Thesis Proposal: Reinforcement Learning for Text Simplification using the rules of Leichte Sprache

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Text simplification refers to the problem of taking a sentence or a text and transferring it to a text that is easier to read. It is often implemented as a supervised sequence-to-sequence task, but it can also be done using reinforcement learning, by applying some measurement of "simplicity". Zhang and Lapata use a reward function combining measurements for simplicity, relevance, and fluency. In a similar vein, Nakamachi et al. train BERT models to predict the grammaticality, meaning preservation, and simplicity and use these to build a reward function.

Simplification through reinforcment learning has the advantage over supervised learning with cross-entropy loss that it "nudges" the model towards producing simplified versions of text instead of (or in addition to) trying to produce text that is similar to the target. In addition, it could also be useful for languages for which few annotated examples exist (although e.g. Nakamachi et al. pre-train their model in a supervised manner).

These approaches use different measurements for simplicity. Zhang and Lapata use the SARI score (7), which is compares the system output both to the non-simple input sentence and to reference sentences. Nakamachi et al. train a BERT model to estimate the simplicity level of a sentence in the Newsela dataset (6). Cramerus et al. use a neural network to aggregate a number of different features, like results of dependency parsing, POS tags, lexical complexity, and more classical readability features like sentence length.

Generally speaking, there is no one clear concensus about what features simplified text should include.

However, there are specific guidelines on how to write simplified text, like the Regelwerk für Leichte Sprache by the Gesellschaft für Leichte Sprache for German, which is based on scientific research on simple language and on the experiences of professional simple-language translators. I plan to use the rules from the Regelwerk to build a reward function.

The Regelwerk is proprietary, but I have already requested the usage rights from the Gesellschaft für Leichte Sprache and hope that they will be granted.

Since a number of the rules in the Regelwerk apply to documents rather than sentences, I plan to build a system working on a document-to-document level.

I plan to use the simplified German corpus by Battisti et al. for testing (and possibly pre-training). This corpus is not publicly available, but I have already obtained the scripts that the authors used to scrape the texts.

The reward function will also have to include a measure of semantic similarity between the texts, for which I intend to train a Doc2Vec model (3) on the simplified German corpus.

I would also like to compare this reward function to some of the other approaches, namely:

- supervised training with cross-entropy loss,
- the reward function of Nakamachi et al., and
- a supervised loss function like that by Cramerus et al. but using the criteria of the Regelwerk.

For analysis of the outputs, I want to do three things:

- Use the SARI score. SARI is sentence-based, so I plan to sentence-align the input, output, and reference text and average the scores over the sentences of a document.
- Automatically check for each rule in the Regelwerk, to find out, how well (or badly) the training worked for each aspect of simple language.
- Manual analysis, since the two other points do not cover all possible issues, such as long-term dependencies.

References

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