

[KICSV Special AI Lecture]
Core AI Concepts and Modern Architectures

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About Speaker

- *Co-Founder & CTO @ Erudio Bio, San Jose & Novato, CA, USA*
- *Advisor & Evangelist @ CryptoLab, Inc., San Jose, CA, USA*
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- Advisory Professor, Electrical Engineering and Computer Science @ DGIST, Korea
- Adjunct Professor, Electronic Engineering Department @ Sogang University, Korea
- Global Advisory Board Member @ Innovative Future Brain-Inspired Intelligence System Semiconductor of Sogang University, Korea
- *KFAS-Salzburg Global Leadership Initiative Fellow @ Salzburg Global Seminar, Salzburg, Austria*
- Technology Consultant @ Gerson Lehrman Group (GLG), NY, USA
- *Co-Founder & CTO / Head of Global R&D & Chief Applied Scientist / Senior Fellow @ Gauss Labs, Inc., Palo Alto, CA, USA*
2020 ~ 2023

- Senior Applied Scientist @ Amazon.com, Inc., Vancouver, BC, Canada ~ 2020
- Principal Engineer @ Software R&D Center, DS Division, Samsung, Korea ~ 2017
- Principal Engineer @ Strategic Marketing & Sales Team, Samsung, Korea ~ 2016
- Principal Engineer @ DT Team, DRAM Development Lab, Samsung, Korea ~ 2015
- Senior Engineer @ CAE Team, Samsung, Korea ~ 2012
- PhD - Electrical Engineering @ Stanford University, CA, USA ~ 2004
- Development Engineer @ Voyan, Santa Clara, CA, USA ~ 2001
- MS - Electrical Engineering @ Stanford University, CA, USA ~ 1999
- BS - Electrical & Computer Engineering @ Seoul National University 1994 ~ 1998

Highlight of Career Journey

- BS in EE @ SNU, MS & PhD in EE @ Stanford University
 - *Convex Optimization - Theory, Algorithms & Software*
 - advised by *Prof. Stephen P. Boyd*
- Principal Engineer @ Samsung Semiconductor, Inc.
 - AI & Convex Optimization
 - collaboration with *DRAM/NAND Design/Manufacturing/Test Teams*
- Senior Applied Scientist @ Amazon.com, Inc.
 - e-Commerce AIs - anomaly detection, deep RL, and recommender system
 - Bezos's project - drove *\$200M* in additional sales via Amazon Mobile Shopping App
- *Co-Founder & CTO / Global R&D Head & Chief Applied Scientist @ Gauss Labs, Inc.*
- *Co-Founder & CTO* - AI Technology & Business Development @ Erudio Bio, Inc.

Today

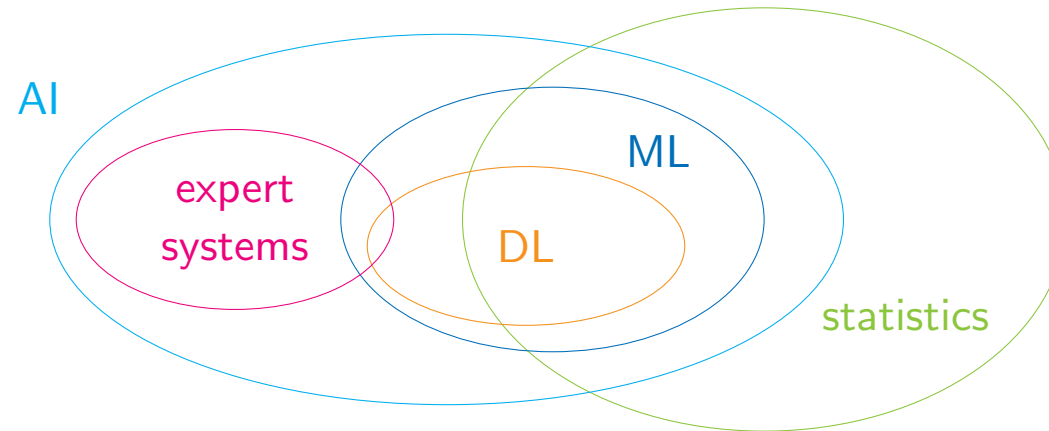
- Artificial Intelligence - 5
 - AI history & recent significant achievements
 - evidences for unprecedented AI progress - market & industry
- LLM - 30
 - language models, seq2seq models
 - LLM, (variants of) Transformer, challenges of LLMs
- Generative AI (genAI) - 60
 - history of genAI, many views on genAI
 - current trend & future perspectives
- Selected references - 78
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Artificial Intelligence

Definition and History

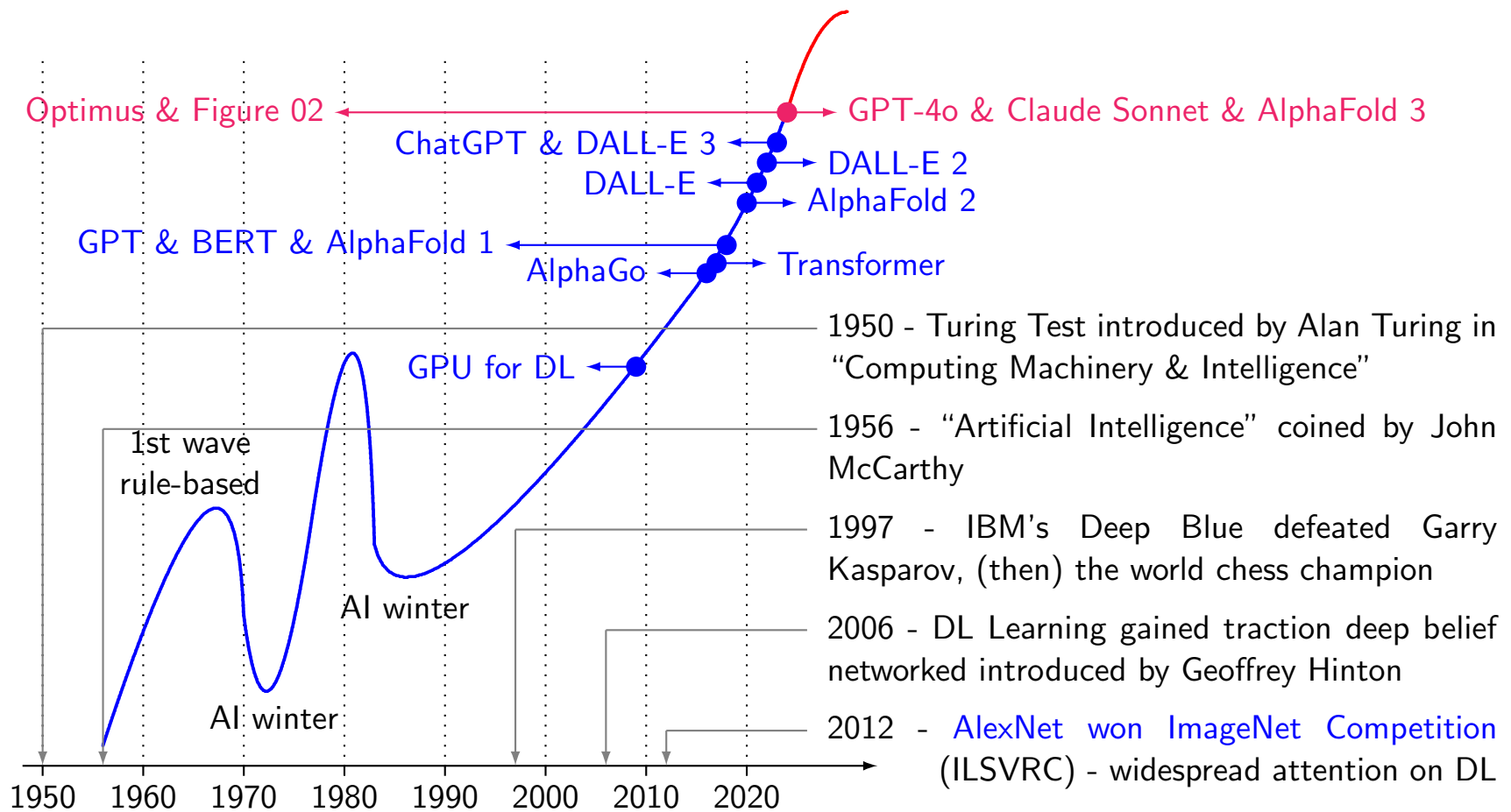
Definition & relation to other technologies

- AI
 - is technology doing tasks requiring human intelligence, such as learning, problem-solving, decision-making & language understanding
 - encompasses *range of technologies, methodologies, applications & products*
- AI, ML, DL, statistics & expert system¹ [HGH⁺22]



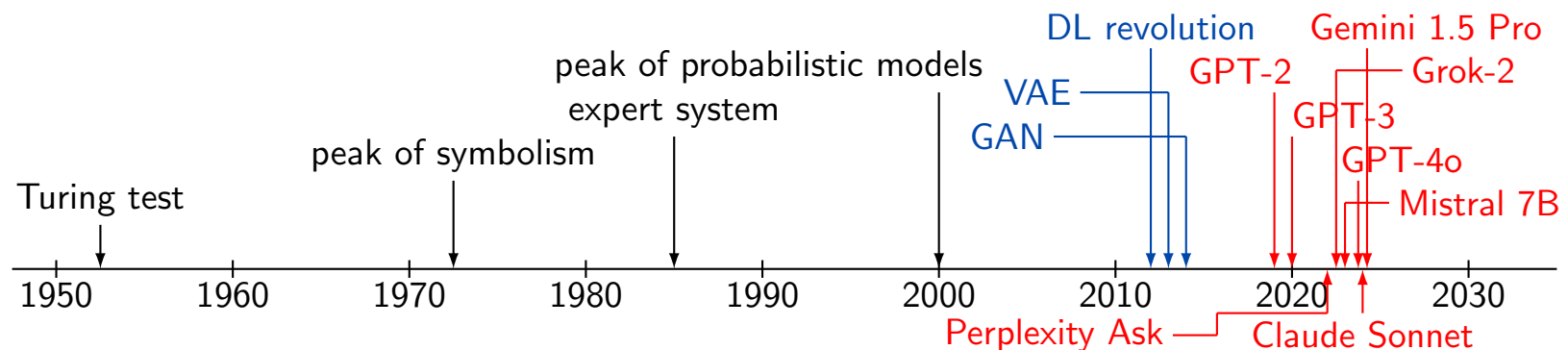
¹ML: machine learning & DL: deep learning

History



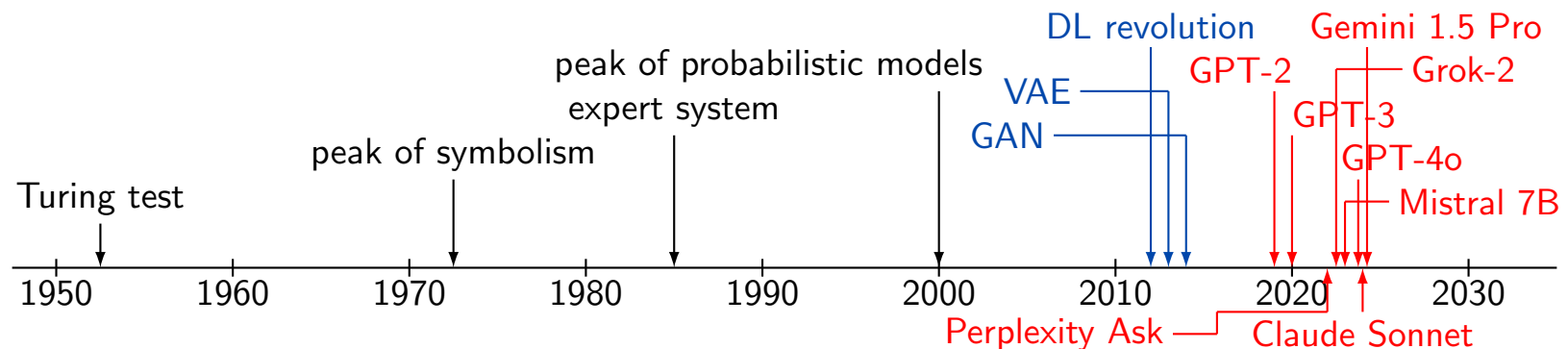
Birth of AI - early foundations & precursor technologies

- 1950s ~ 1970s
 - Alan Turing - concept of *“thinking machine”* & *Turing test* to evaluate machine intelligence (1950s)
 - *symbolists* (as opposed to connectionists) - early AI focused on symbolic reasoning, logic & problem-solving - Dartmouth Conference in 1956 by *John McCarthy, Marvin Minsky, Allen Newell & Herbert A. Simon*
 - precursor technologies - genetic algorithms (GAs), Markov chains & *hidden Markov models (HMMs)* - laying foundation for generative processes (1970s ~)



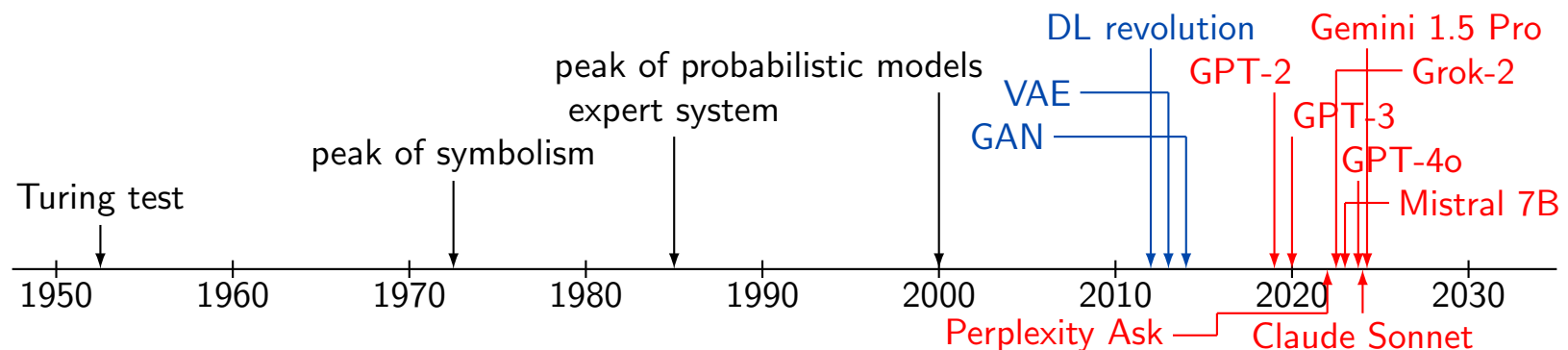
Rule-based systems & probabilistic models

- 1980s ~ early 2000s
 - *expert systems* (1980s) - AI systems designed to mimic human decision-making in specific domains
 - development of neural networks (NN) w/ backpropagation *training multi-layered networks* - setting stage for way more complex generative models
 - *probabilistic models* (including network models, *i.e.*, Bayesian networks) & Markov models - laying groundwork for data generation & pattern prediction



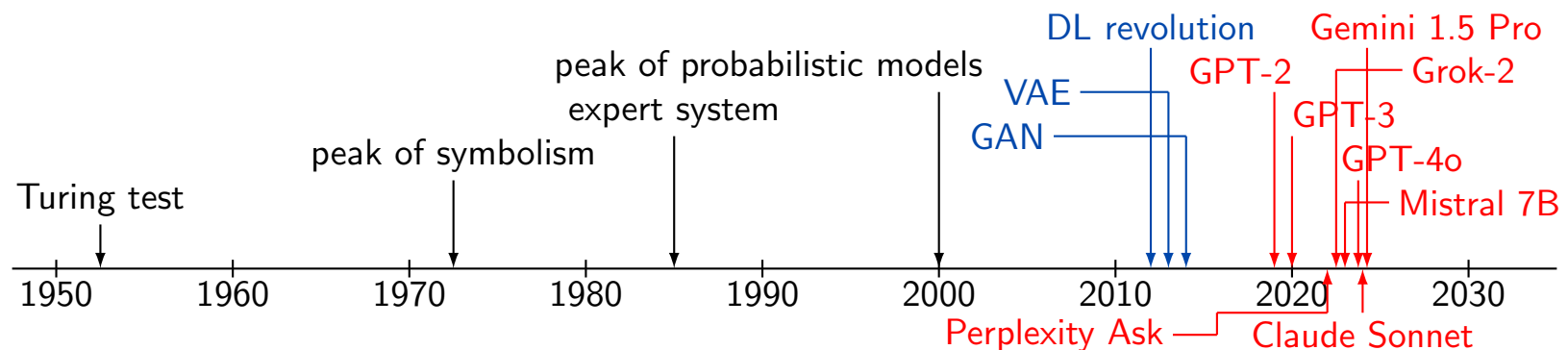
Rise of deep learning & generative models

- 2010s - breakthrough in genAI
 - *deep learning (DL) revolution* - advances in GPU computing and data availability led to the rapid development of deep neural networks.
 - *variational autoencoder (VAE)* (2013) - by Kingma and Welling - learns mappings between input and latent spaces
 - *generative adversarial network (GAN)* (2014) - by Ian Goodfellow - game-changer in generative modeling where two NNs compete each other to create realistic data
 - widely used in image generation & creative tasks



Transformer models & multimodal AI

- late 2010s ~ Present
 - Transformer architecture (2017) - by Vaswani et al.
 - *revolutionized NLP*, e.g., LLM & various genAI models
 - GPT series - generative pre-trained transformer
 - GPT-2 (2019) - generating human-like texts - *marking leap in language models*
 - GPT-3 (2020) - 175B params - set *new standards for LLM*
 - multimodal systems - DALL-E & CLIP (2021) - *linking text and visual data*
 - emergence of diffusion models (2020s) - new approach for generating high-quality images - progressively “denoising” random noise (DALL-E 2 & Stable Diffusion)



Significant AI Achievements - 2014 – 2025

Deep learning revolution

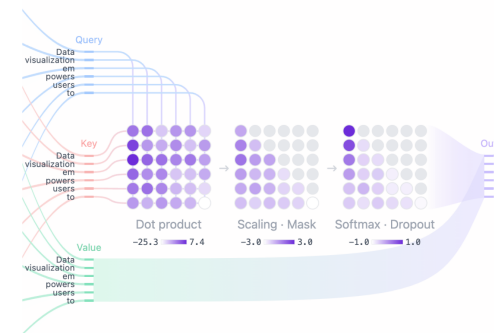
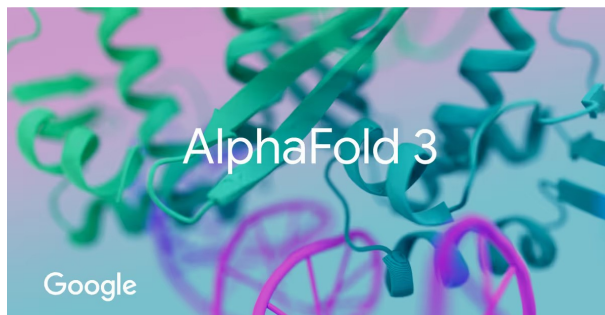
- 2012 – 2015 - DL revolution²
 - CNNs demonstrated exceptional performance in image recognition, *e.g.*, *AlexNet's victory in ImageNet competition*
 - widespread adoption of DL learning in CV transforming industries
- 2016 - AlphaGo defeats human Go champion
 - DeepMind's AlphaGo defeated world champion in Go, extremely complex game *believed to be beyond AI's reach*
 - significant milestone in RL - AI's potential in solving complex & strategic problems



²CV: computer vision, NN: neural network, CNN: convolutional NN, RL: reinforcement learning

Transformer changes everything

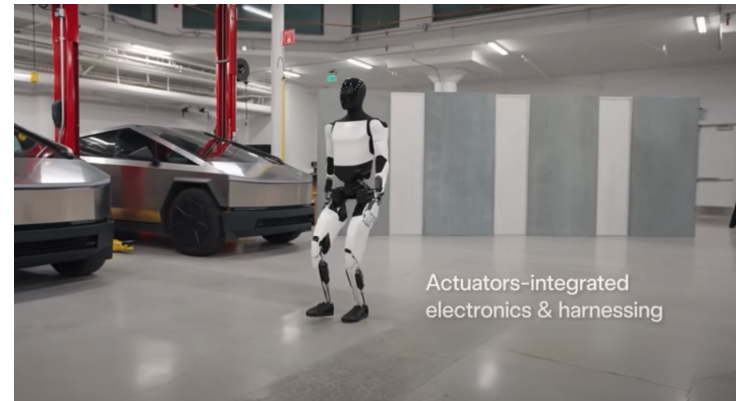
- 2017 – 2018 - Transformers & NLP breakthroughs³
 - *Transformer (e.g., BERT & GPT) revolutionized NLP*
 - major advancements in, e.g., machine translation & chatbots
- 2020 - AI in healthcare – AlphaFold & beyond
 - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting 3D protein structures with remarkable accuracy
 - accelerates drug discovery and personalized medicine - offering new insights into diseases and potential treatments



³NLP: natural language processing, GPT: generative pre-trained transformer

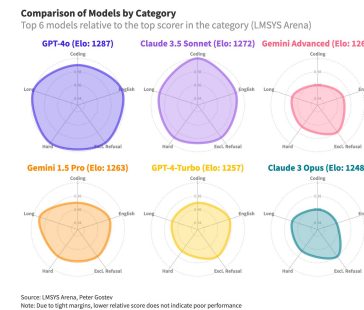
Lots of breakthroughs in AI technology and applications in 2024

- proliferation of advanced AI models
 - GPT-4o, Claude Sonnet, Claude 3 series, Llama 3, Sora, Gemini
 - *transforming industries* such as content creation, customer service, education, *etc.*
- breakthroughs in specialized AI applications
 - Figure 02, Optimus, AlphaFold 3
 - driving unprecedented advancements in automation, drug discovery, scientific understanding - *profoundly affecting healthcare, manufacturing, scientific research*



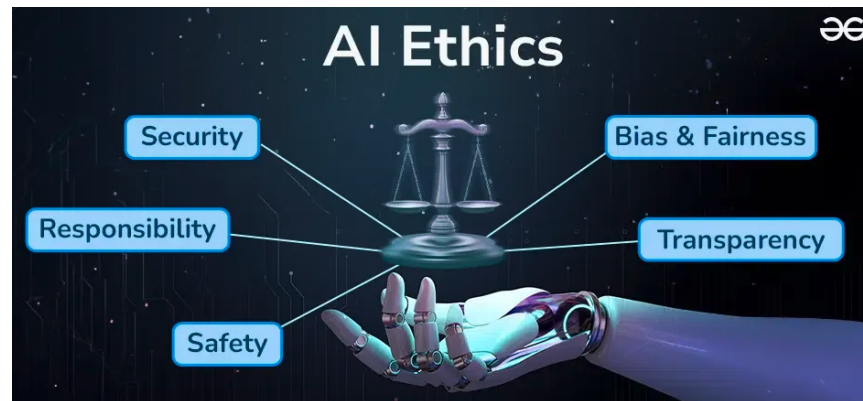
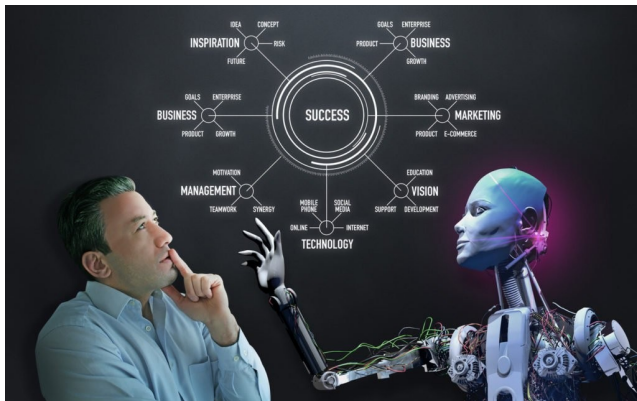
Major AI Breakthroughs in 2025

- next-generation foundation models
 - GPT-5 and Claude 4 demonstrate emergent reasoning abilities
 - open-source models achieving parity with leading commercial systems from 2024
- hardware innovations
 - NVIDIA's Blackwell successor architecture delivering 3-4x performance improvement
 - AMD's MI350 accelerators challenging NVIDIA's market dominance
- AI-human collaboration systems
 - seamless multimodal interfaces enabling natural human-AI collaboration
 - AI systems effectively explaining reasoning and recommendations
 - augmented reality interfaces providing real-time AI assistance in professional contexts



Transformative impact of AI - reshaping industries, work & society

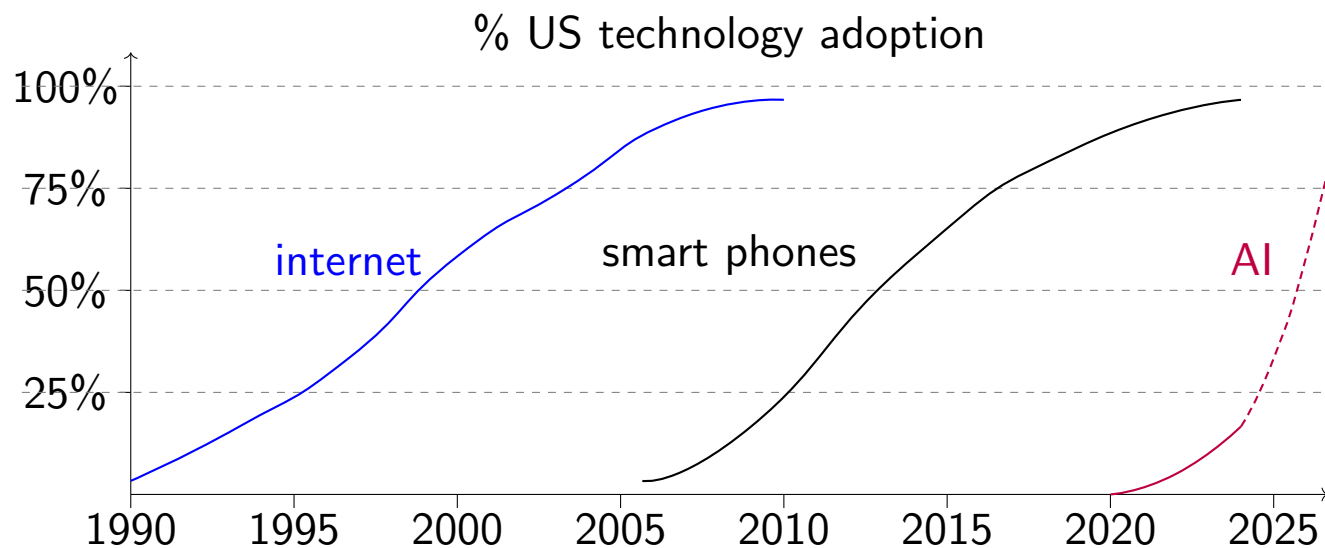
- accelerating human-AI collaboration
 - not only reshaping industries but *altering how humans interact with technology*
 - AI's role as collaborator and augmentor redefines productivity, creativity, the way we address global challenges, *e.g.*, *sustainability & healthcare*
- AI-driven automation *transforms workforce dynamics* - creating new opportunities while challenging traditional job roles
- *ethical AI considerations* becoming central not only to business strategy, but to society as a whole - *influencing regulations, corporate responsibility & public trust*



Measuring AI's Ascent

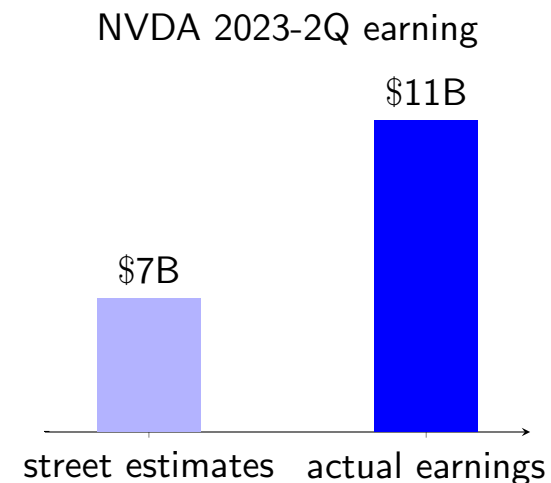
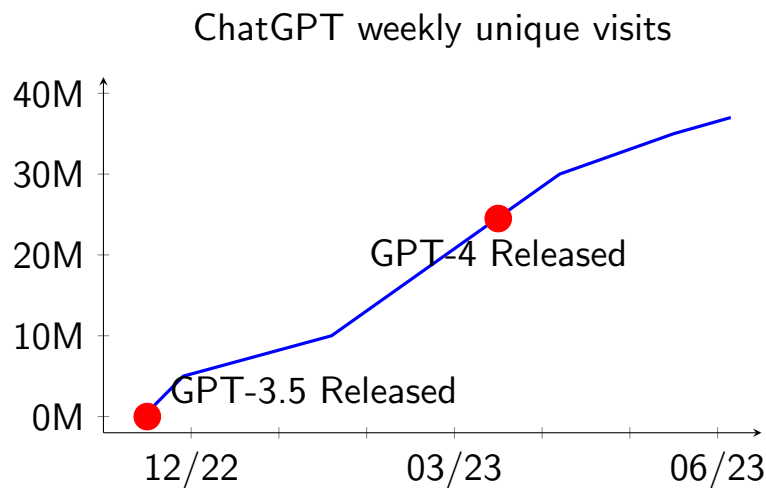
Where are we in AI today?

- sunrise phase - currently experiencing dawn of AI era with significant advancements and increasing adoption across various industries
- early adoption - in early stages of AI lifecycle with widespread adoption and innovation across sectors marking significant shift in technology's role in society



Explosion of AI ecosystems - ChatGPT & NVIDIA

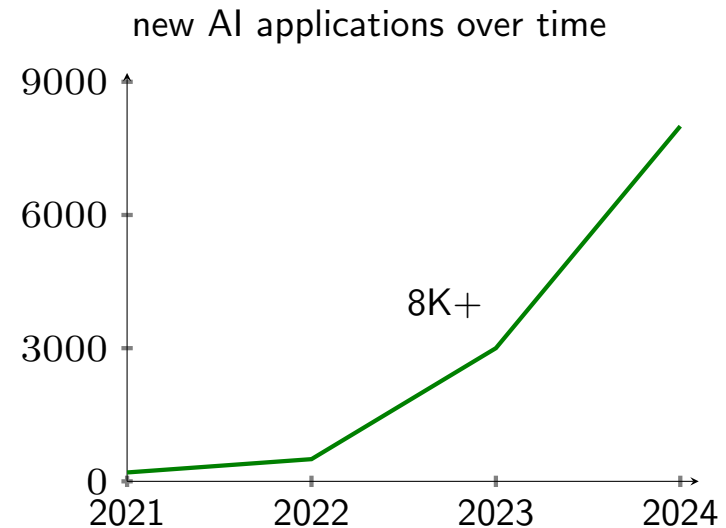
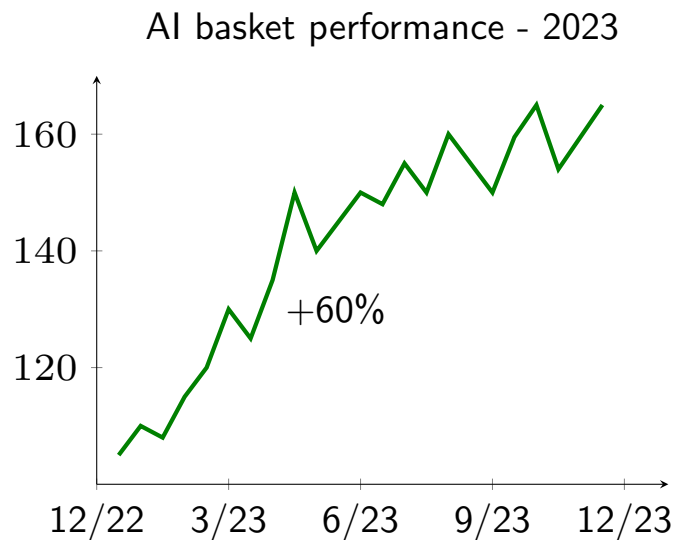
- took only *5 months for ChatGPT users to reach 35M*
- NVIDIA 2023 Q2 earning exceeds market expectation by big margin - \$7B vs \$13.5B
 - surprisingly, *101% year-to-year growth*
 - even more surprisingly *gross margin was 71.2%* - up from 43.5% in previous year⁴



⁴source - Bloomberg

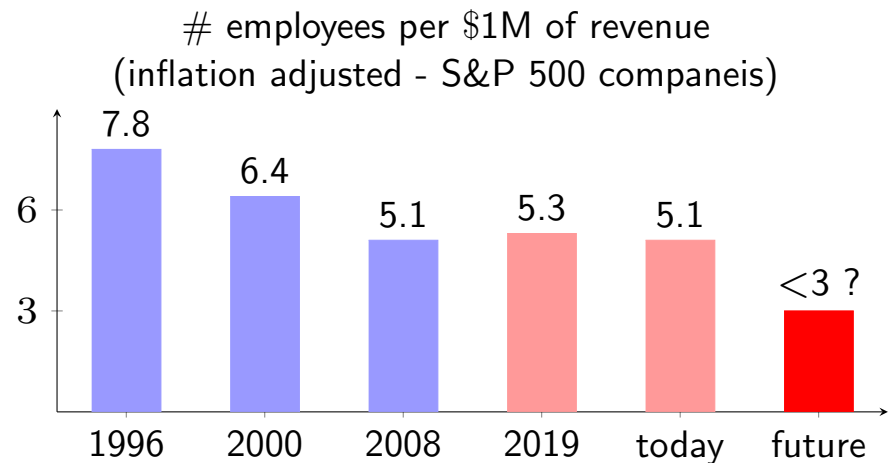
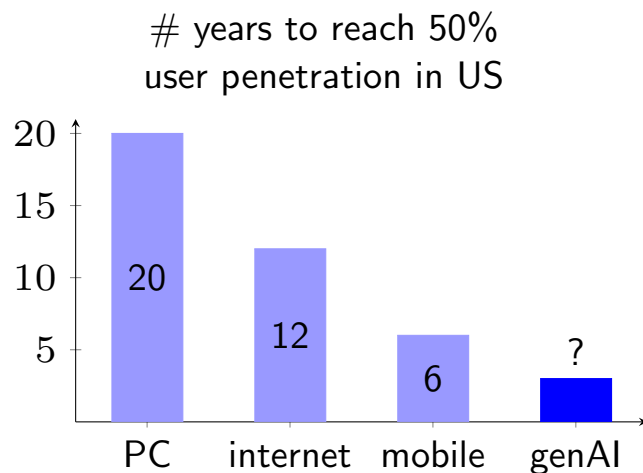
Explosion of AI ecosystems - AI stock market

- *AI investment surge in 2023 - portfolio performance soars by 60%*
 - AI-focused stocks significantly outpaced traditional market indices
- *over 8,000 new AI applications* developed in last 3 years
 - applications span from healthcare and finance to manufacturing and entertainment



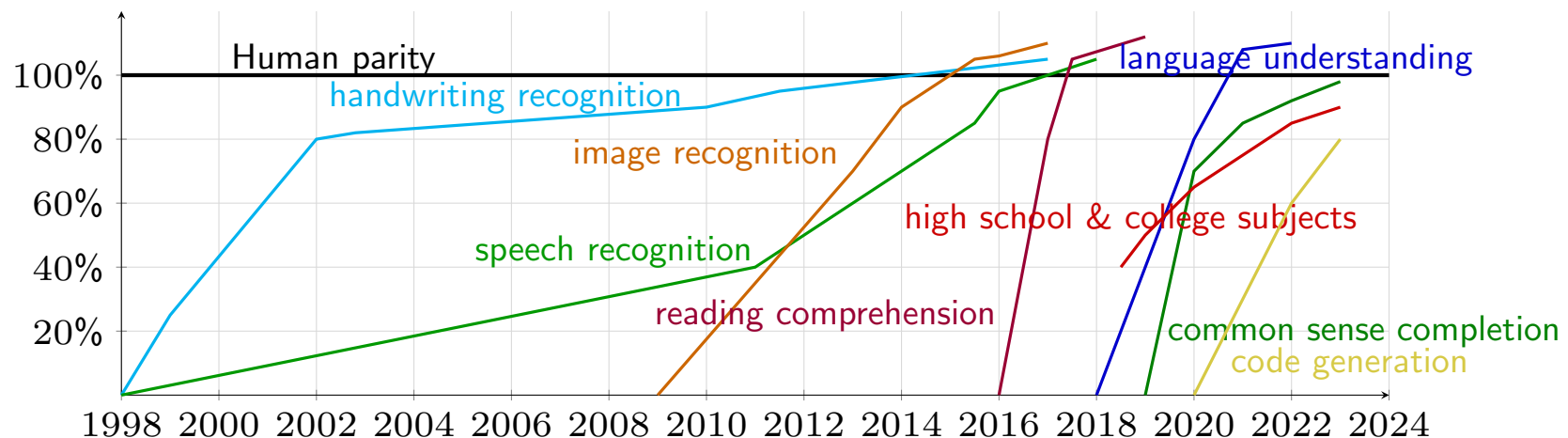
AI's transformative impact - adoption speed & economic potential

- adoption - has been twice as fast with platform shifts suggesting
 - increasing demand and readiness for new technology improved user experience & accessibility
- AI's potential to drive economy for years to come
 - 35% improvement in productivity driven by introduction of PCs and internet
 - greater gains expected with AI proliferation



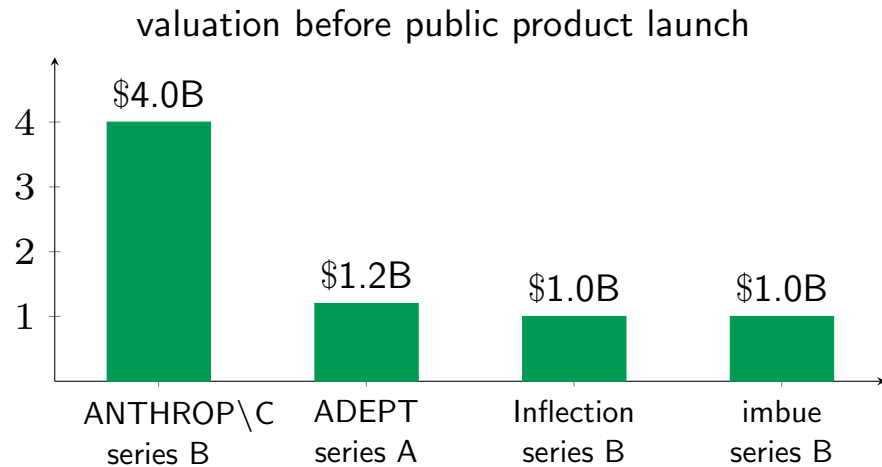
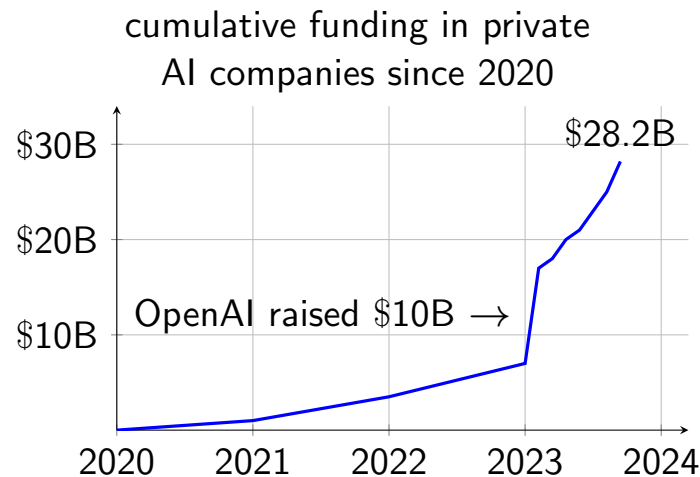
AI getting more & more faster

- steep upward slopes of AI capabilities highlight accelerating pace of AI development
 - period of exponential growth with AI potentially mastering new skills and surpassing human capabilities at ever-increasing rate
- closing gap to human parity - some capabilities approaching or arguably reached human parity, while others having still way to go
 - achieving truly human-like capabilities in broad range remains a challenge



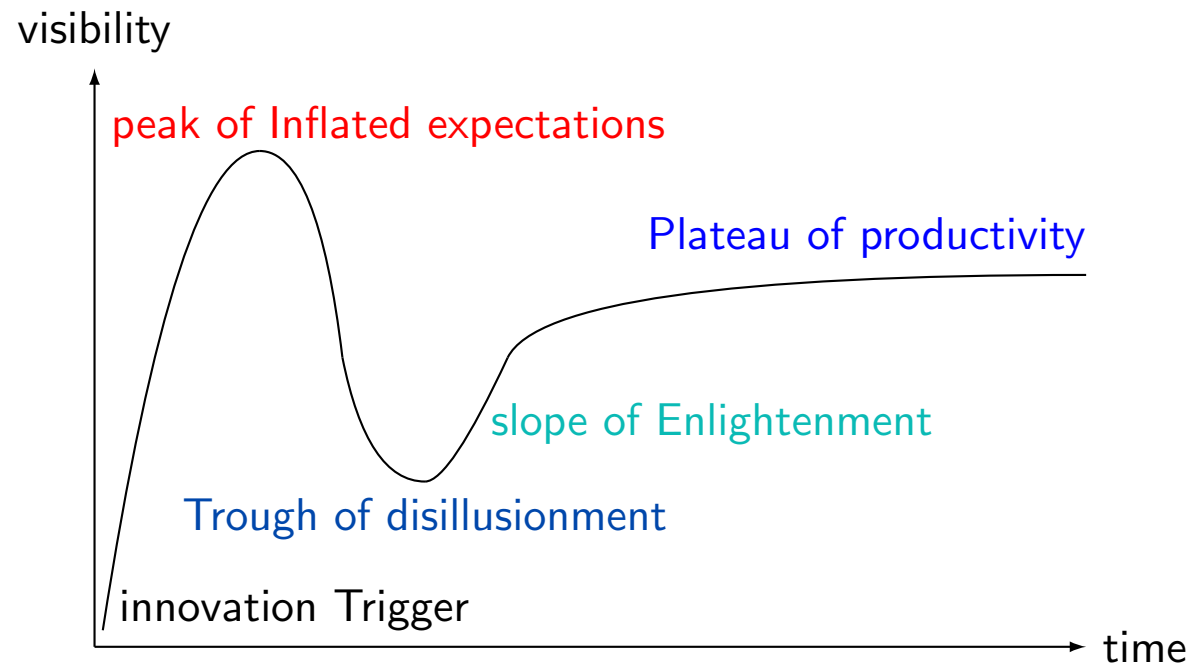
Massive investment in AI

- *explosive growth* - cumulative funding skyrocketed reaching staggering \$28.2B
- OpenAI - significant fundraising (=\$10B) fueled rapid growth
- *valuation surge* - substantial valuations even before public products for stellar companies
- *fierce competition for capital* among AI startups driving innovation & accelerating development
- massive investment indicates *strong belief in & optimistic outlook for potential of AI* to revolutionize industries & drive economic growth



Is AI hype?

Technology hype cycle



- innovation trigger - technology breakthrough kicks things off
- peak of inflated expectations - early publicity induces many successes followed by even more
- trough of disillusionment - expectations wane as technology producers shake out or fail
- slope of enlightenment - benefit enterprise, technology better understood, more enterprises fund pilots

Fiber vs cloud infrastructure

- fiber infrastructure - 1990s

- Telco Co's raised \$1.6T of equity & \$600B of debt
- bandwidth costs decreased 90% within 4 years
- companies - Covage, NothStart, Telligent, Electric Lightwave, 360 networks, Nextlink, Broadwind, UUNET, NFS Communications, Global Crossing, Level 3 Communications
- became *public good*

- cloud infrastructure - 2010s

- entirely new computing paradigm
- mostly public companies with data centers
- *big 4 hyperscalers generate* \$150B + annual revenue



Yes & No

characteristics of hype cycles	speaker's views
value accrual misaligned with investment	● OpenAI still operating at a loss; business model <i>still</i> not clear ● gradual value creation across broad range of industries and technologies (<i>e.g.</i>, CV, LLMs, RL) unlike fiber optic bubble in 1990s
overestimating timeline & capabilities of technology	● self-driving cars delayed for over 15 years, with limited hope for achieving level 5 autonomy ● AI, however, has proven useful within a shorter 5-year span, with enterprises eagerly adopting
lack of widespread utility due to technology maturity	● AI already providing significant utility across various domains ● vs quantum computing remains promising in theory but lacks widespread practical utility

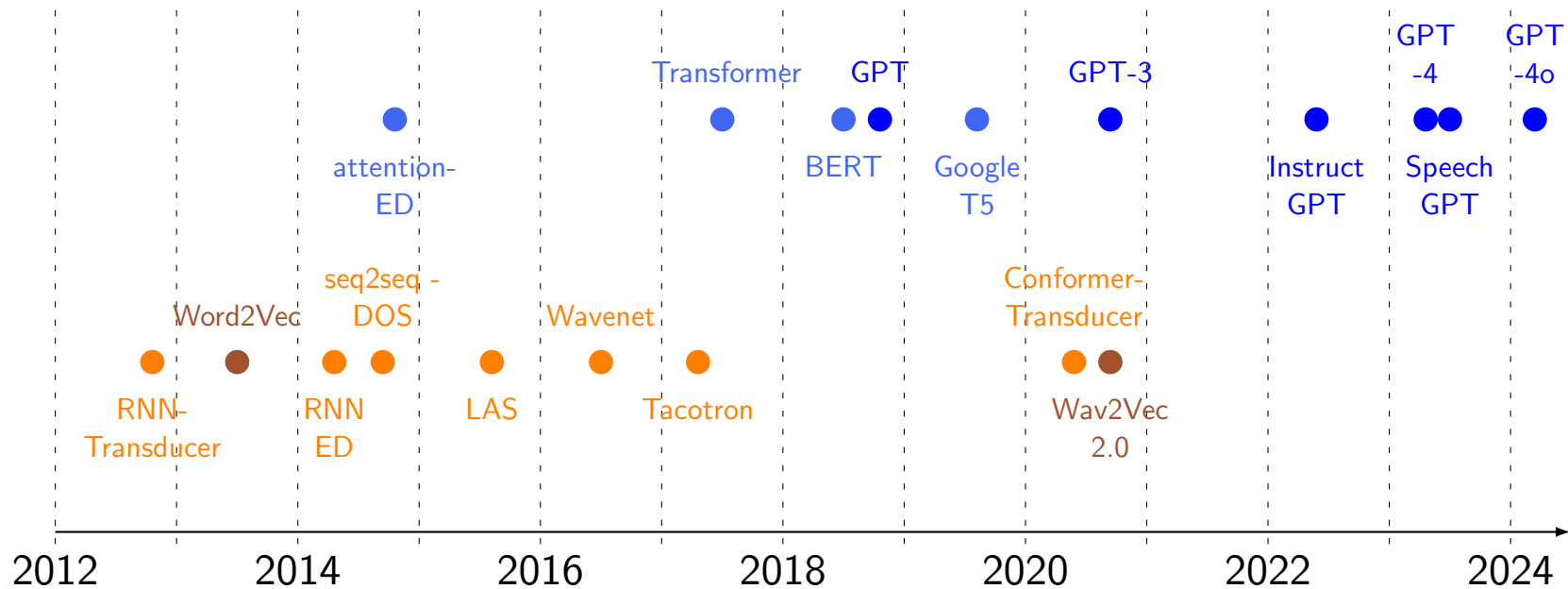
LLM

Language Models

History of language models

- bag of words - first introduced – 1954
- word embedding – 1980
- RNN based models - conceptualized by David Rumelhart – 1986
- LSTM (based on RNN) – 1997
- 380M-sized seq2seq model using LSTMs proposed – 2014
- 130M-sized seq2seq model using gated recurrent units (GRUs) – 2014
- Transformer - Attention is All You Need - A. Vaswani et al. @ Google – 2017
 - 100M-sized encoder-decoder multi-head attention model for machine translation
 - non-recurrent architecture, handle arbitrarily long dependencies
 - parallelizable, *simple* (linear-mapping-based) attention model

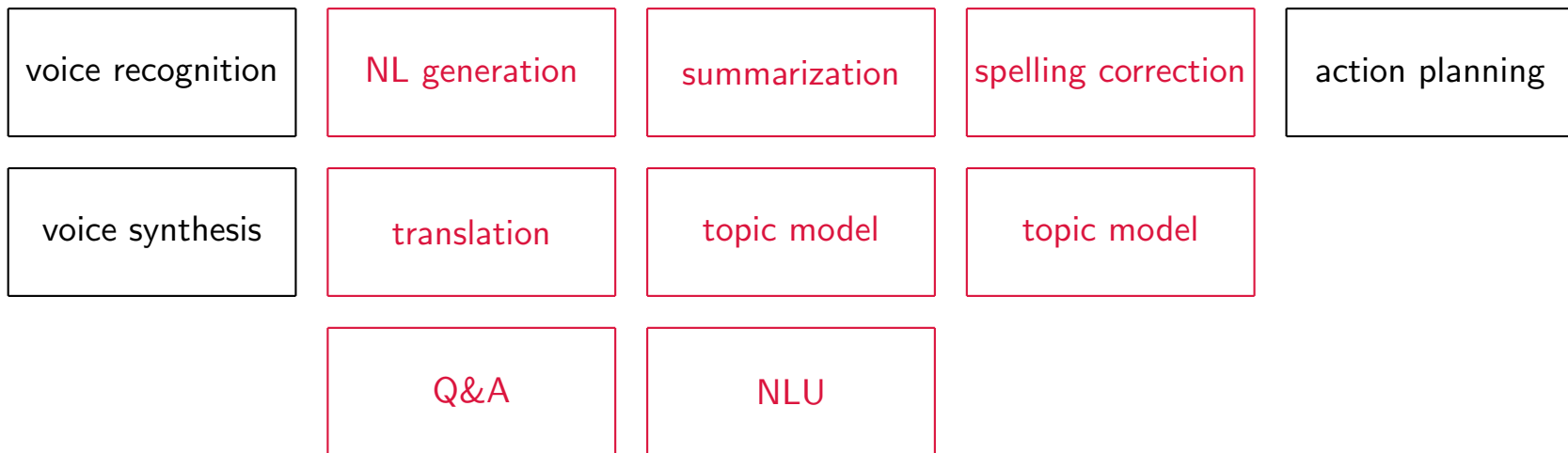
Recent advances in speech & language processing



- LAS: listen, attend, and spell, ED: encoder-decoder, DOS: decoder-only structure

Types of language models

- many of language models have **common requirements** - language representation learning
- can be learned via pre-training *high performing model* and fine-tuning/transfer learning/domain adaptation
- this *high performing model* learning essential language representation *is* (language) foundation model
- actually, same for other types of learning, *e.g.*, CV



NLP Market

NLP market size

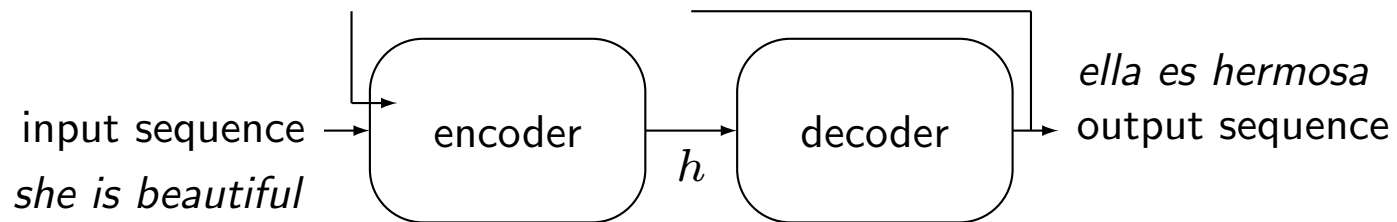
- global NLP market size estimated at USD 16.08B in 2022, is expected to hit USD 413.11B by 2032 - *CAGR of 38.4%*
- in 2022
 - north america NLP market size valued at USD 8.2B
 - high tech and telecom segment accounted revenue share of over 23.1%
 - healthcare segment held a 10% market share
 - (by component) solution segment hit 76% revenue share
 - (deployment mode) on-premise segment generated 56% revenue share
 - (organizational size) large-scale segment contributed highest market share
- source - [Precedence Research](#)



Sequence-to-Sequence Models

Sequence-to-sequence (seq2seq) model

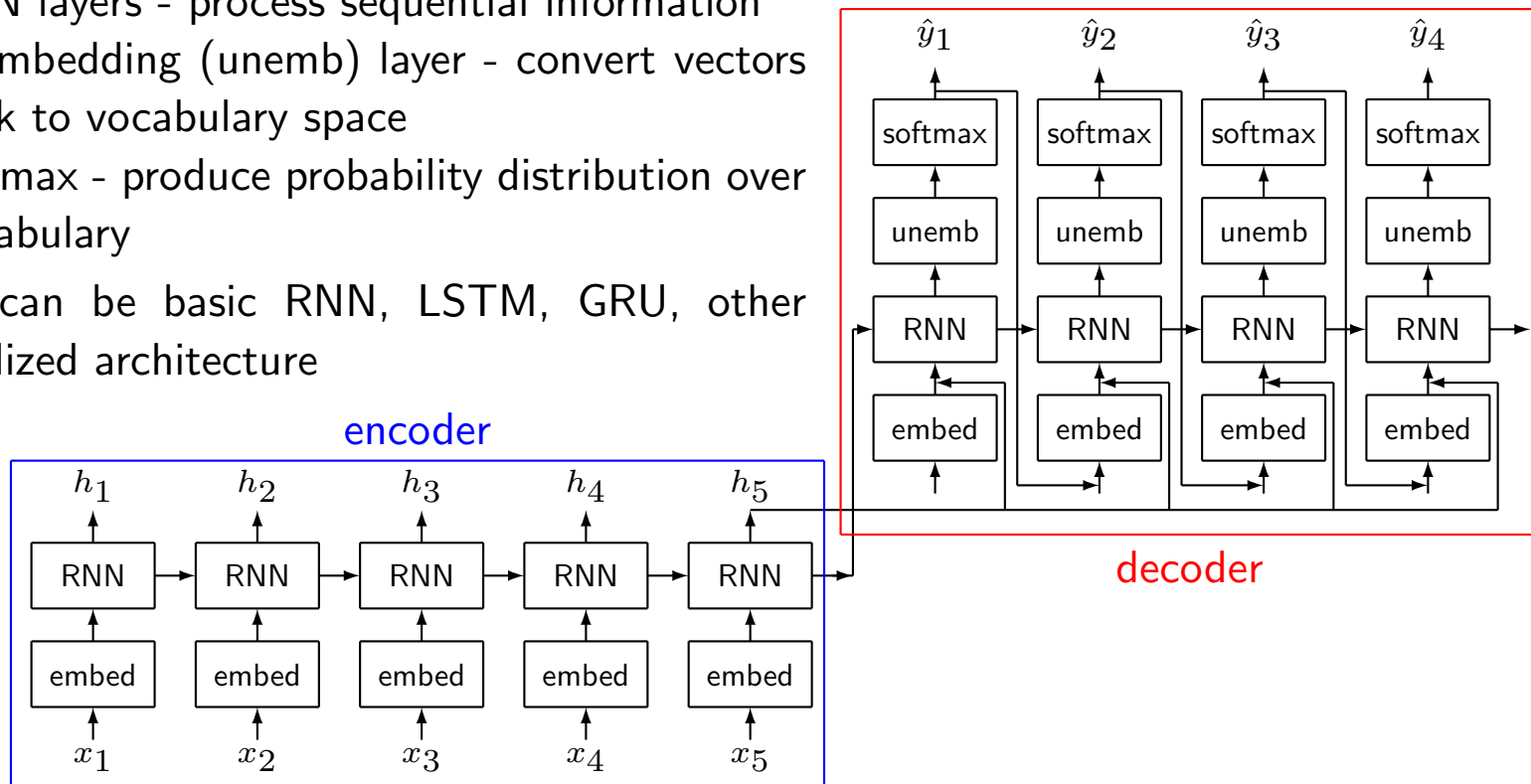
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



- encoder & decoder can be RNN-type models
- $h \in \mathbf{R}^n$ - hidden state - *fixed length* vector
- (try to) condense and store information of input sequence (losslessly) in (fixed-length) hidden states
 - finite hidden state - not flexible enough, *i.e.*, cannot handle arbitrarily large information
 - memory loss for long sequences
 - LSTM was promising fix, but with (inevitable) limits

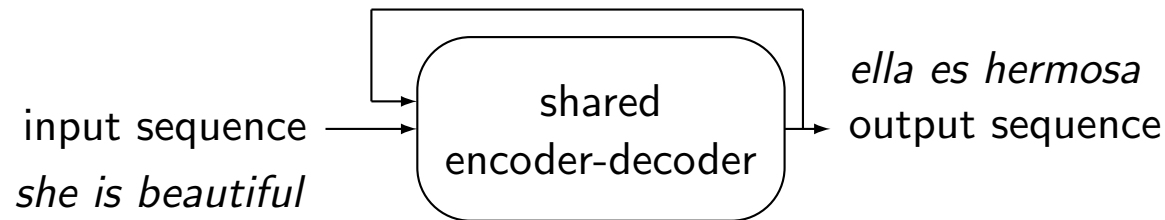
RNN-type encoder-decoder architecture

- components
 - embedding layer - convert input tokens to vector representations
 - RNN layers - process sequential information
 - unembedding (unemb) layer - convert vectors back to vocabulary space
 - softmax - produce probability distribution over vocabulary
- RNN can be basic RNN, LSTM, GRU, other specialized architecture



Shared encoder-decoder model

- single neural network structure can handle both encoding & decoding tasks
 - efficient architecture reducing model complexity
 - allow for better parameter sharing across tasks
- widely used in modern LLMs to process & generate text sequences
 - applications - machine translation, text summarization, question answering
- advantages
 - efficient use of parameters, versatile for multiple NLP tasks



Large Language Models

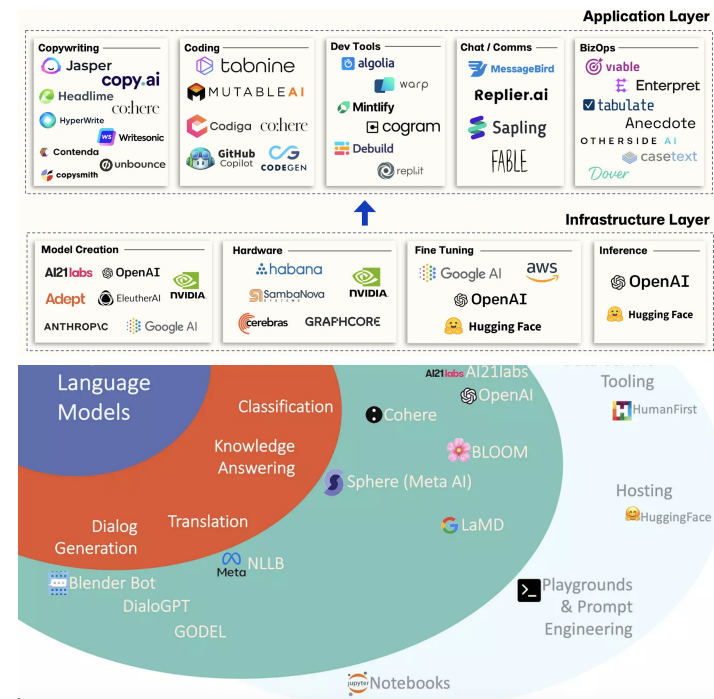
LLM

- LLM
 - type of AI aimed for NLP trained on massive corpus of texts & programming code
 - allow learn statistical relationships between words & phrases, *i.e.*, conditional probabilities
 - *amazing performance shocked everyone - unreasonable effectiveness of data (Halevry et al., 2009)*
- applications
 - conversational AI agent / virtual assistant
 - machine translation / text summarization / content creation / sentiment analysis / question answering
 - code generation
 - market research / legal service / insurance policy / triange hiring candidates
- + virtually infinite # of applications



LLMs

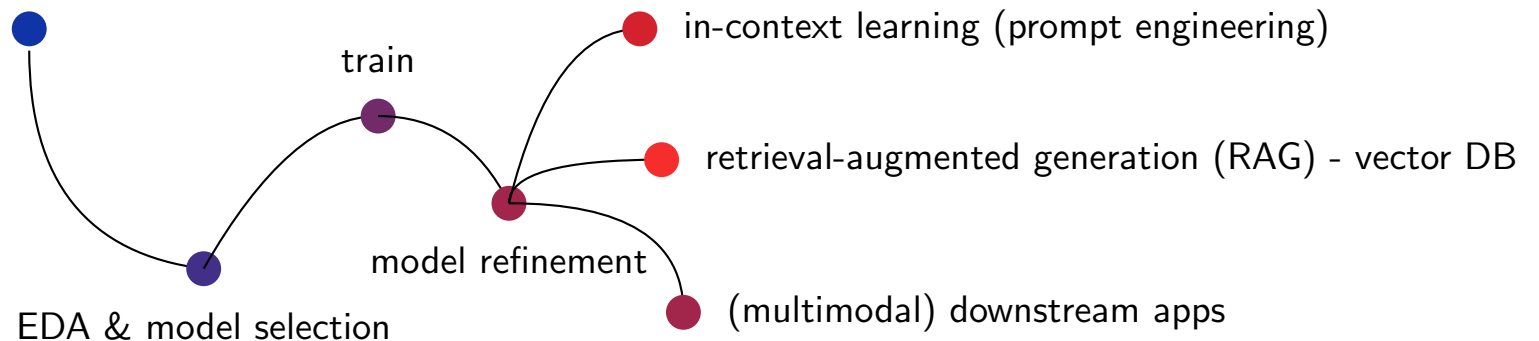
- Foundation Models
 - GPT-x/Chat-GPT - OpenAI, Llama-x - Meta, PaLM-x (Bard) - Google
- # parameters
 - generative pre-trained transformer (GPT) - GPT-1: 117M, GPT-2: 1.5B, GPT-3: 175B, GPT-4: 100T, GPT-4o: 200B
 - large language model Meta AI (Llama) - Llama1: 65B, Llama2: 70B, Llama3: 70B
 - scaling language modeling with pathways (PaLM) - 540B
- burns lots of cash on GPUs!
- applicable to many NLP & genAI applications



LLM building blocks

- data - trained on massive datasets of text & code
 - quality & size critical on performance
- architecture - GPT/Llama/Mistral
 - can make huge difference
- training - self-supervised/supervised learning
- inference - generates outputs
 - in-context learning, prompt engineering

goal and scope of LLM project



Transformer

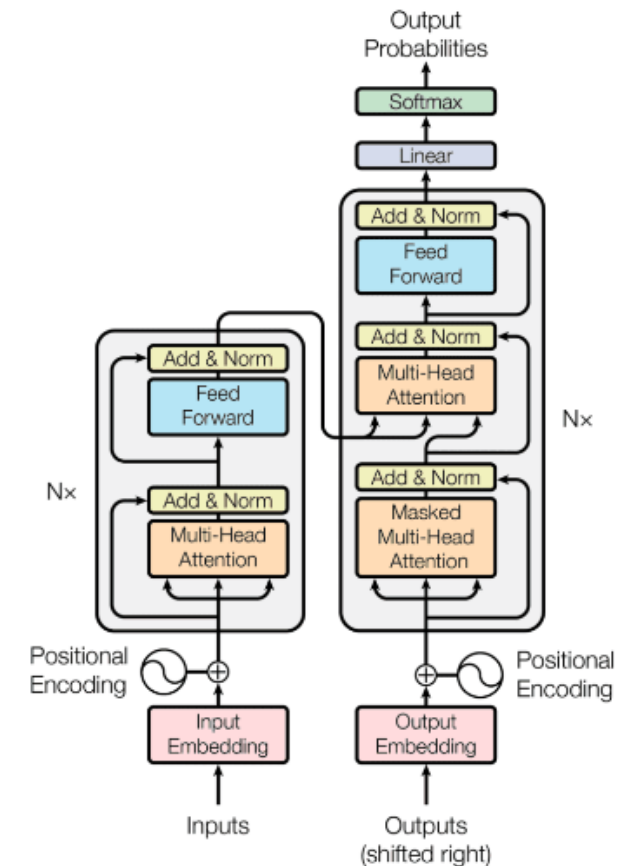
LLM architectural secret (or known) sauce

Transformer - simple parallelizable attention mechanism

A. Vaswani, et al. Attention is All You Need, 2017

Transformer architecture

- encoding-decoding architecture
 - input embedding space → multi-head & multi-layer representation space → output embedding space
- additive positional encoding - information regarding order of words @ input embedding
- multi-layer and multi-head attention followed by addition / normalization & feed forward (FF) layers
- *(relatively simple) attentions*
 - single-head (scaled dot-product) / multi-head attention
 - self attention / encoder-decoder attention
 - masked attention
- benefits
 - *evaluate dependencies between arbitrarily distant words*
 - has recurrent nature w/o recurrent architecture → parallelizable → fast w/ additional cost in computation



Single-head scaled dot-product attention

- values/keys/queries denote value/key/query *vectors*, d_k & d_v are lengths of keys/queries & vectors
- we use *standard* notions for matrices and vectors - not transposed version that (almost) all ML scientists (wrongly) use
- output: weighted-average of values where weights are attentions among tokens
- assume n queries and m key-value pairs

$$Q \in \mathbf{R}^{d_k \times n}, K \in \mathbf{R}^{d_k \times m}, V \in \mathbf{R}^{d_v \times m}$$

- attention! outputs n values (since we have n queries)

$$\text{Attention}(Q, K, V) = V \text{softmax} \left(K^T Q / \sqrt{d_k} \right) \in \mathbf{R}^{d_v \times n}$$

- *much simpler attention mechanism than previous work*
 - attention weights were output of complicated non-linear NN

Single-head - close look at equations

- focus on i th query, $q_i \in \mathbf{R}^{d_k}$, $Q = \begin{bmatrix} - & q_i & - \end{bmatrix} \in \mathbf{R}^{d_k \times n}$
- assume m keys and m values, $k_1, \dots, k_m \in \mathbf{R}^{d_k}$ & $v_1, \dots, v_m \in \mathbf{R}^{d_v}$

$$K = \begin{bmatrix} k_1 & \cdots & k_m \end{bmatrix} \in \mathbf{R}^{d_k \times m}, V = \begin{bmatrix} v_1 & \cdots & v_m \end{bmatrix} \in \mathbf{R}^{d_v \times m}$$

- then

$$K^T Q / \sqrt{d_k} = \begin{bmatrix} - & k_j^T q_i / \sqrt{d_k} & - \\ & \vdots & \\ & k_j^T q_i / \sqrt{d_k} & - \\ & \vdots & \end{bmatrix}$$

e.g., dependency between i th output token and j th input token is

$$a_{ij} = \exp \left(k_j^T q_i / \sqrt{d_k} \right) / \sum_{j=1}^m \exp \left(k_j^T q_i / \sqrt{d_k} \right)$$

- value obtained by i th query, q_i in $\text{Attention}(Q, K, V)$

$$a_{i,1}v_1 + \cdots + a_{i,m}v_m$$

Multi-head attention

- evaluate h single-head attentions (in parallel)
- d_e : dimension for embeddings
- embeddings

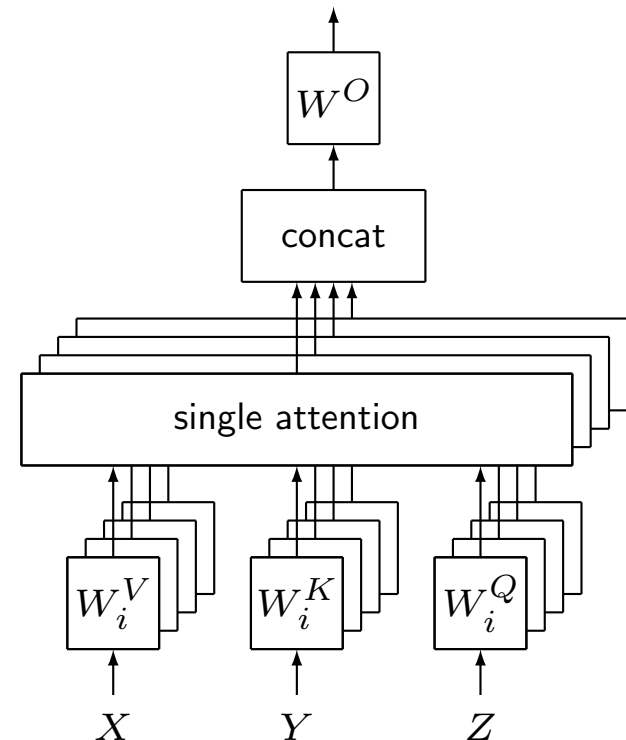
$$X \in \mathbf{R}^{d_e \times m}, Y \in \mathbf{R}^{d_e \times m}, Z \in \mathbf{R}^{d_e \times n}$$

e.g., n : input sequence length & m : output sequence length in machine translation

- h key/query/value weight matrices: $W_i^K, W_i^Q \in \mathbf{R}^{d_k \times d_e}$, $W_i^V \in \mathbf{R}^{d_v \times d_e}$ ($i = 1, \dots, h$)
- linear output layers: $W^O \in \mathbf{R}^{d_e \times h d_v}$
- *multi-head attention!*

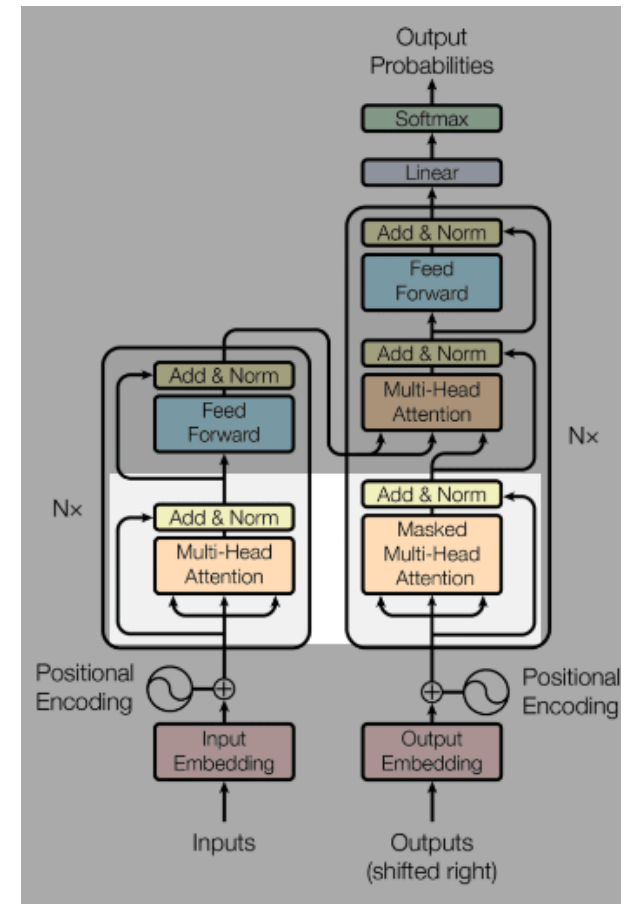
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbf{R}^{d_e \times n},$$

$$A_i = \text{Attention}(W_i^Q Z, W_i^K Y, W_i^V X) \in \mathbf{R}^{d_v \times n}$$



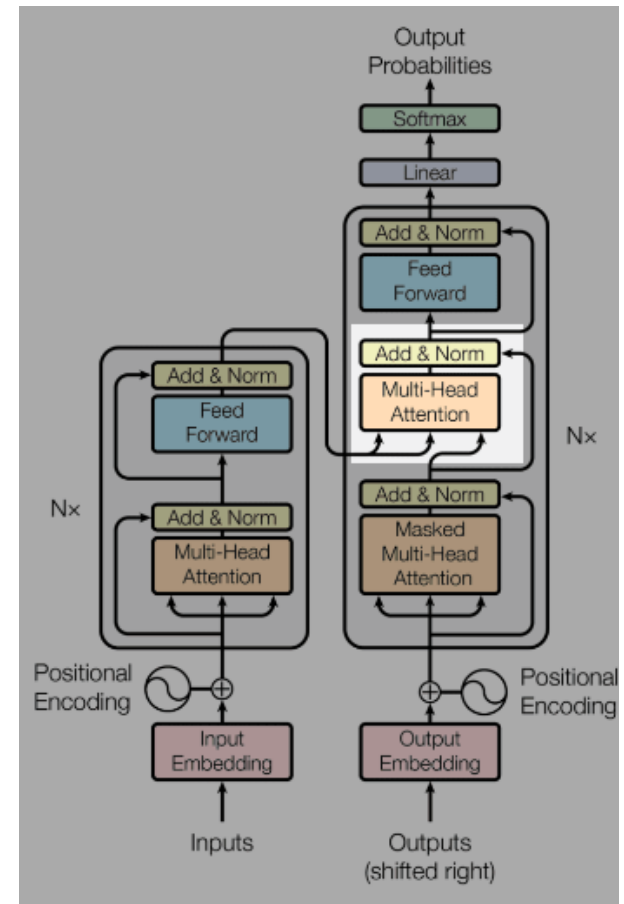
Self attention

- $m = n$
- encoder
 - keys & values & queries (K, V, Q) come from same place (from previous layer)
 - every token attends to every other token in input sequence
- decoder
 - keys & values & queries (K, V, Q) come from same place (from previous layer)
 - every token attends to other tokens up to that position
 - prevent leftward information flow to right to preserve causality
 - assign $-\infty$ for illegal connections in softmax (masking)



Encoder-decoder attention

- m : length of input sequence
- n : length of output sequence
- n queries (Q) come from previous decoder layer
- m keys / m values (K, V) come from output of encoder
- every token in output sequence attends to every token in input sequence

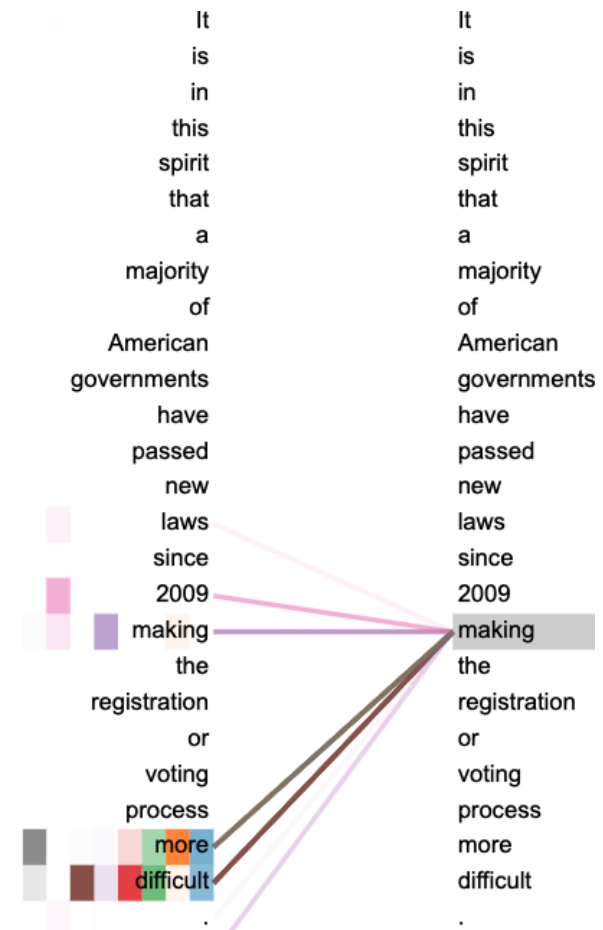


Visualization of self attentions

example sentence

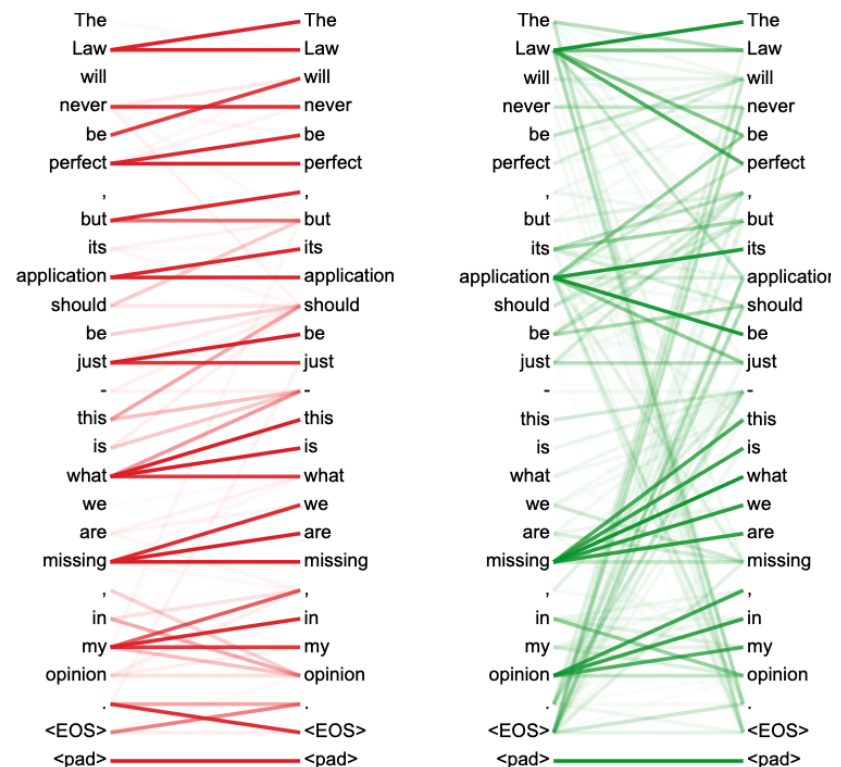
“It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult.”

- self attention of encoder (of a layer)
 - right figure
 - show dependencies between “making” and other words
 - different columns of colors represent different heads
 - “making” has strong dependency to “2009”, “more”, and “difficult”

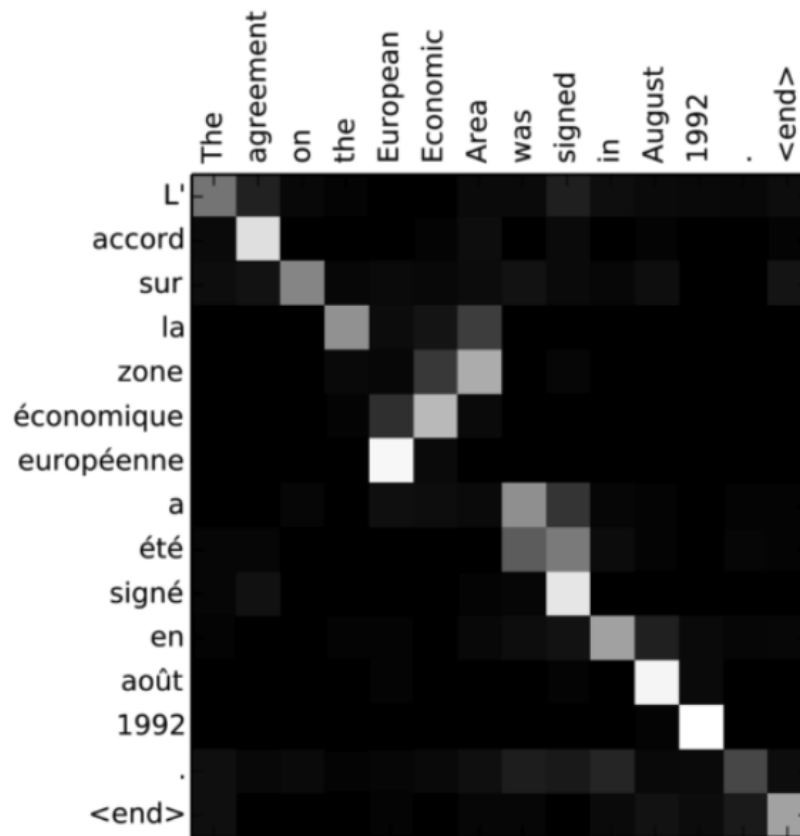


Visualization of multi-head self attentions

- self attentions of encoder for two heads (of a layer)
 - different heads represent different structures
→ advantages of multiple heads
 - multiple heads work together to collectively yield good results
 - dependencies *not* have absolute meanings (like embeddings in collaborative filtering)
 - randomness in resulting dependencies exists due to stochastic nature of ML training



Visualization of encoder-decoder attentions



- machine translation: English → French

- input sentence: “The agreement on the European Economic Area was signed in August 1992.”
- output sentence: “L’ accord sur la zone économique européenne a été signé en août 1992.”

- encoder-decoder attention reveals relevance between

- European ↔ européenne
- Economic ↔ européenne
- Area ↔ zone

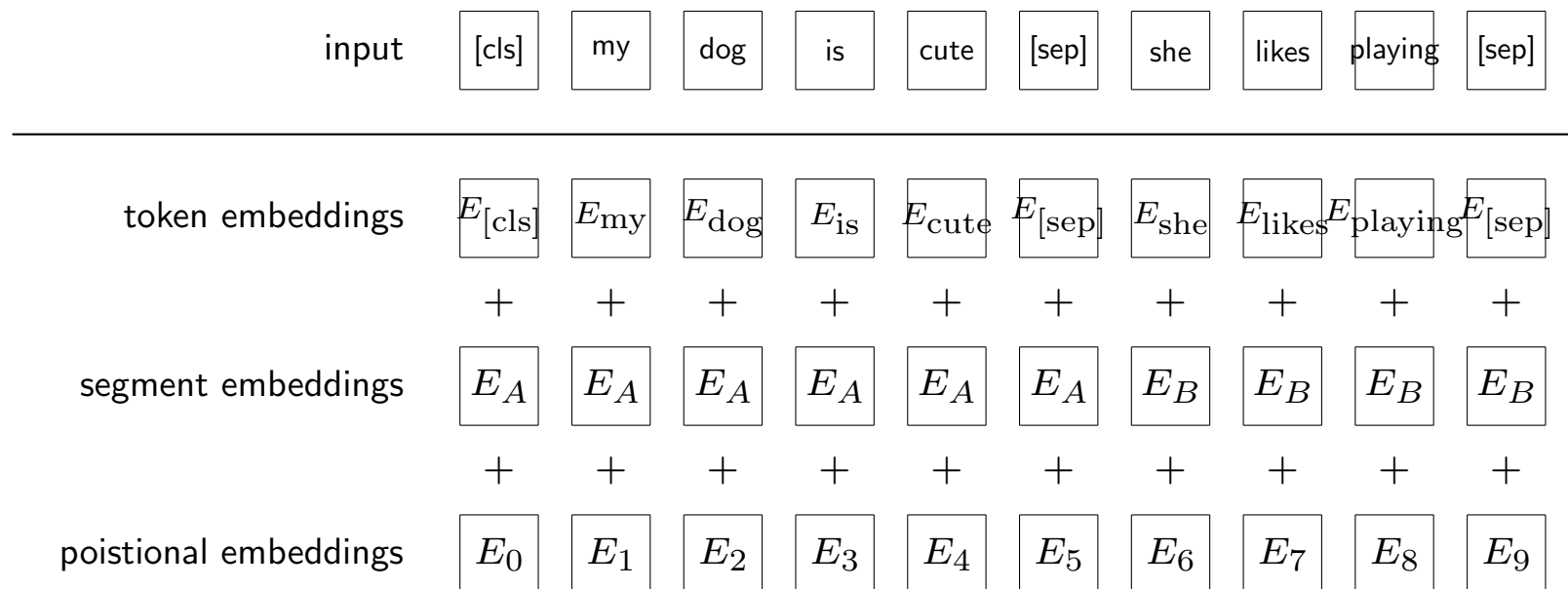
Model complexity

- computational complexity
 - n : sequence length, d : embedding dimension
 - complexity per layer - self-attention: $\mathcal{O}(n^2d)$, recurrent: $\mathcal{O}(1)$
 - sequential operations - self-attention: $\mathcal{O}(1)$, recurrent: $\mathcal{O}(n)$
 - maximum path length - self-attention: $\mathcal{O}(1)$, recurrent: $\mathcal{O}(n)$
- *massive parallel processing, long context windows*
 - *makes NVidia more competitive, hence profitable!*
 - *makes SK Hynix prevail HBM market!*

Variants of Transformer

Bidirectional encoder representations from transformers (BERT)

- Bidirectional Encoder Representations from Transformers [DCLT19]
- pre-train deep bidirectional representations from unlabeled text
- fine-tunable for multiple purposes



Challenges in LLMs

- *hallucination - can give entirely plausible outcome that is false*
- data poison attack
- unethical or illegal content generation
- huge resource necessary for both training & inference
- model size - need compact models
- outdated knowledge - can be couple of years old
- lack of reproducibility
- *biases - more on this later . . .*

do not, though, focus on downsides but on *infinite possibilities!*

- it evolves like internet / mobile / electricity
- only “tip of the iceberg” found & released

genAI

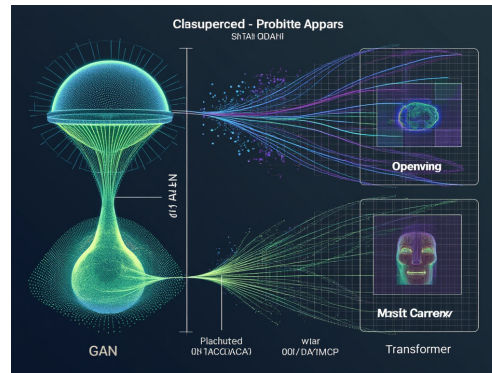
Definition of genAI

Generative AI

- genAI refers to systems capable of producing new (& original) contents based on patterns learned from training data (representation learning)
 - as opposed to discriminative models for, *e.g.*, classification, prediction & regression
 - here content can be text, images, audio, video, *etc.* - what about smell & taste?
- genAI model examples
 - generative adversarial networks (GANs), variational autoencoders (VAEs), diffusion models, Transformers



by Midjourney



by Grok 2 mini



by Generative AI Lab

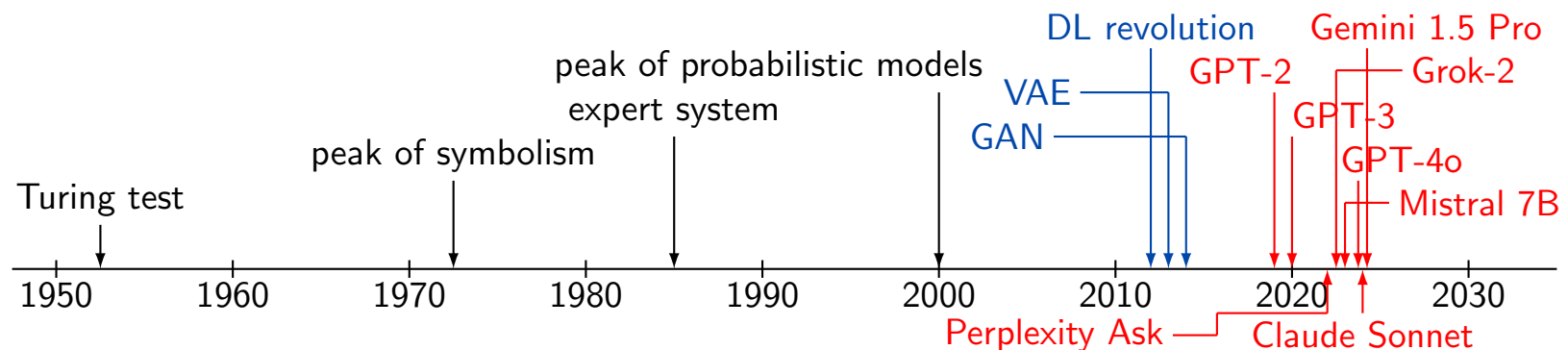
Examples of genAI in action

- text generation
 - Claude, ChatGPT, Mistral, Perplexity, Gemini, Grok
 - conversational agent writing articles, code & even poetry
- image generation
 - DALL-E - creates images based on textual descriptions
 - Stable Diffusion - uses diffusion process to generate high-quality images from text prompts (by denoising random noise)
 - MidJourney - art and visual designs generated through deep learning
- music generation
 - Amper Music - generates unique music compositions
- code generation
 - GitHub Copilot - generates code snippets based on natural language prompts

History of genAI

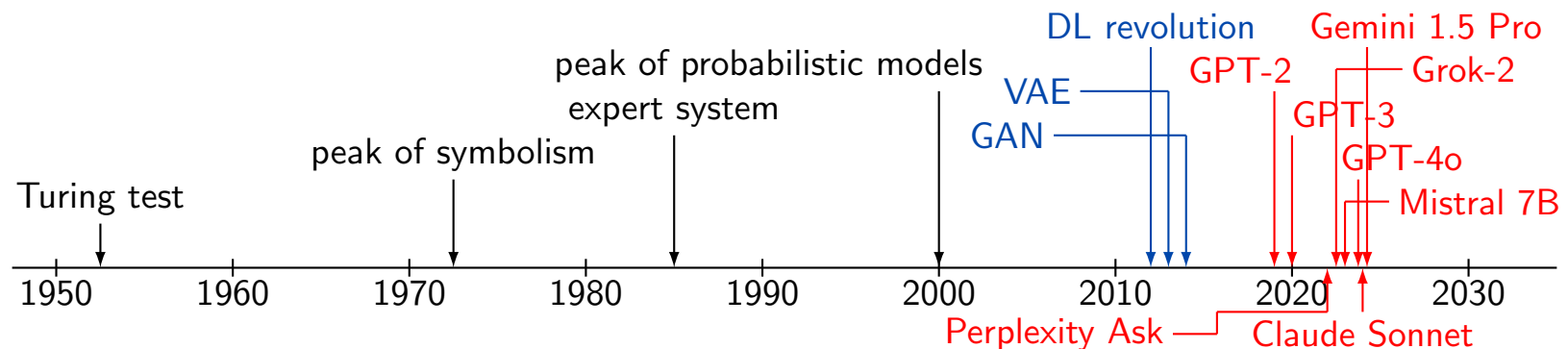
Birth of AI - early foundations & precursor technologies

- 1950s ~ 1970s
 - Alan Turing - concept of “*thinking machine*” & *Turing test* to evaluate machine intelligence (1950s)
 - *symbolists* (as opposed to connectionists) - early AI focused on symbolic reasoning, logic & problem-solving - Dartmouth Conference in 1956 by *John McCarthy, Marvin Minsky, Allen Newell & Herbert A. Simon*
 - precursor technologies - genetic algorithms (GAs), Markov chains & *hidden Markov models (HMMs)* - laying foundation for generative processes (1970s ~)



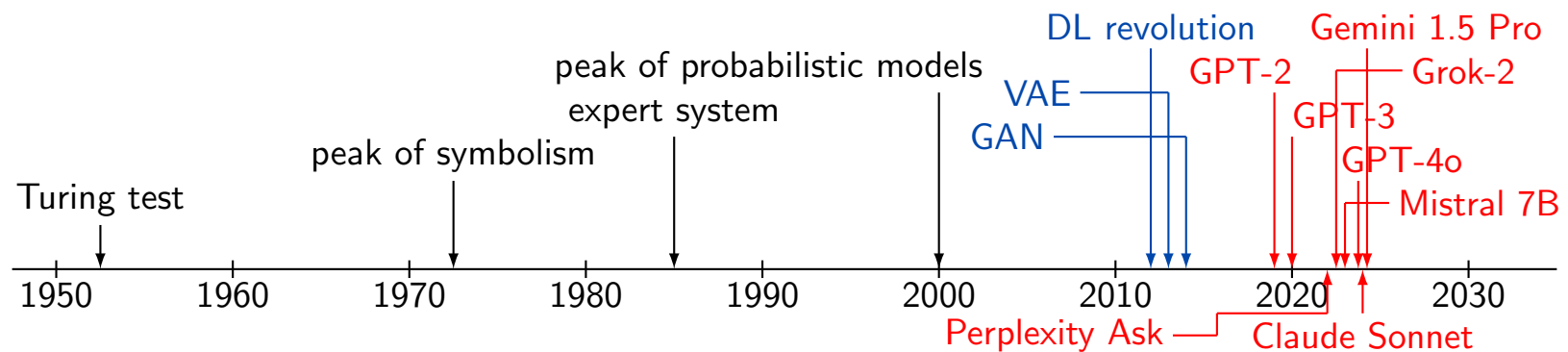
Rule-based systems & probabilistic models

- 1980s ~ early 2000s
 - *expert systems* (1980s) - AI systems designed to mimic human decision-making in specific domains
 - development of neural networks (NN) w/ backpropagation *training multi-layered networks* - setting stage for way more complex generative models
 - *probabilistic models* (including network models, *i.e.*, Bayesian networks) & Markov models - laying groundwork for data generation & pattern prediction



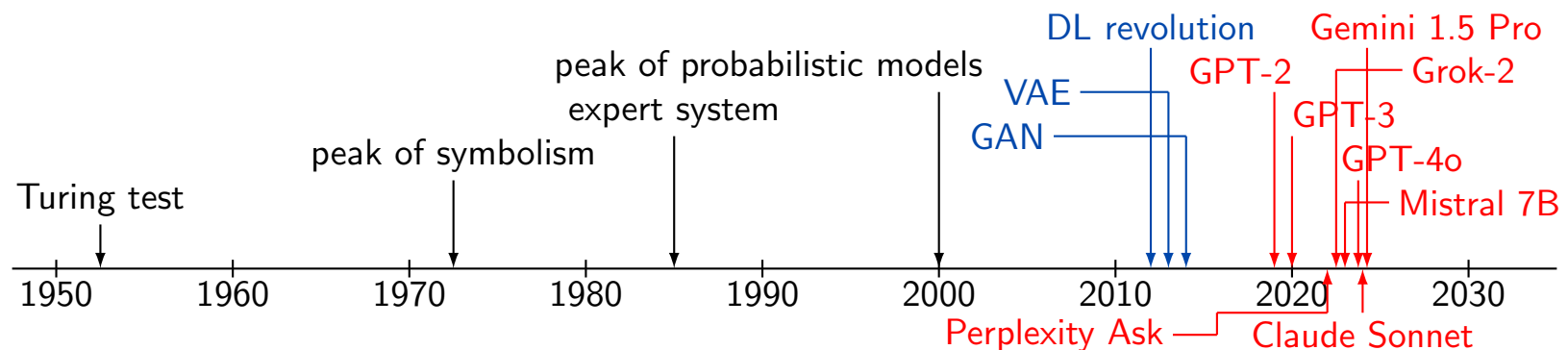
Rise of deep learning & generative models

- 2010s - breakthrough in genAI
 - *deep learning (DL) revolution* - advances in GPU computing and data availability led to the rapid development of deep neural networks.
 - *variational autoencoder (VAE)* (2013) - by Kingma and Welling - learns mappings between input and latent spaces
 - *generative adversarial network (GAN)* (2014) - by Ian Goodfellow - game-changer in generative modeling where two NNs compete each other to create realistic data
 - widely used in image generation & creative tasks



Transformer models & multimodal AI

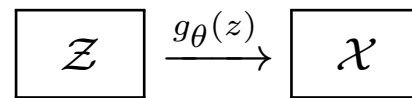
- late 2010s ~ Present
 - Transformer architecture (2017) - by Vaswani et al.
 - *revolutionized NLP*, e.g., LLM & various genAI models
 - GPT series - generative pre-trained transformer
 - GPT-2 (2019) - generating human-like texts - *marking leap in language models*
 - GPT-3 (2020) - 175B params - set *new standards for LLM*
 - multimodal systems - DALL-E & CLIP (2021) - *linking text and visual data*
 - emergence of diffusion models (2020s) - new approach for generating high-quality images - progressively “denoising” random noise (DALL-E 2 & Stable Diffusion)



Mathy Views on genAI

genAI models

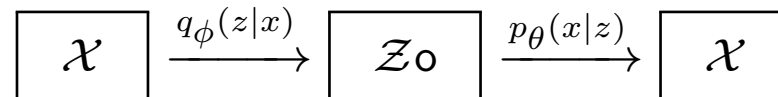
- definition of generative model



- *generate samples in original space, $\mathcal{X}$, from samples in latent space, $\mathcal{Z}$*
- g_{θ} is parameterized model *e.g.*, CNN / RNN / Transformer / diffusion-based model
- training
 - finding θ that minimizes/maximizes some (statistical) loss/merit function so that $\{g_{\theta}(z)\}_{z \in \mathcal{Z}}$ generates plausible point in $\mathcal{X}$
- inference
 - random samples z to generated target samples $x = g_{\theta}(z)$
 - *e.g.*, image, text, voice, music, video

VAE - early genAI model

- variational auto-encoder (VAE) [KW19]



- log-likelihood & ELBO - for any $q_{\phi}(z|x)$

$$\begin{aligned} \log p_{\theta}(x) &= \mathbf{E}_{z \sim q_{\phi}(z|x)} \log p_{\theta}(x) = \mathbf{E}_{z \sim q_{\phi}(z|x)} \log \frac{p_{\theta}(x, z)}{q_{\phi}(z|x)} \cdot \frac{q_{\phi}(z|x)}{p_{\theta}(z|x)} \\ &= \mathcal{L}(\theta, \phi; x) + D_{KL}(q_{\phi}(z|x) \| p_{\theta}(z|x)) \geq \mathcal{L}(\theta, \phi; x) \end{aligned}$$

- (indirectly) maximize likelihood by maximizing evidence lower bound (ELBO)

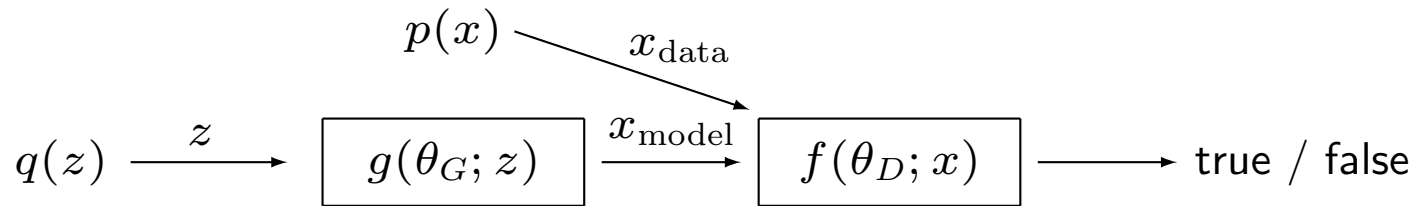
$$\mathcal{L}(\theta, \phi; x) = \mathbf{E}_{z \sim q_{\phi}(z|x)} \log \frac{p_{\theta}(x, z)}{q_{\phi}(z|x)}$$

- generative model

$$p_{\theta}(x|z)$$

GAN - early genAI model

- generative adversarial networks (GAN) [GPAM⁺14]



- value function

$$V(\theta_D, \theta_G) = \mathbf{E}_{x \sim p(x)} \log f(\theta_D; x) + \mathbf{E}_{z \sim q(z)} \log(1 - f(\theta_D; g(\theta_G; z)))$$

- modeling via playing min-max game

$$\min_{\theta_G} \max_{\theta_D} V(\theta_D, \theta_G)$$

- generative model

$$g(\theta_G; z)$$

- variants: conditional / cycle / style / Wasserstein GAN

genAI - LLM

- *maximize conditional probability*

$$\underset{\theta}{\text{maximize}} \quad d(p_{\theta}(x_t|x_{t-1}, x_{t-2}, \dots), p_{\text{data}}(x_t|x_{t-1}, x_{t-2}, \dots))$$

where $d(\cdot, \cdot)$ distance measure between probability distributions

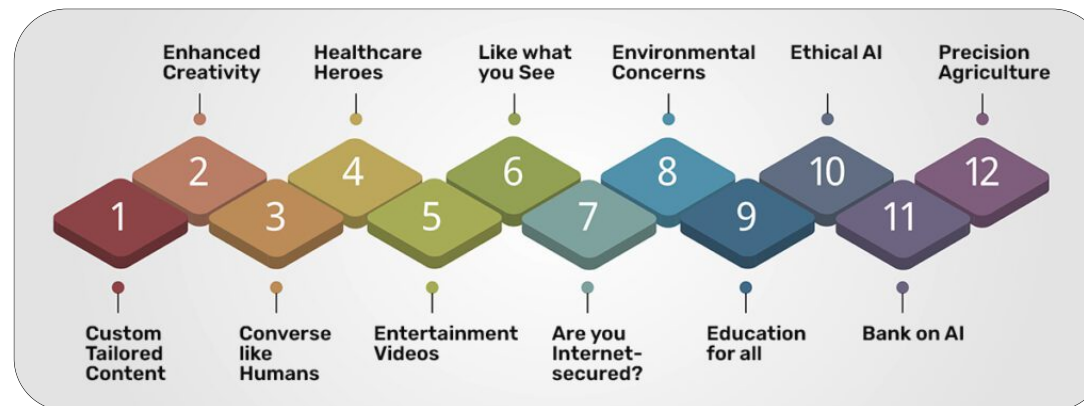
- previous sequence: $x_{t-1}, x_{t-2}, \dots$
- next token: x_t
- p_{θ} represented by (extremely) complicated model
 - *e.g.*, containing multi-head & multi-layer Transformer architecture inside
- model parameters, *e.g.*, for Llama2

$$\theta \in \mathbf{R}^{70,000,000,000}$$

Current Trend & Future Perspectives

Current trend of genAI

- rapid advancement in language models & multimodal AI capabilities
- rise of AI-assisted creativity & productivity tools
- growing adoption across industries
 - creative industries - design, entertainment, marketing, software development
 - life sciences - healthcare, medical, biotech
- infrastructure & accessibility, *e.g.*, Hugging Face democratizes AI development
- integration with cloud platforms & enterprise-level tools
- increased focus on AI ethics & responsible development



Industry & business impacts

- how genAI is transforming industries
 - creative industries - content creation - advertising, gaming, film
 - life science - enhance research, drug discovery & personalized treatments
 - finance - automating document generation, risk modeling & fraud detection
 - manufacturing & Design - rapid prototyping, 3D modeling & optimization
 - business operations - automate routine tasks to boost productivity



Future perspectives of genAI

- hyper-personalization - highly personalized content for individual users - music, products & services
- AI ethics & governance - concerns over deepfakes, misinformation & bias
- interdisciplinary synergies - integration with other fields such as quantum computing, neuroscience & robotics
- human-AI collaboration - augment human creativity rather than replace it
- energy efficiency - have to figure out how to dramatically reduce power consumption



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Thank You