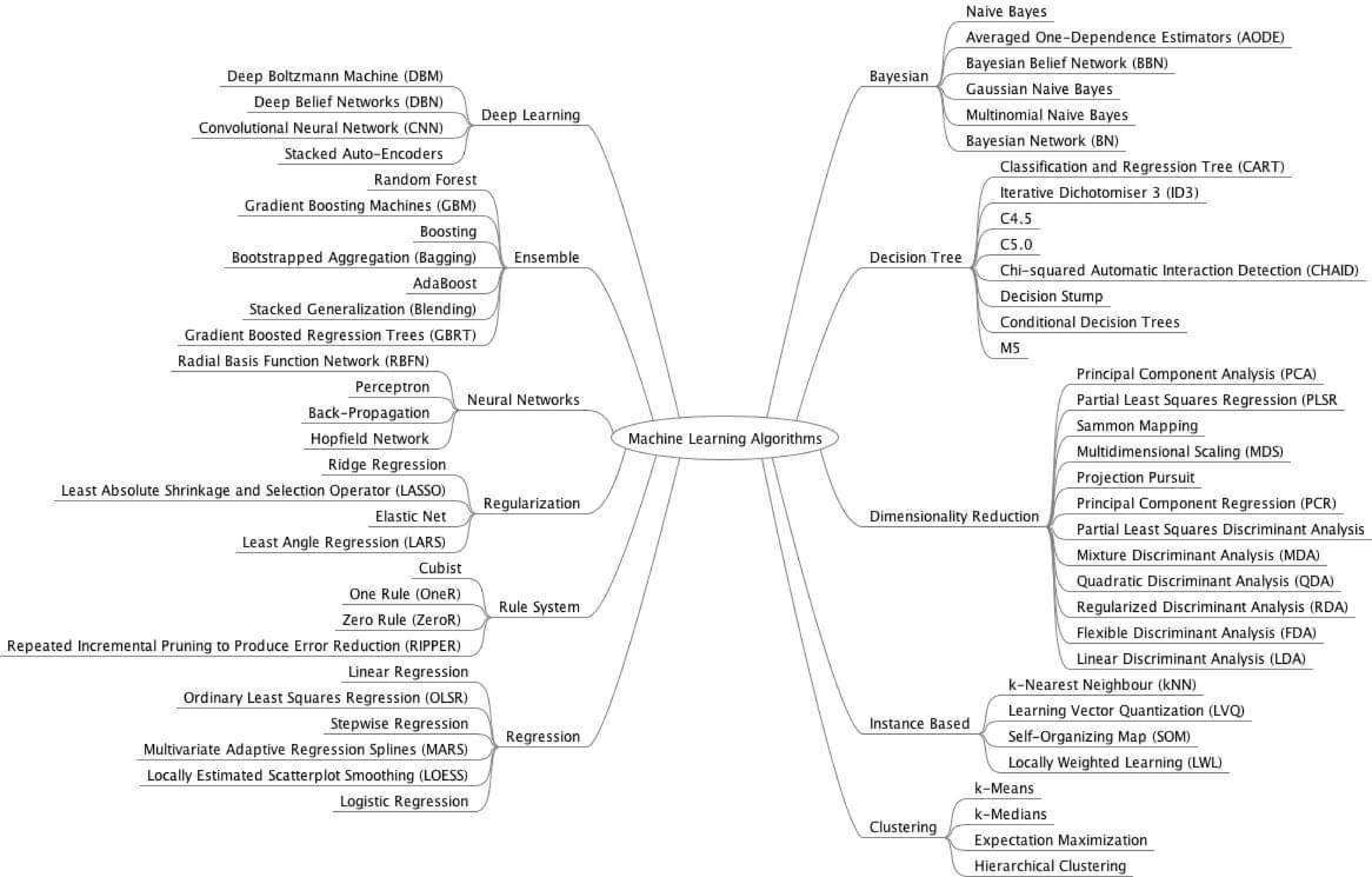


Machine Learning Algorithms
Deep Learning
Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders
Ensemble
Random Forest
Gradient Boosting Machines (GBM)
Boosting
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (Blending)
Gradient Boosted Regression Trees (GBRT)
Neural Networks
Radial Basis Function Network (RBFN)
Perceptron
Back-Propagation
Hopfield Network
Regularization
Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least Angle Regression (LARS)
Rule System
Cubist
One Rule (OneR)
Zero Rule (ZeroR)
Repeated Incremental Pruning to Produce Error Reduction (RIPPER)
Regression
Linear Regression
Ordinary Least Squares Regression (OLSR)
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Logistic Regression
Bayesian
Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Gaussian Naive Bayes
Multinomial Naive Bayes
Bayesian Network (BN)
Decision Tree
Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5
C5.0
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
Conditional Decision Trees
M5
Dimensionality Reduction
Principal Component Analysis (PCA)
Partial Least Squares Regression (PLSR
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Principal Component Regression (PCR)
Partial Least Squares Discriminant Analysis
Mixture Discriminant Analysis (MDA)
Quadratic Discriminant Analysis (QDA)
Regularized Discriminant Analysis (RDA)
Flexible Discriminant Analysis (FDA)
Linear Discriminant Analysis (LDA)
Instance Based
k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)
Clustering
k-Means
k-Medians
Expectation Maximization
Hierarchical Clustering

data iku

TOP PREDICTION ALGORITHMS

TYPE	NAME	DESCRIPTION	ADVANTAGES	DISADVANTAGES
Linear	Linear regression	**The "best fit" line** through all data points. Predictions are numerical.	Easy to understand -- you clearly see what the biggest drivers of the model are.	X Sometimes too simple to capture complex relationships between variables. X Tendency for the model to "overfit".
Linear	Logistic regression	The adaptation of **linear regression** to problems of classification (e.g., yes/no questions, groups, etc.)	Also easy to understand.	X Sometimes too simple to capture complex relationships between variables. X Tendency for the model to "overfit".
Tree-based	Decision tree	A graph that uses a **branching method** to match all possible outcomes of a decision.	Easy to understand and implement.	X Not often used on its own for prediction because it's also often too simple and not powerful enough for complex data.
Tree-based	Random Forest	Takes the average of many decision trees, each of which is made with a sample of the data. Each tree is weaker than a full decision tree, but **by combining them we get better overall performance.**	A sort of "wisdom of the crowd". Tends to result in very high quality models. Fast to train.	X Can be slow to output predictions relative to other algorithms. X Not easy to understand predictions.
Tree-based	Gradient Boosting	Uses even weaker decision trees, that are increasingly **focused on "hard" examples.**	High-performing.	X A small change in the feature set or training set can create radical changes in the model. X Not easy to understand predictions.
Neural networks	Neural networks	Mimics the behavior of the brain. Neural networks are interconnected neurons that pass messages to each other. Deep learning uses several **layers of neural networks put one after the other.**	Can handle extremely complex tasks - no other algorithm comes close in image recognition.	X Very, very slow to train, because they have so many layers. Require a lot of power. X Almost impossible to understand predictions.

the world of machine learning algorithms – a summary

think big data

regression

Ordinary Least Squares Regression (OLSR)
Linear Regression
Logistic Regression
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Jackknife Regression

regularization

Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least-Angle Regression (LARS))

instance based

also called **cake-based, memory-based**

k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)

dimesionality reduction

Principal Component Analysis (PCA)
Principal Component Regression (PCR)
Partial Least Squares Regression (PLSR)
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Discriminant Analysis (LDA, MDA, QDA, FDA)

deep learning

Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders

associated rule

Apriori
Eclat
FP-Growth

ensemble

Logit Boost (Boosting)
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (blending)
Gradient Boosting Machines (GBM)
Gradient Boosted Regression Trees (GBRT)
Random Forest

bayesian

Naive Bayes
Gaussian Naive Bayes
Multinomial Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Bayesian Network (BN)
Hidden Markov Models
Conditional random fields (CRFs)

decision tree

Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5 and C5.0 (different versions of a powerful approach)
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
M5
Random Forests
Conditional Decision Trees

clustering

Single-linkage clustering
k-Means
k-Medians
Expectation Maximisation (EM)
Hierarchical Clustering
Fuzzy clustering
DBSCAN
OPTICS algorithm
Non Negative Matrix Factorization
Latent Dirichlet allocation (LDA)

neural networks

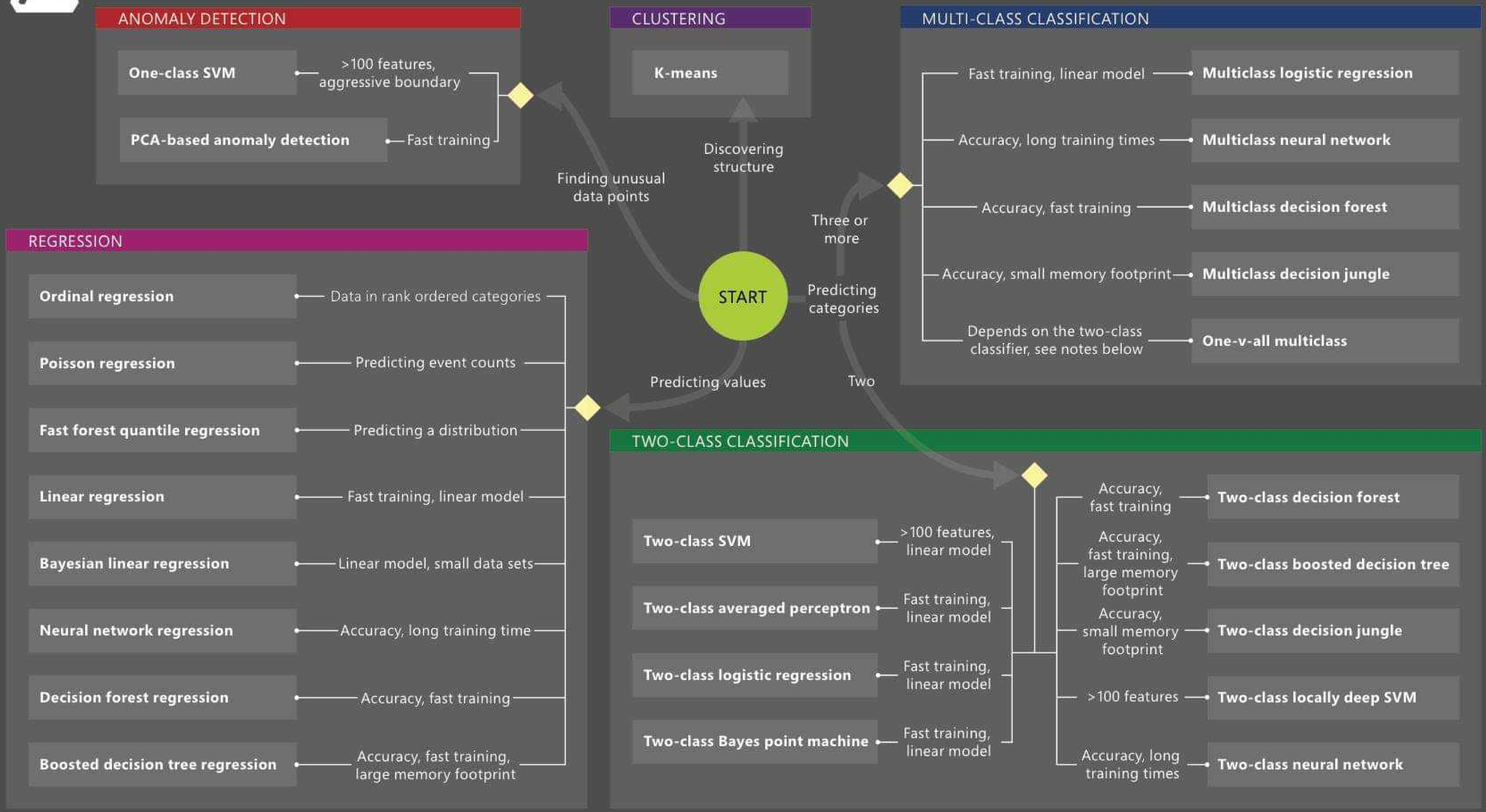
Self Organizing Map
Perceptron
Back-Propagation
Hopfield Network
Radial Basis Function Network (RBFN)
Backpropagation
Autoencoders
Hopfield networks
Boltzmann machines
Restricted Boltzmann Machines
Spiking Neural Networks
Learning Vector quantization (LVQ)

...and others

Support Vector Machines (SVM)
Evolutionary Algorithms
Inductive Logic Programming (ILP)
Reinforcement Learning (Q-Learning, Temporal Difference,
State-Action-Reward-State-Action (SARSA))
ANOVA
Information Fuzzy Network (IFN)
Page Rank
Conditional Random Fields (CRF)

Microsoft Azure Machine Learning: Algorithm Cheat Sheet

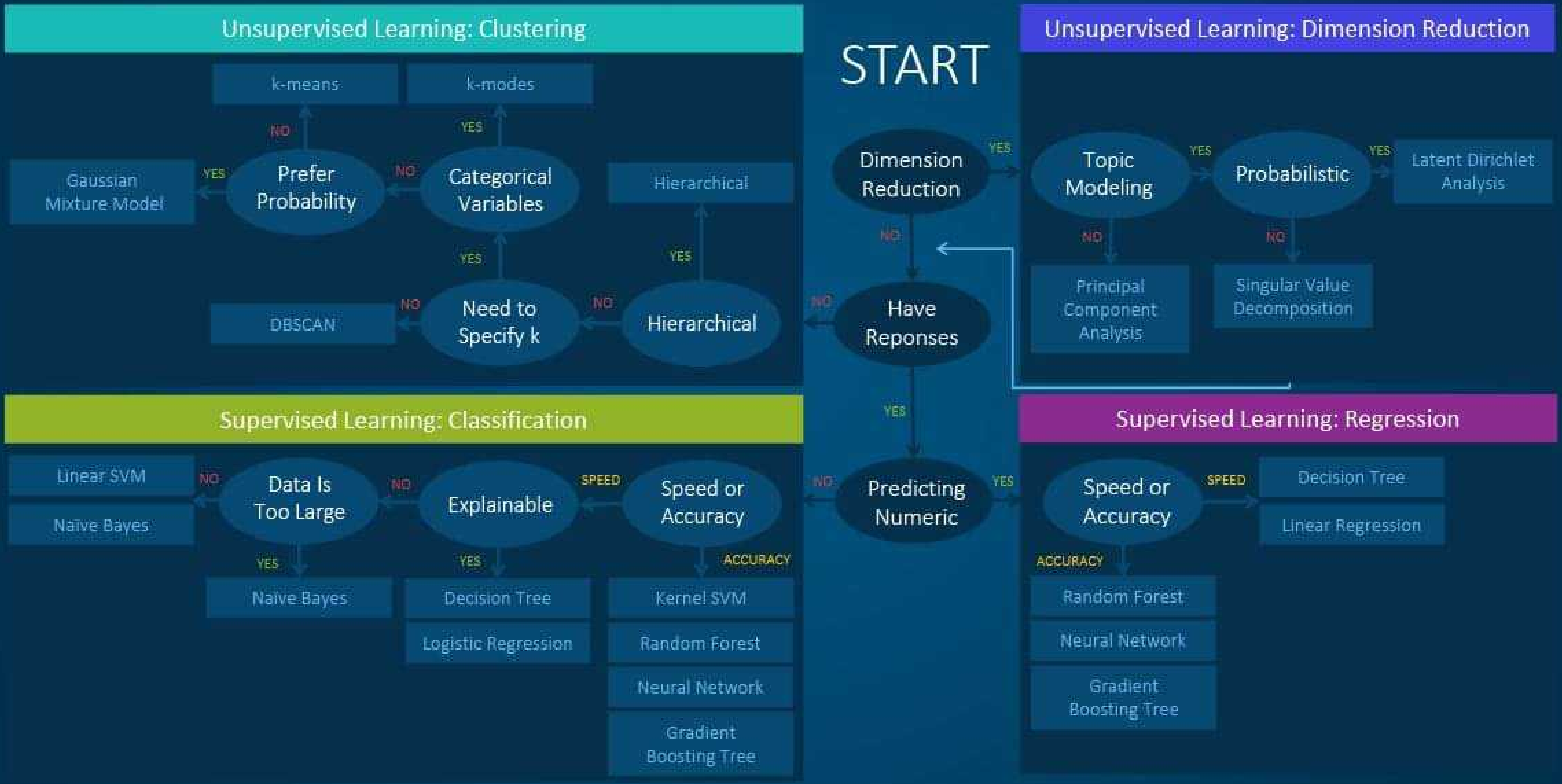
This cheat sheet helps you choose the best Azure Machine Learning Studio algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the question you're trying to answer.



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


A mostly complete chart of
Neural Networks
©2016 Fjodor van Veen - asimovinstitute.org
Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probablistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Different Memory Cell
Kernel
Convolution or Pool
Perceptron (P)
Feed Forward (FF)
Radial Basis Network (RBF)
Deep Feed Forward (DFF)
Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)
Auto Encoder (AE)
Variational AE (VAE)
Denoising AE (DAE)
Sparse AE (SAE)
Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

Machine Learning Algorithms Cheat Sheet



CHEATSHEET

Machine Learning Algorithms

(Python and R Codes)

Types

Supervised Learning
- Decision Tree
- Random Forest
- kNN
- Logistic Regression

Unsupervised Learning
- Apriori algorithm
- k-means
- Hierarchical Clustering

Reinforcement Learning
- Markov Decision Process
- Q Learning

Python Code	R Code

Linear Regression

Python Code:

```python
#Import Library
#Import other necessary libraries like pandas,
#numpy...
from sklearn import linear_model
#Load Train and Test datasets
#Identify feature and response variable(s) and
#values must be numeric and numpy arrays
x_train=input_variables_values_training_datasets
y_train=target_variables_values_training_datasets
x_test=input_variables_values_test_datasets
#Create linear regression object
linear = linear_model.LinearRegression()
#Train the model using the training sets and
#check score
linear.fit(x_train, y_train)
linear.score(x_train, y_train)
#Equation coefficient and Intercept
print('Coefficient: \n', linear.coef_)
print('Intercept: \n', linear.intercept_)
#Predict Output
predicted= linear.predict(x_test)
```

R Code:

```r
#Load Train and Test datasets
#Identify feature and response variable(s) and
#values must be numeric and numpy arrays
x_train <- input_variables_values_training_datasets
y_train <- target_variables_values_training_datasets
x_test <- input_variables_values_test_datasets
x <- cbind(x_train,y_train)
#Train the model using the training sets and
#check score
linear <- lm(y_train ~ ., data = x)
summary(linear)
#Predict Output
predicted= predict(linear,x_test)
```

Logistic Regression

Python Code:

```python
#Import Library
from sklearn.linear_model import LogisticRegression
#Assumed you have, X (predictor) and Y (target)
#for training data set and x_test(predictor)
#of test_dataset
#Create logistic regression object
model = LogisticRegression()
#Train the model using the training sets
#and check score
model.fit(X, y)
model.score(X, y)
#Equation coefficient and Intercept
print('Coefficient: \n', model.coef_)
print('Intercept: \n', model.intercept_)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
x <- cbind(x_train,y_train)
#Train the model using the training sets and check
#score
logistic <- glm(y_train ~ ., data = x,family='binomial')
summary(logistic)
#Predict Output
predicted= predict(logistic,x_test)
```

Decision Tree

Python Code:

```python
#Import Library
#Import other necessary libraries like pandas, numpy...
from sklearn import tree
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of
#test_dataset
#Create tree object
model = tree.DecisionTreeClassifier(criterion='gini')
#for classification, here you can change the
#algorithm as gini or entropy (information gain) by
#default it is gini
#model = tree.DecisionTreeRegressor() for
#regression
#Train the model using the training sets and check
#score
model.fit(X, y)
model.score(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(rpart)
x <- cbind(x_train,y_train)
#grow tree
fit <- rpart(y_train ~ ., data = x,method="class")
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

SVM (Support Vector Machine)

Python Code:

```python
#Import Library
from sklearn import svm
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create SVM classification object
model = svm.svc()
#there are various options associated
with it, this is simple for classification.
#Train the model using the training sets and check
#score
model.fit(X, y)
model.score(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(e1071)
x <- cbind(x_train,y_train)
#Fitting model
fit <-svm(y_train ~ ., data = x)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

Naive Bayes

Python Code:

```python
#Import Library
from sklearn.naive_bayes import GaussianNB
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create SVM classification object model = GaussianNB()
#there is other distribution for multinomial classes
like Bernoulli Naive Bayes
#Train the model using the training sets and check
#score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(e1071)
x <- cbind(x_train,y_train)
#Fitting model
fit <-naiveBayes(y_train ~ ., data = x)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

kNN (k- Nearest Neighbors)

Python Code:

```python
#Import Library
from sklearn.neighbors import KNeighborsClassifier
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create KNeighbors classifier object model
KNeighborsClassifier(n_neighbors=6)
#default value for n_neighbors is 5
#Train the model using the training sets and check score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(knn)
x <- cbind(x_train,y_train)
#Fitting model
fit <-knn(y_train ~ ., data = x,k=5)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

k-Means

Python Code:

```python
#Import Library
from sklearn.cluster import KMeans
#Assumed you have, X (attributes) for training data set
#and x_test(attributes) of test_dataset
#Create KNeighbors classifier object model
k_means = KMeans(n_clusters=3, random_state=0)
#Train the model using the training sets and check score
model.fit(X)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(cluster)
fit <- kmeans(X, 3)
#5 cluster solution
```

Random Forest

Python Code:

```python
#Import Library
from sklearn.ensemble import RandomForestClassifier
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create Random Forest object
model= RandomForestClassifier()
#Train the model using the training sets and check score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(randomForest)
x <- cbind(x_train,y_train)
#Fitting model
fit <- randomForest(Species ~ ., x,ntree=500)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

Dimensionality Reduction Algorithms

Python Code:

```python
#Import Library
from sklearn import decomposition
#Assumed you have training and test data set as train and
#test
#Create PCA object pca= decomposition.PCA(n_components=k)
#default value of k =min(n_sample, n_features)
#For Factor analysis
#fa= decomposition.FactorAnalysis()
#Reduced the dimension of training dataset using PCA
train_reduced = pca.fit_transform(train)
#Reduced the dimension of test dataset
test_reduced = pca.transform(test)
```

R Code:

```r
#Import Library
library(stats)
pca <- princomp(train, cor = TRUE)
train_reduced  <- predict(pca,train)
test_reduced  <- predict(pca,test)
```

Gradient Boosting & AdaBoost

Python Code:

```python
#Import Library
from sklearn.ensemble import GradientBoostingClassifier
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create Gradient Boosting Classifier object
model= GradientBoostingClassifier(n_estimators=100, \
       learning_rate=1.0, max_depth=1, random_state=0)
#Train the model using the training sets and check score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code:

```r
#Import Library
library(caret)
x <- cbind(x_train,y_train)
#Fitting model
fitControl <- trainControl( method = "repeatedcv",
+ number = 4, repeats = 4)
fit <- train(y ~ ., data = x, method = "gbm",
+ trControl = fitControl,verbose = FALSE)
predicted= predict(fit,x_test,type= "prob")[,2]
```

Python Cheat Sheet

JUST THE BASICS

CREATED BY: ARIANNE COLTON AND SEAN CHEN

GENERAL

- Python is case sensitive
- Python index starts from 0
- Python uses whitespace (tabs or spaces) to indent code instead of using braces.

HELP

Help Home Page	`help()`
Function Help	`help(str.replace)`
Module Help	`help(re)`

MODULE (AKA LIBRARY)

Python module is simply a '.py' file

List Module Contents	`dir(module1)`
Load Module	`import module1` *
Call Function from Module	`module1.func1()`

* import statement creates a new namespace and executes all the statements in the associated .py file within that namespace. If you want to load the module's content into current namespace, use 'from module1 import *'

SCALAR TYPES

Check data type : `type(variable)`

SIX COMMONLY USED DATA TYPES

1. **int/long*** - Large int automatically converts to long
2. **float*** - 64 bits, there is no 'double' type
3. **bool*** - True or False
4. **str*** - ASCII valued in Python 2.x and Unicode in Python 3
   - String can be in single/double/triple quotes
   - String is a sequence of characters, thus can be treated like other sequences
   - Special character can be done via \ or preface with r

   ```
   str1 = r'this\f?ff'
   ```

   - String formatting can be done in a number of ways

   ```
   template = '%.2f %s haha $%d';
   str1 = template % (4.88, 'hola', 2)
   ```

SCALAR TYPES

* str(), bool(), int() and float() are also explicit type cast functions.

5. **NoneType(None)** - Python 'null' value (ONLY one instance of None object exists)
   - None is not a reserved keyword but rather a unique instance of 'NoneType'
   - None is common default value for optional function arguments :

   ```
   def func1(a, b, c = None)
   ```

   - Common usage of None :

   ```
   if variable is None :
   ```

6. **datetime** - built-in python 'datetime' module provides 'datetime', 'date', 'time' types.
   - 'datetime' combines information stored in 'date' and 'time'

Create datetime from String	`dt1 = datetime.strptime('20091031', '%Y%m%d')`
Get 'date' object	`dt1.date()`
Get 'time' object	`dt1.time()`
Format datetime to String	`dt1.strftime('%m/%d/%Y %H:%M')`
Change Field Value	`dt2 = dt1.replace(minute = 0, second = 30)`
Get Difference	`diff = dt1 - dt2` # diff is a 'datetime.timedelta' object

Note : Most objects in Python are mutable except for 'strings' and 'tuples'

DATA STRUCTURES

Note : All non-Get function call i.e. `list1.sort()` examples below are in-place (without creating a new object) operations unless noted otherwise.

TUPLE

One dimensional, fixed-length, **immutable** sequence of Python objects of ANY type.

DATA STRUCTURES

Create Tuple	`tup1 = 4, 5, 6` or `tup1 = (6,7,8)`
Create Nested Tuple	`tup1 = (4,5,6), (7,8)`
Convert Sequence or Iterator to Tuple	`tuple([1, 0, 2])`
Concatenate Tuples	`tup1 + tup2`
Unpack Tuple	`a, b, c = tup1`

Application of Tuple

Swap variables	`b, a = a, b`

LIST

One dimensional, variable length, **mutable** (i.e. contents can be modified) sequence of Python objects of ANY type.

Create List	`list1 = [1, 'a', 3]` or `list1 = list(tup1)`
Concatenate Lists*	`list1 + list2` or `list1.extend(list2)`
Append to End of List	`list1.append('b')`
Insert to Specific Position	`list1.insert(posIdx, 'b')` **
Inverse of Insert	`valueAtIdx = list1.pop(posIdx)`
Remove First Value from List	`list1.remove('a')`
Check Membership	`3 in list1 => True` ***
Sort List	`list1.sort()`
Sort with User-Supplied Function	`list1.sort(key = len)` # sort by length

* List concatenation using '+' is expensive since a new list must be created and objects copied over. Thus, `extend()` is preferable.

** Insert is computationally expensive compared with append.

*** Checking that a list contains a value is lot slower than dicts and sets as Python makes a linear scan where others (based on hash tables) in constant time.

Built-in 'bisect module‡

- Implements binary search and insertion into a sorted list
- 'bisect.bisect' finds the location, where 'bisect.insort' actually inserts into that location.

‡ WARNING : bisect module functions do not check whether the list is sorted, doing so would be computationally expensive. Thus, using them in an unsorted list will succeed without error but may lead to incorrect results.

SLICING FOR SEQUENCE TYPES†

† Sequence types include 'str', 'array', 'tuple', 'list', etc.

Notation	`list1[start:stop]`
	`list1[start:stop:step]` (If step is used) §

Note :

- 'start' index is included, but 'stop' index is NOT.
- start/stop can be omitted in which they default to the start/end.

§ Application of 'step' :

Take every other element	`list1[::2]`
Reverse a string	`str1[::-1]`

DICT (HASH MAP)

Create Dict	`dict1 = {'key1' :'value1', 2 :[3, 2]}`
Create Dict from Sequence	`dict(zip(keyList, valueList))`
Get/Set/Insert Element	`dict1['key1']`* `dict1['key1'] = 'newValue'`
Get with Default Value	`dict1.get('key1', defaultValue)` **
Check if Key Exists	`'key1' in dict1`
Delete Element	`del dict1['key1']`
Get Key List	`dict1.keys()` ***
Get Value List	`dict1.values()` ***
Update Values	`dict1.update(dict2)` # dict1 values are replaced by dict2

* 'KeyError' exception if the key does not exist.

** 'get()' by default (aka no 'defaultValue') will return 'None' if the key does not exist.

*** Returns the lists of keys and values in the same order. However, the order is not any particular order, aka it is most likely not sorted.

Valid dict key types

- Keys have to be immutable like scalar types (int, float, string) or tuples (all the objects in the tuple need to be immutable too)
- The technical term here is 'hashability', check whether an object is hashable with the `hash('this is string'), hash([1, 2])` - this would fail.

SET

- A set is an **unordered** collection of UNIQUE elements.
- You can think of them like dicts but keys only.

Create Set	`set([3, 6, 3])` or `{3, 6, 3}`
Test Subset	`set1.issubset(set2)`
Test Superset	`set1.issuperset(set2)`
Test sets have same content	`set1 == set2`

- **Set operations :**

Union(aka 'or')	`set1 | set2`
Intersection (aka 'and')	`set1 & set2`
Difference	`set1 - set2`
Symmetric Difference (aka 'xor')	`set1 ^ set2`

Python For Data Science *Cheat Sheet*

Python Basics

Learn More Python for Data Science Interactively at www.datacamp.com

Variables and Data Types

Variable Assignment

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

Calculations With Variables

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

Types and Type Conversion

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

Asking For Help

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

Strings

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

String Operations

```
>>> my_string * 2
 'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'Innit'
 'thisStringIsAwesomeInnit'
>>> 'm' in my_string
 True
```

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_list2[1][:2]`	my_list[list][itemOfList]

List Operations

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

List Methods

`>>> my_list.index(a)`	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

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 whitespace from ends

Libraries

Import libraries

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

Selective import

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

pandas — Data analysis

scikit-learn — Machine learning

NumPy — Scientific computing

matplotlib — 2D plotting

Install Python

ANACONDA — Leading open data science platform powered by Python

spyder — Free IDE that is included with Anaconda

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

Numpy Arrays

Also see Lists

```
>>> my_list = [1, 2, 3, 4]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[4,5,6]])
```

Selecting Numpy Array Elements

Index starts at 0

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

Numpy Array Operations

```
>>> my_array > 3
 array([False, False, False,  True], dtype=bool)
>>> my_array * 2
 array([2, 4, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
 array([6, 8, 10, 12])
```

Numpy Array Functions

`>>> my_array.shape`	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

Python For Data Science *Cheat Sheet*

Matplotlib

Learn Python Interactively at www.DataCamp.com

Matplotlib

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

1 Prepare The Data

Also see Lists & NumPy

1D Data

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

2D Data or Images

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

2 Create Plot

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

Figure

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

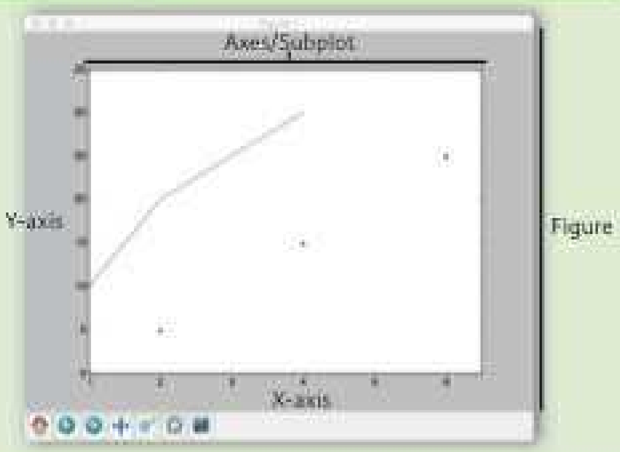
Axes

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

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

Plot Anatomy & Workflow

Plot Anatomy



Workflow

The basic steps to creating plots with matplotlib are:

1 Prepare data 2 Create plot 3 Plot 4 Customize plot 5 Save plot 6 Show plot

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

4 Customize Plot

Colors, Color Bars & Color Maps

```
>>> plt.plot(x, x, x, x**2, x, x**3)
>>> ax.plot(x, y, alpha = 0.4)
>>> ax.plot(x, y, c='k')
>>> fig.colorbar(im, orientation='horizontal')
>>> im = ax.imshow(img,
                   cmap='seismic')
```

Markers

```
>>> fig, ax = plt.subplots()
>>> ax.scatter(x,y,marker=".")
>>> ax.plot(x,y,marker="o")
```

Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--')
>>> plt.plot(x,y,'--',x**2,y**2,'-.')
>>> plt.setp(lines,color='r',linewidth=4.0)
```

Text & Annotations

```
>>> ax.text(1,
            -2.1,
            'Example Graph',
            style='italic')
>>> ax.annotate("Sine",
                xy=(8, 0),
                xycoords='data',
                xytext=(10.5, 0),
                textcoords='data',
                arrowprops=dict(arrowstyle="->",
                                connectionstyle="arc3"),)
```

Mathtext

```
>>> plt.title(r'$sigma_i=15$', fontsize=20)
```

Limits, Legends & Layouts

Limits & Autoscaling

`>>> ax.margins(x=0.0,y=0.1)`	Add padding to a plot
`>>> ax.axis('equal')`	Set the aspect ratio of the plot to 1
`>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5])`	Set limits for x-and y-axis
`>>> ax.set_xlim(0,10.5)`	Set limits for x-axis

Legends

`>>> ax.set(title='An Example Axes', 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"])`	Manually set x-ticks
`>>> ax.tick_params(axis='y', direction='inout', length=10)`	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)`	Adjust the spacing between subplots
`>>> fig.tight_layout()`	Fit subplot(s) in to the figure area

Axis Spines

`>>> ax1.spines['top'].set_visible(False)`	Make the top axis line for a plot invisible
`>>> ax1.spines['bottom'].set_position(('outward',10))`	Move the bottom axis line outward

3 Plotting Routines

1D Data

`>>> 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

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

2D Data or Images

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

`>>> axes2[0].pcolor(data2)`	Pseudocolor plot of 2D array
`>>> axes2[0].pcolormesh(data)`	Pseudocolor plot of 2D array
`>>> CS = plt.contour(Y,X,U)`	Plot contours
`>>> axes2[2].contourf(data1)`	Plot filled contours
`>>> axes2[2]= ax.clabel(CS)`	Label a contour plot

5 Save Plot

Save figures

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

Save transparent figures

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

6 Show Plot

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

Close & Clear

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

Data Science Cheat Sheet

NumPy

KEY
We'll use shorthand in this cheat sheet
`arr` - A numpy Array object

IMPORTS
Import these to start
`import numpy as np`

IMPORTING/EXPORTING
`np.loadtxt('file.txt')` - From a text file
`np.genfromtxt('file.csv',delimiter=',')` - From a CSV file
`np.savetxt('file.txt',arr,delimiter=' ')` - Writes to a text file
`np.savetxt('file.csv',arr,delimiter=',')` - Writes to a CSV file

CREATING ARRAYS
`np.array([1,2,3])` - One dimensional array
`np.array([(1,2,3),(4,5,6)])` - Two dimensional array
`np.zeros(3)` - 1D array of length `3` all values `0`
`np.ones((3,4))` - 3x4 array with all values `1`
`np.eye(5)` - 5x5 array of `0` with `1` on diagonal (Identity matrix)
`np.linspace(0,100,6)` - Array of `6` evenly divided values from `0` to `100`
`np.arange(0,10,3)` - Array of values from `0` to less than `10` with step `3` (eg `[0,3,6,9]`)
`np.full((2,3),8)` - 2x3 array with all values `8`
`np.random.rand(4,5)` - 4x5 array of random floats between `0-1`
`np.random.rand(6,7)*100` - 6x7 array of random floats between `0-100`
`np.random.randint(5,size=(2,3))` - 2x3 array with random ints between `0-4`

INSPECTING PROPERTIES
`arr.size` - Returns number of elements in `arr`
`arr.shape` - Returns dimensions of `arr` (rows, columns)
`arr.dtype` - Returns type of elements in `arr`
`arr.astype(dtype)` - Convert `arr` elements to type `dtype`
`arr.tolist()` - Convert `arr` to a Python list
`np.info(np.eye)` - View documentation for `np.eye`

COPYING/SORTING/RESHAPING
`np.copy(arr)` - Copies `arr` to new memory
`arr.view(dtype)` - Creates view of `arr` elements with type `dtype`
`arr.sort()` - Sorts `arr`
`arr.sort(axis=0)` - Sorts specific axis of `arr`
`two_d_arr.flatten()` - Flattens 2D array `two_d_arr` to 1D
`arr.T` - Transposes `arr` (rows become columns and vice versa)
`arr.reshape(3,4)` - Reshapes `arr` to `3` rows, `4` columns without changing data
`arr.resize((5,6))` - Changes `arr` shape to `5x6` and fills new values with `0`

ADDING/REMOVING ELEMENTS
`np.append(arr,values)` - Appends `values` to end of `arr`
`np.insert(arr,2,values)` - Inserts `values` into `arr` before index `2`
`np.delete(arr,3,axis=0)` - Deletes row on index `3` of `arr`
`np.delete(arr,4,axis=1)` - Deletes column on index `4` of `arr`

COMBINING/SPLITTING
`np.concatenate((arr1,arr2),axis=0)` - Adds `arr2` as rows to the end of `arr1`
`np.concatenate((arr1,arr2),axis=1)` - Adds `arr2` as columns to end of `arr1`
`np.split(arr,3)` - Splits `arr` into `3` sub-arrays
`np.hsplit(arr,5)` - Splits `arr` horizontally on the `5`th index

INDEXING/SLICING/SUBSETTING
`arr[5]` - Returns the element at index `5`
`arr[2,5]` - Returns the 2D array element on index `[2][5]`
`arr[1]=4` - Assigns array element on index `1` the value `4`
`arr[1,3]=10` - Assigns array element on index `[1][3]` the value `10`
`arr[0:3]` - Returns the elements at indices `0,1,2` (On a 2D array: returns rows `0,1,2`)
`arr[0:3,4]` - Returns the elements on rows `0,1,2` at column `4`
`arr[:2]` - Returns the elements at indices `0,1` (On a 2D array: returns rows `0,1`)
`arr[:,1]` - Returns the elements at index `1` on all rows
`arr<5` - Returns an array with boolean values
`(arr1<3) & (arr2>5)` - Returns an array with boolean values
`~arr` - Inverts a boolean array
`arr[arr<5]` - Returns array elements smaller than `5`

SCALAR MATH
`np.add(arr,1)` - Add `1` to each array element
`np.subtract(arr,2)` - Subtract `2` from each array element
`np.multiply(arr,3)` - Multiply each array element by `3`
`np.divide(arr,4)` - Divide each array element by `4` (returns `np.nan` for division by zero)
`np.power(arr,5)` - Raise each array element to the `5`th power

VECTOR MATH
`np.add(arr1,arr2)` - Elementwise add `arr2` to `arr1`
`np.subtract(arr1,arr2)` - Elementwise subtract `arr2` from `arr1`
`np.multiply(arr1,arr2)` - Elementwise multiply `arr1` by `arr2`
`np.divide(arr1,arr2)` - Elementwise divide `arr1` by `arr2`
`np.power(arr1,arr2)` - Elementwise raise `arr1` raised to the power of `arr2`
`np.array_equal(arr1,arr2)` - Returns `True` if the arrays have the same elements and shape
`np.sqrt(arr)` - Square root of each element in the array
`np.sin(arr)` - Sine of each element in the array
`np.log(arr)` - Natural log of each element in the array
`np.abs(arr)` - Absolute value of each element in the array
`np.ceil(arr)` - Rounds up to the nearest int
`np.floor(arr)` - Rounds down to the nearest int
`np.round(arr)` - Rounds to the nearest int

STATISTICS
`np.mean(arr,axis=0)` - Returns mean along specific axis
`arr.sum()` - Returns sum of `arr`
`arr.min()` - Returns minimum value of `arr`
`arr.max(axis=0)` - Returns maximum value of specific axis
`np.var(arr)` - Returns the variance of array
`np.std(arr,axis=1)` - Returns the standard deviation of specific axis
`arr.corrcoef()` - Returns correlation coefficient of array

Numpy Cheat Sheet

Python Package

Created By: Arianne Colton and Sean Chen

Numpy (Numerical Python)

What is NumPy?

Foundation package for scientific computing in Python

Why NumPy?

- Numpy **'ndarray'** is a much more efficient way of storing and manipulating **"numerical data"** than the built-in Python data structures.
- Libraries written in lower-level languages, such as C, can operate on data stored in Numpy **'ndarray'** without copying any data.

N-Dimensional Array (NDArray)

What is NdArray?

Fast and space-efficient multidimensional array (container for homogeneous data) providing vectorized arithmetic operations

Create NdArray	`np.array(seq1)` # seq1 - is any sequence like object, i.e. [1, 2, 3]

Create Special NdArray	`1, np.zeros(10)`
	# one dimensional ndarray with 10 elements of value 0
	`2, np.ones(2, 3)`
	# two dimensional ndarray with 6 elements of value 1
	`3, np.empty(3, 4, 5) *`
	# three dimensional ndarray of uninitialized values
	`4, np.eye(N) or np.identity(N)`
	# creates N by N identity matrix

NdArray version of Python's `range`	`np.arange(1, 10)`
Get # of Dimension	`ndarray1.ndim`
Get Dimension Size	`dim1size, dim2size, .. = ndarray1.shape`
Get Data Type **	`ndarray1.dtype`
Explicit Casting	`ndarray2 = ndarray1. astype(np.int32) ***`

- * Cannot assume empty() will return all zeros. It could be garbage values.

- ** Default data type is **'np.float64'**. This is equivalent to Python's float type which is 8 bytes (64 bits); thus the name 'float64'.
- *** If casting were to fail for some reason, **'TypeError'** will be raised.

Slicing (Indexing/Subsetting)

- Slicing (i.e. `ndarray1[2:6]`) is a **'view'** on the original array. **Data is NOT copied.** Any modifications (i.e. `ndarray1[2:6] = 8`) to the 'view' will be reflected in the original array.
- Instead of a 'view', explicit copy of slicing via :

```
ndarray1[2:6].copy()
```

- Multidimensional array indexing notation :

`ndarray1[0][2]` or `ndarray1[0, 2]`

*** Boolean indexing :**

```
ndarray1[(names == 'Bob') | (names == 'Will'), 2:]
# '2:' means select from 3rd column on
```

- * Selecting data by boolean indexing **ALWAYS** creates a copy of the data.
- * The 'and' and 'or' keywords do NOT work with boolean arrays. Use & and |.

*** Fancy indexing** (aka 'indexing using integer arrays')

Select a subset of rows in a particular order :

```
ndarray1[ [3, 8, 4] ]
ndarray1[ [-1, 6] ]
# negative indices select rows from the end
```

- * Fancy indexing **ALWAYS** creates a copy of the data.

Numpy (Numerical Python)

Setting data with assignment :

```
ndarray1[ndarray1 < 0] = 0 *
```

- * If ndarray1 is two-dimensions, ndarray1 < 0 creates a two-dimensional boolean array.

Common Operations

1. Transposing

- A special form of reshaping which returns a **'view'** on the underlying data without copying anything.

```
ndarray1.transpose()      or
ndarray1.T                or
ndarray1.swapaxes(0, 1)
```

2. Vectorized wrappers (for functions that take scalar values)

- `math.sqrt()` works on only a `scalar`

`np.sqrt(seq1)` # any sequence (list, ndarray, etc) to return a ndarray

3. Vectorized expressions

- `np.where(cond, x, y)` is a vectorized version of the expression 'x if condition else y'

```
np.where([True, False], [1, 2], [2, 3]) => ndarray (1, 3)
```

- Common Usages :

`np.where(matrixArray > 0, 1, -1)`
=> a new array (same shape) of 1 or -1 values

`np.where(cond, 1, 0).argmax() *`
=> Find the first True element

- * `argmax()` can be used to find the index of the maximum element. Example usage is find the first element that has a "price > number" in an array of price data.

4. Aggregations/Reductions Methods (i.e. mean, sum, std)

Compute mean	`ndarray1.mean()` or `np.mean(ndarray1)`
Compute statistics over axis *	`ndarray1.mean(axis = 1)` `ndarray1.sum(axis = 0)`

- * axis = 0 means column axis, 1 is row axis.

5. Boolean arrays methods

Count # of 'Trues' in boolean array	`(ndarray1 > 0).sum()`
If at least one value is 'True'	`ndarray1.any()`
If all values are 'True'	`ndarray1.all()`

Note: These methods also work with non-boolean arrays, where non-zero elements evaluate to True.

6. Sorting

Inplace sorting	`ndarray1.sort()`
Return a sorted copy instead of inplace	`sorted1 = np.sort(ndarray1)`

7. Set methods

Return sorted unique values	`np.unique(ndarray1)`
Test membership of ndarray1 values in [2, 3, 6]	`resultBooleanArray = np.in1d(ndarray1, [2, 3, 6])`

- Other set methods : `intersect1d()`, `union1d()`, `setdiff1d()`, `setxor1d()`

8. Random number generation (np.random)

- Supplements the built-in Python random * with functions for efficiently generating whole arrays of sample values from many kinds of probability distributions.

```
samples = np.random.normal(size =(3, 3))
```

- * Python built-in random ONLY samples one value at a time.

Created by Arianne Colton and Sean Chen

www.datasciencefree.com

Based on content from 'Python for Data Analysis' by Wes McKinney

Updated: August 18, 2016

Python For Data Science *Cheat Sheet*

NumPy Basics

Learn Python for Data Science **Interactively** at www.DataCamp.com

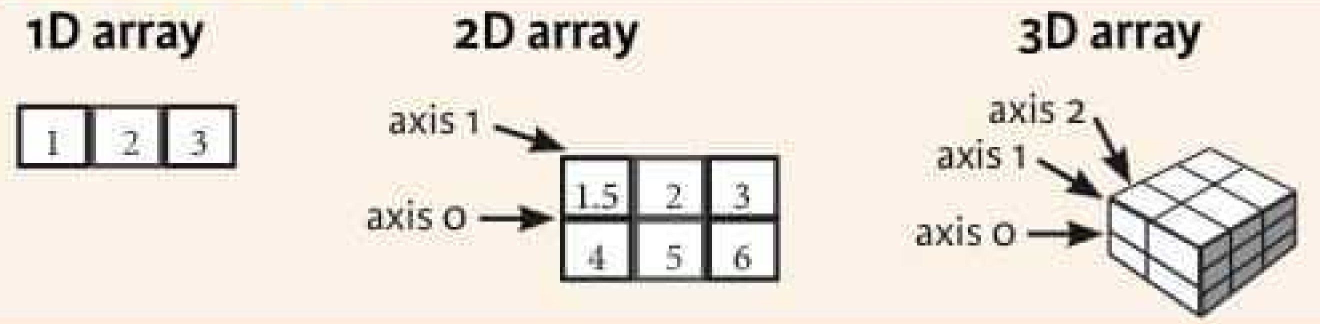
NumPy

The **NumPy** library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Use the following import convention:

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

NumPy Arrays



Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]],
                 dtype = float)
```

Initial Placeholders

`>>> np.zeros((3,4))`	Create an array of zeros
`>>> np.ones((2,3,4),dtype=np.int16)`	Create an array of ones
`>>> d = np.arange(10,25,5)`	Create an array of evenly spaced values (step value)
`>>> np.linspace(0,2,9)`	Create an array of evenly spaced values (number of samples)
`>>> e = np.full((2,2),7)`	Create a constant array
`>>> f = np.eye(2)`	Create a 2X2 identity matrix
`>>> np.random.random((2,2))`	Create an array with random values
`>>> np.empty((3,2))`	Create an empty array

I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv", delimiter=',')
>>> np.savetxt("myarray.txt", a, delimiter=" ")
```

Data Types

`>>> np.int64`	Signed 64-bit integer types
`>>> np.float32`	Standard double-precision floating point
`>>> np.complex`	Complex numbers represented by 128 floats
`>>> np.bool`	Boolean type storing `TRUE` and `FALSE` values
`>>> np.object`	Python object type
`>>> np.string_`	Fixed-length string type
`>>> np.unicode_`	Fixed-length unicode type

Inspecting Your Array

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

Asking For Help

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

Array Mathematics

Arithmetic Operations

`>>> g = a - b`
`array([[-0.5, 0. , 0. ],`
`[-3. , -3. , -3. ]])`
	Subtraction

`>>> np.subtract(a,b)`	Subtraction

`>>> b + a`
`array([[ 2.5, 4. , 6. ],`
`[ 5. , 7. , 9. ]])`
	Addition

`>>> np.add(b,a)`	Addition

`>>> a / b`
`array([[ 0.66666667, 1. , 1. ],`
`[ 0.25 , 0.4 , 0.5 ]])`
	Division

`>>> np.divide(a,b)`	Division

`>>> a * b`
`array([[ 1.5, 4. , 9. ],`
`[ 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)`
`array([[ 7., 7.],`
`[ 7., 7.]])`
	Dot product

Comparison

`>>> a == b`
`array([[False, True, True],`
`[False, False, False]], dtype=bool)`
	Element-wise comparison

`>>> a < 2` `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
`>>> a.corrcoef()`	Correlation coefficient
`>>> np.std(b)`	Standard deviation

Copying Arrays

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

Sorting Arrays

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

Subsetting, Slicing, Indexing

Also see Lists

Subsetting

`>>> a[2]` `3`	Select the element at the 2nd index
`>>> b[1,2]` `6.0`	Select the element at row 0 column 2 (equivalent to `b[1][2]`)

Slicing

`>>> a[0:2]` `array([1, 2])`	Select items at index 0 and 1
`>>> b[0:2,1]` `array([ 2., 5.])`	Select items at rows 0 and 1 in column 1
`>>> b[:1]` `array([[1.5, 2., 3.]])`	Select all items at row 0 (equivalent to `b[0:1, :]`)

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

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

Boolean Indexing

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

Fancy Indexing

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

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

Array Manipulation

Transposing Array

`>>> i = np.transpose(b)`	Permute array dimensions
`>>> i.T`	Permute array dimensions

Changing Array Shape

`>>> b.ravel()`	Flatten the array
`>>> g.reshape(3,-2)`	Reshape, but don't change data

Adding/Removing Elements

`>>> h.resize((2,6))`	Return a new array with shape (2,6)
`>>> np.append(h,g)`	Append items to an array
`>>> np.insert(a, 1, 5)`	Insert items in an array
`>>> np.delete(a,[1])`	Delete items from an array

Combining Arrays

`>>> np.concatenate((a,d),axis=0)` `array([ 1, 2, 3, 10, 15, 20])`	Concatenate arrays

`>>> np.vstack((a,b))`
`array([[ 1. , 2. , 3. ],`
`[ 1.5, 2. , 3. ],`
`[ 4. , 5. , 6. ]])`
	Stack arrays vertically (row-wise)

`>>> np.r_[e,f]`	Stack arrays vertically (row-wise)

`>>> np.hstack((e,f))`
`array([[ 7., 7., 1., 0.],`
`[ 7., 7., 0., 1.]])`
	Stack arrays horizontally (column-wise)

`>>> np.column_stack((a,d))`
`array([[ 1, 10],`
`[ 2, 15],`
`[ 3, 20]])`
	Create stacked column-wise arrays

`>>> np.c_[a,d]`	Create stacked column-wise arrays

Splitting Arrays

`>>> np.hsplit(a,3)` `[array([1]),array([2]),array([3])]`	Split the array horizontally at the 3rd index

`>>> np.vsplit(c,2)`
`[array([[[ 1.5, 2. , 1. ],`
`[ 4. , 5. , 6. ]]]),`
`array([[[ 3., 2., 3.],`
`[ 4., 5., 6.]]])]`
	Split the array vertically at the 2nd index

Data Analysis with PANDAS

CHEAT SHEET

CREATED BY: ARIANNE COLTON AND SEAN CHEN

DATA STRUCTURES

SERIES (1D)

One-dimensional array-like object containing an array of data (of any **NumPy** data type) and an associated array of data labels, called its **"index"**. If index of data is not specified, then a default one consisting of the integers 0 through N-1 is created.

Create Series	`series1 = pd.Series ([1, 2], index = ['a', 'b'])` `series1 = pd.Series(dict1)*`
Get Series Values	`series1.values`
Get Values by Index	`series1['a']` `series1[['b','a']]`
Get Series Index	`series1.index`
Get Name Attribute (None is default)	`series1.name` `series1.index.name`
** Common Index Values are Added	`series1 + series2`
Unique But Unsorted	`series2 = series1.unique()`

- * Can think of Series as a fixed-length, ordered dict. Series can be substitued into many functions that expect a dict.
- ** Auto-align differently-indexed data in arithmetic operations

DATAFRAME (2D)

Tabular data structure with ordered collections of columns, each of which can be different value type.

Data Frame (DF) can be thought of as a dict of Series.

Create DF
(from a dict of equal-length lists or NumPy arrays)
	`dict1 = {'state': ['Ohio', 'CA'], 'year': [2000, 2010]}`
	
	`df1 = pd.DataFrame(dict1)`
	# columns are placed in sorted order
	`df1 = pd.DataFrame(dict1, index = ['row1', 'row2']))`
	# specifying index
	`df1 = pd.DataFrame(dict1, columns = ['year', 'state'])`
	# columns are placed in your given order

* Create DF (from nested dict of dicts) The inner keys as row indices	`dict1 = {'col1': {'row1': 1, 'row2': 2}, 'col2': {'row1': 3, 'row2': 4}}` `df1 = pd.DataFrame(dict1)`

Get Columns and Row Names	`df1.columns` `df1.index`
Get Name Attribute (None is default)	`df1.columns.name` `df1.index.name`
Get Values	`df1.values` # returns the data as a 2D ndarray, the dtype will be chosen to accomandate all of the columns
** Get Column as Series	`df1['state'] or df1.state`
** Get Row as Series	`df1.ix['row2'] or df1.ix[1]`
Assign a column that doesn't exist will create a new column	`df1['eastern'] = df1.state == 'Ohio'`
Delete a column	`del df1['eastern']`
Switch Columns and Rows	`df1.T`

- * Dicts of Series are treated the same as Nested dict of dicts.
- ** Data returned is a 'view' on the underlying data, NOT a copy. Thus, any in-place modificatons to the data will be reflected in df1.

PANEL DATA (3D)

Create Panel Data : (Each item in the Panel is a DF)

```
import pandas_datareader.data as web
panel1 = pd.Panel({stk : web.get_data_
yahoo(stk, '1/1/2000', '1/1/2010')
for stk in ['AAPL', 'IBM']})
# panel1 Dimensions : 2 (item) * 861 (major) * 6 (minor)
```

"Stacked" DF form : (Useful way to represent panel data)

```
panel1 = panel1.swapaxes('item', 'minor')
panel1.ix[:, '6/1/2003', :].to_frame() *
=> Stacked DF (with hierarchical indexing **) :
#                   Open High Low Close Volume Adj-Close
# major       minor
# 2003-06-01  AAPL
#             IBM
# 2003-06-02  AAPL
#             IBM
```

DATA STRUCTURES CONTINUED

- * DF has a "to_panel()" method which is the inverse of "to_frame()".
- ** Hierarchical indexing makes N-dimensional arrays unnecessary in a lot of cases. Aka prefer to use Stacked DF, not Panel data.

INDEX OBJECTS

Immutable objects that hold the axis labels and other metadata (i.e. axis name)

- i.e. Index, MultiIndex, DatetimeIndex, PeriodIndex
- Any sequence of labels used when constructing Series or DF internally converted to an Index.
- Can functions as fixed-size set in additional to being array-like.

HIERARCHICAL INDEXING

Multiple index levels on an axis : A way to work with higher dimensional data in a lower dimensional form.

MultiIndex :

```
series1 = Series(np.random.randn(6), index =
[['a', 'a', 'a', 'b', 'b', 'b'], [1, 2, 3,
1, 2, 3]])
series1.index.names = ['key1', 'key2']
```

Series Partial Indexing	`series1['b']` # Outer Level `series1[:, 2]` # Inner Level

DF Partial Indexing	`df1['outerCol3','InnerCol2']`
	Or
	`df1['outerCol3']['InnerCol2']`

Swaping and Sorting Levels

Swap Level (level interchanged) *	`swapSeries1 = series1.swaplevel('key1', 'key2')`
Sort Level	`series1.sortlevel(1)` # sorts according to first inner level

Common Ops : Swap and Sort **	`series1.swaplevel(0, 1).sortlevel(0)` # the order of rows also change

- * The order of the rows do not change. Only the two levels got swapped.
- ** Data selection performance is much better if the index is sorted starting with the outermost level, as a result of calling `sortlevel(0)` or `sort_index()`.

Summary Statistics by Level

Most stats functions in DF or Series have a "level" option that you can specify the level you want on an axis.

Sum rows (that have same 'key2' value)	`df1.sum(level = 'key2')`
Sum columns ..	`df1.sum(level = 'col3', axis = 1)`

- Under the hood, the functionality provided here utilizes panda's **"groupby"**.

DataFrame's Columns as Indexes

DF's "set_index" will create a new DF using one or more of its columns as the index.

New DF using columns as index	`df2 = df1.set_index(['col3', 'col4'])` * ‡ # col3 becomes the outermost index, col4 becomes inner index. Values of col3, col4 become the index values.

- * "reset_index" does the opposite of "set_index", the hierarchical index are moved into columns.
- ‡ By default, 'col3' and 'col4' will be removed from the DF, though you can leave them by option : `'drop = False'`.

MISSING DATA

Python	`NaN = np.nan` (not a number)
Pandas *	`NaN` or python built-in `None` mean missing/NA values

* Use `pd.isnull()`, `pd.notnull()` or `series1/df1.isnull()` to detect missing data.

FILTERING OUT MISSING DATA

`dropna()` returns with ONLY non-null data, source data NOT modified.

`df1.dropna()` # drop any row containing missing value
`df1.dropna(axis = 1)` # drop any column containing missing values
`df1.dropna(how = 'all')` # drop row that are all missing
`df1.dropna(thresh = 3)` # drop any row containing < 3 number of observations

FILLING IN MISSING DATA

`df2 = df1.fillna(0)` # fill all missing data with 0 `df1.fillna('inplace = True')` # modify in-place
Use a different fill value for each column : `df1.fillna({'col1' : 0, 'col2' : -1})`
Only forward fill the 2 missing values in front : `df1.fillna(method = 'ffill', limit = 2)` i.e. for column1, if row 3-6 are missing. so 3 and 4 get filled with the value from 2, NOT 5 and 6.

Python For Data Science *Cheat Sheet*

Pandas Basics

Learn Python for Data Science Interactively at www.DataCamp.com

Pandas

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

Use the following import convention:

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

Pandas Data Structures

Series

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

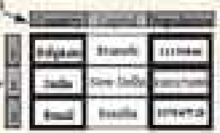
Index

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

DataFrame

Columns

Index



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

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

Asking For Help

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

Selection

Also see NumPy Arrays

Getting

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

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

Selecting, Boolean Indexing & Setting

By Position

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

By Label

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

By Label/Position

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

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

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

Boolean Indexing

`>>> s[~(s > 1)]` `>>> s[(s < -1) | (s > 2)]`	Series s where value is not >1 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

I/O

Read and Write to CSV

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

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> pd.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')
```

Read multiple sheets from the same file

```
>>> xlsx = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite:///:memory:')
>>> pd.read_sql("SELECT * FROM my_table;", engine)
>>> pd.read_sql_table('my_table', engine)
>>> pd.read_sql_query("SELECT * FROM my_table;", engine)
```

`read_sql()` is a convenience wrapper around `read_sql_table()` and `read_sql_query()`

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

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(by='Country')`	Sort by row or column index
`>>> s.order()`	Sort a series by its values
`>>> df.rank()`	Assign ranks to entries

Retrieving Series/DataFrame Information

Basic Information

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

Summary

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

Applying Functions

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

Data Alignment

Internal Data Alignment

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

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

Arithmetic Operations with Fill Methods

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

```
>>> s.add(s3, fill_value=0)
  a    10.0
  b    -5.0
  c    5.0
  d    7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

Python For Data Science *Cheat Sheet*

Scikit-Learn

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

Scikit-learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.

A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>> iris = datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y_test, y_pred)
```

Loading The Data

Also see NumPy & Pandas

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable.

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

Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        random_state=0)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>> svc = SVC(kernel='linear')
```

Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>> pca = PCA(n_components=0.95)
```

K Means

```
>>> from sklearn.cluster import KMeans
>>> k_means = KMeans(n_clusters=3, random_state=0)
```

Model Fitting

Supervised learning

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

Unsupervised Learning

```
>>> k_means.fit(X_train)              Fit the model to the data
>>> pca_model = pca.fit_transform(X_train)   Fit to data, then transform it
```

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.random((2,5)))   Predict labels
>>> y_pred = lr.predict(X_test)                     Predict labels
>>> y_pred = knn.predict_proba(X_test)              Estimate probability of a label
```

Unsupervised Estimators

```
>>> y_pred = k_means.predict(X_test)   Predict labels in clustering algos
```

Preprocessing The Data

Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test = scaler.transform(X_test)
```

Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>> scaler = Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X_train)
>>> normalized_X_test = scaler.transform(X_test)
```

Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>> enc = LabelEncoder()
>>> y = enc.fit_transform(y)
```

Imputing Missing Values

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

Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>> poly = PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

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

Classification Report

```
>>> from sklearn.metrics import classification_report   Precision, recall, f1-score
>>> print(classification_report(y_test, y_pred))        and support
```

Confusion Matrix

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

Regression Metrics

Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5, 2]
>>> mean_absolute_error(y_true, y_pred)
```

Mean Squared Error

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

R^2 Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_pred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(y_true, y_pred)
```

Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

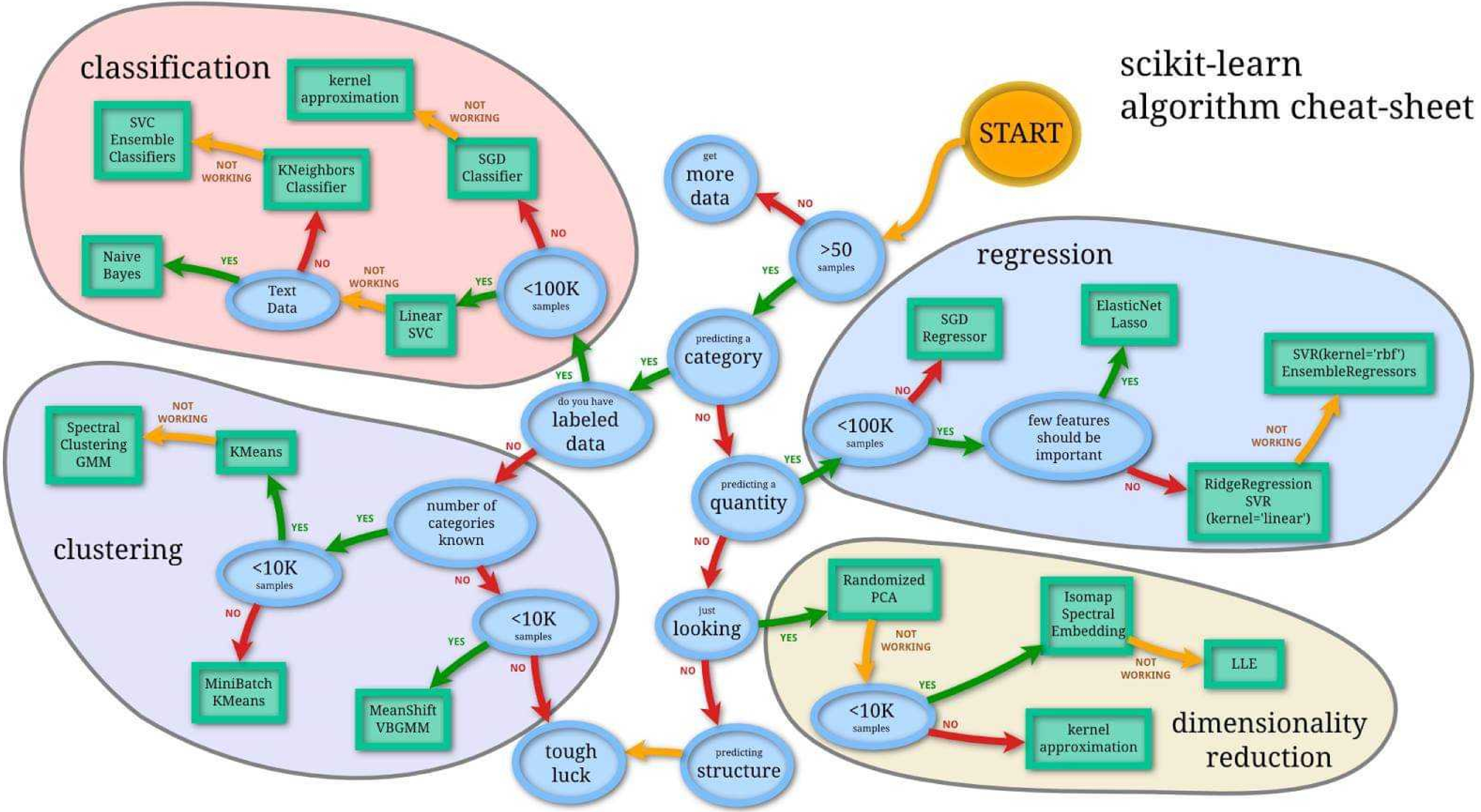
Tune Your Model

Grid Search

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

Randomized Parameter Optimization

```
>>> from sklearn.grid_search import RandomizedSearchCV
>>> params = {"n_neighbors": range(1,5),
              "weights": ["uniform", "distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn,
                                 param_distributions=params,
                                 cv=4,
                                 n_iter=8,
                                 random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```


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