

AI Slides Viewer & Checker

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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*

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)



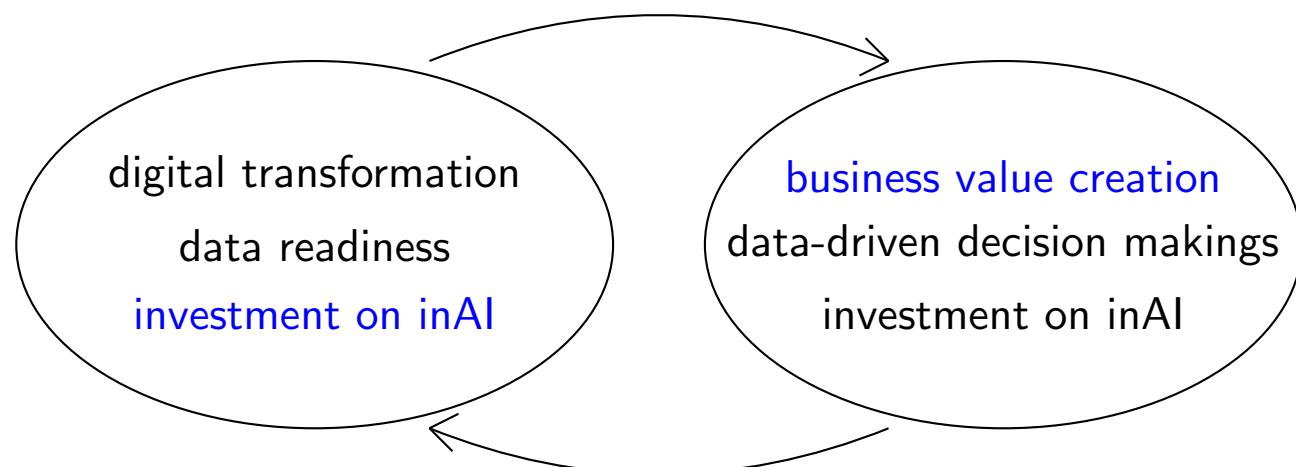
inAI fields

- 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

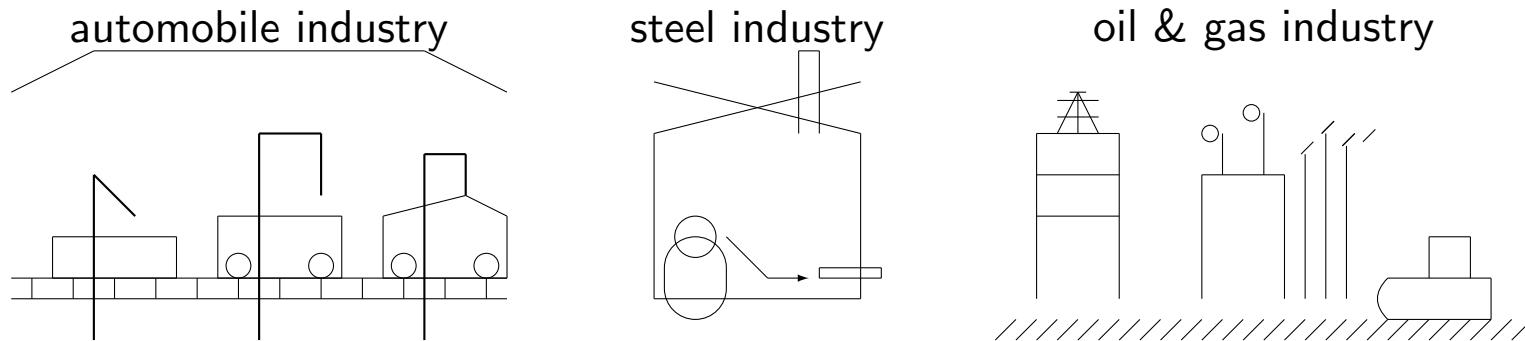
Vicious (or virtuous) cycle

- 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

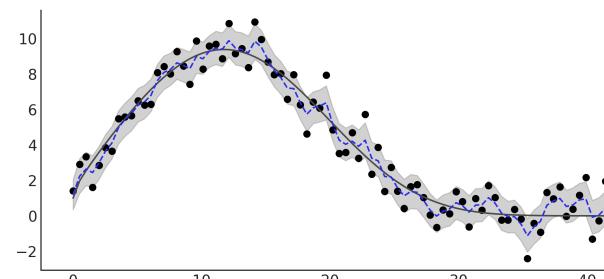
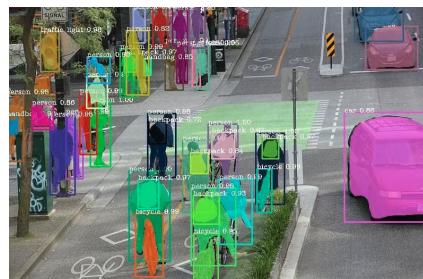
- huge volume
- data multi-modality
- high velocity requirement
- very fat data
- sever data shift & drift (in many cases)
- label imbalance
- data quality



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

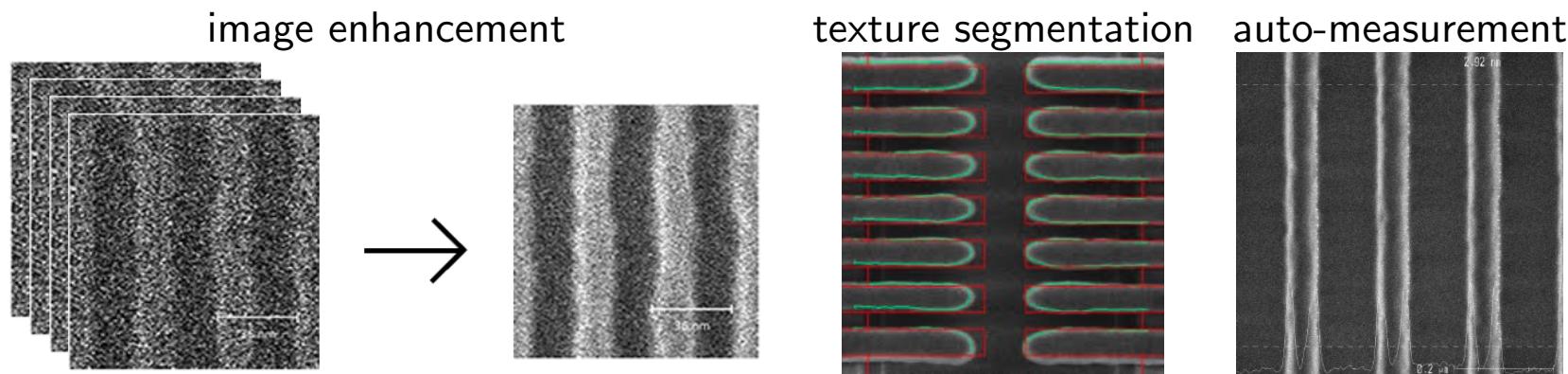


Image enhancement

- 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

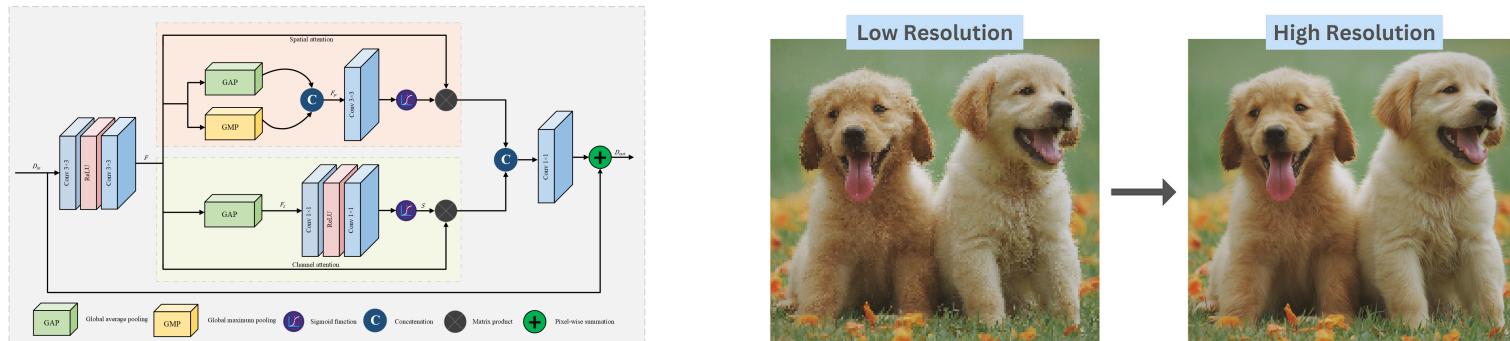
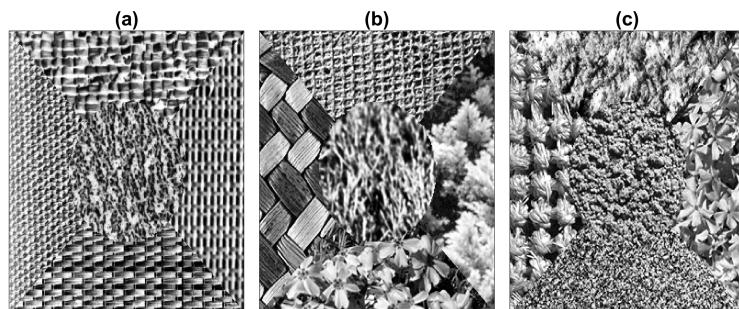


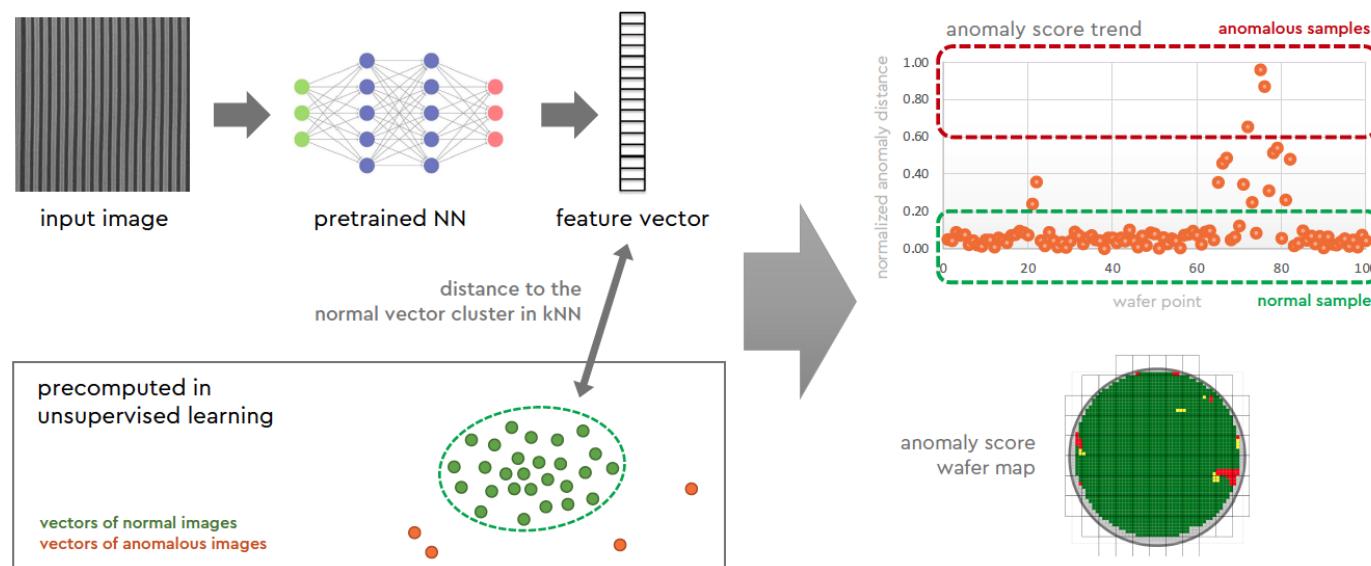
Image segmentation

- 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



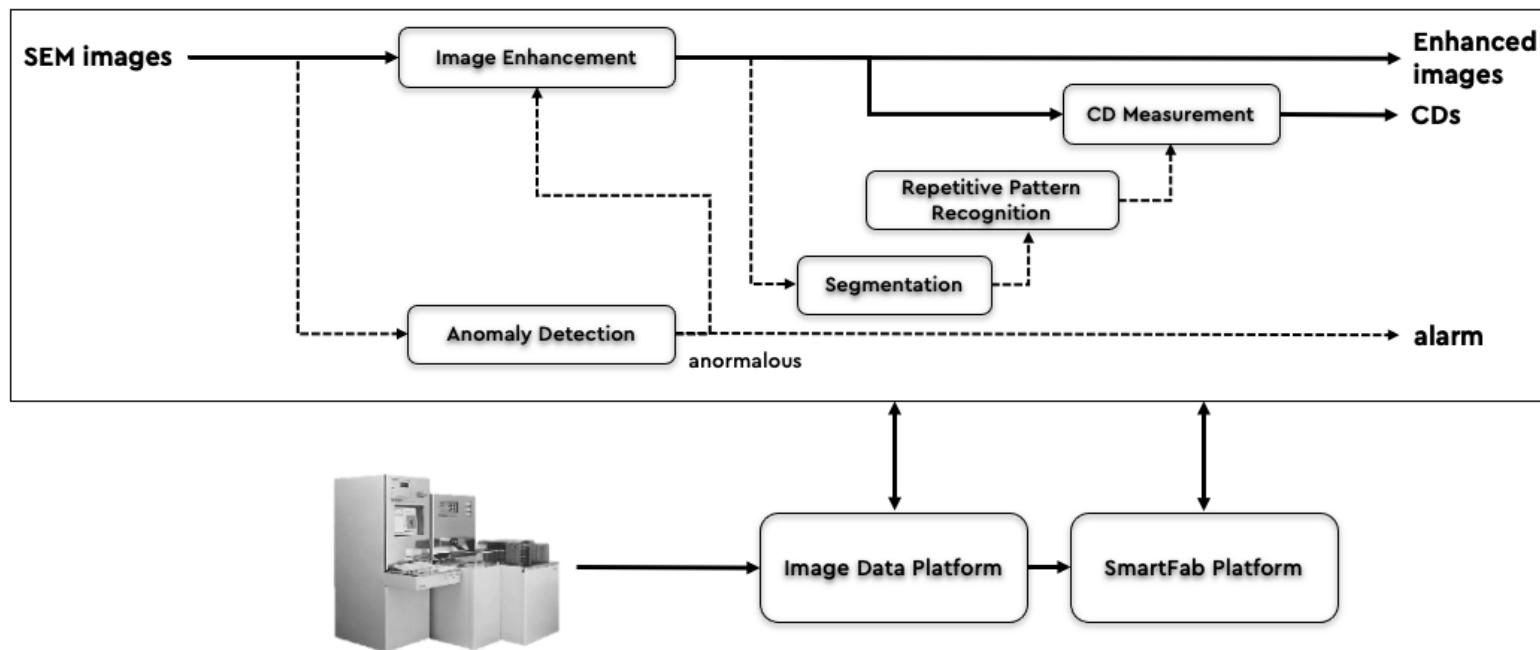
Anomaly detection using side product

- 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



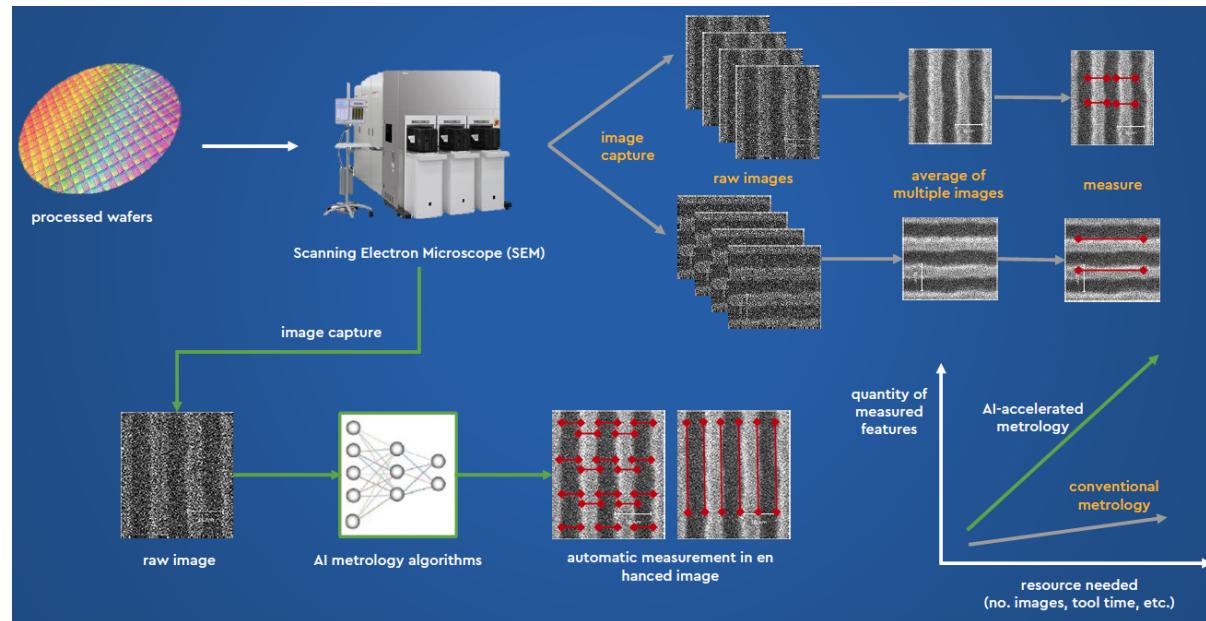
AI-enabled metrology system

- integration of separate components creates AI-enabled metrology system



Benefits of new system

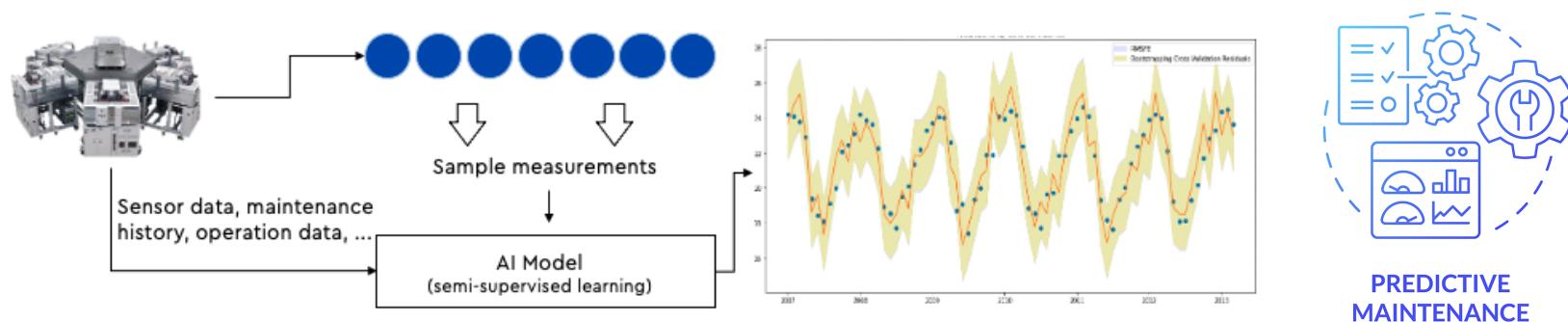
- new system provides
 - improved accuracy and reliability
 - improved throughput
 - savings on investment on measurement equipment



TS ML in manAI

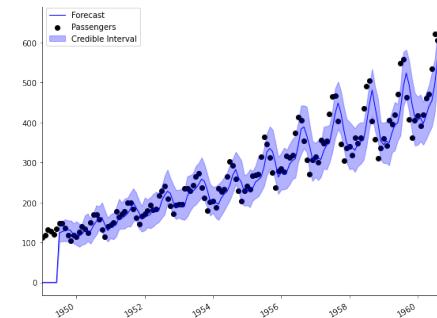
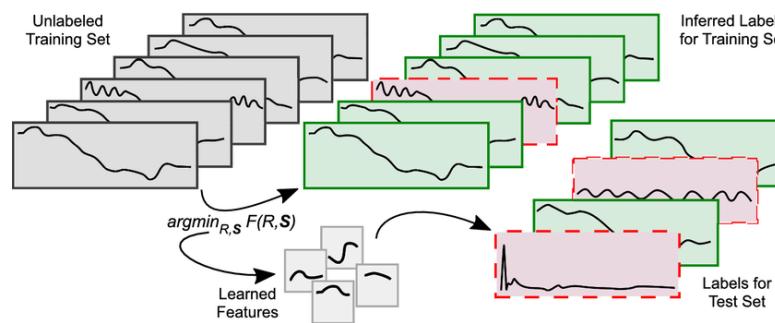
Time-series ML applications in manAI

- 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

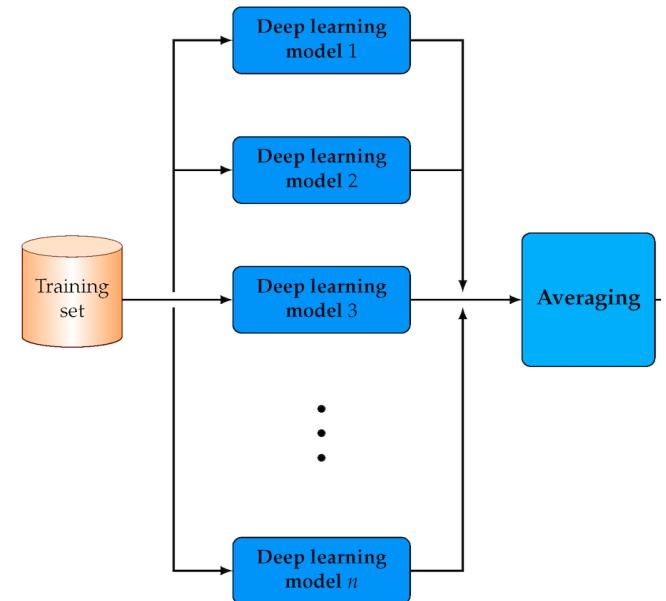


Difficulties with TS ML

- 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



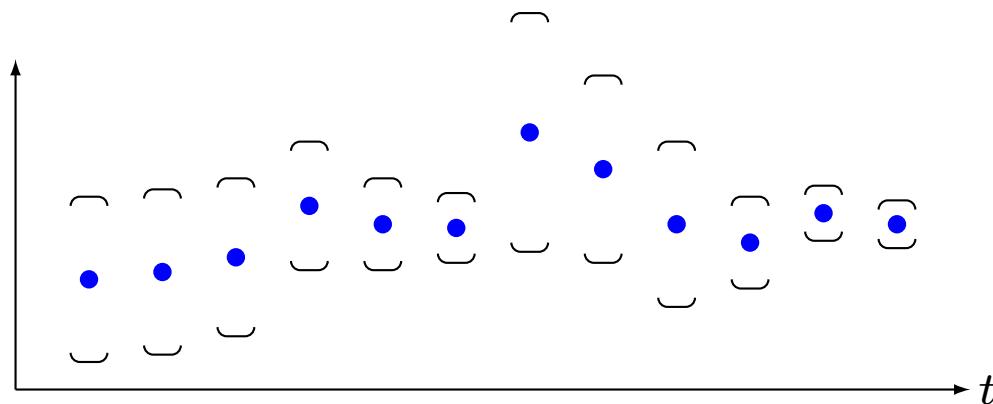
$$g_k = w_{1,k}f_{1,k} + w_{2,k}f_{2,k} + \dots + w_{p_k,k}f_{p_k,k} = \sum_{i=1}^{p_k} w_{i,k}f_{i,k}$$

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*



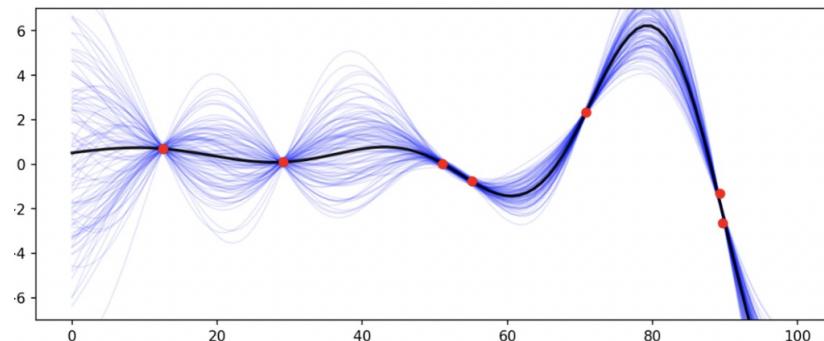
Bayesian approach for credibility interval evaluation

- 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

- situation
 - 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 $x_{t_k}, x_{t_{k-1}}, \dots, y_{t_{k-1}}, y_{t_{k-2}}, \dots$

- (one) problem formulation

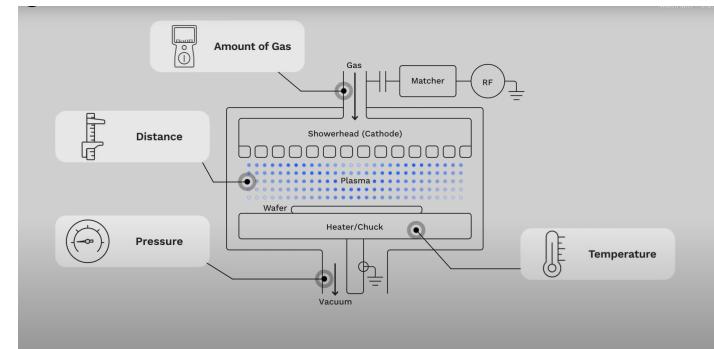
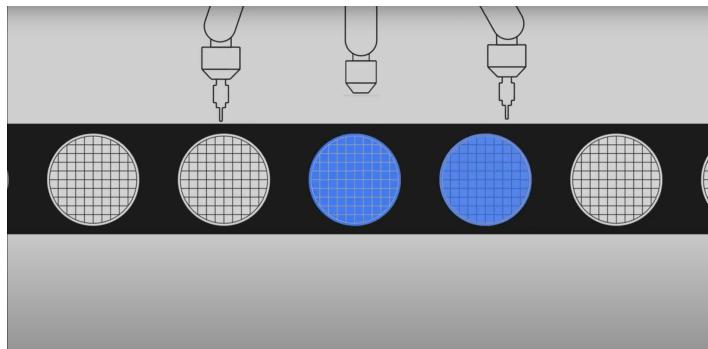
$$\begin{aligned} & \text{minimize} && \sum_{k=1}^K w_{k,K-k} l(y_{t_k}, \hat{y}_{t_k}) \\ & \text{subject to} && \hat{y}_{t_k} = g_k(x_{t_k}, x_{t_{k-1}}, \dots, y_{t_{k-1}}, y_{t_{k-2}}, \dots) \end{aligned}$$

where

- optimization variables - $g_1, g_2, \dots : \mathcal{D} \rightarrow \mathbf{R}^m$
- domain of g_k - $\mathcal{D} = \mathbf{R}^n \times \mathbf{R}^n \times \dots \times Q \times Q \times \dots$ where $Q = \mathbf{R}^m \cup \{\text{null}\}$
- loss function - $l : \mathbf{R}^m \times \mathbf{R}^m \rightarrow \mathbf{R}_+$
- weight on loss - $w_{k,0}, w_{k,1}, \dots$

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



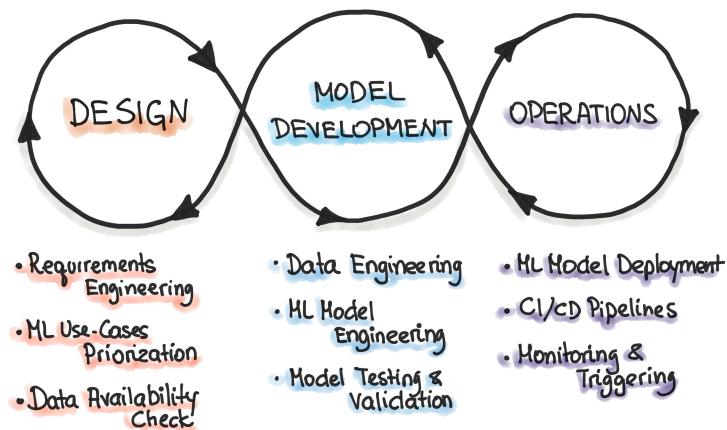
Manufacturing AI Productionization

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

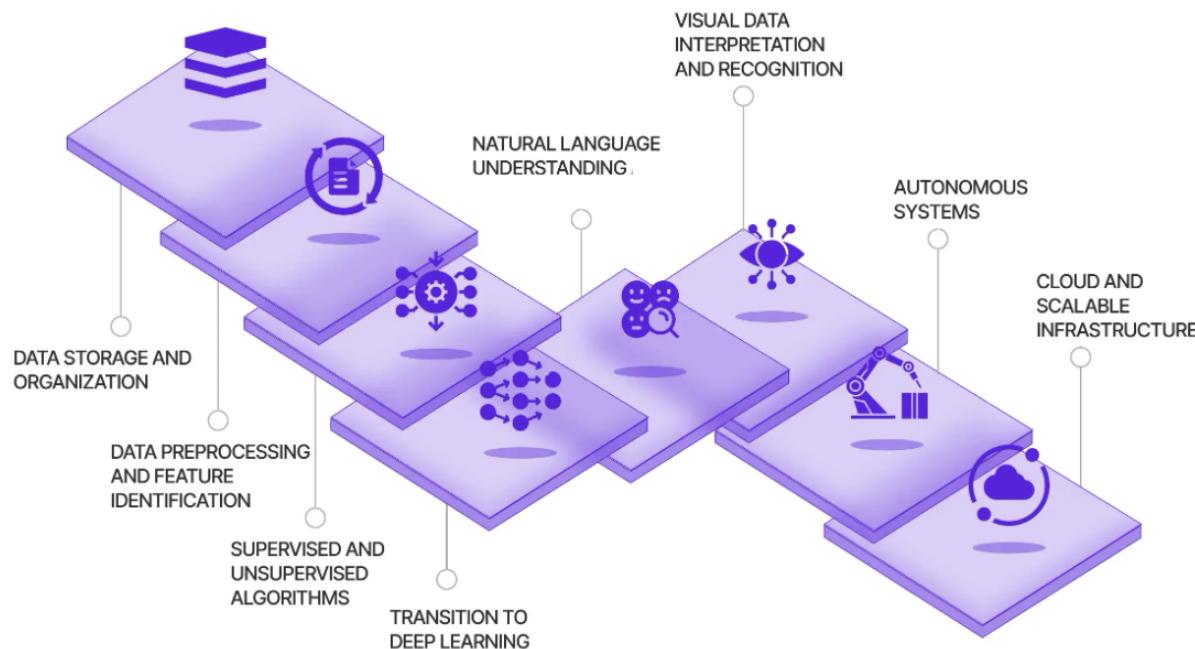
- environment for flexible and agile exploration - EDA³
- fast & efficient iteration of algorithm selection, experiments, & analysis
- correct training / validation / test data sets critical!
- seamless productionization from, e.g., Jupyter notebook to production-ready code
- monitoring, *right* metrics,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



³EDA - exploratory data analysis

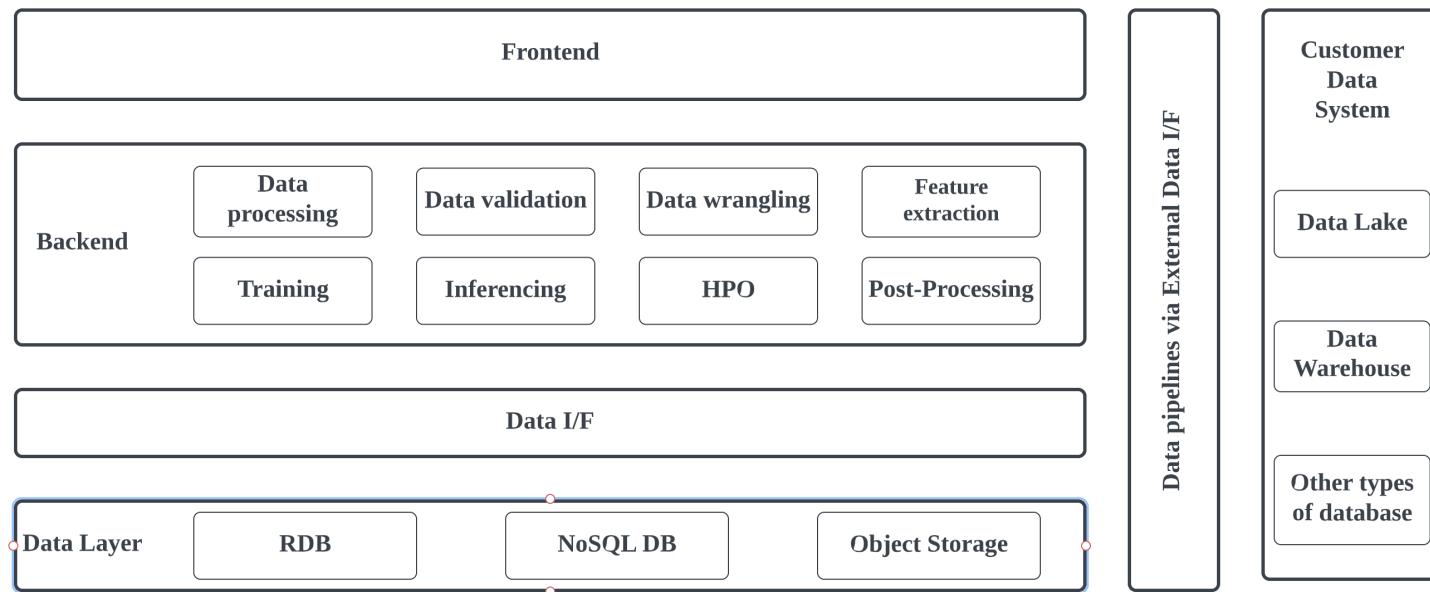
manAI software system

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



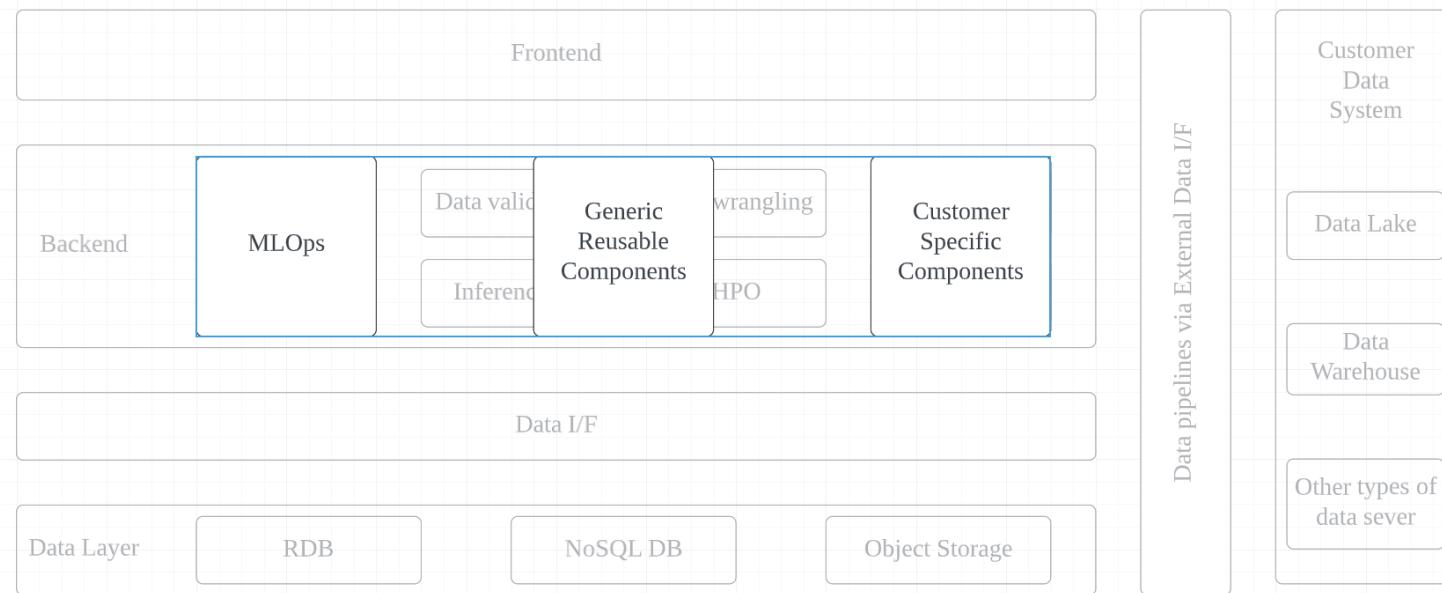
manAI system architecture

- 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

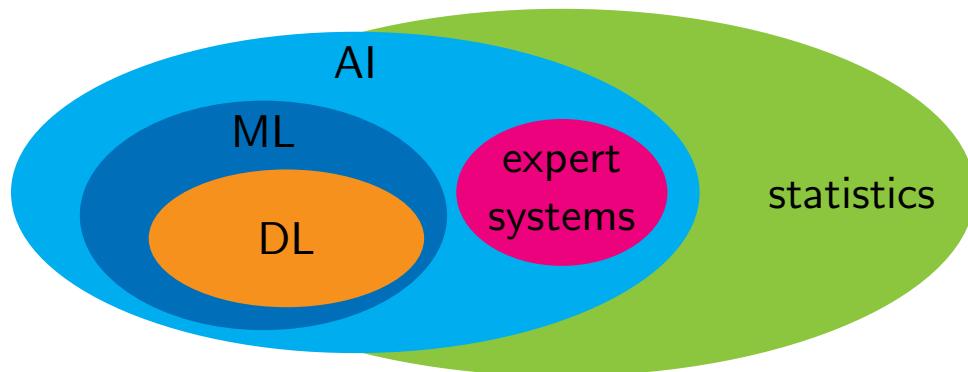
- various CV MLs used for inAI applications
- TS ML applications found in every place in manufacturing
- drift/shift & data noise make TS MLs very challenging, but working solutions found
- in reality, crucial bottlenecks are
 - data quality, preprocessing, monitoring, notification, and retraining
 -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

AI & Bio

AI in Bio

AI

- AI technologies, methodologies & applications used throughout biological sciences and biology R&D
- AI is *not* one thing - encompass range of technologies, methodologies & applications
- ML, DL & NN [HGH⁺22]
 - ML - umbrella term for training computer systems to solve complex problems, using large amount of data, learning algorithms, statistical models
 - DL (subset of ML) - using techniques such as multi-layer neural networks (NN) for computer vision (CV), natural language processing (NLP), time-series predictions to improve the performance and



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.

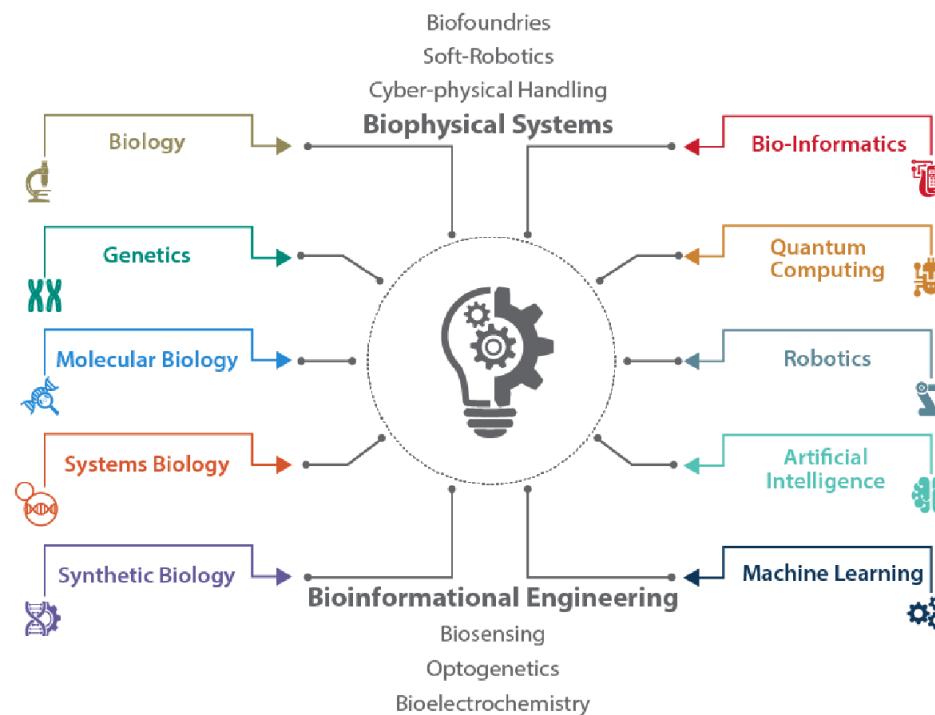
Biotechnology

Biotechnology

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

biotechnology - multidisciplinary field

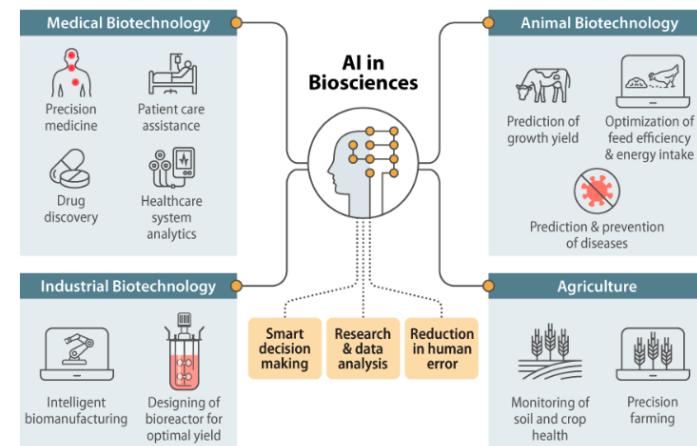
- sciences and technologies enabling biotechnology include, but not limited to,
 - (molecular) biology, genetics, systems biology, synthetic biology, bio-informatics, quantum computing, robotics [DFJ22]



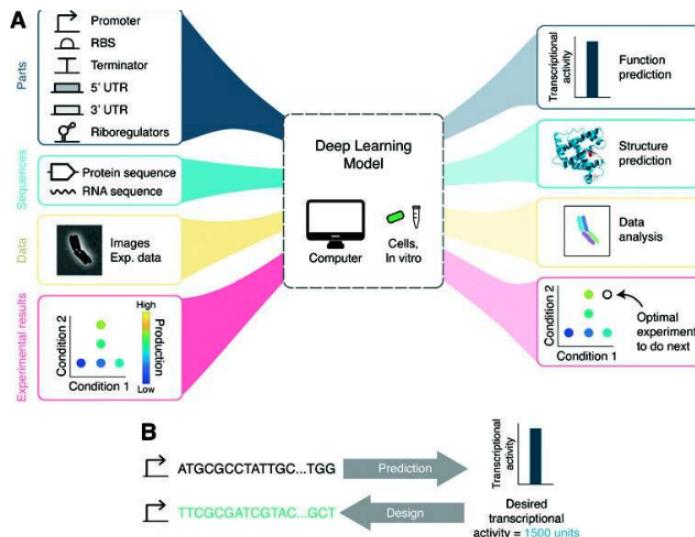
Convergence of AI and biological design

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

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



Multi-source genetic sequence data



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

Quality & quantity of biological data

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

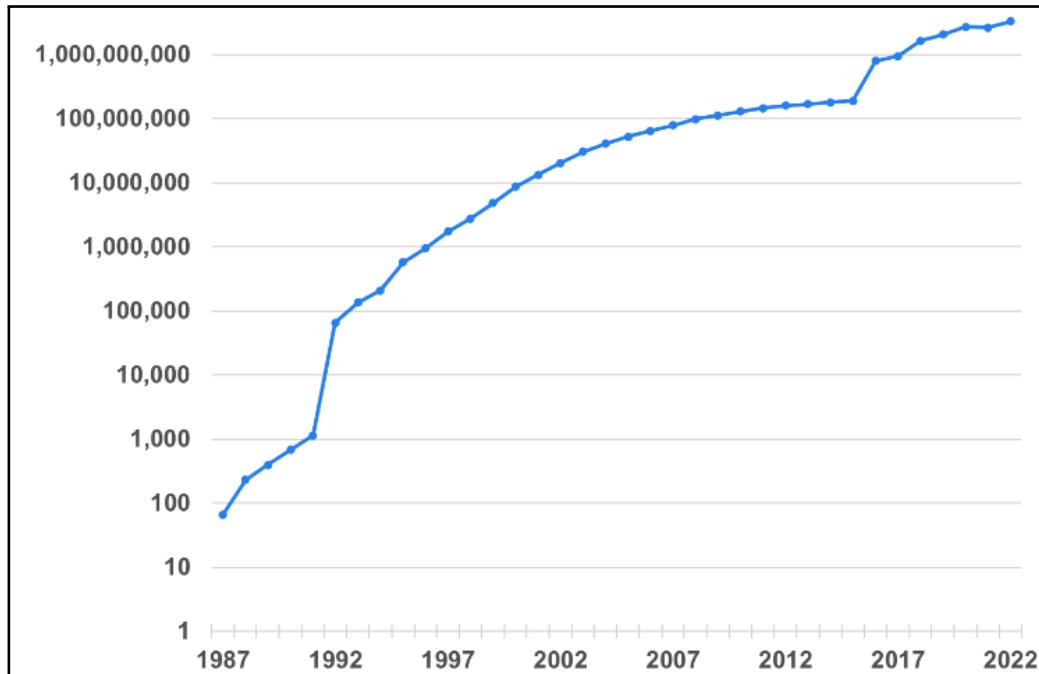
Rapid growth of biological data

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

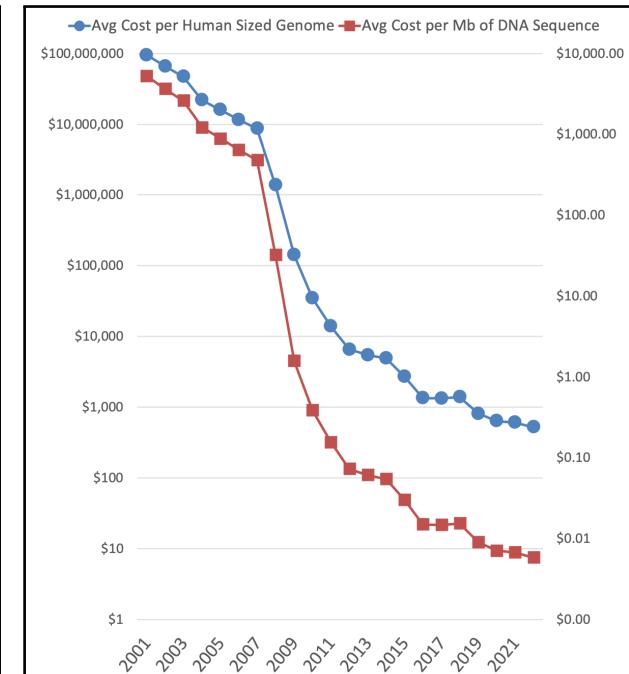
Volume and sequencing cost of DNA over time

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

sequences in INSDC



DNA sequencing cost



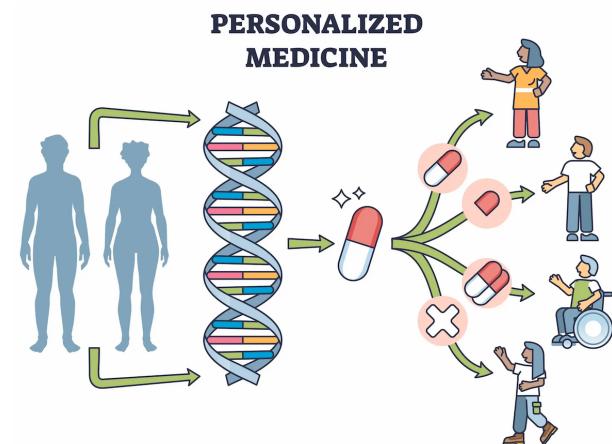
Bio data availability and bias

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

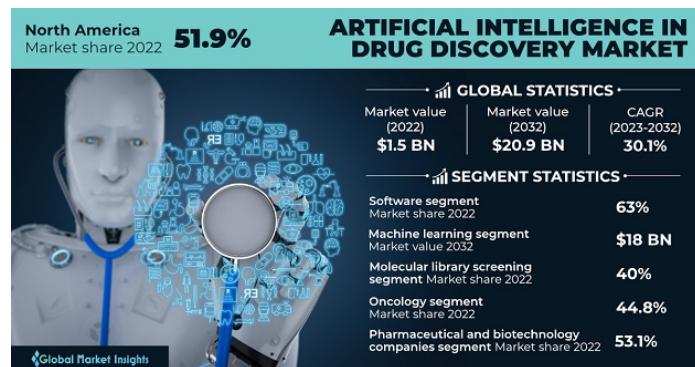
Emerging Trends in Biotech

Personalized medicine

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



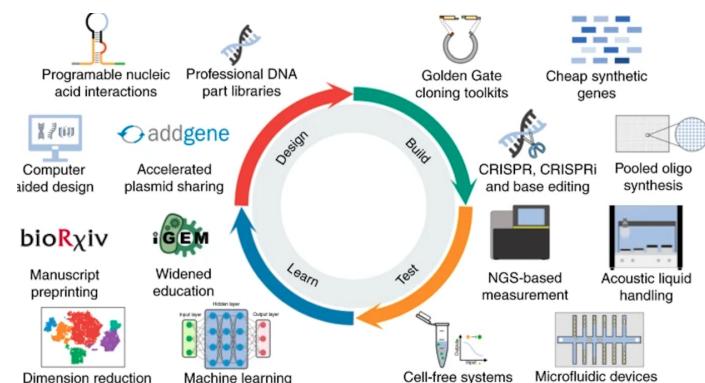
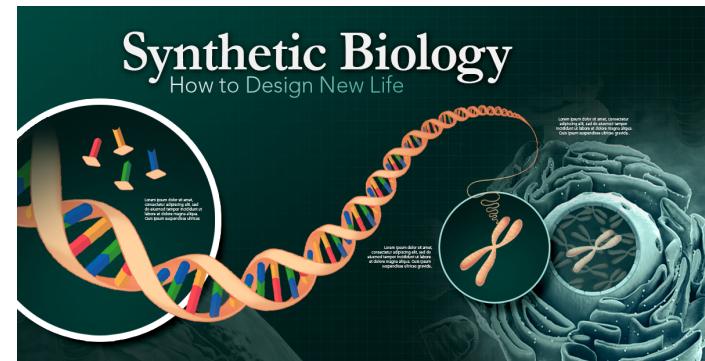
AI-driven drug discovery



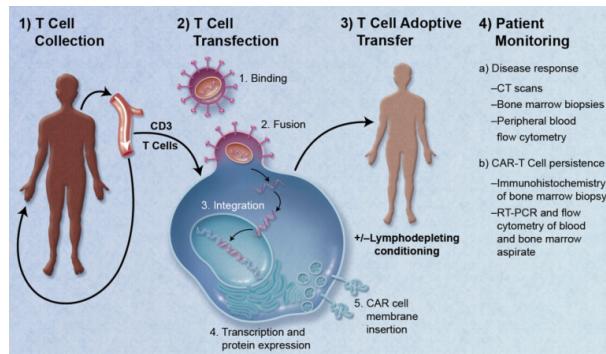
- traditional drug discovery process - time-consuming and costly often taking decades and billions of dollars
- AI streamlines this process by predicting the efficacy and safety of potential compounds with more speed and accuracy
- AI models analyze chemical databases to identify new drug candidates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

Synthetic biology

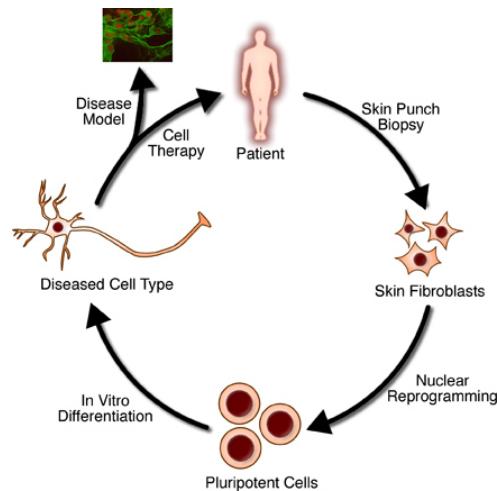
- use AI for gene editing, biomaterial production and synthetic pathways
- combine principles of biology and engineering to design and construct new biological entities
- AI optimizes synthetic biology processes from designing genetic circuits to scaling up production
- company - Ginkgo Bioworks uses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



Regenerative medicine

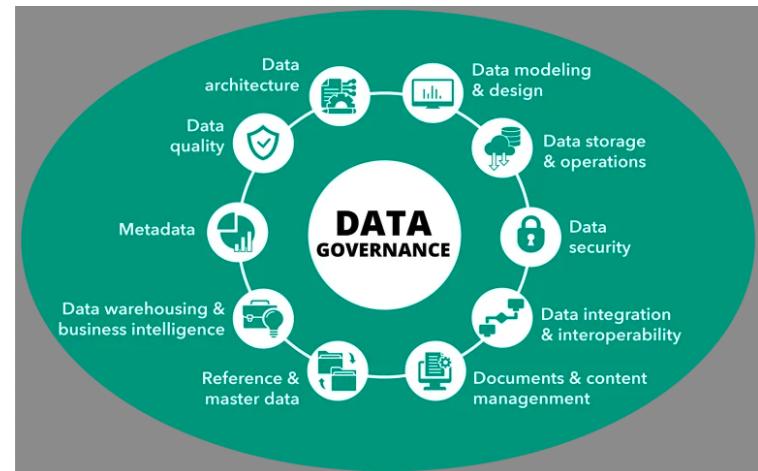


- AI advances development of stem cell therapies & tissue engineering
- AI algorithms assist in identifying optimal cell types, predicting cell behavior & personalized treatments
- particularly for conditions such as neurodegenerative diseases, heart failure and orthopedic injuries
- company - Organovo leverages AI to potentially improve the efficacy and scalability of regenerative therapies, developing next-generation treatments

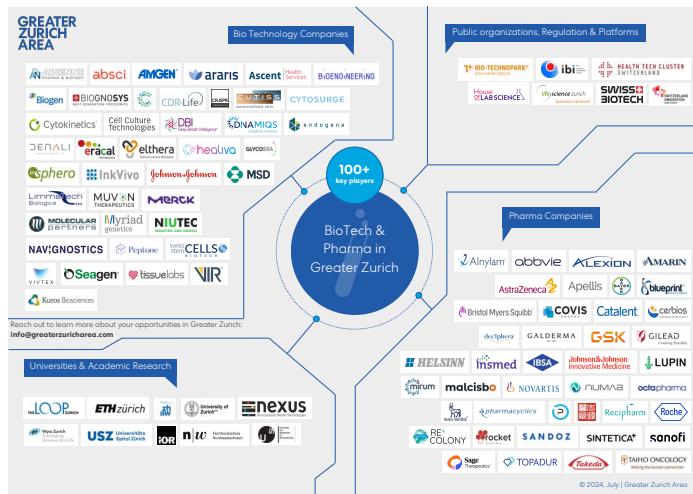


Bio data integration

- 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

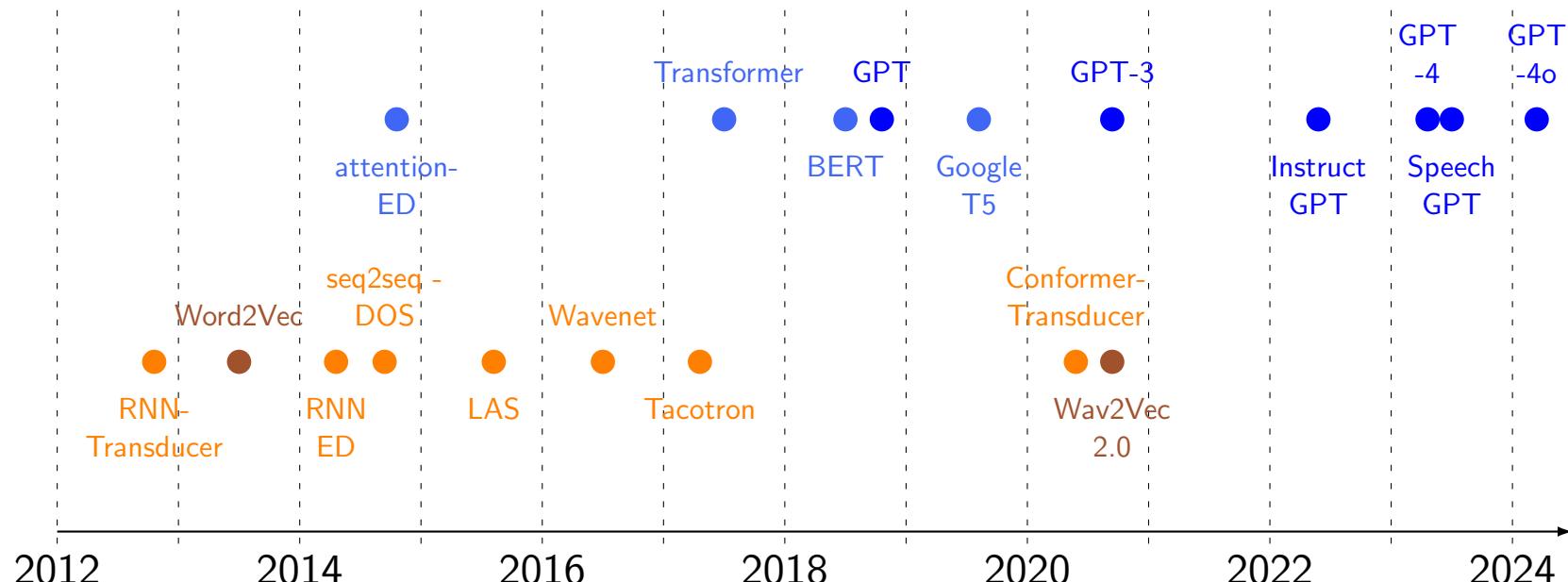
LLM

Language Models

History of language models

- bag of words - first introduced – 1954
- word embedding – 1980
- RNN based models - conceptualized by David Rumelhart – 1986
- LSTM (based on RNN) – 1997
- 380M-sized seq2seq model using LSTMs proposed – 2014
- 130M-sized seq2seq model using gated recurrent units (GRUs) – 2014
- Transformer - Attention is All You Need - A. Vaswani et al. @ Google – 2017
 - 100M-sized encoder-decoder multi-head attention model for machine translation
 - non-recurrent architecture, handle arbitrarily long dependencies
 - parallelizable, *simple* (linear-mapping-based) attention model

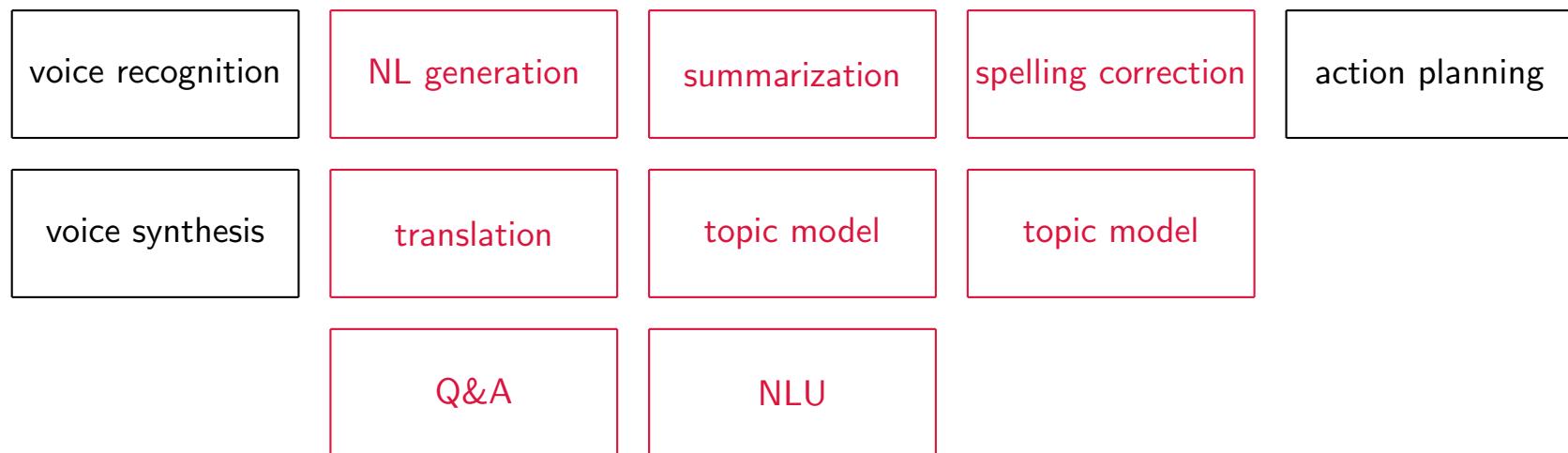
Recent advances in speech & language processing



- LAS: listen, attend, and spell, ED: encoder-decoder, DOS: decoder-only structure

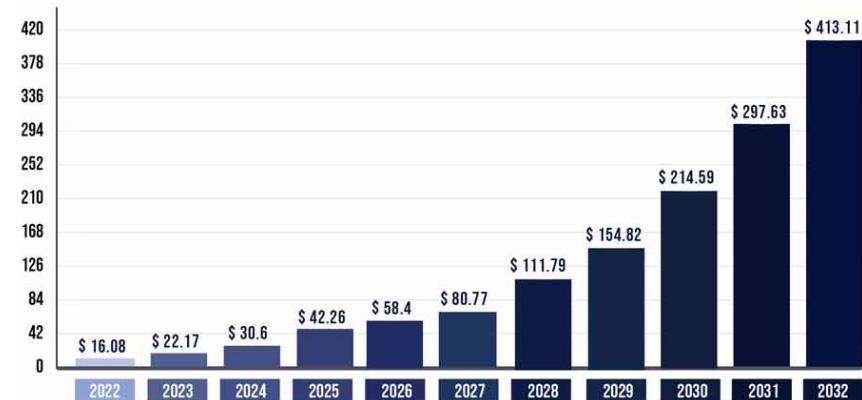
Types of language models

- many of language models have **common requirements** - language representation learning
- can be learned via pre-training *high performing model* and fine-tuning/transfer learning/domain adaptation
- this *high performing model* learning essential language representation *is* (language) foundation model
 - actually, same for other types of learning, e.g., CV



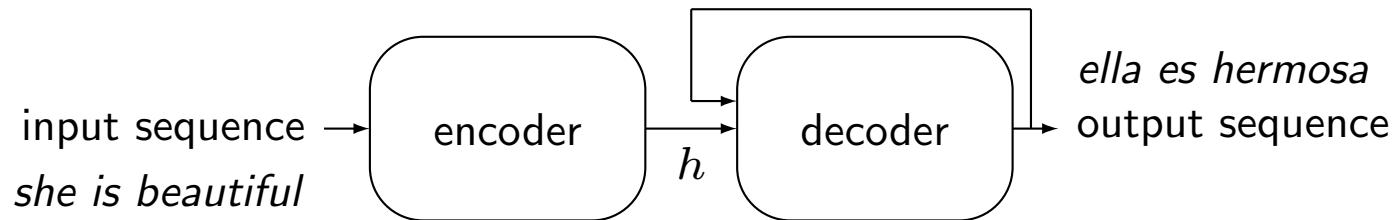
NLP market size

- global NLP market size estimated at USD 16.08B in 2022, is expected to hit USD 413.11B by 2032 - *CAGR of 38.4%*
- in 2022
 - north america NLP market size valued at USD 8.2B
 - high tech and telecom segment accounted revenue share of over 23.1%
 - healthcare segment held a 10% market share
 - (by component) solution segment hit 76% revenue share
 - (deployment mode) on-premise segment generated 56% revenue share
 - (organizational size) large-scale segment contributed highest market share
- source - Precedence Research



RNN-type sequence to sequence (seq2seq) model

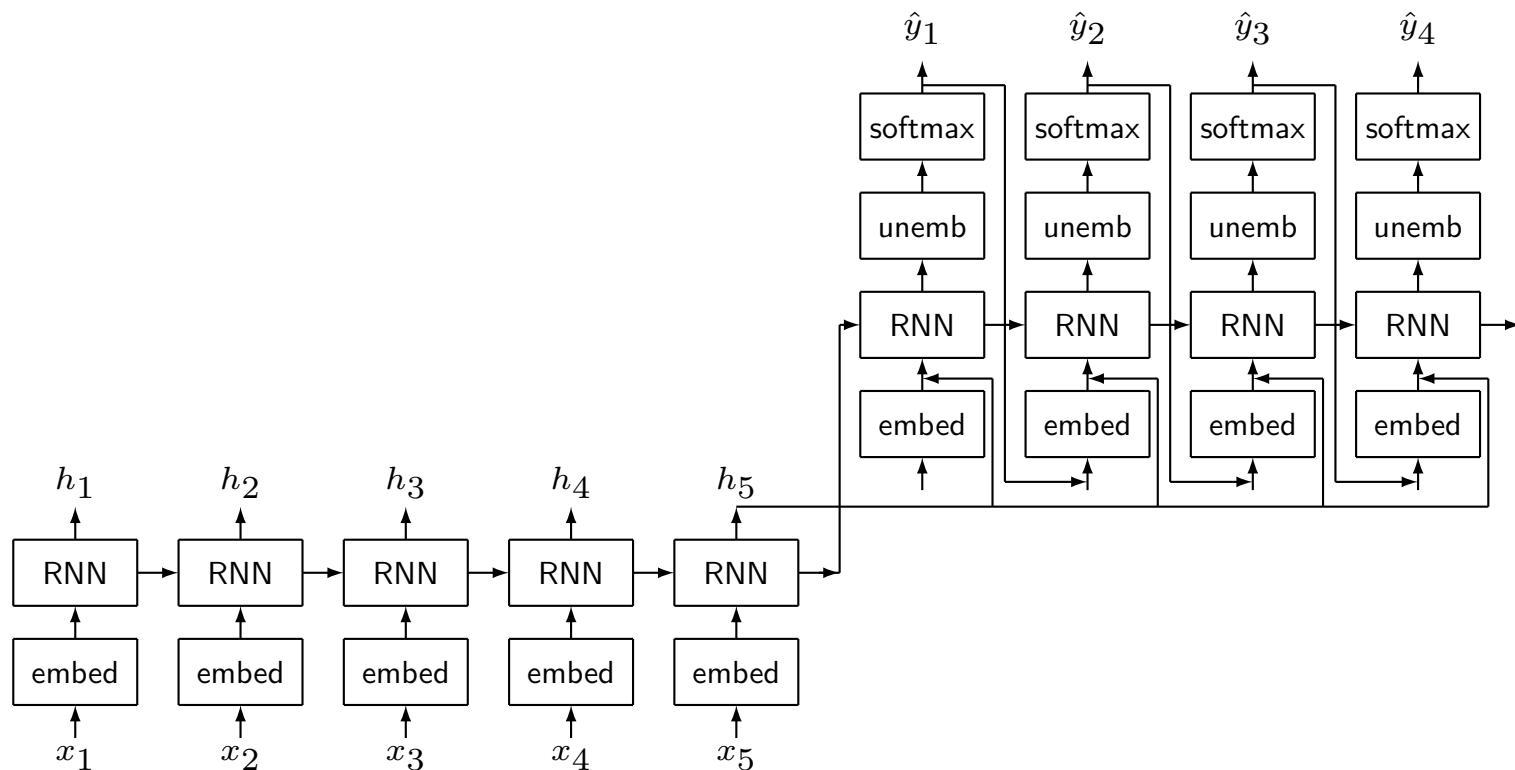
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



- encoder & decoder is RNN-type model
- $h \in \mathbf{R}^n$ - hidden state - *fixed length* vector
- (try to) condense and store information of input sequence (losslessly) in (fixed-length) hidden states
 - finite hidden state - not flexible enough, *i.e.*, cannot handle arbitrarily large information
 - memory loss for long sequences
 - LSTM was promising fix, but with (inevitable) limits

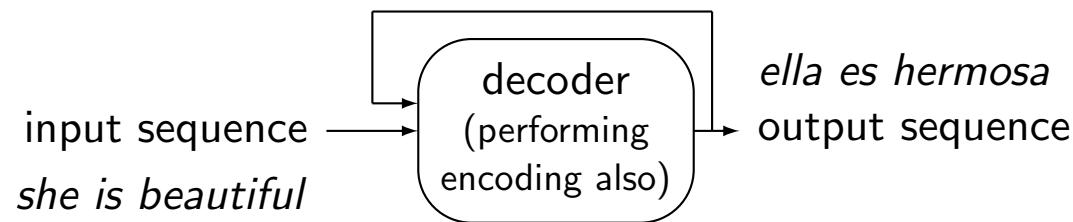
RNN-type encoder-decoder example

- RNN can be basic RNN, LSTM, GRU, etc.



Shared encoder/decoder model

- may use single structure to perform both encoding & decoding
- LLMs are built in this way



Large Language Models

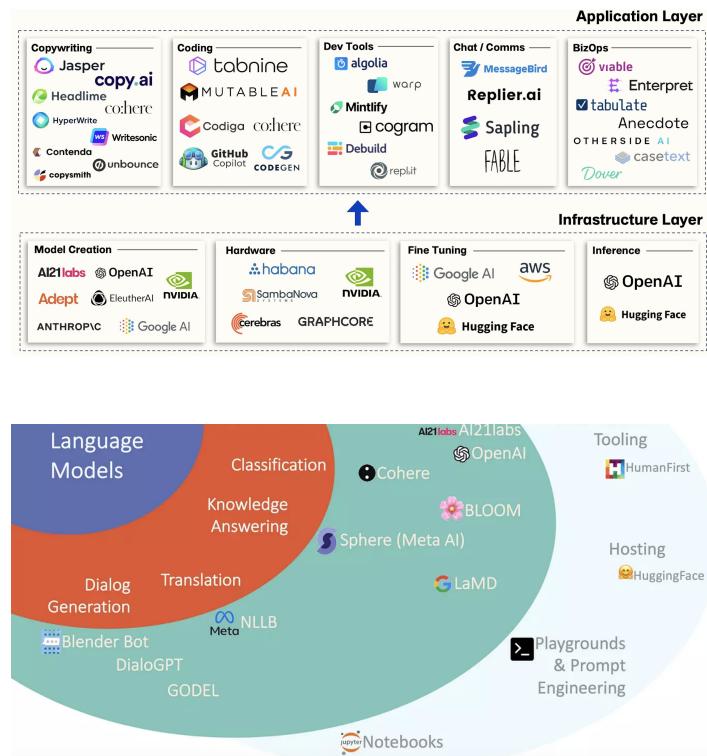
LLM

- LLM
 - type of AI aimed for NLP trained on massive corpus of texts & programming code
 - allow learn statistical relationships between words & phrases, *i.e.*, conditional probabilities
 - *amazing performance shocked everyone - unreasonable effectiveness of data (Halevy et al., 2009)*
 - applications
 - conversational AI agent / virtual assistant
 - machine translation / text summarization / content creation / sentiment analysis
 - code generation
 - market research / legal service / insurance policy / triange hiring candidates
 - + virtually infinite # of applications



LLMs

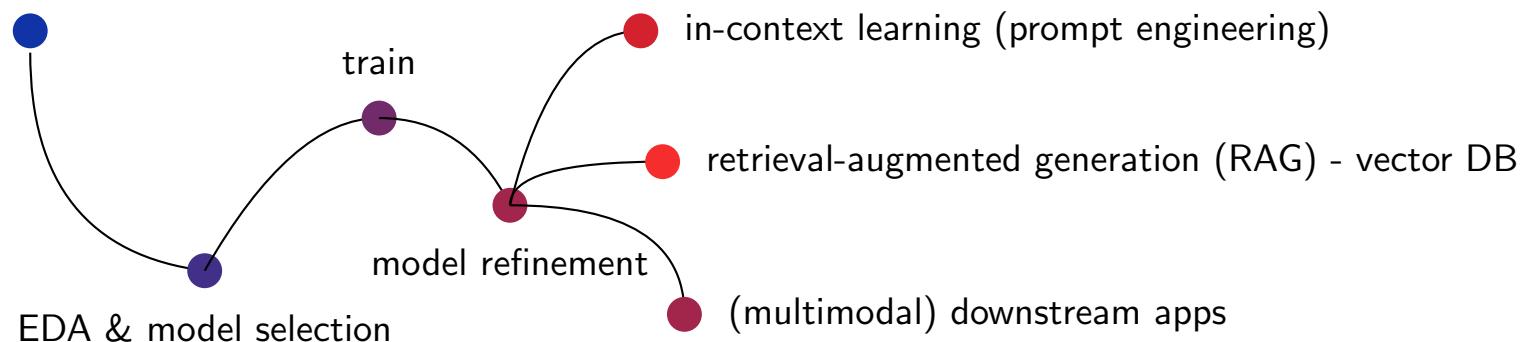
- Foundation Models
 - GPT-x/Chat-GPT - OpenAI, Llama-x - Meta, PaLM-x (Bard) - Google
- # parameters
 - generative pre-trained transformer (GPT) - GPT-1: 117M, GPT-2: 1.5B, GPT-3: 175B, GPT-4: 100T, GPT-4o: 200B
 - large language model Meta AI (Llama) - Llama1: 65B, Llama2: 70B, Llama3: 70B
 - scaling language modeling with pathways (PaLM) - 540B
- burns lots of cash on GPUs!
- applicable to many NLP & genAI applications



LLM building blocks

- data - trained on massive datasets of text & code
 - quality & size critical on performance
- architecture - GPT/Llama/Mistral
 - can make huge difference
- training - self-supervised/supervised learning
- inference - generates outputs
 - in-context learning, prompt engineering

goal and scope of LLM project



Transformer

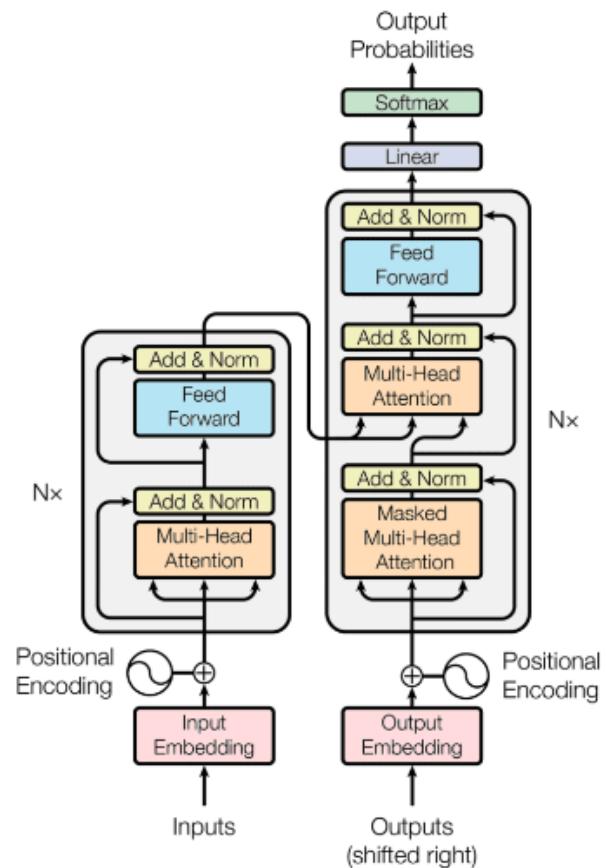
LLM architectural secret (or known) sauce

Transformer - simple parallelizable attention mechanism

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

Transformer architecture

- encoding-decoding architecture
 - input embedding space → multi-head & mult-layer representation space → output embedding space
- additive positional encoding - information regarding order of words @ input embedding
- multi-layer and multi-head attention followed by addition / normalization & feed forward (FF) layers
- *(relatively simple) attentions*
 - single-head (scaled dot-product) / multi-head attention
 - self attention / encoder-decoder attention
 - masked attention
- benefits
 - *evaluate dependencies between arbitrarily distant words*
 - has recurrent nature w/o recurrent architecture → parallelizable → fast w/ additional cost in computation



Single-head scaled dot-product attention

- values/keys/queries denote value/key/query *vectors*, d_k & d_v are lengths of keys/queries & vectors
- we use *standard* notions for matrices and vectors - not transposed version that (almost) all ML scientists (wrongly) use
- output: weighted-average of values where weights are attentions among tokens
- assume n queries and m key-value pairs

$$Q \in \mathbf{R}^{d_k \times n}, K \in \mathbf{R}^{d_k \times m}, V \in \mathbf{R}^{d_v \times m}$$

- attention! outputs n values (since we have n queries)

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

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

Single-head - close look at equations

- focus on i th query, $q_i \in \mathbf{R}^{d_k}$, $Q = [\quad - \quad q_i \quad - \quad] \in \mathbf{R}^{d_k \times n}$
- assume m keys and m values, $k_1, \dots, k_m \in \mathbf{R}^{d_k}$ & $v_1, \dots, v_m \in \mathbf{R}^{d_v}$

$$K = [\quad k_1 \quad \cdots \quad k_m \quad] \in \mathbf{R}^{d_k \times m}, V = [\quad v_1 \quad \cdots \quad v_m \quad] \in \mathbf{R}^{d_v \times m}$$

- then

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

e.g., dependency between i th output token and j th input token is

$$a_{ij} = \exp \left(k_j^T q_i / \sqrt{d_k} \right) / \sum_{j=1}^m \exp \left(k_j^T q_i / \sqrt{d_k} \right)$$

- value obtained by i th query, q_i in $\text{Attention}(Q, K, V)$

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

Multi-head attention

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

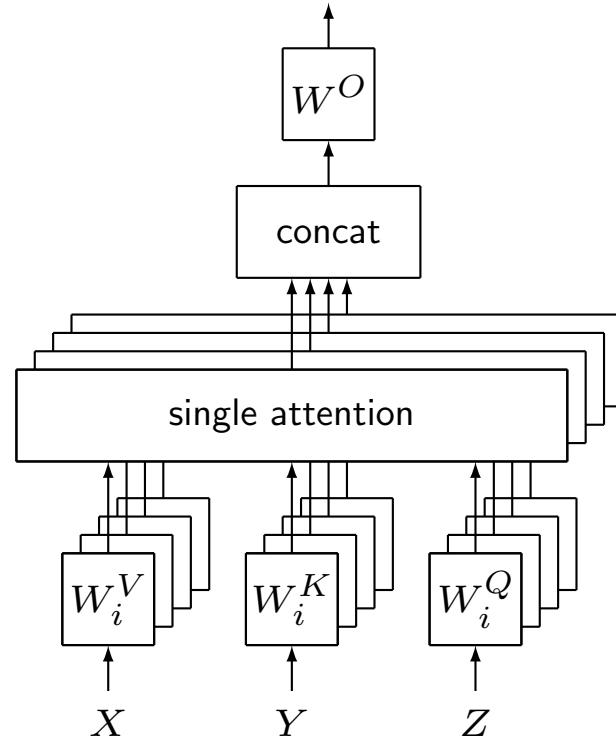
$$X \in \mathbb{R}^{d_e \times m}, Y \in \mathbb{R}^{d_e \times m}, Z \in \mathbb{R}^{d_e \times n}$$

e.g., n : input sequence length & m : output sequence length in machine translation

- h key/query/value weight matrices: $W_i^K, W_i^Q \in \mathbb{R}^{d_k \times d_e}$, $W_i^V \in \mathbb{R}^{d_v \times d_e}$ ($i = 1, \dots, h$)
- linear output layers: $W^O \in \mathbb{R}^{d_e \times hdv}$
- *multi-head attention!*

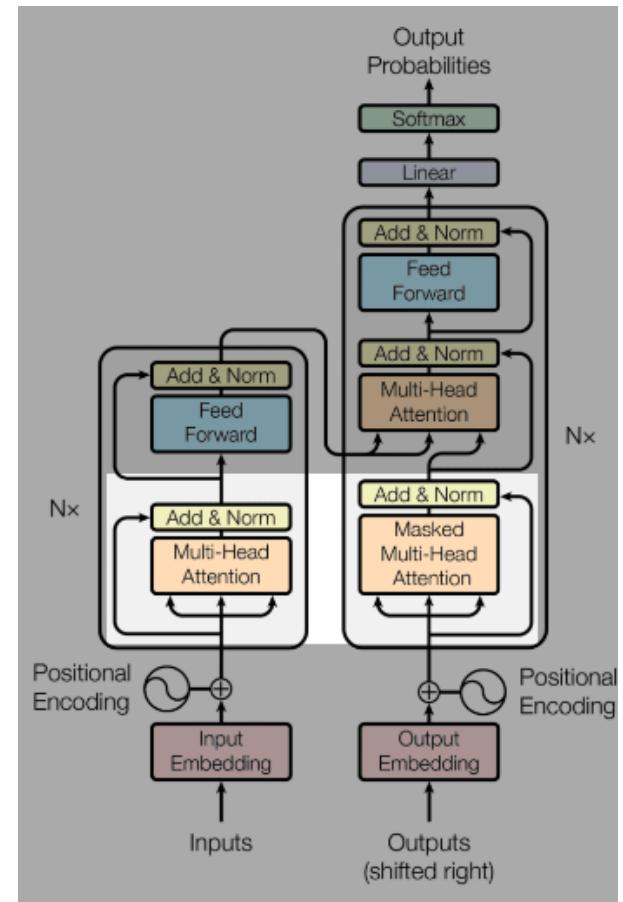
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbb{R}^{d_e \times n},$$

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



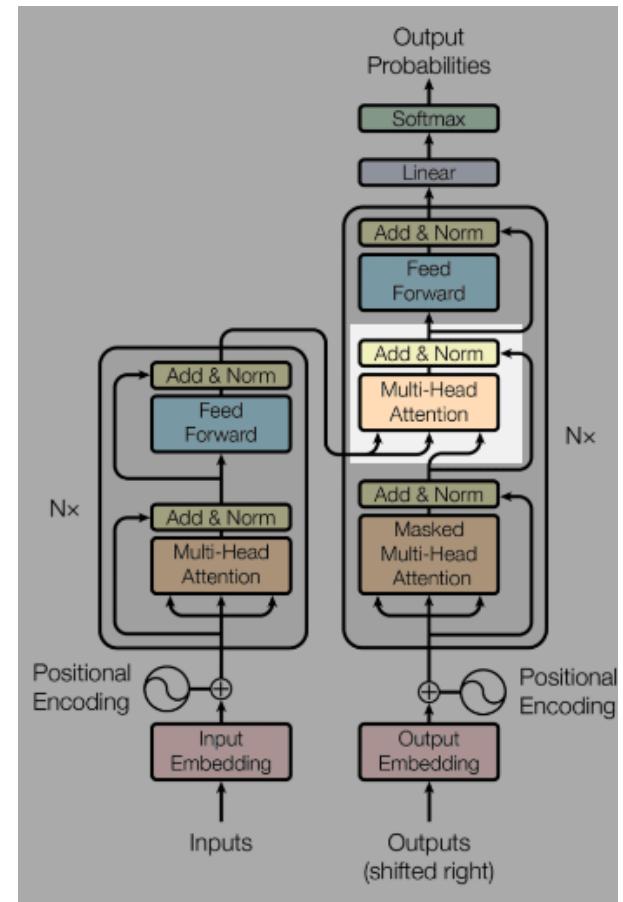
Self attention

- $m = n$
- encoder
 - keys & values & queries (K, V, Q) come from same place (from previous layer)
 - every token attends to every other token in input sequence
- decoder
 - keys & values & queries (K, V, Q) come from same place (from previous layer)
 - every token attends to other tokens up to that position
 - prevent leftward information flow to right to preserve causality
 - assign $-\infty$ for illegal connections in softmax (masking)



Encoder-decoder attention

- m : length of input sequence
- n : length of output sequence
- n queries (Q) come from previous decoder layer
- m keys / m values (K, V) come from output of encoder
- every token in output sequence attends to every token in input sequence

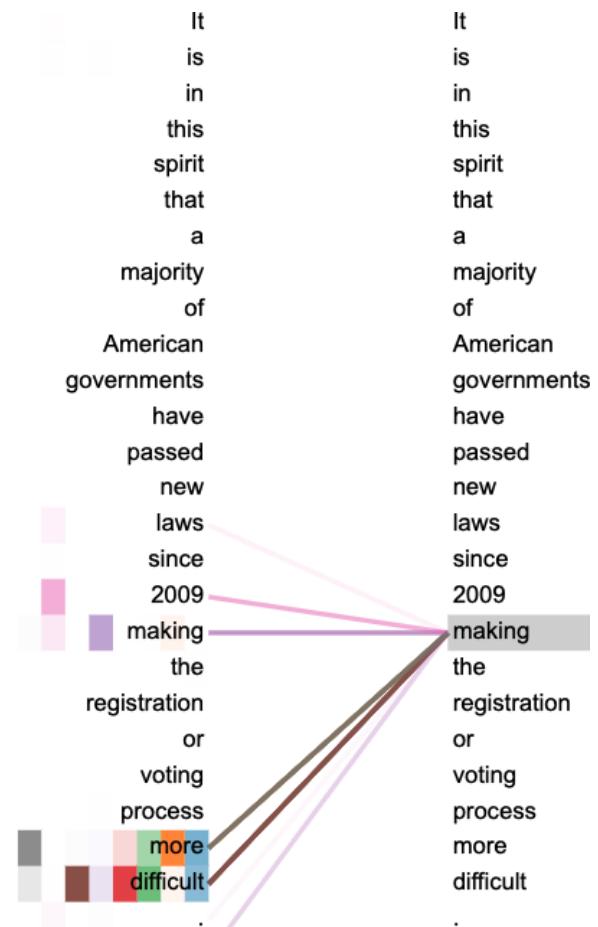


Visualization of self attentions

example sentence

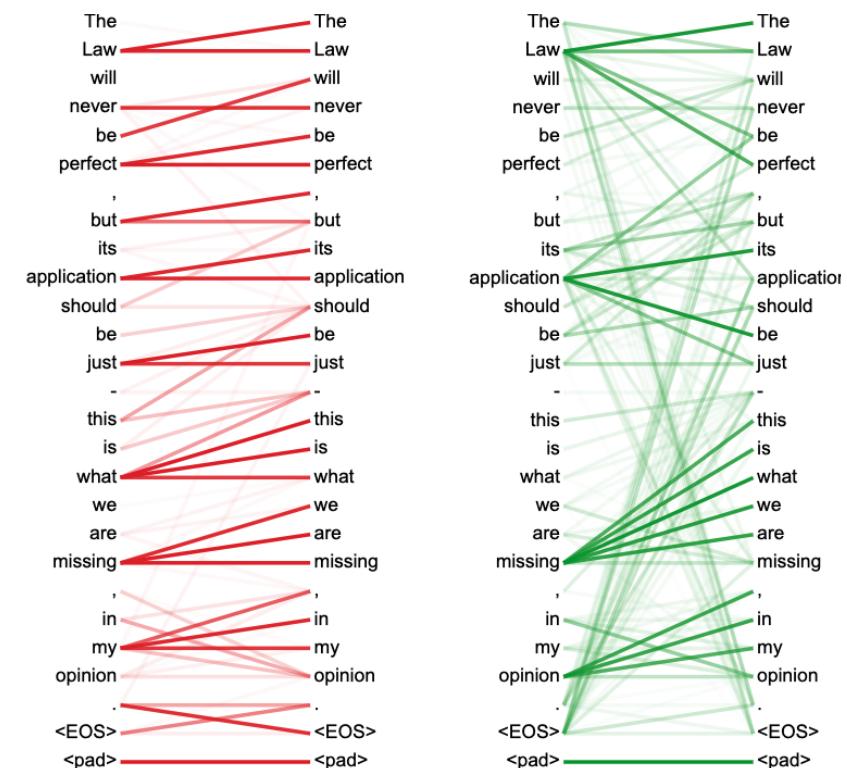
"It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult."

- self attention of encoder (of a layer)
 - right figure
 - show dependencies between "making" and other words
 - different columns of colors represent different heads
 - "making" has strong dependency to "2009", "more", and "difficult"

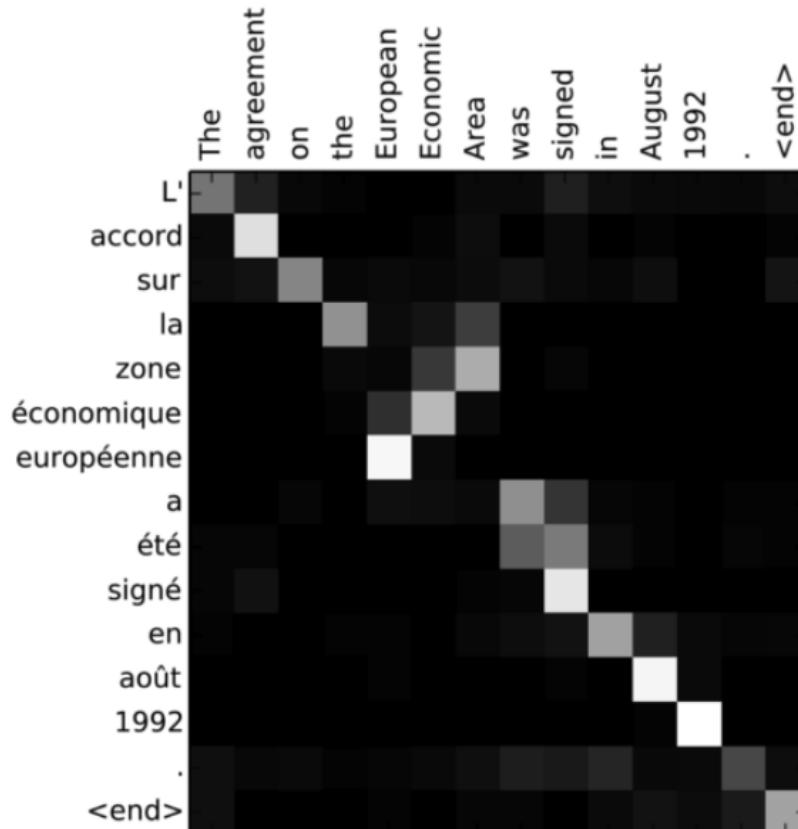


Visualization of multi-head self attentions

- self attentions of encoder for two heads (of a layer)
 - different heads represent different structures
→ advantages of multiple heads
 - multiple heads work together to collectively yield good results
 - dependencies *not* have absolute meanings (like embeddings in collaborative filtering)
 - randomness in resulting dependencies exists due to stochastic nature of ML training



Visualization of encoder-decoder attentions



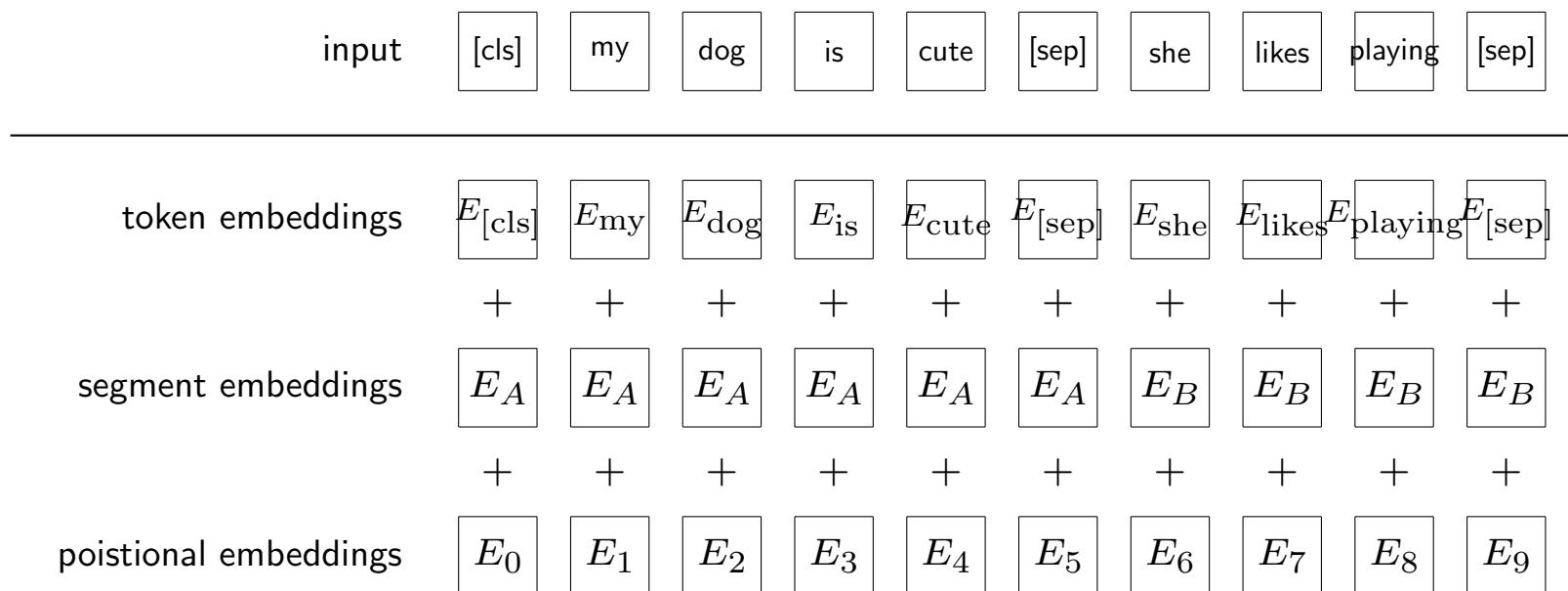
- machine translation: English → French
 - input sentence: "The agreement on the European Economic Area was signed in August 1992."
 - output sentence: "L'accord sur la zone économique européenne a été signé en août 1992."
- encoder-decoder attention reveals relevance between
 - European ↔ européenne
 - Economic ↔ européenne
 - Area ↔ zone

Model complexity

- computational complexity
 - n : sequence length, d : embedding dimension
 - complexity per layer - self-attention: $\mathcal{O}(n^2d)$, recurrent: $\mathcal{O}(1)$
 - sequential operations - self-attention: $\mathcal{O}(1)$, recurrent: $\mathcal{O}(n)$
 - maximum path length - self-attention: $\mathcal{O}(1)$, recurrent: $\mathcal{O}(n)$
- *massive parallel processing, long context windows*
 - makes NVidia more competitive, hence profitable!
 - makes SK Hynix prevail HBM market!

Derivatives of Transformer - BERT

- Bidirectional Encoder Representations from Transformers [DCLT19]
- pre-train deep bidirectional representations from unlabeled text
- fine-tunable for multiple purposes



Implications & Challenges

Multimodal learning

- understand information from multiple modalities, *e.g.*, text, images, audio, and video
- representation learning
 - language representation + image / video / text / audio representation
 - learn multimodal representations together
- outputs
 - captions for images, videos with narration, musics with lyrics
- collaboration among different modalities
 - understand image world (open system) using language (closed system)



Implications of success of LLMs

- (very) many researchers change gears towards LLM
 - from computer vision (CV), speech, music, video, even reinforcement learning
- *LLM is not (only) about languages . . .*
 - humans have . . .
 - evolved and optimized (natural) language structures for eons
 - handed down knowledge using natural languages for thousands of years
 - natural language optimized (in human brains) through *thousands of generations by evolution*
 - *can connect non-linguistic world (open system) using language structures (closed system)*

Challenges in LLMs

- *hallucination - can give entirely plausible outcome that is false*
- data poison attack
- unethical or illegal content generation
- huge resource necessary for both training & inference
- model size - need compact models
- outdated knowledge - can be couple of years old
- lack of reproducibility
- *biases - more on this later . . .*

do not, though, focus on downsides but on *infinite possibilities!*

- it evolves like internet / mobile / electricity
- only “tip of the iceberg” found & released

genAI

Generative AI (genAI)

- definition of generative model

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

- *generate samples in original space, \mathcal{X} , from samples in latent space, \mathcal{Z}*
- g_{θ} is parameterized model *e.g.*, CNN / RNN / Transformer / diffuction-based model
- training
 - finding θ that minimizes/maximizes some (statistical) loss/merit function so that $\{g_{\theta}(z)\}_{z \in \mathcal{Z}}$ generates plausible point in \mathcal{X}
- inference
 - random samples z to generated target samples $x = g_{\theta}(z)$
 - *e.g.*, image, text, voice, music, video

VAE - early genAI model

- variational auto-encoder (VAE) [KW19]

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

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

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

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

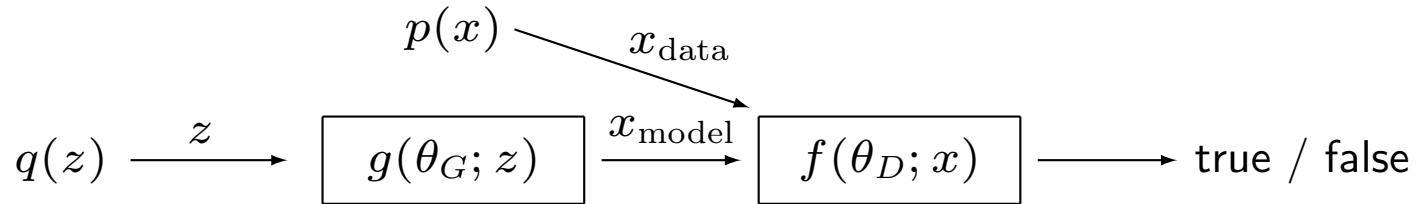
$$\mathcal{L}(\theta, \phi; x) = \mathbf{E}_{z \sim q_\phi(z|x)} \log \frac{p_\theta(x, z)}{q_\phi(z|x)}$$

- generative model

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

GAN - early genAI model

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



- value function

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

- modeling via playing min-max game

$$\min_{\theta_G} \max_{\theta_D} V(\theta_D, \theta_G)$$

- generative model

$$g(\theta_G; z)$$

- variants: conditional / cycle / style / Wasserstein GAN

genAI - LLM

- *maximize conditional probability*

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

where $d(\cdot, \cdot)$ distance measure between probability distributions

- previous sequence: x_{t-1}, x_{t-2}, \dots
- next token: x_t
- p_{θ} represented by (extremely) complicated model
 - e.g., containing multi-head & multi-layer Transformer architecture inside
- model parameters, e.g., for Llama2

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

AI Research

AI research race gets crazy

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



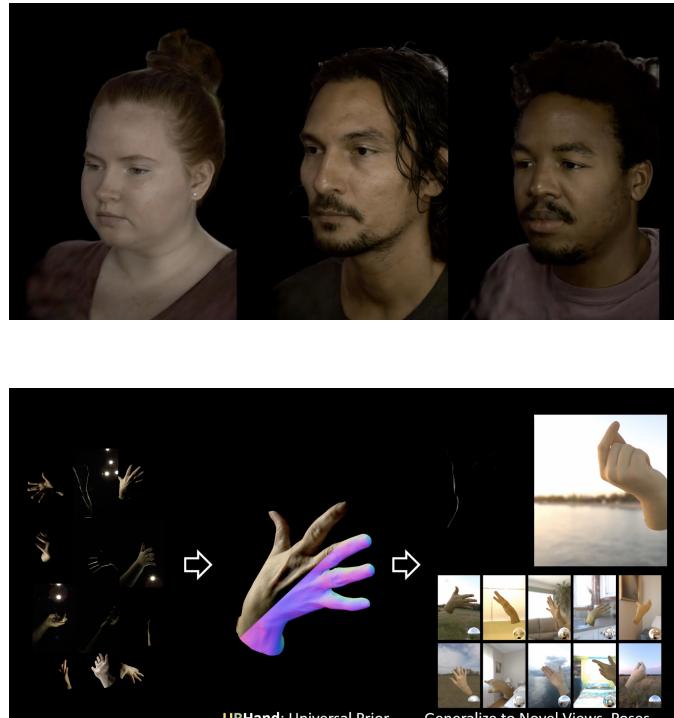
AI progress within a month - March, 2024

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

Papers of single company accepted by single conference

- CVPR 2024

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



AI Applications

genAI applications

- ChatGPT, Cohere
- Anthropic, Dolly, Mosaic MPT
- Stable Diffusion
- Midjourney, DALL-E, LLaMA 2
- Mistral AI, Amazon Bedrock, and Falcon



ChatGPT & VR/AR

- new appropriately to teaching
- power of ChatGPT and VR/AR unlocks immersive learning
 - *learning language* - immersive VR environment provides immediate feedback, responding to inquiries & interactive discussions
 - *medical education* - experience diagnosing and treating patients in lifelike scenarios
 - *investigating history & culture* - integration of ChatGPT into VR enables virtual visit to historical places and cultural landmarks
 - *development of soft skills* - practice and hone soft skills, *e.g.*, leadership, teamwork & communication through VR simulations augmented by ChatGPT
 - *extracurricular activities*
 - personalized learning, gamification of education, international cooperation, educator empowerment
- *VR & ChatGPT integration opens up new training and educational opportunities!*

AI Hardware

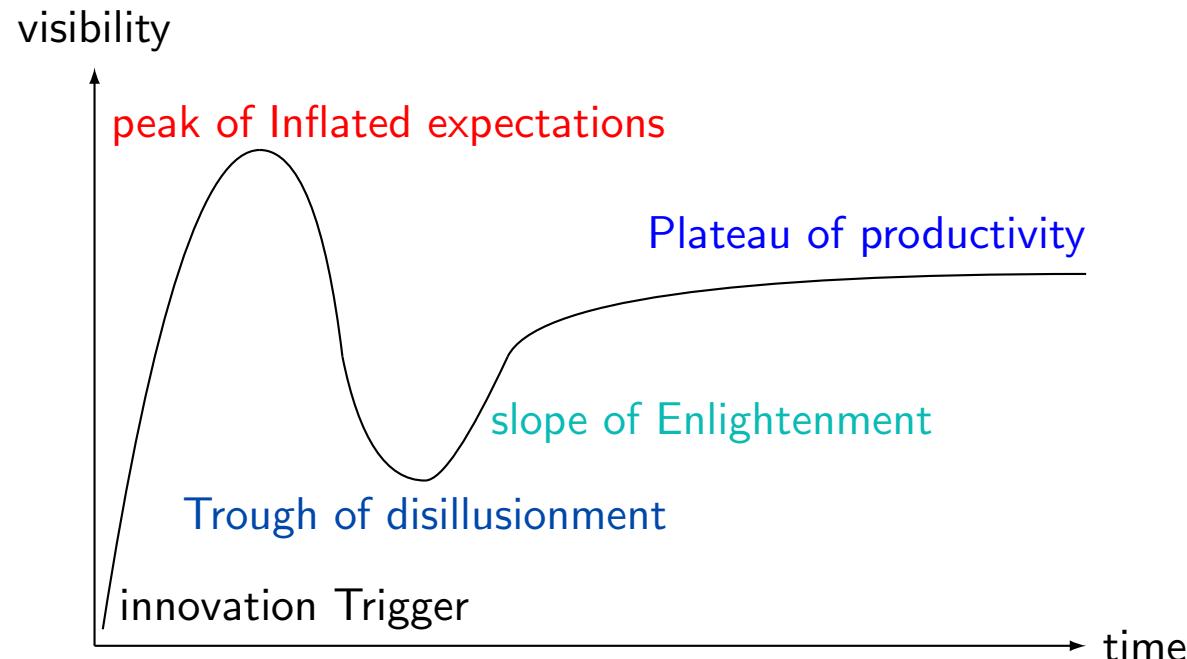
Case study - AMD - Nvidia's new competitor

- Instint MI300X - launched on 06-Dec-2023
 - 50% more HBM3 capacity than its predecessor, MI250X (128 GB)
 - *outperform Nvidia's H100 TensorRT-LLM* (when using optimized AI software stack)
 - 1.6X Higher Memory Bandwidth - 1.3X FP16 TFLOPS
 - up to 40% faster vs H100 (Llama-2 70B) in 8v8 server
- *great timing when Nvidia's order backlogs stuck*
- AMD stocks soars as of Jan-2024
- potential risks: ROCm vs CUDA, speed of customer adoption, production coverage



AI Market

AI hype cycle



- innovation trigger - technology breakthrough kicks things off
- peak of inflated expectations - early publicity induces many successes followed by even more
- trough of disillusionment - expectations wane as technology producers shake out or fail
- slope of enlightenment - benefit enterprise, technology better understood, more enterprises fund pilots

genAI products

- DALL-E (OpenAI)
 - trained on a diverse range of images
 - *generate unique and detailed images based on textual descriptions*
 - understanding context and relationships between words

- Midjourney
 - let people *create imaginative artistic images*
 - can interactively guide the generative process, providing high-level directions



genAI products

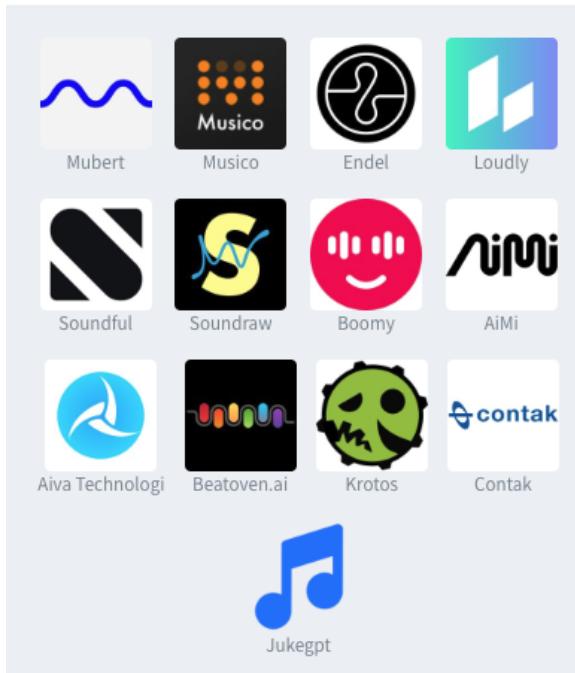


- Dream Studio
 - enables people to create music
 - *analyze patterns in music data and generates novel compositions based on input and style*
 - *allows musicians to explore new ideas and enhance their creative processes*
 - offer open-source free version
- Runway
 - provide range of generative AI tools for creative professionals
 - *realistic images, manipulate photos, create 3D models, automate filmmaking, . . .*
 - “artificial intelligence brings automation at every scale, introducing dramatic changes in how we create”

AI products

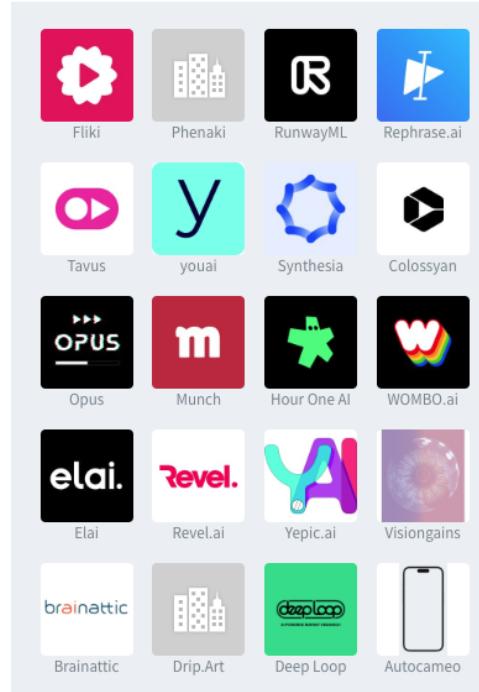
Audio: music generation

Combined funding \$ 61M



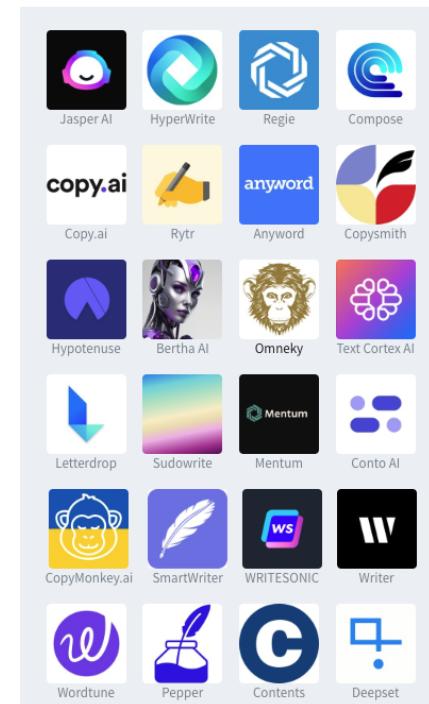
Video

Combined funding \$ 428M



Text: copy & writing

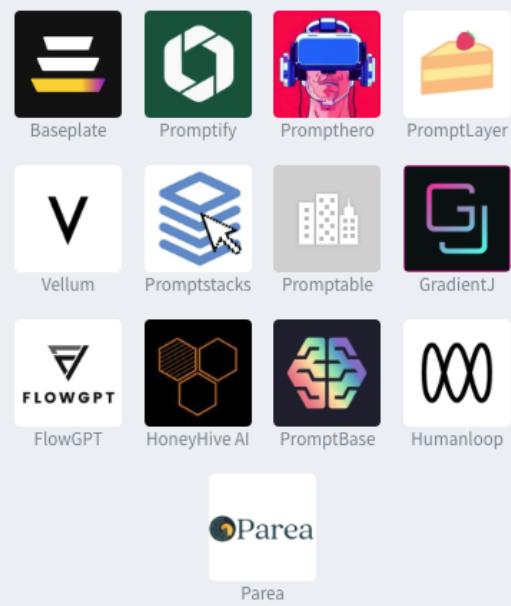
Combined funding \$ 863M



AI products

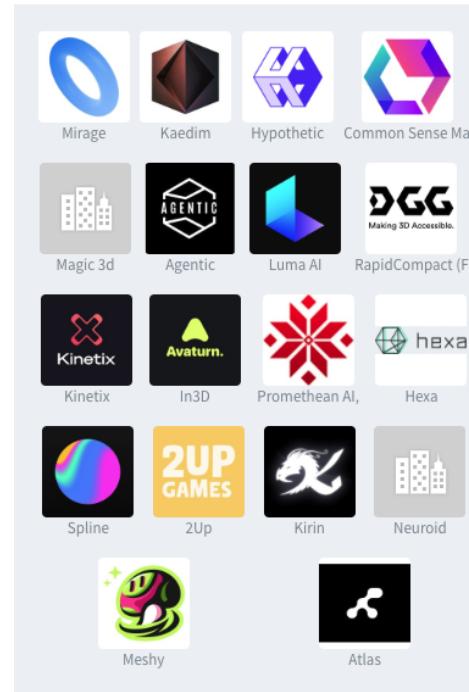
LLMs tools: Prompt Engineering and Management

Combined funding \$ 7.5M



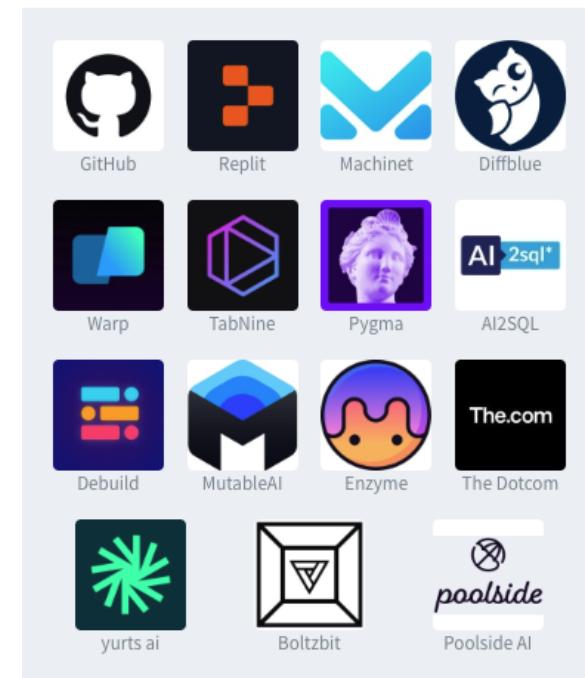
Gaming & design: 3d assets & worlds

Combined funding \$ 117M



Code: code generation

Combined funding \$ 828M



AI companies

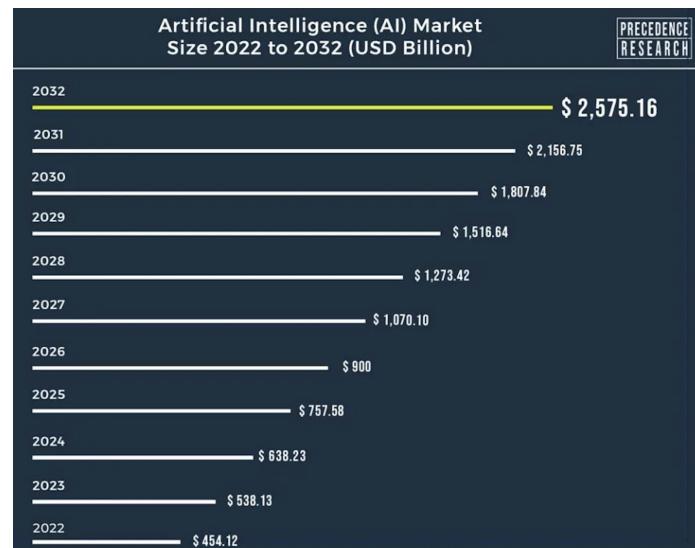
- big tech companies
 - OpenAI, Microsoft, Google, Meta - foundation models
- small(er) players
 - Figure AI, Mistral AI
- AI hardware companies - benefiting from LLM and genAI market dominance
 - Nvidia, AMD, Samsung, SK hynix, Micron, Intel, TSMC (AI processors & memory chips)
- *tiny fraction of Silicon Valley startups gets majority of total funding*
 - Anthropic - \$3.5B - large-scale AI systems - Claude
 - AssemblyAI - \$58M - speech AI
 - Hugging Face - \$400M - AI model/data platforms
 - Inflection AI - \$1.5B - conversational AI - Pi

Opportunities among big tech's domination

- OpenAI/Microsoft, Meta, Google's races for foundation models heated up!
- no small players can compete with rare exceptions, *e.g.*, Mistral AI
- hyperscalers stand strong - AWS, Azure, and Google Cloud
- *speaker's proposals for strategies*
 - accurately (or roughly) predict how far & up to where big players will reach
 - target niche markets
 - focus on (creative) downstream applications of LLMs and/or genAIs

AI market outlook in 2024

- global AI market expected to reach *USD 0.5T by 2024* (IDC @ Mar-2023) & expected to reach around *USD 2.5T by 2032* (Precedence Research @ Dec-2023) [P.R23]
 - was valued at USD 454B in 2022, expanding at *double-digit CAGR of 19%* from 2023 to 2032
- *AI funding soars to USD 17.9B for Q3 in 2023 in Silicon Valley while rest of tech slumps* (PitchBook data, Bloomberg @ Oct-2023) [Blo23]
 - multibillion-dollar investment in AI startups almost commonplace in Silicon Valley
 - genAI dazzles users and investors with photo-realistic images & human-sounding text
- genAI software sales could surge *18,647% by 2032*



Productivity, inflation & jobs

- Federal Reserve probes AI's impact on productivity, inflation & jobs - Jul-2024
 - feds acknowledging significant AI investments
 - Jerome Powell emphasizes uncertainties on whether AI will eliminate, augment, or create jobs - stating it's too early to predict
 - Powell acknowledges limited influence of central banks like the Fed on AI's technological shifts
 - fed actively researching various AI forms beyond genAI to understand potential economic impacts
 - IMF predicts AI (could) impact up to 60% of jobs in advanced economies potentially lowering labor demand and wages in sectors like finance and insurance

AI & global economy

- five ways AI is transforming global economy
 - reshape job markets, creating new roles while rendering some obsolete
 - enhance productivity across industries
 - contribute to global economy by optimizing processes and innovation
 - *may widen economic disparities if not managed inclusively*
 - *governments* has to develop policies to address AI's economic and social impacts



Global Semiconductor Business

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 and China
 - export controls on advanced chips and equipment to China
 - investment restrictions in both directions
- CHIPS & Science Act (Aug, 2022)
 - \$52B in subsidies for domestic semiconductor production, 25% investment tax credit for chip plants
 - (coerce) world-best semiconductor companies build factories in US with support of government and states
 - GlobalFoundries - \$1.5B @ Feb-2024 - Global Foundary
 - Intel - \$8.5B @ Apr-2024 - Ohio - two fabs expandable to \$100B
 - Samsung - \$6.4B @ Apr-2024 - Talor, Texas - advanced logic chips
 - 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 Startups

Incubators

- Y Combinator
 - invests \$500,000 in each startup receiving 7% equity
 - program culminates in “Demo Day” where startups present to investors
 - helped Airbnb, Dropbox, DoorDash, Reddit, Stripe, . . .
 - highly competitive - acceptance rate of 1.5% – 2% - 10k applicants per six months
 - significantly higher survival rate - around 18% valued at over \$100M and 4% becoming unicorns—valued at over \$1B
- XXX

We're not talking about AI chip startups enough

- *not talking about AI chip startups enough*
 - Etched - specializes in AI accelerator chips for LLMs - Sohu chip embeds transformer architecture into silicon
 - Tenstorrent - develops high-performance AI processors focused on efficient training and inference
 - Axelera AI - specializes in high-performance AI hardware for edge computing, excelling in CV applications
 - Recogni - develops high-performance AI chips for edge computing applications focusing on low-latency processing for autonomous vehicles
- *global AI chip market will gross \$30B in 2024 and become \$300B in next 10 years*



Serendipities around Als

Serendipity or inevitability

- What if Geoffrey Hinton had not been persistent researcher?
- What if symbolists won AI race over connectionists?
- What if attention mechanism did not perform well?
- What if Transformer architecture did not perform super well?
- What if Jensen Hwang had not been crazy about making hardware for professional gamers?
- Is it like Alexander Fleming's Penicillin?
- Or more like Inevitability?

Some Important Questions

Some important questions around AI

- why human-level AI in the first place?
- what lies in very core of DL architecture? what makes it work amazingly well?
- biases that can hurt judgement, decision making, social good?
- ethical and legal issues
- consciousness, knowledge, belief, reasoning
- future of AI

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, . . .

Biases - by Humans & Machines

Cognitive biases

- 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,



LLM biases

- plausible with LLM
 - 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 inferencing 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

Ethical and Legal Issues

Ethics - possibilities & questions

- 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

Ethically controversial issues

- AI girlfriends
 - lots of AI girlfriend apps already developed
 - ethical considerations and provisions for user privacy with AI partners imperative - as with every technology involving personal data and emotional interaction
 - prospect of developing lifelike digital companions will grow better with evolution of AI
 - perhaps changing ways relationships and companionship perceived in digital age one day
 - why not many AI boyfriend apps? is this sexual discrimination issue (at all)?

Legal issues with ethical consideration - (hypothetical) scenarios

- 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 & humanistic 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?
 - will to survive?
- no agreed definition on consciousness exists yet
 - . . . and will be so forever
- can it be separated from fact that humans are biological living beings?
 - (speaker) doesn't think so . . .
- is SKYNET ever plausible (without someone's intention)?
 - can AI have *desire* to survive (or save earth)?



Utopia or dystopia



- not important questions (speaker thinks)
 - what we should worry about is not doomsday or destroying humankind
- but rather we should focus on
 - our limit in controlling or unintended consequences of AI
 - misuse by those possessing social, economic, political power
 - social good and welfare impaired by (exploiting of) AI
 - choice among utilitarianism / humanism / justice / equity
 - handle ethical and legal issues

Knowledge, Belief, and Reasoning of AI

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

What categories of questions should they be?

Philosophical? Cognitive scientific?

Three surprises of LLM

- 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
 - “*does LLM have knowledge and belief?*”
 - “*can it reason?*”

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

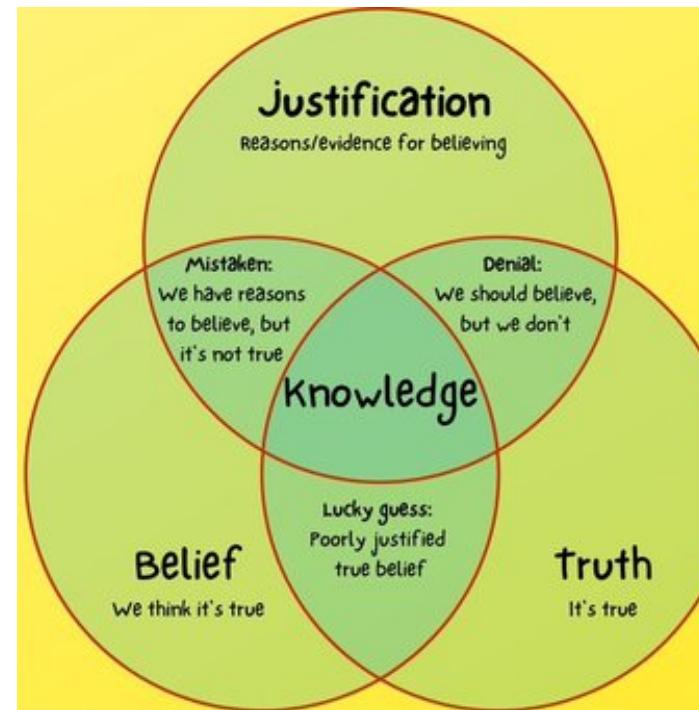
does ChatGPT have belief?
or
do humans have knowledge?
- let us discuss them in two different perspectives
 - laymen's perspective
 - cognitive scientific perspective

Laymen's perspective on knowledge, belief & reasoning

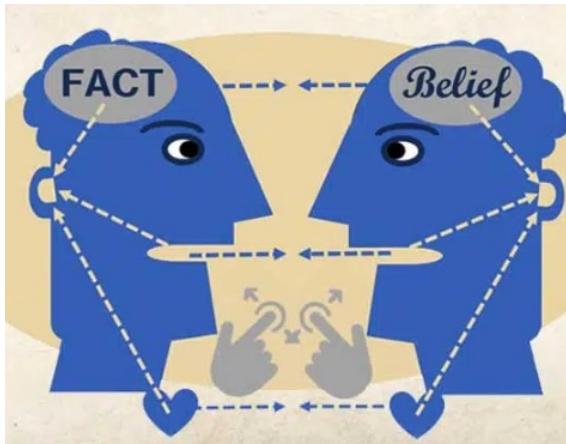
- does (good) LLM have knowledge?
 - Grandmother - looks like it cuz when instructed “*explaining big bang*”, it says
“The Big Bang theory is prevailing cosmological model that explains the origin and evolution of the universe. . . . 13.8 billion years ago . . .”
- does it have belief?
 - Grandmother: 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!

Cognitive scientific perspective on knowledge

- does LLM have knowledge?
 - Speaker: I don't think so.
- why?
 - Speaker: 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."
 - LLM *cannot* do this.
 - Speaker: also 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* following words after "*Tom Cruise's mother is.*"
 - Speaker: so we *cannot say it really knows the fact!*



Cognitive scientific perspective on belief



- for the discussion
 - we do not concern *any specific belief*
 - we concern prerequisites for ascribing any beliefs to AI system
- so does it have belief?
 - Speaker: 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, an essential aspect of the capacity to distinguish truth from falsehood.
 - Speaker: when a human being takes to Wikipedia and confirms some fact, what happens is not her language model update, but

reflection of her nature as language-using animal inhabiting shared world with a community of other language-users.
 - Speaker: LLM does not have this ground, an essential consideration when deciding whether it *really* had beliefs.
 - Speaker: so *no, LLM cannot have belief!*

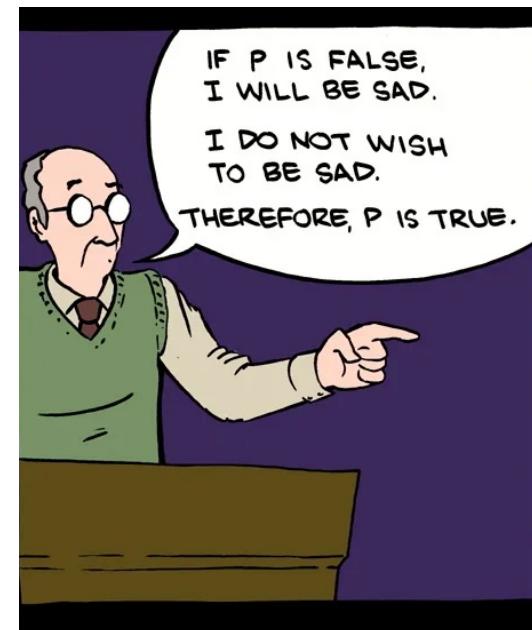
Cognitive scientific perspective on reasoning

- note reasoning is *content neutral*
 - e.g., following logic is perfect regardless of truth of premises

$$\text{if Socrates is a human and humen are immortal, then}\\ \text{Socrates would have survived today.}$$
- Speaker: when asked “*if humans are immortal, would Socrates have survived today?*”, LLM says

$$\text{“... it's logical to conclude that Socrates would likely still}\\ \text{be alive today. ...”}$$
 - however, remember, once again, what we just asked it to do is *not* “deductive inference”, but

$$\text{given the statistical distribution of words in public corpus,}\\ \text{what words are likely to follow the sequence, “humans are}\\ \text{immortal and Socrates is human therefore.”}$$
- Speaker: so LLM *cannot* or rather *does not* reason
- however, LLM can *mimic even multi-step reasoning whose inferencing structure is complicated* using *in-context learning* or *few-short prompting!*



A simple example supporting reasoning incapability



- You

"Who is Tom Cruise's mother?"

- ChatGPT

"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,"

- You

"Who is Mary Lee Pfeiffer's son?"

- ChatGPT

"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. . . ."

Future of AI

Aschenbrenner's essay

- Leopold Aschenbrenner, who left OpenAI showing concerns about safety, wrote *epic 165-page treatise* - Jun-2024
 - rapid progress
 - AI development (is) accelerating at unprecedented rate, predicting by 2027, AI models lead to intelligence explosion surpassing human intelligence
 - economic and security implications
 - trillions of dollars being invested into infrastructure supporting AI systems
 - critical need for securing technologies to prevent misuse, *e.g.*, by state actors like Chinese Communist Party (CCP)
 - technical and ethical challenges
 - significant challenges in controlling AI (smarter than humans), *i.e.*, “superalignment” problem, to prevent catastrophic outcomes
 - predictions and societal impact
 - few people truly understand scale of change by AI
 - potential for AI to reshape industries, enhance national security
 - pose new ethical and governance challenges

More about Aschenbrenner's essay

- AGI by 2027
 - seen AI advancing from preschool-level to high-schooler abilities in 4 years highlighting rapid progress from GPT-2 to GPT-4
- superintelligence following AGI - post AGI
 - rapid advancement from human-level to superhuman capabilities
- G-dollar investment on AI clusters
- national & global security dynamics
 - may lead to all-out war, *e.g.*, with China, if not managed properly
- superalignment challenges
 - keeping superintelligent AI aligned with human values and interests - “one of the most critical predictions”
- societal and economic transformations, project involvement by US government, technological mobilization

Moral

Moral

- AI, *e.g.*, LLM, shows incredible utility and commercial potentials, hence we should
 - make informed decisions about trustworthiness and safety
 - avoid ascribing capacities they lack
- today's AI is 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, policy makers, media people*

Recent AI Research and New Development

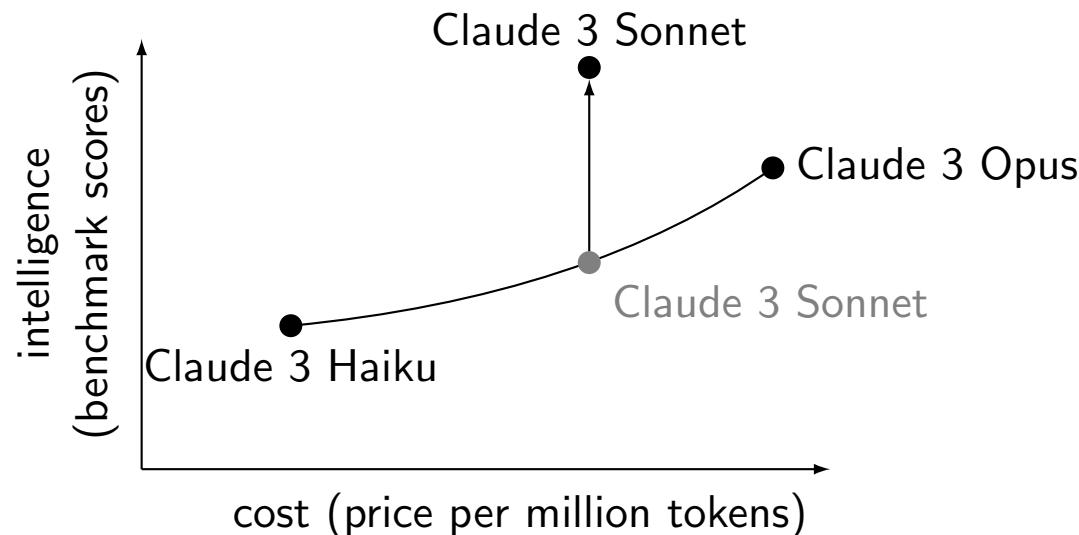
Notable recent AI research and new development

- 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*

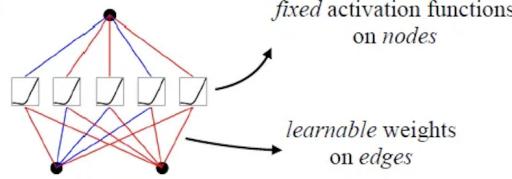
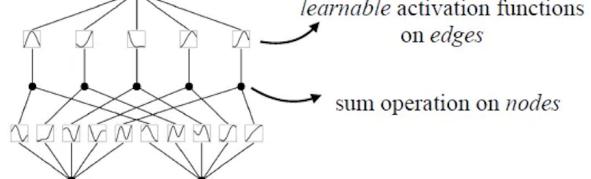
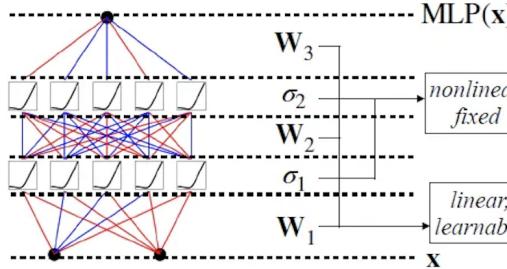
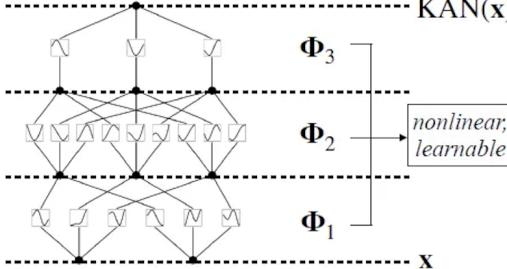
| | Claude 3.5 Sonnet | Claude 3 Opus | GPT-4o | Gemini 1.5 Pro |
|---------------------------|----------------------|------------------|--------|-------------------|
| visual math reasoning | 67.7% | 50.5% | 63.8% | 63.9% |
| science diagrams | 94.7% | 88.1% | 94.2% | 94.4% |
| visual question answering | 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

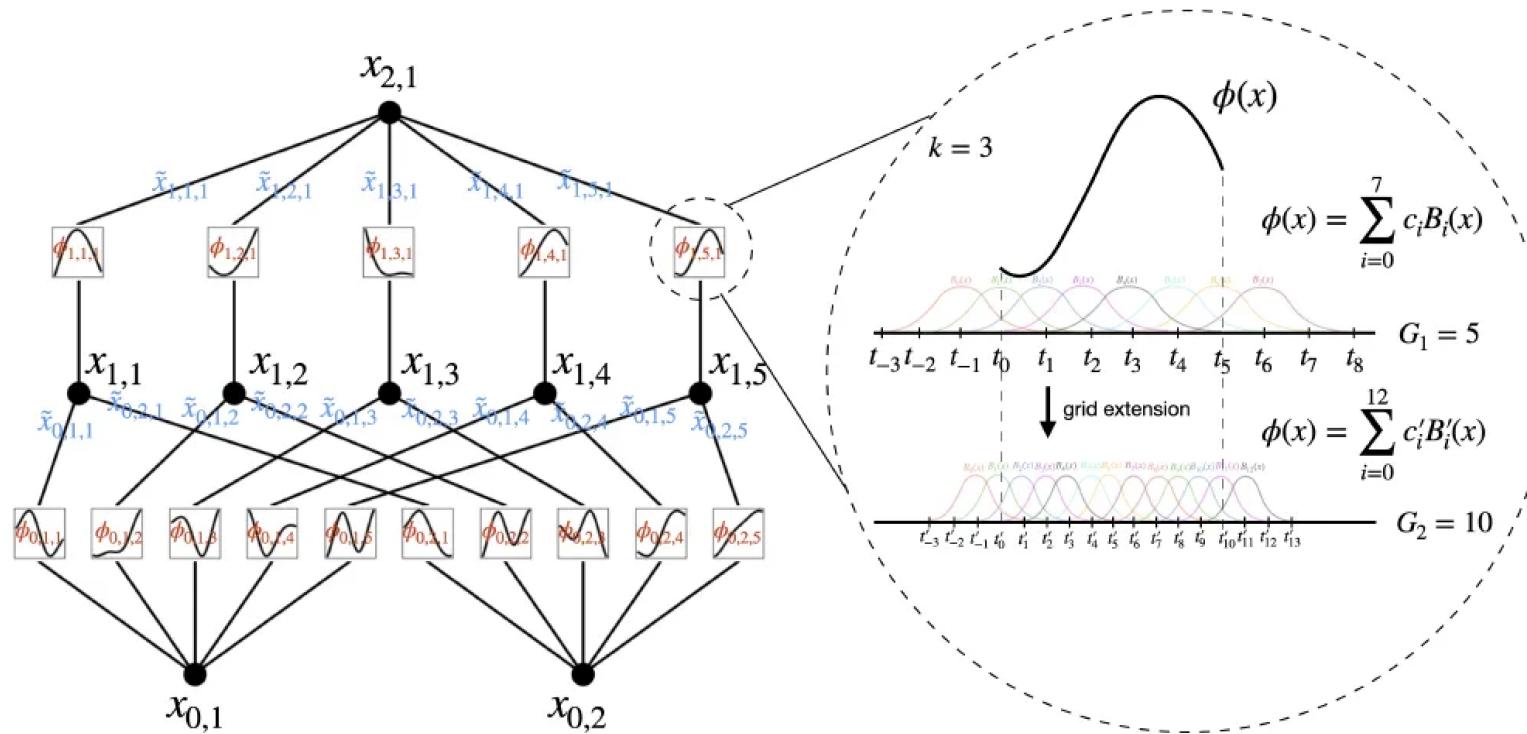
Kolmogorov–Arnold networks (KAN)

- 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

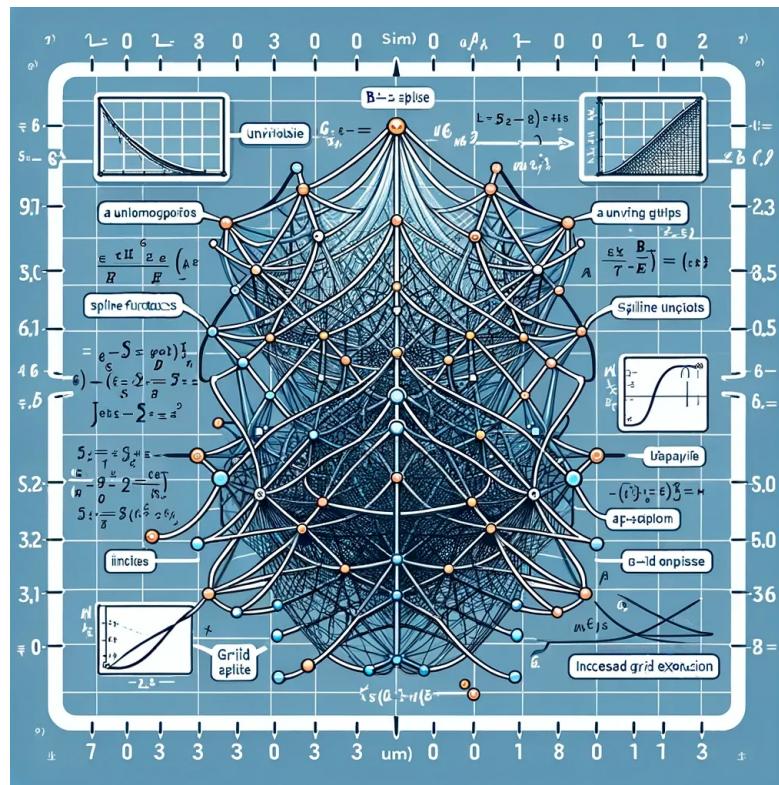
MLP vs KAN

| 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) | (a)  | (b)  |
| 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) | (c)  | (d)  |

KAN architecture with spline parametrization unit layer



Future work on KAN



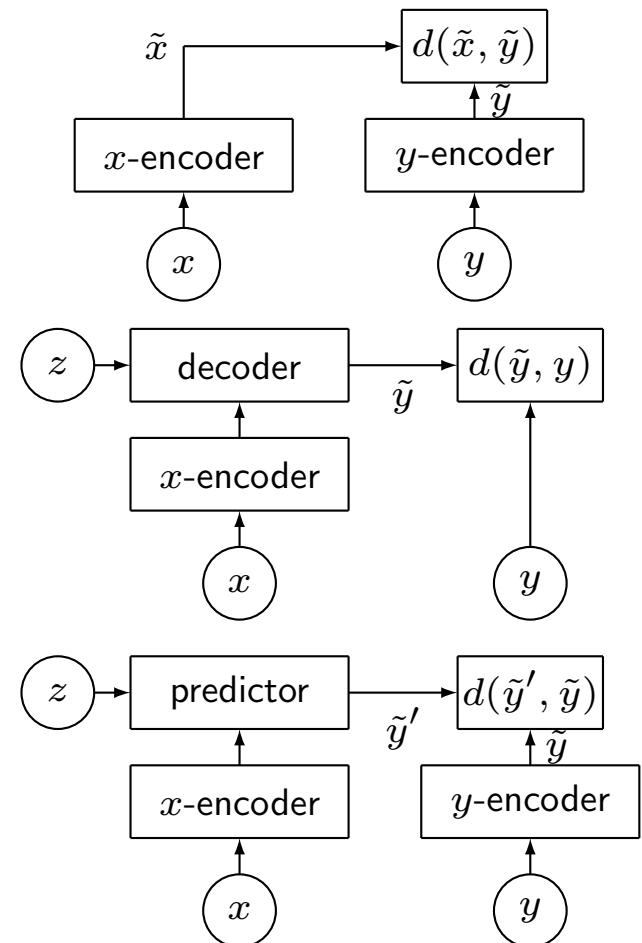
- natural question is
 - what if use both MLP and KAN?
 - what if use other types of splines?
 - how to control forgetfulness of continual learning?
 - why functions of one variable? possible to use functions of two variables?

(figure created by DALLE-3)

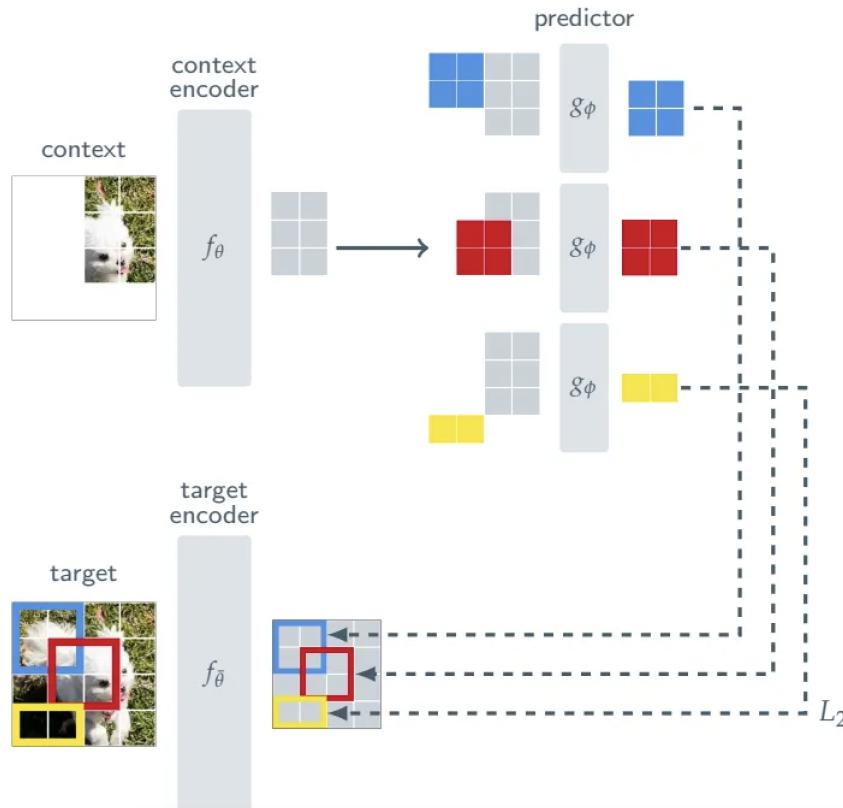
JEPA

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



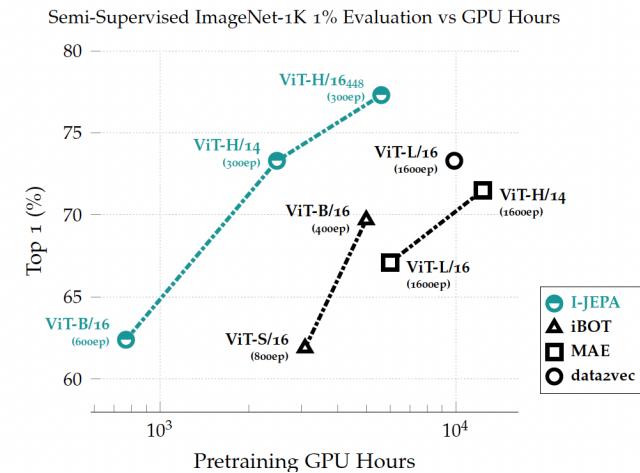
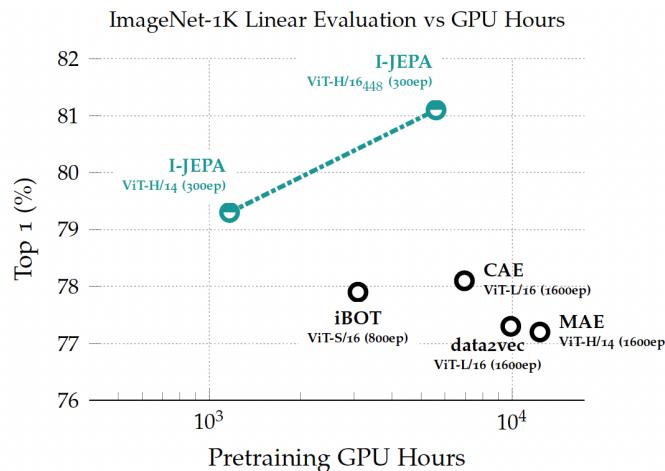
- I-JEPA

- 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

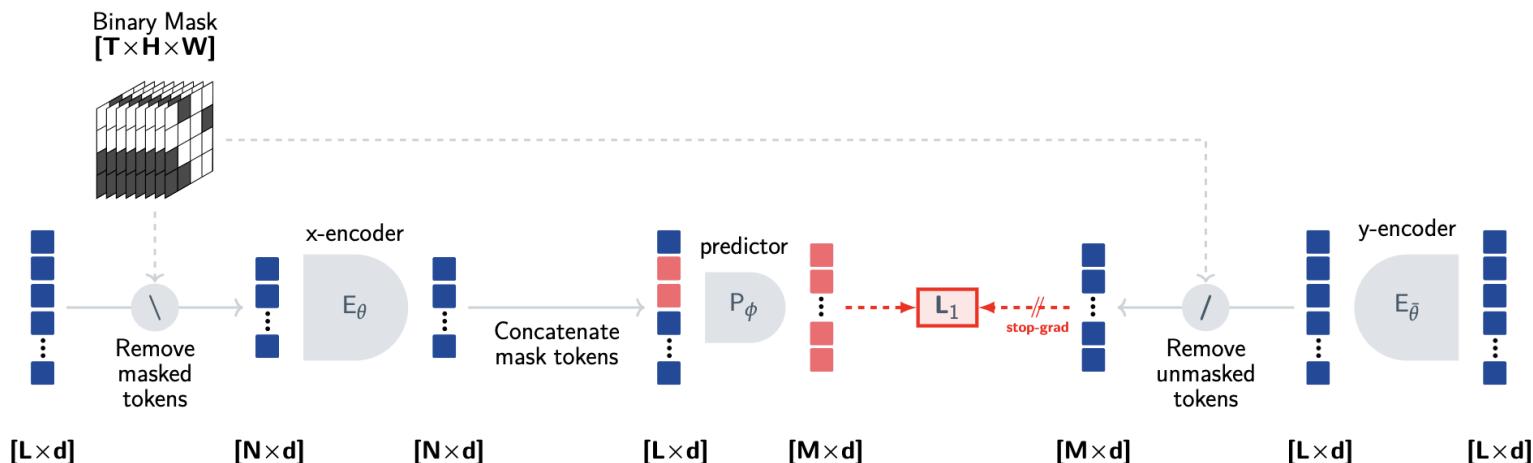
| Method | Arch. | CIFAR100 | Places205 | iNat18 |
|--|----------|-------------|-------------|-------------|
| <i>Methods without view data augmentations</i> | | | | |
| data2vec [8] | ViT-L/16 | 81.6 | 54.6 | 28.1 |
| MAE [36] | ViT-H/14 | 77.3 | 55.0 | 32.9 |
| I-JEPA | ViT-H/14 | 87.5 | 58.4 | 47.6 |
| <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

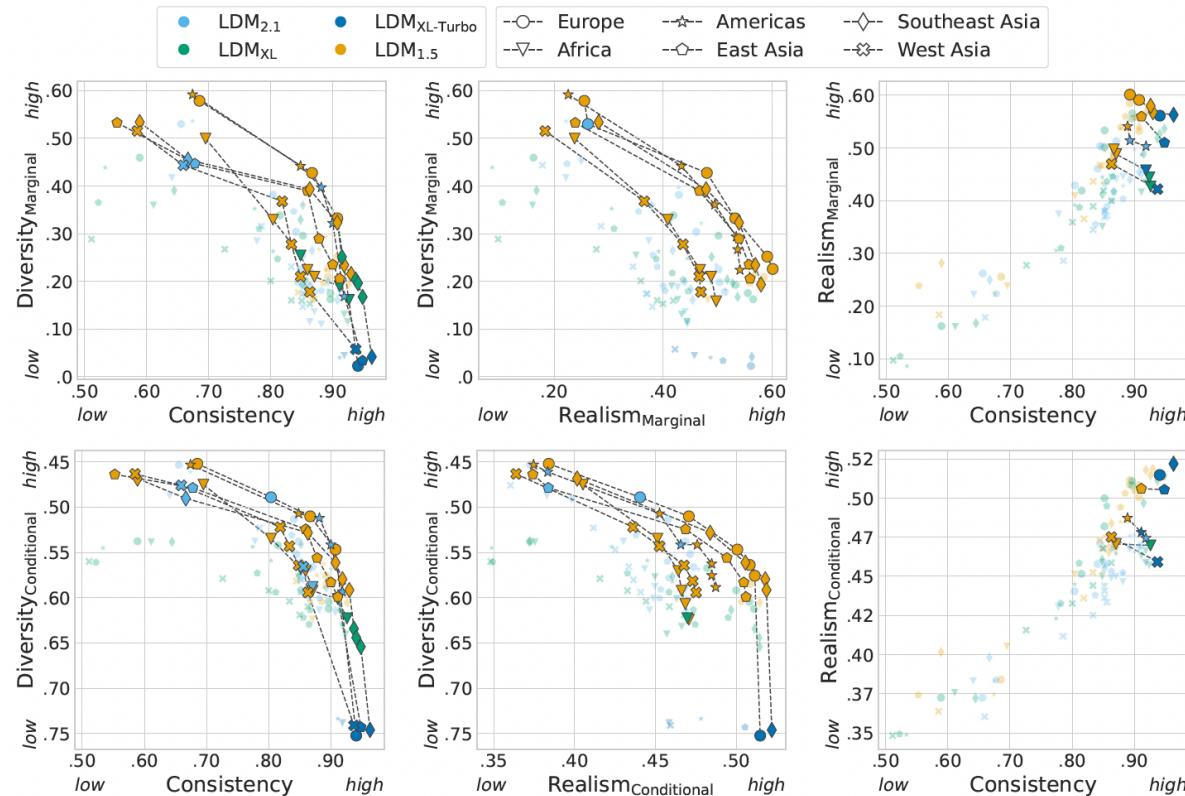
- Revisiting Feature Prediction for Learning Visual Representations from Video - Yann LeCun et al. - Feb-2024
 - essentially same ideas of JEPA - loss function is calculated in embedding space - for better semantic representation learning (rather than pixel-wise learning)



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



Learning ML & AI

Best ways to learn ML & AI

- first, learn basics - college classes, online courses, (easy) books
- hands-on is MUST!
 - learn and practice coding - Python is MUST; do not do R or at least R only
 - learn git - should not do everything yourself - import others' work
- *(I think) online courses are blessing to mankind!*
 - you *can't* say “I can't do it because resource is not available or classes of good schools are not available” because . . . they are available! :)
 - getting (expensive) certificates is good idea because . . . otherwise you wouldn't finish it! :) plus you can post it on your LinkedIn
- I think this is enough for now . . .
- would be best if your task at work is related to ML
- however, even if that's not the case or can't be the case, can always do your own personal projects – or contribute to public projects (to github)! (if you're really good)

Andrew Ng!

- Andrew Ng
 - (co-)founder of “Deep Learning.AI” and “Coursera”, prominent figure in ML & AI
 - his courses highly regarded because well-structured and provide insights
- latest Andrew Ng courses
 - AI Agents in LangGraph
 - AI Agentic Design Patterns with AutoGen
 - Introduction to On-device AI
 - Multi AI Agent Systems with Crew AI
 - Building Multimodal Search and RAG - contrastive learning, multimodality to RAG
 - Building Agentic RAG with LlamaIndex
 - Quantisation In Depth
 - In Prompt Engineering for Vision Models
 - Getting Started with Mistral - open-source models (Mistral 7B, Mixtral 8x7B)
 - Preprocessing Unstructured Data for LLM

Selected References & Sources

Selected references & sources

- Daniel Kahneman, Thinking, Fast and Slow, 2011
- T. Kuiken, Artificial Intelligence in the Biological Sciences: Uses, Safety, Security, and Oversight, 2023
- S. Yin, et. al., A Survey on Multimodal LLMs, 2023
- M. Shanahan, Talking About Large Language Models, 2022
- A. Vaswani, et al., Attention is all you need, NeurIPS, 2017
- I.J. Goodfellow, . . . , Y. Bengio, Generative adversarial networks (GAN), 2014
- A.Y. Halevy, P. Norvig, and F. Pereira. Unreasonable Effectiveness of Data, 2009
- Stanford Venture Investment Groups
- CEOs & CTOs @ startup companies in Silicon Valley
- VCs on Sand Hill Road - Palo Alto, Menlo Park, Woodside in California

References

References

- [ACH⁺24] Pietro Astolfi, Marlène Careil, Melissa Hall, Oscar Mañas, Matthew Muckley, Jakob Verbeek, Adriana Romero Soriano, and Michal Drozdzal. Consistency-diversity-realism pareto fronts of conditional image generative models, 2024.
- [ADM⁺23] Mahmoud Assran, Quentin Duval, Ishan Misra, Piotr Bojanowski, Pascal Vincent, Michael Rabbat, Yann LeCun, and Nicolas Ballas. Self-supervised learning from images with a joint-embedding predictive architecture, 2023.
- [BGP⁺24] Adrien Bardes, Quentin Garrido, Jean Ponce, Xinlei Chen, Michael Rabbat, Yann LeCun, Mahmoud Assran, and Nicolas Ballas. Revisiting feature prediction for learning visual representations from video, 2024.
- [BKP22] Abhaya Bhardwaj, Shristi Kishore, and Dhananjay K. Pandey. Artificial intelligence in biological sciences. *Life*, 12(1430), 2022.
- [Blo23] Bloomberg. Bloomberg, 2023.

- [DCLT19] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.
- [DFJ22] Thomas A. Dixon, Paul S. Freemont, and Richard A. Johnson. A global forum on synthetic biology: The need for international engagement. *Nature Communications*, 13(3516), 2022.
- [GPAM⁺14] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks, 2014.
- [HGH⁺22] Sue Ellen Haupt, David John Gagne, William W. Hsieh, Vladimir Krasnopolksy, Amy McGovern, Caren Marzban, William Moninger, Valliappa Lakshmanan, Philippe Tissot, and John K. Williams. The history and practice of AI in the environmental sciences. *Bulletin of the American Meteorological Society*, 103(5):E1351 – E1370, 2022.
- [HM24] Guadalupe Hayes-Mota. Emerging trends in AI in biotech. *Forbes*, June 2024.
- [HNF09] Alon Halevy, Peter Norvig, and Nanediri Fernando. The unreasonable effectiveness of data. *Intelligent Systems, IEEE*, 24:8 – 12, 05 2009.

- [Kah11] Daniel Kahneman. *Thinking, fast and slow*. Farrar, Straus and Giroux, New York, 2011.
- [Kui23] Todd Kuiken. Artificial intelligence in the biological sciences: Uses, safety, security, and oversight. *Congressional Research Service*, Nov 2023.
- [KW19] Diederik P. Kingma and Max Welling. An introduction to variational autoencoders. *Foundations and Trends in Machine Learning*, 12(4):307–392, 2019.
- [KXS⁺24] Tzofi Klinghoffer, Xiaoyu Xiang, Siddharth Somasundaram, Yuchen Fan, Christian Richardt, Ramesh Raskar, and Rakesh Ranjan. Platonerf: 3d reconstruction in plato's cave via single-view two-bounce lidar, 2024.
- [LWV⁺24] Ziming Liu, Yixuan Wang, Sachin Vaidya, Fabian Ruehle, James Halverson, Marin Soljačić, Thomas Y. Hou, and Max Tegmark. KAN: Kolmogorov-arnold networks, 2024.
- [Mil22] Chris Miller. *Chip war: fight for the world's most critical technology*. New York: Scribner, 2022.
- [MLZ22] Louis-Philippe Morency, Paul Pu Liang, and Amir Zadeh. Tutorial on multimodal machine learning. In Miguel Ballesteros, Yulia Tsvetkov, and

- Cecilia O. Alm, editors, *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Tutorial Abstracts*, pages 33–38, Seattle, United States, July 2022. Association for Computational Linguistics.
- [P.R23] P.R. Precedence research, 2023.
- [RAB⁺23] Ziaur Rahman, Muhammad Aamir, Jameel Ahmed Bhutto, Zhihua Hu, and Yurong Guan. Innovative dual-stage blind noise reduction in real-world images using multi-scale convolutions and dual attention mechanisms. *Symmetry*, 15(11), 2023.
- [Say21] Kelley M. Sayler. Defense primer: Emerging technologies. *Congressional Research Service*, 2021.
- [Sha23] Murray Shanahan. Talking about large language models, 2023.
- [SSS⁺24] Shunsuke Saito, Gabriel Schwartz, Tomas Simon, Junxuan Li, and Giljoo Nam. Relightable gaussian codec avatars, 2024.
- [Toe23] Rob Toews. The next frontier for large language models is biology. *Forbes*, July 2023.
- [VSP⁺17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones,

Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of 31st Conference on Neural Information Processing Systems (NIPS)*, 2017.

- [Wet23] Kris A. Wetterstrand. Dna sequencing costs: Data, 2023.
- [YFZ⁺24] Shukang Yin, Chaoyou Fu, Sirui Zhao, Ke Li, Xing Sun, Tong Xu, and Enhong Chen. A survey on multimodal large language models, 2024.
- [ZBX⁺24] Siwei Zhang, Bharat Lal Bhatnagar, Yuanlu Xu, Alexander Winkler, Petr Kadlecak, Siyu Tang, and Federica Bogo. Rohm: Robust human motion reconstruction via diffusion, 2024.