

CSCE 638 Natural Language Processing Foundation and Techniques

Lecture 20: Hallucinations

Kuan-Hao Huang

Spring 2025



Invited Talk



- **Speaker:** [Pan Lu](#), Postdoctoral Scholar at Stanford University
- **Title:** Advancing Complex Reasoning with Language Models and Agentic Systems
- **Date:** 4/16
- **Online @ Zoom:**
 - <https://tamu.zoom.us/my/khhuang?pwd=oAdWOKVOCGPapqDbJnVtktdW2AE6nb.1>

Invited Talk

Abstract: Complex reasoning is fundamental to human intelligence and plays a crucial role in advancing education, science, and technology. This talk explores the development of language model systems that exhibit robust mathematical reasoning and facilitate scientific reasoning, marking a significant step toward general artificial intelligence. We introduce novel multi-modal and knowledge-intensive benchmarks designed to assess the reasoning capabilities of large language models (LLMs) and vision-language models (VLMs) in real-world scenarios, including those involving visual data, tabular information, and scientific applications. The talk highlights recent advancements in mathematical reasoning within visual contexts and addresses key unresolved challenges. Additionally, we present cutting-edge retrieval and tool-augmented algorithms that significantly enhance LLM performance in mathematical reasoning tasks. Finally, we explore how agentic systems, leveraging test-time optimization and external tools, can further advance mathematical reasoning and scientific discovery.

Invited Talk



Evaluating Math Reasoning in Visual Contexts

Pan Lu¹, Hritik Bansal¹, Tony Xia¹, Jiacheng Liu², Chunyuan Li³, Hannaneh Hajishirzi², Hao Cheng³,
Kai-Wei Chang¹, Michel Galley³, Jianfeng Gao³

¹University of California, Los Angeles,

²University of Washington, ³Microsoft Research

ICLR 2024 Oral (85 in 7304, 1.2%)

[Paper](#)

[arXiv](#)

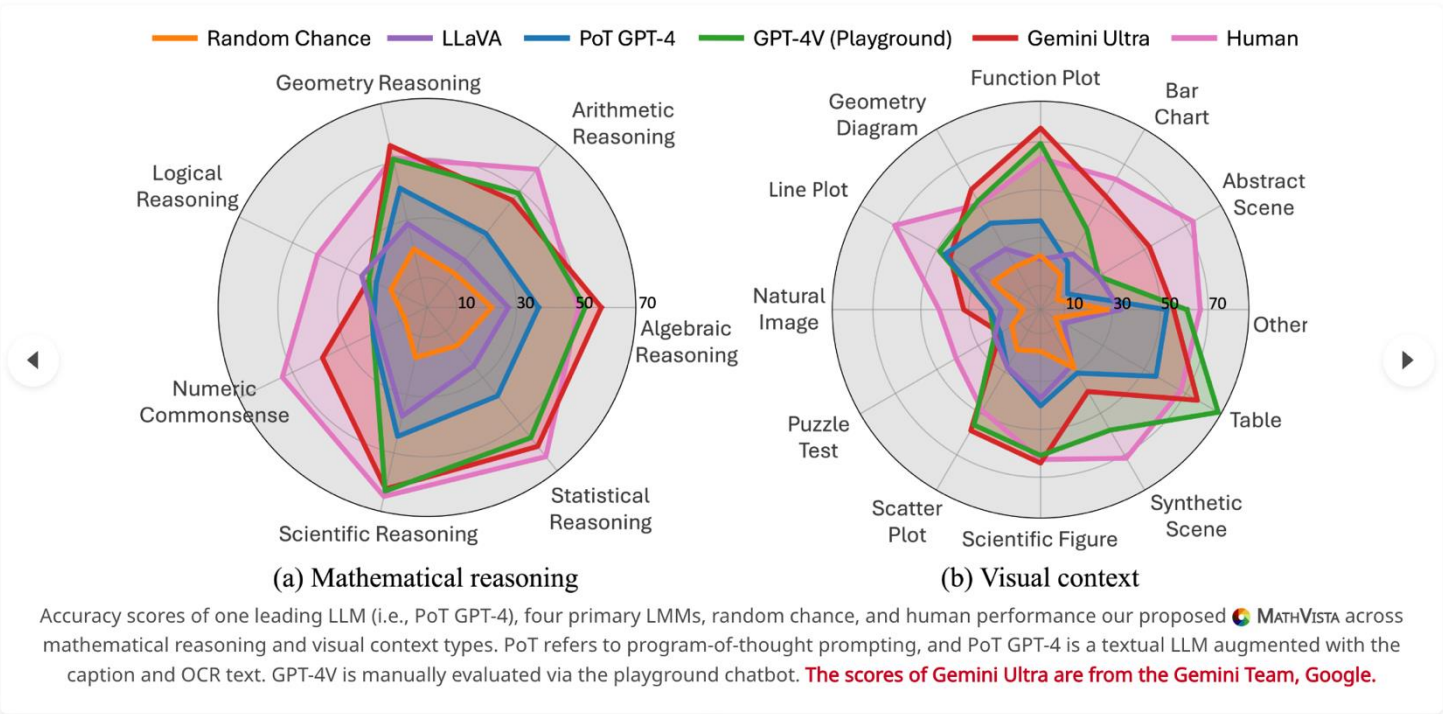
[Code](#)

[Dataset](#)

[Visualize](#)

[Leaderboard](#)

[Twitter](#)



Quiz 3

- Date: 4/14
 - 15 minutes before the end of the lecture
 - 5 questions focusing on high-level concepts
- Pay attention to how methods work and the difference between them

W10	3/17	L15	Multilingual NLP [slides]
	3/19	L16	Vision-Language Models [slides]
W11	3/24	L17	Adversarial Attack and Defense [slides]
	3/26	L18	AI-Generated Text Detection [slides]
W12	3/31		Invited Talk (Minhao Cheng)
	4/2	L19	Bias Detection and Mitigation [slides]
W13	4/7	L20	Hallucinations and Misinformation Control
	4/9	L21	Controlled Generation, Non-Autoregressive Generation

Course Project – Final Report

- Due: 4/30
- Page limit: 9 pages (references are not counted for page limit)
- The report should include
 - Introduction to the topic you choose
 - Related literature
 - Novelty and challenges
 - Your approach
 - Experimental settings
 - Results, findings, and insights
 - Future directions
- A .zip file containing all the code

Course Project – Final Report

- Introduce all the components of the proposed approaches
 - Your classmates should be able to easily understand what you have done by reading it
 - If your method is based on previous work A, introduce work A a little bit
 - If you collect data by your own, clearly describe the format and how they are being collected
- All contributions need to be grounded in evidence
 - [X] We implement XXX and it has promising performance
 - [O] We implement XXX and it has promising performance, as shown in Figure Y and Table Z
- Properly cite everything


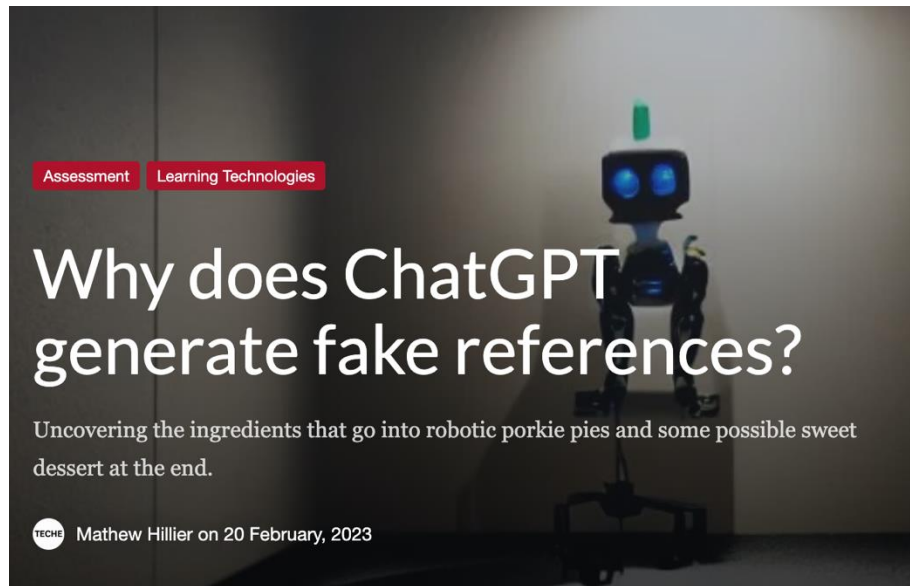
Final Presentation

- Each team has 7 minutes for presentation
 - You have to stop once you reach 7 minutes
- The presentation should include
 - The topic you choose
 - Novelty and challenges compared to previous literature
 - Your approach
 - Experimental settings
 - Results, findings, and insights
- Your classmates should be able to easily understand what you have done

Final Presentation

Date	Order 1	Order 2	Order 3	Order 4	Order 5	Order 6	Order 7	Order 8	Order 9
4/21	Team 2	Team 10	Team 4	Team 9	Team 26	Team 18	Team 1	Team 24	Team 12
4/23	Team 25	Team 14	Team 11	Team 23	Team 13	Team 5	Team 16	Team 15	Team 21
4/28	Team 8	Team 20	Team 19	Team 17	Team 27	Team 7	Team 6	Team 3	Team 22

Hallucinations




What is an AI Hallucination?

An AI hallucination is a false or misleading output generated by an artificial intelligence system. It can be a confident response by an AI that does not seem to be justified by its training data.

Example:

When asked about Microsoft's annual revenue in **2021**, a hallucinating chatbot falsely states that the figure is **\$10 billion** (the right answer should have been **\$168.1 billion**).

 Techopedia

What is Hallucination?

- The generation of content that is irrelevant, made-up, or inconsistent with the input data

What is Hallucination?



Who was the first person to walk on the moon?



Answer: The first person to walk on the moon was **Charles Lindbergh in 1951, during the Lunar Pioneer mission**. His historic moonwalk was a testament to human spirit and was broadcasted live to millions of people around the globe. ❌



Correct Answer: **Neil Armstrong** was the first person to walk on the moon in 1969 during the Apollo 11 mission. ✅

(a) Factuality Hallucination



Please summarize the following news article:



Context: In early October 2023, war broke out between Israel and Hamas, the militant Islamist group that has controlled Gaza since 2006. Hamas fighters fired rockets ... civilians and taking dozens of hostages.

Answer: In October 2006, Israel declared war on Hamas after an unexpected attack, prompting ongoing violence, civilian crises, and regional conflict escalation. ❌

(b) Faithfulness Hallucination

What is Hallucination?



Give me a list of 10 articles as references about the advantages of DIY home-based surgery. Include only publications from high impact factor journals.



1. "The Benefits of Home-Based Surgery: A Review of the Literature" by J. Kim, D. Kim, and J. Yoon in the Journal of Surgical Research (Impact Factor: 2.31).
2. "DIY Surgery: A Review of the Advantages and Disadvantages" by P. R. Smith and J. T. Smith in the Journal of Medical Ethics (Impact Factor: 3.54).
3. "Self-Surgery: A Comparative Study of Outcomes and Costs" by M. S. Cohen and C. L. Smith in the American Journal of Surgery (Impact Factor: 3.24).
4. "DIY Surgery: A Review of the Evidence and Clinical Implications" by L. R. Jones and J. E. Smith in the British Medical Journal (Impact Factor: 23.50).
5. "The Pros and Cons of Home-Based Surgery: A Systematic Review" by R. J. Brown and T. M. Davis in the Annals of Surgery (Impact Factor: 10.23).
6. "DIY Surgery: A Review of the Ethical and Legal Implications" by J. R. Williams and M. K. Jones in the Journal of Medical Ethics (Impact Factor: 3.54).
7. "The Case for Home-Based Surgery: A Review of the Literature" by S. A. Smith and D. J. Smith in the Journal of the American Medical Association (Impact Factor: 50.58).
8. "Self-Surgery: A Review of the Literature and Clinical Implications" by M. T. Jones and J. R. Williams in the Journal of Surgical Oncology (Impact Factor: 3.73).
9. "DIY Surgery: A Review of the Evidence and Clinical Implications" by J. E. Smith and L. R. Jones in the British Journal of Surgery (Impact Factor: 6.62).
10. "The Advantages and Disadvantages of Home-Based Surgery: A Review of the Literature" by D. J. Smith and S. A. Smith in the New England Journal of Medicine (Impact Factor: 70.59).

Hallucination Can Be Serious

JO

Can i get some medical advice please? My right calf is red and swollen and hurts a bit. What's wrong with me? I feel short of breath too



I'm not a doctor, but I can provide some general information. It's important to note that when you're experiencing symptoms like a red and swollen calf, pain, and shortness of breath, it can be indicative of a potentially serious medical issue. These symptoms may suggest a deep vein thrombosis (DVT), which is a blood clot in a deep vein, typically in the leg. DVT can lead to pain, redness, and swelling in the affected leg and can sometimes cause shortness of breath if a clot breaks off and travels to the lungs (pulmonary embolism).

Given the seriousness of these symptoms, it is crucial that you seek immediate medical attention. DVT and pulmonary embolism are both potentially life-threatening conditions and require prompt diagnosis and treatment. Please go to the nearest emergency room or contact your healthcare provider immediately for a proper evaluation and diagnosis. They can perform the necessary tests, such as ultrasound or blood tests, to confirm or rule out DVT and take appropriate action to address your condition. Do not delay seeking medical help in this situation.

Factuality Hallucination

Sub-Type	User Input	Model Output	Explanation
Factual Inconsistency	Tell me about the first person to land on the Moon.	Yuri Gagarin was the first person to land on the Moon	The LLM's response is factual inconsistency as Neil Armstrong was the first person to land on the Moon , not Yuri Gagarin, who was the first human in space
Factual Fabrication	Tell me about the historical origins of unicorns	Unicorns were documented to have roamed the plains of Atlantis around 10,000 BC, where they were considered sacred creatures and were often associated with royalty.	The LLM's response is a fabricated claim since there's no verified, real-world evidence supporting the existence of unicorns in Atlantis , especially in connection with royalty

Faithfulness Hallucination

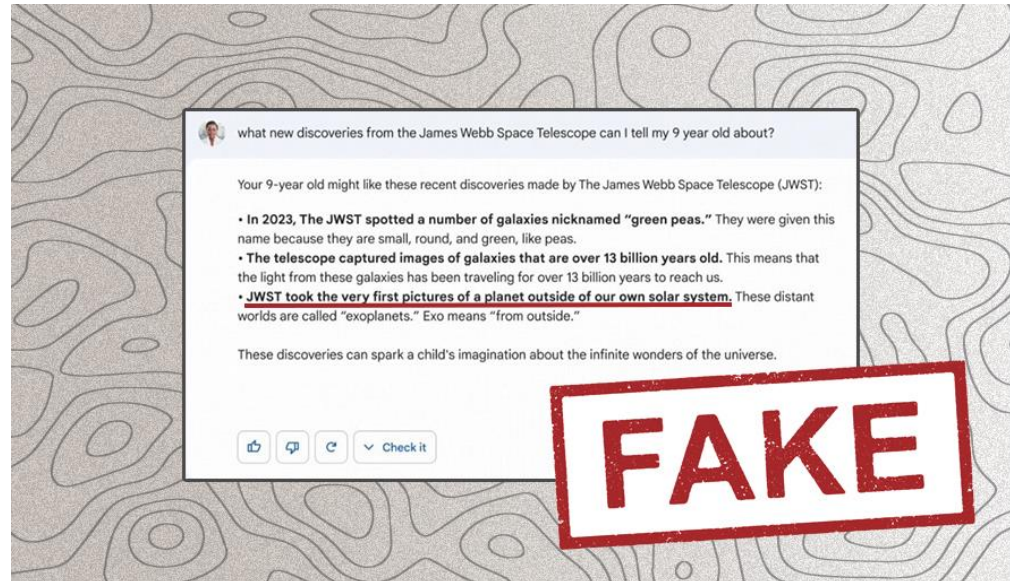
Sub-Type	User Input	Model Output	Explanation
Instruction Inconsistency	Translate the following English question into Spanish: "What is the capital of France?"	The capital of France is Paris.	The user explicitly provided an instruction to translate the English question into Spanish. Instead of performing the translation as instructed, the LLM chose to answer the question.
Context Inconsistency	Summarize the following paragraph about the Nile: The Nile is a major north-flowing river in northeastern Africa. It's traditionally considered the longest river in the world. Originating in the Great Lakes region of central Africa, it flows through several countries before emptying into the Mediterranean Sea	The Nile originates from the mountain ranges of central Africa and flows into the Mediterranean.	The LLM's summary incorrectly states that the Nile originates from the "mountain ranges of Central Africa," while the paragraph clearly mentions that the Nile originates in the Great The Lakes region of central Africa.
Logical Inconsistency	Solve the equation $2x + 3 = 11$ step by step.	Step 1: Subtract 3 from both sides to get: $2x = 8$. Step 2: Divide both sides by 2 to get $x = 3$. So, the result of the equation is $x=3$.	The first step correctly isolates the term with x to get $2x = 8$. However, the next step inaccurately divides 8 by 2 to yield a result of $x = 3$, which is inconsistent with the earlier reasoning.

Causes of Hallucinations in LLMs

- Training data issues
- Inference stage challenges
- Prompt Engineering

Training Data Issues

- Verifying data's fairness, unbiasedness, and factual correctness is challenging
 - Models cannot distinguish between truth and fiction
- Internet-sourced datasets may include biased or incorrect information
 - propagate into the model's outputs



Inference Stage Challenges

- Defective decoding strategies
- Inherent randomness in the sampling methods

Inputs and Prompt Engineering

- LLMs may generate hallucinated content when faced with unclear or imprecise input
- LLMs might generate an incorrect or unrelated answer if a prompt lacks adequate context or is ambiguously worded

FACTSCORE: Fine-grained Atomic Evaluation of Factual Precision in Long Form Text Generation

**Sewon Min^{†1} Kalpesh Krishna^{†2} Xinxi Lyu¹ Mike Lewis⁴ Wen-tau Yih⁴
Pang Wei Koh¹ Mohit Iyyer² Luke Zettlemoyer^{1,4} Hannaneh Hajishirzi^{1,3}**

¹University of Washington ²University of Massachusetts Amherst

³Allen Institute for AI ⁴Meta AI

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{kalpesh,miyyer}@cs.umass.edu {mikelewis,scotttyih}@meta.com

Evaluation of Hallucinations

Input: Tell me a bio of Bridget Moynahan.

This is true

Bridget Moynahan is an American actress, model and

This is not

producer. She is best known for her roles in Grey's Anatomy,

Again, false

but these are all correct

The Recruit, I, Robot and Blue Bloods. She studied acting at

the American Academy of Dramatic Arts, and ...

She did study acting

but at the different institution...

FActScore: Factual Precision in Atomicity Score

Bridget Moynahan is an American actress, model and producer. She is best known for her roles in Grey's Anatomy, I, Robot and Blue Bloods. She studied acting at the American Academy of Dramatic Arts, and ...

Atomic facts



- Bridget Moynahan is American.
- Bridget Moynahan is an actress.
- Bridget Moynahan is a model.
- Bridget Moynahan is a producer.
- She is best known for her roles in Grey's Anatomy.
- She is best known for her roles in I, Robot.
- She is best known for her roles in Blue Bloods.
- She studied acting.
- She studied at the American Academy of Dramatic Arts.
- ...

FActScore: Factual Precision in Atomicity Score

Bridget Moynahan is an American actress, model and producer. She is best known for her roles in Grey's Anatomy, I, Robot and Blue Bloods. She studied acting at the American Academy of Dramatic Arts, and ...

Atomic facts

- Bridget Moynahan is American. ✓
- Bridget Moynahan is an actress. ✓
- Bridget Moynahan is a model. ✓
- Bridget Moynahan is a producer. ✗
- She is best known for her roles in Grey's Anatomy. ✗
- She is best known for her roles in I, Robot. ✓
- She is best known for her roles in Blue Bloods. ✓
- She studied acting. ✓
- She studied at the American Academy of Dramatic Arts. ✗
- ...


66.7%



FActScore: Factual Precision in Atomicity Score

Bridget Moynahan is an American filmmaker and writer. She is best known for her work on the soap opera General Hospital, which she co-created with husband Charles Kelly. Moynahan was raised in a middle-class family in Los Angeles, ...

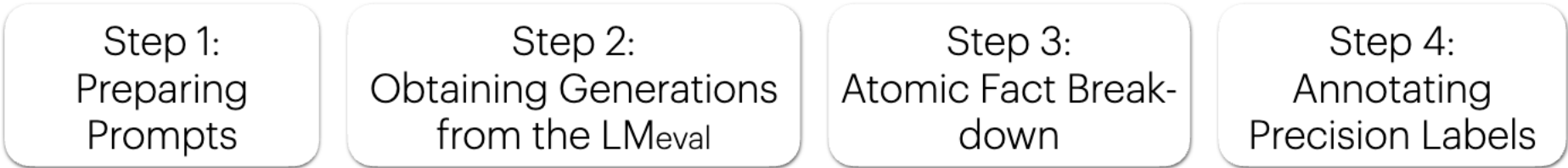
Atomic facts

- 
- Bridget Moynahan is American. ✓
 - Bridget Moynahan is a filmmaker. ✗
 - Bridget Moynahan is a writer. ✗
 - She is best known for her work on General Hospital. ✗
 - General Hospital is the soap opera. ✗
 - She co-created General Hospital. ✗
 - She co-created General Hospital with her husband. ✗
 - Her husband is Charles Kelly. ✗
 - Moynahan was raised in a middle-class family. ✗
 - Moynahan was raised in Los Angeles. ✗
 - ...

10.0%



FActScore: Factual Precision in Atomicity Score



Bridget Moynahan is an American.
Bridget Moynahan is an actress.
Bridget Moynahan is a model.
Bridget Moynahan is a producer.
...
She studied acting at the American Academy of Dramatic Arts.
She began her career in the late 1990s.

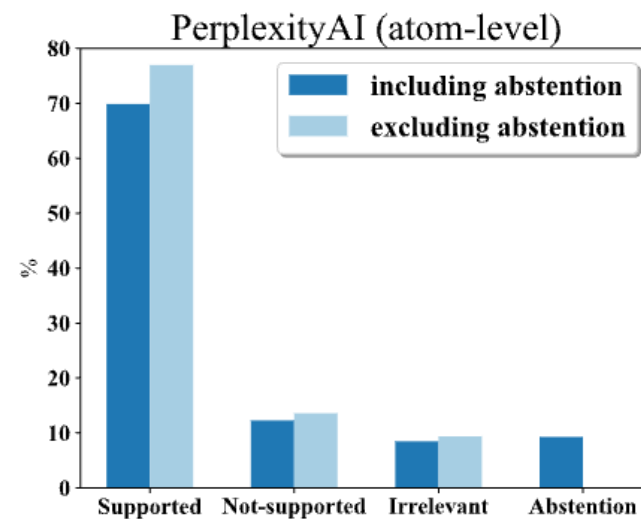
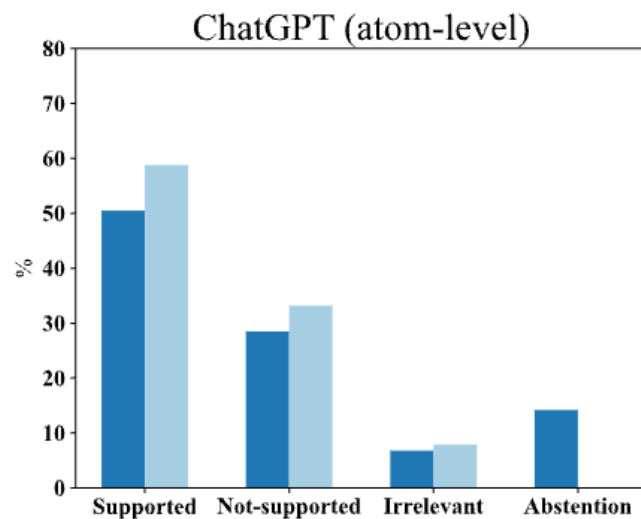
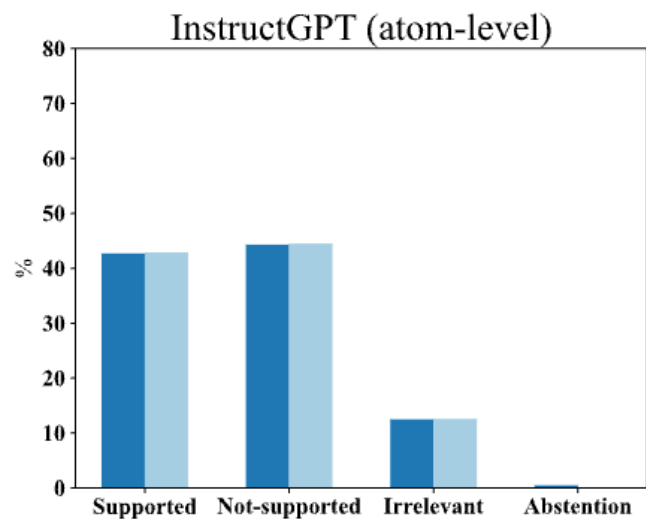


Irrelevant

Supported

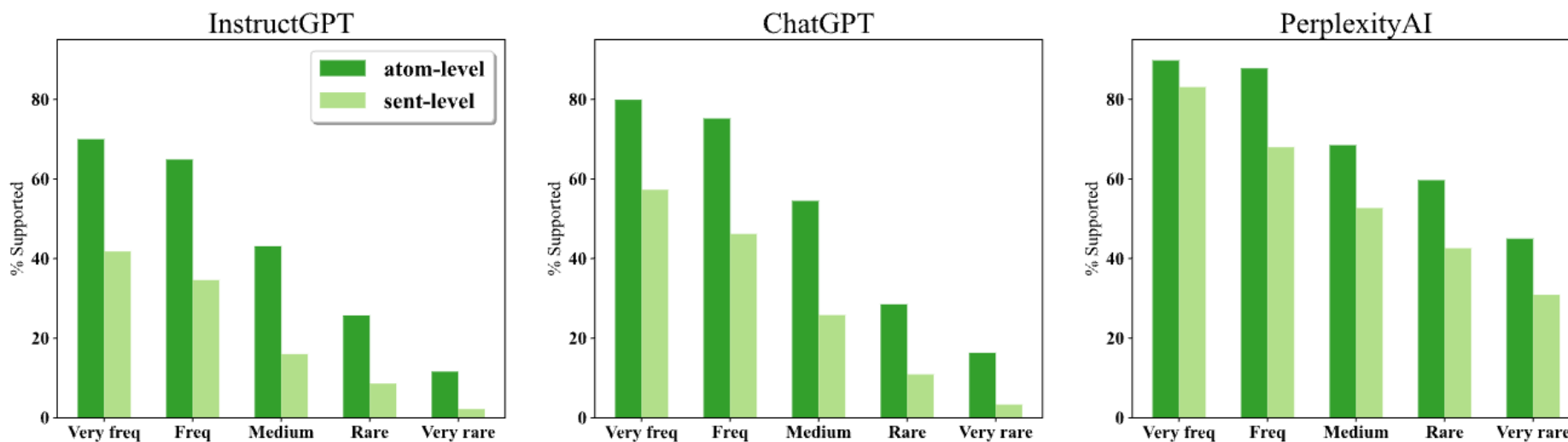
Not-supported

Results



All models make substantial precision errors

Results



More errors as the rarity of entities increases

How Language Model Hallucinations Can Snowball

Muru Zhang[♡] Ofir Press[♡] William Merrill[♠] Alisa Liu[♡] Noah A. Smith^{♡♣}

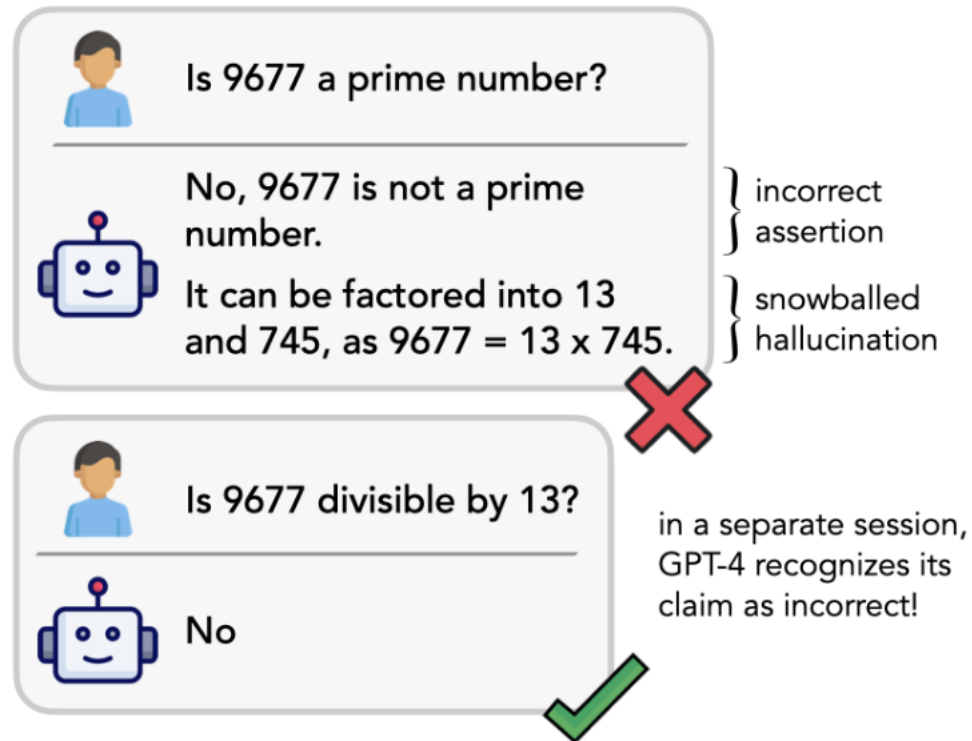
[♡]Paul G. Allen School of Computer Science and Engineering, University of Washington

[♠]New York University




[♣]Allen Institute for Artificial Intelligence

nanami17@cs.washington.edu

Hallucination Snowballing



Verification

Dataset	Original Question	Verification Question
 Primality Testing	<p>User: Is 10733 a prime number?</p> <p>GPT-4: No... It can be <u>factored</u> into 3×3577.</p>	<p>User: Is 10733 divisible by 3? Answer with either Yes or No.</p> <p>GPT-4: <u>No</u></p>
 Senator Search	<p>User: Was there ever a US senator that represented the state of New Hampshire and whose alma mater was the University of Pennsylvania?</p> <p>GPT-4: Yes... His name was <u>John P. Hale</u></p>	<p>User: Was John P. Hale's alma mater University of Pennsylvania?</p> <p>GPT-4: <u>No</u>... [it] was Bowdoin</p>
 Graph Connectivity	<p>User: Current flight information (the following flights are one-way only, and all the flights available are included below):</p> <p>There is a flight from city F to city K</p> <p>There is a flight from city H to city A</p> <p>[... 10 other rules cut for space ...]</p> <p>Question: Is there a series of flights that goes from city B to city E?</p> <p>GPT-4: Yes... the route is as follows: ... <u>City K to City G</u>...</p>	<p>User: [...flight information given in the context...]</p> <p>Based on the above flight information, is City K to City G a valid flight?</p> <p>GPT-4: <u>No</u>, based on the above flight information, there is no direct flight from City K to City G.</p>

Results

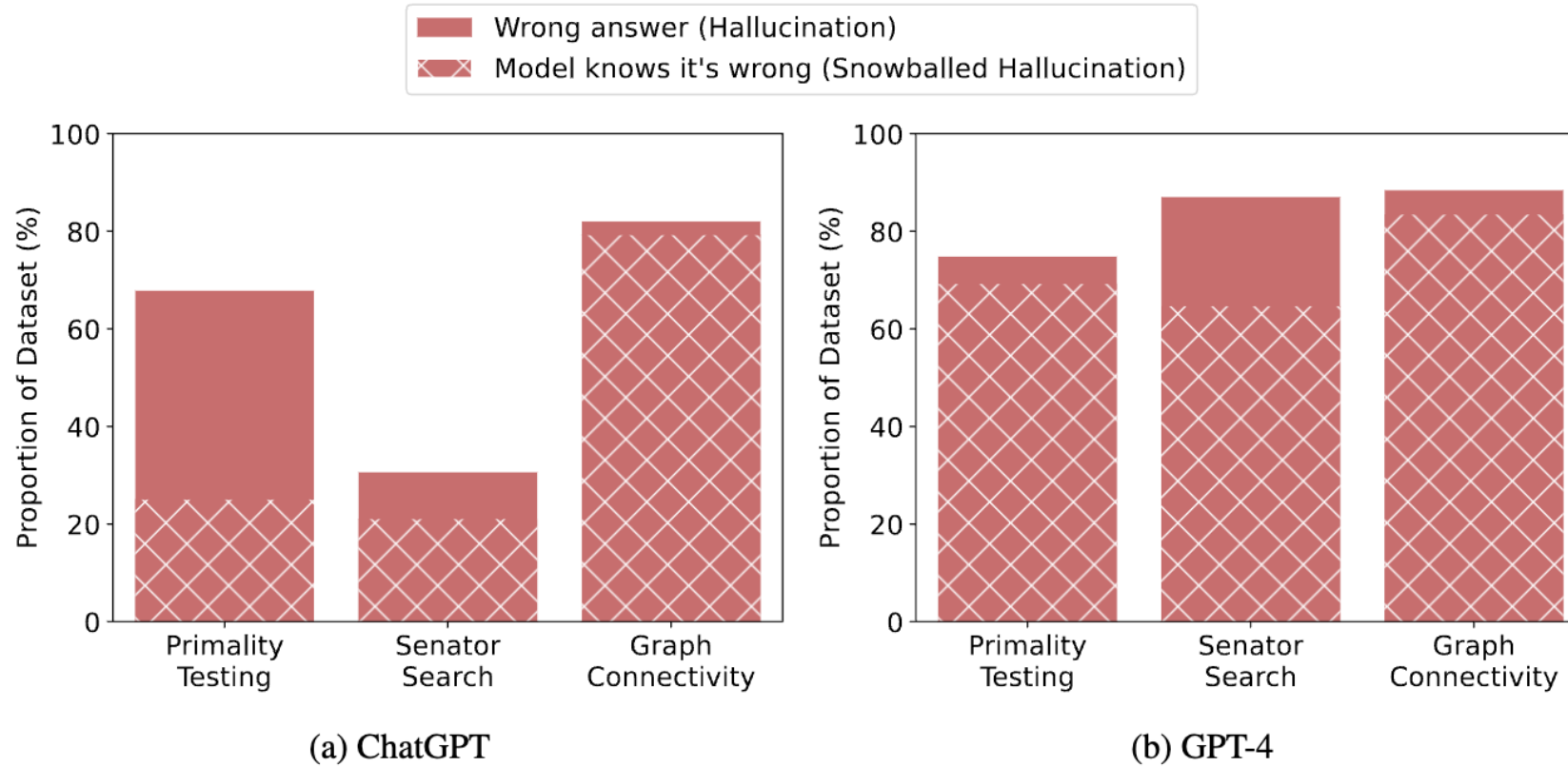


Figure 2: Percentage of hallucination and percentage of snowballed hallucination (both calculated with respect to the entire dataset) for ChatGPT and GPT-4. The precise numbers for this plot are available in [Table 6](#) and [Table 7](#) in the Appendix.

Chain-of-Thought Helps!

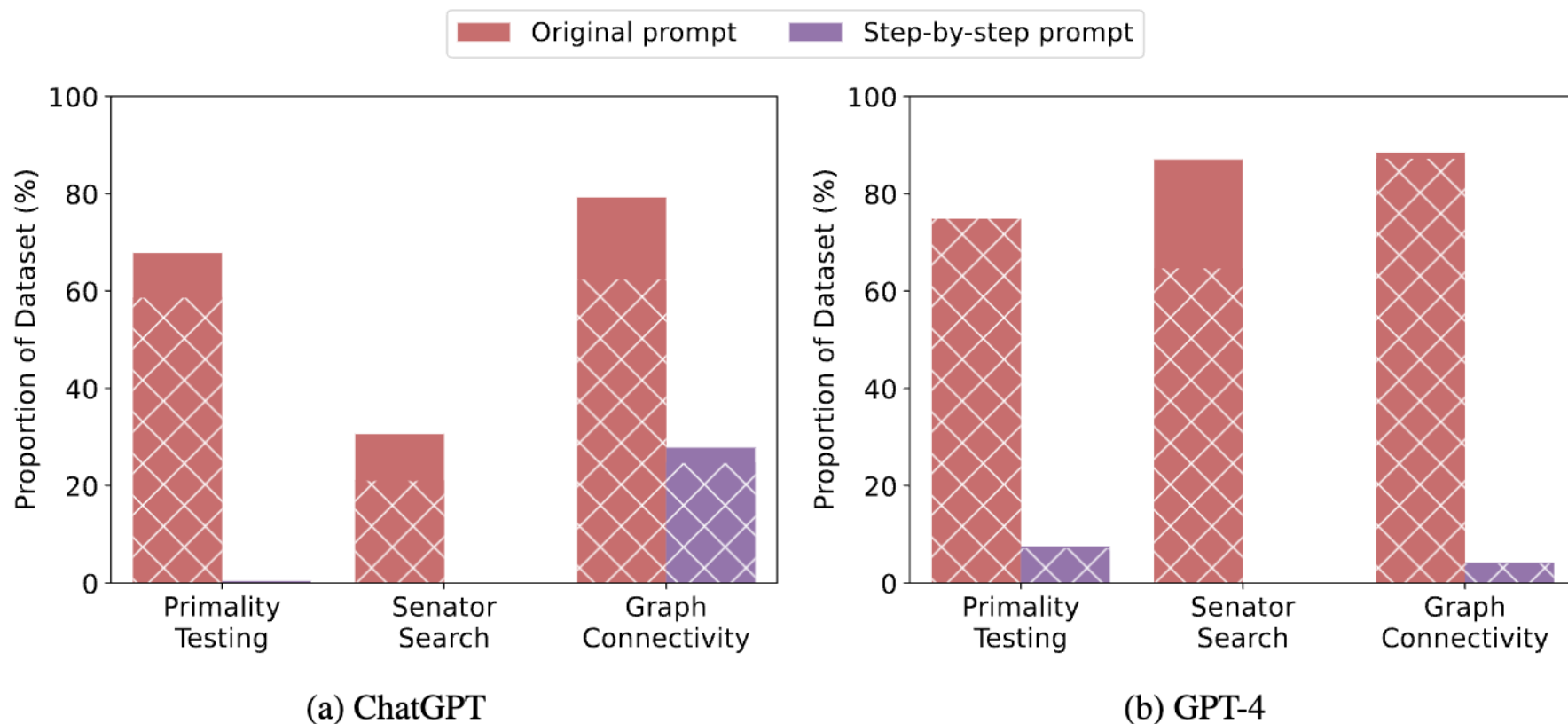
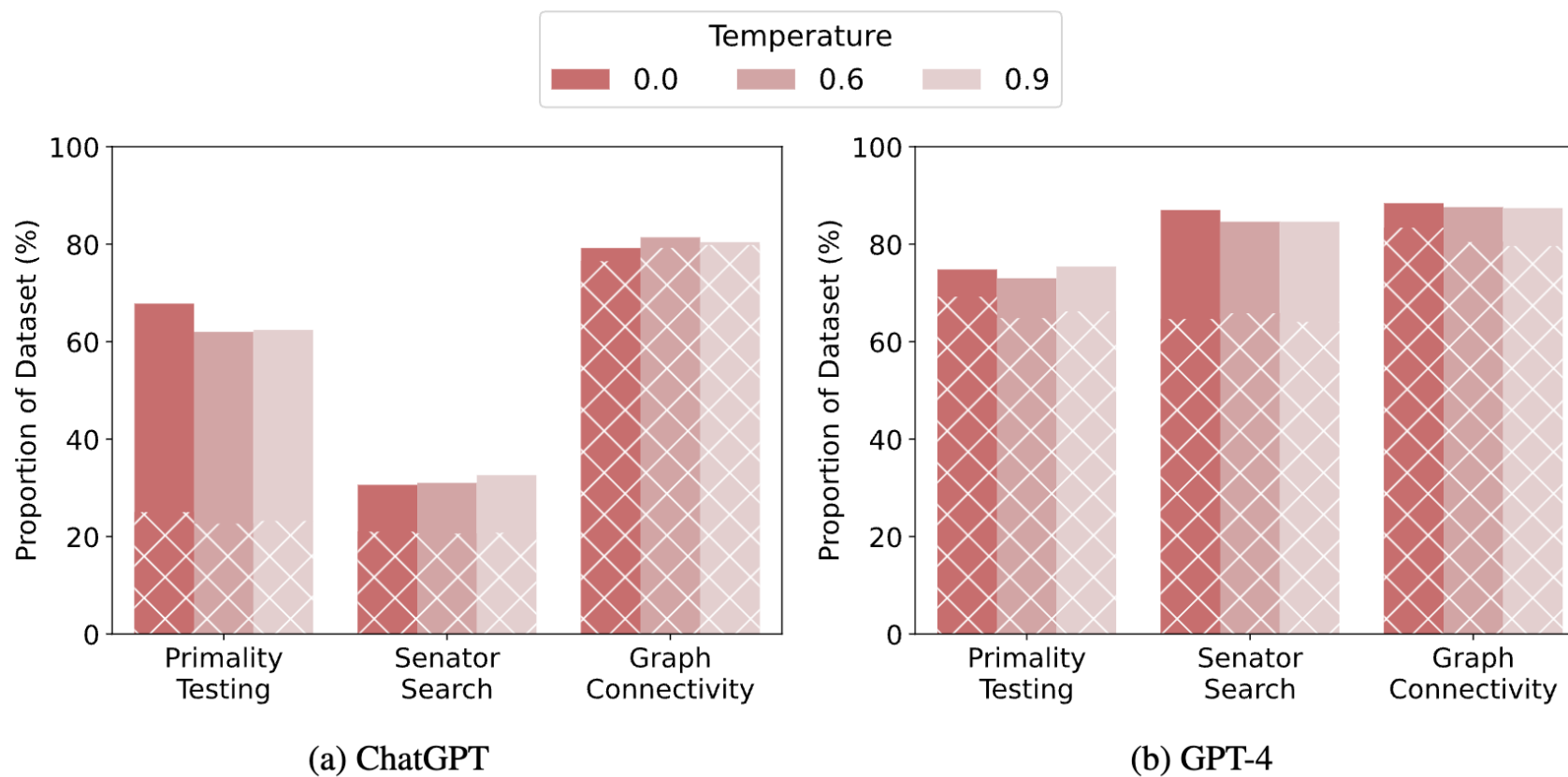


Figure 3: Error rate and snowballed hallucination rate (hatch pattern) for ChatGPT and GPT-4, when using the original prompt versus “*Let’s think step by step*”. See Appendix [Table 8](#) and [Table 9](#) for the exact numbers.

How About Tuning Temperature?

$$p_i = \text{softmax}(z_i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$



SELF CHECKGPT: Zero-Resource Black-Box Hallucination Detection for Generative Large Language Models

Potsawee Manakul, Adian Liusie, Mark J. F. Gales

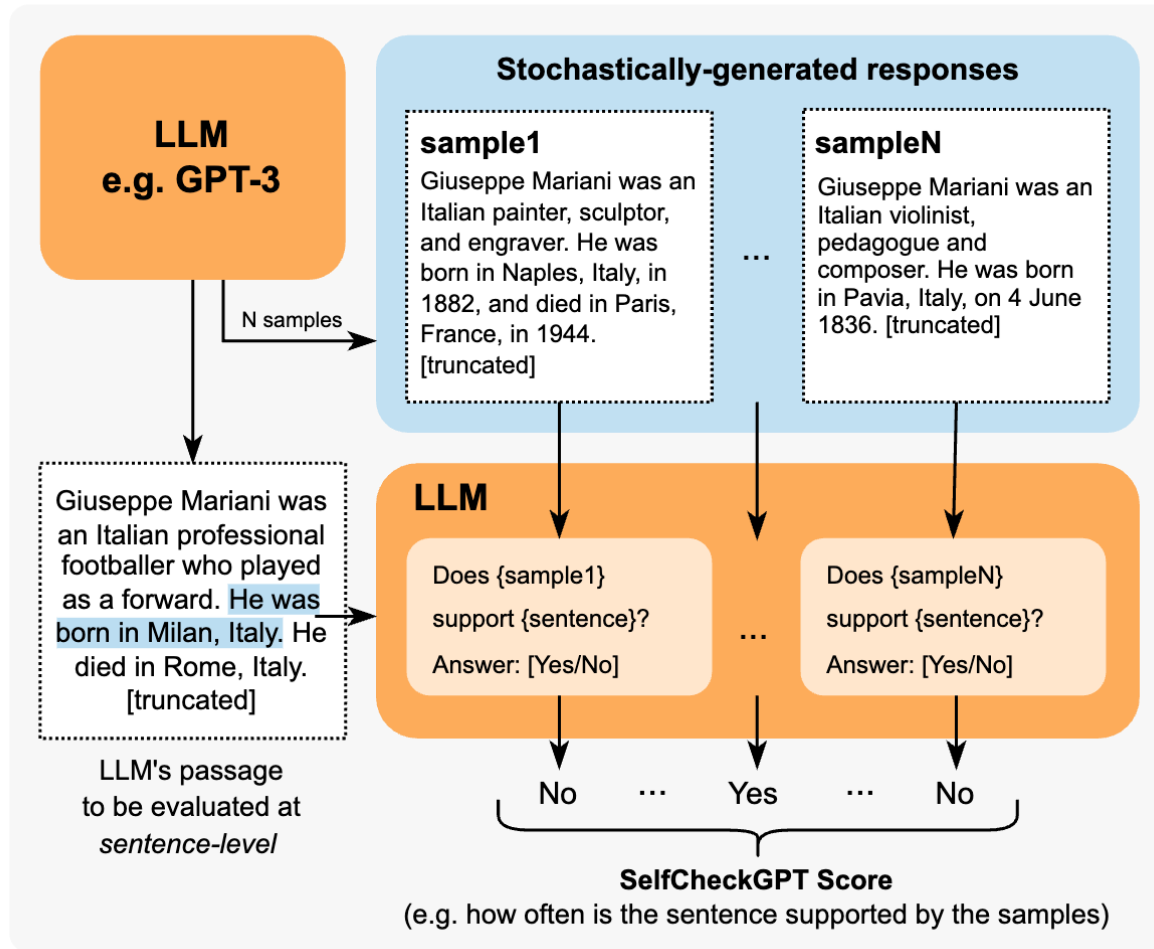
ALTA Institute, Department of Engineering, University of Cambridge

pm574@cam.ac.uk, al826@cam.ac.uk, mjfg@eng.cam.ac.uk

LLMs Can Verify

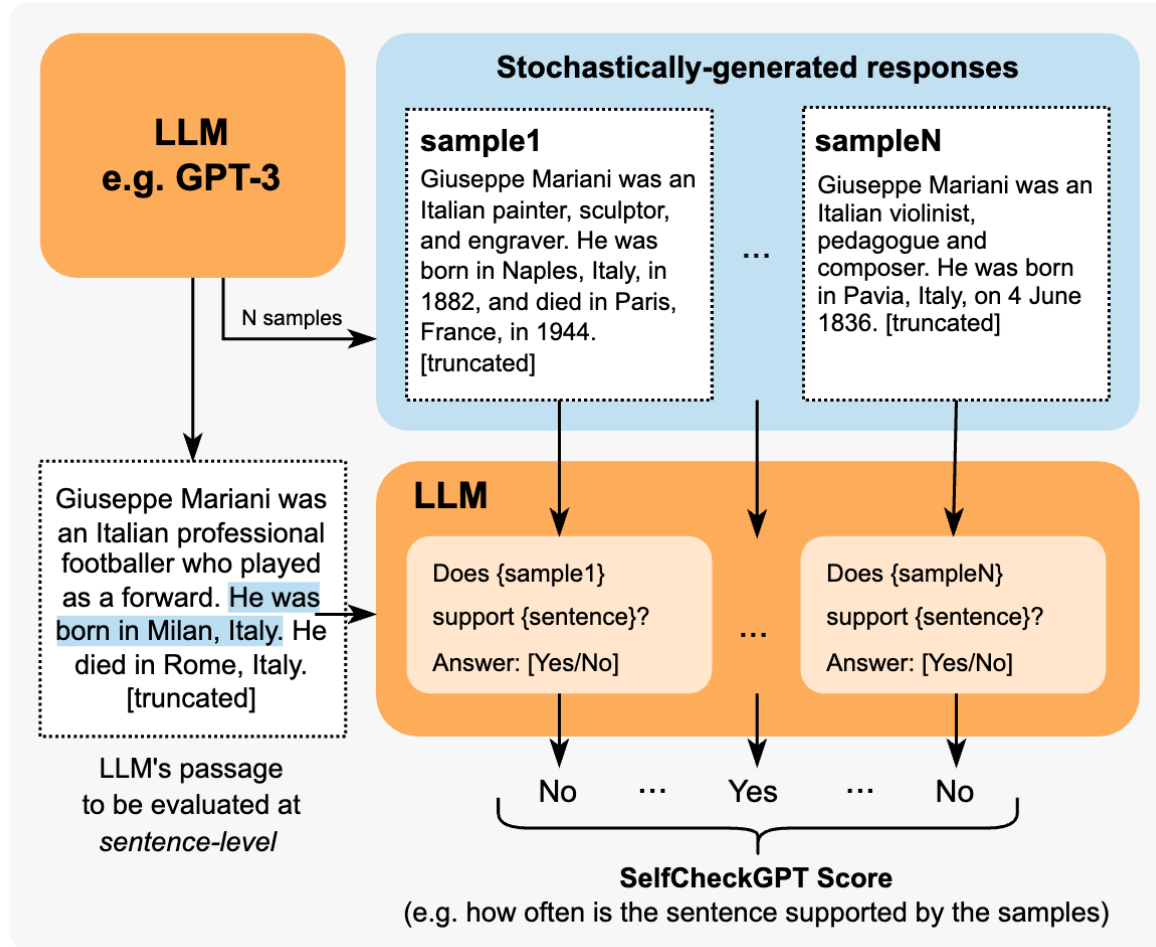
- If an LLM has knowledge of a given concept, sampled responses are likely to be similar and contain consistent facts

SelfCheckGPT with BERTScore



$$\mathcal{S}_{\text{BERT}}(i) = 1 - \frac{1}{N} \sum_{n=1}^N \max_k (\mathcal{B}(r_i, s_k^n))$$

SelfCheckGPT with Prompt



Context: {}
Sentence: {}
Is the sentence supported by the context above?
Answer Yes or No:

$$\mathcal{S}_{\text{Prompt}}(i) = \frac{1}{N} \sum_{n=1}^N x_i^n$$

Results

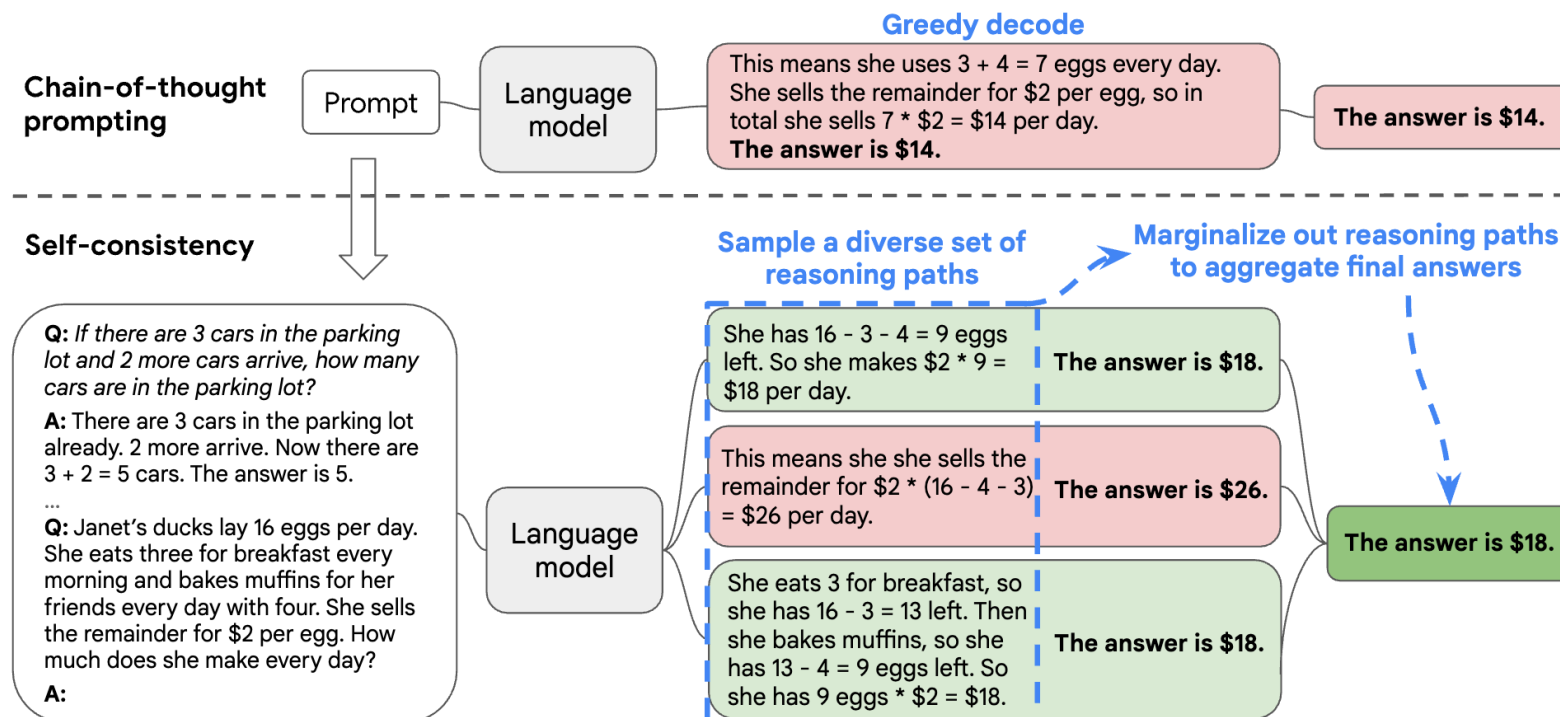
Method	Sentence-level (AUC-PR)			Passage-level (Corr.)	
	NonFact	NonFact*	Factual	Pearson	Spearman
Random	72.96	29.72	27.04	-	-
GPT-3 (text-davinci-003)'s probabilities (<i>LLM, grey-box</i>)					
Avg($-\log p$)	83.21	38.89	53.97	57.04	53.93
Avg(\mathcal{H}) [†]	80.73	37.09	52.07	55.52	50.87
Max($-\log p$)	87.51	35.88	50.46	57.83	55.69
Max(\mathcal{H}) [†]	85.75	32.43	50.27	52.48	49.55
LLaMA-30B's probabilities (<i>Proxy LLM, black-box</i>)					
Avg($-\log p$)	75.43	30.32	41.29	21.72	20.20
Avg(\mathcal{H})	80.80	39.01	42.97	33.80	39.49
Max($-\log p$)	74.01	27.14	31.08	-22.83	-22.71
Max(\mathcal{H})	80.92	37.32	37.90	35.57	38.94
SelfCheckGPT (<i>black-box</i>)					
w/ BERTScore	81.96	45.96	44.23	58.18	55.90
w/ QA	84.26	40.06	48.14	61.07	59.29
w/ Unigram (max)	85.63	41.04	58.47	64.71	64.91
w/ NLI	92.50	45.17	66.08	74.14	73.78
w/ Prompt	93.42	53.19	67.09	78.32	78.30

SELF-CONSISTENCY IMPROVES CHAIN OF THOUGHT REASONING IN LANGUAGE MODELS

Xuezhi Wang^{†‡} Jason Wei[†] Dale Schuurmans[†] Quoc Le[†] Ed H. Chi[†]
Sharan Narang[†] Aakanksha Chowdhery[†] Denny Zhou^{†§}

[†]Google Research, Brain Team

[‡]xuezhiw@google.com, [§]dennyzhou@google.com



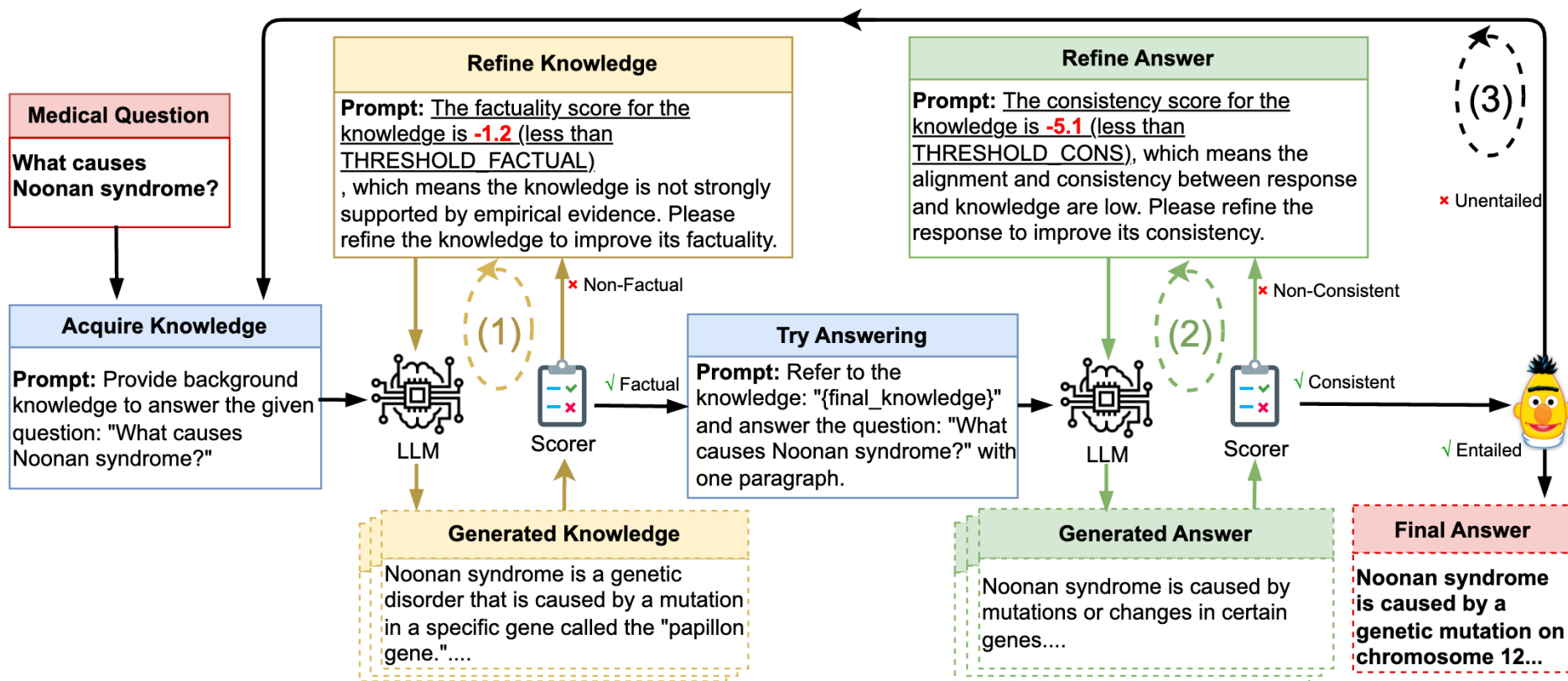
Towards Mitigating Hallucination in Large Language Models via Self-Reflection

Ziwei Ji, Tiezheng Yu, Yan Xu, Nayeon Lee, Etsuko Ishii, Pascale Fung

Center for Artificial Intelligence Research (CAiRE)

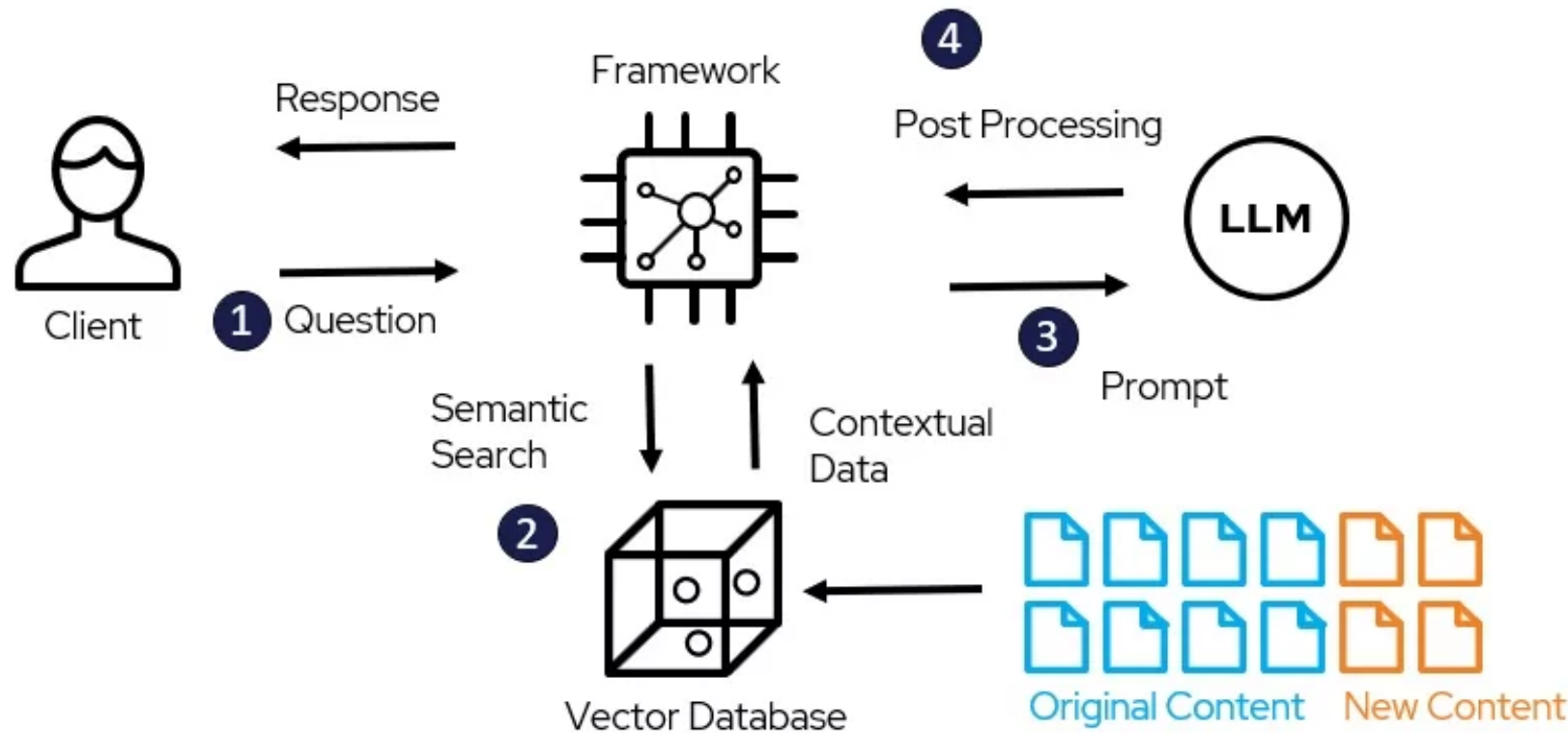
Hong Kong University of Science and Technology

zjiad@connect.ust.hk, pascale@ece.ust.hk

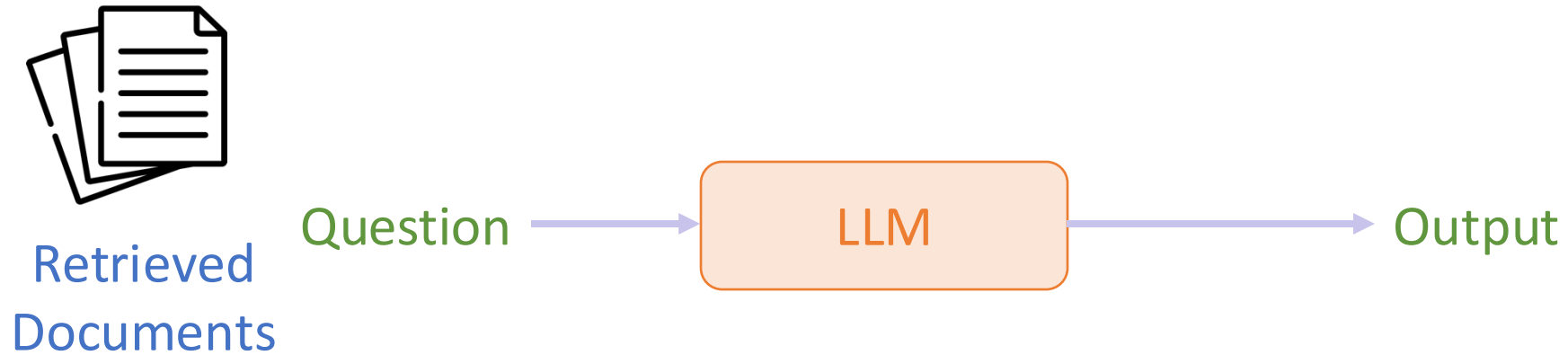


Recap: Retrieval-Augmented Generation (RAG)

RAG Architecture Model



From Factuality to Faithfulness



Recap: Factuality vs. Faithfulness



Who was the first person to walk on the moon?



Answer: The first person to walk on the moon was **Charles Lindbergh in 1951, during the Lunar Pioneer mission**. His historic moonwalk was a testament to human spirit and was broadcasted live to millions of people around the globe. ❌



Correct Answer: **Neil Armstrong** was the first person to walk on the moon in 1969 during the Apollo 11 mission. ✅

(a) Factuality Hallucination



Please summarize the following news article:

Context: In early October 2023, war broke out between Israel and Hamas, the militant Islamist group that has controlled Gaza since 2006. Hamas fighters fired rockets ... civilians and taking dozens of hostages.



Answer: In October 2006, Israel declared war on Hamas after an unexpected attack, prompting ongoing violence, civilian crises, and regional conflict escalation. ❌

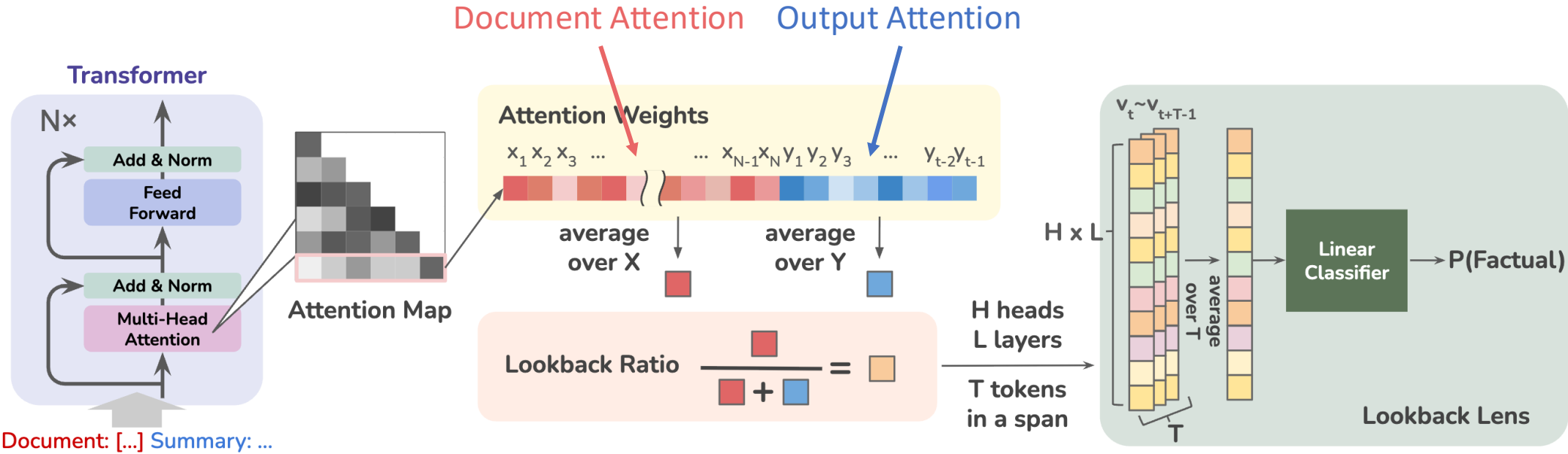
(b) Faithfulness Hallucination

Lookback Lens: Detecting and Mitigating Contextual Hallucinations in Large Language Models Using *Only* Attention Maps

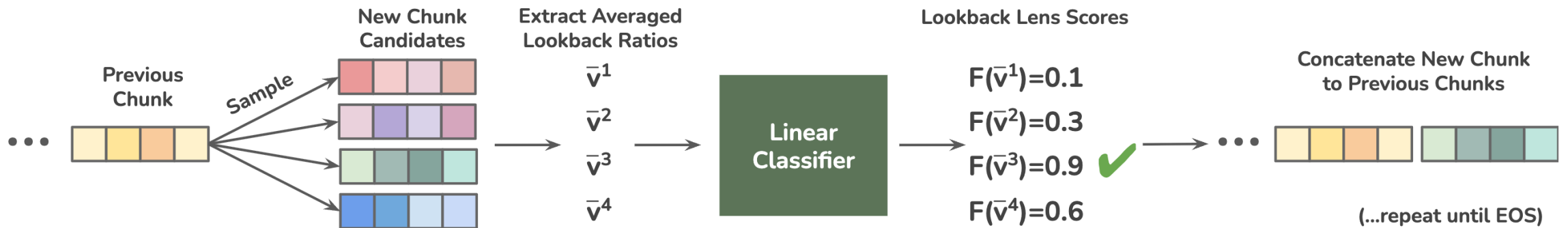
**Yung-Sung Chuang[†] Linlu Qiu[†] Cheng-Yu Hsieh[‡] Ranjay Krishna[‡]
Yoon Kim[†] James Glass[†]**

Massachusetts Institute of Technology[†] University of Washington[‡]
yungsung@mit.edu

Lookback Ratio



Lookback Lens Guided Decoding



Trusting Your Evidence: Hallucinate Less with Context-aware Decoding

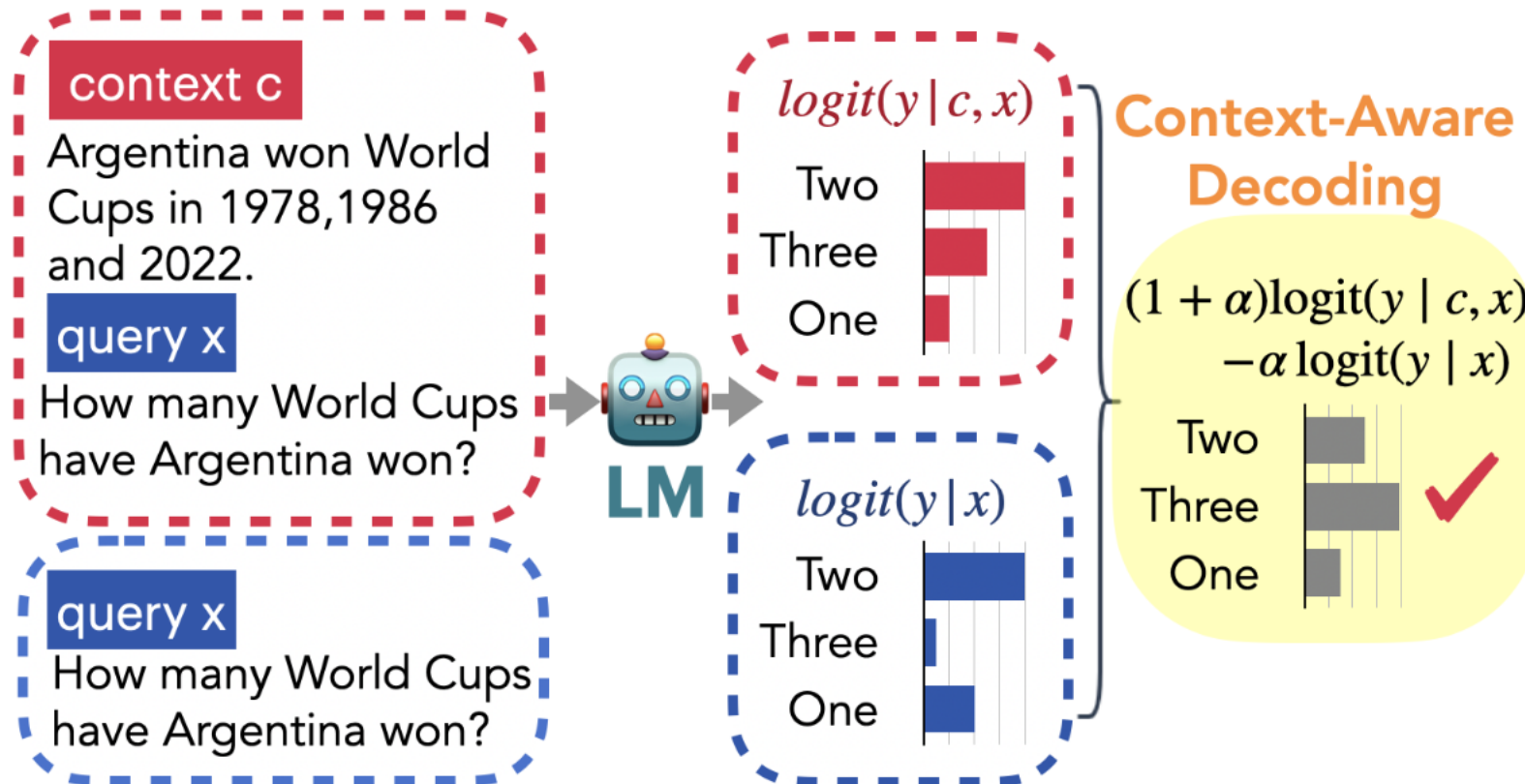
Weijia Shi^{1 *} **Xiaochuang Han**^{1 *}
Mike Lewis² **Yulia Tsvetkov**¹ **Luke Zettlemoyer**¹ **Scott Yih**²

¹ University of Washington, Seattle, WA, ² Meta AI
{swj0419, xhan77}@cs.washington.edu

Context-Aware Decoding



Context-Aware Decoding



$$y_t \sim \text{softmax}[(1 + \alpha) \text{logit}_\theta(y_t | \mathbf{c}, \mathbf{x}, \mathbf{y}_{<t}) - \alpha \text{logit}_\theta(y_t | \mathbf{x}, \mathbf{y}_{<t})]$$

Results

			CNN-DM			XSUM		
Model		Decoding	ROUGE-L	factKB	BERT-P	ROUGE-L	factKB	BERT-P
OPT	13B	Regular	22.0	77.8	86.5	16.4	47.2	85.2
		CAD	27.4	84.1	90.8	18.2	64.9	87.5
	30B	Regular	22.2	81.7	87.0	17.4	38.2	86.1
		CAD	28.4	87.0	90.2	19.5	45.6	89.3
GPT-Neo	3B	Regular	24.3	80.5	87.5	17.6	54.0	86.6
		CAD	27.7	87.5	90.6	18.1	65.1	89.1
	20B	Regular	18.7	68.3	85.2	14.9	42.2	85.7
		CAD	24.5	77.5	89.4	19.0	63.3	90.6
LLaMA	13B	Regular	27.1	80.2	89.5	19.0	53.5	87.8
		CAD	32.6	90.8	93.0	21.1	73.4	91.7
	30B	Regular	25.8	76.8	88.5	18.7	47.7	87.1
		CAD	31.8	87.8	92.2	22.0	66.4	90.3
FLAN	3B	Regular	25.5	90.2	91.6	18.8	31.9	88.2
		CAD	26.1	93.9	92.1	19.5	35.9	88.8
	11B	Regular	25.4	90.4	91.4	19.4	29.8	88.3
		CAD	27.1	93.1	92.2	20.0	35.0	88.8

SELF-RAG: LEARNING TO RETRIEVE, GENERATE, AND CRITIQUE THROUGH SELF-REFLECTION

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Self-Reflective Retrieval-Augmented Generation

Retrieval-Augmented Generation (RAG)

Prompt How did US states get their names?

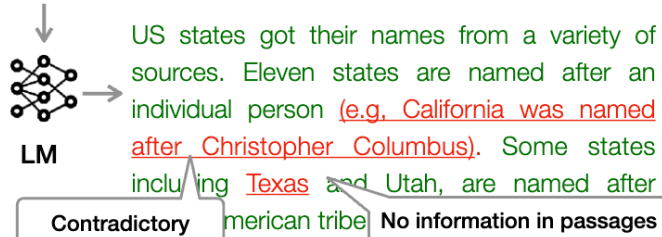
Step 1: Retrieve K documents

- 1 Of the fifty states, eleven are named after an individual person.
- 2 Popular names by states. In Texas, Emma is a popular baby name.
- 3 California was named after a fictional island in a Spanish book.

Retriever

Step 2: Prompt LM with K docs and generate

Prompt How did US states get their names? + 1 2 3



Prompt: Write an essay of your best summer vacation



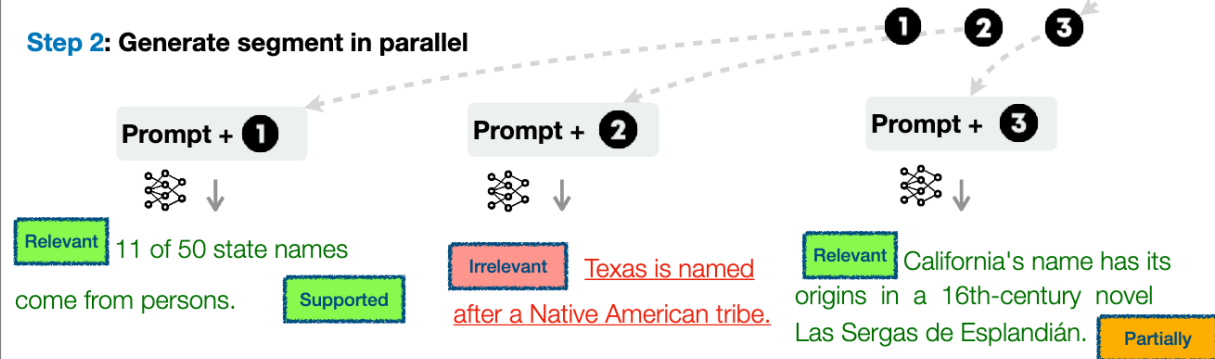
Ours: Self-reflective Retrieval-Augmented Generation (Self-RAG)

Prompt How did US states get their names?

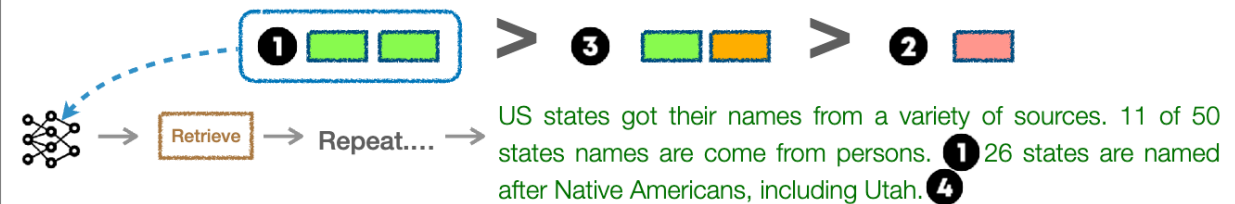
Step 1: Retrieve on demand



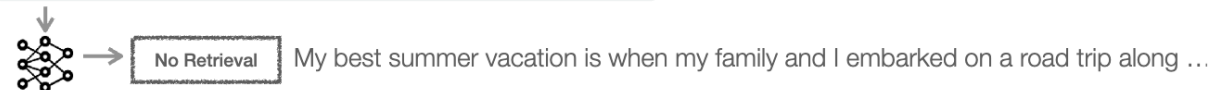
Step 2: Generate segment in parallel



Step 3: Critique outputs and select best segment



Prompt: Write an essay of your best summer vacation



Enabling Large Language Models to Generate Text with Citations

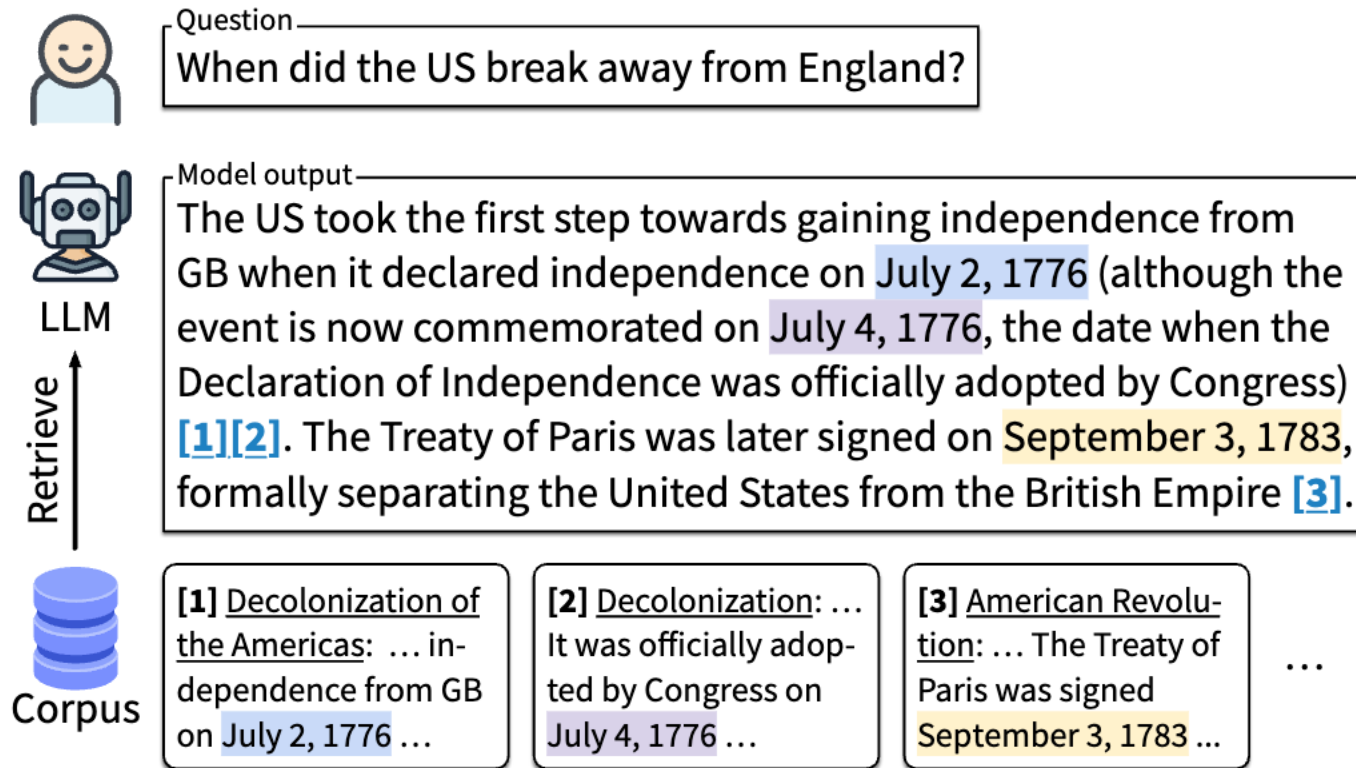
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Grounded Generation



Examples

Dataset	Corpus (#passages)	Question type	Example
ASQA	Wikipedia (21M)	Factoid (ambiguous)	Q: When did the US break away from England? A: The US declared independence on July 2, 1776 [1][2] ... The Treaty of Paris was later signed on September 3, 1783 [3].
QAMPARI	Wikipedia (21M)	Factoid (list)	Q: Which films have Gong Li as a member of their cast? A: The Story of Qiu Ju [1], Farewell My Concubine [2], The Monkey King 2 [3], Mulan [3], Saturday Fiction [3] ...
ELI5	Sphere (899M)	Why/How/What	Q: How do student loans affect getting a mortgage? A: Student loans can affect the debt to income ratio [1], which is a key factor in determining the amount that ... [2][3]

Evaluation Goal

- **Fluency:** whether the model's generated text is fluent and coherent
- **Correctness:** whether the answer is accurate and covers all aspects of interest
- **Citation quality:** whether the answer is well supported by the cited passages and no irrelevant passages are cited

Citation Quality

Question

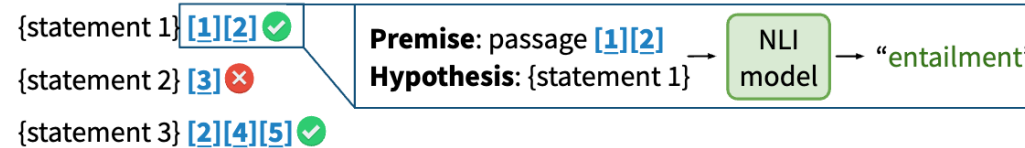
When did the US break away from England?

Model output

{statement 1} [1][2]. {statement 2} [3]. {statement 3} [2][4][5].

Citation Recall

Recall = 1 if the concatenation of all cited passages fully supports the segment.
We use an NLI model to determine "fully support".



For this question, **citation recall** = 2 / 3 = **66%**

Citation Precision

Detect "irrelevant" citation: one citation alone does not support the claim, and removing it does not affect other citations combined to support the claim.

{statement 1} [1][2] ✓:

[1] ✗ [2] ✗ → Precision = 1

[2] ✗ [1] ✗ → Precision = 1

{statement 2} [3] ✗ → If recall = 0, then precision = 0

{statement 3} [2][4][5] ✓:

[2] ✗ [4][5] ✓ → [2] is "irrelevant". Precision = 0

[4] ✗ [2][5] ✗ → Precision = 1

[5] ✗ [2][4] ✗ → Precision = 1

For this question, **citation precision** = 4 / 6 = **66%**

CaLM: Contrasting Large and Small Language Models to Verify Grounded Generation

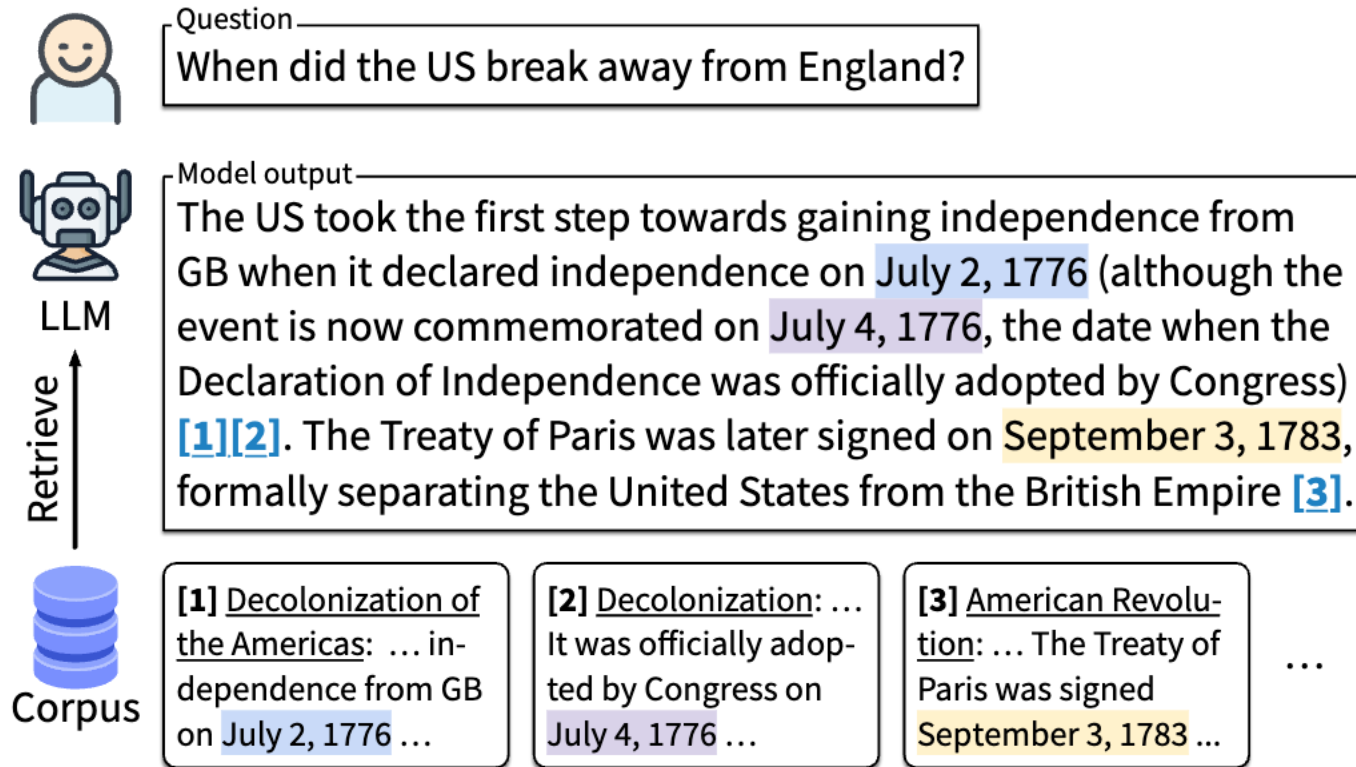


**I-Hung Hsu^{1*}, Zifeng Wang², Long T. Le², Lesly Miculicich²,
Nanyun Peng³, Chen-Yu Lee², Tomas Pfister²**

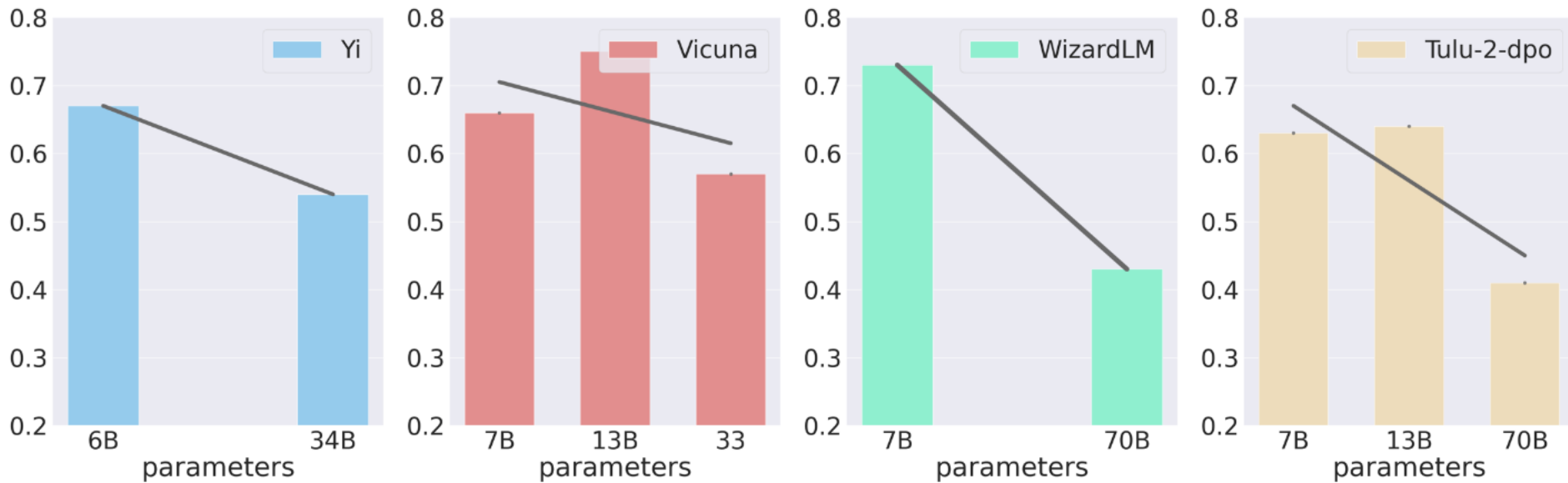
¹University of Southern California, ²Google Cloud AI Research,

³University of California, Los Angeles

Grounded Generation



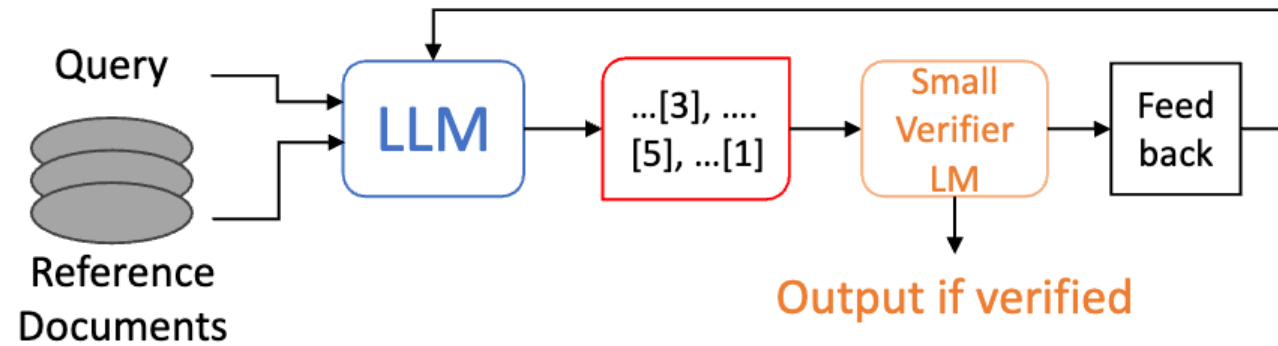
Sensitivity to Retrieved Documents



Small LMs are more sensitive to documents

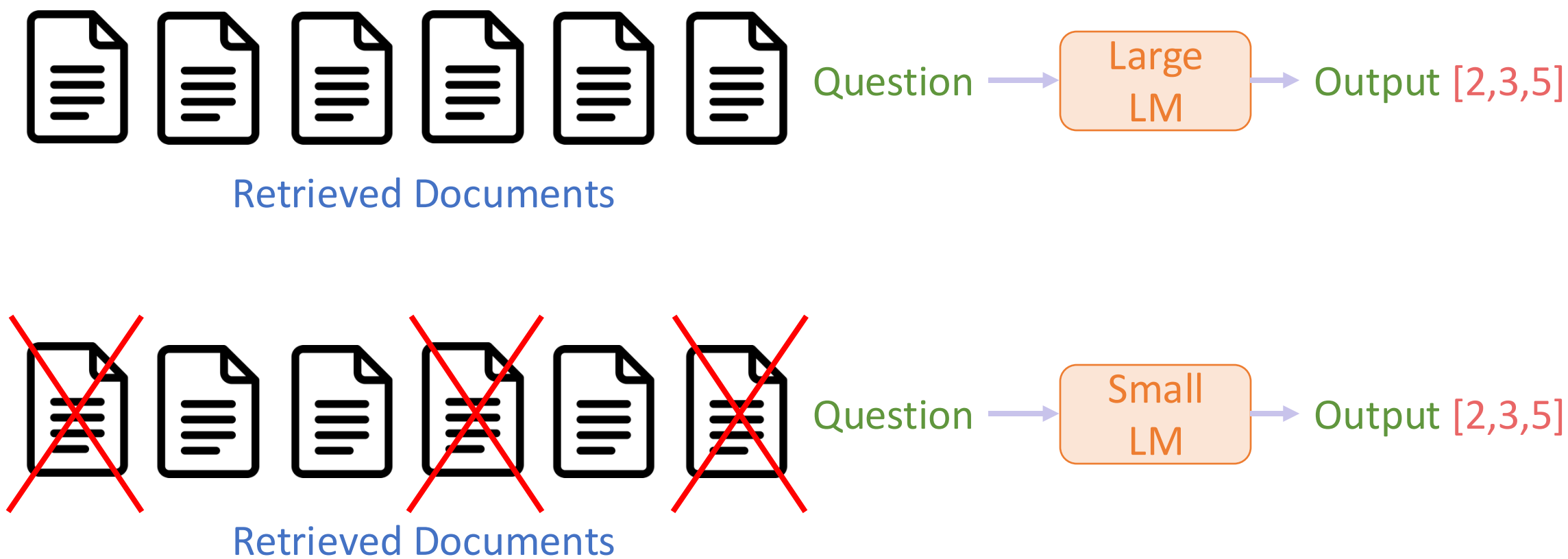
Overview

(c) Ours: Post verification on LLM's output ensure output quality



Key idea: using small LMs as verifiers

Key Idea



Results

Method	Method Type	# Main LM Call	# Verifier LM Call	DPR as retriever					GTR as retriever				
				Fluency mauve	Correct. EM Rec.	Citation Prec.	Rec.	Average	Fluency mauve	Correct. EM Rec.	Citation Prec.	Rec.	Average
GPT-3.5-Turbo-1106 as Main LM													
ICLCite (Gao et al., 2023b)	Single Run	1	-	74.73	39.32	67.36	69.48	62.72	71.85	41.92	73.14	77.90	66.20
Summ + ICLCite (Gao et al., 2023b)	Preprocess	10	-	48.95	29.30	60.14	54.52	48.23 (-14.49)	68.01	41.11	66.04	74.43	62.40 (-3.8)
Snippet + ICLCite (Gao et al., 2023b)		10	-	48.56	29.48	59.52	53.84	47.85 (-14.87)	68.84	39.89	62.05	71.06	60.46 (-5.74)
ICLCite + USC (Chen et al., 2023)*	Postprocess	10	-	77.50	40.71	61.20	64.07	60.87 (-1.85)	77.31	42.75	67.08	71.64	64.69 (-1.51)
CaLM (ours)		≤ 4	≤ 3	81.35	43.56	66.00	69.95	64.71 (+1.99)	83.98	45.01	72.59	78.03	68.98 (+2.78)
text-unicorn as Main LM													
ICLCite (Gao et al., 2023b)	Single Run	1	-	62.01	37.09	62.42	60.35	55.46	63.25	39.83	69.39	67.98	60.11
Summ + ICLCite (Gao et al., 2023b)	Preprocess	10	-	63.21	38.67	52.41	59.45	53.43 (-2.03)	75.68	42.65	61.18	68.91	62.11 (+2.00)
Snippet + ICLCite (Gao et al., 2023b)		10	-	59.03	37.69	54.62	59.44	52.69 (-2.77)	72.50	40.97	60.88	68.02	60.59 (+0.48)
ICLCite + USC (Chen et al., 2023)	Postprocess	10	-	57.92	37.16	62.05	60.00	54.28 (-1.18)	63.27	40.75	68.90	67.60	60.13 (+0.02)
CaLM (ours)		≤ 4	≤ 3	77.18	42.24	63.71	64.99	62.03 (+6.57)	82.08	44.21	70.55	72.37	67.30 (+7.19)
Finetune Llama-2 Baseline													
Self-RAG (7B) †	Finetune LM	-	-	-	-	-	-	-	74.3	30.0	66.9	67.8	59.8
Self-RAG (13B) †	Finetune LM	-	-	-	-	-	-	-	71.6	31.7	70.3	71.3	61.2