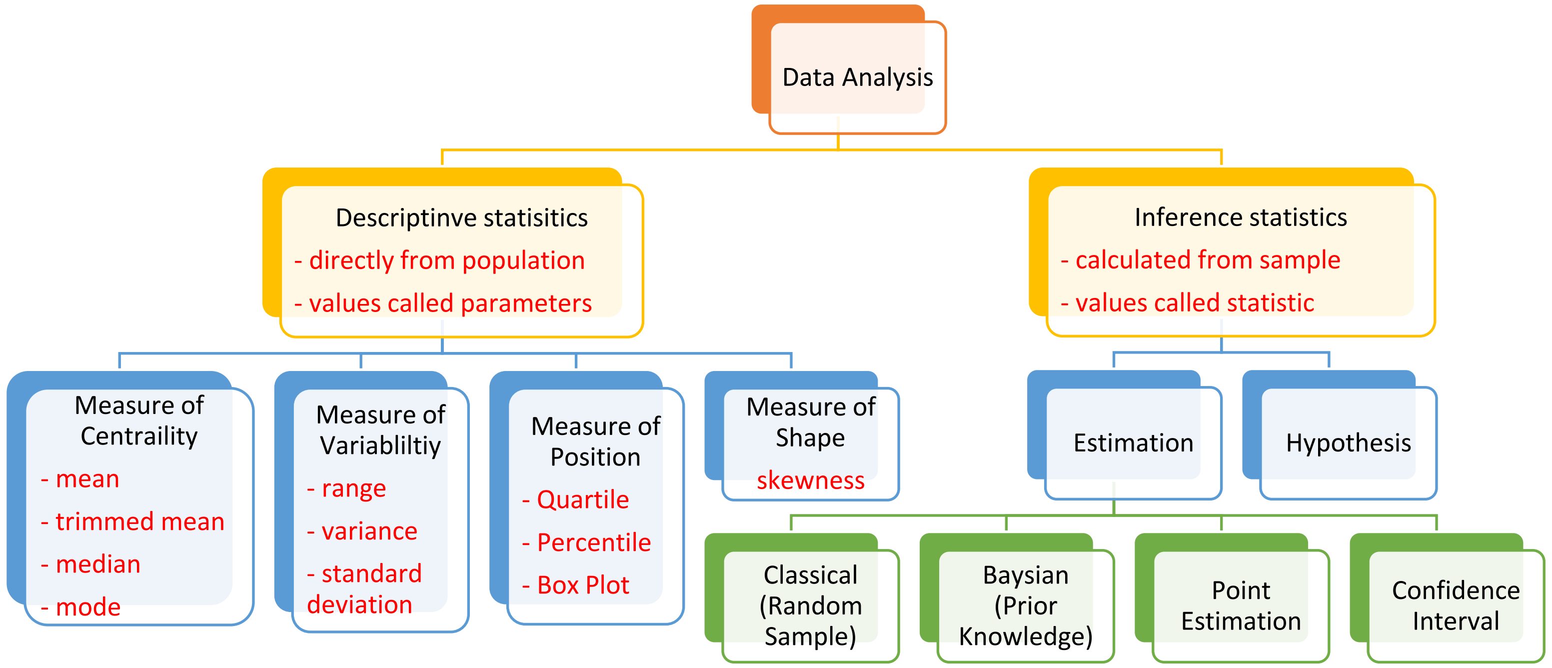
Basic formulas for statistical measures

Law	**Discrete**		**Continuous**
Mean (μ) **Expected Value**	$\mu = E(X) = \Sigma\ (x\ f(x))$		$\mu = E(X) = \int (x\ f(x))\ dx$
Joint Mean **Expected Value**	$\mu_{g(x,y)} = \Sigma\Sigma\ (g(x,y) * f(x,y))$		$\mu_{g(x,y)} = \int\int (g(x,y) * f(x,y))\ dx\ dy$
Variance (σ^2)	$\sigma^2 = \Sigma\ (x^2 * f(x)) - \mu^2$		$\sigma^2 = \int (x^2 * f(x))\ dx - \mu^2$
	$\sigma^2 = E\ (x^2) - \mu^2$		
Covariance (σ_{xy}) **check linearity** $-\infty < \sigma_{xy} < \infty$	$\sigma_{xy} = \Sigma\Sigma\ [(xy)\ f(x,y)] - \mu_x\mu_y$		$\sigma_{xy} = \int\int [(xy)\ f(x,y)]\ dx\ dy - \mu_x\ \mu_y$
	$\mu_x = \Sigma\ (\ x * g(x)\ )$ $\mu_y = \Sigma\ (\ y * h(y)\ )$		$\mu_x = \int (\ x * g(x)\ )\ dx$ $\mu_y = \int (\ y * h(y)\ )\ dy$
	$\sigma_{xy} = E(XY) - \mu_x\ \mu_y$		
Correlation (ρ_{xy}) **Measure linearity** $-1 < \rho_{xy} < 1$	$\sigma_x^2 = E(x^2) - \mu_x^2$	$\sigma_y^2 = E(y^2) - \mu_y^2$	
	$\rho_{xy} = \sigma_{xy} / (\sigma_x\ \sigma_y)$		

Summary of Common Probability Distributions

Name	Probability Distribution	Mean	Variance
Discrete			
Uniform	$\frac{1}{n}, a \le b$	$\frac{(b+a)}{2}$	$\frac{(b-a+1)^2-1}{12}$
Binomial	$\binom{n}{x} p^x(1-p)^{n-x}$, $x = 0, 1, \ldots, n, 0 \le p \le 1$	np	$np(1-p)$
Geometric	$(1-p)^{x-1}p$, $x = 1, 2, \ldots, 0 \le p \le 1$	$1/p$	$(1-p)/p^2$
Negative binomial	$\binom{x-1}{r-1}(1-p)^{x-r}p^r$ $x = r, r+1, r+2, \ldots, 0 \le p \le 1$	r/p	$r(1-p)/p^2$
Hypergeometric	$\frac{\binom{K}{x}\binom{N-K}{n-x}}{\binom{N}{n}}$ $x = \max(0, n-N+K), 1, \ldots$ $\min(K, n), K \le N, n \le N$	np, where $p = \frac{K}{N}$	$np(1-p)\left(\frac{N-n}{N-1}\right)$
Poisson	$\frac{e^{-\lambda}\lambda^x}{x!}, x = 0, 1, 2, \ldots, 0 < \lambda$	λ	λ
Continuous			
Uniform	$\frac{1}{b-a}, a \le x \le b$	$\frac{(b+a)}{2}$	$\frac{(b-a)^2}{12}$
Normal	$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$ $-\infty < x < \infty, -\infty < \mu < \infty, 0 < \sigma$	μ	σ^2
Exponential	$\lambda e^{-\lambda x}, 0 \le x, 0 < \lambda$	$1/\lambda$	$1/\lambda^2$
Erlang	$\frac{\lambda^r x^{r-1} e^{-\lambda x}}{(r-1)!}, 0 < x, r = 1, 2, \ldots$	r/λ	r/λ^2
Gamma	$\frac{\lambda x^{r-1} e^{-\lambda x}}{\Gamma(r)}, 0 < x, 0 < r, 0 < \lambda$	r/λ	r/λ^2
Weibull	$\frac{\beta}{\delta}\left(\frac{x}{\delta}\right)^{\beta-1} e^{-(x/\delta)^\beta}$, $0 < x, 0 < \beta, 0 < \delta$	$\delta\Gamma\left(1+\frac{1}{\beta}\right)$	$\delta^2\Gamma\left(1+\frac{2}{\beta}\right)$ $-\delta^2\left[\Gamma\left(1+\frac{1}{\beta}\right)\right]^2$
Lognormal	$\frac{1}{x\sigma\sqrt{2\pi}}\exp\left(\frac{-[\ln(x)-\theta]^2}{2\omega^2}\right)$	$e^{\theta+\omega^2/2}$	$e^{2\theta+\omega^2}(e^{\omega^2}-1)$



Frequency Table

- Range = Upper value – Lower value.
- Sturges's formula for class count: k =1+3.322log(n) → n number of items.
- Calculate class width: R / K.
- Assign data points to classes to build the frequency table.

Quartile

- Count the data points.
- Order them from smallest to largest.
- Locate the median (Q2).
- Divide the dataset into two at the median.
- For odd-sized datasets, exclude the median for the next steps.
- For even-sized datasets, include both middle values in the halves.
- The median of the lower half is Q1.
- The median of the upper half is Q3

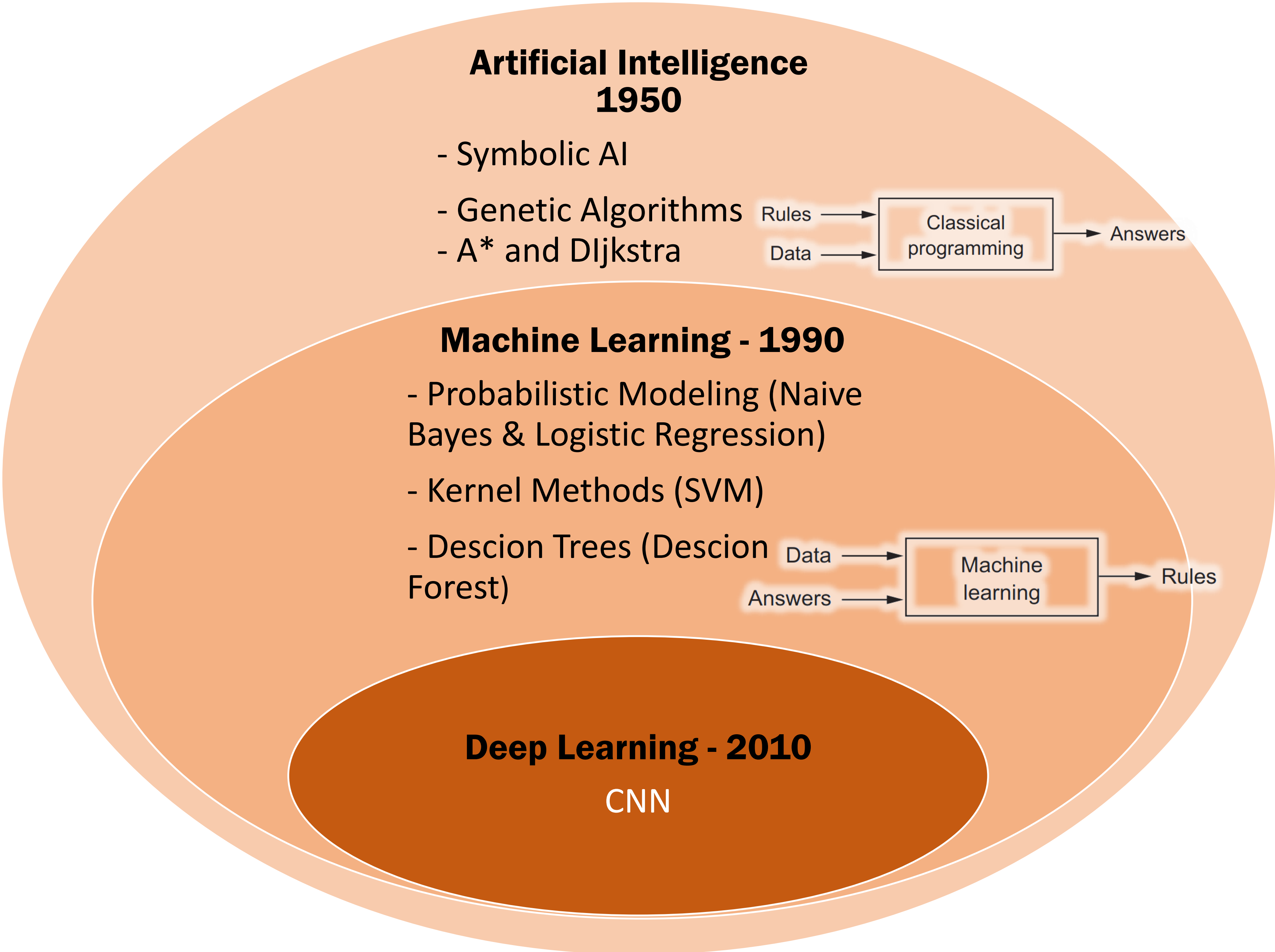
- Binominal (Bernolli) used for x success in n trials (true and false trials)
- Geometric is used for x trials to get the first success
- Negative binonminal is used for kth success in x trials
- Poission is used for number of outcomes in a region with average or rate
- Uniform is used when the outcomes have equal likelihood
- Exponential is used for time between events with average
- Standard Normal Distribution has the following equation to convert its table0 values to any other normal distribution system

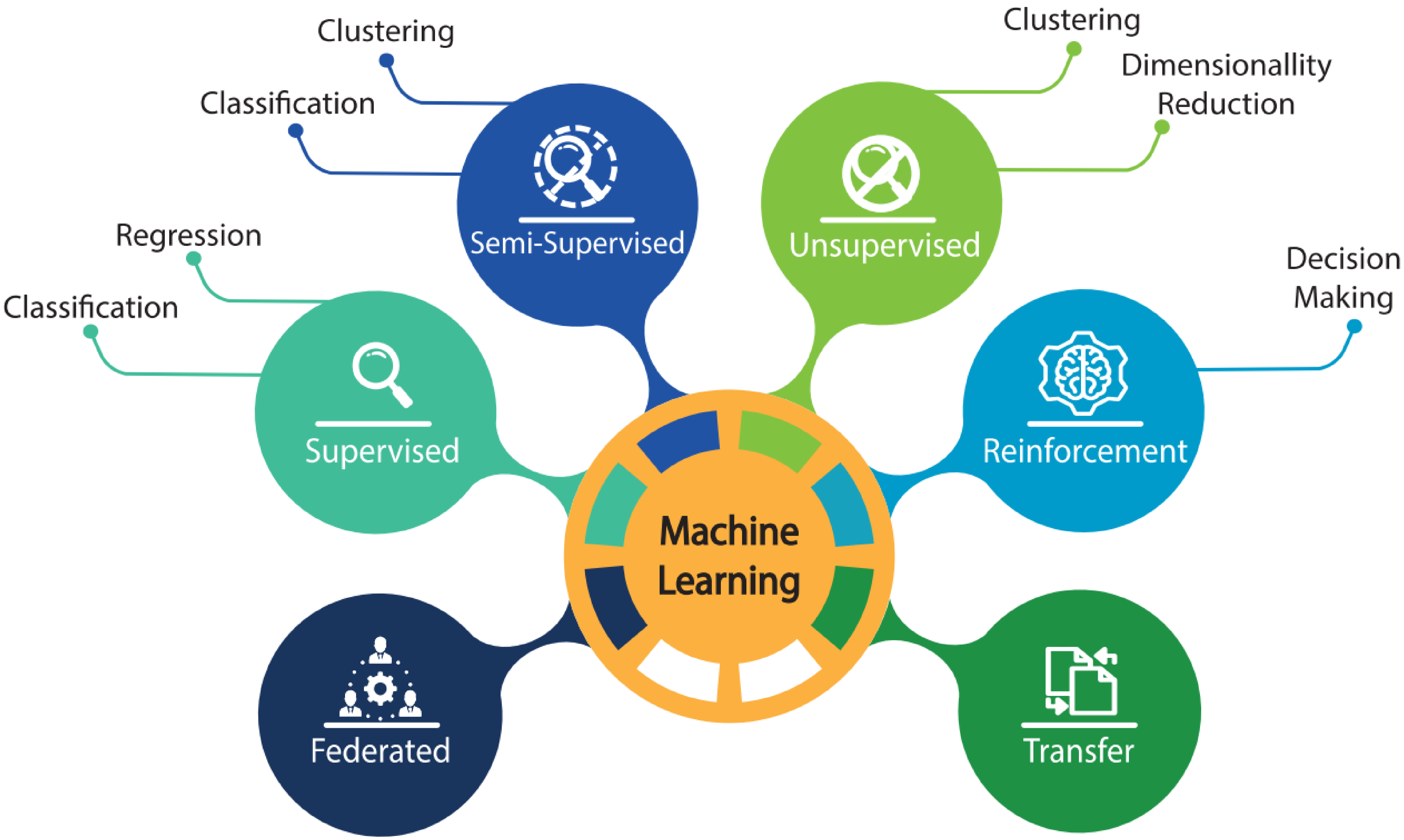
$$f(z) = \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}}$$

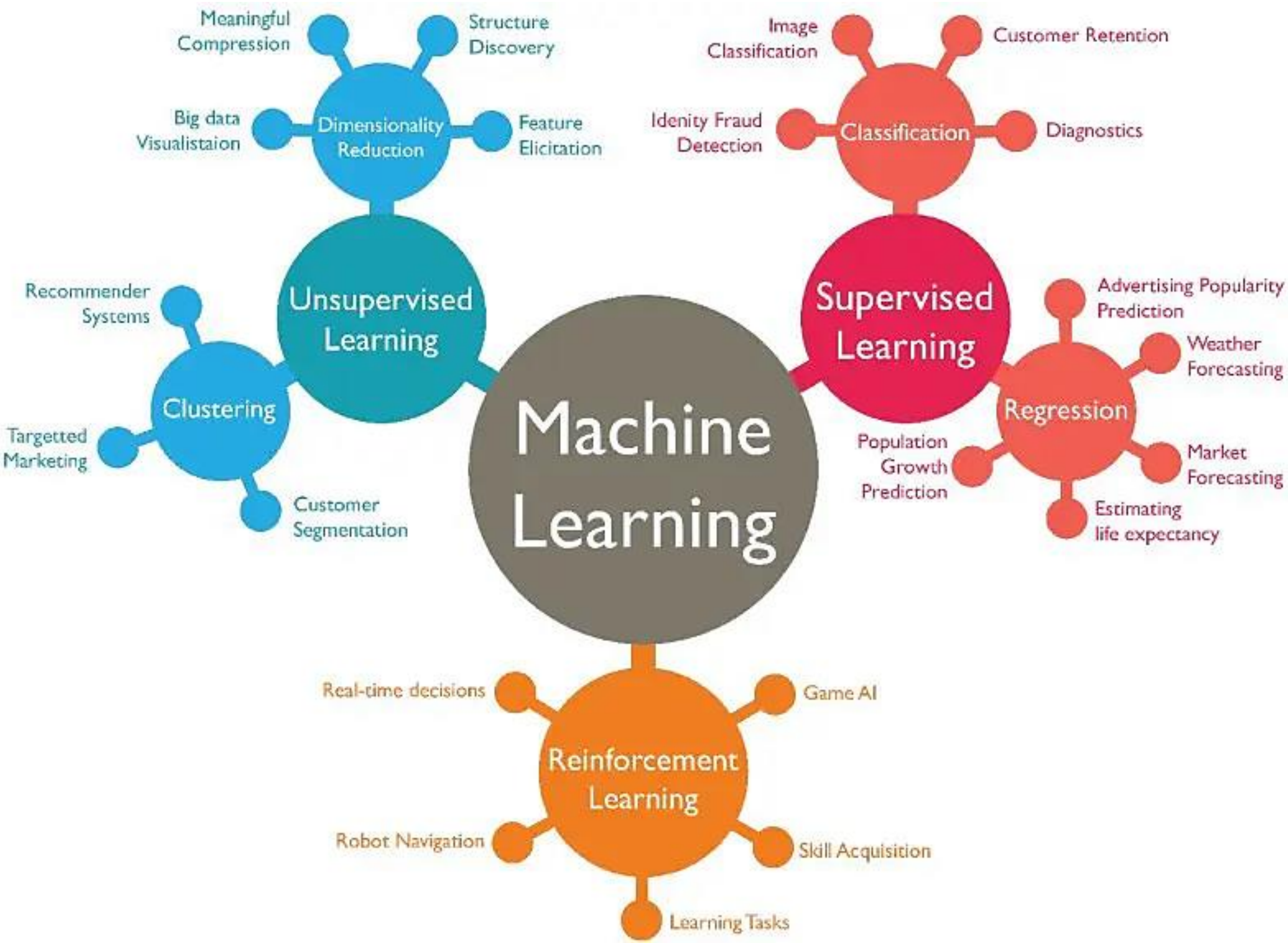
$$Z = \frac{X - \mu}{\sigma}$$

- Where μ is the mean of population
- σ is the standard deviation of the population
- x is the value from foreign system with normal distribution
- z is the result equivalent from standard normal distribution

	Category	Algorithm	When to Use
	Sorting	Bubble Sort	Simple sorting, small datasets
		Insertion Sort	Small datasets, mostly sorted data
		Selection Sort	Small datasets, simplicity over efficiency
		Merge Sort	Large datasets, require stable sort
		Quick Sort	Large datasets, average case speed
		Heap Sort	Need to sort large datasets in place
		Radix Sort	Large datasets with fixed-length keys
		Bucket Sort	Large datasets, uniformly distributed
		External Sort	Very large datasets that don't fit in memory
	Searching	Linear Search	Unsorted data, small datasets
		Binary Search	Sorted data, large datasets
		Depth-First Search (DFS)	Graphs, exploring edges/node paths
		Breadth-First Search (BFS)	Graphs, finding shortest path
	Data Structures	Arrays, Linked Lists, queue, stack, priority queue	
	String Manipulation		
Hierarchical data	**Tree and BST**	Tree Traversal	Accessing/Searching/Manipulating tree data
		BST Operations	Efficient search, insert, delete in sorted data
		AVL Trees	Self-balancing BST where lookup speed is critical
networks, paths, and relationships	**Graph**	Dijkstra's Algorithm	Shortest path in weighted graph without negative edges
		Kruskal's Algorithm	Minimum spanning tree in sparse graphs
		Prim's Algorithm	Minimum spanning tree in dense graphs
sequence of decisions	**Greedy**		
Can be divided to sub problems	**Divide and conquer**	Quick Sort	When average case performance is key
		Merge Sort	Large datasets where stability is key
		Binary Search	Quickly finding an item in sorted data
		Strassen's Matrix Multiplication	Large matrix multiplication
		Karatsuba Algorithm	Fast multiplication of large numbers
Permutations Combinations	**Backtracking**		
Overlapping Subproblems Optimal Substructure	**Dynamic Programming**	Fibonacci, knapsack and palindromes	


Artificial Intelligence
1950
- Symbolic AI
- Genetic Algorithms
- A* and DIjkstra
Rules
Data
Classical
programming
Answers
Machine Learning - 1990
- Probabilistic Modeling (Naive
Bayes & Logistic Regression)
- Kernel Methods (SVM)
- Descion Trees (Descion
Forest)
Data
Answers
Machine
learning
Rules
Deep Learning - 2010
CNN


Clustering
Classification
Semi-Supervised
Regression
Classification
Supervised
Clustering
Dimensionallity
Reduction
Unsupervised
Decision
Making
Reinforcement
Machine
Learning
Federated
Transfer



Machine Learning
Unsupervised Learning
Dimensionality Reduction
Meaningful Compression
Structure Discovery
Big data Visualistaion
Feature Elicitation
Clustering
Recommender Systems
Targetted Marketing
Customer Segmentation
Supervised Learning
Classification
Image Classification
Customer Retention
Idenity Fraud Detection
Diagnostics
Regression
Advertising Popularity Prediction
Weather Forecasting
Population Growth Prediction
Market Forecasting
Estimating life expectancy
Reinforcement Learning
Real-time decisions
Game AI
Robot Navigation
Skill Acquisition
Learning Tasks

CNN and RNNS for high-dimensional, large, complex dataset (low interpretability and higher computational resources)

TYPE , Learning, Function, Complextity

1. **Type:**
   1) SVM (Support Vector Machine)
   2) PCA (Principal Component Analysis)
   3) Decision Forests
   4) Naive Bayes
   5) Linear Regression
   6) Logistic Regression
   7) KNN (K-Nearest Neighbors)
   8) K-Means
   9) Small CNN → SqueezeNet & MobileNet
   10) Large CNN → DenseNet & EfficientNet & NASNet & AlexNet & GoogleNet & VGG
   11) RNN → LSTM & BiLSTM & GRU & ResNet
   12) CNN + RNN → Attention-based models & Transformers
   13) GANs (Generative Adversarial Networks)
   14) Autoencoder

2. **Learning**:

   - **Supervised Learning**: Algorithms learn from labeled data, with input-output pairs provided during training.
   - **Unsupervised Learning**: Algorithms learn patterns and structures in unlabeled data without explicit supervision.
   - **Semi-supervised learning** exists between supervised and unsupervised learning
   - **Reinforcement Learning**: Agents learn to interact with an environment to maximize rewards through trial and error.

3. **Function**:

   - **Classification**: Algorithms predict discrete class labels for given input data.
   - **Regression**: Algorithms predict continuous values based on input data.
   - **Clustering**: Algorithms group similar data points together based on some similarity measure.
   - **Dimensionality Reduction**: Techniques reduce the number of input variables while preserving important information.
   - **Computer Vision**: Algorithms designed to process and interpret visual data.
   - **Natural Language Processing (NLP)**: Algorithms designed to understand and process human language.
   - **Speech Recognition**: Algorithms designed to transcribe spoken language into text.
   - **Recommendation Systems**: Algorithms designed to recommend items or content to users based on their preferences.
   - **Ensemble Learning**: Techniques that combine multiple machine learning models to improve prediction accuracy or robustness
   - **Anomaly Detection**

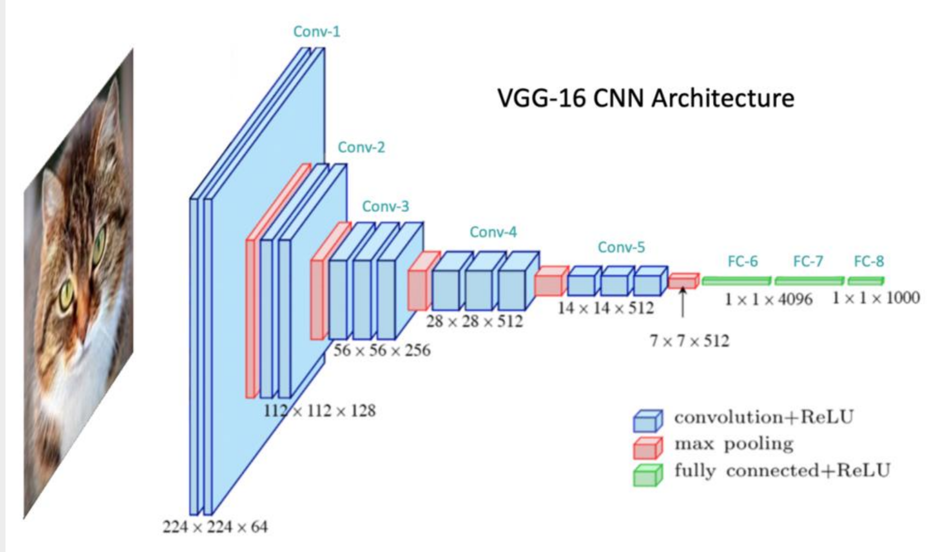
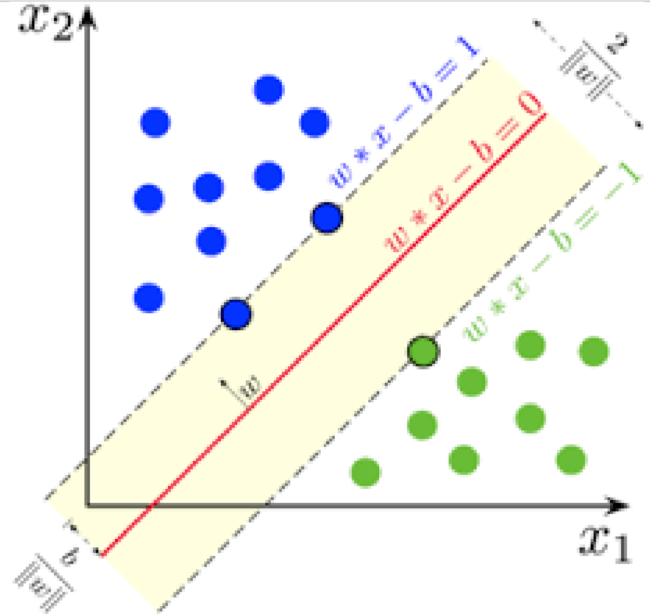
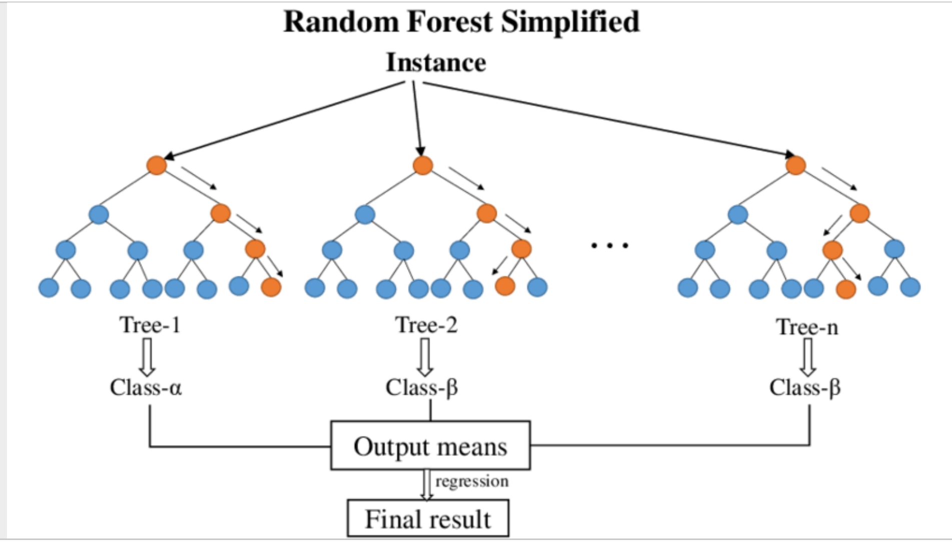
4. **Complexity**:

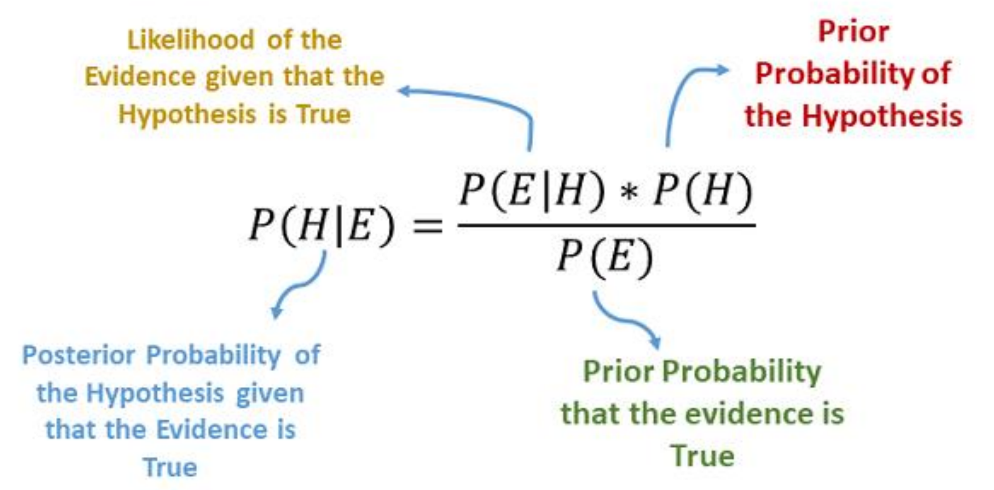
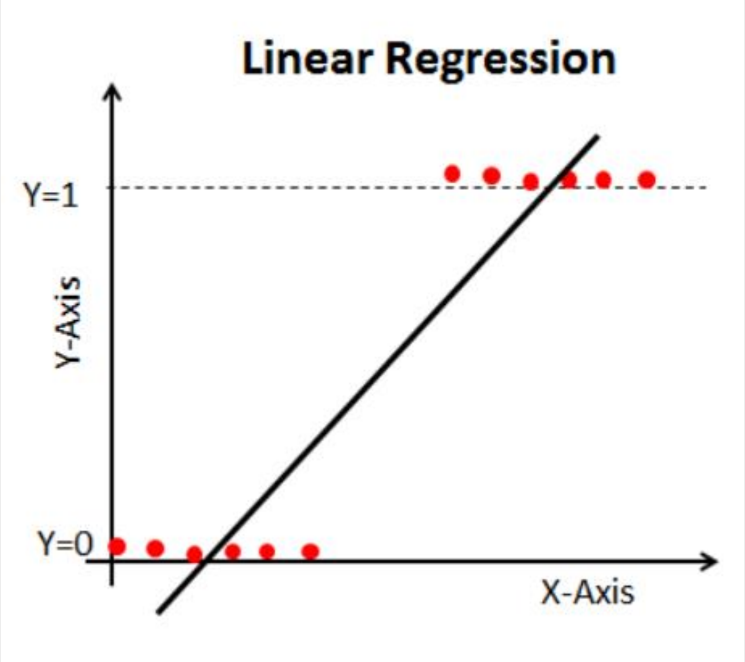
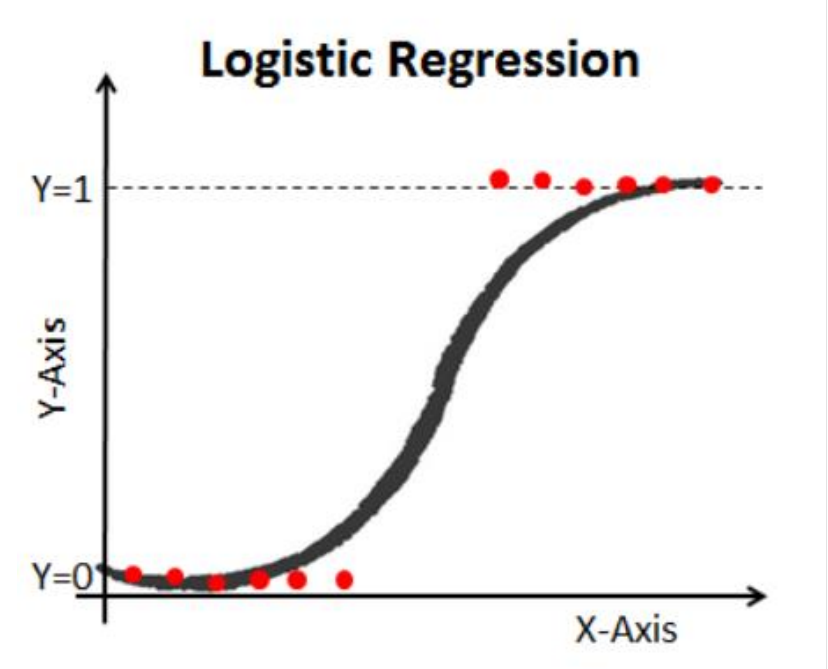
   - **Parametric Models**: Models have a fixed number of parameters and a predefined structure, such as linear regression.
   - **Non-parametric Models**: Models have a flexible number of parameters, such as decision trees and k-nearest neighbors.
   - **Deep Learning**: Neural networks with multiple hidden layers, capable of learning intricate patterns and representations from data.

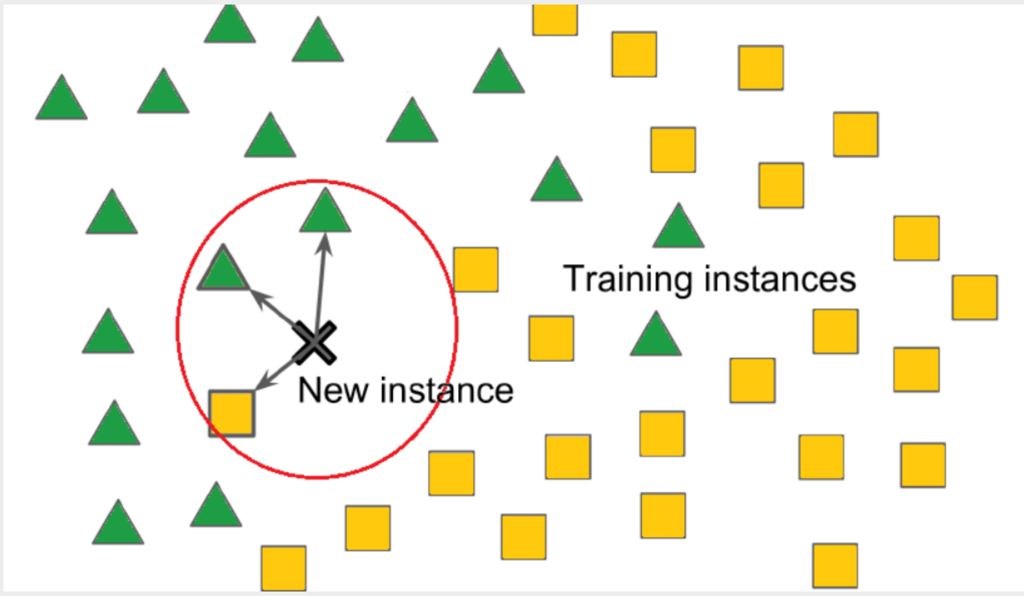
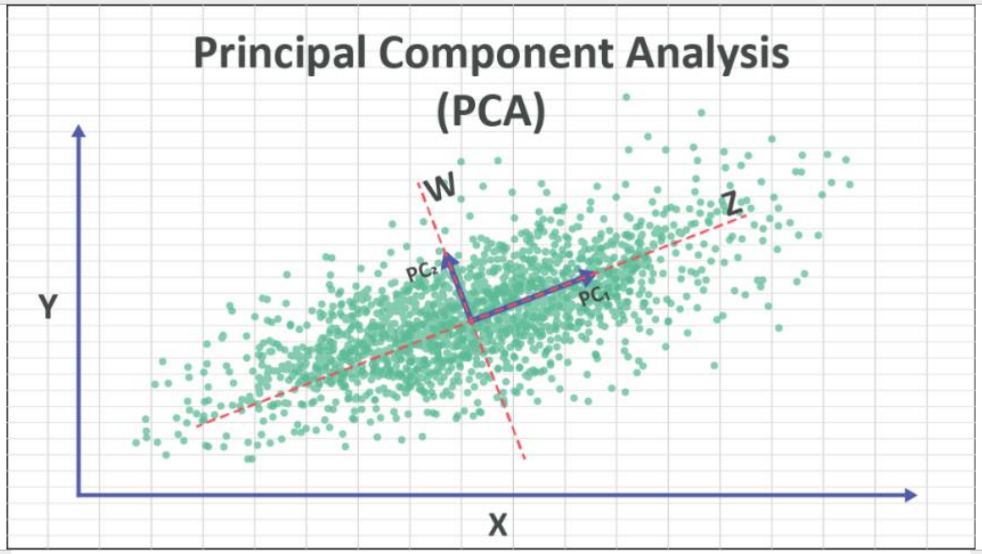
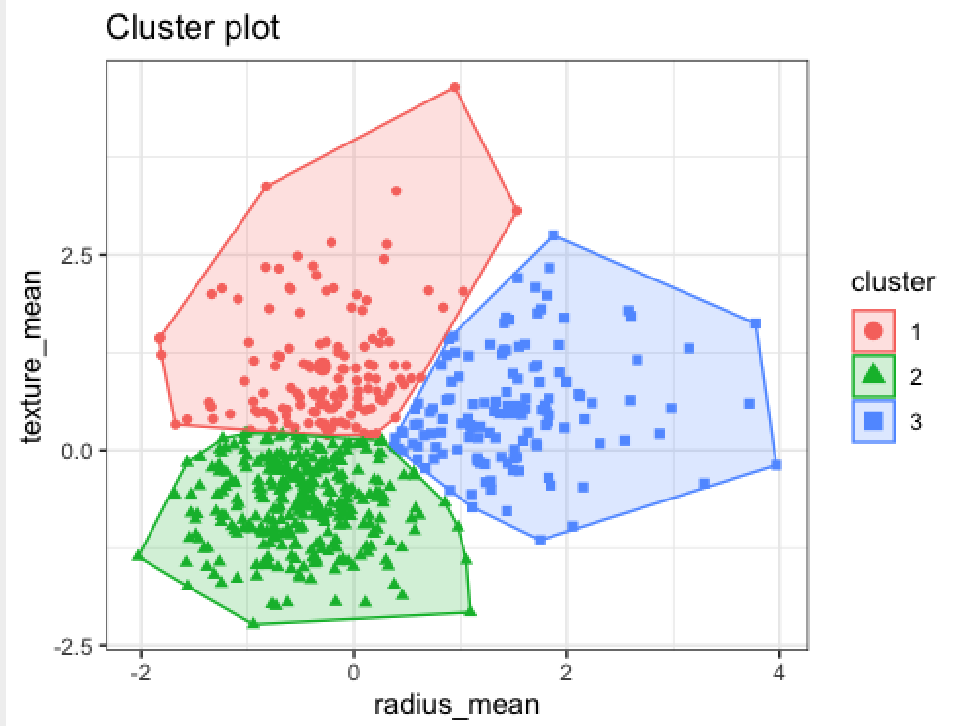
- Let's say you're working on predicting the price of a house based on various features such as square footage, number of bedrooms, number of bathrooms, and location. In this case, you have a continuous target variable (price) that you want to predict, and the relationship between the features and the target variable is likely to be linear.
- Using linear regression would be appropriate in this scenario because it models the relationship between the input features and the target variable as a linear function. Linear regression would allow you to estimate the coefficients of each feature, which represent the change in the target variable for a one-unit change in each feature, holding all other features constant.
- On the other hand, logistic regression is used for binary classification problems where the target variable is categorical (e.g., yes/no, 1/0). If the target variable is not binary or if the relationship between the features and the target variable is not linear, logistic regression would not be suitable.

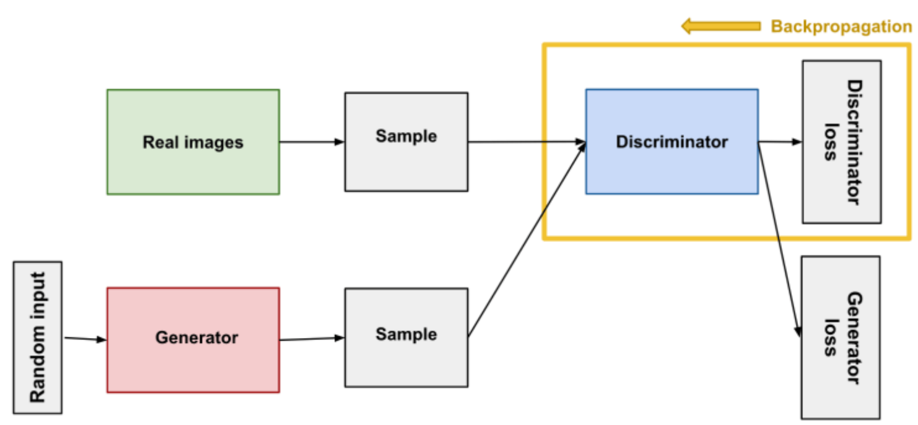
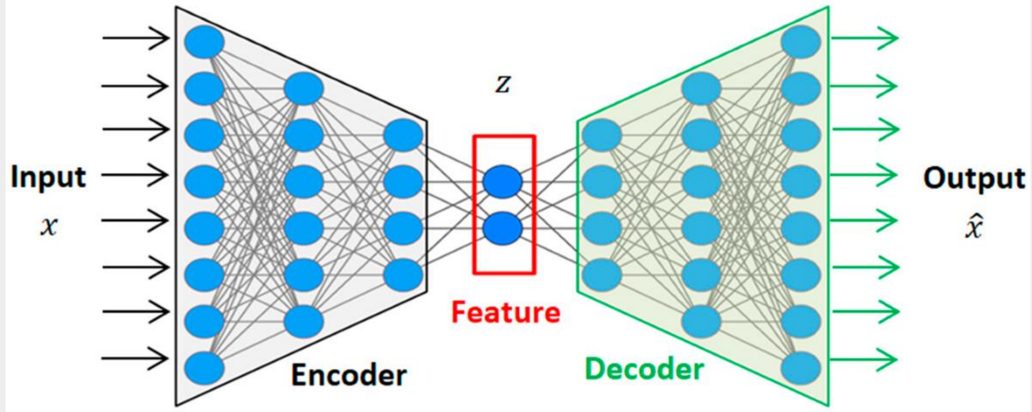
- Let's consider a scenario where you have a dataset with high-dimensional features, such as images represented as pixel values. You want to perform binary classification to distinguish between images of cats and dogs. Each image is represented by a large number of features (e.g., pixel values), making the dataset high-dimensional.
- In this case, using SVM with a kernel function, such as the radial basis function (RBF) kernel, can effectively handle high-dimensional data and find complex nonlinear decision boundaries between the classes. SVM with the RBF kernel is capable of capturing intricate patterns in the data, which may be necessary for distinguishing between images of cats and dogs with high accuracy.
- On the other hand, PCA is a dimensionality reduction technique that aims to reduce the dimensionality of the dataset by finding a lower-dimensional representation while preserving most of the variance in the data. However, PCA may not be as effective in capturing complex nonlinear relationships in the data, especially in cases where the decision boundary between classes is highly nonlinear or intricate.

- Consider a text classification problem where you want to classify emails as either spam or not spam based on the words contained in the email. Each email is represented by a bag-of-words representation, where the presence or absence of words in the email is used as features for classification. In this scenario:
- Naive Bayes: Naive Bayes classifiers are well-suited for text classification tasks because they assume that features are conditionally independent given the class label. Despite this simplifying assumption, Naive Bayes classifiers often perform well on text data and are computationally efficient. They calculate the probability of each class given the features and select the class with the highest probability.

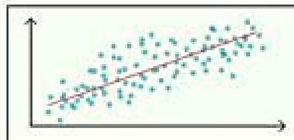
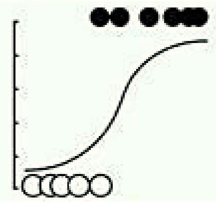
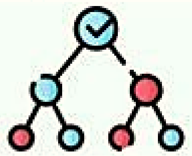
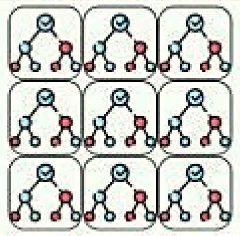
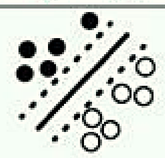
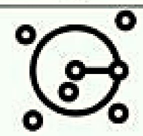
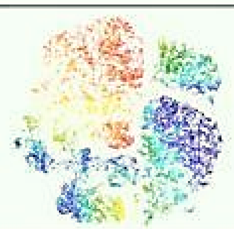
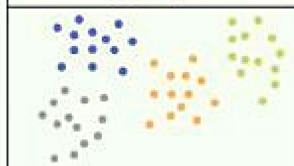
Algorithm	Type	Functionality	Deep Learning	Model Complexity	Code example	image
CNN	Supervised	Classification, Regression	Yes	Deep	from keras.models import Sequential from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense model = Sequential() model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3))) model.add(MaxPooling2D((2, 2))) model.add(Conv2D(64, (3, 3), activation='relu')) model.add(MaxPooling2D((2, 2))) model.add(Flatten()) model.add(Dense(64, activation='relu')) model.add(Dense(10, activation='softmax'))	
SVM (Support Vector Machine)	Supervised	Classification, Regression	No	Parametric	from sklearn import datasets from sklearn.model_selection import train_test_split from sklearn.svm import SVC iris = datasets.load_iris() X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.3, random_state=42) svm_model = SVC(kernel='linear') svm_model.fit(X_train, y_train) accuracy = svm_model.score(X_test, y_test) print("Accuracy:", accuracy)	
Decision Forests	Supervised	Classification, Regression	No	Non-parametric	from sklearn import datasets from sklearn.model_selection import train_test_split from sklearn.ensemble import RandomForestClassifier iris = datasets.load_iris() X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.3, random_state=42) rf_model = RandomForestClassifier(n_estimators=100) rf_model.fit(X_train, y_train) accuracy = rf_model.score(X_test, y_test) print("Accuracy:", accuracy)	

Naive Bayes	Supervised	Classification	No	Parametric	from sklearn import datasets from sklearn.model_selection import train_test_split from sklearn.naive_bayes import GaussianNB iris = datasets.load_iris() X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.3, random_state=42) nb_model = GaussianNB() nb_model.fit(X_train, y_train) accuracy = nb_model.score(X_test, y_test) print("Accuracy:", accuracy)	
Linear Regression	Supervised	Regression	No	Parametric	from sklearn.datasets import load_boston from sklearn.model_selection import train_test_split from sklearn.linear_model import LinearRegression boston = load_boston() X_train, X_test, y_train, y_test = train_test_split(boston.data, boston.target, test_size=0.3, random_state=42) lr_model = LinearRegression() lr_model.fit(X_train, y_train) accuracy = lr_model.score(X_test, y_test) print("Accuracy:", accuracy)	
Logistic Regression	Supervised	Classification	No	Parametric	from sklearn import datasets from sklearn.model_selection import train_test_split from sklearn.linear_model import LogisticRegression iris = datasets.load_iris() X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.3, random_state=42) lr_model = LogisticRegression() lr_model.fit(X_train, y_train) accuracy = lr_model.score(X_test, y_test) print("Accuracy:", accuracy)	

KNN (K-Nearest Neighbors)	Supervised	Classification	No	Non-parametric	from sklearn.datasets import load_iris from sklearn.model_selection import train_test_split from sklearn.neighbors import KNeighborsClassifier iris = load_iris() X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.3, random_state=42) knn_model = KNeighborsClassifier(n_neighbors=5) knn_model.fit(X_train, y_train) accuracy = knn_model.score(X_test, y_test) print("Accuracy:", accuracy)	
PCA (Principal Component Analysis)	Unsupervised	Dimension Reduction	No	Non-parametric	from sklearn.datasets import load_iris from sklearn.decomposition import PCA iris = load_iris() pca = PCA(n_components=2) X_reduced = pca.fit_transform(iris.data)	
K-Means	Unsupervised	Clustering	No	Non-parametric	from sklearn.datasets import make_blobs from sklearn.cluster import KMeans X, _ = make_blobs(n_samples=300, centers=4, cluster_std=0.60, random_state=0) kmeans = KMeans(n_clusters=4) kmeans.fit(X)	

GANs (Generative Adversarial Networks)	Unsupervised	Generation	Yes	Deep		
Autoencoder	Unsupervised	Dimension Reduction, Generation	Yes	Deep		

Time Complexity of 10 Most Popular ML Algorithms

	Linear Regression (OLS)	$O(nm^2 + m^3)$	$O(m)$
	Linear Regression (SGD)	$O(n_{epoch}nm)$	$O(m)$
	Logistic Regression (Binary)	$O(n_{epoch}nm)$	$O(m)$
	Logistic Regression (Multiclass OvR)	$O(n_{epoch}nmc)$	$O(mc)$
	Decision Tree	$O(n \cdot \log(n) \cdot m)$ $O(n^2 \cdot m)$	$O(d_{tree})$
	Random Forest Classifier	$O(n_{trees} \cdot n \cdot \log(n) \cdot m)$	$O(d_{trees} * d_{tree})$
	Support Vector Machines (SVMs)	$O(nm^2 + m^3)$	$O(m * n_{sv})$
	k-Nearest Neighbors	—	$O(nm)$
$P(A\|B) = \frac{P(B\|A) * P(A)}{P(B)}$	Naive Bayes	$O(nm)$	$O(mc)$
	Principal Component Analysis (PCA)	$O(nm^2 + m^3)$	—
	t-SNE	$O(n^2m)$	—
	KMeans Clustering	$O(iknm)$	??

n: samples | m: dimensions | n_{epoch}: epochs | c: classes

d_{tree}: depth | n_{sv}: Support vectors | k: clusters | i: iterations

Advanced CNNs

Model	Type	Best Case to Use	Model Size
SqueezeNet	CNN	When limited computational resources are available	Small
MobileNet	CNN	Mobile and edge devices, real-time applications	Small
BiLSTM (Bidirectional LSTM)	RNN	Sequential data with bidirectional context	Medium
GRU (Gated Recurrent Unit)	RNN	Sequences with less complex dependencies	Medium
LSTM (Long Short-Term Memory)	RNN	Long sequences with complex dependencies	Medium
DenseNet	CNN	Image classification tasks	Large
EfficientNet	CNN	State-of-the-art performance with efficient use of resources	Large
NASNet (Neural Architecture Search Network)	CNN	High-performance image classification tasks	Large
AlexNet	CNN	Legacy image classification tasks	Large
GoogLeNet (Inception)	CNN	Tasks requiring strong generalization	Large
VGG (Visual Geometry Group) networks (e.g., VGG16, VGG19)	CNN	Image classification tasks, benchmarking	Large
Attention-based models (e.g., Transformer with Attention Mechanisms)	RNN/CNN	NLP tasks, sequence-to-sequence learning	Varies
Transformer	RNN/CNN	NLP tasks, language translation	Varies

History Table

1950	AI started
1990	Machine Learning Started
1997	LSTM
2010	Deep Learning Started
2012	CNN started

- Machine learning is not a science or mathematics where advancements is achieved by paper and pen it’s an engineering
- If machine learning is an engine so the data is its coal
- Neural netword core is a layer and its like a data filter with activation function
- Each model should have (loss function, optimizer, metric to monitor during training)
- Preprocessing: one of the best ones is to make any parameter value ranging from 0 to 1 by normalization

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F-measure} = \frac{2 \cdot TP}{2 \cdot TP+FN+FP}$$

$$\text{Cost} = TP \times Cost_{TP} + FN \times Cost_{FN} + TN \times Cost_{TN} + FP \times Cost_{FP}$$

$$\text{Sensitivity} = \text{Recall}$$

$$\text{Specificity} = 1 - \frac{FP}{FP+TN} = \frac{TN}{TN+FP}$$

$$\text{False Positive Rate} = 1 \text{ - Specificity}$$

Neural Network	Training Time Complexity	Classification Time Complexity	Space Complexity (Missing Data)
Feedforward Network	O(n * E * I * H * O)	O(n * I * H * O)	O(E * I * H * O)
Convolutional Network	O(n * E * I * K * O)	O(n * I * K * O)	O(E * I * K * O)
Recurrent Network	O(n * E * I * H^2)	O(n * I * H^2)	O(E * I * H^2)
Generative Adversarial Network (GAN)	O(n * E * G * D)	O(n * G * D)	O(E * G * D)
Long Short-Term Memory (LSTM)	O(n * E * I * H^2)	O(n * I * H^2)	O(E * I * H^2)
Transformer Network	O(n * E * I^2 * H)	O(n * I^2 * H)	O(E * I^2 * H)

In the table:

- "n" represents the number of training examples
- "E" denotes the number of training epochs
- "I" refers to the number of input features
- "H" represents the number of hidden units or layers
- "O" denotes the number of output units
- "K" represents the kernel size (for Convolutional Networks)
- "G" denotes the number of generator iterations (for GANs)
- "D" represents the number of discriminator iterations (for GANs)