Identifying Non-explicit Citing Sentences for Citation-based Summarization

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Abstract

Identifying background (context) information in scientific articles can help scholars understand major contributions in their research area more easily. In this paper, we propose a general framework based on probabilistic inference to extract such context information from scientific papers. We model the sentences in an article and their lexical similarities as a Markov Random Field tuned to detect the patterns that context data create, and employ a Belief Propagation mechanism to detect likely context sentences. We also address the problem of generating surveys of scientific papers. Our experiments show greater pyramid scores for surveys generated using such context information rather than citation sentences alone.

1 Introduction

In scientific literature, scholars use citations to refer to external sources. These secondary sources are essential in comprehending the new research. Previous work has shown the importance of citations in scientific domains and indicated that citations include survey-worthy information (Siddharthan and Teufel, 2007; Elkiss et al., 2008; Qazvinian and Radev, 2008; Mohammad et al., 2009; Mei and Zhai, 2008).

A citation to a paper in a scientific article may contain explicit information about the cited research. The following example is an excerpt from a CoNLL paper1 that contains information about Eisner’s work on bottom-up parsers and the notion of span in parsing:

“Another use of bottom-up is due to Eisner (1996), who introduced the notion of a span.”

However, the citation to a paper may not always include explicit information about the cited paper: 

“This approach is one of those described in Eisner (1996)”

Although this sentence alone does not provide any information about the cited paper, it suggests that its surrounding sentences describe the proposed approach in Eisner’s paper:

“... In an all pairs approach, every possible pair of two tokens in a sentence is considered and some score is assigned to the possibility of this pair having a (directed) dependency relation. Using that information as building blocks, the parser then searches for the best parse for the sentence. This approach is one of those described in Eisner (1996).”

We refer to such implicit citations that contain information about a specific secondary source but do not explicitly cite it, as sentences with context information or context sentences for short. We look at the patterns that such sentences create and observe that context sentences occur with a small neighborhood of explicit citations. We also discuss the problem of extracting context sentences for a source-reference article pair. We propose a general framework that looks at each sentence as a random variable whose value determines its state about the target paper. In summary, our proposed model is based on the probabilistic inference of these random variables using graphical models. Finally we give evidence on how such sentences can help us produce better surveys of research areas. The rest of this paper is organized as follows. Preceded by a review of prior work in Section 2, we explain the data collection and our annotation process in Section 3. Section 4 explains our methodology and is followed by experimental setup in Section 5.

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1Buchholz and Marsi “CoNLL-X Shared Task On Multilingual Dependency Parsing”, CoNLL 2006
Table 1: Papers chosen from AAN as source papers for the evaluation corpus, together with their publication year, number of references (in AAN) and number of sentences. Papers marked with * are used to calculate inter-judge agreement.

| ACL-ID   | Author                      | Title                                    | Year | #Refs | #Sents |
|----------|-----------------------------|------------------------------------------|------|-------|--------|
| P08-2026 | McClosky & Charniak         | Self-Training for Biomedical Parsing      | 2008 | 12    | 8      |
| N07-1025 | Mihalcea                    | Using Wikipedia for Automatic ...         | 2007 | 21    | 12     |
| N07-3002 | Wang                        | Learning Structured Classifiers ...       | 2007 | 22    | 14     |
| P06-1101 | Snow et. al.                | Semantic Taxonomy Induction ...           | 2006 | 19    | 9      |
| P06-1116 | Abdalla & Teufel            | A Bootstrapping Approach To ...           | 2006 | 24    | 10     |
| W06-2933 | Nivre et. al.               | Labeled Pseudo-Projective Dependency ... | 2006 | 27    | 5      |
| P05-1044 | Smith & Eisner              | Contrastive Estimation: Training Log-Linear ... | 2005 | 30    | 13     |
| P05-1073 | Toutanova et. al.           | Joint Learning Improves Semantic Role Labeling | 2005 | 14    | 10     |
| N03-1003 | Barzilay & Lee              | Learning To Paraphrase: An Unsupervised ... | 2003 | 26    | 13     |
| N03-2016 | Kondrak et. al.             | Cognates Can Improve Statistical Translation ... | 2003 | 8     | 5      |

2 Prior Work

Analyzing the structure of scientific articles and their relations has received a lot of attention recently. The structure of citation and collaboration networks has been studied in (Teufel et al., 2006; Newman, 2001), and summarization of scientific documents is discussed in (Teufel and Moens, 2002). In addition, there is some previous work on the importance of citation sentences. Elkiss et al., (Elkiss et al., 2008) perform a large-scale study on citations in the free PubMed Central (PMC) and show that they contain information that may not be present in abstracts. In other work, Nanba et al., (Nanba and Okumura, 1999; Nanba et al., 2004b; Nanba et al., 2004a) analyze citation sentences and automatically categorize them in order to build a tool for survey generation.

The text of scientific citations has been used in previous research. Bradshaw (Bradshaw, 2002; Bradshaw, 2003) uses citations to determine the content of articles. Similarly, the text of citation sentences has been directly used to produce summaries of scientific papers in (Qazvinian and Radev, 2008; Mei and Zhai, 2008; Mohammad et al., 2009). Determining the scientific attribution of an article has also been studied before. Siddharthan and Teufel (Siddharthan and Teufel, 2007; Teufel, 2005) categorize sentences according to their role in the author’s argument into predefined classes: Own, Other, Background, Textual, Aim, Basis, Contrast.

Little work has been done on automatic citation extraction from research papers. Kaplan et al., (Kaplan et al., 2009) introduces “citation-site” as a block of text in which the cited text is discussed. The mentioned work uses a machine learning method for extracting citations from research papers and evaluates the result using 4 annotated articles.

In our work we use graphical models to extract context sentences. Graphical models have a number of properties and corresponding techniques and have been used before on Information Retrieval tasks. Romanello et al, (Romanello et al., 2009) use Conditional Random Fields (CRF) to extract references from unstructured text in digital libraries of classic texts. Similar work include term dependency extraction (Metzler and Croft, 2005), query expansion (Metzler and Croft, 2007), and automatic feature selection (Metzler, 2007).

3 Data

The ACL Anthology Network (AAN)\textsuperscript{2} is a collection of papers from the ACL Anthology\textsuperscript{3} published in the Computational Linguistics journal and proceedings from ACL conferences and workshops and includes more than 14,000 papers over a period of four decades (Radev et al., 2009). AAN includes the citation network of the papers in the ACL Anthology. The papers in AAN are publicly available in text format retrieved by an OCR process from the original pdf files, and are segmented into sentences.

To build a corpus for our experiments we picked 10 recently published papers from various areas in NLP\textsuperscript{4}, each of which had references for a total of 203 candidate paper-reference pairs. Table 1 lists these papers together with their authors, titles, publication year, number of references, number of references within AAN, and the number of sen-

\textsuperscript{2} http://clair.si.umich.edu/clair/anthology/

\textsuperscript{3} http://www.aclweb.org/anthology-new/

\textsuperscript{4} Regardless of data selection, the methodology in this work is applicable to any of the papers in AAN.
While this is appropriate for other applications, deciding whether 
Jacquemin (1999) and Barzilay and McKeown (2001) identify 
like us (and unlike Lin and Pantel, who employ a single large 
vector size) annotations that we did, and the Kappa coefficient (\(\kappa\)) was calculated. The \(\kappa\) statistic is formulated as

\[
\kappa = \frac{Pr(a) - Pr(e)}{1 - Pr(e)}
\]

where \(Pr(a)\) is the relative observed agreement among raters, and \(Pr(e)\) is the probability that annotators agree by chance if each annotator is randomly assigning categories. To calculate \(\kappa\), we ignored all explicit citations (since they were provided to the external annotator) and used the binary categories (i.e., 1 for context sentences, and 0 otherwise) for all other sentences. Table 3 shows the annotation vector size (i.e., number of sentences), number of annotation instances (i.e., number of references), and average \(\kappa\) for each set. The average \(\kappa\) is above 0.85 in both cases, suggesting that the annotation process has a low degree of subjectivity and can be considered reliable.

### 3.2 Analysis

In this section, we describe our analysis. First, we look at the number of explicit citations each reference has received in a paper. Figure 1 (a) shows the histogram corresponding to this distribution. It indicates that the majority of references get cited in only 1 sentence in a scientific article, while the maximum being 9 in our collected dataset with only 1 instance (i.e., there is only 1 reference that gets cited 9 times in a paper). Moreover, the data exhibits a highly positive-skewed distribution. This is illustrated on a log-log scale in Figure 1 (b). This highly skewed distribution indicates that the majority of references get cited only once in a citing paper. The very small number of citing sentences can not make a full inventory of the contributions of the cited paper, and therefore, extracting explicit citations alone without context

| Table 2: Part of the annotation for N03-1003 with respect to two of its references “Lin and Pantel (2001)” (the first column) “Shinyama et al. (2002)” (the second column). Cs indicate explicit citations, Is indicate implicit citations and Os are none.

| Sentence | Cs | Cs’ | O
|-----------|----|-----|---
| ...Jacquemin (1999) and Barzilay and McKeown (2001) identify phrase level paraphrases, while Lin and Pantel (2001) and Shinyama et al. (2002) acquire structural paraphrases encoded as templates. | 1 | 1 | 0
| ...| 1 | 0 | 1
| ...Lin and Pantel (2001) extract inference rules, which are related to paraphrases (for example, X wrote Y implies X is the author of Y), to improve question answering. | 0 | 0 | 1
| ...They assume that paths in dependency trees that take similar arguments (leaves) are close in meaning. | 1 | 1 | 0
| ...However, only two-argument templates are considered. | 0 | 0 | 1
| ...Shinyama et al. (2002) also use dependency-tree information to extract templates of a limited form (in their case, determined by the underlying information extraction application). | 0 | 1 | 0
| ...Like us (and unlike Lin and Pantel, who employ a single large corpus), they use articles written about the same event in different newspapers as data. | 1 | 1 | 0
| ...Our approach shares two characteristics with the two methods just described: pattern comparison by analysis of the patterns respective arguments, and use of nonparallel corpora as a data source. | 0 | 0 | 1
| ...However, extraction methods are not easily extended to generation methods. | 1 | 1 | 0
| ...One problem is that their templates often only match small fragments of a sentence. | 0 | 0 | 1
| ...While this is appropriate for other applications, deciding whether to use a given template to generate a paraphrase requires information about the surrounding context provided by the entire sentence. | 1 | 1 | 0

| ACL-ID | vector size | # Annotations | \(\pi\) |
|--------|-------------|--------------|-------|
| N07-1025 | 133 | 21 | 0.889 ± 0.30 |
| N03-2016* | 92 | 8 | 0.853 ± 0.35 |

Table 3: Average \(\kappa\) coefficient as inter-judge agreement for annotations of two sets

3Someone not involved with the paper but an expert in NLP.
sentences may result in information loss about the contributions of the cited paper.

Table 4: The distribution of gaps in the annotated data

| gap size | 0  | 1  | 2  | 4  | 9  | 10 | 15 | 16 |
|----------|----|----|----|----|----|----|----|----|
| instance | 273| 14 | 2  | 1  | 2  | 1  | 1  | 1  |

Next, we investigate the distance between context sentences and the closest citations. For each context sentence, we find its distance to the closest context sentence or explicit citation. Formally, we define the gap to be the number of sentences between a context sentence (marked with 1) and the closest context sentence or explicit citation (marked with either C or 1) to it. For example, the second column of Table 2 shows that there is a gap of size 1 in the 9th sentence in the set of context and citation sentences about Shinyama et al. (2002). Table 4 shows the distribution of gap sizes in the annotated data. This observation suggests that the majority of context sentences directly occur after or before a citation or another context sentence. However, it shows that gaps between sentences describing a cited paper actually exist, and a proposed method should have the capability to capture them.

4 Proposed Method

In this section we propose our methodology that enables us to identify the context information of a cited paper. Particularly, the task is to assign a binary label $X_C$ to each sentence $S_i$ from a paper $S$, where $X_C = 1$ shows a context sentence related to a given cited paper, $C$. To solve this problem we propose a systematic way to model the network level relationship between consecutive sentences. In summary, each sentence is represented with a node and is given two scores (context, non-context), and we update these scores to be in harmony with the neighbors’ scores.

A particular class of graphical models known as Markov Random Fields (MRFs) are suited for solving inference problems with uncertainty in observed data. The data is modeled as an undirected graph with two types of nodes: hidden and observed. Observed nodes represent values that are known from the data. Each hidden node $x_u$, corresponding to an observed node $y_u$, represents the true state underlying the observed value. The state of a hidden node is related to the value of its corresponding observed node as well as the states of its neighboring hidden nodes.

The local Markov property of an MRF indicates that a variable is conditionally independent on all other variables given its neighbors: $x_v \perp \perp x_{V \setminus cl(v)} | ne(v)$, where $ne(v)$ is the set of neighbors of $v$, and $cl(v) = \{v\} \cup ne(v)$ is the closed neighborhood of $v$. Thus, the state of a node is assumed to statistically depend only upon its hidden node and each of its neighbors, and independent of any other node in the graph given its neighbors.

Dependencies in an MRF are represented using two functions: Compatibility function ($\psi$) and Potential function ($\phi$). $\psi_{uv}(x_c, x_d)$ shows the edge potential of an edge between two nodes $u, v$ of classes $x_c$ and $x_d$. Large values of $\psi_{uv}$ would indicate a strong association between $x_c$ and $x_d$ at nodes $u, v$. The Potential function, $\phi_i(x_c, y_c)$, shows the statistical dependency between $x_c$ and $y_c$ at each node $i$ assumed by the MRF model.

In order to find the marginal probabilities of $x_i$s in a MRF we can use Belief Propagation (BP) (Yedidia et al., 2003). If we assume the $y_i$s are fixed and show $\phi_i(x_i, y_i)$ by $\phi_i(x_i)$, we can find the joint probability distribution for unknown variables $x_i$ as

$$p(\{x\}) = \frac{1}{Z} \prod_{ij} \psi_{ij}(x_i, x_j) \prod_i \phi_i(x_i)$$

In the BP algorithm a set of new variables $m$ is introduced where $m_{ij}(x_j)$ is the message passed from $i$ to $j$ about what state $x_j$ should be in. Each message, $m_{ij}(x_j)$, is a vector with the same dimensionality of $x_j$ in which each dimension shows $i$’s opinion about $j$ being in the corresponding class. Therefore each message could be considered as a probability distribution and its components should sum up to 1. The final belief at a
Elements that make up the message from a node $i$ to another node $j$: messages from $i$’s neighbors, local evidence at $i$, and propagation function between $i, j$ summed over all possible states of node $i$.

node $i$, in the BP algorithm, is also a vector with the same dimensionality of messages, and is proportional to the local evidence as well as all messages from the node’s neighbors:

$$b_i(x_i) \leftarrow k \phi_i(x_i) \prod_{j \in \text{ne}(i)} m_{ji}(x_i)$$

where $k$ is the normalization factor of the beliefs about different classes. The message passed from $i$ to $j$ is proportional to the propagation function between $i, j$, the local evidence at $i$, and all messages sent to $i$ from its neighbors except $j$:

$$m_{ij}(x_j) \leftarrow \sum_{x_i} \phi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{k \in \text{ne}(i) \setminus j} m_{ki}(x_i)$$

Figure 2 illustrates the message update rule.

Convergence can be determined based on a variety of criteria. It can occur when the maximum change of any message between iteration steps is less than some threshold. Convergence is guaranteed for trees but not for general graphs. However, it typically occurs in practice (McGlohon et al., 2009). Upon convergence, belief scores are determined by Equation 1.

### 4.1 MRF construction

To find the sentences from a paper that form the context information of a given cited paper, we build an MRF in which a hidden node $x_i$ and an observed node $y_i$ correspond to each sentence. The structure of the graph associated with the MRF is dependent upon the validity of a basic assumption. This assumption indicates that the generation of a sentence (in form of its words) only depends on its surrounding sentences. Said differently, each sentence is written independently of all other sentences given a number of its neighbors. This local dependence assumption can result in a number of different MRFs, each built assuming a dependency between a sentence and all sentences within a particular distance. Figure 3 shows the structure of the two MRFs at either extreme of the local dependence assumption. In Figure 3 a, each sentence only depends on one following and one preceding sentence, while Figure 3 b shows an MRF in which sentences are dependent on each other regardless of their position. We refer to the former by $\text{BP}_1$, and to the latter by $\text{BP}_n$. Generally, we use $\text{BP}_i$ to denote an MRF in which each sentence is connected to $i$ sentences before and after.

$$
\begin{array}{c|c|c}
\psi_{ij}(x_c, x_d) & x_d = 0 & x_d = 1 \\
x_c = 0 & 0.5 & 0.5 \\
x_c = 1 & 1 - S_{ij} & S_{ij}
\end{array}
$$

Table 5: The compatibility function $\psi$ between any two nodes in the MRFs from the sentences in scientific papers

### 4.2 Compatibility Function

The compatibility function of an MRF represents the association between the hidden node classes. A node’s belief to be in class 1 is its probability to be included in the context. The belief of a node $i$, about its neighbor $j$ to be in either classes is assumed to be 0.5 if $i$ is in class 0. In other words, if a node is not part of the context itself, we assume
it has no effect on its neighbors’ classes. In contrast, if $i$ is in class 1 its belief about its neighbor $j$ is determined by their mutual lexical similarity. If this similarity is close to 1 it indicates a stronger tie between $i, j$. However, if $i, j$ are not similar, $i$’s probability of being in class 1, should not affect that of $j$’s. To formalize this assumption we use the sigmoid of the cosine similarity of two sentences to build $\psi$. More formally, we define $S$ to be

$$S_{ij} = \frac{1}{1 + e^{-\cosine(i,j)}}$$

The sigmoid function obtains a value of 0.5 for a cosine of 0 indicating that there is no bias in the association of the two sentences. The matrix in Table 5 shows the compatibility function built based on the above arguments.

4.3 Potential Function

The node potential function of an MRF can incorporate some other features observable from data. Here, the goal is to find all sentences that are about a specific cited paper, without having explicit citations. To build the node potential function of the observed nodes, we use some sentence level features. First, we use the explicit citation as an important feature of a sentence. This feature can affect the belief of the corresponding hidden node, which can in turn affect its neighbors’ beliefs. For a given paper-reference pair, we flag (with a 1) each sentence that has an explicit citation to the reference.

The second set of features that we are interested in are discourse-based features. In particular we match each sentence with specific patterns and flag those that match. The first pattern is a bigram in which the first term matches any of “this; that; those; these; his; her; their; such; previous”, and the second term matches any of “work; approach; system; method; technique; result; example”. The second pattern includes all sentences that start with “this; such”.

Finally, the similarity of each sentence to the reference is observable from the data and can be used as a sentence-level feature. Intuitively, if a sentence has higher similarity with the reference paper, it should have a higher potential of being in class 1 or $C$. The flag of each sentence here is a value between 0 and 1 and is determined by its cosine similarity to the reference. Once the flags for each sentence, $S_i$ are determined, we calculate normalized $f_i$ as the unweighted linear combination of individual features. Based on $f_i$s, we compute the potential function, $\phi$, as shown in Table 6.

$$
\phi_i(x_c, y_c) = \begin{cases} 
0 & x_c = 0 \\
1 - f_i & x_c = 1
\end{cases}
$$

Table 6: The node potential function $\phi$ for each node in the MRFs from the sentences in scientific papers is built using the sentences’ flags computed using sentence level features.

5 Experiments

The intrinsic evaluation of our methodology means to directly compare the output of our method with the gold standards obtained from the annotated data. Our methodology finds the sentences that cite a reference implicitly. Therefore the output of the inference method is a vector, $v$, of 1’s and 0’s, whereby a 1 at element $i$ means that sentence $i$ in the source document is a context sentence about the reference while a 0 means an explicit citation or neither. The gold standard for each paper-reference pair, $\omega$ (obtained from the annotated vectors in Section 3.1 by changing all $C$s to 0s), is also a vector of the same format and dimensionality.

Precision, recall, and $F_\beta$ for this task can be defined as

$$
p = \frac{v \cdot \omega}{v \cdot T} ; \quad r = \frac{v \cdot \omega}{\omega \cdot T} \quad F_\beta = \frac{(1 + \beta^2)p \cdot r}{\beta^2p + r} \quad (3)
$$

where $T$ is a vector of 1’s with the same dimensionality and $\beta$ is a non-negative real number.

5.1 Baseline Methods

The first baseline that we use is an IR-based method. This baseline, $B_1$, takes explicit citations as an input but use them to find context sentences. Given a paper-reference pair, for each explicit citation sentence, marked with $C$, $B_1$ picks its preceding and following sentences if their similarities to that sentence is greater than a cutoff (the median of all such similarities), and repeats this for neighboring sentences of newly marked sentences. Intuitively, $B_1$ tries to find the best chain (window) around citing sentences.

As the second baseline, we use the hand-crafted discourse based features used in MRF’s potential function. Particularly, this baseline, $B_2$, marks
Table 7: Average $F_{\beta=3}$ for similarity based baseline ($B_1$), discourse-based baseline ($B_2$), a supervised method (SVM) and three MRF-based methods.

| paper         | $B_1$   | $B_2$ | SVM | $B_{P1}$ | $B_{P4}$ | $B_{Pn}$ |
|---------------|---------|-------|-----|----------|----------|----------|
| P08-2026      | 0.441   | 0.237 | 0.249 | 0.470    | **0.613**| 0.285    |
| N07-1025      | 0.388   | 0.102 | 0.124 | 0.313    | **0.466**| 0.138    |
| N07-3002      | 0.521   | 0.339 | 0.232 | **0.742**| 0.627    | 0.315    |
| P06-1101      | 0.125   | 0.388 | 0.127 | 0.649    | **0.889**| 0.193    |
| P06-1116      | 0.283   | 0.104 | 0.100 | 0.307    | **0.341**| 0.130    |
| W06-2933      | 0.313   | 0.100 | 0.176 | 0.338    | **0.413**| 0.160    |
| P05-1044      | 0.225   | 0.100 | 0.060 | 0.172    | **0.586**| 0.094    |
| P05-1073      | 0.144   | 0.100 | 0.144 | 0.433    | **0.518**| 0.171    |
| N03-1003      | 0.245   | 0.249 | 0.126 | **0.523**| 0.466    | 0.125    |
| N03-2016      | 0.100   | 0.181 | 0.224 | 0.439    | **0.482**| 0.185    |

Each sentence that is within a particular distance (4 in our experiments) of an explicit citation and matches one of the two patterns mentioned in Section 4.3. After marking all such sentences, $B_2$ also marks all sentences between them and the closest explicit citation, which is no farther than 4 sentences away. This baseline helps us understand how effectively this sentence level feature can work in the absence of other features and the network structure.

Finally, we use a supervised method, SVM, to classify sentences as context/non-context. We use 4 features to train the SVM model. These 4 features comprise the 3 sentence level features used in MRF’s potential function (i.e., similarity to reference, explicit citation, matching certain regular-expressions) and a network level feature: distance to the closes explicit citation. For each source paper, $P$, we use all other source papers and their source-reference annotation instances to train a model. We then use this model to classify all instances in $P$. Although the number of references and thus source-reference pairs are different for different papers, this can be considered similar to a 10-fold cross validation scheme, since for each source paper the model is built using all source-reference pairs of all other 9 papers.

We compare these baselines with 3 MRF-based systems each with a different assumption about independence of sentences. $B_{P1}$ denotes an MRF in which each sentence is only connected to 1 sentence before and after. In $B_{P4}$ locality is more relaxed and each sentence is connected to 4 sentences on each sides. $B_{Pn}$ denotes an MRF in which all sentences are connected to each other regardless of their position in the paper.

Table 7 shows $F_{\beta=3}$ for our experiments and shows how $B_{P4}$ outperforms the other methods on average. The value 4 may suggest the fact that although sentences might be independent of distant sentences, they depend on more than one sentence on each side.

The final experiment we do to intrinsically evaluate the MRF-base method is to compare different sentence-level features. The first feature used to build the potential function is explicit citations. This feature does not directly affect context sentences (i.e., it affects the marginal probability of context sentences through the MRF network connections). Therefore, we do not alter this feature in comparing different features. However, we look at the effect of the second and the third features: hand-crafted regular expression-based features and similarity to the reference. For each paper, we use $B_{P4}$ to perform 3 experiments: two in absence of each feature and one including all features. Figure 4 shows the average $F_{\beta=3}$ for each experiment. This plot shows that the features lead to better results when used together.

6 Impact on Survey Generation

We also performed an extrinsic evaluation of our context extraction methodology. Here we show how context sentences add important survey-worthy information to explicit citations. Previous work that generate surveys of scientific topics use the text of citation sentences alone (Mohammad et al., 2009; Qazvinian and Radev, 2008). Here, we show how the surveys generated using citations and their context sentences are better than those generated using citation sentences alone.

We use the data from (Mohammad et al., 2009)
... Naturally, our current work on question answering for the reading comprehension task is most related to those of (Hirschman et al., 1999; Charniak et al., 2000; Riloff and Thelen, 2000; Wang et al., 2000). In fact, all of this body of work as well as ours are evaluated on the same set of test stories, and are developed (or trained) on the same development set of stories. The work of (Hirschman et al., 1999) initiated this series of work, and it reported an accuracy of 36.3% on answering the questions in the test stories. Subsequently, the work of (Riloff and Thelen, 2000) and (Charniak et al., 2000) improved the accuracy further to 39.7% and 41%, respectively. However, all of these three systems used handcrafted, deterministic rules and algorithms...

The cross-model comparison showed that the performance ranking of these models was: U-SVM > PatternM > S-SVM > Retrieval-M. Compared with retrieval-based [Yang et al., 2003], pattern-based [Ravichandran et al. 2002 and Soubbotin et al. 2002], and deep NLP-based [Moldovan et al. 2002; Hovy et al. 2001; and Pasca et al. 2001] answer selection, machine learning techniques are more effective in constructing QA components from scratch. These techniques suffer, however, from the problem of requiring an adequate number of handtagged question-answer training pairs. It is too expensive and labor intensive to collect such training pairs for supervised machine learning techniques...

As expected, the definition and person-bio answer types are covered well by these resources. The web has been employed for pattern acquisition (Ravichandran et al., 2003), document retrieval (Dumais et al., 2002), query expansion (Yang et al., 2003), structured information extraction, and answer validation (Magnini et al., 2002). Some of these approaches enhance existing QA systems, while others simplify the question answering task, allowing a less complex approach to find correct answers...

Table 8: A portion of the QA survey generated by LexRank using the context information.

|              | Citation Survey | Context Survey |
|--------------|----------------|---------------|
| **QA**       |                |               |
| CT nuggets   | 0.416          | 0.634         |
| AB nuggets   | 0.397          | 0.594         |
| **DP**       |                |               |
| CT nuggets   | 0.324          | 0.379         |

Figure 4: Average $F_{\beta=3}$ for $BP_4$ employing different features.

Table 9: Pyramid $F_{\beta=3}$ scores of automatic surveys of QA and DP data. The QA surveys are evaluated using nuggets drawn from citation texts (CT), or abstracts (AB), and DP surveys are evaluated using nuggets from citation texts (CT).

that contains two sets of cited papers and corresponding citing sentences, one on Question Answering (QA) with 10 papers and the other on Dependency Parsing (DP) with 16 papers. The QA set contains two different sets of nuggets extracted by experts respectively from paper abstracts and citation sentences. The DP set includes nuggets extracted only from citation sentences. We use these nugget sets, which are provided in form of regular expressions, to evaluate automatically generated summaries. To perform this experiment we needed to build a new corpus in which each explicit citation sentence is replaced with the same sentence attached to at most 4 sentence on each side.

After building the context corpus, we use LexRank (Erkan and Radev, 2004) to generate 2 QA and 2 DP surveys using the citation sentences only, and the new context corpus explained above. LexRank is a multidocument summarization system, which first builds a cosine similarity graph of all the candidate sentences. Once the network is built, the system finds the most central sentences by performing a random walk on the graph. We limit these surveys to be of a maximum length of 1000 words. Table 8 shows a portion of the survey generated from the QA context corpus. This example shows how context sentences add meaningful and survey-worthy information along with citation sentences. Table 9 shows the Pyramid $F_{\beta=3}$ score of automatic surveys of QA and DP.
data. The QA surveys are evaluated using nuggets drawn from citation texts (CT), or abstracts (AB), and DP surveys are evaluated using nuggets from citation texts (CT). In all evaluation instances the surveys generated with the context corpora excel at covering nuggets drawn from abstracts or citation sentences.

7 Conclusion

In this paper we proposed a framework based on probabilistic inference to extract sentences that appear in the scientific literature, and which are about a secondary source, but which do not contain explicit citations to that secondary source. Our methodology is based on inference in an MRF built using the similarity of sentences and their lexical features. We show, by numerical experiments, that an MRF in which each sentence is connected to only a few adjacent sentences properly fits this problem. We also investigate the usefulness of such sentences in generating surveys of scientific literature. Our experiments on generating surveys for Question Answering and Dependency Parsing show how surveys generated using such context information along with citation sentences have higher quality than those built using citations alone.

Generating fluent scientific surveys is difficult in absence of sufficient background information. Our future goal is to combine summarization and bibliometric techniques towards building automatic surveys that employ context information as an important part of the generated surveys.

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References

Shannon Bradshaw. 2002. Reference Directed Indexing: Indexing Scientific Literature in the Context of Its Use. Ph.D. thesis, Northwestern University.

Shannon Bradshaw. 2003. Reference directed indexing: Redeeming relevance for subject search in citation indexes. In Proceedings of the 7th European Conference on Research and Advanced Technology for Digital Libraries.

Aaron Elkiss, Siwei Shen, Anthony Fader, Güneş Erkan, David States, and Dragomir R. Radev. 2008. Blind men and elephants: What do citation summaries tell us about a research article? Journal of the American Society for Information Science and Technology, 59(1):51–62.

Güneş Erkan and Dragomir R. Radev. 2004. Lexrank: Graph-based centrality as salience in text summarization. Journal of Artificial Intelligence Research (JAIR).

Dain Kaplan, Ryu Iida, and Takenobu Tokunaga. 2009. Automatic extraction of citation contexts for research paper summarization: A coreference-chain based approach. In Proceedings of the 2009 Workshop on Text and Citation Analysis for Scholarly Digital Libraries, pages 88–95, Suntec City, Singapore, August. Association for Computational Linguistics.

Mary McGlohon, Stephen Bay, Markus G. Anderle, David M. Steier, and Christos Faloutsos. 2009. Snare: a link analytic system for graph labeling and risk detection. In KDD ’09: Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 1265–1274.

Qiaozhu Mei and Cheng-Xiang Zhai. 2008. Generating impact-based summaries for scientific literature. In Proceedings of ACL ’08, pages 816–824.

Donald Metzler and W. Bruce Croft. 2005. A markov random field model for term dependencies. In SIGIR ’05: Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval, pages 472–479.

Donald Metzler and W. Bruce Croft. 2007. Latent concept expansion using markov random fields. In SIGIR ’07: Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, pages 311–318.

Donald A. Metzler. 2007. Automatic feature selection in the markov random field model for information retrieval. In CIKM ’07: Proceedings of the sixteenth ACM conference on Conference on information and knowledge management, pages 253–262.

Saif Mohammad, Bonnie Dorr, Melissa Egan, Ahmed Hassan, Pradeep Muthukrishnan, Vahed Qazvinian, Dragomir Radev, and David Zajic. 2009. Using citations to generate surveys of scientific paradigms.
In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, pages 584–592, Boulder, Colorado, June. Association for Computational Linguistics.

Hidetsugu Nanba and Manabu Okumura. 1999. Towards multi-paper summarization using reference information. In *IJCAI1999*, pages 926–931.

Hidetsugu Nanba, Takeshi Abekawa, Manabu Okumura, and Suguru Saito. 2004a. Bilingual presri: Integration of multiple research paper databases. In *Proceedings of RIAO 2004*, pages 195–211, Avignon, France.

Hidetsugu Nanba, Noriko Kando, and Manabu Okumura. 2004b. Classification of research papers using citation links and citation types: Towards automatic review article generation. In *Proceedings of the 11th SIG Classification Research Workshop*, pages 117–134, Chicago, USA.

Mark E. J. Newman. 2001. The structure of scientific collaboration networks. *PNAS*, 98(2):404–409.

Vahed Qazvinian and Dragomir R. Radev. 2008. Scientific paper summarization using citation summary networks. In *COLING 2008*, Manchester, UK.

Dragomir R. Radev, Pradeep Muthukrishnan, and Vahed Qazvinian. 2009. The ACL anthology network corpus. In *ACL workshop on Natural Language Processing and Information Retrieval for Digital Libraries*.

Matteo Romanello, Federico Boschetti, and Gregory Crane. 2009. Citations in the digital library of classics: Extracting canonical references by using conditional random fields. In *Proceedings of the 2009 Workshop on Text and Citation Analysis for Scholarly Digital Libraries*, pages 80–87, Suntec City, Singapore, August. Association for Computational Linguistics.

Advaith Siddharthan and Simone Teufel. 2007. Whose idea was this, and why does it matter? attributing scientific work to citations. In *Proceedings of NAACL/HLT-07*.

Simone Teufel and Marc Moens. 2002. Summarizing scientific articles: experiments with relevance and rhetorical status. *Comput. Linguist.*, 28(4):409–445.

Simone Teufel, Advaith Siddharthan, and Dan Tidhar. 2006. Automatic classification of citation function. In *Proceedings of the EMNLP*, Sydney, Australia, July.

Simone Teufel. 2005. Argumentative Zoning for Improved Citation Indexing. *Computing Attitude and Affect in Text: Theory and Applications*, pages 159–170.

Jonathan S. Yedidia, William T. Freeman, and Yair Weiss. 2003. Understanding belief propagation and its generalizations. pages 239–269.