

**[SNU ECS Four-Departments Joint Seminar]
AI Pulse Check - What Silicon Valley Is Actually
Building Right Now**

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About Speaker

- *Co-Founder & CTO @ Erudio Bio, Inc., San Jose & Novato, CA, USA*
- *Co-Founder & CEO @ Erudio Bio Korea, Inc., Korea*
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- *Global Advisory Board Member @ Innovative Future Brain-Inspired Intelligence System Semiconductor of Sogang University, Korea*
- Technology Consultant @ Gerson Lehrman Group (GLG), NY, USA
- Chief Business Development Officer @ WeStory.ai, Cupertino, CA, USA
- Advisor @ CryptoLab, Inc., San Jose, CA, 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
 - *Jeff 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.
- *Co-Founder & CEO* - AI Technology & Business Development @ Erudio Bio Korea, Inc.

Today

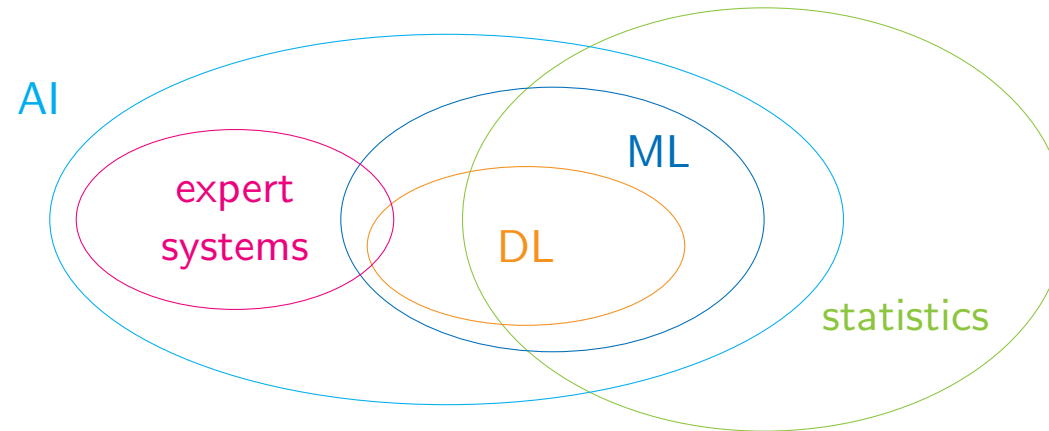
- Artificial Intelligence - 5
 - AI history & recent significant achievements
 - market indicators for unprecedented AI progress
- AI Agents - 30
 - Big Data → ML/DL → LLM & genAI → Agentic AI
 - implication of grand success of LLM in multimodal AI
- Silicon Valley's Cultural Engine of Innovation and Disruption - 38
 - My journey from Samsung & Amazon to Gauss Labs & Erudio Bio
 - Innovation ecosystem of Silicon Valley / Founding and scaling startups
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Artificial Intelligence

Definition and History

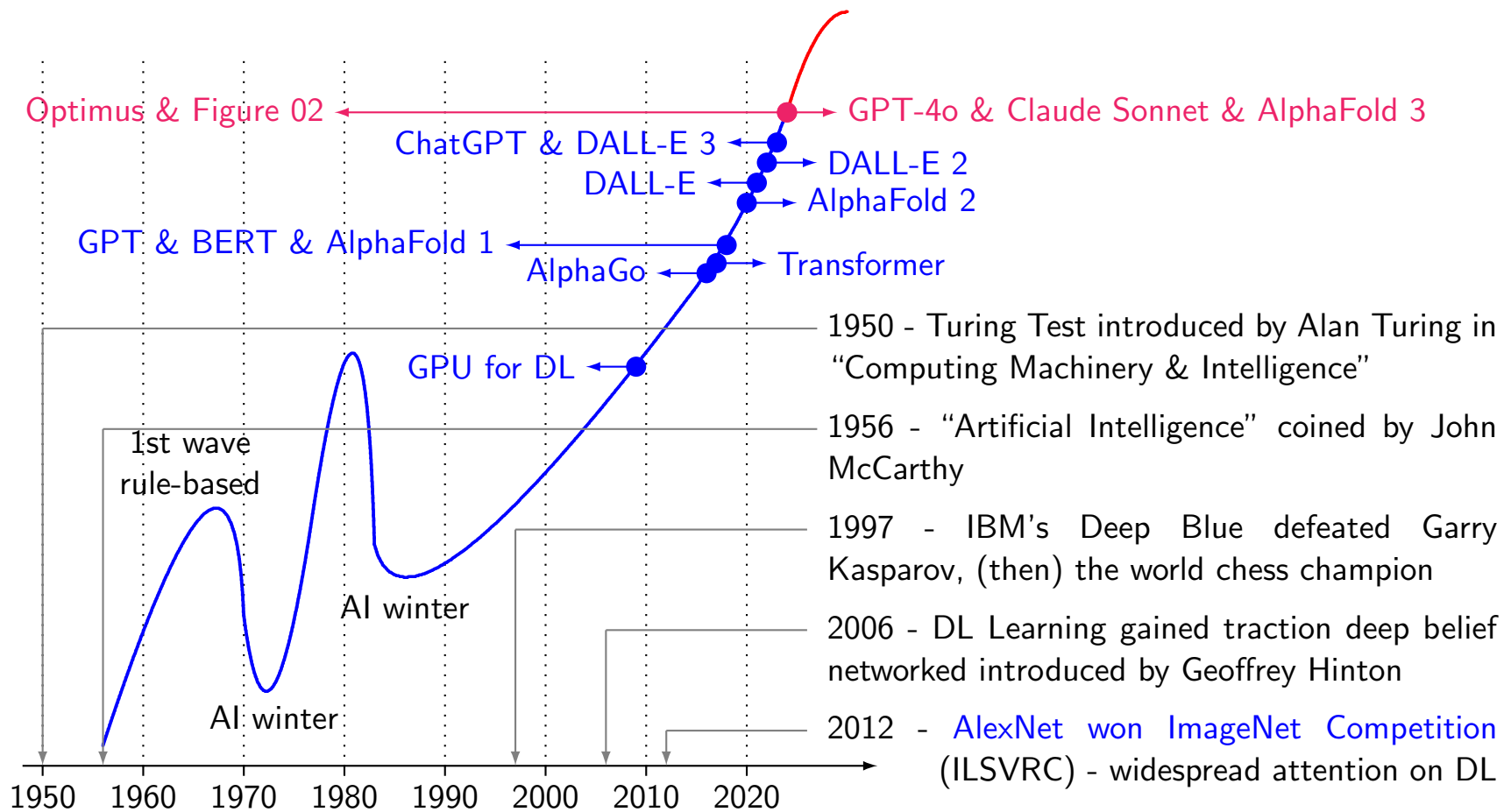
Definition & relation to other technologies

- 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]



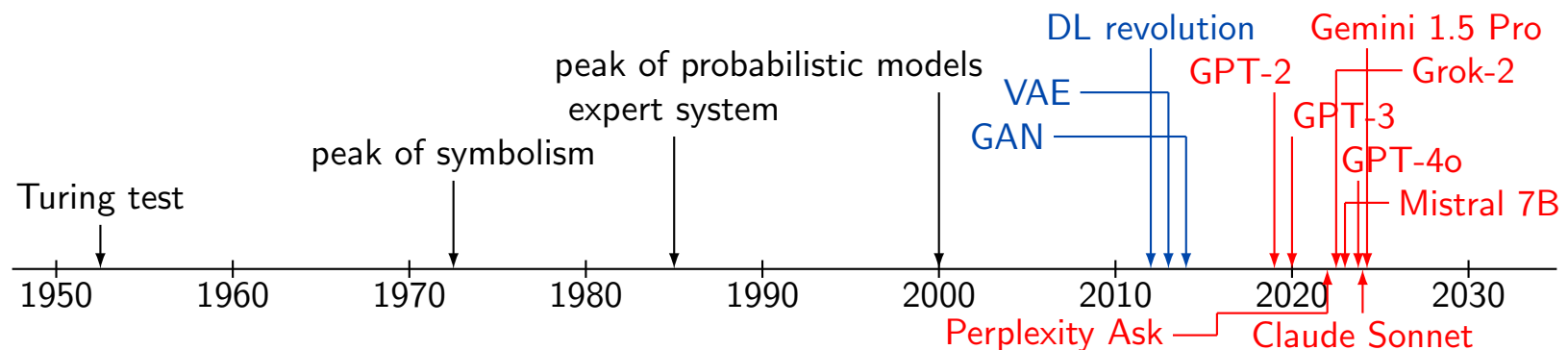
¹ML: machine learning & DL: deep learning

History



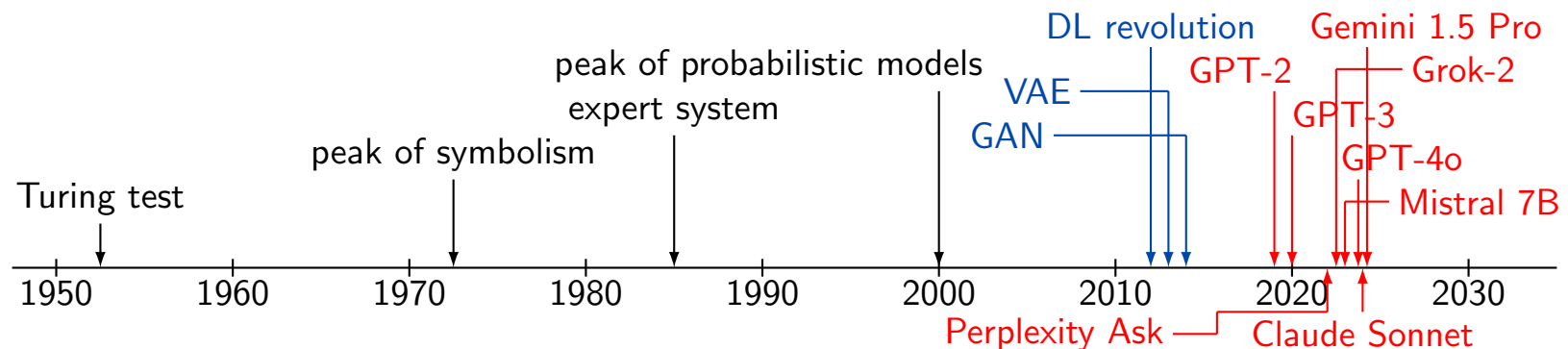
Birth of AI - early foundations & precursor technologies

- 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 ~)



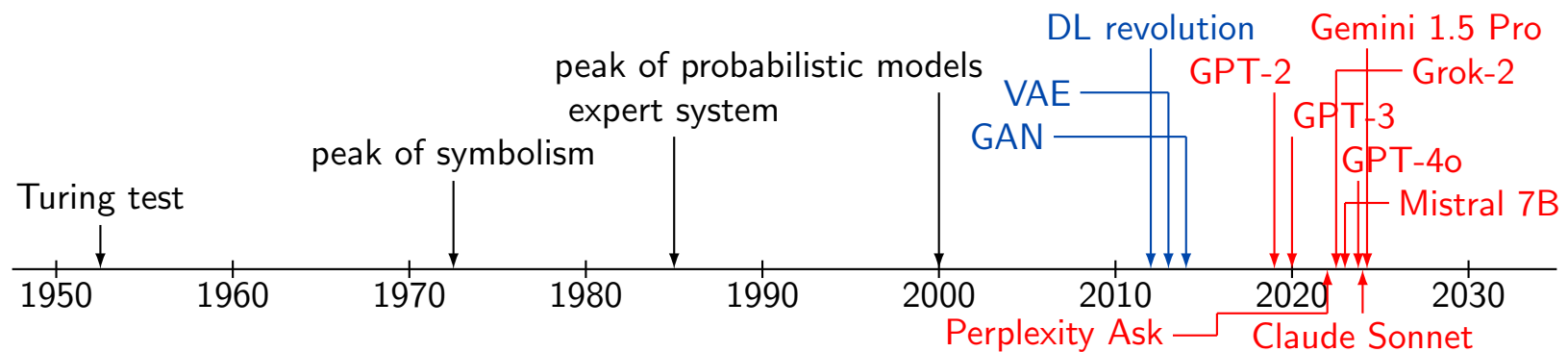
Rule-based systems & probabilistic models

- 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



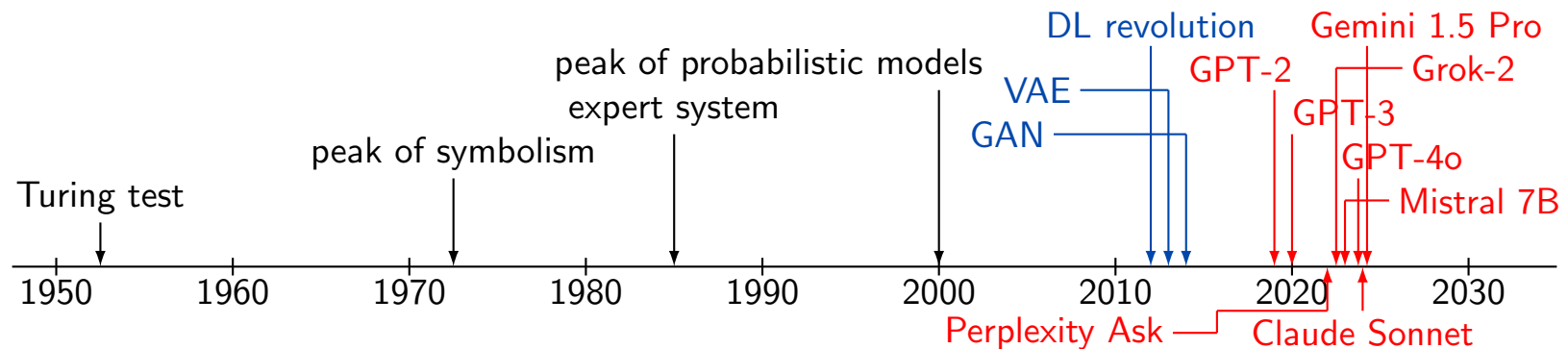
Rise of deep learning & generative models

- 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

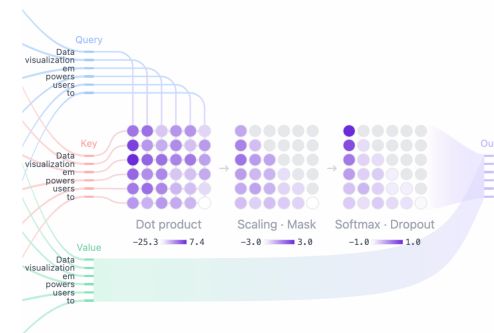
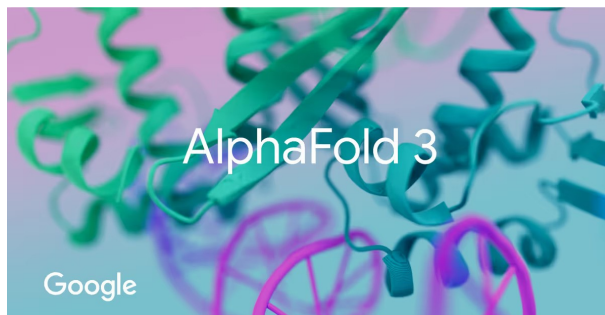
- 2012 – 2015 - DL revolution²
 - CNNs demonstrated exceptional performance in image recognition, *e.g.*, *AlexNet's victory in ImageNet competition*
 - widespread adoption of DL learning in CV transforming industries
- 2016 - AlphaGo defeats human Go champion
 - DeepMind's AlphaGo defeated world champion 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

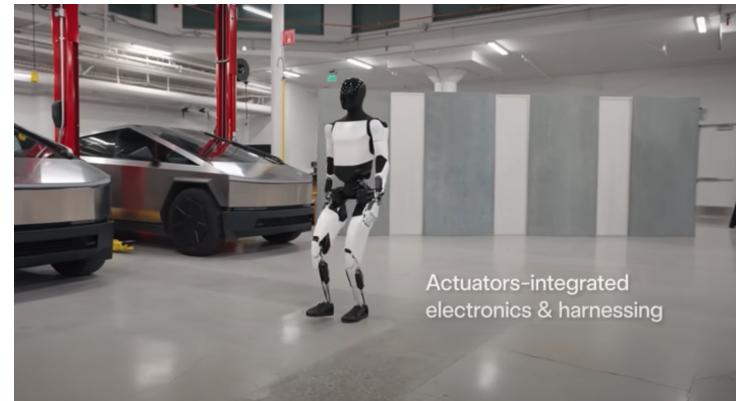
- 2017 – 2018 - Transformers & NLP breakthroughs³
 - *Transformer (e.g., BERT & GPT) revolutionized NLP*
 - major advancements in, e.g., machine translation & chatbots
- 2020 - AI in healthcare – AlphaFold & beyond
 - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting 3D protein 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

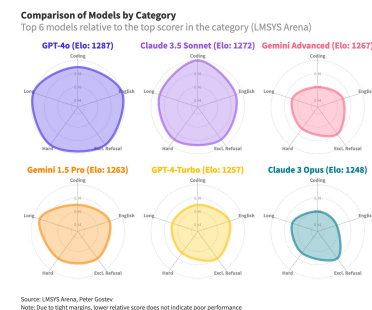
Lots of breakthroughs in AI technology and applications in 2024

- 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*



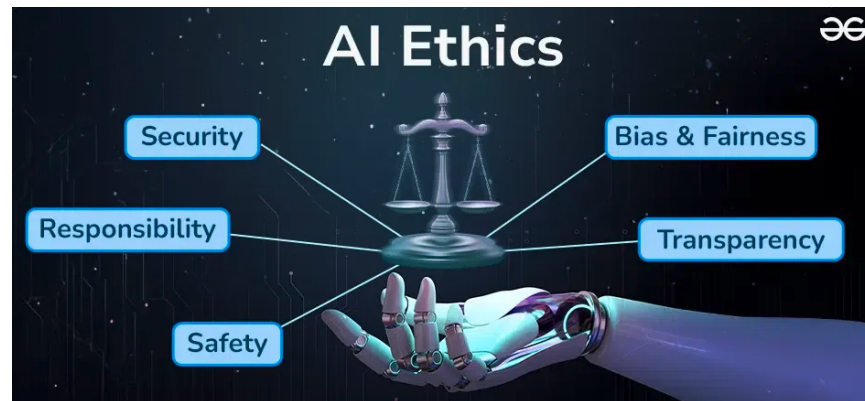
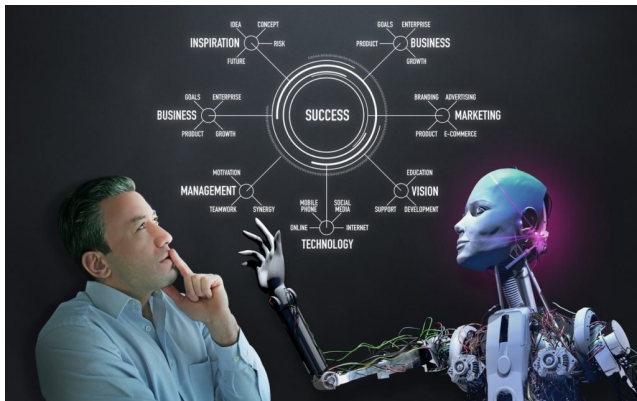
Major AI Breakthroughs in 2025

- 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

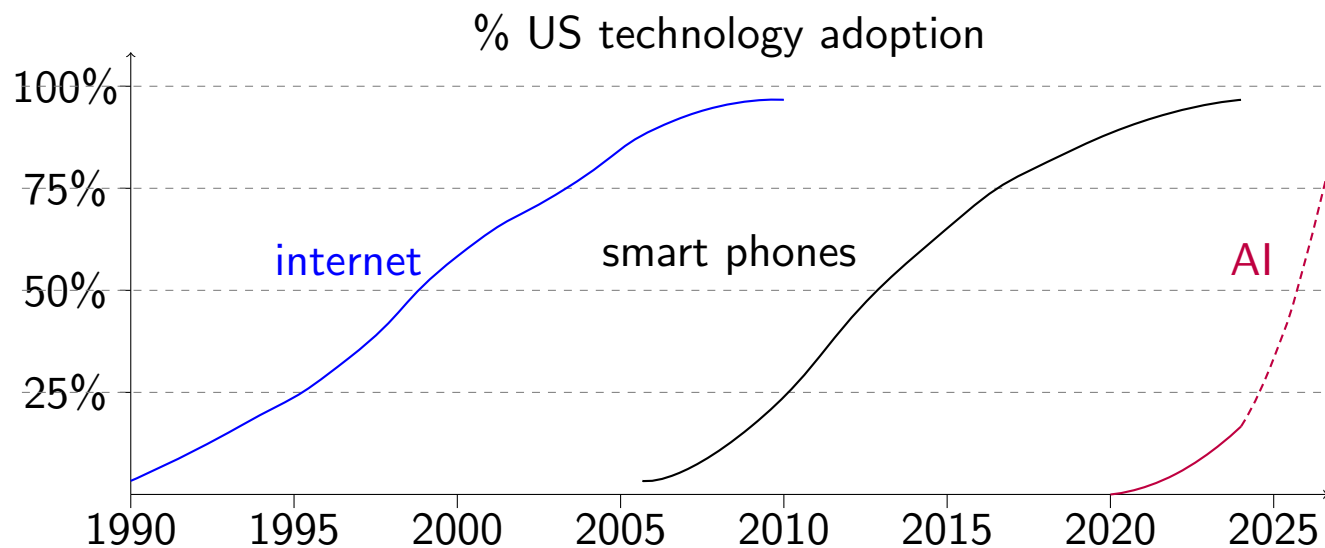
- accelerating human-AI collaboration
 - not only reshaping industries but *altering how humans interact with technology*
 - AI's role as collaborator and augmentor redefines productivity, creativity, the way we address global challenges, *e.g.*, *sustainability & healthcare*
- AI-driven automation *transforms 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

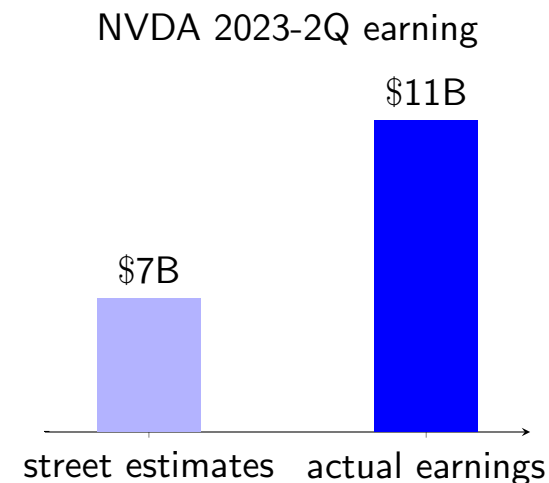
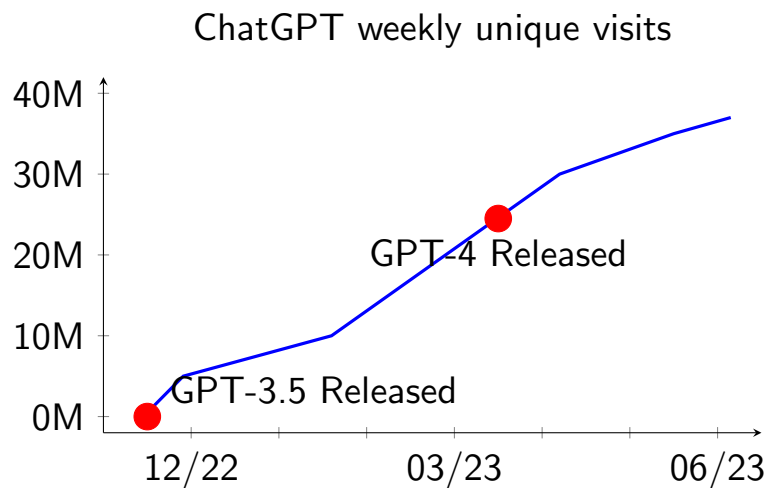
Where are we in AI today?

- 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

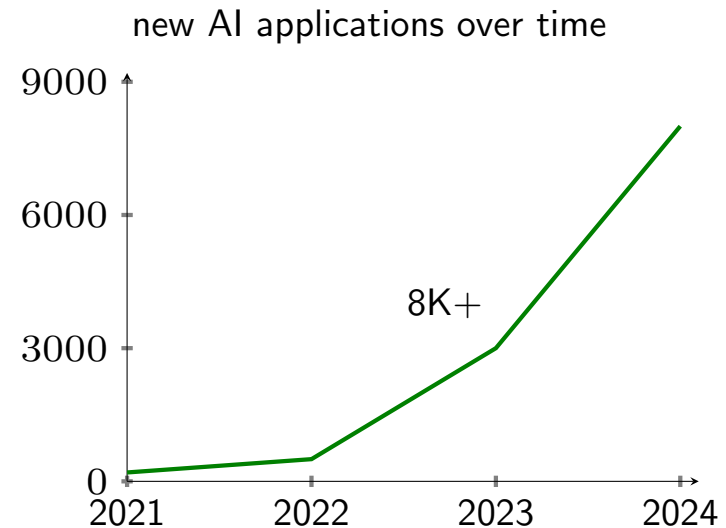
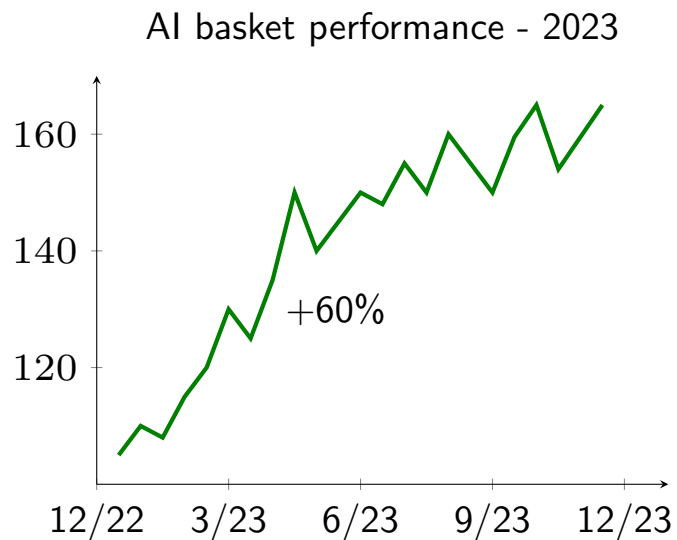
- took only *5 months for ChatGPT users to reach 35M*
- NVIDIA 2023 Q2 earning exceeds market expectation by big margin - \$7B vs \$13.5B
 - surprisingly, *101% year-to-year growth*
 - even more surprisingly *gross margin was 71.2%* - up from 43.5% in previous year⁴



⁴source - Bloomberg

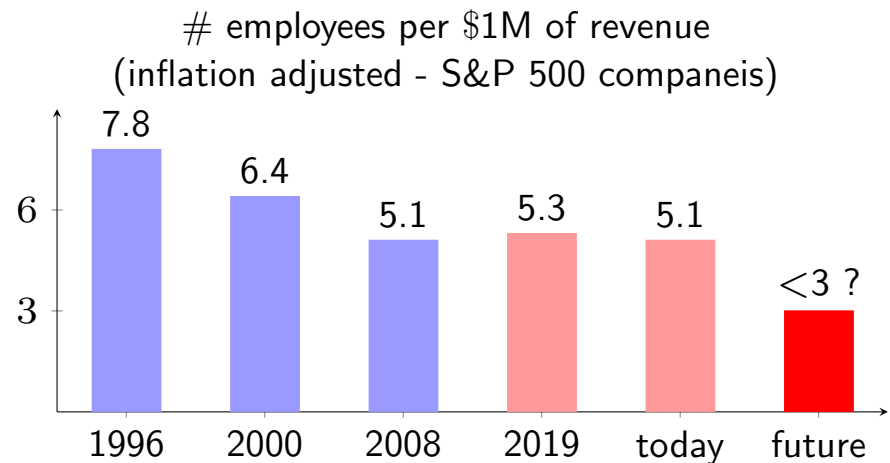
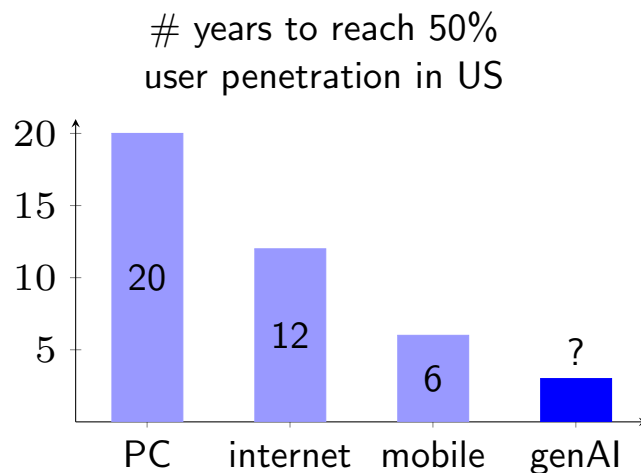
Explosion of AI ecosystems - AI stock market

- *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



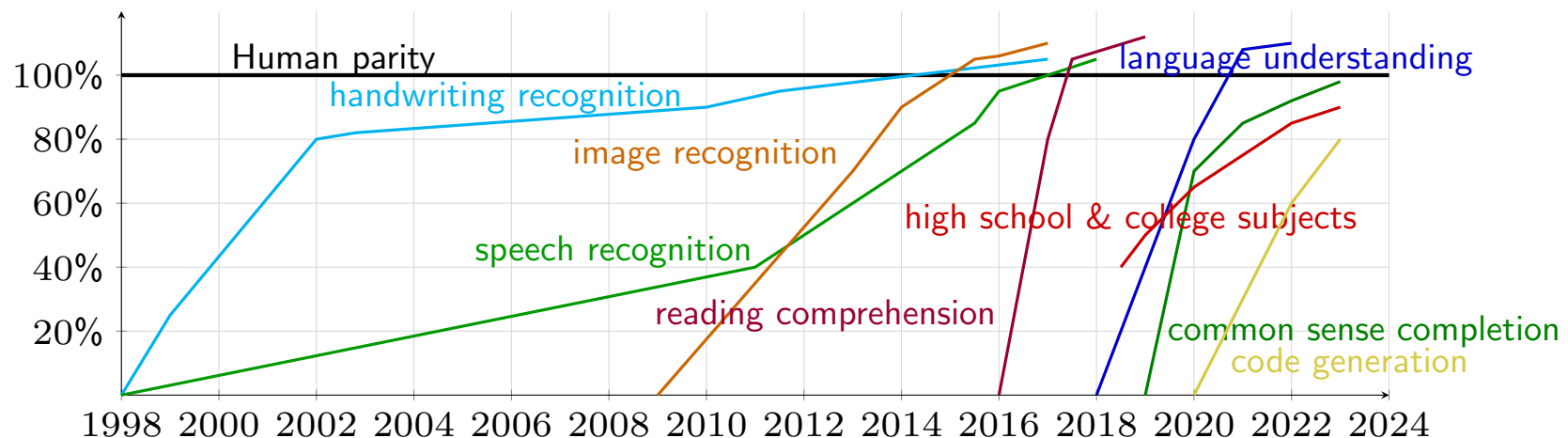
AI's transformative impact - adoption speed & economic potential

- 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



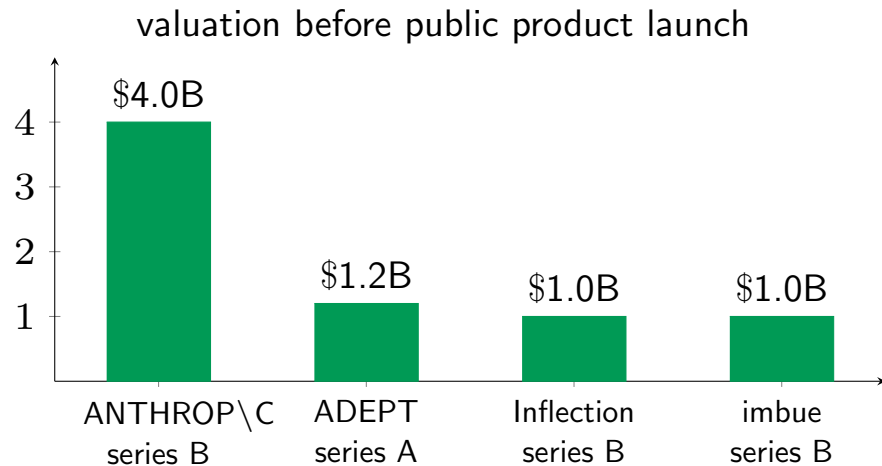
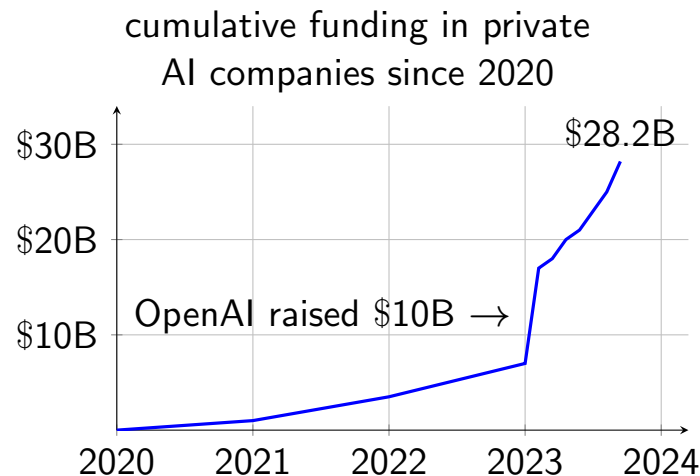
AI getting more & more faster

- 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



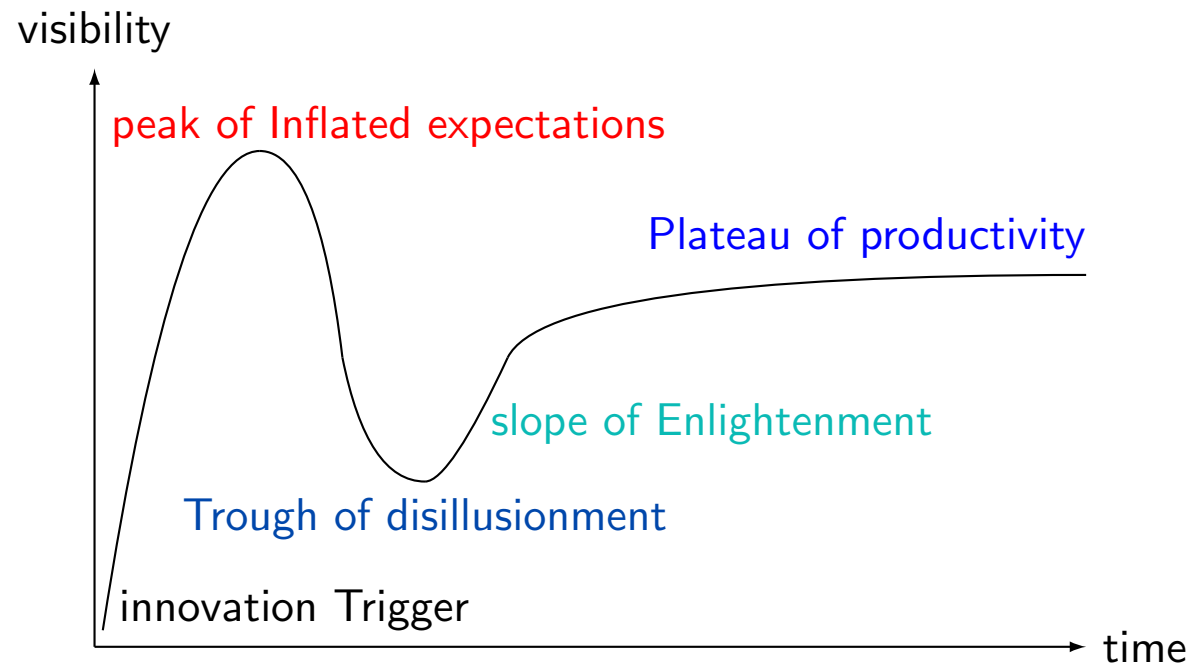
Massive investment in AI

- *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



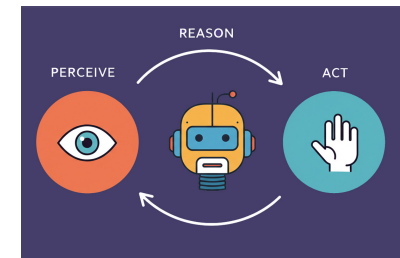
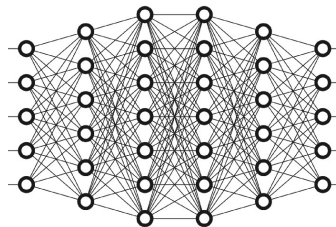
Yes & No

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

AI Agents

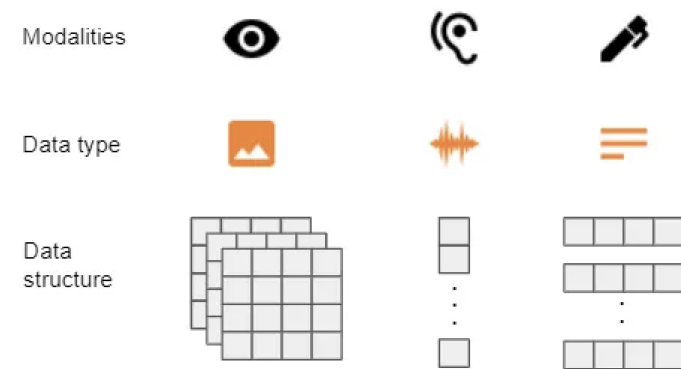
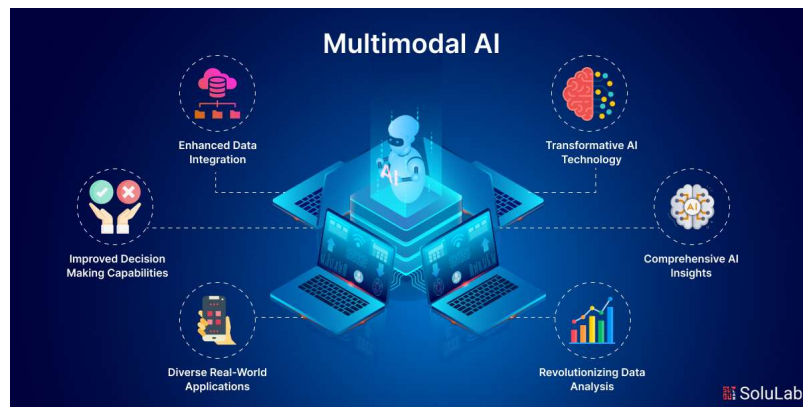
AI progress in 21st century in keywords

- 2010 ~ Big Data
- 2012 ~ Deep Learning
- 2017 ~ Transformer - Attention is All you need!
- 2022 ~ LLM & genAI
- 2024 ~ AI Agent (Agentic AI)



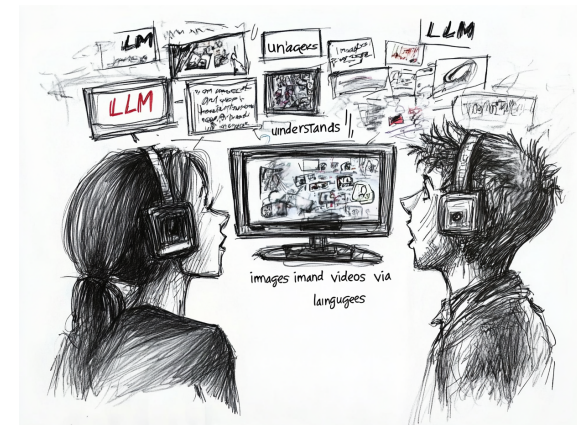
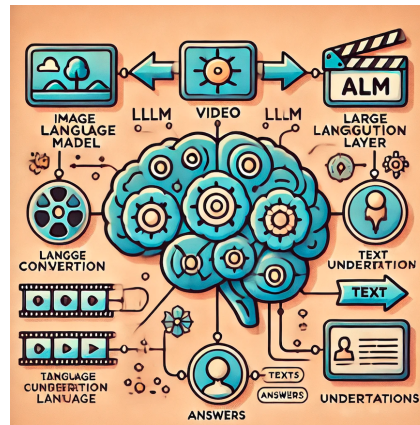
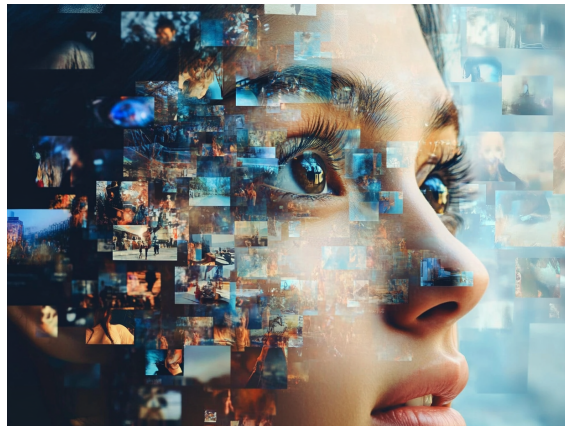
Multimodal learning

- understand information from multiple modalities, *e.g.*, text, images, audio, video
- representation learning methods
 - combine multiple representations or learn multimodal representations simultaneously
- applications
 - images from text prompt, videos with narration, musics with lyrics
- collaboration among different modalities
 - understand image world (open system) using language (closed system)



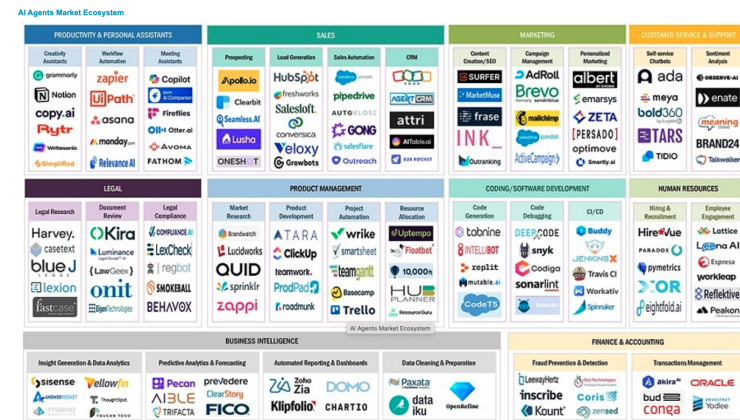
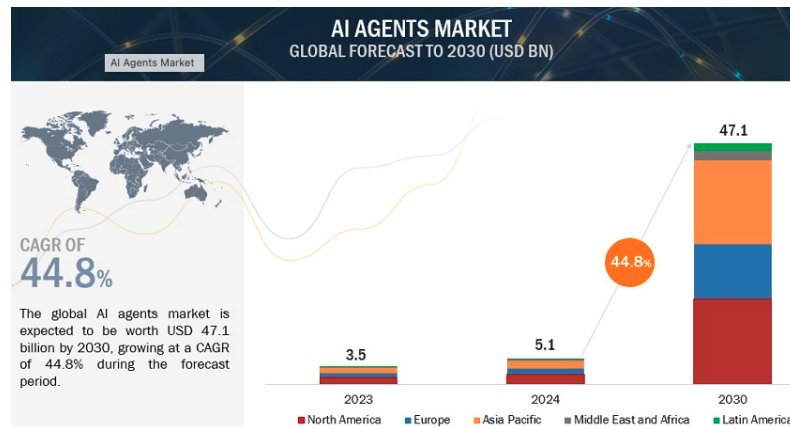
Implications of success of LLMs

- many researchers change gears towards LLM
 - from computer vision (CV), speech, music, video, even reinforcement learning
- *LLM is not only about NLP . . .* humans have . . .
 - evolved to optimize natural language structures for eons
 - handed down knowledge using *this natural languages* for thousands of years
 - internal structure (or equivalently, representation) of natural languages optimized via *thousands of generation by evolution*
- LLM *connects non-linguistic world (open system) via natural languages (closed system)*



Multimodal AI (mmAI)

- mmAI - systems processing & integrating data from multiple sources & modalities, to generate unified response / decision
- 1990s – 2000s - early systems - initial research combining basic text & image data
- 2010s - CNNs & RNNs enabling more sophisticated handling of multimodality
- 2020s - modern multimodal models - Transformer-based architectures handling complex multi-source data at highly advanced level
- mmAI *mimics human cognitive ability* to interpret and integrate information from various sources, leading to holistic decision-making

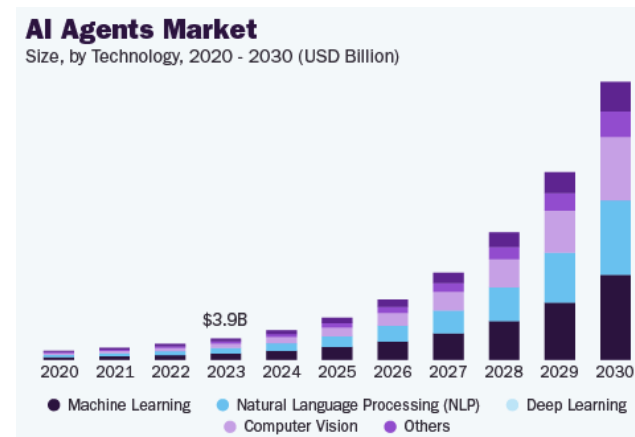
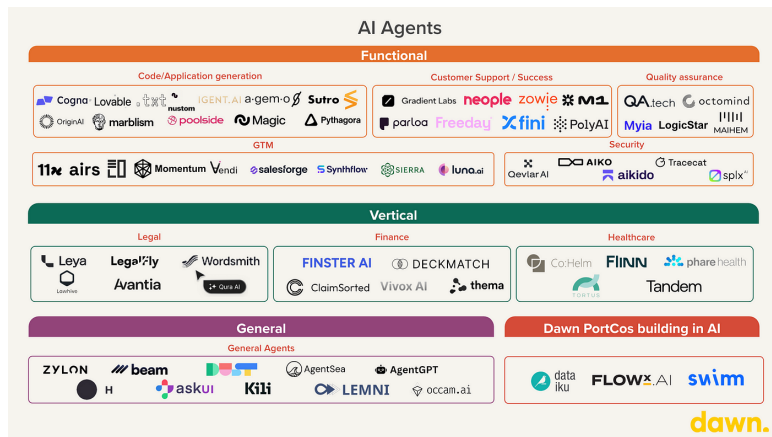


mmAI Technology

- core components
 - data preprocessing - images, text, audio & video
 - architectures - unified Transformer-based (*e.g.*, ViT) & cross-attention mechanisms / hybrid architectures (*e.g.*, CNNs + LLMs)
 - integration layers - fusion methods for combining data representations from different modalities
- technical challenges
 - data alignment - accurate alignment of multimodal data
 - computational demand - high-resource requirements for training and inferencing
 - diverse data quality - manage variations in data quality across modalities
- advancements
 - multimodal embeddings - shared feature spaces interaction between modalities
 - self-supervised learning - leverage unlabeled data to learn representations across modalities

AI agents powered by multimodal LLMs

- foundation
 - integrate multimodal AI capabilities for enhanced interaction & decision-making
- components
 - perceive environment through multiple modalities (visual, audio, text), process using LLM technology, generate contextual responses & take actions
- capabilities
 - understand complex environments, reason across modalities, engage in natural interactions, adapt behavior based on context & feedback



AI agents - Present & Future

- emerging applications
 - scientific research - agents analyzing & running experiments & generating hypotheses
 - creative collaboration - AI partners in design & art combining multiple mediums
 - environmental monitoring - processing satellite sensor data for climate analysis
 - healthcare - enhanced diagnostic combining imaging, *e.g.*, MRI, with patient history
 - customer experience - virtual assistants understanding spoken language & visual cues
 - autonomous vehicles - integration of visual, radar & audio data
- future
 - ubiquitous AI agents - seamless integration into everyday devices
 - highly tailored personalized experience - in education, entertainment & healthcare



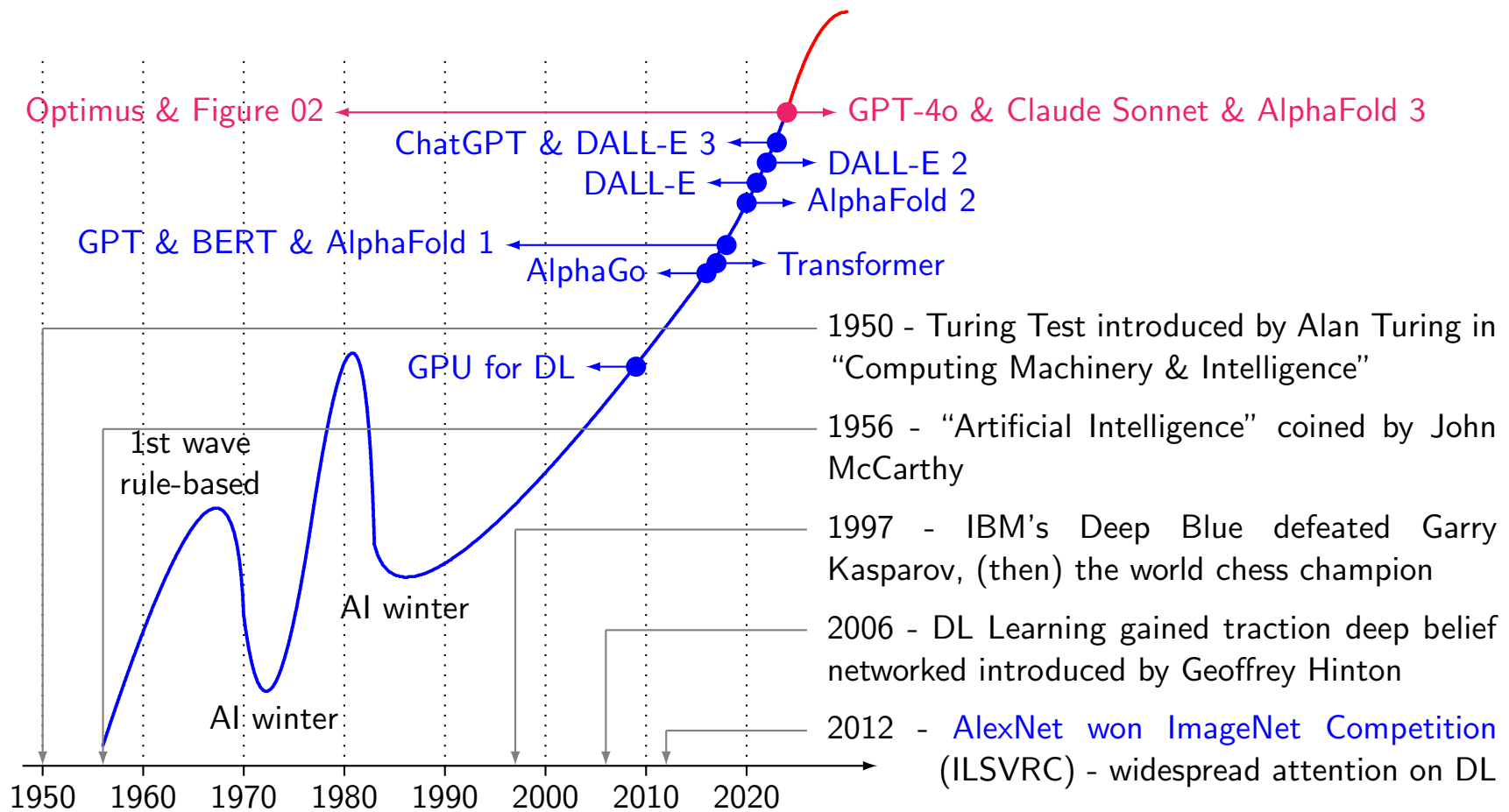
Silicon Valley's Cultural Engine of Innovation and Disruption

My journey from Samsung & Amazon to Gauss Labs & Erudio Bio

- Samsung Semiconductor, Inc.
 - inception into industry from academia, the world's best memory chip maker!
- Amazon.com, Inc.
 - experience so-called Silicon Valley big tech culture and technology
 - set tone for my future career trajectory!
- Gauss Labs, Inc.
 - found & operate AI startup, shaping corporate culture & spearheading R&D as CTO
 - inherent challenges of Korean conglomerate spin-off startup - cultural constraints, over-capitalization, and leadership limitations
- Erudio Bio, Inc.
 - concrete & tangible bio-technology in addition to AI
 - great decisions regarding business development; business models, market fit, go-to-market (GTM) strategies based on lessons learned *in a hard way* 😊

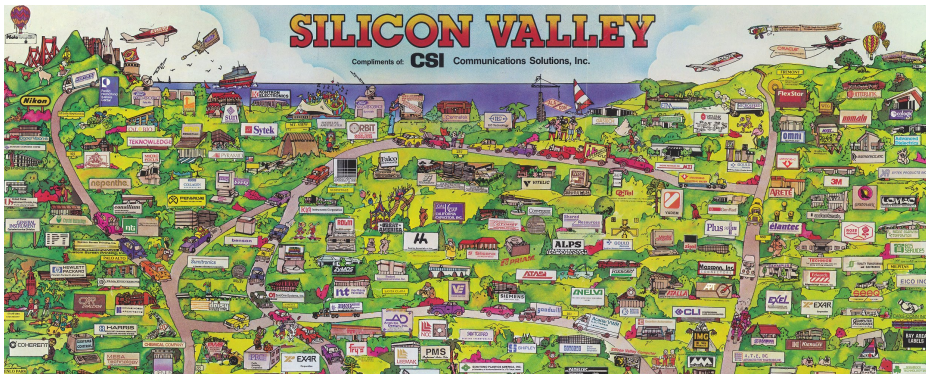


Joining Amazon.com, Inc. at the inflection point of AI



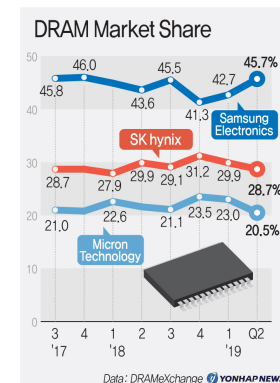
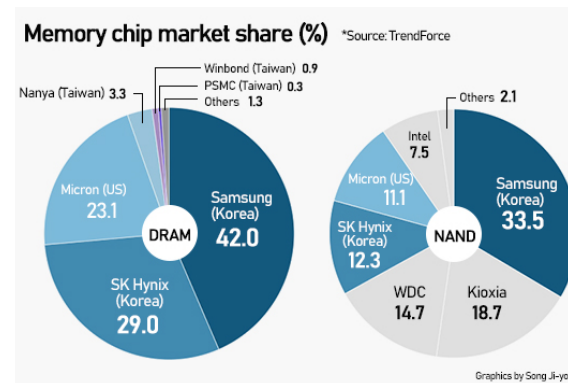
Innovation ecosystem of Silicon Valley

- key characteristics
 - risk-taking culture, *trust* in technology → *genuine* respect for engineers and scientists
 - easy access to huge capital - VCs, angel investors alike
 - talent density - engineers, researchers, scientists, entrepreneurs, PMs, TPMs, . . .
 - diversity, “collision density” of ideas
 - ecosystem of collaboration and competition - startups, academia, industry leaders
- what they mean for global big tech
 - set trends in AI, software & hardware (and or hence) product & industry innovation
 - act as testing ground for disruptive ideas



Case study: Amazon - amazing differentiators of big techs

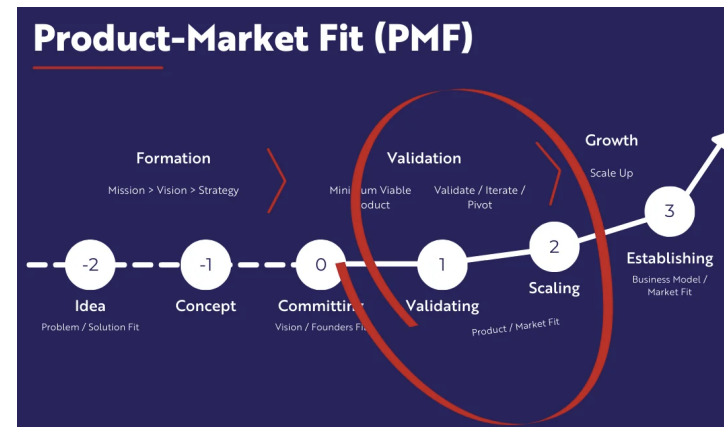
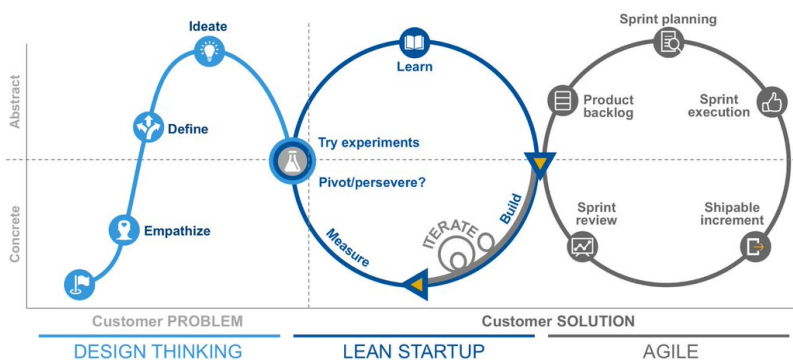
- Amazon's culture & leadership principles
 - customer obsession as driver of innovation
 - high standards & ownership culture, disagree & commit
 - bias for action and long-term thinking - sounds contradictory?
 - mechanisms like “two-pizza teams” & “Day One” for (or rather despite) scalability
- lessons for Korean corporations
 - applying customer-centric innovation in hardware & AI, *e.g.*, on-device AI
 - balancing agility with long-term R&D
 - *build / adapt / apply on the core strength of Samsung that no other company has!*



Founding and scaling startups

- challenges
 - competence of and chemistry among co-founders crucial
 - technology & great team are *necessary*, but *not sufficient (at all!)* for success
 - business models, market fit, timing, agility, flexibility for pivoting / perseverance
- insight
 - importance of domain expertise in addition to AI
 - balancing innovation with good business decisions

Combine Design Thinking, Lean Startup and Agile



Bridging Silicon Valley & Korea

- cultural differences
 - risk appetite & failure tolerance
 - decision-making speed vs hierarchy
 - innovation vs execution focus
- opportunities for collaboration
 - leveraging Korea's manufacturing expertise with Silicon Valley's software/AI strengths
 - building global teams with diverse perspectives



To be successful . . .

- embrace customer/market-centric mindset in innovation and for business decisions
- balance agility with long-term vision
- foster cross-cultural collaboration for global impact
- ((very) strategically and carefully) leverage AI to solve real-world industrial challenges



Appendix

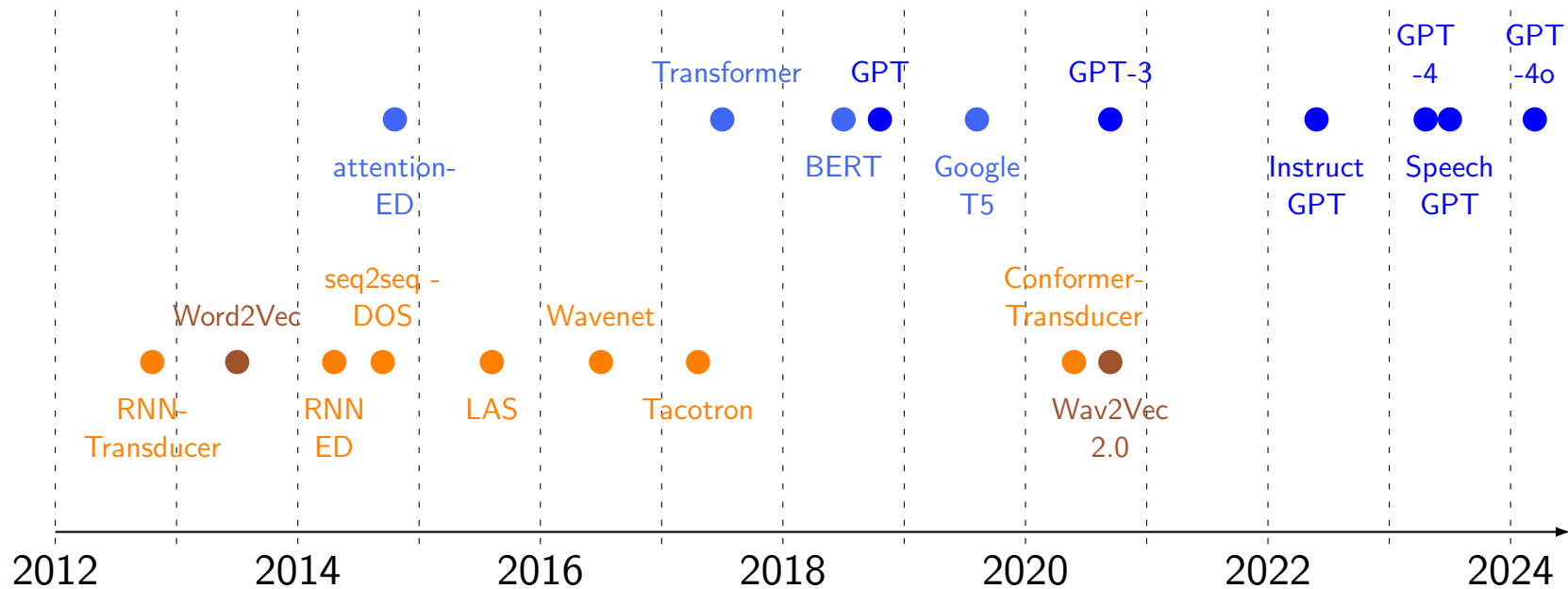
LLM

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

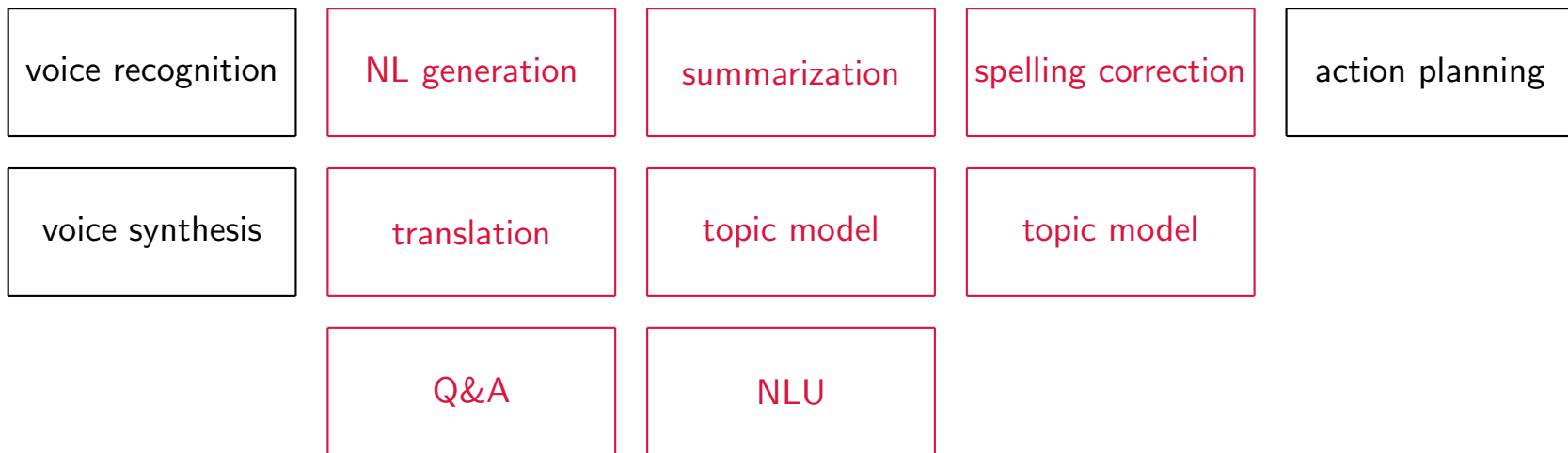
Recent advances in speech & language processing



- 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

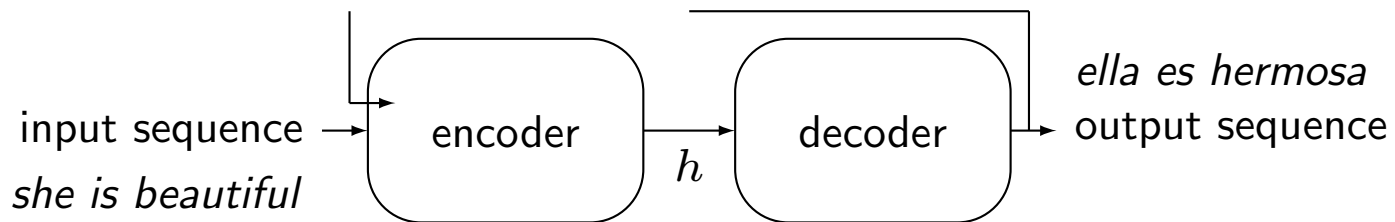
- global NLP market size estimated at USD 16.08B in 2022, is expected to hit USD 413.11B by 2032 - *CAGR of 38.4%*
- in 2022
 - north america NLP market size valued at USD 8.2B
 - high tech and telecom segment accounted revenue share of over 23.1%
 - healthcare segment held a 10% market share
 - (by 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

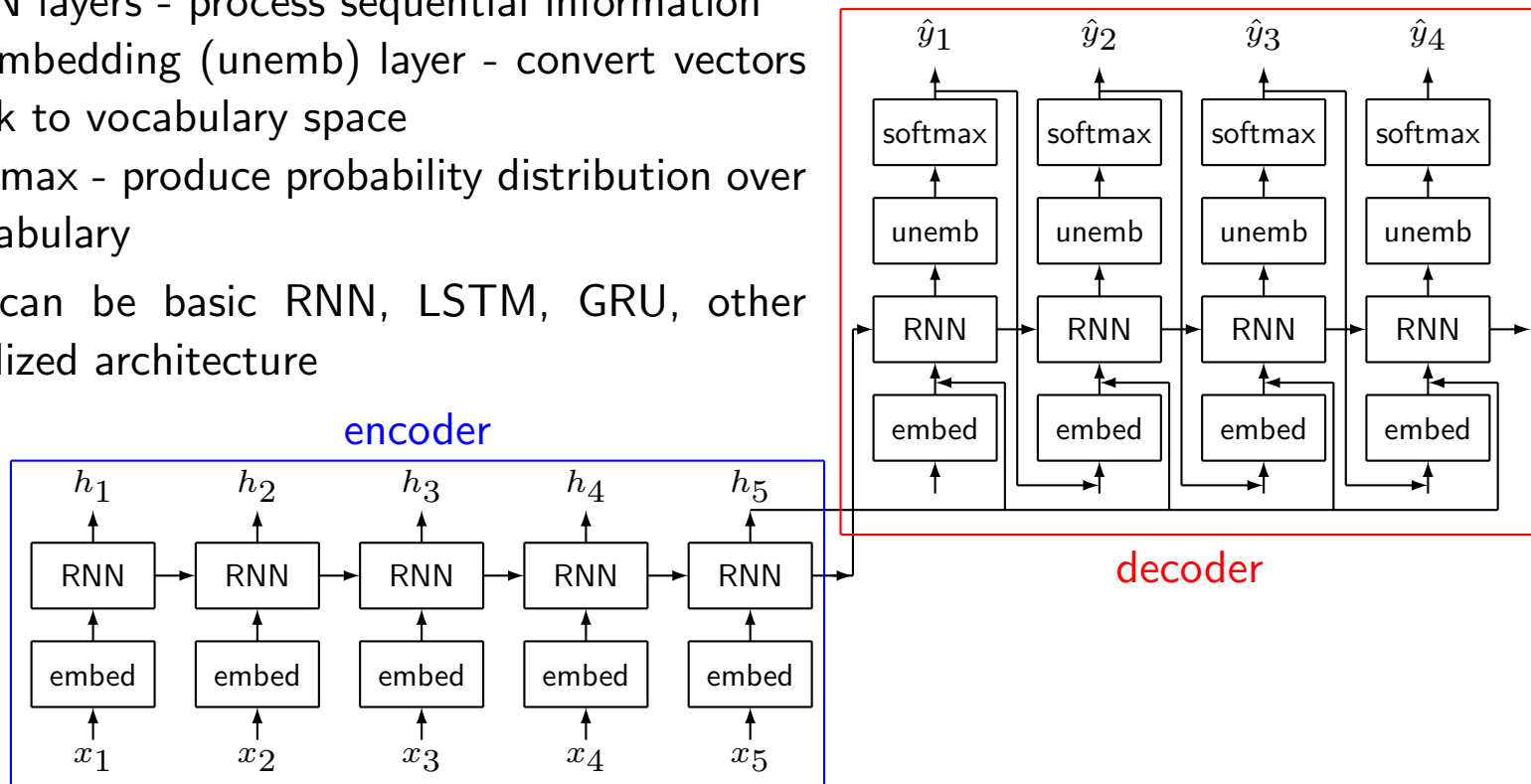
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



- 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

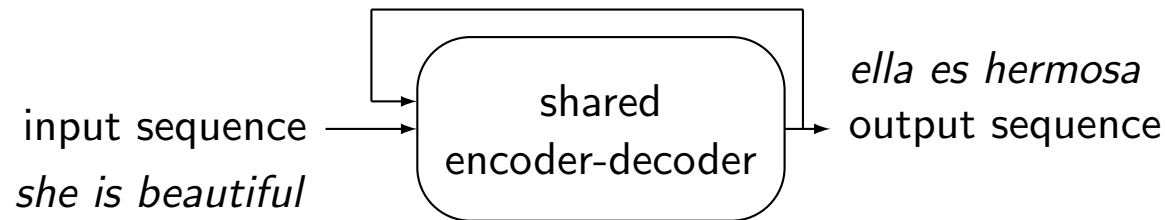
RNN-type encoder-decoder architecture

- 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

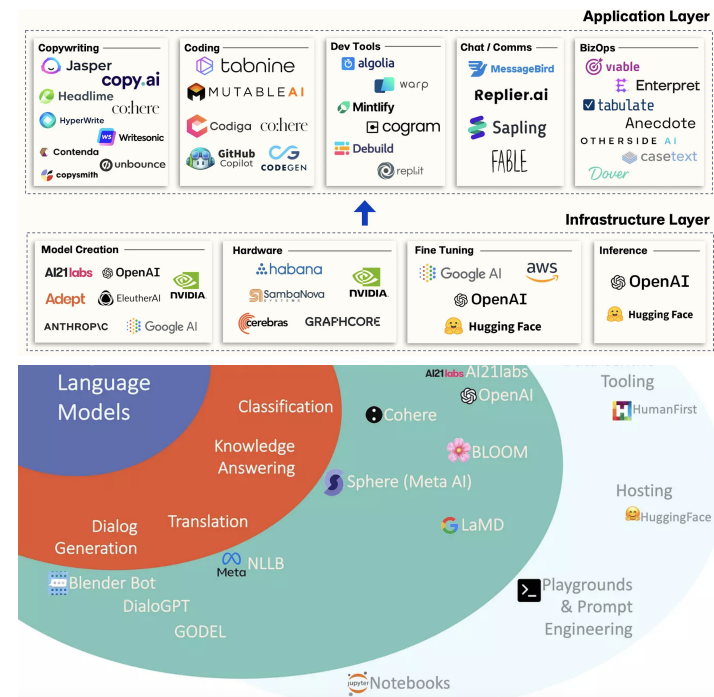
LLM

- 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

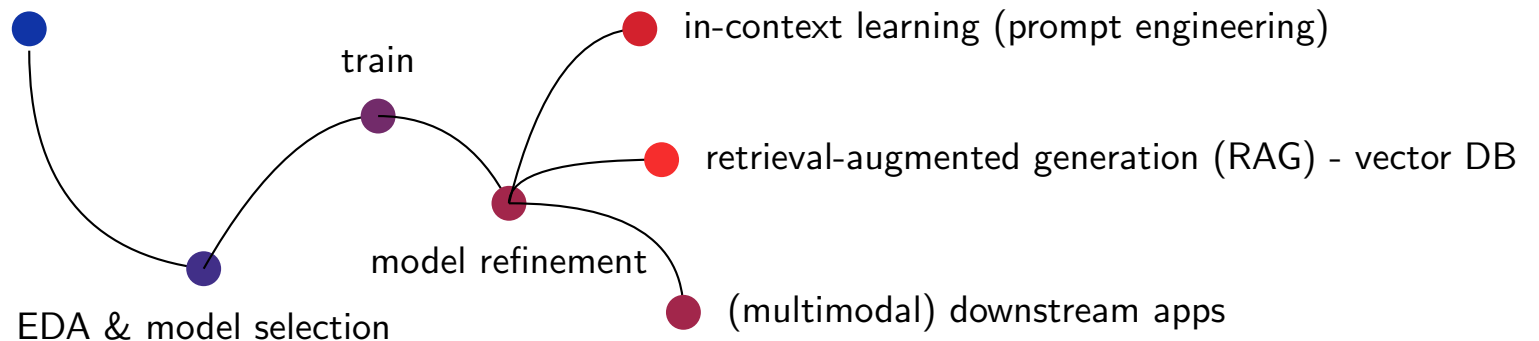
- Foundation Models
 - GPT-x/Chat-GPT - OpenAI, Llama-x - Meta, PaLM-x (Bard) - Google
- # parameters
 - generative pre-trained transformer (GPT) - GPT-1: 117M, GPT-2: 1.5B, GPT-3: 175B, GPT-4: 100T, GPT-4o: 200B
 - large language model Meta AI (Llama) - Llama1: 65B, Llama2: 70B, Llama3: 70B
 - scaling 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

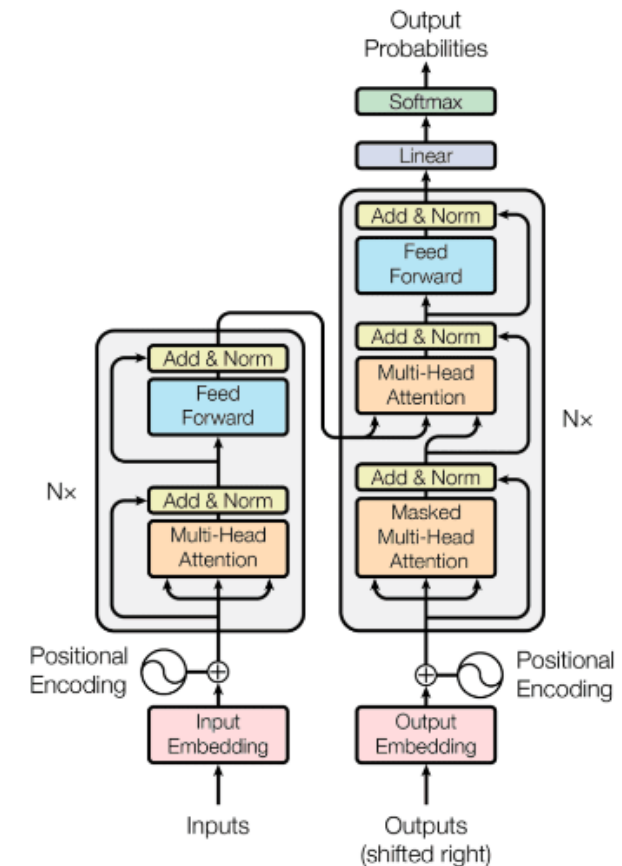
LLM architectural secret (or known) sauce

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

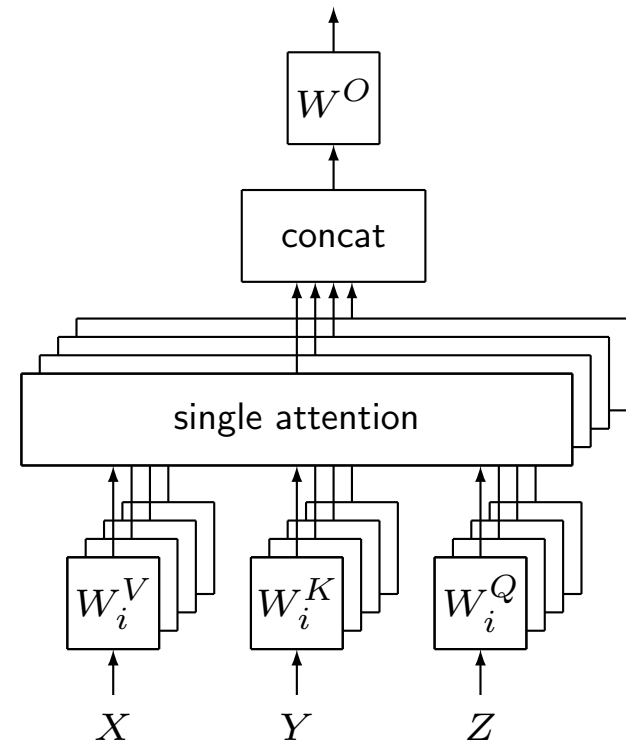
$$X \in \mathbf{R}^{d_e \times m}, Y \in \mathbf{R}^{d_e \times m}, Z \in \mathbf{R}^{d_e \times n}$$

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!*

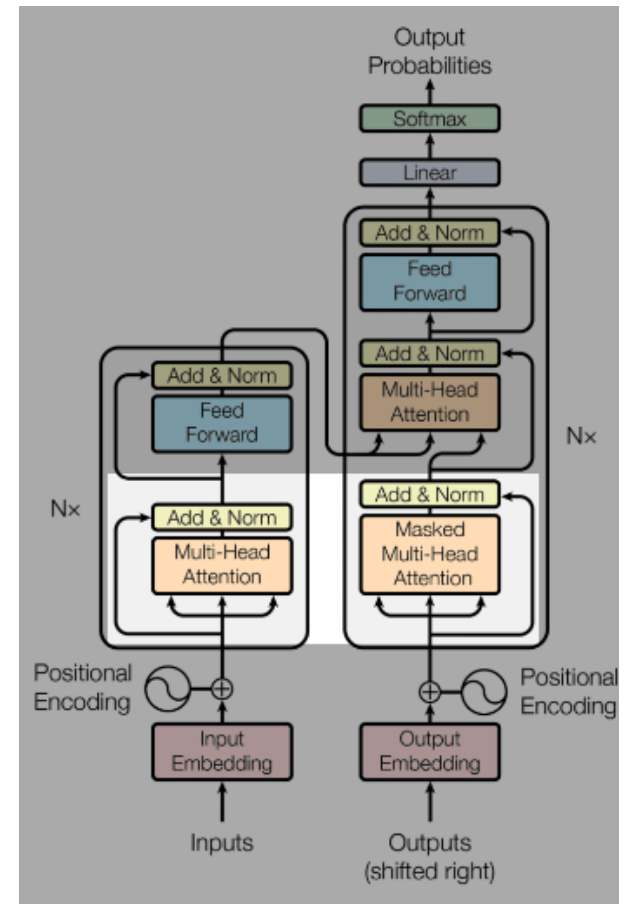
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbf{R}^{d_e \times n},$$

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



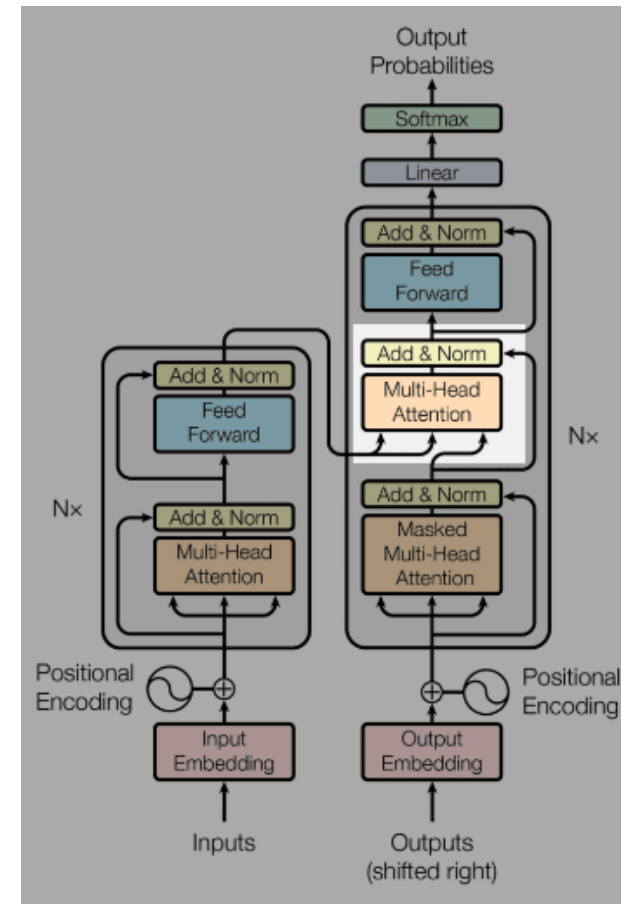
Self attention

- $m = n$
- 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

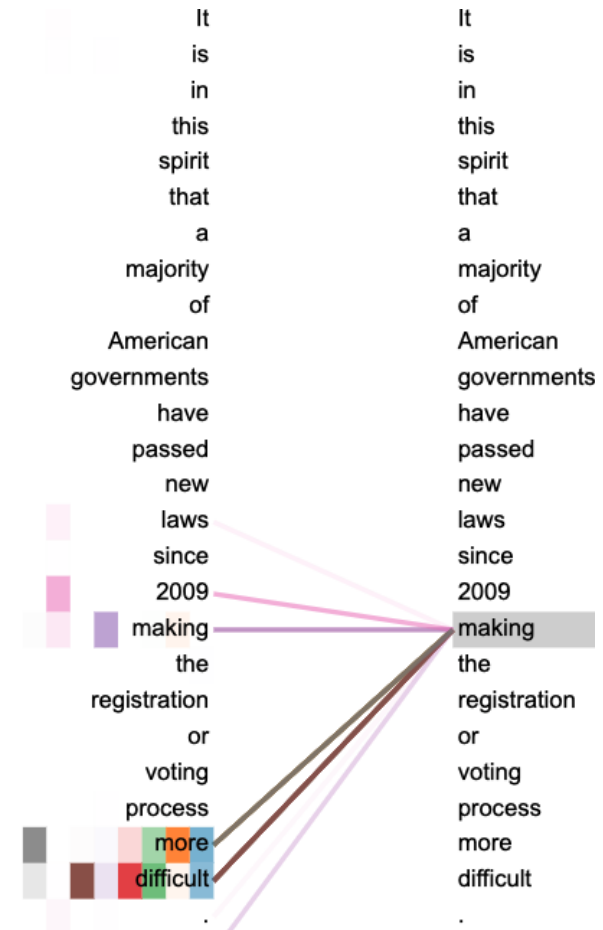


Visualization of self attentions

example sentence

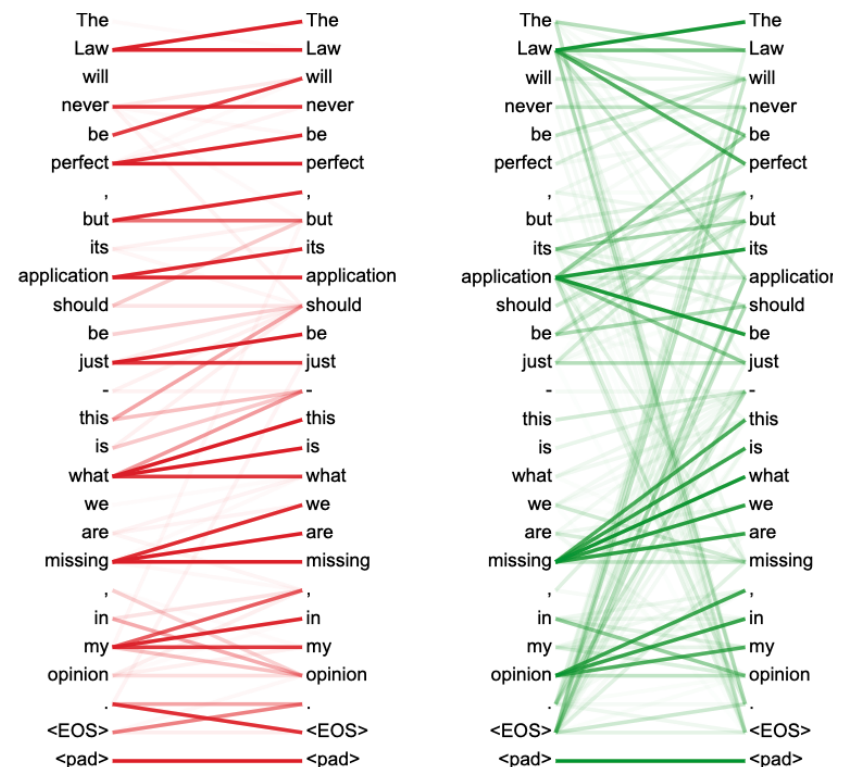
“It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult.”

- 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”

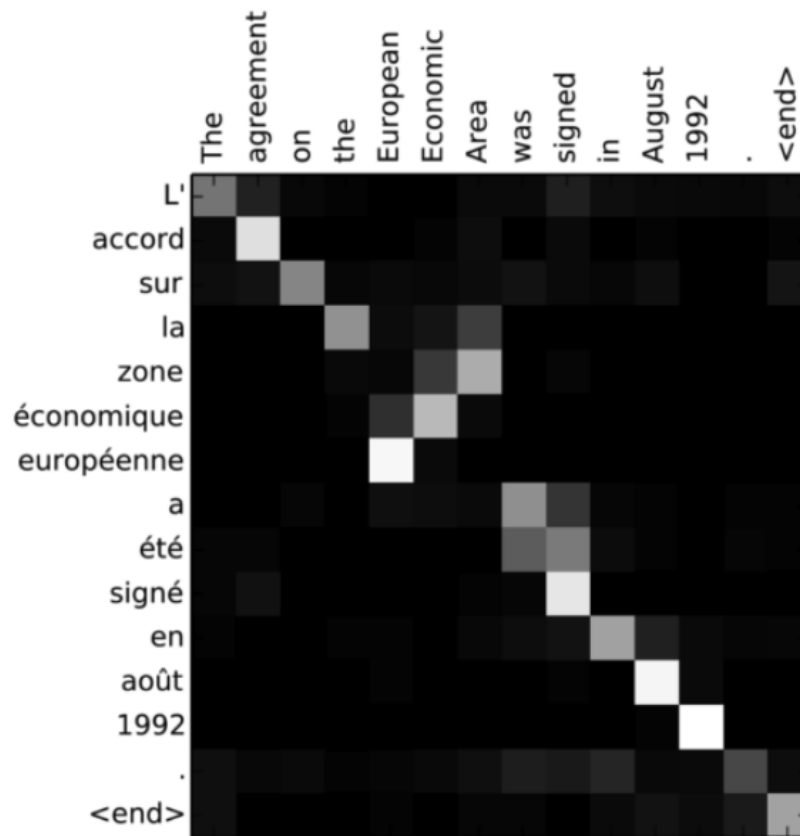


Visualization of multi-head self attentions

- 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

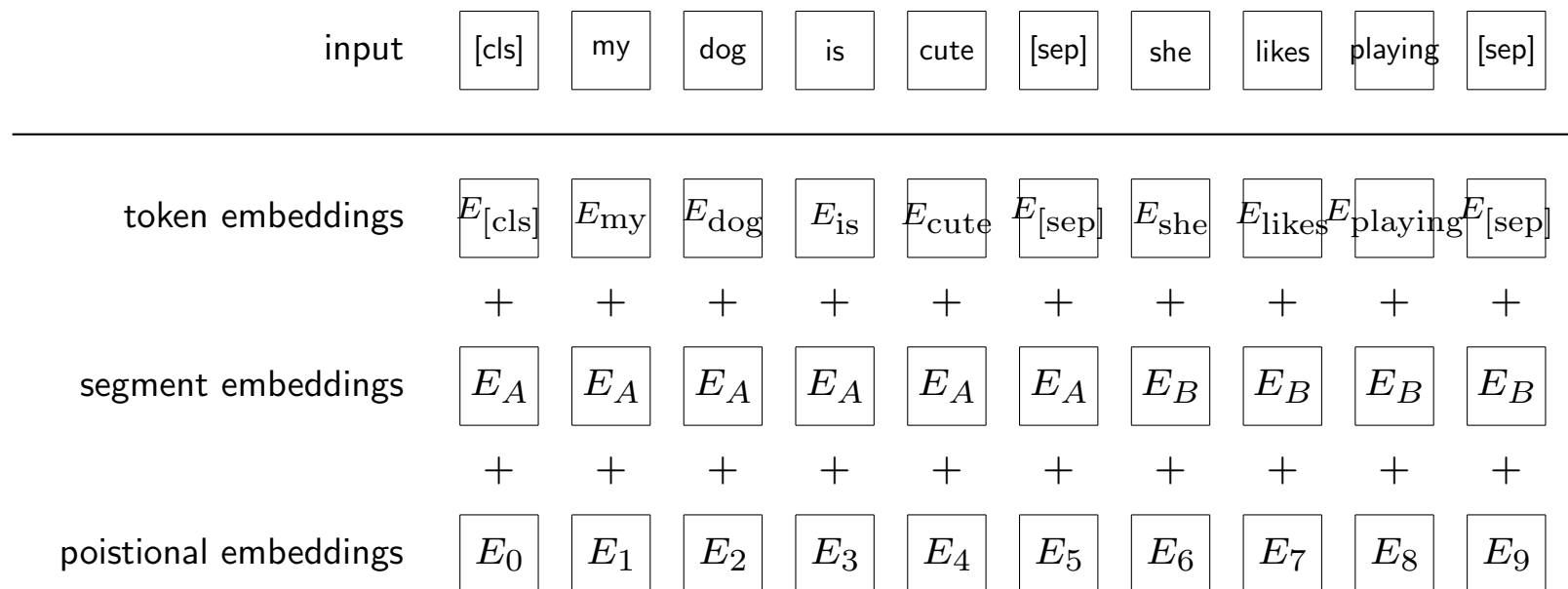
Model complexity

- 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 & relieved

genAI

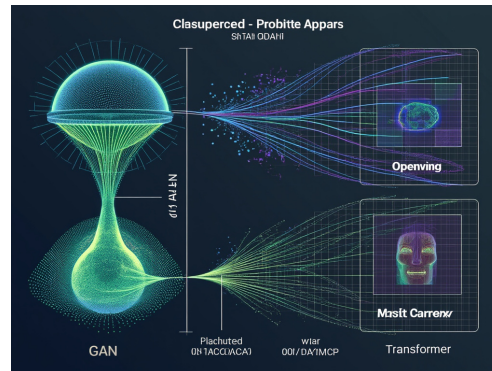
Definition of genAI

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

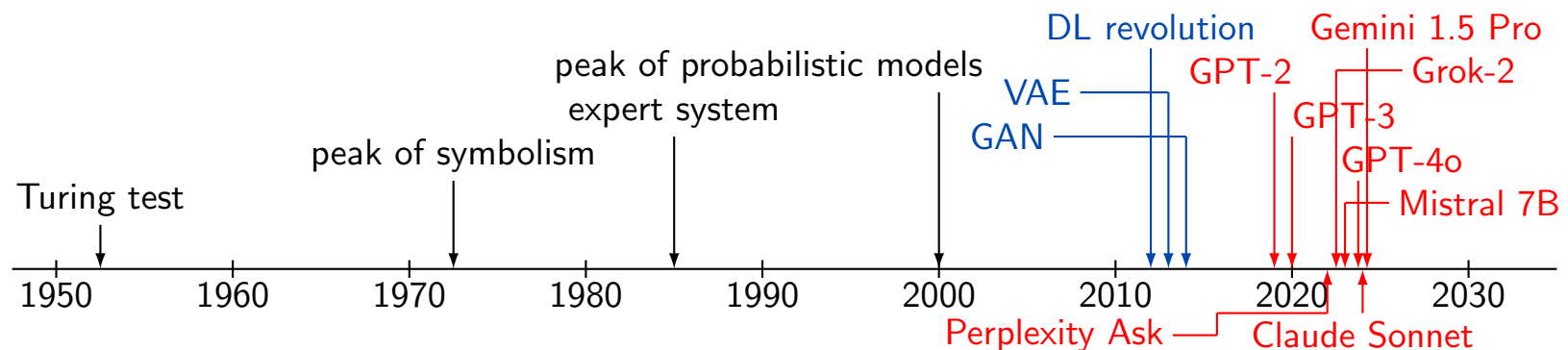
Examples of genAI in action

- 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

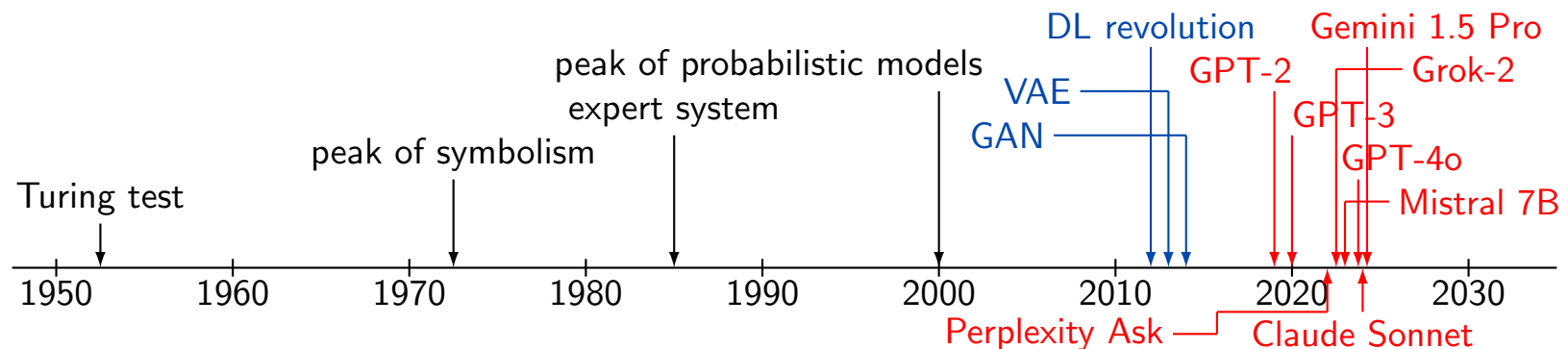
Birth of AI - early foundations & precursor technologies

- 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 ~)



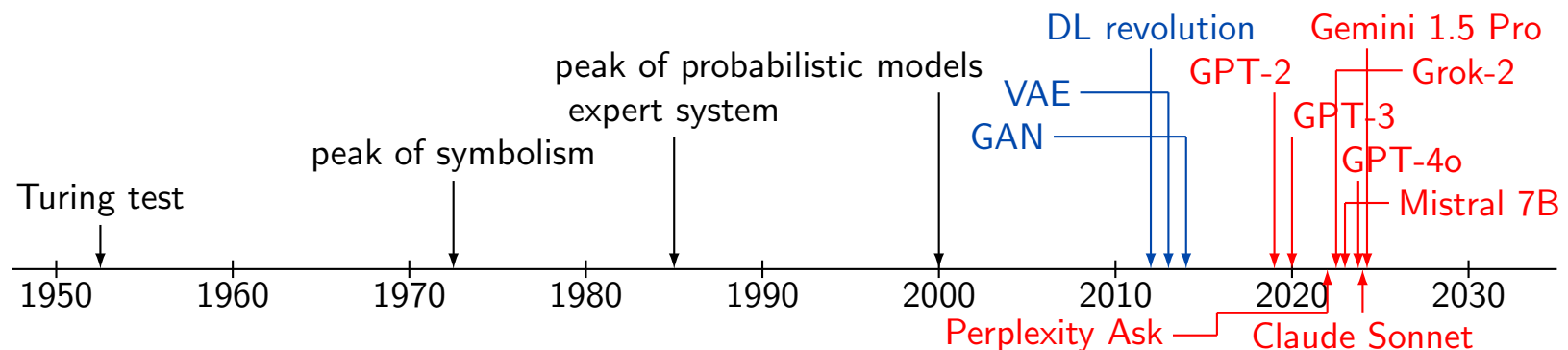
Rule-based systems & probabilistic models

- 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



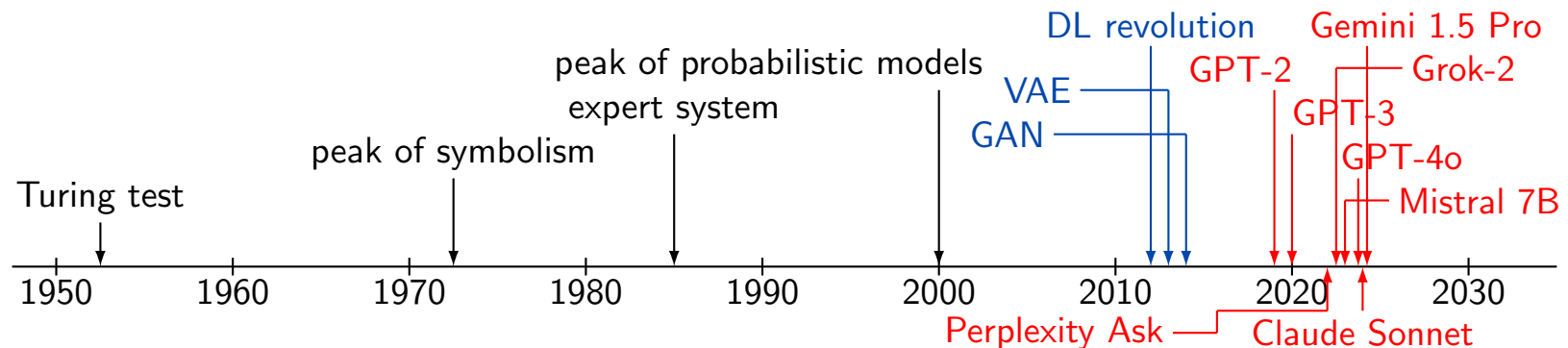
Rise of deep learning & generative models

- 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

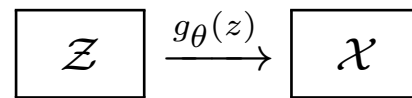
- late 2010s ~ Present
 - Transformer architecture (2017) - by Vaswani et al.
 - *revolutionized NLP*, e.g., LLM & various genAI models
 - GPT series - generative pre-trained transformer
 - GPT-2 (2019) - generating human-like texts - *marking leap in language models*
 - GPT-3 (2020) - 175B params - 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

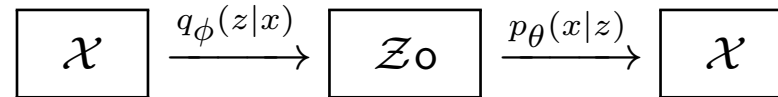
- definition of generative model



- *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)

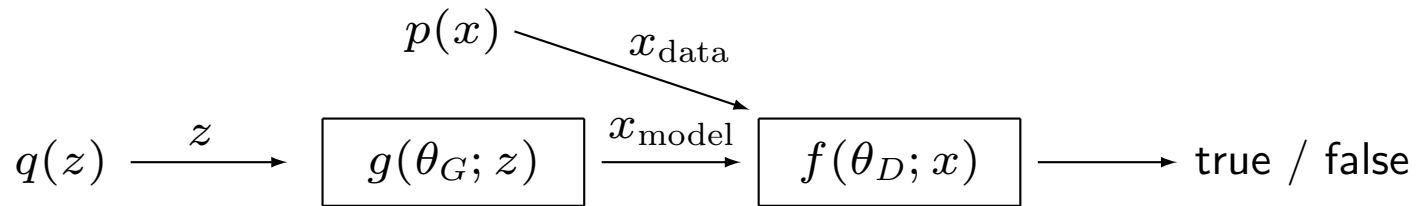
$$\mathcal{L}(\theta, \phi; x) = \mathbf{E}_{z \sim q_{\phi}(z|x)} \log \frac{p_{\theta}(x, z)}{q_{\phi}(z|x)}$$

- 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

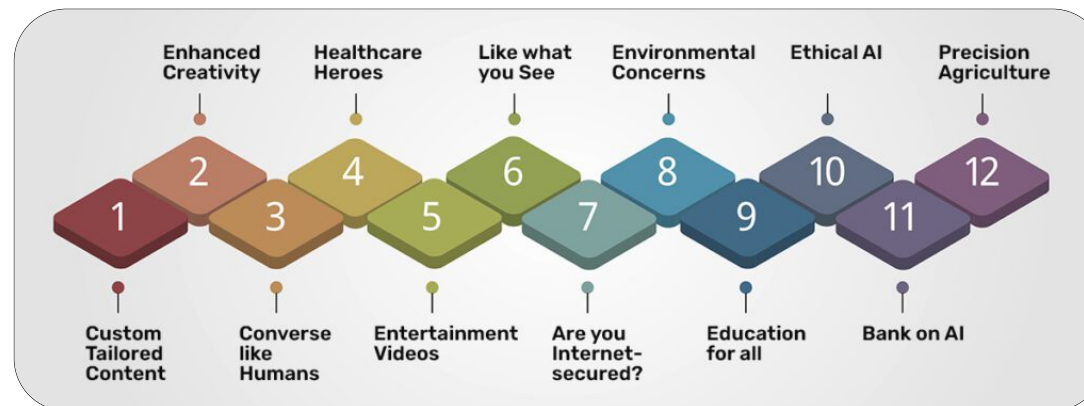
- previous sequence: $x_{t-1}, x_{t-2}, \dots$
- next token: x_t
- p_{θ} represented by (extremely) complicated model
 - *e.g.*, containing multi-head & multi-layer Transformer architecture inside
- model parameters, *e.g.*, for Llama2

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

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

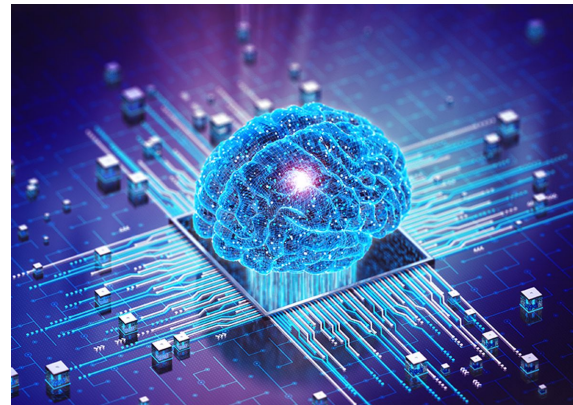
- hyper-personalization - highly personalized content for individual users - music, products & services
- AI ethics & governance - concerns over deepfakes, misinformation & bias
- interdisciplinary synergies - integration with other fields such as quantum computing, neuroscience & robotics
- human-AI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



AI & Biotech

AI in biology

- AI has been used in biological sciences, and science in general
- AI's ability to process large amounts of raw, unstructured data (*e.g.*, DNA sequence data)
 - reduces time and cost to conduct experiments in biology
 - enables others types of experiments that previously were unattainable
 - contributes to broader field of engineering biology or biotechnology
- AI increases human ability to make direct changes at cellular level and create novel genetic material (*e.g.*, DNA and RNA) to obtain specific functions



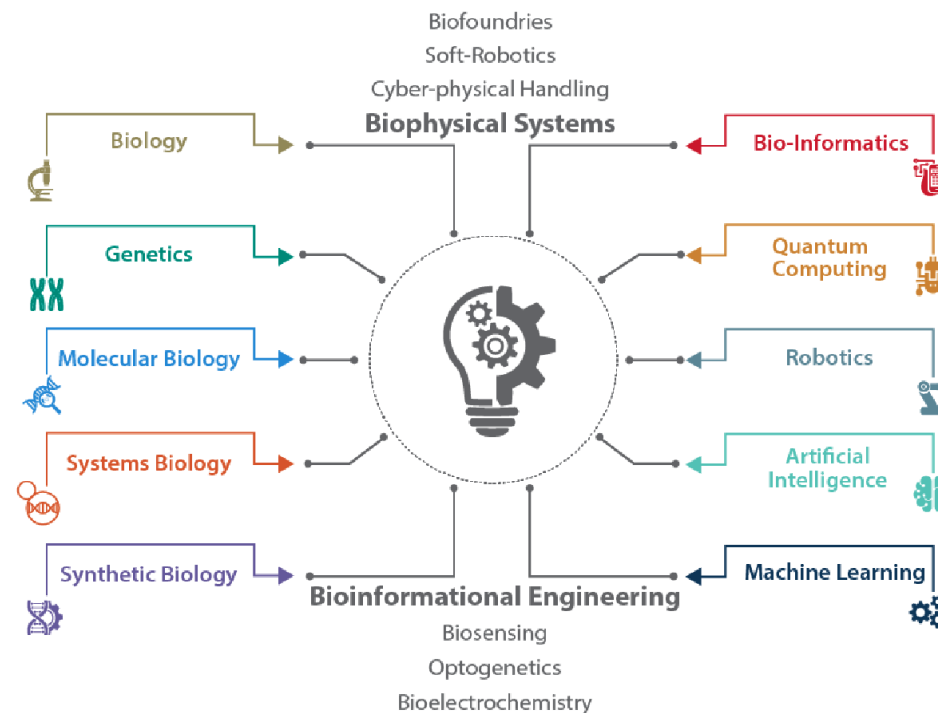
Biotech

Biotech

- biotechnology
 - is multidisciplinary field leveraging broad set of sciences and technologies
 - relies on and builds upon advances in other fields such as nanotechnology & robotics, and, increasingly, AI
 - enables researchers to read and write DNA
 - sequencing technologies “read” DNA while gene synthesis technologies take sequence data and “write” DNA turning data into physical material
- 2018 National Defense Strategy & Senior US Defense and Intelligence Officials identified emerging technologies that could have disruptive impact on US national security [[Say21](#)]
 - [AI](#), lethal autonomous weapons, hypersonic weapons, directed energy weapons, [biotechnology](#), quantum technology
- other names for biotechnology are engineering biology, synthetic biology, biological science (when discussed in context of AI)

Biotech - multidisciplinary field

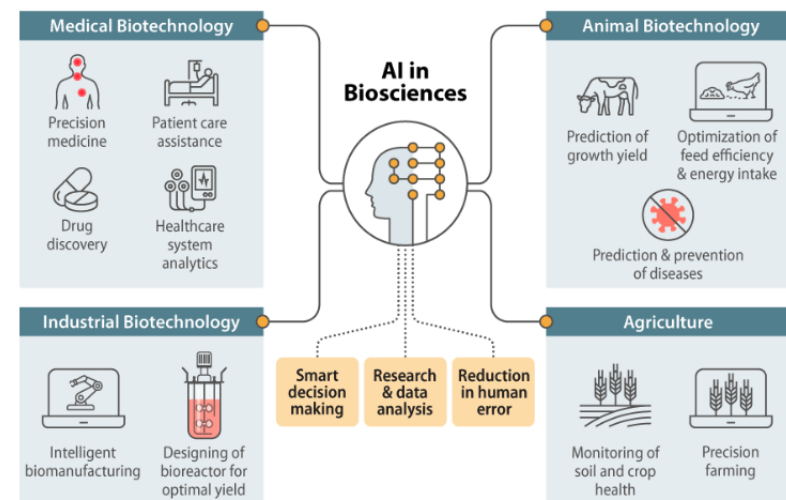
- sciences and technologies enabling biotechnology include (but not limited to)
 - (molecular) biology, genetics, systems biology, synthetic biology, bio-informatics, quantum computing, robotics [DFJ22]



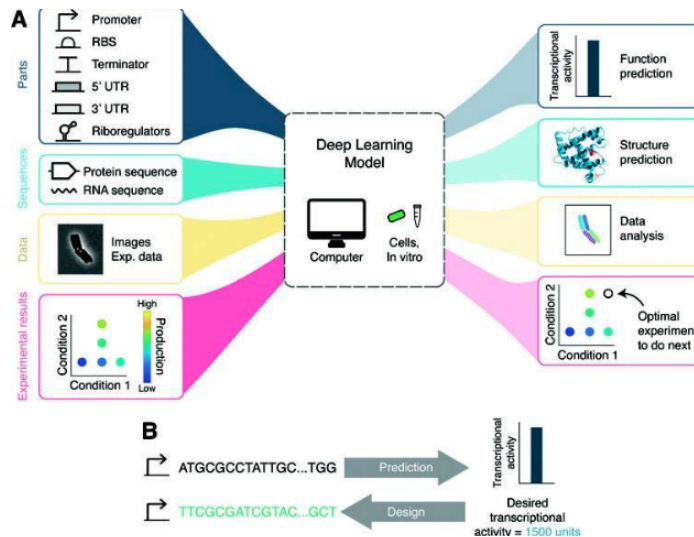
Convergence of AI and biological design

- AI & biological sciences converging [BKP22]
 - each building upon the other's capabilities for new research and development across multiple areas
- Demis Hassabis, CEO & cofounder of DeepMind, said of biology [Toe23]

“. . . biology can be thought of as information processing system, albeit extraordinarily complex and dynamic one . . . just as mathematics turned out to be the right description language for physics, biology may turn out to be *the perfect type of regime for the application of AI!*”
- both AI & biotech rely on and build upon advances in other scientific disciplines and technology fields, such as nanotechnology, robotics, and increasingly big data (*e.g.*, genetic sequence data)
 - each of these fields itself convergence of multiple sciences and technologies
- so *their impacts can combine to create new capabilities*



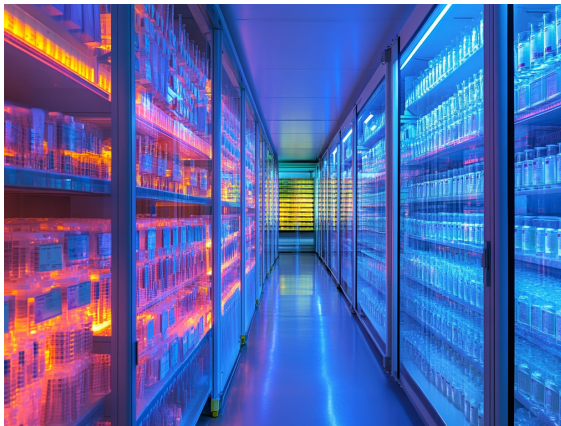
Multi-source genetic sequence data



- AI, essential to analyzing exponential growth of genetic sequence data
 - “AI will be essential to fully understanding how genetic code interacts with biological processes” - US National Security Commission on Artificial Intelligence (NSCAI)
 - process huge amounts of biological data, *e.g.*, genetic sequence data, coming from different biological sources for understanding complex biological systems
 - sequence data, molecular structure data, image data, time-series, omics data
- *e.g.*, analyze genomic data sets to determine the genetic basis of particular trait and potentially uncover genetic markers linked with that trait

Quality & quantity of biological data

- limiting factor, however, is *quality and quantity* of biological data, *e.g.*, DNA sequences, that AI is trained on
 - *e.g.*, accurate identification of particular species based on DNA requires reference sequences of *sufficient quality* to exist and be available
- databases have varying standards - access, type, and quality of information
- design, management, quality standards, and data protocols for reference databases can affect utility of particular DNA sequence



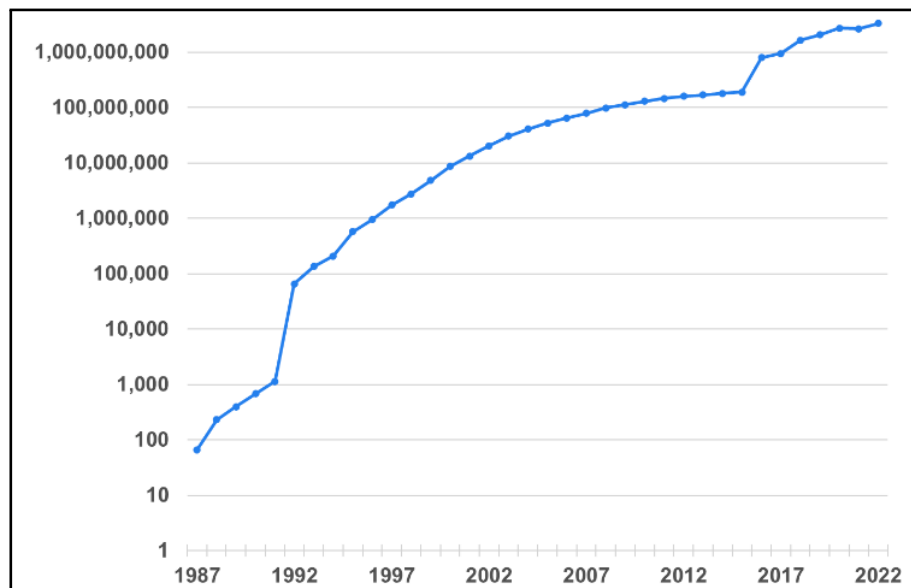
Rapid growth of biological data

- volume of genetic sequence data grown exponentially as sequencing technology evolved
- more than 1,700 databases incorporating data on genomics, protein sequences, protein structures, plants, metabolic pathways, *etc.*, *e.g.*
 - open-source public database
 - Protein Data Bank, US-funded data center - more than *terabyte of three-dimensional structure data* for biological molecules, *e.g.*, proteins, DNA, RNA
 - proprietary database
 - Gingko Bioworks - more than *2B protein sequences*
 - public research groups
 - Broad Institute - produces roughly *500 terabases of genomic data per month*
- great potential value in aggregate volume of genetic datasets that can be collectively mined to discover and characterize relationships among genes

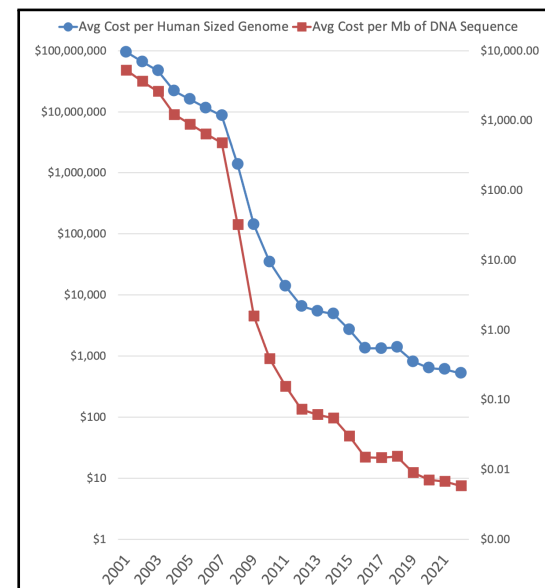
Volume and sequencing cost of DNA over time

- volume of DNA sequences & DNA sequencing cost
 - data source: National Human Genome Research Institute (NHGRI) [Wet23] & International Nucleotide Sequence Database Collaboration (INSDC)
- *more dramatic than Moore's law!*

sequences in INSDC



DNA sequencing cost



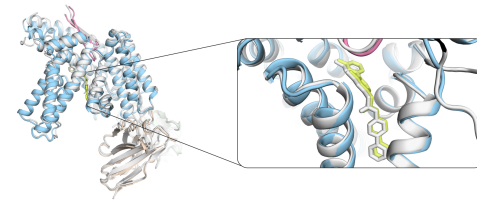
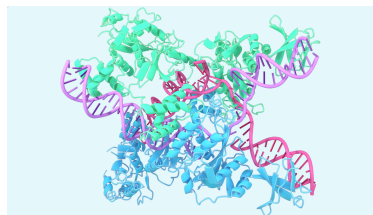
Bio data availability and bias

- US National Security Commission on Artificial Intelligence (NSCAI) recommends
 - US fund and prioritize development of a biobank containing *“wide range of high-quality biological and genetic data sets securely accessible by researchers”*
 - establishment of database of broad range of human, animal, and plant genomes would
 - *enhance and democratize biotechnology innovations*
 - *facilitate new levels of AI-enabled analysis of genetic data*
- bias - availability of genetic data & decisions about selection of genetic data can introduce bias, *e.g.*
 - training AI model on datasets emphasizing or omitting certain genetic traits can affect how information is used and types of applications developed - *potentially privileging or disadvantaging certain populations*
 - access to data and to AI models themselves may impact communities of differing socioeconomic status or other factors unequally

Emerging Trends in Biotech

AlphaFold

- solving 50-year-old protein folding problem, *“one of biology’s grand challenges”*
 - definition - given amino acid sequence, predict how it folds into a 3D structure
 - proteins fold in microseconds, but predicting computationally nearly impossible
- AlphaFold 1 (2018) - DL + physics-based energy functions → AlphaFold 2 (2020)
 - attention-based NN solving protein folding “in principle” → AlphaFold 3 (2024) - diffusion-based DL, drug-protein interactions, protein complexes
- AlphaFold protein structure database
 - >200MM protein structures - nearly every known protein, used by >2MM researchers
- Applications & implications
 - drug discovery - target identification, lead optimization, side effect prediction
 - enzyme engineering, agriculture, environmental, vaccine development



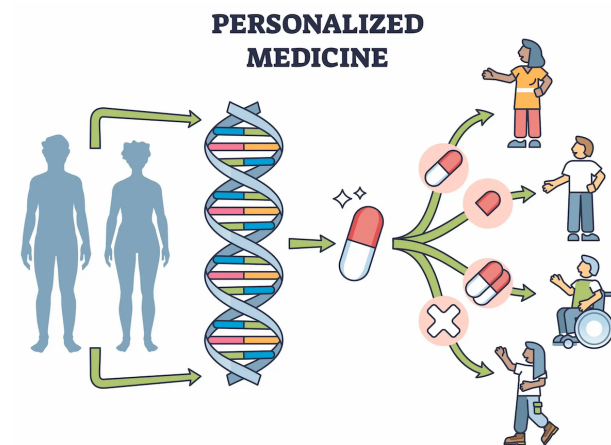
AlphaGo

- [illegible]

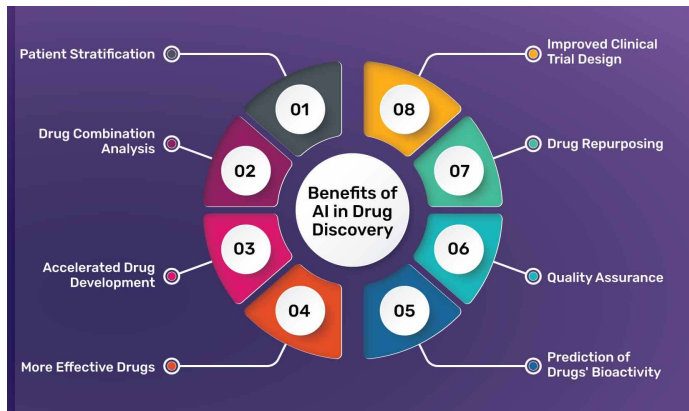


Personalized medicine

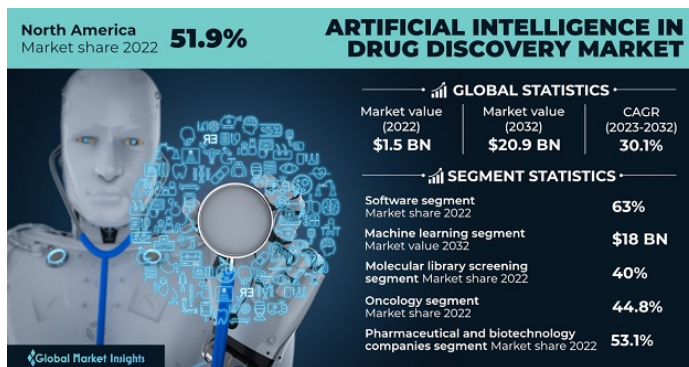
- *shift from one-size-fits-all approach to tailored treatments*
- based on individual genetic profiles, lifestyles & environments
- AI enables analysis of vast data to predict patient responses to treatments, thus enhancing efficacy and reducing adverse effects
- *e.g.*
 - custom cancer therapies
 - personalized treatment plans for rare diseases
 - precision pharmacogenomics
- companies - Tempus, Foundation Medicine, *etc.*



AI-driven drug discovery

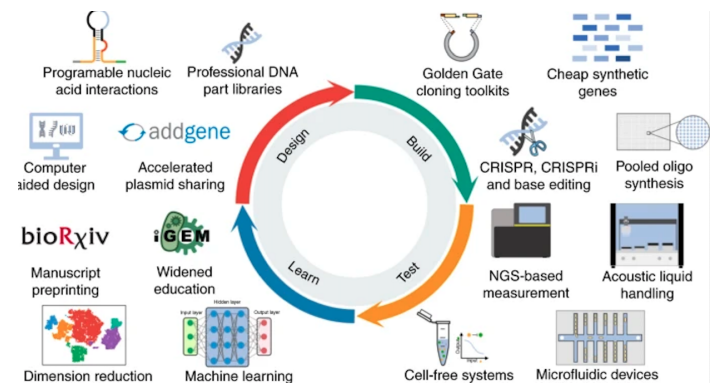


- traditional drug discovery process - time-consuming and costly often taking decades and billions of dollars
- AI streamlines this process by predicting the efficacy and safety of potential compounds with more speed and accuracy
- AI models analyze chemical databases to identify new drug candidates or repurpose existing drugs for new therapeutic uses
- companies - Insilco Medicine, Atomwise.

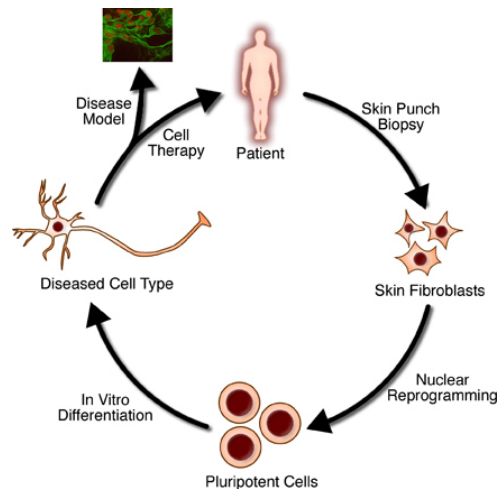
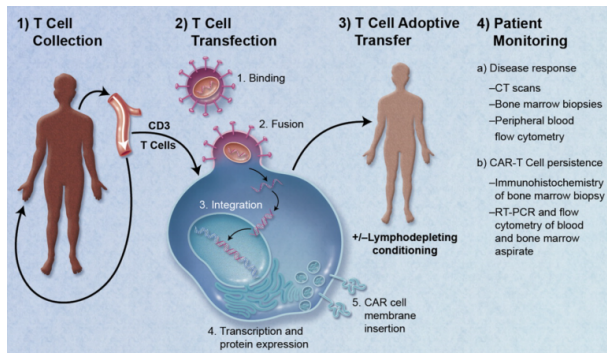


Synthetic biology

- use AI for gene editing, biomaterial production and synthetic pathways
- combine principles of biology and engineering to design and construct new biological entities
- AI optimizes synthetic biology processes from designing genetic circuits to scaling up production
- company - Ginkgo Bioworks uses AI to design custom microorganisms for applications ranging from pharmaceuticals to industrial chemicals



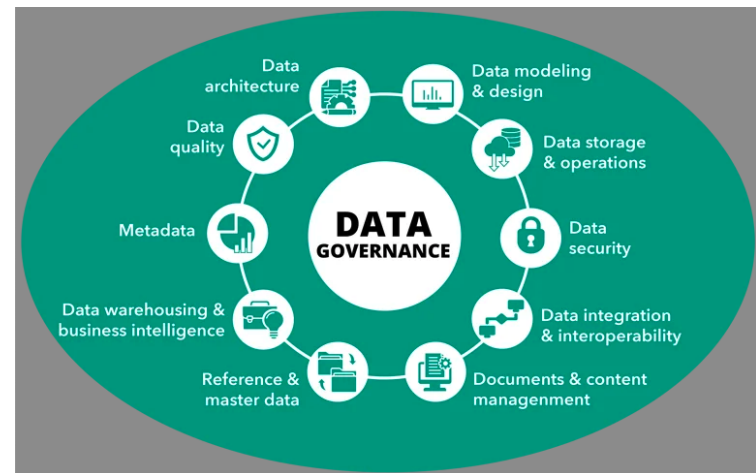
Regenerative medicine



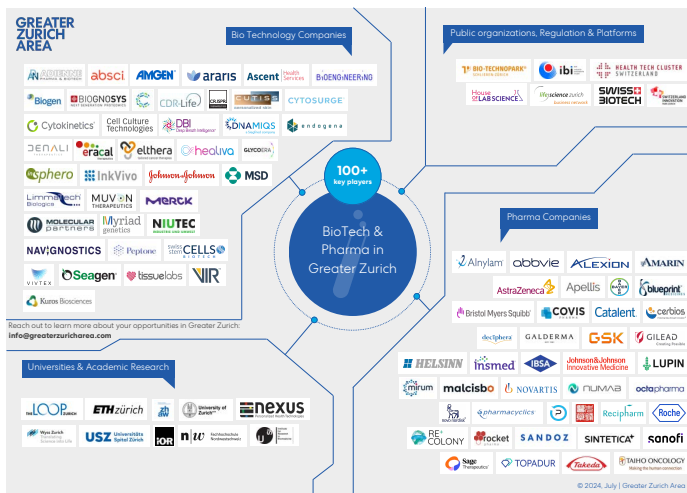
- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo leverages AI to potentially improve the efficacy and scalability of regenerative therapies, developing next-generation treatments

Bio data integration

- integration of disparate data sources, including genomic, proteomic & clinical data - one of biggest challenges in biotech & healthcare
- AI delivers meaningful insights *only when* seamless data integration and interoperability realized
- developing platforms facilitating comprehensive, longitudinal patient data analysis - vital enablers of AI in biotech
- company - Flatiron Health working on integrating diverse datasets to provide holistic view of patient health



Biotech companies



- Atomwise - small molecule drug discovery
- Cradle - protein design
- Exscientia - precision medicine
- Iktos - small molecule drug discovery and design
- Insilico Medicine - full-stack drug discovery system
- Schrödinger, Inc. - use physics-based models to find best possible molecule
- Absci Corporation - antibody design, creating new from scratch antibodies, *i.e.*, “de novo antibodies”, and testing them in laboratories

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Thank You