# Context matters: Towards extracting a citation's context using linguistic features



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## TL;DR

- **Aim:** recommend potential citations at a particular location in a draft paper.
- **Task**: select the context for which to recommend citations **Evaluation**: attempt to recover original citations in existing published papers from the whole document collection
- **Previous work**: traditionally all contexts are extracted using symmetric windows over words or sentences
- **Approach:** compare symmetrical methods for extracting a citation's context: window-of-words and window-ofsentences with a human oracle selecting relevant sentences **Corpus:** ACL Anthology Corpus (AAC)

#### A variety of coherence theories have been developed over the years [...] and their principles have found application in many symbolic text generation systems (e.g. CITATION NEEDED)

(Adapted from Barzilay and Lapata, 2005)

#### Recommendations

1. Motivation

- D. Scott, C. S. de Souza. 1990. Getting the message across in RSTbased text generation. In R. Dale, C. Mellish, M. Zock, eds., Current Research in Natural Language Generation, 47–73. Academic Press.
- R. Kibble, R. Power. 2004. Optimising referential coherence in text generation. Computational Linguistics, 30(4):401–416.
- E. H. Hovy. 1987. Generating natural language under pragmatic constraints. Journal of Pragmatics, 11(6), 689-719.
- All previous work on citation recommendation uses symmetric methods to extract the context of a citation
- Are symmetric methods optimal?

### 2. Annotated citation contexts

**Athar and Teufel (2012) –** *Context-Enhanced Citation* Sentiment Detection

- **Corpus**: ACL Anthology
- Annotated contexts: ~1800 (citations to 20 selected papers)
- Per-sentence **annotations**:
- **relevant** (3115 sentences)
- sentiment:
  - (**p**)ositive (261)
  - (**n**)egative (365) ullet
  - (**o**)bjective (2489)
- Most sentences containing a citation are labelled objective. (1929)

## 3. Evaluation

#### 1. Index document collection

AAC: ~28k documents, excluding annotated documents

#### 2. Generate queries

From each of the annotated citation contexts, remove stopwords and generate one query using:

- Window of words (30, 50, 100, 500)
- Window of sentences (1 only, 1 up, 1 down, 1 up + 1 down, 2up+2down, paragraph)
- Oracle / human annotations (all relevant, combinations of positive, negative and objective)

#### 3. Evaluate queries

Run queries, attempt to retrieve original citation from document collection, measure Mean Reciprocal Rank (MRR)

#### 4. Context extraction methods

#### **Annotation Sentence**

This suggests that the performance which may be obtained for this task may be

## **Extraction methods**

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^	lower than has been achieved for standard text.	s lask may be	(30 up, 30 down)
Х	Further insight into the task can be gained from determining the d	egree to which the	(30 up, 30 uovii)
	subjects agreed.		
Ο	<b>Carletta (1996)</b> argues that the kappa statistic (a) should be adopted to judge annotator consistency for classification tasks in the area of discourse and dialogue		
	analysis.	se and dialogue	
Х	It is worth noting that the problem of sentence boundary detection presented so far		Window of <b>sentences</b> (2 up, 2 down)
	in this paper has been formulated as a classification task in which each token boundary has to be classified as either being a sentence boundary or not.		
Ο	Carletta argues that several incompatible measures of annotator agreement have		
	been used in discourse analysis, making comparison impossible.		Oracle - <b>annotated</b>
0	Her solution is to look to the field of content analysis, which has already experienced		<b>sentences</b> (p + n + o)
	these problems, and adopt their solution of using the kappa statist	tic.	
	(from Stevenson and Gaizauskas (2000) - Experiments on Sentence Boundary Detection)		
	5. Results		6. Discussion
	Evaluation: Mean Reciprocal Rank		
nnotated sentence n 0.0134		Findings:	la autoarforme all evenetrical
		$\blacksquare$ $\blacksquare$ $\Box$	TO AUTRARTARME ALLEVIMMATRICAL

0.147

0.1505

0.16

0.12

0.14

0.1533

0.1575

0.18



0.02

0

0.04

0.06

0.08

0.1

- Human oracle outperiornis all symmetrical methods. Symmetrical windows of either tokens or sentences are therefore not optimal.
- The annotated sentiment of sentences was not useful for query extraction. The more sentences we include that were annotated as relevant, the higher the score.
- More query terms is not always better. Carefully selecting relevant text spans for context extraction improves results.

**Future work:** keyword extraction using linguistic features. Train a machine learning classifier to generate queries from sub-sentence-length spans.