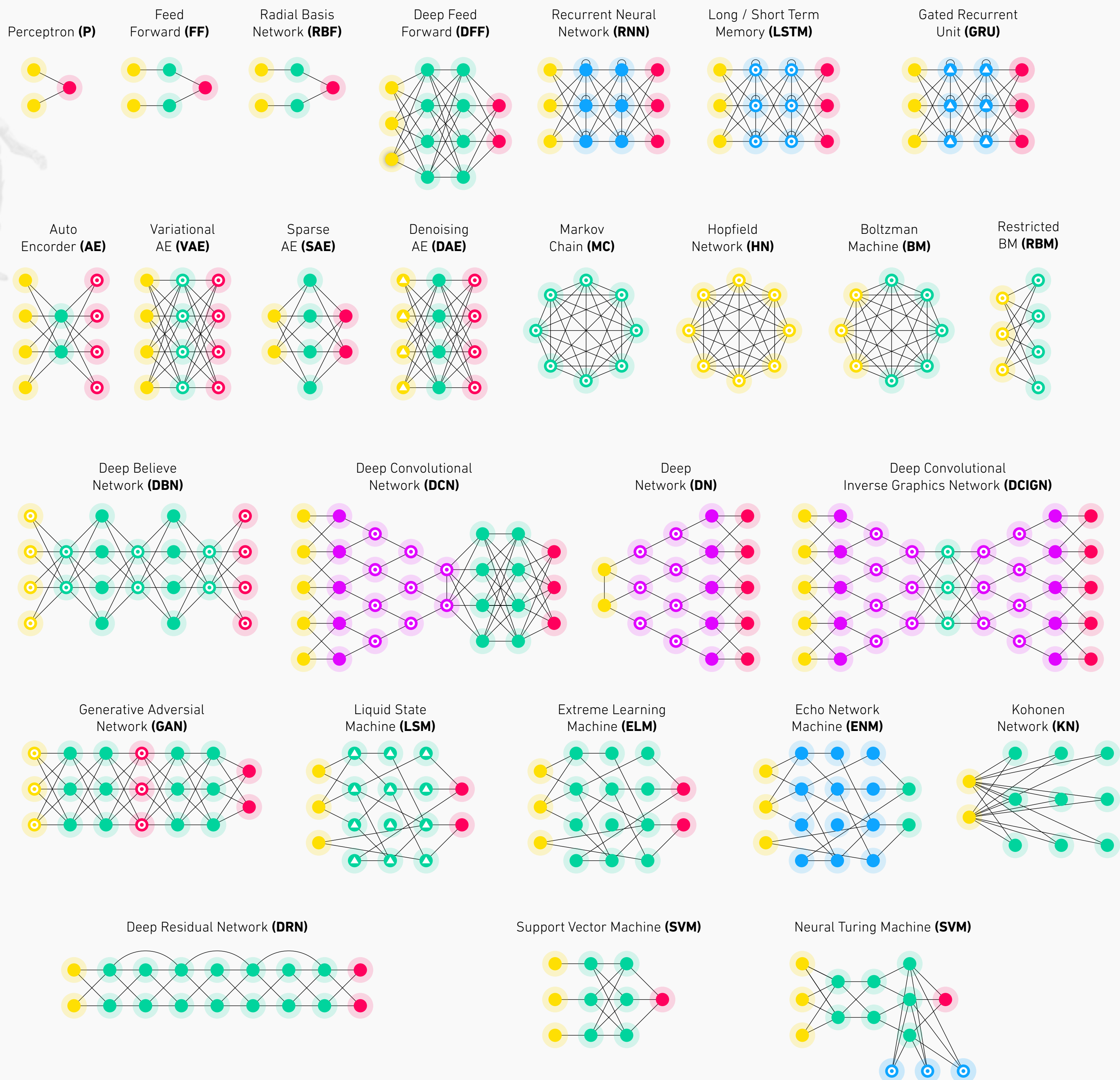
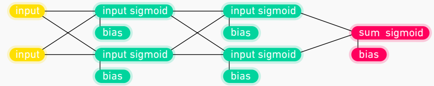
## Index

- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablisticc Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolutional or Pool

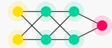


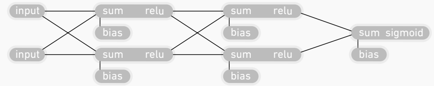
# Neural Networks Graphs Cheat Sheet

## BecomingHuman.AI

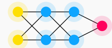


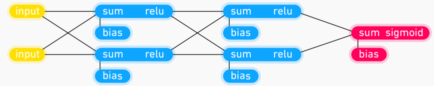
Deep Feed Forward Example



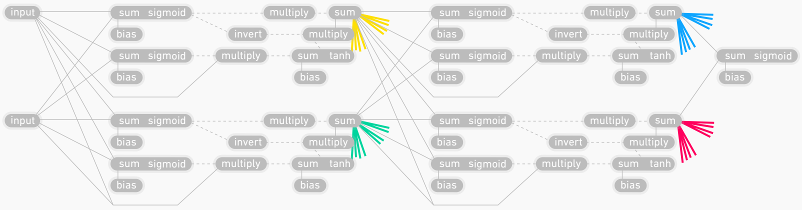


Deep Recurrent Example (previous literation)

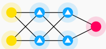


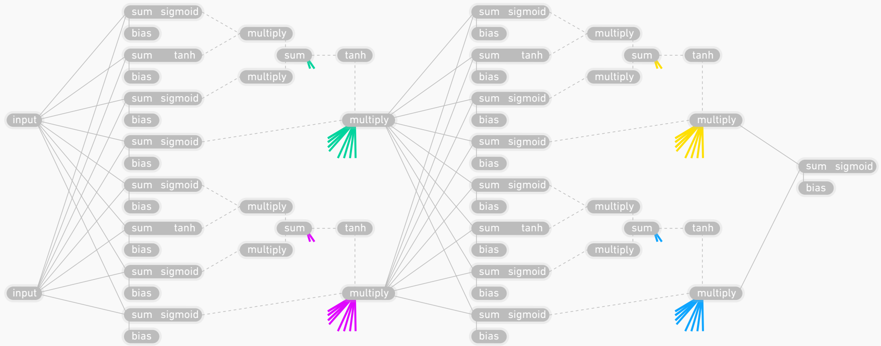


Deep Recurrent Example

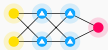


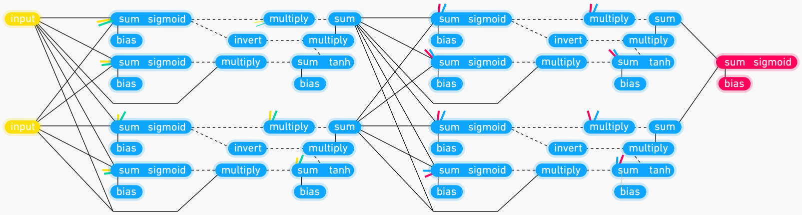
Deep GRU Example (previous literation)



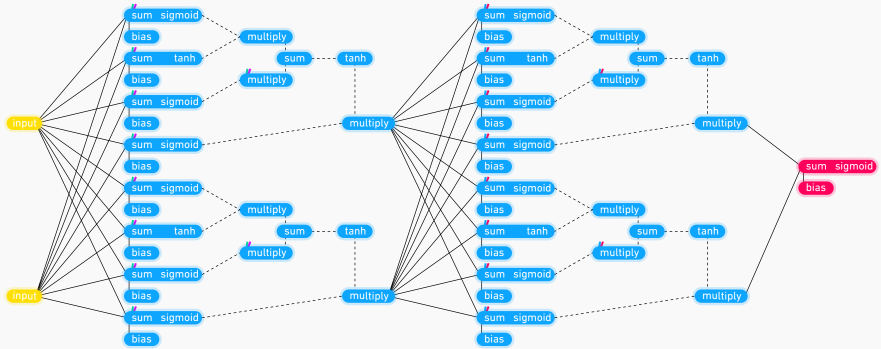


Deep LSTM Example (previous literation)





Deep GRU Example



Deep LSTM Example

**Part 2**

# Machine Learning

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

### LOGISTIC
linear_model.LogisticRegression()
Target variable is categorical

## CLUSTER ANALYSIS

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

### ANOMALY DETECTION
covariance.EllipticalEnvelope()
Finding outliers through grouping

## 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() MultinominalNB() BernoulliNB()
Updating knowledge step by step with new info

## 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()

**SPECIFICITY FUNCTION**
TN / (FP+TN)

**SENSITIVITY FUNCTION**
TP / (TP+FN)

Originally Created by Emily Barry. **See original here**.

# Cheat-Sheet Skicit learn

# Phyton For Data Science

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## 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)))
>>> y_pred = lr.predict(X_test)
>>> y_pred = knn.predict_proba(X_test)
```

**Predict labels**
**Predict labels**
**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 comvertible to numeric arrays, such as Pandas Dataframe, are also acceptable**

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

## 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)
```

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

**Estimator score method**
**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))
```

## Model Fitting

**Supervised learning**

```
>>> lr.fit(X, y)
>>> knn.fit(X_train, y_train)
>>> svc.fit(X_train, y_train)
```

**Fit the model to the data**

**Unsupervised Learning**

```
>>> k_means.fit(X_train)
>>> pca_model = pca.fit_transform(X_train)
```

**Fit the model to the data**
**Fit to data, then transform it**

## 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,
                                 cv=4,
                                 n_iter=8,
                                 random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```

# Skicit-learn Algorithm

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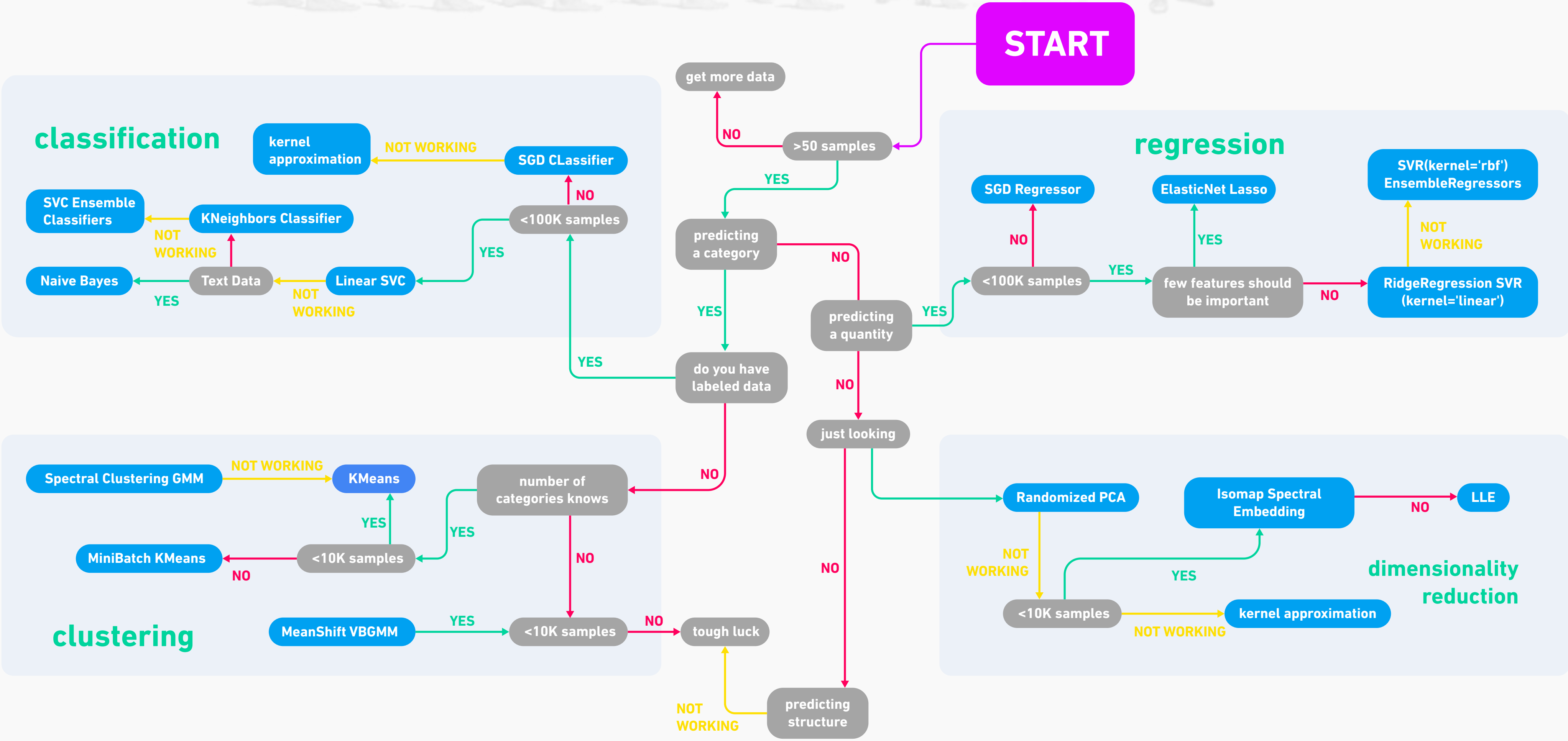
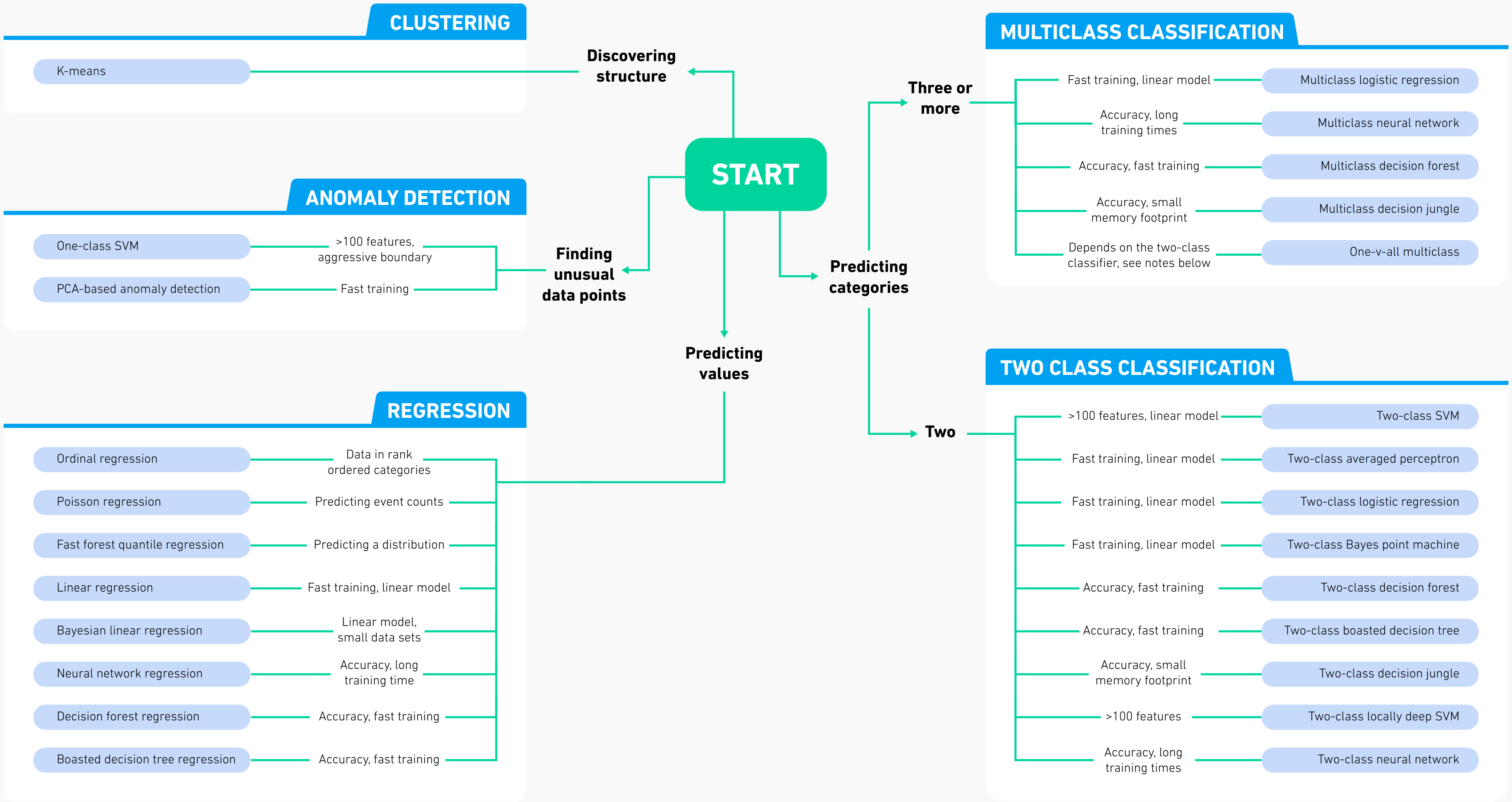


# Algorithm Cheat Sheet

## BecomingHuman.AI

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

# Tensor Flow Cheat Sheet

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TensorFlow

In May 2017 Google announced the second-generation of the TPU, as well as the availability of the TPUs in Google Compute Engine.[12] The second-generation TPUs deliver up to 180 teraflops of performance, and when organized into clusters of 64 TPUs provide up to 11.5 petaflops.

## Info

### TensorFlow

TensorFlow™ is an open source software library created by Google for numerical computation and large scale computation. Tensorflow bundles together Machine Learning, Deep learning models and frameworks and makes them useful by way of common metaphor.

### Keras

Keras is an open sourced neural networks library, written in Python and is built for fast experimentation via deep neural networks and modular design. It is capable of running on top of TensorFlow, Theano, Microsoft Cognitive Toolkit, or PlaidML.

### Skflow

Scikit Flow is a high level interface base on tensorflow which can be used like sklearn. You can build you own model on your own data quickly without rewriting extra code.provides a set of high level model classes that you can use to easily integrate with your existing Scikit-learn pipeline code.

Originally created by Altoros. **See Original here.**

## 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
sudo pip install

### 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

## Tensor Flow

### 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
TensorFlowLinearClassififier
TensorFlowLinearRegressor
TensorFlowRNNClassifier
TensorFlowRNNRegressor
TensorFlowEstimator

### Each classifier and regressor have following fields n_classes=0 (Regressor), n_classes are expected to be input (Classifier)

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

### Each class has a method fit

fit(X, y, monitor=None, logdir=None)

**X:** matrix or tensor of shape [n_samples, n_features...]. Can be iterator that returns arrays of features. The training input samples for fitting the model.

**Y:** vector or matrix [n_samples] or [n_samples, n_outputs]. Can be iterator that returns array of targets. The training target values (class labels in classification, real numbers in regression).

**monitor:** Monitor object to print training progress and invoke early stopping

**logdir:** the directory to save the log file that can be used for optional visualization.

predict (X, axis=1, batch_size=None)
Args:

**X:** array-like matrix, [n_samples, n_features...] or iterator.
axis: Which axis to argmax for classification.
By default axis 1 (next after batch) is used. Use 2 for sequence predictions.

**batch_size:** If test set is too big, use batch size to split it into mini batches. By default the batch_size member variable is used.
Returns:
y: array of shape [n_samples]. The predicted classes or predicted value.

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

### 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** |

## Asking For Help

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

## Lists

Also see NumPy Arrays

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

### Selecting List Elements

Index starts at 0

**Subset**

| | |
|---|---|
| >>> my_list[1] | **Select item at index 1** |
| >>> my_list[-3] | **Select 3rd last item** |

**Slice**

| | |
|---|---|
| >>> my_list[1:3] | **Select items at index 1 and 2** |
| >>> my_list[1:] | **Select items after index 0** |
| >>> my_list[:3] | **Select items before index 3** |
| >>> my_list[:] | **Copy my_list** |

**Subset Lists of Lists**

| | |
|---|---|
| >>> my_list2[1][0] | **my_list[list][itemOfList]** |
| >>> my_list2[1][:2] | |

### List Operations

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

### List Methods

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

## 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]<br>2 | **Select item at index 1** |

**Slice**

| | |
|---|---|
| >>> my_array[0:2]<br>array([1, 2]) | **Select items at index 0 and 1** |

**Subset 2D Numpy arrays**

| | |
|---|---|
| >>> my_2darray[:,0]<br>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 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** |
| >>> np.median(my_array) | **Median of the array** |
| >>> my_array.corrcoef() | **Correlation coefficient** |
| >>> np.std(my_array) | **Standard deviation** |

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

# Python For Data Science Cheat Sheet

# 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.**

```
$ ./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 whole**TextFiles()**.**

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

## Selecting Data

### Getting

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

### Sampling

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

### Filtering

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

## Iterating

### Getting

```
>>> def g(x): print(x)
>>> rdd.foreach(g)
('a', 7)
('b', 2)
('a', 2)
```

## Retrieving RDD Information

### Basic Information

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

### Summary

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

## Applying Functions

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

## Mathematical Operations

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

## Sort

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

## Reshaping Data

### Reducing

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

### Grouping by

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

### Aggregating

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

## 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()
```

## Execution

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

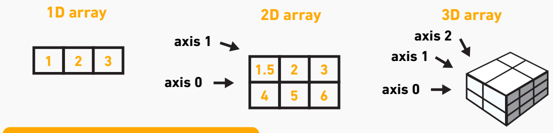
# NumPy Basics **Cheat Sheet**

## BecomingHuman.AI

DataCamp

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

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

## Data Types

| | |
|---|---|
| >>> np.int64 | **Signed 64-bit integer types** |
| >>> np.float32 | **Standard double-precision floating point** |
| >>> np.complex | **Complex numbers represented by 128 floats** |
| >>> np.bool | **Boolean type storing TRUE and FALSE** |
| >>> 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<br>array([[-0.5, 0. , 0. ],<br>[-3. , -3. , -3. ]]) | **Subtraction** |
| >>> np.subtract(a,b) | **Subtraction** |
| >>> b + a<br>array([[ 2.5, 4. , 6. ],<br>[ 5. , 7. , 9. ]]) | **Addition** |
| >>> np.add(b,a) | **Addition** |
| >>> a / b<br>array([[ 0.66666667, 1. , 1. ],<br>[ 0.25 , 0.4 , 0.5 ]]) | **Division** |
| >>> np.divide(a,b) | **Division** |
| >>> a * b<br>array([[ 1.5, 4. , 9. ],<br>[ 4. , 10. , 18. ]]) | **Multiplication** |
| >>> 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)<br>array([[ 7., 7.],<br>[ 7., 7.]]) | **Dot product** |

### Comparison

| | |
|---|---|
| >>> a == b<br>array([[False, True, True],<br>[False, False, False]], dtype=bool) | **Element-wise comparison** |
| >>> a < 2<br>array([True, False, False], dtype=bool) | **Element-wise comparison** |
| >>> 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** |

## 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]<br>3 | **Select the element at the 2nd index** |
| >>> b[1,2]<br>6.0 | **Select the element at row 1 column 2 (equivalent to** b[1][2]**)** |

### Slicing

| | |
|---|---|
| >>> a[0:2]<br>array([1, 2]) | **Select items at index 0 and 1** |
| >>> b[0:2,1]<br>array([ 2., 5.]) | **Select items at rows 0 and 1 in column 1** |
| >>> b[:1]<br>array([[1.5, 2., 3.]]) | **Select all items at row 0 (equivalent to** b[0:1, :]**)** |
| >>> c[1,...]<br>array([[[ 3., 2., 1.],<br>[ 4., 5., 6.]]]) | **Same as** [1,:,:] |
| >>> a[ : :-1]<br>array([3, 2, 1]) | **Reversed array** a |

### Boolean Indexing

| | |
|---|---|
| >>> a[a<2]<br>array([1]) | **Select elements from** a **less than 2** |

### Fancy Indexing

| | |
|---|---|
| >>> b[[1, 0, 1, 0],[0, 1, 2, 0]]<br>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]]<br>array([[ 4. ,5. , 6. , 4. ],<br>[ 1.5, 2. , 3. , 1.5],<br>[ 4. , 5. , 6. , 4. ],<br>[ 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** |
| >>> np.delete(a,[1]) | **Delete items from an array** |

### Combining Arrays

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

### Splitting Arrays

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

# **Bokeh** Cheat Sheet

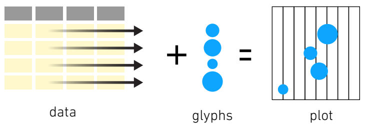
BecomingHuman.AI

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]                          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
```

## 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()
```

## Show or Save Your Plots

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

## 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")
```

### 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]])
```

### 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'))
```

### 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
>>> html = file_html(p, CDN, "my_plot")
```

**Components**

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

## 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',
```

# **Keras** Cheat Sheet

## BecomingHuman.AI

DataCamp

Keras is a powerfuland 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'])
```

## 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
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

### 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'))
```

## 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])
```

## 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'])
```

## Save/ Reload Models

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

## 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** |

## Prediction

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

## 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)
```

## Preprocessing

### 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)
```

# Pandas Basics

# Cheat Sheet

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

| | |
|---|---|
| a | 3 |
| b | -5 |
| c | 7 |
| d | 4 |

index

```
>>> 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'])
```

## 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

**Get one element**
```
>>> s['b']
 -5
```

**Get subset of a DataFrame**
```
>>> df[1:]
   Country Capital     Population
 1 India   New Delhi  1303171035
 2 Brazil  Brasília   207847528
```

### Selecting, Boolean Indexing & Setting

**By Position**

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

**By Label**

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

**By Label/Position**

**Select single row of subset of rows**
```
>>> df.ix[2]
 Country      Brazil
 Capital      Brasília
 Population   207847528
```

**Select a single column of subset of columns**
```
>>> df.ix[:,'Capital']
 0 Brussels
 1 New Delhi
 2 Brasília
```

**Select rows and columns**
```
>>> df.ix[1,'Capital']
 '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

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

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

## 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 | Brasilia | 207847528 |
| 3 | Brazil | Brasilia | 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()
>>> df4.groupby(level=0).sum()
>>> df4.groupby(level=0).agg({'a':lambda x:sum(x)/len(x), 'b': np.sum})
```

**Transformation**

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

## Missing Data

```
>>> df.dropna()                Drop NaN value
>>> df3.fillna(df3.mean())     Fill NaN values with a predetermined value
>>> df2.replace("a", "f")      Replace values with others
```

## Combining Data

data1

| X1 | X2 |
|---|---|
| a | 11.432 |
| b | 1.303 |
| c | 99.906 |

data2

| X1 | X3 |
|---|---|
| a | 20.784 |
| b | NaN |
| d | 20.784 |

### 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')
```

## Visualization

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

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

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

# Data Wrangling with pandas Cheat Sheet

BecomingHuman.AI

## 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')
)
```

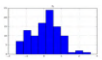
## Windows

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

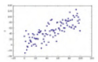
**df.rolling(n)**
Return a Rolling object allowing summary functions to be applied to windows of length n.

## Windows

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

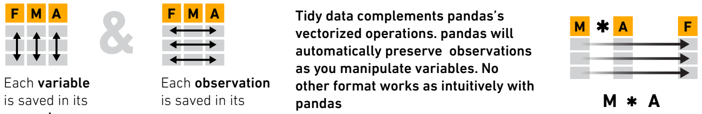


**df.plot.scatter(x='w',y='h')**
Scatter chart using pairs of points



## 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 .

## Windows

**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

## 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.

Vector function

Vector function

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

ydf

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |

+ zdf

| x1 | x2 |
|---|---|
| B | 2 |
| C | 3 |
| D | 4 |

=

### Set 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(columns=['_merge'])**
Rows that appear in ydf but not zdf (Setdiff)

adf

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |

+ bdf

| x1 | x3 |
|---|---|
| A | T |
| B | F |
| C | T |

=

### Standard Joins

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

**dpd.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

# Data Wrangling with 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)

iris × Filter

| | 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:**

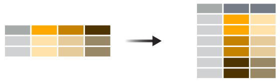

Each **variable** is saved in its own **column**

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

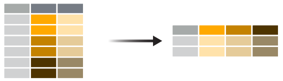
Tidy data complements R's vectorized operations. R will automatically preserve observations as you manipulate variables. No other format works as intuitively with R


**M * A**

## 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.

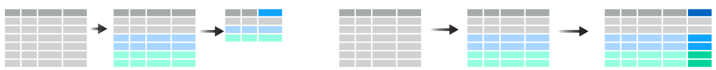
## Group Data

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

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

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

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

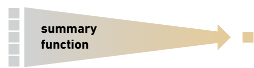


## Summarise Data

**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

A

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |

\+ B

| x1 | x2 |
|---|---|
| A | T |
| B | F |
| C | T |

=

Y

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |

\+ Z

| x1 | x2 |
|---|---|
| B | 2 |
| C | 3 |
| D | 4 |

=

### Mutating Joins

**dplyr::lef_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.

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.

# 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` | |
| `>>> 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` | 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

| | |
|---|---|
| `>>> 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 |

### 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

| | |
|---|---|
| `>>> 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 |

### 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 |

## Asking For Help

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

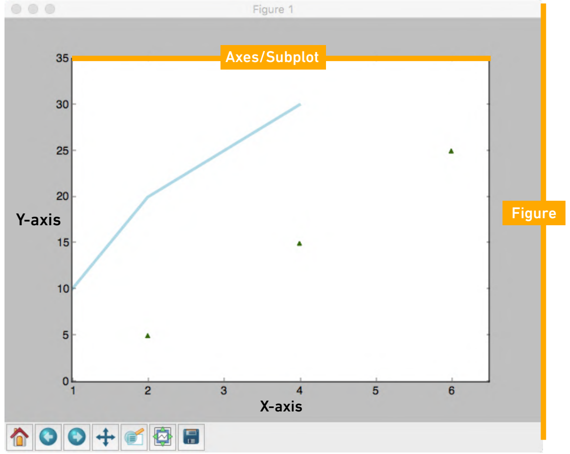
Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

# Matplotlib Cheat Sheet

**BecomingHuman.AI**

## 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
>>> 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 5
```

## 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

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

### 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** |
| `>>> 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** |

## Save Plot

### Save figures

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

### Save transparent figures

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

## Show Plot

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

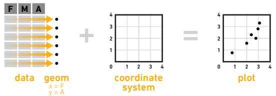
## Close & Clear

```
>>> plt.cla()
>>> plt.clf()
>>> plt.close()
```

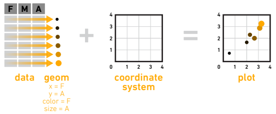
# Data Visualisation with ggplot2 Cheat Sheet

## 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

```
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

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

### 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

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

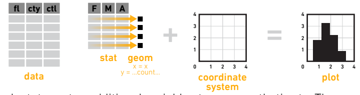
m + **geom_contour**(aes(z = z))
x, y, z, alpha, colour, linetype, size, weight

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

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**()

## 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))

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


### 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 + 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.

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.)

## 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

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

| fl: c | fl: d | fl: e | fl: p | fl: r |
|---|---|---|---|---|

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

| $\alpha^c$ | $\alpha^d$ | $\alpha^e$ | $\alpha^p$ | $\alpha^r$ |
|---|---|---|---|---|

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

| c | d | e | p | r |
|---|---|---|---|---|

## 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**

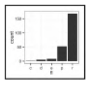
## Legends

t + **theme**(legend.position = "bottom")
Place legend at "bottom", "top", "left", or "right"

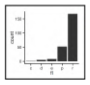
t + **guides**(color = "none")
Set legend type for each aesthetic: colorbar, legend, or none (no legend)

t + **scale_fill_discrete**(name = "Title", labels = c("A", "B", "C"))
Set legend title and labels with a scale function.

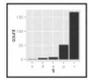
## Themes



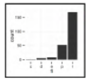
r + **theme_bw**()
White background with grid lines



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



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

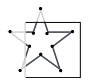


r + **theme_minimal**()
Minimal theme

**ggthemes** - Package with additional ggplot2 themes

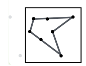
## Zooming

### Without clipping (preferred)



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

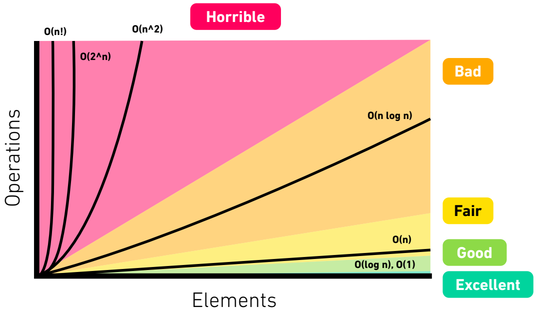
### With clipping (removes unseen data points)



t + **xlim(0, 100) + ylim(10, 20)**

t + **scale_x_continuous**(limits = c(0, 100)) +
**scale_y_continuous**(limits = c(0, 100))

## Big-O Complexity Chart




# Big-O Cheat Sheet

BecomingHuman.AI

## Data Structure Operation

| Data Structure | Time Complexity: Average Access | Average Search | Average Insertion | Average Deletion | Worst Access | Worst Search | Worst Insertion | Worst Deletion | Space Complexity: Worst |
|---|---|---|---|---|---|---|---|---|---|
| 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)) | Θ(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) |
| Binary Search Tree | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(n) | Θ(n) | Θ(n) | Θ(n) | Θ(n) |
| Cartesian Tree | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | N/A | Θ(n) | Θ(n) | Θ(n) | Θ(n) |
| B-Tree | N/A | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(n) |
| Red-Black Tree | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(n) |
| Splay Tree | N/A | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | N/A | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(n) |
| AVL Tree | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(n) |
| KD Tree | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(log(n)) | Θ(n) | Θ(n) | Θ(n) | Θ(n) | Θ(n) |

## Array Sorting Algorithms

| Algorithm | Time Complexity: Best | Average | Worst | Space Complexity: 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) |
| Tree Sort | Ω(n log(n)) | Θ(n log(n)) | O(n^2) | O(n log(n)) |
| Shell Sort | Ω(n log(n)) | Θ(n(log(n))^2) | O(n(log(n))^2) | O(n log(n)) |
| Bucket Sort | Ω(n+k) | Θ(n+k) | O(n^2) | Ω(n+k) |
| Radix Sort | Ω(n+k) | Θ(n+k) | Ω(n+k) | Ω(n+k) |
| Counting Sort | Ω(n+k) | Θ(n+k) | Ω(n+k) | Ω(n+k) |
| Cubesort | Ω(n) | Θ(n log(n)) | O(n log(n)) | O(n log(n)) |

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