Master's Thesis

Semantic approaches to citation recommendation

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April 30th, 2019

Writing Period

15. 10. 2018 – 30. 04. 2019

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30. April 2019

Bearbeitungszeit

15. 10. 2018 – 30. 04. 2019

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Declaration

I hereby declare, that I am the sole author and composer of my thesis and that no other sources or learning aids, other than those listed, have been used. Furthermore, I declare that I have acknowledged the work of others by providing detailed references of said work. I hereby also declare, that my Thesis has not been prepared for another examination or assignment, either wholly or excerpts thereof.

Place, Date

Signature

Abstract

foo bar

Zusammenfassung

fu bar

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1 Introduction

1.1 Motivation

Citations are a central building block of scholarly discourse. They are the means by which scholars relate their research to existing work—be it in backing up claims, criticising, naming examples or engaging in any other form. Citing in a meaningful way requires an author to be aware of publications relevant to their work. Here, the ever increasing amount of new reseach publications per year poses a serious challenge. Even with academic search engines like Goolge Scholar and CiteSeerX at our disposal, identifying publications that are worthwhile to examine and appropriate to reference remains a time consuming task.

It is therefore not suprising that methods to aid researchers in these tasks have been and still are being actively researched. While diverse in nature, the common core of these efforts is the goal to utilize the automated processing of publications. This can be achieved by either extracting information from publications as they are [1, 2], or by introducing explicit semantic representations of their content to facilitate automated processing [3, 4]. Once processed, a typical method is to harvest human made citations, analyze them [5, 6] and use them for example to recommend papers [2] or aid in document exploration [7]. Although systems like this have existed for over 20 years [8, 2], there is not a lot of work looking into the use of explicit semantic representations for the recommendation of papers. This is why this thesis will investiage their application. More specifically, we will concentrate on the task of recommending papers for citation—as opposed to, for example, discovery. What this encompasses will be described in more detail in the following section.

1.2 Problem setting

In the boradest sense, recommending papers for citation means given an input text, suggest publications that can be referred to from within that text. In scale this can vary from specific recommendations for a section of a sentence (*local* or *context-based*), to general recommendations for a whole input document (*global*). The task can also include deciding whether or not the input contains parts that would justify inserting a citation in the first place [9]. In this thesis, we will focus on local citation recommendation with the assumption that the input always allows for/requires a citation to be put in.

Another distinction to be made is between personalized and general citation recommendation. Some approaches make use of user specific information such as an author's prior citations. Collaborative filtering approaches by nature include a user model and therfore fall into this category. While personalization can improve recommendation, it limits the approach to users that are willing to share personal information. We therefore limit ourselves to purely content based filtering approaches.

A last clarification has to be made concerning the term *explicit semantic representations*. This is to be understood as a differentiation from the mere use of unstructured text. A most prominent example for explicit semantic representations would be the structure of the Semantic Web [10]. In the context of citation recommendation as briefly outlined above this means representing citations in a semantically meaningful way as opposed to just relying on syntactical information like n-grams or bag-of-words representations.

The problem setting can be summarized as follows. To investigate is, the applicability of and requirements for the use of explicit semantic representations for content based, local citation recommendation. The following section will outline how this investigation is performed.

1.3 Method

In order to assess if and how explicit semantic representations can benefit citation recommendation we investigate the use of named entities as well as claim structures. For the evaluation of our models in a realistic setting we generate a large data set that allows for the extraction of precise citation marker positions. To ensure comparability with other approaches we also perform evaluations on existing data sets as far as possible.

Extend to mention offline and online eval

Extend moar

1.4 Contributions

The data set

Two models (even though they don't perform that well)

Insights into open problems with building claim models around citations (b/c of non-integral citation styles)

1.5 Document structure

foo bar

Copypasta of useful stuff below.

- Put a tilde (nbsp) in front of citations [11].
- **(TODO: Do this!)**
- **(EXTEND: Write more when new results are out!)**
- **(DRAFT: Hacky text!)**

- Chapter 1
- the colors of the Uni
  - UniBlue
  - UniRed
  - UniGrey
- a command for naming matrices $\mathbf{G}$, and naming vectors $\mathbf{a}$. This overwrites the default behavior of having an arrow over vectors, sticking to the naming conventions normal font for scalars, bold-lowercase for vectors, and bold-uppercase for matrices.
- named equations:

$$d(a, b) = d(b, a) \tag{1}$$

symmetry

- Use “these” for citing, not "these"
- If an equation is at the end of a sentence, add a full stop. If it’s not the end, add a comma: $a = b + c \quad (1)$,
- `https://en.wikipedia.org`
- Do not overuse footnotes[1] if possible.

[1] `https://en.wikipedia.org`

2 Related Work

To the best of our knowledge there is, so far, almost no work investigating (1) the use of explicit senamtic representations for (2) the task of local citation recommendation. We will therefore present related work in two areas. First, semantic approaches to citation/paper recommendation in general (global as well as local). Second, local citation recommendation regardless of the specifics of the approach taken.

Note that SemCir [12] (see below) is the only case of a semantic approach to local citation recommendation we are aware of. The explicit semantic representations are, however, not generated from citation contexts (local) but from papers (global) that are textually (not necessarily semantically) similar to the citation contexts.

2.1 Semantic approaches to citation recommendation

At a point in time where publishing research papers online was an emerging trend, Middleton et al. [13] propose a system for paper recommendation making use of a topic ontology. Based on classifying papers into topics and recording which papers a researcher would access on the web, they employ content-based filtering, collaborative filtering and a feedback mechanism to suggest papers from new topics to users. Comparing the topic ontology to a flat list of topics in two user studies, they report 7–15% more user satisfaction for the ontology case.

In a similar vein, Zhang et al. [14] propose a hybrid recommender system for papers based on semantic concept similarity. They derive concepts from CiteULike[1] tags and use these to measure the semantic similarity of papers and users' interest. In their evaluation they compare different settings of the approach but do not compare to other work or alternative techniques.

Jiang et al. [15] use CiteULike tags as academic concepts to build a topic model applied to paper abstracts. In a content-based recommendation setting they let volunteers judge the relevance of recommendations for a test set of 30 papers. The evaluation includes a TFIDF baseline, latent Dirichlet allocation (LDA) and an approach combining LDA with their concept model. The reported MAP@5 and NDCG@5 values are best for the LDA+concept method.

In [16] Zarrinkalam et al. enrich their metadata on research papers using multiple Linked Open Data (LOD) sources to drive a hybrid recommender system. They compare a purely content-based method using only text similarity with a second method additionally utilizing collaborative filtering and a third method furthermore using the LOD enriched data. They report recall, co-cited probability and NDCG values for various cut-off values for which the LOD enriched method consistently achieves the best performance.

With SemCiR [12] Zarrinkalam et al. introduce a content-based, global citation recommendation approach that utilizes a semantic distance measure between papers. They furthermore introcude a method for extending the measure to determine the semantic distance between an input text and a paper, which is achieved by representing the input by textually similar papers. The distance measure suggested builds on six different relational features including shared authors, venue, and overlapping in- and outgoing citations. The approach is evaluated on a 12,500 paper subset of CiteSeerX [17] in a citation re-prediction setting, using as input a paper's title, abstract and contexts in other papers where it was referred to. An evaluation of different scenarios measuring recall, co-cited probability and NDCG leads the authors to conclude that recommendation results can be improved by

[1] See `http://citeulike.org/`.

using their semantic distance measure and including citation contexts in the measurement textual similarity.

2.2 Local citation recommendation

Probably one of the first investigations into local citation recommendation is the work of He et al. [18]. They propose a two-step system that first identifies recommendation candidates and then re-ranks them by concept similarity. While also discussing global citation recommendation in detail, for the local case they compare recommending for a single context and recommending for all contexts within a document simultaneously. In an evaluation on the CiteSeerX data set measured by recall, co-cited probability and NDCG they find that the single context task is harder, but also, that their approach to the all contexts task achieves results comparable to and even better than some global citation recommendation methods.

In a follow-up work Huang et al. [19] build upon above work by swapping out the computationally complex concept based re-ranking method with a translational model. In this model citation contexts are treated as the source language and cited papers as words in the target language. The resulting system, RefSeer, is evaluated on two smaller data sets (CiteULike and a CiteSeer subset) and one large one (all of CiteSeer). The authors report precision, recall, Bpref and MRR values for the two smaller data sets and conclude that their system can give correct recommendations in a realistic setting—such as when only the top 10 recommendations are shown.

Huang et al. improve RefSeer with a neural probabilistic model that learns distributed representations of words and documents in [20]. They evaluate their model for local citation recommendation on the whole of CiteSeer, splitting between train and test set at the year 2011 (9M contexts train, 1.5M contexts test). Measuring MAP, MRR and NDCG they show that their model outperforms 4 different state-of-the-art approaches. An analysis on the

influence of papers' citation counts on recommendation performance shows that their approach especially exceeds other work in case of lesser cited papers (<100 citations).

In [21] Duma et al. test the effectiveness of using a variety of document internal and external text inputs to a TF-IDF model. Their data set is built from the ACL Anthology and contains 5446 citations. In a re-prediction setting the authors measure how reliably their models rank the correct paper at the top position. They conclude that a mixture of internal and external inputs outperforms either of the aforementioned used on their own.

The work presented in [22] by Duma et al. focusses on the rethorical function of sentences. The authors classify sentences using the Core Scientific Concepts (CoreSC) scheme and investigate how their distinction can be used to improve recommendation. Evaluating on one million papers from the PubMed Central Open Access Subset they measure NDCG values and find that for several classes of input sentences significant gains in recommendation quality can be made by focussing on certain rethoric passages of candidate documents when ranking text similarity.

The Neural Citation Network (NCN) proposed by Ebesu et al. in [23] is inspired by neural machine translation, learns citation context representations as well as auhtor representations and includes an attention mechanism. For their evaluation the authors use 4.5 million citation contexts from the RefSeer data set and report NDCG, MAP, MRR and recall values. They compare against a BM25 baseline, a citation translation model as well as two variations of their model that do not make use of author representations. While BM25 is outperformed by all of the other approaches to some degree the NCN's results lead the evaluation by a distinct margin.

Kobayashi et al. [24] describe a variation of local citation recommendation they call *context-based co-citation recommendation*. The input here is a citation context *plus* one publication referred to in that contexts. The goal then is to recommend other publications that also can be used as citations in that contexts. By classifying text sections into the discourse facets "objective", "method", and "result" the authors are able to train distributed vector

representations per facet which are then used for the recommendation. They evaluate their approach on contexts from the ACL Anthology containing "enumerated co-citations" (e.g. *[27,42]*) and report NDCG values at a cut-off of 100. In comparison with two baseline methods their discourse facets are shown to be effective.

In [25] Jeong et al. introduce an appraoch to local citation recommendation using Graph Convolutional Networks (GCN) and Bidirectional Encoder Representations from Transformers (BERT). The GCN is used to capture information from the citation relationships between papers, while the pre-trained BERT is applied on the citation contexts themselves. The authors evaluate their approach on a subset of 6500 papers from the ACL Anthology and a self-created data set of close to 5000 papers. They report MAP, MRR and recall values at different cut-offs demostrating that their BERT+CGN approach outperforms several reduced versions of the aforementioned as well as a baseline model.

3 Background

explain all the things.

Algorithm 1 Stochastic Gradient Descent: Neural Network

Create a mini batch of m samples $\mathbf{x}_0 \dots \mathbf{x}_{m-1}$
foreach sample $\mathbf{x}$ **do**
  $\mathbf{a}^{\mathbf{x},0} \leftarrow \mathbf{x}$ ▷ Set input activation
  foreach Layer $l \in \{1 \dots L-1\}$ **do** ▷ Forward pass
    $\mathbf{z}^{\mathbf{x},l} \leftarrow \mathbf{W}^l \mathbf{a}^{\mathbf{x},l-1} + \mathbf{b}^l$
    $\mathbf{a}^{\mathbf{x},l} \leftarrow \varphi(\mathbf{z}^{\mathbf{x},l})$
  end for
  $\boldsymbol{\delta}^{\mathbf{x},L} \leftarrow \nabla_{\mathbf{a}} C_{\mathbf{x}} \odot \varphi'(\mathbf{z}^{\mathbf{x},L})$ ▷ Compute error
  foreach Layer $l \in L-1, L-2 \dots 2$ **do** ▷ Backpropagate error
    $\boldsymbol{\delta}^{\mathbf{x},l} \leftarrow ((\mathbf{W}^{l+1})^T \boldsymbol{\delta}^{\mathbf{x},l+1}) \odot \varphi'(\mathbf{z}^{\mathbf{x},l})$
  end for
end for
foreach $l \in L, L-1 \dots 2$ **do** ▷ Gradient descent
  $\mathbf{W}^l \leftarrow \mathbf{W}^l - \frac{\eta}{m} \sum_{\mathbf{x}} \boldsymbol{\delta}^{\mathbf{x},l} (\mathbf{a}^{\mathbf{x},l-1})^T$
  $\mathbf{b}^l \leftarrow \mathbf{b}^l - \frac{\eta}{m} \sum_{\mathbf{x}} \boldsymbol{\delta}^{\mathbf{x},l}$
end for

4 Data set

Recommender systems rely on data for their development, training and evaluation. It is therefore important to properly assess potential data sets in terms of their strengths and shortcomings—especially with regards to the task at hand. In citation recommendation, the goal is to identify papers relevant to a user input. Because of the large amount of available research, this means a recommender has to be able to find relevant publications in a large set of possible candidates in order to be considered fit for the task. As a comsequence, evaluation results are likely to be more meaningful when a large data set is used. Apart from the size, the quality of data is also crucial. For local citation recommendation this means that a clean citation context, precise position of citaiton markers and valid citation information are desirable. With these criteria in mind we assessed existing data sets, leading us to the conclusion that—for the relatively new task of local citation recommendation—it would be worth the effort to create a new data set.

The following sections describe the details of our assessment as well as the creation process and evaluation of our new data set.

4.1 Existing data sets

Table 1 gives an overview of relevant existing data sets. While various recommendation domains have established quasi standard data sets, this is not yet the case in citation

[1] https://www.ncbi.nlm.nih.gov/pmc/tools/openftlist/
[2] http://www.comp.nus.edu.sg/~sugiyama/SchPaperRecData.html

Table 1: Overview of existing data sets.

Data set	#Papers	Cit. context	Disciplines	Ref. IDs
CiteSeerX [17] / RefSeer [19]	5M	400 chars	(unrestricted)	internal
PubMed Central OAS[1]	2.3M	extractable	Biomed./Life Sci.	mixed
arXiv CS [26]	90K	1 sentence	CS	DBLP
Scholarly v2[2]	100K	extractable	CS	no
ACL-ARC	11K	extractable	CS/Comp. Ling.	no
ACL-AAN	18K	extractable	CS/Comp. Ling.	no

recommendation. CiteSeerX is currently the most used in the field [2]. It is comparatively large, but many approaches only use subsets and generate them with varying filtering criteria. Furthermore, there are several quality issues. The main problems are inaccurate citaion information, noisy citation contexts and cut off words at the borders of citation contexts.

The PubMed Central Open Access Subset is another large data set that has been used for citation based tasks [22, 27, 28, 29]. Contained publications are already processed and available in XML format. While the data set overall is comparatively clean, heterogeneous annotation of citations within the text and mixed usage of global reference identifiers (PubMed, MEDLINE, DOI, ...) make it difficult to retrieve high quality citation interlinkings of documents from the data set[3] [27].

4.2 Data set creation

arXiv operates since 1991[30]

[3]To be more precise, the heterogeneity makes the usage of the data set *as is* problematic. Resolving references retrospectively would be an option but comparatively challenging in the case of PubMed because of the frequent usage of special notation in publication titles; see also: `http://www.sciplore.org/files/citrec/CITREC_Parser_Documentation.pdf`

system to automatically extract citation interlinks from arXiv sources by parsing LaTeX files as early as 1998[31]

survey paper on extraction of meta data (author, year, ...) and classification of sentences (method, goal, ...) from publications[1]

evaluation of reference string parsers[32], a dataset for reference string parsing[33]

4.3 Data set evaluation

Scientific publications are usually distributed in formats targeted at human consumption (e.g. PDF) or, in cases like arXiv.org, also as source files *for* the aforementioned (e.g. LaTeX sources for generating a PDF). Citation recommendation, in contrast, requires automated processing of publications' textual contents as well as documents' interlinking through citations. The creation of a data set for citation recommendation therefore encompasses two main steps: extraction of plain text and resolution of references. In the following we will describe how we approached these two steps using arXiv.org publication sources and the Microsoft Academic Graph (MAG)[34].

4.3.1 arXiv.org sources and the MAG

The following two resources are the basis of the data set creation process.

arXiv.org hosts over 1.4 million submissions from August 1991 onward[4]. They are available not only as PDF, but (in most cases) also as LaTeX source files. The discipline most prominently represented is physics, followed by mathematics, with computer science seeing a continued increase in percentage of submissions ranking third. The availability of

[4]https://arxiv.org/stats/monthly_submissions

LaTeX sources makes arXiv.org submissions particularly well suited for extracting plain text and accurate citation information.

Microsoft Academic Graph is a very large[5], automatically generated data set on publications, related entities (authors, venues, etc.) and their interconnections through citation. While citation contexts are available, full text is not. The size of the MAG makes it a good target for matching reference items against it. Especially given that arXiv.org spans several fields of study.

4.3.2 Pipeline overview

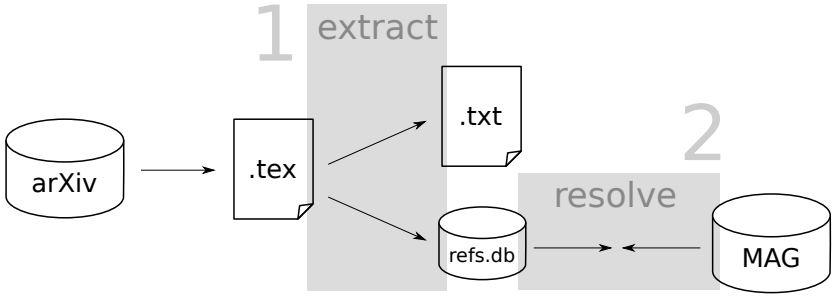
To create the data set we start out with arXiv sources. From these we generate, per publication, a plain text file with the document's textual contents and a set of database entries reflecting the document's reference section[6]. In a second step we then iterate through all reference items in the database and match them against paper metadata records in the MAG (See figure 1). The result of this process are MAG paper records associated with one or more reference items, who in turn are associated with citation contexts in the plain text files. In other words, we end up with descriptions of cited documents, consisting of the sections of citing documents aforementioned are referenced in.

4.3.3 LaTeX parsing

LaTeX code, albeit structured and guided by rules, is written by humans and offers many possibilities and freedoms, which makes parsing it a non trivial task. Moreover, the generation of a large data set necessitates parsing large quantities of LaTeX sources in a limited amount of time. This means fault tolerance, quality of output and speed are three goals for LaTeX parsing. In the following we will describe the tools considered for this task,

[5] At the time of writing the MAG contains data on over 200 million publications.

[6] Association between reference items and citations in the text are preserved by placing citation markers in the text.



(a) subfloat

Figure 1: Schematic representation of the data set generation process.

Table 2: Comparison of tools for parsing LaTeX.

Tool	Output	Robust	Usable w/o modification
plastex[7]	DOM	no	yes
TexSoup[8]	document tree	no	yes
opendetex[9]/detex[10]	plain text	no	yes
GrabCite [26]	plain text + resolved ref.	yes	no
LaTeXML[11]	XML	yes	yes
Tralics[12]	XML	yes	yes

the challenges we faced in general and with regard to arXiv sources in particular and the resulting approach.

Tools

We considered several tools for direct conversion to plain text or to intermediate formats. Table 2 gives an overview.

Based on this evaluation we chose to use Tralics to convert the arXiv sources to XML and from there generate plain text and reference item database records. Compared to LaTeXML the output contained a bit more noise—particularly from LaTeX preambles—but

[7] https://github.com/tiarno/plastex
[8] https://github.com/alvinwan/texsoup
[9] https://github.com/pkubowicz/opendetex
[10] https://www.freebsd.org/cgi/man.cgi?query=detex
[11] https://github.com/brucemiller/LaTeXML
[12] https://www-sop.inria.fr/marelle/tralics/

the immense speed gain would allow for the generation of a large data set in a reasonable time frame.

Challenges

Challenges faced in getting from arXiv sources to plain text range from the source files themselves, over their LaTeX contents to specifics concerning the parsing tool. For some portion of arXiv submissions, LaTeX sources are straight up not available. This can mean that source files are in a different format (like HTML or TeX) or just a PDF is present. In cases where LaTeX sources are available, these have to be correctly identified (file encodings, unorthodox choices of file extensions etc. can be a challenge here) and then can be parsed. In few cases, where the source consists of a single `\includepdf` command, there can be no sensible output. The majority fortunately is proper LaTeX code. Challenges in such cases include the usage of unusual extra packages not included in the source and convoluted (re-)definition of macros. An illustrating and easy to understand case of this is a paper we noticed, where the author chose to create a new command *for the macro* `\newcommand` which they then used to create new commands for adding items to the reference section of the paper.

Detailed description

In a first step we go from the various shapes of sources to a single LaTeX file per arXiv submission. If the source consists of a single file, we determine whether or not it's a LaTeX file. In case of more than one file we search for a main LaTeX file, look if a `.bbl` file is present[13] and then flatten the LaTeX project to a single file using latexpand[14][15]. To

[13] If so, it has to be the same name as the main LaTeX file: https://arxiv.org/help/submit_tex#bibtex

[14] https://ctan.org/pkg/latexpand

[15] We also tested flatex (https://ctan.org/pkg/flatex) and flap (https://github.com/fchauvel/flap) but got the best results with latexpand.

prevent parsing problems later on we then normalize `\cite` and `\bibitem` commands (many papers use variations of these commands defined in e.g. the `natbib` package).

The second step is to convert each LaTeX source to plain text while keeping track of citation markers and reference items. Using Tralics we generate an XML representation of each LaTeX document and replace formulas, figures, tables and non citation references with replacement tokens. The plain text is then extracted, each reference item is assigend a UUID, its text stored in a database and corresponding citation markers are placed in the plain text.

4.3.4 Reference resolution

A single publication's reference section follows a coherent style, many publications can follow many different bibliography styles though. Furthermore, the amount of information included in a reference item is variable and can range from the inclusion of unique identifiers like a DOI up to the omission of the cited work's title. This makes the automated identification of cited documents based on reference items a challenging and still unsolved task[1].

Given it is, by itself, the most distinctive part of a publication, we base our reference resolution on the title of the cited work and use other pieces of information (e.g. authors' names) only in secondary steps. In the following we will describe the challenges we faced, matching arXiv.org submissions' reference items against MAG paper records and how we approached the task.

Challenges

The reference resolution process depends on three pieces. Both data records (arXiv side and MAG side) and the matching procedure. Considering the arXiv side, reference items can be problematic when they do not contain a title or contain formulas in the title. Citing

by only authors, journal name, volume and article number was often observed by us in physics papers. Formulas can become problematic because of inconsistent ways of transcribing them as plain text. One also comes across reference items that are mere comments (and would have probably better been included as footnotes) or ones that refer to non publications. These cases are less problematic because they just fail to match. The most significant challenge on the MAG side is noise. This can either prevent matches or lead to false matches.

The matching procedure ideally has a certain tolerance for minor inconsistencies (abbreviations or typos for example) while remaining accurate. Another requirement, because of the amount of data, is again speed. As every citing document can have many reference items, the number of reference items to process can easily be an order of magnitude higher than the number of citing documents. This circumstance required us to implement the matching procedure in a parallelized fashion which brought its own set of technical challenges.

Detailed description

Our reference resolution approach can be broken down in two steps: title identification and matching. For identification of the title we first look for arXiv IDs and DOIs within the reference item. If such an ID is present we obtain the cited work's title from an arXiv metadata dump or via crossref.org[16] respectively. Otherwise we use Neural ParsCit[?] to identify the portion of the item that makes up the title. Because there are cases where the identified range is just slightly off, we identify several title candidates, beginning with the one identified by Neural ParsCit and then varying the range by a few words. For the matching we then normalize the title the same way the MAG's normalized titles are generated. This means replacing everything not matching the regex word character class `\w` with a space, normalizing modified alphabet characters like umlauts (ö→o) and finally replacing multiple spaces with single ones. The normalized title is matched against all MAG papers. The resulting match candidates are then checked by author names. A candidate

[16] https://www.crossref.org/

is considered good, if at least of of the author's normalized names in the MAG appears in the normalized reference item string. If, after this, still multiple candidates are left, we order them by the citation count given in the MAG and choose the first one. The last step particularly helps to mitigate rouge almost-duplicate entries in the MAG that often have few to no citations.

4.4 Key figures

4.4.1 Creation process

We used an arXiv.org source dump containing all submissions up until the end of 2017 (1,340,770 documents). 100,240 of these were only available in PDF format, leaving 1,240,530 sources. Our pipeline output 1,151,707 (92.8%) plain text files, 1,018,976 (82.1%) of which contained citation markers (for the missing 10% the parsing of `\cite` and `\bibitem` commands most likely failed). The number of reference items identified is 35,053,329, for which 56,077,906 citation markers were placed within the plain text files. This first part of the process took 59 hours to run, unparallalized on a 8 core Intel Core i7-7700 3.60GHz machine with 60 GB of memory.

Of the 35.053.329 reference items, we were able to match 14,046,239 (40.07%). For 33.14% of the reference items we could neither find an arXiv ID or DOI, nor was Neural ParsCit able to identify a title. For the remaining 26.79% a title was identified but could not be matched with the MAG. Of the matched 14 million items' titles, 50.67% were identified via Neural ParsCit. 29.67% by DOI and 19.66% by arXiv ID. Of the identified DOIs 26.8% were found as is while 73.2% were heuristically determined[17]. The matching process took 103 hours, run in 10 parallel processes on a 64 core Intel Xeon Gold 6130 @ 2.10GHz machine with 500 GB of memory.

[17] This was possible because the DOIs of articles in journals of the American Physical Society follow predictable patterns.

Table 3: Confidence intervals for a sample size of 300 with 297 positive results as given by Wilson score interval and Jeffreys interval [35].

Confidence level	Method	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

Quality assessment of matches

To test the quality of our matches we take a random sample of 300 matched reference items and manually check if the correct record in the MAG was identified. For 300 items we note 3 errors, giving us an accuracy estimate of 96% at the worst, as shown in table 3.

The three incorrectly identified references were as follows (MAG IDs in square brackets):

1. *"Eddy, J.A.: 1983, The maunder minimum - a reappraisal. Solar Phys. 89, 195. ADS."*
   - matched: [2024069573]
     "The Maunder Minimum" (John A. Eddy; 1976)
   - correct: [2080336740]
     "The Maunder Minimum: A reappraisal" (John A. Eddy; 1983)
2. *"J. Zhu, S. Rosset, T. Hastie, and R. Tibshirani. 1-norm support vector machines. In Advances in Neural Information Processing Systems (NIPS), volume 16, pages 49–56, 2004."*
   - matched: [2249237221]
     "Support Vector Machines" (Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani; 2013)
   - correct: [2130698119]
     "1-norm Support Vector Machines" (Ji Zhu, Saharon Rosset, Robert Tibshirani, Trevor J. Hastie; 2003)

3. *"D. T. Limmer and D. Chandler. The putative liquid-liquid transition is a liquid-solid transition in atomistic models of water. The Journal of Chemical Physics, 135(13):134503, 2011."*
    - matched: [2599889364]
      "The Putative Liquid-Liquid Transition is a Liquid-Solid Transition in Atomistic Models of Water" (David Chandler, David Limmer; 2013)
    - correct: [1977410206]
      "The putative liquid-liquid transition is a liquid-solid transition in atomistic models of water. II" (David T. Limmer, David Chandler; 2011)

4.4.2 Resulting data set

For the resulting data set we first report the number of cited papers, citing papers, references and citation contexts. Figure 2 illustrates these four types of numbers in a small toy example for ease of understanding. For our data set we ended up with 2,343,585 cited papers, 926.644 citing papers, 13,303,373 references and 24,558,560 citation contexts. Note that these numbers do not reflect the ones reported for the generation process exactly. This is because references can end up with no associated citation contexts due to parsing problems. Such cases are not counted for the data set.

Figure 3 shows the number of citing documents for all cited documents. There is one document with close to 10,000 citations, another 3 with more than 5,000 and another 10 with more than 3,000. 1,262,861 (53.89%) of the documents have at least 2 citations, 547,036 (23.34%) have at least 5. The mean number of citations is 5.68 (SD 26.82). Figure 4 shows the number of citation context per reference. 8,722,795 (65.57%) references have only one citation context, the maximum is 278, the mean 1.85 (SD 2.02). This means a cited document is described by on average $1.85 \times 5.68 \approx 10.5$ citation contexts.

Figure 5 shows the flow of citations by field of study for all 13.3 million matched reference items. Fields of study with very small numbers of references are combined to *other* for

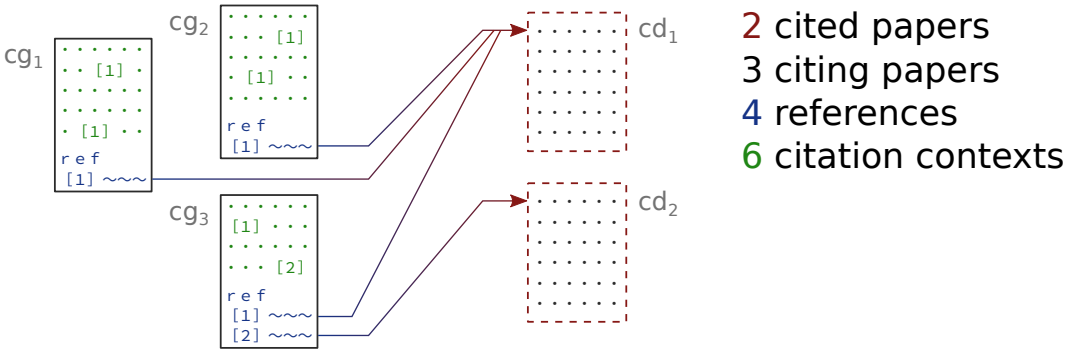


Figure 2: Four types of numbers. A toy example with citation pairs $cg_1 \longrightarrow cd_1$, $cg_2 \longrightarrow cd_1$, $cg_3 \longrightarrow cd_1$, $cg_3 \longrightarrow cd_2$ resulting in 2 cited papers, 3 citing papers, 4 references and 6 citation contexts.

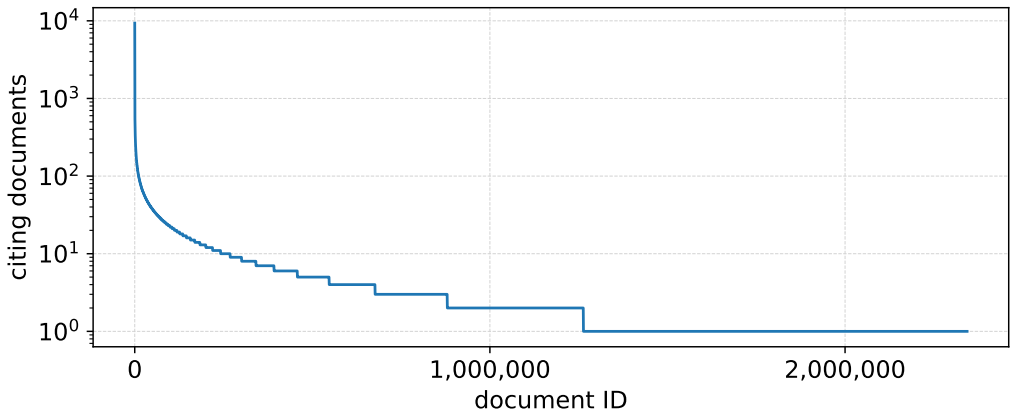


Figure 3: Number of citing documents per cited document.

legibility reasons. For the citing document's side, these are economics, electrical engineering and systems science, quantitative biology, quantitative finance and statistics. Combined on the cited document's side are chemistry, biology, engineering, materials science, economics, geology, psychology, medicine, business, geography, sociology, political science, philosophy, environmental science and art. In rare cases[18] papers in the MAG (cited document's side) can have multiple main fields of study assigned. In such an event we assigned the first one we retrieved from the MAG.

[18]Exact numbers for the whole MAG are as follows: physics 8,682,931; math 6,701,038; cs 14,225,297; cs+math 2,254; math+phys 1,737; phys+cs 287.

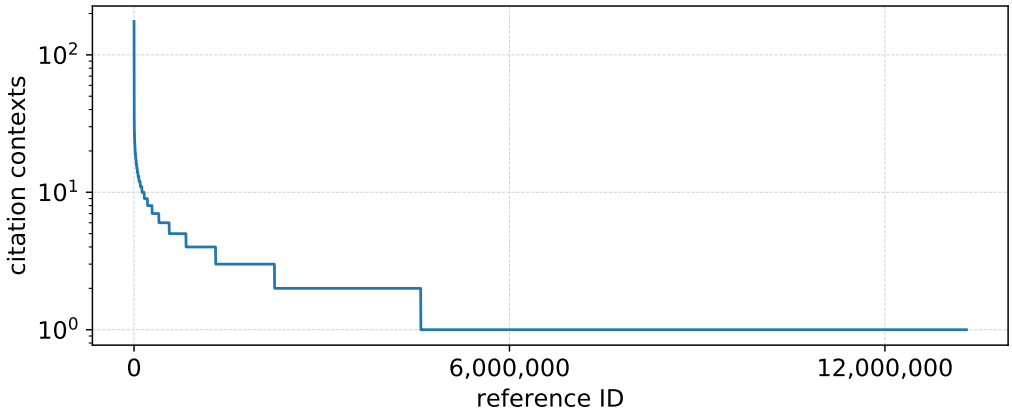


Figure 4: Number of citation contexts per reference.

To no surprise, publications in each field are cited the most from within the field itself. Notable is, however, that the incoming citations in mathematics are the most varied (physics and computer science combined make up 38% of the citations).

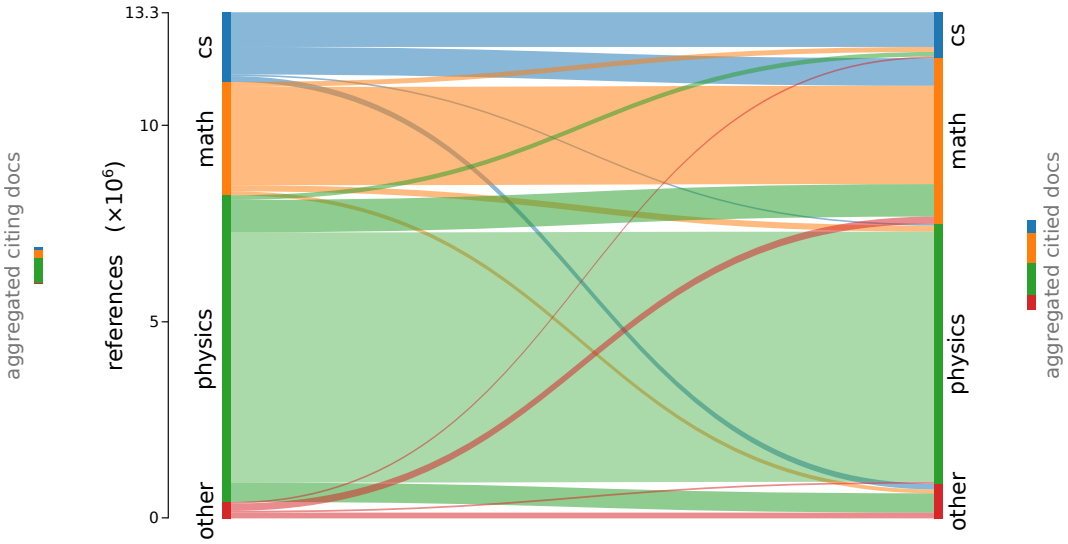


Figure 5: Citation flow by field of study for 13.3 million reference items. For reference, the number of citing and cited documents per field of study are plotted on the sides.

5 Semantic approaches to citation recommendation

types of citations (naming an entity, backing up a claim, etc.)

how citations are embedded in sentences (integral/non-integral[36, 37, 38, 39, 40])

5.1 Fields of Study as names entities

name name

5.2 Claims

5.2.1 Tools for extracting claims

tools tools

also: Survey on open information extraction[41]

context specific claim detection[42]

if only papers where semantically annotated as proposed in [3]

5.2.2 A model of aboutness closely tied to claim structure

predpatt[43, 44]

unfeasibility of use of PredPatt output as is

loosened predicate:parameter model

predicates could be grouped/clustered to represent functions as in [45]

alternative view: model gives a selective citation context derived from claim structure (cf. concept of reference scope as sub part of citation context sentence[46, 47]

6 Evaluation

evaluate evaluate

implemetation pain and bad evaluation scores[48]

6.1 Special considerations for citation recommendation

train/test splitting (per cited doc, temporal, ...), re-recommendation, number of contexts describing a recommendation item, ...

a cited doc's role (how it is cited) can develop over time[49, 50]

relevance of time[51]

candidates are only citations within current paper[21]

6.2 Offline evaluation

pre-filtering experiments (knn[29], lsi, lda, fos, ...)

different evaluation settings (all, CSonly, comparison to MAG, ACL (data from [**?**])...)

FoS alone, restrictively combined w/ BOW, only directly preceeding, ...

PP model alone, combined, ...

-> not *generally* applicable/beneficial but for certain citation types ...

also mention [24] here b/c they specifically target cases where more than one citation is applicable (could be interpreted as either *multiple (simultaneously)* for one context or *several options that are all valid by themselves but in the end a single one is to be chosen* for one contexts)

6.3 Online evaluation

online online

7 Conclusion

conclude conclude.

8 Future work

As a first step identify types of citations more systematically.

For different types, different models.

Proper claim model. (that could also include assessing credibility[52])

Argumentative structures. (Argumentation mining[53, 54, 55])

Bibliography

[1] Z. Nasar, S. W. Jaffry, and M. K. Malik, "Information extraction from scientific articles: a survey," *Scientometrics*, vol. 117, pp. 1931–1990, Dec 2018.

[2] J. Beel, B. Gipp, S. Langer, and C. Breitinger, "Research-paper recommender systems: a literature survey," *International Journal on Digital Libraries*, vol. 17, pp. 305–338, Nov 2016.

[3] S. Buckingham Shum, E. Motta, and J. Domingue, "Scholonto: an ontology-based digital library server for research documents and discourse," *International Journal on Digital Libraries*, vol. 3, pp. 237–248, Oct 2000. r (ch 1-3).

[4] J. Schneider, T. Groza, and A. Passant, "A review of argumentation for the social semantic web," *Semant. web*, vol. 4, pp. 159–218, Apr. 2013.

[5] A. Abu-Jbara, J. Ezra, and D. Radev, "Purpose and polarity of citation: Towards nlp-based bibliometrics," in *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 596–606, Association for Computational Linguistics, 2013.

[6] S. Teufel, A. Siddharthan, and D. Tidhar, "Automatic classification of citation function," in *Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing*, EMNLP '06, (Stroudsburg, PA, USA), pp. 103–110, Association for Computational Linguistics, 2006.

[7] M. Berger, K. McDonough, and L. M. Seversky, "Cite2vec: Citation-driven document exploration via word embeddings," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, pp. 1–1, 01 2016.

[8] K. D. Bollacker, S. Lawrence, and C. L. Giles, "Citeseer: An autonomous web agent for automatic retrieval and identification of interesting publications," in *Proceedings of the Second International Conference on Autonomous Agents*, AGENTS '98, (New York, NY, USA), pp. 116–123, ACM, 1998.

[9] Q. He, D. Kifer, J. Pei, P. Mitra, and C. L. Giles, "Citation recommendation without author supervision," in *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining*, WSDM '11, (New York, NY, USA), pp. 755–764, ACM, 2011.

[10] T. Berners-Lee, J. Hendler, O. Lassila, *et al.*, "The semantic web," *Scientific american*, vol. 284, no. 5, pp. 28–37, 2001.

[11] M. J. Moravcsik and P. Murugesan, "Some results on the function and quality of citations," *Social Studies of Science*, vol. 5, no. 1, pp. 86–92, 1975.

[12] F. Zarrinkalam and M. Kahani, "Semcir: A citation recommendation system based on a novel semantic distance measure," *Program: Electronic Library and Information Systems*, vol. 47, pp. 92–112, 2013.

[13] S. E. Middleton, D. D. Roure, and N. Shadbolt, "Capturing knowledge of user preferences: ontologies in recommender systems," in *K-CAP*, 2001.

[14] M. Zhang, W. Wang, and X. Li, "A paper recommender for scientific literatures based on semantic concept similarity," in *Digital Libraries: Universal and Ubiquitous Access to Information* (G. Buchanan, M. Masoodian, and S. J. Cunningham, eds.), (Berlin, Heidelberg), pp. 359–362, Springer Berlin Heidelberg, 2008.

[15] Y. Jiang, A. Jia, Y. Feng, and D. Zhao, "Recommending academic papers via users' reading purposes," *RecSys'12 - Proceedings of the 6th ACM Conference on Recommender Systems*, 09 2012.

[16] F. Zarrinkalam and M. Kahani, "A multi-criteria hybrid citation recommendation system based on linked data," in *2012 2nd International eConference on Computer and Knowledge Engineering (ICCKE)*, pp. 283–288, IEEE, 2012.

[17] C. Caragea, J. Wu, A. Ciobanu, K. Williams, J. Fernández-Ramírez, H.-H. Chen, Z. Wu, and L. Giles, "Citeseerx: A scholarly big dataset," in *Advances in Information Retrieval* (M. de Rijke, T. Kenter, A. P. de Vries, C. Zhai, F. de Jong, K. Radinsky, and K. Hofmann, eds.), (Cham), pp. 311–322, Springer International Publishing, 2014.

[18] Q. He, J. Pei, D. Kifer, P. Mitra, and L. Giles, "Context-aware citation recommendation," in *Proceedings of the 19th International Conference on World Wide Web*, WWW '10, (New York, NY, USA), pp. 421–430, ACM, 2010.

[19] W. Huang, , P. Mitra, and C. L. Giles, "Refseer: A citation recommendation system," in *IEEE/ACM Joint Conference on Digital Libraries*, pp. 371–374, Sep. 2014.

[20] W. Huang, Z. Wu, C. Liang, P. Mitra, and C. L. Giles, "A neural probabilistic model for context based citation recommendation," in *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, AAAI'15, pp. 2404–2410, AAAI Press, 2015.

[21] D. Duma and E. Klein, "Citation resolution: A method for evaluating context-based citation recommendation systems," in *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, vol. 2, pp. 358–363, 2014.

[22] D. Duma, E. Klein, M. Liakata, J. Ravenscroft, and A. Clare, "Rhetorical classification of anchor text for citation recommendation," *D-Lib Magazine*, vol. 22, 2016.

[23] T. Ebesu and Y. Fang, "Neural citation network for context-aware citation recommendation," in *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '17, (New York, NY, USA), pp. 1093–1096, ACM, 2017.

[24] Y. Kobayashi, M. Shimbo, and Y. Matsumoto, "Citation recommendation using distributed representation of discourse facets in scientific articles," in *Proceedings of the 18th ACM/IEEE on Joint Conference on Digital Libraries*, JCDL '18, (New York, NY, USA), pp. 243–251, ACM, 2018. r (ch 1-2).

[25] C. Jeong, J. Sion, H. Shin, E. Park, and S. Choi, "A context-aware citation recommendation model with bert and graph convolutional networks," 02 2019.

[26] M. Färber, A. Thiemann, and A. Jatowt, "A High-Quality Gold Standard for Citation-based Tasks," in *Proceedings of the 11th International Conference on Language Resources and Evaluation*, LREC 2018, 2018. r.

[27] B. Gipp, N. Meuschke, and M. Lipinski, "Citrec : An evaluation framework for citation-based similarity measures based on trec genomics and pubmed central," in *iConference 2015 Proceedings*, iSchools, 2015.

[28] L. Galke, F. Mai, I. Vagliano, and A. Scherp, "Multi-modal adversarial autoencoders for recommendations of citations and subject labels," in *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*, UMAP '18, (New York, NY, USA), pp. 197–205, ACM, 2018.

[29] C. Bhagavatula, S. Feldman, R. Power, and W. Ammar, "Content-based citation recommendation," in *NAACL-HLT*, 2018.

[30] P. Ginsparg, "First steps towards electronic research communication," *Computers in Physics*, vol. 8, pp. 390–396, July 1994.

[31] H. Nanba, "Towards multi-paper summarization using reference information," Master's thesis, Japan Advanced Institute of Science and Technology, 2 1998. (in Japanese).

[32] D. Tkaczyk, A. Collins, P. Sheridan, and J. Beel, "Machine learning vs. rules and out-of-the-box vs. retrained: An evaluation of open-source bibliographic reference and citation parsers," in *Proceedings of the 18th ACM/IEEE on Joint Conference on Digital Libraries*, JCDL '18, (New York, NY, USA), pp. 99–108, ACM, 2018.

[33] S. Anzaroot and A. McCallum, "A new dataset for fine-grained citation field extraction," in *ICML Workshop on Peer Reviewing and Publishing Models*, 2013.

[34] A. Sinha, Z. Shen, Y. Song, H. Ma, D. Eide, B.-J. P. Hsu, and K. Wang, "An overview of microsoft academic service (mas) and applications," in *Proceedings of the 24th International Conference on World Wide Web*, WWW '15 Companion, (New York, NY, USA), pp. 243–246, ACM, 2015. r.

[35] L. D. Brown, T. T. Cai, and A. DasGupta, "Interval estimation for a binomial proportion," *Statistical Science*, vol. 16, no. 2, pp. 101–133, 2001.

[36] J. Swales, *Genre analysis: English in academic and research settings*. Cambridge University Press, 1990.

[37] K. Hyland, "Academic attribution: citation and the construction of disciplinary knowledge," *Applied Linguistics*, vol. 20, no. 3, pp. 341–367, 1999.

[38] P. Thompson, *A pedagogically-motivated corpus-based examination of PhD theses: Macrostructure, citation practices and uses of modal verbs*. PhD thesis, University of Reading, 2001.

[39] A. Okamura, "Citation forms in scientific texts: Similarities and differences in l1 and l2 professional writing," *Nordic Journal of English Studies*, vol. 7, no. 3, pp. 61–81, 2008.

[40] W. Lamers, N. J. v. Eck, L. Waltman, and H. Hoos, "Patterns in citation context: the case of the field of scientometrics," in *STI 2018 Conference proceedings*, pp. 1114–1122, Centre for Science and Technology Studies (CWTS), 2018.

[41] C. Niklaus, M. Cetto, A. Freitas, and S. Handschuh, "A survey on open information extraction," in *Proceedings of the 27th International Conference on Computational Linguistics*, pp. 3866–3878, Association for Computational Linguistics, 2018.

[42] R. Levy, Y. Bilu, D. Hershcovich, E. Aharoni, and N. Slonim, "Context dependent claim detection," in *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*, (Dublin, Ireland), pp. 1489–1500, Dublin City University and Association for Computational Linguistics, August 2014. r.

[43] A. S. White, D. Reisinger, K. Sakaguchi, T. Vieira, S. Zhang, R. Rudinger, K. Rawlins, and B. Van Durme, "Universal decompositional semantics on universal dependencies," in *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pp. 1713–1723, Association for Computational Linguistics, 2016.

[44] S. Zhang, R. Rudinger, and B. V. Durme, "An evaluation of predpatt and open ie via stage 1 semantic role labeling," in *IWCS 2017 — 12th International Conference on Computational Semantics — Short papers*, 2017.

[45] K. Gábor, D. Buscaldi, A.-K. Schumann, B. QasemiZadeh, H. Zargayouna, and T. Charnois, "Semeval-2018 task 7: Semantic relation extraction and classification in scientific papers," in *Proceedings of The 12th International Workshop on Semantic Evaluation*, pp. 679–688, Association for Computational Linguistics, 2018.

[46] A. Abu-Jbara and D. Radev, "Reference scope identification in citing sentences," in *Proceedings of the 2012 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, NAACL HLT '12, (Stroudsburg, PA, USA), pp. 80–90, Association for Computational Linguistics, 2012.

[47] R. Jha, A.-A. Jbara, V. Qazvinian, and D. R. Radev, “Nlp-driven citation analysis for scientometrics,” *Natural Language Engineering*, vol. 23, no. 1, p. 93–130, 2017.

[48] J. Beel and S. Dinesh, “Real-world recommender systems for academia: The pain and gain in building, operating, and researching them [long version],” *CoRR*, vol. abs/1704.00156, 2017.

[49] J. Swales, “Citation analysis and discourse analysis,” *Applied Linguistics*, vol. 7, no. 1, pp. 39–56, 1986.

[50] J. He and C. Chen, “Temporal representations of citations for understanding the changing roles of scientific publications,” in *Front. Res. Metr. Anal.*, 2018.

[51] J. Beel, “It’s time to consider "time" when evaluating recommender-system algorithms [proposal],” *CoRR*, vol. abs/1708.08447, 2017.

[52] K. Popat, S. Mukherjee, J. Strötgen, and G. Weikum, “Credibility assessment of textual claims on the web,” in *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*, CIKM ’16, (New York, NY, USA), pp. 2173–2178, ACM, 2016.

[53] C. Stab and I. Gurevych, “Parsing argumentation structures in persuasive essays,” *CoRR*, vol. abs/1604.07370, 2016.

[54] M. Lippi and P. Torroni, “Argumentation mining: State of the art and emerging trends,” *ACM Trans. Internet Technol.*, vol. 16, pp. 10:1–10:25, Mar. 2016.

[55] I. Habernal and I. Gurevych, “Argumentation mining in user-generated web discourse,” *Comput. Linguist.*, vol. 43, pp. 125–179, Apr. 2017.