



take[lab];

Event and Temporal Relation Extraction from Croatian Newspaper Texts

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- **Event extraction (EE)** and **temporal relation extraction (TRE)** – non-trivial information extraction tasks
- Important role in various NLP applications
- EE: event identification or event classification
- TRE: classification of temporal relations between extracted pairs of events

Our goal

Develop and evaluate **EE** and **TRE** from Croatian newspaper text using **supervised machine learning** with simple features

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Develop and evaluate **EE** and **TRE** from Croatian newspaper text using **supervised machine learning** with simple features

- Sketch of related work
- Corpus annotation
- Models and features
- Results
- Conclusion

- [Vendler, 1957] – *states, activities, accomplishments, achievements*
- [Pustejovsky, 1991] – structural event hierarchy
- [Siegel & McKeown, 2000] – machine learning for determining the aspectual properties of verbs
- [Pustejovsky et al., 2003a] – *TimeML*, eight classes of events
- [Pustejovsky et al., 2003b] – *TimeBank* manually annotated for events
 - [Saurí et al., 2005], [Boguraev & Ando, 2005], [Bethard & Martin, 2006]

- [Allen, 1983] – interval temporal algebra
- [Pustejovsky et al., 2003a] – *TimeML*, eight labels for relations
- [Pustejovsky et al., 2003b] – *TimeBank* annotated with low inter-annotator agreement
- [Mani et al., 2006] – expanded TimeBank using a temporal closure algorithm
- [Lapata & Lascarides, 2004, Lapata & Lascarides, 2006] – probabilistic models for inserting temporal connectives (*during*, *after*, ...) into sentences
- [Verhagen et al., 2007], and [Verhagen et al., 2010]– *TempEval* and *TempEval-2* evaluation exercises

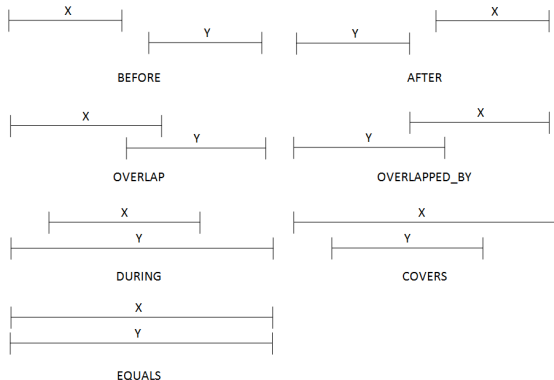
- **230** newspaper articles from the Croatian newspaper *Vjesnik* spanning years 1999—2009
- Avg. article length: 500 tokens (including words and punctuation marks)
- Topics: daily news, sports, politics, and culture
- Opinionated text (i.e., columns, reviews) was not considered
- **102,830** words, **26,095** word-form types, **10,963** lemma types

- Because we focus on **news corpora**, we introduce three modifications to TimeML guidelines:
 1. only **realis** events
 2. no generic events
 3. no states (only state changes)
- Events considered on a single word basis
- 7 event classes

- 5 annotators
- Inter-annotator agreement: $F_1 = 0.7951$

Event Class	Frequency	IAA
OCCURRENCE	6,867	0.6537
REPORTING	1,303	0.8207
I_ACTION	1,124	0.3341
HALF_GENERIC	642	0.2080
STATE_CHANGE	348	0.2349
ASPECTUAL	301	0.4272
PERCEPTION	58	0.3383
<i>Total</i>	10,643	

- Based on Allen's relation, but with some conflationions
- 8 relations



- 4 annotators
- Inter-annotator agreement: $\kappa = 0.5855$

Relation Type	Frequency	IAA
BEFORE	4,860	0.7660
AFTER	3,500	0.8676
EQUALS	1,880	0.4968
COVERS	1,597	0.5847
DURING	1,341	0.5775
NON-DETERMINABLE	763	0.1813
OVERLAP	46	0.0000
OVERLAPPED_BY	24	0.0833
<i>Total</i>	14,011	

- Naive Bayes (NB), k -nearest neighbors (k -NN) with $k = 3$, and support vector machine (SVM)
- Baseline: word-conditioned majority class (events) and majority class (temporal relations)
- Event extraction features:
 - word, lemma, stem, POS tag, case, number, modality, auxiliary words, verb form, verb valence class (from CROVALLEX), negation, surrounding words
- Temporal relation extraction features:
 - word, lemma, stem, POS tag, modality, auxiliary words, verb valence class (from CROVALLEX), event class, binary feature vector for words between events

- Event extraction: two experiments
 - binary classification (event identification)
 - multiclass classification (event classification)
- Temporal relation extraction: classification of relations between all pairs of events within the same sentence
- Performance estimates: ten-fold cross-validation
- Results: macro-averaged F_1 scores averaged over ten folds

	Baseline	NB	<i>k</i> -NN	SVM
Event identification	5.82 ± 0.69	68.85 ± 0.63	71.07 ± 1.31	77.40 ± 0.80
Event classification	0.84 ± 0.20	33.56 ± 1.27	43.63 ± 2.93	48.04 ± 3.21
OCCURRENCE	3.10 ± 0.76	55.40 ± 2.04	53.33 ± 2.14	62.34 ± 1.23
REPORTING	0.69 ± 0.87	75.28 ± 1.09	76.44 ± 3.32	79.91 ± 2.36
ASPECTUAL	0.39 ± 1.24	12.25 ± 2.31	58.42 ± 7.37	59.21 ± 5.48
PERCEPTION	0.00 ± 0.00	24.66 ± 8.65	50.80 ± 15.64	56.32 ± 18.18
I_ACTION	0.99 ± 0.90	28.63 ± 1.88	24.21 ± 4.26	24.28 ± 2.40
STATE_CHANGE	0.72 ± 0.93	25.11 ± 3.62	23.18 ± 8.04	23.17 ± 6.49
HALF_GENERIC	0.00 ± 0.00	13.59 ± 2.11	18.99 ± 5.70	31.04 ± 6.15

- Comparison difficult due to differences in comparison schemes
- [Saurí et al., 2005]
 - Slightly higher event identification results (80%), based on word chunking, whereas we consider only single words
 - Much better results for event classification (86%), but with a different set of event classes, unfair performance estimate [Bethard & Martin, 2006]
- [Bethard & Martin, 2006] – F_1 scores of up to 76% for event identification, 58% for event classification
- [Verhagen et al., 2010] – F_1 scores for Spanish and English – 88% and 80% for event identification, 66% and 79% for event classification

	Baseline	Bayes	k-NN	SVM
Temp. relation classif.	6.44 ± 0.01	38.77 ± 1.87	32.17 ± 1.86	51.16 ± 2.94
BEFORE	51.43 ± 0.05	63.63 ± 1.74	59.61 ± 3.47	73.12 ± 0.85
AFTER	—	59.35 ± 2.18	56.16 ± 3.83	71.08 ± 1.46
OVERLAP	—	$11,88 \pm 11.70$	0.00 ± 0.00	32.07 ± 19.44
OVERLAPPED_BY	—	2.64 ± 2.37	0.00 ± 0.00	20.67 ± 23.82
DURING	—	55.59 ± 3.14	46.16 ± 4.26	60.41 ± 2.89
COVERS	—	36.51 ± 2.52	24.49 ± 3.72	50.83 ± 3.49
EQUALS	—	36.91 ± 3.54	33.87 ± 2.30	46.01 ± 3.43
NON-DETERM.	—	43.63 ± 3.71	37.05 ± 7.22	55.11 ± 8.20

- Comparison difficult due to differences in relation types and the pairs of events considered
- [Verhagen et al., 2010] – F_1 scores of 58% and 66% for the relevant temporal relation extraction tasks
- Higher results are expected because only specific event pairs are considered

- We've addressed EE and TRE for Croatian
- F_1 scores of **77%** for event identification, **48%** for event classification, and **51%** for temporal relation classification
- Difficult to compare to work of others, but satisfactory given the simplicity of features
- We believe results are indicative for other Slavic languages
- Future work
 - a more detailed analysis of the annotation scheme and guidelines
 - use of more sophisticated features (syntactic functions)
 - relating events to normalized TIMEXes

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Thanks for your attention!

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