Introduction to Generative AI

Generative AI and Prompt Engineering

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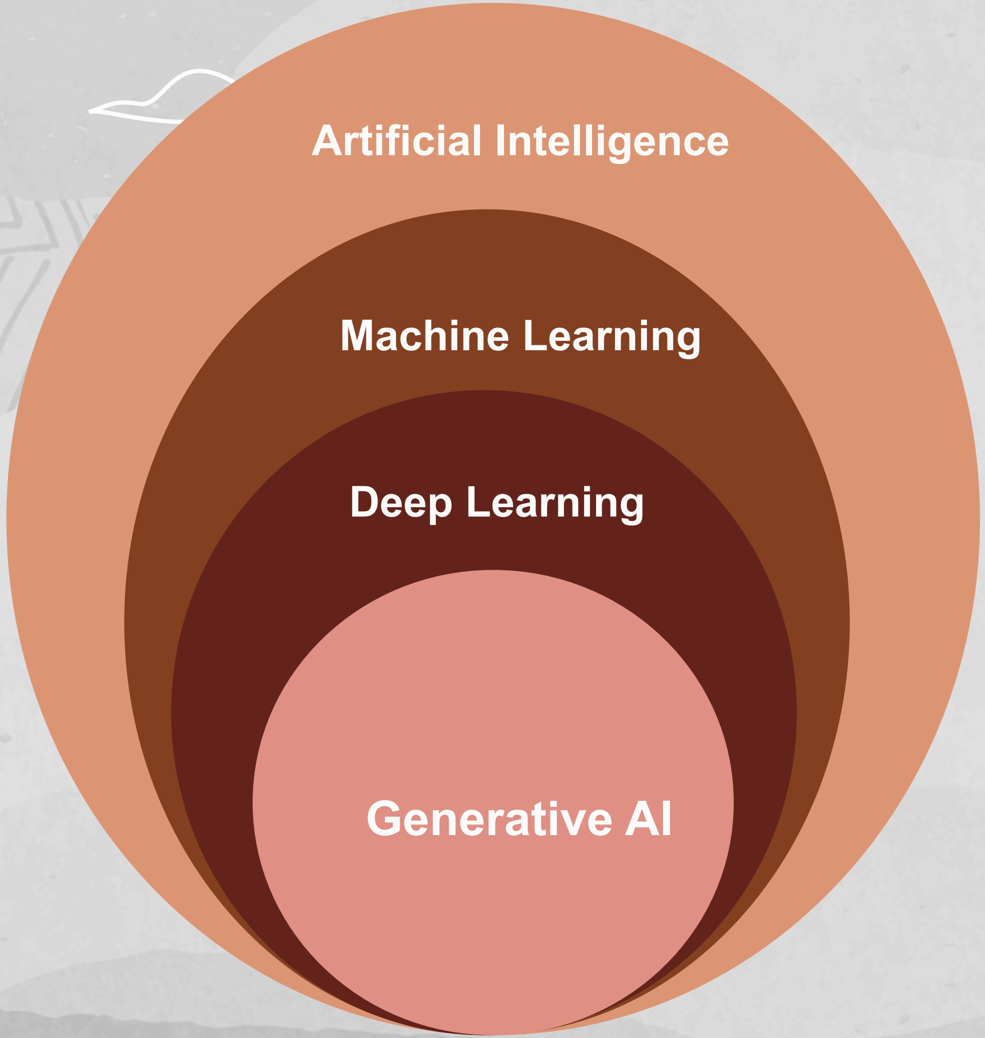
What is Generative AI

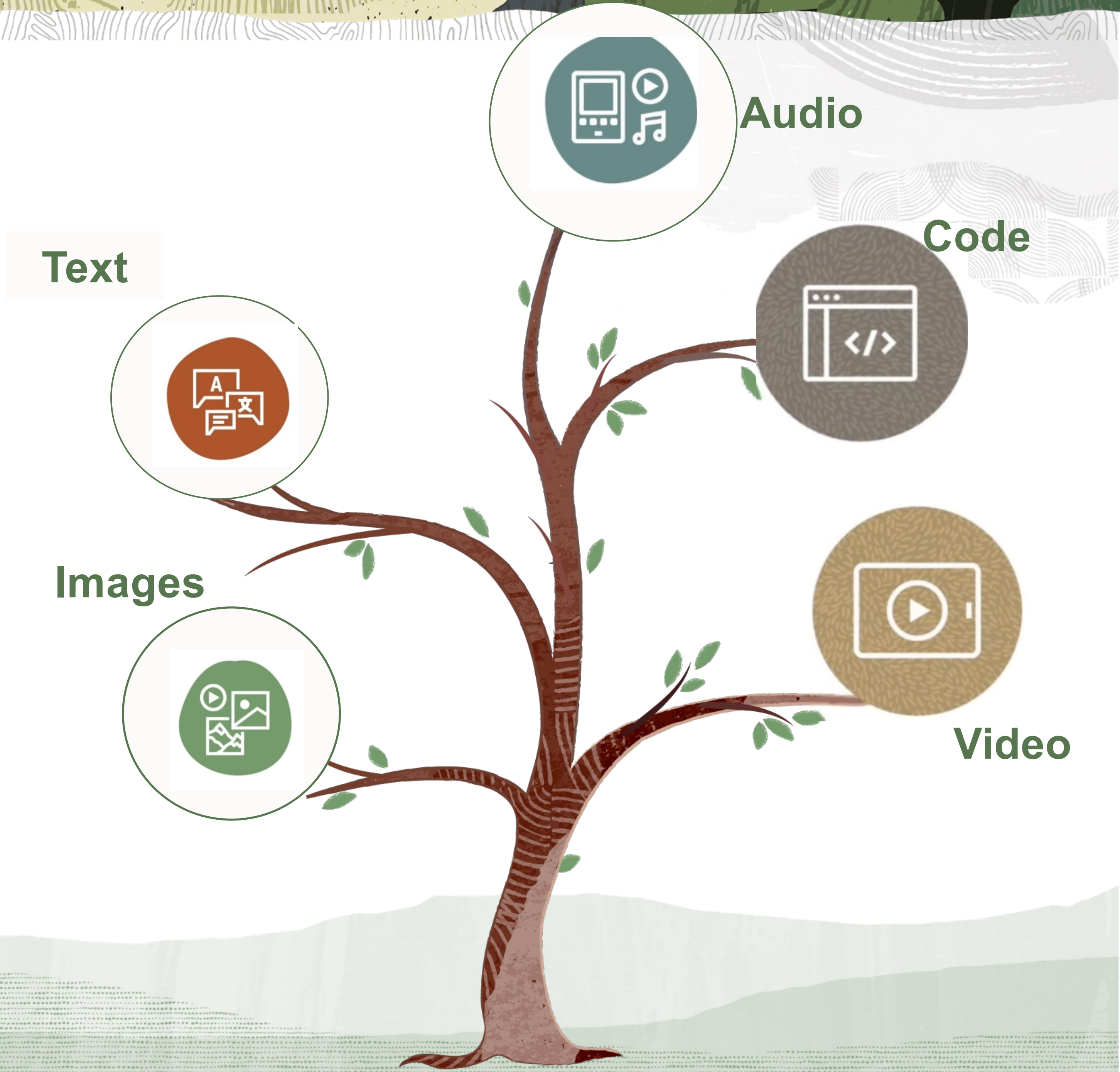


Generative AI refer to a set of AI methodologies that can create content that resembles the training data they were exposed to.

- A type of AI that can create new content.
- Subset of Deep Learning where the models are trained to generate output on their own.
- Models that can create a wide range of outputs such as images, music, speech, text and other types of data.

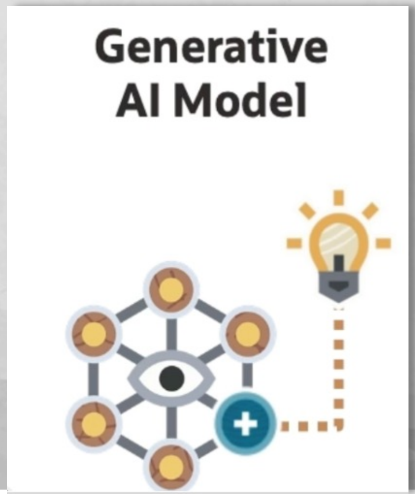
Generative AI

Machine Learning that can produce contents such as audio, text, code, video, images and other data.



How does Generative AI Work?

Learns the underlying patterns in a given data set and uses that knowledge to create new data that shares those patterns.



Training Data

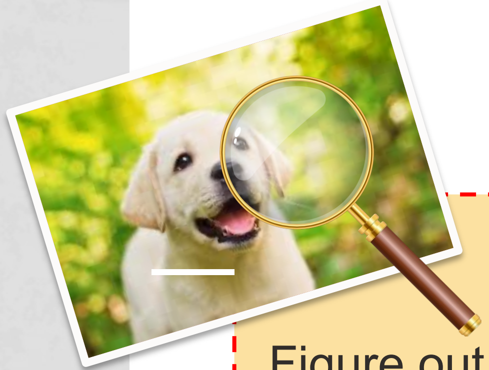
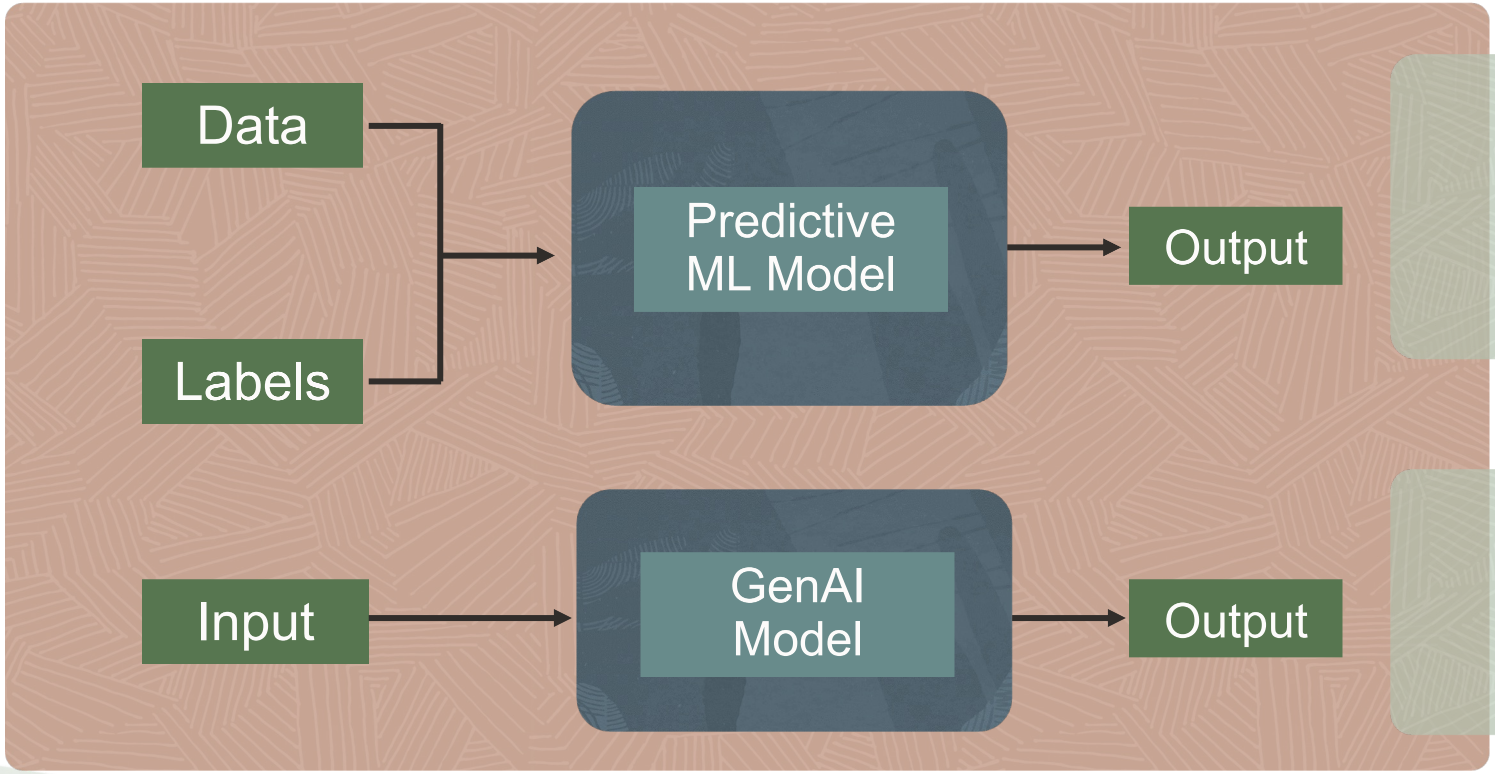


Figure out common dog patterns and features

“Draw a picture of a Dog”

Generative AI and Other AI Approaches



- Classification
- Recommendation System
- Game Playing

- Image Synthesis
- Text Generation
- Music Composition

Types of Generative AI Models

Image Based

- Generates Visual Content
- Learns from Large collection of images

Text-Based

- Generates Textual Content
- Learns from large collection of text data

Generative Adversarial Network (GAN)

https://www.christies.com/lot/lot-edmond-de-belamy-from-la-famille-de-6166184/

- Generate realistic images that resemble training data.
- Create high-quality images and original artworks.
- Imagine you have a bunch of **cat images**, and you want a machine learning model to create similar images.
- This is exactly what a GAN does.

Generative Adversarial Networks (GANs)

Generator

- Takes in random numbers as input and generates the images of interest (**the forger**)

Discriminator

- Takes both the images from the generator and the real images from the data and spots the difference between them (**the detective**)

Adversarial Objective

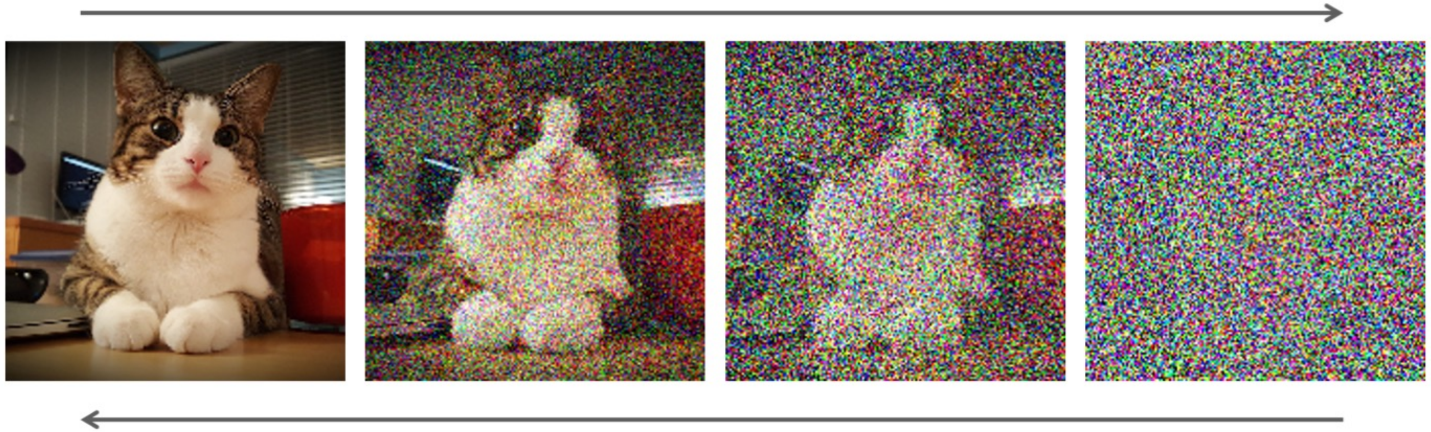
- These two networks are pitted against each other where the **generator creates more realistic synthetic images to fool the discriminator** while the **discriminator networks tries to get better at detecting fake images**.

- Both the generator and the discriminator are trained together.
- And, over the duration of training, the generator gets better at creating images which look real, and the discriminator gets better at spotting fakes.

- This back-and-forth strategy forces both the networks to improve until the generator can create highly realistic synthetic images, that indistinguishable from real images

Diffusion Models

- Work by adding noise to the images in the training data by **forward diffusion process** and then reversing the process to recover the original image using **reverse diffusion.**
- These models can be trained on **large un-labeled datasets in an unsupervised manner.**



Transformers and Large Language Models

LLMs

…d
process human language at a massive scale

LLMs and Transformers

Based on Deep Learning architecture such as Transformers

Generative AI Real-World Use Cases

Visual

- Image generation
- Video Generation
- Design

Language

- Content Creation
- Code Generation
- Conversational AI

Drug Discovery

- New molecular Structure

Music

- Music Generation

Email Spam Classification Model

Data: Examples of emails either tagged as Spam or not Spam

Training

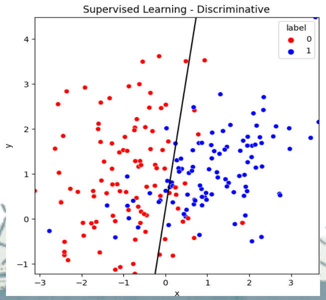
Discriminative – Learns the boundary that separates “spam” vs “not spam”

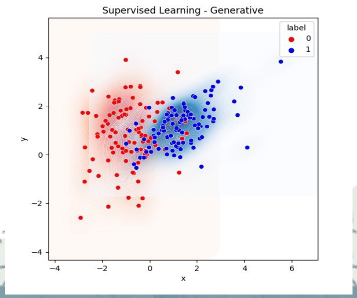
Generative – Learns the distribution of “spam” and “not spam” emails to understand how each class generates content

Inference

Discriminative – Determine on which side of the boundary a new email falls

Generative – Based on learned distributions compute the likelihood of the new email being “spam” vs “not spam”





Difference Between Discriminative and Generative Models

Aspect	Generative Models	Discriminative Models
Purpose	Model data distribution	Model conditional probability of labels given data
Use Cases	Data generation, denoising, unsupervised learning	Classification, supervised learning tasks
Common Examples	Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs)	Logistic Regression, Support Vector Machines, Deep Neural Networks
Training Focus	Maximize likelihood of observed data, Capture data structure	Learn decision boundary, Differentiate between classes
Example Task	Image generation, Inpainting (e.g., GANs, VAEs)	Text classification, Object detection (e.g., Deep Neural Networks)

Mechanics of Generative AI

Generative Models

Can generate new instances based on what they have learned. E.g. Variational Autoencoders, GANs, and RNNs.

Training Data

The quality of dataset directly impacts the performance of the generated outputs.

Loss Functions

Mathematical functions that measure the difference between the generated output and a desired target.

- Guide the learning process by providing feedback on how well the model is performing.

Optimization Algorithms

Adjust the parameters of the generative model to minimize the loss function during training. E.g. Stochastic Gradient Descent (SGD), Adam, and RMSProp.

Evaluation Metrics

Metrics such as perplexity for language models or Inception Score for image generation tasks.

Hyperparameters and Tuning

Settings that control the behaviour of the learning process. E.g. learning rate, batch size, number of layers in the network, etc.

Mechanics of Generative AI

Regularization Techniques

Help prevent overfitting by adding constraints to the model's parameters or architecture during training. E.g. dropout, weight decay (L2), and early stopping.

Data Augmentation

Involves generating additional training data from existing instances by applying transformations such as rotation, scaling, flipping, etc. It can help improve the generalization ability of generative models.

Potential of Generative AI

- Low Resource Languages
- Personalized Content Generation
- AI Tutors
- Intelligent Assistants
- Accelerating Scientific Discovery

Thank You