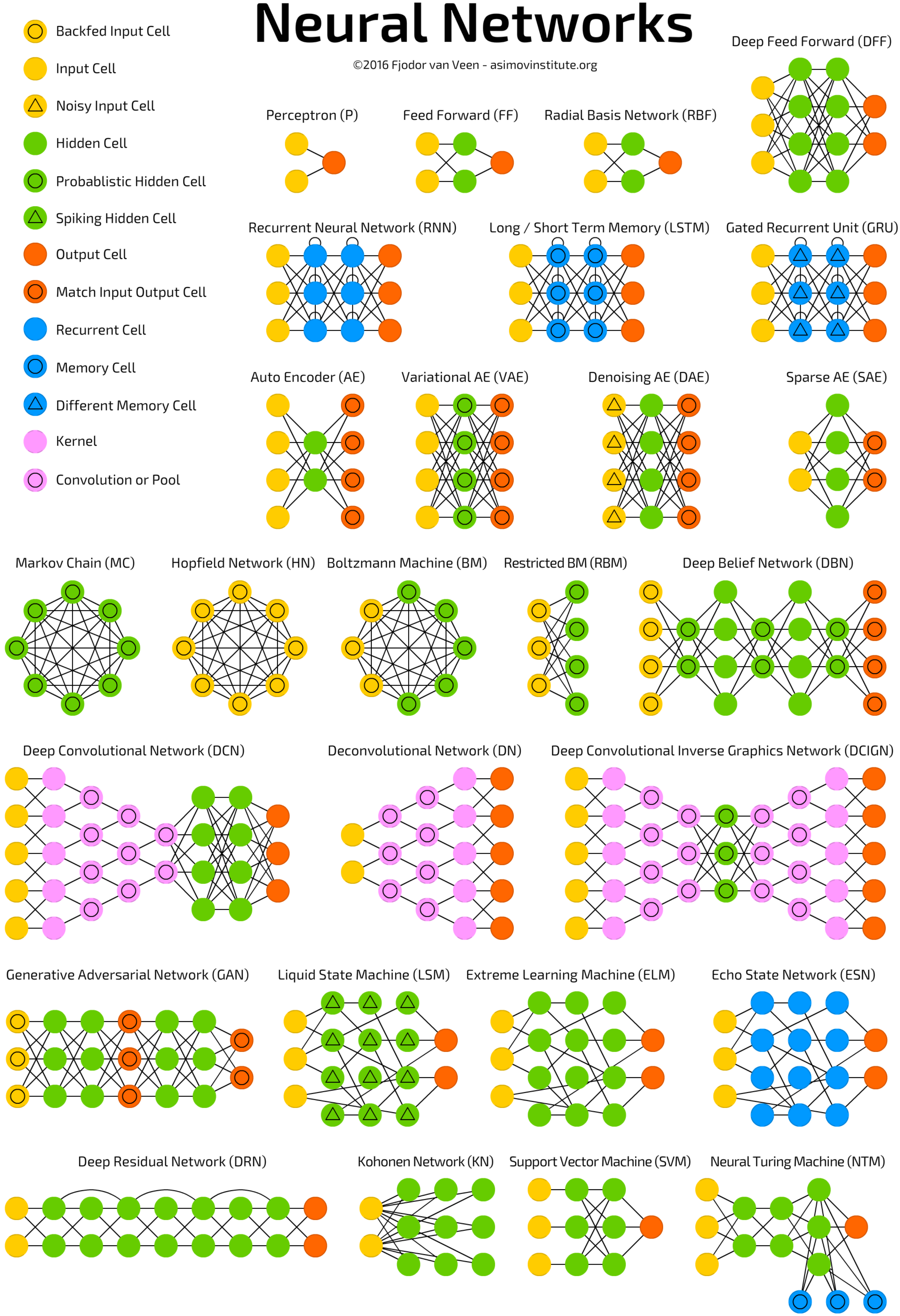
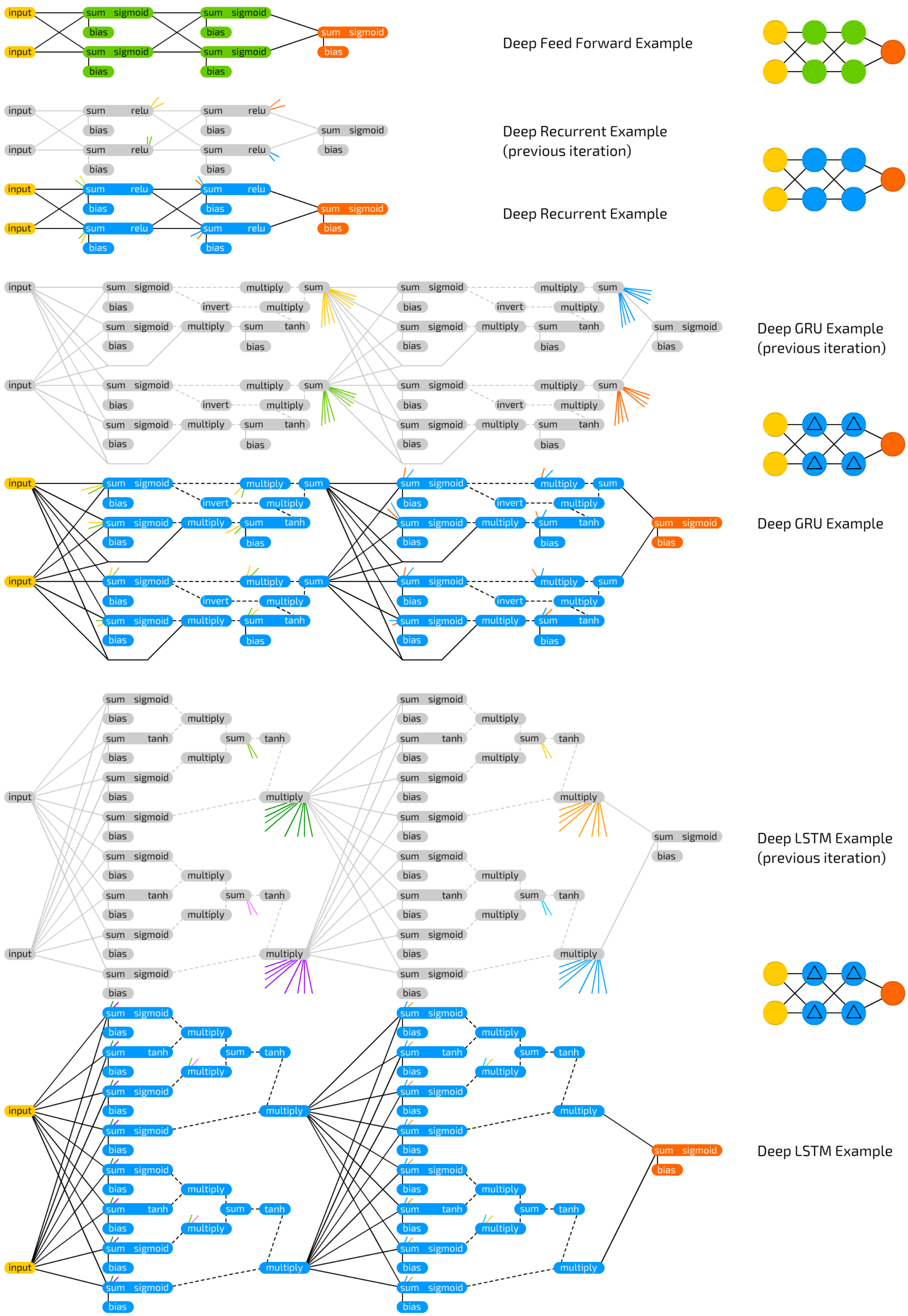
A mostly complete chart of

Neural Networks



An informative chart to build

Neural Network Graphs



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 $\{x_1, x_2, \ldots, x_n\}$. If there exists n scalars $a_1, a_2, \ldots, a_n$, at least one of which is nonzero, such that $a_1x_1 + a_2x_2 + \ldots + a_nx_n = 0$, then the $\{x_i\}$ are linearly dependent.

Spanning a Space:

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

Inner Product:

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

1. $(x,y) = (y,x)$ 2. $(x, ay_1 + by_2) = a(x,y_1) + b(x,y_2)$
3. $(x,x) \geq 0$, where equality holds iff x 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 $y_1, y_2, \ldots, y_n$. From these vectors we will obtain n orthogonal vectors $v_1, v_2, \ldots, v_n$.

$$v_1 = y_1, \quad v_k = y_k - \sum_{i=1}^{k-1} \frac{(v_i, y_k)}{(v_i, v_i)} v_i,$$

$$where\ \frac{(v_i, y_k)}{(v_i, v_i)} v_i\ is\ the\ projection\ of\ y_k\ on\ v_i$$

Vector Expansions:

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

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

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 $\mathbf{B} = [\mathrm{v}_1\ \mathrm{v}_2\ \ldots\ \mathrm{v}_n]$,

$\mathbf{R} = [\mathrm{r}_1\ \mathrm{r}_2 \ldots\ \mathrm{r}_n]$, $\mathbf{R}^T = \mathbf{B}^{-1}$ In matrix form: $\mathbf{x}^v = \mathbf{B}^{-1}\,\mathbf{x}^s$

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 $\{v_1, v_2, \ldots, v_n\}$ be a basis for vector space X, and let $\{u_1, u_2, \ldots, u_n\}$ 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

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

Change of Basis: $\mathbf{B}_t = [\mathbf{t}_1\ \mathbf{t}_2\ \ldots\mathbf{t}_n]$, $\mathbf{B}_w = [\mathbf{w}_1\ \mathbf{w}_2\ \ldots\mathbf{w}_n]$

$$\mathbf{A}' = [\mathbf{B}_w^{-1}\mathbf{A}\mathbf{B}_t]$$

Eigenvalues & Eigenvectors: $\mathbf{Az} = \lambda\mathbf{z}$, $|[\mathbf{A} - \lambda\mathbf{I}]| = 0$

Diagonalization: $\mathbf{B} = [\mathbf{z}_1\ \mathbf{z}_2\ \ldots\mathbf{z}_n]$,

where $\{\mathbf{z}, \mathbf{z}_2, \ldots, \mathbf{z}_n\}$ are the eigenvectors of a square matrix A,

$$[\mathbf{B}^{-1}\mathbf{AB}] = \mathrm{diag}([\lambda_1\ \lambda_2 \ldots \lambda_n])$$

Perceptron Architecture:

$\mathbf{a} = hardlim(\mathbf{Wp} + \mathbf{b})$, $\mathbf{W} = [\,{}_1\mathbf{w}^T\ {}_2\mathbf{w}^T\ \ldots\ {}_S\mathbf{w}^T]^T$,

$$a_i = hardlim(n_i) = hardlim(\,{}_i\mathbf{w}^T\,\mathrm{p} + b_i)$$

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

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

Perceptron Learning Rule

$$\mathbf{W}^{new} = \mathbf{W}^{old} + \mathbf{e}\mathbf{p}^T, \mathbf{b}^{new} = \mathbf{b}^{old} + \mathbf{e},$$

$$where\quad \mathbf{e} = \mathbf{t} - \mathbf{a}$$

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: $\mathbf{a} = purelin(\mathbf{Wp})$

The Hebb Rule: *Supervised Form:* $\mathrm{w}_{ij}^{new} = \mathrm{w}_{ij}^{old} + t_{qi}P_{qi}$

$$\mathbf{W} = \boldsymbol{t}_1\boldsymbol{P}_1^T + \boldsymbol{t}_2\boldsymbol{P}_2^T + \cdots + \boldsymbol{t}_Q\boldsymbol{P}_Q^T$$

$$\mathbf{W} = [\mathbf{t}_1\ \mathbf{t}_2 \ldots \mathbf{t}_Q] \begin{bmatrix} \mathbf{p}_1^T \\ \mathbf{p}_2^T \\ \vdots \\ \mathbf{p}_Q^T \end{bmatrix} = \mathbf{TP}^T$$

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

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

Variations of Hebbian Learning:

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

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

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

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

Grad $\nabla F(\mathbf{x}) = \left[\frac{\partial}{\partial \mathrm{x}_1}F(\mathbf{x})\ \ \frac{\partial}{\partial \mathrm{x}_2}F(\mathbf{x})\ \ \ldots\ \frac{\partial}{\partial \mathrm{x}_n}F(\mathbf{x})\right]^T$

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

$$\begin{bmatrix} \frac{\partial}{\partial \mathrm{x}_1{}^2}F(\mathbf{x}) & \frac{\partial}{\partial \mathrm{x}_1\,\partial \mathrm{x}_2}F(\mathbf{x}) \ldots & \frac{\partial}{\partial \mathrm{x}_1\,\partial \mathrm{x}_n}F(\mathbf{x}) \\ \frac{\partial}{\partial \mathrm{x}_2\,\partial \mathrm{x}_1}F(\mathbf{x}) & \frac{\partial}{\partial \mathrm{x}_2{}^2}F(\mathbf{x}) \ldots & \frac{\partial}{\partial \mathrm{x}_2\,\partial \mathrm{x}_n}F(\mathbf{x}) \\ \vdots & \vdots & \vdots \\ \frac{\partial}{\partial \mathrm{x}_n\,\partial \mathrm{x}_1}F(\mathbf{x}) & \frac{\partial}{\partial \mathrm{x}_n\,\partial \mathrm{x}_2}F(\mathbf{x}) \ldots & \frac{\partial}{\partial \mathrm{x}_n{}^2}F(\mathbf{x}) \end{bmatrix}$$

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 $\delta > \|\Delta x\| > 0$.

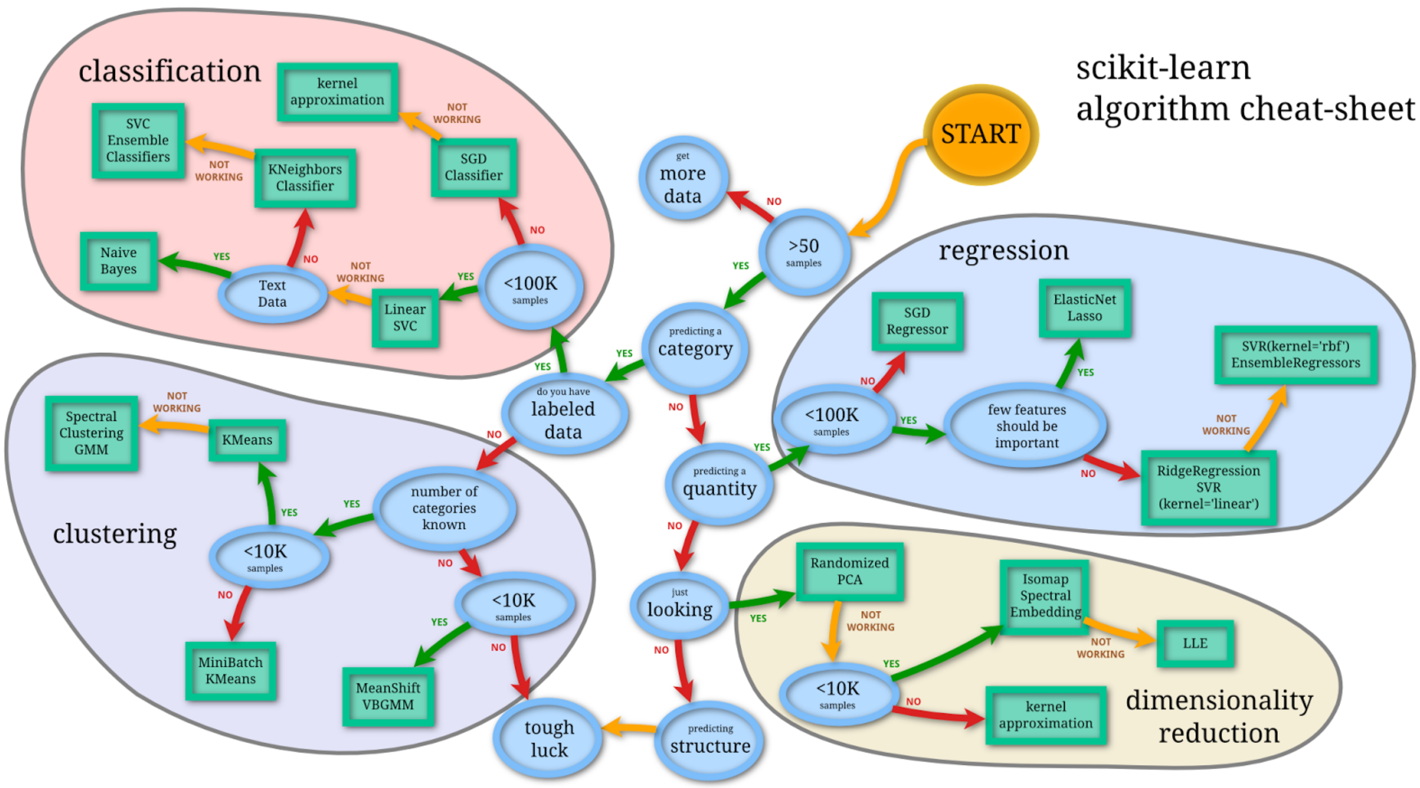
Necessary Conditions for Optimality:

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

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

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

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


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

Python For Data Science *Cheat Sheet*

Scikit-Learn

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

Scikit-learn

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

A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.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','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)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

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

Support Vector Machines (SVM)

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

Naive Bayes

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

KNN

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

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

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

K Means

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

Model Fitting

Supervised learning	
`>>> lr.fit(X, y)`	Fit the model to the data
`>>> knn.fit(X_train, y_train)`	
`>>> svc.fit(X_train, y_train)`	
Unsupervised Learning	
`>>> k_means.fit(X_train)`	Fit the model to the data
`>>> pca_model = pca.fit_transform(X_train)`	Fit to data, then transform it

Prediction

Supervised Estimators	
`>>> y_pred = svc.predict(np.random.random((2,5)))`	Predict labels
`>>> y_pred = lr.predict(X_test)`	Predict labels
`>>> y_pred = knn.predict_proba(X_test)`	Estimate probability of a label
Unsupervised Estimators	
`>>> y_pred = k_means.predict(X_test)`	Predict labels in clustering algos

Preprocessing The Data

Standardization

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

Normalization

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

Binarization

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

Encoding Categorical Features

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

Imputing Missing Values

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

Generating Polynomial Features

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

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score	
`>>> knn.score(X_test, y_test)`	Estimator score method
`>>> from sklearn.metrics import accuracy_score`	Metric scoring functions
`>>> accuracy_score(y_test, y_pred)`	
Classification Report	
`>>> from sklearn.metrics import classification_report`	Precision, recall, f1-score
`>>> print(classification_report(y_test, y_pred))`	and support
Confusion Matrix	
`>>> from sklearn.metrics import confusion_matrix`	
`>>> print(confusion_matrix(y_test, y_pred))`	

Regression Metrics

Mean Absolute Error

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

Mean Squared Error

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

R^2 Score

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

Clustering Metrics

Adjusted Rand Index

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

Homogeneity

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

V-measure

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

Cross-Validation

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

Tune Your Model

Grid Search

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

Randomized Parameter Optimization

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