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› Research Project Presentation

Automated Collection and Review of Academic Papers Using AI

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Agenda

1. Introduction
2. Program flow
3. Evaluation
4. Lessons Learnt and Future work

Introduction

Current Problem:

- The essential task of gathering relevant literature for new research or a review paper is becoming difficult in the academic field due to the increasing number of published works.

- The researchers to adapt their search strategies for each platform, leading to increased time investment and the risk of encountering duplicate entries of the same paper across different databases.

Introduction

Solution:

- We have developed a program that quickly collects related article information by simply entering specific search conditions such as keywords and desired database and organizes it into an Excel list for easy viewing.

- The program also goes beyond simple aggregation and utilizes advanced clustering algorithms to categorize literature into thematic groups, providing a structured and insightful overview of the research landscape.

Program Flow

Overview:

We utilize the Findpaper library to gather information on research papers and perform clustering based on the abstracts' information using TF-IDF.

The steps involved are as follows:

Step 1. Data Collection using Findpapers

Step 2. Converting data from JSON to Excel

Step 3. Cleaning Abstract Text

Step 4. Generating TF-IDF Feature Matrices

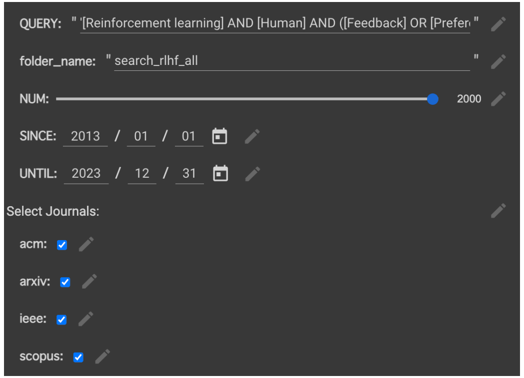
Step 5. Determining the Number of Clusters and Clustering

Step 6. Refining Research Papers by the PRISMA Framework

Program Flow

Step 1. Data Collection using Findpapers

- Findpapers library facilitates efficient literature search for researchers across multiple databases.
- It generates a JSON file with detailed information on identified research papers.




```
      "abstract": "In this work, we consider the offline preference-based reinforcement learning problem. We
focus on the two-phase learning approach that is prevalent in previous reinforcement learning from human
preference works. We find a challenge in applying two-phase learning in the offline PBRL setting that the
learned utility model can be too hard for the learning agent to optimize during the second learning phase. To
overcome the challenge, we propose a two-phasing learning approach under behavior regularization through
action clipping. The insight is that the state-actions which are poorly covered by the dataset can only
provide limited information and increase the complexity of the problem in the second learning phase. Our
method ignores such state-actions during the second learning phase to achieve higher learning efficiency. We
empirically verify that our method has high learning efficiency on a variety of datasets in robotic control
environments.",
      "authors": [
        "Xu, Yinglun",
        "Singh, Gagandeep"
      ],
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      "citations": null,
      "comments": null,
      "databases": [
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      ],
      "doi": null,
      "keywords": [],
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      "publication": null,
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      "selected": null,
      "title": "Efficient Two-Phase Offline Deep Reinforcement Learning from Preference Feedback",
```

Program Flow

Step 2. Converting data from JSON to Excel

Imported the JSON data and parsed it to extract key information from each paper, including title, publication date, authors, databases, journal, keywords, DOI (Digital Object Identifier), citation and save as an Excel file.


```
      "abstract": "In this work, we consider the offline preference-based reinforcement learning problem. We
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      "databases": [
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      ],
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      "keywords": [],
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      "title": "Efficient Two-Phase Offline Deep Reinforcement Learning from Preference Feedback",
```


Title	Year	Abstract	Authors	Databases	Publisher	Journal	Keywords	DOI	Citations
2023 American Co	2023-01-01	The proceedings contain 66		Scopus		Proceedings of the American Contr			0
Using Adversarial F	2023-01-01	The paper prc	Antonelli, Dar	Scopus	Springer Ne	IFIP Advanc	Cobots/ Ad	10.1007/9	0
Human-in-the-Loo	2023-01-01	One goal of ar	Huai-Ning Wu	IEEE/ Scopu	IEEE Compu	IEEE Transa	human beh	10.1109/TI	1
A novel explainabl	2023-01-01	Rise of unmar	Sanket Lokhar	Scopus	SPIE	Artificial In	Explainable	10.1117/1	0
ADVERT: Defendin	2023-01-01	Following the	Huang, Linan/	Scopus	Springer In	SpringerBriefs in Comp		10.1007/9	0
Generating Diverse	2023-01-01	Title: Generat	Soo-Hyun Joo	Scopus	Fuji Techno	Journal of D	road restor	10.20965/	0
A Cognitive Compu	2023-01-01	Collective dy	Tump, A.N./ D	Scopus	SAGE Publi	Perspective	groups/ rei	10.1177/1	1
Vision-force-fused	2023-01-01	Contact-rich	Jin, Piaopiao/	Scopus	Frontiers M	Frontiers ir	curriculum	10.3389/fr	0
Muddling-Through	2023-01-01	Large-scale, g	Cox Jr., Louis	Scopus		International Series in		10.1007/9	0
A rubric for humar	2023-01-01		Momennejad	Scopus	The Royal S	Philosophical Transacti		10.1098/rs	4
Episode-Fuzzy-COA	2023-01-01	To realize rob	Li, B./ Liu, X./	Scopus		IEEE Transa	Costs/ robc	10.1109/TI	0
A Novel Framewor	2023-01-01		Alili A.	Scopus	Institute of	IEEE Transactions on Ne		10.1109/TI	7
Human-Centered F	2023-01-01	In cognitive b	Greco, Emilio,	Scopus	Springer In	Internet of Things		10.1007/9	1
2023 Internationa	2023-01-01			Scopus		2023 International Conference on			0
A Reinforcement L	2023-01-01	This article in	Hao Wang/ Sh	IEEE/ Scopu	IEEE	IEEE Journa	underwate	10.1109/JC	13
Provable Safe Rein	2023-01-01		Bennett A.	Scopus		Proceedings of Machine Learning R			0
Energy-Saving Con	2023-01-01	Due to the co	Chen, Lihan/ X	Scopus	Multidiscip	Agriculture (Switzerlan		10.3390/ag	2
Editorial: Bringing	2023-01-01	Editorial: Brir	Kaplun, Dmitr	Scopus	Frontiers	Frontiers ir	artificial in	10.3389/fr	1
Interactive Robot I	2023-01-01	How do peop	Chetouani, M	Scopus	Springer Ve	Lecture Notes in Comp		10.1007/9	1
Few-Shot Preferen	2023-01-01		Hejna J.	Scopus		Proceedings of Machine Learning R			3
PAL to Lend a Help	2023-01-01	The World He	Mishra, K./ Pr	Scopus		Proceedings of the Annual Meeting			1
Brain-inspired neu	2023-01-01	In biological	Shen, G./ Zhac	Scopus	National Ac	Proceeding	brain-inspi	10.1073/p	1
Proceedings of the	2023-01-01	The proceedings contain 36		Scopus	Springer Ve	Lecture Notes in Computer Science			0
Leveraging conscic	2023-01-01	Various inter	St. Clair, Rach	Scopus	Frontiers M	Frontiers in Computati		10.3389/fr	0
A Pilot Study on Ar	2023-01-01	The task of su	Gooding, S./ V	Scopus		Proceedings of the Annual Meeting			0
A Reinforcement L	2023-01-01	Temporal diff	Natsheh, A.Y./	Scopus		2023 Intern	feedback-b	10.1109/IC	0
Learning to identif	2023-01-01	Artificial Inte	Chaput, R./ M	Scopus		Proceeding	Human Pre	10.1109/IC	0
Factually Consister	2023-01-01	Despite the se	Roit, P./ Ferre	Scopus		Proceedings of the Annual Meeting			1
Realizing Human-li	2023-01-01	Locomotion	Ye, Linqi/ War	Scopus	Springer Ve	Lecture No	Reinforcem	10.1007/9	0

Program Flow

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Step 3. Cleaning Abstract Text

- Checks for and handles missing values by returning an empty string
- Retaining only alphabetic characters and converts all text to lowercase to ensure consistency in the dataset.
- Removes any HTML tags from the text.

Abstract	Clean Abstract
Large language models (LLMs) are fine-	large language models llms are fine tunec
<p>Introductionâ??Large lang	introduction large language models llms
Learning from human feedback is an ef	learning from human feedback is an effec
We present DRESS, a large vision langu	we present dress a large vision language r
Large Language Models (LLMs) often st	large language models llms often struggle
Reinforcement Learning with Human F	reinforcement learning with human feed
Grey-box fuzzing is the lightweight app	grey box fuzzing is the lightweight appro:
Effective conversation requires comm	effective conversation requires common
Reinforcement learning from human fe	reinforcement learning from human feed
Reinforcement Learning from Human I	reinforcement learning from human feed
Understanding people's preferences fo	understanding people s preferences for fa
Recently, diffusion-based deep generat	recently diffusion based deep generative
While recent advances have boosted L	while recent advances have boosted lm p

Program Flow

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Step 4. Generating TF-IDF Feature Matrices

TF-IDF(Term Frequency-Inverse Document Frequency):
It is a statistical measure used to evaluate the importance of a word in a document within a collection of documents.

The TF part counts **how often** a term appears in a specific document.
The IDF part assesses **the rarity** of the term across all documents.

This method making it easier to understand the significance of each term in its context.

Program Flow

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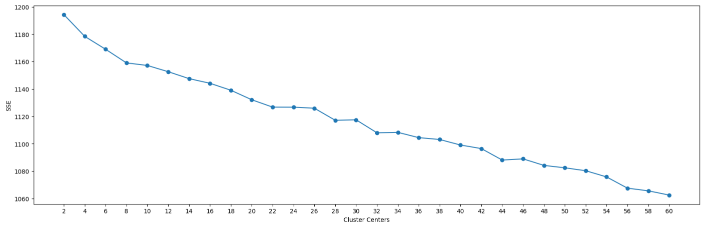
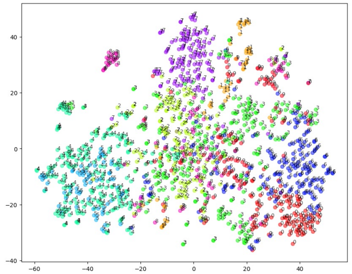
Step 5. Determining the Number of Clusters and Clustering

- Employed the elbow method to identify the optimal number of clusters in the dataset by plotting the sum of squared distances against the number of clusters.
- Apply K-Means clustering to the TF-IDF feature matrix generated from cleaned abstract texts.
- After clustering, saved the dataset with predicted cluster labels for each document to an Excel file.





Program Flow

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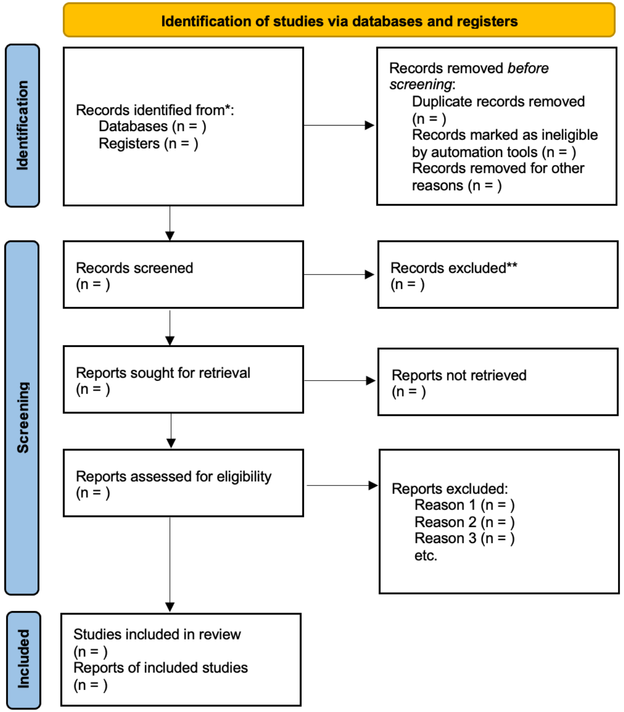
Step 6. Refining Research Papers using the PRISMA Framework as a reference

The PRISMA framework is a methodology designed for conducting systematic reviews and meta-analyses, ensuring comprehensive and transparent reporting.

Using it as a reference, the paper filtration process involves clustering the collected research papers are analyzed to identify the topics within that cluster.

This approach facilitates the refinement and selection of relevant papers necessary for the research.



Evaluation

Condition

To validate the utility of this automated system, we implemented the following criteria:

Query: "[Reinforcement learning] AND [Human] AND ([Feedback] OR [Preference])
Period: 2013 to 2023.
Selected databases: ACM, arXiv, IEEE, and Scopus

the system successfully collected 1,728 records.

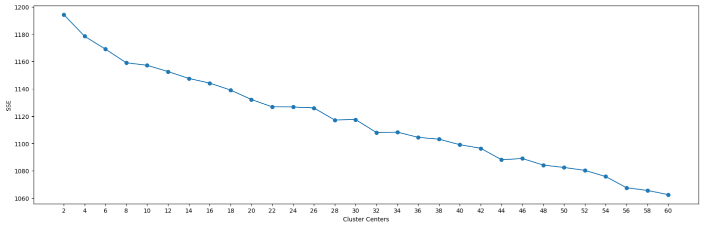
This dataset served as a basis for conducting a review paper, providing a test case to evaluate the utility of the automated system in a research review context.

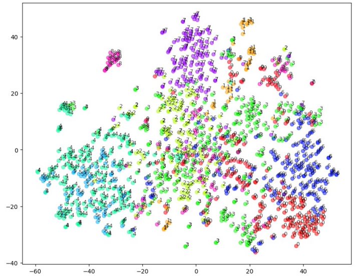
Evaluation

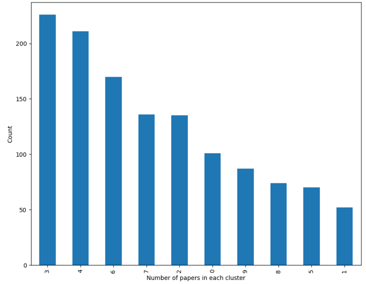
1. Clustering

Attempted to determine the optimal number of clusters using the elbow method
-> unclear distribution boundaries.
-> Decided to set the number of clusters to 10 to narrow down clusters to around 100 papers each, making it manageable for review or reference searching.

Despite not achieving precise categorization, the clustering distributed papers across clusters with 52 to 226 papers per cluster, providing a broad literature overview suitable for review paper writing.







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Evaluation

2. Quality of Paper Collection

Prepared a set of 41 "control papers" as model cases for the research topic to assess the quality of the collected dataset.
Approximately 56% (23 out of 41) of the control papers were included in the generated list, indicating coverage of these model cases.

For the Included List:
Papers had query words such as "Reinforcement Learning" and "Human Feedback" or "Preference" (RLHF) in their abstracts, indicating relevance to the search criteria.

Evaluation

2. Quality of Paper Collection

For the Excluded List:

- Papers typically excluded lacked explicit mentions of key query terms like "Reinforcement Learning" or "Human Feedback" in their content or abstracts.
- Some papers on topics related to Large Language Models (LLMs) or GPT, which may inherently involve elements of RLHF, were overlooked due to the absence of explicit keyword mentions in their abstracts.
- Papers that used abbreviations (e.g., "RL from human feedback") instead of the full terms were likely missed, impacting the comprehensiveness of the search results.

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Evaluation

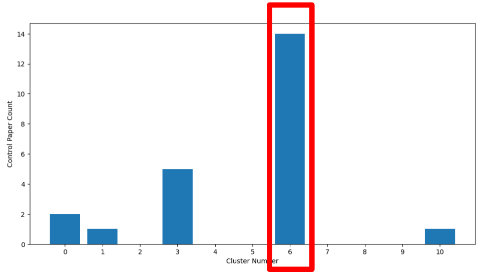
3. Evaluation Regarding the Creation of a Review Paper

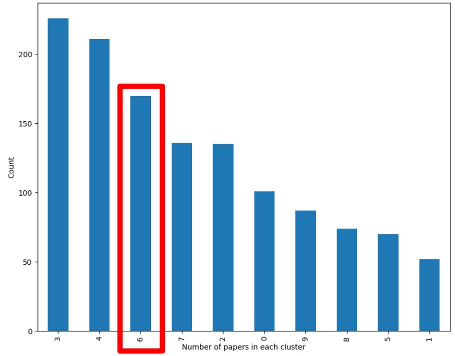
Referenced the PRISMA Framework for conducting literature collection and evaluation for a review paper.

1. Initially collected a total of 1,728 papers.

2. Cluster No. 6 contained 14 control papers
➔ the total list for this cluster included 170 papers.

3. A review of the top 10 keywords in Cluster No. 6 (e.g., 'rl,' 'feedback,' 'language,' 'preferences,' 'human,' 'models,' 'reward,' 'model,' 'rlhf') suggested a strong relation to RLHF topics.





Evaluation

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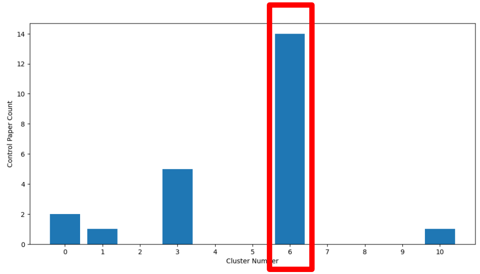
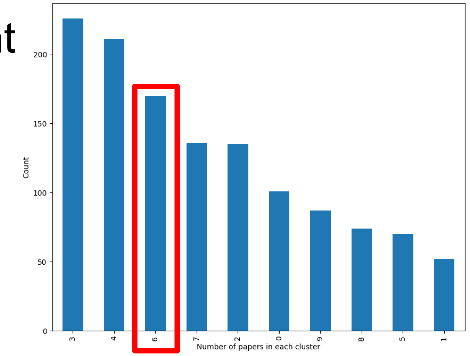
3. Evaluation Regarding the Creation of a Review Paper



Selecting around 100 papers from this cluster would likely suffice for writing a review paper, given its thematic relevance.



The program's effectiveness in facilitating review paper creation is affirmed by efficiently narrowing down to a manageable and relevant subset of papers.

Lessons Learnt

- Utilized the "Findpaper" tool for collecting research papers, with some titles lacking crucial information.

- Clustering was based on abstracts, but not all relevant papers included search query keywords in their abstracts, suggesting a potential expansion to full-text clustering.

- The use of TF-IDF and K-means clustering for this study did not yield optimal cluster distribution, indicating the need for alternative methods.

Future work

- Consider direct scraping from individual websites to recover missing data from research papers.
- Expand clustering analysis from abstracts to full texts to incorporate a broader range of information and improve clustering results.
- Investigate alternative clustering methods such as DBSCAN, LLMs, or BERT to capture semantic similarities between papers more effectively, focusing on contextual meaning and comprehensive understanding of textual content.

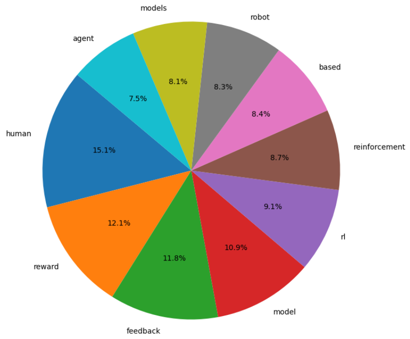
THANK YOU!

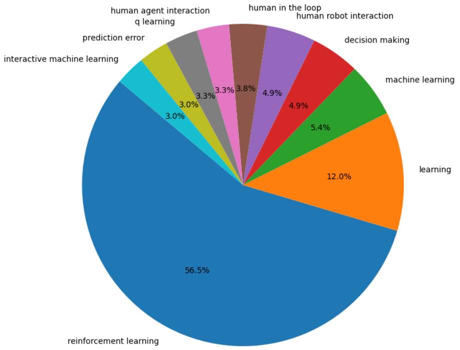
TREND ANALYSIS

1. Keyword

- Conducted a comparative analysis using pie charts, comparing the top 10 high TF-IDF score words to the top 10 keywords provided by authors.

- Noted difficulty in determining the context of words such as "learning" from the TF-IDF graph, as it doesn't specify whether they relate to "reinforcement learning" or other terms.





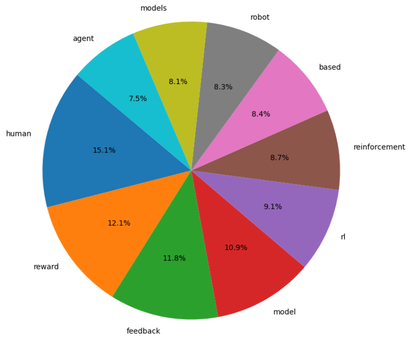
TREND ANALYSIS

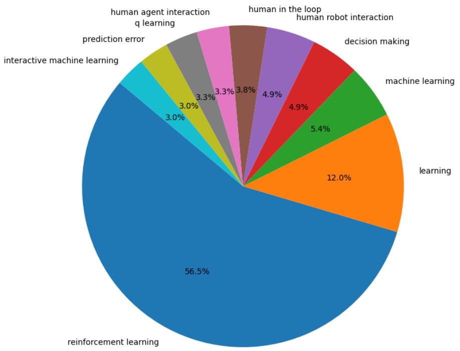
1. Keyword

- Observed that TF-IDF-based analysis was less informative than author-provided keywords.

- Identified frequent appearance of standard machine learning terms like "reward" or "model" with high TF-IDF scores, which hindered meaningful insight extraction.

- Found that adjusting TF-IDF parameters was ineffective in resolving these issues, indicating a need for more nuanced keyword analysis methods.





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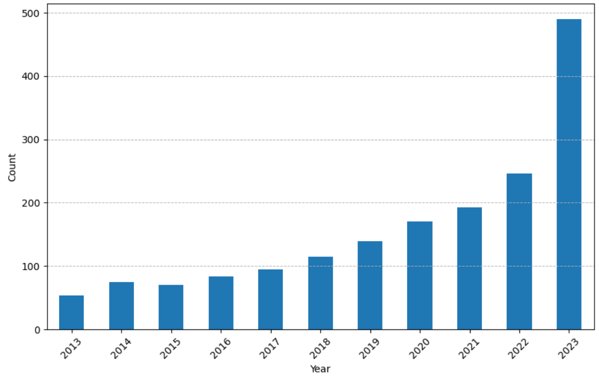
TREND ANALYSIS

2. Publication Number by Year

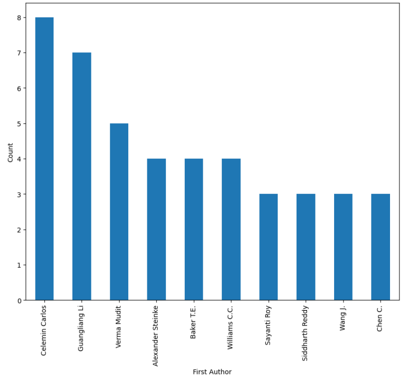
- Publications increased from 55 in 2013 to 510 in 2023, marking a nearly tenfold increase over the decade.
- There was a significant rise in publications from 266 to 510 between 2022 and 2023, almost doubling in just one year.
- The trend reflects a growing interest in the field of RLHF.



TREND ANALYSIS

3. Author Analysis

- Attempted to aggregate data on the first authors of RLHF papers.
- Encountered challenges due to variations in author name representations, like abbreviations or omissions.
- This issue highlights the need for more sophisticated methods, such as GPT, to standardize author names.



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TREND ANALYSIS

4. Journal Distribution

- Journals publishing RLHF papers show diversity in engaged fields.
- Significant presence in neuroscience-related journals, indicating strong interest in RLHF within neuroscience.
- Other prominent fields include robotics and psychophysiology, demonstrating RLHF's interdisciplinary application.
- The distribution underscores RLHF's broad impact and relevance across different scientific and research domains.

	Count
PLoS ONE	23
Journal of Neuroscience	20
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	20
Cognitive, Affective and Behavioral Neuroscience	20
Psychophysiology	19
Frontiers in Neuroscience	18
Frontiers in Human Neuroscience	17
NeuroImage	17
Proceedings - IEEE International Conference on Robotics and Automation	17
RSJ International Conference on Intelligent Robots and Systems (IROS)	17
Scientific Reports	17
Advances in Neural Information Processing Systems	15