

Multi-Disciplinary Dataset Discovery

FROM

Citation-Verified Literature Contexts

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Motivation



Where can we find datasets for a specific research topic?

A reliable way is to trace datasets through relevant papers.



But there are so many relevant papers. All of them?

Not manually.



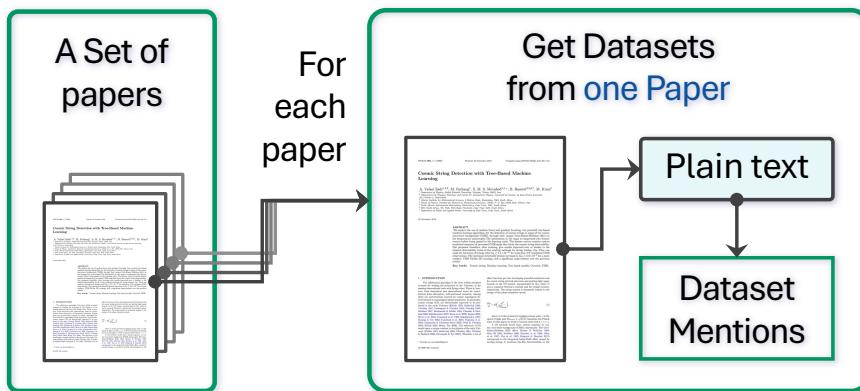
So... is there a way to do this automatically?

Related Work



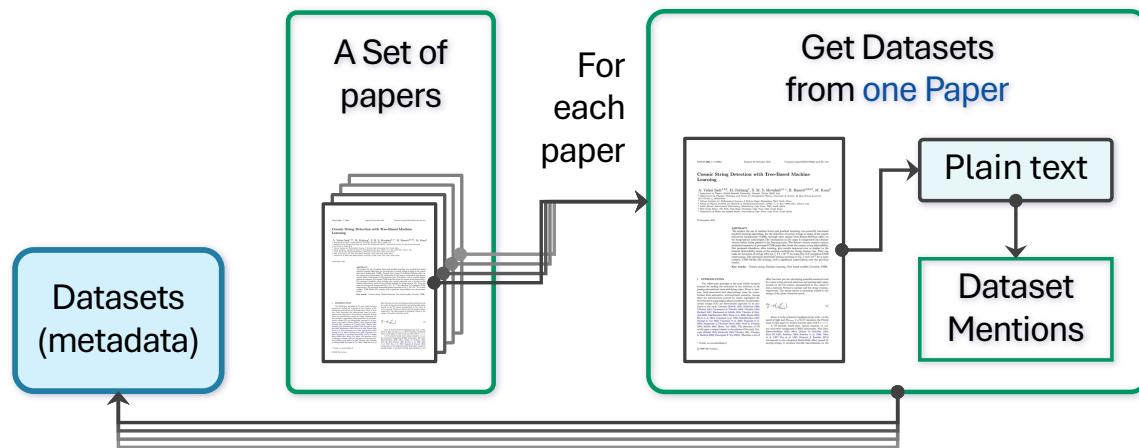
A common paradigm is to first collect a **fixed set of papers**,

Related Work



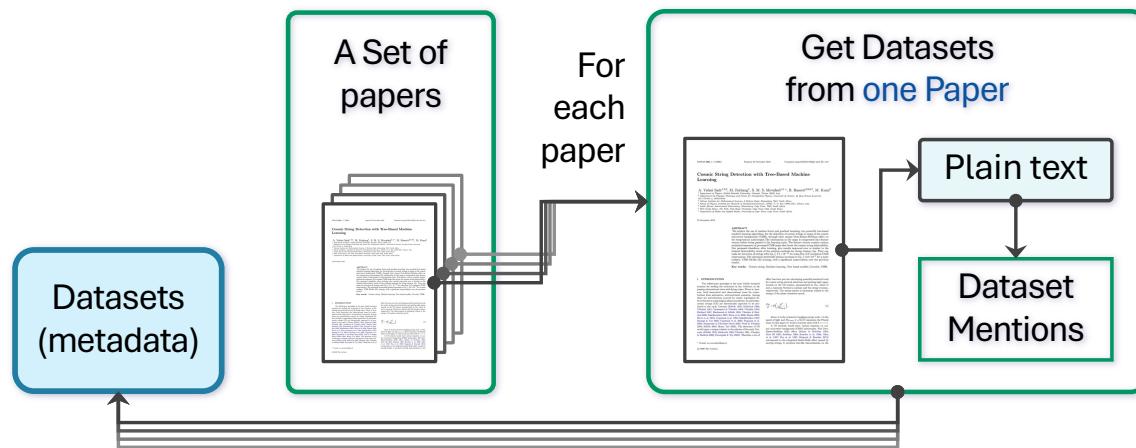
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SciREX (2020):
Extract dataset mention with supervised sequence labelling from ML papers

DMDD (2023):
large-scale NER over S2ORC full text across AI-related domains

RAGing Against the Literature (2024):
retrieval-augmented LLM extraction built on DMDD

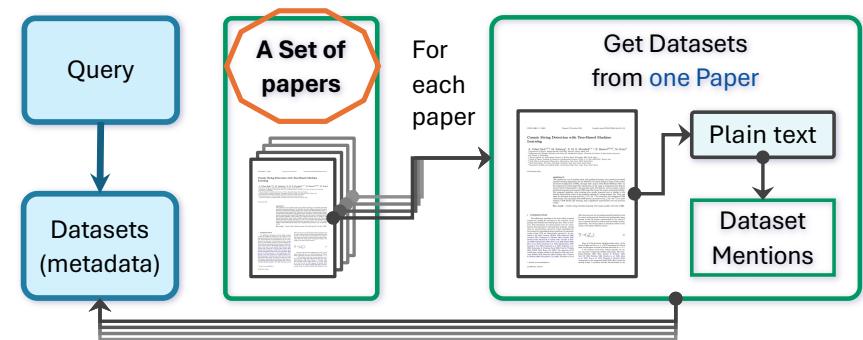
ChatPD (2025):
LLM-based extraction with entity resolution from arXiv full text

Challenges

1: Domain-limited / Static Paper Collections

Most existing approaches operate on **pre-defined, domain-limited paper collections**, which are typically fixed and updated infrequently.

As a result, they struggle to support **open-ended queries** or to keep pace with updated published work.



Our approach directly interfaces with academic search engines to dynamically retrieve papers relevant to a given query.

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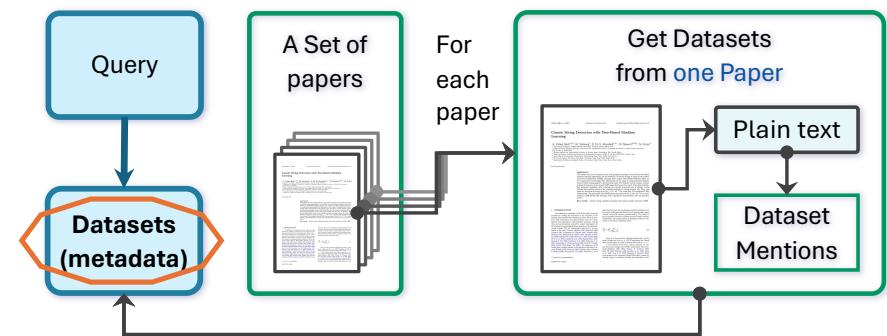
Challenges

2: Shallow Matching Based on Dataset Metadata

Many existing systems rely on matching a user query against **pre-extracted dataset metadata**, which typically contains limited information such as names, tasks, or brief descriptions.

Such metadata is often insufficient to capture the nuanced ways in which datasets are discussed and used in the literature.

To address this, we move the **matching stage earlier** and extend it over textual evidence, rather than relying solely on static metadata.



Google Dataset Search

 DataCite
Commons

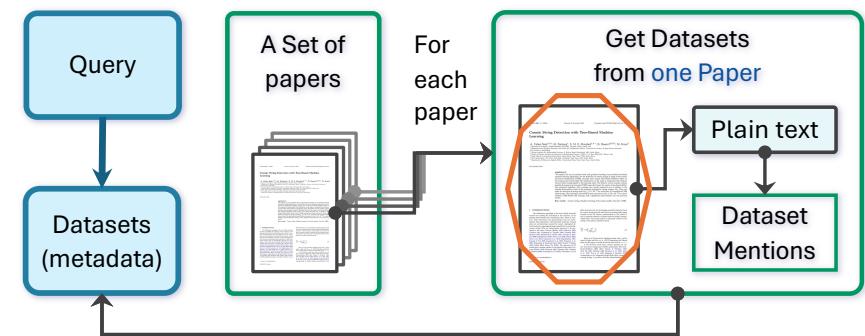
Challenges

3: Scalability of Full-text Processing

A natural solution is to dynamically process the **full text** of all retrieved papers. However, this quickly becomes **computationally heavy at scale**.

Instead, we leverage **citation contexts** from **Semantic Scholar**, which are **updated on a weekly basis**.

Compared to full text, citation contexts are **substantially shorter**, yet provide an **informative textual representation** of each paper, while **preserving high-quality signals about dataset usage**.



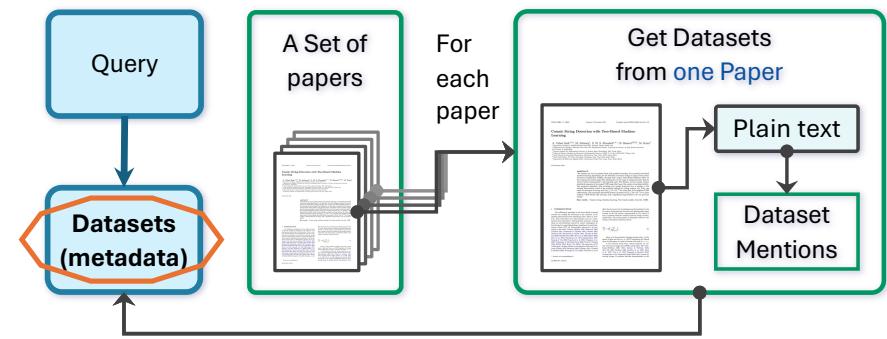
Challenges

4: Dataset Validity and Practical Usability

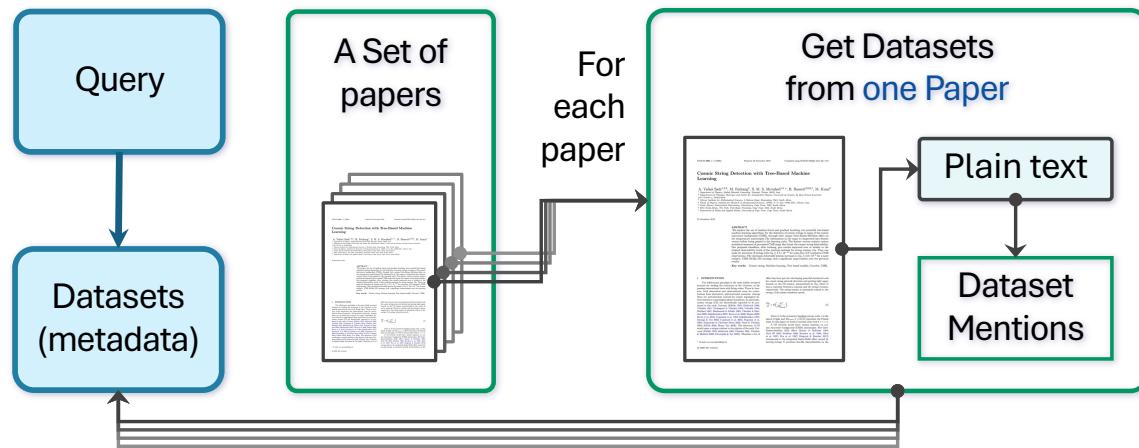
A less discussed but critical issue is that **many datasets mentioned in papers are no longer usable**, a problem that is particularly severe in the social sciences (e.g. Chen & Wu 2025 presented yesterday).

Starting from **citation contexts** provides an important advantage:

a dataset must have been **examined by at least one expert**, significantly reducing the need for manual filtering of unusable datasets.

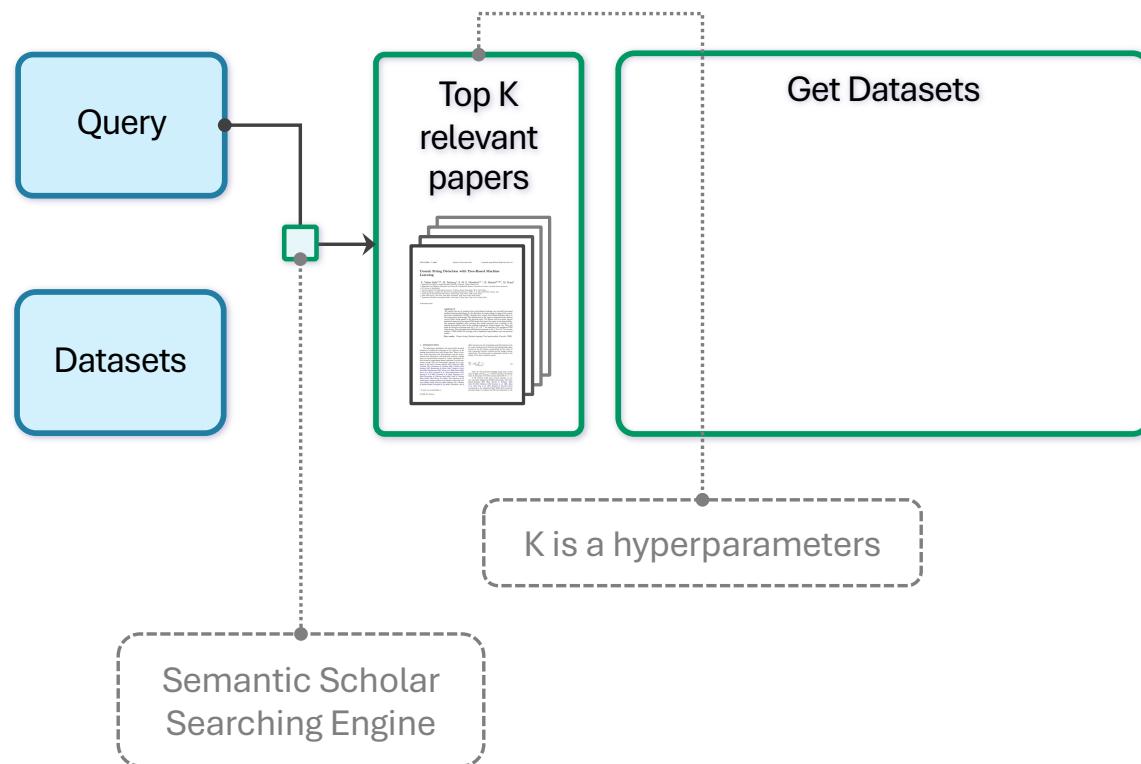


Challenges



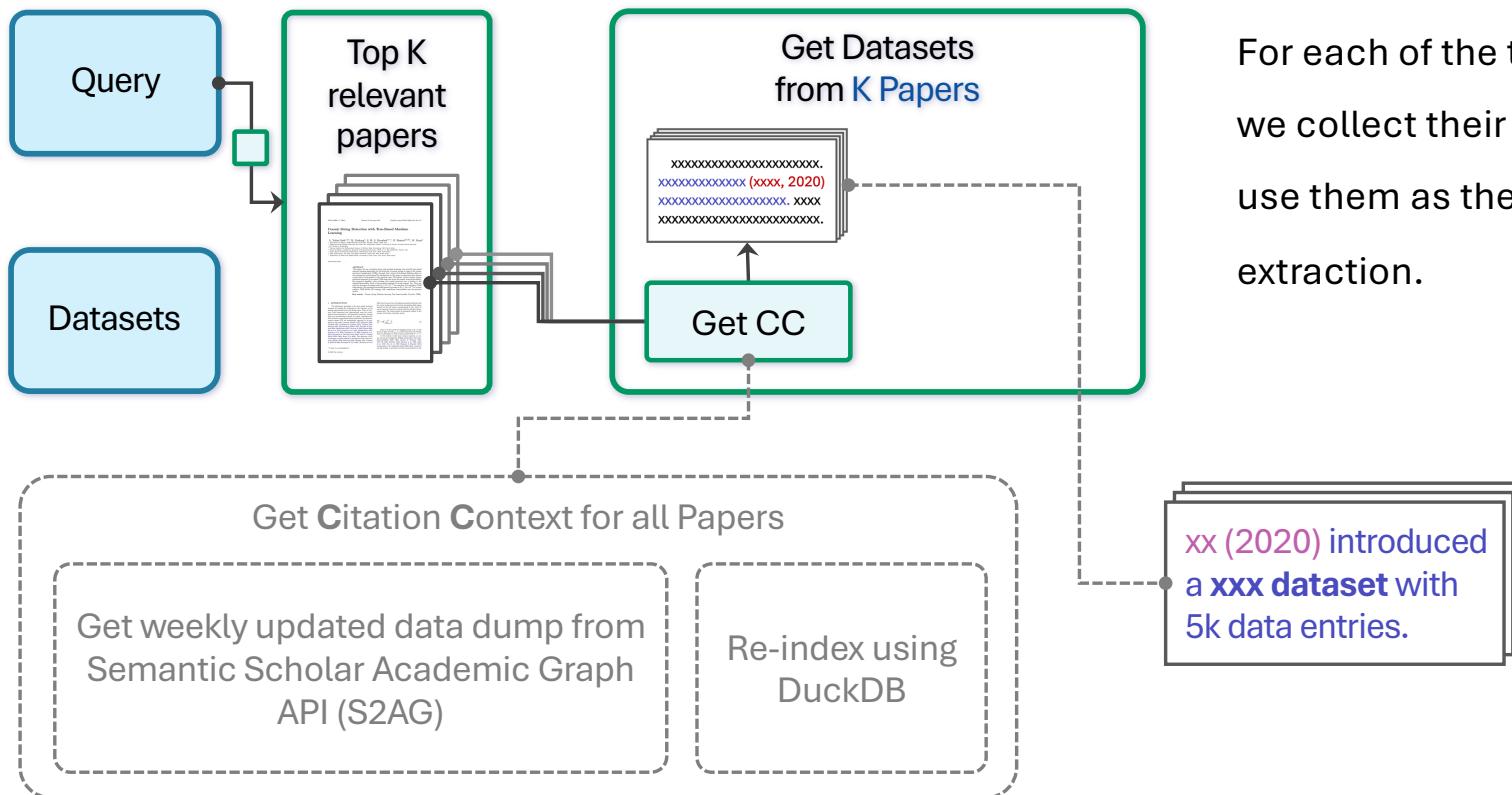
These challenges call for a **query-driven** and **scalable** approach for tracing datasets through the literature.

Our Approach



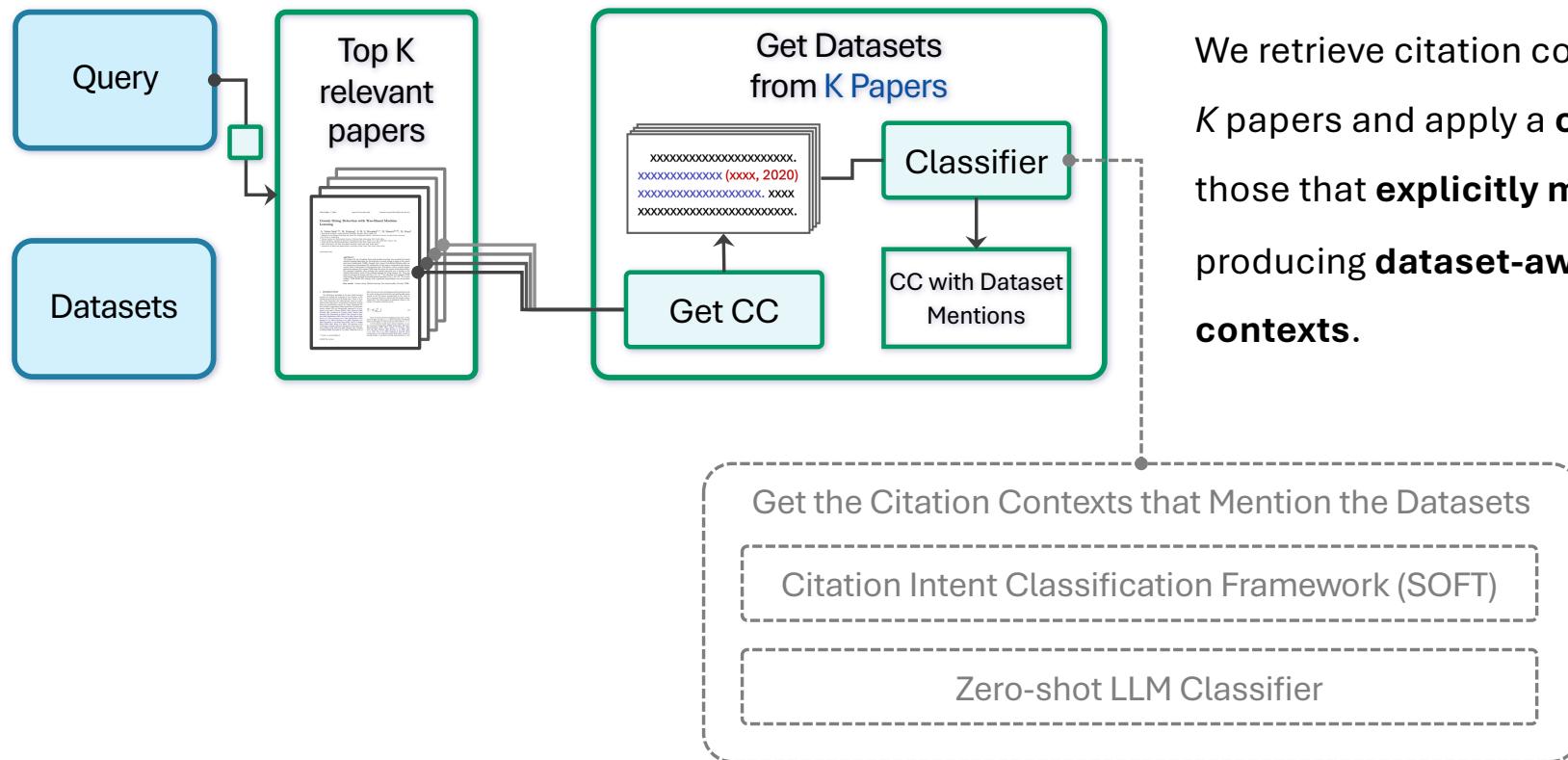
Given a query,
we first retrieve the **top- K relevant papers**
using an academic search engine,
forming the input to our dataset tracing
pipeline.

Our Approach

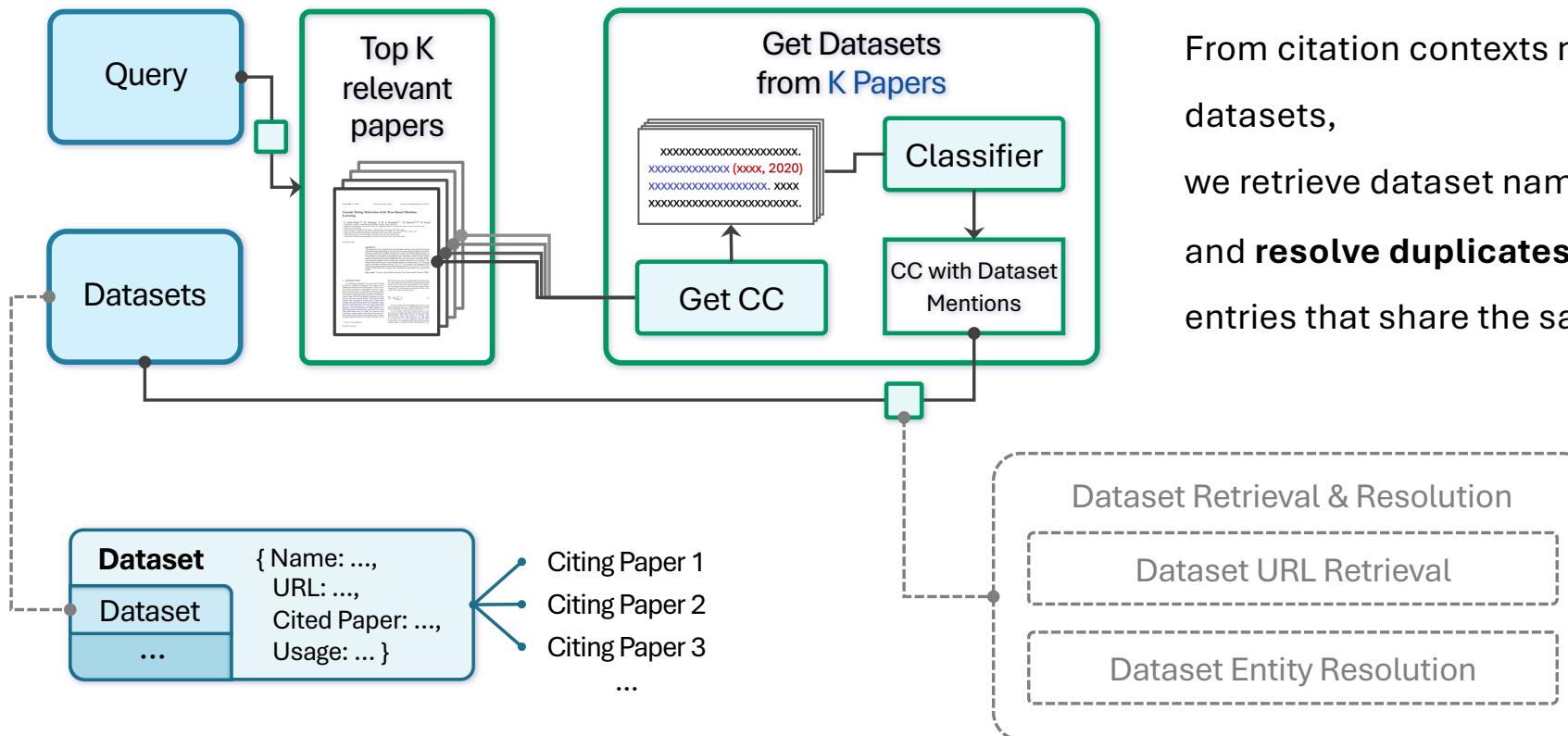


For each of the top- K retrieved papers, we collect their **citation contexts** and use them as the textual basis for dataset extraction.

Our Approach



Our Approach



Experiments

Data

Multi-Disciplinary: [**Revised Field of Science and Technology \(FOS\)**](#)

| Field | Sub-field |
|--------------------------------|--|
| 1. Natural sciences | 1.2 Computer and information sciences |
| 2. Engineering and technology | 2.11 Other engineering and technologies (Food and beverages) |
| 3. Medical and Health sciences | 3.2 Clinical medicine |
| 4. Agricultural sciences | 4.1 Agriculture, Forestry, and Fisheries |
| 5. Social sciences | 5.3 Educational sciences |
| 6. Humanities | 6.4 Arts (arts, history of arts, performing arts, music) |

Datasets listed in **survey papers** as **gold standard**

Evaluated via **expert assessments**

Experiments

Data

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| 1. Natural sciences | 1.2 Computer and information sciences |

Datasets listed in **survey papers** as **gold standard**

| Research Question | Gold |
|--|------|
| Multi-modal Knowledge Graph Reasoning [28] | 11 |
| All-in-One Image Restoration [29] | 30 |
| Planning Capabilities of LLM [30] | 38 |
| Event-based Stereo Depth Estimation [31] | 17 |
| Patent Classification in NLP [32] | 7 |
| Document-level Event Extraction [33] | 23 |
| Text Line Segmentation for Historical Documents [34] | 43 |
| Personalized Text Generation [35] | 16 |

Survey title as queries

Experiments

Data

Multi-Disciplinary: [**Revised Field of Science and Technology \(FOS\)**](#)

| Field | Sub-field |
|--------------------------------|---|
| 1. Natural sciences | 1.2 Computer and information sciences |
| 2. Engineering and technology | <ul style="list-style-type: none">- Plant Disease Diagnosis or pest detection image dataset |
| 3. Medical and Health sciences | <ul style="list-style-type: none">- Laban Movement Analysis for Dance Emotion- Antioxidant Peptides Sequence and activity relationship |
| 4. Agricultural sciences | <ul style="list-style-type: none">- Salty-enhancing Peptides- Colorectal Liver Metastases CRLM Single Cell RNA Sequencing |
| 5. Social sciences | <ul style="list-style-type: none">- Statistical Learning Non-native |
| 6. Humanities | |

Evaluated via **expert assessments**

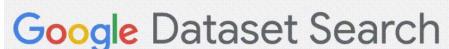
Expert-provided queries
(Requested to provide a familiar research topic)

Experiments

Data

Multi-Disciplinary: [Revised Field of Science and Technology \(FOS\)](#)

Baseline

 Google Dataset Search

 DataCite Commons

Evaluation Metric

Statistical: Recall (survey-based)

Expert Assessments:

- Educational Background: Doctoral Degree Holder (3), Doctoral Candidate (4), Master's Candidate (3)
- Method: double-blind Google Form
- Evaluation: 1-5 Scale for Relevance, Utility, Accessibility, Trustworthiness, Novelty

Results

For statistical-based evaluation:

- Our literature-based approach achieves substantially higher average recall (**47.47%**) than Google Dataset Search (2.70%) and DataCite (0.00%).
- On individual survey-derived tasks, recall reaches up to **81.82%**.

| Research Question | Gold | Matched | | | Recall (%) | | |
|--|------|---------|--------|----------|--------------|--------|----------|
| | | Ours | Google | DataCite | Ours | Google | DataCite |
| Multi-modal Knowledge Graph Reasoning [28] | 11 | 9 | 0 | 0 | 81.82 | 0.00 | 0.00 |
| All-in-One Image Restoration [29] | 30 | 10 | 0 | 0 | 33.33 | 0.00 | 0.00 |
| Planning Capabilities of LLM [30] | 38 | 21 | 0 | 0 | 55.26 | 0.00 | 0.00 |
| Event-based Stereo Depth Estimation [31] | 17 | 9 | 0 | 0 | 52.94 | 0.00 | 0.00 |
| Patent Classification in NLP [32] | 7 | 3 | 0 | 0 | 42.86 | 0.00 | 0.00 |
| Document-level Event Extraction [33] | 23 | 9 | 3 | 0 | 39.13 | 13.04 | 0.00 |
| Text Line Segmentation for Historical Documents [34] | 43 | 13 | 1 | 0 | 30.23 | 2.33 | 0.00 |
| Personalized Text Generation [35] | 16 | 1 | 1 | 0 | 6.25 | 6.25 | 0.00 |
| Average Recall | | | | | 47.47 | 2.70 | 0.00 |

Results

For expert-based evaluation:

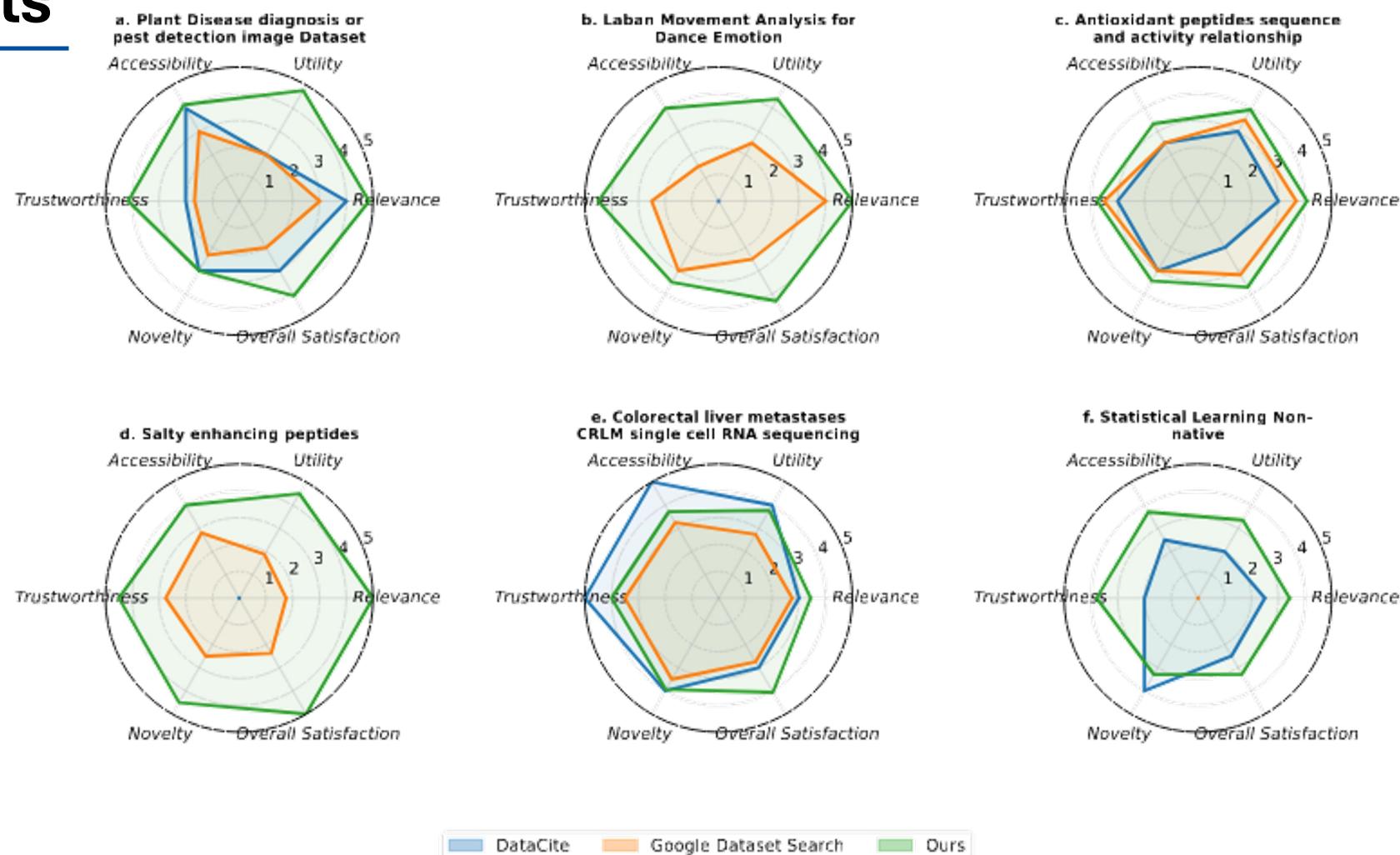
Experts evaluated datasets on six 5-point dimensions,

- Across all research queries, our system is consistently rated highest in relevance and utility, with strong gains in trustworthiness and overall quality.
- Among all expert-rated datasets, our method surfaces 45 out of 105 datasets (**42.9%**) rated **at least 4** on both utility and novelty, compared to **12.9%** for Google Dataset Search and **33.3%** for DataCite.

TABLE III: Aggregate expert mean ratings (1–5).

| Dimension | Ours | Google | DataCite |
|-----------------|-------------|--------|----------|
| Relevance | 4.33 | 3.07 | 2.60 |
| Utility | 4.09 | 2.46 | 2.66 |
| Accessibility | 3.80 | 2.87 | 3.17 |
| Trustworthiness | 4.13 | 2.49 | 2.84 |
| Novelty | 3.64 | 2.92 | 3.50 |
| Overall | 4.07 | 2.60 | 2.48 |

Results



Acknowledgement

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