[KIST AI Policy Seminar]
Cross-Industry AI Innovation - Silicon Valley's Model for AI-Driven Technology Transfer Across Industries

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About Speaker

- *Co-Founder & CTO @ Erudio Bio, San Jose & Novato, CA, USA*
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- *KFAS-Salzburg Global Leadership Initiative Fellow @ Salzburg Global Seminar*, Salzburg, Austria
- Technology Consultant @ Gerson Lehrman Gruop (GLG), NY, USA
- *Co-Founder & CTO / Head of Global R&D & Chief Applied Scientist / Senior Fellow @ Gauss Labs, Inc., Palo Alto, CA, USA* *2020 ∼ 2023*

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

Highlight of Career Journey

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

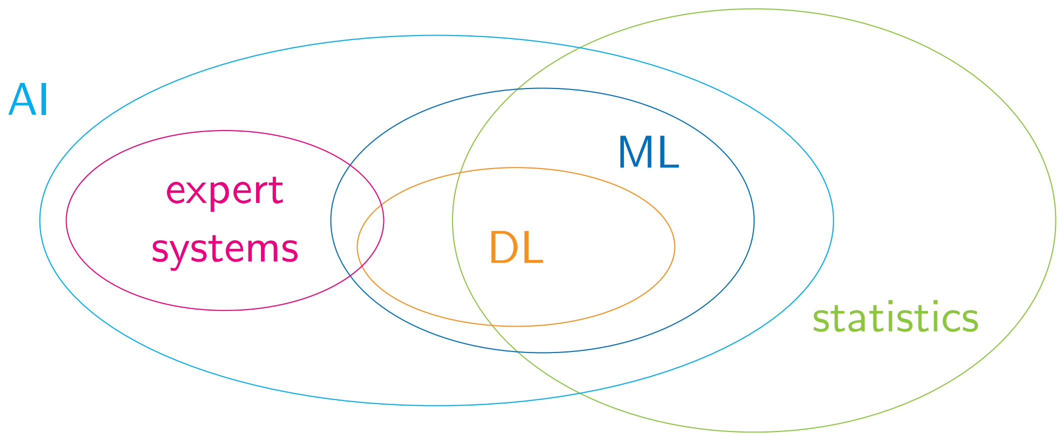
Today

Artificial Intelligence

Definition and History

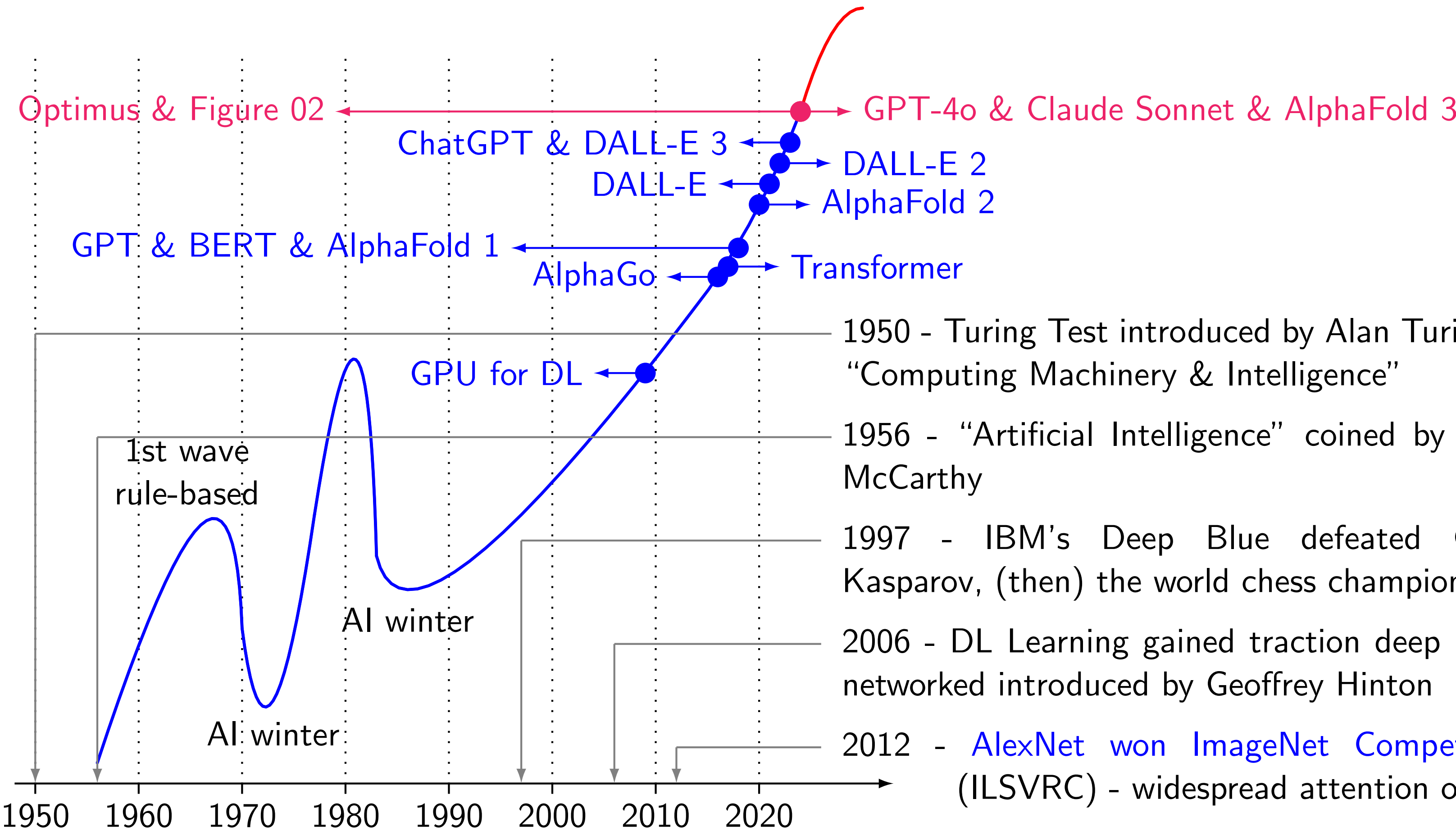
Definition & relation to other technologies

- 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



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

1956 - "Artificial Intelligence" coined by John McCarthy

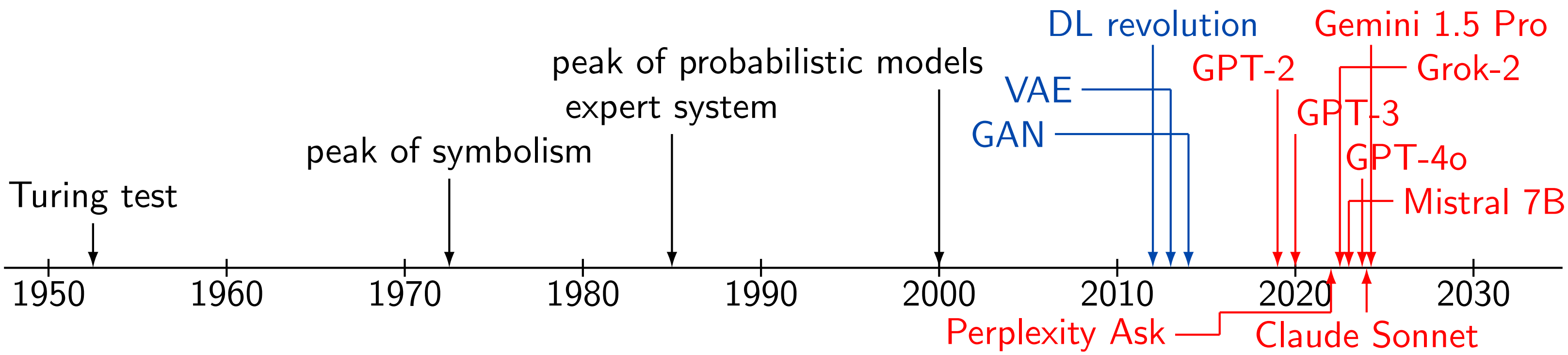
1997 - IBM's Deep Blue defeated Garry Kasparov, (then) the world chess champion

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

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

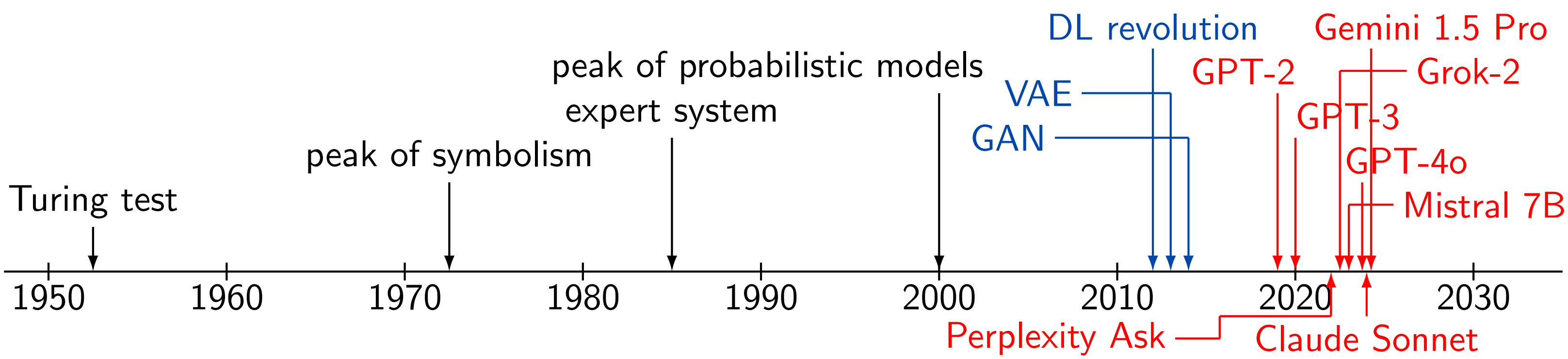
Birth of AI - early foundations & precursor technologies

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



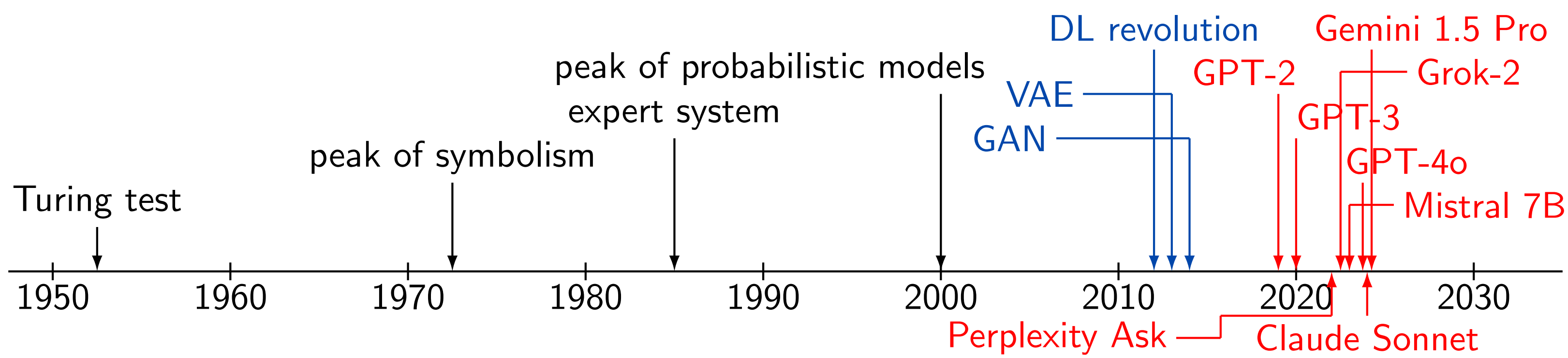
Rule-based systems & probabilistic models

- 1980s $\sim$ 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



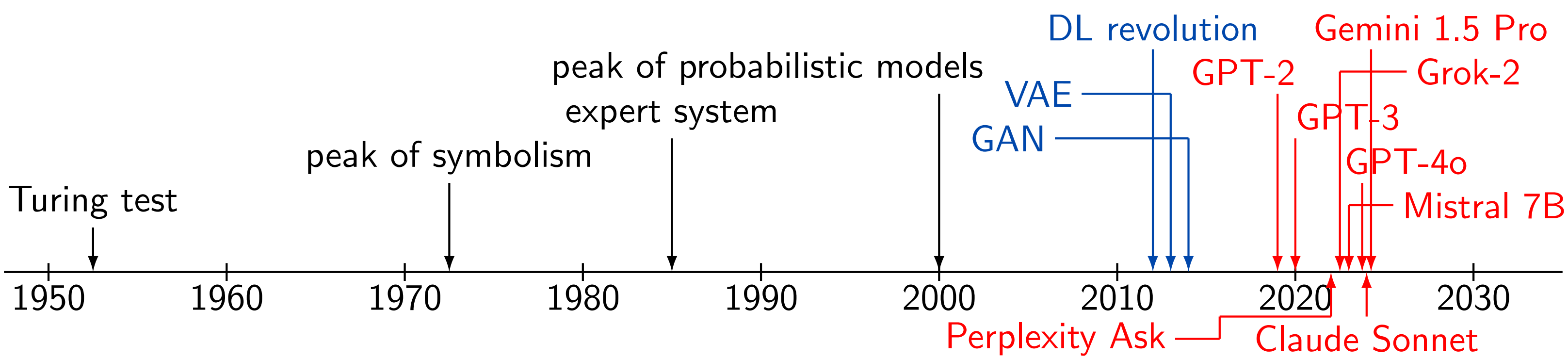
Rise of deep learning & generative models

- 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 ∼ 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

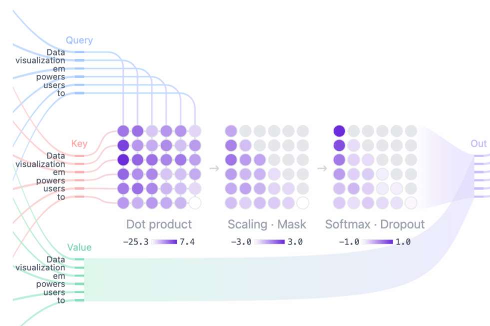
Deep learning revolution

- 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

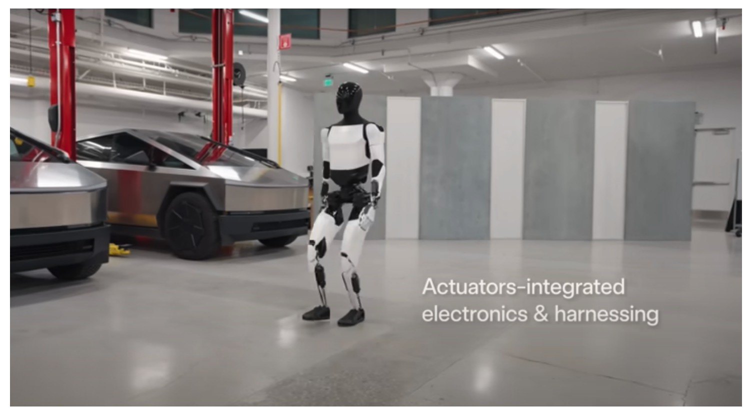
- 2017 – 2018 - Transformers & NLP breakthroughs[3]
  - *Transformer (e.g., BERT & GPT) revolutionized NLP*
  - major advancements in, *e.g.*, machine translation & chatbots
- 2020 - AI in healthcare – AlphaFold & beyond
  - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting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

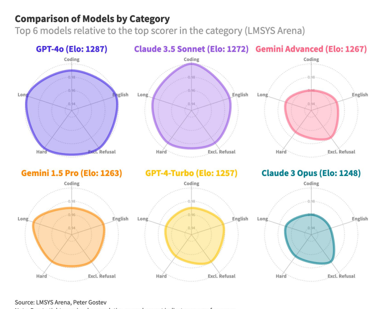
Lots of breakthroughs in AI technology and applications in 2024

- 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*



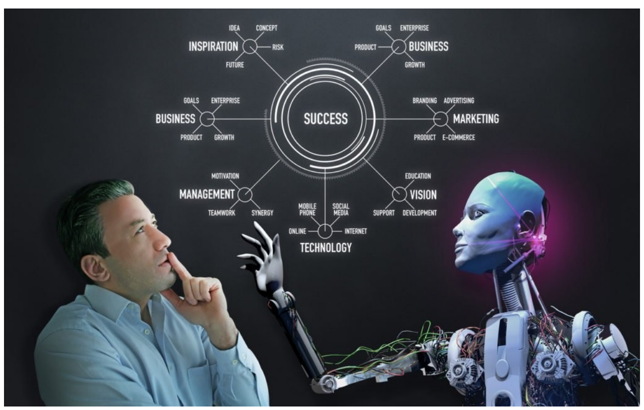
Major AI Breakthroughs in 2025

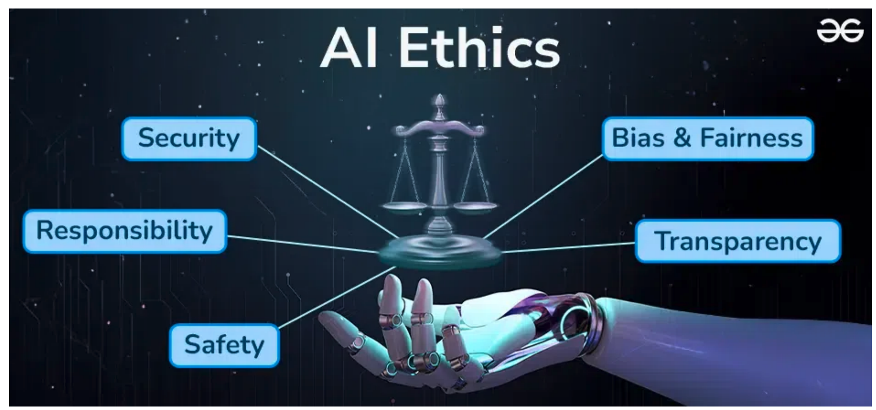
- next-generation foundation models
  - GPT-5 and Claude 4 demonstrate emergent reasoning abilities
  - open-source models achieving parity with leading commercial systems from 2024
- hardware innovations
  - NVIDIA's Blackwell successor architecture delivering 3-4x performance improvement
  - AMD's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

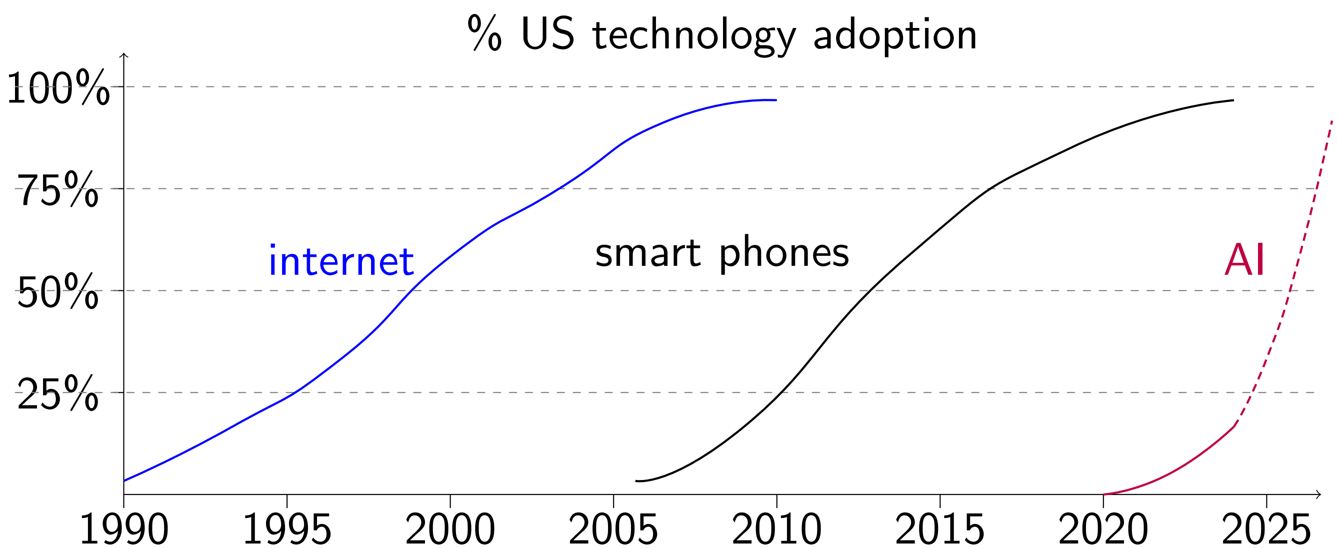




Measuring AI's Ascent

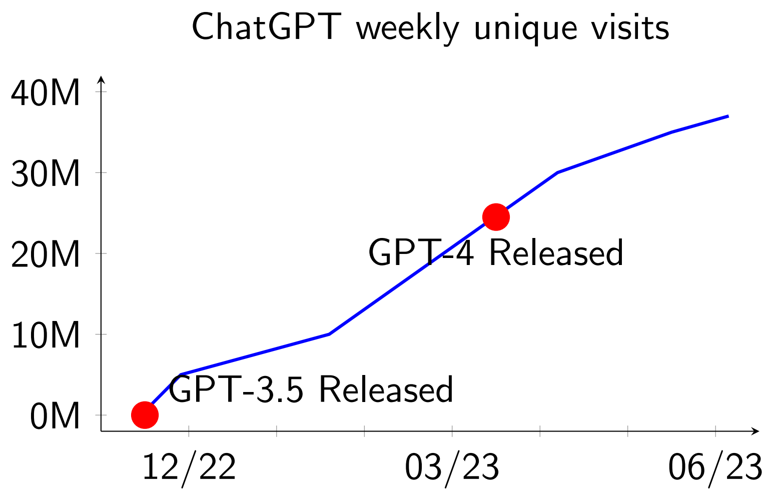
Where are we in AI today?

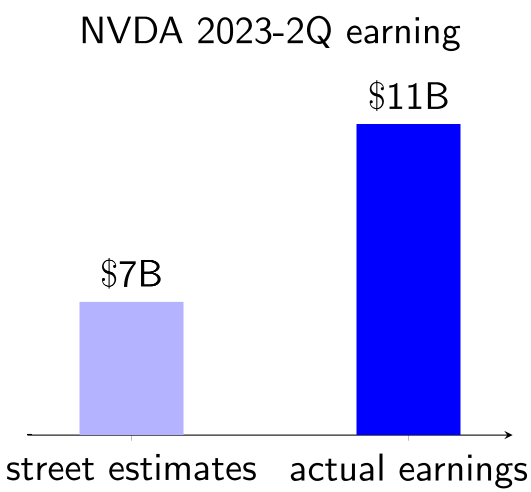
- sunrise phase - currently experiencing dawn of AI era with significant advancements and increasing adoption across various industries
- early adoption - in early stages of AI lifecycle with widespread adoption and innovation across sectors marking significant shift in technology's role in society



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]

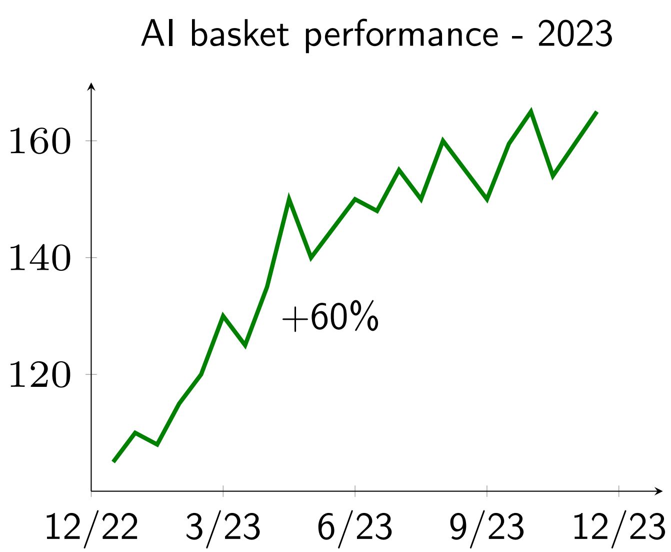


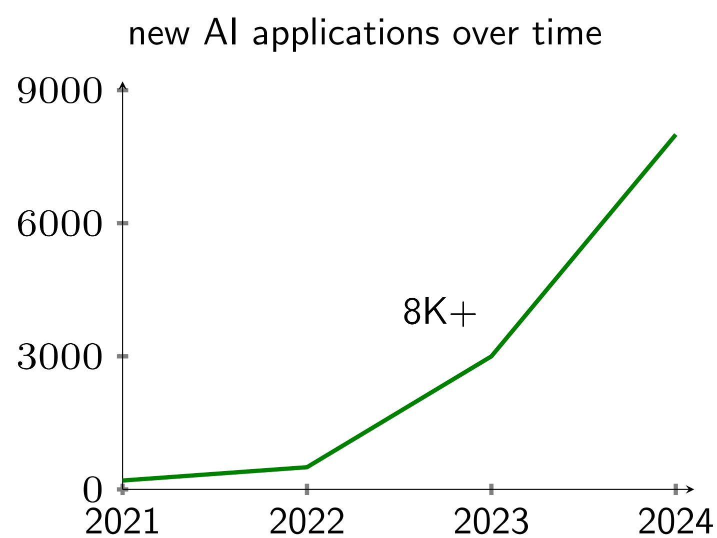


[4] source - Bloomberg

Explosion of AI ecosystems - AI stock market

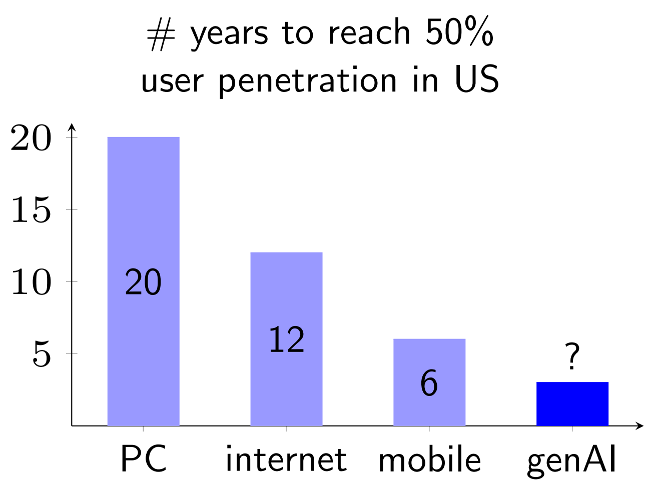
- *AI investment surge in 2023 - portfolio performance soars by 60%*
  - AI-focused stocks significantly outpaced traditional market indices
- *over 8,000 new AI applications* developed in last 3 years
  - applications span from healthcare and finance to manufacturing and entertainment

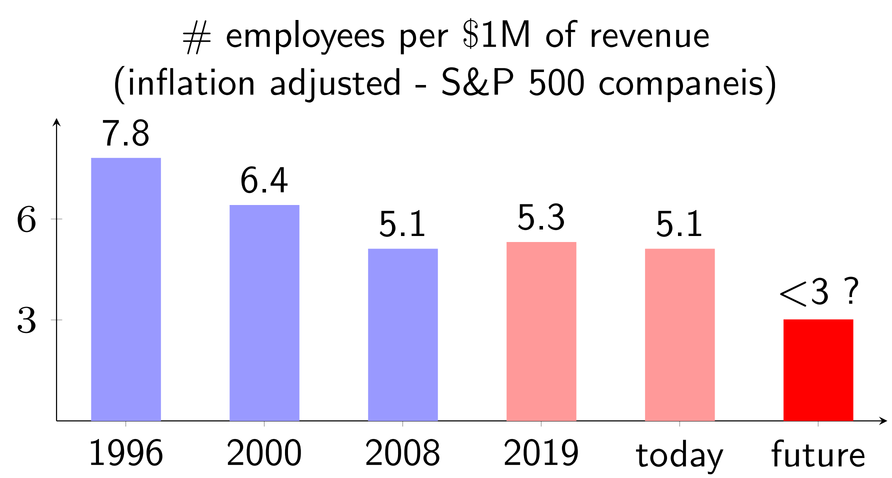




AI's transformative impact - adoption speed & economic potential

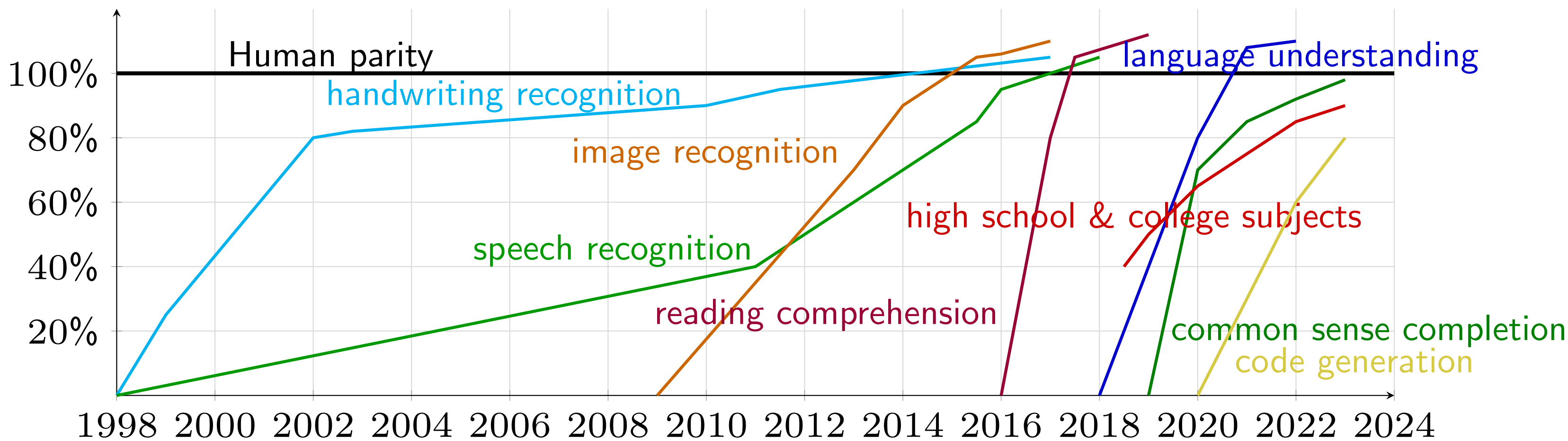
- adoption - has been twice as fast with platform shifts suggesting
  - increasing demand and readiness for new technology improved user experience & accessibility
- AI's potential to drive economy for years to come
  - 35% improvement in productivity driven by introduction of PCs and internet
  - greater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





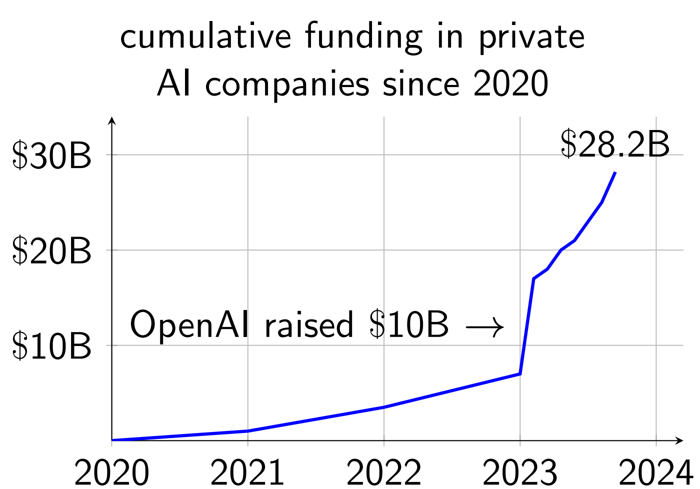
AI getting more & more faster

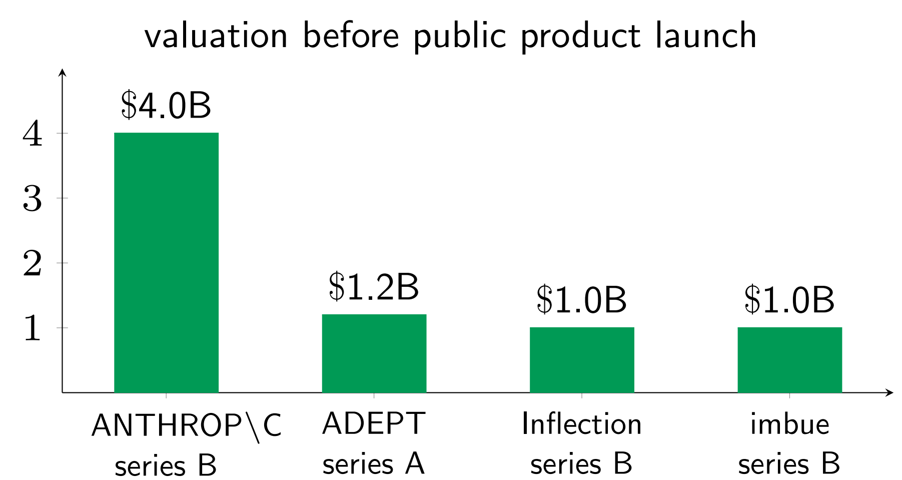
- steep upward slopes of AI capabilities highlight accelerating pace of AI development
  - period of exponential growth with AI potentially mastering new skills and surpassing human capabilities at ever-increasing rate
- closing gap to human parity - some capabilities approaching or arguably reached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



Massive investment in AI

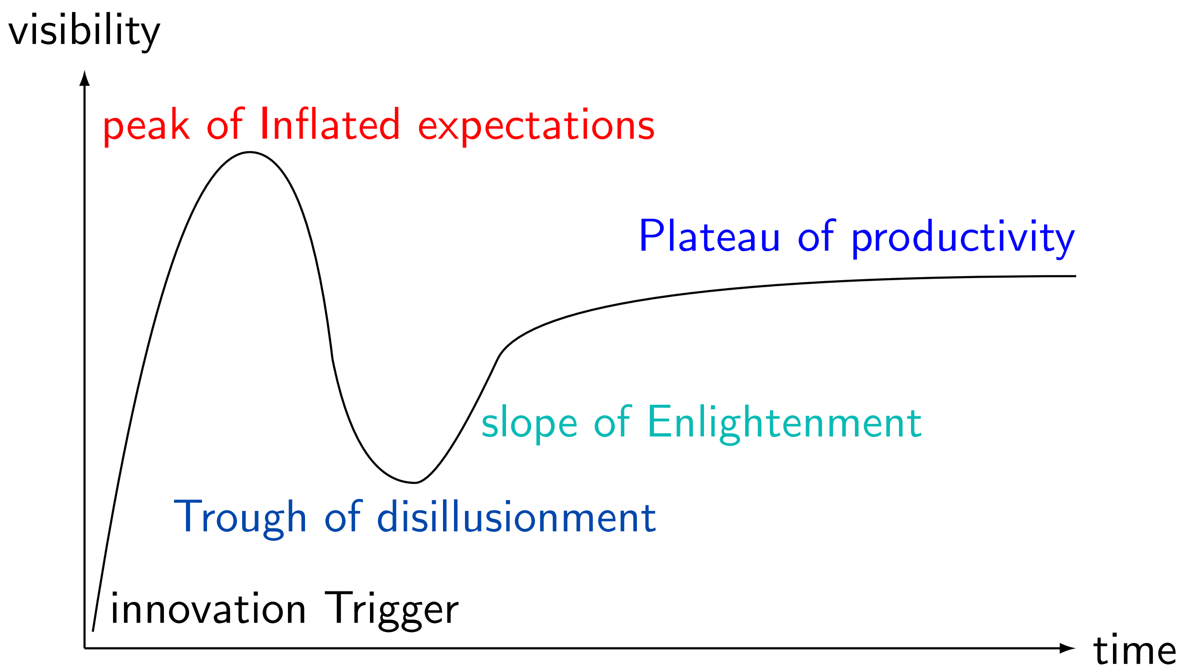
- *explosive growth* - cumulative funding skyrocketed reaching staggering \$28.2B
- OpenAI - significant fundraising (=\$10B) fueled rapid growth
- *valuation surge* - substantial valuations even before public products for stella companies
- *fierce competition for capital* among AI startups driving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





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

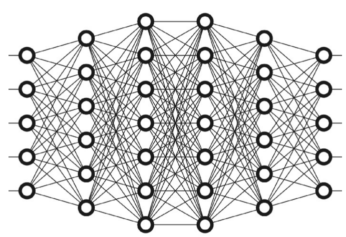
Yes & No

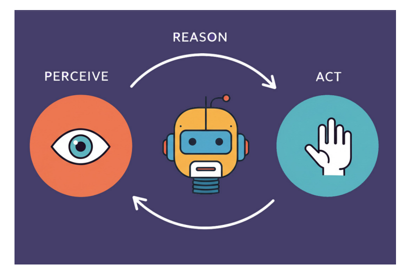
characteristics of hype cycles	speaker's views
value accrual misaligned with investment	• OpenAI still operating at a loss; business model *still* not clear • gradual value creation across broad range of industries and technologies (*e.g.*, CV, LLMs, RL) unlike fiber optic bubble in 1990s
overestimating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

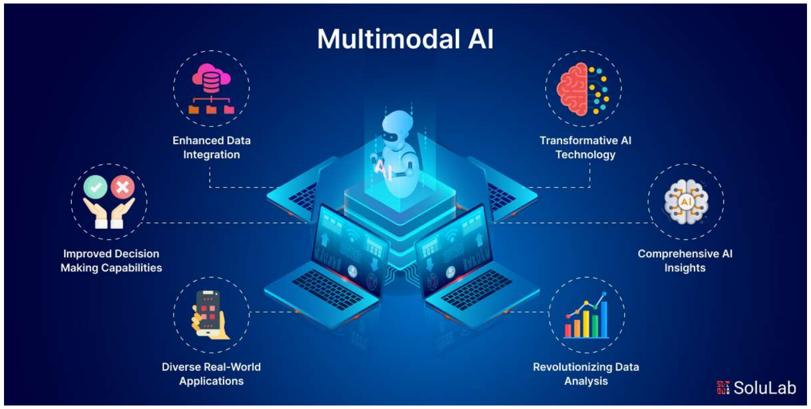
- 2010 $\sim$ Big Data
- 2012 $\sim$ Deep Learning
- 2017 $\sim$ Transformer - Attention is All you need!
- 2022 $\sim$ LLM & genAI
- 2024 $\sim$ AI Agent (Agentic AI)

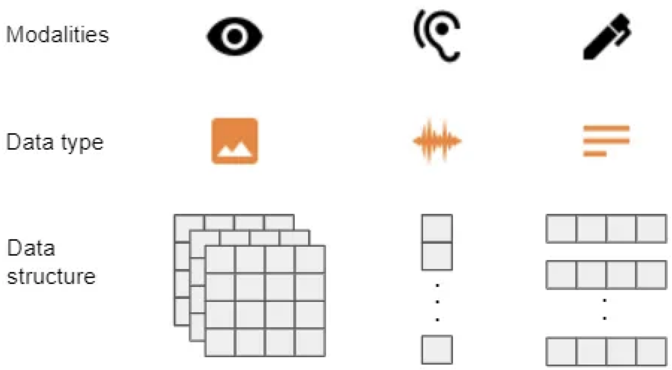




Multimodal learning

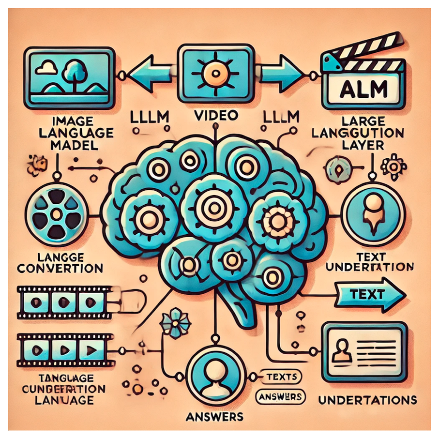
- understand information from multiple modalities, *e.g.*, text, images, audio, video
- representation learning methods
  - combine multiple representations or learn multimodal representations simultaneously
- applications
  - images from text prompt, videos with narration, musics with lyrics
- collaboration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

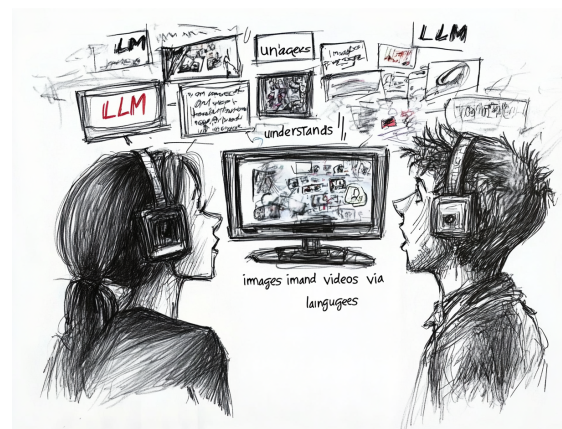




Implications of success of LLMs

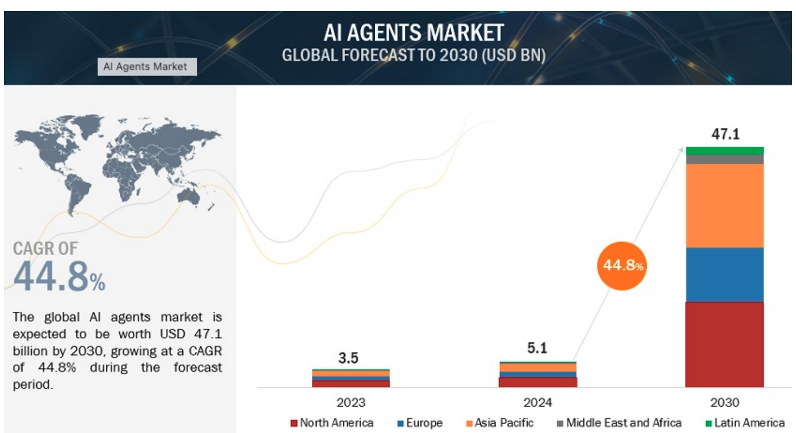
- many researchers change gears towards LLM
  - from computer vision (CV), speach, music, video, even reinforcement learning
- *LLM is not only about NLP . . .* humans have . . .
  - evolved to optimize natural language structures for eons
  - handed down knowledge using *this natural languages* for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

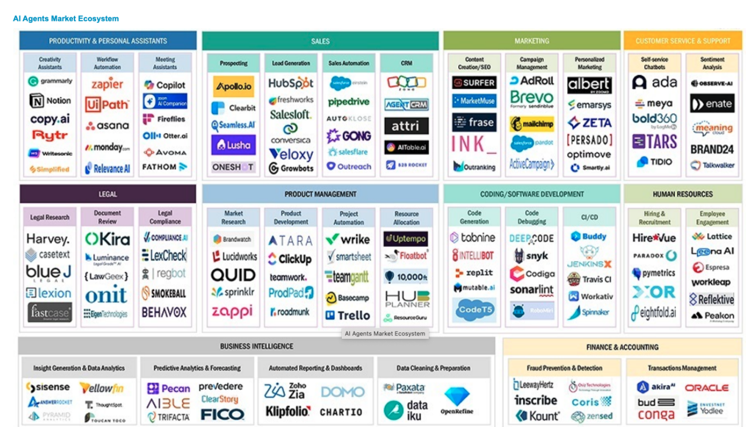




Multimodal AI (mmAI)

- 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



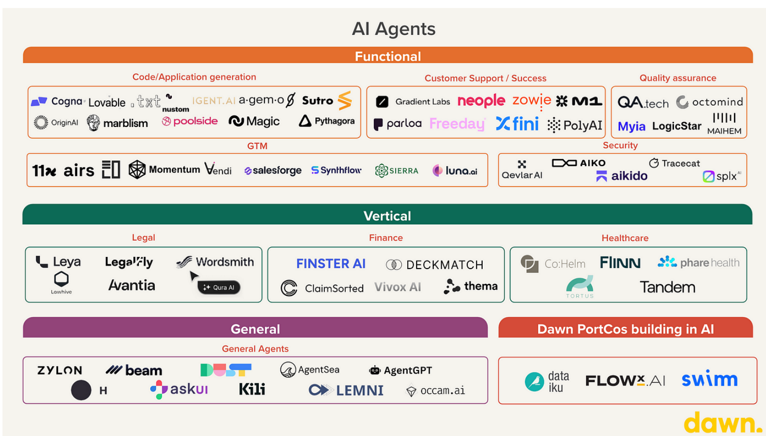


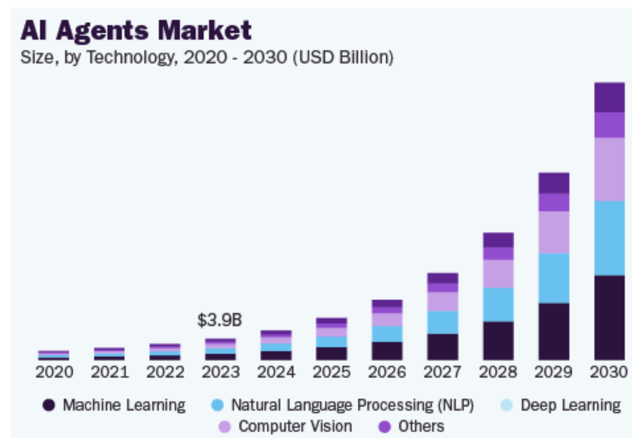
mmAI Technology

- 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





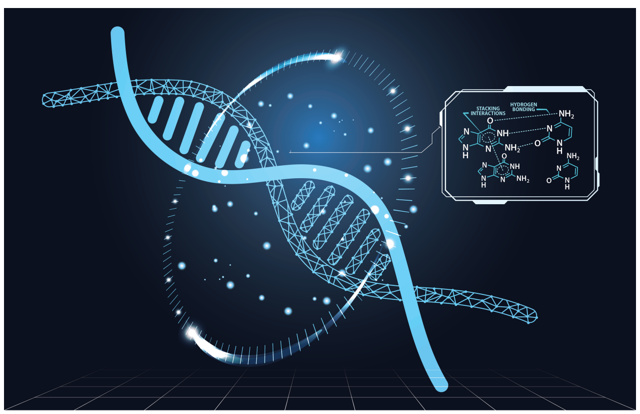
AI agents - Present & Future

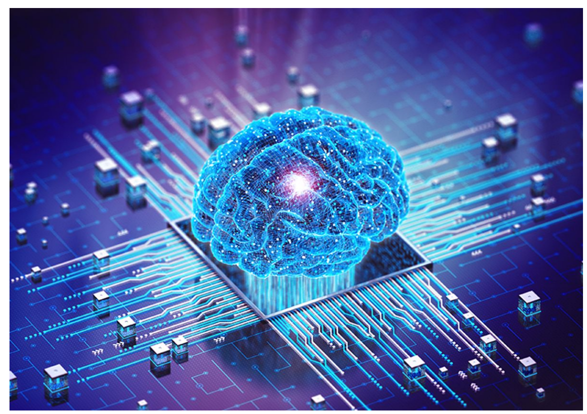
- emerging applications
  - scientific research - agents analyzing & running experiments & generating hypotheses
  - creative collaboration - AI partners in design & art combining multiple mediums
  - environmental monitoring - processing satellite sensor data for climate analysis
  - healthcare - enhanced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

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





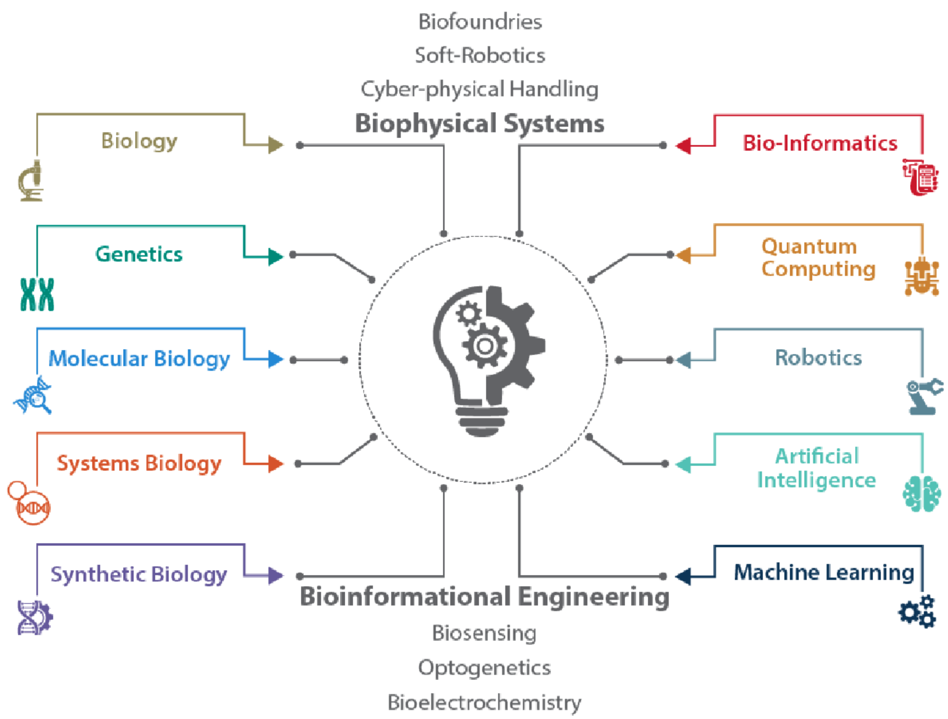
Biotech

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]

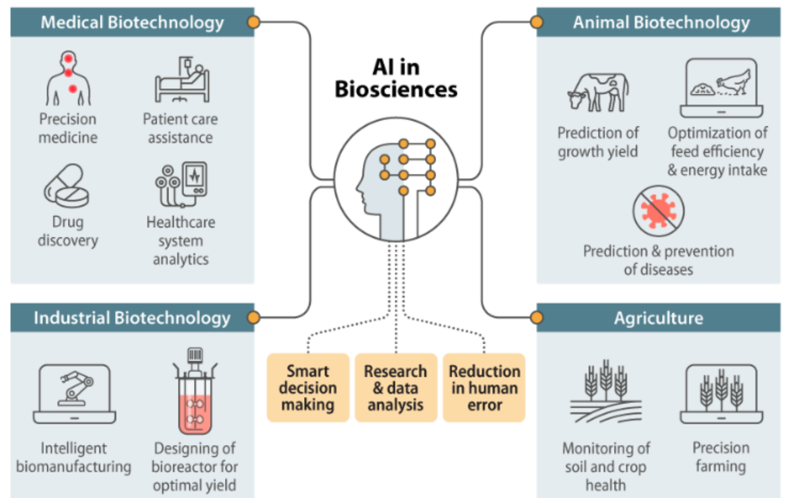


Convergence of AI and biological design

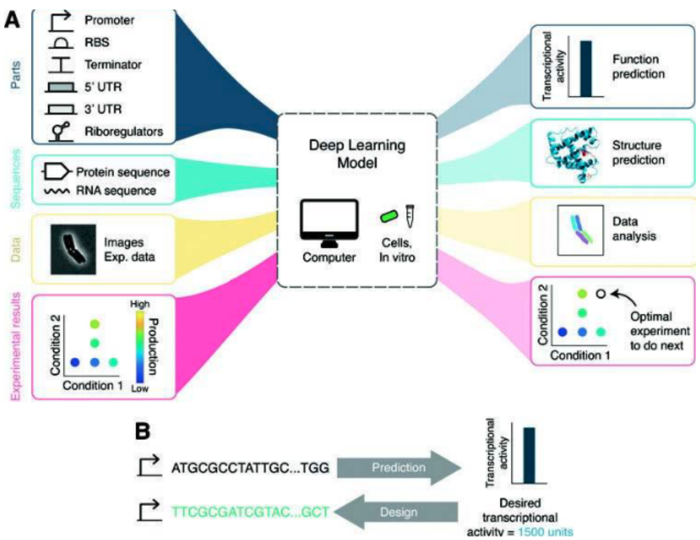
- AI & biological sciences converging [BKP22]
  - each building upon the other's capabilities for new research and development across multiple areas
- Demis Hassabis, CEO & cofounder of DeepMind, said of biology [Toe23]

  > ". . . 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



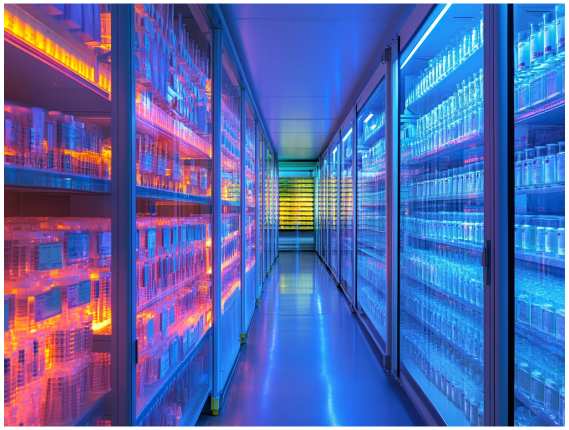
- AI, essential to analyzing exponential growth of genetic sequence data

  > "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



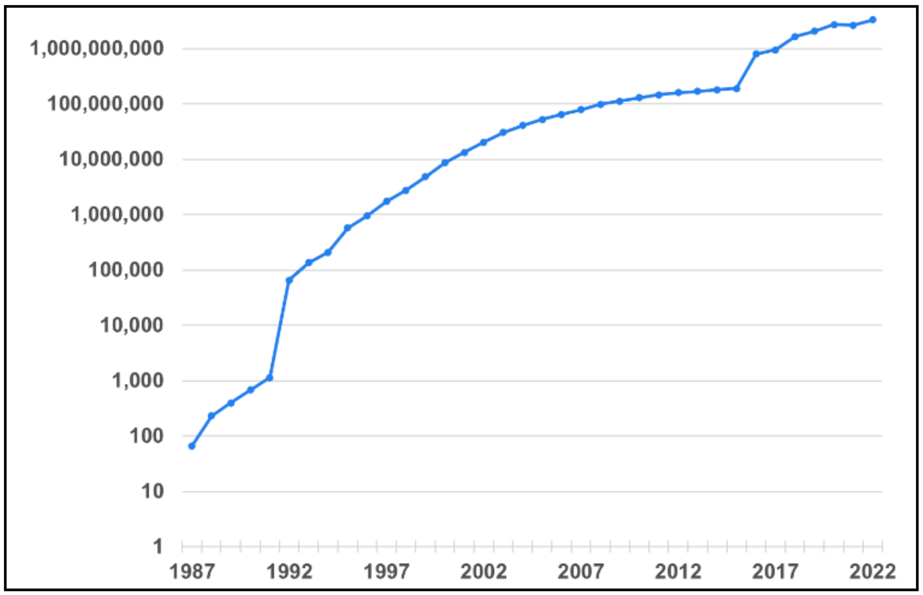
Rapid growth of biological data

- 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

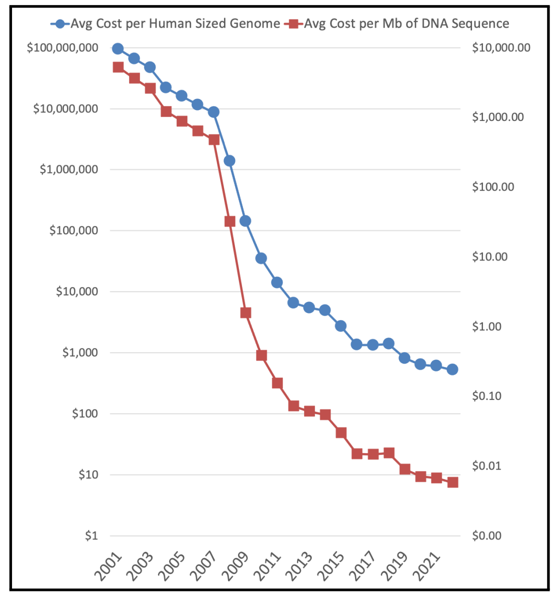
Volume and sequencing cost of DNA over time

- 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



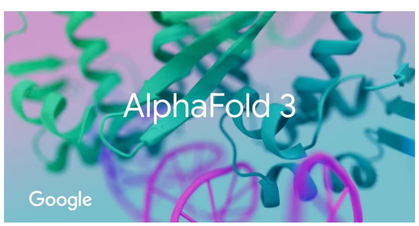
Bio data availability and bias

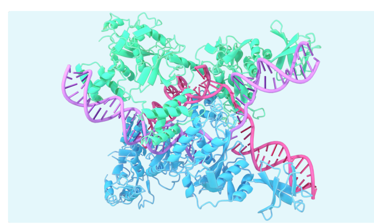
- US National Security Commission on Artificial Intelligence (NSCAI) recommends
  - US fund and prioritize development of a biobank containing *"wide range of high-quality biological and genetic data sets securely accessible by researchers"*
  - establishment of database of broad range of human, animal,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

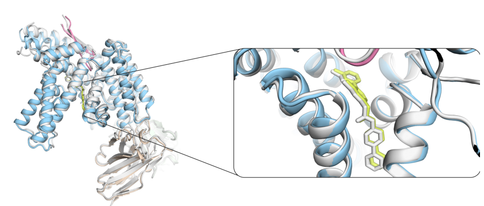
Emerging Trends in Biotech

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 $\rightarrow$ AlphaFold 2 (2020) - attention-based NN solving protein folding "in principle" $\rightarrow$ 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





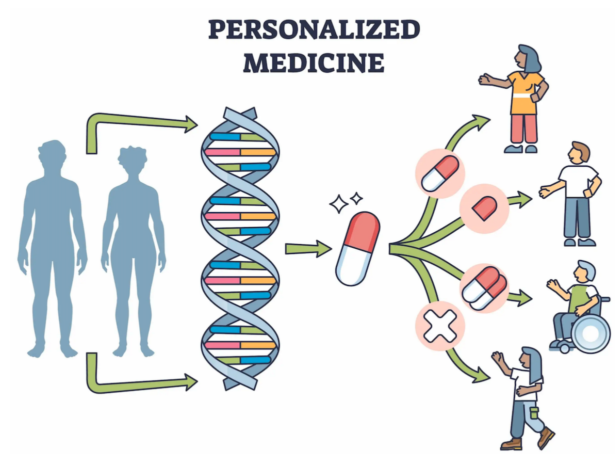


AlphaGo

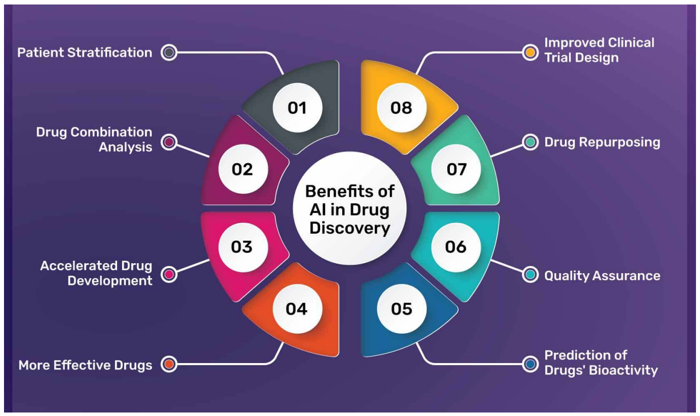
- Go board marked with 19×19 grid - $(19 \times 19)! = 361! \approx 1.44 \times 10^{768}$
  1437923258884890654832362511499863354754907538644755876127282765299227795534389618856841908003141196
  0714137944348905859683839682333043216077138088370565578796691924861827097800358990211005794501073330
  5079262777172275041226808677528136885057526541812043502150623466302643442673632627092764643302557772
  2695595343233942204301825548143785112222186834487969871267194205609533306413935710635197200721473378
  7338269803085351043174203653673779887217565513450041291061650506154496265581102824241428406627054585
  5623101563752892899924857388316647687165212001536218913733713768261861456295440900774337589490771443
  9917299937133680728459000034496420337066440853337001284286412654394495050773954560000000000000000000
  000000000000000000000000000000000000000000000000000000000000000000000
- 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

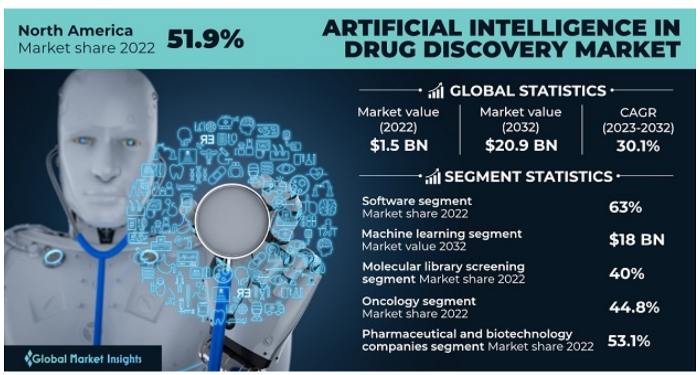
Personalized medicine

- *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.

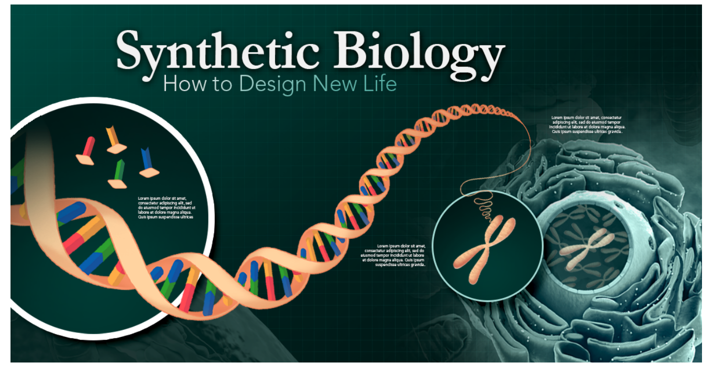
Synthetic biology

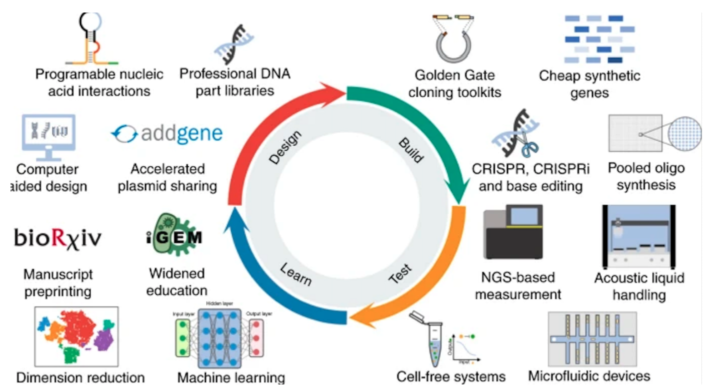
- use AI for gene editing, biomaterial production and synthetic pathways

- combine principles of biology and engineering to design and construct new biological entities

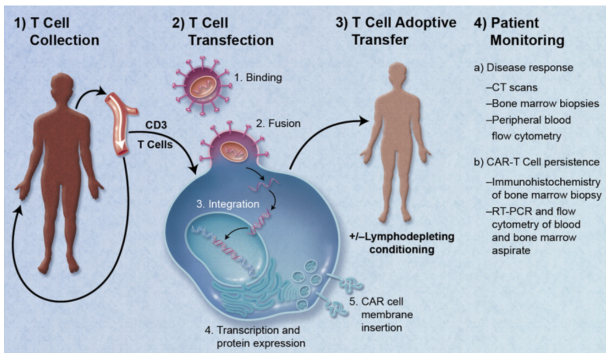
- AI optimizes synthetic biology processes from designing genetic circuits to scaling up production

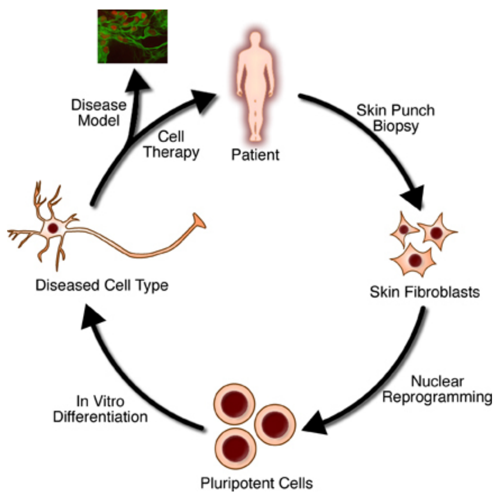
- company - Ginkgo Bioworks uses AI to design custom microorganisms for applications ranging from pharmaceuticals to industrial chemicals





Regenerative medicine

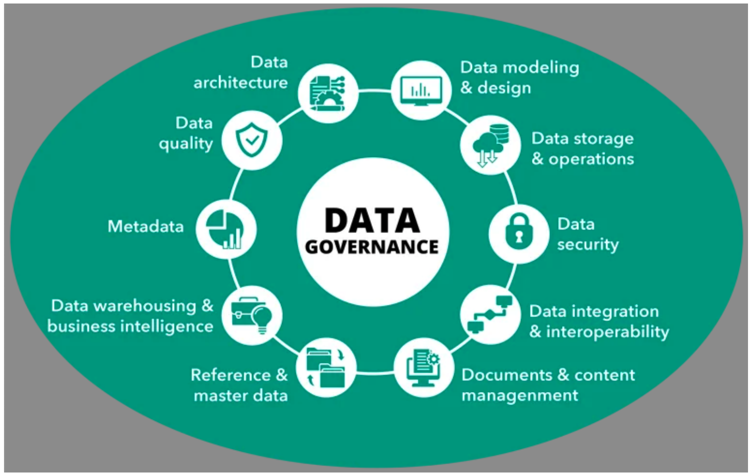




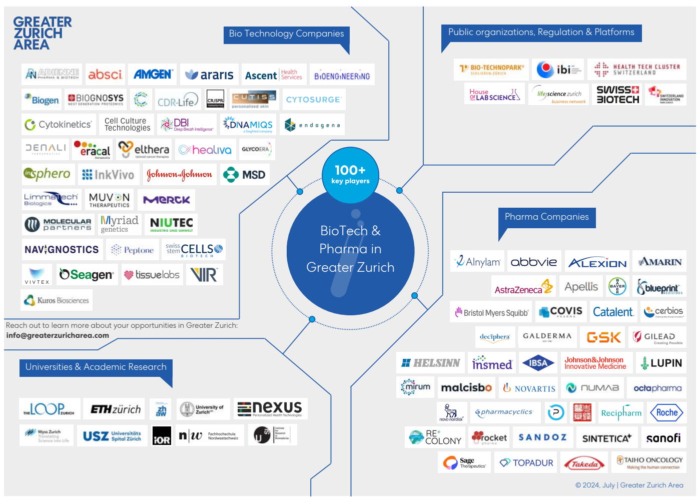
- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo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

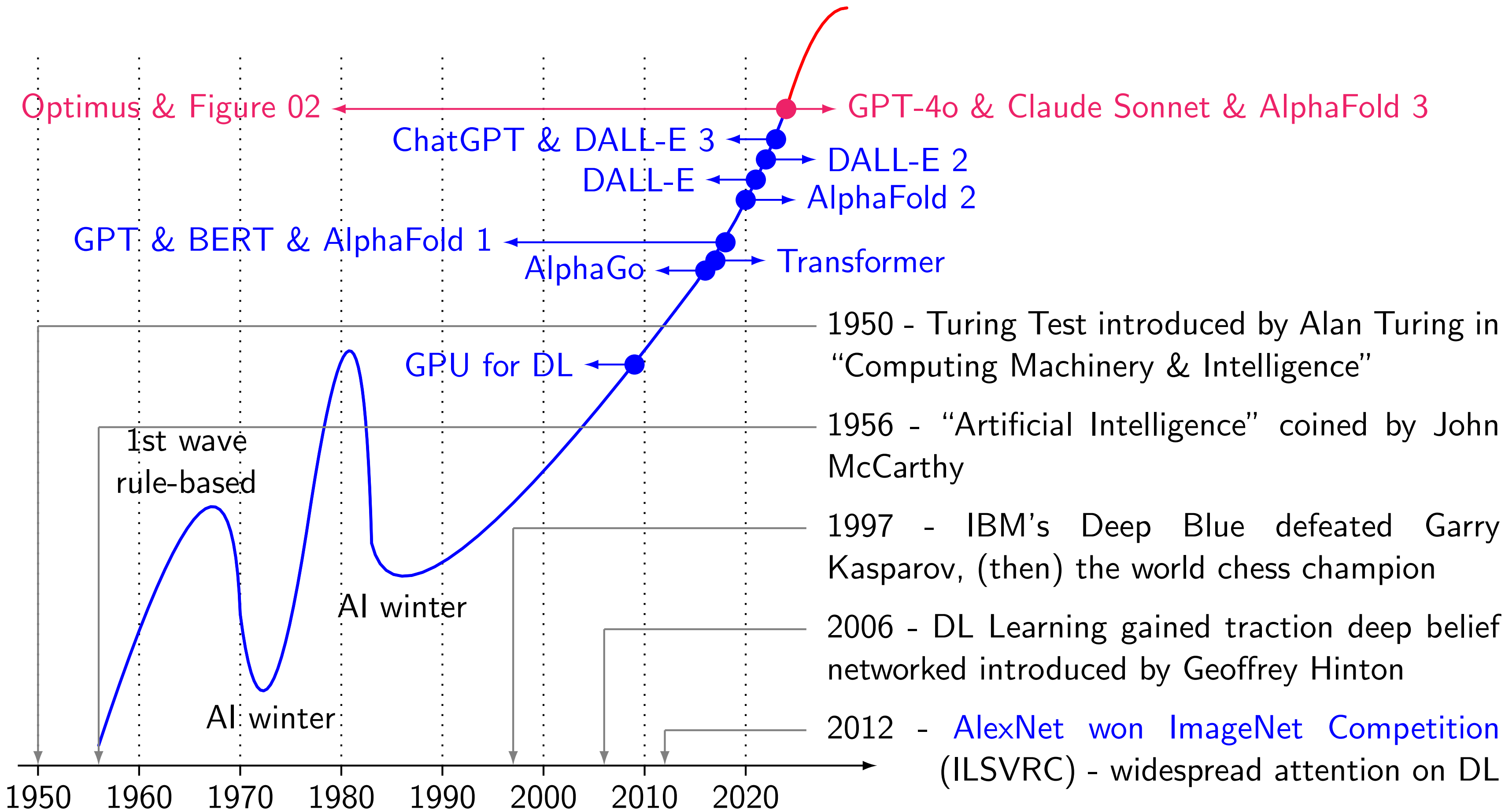
Appendices

Silicon Valley's Cultural Engine of Innovation and Disruption

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

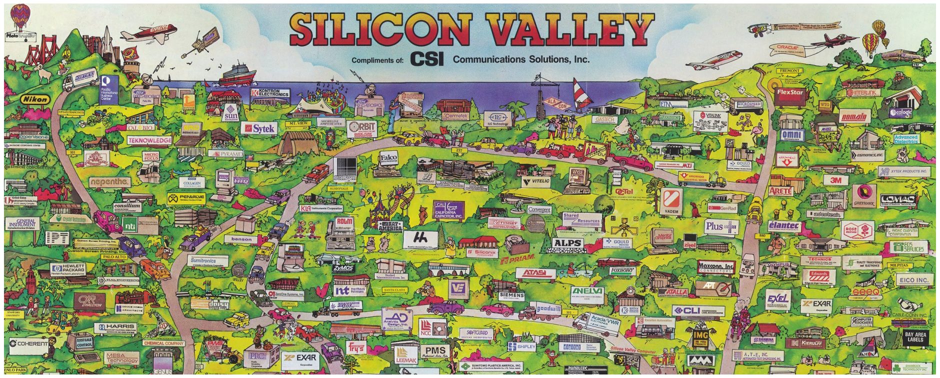
- Samsung Semiconductor, Inc.
  - inception into industry from academia, the world's best memory chip maker!
- Amazon.com, Inc.
  - experience so-called Silicon Valley big tech culture and technology
  - set tone for my future career trajectory!
- Gauss Labs, Inc.
  - found & operate AI startup, shaping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

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



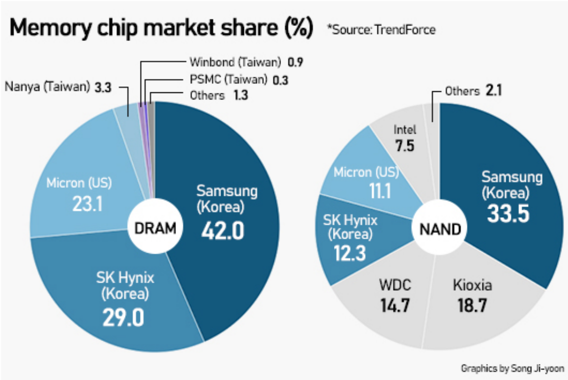
Innovation ecosystem of Silicon Valley

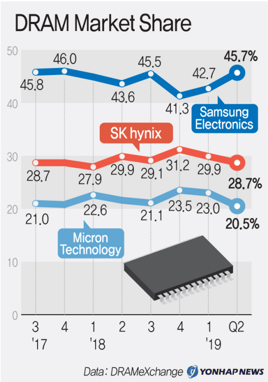
- key characteristics
  - risk-taking culture, *trust* in technology → *genuine* respect for engineers and scientists
  - easy access to huge capital - VCs, angel investors alike
  - talent density - engineers, researchers, scientists, entrepreneurs, PMs, TPMs, . . .
  - diversity, "collision density"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



Case study: Amazon - amazing differentiators of big techs

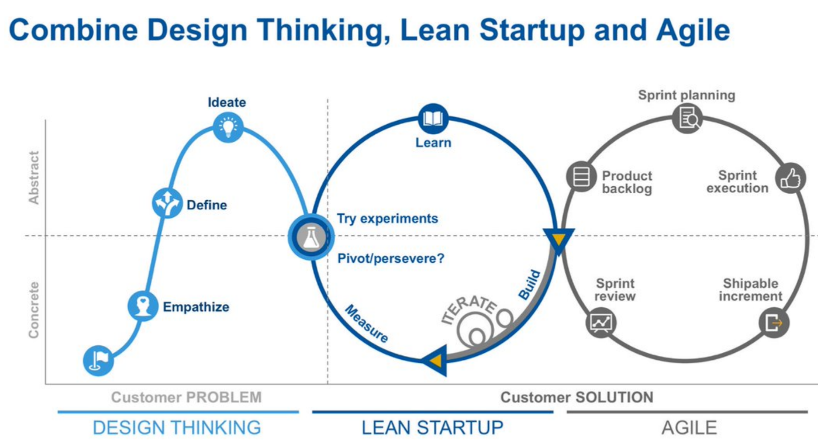
- Amazon's culture & leadership principles
  - customer obsession as driver of innovation
  - high standards & ownership culture, disagree & commit
  - bias for action and long-term thinking - sounds contradictory?
  - mechanisms like "two-pizza teams" & "Day One" for (or rather despite) scalability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

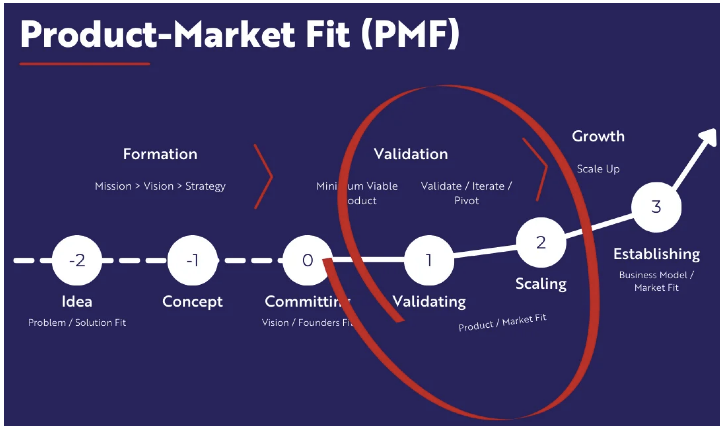




Founding and scaling startups

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





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

Industrial AI

Industrial AI (inAI)

- inAI (collectively) refers to AI technology & software and their products developed for
  - *customer values creation, productivity improvement, cost reduction, production optimization, predictive analysis, insight discovery*

  in industries such as
  - *semiconductor, steel, oil & gas, cement, and other various manufacturing industries*

  (unlike general AI, which is frontier research discipline striving to achieve human-level intelligence)

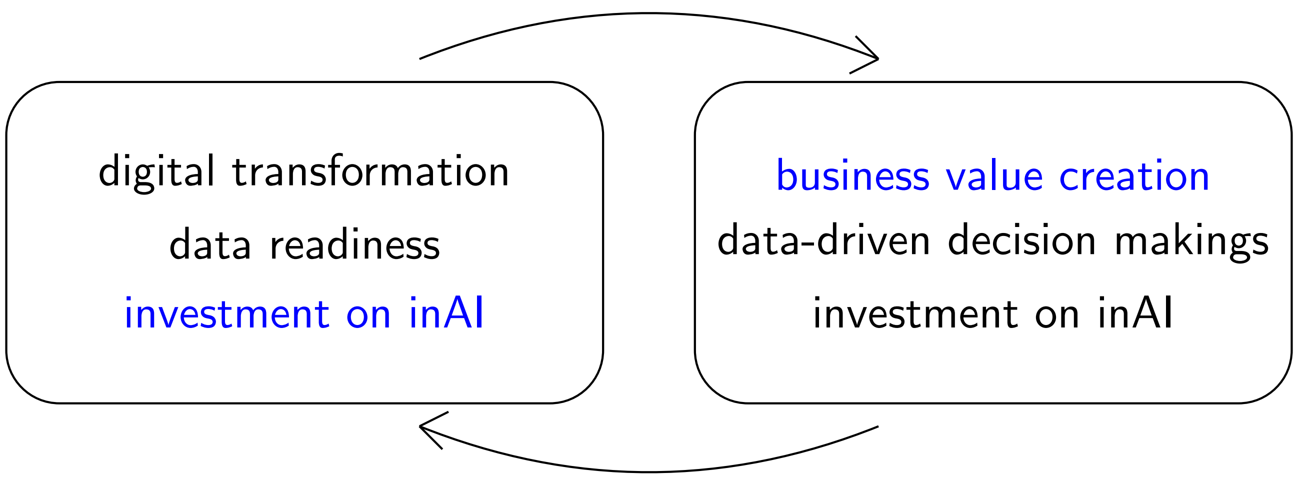
inAI fields

- product
  - product design & innovation, adaptability & advancement, product quality & validation, design for reusability & recyclability, performance optimization
- production process
  - *production quality,* process management, inter-process relations, process routing & scheduling, process design & innovation, *traceability, predictive process control*
- machinery & equipment
  - *predictive maintenance, monitoring & diagnosis,* component development, *ramp-up optimization,* material consumption prediction
- supply chain
  - supply chain monitoring, material requirements planning, customer management, supplier management, logistics, reusability & recyclability

Characteristics of inAI

Vicious (or virtuous) cycle

- integration of inAI with customers' business creates monetary values and encourages data-driven decisions
- however, to do so, digital transformation with data-readiness is MUST-have
- created values, in turn, can be invested into infrastructure required for digital transformation and success of inAI!

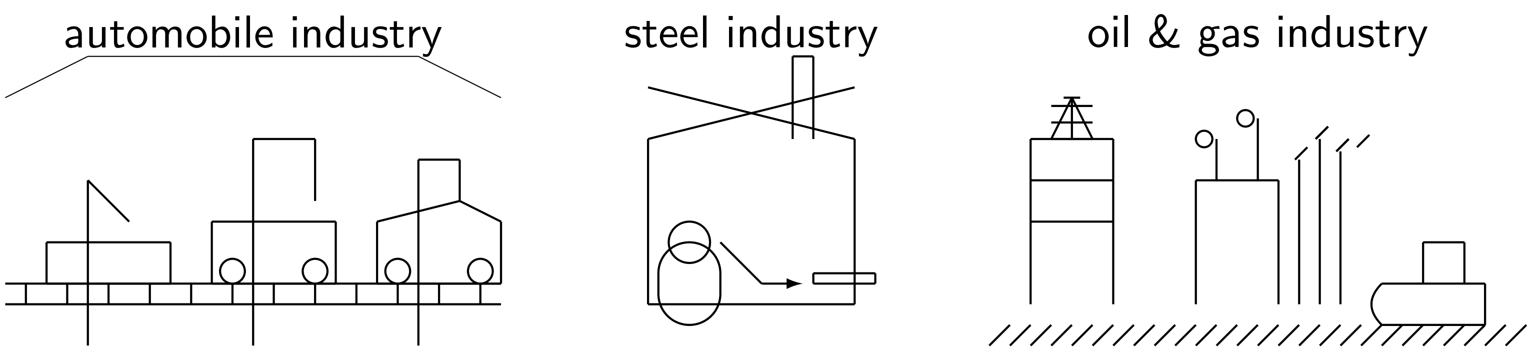


Data-centric AI

- unlike many ML disciplines where foundation models do generic representation learning, $i.e.$, learn universal features
- each equipment has (gradually) different data characteristics, hence need data-centric AI

  ". . . need 1,000 models for 1,000 problems" - Andrew Ng

  - data-centric AI - discipline of systematically engineering the data used to build AI system



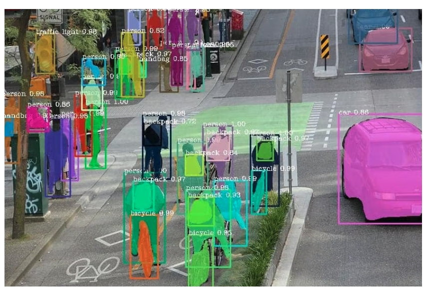
Challenging data characteristics

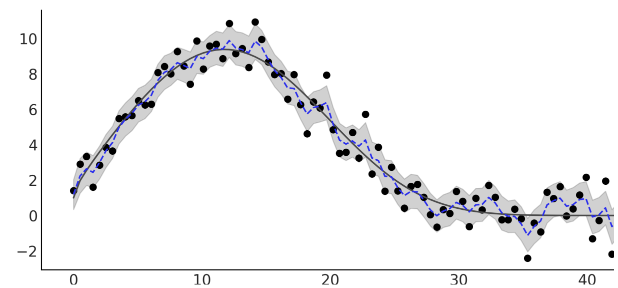
- huge volume
- data multi-modality
- high velocity requirement
- very fat data
- sever data shift & drift (in many cases)
- label imbalance
- data quality

Manufacturing AI

MLs in manufacturing AI (manAI)

- *image data* - huge amount of image data measured and inspected
  - SEM/TEM images, wafer defect maps, test failure pattern maps [5]
  - → semantic segmentation, defect inspection, anomaly detection
- *time-series (TS) data* - *all the data* coming out of manufacturing is TS
  - equipment sensor data, process times, various measurements, MES data [6]
  - → regression, anomaly detection, semi-supervised learning, Bayesian inference





[5] SEM: scanning electron miscroscope, TEM: transmission electron miscroscope
[6] MES: manufacturing execution system

CV ML in manAI

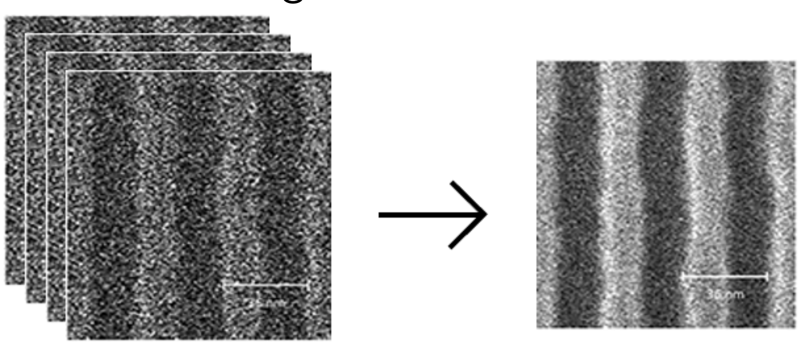
Computer vision ML in manAI

- measurement and inspection (MI)
  - metrology - measurement of critical features
  - inspection - defect inspection, defect localization, defect classification
  - failure pattern analysis
- applications
  - automatic feature measurement
  - anomaly detection
  - defect inspection

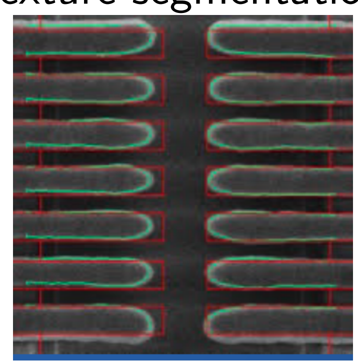
Automatic feature measurement

- ML techniques
  - image enhancement (denoising)
  - texture segmentation
  - repetitive pattern recognition
  - automatic measurement

image enhancement



texture segmentation



auto-measurement

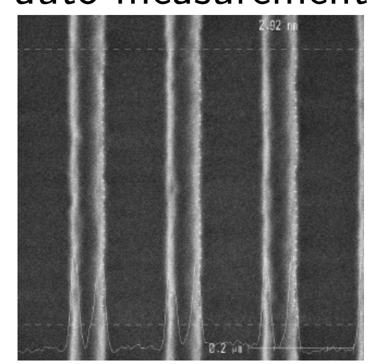
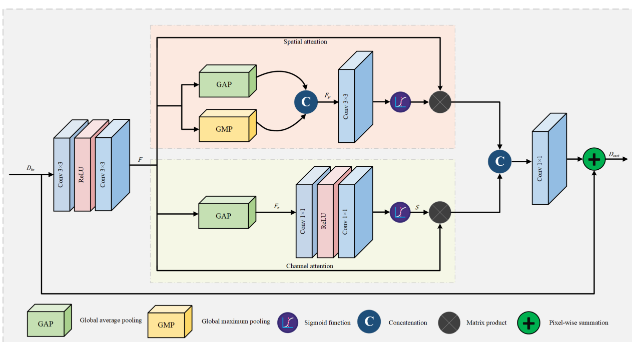


Image enhancement

- image enhancement techniques
  - general supervised denoising using DL
  - blind denoising using DL - remove noise without prior knowledge of noise adapting to various noise types
  - super-resolution - upscale low-resolution images, add realistic details for sharper & higher-quality images



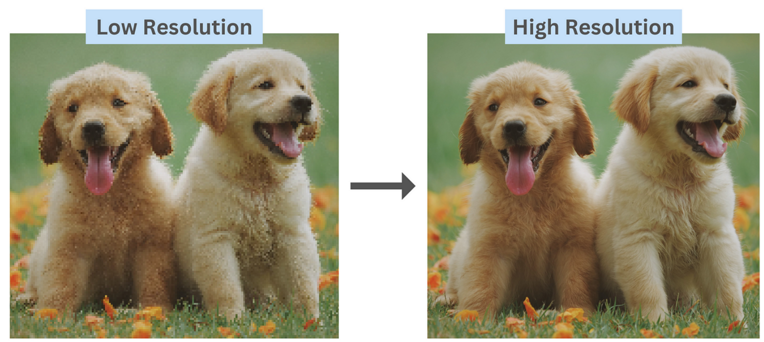
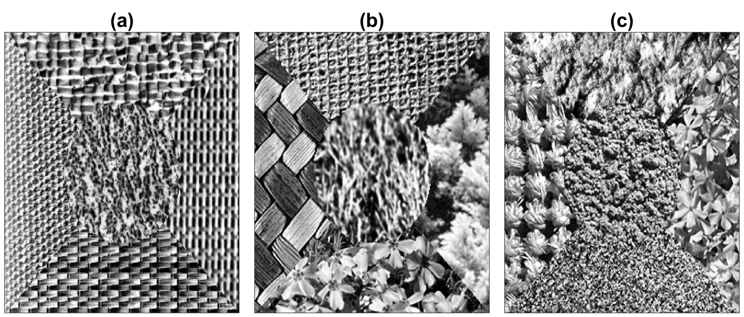


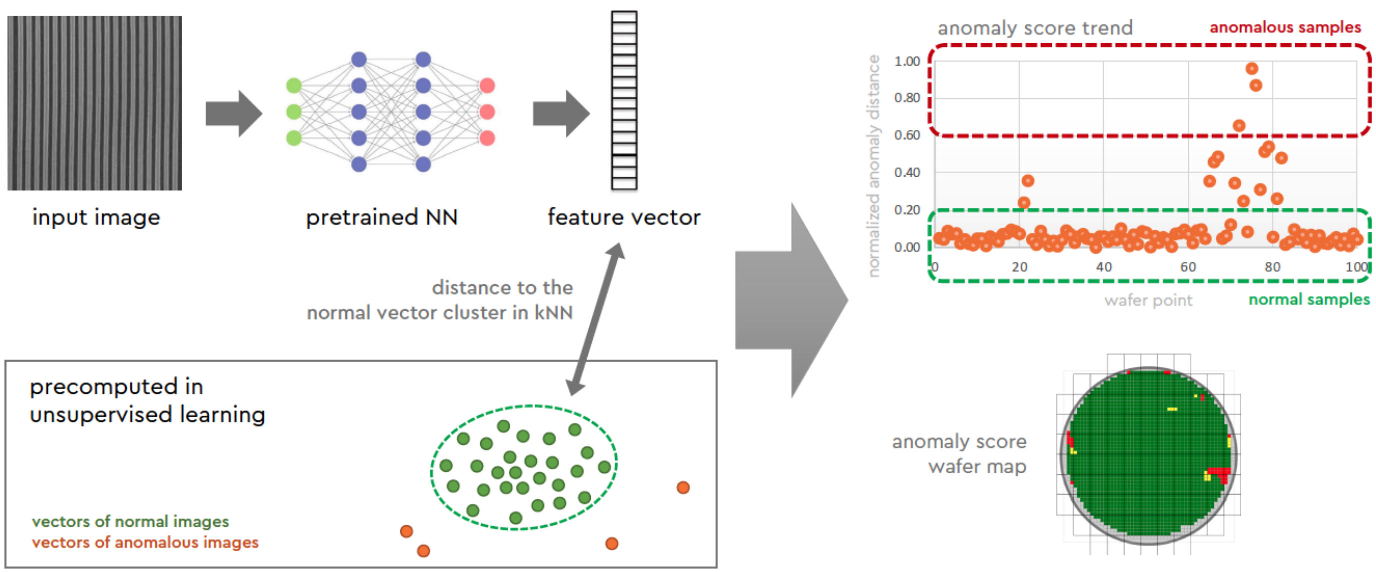
Image segmentation

- texture segmentation
  - distinguish areas based on texture patterns - identifying regions with similar textural features - used for material classification, surface defect detection, medical imaging
  - methods - Gabor filters, wavelet transforms, DL
- semantic segmentation
  - assign class labels to every pixel - enabling precise object and region identification - used for autonomous driving, scene understanding, medical diagnostics
  - methods - fully convolutional network (FCN), U-net, DeepLab



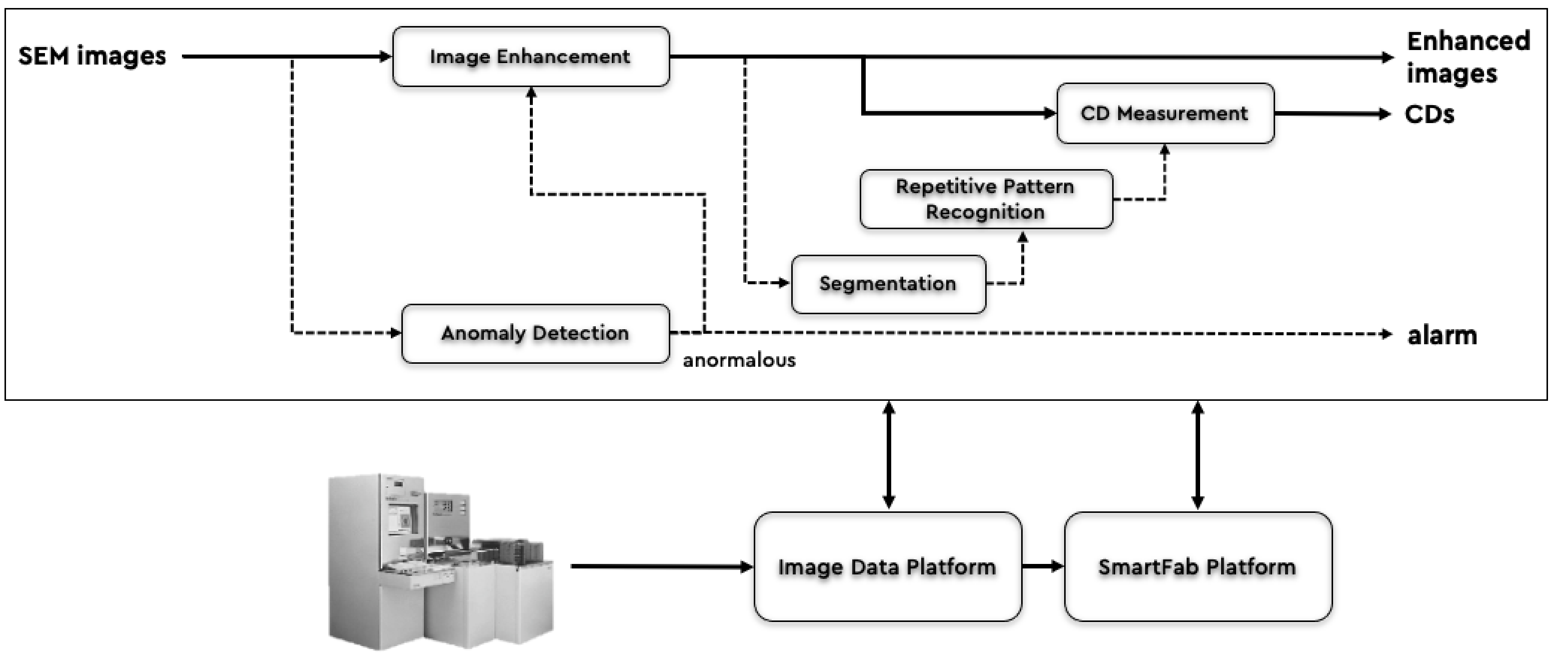
Anomaly detection using side product

- representation in embedding space obtained as side product from previous processes
- distance from normal clusters used for anomaly detection
- can be used for yield drop prediction and analysis



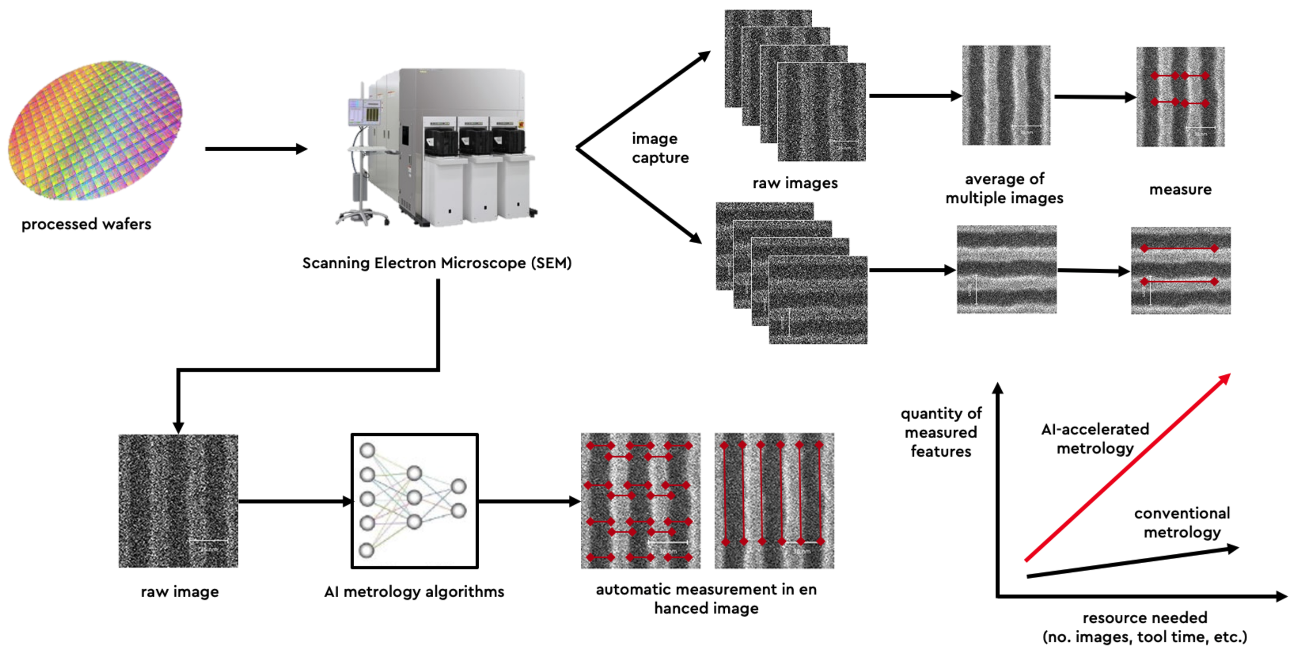
AI-enabled metrology system

- integration of separate components creates AI-enabled metrology system



Benefits of new system

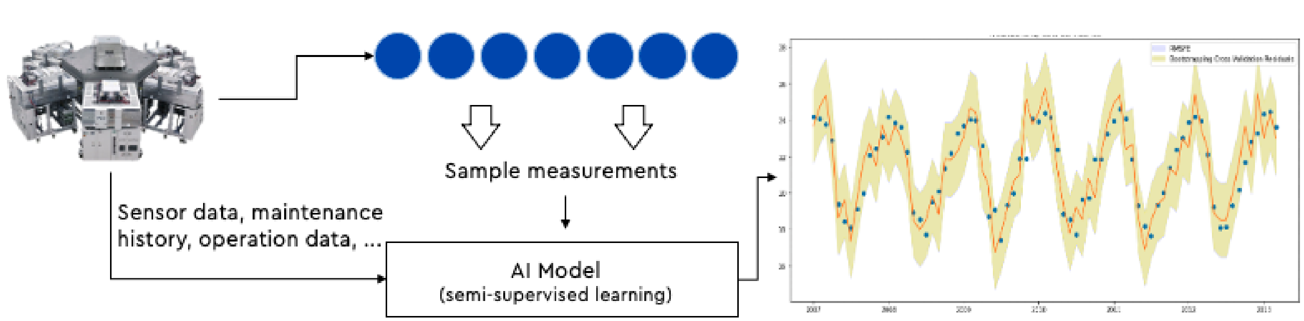
- new system provides
  - improved accuracy and reliability
  - improved throughput
  - savings on investment on measurement equipment



TS ML in manAI

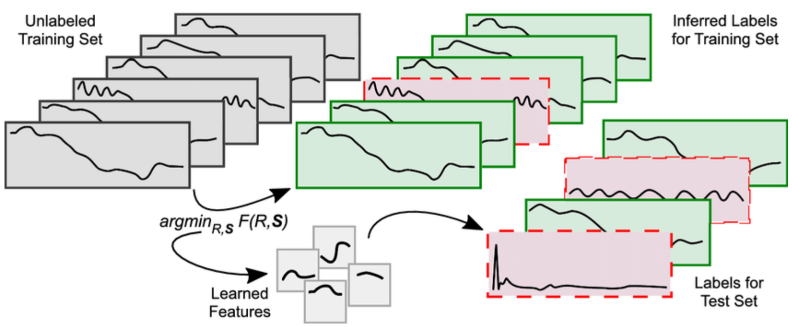
Time-series ML applications in manAI

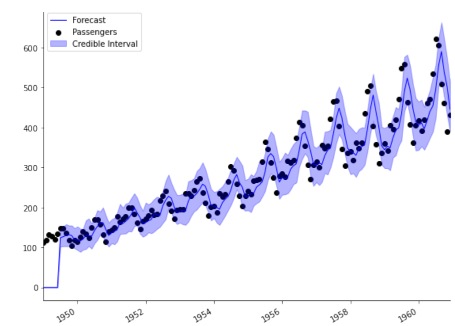
- estimation of TS values
  - virtual metrology - estimate measurement without physically measuring things
- anomaly detection on TS
  - predictive maintenance - predict maintenance times ahead
- multi-modal ML using LLM & genAI
  - root cause analysis and recommendation system



TS MLs in manAI

- TS regression/prediction/estimation
  - LSTM, GRU, attention-based models, Transformer-based architecture for capturing long-term dependencies and patterns
- anomaly detection
  - isolation forest, autoencoders, one-class SVM
- TS regression providing credibility intervals
  - Bayesian-based approaches offering uncertainty estimation alongside predictions



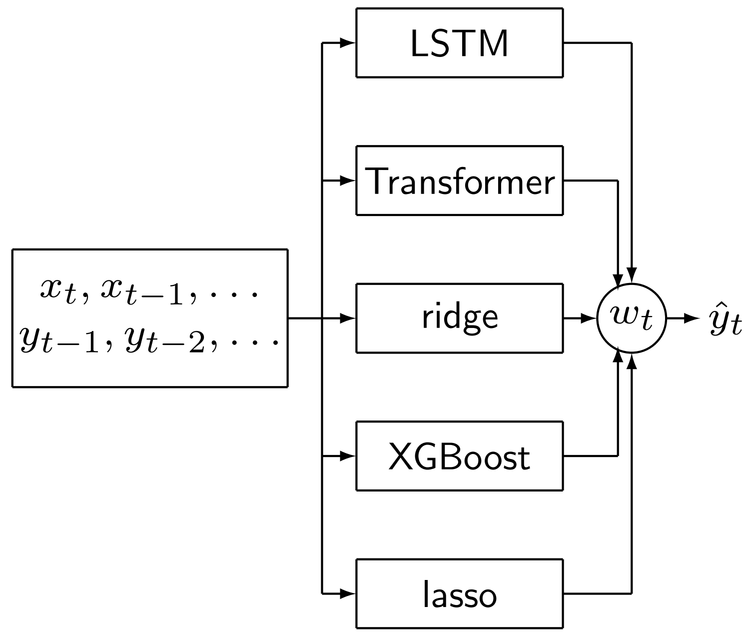


Difficulties with TS ML

- no definition exists for general TS data
- data drift & shift
  - $p(x_{t_k}, x_{t_{k-1}}, \ldots)$ changes over time
  - $p(y_{t_k} | x_{t_k}, x_{t_{k-1}}, \ldots, y_{t_{k-1}}, y_{t_{k-2}}, \ldots)$ changes over time
- (extremely) fat data, poor data quality, huge volume of data to process
- not many research results available
- none of algorithms in academic papers work / no off-the-shelf algorithms work

Online learning for TS regression

- use multiplie experts - $f_{1,k}, \ldots, f_{p_k,k}$ for each time step $t = t_k$ where $f_{i,k}$ can be any of following
  - seq2seq models ($e.g.$, LSTM, Transformer-based models)
  - non-DL statistical learning models ($e.g.$, online ridge regression)
- model predictor for t_k, $g_k : \mathbf{R}^n \to \mathbf{R}^m$ as weighted sum of experts



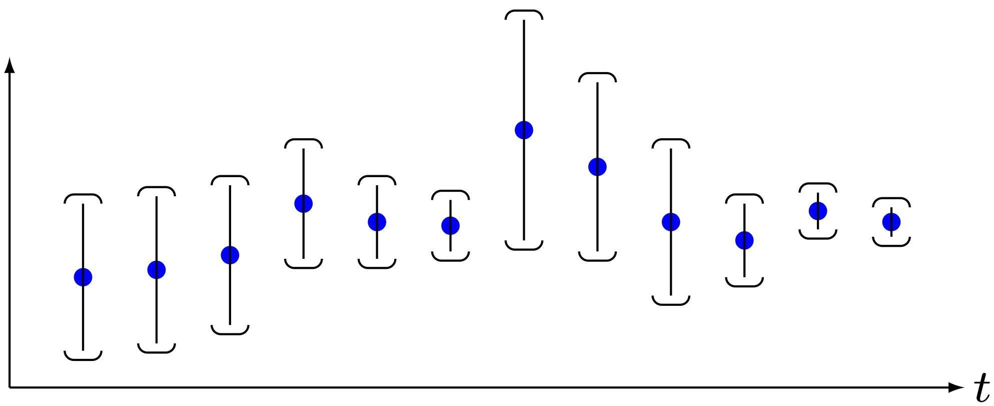
$$g_k = w_{1,k} f_{1,k} + w_{2,k} f_{2,k} + \cdots + w_{p_k,k} f_{p_k,k} = \sum_{i=1}^{p_k} w_{i,k} f_{i,k}$$

Credibility intervals

- every point prediction is wrong, $i.e.$

$$\mathbf{Prob}(\hat{y}_t = y_t) = 0$$

- reliability of prediction matters, however, *none* literature deals with this (properly)
- critical for our customers, $i.e.$, *such information is critical for downstream applications*
  - $e.g.$, when used for feedback control, need to know how reliable prediction resuilts are
  - sometimes *more crucial than algorithm accuracy*



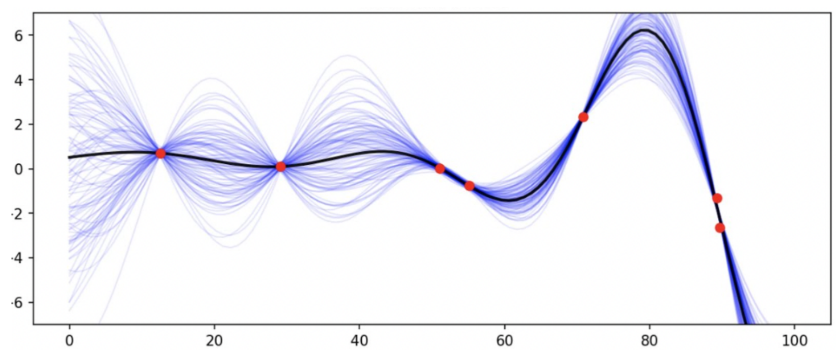
Bayesian approach for credibility interval evaluation

- assume conditional distribution ith predictor parameterized by $\theta_{i,k} \in \Theta$

$$p_{i,k}(y(t_k)|x_{t_k}, x_{t_{k-1}}, \ldots, y(t_{k-1}), y(t_{k-2}), \ldots) = p_{i,k}(y(t_k); x_{t_k}, \theta_{i,k})$$

  – depends on prior & current input, $i.e.$, $\theta_{i,k}$ & x_{t_k}
- update $\theta_{i,k+1}$ from $\theta_{i,k}$ after observing true $y(t_k)$ using Bayesian rule

$$p(w; \theta_{i,k+1}) := p(w|y(t_k); x_{t_k}, \theta_{i,k}) = \frac{p(y(t_k)|w, x_{t_k})p(w; \theta_{i,k})}{\int p(y(t_k)|w, x_{t_k})p(w; \theta_{i,k})dw}$$



Virtual Metrology

VM

- background
  - every process engineer wants to (so badly) measure every material processed - make sure process done as desired
    - $e.g.$, in semiconductor manufacturing, photolithography engineer wants to make sure diameter of holes or line spacing on wafers done correctly to satisfy specification for GPU or memory chips
  - however, various constraints prevent them from doing it, $e.g.$, in semiconductor manufacturing
    - measurement equipment requires investment
    - incur intolerable throughput
    - fab space does not allow
- GOAL - *measure every processed material without physically measuring them*

VM - problem formulation

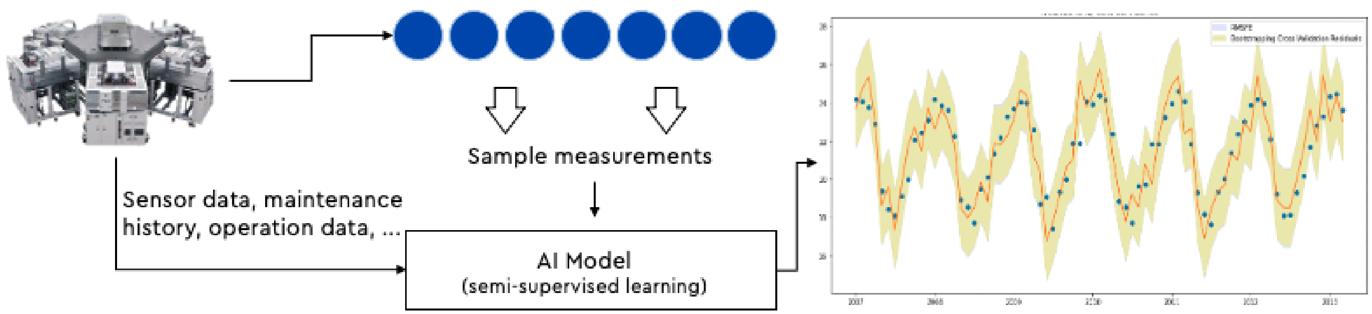
- problem description

$$\begin{array}{rl} \text{(stochastically) predict} & y_{t_k} \\ \text{given} & x_{t_k}, x_{t_{k-1}}, \ldots, y_{t_{k-1}}, y_{t_{k-2}}, \ldots \end{array}$$

- our problem formulation

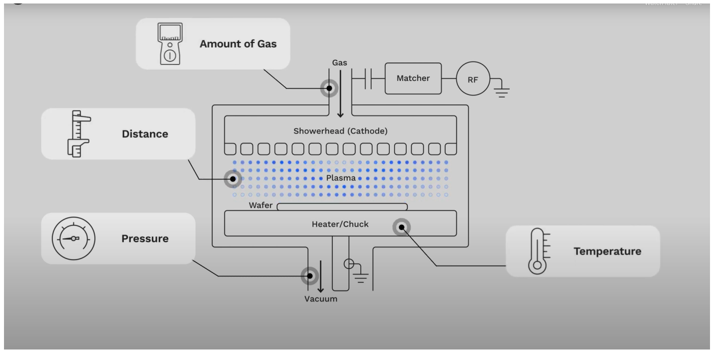
$$\begin{array}{ll} \text{minimize} & \sum_{k=1}^{K} w_{k,K-k}\, l(y_{t_k}, \hat{y}_{t_k}) \\ \text{subject to} & \hat{y}_{t_k} = g_k(x_{t_k}, x_{t_{k-1}}, \ldots, y_{t_{k-1}}, y_{t_{k-2}}, \ldots) \end{array}$$

where optimization variables - $g_1, g_2, \ldots : \mathcal{D} \to \mathbf{R}^m$



VM - Gauss Labs' inAI success story

- Gauss Labs' ML solution & AI product
  - fully home-grown online TS adpative ensemble learning method
  - outperform competitors and customer inhouse tools, *e.g.*, *Samsung, Intel, Lam Research*
  - published & patented in US, Europe, and Korea
- business impacts
  - improve process quality - reduction of process variation by tens of percents
  - (indirectly) contribute to better product quality and yield
  - Gauss Labs' main revenue source



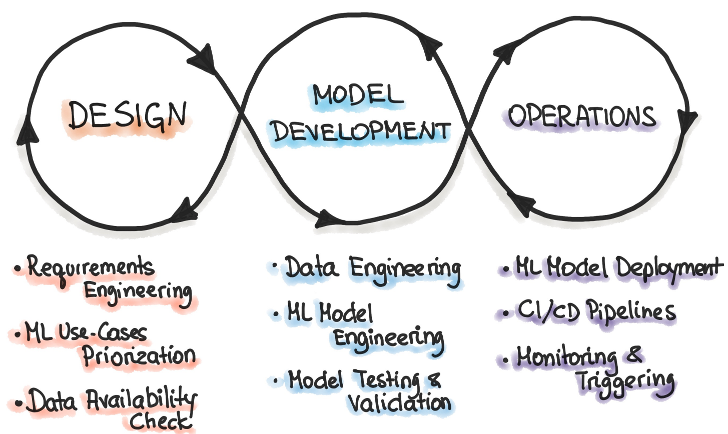
Manufacturing AI Productionization

Minimally required efforts for manAI

- MLOps - for CI/CD
- data preprocessing - missing values, inconsistent names, difference among different systems
- feature extraction & selection
- monitoring & retraining
- notification, via messengers or emails
- mainline merge approvals by humans
- data latency, data reliability, & data availability

MLOps for manAI

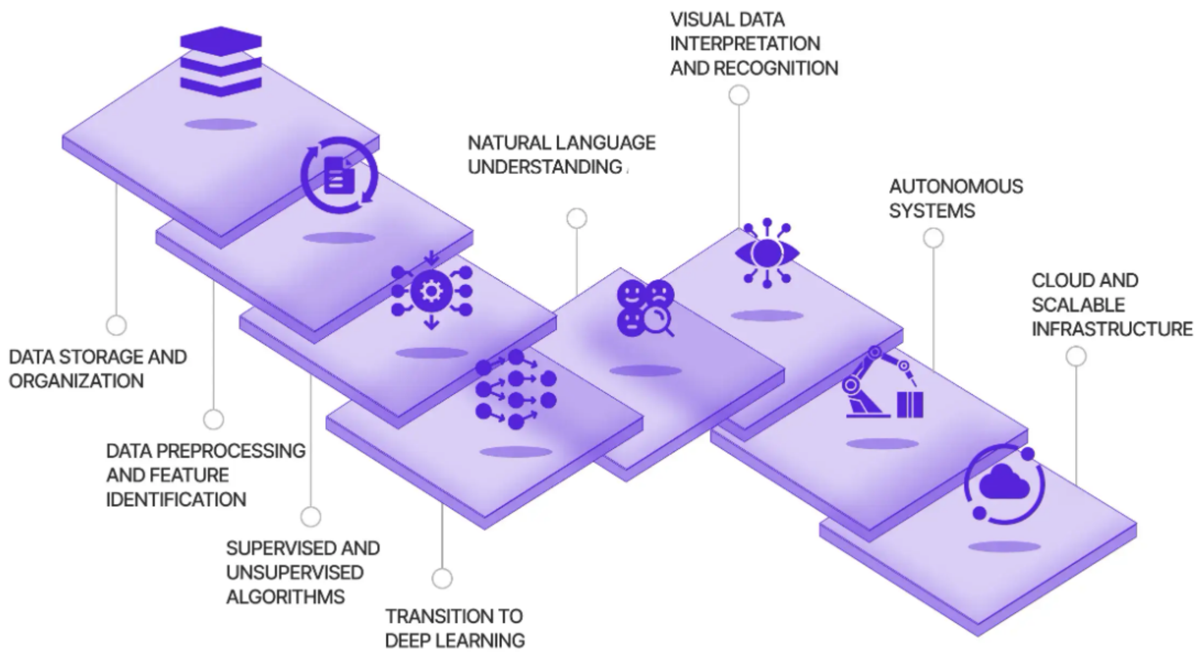
- environment for flexible and agile exploration - EDA[7]
- fast & efficient iteration of algorithm selection, experiements, & analysis
- correct training / validation / test data sets critical!
- seamless productionization from, *e.g.*, Jupyter notebook to production-ready code
- monitorning, *right* metrics, notification, re-training



[7] EDA - exploratory data analysis

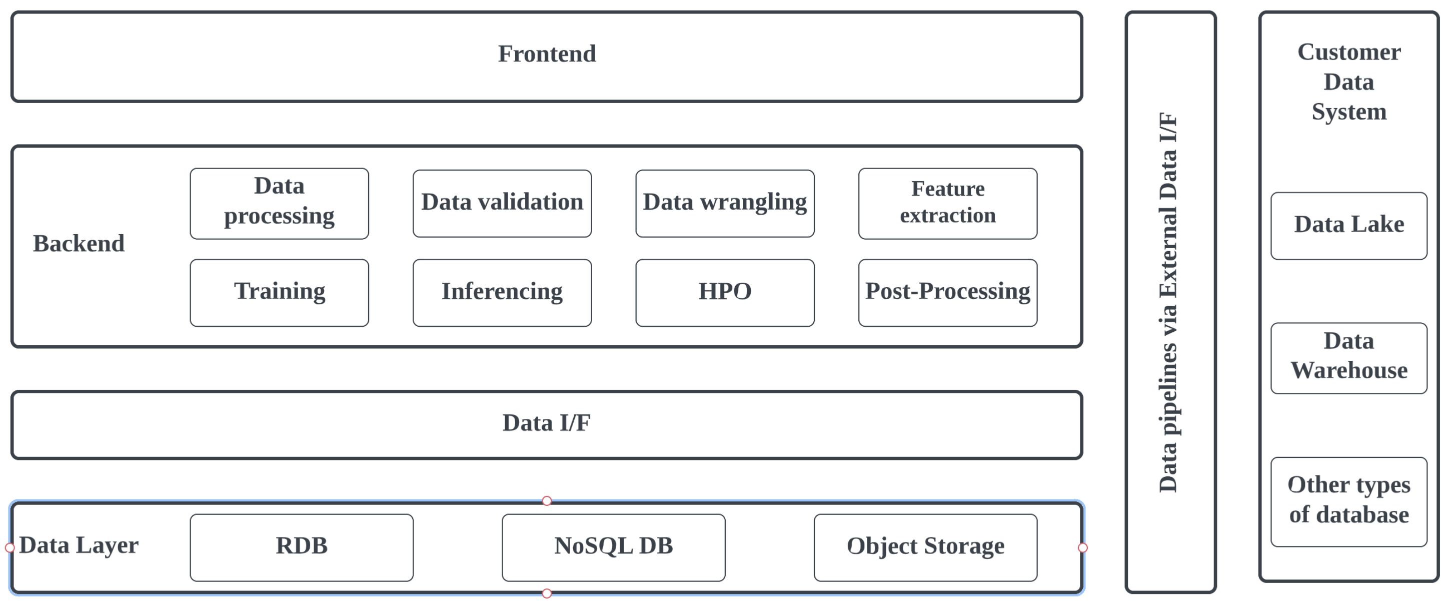
manAI software system

- data, data, data! – store, persist, retrieve, data quality
- seamless pipeline for development, testing, running deployed services
- development envinroment should be built separately



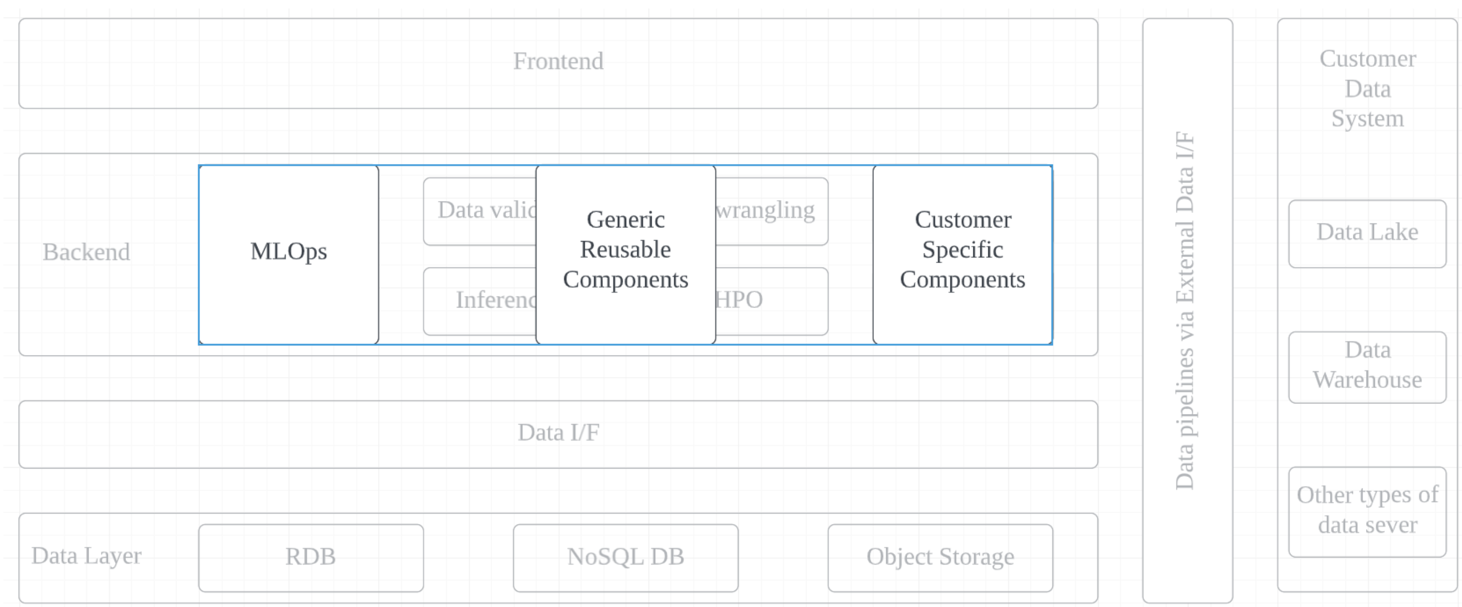
manAI system architecture

- frontend / backend / data I/F / data layer
- efficient and effective MLOps in backend or development environment



Reusuable components vs customer specific components

- make sure to build two components separate - generic reusable and customer specific
- generic models should be tuned for each use case
- generic model library grows as interacting with more and more customers



My Two Cents

Recommendations for maximum impact via inAI

- concrete goals of projects
  - north star – yield improvement, process quality, making engineers' lives easier
  - hard problem – scheduling and optimization
- be strategic!
  - learn from others – lots of successes & failures of inAI
  - ball park estimation for ROI cricial – efforts, time, expertise, data
  - utilities vs technical excellency / uniqueness vs common technology
  - home-grown vs off-the-shelf

Remember . . .

- data, data, data! – readiness, quality, procurement, pre-processing, DB
- *never* underestimate domain knowledge & expertise – data do NOT tell you everything
- EDA
- do *not* over-optimize your algorithms – ML is all about trials-&-errors
- overfitting, generalization, concept drift/shift - way more important than you could ever imagine
- devOps, MLOps, agile dev, software development & engineering

Conclusion

Conclusion

- various CV MLs used for inAI applications
- TS ML applications found in every place in manufacturing
- drift/shift & data noise make TS MLs very challenging, but working solutions found
- in reality, crucial bottlenecks are
  - data quality, prepocessing, monitoring, notification, and retraining
  - data latency, avaiability, and reliability
  - excellency in software platform design and development using cloud services

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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