

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

A	3
B	-5
C	7
D	4

Index →

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

DataFrame

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

Columns →

Index →

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'])
```

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')
```

Asking For Help

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

Selection

Getting

```
>>> s['b']
-5
>>> df[1:]
   Country    Capital  Population
1  India      New Delhi     1303171035
2  Brazil    Brasilia     207847528
```

Also see NumPy Arrays

Get one element
Get subset of a DataFrame

Selecting, Boolean Indexing & Setting

By Position

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

By Label

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

By Label/Position

```
>>> df.ix[2]
   Country      Brazil
   Capital    Brasilia
   Population  207847528
```

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

```
>>> df.ix[1, 'Capital']
'New Delhi'
```

Boolean Indexing

```
>>> s[~(s > 1)]
>>> s[(s < -1) | (s > 2)]
>>> df[df['Population'] > 12000000000]
```

Setting

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

Select single value by row & column

Select single value by row & column labels

Select single row of subset of rows

Select a single column of subset of columns

Select rows and columns

Series s where value is not >1
s where value is <-1 or >2

Use filter to adjust DataFrame

Set index a of Series s to 6

Dropping

```
>>> s.drop(['a', 'c'])
>>> df.drop('Country', axis=1)
```

Drop values from rows (axis=0)
Drop values from columns (axis=1)

Sort & Rank

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

Sort by row or column index
Sort a series by its values
Assign ranks to entries

Retrieving Series/DataFrame Information

Basic Information

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

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

Summary

```
>>> df.sum()
>>> df.cumsum()
>>> df.min() / df.max()
>>> df.idmin() / df.idmax()
>>> df.describe()
>>> df.mean()
>>> df.median()
```

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

Applying Functions

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

Apply function
Apply function element-wise

Data Alignment

Internal Data Alignment

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

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

Arithmetic Operations with Fill Methods

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

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



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Select a single column of subset of columns

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Drop values from columns (axis=1)

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>>> s + s3
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b    NaN
c     5.0
d     7.0
```

Arithmetic Operations with Fill Methods

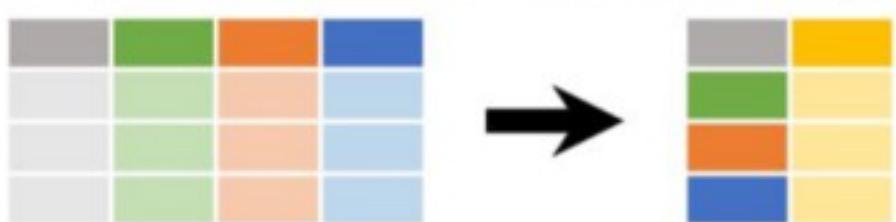
You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> 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)
```



Summarize Data

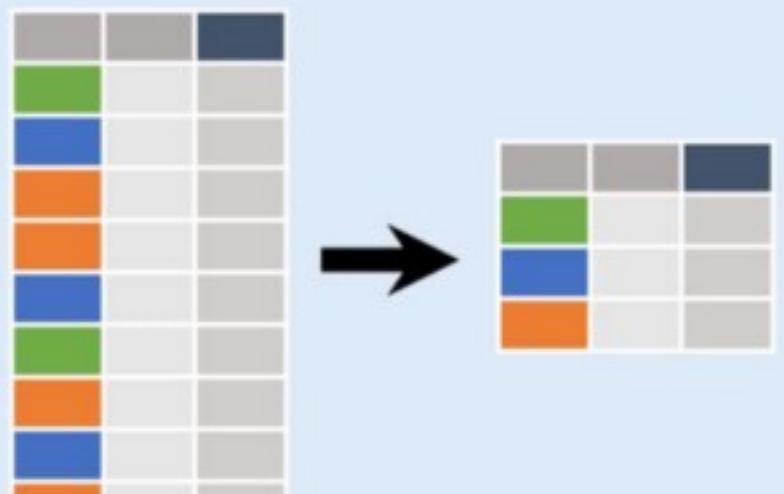
```
df['w'].value_counts()
Count number of rows with each unique value of variable
len(df)
# of rows in DataFrame.
df['w'].nunique()
# of distinct values in a column.
df.describe()
Basic descriptive statistics for each column (or GroupBy)
```



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

sum()	min()
Sum values of each object.	Minimum value in each object.
count()	max()
Count non-NA/null values of each object.	Maximum value in each object.
median()	mean()
Median value of each object.	Mean value of each object.
quantile([0.25,0.75])	var()
Quantiles of each object.	Variance of each object.
apply(function)	std()
Apply function to each object.	Standard deviation of each object.

Group Data



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

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

Additional GroupBy functions:

size()	agg(function)
Size of each group.	Aggregate group using function.

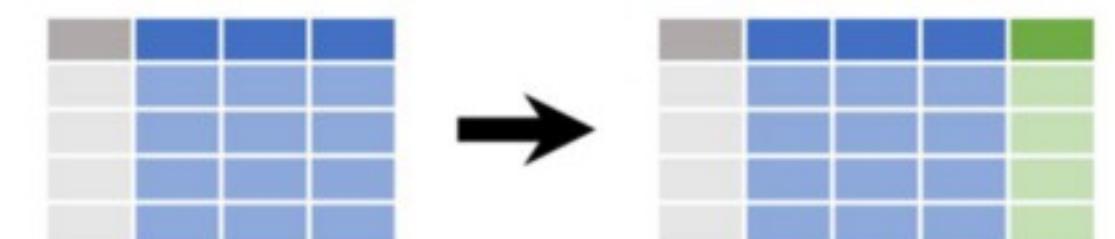
Windows

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.

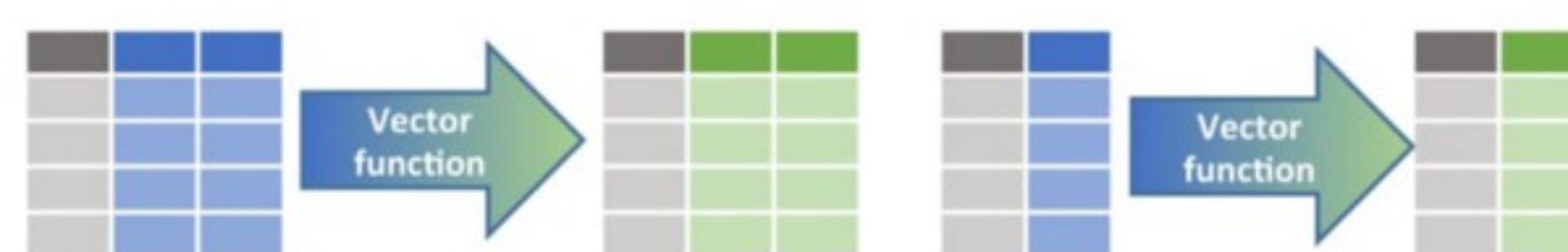
Handling Missing Data

df.dropna()	Drop rows with any column having NA/null data.
df.fillna(value)	Replace all NA/null data with value.

Make New Columns



df.assign(Area=lambda df: df.Length*df.Height)	Compute and append one or more new columns.
df['Volume'] = df.Length*df.Height*df.Depth	Add single column.
pd.qcut(df.col, n, labels=False)	Bin column into n buckets.



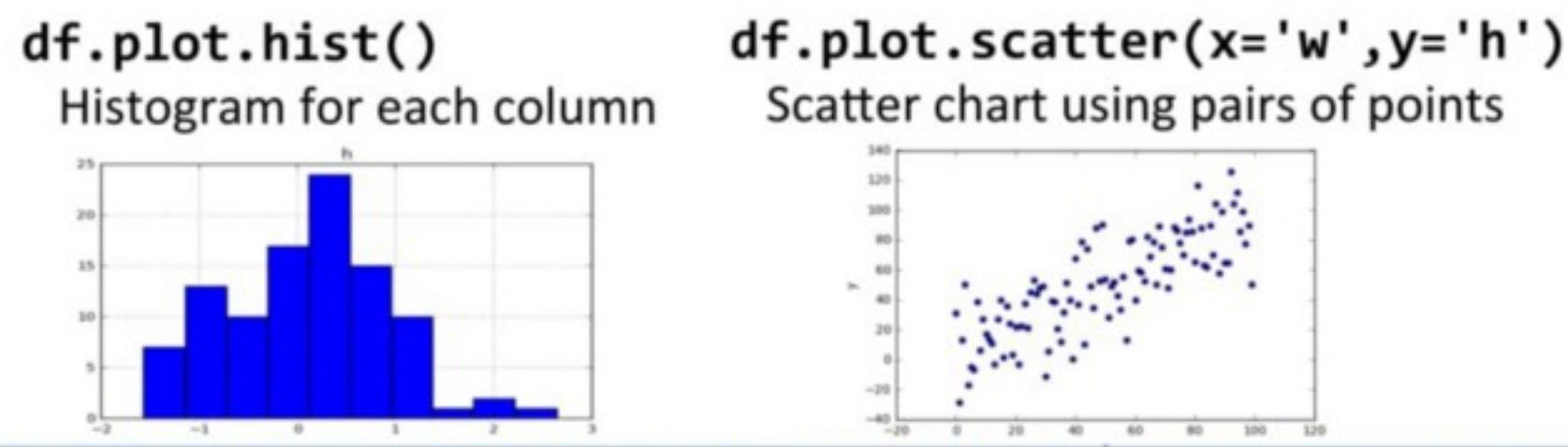
pandas provides a large set of **vector functions** that operate on all columns of a DataFrame or a single selected column (a pandas Series). These functions produce vectors of values for each of the columns, or a single Series for the individual Series. Examples:

max(axis=1)	min(axis=1)
Element-wise max.	Element-wise min.
clip(lower=-10,upper=10)	abs()
Trim values at input thresholds	Absolute value.

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)	shift(-1)
Copy with values shifted by 1.	Copy with values lagged by 1.
rank(method='dense')	cumsum()
Ranks with no gaps.	Cumulative sum.
rank(method='min')	cummax()
Ranks. Ties get min rank.	Cumulative max.
rank(pct=True)	cummin()
Ranks rescaled to interval [0, 1].	Cumulative min.
rank(method='first')	cumprod()
Ranks. Ties go to first value.	Cumulative product.

Plotting



Combine Data Sets

adf	bdf
x1	x2
A	1
B	2
C	3

x1	x3
A	T
B	F
D	T

Standard Joins

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

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

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

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

x1	x2	x3
A	1	T
B	2	F

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

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

x1	x2
A	1
B	2

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

x1	x2
C	3

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

ydf	zdf
x1	x2
A	1
B	2
C	3
D	4

Set-like Operations

x1	x2
B	2
C	3

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

x1	x2
A	1
B	2
C	3
D	4

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

x1	x2
A	1

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

General Minimization Algorithm:

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

Steepest Descent Algorithm:

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

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

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

Learning Rate to Minimize Along the Line:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k \xrightarrow{ts} \alpha_k = -\frac{\mathbf{g}_k^T \mathbf{p}_k}{\mathbf{p}_k^T \mathbf{A} \mathbf{p}_k} \quad (\text{For quadratic fn.})$$

After Minimization Along the Line:

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

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

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

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

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

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

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

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

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

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

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

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

Adaptive Filter ADALINE:

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

Backpropagation Algorithm:

Performance Index:

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

Approximate Performance Index: (single sample)

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

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

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

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

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

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

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

$$\dot{\mathbf{F}}^m(\mathbf{n}^m) = \text{diag}([\dot{f}^m(n_1^m) \quad \dot{f}^m(n_2^m) \quad \dots \quad \dot{f}^m(n_{S^m}^m)])$$

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

Weight Update (Approximate Steepest Descent):

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

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

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

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

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

*Heuristic Variations of Backpropagation:

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

Backpropagation with Momentum (MOBP):

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

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

Variable Learning Rate Backpropagation (VLBP)

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

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

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

Associative Learning Rules:

Unsupervised Hebb Rule:

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

Hebb with Decay:

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

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

The instar is activated for ${}_1 \mathbf{w}^T \mathbf{p} = \| {}_1 \mathbf{w} \| \| \mathbf{p} \| \cos \theta \geq -b$ where θ is the angle between \mathbf{p} and ${}_1 \mathbf{w}$.

Instar Rule:

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

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

Kohonen Rule:

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

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

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

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

Competitive Learning with the Kohonen Rule:

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

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

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

Self-Organizing with the Kohonen Rule:

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

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

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

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

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

LVQ Network Learning with the Kohonen Rule:

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

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

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

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

**HINT:

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

Python For Data Science Cheat Sheet

SciPy - Linear Algebra

Learn More Python for Data Science [Interactively](#) at [www.datacamp.com](#)



SciPy

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



Interacting With NumPy

[Also see NumPy](#)

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[1.5,2,3], [4,5,6], [(3,2,1), (4,5,6)]])
```

Index Tricks

>>> np.mgrid[0:5,0:5]	Create a dense meshgrid
>>> np.ogrid[0:2,0:2]	Create an open meshgrid
>>> np.r_[3,[0]*5,-1:1:10j]	Stack arrays vertically (row-wise)
>>> np.c_[b,c]	Create stacked column-wise arrays

Shape Manipulation

>>> np.transpose(b)	Permute array dimensions
>>> b.flatten()	Flatten the array
>>> np.hstack((b,c))	Stack arrays horizontally (column-wise)
>>> np.vstack((a,b))	Stack arrays vertically (row-wise)
>>> np.hsplit(c,2)	Split the array horizontally at the 2nd index
>>> np.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.unwrap(g)	Create an array of evenly spaced values (log scale)
>>> np.logspace(0,10,3)	Return values from a list of arrays depending on conditions
>>> np.select([c<4],[c*2])	Factorial
>>> misc.factorial(a)	Combine N things taken at k time
>>> misc.comb(10,3,exact=True)	Weights for N-point central derivative
>>> misc.central_diff_weights(3)	Find the n-th derivative of a function at a point

Linear Algebra

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
>>> linalg.inv(A)
```

Transposition

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

Trace

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

Norm

```
>>> linalg.norm(A)
>>> linalg.norm(A,1)
>>> linalg.norm(A,np.inf)
```

Rank

```
>>> np.linalg.matrix_rank(C)
```

Determinant

```
>>> linalg.det(A)
```

Solving linear problems

```
>>> linalg.solve(A,b)
>>> E = np.mat(a).T
>>> linalg.lstsq(F,E)
```

Generalized inverse

```
>>> linalg.pinv(C)
```

```
>>> linalg.pinv2(C)
```

Creating Sparse Matrices

```
>>> F = np.eye(3, k=1)
>>> G = np.mat(np.identity(2))
>>> C[C > 0.5] = 0
>>> H = sparse.csr_matrix(C)
>>> I = sparse.csc_matrix(D)
>>> J = sparse.dok_matrix(A)
>>> E.todense()
>>> sparse.isspmatrix_csc(A)
```

Sparse Matrix Routines

Inverse

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

Norm

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

Solving linear problems

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

Sparse Matrix Functions

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

Inverse

Inverse
Transpose matrix
Conjugate transposition

Trace

Frobenius norm
L1 norm (max column sum)
L inf norm (max row sum)

Matrix rank

Determinant

Solver for dense matrices
Solver for dense matrices
Least-squares solution to linear matrix equation

Compute the pseudo-inverse of a matrix (least-squares solver)
Compute the pseudo-inverse of a matrix (SVD)

Create a 2X2 identity matrix
Create a 2x2 identity matrix

Compressed Sparse Row matrix
Compressed Sparse Column matrix
Dictionary Of Keys matrix
Sparse matrix to full matrix
Identify sparse matrix

Inverse

Norm

Solver for sparse matrices

Sparse matrix exponential

Matrix Functions

Addition

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

Subtraction

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

Division

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

Multiplication

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

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

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

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

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

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

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

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

Exponential Functions

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

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

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

Logarithm Function

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

Trigonometric Functions

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

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

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

Hyperbolic Trigonometric Functions

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

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

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

Matrix Sign Function

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

Matrix Square Root

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

Arbitrary Functions

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

Decompositions

Eigenvalues and Eigenvectors

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

```
>>> l1, l2 = la
```

```
>>> v[:,0]
```

```
>>> v[:,1]
```

```
>>> linalg.eigvals(A)
```

Singular Value Decomposition

```
>>> U,s,Vh = linalg.svd(B)
```

```
>>> M,N = B.shape
```

```
>>> Sig = linalg.diagsvd(s,M,N)
```

LU Decomposition

```
>>> P,L,U = linalg.lu(C)
```

Sparse Matrix Decompositions

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

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

Addition

Subtraction

Division

Multiplication operator (Python 3)

Multiplication

Dot product

Vector dot product

Inner product

Outer product

Tensor dot product

Kronecker product

Matrix exponential

Matrix exponential (Taylor Series)

Matrix exponential (eigenvalue decomposition)

Matrix logarithm

Matrix sine

Matrix cosine

Matrix tangent

Hypberbolic matrix sine

Hyperbolic matrix cosine

Hyperbolic matrix tangent

Matrix sign function

Matrix square root

Solve ordinary or generalized eigenvalue problem for square matrix

Unpack eigenvalues

First eigenvector

Second eigenvector

Unpack eigenvalues

Singular Value Decomposition (SVD)

Construct sigma matrix in SVD

LU Decomposition

Eigenvalues and eigenvectors SVD

Asking For Help

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

</

About

TensorFlow

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

Skflow

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

Keras

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

Installation

How to install new package in Python:

```
pip install <package-name>
```

Example: pip install requests

How to install tensorflow?

device = cpu/gpu

python_version = cp27/cp34

sudo pip install

[https://storage.googleapis.com/tensorflow/linux/\\$device/tensorflow-0.8.0-\\$python_version-none-linux_x86_64.whl](https://storage.googleapis.com/tensorflow/linux/$device/tensorflow-0.8.0-$python_version-none-linux_x86_64.whl)

How to install Skflow

pip install sklearn

How to install Keras

pip install keras

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

Helpers

Python helper

Important functions

type(object)

Get object type

help(object)

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

dir(object)

Get list of object attributes (fields, functions)

str(object)

Transform an object to string

object?

Shows documentations about the object

globals()

Return the dictionary containing the current scope's global variables.

locals()

Update and return a dictionary containing the current scope's local variables.

id(object)

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

**import __builtin__
dir(__builtin__)**

Other built-in functions

TensorFlow

Main classes

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

Some useful functions

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

TensorFlow Optimizers

**GradientDescentOptimizer
AdadeltaOptimizer
AdagradOptimizer
MomentumOptimizer
AdamOptimizer
FtrlOptimizer
RMSPropOptimizer**

Reduction

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

Activation functions

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

Skflow

Main classes

**TensorFlowClassifier
TensorFlowRegressor
TensorFlowDNNClassifier
TensorFlowDNNRegressor
TensorFlowLinearClassifier
TensorFlowLinearRegressor
TensorFlowRNNClassifier
TensorFlowRNNRegressor**

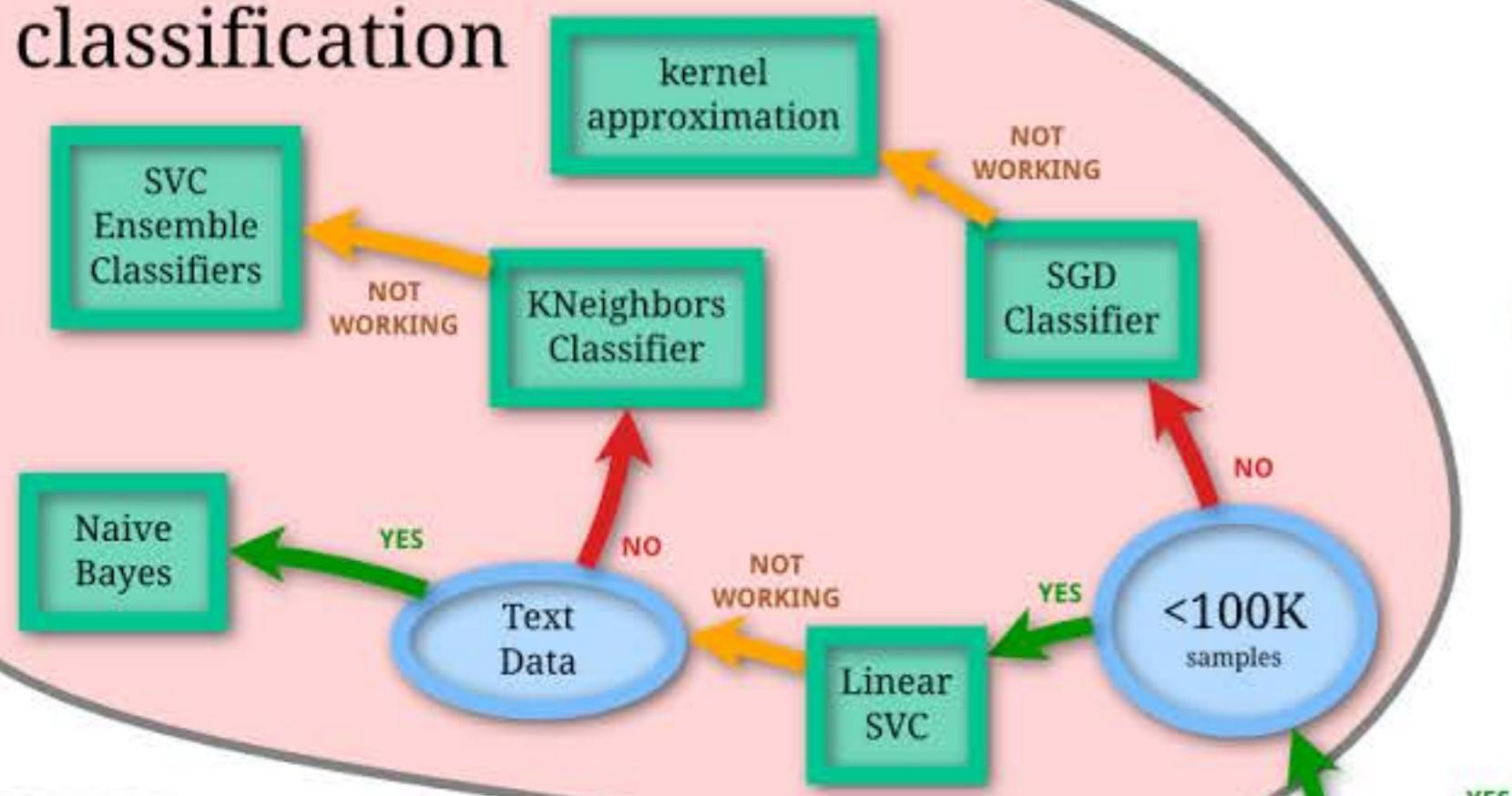
TensorFlowEstimator

Each classifier and regressor have following fields

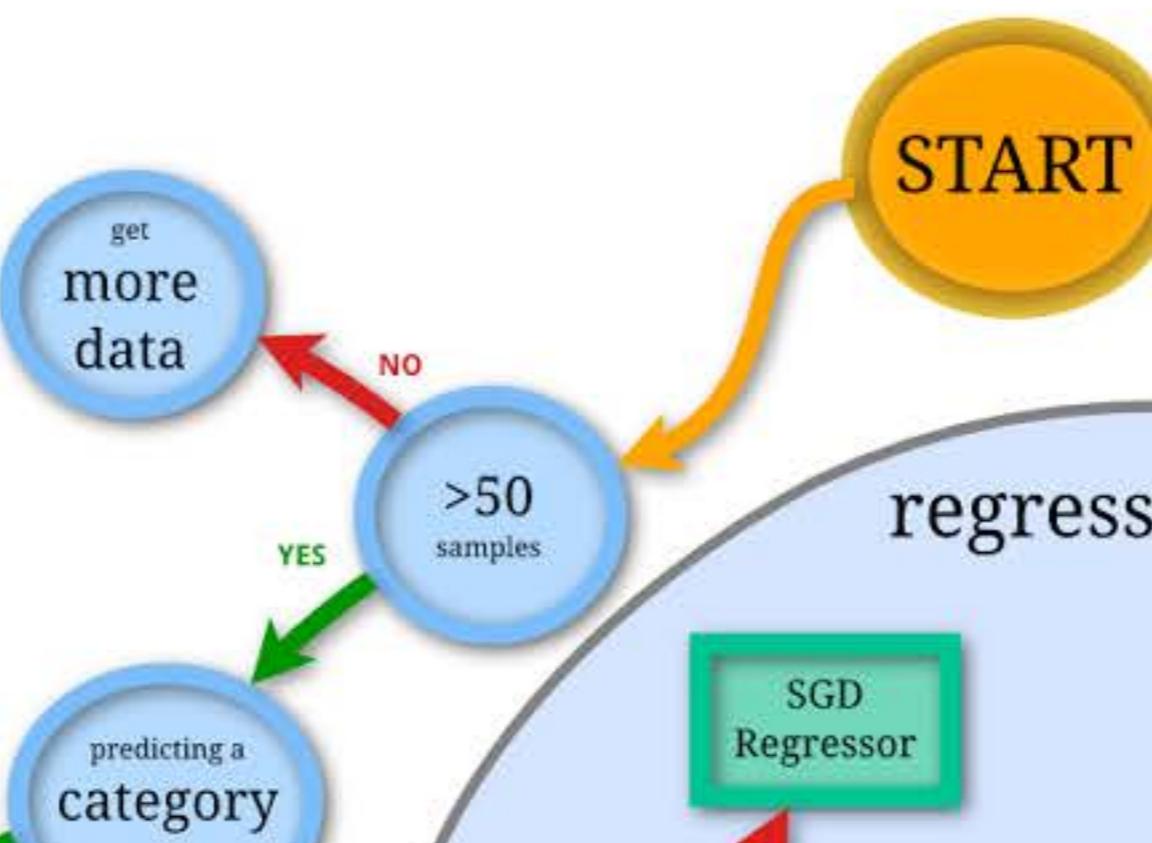
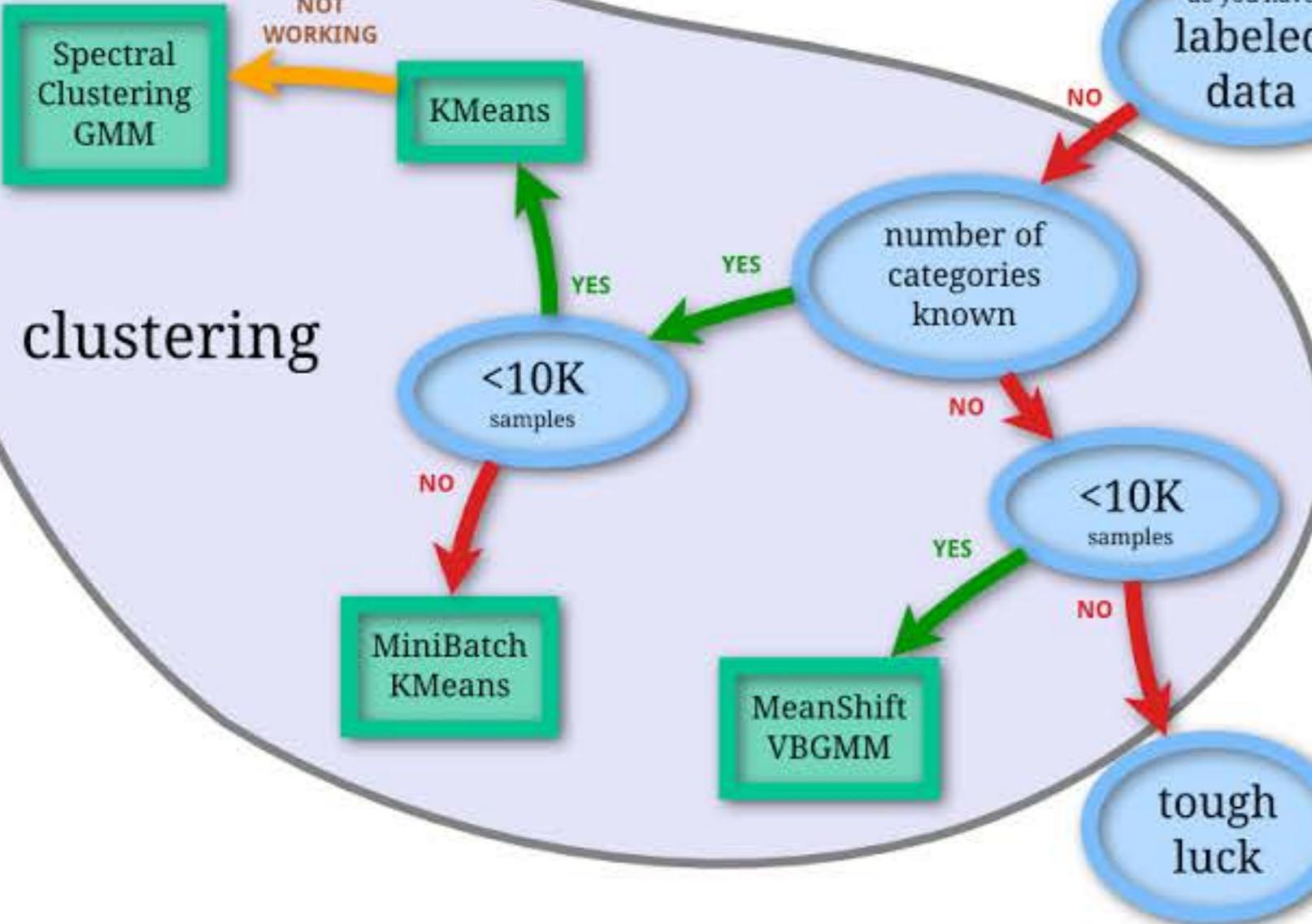
n_classes=0 (Regressor), n_classes are expected to be input (Classifiers)
batch_size=32,
steps=200, // except
TensorFlowRNNClassifier - there is 50
optimizer='Adagrad',
learning_rate=0.1,

scikit-learn algorithm cheat-sheet

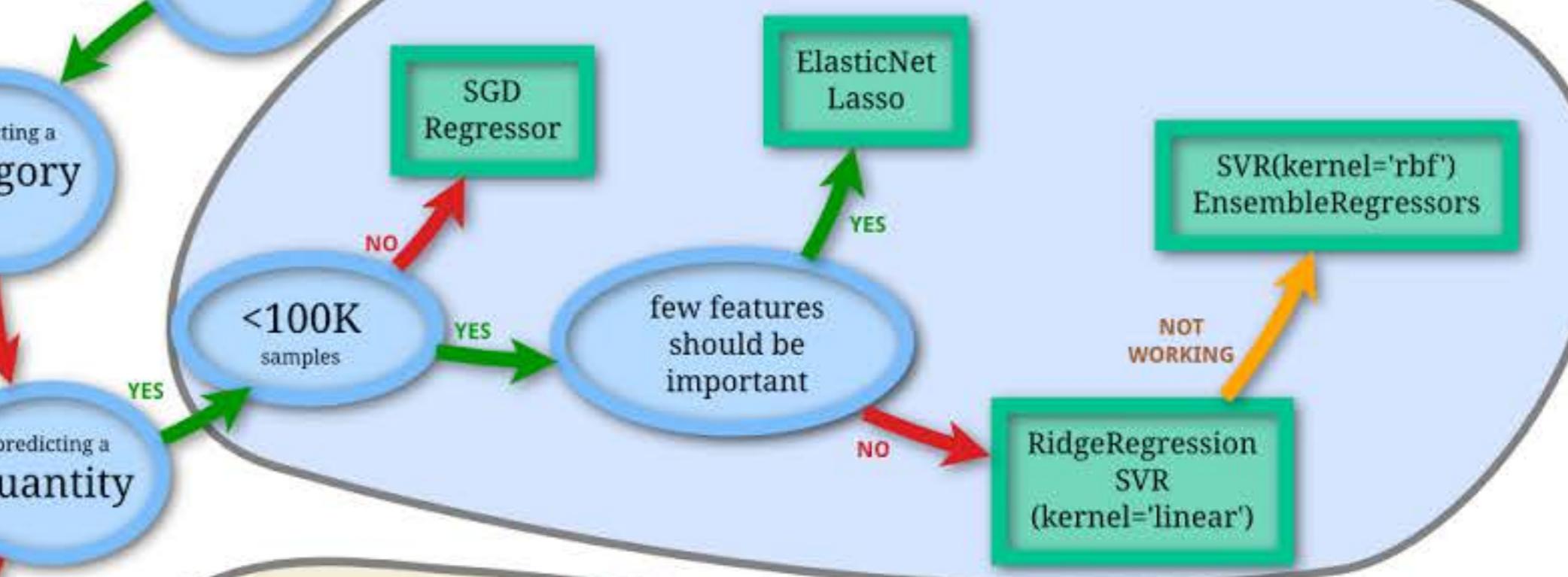
classification



clustering



regression



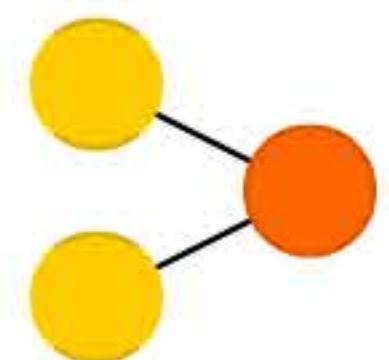
dimensionality reduction

A mostly complete chart of
Neural Networks

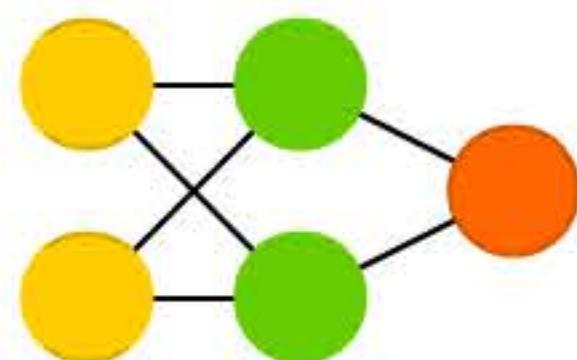
©2016 Fjodor van Veen - asimovinstitute.org

-  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
-  Convolution or Pool

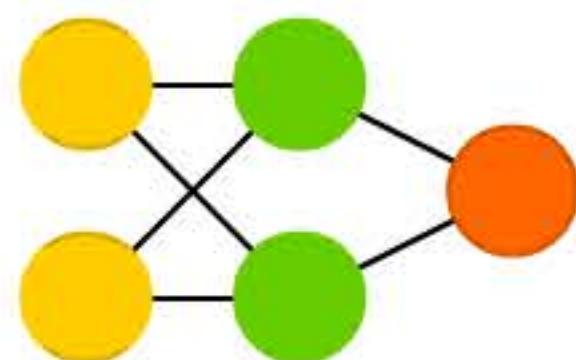
Perceptron (P)



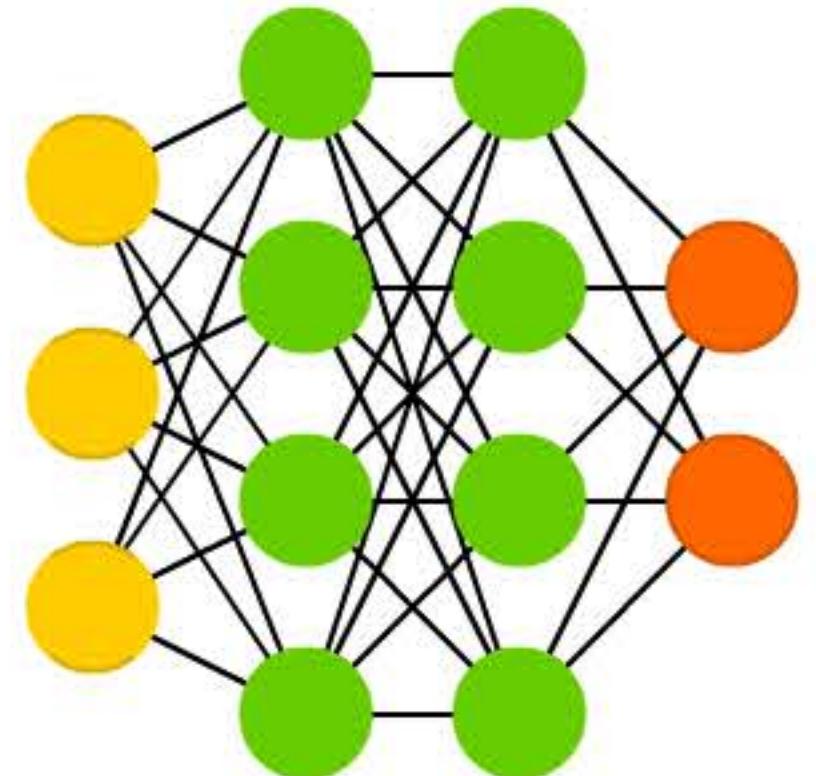
Feed Forward (FF)



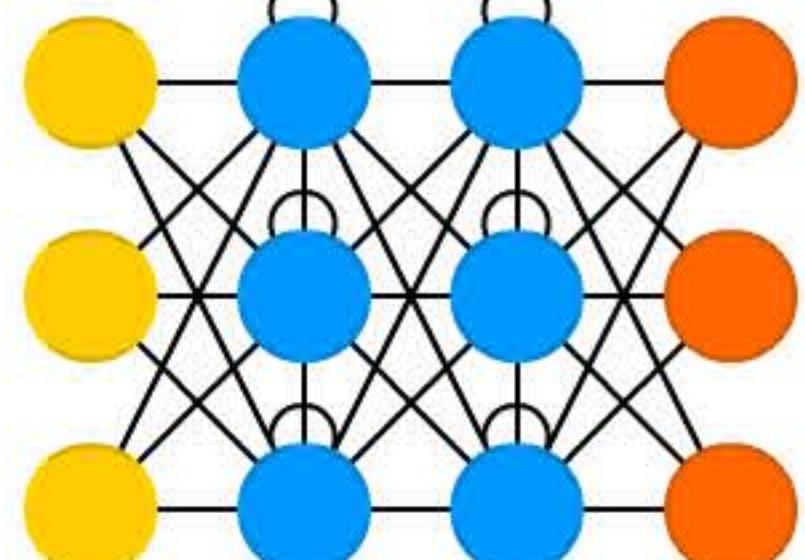
Radial Basis Network (RBF)



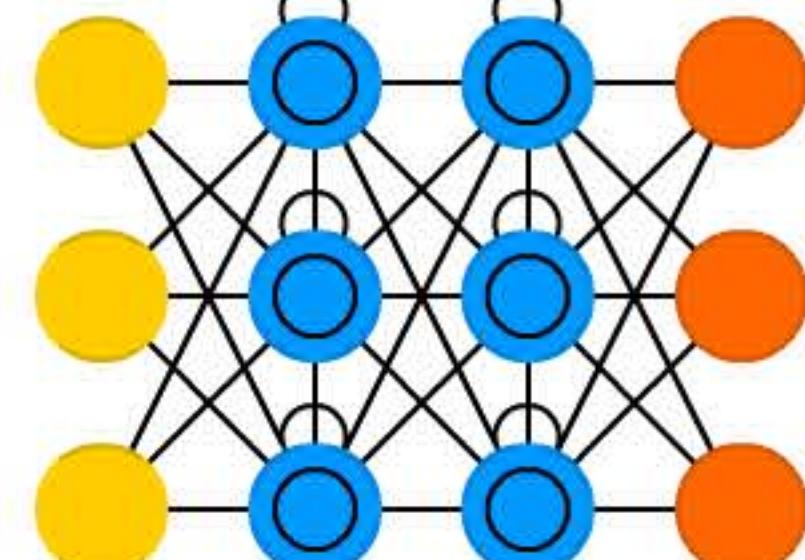
Deep Feed Forward (DFF)



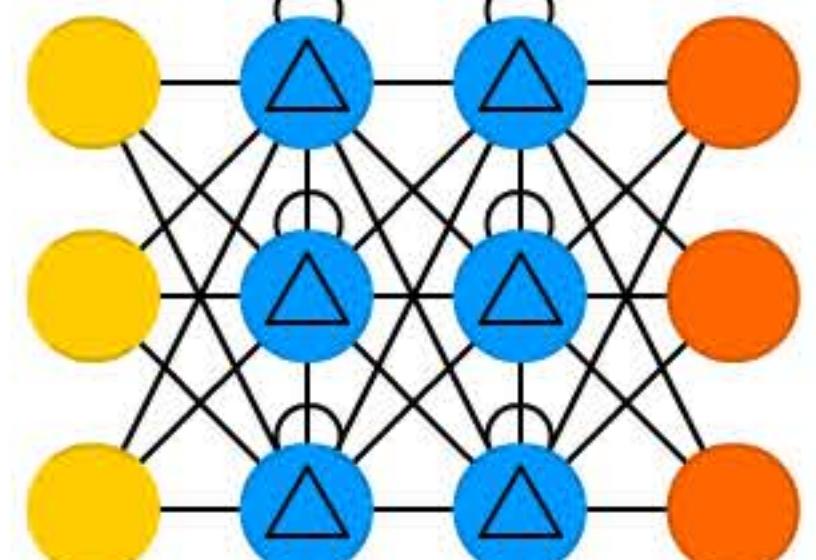
Recurrent Neural Network (RNN)



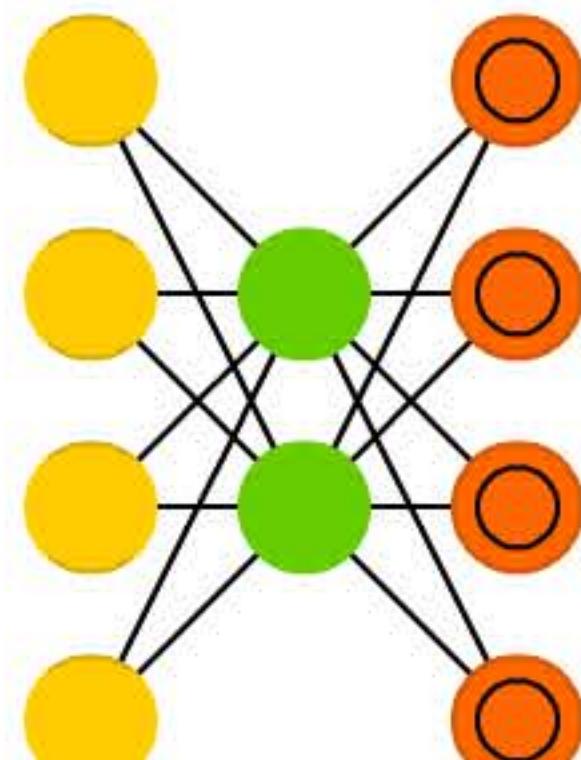
Long / Short Term Memory (LSTM)



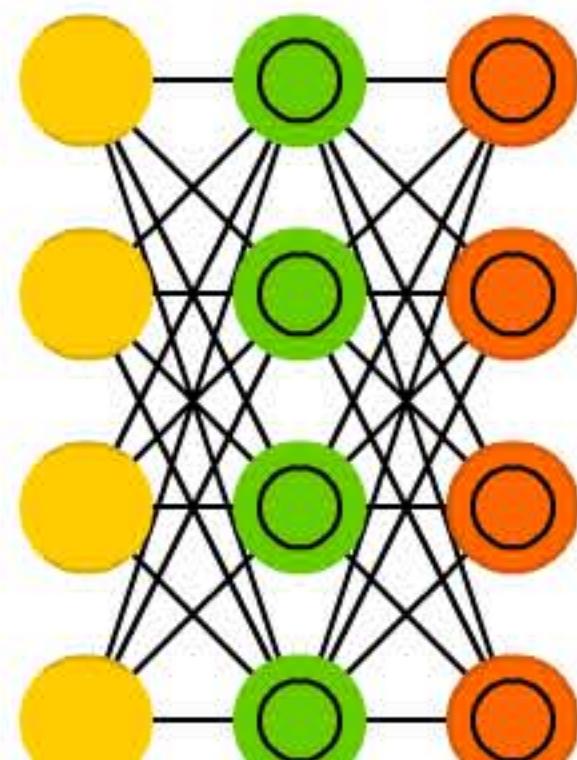
Gated Recurrent Unit (GRU)



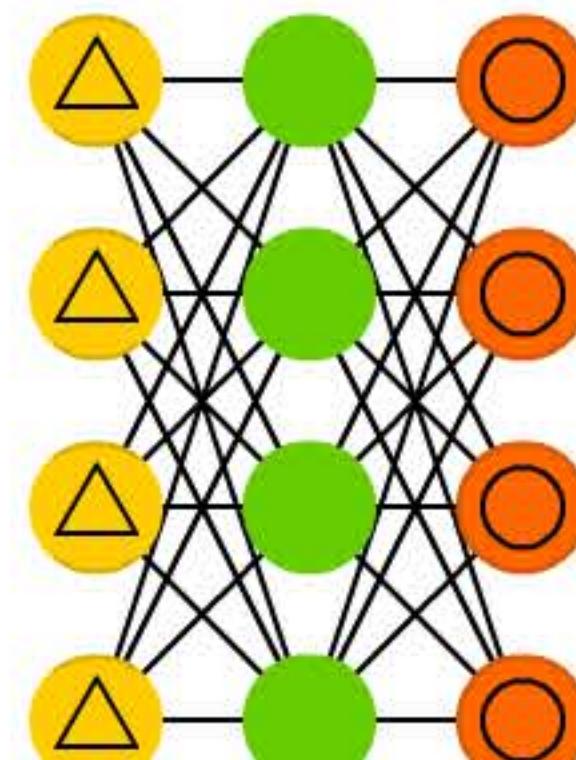
Auto Encoder (AE)



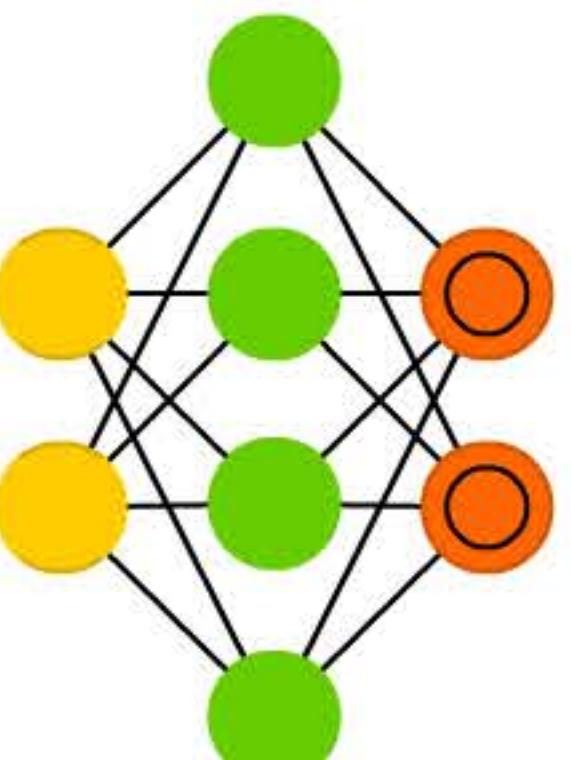
Variational AE (VAE)



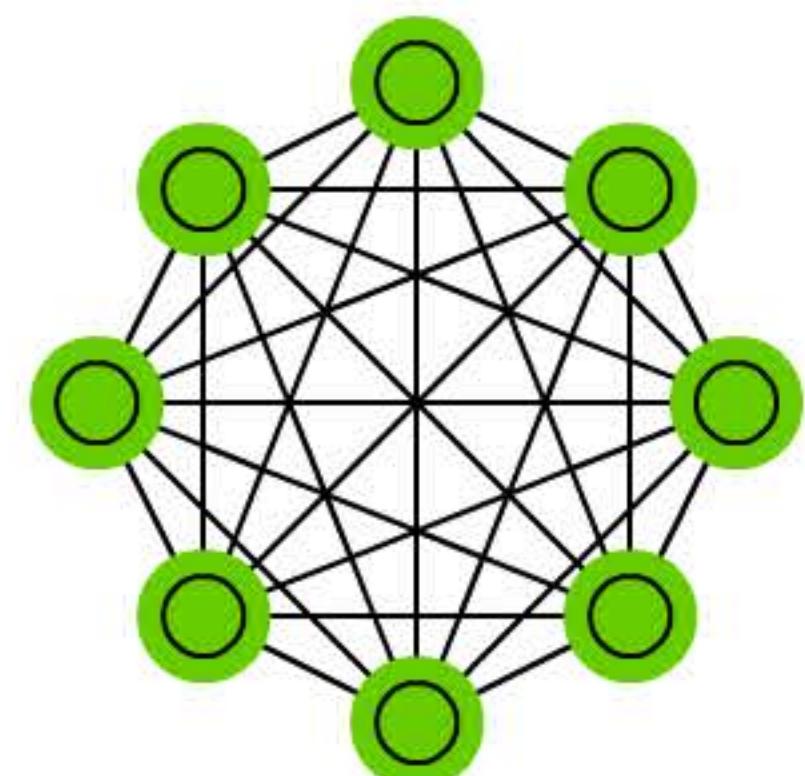
Denoising AE (DAE)



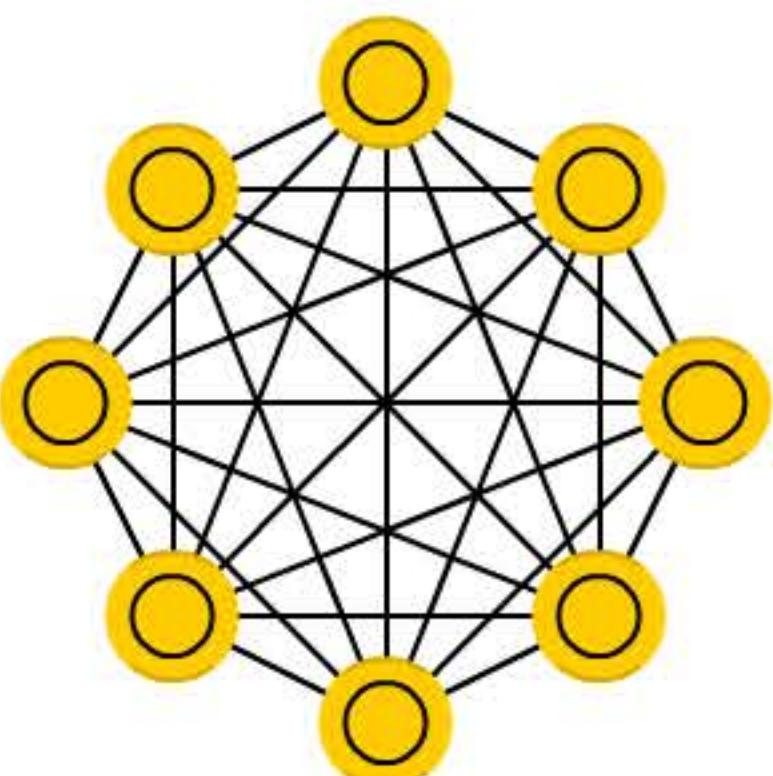
Sparse AE (SAE)



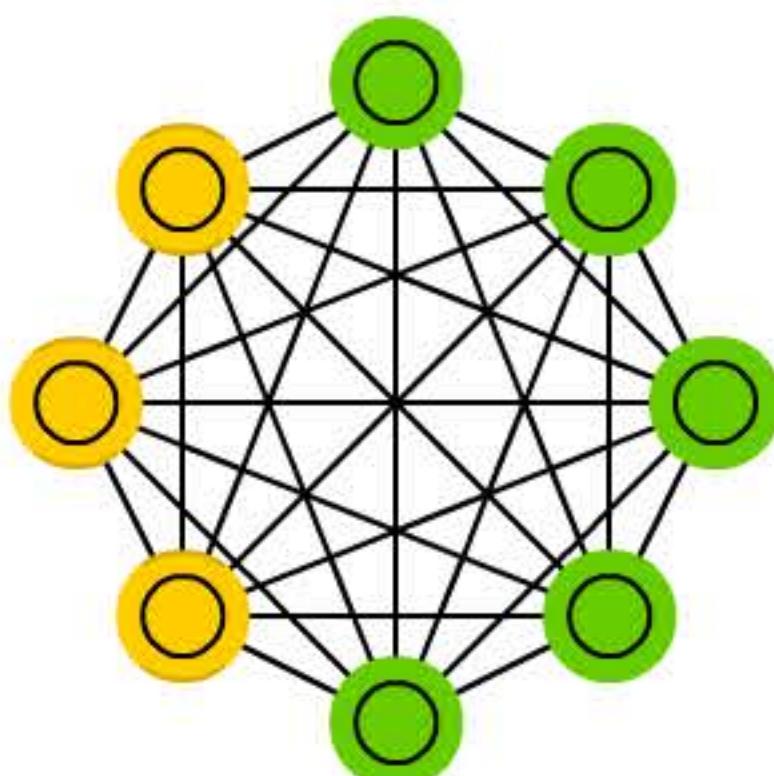
Markov Chain (MC)



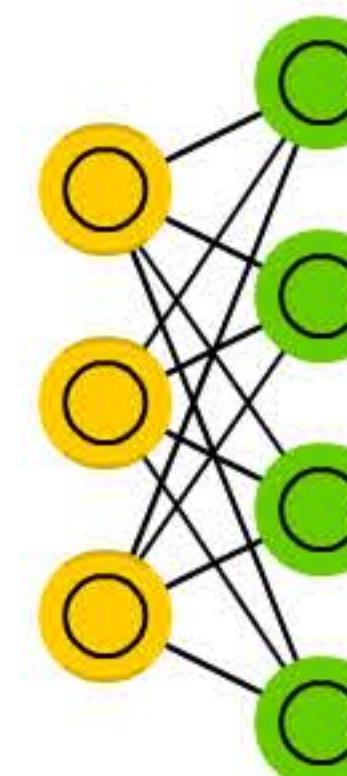
Hopfield Network (HN)



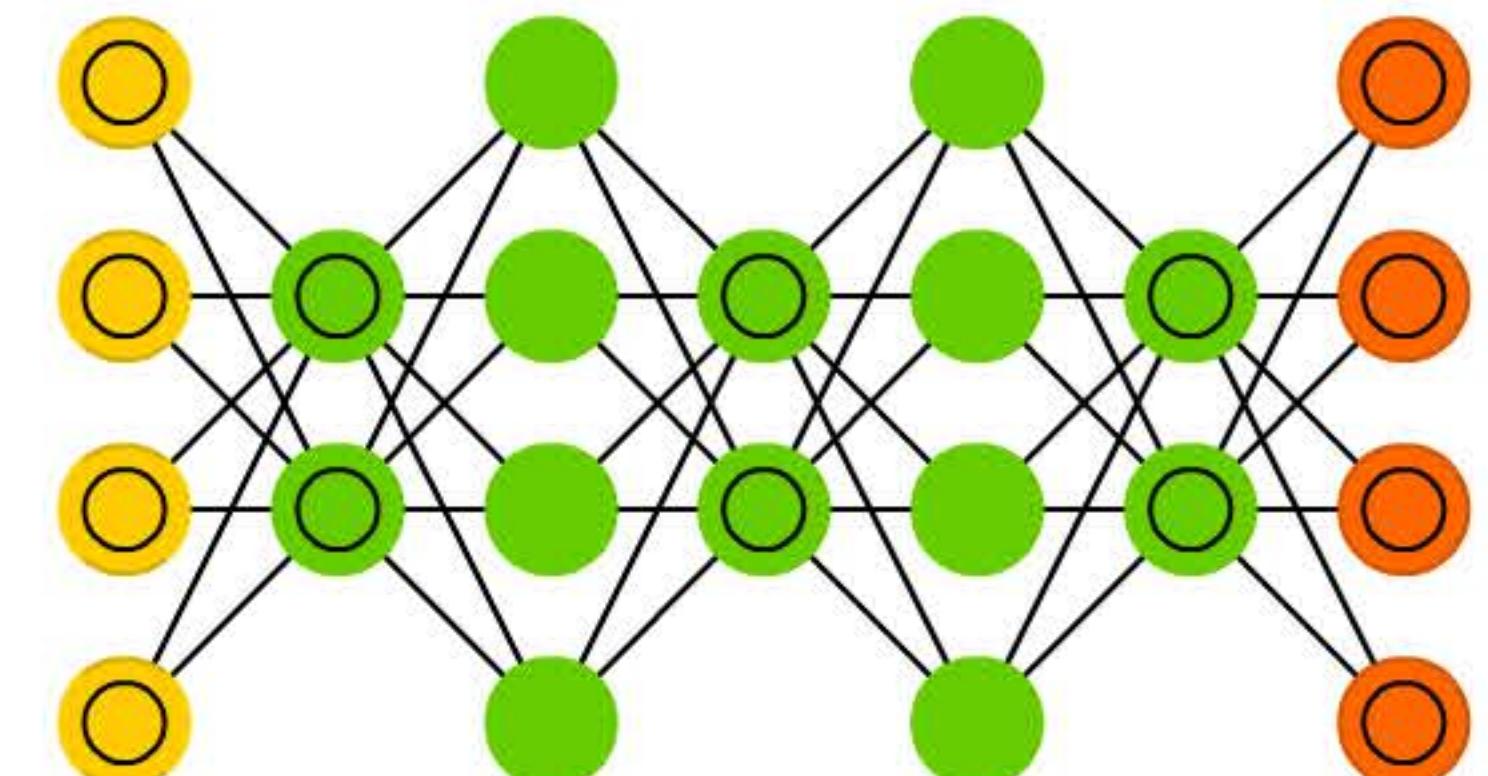
Boltzmann Machine (BM)



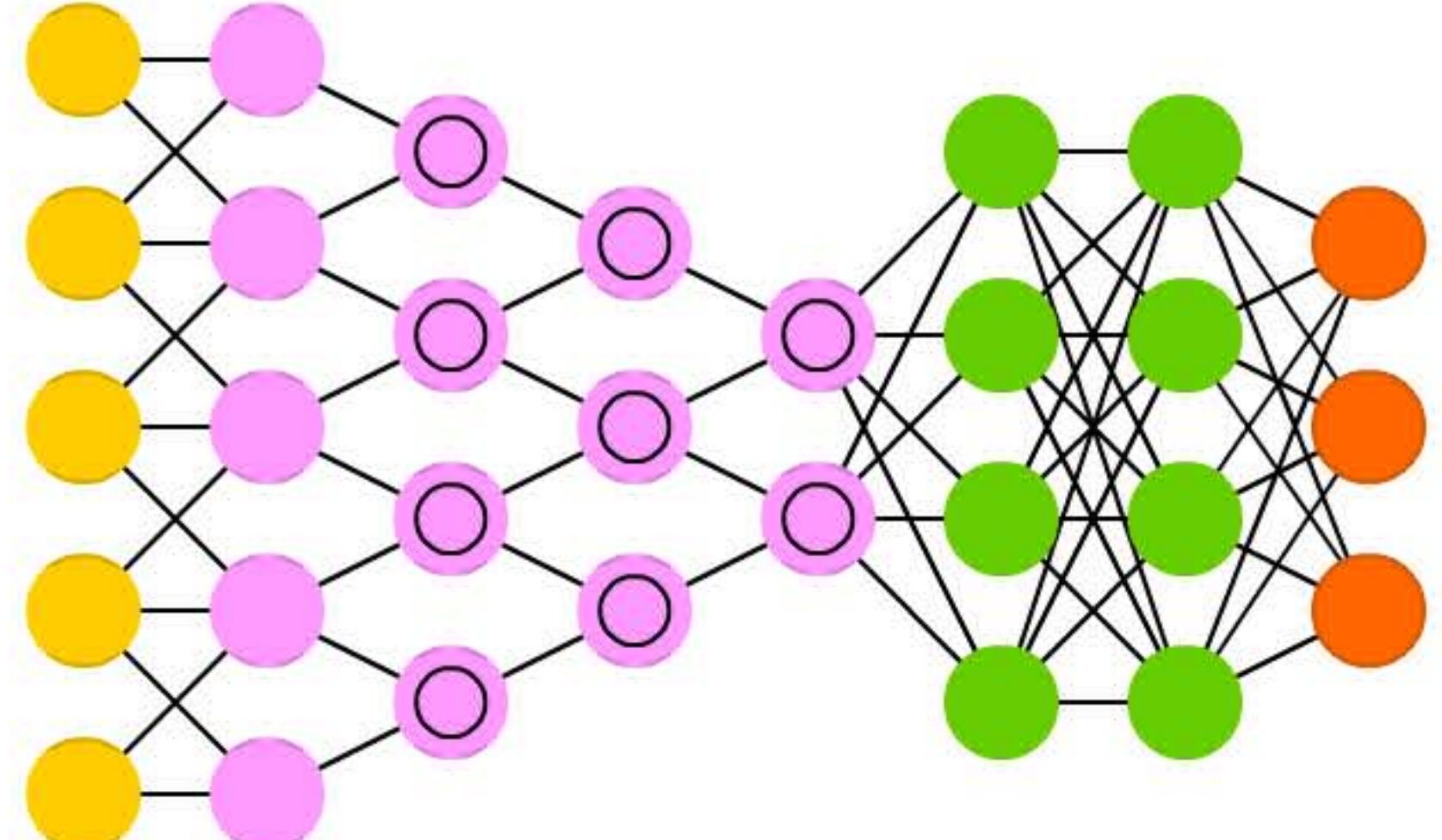
Restricted BM (RBM)



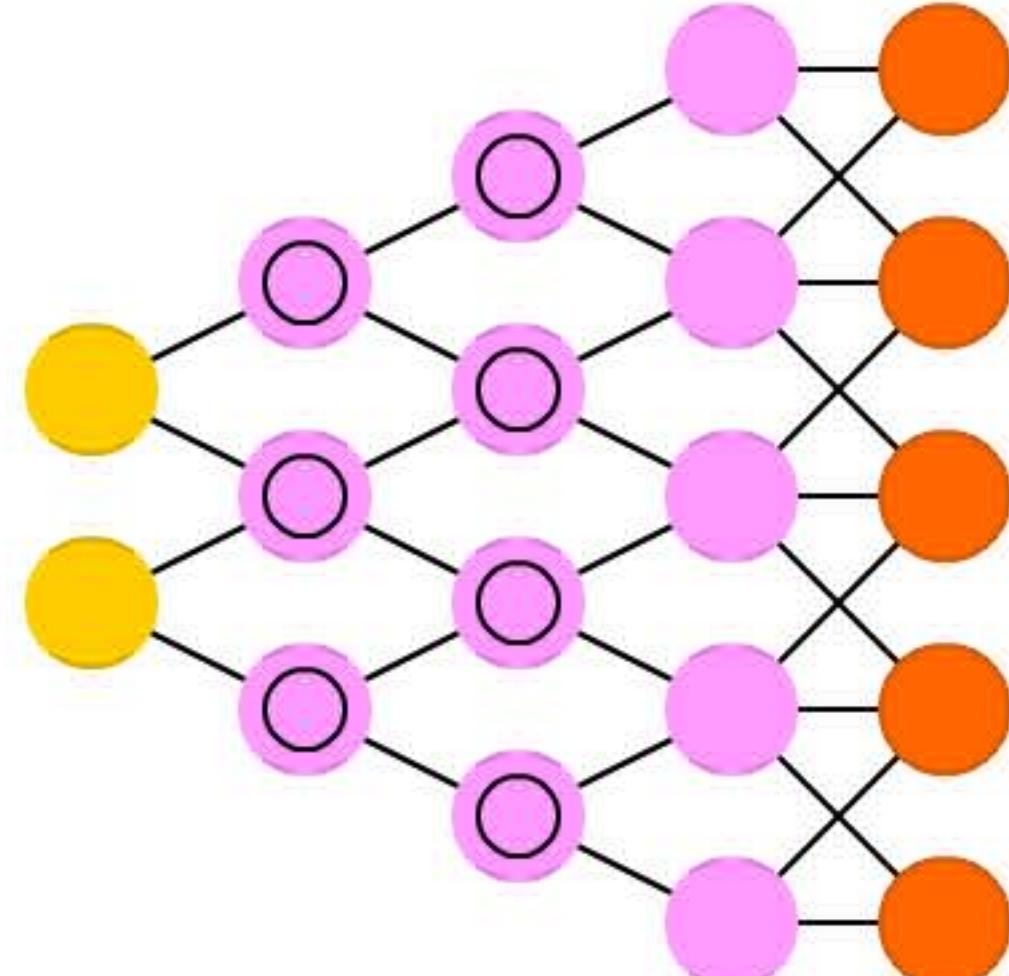
Deep Belief Network (DBN)



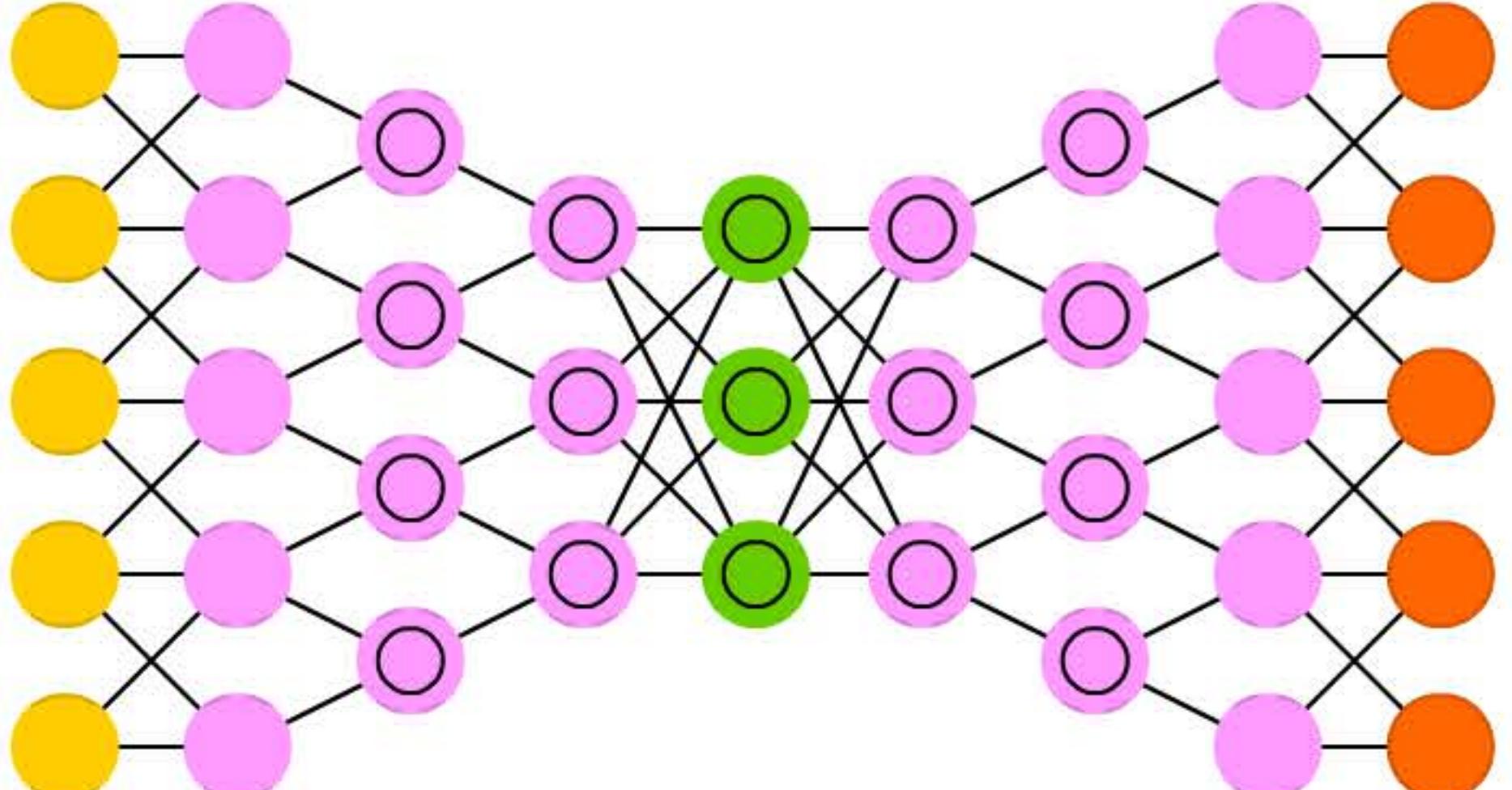
Deep Convolutional Network (DCN)



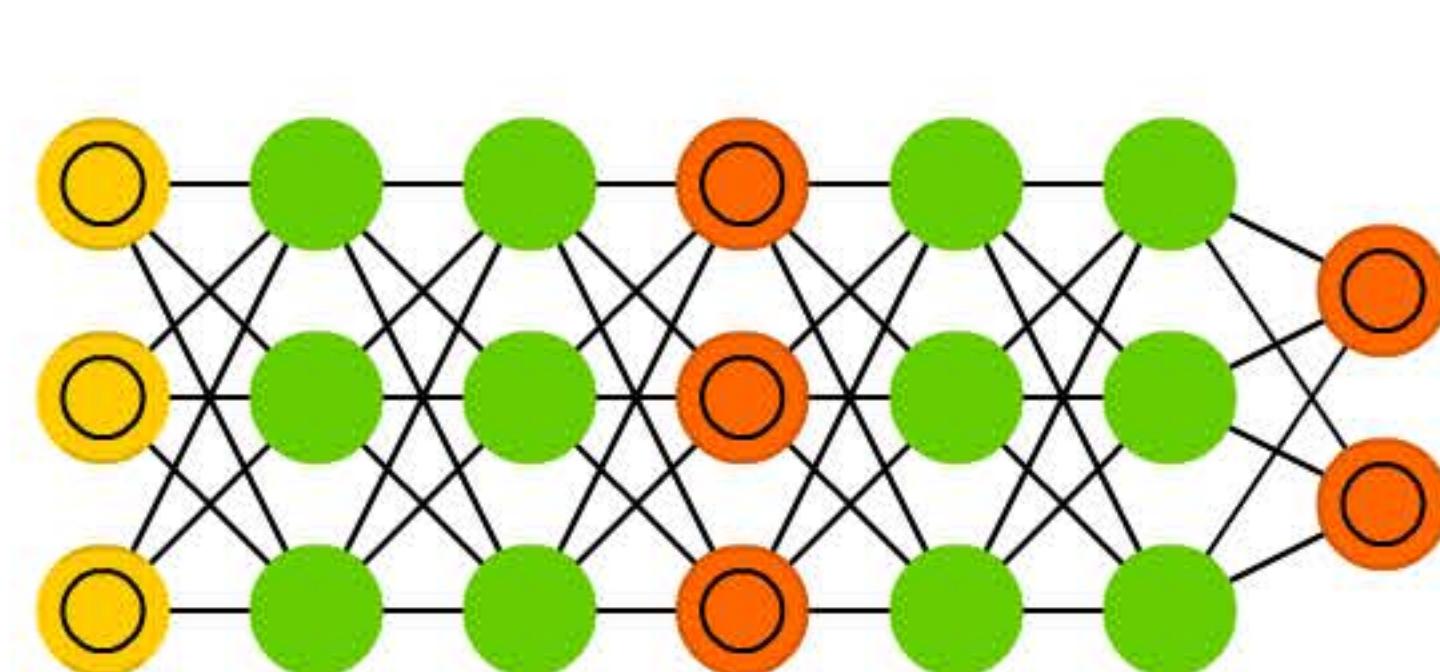
Deconvolutional Network (DN)



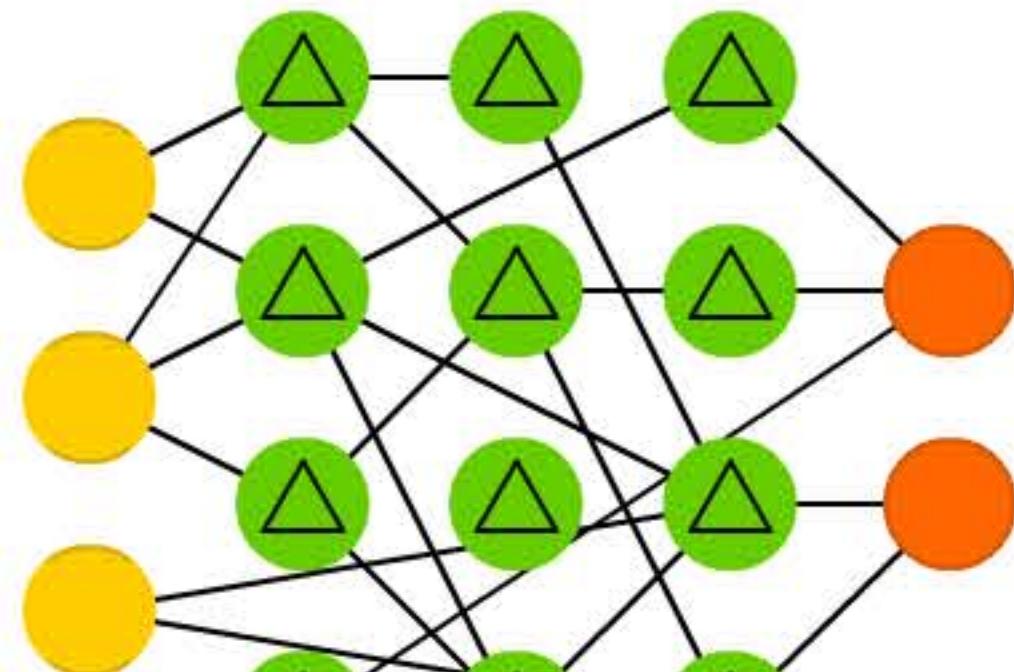
Deep Convolutional Inverse Graphics Network (DCIGN)



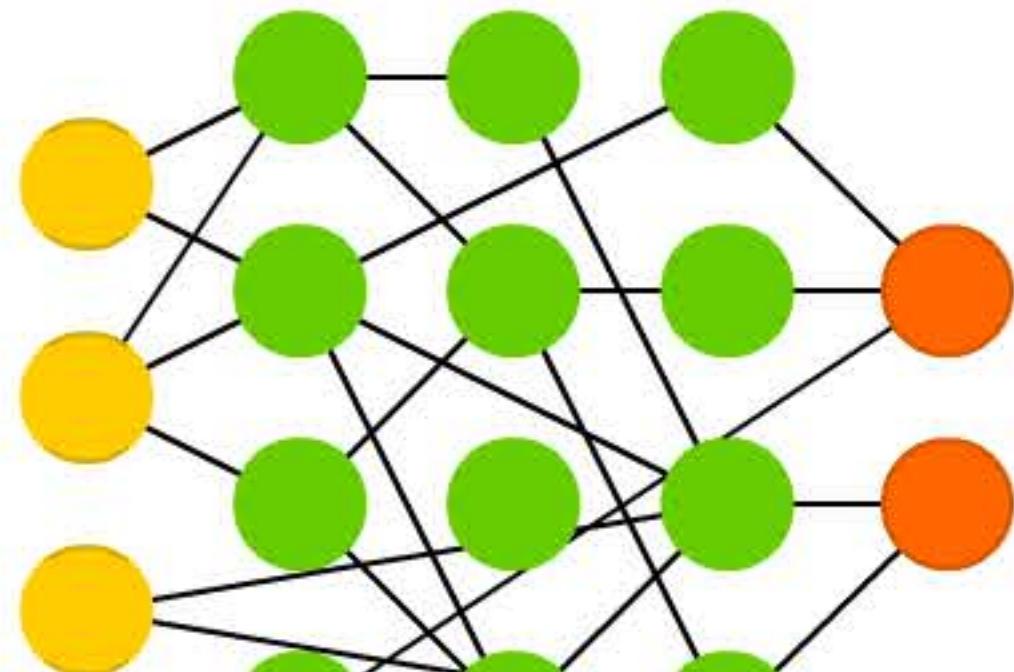
Generative Adversarial Network (GAN)



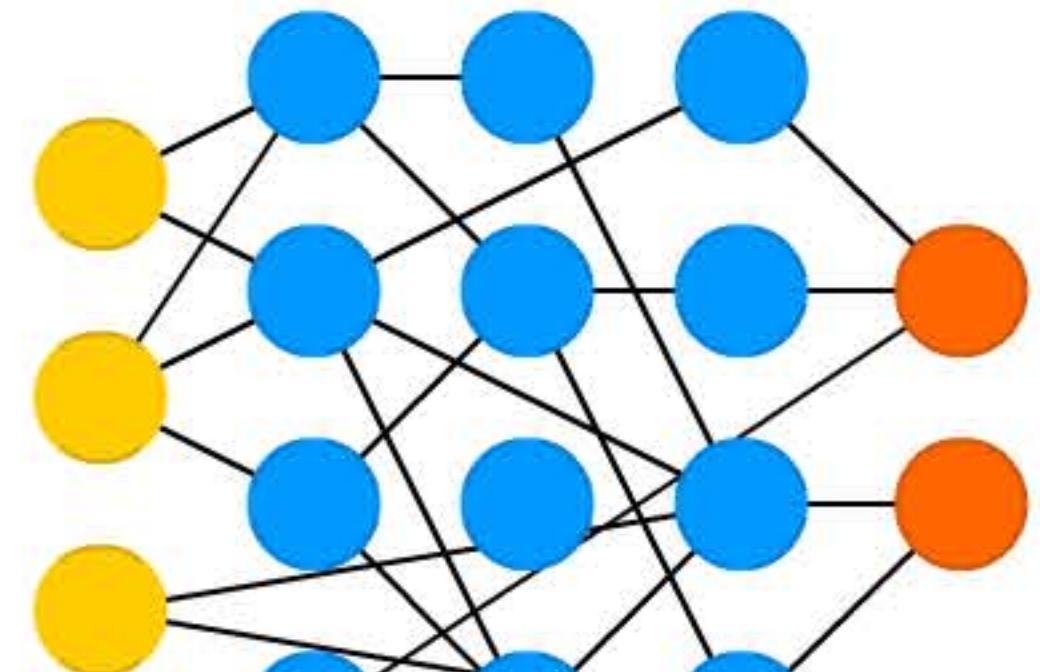
Liquid State Machine (LSM)



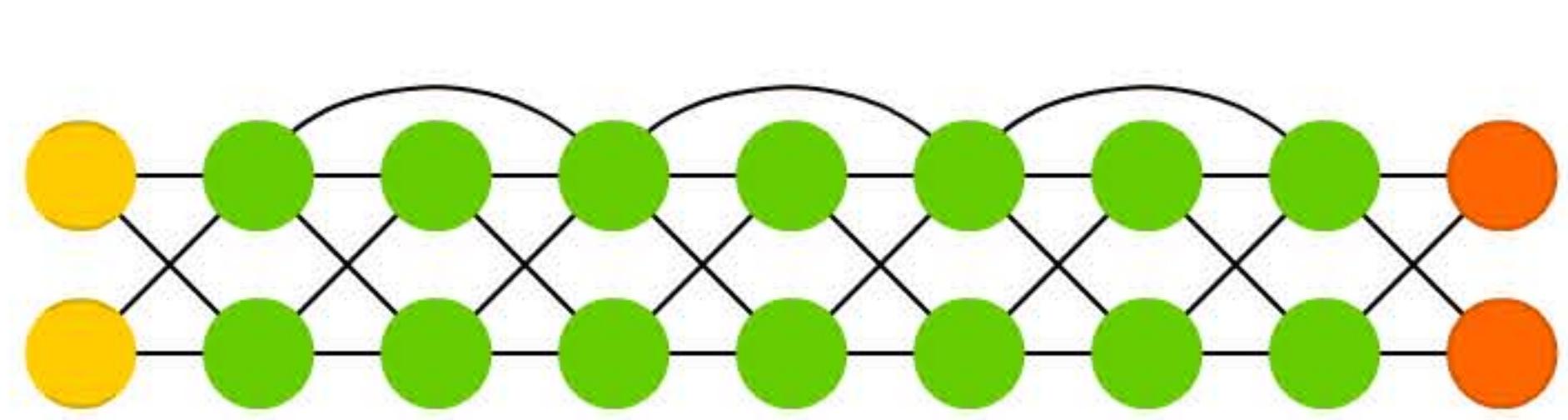
Extreme Learning Machine (ELM)



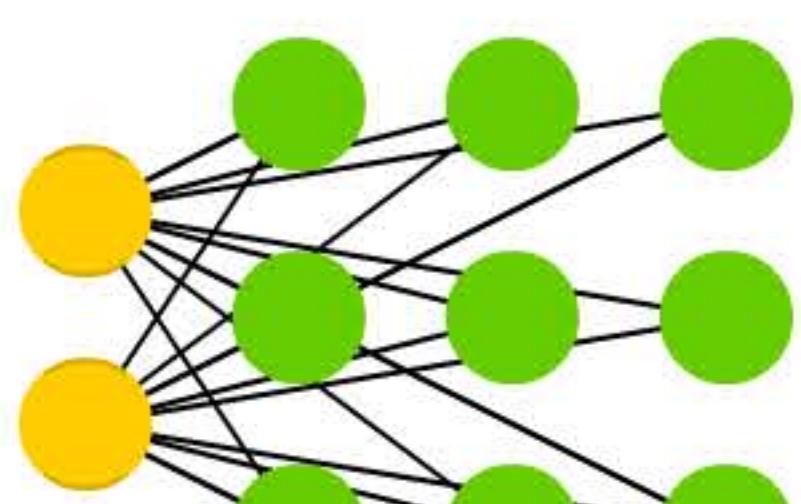
Echo State Network (ESN)



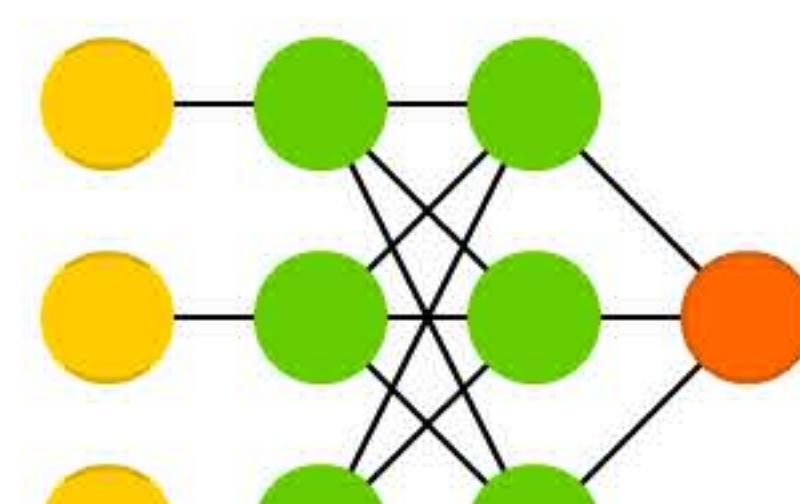
Deep Residual Network (DRN)



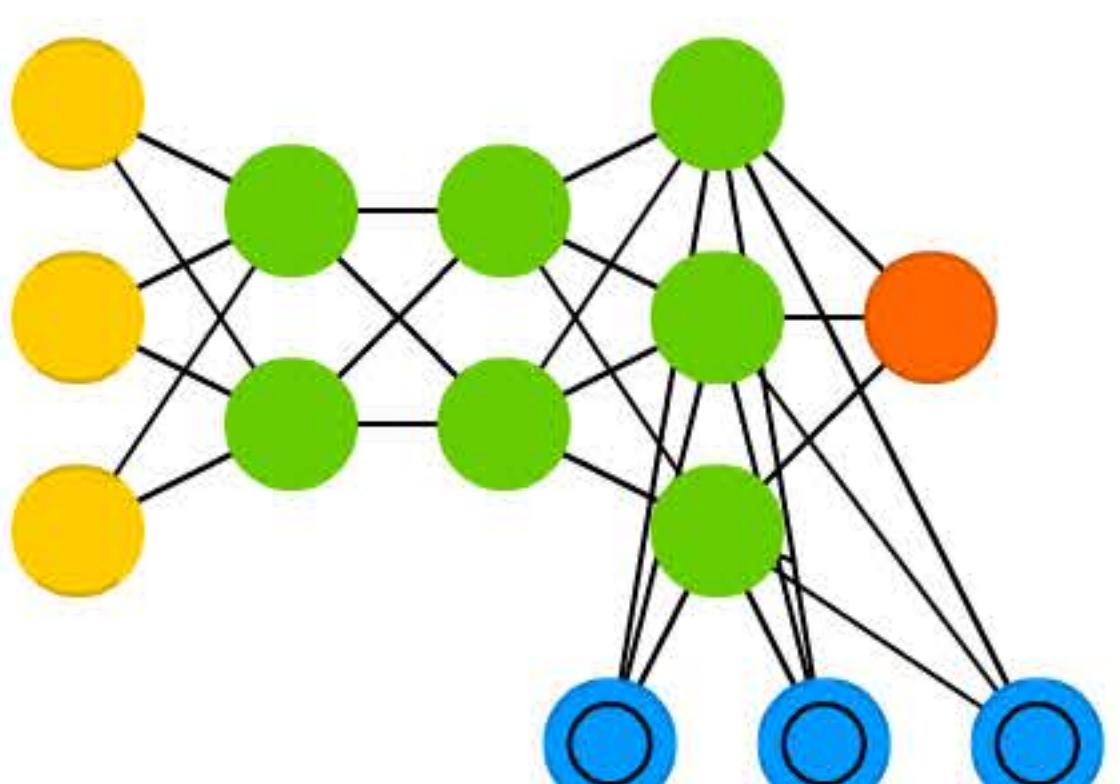
Kohonen Network (KN)



Support Vector Machine (SVM)



Neural Turing Machine (NTM)



Array Sorting Algorithms

Algorithm	Time Complexity			Space Complexity
	Best	Average	Worst	
<u>Quicksort</u>	$\Omega(n \log(n))$	$\Theta(n \log(n))$	$O(n^2)$	$O(\log(n))$
<u>Mergesort</u>	$\Omega(n \log(n))$	$\Theta(n \log(n))$	$O(n \log(n))$	$O(n)$
<u>Timsort</u>	$\Omega(n)$	$\Theta(n \log(n))$	$O(n \log(n))$	$O(n)$
<u>Heapsort</u>	$\Omega(n \log(n))$	$\Theta(n \log(n))$	$O(n \log(n))$	$O(1)$
<u>Bubble Sort</u>	$\Omega(n)$	$\Theta(n^2)$	$O(n^2)$	$O(1)$
<u>Insertion Sort</u>	$\Omega(n)$	$\Theta(n^2)$	$O(n^2)$	$O(1)$
<u>Selection Sort</u>	$\Omega(n^2)$	$\Theta(n^2)$	$O(n^2)$	$O(1)$
<u>Tree Sort</u>	$\Omega(n \log(n))$	$\Theta(n \log(n))$	$O(n^2)$	$O(n)$
<u>Shell Sort</u>	$\Omega(n \log(n))$	$\Theta(n(\log(n))^2)$	$O(n(\log(n))^2)$	$O(1)$
<u>Bucket Sort</u>	$\Omega(n+k)$	$\Theta(n+k)$	$O(n^2)$	$O(n)$
<u>Radix Sort</u>	$\Omega(nk)$	$\Theta(nk)$	$O(nk)$	$O(n+k)$
<u>Counting Sort</u>	$\Omega(n+k)$	$\Theta(n+k)$	$O(n+k)$	$O(k)$
<u>Cubesort</u>	$\Omega(n)$	$\Theta(n \log(n))$	$O(n \log(n))$	$O(n)$

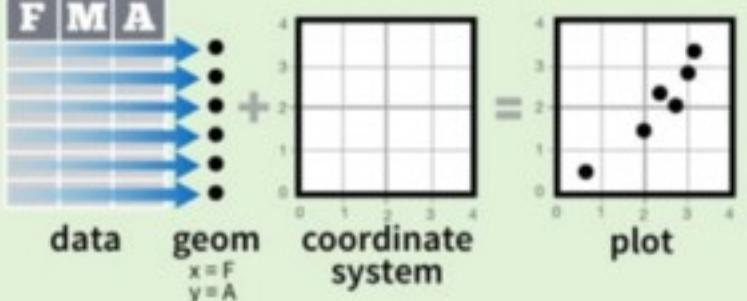
Data Visualization with ggplot2

Cheat Sheet

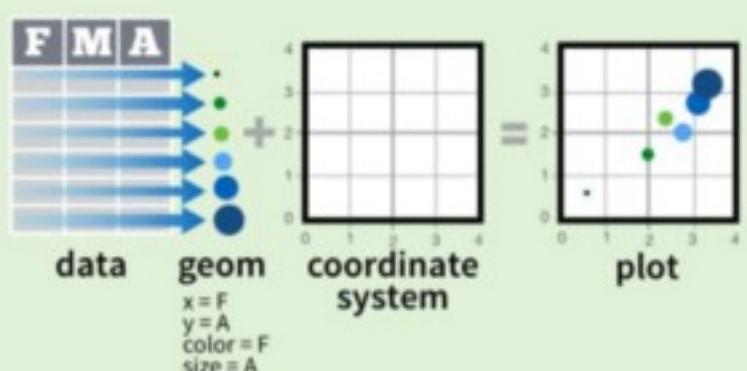


Basics

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



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



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

aesthetic mappings **data** **geom**

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

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

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

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

data

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

add layers, elements with +

layer = geom + default stat + layer specific mappings

additional elements

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

last_plot()

Returns the last plot

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

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

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

One Variable

Continuous

	a + geom_area(stat = "bin") x, y, alpha, color, fill, linetype, size b + geom_area(aes(y = ..density..), stat = "bin")
	a + geom_density(kernel = "gaussian") x, y, alpha, color, fill, linetype, size, weight b + geom_density(aes(y = ..county..))
	a + geom_dotplot() x, y, alpha, color, fill
	a + geom_freqpoly() x, y, alpha, color, linetype, size b + geom_freqpoly(aes(y = ..density..))
	a + geom_histogram(binwidth = 5) x, y, alpha, color, fill, linetype, size, weight b + geom_histogram(aes(y = ..density..))

Discrete

	b <- ggplot(mpg, aes(fl))
	b + geom_bar() x, alpha, color, fill, linetype, size, weight

Graphical Primitives

	c <- ggplot(map, aes(long, lat))
	c + geom_polygon(aes(group = group)) x, y, alpha, color, fill, linetype, size
	d <- ggplot(economics, aes(date, unemploy))
	d + geom_path(lineend = "butt", linejoin = "round", linemitre = 1) x, y, alpha, color, linetype, size
	d + geom_rect(aes(ymin = unemploy - 900, ymax = unemploy + 900)) x, y, alpha, color, fill, linetype, size
	e <- ggplot(seals, aes(x = long, y = lat))
	e + geom_segment(aes(xend = long + delta_long, yend = lat + delta_lat)) x, y, alpha, color, linetype, size
	e + geom_rect(aes(xmin = long, ymin = lat, xmax = long + delta_long, ymax = lat + delta_lat)) x, y, alpha, color, fill, linetype, size

Two Variables

Continuous X, Continuous Y

	f <- ggplot(mpg, aes(cty, hwy))
	f + geom_jitter() x, y, alpha, color, fill, shape, size
	f + geom_point() x, y, alpha, color, fill, shape, size
	f + geom_quantile() x, y, alpha, color, linetype, size, weight
	f + geom_rug(sides = "bl") alpha, color, linetype, size
	f + geom_smooth(model = lm) x, y, alpha, color, fill, linetype, size, weight
	f + geom_text(aes(label = cty)) x, y, label, alpha, angle, color, family, fontface, hjust, lineheight, size, vjust

Discrete X, Continuous Y

	g <- ggplot(mpg, aes(class, hwy))
	g + geom_bar(stat = "identity") x, y, alpha, color, fill, linetype, size, weight
	g + geom_boxplot() lower, middle, upper, x, y, alpha, color, fill, linetype, shape, size, weight
	g + geom_dotplot(binaxis = "y", stackdir = "center") x, y, alpha, color, fill
	g + geom_violin(scale = "area") x, y, alpha, color, fill, linetype, size, weight

Discrete X, Discrete Y

	h <- ggplot(diamonds, aes(cut, color))
	h + geom_jitter() x, y, alpha, color, fill, shape, size

Three Variables

	seals\$z <- with(seals, sqrt(delta_long^2 + delta_lat^2))
	m <- ggplot(seals, aes(long, lat))
	m + geom_contour(aes(z = z)) x, y, z, alpha, colour, linetype, size, weight

Continuous Bivariate Distribution

	i <- ggplot(movies, aes(year, rating))
	i + geom_hex(binwidth = c(5, 0.5)) xmax, xmin, ymax, ymin, alpha, color, fill, linetype, size, weight
	i + geom_hex() x, y, alpha, colour, linetype, size
	i + geom_hex() x, y, alpha, colour, fill size

Continuous Function

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

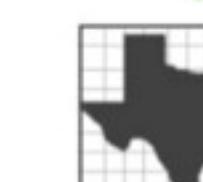
Visualizing error

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

	k + geom_crossbar(fatten = 2) x, y, ymax, ymin, alpha, color, fill, linetype, size
	k + geom_errorbar() x, y, ymax, ymin, alpha, color, linetype, size, width (also geom_errorbarh())
	k + geom_linerange() x, y, ymin, ymax, alpha, color, linetype, size
	k + geom_pointrange() x, y, ymin, ymax, alpha, color, fill, linetype, shape, size

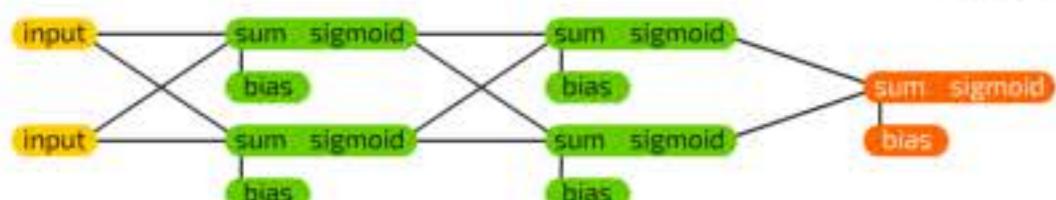
Maps

```
data <- data.frame(murder = USArrests$Murder,
                    state = tolower(rownames(USArrests)))
map <- map_data("state")
l <- ggplot(data, aes(fill = murder))
l + geom_map(aes(map_id = state), map = map) +
  expand_limits(x = map$long, y = map$lat)
```

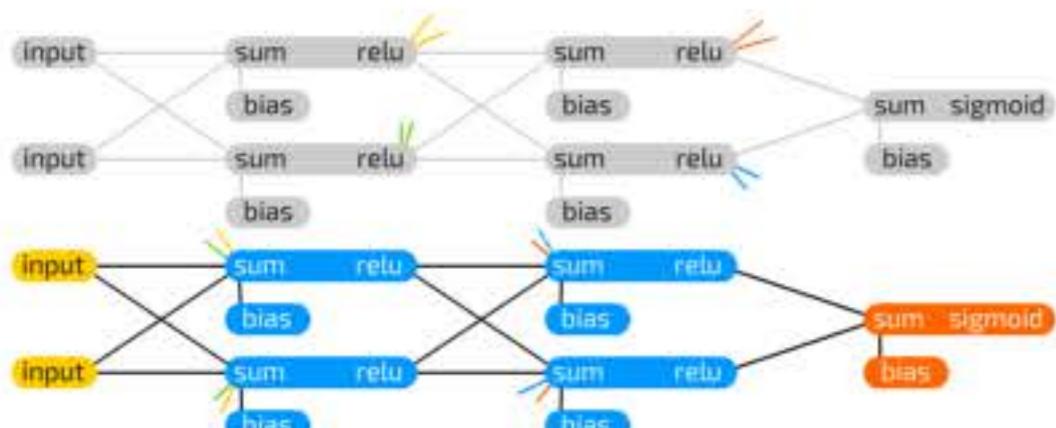
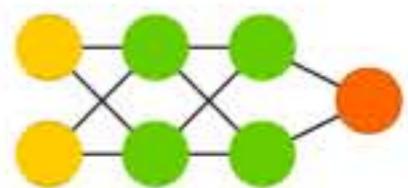
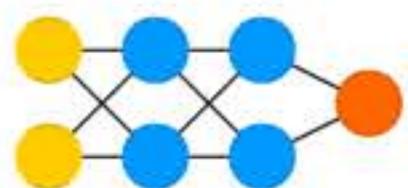


Neural Network Graphs

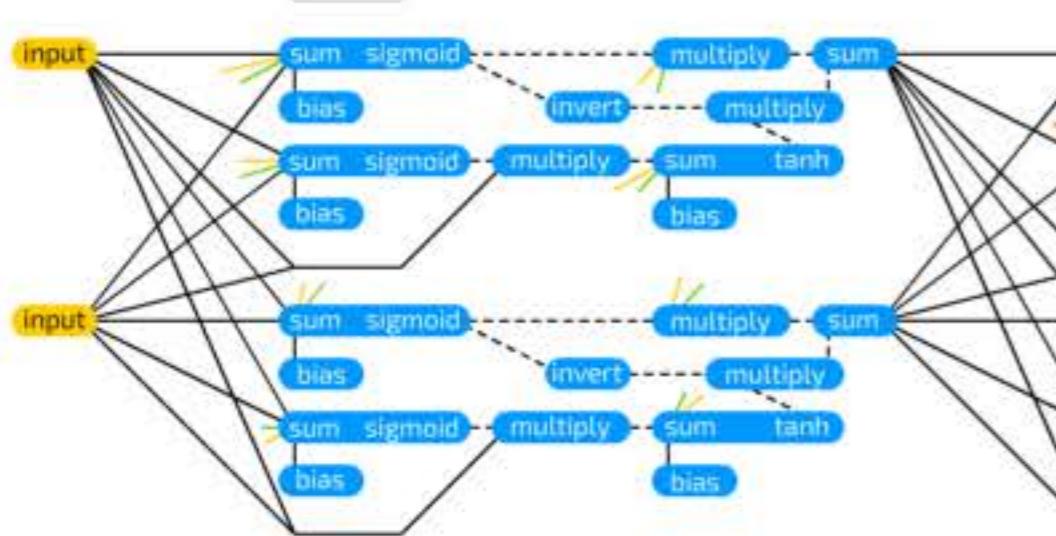
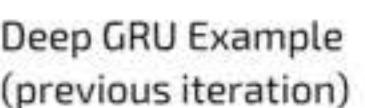
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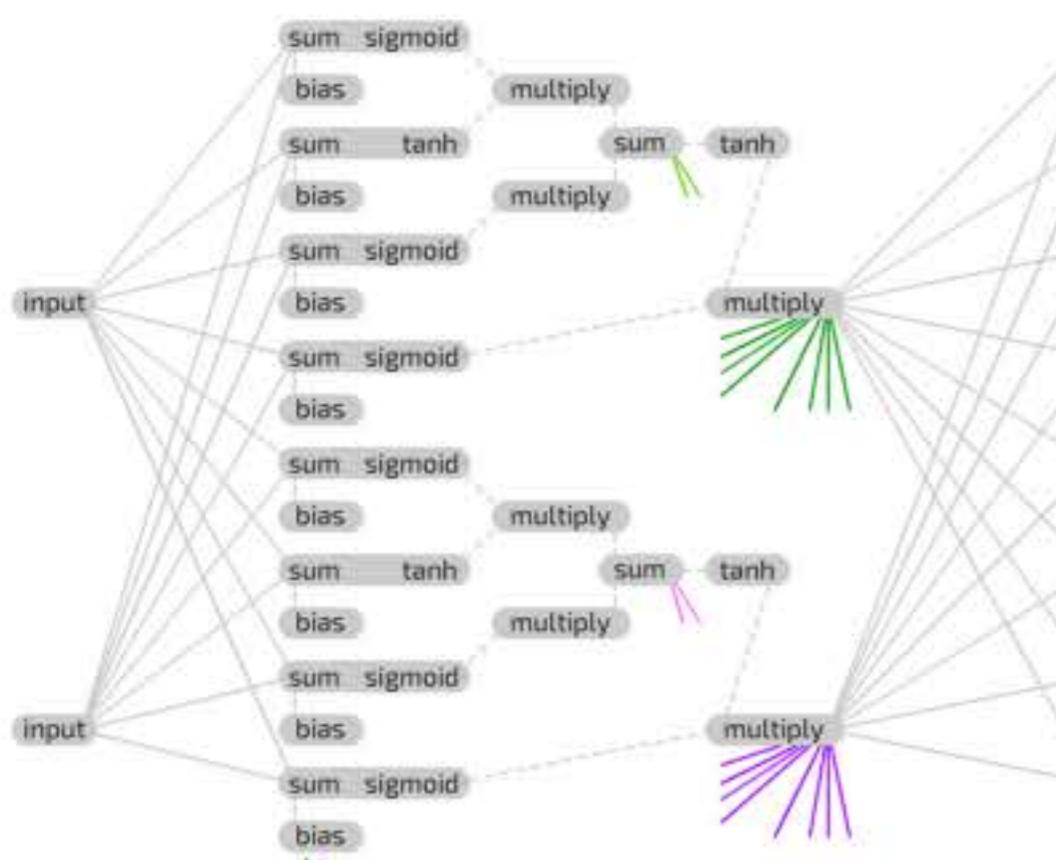
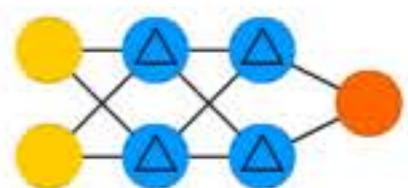
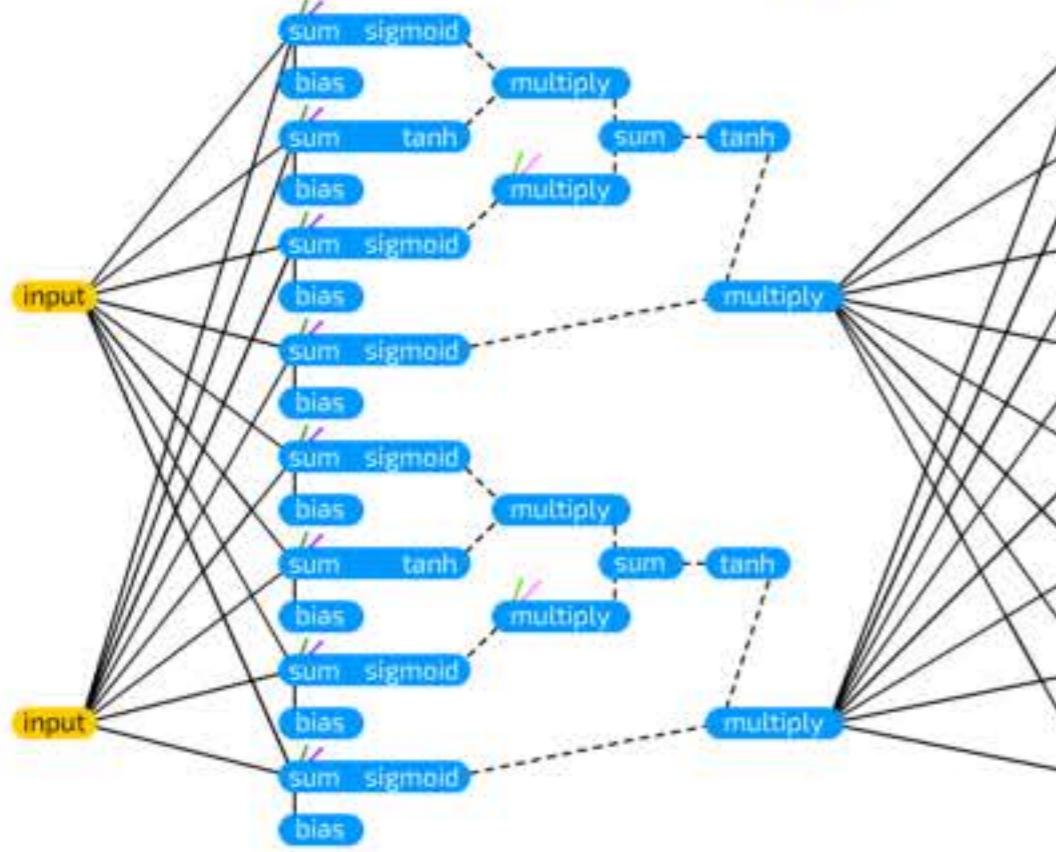
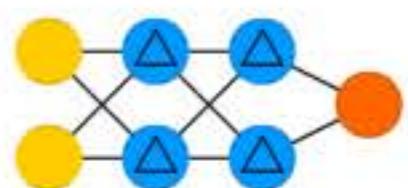
Deep Feed Forward Example

Deep Recurrent Example
(previous iteration)

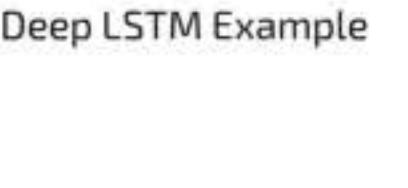
Deep Recurrent Example



Deep GRU Example

Deep LSTM Example
(previous iteration)

Deep LSTM Example



Common Data Structure Operations

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

Python For Data Science Cheat Sheet

PySpark Basics

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Spark

PySpark is the Spark Python API that exposes the Spark programming model to Python



Initializing Spark

SparkContext

```
>>> from pyspark import SparkContext  
>>> sc = SparkContext(master = 'local[2]')
```

Inspect SparkContext

```
>>> sc.version  
>>> sc.pythonVer  
>>> sc.master  
>>> str(sc.sparkHome)  
>>> str(sc.sparkUser())  
  
>>> sc.appName  
>>> sc.applicationId  
>>> sc.defaultParallelism  
>>> sc.defaultMinPartitions
```

Retrieve SparkContext version
Retrieve Python version
Master URL to connect to
Path where Spark is installed on worker nodes
Retrieve name of the Spark User running SparkContext
Return application name
Retrieve application ID
Return default level of parallelism
Default minimum number of partitions for RDDs

Configuration

```
>>> from pyspark import SparkConf, SparkContext  
>>> conf = (SparkConf()  
           .setMaster("local")  
           .setAppName("My app")  
           .set("spark.executor.memory", "1g"))  
>>> sc = SparkContext(conf = conf)
```

Using The Shell

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

```
$ ./bin/spark-shell --master local[2]  
$ ./bin/pyspark --master local[4] --py-files code.py
```

Set which master the context connects to with the `--master` argument, and add Python .zip, .egg or .py files to the runtime path by passing a comma-separated list to `--py-files`.

Loading Data

Parallelized Collections

```
>>> rdd = sc.parallelize([('a', 7), ('a', 2), ('b', 2)])  
>>> rdd2 = sc.parallelize([('a', 2), ('d', 1), ('b', 1)])  
>>> rdd3 = sc.parallelize(range(100))  
>>> rdd4 = sc.parallelize([('a', ["x", "y", "z"]),  
                         ("b", ["p", "r"])]))
```

External Data

Read either one text file from HDFS, a local file system or any Hadoop-supported file system URI with `textFile()`, or read in a directory of text files with `wholeTextFiles()`.

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

Retrieving RDD Information

Basic Information

```
>>> rdd.getNumPartitions()  
>>> rdd.count()  
3  
>>> rdd.countByKey()  
defaultdict(<type 'int'>, {'a':2, 'b':1})  
>>> rdd.countByValue()  
defaultdict(<type 'int'>, {'b':2, 'a':1, 'a':1, 'a':7})  
>>> rdd.collectAsMap()  
{'a': 2, 'b': 1}  
>>> rdd3.sum()  
4950  
>>> sc.parallelize([]).isEmpty()  
True
```

List the number of partitions
Count RDD instances
Count RDD instances by key
Count RDD instances by value
Return (key,value) pairs as a dictionary
Sum of RDD elements
Check whether RDD is empty

Summary

```
>>> rdd3.max()  
99  
>>> rdd3.min()  
0  
>>> rdd3.mean()  
49.5  
>>> rdd3.stdev()  
28.866070047722118  
>>> rdd3.variance()  
833.25  
>>> rdd3.histogram(3)  
([0,33,66,99], [33,33,34])  
>>> rdd3.stats()
```

Maximum value of RDD elements
Minimum value of RDD elements
Mean value of RDD elements
Standard deviation of RDD elements
Compute variance of RDD elements
Compute histogram by bins
Summary statistics (count, mean, stdev, max & min)

Applying Functions

```
>>> rdd.map(lambda x: x+(x[1],x[0]))  
     .collect()  
[(('a',7,7,'a'), ('a',2,2,'a'), ('b',2,2,'b'))]  
>>> rdd5 = rdd.flatMap(lambda x: x+(x[1],x[0]))  
  
>>> rdd5.collect()  
[('a',7,7,'a','a',2,2,'a','b',2,2,'b')]  
>>> rdd4.flatMapValues(lambda x: x)  
     .collect()  
[('a','x'),('a','y'),('a','z'),('b','p'),('b','r')]
```

Apply a function to each RDD element
Apply a function to each RDD element and flatten the result
Apply a flatMap function to each (key,value) pair of rdd4 without changing the keys

Selecting Data

Getting

```
>>> rdd.collect()  
[('a', 7), ('a', 2), ('b', 2)]  
>>> rdd.take(2)  
[('a', 7), ('a', 2)]  
>>> rdd.first()  
('a', 7)  
>>> rdd.top(2)  
[('b', 2), ('a', 7)]
```

Sampling

```
>>> rdd3.sample(False, 0.15, 81).collect()  
[3,4,27,31,40,41,42,43,60,76,79,80,86,97]
```

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']
```

Return a list with all RDD elements
Take first 2 RDD elements
Take first RDD element
Take top 2 RDD elements
Return sampled subset of rdd3
Filter the RDD
Return distinct RDD values
Return (key,value) RDD's keys

Iterating

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

Apply a function to all RDD elements

Reshaping Data

Reducing

```
>>> rdd.reduceByKey(lambda x,y : x+y)  
     .collect()  
[('a',9), ('b',2)]  
>>> rdd.reduce(lambda a, b: a + b)  
('a',7, 'a',2, 'b',2)
```

Merge the rdd values for each key

Merge the rdd values

Return RDD of grouped values

Group rdd by key

Grouping by

```
>>> rdd3.groupBy(lambda x: x % 2)  
     .mapValues(list)  
     .collect()  
>>> rdd.groupByKey()  
     .mapValues(list)  
     .collect()  
[('a',[7,2]), ('b',[2])]
```

Aggregate RDD elements of each partition and then the results

Aggregate values of each RDD 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)  
>>> rdd.aggregateByKey((0,0),seqOp,combOp)  
     .collect()  
[('a',(9,2)), ('b',(2,1))]  
>>> rdd3.fold(0,add)  
4950  
>>> rdd.foldByKey(0, add)  
     .collect()  
[('a',9), ('b',2)]  
>>> rdd3.keyBy(lambda x: x+x)  
     .collect()
```

Aggregate the elements of each partition, and then the results

Merge the values for each key

Create tuples of RDD elements by applying a function

Mathematical Operations

```
>>> rdd.subtract(rdd2)  
     .collect()  
[('b',2), ('a',7)]  
>>> rdd2.subtractByKey(rdd)  
     .collect()  
[('d', 1)]  
>>> rdd.cartesian(rdd2).collect()
```

Return each rdd value not contained in rdd2

Return each (key,value) pair of rdd2 with no matching key in rdd

Return the Cartesian product of rdd and rdd2

Sort

```
>>> rdd2.sortBy(lambda x: x[1])  
     .collect()  
[('d',1), ('b',1), ('a',2)]  
>>> rdd2.sortByKey()  
     .collect()  
[('a',2), ('b',1), ('d',1)]
```

Sort RDD by given function

Sort (key, value) RDD by key

Repartitioning

```
>>> 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
```



Python For Data Science Cheat Sheet

Scikit-Learn

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Scikit-learn

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



A Basic Example

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

Loading The Data

Also see NumPy & Pandas

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

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

Training And Test Data

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

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)
```

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)
>>> knn.fit(X_train, y_train)
>>> svc.fit(X_train, y_train)
```

Unsupervised Learning

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

Fit the model to the data

Fit the model to the data

Fit to data, then transform it

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.random((2,5)))
>>> y_pred = lr.predict(X_test)
>>> y_pred = knn.predict_proba(X_test)
```

Unsupervised Estimators

```
>>> y_pred = k_means.predict(X_test)
```

Predict labels

Predict labels

Estimate probability of a label

Predict labels in clustering algos

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test)
>>> from sklearn.metrics import accuracy_score
>>> accuracy_score(y_test, y_pred)
```

Estimator score method
Metric scoring functions

Classification Report

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

Precision, recall, f1-score and support

Confusion Matrix

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

Regression Metrics

Mean Absolute Error

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

Mean Squared Error

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

R² Score

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

Clustering Metrics

Adjusted Rand Index

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

Homogeneity

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

V-measure

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

Cross-Validation

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

Tune Your Model

Grid Search

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

Randomized Parameter Optimization

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



Python For Data Science Cheat Sheet

Python Basics

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Variables and Data Types

Variable Assignment

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

Calculations With Variables

>>> x+2	Sum of two variables
>>> x-2	Subtraction of two variables
>>> x*2	Multiplication of two variables
>>> x**2	Exponentiation of a variable
>>> x%2	Remainder of a variable
>>> x/float(2)	Division of a variable
2.5	

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 + 'Init'  
'thisStringIsAwesomeInit'  
>>> '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]  
>>> my_list[-3]
```

Slice

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

Subset Lists of Lists

```
>>> my_list2[1][0]
```

```
>>> my_list2[1][1:-1]
```

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[list][itemOfList]

List Operations

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

List Methods

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

Get the index of an item
Count an item
Append an item at a time
Remove an item
Remove an item
Reverse the list
Append an item
Remove an item
Insert an item
Sort the list

Libraries

Import libraries

```
>>> import numpy  
>>> import numpy as np  
>>> from math import pi
```

pandas Data analysis

Machine learning

NumPy Scientific computing

matplotlib 2D plotting

Install Python



Leading open data science platform
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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

NumPy Basics

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NumPy

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

Use the following import convention:

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



NumPy Arrays

1D array

1	2	3
---	---	---

2D array

axis 0	1.5	2	3
axis 1	4	5	6

3D array

axis 0	1.5	2	3
axis 1	4	5	6
axis 2	7	8	9

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))
>>> np.ones((2,3,4),dtype=np.int16)
>>> d = np.arange(10,25,5)

>>> np.linspace(0,2,9)

>>> e = np.full((2,2),7)
>>> f = np.eye(2)
>>> np.random.random((2,2))
>>> np.empty((3,2))
```

Create an array of zeros
Create an array of ones
Create an array of evenly spaced values (step value)
Create an array of evenly spaced values (number of samples)
Create a constant array
Create a 2X2 identity matrix
Create an array with random values
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
>>> np.float32
>>> np.complex
>>> np.bool
>>> np.object
>>> np.string_
>>> np.unicode_
```

Signed 64-bit integer types
Standard double-precision floating point
Complex numbers represented by 128 floats
Boolean type storing TRUE and FALSE values
Python object type
Fixed-length string type
Fixed-length unicode type

Inspecting Your Array

```
>>> a.shape
>>> len(a)
>>> b.ndim
>>> e.size
>>> b.dtype
>>> b.dtype.name
>>> b.astype(int)
```

Array dimensions
Length of array
Number of array dimensions
Number of array elements
Data type of array elements
Name of data type
Convert an array to a different type

Asking For Help

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

Array Mathematics

Arithmetic Operations

```
>>> g = a - b
>>> np.subtract(a,b)
>>> b + a
>>> np.add(b,a)
>>> a / b
>>> np.divide(a,b)
>>> a * b
>>> np.multiply(a,b)
>>> np.exp(b)
>>> np.sqrt(b)
>>> np.sin(a)
>>> np.cos(b)
>>> np.log(a)
>>> e.dot(f)
>>> array([[ 7.,  7.], [ 7.,  7.]])
```

Subtraction

Subtraction
Addition

Addition
Division

Division
Multiplication

Multiplication
Exponentiation
Square root
Print sines of an array
Element-wise cosine
Element-wise natural logarithm
Dot product

Comparison

```
>>> a == b
>>> array([[False, True, True],
           [False, False, False]], dtype=bool)
>>> a < 2
>>> array([True, False, False], dtype=bool)
>>> np.array_equal(a, b)
```

Element-wise comparison

Element-wise comparison

Array-wise comparison

Aggregate Functions

```
>>> a.sum()
>>> a.min()
>>> b.max(axis=0)
>>> b.cumsum(axis=1)
>>> a.mean()
>>> b.median()
>>> a.corrcoef()
>>> np.std(b)
```

Array-wise sum
Array-wise minimum value
Maximum value of an array row
Cumulative sum of the elements
Mean
Median
Correlation coefficient
Standard deviation

Copying Arrays

```
>>> h = a.view()
>>> np.copy(a)
>>> h = a.copy()
```

Create a view of the array with the same data
Create a copy of the array
Create a deep copy of the array

Sorting Arrays

```
>>> a.sort()
>>> c.sort(axis=0)
```

Sort an array
Sort the elements of an array's axis

Subsetting, Slicing, Indexing

Subsetting

```
>>> a[2]
>>> 3
```

1	2	3
4	5	6

Select the element at the 2nd index
Select the element at row 0 column 2 (equivalent to b[1][2])

Slicing

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

1	2	3
4	5	6

Select items at index 0 and 1
Select items at rows 0 and 1 in column 1

```
>>> b[:1]
>>> array([[1.5, 2., 3.]])
```

1.5	2	3
4	5	6

Select all items at row 0 (equivalent to b[0:1, :])
Same as [1,:,:]

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

3	2	1
4	5	6

Reversed array a

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

1	2	3
4	5	6

Select elements from a less than 2
Select elements (1,0),(0,1),(1,2) and (0,0)

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

4	2	6	1.5
1.5	2	3	1.5

Select a subset of the matrix's rows and columns

Array Manipulation

Transposing Array

```
>>> i = np.transpose(b)
>>> i.T
```

Permute array dimensions
Permute array dimensions

Changing Array Shape

```
>>> b.ravel()
>>> g.reshape(3,-2)
```

Flatten the array
Reshape, but don't change data

Adding/Removing Elements

```
>>> h.resize((2,6))
>>> np.append(h,g)
>>> np.insert(a, 1, 5)
>>> np.delete(a, [1])
```

Return a new array with shape (2,6)
Append items to an array
Insert items in an array
Delete items from an array

Combining Arrays

```
>>> np.concatenate((a,d),axis=0)
>>> array([ 1,  2,  3, 10, 15, 20])
>>> np.vstack((a,b))
>>> array([[ 1.,  2.,  3.],
           [ 1.5,  2.,  3.],
           [ 4.,  5.,  6.]])
>>> np.r_[e,f]
>>> np.hstack((e,f))
>>> array([[ 7.,  7.,  1.,  0.],
           [ 7.,  7.,  0.,  1.]])
>>> np.column_stack((a,d))
>>> array([[ 1, 10],
           [ 2, 15],
           [ 3, 20]])
>>> np.c_[a,d]
```

Concatenate arrays
Stack arrays vertically (row-wise)
Stack arrays vertically (row-wise)
Stack arrays horizontally (column-wise)
Create stacked column-wise arrays
Create stacked column-wise arrays

Splitting Arrays

```
>>> np.hsplit(a,3)
>>> [array([1]),array([2]),array([3])]
>>> np.vsplit(c,2)
>>> [array([[ 1.5,  2.,  1. ]]),
           [array([[ 4.,  5.,  6. ]])]
```

Split the array horizontally at the 3rd index
Split the array vertically at the 2nd index



LEGEND

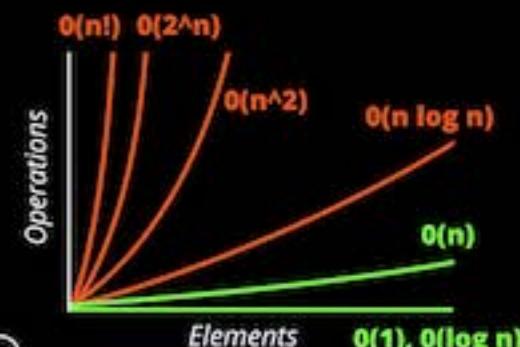
TIME Complexity VS. SPACE Complexity

Good Fair Bad

Good Fair Bad



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Operations

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ARRAY SORTING
Algorithms

DATA Structure

TIME Complexity

SPACE Complexity

Operations

Average

Access Search Insertion Deletion

Worst

Access Search Insertion Deletion

Operations

Operations

Array $\Theta(1)$ $\Theta(n)$ $\Theta(n)$ $\Theta(n)$

Operations

Stack $\Theta(n)$ $\Theta(n)$ $\Theta(1)$ $\Theta(1)$

Operations

Queue $\Theta(n)$ $\Theta(n)$ $\Theta(1)$ $\Theta(1)$

Operations

Singly-Linked List $\Theta(n)$ $\Theta(n)$ $\Theta(1)$ $\Theta(1)$

Operations

Doubly-Linked List $\Theta(n)$ $\Theta(n)$ $\Theta(1)$ $\Theta(1)$

Operations

Skip List $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$

Operations

Hash Table N/A $\Theta(1)$ $\Theta(1)$ N/A

Operations

Binary Search Tree $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(n)$

Operations

Cartesian Tree N/A $\Theta(\log(n))$ $\Theta(\log(n))$ N/A

Operations

B-Tree $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$

Operations

Red-Black Tree $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$

Operations

Splay Tree N/A $\Theta(\log(n))$ $\Theta(\log(n))$ N/A

Operations

AVL Tree $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$

Operations

KD Tree $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(\log(n))$ $\Theta(n)$

ARRAY Algorithms

TIME Complexity

SPACE Complexity

Operations

Best

 $\Theta(n \log(n))$

Average

 $\Theta(n \log(n))$

Worst

 $\Theta(n^2)$

Operations

 $\Theta(n \log(n))$

Worst

 $\Theta(n^2)$

Operations

Quicksort

Operations

 $\Theta(n \log(n))$

Average

 $\Theta(n \log(n))$

Worst

 $\Theta(n^2)$

Operations

Mergesort

Operations

 $\Theta(n \log(n))$

Average

 $\Theta(n \log(n))$

Worst

 $\Theta(n \log(n))$

Operations

Timsort

Operations

 $\Theta(n)$

Average

 $\Theta(n \log(n))$

Worst

 $\Theta(n \log(n))$

Operations

Heapsort

Operations

 $\Theta(n \log(n))$

Average

 $\Theta(n \log(n))$

Worst

 $\Theta(n \log(n))$

Operations

Bubble Sort

Operations

 $\Theta(n)$

Average

 $\Theta(n^2)$

Worst

 $\Theta(n^2)$

Operations

Insertion Sort

Operations

 $\Theta(n)$

Average

 $\Theta(n^2)$

Worst

 $\Theta(n^2)$

Operations

Selection Sort

Operations

 $\Theta(n^2)$

Average

 $\Theta(n^2)$

Worst

 $\Theta(n^2)$

Operations

Tree Sort

Operations

 $\Theta(n \log(n))$

Average

 $\Theta(n^2)$

Worst

 $\Theta(n^2)$

Operations

Shell Sort

Operations

 $\Theta(n \log(n))$

Average

 $\Theta(n(\log(n))^2)$

Worst

 $\Theta(n(\log(n))^2)$

Operations

Bucket Sort

Operations

 $\Theta(n+k)$

Average

 $\Theta(n+k)$

Worst

 $\Theta(n^2)$

Operations

Radix Sort

Operations

 $\Theta(nk)$

Average

 $\Theta(nk)$

Worst

 $\Theta(nk)$

Operations

Counting Sort

Operations

 $\Theta(n+k)$

Average

 $\Theta(n+k)$

Worst

 $\Theta(n+k)$

Operations

Cubesort

Operations

 $\Theta(n)$

Average

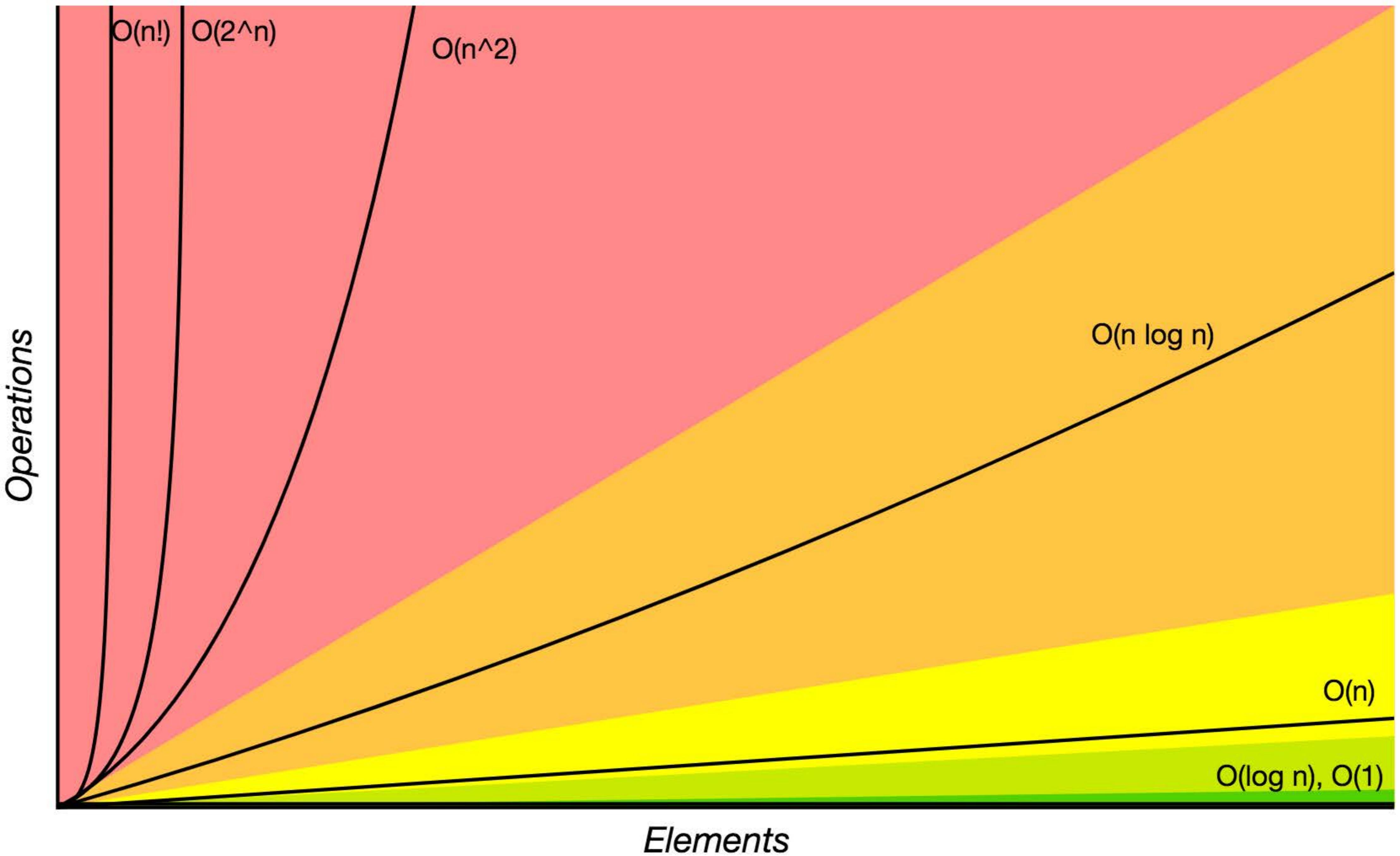
 $\Theta(n \log(n))$

Worst

 $\Theta(n \log(n))$

Big-O Complexity Chart

Horrible Bad Fair Good Excellent



MACHINE LEARNING IN EMOJI

SUPERVISED

UNSUPERVISED

REINFORCEMENT

	SUPERVISED	human builds model based on input / output
	UNSUPERVISED	human input, machine output human utilizes if satisfactory
	REINFORCEMENT	human input, machine output human reward/punish, cycle continues

BASIC REGRESSION

	LINEAR	<code>linear_model.LinearRegression()</code>
	Lots of numerical data	
	LOGISTIC	<code>linear_model.LogisticRegression()</code>
	Target variable is categorical	or

CLASSIFICATION

	NEURAL NET	<code>neural_network.MLPClassifier()</code>
	Complex relationships. Prone to overfitting	
	Basically magic.	
	K-NN	<code>neighbors.KNeighborsClassifier()</code>
	Group membership based on proximity	
	DECISION TREE	<code>tree.DecisionTreeClassifier()</code>
	If/then/else. Non-contiguous data	
	Can also be regression	
	RANDOM FOREST	<code>ensemble.RandomForestClassifier()</code>
	Find best split randomly	
	Can also be regression	
	SVM	<code>svm.SVC()</code> <code>svm.LinearSVC()</code>
	Maximum margin classifier. Fundamental Data Science algorithm	
	NAIVE BAYES	<code>GaussianNB()</code> <code>MultinomialNB()</code> <code>BernoulliNB()</code>
	Updating knowledge step by step with new info	

CLUSTER ANALYSIS

	K-MEANS	<code>cluster.KMeans()</code>
	Similar datum into groups based on centroids	
	ANOMALY DETECTION	<code>covariance.EllipticalEnvelope()</code>
	Finding outliers through grouping	

FEATURE REDUCTION

T-DISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING	<code>manifold.TSNE()</code>
Visualize high dimensional data. Convert similarity to joint probabilities	
PRINCIPLE COMPONENT ANALYSIS	<code>decomposition.PCA()</code>
Distill feature space into components that describe greatest variance	
CANONICAL CORRELATION ANALYSIS	<code>decomposition.CCA()</code>
Making sense of cross-correlation matrices	
LINEAR DISCRIMINANT ANALYSIS	<code>lda.LDA()</code>
Linear combination of features that separates classes	

OTHER IMPORTANT CONCEPTS

BIAS VARIANCE TRADEOFF	
UNDERFITTING / OVERFITTING	
INERTIA	
ACCURACY FUNCTION	$(TP + TN) / (P + N)$
Precision Function	$TP / (TP + FP)$
Specificity Function	$TN / (FP + TN)$
Sensitivity Function	$TP / (TP + FN)$

Python For Data Science Cheat Sheet

Keras

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Keras

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

A Basic Example

```
>>> import numpy as np
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>> data = np.random.random((1000,100))
>>> labels = np.random.randint(2,size=(1000,1))
>>> model = Sequential()
>>> model.add(Dense(32,
    activation='relu',
    input_dim=100))
>>> model.add(Dense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop',
    loss='binary_crossentropy',
    metrics=['accuracy'])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

Data

Also see NumPy, Pandas & Scikit-Learn

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the `train_test_split` module of `sklearn.cross_validation`.

Keras Data Sets

```
>>> from keras.datasets import boston_housing,
    mnist,
    cifar10,
    imdb

>>> (x_train,y_train),(x_test,y_test) = mnist.load_data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

Other

```
>>> from urllib.request import urlopen
>>> data = np.loadtxt(urlopen("http://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes.data"),delimiter=",")
>>> X = data[:,0:8]
>>> y = data[:,8]
```

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)
```

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'))
```

Also see NumPy & Scikit-Learn

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)
```

Inspect Model

```
>>> model.output_shape
>>> model.summary()
>>> model.get_config()
>>> model.get_weights()
```

Model output shape
Model summary representation
Model configuration
List all weight tensors in the model

Compile Model

MLP: Binary Classification

```
>>> model.compile(optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy'])
```

MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
    loss='categorical_crossentropy',
    metrics=['accuracy'])
```

MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
    loss='mse',
    metrics=['mae'])
```

Recurrent Neural Network

```
>>> model3.compile(loss='binary_crossentropy',
    optimizer='adam',
    metrics=['accuracy'])
```

Model Training

```
>>> model3.fit(x_train4,
    y_train4,
    batch_size=32,
    epochs=15,
    verbose=1,
    validation_data=(x_test4,y_test4))
```

Evaluate Your Model's Performance

```
>>> score = model3.evaluate(x_test,
    y_test,
    batch_size=32)
```

Prediction

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

Save/ Reload Models

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

Model Fine-tuning

Optimization Parameters

```
>>> from keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss='categorical_crossentropy',
    optimizer=opt,
    metrics=['accuracy'])
```

Early Stopping

```
>>> from keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
    y_train4,
    batch_size=32,
    epochs=15,
    validation_data=(x_test4,y_test4),
    callbacks=[early_stopping_monitor])
```



Python For Data Science Cheat Sheet

Bokeh

Learn Bokeh [Interactively](#) at www.DataCamp.com, taught by Bryan Van de Ven, core contributor

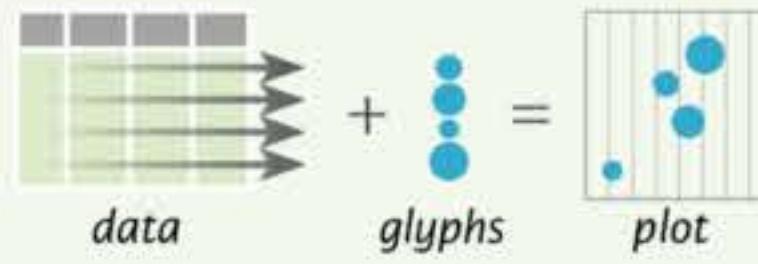


Plotting With Bokeh

The Python interactive visualization library Bokeh enables high-performance visual presentation of large datasets in modern web browsers.



Bokeh's mid-level general purpose `bokeh.plotting` interface is centered around two main components: data and glyphs.



The basic steps to creating plots with the `bokeh.plotting` interface are:

1. Prepare some data:
Python lists, NumPy arrays, Pandas DataFrames and other sequences of values
2. Create a new plot
3. Add renderers for your data, with visual customizations
4. Specify where to generate the output
5. Show or save the results

```
>>> from bokeh.plotting import figure
>>> from bokeh.io import output_file, show
>>> x = [1, 2, 3, 4, 5]          Step 1
>>> y = [6, 7, 2, 4, 5]
>>> p = figure(title="simple line example",      Step 2
              x_axis_label='x',
              y_axis_label='y')
>>> p.line(x, y, legend="Temp.", line_width=2)    Step 3
>>> output_file("lines.html")                    Step 4
>>> show(p)                                     Step 5
```

1 Data

Also see Lists, NumPy & Pandas

Under the hood, your data is converted to Column Data Sources. You can also do this manually:

```
>>> import numpy as np
>>> import pandas as pd
>>> df = pd.DataFrame(np.array([[33.9, 4, 65, 'US'],
                               [32.4, 4, 66, 'Asia'],
                               [21.4, 4, 109, 'Europe']]),
                     columns=['mpg', 'cyl', 'hp', 'origin'],
                     index=['Toyota', 'Fiat', 'Volvo'])

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

2 Plotting

```
>>> from bokeh.plotting import figure
>>> p1 = figure(plot_width=300, tools='pan,box_zoom')
>>> p2 = figure(plot_width=300, plot_height=300,
               x_range=(0, 8), y_range=(0, 8))
>>> p3 = figure()
```

3 Renderers & Visual Customizations

Glyphs

Scatter Markers

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

Line Glyphs

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

Rows & Columns Layout

Rows

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

Nesting Rows & Columns

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

Columns

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

Grid Layout

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

Tabbed Layout

```
>>> from bokeh.models.widgets import Panel, Tabs
>>> tab1 = Panel(child=p1, title="tab1")
>>> tab2 = Panel(child=p2, title="tab2")
>>> layout = Tabs(tabs=[tab1, tab2])
```

Legends

Legend Location

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

Outside Plot Area

```
>>> r1 = p2.asterisk(np.array([1,2,3]), np.array([3,2,1]))
>>> r2 = p2.line([1,2,3,4], [3,4,5,6])
>>> legend = Legend(items=[("One", [p1, r1]), ("Two", [r2])], location=(0, -30))
>>> p.add_layout(legend, 'right')
```

4 Output

Output to HTML File

```
>>> from bokeh.io import output_file, show
>>> output_file('my_bar_chart.html', mode='cdn')
```

Notebook Output

```
>>> from bokeh.io import output_notebook, show
>>> output_notebook()
```

Embedding

Standalone HTML

```
>>> from bokeh.embed import file_html
>>> html = file_html(p, CDN, "my_plot")
```

Components

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

5 Show or Save Your Plots

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

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

Customized Glyphs

Selection and Non-Selection Glyphs

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

Hover Glyphs

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

Colormapping

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

[Also see Data](#)

[Also see Data](#)

[Also see Data](#)

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='hp', marker='square',
                xlabel='Miles Per Gallon',
                ylabel='Horsepower')
```

DataCamp

Learn Python for Data Science [Interactively](#)



Data Wrangling with dplyr and tidyr

Cheat Sheet



Syntax - Helpful conventions for wrangling

`dplyr::tbl_df(iris)`

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

```
Source: local data frame [150 x 5]
  Sepal.Length Sepal.Width Petal.Length
1          5.1        3.5         1.4
2          4.9        3.0         1.4
3          4.7        3.2         1.3
4          4.6        3.1         1.5
5          5.0        3.6         1.4
...
Variables not shown: Petal.Width (dbl), Species (fctr)
```

`dplyr::glimpse(iris)`

Information dense summary of `tbl` data.

`utils::View(iris)`

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

iris					
	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
...	
8	5.0	3.4	1.5	0.2	setosa

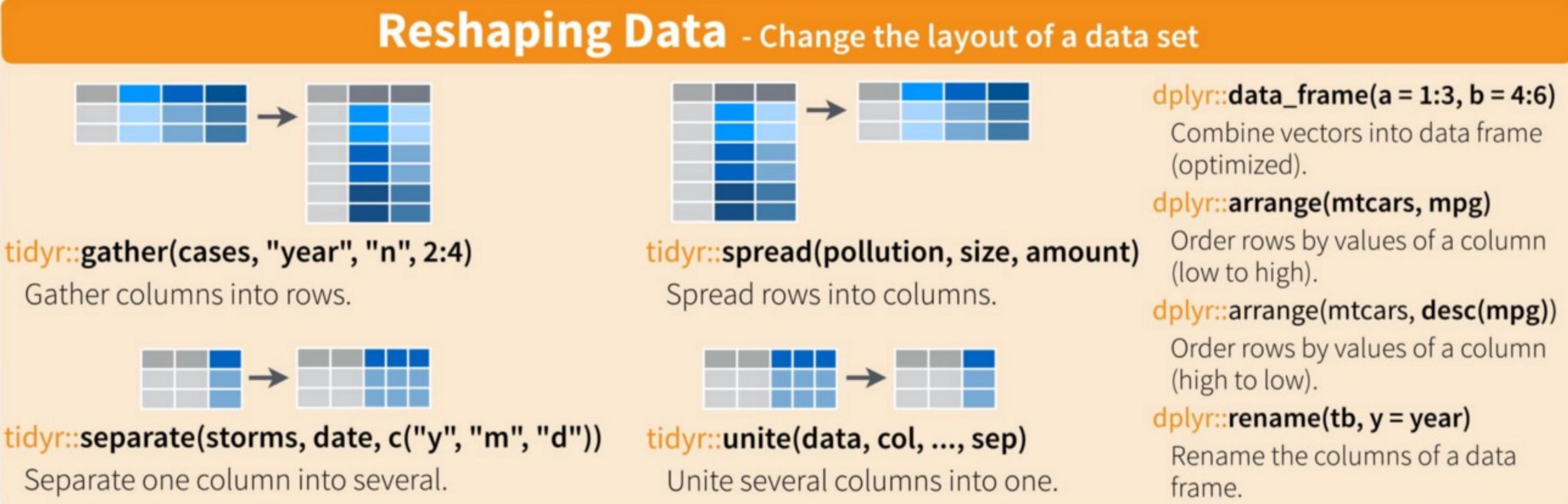
`dplyr::%>%`

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

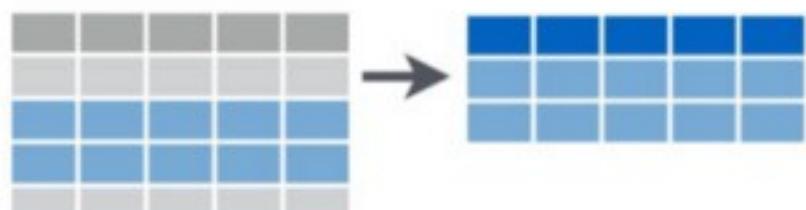
`x %>% f(y)` is the same as `f(x, y)`
`y %>% f(x, ., z)` is the same as `f(x, y, z)`

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

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



Subset Observations (Rows)



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

Extract rows that meet logical criteria.

`dplyr::distinct(iris)`

Remove duplicate rows.

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

Randomly select fraction of rows.

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

Randomly select n rows.

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

Select rows by position.

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

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

Logic in R - ?Comparison, ?base::Logic			
<	Less than	!=	Not equal to
>	Greater than	%in%	Group membership
==	Equal to	is.na	Is NA
<=	Less than or equal to	!is.na	Is not NA
>=	Greater than or equal to	&, , !, xor, any, all	Boolean operators

Subset Variables (Columns)



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

Select columns by name or helper function.

Helper functions for select - ?select

`select(iris, contains("."))`

Select columns whose name contains a character string.

`select(iris, ends_with("Length"))`

Select columns whose name ends with a character string.

`select(iris, everything())`

Select every column.

`select(iris, matches(".t.))`

Select columns whose name matches a regular expression.

`select(iris, num_range("x", 1:5))`

Select columns named x1, x2, x3, x4, x5.

`select(iris, one_of(c("Species", "Genus")))`

Select columns whose names are in a group of names.

`select(iris, starts_with("Sepal"))`

Select columns whose name starts with a character string.

`select(iris, Sepal.Length:Petal.Width)`

Select all columns between Sepal.Length and Petal.Width (inclusive).

`select(iris, -Species)`

Select all columns except Species.

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.

`min`

Minimum value in a vector.

`dplyr::last`

Last value of a vector.

`max`

Maximum value in a vector.

`dplyr::nth`

Nth value of a vector.

`dplyr::n`

of values in a vector.

`dplyr::n_distinct`

of distinct values in a vector.

`IQR`

IQR of a vector.

Group Data

`dplyr::group_by(iris, Species)`

Group data into rows with the same value of Species.

`dplyr::ungroup(iris)`

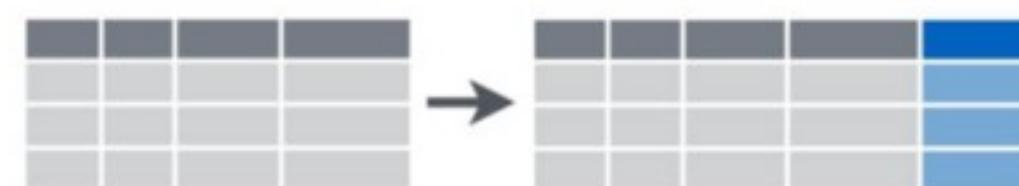
Remove grouping information from data frame.

`iris %>% group_by(Species) %>% summarise(...)`

Compute separate summary row for each group.



Make New Variables



`dplyr::mutate(iris, sepal = Sepal.Length + Sepal.Width)`

Compute and append one or more new columns.

`dplyr::mutate_each(iris, funs(min_rank))`

Apply window function to each column.

`dplyr::transmute(iris, sepal = Sepal.Length + Sepal.Width)`

Compute one or more new columns. Drop original columns.



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

`dplyr::lead`

Copy with values shifted by 1.

`dplyr::lag`

Copy with values lagged by 1.

`dplyr::dense_rank`

Ranks with no gaps.

`dplyr::min_rank`

Ranks. Ties get min rank.

`dplyr::percent_rank`

Ranks rescaled to [0, 1].

`dplyr::row_number`

Ranks. Ties got to first value.

`dplyr::ntile`

Bin vector into n buckets.

`dplyr::between`

Are values between a and b?

`dplyr::cume_dist`

Cumulative distribution.

`dplyr::cumall`

Cumulative all

`dplyr::cumany`

Cumulative any

`dplyr::cummean`

Cumulative mean

`cumsum`

Cumulative sum

`cummax`

Cumulative max

`cummin`

Cumulative min

`cumprod`

Cumulative prod

`pmax`

Element-wise max

`pmin`

Element-wise min

Combine Data Sets

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

+	=
---	---

Mutating Joins

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

x1	x3	x2
A	T	1
B	F	2
D	T	NA

x1	x2	x3
A	1	T
B	2	F

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

Filtering Joins

x1	x2
A	1
B	2

x1	x2
C	3

`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.

y	z		
x1	x2	x1	x2
A	1	B	2
B	2	C	3
C	3	D	4

x1	x2
B	2
C	3
D	4

x1	x2
A	1

x1	x2	x1	x2
A	1	B	2
B	2	C	3
C	3	D	4

`dplyr::intersect(y, z)`

Rows that appear in both y and z.

`dplyr::union(y, z)`

Rows that appear in either or both y and z.

`dplyr::setdiff(y, z)`

Rows that appear in y but not z.

Binding

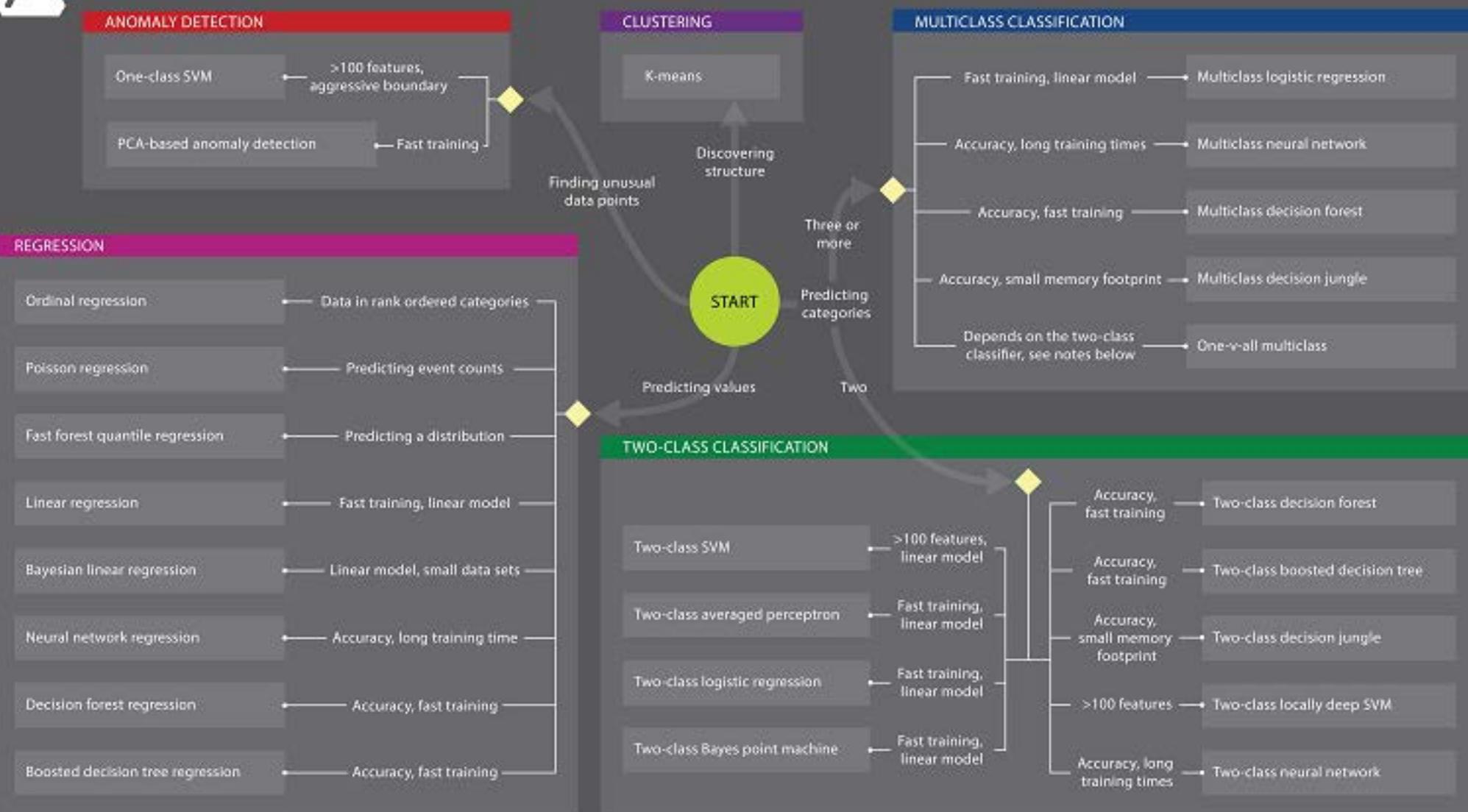
x1	x2
A	1
B	2
C	3
B	2
C	3
D	4

x1	x2	x1	x2

<tbl_r cells="4

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.



Data Wrangling

with pandas

Cheat Sheet

<http://pandas.pydata.org>

Syntax – Creating DataFrames

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

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

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

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

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

Method Chaining

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

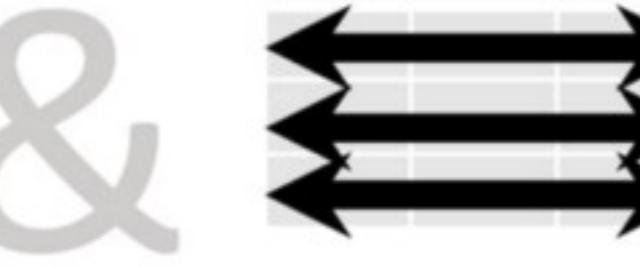
```
df = (pd.melt(df)
      .rename(columns={
          'variable' : 'var',
          'value' : 'val'})
      .query('val >= 200')
)
```

Tidy Data – A foundation for wrangling in pandas

In a tidy data set:



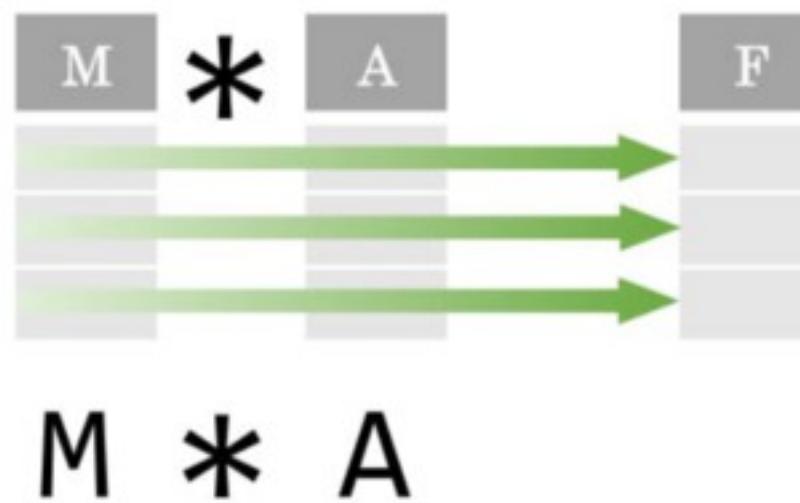
&



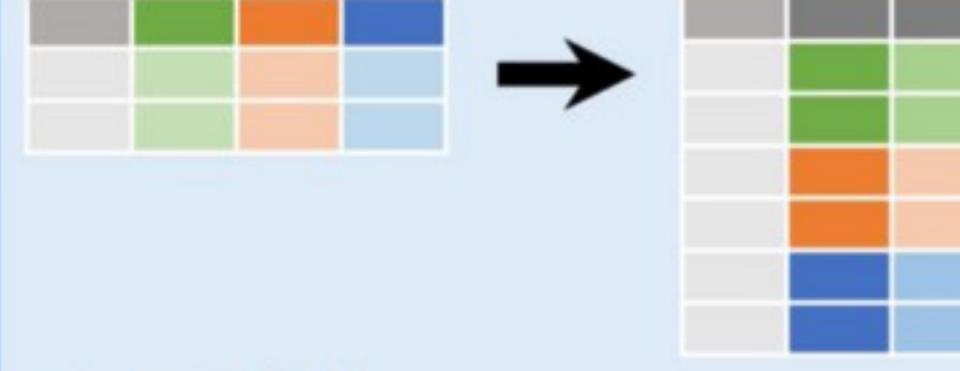
Each **variable** is saved in its own **column**

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

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

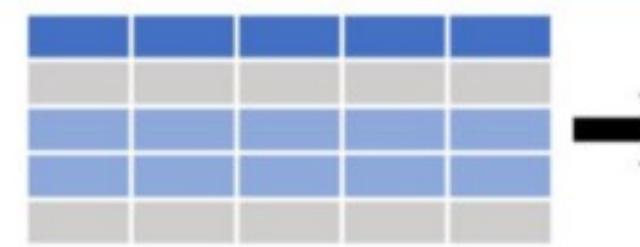
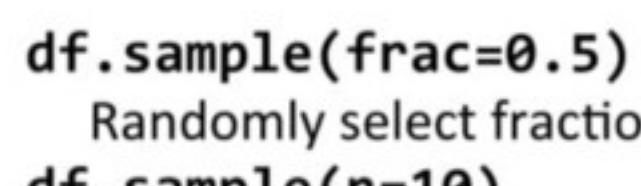
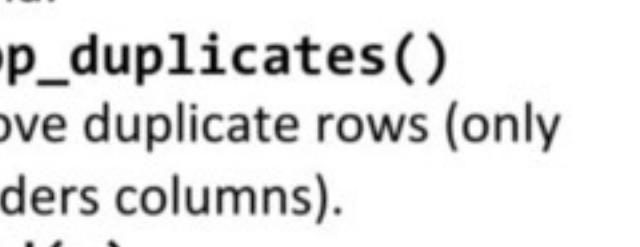
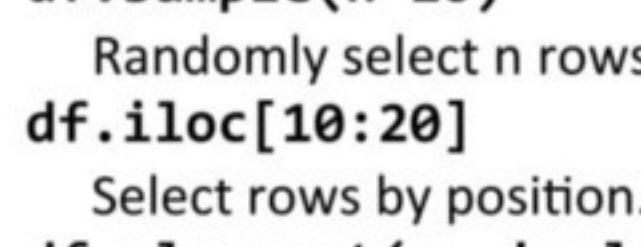


Reshaping Data – Change the layout of a data set

	pd.melt(df) Gather columns into rows.		df.pivot(columns='var', values='val') Spread rows into columns.
	pd.concat([df1,df2]) Append rows of DataFrames		pd.concat([df1,df2], axis=1) Append columns of DataFrames

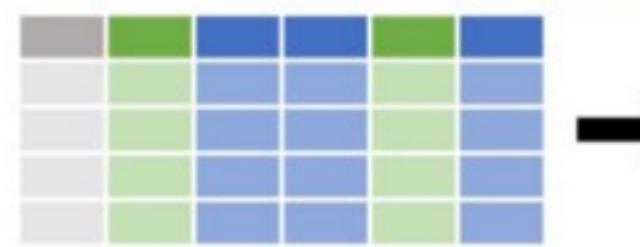
- df.sort_values('mpg')**
Order rows by values of a column (low to high).
- df.sort_values('mpg', ascending=False)**
Order rows by values of a column (high to low).
- df.rename(columns = {'y':'year'})**
Rename the columns of a DataFrame
- df.sort_index()**
Sort the index of a DataFrame
- df.reset_index()**
Reset index of DataFrame to row numbers, moving index to columns.
- df.drop(['Length','Height'], axis=1)**
Drop columns from DataFrame

Subset Observations (Rows)

	df[df.Length > 7] Extract rows that meet logical criteria.
	df.sample(frac=0.5) Randomly select fraction of rows.
	df.sample(n=10) Randomly select n rows.
	df.iloc[10:20] Select rows by position.
	df.nlargest(n, 'value') Select and order top n entries.

- df.sample(frac=0.5)**
Randomly select fraction of rows.
- df.sample(n=10)**
Randomly select n rows.
- df.iloc[10:20]**
Select rows by position.
- df.nlargest(n, 'value')**
Select and order top n entries.
- df.nsmallest(n, 'value')**
Select and order bottom n entries.

Subset Variables (Columns)



- df[['width', 'length', 'species']]**
Select multiple columns with specific names.
- df['width'] or df.width**
Select single column with specific name.
- df.filter(regex='regex')**
Select columns whose name matches regular expression regex.

regex (Regular Expressions) Examples

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

- df.loc[:, 'x2':'x4']**
Select all columns between x2 and x4 (inclusive).
- df.iloc[:, [1,2,5]]**
Select columns in positions 1, 2 and 5 (first column is 0).
- df.loc[df['a'] > 10, ['a', 'c']]**
Select rows meeting logical condition, and only the specific columns .

Logic in Python (and pandas)		
<	Less than	!=
>	Greater than	df.column.isin(values)
==	Equals	pd.isnull(obj)
<=	Less than or equals	pd.notnull(obj)
>=	Greater than or equals	&, , ~, ^, df.any(), df.all()

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)
```

3 Plotting Routines

1D Data

```
>>> fig, ax = plt.subplots()  
>>> lines = ax.plot(x,y)  
>>> ax.scatter(x,y)  
>>> axes[0,0].bar([1,2,3],[3,4,5])  
>>> axes[1,0].barh([0.5,1,2.5],[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')
```

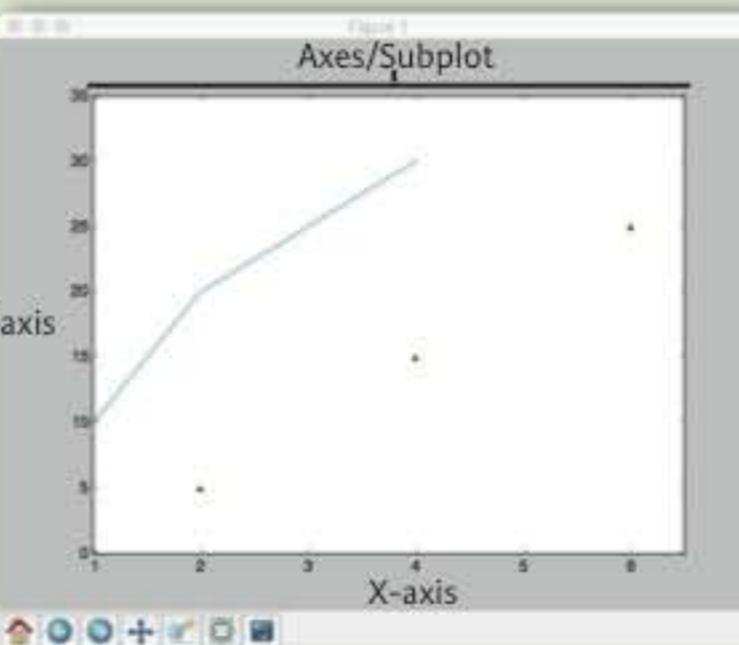
2D Data or Images

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

Colormapped or RGB arrays

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] Step 2  
>>> fig = plt.figure() Step 3  
>>> 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='^') Step 4  
>>> ax.set_xlim(1, 6.5)  
>>> plt.savefig('foo.png') Step 5  
>>> 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"),)
```

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)
```

Mathtext

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

Limits, Legends & Layouts

Limits & Autoscaling
>>> ax.margins(x=0.0,y=0.1)
>>> ax.axis('equal')
>>> ax.set_xlim=[0,10.5], ylim=[-1.5,1.5])
>>> ax.set_xlim(0,10.5)

Legends

```
>>> ax.set(title='An Example Axes',  
           ylabel='Y-Axis',  
           xlabel='X-Axis')  
>>> ax.legend(loc='best')
```

Ticks

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

Subplot Spacing

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

```
>>> fig.tight_layout()
```

Axis Spines

```
>>> ax1.spines['top'].set_visible(False)  
>>> ax1.spines['bottom'].set_position(('outward',10))
```

Add padding to a plot
Set the aspect ratio of the plot to 1
Set limits for x-and y-axis
Set limits for x-axis

Set a title and x-and y-axis labels

No overlapping plot elements

Manually set x-ticks

Make y-ticks longer and go in and out

Adjust the spacing between subplots

Fit subplot(s) in to the figure area

Make the top axis line for a plot invisible
Move the bottom axis line outward

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

Clear an axis
Clear the entire figure
Close a window



Linear Vector Spaces:

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

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

Linear Independence: Consider n vectors $\{x_1, x_2, \dots, x_n\}$. If there

exists n scalars a_1, a_2, \dots, a_n , at least one of which is nonzero, such that $a_1x_1 + a_2x_2 + \dots + a_nx_n = 0$, then the $\{x_i\}$ are linearly dependent.

Spanning a Space:

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

Inner Product: (x, y) for any scalar function of x and y .

$$1. (x, y) = (y, x) \quad 2. (x, ay_1 + by_2) = a(x, y_1) + b(x, y_2)$$

$$3. (x, x) \geq 0, \text{ where equality holds iff } x \text{ is the zero vector.}$$

Norm: A scalar function $\|x\|$ is called a norm if it satisfies:

1. $\|x\| \geq 0$
2. $\|x\| = 0$ if and only if $x = 0$.
3. $\|ax\| = |a|\|x\|$
4. $\|x + y\| \leq \|x\| + \|y\|$

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

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

Gram Schmidt Orthogonalization:

Assume that we have n independent vectors y_1, y_2, \dots, y_n . From these vectors we will obtain n orthogonal vectors v_1, v_2, \dots, v_n .

$$v_1 = y_1, \quad v_k = y_k - \sum_{i=1}^{k-1} \frac{(v_i, y_k)}{(v_i, v_i)} v_i, \\ \text{where } \frac{(v_i, y_k)}{(v_i, v_i)} v_i \text{ is the projection of } y_k \text{ on } v_i$$

Vector Expansions:

$$x = \sum_{i=1}^n x_i v_i = x_1 v_1 + x_2 v_2 + \dots + x_n v_n,$$

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

Reciprocal Basis Vectors:

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

To compute the reciprocal basis vectors: set $B = [v_1 \ v_2 \ \dots \ v_n]$,

$$R = [r_1 \ r_2 \ \dots \ r_n], \quad R^T = B^{-1} \quad \text{In matrix form: } x^v = B^{-1} x^s$$

Transformations:

A transformation consists of three parts:

domain: $X = \{x_i\}$, range: $Y = \{y_i\}$, and a rule relating each $x_i \in X$ to an element $y_i \in Y$.

Linear Transformations: transformation A is linear if:

1. for all $x_1, x_2 \in X$, $A(x_1+x_2) = A(x_1) + A(x_2)$
2. for all $x \in X$, $a \in R$, $A(ax) = aA(x)$

Matrix Representations:

Let $\{v_1, v_2, \dots, v_n\}$ be a basis for vector space X , and let $\{u_1, u_2, \dots, u_n\}$ be a basis for vector space Y . Let A be a linear transformation with domain X and range Y : $A(x) = y$

The coefficients of the matrix representation are obtained from

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

$$\text{Change of Basis: } B_t = [t_1 \ t_2 \ \dots \ t_n], \quad B_w = [w_1 \ w_2 \ \dots \ w_n] \\ A' = [B_w^{-1} A B_t]$$

Eigenvalues & Eigenvectors: $Az = \lambda z$, $|(A - \lambda I)| = 0$

Diagonalization: $B = [z_1 \ z_2 \ \dots \ z_n]$,

where $\{z_1, z_2, \dots, z_n\}$ are the eigenvectors of a square matrix A , $[B^{-1} A B] = \text{diag}([\lambda_1 \ \lambda_2 \ \dots \ \lambda_n])$

Perceptron Architecture:

$$\mathbf{a} = \text{hardlim}(\mathbf{W}\mathbf{p} + \mathbf{b}), \quad \mathbf{W} = [w_1^T \ w_2^T \ \dots \ w_s^T]^T, \\ a_i = \text{hardlim}(n_i) = \text{hardlim}(\mathbf{w}_i^T \mathbf{p} + b_i)$$

Decision Boundary: $\mathbf{w}_i^T \mathbf{p} + b_i = 0$

The decision boundary is always orthogonal to the weight vector. Single-layer perceptrons can only classify linearly separable vectors.

Perceptron Learning Rule

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

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

Linear Associator: $\mathbf{a} = \text{purelin}(\mathbf{W}\mathbf{p})$

$$\text{The Hebb Rule: Supervised Form: } w_{ij}^{\text{new}} = w_{ij}^{\text{old}} + t_{qi}P_{qi} \\ \mathbf{W} = t_1 P_1^T + t_2 P_2^T + \dots + t_Q P_Q^T$$

$$\mathbf{W} = [t_1 \ t_2 \ \dots \ t_Q] \begin{bmatrix} \mathbf{p}_1^T \\ \mathbf{p}_2^T \\ \vdots \\ \mathbf{p}_Q^T \end{bmatrix} = \mathbf{T} \mathbf{P}^T$$

Pseudoinverse Rule: $\mathbf{W} = \mathbf{T} \mathbf{P}^+$

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

Variations of Hebbian Learning:

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

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

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

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

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

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

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

Directional Derivatives:

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

Minima:

Strong Minimum: if a scalar $\delta > 0$ exists, such that $F(x) < F(x + \Delta x)$ for all Δx such that $\delta > \|\Delta x\| > 0$.

Global Minimum: if $F(x) < F(x + \Delta x)$ for all $\Delta x \neq 0$

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

Necessary Conditions for Optimality:

1st-Order Condition: $\nabla F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}^*} = 0$ (Stationary Points)

2nd-Order Condition: $\nabla^2 F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}^*} \geq 0$ (Positive Semi-definite Hessian Matrix).

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

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