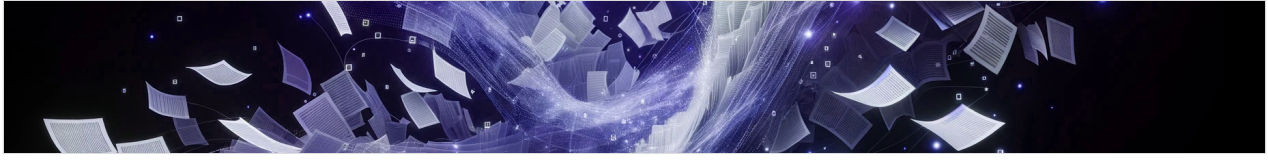
Data Mining and Information Extraction Methods for Large-Scale High Quality Representations of Scientific Publications

Disputation

Tarek Saier | 22. April 2024

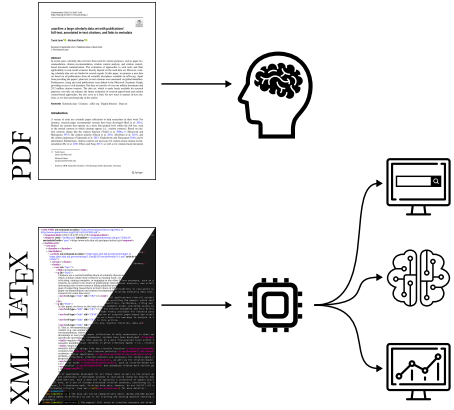


Data Mining and Information Extraction Methods for Large-Scale High Quality Representations of Scientific Publications

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

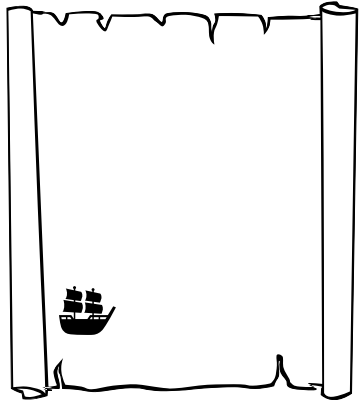
Scholarly Data

- **Usage**
  - Services (Search, Recommendation, Stats)
  - 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



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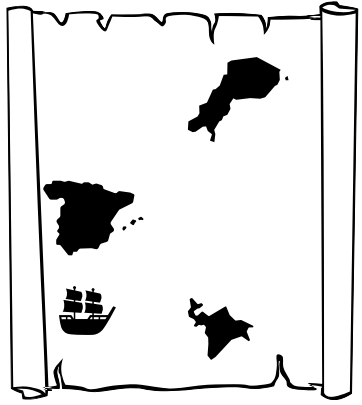

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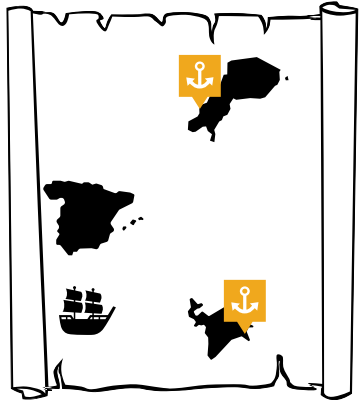
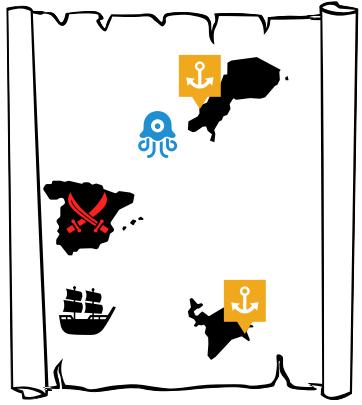
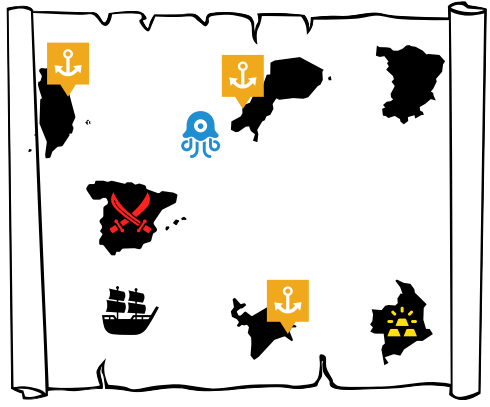


Maps of the Sea



Maps of the Sea



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

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better maps[1] $\Rightarrow$ **better decisions**

[1] Abstract representations of the real world

Maps of the Sea / Maps of Science

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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[1]

[1] Used data sets are small, incomplete, noisy, etc.

Maps of the Sea / Maps of Science

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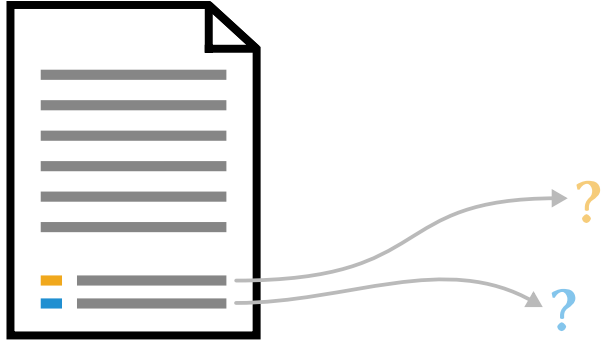
RQ How can large-scale scholarly data be improved?

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

Maps of Science

Maps of Science



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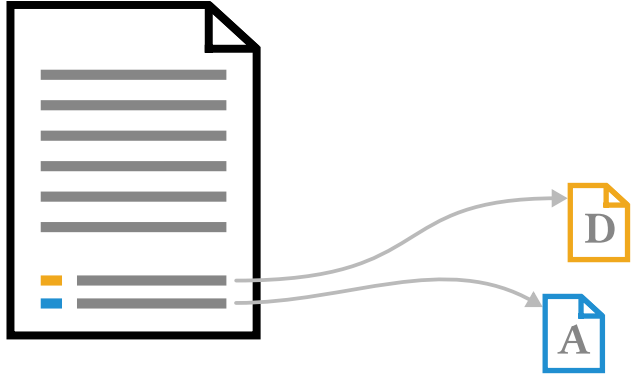

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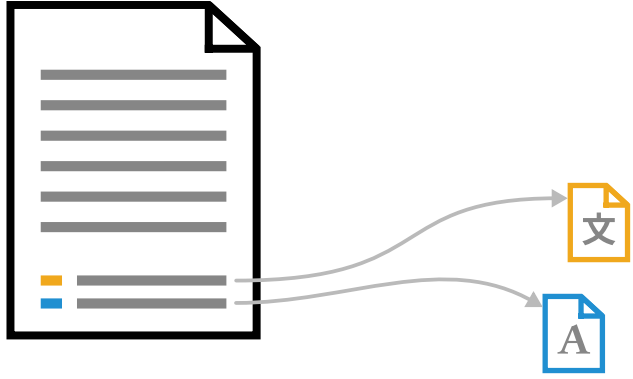

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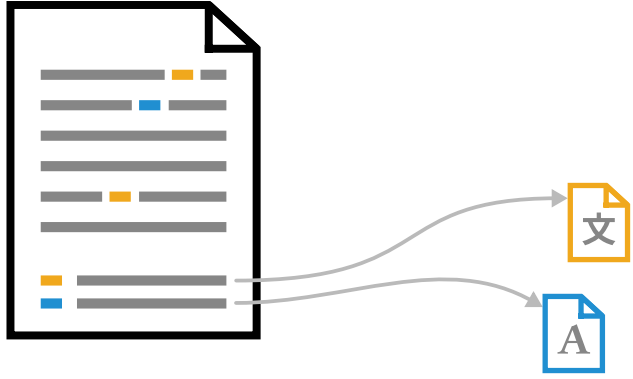

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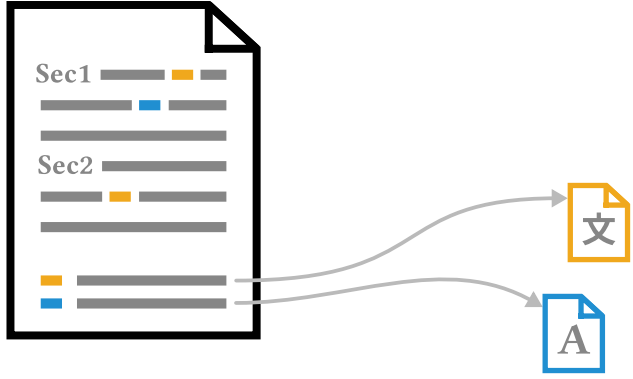

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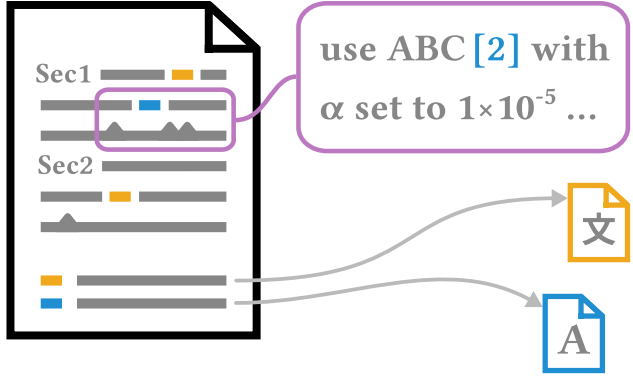

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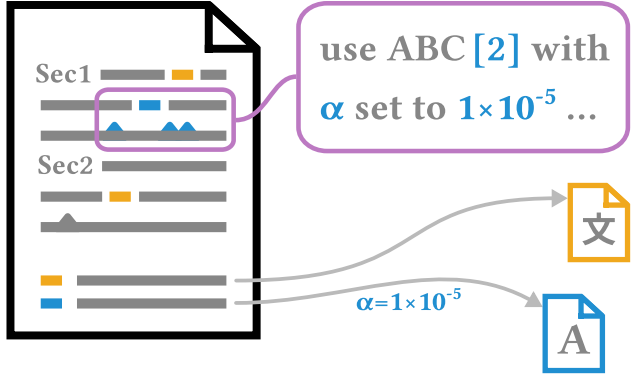

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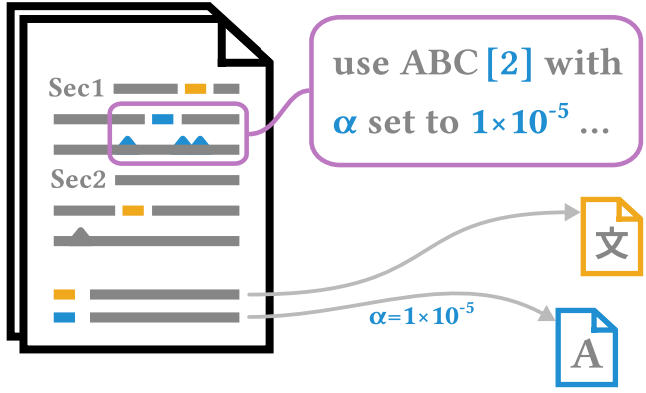
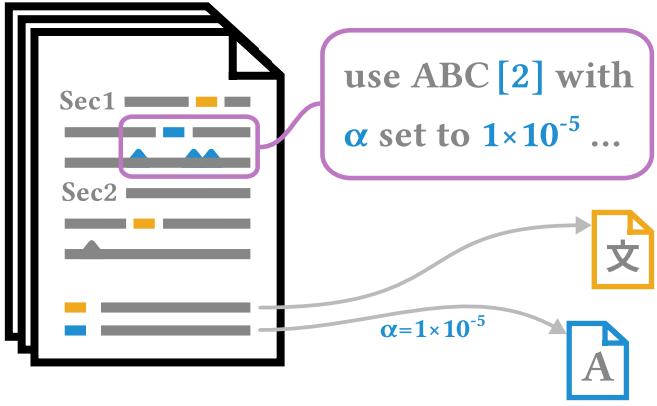
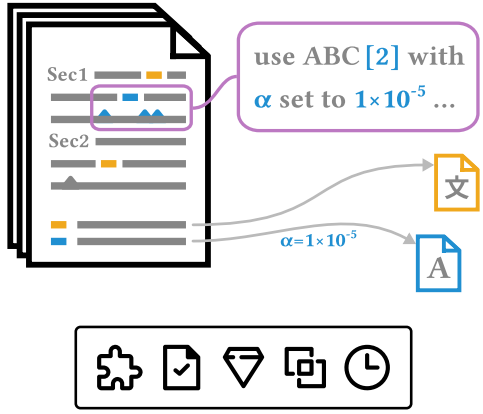


Maps of Science



Quality Aspects



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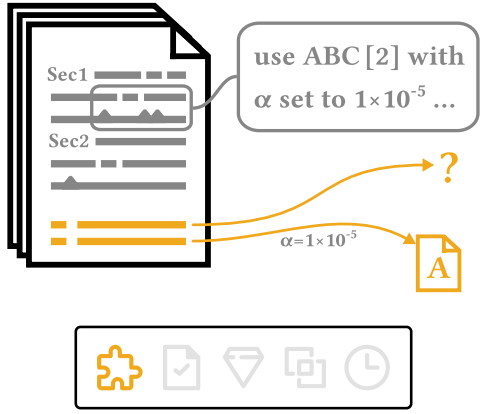

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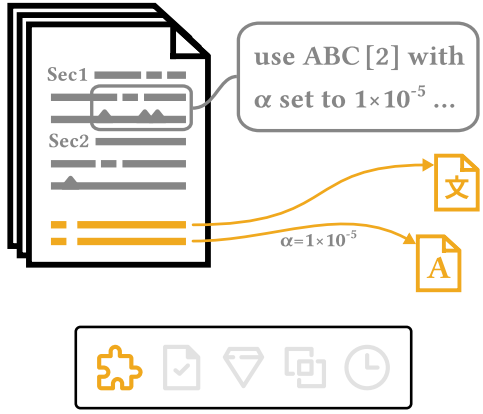

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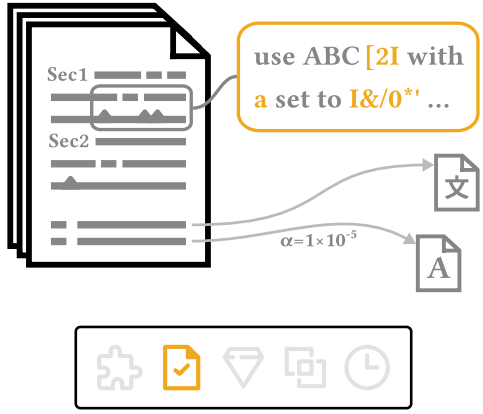

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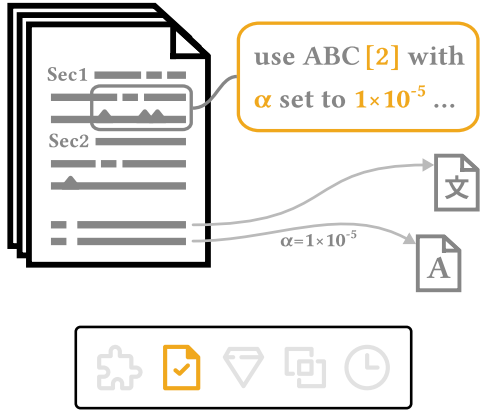

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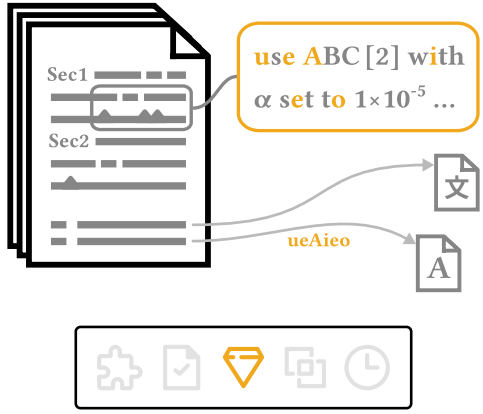

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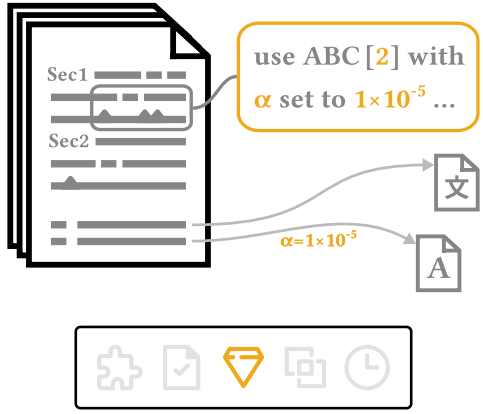

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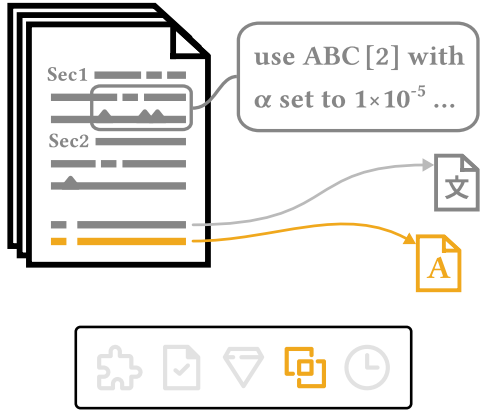

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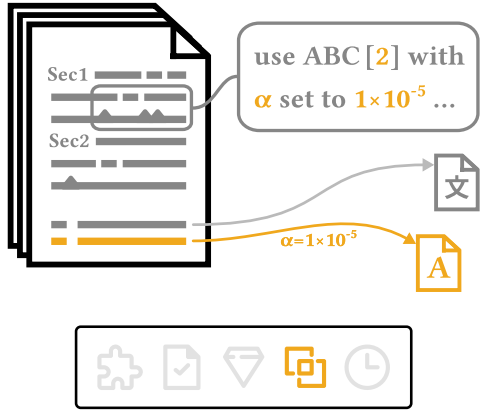

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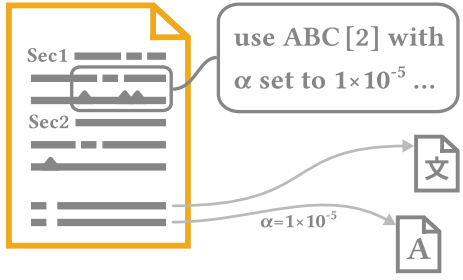

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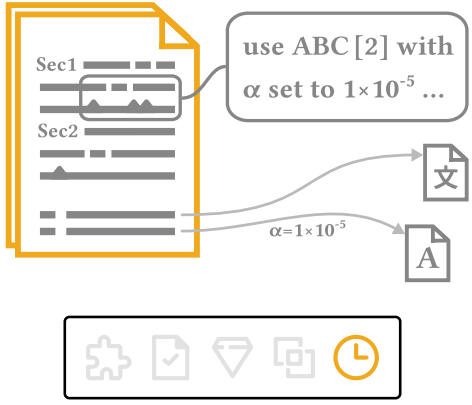

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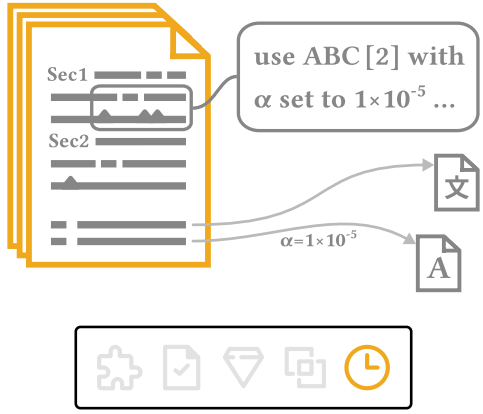
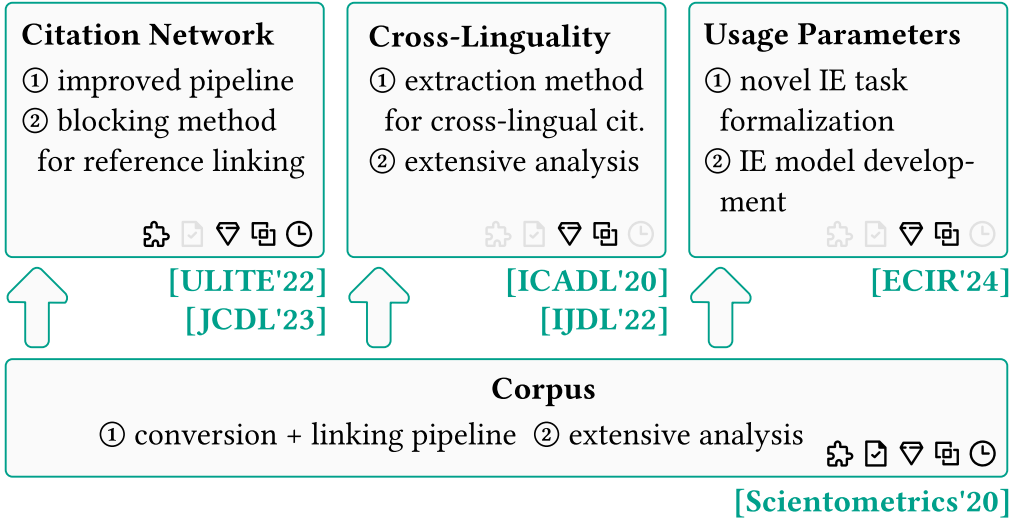


Data Mining and Information Extraction Methods

for Large-Scale High Quality Representations of Scientific Publications


Citation Network
① improved pipeline
② blocking method for reference linking
[ULITE'22]
[JCDL'23]
Cross-Linguality
① extraction method for cross-lingual cit.
② extensive analysis
[ICADL'20]
[IJDL'22]
Usage Parameters
① novel IE task formalization
② IE model development
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Corpus
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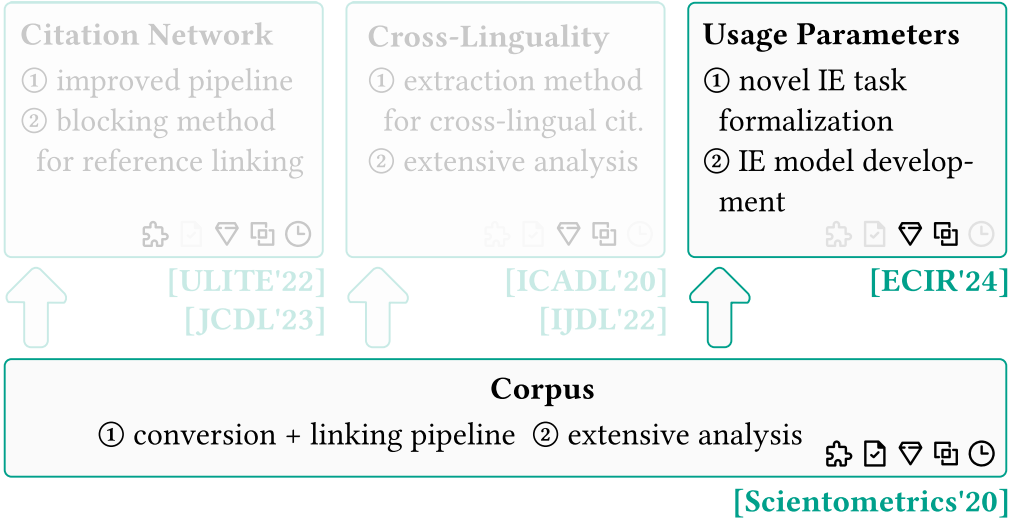
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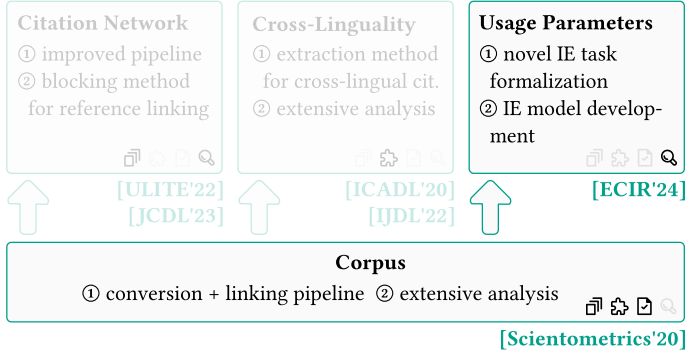
Outline

- **Corpus**
  - Challenges
  - Solutions
  - Resulting Corpus
- **Citation Network**
- **Cross-Linguality**
- **Usage Parameters**
  - Task Definition
  - Methods
  - Results
- **Conclusion**
  - Contributions
  - Impact

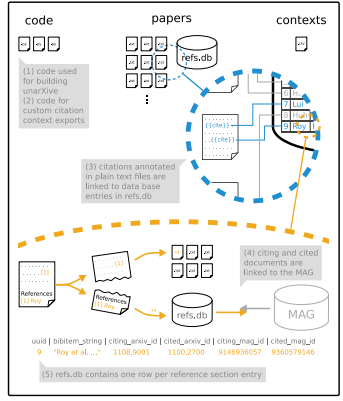


Corpus

unarXive

Corpus - Digest

- **Research gap**
  - Corpus size
  - Data cleanliness
  - Reference linking
- **Approach**
  - Joint handling of text + references
  - Conversion of / IE from LaTeX
  - Reference parsing + linking to MAG
- **Results**
  - Corpus creation methodology
  - More extensive, complete; less noisy data
  - Large corpus for further research



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
  - LaTeXis powerful and people are creative
- **Reference linking**
  - Choice of target set
  - Parsing (`bbl`, not `bib`)
  - Variance and information sparsity

```
\begin{document}
\newcommand{\nc}{\newcommand}
\nc{\be}{\begin{equation}}
\nc{\ee}{\end{equation}}
\nc{\bib}{\bibitem}
```

[10] I. Bonalde et al., Phys. Rev. Lett. **85**, 4775 (2000).

⇕

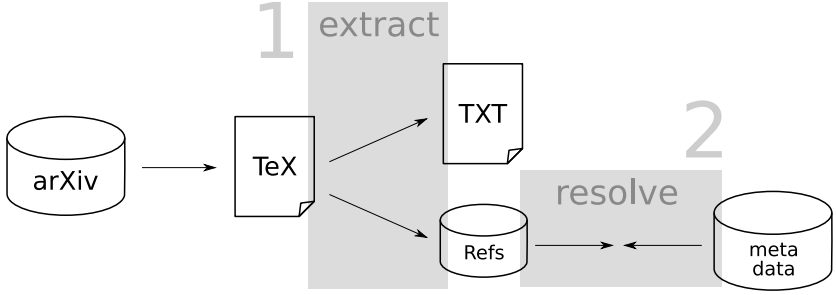
[25] Bonalde I, Yanoff B D, Salamon M B, Van Harlingen D J, Chia E M E, Mao Z Q and Maeno Y 2000 Phys. Rev. Lett. **85** 4775

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

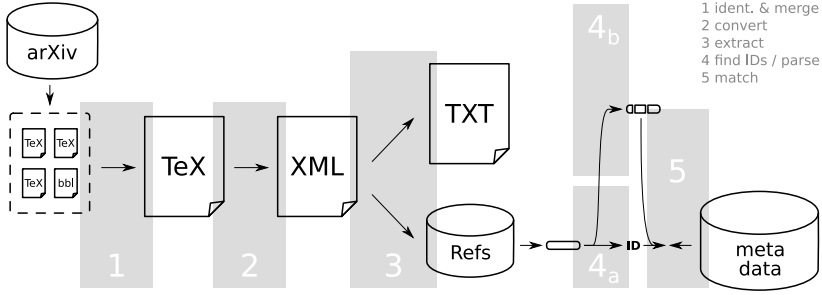
⇕

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 - Solutions



Corpus - Solutions



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	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 (2022)

Data Set	Source		Citation Network[a]		# Docs	Disciplines	Purpose
	Data	Format	general	compare			
CORE [10]	multiple	PDF	0%	-	>100 M	various	general NLP
S2ORC (PDF) [11]	multiple	PDF	69.4%	-	12 M	various	general NLP
unarXive 2020 [1]	arXiv.org	LaTeX	42.6%	42.6%	1.2 M	phys., maths, CS	general NLP
S2ORC (LaTeX) [11]	arXiv.org	LaTeX	31.1%	31.1%	1.5 M	phys., maths, CS	general NLP
arXMLiv [12]	arXiv.org	LaTeX	0%	0%	1.6 M	phys., maths, CS	maths linguistics
SciXGen [13]	arXiv.org	LaTeX	41.6%	-	205 k	CS	text generation
PMC-OAS [7]	PubMed	XML	mixed[b]	-	**3.3 M**	**biomedical**	not NLP specific
unarXive 2022 [14]	arXiv.org	LaTeX	44.4%	**44.4%**	**1.9 M**	**phys., maths, CS**	general NLP

[a] "general": whole data set; not directly comparable. "compare": arXiv.org data from 1991–2020; directly comparable.
[b] No citation network due to mixed set of IDs (PubMed, MEDLINE, DOI) [9].

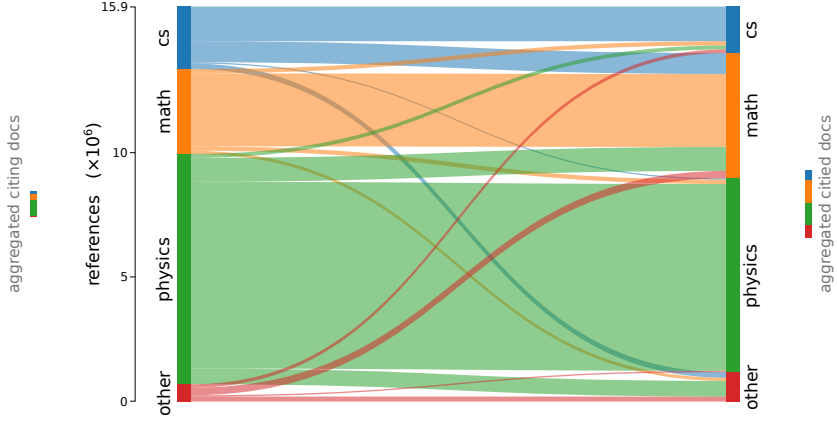
Corpus - Link Correctness

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 - Citation Flow



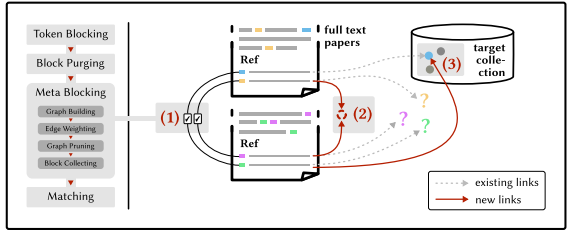
Corpus - Conclusion

- **Advancements**
  - More extensive
    - single domain vs multi domain
    - 90 k vs 1.2 M / 2022: 1.6 M vs 1.9 M
  - More complete, high quality citation network
    - 13.3% increase in matched references
  - Less noise due to LaTeX as source
  - Novel types of analyses possible
- **Foundation for further studies**

Cit. Netw. & Cross-Ling.

Citation Network - Digest

- **Research gap**
  - Reference linking coverage
  - Reliance on target data set
- **Approach**
  - Use unarXive data
  - Improved reference parsing pipeline
  - Blocking approach used within set of references
- **Results**
  - 2% increase in base matching success
  - Manifold increase in bibliographic coupling matches

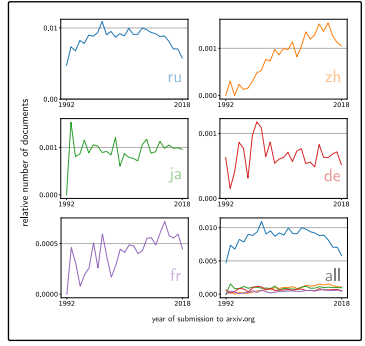


ULITE'22 [16]

JCDL'23 [14]

Cross-Linguality - Digest

- **Research gap**
  - Restriction of existing work to English
  - Limited scale of existing studies
- **Approach**
  - Use unarXive data
  - Document language from raw reference strings
  - Temporal and geographic analyses
- **Results**
  - Reliable method for identification
  - Largest study so far (<1k → >1M)
  - Identification of trends and challenges

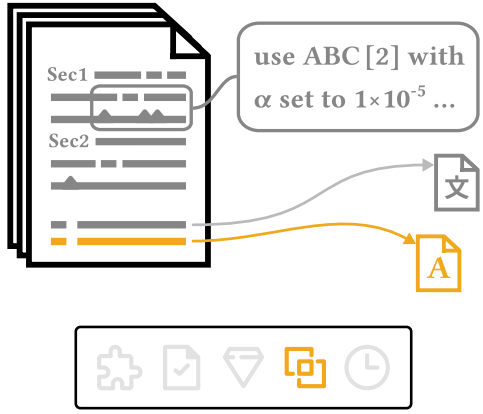


ICADL'20 [17]

IJDL'22 [18]

Parameters

Parameters



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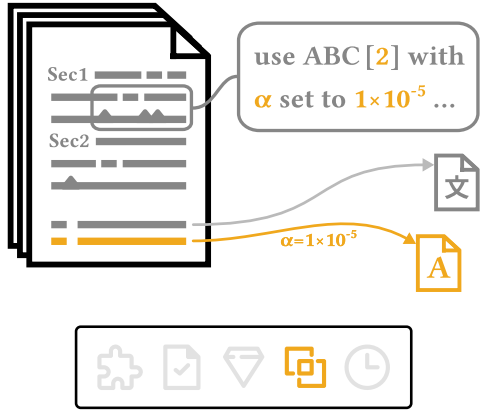
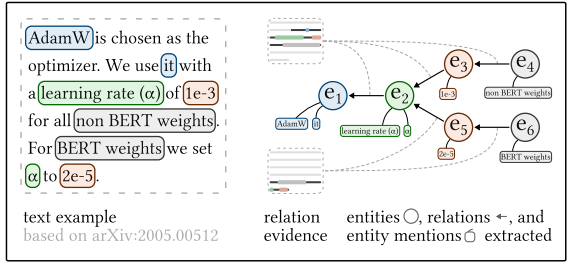


Parameters - Digest

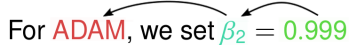
- **Research gap**
  - Important information not considered
  - Lack of link granularity
  - No formalization/approaches
- **Approach**
  - Task formalization
  - Data annotation (data from unarXive)
  - Two lines of approaches
    - BERT based model approach
    - LLM based approach
- **Results**
  - Novel task, novel data
  - Improvements over SOTA baselines



ECIR'24 [19]

Parameters - Task Definition

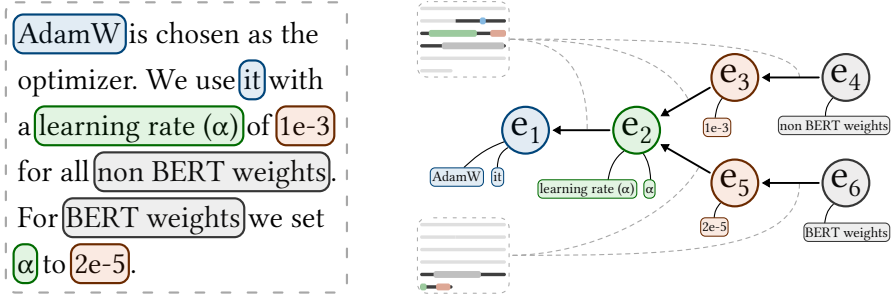
- **Goal**
  - Automatically extract parameter information from paper text
- **Motivation**
  - Reproducibility indication [20], automation [21]
  - Uncover conventions and trends
  - More fine-grained paper representations (similarity measures, recommendation, search)
- **Task Type**
  - (Named) Entity Recognition, Relation Extraction



Parameters - Scope & Annotation Scheme

- 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
- out of scope
  - measurements (*"We obtain an AUC value of 0.75"*)

Scope & Annotation Scheme



text example
based on arXiv:2005.00512

relation evidence

entities ◯, relations ←, and entity mentions ⎙ extracted

Parameters - Data

- Annotation approach
  - Guidelines based on ACL RD-TEC guidelines [22]
  - Paragraph level, whole papers
- Extent
  - 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

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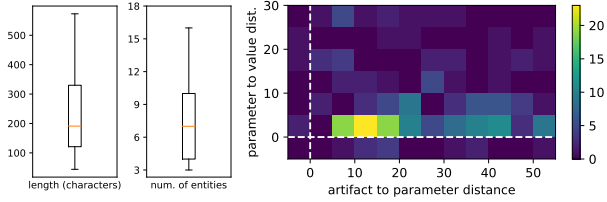
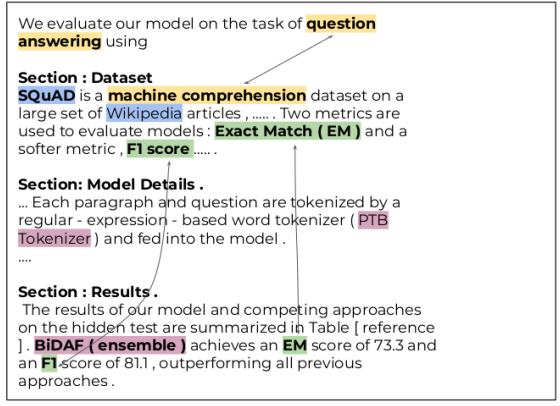


(a) text segments (b) relation distances (#chars)

Figure: Observations of initial annotation round

Parameters - Related Work: Fine-tuned models

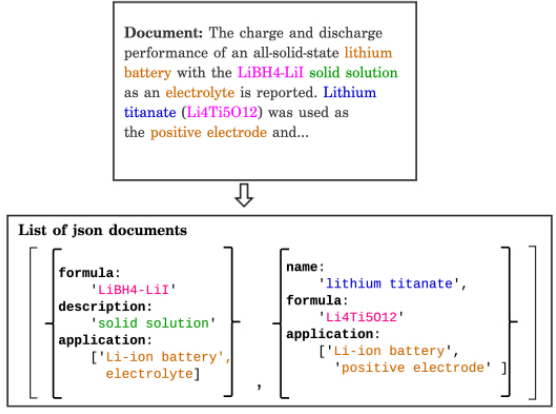
- SciERC dataset
  - SCIIE [23]
  - PL-Marker [24]
  - → **overlap**
- SciREX dataset
  - TempGen [25] (only RE)
- SemEval 2022 (math symb. to descr.)
  - JBNU-CCLab [26]
  - AIFB [27]
- SemEval 2021 (measurements)
  - LIORI [28]
  - → **mention patterns**



Parameters - Related Work: LLMs

- Medical science [29]
  - singular values
  - lists
- Material science [30–32]
  - singular values
  - lists
  - complex [32] (see right)

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

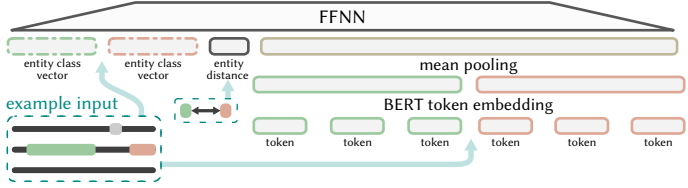


Parameters - Approach

- **Fine-tuned, supervised**
  - PL-Marker (SciERC SOTA)
  - Mention pattern aware RE (ours)
- **LLM, zero-/few-shot**
  - 6 models
  - JSON approach (MatSci)
  - YAML approach (ours)

Parameters - Methods: Fine-tuned models

- Based on PL-Marker
- New RE module
- Include entity class emb. + distance in model input



Parameters - Methods: LLMs

- Test various prompting techniques
  - Multi-stage
  - In-text annitation
  - Data serialization format ✓
- Compare 6 models
- Base prompt + tuning for each
- Few-shot only with Vicuna_{16k}

Model	Variant	Size
WizardLM [33]	`WizardLM-13B-V1.1`	13 B
Vicuna_{4k} [34]	`vicuna-13b-v1.3`	13 B
Vicuna_{16k} [34]	`vicuna-13b-v1.5-16k`	13 B
Falcon [35]	`falcon-40b-instruct`	40 B
GALACTICA [36]	`galactica-120b`	120 B
GPT-3.5 [37]	`text-davinci-003`	175 B

Parameters - Methods: 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:
```

Parameters - Experiments: Fine-tuned models

5-fold cross-validation, stratified sampling

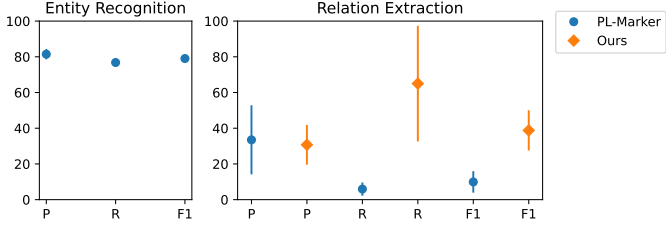


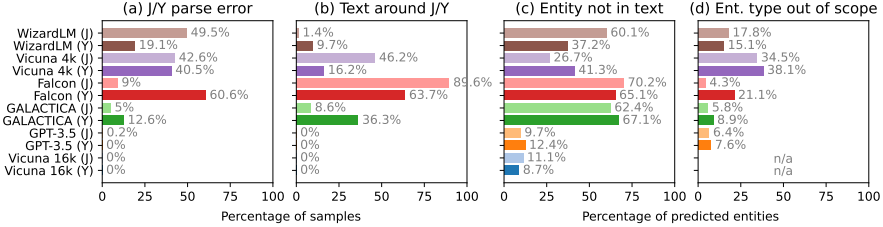
Table: Ablation study results (model inputs are: T = BERT token embeddings, C = entity class embeddings, D = entity distance)

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**

Parameters - Experiments: LLMs

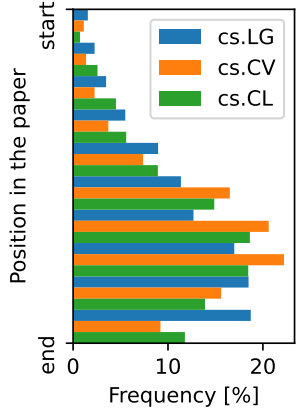
Zero-shot		Entity Recognition			Relation Extraction		
Model	Output	P [%]	R [%]	F_1 [%]	P [%]	R [%]	F_1 [%]
WizardLM	JSON	6.9	11.3	8.6	0.1	0.8	0.1
	YAML	9.7	35.6	15.3 $\Delta_{+6.7}$	0.1	1.5	0.1 $\Delta_{+0.0}$
$Vicuna_{4k}$	JSON	15.1	9.3	11.5	0.7	3.8	1.2
	YAML	17.3	31.5	22.3 $\Delta_{+10.8}$	0.0	0.8	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** $\Delta_{+4.8}$

Parameters - Experiments: LLMs



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 accross disciplines



Parameters - Discussion

- Applicable on large scale
- LLMs not on par with BERT based model
- **Advancements**
  - Task formalization (scope, data scheme, annotation guidelines)
  - High quality manually annotated data set
  - BERT model based approach
    - 29% F_1 increase for RE
  - LLM approach
    - avg. 5.5% F_1 increase for NER
    - consistent across all LLMs

Conclusion

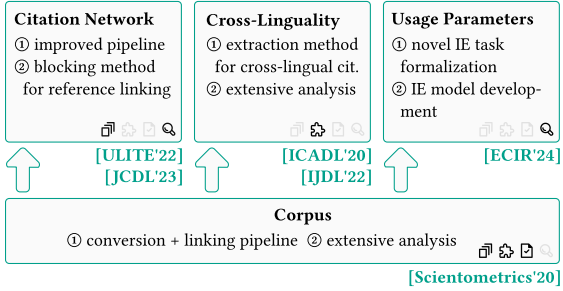
Overall Conclusion

RQ How can large-scale scholarly data be improved?

Overall Conclusion

RQ How can large-scale scholarly data be improved?

like this:



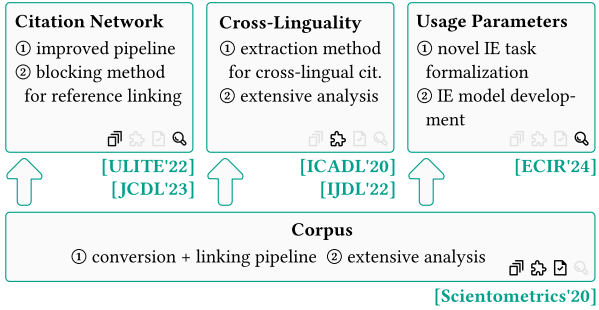
Overall Conclusion

RQ How can large-scale scholarly data be improved?

- Scholarly data from source formats
- Joint handling of docs & references
- Identifier aware references parsing
- Intra references clustering & matching
- Extraction of non-English content
- Identification of cross-lingual references from raw references
- Extraction of usage parameters from full text
- Mention pattern aware relation extraction

Overall Conclusion

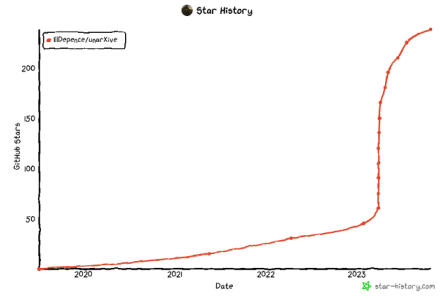
- **Big Picture**
  - Corpus creation method
  - Advances in three focus areas
    - Citation Network
    - Cross-Linguality
    - Usage Parameters
- **Improved**
  - Volume
  - Completeness
  - Correctness
  - Granularity
- **Impact on research community**



Impact

Adoption by the research community.

- **Methodology**
  - Document Parsing Methodology [11]
- **Model dev/eval**
  - Citation Recommendation [38] ([39, 40])
  - Citation Analysis [41, 42] ([17, 18])
  - Document Retrieval [43]
  - Researcher Profile Embeddings [44]
  - Reference Linking ([16])
- **Dataset extension**
  - Link Prediction ([45])
  - NER+RE ([19])



Thank You ☺

Questions?

References I

1. Saier, T. & Färber, M. unarXive: A Large Scholarly Data Set with Publications' Full-Text, Annotated In-Text Citations, and Links to Metadata. *Scientometrics* **125,** 3085–3108. ISSN: 1588-2861 (Dec. 2020).
2. Bird, S. *et al. The ACL Anthology Reference Corpus: A Reference Dataset for Bibliographic Research in Computational Linguistics.* in *Proceedings of the Sixth International Conference on Language Resources and Evaluation* (Marrakech, Morocco, 2008).
3. Radev, D. R., Muthukrishnan, P., Qazvinian, V. & Abu-Jbara, A. The ACL anthology network corpus. *Language Resources and Evaluation* **47,** 919–944 (2013).
4. Sugiyama, K. & Kan, M. A Comprehensive Evaluation of Scholarly Paper Recommendation Using Potential Citation Papers. *International Journal on Digital Libraries* **16,** 91–109 (2015).
5. Caragea, C. *et al. CiteSeer x : A Scholarly Big Dataset.* in *Proceedings of the 36th European Conference on IR Research* (Amsterdam, The Netherlands, 2014), 311–322.
6. Huang, W., Wu, Z., Liang, C., Mitra, P. & Giles, C. L. *A Neural Probabilistic Model for Context Based Citation Recommendation.* in *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence* (AAAI Press, Austin, Texas, 2015), 2404–2410. ISBN: 0-262-51129-0.
7. Of Medicine, B. (N. L. *PMC Open Access Subset.* [Internet]. B. 2003 - [cited 2023 Feb 7]. https://www.ncbi.nlm.nih.gov/pmc/tools/openftlist/.
8. Färber, M., Thiemann, A. & Jatowt, A. *A High-Quality Gold Standard for Citation-based Tasks.* in *Proceedings of the 11th International Conference on Language Resources and Evaluation* (Miyazaki, Japan, 2018).

References II

9. Gipp, B., Meuschke, N. & Lipinski, M. *CITREC : An Evaluation Framework for Citation-Based Similarity Measures based on TREC Genomics and PubMed Central.* in *iConference 2015 Proceedings* (iSchools, 2015).
10. Pontika, N., Knoth, P., Cancellieri, M. & Pearce, S. Developing Infrastructure to Support Closer Collaboration of Aggregators with Open Repositories. *LIBER Quarterly* **25,** 172–188 (Apr. 2016).
11. Lo, K., Wang, L. L., Neumann, M., Kinney, R. & Weld, D. *S2ORC: The Semantic Scholar Open Research Corpus.* in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (Association for Computational Linguistics, July 2020), 4969–4983.
12. Ginev, D. *arXMLiv:2020 dataset, an HTML5 conversion of arXiv.org.* hosted at `https://sigmathling.kwarc.info/resources/arxmliv-dataset-2020/`. SIGMathLing – Special Interest Group on Math Linguistics. 2020.
13. Chen, H., Takamura, H. & Nakayama, H. *SciXGen: A Scientific Paper Dataset for Context-Aware Text Generation.* in *Findings of the Association for Computational Linguistics: EMNLP 2021* (Nov. 2021), 1483–1492. doi:`10.18653/v1/2021.findings-emnlp.128`.
14. Saier, T., Krause, J. & Färber, M. *unarXive 2022: All arXiv Publications Pre-Processed for NLP, Including Structured Full-Text and Citation Network.* in *2023 ACM/IEEE Joint Conference on Digital Libraries (JCDL)* (IEEE Computer Society, Los Alamitos, CA, USA, June 2023), 66–70. doi:`10.1109/JCDL57899.2023.00020`.
15. Brown, L. D., Cai, T. T. & DasGupta, A. Interval Estimation for a Binomial Proportion. *Statistical Science* **16,** 101–133 (2001).
16. Saier, T., Luan, M. & Färber, M. *A Blocking-Based Approach to Enhance Large-Scale Reference Linking.* in *Proceedings of the workshop on understanding literature references in academic full text (ULITE) at JCDL 2022* (June 2022).

References III

17. Saier, T. & Färber, M. *A Large-Scale Analysis of Cross-lingual Citations in English Papers.* in *Digital Libraries at Times of Massive Societal Transition* (Springer International Publishing, 2020), 122–138. ISBN: 978-3-030-64452-9. doi:10.1007/978-3-030-64452-9_11.

18. Saier, T., Färber, M. & Tsereteli, T. Cross-Lingual Citations in English Papers: A Large-Scale Analysis of Prevalence, Formation, and Ramifications. en. *International Journal on Digital Libraries* **23,** 179–195. ISSN: 1432-1300 (June 2022).

19. Saier, T., Ohta, M., Asakura, T. & Färber, M. *HyperPIE: Hyperparameter Information Extraction from Scientific Publications.* in *Advances in Information Retrieval* **14609** (Springer Nature Switzerland, Mar. 2024), 254–269. ISBN: 978-3-031-56060-6. doi:10.1007/978-3-031-56060-6_17.

20. Raff, E. *A Step Toward Quantifying Independently Reproducible Machine Learning Research.* in *Advances in Neural Information Processing Systems* **32** (Curran Associates, Inc., 2019).

21. Sethi, A., Sankaran, A., Panwar, N., Khare, S. & Mani, S. DLPaper2Code: Auto-Generation of Code From Deep Learning Research Papers. *Proceedings of the AAAI Conference on Artificial Intelligence* **32.** doi:10.1609/aaai.v32i1.12326 (Apr. 2018).

22. QasemiZadeh, B. & Schumann, A.-K. *The ACL RD-TEC 2.0: A Language Resource for Evaluating Term Extraction and Entity Recognition Methods.* in *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)* (European Language Resources Association (ELRA), May 2016), 1862–1868.

23. Luan, Y., He, L., Ostendorf, M. & Hajishirzi, H. *Multi-Task Identification of Entities, Relations, and Coreferencefor Scientific Knowledge Graph Construction.* in *Proc. Conf. Empirical Methods Natural Language Process. (EMNLP)* (2018).

References IV

24. Ye, D., Lin, Y., Li, P. & Sun, M. *Packed Levitated Marker for Entity and Relation Extraction.* in *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (Association for Computational Linguistics, May 2022), 4904–4917. doi:10.18653/v1/2022.acl-long.337.

25. Huang, K.-H., Tang, S. & Peng, N. *Document-level Entity-based Extraction as Template Generation.* in *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing* (Nov. 2021), 5257–5269. doi:10.18653/v1/2021.emnlp-main.426.

26. Lee, S.-M. & Na, S.-H. *JBNU-CCLab at SemEval-2022 Task 12: Machine Reading Comprehension and Span Pair Classification for Linking Mathematical Symbols to Their Descriptions.* in *Proceedings of the 16th International Workshop on Semantic Evaluation (SemEval-2022)* (July 2022), 1679–1686. doi:10.18653/v1/2022.semeval-1.231.

27. Popovic, N., Laurito, W. & Färber, M. *AIFB-WebScience at SemEval-2022 Task 12: Relation Extraction First - Using Relation Extraction to Identify Entities.* in *Proceedings of the 16th International Workshop on Semantic Evaluation (SemEval-2022)* (July 2022), 1687–1694. doi:10.18653/v1/2022.semeval-1.232.

28. Davletov, A., Gordeev, D., Arefyev, N. & Davletov, E. *LIORI at SemEval-2021 Task 8: Ask Transformer for measurements.* in *Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021)* (Aug. 2021), 1249–1254. doi:10.18653/v1/2021.semeval-1.178.

29. Agrawal, M., Hegselmann, S., Lang, H., Kim, Y. & Sontag, D. *Large language models are few-shot clinical information extractors.* in *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing* (Dec. 2022), 1998–2022.

30. Xie, T. *et al. Large Language Models as Master Key: Unlocking the Secrets of Materials Science with GPT.* Apr. 2023. doi:10.48550/arXiv.2304.02213.

References V

31. Polak, M. P. & Morgan, D. *Extracting Accurate Materials Data from Research Papers with Conversational Language Models and Prompt Engineering – Example of ChatGPT.* Mar. 2023. doi:10.48550/arXiv.2303.05352.
32. 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.
33. Xu, C. *et al. WizardLM: Empowering Large Language Models to Follow Complex Instructions.* 2023.
34. Chiang, W.-L. *et al. Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%* ChatGPT Quality.* Mar. 2023. https://lmsys.org/blog/2023-03-30-vicuna/.
35. Almazrouei, E. *et al. Falcon-40B: an open large language model with state-of-the-art performance.* 2023.
36. Taylor, R. *et al. GALACTICA: A Large Language Model for Science.* 2022.
37. Brown, T. B. *et al. Language Models Are Few-Shot Learners.* in *Proceedings of the 34th International Conference on Neural Information Processing Systems* (2020).
38. Meyer, M., Frey, J., Laub, T., Wrzalik, M. & Krechel, D. *Citcom – Citation Recommendation.* in *INFORMATIK 2020* (eds Reussner, R. H., Koziolek, A. & Heinrich, R.) (Gesellschaft für Informatik, Bonn, 2021), 907–914. doi:10.18420/inf2020_82.
39. Saier, T. & Färber, M. *Bibliometric-Enhanced arXiv: A Data Set for Paper-Based and Citation-Based Tasks.* in *Proceedings of the 8th International Workshop on Bibliometric-enhanced Information Retrieval (BIR) co-located with the 41st European Conference on Information Retrieval (ECIR 2019)* (Cologne, Germany, 2019), 14–26.

References VI

40. Färber, M. & Sampath, A. *HybridCite: A Hybrid Model for Context-Aware Citation Recommendation.* in *Proceedings of the ACM/IEEE Joint Conference on Digital Libraries in 2020* (2020), 117–126. doi:10.1145/3383583.3398534.

41. Veneri, M. D. *et al.* How Have Astronomers Cited Other Fields in the Last Decade? *Research Notes of the AAS* **6,** 113 (June 2022).

42. Xue, J. *An analysis of the semantic shifts of citations.* MA thesis (University of Helsinki, Faculty of Science, June 2021). http://urn.fi/URN:NBN:fi:hulib-202107263435.

43. Parisot, M. & Zavrel, J. *Multi-objective Representation Learning for Scientific Document Retrieval.* in *Proceedings of the Third Workshop on Scholarly Document Processing* (Association for Computational Linguistics, Gyeongju, Republic of Korea, Oct. 2022), 80–88. https://aclanthology.org/2022.sdp-1.9.

44. Mochihashi, D. *Researcher2Vec: Neural Linear Model of Scholar Recommendation for Funding Agency.* in *Proceedings of the International Society of Scientometrics and Informetrics Conference 2023* (July 2023).

45. Saier, T., Dong, Y. & Färber, M. *CoCon: A Data Set on Combined Contextualized Research Artifact Use.* in *2023 ACM/IEEE Joint Conference on Digital Libraries (JCDL)* (IEEE Computer Society, Los Alamitos, CA, USA, June 2023), 47–50. doi:10.1109/JCDL57899.2023.00016.

46. Jurgens, D., Kumar, S., Hoover, R., McFarland, D. & Jurafsky, D. Measuring the Evolution of a Scientific Field through Citation Frames. *Transactions of the Association for Computational Linguistics* **6,** 391–406 (2018).

47. Saier, T. & Färber, M. *Semantic Modelling of Citation Contexts for Context-Aware Citation Recommendation.* in *Advances in Information Retrieval* (Springer International Publishing, 2020), 220–233. doi:10.1007/978-3-030-45439-5_15.

References VII

48. Krause, J., Shapiro, I., Saier, T. & Färber, M. *Bootstrapping Multilingual Metadata Extraction: A Showcase in Cyrillic.* in *Proceedings of the Second Workshop on Scholarly Document Processing* (Association for Computational Linguistics, Online, June 2021), 66–72. doi:10.18653/v1/2021.sdp-1.8. https://aclanthology.org/2021.sdp-1.8.

49. Shapiro, I., Saier, T. & Färber, M. *Sequence Labeling for Citation Field Extraction from Cyrillic Script References.* in *SDU 2022: Scientific Document Understanding 2022; Proceedings of the Workshop on Scientific Document Understanding; co-located with 36th AAAI Conference on Artificial Inteligence (AAAI 2022)* (Mar. 2022).

50. Nishioka, C., Färber, M. & Saier, T. *How Does Author Affiliation Affect Preprint Citation Count? Analyzing Citation Bias at the Institution and Country Level.* in *Proceedings of the 22nd ACM/IEEE Joint Conference on Digital Libraries* (Association for Computing Machinery, 2022). ISBN: 9781450393454. doi:10.1145/3529372.3530953.

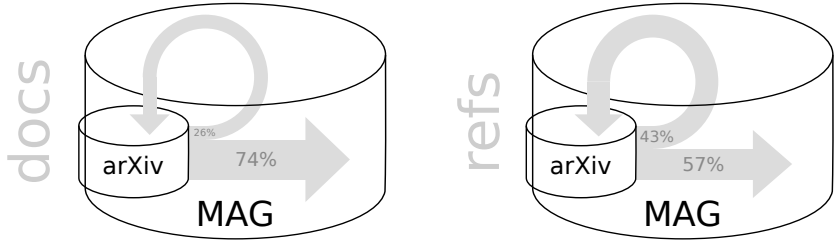
Extra Slides

Corpus - Stats

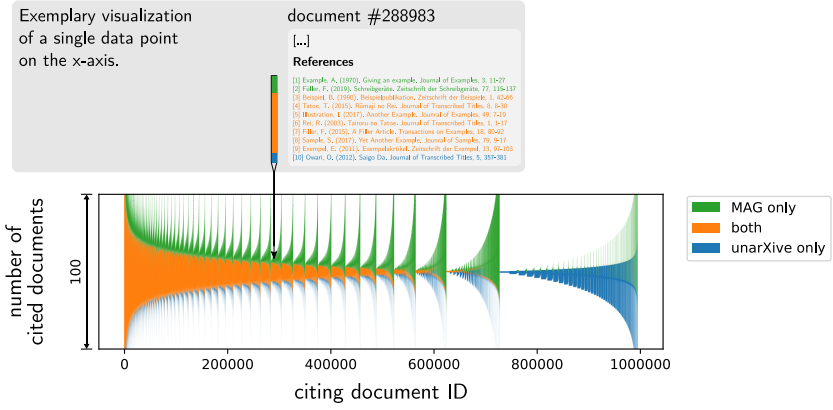
	citing documents	references		cited documents
		outgoing	incoming	
full data set:	**1,043,126**	15,954,664	15,954,664	**2,746,288**
full text	1,043,126	15,954,664	7,181,576	736,597
linked to MAG	994,351	15,846,351	15,954,664	2,746,288
by discipline:				
physics	662,894	9,300,576	7,827,072	921,852
mathematics	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	$\underline{\text{Math}^{\dagger} \rightarrow \text{Math}^{\ddagger}}$	200,859	5.41	6.81
	$\text{Math}^{\dagger} \rightarrow \text{CS}$	5,134	92.13	2.96
	$\text{Math}^{\dagger} \rightarrow \text{Phys}$	3,114	89.88	1.75
	$\text{CS} \rightarrow \text{Math}^{\ddagger}$	3,456	18.82	0.41
	$\text{Phys} \rightarrow \text{Math}^{\ddagger}$	3,859	16.49	0.40
	$\underline{\text{CS} \rightarrow \text{CS}}$	2,500	11.38	0.18
	$\underline{\text{Phys} \rightarrow \text{Phys}}$	10,374	2.12	0.14
	$\underline{\text{CS} \rightarrow \text{Phys}}$	50	307.16	0.10
	$\text{Phys} \rightarrow \text{CS}$	137	101.40	0.09

[a] †: Mathematics citing document, ‡: Mathematics cited document, $\underline{\text{X} \rightarrow \text{X}}$: Citing and cited document are from the same discipline).

Parameters - Motivation

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)

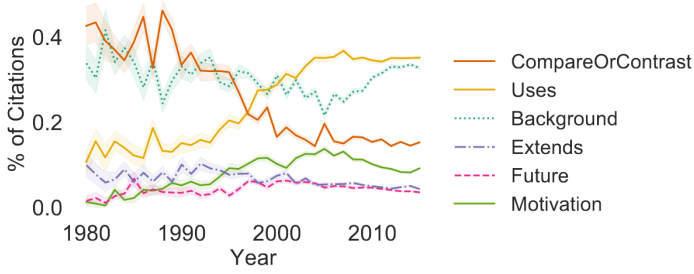
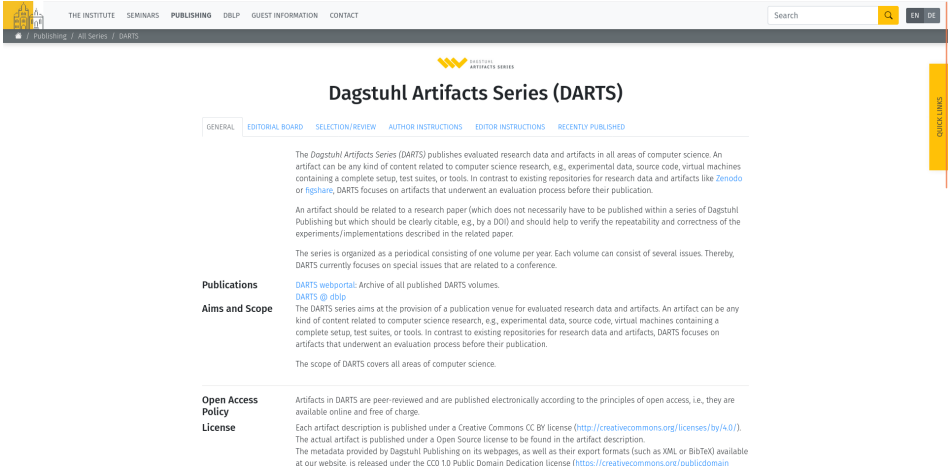


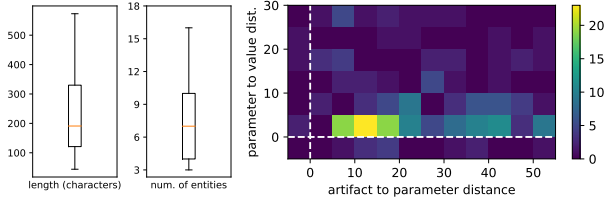
Figure 5: Changes in the average citation frame in ACL papers reveals a continued decline in the percentage of COMPARISON OR CONTRAST and increase in USES citations. The increase in BACKGROUND citations circa 2010 marks the start of the era of unlimited references in ACL conferences. Shaded regions show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

Parameters - Motivation



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

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)	*	Conference	Full	1 of 4	Core A	[19]

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	[39]
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*	[45]

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 [39] and [48], which constitute the results of the master's thesis preceding the doctoral research period, paved the way for the dissertation.

Limitations

- **Corpus**
  - LaTeXrequired (no humanities)
- **Cit. Netw.**
  - Blocking method scalability
- **Cross.-Ling.**
  - Single “direction”
  - Dependency on author notation
- **Parameters**
  - IE from text, not tables, code, etc.
  - ML specific
  - English only