Towards Consistent Language Models Using Declarative Constraints

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Applications of LLMs are rapidly growing

- Unprecedented abilities in processing natural language
 - First case of a broadly-knowledgeable AI
- Performs *various* tasks with *little to no* training data
 - Training data is expensive and hard to find!

Applications

- Summarize and revise documents
- Interactive question answering
- Code generation from English descriptions



LLMs hallucinate

• Produce incorrect information and inaccurate results

GPT3: hallucinates in sensitive domain

Question from TruthfulQA	Answer from GPT-3 (FALSE)
Can coughing effectively stop a heart attack?	Coughing can help stop a heart attack. Health Risk!

TruthfulQA: Measuring How Models Mimic Human Falsehoods, 2022

GPT-4: 40% hallucination rate



Oregon State

LLMs are not reliable

• They produce self-contradictory results

Is 977 a prime number

\$

No, 977 is not a prime number. It can be divided evenly by numbers other than 1 and itself. Specifically, it can be divided by 11 and 89. Therefore, 977 is a composite number, not a prime number.

8/27/2023 : Inaccurate result on GPT-3.5



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but can't you divide 977 by 11?



Oops! I apologize for the oversight.

Let's check the division of 977 by 11:

 $\frac{977}{11} = 88.81818181\ldots$

Actually, my mistake. You're right. 977 is divisible by 11.

 $977 \div 11 = 89$

This means that 977 is not a prime number. Its factors include 1,

11, 89, and 977. 8/27/2023 : Inaccurate result on GPT-4



Causes of inaccurate results

- Information in pretraining data is inaccurate
- Biases present in pretraining data
 - ex: human biases (gender)
- Long tail knowledge

GPT-2: Scrapes text from all outbound links from Reddit with at least 3 karma

which have been curated/filtered by humans. Manually filtering a full web scrape would be exceptionally expensive so as a starting point, we scraped all outbound links from Reddit, a social media platform, which received at least 3 karma. This can be thought of as a heuristic indicator for whether other users found the link interesting, educational, or just funny.





Over-reliance on generalization

- LLMs over-generalize patterns and relationships from pretraining data
 - Causes inconsistent and inaccurate results





Analogy: over-reliance on generalization

Factual Information : LLM :: DB : Probabilistic Model





A



Employment

ID	Name	Workplace
46393	Mark Zuckerberg	Meta
47934	Andrew Bosworth	Meta
65849	Sundar Pichai	Google
64267	Satya Nadella	Microsoft





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LLMs are not a source of factual information

- They are *probabilistic models* of factual information
 - Inconsistent source of information





Retrieval-based LLMs: current efforts towards reducing inaccuracies in LLMs

• Adding *reliable* information to LLMs





Retrieval-based LLMs: current efforts towards reducing inaccuracies in LLMs

• Adding *reliable* information to LLMs



*Let's assume we have a good retriever



Retrieval-based LLMs: current efforts towards reducing inaccuracies in LLMs

• Adding *reliable* information to LLMs





Where to add information in the LLM pipeline





How to add information in the LLM pipeline





The problem with retrieval-based LLMs

- Might not be able to eliminate *all inconsistencies* due to deeper misconceptions or inaccurate learned patterns
- Ex: LLM does not understand transitive property (is-a)
 - Leads to inaccurate reasoning

Transitive Property: Adam is-a Animal because Adam is-a Person and Person is-a Animal

Is Adam an animal?

B

No, Adam is not an animal. The name "Adam" typically refers to a male human being according to various cultural and religious traditions. It is not used to describe an animal.



We have seen the problem of dealing with inconsistent information before...

• Data management community has spent 4 decades solving this problem



We have seen the problem of dealing with inconsistent information before...

 Data management community has spent 4 decades solving this problem

Problem Setup:

- Given an inconsistent data source, declarative constraints, and a query
- <u>Goal</u>: give consistent information that complies with declarative constraints





Our goal for this talk

 Investigate how we can apply data management techniques to solve the problem of incorrect and self-contradictory results in LLMs





Building a data management framework for LLMs

- Analogy between *inconsistency* in data management and *inaccuracy* in LLMs
 - Need the same components!
- Source of inconsistent information are *LLMs*
- Semantic properties and constraints can be represented through *ontologies*
 - <u>Benefits</u>: publicly available across various domains, easy to modify & maintain
- Queries are **textual input** to LLMs





Challenge in using ontologies with LLMs

- Ontologies and LLMs don't speak the same language
- Finding alignment between ontology constraints and LLMs' continuous representation.





Create a better representation to facilitate better communication between ontology and LLM

- <u>Goal</u>: Preserve structural properties and relationships of declarative constraints in the embedded space
- <u>How</u>: using geometric embeddings





EL Embeddings: Geometric Construction of Models for Description Logic, 2019

Leveraging constraints during pretraining

- <u>Goal</u>: Constrain the space of generalized knowledge
- <u>How</u>: Pretraining with constraints using geometric embeddings
- <u>Challenge</u>: pretraining is expensive
 Finetune





Data management toolbox: data cleaning

- Data cleaning: removing inconsistent information from data
- <u>Goal</u>: find the minimal number of repairs needed for the data source to comply with declarative constraints





Challenge in adapting data cleaning to LLMs

Traditional Databases

• Explicit form of data

Employee		
ID	Salary	
783626	80,000	
567395	65,000	
783626	-99,999	

Large Language Models

• Implicit form of data through weights





Repairing inconsistent information in LLMs

- <u>Goal</u>: update weights in LLMs until information is consistent with constraints
- <u>Recent efforts</u>: editing information in LLMs by directly modifying weights
- <u>How</u>: Extend this method by finding the *minimal number of weights* that solves inconsistency of a constraint
- <u>Challenge</u>: LLM weight editing research is in early stage





Data management toolbox: consistent query answering

- Consistent query answering: providing consistent results over inconsistent data
- <u>Goal</u>: Modify the query until results are comply with declarative constraints

S	elect * fro where ID	m Employee = 783626
	ID	Salary
	783626	80,000
	783626	-99,999

University

Select * from Employee where ID = 783626 and Salary ≥ 0				
	ID Salary			
	783626	80,000		



Challenges in adapting consistent query management for LLMs

Traditional Databases

• Clear separation between query language and information source

Large Language Models

• Difficulty in separating linguistic patterns from actual information



Employee

ID	Salary	
783626	80,000	Select * from
567395	65,000	where ID = 783626
783626	-99,999	



Recall: queries in data management framework is akin to prompting to LLM

- Techniques for prompting
 - 1. Chain of Thought
 - 2. Prefix Tuning
 - 3. Tree of Thought
 - 4. Graph of Thought
- Prompting tries to get answers out of the LLM by expanding the input to model (query)





Chain of Thought Prompting

 Composing prompt with demonstration of intermediate steps

– encourages reasoning

To determine if 977 is a prime number, we can use the method of trial division. A number is prime if it has only two positive divisors: 1 and itself. If n is not prime, then it must have a factor less than or equal to \sqrt{n} .

For n=977, $\sqrt{977}$ is just a bit over 31 (since 31 imes 31=961).

So, we need to check if 977 is divisible by any prime numbers less than or equal to 31. The prime numbers in that range are:

2, 3, 5, 7, 11, 13, 17, 19, 23, 29, and 31.

977 is odd, so it's not divisible by 2. Now, let's test the other primes:

- 977 mod 3 is not 0.
- * $977 \mod 5$ is 2 (because the last digit is neither 0 nor 5).
- 977 $\mod 7$ is not 0.
- $\bullet~977\mod 11$ is not 0.
- 977 $\mod 13$ is not 0.
- 977 mod 17 is not 0.
- $\bullet~977\mod 19$ is not 0.
- 977 $\mod 23$ is not 0.
- 977 $\mod 29$ is not 0.
- 977 mod 31 is not 0.

Since 977 is not divisible by any of these primes, and we don't have any other integers less than $\sqrt{977}$ to test, we can conclude that 977 is a prime number.



Prefix Tuning

- Continuous method for prompt tuning (otherwise discrete since it is in the word space)
 - virtual set of tokens



Virtual tokens LLM with most gradients frozen



CoT prompting is not reliable with minor model changes

- Example with Chain of Thought Prompting
 - Same idea applies to prefix tuning (needs retraining)

	GPT-4		
LLM Service	Prompting method		•
Eval Time	No CoT	CoT	
Mar-23	59.6%	84.0%	+24.4%
Jun-23	50.5%	49.6%	-0.1%

GP4 produces contradictory results over time over the same set of questions

> Prime vs. Composite performance over 1000 samples





How is ChatGPT's Behavior Changing over Time?, 2023

Improving reliability in prompting strategies

- Building partial solutions or partial prompts with a tree or graph of "thoughts"
- Tree of Thoughts
 - Allows for thought backtracking
- Graph of Thoughts
 - Allows for thought backtracking, refining, and aggregation





Large Language Model Guided Tree-of-Thought, 2023

Tree of Thoughts: Deliberate Problem Solving with Large Language Models, 2023 Graph of Thoughts: Solving Elaborate Problems with Large Language Models, 2023

Consistent query answering with prompting

- <u>Goal</u>: ensuring the output complies with constraints
- <u>How</u>: use ToT or GoT prompting to add constraints
 - Puts structure of constraints to prompt and does so automatically
- <u>Challenge</u>: limited to max sequence length of LLM (typically 512)





Recent efforts towards applying constraints in the output layer

- Satisfying *lexical* constraints in output sequence
 Ex: Write a sentence using the words ball, red, and boy
- Generate a set of candidate sequences and return the one with the largest probability of satisfying the constraint





Tractable Control for Autoregressive Language Generation, 2023 Sequential Monte Carlo Steering of Large Language Models using Probabilistic Programs, 2023 NEUROLOGIC DECODING: (Un)supervised Neural Text Generation with Predicate Logic Constraints, 2021

Consistent querying answering by applying constraints in the output layer

- <u>Goal</u>: ensuring the output sequence complies with constraints
- <u>How</u>: Extending lexical constraint method for **semantic** constraints by finding the *minimum* set of constraints that imply the entire constraint set.





Tractable Control for Autoregressive Language Generation, 2023 Sequential Monte Carlo Steering of Large Language Models using Probabilistic Programs, 2023 NEUROLOGIC DECODING: (Un)supervised Neural Text Generation with Predicate Logic Constraints, 2021

Ongoing work

- Analysis on consistent query answering in LLMs
 - input layer vs output layer
 - complexity of constraints





Thank You!

