# Comparison of Machine Learning Types

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| **Aspect** | **Supervised Learning** | **Unsupervised Learning** | **Reinforcement Learning** | **Semi-Supervised Learning** | **Self-Supervised Learning** | **Deep Learning** |
| Definition | Learns from labeled data (input-output pairs). | Finds patterns in unlabeled data. | Learns by interacting with an environment and receiving rewards or penalties. | Uses a small amount of labeled data and a large amount of unlabeled data. | Learns by generating its own labels from raw data. | Uses deep neural networks for complex patterns. |
| Data Type | Labeled (X, Y) | Unlabeled (X only) | State-action-reward-based | Partially labeled | Unlabeled but auto-labeled | Labeled or unlabeled |
| Goal | Predict outputs for new data. | Discover hidden structures in data. | Maximize cumulative reward. | Improve learning with limited labels. | Learn high-level features automatically. | Model complex patterns from big data. |
| Learning Process | Maps inputs to outputs based on past data. | Groups similar data points or reduces data dimensions. | Learns through trial and error (feedback loop). | Leverages both labeled and unlabeled data for learning. | Self-generates supervision signals from data. | Uses multiple layers of neurons to extract deep features. |
| Common Techniques | Regression, Classification | Clustering, Dimensionality Reduction, Association | Q-Learning, Deep Q Networks (DQN), Policy Gradient | Self-training, S3VM (Semi-Supervised SVM) | Contrastive Learning, BERT (for NLP) | CNNs, RNNs, Transformers |
| Examples | Spam detection, Fraud detection, Medical diagnosis | Customer segmentation, Anomaly detection | Game-playing AI (AlphaGo, Dota 2 AI), Robotics | Google Photos face recognition with limited labeled images | GPT-4, BERT, Vision Transformers | Tesla self-driving, ChatGPT, Image recognition |
| Strengths | High accuracy with labeled data. | Works well for pattern discovery. | Adapts dynamically to new environments. | Balances efficiency with minimal labeled data. | Efficient for large-scale learning without human annotation. | Handles large, complex datasets with high accuracy. |
| Limitations | Needs a lot of labeled data. | Difficult to interpret patterns. | Computationally expensive and slow to train. | Requires a balance of labeled/unlabeled data. | Requires large computing power and data. | Needs huge datasets and long training times. |