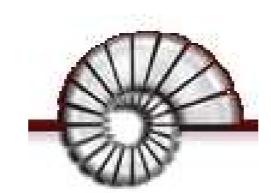
# Local Context Selection for Aligning Sentences in Parallel Corpora

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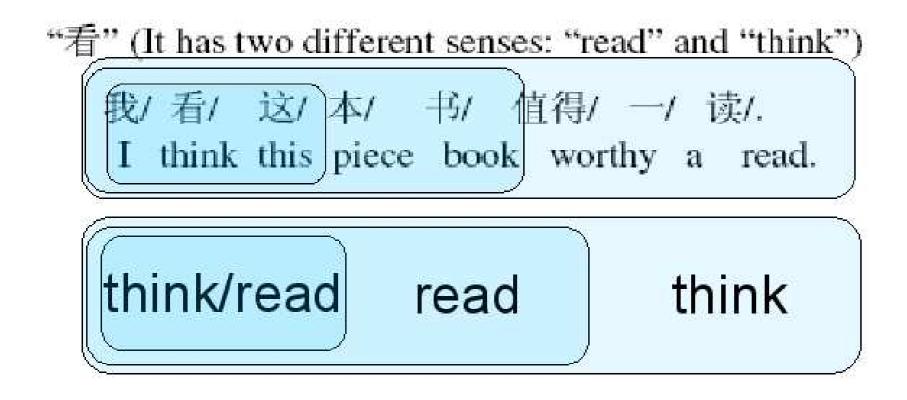
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#### Abstract

A novel language-independent context-based sentence alignment technique, which uses the context of sentences and Zipfian word vectors, is presented. Alternatives for local context models examined and a demonstration of better performance when compared with prominent sentence alignment techniques is given. The local context for a pair of set of sentences which maximizes the correlation is dynamically selected. Our system performs 1.1951 to 1.5404 times better in reducing the error rate in alignment accuracy and coverage.

#### Motivation

- Sentence alignment: mapping the sentences of two given parallel corpora which are known to be translations of each other.
- Mappings are not necessarily 1-to-1, monotonic, or continuous.
- Dynamic nature of the context is noticed for many NLP tasks, including WSD [1]:



## Zipfian Word Vectors

- Zipf's Law: "a few words occur frequently while many occur rarely" [2].
- Zipfian Word Vector (ZWV) turns a given sentence to bins where each bin contains the number of words with similar frequencies in the given corpus.
- Thus, for a single sentence as in:
  - $S=\mbox{"}$  big brother is watching you " , the caption beneath it ran .,

the Zipfian word vector becomes:

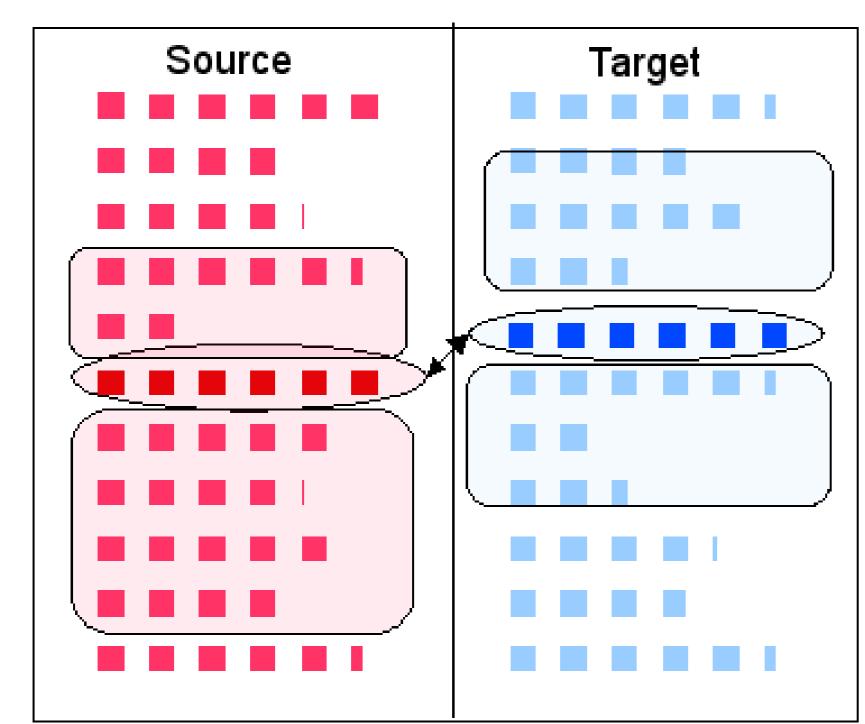
$$ZWV(S) = [14, 1, 3, 0, 1, 3, 2, 0, 1, 1, 2],$$

where the sentence length in the number of tokens is added to the beginning as well.

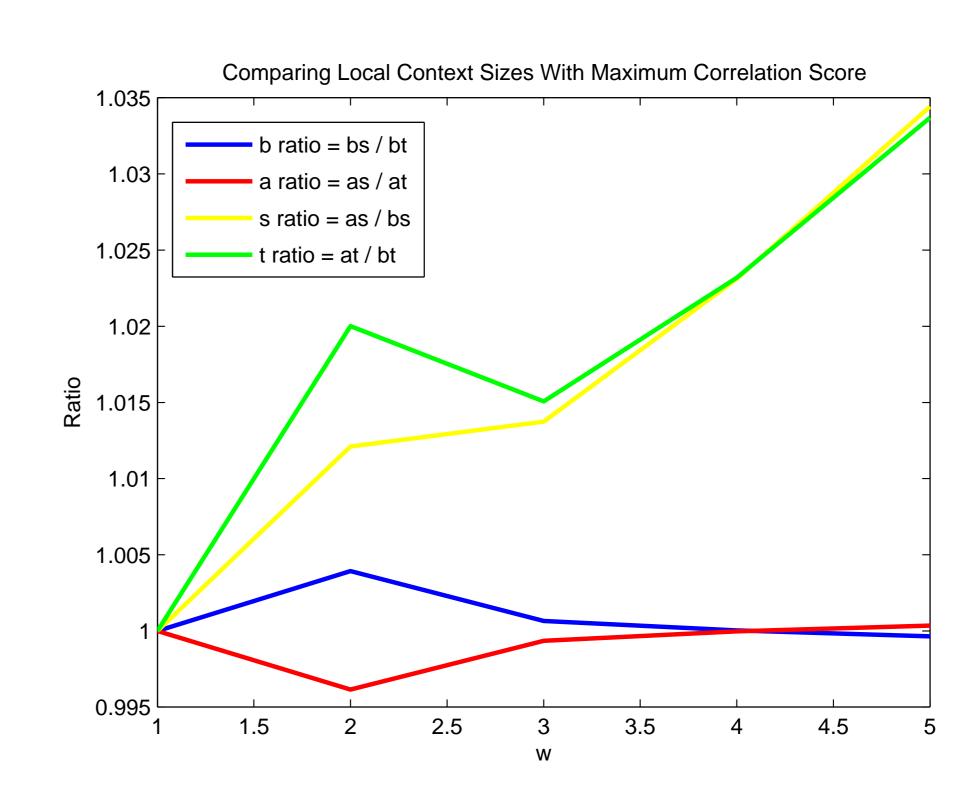
- For each set of sentences we create the *Zipfian word matrix*, which is the concatenation of ZWVs surrounding S based on S's local context, which contains at most  $2 \times w + 1$  rows for a given window size of w.
- $\blacksquare$  Weight decaying 2D Pearson correlation coefficient is used for comparing candidate T's.

# Context in Sentence Alignment

Example sentence alignment scenario is given below:



- $\blacksquare$  The local contexts for the scenario are (2,4) and (3,3) respectively.
- Full local context search considers all  $w^3$  possibilities for  $(b_s, a_s)$  and  $(b_t, b_s + a_s b_t)$ .
- Symmetric local context search considers  $w^2$  symmetric possibilities:  $(b_s = b_t, a_s = a_t)$
- From C local context configurations, choose **maximum**, **average**, or **average top** k?



- The sentences that come before have a larger role in determining the context?
- In nearly two thirds of  $\mathcal{C}$ , the local context sizes for S and T are exactly the same.

Dataset	b	a	Increase
Bulgarian	1.9564	1.9936	1.9%
Czech	1.9610	1.9961	1.8%
Estonian	1.9563	2.0129	2.9%
Hungarian	1.9723	1.9964	1.2%
Lithuanian	1.9720	2.0246	2.7%
Latvian	1.9667	2.0043	1.9%
Romanian	1.9275	1.9688	2.1%
Serbo-Croatian	1.9424	1.9755	1.7%
Slovene	1.9486	1.9765	1.4%

Table 1: Local symmetric context sizes per language - English pairs

# Results

	Sentence Alignment Accuracy						
Language	hunalign	Moore	static	maximum	average	average top 5	
Bulgarian	$96.74 \ / \ 3.26$	96.09 / 3.91	96.09 / 3.91	95.77 / 4.23	$96.74 \ / \ 3.26$	$96.74 \ / \ 3.26$	
Czech	96.14 / 3.86	95.82 / 4.18	96.78 / 3.22	96.78 / 3.22	96.78 / 3.22	96.78 / 3.22	
Estonian	99.68 / 0.32	98.39 / 1.61	98.39 / 1.61	99.04 / 0.96	98.39 / 1.61	99.04 / 0.96	
Hungarian	87.86 / 12.14	88.96 / 11.04	92.98 / 7.02	91.30 / 8.70	93.98 / 6.02	91.64 / 8.36	
Latvian	95.71 / 4.29	92.74 / 7.26	96.70 / 3.30	96.70 / 3.30	96.70 / 3.30	$97.03 \ / \ 2.97$	
Lithuanian	88.44 / 11.56	82.31 / 17.69	92.18 / 7.82	92.52 / 7.48	91.84 / 8.16	92.52 / 7.48	
Romanian	89.86 / 10.14	$95.27 \ / \ 4.73$	91.22 / 8.78	90.54 / 9.46	91.22 / 8.78	92.23 / 7.77	
Serbo-Croatian	98.70 / 1.30	97.08 / 2.92	97.73 / 2.27	98.05 / 1.95	97.73 / 2.27	97.73 / 2.27	
Slovene	97.70 / 2.30	97.04 / 2.96	98.68 / 1.32	98.36 / 1.64	99.34 / 0.64	98.36 / 1.64	

Table 2: Sentence alignment accuracy per English - language alignments

	Sentence Alignment Coverage						
Language	hunalign	Moore	static	maximum	average	average top 5	
Bulgarian	95.34 / 4.66	94.86 / 5.14	95.18 / 4.82	94.86 / 5.14	95.99 / 4.01	95.99 / 4.01	
Czech	94.92 / 5.08	95.24 / 4.76	96.35 / 3.65	96.35 / 3.65	96.35 / 3.65	$96.35 \ / \ 3.65$	
Estonian	99.52 / 0.48	98.08 / 1.92	98.08 / 1.92	98.88 / 1.12	98.08 / 1.92	98.88 / 1.12	
Hungarian	84.30 / 15.70	85.90 / 14.10	91.51 / 8.49	89.10 / 10.90	92.63 / 7.37	89.42 / 10.58	
Latvian	92.65 / 7.35	90.26 / 9.74	95.37 / 4.63	95.37 / 4.63	95.37 / 4.63	95.69 / 4.31	
Lithuanian	84.85 / 15.15	79.15 / 20.85	90.23 / 9.77	90.72 / 9.28	89.90 / 10.10	90.72 / 9.28	
Romanian	86.79 / 13.21	93.64 / 6.36	89.72 / 10.28	89.07 / 10.93	89.72 / 10.28	90.86 / 9.14	
Serbo-Croatian	97.75 / 2.25	96.46 / 3.54	97.27 / 2.73	97.59 / 2.41	97.27 / 2.73	97.27 / 2.73	
Slovene	95.81 / 4.19	95.64 / 4.36	98.06 / 1.94	97.58 / 2.42	98.71 / 1.29	97.58 / 2.42	

Table 3: Sentence alignment coverage per English - language alignments

### Conclusions

- Provided formalizations of context for the sentence alignment task.
- Introduced Zipfian word vectors, which effectively presents an order-free representation of the distributional properties of a given sentence.
- Defined 2D weight decaying correlation for calculating the similarities between sentences.
- Our system dynamically selects the local context for a pair of set of sentences which maximizes the correlation.
- The system performs 1.1951 to 1.5404 times better in reducing the error rate in alignment accuracy and coverage.

#### References

[1] Xiaojie Wang. Robust utilization of context in word sense disambiguation. In Anind Dey, Boicho Kokinov, David Leake, and Roy Turner, editors, Modeling and Using Context: 5th International and Interdisciplinary Conference, pages 529541. Springer-Verlag, Berlin, 2005.

[2] George Kingsley Zipf. The meaning-frequency relationship of words. The Journal of General Psychology, 33:251256, 1945.