

Welcome!

The program will begin soon.
You will not hear audio until we begin.



Unlocking the Potential of Generative Artificial Intelligence in the Oil and Gas Industry

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Leader

Artificial Intelligence Center of Excellence

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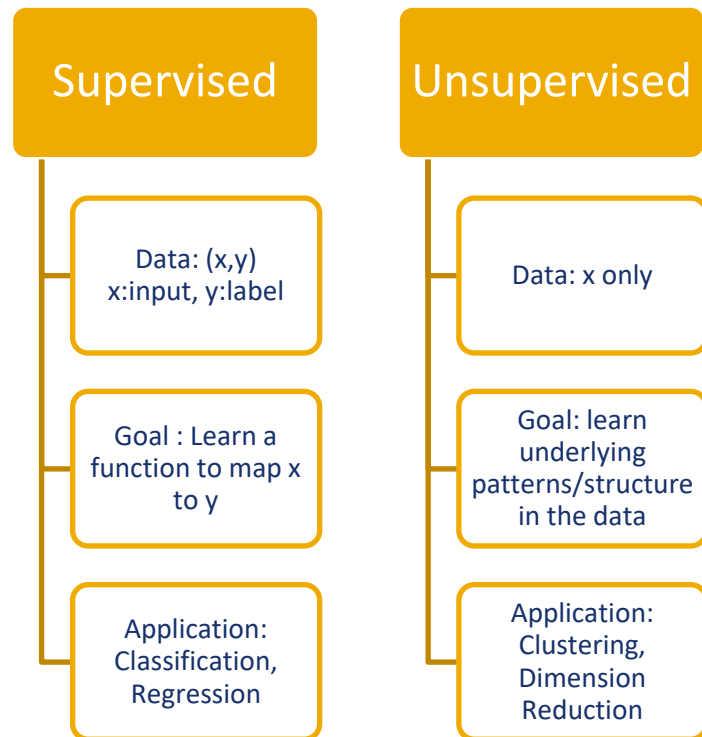
Agenda



- What is Generative AI
- Evolution of Generative AI
- Generative AI Landscape
- Transformer Architecture
- Unimodal and Multimodal Gen AI
- Responsible AI Practice
- Gen AI Applications in Oil and Gas Industry



What is Generative Machine Learning



	Discriminative model	Generative model
Goal	Directly estimate $P(y x)$	Estimate $P(x y)$ to then deduce $P(y x)$
What's learned	Decision boundary	Probability distributions of the data
Illustration		
Examples	Regressions, SVMs	GDA, Naive Bayes

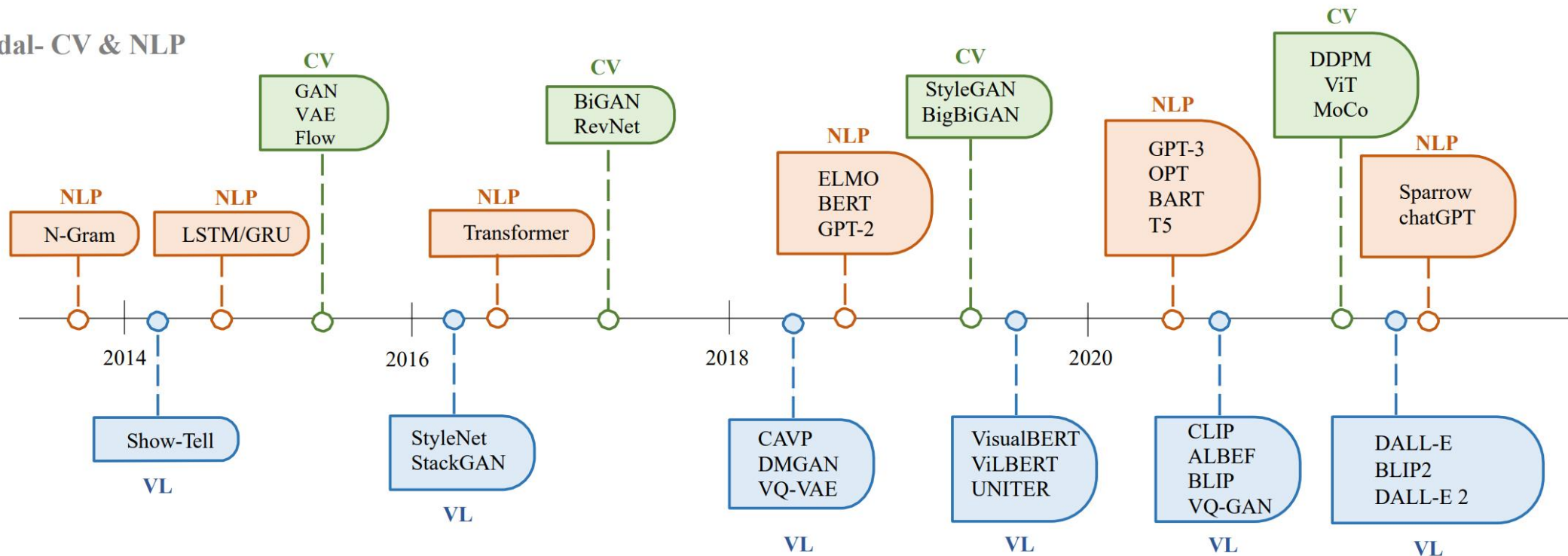
Source: [CS 229 - Supervised Learning Cheatsheet \(stanford.edu\)](#)

- A discriminative machine learning model learns parameters that maximize the conditional probability $P(Y|X)$,
- A generative machine learning model learns parameters that maximize the joint probability $P(X,Y)$.



Evolution of Generative AI

Unimodal- CV & NLP

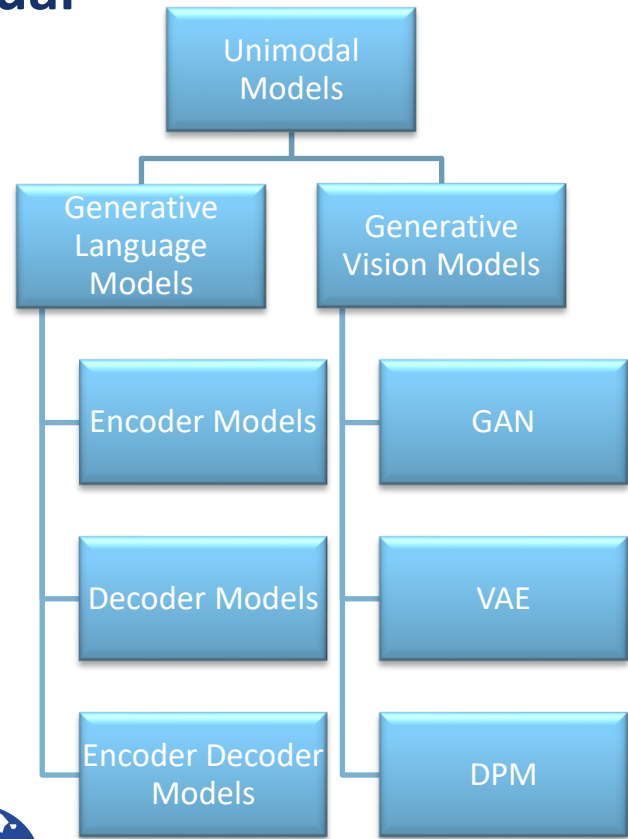


Multimodal – Vision Language

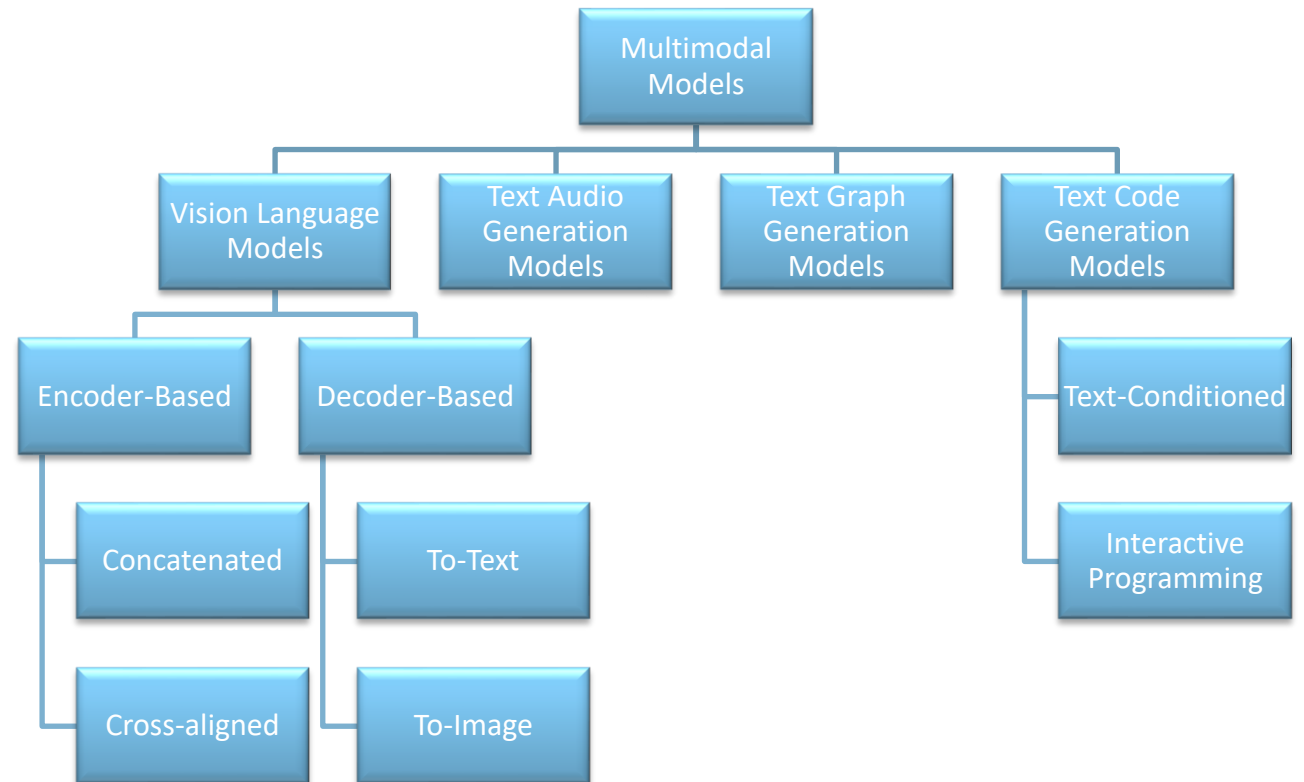
Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

Generative AI Landscape

Unimodal

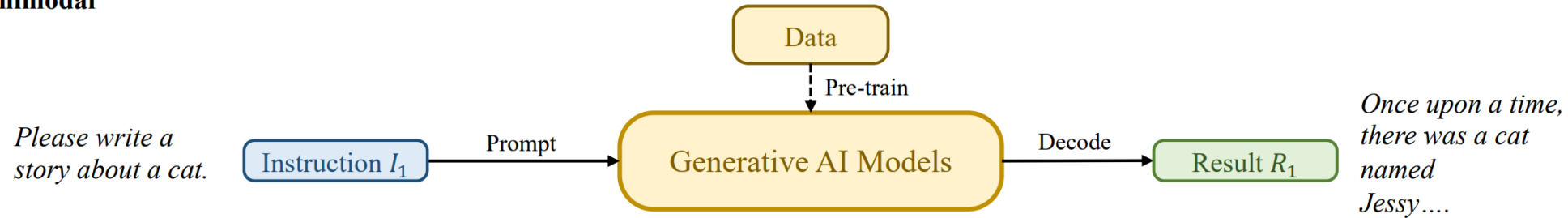


Multimodal

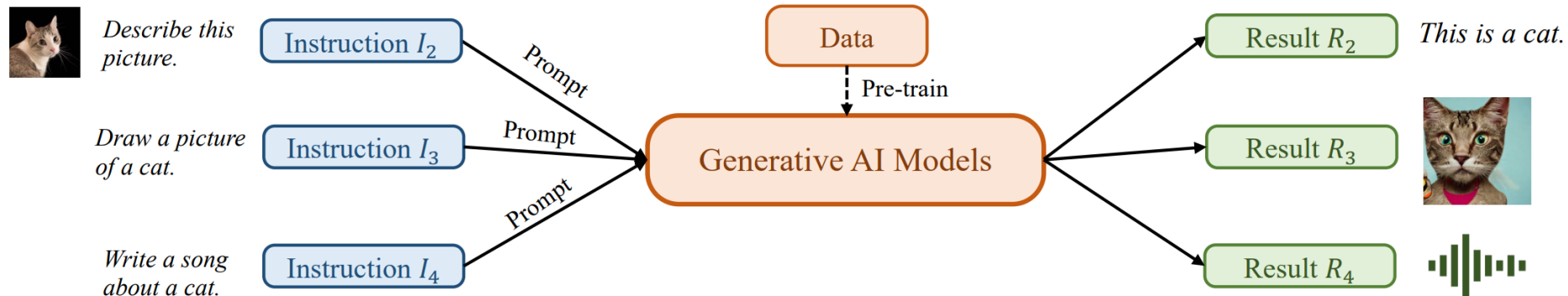


Generative AI Scenarios

Unimodal

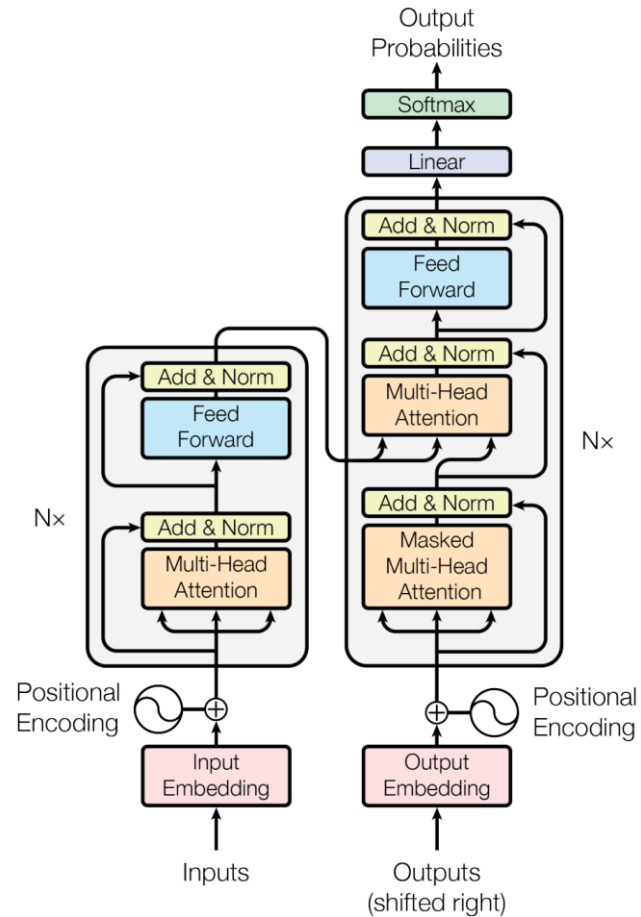


Multimodal



Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

Transformer Model Architecture



- Embedding
- Positional Encoding
- Encoder
- Decoder
- Multi-head Attention

Multimodal Vision Language Generation



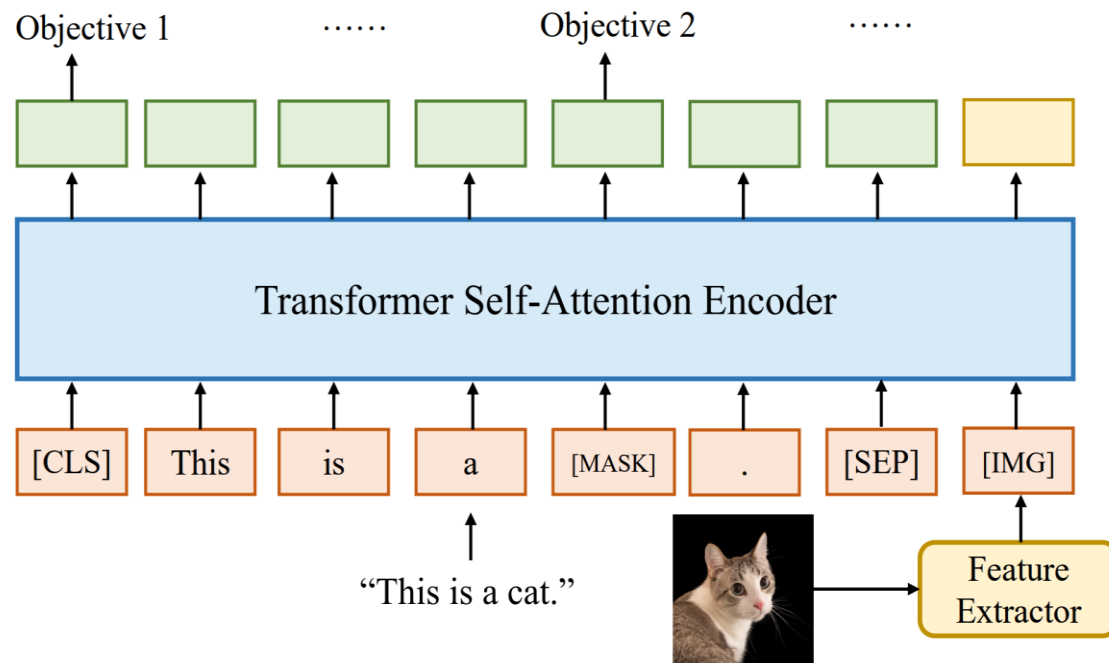
- Vision Language Encoders
 - Concatenated Encoders
 - by concatenating the embeddings from single encoders.
 - VisualBERT
 - Cross-aligned Encoders
 - Two tower for each modality and learn joint representation space by using a cross-modality encoder.
 - LXMERT
 - ViLBERT
- Vision Language Decoders
 - To-Text Decoders
 - To-Image Decoders



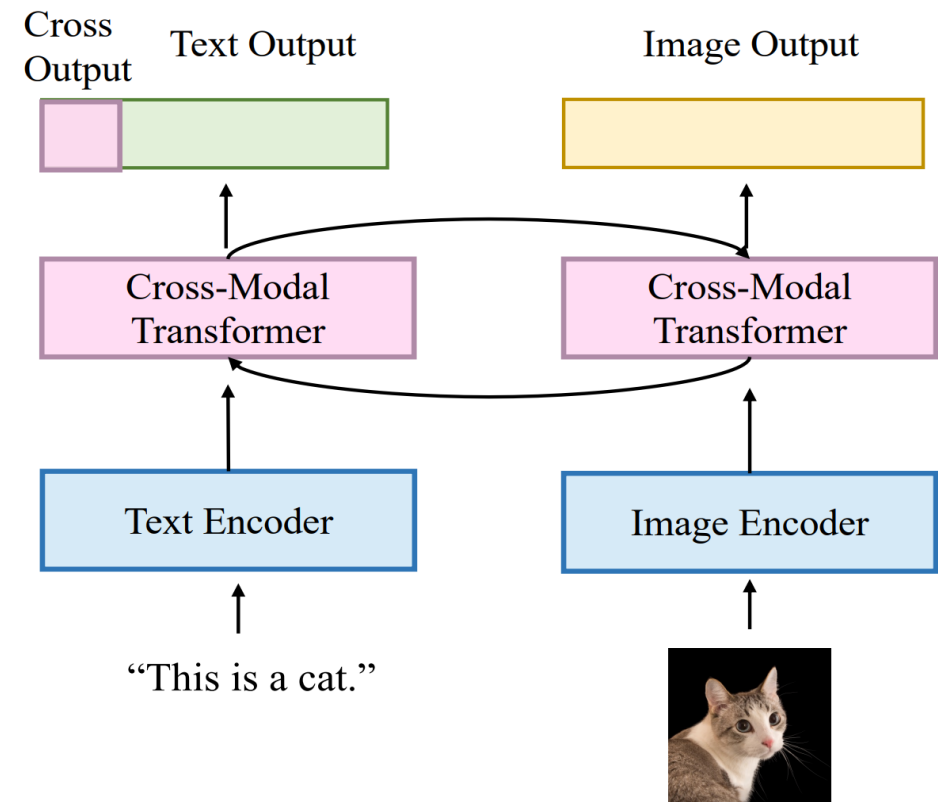
Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

Vision Language Encoders

- Concatenated Encoder



- Cross-aligned Encoder



Vision Language Decoders

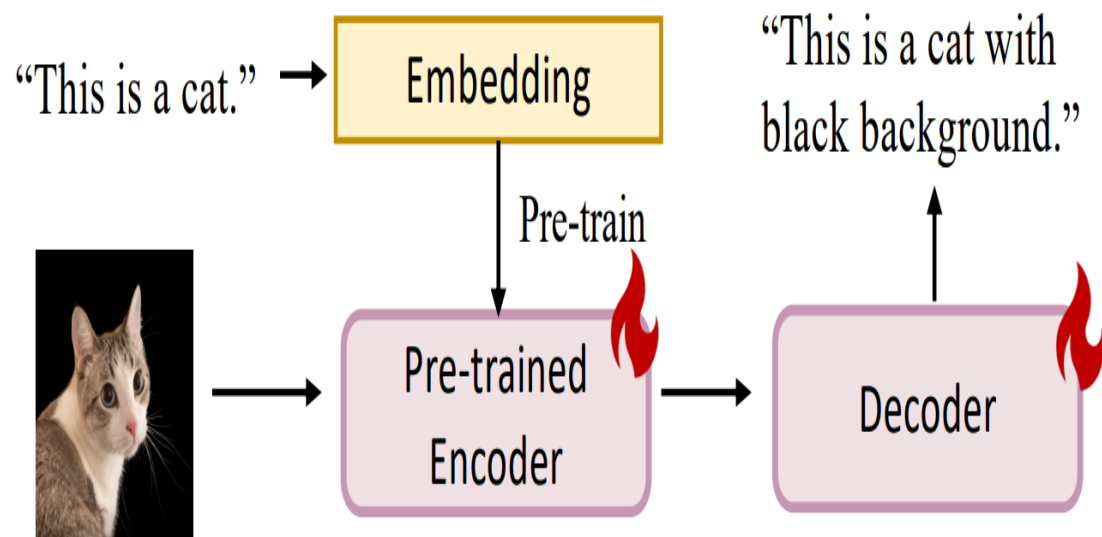
- To Text Decoders
 - Jointly-trained Decoders
 - Frozen Decoders
- To Image Decoders
 - GAN-based Decoders
 - StackGAN: two stage
 - AttnGAN: Attn+StackGAN
 - Diffusion-based Decoders
 - GLIDE



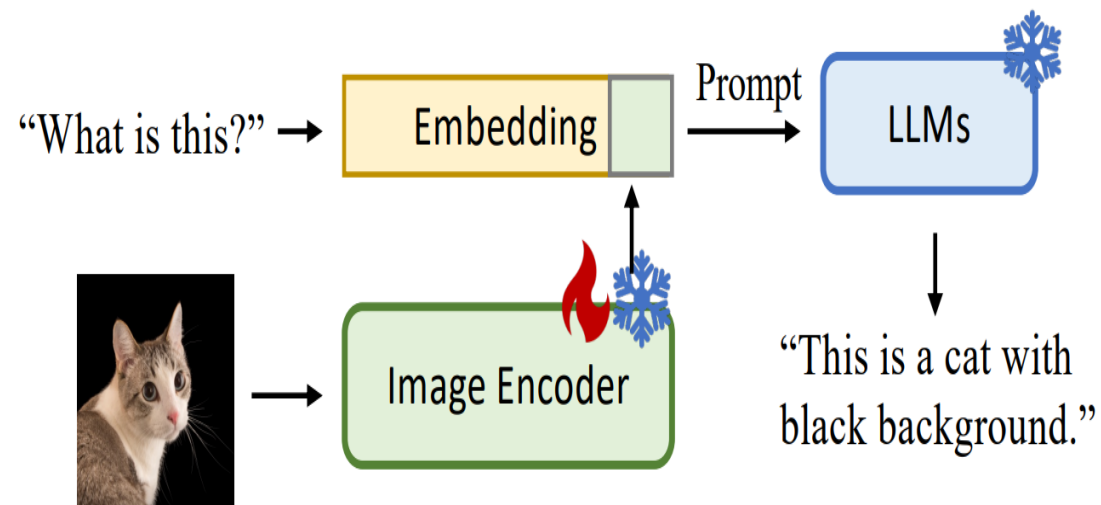
Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

Vision Language Decoders

- Jointly Trained Decoders



- Frozen Decoders



Multimodal Text Code Generation



- Text-conditioned Programming Code Generation
 - CodeBERT
 - CuBERT
 - CodeT5
 - PLBART



Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

Selected Generative AI Models



- Large Language Models (LLMs)
- Generative Adversarial Networks (GANs)
- Variational Autoencoders (VAEs)
- Diffusion Probabilistic Models (DPMs)



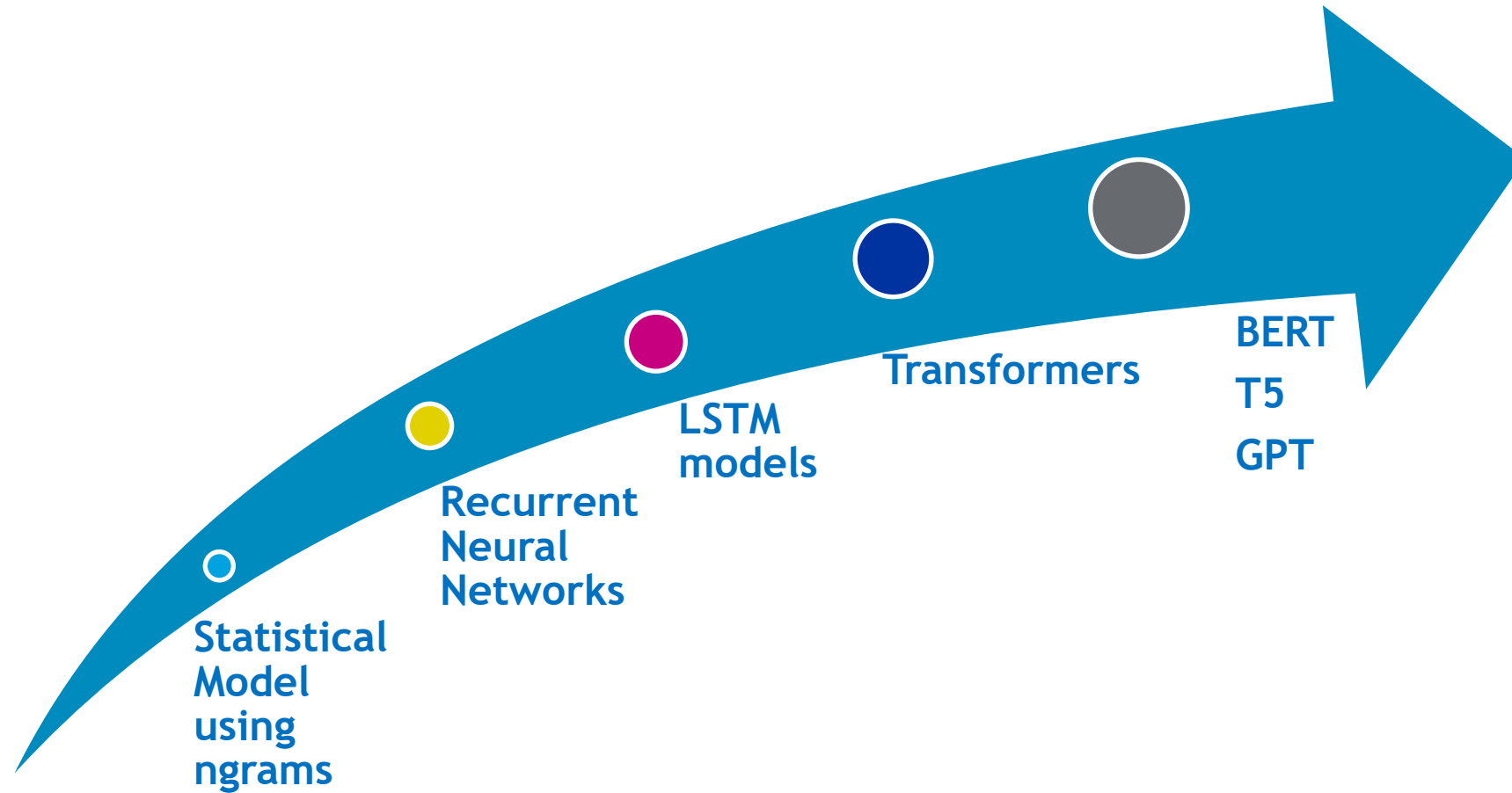
What is a Language Model ?



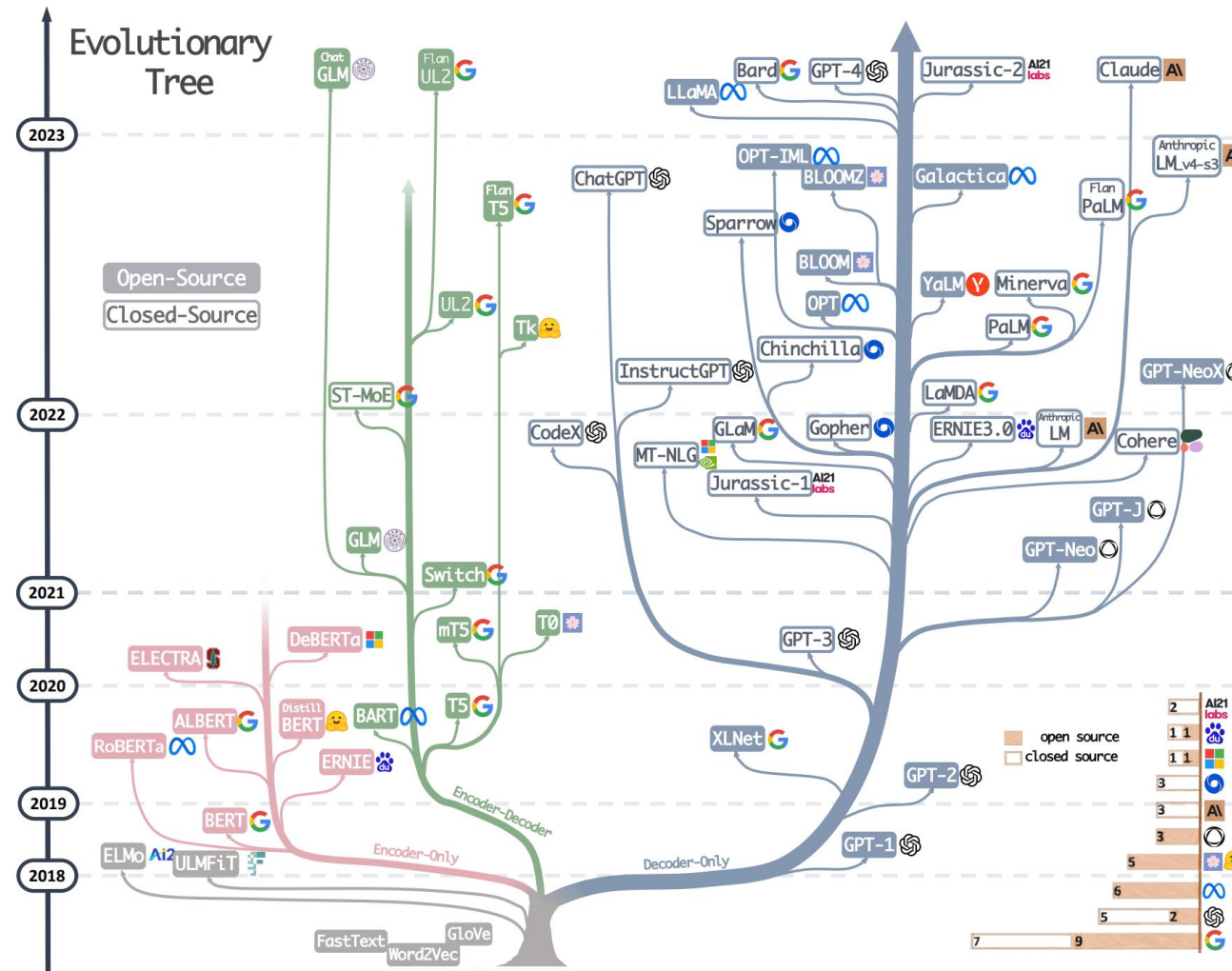
A Language Model is a probabilistic model that defines a probability distribution over the sequence of words to predict the next _____ in a sentence.



Evolution of Large Language Models

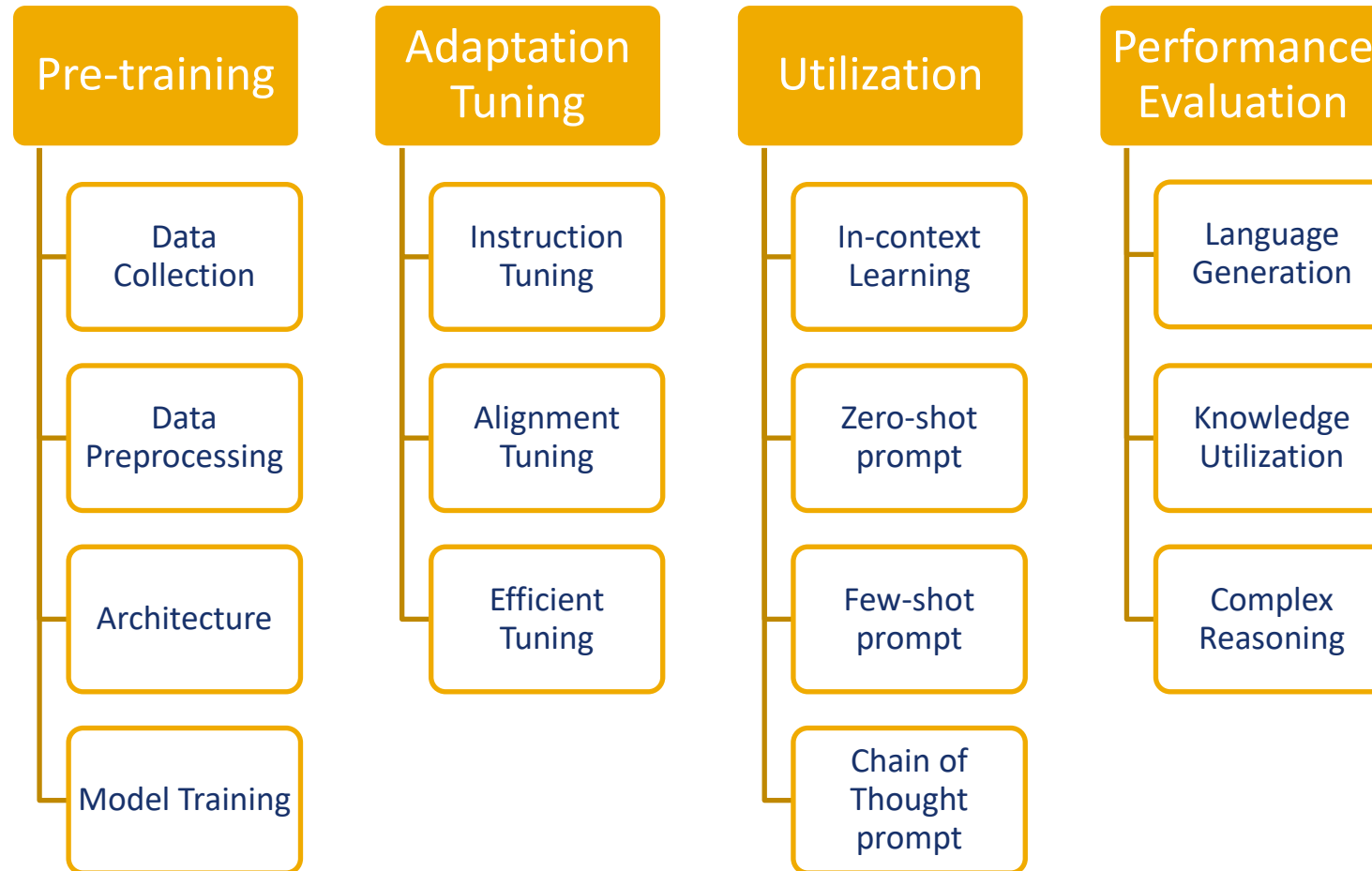


Large Language Models Landscape



Source: [2304.13712] Harnessing the Power of LLMs in Practice: A Survey on ChatGPT and Beyond (arxiv.org)

Training Lifecycle of LLM

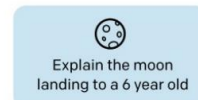


What is ChatGPT?

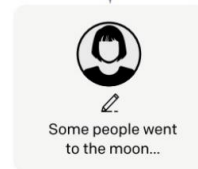
Step 1

Collect demonstration data, and train a supervised policy.

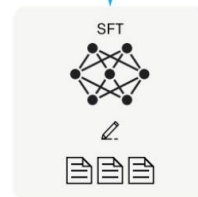
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



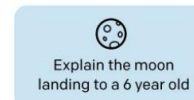
This data is used to fine-tune GPT-3 with supervised learning.



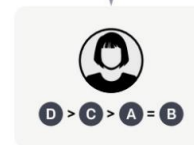
Step 2

Collect comparison data, and train a reward model.

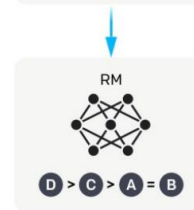
A prompt and several model outputs are sampled.



A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



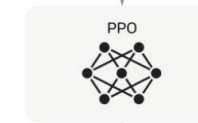
Step 3

Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

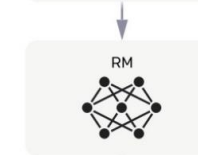


The policy generates an output.

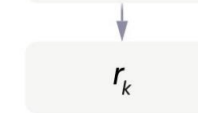


The reward model calculates a reward for the output.

Once upon a time...



The reward is used to update the policy using PPO.



Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

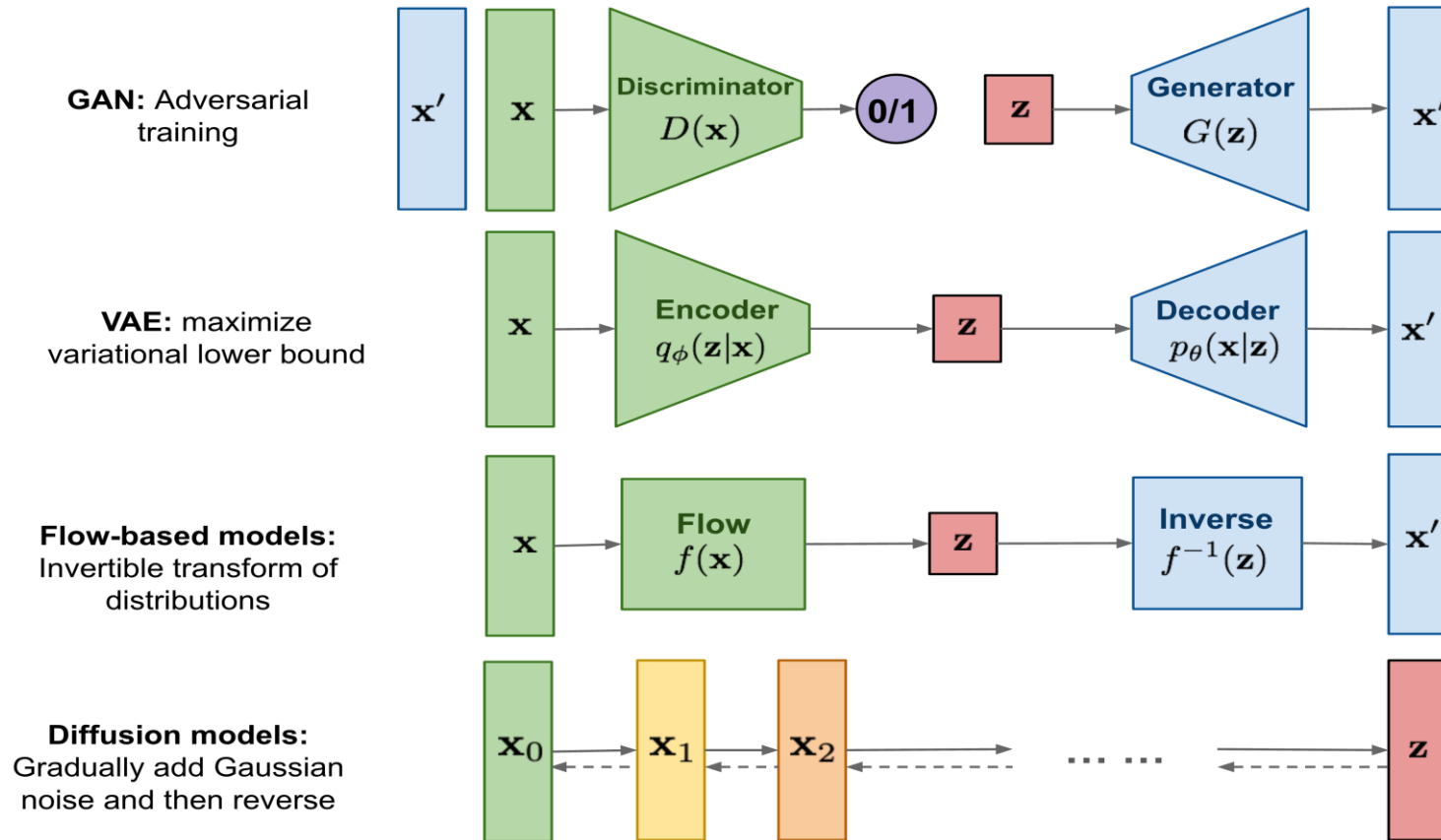
Prompt Design and Engineering



- Prompt Engineering is a technique for improving the performance of LLMs by providing them with additional input in the form of prompts or instructions.
- The idea behind Prompt Engineering is to guide the model towards generating more relevant and coherent text by providing it with context-specific information.
- Prompt Engineering can be used to improve the performance of LLMs on specific tasks such as question answering or summarization.
- Zero-shot Prompting
 - No examples
- Few-shot Prompting
 - One or more examples
- Chain of Thought Prompting
 - Steps for guidance



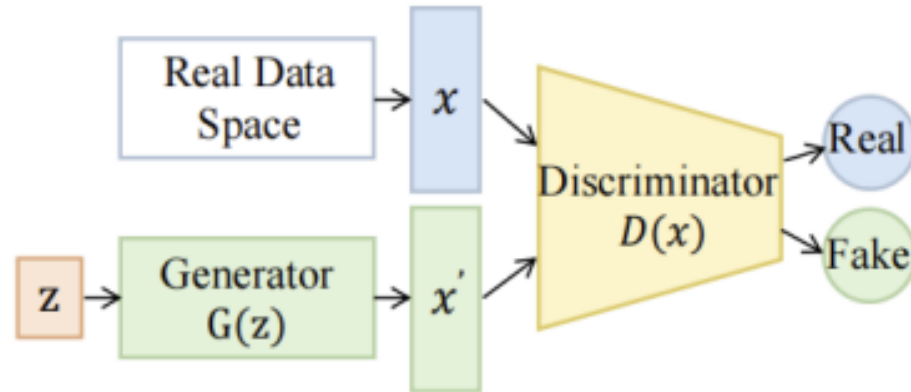
Unimodal Image Generative AI Modeling



Source: A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT

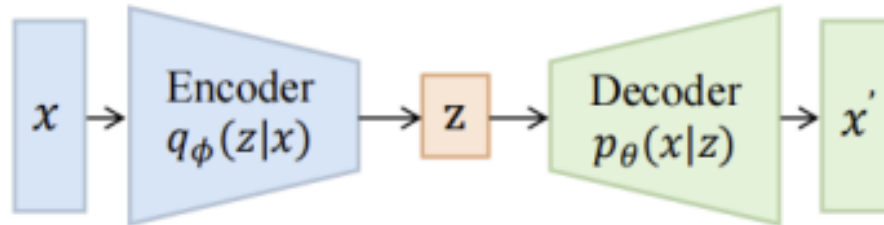
[What are Diffusion Models? | Lil'Log \(lilianweng.github.io\)](https://lilianweng.github.io/lil-log/)

Generative Adversarial Networks



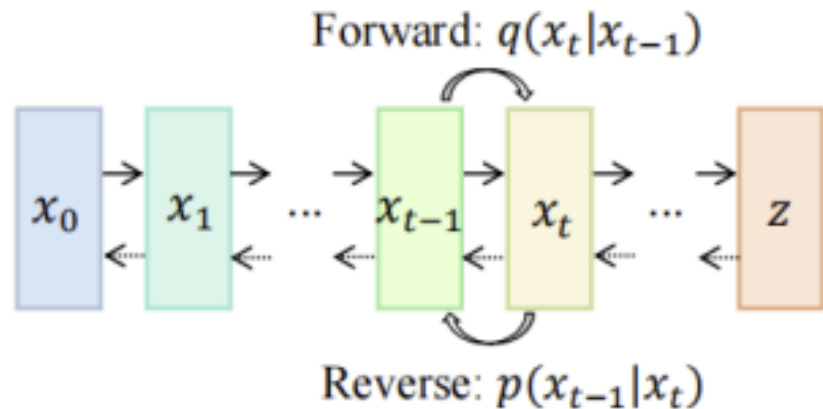
- Generator
- Discriminator

Variational Autoencoders



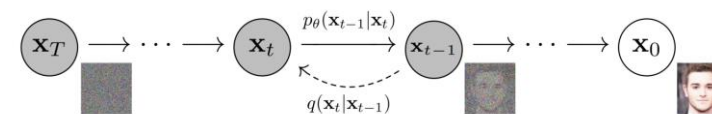
- Variational Inference
- Mean and Variance
- Latent Space

Diffusion Probabilistic Models



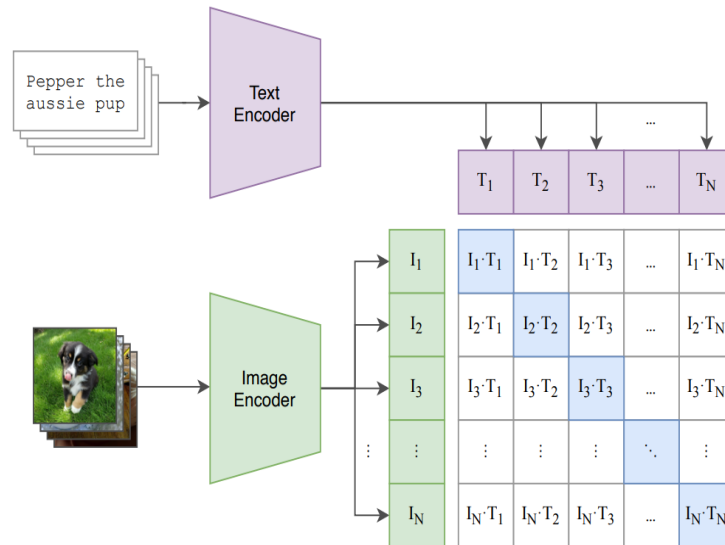
$$X_1 = \sqrt{1-p} X_0 + \sqrt{p} u_1, \quad u_1 \sim \mathcal{N}(0, I)$$

- Diffusion Mechanism
- Parametrized as Markov Chain
- Gaussian Noise
- Forward Process
- Reverse Process

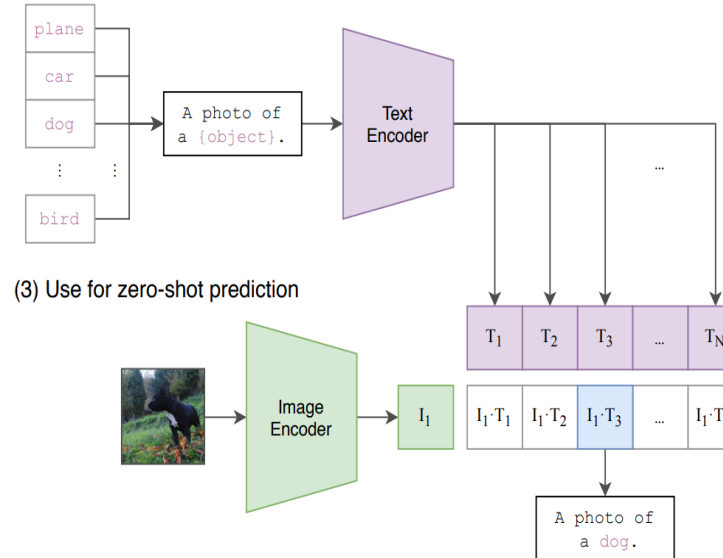


CLIP: Contrastive Language-Image Pre-training

(1) Contrastive pre-training



(2) Create dataset classifier from label text



(3) Use for zero-shot prediction

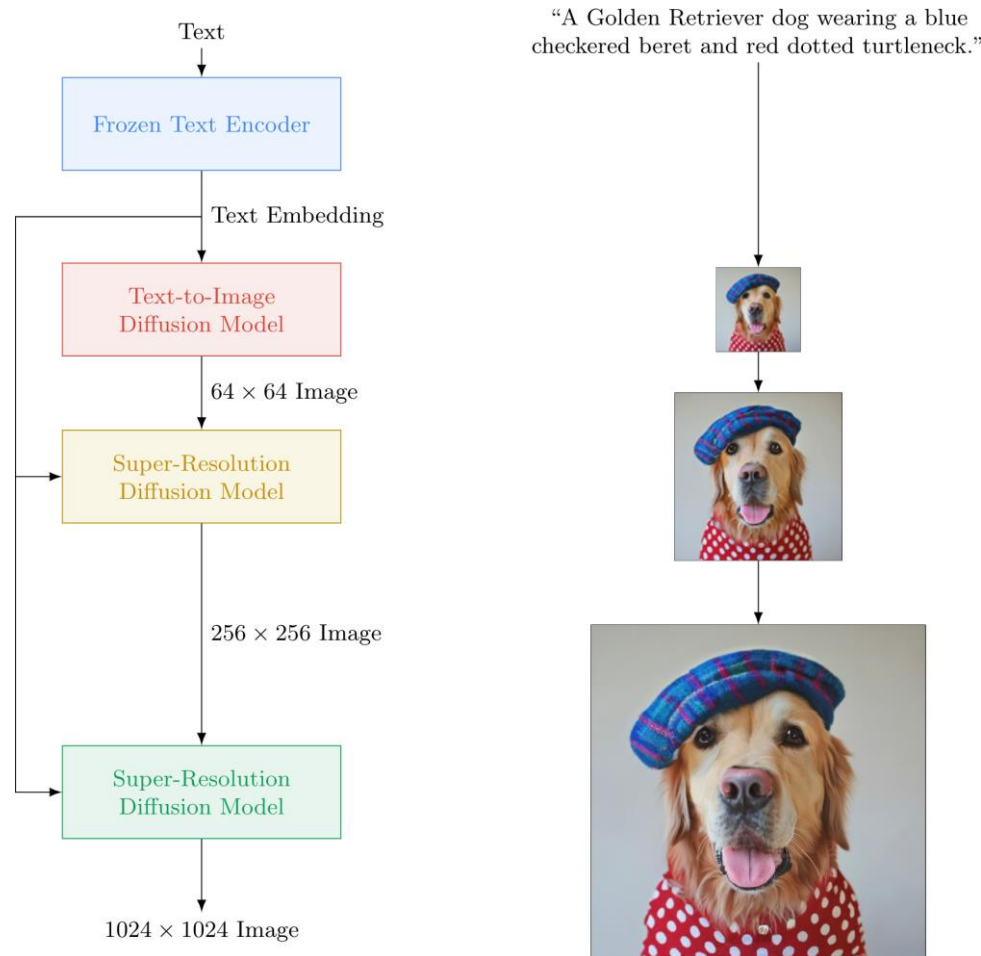
CLIP jointly trains an image encoder and a text encoder to predict the correct pairings of a batch of (image, text) training examples. At test time the learned text encoder synthesizes a zero-shot linear classifier by embedding the names or descriptions of the target dataset's classes.

[Source: Learning Transferable Visual Models From Natural Language Supervision \(arxiv.org\)](https://arxiv.org/abs/2103.00020)

Imagen



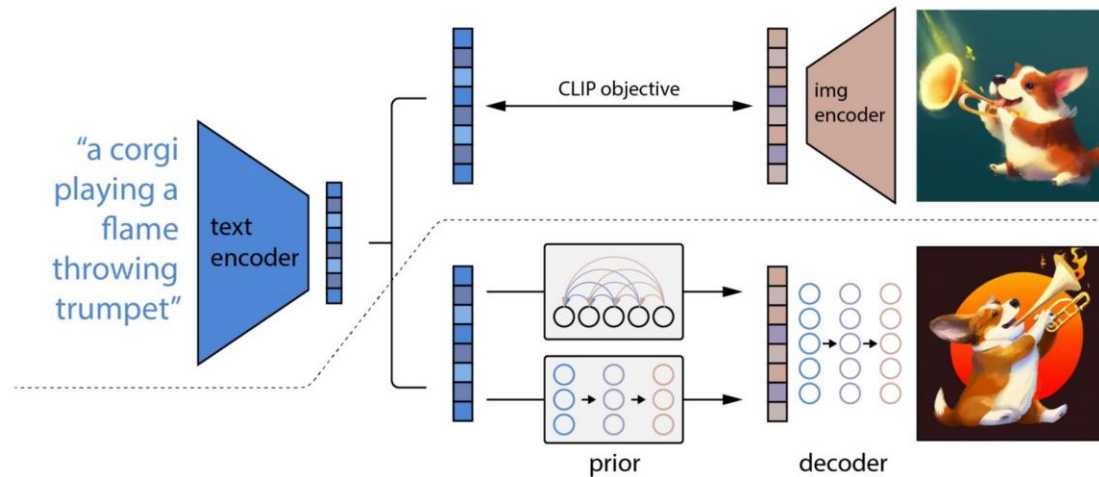
extremely angry bird



Source: <https://imagen.research.google/>

- Imagen uses a large frozen T5-XXL encoder to encode the input text into embeddings.
- A conditional diffusion model maps the text embedding into a 64×64 image.
- Imagen further utilizes text-conditional super-resolution diffusion models to upsample the image
- 64×64→256×256 and 256×256→1024×1024.

DALL-E 2



- The model structure of DALL-E-2. Above the dotted line is the CLIP pre-training process, which aims to align the vision and language modalities. And below the dotted line is the image generation process. The text encoder accepts an instruction and encodes it into a representation, then the prior network and diffusion model decodes this representation to generate the final output.

Responsible Artificial Intelligence



Transparency:

The ability to explain how an AI system works and what data it uses to make decisions. This includes making the decision-making process clear and understandable to users and stakeholders.

Fairness:

The principle that AI systems should not discriminate against individuals or groups based on their race, gender, age, or other characteristics. This requires careful consideration of the data used to train AI systems and the algorithms used to make decisions.

Accountability:

The principle that AI systems should be designed to take responsibility for their actions and decisions. This includes providing clear lines of responsibility for the development and deployment of AI systems.

Reliability:

The principle that AI systems should be designed to work consistently and accurately over time. This requires careful testing and validation of AI systems before they are deployed.

Representation and Equitable:

The principle that AI systems should be designed to represent all individuals and groups fairly and equitably. This requires careful consideration of the data used to train AI systems and the algorithms used to make decisions.

Explainable and Interpretable:

The principle that AI systems should be designed to provide clear explanations of their decisions and actions. This includes providing users with information about how decisions are made and what data is used to make them.



Responsible Generative Artificial Intelligence



Transparency:

GAI systems should be designed to provide clear explanations of how they generate content and what data they use to do so. This includes making the decision-making process clear and understandable to users and stakeholders.

Fairness:

GAI systems should be designed to generate content that does not discriminate against individuals or groups based on their race, gender, age, or other characteristics. This requires careful consideration of the data used to train GAI systems and the algorithms used to generate content.

Accountability:

GAI systems should be designed to take responsibility for the content they generate. This includes providing clear lines of responsibility for the development and deployment of GAI systems.

Reliability:

GAI systems should be designed to generate content consistently and accurately over time. This requires careful testing and validation of GAI systems before they are deployed.

Representation and Equitable:

GAI systems should be designed to represent all individuals and groups fairly and equitably in the content they generate. This requires careful consideration of the data used to train GAI systems and the algorithms used to generate content.

Explainable and Interpretable:

GAI systems should be designed to provide clear explanations of how they generate content. This includes providing users with information about how decisions are made and what data is used to generate content.



LLM Applications in Oil & Gas Industry

- [NLP applications in the oil and natural gas industry | Second International Meeting for Applied Geoscience & Energy \(seg.org\)](#)
 - Attribute Extraction
 - Semantic Information Retrieval
 - Query Intent Translation
 - User-Defined Classification of O&G Documents
- [Geoscience Language Processing for Exploration | Abu Dhabi International Petroleum Exhibition and Conference | OnePetro](#)
 - GeoBERT
 - Geoscience Q&A
 - Query based Summarization



GAN Applications in Oil & Gas Industry



- Geophysical model generation with generative adversarial networks | Geoscience Letters | Full Text (springeropen.com)
 - 2D density and stratigraphic models generated using StyleGAN2 and StyleGAN2 ADA



VAE Applications in Oil & Gas Industry



- Machine learning inversion of geophysical data by a conditional variational autoencoder | SEG International Exposition and Annual Meeting | OnePetro
 - Prior Geological knowledge is incorporated into geophysical inversions using conditional VAE.



Diffusion Applications in Oil & Gas Industry



- [\[2207.10451\] Deep Diffusion Models for Seismic Processing \(arxiv.org\)](#)
 - DPM used to process the seismic data for demultiple, denoising and interpolation.



Questions

