Introduction to Artificial Intelligence

Artificial Intelligence (AI) is a broad field of computer science focused on creating systems capable of performing tasks that typically require human intelligence. These tasks include reasoning, learning, perception, decision-making, language understanding, and problem-solving. AI systems range from simple rule-based systems to highly complex self-learning models that adapt based on data.

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Machine Learning (ML)

Machine Learning is a subset of AI that focuses on enabling machines to learn patterns from data without being explicitly programmed. Instead of writing fixed rules, ML algorithms use statistical techniques to infer relationships from data. Common ML paradigms include supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning uses labeled data, unsupervised learning works with unlabeled data, and reinforcement learning optimizes decisions through rewards and penalties.

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Common Machine Learning Algorithms

Key ML algorithms include Linear Regression, Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, K-Nearest Neighbors, Naive Bayes, Gradient Boosting, and Clustering algorithms such as K-Means and Hierarchical Clustering. Each algorithm has strengths, weaknesses, assumptions, and suitable use cases depending on the nature of the data, feature space, and problem constraints.

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Neural Networks (NN)

Neural Networks are inspired by the structure of the human brain. They consist of interconnected nodes called neurons, organized into layers: input layer, hidden layers, and output layer. Each neuron performs a weighted sum of inputs, adds a bias, and applies an activation function. Training a neural network involves adjusting weights using optimization algorithms such as Gradient Descent and Backpropagation.

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Deep Learning (DL)

Deep Learning is a specialized subset of machine learning that uses deep neural networks with many hidden layers. DL excels at learning hierarchical feature representations from large datasets. It has driven breakthroughs in computer vision, natural language processing, speech recognition, and generative modeling. Popular architectures include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), LSTMs, GRUs, Transformers, and Autoencoders.

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Training, Optimization, and Loss Functions

Training ML and DL models involves defining a loss function that measures prediction error, selecting an optimizer, and iteratively updating parameters. Common loss functions include Mean Squared Error, Cross-Entropy Loss, and Hinge Loss. Optimizers include SGD, Adam, RMSProp, and Adagrad. Concepts such as learning rate, batch size, epochs, overfitting, underfitting, regularization, dropout, and early stopping are critical for model performance.

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Model Evaluation and Metrics

Model evaluation ensures that learned patterns generalize to unseen data. Common metrics include accuracy, precision, recall, F1-score, ROC-AUC, confusion matrix, mean absolute error, and R-squared. Cross-validation techniques such as k-fold cross-validation are widely used to obtain reliable performance estimates.

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MLOps, Deployment, and Scaling

MLOps integrates machine learning with DevOps principles to manage the lifecycle of ML models in production. It includes data versioning, model versioning, continuous training, monitoring, drift detection, and retraining. Deployment strategies include REST APIs, batch inference, edge deployment, and cloud-based serving.

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Large-Scale Knowledge Bases and RAG Systems

Retrieval-Augmented Generation (RAG) systems combine information retrieval with generative models. Large textual knowledge bases are chunked, embedded into vector representations, and stored in vector databases. During inference, relevant chunks are retrieved and injected into prompts to ground responses in factual data. Well-structured, diverse, and comprehensive documents improve retrieval quality and downstream reasoning.

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