# Generative AI and LLM

Introduction to Generative AI: From Imagination to Impact
CS5202

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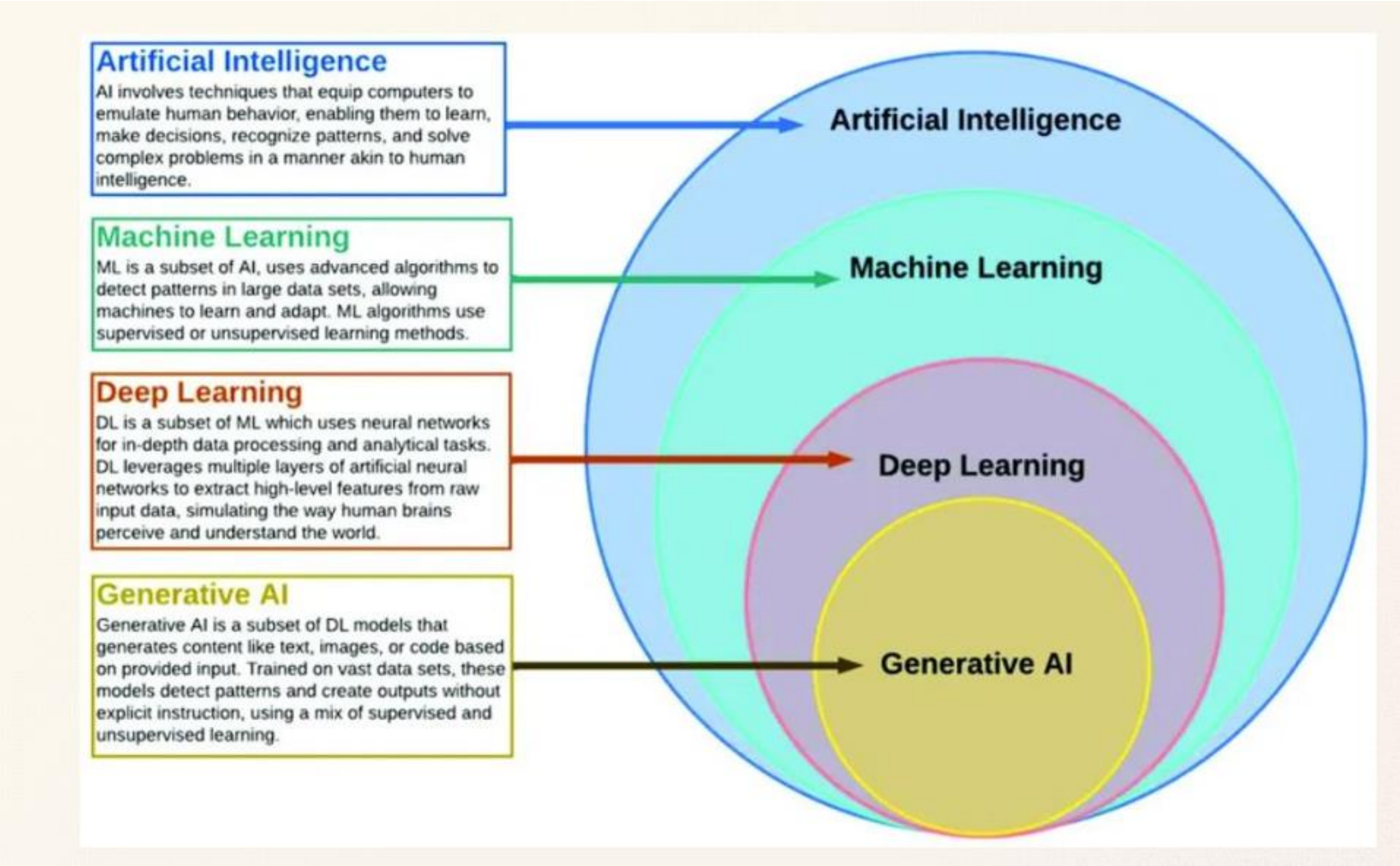
Global Thinkers. Engaged Leaders.

# Lecture Plan

- Impact of Generative AI
- Traditional Ai vs Generative AI
- Evolution of GenAI
- GenAI Taxonomy
- References

# The AI Landscape



# What If Machines Could Create?

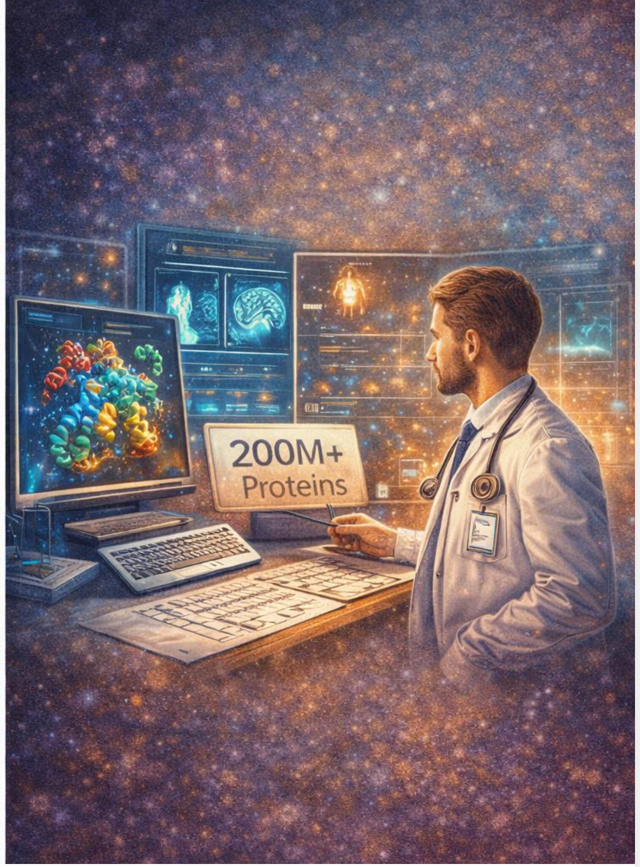
- Write poems, generate code, design drugs
- Diagnose diseases
- Simulate the brain
- Imagine solutions humans haven’t thought of

*Generative AI is not about automation — it’s about* ***augmentation of human intelligence***

# The GenAI Revolution – ChatGPT

- Single powerful statistic: "***From 0 to 100M users in 2 months - ChatGPT's unprecedented adoption"***
- Brief statement:

**Generative AI is not hype—it's already solving problems that were unsolvable 3 years ago**




# Revolutionizing Medicine and Drug Discovery

- **Key Problems:**
- Slow drug discovery (10–15 years)
- Limited medical expertise in rural areas
- Personalized treatment gaps

**GenAI Solutions:**

- **DeepMind’s AlphaFold**
    - Predicted structures of **200M+ proteins**
    - Accelerated biology & medicine research
- **OpenAI’s** medical reasoning models
    - Assist doctors in clinical reasoning
    - Summarize patient histories

# Environment & Climate

**Problems:**

- Climate modeling is computationally expensive
- Deforestation monitoring is slow
- Energy optimization is complex

**GenAI in Action:**

- **Google DeepMind** AI for weather & flood prediction
- Generative models for:
    - Climate simulations
    - Smart energy grid optimization
    - Satellite image generation & restoration

# Neuroscience & Human Mind

**Challenges:**

- Brain is complex, noisy, high-dimensional
- Limited labeled neural data
- Understanding cognition & consciousness

**GenAI Applications:**

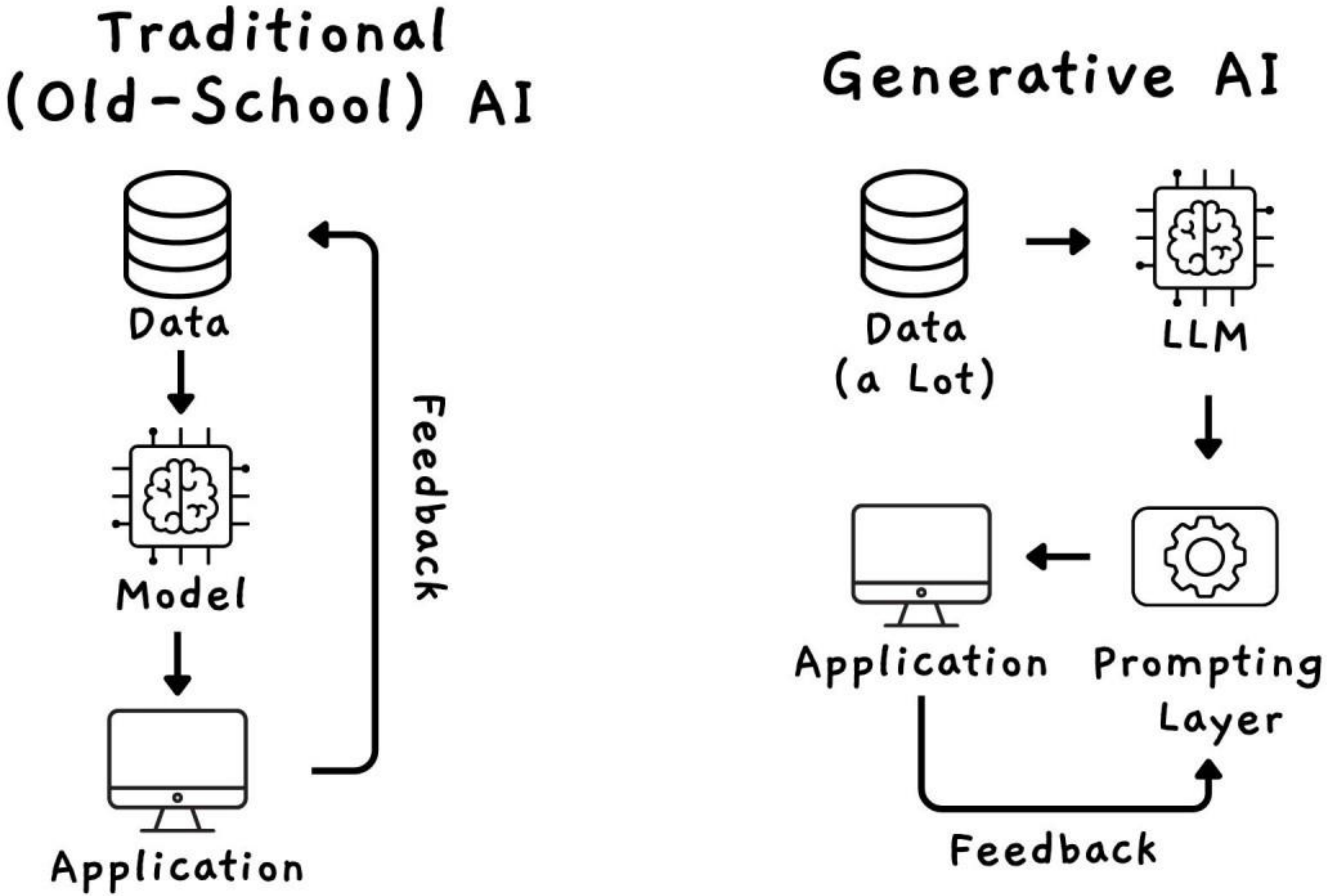
- Generative models for **EEG / fMRI data synthesis**
- Brain-to-text and brain-to-image decoding
- Simulation of neural activity patterns

**Examples:**

- Reconstructing images from brain signals
- Generating synthetic neural data for research

# From Impact to Understanding

Now that we've seen what GenAI can achieve, let's explore the fundamentals behind these remarkable capabilities


Traditional
(Old-School) AI
Data
Model
Application
Feedback
Generative AI
Data
(a Lot)
LLM
Prompting
Layer
Application
Feedback

# What Is Generative AI?

- Generative AI refers to machine learning models that **create new content-**text, images, audio, video, code or data by learning patterns from existing examples.

- **Key distinction:** Unlike traditional AI that classifies or predicts, GenAI *generates* novel outputs that didn't exist before

# Discriminative VS Generative AI

- **Discriminative Models**
- **Goal:** Learn boundaries between classes
- **Question:** "Is this a cat or dog?"
- **Examples:** SVM, Logistic Regression, CNNs for classification

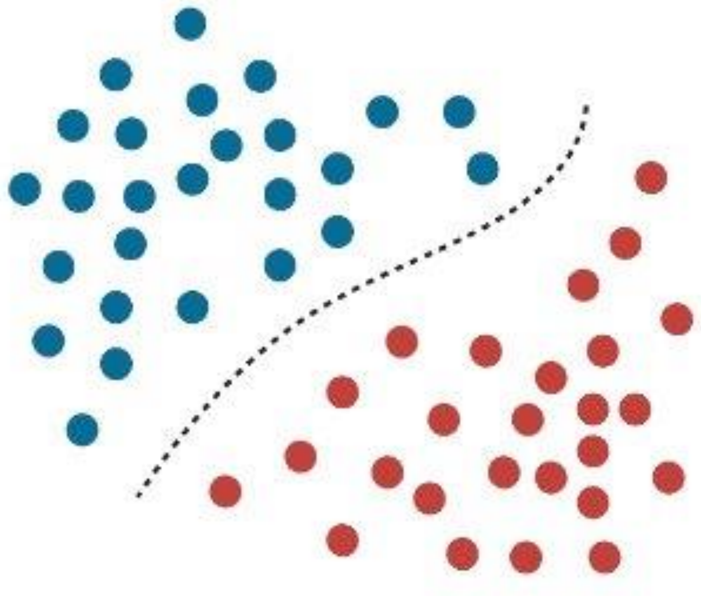
- **Generative Models**
- **Goal:** Learn the data distribution itself
- **Question:** "Can you create a new cat image?"
- **Examples:** GANs, VAEs, Diffusion Models, Transformers

# Discriminative vs Generative AI Models

## Discriminative (classic)

Predict a label/class given the features of input data

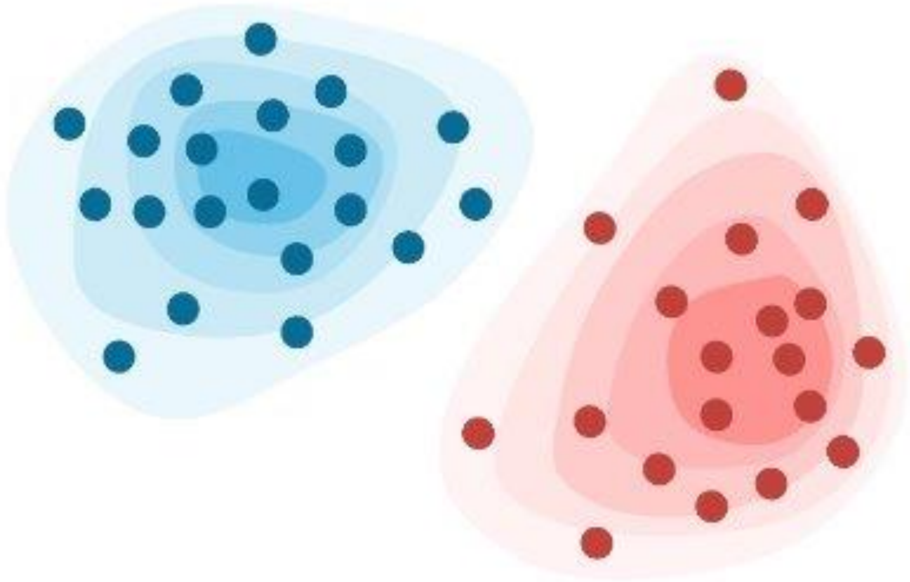
**What's learned?:** Decision boundary



## Generative

Abstract underlying patterns in input data in order to generate new content

**What's learned?:** Probability distributions of the data



# Evolution of Generative Models

1. **1950s-1980s**

   **Early Foundations**

   Rule-based systems, Markov chains, basic statistical models

2. **1986**

   **Backpropagation**

   Rumelhart, Hinton & Williams—enabling deep learning

3. **2014**

   **GANs Introduced**

   Ian Goodfellow's revolutionary adversarial training approach

4. **2017**

   **Transformer Architecture**

   "Attention Is All You Need"—foundation of modern LLMs

5. **2020-Present**

   **Diffusion Models Era**

   Stable Diffusion, DALL-E, GPT-4, and explosive growth

# Key Milestones in the Evolution

### Variational Autoencoders (2013)

Kingma & Welling introduce probabilistic latent space learning

### GANs Revolution (2014)

Generator vs. Discriminator paradigm produces photorealistic images

### Attention Mechanism (2017)

Transformers unlock unprecedented language understanding and generation

### Diffusion Models (2020)

Denoising approach achieves state-of-the-art image synthesis

### Foundation Models (2022+)

GPT-4, Claude, Gemini—massive scale, multi-modal capabilities

# Why Now? Why Not 10 Years Ago?

- Big data 📊
- GPUs & TPUs ⚙️
- Transformers 🧠
- Self-supervised learning
- Open research & scaling laws

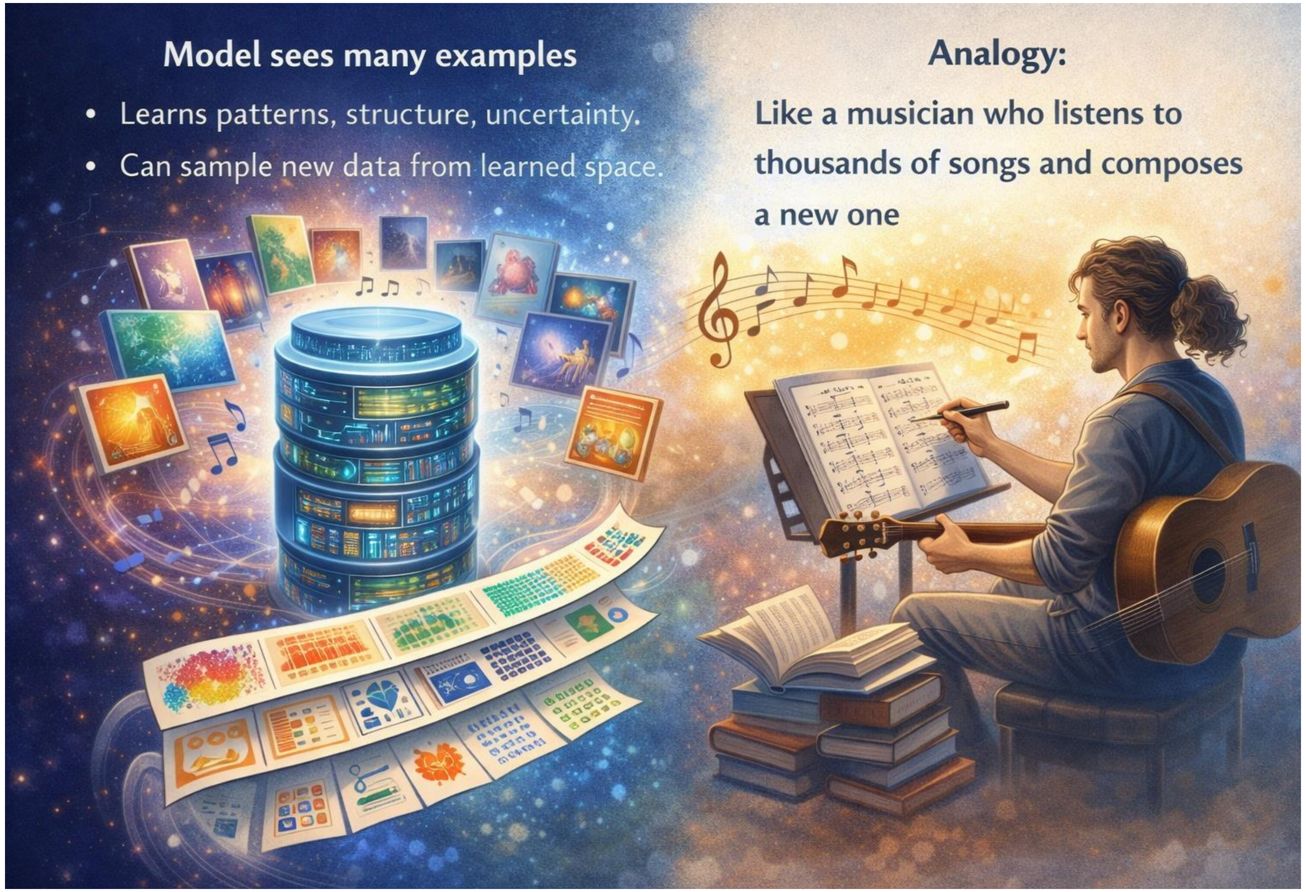
# Intuition Behind Generative Learning

**Core Concept:**

- Model sees many examples
- Learns *patterns, structure, uncertainty*
- Can sample new data from learned space

**Analogy:**

- Like a musician who listens to thousands of songs and composes a new one



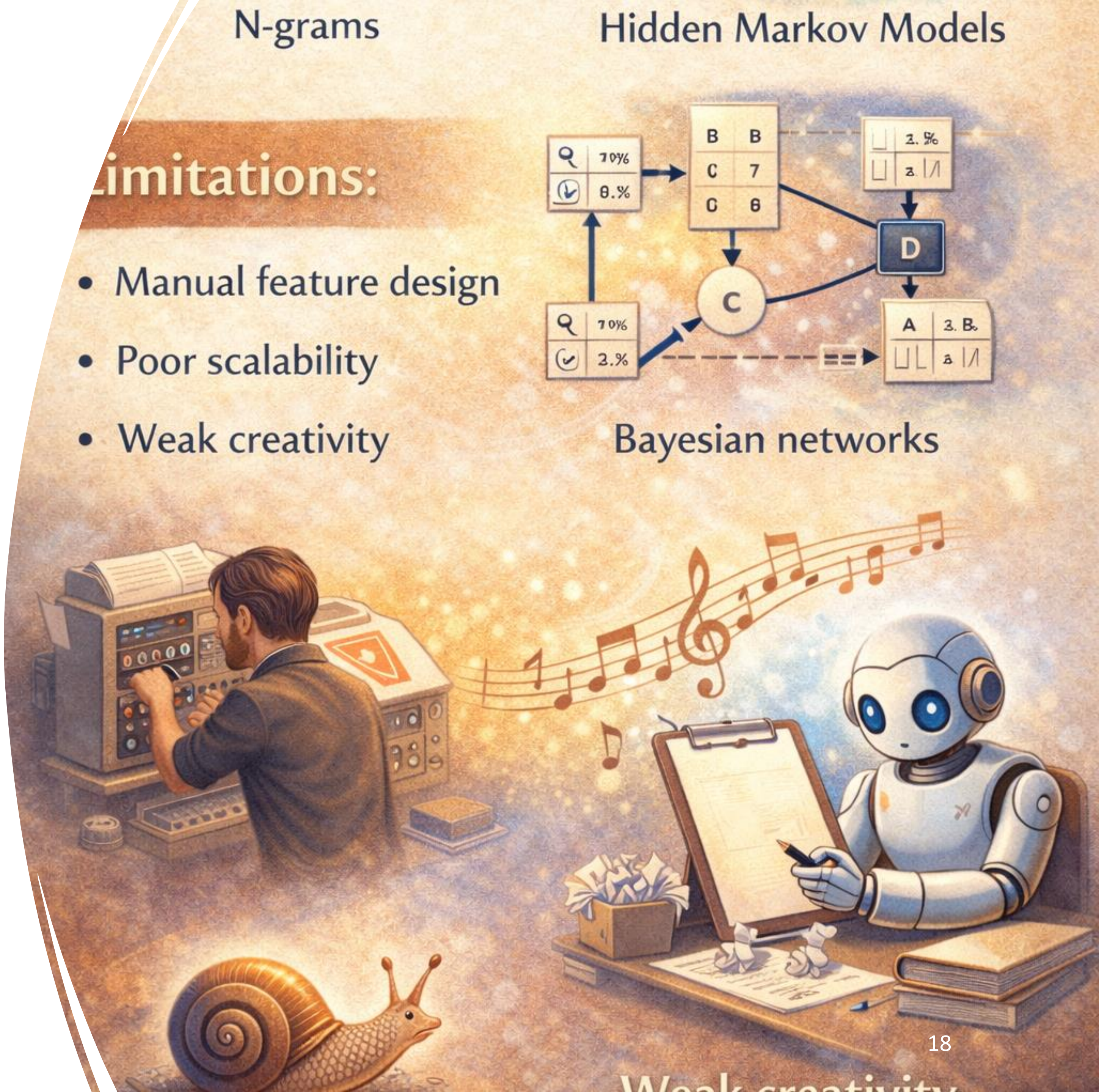
# Early Era of GenAI (Pre-2010)

**Rule-based & probabilistic models**

- N-grams
- Hidden Markov Models
- Bayesian networks

**Limitations:**

- Manual feature design
- Poor scalability
- Weak creativity



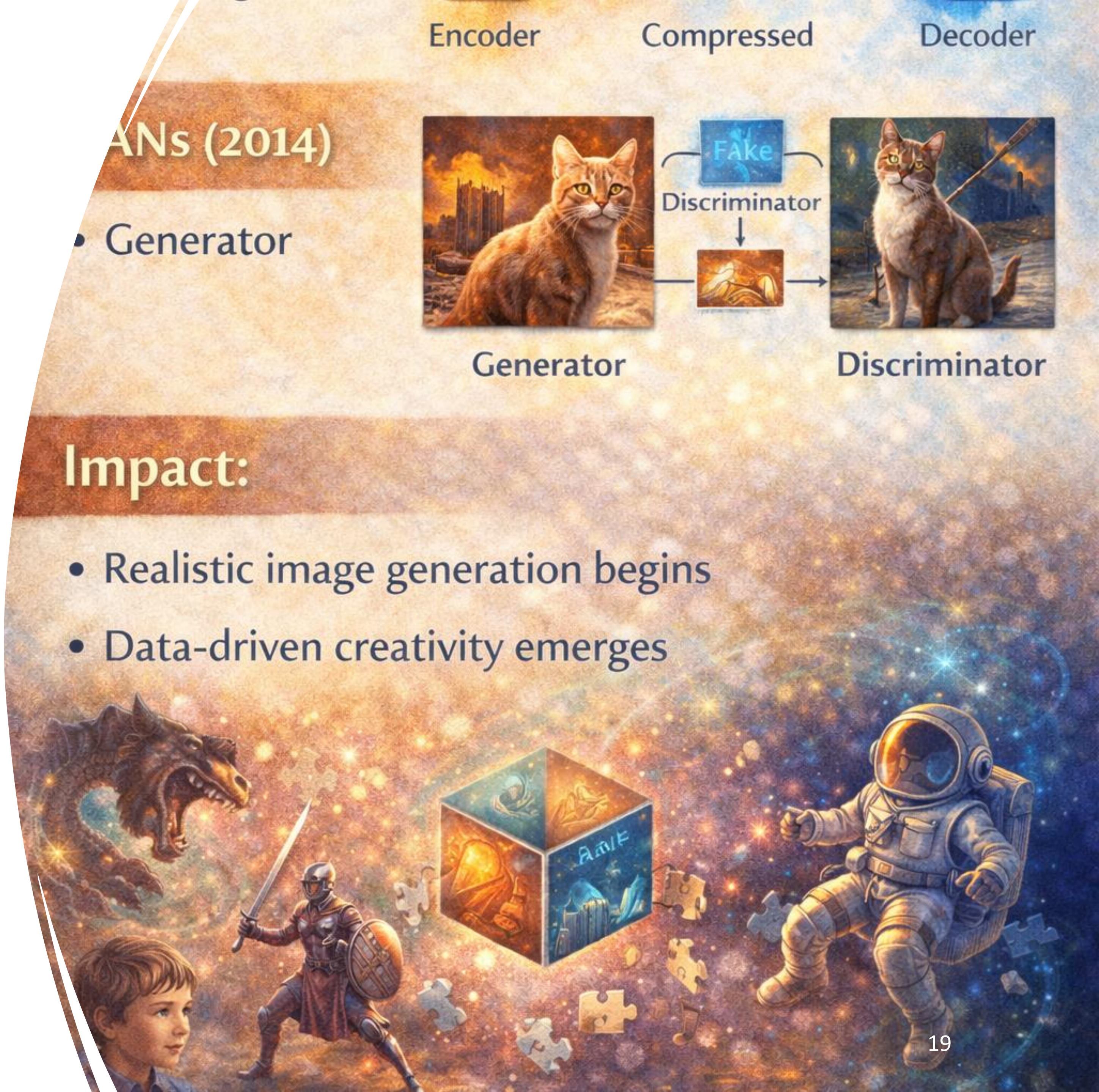
# Rise of Deep Generative Models (2013–2016)

**Breakthroughs:**

- Autoencoders
- **GANs** (2014)
- Representation learning

**Impact:**

- Realistic image generation begins
- Data-driven creativity emerges



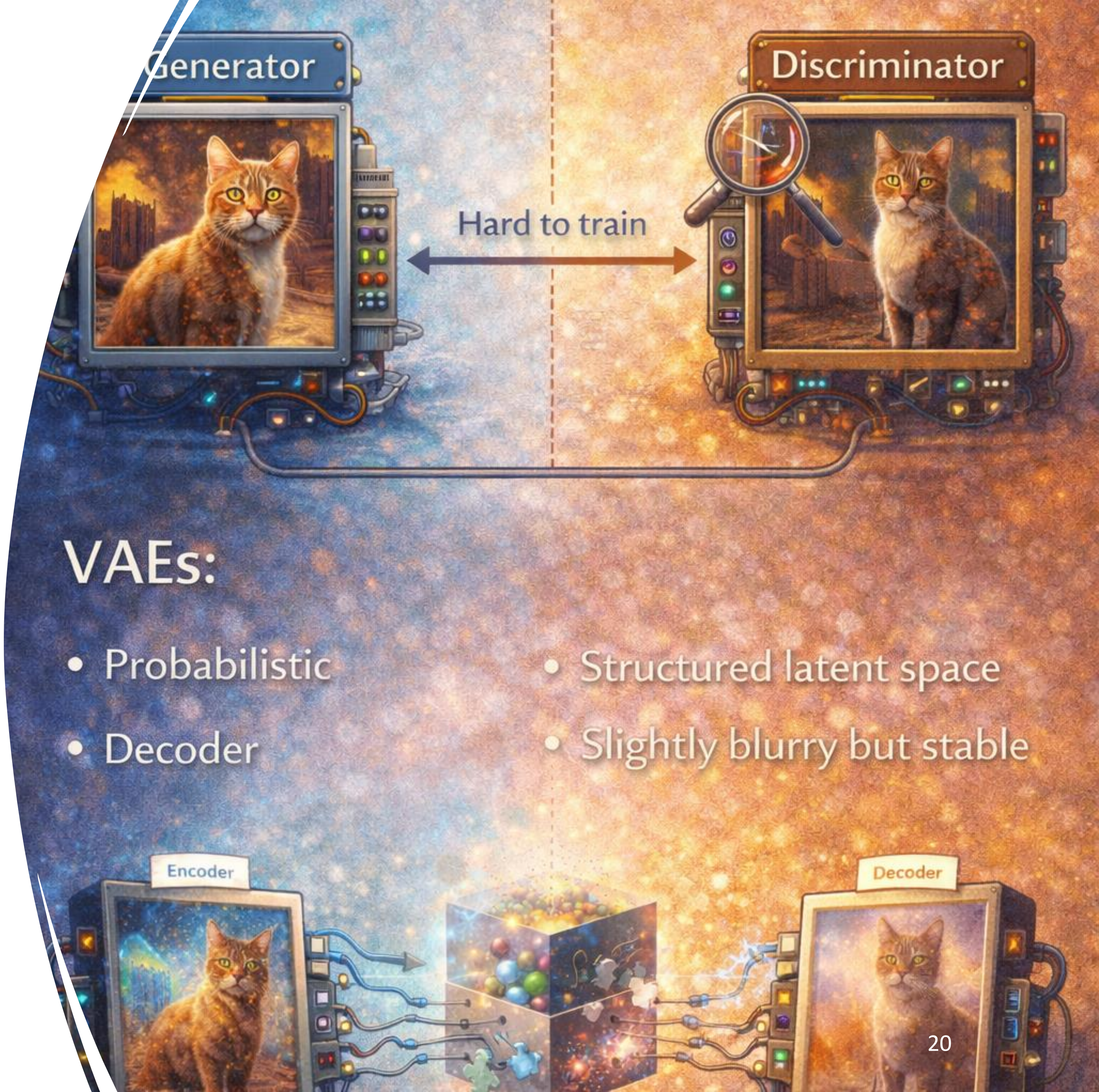
# GANs & VAEs

**GANs:**

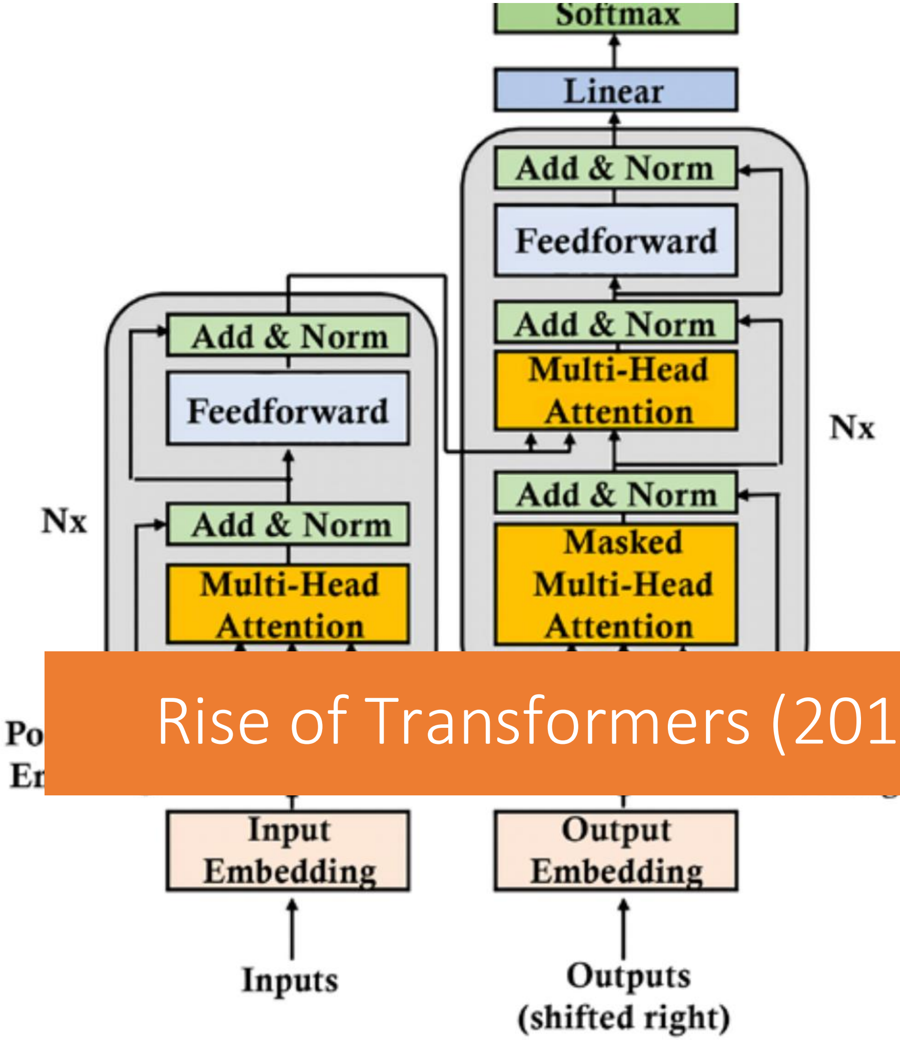
- Generator vs Discriminator
- Sharp images
- Hard to train

**VAEs:**

- Probabilistic
- Structured latent space
- Slightly blurry but stable



# Rise of Transformers (2017)

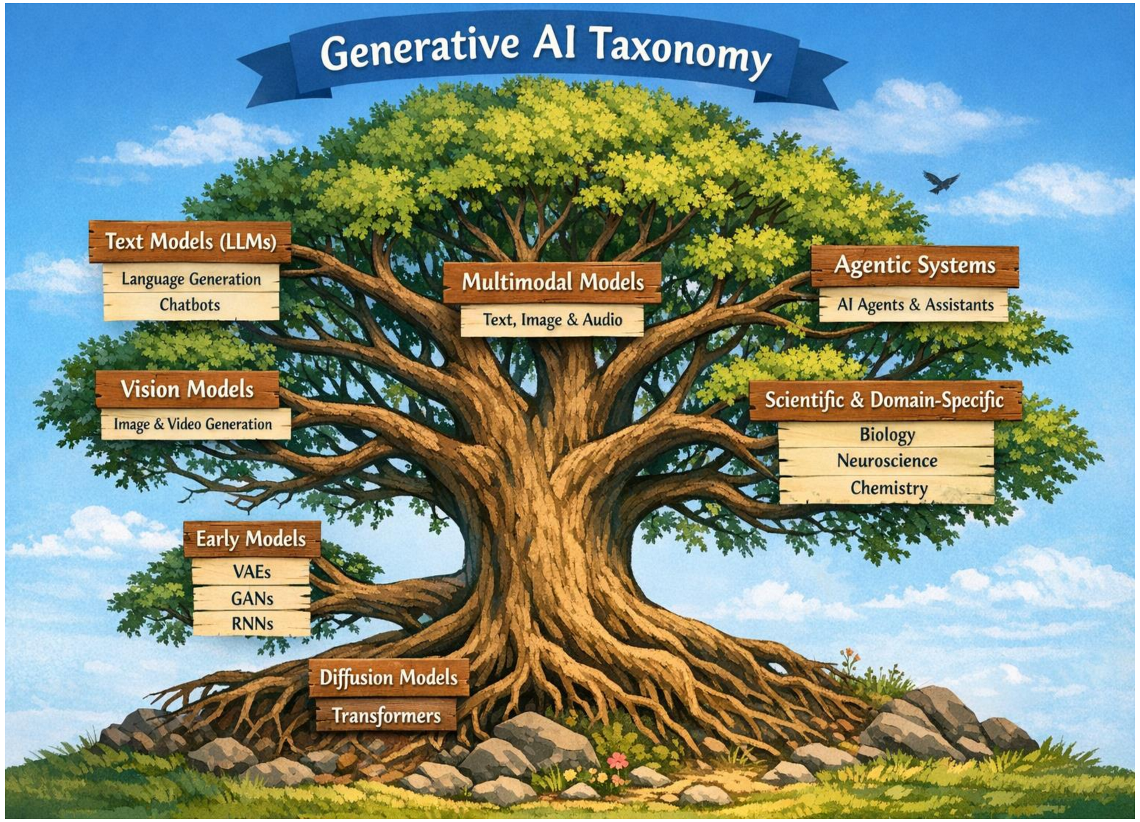



# Current GenAI (2020–Now)

**Modern Classification:**

- Text-only (LLMs)
- Vision-only
- Multimodal (text + image + audio)
- Agentic systems
- Domain-specific GenAI (biology, neuroscience)

# GenAI Taxonomy



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