Evaluating Answers to Reading Comprehension Questions in Context

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Research Questions

- What linguistic representations can be used robustly and efficiently in an automatic meaning comparison?
- What is the role of context and how can we utilize knowledge about it in comparing meaning automatically?
  Context here means questions and reading texts in reading comprehension tasks.

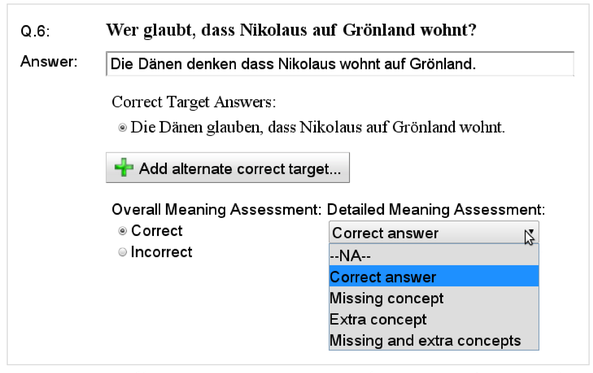
Why Reading Comprehension Exercises?

- Answers are different realizations of the same meaning.
- Meaning is clearly restricted by the task context (question, text).
- Learner language is not necessarily well-formed

➥ requires robust computational processing.

Corpus: CREG

- Corpus of Reading comprehension Exercises in German
- Is being collected in the German programs of the Ohio State University and Kansas University: almost only English L1.
- Meta data: information about students collected term by term.
- All learner answers are rated with respect to meaning (not form) by two annotators at the corresponding universities:



Assessment of learner answers in WELCOME (Meurers, Ott & Ziai, 2010)

- Agreement study based on a snapshot of the data from May 25, 2011 (Ott, Ziai & Meurers, to appear):

	# Student Answers	# Questions	% agreement binary	% agreement detailed	κ agreement binary	κ agreement detailed
KU:	5257	202	88.5%	86.6%	0.712	0.771
OSU:	4826	142	85.7%	70.6%	0.572	0.473

- Binary assessment is the observation of a task that teachers usually perform in grading: good percentage agreement.
- Detailed assessment: agreement drop in OSU data.
- Further research: have one team annotate a balanced subset of the data from the other team in order to level out effects of skewed category distribution ($\rightarrow$ low κ) in agreement study.

CoMiC: A Content Assessment System

Comparing Meaning in Context (CoMiC)

- CoMiC automatically judges whether or not a student answer is a correct answer to a reading comprehension question on basis of meaning comparison to a pre-defined target answer.
- CoMiC is a re-implementation and successor of the Content Assessment Module (CAM) by Bailey & Meurers (2008).

A Three-Phase Approach

1. Automatic Annotation enriches student and target answers as well as questions with information on different levels and types of abstraction.
2. Alignment maps elements of the learner answer to elements of the target response using annotation.
3. Classification analyzes the possible alignments and labels the learner response with a binary content assessment and a detailed diagnosis code.
   - Machine learning (TiMBL, Daelemans et al. 2007)

Example Alignment

Q: **Was sind die Kritikpunkte, die Leute über Hamburg äußern?**
'What are the objections people have about Hamburg?'

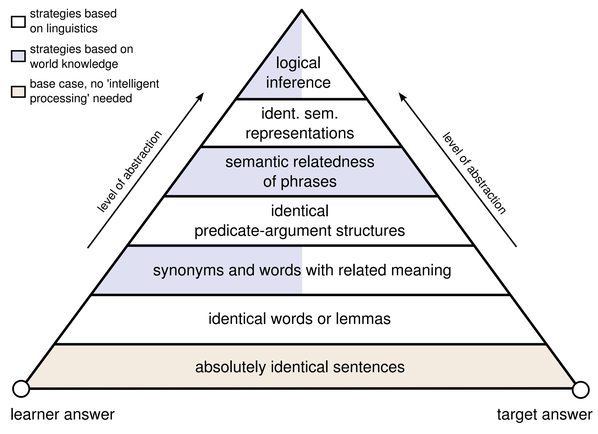
TA: **Der Gestank von Fisch und Schiffsdiesel an den Kais .**
The stink of fish and fuel on the quays .
SemType, Spelling, Spelling, Ident, Ident, Similarity

SA: **Der Geruch zon Fish und Schiffsdiesel beim Hafen .**
The smell of$_{err}$ fish$_{err}$ and fuel at the port .

Performance

- CoMiC-DE performs with an accuracy of 84,6% in an experiment with 1032 learner answers to 177 questions with 223 target answers (Meurers, Ziai, Ott & Kopp, 2011).
  - With correct and incorrect answers being equally distributed in the test data ($\rightarrow$ 50% random baseline).
- This is state-of-the-art compared to other systems for English, e. g., C-Rater (Leacock & Chodorow, 2003) or CAM (Bailey & Meurers, 2008)

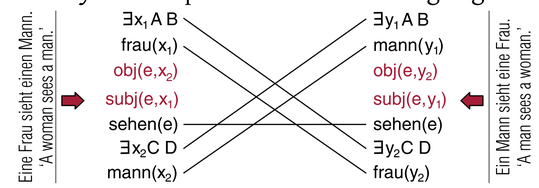
Levels of Abstraction in Meaning Comparison



Current Work in Progress

Semantic Representations in Meaning Comparison

- Basic idea: alignment (of parts) of PARTS-lists in Lexical Resource Semantics representations (LRS, Richter & Sailer 2004).
- Only 'structurally similar' parts of terms are being aligned:



(Hahn & Meurers, 2011)

Using Information Structure

- Focussed parts of answers encode requested information:

Q: **An was denken viele Menschen, wenn sie von Weißrussland hören?**
'What do many people think of when they hear about Belarus?'

TA: **Sie denken an die Tschernobyl-Katastrophe von 1986.**
'They think of the Chernobyl disaster of 1986.'

SA: **Ausländer denken bei Weißrussland weniger an Urlaub, sondern eher an die Tschernobyl-Katastrophe von 1986. Damals explodierten in der Sowjetunion Teile eines Atomkraftwerks und wurden einige Regionen Weißrusslands von der radioaktiven Strahlung verseucht.**
'Foreigners thinking about Belarus think less of vacation but rather of the Chernobyl disaster of 1986. Back then, parts of a nuclear plant exploded and some areas of Belarus were polluted by the radioactivity.'

- Distinguishing given and new information is not sufficient:

Q: **Ist die Wohnung in einem Neubau oder in einem Altbau?**
'Is the flat in a new building or in an old building?'

TA: **Die Wohnung ist in einem Neubau.**
'The flat is in a new building.'

SA: **Die Wohnung ist in einem Neubau**
'The flat is in a new building.'

Distributional Semantics of Phrasal Elements

- Semantic relatedness measures that use large corpora (e. g., PMI-IR, Turney 2001) are mostly used on the word level.
- Transfer of these approaches to phrases for non-compositional elements requiring world knowledge, e. g., *at home* vs. *in my house*.

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