AAI Last Sem

Overview of generative models and their importance in AI

Generative models are a type of machine learning model that learns to generate new data similar to a given dataset. Unlike traditional discriminative models, which classify or predict labels based on input data, generative models **create new instances** of data by capturing the **underlying probability distribution** of the training data.

Types of Generative Models

1. **Generative Adversarial Networks (GANs) :**
    - Composed of a Generator and a Discriminator in a competitive setting.
    - Used in image generation, video synthesis, and data augmentation.
    - Example: A **Generative Adversarial Network (GAN)** can generate **realistic images of human faces** that never existed before.
2. **Variational Autoencoders (VAEs) :**
    - Probabilistic models that encode input data into a latent space and decode it back.
    - Useful in image generation, anomaly detection, and latent space exploration.
    - Example: Generating realistic handwritten digits (MNIST dataset).
3. **Autoregressive Models:**
    - Generate data sequentially, predicting one pixel or one sample at a time.
    - Used in speech synthesis and image generation.
    - Example: OpenAI's WaveNet for natural-sounding voice synthesis.

Importance of Generative Models in AI

1. **Content Creation**
    - AI-generated images, videos, and music are widely used in media, entertainment, and design industries.
    - Example: AI-generated art competitions, AI music composers.
2. **Data Augmentation**
    - Helps in training machine learning models when data is scarce by generating synthetic yet realistic data.
    - Example: Medical imaging datasets, self-driving car simulations.

3. **AI-Assisted Creativity**
    - Supports human creativity by generating ideas, designs, and even writing drafts.
    - Example: GPT models used for story writing, marketing copy.
4. **Healthcare & Drug Discovery**
    - AI-generated molecular structures accelerate drug discovery processes.
    - Example: AI-assisted protein folding solutions (AlphaFold).
5. **Realistic Simulations**
    - Used in gaming, VR, and AI training environments.
    - Example: AI-generated virtual worlds, game character animations.
6. **Personalization & Recommendation**
    - Generative models help create personalized content for users, improving engagement.
    - Example: AI-generated personalized news, advertisements, and fashion designs.

Overview of generative models and their importance in AI

🔹 Why Is Probability Important in Generative Models?

- Generative models learn the **probability distribution** of data instead of just mapping inputs to outputs.
- Instead of predicting labels, they **sample from the learned distribution** to generate new data points.
- **Probability theory is the foundation of generative models, allowing AI to model randomness and create realistic new samples.**

🔹 Example:

- In a **face-generating AI**, the model doesn't classify "face vs. no face." Instead, it learns the probability distribution of **human face features** and generates new faces.

Probability Distributions

- Gaussian (Normal) Distribution:
    - Applies to continuous data and has a bell-shaped curve.
    - Used in GMMs, VAEs
    - Eg: Modeling pixel intensity in images

- Bernoulli Distribution
    - Binary classification tasks, Applies to binary outcomes (e.g., success or failure).
    - EG: Fraud detection (Yes/No)

- Multivariate Gaussian Distribution:
    - Extends the Gaussian distribution to multiple dimensions (e.g., when working with multiple features).

Connection between Probability Theory and Generative Modelling

- Generative models, particularly **VAEs** and **GANs**, are grounded in probability theory. They model data generation as a probabilistic process.
- In **GANs**, the generator attempts to produce data that is indistinguishable from real data, which involves learning the underlying data distribution.
- **VAEs** explicitly model the data generation process as a probabilistic procedure, capturing the uncertainty in data generation.
- **Bayes' Theorem** is used in **Bayesian GANs** and **VAEs** to update beliefs about latent variables and data.
- Probabilistic models are used for **likelihood estimation**, and sampling from probability distributions is a fundamental aspect of generative modeling.
- The **expected value** and **variance** are used to assess the quality of generated data and measure how well generative models capture the data distribution.

Introduction to GANs (Generative Adversarial Networks)

Generative Adversarial Networks (GANs) are a class of deep learning models designed for generating new, realistic data samples similar to a given dataset. Introduced by **Ian Goodfellow in 2014**, GANs have revolutionized fields like image synthesis, video generation, and data augmentation.

The Concept of GANs

Generative Adversarial Networks (GANs) consist of **two neural networks**—the **generator** and the **discriminator**—which are trained simultaneously in a **competitive** process.

The goal of a GAN is for the **generator** to create data samples that are indistinguishable from real data, while the **discriminator** learns to differentiate between real and generated samples. Through this adversarial training, both networks improve over time.

Key Components of GANs

1. **Generator (G):**
    - Takes random noise as input and generates synthetic data samples.
    - Learns to map the noise to realistic data that resembles the training distribution.
2. **Discriminator (D):**
    - Receives both real and generated data as input.
    - Learns to classify inputs as real or fake, providing feedback to improve the generator.

How GANs Work

Training Process:

1. The generator starts with random noise and produces fake data.
2. Both real and fake data samples are fed into the discriminator.
3. The discriminator learns to distinguish real from generated data.
4. Simultaneously, the generator is trained to create more convincing samples that can fool the discriminator.
5. This adversarial process continues iteratively, refining both networks.

Objective Functions:

- The **generator** aims to **minimize** the probability that the discriminator correctly classifies generated data as fake.
- The **discriminator** aims to **maximize** the probability of correctly identifying real and fake samples.
- **Nash Equilibrium:** In an ideal scenario, the generator produces data so realistic that the discriminator **cannot reliably distinguish** between real and generated samples. This state is known as the **Nash Equilibrium**.

Application of GAN

1. **Image Generation**
2. **Data Augmentation**
3. **Super-Resolution Imaging**
4. **DeepFakes & Face Synthesis**
5. **Text-to-Image Synthesis**
6. **3D Object Generation**
7. **Video Prediction & Generation**
8. **Medical Image Synthesis & Enhancement**
9. **Music & Audio Generation**
10. **Anomaly Detection & Fraud Detection**

Variational Autoencoders (VAEs)

🔹 **Definition:**

- **VAEs are another type of generative model that learns a compressed representation of data and generates new data samples from it.**
- **Unlike GANs, VAEs use probabilistic encoding and decoding.**

🔹 **How VAEs Work:**

1️⃣ **Encoder – Compresses input data into a smaller representation (latent space).**
2️⃣ **Latent Space – Represents different variations of the input.**
3️⃣ **Decoder – Reconstructs realistic data from latent space.**

🔹 **Example:** VAEs can generate new handwritten digits that resemble real ones but are not exact copies.

🔹 **Application:** *VAEs are used in medical imaging, speech synthesis, and text generation.*

Other Generative Models

Model	Description	Example
Autoregressive Models	Predict the next value in a sequence	GPT (text generation)
Flow-Based Models	Learn transformations from simple to complex distributions	RealNVP (image generation)
Energy-Based Models	Use energy functions to model distributions	Restricted Boltzmann Machines

4️⃣ *Challenges with Generative Models*

📌 *1. Training Instability*

- *GANs require **careful balancing** between the Generator and Discriminator.*
- *If the **Discriminator gets too strong**, the Generator stops learning.*

📌 *2. Mode Collapse*

- *The Generator **fails to generate diverse outputs** and produces **repetitive samples**.*
- *Example: A face-generating GAN only produces **male faces** instead of both male and female faces.*

📌 *3. High Computational Cost*

- *Training generative models **requires high-end GPUs/TPUs**.*
- *Example: Training **StyleGAN** to generate human faces takes **days to weeks** on powerful hardware.*

📌 *4. Difficult Evaluation Metrics*

- *Unlike classifiers, evaluating generative models is **subjective**.*
- *Common metrics:*
  ✅ ***FID (Fréchet Inception Distance)** – Measures how close generated images are to*

real ones.
✅ ***Inception Score (IS)*** *– Evaluates image* ***diversity and quality****.*

📌 *5. Ethical Concerns*

- *Generative models can be used to create* ***deep fakes, misinformation, and fake identities****.*
- *Example:* ***Fake news articles generated by AI****.*

💡 *Despite these challenges, advancements in GANs and VAEs continue to improve generative AI applications.*

Gaussian Mixture Models

Gaussian Mixture Models (GMMs) are probabilistic models used for representing data that is assumed to be generated from a mixture of several Gaussian distributions. Here are some key points about GMMs:

1. **Definition**:
    - GMMs are a type of unsupervised learning algorithm that models the probability distribution of data as a weighted sum of multiple Gaussian distributions.
2. **Components**:
    - **Gaussian Distributions**: Each component in the mixture is a Gaussian (normal) distribution with its own mean and variance.
    - **Weights**: Each Gaussian component has a weight that represents the probability of that component generating a data point.
3. **Parameters**:
    - The parameters of a GMM include the means, variances (or covariances for multivariate data), and weights of the Gaussian components.
4. **Expectation-Maximization (EM) Algorithm**:
    - GMMs are typically trained using the EM algorithm, which iteratively estimates the parameters of the Gaussian components.
    - **E-step**: Estimates the probability that each data point belongs to each Gaussian component.
    - **M-step**: Updates the parameters of the Gaussian components based on these probabilities.
5. **Applications**:
    - **Clustering**: GMMs can be used for clustering data points into different groups based on their probability distributions.
    - **Density Estimation**: GMMs can model the probability density function of data, which is useful for anomaly detection and generating new data points.

    - **Speech Recognition**: GMMs are used in modeling the distribution of speech features for speaker identification and speech recognition.
    - **Image Segmentation**: GMMs can be used to segment images into different regions based on pixel intensity distributions.
6. **Advantages**:
    - Flexibility: GMMs can model complex data distributions by combining multiple Gaussian components.
    - Probabilistic Framework: Provides a probabilistic approach to clustering and density estimation.
7. **Limitations**:
    - Sensitivity to Initialization: The EM algorithm can converge to local optima, making the results sensitive to initial parameter values.
    - Computational Complexity: Training GMMs can be computationally expensive, especially for high-dimensional data.

GMMs are a powerful tool in machine learning and statistics, offering a flexible and probabilistic approach to modeling complex data distributions.

HMM(Hidden Markov Model)

A **Hidden Markov Model (HMM)** is a statistical model used to represent systems that transition between states in a probabilistic manner. It is widely used in artificial intelligence, machine learning, and pattern recognition. HMMs are particularly useful for modeling sequential data where the underlying process is assumed to be a Markov process with hidden (unobserved) states.

Key Components of an HMM

1. **States (Hidden States)**:
    - These are the unobservable states of the system. The system is assumed to be in one of these states at any given time.
    - Example: In weather prediction, states could be "Sunny," "Cloudy," or "Rainy."
2. **Observations**:
    - These are the visible outputs or emissions that depend on the hidden states.

    - Example: If the hidden state is "Rainy," the observation could be "Carrying an umbrella."
3. **State Transition Probability Matrix (A)**:
    - This matrix defines the probability of transitioning from one state to another.
    - Example: The probability of transitioning from "Sunny" to "Rainy" might be 0.1.
4. **Emission Probability Matrix (B)**:
    - This matrix defines the probability of an observation being generated from a particular state.
    - Example: The probability of "Carrying an umbrella" given the state is "Rainy" might be 0.8.
5. **Initial State Probability Distribution (π)**:
    - This defines the probability of the system starting in each state.
    - Example: The probability of the day starting as "Sunny" might be 0.6.

Working of an HMM

1. **Initialization**:
    - The system starts in an initial state based on the initial state probability distribution (π).
2. **State Transition**:
    - At each time step, the system transitions to a new state based on the state transition probability matrix (A).
3. **Emission of Observations**:
    - After transitioning to a new state, the system emits an observation based on the emission probability matrix (B).
4. **Sequence Generation**:
    - This process repeats over time, generating a sequence of hidden states and corresponding observations.

Example of an HMM

Scenario: Weather Prediction

- **Hidden States**: {Sunny, Cloudy, Rainy}
- **Observations**: {Carrying an umbrella, Not carrying an umbrella}

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- **State Transition Matrix (A)**:

	Sunny	Cloudy	Rainy
Sunny	0.7	0.2	0.1
Cloudy	0.3	0.5	0.2
Rainy	0.2	0.3	0.5

- **Emission Matrix (B)**:

	Umbrella	No Umbrella
Sunny	0.1	0.9
Cloudy	0.3	0.7
Rainy	0.8	0.2

- **Initial State Distribution (π)**:

  Sunny: 0.6, Cloudy: 0.3, Rainy: 0.1

Sequence Generation

1. Start with an initial state (e.g., "Sunny").
2. Transition to a new state based on the transition matrix (e.g., "Sunny" → "Cloudy").
3. Emit an observation based on the emission matrix (e.g., "Cloudy" → "No Umbrella").
4. Repeat the process to generate a sequence of observations.

Applications of HMMs

1. **Speech Recognition**:
   - HMMs are used to model phonemes and words in speech signals.
   - Example: Google Assistant, Siri.
2. **Natural Language Processing (NLP)**:
   - Used for part-of-speech tagging, named entity recognition, and text segmentation.
3. **Bioinformatics**:
   - Used for DNA sequence analysis, protein structure prediction, and gene finding.

4. **Finance**:
    - Used for stock market prediction and modeling financial time series.
5. **Gesture Recognition**:
    - Used in computer vision to recognize gestures or movements.
6. **Robotics**:
    - Used for robot localization and mapping.

Advantages of HMMs

1. **Efficient for Sequential Data**:
    - HMMs are well-suited for modeling sequential data like time series, speech, and text.
2. **Probabilistic Framework**:
    - Provides a probabilistic approach to handle uncertainty in observations and states.
3. **Wide Range of Applications**:
    - Versatile and applicable in various domains like speech recognition, bioinformatics, and finance.
4. **Mathematically Sound**:
    - Based on well-established statistical principles.

Disadvantages of HMMs

1. **Assumption of Markov Property**:
    - HMMs assume that the next state depends only on the current state, which may not always be true.
2. **Limited Representation Power**:
    - HMMs struggle to model long-term dependencies in data.
3. **Scalability Issues**:
    - For large state spaces, the computation of probabilities becomes computationally expensive.
4. **Difficulty in Training**:
    - Requires a large amount of labeled data for training, and the Baum-Welch algorithm (EM algorithm) can get stuck in local optima.
5. **Sensitivity to Initial Parameters**:
    - The performance of HMMs can be highly dependent on the initial choice of parameters.

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Bayesian Networks

- Bayesian Belief Networks is a key computer technology for dealing with probabilistic events and to solve problems which have uncertainty.
- Bayesian network is defined as "**A Bayesian Network is a probabilistic graphical model which represents a set of variables and their conditional dependencies through a directed acyclic graph.**" It is also called the Bayes network, belief network, decision network or Bayesian model.
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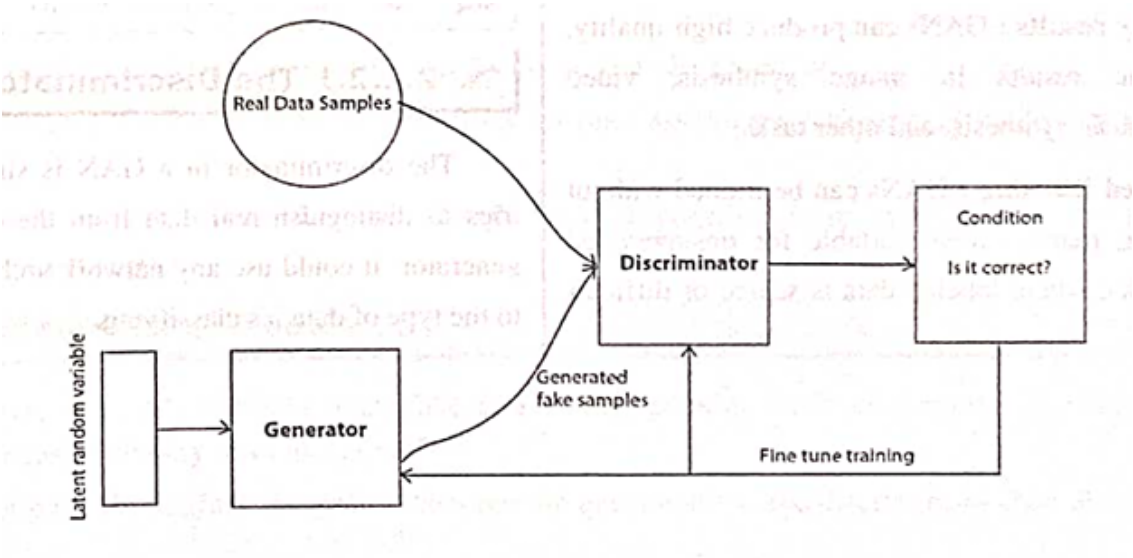
Generative Adversarial Networks (GANs) architecture

Generative Adversarial Network (GAN) Architecture

- A generative adversarial network (GAN) is a machine learning (ML) model in which two neural networks compete with each other by using deep learning methods to become more accurate in their predictions.
- GANs typically run unsupervised and use a cooperative zero-sum game framework to learn, where one person's gain equals another person's loss.
- The two neural networks that make up a GAN are referred to as the generator and the discriminator. The generator is a convolutional neural network and the discriminator is a deconvolutional neural network.

- The goal of the generator is to artificially manufacture outputs that could easily be mistaken for real data. The goal of the discriminator is to identify which of the outputs it receives have been artificially created.



- **Mathematical Formulation**

The objective function of GANs is based on a **min-max optimization** problem:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x \sim P_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim P_z(z)}[\log(1 - D(G(z)))]$$

where:

- x is real data sampled from the actual data distribution $P_{data}(x)$.
- z is random noise sampled from a prior distribution $P_z(z)$.
- $G(z)$ is the fake data generated by the Generator.
- $D(x)$ and $D(G(z))$ are the probabilities assigned by the Discriminator to real and fake data, respectively.

Advantages of Generative Adversarial Networks (GANs)

1. **Synthetic data generation**: GANs can generate new, synthetic data that resembles some known data distribution, which can be useful for data augmentation, anomaly detection, or creative applications.

2. **High-quality results**: GANs can produce high-quality, photorealistic results in image synthesis, video synthesis, music synthesis, and other tasks.
3. **Unsupervised learning**: GANs can be trained without labeled data, making them suitable for unsupervised learning tasks, where labeled data is scarce or difficult to obtain.
4. **Versatility**: GANs can be applied to a wide range of tasks, including image synthesis, text-to-image synthesis, image-to-image translation, anomaly detection, data augmentation, and others.

Disadvantages of Generative Adversarial Networks (GANs)

1. **Training Instability**: GANs can be difficult to train, with the risk of instability, mode collapse, or failure to converge.
2. **Computational Cost**: GANs can require a lot of computational resources and can be slow to train, especially for high-resolution images or large datasets.
3. **Overfitting**: GANs can overfit the training data, producing synthetic data that is too similar to the training data and lacking diversity.
4. **Bias and Fairness**: GANs can reflect the biases and unfairness present in the training data, leading to discriminatory or biased synthetic data.
5. **Interpretability and Accountability**: GANs can be opaque and difficult to interpret or explain, making it challenging to ensure accountability, transparency, or fairness in their applications.

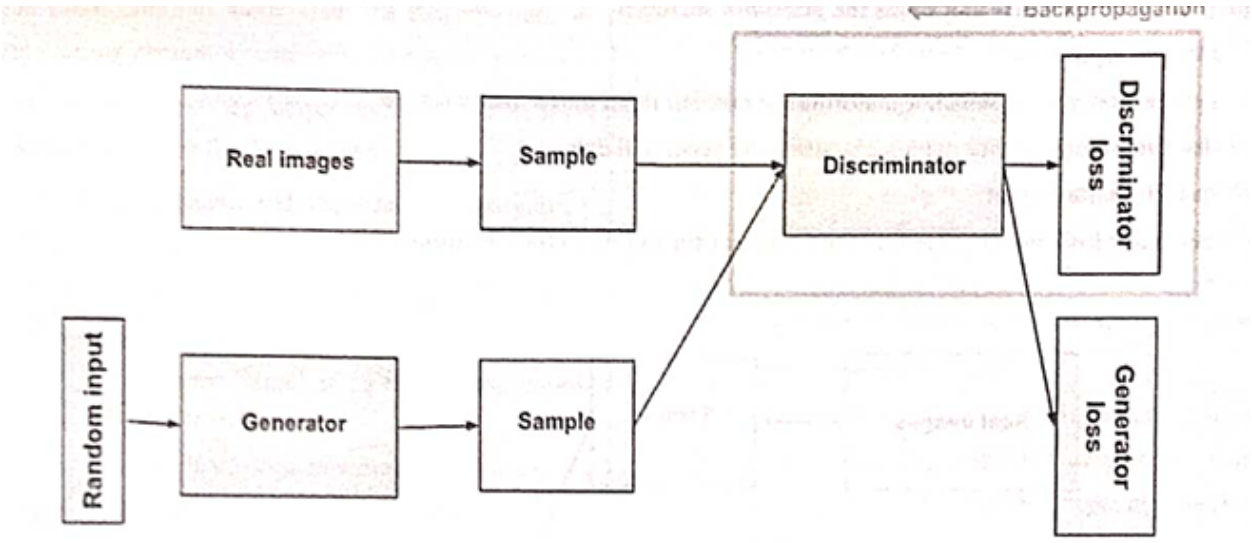


Fig. 2.1.2 : Generator Discriminator Architecture

The Discriminator Model

- The discriminator in a GAN is a classifier that distinguishes real data from data created by the generator.
- It can use any network architecture suitable for the type of data it is classifying.

Discriminator Training Data

- The discriminator's training data comes from two sources:
    - **Real data instances**: Used as positive examples during training (e.g., real pictures of people).
    - **Fake data instances**: Created by the generator and used as negative examples during training.
- During discriminator training, the generator does not train; its weights remain constant while it produces examples for the discriminator.

Training the Discriminator

- The discriminator connects to two loss functions but only uses the discriminator loss during its training.
- Steps during discriminator training:
    1. The discriminator classifies both real and fake data.
    2. The discriminator loss penalizes misclassifications (e.g., classifying real data as fake or fake data as real).
    3. The discriminator updates its weights through backpropagation based on the discriminator loss.

The Generator Model

- The generator in a GAN learns to create fake data by incorporating feedback from the discriminator.
- Its goal is to make the discriminator classify its output as real.
- Generator training requires tighter integration between the generator and the discriminator compared to discriminator training.

Generator Training

- The generator learns to create fake data by receiving feedback from the discriminator.
- It aims to produce data that the discriminator classifies as real.

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- Generator training involves:
    - Random input.
    - The generator network, which transforms the random input into a data instance.
    - The discriminator network, which classifies the generated data.
    - The generator loss, which penalizes the generator for failing to fool the discriminator.

Key Components of GAN Training

- **Discriminator Loss**: Used during discriminator training to improve classification accuracy.
- **Generator Loss**: Used during generator training to improve the quality of generated data.
- **Integration**: Generator training requires close interaction with the discriminator to refine its outputs.

Training GANs

1. **Alternating Training**:
    - GAN training alternates between training the discriminator and the generator.
    - **Discriminator Training**: The discriminator is trained for one or more epochs to distinguish between real data and fake data generated by the generator. The generator's weights remain fixed during this phase.
    - **Generator Training**: The generator is trained for one or more epochs to produce data that fools the discriminator. The discriminator's weights remain fixed during this phase.
    - This alternating process continues iteratively to improve both networks.
2. **Generator Training Process**:
    - Sample random noise as input.
    - Generate fake data from the noise using the generator.
    - Pass the generated data to the discriminator for classification ("Real" or "Fake").
    - Calculate the loss based on the discriminator's classification.
    - Backpropagate the loss to update only the generator's weights.
3. **Convergence**:
    - As the generator improves, the discriminator's ability to distinguish real from fake data decreases.
    - Ideally, the discriminator's accuracy drops to 50% (random guessing), indicating the generator is producing highly realistic data.

    - However, if training continues beyond this point, the generator may start receiving meaningless feedback, leading to a collapse in the quality of generated data.
4. **Key Points**:
    - The discriminator and generator are trained separately but depend on each other's feedback.
    - The generator aims to produce data indistinguishable from real data, while the discriminator aims to correctly classify real vs. fake data.
    - Proper balance and alternating training are crucial for successful GAN convergence.

This alternating training process allows GANs to tackle complex generative tasks by breaking them into simpler classification problems.

EXTRA

Probability Theory: An Overview

Probability theory is a branch of mathematics that deals with uncertainty and randomness. It provides a framework for modeling and analyzing uncertain events and their outcomes. Probability theory is essential in various fields, including statistics, machine learning, physics, economics, and more.

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1. Sample Space and Events

Sample Space (S):

The sample space is the set of all possible outcomes of a random experiment. It is denoted by **S**.

Event (E):

An event is a subset of the sample space, representing a particular outcome or a combination of outcomes.

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2. Probability of an Event

The probability of an event **E**, denoted as **P(E)**, is a measure of the likelihood that event **E** will occur.

- Probability values range from **0** (impossible event) to **1** (certain event).

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3. Probability Axioms

Probability theory is based on three fundamental axioms:

- **Non-Negativity:** For any event E, the probability **P(E)** is greater than or equal to 0:
  $P(E) \geq 0$.
- **Normalization:** The probability of the entire sample space is 1:
  $P(S) = 1$.
- **Additivity:** For a sequence of mutually exclusive events (events that cannot occur simultaneously), the probability of the union of these events is the sum of their individual probabilities:
  $P(E_1 \cup E_2) = P(E_1) + P(E_2)$.

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4. Complementary Probability

The probability of the complement of an event E (not E) is given by:
$P(\text{not } E) = 1 - P(E)$.

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5. Conditional Probability

- Conditional probability measures the probability of one event happening given that another event has already occurred.
- It is denoted as **$P(A \mid B)$**, where **A** is the event of interest, and **B** is the event that has already occurred.
- The formula for conditional probability is:
  $P(A \mid B) = P(A \cap B) / P(B)$, where $P(B) > 0$.

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6. Independence

- Two events **A** and **B** are independent if the occurrence of one event does not affect the probability of the other event.
- Mathematically,
  P(A | B) = P(A)
  and
  P(B | A) = P(B) if A and B are independent.

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7. Multiplication Rule

The probability of two events **A** and **B** occurring together (joint probability) is given by:

- **P(A ∩ B) = P(A) * P(B | A)**
  or
  P(B) * P(A | B).

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8. Bayes' Theorem

- Bayes' Theorem is a fundamental formula in probability theory that relates conditional probabilities. It is used for updating beliefs based on new evidence.
- It is expressed as:
  P(A | B) = [P(B | A) * P(A)] / P(B).