

Knowledge Curation

Stanford CS224V Course

Conversational Virtual Assistants with Deep Learning

Monica Lam, Yucheng Jiang

Announcement

1. Student intro form due **today**
2. HW1 released today (Due: October 2nd)
 - Get familiar with tool stack of knowledge curation pipeline
 - Have hands-on experience designing LLM-enpowered system

Lecture Plan

1. **Knowledge Curation (STORM)**

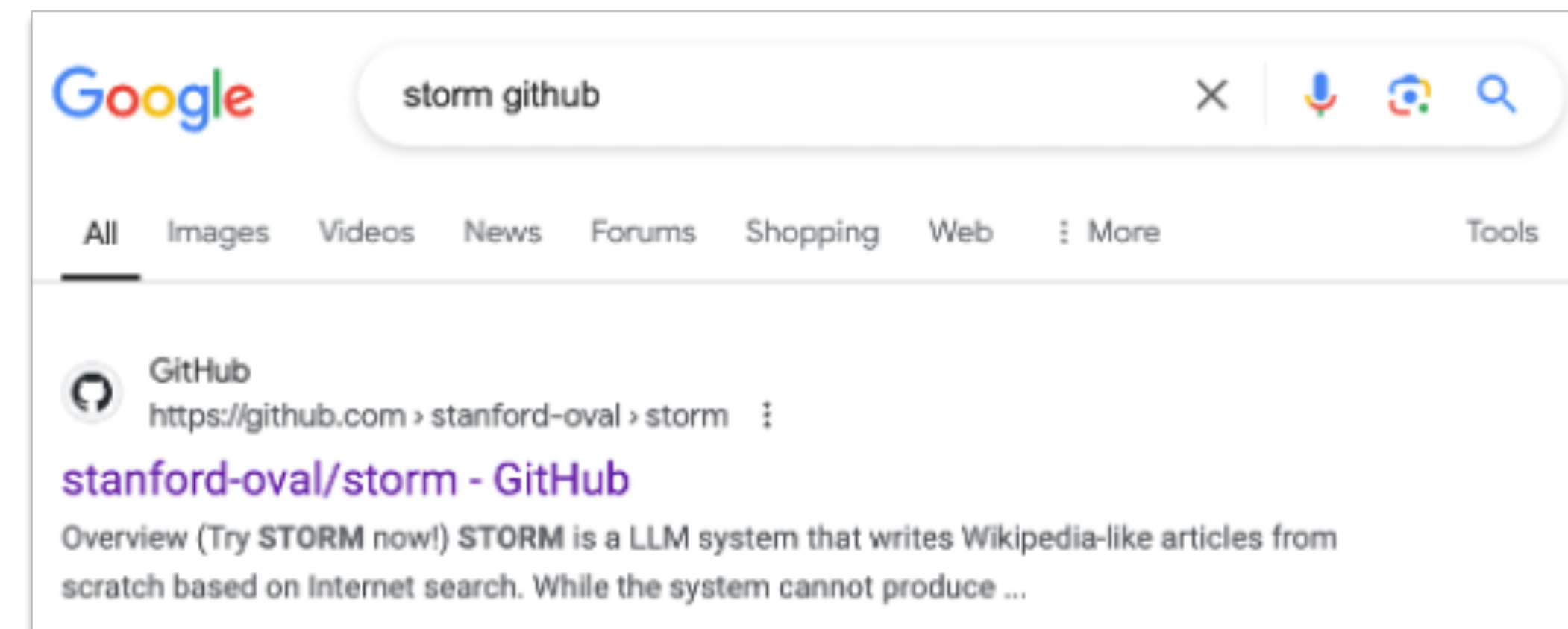
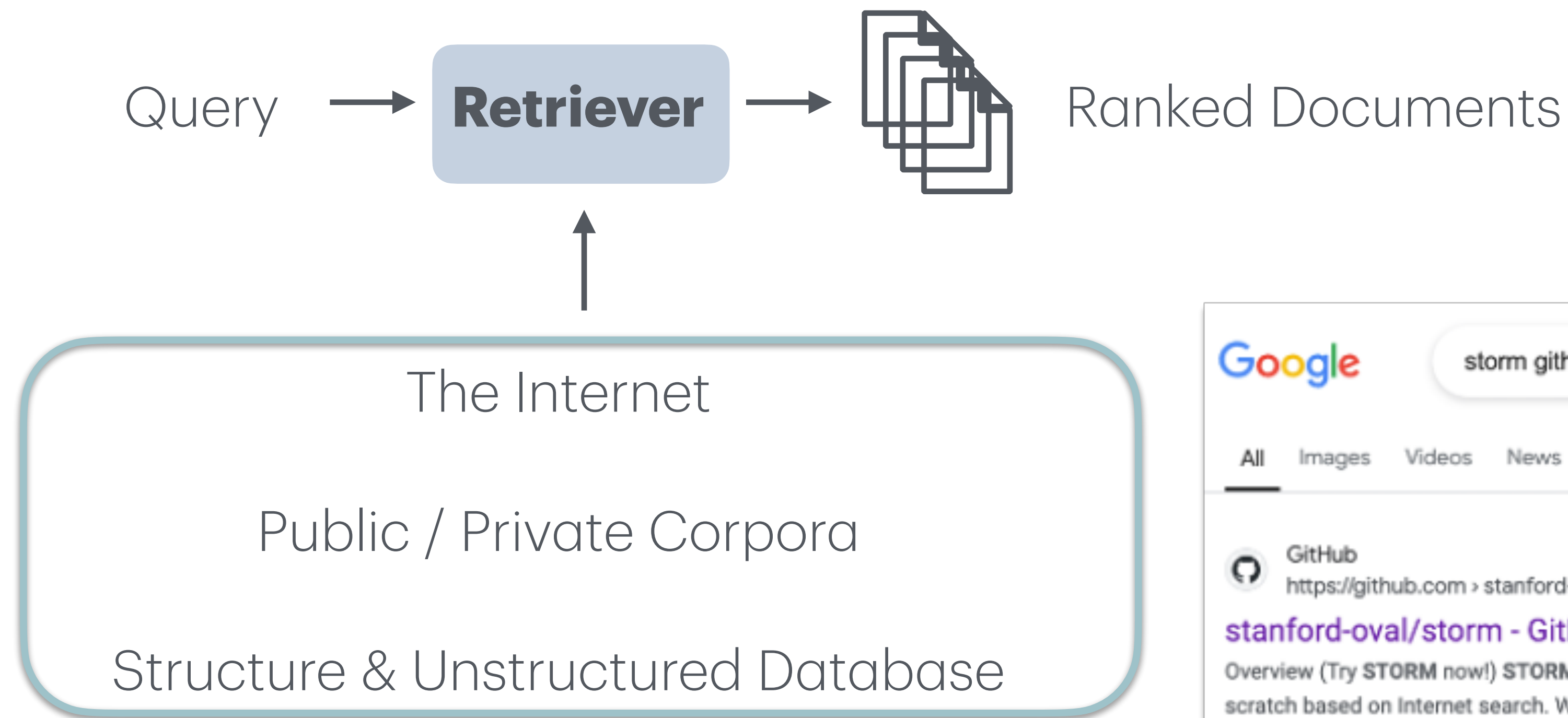
- Information Retrieval & RAG at a Glance
- Evaluation? Evaluation!

2. **Bring Human into the Loop (Co-STORM)**

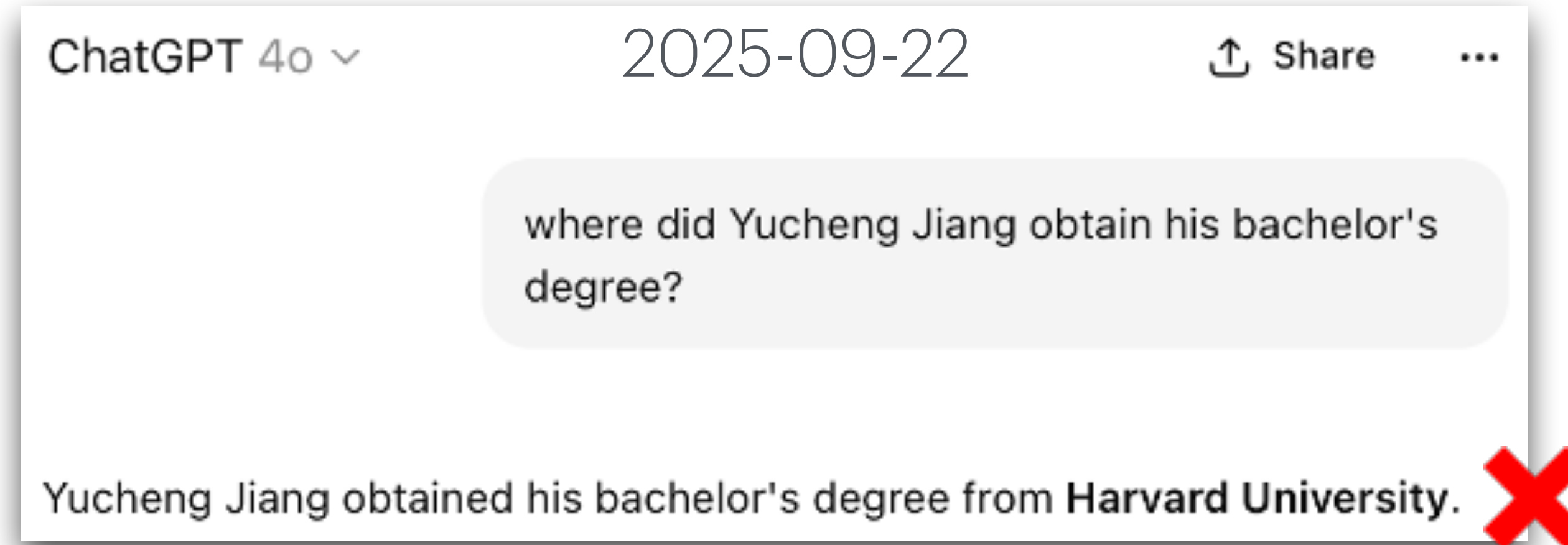
3. **HW1 Overview**

Information Retrieval at a Glance

When we have an information-seeking need,



Information Retrieval at a Glance



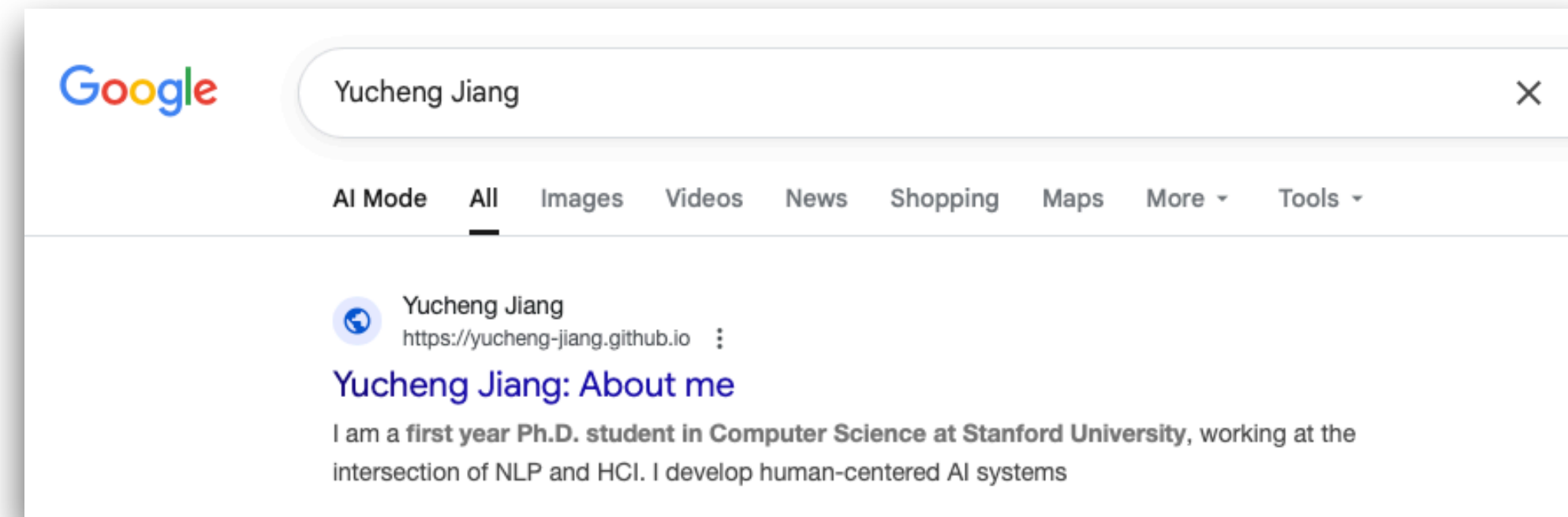
The major issue of using LLMs for knowledge tasks: **Hallucination**

- Long-tail information
- Knowledge cutoffs
- Private data

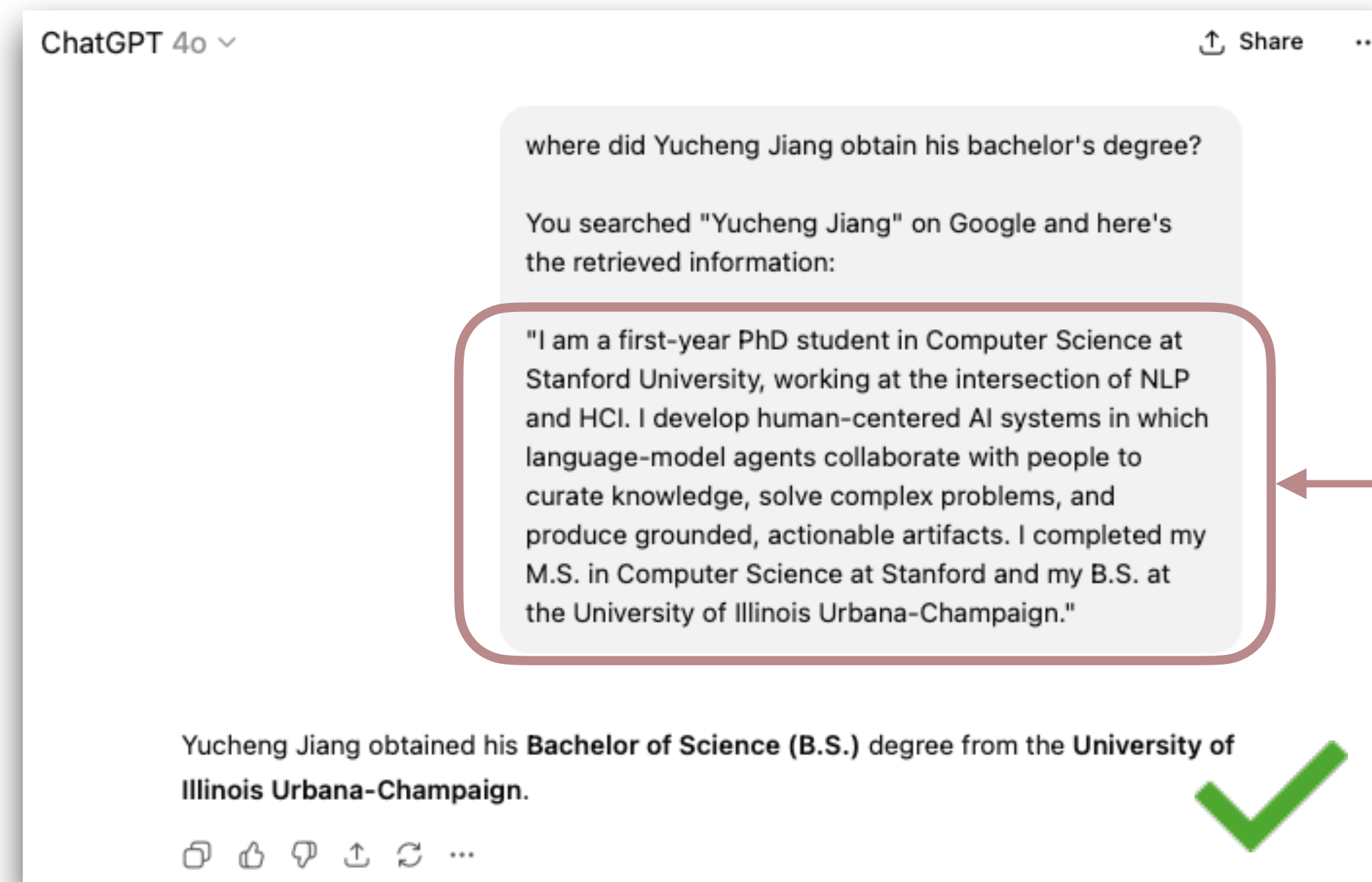
A response that is not faithful to the facts of the world.

Retrieval Augmented Generation

Step 1: **Retrieve**



Step 2: **Augment**



Step 3: **Generate**

Yucheng Jiang obtained his **Bachelor of Science (B.S.)** degree from the **University of Illinois Urbana-Champaign**.



Retrieval Augmented Generation

Retrievers

Data sources

HW1

10/22, 10/27 Lecture

Structured and Unstructured database

10/29 Lecture

Public/Private corpora

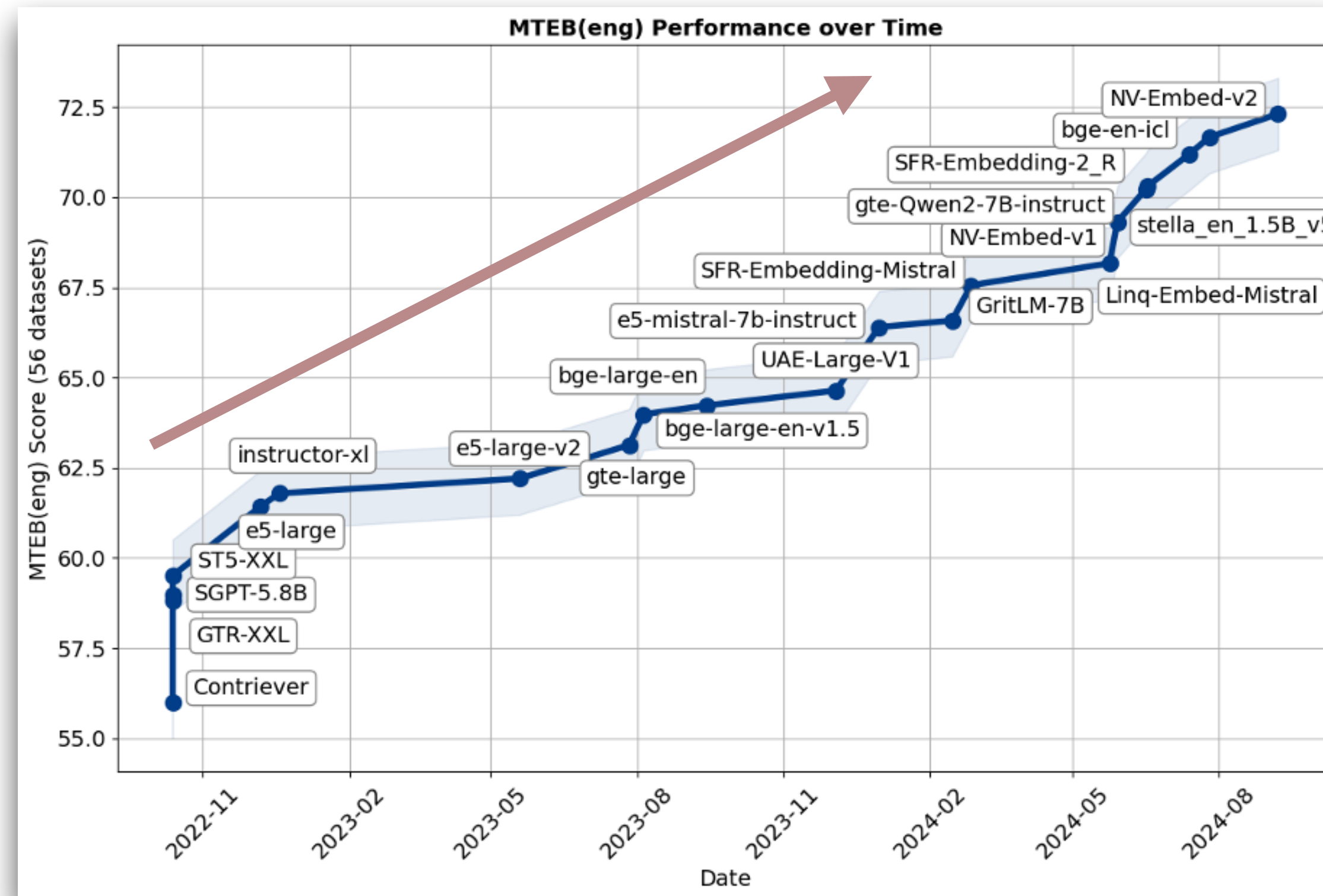
11/12 Lecture

Hand-written documents

The Internet

Indexing → Chunking → Reranking

Retrieval Augmented Generation



MTEB: Massive Text Embedding Benchmark, Niklas et al. 2023 (This illustration is contributed by Niklas Muennighoff.)

We have better embedding models and infrastructure for Information Retrieval over time.

Retrieval Augmented Generation

Humanity's Last Exam:

2,500 challenging questions across
over a hundred subjects, at the
frontier of human knowledge



GPT-5 (2025.08) score: 25.32

O4-mini (2025.04) score: 14.28

GPT-4o (2024.11) score: 2.72

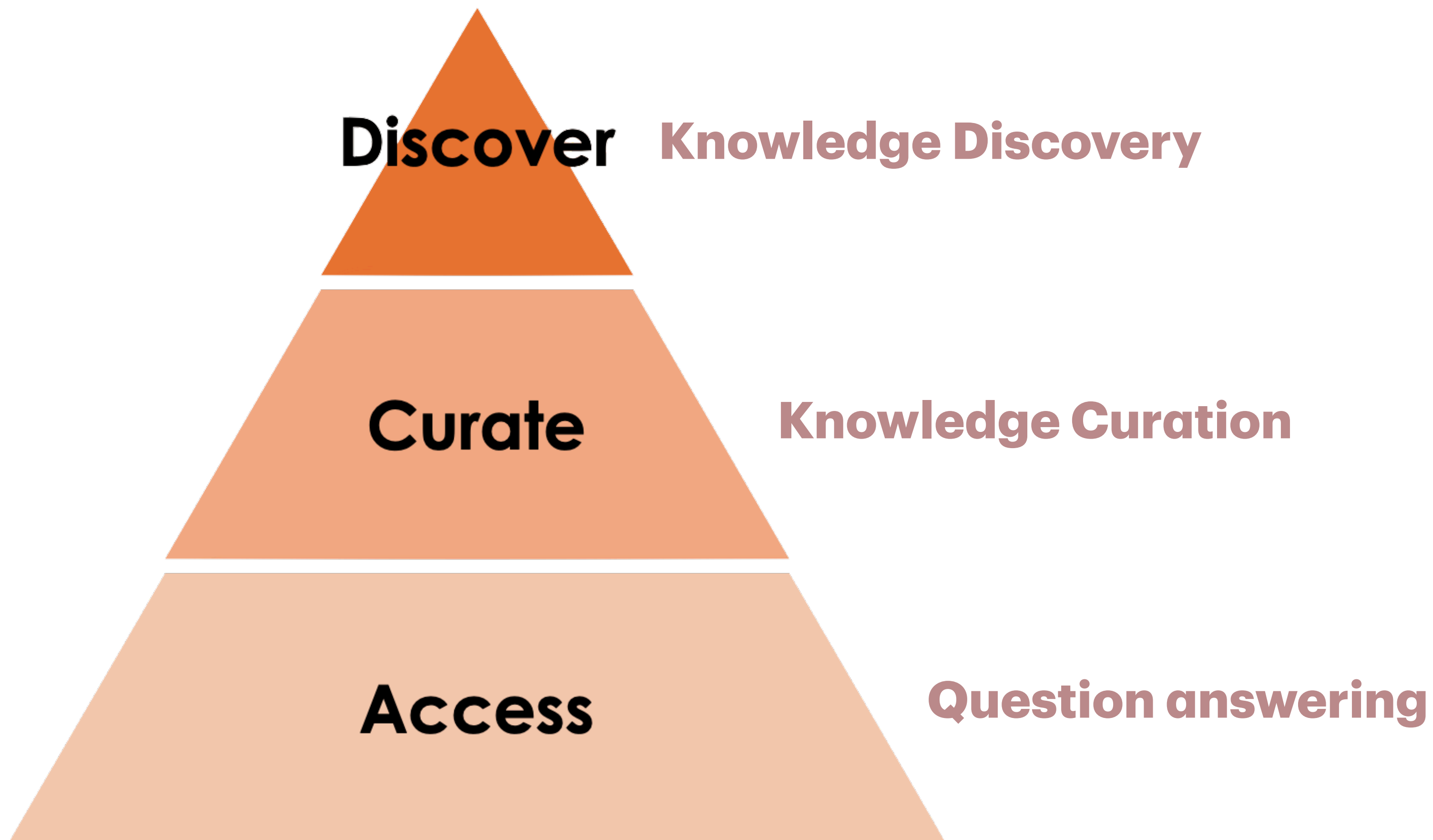
We have stronger, more intelligent language models.

Meta question

Are people's information needs satisfied?



The illustration is co-created with DALL-E.



Real Unknowns:

Knowledge that does not exist

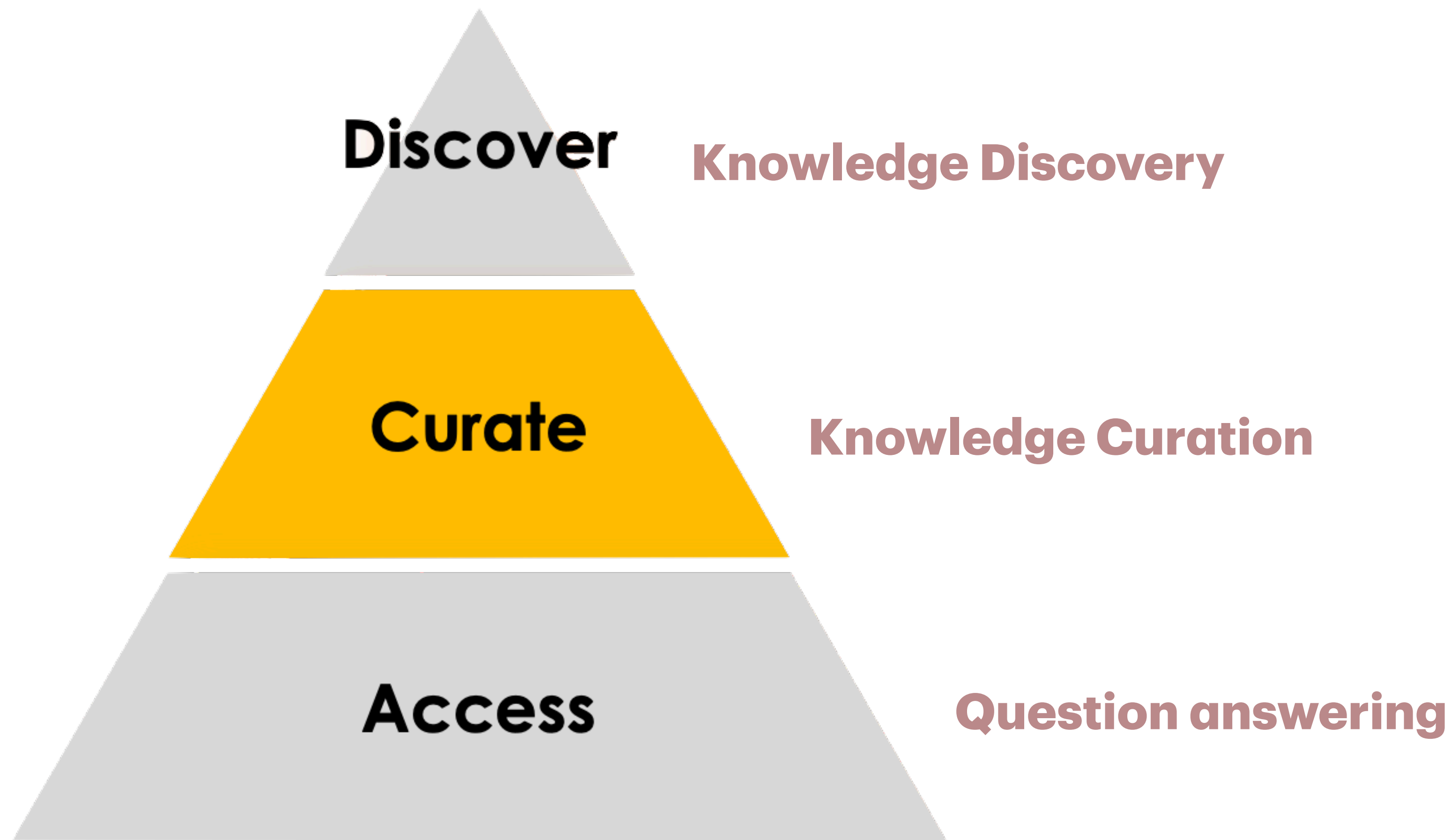
Unknown Unknowns:

Things you don't know and aren't aware of

Known Unknowns:

Things you know you don't have knowledge

The illustration is contributed by Yijia Shao



Real Unknowns:

Knowledge that does not exist

Unknown Unknowns:

Things you don't know and aren't aware of

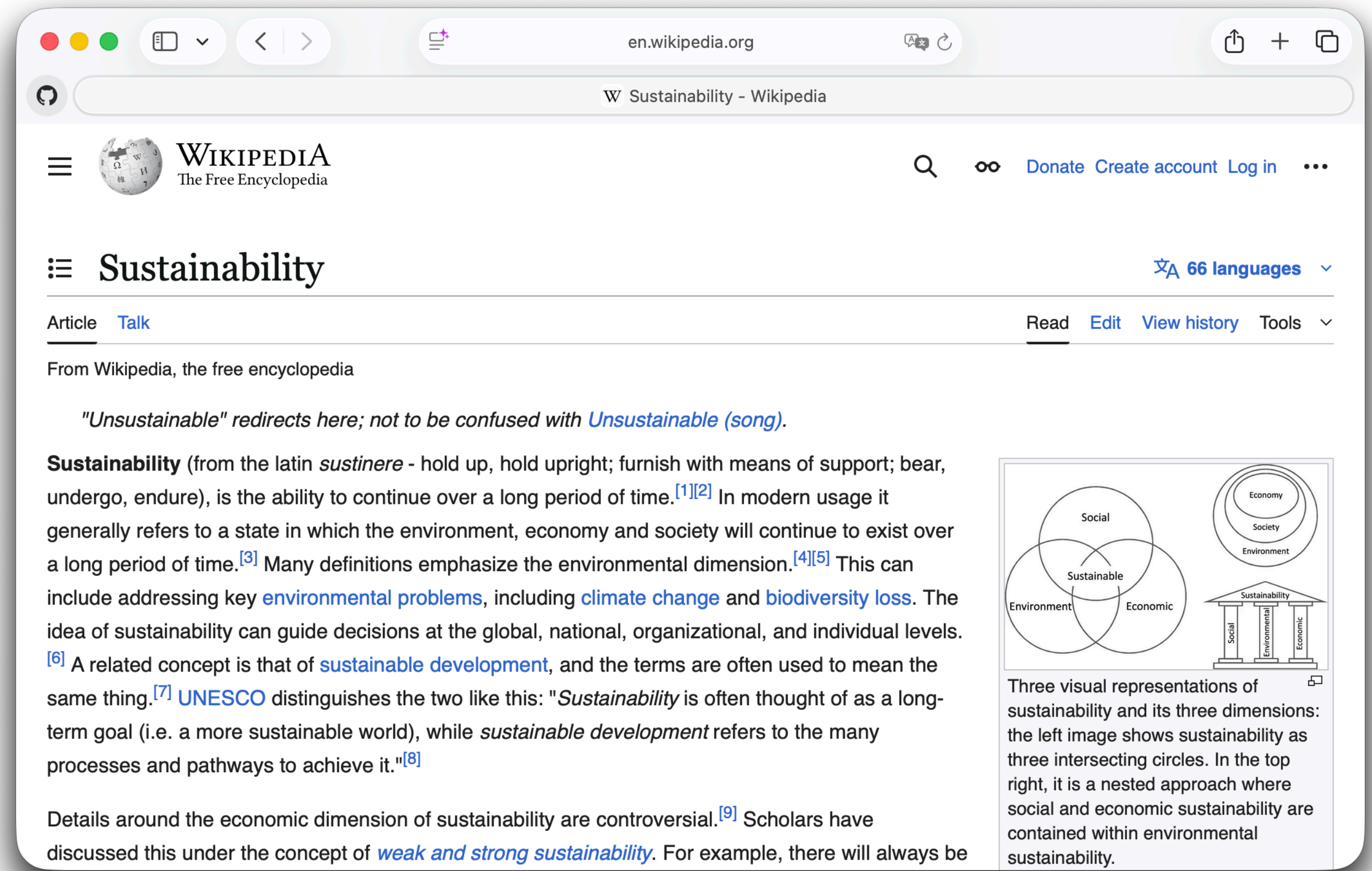
Known Unknowns:

Things you know you don't have knowledge

Knowledge Curation

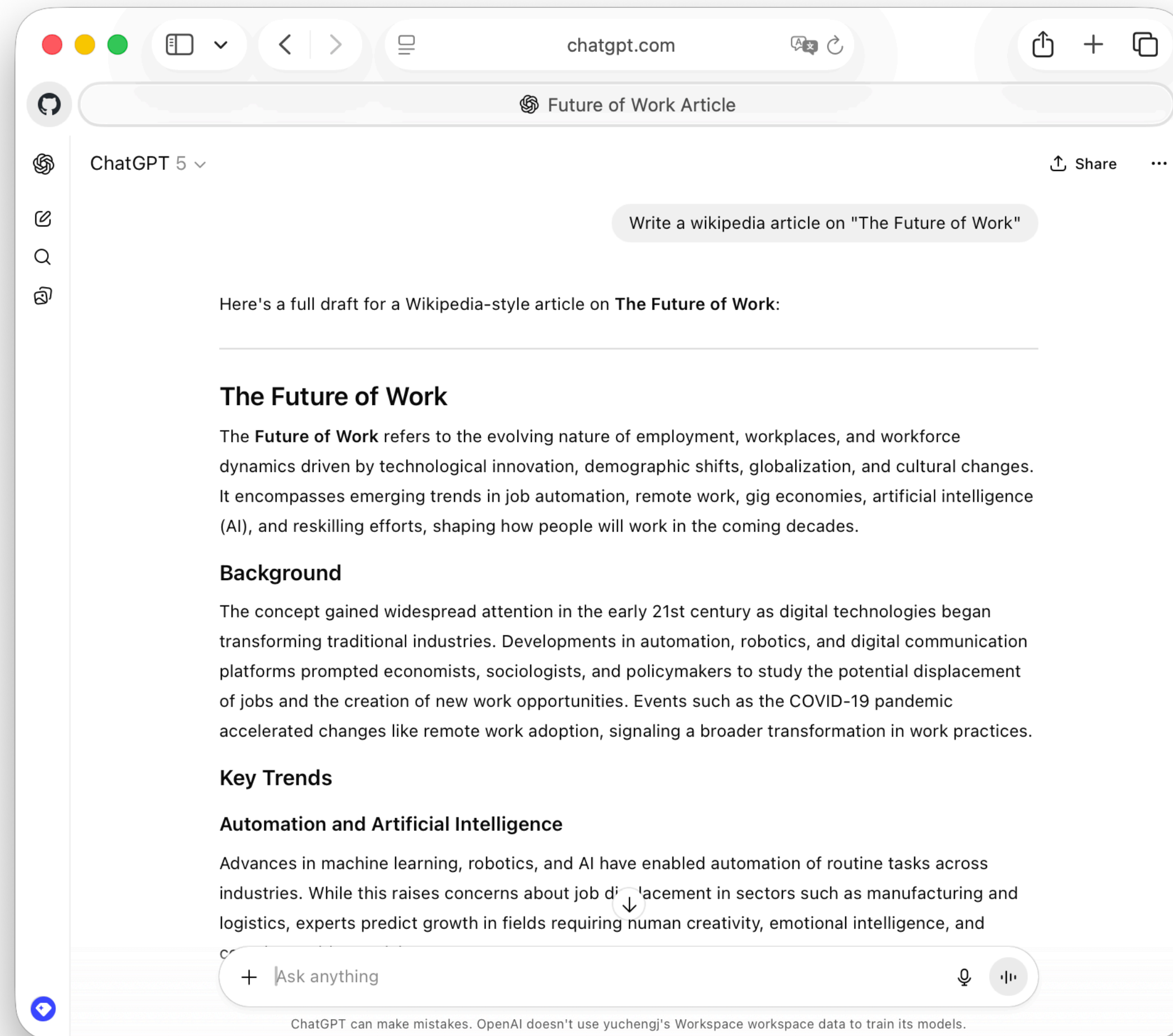
Wikipedia is a good example of knowledge curation.

- Comprehensive
- Organized
- Reliable
- Verifiable



Knowledge Curation

Generating wikipedia-like article is non-trivial



 Lack of details

 Hard to verify

Knowledge Curation

Early stage long form generation methods (1/2) - Training Neural Models

Given the ordered paragraphs $\{p_{R_{i(j)}}^i\}$

Encode, concatenate, and truncate

$$\text{text}_i = T(a_i) || \{p_{R_{i(j)}}^i\}$$

$$\text{tokenize}(\text{text}_i) = x_i = (x_i^1, x_i^2, \dots, x_i^{n_i})$$

$$m_i^L = (x_i^1, \dots, x_i^{\min(L, n_i)})$$

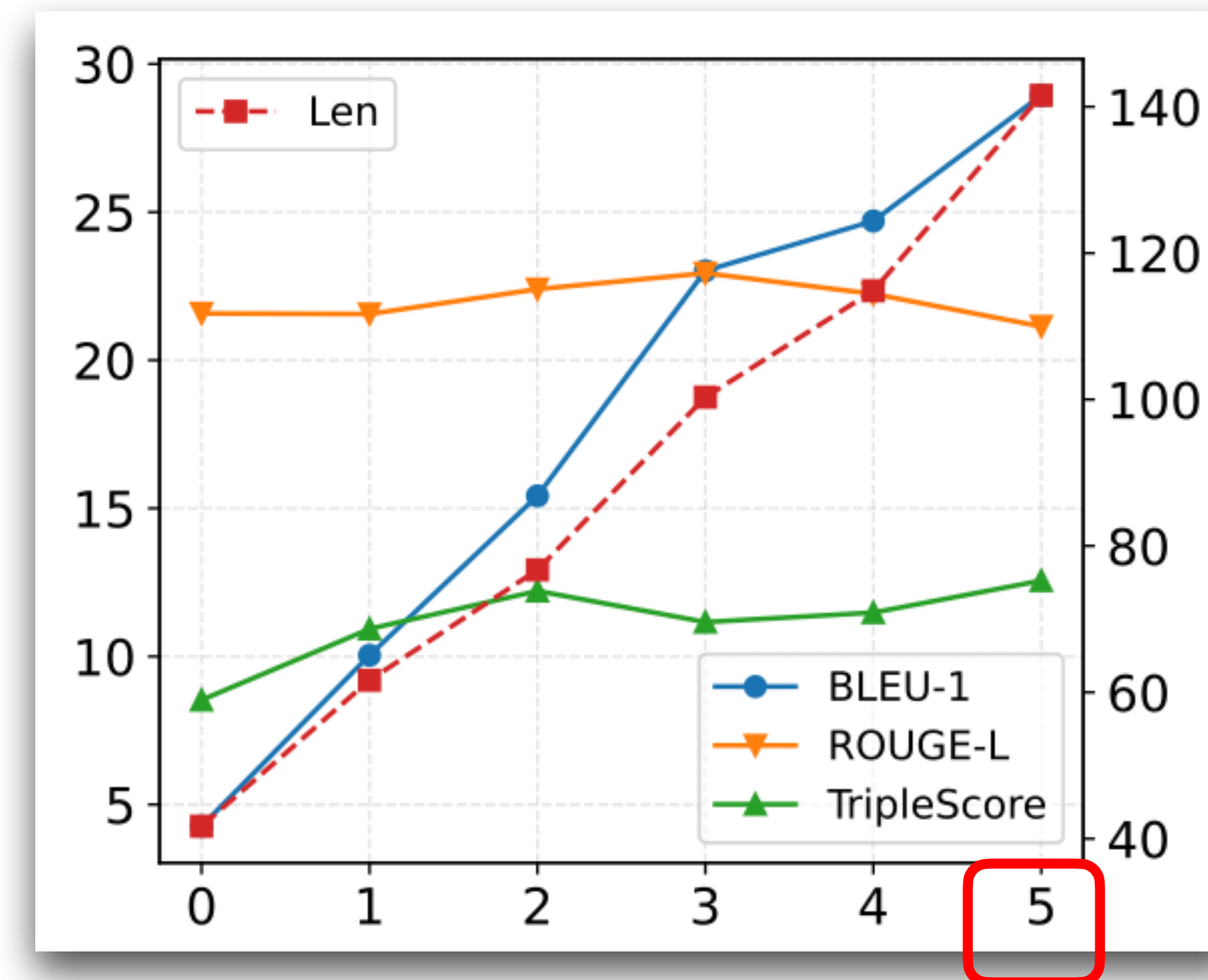
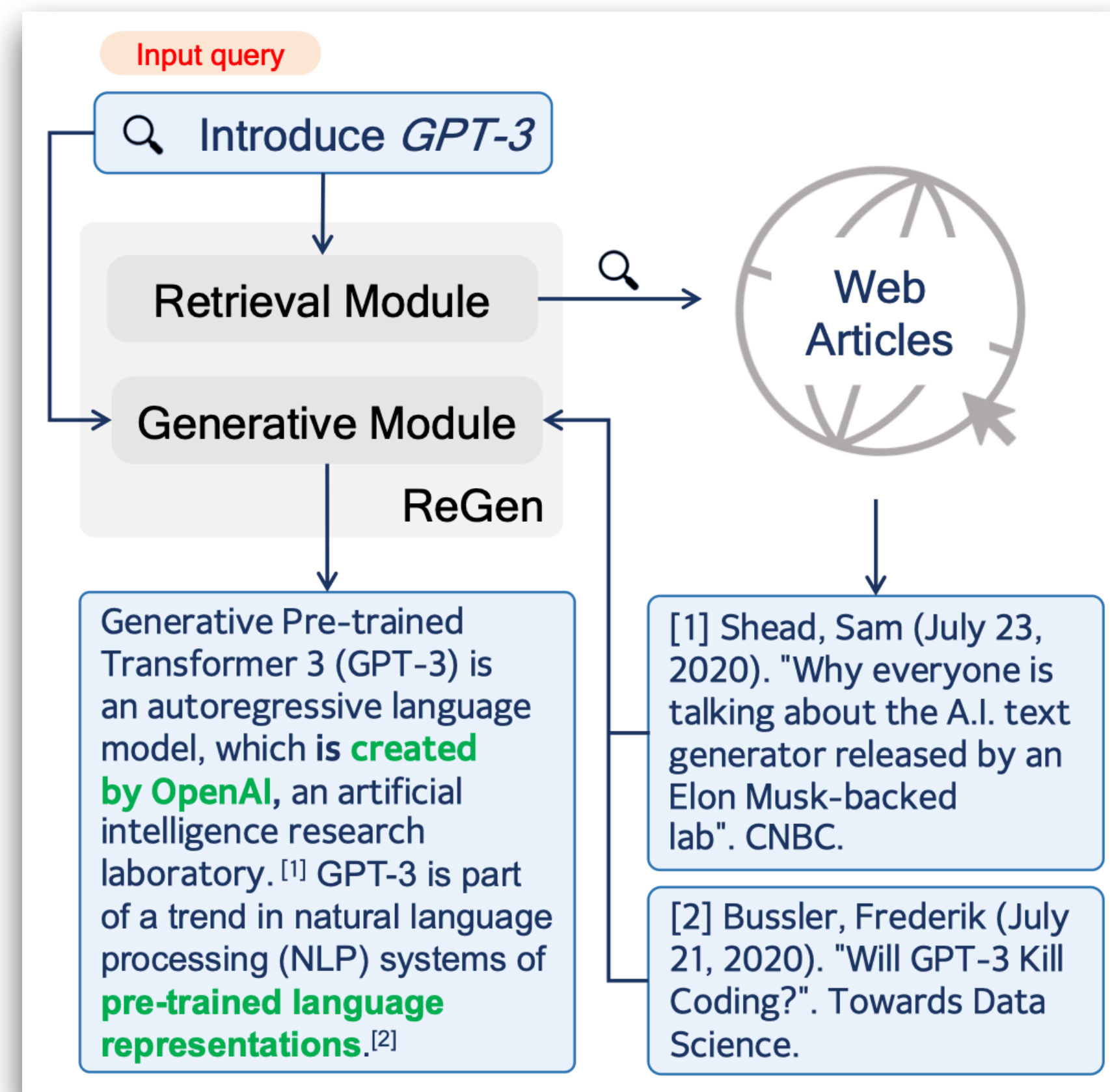
Train an abstractive model W that learns to write articles, $a_i = W(m_i^L)$

Early prior works usually **assumes** the references are given.

However, collecting references requires literature research which is non-trivial

Knowledge Curation

Early stage long form generation methods (2/2) - Prompting an LLM



Limited length, only a few citations

Knowledge Curation

STORM: Assist in writing Wikipedia-like articles from scratch with LLMs

2024/02: **STORM** - First open source knowledge curation system - Beginning of Deep Research

2024/12: Gemini Deep Research

2025/02: OpenAI Deep Research, Perplexity Deep Research

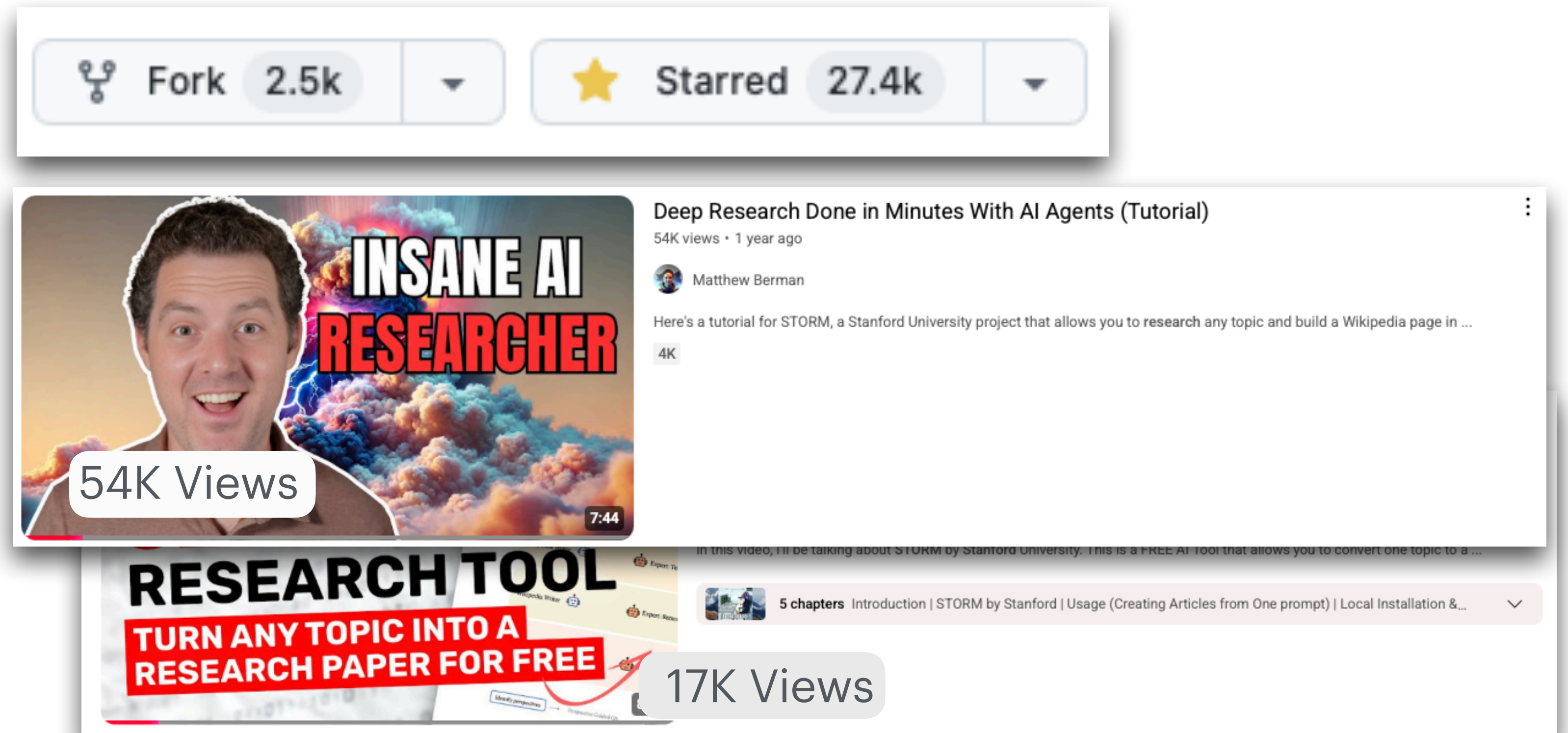
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Knowledge Curation

STORM: Assist in writing Wikipedia-like articles from scratch with LLMs

**STORM has
aroused interest
across various
communities**



Shao, Yijia, Yucheng Jiang, Theodore A. Kanell, Peter Xu, Omar Khattab, and Monica S. Lam. "Assisting in writing Wikipedia-like articles from scratch with large language models.", In NAACL 2024

Knowledge Curation

STORM: How to generate grounded articles with good breadth & depth

Key Idea: Mimic Human Writing Process

How do humans write?

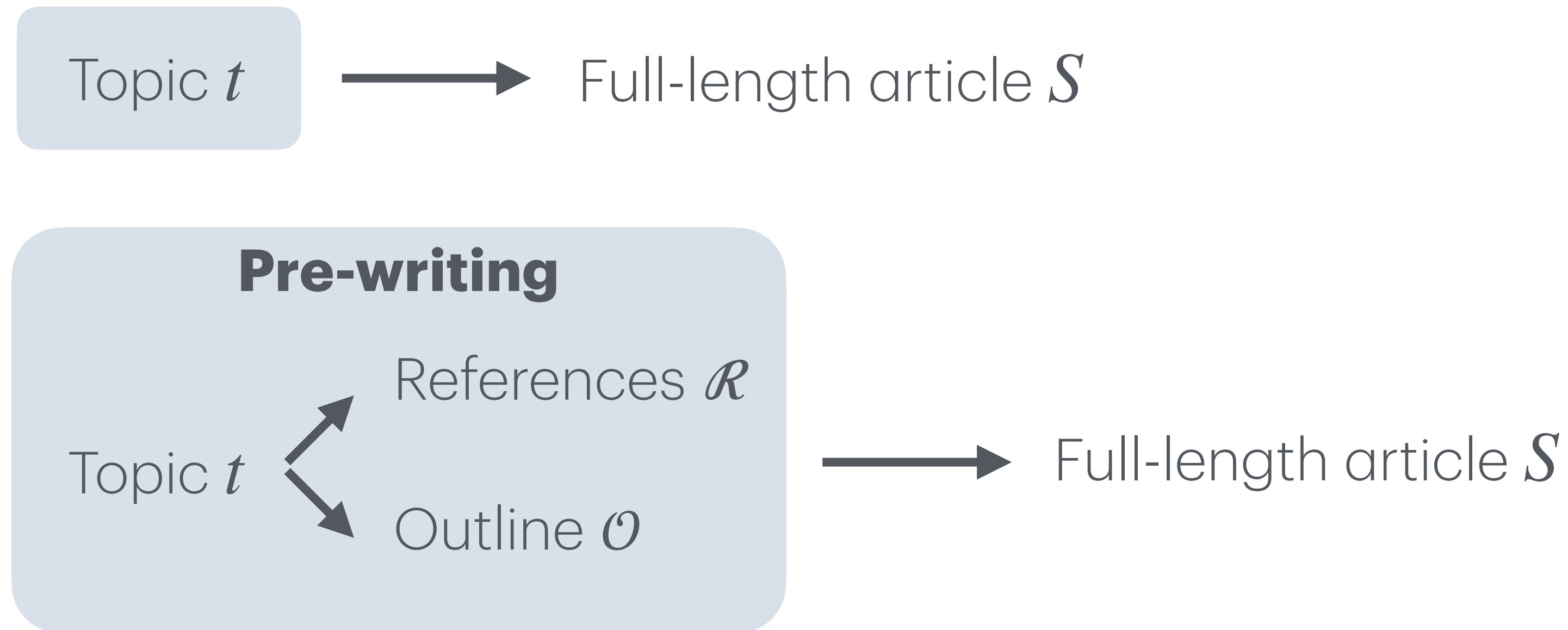
Rohman, 1965: **Pre-Writing** the Stage of Discovery in the Writing Process

How do humans do literature search?

Booth et al., 2003: The Craft of Research “Chapter II: **Asking Questions**, Finding Answers”

Knowledge Curation

STORM: Pre-writing



The pre-writing task:

Give a topic t , the pre-writing task is to find a set of references \mathcal{R} , and create an outline \mathcal{O} , which is defined as a list of multi-level section headings, to organize \mathcal{R} .

Knowledge Curation

STORM: Literature research via question asking

Topic: 2022 Winter Olympics Opening Ceremony

Prompt: Ask 30 questions about the given topic

1. **When** was the opening ceremony held?
2. **Where** was the opening ceremony held?
3. **How many** countries participated in the opening ceremony?

Direct prompting results in questions that lack breadth and depth

We cannot simply rely on “brute force” or inference-time scaling

Knowledge Curation

STORM: Literature research via perspective guided QA

STORM uses **perspective** as a latent variable to control the breadth of the search.

Topic: 2022 Winter Olympics Opening Ceremony

Survey related topics:

wiki/2020_summer_olympics

wiki/2018_winter_olympics

Identify perspectives:

(e.g. Economist: this editor will bring in the economic perspective, focusing on topics such as national macro economic effects...)

Knowledge Curation

STORM: Simulating conversations to allow follow-up questions

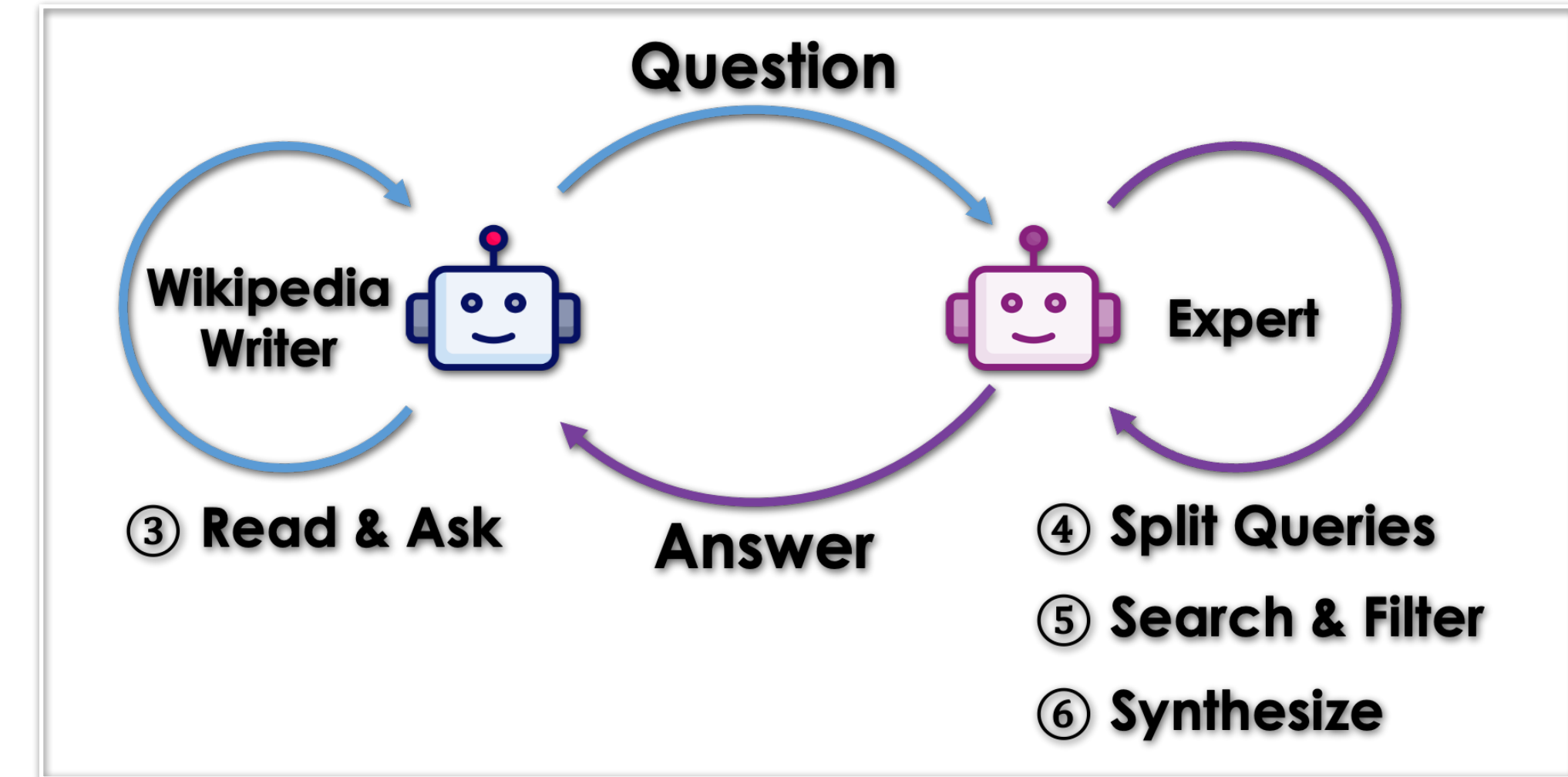
Some in-**depth** questions arise only after reading the information gathered in previous rounds.

Topic: 2022 Winter Olympics Opening Ceremony

Q: Can you provide me with a list of the participating countries in the 2022 Winter Olympics opening ceremony?

A: The 2022 Winter Olympics featured a diverse group of countries... Athletes from over 90 countries will enter the stadium **in a specific order**.

Q: **How is the order** of participating countries in the 2022 Winter Olympics opening ceremony **determined**?



Knowledge Curation

STORM: Conducting meaningful evaluations

What should we evaluate? and how?

Do we have ground truth / golden answer?

Besides the final report, what else should we evaluate?

Knowledge Curation

STORM: Automatic evaluation - Outline quality

Introduce **outline coverage metrics** as a proxy of the pre-writing stage quality for **fast prototyping**

Given the human-written wikipedia article on topic t

1. **Heading soft recall**

Compare embedding of headings in \mathcal{O} and the human-written article

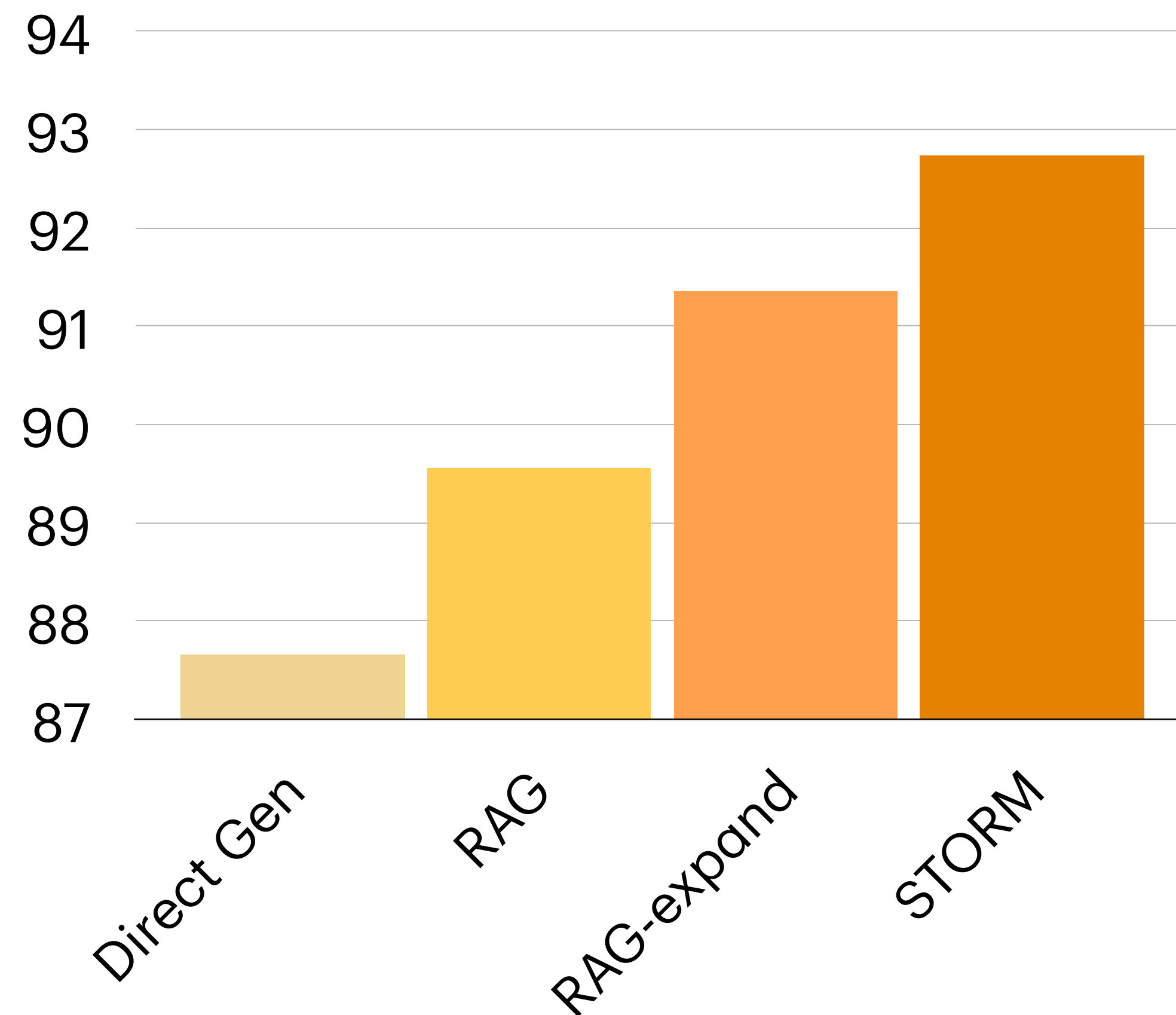
2. **Heading entity recall**

The percentage of named entities in the human-written article covered by \mathcal{O}

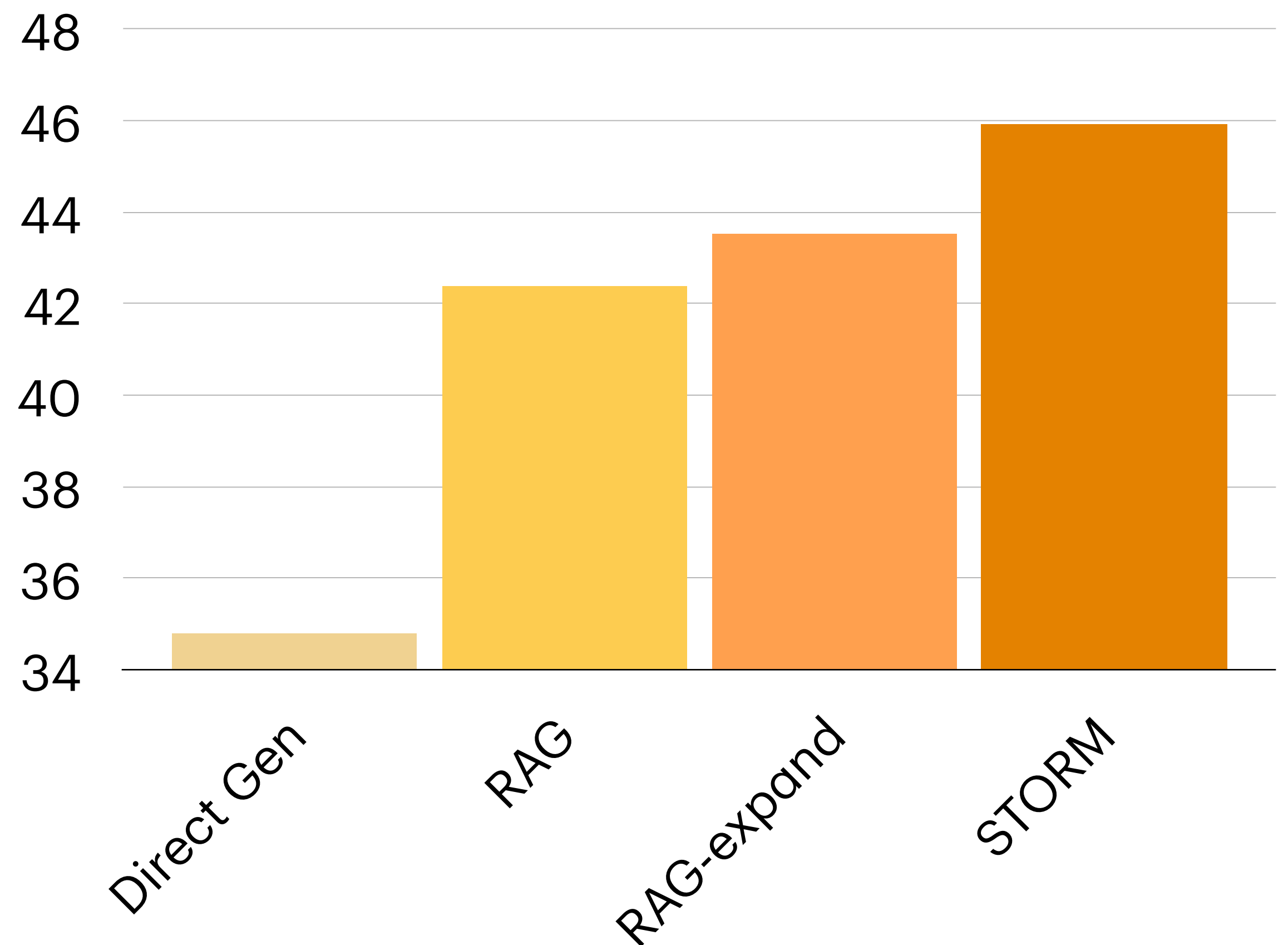
Knowledge Curation

STORM: Automatic evaluation - Outline quality

Heading Soft Recall



Heading Entity Recall



Knowledge Curation

STORM: Automatic evaluation - Outline quality

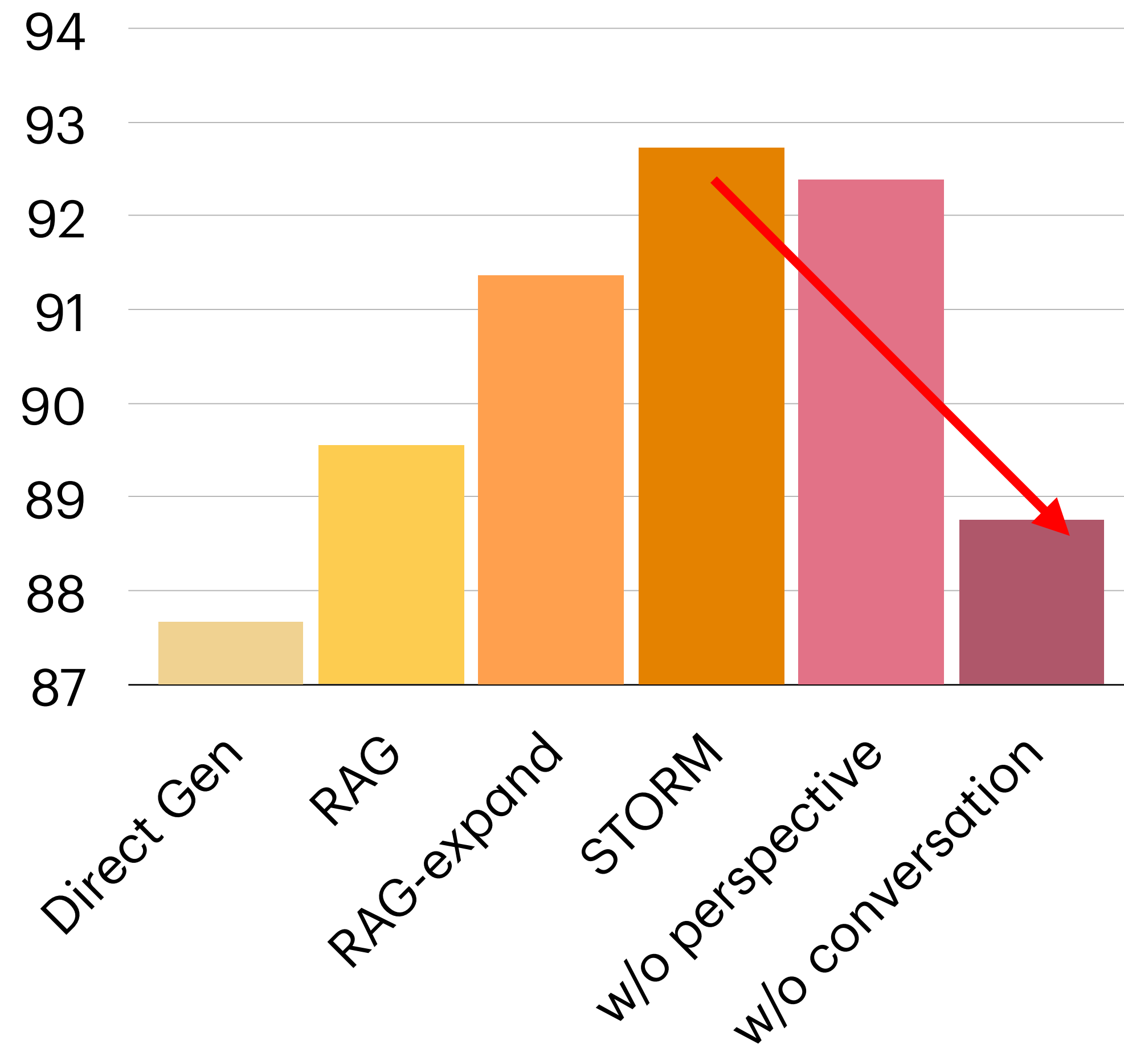
Ablation study is important!

Ablation study help us to understand how different parts of a system contribute to its overall performance

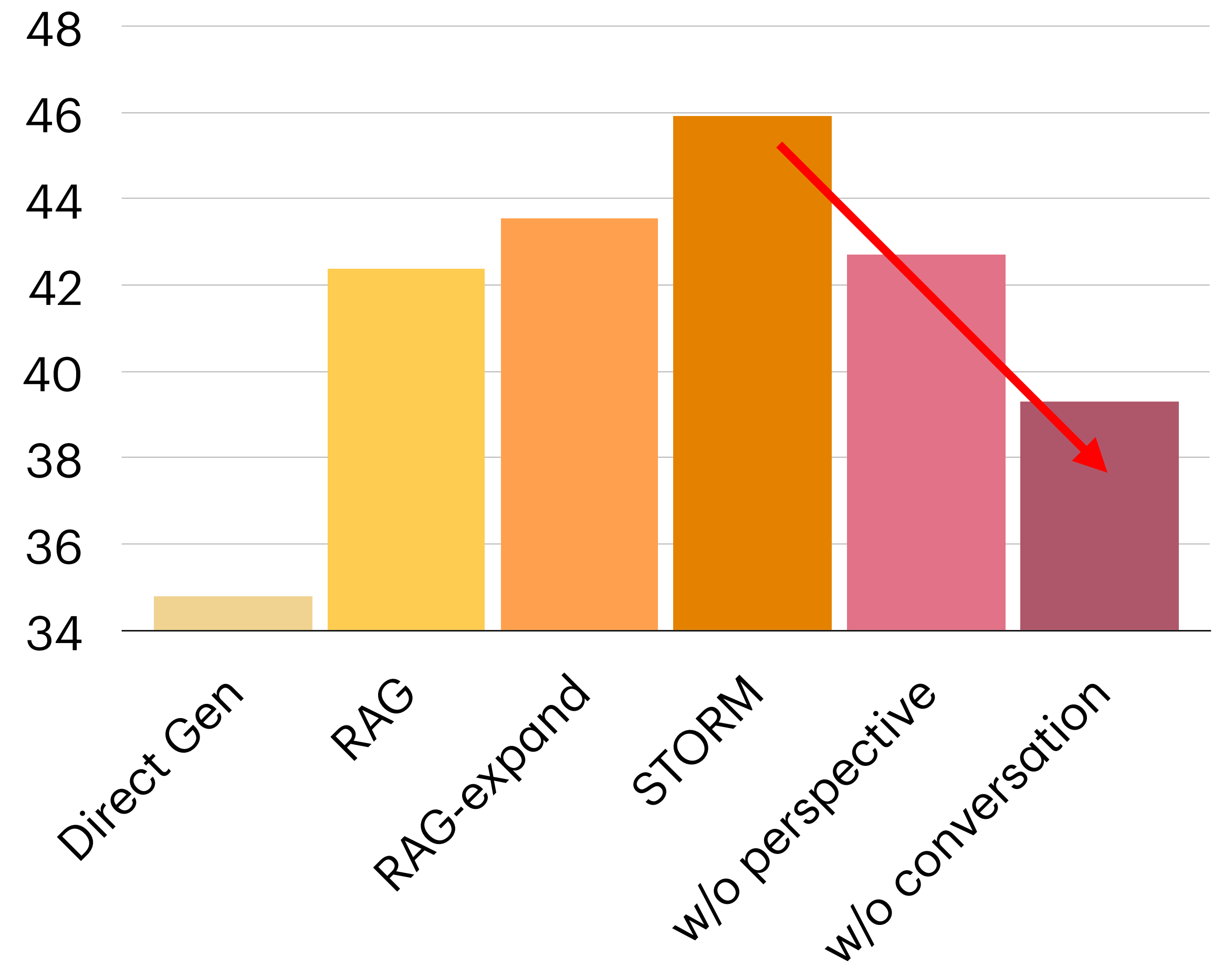
Knowledge Curation

STORM: Automatic evaluation - Outline quality

Heading Soft Recall



Heading Entity Recall



Knowledge Curation

STORM: Human evaluation - Wikipedia editor evaluation

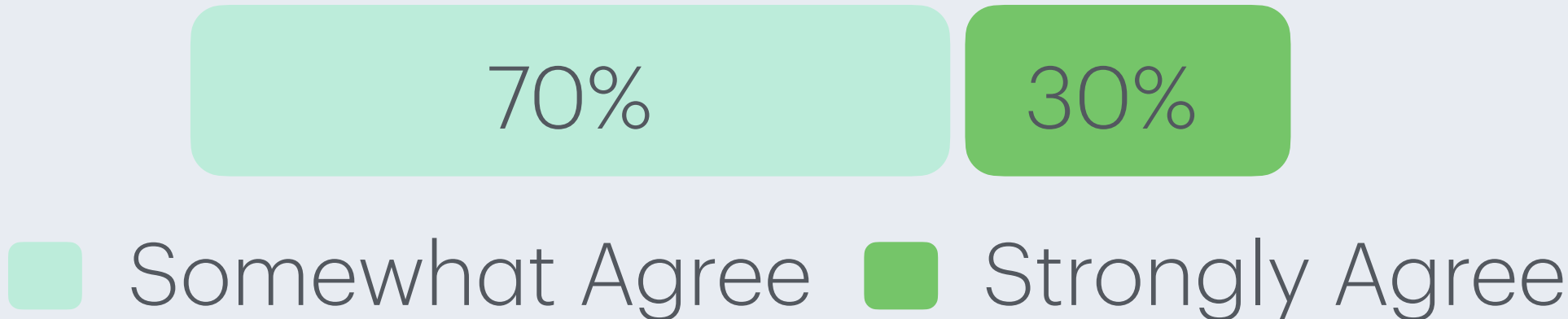
**Careful human evaluation is necessary
to evaluate LM-empowered systems.**

Knowledge Curation

STORM: Human evaluation - Wikipedia editor evaluation

**Experienced Wikipedia editors
favor articles produced by STORM.**

“I (Wikipedia Editor) think it can be specifically helpful for my pre-writing stage.”



≥ 4 Rate (1-7 Scale)	Interest Level	Organization	Relevance	Coverage	Verifiability
oRAG	57.5%	45.0%	62.5%	57.5%	67.5%
STORM	70.0%	70.0%	65.0%	67.5%	67.5%

Knowledge Curation

STORM: Human evaluation - In the wild evaluation

UIUX design is critical for larger scale human evaluation in the wild

<https://storm.genie.stanford.edu>

820,000 Users

1,400,000 Articles

2,700,000 Browsing

250,000 Feedbacks

Knowledge Curation

STORM: Human evaluation - In the wild evaluation

People have used STORM across a diverse range of topics & use cases

Agriculture

Fitness

Design

Management

Computer Science

Medicare

Gaming

Business

Environment science

Law

Music

Animal science

Biology

News

Food

Transportation

Physics

Politics

Travel

Emergency management

Geology

Cultural study

Education

...

Revisit: Meta question

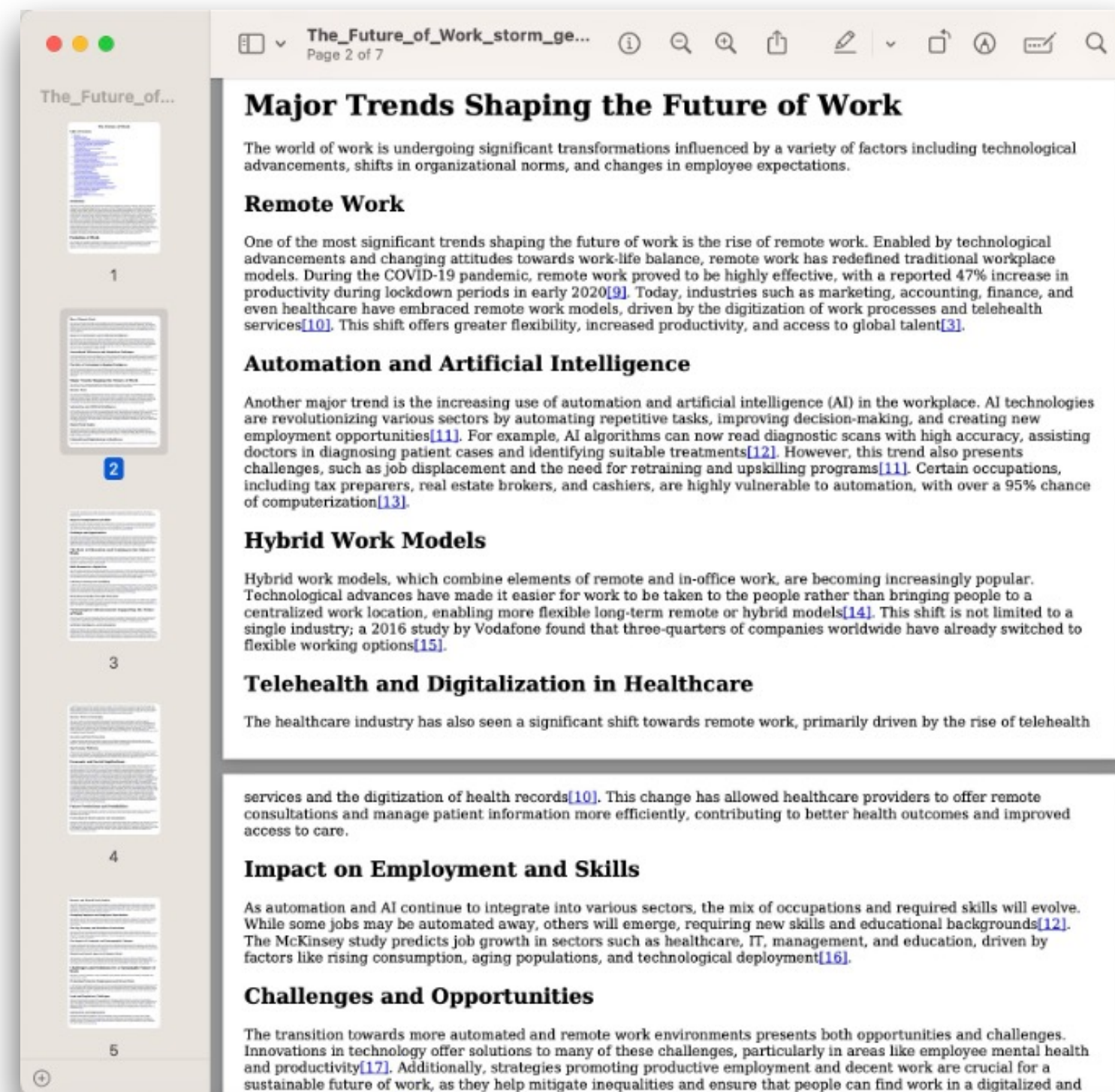
Are people's information needs satisfied?



The illustration is co-created with DALL-E.

Revisit: Meta question

Are people's information needs satisfied?

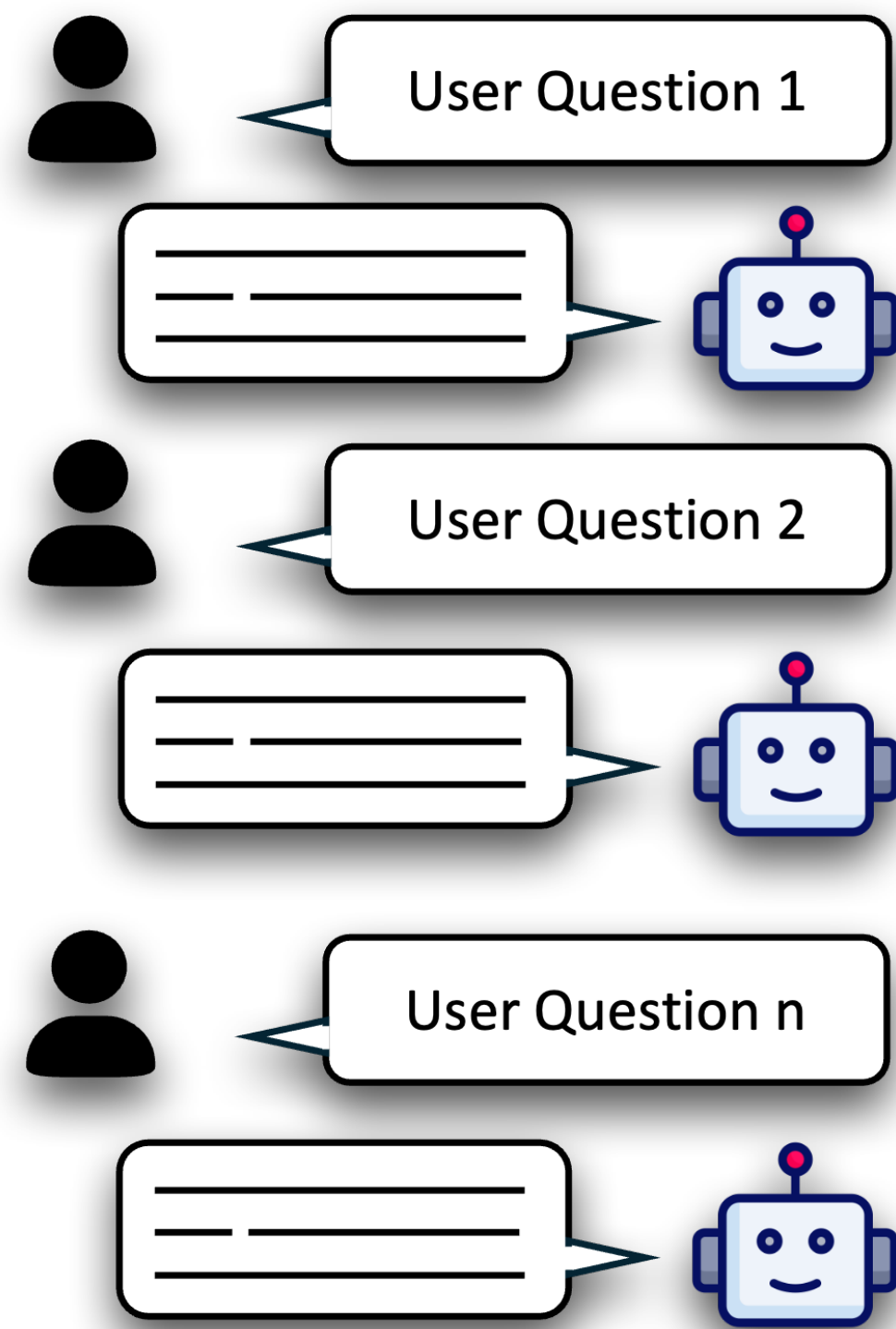


My thoughts evolve, so I want to update my queries.

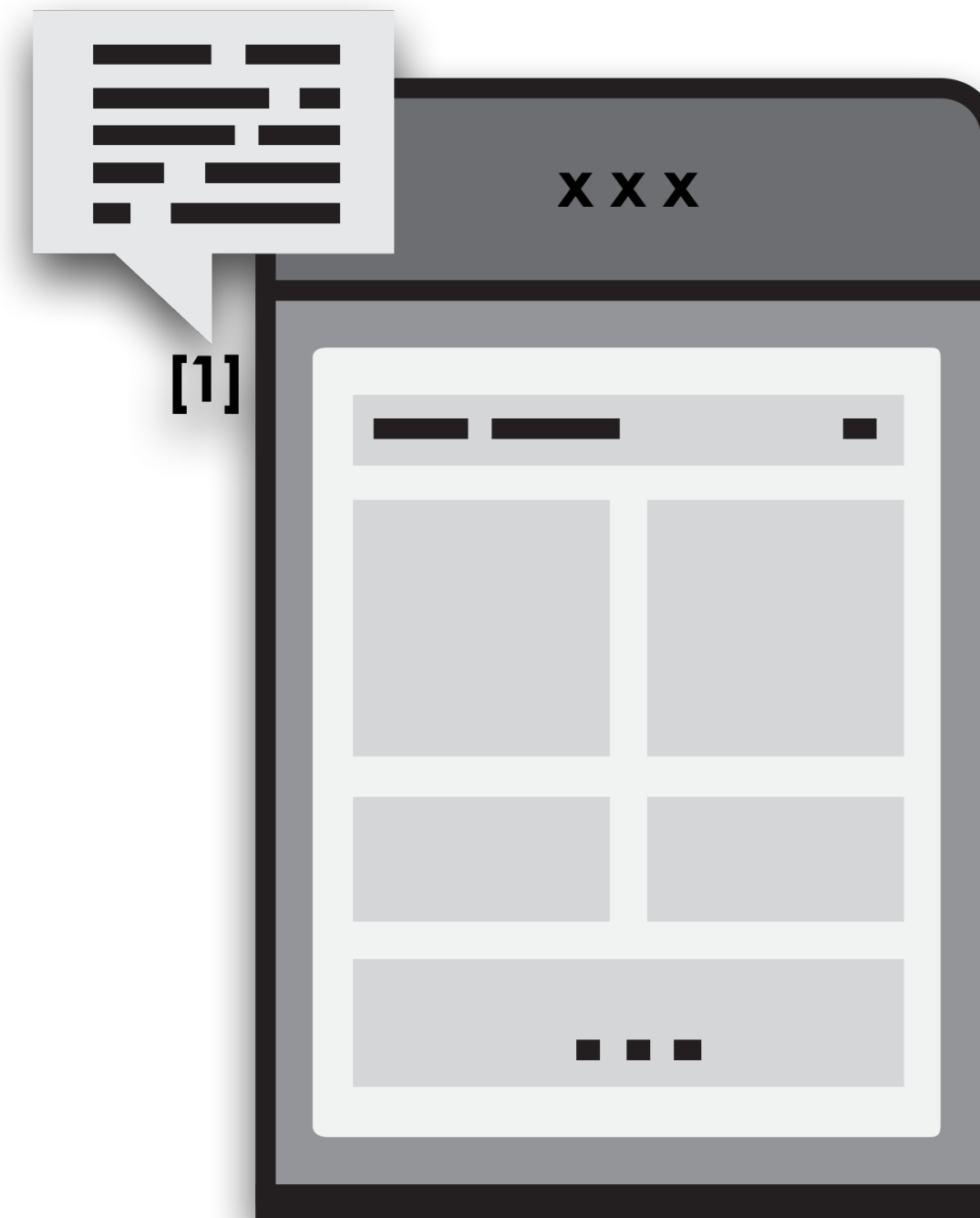
I am inspired by this link and hope to learn more about it.

I know this topic is also relevant. Can you include it?

Human-AI interaction/collaboration



Convert STORM into a hallucination-free question answering system



After the long report is generated, allow the user to edit or ask questions.

Human-AI interaction/collaboration



The diagram illustrates a user-initiative interaction. It shows a vertical sequence of three user questions: 'User Question 1', 'User Question 2', and 'User Question n'. Each question is represented by a speech bubble coming from a user icon. Below each question is a corresponding response from a chatbot icon, represented by a speech bubble with horizontal lines indicating text.

User-initiative design

(Baseline 1: RAG Chatbot)

Convert STORM into a hallucination-free question answering system



The diagram illustrates a system-initiative interaction. It shows a large document icon with a speech bubble containing '[1]' pointing to it. Below this, there is a smaller document icon with a speech bubble containing 'x x x' pointing to it. This is followed by a larger document icon with a speech bubble containing '...' pointing to it. The entire sequence is enclosed in a rounded rectangle.

System-initiative design

(Baseline 2: STORM + QA)

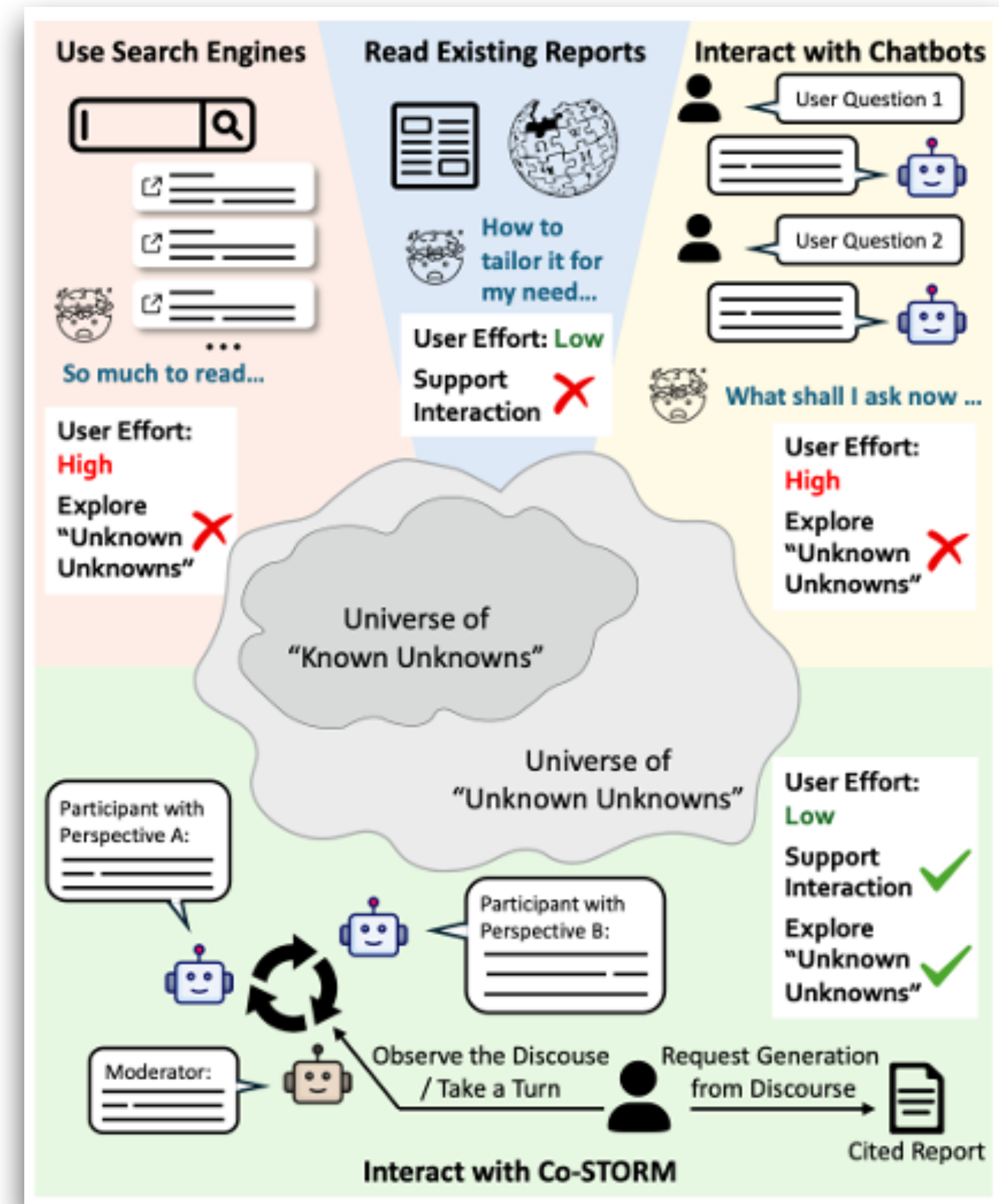
After the long report is generated, allow the user to edit or ask questions.

Human-AI interaction/collaboration

CoSTORM:

Engaged human learning through Participation in LM agent conversations

Jiang, Yucheng, Yijia Shao, Dekun Ma, Sina J. Semnani, and Monica S. Lam. "Into the Unknown Unknowns: Engaged Human Learning through Participation in Language Model Agent Conversations.", In EMNLP 2024



Human-AI interaction/collaboration

CoSTORM: Human learning, unknown unknowns discovery

Key Idea: Mimic Human Learning Process

How do children/students learn?

Nussbaum, 2008: **Collaborative discourse** and collaborative argumentation is important for promoting students' deep-level understanding of contents.

How do humans retain information?

Buzan, 1974: Using **mind map** for note taking to help recall and critical thinking.

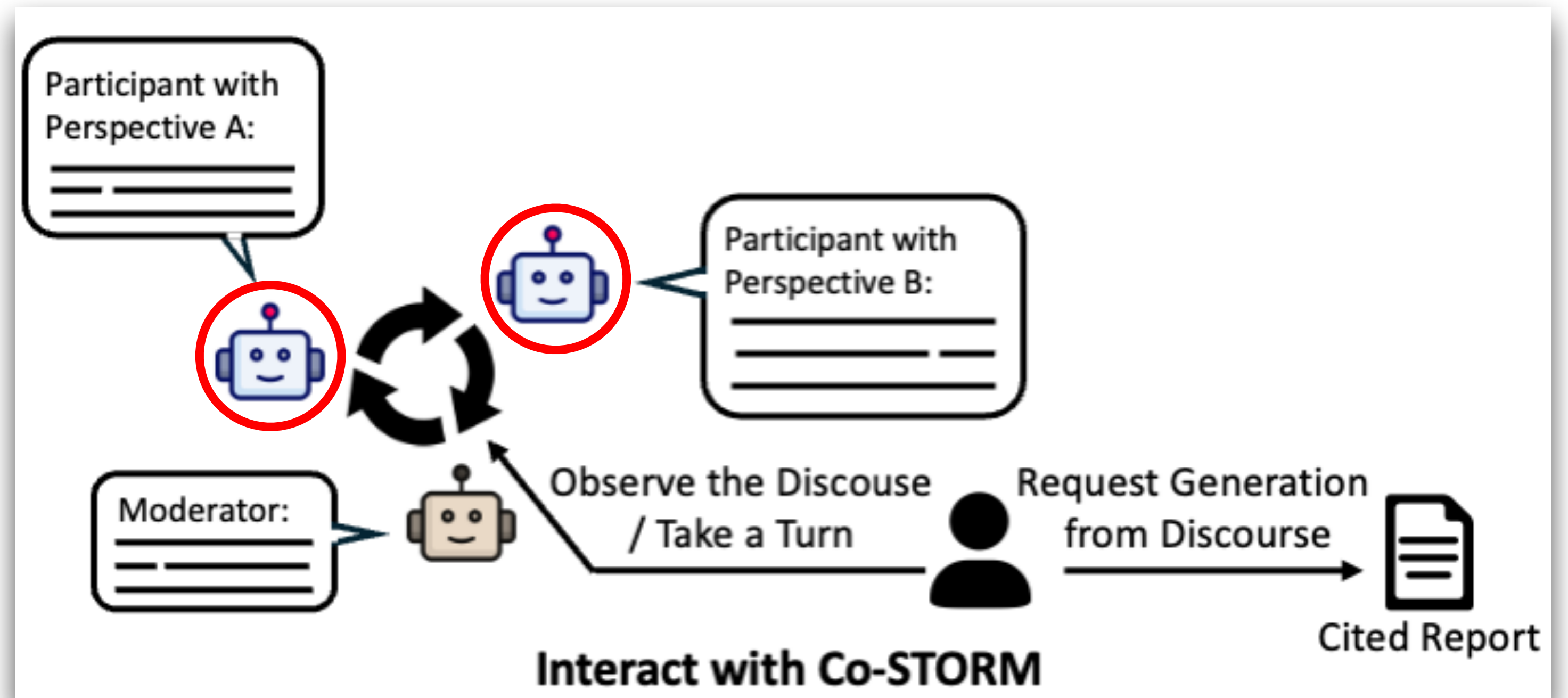
Human-AI interaction/collaboration

CoSTORM: Collaborative Discourse Protocol Design

Agents form a roundtable,
answering and **asking**
questions grounded on external
sources

The user can jump in at any
time to steer the discourse and
inject questions and opinions.

Maintains a dynamic,
hierarchical mind map so users
can easily follow and engage.



Input Optional Design

Human-AI interaction/collaboration

CoSTORM: Collaborative Discourse Protocol Design

However, the agent almost always choose **question answering**, causing the conversation to focus on a narrow topic, which can result in **overly niche content**.

How do human ask follow up questions during information seeking?

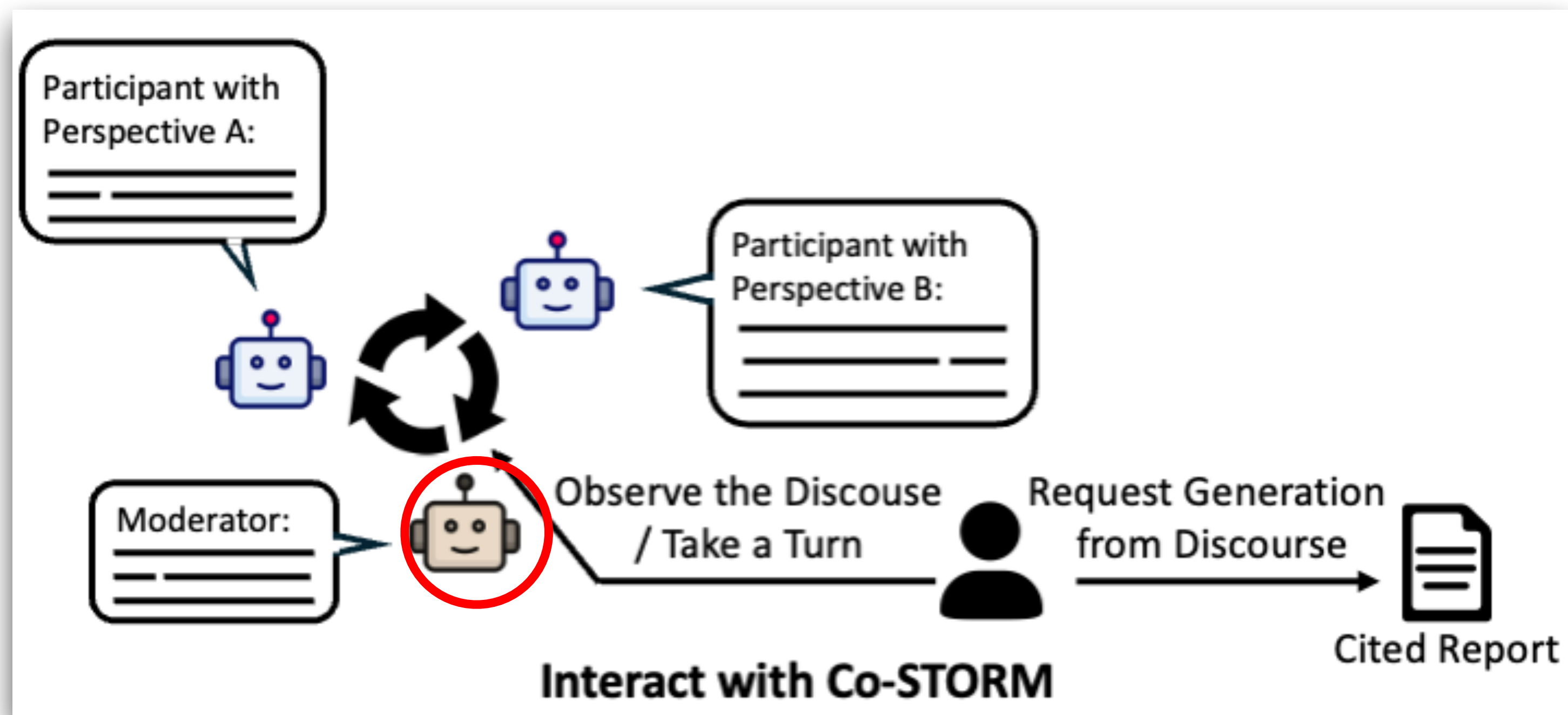
Serendipidity: We may discover topics not directly related but particularly interesting

For example, when we search for “improving software engineering practices”, we might stumble upon an article about “the cognitive psychology behind team decision-making”.

Human-AI interaction/collaboration

CoSTORM: Collaborative Discourse Protocol Design

Solution: Ask thought provoking questions via **Moderator** role



Human-AI interaction/collaboration

CoSTORM: Collaborative Discourse Protocol Design

Solution: Ask thought provoking questions via **Moderator** role

Step 1: Extract and rerank unused information throughout discourse history

$$\cos(i, t)^\alpha [1 - \cos(i, q)]^{1-\alpha}$$

(where i, q, t are embeddings of the information, question, and topic)

Step 2: Generate thought-provoking questions & polish the utterance

Human-AI interaction/collaboration

CoSTORM: Conducting meaningful evaluations

What should we evaluate? and how?

Do we have ground truth / golden answer?

Besides the final report, what else should we evaluate?

Human-AI interaction/collaboration

CoSTORM: Automatic evaluation - Discourse quality

	Question-Answering Turn Quality		
	Consistency	Engagement	# Unique URLs
RAG Chatbot	4.37	4.13	2.94
STORM + QA	4.34	4.11	2.89
Co-STORM	4.40[†]	4.33[†]	6.04[†]
w/o Multi-Expert	4.40	4.32	5.91
w/o Moderator	4.39	4.28	5.67

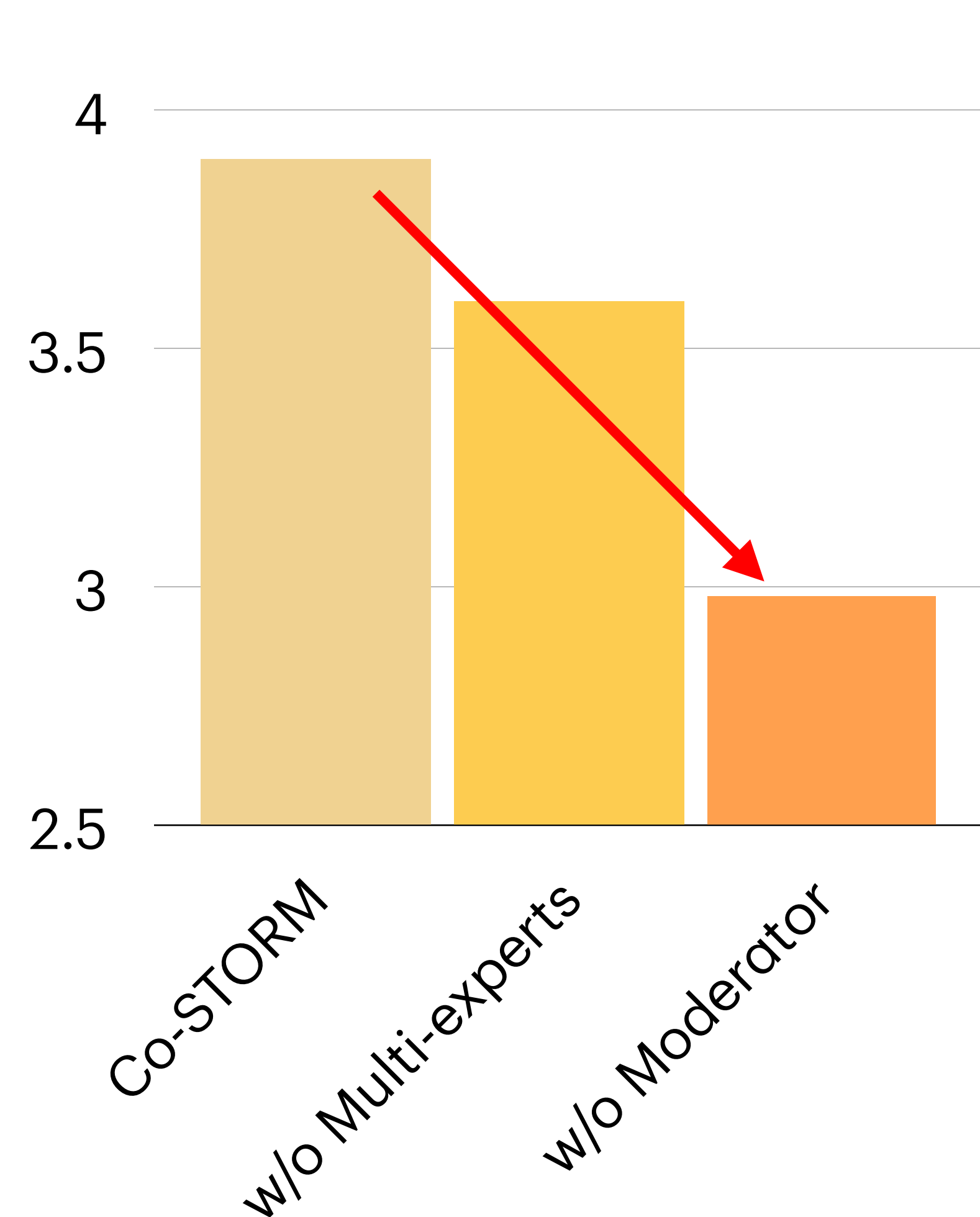
Human-AI interaction/collaboration

CoSTORM: Automatic evaluation - Final report quality

	Report Quality				
	Relevance	Breadth	Depth	Novelty	Info Diversity
RAG Chatbot	3.57	3.50	3.26	2.44	0.595
STORM + QA	3.61	3.61	3.43	2.50	0.592
Co-STORM	3.78	3.79	3.77†	3.05†	0.602
w/o Multi-Expert	3.73	3.75	3.77	2.93	0.589
w/o Moderator	3.56	3.69	3.41	2.89	0.577

Human-AI interaction/collaboration

CoSTORM: Automatic evaluation - Ablation study



	# User	# expert agent	# moderator
Co-STORM	1	N	1
w/o multi-experts	1	1	1
w/o multi-agent	1	N	0

Having just one expert and one moderator can already provide most of the benefits

Human-AI interaction/collaboration

CoSTORM: Human Evaluation

	Co-STORM v.s. Search Engine				Co-STORM v.s. RAG Chatbot			
	Search Engine	Co-STORM	Win % (Lose %)	<i>p</i> -value	RAG Chatbot	Co-STORM	Win % (Lose %)	<i>p</i> -value
Relevance	3.90	4.00	30% (30%)	0.758	3.89	4.22	33% (0%)	0.081
Breadth	3.60	4.10	50% (10%)	0.096	3.11	4.22	67% (0%)	0.013
Depth	3.10	4.00	60% (10%)	0.081	3.11	4.00	56% (33%)	0.069
Serendipity	2.70	3.90	70% (10%)	0.030	2.78	3.78	67% (0%)	0.009

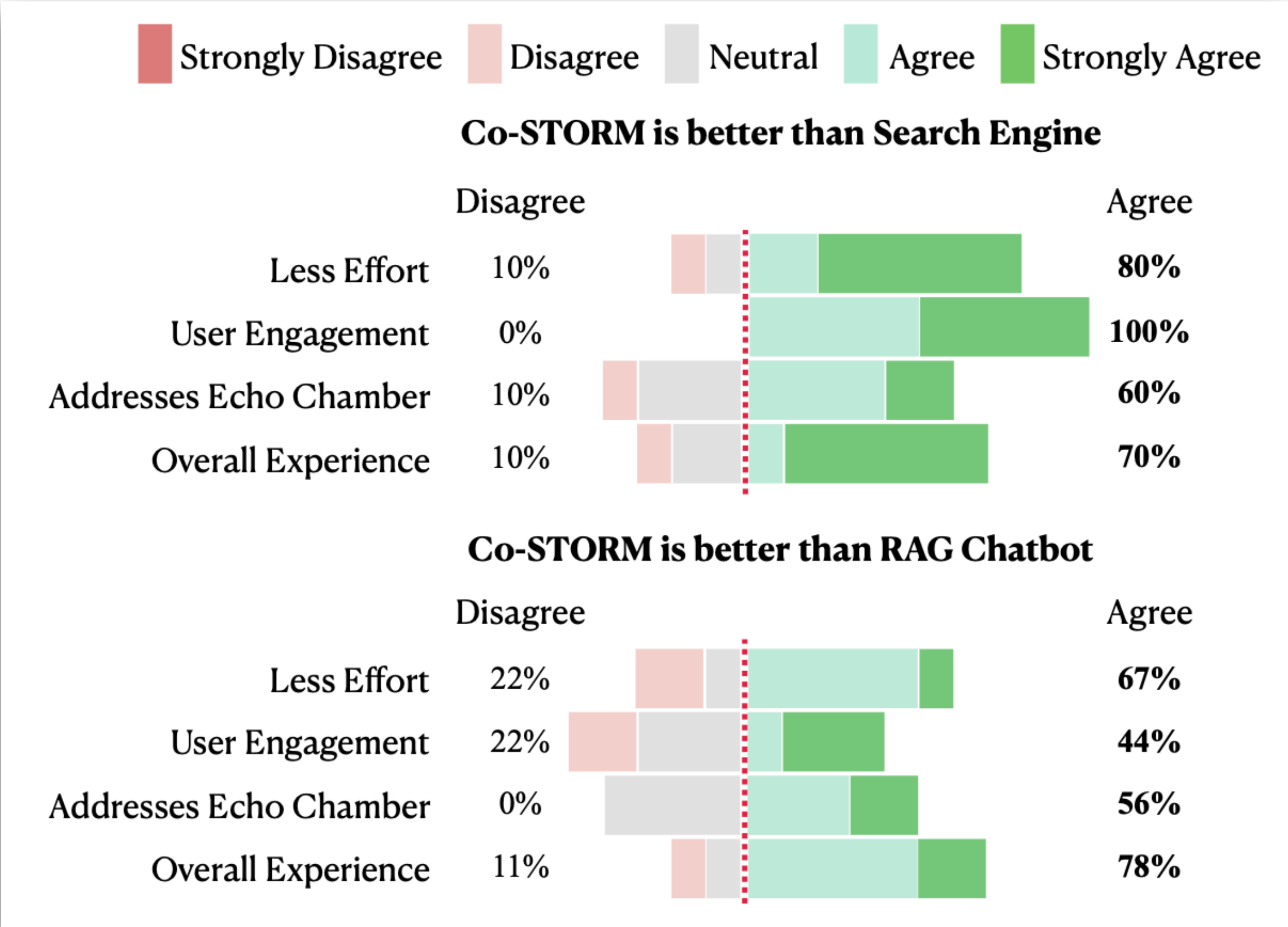
Table 4: Human ratings on different aspects of the information-seeking experience with Co-STORM and Search Engine (n=10) and with Co-STORM and RAG Chatbot (n=9)⁶. The ratings are given on a scale from 1 to 5 with 3 as “Average”. We report the win rate of Co-STORM in pairwise comparison and the *p*-value in a paired *t*-test.

Human-AI interaction/collaboration

CoSTORM: Automatic evaluation - Human Evaluation

Co-STORM allows for almost full automation and much better understanding as it brings up topics that the user may not even think of.

“Co-STORM is so much less mentally taxing for me to use”



DataSTORM and HW 1

HW1 Overview

STORM and other deep research systems focus on **literature search (or literature review of research)** and summarizing existing information.

In HW1 we will go further—conducting **original research** to produce an investigative journalism article on a real-time world conflict.

DataSTORM and HW 1

HW1 Overview - Provided building blocks

1. Internet based literature search (similar to STORM)

2. Database exploration agent (DataSTORM)

Given a topic and an initial set of research questions, it interacts with the database, autonomously generating and refining questions, retrieving answers, and returning a curated set of interesting search results throughout the process.

DataSTORM and HW 1

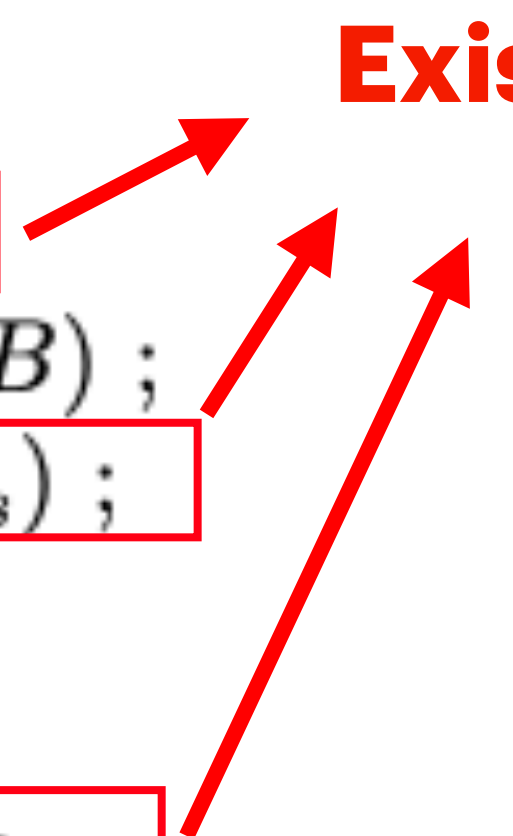
HW1 Algorithm overview

Algorithm 1: HW1

Input : Topic t

Output: Report R

```
 $B \leftarrow \text{RUNLITERATURESEARCH}(t) ;$  // Background report on topic  
 $Q_s \leftarrow \text{GENERATESEEDQUESTIONS}(B) ;$  // Initial research questions  
 $D \leftarrow \text{DATABASEEXPLORATION}(t, Q_s) ;$  // Curated retrieved results  
 $T \leftarrow \text{GENERATETHESES}(D) ;$  // Set of proposed theses  
 $\tau^* \leftarrow \text{SELECTBESTTHESIS}(T) ;$  // Select most promising thesis  
 $S \leftarrow \text{RUNLITERATURESEARCH}(\tau^*) ;$  // Evidence supporting selected thesis  
 $R \leftarrow \text{CONSOLIDATEFINDINGS}(B, D, \tau^*, S) ;$  // Comprehensive final report  
return  $R$ ;
```



Existing building blocks

DataSTORM and HW 1

HW1: Your tasks

Algorithm 1: HW1

Input : Topic t

Output: Report R

$B \leftarrow \text{RUNLITERATURESEARCH}(t) ;$

$Q_s \leftarrow \text{GENERATESEEDQUESTIONS}(B) ;$

$D \leftarrow \text{DATABASEEXPLORATION}(t, Q_s) ;$

$T \leftarrow \text{GENERATETHESES}(D) ;$

$\tau^* \leftarrow \text{SELECTBESTTHESIS}(T) ;$

$S \leftarrow \text{RUNLITERATURESEARCH}(\tau^*) ;$

$R \leftarrow \text{CONSOLIDATEFINDINGS}(B, D, \tau^*, S) ;$

return R ;

Implement these small building blocks

// Background report on topic

// Initial research questions

// Curated retrieved results

// Set of proposed theses

// Select most promising thesis

// Evidence supporting selected thesis

// Comprehensive final report

Takeaways

Build LM-empowered systems.

An emerging paradigm in the era of foundation models.

Crafting LM pipelines resembles how we observe human workflows.

STORM resembles how human write.

Co-STORM resembles collaborative discourse in education.

Conduct user study in addition to automatic evaluation.

STORM invites 20 Wikipedia editors during paper writing.

Co-STORM invites 20 users in the wild during paper writing

STORM & Co-STORM deployed in the wild, tested by over 800,000 users.

Questions

Feel free to reach out to **yuchengj@stanford.edu** for more questions/thoughts.