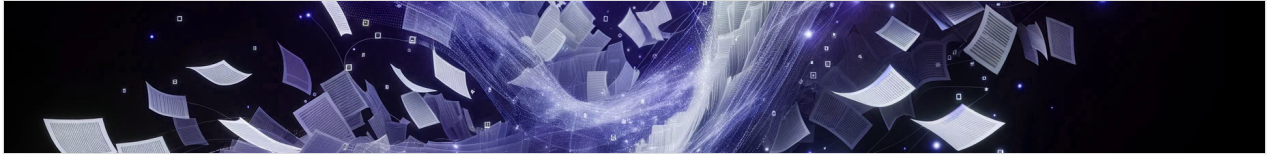
Data Mining and Information Extraction Methods for Large-Scale High Quality Representations of Scientific Publications

Dissertation Defense

Tarek Saier | 22. April 2024

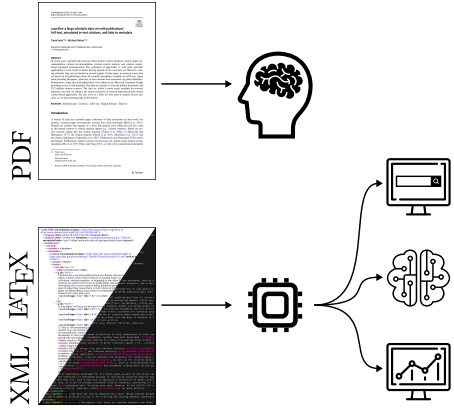


Data Mining and Information Extraction Methods for Large-Scale High Quality Representations of Scientific Publications

Data Mining and Information Extraction Methods for Large-Scale High Quality Scholarly Data

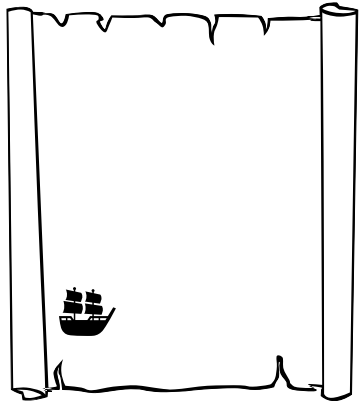
Scholarly Data

- **Usage**
  - Services (search, recommendation, statistics)
  - ML models (LLMs, sumarization, recommender systems)
  - Analyses (temporal, geographic, institutional)
- **Flavors**
  - Metadata (MAG, OpenAlex, ORKG, crossref)
  - Documents (Core, arXMLiv, PMC)
  - Linked Documents (unarXive, S2ORC)
- **Data Sources**
  - PDF (Core, ACL Anthology)
  - XML (PubMed, PLOS, publisher internal)
  - LaTeX (arXiv)

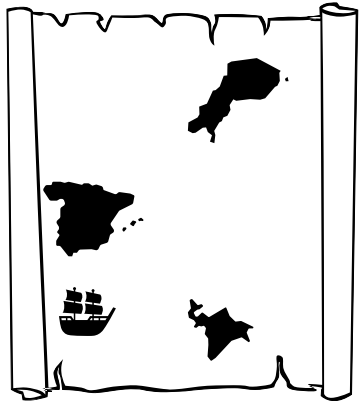


Analogy

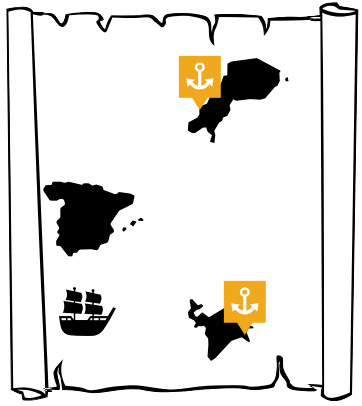
Maps of the Sea



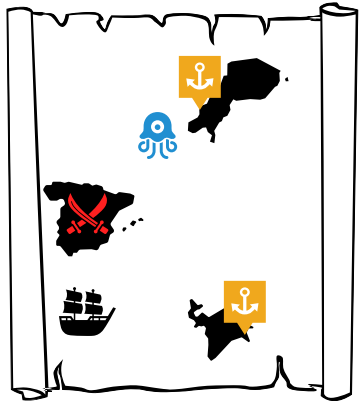
Maps of the Sea



Maps of the Sea



Maps of the Sea



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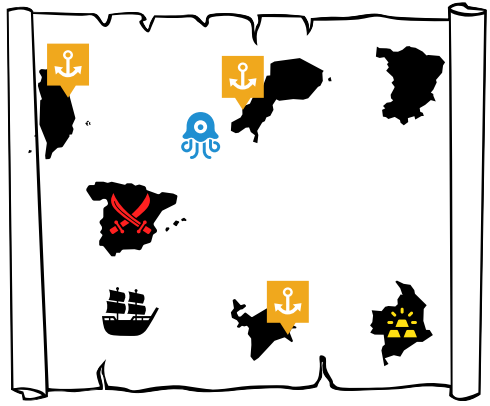

Maps of the Sea / Maps of Science

The Sailor looks for

- Port to trade
- Island to explore

The Scientist looks for

- Paper to read
- Venue to publish at
- Research idea to explore

Maps of the Sea / Maps of Science

The Trade Company looks for

- Routes to expand
- Ports to build
- Sailor to hire

The University/Funding Body looks for

- Research to fund
- Researcher to hire
- Policy to establish

Maps of the Sea / Maps of Science

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better maps ⇒ better decisions

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false maps ⇒ misleading/false analyses, models, etc.

Maps of the Sea / Maps of Science

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our maps of science are insufficient

Maps of the Sea / Maps of Science

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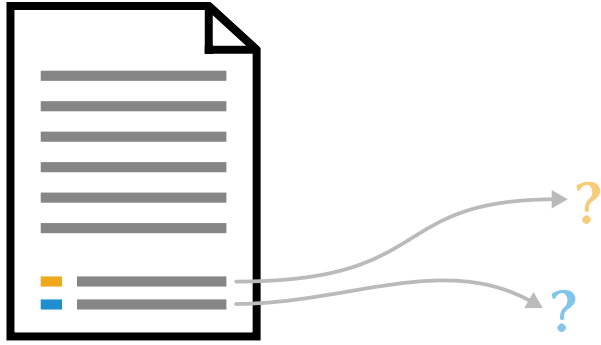
Research Objective
Develop methods for generating large-scale, high quality scholarly data.

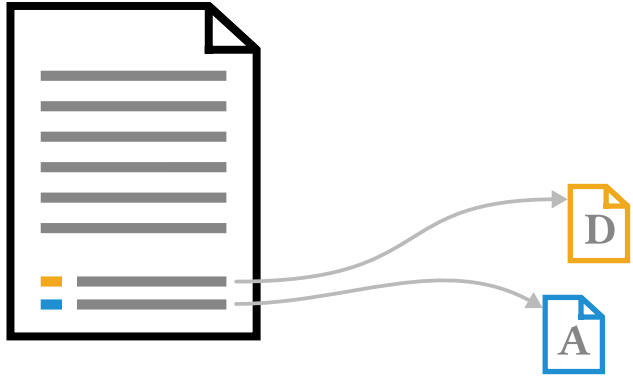
Data Mining and Information Extraction Methods for **Large-Scale High Quality** Representations of Scientific Publications

Maps of Science

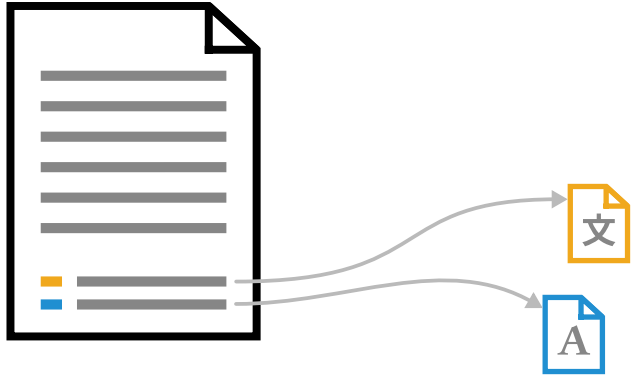
Maps of Science



Maps of Science



Maps of Science



Maps of Science

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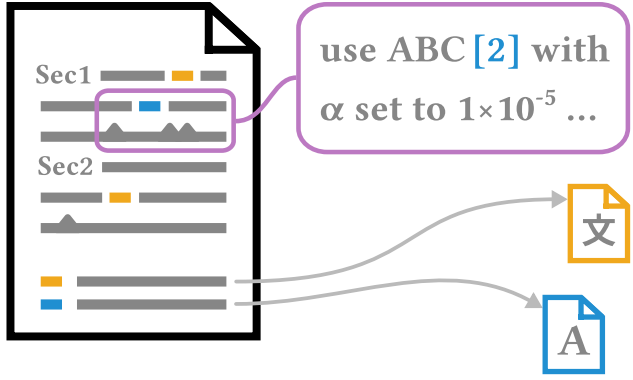
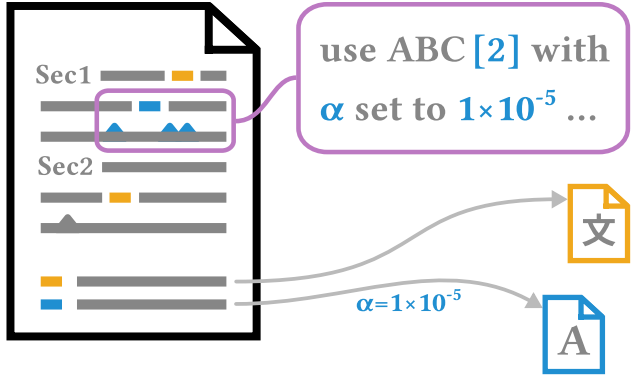
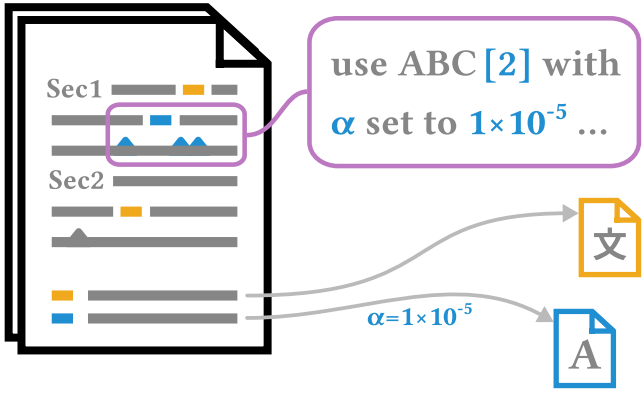


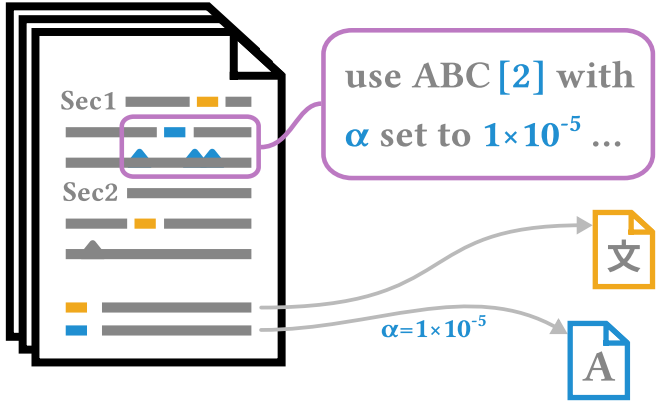
Maps of Science



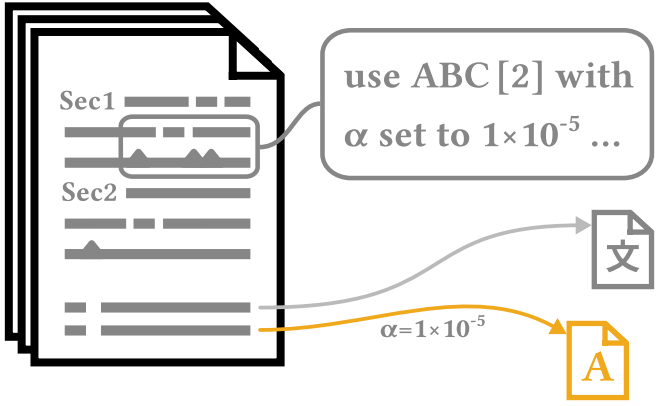
Maps of Science



Maps of Science



Research Gap: Citation Network



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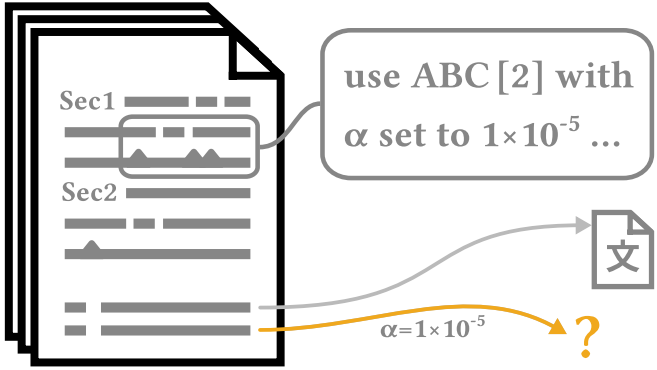
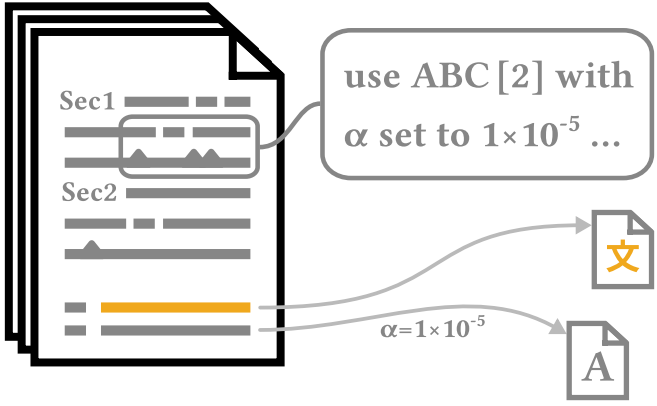


Research Gap: Non-English Documents



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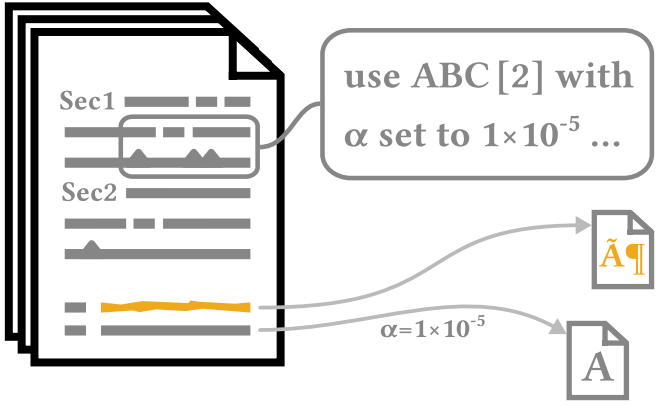

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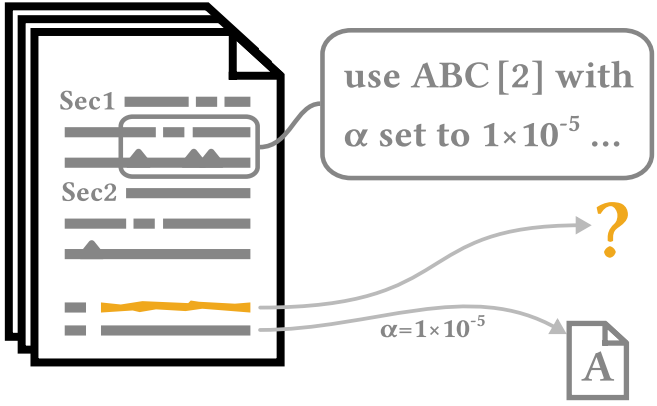

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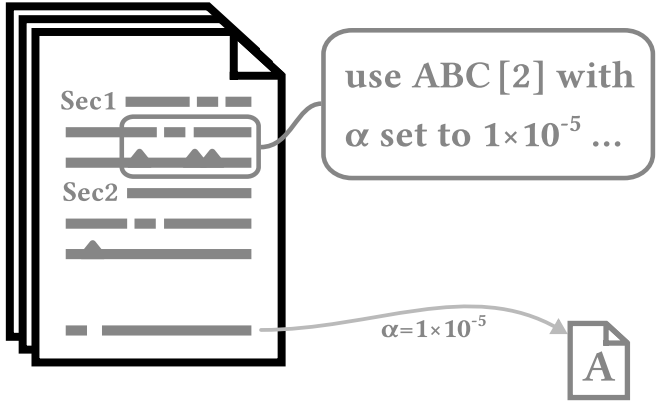
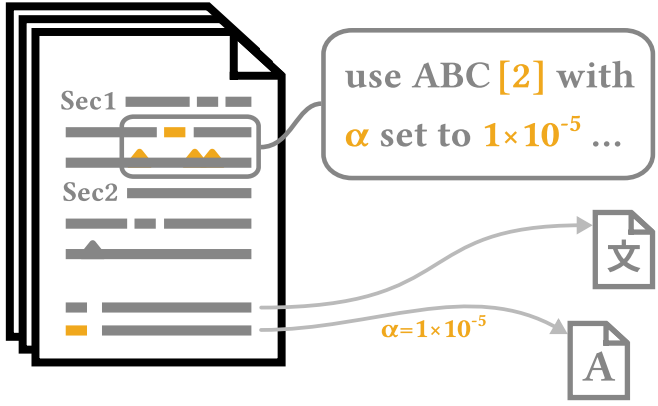


Research Gap: Artifact Parameters



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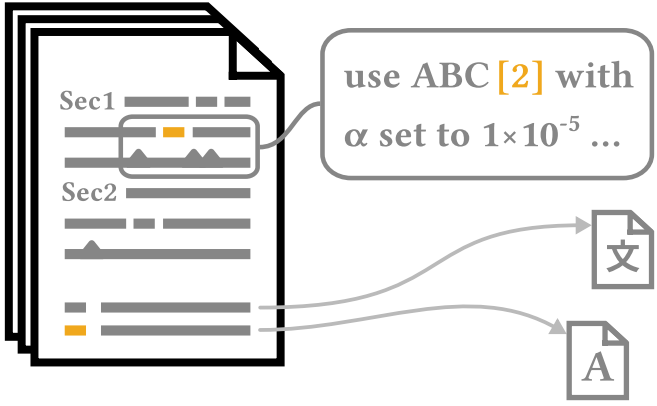


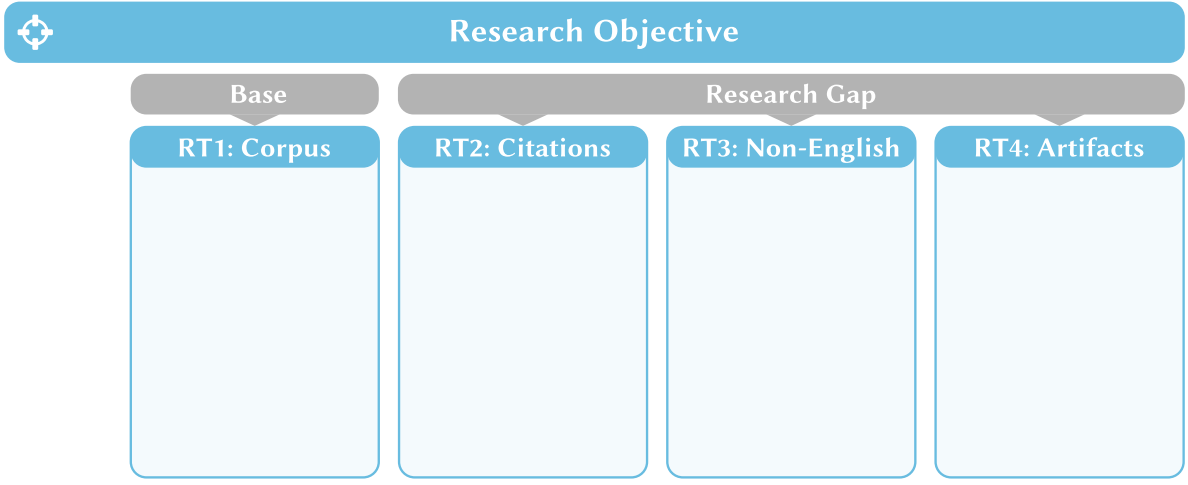
Data Mining and Information Extraction Methods

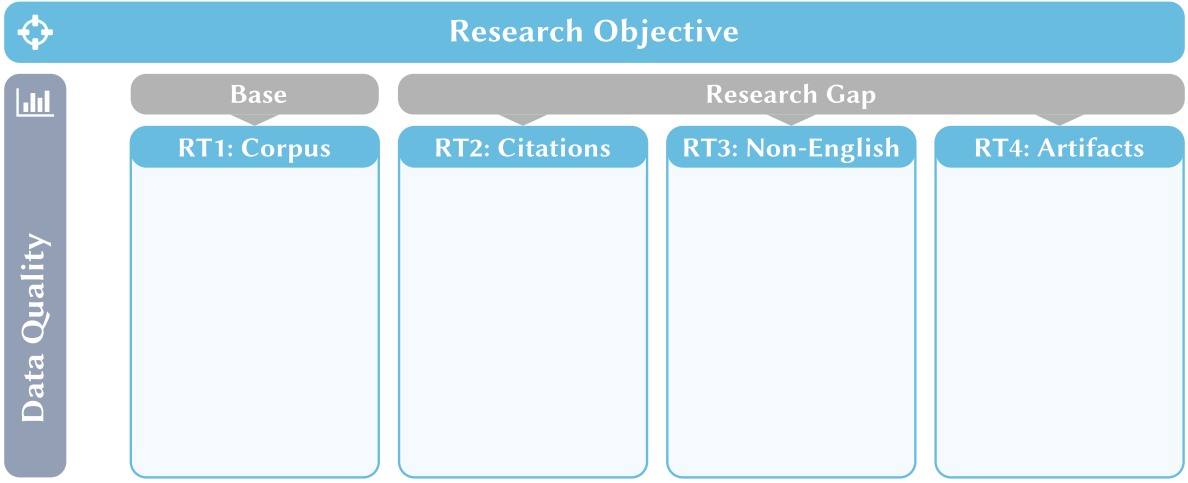
for Large-Scale High Quality Representations of Scientific Publications

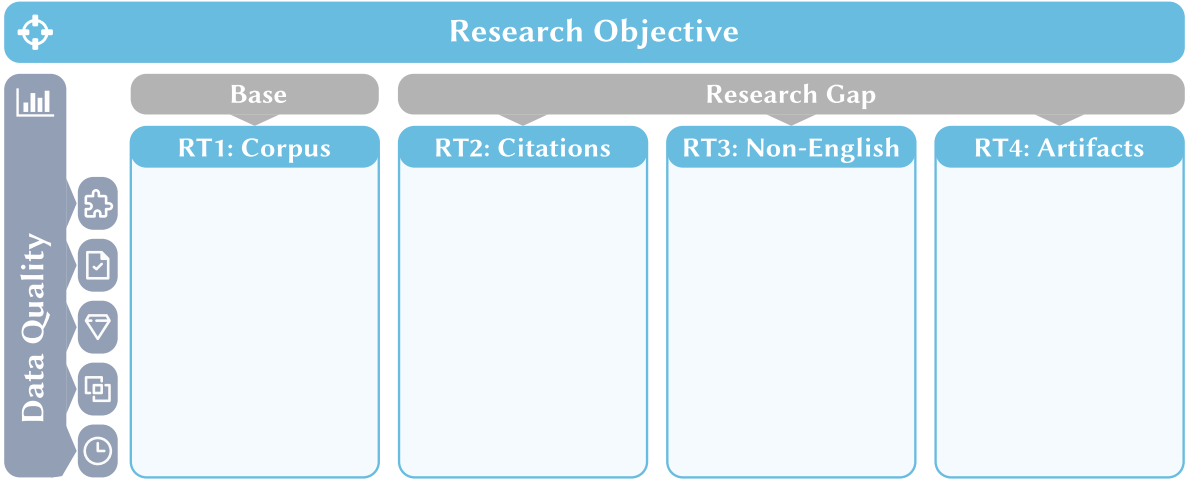
Research Objective

Research Objective

Research Gap


Research Objective
Base
Research Gap
RT1: Corpus
RT2: Citations
RT3: Non-English
RT4: Artifacts


Research Objective
Data Quality
Base
Research Gap
RT1: Corpus
RT2: Citations
RT3: Non-English
RT4: Artifacts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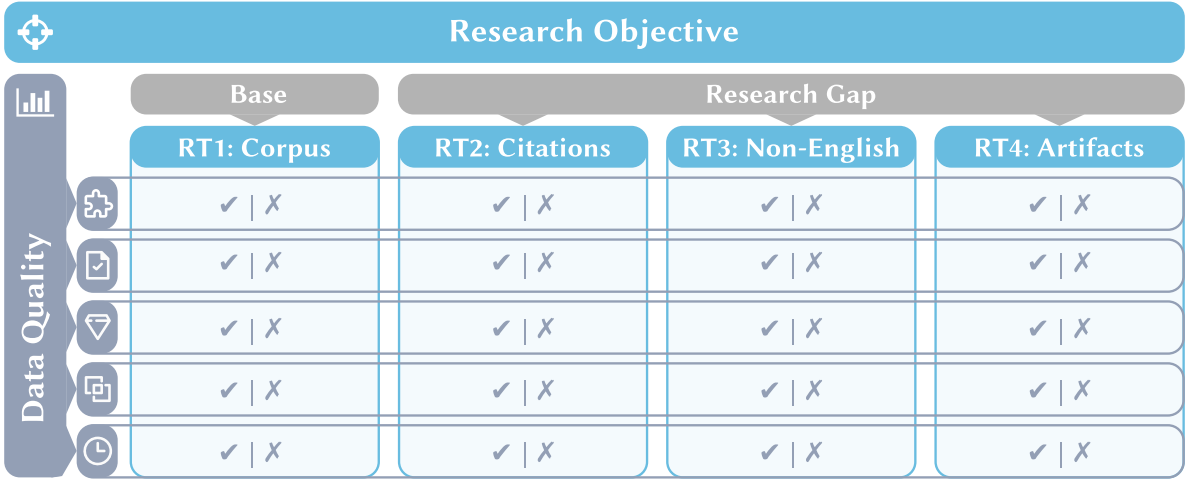
Data Quality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Base
Research Gap
RT1: Corpus
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RT3: Non-English
RT4: Artifacts
Data Quality
✔ | ✗
✔ | ✗
✔ | ✗
✔ | ✗
✔ | ✗
✔ | ✗
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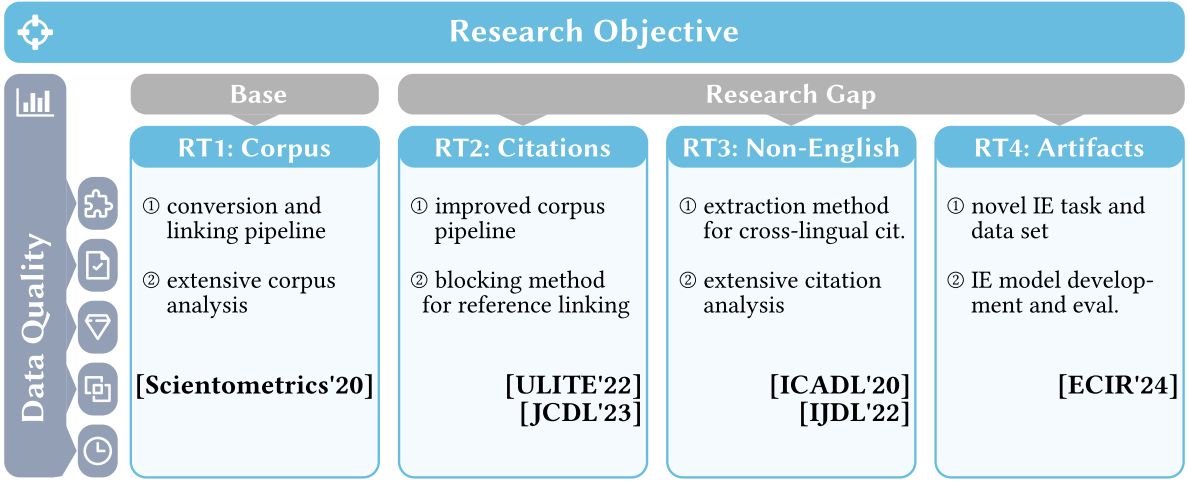
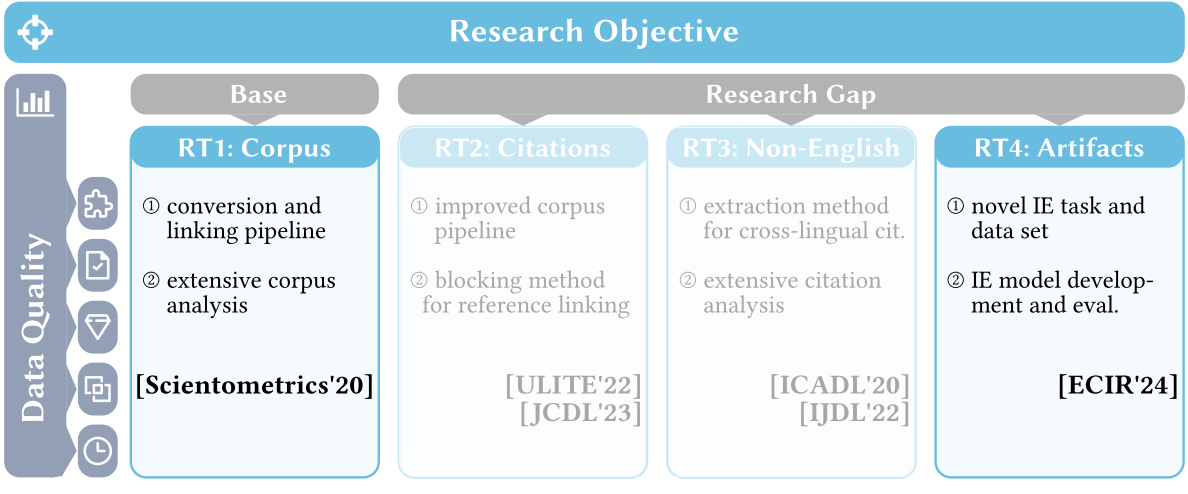

Research Objective
Data Quality
Base
Research Gap
RT1: Corpus
① conversion and linking pipeline
② extensive corpus analysis
[Scientometrics'20]
RT2: Citations
① improved corpus pipeline
② blocking method for reference linking
[ULITE'22]
[JCDL'23]
RT3: Non-English
① extraction method for cross-lingual cit.
② extensive citation analysis
[ICADL'20]
[IJDL'22]
RT4: Artifacts
① novel IE task and data set
② IE model development and eval.
[ECIR'24]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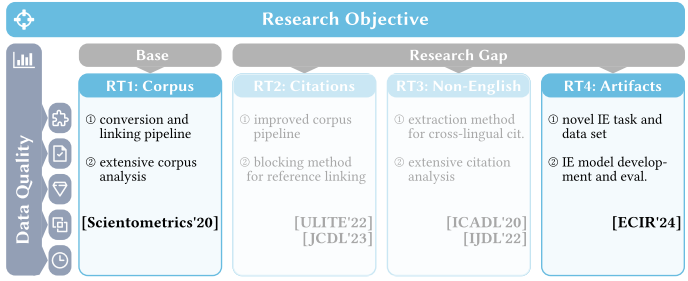
Outline

- **Corpus**
  - Challenges
  - Methods
  - Resulting Corpus
- **Citation Network**
- **Non-English Documents**
- **Artifact Parameters**
  - Task Definition
  - Methods
  - Results
- **Conclusion**
  - Contributions
  - Impact

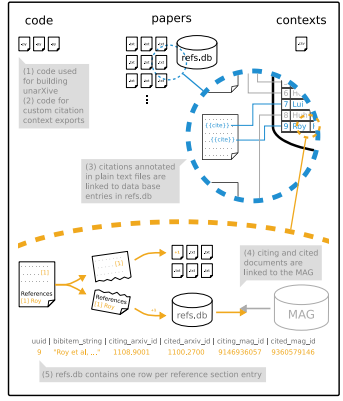


Corpus

unarXive

Corpus - Digest

- **Research Task**
  Develop a method for creating large-scale, high quality “base corpus”
- **Method**
  - LaTeX as data source
  - Joint handling of text + references
  - Reference parsing + linking to metadata records
- **Results**
  - Corpus among 3 largest full-text corpora
  - More extensive, complete, less noisy
  - State of the art citation network



Scientometrics’20 [1]

Corpus - Challenges

- **General**
  - Volume ($\sim 10^6$ docs, $\sim 10^7$ refs)
  - Bridging visual medium and text information
- **Parsing**
  - Parser efficiency
  - Typesetting info ≠ semantic info
  - LaTeX is powerful and people are creative
- **Reference linking**
  - Choice of target set
  - Parsing (`bbl`, not `bib`)
  - Variance and information sparsity

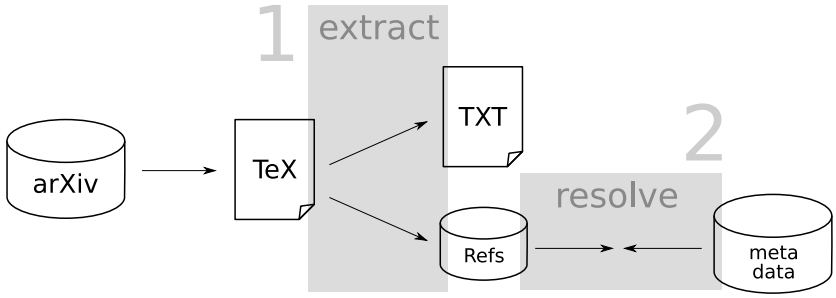
```
% Bonnet et al., 2001
\begin{document}
\newcommand{\nc}{\newcommand}
\nc{\be}{\begin{equation}}
```

[4] Jaume, S.C. and Sykes, L.R., Pure and Applied Geophysics **155**, 279-305.

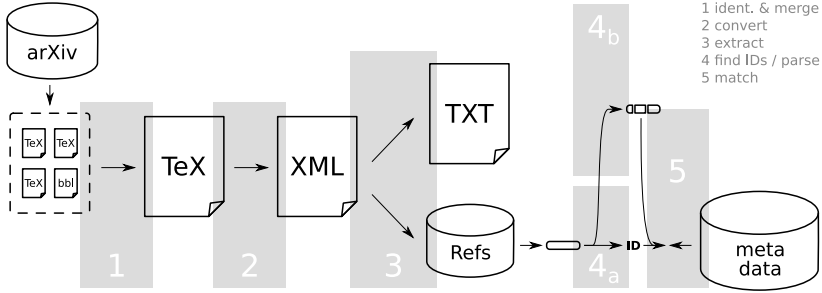
↕

Jaume, S.C. and L.R. Sykes, Evolving Towards a Critical Point: A Review of Accelerating Seismic Moment/Energy Release Prior to Large and Great Earthquakes, Pure Appl.Geophys., 155, 279, 1999.

Corpus - Methods



Corpus - Methods



Corpus - Result

- **Size**
  - 1.2 M documents (2.7 M cited)
  - 16 M references
  - 29 M in-text citation markers
- **Scope**
  - 1991–2018 (current: 2022)
  - physics (63%), maths (23%), CS (11%), other (3%)
- **Reference matching**
  - 53% by parsing + matching
  - 28% by DOI
  - 19% by arXiv ID

Corpus - Result

Data Set	# Docs	Cit. Markers	Linked	Link Succ.	Link Acc.
ACL-ARC [2]	11 k	×	×	n/a	n/a
ACL-AAN [3]	18 k	×	×	n/a	n/a
Scholarly Dataset 2 [4]	100 k	×	×	n/a	n/a
CiteSeerX [5] / RefSeer [6]	1 M	ambiguous	×	n/a	n/a
PMC OAS [7]	**2.3 M**	exact	mixed[a]	-	-
arXiv CS [8]	90 k	exact	✓	39.3%	-
unarXive [1]	1.2 M	exact	✓	**42.6%**	**96%**

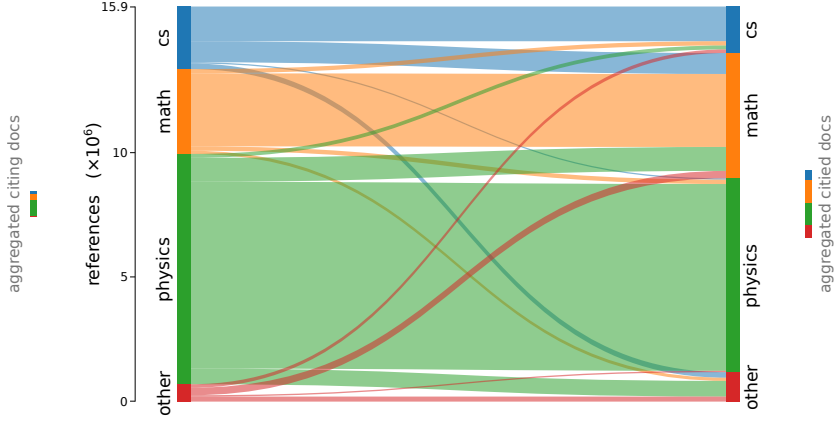
[a] No citation network due to mixed set of IDs (PubMed, MEDLINE, DOI) [9].

Corpus - Result (2022)

Data Set	# Docs	Cit. Markers	Linked	Link Succ.	Link Acc.
arXMLiv [12]	1.6 M	exact	×	n/a	n/a
PMC-OAS [7]	**3.3 M**	exact	mixed[a]	-	-
SciXGen [13]	205 k	exact	✓	41.6%	-
S2ORC (LaTeX) [11]	1.5 M	exact	✓	31.1%	92%
unarXive 2022 [14]	1.9 M	exact	✓	**44.4%**	**96%**

[a] No citation network due to mixed set of IDs (PubMed, MEDLINE, DOI) [9].

Corpus - Citation Flow



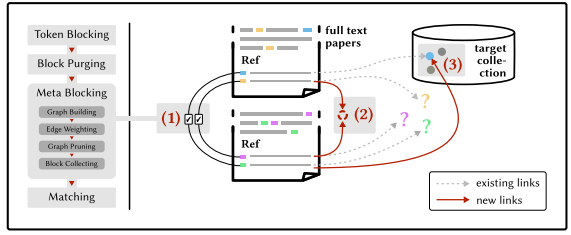
Corpus - Conclusion

- **Advancements**
  - More extensive
    - single domain vs multi domain
  - More complete, high quality citation network
    - 13.3% increase in linked references (↔ S2ORC$_{\text{LaTeX}}$)
    - 4% more accurate reference links (↔ S2ORC$_{\text{LaTeX}}$)
  - Less noise due to LaTeX as source
  - Novel types of analyses possible
- **Foundation for further studies**
- → **RT1**✓

Citations & Non-English

Citation Network - Digest

- **Research Task**
  Develop a method linking references more successfully without compromising accuracy
- **Method**
  - Use unarXive data
  - Improved reference linking pipeline (parser & target set choice, heuristics)
  - Blocking & matching within set of references
- **Results**
  - +2% in base matching success (SOTA)
  - Manifold increase in bibl. couplings
- → **RT2**✓

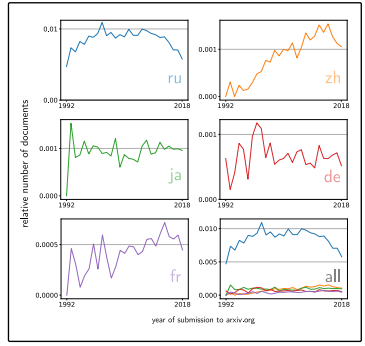


ULITE'22 [16]

JCDL'23 [14]

Non-English Documents - Digest

- **Research Task**
  Develop an approach to include non-English publications into large-scale scholarly data
- **Method**
  - Use unarXive data
  - Identify cross-lingual citations by reference strings
  - Temporal and geographic analyses
- **Results**
  - Reliable method for identification
  - Largest study so far (<1k → >1M)
  - Identification of trends and challenges
- → **RT3**✓

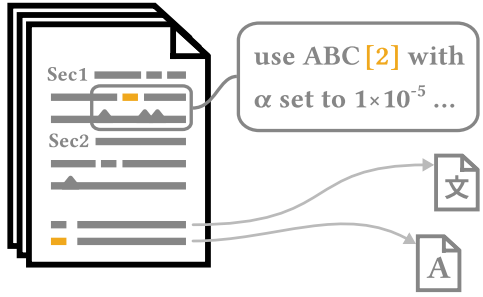


ICADL'20 [17]

IJDL'22 [18]

Artifact Parameters

Artifact Parameters



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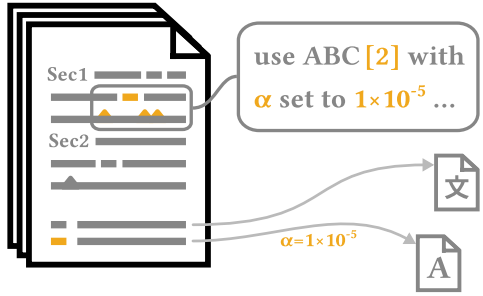
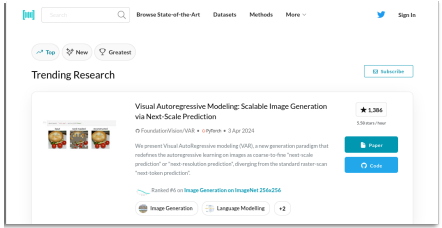
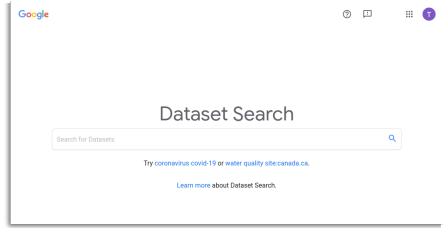
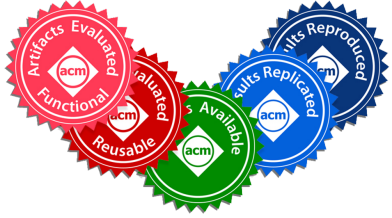


Artifact Parameters - Motivation







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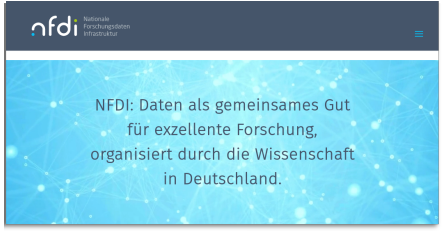
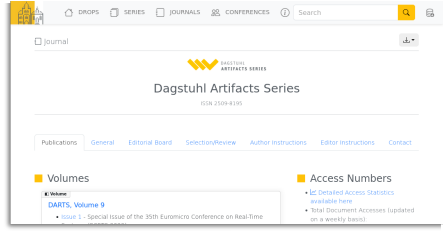




Artifact Parameters - Motivation

NLP field increasing focus on **data** and its **algorithmic processing**

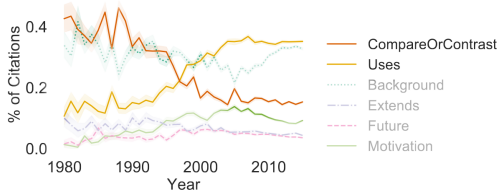
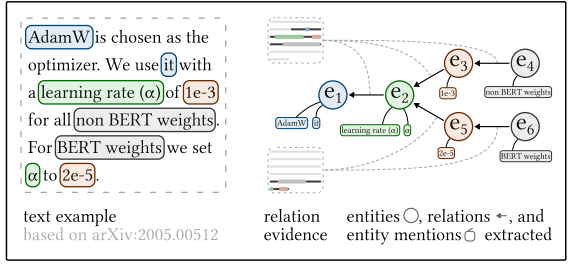


Figure 5: Changes in the average citation frame in ACL papers reveals a continued decline in the percentage of COMPARISON OR CONTRAST and increase in USES citations. The increase in BACKGROUND citations circa 2010 marks the start of the era of unlimited references in ACL conferences. Shaded regions show bootstrapped 95% confidence intervals.

Jurgens, D. *et al.* Measuring the Evolution of a Scientific Field through Citation Frames. *Transactions of the Association for Computational Linguistics* **6,** 391–406 (2018)

Artifact Parameters - Digest

- **Research Task**
  Develop a method to extract fine-grained research artifacts information
- **Method**
  - Task formalization
  - Data annotation (data from unarXive)
  - Two lines of approaches
    - BERT based model approach
    - LLM based approach
- **Results**
  - Novel task, novel data
  - Improvements over SOTA baselines
  - Methods applicable to large data sets



ECIR'24 [20]

Artifact Parameters - Task

AdamW is chosen as the optimizer. We use it with a learning rate (α) of 1e-3 for all non BERT weights. For BERT weights we set α to 2e-5.

text example
based on arXiv:2005.00512

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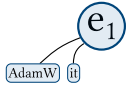

entity type
artifact

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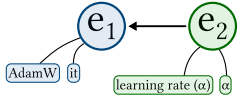

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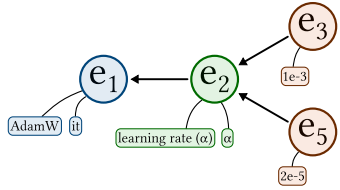

entity type
artifact parameter value

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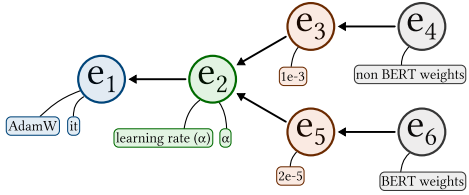
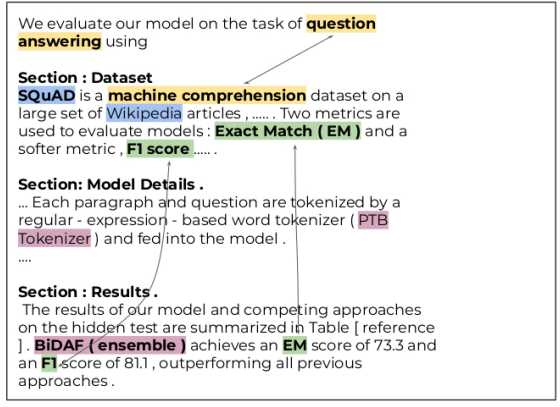


entity type
artifact parameter value context

Artifact Parameters - Related Work

- Fine-tuned Models
  - SciERC dataset [21]
  - SOTA: PL-Marker [22]
    → **entity type overlap**
- LLMs
  - Mostly singular values/lists [24–26]
  - Hierarchical [27] (see right)
    → **data serialization format**



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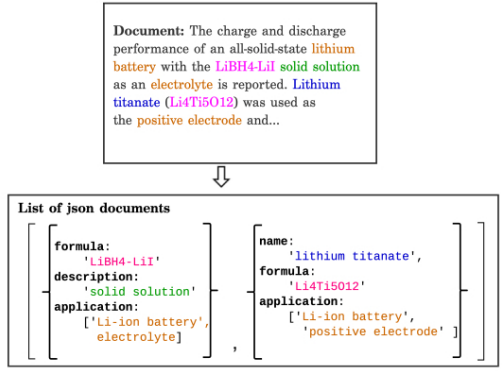
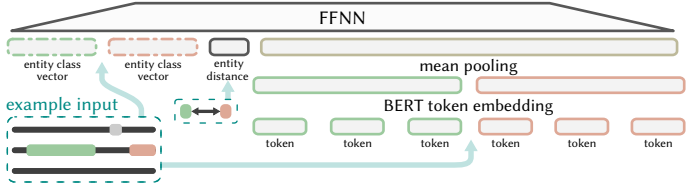
Note: all related LLM work is evaluated on **GPT models only**.



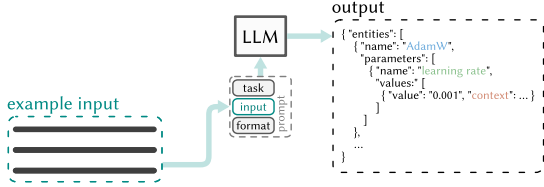
Approach: Fine-tuned models

- Based on PL-Marker (SciERC SOTA)
- (N)ER: used as is
- RE: new module, utilizing
  - Entity class embeddings
  - Entity distance



Approach: LLMs

- Data serialization format
  - JSON → YAML
- Compare 6 models
- Base prompt + tuning for each
- Zero-shot: all
- Few-shot: only Vicuna$_{16k}$



Approach: LLMs

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Model	Size
WizardLM [28]	13 B
Vicuna_{4k} [29]	13 B
Vicuna_{16k} [29]	13 B
Falcon [30]	40 B
GALACTICA [31]	120 B
GPT-3.5 [32]	175 B

Artifact Parameters - Data

- No existing data sets
  → **use unarXive** ML/CV/CL/DL
- Annotation approach
  - Paragraph level, whole papers
- **Data Set Size**
  - 444 paragraphs
  - 1,971 entities
  - 614 relations
- IAA
  - 0.867 for entities
  - 0.737 for relations
  - → **high quality**

Artifact Parameters - Experiments: Fine-tuned models

- **Setting**
  - 5-fold cross-validation
  - Stratified sampling
- **Results** (F_1 [%])
  - ER: 78.0
  - RE: 9.9 → 38.8
- **Analysis**
  - Parameter: low performance
  - Contexts: not predicted

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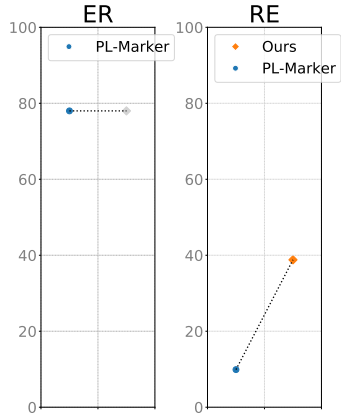

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Table: Ablation study results (model inputs are: T = BERT token embeddings, C = entity class embeddings, D = entity distance)

Used	P [%]	R [%]	F_1 [%]
␣CD	15.5	8.8	11.1
T␣D	16.6	29.8	19.6
TC␣	26.5	65.0	35.5
TCD	**30.7**	**65.0**	**38.8**

Artifact Parameters - Experiments: LLMs

- **Setting**
  - Zero-/Few-shot
  - Compare JSON w/ YAML variant
- **Results** (best F_1 [%]) (zero-shot)
  - ER: 44.0 (37.4)
  - RE: 7.8 (6.1)
- **Analysis**
  - Very low RE performance
  - YAML: avg. +5% in ER
  - Format adherence
    + entity hallucinations

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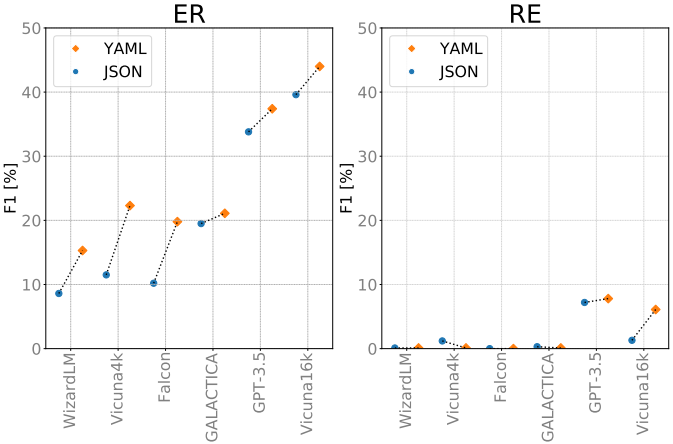
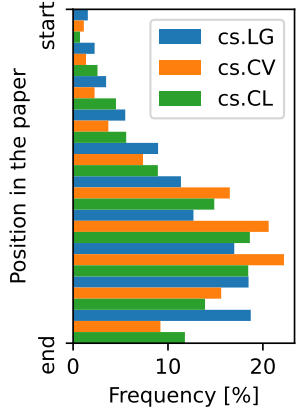


Artifact Parameters - Experiments: Application

- Apply best model (BERT based) on 15k paper sample
- Parameters information given in
  - 36% of ML papers
  - 42% of CV papers
  - 36% of CL papers
  - 7% of DL papers
- Distribution towards second half of paper across disciplines



Artifact Parameters - Conclusion

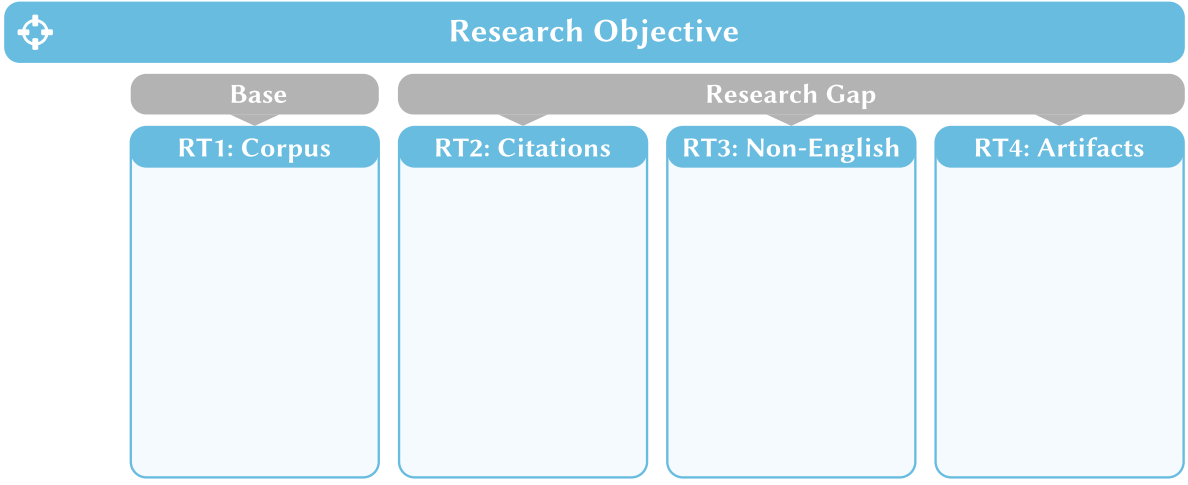
- **Advancements**
  - Novel, relevant task
    (data scheme, annotation guidelines)
  - High quality manually annotated data set
  - Approaches based on BERT, LLMs
    - BERT model based approach
      29% F_1 increase for RE
    - LLM approach
      Avg. 5.5% F_1 increase for ER
      (consistent across all used LLMs)
  - Trained model applicable on large scale
- → **RT4**✓

Conclusion

Research Objective

Research Objective

Research Gap


Research Objective
Base
Research Gap
RT1: Corpus
RT2: Citations
RT3: Non-English
RT4: Artifacts

Research Objective

Base

RT1: Corpus

① conversion and linking pipeline

② extensive corpus analysis

[Scientometrics'20]

Research Gap

RT2: Citations

① improved corpus pipeline

② blocking method for reference linking

[ULITE'22]
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① extraction method for cross-lingual cit.

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① novel IE task and data set

② IE model development and eval.

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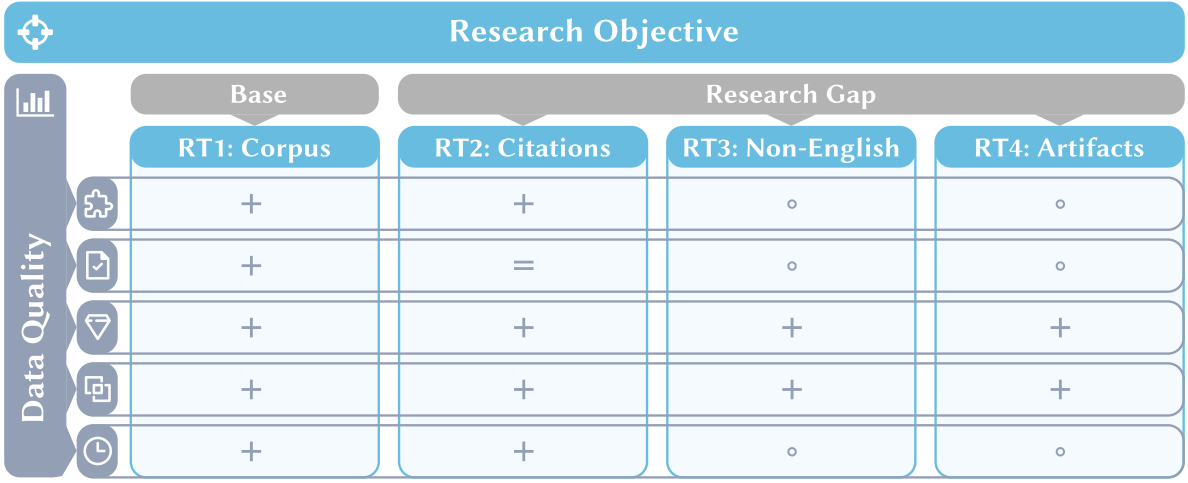
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Data Quality
+
+
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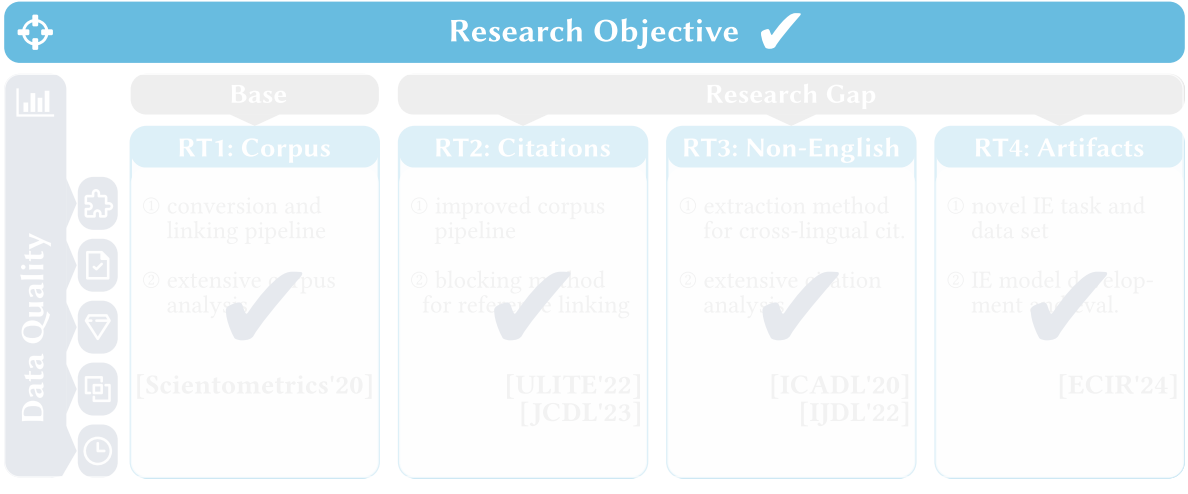
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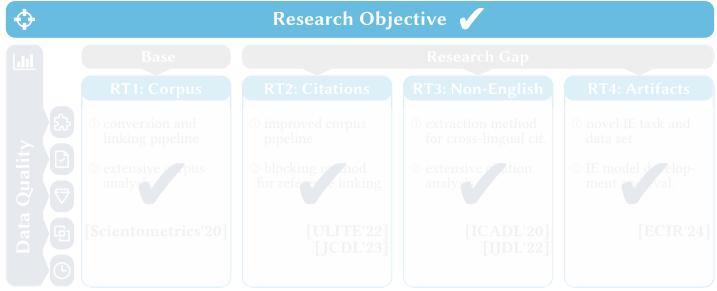
Overall Conclusion

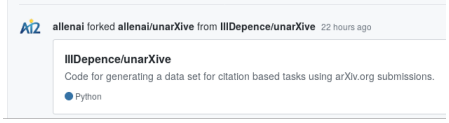
- **Research Objective**
  - Addressed research gaps in 3 areas of key importance
  - All developed methods demonstrably applicable to large-scale data
  - Comprehensive improvements of data quality
- **Impact on research community**

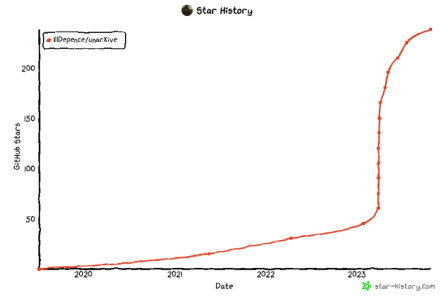


Impact

Adoption by the research community.

- **Methodology**
  - Document Parsing Methodology [11]
  - Reference Matching Methodology [13]
- **Model dev/eval**
  - Citation Recommendation [33]
  - Document Retrieval [34]
  - Researcher Profile Embeddings [35]
- **Analyses**
  - Interdisciplinary Citations [36]
  - Citation Context Semantic Shifts [37]
  - Obliteration by Incorporation [38]





Big Picture

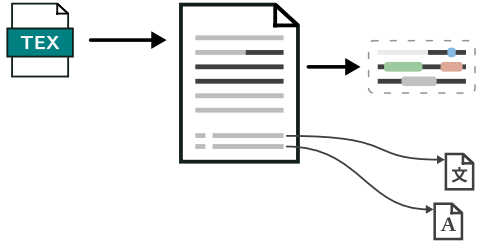
Compared to others

- **S2ORC** (Allen AI)
  - larger
  - less granular (maths), more noisy (PDF)
- **arXMLiv** (FAU KWARC)
  - more structured
  - no citation network
- **ORKG** (TIB)
  - more rigorously semantic
  - smaller (manual/semi-automated input)

Our work combines (1) **accurate, fine-granular** document representations,
(2) a **citation network**, and (3) applicability on a **large scale** due to being automated.

Outlook

- **Data Sources**
  - JATS-XML
- **Non-English Publications**
  - English citing docs
- **Artifact Parameters**
  - Applications
- **Long-term**
  - Digital record of science



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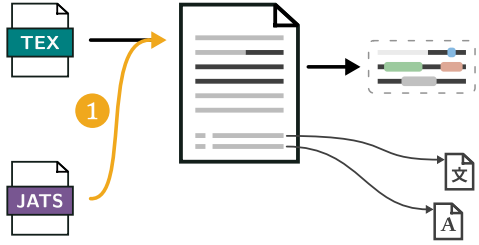

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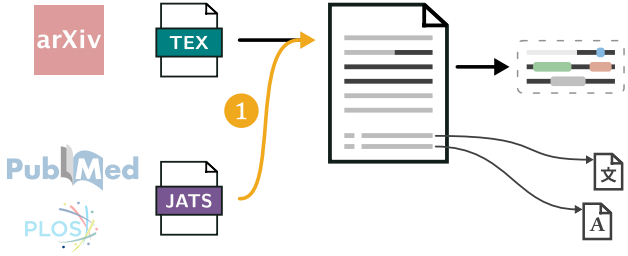

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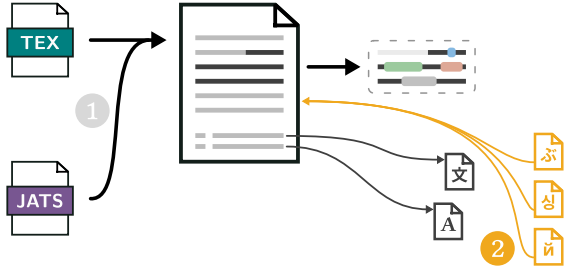

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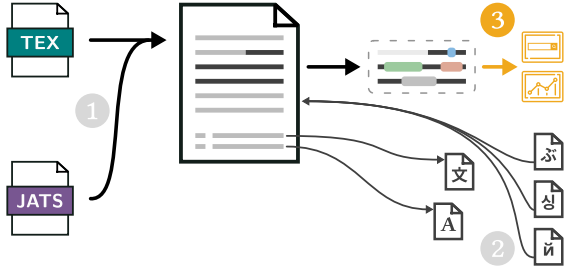
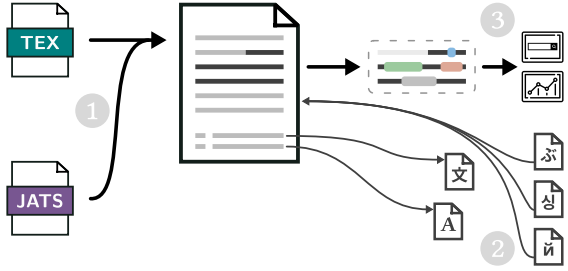
- **Long-term**
  - Digital record of science



Outlook

- **Data Sources**
  - JATS-XML
- **Non-English Publications**
  - English citing docs
- **Artifact Parameters**
  - Applications
- **Long-term**
  - Digital record of science



Thank You ☺

Questions Discussion Comments

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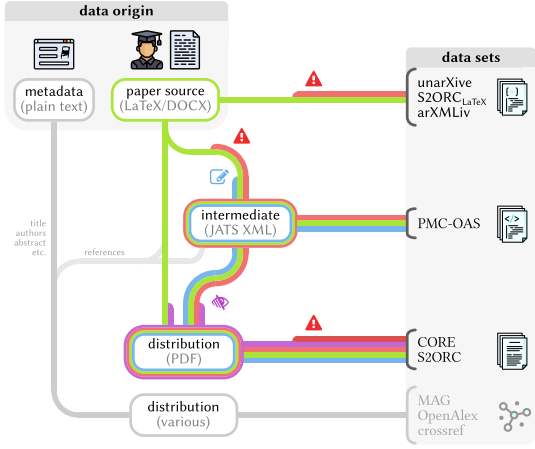
Extra Slides

Scholarly Data IE

Scholarly Data Origins



Corpus - Result Full

Data set	# Docs	Cit. markers	Disciplines	Full text	Linked
ACL-ARC [2]	11 k	no	comp. ling.	PDF	×
ACL-AAN [3]	18 k	no	comp. ling.	PDF	×
Scholarly Dataset 2 [4]	100 k	no	CS	PDF	×
CiteSeerX [5] / RefSeer [6]	1 M	ambiguous	mixed	400 char excerpts	×
PMC OAS [7]	2.3 M	exact	biomedical	XML	mixed[a]
arXiv CS [8]	90 k	exact	CS	text	✓
unarXive [1]	1.2 M	exact	phys., maths, CS	text	✓

[a] No citation network due to mixed set of IDs (PubMed, MEDLINE, DOI) [9].

Corpus - Result Full (2022)

Data Set	Source Data	Source Format	Citation Network[a] general	Citation Network[a] compare	# Docs	Disciplines
CORE [10]	multiple	PDF	0%	-	>100 M	various
S2ORC (PDF) [11]	multiple	PDF	69.4%	-	12 M	various
unarXive 2020 [1]	arXiv.org	LaTeX	42.6%	42.6%	1.2 M	phys., maths, CS
S2ORC (LaTeX) [11]	arXiv.org	LaTeX	31.1%	31.1%	1.5 M	phys., maths, CS
arXMLiv [12]	arXiv.org	LaTeX	0%	0%	1.6 M	phys., maths, CS
SciXGen [13]	arXiv.org	LaTeX	41.6%	-	205 k	CS
PMC-OAS [7]	PubMed	XML	mixed[b]	-	**3.3 M**	**biomedical**
unarXive 2022 [14]	arXiv.org	LaTeX	44.4%	**44.4%**	**1.9 M**	**phys., maths, CS**

[a] "general": all data; incomparable. "compare": arXiv.org data 1991–2020; directly comparable.
[b] No citation network due to mixed set of IDs (PubMed, MEDLINE, DOI) [9].

Corpus - Link Correctness Full

Table: Link correctness (n = 300)

Confidence level	Method[a]	Lower limit	Upper limit
0.99	Wilson	0.9613	0.9975
	Jeffreys	0.9666	0.9983
0.95	Wilson	0.9710	0.9966
	Jeffreys	0.9736	0.9972

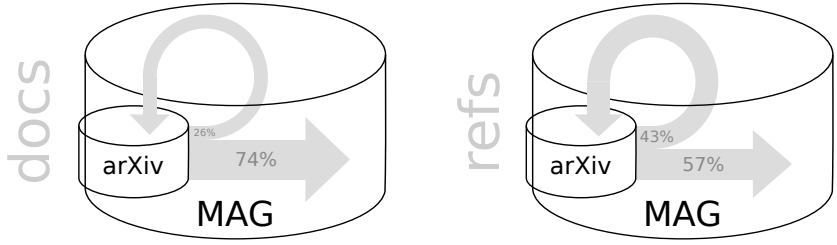
[a] Confidence interval given as Wilson score interval and Jeffreys interval [15].

Corpus - Stats

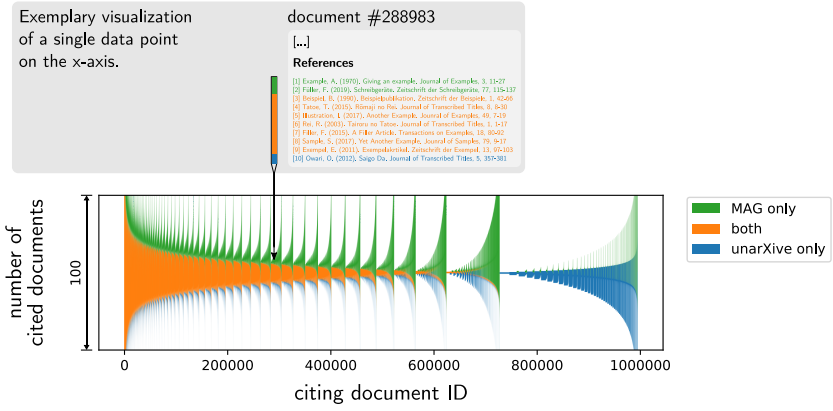
	citing documents	references		cited documents
		outgoing	incoming	
full data set:	**1,043,126**	15,954,664	15,954,664	**2,746,288**
full text	1,043,126	15,954,664	7,181,576	736,597
linked to MAG	994,351	15,846,351	15,954,664	2,746,288
by discipline:				
physics	662,894	9,300,576	7,827,072	921,852
mathematics	237,422	3,426,117	5,062,033	906,301
computer science	111,694	2,526,656	1,876,401	425,860
other	31,116	701,315	1,189,158	492,275

data: `http://doi.org/10.5281/zenodo.3385851`
code: `https://github.com/IllDepence/unarXive`

Corpus - Citation Flow



Corpus - Reference Composition

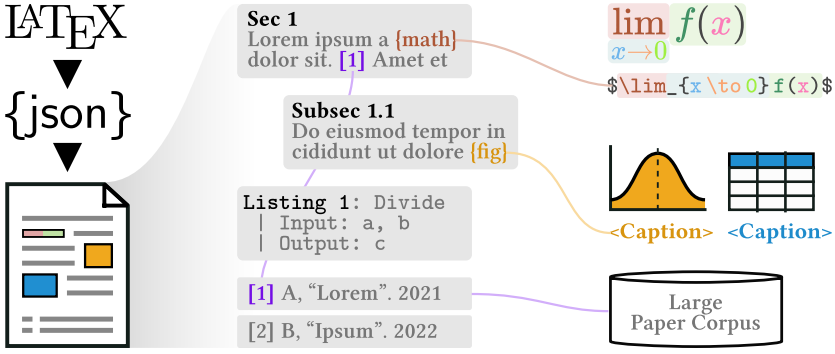


Corpus - Target Sec. Specific Refs

	Discipline[a]	Count	Normalization factor	Normalized ratio (%)
Citing	Mathematics	298,009	4.66	8.70
	CS	9,123	6.31	0.36
	Physics	30,593	1.72	0.33
Cited	Mathematics	313,651	3.15	6.20
	CS	12,179	8.50	0.65
	Physics	31,087	2.04	0.40
Pairs	Math†→Math‡	200,859	5.41	6.81
	Math†→CS	5,134	92.13	2.96
	Math†→Phys	3,114	89.88	1.75
	CS→Math‡	3,456	18.82	0.41
	Phys→Math‡	3,859	16.49	0.40
	CS→CS	2,500	11.38	0.18
	Phys→Phys	10,374	2.12	0.14
	CS→Phys	50	307.16	0.10
	Phys→CS	137	101.40	0.09

[a] †: Mathematics citing document, ‡: Mathematics cited document, X→X: Citing and cited document are from the same discipline.

unarXive 2022 Schema



- **Created from LaTeX sources**
- **Document structure and content types preserverd**
- **Math, figures, tables, references linked**

Artifact Parameters - Task

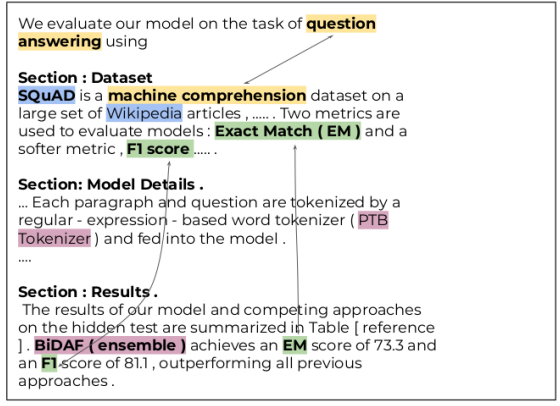
- **Task Type**
  - (Named) Entity Recognition, Relation Extraction
- 4 entity classes
  - (1) research **artifact**: model, method, data set, ...
  - descriptions of how authors use the artifacts
    (2) **parameter** (α, learning rate, k, ...)
    (3) **value** (1e-3, five, $\frac{1}{3}$, ...)
    (4) **context** (for fine-tuning, during grid search, ...)
- 1 relation type
  - Given by entity type pair

Artifact Parameters - Task (ext)

- **Goal**
  - Automatically extract hyperparameter information from paper text
- **Motivation**
  - Reproducibility indication [39], automated reproduction [40]
  - Uncover conventions and trends
  - More fine-grained paper representations (similarity measures, recommendation, search)
- **Task Type**
  - (Named) Entity Recognition, Relation Extraction

Artifact Parameters - Related Work: Fine-tuned models

- SciERC dataset
  - SCIIE [21]
  - PL-Marker [22]
  - → **entity type overlap**
- SciREX dataset
  - TempGen [41] (only RE)
- SemEval 2022 (math symb. to descr.)
  - JBNU-CCLab [42]
  - AIFB [43]
- SemEval 2021 (measurements)
  - LIORI [23]
  - → **utilize mention pattern regularities**



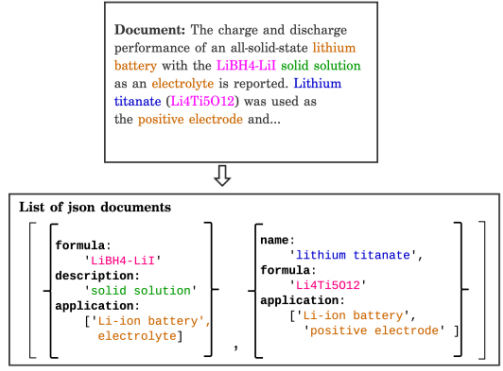
Artifact Parameters - Related Work: Fine-tuned models (other data sources)

- From code documentation [44]
- From code [45]

Artifact Parameters - Related Work: LLMs

- Medical science [24]
  - singular values
  - lists
- Material science [25–27]
  - singular values
  - lists
  - hierarchical [27] (see right)
    → **data serialization format**

Note: all of the above evaluate on **GPT models only**.



Dunn, A. *et al. Structured information extraction from complex scientific text with fine-tuned large language models.* Dec. 2022. doi:10.48550/arXiv.2212.05238

Artifact Parameters - Approach: LLMs

```
In the context of machine learning and related fields, what (if any) are the entities (datasets, models,
methods, loss functions, regularization techniques) mentioned in the LaTeX Input Text below? What (if any)
are their parameters and values?

[LaTeX Input Text start]
We use AdamW with a learning rate ($\alpha$) of 1e-3 for /* [...] */
[LaTeX Input Text end]

Answer in the following YAML format.

Format:
---
text_contains_entities: true/false
entities:
  - entity<N>:
      id: e<N>
      name: "<entity name>"
      type: dataset/model/method/loss function/regularization technique
      has_parameters: true/false
      parameters:
        - parameter<M>:
            id: p<N.M>
/* [...] */
...

Only include entities that are of type dataset, model, method, loss function, or regularization technique.
Do not output entities that are of another type. Do not include entities of type task, metric, library,
software, or API.
Only produce output in the YAML format specified above. Output no additional text.

Output:
```

Artifact Parameters - Approach: LLMs

```
In the context of machine learning and related fields, what (if any) are the entities (datasets, models,
methods, loss functions, regularization techniques) mentioned in the LaTeX Input Text below? What (if any)
are their parameters and values?
```
Task

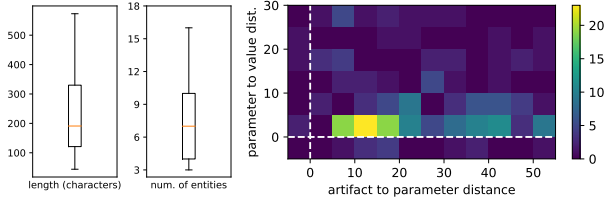
```
[LaTeX Input Text start]
We use AdamW with a learning rate ($\alpha$) of 1e-3 for /* [...] */
[LaTeX Input Text end]
```
Input Text

```
Answer in the following YAML format.

Format:
---
text_contains_entities: true/false
entities:
  - entity<N>:
      id: e<N>
      name: "<entity name>"
      type: dataset/model/method/loss function/regularization technique
      has_parameters: true/false
      parameters:
        - parameter<M>:
            id: p<N.M>
/* [...] */
...
```
Format

```
Only include entities that are of type dataset, model, method, loss function, or regularization technique.
Do not output entities that are of another type. Do not include entities of type task, metric, library,
software, or API.
Only produce output in the YAML format specified above. Output no additional text.

Output:
```
Output Prefix

Artifact Parameters - Data

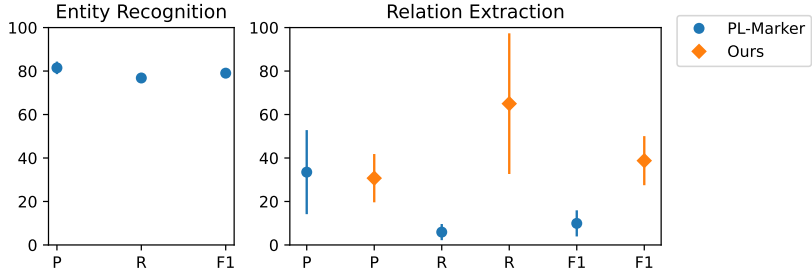
- Two annotation rounds
- Initial (pre-filtered text, exploratory, to fine-adjust scheme)
  - 151 text segments
  - 1,345 entities
  - 1,110 relations
- Main (full papers, eval data)
  - 444 paragraphs
  - 1,971 entities
    (1,134 a, 131 p, 662 v, 44 c)
  - 614 relations
- IAA
  - 0.867 for entities
  - 0.737 for relations



(a) text segments (b) relation distances (#chars)

Figure: Observations of initial annotation round

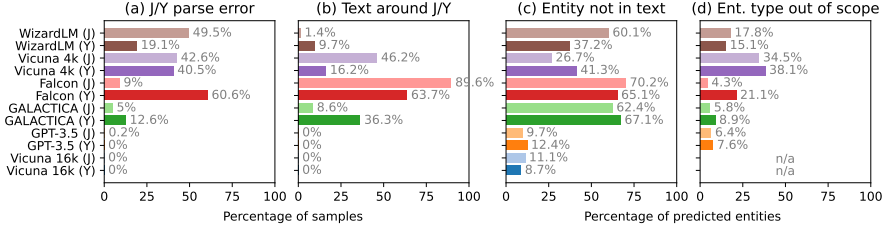
Artifact Parameters - Experiments: Fine-tuned models



Artifact Parameters - Experiments: LLMs

Zero-shot		Entity Recognition			Relation Extraction		
Model	Output	P [%]	R [%]	F_1 [%]	P [%]	R [%]	F_1 [%]
WizardLM	JSON	6.9	11.3	8.6	0.1	0.8	0.1
	YAML	9.7	35.6	15.3 $\Delta_{+6.7}$	0.1	1.5	0.1 $\Delta_{+0.0}$
$Vicuna_{4k}$	JSON	15.1	9.3	11.5	0.7	3.8	1.2
	YAML	17.3	31.5	22.3 $\Delta_{+10.8}$	0.0	0.8	0.1 $\Delta_{-1.1}$
Falcon	JSON	**37.1**	5.9	10.2	0.0	0.0	0.0
	YAML	32.7	14.2	19.8 $\Delta_{+9.6}$	0.0	0.0	0.0 $\Delta_{+0.0}$
GALACTICA	JSON	25.9	15.7	19.5	0.1	2.3	0.3
	YAML	23.1	19.5	21.1 $\Delta_{+1.6}$	0.0	0.8	0.1 $\Delta_{-0.2}$
GPT-3.5	JSON	27.9	**42.8**	33.8	5.4	10.7	7.2
	YAML	34.0	41.7	**37.4** $\Delta_{+3.6}$	**5.8**	**12.2**	**7.8** $\Delta_{+0.6}$
5-shot		Entity Recognition			Relation Extraction		
$Vicuna_{16k}$	JSON	34.4	46.7	39.6	0.8	4.6	1.3
	YAML	**43.9**	**44.1**	**44.0** $\Delta_{+0.4}$	**4.5**	**9.9**	**6.1** $\Delta_{+4.8}$

Artifact Parameters - Experiments: LLMs



Publications - primary

Chap.	Venue	Year	Type	Length	Author Position	Venue Rating	Ref.
3	Scientometrics	2020	Journal	Full	1 of 2	SJR Q1	[1]
4	JCDL	2022	Workshop	Full	1 of 3	Core A*	[16]
	JCDL	2023	Conference	Short	1 of 3	Core A*	[14]
5	ICADL	2020	Conference	Full	1 of 2	Core A	[17]
	IJDL	2022	Journal	Full	1 of 3	SJR Q2	[18]
6	ECIR	2024	Conference	Full	1 of 4	Core A	[20]

Venue ranks from Core[1] (conferences) and SJR[2] (journals).[3]

[1] See `http://portal.core.edu.au/conf-ranks/` (last accessed 2023-10-12).

[2] See `https://www.scimagojr.com/` (last accessed 2023-10-12).

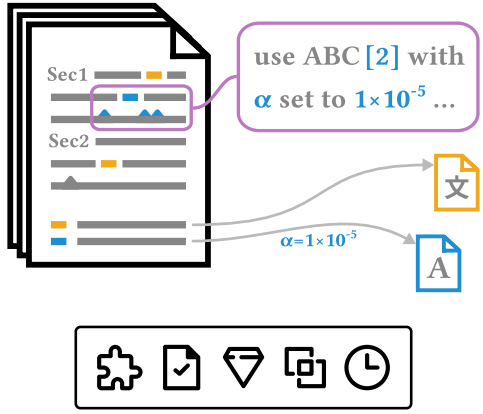
[3] Ratings for publication year or, if not listed, most up-to-date ranking. Workshops ranks are that of the hosting conference.

Publications - secondary

Venue	Year	Type	Length	Author Position	Venue Rating	Ref.
ECIR	2019	Workshop	Full	1 of 2	Core A	[46]
ECIR	2020	Conference	Full	1 of 3	Core A	[47]
NAACL	2021	Workshop	Short	3 of 4	Core A	[48]
AAAI	2022	Workshop	Full	2 of 3	Core A*	[49]
JCDL	2022	Conference	Full	3 of 3	Core A*	[50]
JCDL	2023	Conference	Short	1 of 3	Core A*	[51]

Additional publications (co-)authored leading up to and during the research period which are not a direct part of the dissertation, but nevertheless informed the overall research trajectory. Especially [46] and [48], which constitute the results of the master's thesis preceding the doctoral research period, paved the way for the dissertation.

Quality Dimensions



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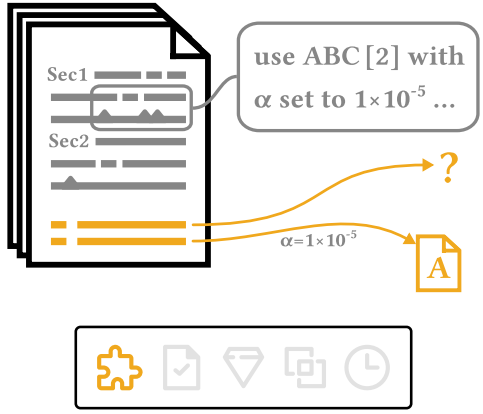

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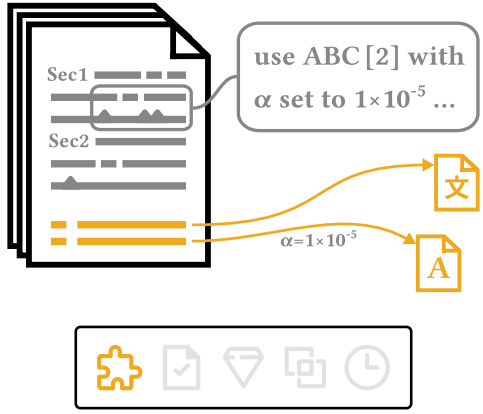
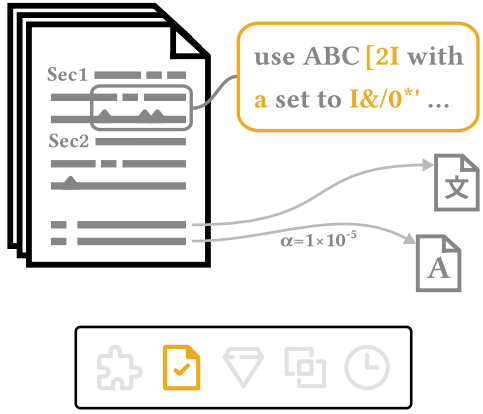


Quality Dimensions: Accuracy



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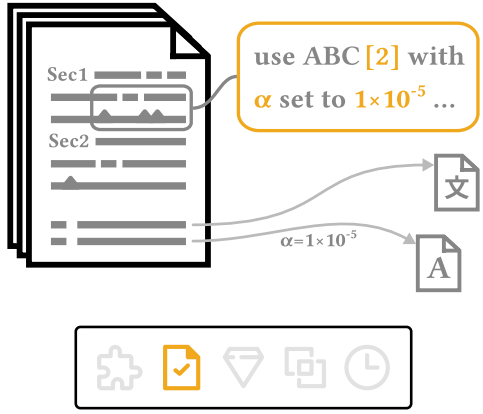

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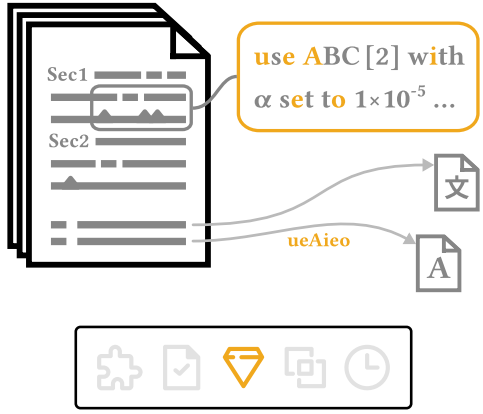

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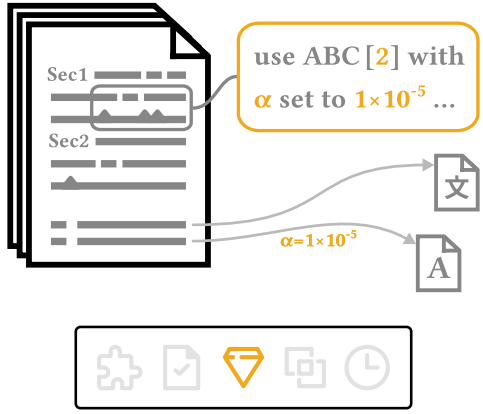

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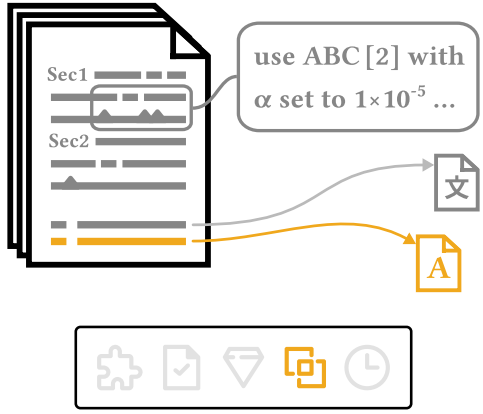

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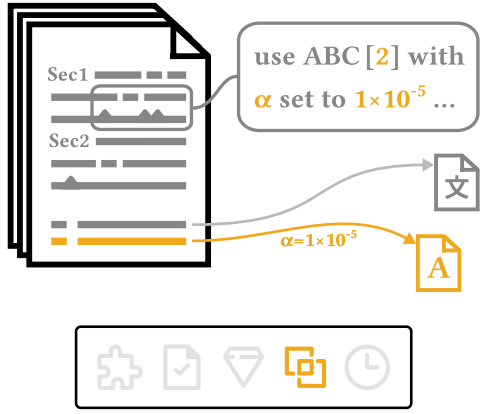
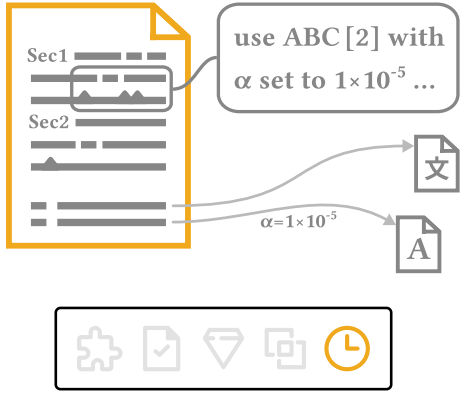


Quality Dimensions: Timeliness



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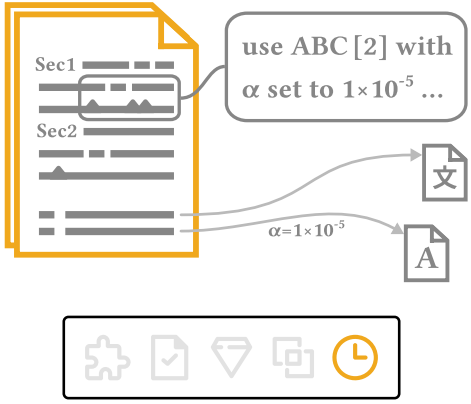

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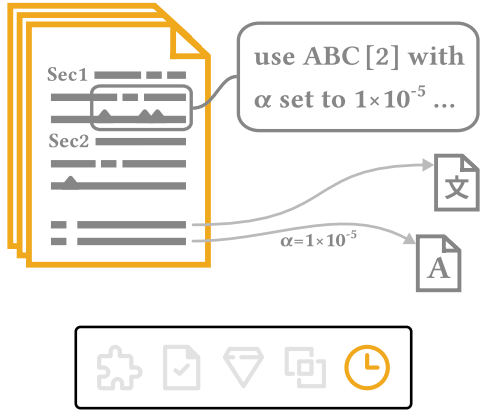

Limitations

- **Corpus**
  - LaTeX required (no humanities)
- **Citation Network**
  - Blocking method scalability
- **Non-English Documents**
  - Single “direction”
  - Dependency on author notation
- **Artifact Parameters**
  - IE from text, not tables, code, etc.
  - ML specific
  - English only