Evaluating the Meaning of Answers to Reading Comprehension Questions: A Semantics-Based Approach

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    + they precisely expose meaning distinctions and support linking meaning to discourse

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    + semantic representations abstract away from lexical and syntactic variation in the realization of the same meaning
    + they precisely expose meaning distinctions and support linking meaning to discourse
- We present a short answer assessment approach based on underspecified formal semantic representations.

Outline

Empirical challenge: CREG

- Empirical basis: Corpus of Reading Comprehension Exercises in German (CREG; Ott, Ziai & Meurers 2012)
  - CREG consists of texts, questions, target answers, and student answers written by learners of German.

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- CREG data was collected and assessed in two large German programs in the US: KU and OSU
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  - For each student answer, two independent annotators evaluated whether it correctly answers the question.
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- Data freely available, and reference results available for CoMiC-DE system (Meurers, Ziai, Ott & Kopp 2011),
  - a system not using formal semantic representations

Representations: Lexical Resource Semantics

- LRS (Richter & Sailer 2003) is an underspecified semantic formalism:
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- LRS (Richter & Sailer 2003) is an underspecified semantic formalism:
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  - semantic representations are not completely specified but subsume a set of possible resolved expressions
- Advantage of an underspecified semantic formalism for content assessment:
  - provides access to fine-grained semantic distinctions
    - all parts of the semantic representation are accessible in a flat representation
  - how the parts are combined is separately encoded (variable bindings, dominance)
    - avoids costly computation of all readings
    - similar parts can be compared independent of where they appear in the overall semantics

Example for LRS representation

(1) *Alle Zimmer haben nicht eine Dusche.*
all rooms have not a shower

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- INTERNAL CONTENT: core semantic contribution of head
- EXTERNAL CONTENT: semantic representation of sentence
- PARTS: all subterms of the representation

$$\begin{bmatrix} \textsc{incont} & \textit{have(e)} \\ \textsc{excont} & \mathrm{A} \\ \textsc{parts} & \left\langle \begin{array}{l} \mathrm{A},\ \mathrm{have(e)},\ \forall x_1(\mathrm{B} \rightarrow \mathrm{C}),\ \exists x_2\ (\mathrm{D} \wedge \mathrm{E}),\ \neg\ \mathrm{F}, \\ \mathrm{room}(x_1),\ \mathrm{shower}(x_2),\ \mathrm{subj(e,}x_1\mathrm{)},\ \mathrm{obj(e,}x_2\mathrm{)} \\ \exists \mathrm{e}(\mathrm{have(e)} \wedge \mathrm{subj(e,}x_1\mathrm{)} \wedge \mathrm{obj(e,}x_2\mathrm{)}) \end{array} \right\rangle \end{bmatrix}$$

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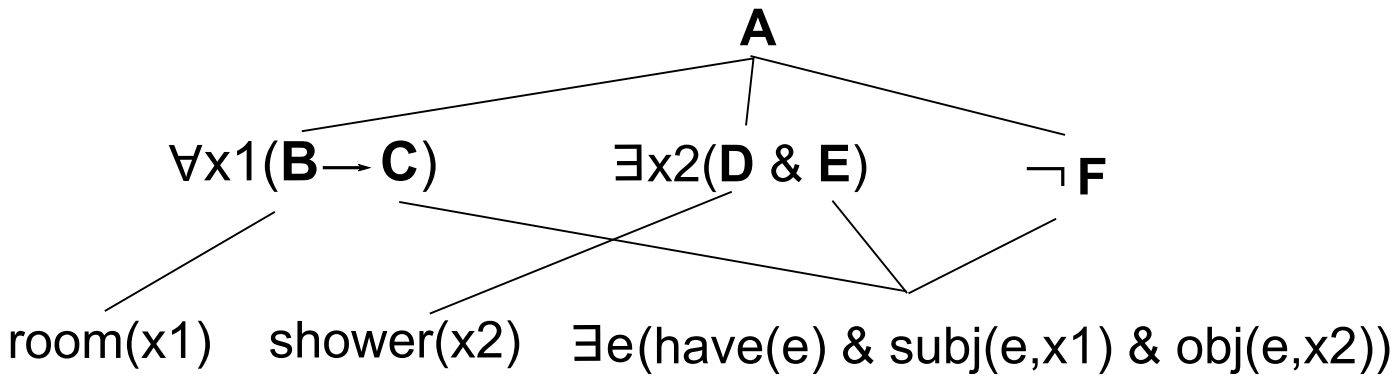
- LRS representations include dominance constraints, which restrict possible identifications, e.g.:



Our general approach

1. automatically derive LRS representations for the student answer, the target answer, and the question
   - method described in Hahn & Meurers (2011)
   - based on statistical dependency parsing
   - always results in an LRS structure, also for ill-formed input

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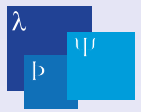

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   alignments also computed between answers and question
3. perform overall meaning comparison based on numerical scores representing quality of alignment

Aligning Meaning Representations

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- A simple example: “John left.” vs. “Jon vanished.”

∃x A B	——	∃y E F
john(x)	——	jon(y)
∃e C D	——	∃f G H
subj(e,x)	——	subj(f,y)
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- Best alignment is determined automatically using a maximization criterion.

Automatically Deriving Alignments

Maximization criterion

- combines three measures of alignment quality:
  - **LinkScore**: similarity of the alignment links
  - **VariableScore**: consistency of alignments with respect to the induced variable bindings θ
  - **DominanceScore**: consistency with respect to dominance constraints
- $Q(a, \theta | S, T) = \quad LinkScore(a|S,T) \cdot VariableScore(\theta) \cdot DominanceScore(a|S,T)$
- The alignment maximizing the criterion is found efficiently using the A* algorithm.

LinkScore: Similarity for Alignment Links

- Base cases:
  - Variables can be matched with any variable of same type.
  - For other semantic terms, compute the maximum score of
    - Levenshtein distance, to account for spelling errors
    - Synonyms: score 1 if in GermaNet (Hamp & Feldweg 1997)
    - Dissimilar elements of same category: constant costs, empirically determined for pairs of
      – grammatical function terms
      – special terms (affirmative or negative natural language expressions and logical negation)
    - ...

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$\Rightarrow$ Overall **LinkScore** = sum of similarity of all alignment links

- unaligned elements: constant cost μ_{NULL} (may be smaller than costly alignment link in another overall alignment)

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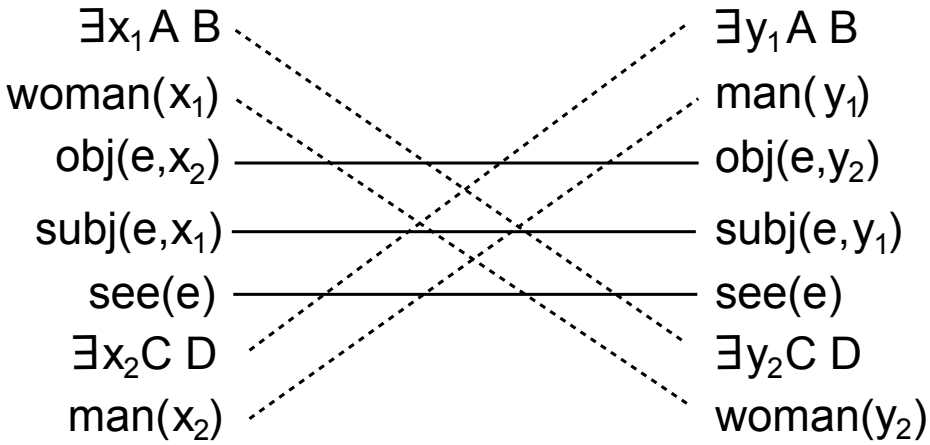

  - line links require unifying x_1 with y_1 and x_2 with y_2
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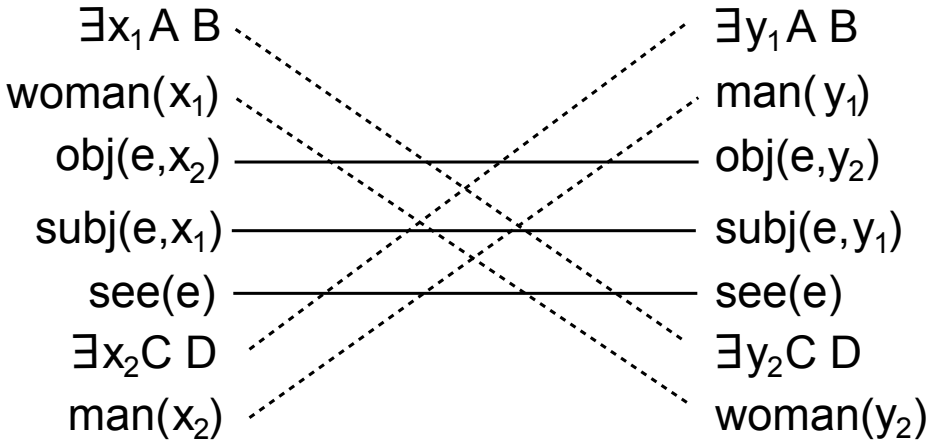

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  - adding the dotted links would result in unifying all variables

- An alignment which preserves the structure will not unify two distinct variables from the same LRS representation.

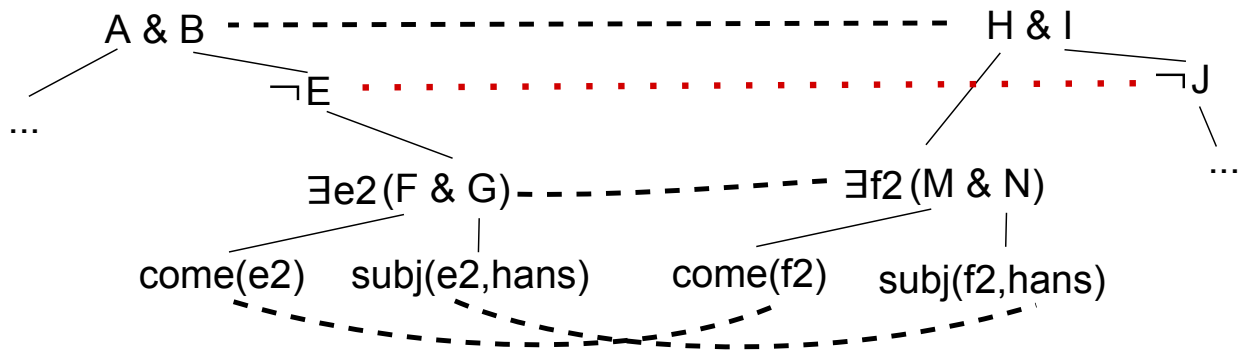
$\Rightarrow$ **VariableScore** = information loss resulting from unification

DominanceScore

- Mismatches in the structure of the linked semantic representations need to be taken into account.
- For example:

(2) a. *Peter will come but Hans will **not** come.*

b. *Peter will **not** come but Hans will come.*



⇒ **DominanceScore** = extent to which an alignment defines an isomorphism

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From Alignment to Meaning Comparison

Basic measures

- Based on the best overall alignment identified using A*, we compute several measures for meaning comparison.
- **ALIGN** measure, based on alignment quality Q:

$$\text{ALIGN} = \frac{\text{alignment quality(student answer, target answer)}}{\text{\# of elements in shorter PARTS list}}$$

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- **EQUAL** measure, based on number of alignment links:

$$\text{Student} = \frac{\text{\# of alignment links(student answer, target answer)}}{\text{\# of elements on PARTS list of } \textit{student} \text{ answer}}$$

$$\text{Target} = \frac{\text{\# of alignment links(student answer, target answer)}}{\text{\# of elements of PARTS list of } \textit{target} \text{ answer}}$$

Average = average of Student and Target measures

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Studying Impact of Functional Elements

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- **IGNORE** measures: ignore all functional elements
- **WEIGHTED** measures: weight elements so that functional and non-functional ones differ in impact
  - weights are empirically determined using grid search on a development set

From Alignment to Meaning Comparison

Studying Impact of Information Structure

- Information Structure (Krifka 2008): structuring of the meaning of a response in relation to the discourse
  - *given* (vs. *new*): part of meaning known from question
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- Some previous approaches exclude *given* material from alignment (Bailey & Meurers 2008; Mohler et al. 2011):
  - greatly improves classification accuracy
- Meurers, Ziai, Ott & Kopp (2011) show that the relevant linguistic aspect here is not *givenness* but *focus*.

From Alignment to Meaning Comparison

How we integrate information structure

- Needed: A component which automatically identifies the focus of an answer in a question-answer pair.
  - First approximation: an element on the PARTS lists of an answer is marked as focused if it is not aligned to the question, except for alignment with explicit alternatives.

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  - First approximation: an element on the PARTS lists of an answer is marked as focused if it is not aligned to the question, except for alignment with explicit alternatives.
- **FOCUS** measures: BASIC measures counting only those elements which are recognized as focused
- **GIVEN** measures: BASIC measures counting only elements not aligned to the question

Experiments

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- Experiment
  - explored all measures for meaning assessment
  - binary classification is based on a threshold
    - arithmetic mean of the average result of correct and the average result of incorrect answers
  - training and testing performed using the leave-one-out scheme Weiss & Kulikowski (1991)

Results

	BASIC	GIVEN	FOCUS
WEIGHTED Average	80.9	86.1	**86.3**
IGNORE Average	79.8	84.7	84.9
EQUAL Average	76.6	80.8	80.7
ALIGN	77.1		
CoMiC-DE		84.6	

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- Information Structure
  - Focus helps target relevant part of answer (+5.4%)
- Outperforms CoMiC-DE, also integrating givenness
  - supports usefulness of semantic representations

Results

Experiment testing impact of grammaticality

- We manually annotated 220 student answers for grammatical well-formedness.
  - 66% were ungrammatical
- Accuracy on this sample:
  - 83% for ungrammatical answers
  - 81% for grammatical answers

$\Rightarrow$ semantics-based approaches can be robust, not directly linked to grammaticality

Conclusion

- We presented a system for evaluating the content of answers to reading comprehension questions.
- Unlike previous content assessment systems, it is based on comparing formal semantic representations.
  - integrates a novel approach for comparing underspecified semantic representations
- Formal semantic representations readily support the integration of information structural differences.
  - connects content-assessment to information structure research in formal semantics and pragmatics
- The system presented outperforms our shallower CoMiC-DE system on the same CREG data set.
  - formal semantic representations can be competitive for content assessment in real-world contexts

References

Bailey, S. & D. Meurers (2008). Diagnosing meaning errors in short answers to reading comprehension questions. In J. Tetreault, J. Burstein & R. D. Felice (eds.), *Proceedings of the 3rd Workshop on Innovative Use of NLP for Building Educational Applications (BEA-3) at ACL'08*. Columbus, Ohio, pp. 107–115. URL http://aclweb.org/anthology/W08-0913.

Haghighi, A. D., A. Y. Ng & C. D. Manning (2005). Robust textual inference via graph matching. In *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, pp. 387–394.

Hahn, M. & D. Meurers (2011). On deriving semantic representations from dependencies: A practical approach for evaluating meaning in learner corpora. In K. Gerdes, E. Hajicová & L. Wanner (eds.), *Depling 2011 Proceedings*. Barcelona, pp. 94–103.

Hamp, B. & H. Feldweg (1997). GermaNet - a Lexical-Semantic Net for German. In *Proceedings of ACL workshop Automatic Information Extraction and Building of Lexical Semantic Resources for NLP Applications*. pp. 9–15.

Krifka, M. (2008). Basic notions of information structure. *Acta Linguistica Hungarica* 55(3), 243–276.

MacCartney, B., M. Galley & C. D. Manning (2008). A phrase-based alignment model for natural language inference. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, pp. 802–811.

Meurers, D., R. Ziai, N. Ott & J. Kopp (2011). Evaluating Answers to Reading Comprehension Questions in Context: Results for German and the Role of Information Structure. In *Proceedings of the TextInfer 2011 Workshop on Textual Entailment*. Edinburgh, Scotland, UK: Association for Computational Linguistics, pp. 1–9. URL http://www.aclweb.org/anthology/W11-2401.

Mohler, M., R. Bunescu & R. Mihalcea (2011). Learning to Grade Short Answer Questions using Semantic Similarity Measures and Dependency Graph Alignments. In *Proceedings of the 49th Annual Meeting of the Association for Comnputational Linguistics*. pp. 752–762.

Ott, N., R. Ziai & D. Meurers (2012). Creation and Analysis of a Reading Comprehension Exercise Corpus: Towards Evaluating Meaning in Context. In T. Schmidt & K. Wörner (eds.), *Multilingual Corpora and Multilingual Corpus Analysis*, Amsterdam: Benjamins, Hamburg Studies in Multilingualism (HSM). URL http://purl.org/dm/papers/ott-ziai-meurers-12.html.

Richter, F. & M. Sailer (2003). Basic Concepts of Lexical Resource Semantics. In A. Beckmann & N. Preining (eds.), *ESSLLI 2003 – Course Material I*. Wien: Kurt Gödel Society, vol. 5 of *Collegium Logicum*, pp. 87–143.

Rus, V., A. Graesser & K. Desai (2007). Lexico-syntactic subsumption for textual entailment. *Recent Advances in Natural Language Processing IV: Selected Papers frp, RANLP 2005* pp. 187–196.

Sammons, M., V. Vydiswaran et al. (2009). Relation Alignment for Textual Entailment Recognition. In *Text Analysis Conference (TAC)*.

Weiss, S. M. & C. A. Kulikowski (1991). *Computer systems that learn*. San Mateo, CA: Morgan Kaufmann.

Ziai, R., N. Ott & D. Meurers (2012). Short Answer Assessment: Establishing Links Between Research Strands. In *Proceedings of the 7th Workshop on Innovative Use of NLP for Building Educational Applications (BEA-7) at NAACL-HLT 2012*. Montreal. URL http://purl.org/dm/papers/ziai-ott-meurers-12.html.

Full Results

Measure	BASIC	GIVEN	FOCUS
ALIGN	77.1		
EQUAL			
Student	69.8	75.3	75.2
Target	70.0	75.5	75.2
Average	76.6	80.8	80.7
IGNORE			
Student	75.8	80.1	80.3
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Target	76.1	83.3	83.3
Average	80.9	86.1	**86.3**
CoMiC-DE	84.6		

From Alignment to Meaning Comparison

Information Structure: Example for Focus vs. Given

- Alternative questions: focused information determining whether answer is correct is explicitly given in question.

(3) *Ist die Wohnung in einem Altbau oder Neubau?*
is the flat in a old house or new house

(4) a. *Die Wohnung ist in einem* ***Altbau****.*
the flat is in a old house

b. *Die Wohnung ist in einem* ***Neubau****.*
the flat is in a new house

- All words in answers mentioned in the question, but some are **focused**, shown in boldface.