

AI - Industry & Society

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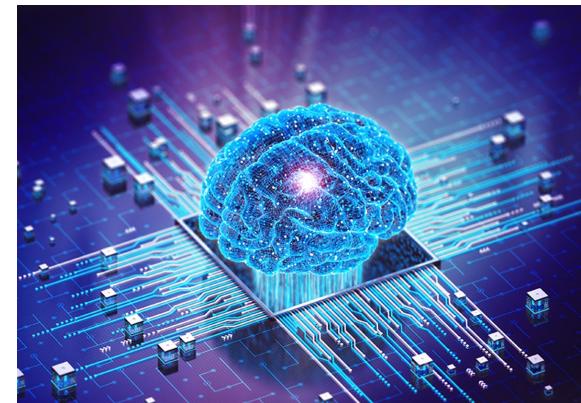
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AI & Biotech

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 other types of experiments that previously were unattainable
 - contributes to broader field of engineering biology or biotechnology
- AI increases human ability to make direct changes at cellular level and create novel genetic material (*e.g.*, DNA and RNA) to obtain specific functions



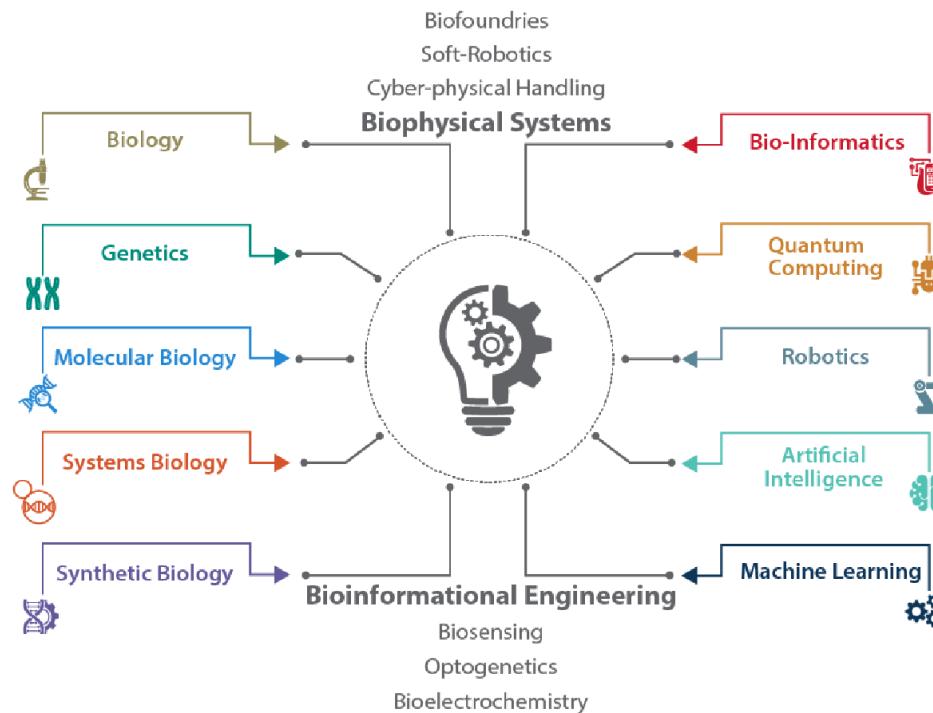
Biotech

Biotech

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

Biotech - multidisciplinary field

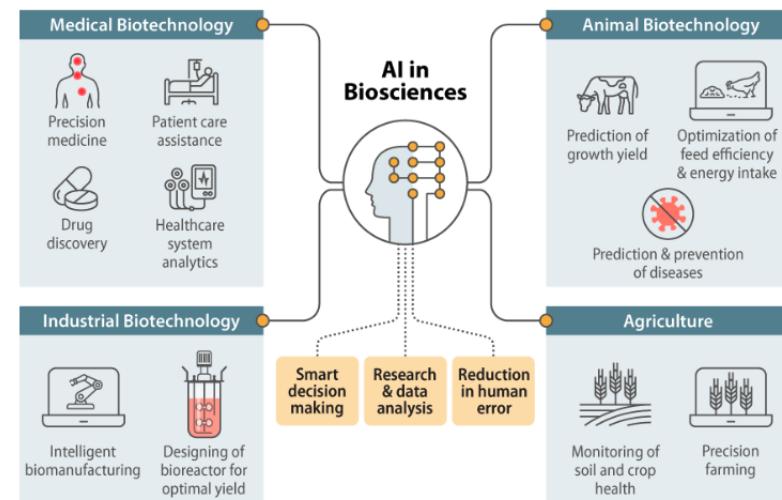
- sciences and technologies enabling biotechnology include (but not limited to)
 - (molecular) biology, genetics, systems biology, synthetic biology, bio-informatics, quantum computing, robotics [DFJ22]



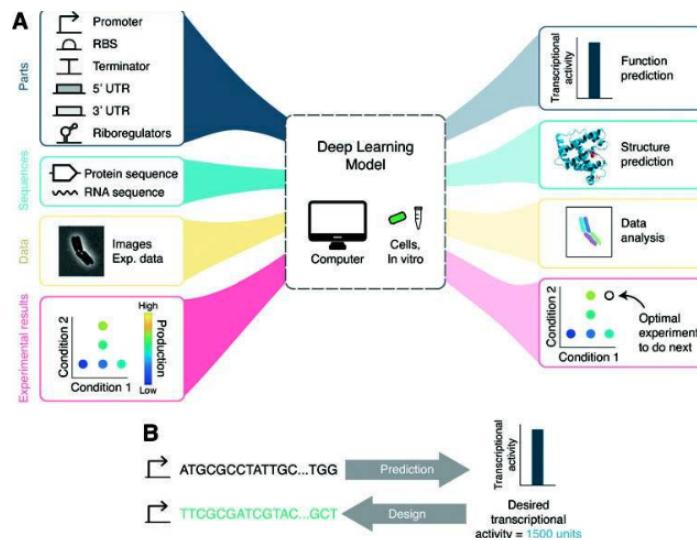
Convergence of AI and biological design

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

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



Multi-source genetic sequence data



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

“AI will be essential to fully understanding how genetic code interacts with biological processes” - US National Security Commission on Artificial Intelligence (NSCAI)

 - process huge amounts of biological data, *e.g.*, genetic sequence data, coming from different biological sources for understanding complex biological systems
 - sequence data, molecular structure data, image data, time-series, omics data
- *e.g.*, analyze genomic data sets to determine the genetic basis of particular trait and potentially uncover genetic markers linked with that trait

Quality & quantity of biological data

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



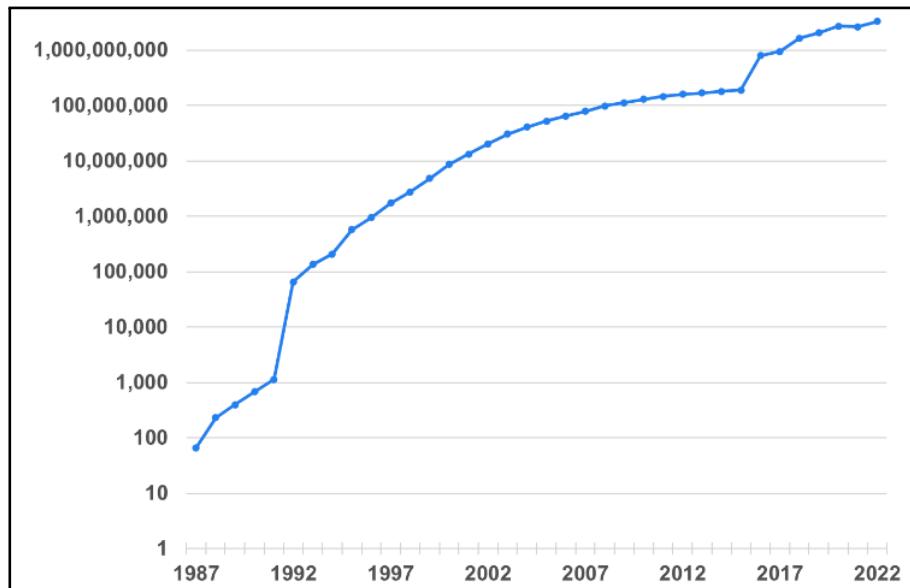
Rapid growth of biological data

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

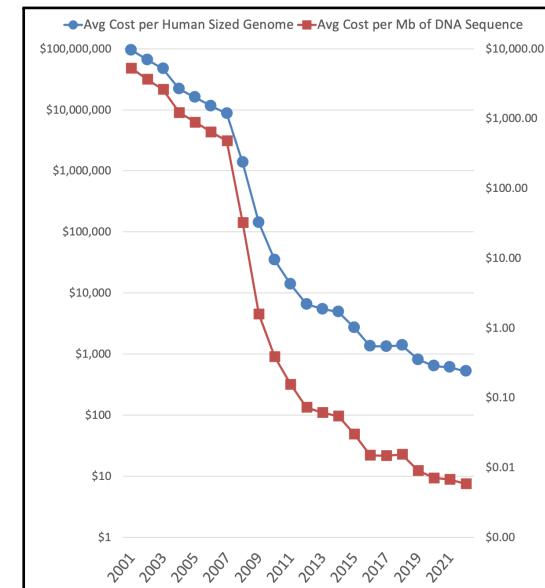
Volume and sequencing cost of DNA over time

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

sequences in INSDC



DNA sequencing cost



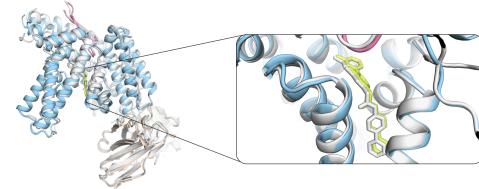
Bio data availability and bias

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

Emerging Trends in Biotech

AlphaFold

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

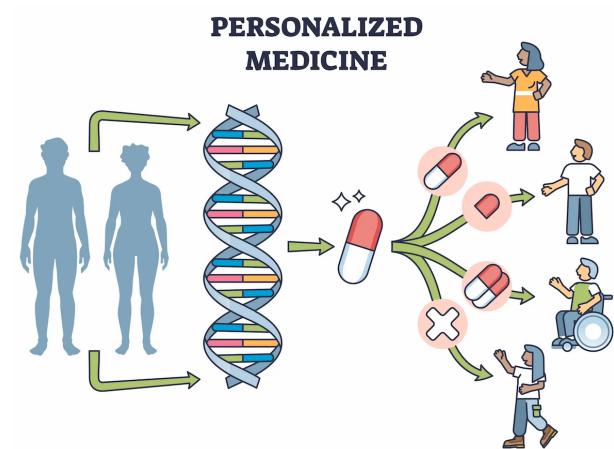


AlphaGo

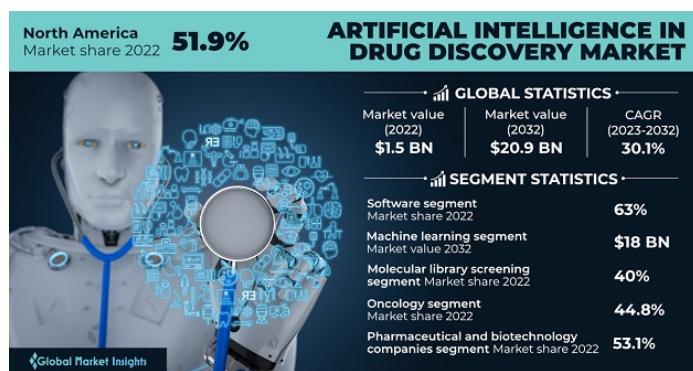
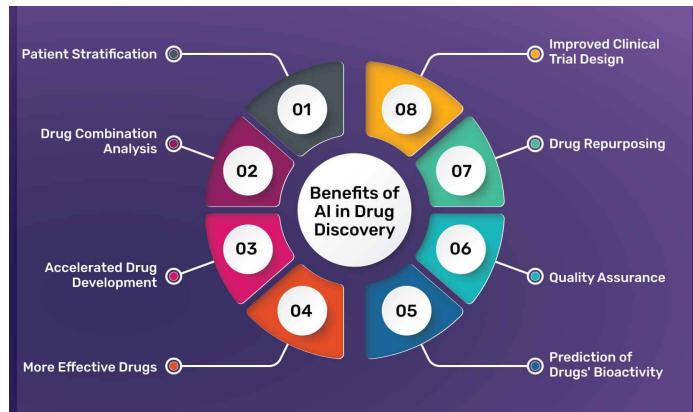


Personalized medicine

- *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.



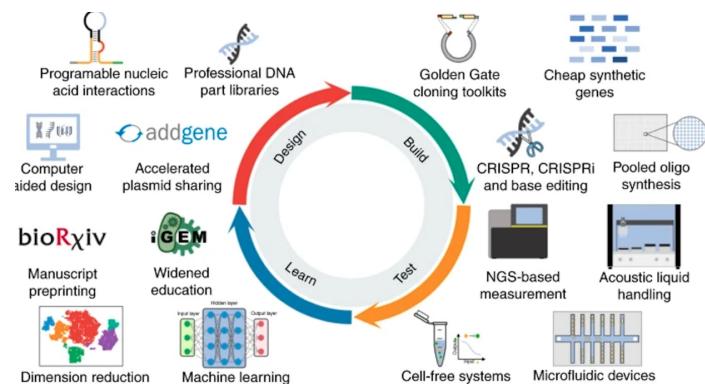
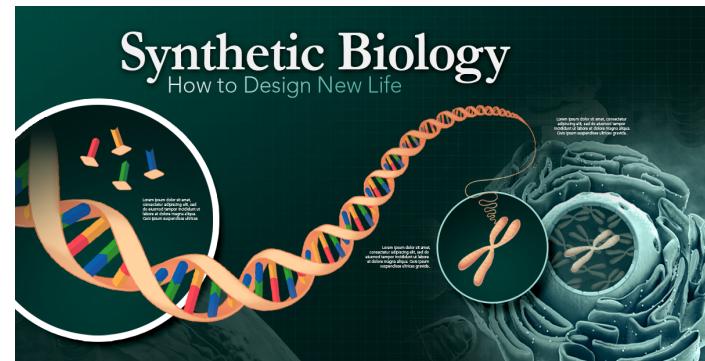
AI-driven drug discovery



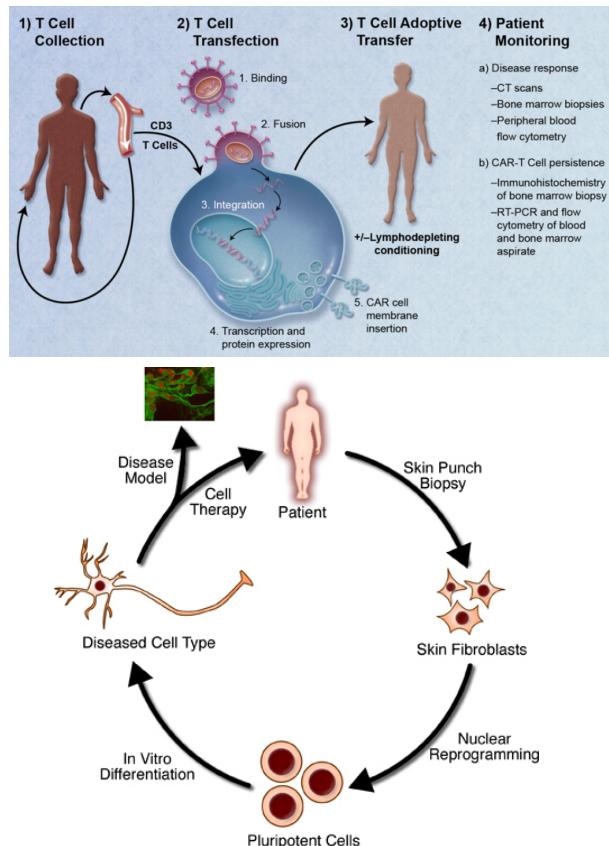
- traditional drug discovery process - time-consuming and costly often taking decades and billions of dollars
- AI streamlines this process by predicting the efficacy and safety of potential compounds with more speed and accuracy
- AI models analyze chemical databases to identify new drug candidates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



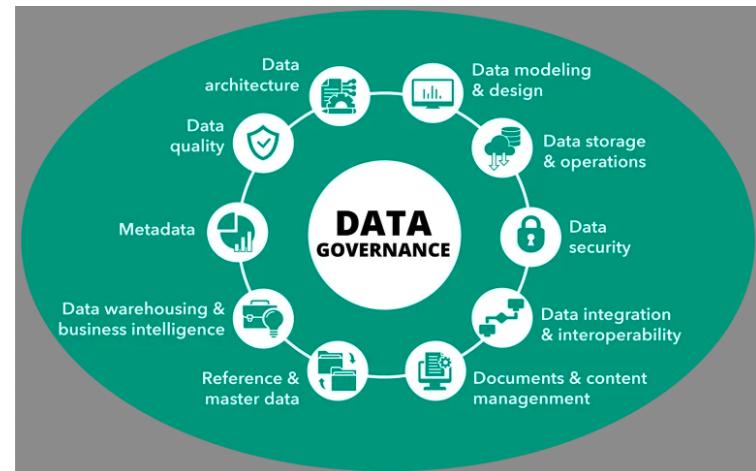
Regenerative medicine



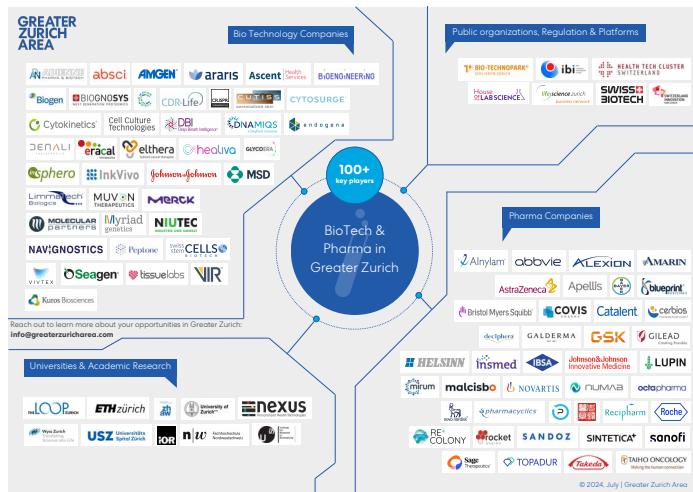
- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo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



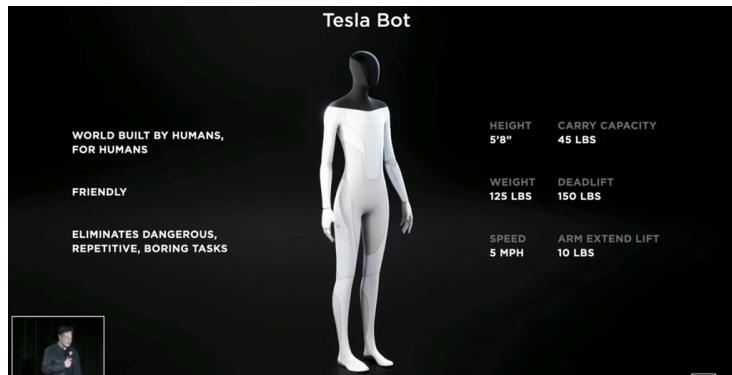
- Atomwise - small molecule drug discovery
- Cradle - protein design
- Exscientia - precision medicine
- Iktos - small molecule drug discovery and design
- Insilico Medicine - full-stack drug discovery system
- Schrödinger, Inc. - use physics-based models to find best possible molecule
- Absci Corporation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

AI-powered Humanoid Robots

Tesla Optimus

Tesla Optimus

- humanoid robot developed by Tesla intended to handle repetitive & dangerous tasks
- objective - *revolutionize automation* & assist in human labor across various industries
- features - [YouTube - Optimus - Gen 2](#)
 - dimensions - 5'8" tall & 125 lbs
 - capabilities - lifting weights, walking at 5 MPH & performing everyday tasks
 - AI-powered - runs on Tesla's AI leveraging same technology used in self-driving cars
 - power source - 2.3 KWH battery designed for efficient power management
 - launch year - announced by Elon Musk during Tesla AI Day in 2021
 - *price* - \$25,000~\$30,000 expected to decrease over time



History of Tesla Optimus

- inception - first conceptualized as extension of Tesla's AI & robotics capabilities
- AI day 2021 - *officially announced by Elon Musk* w/ vision to solve labor shortages & improve productivity
- Sep 2022 - prototype unveiled
- gen 2 introduced in 2023 - improved capabilities
- Jun 2024 w/ more advanced tasks - *towards mass production for commercial applications*

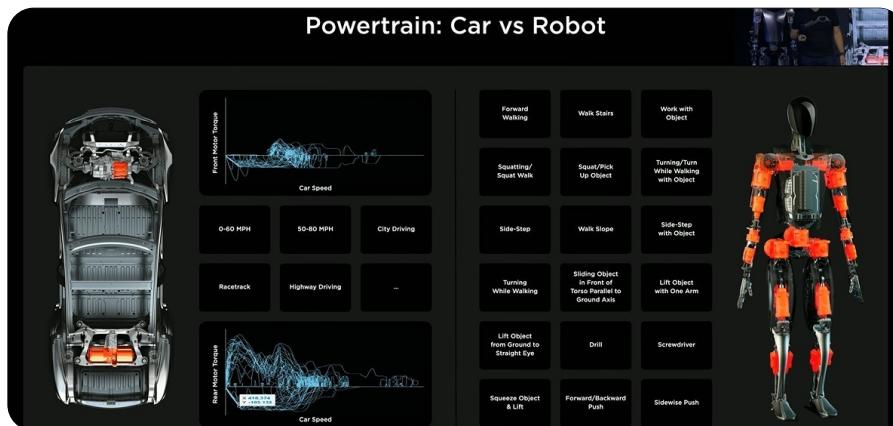
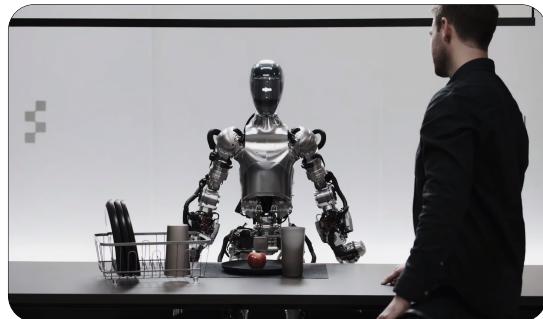


Figure A1

Figure AI robots

- Figure AI
 - founded in 2022 as Silicon Valley startup company by Brett Adcock - serial entrepreneur with successful Archer Aviation & Vetter
 - vision of enhancing productivity by integrating AI and robotics into both industrial & personal spaces
- Figure 02
 - 5'6" tall, 154 lbs, payload of 44 lbs, 5 hr runtime, 1.2 m/s speed
 - imitation learning
 - capabilities - advanced cognition, STS task, dexterous hands w/ 16 degrees of freedom



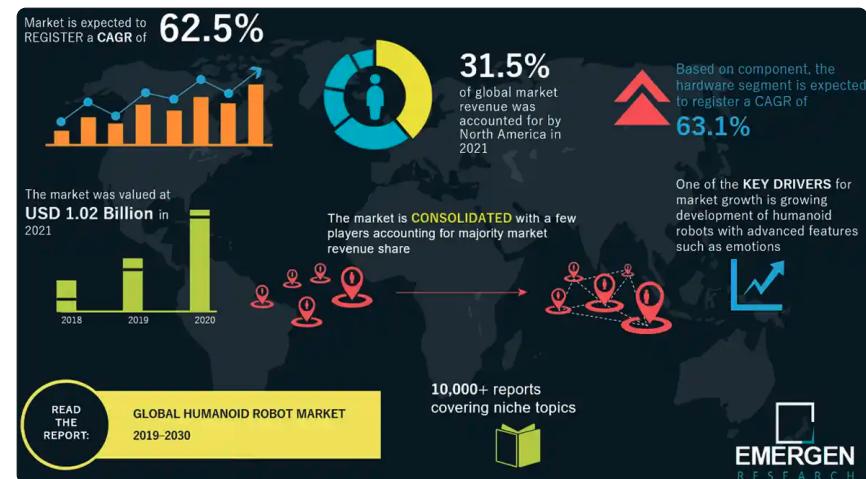
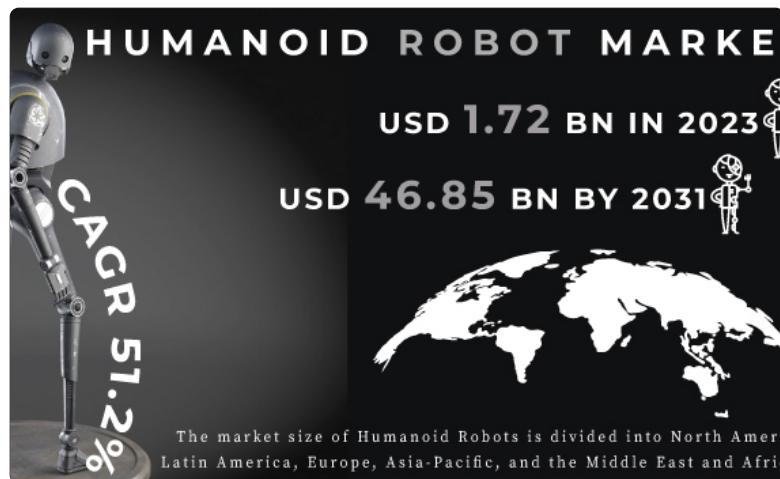
History of Figure AI

- 2022 - founded by Brett Adcock - previously co-founded Archer Aviation & Vetter
- 2022-2023 - early development - stealth mode focusing on developing their own technology
- May 2023 - public announcement - officially announces mission to develop general-purpose humanoid robots - already raised \$70M @ announcement
- Aug 2023 - unveils Figure 01, first prototype w/ basic mobility & manipulation capabilities
- Oct 2023 - series B funding - raised \$675M beyond initial goal of \$500M - Jeff Bezos, Microsoft, OpenAI - valuation of ~ \$2.6B
- late 2023 ~ early 2024 - partnership announcements - refines humanoid robot technology in locomotion, object manipulation & human-robot interaction
- 2024 - significant strides in robot control & decision-making

Impacts & Future

Impacts on industries & markets

- impacts on robotics history
 - competitor benchmark - competes with robotics giants such as Boston dynamics
 - affordability & scale - predict to lead to *lower costs & higher adoption*
- impacts on labor market
 - task automation - replace human labor in *high-risk & repetitive roles*
 - *job displacement vs creation* - new roles in AI, robot maintenance & oversight
- impacts on consumer market - home automation



Future outlook & predictions

- widespread industrial adoption - expected to become common tool in factories by 2030
- market valued @ **\$1.02B in 2021** - expected *CAGR of 62.5%, 63.1% in hardware segment by 2030 - 31.5% revenue increase in 2021* North America - **10,000 humanoid robots** will be shipped worldwide each year by 2027
- AI evolution - continuous learning and AI enhancements will lead to greater efficiency & adaptability
- consumer integration - long-term vision includes personal assistant
- societal impact - could redefine human roles in industries & homes *raising philosophical & ethical questions on human-robot collaboration*



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*
 - *semiconductor, steel, oil & gas, cement, and other various manufacturing industries* (unlike general AI, which is frontier research discipline striving to achieve human-level intelligence)



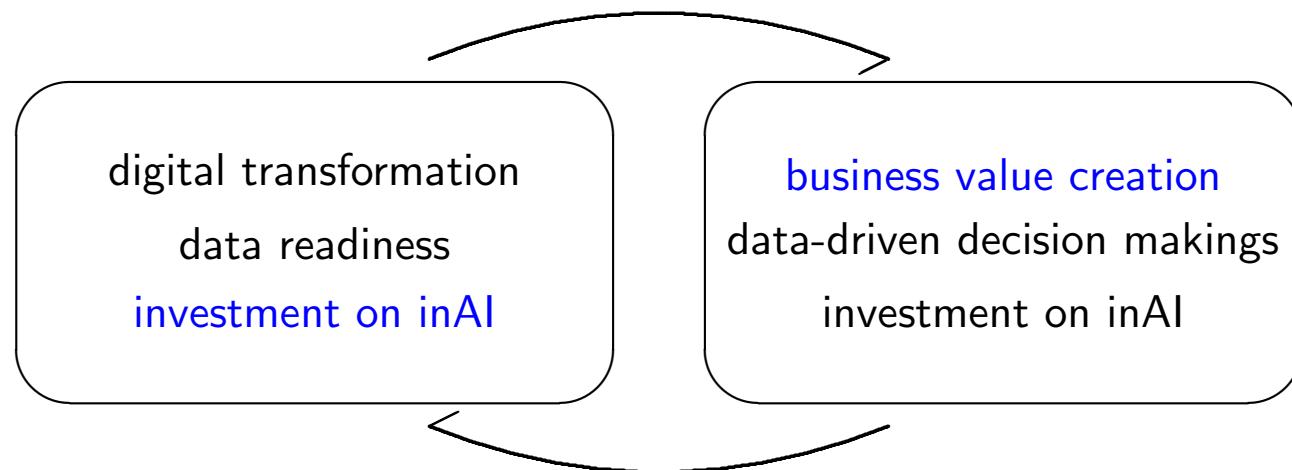
inAI fields

- 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

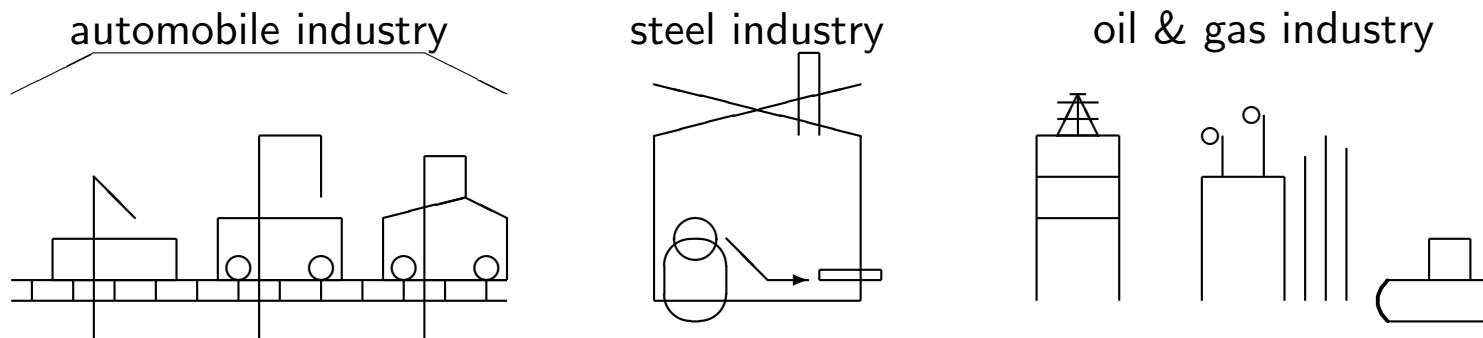
Vicious (or virtuous) cycle

- 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

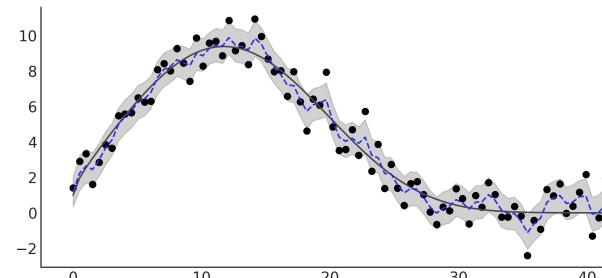
- huge volume
- data multi-modality
- high velocity requirement
- very fat data
- sever data shift & drift (in many cases)
- label imbalance
- data quality



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 maps¹
→ 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 data²
→ regression, anomaly detection, semi-supervised learning, Bayesian inference



¹SEM: scanning electron microscope, TEM: transmission electron microscope

²MES: 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

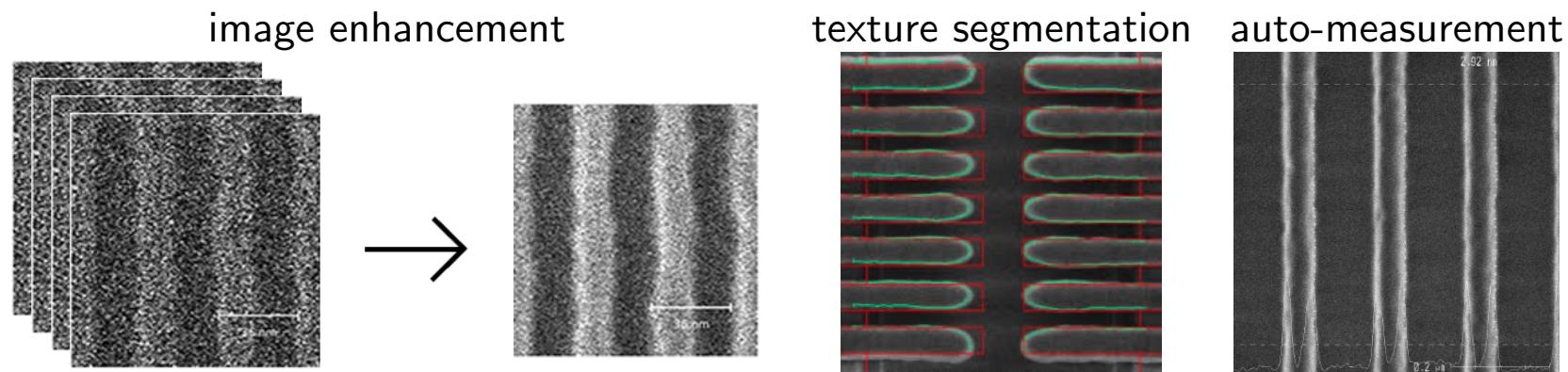


Image enhancement

- 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

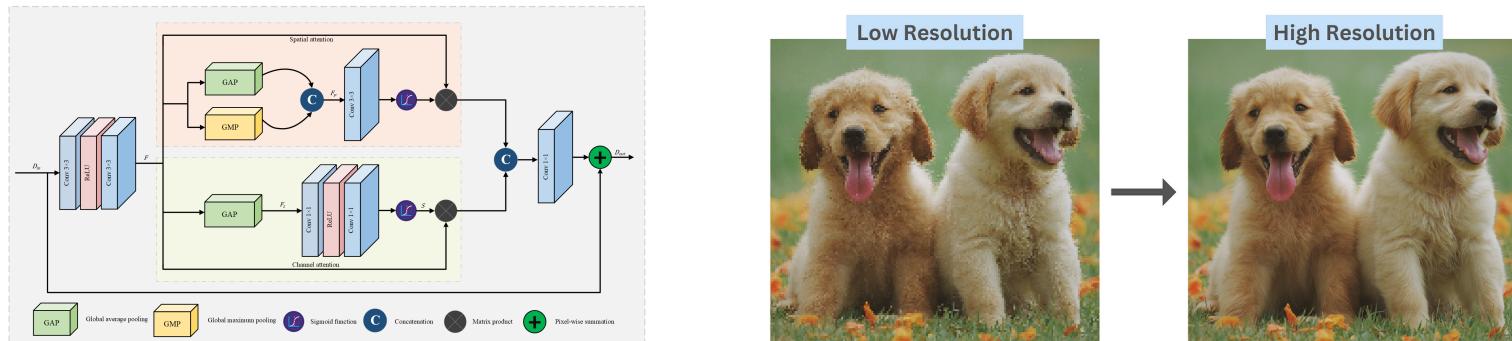
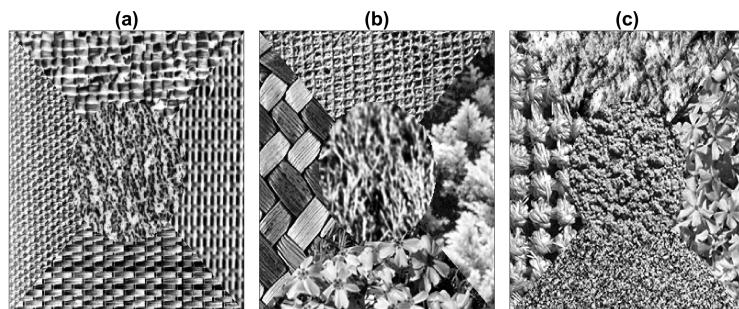


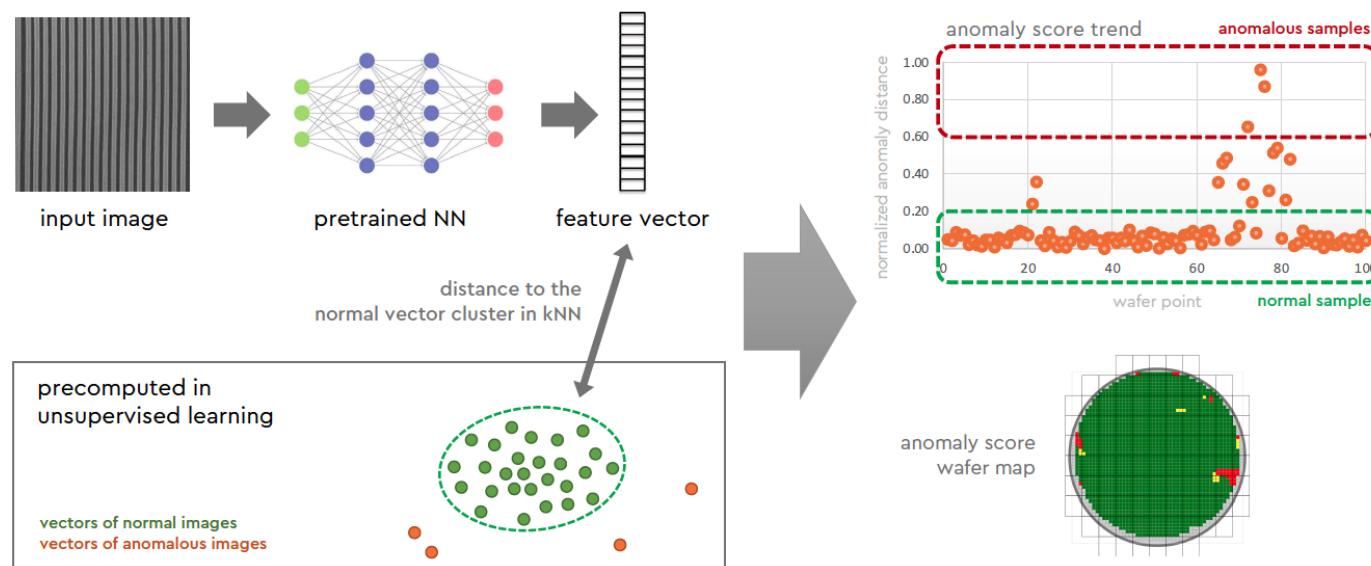
Image segmentation

- 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



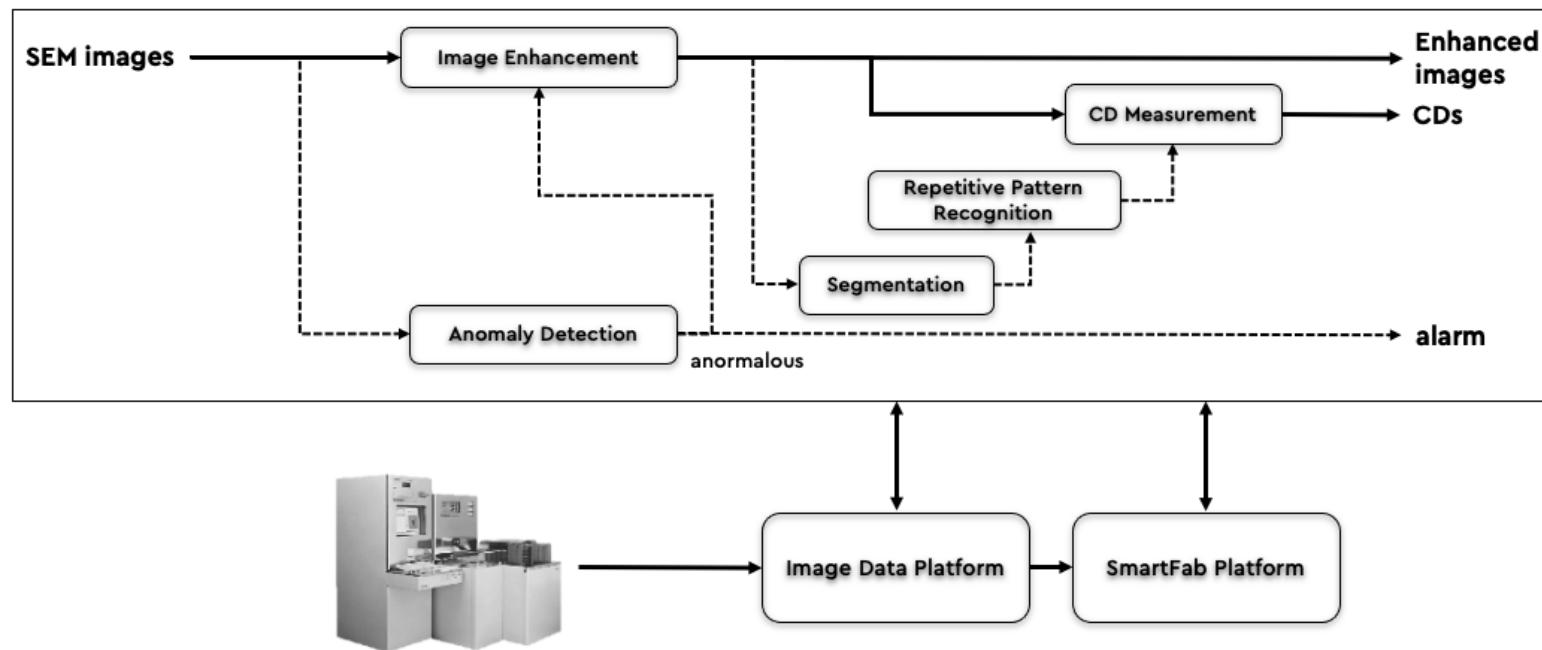
Anomaly detection using side product

- 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



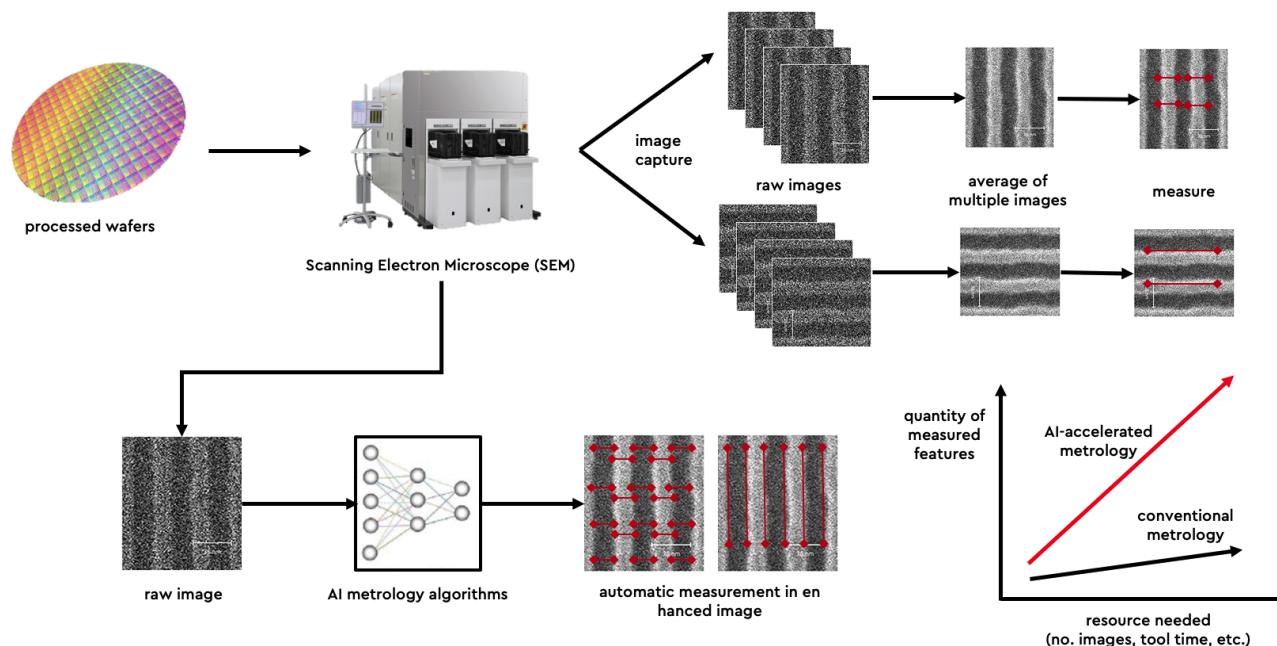
AI-enabled metrology system

- integration of separate components creates AI-enabled metrology system



Benefits of new system

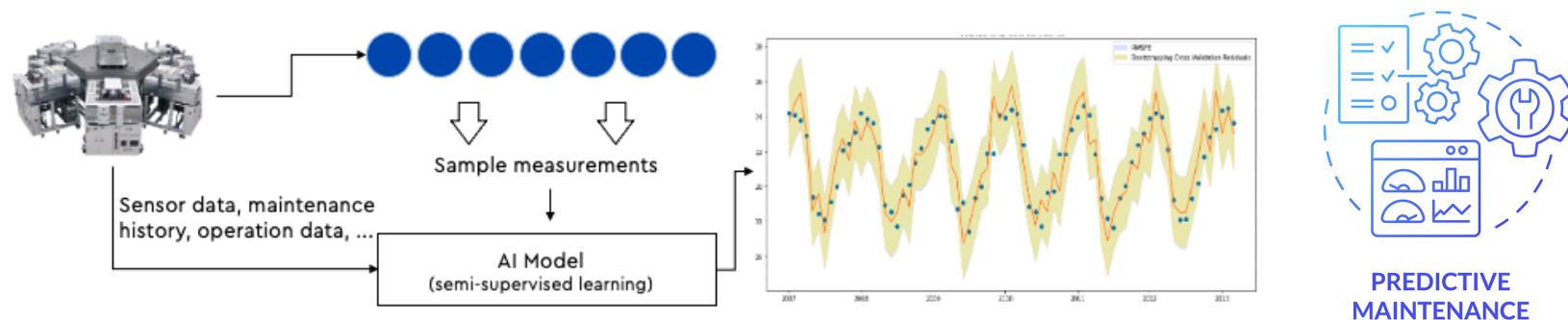
- new system provides
 - improved accuracy and reliability
 - improved throughput
 - savings on investment on measurement equipment



TS ML in manAI

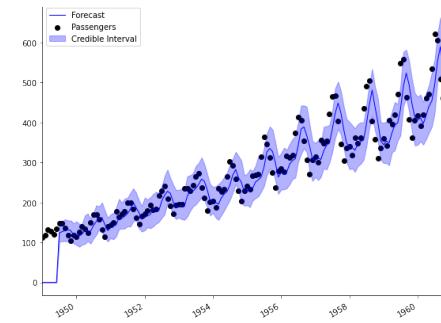
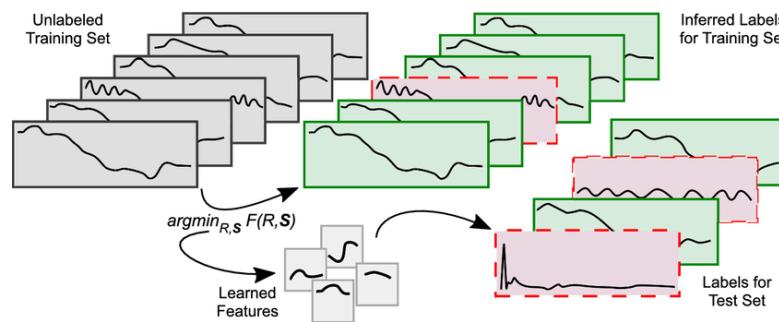
Time-series ML applications in manAI

- 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

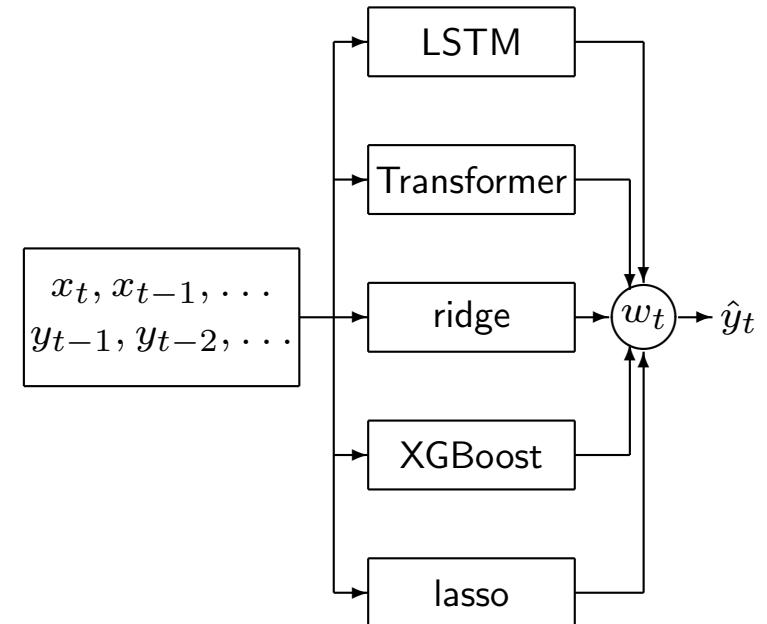


Difficulties with TS ML

- no definition exists for general TS data
- data drift & shift
 - $p(x_{t_k}, x_{t_{k-1}}, \dots)$ changes over time
 - $p(y_{t_k} | x_{t_k}, x_{t_{k-1}}, \dots, y_{t_{k-1}}, y_{t_{k-2}}, \dots)$ 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 multiple experts - $f_{1,k}, \dots, f_{p_k,k}$ 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 , $g_k : \mathbf{R}^n \rightarrow \mathbf{R}^m$ as weighted sum of experts



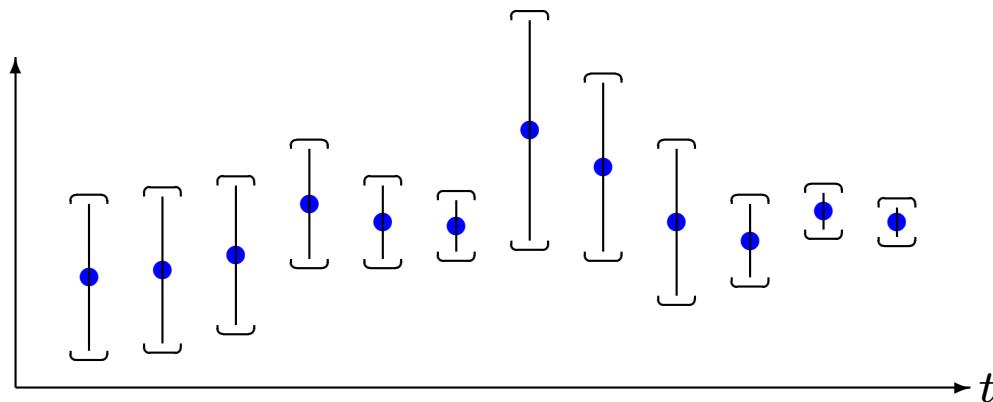
$$g_k = w_{1,k}f_{1,k} + w_{2,k}f_{2,k} + \cdots + w_{p_k,k}f_{p_k,k} = \sum_{i=1}^{p_k} w_{i,k}f_{i,k}$$

Credibility intervals

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

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

- 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 results are
 - sometimes *more crucial than algorithm accuracy*



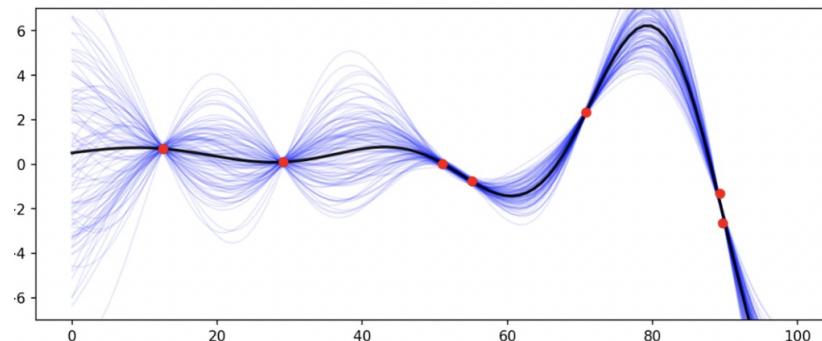
Bayesian approach for credibility interval evaluation

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

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

- 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

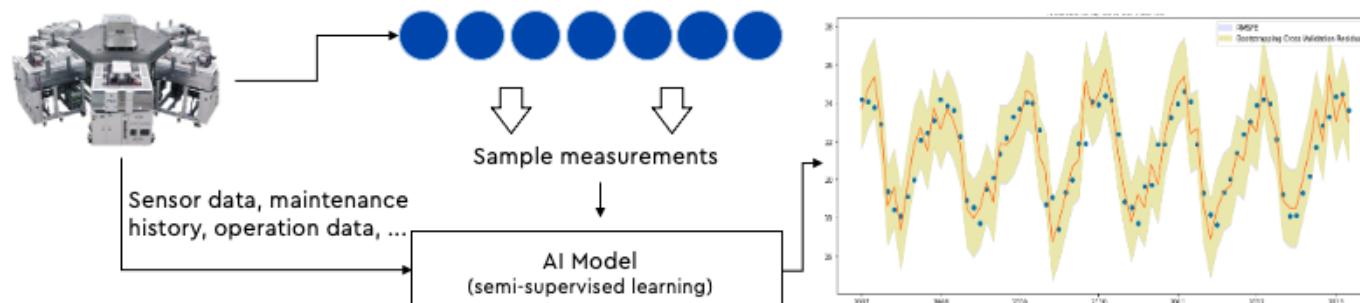
- problem description

(stochastically) predict y_{t_k}
 given $x_{t_k}, x_{t_{k-1}}, \dots, y_{t_{k-1}}, y_{t_{k-2}}, \dots$

- our problem formulation

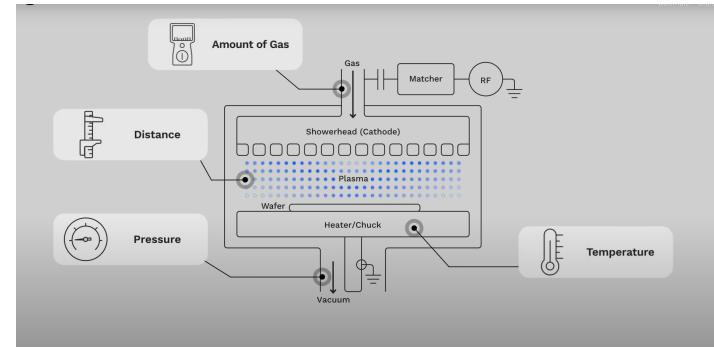
$$\begin{aligned} & \text{minimize} && \sum_{k=1}^K w_{k,K-k} l(y_{t_k}, \hat{y}_{t_k}) \\ & \text{subject to} && \hat{y}_{t_k} = g_k(x_{t_k}, x_{t_{k-1}}, \dots, y_{t_{k-1}}, y_{t_{k-2}}, \dots) \end{aligned}$$

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



VM - Gauss Labs' inAI success story

- **Gauss Labs' ML solution & AI product**
 - fully home-grown online TS adaptive 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



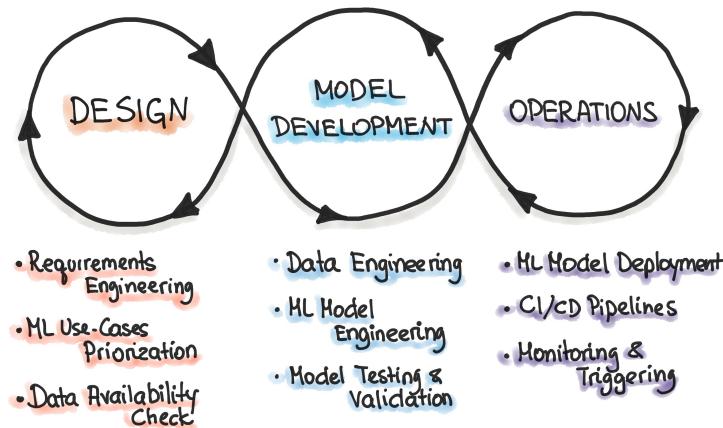
Manufacturing AI Productionization

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

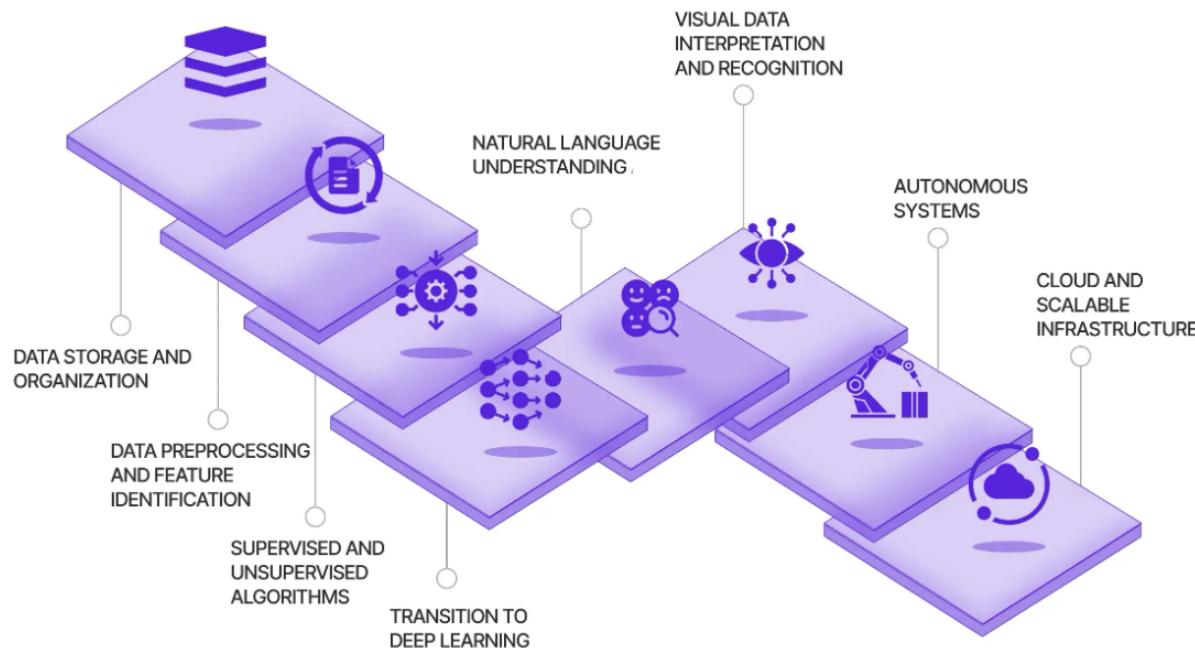
- environment for flexible and agile exploration - EDA³
- fast & efficient iteration of algorithm selection, experiments, & analysis
- correct training / validation / test data sets critical!
- seamless productionization from, e.g., Jupyter notebook to production-ready code
- monitoring, *right* metrics, notification, re-training



³EDA - exploratory data analysis

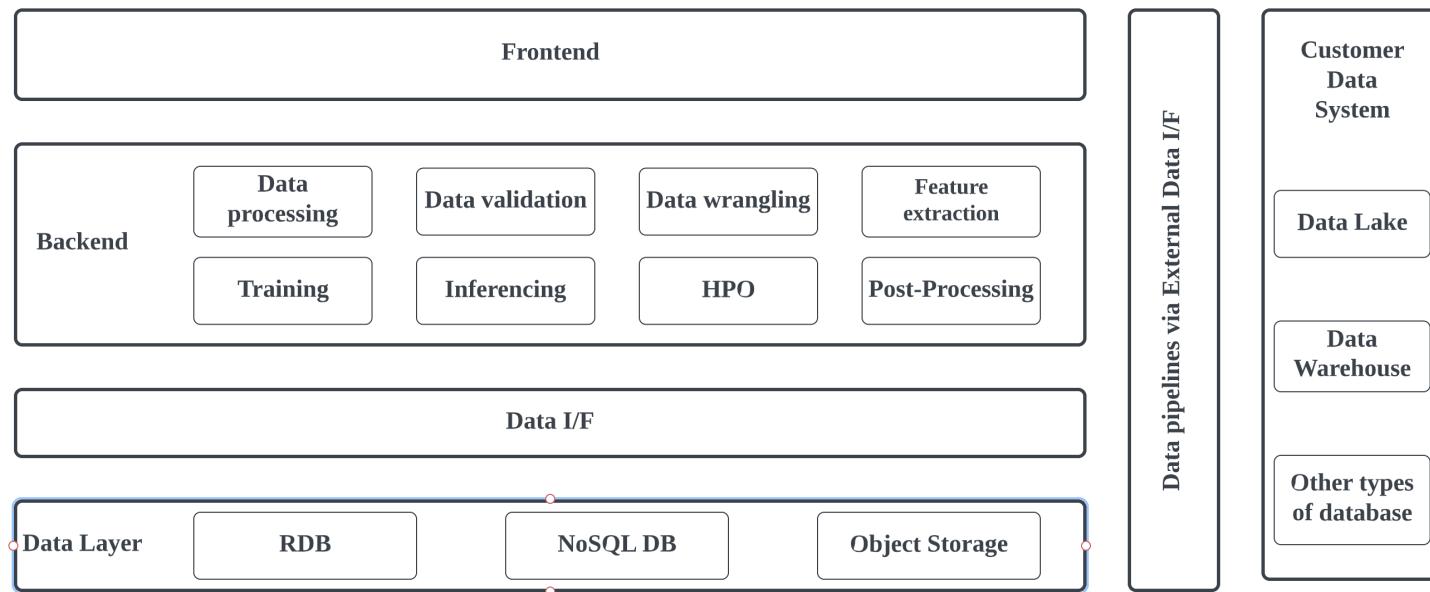
manAI software system

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



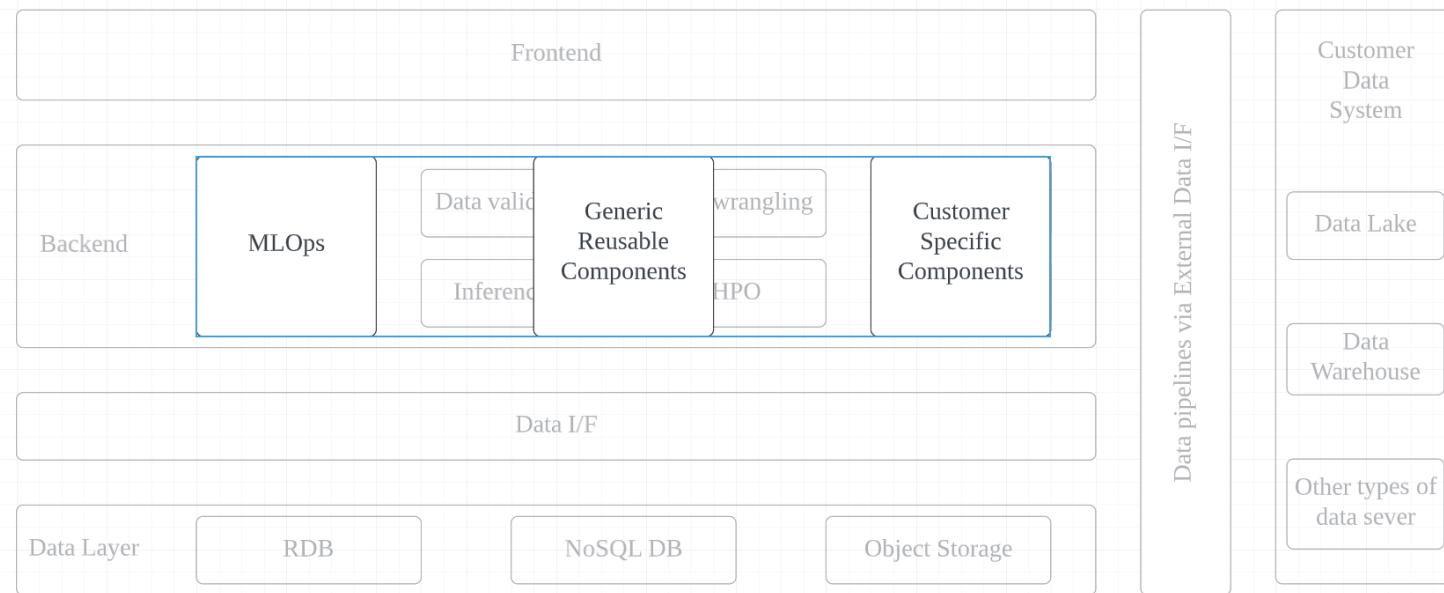
manAI system architecture

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



Reusable 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 crucial – 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, preprocessing, monitoring, notification, and retraining
 - data latency, availability, and reliability
 - excellency in software platform design and development using cloud services

Global Semiconductor Industry

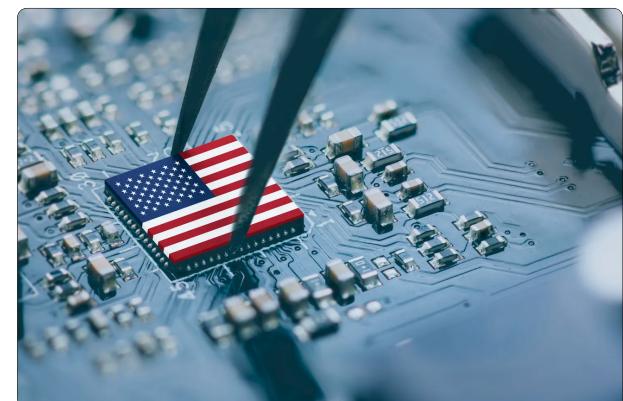
Hard-to-predict AI hardware markets

- US
 - birthplace for modern semiconductor chips driving PC market, internet, multi-media, mobile phones, and AI . . .
 - Intel, Texas Instrument (TI), Global Foundry
 - traditionally strong with design houses - NVIDIA, AMD, Broadcom, Apple, . . .
 - threatened experiencing global chip shortage & vulnerable supply chain via COVID
 - national security concerns & economic competitiveness
- China
 - strong fast followers - SMIC⁴, Huawei, Hua Hong Semiconductor (foundry)
- South Korea
 - best memory chip makers - Samsung, SK hynix
 - struggling with LSI and foundry business

⁴SMIC - Semiconductor Manufacturing International Corporation

Reshoring semiconductor manufacturing industry

- trade & semiconductor WAR between US & China
 - export controls on advanced chips and equipment
- CHIPS & Science Act (Aug, 2022)
 - \$52B in subsidies for domestic production, 25% investment tax credit for chip plants
 - (coerce) world-best semiconductor manufacturers build factories in US with support
 - GlobalFoundries - \$1.5B @ Feb-2024
 - Intel - \$8.5B @ Apr-2024 - Ohio - two fabs expandable to \$100B
 - Samsung - \$6.4B @ Apr-2024 - Talor, Texas
 - TSMC - \$6.6B @ Apr-2024 - Phoenix, Arizona
 - two foundry fabs (3nm & 4nm)



Turmoils in global semiconductor business

- global context
 - EU Chips Act - €43B to boost European chip production
 - Japan & South Korea - significant investments in domestic capacity
- industry dynamics
 - Intel's foundry ambitions - targeting 50% global market share by 2030
 - TSMC expanding global footprint (US, Japan, possibly Germany)
- future outlook
 - projected shift in global semiconductor manufacturing landscape
 - increased geographical diversification of chip production

Export controls on US chip technology to China



- goal - limit China's access to advanced semiconductor tech to maintain US strategic advantage
- impacts on
 - China - advanced chips and equipment not allowed, domestic innovation increased
 - US - short-term - US lose market share and revenue in China
 - US - long-term - potential decline in US global competitiveness
- Chinese response - circumvent controls and adapt supply chains
- conclusion
 - US-China chip rivalry transforms global supply chains with deep implications for *security & industry*
 - US success hinges on better coordination and policy analysis
- reference - [Balancing the Ledger - Center for Strategic & International Studies \(CSIS\)](#)

China strikes back on US sanction

- **Huawei's launch of Mate 60 Pro smartphone**
 - these domestically produced chips represent major breakthrough against US sanctions
 - its success with *advanced 7nm Kirin 9000S chip* demonstrates significant progress in China's self-reliance in high-tech manufacturing - narrowing the technological gap with global leaders
- **Huawei case highlights potential failure of US sanctions potentially leading to more aggressive US measures**
 - US export controls on China's semiconductor industry are effective in the short term but insufficient to halt China's progress especially in legacy chip manufacturing
 - to maintain technological edge, US must balance further restrictions with supporting its semiconductor industry to avoid overreliance on export controls



Chinese semiconductor companies

- Chinese major semiconductor companies
 - SMIC - China's largest chip foundry, advancing 7nm technology
 - HiSilicon - Huawei's chip design arm, crucial for the Kirin processors
 - YMTC - leader in 3D NAND memory chip production
 - Huahong Group, CXMT, SMEE, GigaDevice, UniIC Semiconductors, ASMC, etc.
- *SMIC shows significant progress in producing 7nm chips* & YMTC leads memory chip manufacturer - both face challenges from US export controls
- industry faces internal challenges, e.g., corruption & misallocation of resources
- but remains crucial to China's goal of technological self-reliance



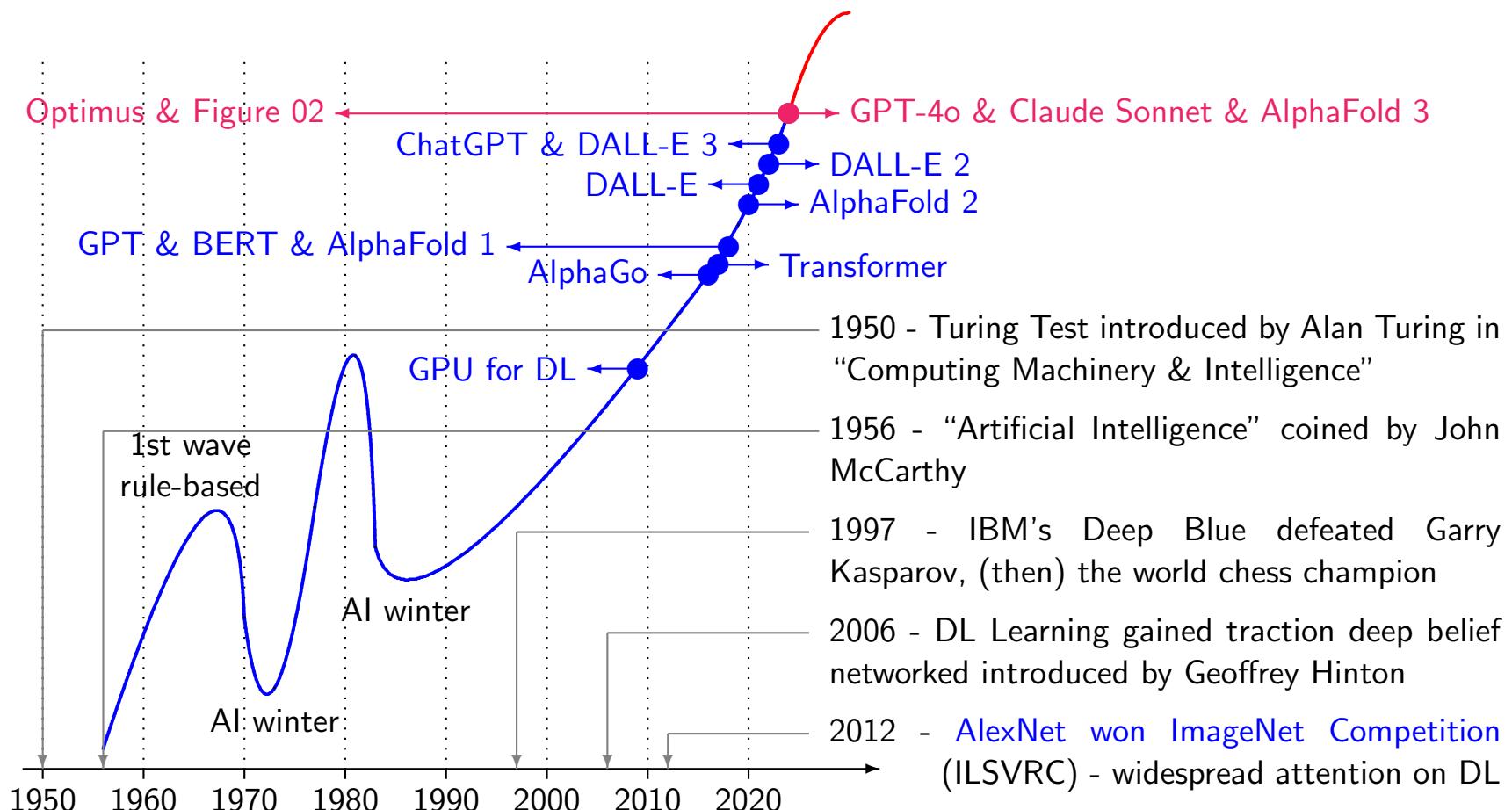
Silicon Valley's Cultural Engine of Innovation and Disruption

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

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

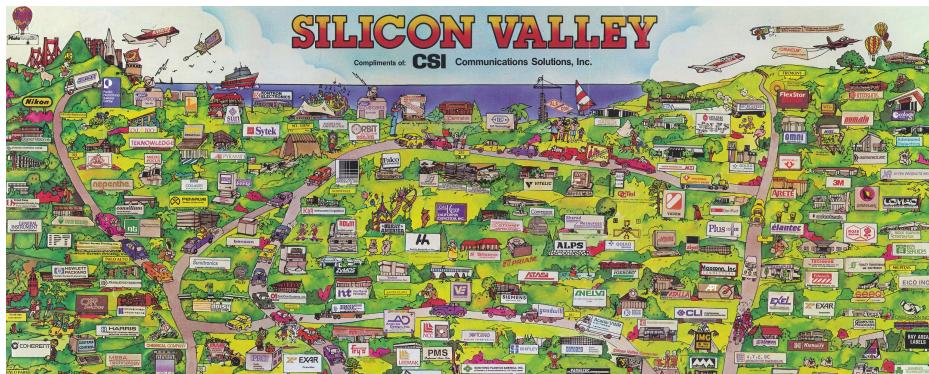


Joining Amazon.com, Inc. at the inflection point of AI



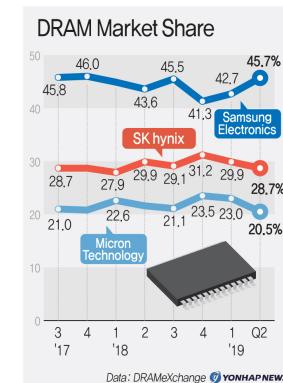
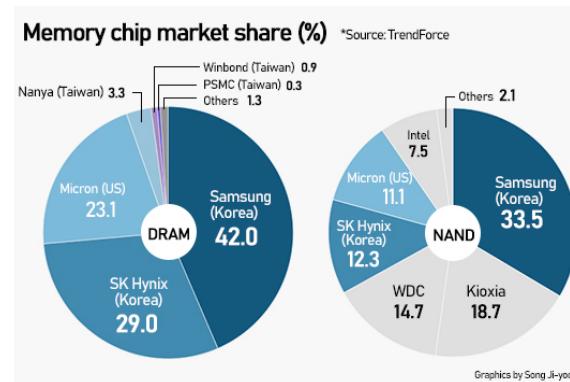
Innovation ecosystem of Silicon Valley

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



Case study: Amazon - amazing differentiators of big techs

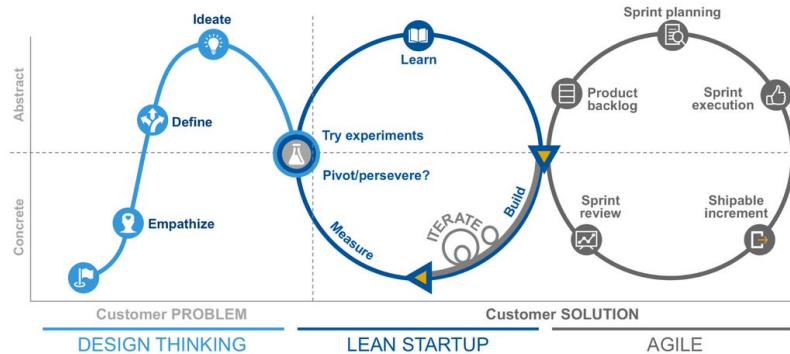
- Amazon's culture & leadership principles
 - customer obsession as driver of innovation
 - high standards & ownership culture, disagree & commit
 - bias for action and long-term thinking - sounds contradictory?
 - mechanisms like “two-pizza teams” & “Day One” for (or rather despite) scalability
- lessons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



Founding and scaling startups

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

Combine Design Thinking, Lean Startup and Agile



Product-Market Fit (PMF)



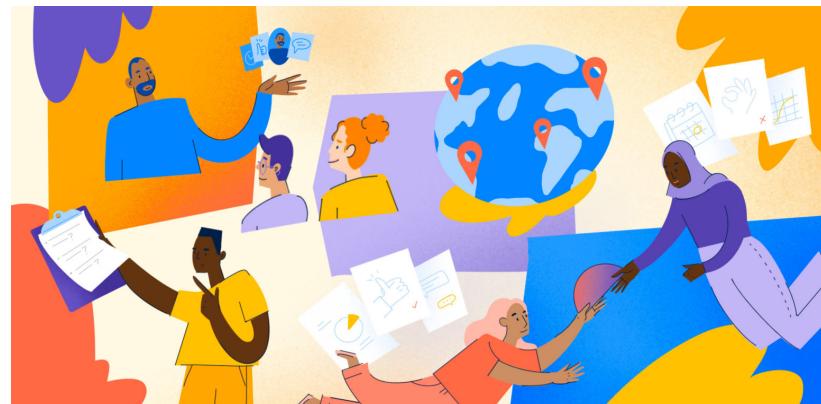
Bridging Silicon Valley & Korea

- 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



Some Important Questions around AI

Some important questions around AI

- why human-level AI?
- what lies in very core of DL architecture? what makes it work amazingly well?
- biases that can hurt judgement, decision making, social good?
- AI ethics & legal issues
- consciousness
- utopia vs dystopia
- knowledge, belief, reasoning
- risk of anthropomorphization

Human-level AI?

Why human-level in the first place?

- lots of times, when we measure AI performance, we say
 - how can we achieve human-level performance, *e.g.*, CV models?
- why human-level?
 - are all human traits desirable? are humans flawless?
 - aren't humans still evolving?
- advantage of AI over humans
 - *e.g.*, self-driving cars can use extra eyes, GPS, computer network
 - *e.g.*, recommendation system runs for hundreds of millions of people overnight
 - AI is available 24 / 7 while humans cannot
 - . . . critical advantages for medical assistance, emergency handling
 - AI does not make more mistakes because task is repetitive and tedious
 - AI does not request salary raise or go on strike

What makes DL so successful?

Factors contributing to astonishing success of DL

- analysis based on speaker's mathematical, numerical algorithmic & statistical perspectives considering hardware innovations

30% universal approximation theorem? - (partially) yes! but that's not all

- function space of neural network is *dense* (math theory), *i.e.*, for every $f : \mathbf{R}^n \rightarrow \mathbf{R}^m$, exists $\langle f_n \rangle$ such that $\lim_{n \rightarrow \infty} f_n = f$

25% architectures/algorithms tailored for each class of applications, *e.g.*, CNN, RNN, Transformer, NeRF, diffusion, GAN, VAE, . . .

20% data labeling - expensive, data availability - unlimited web text corpus

15% computation power/parallelism - AI accelerators, *e.g.*, GPU, TPU & NPU

10% rest - Python, open source software, cloud computing, MLOps, . . .

Sudden leap in LLM performance

Probability inferred sequence is correct

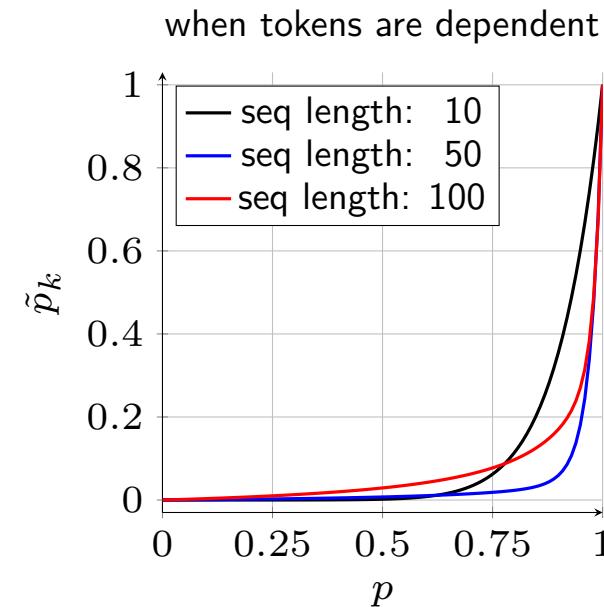
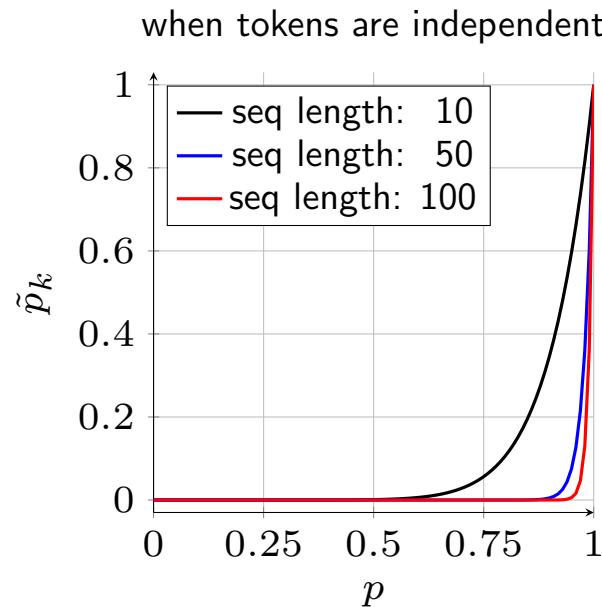
- assume
 - t_i - i th token
 - p_i - probability that t_i is correct
 - ρ_i - correlation coefficient between t_{i-1} & t_i
 - \tilde{p}_k - probability that (t_1, \dots, t_k) are correct
- recursion

$$\rho_i = \frac{\tilde{p}_i - \tilde{p}_{i-1}p_i}{\sqrt{\tilde{p}_{i-1}(1 - \tilde{p}_{i-1})p_i(1 - p_i)}}$$

$$\Leftrightarrow \quad \tilde{p}_i = \tilde{p}_{i-1}p_i + \rho_i \sqrt{\tilde{p}_{i-1}(1 - \tilde{p}_{i-1})p_i(1 - p_i)}$$

Dramatic improvement of LLM near saturation

- do simulations for both independent & dependent cases
 - assume p_i are same for all i
- (for both cases) sequence inference improves dramatically as p approaches 1
- this explains *why we have observed sudden dramatic performance improvement of certain seq2seq learning technologies*, e.g., LLM



Biases

Cognitive biases attributed to humans

- cognitive biases [Kah11]
 - confirmation bias, availability bias
 - hindsight bias, confidence bias, optimistic bias
 - anchoring bias, halo effect, framing effect, outcome bias
 - belief bias, negativity bias, false consensus



Biases of LLMs

- LLMs subject to
 - availability bias - biased by imbalancedly available information
 - LLM trained by imbalanced # articles for specific topics
 - belief bias - derive conclusion not by reasoning, but by what it saw
 - LLM easily inferring what it saw, *i.e.*, data it trained on
 - halo effect - overemphasize on what prestigious figures say
 - LLM trained by imbalanced # reports about prestigious figures
- similar facts true for other types of ML models,
 - *e.g.*, video caption, text summarization, sentiment analysis
- cognitive biases only humans represent
 - confirmation bias, hindsight bias, confidence bias, optimistic bias, anchoring bias, negativity bias, framing effect

AI Ethics

Ethical issues related to AI

- AI can be exploited by those who have bad intention to
 - manipulate / deceive people - using manipulated data corpus for training
 - *e.g.*, spread false facts
 - induce unfair social resource allocation
 - *e.g.*, medical insurance, taxation
 - exploit advantageous social and economic power
 - *e.g.*, unfair wealth allocation, mislead public opinion
- AI for Good - advocated by Andrew Ng
 - *e.g.*, public health, climate change, disaster management
- should scientists and engineers be morally & politically conscious?
 - *e.g.*, Manhattan project

AI related Legal Issues

Legal issues with ethical consideration

- scenario 1 - full self-driving algorithm causes traffic accident killing people
 - who is responsible? - car maker, algorithm developer, driver, algorithm itself?
- scenario 2 - self-driving cars kill less people than human drivers
 - *e.g.*, human drivers kill 1.5 people for 100,000 miles & self-driving cars kill 0.2 people for 100,000 miles
 - how should law makers make regulations?
 - utilitarian & humanitarian perspectives
- scenario 3 - someone is not happy with their data being used for training
 - “The Times sues OpenAI and Microsoft over AI use of copyrighted work” (Dec-2023)
 - “Newspaper publishers in California, Colorado, Illinois, Florida, Minnesota and New York said Microsoft and OpenAI used millions of articles without payment or permission to develop ChatGPT and other products” (Apr-2024)

Consciousness

Consciousness

- what is consciousness, anyway?
 - recognizes itself as independent, autonomous, valuable entity?
 - recognizes itself as living being, unchangeable entity?
- no agreed definition on consciousness exists yet
 - . . . and will be so forever
- does it have anything to do with the fact that humans are biologically living being?
- is SKYNET ever plausible?
 - can AI have *desire* to survive (or save earth)?



Utopia vs Dystopia

Utopia vs dystopia



- not important questions (at all) *I think . . .*
- what we should focus on is *not* the possibilities of doomsday or Judgment Day, but rather
 - our limits on controlling unintended impacts of AI
 - *misuse* by (greedy, immoral, and unethical) people possessing social, economic & political power
 - *social good and welfare impaired* by either exploiting AI or ignorance of (inner workings of) AI
- should concern
 - choice or balance among utilitarianism, humanitarianism & values
 - amend or improve laws/regulations
 - ethical issues caused by AI

Knowledge, Belief, and Reasoning

Does AI (LLM) have knowledge or belief? Can it reason?

**What categories of questions do they belong to?
engineering, scientific, philosophical, cognitive scientific, . . . ?**

LLMs . . .

- LLM is very different sort of animal . . . except that it is *not* an animal!
- *unreasonable* effectiveness of data [HNF09]
 - *performance scales with size of training data*
 - *qualitative leaps* in capability as models scale
 - tasks demanding human intelligence *reduced to next token prediction*
- focus on third surprise

conditional probability model looks like human with intelligence

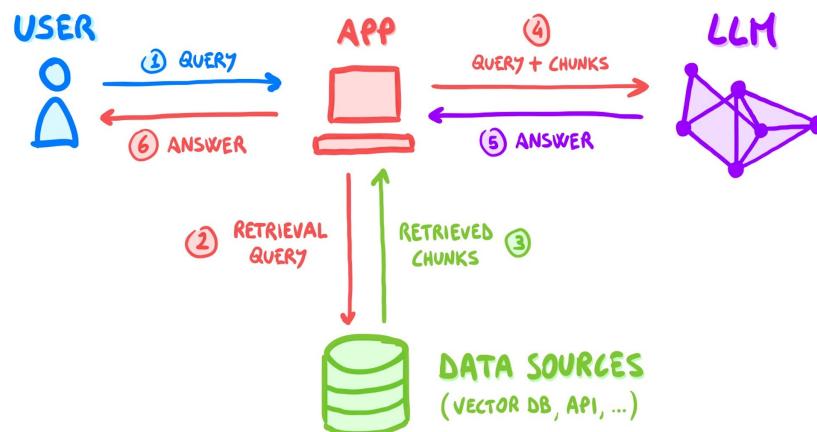
- making vulnerable to anthropomorphism
- examine it by throwing questions such as
 - “*does LLM have knowledge and belief?*”
 - “*can it reason?*”

What LLM really does!

- given prompt “the first person to walk on the Moon was”, LLM responds with “Neil Armstrong”. . . strictly speaking
 - it’s *not* being asked *who* was the first person to walk on the Moon
 - what are being *really* asked is “*given statistical distribution of words in vast public corpus of text, what words are most likely to follow ‘The first person to walk on the Moon was’?*”
- given prompt “after ring was destroyed, Frodo Baggins returned to”, LLM responds with “the Shire”
 - on one level, it seems fair to say, you might be testing LLM’s knowledge of fictional world of Tolkien’s novels
 - what are being *really* asked is “*given statistical distribution of words in vast public corpus of text, what words are most likely to follow ‘After the ring was destroyed, Frodo Baggins returned to’?*”

LLMs vs systems in which they are embedded

- crucial to distinguish between the two (for philosophical clarity)
 - LLM (bare-bones model) - highly specific & well-defined function, which is *conditional probability estimator*
 - systems in which LLMs are embedded, *e.g.*, for question-answering, news article summarization, screenplays generation, language translation



How ChatBot works?

- conversational AI agent does *in-context learning* or *few-shot prompting*
- for example,

- when the user enters

- who is the first person to walk on the Moon?

- ChatBot, LLM-embedded system, feeds the following to LLM

- User, a human, and BOT, a clever and knowledgeable AI agent.

- User: what is 2+2?

- BOT: the answer is 4.

- User: where was Albert Einstein born?

- BOT: he was born in Germany.

- User: who is the first person to walk on the Moon?

- BOT:

Knowledge, belief & reasoning around LLM

- *not* easy topic to discuss, or even impossible because
 - we *do not have agreed definition* of these terms especially in context of being asked questions like

does LLM have belief?
or
do humans have knowledge?
- let us discuss them in two different perspectives
 - laymen's perspectives
 - cognitive scientific & philosophical perspectives

Laymen's perspectives on knowledge, belief & reasoning

- does (good) LLM have knowledge?
 - Grandmother: looks like it cuz when instructed “*explaining big bang*”, it says
“*The Big Bang theory is prevailing cosmological model that explains the origin and evolution of the universe. . . . 13.8 billion years ago . . .*”
- does it have belief?
 - Grandmother: I don't think so, e.g., it does not believe in God!
- can it reason?
 - Grandmother: seems like it! e.g., when asked “*Sunghee is a superset of Alice and Beth is a superset of Sunghee. Is Beth a superset of Alice?*”, it says
“*Yes, based on information provided, if Sunghee is a superset of Alice and Beth is a superset of Sunghee, then Beth is indeed a superset of Alice . . .*”
- can it reason to prove theorem whose inferential structure is more complicated?
 - Grandmother: I'm not sure – actually, I don't know what you're talking about!

Knowledge

- could argue LLM “knows” which words follow which other words with high probability
- but, only *in context of capacity to distinguish truth from falsehood* can we legitimately speak of “knowledge” !
- LLM(-embedded BOT)
 - can be said to “*encode*”, “*store*”, or “*contain*” knowledge
 - lacks means to use words “true” & “false” in all ways & in all contexts because . . .
 - *does not inhabit the world* we human language-users share!



Belief

- nothing can count as *belief about the world* we share unless
 - is against backdrop of “*ability to update beliefs appropriately in light of evidence from that world*” - (again) essential capacity to distinguish truth from falsehood
- change taking place in humans when acquiring or updating belief is
 - reflection of their nature as language-using animals inhabiting shared world with community of language-users
- then, *what if LLM-embedded system updates LLM with outside world information?*
 - even so, when interacting with AI systems based on LLMs, these grounds are *absent!*



can you provide me up-to-date information about AI agent perplexity?

Sources

- Perplexity AI: A Guide for Beginners - Jeff Su
- Perplexity AI's value to our AI team as it realizes new \$800K funding - siliconangle
- Perplexity At A Deep Dive - Reflections
- anopose

Show all

Perplexity

Perplexity AI is an AI-powered search engine and answer engine that has gained significant traction in recent years. Founded in 2022, Perplexity uses large language models (LLMs) to generate answers to user queries, citing sources from the web within the text response. As of Q1 2024, Perplexity had reached 15 million monthly users.

Key features and developments of Perplexity AI include:

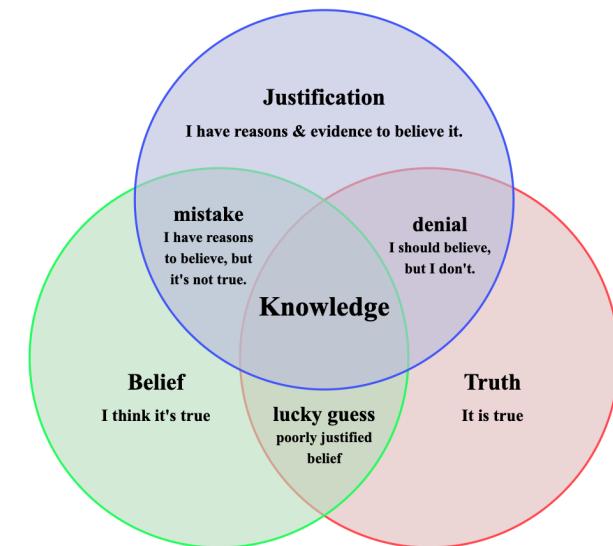
- Search functionality: Perplexity summarizes search results and produces text with inline citations, providing personalized results based on the context of user queries

Ask follow-up



Knowledge in philosophical and cognitive scientific sense

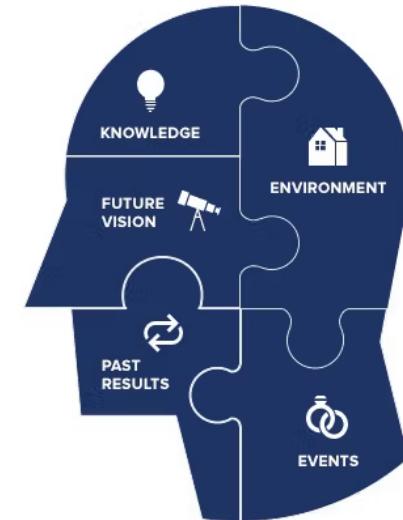
- does LLM have knowledge?
 - Sunghee: *I don't think so!*
- why?
 - we say we have “knowledge” when
“we do so against ground of various human capacities that we all take for granted when we engage in everyday conversation with each other.”
 - when asked *“who is Tom Cruise’s mother?”*, it says *“Tom Cruise’s mother is Mary Lee Pfeiffer.”*
 However, this is nothing but
“guessing” by conditional probability model the most likely words following “Tom Cruise’s mother is.”
 - so *we cannot say it really knows the fact!*



Belief in philosophical and cognitive scientific sense

- for the discussion
 - do *not* concern any specific belief
 - but concern *prerequisites for ascribing any beliefs to AI system*
- so does it have belief?
 - nothing can count as belief about the world we share unless
 - it is against ground of the ability to update beliefs appropriately in light of evidence from that world, essential aspect of the capacity to distinguish truth from falsehood*
 - LLM does not have this ground, essential consideration when deciding whether it *really* had beliefs.
- Sunghee: so *no, LLM cannot have belief!*

WHERE DO YOUR
BELIEFS COME FROM?



Reasoning in philosophical and cognitive scientific sense

- note reasoning is *content neutral*
 - e.g., following logic is perfect regardless of truth of premises
 - hence, no access to outside world does *not* disqualify
- when asked “*if humans are immortal, would Socrates have survived today?*”, LLM says “*... it's logical to conclude that Socrates would likely still be alive today. ...*”
- however, remember, once again, what we just asked it to do is *not* “deductive inference”
given the statistical distribution of words in public corpus, what words are likely to follow the sequence, “humans are immortal and Socrates is human therefore.”
- Sunghee: so *no, LLM cannot reason, either!*
- but, LLM
 - pretends to reason, and from which capabilities, we can benefit!
 - also, can *mimic even multi-step reasoning whose inferencing structure is complicated* using *chain-of-thoughts prompting*, i.e., *in-context learning* or *few-short prompting*

Simple example showing LLM not possessing knowledge



- User
"Who is Tom Cruise's mother?"
- LLM(-embedded question-answering system) (as of Jan 2022)
"Tom Cruise's mother is Mary Lee Pfeiffer. She was born Mary Lee South. . . . Information about his family, including his parents, has been publicly available, . . . "
- User
"Who is Mary Lee Pfeiffer's son?"
- LLM(-embedded question-answering system) (as of Jan 2022)
"As of my last knowledge update in January 2022, I don't have specific information about Mary Lee Pfeiffer or her family, including her son. . . . "

Risk of anthropomorphization

- unfortunately, contemporary LLMs are *too powerful, too versatile, and too useful for most people to accept (after understanding) previous arguments!*
- maybe, o.k. for laymen to (mistakenly) anthropomorphize LLM(-embedded systems)
- however, *imperative for (important, smart, and responsible) AI researchers, scientists, engineers & practitioners* to have rigorous understanding in these aspects especially when
 - advise and be consulted by law makers, policy makers, journalists, and various stakeholders responsible for *critical business decisions (in private sectors) and public policies (in public sectors)*
 - collaborate with or/and help professionals in liberal arts, such as *philosophy, ethics, law, religion, literature, history, music, cultural studies, psychology, sociology, anthropology, political science, economics, archaeology, linguistics, media studies, natural sciences, fine arts, . . .*
 - to address negative societal and economic impacts

Moral

- AI shows incredible utility and commercial potentials, hence should
 - make informed decisions about trustworthiness and safety
 - avoid ascribing capacities they lack
 - *take best utilization of remarkable capabilities of AI*
- today's AI so powerful, so (seemingly) convincingly intelligent
 - obfuscate mechanism
 - actively encourage *anthropomorphism* with philosophically loaded words like “*believe*” and “*think*”
 - easily mislead people about character and capabilities of AI
- matters not only to scientists, engineers, developers, and entrepreneurs, but also
 - *general public, law & policy makers, journalists, . . .*

Empowering Humanity for Future Enriched by AI

Blessings & Curses of AI

Blessings

- advancements in healthcare & improved quality of life
 - much faster & more accurate diagnosis, far superior personalized medicine, accelerated drug discovery, assistive technologies
- economic growth & efficiency
 - automation to increase productivity and reduce cost, far superior decision-making
- environmental solutions
 - climate change prediction, global warming effect mitigation, solutions for sustainability
- safety & security
 - natural disaster prediction & relief, cybersecurity



Curses

- job displacement & overall impacts on labor market
 - millions of jobs threatened, wealth gap widened
- bias & inequality, misinformation & manipulation
 - existing human biases, both conscious and unconscious, perpetuated through AIs, asymmetric accessibility to advanced AI technologies by nations & corporations
- ethical dilemmas
 - infringing privacy & human rights, accountability for weapon uses and damages by AI
- environmental costs
 - significant energy for training AI models, waste generated by obsolescent AI hardware



Salzburg Global Seminar

KFAS-Salzburg Global Leadership Initiative

- “Uncertain Futures and Connections Reimagined: Connecting Technologies” - 41 global leaders convened from 4-Dec to 8-Dec, 2024 @ Schloss Leopoldskron in Salzburg, Austria
- My working group was “Technology, Growth, and Inequality: The Case of AI”
 - International Cooperation Officer (Portugal)
 - Gender Equality, Disability Inclusion Consultant, UN Women (Lithuania)
 - Assistant Professor @ Lincoln Alexander School of Law (Canada)
 - Research Associate @ Luxembourg Institute of Socio-Economic Research
 - Policy Officer & Delegation of the EU Union (India)
- blog: [Bridging Technology & Humanity - Reflections from Lyon, Salzburg, and München](#)



KFAS-Salzburg Global Leadership Initiative

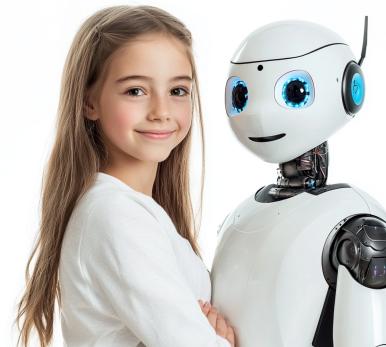
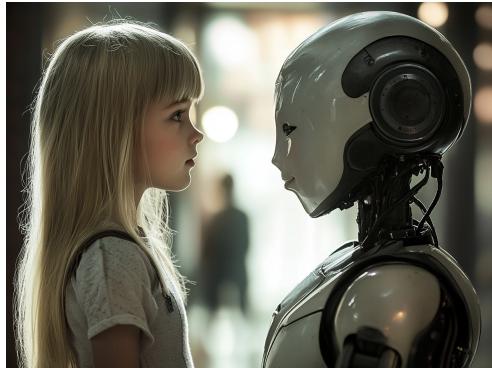
Salzburg Global photo collections



Empowering Humanity

AI capacity building - scientists, engineers & practitioners

- ethics and responsible AI education or campaign via interdisciplinary collaboration
 - foster continuous learning programs on AI risks, bias & societal impacts
- bias detection & mitigation
 - bias-detection tools to identify & reduce discrimination in data & models
 - regular fairness audits
- transparency & explainability
 - explainable AI (xAI) techniques, frameworks like Model Cards for transparency
- environmental impact awareness
 - reduce AI's carbon footprint, advocate for sustainable AI development practices



AI capacity building - lawmakers & policy makers

- problems
 - difficulties in understanding of rapidly evolving AI technologies
 - lead to reactive or insufficient regulation
- proposed solutions
 - develop comprehensive regulatory frameworks addressing transparency, bias & privacy concerns
 - gender bias, racial bias, hallucinations
 - foster public debates on ethical AI use & societal implications
 - introduce policies to limit spread of AI-generated misinformation,



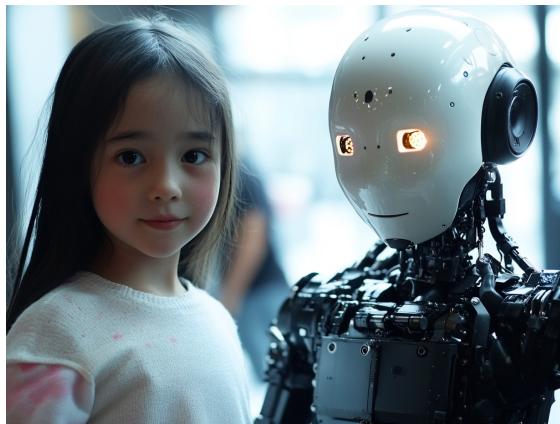
Participatory social agreements

- open data frameworks including data sovereignty, regulation of data transfer, storage & localization
- corporate social responsibility, extra-territorial obligations & environmental protection
 - including outside the jurisdiction of the country
- labour and employment displacements, tax cuts & algorithmic impact assessments
 - including remedies for AI harms and enforcements



Reclaiming technology for Humanity

- strategic approach to AI development
 - *leverage very technologies alienating humans to strengthen human connection*
 - transform automation from replacement to *enhancement of human capabilities*
 - leverage technological scale to address fundamental human needs
- *paradigm shift* in technological implementation
 - recognize the duality of advanced technologies
 - *systematically channel AI capabilities toward human-centric solutions*
 - convert technological challenges into opportunities for human advancement



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