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

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About Speaker

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- *Co-Founder & CEO @ Erudio Bio Korea, Inc., Korea*
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- *Advisory Professor, Electrical Engineering and Computer Science @ DGIST, Korea*
- *Global Advisory Board Member @ Innovative Future Brain-Inspired Intelligence System Semiconductor of Sogang University, Korea*
- Technology Consultant @ Gerson Lehrman Gruop (GLG), NY, USA
- Advisor & Evangelist @ CryptoLab, Inc., San Jose, CA, USA
- Chief Business Development Officer @ WeStory.ai, Cupertino, 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 $\sim$ 2020
- Principal Engineer @ Software R&D Center, DS Division, Samsung, Korea $\sim$ 2017
- Principal Engineer @ Strategic Marketing & Sales Team, Samsung, Korea $\sim$ 2016
- Principal Engineer @ DT Team, DRAM Development Lab, Samsung, Korea $\sim$ 2015
- Senior Engineer @ CAE Team, Samsung, Korea $\sim$ 2012
- PhD - Electrical Engineering @ Stanford University, CA, USA $\sim$ 2004
- Development Engineer @ Voyan, Santa Clara, CA, USA $\sim$ 2001
- MS - Electrical Engineering @ Stanford University, CA, USA $\sim$ 1999
- BS - Electrical & Computer Engineering @ Seoul National University 1994 $\sim$ 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.

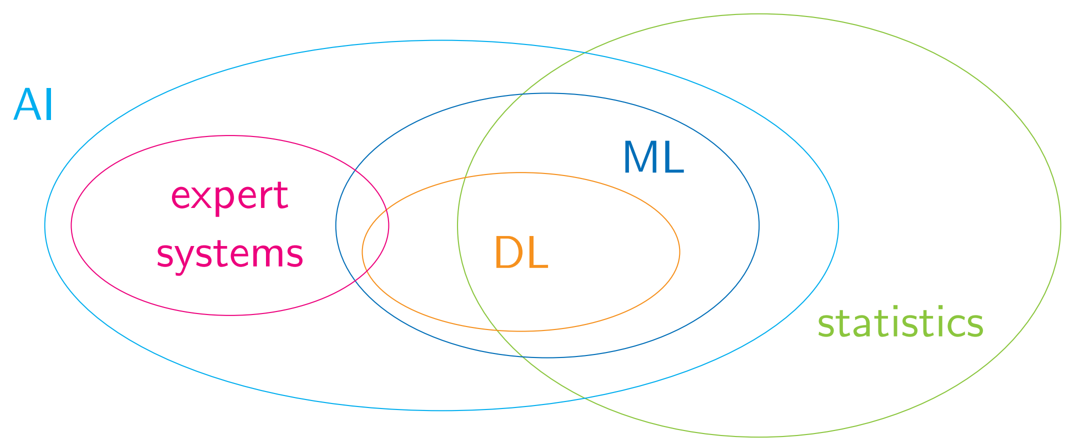
Today

Artificial Intelligence

Definition and History

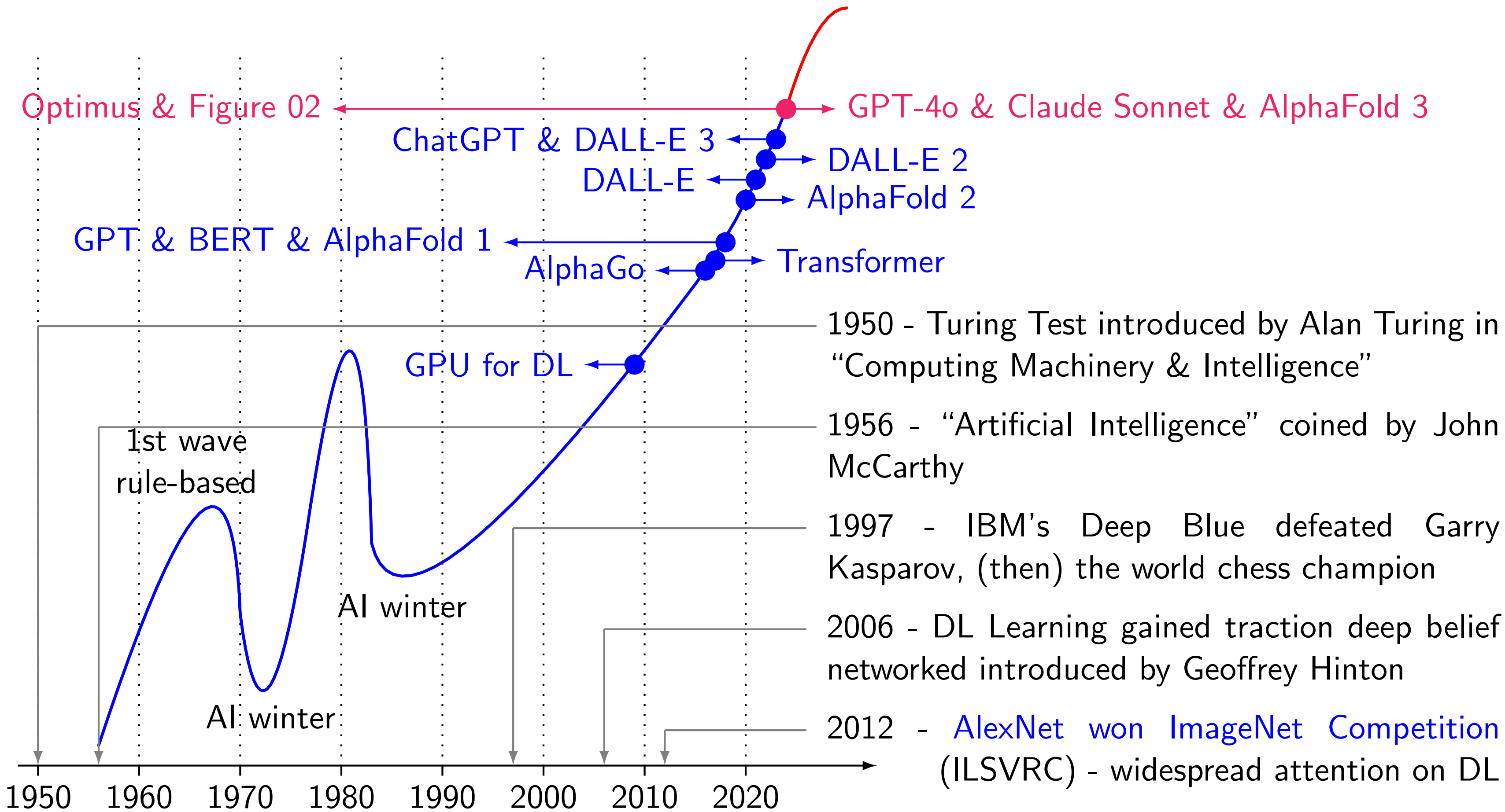
Definition & relation to other technologies

- 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 system[1] [HGH+22]



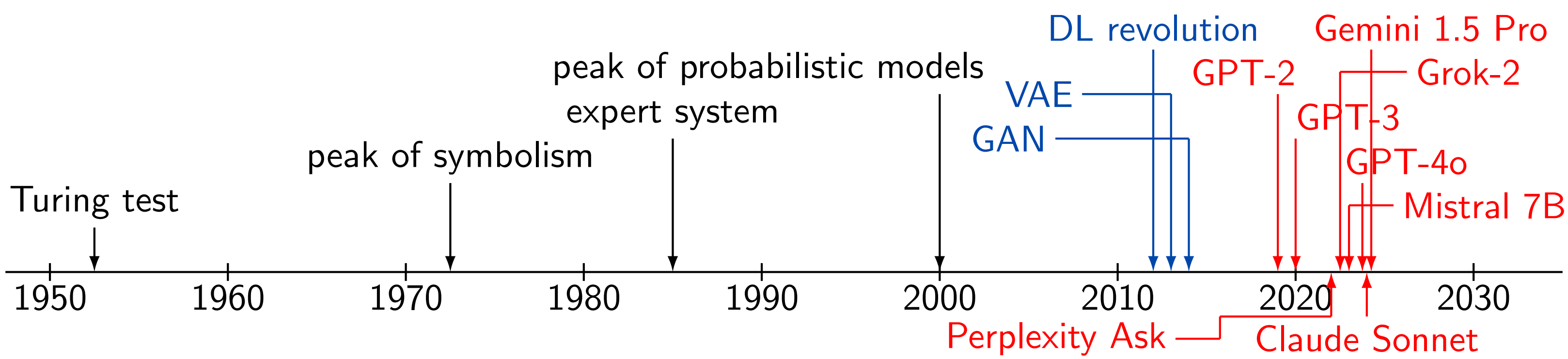
[1] ML: machine learning & DL: deep learning

History


Optimus & Figure 02
GPT-4o & Claude Sonnet & AlphaFold 3
ChatGPT & DALL-E 3
DALL-E 2
DALL-E
AlphaFold 2
GPT & BERT & AlphaFold 1
AlphaGo
Transformer
GPU for DL
1st wave
rule-based
AI winter
AI winter
1950 - Turing Test introduced by Alan Turing in "Computing Machinery & Intelligence"
1956 - "Artificial Intelligence" coined by John McCarthy
1997 - IBM's Deep Blue defeated Garry Kasparov, (then) the world chess champion
2006 - DL Learning gained traction deep belief networked introduced by Geoffrey Hinton
2012 - AlexNet won ImageNet Competition (ILSVRC) - widespread attention on DL
1950
1960
1970
1980
1990
2000
2010
2020

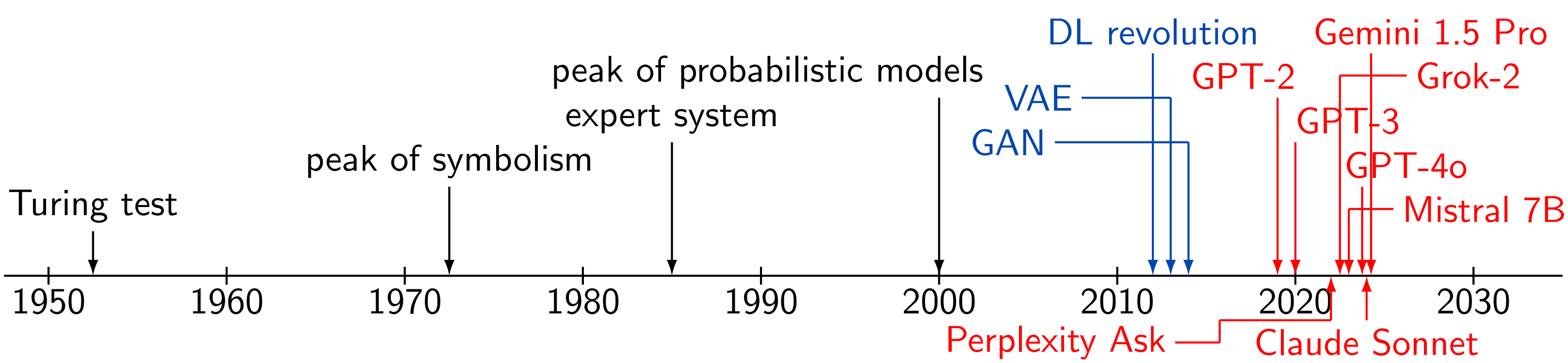
Birth of AI - early foundations & precursor technologies

- 1950s $\sim$ 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 $\sim$)



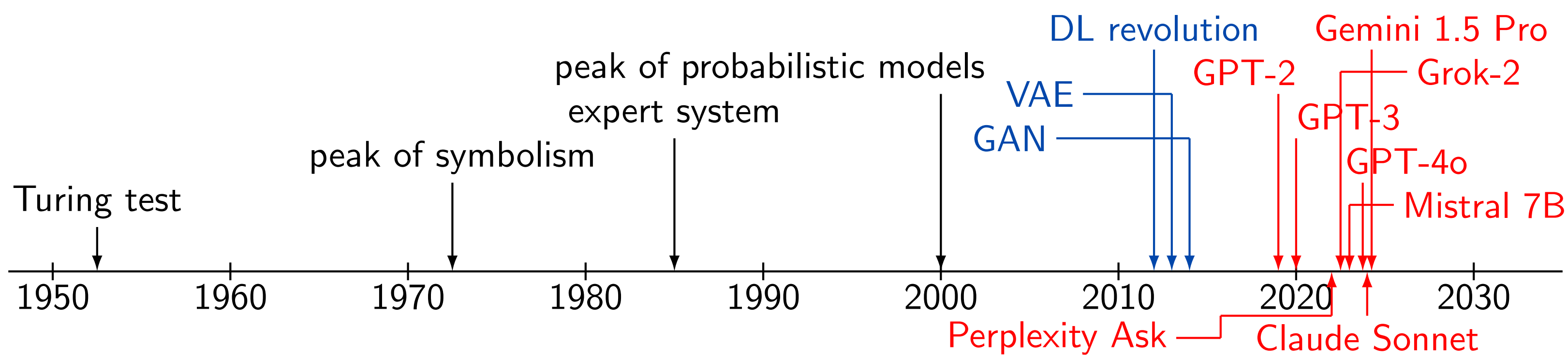
Rule-based systems & probabilistic models

- 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



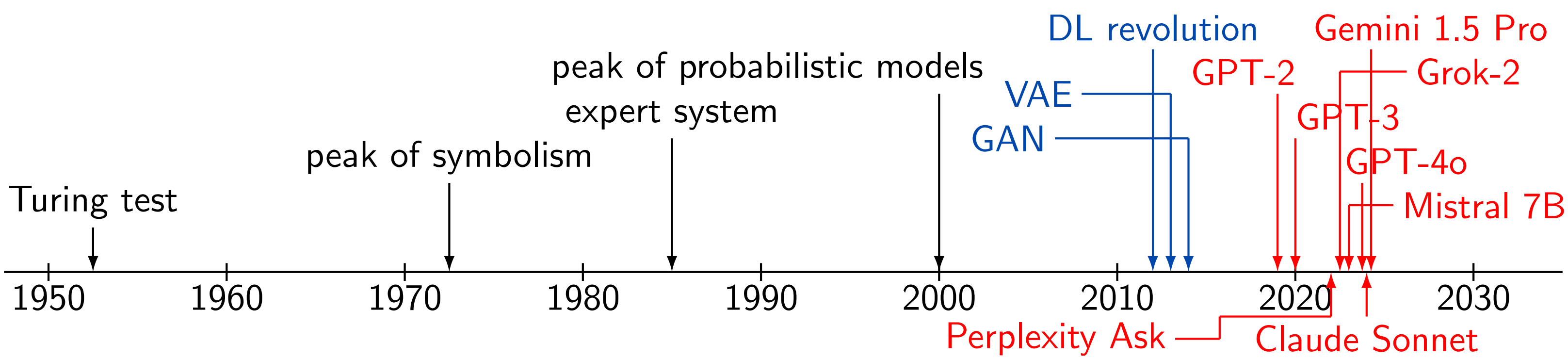
Rise of deep learning & generative models

- 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 $\sim$ 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

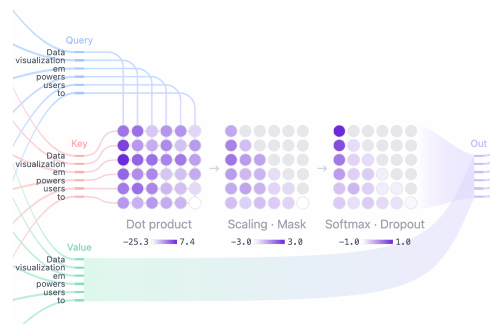
Deep learning revolution

- 2012 – 2015 - DL revolution[2]
  - 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

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

Transformer changes everything

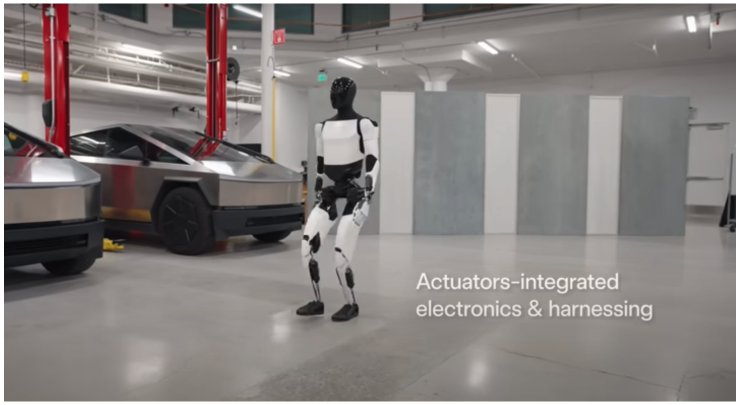
- 2017 – 2018 - Transformers & NLP breakthroughs[3]
  - *Transformer ($e.g.$, BERT & GPT) revolutionized NLP*
  - major advancements in, $e.g.$, machine translation & chatbots
- 2020 - AI in healthcare – AlphaFold & beyond
  - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting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



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

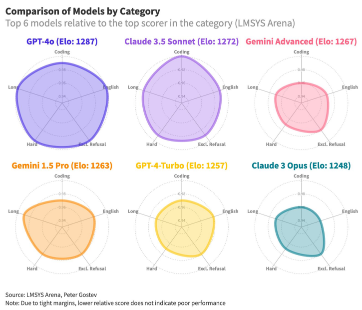
Lots of breakthroughs in AI technology and applications in 2024

- 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*



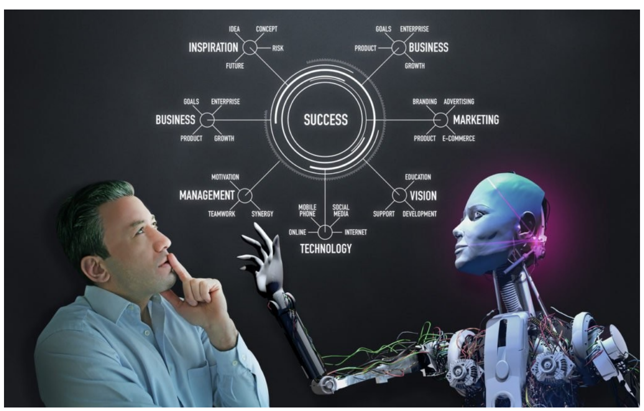
Major AI Breakthroughs in 2025

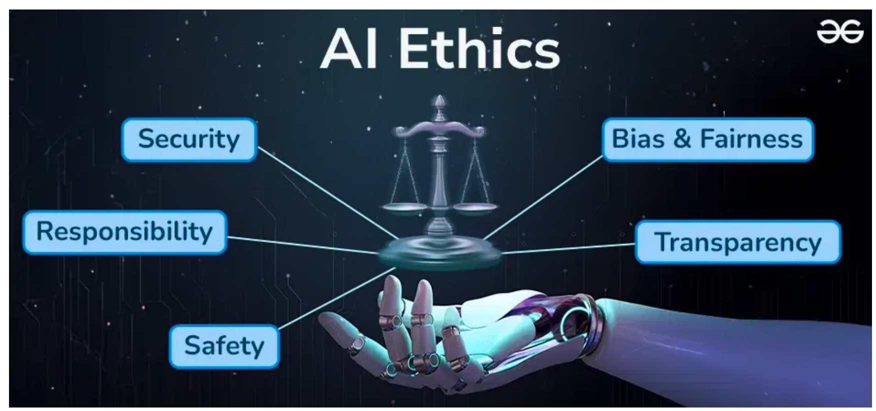
- next-generation foundation models
  - GPT-5 and Claude 4 demonstrate emergent reasoning abilities
  - open-source models achieving parity with leading commercial systems from 2024
- hardware innovations
  - NVIDIA's Blackwell successor architecture delivering 3-4x performance improvement
  - AMD's 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*

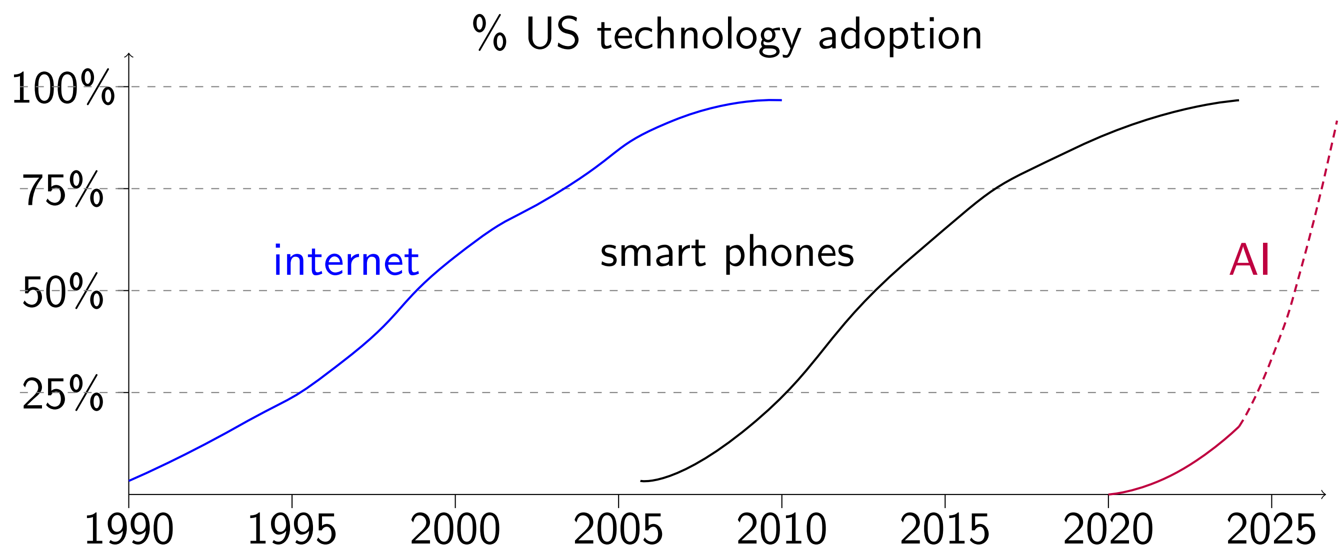




Measuring AI's Ascent

Where are we in AI today?

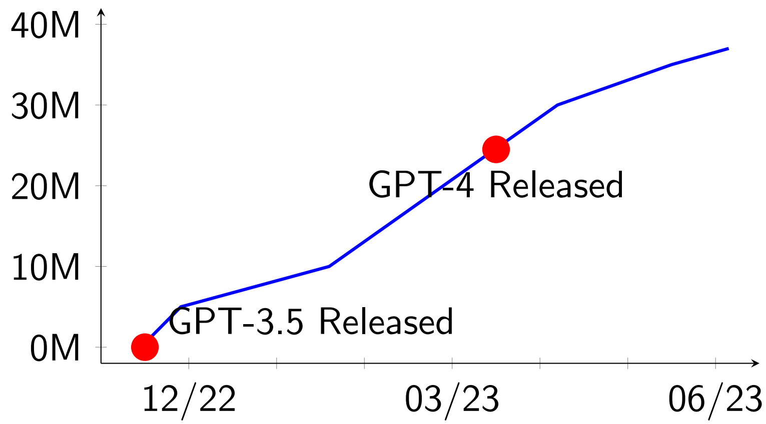
- sunrise phase - currently experiencing dawn of AI era with significant advancements and increasing adoption across various industries
- early adoption - in early stages of AI lifecycle with widespread adoption and innovation across sectors marking significant shift in technology's role in society



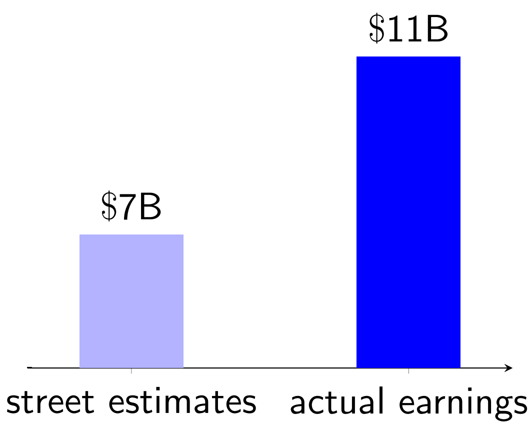
Explosion of AI ecosystems - ChatGPT & NVIDIA

- took only *5 months for ChatGPT users to reach 35M*
- NVDIA 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 year[4]

ChatGPT weekly unique visits



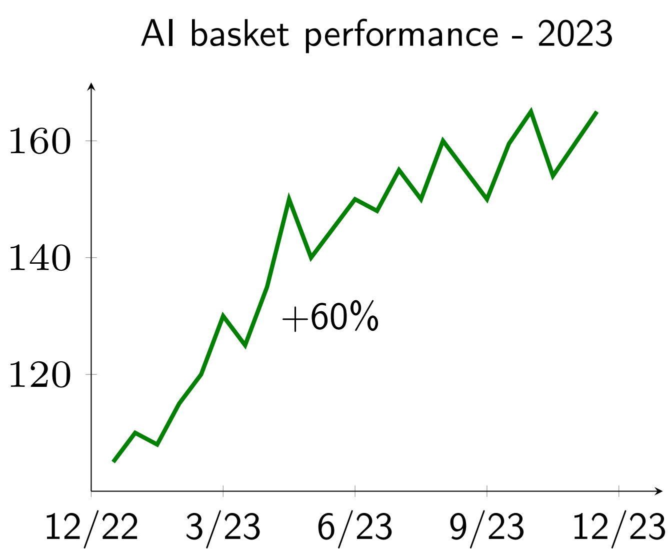
NVDA 2023-2Q earning

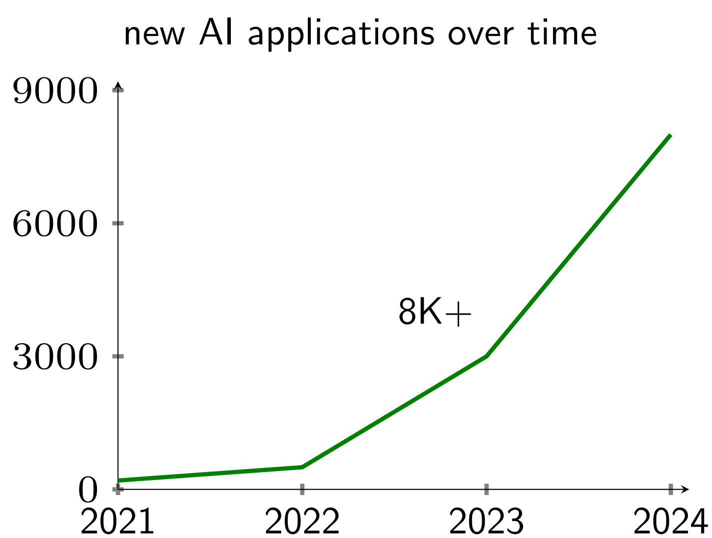


[4] source - Bloomberg

Explosion of AI ecosystems - AI stock market

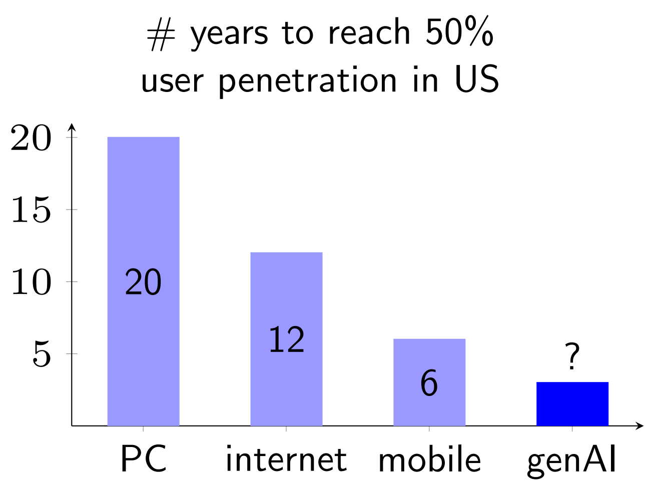
- *AI investment surge in 2023 - portfolio performance soars by 60%*
  - AI-focused stocks significantly outpaced traditional market indices
- *over 8,000 new AI applications* developed in last 3 years
  - applications span from healthcare and finance to manufacturing and entertainment

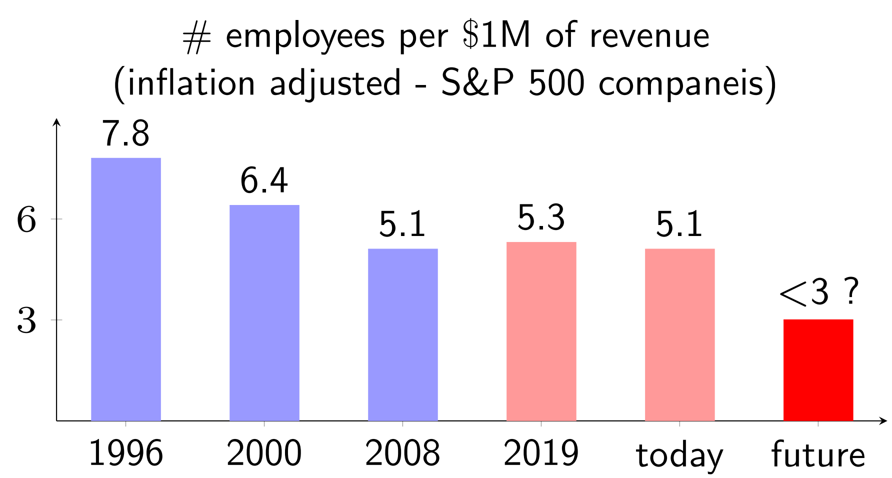




AI's transformative impact - adoption speed & economic potential

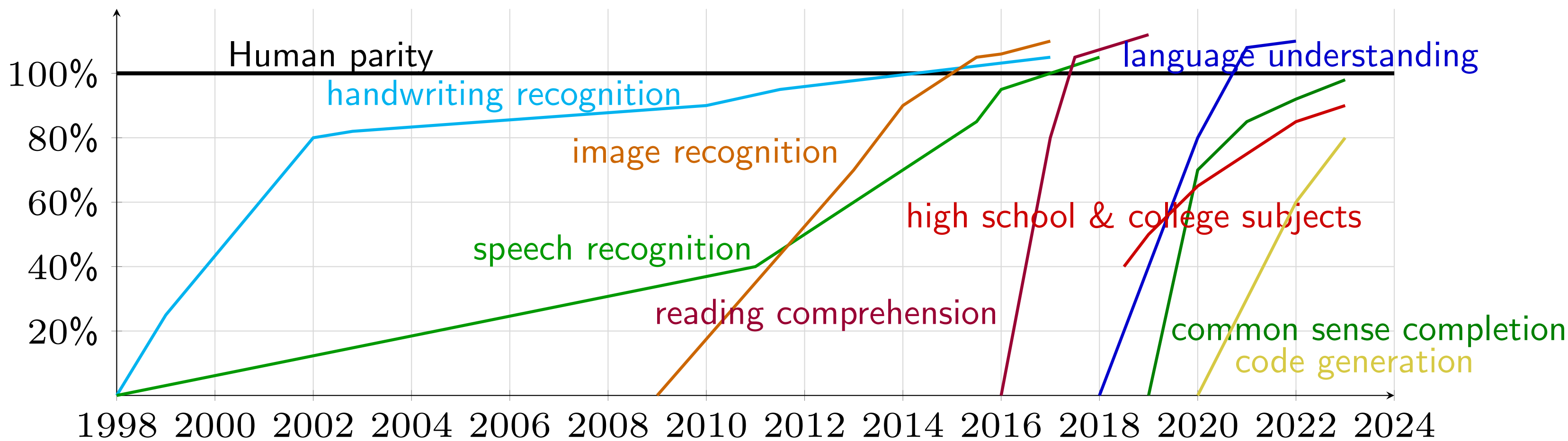
- adoption - has been twice as fast with platform shifts suggesting
  - increasing demand and readiness for new technology improved user experience & accessibility
- AI's potential to drive economy for years to come
  - 35% improvement in productivity driven by introduction of PCs and internet
  - greater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





AI getting more & more faster

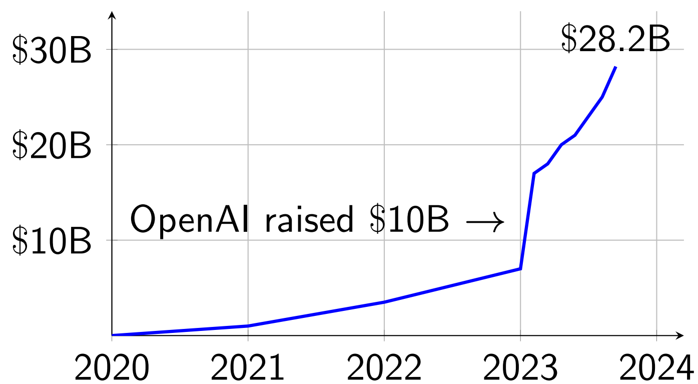
- steep upward slopes of AI capabilities highlight accelerating pace of AI development
  - period of exponential growth with AI potentially mastering new skills and surpassing human capabilities at ever-increasing rate
- closing gap to human parity - some capabilities approaching or arguably reached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



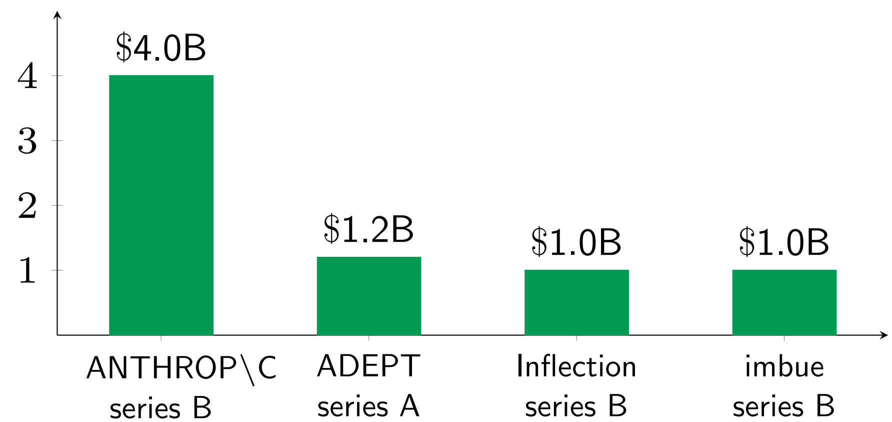
Massive investment in AI

- *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 stella 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

cumulative funding in private
AI companies since 2020

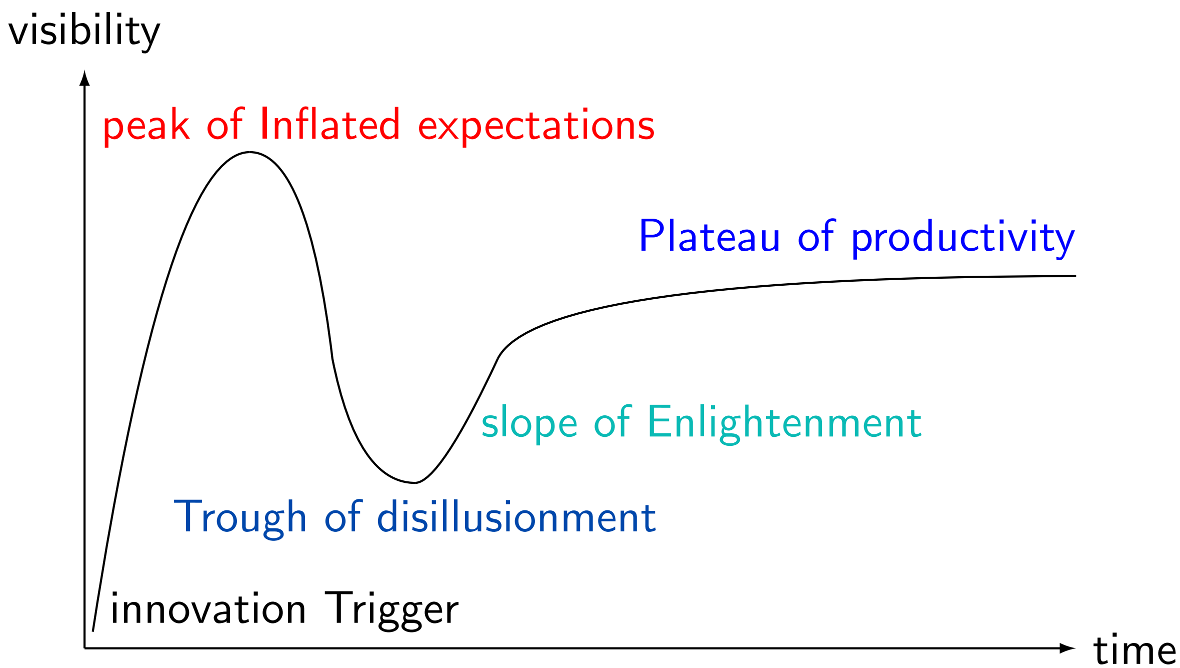


valuation before public product launch



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 companeis with data centers
  - *big 4 hyperscalers generate* $150B + annual revenue

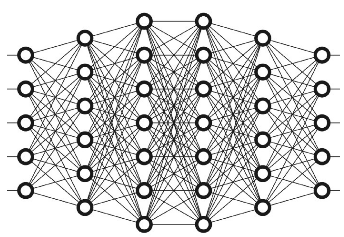
Yes & No

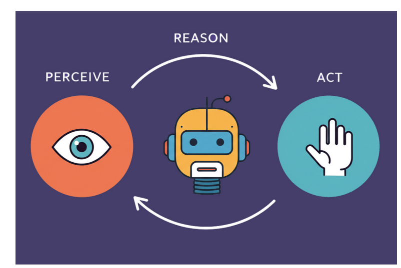
characteristics of hype cycles	speaker's views
value accrual misaligned with investment	• OpenAI still operating at a loss; business model *still* not clear • gradual value creation across broad range of industries and technologies (*e.g.*, CV, LLMs, RL) unlike fiber optic bubble in 1990s
overestimating 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

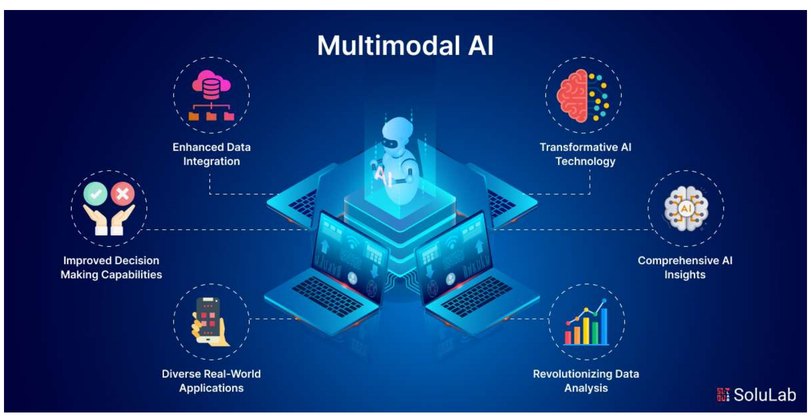
- 2010 $\sim$ Big Data
- 2012 $\sim$ Deep Learning
- 2017 $\sim$ Transformer - Attention is All you need!
- 2022 $\sim$ LLM & genAI
- 2024 $\sim$ AI Agent (Agentic AI)

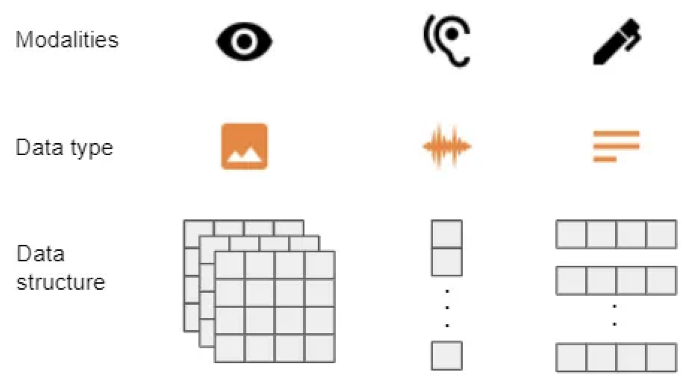




Multimodal learning

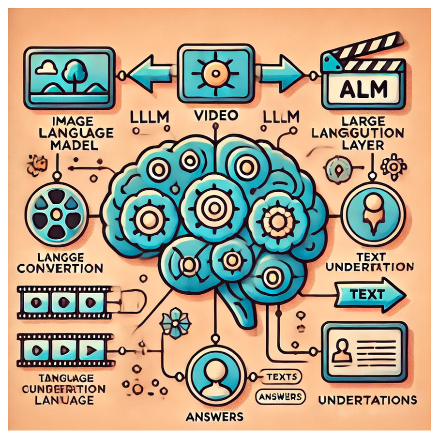
- understand information from multiple modalities, *e.g.*, text, images, audio, video
- representation learning methods
  - combine multiple representations or learn multimodal representations simultaneously
- applications
  - images from text prompt, videos with narration, musics with lyrics
- collaboration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

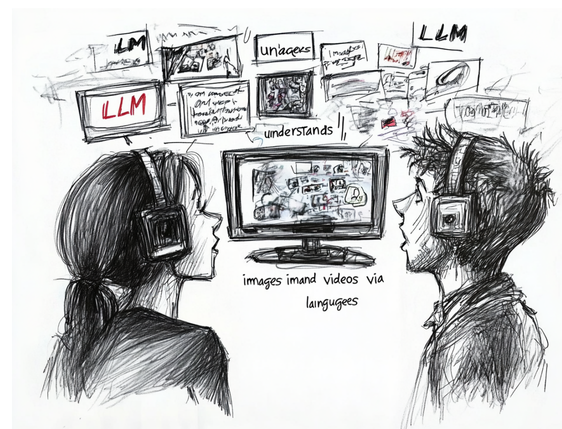




Implications of success of LLMs

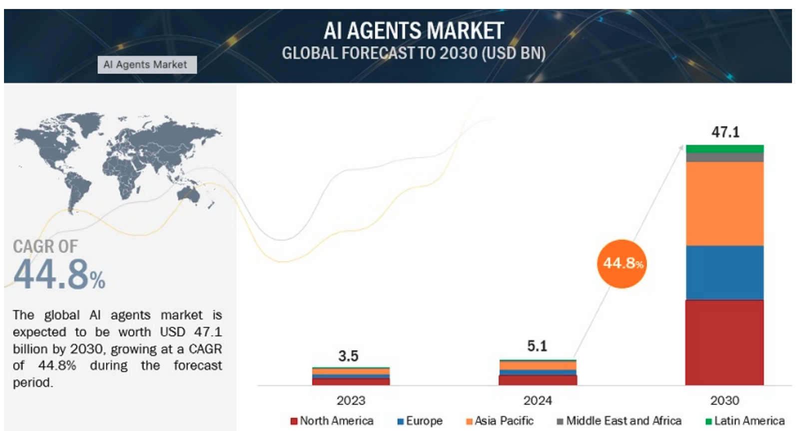
- many researchers change gears towards LLM
  – from computer vision (CV), speach, music, video, even reinforcement learning
- *LLM is not only about NLP . . .* humans have . . .
  - evolved to optimize natural language structures for eons
  - handed down knowledge using *this natural languages* for 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)*

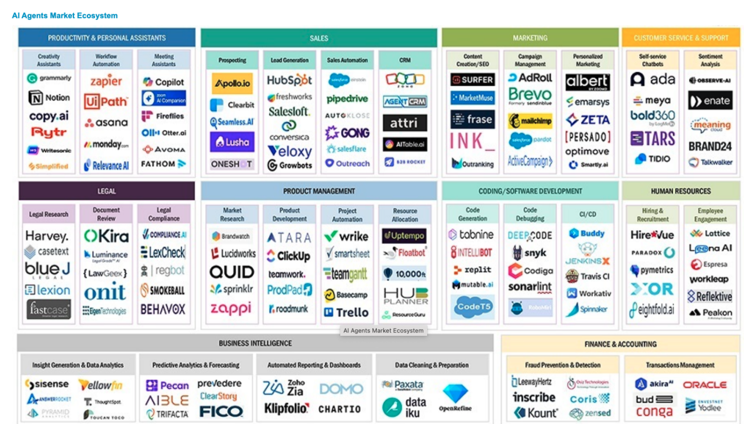




Multimodal AI (mmAI)

- 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



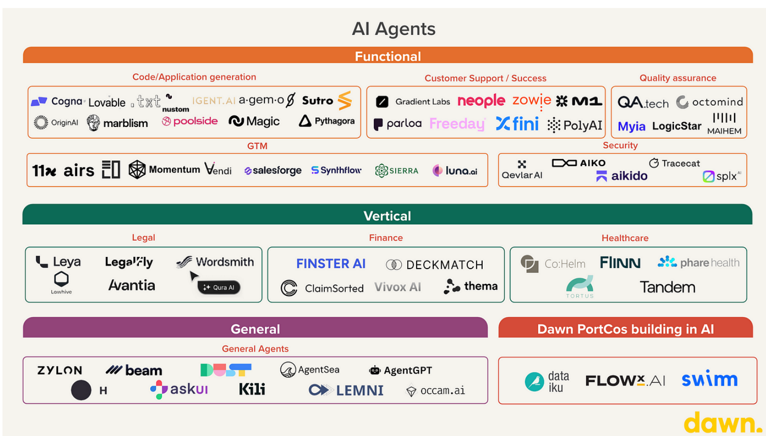


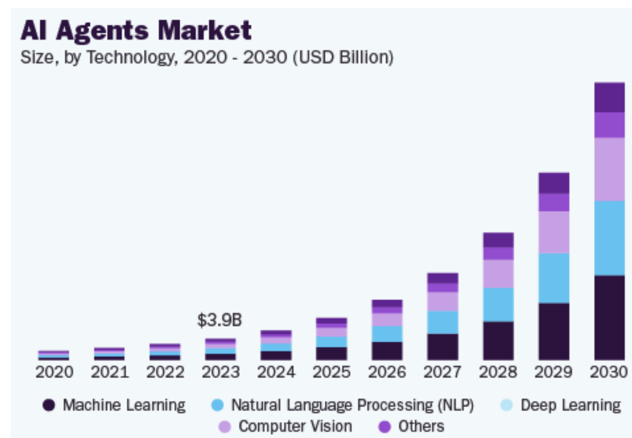
mmAI Technology

- 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

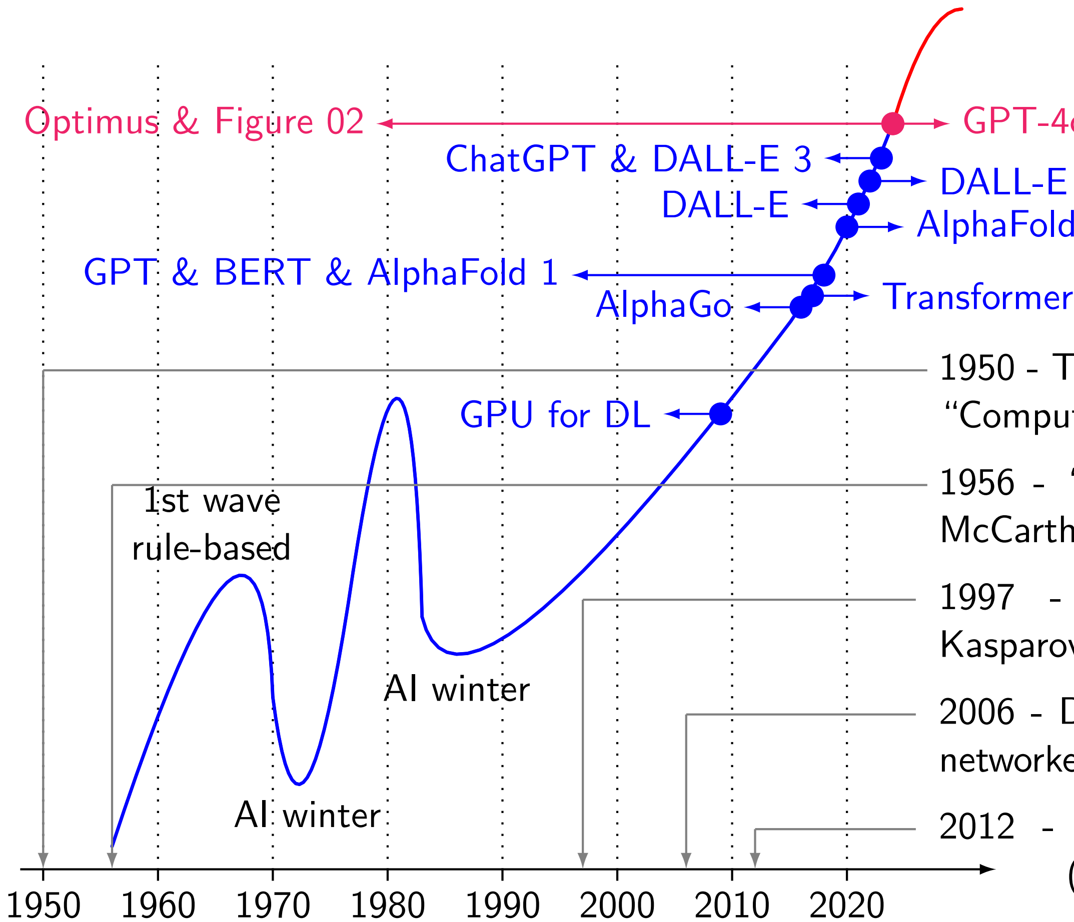
- emerging applications
  - scientific research - agents analyzing & running experiments & generating hypotheses
  - creative collaboration - AI partners in design & art combining multiple mediums
  - environmental monitoring - processing satellite sensor data for climate analysis
  - healthcare - enhanced 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



1950 - Turing Test introduced by Alan Turing in "Computing Machinery & Intelligence"

1956 - "Artificial Intelligence" coined by John McCarthy

1997 - IBM's Deep Blue defeated Garry Kasparov, (then) the world chess champion

2006 - DL Learning gained traction deep belief networked introduced by Geoffrey Hinton

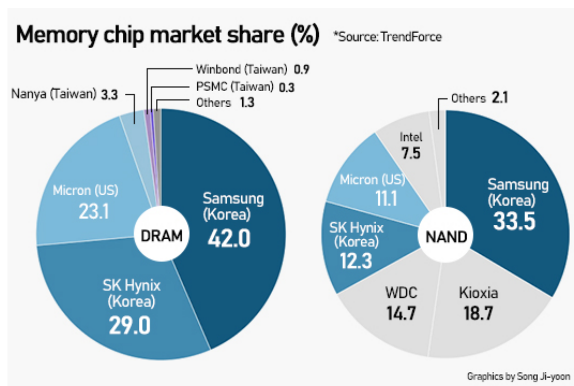
2012 - AlexNet won ImageNet Competition (ILSVRC) - widespread attention on DL

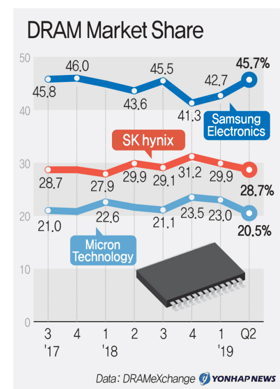
Innovation ecosystem of Silicon Valley

- 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

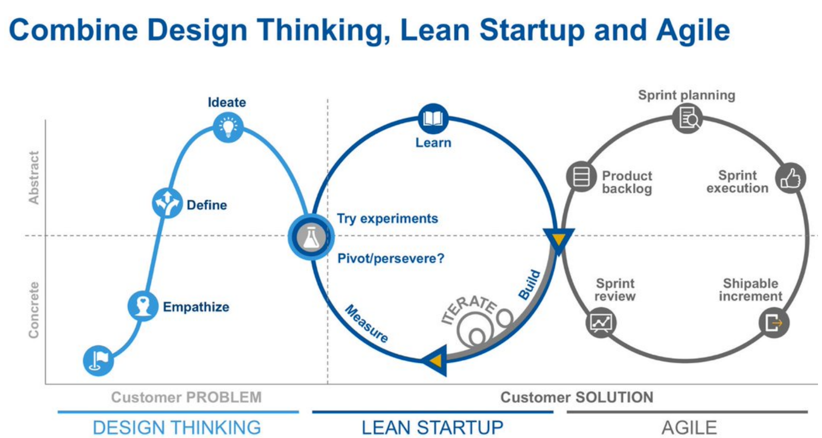
- Amazon's culture & leadership principles
  - customer obsession as driver of innovation
  - high standards & ownership culture, disagree & commit
  - bias for action and long-term thinking - sounds contradictory?
  - mechanisms like "two-pizza teams" & "Day One" for (or rather despite) scalability
- 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!*

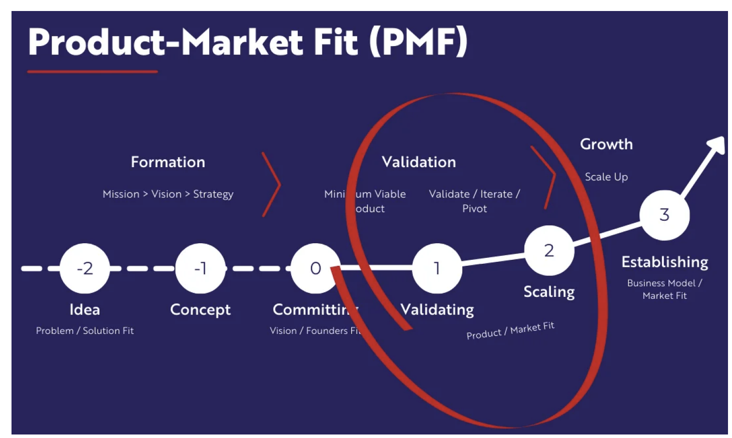




Founding and scaling startups

- 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





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

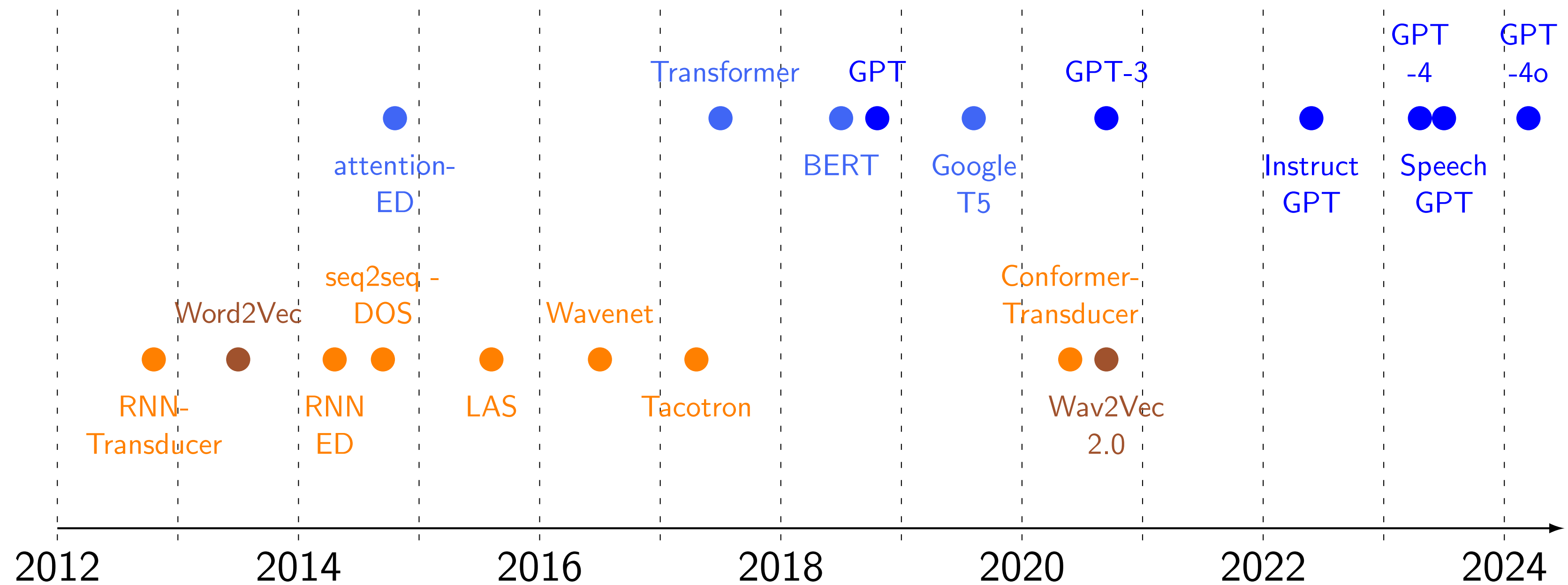
LLM

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-tranining *high performing model* and fine-tuning/transfer learning/domain adaptation
- this *high performing model* learning essential language representation *is* (lanauge) foundation model

– actually, same for other types of learning, $e.g.$, CV

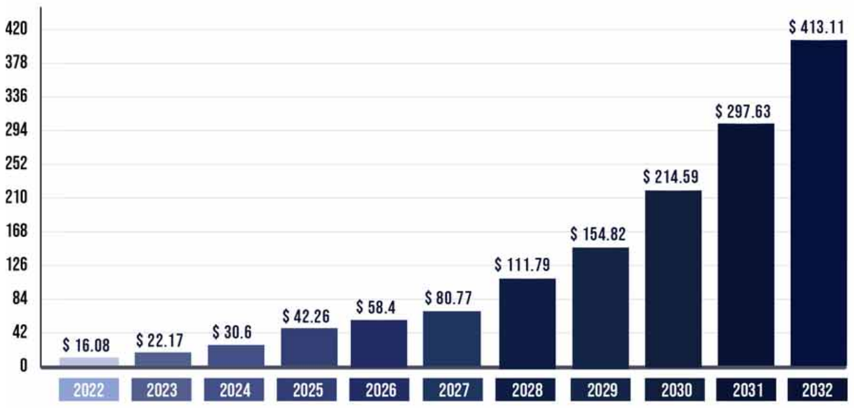
voice recognition	NL generation	summarization	spelling correction	action planning
voice synthesis	translation	topic model	topic model	
	Q&A	NLU		

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

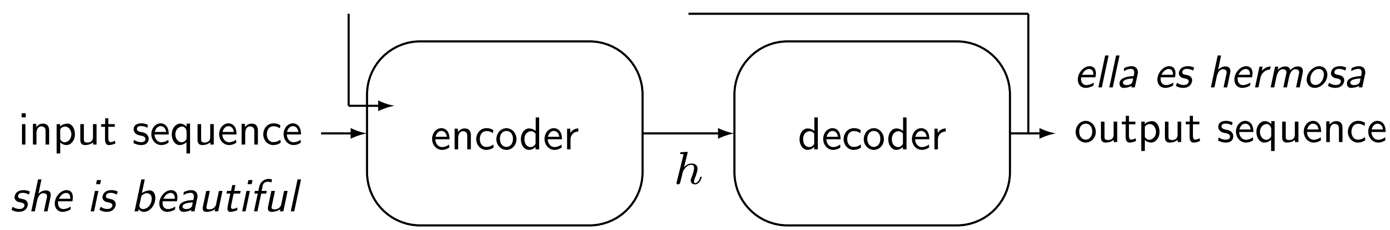
- source - Precedence Research



Sequence-to-Sequence Models

Sequence-to-sequence (seq2seq) model

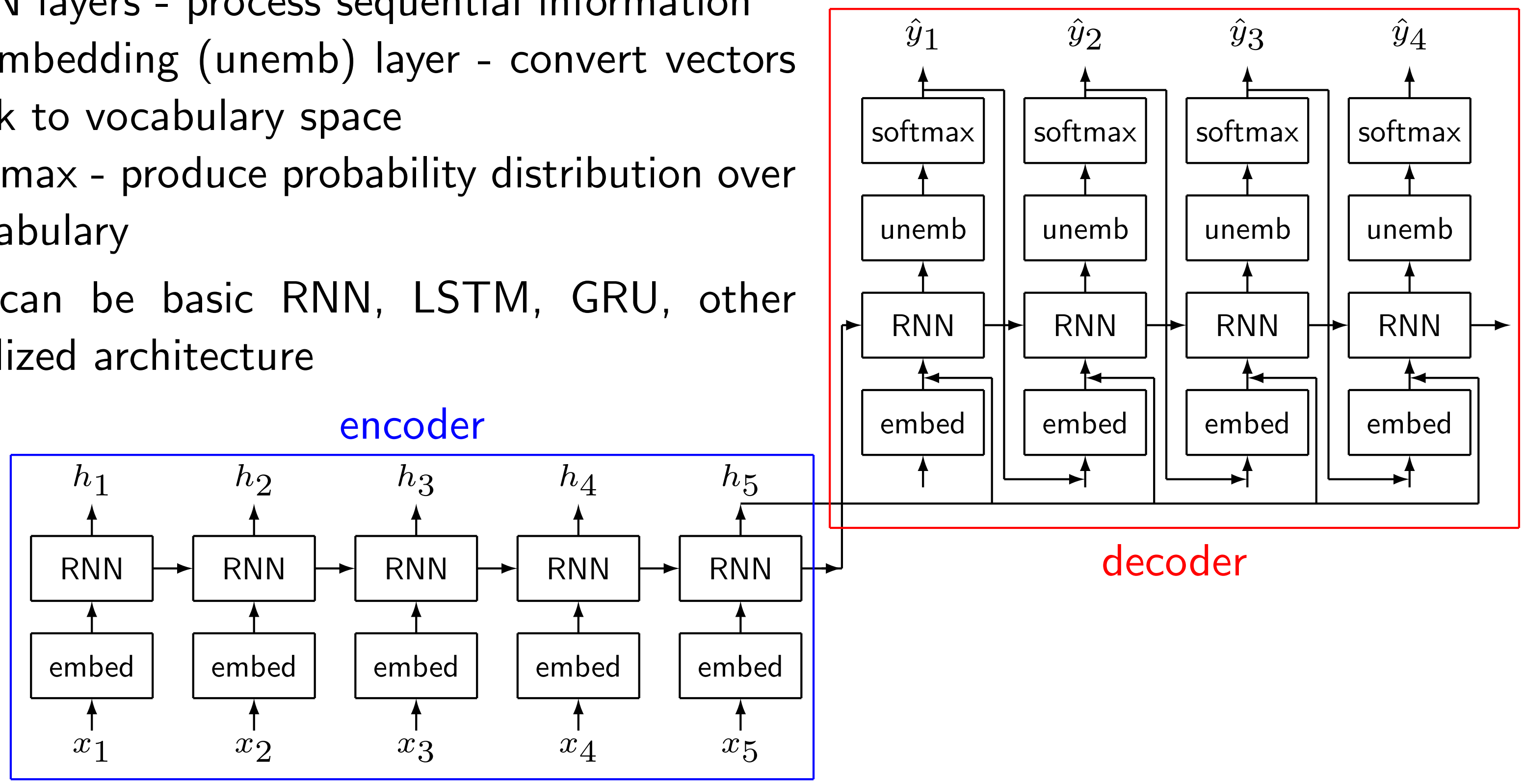
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



  - 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

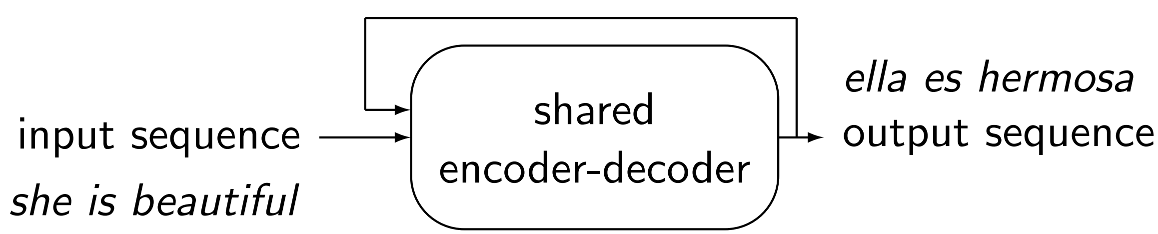
RNN-type encoder-decoder architecture

- 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

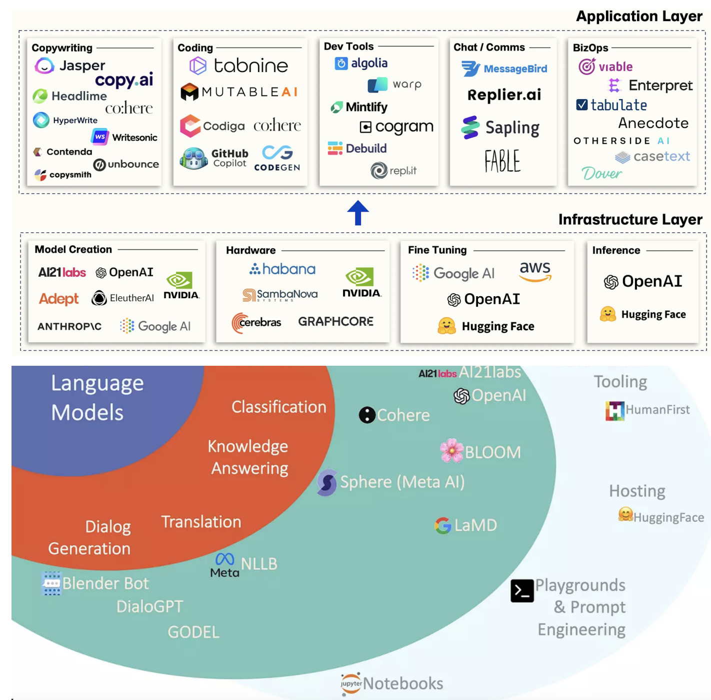
- LLM
  - type of AI aimed for NLP trained on massive corpus of texts & programming code
  - allow learn statistical relationships between words & phrases, $i.e.$, conditional probabilities
  - *amazing performance shocked everyone - unreasonable effectiveness of data (Halevry et al., 2009)*

- 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

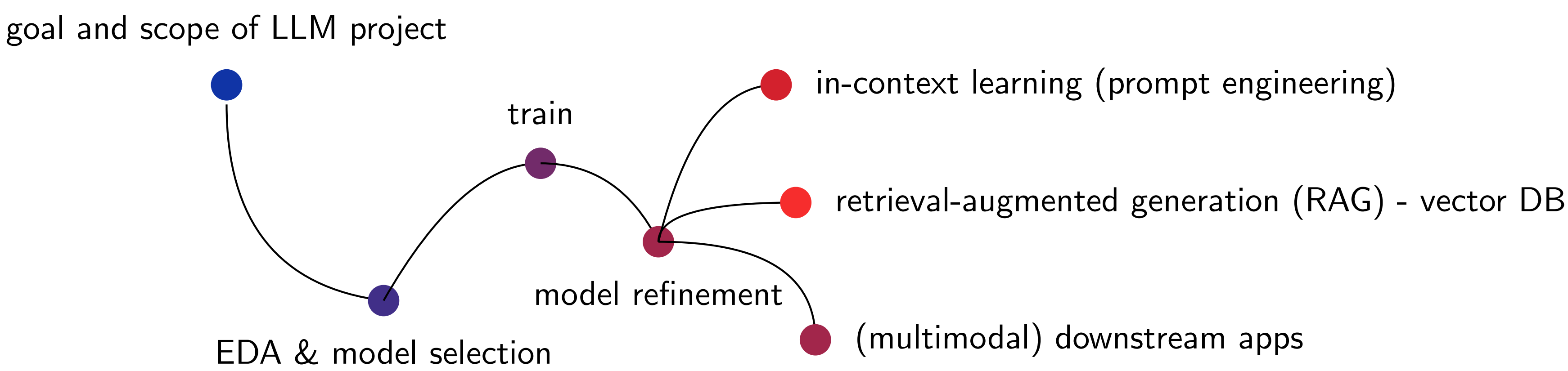
LLMs

- Foundation Models
  - GPT-x/Chat-GPT - OpenAI, Llama-x - Meta, PaLM-x (Bard) - Google
- # parameters
  - generative pre-trained transfomer (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



Transformer

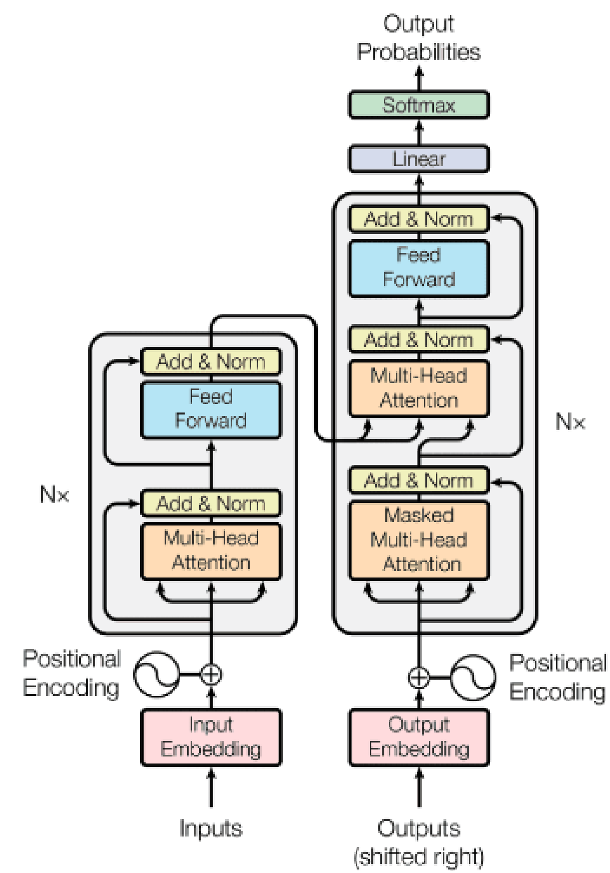
LLM architectural secret (or known) sauce

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 & mult-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)

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

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

Single-head - close look at equations

- focus on ith 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, $k_1, \ldots, k_m \in \mathbf{R}^{d_k}$ & $v_1, \ldots, v_m \in \mathbf{R}^{d_v}$

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

- then

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

$e.g.$, dependency between ith output token and jth 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 ith query, q_i in $\mathrm{Attention}(Q, K, V)$

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

Multi-head attention

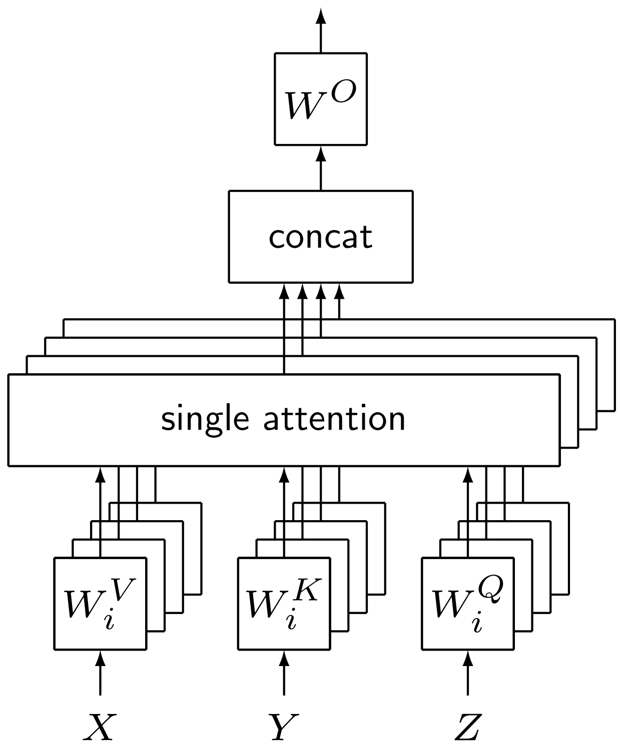
- evaluate h single-head attentions (in parallel)
- d_e: dimension for embeddings
- embeddings

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

  e.g., n: input sequence length & m: output sequence length in machine translation
- h key/query/value weight matrices: $W_i^K, W_i^Q \in \mathbf{R}^{d_k \times d_e}$, $W_i^V \in \mathbf{R}^{d_v \times d_e}$ $(i = 1, \ldots, h)$
- linear output layers: $W^O \in \mathbf{R}^{d_e \times h d_v}$
- *multi-head attention!*

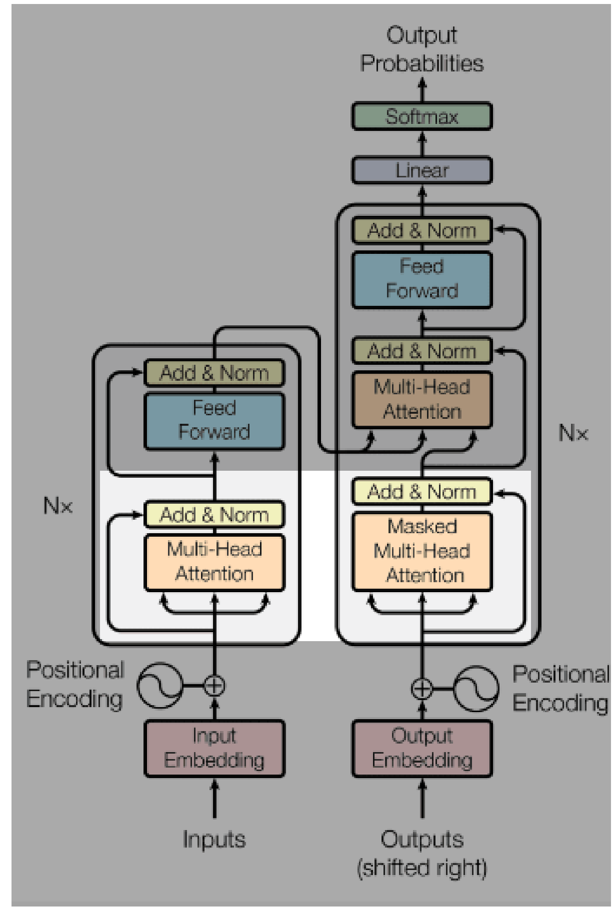
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbf{R}^{d_e \times n},$$

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



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

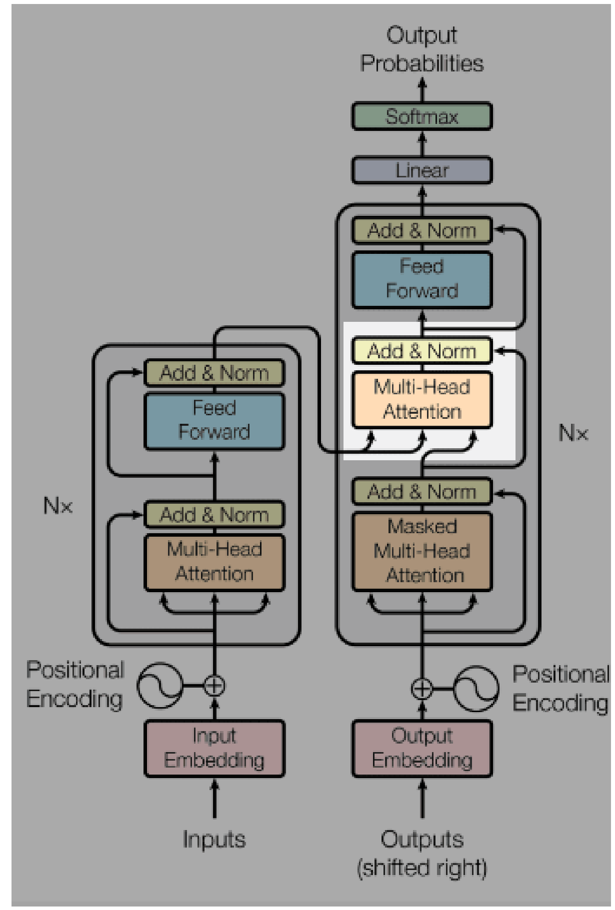
- m: length of input sequence

- 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

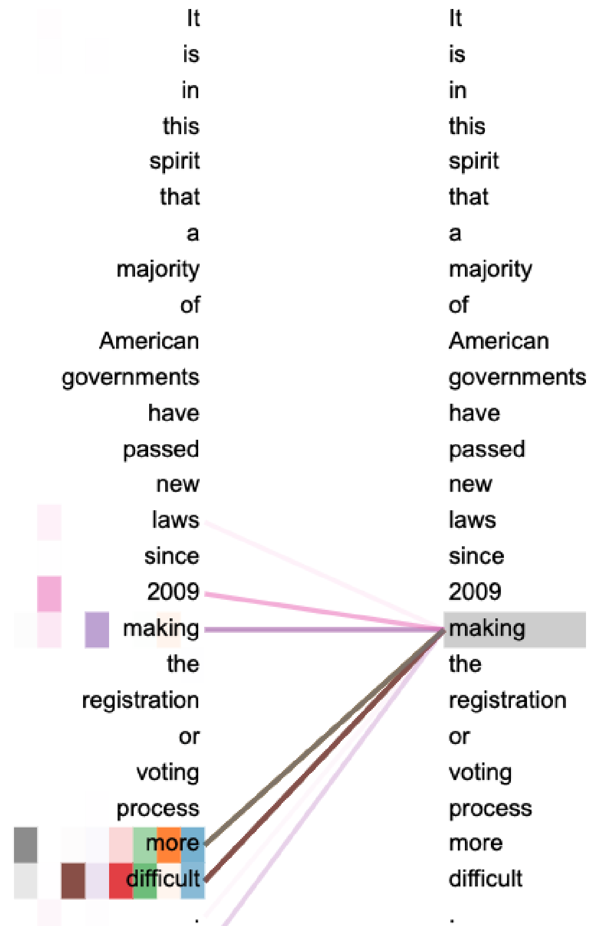


Visualization of self attentions

example sentence

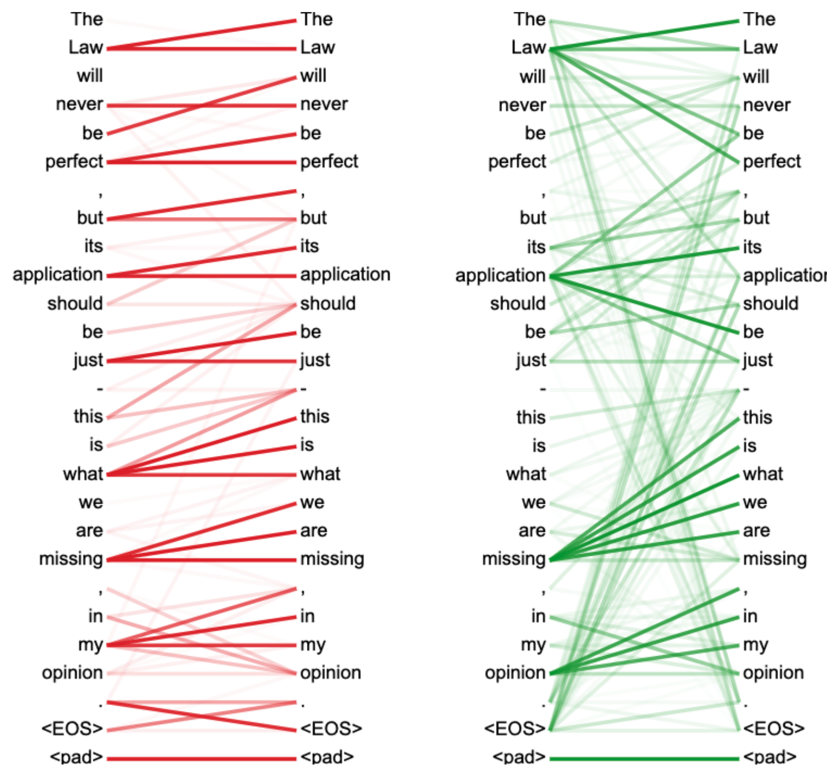
"It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult."

- 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"

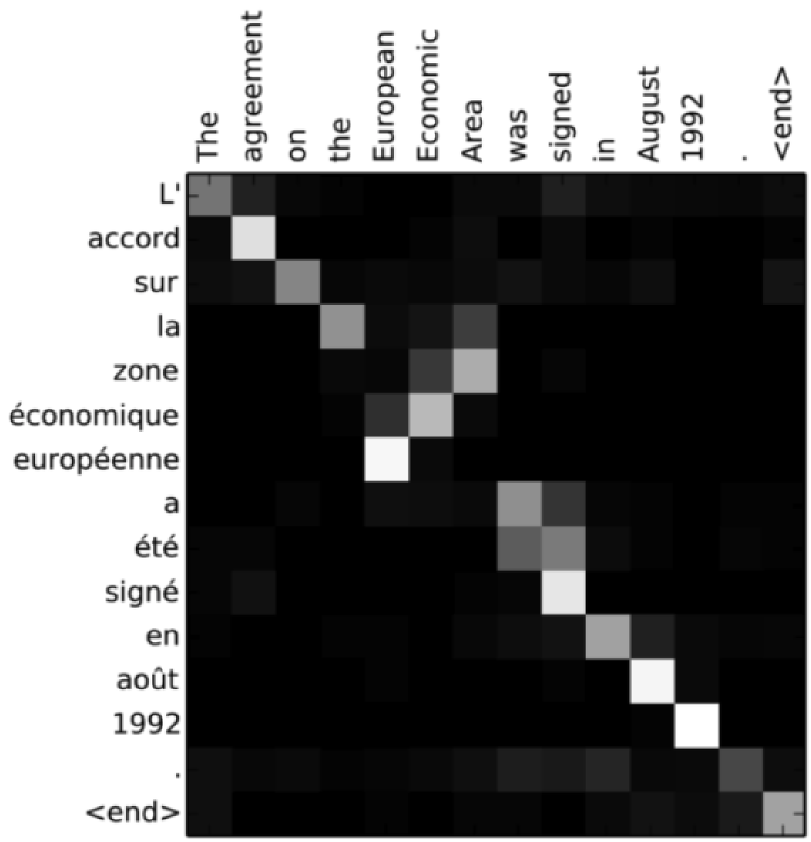


Visualization of multi-head self attentions

- self attentions of encoder for two heads (of a layer)
  - different heads represent different structures
    $\rightarrow$ advantages of multiple heads
  - multiple heads work together to colletively 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 $\rightarrow$ 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 $\leftrightarrow$ européenne
  - Economic $\leftrightarrow$ européconomique
  - Area $\leftrightarrow$ zone

Model complexity

- computational complexity
  - n: sequence length, d: embedding dimension
  - complexity per layer - self-attention: $\mathcal{O}(n^2 d)$, 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*

  $\longrightarrow$ *makes NVidia more competitive, hence profitable!*

  $\longrightarrow$ *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

input	[cls]	my	dog	is	cute	[sep]	she	likes	playing	[sep]
token embeddings	$E_{\text{[cls]}}$	E_{my}	E_{dog}	E_{is}	E_{cute}	$E_{\text{[sep]}}$	E_{she}	E_{likes}	E_{playing}	$E_{\text{[sep]}}$
	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$
segment embeddings	E_A	E_A	E_A	E_A	E_A	E_A	E_B	E_B	E_B	E_B
	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$
poistional embeddings	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9

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 iceburg" found & releaved

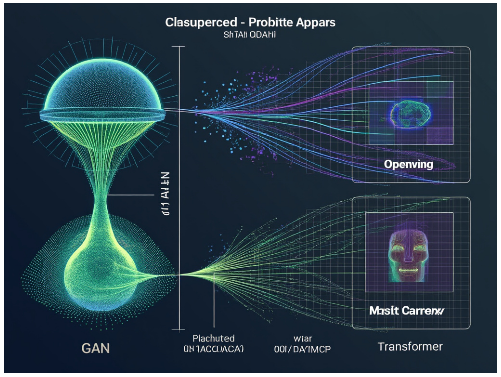
genAI

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

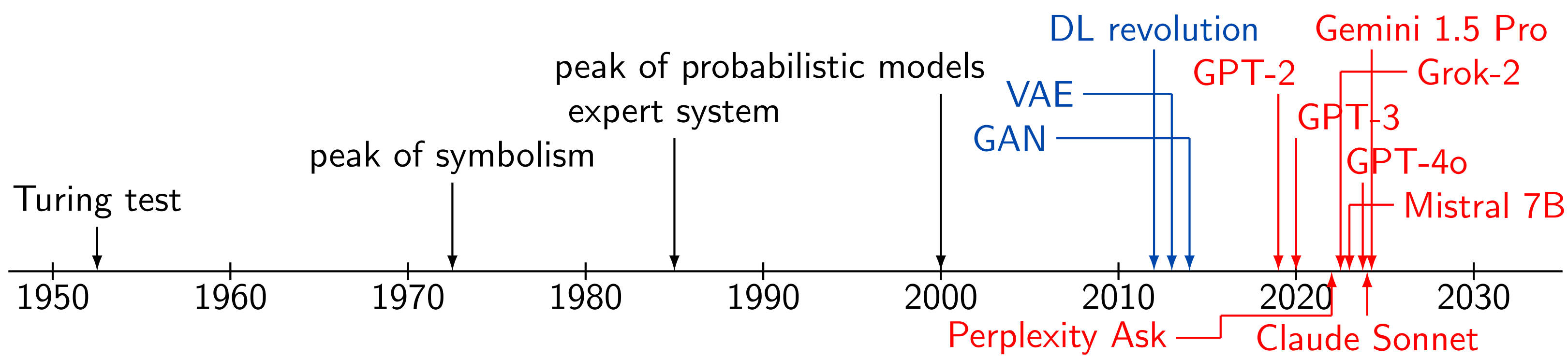
Examples of genAI in action

- 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

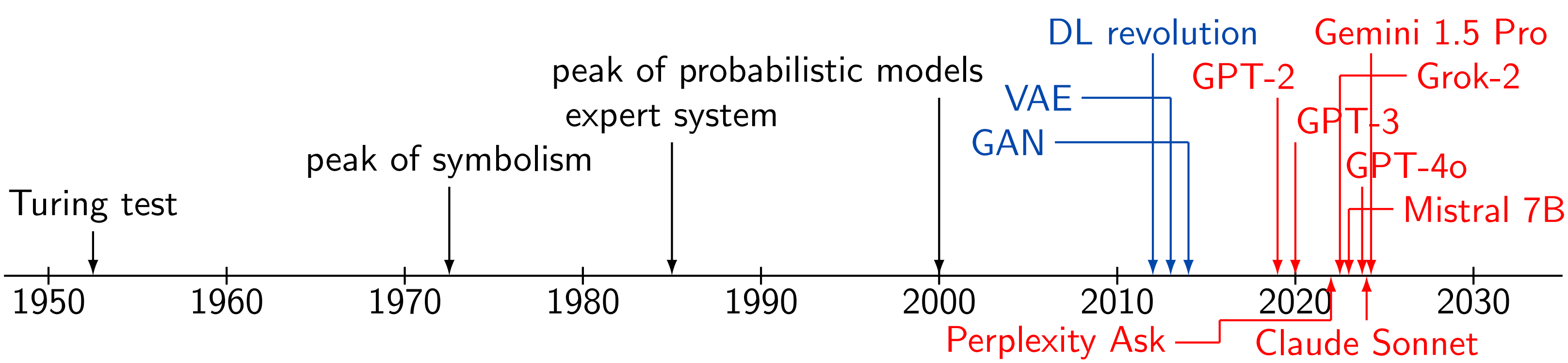
Birth of AI - early foundations & precursor technologies

- 1950s $\sim$ 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 $\sim$)



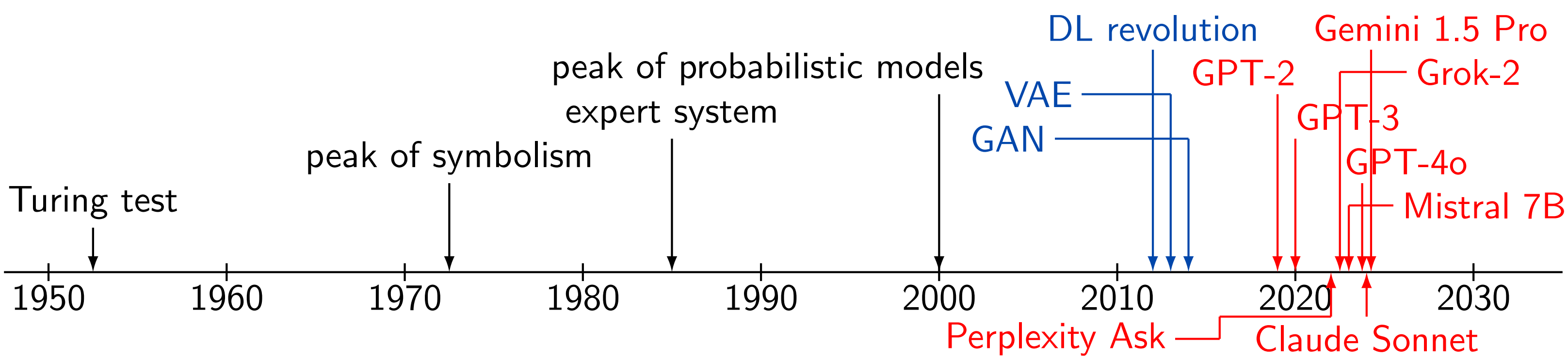
Rule-based systems & probabilistic models

- 1980s $\sim$ 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



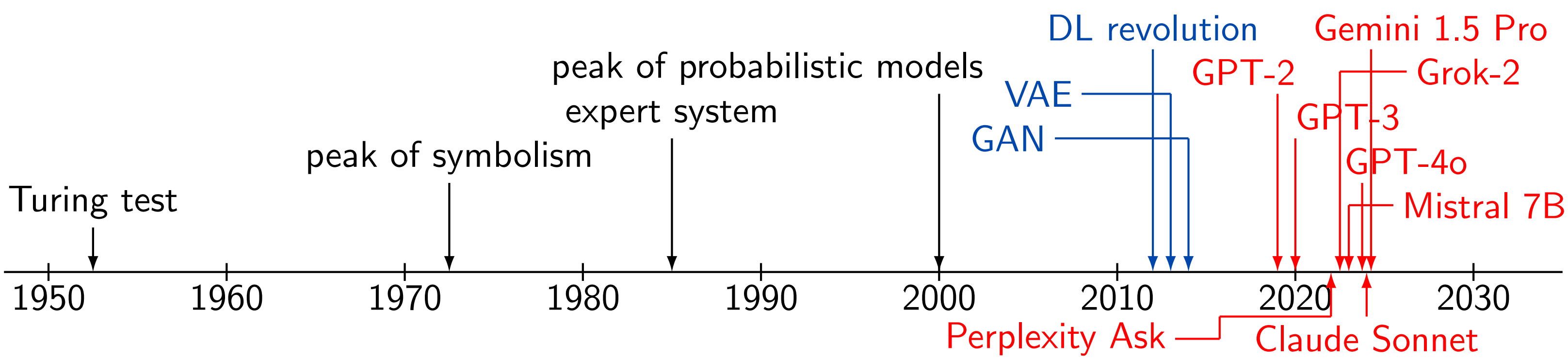
Rise of deep learning & generative models

- 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 $\sim$ 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

$$\boxed{\mathcal{Z}} \xrightarrow{g_\theta(z)} \boxed{\mathcal{X}}$$

- *generate samples in original space, $\mathcal{X}$, from samples in latent space, $\mathcal{Z}$*
- g_θ is parameterized model $e.g.$, CNN / RNN / Transformer / diffuction-based model
- training
  - finding θ that minimizes/maximizes some (statistical) loss/merit function so that $\{g_\theta(z)\}_{z\in\mathcal{Z}}$ generates plausiable 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]

$$\boxed{\mathcal{X}} \xrightarrow{q_\phi(z|x)} \boxed{\mathcal{Z}\text{o}} \xrightarrow{p_\theta(x|z)} \boxed{\mathcal{X}}$$

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

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

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

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

- generative model

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

GAN - early genAI model

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

$$\begin{tikzcd} & & p(x) \arrow[dr, "x_{\mathrm{data}}"] & & \\ q(z) \arrow[r, "z"] & \boxed{g(\theta_G; z)} \arrow[rr, "x_{\mathrm{model}}"] & & \boxed{f(\theta_D; x)} \arrow[r] & \text{true / false} \end{tikzcd}$$

  – value function

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

  – 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*

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

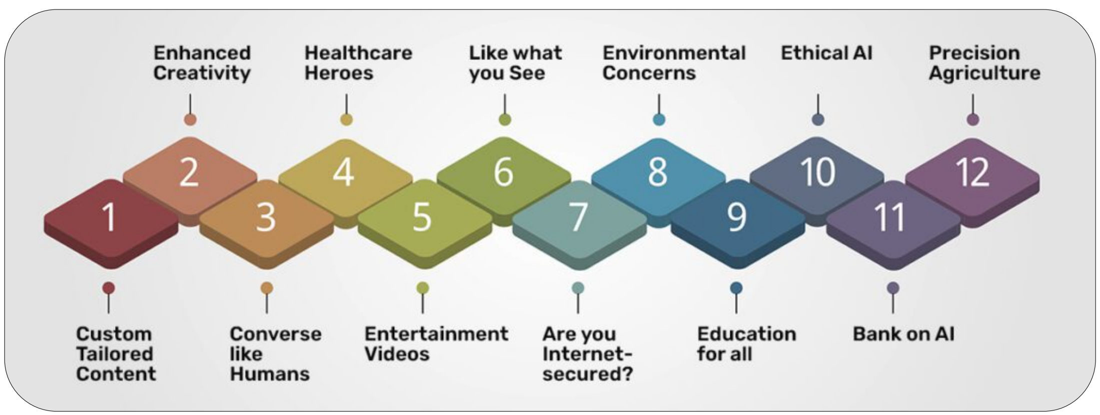
  where $d(\cdot,\cdot)$ distance measure between probability distributions
  - previous sequence: $x_{t-1}, x_{t-2}, \ldots$
  - next token: x_t
- p_θ represented by (extremely) complicated model
  - $e.g.$, containing multi-head & multi-layer Transformer architecture inside
- model parameters, $e.g.$, for Llama2

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

Current Trend & Future Perspectives

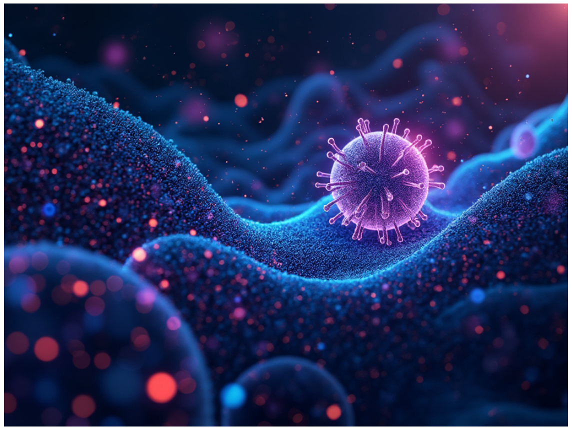
Current trend of genAI

- 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



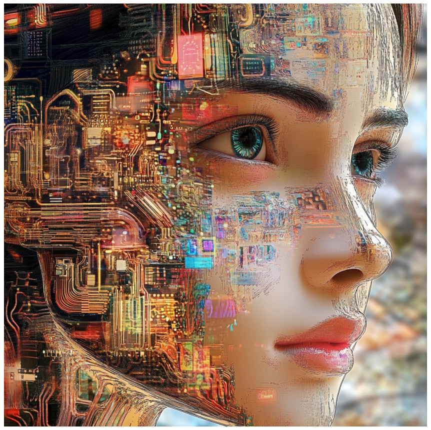
Industry & business impacts

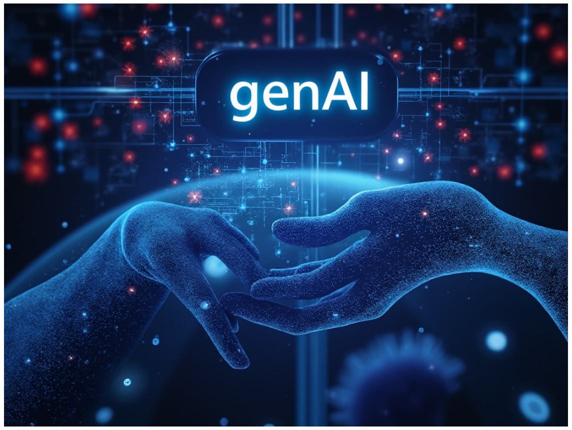
- how genAI is transforming industries
  - creative industries - content creation - advertising, gaming, film
  - life science - enhance research, drug discovery & personalized treatments
  - finance - automating document generation, risk modeling & fraud detection
  - manufacturing & Design - rapid 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

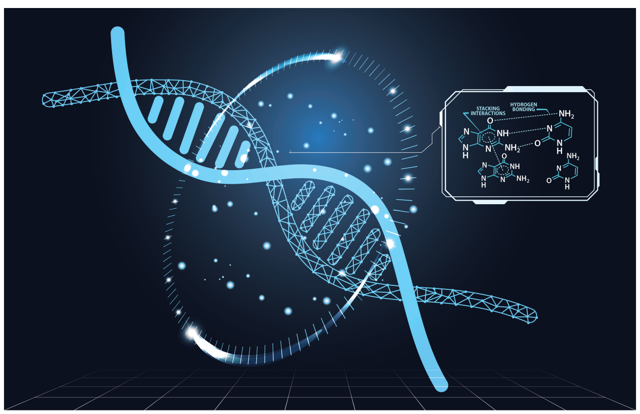


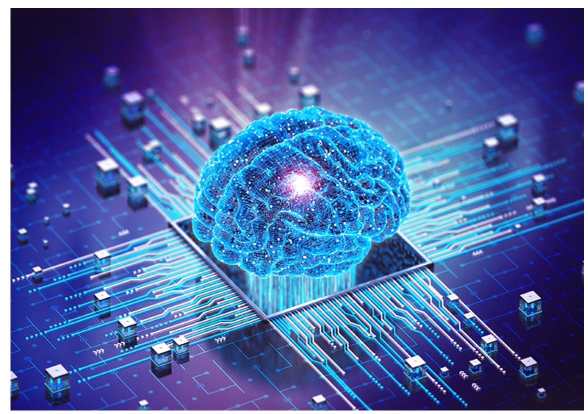


AI & Biotech

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





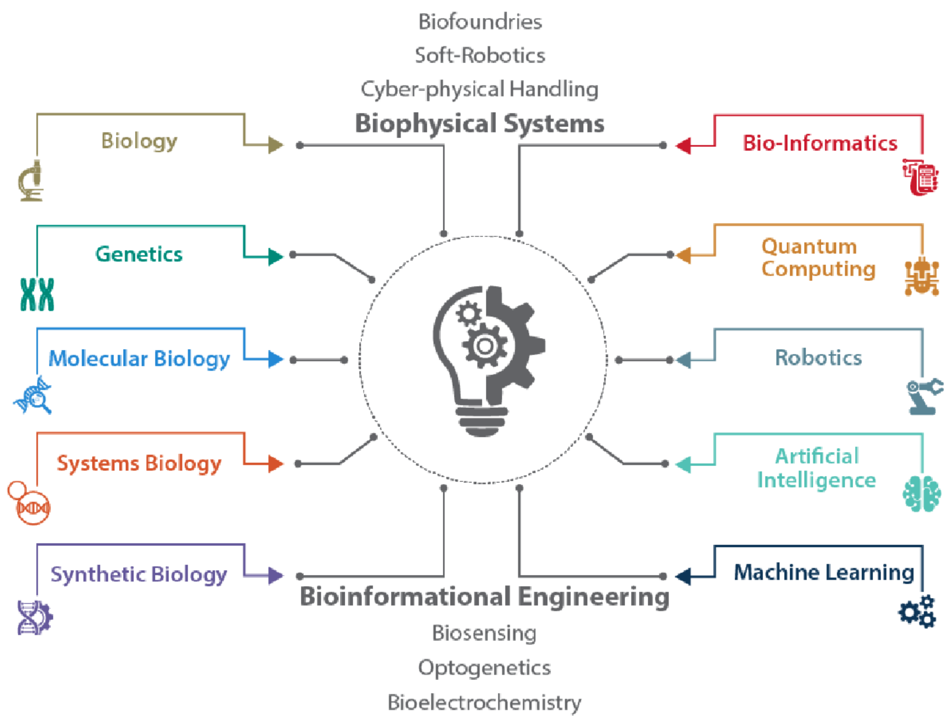
Biotech

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]

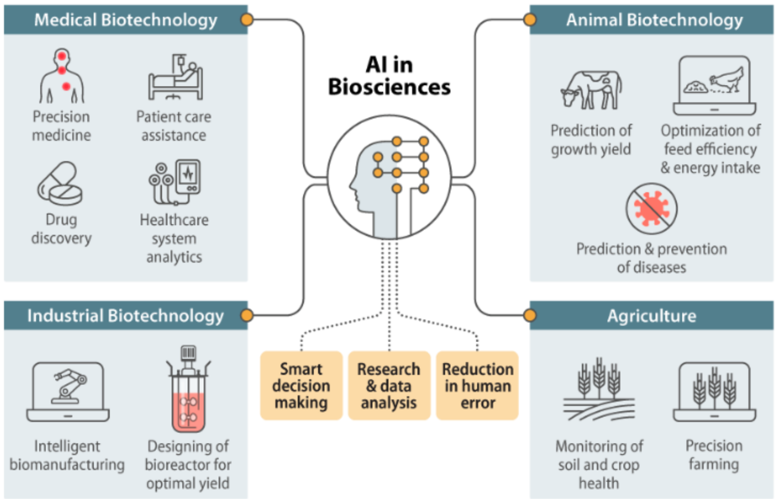


Convergence of AI and biological design

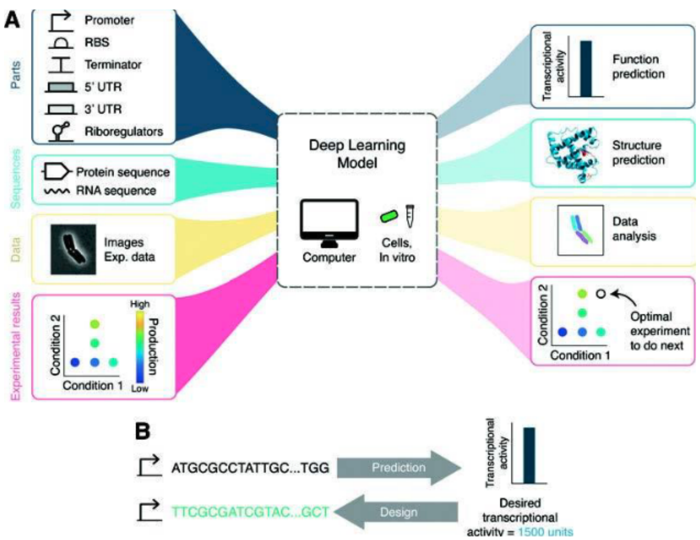
- AI & biological sciences converging [BKP22]
  - each building upon the other's capabilities for new research and development across multiple areas
- Demis Hassabis, CEO & cofounder of DeepMind, said of biology [Toe23]

  > ". . . 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



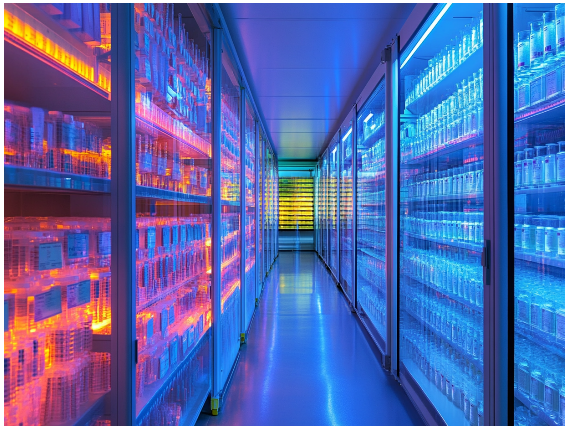
- AI, essential to analyzing exponential growth of genetic sequence data

  "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



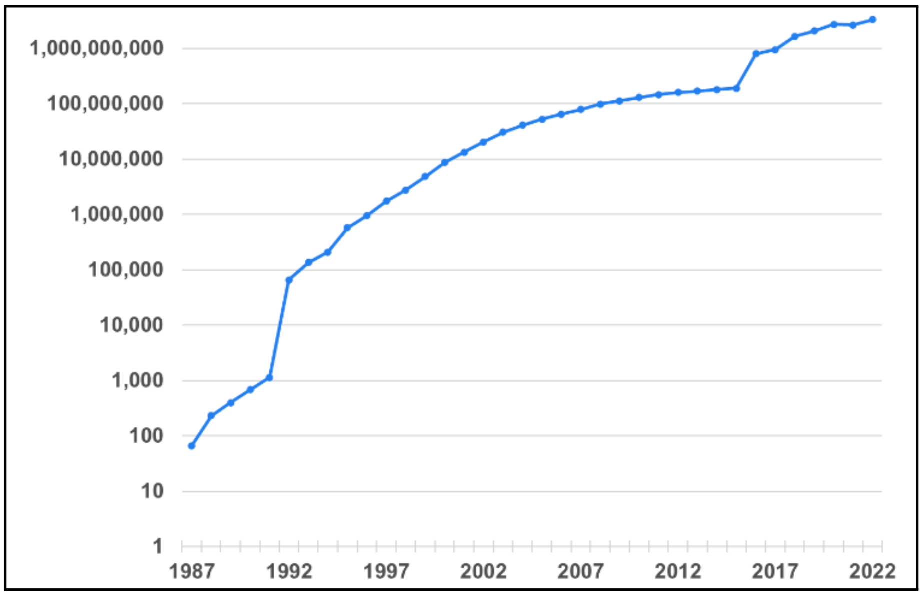
Rapid growth of biological data

- 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

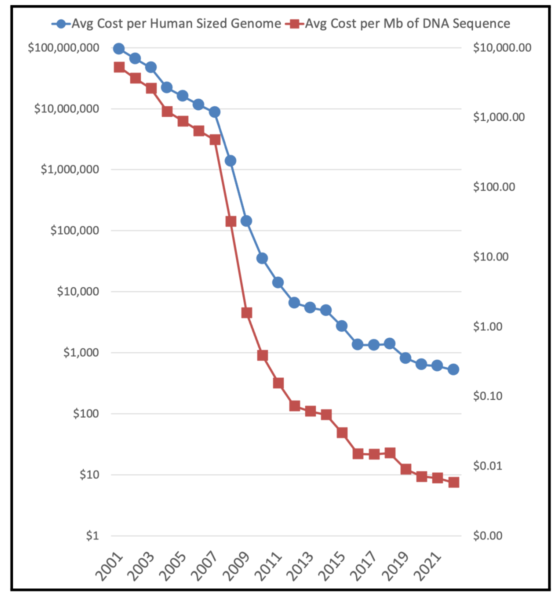
Volume and sequencing cost of DNA over time

- 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



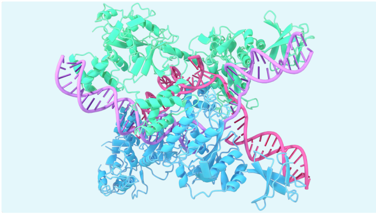
Bio data availability and bias

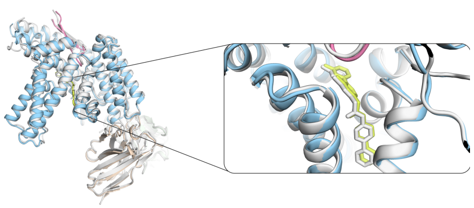
- US National Security Commission on Artificial Intelligence (NSCAI) recommends
  - US fund and prioritize development of a biobank containing *"wide range of high-quality biological and genetic data sets securely accessible by researchers"*
  - establishment of database of broad range of human, animal, 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

- Go board marked with 19×19 grid - $(19 \times 19)! = 361! \approx 1.44 \times 10^{768}$
  1437923258884890654832362511499863354754907538644755876127282765299227795534389618856841908003141196
  0714137944348905859683839682333043216077138088370565578796691924861827097800358990211005794501073330
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  5623101563752892899924857388316647687165212001536218913733713768261861456295440900774337589490771443
  9917299937133680728459000034496420337066440853337001284286412654394495050773954560000000000000000000
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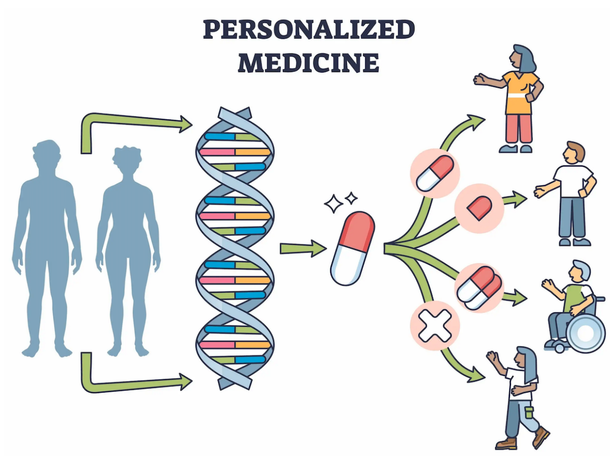
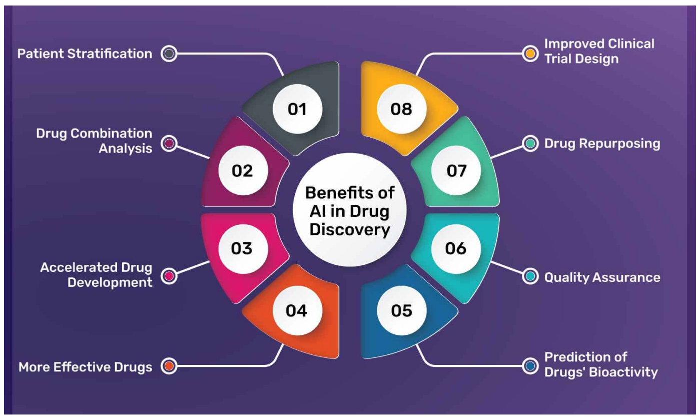
- deep reinforcement learning with Monte Carlo tree search
  - trained on thousands of years of Go game history
  - AlphaGo Zero learns by playing against itself
- development experience, insight, knowledge, know-how transferred to AlphaFold

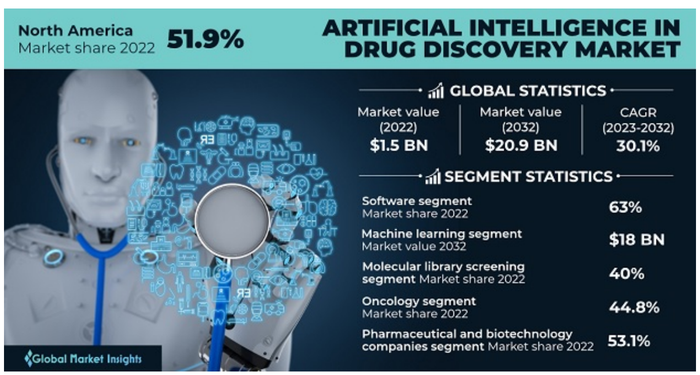
Personalized medicine

- *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

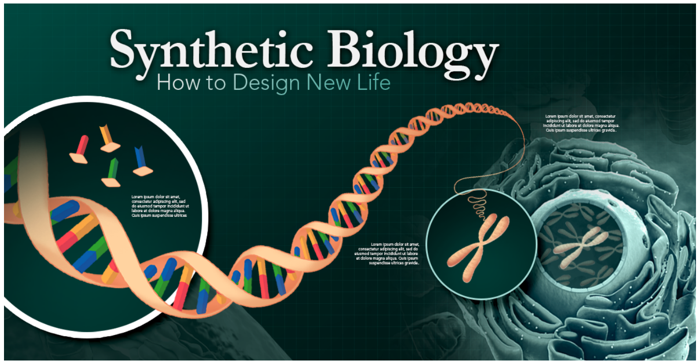


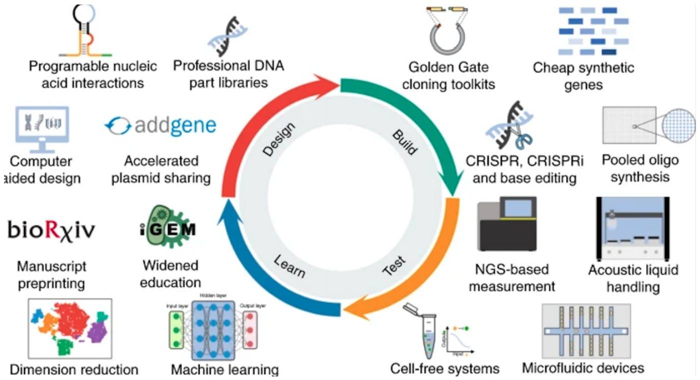


- traditional drug discovery process - time-consuming and costly often taking decades and billions of dollars
- AI streamlines this process by predicting the efficacy and safety of potential compounds with more speed and accuracy
- AI models analyze chemical databases to identify new drug candidates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

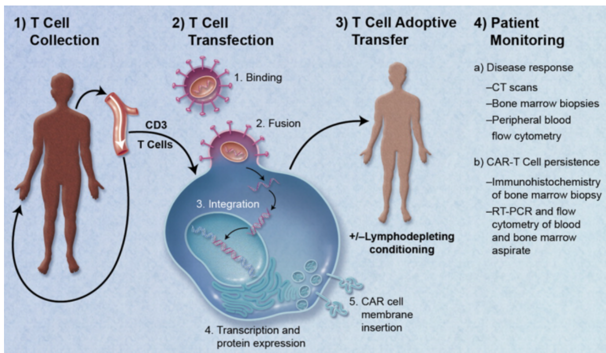
Synthetic biology

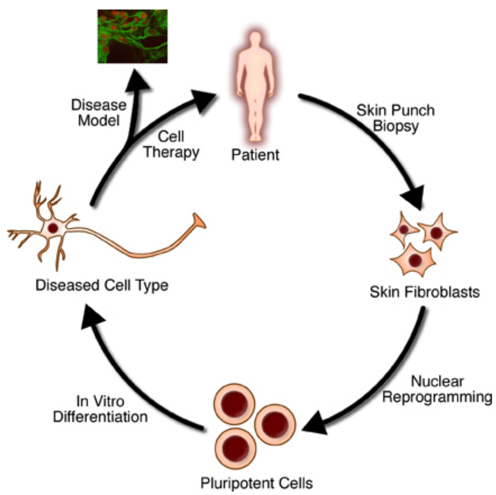
- use AI for gene editing, biomaterial production and synthetic pathways
- combine principles of biology and engineering to design and construct new biological entities
- AI optimizes synthetic biology processes from designing genetic circuits to scaling up production
- company - Ginkgo Bioworks uses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





Regenerative medicine

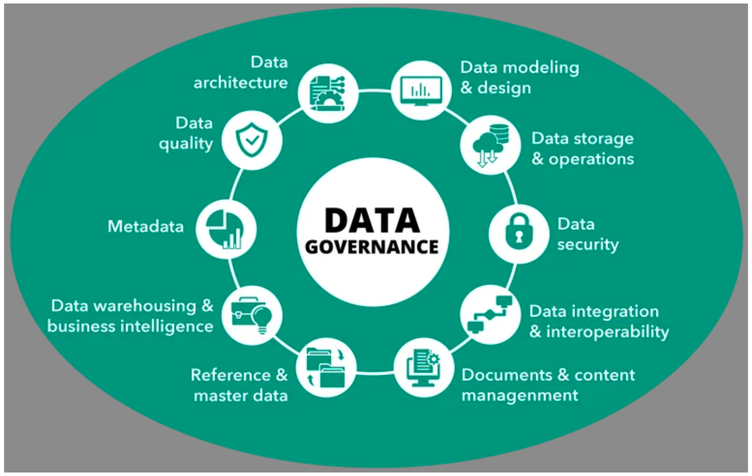




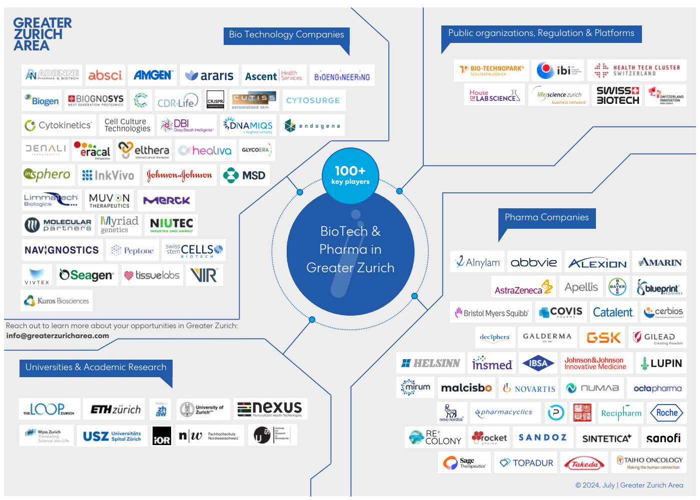
- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo 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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- CEOs, CTOs, CFOs, COOs, CMOs & CCOs @ startup companies in Silicon Valley
- VCs on Sand Hill Road - Palo Alto, Menlo Park, Woodside in California, USA

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Thank You