

Giveme5W1H

A Universal System for Extracting Main Events from News Articles

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Taliban attacks German consulate in northern Afghan city of Mazar-i-Sharif with truck bomb

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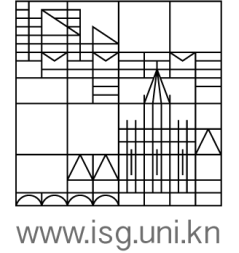
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Who did **what**, **where**, **when**, **why**, and **how**?

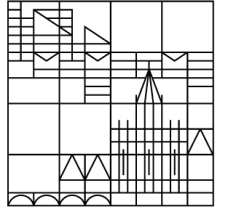
Motivation



- News texts
 - answer the five journalistic W and one H questions (5W1H)
 - to quickly inform readers of the main event
- **5W1Hs useful** for various applications
 - Event detection
 - Finding related articles (clustering)
 - Summarization
 - Other sciences, e.g., frame analyses in the social sciences
 - ...

Content

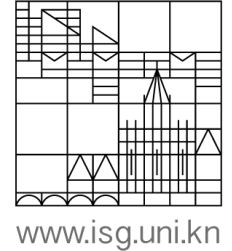
- Background
- Methodology
- Evaluation and results
- Conclusion



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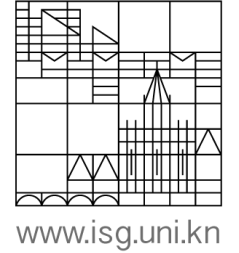
Background

Event Extraction from News Articles



- Current methods
 - extract events **implicitly** (topic modeling, clustering) [2,6,27,32]
 - extract **task-specific** properties [26,32]
 - are **not publicly available** (but **extract explicit event descriptors**) [29,34-36]
 - Sufficient quality: accuracy ranges from 0.65 [29] to 0.89 [36]
- Disadvantages to the research community
 - **Redundant work** for a common task
 - **Non-optimal accuracy**

Research Objective



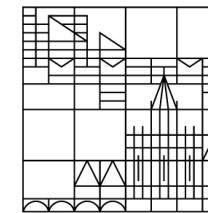
Devise a method that extracts the main event of a single news article

- *explicit main event descriptors*
- that are *usable* by later tasks in the analysis workflow

- ↓
- *publicly available*

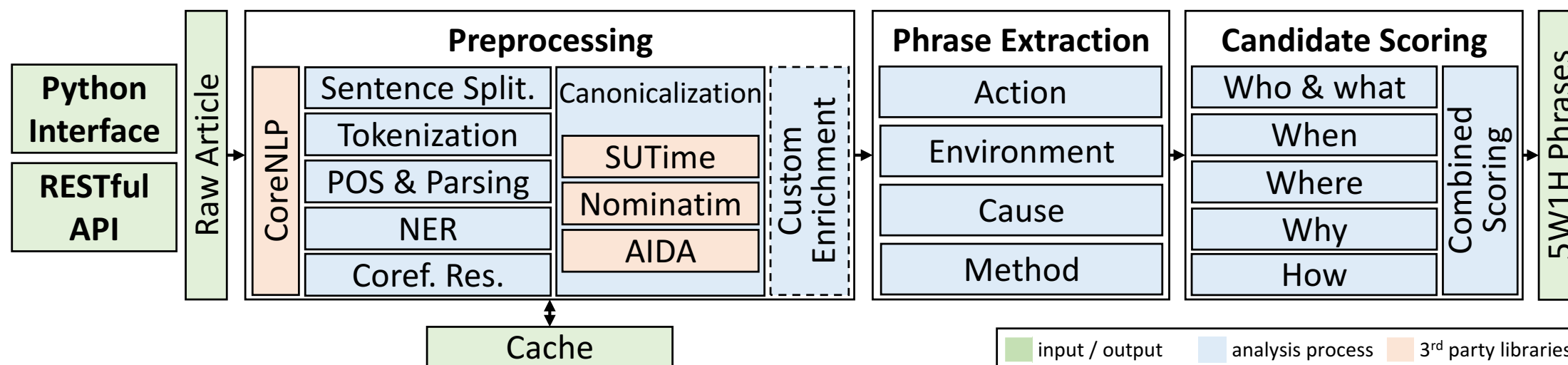
Methodology

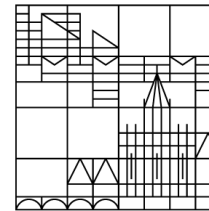
Giveme5W1H



Three Phase Analysis Pipeline

- Syntactic and domain-specific rules for extraction and scoring





Phrase Extraction

• Who

- **Subjects**
(1st noun phrase (NP) in sentence)

• What

- **Predicates** (verb phrase (VP) that is right to 'who' in parse tree)

• Where

- Named entities (NEs) of type **location**, parsed by Nominatim

• When

- NEs of type **date or time**, parsed by SUTime

• Why

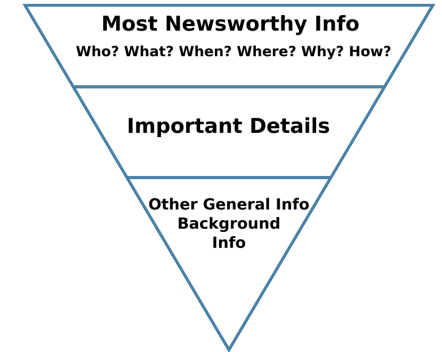
- Causal conjunctions (CC, "due to"), causative Vs and RBs ("implicate")

• How

- Copulative CCs ("after [the train came off]"), fallback: ADJs, RBs

Candidate Scoring: Who and What

- **Early** – inverted pyramid [10], but may contain hooks
- **Often**
- **Contain NE** [12]



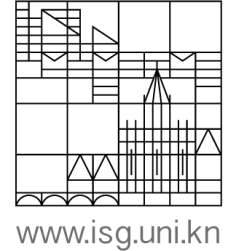
$$s_{\text{who}}(c) = w_0 \left(1 - \frac{n_{\text{pos}}(c)}{d_{\text{len}}}\right) + w_1 \left(\frac{n_f(c)}{\max_{c' \in \mathcal{C}}(n_f(c'))}\right) + w_2 \text{NE}(c)$$

$$w_0 = 0.9, w_1 = 0.095, w_2 = 0.005$$

- What: score jointly with respective who candidate
- Learned model parameters on 100 annotated articles

Evaluation and results

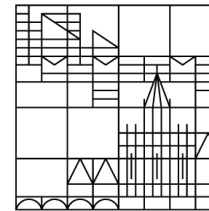
Survey Setup



- Random sample of 120 articles from BBC corpus (2,225 articles) [14]
 - 24 articles for each category
 - business (Bus), entertainment (Ent), politics (Pol), sport (Spo), and tech (Tec)
- Three assessors (graduate IT students)
- 3-point Likert scale
 - Non-relevant: 0
 - Partially relevant: 0.5
 - Relevant: 1

Precision = 0.73 (on 4W: 0.82)

Property	ICR	Bus	Ent	Pol	Spo	Tec	Avg.
Who	.93	.98	.88	.89	.97	.90	.92
What	.88	.85	.69	.89	.84	.66	.79
When	.89	.55	.91	.79	.81	.82	.78
Where	.95	.82	.63	.85	.79	.80	.78
Why	.96	.48	.62	.42	.45	.42	.48
How	.87	.63	.58	.68	.51	.65	.61
Avg.	.91	.72	.72	.75	.73	.71	.73
Avg 4W	.91	.80	.78	.86	.85	.80	.82

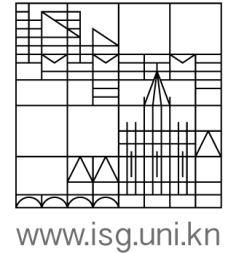


Comparison to State-of-the-Art

- Only on 5W evaluated, Giveme5W1H is
 - 0.05 **better** than Giveme5W [17] (0.70)
 - 0.10 **better** than fraction of “correct” answers in [29] (0.65)
 - 0.14 **worse** than precision in [36] (0.89)
- **However**
 - No gold standard & use of non-disclosed datasets [29, 35, 36]
 - Input translated from other languages [29]
 - Binary relevance assessments [20,36]

Conclusion

First Open-Source 5W1H Extractor



- Syntactic and domain-specific rules
- Precision = 0.73
 - Only on 4W: 0.82
- Get it at github.com/fhamborg/Giveme5W1H
- Future work
 - Improve “what” by scoring more independently from “who”
 - Extract implicit locations, e.g., “Apple HQ” → Cupertino



Thank You!

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