

[KICSV Special AI Lecture]
Core AI Concepts and Modern Architectures

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About Speaker

- *Co-Founder & CTO @ Erudio Bio, San Jose & Novato, CA, USA*
- *Advisor & Evangelist @ CryptoLab, Inc., San Jose, CA, USA*
- Chief Business Development Officer @ WeStory.ai, Cupertino, CA, USA
- Advisory Professor, Electrical Engineering and Computer Science @ DGIST, Korea
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- Global Advisory Board Member @ Innovative Future Brain-Inspired Intelligence System Semiconductor of Sogang University, Korea
- *KFAS-Salzburg Global Leadership Initiative Fellow @ Salzburg Global Seminar*, Salzburg, Austria
- Technology Consultant @ Gerson Lehrman Group (GLG), NY, USA
- *Co-Founder & CTO / Head of Global R&D & Chief Applied Scientist / Senior Fellow @ Gauss Labs, Inc., Palo Alto, CA, USA* 2020 ~ 2023

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

Highlight of Career Journey

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

Today

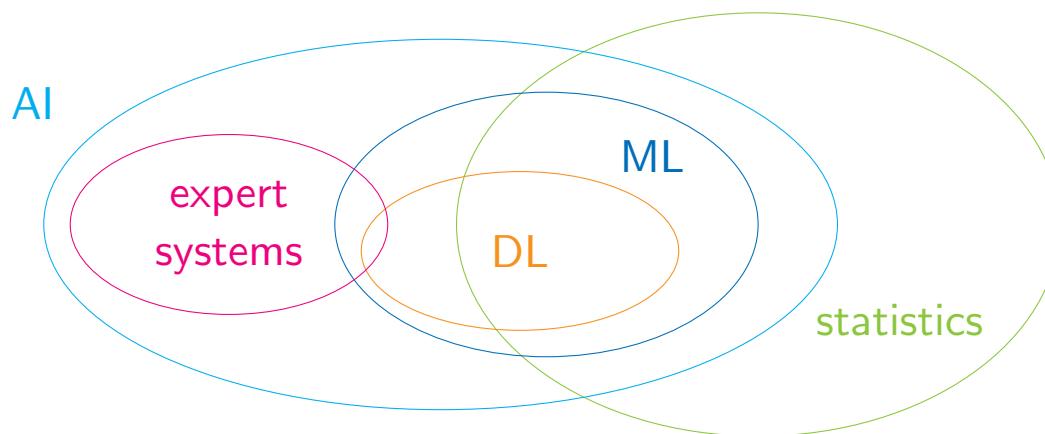
- Artificial Intelligence - 5
 - AI history & recent significant achievements
 - evidences for unprecedented AI progress - market & industry
- Machine Learning Basics - 30
 - ML, DL, CNN, RNN
 - DNN training using stochastic gradient descent (SGD), backpropagation
- LLM - 54
 - language models, seq2seq models
 - LLM, (variants of) Transformer, challenges of LLMs
- Generative AI (genAI) - 84
 - history of genAI, mathy views on genAI
 - current trend & future perspectives
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Artificial Intelligence

Definition and History

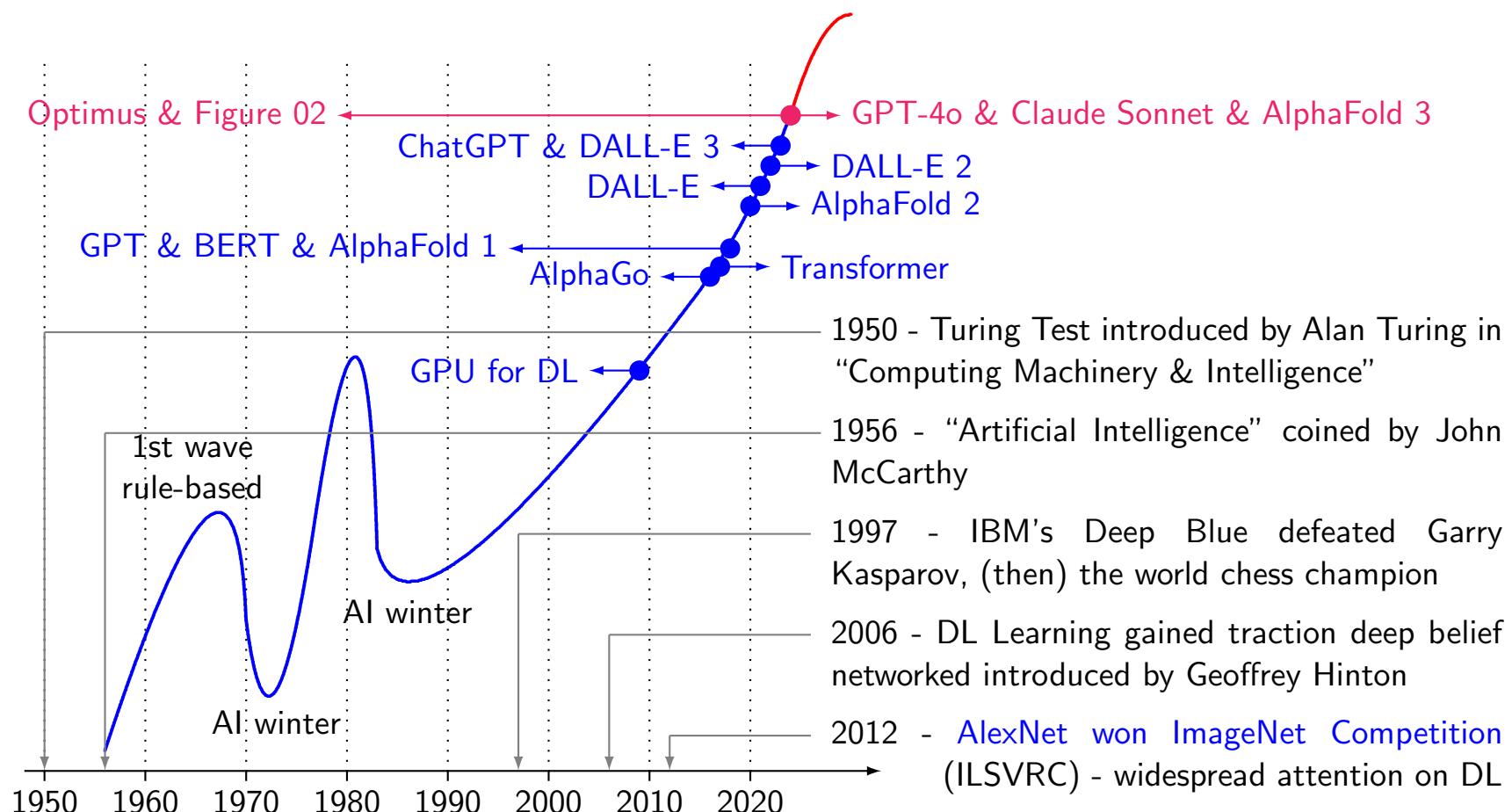
Definition & relation to other technologies

- AI
 - is technology doing tasks requiring human intelligence, such as learning, problem-solving, decision-making & language understanding
 - encompasses *range of technologies, methodologies, applications & products*
- AI, ML, DL, statistics & expert system¹ [HGH⁺22]



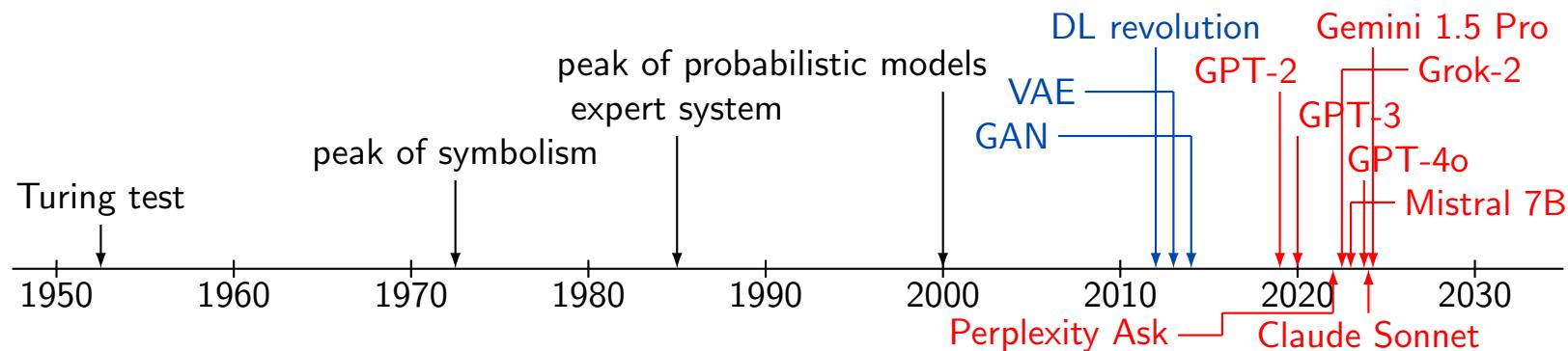
¹ML: machine learning & DL: deep learning

History



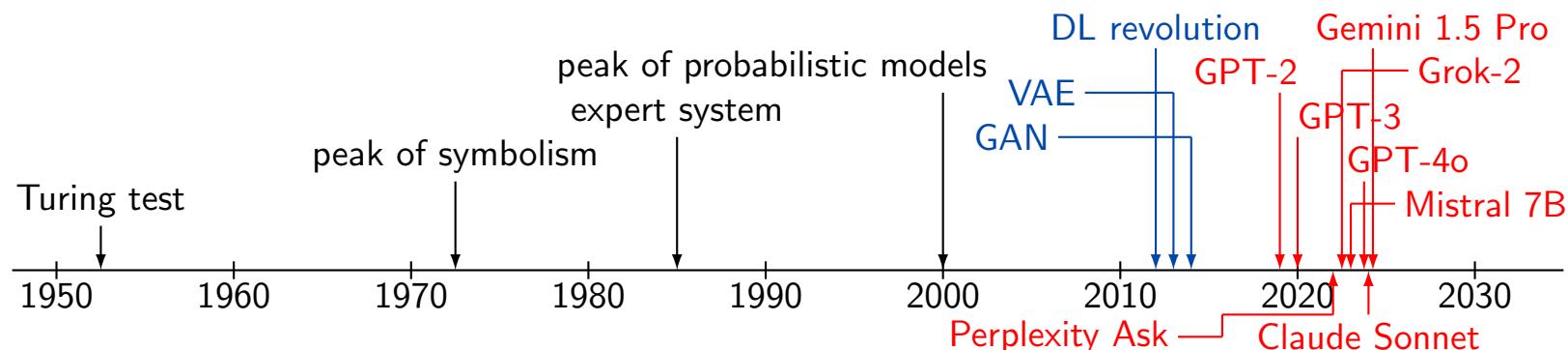
Birth of AI - early foundations & precursor technologies

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



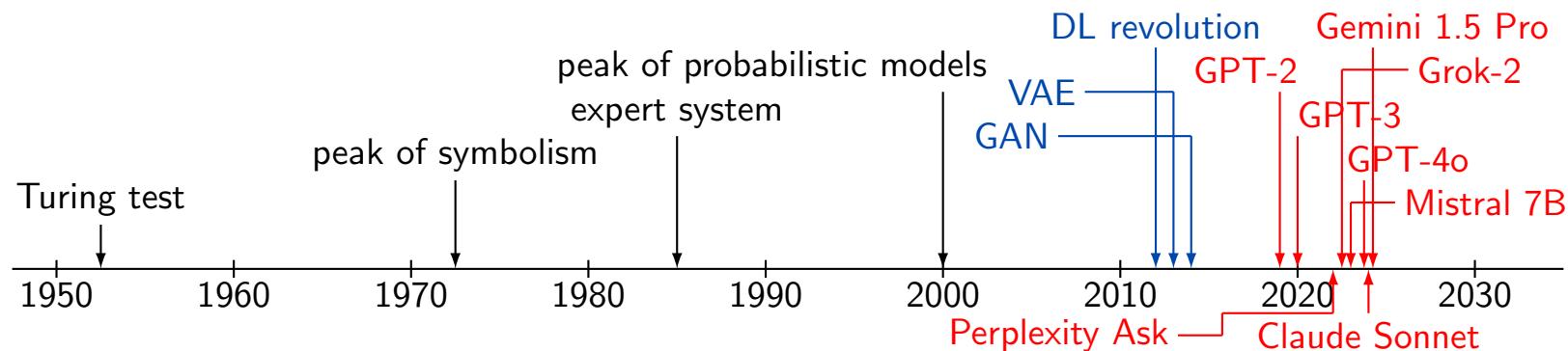
Rule-based systems & probabilistic models

- 1980s ~ early 2000s
 - *expert systems* (1980s) - AI systems designed to mimic human decision-making in specific domains
 - development of neural networks (NN) w/ backpropagation *training multi-layered networks* - setting stage for way more complex generative models
 - *probabilistic models* (including network models, *i.e.*, Bayesian networks) & Markov models - laying groundwork for data generation & pattern prediction



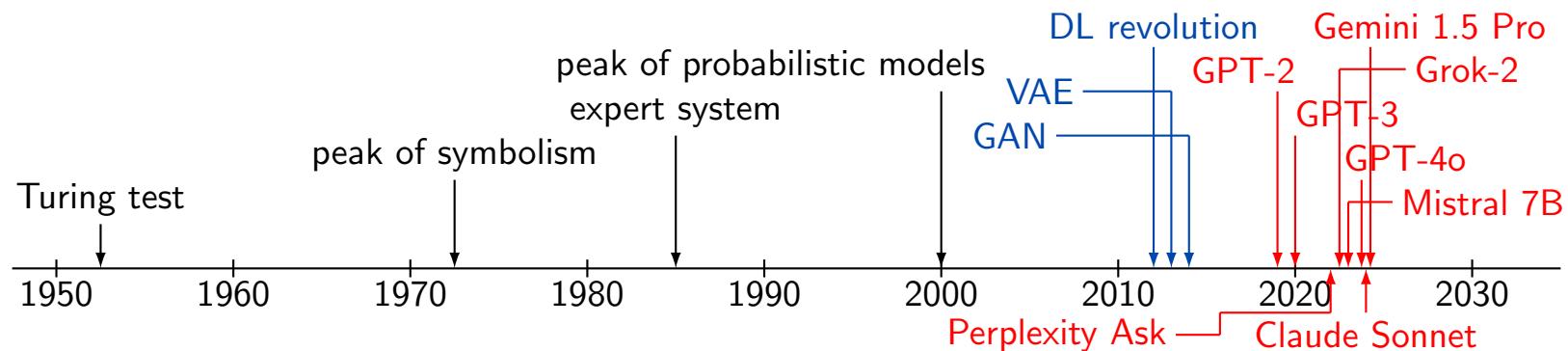
Rise of deep learning & generative models

- 2010s - breakthrough in genAI
 - *deep learning (DL) revolution* - advances in GPU computing and data availability led to the rapid development of deep neural networks.
 - *variational autoencoder (VAE)* (2013) - by Kingma and Welling - learns mappings between input and latent spaces
 - *generative adversarial network (GAN)* (2014) - by Ian Goodfellow - game-changer in generative modeling where two NNs compete each other to create realistic data
 - widely used in image generation & creative tasks



Transformer models & multimodal AI

- late 2010s ~ Present
 - Transformer architecture (2017) - by Vaswani et al.
 - *revolutionized NLP*, e.g., LLM & various genAI models
 - GPT series - generative pre-trained transformer
 - GPT-2 (2019) - generating human-like texts - *marking leap in language models*
 - GPT-3 (2020) - 175B params - set *new standards for LLM*
 - multimodal systems - DALL-E & CLIP (2021) - *linking text and visual data*
 - emergence of diffusion models (2020s) - new approach for generating high-quality images - progressively “denoising” random noise (DALL-E 2 & Stable Diffusion)



Significant AI Achievements - 2014 – 2025

Deep learning revolution

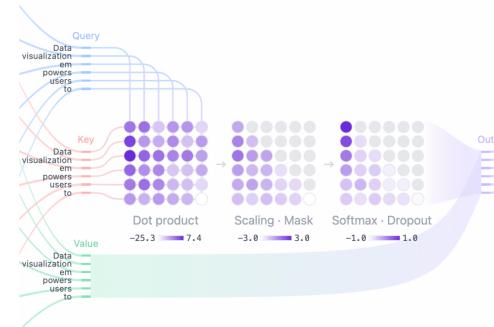
- 2012 – 2015 - DL revolution²
 - CNNs demonstrated exceptional performance in image recognition, e.g., *AlexNet's victory in ImageNet competition*
 - widespread adoption of DL learning in CV transforming industries
- 2016 - AlphaGo defeats human Go champion
 - DeepMind's AlphaGo defeated world champion in Go, extremely complex game *believed to be beyond AI's reach*
 - significant milestone in RL - AI's potential in solving complex & strategic problems



²CV: computer vision, NN: neural network, CNN: convolutional NN, RL: reinforcement learning

Transformer changes everything

- 2017 – 2018 - Transformers & NLP breakthroughs³
 - *Transformer (e.g., BERT & GPT) revolutionized NLP*
 - major advancements in, *e.g.*, machine translation & chatbots
- 2020 - AI in healthcare – AlphaFold & beyond
 - DeepMind's *AlphaFold solves 50-year-old protein folding problem* predicting 3D protein structures with remarkable accuracy
 - accelerates drug discovery and personalized medicine - offering new insights into diseases and potential treatments



³NLP: natural language processing, GPT: generative pre-trained transformer

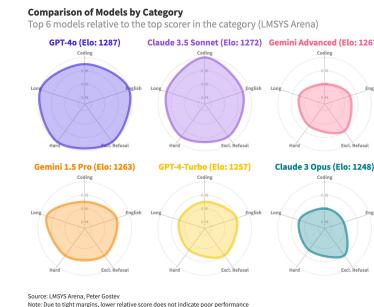
Lots of breakthroughs in AI technology and applications in 2024

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



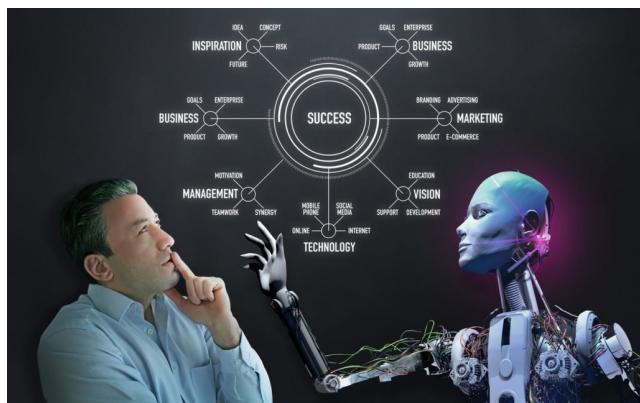
Major AI Breakthroughs in 2025

- next-generation foundation models
 - GPT-5 and Claude 4 demonstrate emergent reasoning abilities
 - open-source models achieving parity with leading commercial systems from 2024
- hardware innovations
 - NVIDIA's Blackwell successor architecture delivering 3-4x performance improvement
 - AMD's MI350 accelerators challenging NVIDIA's market dominance
- AI-human collaboration systems
 - seamless multimodal interfaces enabling natural human-AI collaboration
 - AI systems effectively explaining reasoning and recommendations
 - augmented reality interfaces providing real-time AI assistance in professional contexts



Transformative impact of AI - reshaping industries, work & society

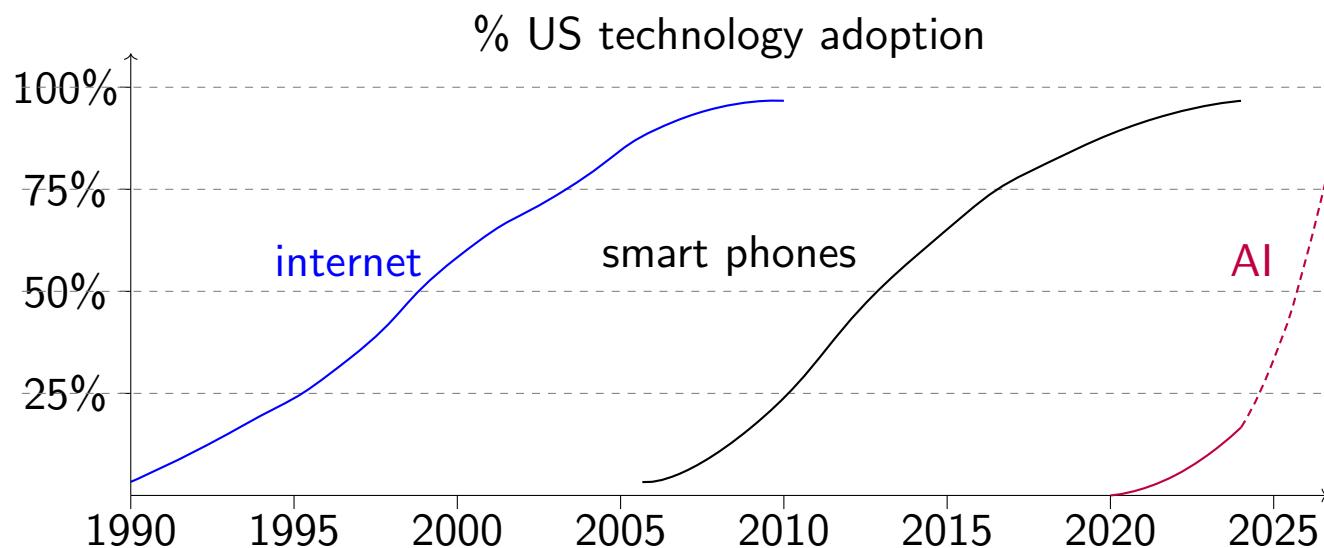
- accelerating human-AI collaboration
 - not only reshaping industries but *altering how humans interact with technology*
 - AI's role as collaborator and augmentor redefines productivity, creativity, the way we address global challenges, e.g., *sustainability & healthcare*
- AI-driven automation *transforms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



Measuring AI's Ascent

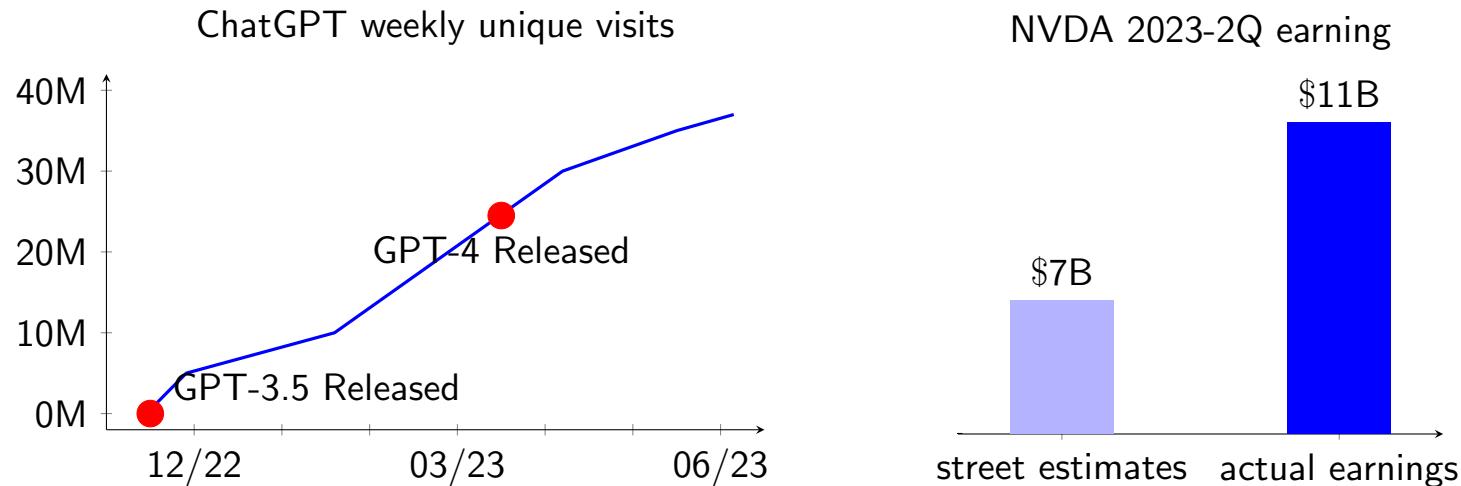
Where are we in AI today?

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



Explosion of AI ecosystems - ChatGPT & NVIDIA

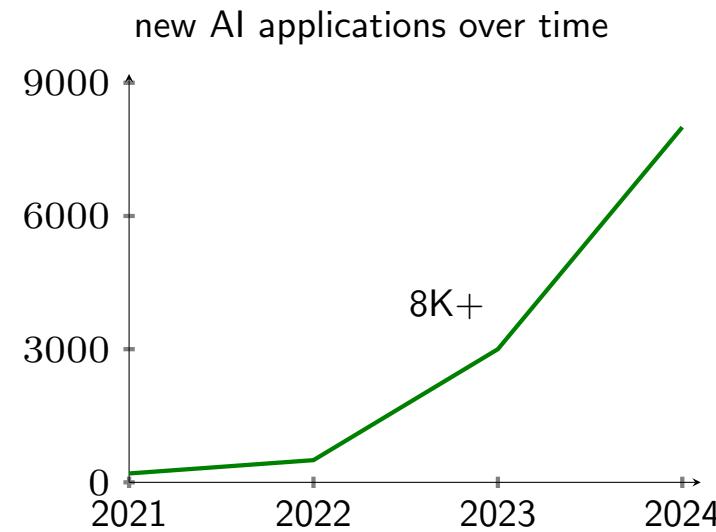
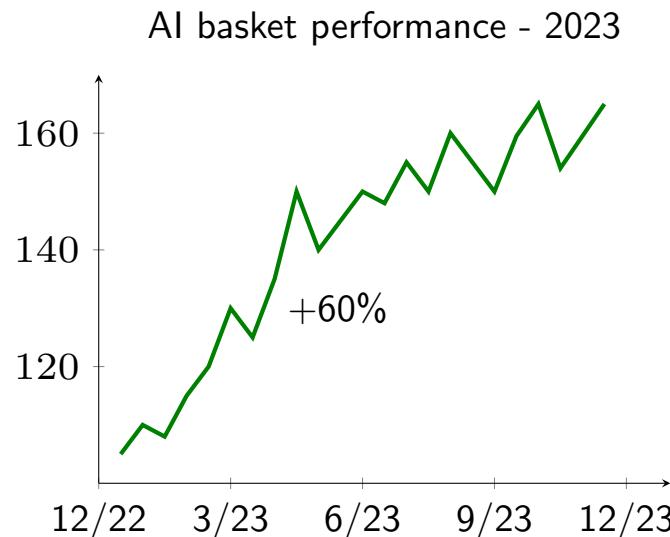
- took only *5 months for ChatGPT users to reach 35M*
- NVIDIA 2023 Q2 earning exceeds market expectation by big margin - \$7B vs \$13.5B
 - surprisingly, *101% year-to-year growth*
 - even more surprisingly *gross margin was 71.2%* - up from 43.5% in previous year⁴



⁴source - Bloomberg

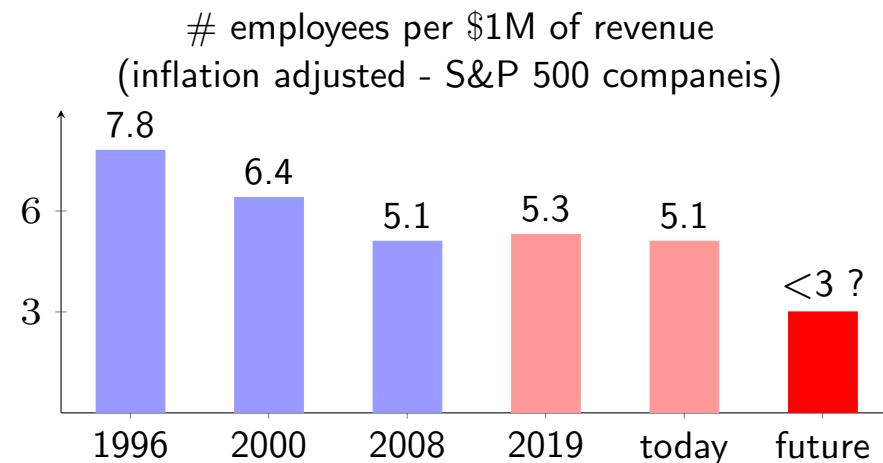
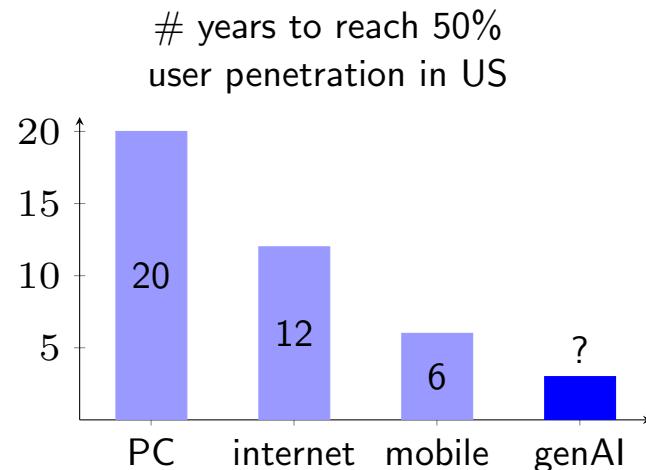
Explosion of AI ecosystems - AI stock market

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



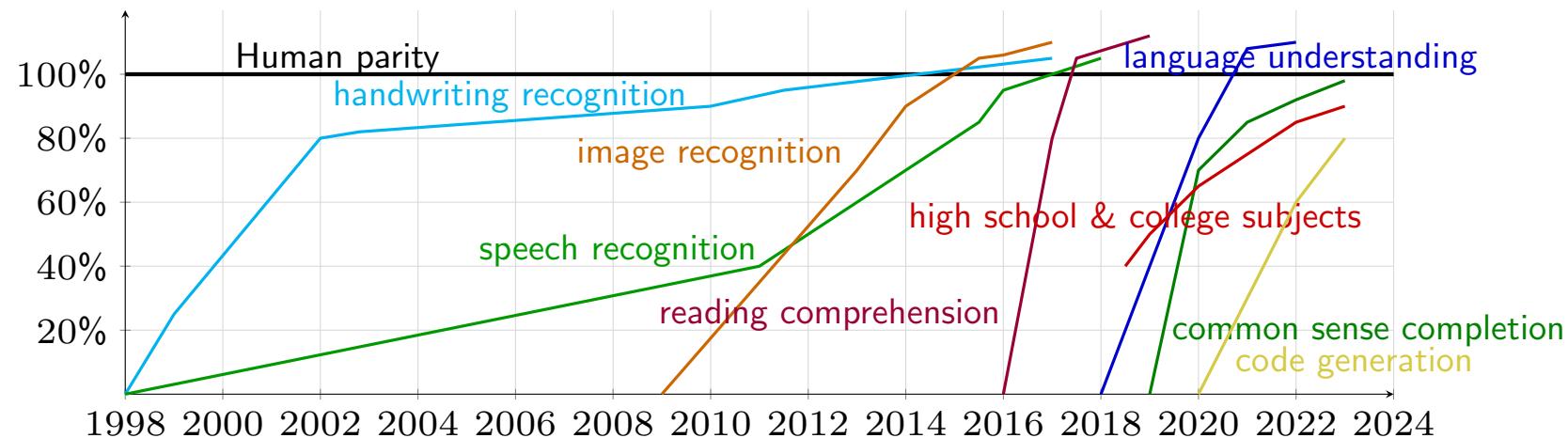
AI's transformative impact - adoption speed & economic potential

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



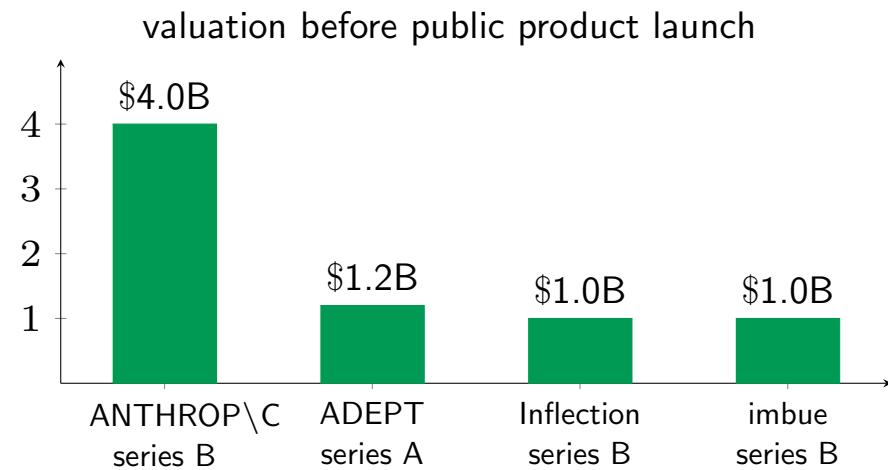
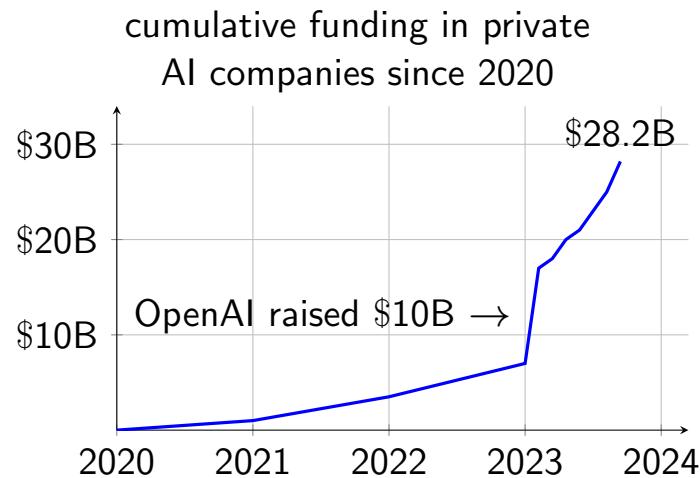
AI getting more & more faster

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



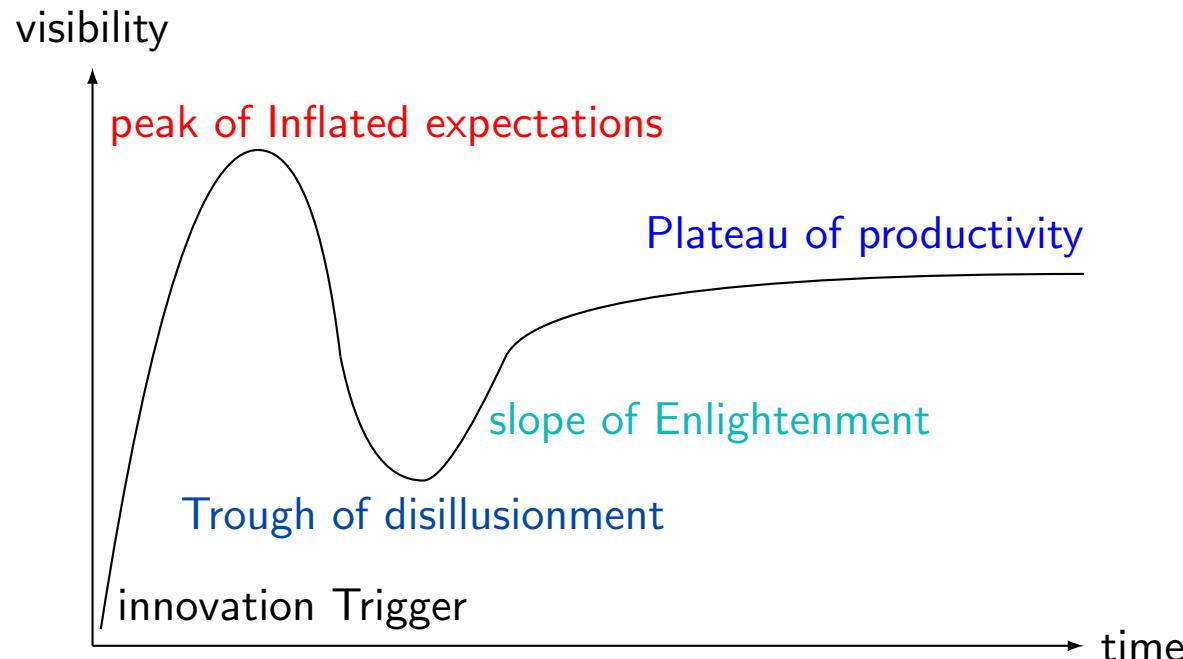
Massive investment in AI

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



Is AI hype?

Technology hype cycle



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

Fiber vs cloud infrastructure

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



Yes & No

characteristics of hype cycles	speaker's views
value accrual misaligned with investment	<ul style="list-style-type: none">• OpenAI still operating at a loss; business model <i>still</i> not clear• gradual value creation across broad range of industries and technologies (<i>e.g.</i>, CV, LLMs, RL) unlike fiber optic bubble in 1990s
overestimating timeline & capabilities of technology	<ul style="list-style-type: none">• self-driving cars delayed for over 15 years, with limited hope for achieving level 5 autonomy• AI, however, has proven useful within a shorter 5-year span, with enterprises eagerly adopting
lack of widespread utility due to technology maturity	<ul style="list-style-type: none">• AI already providing significant utility across various domains• vs quantum computing remains promising in theory but lacks widespread practical utility

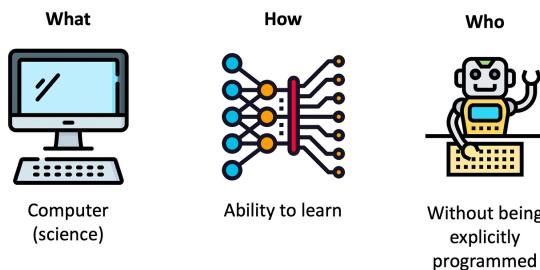
ML Basics

Machine learning

Machine Learning

- ML

- is subfield of computer science that
“gives computers the ability to learn without being explicitly programmed.”
- Arthur Samuel (1959)
- is *not* magic, still less intelligent than humans for many cases
- *numerically minimizes* certain (mathematical) loss function to (indirectly) solve *some statistically meaningful* problems



Machine learning is the subfield of computer science that gives “computers the ability to learn without being explicitly programmed.”



Arthur Samuel

Two famous quotes

- Albert Einstein

The grand aim of all science is to cover the greatest number of empirical facts by logical deduction from the smallest possible number of hypotheses or axioms.

- Alfred North Whitehead

Civilization advances by extending the number of important operations which we can perform without thinking about them. - Operations of thought are like cavalry charges in a battle – they are strictly limited in number, they require fresh horses, and must only be made at decisive moments.

Statistical problem formulation

- assume data set $X_m = \{x^{(1)}, \dots, x^{(m)}\}$
 - drawn independently from (true, but unknown) data generating distribution $p_{\text{data}}(x)$
- maximum likelihood estimation (MLE) is to solve

$$\text{maximize } p_{\text{model}}(X; \theta) = \prod_{i=1}^m p_{\text{model}}(x^{(i)}; \theta)$$

- equivalent (but numerically friendly) formulation

$$\text{maximize } \log p_{\text{model}}(X; \theta) = \sum_{i=1}^m \log p_{\text{model}}(x^{(i)}; \theta)$$

MLE & KL divergence

- in (context of) information theory, Kullback-Leibler (KL) divergence defines distance between two probability distributions p & q

$$D_{\text{KL}}(p\|q) = \mathbf{E}_{X \sim p} \log p(X)/q(X) = \int_{x \in \Omega} p(x) \log \frac{p(x)}{q(x)} dx$$

- KL divergence between data distribution p_{data} & model distribution p_{model} can be approximated by Monte Carlo method as

$$D_{\text{KL}}(p_{\text{data}}\|p_{\text{model}}) \simeq \frac{1}{m} \sum_{i=1}^m (\log p_{\text{data}}(x^{(i)}) - \log p_{\text{model}}(x^{(i)}; \theta))$$

- *minimizing KL divergence is equivalent to solving MLE problem!*

Equivalence of MLE to MSE

- assume model is Gaussian, *i.e.*, $y \sim \mathcal{N}(g_\theta(x), \Sigma)$ ($g_\theta(x) \in \mathbf{R}^p$, $\Sigma \in \mathbf{S}_{++}^p$)

$$p(y|x; \theta) = \frac{1}{\sqrt{2\pi}^p |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (y - g_\theta(x))^T \Sigma^{-1} (y - g_\theta(x)) \right)$$

- assuming that $\Sigma = \alpha I_p$, log-likelihood becomes

$$\begin{aligned} \sum_{i=1}^m \log p(x^{(i)}, y^{(i)}; \theta) &= \sum_{i=1}^m \log p(y^{(i)}|x^{(i)}; \theta) p(x^{(i)}) \\ &= - \sum_{i=1}^m \|y^{(i)} - g_\theta(x^{(i)})\|_2^2 / 2\alpha - \frac{pm}{2} \log(2\pi\alpha) + \sum_{i=1}^m \log p(x^{(i)}) \end{aligned}$$

- minimizing mean-square-error (MSE) is equivalent to solving MLE problem!*

Numerical optimization problem formulation

- (true) problem to solve

$$\text{minimize } \mathbf{E} l(g_\theta(X), Y)$$

- *impossible* to solve

- basic formulation - surrogate problem to solve

$$\text{minimize } f(\theta) = \frac{1}{m} \sum_{i=1}^m l(g_\theta(x^{(i)}), y^{(i)})$$

- formulation with regularization

$$\text{minimize } f(\theta) = \frac{1}{m} \sum_{i=1}^m l(g_\theta(x^{(i)}), y^{(i)}) + \gamma r(\theta)$$

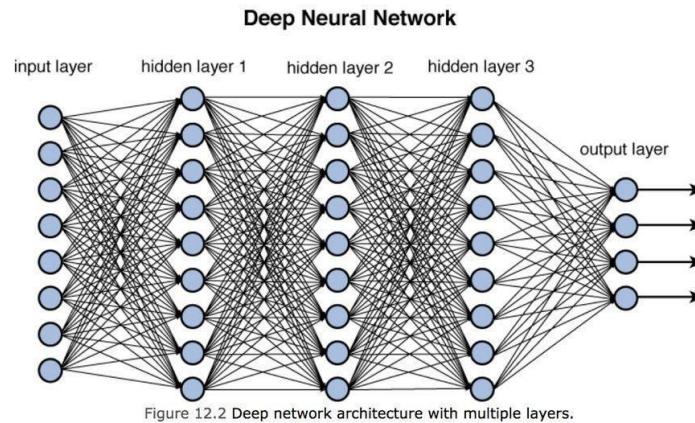
- stochastic gradient descent (SGD)

$$\theta^{(k+1)} = \theta^{(k)} - \alpha_k \nabla f(\theta^{(k)})$$

Deep Learning

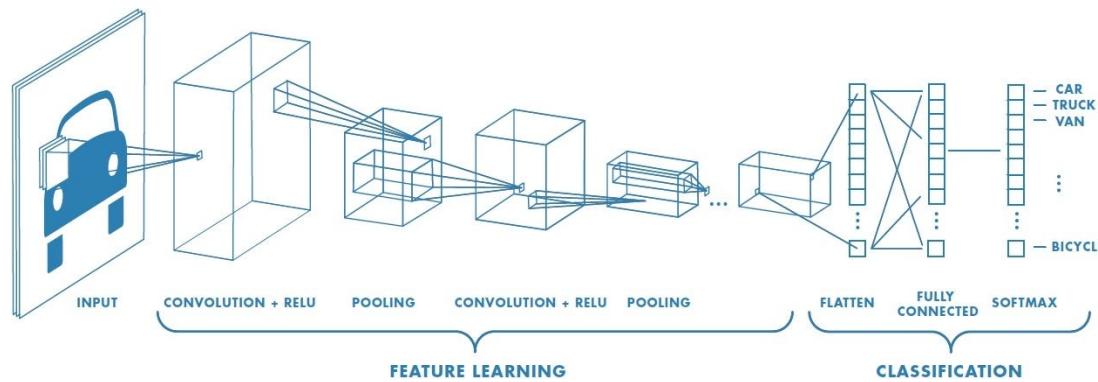
Deep learning (DL)

- machine learning using artificial neural networks with multiple layers for
 - automatically learning hierarchical representations of data
- key components
 - deep neural networks, hidden layers, backpropagation, activation functions
 - hierarchical feature learning, representation learning, end-to-end learning
- key breakthroughs enabling DL
 - massively available data, GPU computing, algorithmic advances



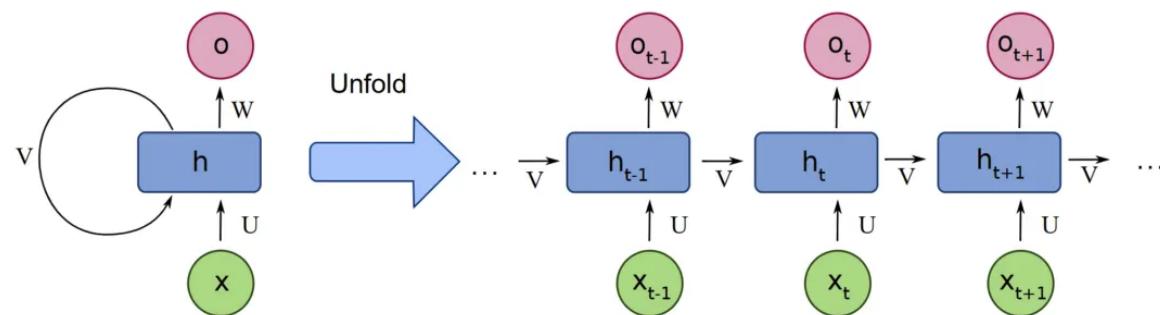
Convolutional neural network (CNN)

- specialized DL learning architecture designed for
 - processing grid-like data such as images
 - where spatial relationships between pixels matter
- key components
 - convolutional layers, pooling layers, activation functions, fully connected layers
- how it works
 - feature extraction, translation invariance, parameter sharing
- why it excels
 - local connectivity, hierarchical learning



Recurrent neural network (RNN)

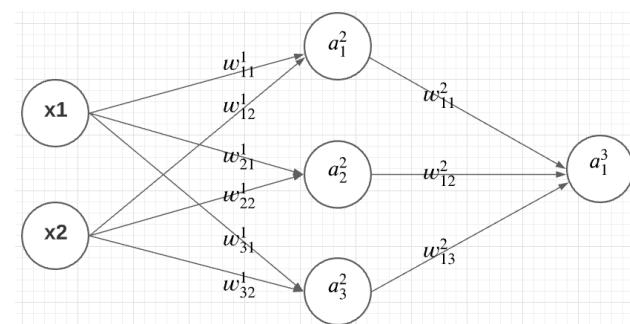
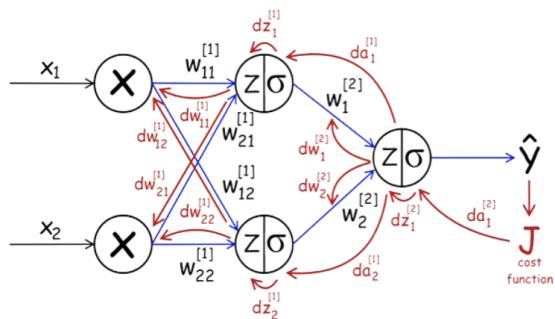
- neural network designed for
 - processing sequential data by maintaining memory of previous inputs
- key components
 - hidden states, recurrent connections, input/output layers, weight sharing
- how it works
 - sequential processing, memory mechanism, temporal dependencies
- why it excels
 - variable length input, context awareness, flexible architecture
- variants - long short-term memory (LSTM), gated recurrent unit (GRU)



Training DNN using SGD

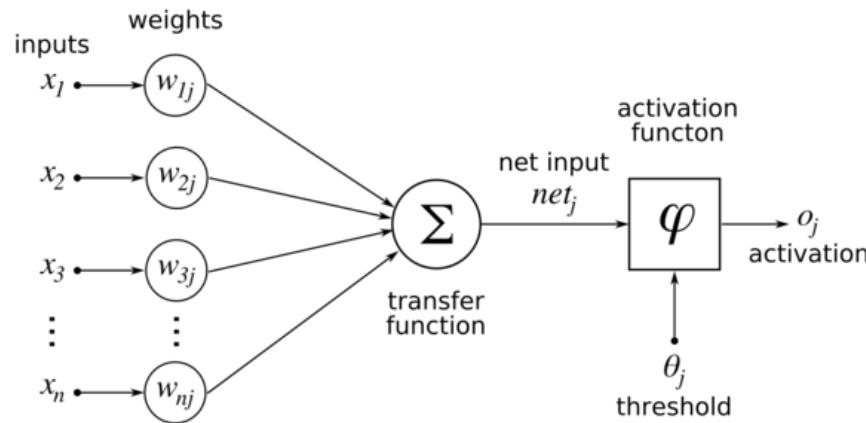
Notations

- p / q - dimension of input / output spaces
- $l : \mathbf{R}^q \times \mathbf{R}^q \rightarrow \mathbf{R}_+$ - loss function
- d - depth of neural network
- n_i ($1 \leq i \leq d$) - number of perceptrons in i th layer
- $z^{[i]} \in \mathbf{R}^{n_i}$ - input to i th layer
- $o^{[i]} \in \mathbf{R}^{n_i}$ - output of i th layer
- $W^{[i]} \in \mathbf{R}^{n_i \times n_{i-1}}$ - weights of connections between $(i-1)$ th and i th layer
- $w^{[i]} \in \mathbf{R}^{n_i \times n_{i-1}}$ - bias weights of i th layer
- $\phi^{[i]} : \mathbf{R}^{n_i} \rightarrow \mathbf{R}^{n_i}$ - activation functions of i th layer

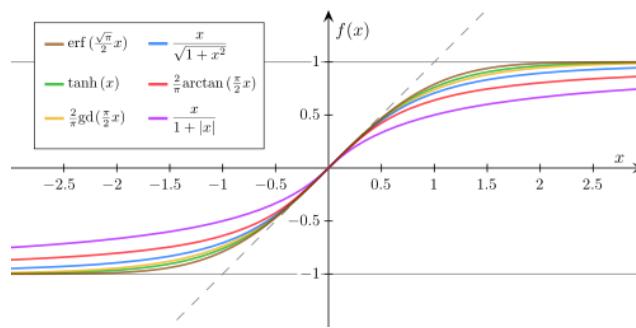


Basic unit & activation function

- basic unit



- activation function



Neural net equations

- modeling function for the (deep) neural network $g_\theta : \mathbf{R}^p \rightarrow \mathbf{R}^q$

$$g_\theta = \phi_\theta^{[d]} \circ \psi_\theta^{[d]} \circ \cdots \circ \phi_\theta^{[1]} \circ \psi_\theta^{[1]}$$

or equivalently

$$g_\theta(x) = \phi_\theta^{[d]}(\psi_\theta^{[d]}(\cdots(\phi_\theta^{[1]}(\psi_\theta^{[1]}(x)))))$$

- for i th layer
 - output via (componentwise) activation function

$$o^{[i]} = \phi^{[i]}(z^{[i]}) \Leftrightarrow o_j^{[i]} = \phi_j^{[i]}(z_j^{[i]}) \quad (1 \leq j \leq n_i)$$

- input via affine transformation $\psi^{[i]} : \mathbf{R}^{n_{i-1}} \rightarrow \mathbf{R}^{n_i}$

$$z^{[i]} = \psi^{[i]}(o^{[i-1]}) = W^{[i]}o^{[i-1]} + w^{[i]}$$

Stochastic gradient descent

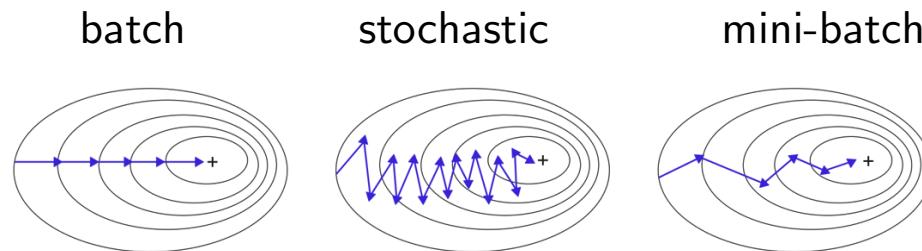
- ML training tries to minimize some loss function - $f(\theta)$ depends on (not only θ , but also) batch of data $(x^{(1)}, y^{(1)}), \dots, (x^{(m)}, y^{(m)})$

$$\text{minimize } f(\theta)$$

- while exist hundreds of optimization methods solving this problem
 - the only method used widely* is stochastic *gradient descent!*
- (stochastic) gradient descent

$$f(\theta^{k+1}) = f(\theta^k) - \alpha^k \nabla f(\theta^k)$$

- backpropagation* is used to evaluate this (stochastic) *gradient* using *chain rule*



Chain rule

- suppose
 - two functions $f : \mathbf{R}^n \rightarrow \mathbf{R}^m$ & $g : \mathbf{R}^m \rightarrow \mathbf{R}$
 - Jacobian of f - $Df : \mathbf{R}^n \rightarrow \mathbf{R}^{m \times n}$
 - gradient of g - $\nabla g : \mathbf{R}^m \rightarrow \mathbf{R}^m$
- gradient of composite function $h = g \circ f$

$$\nabla h(\theta) = Df(\theta)^T \nabla g(f(\theta)) \in \mathbf{R}^n \quad (\text{using matrix-vector multiplication})$$

in other words

$$\frac{\partial}{\partial \theta_i} h(\theta) = \sum_{j=1}^m \frac{\partial}{\partial \theta_i} f_j(\theta) \nabla_j g(f(\theta)) \quad (\text{scalar version})$$

Loss function & its gradient

- assume cost function of deep neural network is

$$f(\theta) = \frac{1}{m} \sum_{k=1}^m l(g_\theta(x^{(k)}), y^{(k)}) = \frac{1}{m} \sum_{k=1}^m f_k(\theta)$$

where

$$f_k(\theta) = l(g_\theta(x^{(k)}), y^{(k)})$$

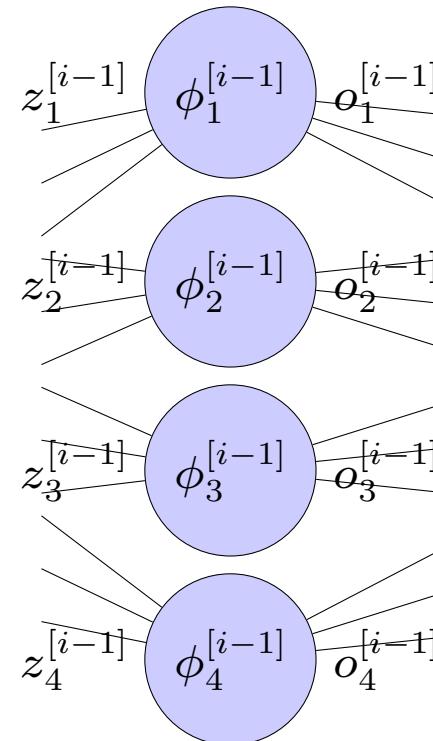
- gradient is

$$m \nabla_\theta f(\theta) = \sum_{k=1}^m \nabla_\theta l(g_\theta(x^{(k)}), y^{(k)}) = \sum_{k=1}^m \nabla_\theta f_k(\theta)$$

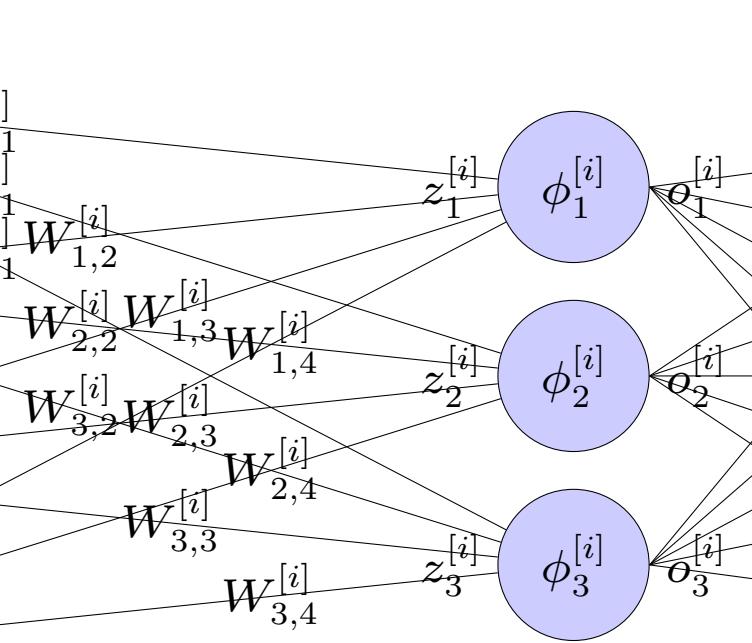
- i.e., evaluate gradient $\nabla_\theta f_k(\theta)$ for each data point $(x^{(k)}, y^{(k)})$

Hidden layers

$(i - 1)$ th hidden layer



i th hidden layer



Backpropagation formula using chain rule

- for each data $(x^{(k)}, y^{(k)})$
 - via activation function

$$\frac{\partial}{\partial z_j^{[i]}} f_k(\theta) = \frac{\partial}{\partial o_j^{[i]}} f_k(\theta) \phi_j^{[i]'}(o_j^{[i]}) \quad \text{for } 1 \leq j \leq n_i \quad (1)$$

where $\phi_j^{[i]'}(o_j^{[i]})$ is derivative of activation function $\phi_j^{[i]}$ evaluated at $o_j^{[i]}$

- via affine transformation

$$\frac{\partial}{\partial W_{j,l}^{[i]}} f_k(\theta) = o_l^{[i-1]} \frac{\partial}{\partial z_j^{[i]}} f_k(\theta) \quad \text{for } 1 \leq j \leq n_i \text{ & } 1 \leq l \leq n_{i-1} \quad (2)$$

$$\frac{\partial}{\partial w_j^{[i]}} f_k(\theta) = \frac{\partial}{\partial z_j^{[i]}} f_k(\theta) \quad \text{for } 1 \leq j \leq n_i \quad (3)$$

$$\frac{\partial}{\partial o_l^{[i-1]}} f_k(\theta) = \sum_{j=1}^{n_i} W_{j,l}^{[i]} \frac{\partial}{\partial z_j^{[i]}} f_k(\theta) \quad \text{for } 1 \leq l \leq n_{i-1} \quad (4)$$

Backpropagation formula using matrix-vector multiplication

- for each data $(x^{(k)}, y^{(k)})$

- via activation function

$$\nabla_{z^{[i]}} f_k(\theta) = D\phi^{[i]} \nabla_{o^{[i]}} f_k(\theta) \quad (5)$$

where $D\phi^{[i]} = \text{diag}(\phi_1^{[i]'}(o_1^{[i]}), \dots, \phi_{n_i}^{[i]'}(o_{n_i}^{[i]}))$ is Jacobian of $\phi^{[i]}$ evaluated at $o^{[i]}$

- via affine transformation

$$\nabla_{W^{[i]}} f_k(\theta) = \nabla_{z^{[i]}} f_k(\theta) o^{[i-1]T} \in \mathbf{R}^{n_i \times n_{i-1}} \quad (6)$$

$$\nabla_{w^{[i]}} f_k(\theta) = \nabla_{z^{[i]}} f_k(\theta) \in \mathbf{R}^{n_i} \quad (7)$$

$$\nabla_{o^{[i-1]}} f_k(\theta) = W^{[i]T} \nabla_{z^{[i]}} f_k(\theta) \in \mathbf{R}^{n_{i-1}} \quad (8)$$

Backpropagation formula using Python numpy package

- for each data $(x^{(k)}, y^{(k)})$
 - via activation function

$$\text{grad_z} = \text{phi_dir} * \text{grad_o} \quad (9)$$

- where grad_z , phi_dir , grad_o are 1d numpy.ndarray of size n_i
- via affine transformation

$$\text{grad_W} = \text{numpy.dot}(\text{grad_z}, \text{val_o.T}) \quad (10)$$

$$\text{grad_w} = \text{grad_z.copy()} \quad (11)$$

$$\text{grad_o_prev} = \text{numpy.dot}(\text{grad_z}, \text{W}) \quad (12)$$

where val_o , grad_w are 1d numpy.ndarray of size n_i , grad_o_prev is 1d numpy.ndarray of size n_{i-1} , grad_W is 2d numpy.ndarray of shape (n_i, n_{i-1})

Gradient evaluation using backpropagation

- forward propagation - evaluate for each $(x^{(k)}, y^{(k)})$

$$g_{\theta}(x^{(k)}) = \phi_{\theta}^{[d]}(\psi_{\theta}^{[d]}(\cdots(\phi_{\theta}^{[1]}(\psi_{\theta}^{[1]}(x^{(k)})))))$$

- *backpropagation - evaluate partial derivatives backward*

- evaluate gradient with respect to output of output layer $o^{[d]} = g_{\theta}(x^{(k)})$

$$\nabla_{o^{[d]}} f_k(\theta) = \nabla_{y_1} l(g_{\theta}(x^{(k)}), y^{(k)})$$

- evaluate gradient with respect to input from that with respect to output using (1), or equivalently, using (5) *i.e.*, evaluate $\nabla_{z^{[i]}} f_k(\theta)$ from $\nabla_{o^{[i]}} f_k(\theta)$
- evaluate gradient with respect to weights, bias, and intput of previous layer using (3), (4), & (2) or equivalently, using (7), (8), & (6) *i.e.*, evaluate $\nabla_{W^{[i]}} f_k(\theta)$, $\nabla_{w^{[i]}} f_k(\theta)$ & $\nabla_{o^{[i-1]}} f_k(\theta)$ from $\nabla_{z^{[i]}} f_k(\theta)$
- repeat back to input layer to evaluate all

$$\nabla_{W^{[1]}} f_k(\theta), \nabla_{w^{[1]}} f_k(\theta), \dots, \nabla_{W^{[d]}} f_k(\theta), \nabla_{w^{[d]}} f_k(\theta)$$

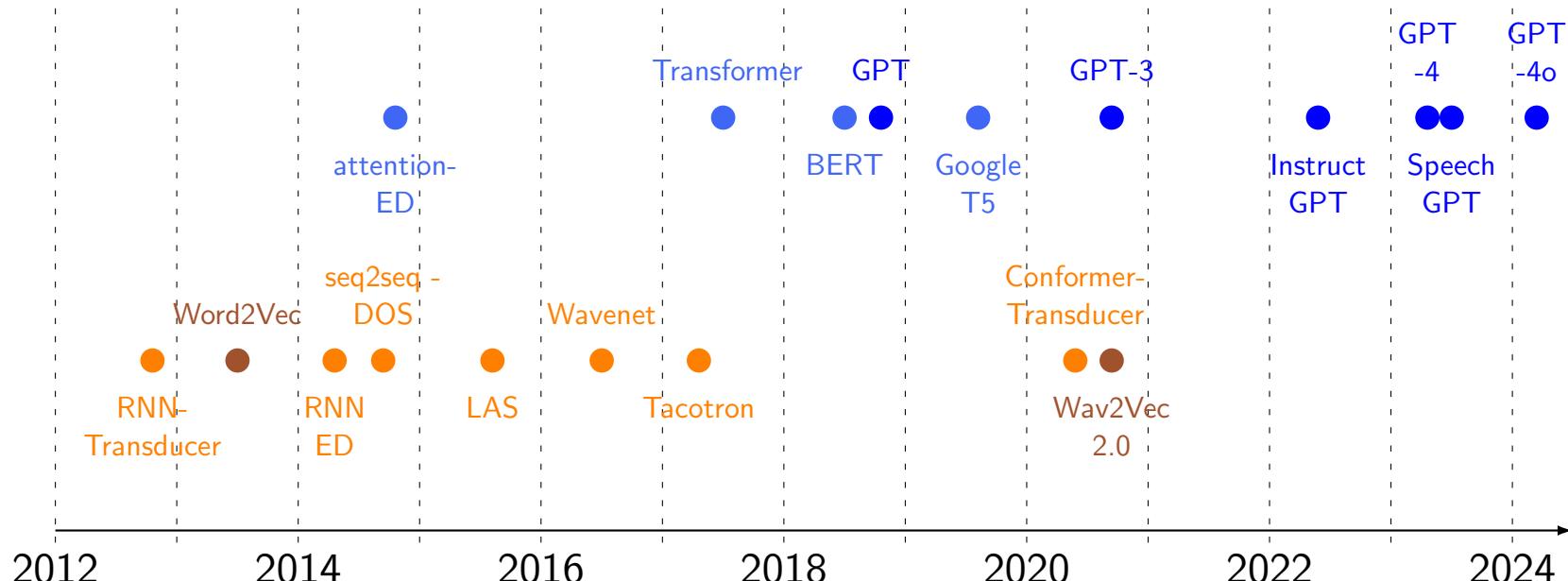
LLM

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

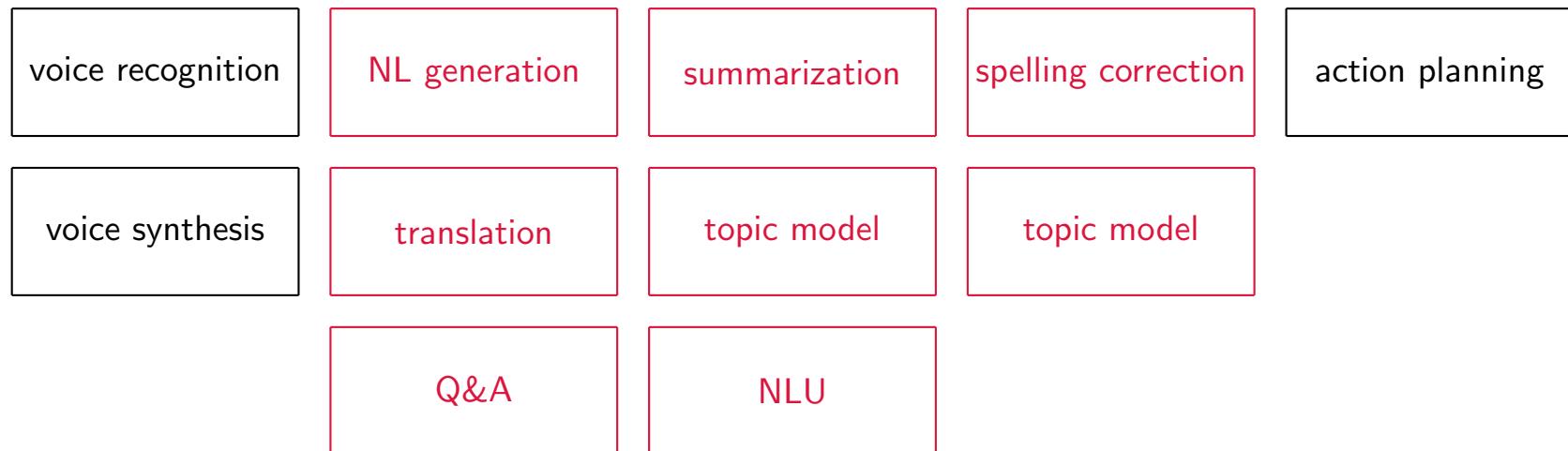
Recent advances in speech & language processing



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

Types of language models

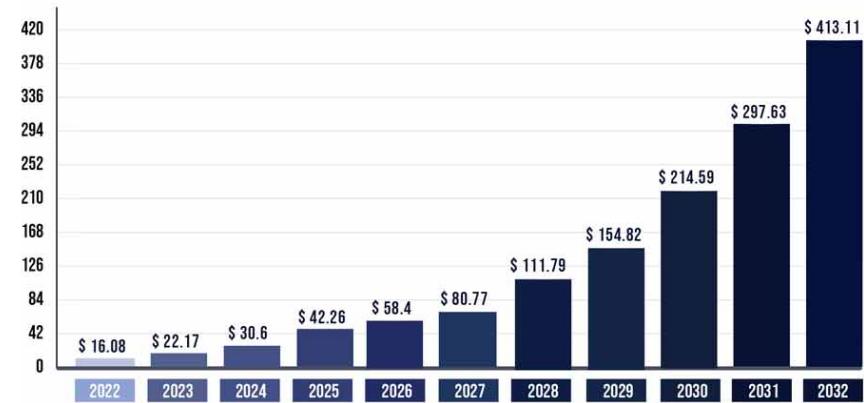
- many of language models have **common requirements** - language representation learning
- can be learned via pre-training *high performing model* and fine-tuning/transfer learning/domain adaptation
- this *high performing model* learning essential language representation *is* (language) foundation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



NLP Market

NLP market size

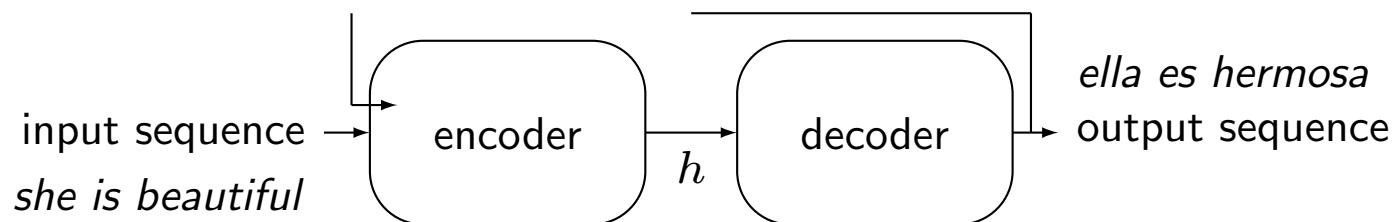
- global NLP market size estimated at USD 16.08B in 2022, is expected to hit USD 413.11B by 2032 - *CAGR of 38.4%*
- in 2022
 - north america NLP market size valued at USD 8.2B
 - high tech and telecom segment accounted revenue share of over 23.1%
 - healthcare segment held a 10% market share
 - (by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



Sequence-to-Sequence Models

Sequence-to-sequence (seq2seq) model

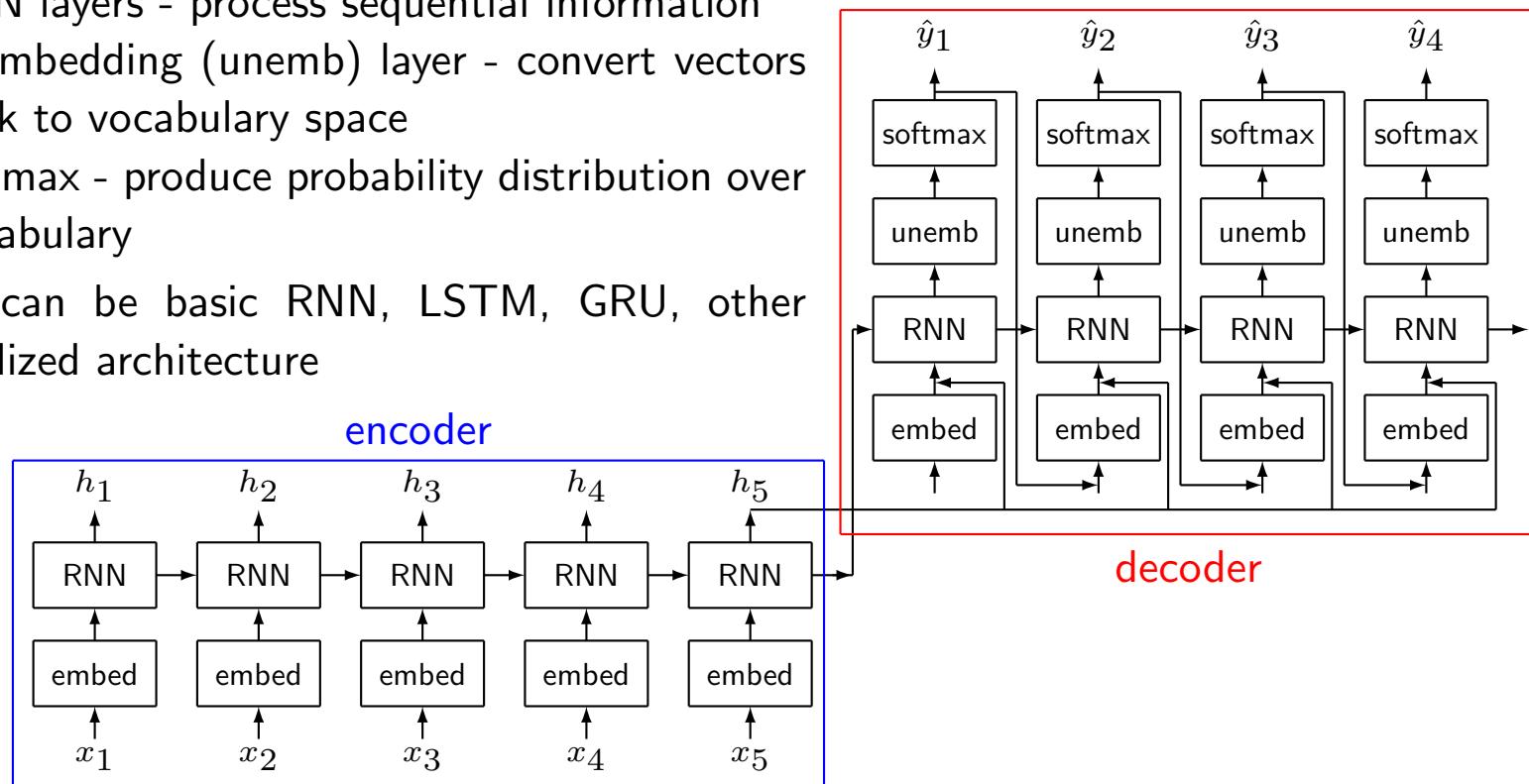
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



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

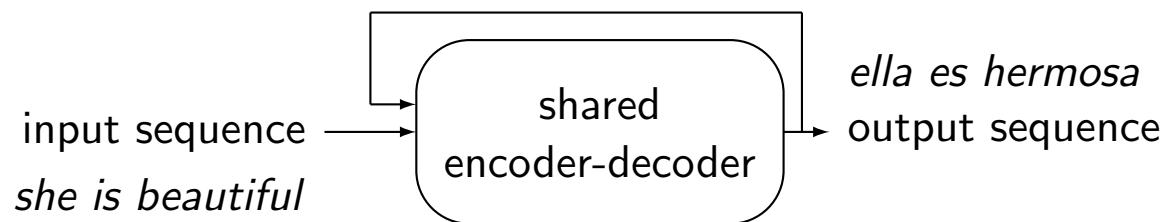
RNN-type encoder-decoder architecture

- components
 - embedding layer - convert input tokens to vector representations
 - RNN layers - process sequential information
 - unembedding (unemb) layer - convert vectors back to vocabulary space
 - softmax - produce probability distribution over vocabulary
- RNN can be basic RNN, LSTM, GRU, other specialized architecture



Shared encoder-decoder model

- single neural network structure can handle both encoding & decoding tasks
 - efficient architecture reducing model complexity
 - allow for better parameter sharing across tasks
- widely used in modern LLMs to process & generate text sequences
 - applications - machine translation, text summarization, question answering
- advantages
 - efficient use of parameters, versatile for multiple NLP tasks



Large Language Models

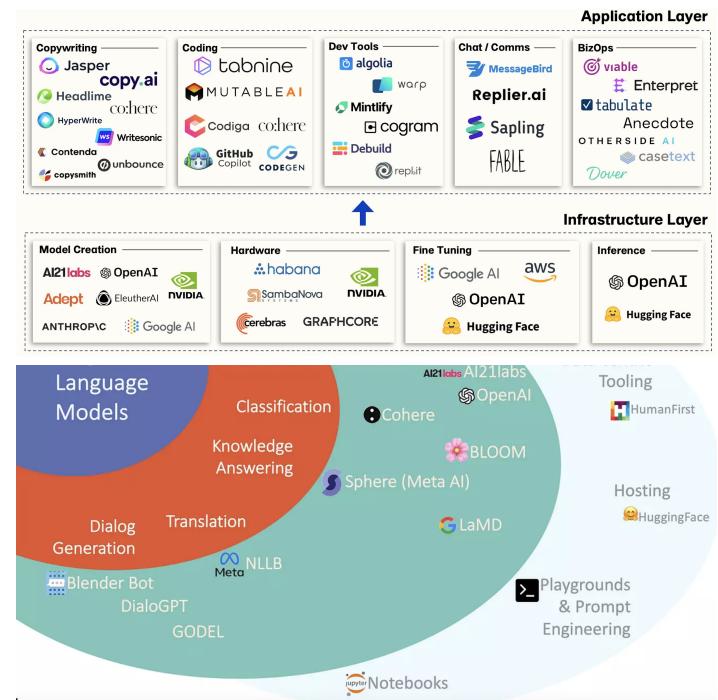
LLM

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



LLMs

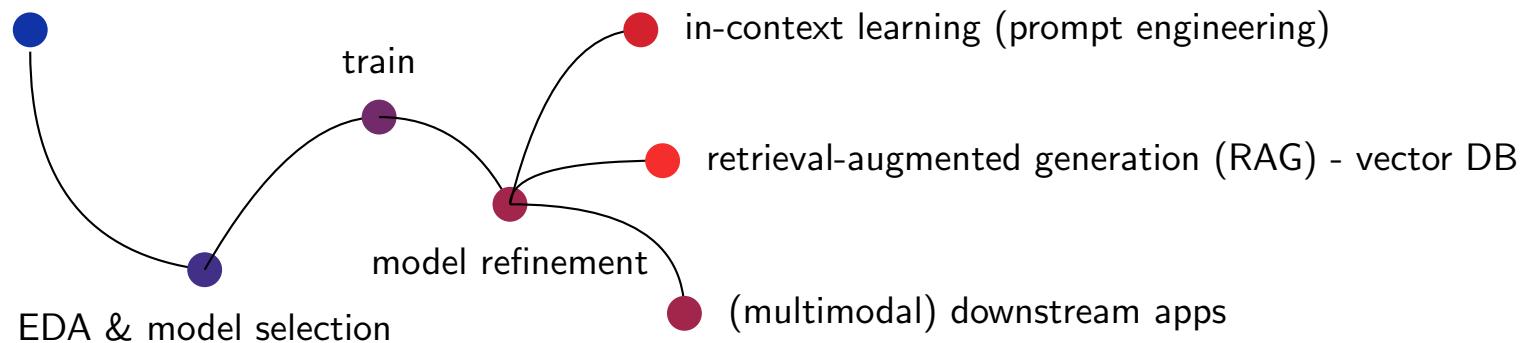
- Foundation Models
 - GPT-x/Chat-GPT - OpenAI, Llama-x - Meta, PaLM-x (Bard) - Google
- # parameters
 - generative pre-trained transformer (GPT) - GPT-1: 117M, GPT-2: 1.5B, GPT-3: 175B, GPT-4: 100T, GPT-4o: 200B
 - large language model Meta AI (Llama) - Llama1: 65B, Llama2: 70B, Llama3: 70B
 - scaling 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

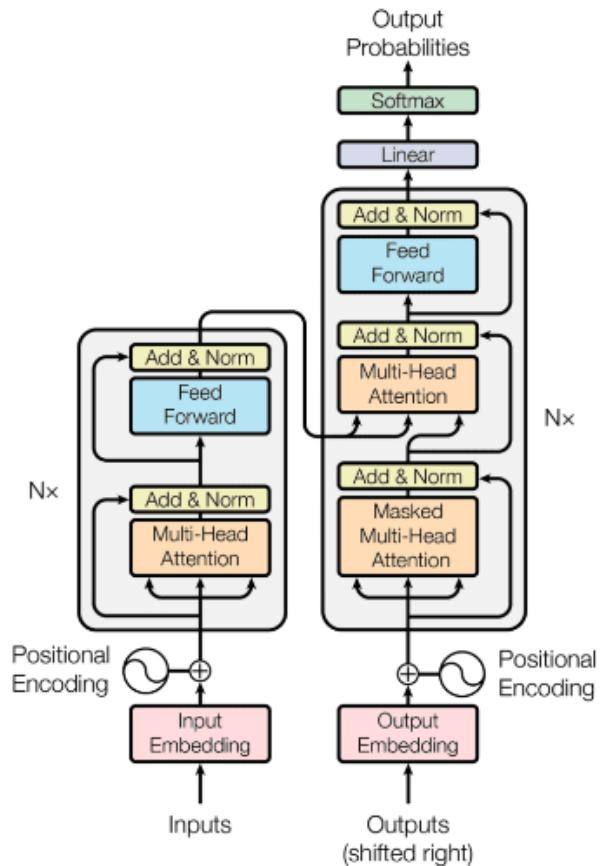
LLM architectural secret (or known) sauce

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

- then

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

e.g., dependency between 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

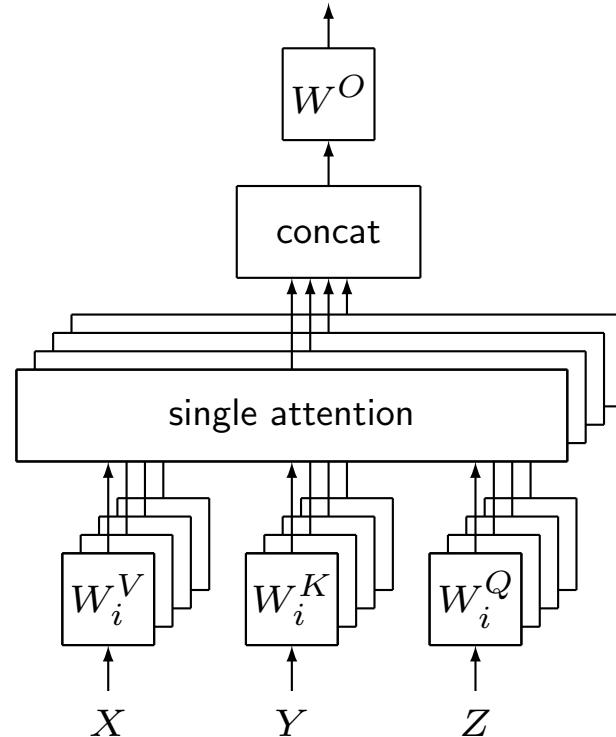
$$X \in \mathbf{R}^{d_e \times m}, Y \in \mathbf{R}^{d_e \times m}, Z \in \mathbf{R}^{d_e \times n}$$

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

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

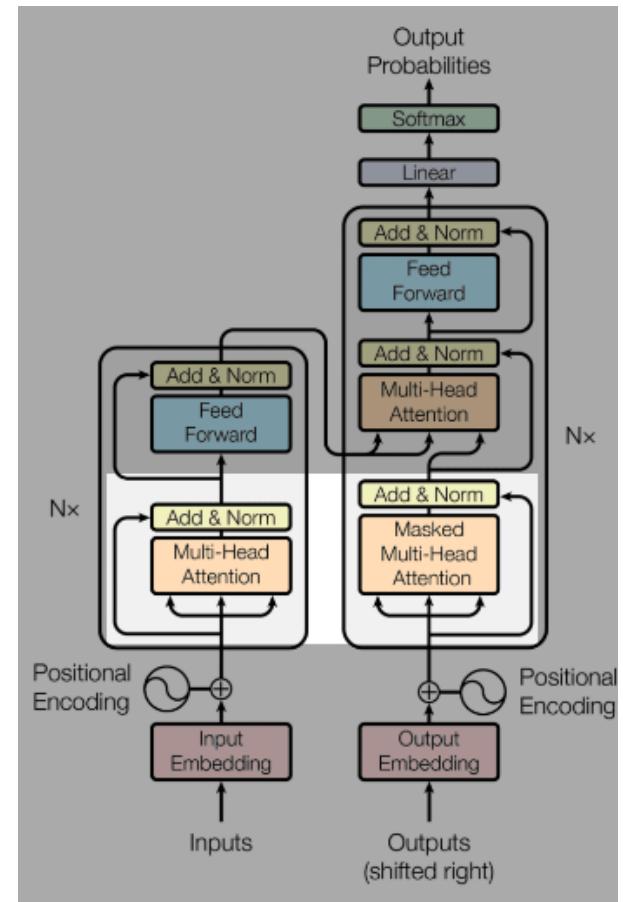
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbf{R}^{d_e \times n},$$

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



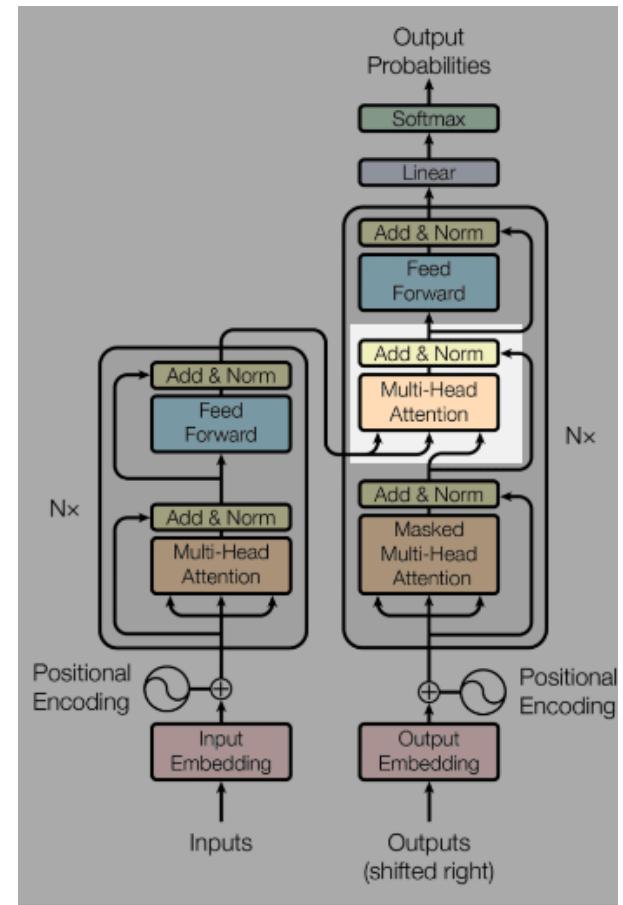
Self attention

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



Encoder-decoder attention

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

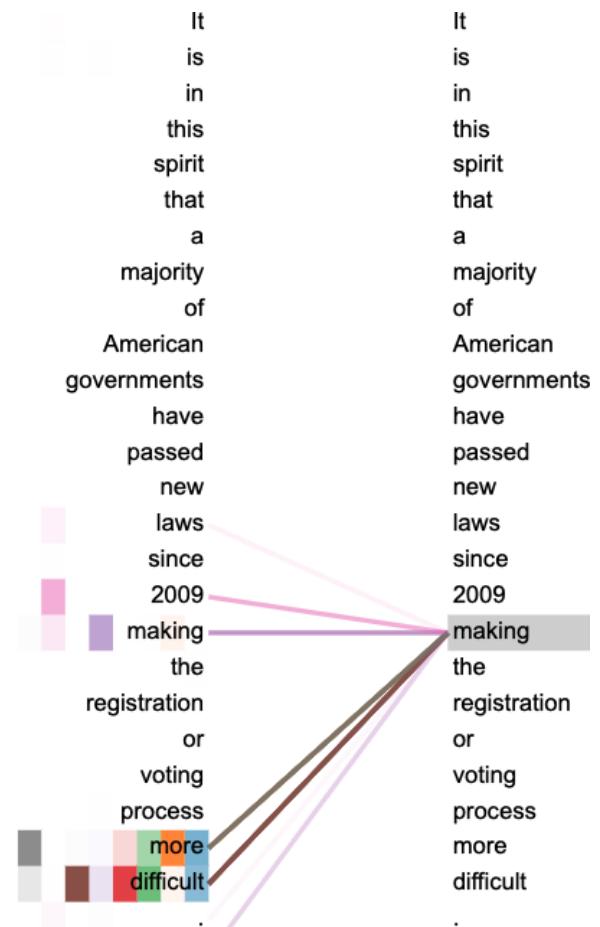


Visualization of self attentions

example sentence

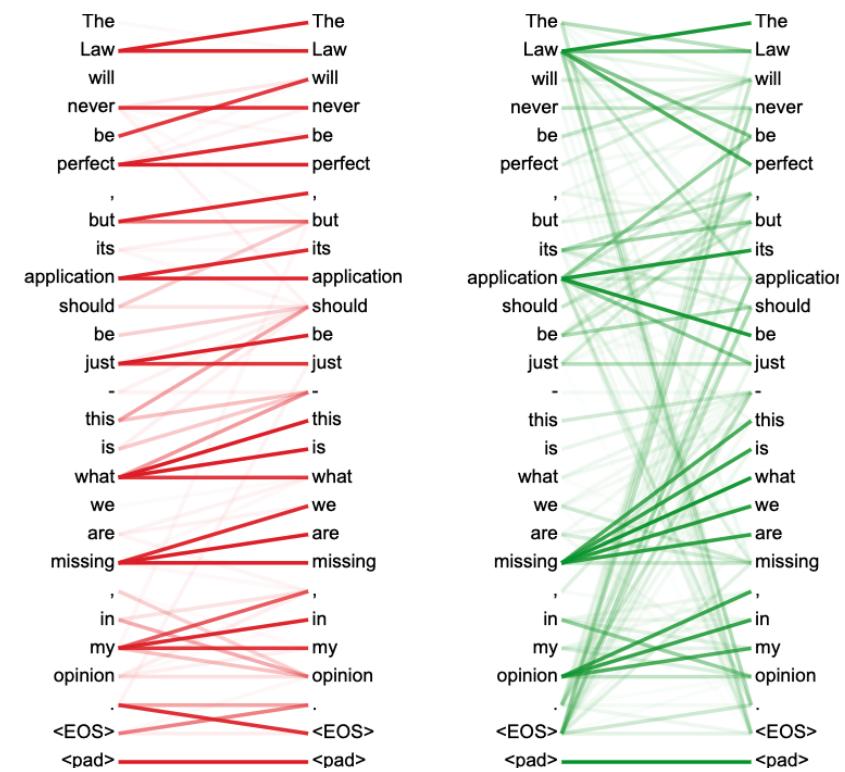
"It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult."

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

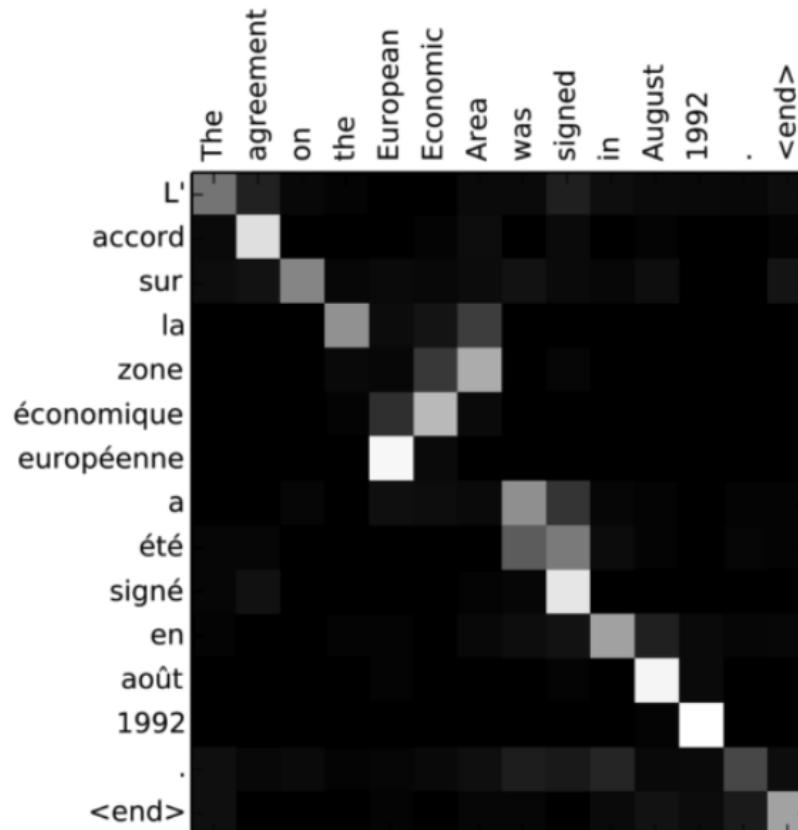


Visualization of multi-head self attentions

- self attentions of encoder for two heads (of a layer)
 - different heads represent different structures
→ advantages of multiple heads
 - multiple heads work together to 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

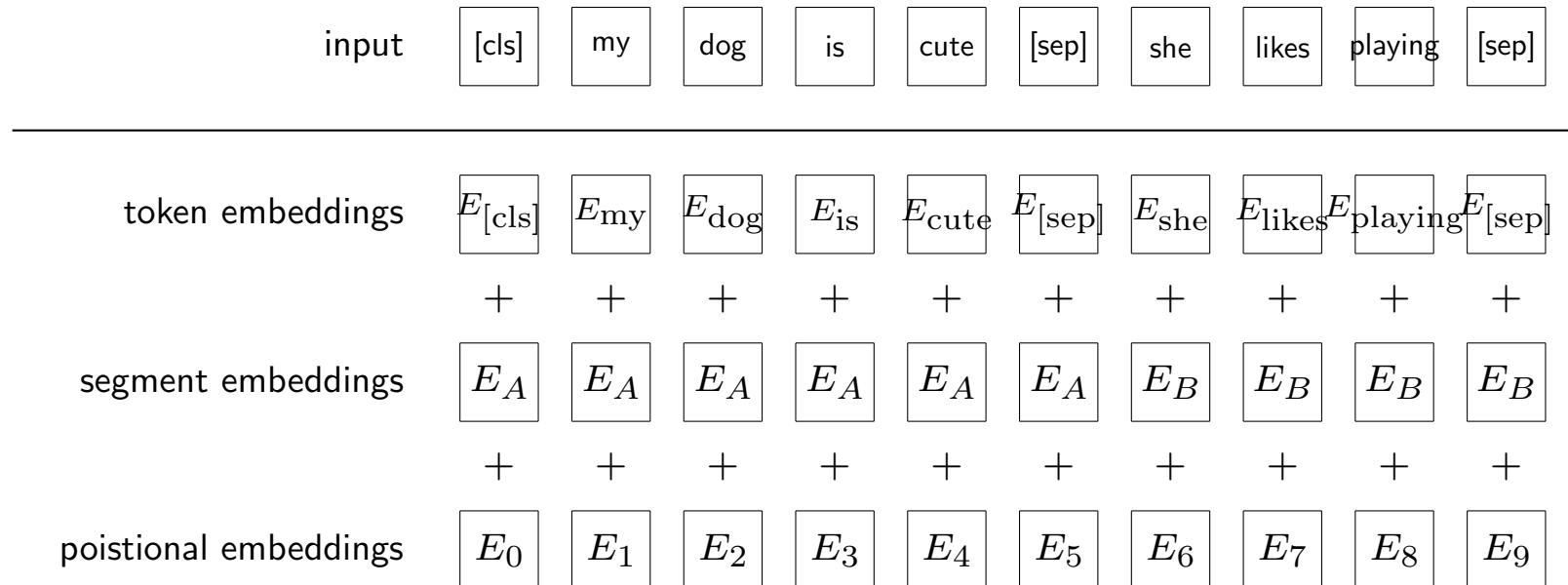
Model complexity

- 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!

Variants of Transformer

Bidirectional encoder representations from transformers (BERT)

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



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

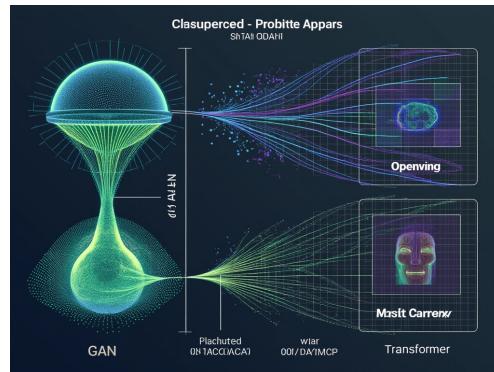
Definition of genAI

Generative AI

- genAI refers to systems capable of producing new (& original) contents based on patterns learned from training data (representation learning)
 - as opposed to discriminative models for, *e.g.*, classification, prediction & regression
 - here content can be text, images, audio, video, *etc.* - what about smell & taste?
- genAI model examples
 - generative adversarial networks (GANs), variational autoencoders (VAEs), diffusion models, Transformers



by Midjourney



by Grok 2 mini



by Generative AI Lab

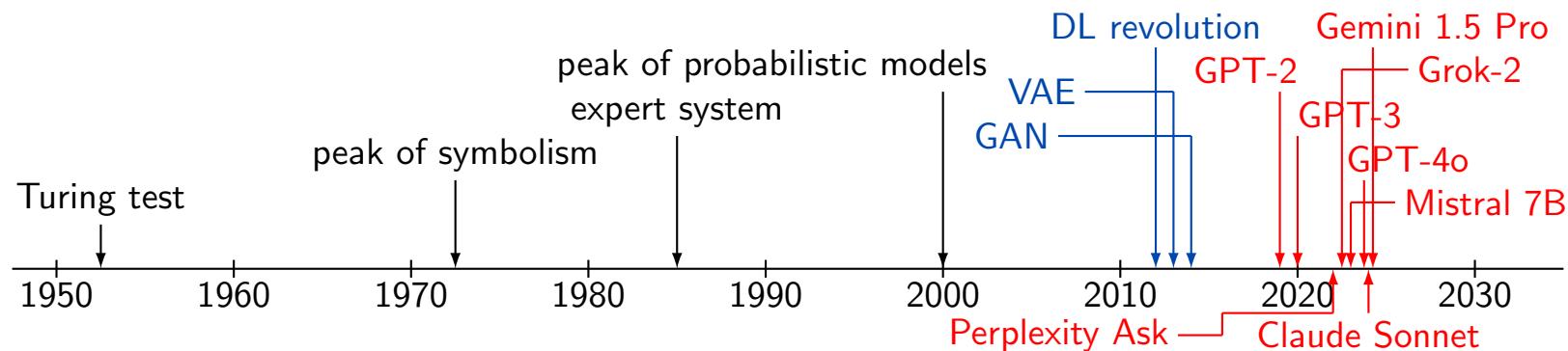
Examples of genAI in action

- text generation
 - Claude, ChatGPT, Mistral, Perplexity, Gemini, Grok
 - conversational agent writing articles, code & even poetry
- image generation
 - DALL-E - creates images based on textual descriptions
 - Stable Diffusion - uses diffusion process to generate high-quality images from text prompts (by denoising random noise)
 - MidJourney - art and visual designs generated through deep learning
- music generation
 - Amper Music - generates unique music compositions
- code generation
 - GitHub Copilot - generates code snippets based on natural language prompts

History of genAI

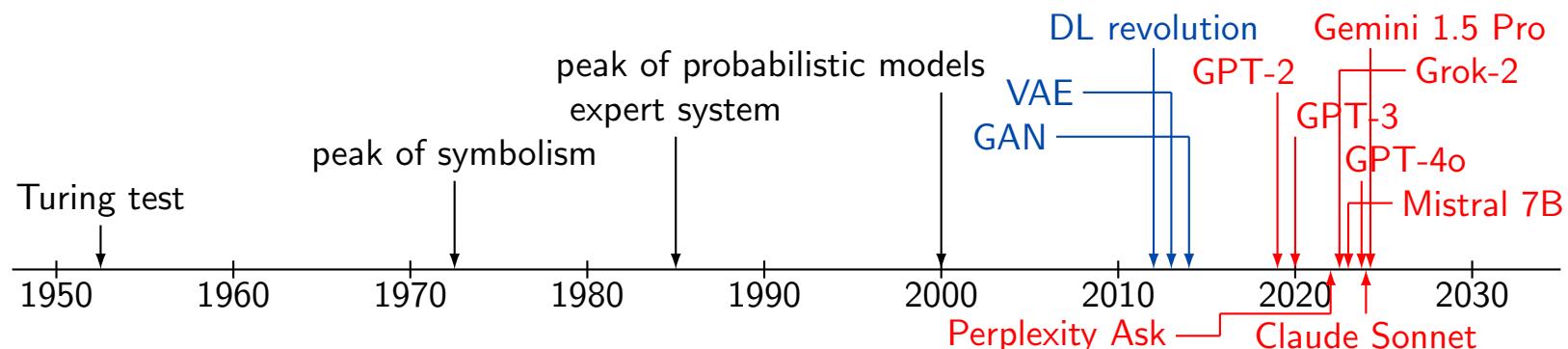
Birth of AI - early foundations & precursor technologies

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



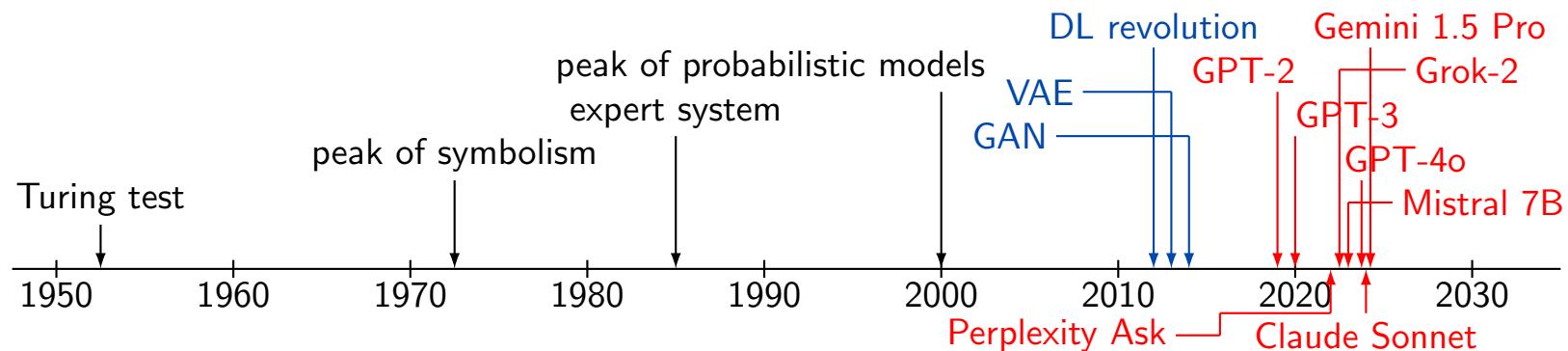
Rule-based systems & probabilistic models

- 1980s ~ early 2000s
 - *expert systems* (1980s) - AI systems designed to mimic human decision-making in specific domains
 - development of neural networks (NN) w/ backpropagation *training multi-layered networks* - setting stage for way more complex generative models
 - *probabilistic models* (including network models, *i.e.*, Bayesian networks) & Markov models - laying groundwork for data generation & pattern prediction



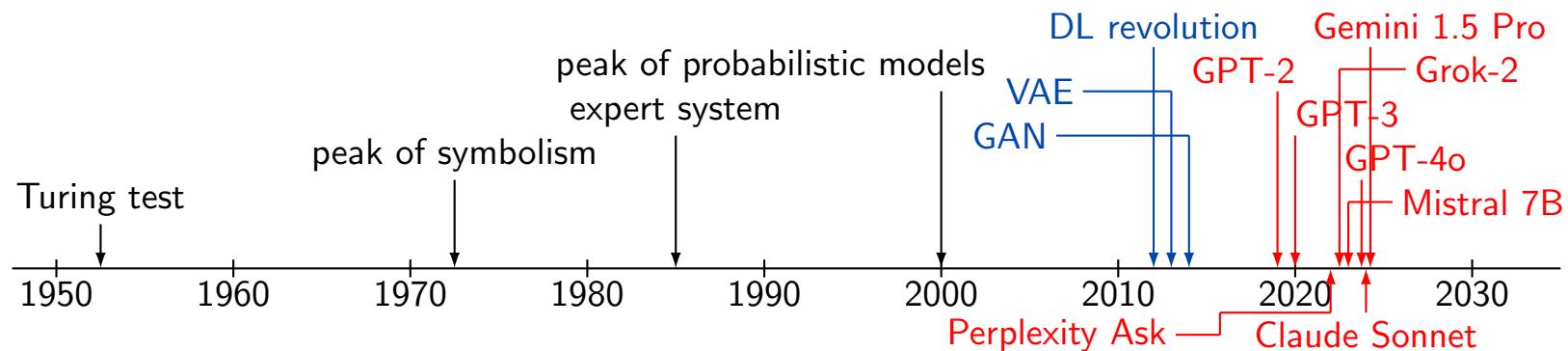
Rise of deep learning & generative models

- 2010s - breakthrough in genAI
 - *deep learning (DL) revolution* - advances in GPU computing and data availability led to the rapid development of deep neural networks.
 - *variational autoencoder (VAE)* (2013) - by Kingma and Welling - learns mappings between input and latent spaces
 - *generative adversarial network (GAN)* (2014) - by Ian Goodfellow - game-changer in generative modeling where two NNs compete each other to create realistic data
 - widely used in image generation & creative tasks



Transformer models & multimodal AI

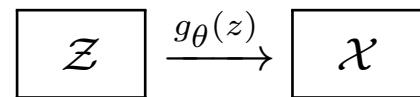
- late 2010s ~ Present
 - Transformer architecture (2017) - by Vaswani et al.
 - *revolutionized NLP*, e.g., LLM & various genAI models
 - GPT series - generative pre-trained transformer
 - GPT-2 (2019) - generating human-like texts - *marking leap in language models*
 - GPT-3 (2020) - 175B params - set *new standards for LLM*
 - multimodal systems - DALL-E & CLIP (2021) - *linking text and visual data*
 - emergence of diffusion models (2020s) - new approach for generating high-quality images - progressively “denoising” random noise (DALL-E 2 & Stable Diffusion)



Mathy Views on genAI

genAI models

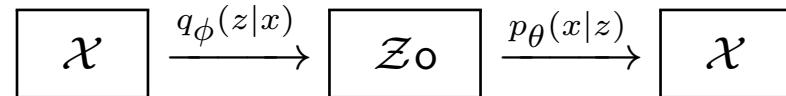
- definition of generative model



- *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]



- 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)

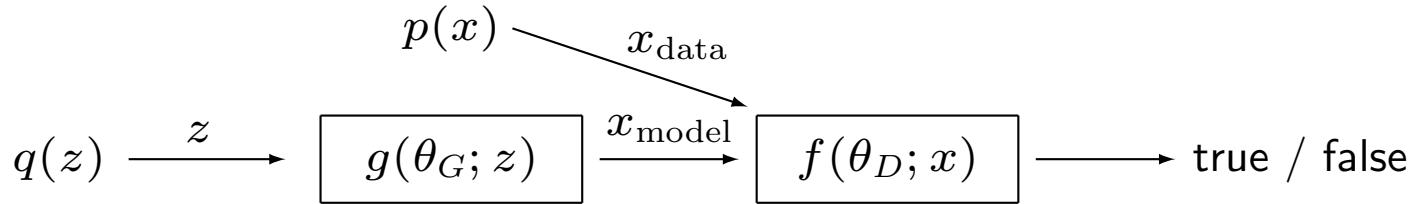
$$\mathcal{L}(\theta, \phi; x) = \mathbf{E}_{z \sim q_\phi(z|x)} \log \frac{p_\theta(x, z)}{q_\phi(z|x)}$$

- 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

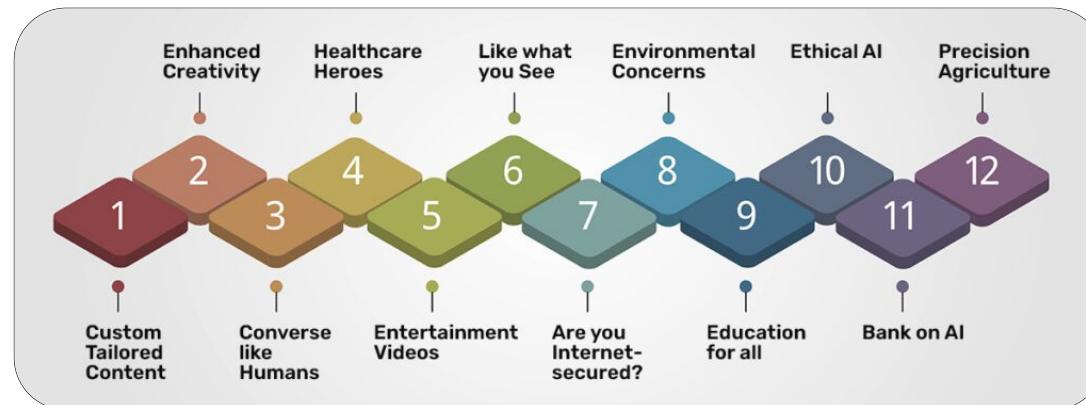
- previous sequence: x_{t-1}, x_{t-2}, \dots
- next token: x_t
- p_{θ} represented by (extremely) complicated model
 - e.g., containing multi-head & multi-layer Transformer architecture inside
- model parameters, e.g., for Llama2

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

Current Trend & Future Perspectives

Current trend of genAI

- rapid advancement in language models & multimodal AI capabilities
- rise of AI-assisted creativity & productivity tools
- growing adoption across industries
 - creative industries - design, entertainment, marketing, software development
 - life sciences - healthcare, medical, biotech
- infrastructure & accessibility, *e.g.*, Hugging Face democratizes AI development
- integration with cloud platforms & enterprise-level tools
- increased focus on AI ethics & responsible development



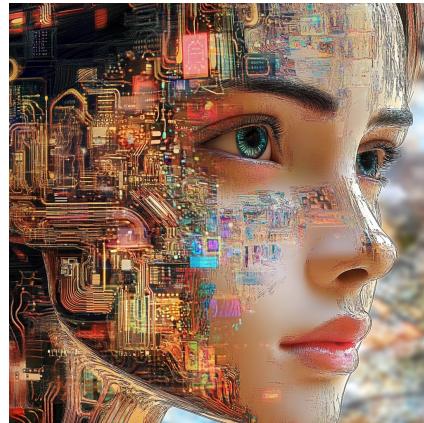
Industry & business impacts

- how genAI is transforming industries
 - creative industries - content creation - advertising, gaming, film
 - life science - enhance research, drug discovery & personalized treatments
 - finance - automating document generation, risk modeling & fraud detection
 - manufacturing & Design - rapid prototyping, 3D modeling & optimization
 - business operations - automate routine tasks to boost productivity



Future perspectives of genAI

- hyper-personalization - highly personalized content for individual users - music, products & services
- AI ethics & governance - concerns over deepfakes, misinformation & bias
- interdisciplinary synergies - integration with other fields such as quantum computing, neuroscience & robotics
- human-AI collaboration - augment human creativity rather than replace it
- energy efficiency - have to figure out how to dramatically reduce power consumption



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Thank You