Master's Thesis

Semantic approaches to citation recommendation

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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

2.1 Semantic approaches to recommendation

At a point in time where publishing research papers online was an emerging trend, Middleton et al. [12] 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. [13] 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. [14] 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

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

concept model. The reported MAP@5 and nDCG@5 values are best for the LDA+concept method.

In [15] 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 [16] 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 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).

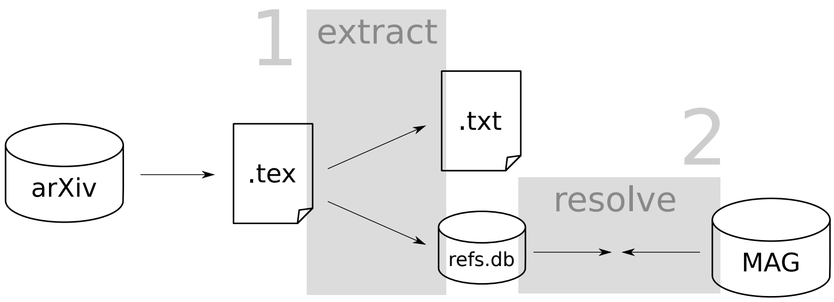
Duma [21, 22] (see notes in Jabref)

Ebesu [23]

Kobayashi [24]

3 Background

explain all the things.



(a) subfloat

Figure 1: Caption that appears under the fig—do I want this in bold tho?

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

---

4 Data set

approach approach.

4.1 Existing data sets

and why a new one was necessary

Data set	#Papers	Cit. context	Disciplines	Full text	Ref. IDs
arXiv CS	90K	1 sentence	CS	yes	DBLP
CiteSeerX /RefSeer	1M	400 chars	all	no	no
PubMed Central OA[1]	2.3M	extractable	Biomed./Life Sci.	yes	mixed
Scholarly v2[2]	100K	extractable	CS	yes	no
ACL-ARC	11k	extractable	CS/comp. ling.	yes	no
ACL-AAN	18k	extractable	CS/comp. ling.	yes	no

Table 1: Table caption. foo bar...

MAG[25] (use/analysis: [26, 27, 28])

use of PMC OAS[29, 22, 30, 31] (PMC OAS problems: [29])

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

4.2 Data set creation

arXiv operates since 1991[32]

system to automatically extract citation interlinks from arXiv sources by parsing LaTeX files as early as 1998[33]

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

evaluation of reference string parsers[34], a dataset for reference string parsing[35]

4.3 Data set evaluation

bar

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[31], 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 ...

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])

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