What makes sense?
Searching for strong WSD predictors in Croatian

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8 Nov 2007

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- SENSEVAL - inter-annotator agreement only around 60%

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- stochastic approach
  - supervised methods - training a model on annotated data set
  - unsupervised methods - clustering on unannotated data set

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- corpus verticalised, sentence boundaries marked

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- manual annotation of 1000 occurences for each lexeme
  60% by both annotators, the rest separatley
- due to strong polysemy -inter-annotator agreement was 100%

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- we do not observe the absoulute accuracy, but the relative shift in regards to the environment size

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  - evaluating impact of sentence border on determining lexeme's sense
- evaluation by accuracy and standard error through 10-fold cross-validation

$$accuracy = \frac{a+d}{a+b+c+d}$$

$$S_E = \frac{\sigma}{\sqrt{N}}$$

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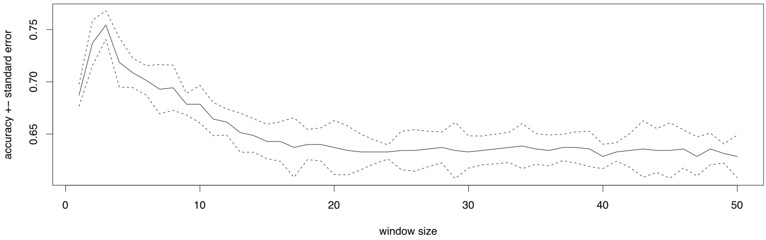
Results

Window size/accuracy for "miš"



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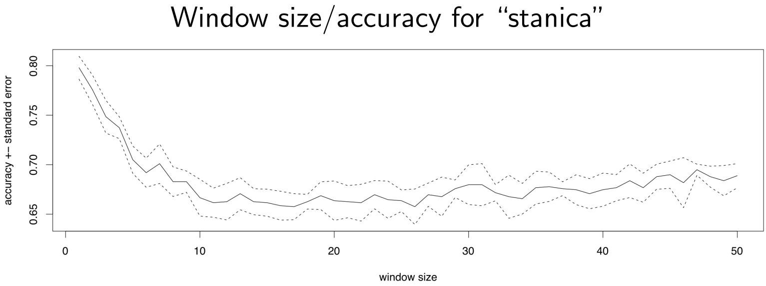
Window size/accuracy for "stanica"
accuracy +− standard error
0.65
0.70
0.75
0.80
0
10
20
30
40
50
window size


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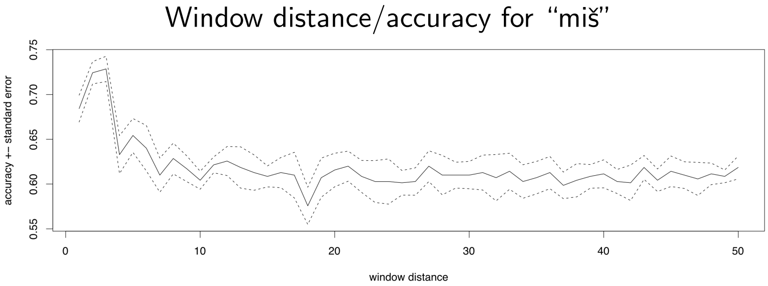
Results



Window distance/accuracy for “miš”
accuracy +- standard error
0.55
0.60
0.65
0.70
0.75
0
10
20
30
40
50
window distance

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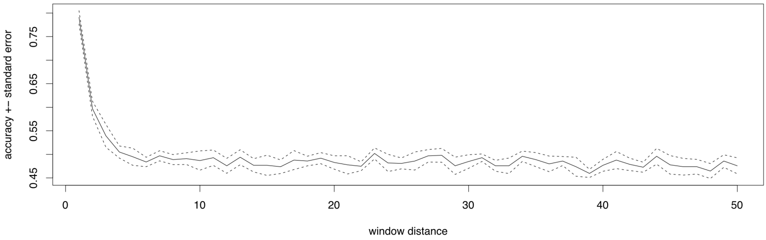
Window distance/accuracy for “stanica”



Results

One-sense-per-discourse method

	Applicability	Accuracy
“miš”	28.92%	88.98%
“stanica”	26.31%	97.10%

Results

Accuracy with standard error in relation to 3 tokens before/after observed lexeme sentence boundary

	Before sentence boundary	After sentence boundary
“miš”	68,00%±1,52%	64,14%±2,09%
“stanica”	57,37%±1,75%	57,27%±1,18%

Conclusion

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  - both window size and window distance experiments confirm the immediate sorrounding of the lexeme as the most informative when determining strong WSD predictors
- good results when applying one-sense-per-discourse method
  - when the observed lexeme appears more than once in a discourse, the probability is very high that it will have the same sense
- sentence border does not appear to be significant for strong WSD predictors

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Questions?