1. Introduction

From translation apps to autonomous vehicles, Machine Learning is the driving force behind these innovations. It's all about training algorithms to make predictions from data. In this chapter, we'll explore different types of machine learning and key terminology.

2. Artificial Intelligence and Machine Learning?

Artificial Intelligence (AI) and Machine Learning (ML) are closely related fields in computer science that focus on developing systems and algorithms to enable computers to perform tasks that typically require human intelligence. While they are related, they have distinct characteristics and purposes:

2.1. Artificial Intelligence (AI)

AI is a computer science field that aims to make machines smart like humans, allowing them to do things independently by learning from experience, understanding language, and solving problems. The main goal of AI is to create machines that can think and make intelligent decisions based on what they know.

2.2. Machine Learning (ML)

ML is a part of AI that helps computers get smarter by learning from data and experience instead of needing explicit instructions. The main aim of ML is to make algorithms and models that can understand patterns in data, so they can make predictions or choices based on new information they haven't seen before. ML algorithms are good at figuring out things from data and can apply this knowledge to new situations.

2.3. Differences between AI and ML

Here are some key differences between AI and ML:

Scope: AI is a broader field encompassing various techniques, including rule-based systems, expert systems, natural language processing (NLP), computer vision, robotics, and more. ML is a subset of AI that specifically deals with learning patterns from data.

Learning: In AI, techniques can be rule-based, heuristic, or rely on pre-programmed knowledge, whereas ML focuses on learning patterns from data.

Training: ML models require training on labeled data to improve their performance. AI systems may not always involve explicit training but may rely on predetermined rules and knowledge.

Flexibility: AI systems can be rule-based and may not adapt to new data without manual intervention. ML models can adapt and improve their performance with more data.

In practice, AI and ML often overlap, with ML techniques being a crucial component of many AI systems. AI systems can incorporate various ML algorithms to enhance their decision-making and adaptability. As technology advances, the boundaries between AI and ML continue to blur, and both fields play a significant role in shaping the future of automation and intelligent systems.

3. Types of Machine Learning

Machine learning algorithms are often divided into three general categories (though other classification schemes are also used): supervised learning, unsupervised learning, and reinforcement learning.

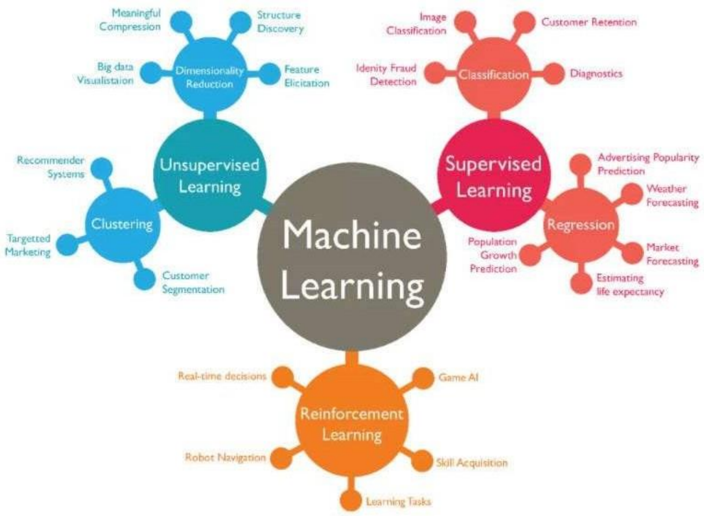


Figure 1: types of machine learning

3.1. Supervised Learning

Supervised Learning is one of the fundamental paradigms in Machine Learning (ML). It is a type of machine learning where an algorithm learns from a labeled dataset, which means that each example in the training data consists of an input (or feature) and the corresponding correct output (or label). The goal of supervised learning is to learn a mapping from inputs to outputs, so that the algorithm can make accurate predictions on new, unseen data.

There are two primary tasks in supervised learning:

3.1.1. Regression

Regression is a type of supervised learning where the target variable is continuous. It's used when you want to predict numerical values. In regression, the algorithm learns a function that maps input features to a continuous output. Key points about regression include:

Examples: Predicting house prices, stock prices, or temperature based on historical data.

Algorithms: Linear regression, polynomial regression, support vector regression, and neural networks.

Evaluation: Common evaluation metrics include mean squared error (MSE) and R-squared (R^2).

3.1.2. Classification

Classification, also a type of supervised learning, is used when the target variable is categorical, falling into predefined classes or categories. In classification, the algorithm assigns data points to discrete classes based on their features. There are two common subtypes:

a. Binary Classification

Binary classification is a specific type of classification where the target variable has only two possible classes. Examples include: Spam email detection (classifying emails as spam or not spam), Medical diagnosis (classifying patients as having a disease or not). In binary classification, the model aims to distinguish between two classes.

b. Multiple Classification

Multiple classification, often referred to as multiclass classification, deals with scenarios where the target variable has more than two classes. Examples include: Identifying the species of flowers (e.g., classifying flowers as roses, daisies, or tulips). In multiple classification, the model assigns data points to one of several possible classes.

Supervised Learning Algorithms

There are various algorithms used in supervised learning, including:

- Linear Regression: Used for regression tasks where the output is a continuous value.
- Logistic Regression: Used for binary classification tasks.
- Decision Trees: Used for both classification and regression tasks.
- Support Vector Machines (SVM): Used for classification and regression.
- Neural Networks: Deep learning models that can handle complex tasks, including image recognition and natural language processing.

3.2. Unsupervised Learning

Unsupervised learning is a category of machine learning where the algorithm learns patterns and structures in data without explicit supervision or labeled output. In other words, it doesn't rely on predefined labels or target values to make predictions or decisions. Instead, unsupervised learning algorithms seek to uncover hidden patterns, group similar data points, or reduce the dimensionality of data.

There are two primary types of unsupervised learning:

Clustering: Clustering algorithms aim to group similar data points together into clusters or segments based on their inherent similarities. The goal is to discover natural groupings in the data. Common clustering algorithms include K-Means, Hierarchical Clustering, and DBSCAN.

Dimensionality Reduction: Dimensionality reduction techniques aim to reduce the number of features or variables in a dataset while preserving its essential characteristics. This is particularly useful when working with high-dimensional data or when trying to visualize data in lower dimensions. Principal Component Analysis (PCA) and t- distributed Stochastic Neighbor Embedding (t-SNE) are popular dimensionality reduction methods.

3.3. Reinforcement Learning

Reinforcement learning (RL) is a type of machine learning paradigm where an agent learns to make sequential decisions by interacting with an environment to achieve a specific goal. Unlike supervised learning, where the model is trained on labeled data, and unsupervised learning, where the model identifies patterns in unlabeled data, RL is about learning through trial and error. The agent learns to take actions in an environment to maximize a cumulative reward signal.

Here are some key components of reinforcement learning:

Agent: The learner or decision-maker that interacts with the environment. It takes actions based on a policy.

Environment: The external system with which the agent interacts. It provides feedback to the agent in the form of rewards and new states.

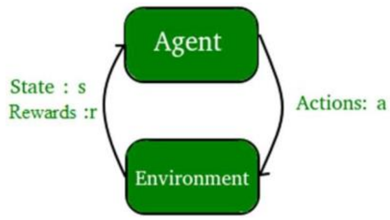
State: A representation of the current situation or configuration of the environment. The state provides information to the agent about its surroundings.

Action: The set of possible choices or decisions that the agent can make in each state. Actions lead to transitions to new states.

Policy: A strategy or mapping that defines the agent's behavior. It determines which actions the agent should take in each state.

Reward: A numerical signal provided by the environment after each action taken by the agent. The reward indicates the immediate benefit or desirability of the action.

Value Function: A function that estimates the expected cumulative reward an agent can achieve from a given state or state-action pair. It helps the agent evaluate the desirability of states or actions.



The goal of reinforcement learning is for the agent to find an optimal policy that maximizes the expected cumulative reward over time. This often involves a trade-off between immediate rewards and long-term goals.

Popular algorithms in reinforcement learning include Q-learning, Deep Q-Networks (DQN), Policy Gradient methods, and more recently, advances in deep reinforcement learning, which combines deep neural networks with RL techniques to handle complex tasks and high-dimensional state spaces.

4. Terminologies of Machine Learning

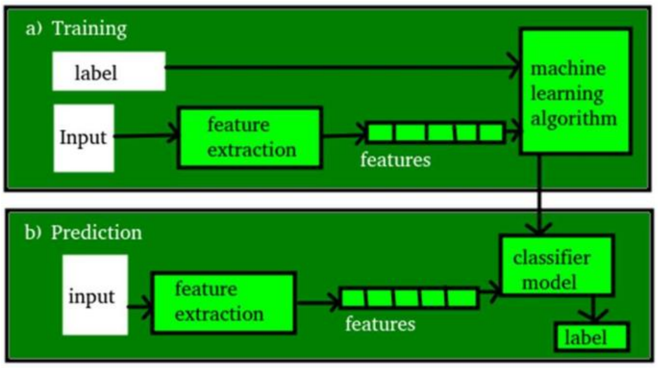
Here are the key characteristics and concepts associated with ML:

- **Model** A model is a **specific representation** learned from data by applying some machine learning algorithm. A model is also called a **hypothesis**.
- **Feature:** is an individual measurable property of our data. A set of numeric features can be conveniently described by a **feature vector**. Feature vectors are fed as input to the model. For example, in order to predict a fruit, there may be features like color, smell, taste, **etc.**

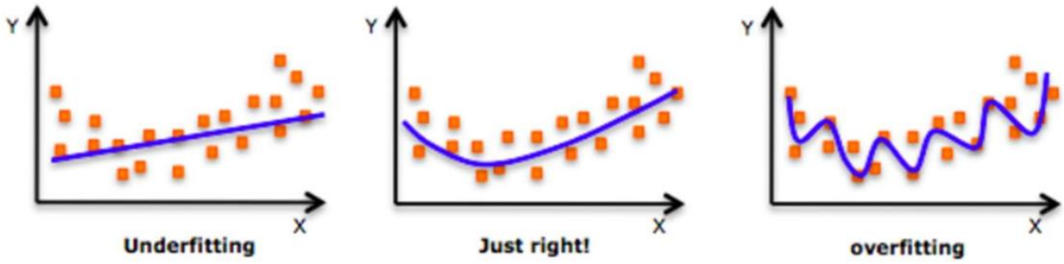
Note: Choosing informative, discriminating and independent features is a crucial step for effective algorithms. We generally employ a **feature extractor** to extract the relevant features from the raw data.

- **Target (Label):** is the value to be predicted by our model. For the fruit example discussed in the features section, the label with each set of input would be the name of the fruit like apple, orange, banana, etc.
- **Training Process:** during the training phase, the algorithm learns from the labeled data. It tries to find patterns, relationships, or a mapping function that connects the input data to the correct output. This is done by adjusting the model's parameters iteratively to minimize a predefined loss or error function.
- **Evaluation:** after training, the model's performance is evaluated on a separate dataset called the validation or test set. This helps assess how well the model generalizes to new, unseen data. Common evaluation metrics include accuracy, precision, recall, F1 score, and mean squared error, depending on the type of task (classification or regression….).
- **Prediction** Once our model is ready, it can be fed a set of inputs to which it will provide a predicted output (label). But make sure if the machine performs well on unseen data, then only we can say the machine performs well.

The figure shown below clears the above concepts:



- **Overfitting and Underfitting**: Overfitting occurs when a model learns the training data too well and performs poorly on new data. Underfitting occurs when a model is too simple to capture the underlying patterns in the data



5. Data in Machine Learning

Data is a crucial component in the field of Machine Learning. It refers to the set of observations or measurements that can be used to train a machine-learning model. Data can be any unprocessed fact, value, text, sound, or picture that is not being interpreted and analyzed. The quality and quantity of data available for training and testing play a significant role in determining the performance of a machine-learning model.

Machine learning algorithms use data to learn patterns and relationships between input variables and target outputs, which can then be used for prediction or classification tasks.

5.1. How do we split data in Machine Learning?

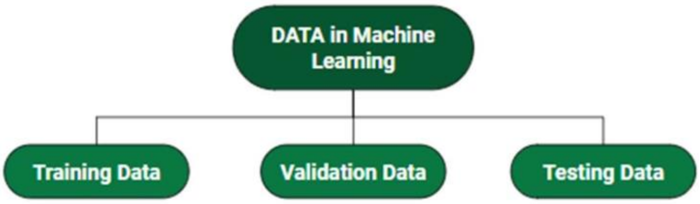
Data can be divided into training, validation and testing sets:

Training Set: Used to train the model (70-80% of data).

Validation Set: Used for hyperparameter tuning and model selection (10-15% of data).

Testing Set: Used to assess the model's performance on unseen data (10-15% of data).

These splits help ensure that the model generalizes well to new, unseen data



5.2. Different Forms of Data

Data can be categorized into four main types based on its structure and nature: structured, unstructured, quantitative, and qualitative data. Here's an overview of each type:

- **Structured Data** is organized in tables with rows and columns, making it easy to analyze. It’s found in databases, spreadsheets, and records, and is great for numerical analysis and reporting.
- **Unstructured data** has no specific format and comes in forms like text, audio, images, or video. Examples include social media posts and documents. Analyzing it requires special methods like natural language processing (NLP) and computer vision.
- **Quantitative Data** is made up of numbers that show quantities or measurements. Examples include temperature, stock prices, age, and test scores. It is used for statistical analysis, hypothesis testing, and data visualization.
- **Qualitative data** is descriptive and non-numeric, representing qualities or categories. Examples include gender, product types, and customer feedback. It is analyzed using methods like coding and sentiment analysis to understand behavior and preferences.

In real-world scenarios, datasets may contain a mix of these data types, requiring data scientists and analysts to use appropriate techniques and tools for each type to extract valuable insights and make informed decisions.

6. Machine Learning Workflow: From Data to Deployment

Using a machine learning model typically involves several steps, from data preparation to model evaluation and deployment. Here's a high-level overview of the common steps involved in using a machine learning model:

1. **Define the Problem:**

Clearly define the problem you want to solve with machine learning. Understand the objectives and goals of your project.

2. **Gather and Prepare Data:**

Collect and organize the data you will use to train and evaluate your model. This may involve data cleaning, preprocessing, and feature engineering to make the data suitable for modeling.

3. **Split the Data:**

Divide your dataset into training, validation, and test sets. The training set is used to train the model, the validation set is used for hyperparameter tuning, and the test set is used to evaluate the model's performance.

4. **Choose a Machine Learning Algorithm:**

Select a machine learning algorithm or model architecture that is appropriate for your problem. The choice of algorithm depends on the nature of the data and the problem type (classification, regression, clustering, etc.).

5. **Feature Selection/Extraction:**

If necessary, select relevant features or perform feature extraction to reduce dimensionality and improve model performance.

6. **Model Training:**

Train the selected machine learning model using the training data. This involves optimizing the model's parameters to minimize the prediction error.

7. **Hyperparameter Tuning:**

Fine-tune the hyperparameters of your model using the validation set to optimize its performance. This may involve techniques like grid search or random search.

8. **Model Evaluation:**

Assess the model's performance using evaluation metrics appropriate for your problem (e.g., accuracy, F1-score, Mean Absolute Error, etc.). Use the test set for this evaluation to get an unbiased estimate of the model's performance.

9. **Iterate and Refine:**

If the model's performance is not satisfactory, iterate through the process, making changes such as selecting different algorithms, adjusting hyperparameters, or gathering more data.

10. **Model Deployment:**

Once you are satisfied with your model's performance, deploy it in a production environment where it can make predictions on new, unseen data. This may involve integrating the model into a web application, mobile app, or other systems.

11. **Monitoring and Maintenance:**

Continuously monitor the deployed model's performance in real-world scenarios. Update the model as needed to maintain its accuracy and effectiveness.

7. Applications of Machine Learning

Machine learning has a wide range of applications across various industries, including but not limited to:

- Healthcare: Predicting disease outcomes, diagnosing medical conditions, and drug discovery.
- Finance: Credit scoring, fraud detection, and algorithmic trading.
- Natural Language Processing (NLP): Language translation, sentiment analysis, and chatbots.
- Computer Vision: Image and video recognition, object detection, and facial recognition.
- Recommendation Systems: Personalized product recommendations in e-commerce and content recommendations in streaming services.
- Autonomous Vehicles: Self-driving cars and drones that use machine learning for navigation and decision-making.

8. Conclusion

This introductory chapter has provided an overview of machine learning, its types, applications, and key concepts. In the following chapters, we will delve deeper into various techniques of machine learning.

Machine learning is a rapidly evolving field, and staying updated with the latest developments and techniques is essential for success. As we progress through this course, you will gain the knowledge and skills needed to apply machine learning to real-world problems.