

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

Sunghee Yun

Co-Founder & CTO @ [Erudio Bio, Inc.](#)

Co-Founder & CEO @ Erudio Bio Korea, Inc.

AI-Korean Medicine Integration Initiative Task Force Member @
[The Association of Korean Medicine](#)

Global Leadership Initiative Fellow @ [Salzburg Global Seminar](#)

Adjunct Professor & Advisory Professor @ Sogang Univ. & DGIST

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
- Adjunct Professor, Electronic Engineering Department @ Sogang University, Korea
- 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
- LLM - 30
 - language models, seq2seq models
 - LLM, (variants of) Transformer, challenges of LLMs
- Generative AI (genAI) - 60
 - history of genAI, mathy views on genAI
 - current trend & future perspectives
- Selected references - 78
- References - 80

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 ~)



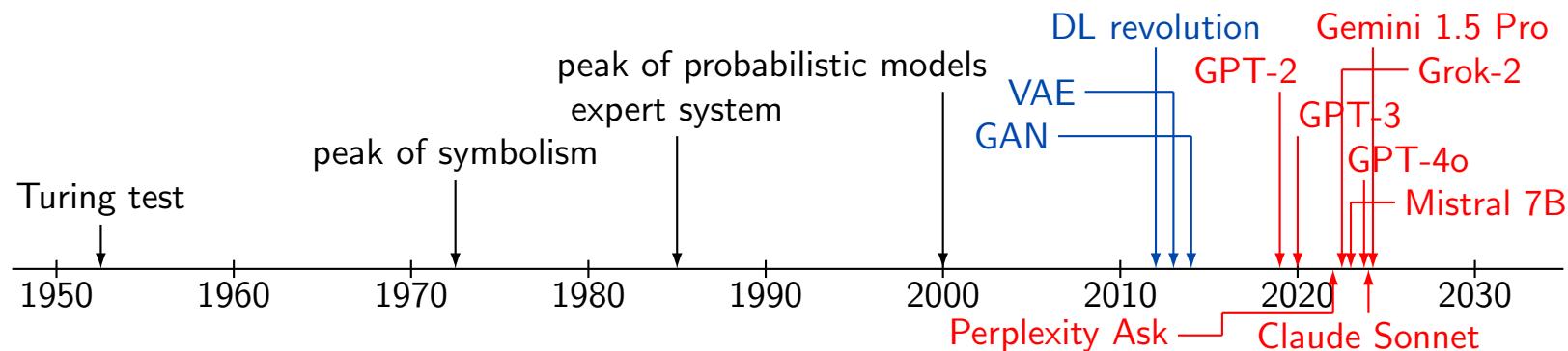
Rule-based systems & probabilistic models

- 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



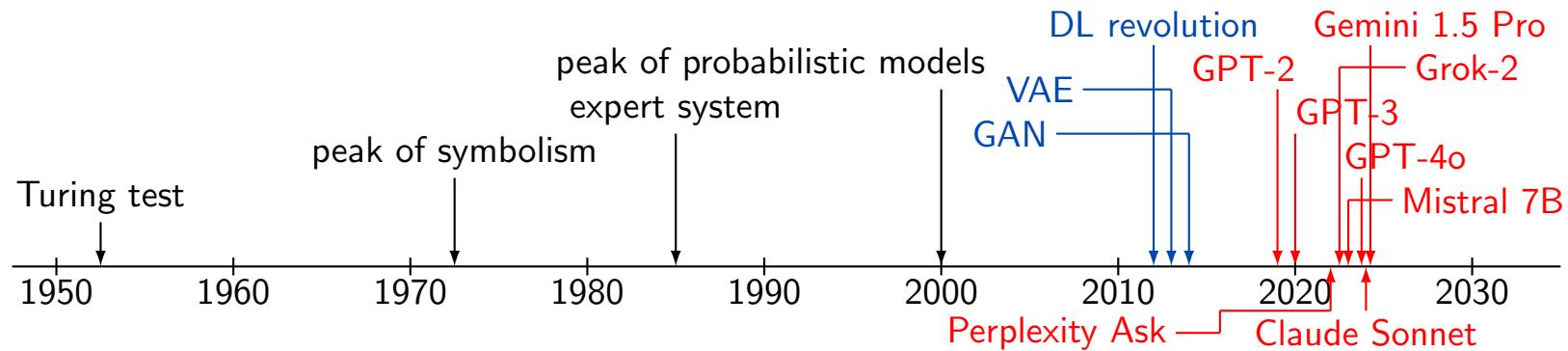
Rise of deep learning & generative models

- 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

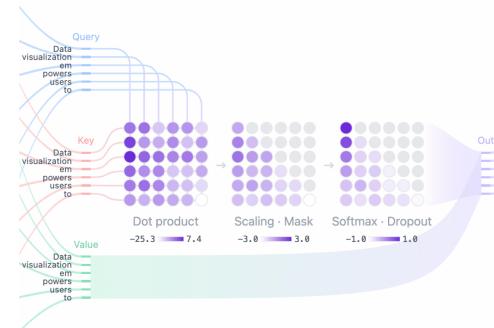
- 2012 – 2015 - DL revolution²
 - CNNs demonstrated exceptional performance in image recognition, e.g., *AlexNet's victory in ImageNet competition*
 - widespread adoption of DL learning in CV transforming industries
- 2016 - AlphaGo defeats human Go champion
 - DeepMind's AlphaGo defeated world champion 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*



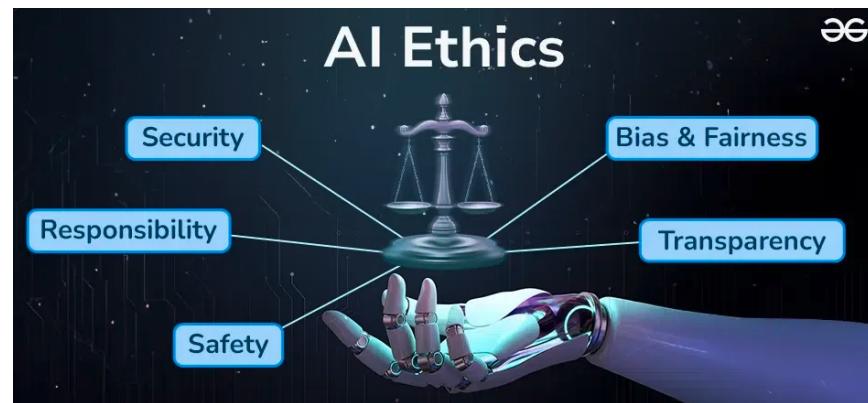
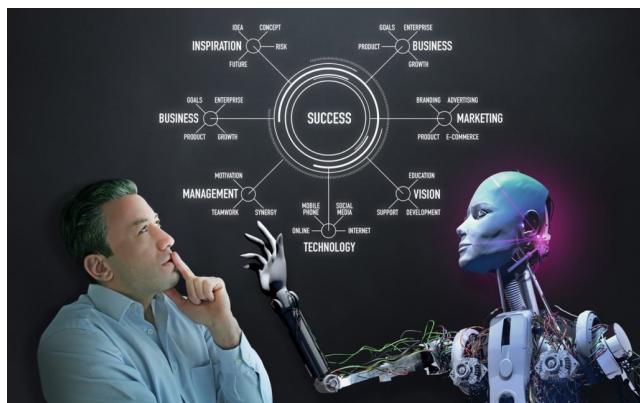
Major AI Breakthroughs in 2025

- 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

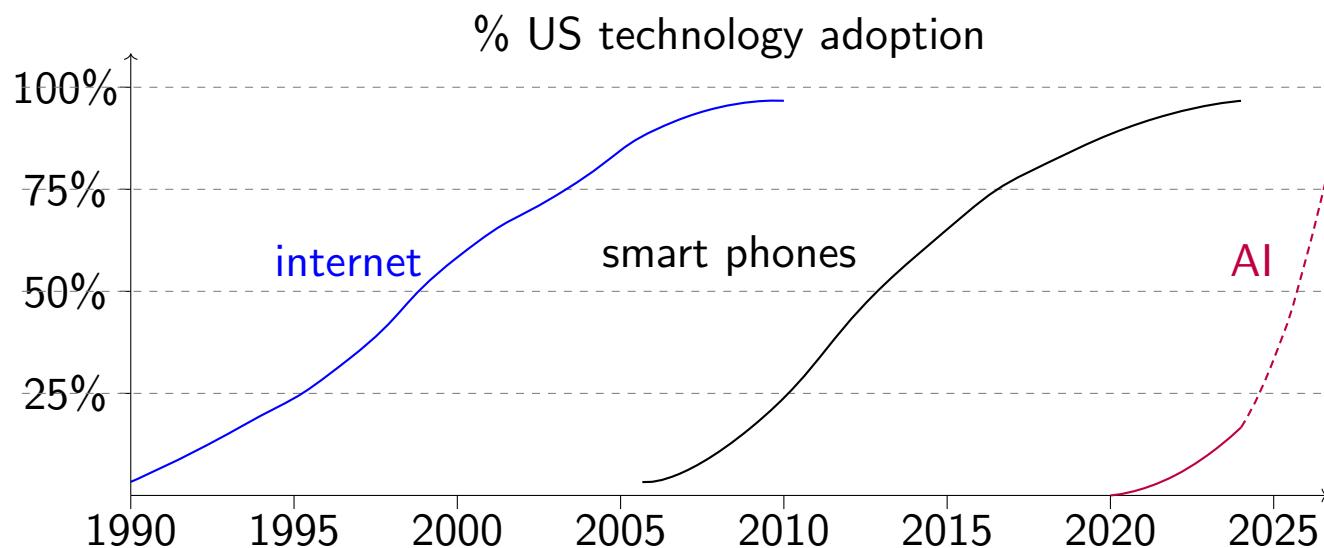
- accelerating human-AI collaboration
 - not only reshaping industries but *altering how humans interact with technology*
 - AI's role as collaborator and augmentor redefines productivity, creativity, the way we address global challenges, e.g., *sustainability & healthcare*
- AI-driven automation *transforms 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

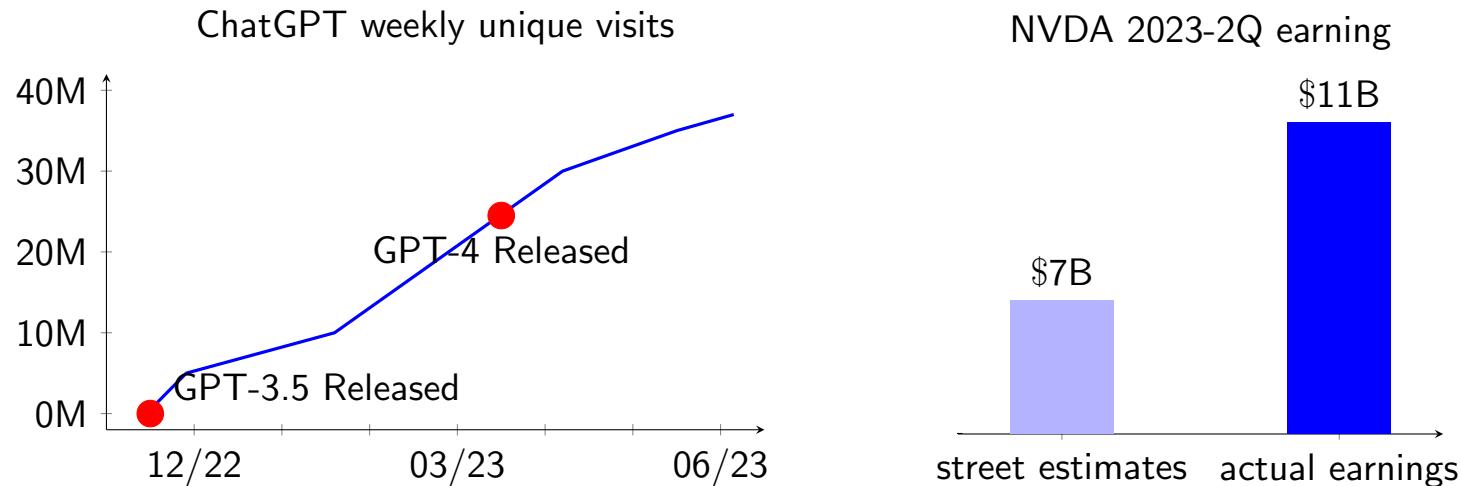
Where are we in AI today?

- 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

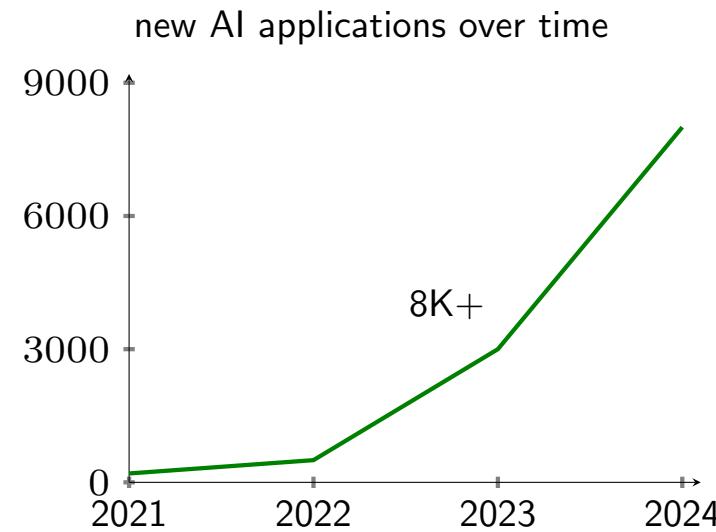
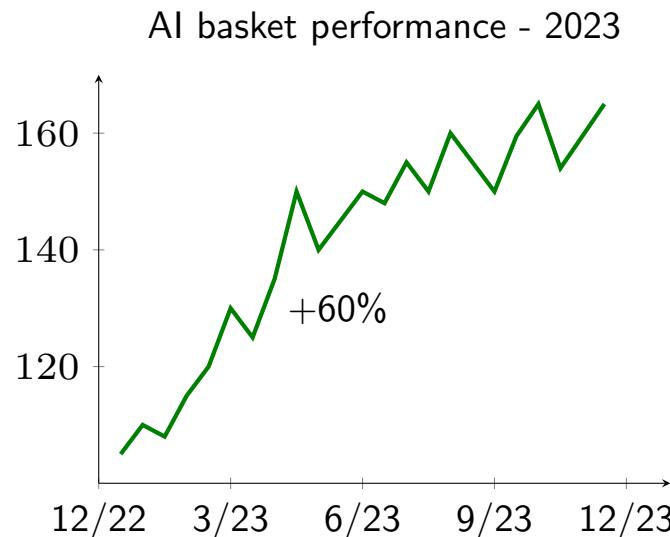
- took only *5 months for ChatGPT users to reach 35M*
- NVIDIA 2023 Q2 earning exceeds market expectation by big margin - \$7B vs \$13.5B
 - surprisingly, *101% year-to-year growth*
 - even more surprisingly *gross margin was 71.2%* - up from 43.5% in previous year⁴



⁴source - Bloomberg

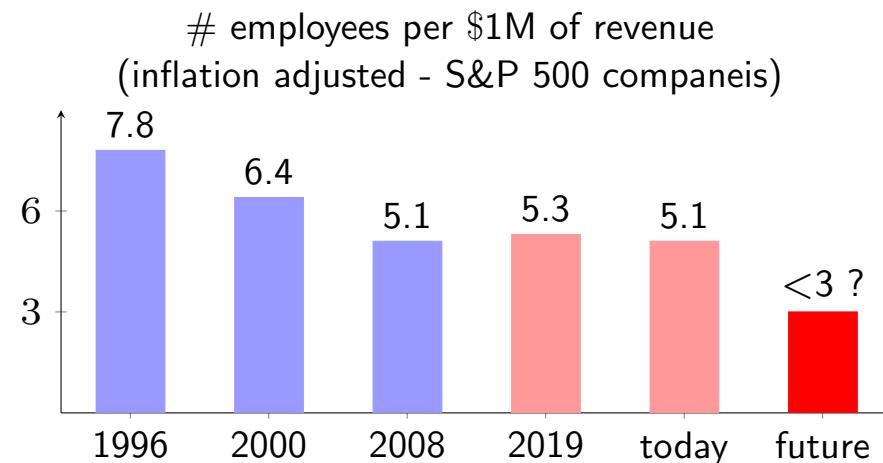
Explosion of AI ecosystems - AI stock market

- *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



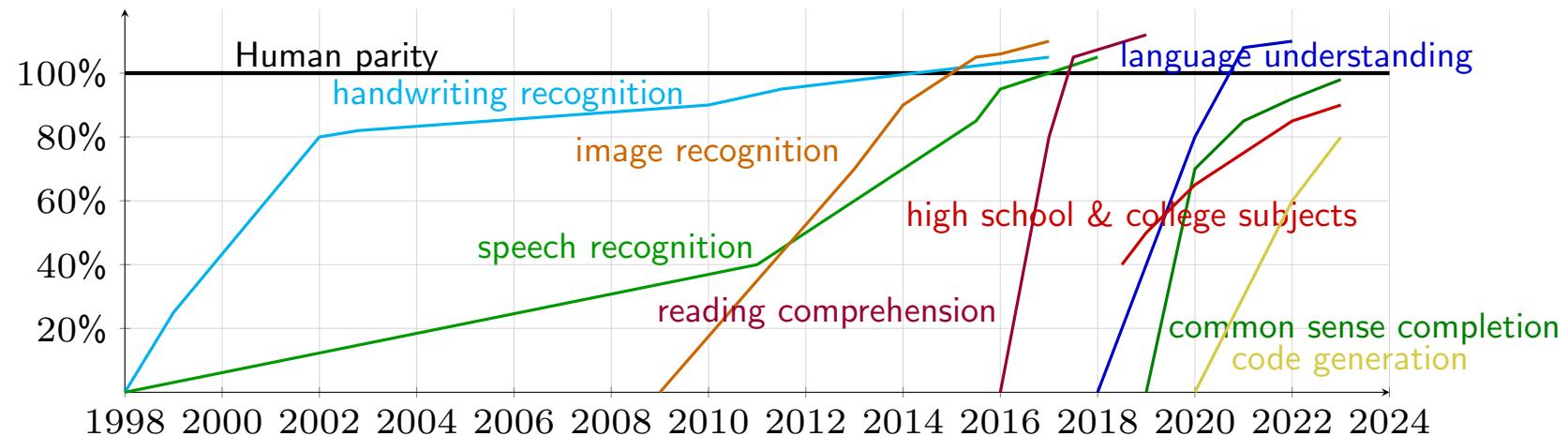
AI's transformative impact - adoption speed & economic potential

- 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



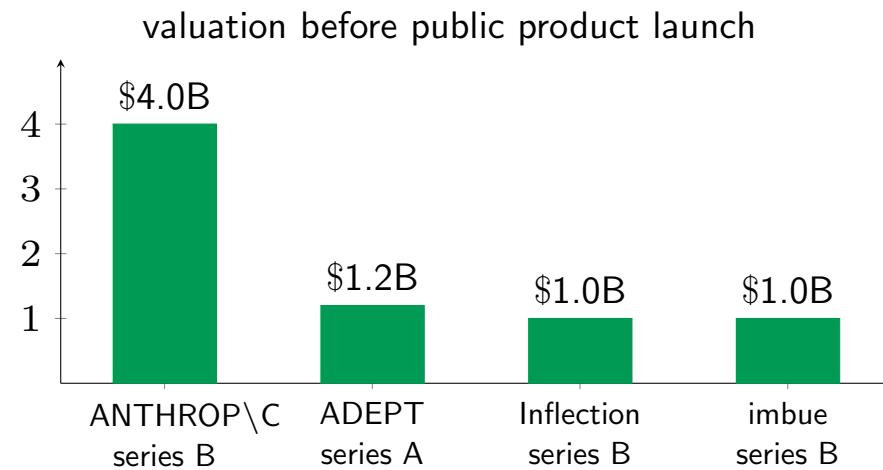
AI getting more & more faster

- 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



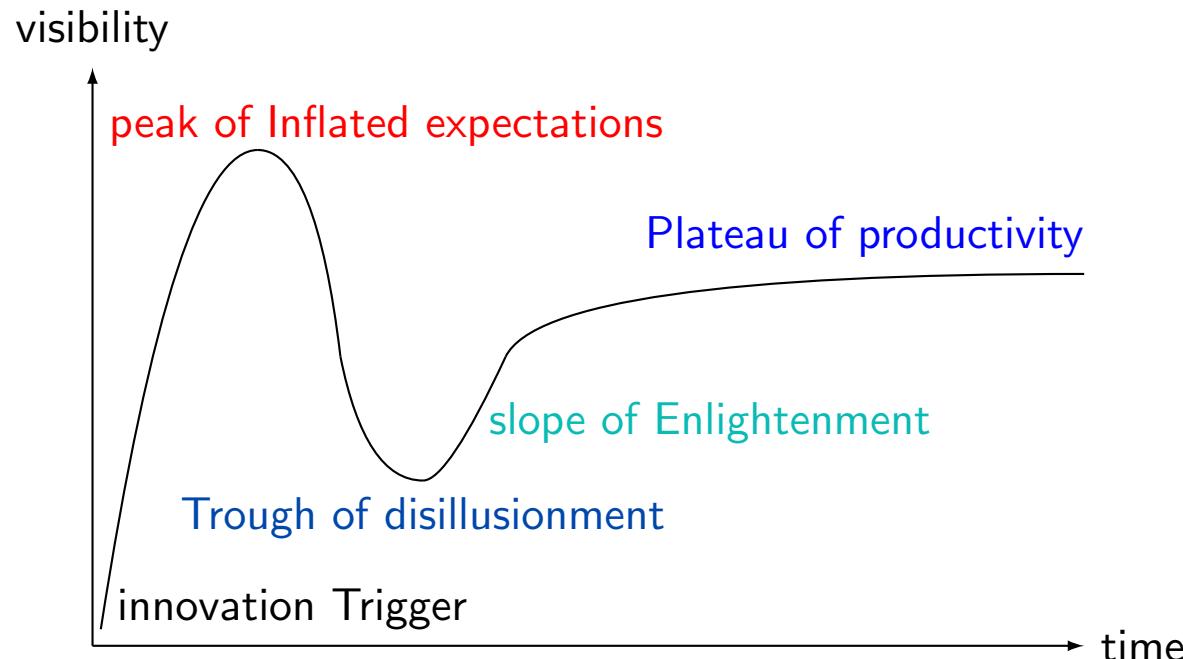
Massive investment in AI

- *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

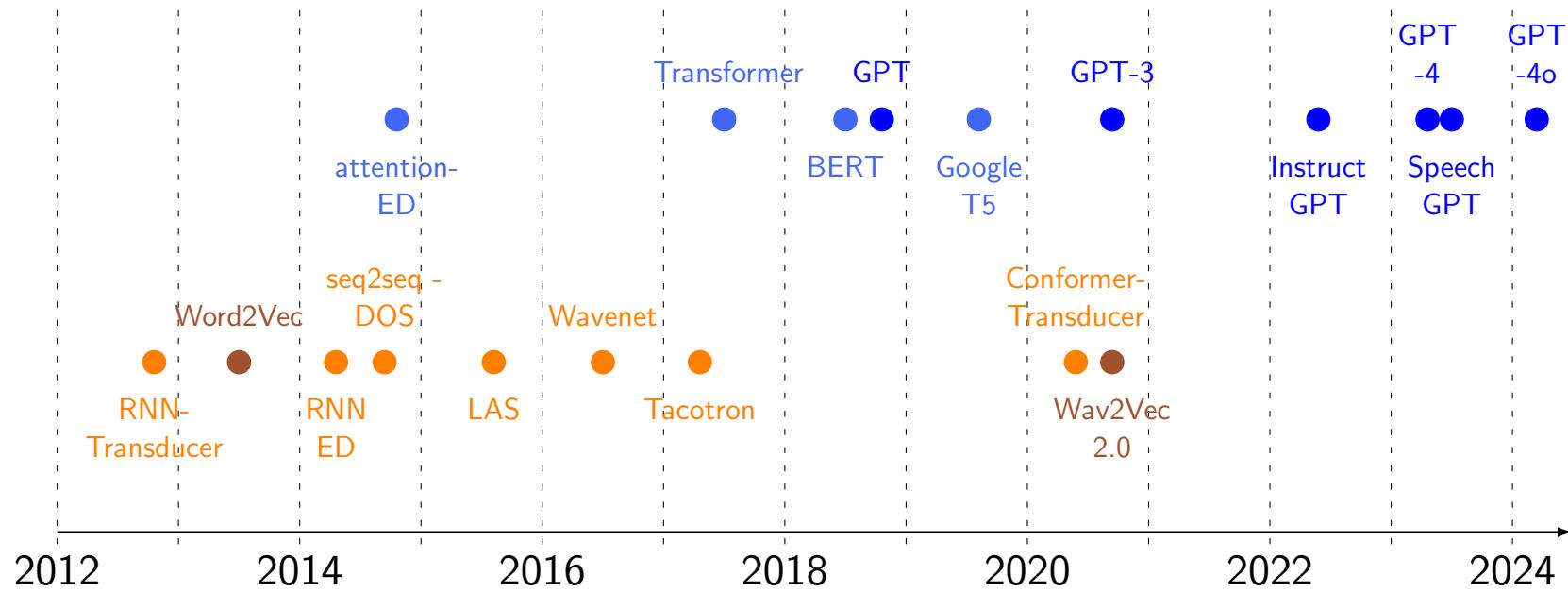
LLM

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

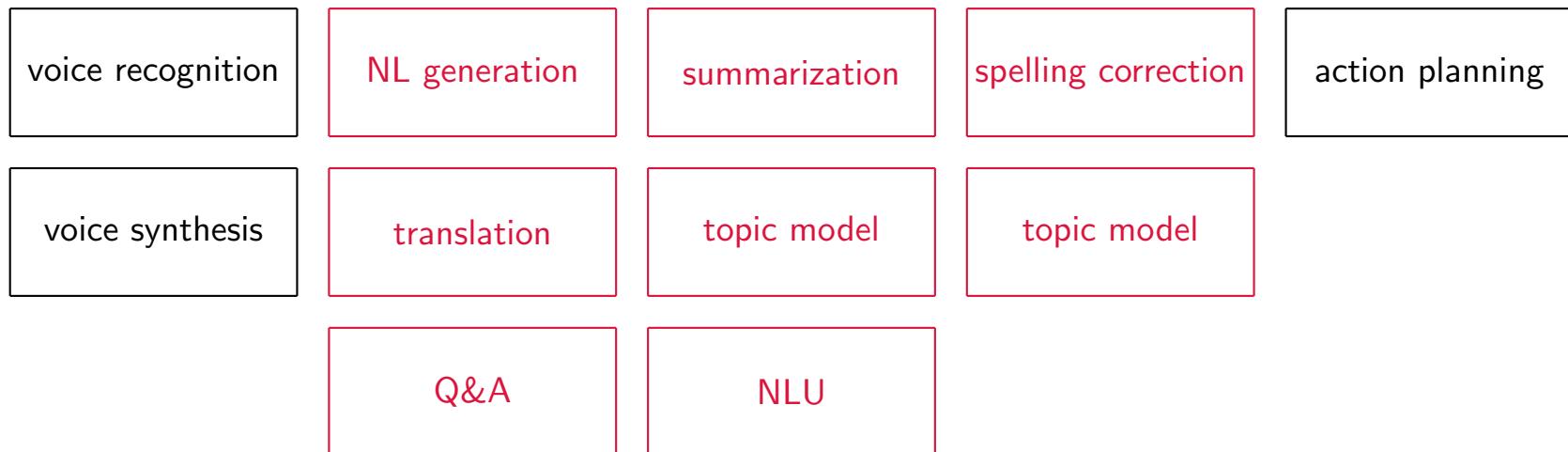
Recent advances in speech & language processing



- 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

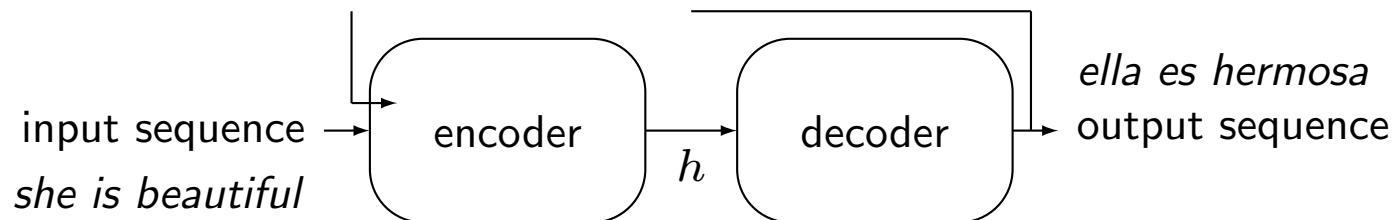
- global NLP market size estimated at USD 16.08B in 2022, is expected to hit USD 413.11B by 2032 - *CAGR of 38.4%*
- in 2022
 - north america NLP market size valued at USD 8.2B
 - high tech and telecom segment accounted revenue share of over 23.1%
 - healthcare segment held a 10% market share
 - (by 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

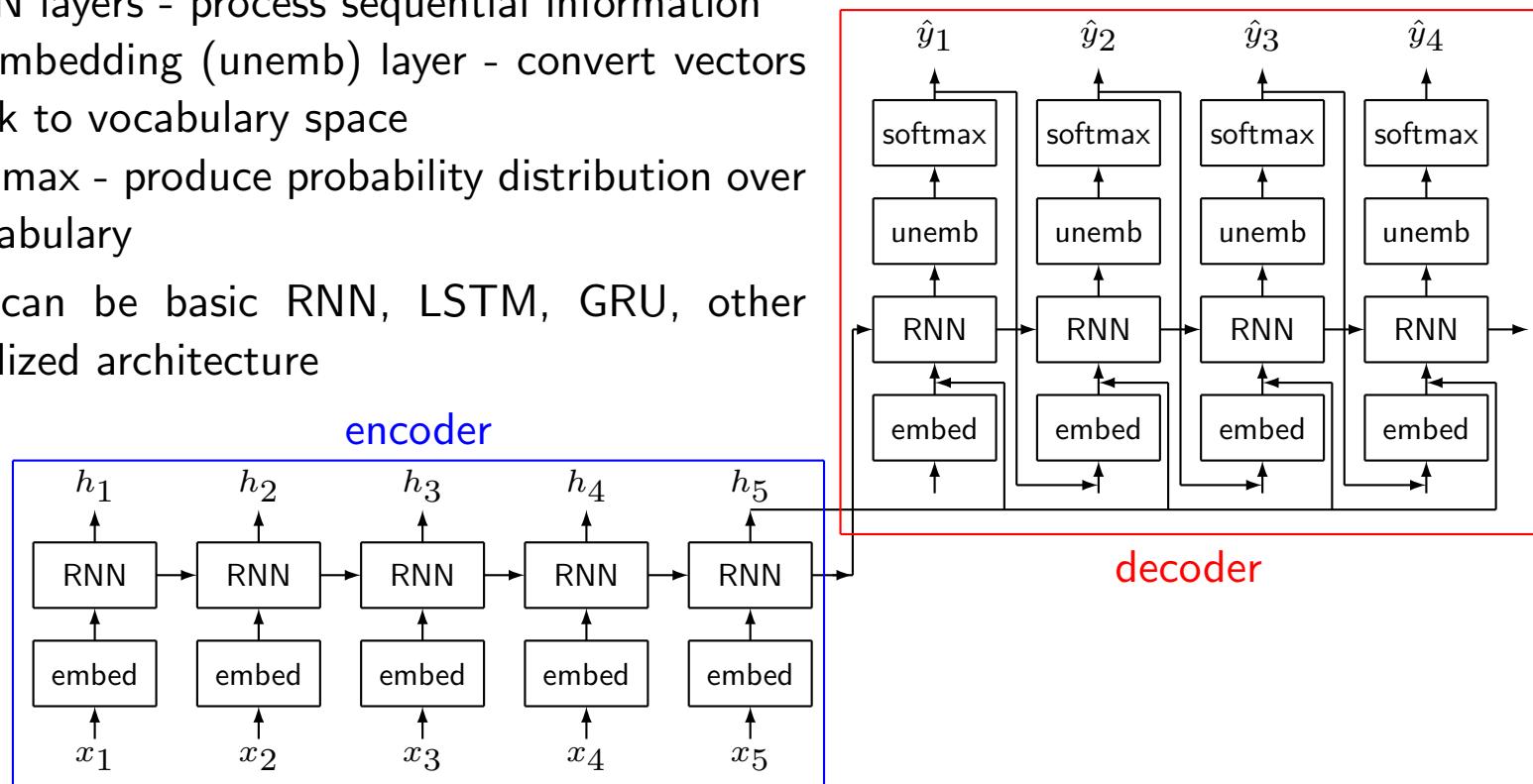
- seq2seq - take sequences as inputs and spit out sequences
- encoder-decoder architecture



- 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

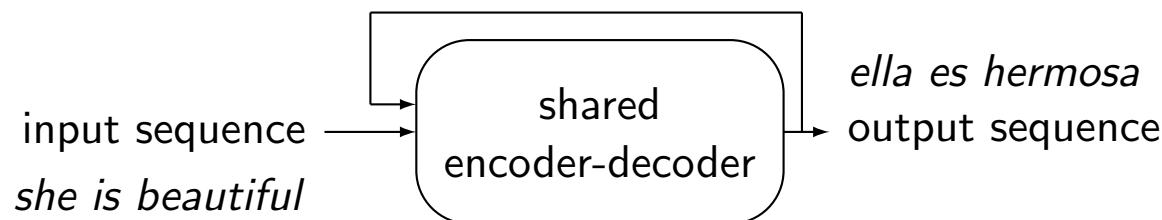
RNN-type encoder-decoder architecture

- 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

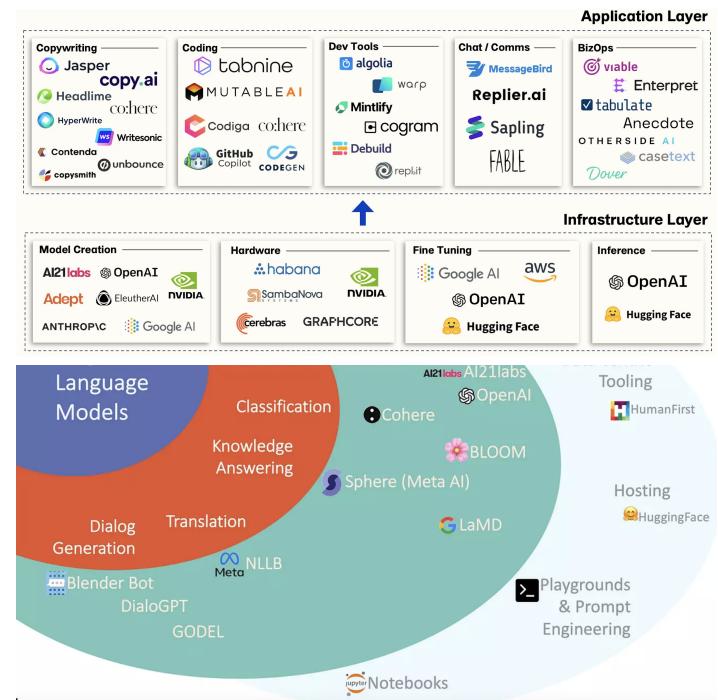
LLM

- 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

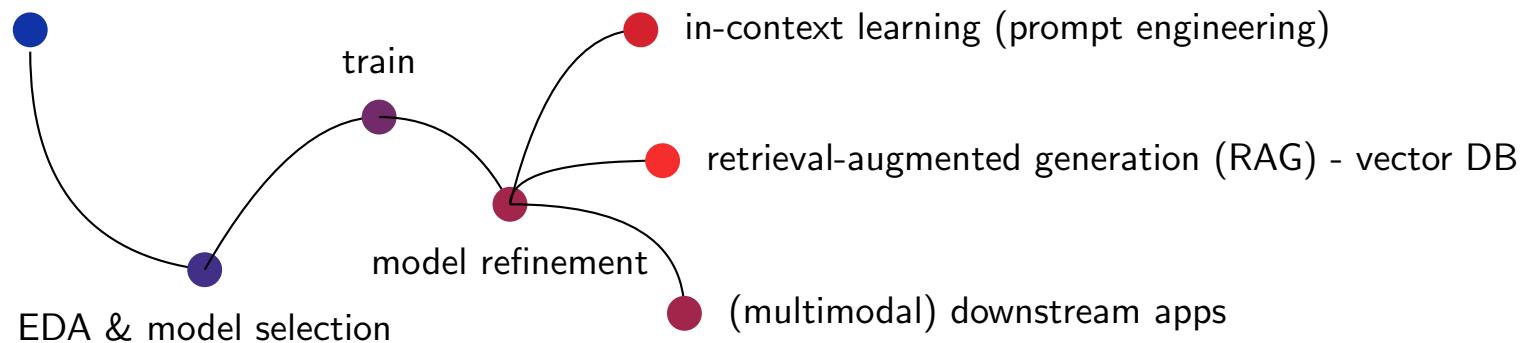
- Foundation Models
 - GPT-x/Chat-GPT - OpenAI, Llama-x - Meta, PaLM-x (Bard) - Google
- # parameters
 - generative pre-trained transformer (GPT) - GPT-1: 117M, GPT-2: 1.5B, GPT-3: 175B, GPT-4: 100T, GPT-4o: 200B
 - large language model Meta AI (Llama) - Llama1: 65B, Llama2: 70B, Llama3: 70B
 - scaling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

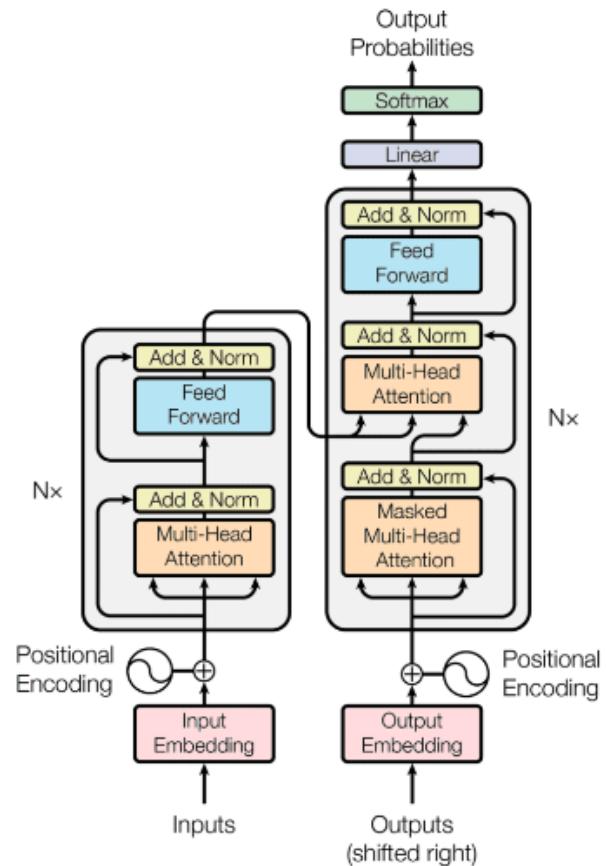
LLM architectural secret (or known) sauce

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

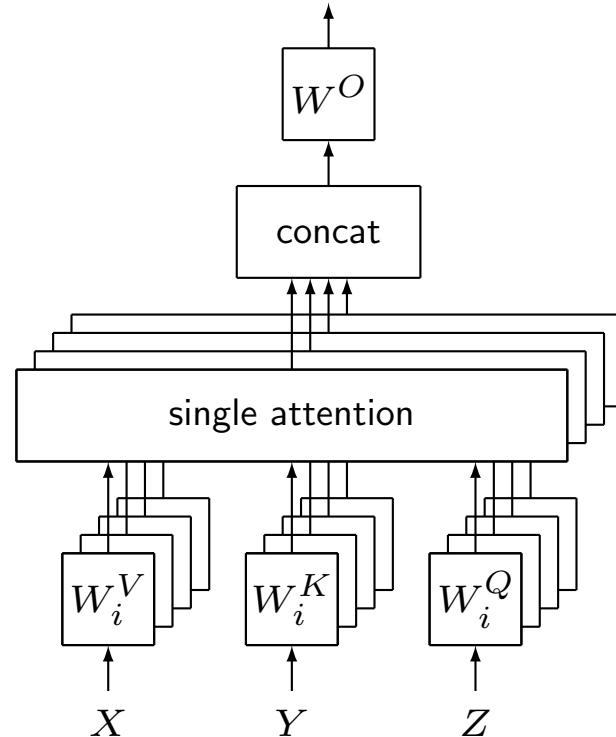
$$X \in \mathbf{R}^{d_e \times m}, Y \in \mathbf{R}^{d_e \times m}, Z \in \mathbf{R}^{d_e \times n}$$

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!*

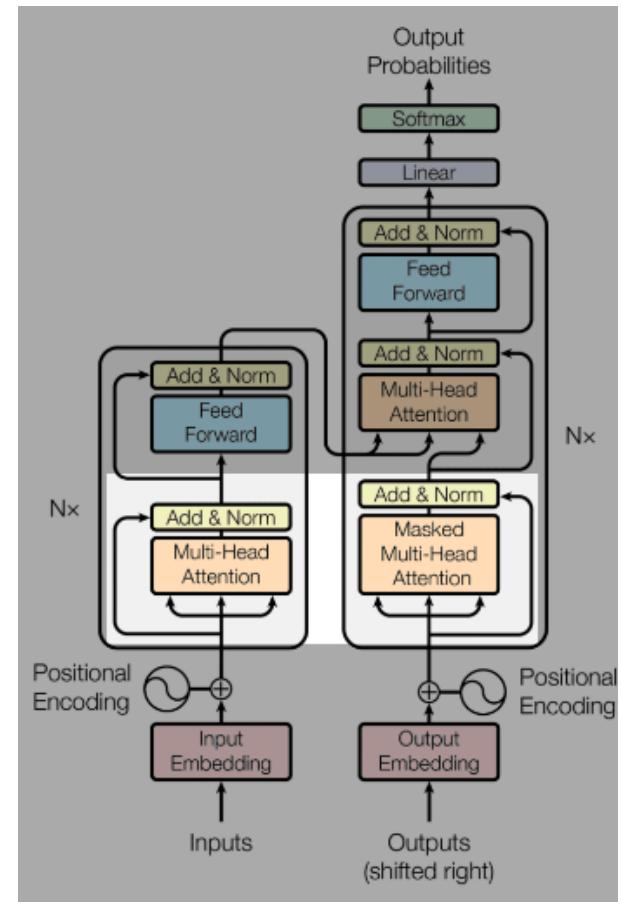
$$W^O \begin{bmatrix} A_1 \\ \vdots \\ A_h \end{bmatrix} \in \mathbf{R}^{d_e \times n},$$

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



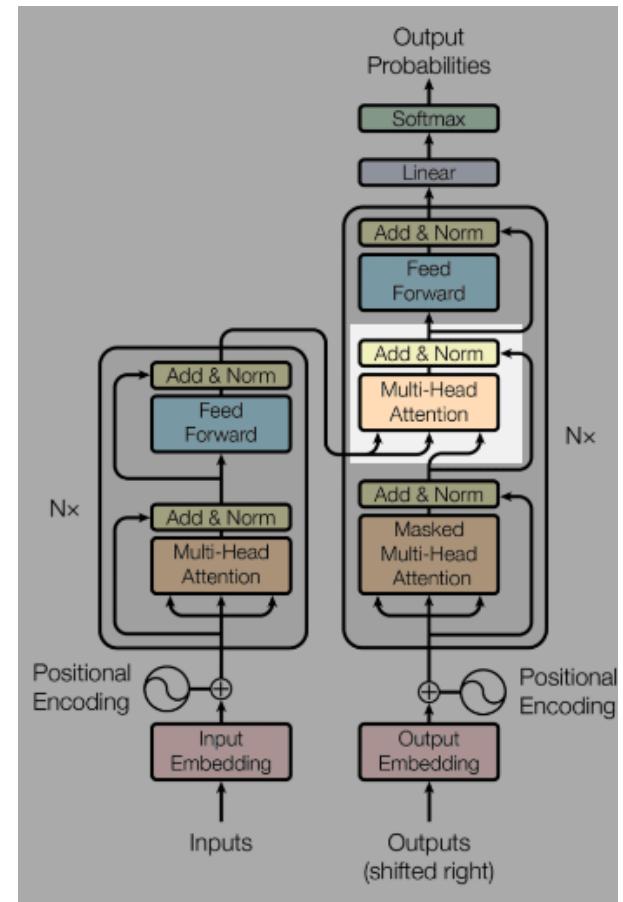
Self attention

- $m = n$
- 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

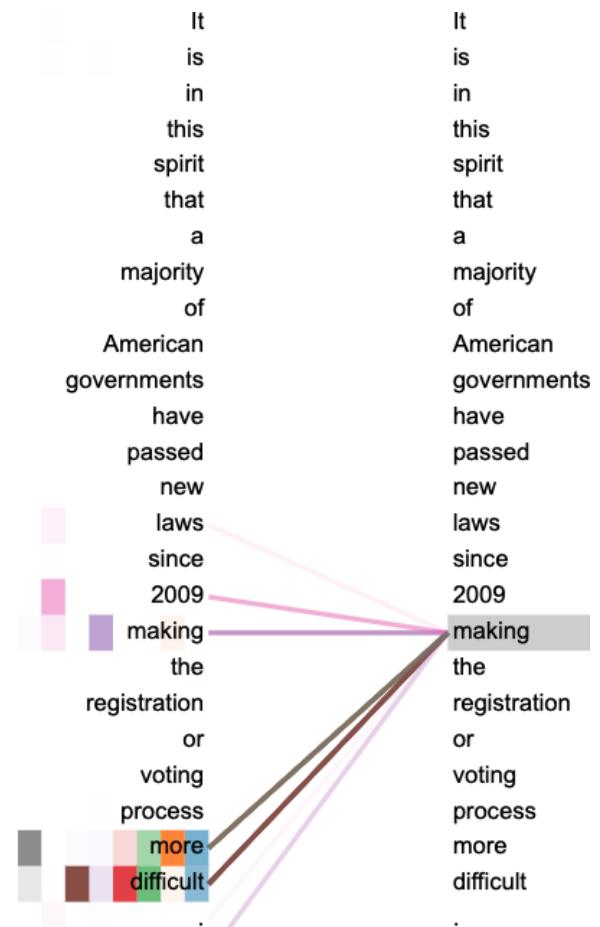


Visualization of self attentions

example sentence

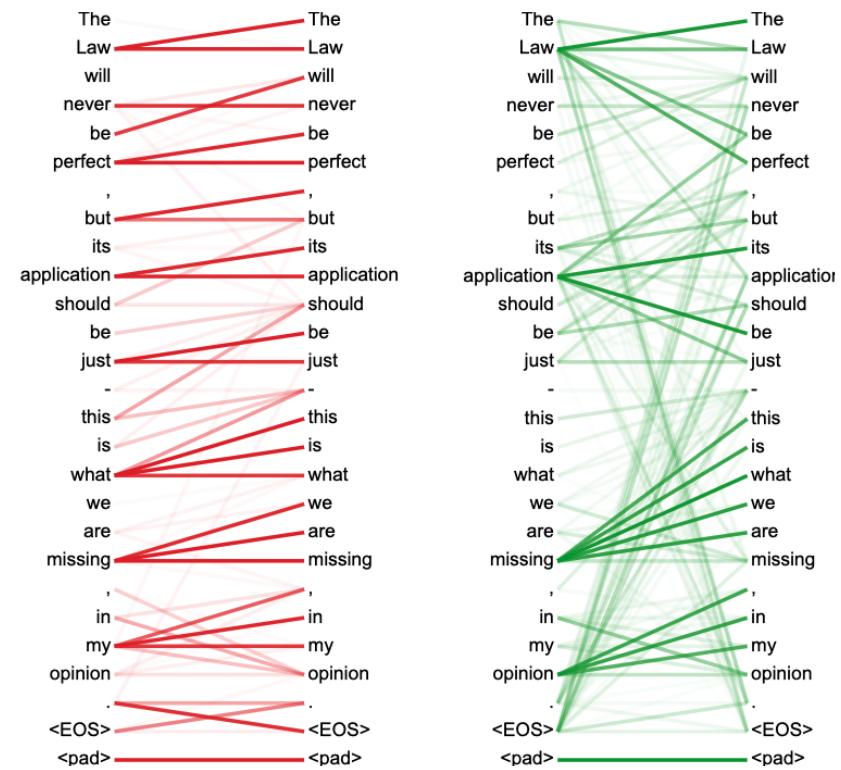
"It is in this spirit that a majority of American governments have passed new laws since 2009 making the registration or voting process more difficult."

- 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"

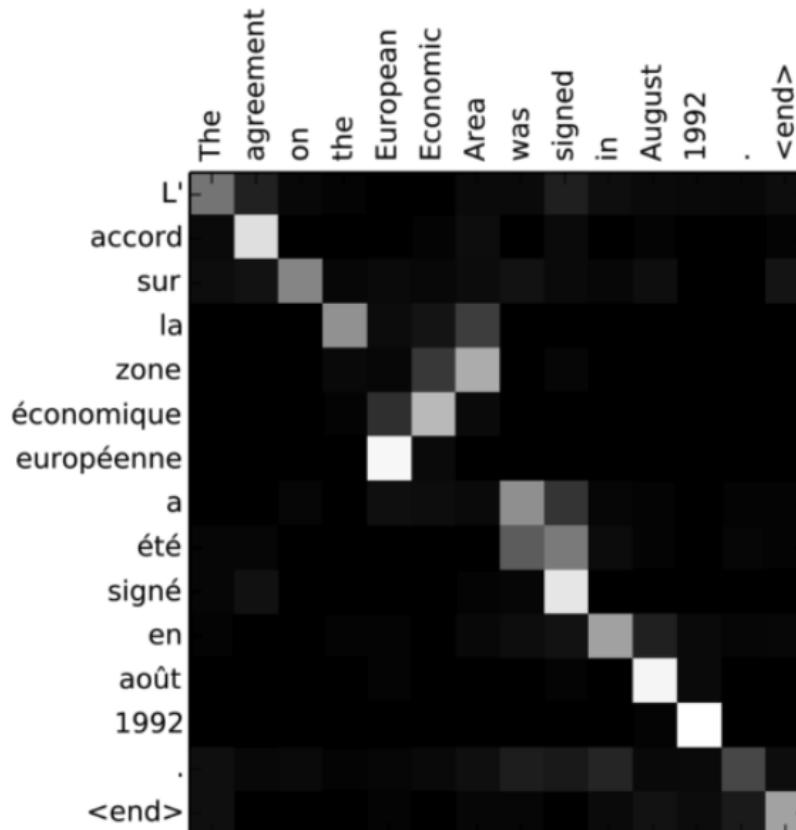


Visualization of multi-head self attentions

- 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

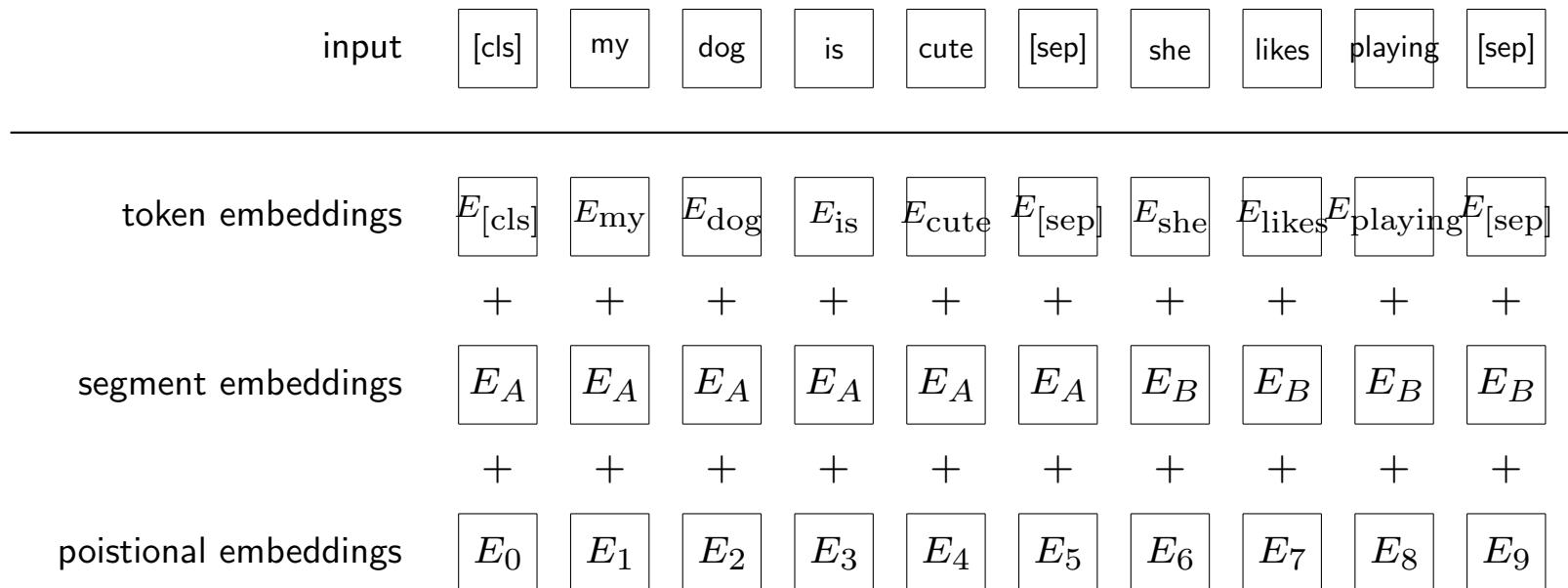
Model complexity

- 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

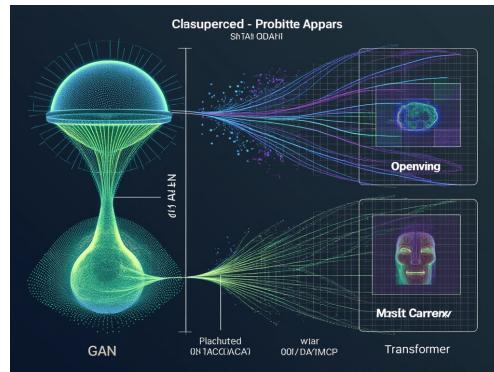
Definition of genAI

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

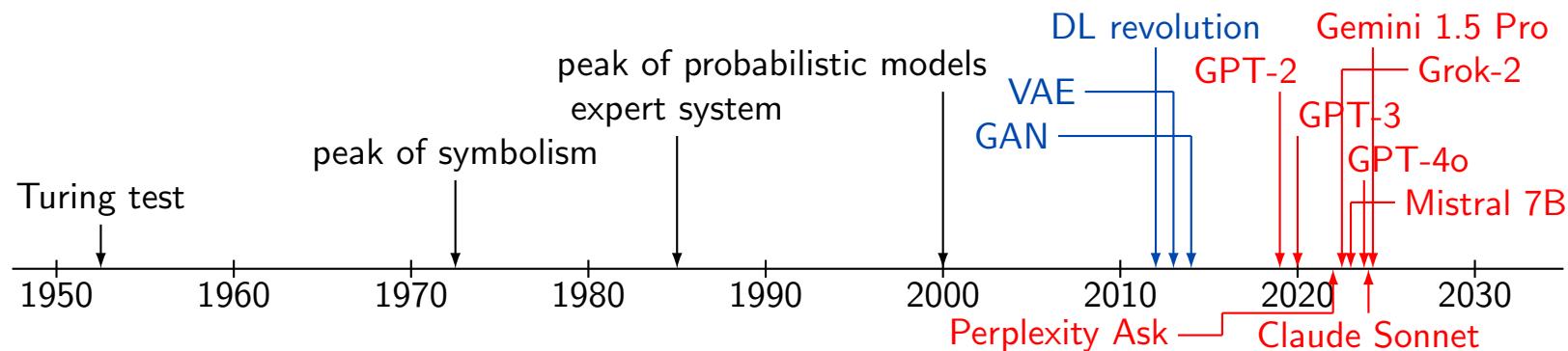
Examples of genAI in action

- 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

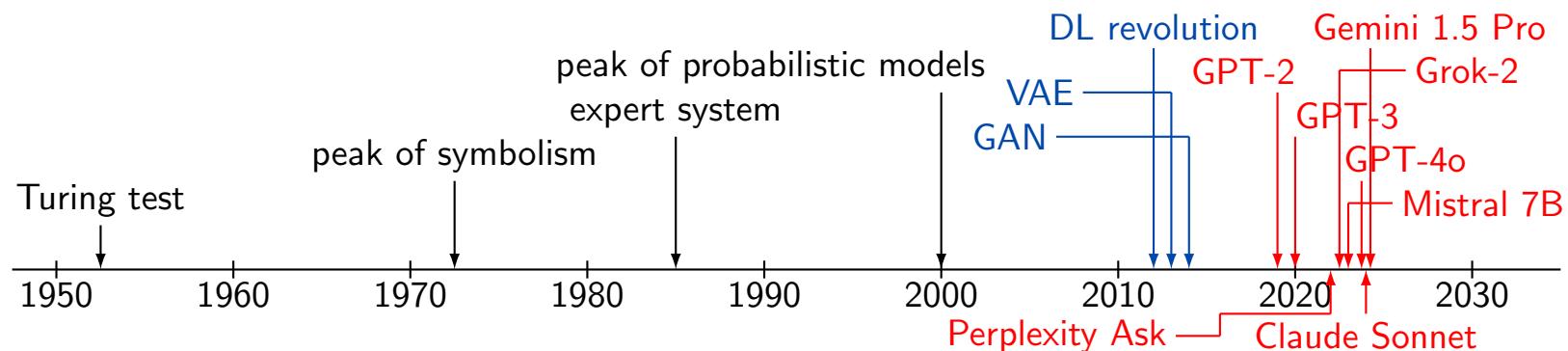
Birth of AI - early foundations & precursor technologies

- 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 ~)



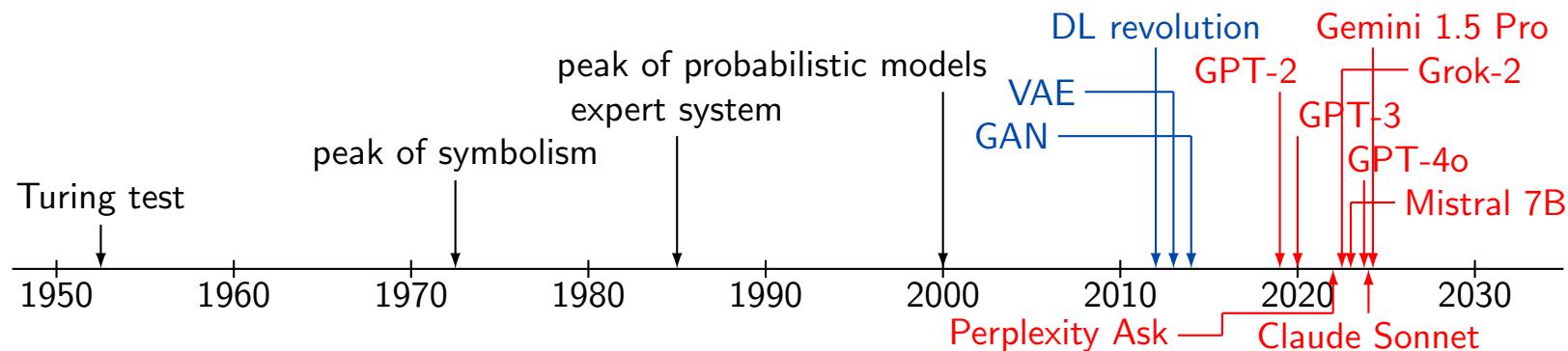
Rule-based systems & probabilistic models

- 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



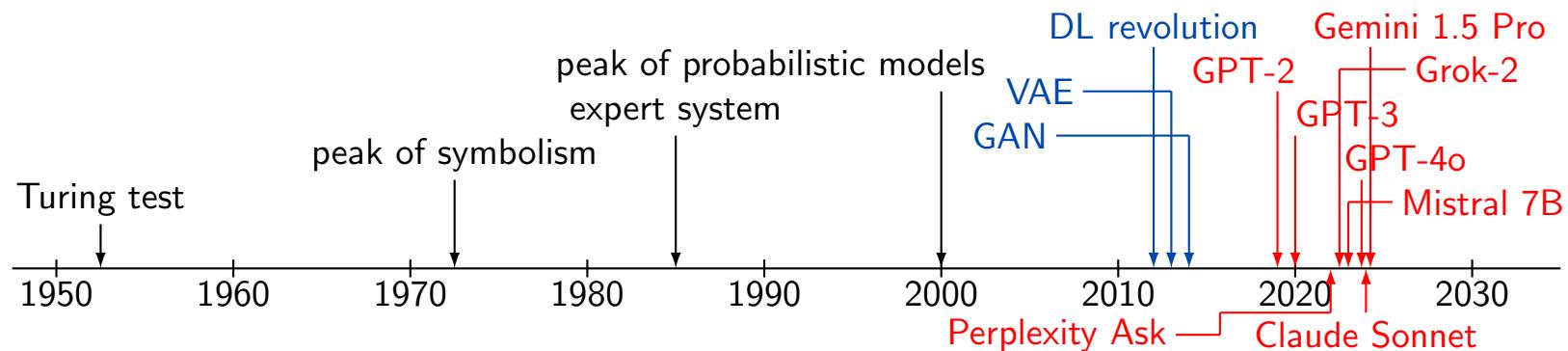
Rise of deep learning & generative models

- 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

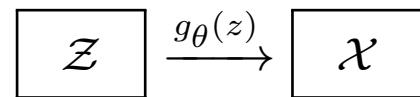
- late 2010s ~ Present
 - Transformer architecture (2017) - by Vaswani et al.
 - *revolutionized NLP*, e.g., LLM & various genAI models
 - GPT series - generative pre-trained transformer
 - GPT-2 (2019) - generating human-like texts - *marking leap in language models*
 - GPT-3 (2020) - 175B params - 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

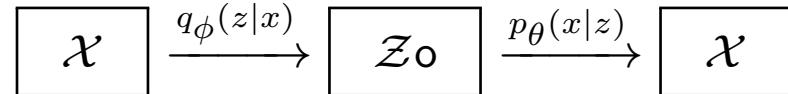
- definition of generative model



- *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)

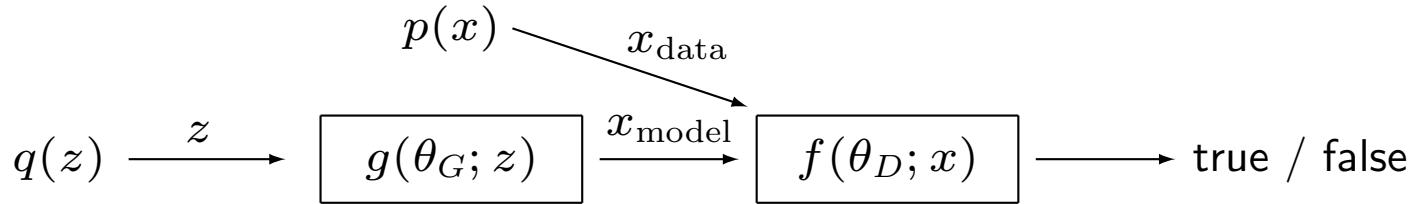
$$\mathcal{L}(\theta, \phi; x) = \mathbf{E}_{z \sim q_\phi(z|x)} \log \frac{p_\theta(x, z)}{q_\phi(z|x)}$$

- 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

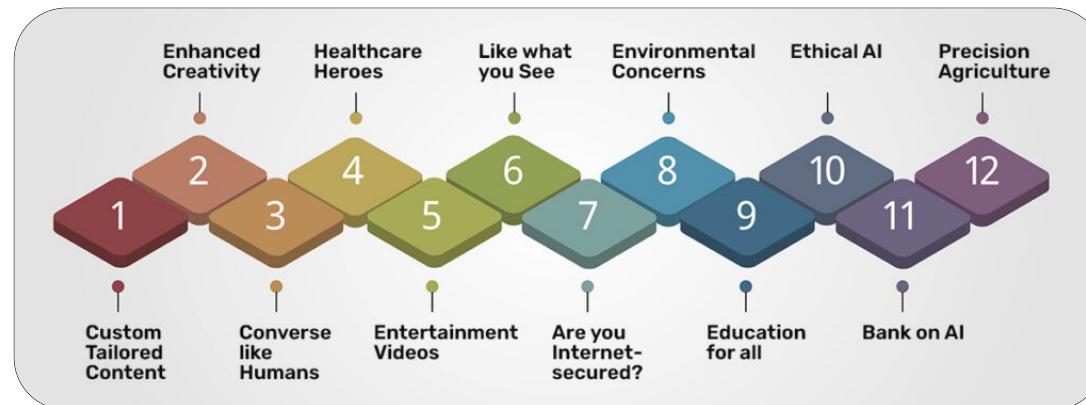
- previous sequence: x_{t-1}, x_{t-2}, \dots
- next token: x_t
- p_{θ} represented by (extremely) complicated model
 - e.g., containing multi-head & multi-layer Transformer architecture inside
- model parameters, e.g., for Llama2

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

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



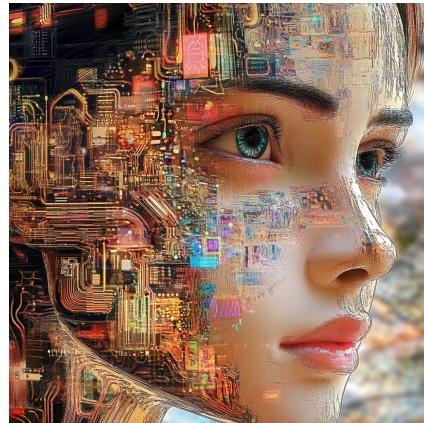
Industry & business impacts

- 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



Selected References & Sources

Selected references & sources

- Robert H. Kane “Quest for Meaning: Values, Ethics, and the Modern Experience” 2013
- Michael J. Sandel “Justice: What’s the Right Thing to Do?” 2009
- Daniel Kahneman “Thinking, Fast and Slow” 2011
- Yuval Noah Harari “Sapiens: A Brief History of Humankind” 2014
- M. Shanahan “Talking About Large Language Models” 2022
- A.Y. Halevy, P. Norvig, and F. Pereira “Unreasonable Effectiveness of Data” 2009
- A. Vaswani, et al. “Attention is all you need” @ NeurIPS 2017
- S. Yin, et. al. “A Survey on Multimodal LLMs” 2023
- Chris Miller “Chip War: The Fight for the World’s Most Critical Technology” 2022
- CEOs, CTOs, CFOs, COOs, CMOs & CCOs @ startup companies in Silicon Valley
- VCs on Sand Hill Road - Palo Alto, Menlo Park, Woodside in California, USA

References

References

- [DCLT19] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2019.
- [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.
- [KW19] Diederik P. Kingma and Max Welling. An introduction to variational autoencoders. *Foundations and Trends in Machine Learning*, 12(4):307–392, 2019.

- [VSP⁺17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of 31st Conference on Neural Information Processing Systems (NIPS)*, 2017.

Thank You