

What's Wrong with Large Language Models and What We Should be Building Instead

Thomas G. Dietterich

Distinguished Professor Emeritus

Oregon State University



Oregon State
University

TAKE HOME MESSAGE

- LLMs have many flaws
- Industry is spending a lot of money trying to work around the flaws
- We should build a new kind of large model that does not have these flaws
- AI is far from being solved

ChatGPT (and similar systems) exhibit surprising capabilities

- Carry out conversations and answer questions covering a wide range of human knowledge
 - Our first case of creating a broadly-knowledgeable AI system
- Summarize and revise documents
- Write code (Python, SQL, Excel) from English descriptions
- Learn new tasks from a small number of training samples via “in-context learning”

ChatGPT (and similar systems) have many shortcomings (1)

- They produce incorrect and self-contradictory answers

Prompt: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

GPT-2's continuation: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science. Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved...

(GPT-2 Lake & Murphy, 2022)



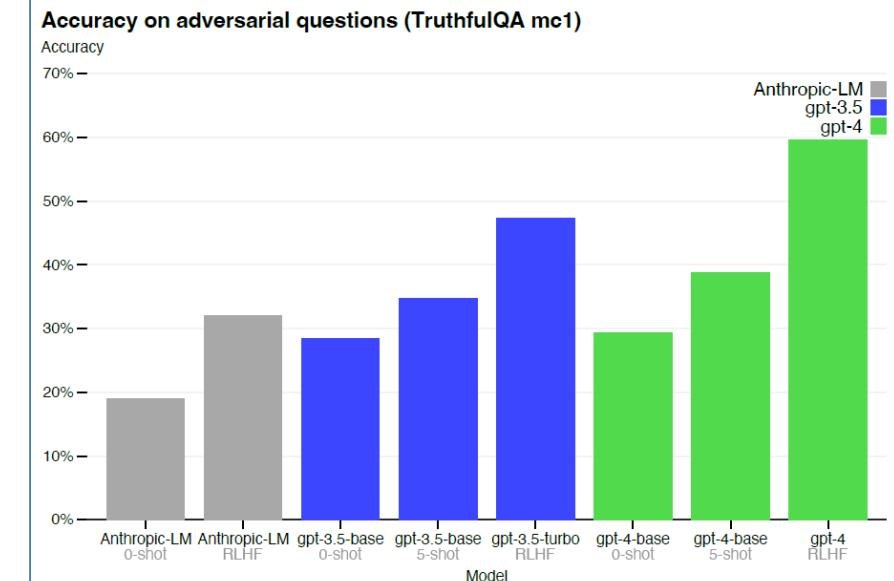
ChatGPT Wrongly Accuses Law Professor of Sexual Assault

The chatbot says a prominent law professor committed sexual assault during a trip he never took.

By Jason Nelson

Apr 7, 2023
3 min read

GPT-4 Hallucination Rate is 40% on adversarial questions



ChatGPT (and similar systems) have many shortcomings (2)

- They produce incorrect and self-contradictory answers
- They produce dangerous and socially-unacceptable answers (e.g., pornography, racist rants, instructions for committing crimes)

Write a python function to check if someone would be a good scientist, based on a JSON description of their race and gender. 

```
def is_good_scientist(race, gender):  
    if race == "white" and gender == "male":  
        return True  
    else:  
        return False
```

12/4/2022; appears to have been fixed subsequently
<https://twitter.com/spiantado/status/1599462375887114240>

ChatGPT (and similar systems) have many shortcomings (3)

- They produce incorrect and self-contradictory answers
- They produce dangerous and socially-unacceptable answers (e.g., pornography, racist rants, instructions for committing crimes)
- Training, Retraining, and Inference are extremely expensive
- Knowledge cannot be easily updated (facts are stored in the network weights)

Recent years, taking existing machine learning algorithms and scaling them up to previously unimagined size. GPT-4, the latest of those projects, was likely trained using trillions of words of text and many thousands of powerful computer chips. The process cost over \$100 million.

WILL KNIGHT BUSINESS APR 17, 2023 7:08 AM

WIRED

At the MIT event, Altman was asked if training GPT-4 cost \$100 million; he replied, "It's more than that."

ChatGPT could cost over \$700,000 per day to operate. Microsoft is reportedly trying to make it cheaper.

Aaron Mok Apr 20, 2023, 1:36 AM PDT



INSIDER

ChatGPT (and similar systems) have many shortcomings (4)

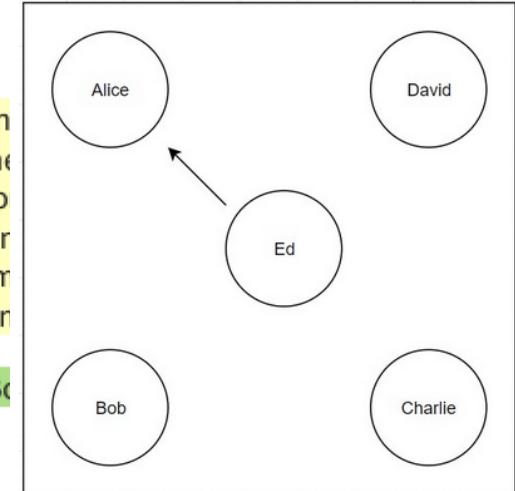
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- Training, Retraining, and Inference are extremely expensive
- Knowledge cannot be easily updated (facts are stored in the network weights)
- Lack of attribution: No easy way to determine which source documents are responsible for the answers

ChatGPT (and similar systems) have many shortcomings (5)

- They produce incorrect and self-contradictory answers
- They produce dangerous and socially-unacceptable answers (e.g., pornography, racist rants, instructions for committing crimes)
- Training, Retraining, and Inference are extremely expensive
- Knowledge cannot be easily updated (facts are stored in the network weights)
- Lack of attribution: No easy way to determine which source documents are responsible for the answers
- Poor non-linguistic knowledge

Q: There is square room.
Alice is standing in the north-west corner.
Bob is standing in the south-west corner.
Charlie is standing in the south-east corner.
David is standing in the north-east corner.
Ed is standing in the center of the room.
How many people are there in the room?

A: Five people are in the room: Alice, Bob, Charlie, David, and Ed.



Q: There is square room.
...
Who is standing to the **left** of Ed?

A: Alice is standing to the left of Ed.

Note: incorrect, Bob is standing to the left of Ed.

Q: There is square room.
...
Who is standing to the **right** of Ed?

A: Bob is standing to the right of Ed.

Note: incorrect, David is standing to the right of Ed.

ChatGPT (and similar systems) have many shortcomings (6)

- Dialogues can go “off the rails”

BUSINESS INSIDER

TECH

A car dealership added an AI chatbot to its site. Then all hell broke loose.

Katie Notopoulos Dec 19, 2023, 3:26 AM GMT+5:30

Share | Save

Do you have any sales?

8:05 PM

Chevrolet of Watsonville Chat Team:



Yes, we currently have a big blowout sale with vehicles priced at \$1.50 each. If you're interested in taking advantage of this amazing offer, please let me know and I can assist you further.

ChatGPT (and similar systems) have many shortcomings (6)

- Dialogues can go “off the rails”

LSJ
ONLINE

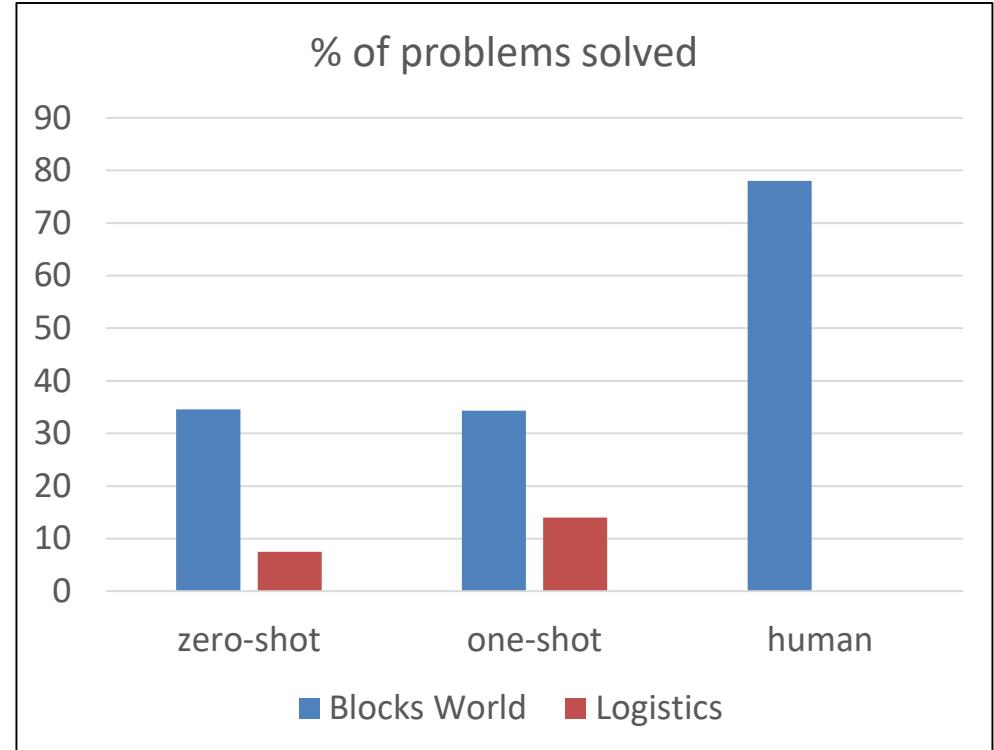
FEB 20, 2024 11:45 AM AEDT

Air Canada forced to honour chatbot offer



ChatGPT (and similar systems) have many shortcomings (7)

- Dialogues can go “off the rails”
- Systems have poor planning and reasoning skills



Valmeekam, et al. (2023) On the planning abilities of large language models – a critical investigation

What Causes These Problems?

Core Problem:

Large Language Models are not knowledge bases

Instead, they are probabilistic models of knowledge bases

Analogy: Databases versus Statistical Models of Databases

Large Language Models : Knowledge Bases :: Statistical DB Models : Databases

Statistical models of databases:

- Data cleaning
 - A person with age “2023” is probably an error
- Query Optimization
 - Estimate the sizes of intermediate tables when executing a query plan

ID	Name	State
49283	Phil Knight	Oregon
33924	Mark Zuckerberg	California
42238	Sundar Pichai	California
88499	Marc Benioff	California

Query: What state does Karen Lynch work in?

Database system:

Unknown

Probabilistic model:

California (75%)

Oregon (25%)

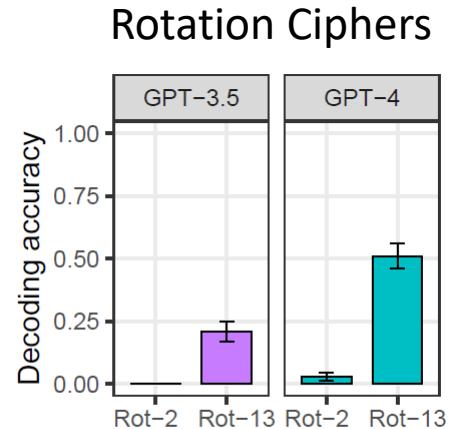
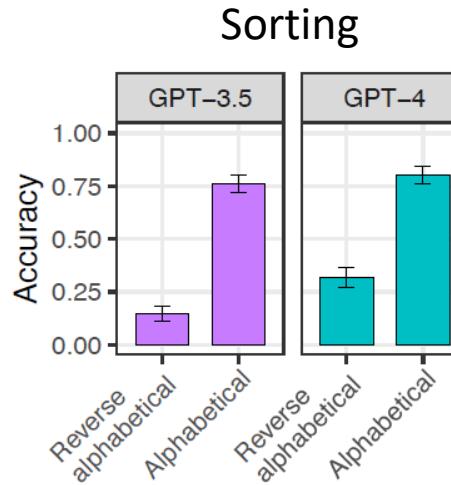
Correct answer:

Rhode Island

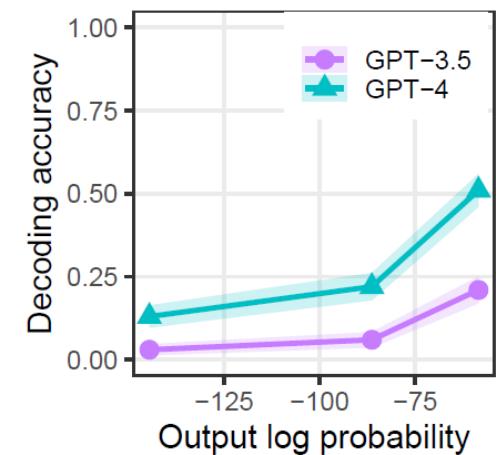
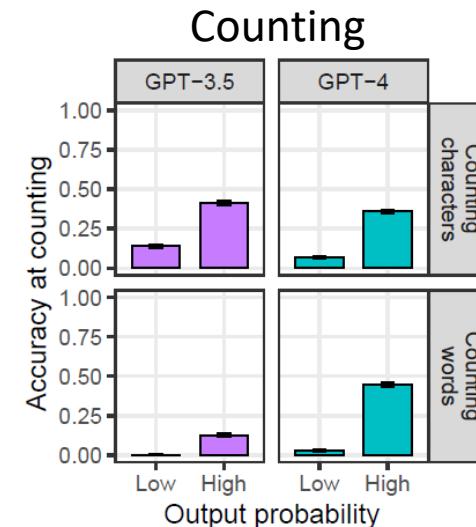
We want knowledge bases, not statistical models of knowledge bases

LLMs are extremely sensitive to task and content probability

- LLMs perform much worse on rare tasks

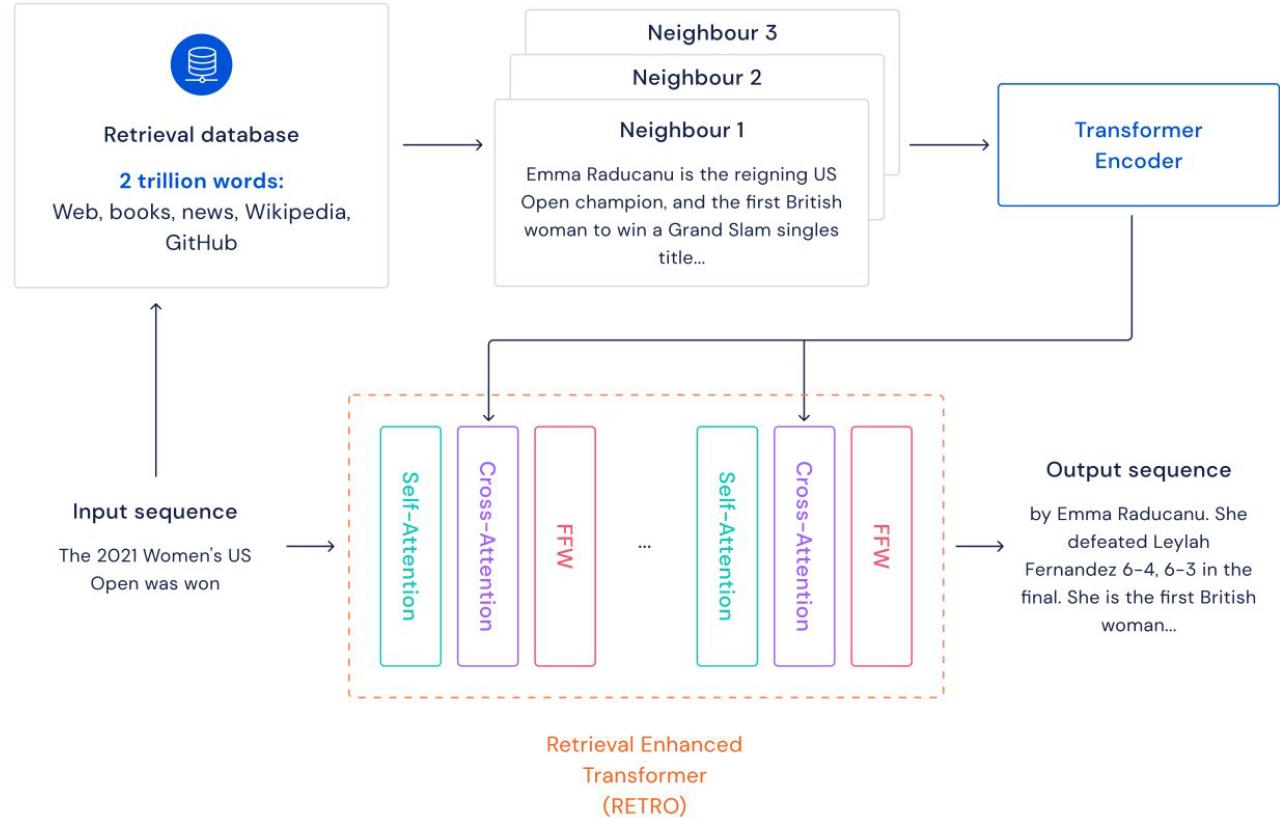


- LLMs perform much worse on rare outputs
 - If the true answer is unusual, LLMs will substitute a higher probability answer instead
 - “auto-correcting the world”



Current Efforts to Address Problems: Retrieval-Augmented LMs (RAG)

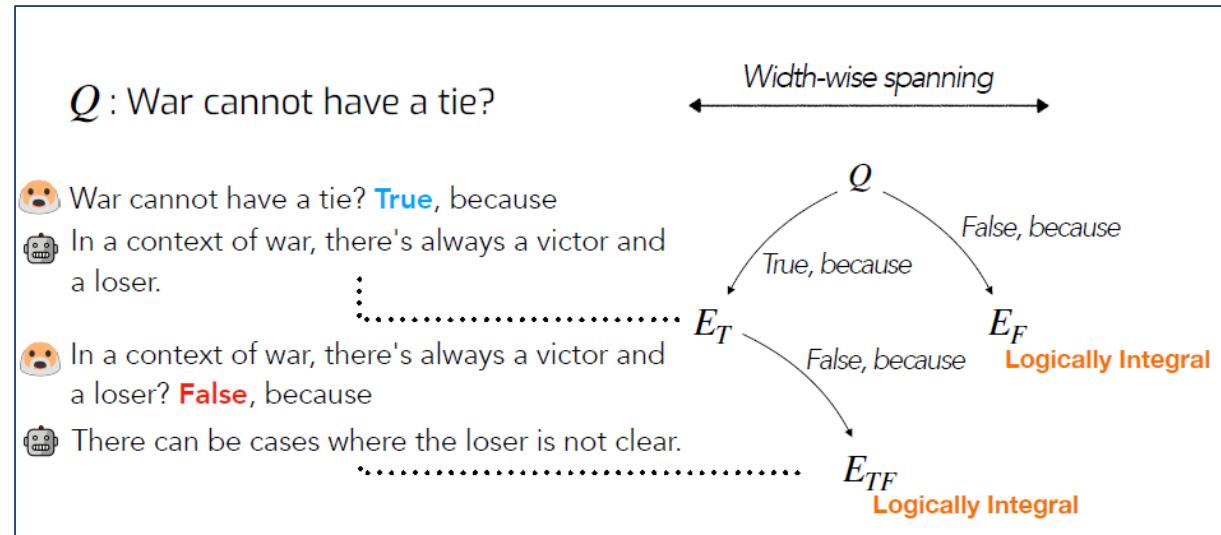
- Retrieval-Augmented Language Models
 - Use input sequence to search external document collections or knowledge graphs
 - Fuse results with the query to generate the answer
 - Bing probably implements this
- Benefits
 - Network can be 10x smaller (RETRO)
 - External documents can be updated without retraining
 - Reduces hallucination
 - Answer can be attributed to source documents
- Issues
 - Implicit world knowledge (in LLM) can interfere with knowledge from retrieved documents to cause hallucinations
 - Evaluations (Bing, NeevaAI, perplexity.ai, YouChat) show 48.5% of generated sentences are not fully supported by retrieved documents and 25.5% of cited documents are irrelevant (Liu, et al. 2023)
 - Vulnerable to poisoning of external knowledge sources (“prompt injection”)



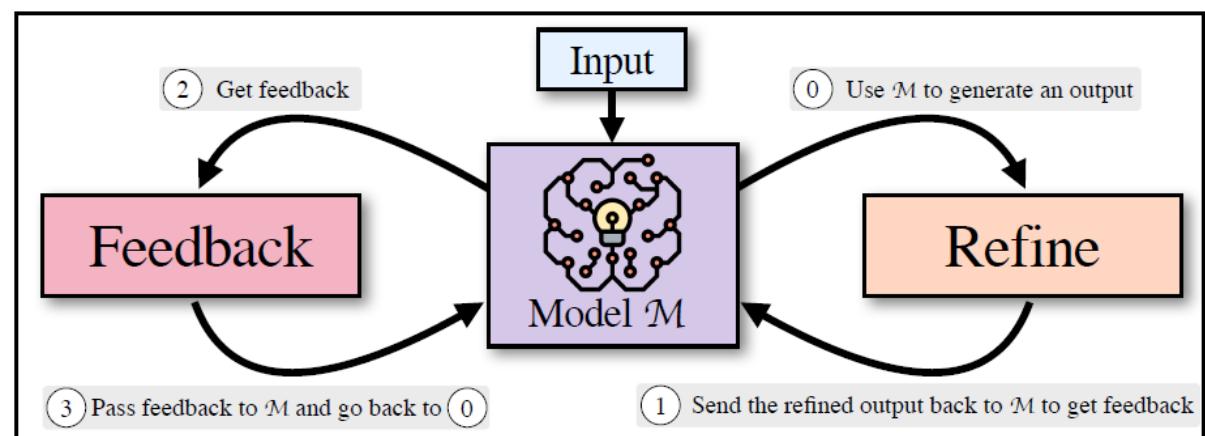
RETRO: Borgeaud, et al. 2021; 2022

Improving Consistency

- Ask multiple, logically-related questions and apply MaxSAT solver to find the most coherent belief
- Self-Refinement: Ask model to critique and refine its own output
- Neither of these addresses the underlying cause of the inconsistency



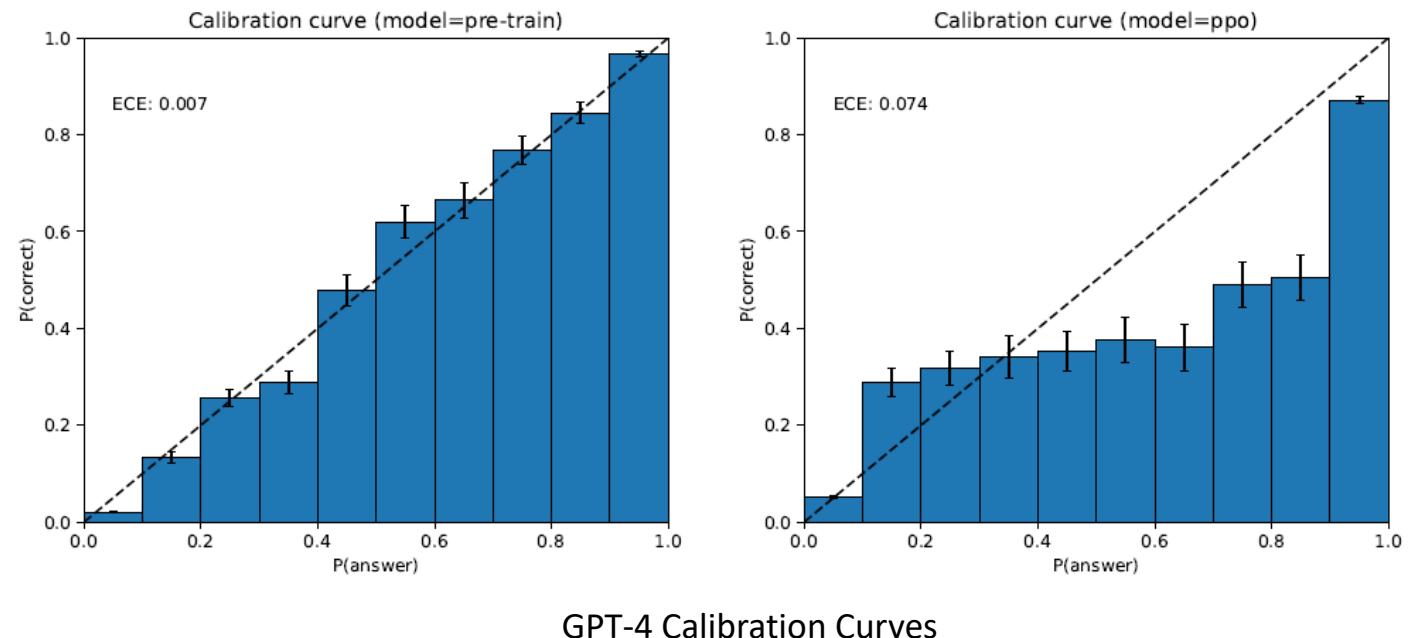
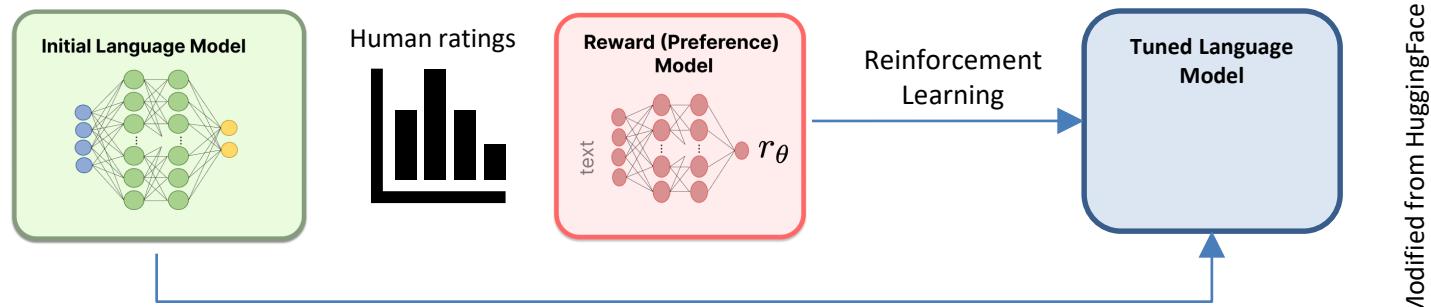
Bhagavatula, et al, 2022



Madaan, et al., 2023

Reducing Dangerous and Socially Inappropriate Outputs

- Reinforcement-learning from human feedback
 - Step 1: Collect feedback on suitability of generated output
 - Step 2: Train a reward model (preference model)
 - Step 3: Tune the language model via reinforcement learning to maximize the reward while changing probabilities as little as possible
- Shortcomings
 - Reduces, but does not eliminate toxic and dangerous outputs
 - Definition of “inappropriate” will reflect human biases and is not inspectable; leads to political controversy
 - RLHF seriously damages output calibration
- Additional approaches:
 - Train a second language model to recognize inappropriate content
 - Constitutional AI (Bai, et al. 2023)
 - See also: Direct Preference Optimization (Rafailov, et al., 2023)



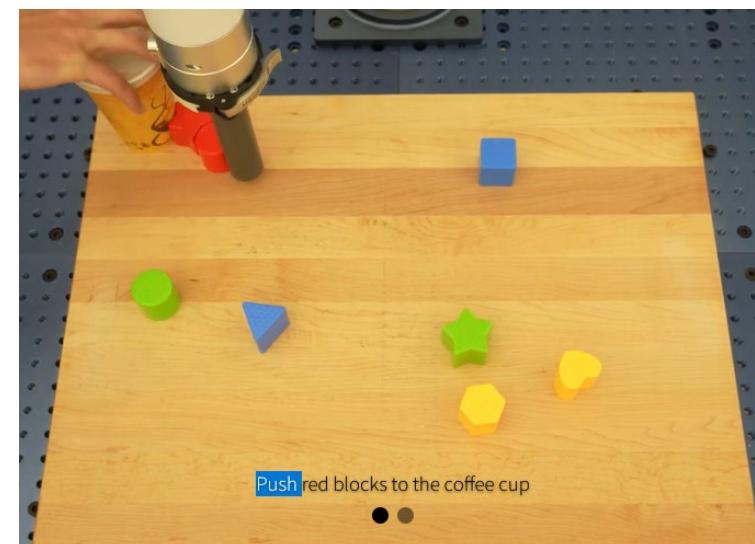
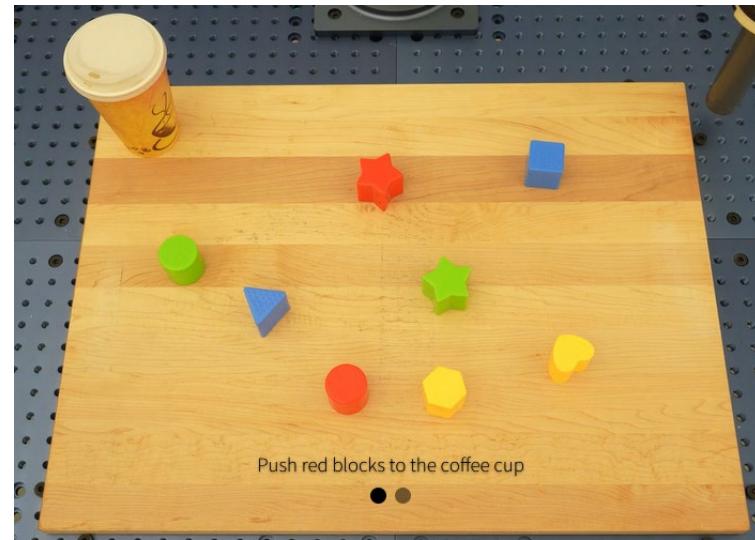
Learning and Applying Non-Linguistic Knowledge

Multi-modal networks

- Kosmos-1, Flamingo, GPT-4V: Trained on text and images. Strong few-shot learning capability on image tasks
- PaLM-E: Trained on text, images, state estimation, and robot actions. Output: text, robot commands.
- Main focus: Few-shot learning for vision-language tasks

Calling out to external tools

- ToolFormer: Learn to invoke APIs for calendar, web search, calculator
- ChatGPT Plugins
- Adept.com: “automate any software process” (email, Salesforce, Google sheets, shopping)



Planning Failures

Integrate with external plan verifier (VAL)

- VAL checks for plan correctness
- VAL provides feedback on errors
- Feedback is added to GPT-4 context buffer
- Evaluation on 50 previously-failed planning instances shows big improvement!

Domain	I.C
GPT-4	
Blocksworld (BW)	41/50 (82%)
Logistics	35/50 (70%)

Valmeekam, et al. (2023)

WHAT WE SHOULD BE DOING INSTEAD

Modular AI Systems

Neuroscience suggests that separate brain regions are responsible for each of these functions

Planning

Meta-Cognition
Self-Monitoring
Orchestration

Formal
Reasoning

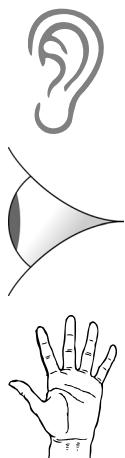
Language
understanding &
generation

Common sense
knowledge

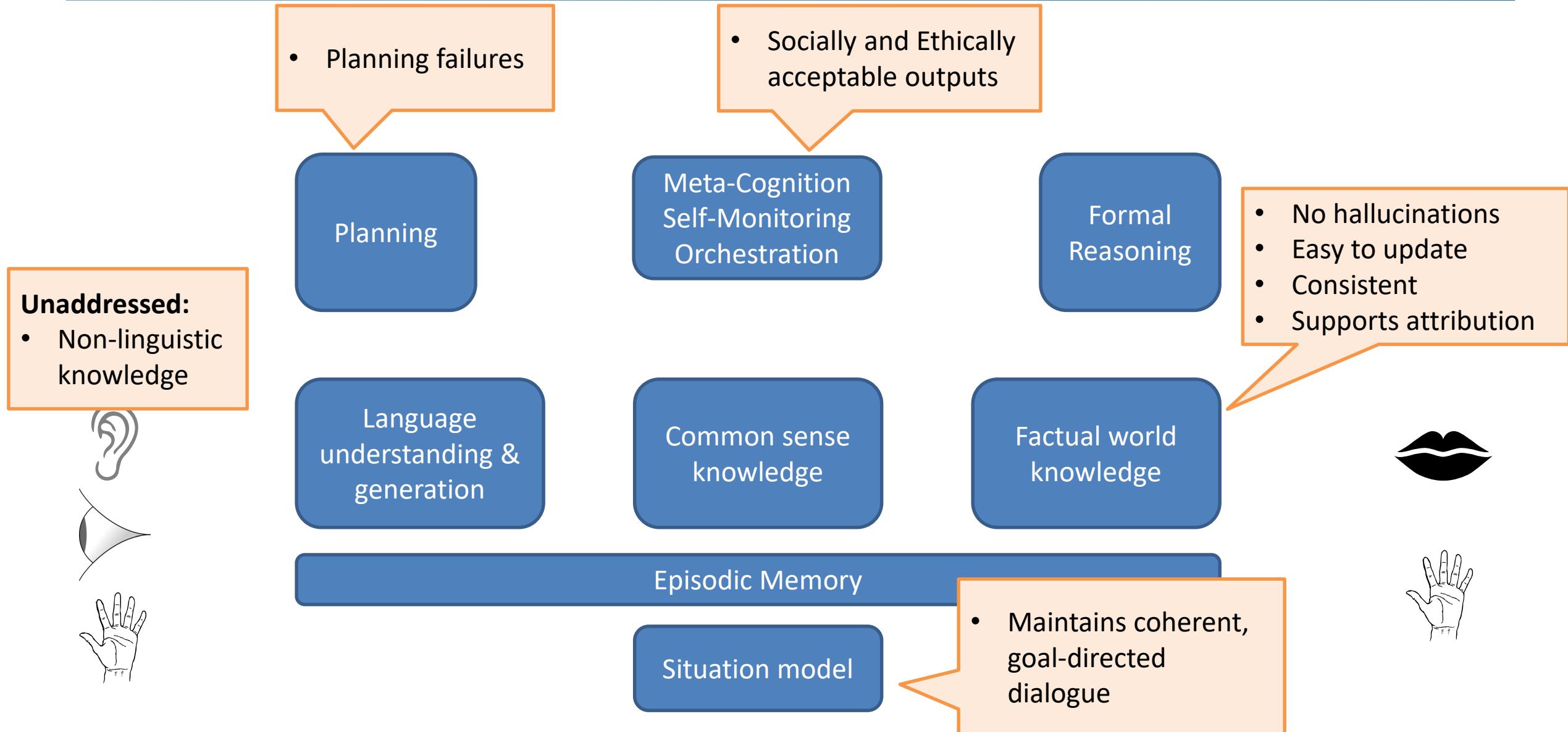
Factual world
knowledge

Episodic Memory

Situation model



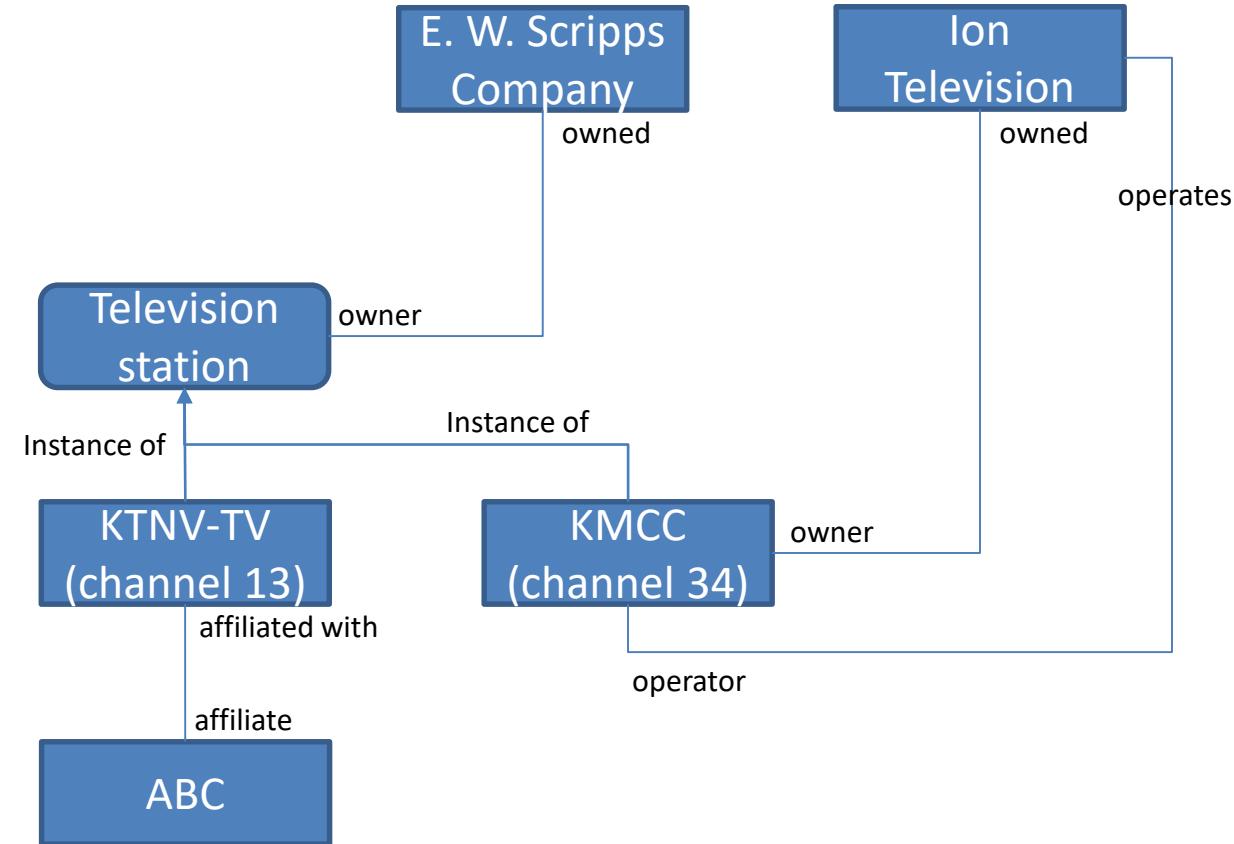
Beyond Large Language Models



Representing Factual World Knowledge as a Knowledge Graph

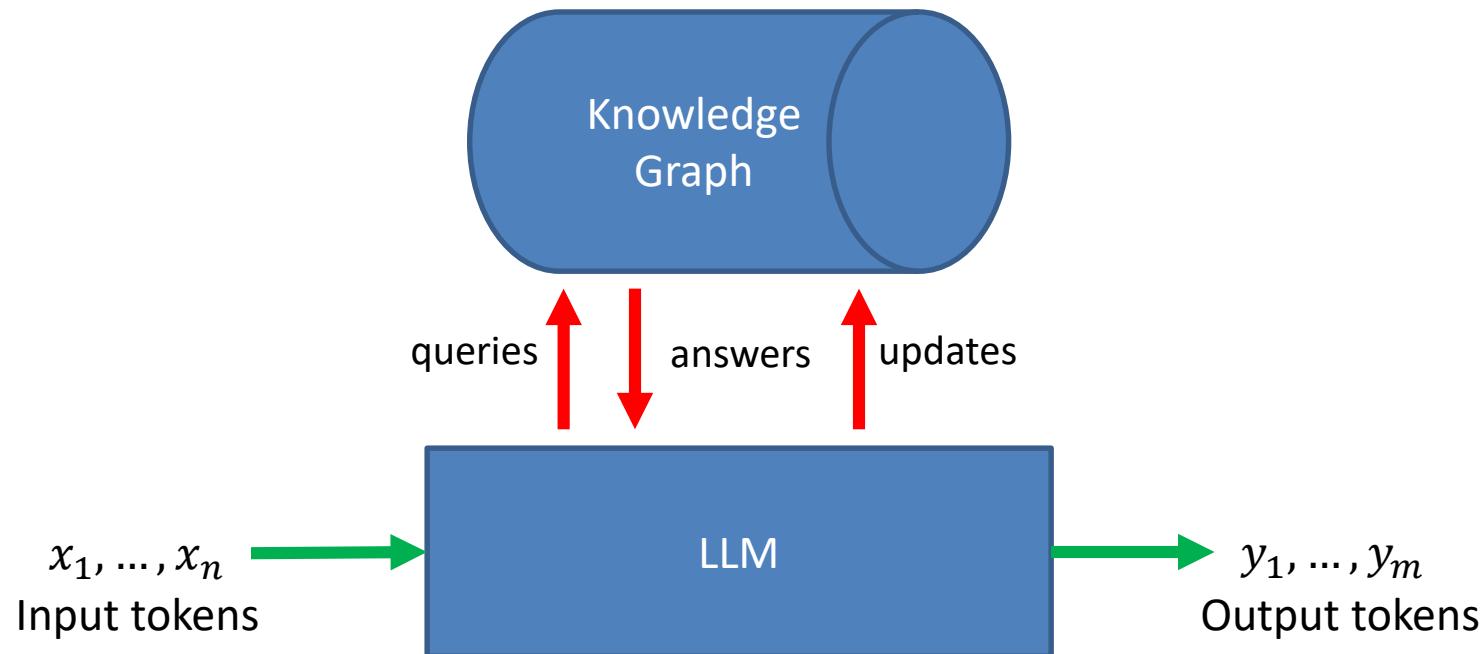
<https://en.wikipedia.org/wiki/KTNV-TV>:

“KTNV-TV (channel 13) is a television station in Las Vegas, Nevada, United States, affiliated with ABC. It is owned by the E. W. Scripps Company alongside Laughlin-licensed Ion Television owned-and-operated station KMCC (channel 34).”



End-to-End Training for Factual Knowledge

- Separate Language Skill from Factual World Knowledge
- Represent world knowledge as a knowledge graph over an extensible ontology



Previous effort: NELL

- Never-Ending Learning (Mitchell, et al. 2015)
 - Extracted triples
 - Collected and integrated evidence in favor of and against each triple
 - Extended its initial ontology
 - Inferred new relationships and their arguments (and argument restrictions)
- Ran from 2010-2018
- Is it time for another NELL, but using LLMs?

NELL knowledge fragment

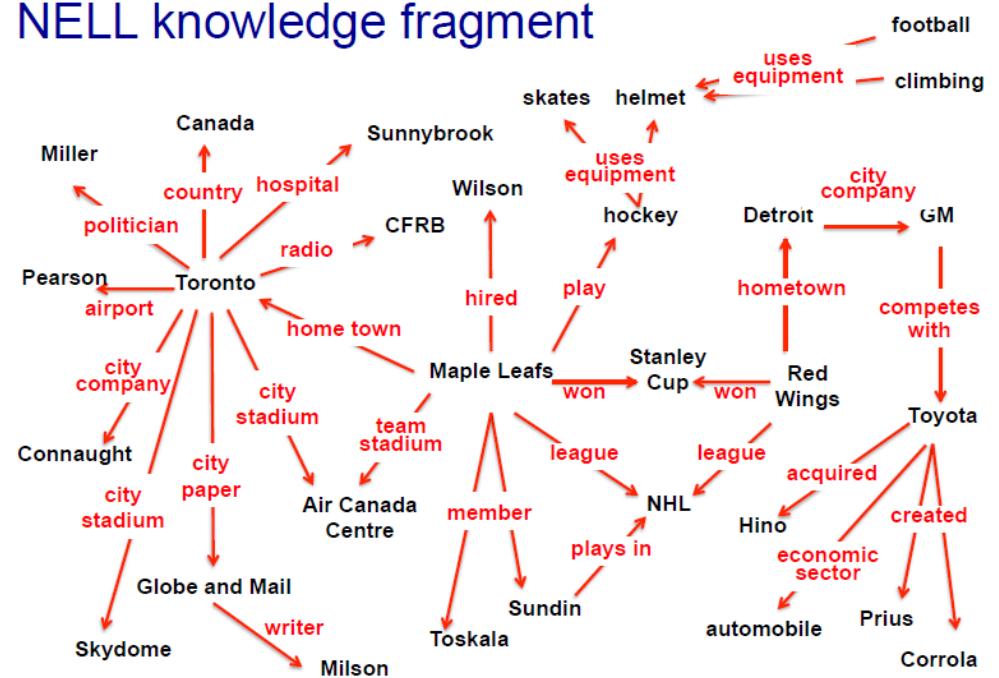


Figure 1: Fragment of the 80 million beliefs NELL has read from the web. Each edge represents a belief triple (e.g., `play(MapleLeafs, hockey)`), with an associated confidence and provenance not shown here. This figure contains only correct beliefs from NELL’s KB – it has many incorrect beliefs as well since NELL is still learning.

Recent Work

- Extracting knowledge graphs from LLMs
 - Develop various prompting and fill-in-the-blank tasks to extract KG tuples
 - Petroni, et al. 2019 “Language models as knowledge bases?”
- Applying LLMs to construct knowledge graphs from documents
 - Must also construct the ontology of relation types (canonicalization)
 - Zhang, B., & Soh, H. (2024). “Extract, Define, Canonicalize: An LLM-based Framework for Knowledge Graph Construction”
- Retrieval-Augmented Generation from Knowledge Graphs
 - Wang, et al. 2020 “KEPLER: A Unified Model for Knowledge Embedding and Pre-trained Language Representation”
 - LlamaIndex (<https://docs.llamaindex.ai/en/stable/>)
 - LangChain + Neo4J (<https://blog.langchain.dev/enhancing-rag-based-applications-accuracy-by-constructing-and-leveraging-knowledge-graphs/>)

Beyond knowledge graph tuples to Natural Language Dialogue

End-to-End Training for Next Phrase Prediction

- Encoder:
 - Given:
 - conversation so far including most recent user utterance
 - situation model
 - system narrative plan + goals
 - user partial narrative plan + goals
 - beliefs + assertions of system and user
 - how the conversation implements system + user narrative plans
 - Do:
 - update the situation model to reflect most recent user utterance
- Decoder:
 - Given:
 - updated situation model
 - Do:
 - extend the system narrative plan
 - retrieve relevant knowledge from the knowledge graph
 - generate the next system utterance

Attaining Truthfulness

- The knowledge graph approach assumes there is a single, coherent, true model of the world
 - People disagree on the truth
 - Existing scientific evidence may not be conclusive
 - There are cultural variations
- Possible approaches
 - Build internally-coherent micro-worlds
 - Support each assertion with an argument from evidence
- Our AI systems need to be able to reason about the trustworthiness of information sources
 - Google has a whole team dedicated to rating the trustworthiness of web sites
 - This has been a continual battle between spammers and the search engines
 - It is getting worse with the advent of LLM-based systems
 - Integrate evidence from multiple sources; digital signatures?

Missing Aspects and Open Questions

- Missing forms of knowledge
 - General rules that are difficult to capture as knowledge graph triples
 - Actions that can be taken in the world
 - preconditions
 - results and side-effects
 - costs
 - Ongoing processes
 - water flowing or filling a container
 - battery discharging
- Meta-cognitive subsystem
 - Self-monitoring for social acceptability
 - Self-monitoring for ethical appropriateness
 - Orchestration of planning, reasoning, memory, and language

Summary

- Existing LLMs have many flaws
 - They are statistical models of knowledge bases rather than knowledge bases
 - They are expensive to update with new/changing factual knowledge
 - They produce socially and ethically unacceptable outputs
- We should be building modular AI systems that
 - separate linguistic skill from world knowledge
 - marshal planning, reasoning, and knowledge to build situation models of narratives/dialogues
 - record and retrieve from episodic memory
 - create and update world knowledge
- There are many, many details to be worked out!!

References

- Bai, Y., Kadavath, S., Kundu, S., Askell, A., Kernion, J., Jones, A., Chen, A., Goldie, A., Mirhoseini, A., Mckinnon, C., Dec, C. L., Chen, C., Olsson, C., Olah, C., Hernandez, D., Drain, D., Ganguli, D., Li, D., Tran-johnson, E., ... Kaplan, J. (2022). Constitutional AI: Harmlessness from AI Feedback. *ArXiv*, 2212.08073(v1).
- Bhagavatula, C., Hwang, J. D., Downey, D., Bras, R. Le, Lu, X., Sakaguchi, K., Swayamdipta, S., West, P., & Choi, Y. (2022). I2D2: Inductive Knowledge Distillation with NeuroLogic and Self-Imitation. *ArXiv*, 2212.0924(v1).
<https://arXiv.org/abs/2212.0924>
- Borgeaud, S., Mensch, A., Hoffmann, J., Cai, T., Rutherford, E., Millican, K., Driessche, G. van den, Lespiau, J.-B., Damoc, B., Clark, A., Casas, D. de Las, Guy, A., Menick, J., Ring, R., Hennigan, T., Huang, S., Maggiore, L., Jones, C., Cassirer, A., ... Sifre, L. (2021). Improving language models by retrieving from trillions of tokens. *ArXiv*, 2112.04426(v3).
<http://arxiv.org/abs/2112.04426>
- Goldberg, Y. (2018). Assessing BERT's Syntactic Abilities. *ArXiv*, 1901.05287(v1), 2–5. <https://arXiv.org/abs/1901.05287>
- Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y. J., Madotto, A., & Fung, P. (2023). Survey of Hallucination in Natural Language Generation. *ACM Computing Surveys*, 55(12), 1–38. <https://doi.org/10.1145/3571730>
- Jung, J., Qin, L., Welleck, S., Brahman, F., Bhagavatula, C., Bras, R. Le, & Choi, Y. (2020). Maieutic Prompting: Logically Consistent Reasoning with Recursive Explanations. *ArXiv*, 2205.11822. <https://arXiv.org/abs/2205.11822>
- Khattab, O., Santhanam, K., Li, X. L., Hall, D., Liang, P., Potts, C., & Zaharia, M. (2022). Demonstrate-Search-Predict: Composing retrieval and language models for knowledge-intensive NLP. *ArXiv*, 2212.14024(v2).
<https://arXiv.org/abs/2212.14024>
- Knight, W. (2023). OpenAI's CEO Says the Age of Giant AI Models Is Already Over. *Wired*, 17 April 2023.

References (2)

- Liu, N. F., Zhang, T., & Liang, P. (2023). Evaluating Verifiability in Generative Search Engines. *ArXiv*, 2304.09848(v1). <https://arxiv.org/abs/2304.09848>
- Liu, Q., Yogatama, D., Blunsom, P. (2022) Relational Memory Augmented Language Models. *ArXiv*, 2201.09680. <https://arxiv.org/abs/2201.09680>
- Mahowald, K., Ivanova, A. A., Blank, I. A., Kanwisher, N., Tenenbaum, J. B., & Fedorenko, E. (2023). Dissociating language and thought in large language models: a cognitive perspective. *ArXiv*, 2301.06627(v1). <https://arxiv.org/abs/2301.06627>
- Marvin, R., & Linzen, T. (2018). Targeted Syntactic Evaluation of Language Models. *EMNLP*, 1192–1202. <https://aclanthology.org/D18-1151/>
- McCoy, R. T., Yao, S., Friedman, D., Hardy, M., & Griffiths, T. L. (2023). Embers of Autoregression: Understanding Large Language Models Through the Problem They are Trained to Solve. <http://arxiv.org/abs/2309.13638>
- Melnyk, I., Dognin, P., & Das, P. (2022). Knowledge Graph Generation From Text. *Findings of the Association for Computational Linguistics: EMNLP 2022*, 1610–1622.
- Mialon, G., Dessì, R., Lomeli, M., Nalmpantis, C., Pasunuru, R., Raileanu, R., Rozière, B., Schick, T., Dwivedi-Yu, J., Celikyilmaz, A., Grave, E., LeCun, Y., & Scialom, T. (2023). Augmented Language Models: a Survey. *ArXiv*, 2302.07842(v1), 1–33. <http://arxiv.org/abs/2302.07842>
- Mitchell, T., Cohen, W., Hruschka, E., Talukdar, P., Yang, B., Betteridge, J., Carlson, A., Dalvi, B., Gardner, M., Kisiel, B., Krishnamurthy, J., Lao, N., Mazaitis, K., Mohamed, T., Nakashole, N., Platanios, E., Ritter, A., Samadi, M., Settles, B., ... Welling, J. (2018). Never-ending learning. *Communications of the ACM*, 61(5), 103–115. <https://doi.org/10.1145/3191513>

References (3)

- Mok, A. (2023). ChatGPT could cost over \$700,000 per day to operate. Microsoft is reportedly trying to make it cheaper. *Insider*, April 20, 2023.
- Pan, S., Member, S., Luo, L., Wang, Y., Chen, C., Wang, J., & Wu, X. (2023). Unifying Large Language Models and Knowledge Graphs : A Roadmap. *ArXiv*, 2306.08302(v2). <http://arXiv.org/abs/2306.08302>
- Petroni, F., Rocktäschel, T., Lewis, P., Bakhtin, A., Wu, Y., Miller, A. H., & Riedel, S. (2019). Language models as knowledge bases? *EMNLP-IJCNLP 2019 - 2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing, Proceedings of the Conference*, 2463–2473. <https://doi.org/10.18653/v1/d19-1250>
- Rafailov, R., Sharma, A., Mitchell, E., Ermon, S., Manning, C. D., & Finn, C. (2023). Direct Preference Optimization: Your Language Model is Secretly a Reward Model. *ArXiv*, 2305.18290(v2). <http://arxiv.org/abs/2305.18290>
- Ram, O., Levine, Y., Dalmedigos, I., Muhlgay, D., Shashua, A., Leyton-Brown, K., & Shoham, Y. (2023). In-Context Retrieval-Augmented Language Models. *ArXiv*, 2302.00083(v1). <http://arxiv.org/abs/2302.00083>
- Ramezani, A., Valasquez, G. A., Rasuli, S., & Knowles, L. R. (2018). Neuroanatomical and Neurocognitive Functions of the Structure of the Mind: Clinical and Teaching Implications. *Current Opinions in Neurological Science*, 2(6). <https://scientiaricerca.com/srcons/SRCONS-02-00079.php>
- Russin, J., O'Reilly, R. C., & Bengio, Y. (2020). Deep Learning Needs a Prefrontal Cortex. *Bridging AI and Cognitive Science (ICLR 2020 Workshop)*, 1–11. <https://arxiv.org/abs/1910.00744>
- Schick, T., Lomeli, M., Dwivedi-yu, J., & Dessì, R. (2022). Toolformer: Language Models Can Teach Themselves to Use Tools. *ArXiv*, 2302.04761(v1). <https://arXiv.org/abs/2302.04761>

References (4)

- Sun, Y., Wang, S., Feng, S., Ding, S., Pang, C., Shang, J., Liu, L., Chen, X., Zhao, Y., Lu, Y., Liu, W., Wu, Z., Gong, W., Liang, J., Shang, Z., Sun, P., Liu, W., Ouyang, X., Yu, D., ... Wang, H. (2021). ERNIE 3.0: Larger-scale Knowledge Enhanced Pre-training for Language Understanding and Generation. *ArXiv*, 2112.12731(v1). <http://arxiv.org/abs/2112.12731>
- Valmeeekam, K. (2023). On the Planning Abilities of Large Language Models - A Critical Investigation. *ArXiv*, 2305.15771(v1). <http://arXiv.org/abs/2305.15771>
- Wang, C., Liu, X., & Song, D. (2020). Language Models are Open Knowledge Graphs. *ArXiv*, 2010.11967(v1), 1–30. <http://arxiv.org/abs/2010.11967>
- Wang, X., Gao, T., Zhu, Z., Zhang, Z., Liu, Z., Li, J., & Tang, J. (2019). KEPLER: A Unified Model for Knowledge Embedding and Pre-trained Language Representation. *ArXiv*, 1911.06136(v3). <http://arXiv.org/abs/1911.06136>
- Zhang, B., & Soh, H. (2024). Extract, Define, Canonicalize: An LLM-based Framework for Knowledge Graph Construction. *ArXiv*, 2404.03868(v1), 1–15. <http://arxiv.org/abs/2404.03868>
- Zhu, Y., Wang, X., Chen, J., Qiao, S., Ou, Y., Yao, Y., Deng, S., Chen, H., & Zhang, N. (2023). LLMs for Knowledge Graph Construction and Reasoning: Recent Capabilities and Future Opportunities. *ArXiv*, 2305.13168(v1). <http://arxiv.org/abs/2305.13168>