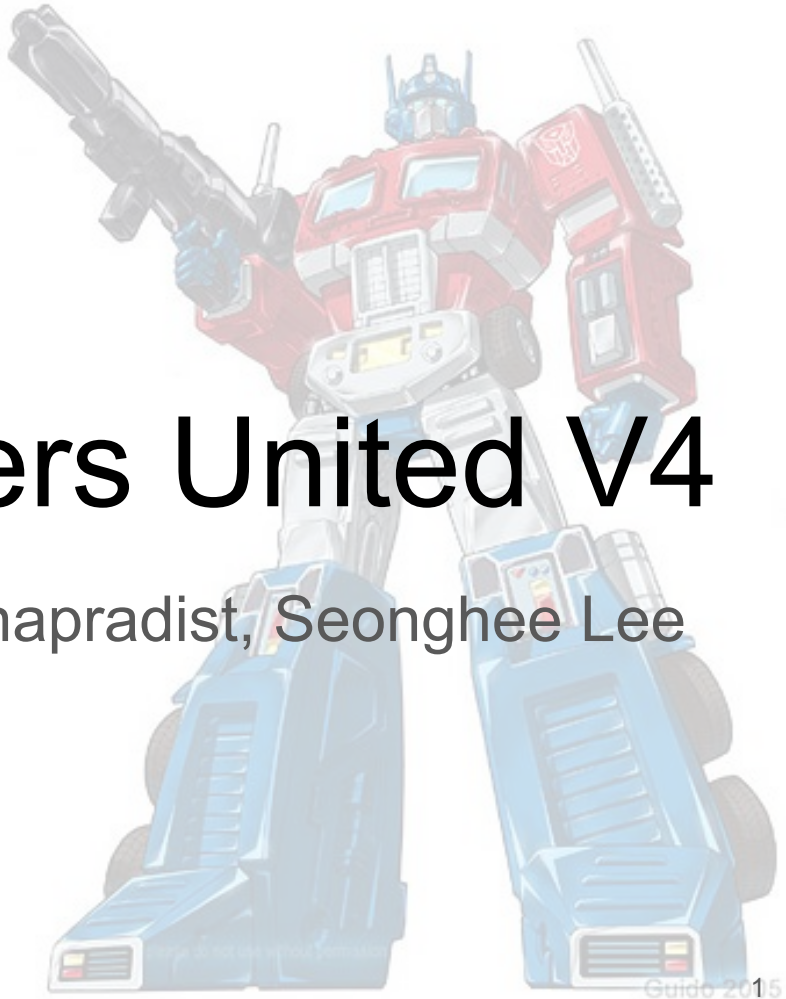
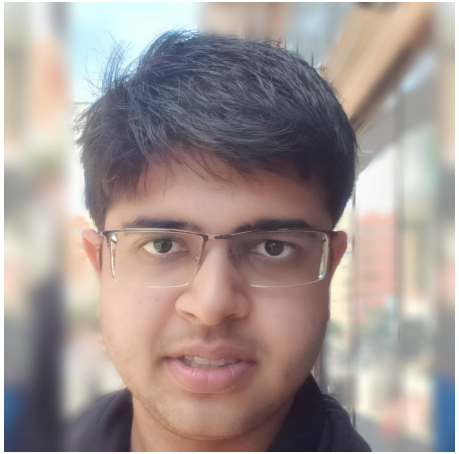
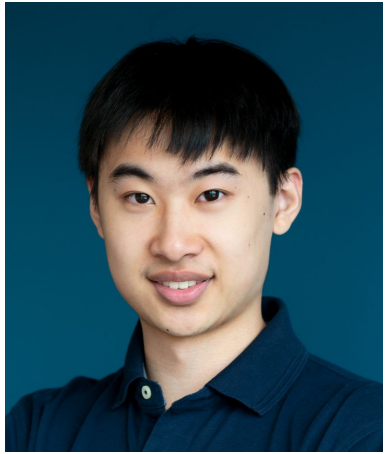
CS 25: Transformers United V4

Div Garg, Steven Feng, Emily Bunnapradist, Seonghee Lee



Instructors

Instructor Bio

Building an Generalist Personal AI Agent (**MultiOn AI**)

On a leave from CS PhD

Passionate about Robotics, AI Agents, and and building efficient learning algorithms

Research interests in RL, and generative modeling.

Previously was working with *Ian Goodfellow*

Publications in RL, robotics, autonomous-driving & 3D vision.

Previously:

- @NvidiaResearch, @GoogleAI, @AppleSPG, @UberATG
- Undergrad @Cornell

Div Garg

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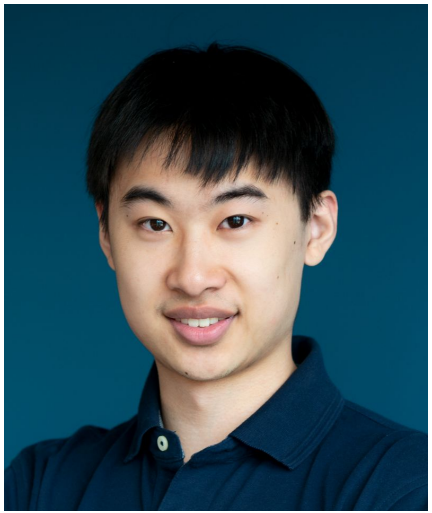
Website: **divyanshgarg.com**
Twitter: **@DivGarg9**

Instructor Bio



Steven Feng

Email: **syfeng@stanford.edu**
Website: **styfeng.github.io**
Twitter: **@stevenyfeng**

2nd-year CS PhD student

Upcoming:

- Research Intern at NVIDIA

Previously:

- Master's at Carnegie Mellon
- Undergrad at University of Waterloo
- Research Intern at Amazon

Research interests:

- NLP and language/text
- Controllability and reasoning of LMs
- Learning efficiency of LLMs
- Text and visual generation
- CV and multimodal grounding
- Cogsci + psych inspired work

For fun:

- Piano/music
  - **Stanford Piano Club!**
  - https://piano.stanford.edu/
  - IG: **@stanfordpiano**

Instructor Bio

Undergrad in Math + CogSci & Master's in CS @ Stanford

Interested in the intersection of artificial intelligence and natural intelligence, as well as neuroscience, philosophy.

Research interests in biologically inspired neural networks, modeling cognition & knowledge acquisition, and machine and human interpretability.

Currently:

NLP Interpretability research @ Stanford

Previously:

Research on computational neuroscience @ Stanford Med & NYU Courant, research on computational cognitive science @ CoCoLab

Emily Bunnapradist

Email: **embunna@stanford.edu**
Twitter: **@emilybunna**

Instructor Bio

Seonghee Lee

Email: **shl1027@stanford.edu**
Website: **https://shljessie.github.io/**

1st year CS masters Student

Research Interests

- Natural Language Processing
- Visual Language Models
- Human AI Interaction
- Accessibility Research

Current Research

- Visual LM based Image Editor with Prof Hari Subramonyam
- Consistency in LLM Agents with Prof Diyi Yang

Previously:

- Incoming @Microsoft Research @Motional @HyundaiMotorCompany
- Undergrad @Cornell

Course Logistics

- Lectures: Thursdays 4:30 - 5:50 pm PDT (Gates B01 and Zoom)
- Enrollment: approx. 190 students max, also waitlist [Axess]
- Only homework: attendance to the lectures!
    - Allowed 3 unexcused absences - track attendance using a Google Form starting next week
- In-person attendance highly encouraged, and required for weeks with in-person speakers
- Ask questions during and after presentation (chat in Zoom or use Slido, no voice on Zoom!)
    - Submit questions to **sli.do** (code: CS25)
- Lectures livestreamed and recorded (released 2 weeks later)
- Contact us at: cs25-spr2324-staff@lists.stanford.edu
- Join our Discord server! https://discord.gg/2vE7gbsjzA

What’s New This Time?

- Large lecture hall and more enrollment
- Professional recording and Zoom livestreaming (to the public)
- Social events (TBD)
- Potential 1-on-1 networking with speakers!
- Auditing open to the public: join the Zoom livestream!
- Attendance form: write 2-3 sentences about what you learned that week

Important Disclaimers: Recording + Livestreaming

- We will be recording + broadcasting + publishing the speaker presentations (Zoom/YouTube)
- You can also access these recordings by logging into the course Canvas site
- Video cameras located in the back of the room will capture the instructor presentations
- While the cameras are positioned with the intention of recording only the instructor, occasionally a part of your image or voice might be incidentally captured
- Before the recordings are published, an editor will review to remove any student appearances
- If you have questions, please contact a member of the teaching team
- TBD: in-person questions, I believe can still raise hand and ask, and we (or the speaker) will repeat them - editors will take care of modifying/blocking out your voice

Important Disclaimers: Auditing & Zoom

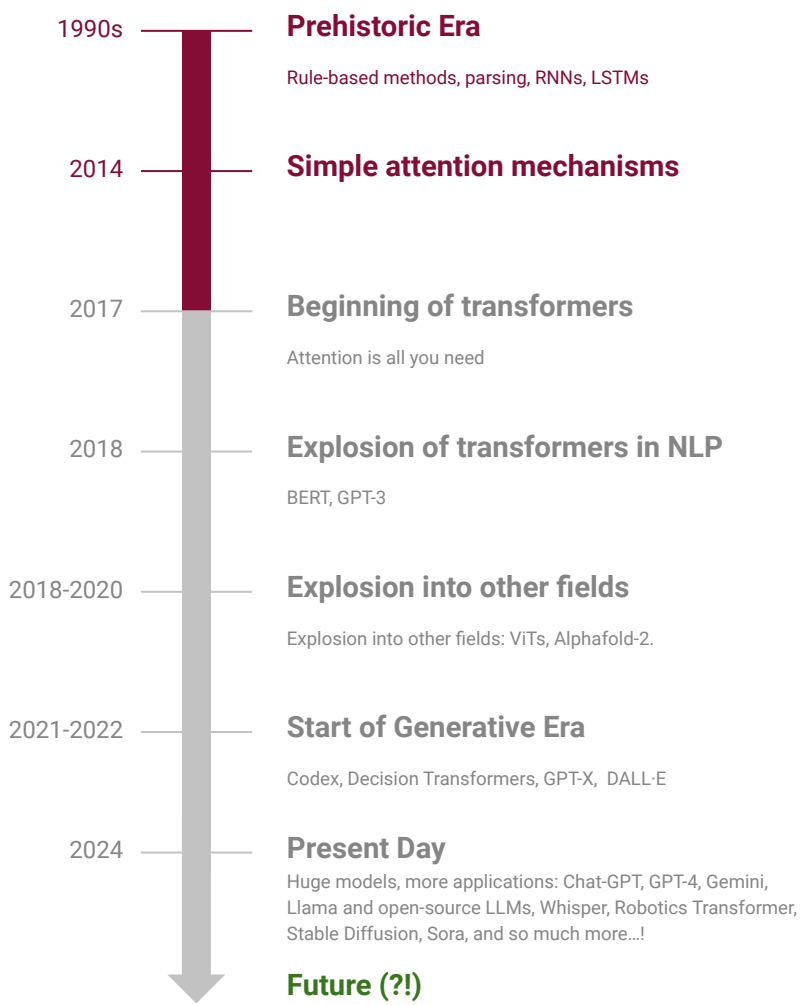
- Zoom meeting has limit of 500 participants, trying to increase to a webinar (1000+)
    - Another reason enrolled students should come in person!
- Do not unmute yourself on Zoom! Any questions/concerns? Send in chat
- In-person auditors: please give seats to enrolled students who have priority
- Inappropriate behavior will result in blacklist from the course (and maybe other consequences with Stanford)

What we hope you will learn

- How transformers work
- How they are being applied (beyond just NLP)
- Some new directions of research…
- Innovative techniques and applications of LLMs
- Remaining challenges/weaknesses

Transformers and LLMs: An Introduction

Attention Timeline



Challenges and Weaknesses

Challenges of NLP:

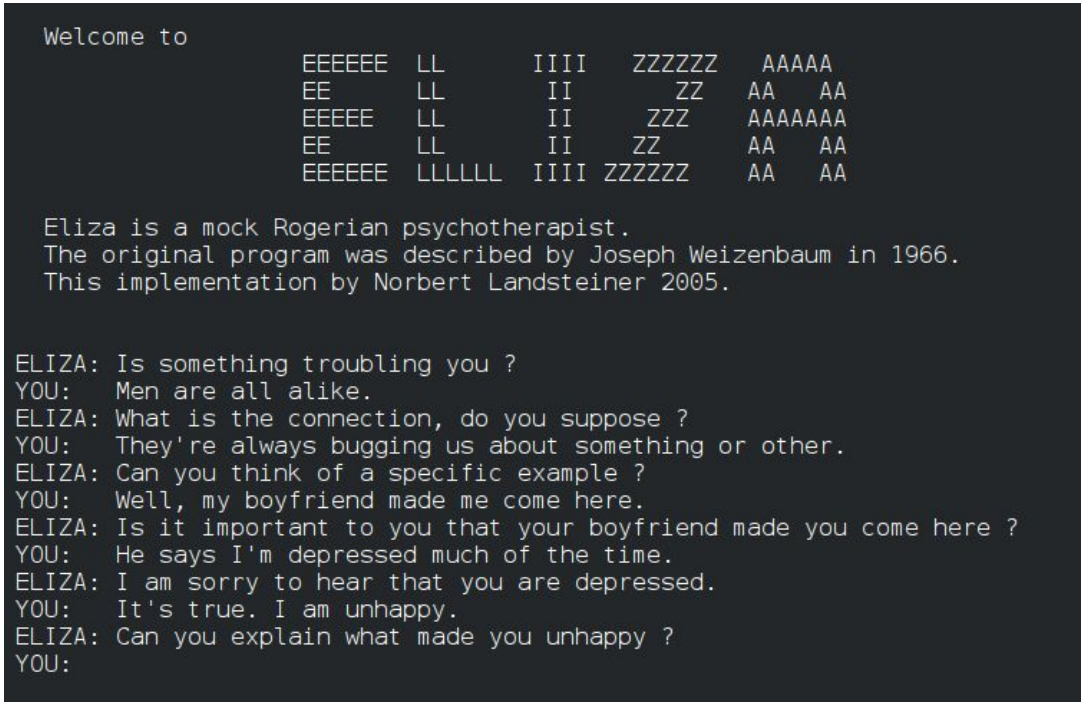
- Discrete nature of text
- More difficult data augmentation
- Text is “precise” - one wrong word changes entire meaning of a sentence
- Potential for long context lengths and memories (e.g. conversations)
- Many more…

Weaknesses of earlier models/apporoaches:

- Short context length
- “Linear” reasoning - no attention mechanism to focus on other parts
- Earlier approaches (e.g. word2vec) do not adapt based on context

NLP Throughout the Years

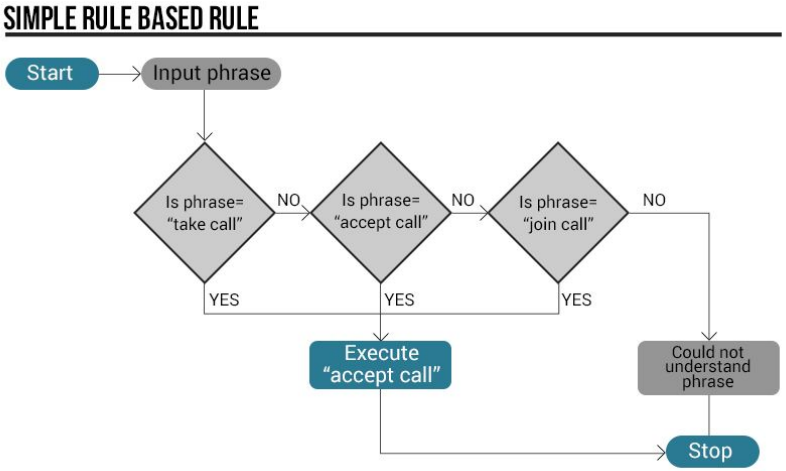
Rule Based NLP Systems

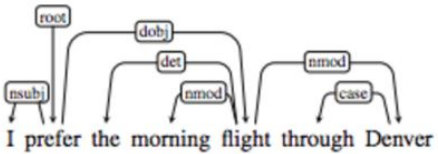


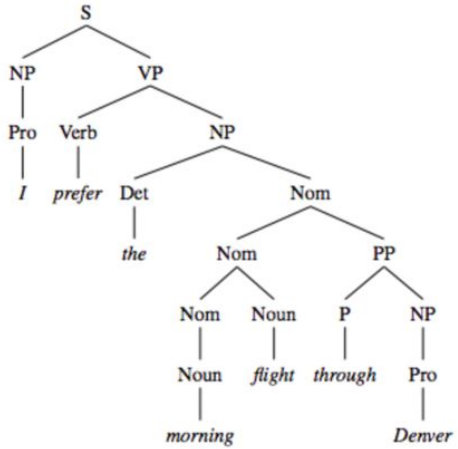
Eliza Chatbot (1966), MIT by Joseph Weizenbaum

Linguistic Foundations

- Rule-based approaches
- Semantic parsing
- Analyzing linguistic structure and grammars of text

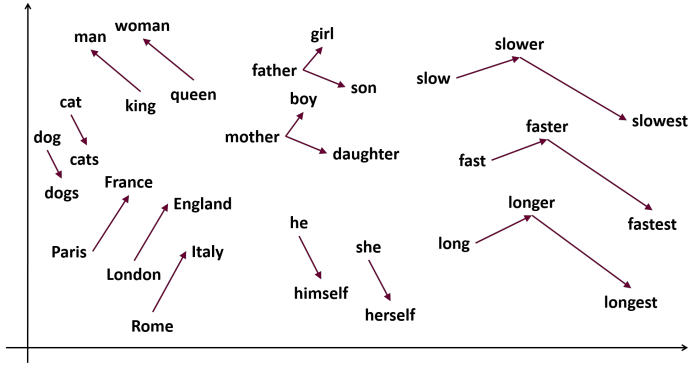






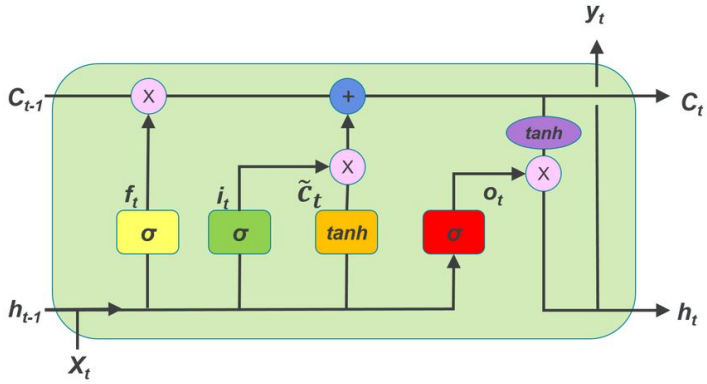
Word Embeddings

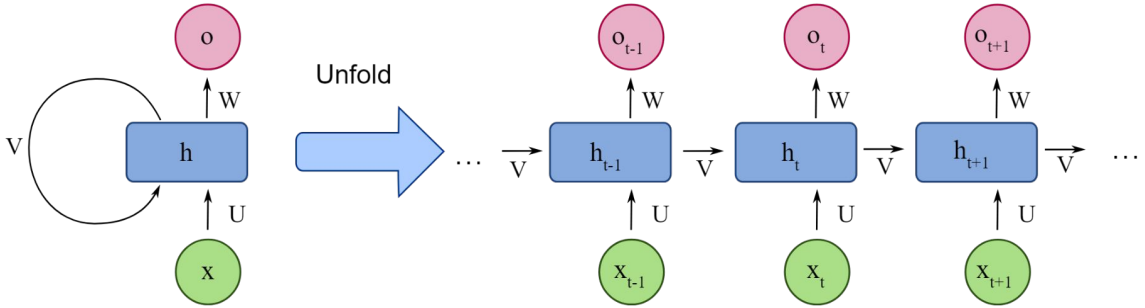
- Represent each word as a “vector” of numbers
- Converts a “discrete” representation to “continuous”, allowing for:
  - More “fine-grained” representations of words
  - Useful computations such as cosine/eucl distance
  - Visualization and mapping of words onto a semantic space
- Examples:
  - Word2Vec (2013), GloVe, BERT, ELMo



Seq2seq Models

- Recurrent Neural Networks (RNNs)
- Long Short-Term Memory Networks (LSTMs)
- “Dependency” and info between tokens
- Gates to “control memory” and flow of information

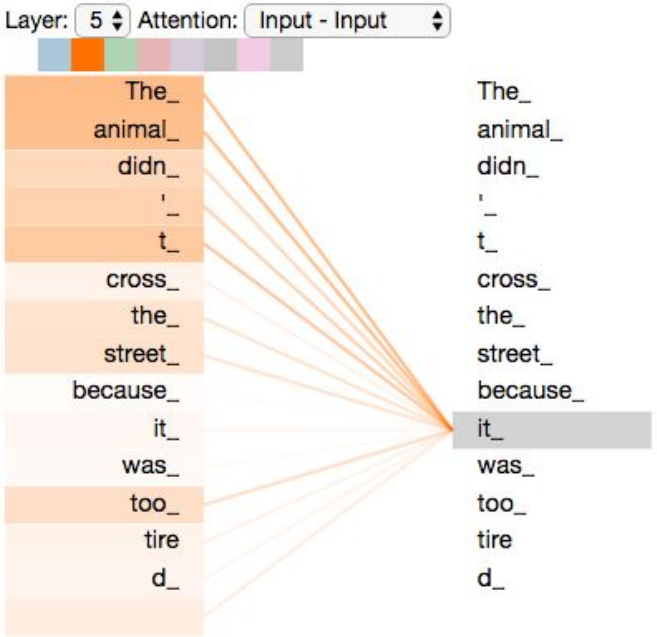




Attention and Transformers

- Allows to “focus attention” on particular aspects of the input text
- Done by using a set of parameters, called "weights," that determine how much attention should be paid to each input at each time step
- These weights are computed using a combination of the input and the current hidden state of the model
- Attention weights are computed (dot product of the query, key and value matrix), then a softmax function is applied to the dot product

$$\text{attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



https://arxiv.org/abs/1706.03762
https://jalammar.github.io/illustrated-transformer/

Analogy for Q, K, V

- Library system
- Imagine you're looking for information on a specific topic (query)
- Each book in the library has a summary (key) that helps identify if it contains the information you're looking for
- Once you find a match between your query and a summary, you access the book to get the detailed information (value) you need
- Here, in Attention, we do a “soft match” across multiple values, e.g. get info from multiple books (“book 1 is most relevant, then book 2, then book 3, etc.”)

$$\text{attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Attention and Transformers

- Attention weights used to compute the context vector, which is a weighted sum of the input at different positions
- Context vector is used to update the hidden state of the model, which is used to generate the final output
- "Pay attention" to different parts of the input, depending on the task at hand → more accurate and natural-sounding output, esp. when working with longer inputs (e.g. paragraphs)

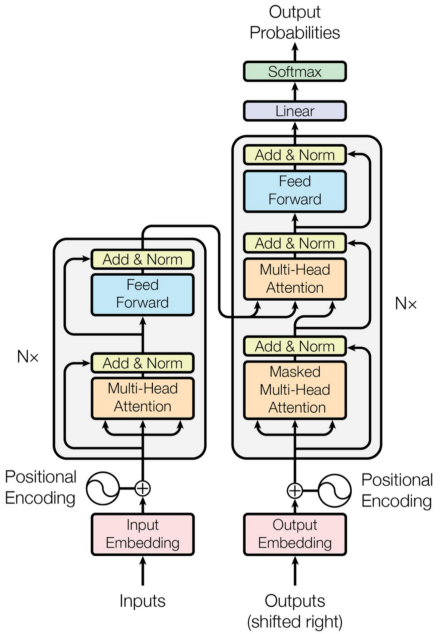
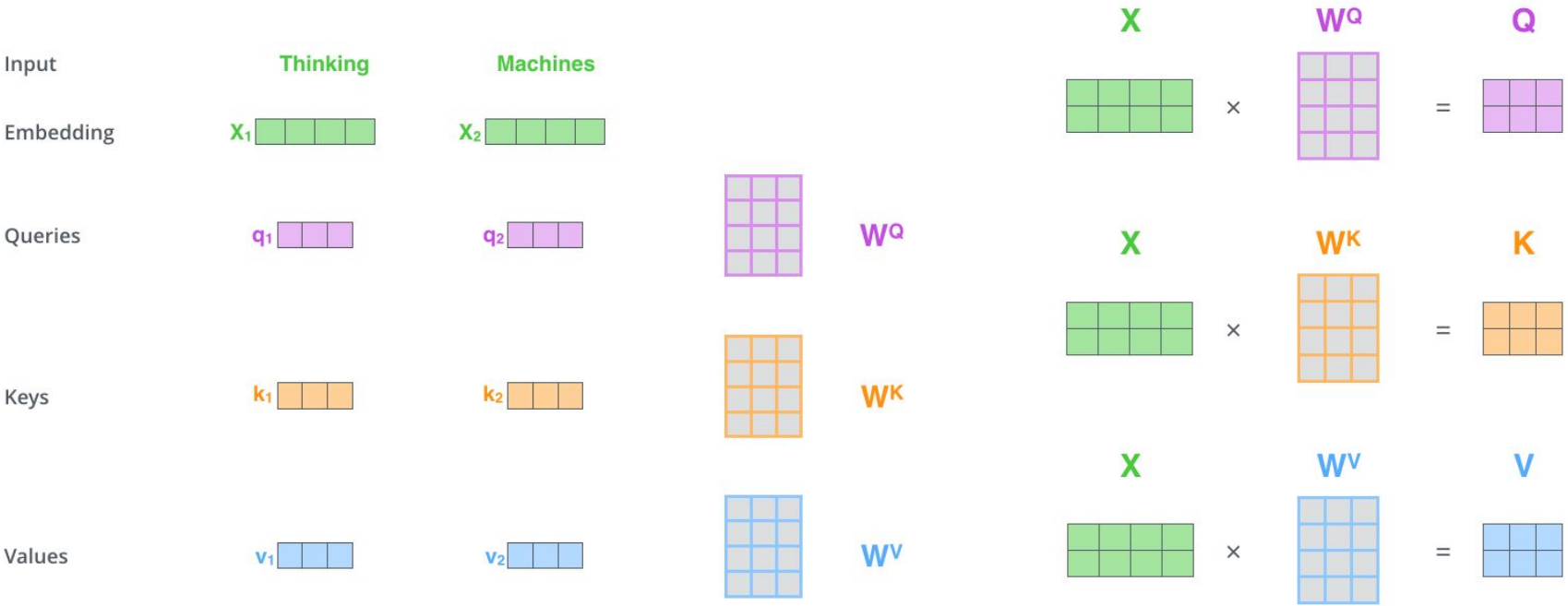


Figure 1: The Transformer - model architecture.

Self-Attention



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Transformer & Multi-Head Attention

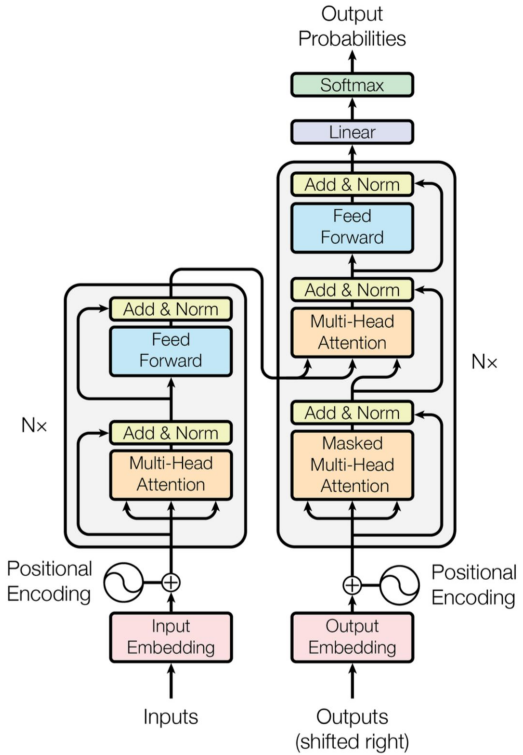
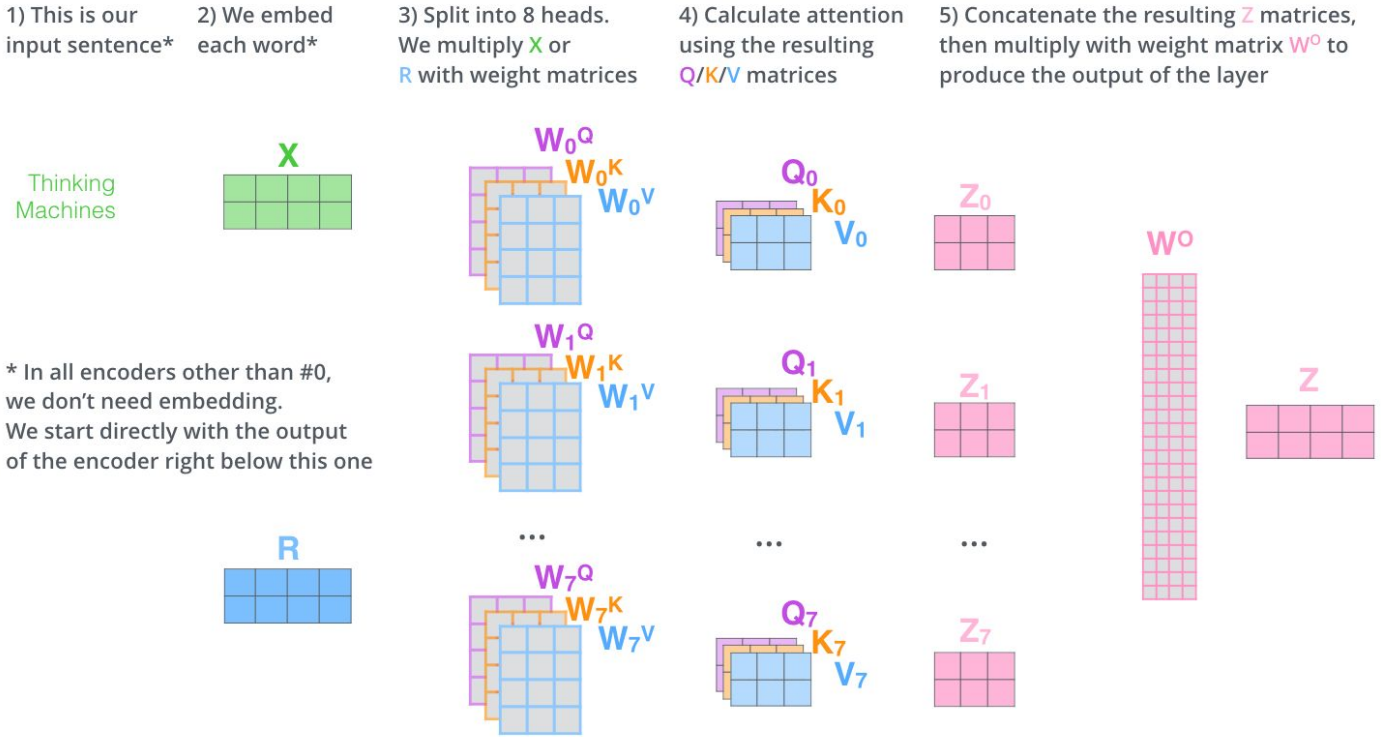


Figure 1: The Transformer - model architecture.

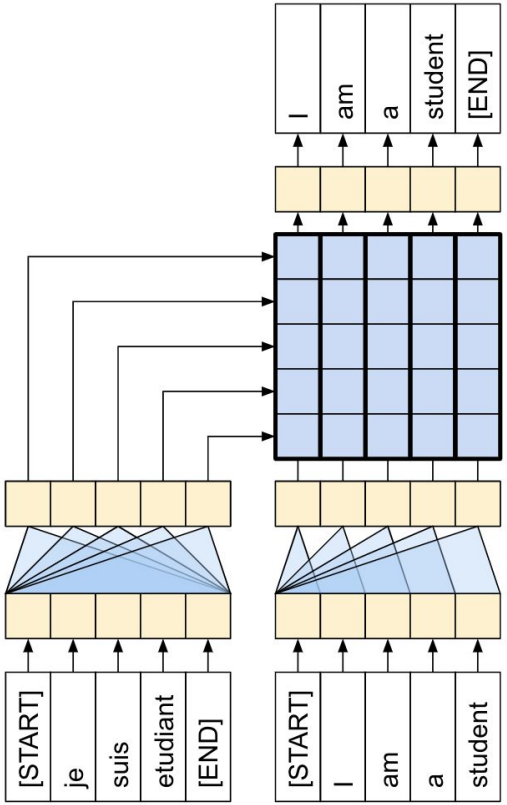
"Attention Is All You Need"
https://arxiv.org/abs/1706.03762

Multi-Head Attention



https://jalammar.github.io/illustrated-transformer/

Cross-Attention (e.g. Machine Translation)



https://jalammar.github.io/illustrated-transformer/

Transformers vs. RNNs

Challenges with RNNs	Transformers
● Long range dependencies ● Gradient vanishing and explosion ● Large # of training steps ● Sequential/recurrence → can't parallelize ● Complexity per layer: $O(n*d^2)$	● Can model long-range dependencies ● No gradient vanishing and explosion ● Fewer training steps ● Can parallelize computation! ● Complexity per layer: $O(n^2*d)$

Large Language Models

- Scaled up versions of Transformer architecture, e.g. millions/billions of parameters
- Typically trained on massive amounts of “general” textual data (e.g. web corpus)
- Training objective is typically “next token prediction”: $P(W_{t+1}|W_t,W_{t-1},...,W_1)$
- Emergent abilities as they scale up (e.g. chain-of-thought reasoning)
- Heavy computational cost (time, money, GPUs)
- Larger general ones: “plug-and-play” with few or zero-shot learning
  - Train once, then adapt to other tasks without needing to retrain
  - E.g. in-context learning and prompting

Emergent Abilities of Large Language Models

- Why do LLMs work so well? What happens as you scale up?
- Potential explanation: emergent abilities!
- An ability is emergent if it is present in larger but not smaller models
- Not have been directly predicted by extrapolating from smaller models
- Performance is near-random until a certain critical threshold, then improves heavily
  - Known as a “phase transition” and would not have been extrapolated

Wei et al., 2022. https://arxiv.org/abs/2206.07682

Few-Shot Prompting

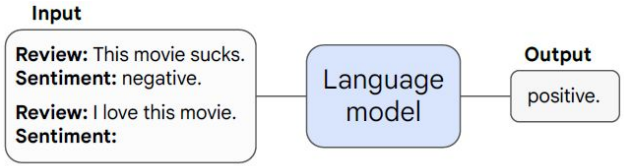


Figure 1: Example of an input and output for few-shot prompting.

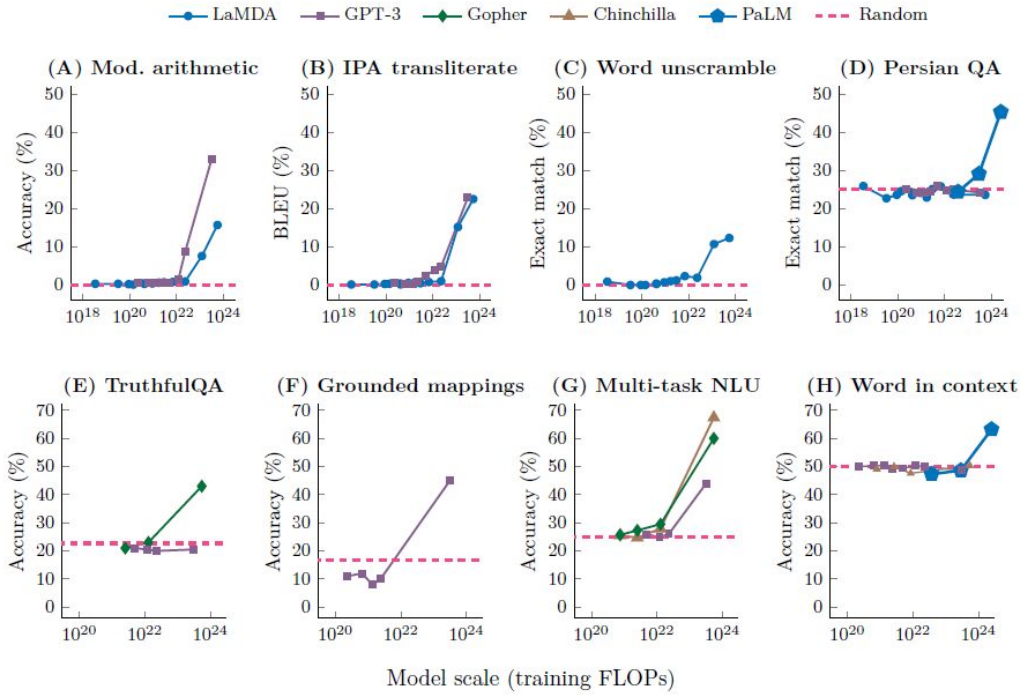


Figure 2: Eight examples of emergence in the few-shot prompting setting. Each point is a separate model. The ability to perform a task via few-shot prompting is emergent when a language model achieves random performance until a certain scale, after which performance significantly increases to well-above random. Note that models that used more training compute also typically have more parameters—hence, we show an analogous figure with number of model parameters instead of training FLOPs as the x-axis in Figure 11. A–D: BIG-Bench (2022), 2-shot. E: Lin et al. (2021) and Rae et al. (2021). F: Patel & Pavlick (2022). G: Hendrycks et al. (2021a), Rae et al. (2021), and Hoffmann et al. (2022). H: Brown et al. (2020), Hoffmann et al. (2022), and Chowdhery et al. (2022) on the WiC benchmark (Pilehvar & Camacho-Collados, 2019).

Potential Explanations of Emergence

- Currently few explanations for why these abilities emerge
- Evaluation metrics used to measure these abilities may not fully explain why they emerge
- Disclaimer: maybe emergent abilities of LLMs are a mirage!!!
  - https://arxiv.org/abs/2304.15004
  - *“Emergent abilities appear due to the researcher's choice of metric rather than due to fundamental changes in model behavior with scale”*

Beyond Scaling

- Further scaling could endow even-larger LMs with new emergent abilities
- While scaling is a factor in emergent abilities, it is not the only factor
- E.g. new architectures, higher-quality data, and improved training procedures, could enable emergent abilities on smaller models
- Further research may make the abilities available for smaller models
- Other directions: improving few-shot prompting abilities of LMs, theoretical and interpretability research, and computational linguistics work

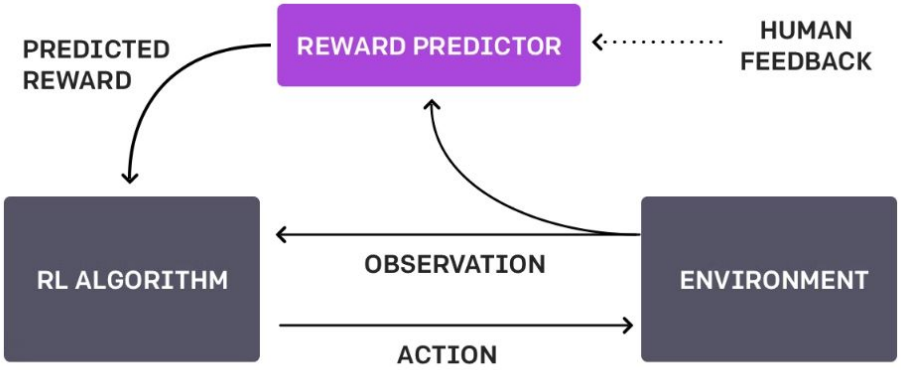
Questions for the Group

- Do you believe emergent abilities will continue to arise with more scale? Will there be a limit? Possibly even diminishing returns?
- What are your thoughts on the current trend of larger models and more data? Do you believe this is a good direction for the research community, or rather “inhibiting our creativity”?
- Thoughts on retrieval-based or retrieval-augmented systems compared to simply “learning everything” within the parameters of the model?

RLHF, ChatGPT, GPT-4, Gemini

Reinforcement Learning with Human Feedback (RLHF)

- RLHF: technique that trains a "reward model" directly from human feedback
- Uses the model as a reward function to optimize an agent's policy using reinforcement learning (RL) through an optimization algorithm
- Ask humans to rank instances of the agent's behavior, e.g. which produced response is better



Direct Preference Optimization (DPO)

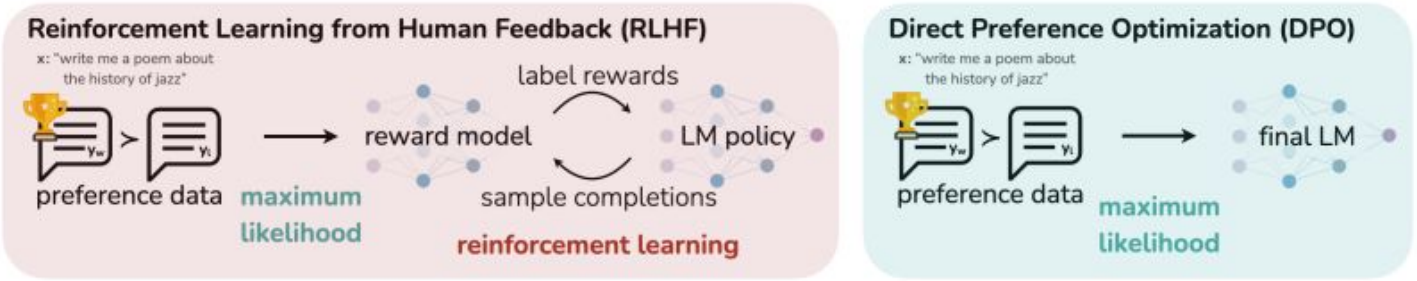
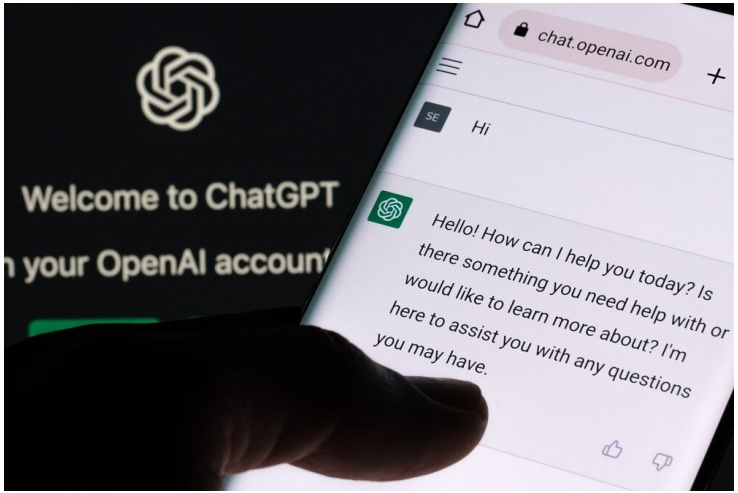


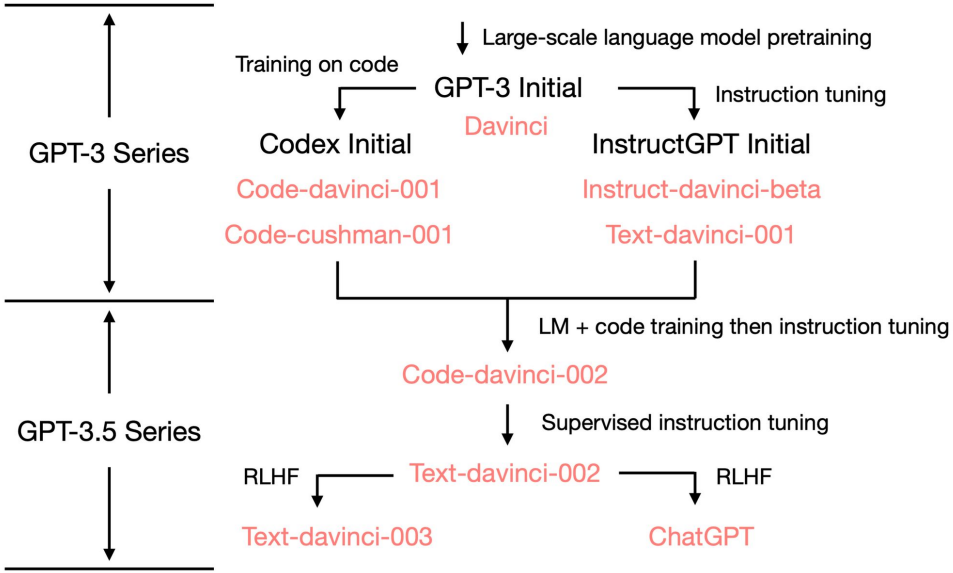
Figure 1: **DPO optimizes for human preferences while avoiding reinforcement learning.** Existing methods for fine-tuning language models with human feedback first fit a reward model to a dataset of prompts and human preferences over pairs of responses, and then use RL to find a policy that maximizes the learned reward. In contrast, DPO directly optimizes for the policy best satisfying the preferences with a simple classification objective, without an explicit reward function or RL.

https://arxiv.org/pdf/2305.18290.pdf

ChatGPT

- Finetuned on GPT-3.5, which is a series of models trained on a mix of text and code using instruction tuning and RLHF
- Taken the world by storm!





GPT-4

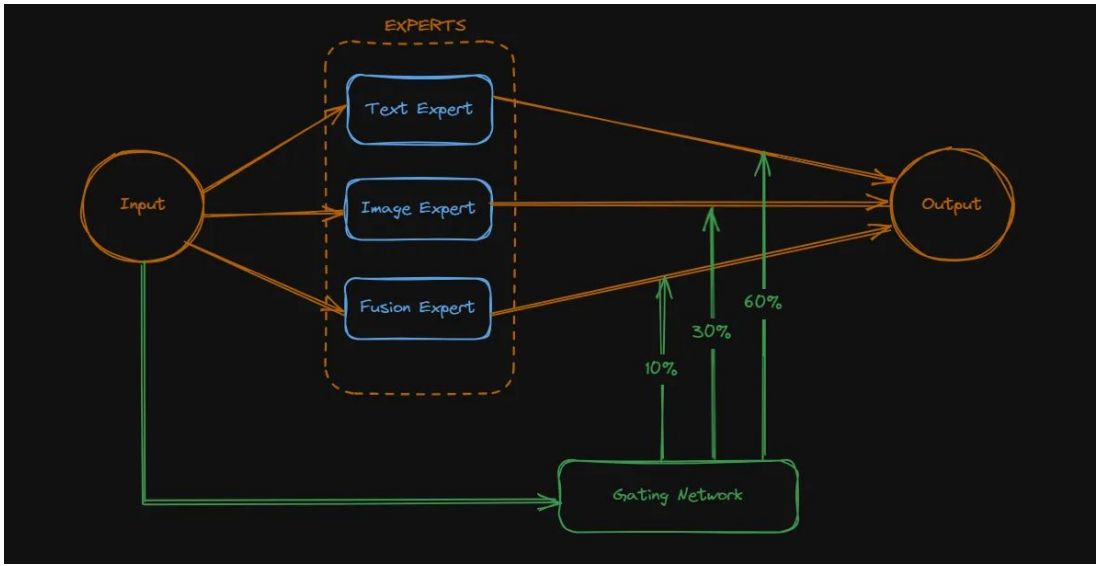
- Supervised learning on large dataset, then RLHF and RLAIF
- GPT-4 trained on both images and text, vision is also out!
  - Discuss humor in images, summarize screenshot text, etc.
- GPT-4 is "more reliable, creative, and able to handle much more nuanced instructions than GPT-3.5”
- Much longer context windows of 8,192 and 32,768 tokens
- Does exceptionally well on standardized tests
- Did not release technical details of GPT-4

Gemini

- Latest: **Gemini 1.5 Pro**
- Gemini Ultra performs better than ChatGPT on 30 of the 32 academic benchmarks in reasoning and understanding it tested on.
- Effectively processes and integrates data from diff modalities:
  - Text, audio, image, video
- Based on a Mixture-of-Experts (MoE) model
  - Significantly improves efficiency in training and application

Gemini

- Based on a Mixture-of-Experts (MoE) model
  - Combination of multiple small Neural networks known as ‘Experts’ which are trained and capable of handling particular data and performing specialised tasks.
  - ‘Gating network’ which predicts which response is best suited to address the request.



Source link

Gemini 1.5

Where we are (2024)

Recently Taken Off:

- LLM boom: ChatGPT, GPT-4, Gemini, open-source models
- Human alignment and interaction
  - Reinforcement learning & human feedback
- Controlling toxicity, bias, and ethics
- More use in unique applications: audio, art/music, neuro/bio, coding, games, physical tasks, etc.
  - Speakers will touch (or have touched) on these!
- Other: diffusion models (e.g. text-to-image/video gen)
  - Also, Diffusion Transformer (DiT)

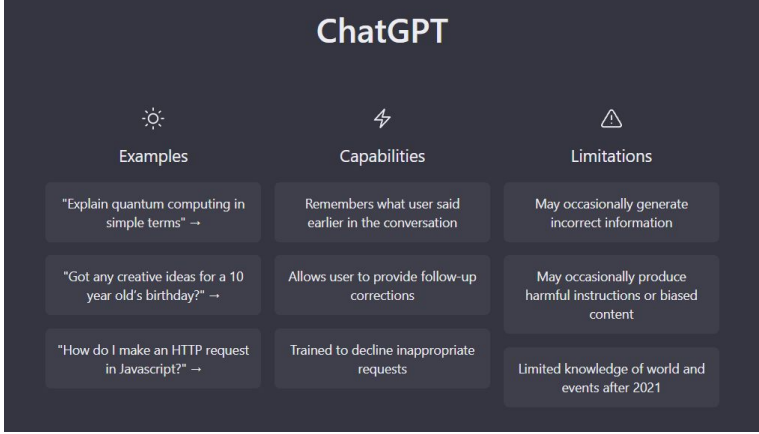
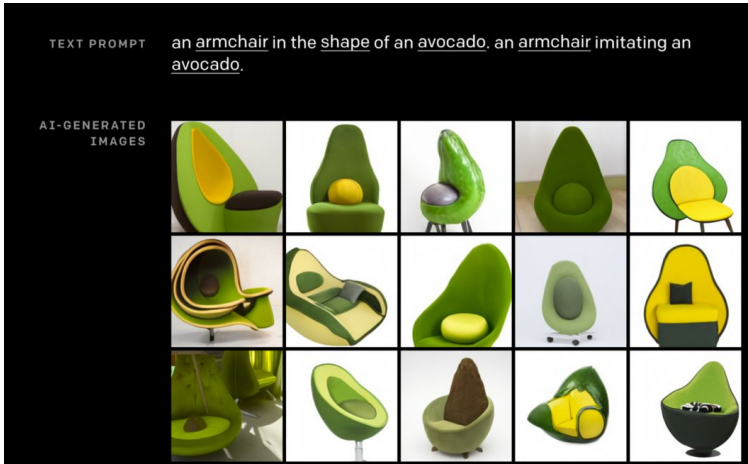


Image source: https://openai.com/blog/chatgpt/



The Future (What's Next?)

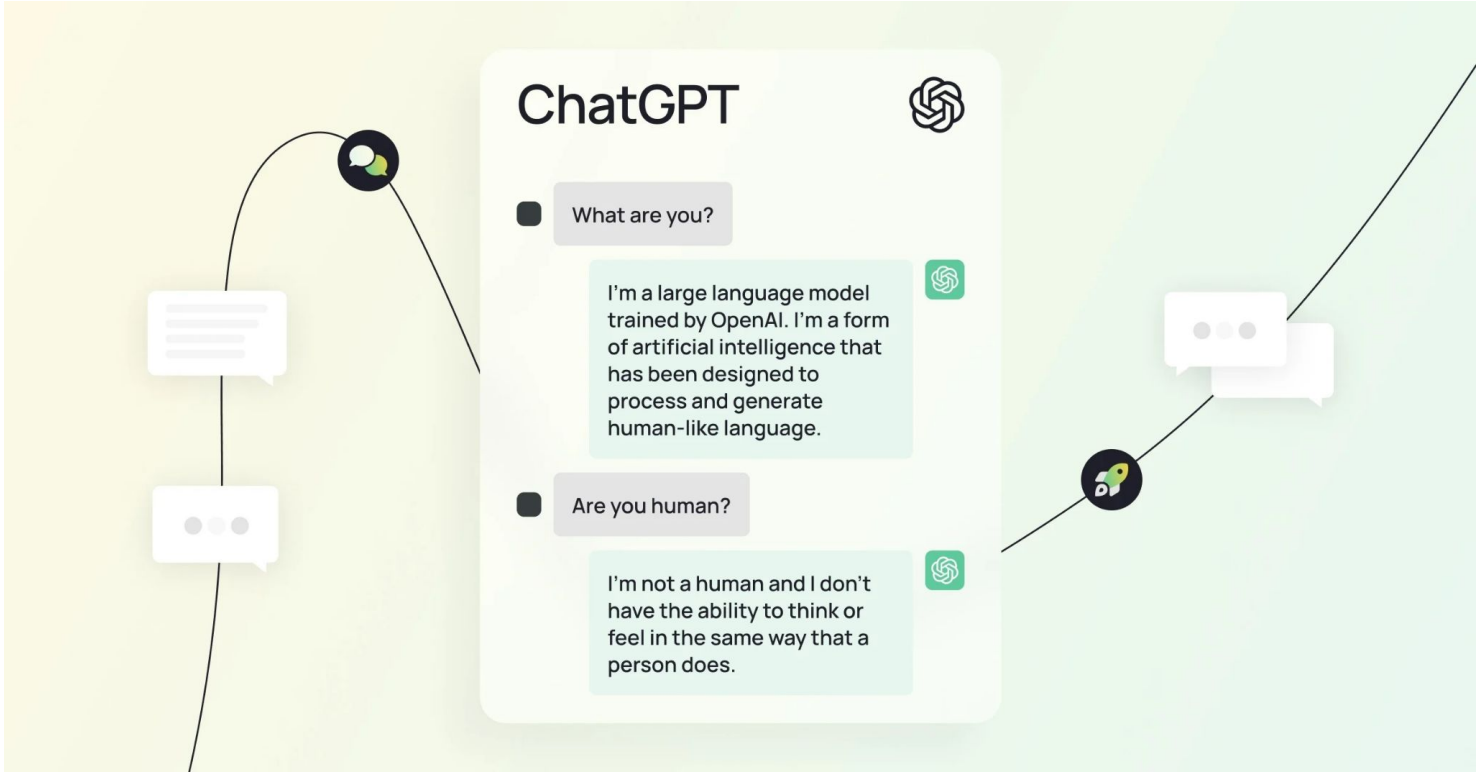
- Can enable a lot more applications:
  - Generalist Agents
  - Longer video understanding and generation, finance + business
  - Incredibly long sequence modeling (GPT authors a novel)
  - Domain-specific "Foundation models" - DoctorGPT, LawyerGPT, …
  - Potential real-world impacts:
    - Personalized education and tutoring systems
    - Advanced healthcare diagnostics, environmental monitoring & protection, etc.
    - Real-time multilingual communication
    - Interactive entertainment & gaming (e.g. NPCs)

The Future (What's Missing?)

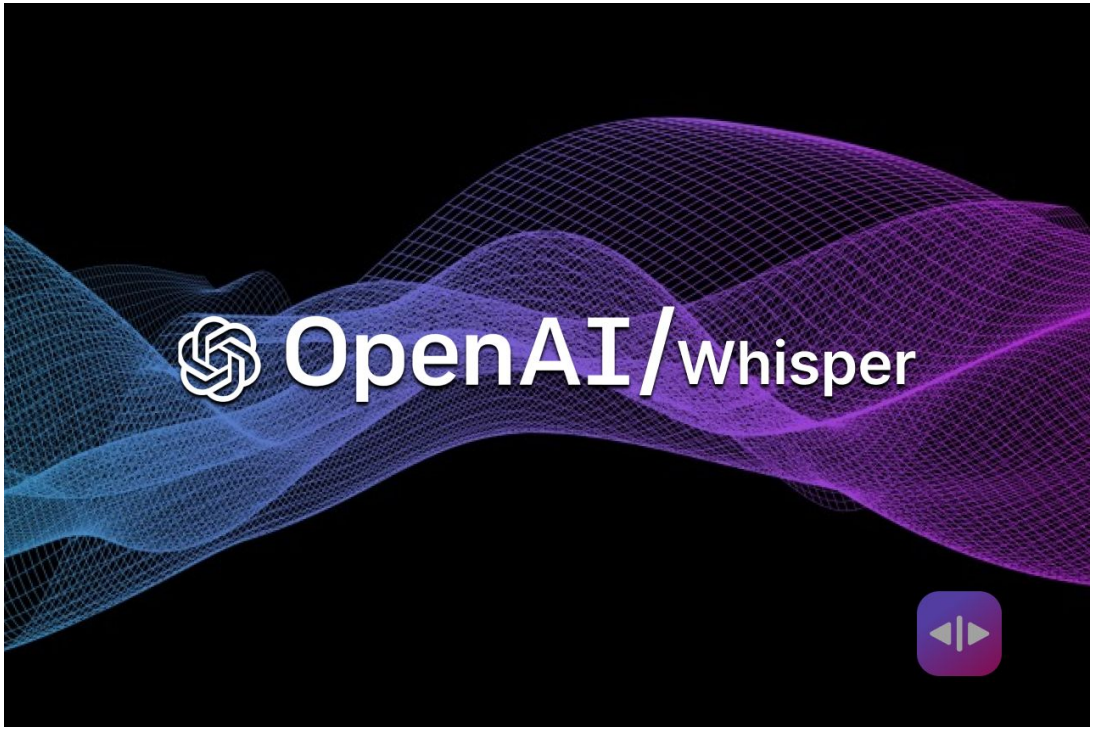
- Missing Ingredients (to AGI/ASI?):
  - Reducing computation complexity
  - Enhanced human controllability
  - Alignment with language models of human brain
  - Adaptive learning and generalization across domains
  - Multi-sensory multimodal embodiment (e.g. intuitive physics and commonsense)
  - Infinite/external memory: like Neural Turing Machines
  - Infinite/constant self-improvement and self-reflection capabilities
  - Complete autonomy and long-horizon decision-making
  - Emotional intelligence and social understanding
  - Ethical reasoning and value alignment

Major Applications of Transformers

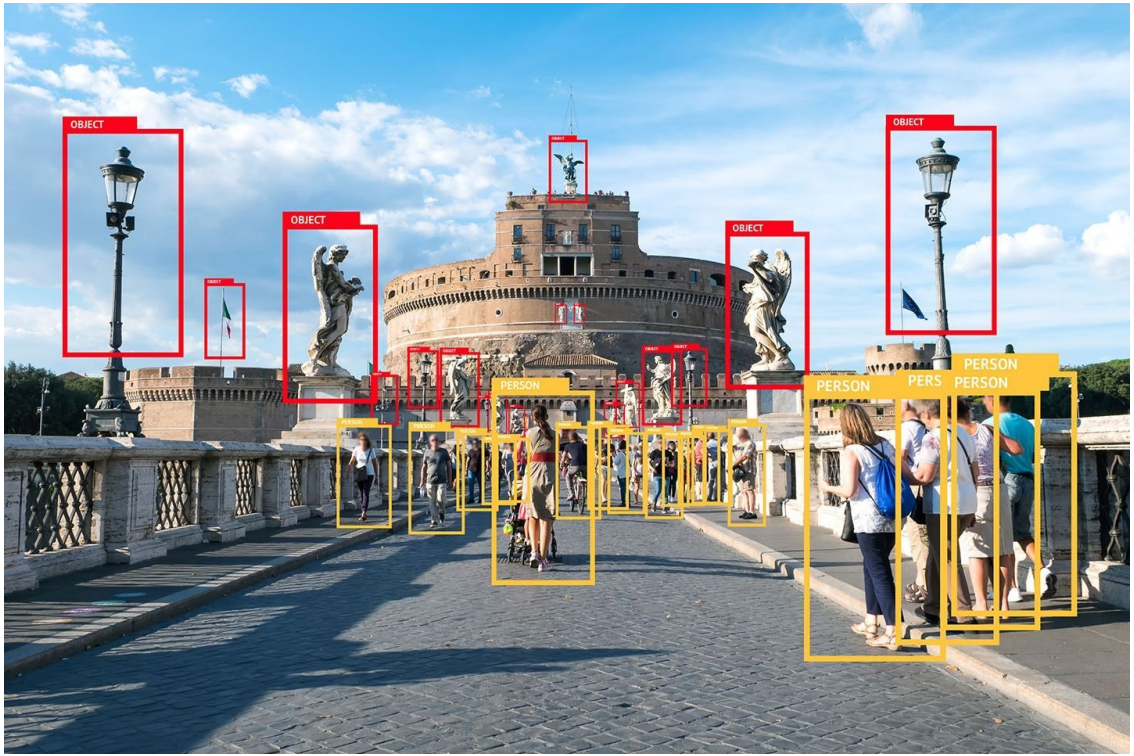
Text and Language



Audio: Speech + Music



Vision: Analyzing Images & Videos



Vision Transformer (ViT)

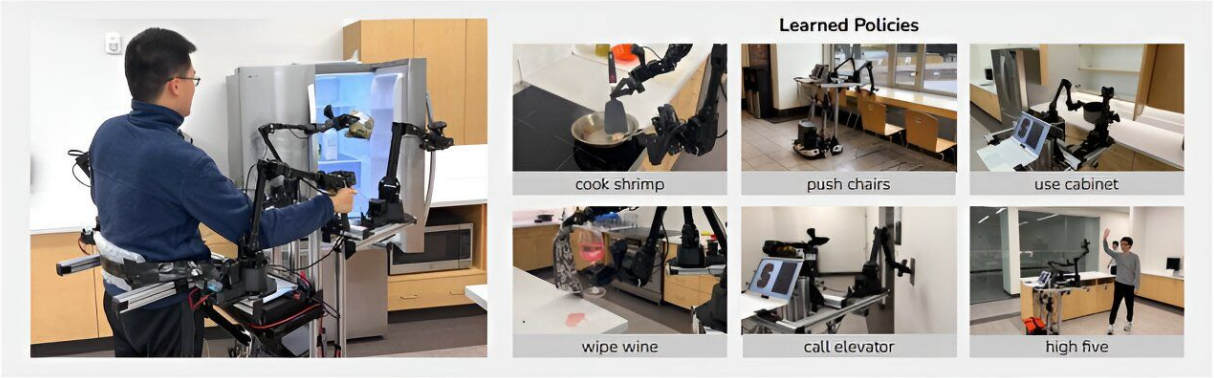
Vision: Generating Images & Video

Images: Stable Diffusion, Dall-E, Midjourney, etc.

Videos: Sora, Pika, etc.

Robotics, Simulations, Physical Tasks

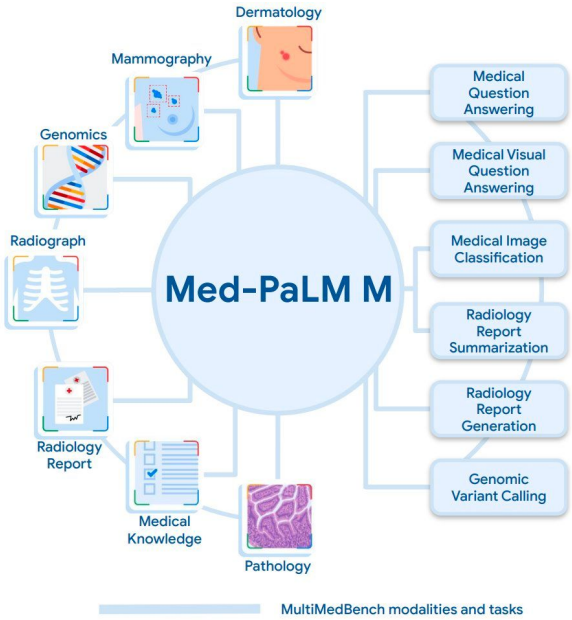
E.g. Voyager, Mobile ALOHA



Playing Games

E.g. AlphaGo, AlphaStar,
AI for MOBAs (e.g. Dota 2 / LoL)

Biology + Healthcare



E.g. Med-PaLM, AlphaFold

Recent Trends and Remaining Weaknesses of LLMs

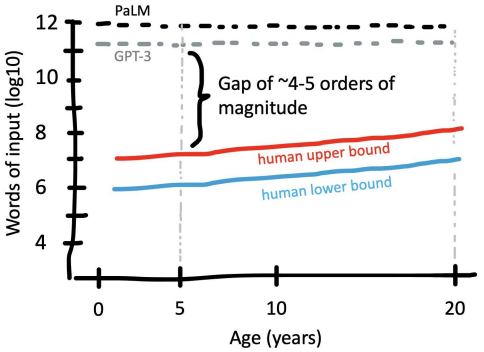
Requiring Large Amounts of Data, Compute, and Cost

- Current LLMs take immense amounts of data, compute, and $ to train
- Requires training over weeks/months over thousands of GPUs
- BabyLM challenge: can we train LLMs using similar amounts of data a baby is exposed to while growing up?

BabyLM: Children vs. LLMs

- Children are different due to several reasons:
  - LMs do statistical learning, which requires more data to learn statistical relations between words and get abstraction/generalization/reasoning
  - Children may learn in smarter, e.g. more explicit compositional/hierarchical manners, learning abstraction/generalization/reasoning more easily

BabyLM: Children vs. LLMs



- Thoughts/ideas from Michael C. Frank's tweet
- 4-5 orders of input magnitude diff b/w human and LLM emergence
- Factor 1: Innate knowledge - relates to priors
- Factor 2: multimodal grounding
- Factor 3: active, social learning
- Factor 4: evaluation differences

Minified LLMs and On-Device LLMs

- Big trend of using LLMs for applications and everyday purposes
- A requirement is ability to run quickly and easily on-devices
- AutoGPT and ChatGPT “plug-ins”
- Right now, work on smaller open-source models (e.g. LLaMA, Mistral)
- In the future: ability to finetune and run models locally, even on your phone!
  - Getting more possible due to more open-source, but still very large and $

Memory Augmentation & Personalization

- Weakness of LLMs is that they are frozen in knowledge at a particular point in time, and don't augment knowledge "on the fly"
- Hope to be able to remember the information while chatting with a particular user, both within the same conversation and across conversations
  - Would help with context window limits and adapting to the particular user
- Widescale: somehow update the model "on the fly" with info from several users
- Further, they usually do not adapt their talking style and persona to the particular user, which could have applications such as mental health therapy

Memory Augmentation & Personalization

- Potential approaches:
  - Memory bank - not feasible/efficient with larger amounts of data
  - Prefix-tuning approaches (finetune a small part of the model) - too expensive
  - Some prompt-based approach - do not see how this would be possible to change the model itself, but can at least help it “personalize” to the user
  - RAG: retrieval-augmented generation (data store, augment context each time)
    - Relies on high-quality external data store
    - Typically not end-to-end
    - Not within the “brain” of the model but outside:
      - Suitable for knowledge/facts, but not fundamental capabilities and skills

Pretraining Data Synthesis & Selection

- Lots of work these days on synthetic data generation (e.g. using GPT-4) to train other models, e.g. smaller models or peer models
- More work on understanding how to best synthesize and select the pretraining data
- Related to model distillation: knowledge from a large complex model (Teacher) is transferred to a smaller, more efficient model (student)
  - Goal: achieve similar performance with less computational cost
- Example: Microsoft Phi models (“Textbooks Are All You Need!”)
  - https://arxiv.org/abs/2306.11644
- Nathan Lambert’s Summary on Synthetic Data in his Interconnect Newsletter

Microsoft Phi-2 Model

- Phi-2, a 2.7 billion-parameter model, excels in reasoning and language understanding, challenging models up to 25x larger
- Emphasizes "textbook-quality" training data and synthetic datasets for teaching common sense and general knowledge
  - Training data mix: synthetic datasets to teach the model commonsense reasoning and general knowledge, including science, daily activities, ToM, etc.
  - Further carefully selected web data filtered by educational value + content quality
- Phi-2 designed as a resource for research on interpretability, safety improvements, and fine-tuning across tasks

New Knowledge or “Memorizing”?

- When LLM is prompted and says something, is what it says truly “novel/new”?
- **Innovation vs. Regurgitation:** ongoing debates about whether LLMs can truly invent new ideas or are primarily recombining existing knowledge (since learn patterns from lots of text)
- **Test-time Contamination**: models might regurgitate rather than synthesize information due to overlap between training and evaluation data, leading to misleading benchmark results
- **Cognitive Simulation:** some argue LLMs mimic human thought processes, suggesting a form of "understanding," while others see this as simply “sophisticated pattern matching”
- **Ethical and Practical Implications**: this impacts trustworthiness, copyright issues, and the educational use of LLM outputs
  - E.g. copyright lawsuit by New York Times (NYT) on OpenAI!

Continual Learning

- AKA, infinite and permanent fundamental self-improvement
- Similar to humans: we constantly learn everyday from every interaction
  - Don’t need to “finetune ourselves” once in a while
- Very challenging, could be the key to AGI!
- Currently work on: finetune a small model based on traces from better model or same model after filtering those traces
  - More like re-training and distillation than true “continual learning”
- Work showing that reasonably sampled data with interjected augmented reasoning and further filtering can be used to further finetune or optimize (e.g. using DPO)
  - E.g. UltraChat-200k and Zephyr
  - E.g. LLMs Can Self-Improve paper

Interpretability of LLMs

- Enormous number of parameters trained on tons of data → “huge black-box” that is hard to interpret and understand
- More work on interpretability is required
- Would allow us to better understand models, leading to better ideas of what/how to improve, easier control, and better alignment/safety
- Mechanistic interpretability: understand how individual components + operations in an ML model contribute to its overall decision-making process
  - Goal: unpack the "black box" of models for clearer insight into how they work

Model Editing & Mechanistic Interpretability

- Also work on mechanistic interpretability and model editing (e.g. edit specific nodes)
- Relevant paper: https://arxiv.org/abs/2202.05262
- Development of a causal intervention method to trace decisive neuron activations for model factual predictions
- Rank-One Model Editing (ROME) to modify model weights for updating factual associations
- Mid-layer feedforward modules play a significant role in storing factual associations
  - Manipulation of these can be a feasible approach for model editing

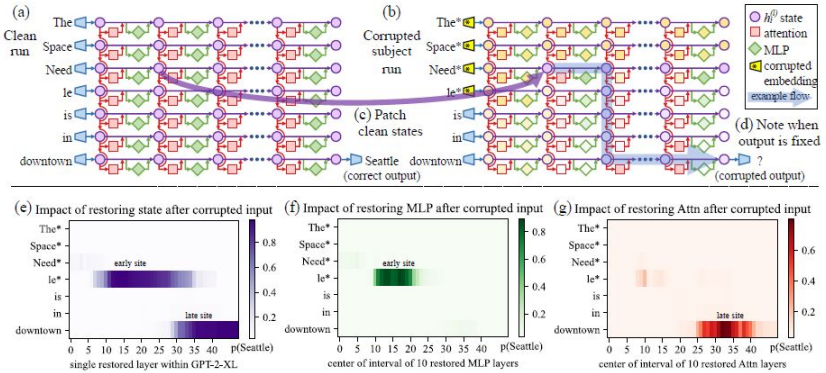
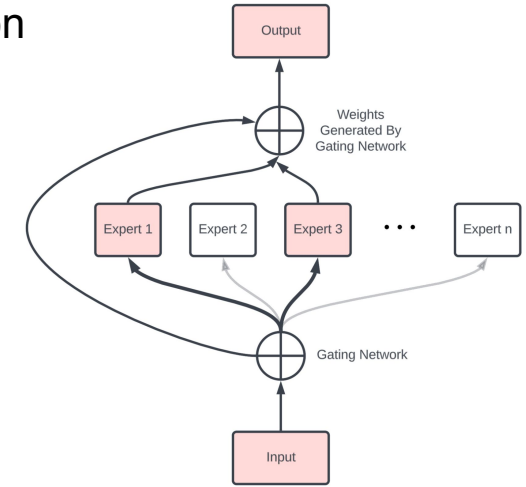


Figure 1: **Causal Traces** compute the causal effect of neuron activations by running the network twice: (a) once normally, and (b) once where we corrupt the subject token and then (c) restore selected internal activations to their clean value. (d) Some sets of activations cause the output to return to the original prediction; the light blue path shows an example of information flow. The causal impact on output probability is mapped for the effect of (e) each hidden state on the prediction, (f) only MLP activations, and (g) only attention activations.

Model Modularity + Mixture of Experts (MoE)

- Mixture of Experts (MoE) very prevalent these days in LLMs:
  - E.g. GPT-4, Gemini, etc.
- Goal: have several models/“experts” work together to solve a problem
  - Each expert may be specialized for a task/purpose
  - Try to use the diff skill-sets together to arrive at a generation
- Research on how to better define and connect these “experts”



Model Modularity + Mixture of Experts (MoE)

- Single model variation (?)
  - Potential to segment/compartmentalize a single NN model into different compartments with their own focus, similar to the human brain?
    - E.g. part of the network for fact-based info, another for spatial reasoning, another for mathematical + logical reasoning, etc.
  - Maybe add more layers on top of the foundation model
    - Particular layers correspond to something (e.g. new domain), and try to tune these new layers specifically

Self-Improvement / Self-Reflection

- Found models can reflect on their own output to iteratively improve/refine them
- Examples of works: ReAct, Reflexion, Self-refine
- Training LMs with Language Feedback: https://arxiv.org/abs/2204.14146

Self-Improvement / Self-Reflection

- Tried multiple layers/levels of self-reflection… showing continual improvement
  - Hypothesize that results will improve to a certain point and then degrade, and depends both on the model scale and the task at hand
  - Some folks believe that AGI is a “constant state of self-reflection”
- Can investigate further improvements to chain-of-thought reasoning and self-reflection

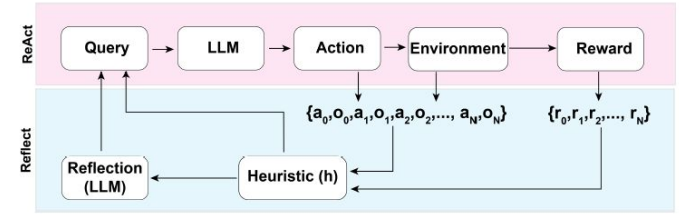
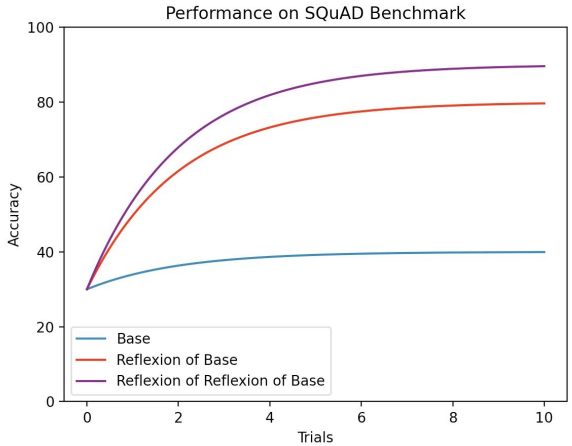


Figure 1: Reflexion can be added to any decision-making approach. We enable ReAct agents to use self-reflection to improve their own performance.



Hallucination Problem

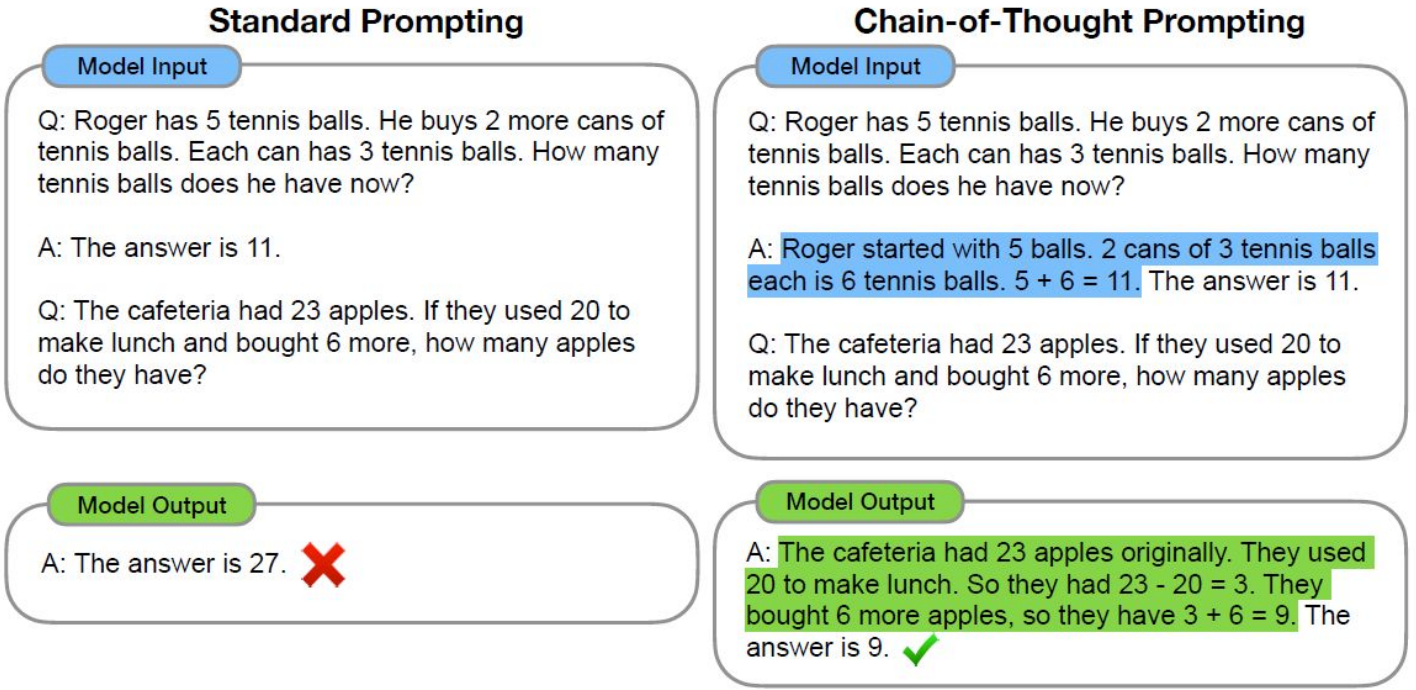
- Model “does not know when it does not know”
- Due to sampling procedure, generates text and sounds confident about it, even when littered with factual errors
- Can enhance through retrieval (e.g. through Google), and also:
  - Internal-based “fact verification”
  - Output verification and regeneration (self-refinement/improvement)
  - Modifying the token sampling to shy away from hallucination
  - Some way to “predict hallucination” before generation and prevent it
- “Confidence” rating would also help check the reliability of the output

Reasoning: Sufficient? Intermediate Guidance Helps…

- Chain-of-thought (CoT) - series of intermediate reasoning steps
- Shown to improve LLM performance on complex reasoning tasks
- Inspired by human thought process: decompose multi-step problems
- Also provides an interpretable window into behavior of the model (how it arrived at an answer, where it goes wrong in its reasoning path)
- CoT exploits the fact that deep down in the model's weights, it knows more about the problem than just prompting it to get a response

Ref: https://arxiv.org/abs/2201.11903

Chain-of-Thought Reasoning



Ref: https://arxiv.org/abs/2201.11903

Improving Chain-of-Thought Reasoning

- CoT results in performance gains for larger LMs, but still remain a non-negligible fraction of errors
- CoT error breakdown:
  - 8% from just a calculator error
  - 16% from symbol mapping error
  - 22% from “one missing step” error
  - Remaining errors due to semantic understanding issues and incoherent CoT
- We can investigate methods to address above errors and improve CoT in general

Ref: https://arxiv.org/abs/2201.11903

Chain-of-Thought Reasoning for Smaller Models

- Currently, CoT works effectively for models of approx. 100B params or more
- Initial paper found “one-step missing” and “semantic understanding” CoT errors to be the most common among smaller models
- 3 potential reasons:
  - Fail at even relatively easy symbol mapping tasks
  - Seem to have inherently weaker arithmetic abilities
  - Often had logical loopholes and did not arrive at a final answer
- Improve CoT for smaller models → significant value to the research community

Ref: https://arxiv.org/abs/2201.11903

Generalizing Chain-of-Thought Reasoning

- Find CoT to have a more rigid definition and format
- Further, its advantages are for particular domains and types of questions
  - Task is challenging and requires multi-step reasoning
  - Scaling curve of the problem/task is relatively flat
- Humans think through different types of problems in multiple ways
- Our “scratchpad” is more flexible and open to different reasoning structures
- Can maybe generalize CoT to be more flexible somehow

Tree of Thoughts

- ToT: “consider multiple different reasoning paths and self-evaluating choices to decide the next course of action, as well as looking ahead or backtracking when necessary to make global choices”

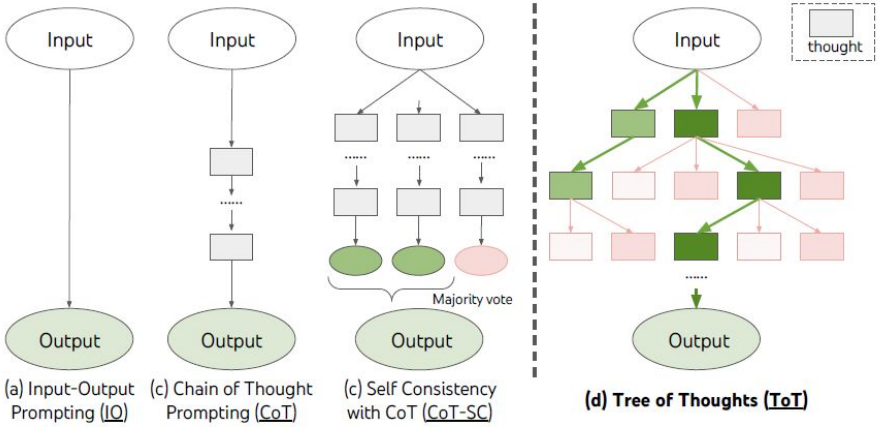


Figure 1: Schematic illustrating various approaches to problem solving with LLMs. Each rectangle box represents a *thought*, which is a coherent language sequence that serves as an intermediate step toward problem solving. See concrete examples of how thoughts are generated, evaluated, and searched in Figures 2,4,6.

Ref: https://arxiv.org/abs/2305.10601

Socratic Questioning

- "Divide-and-conquer fashion algorithm that simulates the self-questioning and recursive thinking process."
- "Self-questioning module using a large-scale LM to propose subproblems related to the original problem as intermediate steps and recursively backtracks and answers the sub-problems to reach the original problem."

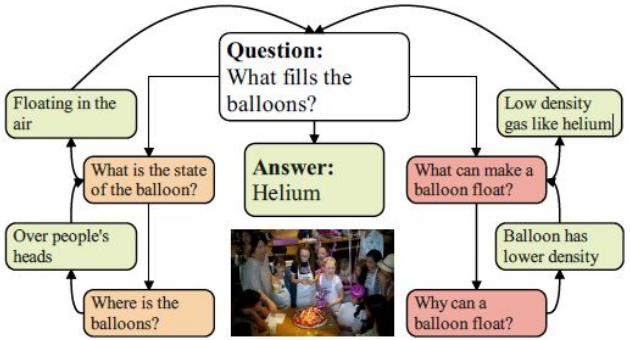


Figure 1: Example of a complex visual question solved in the human thinking process, involving raising visual and commonsense questions.

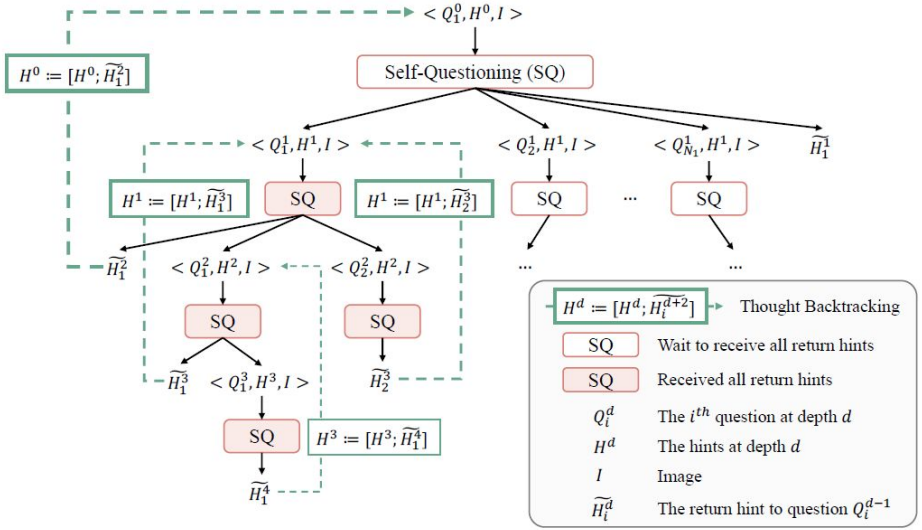


Figure 2: Overview of our SOCRATIC QUESTIONING framework.

Ref: https://arxiv.org/abs/2305.14999

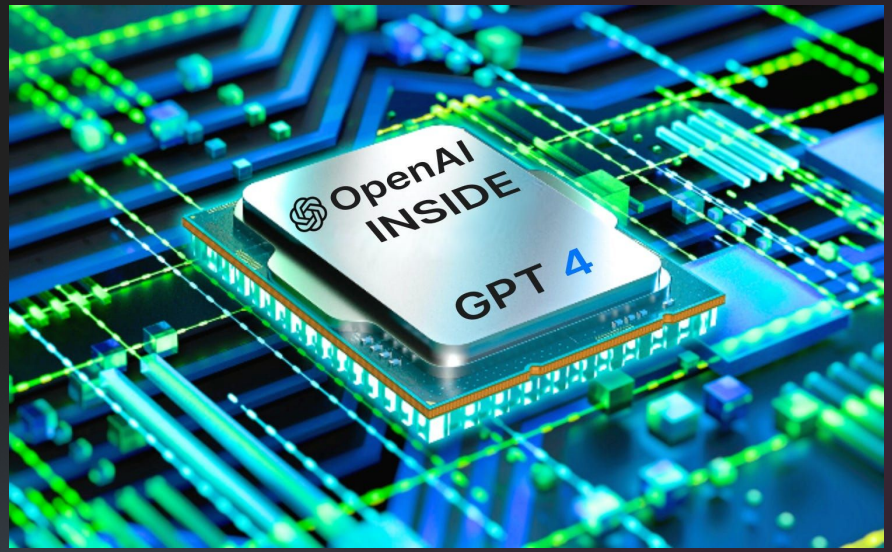
From Language Models to AI Agents

Introduction

- Actions and Emergent Agent Architectures
- Building Human-like AI Agents
- Computer Interactions using AI
- Long-Term Memory and Personalization
- Agent to Agent communication
- Future Directions for Autonomous AI Agents

Building AI Agents

1. Why?
2. How?
3. Ingredients?
4. What can they do?



Key thesis: Humans will communicate with AI using natural language and AI will operate machines allowing for more intuitive and efficient operations

Software 3.0

AI Agents

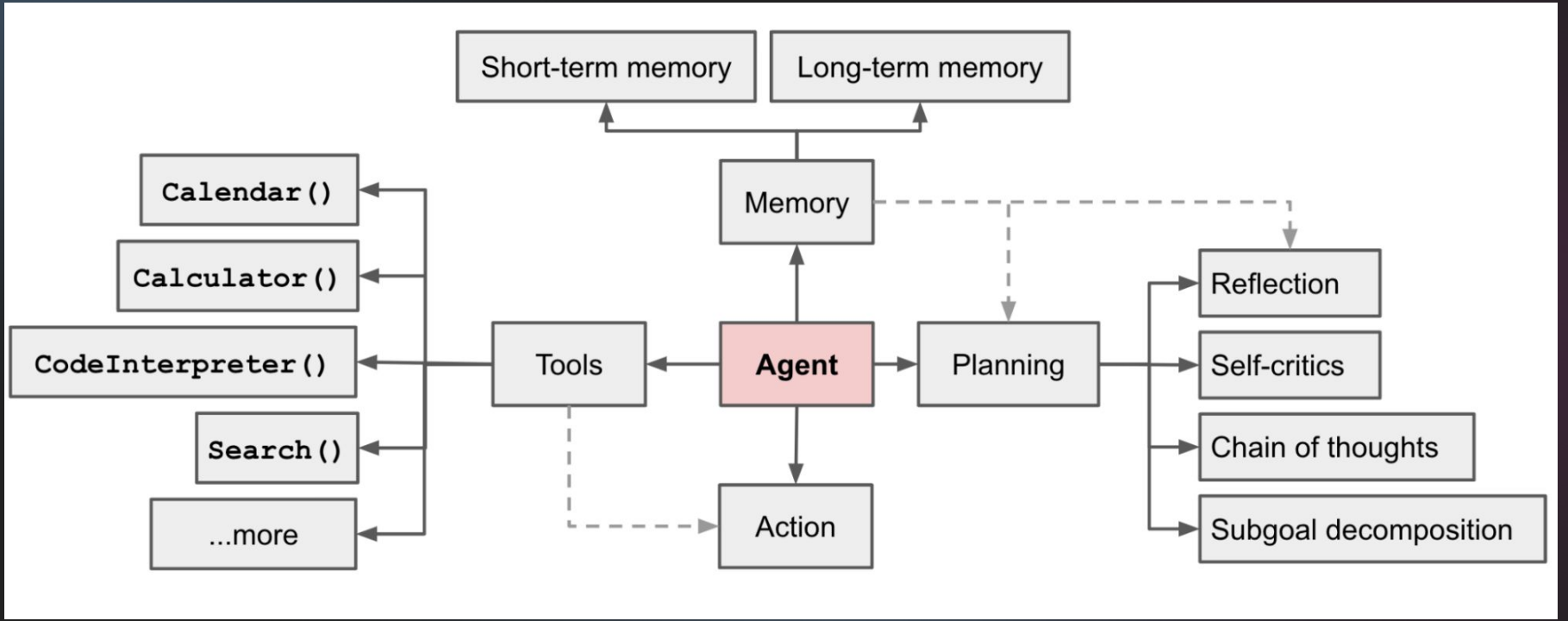
1. **Why?**
   A single call to a large Foundation AI model is not enough. A lot more can be unlocked by building ***AI systems***

2. **How?**
   Using model chaining, reflection & other mechanisms

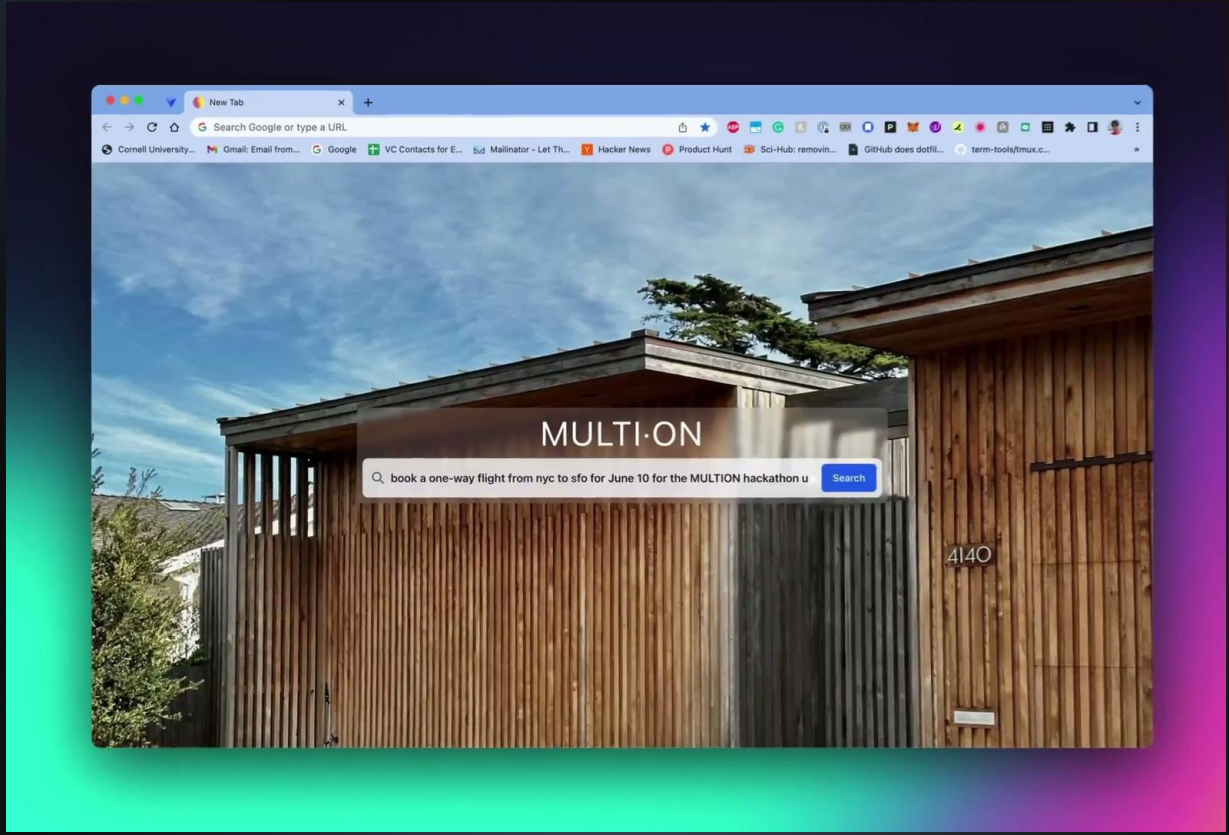
3. **Ingredients?**
   Memory, context length, personalization, actions, internet access…

4. **What can they do?**

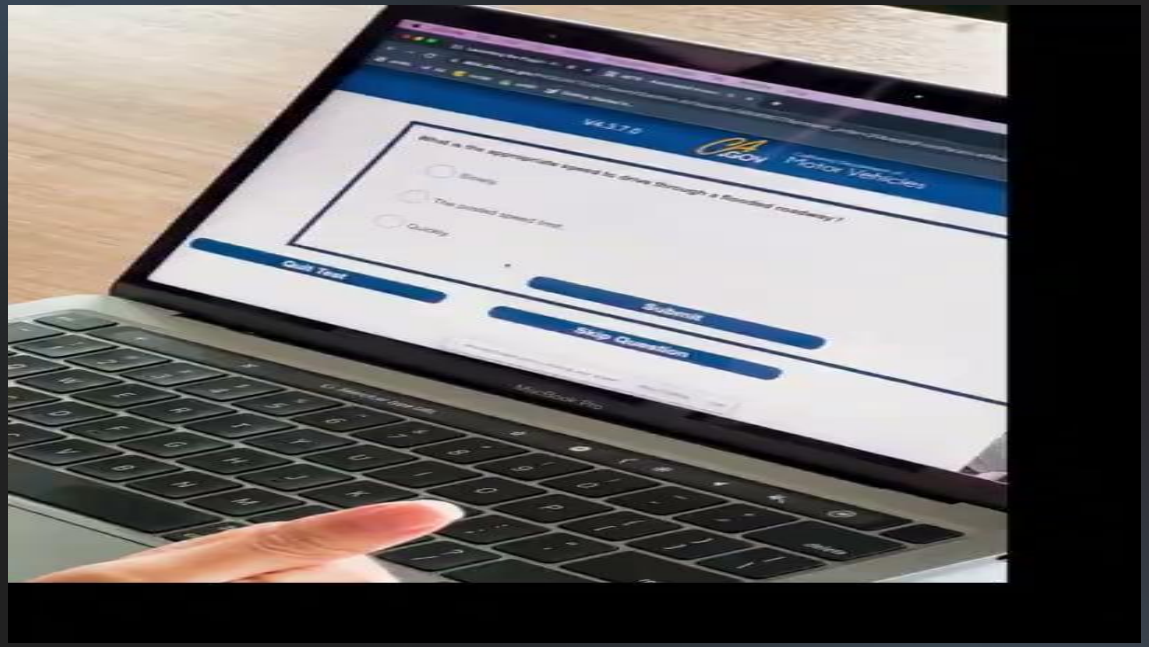
AI Agents


Short-term memory
Long-term memory
Memory
Calendar()
Calculator()
CodeInterpreter()
Search()
...more
Tools
Agent
Planning
Action
Reflection
Self-critics
Chain of thoughts
Subgoal decomposition

The first flight to be fully booked by an AI



AI Agent Passing the Online CA Driving Test

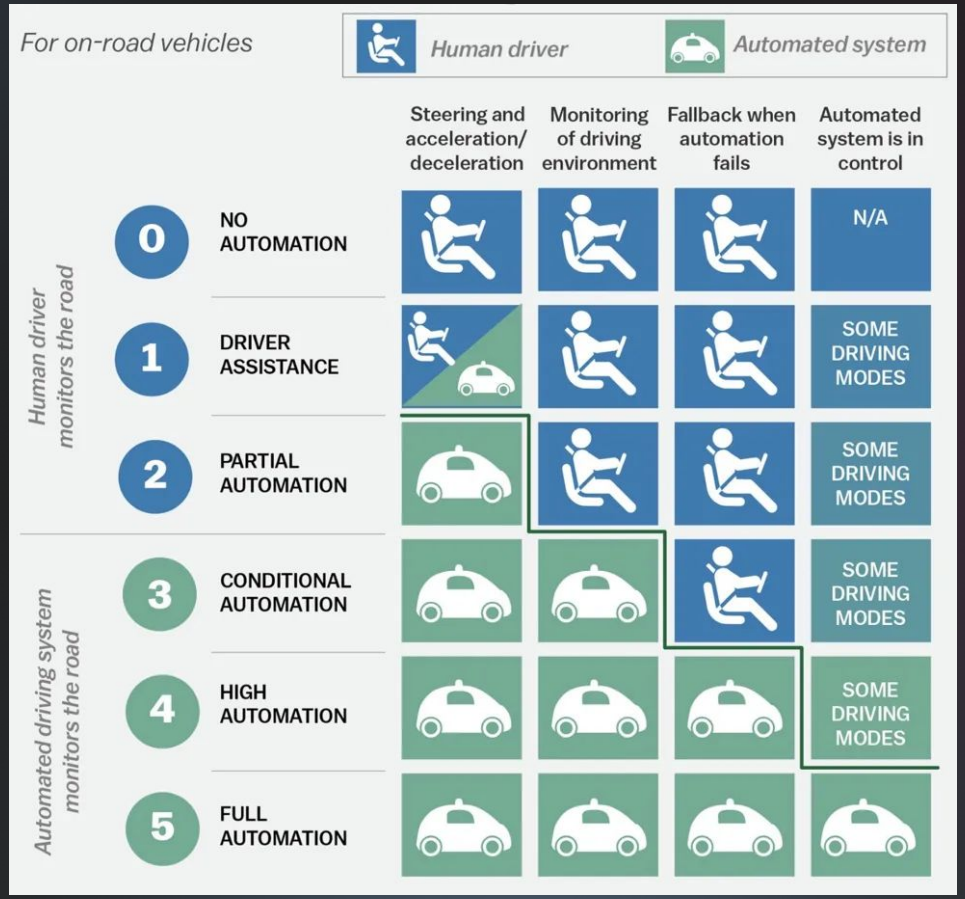


Fully Autonomously passing the official DMV online driving test this week & setting the record as the first AI to obtain a driving permit in CA!

Why **human-like** AI Agents?

1. **Can do what you can do**: Able to use existing interfaces designed for humans & operate outside programmatic boundaries
2. **Digital extension of you**: Can act as an extension of the user and act on their behalf
3. **Less-restrictive boundaries**: Can handle logins, payments, etc. and interact with services without any API restrictions
4. **Simple action space**: Need only click & type action primitives
5. **Self-learning**: Can learn from the user and self-improve with more interactions

5 levels of Autonomy



Computer Interactions

Agent Computer Interaction

Two routes

API (programmatic)

easy to build context
safer & controllable
high variability

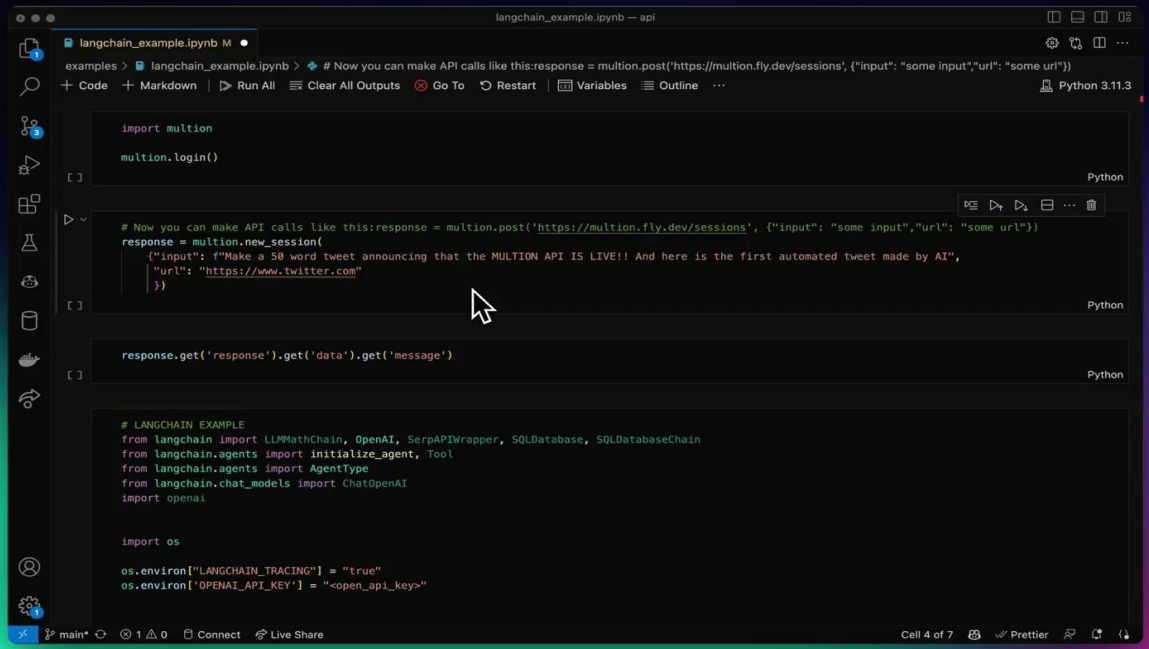
Direct interaction (browser or desktop control)

easy to take actions
free-form interactions
need to provide guarantees

MULTI·ON

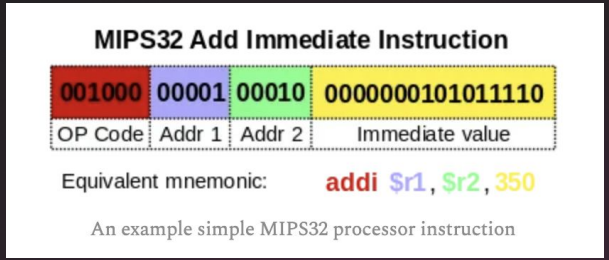
ADEPT

Agent Action API: An universal API for computer interaction



Memory & Personalization

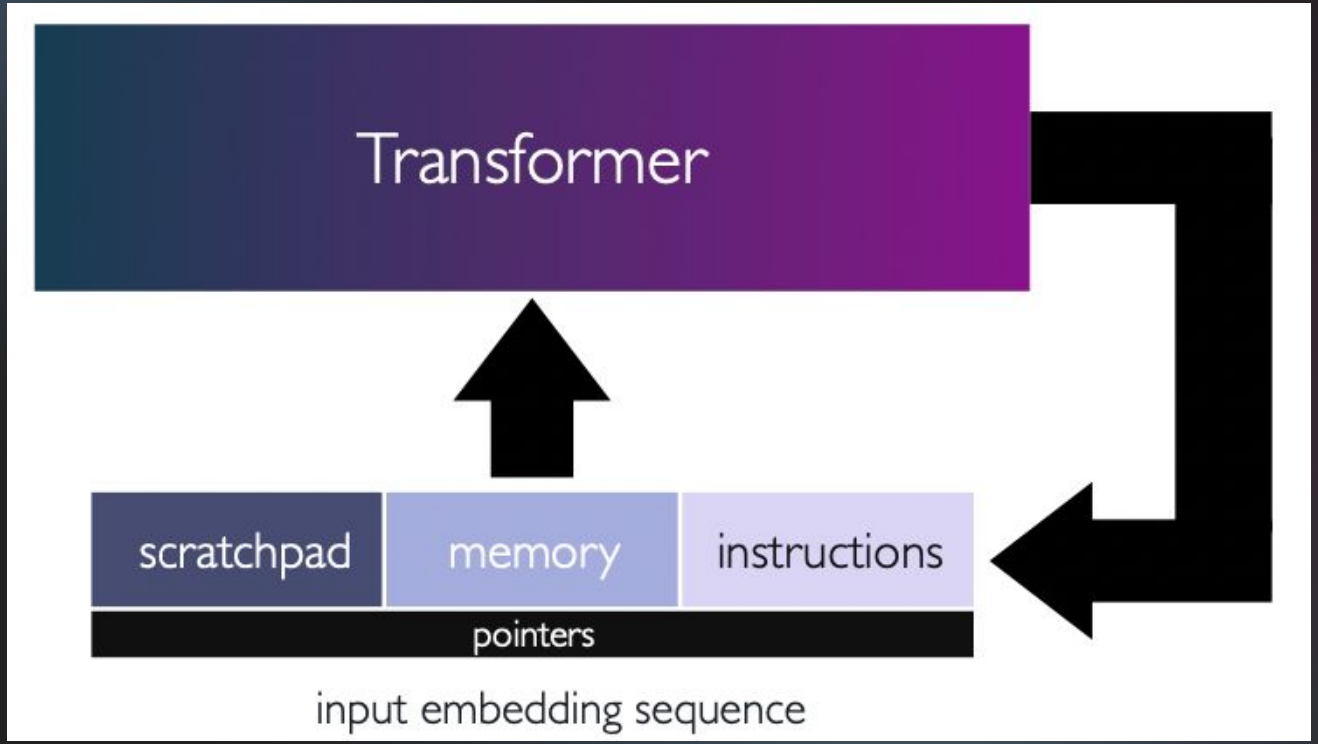
AI Models as Neural Compute Unit



Input Tokens
(max token size)

Output Tokens
(max token size)

AI Models as Neural Compute Unit



Looped Transformers

Long-term Memory

- **Works similar to disk (long-lived & persistent)**

- **Mechanisms**
  - Embeddings
  - Retrieval models

- **Open Questions:**
  - Hierarchy
  - Temporal Coherence
  - Structure
  - Online adaptation

Personalization

- **User-Agent Alignment Problem:** Enable agent to take actions that are aligned with the user preferences

- Everyone has different prefs & likes/dislikes:
  - **Explicit**: allergies, favourite dishes, flight seat prefs, …
  - **Implicit**: choice between brands, out of 10 items in a listing which user likes better

Challenges

- **Collecting user data & preferences:**
  - actively asking for preferences
  - passive learning from interactions

- **Learning from user preferences:** supervised fine-tuning vs human-feedback

- **On-fly adaptation**

- **Privacy**

Agent-to-Agent Communication

Multi Agent Autonomous AI systems





Why Multi-agent Systems

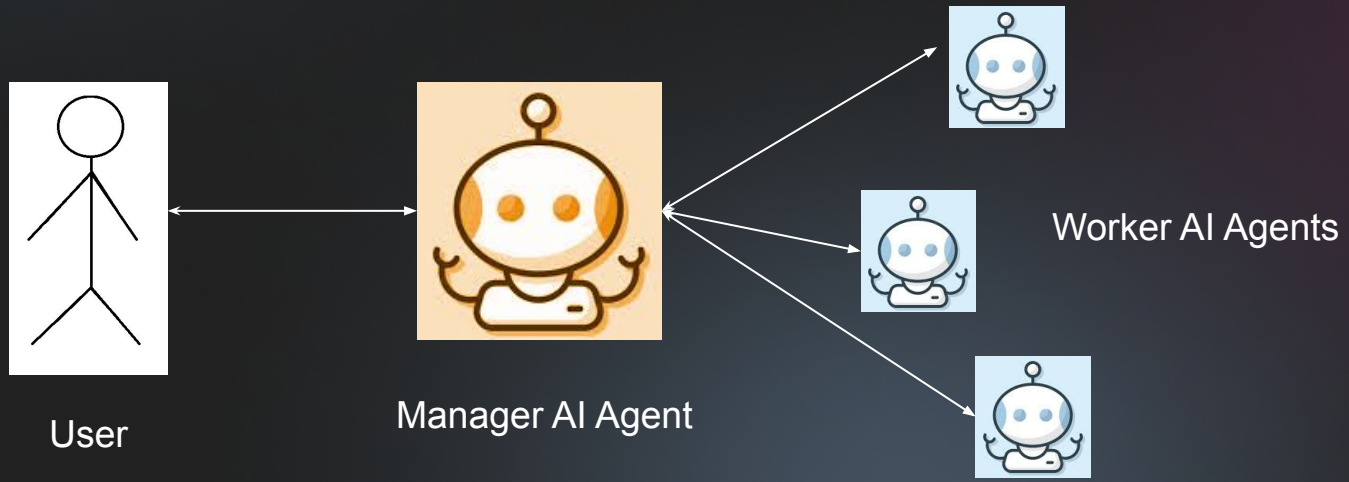
1. **Parallelization unlock**: Breaking a task into smaller chunks and dividing between agents to improve efficiency & speeds

2. **Task Specialization**: An AI agent might seat between the user and each service: e.g. a spreadsheet AI agent, a slack AI agent, a web-browser AI agent, …

3. **Challenges**:
    a. **Agent to Agent Communication**: one AI might want to exchange or request info from another AI agent finish a task

Agent to Agent Communication

- **Exchanging info between fleets of agents**
- **Hierarchies**
- **Syncing primitives**



Agent to Agent Communication

- **Robust communication protocols & Syncing primitives:** Natural language is ambiguous, need mechanisms to reduce miscommunication!

Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**

Manager state

Task X:
(status: not done)

Manager AI Agent

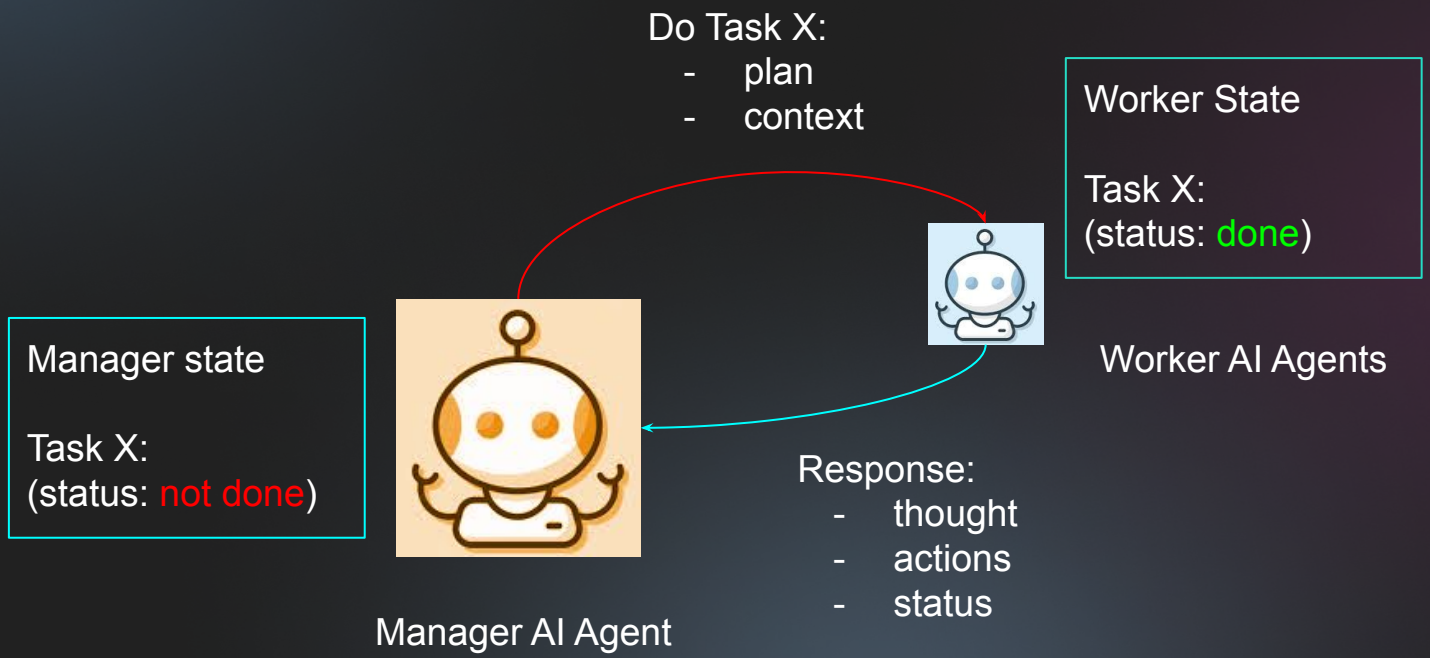
Worker AI Agents

Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**

Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**



Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**

Verify if task was correctly done & follows all specifications

Verify Task X:
- required spec

Worker State

Task X:
(status: done)

Manager state

Task X:
(status: verify done)

Manager AI Agent

Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**

Scenario 1:
Task was correctly done & follows all specifications

Verify Task X:
- required spec

Worker State

Task X:
(status: done)

Manager state

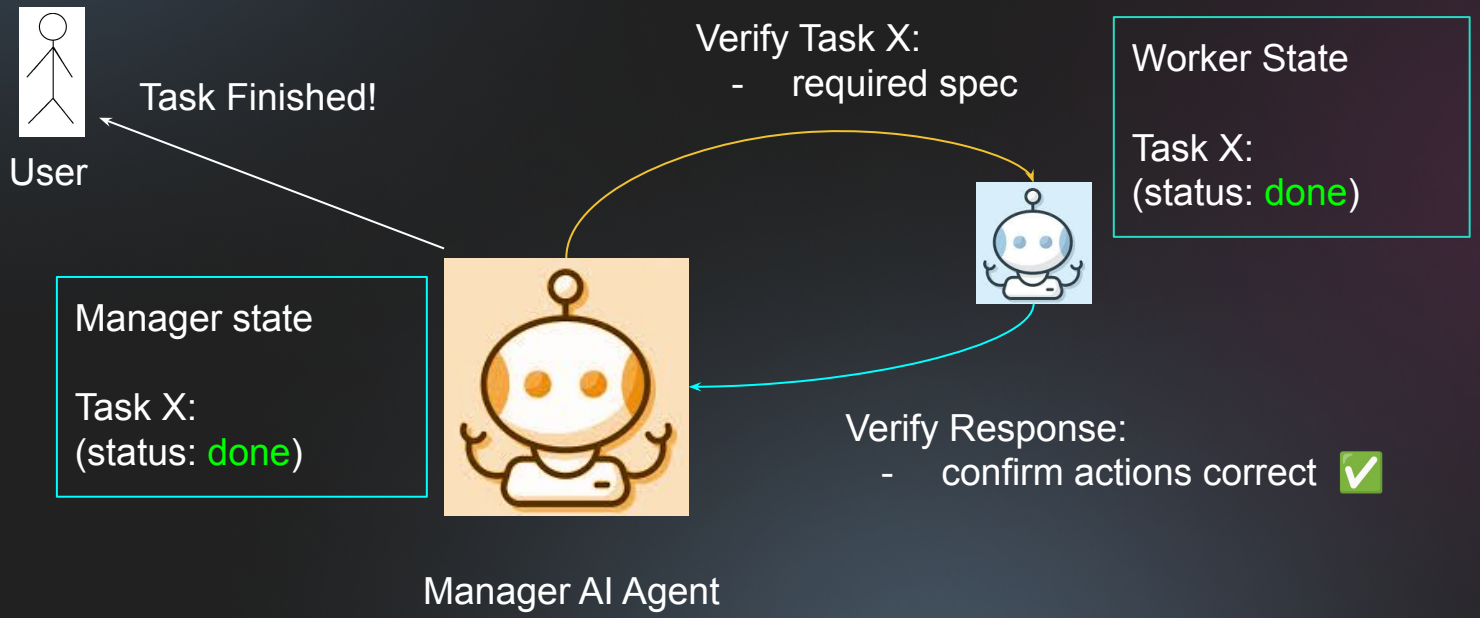
Task X:
(status: verify done)

Verify Response:
- confirm actions correct ✅

Manager AI Agent

Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**



Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**

Scenario 2:
Task was incorrectly done
(Agent Miscommunication)

Verify Task X:
- required spec

Worker State

Task X:
(status: done)

Manager state

Task X:
(status: verify done)

Verify Response:
- actions were not correct ❌

Manager AI Agent

Agent to Agent Communication

- **Robust communication protocols & Syncing primitives**

Scenario 2:
Task was incorrectly done
(Agent Miscommunication)

Re-do Task X:
- plan
- context
- feedback/corrections

Worker State

Task X:
(status: not done)

Manager state

Task X:
(status: not done)

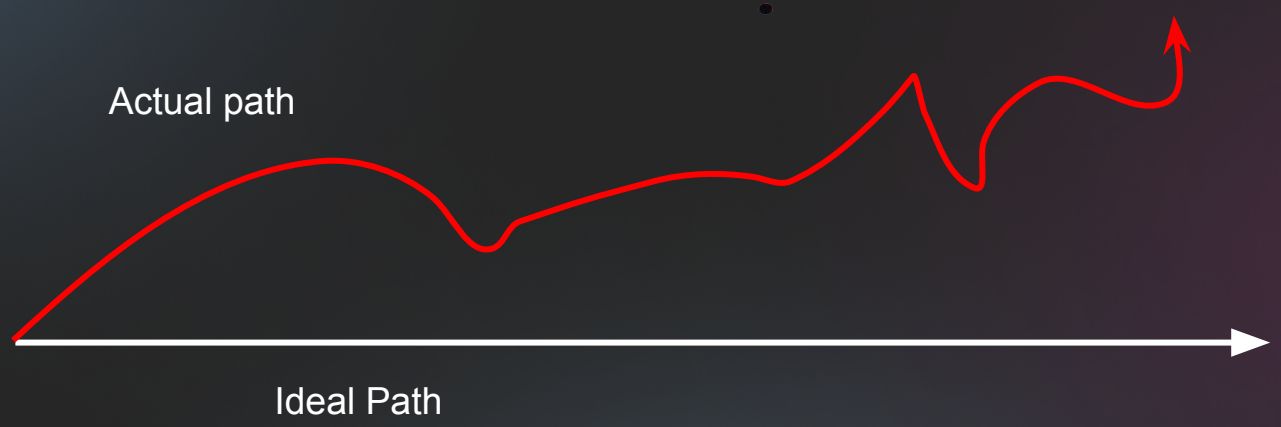
Manager AI Agent

Future Directions

Key Issues with Autonomous Agents

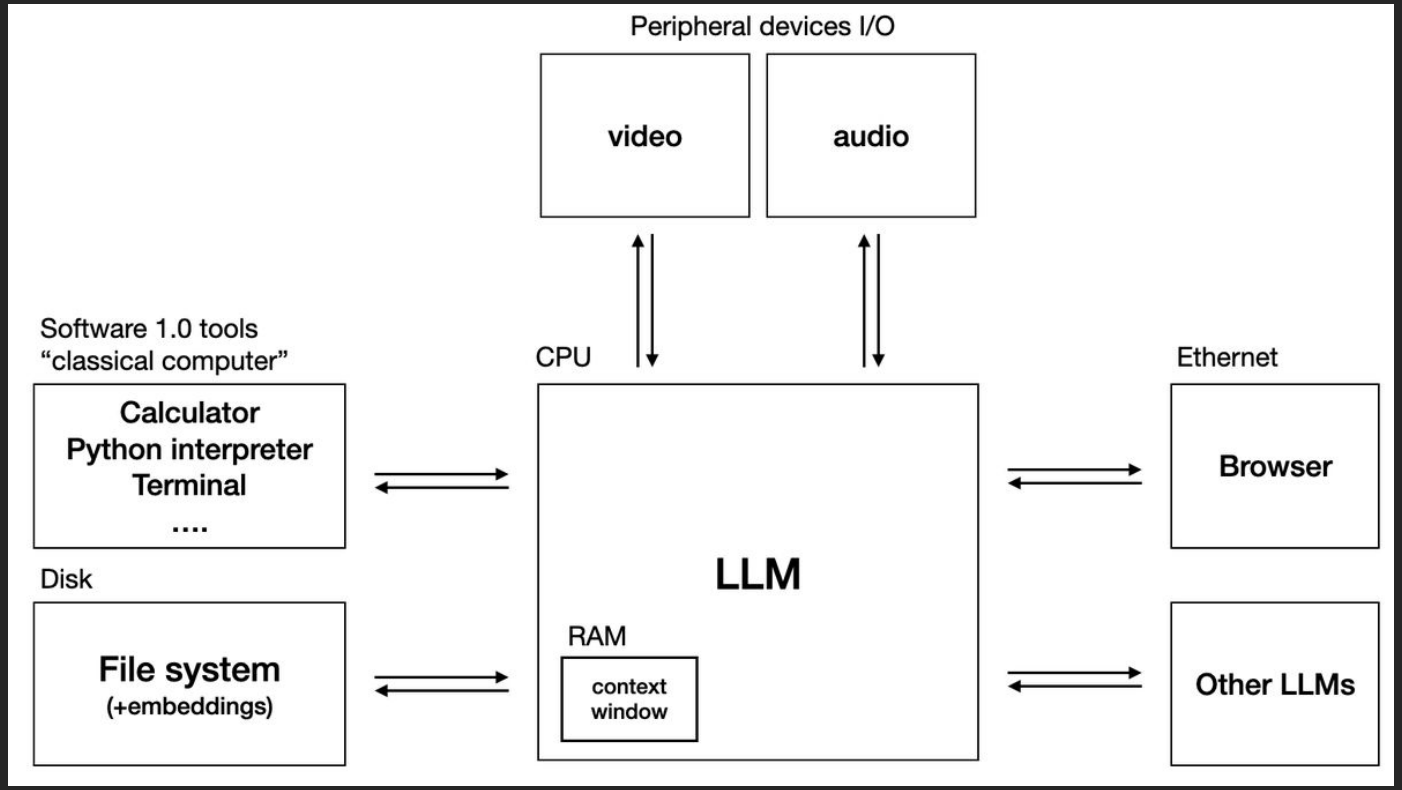
1. **Reliability**
2. **Looping & Plan Divergence**
3. **Testing & Benchmarking**
4. **Real world-deployment & Observability**
    a. How do we trust a fully autonomous AI system
    b. How do we build in human overrides

Plan Divergence

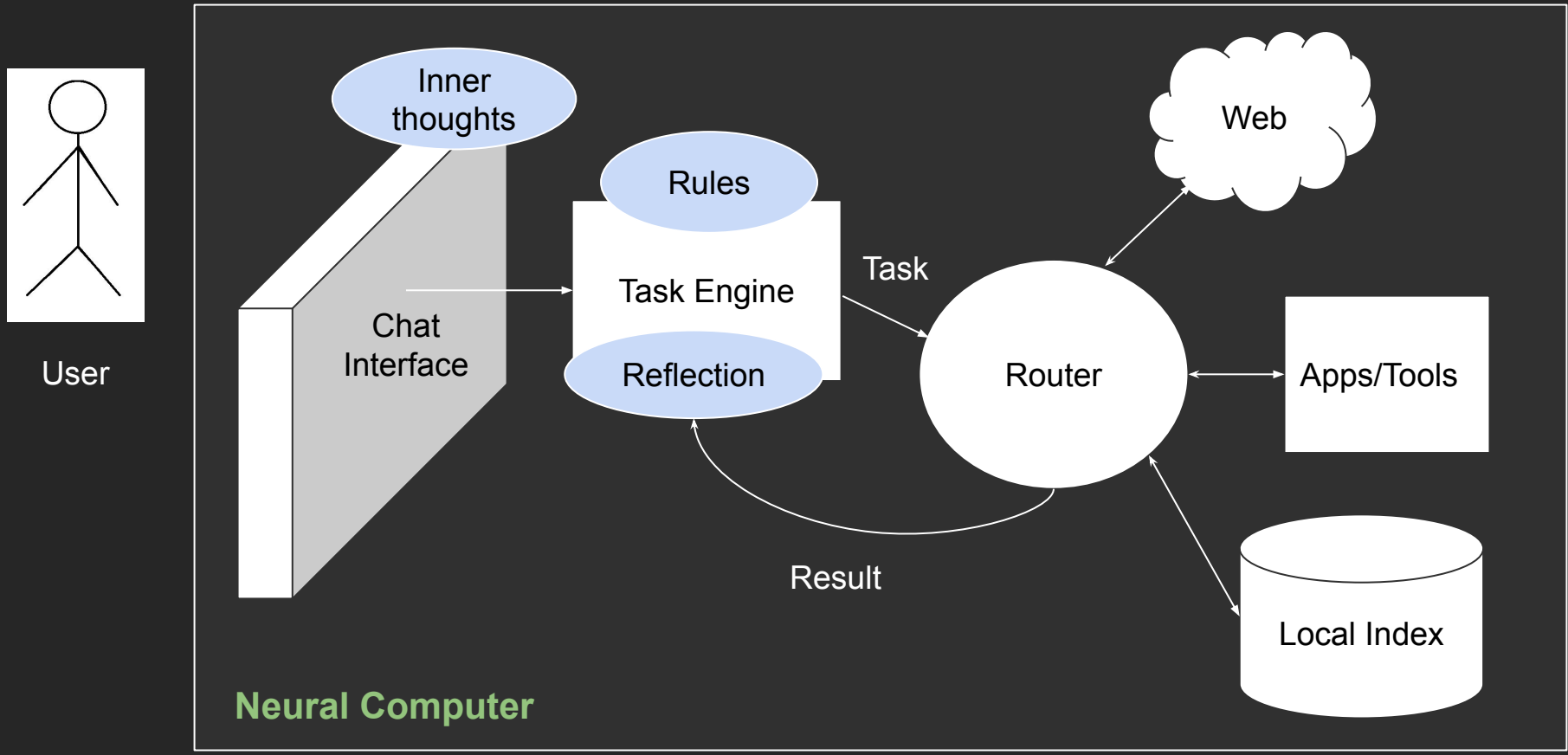


AI Agents like AutoGPT don’t know how to correct on making a mistake!

Karpathy - LLM OS



Building Generalized AI Systems



Future needs for AI agents

- Error correction mechanisms & better agent frameworks
- Security & user permission models
- Sandboxing & deployment in risky settings


That's all Folks!