



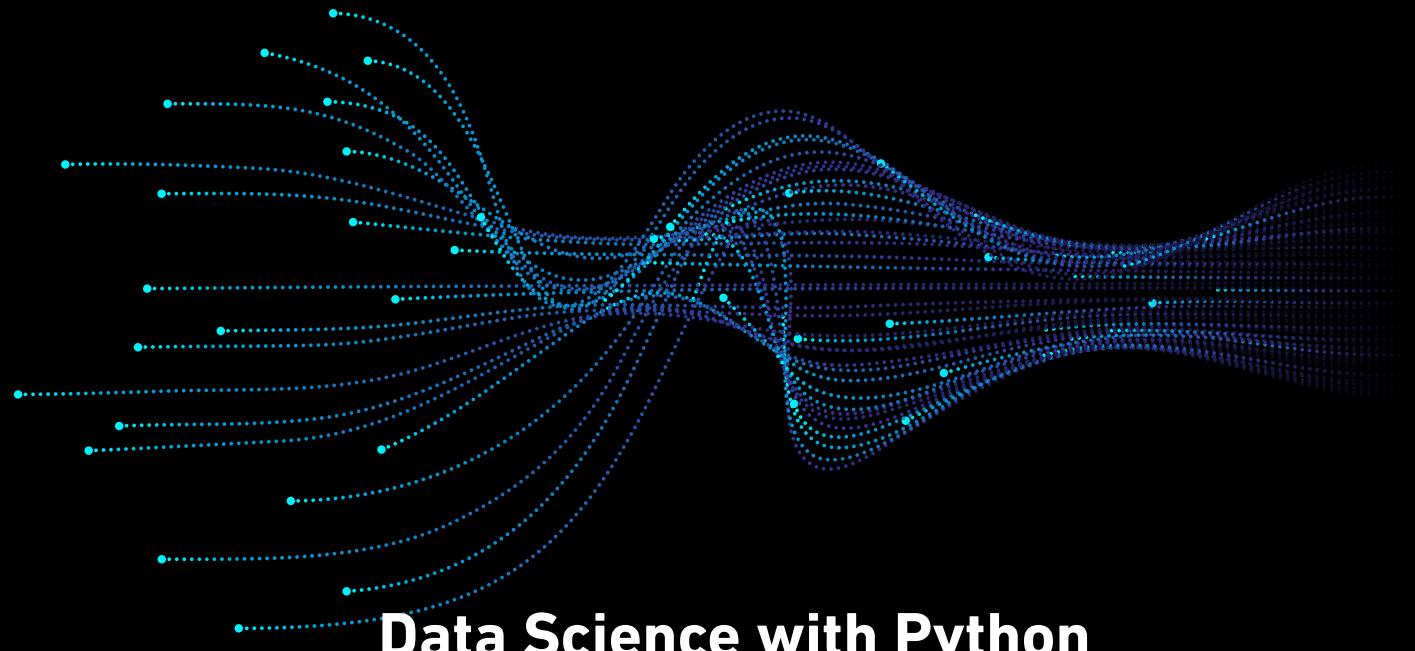
Cheat Sheets for AI

Neural Networks,
Machine Learning,
DeepLearning &
Big Data

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

BecomingHuman.AI

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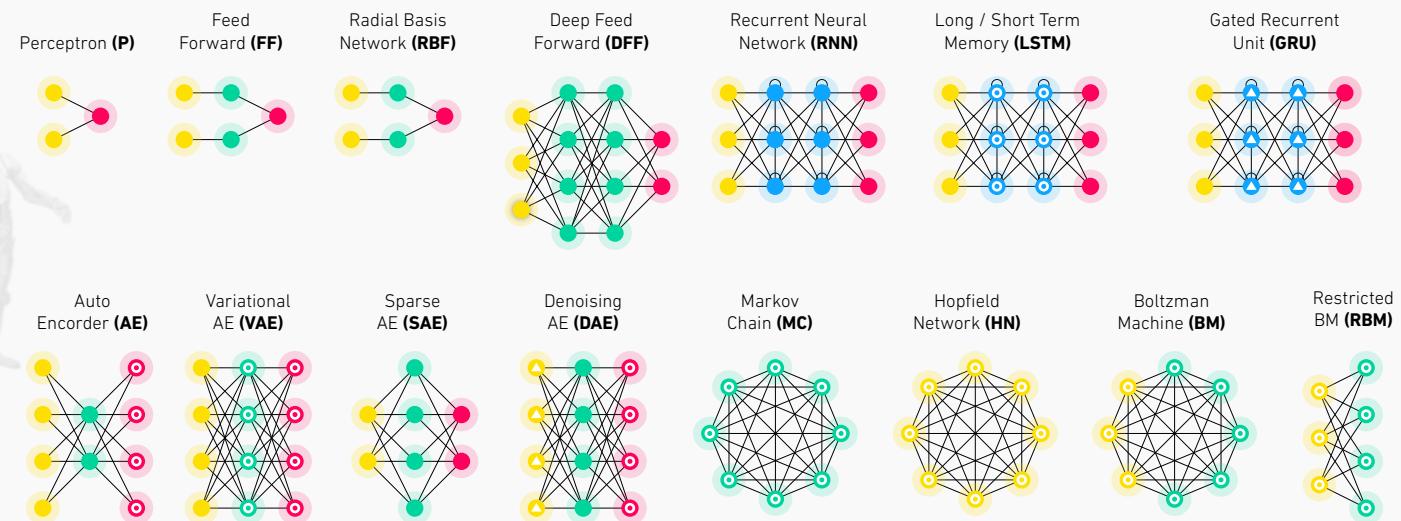


Part 1

Neural Networks

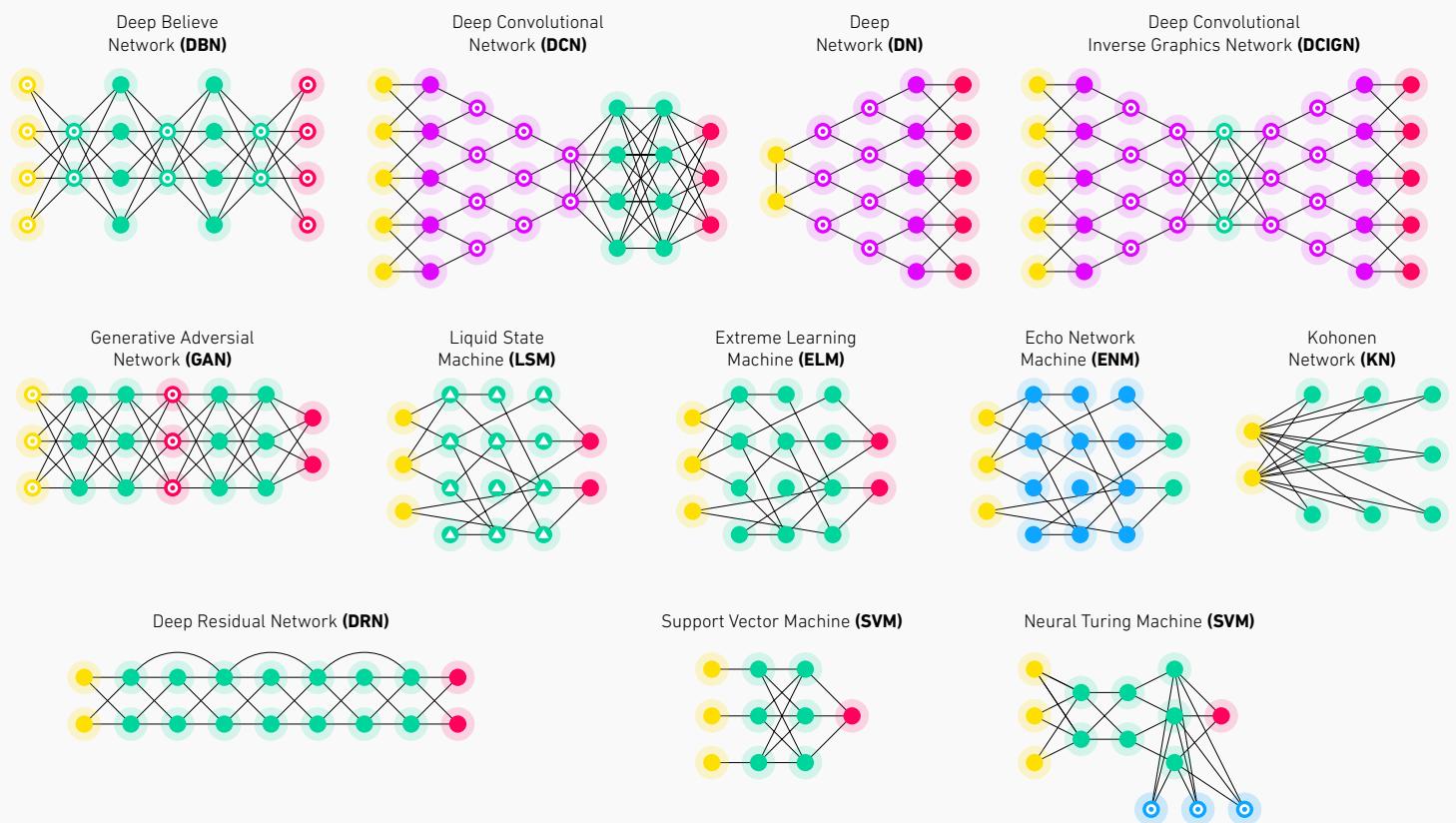
Neural Networks Basic Cheat Sheet

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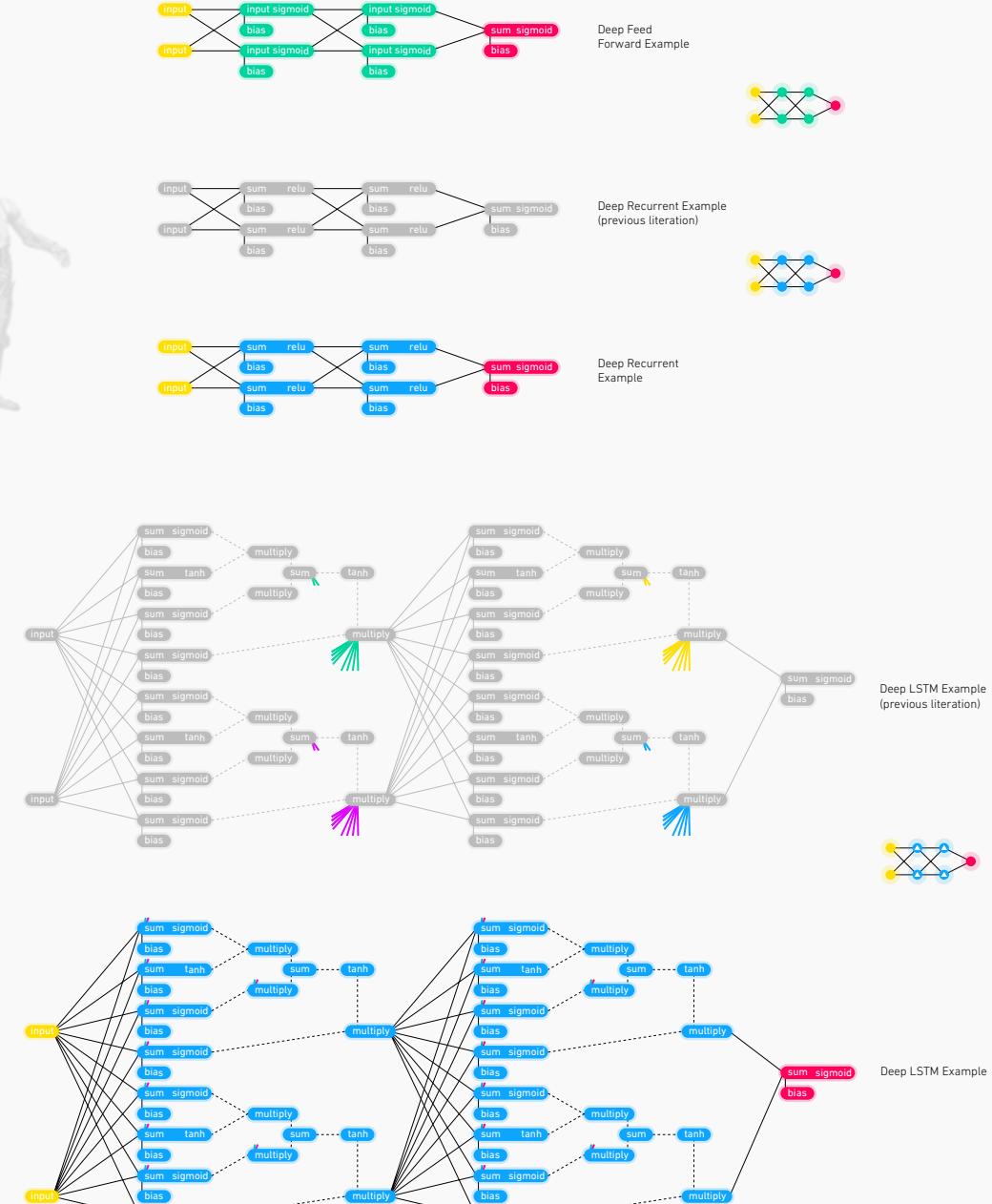
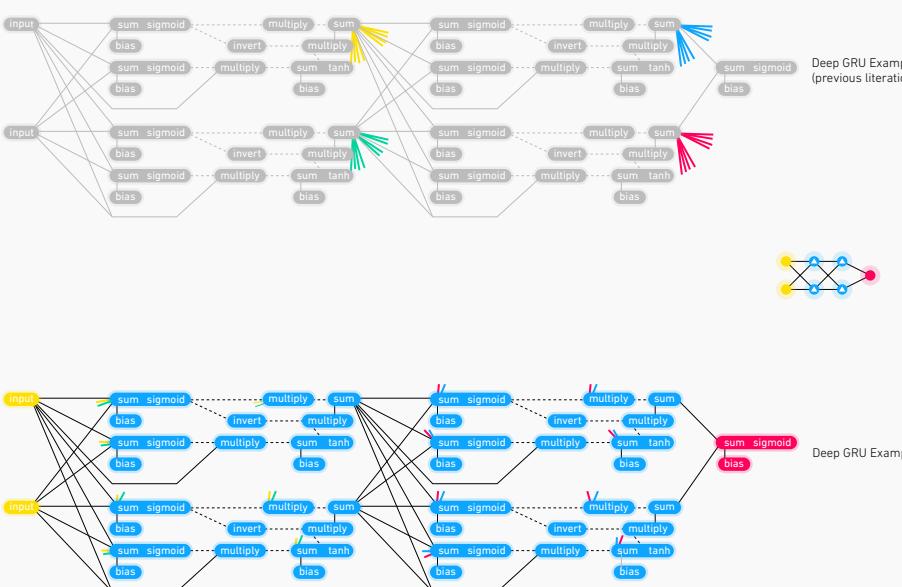
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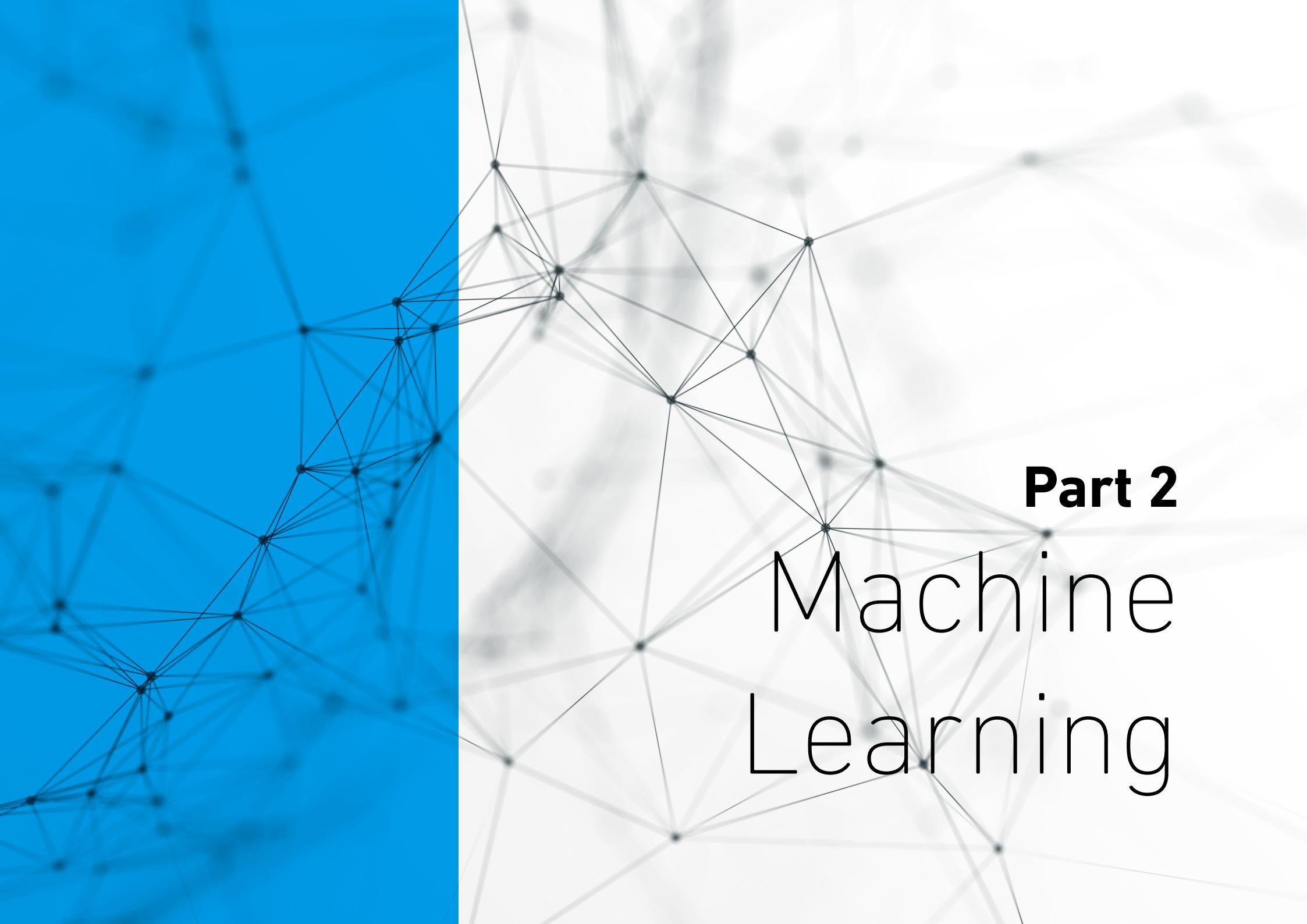
- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolutional or Pool



Neural Networks Graphs Cheat Sheet

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The background of the slide features a complex network graph composed of numerous small, semi-transparent black dots connected by thin gray lines, creating a sense of data points and connections. The left side of the slide has a solid blue vertical bar.

Part 2

Machine Learning

MachineLearning Overview

MACHINE LEARNING IN EMOJI

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SUPERVISED

UNSUPERVISED

REINFORCEMENT

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()` `MultinomialNB()` `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 $TP / (TP+FN)$

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, Xtest, y_train, ytest = train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(ytest, y_pred)
```

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.randn(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 = kmeans.predict(X_test)
```

Predict labels in clustering algos

Loading the Data

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

```
>>> import numpy as np >> X = np.random.random((10,5))
>>> y = np.array(['PH', 'IM', 'F', 'F', 'M', 'F', 'NI', 'tv1', '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(ytest, y_pred)
```

Estimator score method
Metric scoring functions

Classification Report

```
>>> from sklearn.metrics import classification_report
>>> print(classification_report(ytest, y_pred))
```

Precision, recall, f1-score and support

Confusion Matrix

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

R² Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(ytrue, ypred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(ytrue, ypred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(ytrue, ypred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(ytrue, ypred)
```

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

```
>>> kmeans.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
>>> kmeans = KMeans(n_clusters=3, random_state=0)
```

Training And Test Data

```
>>> from sklearn.cross_validation import train_test_split
>>> Xtrain, Xtest, ytrain, ytest = train_test_split(X,
...                                                 y,
...                                                 random_state=0)
```

Tune Your Model

Grid Search

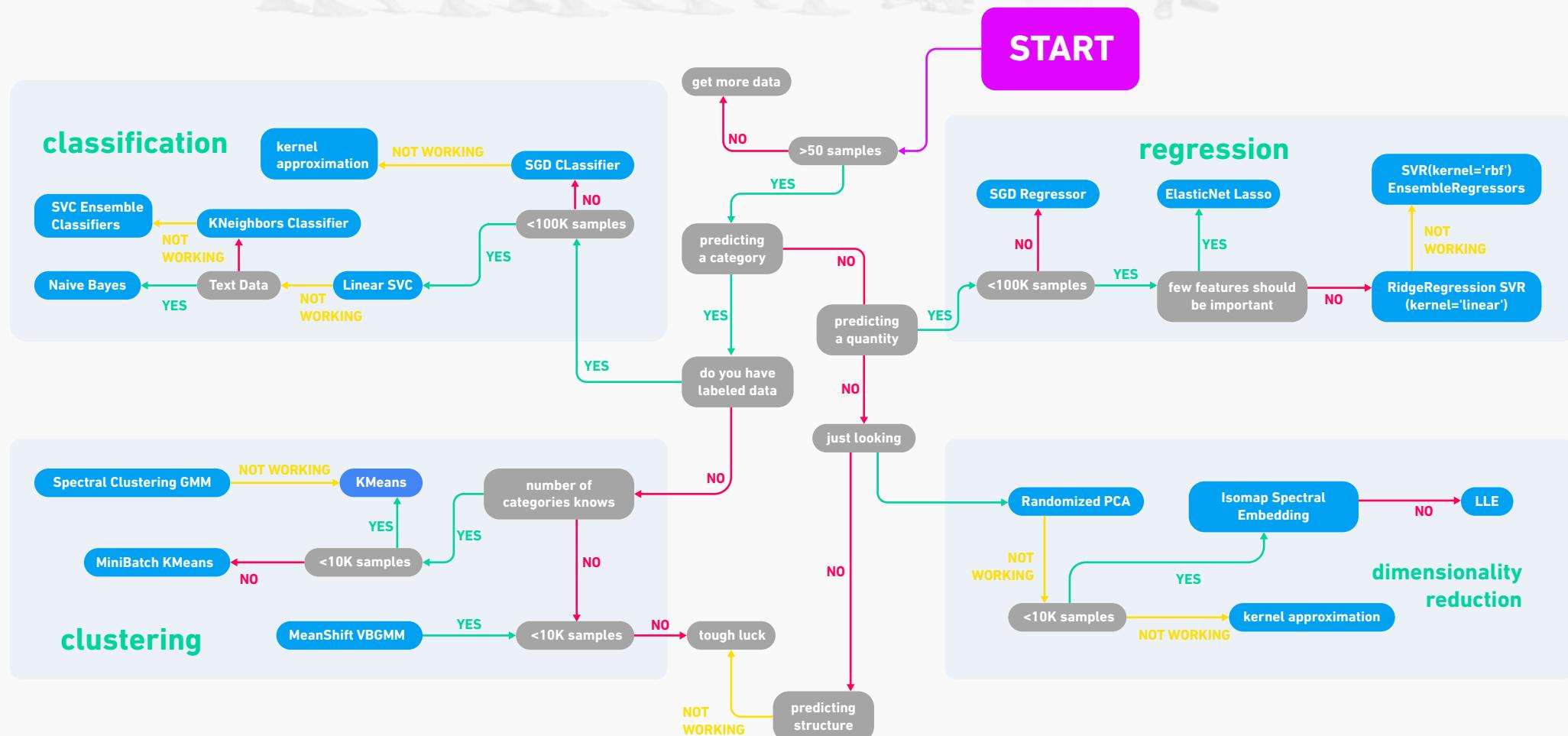
```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {'n_neighbors': np.arange(1,3),
...            'metric': ['euclidean','cityblock']}
>>> grid = GridSearchCV(estimator=knn,
...                      param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)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

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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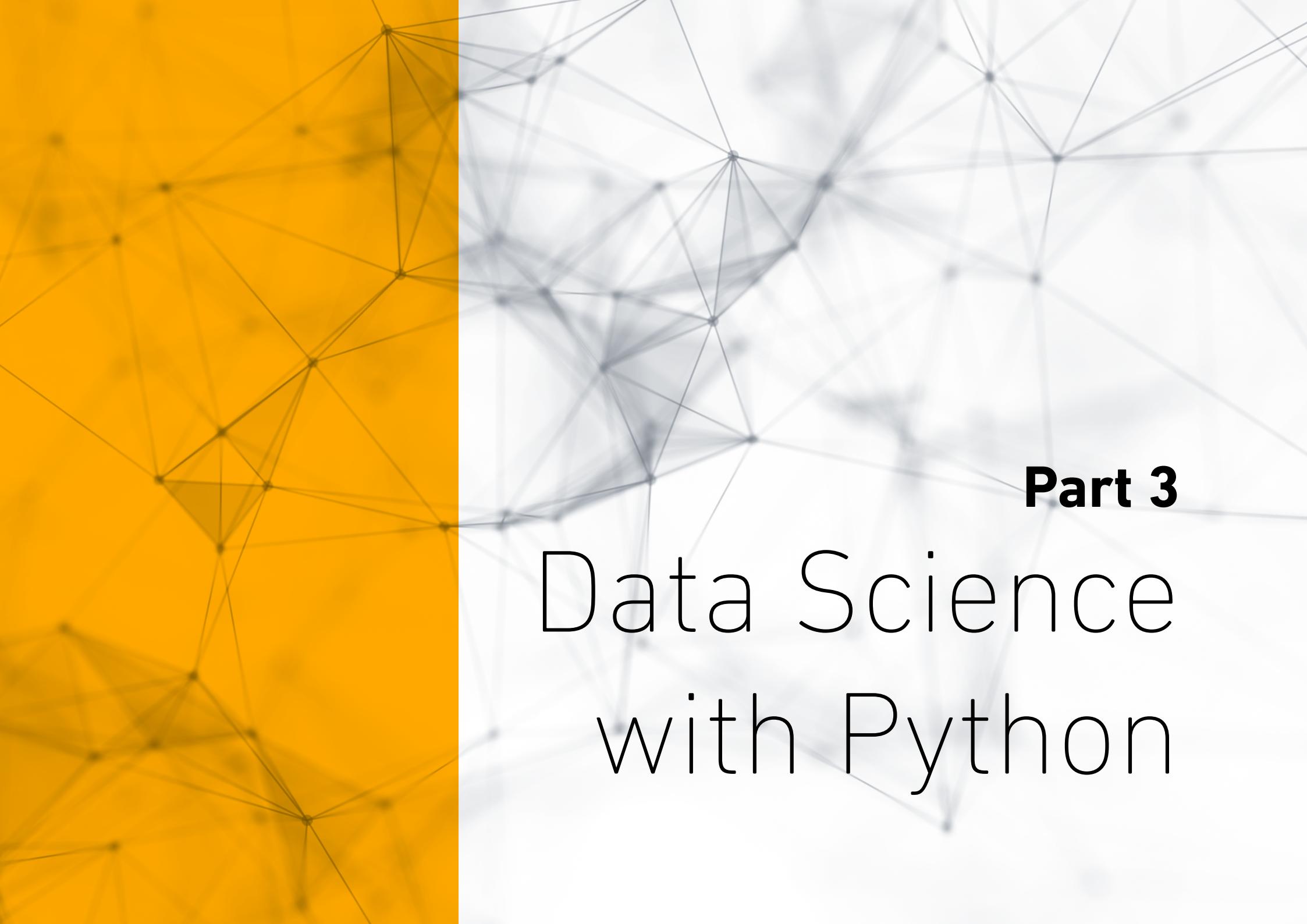


Algorithm Cheat Sheet

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



The background of the slide features a complex network graph composed of numerous small, semi-transparent grey dots connected by thin grey lines, creating a sense of data connectivity and complexity. The left side of the slide has a vertical orange bar running down its entire height, which contains a smaller, identical network graph.

Part 3

Data Science with Python

Tensor Flow Cheat Sheet

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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 your 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.

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

Calculations With Variables

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

Asking For Help

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

Lists

Also see NumPy Arrays

Selecting List Elements

Index starts at 0

Subset

```
>>> my_list[1]  
>>> my_list[-3]
```

Slice

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

List Operations

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

List Methods

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

Select item at index 1
Select 3rd last item

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

my_list[itemOfList]

Numpy Arrays

Also see Lists

Selecting Numpy Array Elements

Index starts at 0

Subset

```
>>> my_array[1]  
2
```

Slice

```
>>> my_array[0:2]  
array([1, 2])
```

Subset 2D Numpy arrays

```
>>> my_2darray[:,0]  
array([1, 4])
```

Select item at index 1

Select items at index 0 and 1

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 + 'Inninit'  
'thisStringIsAwesomeInninit'  
>>> '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



Leading open data science platform
powered by Python



Free IDE that is included
with Anaconda



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] --pyfiles 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 `--pyfiles`.

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 any Hadoop-supported file system URI with `textFile()`, or read in a directory of text files with `wholeTextFiles()`.

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

Selecting Data

Getting

>>> rdd.collect()	Return a list with all RDD elements
>>> rdd.take(2)	Take first 2 RDD elements
>>> rdd.first()	Take first RDD element
>>> rdd.top(2)	Take top 2 RDD elements

Sampling

```
>>> rdd3.sample(False, 0.15, 81).collect()  
[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)  
      .collect()  
[(a,7),(a,2)]  
>>> rdd5.distinct().collect()  
[(a,2),(b,7)]  
>>> rdd.keys().collect()  
[(a, a, b)]
```

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

Summary

>>> rdd3.max() 99	Maximum value of RDD elements
>>> rdd3.min() 0	Minimum value of RDD elements
>>> rdd3.mean() 49.5	Mean value of RDD elements
>>> rdd3.stdev() 28.86670047722118	Standard deviation of RDD elements
>>> rdd3.variance() 833.25	Compute variance of RDD elements
>>> rdd3.histogram(3) ([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])) [(a,7,a),(a,2,a),(b,2,b)]	Apply a function to each RDD element
>>> rdd5 = rdd.flatMap(lambda x: x+(x[1],x[0]))	Apply a function to each RDD element and flatten the result
>>> rdd5.collect() [(a,7,a),(a,2,a),(b,2,b)]	Apply a flatMap function to each (key,value)pair of rdd4 without changing the keys
>>> rdd4.flatMapValues(lambda x: x).collect() [(a,'x),(a,'y),(a,'z),(b,'p),(b,'r)]	Apply a flatMap function to each (key,value)pair of rdd4 without changing the keys

Mathematical Operations

>>> rdd.subtract(rdd2) .collect() in rdd2 [(b,2),(a,7)]	Return each rdd value not contained
>>> rdd2.subtractByKey(rdd) .collect() [(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]) .collect() [(d,1),(b,1),(a,2)]	Sort RDD by given function
>>> rdd2.sortByKey() .collect() [(a,2),(b,1),(d,1)]	RDD by key

Reshaping Data

Reducing

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

Grouping by

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

Aggregating

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

Reshaping Data

>>> rdd.repartition(4) >>> rdd.coalesce(1)	New RDD with 4 partitions
	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



1D array



Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1,2,3), (4,5,6)], dtype = float)
>>> c = np.array([(1,2,3), (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),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.savetxt('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	Subtraction
>>> array([-0.5, 0., 0., 1.], [-3., -3., -3.]))	
>>> np.subtract(a,b)	Subtraction
>>> b + a	Addition
>>> array([[2.5, 4., 6.], [5., 7., 9.]])	
>>> np.add(b,a)	Addition
>>> a / b	Division
>>> array([[0.66666667, 1., 1.], [0.25, 0.4, 0.5]])	
>>> np.divide(a,b)	Division
>>> a * b	Multiplication
>>> array([[1.5, 4., 9.], [4., 10., 18.]])	
>>> np.multiply(a,b)	Multiplication
>>> np.exp(b)	Exponentiation
>>> np.sqrt(b)	Square root
>>> np.sin(a)	Print sines of an array
>>> np.cos(b)	Element-wise cosine
>>> np.log(a)	Element-wise natural logarithm
>>> e.dot(f)	Dot product
>>> array([[7., 7.], [7., 7.]])	

Comparison

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

Aggregate Functions

>>> a.sum()	Array-wise sum
>>> a.min()	Array-wise minimum value
>>> b.max(axis=0)	Maximum value of an array row
>>> b.cumsum(axis=1)	Cumulative sum of the elements
>>> a.mean()	Mean
>>> b.median()	Median

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.argsort(axis=0)      Sort the elements of an array's axis
```

Subsetting, Slicing, Indexing

Subsetting

1 2 3	Select the element at the 2nd index
1.5 2 3 4 5 6	Select the element at row 1 column 2 (equivalent to b[1][2])

Slicing

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

Boolean Indexing

1 2 3	Select elements from a less than 2
-------	------------------------------------

Fancy Indexing

1 2 3	Select elements (1,0),(0,1),(1,2) and (0,0)
	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
```

Combining Arrays

>>> np.concatenate((a,d),axis=0)	Concatenate arrays
>>> np.vstack((a,b))	Stack arrays vertically (row-wise)
>>> np.column_stack((a,d))	Create stacked column-wise arrays
>>> np.r_[e,f]	Stack arrays vertically (row-wise)
>>> np.hsplit(a,3)	Stack arrays horizontally (column-wise)
>>> np.vsplit(a,2)	Split the array vertically at the 2nd index
>>> np.c_[a,d]	Create stacked column-wise arrays



Bokeh Cheat Sheet

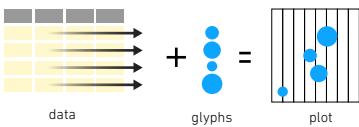
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Data Types

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

Legends

Legend Location

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

Inside 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')
```

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)
```

Customized Glyphs



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

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])
```

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"
```

Statistical Charts With Bokeh

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=hpi,
                marker=square,
                xlabel=Miles Per Gallon,
```

Keras Cheat Sheet

BecomingHuman.AI



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

A Basic Example

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

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

Inspect Model

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

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)
```

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.h5')
>>> my_model = load_model('my_model.h5')
```

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



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 capable of holding any data type

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

Data Frame

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

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

Dropping

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

```
Drop values from columns(axis=1)
```

Sort & Rank

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

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

Retrieving Series/ DataFrame Information

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

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

Summary

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

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

Selection

Also see NumPy Arrays

Getting

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

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]]
'Belgium'
>>> df.at[[0],[0]]
'Belgium'
```

Select single value by row & column

By Label

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

Select single value by row & column labels

By Label/Position

```
>>> df.ix[2]
Country      Brazil
Population  207847528
>>> df.ix[:,['Capital']]
0 Brussels
1 New Delhi
2 Brasilia
>>> df.ix[1,['Capital']]
'New Delhi'
```

Select single row of subset of rows

Boolean Indexing

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

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

Setting

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

Set index a of Series s to 6

Asking For Help

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

Applying Functions

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

Apply function

Apply function element-wise

Data Alignment

Internal Data Alignment

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

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

Arithmetic Operations with Fill Methods

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

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

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')
```

	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

Spread rows into columns



	Type	a	b	c
0	Date			
1	2016-03-01	11.432		
2	2016-03-02		13.031	
3	2016-03-01		20.784	
4	2016-03-03			99.906
5	2016-03-02			1.303
6	2016-03-03			20.784

Pivot Table

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

	0	1
1	0.233482	0.390959
2	0.184713	0.237102
3	0.433522	0.429401

Unstacked

Spread rows into columns



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

Stacked

Melt

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

	Date	Type	Value	Observations
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	

Gather columns into rows



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

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

Indexing With isin

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

Find same elements
Filter on values
Select specific elements

Where

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

Subset the data

Query

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

Query DataFrame

Setting/Resetting Index

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

Set the index
Reset the index
Rename DataFrame

Reindexing

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

Forward Filling

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

Forward Filling

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

Country Capital Population

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

0 3

1 3

2 3

3 3

4 3

Multilabeling

```
>>> arrays = [np.array([1,2,3]),
             np.array([5,4,3,1])]
>>> 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'])
```

Return unique values
Check duplicates
Drop duplicates
Drop duplicates

Duplicate Data

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

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)
```

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

Missing Data

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

Combining Data

data1

X1	X2
a	11.432
b	1.303

data2

X1	X2	X3
a	20.784	
b	NaN	

Pivot

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

X1	X2	X3
a	11.432	20.784
b	1.303	NaN

X1	X2	X3
a	11.432	20.784
b	1.303	NaN

X1	X2	X3
a	11.432	20.784
b	1.303	NaN

X1	X2	X3
a	11.432	20.784
b	1.303	NaN

X1	X2	X3
a	11.432	20.784
b	1.303	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()
```

```
>>> 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(
    [[1, 10],
     [5, 11],
     [6, 12]],
    index=[1, 2, 3],
    columns=['a', 'b', 'c'])
Specify values for each row.
```

	a	b	c
n			
d	1	4	7
e	2	5	8

```
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

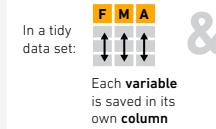
df.plot.hist()
Histogram for each column



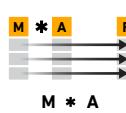
df.plot.scatter(x='w',y='h')
Scatter chart using pairs of points



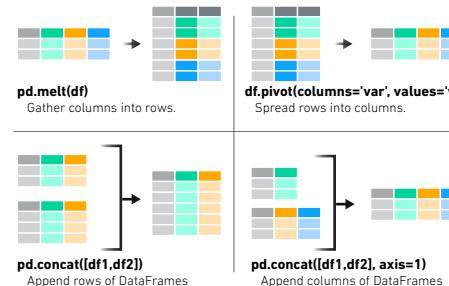
Tidy Data A foundation for wrangling in pandas



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



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.

Logic in Python (and pandas)

<	Less than	is	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=rege)
Select columns whose name matches regular expression regex.

Logic in Python (and pandas)

'.' Matches strings containing a period
'Length\$' Matches strings ending with 'Length'
'\$Sepal' Matches strings beginning with '\$' and 'Sepal'
'^123\$' Matches strings containing 'x' and 'y' 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.

min()
Minimum value in each object.

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

max()
Maximum value in each object.

median()
Median value of each object.

mean()
Mean value of each object.

quantile(q=0.25,0.75)
Quantiles of each object.

var()
Variance of each object.

apply(function)
Apply function to each object

std()
Standard deviation of each object.

Handling Missing Data

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

df.fillna(value)

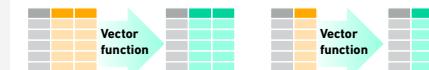
Make New Columns



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

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

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



pandas provides a large set of vector functions that operate on altcolumns 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.

min(axis=1)
Element-wise min.

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

abs()
Absolute value.

Combine Data Sets



Set Operations

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

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

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



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

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

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

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

Filtering Joins

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

adf[~adfx1.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	Petal.Width
1	5.1	3.5	1.4	0.2
2	4.9	3.0	1.4	0.2
3	4.7	3.2	1.3	0.2
4	4.6	3.1	1.5	0.2
5	5.0	3.6	1.4	0.2
..
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 x					
	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa
7	4.6	3.4	1.4	0.3	setosa
8	5.0	3.4	1.5	0.2	setosa

`dplyr::%>%`

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

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

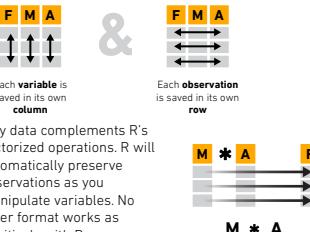
`y %>% f(x, z)` is the same as `f(y, x, z)`

"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:



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

Reshaping Data Change the layout of a data set



`tidy::gather(cases, "year", "n", 2:4)`

Gather columns into rows.



`tidy::spread(pollution, size, amount)`

Spread rows into columns



`tidy::separate(storms, date, c("y", "m", "d"))`

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



`tidy::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(mpq))`

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

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

Rename the columns of a data frame.

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.

`dplyr::var`

Variance of a vector.

`dplyr::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 shifted by 1.

`dplyr::cumall`

Cumulative all

`dplyr::cumany`

Cumulative any

`dplyr::dense_rank`

Ranks with no gaps.

`dplyr::min_rank`

Ranks. Ties get min rank.

`dplyr::cumsum`

Cumulative sum

`dplyr::cummax`

Cumulative max

`dplyr::cummin`

Cumulative min

`dplyr::cumprod`

Cumulative prod

`dplyr::between`

Are values between a and b?

`dplyr::cume_dist`

Cumulative distribution.

`dplyr::pmax`

Element-wise max

`dplyr::pmin`

Element-wise min

Combine Data Sets



`dplyr::left_join(a, b, by = "x1")`

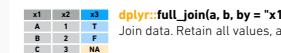
Join matching rows from b to a.



`dplyr::right_join(a, b, by = "x1")`

Join matching rows from a to b.

Filtering Joins



`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.



`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.

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.

`dplyr::group_by(iris, Species) %>% summarise(...)`

Compute separate summary row for each group.

`dplyr::group_by(Species) %>% mutate(...)`

Compute new variables by group.



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



Interacting With NumPy

[Also see NumPy](#)

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2,3), (4j,5j,6j)])
>>> c = np.array([(1,2,3), (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.vsplit(d,2)	Split the array vertically at the 2nd index

Polynomials

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

Create a polynomial object

Vectorizing Functions

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

Vectorize functions

Type Handling

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

Other Useful Functions

>>> np.angle(b,deg=True)	Return the angle of the complex argument
>>> g = np.linspace(0,np.pi,num=5)	Create an array of evenly spaced values (number of samples)
>>> g[3:] += np.pi	Unwrap
>>> np.logspace(0,1,0,3)	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 N-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

Transposition

```
>>> A.T
```

Transpose matrix

Trace

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

Trace

Norm

```
>>> linalg.norm(A)
```

Frobenius norm

```
>>> linalg.norm(A)
```

L1 norm (max column 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	Compressed Sparse Row matrix
>>> H = sparse.csr_matrix(C)	Compressed Sparse Column matrix
>>> I = sparse.csc_matrix(D)	Dictionary Of Keys matrix
>>> J = sparse.dok_matrix(A)	Sparse matrix to full matrix
>>> E.todense()	Identify sparse matrix
>>> sparse.isspmatrix_csc(A)	

Matrix Functions

Addition

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

Addition

Subtraction

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

Subtraction

Division

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

Division

Multiplication

```
>>> A @ D
```

Multiplication operator (Python 3)

```
>>> np.multiply(D,A)
```

Multiplication

```
>>> np.dot(A,D)
```

Dot product

```
>>> np.vdot(A,D)
```

Vector dot product

```
>>> np.inner(A,D)
```

Inner product

```
>>> np.outer(A,D)
```

Outer product

```
>>> np.tensordot(A,D)
```

Tensor dot product

```
>>> np.kron(A,D)
```

Kronecker product

Exponential Functions

```
>>> linalg.expm(A)
```

Matrix exponential

```
>>> linalg.expm2(A)
```

Matrix exponential (Taylor Series)

```
>>> linalg.expm3(D)
```

Matrix exponential (eigenvalue decomposition)

Logarithm Function

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

Matrix logarithm

Trigonometric Functions

```
>>> linalg.sinm(D)
```

Matrix sine

```
>>> linalg.cosm(D)
```

Matrix cosine

```
>>> linalg.tanm(A)
```

Matrix tangent

Hyperbolic Trigonometric Functions

```
>>> linalg.sinhm(D)
```

Hyperbolic matrix sine

```
>>> linalg.coshm(D)
```

Hyperbolic matrix cosine

```
>>> linalg.tanhm(A)
```

Hyperbolic matrix tangent

Matrix Sign Function

```
>>> np.signm(A)
```

Matrix sign function

Matrix Square Root

```
>>> linalg.sqrtm(A)
```

Matrix square root

Arbitrary Functions

```
>>> linalg.fmm(A, lambda x: x*x)
```

Evaluate matrix function

Sparse Matrix Routines

Inverse

```
>>> sparse.linalg.inv(l)
```

Inverse

Norm

```
>>> sparse.linalg.norm(l)
```

Norm

Solving linear problems

```
>>> sparse.linalg.spsolve(H,l)
```

Solver for sparse matrices

Sparse Matrix Functions

```
>>> sparse.linalg.expm(l)
```

Sparse matrix exponential

Decompositions

Eigenvalues and Eigenvectors

```
>>> la, v = linalg.eig(A)
```

Solve ordinary or generalized eigenvalue problem for square matrix

```
>>> l, l2 = la
```

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

Eigenvalues and eigenvectors

```
>>> la, v = sparse.linalg.eigs(F,1)
```

SVD

svds

```
>>> sparse.linalg.svds(H, 2)
```

Asking For Help

>>> help(scipy.linalg.diagsvd)

>>> np.info(np.matrix)

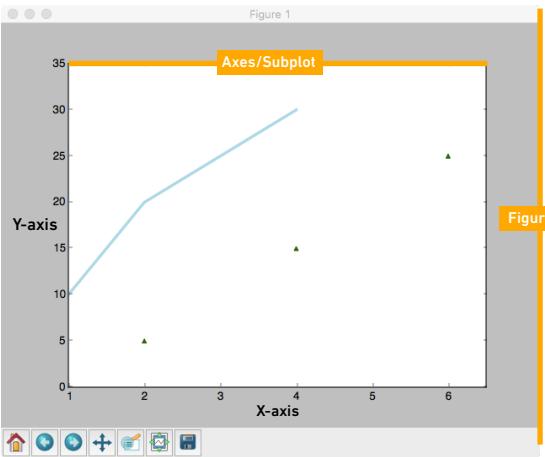
Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

Matplotlib Cheat Sheet

BecomingHuman.AI

Anatomy & Workflow

Plot Anatomy



Workflow

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

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

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)
```

Plotting Routines

1D Data

```
>>> lines = ax.plot(x,y)
>>> ax.scatter(x,y)
>>> axes[0,0].bar([1,2,3],[3,4,5])
>>> axes[1,0].barh([0.5,1.2,2.5],[0,1,2])
>>> axes[1,1].axhline(0.45)
>>> axes[0,1].axvline(0.65)
>>> ax.fill(x,y,color='blue')
>>> ax.fill_between(x,y,color='yellow')
```

Draw points with lines or markers connecting them

Draw unconnected points, scaled or colored

Plot vertical rectangles (constant width)

Plot horizontal rectangles (constant height)

Draw a horizontal line across axes

Draw a vertical line across axes

Draw filled polygons

Fill between y-values and 0

Colormapped or RGB

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

Customize Plot

Colors, Color Bars & Color Maps

```
>>> plt.plot(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'$\sigma_{i,j}=15$', fontsize=20)
```

Vector Fields

```
>>> axes[0,1].arrow(0,0,0.5,0.5)
>>> axes[1,1].quiver(y,z)
>>> axes[0,1].streamplot(X,Y,U,V)
```

Add an arrow to the axes

Plot a 2D field of arrows

Plot 2D vector fields

Data Distributions

```
>>> ax1.hist(y)
>>> ax3.boxplot(y)
>>> ax3.violinplot(z)
```

Plot a histogram

Make a box and whisker plot

Make a violin plot

Pseudocolor

Plot of 2D array
Plot of 2D array
Plot contours
Plot filled contours
Label a contour plot

Pseudocolor plot of 2D array

Pseudocolor plot of 2D array

Plot contours

Plot filled contours

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

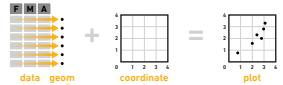
```
>>> plt.clf()
```

```
>>> plt.close()
```

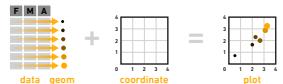
Data Visualisation with ggplot2 Cheat Sheet

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 = ctly, y = hwy, color = cyl, data = mpg, geom = "point")`

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

ggplot(data = mpg, aes(x = cyl, y = hwy))
Begins a plot that you finish by adding layers to. No defaults, but provides more control than `qplot()`.

```
ggplot(mpg, aes(hwy, cyl)) +  
  add layers, elements with +  
  geom_point(aes(color = cyl)) +  
    layer = geom + default stat +  
    geom_smooth(method = "lm") +  
    coord_cartesian() +  
    scale_color_gradient() +  
    theme_bw()
```

additional elements

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

last_plot()
Returns the last plot

ggsave("plot.png", width = 5, height = 5)
Saves last plot as 5" x 5" file named "plot.png" in working directory. Matches file type to file extension.

Coordinate Systems

`r <- b + geom_bar()`

r + coord_cartesian(xlim = c(0, 5))
The default Cartesian coordinate system

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

r + coord_flip()
xmin, xmax, ylim
Flipped Cartesian coordinates

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

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

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

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")  
a + geom_density(kernel = "gaussian")  
a + geom_dotplot()  
a + geom_freqpoly()  
a + geom_hex()  
a + geom_histogram(binwidth = 5)  
a + geom_rug(sides = "bl")  
a + geom_smooth(method = lm)  
a + geom_text(aes(label = cyl))
```

Discrete

```
b <- ggplot(mpg, aes(fct))  
b + geom_bar()
```

Graphical Primitives

```
c <- ggplot(mpg, aes(lng, lat))  
c + geom_polygon(aes(group = group))
```

```
d <- ggplot(economics, aes(date, unemploy))  
d + geom_path(lineend = "butt", linejoin = "round", lineinde
```

```
d + geom_ribbon(aes(ymin = unemploy - 900, ymax = unemploy + 900))
```

```
d <- ggplot(economics, aes(date, unemploy))  
d + geom_segment(aes(xend = long + delta_long, yend = lat + delta_lat))
```

```
d + geom_rect(aes(xmin = long, ymin = lat, xmax = long + delta_long, ymax = lat + delta_lat))
```

Three Variables

```
sealsSz <- with(seals, sqrt(delta_long^2 + delta_lat^2))
```

```
m <- ggplot(seals, aes(long, lat))  
m + geom_contour(aes(z = z))
```

```
m + geom_raster(aes(fill = z), hjust = 0.5, vjust = 0.5, interpolate = FALSE)
```

```
m + geom_tile(aes(fill = z))
```

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, ~ fl)
```

facet into columns based on fl

t + facet_grid(~ year ~ .)

facet into rows based on year

t + facet_grid(~ fl * year ~ .)

facet into both rows and columns

t + facet_wrap(~ fl)

wrap facets into a rectangular layout of one column per discrete variable

Set scales to let axis limits vary across facets

```
t + facet_grid(~ 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 `labeler` to adjust facet labels

```
t + facet_grid(~ fl, labeler = label_both)  
t + facet_grid(~ fl, labeler = label_both)  
t + facet_grid(~ fl, labeler = label_both)  
t + facet_grid(~ fl, labeler = label_both)
```

Two Variables

Continuous X, Continuous Y

```
f <- ggplot(mpg, aes(cty, hwy))  
f + geom_blank()  
f + geom_jitter()  
f + geom_point()  
f + geom_quantile()  
f + geom_rug()  
f + geom_smooth()  
f + geom_text(aes(label = cyl))
```

Discrete X, Continuous Y

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

```
j + geom_line()
```

```
j + geom_smooth()
```

```
j + geom_text(aes(label = cyl))
```

```
j + geom_step(direction = "hv")
```

Continuous Bivariate Distribution

```
i <- ggplot(movies, aes(x = rating, y = count))  
i + geom_bin2d(binwidth = c(0.5, 0.5))  
i + geom_hex()  
i + geom_hex2d()
```

Maps

```
d <- data.frame(murder = USArrests$Murder,  
state = tolower(state.name[USArrests])  
map <- map_data("state")  
(<- ggplot(data, aes(fill = murder))
```

```
d + geom_map(aes(map_id = state), map = map) +  
  expand_limits(x = map$long, y = map$lat)
```

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

```
x, y, alpha, color, fill, linetype, shape, size
```

Position Adjustments

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

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

s + geom_bar(position = "dodge")

Arrange elements side by side

s + geom_bar(position = "fill")

Stack elements on top of one another, normalize height

s + geom_bar(position = "stack")

Stack elements on top of one another

f + geom_point(position = "jitter")

Add random noise to X and Y position of each element to avoid overplotting

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

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

Labels

t + ggtitle("New Plot Title")

Add a main title above the plot

t + xlab("New X Label")

Change the label on the X axis

t + ylab("New Y Label")

Change the label on the Y axis

t + labs(title = "New title", x = "New x", y = "New y")

All of the above

Use scale functions to update legend labels

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 legendTitle and labels with a scale function

Stats

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
geom for layer parameters for stat

a + stat_bin(binwidth = 1, origin = 10)
x, y, count, ..density..
a + stat_bindot(binwidth = 1, binaxis = "x")
x, y, fill, ..count..
a + stat_density(adjust = 1, kernel = "gaussian")
x, y, ..density..

a + stat_bin2d(bins = 30, drop = TRUE)
x, y, fill, ..density..
a + stat_binhex(bins = 30)
x, y, fill, ..count..
a + 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, xend, yend
m + stat_summary_hexes(z = 2, bins = 30, fun = mean)
x, y, ..density.., ..scaled.., ..count.., ..width..

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

a + stat_ecdf(n = 40)
x, y, ..density..
a + stat_quantile(quintiles = c(0.25, 0.5, 0.75), formula = y ~ log(x), method = "nc")
x, y, ..quintile.., ..x.., ..y..

a + 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), n = 101, args = list(d0=5))
f + stat_identity()

ggplot() + stat_qq(aes(sample=1:100), distribution = qt, dparams = list(df=5))
dparams + stat_qq()

f + stat_sum()

f + stat_summary(fun.data = "mean_cl_boot")

f + stat_unique()

Themes

ggthemes - Package with additional ggplot2 themes

White background with grid lines

r + theme_bw()

White background no gridlines

Grey background

r + theme_grey()

Grey background (default theme)

Minimal theme

r + theme_minimal()

Minimal theme

Scales

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

n <- b + geom_bar(aes(fill = fl))
n aesthetic to adjust prepackaged scale
range of values to include in mapping title to use in legend/axis
name = "fuel", labels = c("D", "E", "P", "R")
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 = cfl) - 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(label = 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)
scale_x_date(label = 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

Shape scales

p <- f + geom_point(aes(shape = fl))
p + scale_shape(solid = FALSE)
p + scale_shape_manual(values = cfl)

Size scales

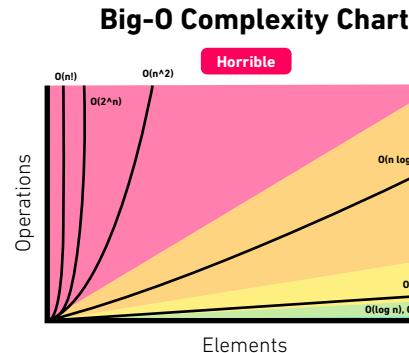
q <- f + geom_point(aes(size = cyl))
q + scale_size_area(max = 6)
Value mapped to area or circle (not radius)

Zooming

Without clipping (preferred)
Without clipping (preferred)
Without clipping (preferred)

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

With clipping (removes unseen data points)
With clipping (removes unseen data points)
With clipping (removes unseen data points)



Data Structure Operation

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

Array Sorting Algorithms

	Time Complexity				Space Complexity			
	Best		Average		Worst		Worst	
	Access	Search	Insertion	Deletion	Access	Search	Insertion	Deletion
Quicksort	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))
Mergesort	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))
Timsort	Θ(n)	Θ(n)	Θ(n log(n))	Θ(n log(n))	Θ(n)	Θ(n log(n))	Θ(n log(n))	Θ(n)
Heapsort	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))
Bubble Sort	Θ(n)	Θ(n)	Θ(n^2)	Θ(n^2)	Θ(n)	Θ(n^2)	Θ(n^2)	Θ(n)
Insertion Sort	Θ(n)	Θ(n)	Θ(n^2)	Θ(n^2)	Θ(n)	Θ(n^2)	Θ(n^2)	Θ(n)
Selection Sort	Θ(n^2)	Θ(n^2)	Θ(n^2)	Θ(n^2)	Θ(n^2)	Θ(n^2)	Θ(n^2)	Θ(n^2)
Tree Sort	Θ(n log(n))	Θ(n log(n))	Θ(n^2)	Θ(n^2)	Θ(n log(n))	Θ(n log(n))	Θ(n^2)	Θ(n log(n))
Shell Sort	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))^2	Θ(n log(n))^2	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))
Bucket Sort	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)
Radix Sort	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)
Counting Sort	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)	Θ(n+k)
Cubesort	Θ(n)	Θ(n)	Θ(n log(n))	Θ(n log(n))	Θ(n)	Θ(n log(n))	Θ(n log(n))	Θ(n log(n))