Generative AI for Beginners

Agenda

In this session, we will learn –

- Fundamentals of Artificial Intelligence

- Basics of Machine Learning

- Introduction to Neural Networks

- Deep Learning Overview

- Large Language Models

- Generative AI Concepts

- Generative Models in AI

- Mathematical Foundations of Generative AI

- Summary

Fundamentals of Artificial Intelligence

AI Fundamentals

- **Defining AI: Computational Intelligence**
    - AI is the creation of algorithms enabling machines to perform tasks requiring human-like intelligence.
    - AI's capabilities include data interpretation, pattern recognition, and decision-making processes.
    - AI's capacity to learn from data, reason out solutions, and perceive environments through sensors.

AI Evolution and Milestones

- **Early AI: Theoretical Beginnings to Initial Models**
  - Tracing AI's roots from Turing's era to its first practical applications in neural networks.
  - The journey through AI winters and technological advancements leading to modern AI capabilities.
- **Contemporary AI: Data-Driven and Deep Learning Paradigms**
  - Highlighting the role of big data and advanced neural networks in shaping today's AI landscape.

AI Types: Narrow vs. General

- **Narrow AI: Specialized and Task-Focused**
  - Focused AI systems designed for specific tasks, exemplified in applications like language translation and game-playing AI.
- **General AI: The Aspiration**
  - The concept of General AI and its goal to replicate broad, human-like cognitive abilities.

AI in the Modern World

- **Everyday Applications of AI**
  - The integration of AI in daily life, evident in digital assistants, smart appliances, and user interface technologies.
- **Invisible Yet Impactful AI**
  - AI's significant yet less visible roles in sectors like finance, logistics, and cybersecurity.

Industry Revolution Through AI

- **AI's Business Transformation**
  - AI's role in revolutionizing business operations, from automated manufacturing to AI-driven strategic analysis.
- **AI in Healthcare: Transformative Innovations**
  - The critical role of AI in advancing healthcare, including diagnostic accuracy and personalized treatment plans.

Limitations and Challenges of Current AI

- **Recognizing the Limitations of Contemporary AI Systems**
  - Addressing AI's dependency on data quality, issues with context recognition, and ethical considerations.
- **Human Oversight in AI Implementation**
  - The critical need for human intervention and judgment in the application and governance of AI systems.

Future Trends in AI Technology

- **AI's Potential in Addressing Global Challenges**
  - Anticipating AI's role in solving complex global issues, such as climate change and resource management.
- **Adapting to an AI-Enhanced Society**
  - Strategies for societal adaptation to AI advancements, emphasizing the importance of policy development and education.

Basics of Machine Learning

Machine Learning: Core Concepts

- **What is Machine Learning?**
  - Machine Learning is a branch of AI where algorithms learn from data to make predictions or decisions.
  - It's an approach to achieve AI through systems that improve with experience.
  - ML algorithms analyze historical data to uncover patterns and insights.
  - These algorithms adjust and improve over time with new data.
  - ML involves transforming data inputs into meaningful outputs or decisions.
  - The accuracy of ML algorithms increases with more data and experience.
  - ML enables automation of decision-making processes in various applications.

Types of Machine Learning

- **Supervised Learning: Labeled Data**
  - Supervised learning uses labeled datasets to train algorithms.
  - Applications: Email spam filtering, speech recognition.

- **Unsupervised Learning: Discovering Patterns**
  - Unsupervised learning finds hidden patterns or structures in unlabeled data.
  - Applications: Customer segmentation, anomaly detection.

- **Semi-Supervised Learning: A Mix**
  - Semi-supervised learning uses a mix of labeled and unlabeled data for training.
  - Applications: Large-scale content classification.

- **Reinforcement Learning: Learning by Doing**
  - Reinforcement learning is about taking actions and learning from the results.
  - Applications: Robotics, gaming strategies.

Machine Learning Algorithms

- **Classification Algorithms**
  - Used for categorizing data into predefined classes.
  - Example: Decision Trees, Support Vector Machines.
- **Regression Algorithms**
  - Predict continuous outcomes based on input variables.
  - Example: Linear Regression, Polynomial Regression.
- **Clustering Algorithms**
  - Group similar data points together.
  - Example: K-Means, Hierarchical Clustering.

Machine Learning Algorithms

- **Dimensionality Reduction**
  - Reduces the number of input variables.
  - Example: Principal Component Analysis, t-SNE.
- **Ensemble Methods**
  - Combine multiple algorithms for better performance.
  - Example: Random Forests, Gradient Boosting.
- **Neural Networks and Deep Learning**
  - Advanced algorithms modeled after the human brain.
  - Example: Convolutional Neural Networks, Recurrent Neural Networks.

Neural Networks in ML

- **Understanding Neural Networks**
  - Composed of layers of interconnected nodes or neurons.
  - Excel in identifying patterns in complex data.
- **Layers in Neural Networks**
  - Include input, hidden, and output layers.
- **Activation Functions**
  - Functions that decide whether a neuron should be activated.
  - Example: ReLU, Sigmoid, Tanh.
- **Backpropagation in Learning**
  - The process of adjusting weights in the network based on the error rate.
- **Deep Learning: A Subset of ML**
  - Involves neural networks with multiple hidden layers.
- **Applications of Neural Networks**
  - Image and speech recognition, natural language processing.

Evaluating Machine Learning Models

- **Accuracy and Precision Metrics**
  - Accuracy measures the overall correctness of the model, while precision focuses on the relevancy of results.
- **Recall and F1-Score**
  - Recall measures the model's ability to detect all relevant instances, and F1-Score balances precision and recall.
- **Confusion Matrix**
  - A table used to describe the performance of a classification model.
- **Cross-Validation Techniques**
  - Methods to evaluate the robustness of ML models, like k-fold cross-validation.
- **Overfitting and Underfitting**
  - Overfitting is when a model learns the training data too well, underfitting is when it doesn't learn enough.
- **Regularization Techniques**
  - Techniques like Lasso and Ridge used to prevent overfitting.

Application - Machine Learning

- **Personalization Algorithms**

  - Tailoring user experiences on platforms like Netflix and Spotify.

- **Predictive Analytics**

  - Forecasting trends and behaviors in various industries.

- **Autonomous Systems**

  - Powering self-driving cars and automated drones.

- **Advanced Healthcare Applications**

  - Assisting in early disease detection and treatment plans.

- **Natural Language Processing**

  - Enhancing language translation and virtual assistants.

- **Fraud Detection Systems**

  - Identifying fraudulent activities in finance and banking.

Challenges in Machine Learning

- **Data Quality Issues**
  - Poor or biased data can lead to inaccurate models.
- **Quantity of Training Data**
  - Insufficient data can hinder the model's ability to learn effectively.
- **Algorithm Complexity**
  - Complex models require greater computational resources and expertise.
- **Model Interpretability**
  - Understanding how and why a model makes certain decisions.
- **Ethical and Bias Concerns**
  - Ensuring fairness and ethical considerations in ML models.
- **Staying Current with Evolving Technologies**
  - The field of ML is rapidly evolving, requiring continuous learning and adaptation.

Introduction to Neural Networks

Introduction to Neural Networks

- **Neural Networks: Mimicking the Human Brain**
  - Neural networks are a set of algorithms, modeled loosely after the human brain, designed to recognize patterns and interpret sensory data.
  - They consist of layers of interconnected nodes (neurons) that process data in a structured and hierarchical manner.

- **The Structure of Neural Networks**
  - A typical neural network consists of an input layer, one or more hidden layers, and an output layer.
  - Each layer contains nodes or neurons, where the actual processing happens through weighted connections.

- **Function of Neurons**
  - Neurons in a neural network process input data, apply activation functions, and pass the output to the next layer.
  - Activation functions like ReLU or Sigmoid determine whether a neuron should be activated based on the input received.

Introduction to Neural Networks

- **Learning in Neural Networks**
  - Neural networks learn by adjusting weights based on the error of their predictions during the training process.
  - This learning process involves backpropagation and gradient descent to minimize the error rate.
- **Types of Neural Networks**
  - There are various types of neural networks, including Convolutional Neural Networks (CNNs) for image processing and Recurrent Neural Networks (RNNs) for sequential data.
- **Applications of Neural Networks**
  - Neural networks are used in a variety of applications, such as image and speech recognition, natural language processing, and autonomous vehicles.

Brief of Deep Learning Concepts

- **What is Deep Learning?**
  - Deep Learning is a subset of Machine Learning where neural networks with many layers (deep neural networks) are used.
  - It excels at processing and learning from large amounts of complex, unstructured data.
- **Deep Neural Networks**
  - Deep neural networks have multiple hidden layers, allowing them to learn complex patterns and perform sophisticated tasks.
  - Each layer extracts different features from the input data, building a detailed understanding of it.
- **Advantages of Deep Learning**
  - Deep Learning models can automatically and effectively learn feature representations from raw data, reducing the need for manual feature extraction.
  - These models scale well with data and become more accurate as the size of the dataset increases.

Deep Learning Concepts

- **Challenges in Deep Learning**
  - Deep Learning requires substantial computational power and large datasets, which can be resource-intensive.
  - Models can become 'black boxes,' making it challenging to interpret how decisions are made.
- **Training Deep Learning Models**
  - Training involves using large datasets to teach models to recognize patterns and make decisions.
  - The training process is computationally expensive and requires sophisticated optimization techniques.
- **Deep Learning in Practice**
  - Practical applications include language translation services, medical diagnosis from imaging, and advanced recommendation systems.

Convolutional Neural Networks (CNNs)

- **Understanding CNNs**
  - CNNs are specialized neural networks for processing data with a grid-like topology, such as images.
  - They use convolutional layers to automatically and adaptively learn spatial hierarchies of features from input images.
- **Architecture of CNNs**
  - The architecture typically includes convolutional layers, pooling layers, and fully connected layers.
  - Each layer in a CNN transforms the input volume to a different volume through its learned weights.
- **Convolutional Layers**
  - Convolutional layers apply a convolution operation to the input, passing the result to the next layer.
  - These layers help the network to focus on small regions of the input and recognize local patterns.

Convolutional Neural Networks (CNNs)

- **Pooling Layers**
  - Pooling layers reduce the spatial size of the representation, decreasing the number of parameters and computation in the network.
  - Common pooling operations include max pooling and average pooling.
- **Feature Learning in CNNs**
  - CNNs learn to identify and recognize features, such as edges in the initial layers and more complex shapes and objects in deeper layers.
- **CNN Applications**
  - Widely used in image and video recognition, image classification, medical image analysis, and facial recognition.

Recurrent Neural Networks (RNNs)

- **RNNs: Specialized for Sequential Data**
  - RNNs are designed to recognize patterns in sequences of data, such as text, genomes, or time series data.
  - They are capable of remembering previous inputs in memory, using them to influence the output.
- **Architecture of RNNs**
  - Unlike standard neural networks, RNNs have a loop that allows information to persist across layers.
  - Each neuron in an RNN can use information from previous steps, making them ideal for sequential data.
- **Challenges with Traditional RNNs**
  - Traditional RNNs often struggle with long-term dependencies, making it hard to retain information from earlier steps as the sequence gets longer.
  - This issue is often addressed with advanced RNNs like LSTMs and GRUs.

Recurrent Neural Networks (RNNs)

- **Long Short-Term Memory Networks (LSTMs)**
  - LSTMs are a type of RNN that are better at remembering long-term dependencies, using gates to control the flow of information.
  - They are particularly effective for applications like speech recognition and language translation.
- **Gated Recurrent Units (GRUs)**
  - GRUs are a variant of LSTMs that use a simplified gating mechanism and have fewer parameters.
  - They are used in similar applications as LSTMs and often offer comparable performance with reduced complexity.
- **Applications of RNNs**
  - RNNs are used in language modeling, text generation, speech recognition, and other tasks involving sequential data.

Deep Learning Overview

Core Concepts of Deep Learning

- Definition: Deep Learning is a subset of machine learning that uses artificial neural networks to simulate human-like decision-making processes.
- Neural Networks: It involves the use of deep neural networks with multiple layers to learn and make predictions. Deep learning relies on interconnected layers of artificial neurons to process and learn from data.
- Training Data: Deep learning models require large datasets for training to improve accuracy.
- Backpropagation: This is the process by which neural networks adjust their parameters to minimize errors.
- Activation Functions: Activation functions introduce non-linearity into the model, enabling complex mapping of inputs to outputs.

Key Features of Deep Learning Systems

- Feature Extraction: Deep learning systems automatically learn and extract relevant features from raw data.
- Scalability: They can handle large-scale data and complex tasks.
- Transfer Learning: Deep learning models can be pre-trained on one task and then fine-tuned for another, saving time and resources.
- High Accuracy: Deep learning models often achieve state-of-the-art accuracy in various applications.

Understanding Deep Learning's Importance

- Applications: Deep Learning is used in image and speech recognition, natural language processing, and autonomous vehicles.
- Innovation Driver: It has revolutionized fields like healthcare, finance, and entertainment.
- Future Relevance: Deep Learning is a critical technology for the future job market.

Real-World Examples

- Image Recognition: Deep learning powers image recognition in smartphones and security systems.
- Language Translation: Services like Google Translate use deep learning for language translation.
- Autonomous Vehicles: Self-driving cars rely on deep learning for perception and decision-making.

Large Language Models (LLMs)

Introduction to Large Language Models (LLMs)

- **Definition of LLMs**
  - Large Language Models are sophisticated AI systems designed to understand, generate, and interact with human language at scale.
  - They process vast amounts of textual data, learning patterns and nuances of language.
- **Evolution and Significance**
  - LLMs represent a significant leap in natural language processing, evolving from simple rule-based models to complex, deep learning systems.
  - Their development marks a paradigm shift in AI's ability to handle linguistic tasks.
- **Core Functionality**
  - LLMs excel in tasks like text generation, translation, and semantic analysis, owing to their extensive training on diverse language data.
  - They can contextually interpret and respond to language inputs with a high degree of accuracy.

Architecture and Design of LLMs

- **Transformer Models**
  - The backbone of modern LLMs is the transformer model, renowned for its ability to handle sequential data efficiently.
  - Transformers use self-attention mechanisms to process words in relation to all other words in a sentence, enhancing context understanding.
- **Training Mechanisms**
  - LLMs are trained using techniques like Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) to grasp language context and flow.
  - This training involves feeding massive text corpora, enabling the model to learn language structures and variations.

Architecture and Design of LLMs

- **Scalability and Parameters**
  - Modern LLMs like GPT-3 boast an unprecedented scale, with hundreds of billions of parameters, allowing nuanced language processing.
  - The scale of these models is a key factor in their ability to generate coherent, contextually relevant text.
- **Fine-Tuning for Specific Tasks**
  - While pretrained on general data, LLMs can be fine-tuned with specific datasets to excel in particular domains or languages.
  - This fine-tuning adapts the model to specialized tasks, from legal document analysis to creative writing.

Applications of Large Language Models

- **Content Creation and Writing Assistance**
  - LLMs are revolutionizing content creation, aiding in writing articles, scripts, and even poetry, often with minimal human input.
  - They offer writing assistance, improving style, grammar, and coherence in text.
- **Conversational AI and Chatbots**
  - Powering advanced chatbots, LLMs enable more natural, context-aware conversations in customer service and virtual assistance.
  - Their ability to understand and generate human-like responses makes them ideal for interactive applications.

Applications of Large Language Models

- **Language Translation and Localization**
  - LLMs drive sophisticated translation tools, handling complex linguistic nuances and idiomatic expressions effectively.
  - They're used for localizing content across different languages, making information more accessible globally.
- **Educational Tools and Learning**
  - In education, LLMs assist in personalized learning, language tutoring, and providing interactive educational content.
  - They can generate practice questions, explain concepts in various subjects, and offer language learning support.

Generative AI Concepts

Introduction to Generative AI

- **Defining Generative AI**
  - Generative AI refers to a subset of AI techniques and models that generate new data instances or content that resembles the training data.
  - Unlike conventional AI, which interprets or classifies data, Generative AI can create novel, realistic outputs, such as images, text, or sound.
- **Key Characteristics of Generative AI**
  - It learns from existing data to generate new data instances that can pass for real-world examples.
  - This technology is particularly adept at understanding and mimicking patterns, styles, and structures in the data it learns from.
- **The Training Process**
  - Generative models are trained using vast datasets, allowing them to capture the complexity and variability of real-world data.
  - The training involves teaching the model to understand and replicate the statistical properties of the input data.

Introduction to Generative AI

- **Applications of Generative AI**
  - Generative AI has diverse applications, from creating art and music to designing new pharmaceuticals and generating synthetic data for training other AI models.
  - Its ability to produce creative and complex outputs has opened new avenues in various fields, including entertainment, healthcare, and technology.
- **Benefits of Generative AI**
  - Offers the ability to automate creative processes, enhance data privacy through synthetic data generation, and assist in innovative product design.
  - It provides solutions where traditional data may be scarce or sensitive, enabling broader AI applications.
- **Challenges and Considerations**
  - Managing the unpredictability of generated content and ensuring ethical use of generative technology are major challenges.
  - The technology raises questions about authenticity, copyright, and ethical implications in content creation.

Generative vs. Discriminative Models

- **Understanding Discriminative Models**
  - Discriminative models predict labels or outcomes based on input data, focusing on differentiating between different classes or categories.
  - They are often used in classification and regression tasks, such as spam detection or price prediction.
- **Characteristics of Discriminative Models**
  - These models learn the boundaries between different classes in the dataset, enabling them to classify new instances effectively.
  - They usually require less computational power than generative models and are more straightforward in their interpretation.
- **Generative Models: A Deeper Dive**
  - Generative models learn the underlying structure and distribution of the data, enabling them to generate new instances.
  - They are capable of capturing complex patterns and generating outputs that closely mimic real-world data.

Generative vs. Discriminative Models

- **Comparison of Capabilities**
  - While discriminative models excel in classification accuracy, generative models offer versatility in creating new content and understanding complex data patterns.
  - The choice between generative and discriminative models depends on the specific task and the nature of the data.
- **Synergy in AI Systems**
  - Combining generative and discriminative models can lead to more robust AI systems, leveraging the strengths of both approaches.
  - For instance, generative models can create training data for discriminative models, enhancing their accuracy and performance.
- **Evolution of AI Modeling**
  - The evolution from purely discriminative to generative modeling signifies a shift towards more creative and autonomous AI capabilities.
  - This evolution reflects the growing complexity and sophistication of AI applications in today's world.

Generative Models in AI

Types of Generative Models in AI

- **Generative Adversarial Networks (GANs)**

  - GANs consist of two parts: a generator that creates images and a discriminator that evaluates them, in a continuous adversarial process.

  - This setup enables GANs to produce highly realistic images, as the generator constantly improves to create outputs that the discriminator can't distinguish from real images.

- **Variational Autoencoders (VAEs)**

  - VAEs are focused on encoding an input into a compressed representation and then reconstructing the input from this representation.

  - They are particularly effective in tasks requiring generation and modification of images, offering a balance between image quality and computational efficiency.

- **Comparison Between GANs and VAEs**

  - GANs are known for generating sharper images, while VAEs are often easier to train and offer more control over the generated outputs.

  - The choice between GANs and VAEs depends on the specific application and desired characteristics of the generated content.

Types of Generative Models in AI

- **Applications of GANs**
  - GANs are used in a variety of creative applications, including art creation, photo-realistic image generation, and style transfer.
  - They are also employed in data augmentation, where they generate new data samples for training machine learning models.
- **Applications of VAEs**
  - VAEs are commonly used in image denoising, anomaly detection, and generative tasks where modeling the distribution of data is crucial.
  - Their ability to learn latent representations makes them suitable for applications like facial recognition and feature extraction.
- **Emerging Trends in Generative Models**
  - Newer types of generative models are emerging, combining the strengths of GANs and VAEs and exploring novel architectures for more efficient and diverse content generation.
  - Research is increasingly focusing on improving the stability and scalability of these models for more practical and widespread applications.

Theoretical Aspects of Generative Models

- **Understanding the Underlying Mathematics**
  - Generative models are grounded in complex mathematical concepts like probability distribution, statistical modeling, and optimization.
  - They aim to learn the probability distribution of the training data, enabling them to generate new data points that follow the same distribution.
- **Training and Optimization Challenges**
  - Training generative models involves dealing with challenges like mode collapse in GANs and ensuring adequate variability in the outputs.
  - Optimization techniques such as gradient descent and backpropagation are crucial in refining these models.
- **Latent Space Representation**
  - Generative models, especially VAEs, operate by mapping input data to a lower-dimensional latent space, capturing the essence of the data.
  - This latent space representation is key to manipulating and generating new content with desired characteristics.

Theoretical Aspects of Generative Models

- **Evaluation of Generative Models**
  - Evaluating generative models is complex and often subjective, as it involves assessing the quality and diversity of generated content.
  - Metrics like Inception Score and Fréchet Inception Distance are used to quantitatively assess the performance of these models.
- **Ethical Considerations and Misuse**
  - The potential misuse of generative models, particularly in creating deepfakes, raises significant ethical concerns.
  - Ensuring responsible use and developing ethical guidelines for generative AI is an ongoing challenge in the field.
- **Future Directions in Generative Model Research**
  - Research is focusing on creating more robust, diverse, and efficient generative models, with applications expanding into more complex domains like 3D content generation and interactive media.
  - There's also a growing emphasis on addressing the ethical implications and ensuring the beneficial use of generative AI technologies.

Mathematical Foundations of Generative AI

Probability and Statistics in Generative AI

- **Role of Probability in Generative AI**
  - Probability theory is central to Generative AI, as it deals with modeling uncertainty and variability in data.
  - Generative models use probabilistic approaches to learn the distribution of training data and to generate new data points that follow this learned distribution.
- **Statistics: Understanding Data Distributions**
  - Statistical analysis helps in understanding and characterizing the data distributions that generative models aim to replicate.
  - Techniques like mean, variance, and standard deviation provide insights into the central tendencies and spread of data, crucial for model training.
- **Bayesian Inference in Generative Models**
  - Bayesian methods provide a framework for updating the model's beliefs about data distributions based on observed data.
  - This approach is particularly useful in generative models for incorporating prior knowledge and handling uncertainty.

Probability and Statistics in Generative AI

- **Random Variables and Distribution Functions**
  - Generative AI heavily relies on the concept of random variables and their probability distribution functions to model data generation processes.
  - Understanding different types of distributions (like Gaussian, Poisson, etc.) is essential for designing and training effective generative models.
- **Sampling Methods**
  - Sampling from complex distributions is a key technique in Generative AI for generating new data instances.
  - Methods like Monte Carlo sampling and Markov Chain Monte Carlo (MCMC) are used to approximate distributions when direct sampling is not feasible.
- **Estimation and Hypothesis Testing**
  - Estimation techniques are used to determine model parameters, while hypothesis testing helps in validating the assumptions made by the model.
  - These statistical methods ensure the reliability and robustness of the generative models.

Theoretical Frameworks of Generative AI Models

- **Information Theory in Generative AI**
  - Information theory concepts like entropy and information gain play a significant role in understanding and optimizing generative models.
  - These concepts help in quantifying the amount of information generated models can capture and reproduce.

- **Machine Learning Algorithms in Generative AI**
  - Generative AI models often build upon foundational machine learning algorithms, adapting them for generative tasks.
  - Understanding these algorithms, including decision trees, neural networks, and support vector machines, is crucial for developing generative models.

- **Deep Learning Architectures**
  - The architecture of deep learning models, particularly those used in generative tasks like GANs and VAEs, is based on complex mathematical and computational principles.
  - Understanding these architectures requires a grasp of concepts like convolution, pooling, and the functioning of neural networks.

Theoretical Frameworks of Generative AI Models

- **Optimization Techniques**
  - Optimization is key in training generative models, involving techniques to find the best parameters for the model to accurately generate new data.
  - Concepts like gradient descent, backpropagation, and learning rate adjustments are fundamental in this process.
- **Regularization and Overfitting**
  - Regularization techniques are used to prevent overfitting, ensuring that generative models generalize well to new, unseen data.
  - Techniques such as dropout, L1/L2 regularization, and early stopping are important in maintaining the model's ability to generate diverse and realistic outputs.
- **Theoretical Limits and Trade-offs**
  - Generative AI involves trade-offs between accuracy, computational efficiency, and the ability to generalize.
  - Understanding these trade-offs and the theoretical limits of generative models is essential for their effective application.

Summary - Generative AI for Beginners

Summary

- AI encompasses systems designed to mimic human intelligence through learning, reasoning, and self-correction.
- Machine Learning is the science of getting computers to learn and act like humans do and improve their learning over time in autonomous fashion by feeding them data and information in the form of observations and real-world interactions.
- Neural networks are a series of algorithms that mimic the operations of a human brain to recognize relationships between vast amounts of data.
- Deep Learning is a subset of ML based on artificial neural networks, with representation learning that transforms inputs through layers to derive meaning.
- Large Language Models are advanced AI tools capable of processing and generating human-like text based on the training from extensive textual datasets.
- Generative AI refers to the AI methods capable of generating new content by learning from existing data patterns.
- Generative models in AI are algorithms that can create new data instances similar to but distinct from the original datasets.
- The mathematical foundations of Generative AI encompass the statistical and probabilistic theories that allow models to generate data with inherent patterns of the training set.