All Machine Learning Algorithm

Explained in One Line →

Supervised Learning Algorithms

Linear Regression: Predicts a continuous output variable based on linear relationships between input features.

Logistic Regression: Classifies input data into discrete categories using a logistic function to model the probabilities.

Decision Trees: Constructs a tree-like model by splitting data based on features to make decisions or predictions.

Random Forests: Ensemble method that combines multiple decision trees to improve prediction accuracy and reduce overfitting.

Support Vector Machines (SVM): Separates data into different classes by finding an optimal hyperplane in a high-dimensional space.

Naive Bayes: Uses Bayes' theorem and assumes independence between features to classify data based on probability calculations.

k-Nearest Neighbors (k-NN): Classifies data based on the majority vote of its k nearest neighbors in the feature space.

Gradient Boosting algorithms: Ensemble methods that sequentially build weak models, minimizing the errors of previous models to improve predictions.

Unsupervised Learning Algorithms

K-means Clustering: Divides data into k clusters based on similarity, aiming to minimize the intra-cluster variance.

Hierarchical Clustering: Builds a hierarchy of clusters by iteratively merging or splitting them based on similarity.

DBSCAN: Density-based clustering algorithm that groups together data points in high-density regions while marking outliers as noise.

Gaussian Mixture Models (GMM): Models data as a combination of Gaussian distributions to perform probabilistic clustering.

Principal Component Analysis (PCA): Reduces the dimensionality of data by transforming it into a new set of uncorrelated variables called principal components.

t-Distributed Stochastic Neighbor Embedding (t-SNE): Dimensionality reduction technique that visualizes high-dimensional data in a lower-dimensional space, emphasizing local structure.

Reinforcement Learning Algorithms

Q-Learning: Reinforcement learning algorithm that learns through trial and error, optimizing actions based on maximizing cumulative rewards.

Deep Q-Network (DQN): Reinforcement learning algorithm that combines Q-learning with deep neural networks for improved performance in complex environments.

Proximal Policy Optimization (PPO): Policy optimization algorithm that iteratively updates policies to maximize rewards and improve sample efficiency.

Monte Carlo Tree Search (MCTS): Search algorithm that simulates and evaluates possible moves in a game tree to determine optimal actions.

Actor-Critic Methods: Reinforcement learning approach that combines a policy network (actor) and a value function (critic) to guide learning.

Deep Learning Algorithms

Convolutional Neural Networks (CNN): Deep learning models designed for image processing, using convolutional layers to extract meaningful features.

Recurrent Neural Networks (RNN): Neural networks that can process sequential data by retaining and using information from previous inputs.

Long Short-Term Memory (LSTM): A type of RNN that addresses the vanishing gradient problem and can retain information over longer sequences.

Generative Adversarial Networks (GAN): Neural network architecture consisting of a generator and a discriminator, trained in competition to produce realistic data.

Transformer Networks: Architecture that employs self-attention mechanisms to process sequences, widely used in natural language processing tasks.

Autoencoders: Neural networks designed to learn compressed representations of input data by training to reconstruct the original input from a reduced-dimensional representation.

Semi-Supervised Learning Algorithms

Expectation-Maximization (EM): Iteratively estimates the parameters of a probabilistic model by alternately computing expected values and maximizing likelihood.

Self-Training: Uses a small amount of labeled data to train a model, which is then used to label a larger amount of unlabeled data for further training iterations.

Co-Training: Simultaneously trains multiple models on different subsets of features or data instances, leveraging their agreement on the unlabeled data.

Label Propagation: Propagates labels from labeled instances to unlabeled instances based on their similarity, utilizing the local structure of the data.

Generative Models with Labeled and Unlabeled Data: Combines generative models with both labeled and unlabeled data to estimate class distributions and make predictions.

Ensemble Learning Algorithms

Bagging: Ensemble technique that combines multiple models trained on different subsets of the training data to make predictions.

Boosting: Ensemble method that combines weak learners sequentially, with each subsequent model focusing on instances that previous models struggled with.

Stacking: Ensemble approach that combines predictions from multiple models by training a meta-model on their outputs.

Voting Classifiers: Ensemble method that combines predictions from multiple models by majority voting or weighted voting.

Dimensionality Reduction Algorithms

Principal Component Analysis (PCA): Reduces the dimensionality of data by transforming it into a new set of uncorrelated variables called principal components.

Linear Discriminant Analysis (LDA): Maximizes class separability by finding linear combinations of features that best discriminate between classes.

t-Distributed Stochastic Neighbor Embedding (t-SNE): Dimensionality reduction technique that visualizes high-dimensional data in a lower-dimensional space, emphasizing local structure.

Independent Component Analysis (ICA): Separates a multivariate signal into additive subcomponents to discover underlying independent sources.

Variational Autoencoders (VAE): Neural network-based generative models that learn low-dimensional representations and reconstruct original data with high fidelity.

Transfer Learning Algorithms

Pre-trained Deep Neural Networks: Deep learning models that are trained on large-scale datasets for specific tasks, often used as a starting point for transfer learning.

Fine-tuning: Technique where a pre-trained model is further trained on a specific task or dataset to improve its performance.

Domain Adaptation: Technique that transfers knowledge from a source domain to a target domain with different distributions, improving generalization.

Multi-task Learning: Simultaneously trains a model on multiple related tasks to improve overall performance by leveraging shared information.