LAVIS | Hochschule RheinMain

Neural Entity Linking on Technical Service Tickets

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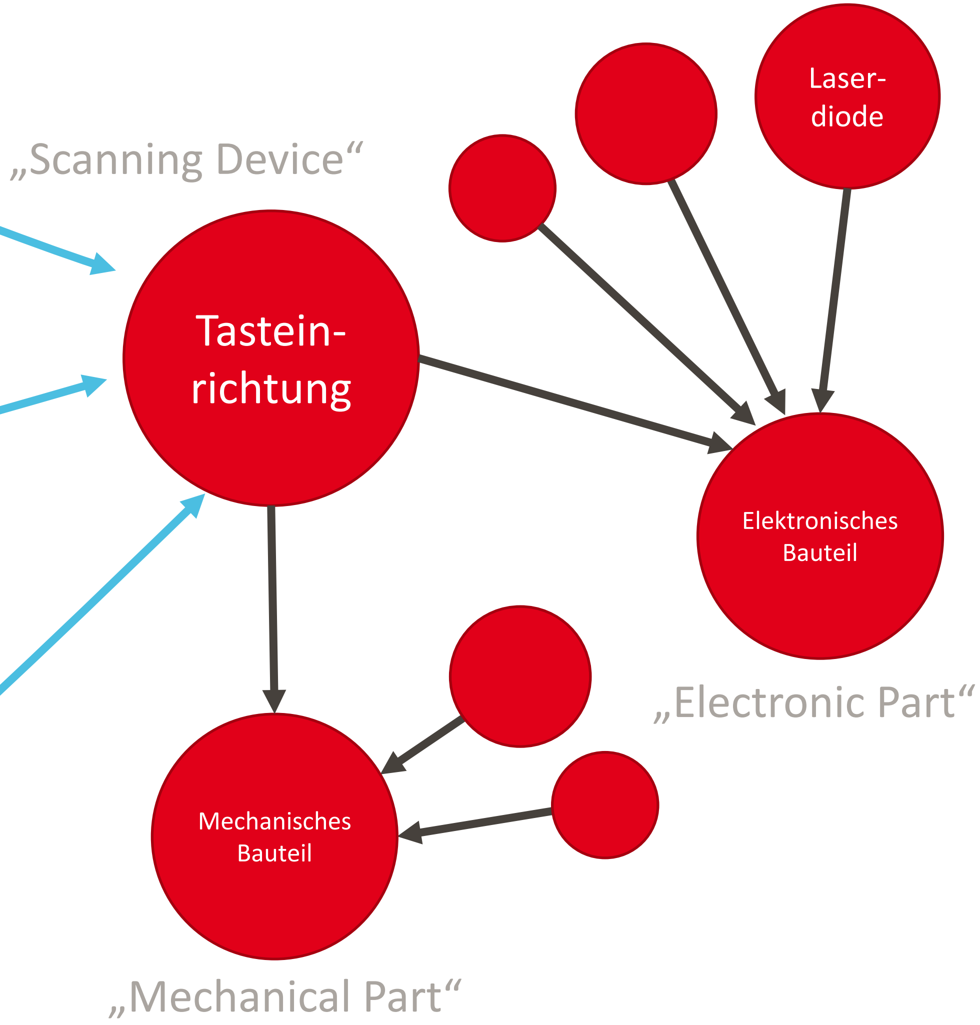
- Documentation is scarce and heterogeneous

Am Verleimteil ist keine Kantentastung im Moment dran. Der 6 mm Schlauch der Tastung hat sich oben in den Niederhalter geklemmt…

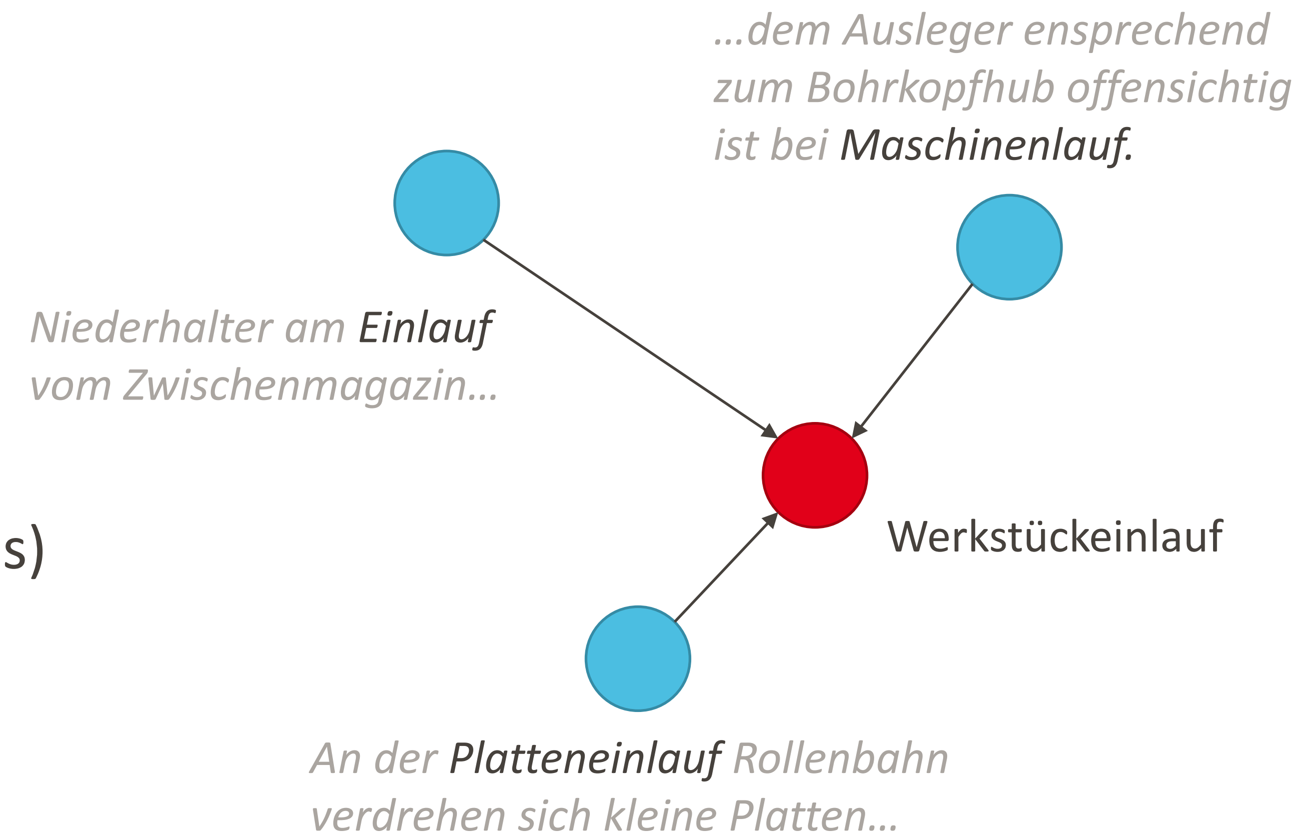
There is no **edge detection** on the gluing part at the moment. The 6 mm hose of the **probe** has clamped itself into the top of the hold-down…

Fehlerauswirkung: Die Vertikalachse (Y-Achse) meldet einen Schleppfehler (nur in Verbindung mit einem Stop der Direktverkettung), eventuell auch die Längstastung…

Error effect: The vertical axis (Y-axis) reports a contouring error (only in connection with a stop of the direct linkage), possibly also the **longitudinal scanner**…



- Task: Link a textual mention to a KB entity [1, 2]
- Easy
  - Spelling Errors
  - Abbreviations
  - Synonyms (general terms)
  - …
- Hard
  - Synonyms (domain specific terms)
  - Hyponyms/Hypernyms
  - Ambiguity
  - …

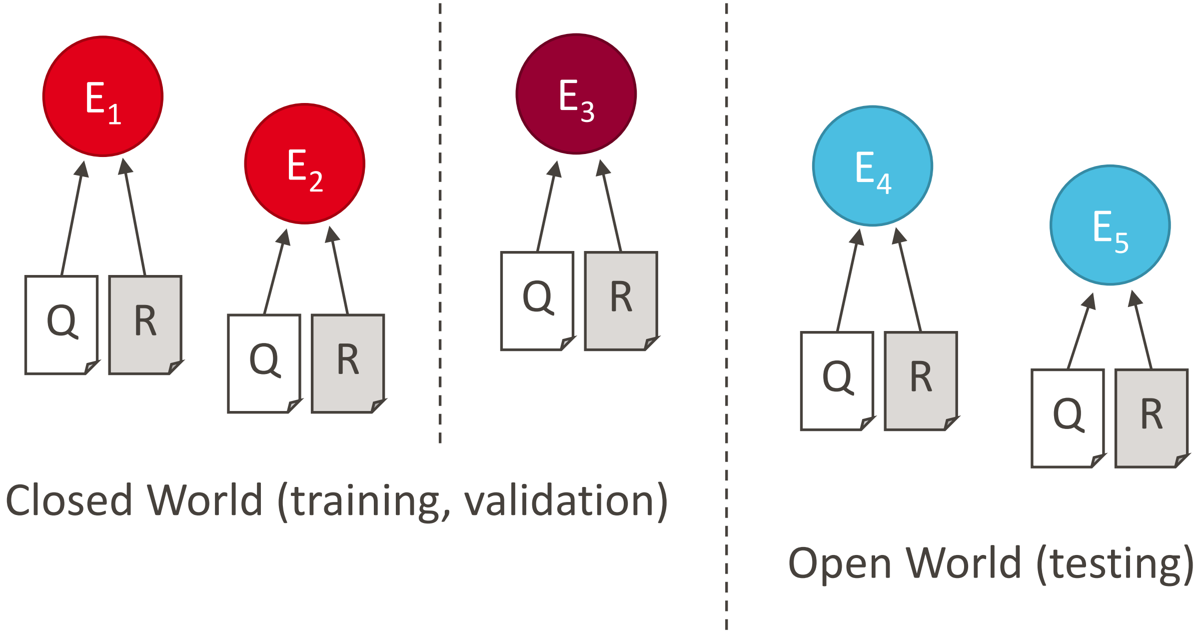


Current State of the Art

- SOTA tackles EL with Representation Learning [3, 4, 5]
  - Unsupervised pre-training on large out-of-domain data (language models)
  - Adaption on target task (transfer learning)
  - Evaluations usually on (high quality) Wikipedia data [6, 7]
- Industry mostly uses heuristics [8]
- Our contribution:
  - Working with low-quality (noisy) data
  - Deep learning in comparison to simple heuristics
  - Zero-shot setting [9, 10]

Data Setup

- Three Open-World datasets (zero-shot)
  - Wikipedia: MIXED, GERÄTE:
    - Mentions selected using the hyperlink structure
  - EMPOLIS: customer issues
    - Mentions selected on human annotated synonym lists



		Entities	Sentences
MIXED	Training	8331	107082
	Validation	1031	13560
	Testing	1027	12853
GERÄTE	Training	5717	65101
	Validation	3231	35823
	Testing	698	7680
EMPOLIS	Training	401	13587
	Validation	201	7680
	Testing	200	6601

Approach 1: Heuristics Pipeline

- Mentions and Entities are both transformed

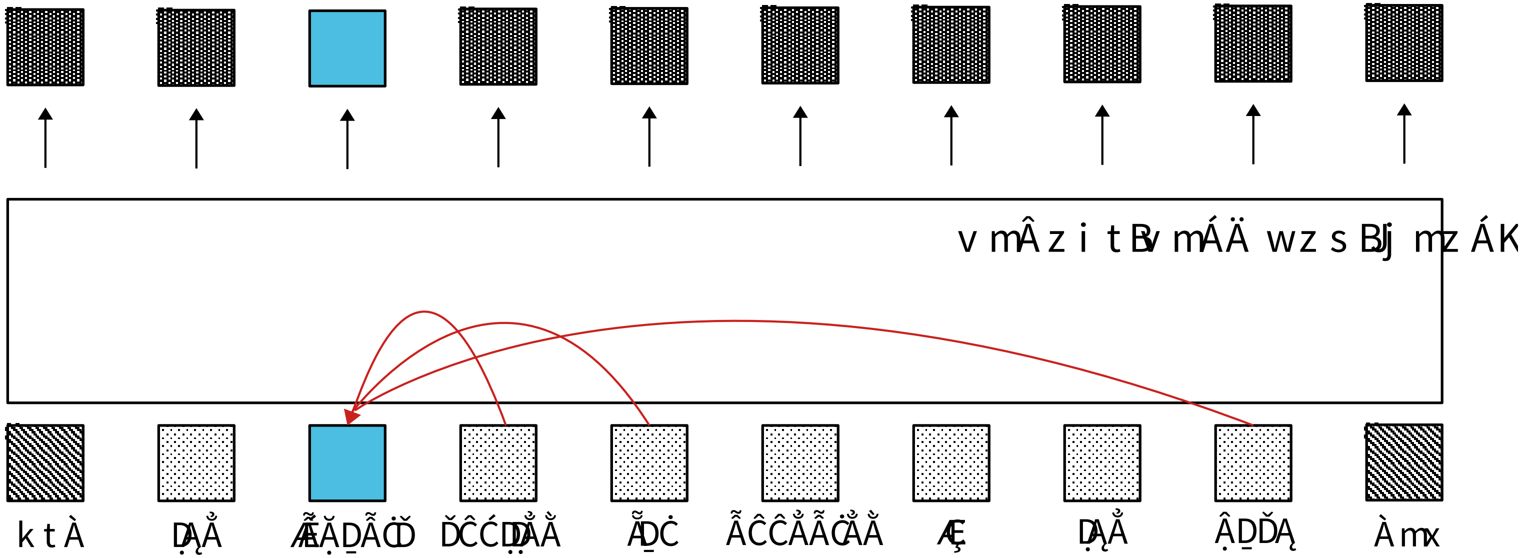
Heuristic	Before	After
Punctuation	CNC-Maschine	CNC Maschine
Corporate Forms	Empolis GmbH	Empolis
Lowercasing	Schwabbelscheibe	schwabbelscheibe
Stemming	astronomische einheit	astronom einheit
Stopword Removal	luren von brudevælte	luren brudevælte
Sorting	linde material handling	handling linde material
Abbreviations*	hohlschaftkegel	hsk

*both token- and compound-based

- Compare by edit distance
- The argmin is returned

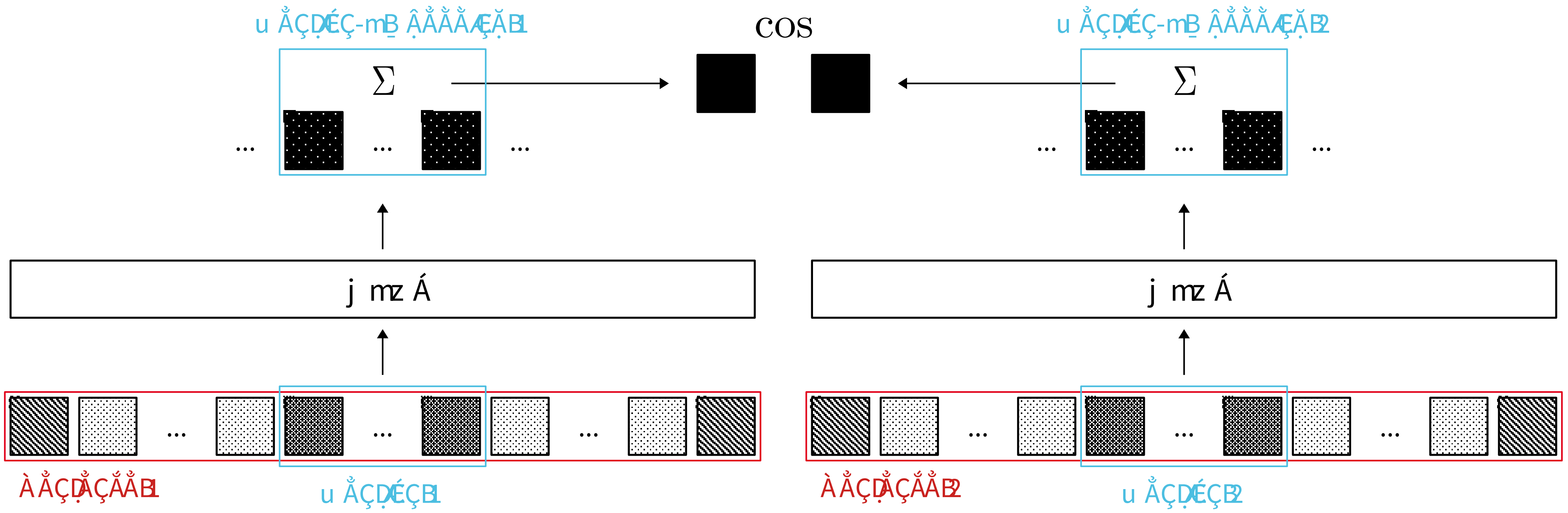
Approach 2: BERT

- Current SOTA: transformer models (self-attention) [11, 12, 13, 14]
- Large & deep models: fine-tuning and inference are expensive



Approach 2a: BERT Bi-Encoder

- Context sentences are successively transformed (caching possible)
- Domain adaption: max-margin loss with negative sampling
- Inference: minimum cosine distance



Evaluation: Heuristics vs. Neural Approach

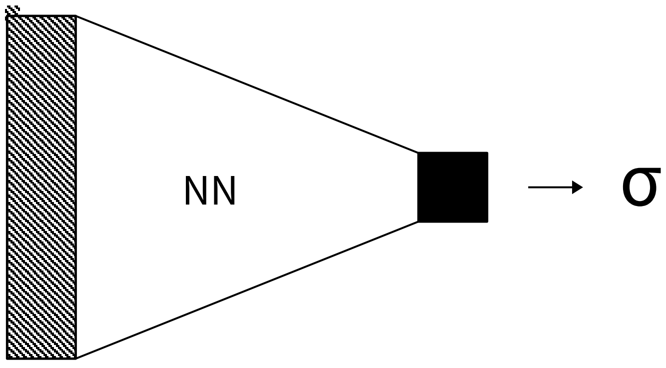
- Measured: Top-1 Accuracy

Classifier	Geräte	Mixed	Empolis
Heuristics	77.87	83.98	51.16
Bi-Encoder	93.30	95.93	40.06
Hybrid	**94.72**	**97.52**	**71.40**

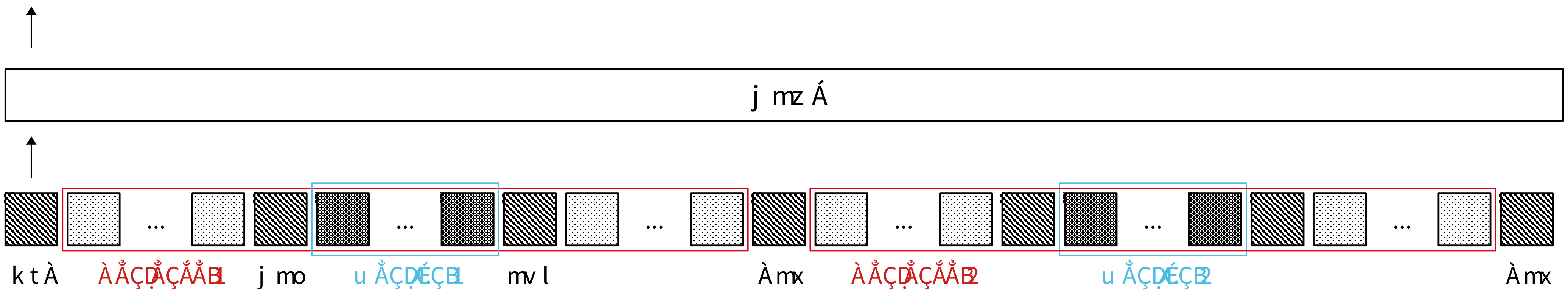
- Hybrid
  - If no suitable candidate was found, fallback to BERT
  - Greatly improves performance on Empolis

Approach 2b: BERT Cross-Encoder

- Context sentences are jointly transformed (no caching)
- Use CLS features for binary classification (feed forward network)



- Domain Adaption: binary cross entropy loss
- Inference: Brute-force search over all candidates



Evaluation: Cross Encoder

- Brute force approach too expensive: reduce number of queries
- Measured: Top-1 Accuracy

Classifier	Geräte	Mixed	Empolis
Bi-Encoder	89.68	93.09	51.53
Cross-Encoder	94.13	96.88	45.41
Hybrid Bi-Encoder	93.41	97.08	80.61
Hybrid Cross-Encoder	**96.42**	**98.05**	**81.63**

- Bi-Encoder with inverted index is much faster (multiple magnitudes)

Thank you!

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