

[Texas A&M Seminar / Intro to Semiconductor & Microelectronics]

Industrial AI - Technological Innovations and Impacts on Semiconductor Manufacturing

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About Speaker

- *Co-founder / CTO - AI Technology & Product Strategy @ Erudio Bio, CA, USA*
- Advisory Professor, Electrical Engineering and Computer Science @ DGIST
- Adjunct Professor, Electronic Engineering Department @ Sogang University
- Technology Consultant @ Gerson Lehrman Group (GLG), NYC, USA
- *Co-founder / CTO & Chief Applied Scientist @ Gauss Labs, CA, USA – 2023*
- Senior Applied Scientist @ Amazon, Vancouver, Canada – 2020
- Principal Engineer @ Software R&D Center of DS Division - Samsung – 2017
- Principal Engineer @ Strategic Marketing Team of Memory Business Unit – 2016
- Principal Engineer @ DT Team of DRAM Development Lab. - Samsung – 2015
- Senior Engineer @ CAE Team - Samsung – 2012
- M.S. & Ph.D. - Electrical Engineering @ Stanford University – 2004
- B.S. - Electrical Engineering @ Seoul National University – 1998

Highlight of career journey

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

Today

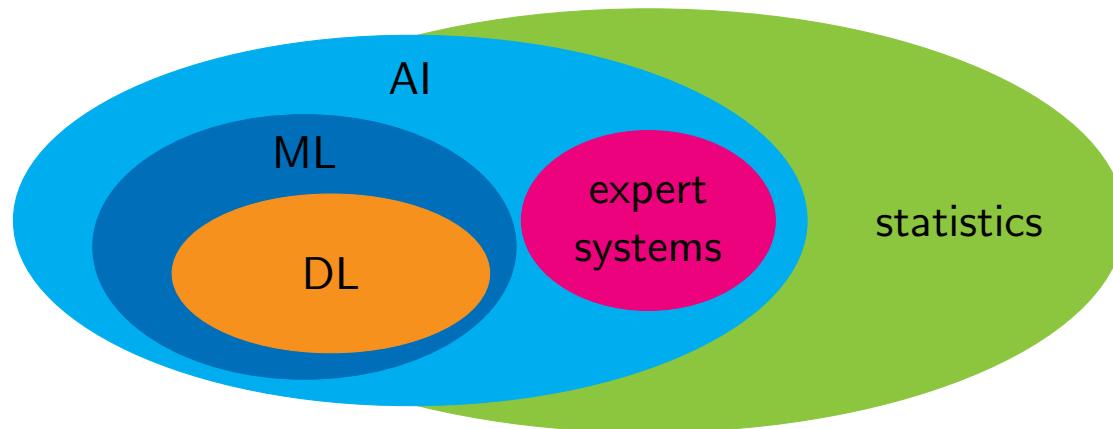
- Artificial Intelligence
 - history
 - AI achievement from 2014 to 2024
- AI research and development trend
- industrial AI (inAI)
 - definition and characteristics of inAI
 - computer vision (CV) and time-series (TS) MLs
 - industrial AI success story - virtual metrology (VM)
- conclusion & speaker's recommendations / advice
- appendices
 - recent AI development & AI in biotech

Artificial Intelligence

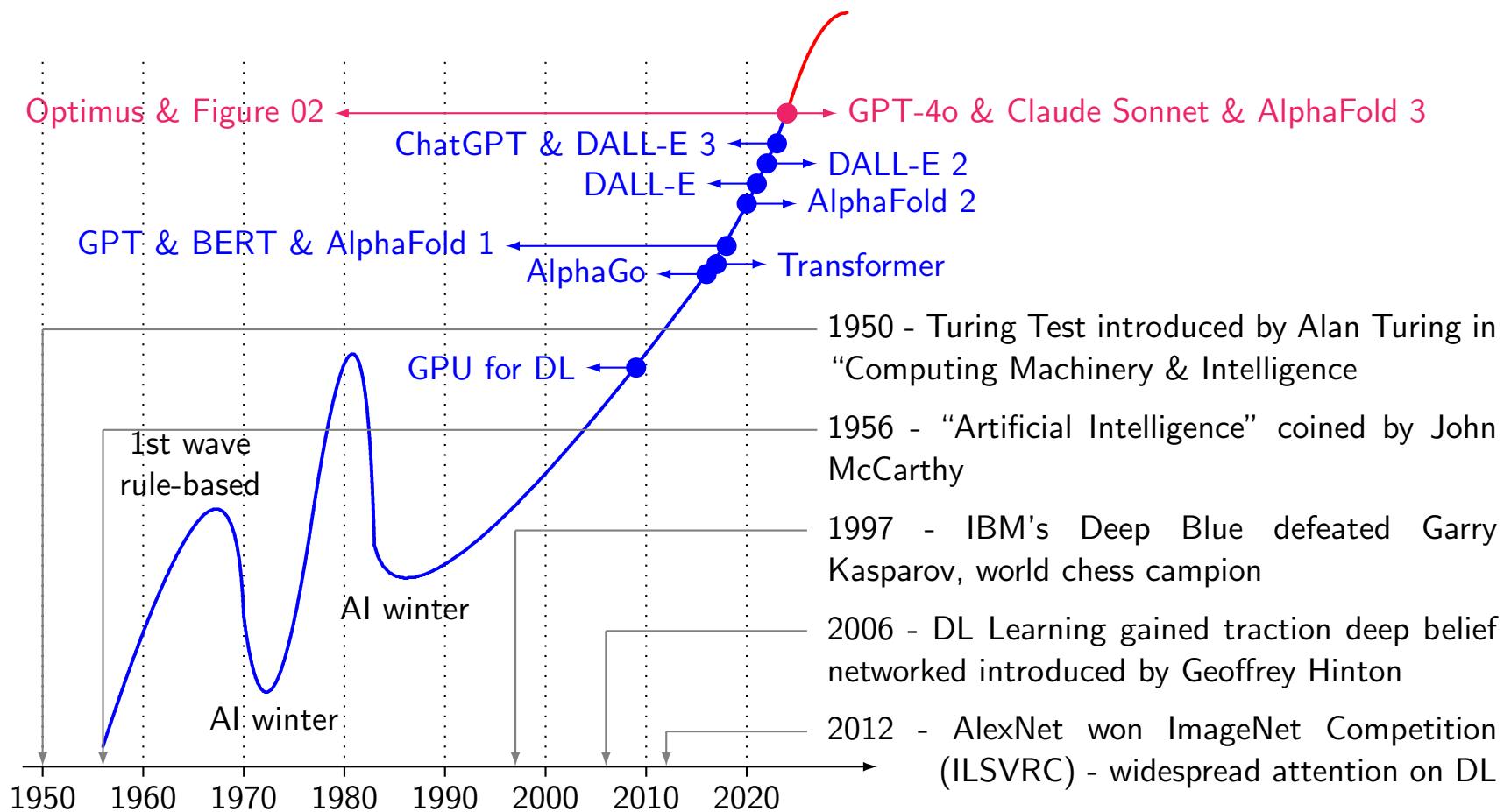
Definition and History

Definition of AI

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



History of AI



Significant AI Achievements - 2014 – 2024

Deep learning revolution

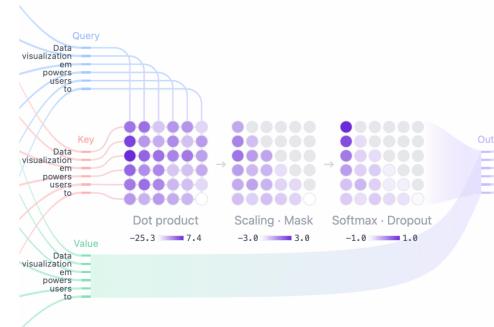
- 2012 – 2015 - Deep Learning Revolution¹
 - CNNs demonstrated exceptional performance in image recognition, e.g., *AlexNet's victory in ImageNet competition*
 - widespread adoption of DL learning in CV transforming industries
- 2016 - AlphaGo Defeats Human Go Champion
 - DeepMind's AlphaGo defeated 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



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

Transformer changes everything

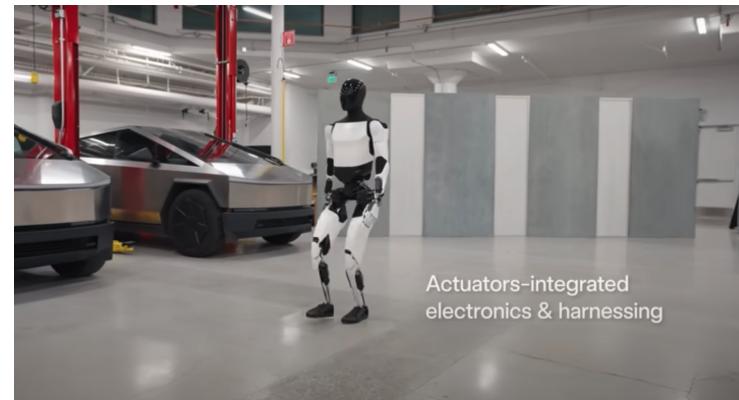
- 2017 – 2018 - Transformers and NLP breakthroughs²
 - *Transformer (e.g., BERT & GPT) revolutionized NLP*
 - major advancements in, *e.g.*, machine translation & chatbots
- 2020 - AI in Healthcare – AlphaFold and Beyond
 - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting 3D protein structures with remarkable accuracy
 - accelerates drug discovery and personalized medicine - offering new insights into diseases and potential treatments



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

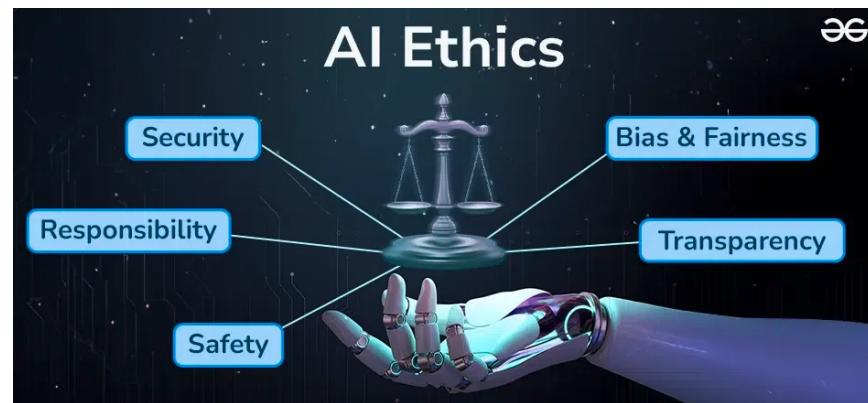
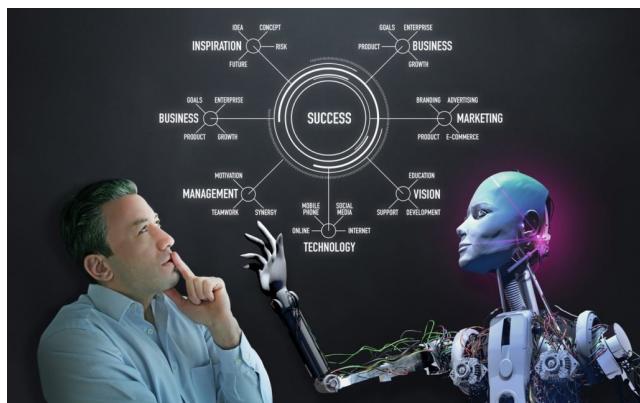
Lots of breakthroughs within 6 months in 2024

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



Transformative impact of AI - reshaping industries, work & society

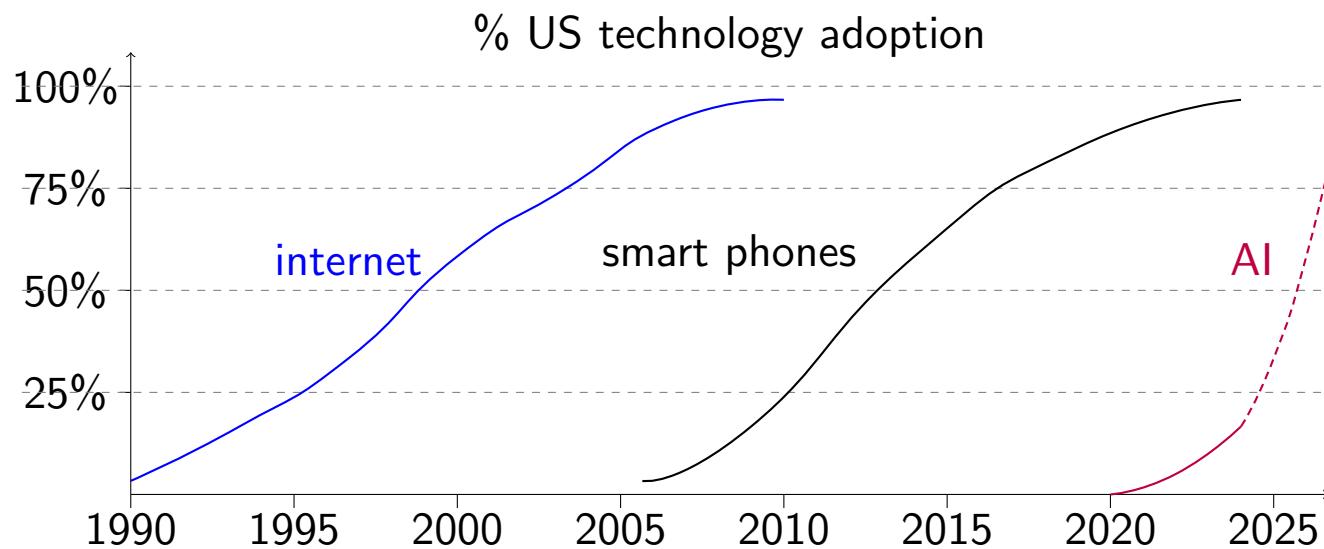
- accelerating human-AI collaboration
 - not only reshaping industries but *altering how humans interact with technology*
 - AI's role as collaborator and augmentor redefines productivity, creativity, the way we address global challenges, e.g., *sustainability & healthcare*
- AI-driven automation *transforms workforce dynamics* - creating new opportunities while challenging traditional job roles
- *ethical AI considerations* becoming central not only to business strategy, but to society as a whole - *influencing regulations, corporate responsibility & public trust*



Recent Advances in AI

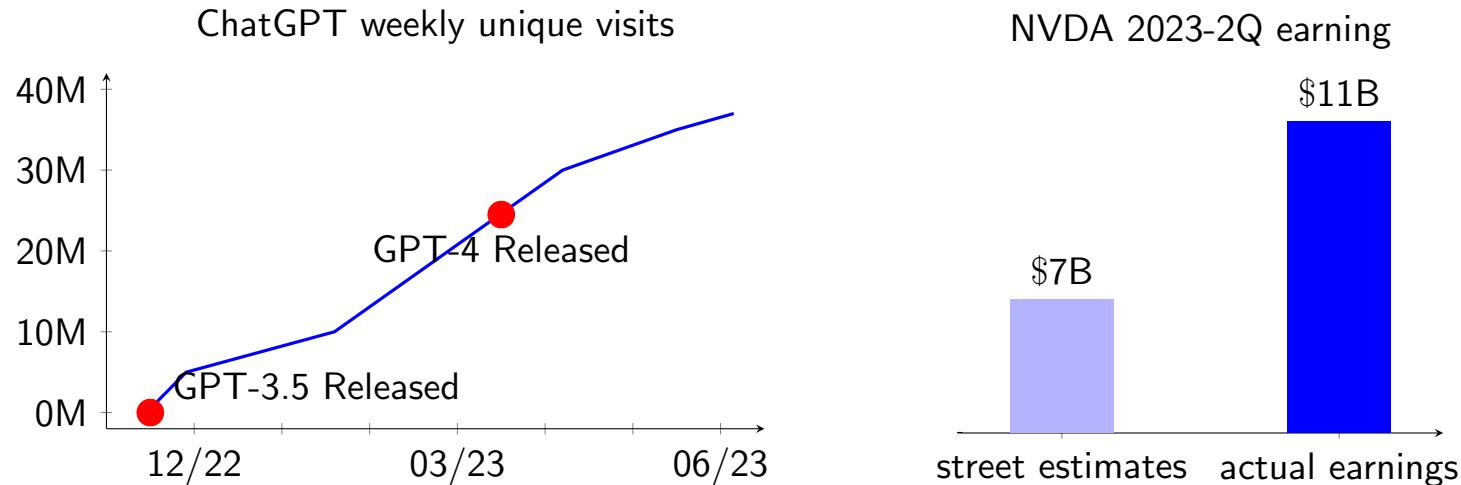
Where are we in AI today?

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



Explosion of AI ecosystems - ChatGPT & NVIDIA

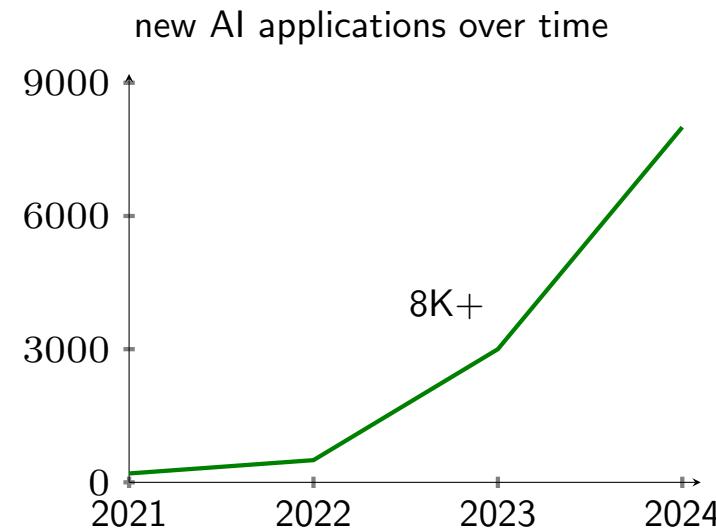
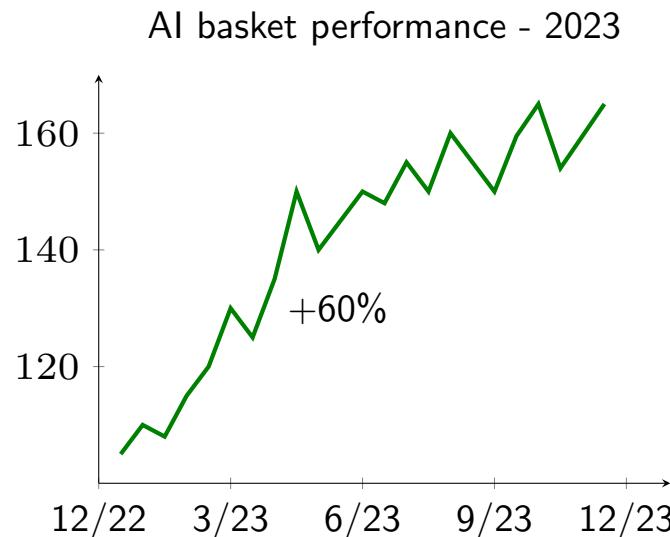
- took only *5 months for ChatGPT users to reach 35M*
- NVIDIA 2023 Q2 earning exceeds market expectation by big margin - \$7B vs \$13.5B
 - surprisingly, *101% year-to-year growth*
 - even more surprisingly *gross margin was 71.2%* - up from 43.5% in previous year³



³source - Bloomberg

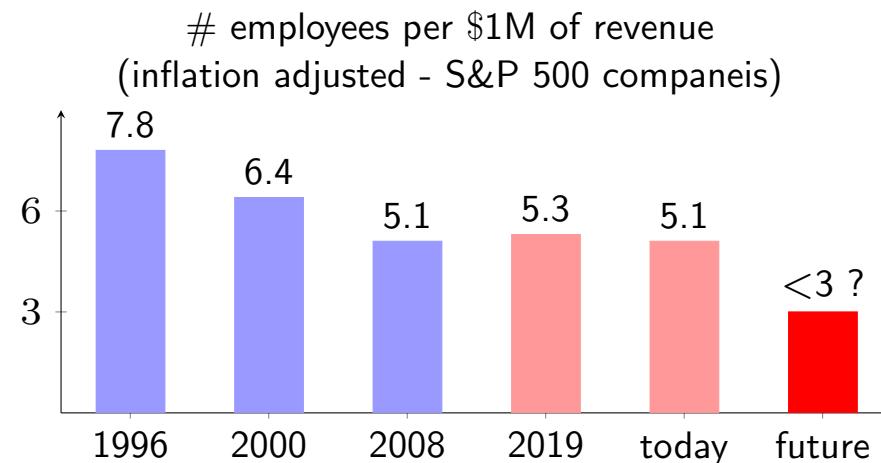
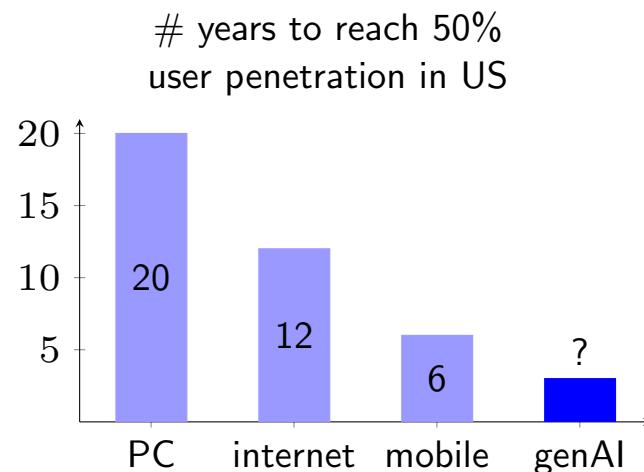
Explosion of AI ecosystems - AI stock market

- *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



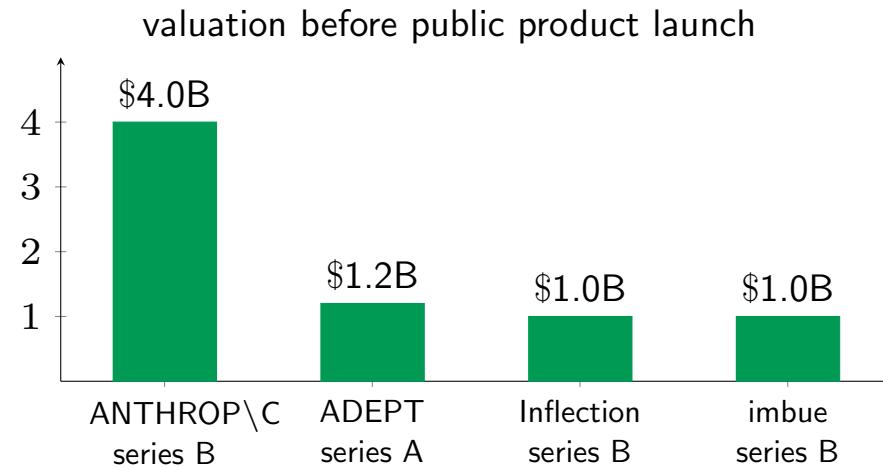
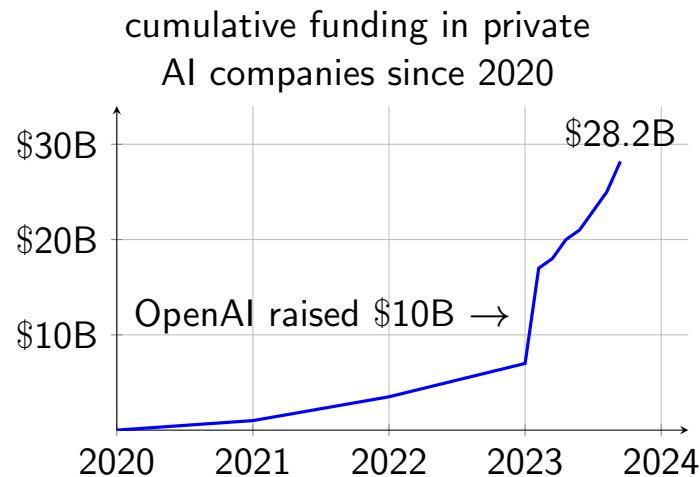
AI's transformative impact - adoption speed & economic potential

- 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



Massive investment in AI

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



AI Market & Values

Fiber vs cloud infrastructure

- fiber infrastructure - 1990s
 - Telco Co's raised \$1.6T of equity & \$600B of debt
 - bandwidth costs decreased 90% within 4 years
 - companies - Covage, NothStart, Telligent, Electric Lightwave, 360 networks, Nextlink, Broadwind, UUNET, NFS Communications, Global Crossing, Level 3 Communications
 - became *public good*
- cloud infrastructure - 2010s
 - entirely new computing paradigm
 - mostly public companies with data centers
 - *big 4 hyperscalers generate \$150B + annual revenue*



Cloud stacks

- SaaS dominates cloud stack - account for 40% of total cloud stack market with estimated TAM of \$260B
- IaaS and PaaS significant players
- semi-cloud's niche presence

cloud stack	companies	estimated TAM	% total in stack
SaaS apps	Salesforce, Adobe	\$260B	40%
PaaS	Confluent, snowflake	\$140B	22%
IaaS	AWS, Azure, GCP	\$200B	30%
cloud semis	AMD, Intel	\$50B	8%

AI stacks

- AI investment landscape - AI sector witnessing significant capital inflow with total funding of approximately \$29 billion across various segments
- models lead pack - AI models, particularly those developed by OpenAI and Anthropic, attracted lion's share of investments, accounting for 60% of total funding
- diverse growth - while models dominate funding, other segments like apps, AI cloud, and AI semis also experiencing substantial growth, indicating broadening AI ecosystem

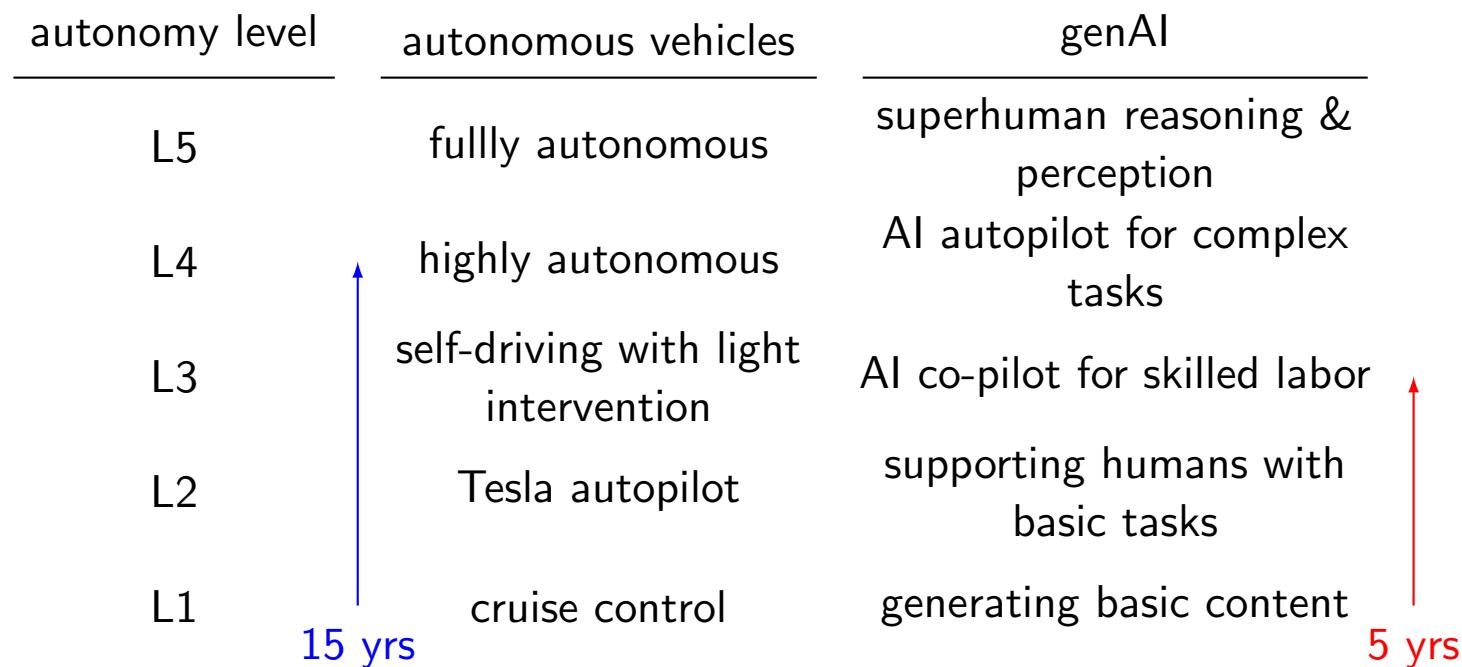
AI stack	companies	total funding	% total in stack
apps	character.io, replit	~\$5B	17%
models	openAI, ANTHROP\ C	~\$17B	60%
Alops	Hugging Face, Weights & Biases	~\$1B	4%
AI cloud	databricks, Lambda	~\$4B	13%
AI semis	cerebras, SambaNova	~\$2B	6%

AI model companies

- AI model companies - competing for which AI model companies will dominate 2020s
- venture funding surge - private AI model companies raised approximately \$17B since 2020, indicating strong investor confidence
- growing open-source presence - becoming increasingly prevalent, adding competition and innovation to AI landscape
- key players - notable companies in AI model space include Adept, OpenAI, Anthropic, Imbue, Inflection, Cohere, and Aleph Alpha
- outcome uncertain - future success is still to be determined, reflecting dynamic and evolving nature of AI industry

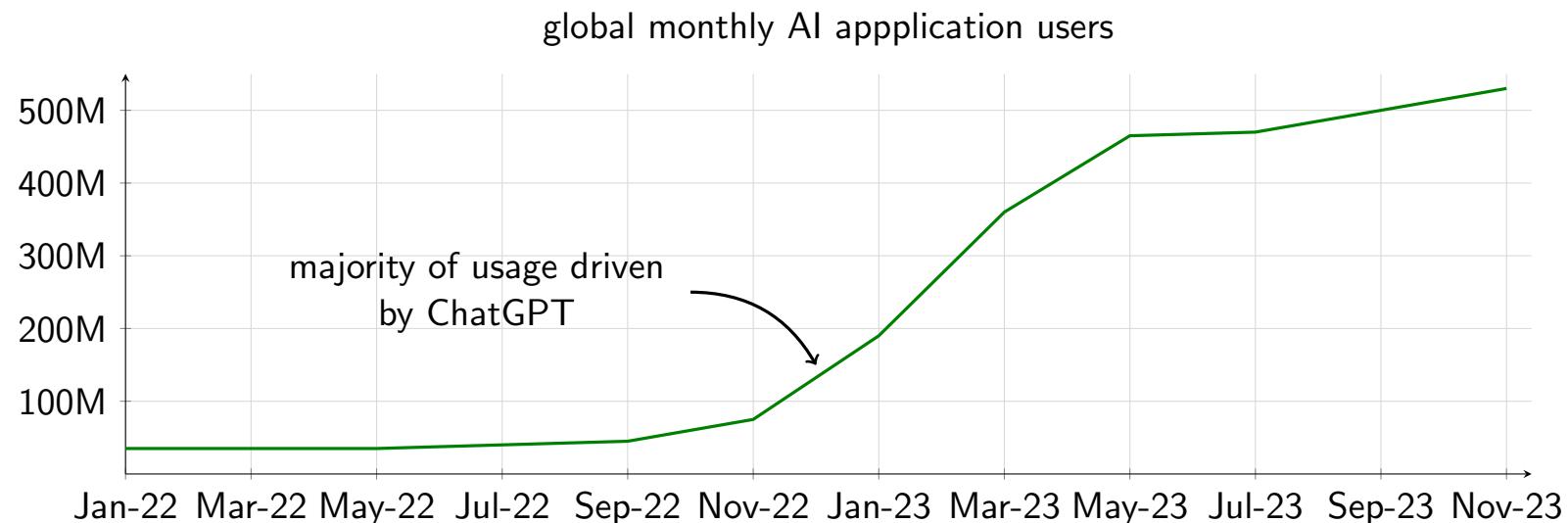
AI advancing much faster

- rapid AI advancement - general AI projected to progress from basic content generation to superhuman reasoning in only 5 years
 - significantly outpacing 15-year timeline for fully autonomous vehicles



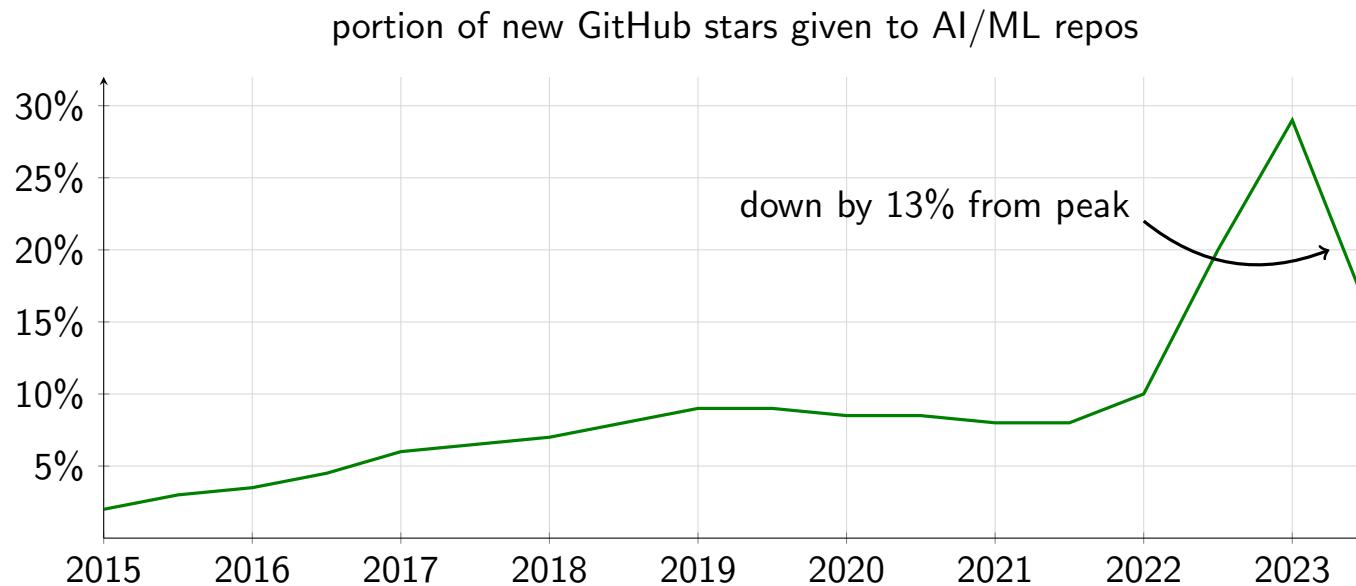
AI interest of users

- AI adoption approaching saturation - initial wave may be nearing saturation
- future growth might come from deeper integration into professional workflows & specialized applications
- potential for market diversification - ChatGPT drove majority of early growth, but now we have other LLMs - Claude, Mistral, Gemini, Grok, Perplexity



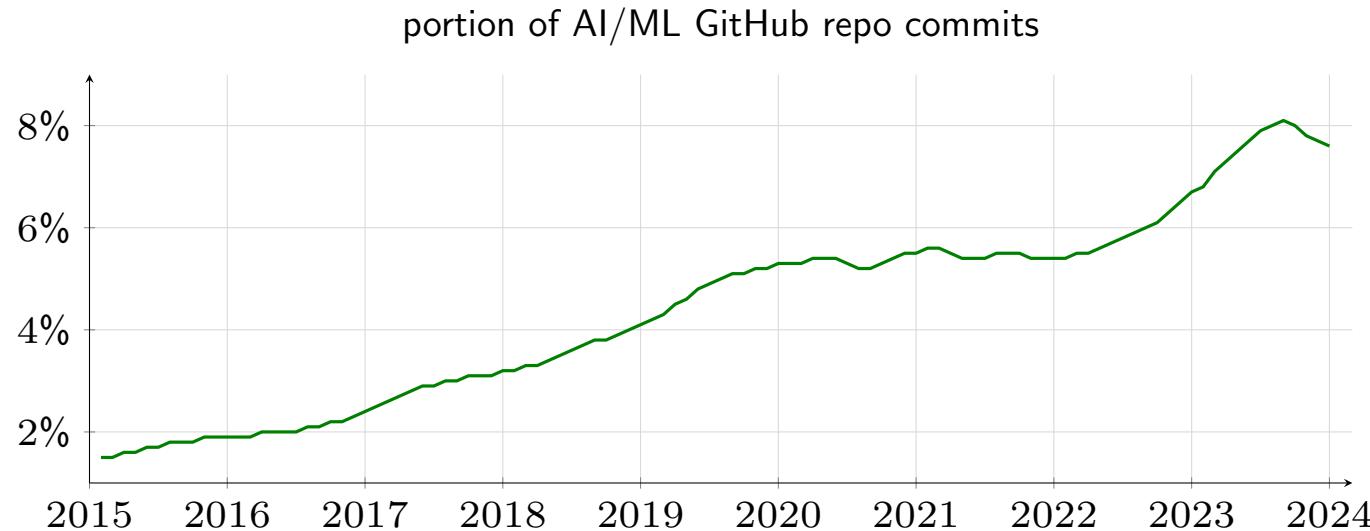
AI interest of developers

- rising popularity - portion of new GitHub stars given to AI/ML repositories steadily increased from 2015 to 2022
- excitement waning & washing out AI “tourists” - decline of 13% from peak in 2022
- could indicate potential factors such as market saturation, economic conditions, or shifts in developer preferences



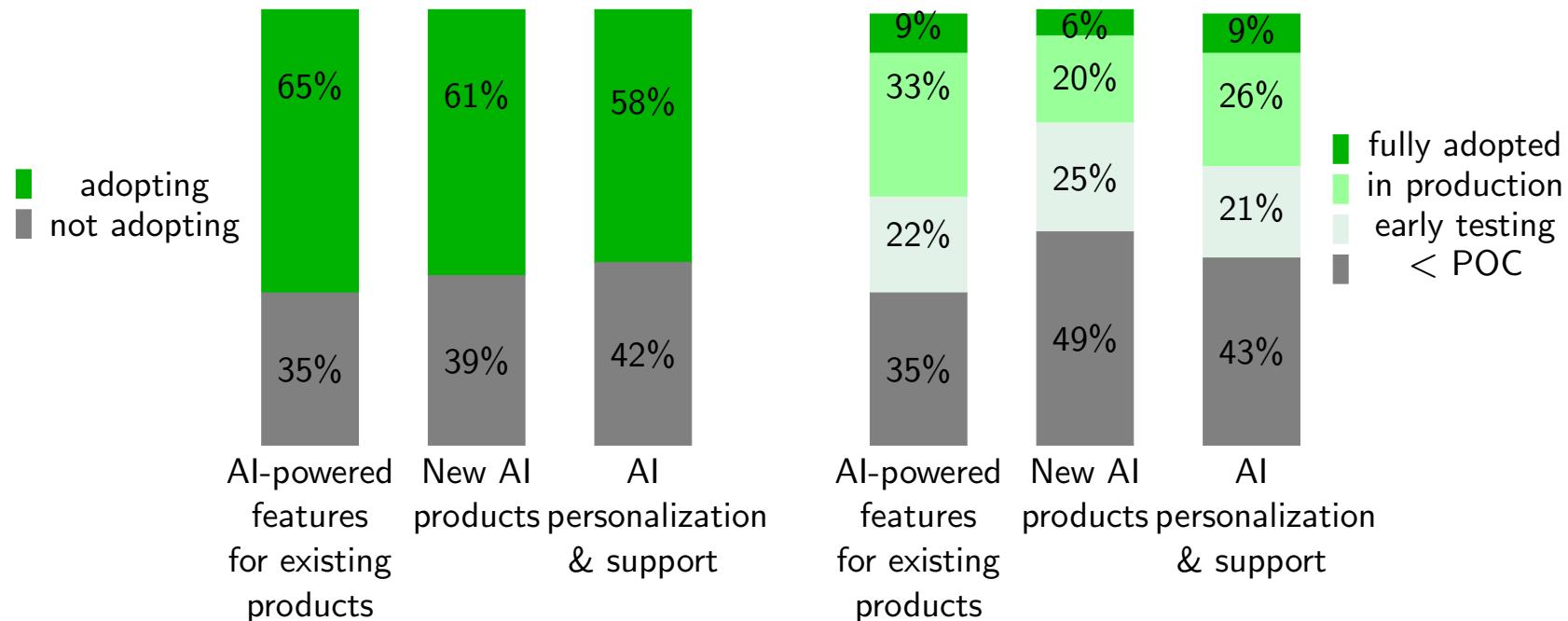
Developers' contribution to software packages

- steep acceleration from 2022 to 2024 correlates with explosion of LLMs & genAI
- suggesting transformative shift in AI landscape beyond gradual growth
- AI/ML still represents relatively small portion (less than 10%)
- indicating significant room for growth and mainstream adoption across various software domains



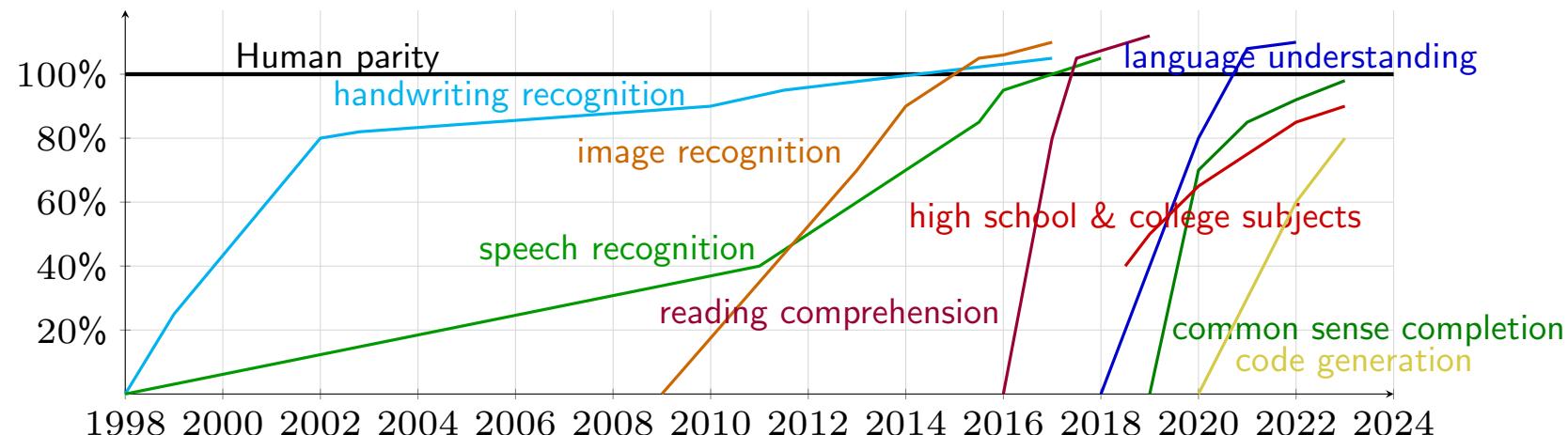
Enterprises adopting AI

- more than 60% of enterprises planning to adopt AI
- full adoption rate is less than 10% - will take long time



AI getting better and 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



AI delivers game-changing values

- time developers save using GitHub Copilot - **55%**
 - **10M+** cumulative downloads as of 2024 & **1.3M** paid subscribers - **30%** Q2Q increase
 - improves developer productivity by **30%+**
- reduction in human-answered customer support requests - **45%**
 - cost per support interaction - **95%** save / \$2.58 (human) vs \$0.13 (AI)
 - median response time - **44 min** faster / 45 min (human) vs 1 min (AI)
 - median customer satisfaction - **14%** higher / 55% (human) vs 69% (AI)
- time saved from editing video in runway - **90%**
- AI chat rated higher quality compared to physician responses - **79%**

Is AI hype?

Yes & No

characteristics of hype cycles

value accrual misaligned with investment

overestimating timeline & capabilities of technology

lack of widespread utility due to technology maturity

speaker's views

- 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
- 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
- AI already providing significant utility across various domains
- vs quantum computing remains promising in theory but lacks widespread practical utility

AI Research

AI research race gets crazy

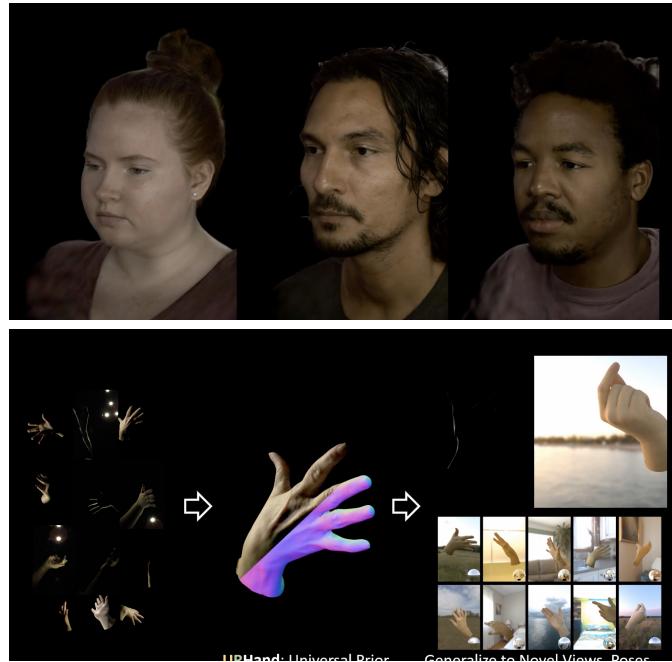
- practically impossible to follow all developments announced everyday
 - new announcement and publication of important work everyday!
- *industry leads research - academia lags behind*
 - trend observed even before 2015
- everyone excited to show off their work to the world
 - conference and github.com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



AI progress within a month - March, 2024

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

Papers of single company accepted by single conference



- CVPR 2024

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

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)



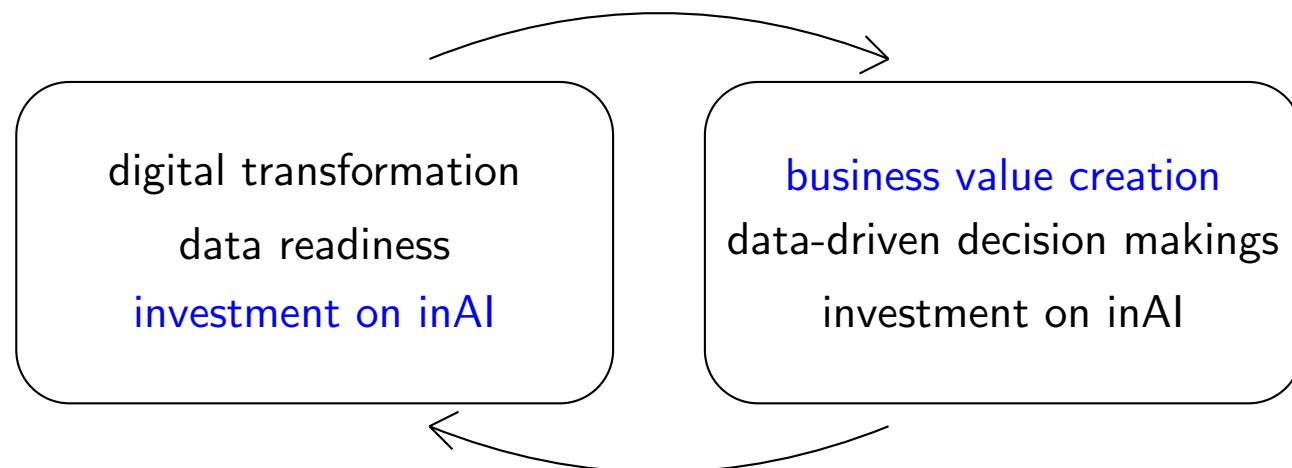
inAI fields

- 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

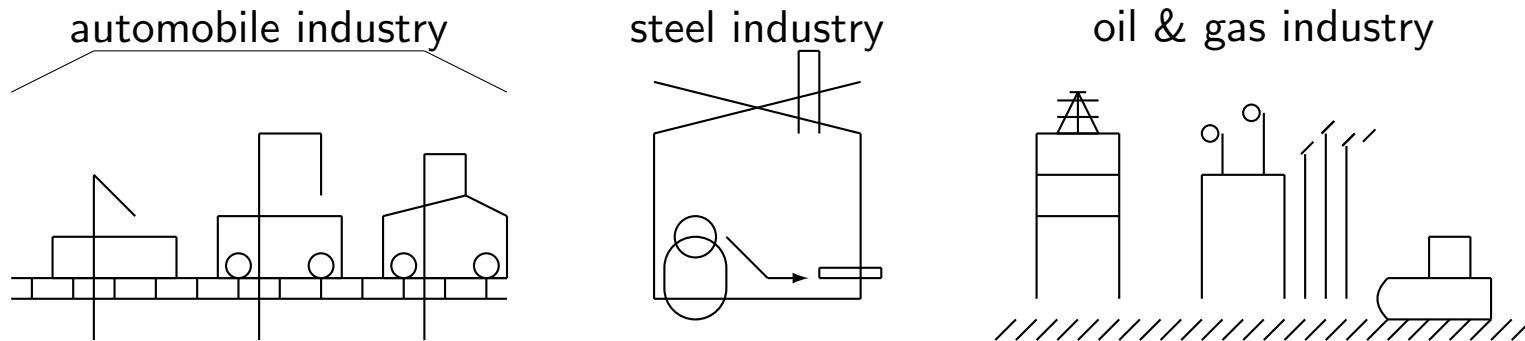
Vicious (or virtuous) cycle

- 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

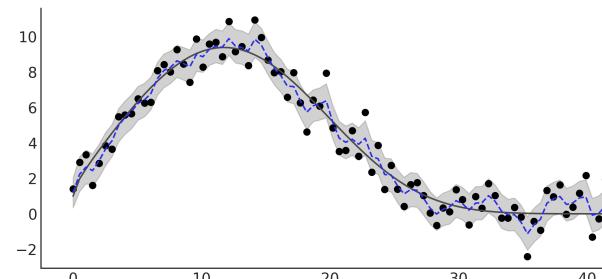
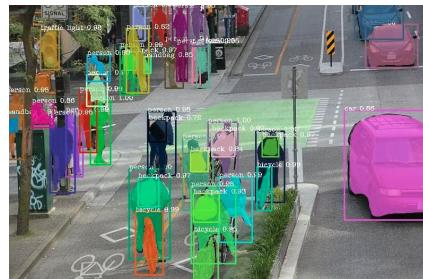
- huge volume
- data multi-modality
- high velocity requirement
- very fat data
- sever data shift & drift (in many cases)
- label imbalance
- data quality



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 maps⁴
→ 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 data⁵
→ regression, anomaly detection, semi-supervised learning, Bayesian inference



⁴SEM: scanning electron microscope, TEM: transmission electron microscope

⁵MES: 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

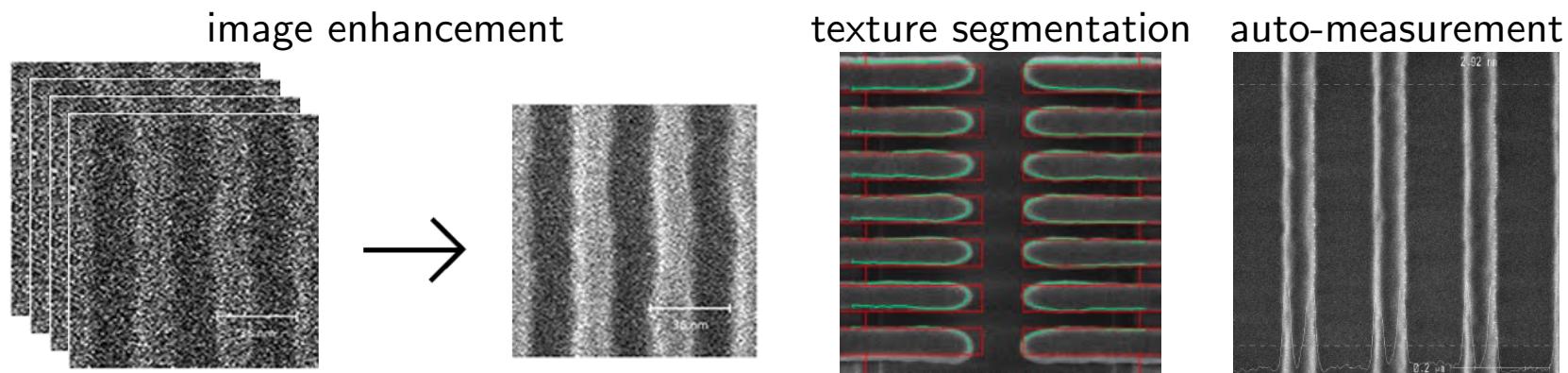


Image enhancement

- 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

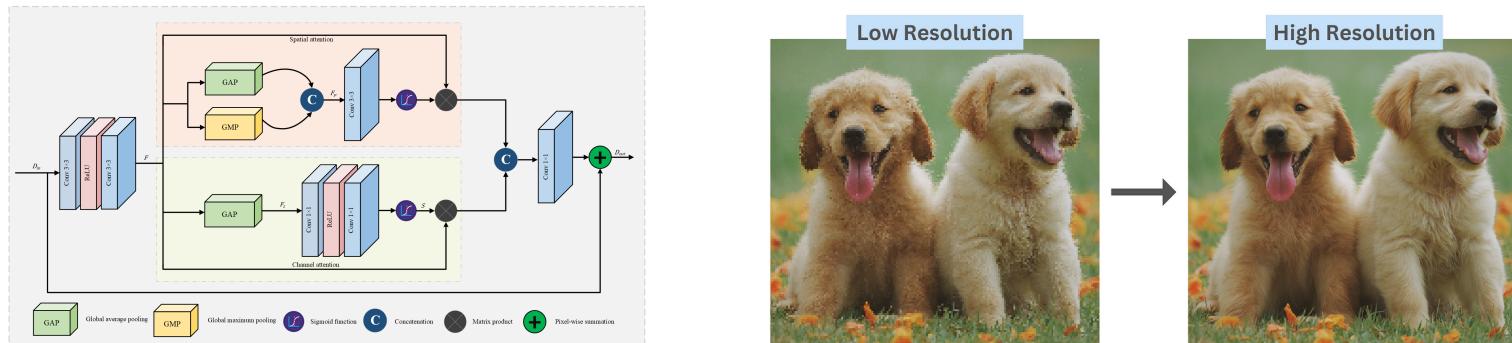
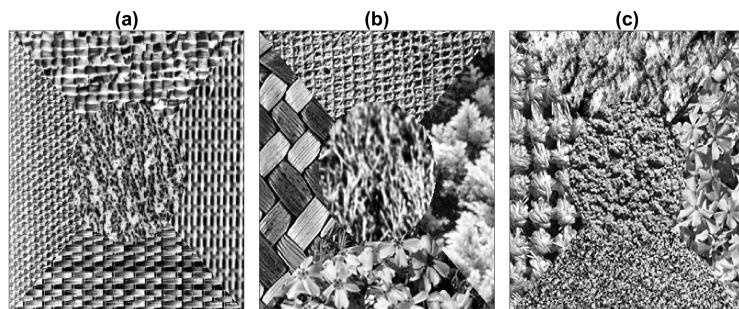


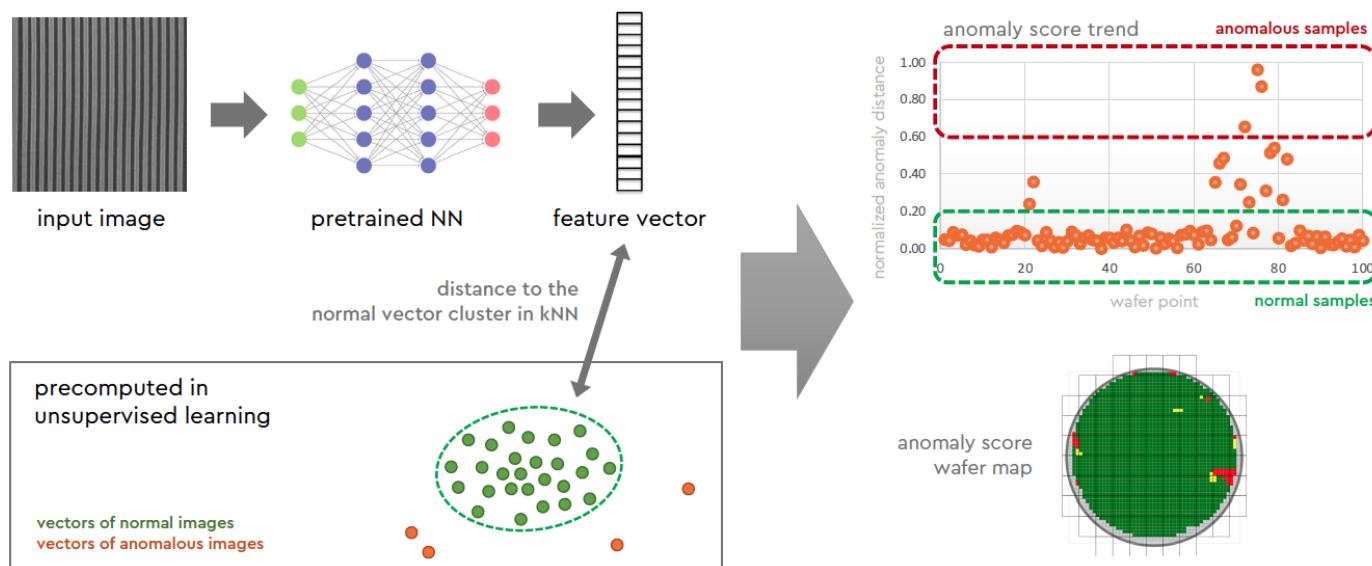
Image segmentation

- 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



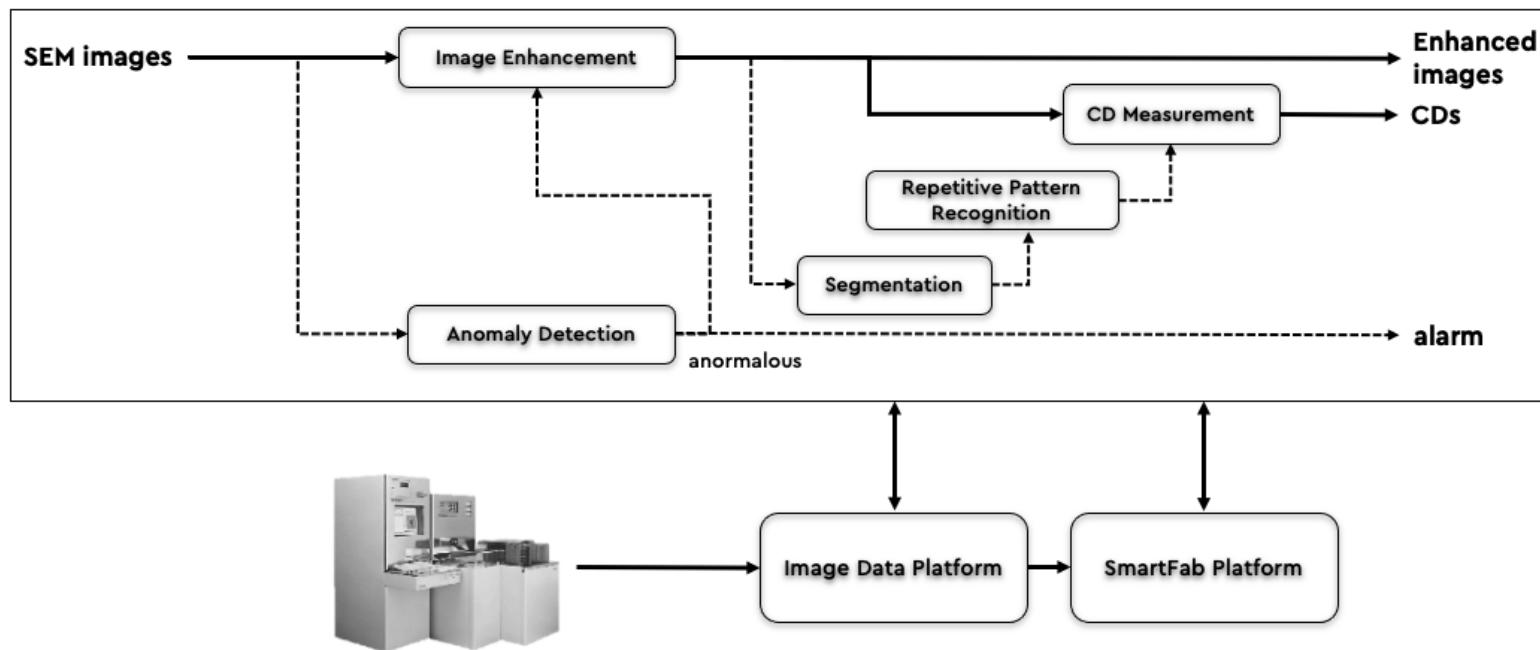
Anomaly detection using side product

- 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



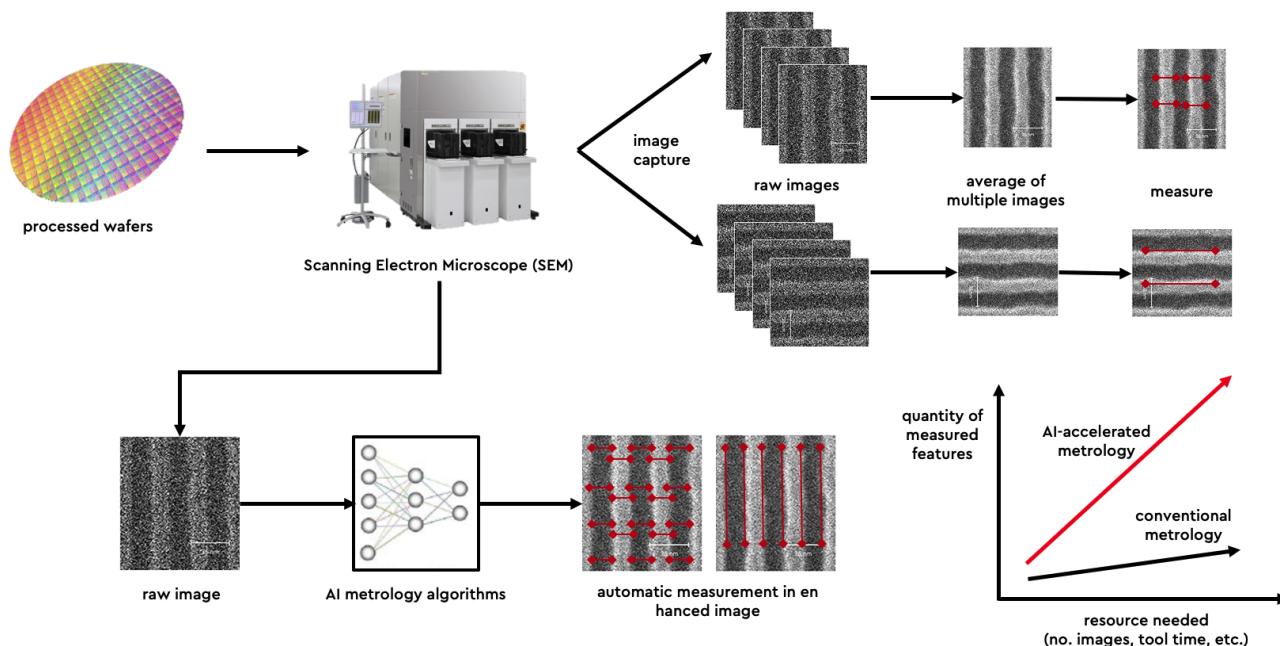
AI-enabled metrology system

- integration of separate components creates AI-enabled metrology system



Benefits of new system

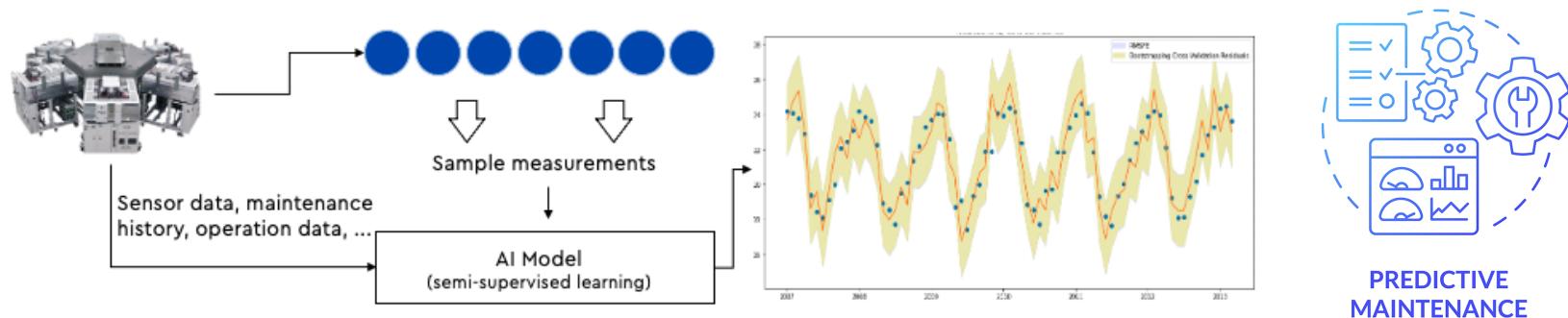
- new system provides
 - improved accuracy and reliability
 - improved throughput
 - savings on investment on measurement equipment



TS ML in manAI

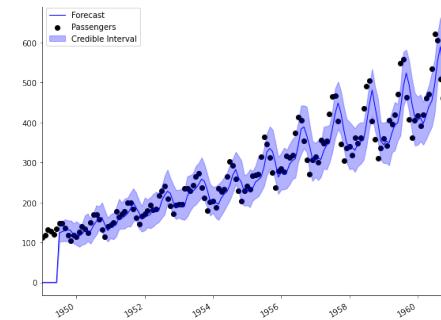
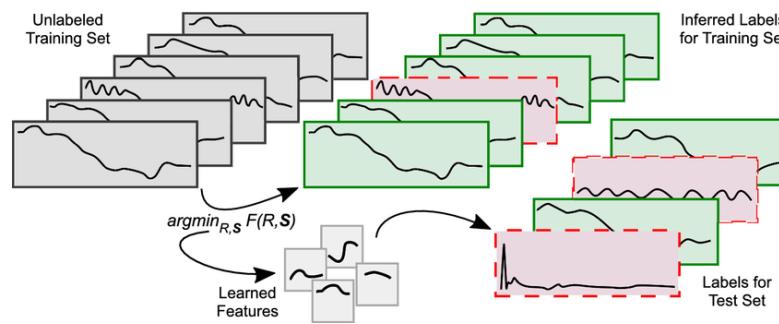
Time-series ML applications in manAI

- 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

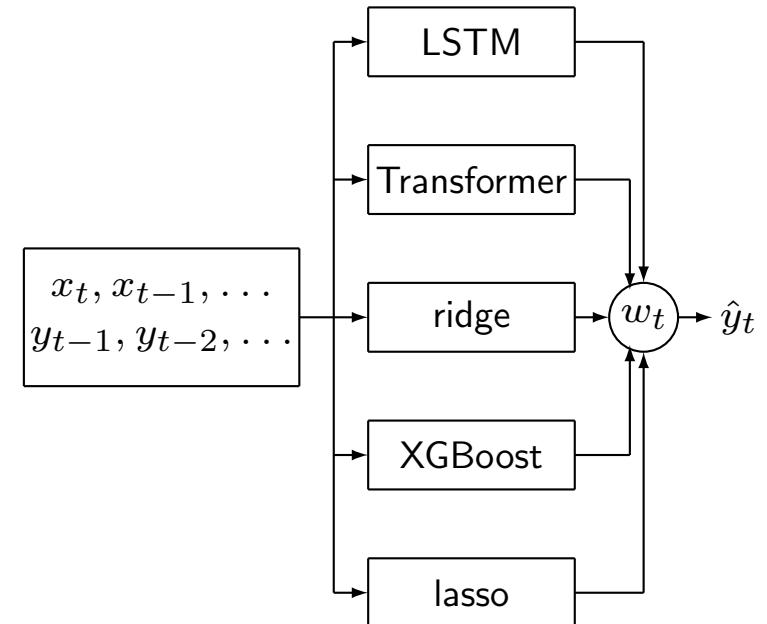


Difficulties with TS ML

- 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



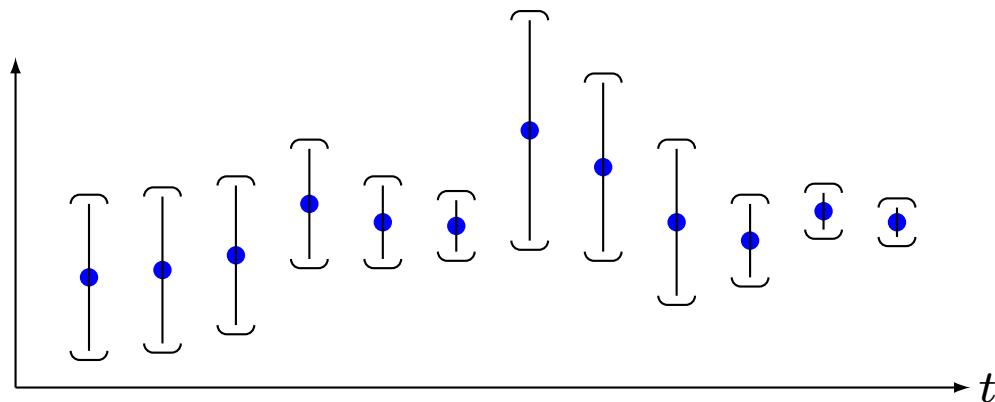
$$g_k = w_{1,k}f_{1,k} + w_{2,k}f_{2,k} + \cdots + w_{p_k,k}f_{p_k,k} = \sum_{i=1}^{p_k} w_{i,k}f_{i,k}$$

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*



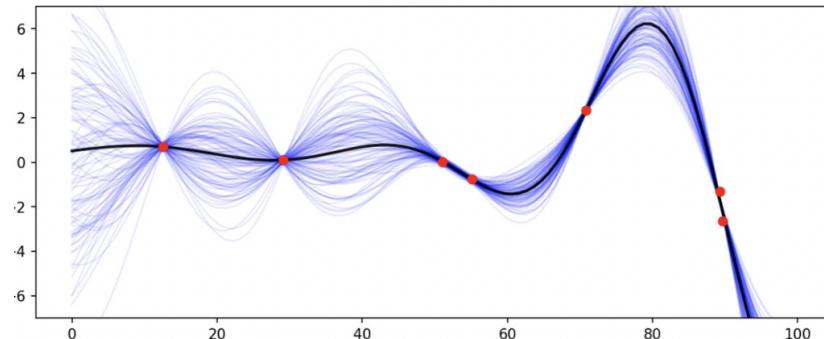
Bayesian approach for credibility interval evaluation

- 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

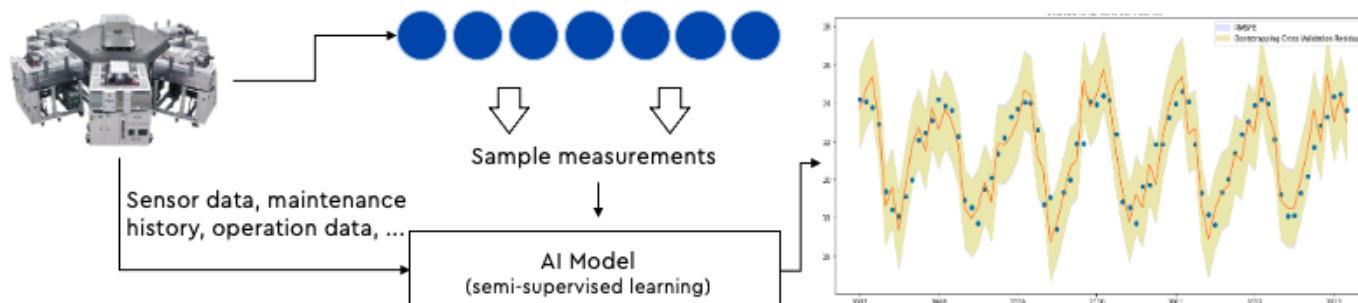
- problem description

(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

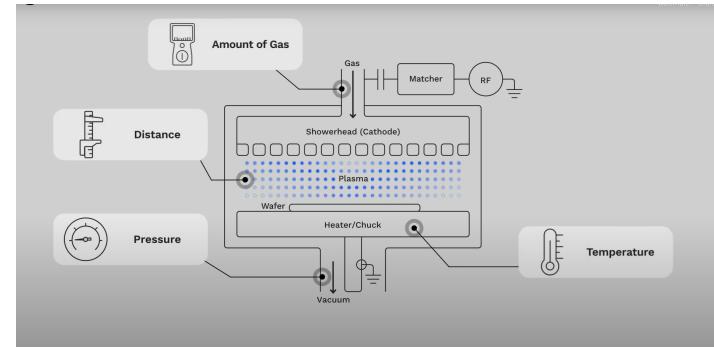
$$\begin{aligned} & \text{minimize} && \sum_{k=1}^K w_{k,K-k} l(y_{t_k}, \hat{y}_{t_k}) \\ & \text{subject to} && \hat{y}_{t_k} = g_k(x_{t_k}, x_{t_{k-1}}, \dots, y_{t_{k-1}}, y_{t_{k-2}}, \dots) \end{aligned}$$

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



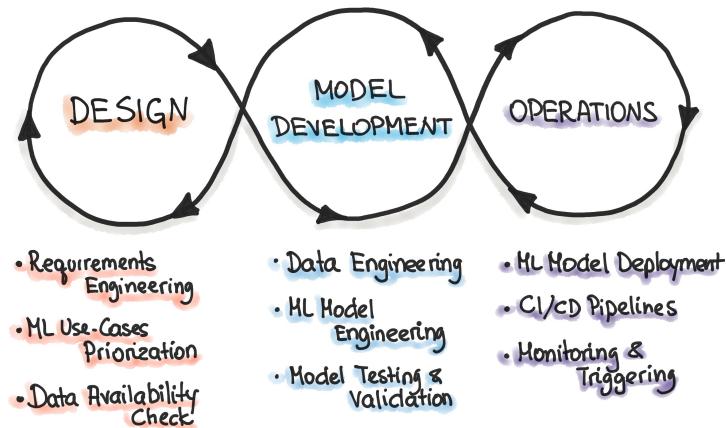
Manufacturing AI Productionization

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

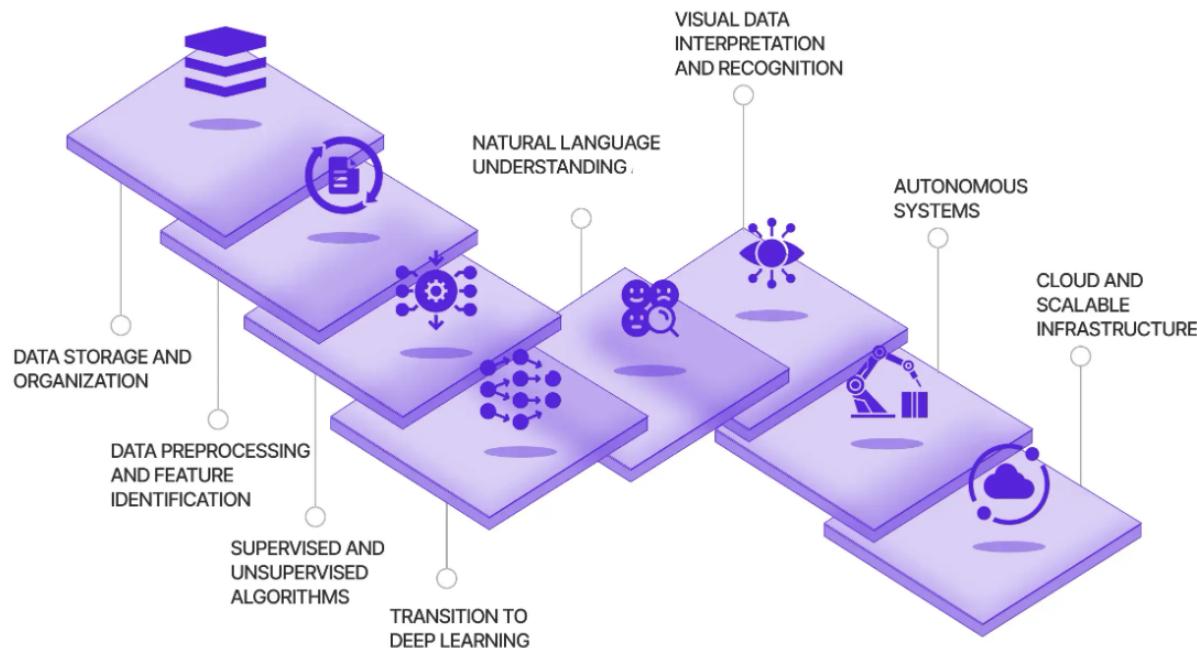
- environment for flexible and agile exploration - EDA⁶
- fast & efficient iteration of algorithm selection, experiments, & analysis
- correct training / validation / test data sets critical!
- seamless productionization from, e.g., Jupyter notebook to production-ready code
- monitoring, *right* metrics, notification, re-training



⁶EDA - exploratory data analysis

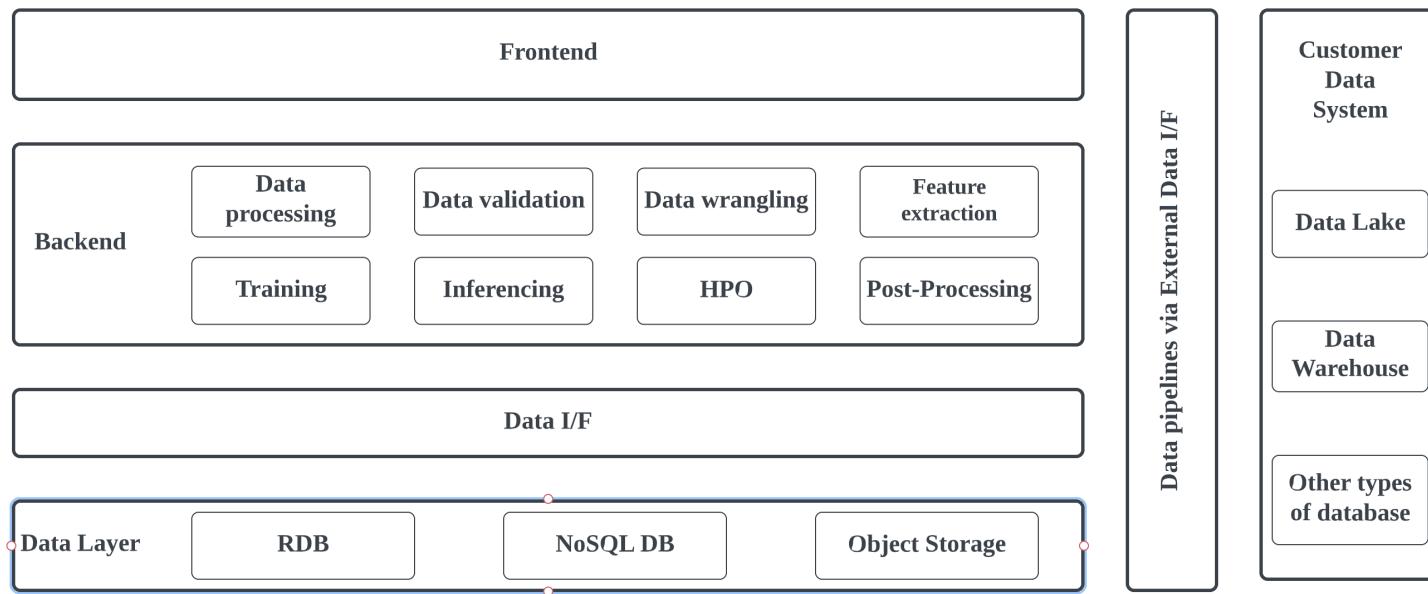
manAI software system

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



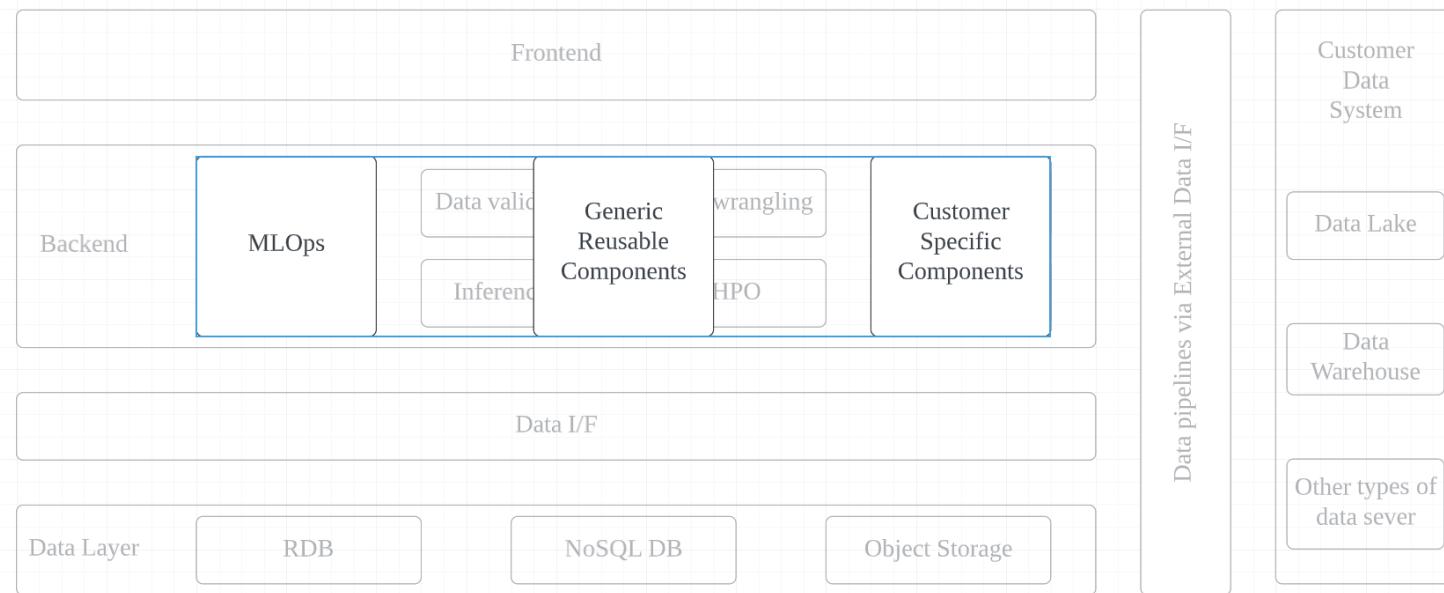
manAI system architecture

- 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

Appendix

Recent AI Development

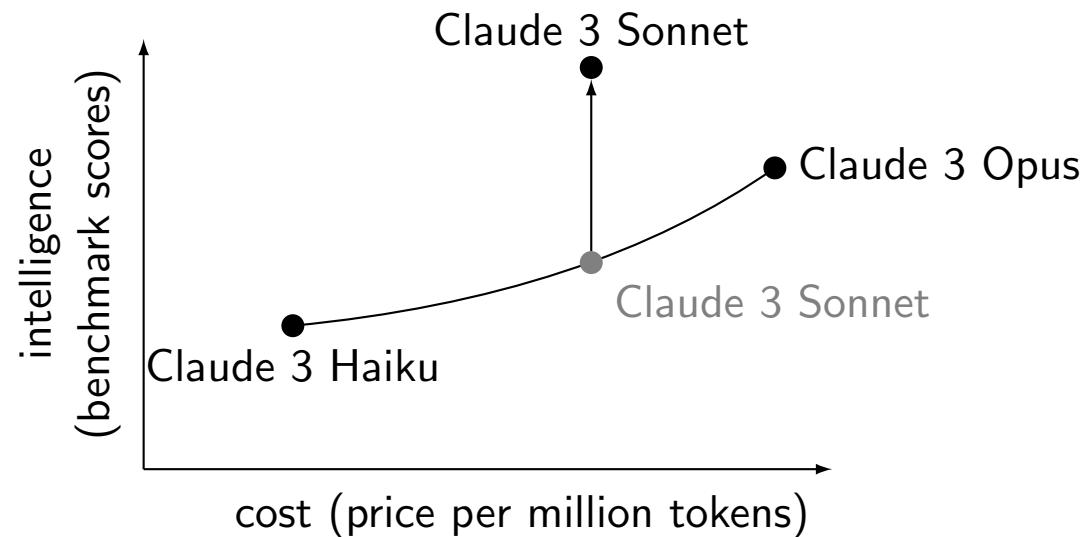
Notable recent AI research and new development

- Claude 3.5 Sonnet
- Kolmogorov–Arnold networks (KAN)
- JEPA (*e.g.*, I-JEPA & V-JEPA) & consistency-diversity-realism trade-off

Claude 3.5 Sonnet

Claude 3.5 Sonnet

- Anthropic
 - releases Claude 3.5 Sonnet (Jul-2024)
 - when! GPT-4o accepted to be default best model for many tasks, e.g., reasoning & summarization
 - claims Claude 3.5 Sonnet sets *new industry standard for intelligence*



Main features & performance

- Claude 3.5 Sonnet shows off
 - improved vision tasks, 2x speed (compared to GPT-4o), artifacts - new UIs for, *e.g.*, code generation & animation
- with GPT-4o, Claude 3.5 Sonnet
 - wins at code generation
 - on par for logical reasoning
 - loses at logical reasoning
 - *wins at generation speed*

	Claude 3.5 Sonnet	Claude 3 Opus	GPT-4o	Gemini 1.5 Pro
visual math reasoning	67.7%	50.5%	63.8%	63.9%
science diagrams	94.7%	88.1%	94.2%	94.4%
visual question answering	68.3%	59.4%	69.1%	62.2%
chart Q&A	90.8%	80.8%	85.7%	87.2%
document visual Q&A	95.2%	89.3%	92.8%	93.1%

KAN

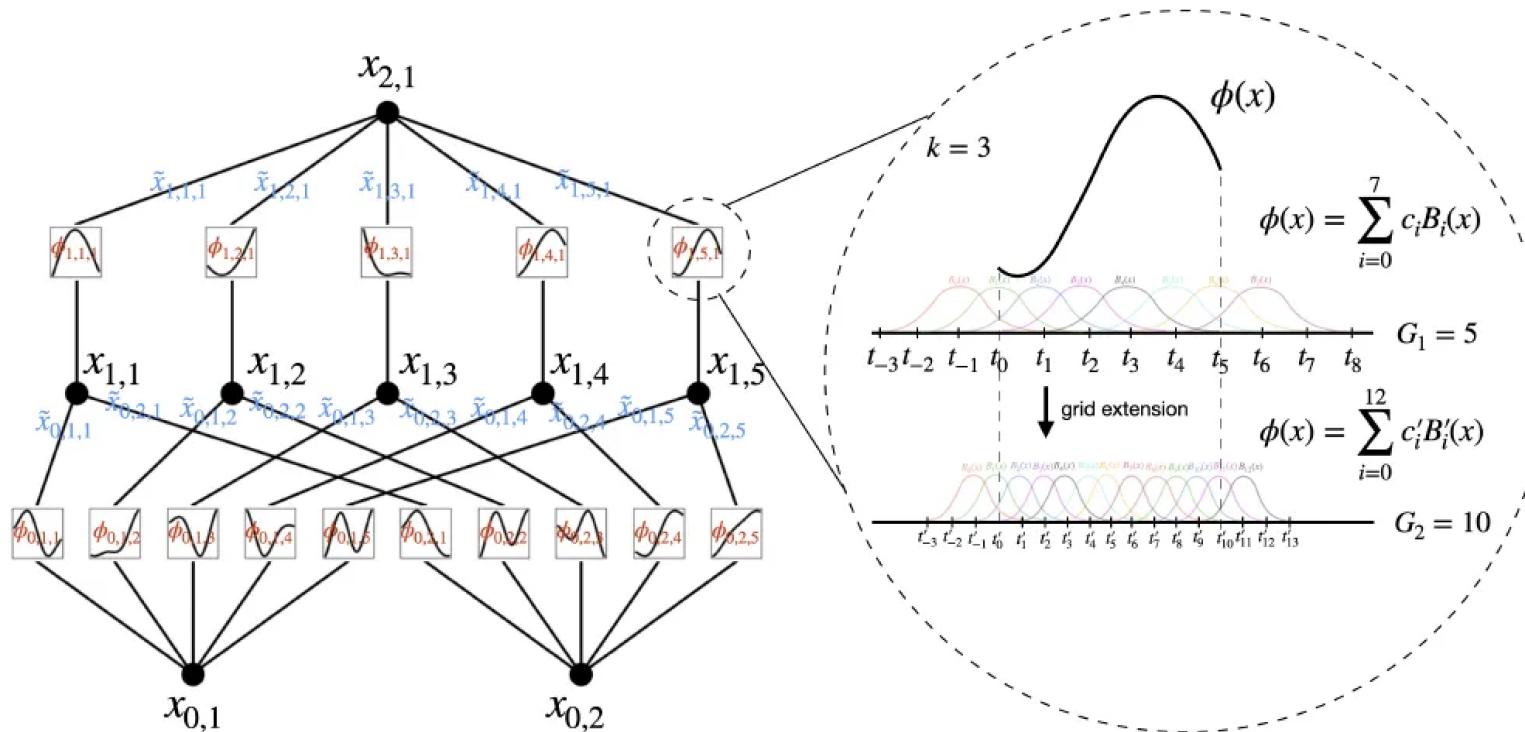
Kolmogorov–Arnold networks (KAN)

- KAN: Kolmogorov-Arnold Networks - MIT, CalTech, Northeastern Univ. & IAIFI
- techniques
 - inspired by Kolmogorov-Arnold representation theorem - every $f : \mathbf{R}^n \rightarrow \mathbf{R}$ can be written as finite composition of continuous functions of single variable, *i.e.*
 - $$f(x) = \sum_{q=0}^{2n} \Phi_q \left(\sum_{p=1}^n \phi_{q,p}(x_p) \right)$$
 - where $\phi_{q,p} : [0, 1] \rightarrow \mathbf{R}$ & $\Phi_q : \mathbf{R} \rightarrow \mathbf{R}$
 - replace (fixed) activation functions with learnable functions
 - use B-splines for learnable (uni-variate) functions - for flexibility & adaptability
- advantages
 - benefits structure of MLP on outside & splines on inside
 - reduce complexity and # parameters to achieve accurate modeling
 - *interpretable* by its nature
 - *better continual learning* - adapt to new data without forgetting thanks to local nature of spline functions

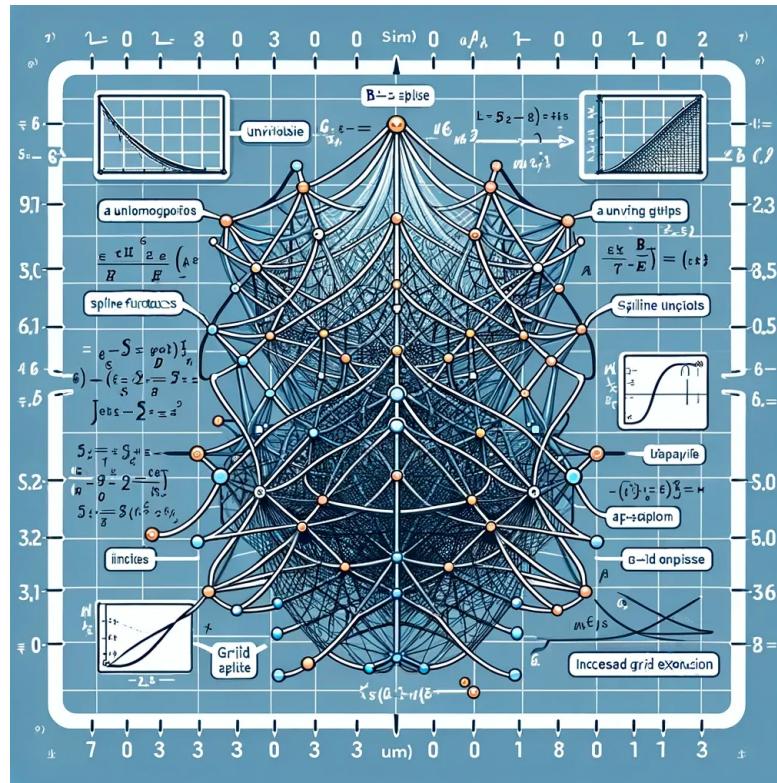
MLP vs KAN

Model	Multi-Layer Perceptron (MLP)	Kolmogorov-Arnold Network (KAN)
Theorem	Universal Approximation Theorem	Kolmogorov-Arnold Representation Theorem
Formula (Shallow)	$f(\mathbf{x}) \approx \sum_{i=1}^{N(e)} a_i \sigma(\mathbf{w}_i \cdot \mathbf{x} + b_i)$	$f(\mathbf{x}) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^n \phi_{q,p}(x_p) \right)$
Model (Shallow)	<p>(a)</p> <p>fixed activation functions on nodes</p> <p>learnable weights on edges</p>	<p>(b)</p> <p>learnable activation functions on edges</p> <p>sum operation on nodes</p>
Formula (Deep)	$\text{MLP}(\mathbf{x}) = (\mathbf{W}_3 \circ \sigma_2 \circ \mathbf{W}_2 \circ \sigma_1 \circ \mathbf{W}_1)(\mathbf{x})$	$\text{KAN}(\mathbf{x}) = (\Phi_3 \circ \Phi_2 \circ \Phi_1)(\mathbf{x})$
Model (Deep)	<p>(c)</p> <p>MLP(\mathbf{x})</p> <p>\mathbf{W}_3</p> <p>σ_2</p> <p>\mathbf{W}_2</p> <p>σ_1</p> <p>\mathbf{W}_1</p> <p>\mathbf{x}</p> <p>nonlinear; fixed</p> <p>linear; learnable</p>	<p>(d)</p> <p>KAN(\mathbf{x})</p> <p>Φ_3</p> <p>Φ_2</p> <p>Φ_1</p> <p>\mathbf{x}</p> <p>nonlinear; learnable</p>

KAN architecture with spline parametrization unit layer



Future work on KAN



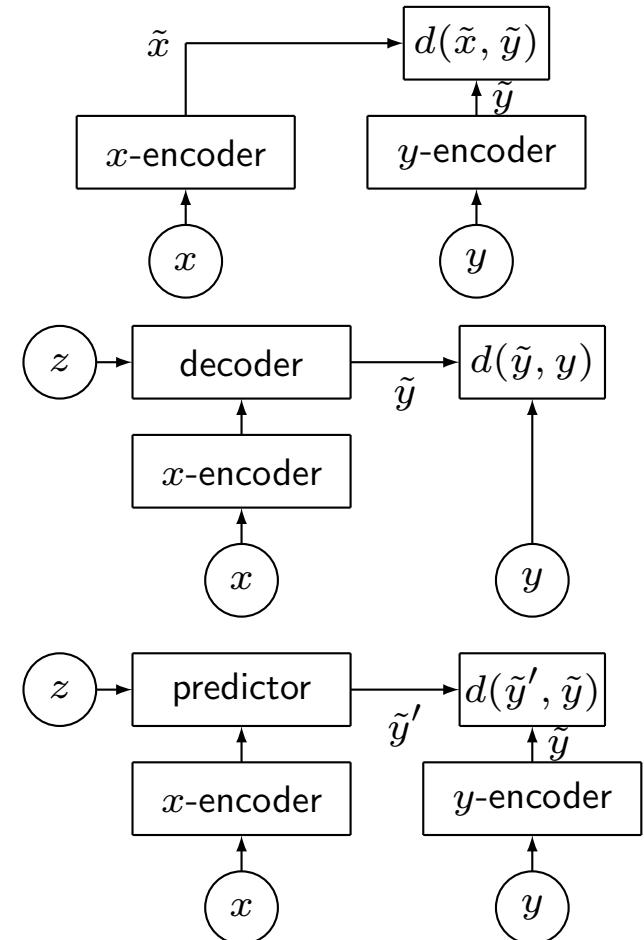
- natural question is
 - what if use both MLP and KAN?
 - what if use other types of splines?
 - how to control forgetfulness of continual learning?
 - why functions of one variable? possible to use functions of two variables?

(figure created by DALLE-3)

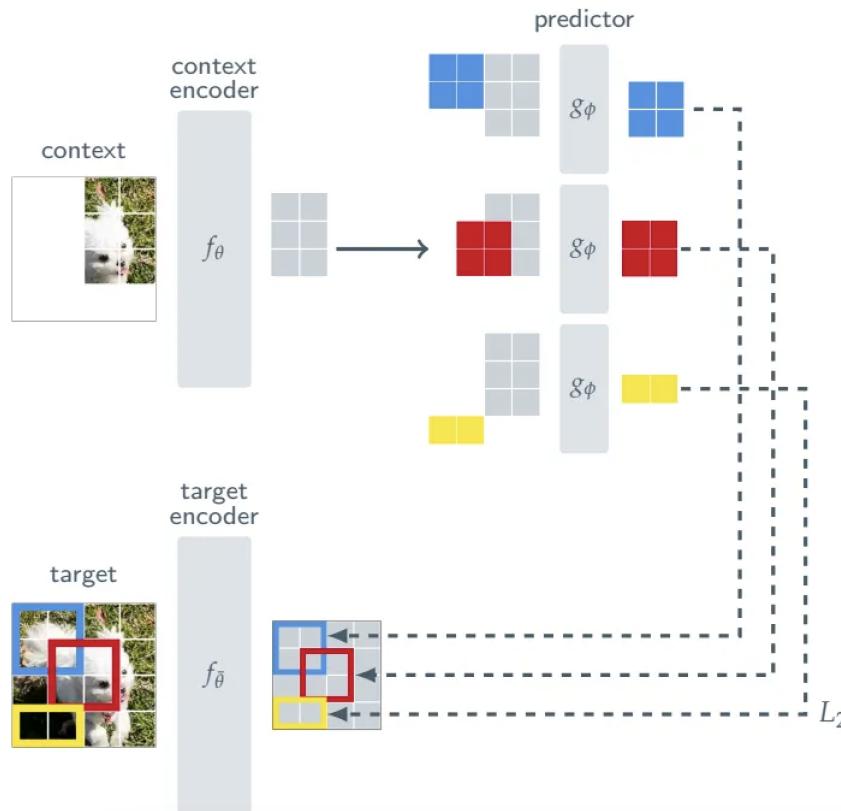
JEPA

Joint-Embedding Predictive Architecture (JEPA)

- Self-Supervised Learning from Images with a Joint-Embedding Predictive Architecture (JEPA) - Yann LeCun et al. - Jan-2023
 - joint-embedding architecture (JEA)
 - output similar embeddings for compatible inputs x, y and dissimilar embeddings for incompatible inputs
 - generative architecture
 - directly reconstruct signal y from compatible signal x using decoder network conditioned on additional variables z to facilitate reconstruction
 - joint-embedding predictive architecture (JEPA)
 - similar to generative architecture, but comparison is done in embedding space
 - e.g., I-JEPA learns y (masked portion) from x (unmasked portion) conditioned on z (position of mask)



Learning semantic representation better



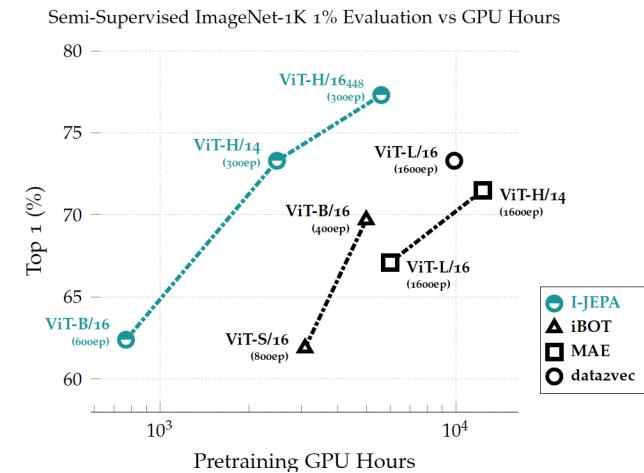
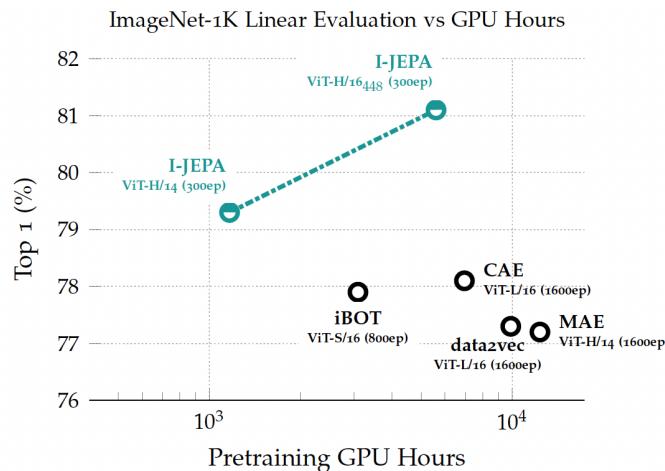
- I-JEPA

- predicts missing information in *abstract representation space*
- e.g., given single context block (unmasked part of the image), predict representations of various target blocks (masked regions of same image) where target representations computed by learned target-encoder
- *generates semantic representations* (not pixel-wise information) potentially eliminating unnecessary pixel-level details & allowing model to concentrate on learning more semantic features

I-JEPA outperforms other algorithms

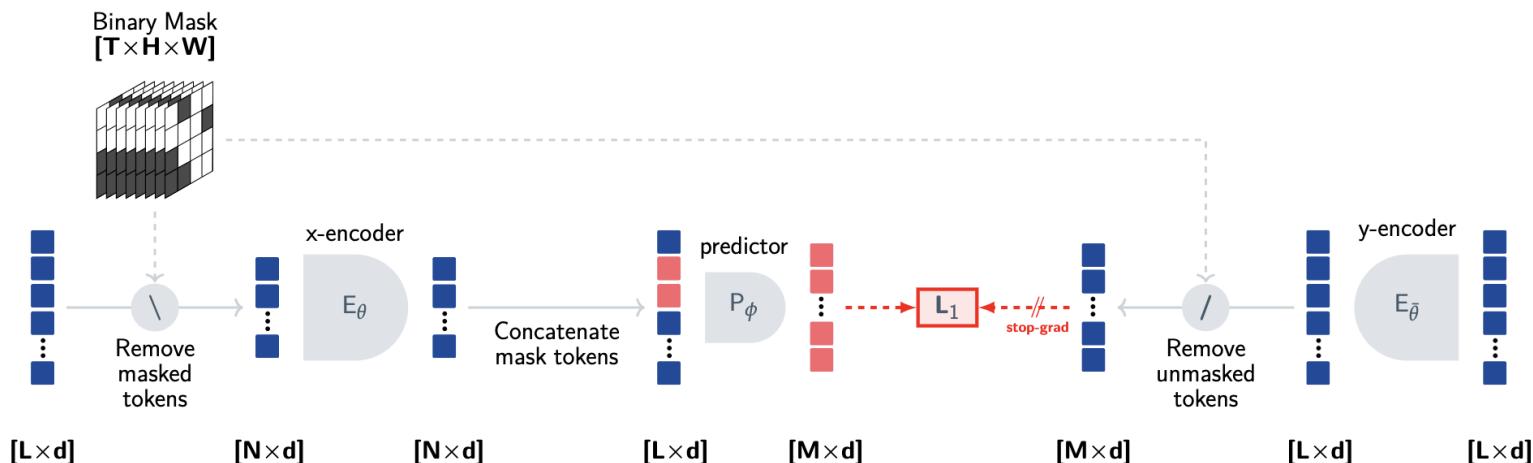
Method	Arch.	CIFAR100	Places205	iNat18
<i>Methods without view data augmentations</i>				
data2vec [8]	ViT-L/16	81.6	54.6	28.1
MAE [36]	ViT-H/14	77.3	55.0	32.9
I-JEPA	ViT-H/14	87.5	58.4	47.6
<i>Methods using extra view data augmentations</i>				
DINO [18]	ViT-B/8	84.9	57.9	55.9
iBOT [79]	ViT-L/16	88.3	60.4	57.3

Method	Arch.	Clevr/Count	Clevr/Dist
<i>Methods without view data augmentations</i>			
data2vec [8]	ViT-L/16	85.3	71.3
MAE [36]	ViT-H/14	90.5	72.4
I-JEPA	ViT-H/14	86.7	72.4
<i>Methods using extra data augmentations</i>			
DINO [18]	ViT-B/8	86.6	53.4
iBOT [79]	ViT-L/16	85.7	62.8



V-JEPA

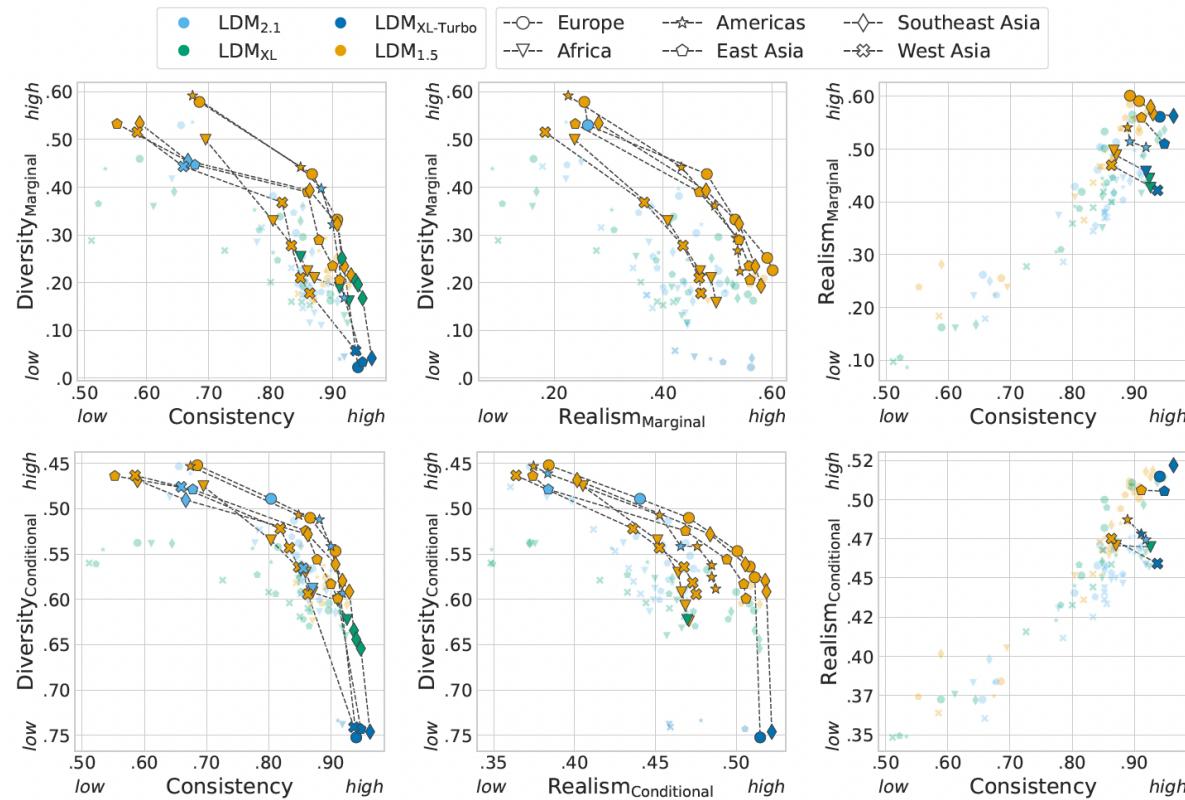
- Revisiting Feature Prediction for Learning Visual Representations from Video - Yann LeCun et al. - Feb-2024
 - essentially same ideas of JEPA - loss function is calculated in embedding space - for better semantic representation learning (rather than pixel-wise learning)



More realistic generative model becomes, less diverse it becomes

- Consistency-diversity-realism Pareto fronts of conditional image generative models - FAIR at Meta - Montreal, Paris & New York City labs, McGill University, Mila, Quebec AI institute, Canada CIFAR AI - Jun-2024
 - realism comes at the cost of coverage, *i.e.*, *the most realistic systems are mode-collapsed!*
 - intuition (or hunch)
 - world models should *not* be generative - should make predictions in representation space - in representation space, unpredictable or irrelevant information is absent
- main argument in favor of JEPA

Consistency-diversity-realism trade-off



AI in Biotech

AI in biology

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

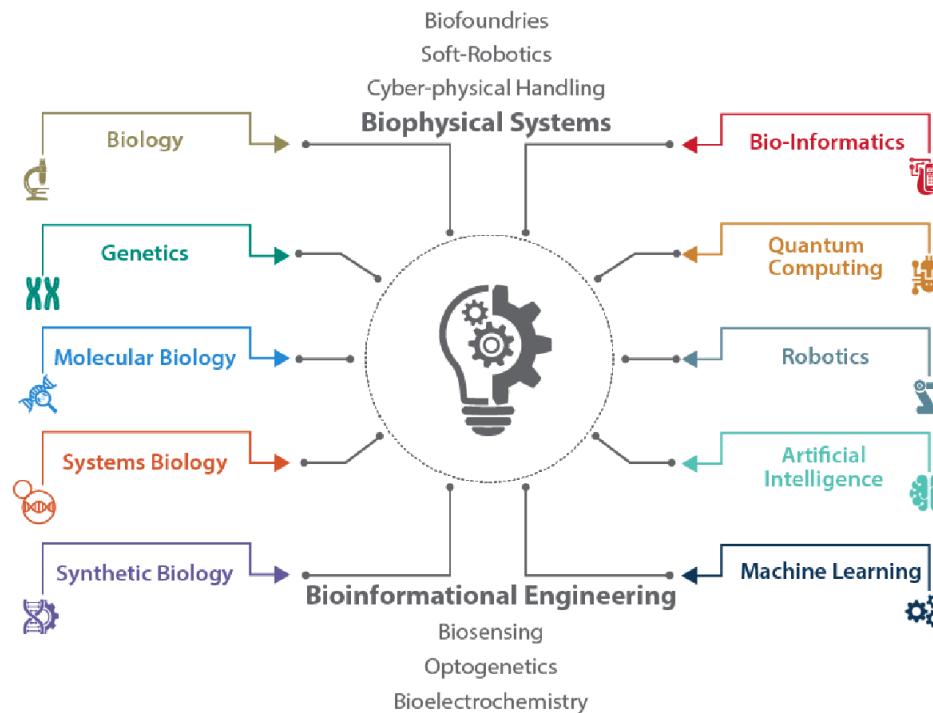
Biotech

Biotech

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

biotech - multidisciplinary field

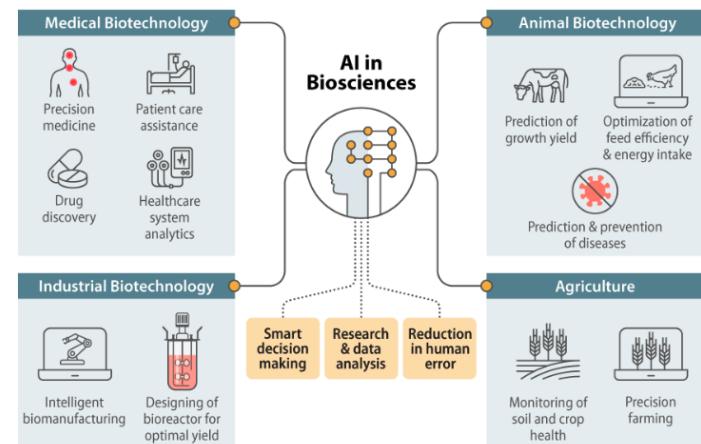
- sciences and technologies enabling biotechnology include, but not limited to,
 - (molecular) biology, genetics, systems biology, synthetic biology, bio-informatics, quantum computing, robotics [?]



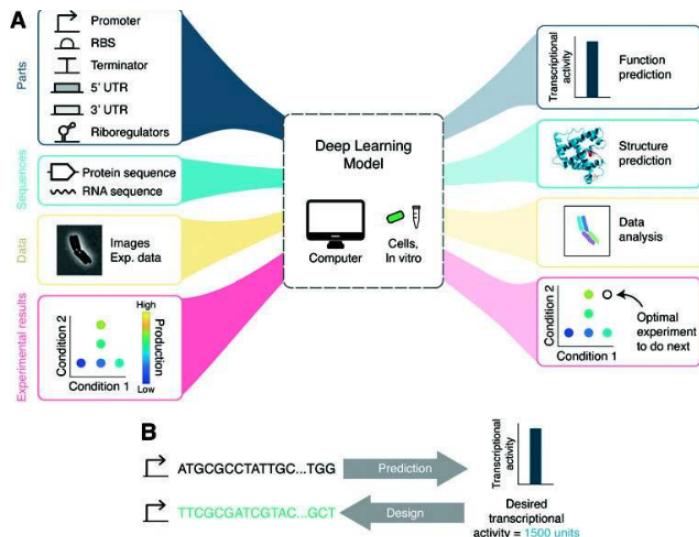
Convergence of AI and biological design

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

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



Multi-source genetic sequence data



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

Quality & quantity of biological data

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

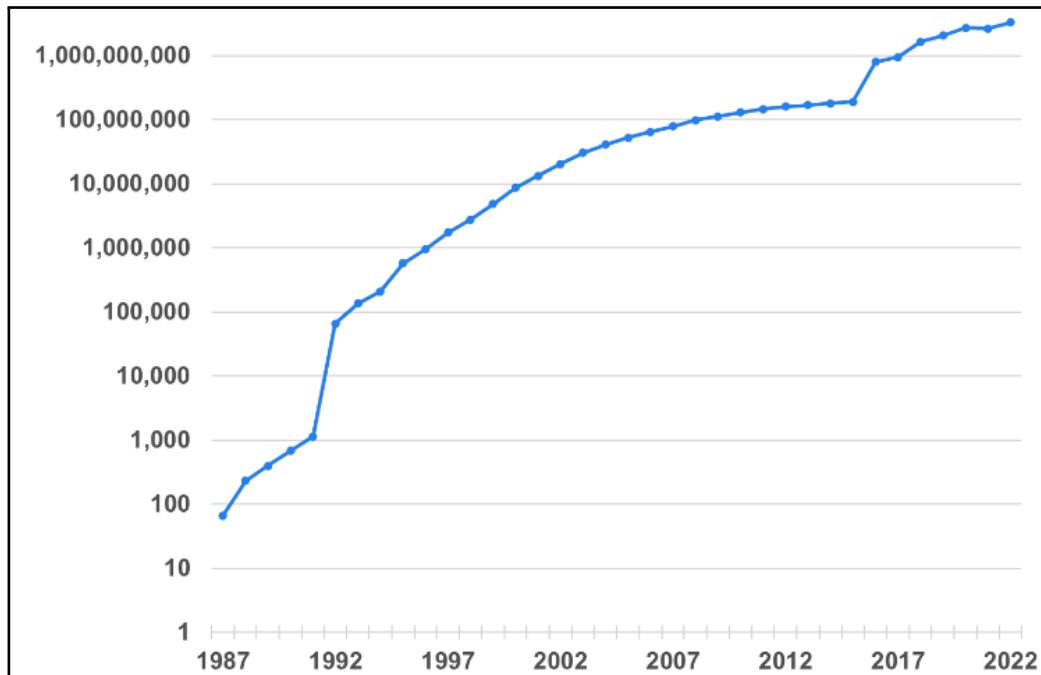
Rapid growth of biological data

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

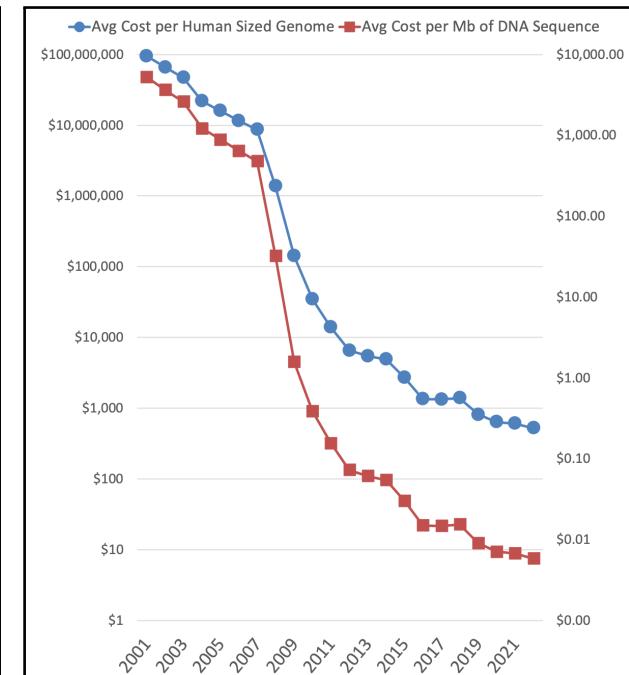
Volume and sequencing cost of DNA over time

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

sequences in INSDC



DNA sequencing cost



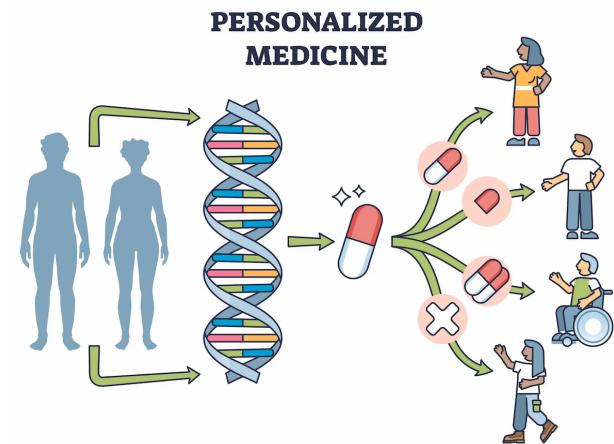
Bio data availability and bias

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

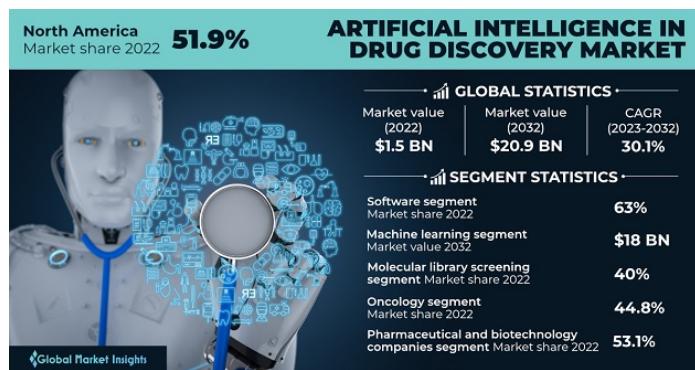
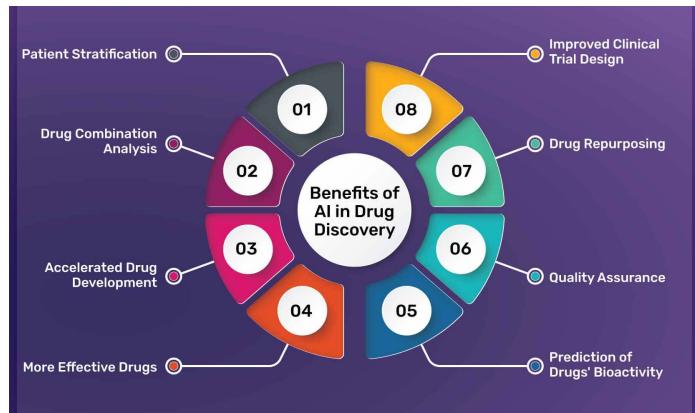
Emerging Trends in Biotech

Personalized medicine

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



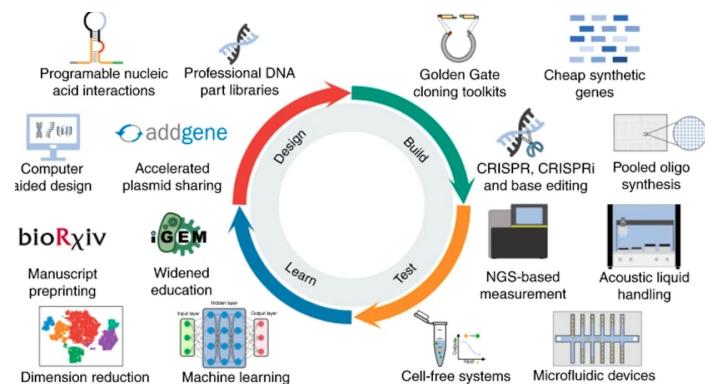
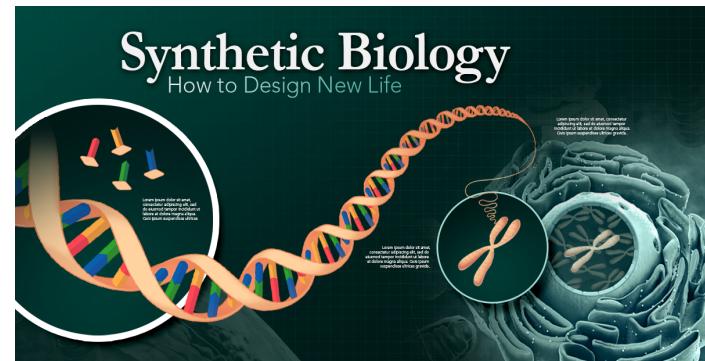
AI-driven drug discovery



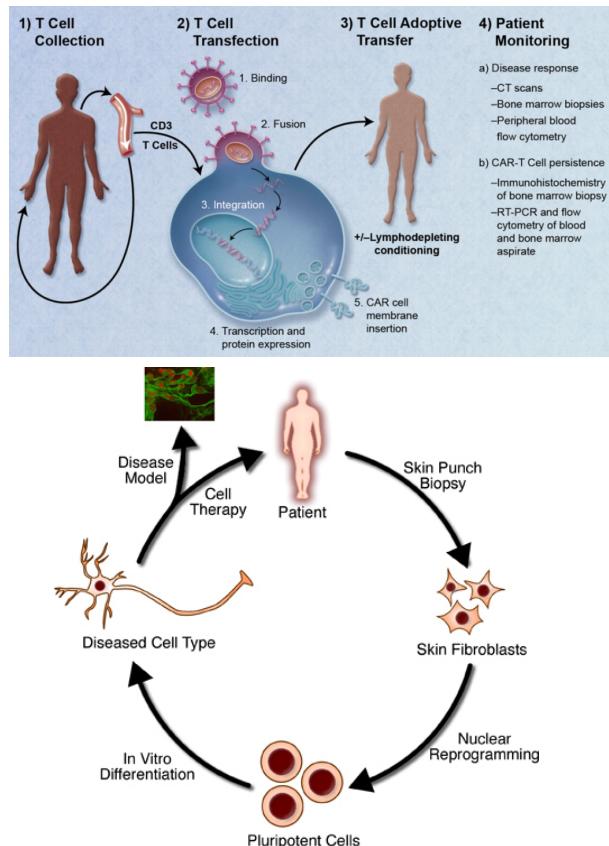
- traditional drug discovery process - time-consuming and costly often taking decades and billions of dollars
- AI streamlines this process by predicting the efficacy and safety of potential compounds with more speed and accuracy
- AI models analyze chemical databases to identify new drug candidates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



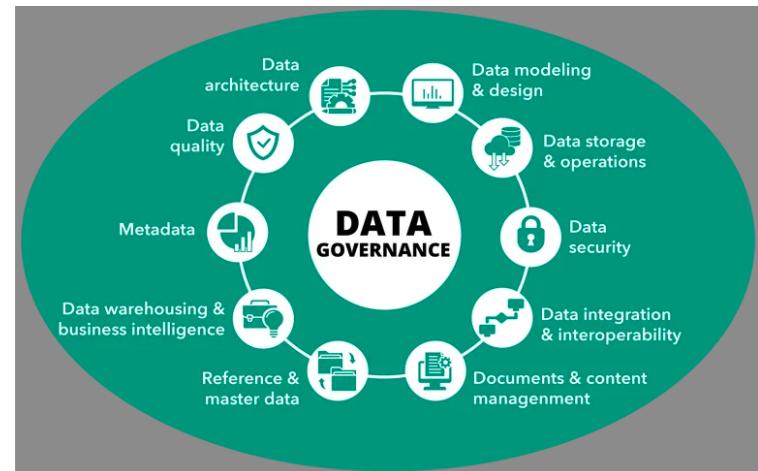
Regenerative medicine



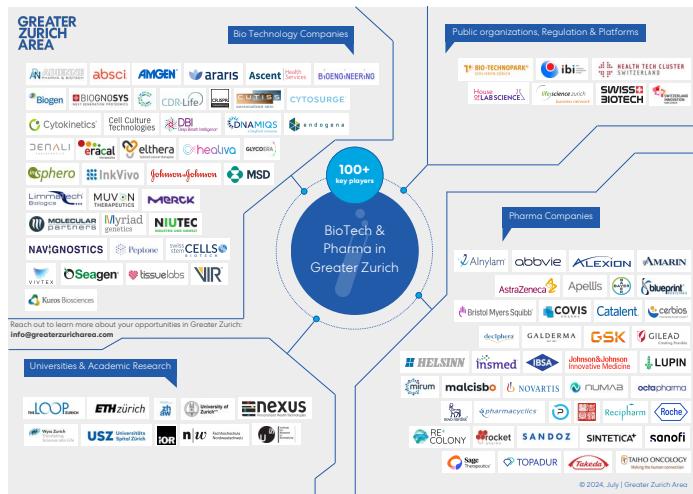
- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo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

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Thank You