Advancing Neural Question Generation for Formal Pragmatics

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Question Generation

- Creating natural questions for a given sentence or paragraph
- Appropriately linking to the meaning of the envisaged answer phrases
- Questions in formal pragmatics:
  - Question-under-Discussion (QuD) approaches
  - link information structure and discourse structure
- Our goal:
  - Partially automate QUD annotation
  - generate all questions that can be answered by a given sentence

Our Approach

- Neural networks can be successfully trained to generate meaningful, well-formed questions (De Kuthy et al., 2020)
- Challenge for a seq2seq architecture: rare or unknown words
  - words are the basic input and output tokens
  - pretrained word embeddings with fixed vocabulary
  - the words in the question to be generated can be selected from source material
- Extend architecture with a pointer component
- Enrich the model with part-of-speech and semantic role information to improve question phrase generation.

⇒ Robust approach with systematic question type coverage

Question-Answer Data

- German QA corpus: 5.24M sentence-question-answer triples
- Sentences from German newspaper *Die Tageszeitung (taz)*
- Transformation-based question generation system (Kolditz 2015)
  - Select potential answer phrases (NPs, PPs, clauses)
  - Replace them with matching question phrases.
  - Transform syntactic representations into questions.

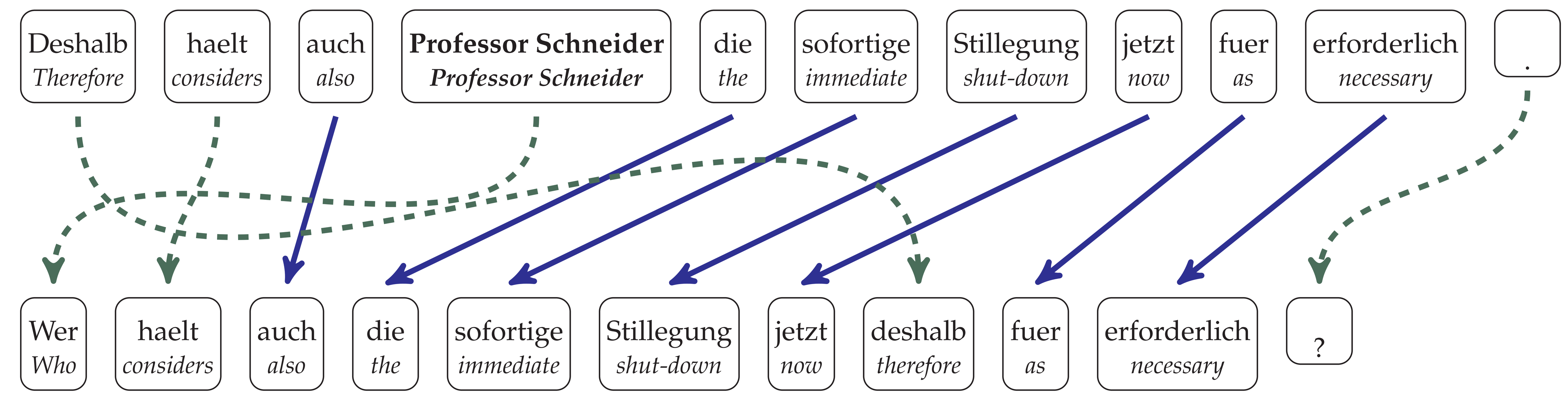
(1) A: Die Kinder essen am Sonntag Kuchen im Garten.
The children eat cake in the garden on Sunday.

Q_1: Wer isst am Sonntag Kuchen im Garten?
Who eats cake in the garden on Sunday?

Q_2: Was essen die Kinder am Sonntag im Garten?
What do the children eat in the garden on Sunday?

Q_3: Wo essen die Kinder am Sonntag Kuchen?
Where do the children eat cake on Sunday?

An Example: Copy vs.Generate Decisions



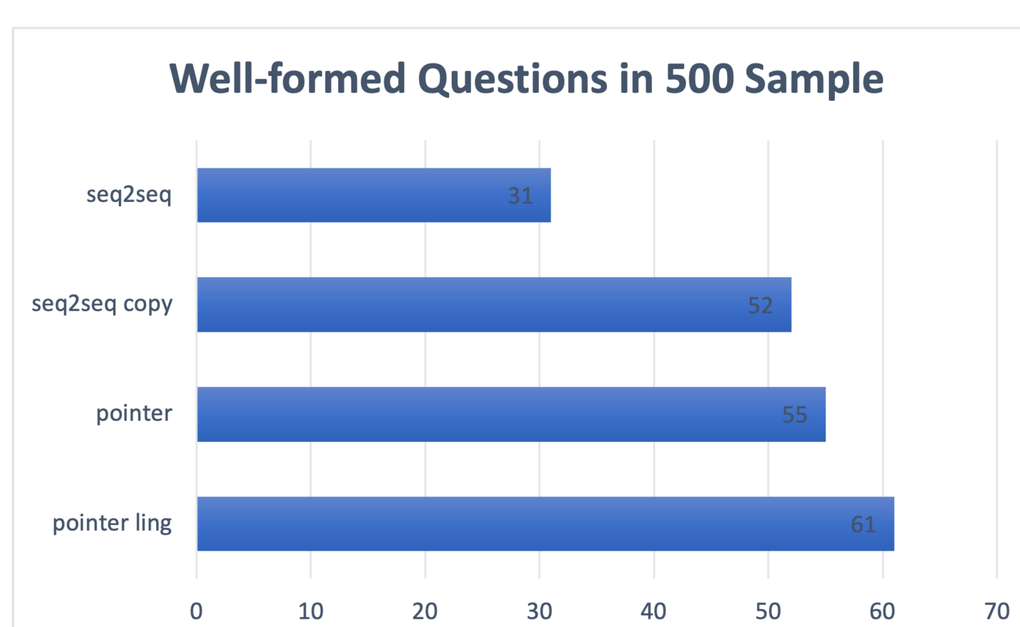
Neural Question Generation

- Basic Sequence-to-sequence architecture (Sutskever et al., 2014):
  - encoder network learns source sequence representation
  - decoder network generates target sequence
  - attention mechanism aligns source and target sequences
- Our Pointer Model:
  - Maxout pointer mechanism with gated self-attention (Zhao et al., 2018)
  - Input sequences: surface tokens, span of answer phrase, parts of speech (POS), semantic role labels (SRL)
  - Copy score: attention scores computed between encoder and decoder hidden state
  - Copy & generation module compete for predicted question

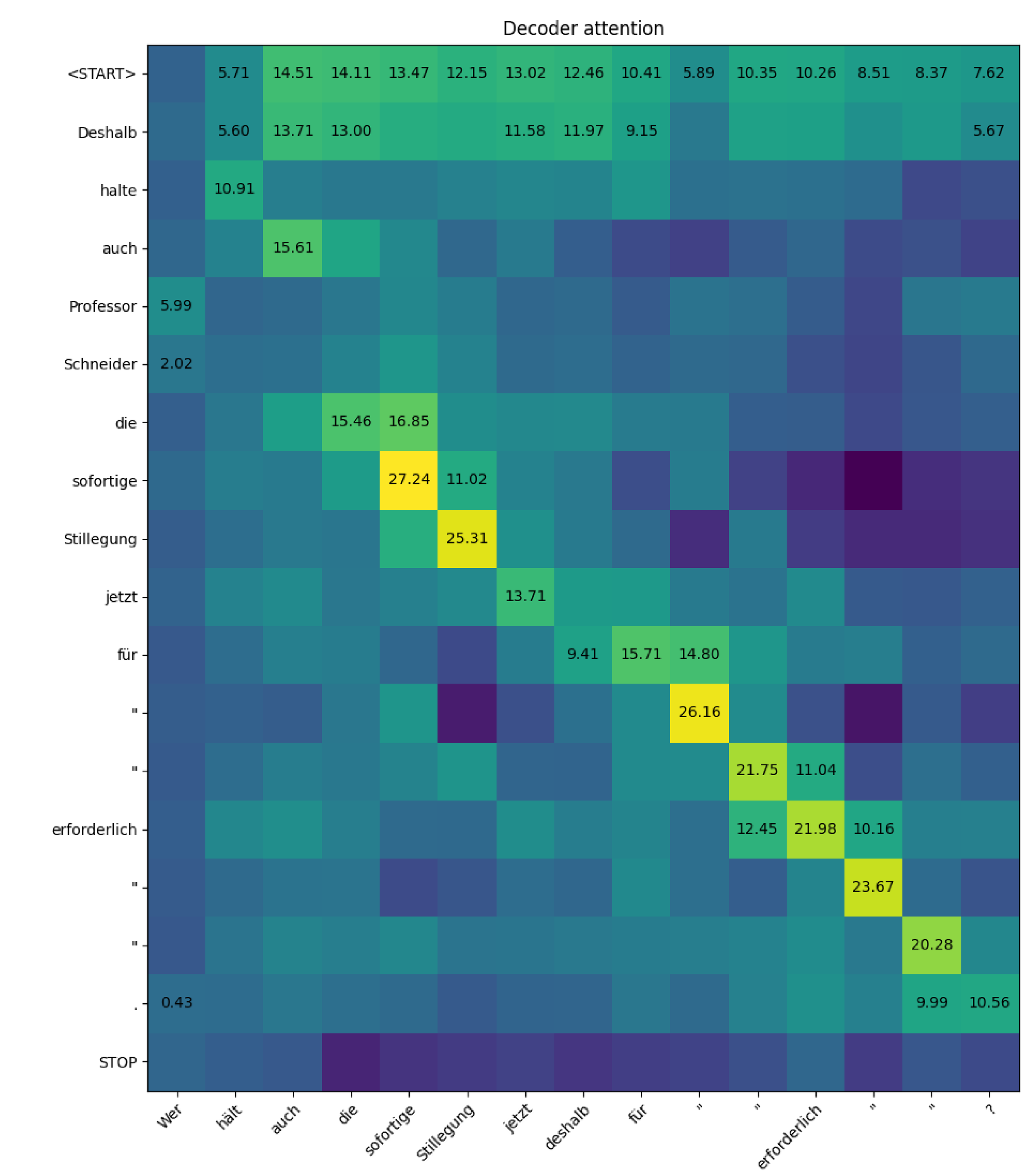
Quantitative Evaluation

- High BLEU score ⇒ high similarity between neural and gold Q

Model	Size	Features	BLEU
Seq2seq	500k	Word, Ans, POS	71.25
Seq2seq + Copy	500k	Word, Ans, POS	84.24
Pointer	500k	Word, Ans	89.40
Pointer	500k	Word, Ans, POS, SRL	**91.45**



Softmaxed Attention Weight



Distribution of Error Types