[CryptoLab Lyon Research Center AI Seminar]
AI - Technology, Research & Products

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About Speaker

- *Co-founder / CTO - AI Technology & Product Strategy @ Erudio Bio, CA, USA*
- Advisory Professor, Electrical Engineering and Computer Science @ DGIST
- Adjunct Professor, Electronic Engineering Department @ Sogang University
- Technology Consultant @ Gerson Lehrman Gruop (GLG)
- *KFAS-Salzburg Global Leadership Initiative Fellow @ Salzburg Global Seminar*
- *Co-founder / CTO & Chief Applied Scientist @ Gauss Labs, CA, USA – 2023*
- Senior Applied Scientist @ Mobile Shopping App Org, Amazon.com, Inc. – 2020
- Principal Engineer @ Software R&D Center of DS Division, Samsung – 2017
- Principal Engineer @ Strategic Marketing & Sales Team, Samsung – 2016
- Principal Engineer @ DT Team of DRAM Development Lab, Samsung – 2015
- Senior Engineer @ CAE Team - Samsung – 2012
- M.S. & Ph.D. - Electrical Engineering @ Stanford University – 2004
- B.S. - Electrical Engineering @ Seoul National University – 1998

Highlight of career journey

- B.S. in EE @ SNU, M.S. & Ph.D. in EE @ Stanford Univ.
  - *Convex Optimization - theory / algorithms / applications* - supervision of *Prof. Stephen P. Boyd*
- Principal Engineer @ Memory Design Technology Team
  - AI & optimization partnering with *DRAM/NAND Design/Process/Test teams*
- Senior Applied Scientist @ Amazon
  - *S-Team Goal (Bezos's) project* - improve customer engagement via Amazon Mobile Shopping App using AI - *increased sales by USD 200M*
- Co-founder / CTO & Chief Applied Scientist @ Gauss Labs
  - *R&D industrial AI products & technology, market/product/investment strategies*
- Co-founder / CTO - AI Technology & Product Strategy @ Erudio Bio
  - *biotech - AI technology & product strategy*

Today

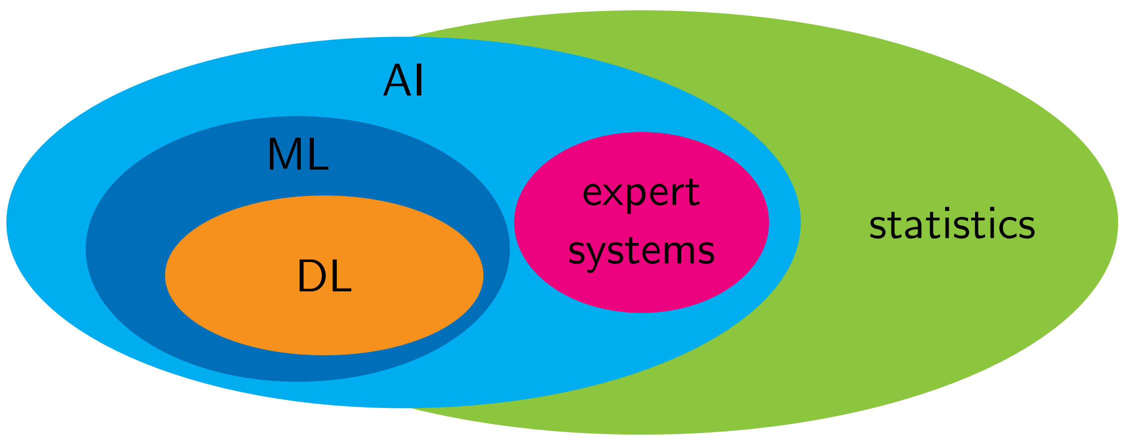
- AI - history and recent progress
- AI research and development trend
- AI products
- Serendipities around AI
- Appendices
  - AI hardware
  - AI & biotech
  - LLM
  - genAI

Artificial Intelligence

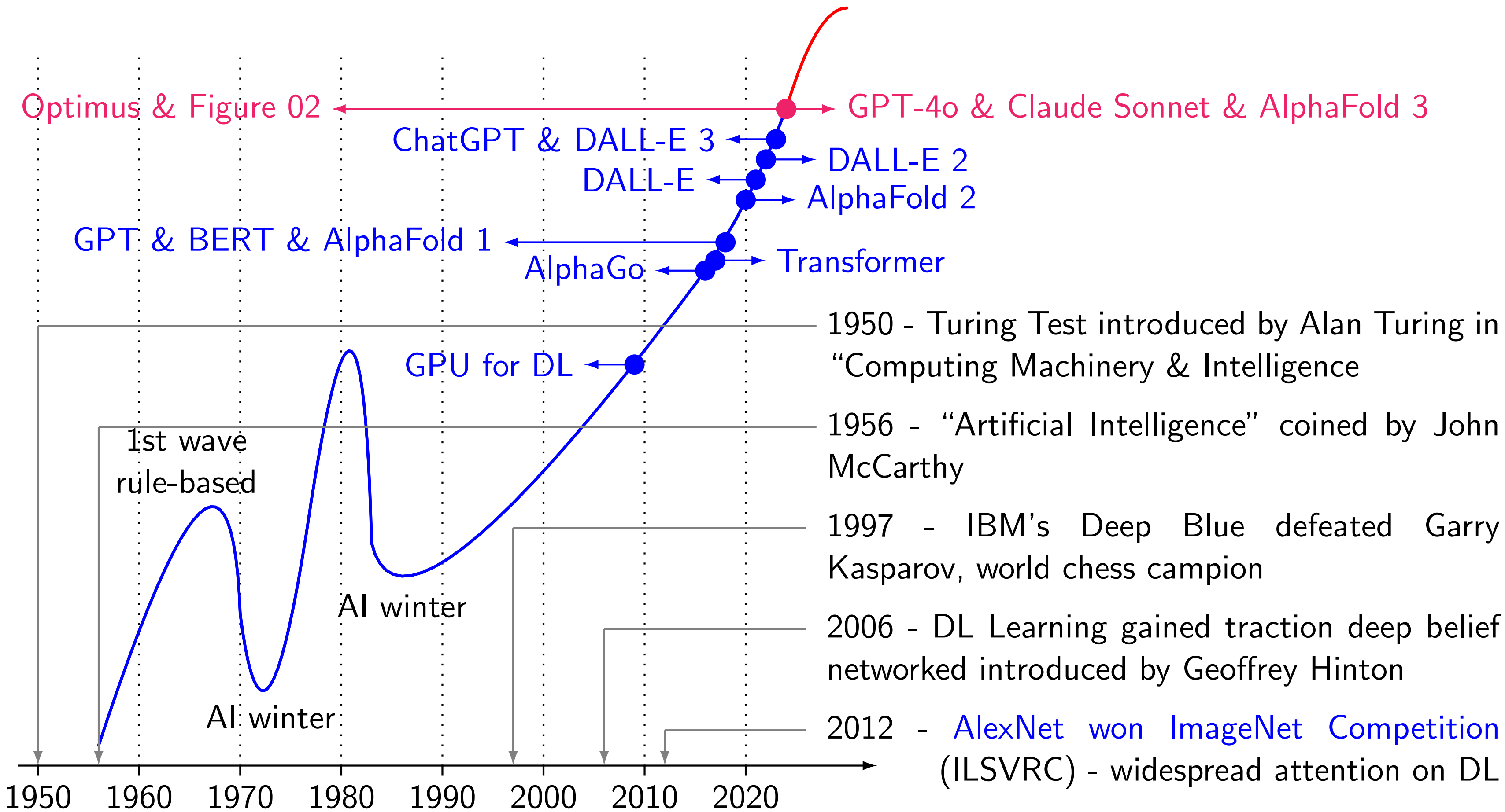
Definition and History

Definition of AI

- AI is
  - technology enabling machines to do tasks requiring human intelligence, such as learning, problem-solving, decision-making & language understanding
  - *not* one thing - encompass range of technologies, methodologies & applications
- relationship of AI, statistics, ML, DL, NN & expert system [HGH+22]



History of AI



Significant AI Achievements - 2014 – 2024

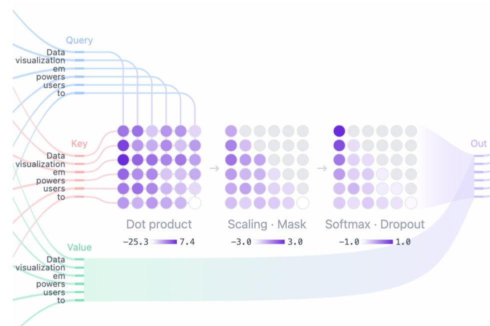
Deep learning revolution

- 2012 – 2015 - DL revolution[1]
  - 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

[1] DL: deep learning, CNN: convolutional neural network, CV: computer vision, RL: reinforcement learning

Transformer changes everything

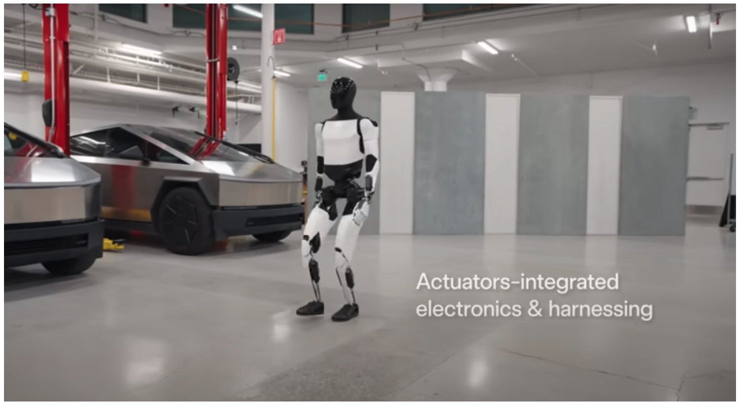
- 2017 – 2018 - Transformers & NLP breakthroughs[2]
  - *Transformer ($e.g.$, BERT & GPT) revolutionized NLP*
  - major advancements in, $e.g.$, machine translation & chatbots
- 2020 - AI in healthcare – AlphaFold & beyond
  - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting 3D protein structures with remarkable accuracy
  - accelerates drug discovery and personalized medicine - offering new insights into diseases and potential treatments



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

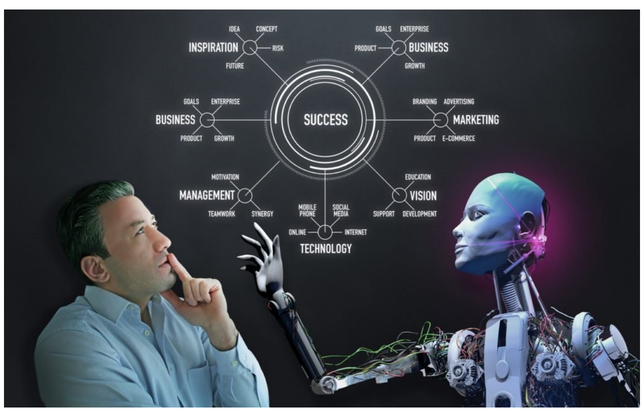
Lots of breakthroughs within 6 months in 2024

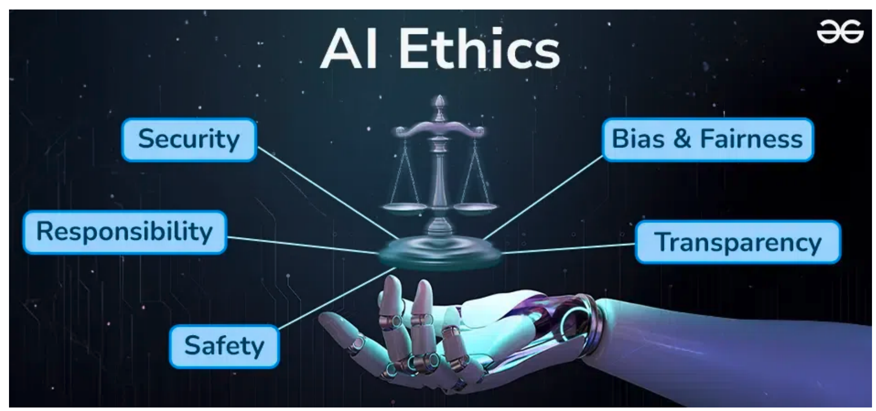
- proliferation of advanced AI models
  - GPT-4o, Claude Sonnet, Llama 3, Sora
  - *transforming industries* such as content creation, customer service, education, *etc.*
- breakthroughs in specialized AI applications
  - Figure 02, Optimus, AlphaFold 3
  - driving unprecedented advancements in automation,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



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*

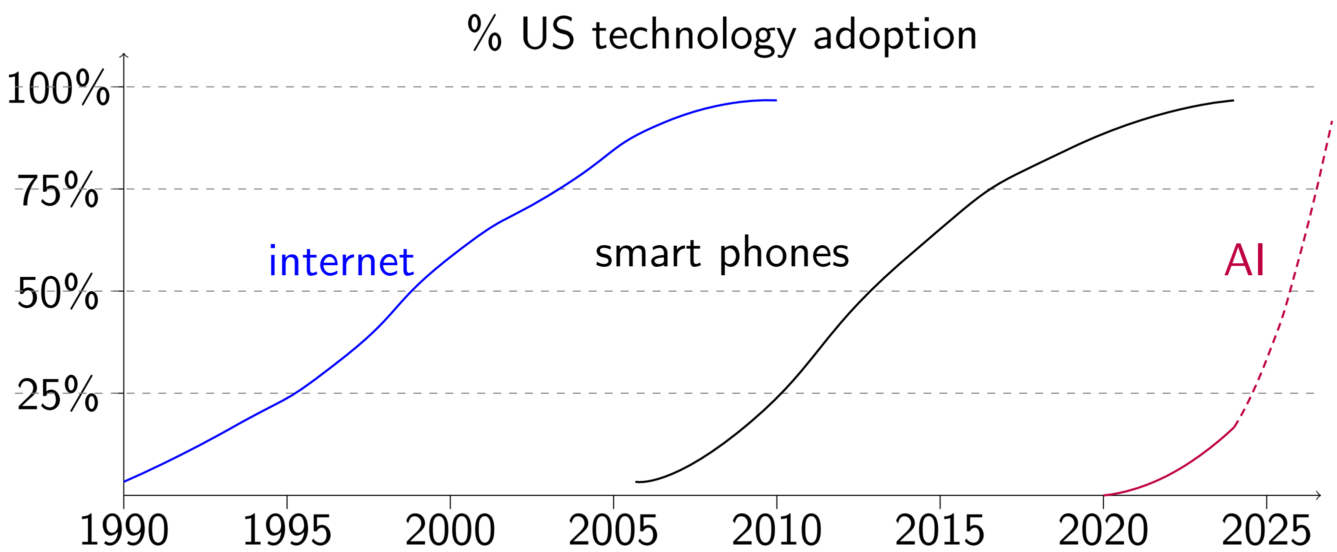




Recent Advances in AI

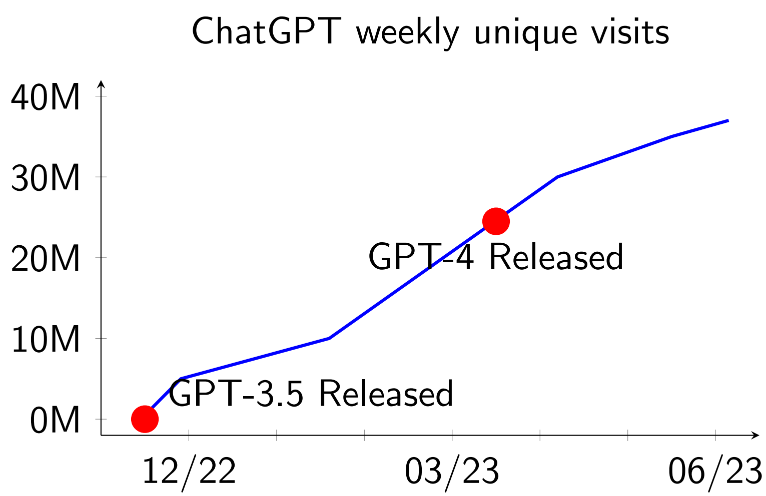
Where are we in AI today?

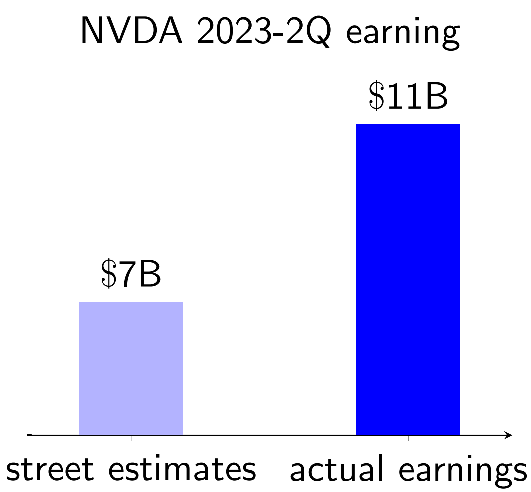
- sunrise phase - currently experiencing dawn of AI era with significant advancements and increasing adoption across various industries
- early adoption - in early stages of AI lifecycle with widespread adoption and innovation across sectors marking significant shift in technology's role in society



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[3]



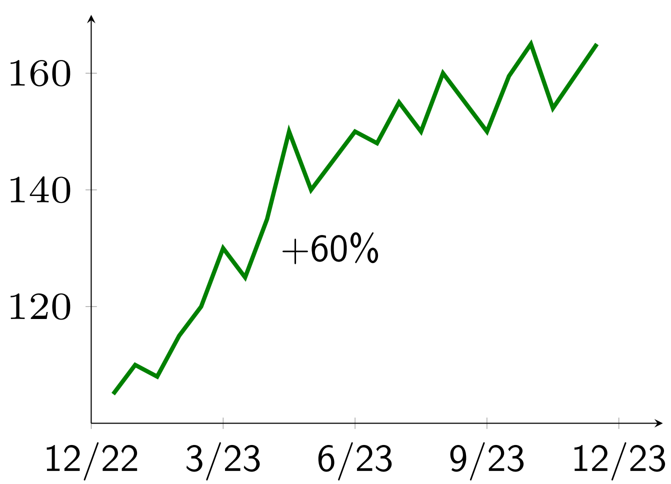


[3] source - Bloomberg

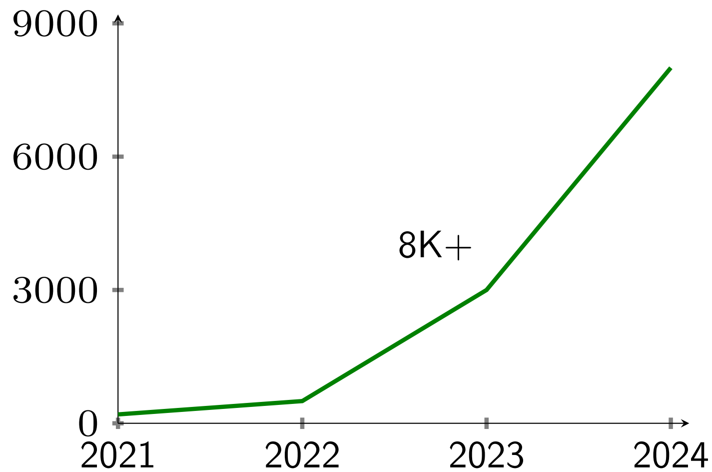
Explosion of AI ecosystems - AI stock market

- *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 basket performance - 2023

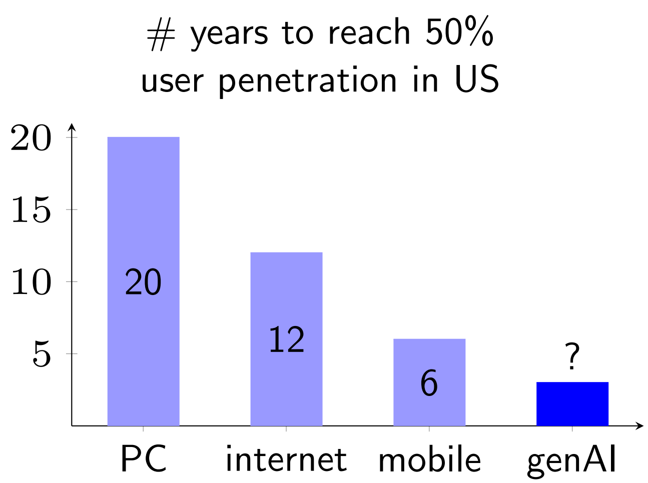


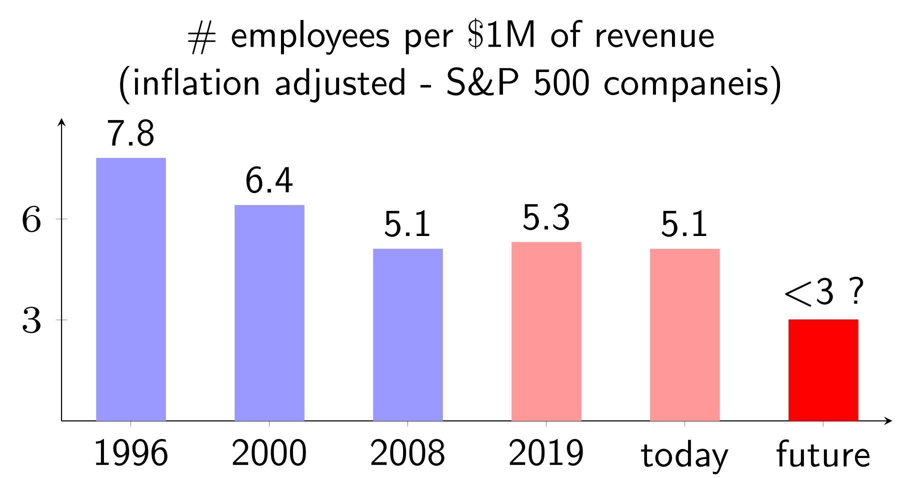
new AI applications over time



AI's transformative impact - adoption speed & economic potential

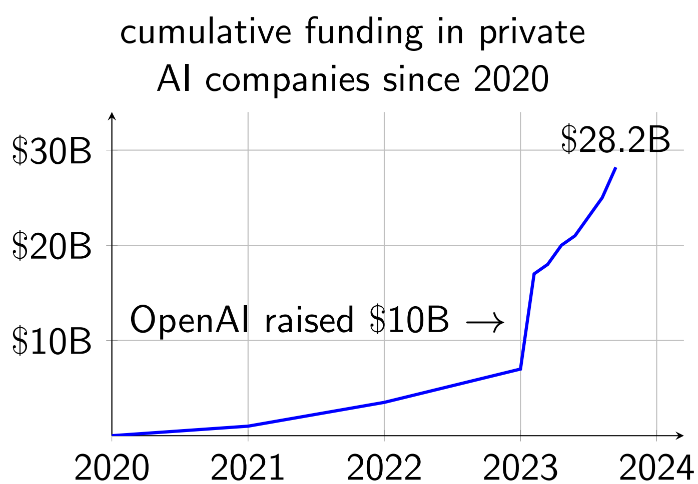
- adoption - has been twice as fast with platform shifts suggesting
  - increasing demand and readiness for new technology improved user experience & accessibility
- AI's potential to drive economy for years to come
  - 35% improvement in productivity driven by introduction of PCs and internet
  - greater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

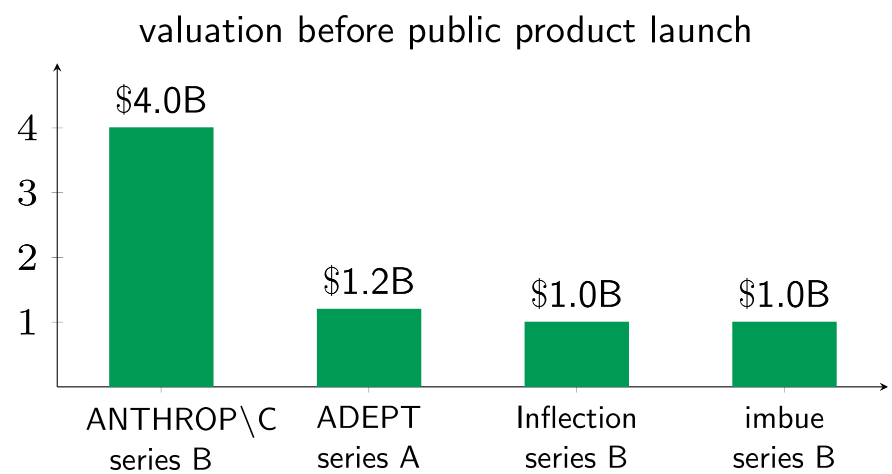




Massive investment in AI

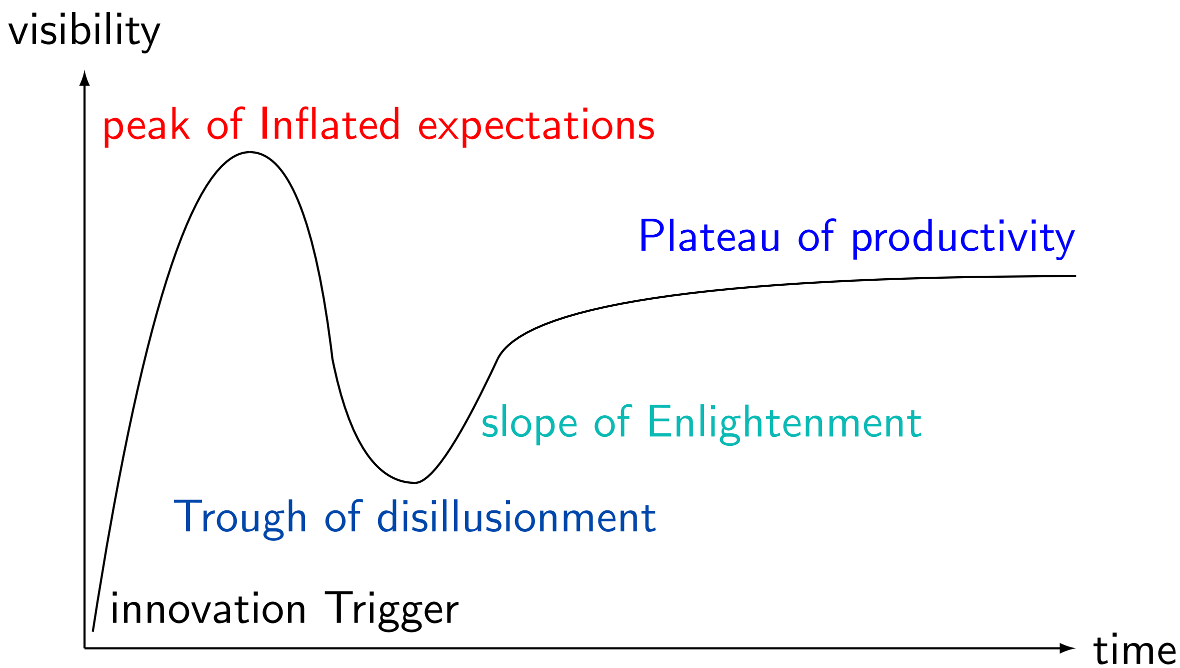
- *explosive growth* - cumulative funding skyrocketed reaching staggering $28.2B
- OpenAI - significant fundraising (=$10B) fueled rapid growth
- *valuation surge* - substantial valuations even before public products for stella companies
- *fierce competition for capital* among AI startups driving innovation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





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 Research

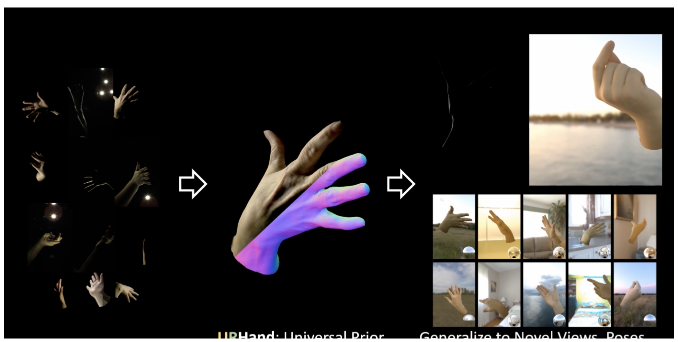
AI research race gets crazy

- practically impossible to follow all developments announced everyday
  - new announcement and publication of important work everyday!
- *industry leads research - academia lags behind*
  - trend observed even before 2015
- everyone excited to show off their work to the world - conference and `github.com`
  - biggest driving force behind unprecedented scale and speed of advancement of AI together with massive investment of capitalists

AI progress within a month - March, 2024

- UBTECH Humanoid Robot Walker S: Workstation Assistant in EV Production Line
- H1 Development of dance function
- Robot Foundation Models (Large Behavior Models) by Toyota Research Institute (TRI)
- Apple Vision Pro for Robotics
- Figure AI & OpenAI
- Human modeling
- LimX Dynamics' Biped Robot P1 Conquers the Wild Based on Reinforcement Learning
- HumanoidBench: Simulated Humanoid Benchmark for Whole-Body Locomotion and Manipulation - UC Berkeley & Yonsei Univ.
- Vision-Language-Action Generative World Model
- RFM-1 - Giving robots human-like reasoning capabilities

Papers of single company accepted by single conference



- CVPR 2024
  - PlatoNeRF: 3D Reconstruction in Plato's Cave via Single-View Two-Bounce Lidar - MIT, Codec Avatars Lab, & Meta [KXS+24]
    - 3D reconstruction from single-view
  - Nymeria Dataset
    - large-scale multimodal egocentric dataset for full-body motion understanding
  - Relightable Gaussian Codec Avatars - Codec Avatars Lab & Meta [SSS+24]
    - build high-fidelity relightable head avatars being animated to generate novel expressions
  - Robust Human Motion Reconstruction via Diffusion (RoHM) - ETH Zürich & Reality Labs Research, Meta [ZBX+24]
    - robust 3D human motion reconstruction from monocular RGB videos

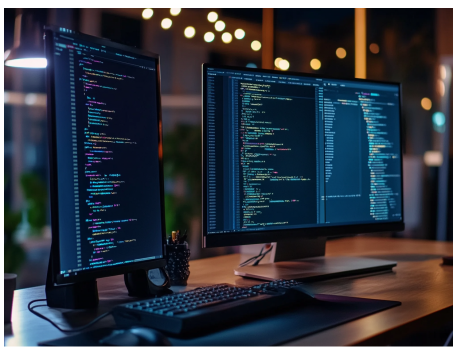
AI Products

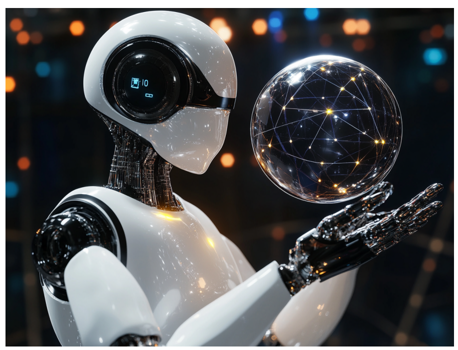
AI product development - trend and characteristics

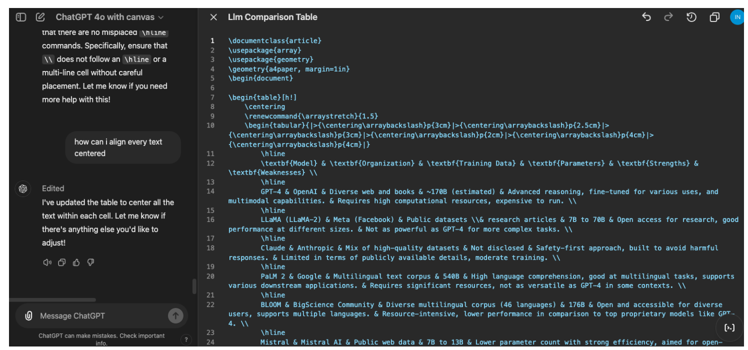
- *rapid pace* of innovation - new AI models & products being released at unprecedented rate, improvements coming in weeks or months (rather than years)
- *LLMs dominating* - models like GPT-4 & Claude pushing boundaries in NLP & genAI
- *multimodal AI* gaining traction - models processing & generating text, images & even video becoming more common, $e.g.$, Grok, GPT-4, Gemini w/ vision capabilities
- *open-source* AI movement - growing trend of open-source AI models and tools, challenging dominance of proprietary systems
- *AI integration in everyday products* - from smartphones to home appliances, AI being integrated into wide array of consumer products

AI product development - trend and characteristics

- *ethical AI & regulatory focus* - increased attention on ethical implications of AI & calls for regulation of AI development and deployment
- AI in enterprise - businesses across industries rapidly adopting AI for various applications
- *specialized AI models* - development of AI models tailored for specific industries or tasks, *e.g.*, healthcare, biotech, financial analysis
- AI-assisted *coding and development* - help software developers write code more efficiently & tools becoming increasingly sophisticated
- *concerns about AI safety & existential risk* - growing debate about potential short & long-term risks of advanced AI







LLM products

- OpenAI - ChatGPT 4o, GPT-4 Turbo Canvas
- Anthropic - Claude 3.5 Sonnet (with Artifacts), Claude 3 Opus, Claude 3 Haiku
- Mistral AI - Mistral 7B, Mistral Large 2, Mistral Small `xx.xx`, Mistral Nemo (12B)
- Google - Gemini (w/ 1.5 Flash), Gemini Advanced (w/ 1.5 Pro)
- X - Grok [mini] [w/ Fun Mode]
- Perplexity AI - Perplexity [Pro] - combines GPT-4, Claude 3.5, and Llama 3
- Liquid AI - Liquid-40B, Liquid-3B (running on small devices)

flying cats generated by Grok, ChatGPT 4o & Gemini

Comparison of LLMs & LLM products

model	developer	training data	# params	strength	weakness
GPT-4	OpenAI	web & books	170B	advanced reasoning & multimodal capabilities	high computational resources
LLaMA-2	Meta	public info & research articles	7∼70B	open access & good performance for different sizes	not powerful for complex tasks
Claude	Anthropic	mix of high-quality datasets	not disclosed	safety-first approach avoiding harmful responses	limited in publicly available details
PaLM 2	Google	multilingual text corpus	540B	high multilingual comprehension supporting various downstream apps	significant resources & not versatile in some contexts

Comparison of LLMs & LLM products

model	developer	training data	# params	strength	weakness
BLOOM	BigScience Community	diverse multilingual corpus	176B	open & support multiple languages	resource-intensive & lower performance
Mistral[4]	Mistral AI	public web data	7∼13B	lower parameter count	limited scalability for specialized apps
Liquid Foundation Model (LFM)	Liquid AI	adaptive datasets	adaptive & dynamic parameters	modular & support more specialized fine-tuning for niche use-cases & adaptable in deployment	complexity in design and implementation

Multimodal genAI products

- DALL-E by OpenAI
  - *generate unique and detailed images based on textual descriptions*
  - understanding context and relationships between words
- Midjourney by Midjourney
  - let people *create imaginative artistic images*
  - can interactively guide the generative process, providing high-level directions

Multimodal genAI products

- Dream Studio by Stability AI
  - *analyze patterns in music data & generates novel compositions*
  - musicians can explore new ideas and enhance their *creative* processes
- Runway by Runway AI
  - *realistic images, manipulate photos, create 3D models & automate filmmaking*

Rise of co-pilot products

- definition - AI-powered tools designed to enhance human productivity across multiple domains including document creation, presentations & coding
- benefits
  - *efficiency* - automate repetitive tasks allowing users to focus on high-value activities
  - *error reduction* - minimize mistakes common in manual work
  - *creativity* - suggestions and prompts help users explore new ideas and approaches
  - *integration* with major productivity suites - Microsoft 365, Google Workspace
- popular products
  - GitHub Copilot, Microsoft 365 Copilot, Grammarly AI, Visual Studio Code Extensions

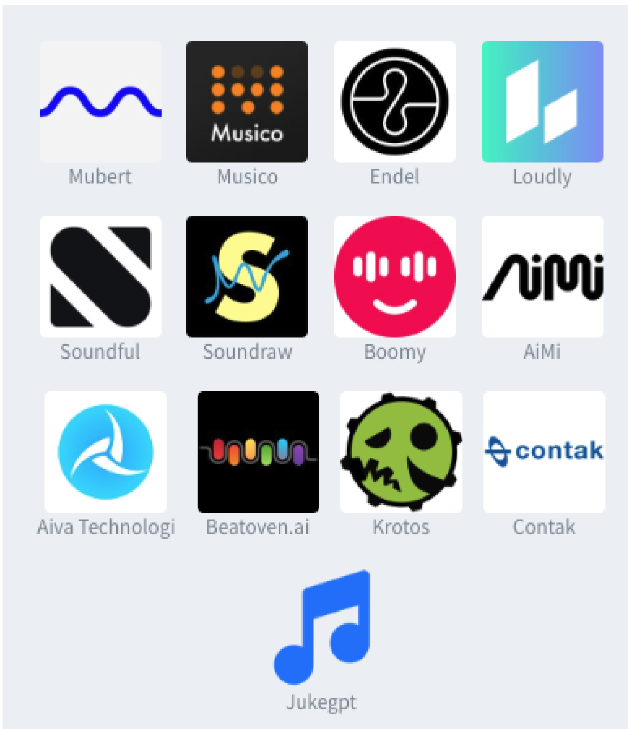
Future of co-pilot products

- potential advancements
  - wider adoption across industries and professions
  - *real-time fully automated collaboration*, *predictive content generation*, personalization
- impact on work environments & creative processes
  - *collaborative human-AI relationships* with augmented reality
  - unprecedented levels of problem-solving due to *augmented cognitive abilities*
- challenges & considerations
  - *ethical concerns around data privacy & AI decision-making*
  - potential impact on *human skills & job markets*

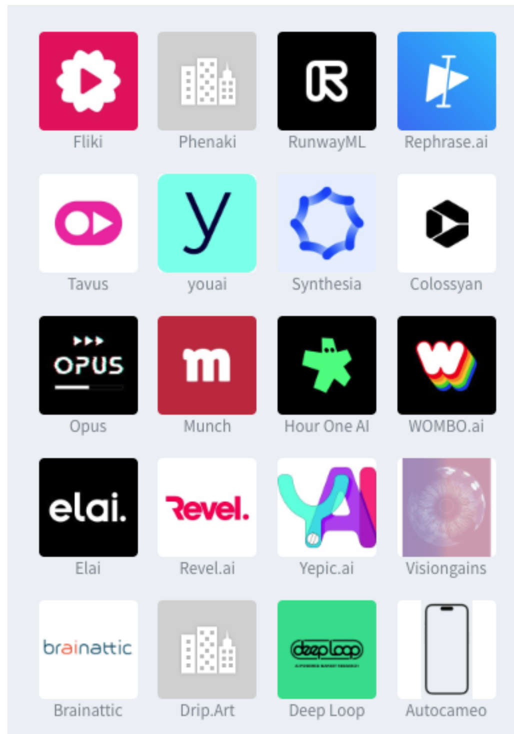


Other AI products - audio/video/text

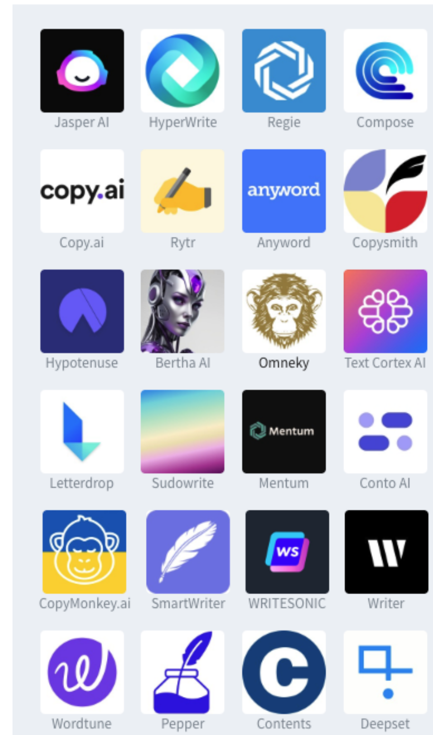
audio



vidio



text



Other AI products - LLM/gaming/design/coding

LLM

Baseplate, Promptify, Promptheo, PromptLayer

Vellum, Promptstacks, Promptable, GradientJ

FlowGPT, HoneyHive AI, PromptBase, Humanloop

Parea

gaming & design

Mirage, Kaedim, Hypothetic, Common Sense Ma

Magic 3d, Agentic, Luma AI, RapidCompact (F

Kinetix, In3D, Promethean AI, Hexa

Spline, 2Up, Kirin, Neuroid

Meshy, Atlas

coding

GitHub, Replit, Machinet, Diffblue

Warp, TabNine, Pygma, AI2SQL

Debuild, MutableAI, Enzyme, The Dotcom

yurts ai, Boltzbit, Poolside AI

Serendipities around AIs

Serendipity or inevitability?

- What if Geoffrey Hinton had not been a persistent researcher?
- What if Geoffrey had been a symbolist (instead of connectionist)?
- What if symbolists won AI race over connectionists?
- What if attention mechanism did not perform well?
- What if Transfomer architecture did not perform super well?
- What if Jensen Hwang had not been crazy about making hardware for professional gamers?

- Is it like Alexander Fleming's Penicillin?
- Or more like Inevitability?

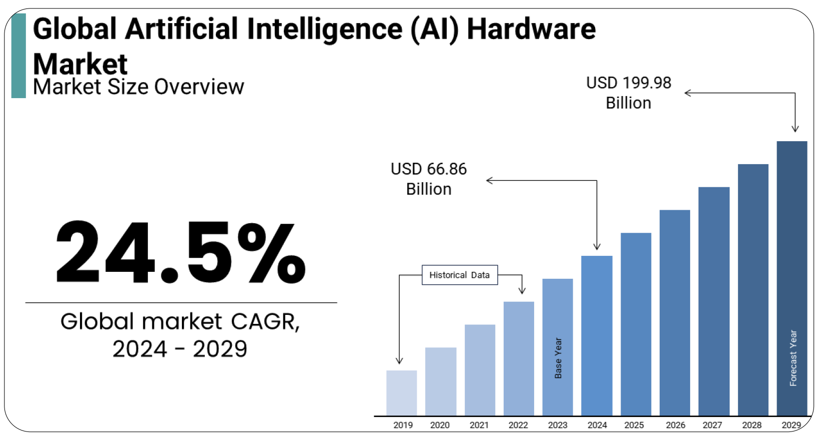
Appendix

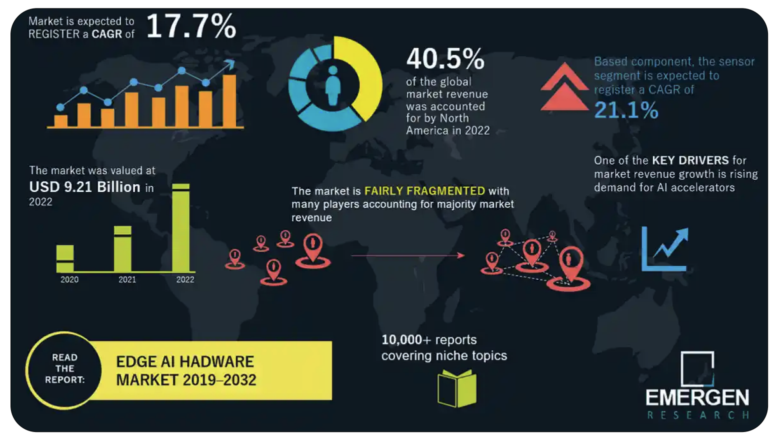
AI Hardware

AI Hardware Industry

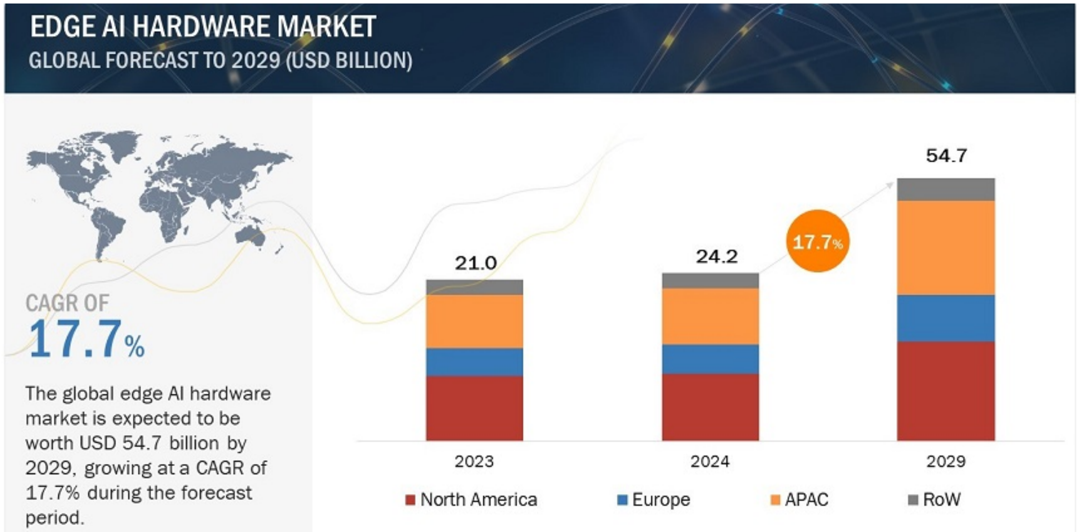
Landscape of AI hardware industry

- global AI hardware market valued at $66.96B in 2024, projected to grow significantly
- major companies - Nvidia, Intel, AMD, Qualcomm, and IBM w/ Nvidia holding substantial market share



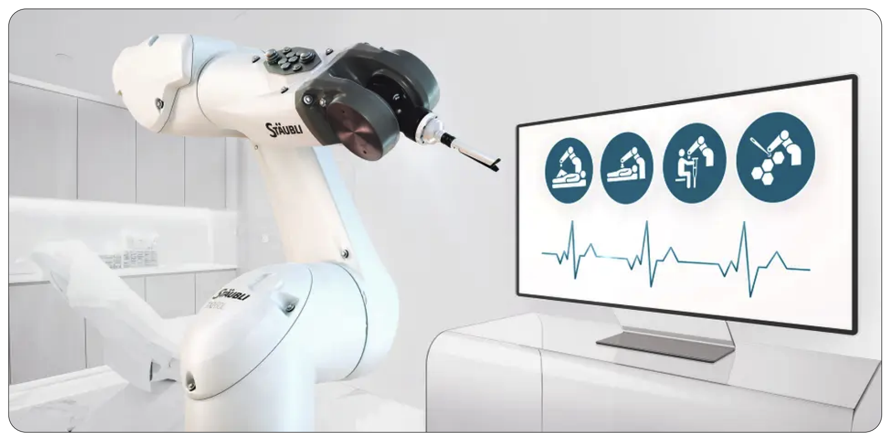


- North America leading market - high R&D investments & key industry players
- Asia Pacific rapidly expanding - strong semiconductor industries in South Korea, China & Japan
- demand for advanced processors such as GPUs, TPUs & AI accelerators rising due to complexity of AI algorithms & high computational power



Predictions for future of AI hardware market

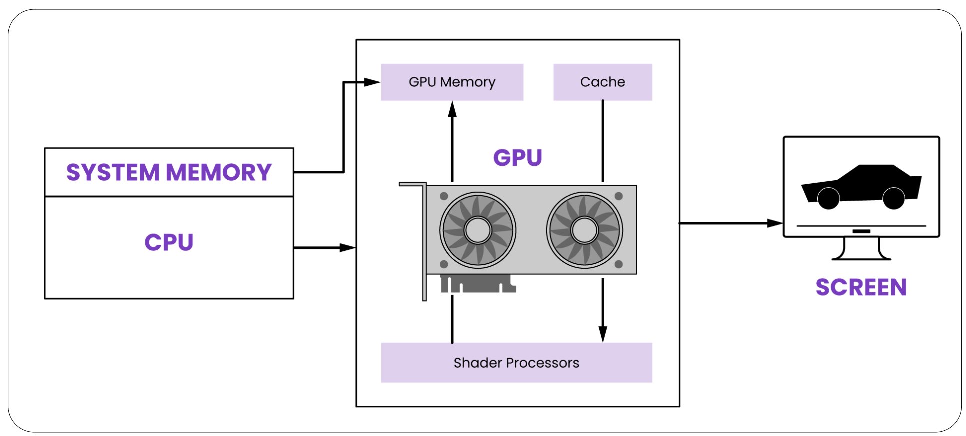
- AI hardware market expected to reach $382B by 2032 - significant growth in data center AI chips
- integration of AI w/ 5G & increased use of AI in edge computing anticipated to drive future demand
- AI hardware becoming crucial in sectors such as autonomous vehicles, robotics & medical devices
- need to address challenges such as heat and power management along with technical complexities



GPUs and AI Accelerators

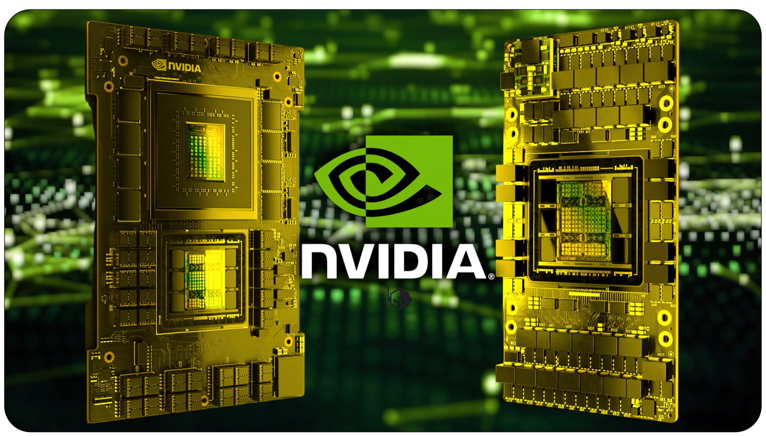
Technical challenges of GPUs & AI accelerators

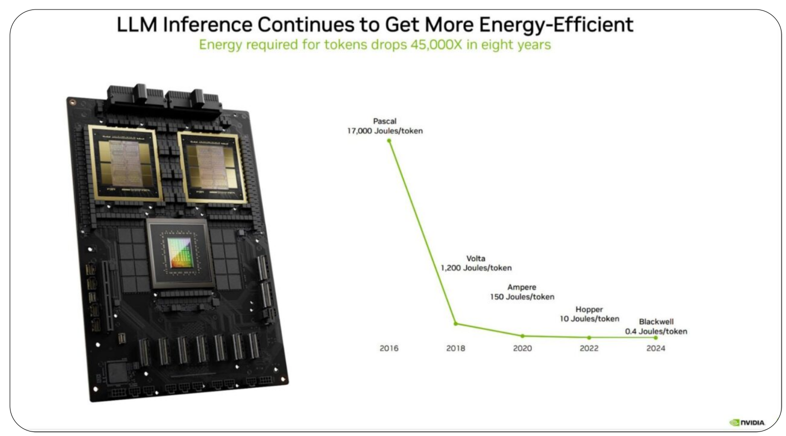
- facing challenges in scaling to handle increasingly large AI models and datasets - traditional architectures struggling w/ massive parallel processing demands of modern AI applications
- AI applications require extensive memory bandwidth often leading to bottlenecks - efficient memory management is crucial
- AI accelerators consume significant power - high operational costs and environmental concerns for both cloud-based & edge AI applications



Potential solutions for overcoming challenges

- development of AI-specific architectures such as tensor cores and custom ASICs to improve efficiency and performance - novel architectures like FPGAs for specific AI tasks, *e.g.*, for RAG & vectorDB
- implementing software optimizations to enhance hardware usability and performance - use of compilers and frameworks that maximize efficiency of existing hardware
- encouraging market competition to drive innovation and reduce monopolistic control - exploring alternative hardware solutions and improving energy efficiency standards





Big tech's in-house chip development

- shift towards in-house AI hardware - major tech companies increasingly developing their own AI chips - move to enhance AI capabilities and reduce dependence

- collaboration with specialized partners - partnering with specialized firms for manufacturing and technology blending in-house expertise with external innovation

	Microsoft	Google	Amazon	Meta
Chip	Maia 100	TPU v5e	Inferentia2	MTIA v1
Launch Date	November, 2023	August, 2023	Early 2023	2025
IP	ARM	ARM	ARM	RISC-V
Process Technology	TSMC 5nm	TSMC 5nm	TSMC 7nm	TSMC 7nm
Transistor Count	105 billion	-	-	-
INT8	-	393 TOPS	-	102.4 TOPS
FP16	-	-	-	51.2 TFLOPS
BF16	-	197 TFLOPS	-	-
Memory	-	-	-	LPDDR5
TDP	-	-	-	25W
Packaging Technology	CoWoS	CoWoS	CoWoS-S	2D
Collaborating Partners	Global Unichip Corp.	Broadcom	Alchip Technologies	Andes Technology
Application	Training/Inference	Inference	Inference	Training/Inference
LLM	GPT-3.5, GPT-4	BERT, PaLM, LaMDA	Titan FM	Llama, Llama2

AMD - Nvidia's new competitor

- key points
  - AMD launched new AI accelerator chip, *Instinct MI300X*, on Dec 6, 2023
  - CDNA 3 architecture, mix of 5nm and 6nm IPs, delivering 153B transistors
  - *outperforms Nvidia's H100 TensorRT-LLM* by 1.6X higher memory bandwidth and 1.3X FP16 TFLOPS
  - up to 40% faster vs Nvidia's Llama-2 70B model in 8x8 server configurations
- market impact
  - significant challenge to Nvidia's dominance in AI accelerator market
  - performance gains over Nvidia's offerings could drive *customer adoption and market share for AMD*
- future prediction
  - *AMD stocks soared* since launch indicating investor confidence in their competitiveness
  - Lisa Su, AMD's CEO, categorized Instinct MI300X as "next big thing" in tech industry
  - potential risks include need to *manage ROCm vs CUDA software ecosystem* & ensure rapid customer adoption and production coverage

AI Accelerator Startups

AI accelerator startups

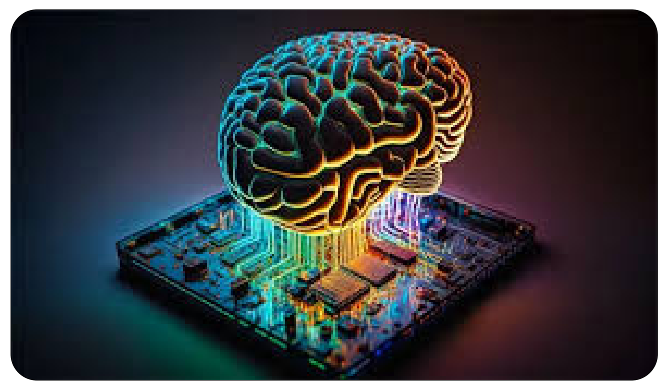
- innovative architectures - startups like Groq, SambaNova & Graphcore leading with *novel architectures designed to accelerate AI workloads*
  - *Groq* - tensor streaming processor (TSP) offering ultra-low latency & high throughput, high-performance AI inference chips enhancing speed & efficiency
  - *SambaNova* - reconfigurable dataflow architecture optimizing for various AI workloads
  - *Graphcore* - intelligence processing unit (IPU) tailored for graph-based computation excelling in sparse data processing
  - *Cerebras Systems* - develop wafer scale engine (WSE), largest chip built for AI workloads, unmatched computational power revolutionizing AI hardware capabilities
  - *Hailo* - specialize for edge devices optimizing AI processes for real-time applications, raised $120M emphasizing potential to disrupt traditional AI chip markets

Technological competitiveness

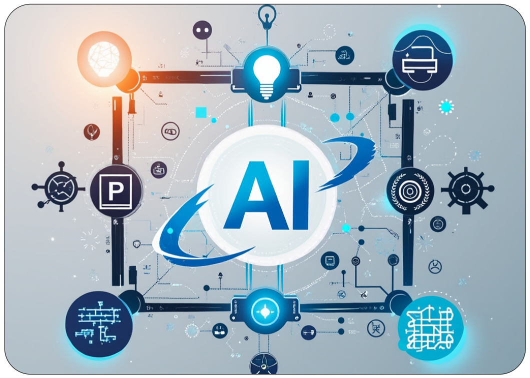
- energy efficiency
  - energy-efficient designs crucial for scalability in data centers and edge devices
  - startups developing solutions significantly reducing power consumption without compromising performance
- customization & flexibility
  - AI accelerators from startups often offer greater customization options for specific AI tasks compared to traditional GPUs
  - flexibility in hardware allows for tailored solutions that can outperform general-purpose accelerators in certain applications
- software integration
  - robust software ecosystems critical - startups investing in developing software stacks that optimize performance for their hardware
  - compatibility with existing AI frameworks is competitive advantage, *e.g.*, `TensorFlow` & `PyTorch`

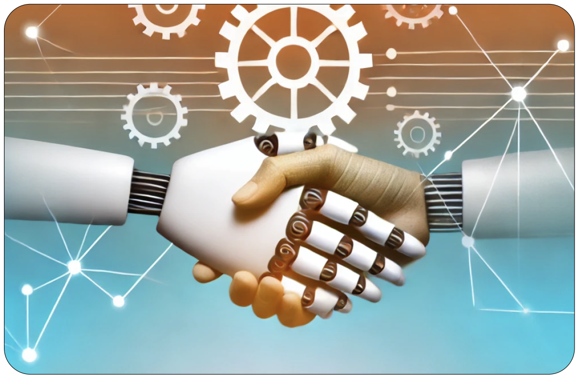
Industry and market influence

- disruption of traditional players
  - challenging dominance of established players like NVIDIA & Intel
  - unique architectures providing specialized solutions traditional GPUs and CPUs cannot efficiently handle
- driving down costs
  - offering competitive alternatives pushing down cost of AI computation
  - could lead to democratization of AI w/ more companies affording high-performance AI capabilities

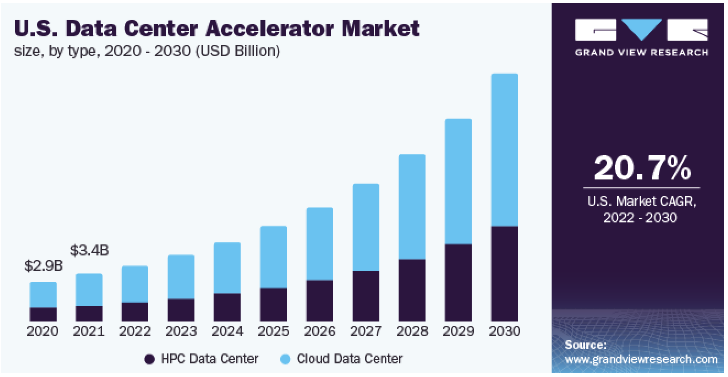


- accelerating AI innovation
  - contributing to rapid innovation providing hardware that can handle emerging AI models & workloads
  - adaptability and specialization enable advancements in AI research & faster development cycles
- strategic partnerships & acquisitions
  - big techs increasingly forming strategic partnerships or acquiring startups to stay competitive
  - collaborations can speed up integration of advanced AI hardware into mainstream products





- market growth & opportunities
  - AI accelerator market expected to grow significantly driven by demand in data centers, edge computing & autonomous systems
  - startups well-positioned to capture significant share of growing market particularly in niche applications
- future outlook
  - dependency on Asia for fabrication might lead to strategic shifts in global tech policies and investments in local manufacturing
  - increasing demand for efficient AI processing on edge devices and in data center.



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.

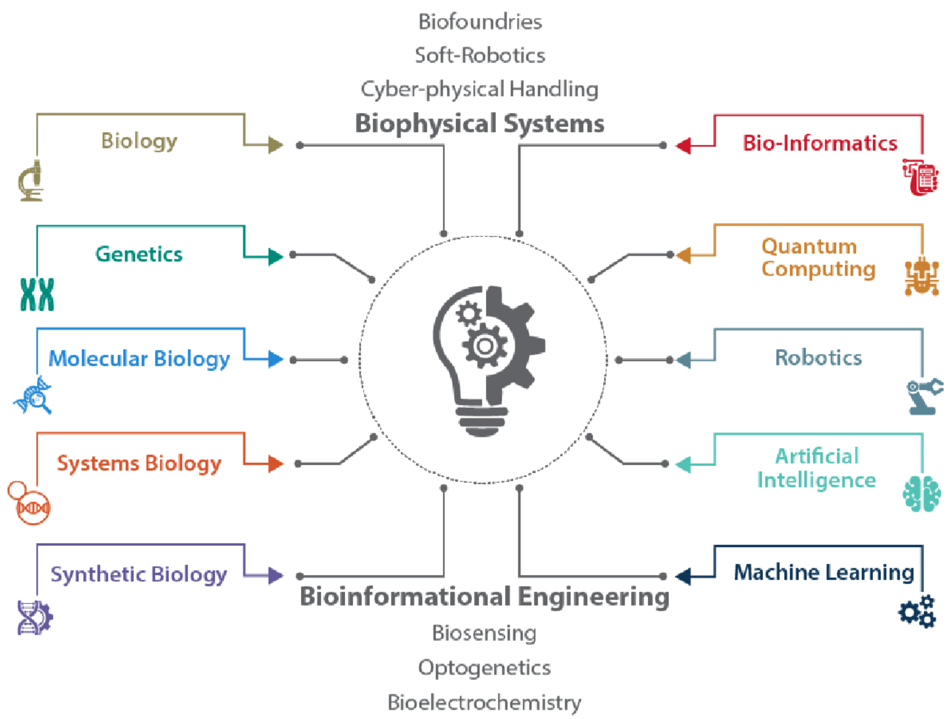
Biotech

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 takes 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]
  - artificial intelligence, 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]

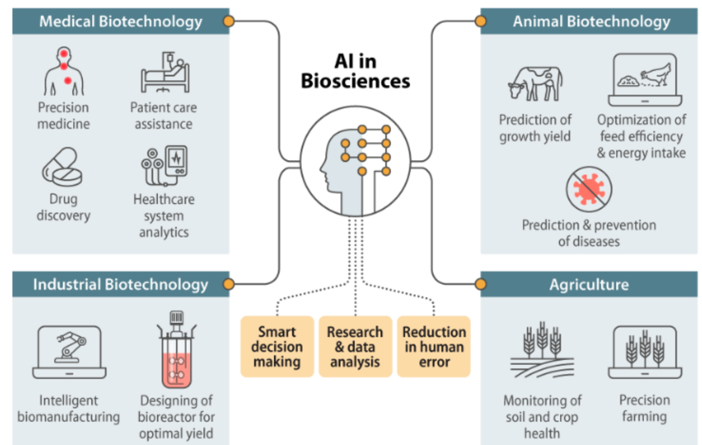


Convergence of AI and biological design

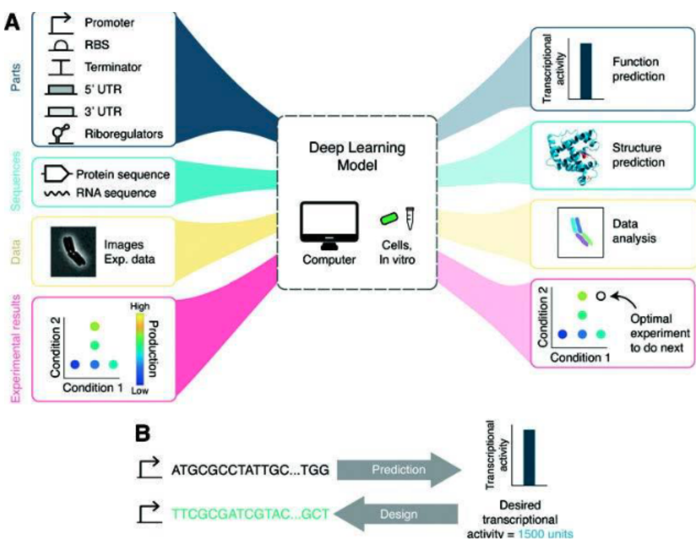
- both AI & biological sciences increasingly converging [BKP22]
  - each building upon the other's capabilities for new research and development across multiple areas
- Demo Hassabis, CEO & cofounder of DeepMind, said of biology [Toe23]

  > ". . . 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 is 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 the 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

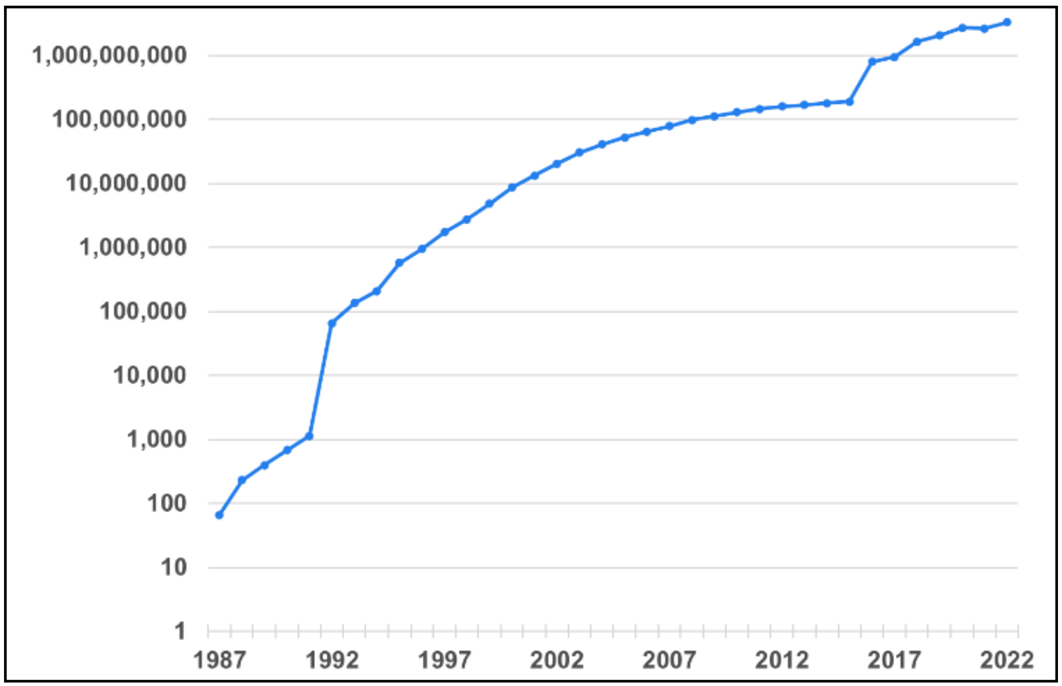
Rapid growth of biological data

- volume of genetic sequence data grown exponentially as sequencing technology has 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, contains more than *terabyte of three-dimensional structure data* for biological molecules, including proteins, DNA, and RNA
  - proprietary database
    - Gingko Bioworks - possesses 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

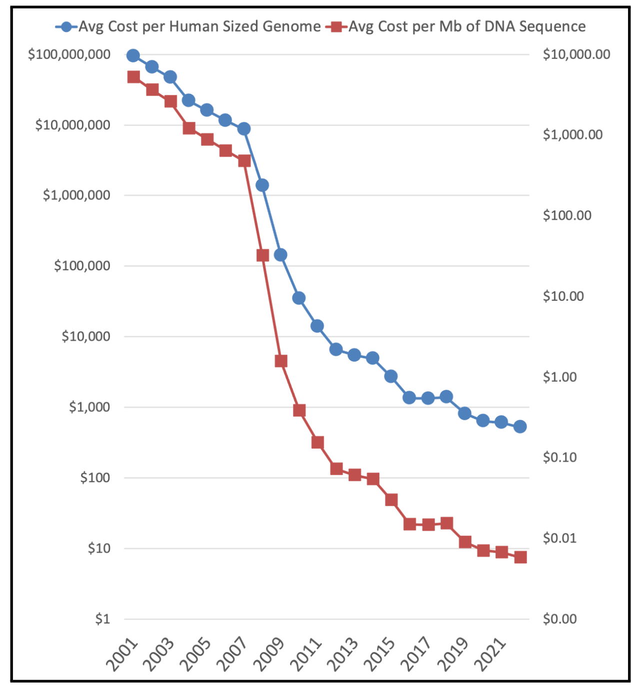
Volume and sequencing cost of DNA over time

- volume of DNA sequences & DNA sequencing cost
  - data source: National Human Genome Research Institute (NHGRI) [Wet23] & International Nucleotide Sequence Database Collaboration (INSDC)

\# sequences in INSDC



DNA sequencing cost



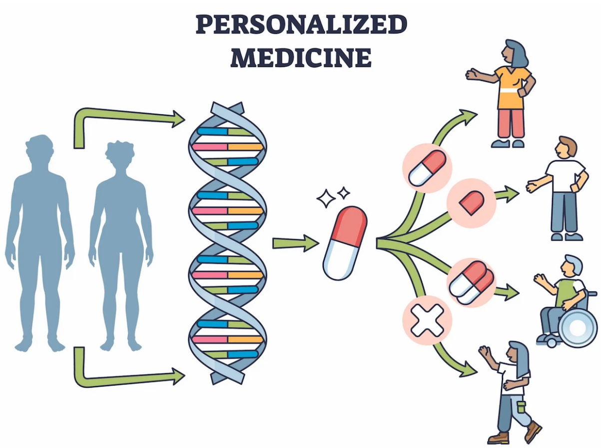
Bio data availability and bias

- 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

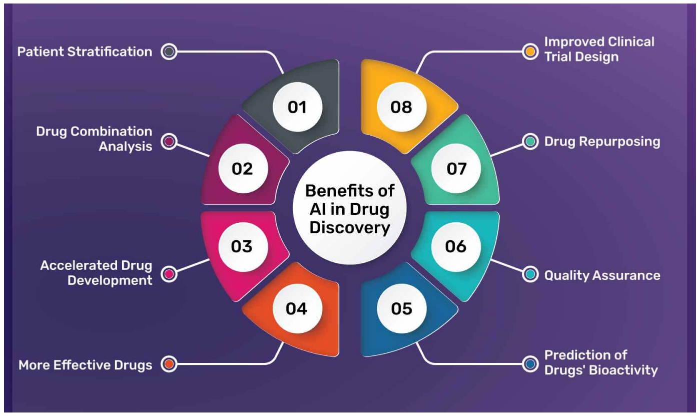
Emerging Trends in Biotech

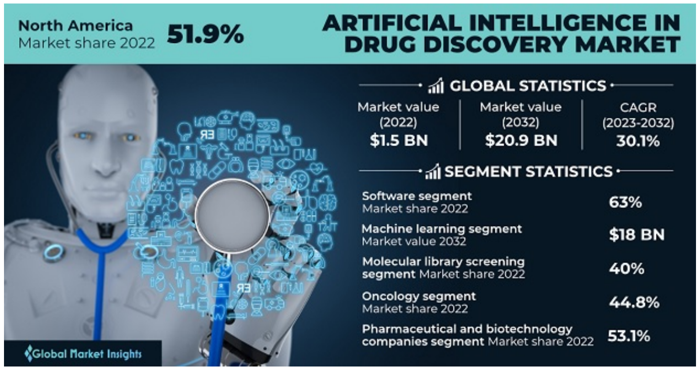
Personalized medicine

- *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

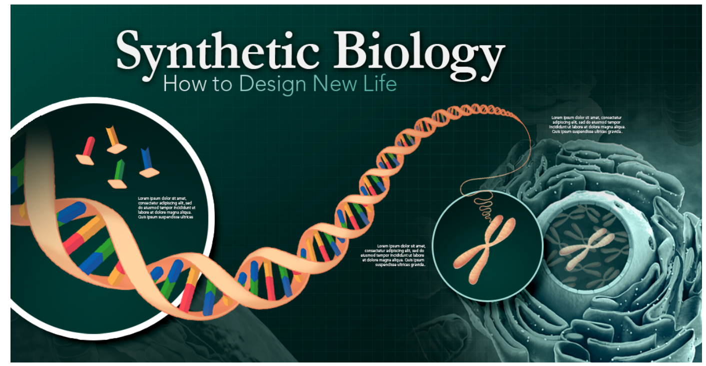


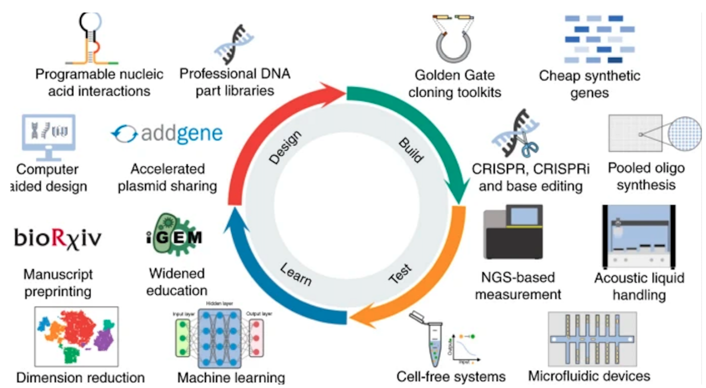


- traditional drug discovery process - time-consuming and costly often taking decades and billions of dollars
- AI streamlines this process by predicting the efficacy and safety of potential compounds with more speed and accuracy
- AI models analyze chemical databases to identify new drug candidates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

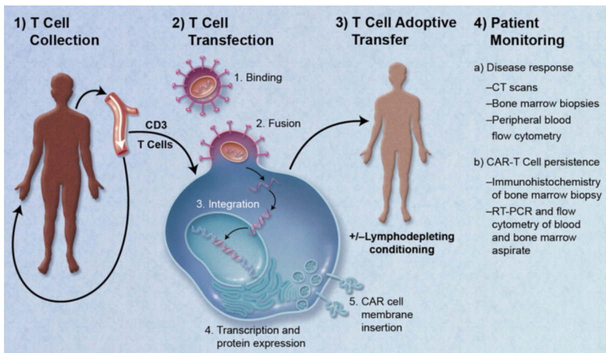
Synthetic biology

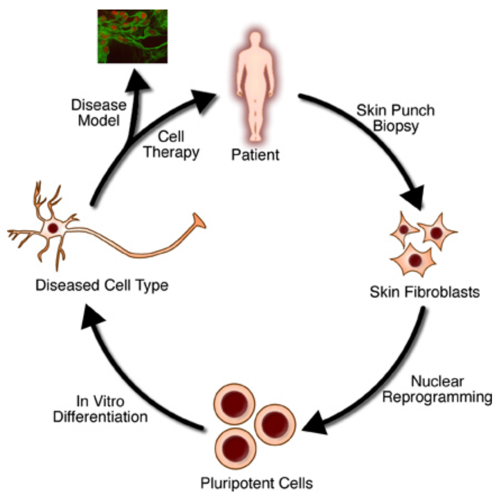
- use AI for gene editing, biomaterial production and synthetic pathways
- combine principles of biology and engineering to design and construct new biological entities
- AI optimizes synthetic biology processes from designing genetic circuits to scaling up production
- company - Ginkgo Bioworks uses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





Regenerative medicine

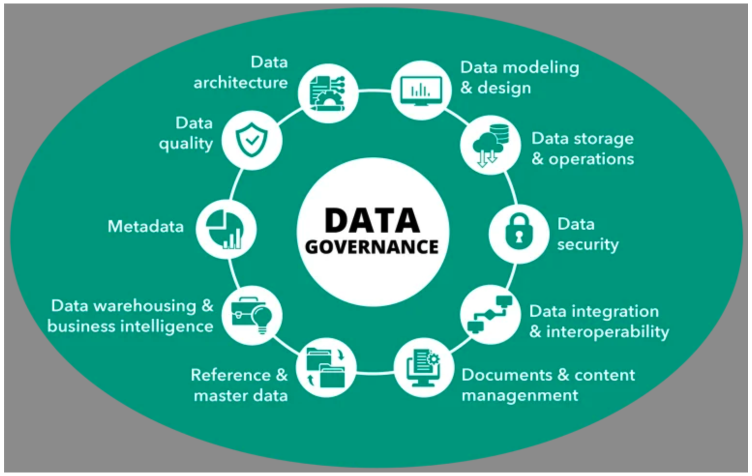




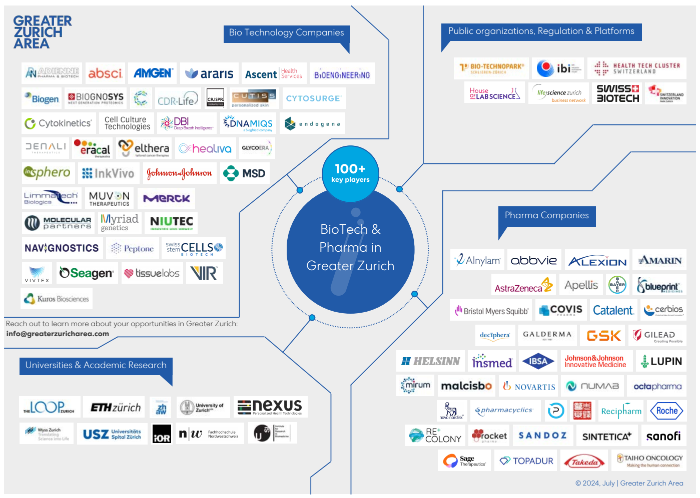
- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo 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

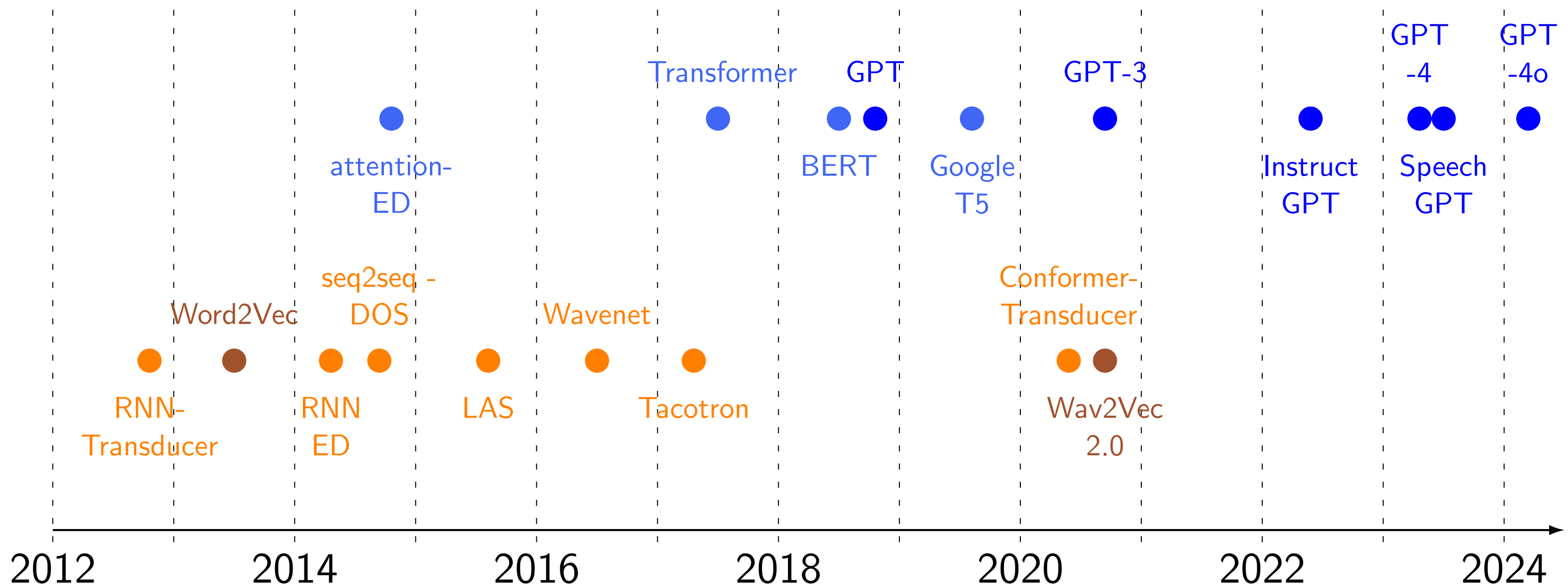
LLM

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

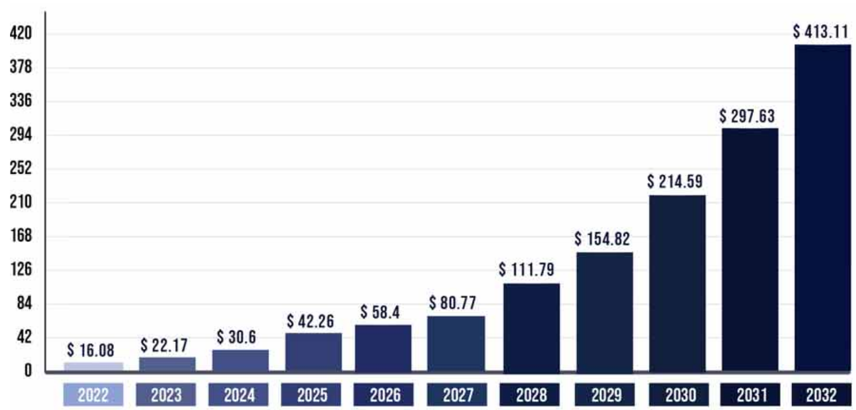
voice recognition	NL generation	summarization	spelling correction	action planning
voice synthesis	translation	topic model	topic model	
	Q&A	NLU		

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

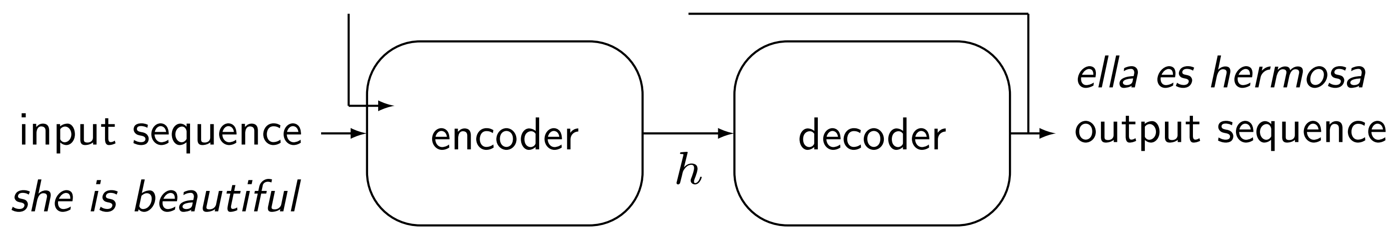
\- source - Precedence Research



Sequence-to-Sequence Models

Sequence-to-sequence (seq2seq) model

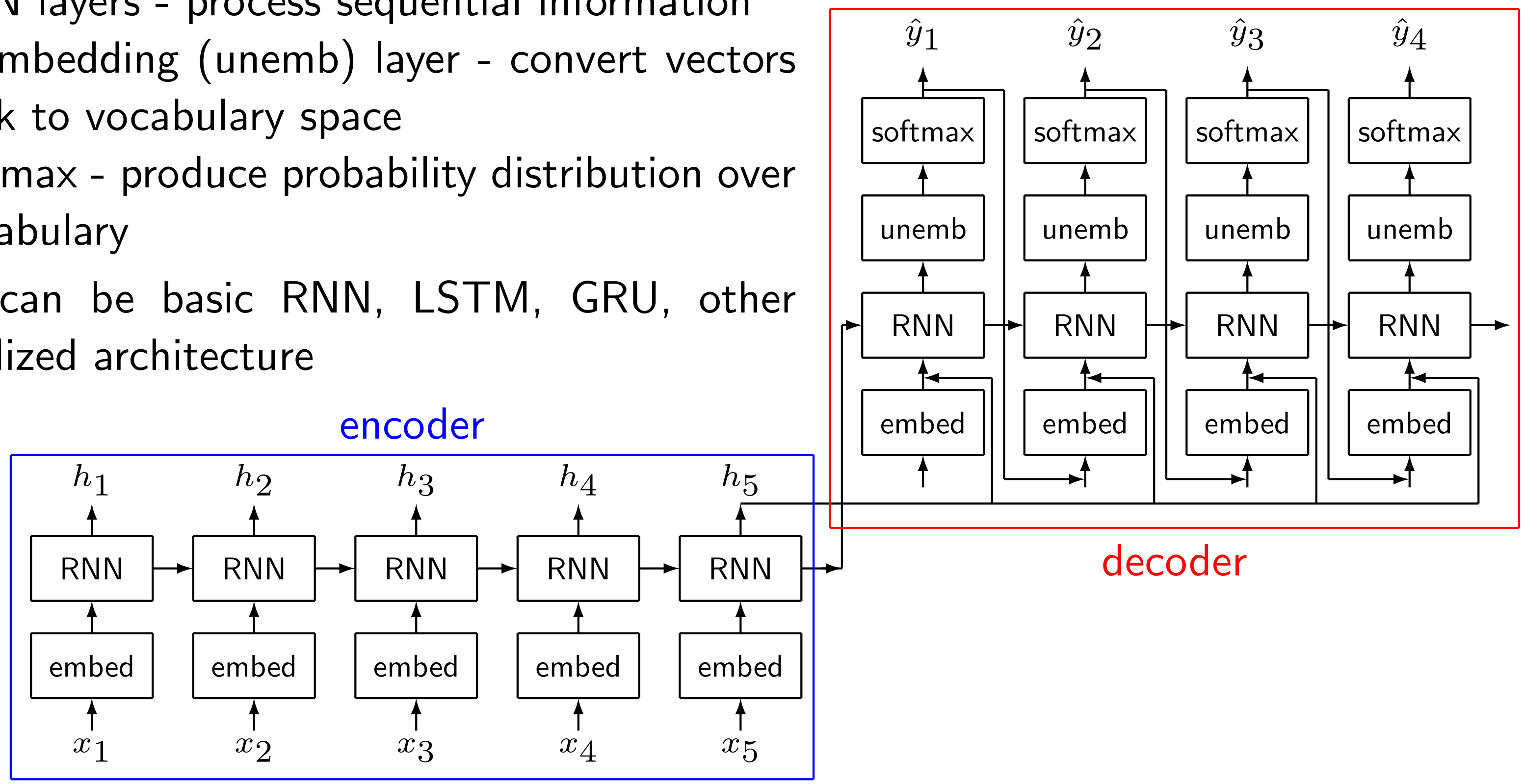
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



  - 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

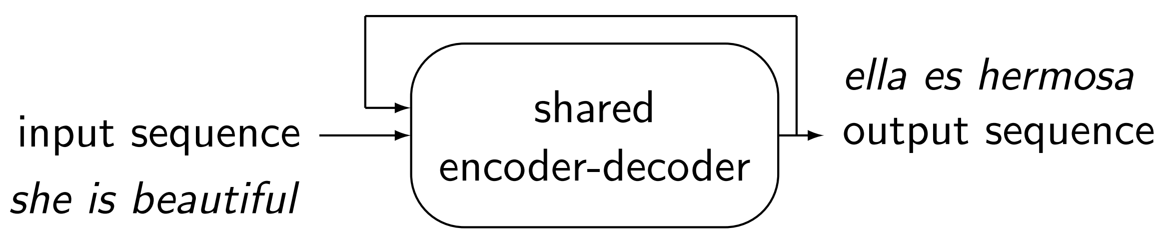
RNN-type encoder-decoder architecture

- 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

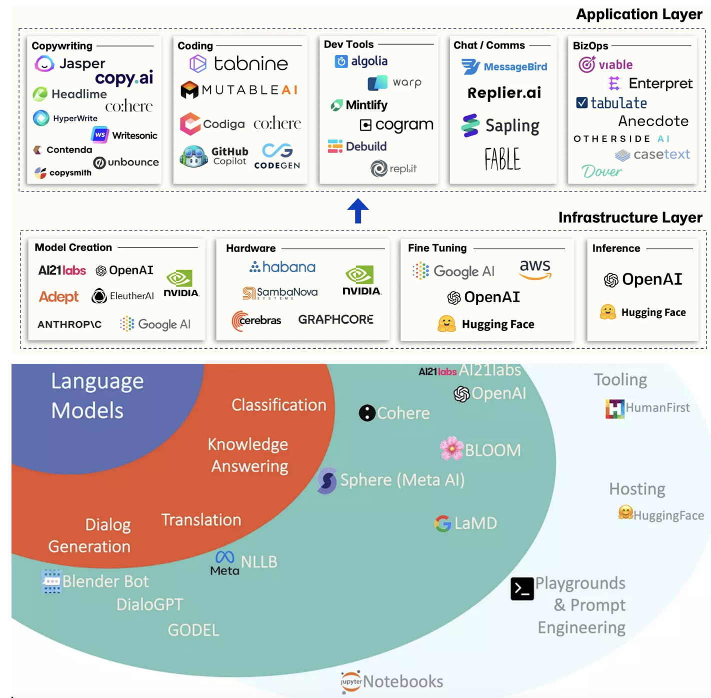
- LLM
  - type of AI aimed for NLP trained on massive corpus of texts & programming code
  - allow learn statistical relationships between words & phrases, $i.e.$, conditional probabilities
  - *amazing performance shocked everyone - unreasonable effectiveness of data (Halevry et al., 2009)*

- 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

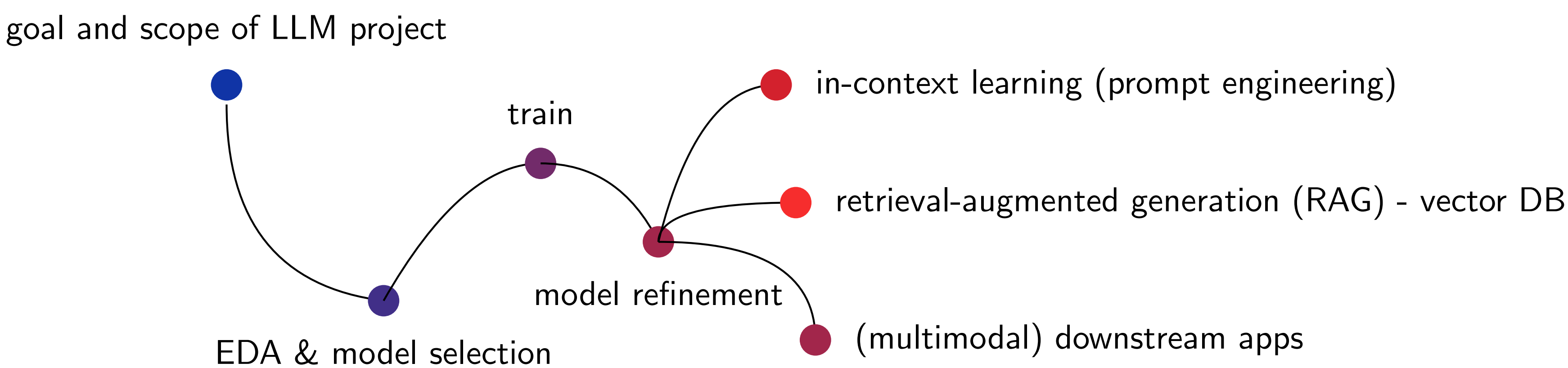
LLMs

- 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

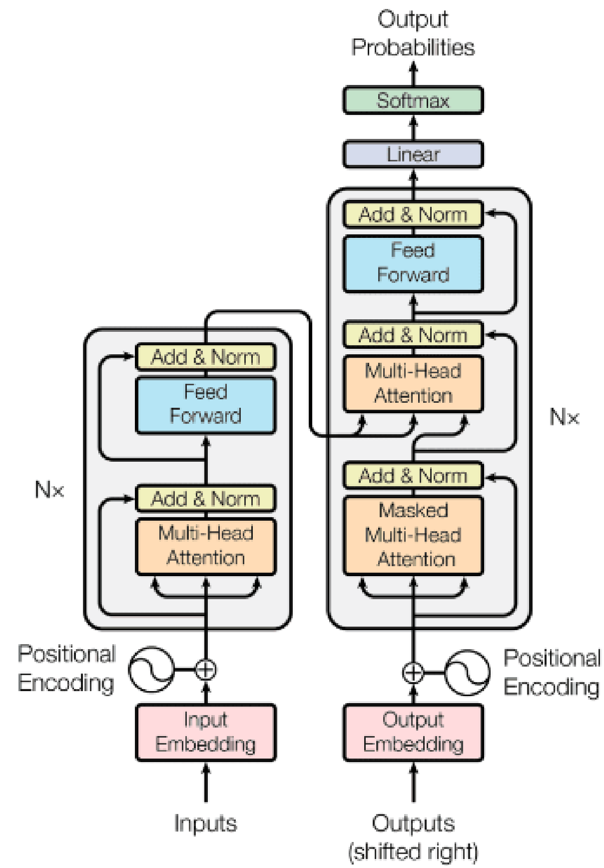
LLM architectural secret (or known) sauce

Transformer - simple parallelizable attention mechanism

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

Transformer architecture

- encoding-decoding architecture
  - input embedding space $\rightarrow$ multi-head & mult-layer representation space $\rightarrow$ 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 $\rightarrow$ parallelizable $\rightarrow$ 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, $q_i \in \mathbf{R}^{d_k}$, $Q = \left[\begin{array}{ccc} - & q_i & - \end{array}\right] \in \mathbf{R}^{d_k \times n}$
- assume m keys and m values, $k_1, \ldots, k_m \in \mathbf{R}^{d_k}$ & $v_1, \ldots, v_m \in \mathbf{R}^{d_v}$

$$K = \left[\begin{array}{ccc} k_1 & \cdots & k_m \end{array}\right] \in \mathbf{R}^{d_k \times m}, V = \left[\begin{array}{ccc} v_1 & \cdots & v_m \end{array}\right] \in \mathbf{R}^{d_v \times m}$$

- then

$$K^T Q / \sqrt{d_k} = \left[\begin{array}{ccc} & \vdots & \\ - & k_j^T q_i / \sqrt{d_k} & - \\ & \vdots & \end{array}\right]$$

$e.g.$, 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

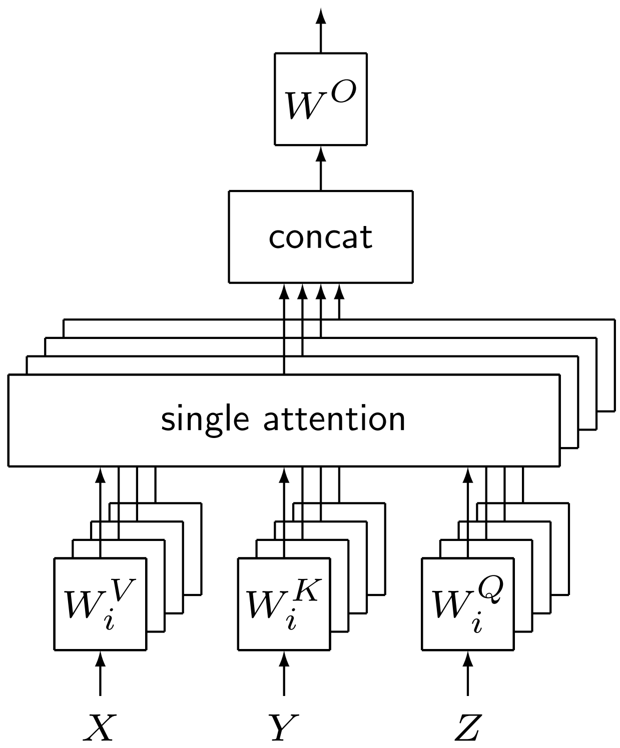
$$X \in \mathbf{R}^{d_e \times m},\ Y \in \mathbf{R}^{d_e \times m},\ Z \in \mathbf{R}^{d_e \times n}$$

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!*

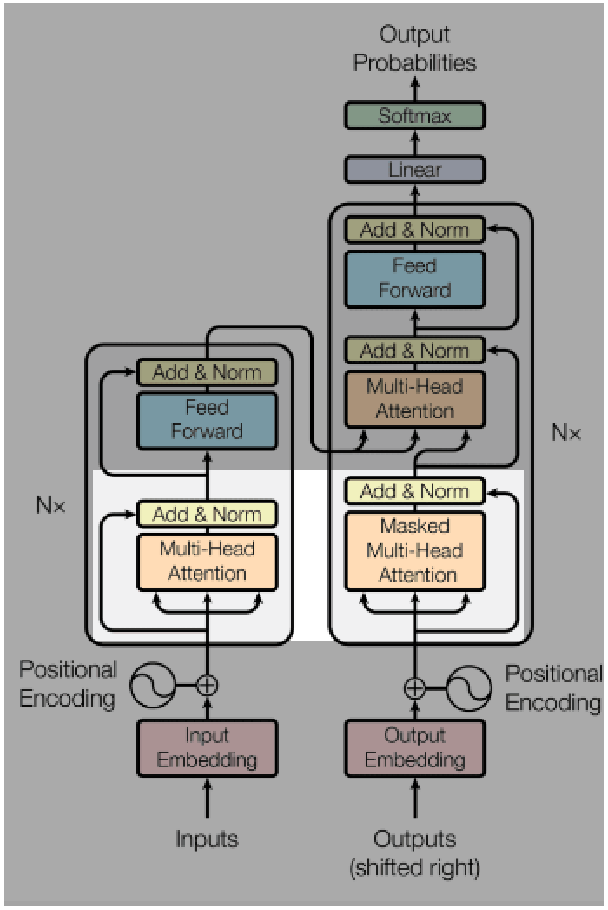
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbf{R}^{d_e \times n},$$

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



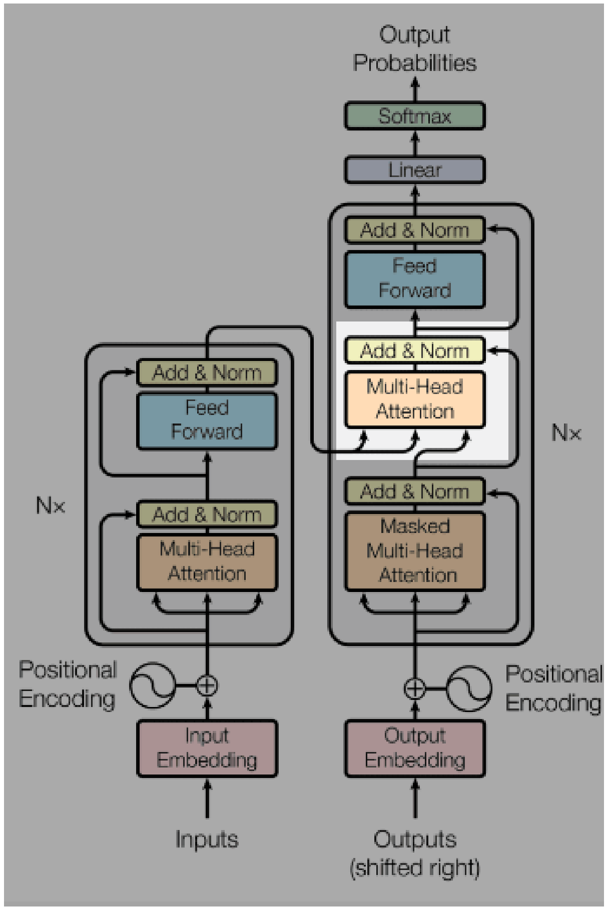
Self attention

- $m = n$
- 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

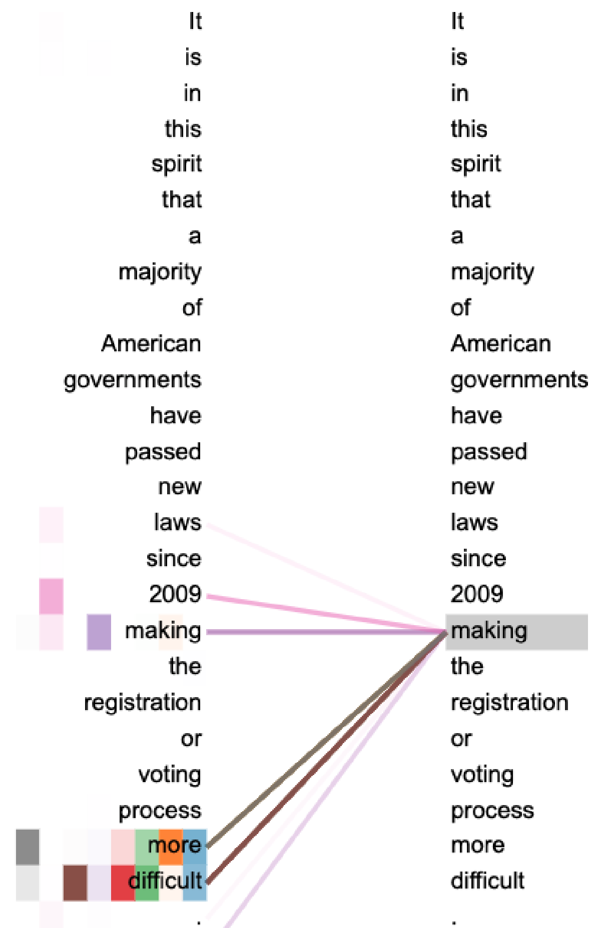


Visualization of self attentions

example sentence

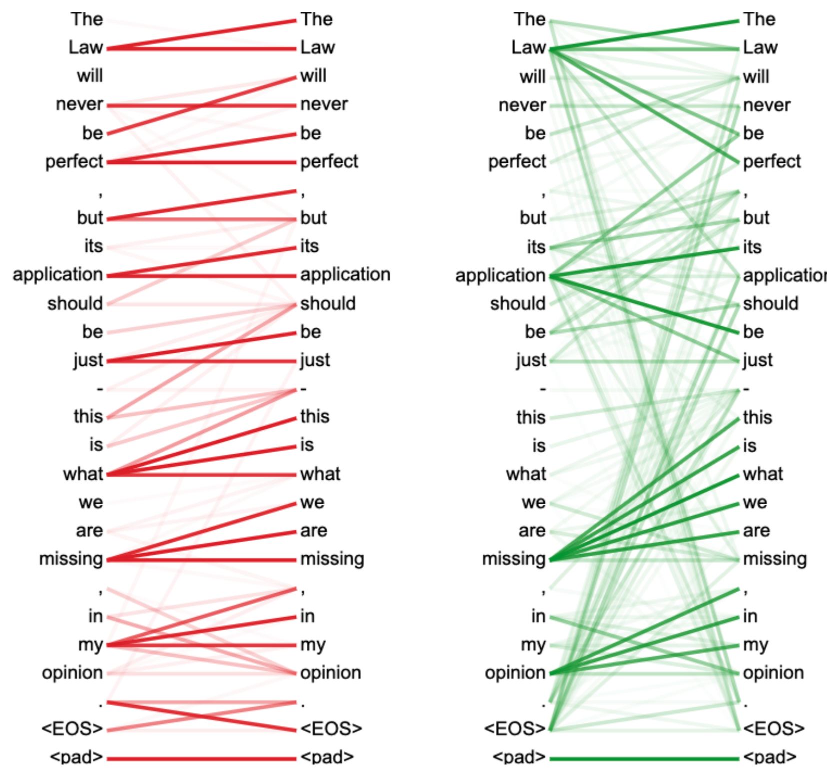
"It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult."

- 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"

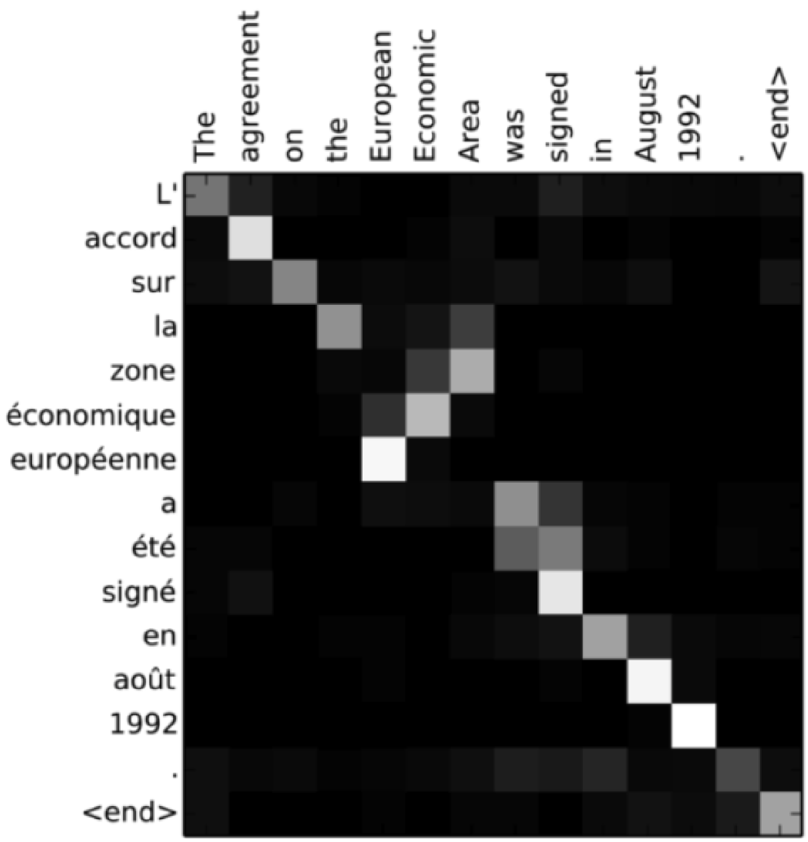


Visualization of multi-head self attentions

- self attentions of encoder for two heads (of a layer)
  - different heads represent different structures
    → 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

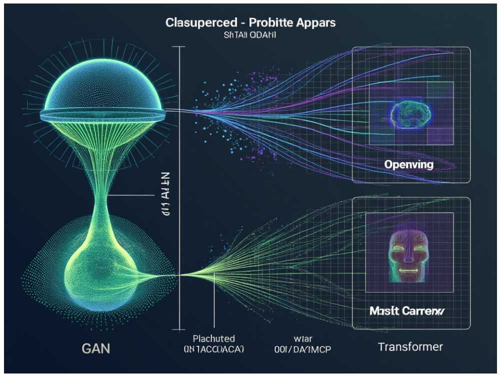
genAI

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

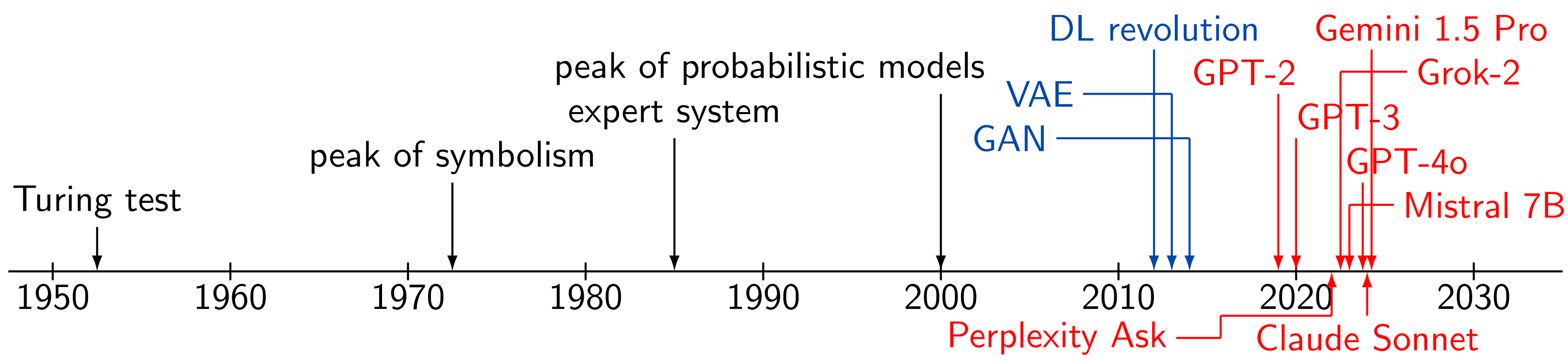
Examples of genAI in action

- 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

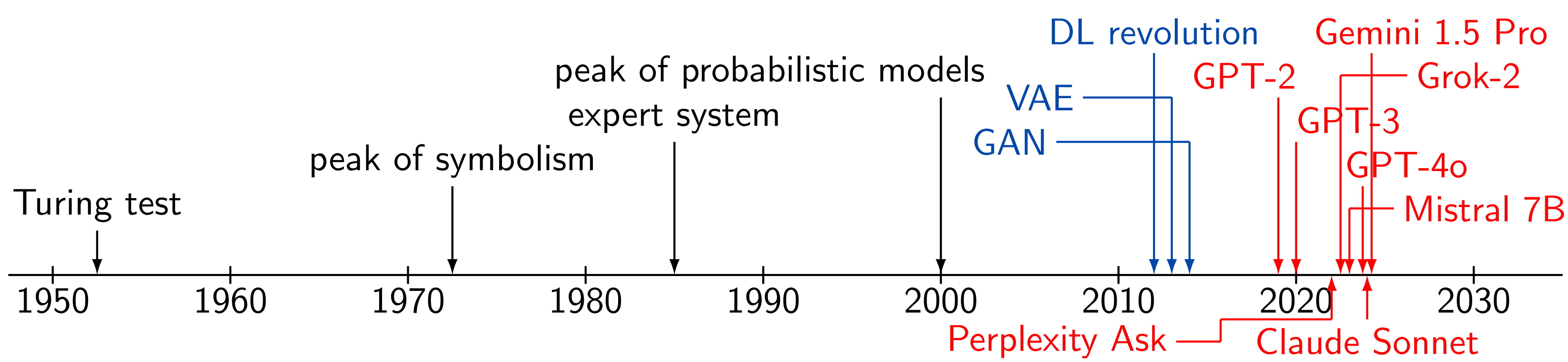
Birth of AI - early foundations & precursor technologies

- 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 $\sim$)



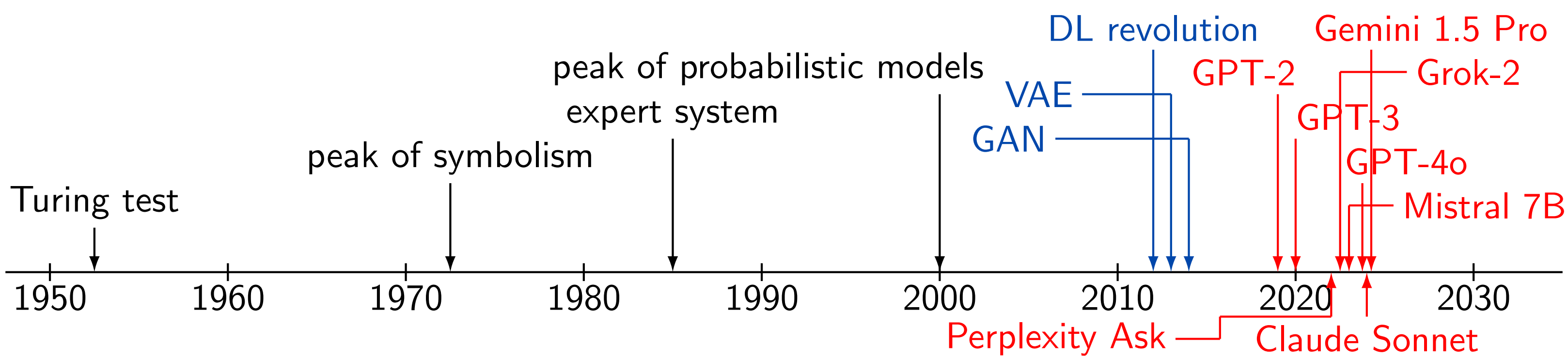
Rule-based systems & probabilistic models

- 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



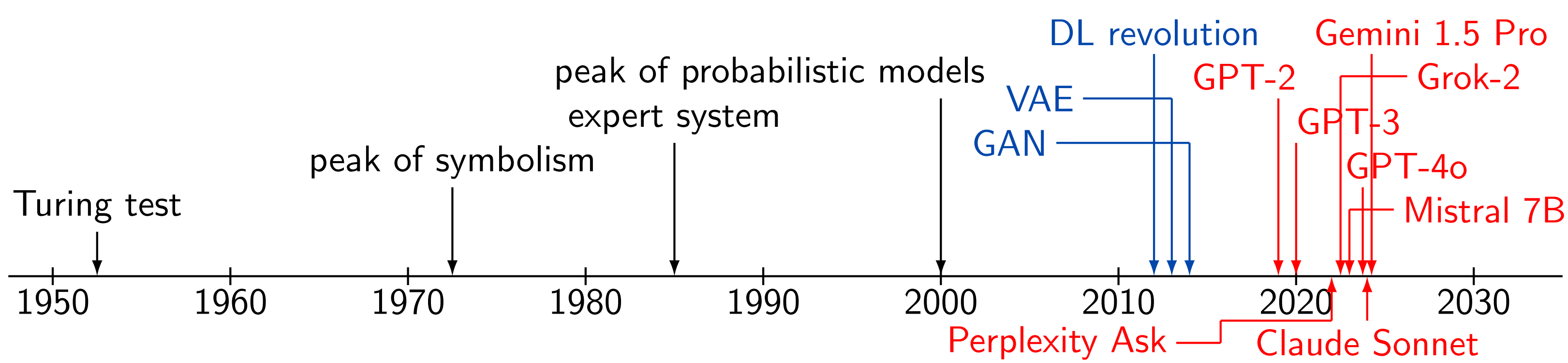
Rise of deep learning & generative models

- 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]

$$\boxed{\mathcal{X}} \xrightarrow{q_\phi(z|x)} \boxed{\mathcal{Z}_0} \xrightarrow{p_\theta(x|z)} \boxed{\mathcal{X}}$$

- 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*

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

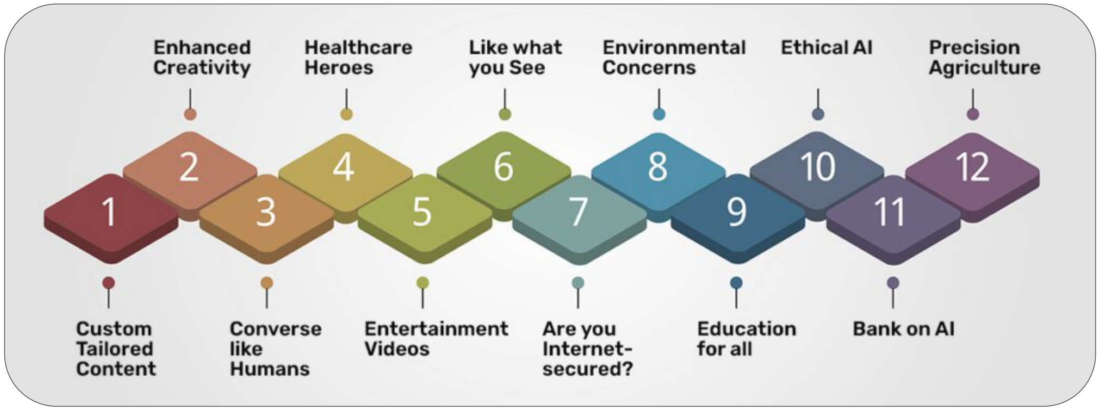
  where $d(\cdot, \cdot)$ distance measure between probability distributions
  - previous sequence: $x_{t-1}, x_{t-2}, \ldots$
  - next token: x_t
- p_θ represented by (extremely) complicated model
  - $e.g.$, containing multi-head & multi-layer Transformer architecture inside
- model parameters, $e.g.$,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

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

Current Trend & Future Perspectives

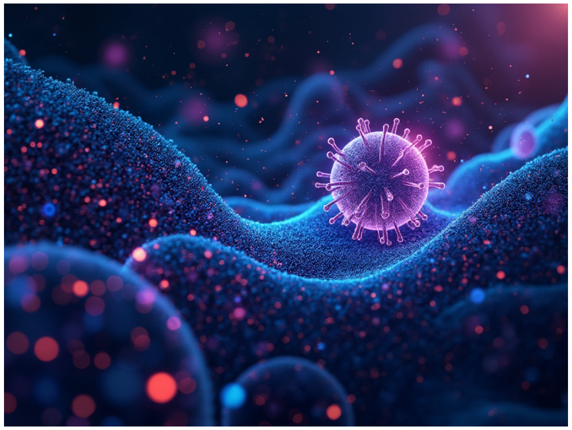
Current trend of genAI

- 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



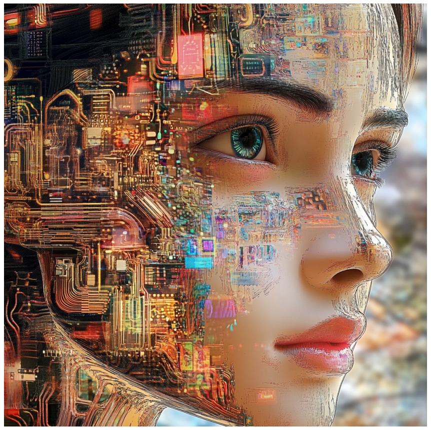
Industry & business impacts

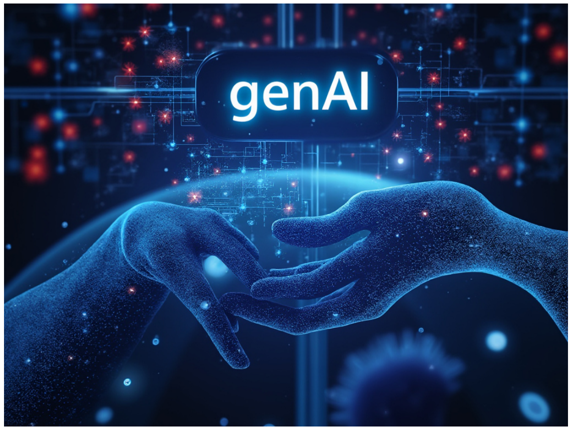
- how genAI is transforming industries
  - creative industries - content creation - advertising, gaming, film
  - life science - enhance research, drug discovery & personalized treatments
  - finance - automating document generation, risk modeling & fraud detection
  - manufacturing & Design - rapid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





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Thank You