

What’s In Your Field?

Mapping Scientific Research with Knowledge Graphs and Large Language Models

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Abstract

The scientific literature’s exponential growth makes it increasingly challenging to navigate and synthesize knowledge across disciplines. Large language models (LLMs) are powerful tools for understanding scientific text, but they fail to capture detailed relationships across large bodies of work. Unstructured approaches, like retrieval augmented generation, can sift through such corpora to recall relevant facts; however, when millions of facts influence the answer, unstructured approaches become cost prohibitive. Structured representations offer a natural complement—enabling systematic analysis across the whole corpus. Recent work enhances LLMs with unstructured or semistructured representations of scientific concepts; to complement this, we try extracting structured representations using LLMs. By combining LLMs’ semantic understanding with a schema of scientific concepts, we prototype a system that answers precise questions about the literature as a whole. Our schema applies across scientific fields and we extract concepts from it using only 20 manually annotated abstracts. To demonstrate the system, we extract concepts from 30,000 papers on arXiv spanning astrophysics, fluid dynamics, and evolutionary biology. The resulting database highlights emerging trends and, by visualizing the knowledge graph, offers new ways to explore the ever-growing landscape of scientific knowledge.

Demo: abby101/surveyor-0 on HF Spaces.
Code: <https://github.com/chiral-carbon/kg-for-science>.

1 Introduction

Consider a researcher seeking to build a multimodal foundation model for astrophysics. They might begin by asking: What are the most important data modalities to support—the most common ones in the field? How would such a researcher go about answering these questions today?

One might hope that LLMs could easily answer such a question, but while they have created unprecedented opportunities for accelerating scientific discovery, they struggle to aggregate reliable statistics and generate systematic analyses across the breadth of scientific literature. Manually reviewing papers or consulting domain experts are not scalable approaches when there are thousands of papers to investigate.

Most current approaches rely on unstructured methods like retrieval augmented generation (RAG) [9, 11, 3]. While these methods excel at broad information retrieval and synthesis, they make it difficult to analyze specific patterns in research across large bodies of literature. The limitations become particularly evident when researchers try to understand how research in a field evolves. They need to track new instruments, identify research problems that require methodological innovation, and understand how theoretical models get validated across disciplines. Unstructured representations struggle to systematically capture these relationships.

Some efforts explore semistructured representations such as: keyphrase extractions based on statistical patterns [5] and LLM-based concept extraction combined with constructing vector-similarity-based knowledge graphs [14]. While valuable, these methods typically treat all concepts uniformly without distinguishing between their functional roles in scientific work, or rely on semantic similarity of concepts using embedding models. This limits the utility of extracted knowledge when a researcher needs a quantitative analysis.

To address this challenge, we introduce a novel approach using LLMs that extracts categorized concepts from scientific papers using a general schema covering key research entities like objects, datasets, methods, and modalities. Our system combines structured knowledge representation with an interactive query interface to enable researchers to

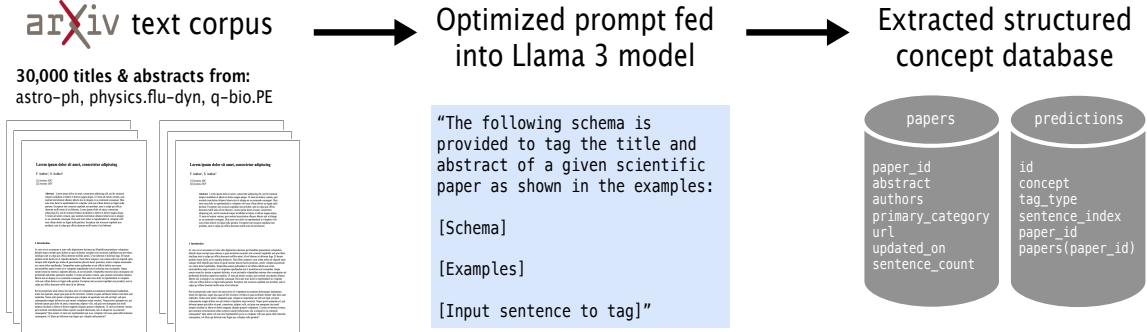


Figure 1: Illustration of the structured concept extraction pipeline: i) the corpus used, ii) running optimized prompt on full corpus, iii) storing model’s outputs and corpus metadata in SQL database.

analyze methodological patterns, track research evolution, and understand relationships between different aspects of scientific work at scale. We visualize the extracted structured information using knowledge graphs that provide key insights into concept co-occurrence in scientific research. The main contributions of this work are: 1) a generic schema for categorizing scientific concepts across different fields, 2) a scalable LLM-based extraction pipeline to mine concepts from papers, 3) an interactive system for querying scientific information, 4) informative knowledge graphs built from the extracted concepts to represent scientific fields.

2 Method

Our system consists of three key components: a *schema* defining different kinds of scientific concepts, a *pipeline* for prompting LLMs to extract these concepts, and a *database* to store this structured knowledge for efficient queries and analysis.

2.1 Schema

Through an iterative discussion process of example selection, comparing manual annotations between the authors, and examining scientific papers across different domains, we developed an annotation schema capturing nine fundamental categories of scientific concepts: *models*, *tasks*, *datasets*, *fields*, *modalities*, *methods*, *objects*, *properties*, and *instruments*. In designing the schema, we aimed for categories that apply across scientific disciplines.

This schema intentionally uses broad category definitions that are immediately understandable to scientists without requiring study of specialized and intricate taxonomies. We opted for coarser categories to avoid the ambiguity and complexity that

model:	representation of a (scientific) phenomenon using mathematical formalism and/or computational simulation
task:	specific problem, objective or goal to be accomplished
dataset:	collection of data, measurements or observations
field:	academic (sub)discipline
modality:	class or type of data/observations with similar or the same structure
method:	approach, technique or procedure to complete a task
object:	entity that can be studied
property:	quantitative or qualitative descriptor, or an inherent attribute of an entity, data, modality or method
instrument:	device or system used for making measurements

Table 1: Definitions for a schema of scientific concepts.

arises when making subtle distinctions between closely related concepts, even though this means some concepts could be described by multiple tags. Rather than implementing complex disambiguation tests, our simple tagging schema allows us to maintain scalability; however, there is always a trade-off between coverage and precision.

Original Sentence

We present an analysis of a new Australia Telescope Compact Array (ATCA) radio-continuum observation of supernova remnant (SNR) G1.9+0.3, which at an age of 181 ± 25 years is the youngest known in the Galaxy.

Tagged Sentence

```
We present an analysis of a new <dataset>  
<instrument>Australia Telescope Compact  
Array (ATCA)</instrument>  
<modality>radio- continuum</modality>  
observation</dataset> of  
<object>supernova remnant (SNR) G1.9+0.3  
</object>, which at an  
<property>age</property> of 181±25  
years is the youngest known in the  
<object>Galaxy</object>.
```

We implemented our extraction pipeline using the open-source Llama-3 70B Instruct model [4], employing few-shot learning to guide concept extraction. For our prompt optimization experiments, we manually annotated 20 papers, using 3 demonstration papers for few-shot examples and the remaining 17 as a development set to iteratively refine the prompts. Above is an example of the manual annotation process sentence-by-sentence.

The pipeline processes the language content sentence-by-sentence using manually annotated examples to demonstrate the target structure (see Fig. 2).

2.2 Pipeline

To optimize extraction reliability, we conducted systematic prompt engineering experiments on the manually annotated set, varying: (i) number and selection of few-shot examples, (ii) structure and ordering of the prompt, (iii) granularity of input text (sentence vs. paragraph), (iv) format of extracted concepts (JSON vs. human-readable).

To guide this iteration, we used a comprehensive set of metrics calculated on our development set, including: precision, recall and F-1 scores, for exact matches. In addition, we also considered the processing time and efficiency of the different approaches. During the annotation process, we found that even simple and broad concepts, such as a modality, encounter ambiguities when applied across scientific fields. As a result, it is likely that no method can achieve complete agreement with the development set annotations. Rather than as an absolute benchmark, we used the development set as a directional signal—a way to see if a given change improved the extraction process. Ultimately, our optimized prompt configuration consisting of instruction, schema and 9 few-shot examples (3 sentences with annotated extractions

Illustration: Prefix + Prompt

The following schema is provided to tag the title and abstract of a given scientific paper as shown in the examples:

\$SCHEMA

Sentence: This magnetic field strength implies a minimum total energy of the synchrotron radiation of $E_{\min} \approx 1.8 \times 10^{48}$ ergs.

Extractions:

property: magnetic field strength, energy

object: synchrotron radiation

... (Total 9 few-shot examples) ...

Sentence: We present HATNet observations of XO-5b, confirming its planetary nature based on evidence beyond that described in the announcement of Burke et al

Ground Truth Tags:

dataset: HATNet observations

instrument: HATNet

object: XO-5b

Predicted Tags:

dataset: HATNet observations

object: XO-5b, planetary nature

Figure 2: Expanded prompt illustration with schema and few-shot examples, along with the sentence to predict tags for.

from each of the 3 demonstration papers) shows promising results. The final results on our development set were: precision of $44\% \pm 12\%$ and recall of $31\% \pm 11\%$ in human-readable response format, with processing times averaging around 2.8 seconds per sentence. When using JSON output format, we observed similar precision levels with slightly higher recall rates of $40\% \pm 12\%$ and processing times of around 4 seconds per sentence. While some noise persisted in the extracted data, the results were sufficient to explore using such structured knowledge from the scientific literature in order to discover relationships and systematically analyze complex statistical questions.

2.3 Database

The extracted concepts and their relationships are stored in a SQL database for scientific analysis queries which enables fast computation of aggregate statistics. The SQL database contains 2 tables: papers and predictions (see Fig. 1). The papers table contains metadata, raw text, author and category information about the papers, and the predictions table contains the information about the tagged concepts, the tag type and the papers they come from. Storing both the extracted information and relevant metadata about where the extractions came from facilitates analyses such as the evolution of methodological approaches over time or the adoption patterns of new experimental techniques across fields.

3 Demo

3.1 Visualization

To explore the relationships between scientific concepts, we built a dynamic visualization using force-directed graph layouts. In this representation, nodes represent individual scientific concepts V (e.g., specific methods, instruments, or objects of study), while edges represent co-occurrences within the same paper E in a graph $G = (V, E)$. A physics-based spring layout algorithm determines the spatial arrangement, with frequently co-occurring concepts drawn closer together.

Our visualization system supports interactive exploration through: 1. Tag-type filtering to focus on specific concept categories (e.g., only methods or instruments), 2. Node highlighting to emphasize specific concepts and their immediate connections, 3. Depth-based exploration to reveal n-hop neighborhoods around concepts of interest, 4. Dynamic force-directed layout updates to reflect filtered sub-graphs.

This graph-based approach enables both targeted investigation of specific concept relationships and broader analysis of methodological patterns across domains. For example, researchers can identify clusters of related experimental techniques, trace the adoption of methods across different subfields, or visualize isolated clusters of objects to understand how they are studied.

3.2 Query Interface

The query interface supports SQL queries for scientific concept exploration, with predefined queries demonstrating use cases like modality distribution

analysis and temporal trends. The interface allows researchers to ask increasingly sophisticated questions by leveraging the structured database. For example, a researcher building an astrophysics foundation model could analyze most-used modalities, examine their current coverage, track usage trends over 5 years, and estimate coverage gains from adding new modalities. This approach helps scientists make data-driven research decisions that would be difficult to achieve through other means.

4 Results

Dataset. We collected the titles and abstracts from 30,000 articles from arXiv comprising 10,000 papers each from astrophysics, fluid dynamics and evolutionary biology, to test across a breadth of scientific disciplines. Titles and abstracts (i.e. article metadata) were used instead of the full text in order to optimize processing efficiency while maintaining representativeness, since the titles and abstracts of papers are likely to be more information dense than the papers’ bodies. After setting aside 20 astrophysics papers for prompt development, we used the optimized prompts refined through this development process to extract concepts from the remaining 9,980 astrophysics papers (from the original 10,000), as well as all 10,000 papers from each of the other two fields (fluid dynamics and evolutionary biology).

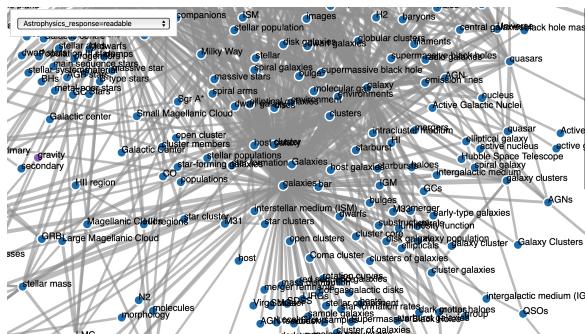
4.1 Graph-based Exploration

Fig. 3 demonstrates the interconnected nature of scientific concepts through co-occurrence knowledge graphs from our analyzed domains.[†]

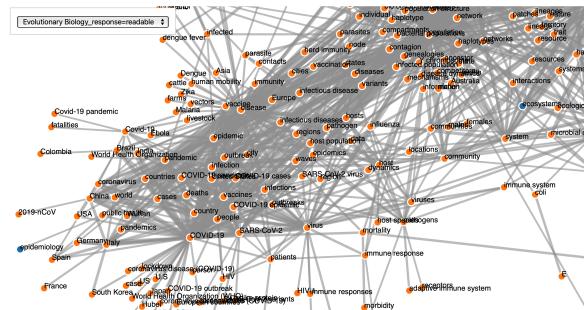
4.2 Demonstrating Example Queries

We examine several key questions to demonstrate the interface’s capability for both exploratory research and targeted investigation in scientific discovery.

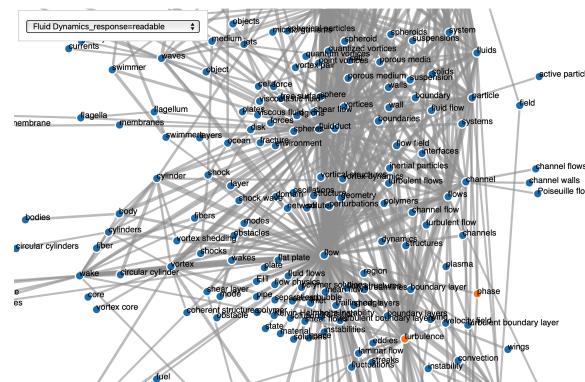
[†]We use the [d3-force](#) library; see documentation for more information on the spring-layout implementation.



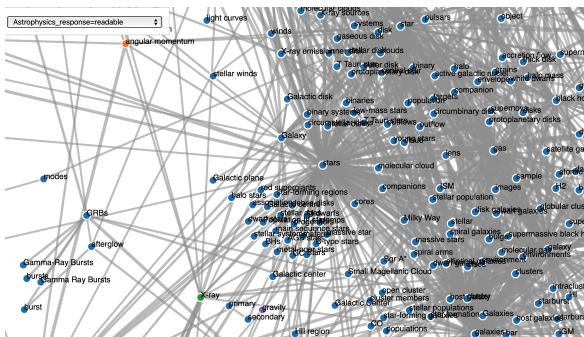
(a) Analysis of galaxy images: various galactic entities, measurement objects, clouds, instruments, and properties.



(b) COVID-19 cluster analysis: geographic distribution of pandemic research and immune health terms indicating research focus areas.



(c) Fluid dynamics clusters centered around "flow," branching into related flow and turbulence-based physical phenomena.



(d) Astrophysical objects and phenomena spanning multiple scales, from individual stars and binaries to galactic structures and clusters.

Figure 3: Co-occurrence graphs: astrophysics (a, d), epidemiology (b), fluid dynamics (c).

Temporal Evolution Analysis

Example: What are the new datasets that came out in fluid dynamics since 2020?

Paper	Dataset	Date
Error propagation of direct pressure gradient interface...	Synthetic velocimetry data	Jul 22 2024
Modelling turbulence in axisymmetric wakes: an approach...	3D laser Doppler anemometry data	Jul 12 2024

Showing 2 of 524 results representing recent fluid dynamics datasets discussed in our corpus. Failure modes included retrievals like “meteorological data” and “wind-tunnel data”, which are generic rather than specific datasets.

Cross-disciplinary Method Application

Example: What are all the datasets in evolutionary biology that use PDEs?

Paper	Dataset	Application
Dynamics of Dengue with human and vector...	Mosquito density data	PDE reaction-diffusion
Detection of correlation between genotypes and env...	genome-wide datasets	INLA-SPDE

Showing 2 of 17 results for datasets in which PDEs were used, thereby finding potential for converging modeling paradigms between fields of study (e.g. dynamical models used in different fields).

Modality Distribution Analysis

Example: What % of papers in astrophysics use only galaxy images, only spectra, both of them, or neither?

Category	Paper Count	Percentage (%)
Neither	901	57.1
Only Spectra	558	35.36
Only Images	88	5.58

Analysis revealed distinct patterns in modality usage: 5.58% of papers used only image data, 35.36% used spectra, and 1.96% used both, while 57.1% used neither, potentially looking at other modalities instead, such as time-series data, which appeared in 1.22% of the papers.

5 Related Work

Large language models (LLMs) [2, 7, 13, 15, 4] have recently demonstrated remarkable capabilities in language tasks, particularly through advances in prompting strategies [2, 16]. These advances have inspired building LLM-based pipelines to engage with complex scientific discovery tasks [8, 1, 10]. Despite these advancements, the problem of hallucinations in LLMs persists [6].

To overcome this, a popular approach is to augment LLMs with unstructured, external knowledge [11, 9], but while RAG excels in retrieving broad context information at scale, it is limited in providing precise information and avenues for systematic analysis, which can be efficiently realized through structured knowledge representations.

Some prior work applies semistructured knowledge representations to the scientific literature, such as Gu and Krenn [5]’s SciMuse system which combines LLMs with the RAKE algorithm to extract concepts as keyword phrases. [14] extended this to astronomy, using LLMs to extract concepts from scientific texts and construct knowledge graphs, grouping the concepts with a vector-based semantic similarity. In biomedicine, [12] integrated domain-specific language models with knowledge graph embeddings, showing improved performance but requiring field-specific finetuning.

Our work differs from these approaches by providing a domain-agnostic framework that combines LLM-powered semantic understanding with queryable structured knowledge curation, and enhanced by graph visualizations. Unlike previous methods, our approach introduces generalizable

categorization schemes that enable cross-domain concept extraction, relationship mapping, and question answering.

6 Discussion

Our tool enables quantitative analysis of research methodologies across scientific domains by organizing concepts into distinct categories like methods, instruments, and data modalities, allowing researchers to systematically investigate patterns that would be difficult to discover through traditional literature review or citation analysis. The combination of SQL queries and graph visualization proves especially valuable for exploring methodological connections. For instance, answering how similar mathematical models get applied across different fields is hard with existing approaches but readily solvable by our system.

While the system shows promise, its current extraction precision leaves room for improvement. At times, the LLM can struggle to distinguish specific named entities (like "Melbourne wind tunnel") from generic concepts (like "wind-tunnel data"), introducing noise into the extracted relationships. Future work could address these limitations through improved prompting strategies, post-training of models by gathering insights from domain experts, and extracting more sophisticated relationships between concepts beyond co-occurrence.

7 Conclusion

This work demonstrates how combining LLMs with structured knowledge representation can enable systematic analysis of scientific literature. Our four key contributions are: a domain-agnostic schema for categorizing scientific concepts, a scalable LLM-based extraction pipeline, a queryable interactive system, and informative knowledge graphs built from the extracted concepts. The results show that even with modest extraction accuracy, our approach can reveal valuable insights about cross-disciplinary connections and research evolution that would be difficult to discover through traditional literature review, opening up new possibilities for navigating scientific research.

Acknowledgments

We thank the Polymathic AI collaboration and the Flatiron Institute, a division of the Simons Foundation, for their generous support and providing the resources required for undertaking this project.

References

- [1] Microsoft Research AI4Science and Microsoft Azure Quantum. 2023. *The Impact of Large Language Models on Scientific Discovery: a Preliminary Study using GPT-4*. *Preprint*, arXiv:2311.07361.
- [2] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. *Language Models are Few-Shot Learners*. *Preprint*, arXiv:2005.14165.
- [3] Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, Meng Wang, and Haofen Wang. 2024. *Retrieval-Augmented Generation for Large Language Models: A Survey*. *Preprint*, arXiv:2312.10997.
- [4] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Alionsius, Daniel Song, Danielle Pintz, Danny Livshits, Danny Wyatt, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Francisco Guzmán, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Govind Thattai, Graeme Nail, Gregoire Milon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jack Zhang, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Jun-teng Jia, Kalyan Vasuden Alwala, Karthik Prasad, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Kushal Lakhota, Lauren Rantala-Yearly, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin Kardas, Maria Tsimpoukelli, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kambadur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Ning Zhang, Olivier Duchenne, Onur Çelebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohan Maheswari, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Raparth, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet, Virginie Do, Vish Vogeti, Vitor Albiero, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaofang Wang, Xiaoqing Ellen Tan, Xide Xia, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Couder, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aayushi Srivastava, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Amos Teo, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Dong, Annie Franco, Anuj Goyal, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Ce Liu, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Cynthia Gao, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Eric-Tuan Le, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Filippos Kokkinos, Firat

- Ozgenel, Francesco Caggioni, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hakan Inan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Hongyuan Zhan, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Ilias Leonardiadis, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Janice Lam, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kiran Jagadeesh, Kun Huang, Kunal Chawla, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabsa, Manav Avalani, Manish Bhatt, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Miao Liu, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikhil Mehta, Nikolay Pavlovich Laptev, Ning Dong, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghatham Murthy, Raghu Nayani, Rahul Mitra, Rangaprabhu Parthasarathy, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Russ Howes, Ruty Rinott, Sachin Mehta, Sachin Siby, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Mahajan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shishir Patil, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Summer Deng, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Koehler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wencheng Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaoqian Wu, Xiaolan Wang, Xilun Wu, Xinbo Gao, Yaniv Kleinman, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yu Zhao, Yuchen Hao, Yundi Qian, Yunlu Li, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, Zhiwei Zhao, and Zhiyu Ma. 2024. [The Llama 3 Herd of Models](#). *Preprint*, arXiv:2407.21783.
- [5] Xuemei Gu and Mario Krenn. 2024. [Interesting Scientific Idea Generation Using Knowledge Graphs and LLMs: Evaluations with 100 Research Group Leaders](#). *Preprint*, arXiv:2405.17044.
- [6] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. 2024. [A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions](#). *ACM Transactions on Information Systems*.
- [7] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2023. [Large Language Models are Zero-Shot Reasoners](#). *Preprint*, arXiv:2205.11916.
- [8] Mario Krenn and Anton Zeilinger. 2020. [Predicting research trends with semantic and neural networks with an application in quantum physics](#). *Proceedings of the National Academy of Sciences*, 117(4):1910–1916.
- [9] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2021. [Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks](#). *Preprint*, arXiv:2005.11401.
- [10] Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, and David Ha. 2024. [The AI Scientist: Towards Fully Automated Open-Ended Scientific Discovery](#). *Preprint*, arXiv:2408.06292.
- [11] Jakub Lála, Odhran O'Donoghue, Aleksandar Shtedritski, Sam Cox, Samuel G. Rodrigues, and Andrew D. White. 2023. [PaperQA: Retrieval-Augmented Generative Agent for Scientific Research](#). *Preprint*, arXiv:2312.07559.
- [12] Rahul Nadkarni, David Wadden, Iz Beltagy, Noah A. Smith, Hannaneh Hajishirzi, and Tom Hope. 2021. [Scientific Language Models for Biomedical Knowledge Base Completion: An Empirical Study](#). *Preprint*, arXiv:2106.09700.
- [13] OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake

- Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Elooundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O’Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotstid, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Shepard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. 2024. [GPT-4 Technical Report](#). *Preprint*, arXiv:2303.08774.
- [14] Zechang Sun, Yuan-Sen Ting, Yaobo Liang, Nan Duan, Song Huang, and Zheng Cai. 2024. [Knowledge Graph in Astronomical Research with Large Language Models: Quantifying Driving Forces in Interdisciplinary Scientific Discovery](#). *Preprint*, arXiv:2406.01391.
- [15] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Biket, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenjin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloemann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Bin Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. [Llama 2: Open Foundation and Fine-Tuned Chat Models](#). *Preprint*, arXiv:2307.09288.
- [16] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. 2023. [Chain-of-Thought Prompting Elicits Reasoning in Large Language Models](#). *Preprint*, arXiv:2201.11903.