A Flexible NLP Pipeline for Computational Narratology in Literary Text

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Context of this Work

Computational Narratology
• context: Digital Humanities
• facilitate annotations from literary scientists
• support hypotheses [1]
• methods: Natural Language Processing

Temporal phenomona
• field of study in narratology
• temporal structure of literary texts
• examples: time shifts, order phenomena (e.g., prolepsis)

The heureCLÉA Project [4]

Cooperation
• BMBF-funded eHumanities project
• narratologists (Hamburg)
• computer scientists (Heidelberg)
• temporal phenomena in literary text

Goals
• collaborative annotation framework that automatically suggests annotations
• reduce manual annotation effort
• analysis of temporal aspects in narrative texts

Temporal Phenomena in Literary Texts

Temporal expressions
• less frequent in literary text (usually)
• can be extracted automatically
• HeidelTime: extraction of explicit temporal expressions [2]

Tense information
• tenses provide information about temporal structures
• shifts in tenses indicate order phenomena
Task: robust annotation of tenses in narrative texts

Prior work
• laborious manual annotations
• automatic systems focus on English
• no existing system for German tense annotation

Data set
• German narrative texts (20th century)
• manual annotation by literary scientists
• tagset: narratological aspects

Component Description and Tools

NLP components
• POS tagging: TreeTagger
• morphology: Morphisto
• time expressions: HeidelTime
• syntactic parsing: Parzu & Stanford parser

CATMA interface
• CATMA: collaborative annotation platform
• flexible CATMA ↔ UIMA interface
• tailored to narratologists

Machine learning interface
• feature extraction and machine learning
• interchangeable algorithms
• goal: predict annotations automatically

Feedback loop on predicted annotations
• manual corrections
• improvement of future predictions (ML)

Use Case: Tense Annotations

Extracting temporal clusters [3]
• temporal cluster: all tokens governed by the same verb
• approach based on morphological features & heuristics
• exploitation of tense markers (e.g., auxiliaries)
• rule set for combinations of morphological features
• heuristic for sentences with unknown tense
• evaluation: comparison to manual annotations
• high inter-annotator agreement ($\kappa > 0.5$)

Evaluation Results

tense correctly tagged verbs

<table>
<thead>
<tr>
<th>tense</th>
<th>correctly tagged verbs</th>
</tr>
</thead>
<tbody>
<tr>
<td>present</td>
<td>93.10</td>
</tr>
<tr>
<td>preterite</td>
<td>95.73</td>
</tr>
<tr>
<td>perfect</td>
<td>96.43</td>
</tr>
<tr>
<td>pluperfect</td>
<td>84.71</td>
</tr>
<tr>
<td>future</td>
<td>90.00</td>
</tr>
</tbody>
</table>

⇒ reliable and robust prediction of tense clusters

Ongoing work
• machine learning based system for additional annotations, e.g., narrative levels
• hybrid, self-improving system: heuristics + machine learning

References


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