The Sources of Text Complexity for NMT

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Original idea of the project: Prof Dr Ruslan Mitkov

Structure of Presentation

- Goals of the research
- Research questions
- Previous work
- Methodology
- Limitations
- Preliminary results
- Acknowledgements
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Goals of the Research

- Although being the state of the art, NMT is still prone to errors
- The study aims to:

1) Identify typical lexical, syntactic, and grammatical patterns which could lead to errors

2) Develop a program capable of detecting some of them before the source language is processed by NMT

Research Questions

- What are the sources of complexity at lexical and syntactic level?
- What types of MWEs are most likely to be mistranslated by NMT?
- Is a transformer-based program able to predict where NMT is most likely to fail?

Previous Work (I)

- First attempts to determine the sources of complexity were made during the era of rule-based machine translation (RBMT)
  - “Translatability indicators“ i.e. text features able to degrade the quality of MT output (Underwood and Jongejan, 2001)
  - Lists of linguistic features contributing to lexical, syntactic, and semantic ambiguity as a set of rules to follow when authoring a text for MT (Bernth and Gdaniec, 2001)

Previous Work (II)

- Controlled language — “a restricted version of a natural language which has been engineered to meet a special purpose“ (Kittredge, 2016, p. 13)
- Confidence Index measuring the level of confidence of an MT system about the quality of its translation (Bernth, 1999)
- Tool able to determine whether a text in English is suitable for MT based on the averaged translatability index which is calculated from all translatability indicators and their weights (Underwood and Jongejan, 2001)

Previous Work (III)

- Several studies consider the correlation between MT and post-editing:
  - Correlation between the quality of MT output and the product analysis and the effort spent on the post-editing (Daems et al., 2017)
  - Correlation between the difficulty of the source text and the cognitive and technical effort of post-editors (O’Brien, 2005; O’Brien, 2006)

Frequent sources of complexity for MT

- Pronominal anaphora (Mitkov and Schmidt, 1998)
- Multi-word expressions (Barreiro et al., 2013)
- Lexical ambiguity i.e. polysemy (Carpuat and Wu, 2007; Ngueng et al., 2018)
- Sentence length (Hung, Ngueng and Shimazu, 2012)
- Difference in sentence structuring between the source and the target (Birch, Osborne and Koehn, 2008; Popović and Arčan, 2015)

Methodology: Investigation

Lexical and syntactic complexities:

- English-Russian NMT of 20 texts from the News Commentary Parallel Corpus (Tiedemann, 2012) by means of DeepL[1] and ModernMT[2]

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- Manual analysis of errors

1 https://www.deepl.com/translator

2 https://www.modernmt.com/translate/

Methodology: Implementation

Hybrid approach

Deep Learning:

BERT (Devlin et al., 2019)

One of the MWE patterns

Rule-based

Syntactic patterns

Methodology: Evaluation

- 2 X F-1 Score will be used

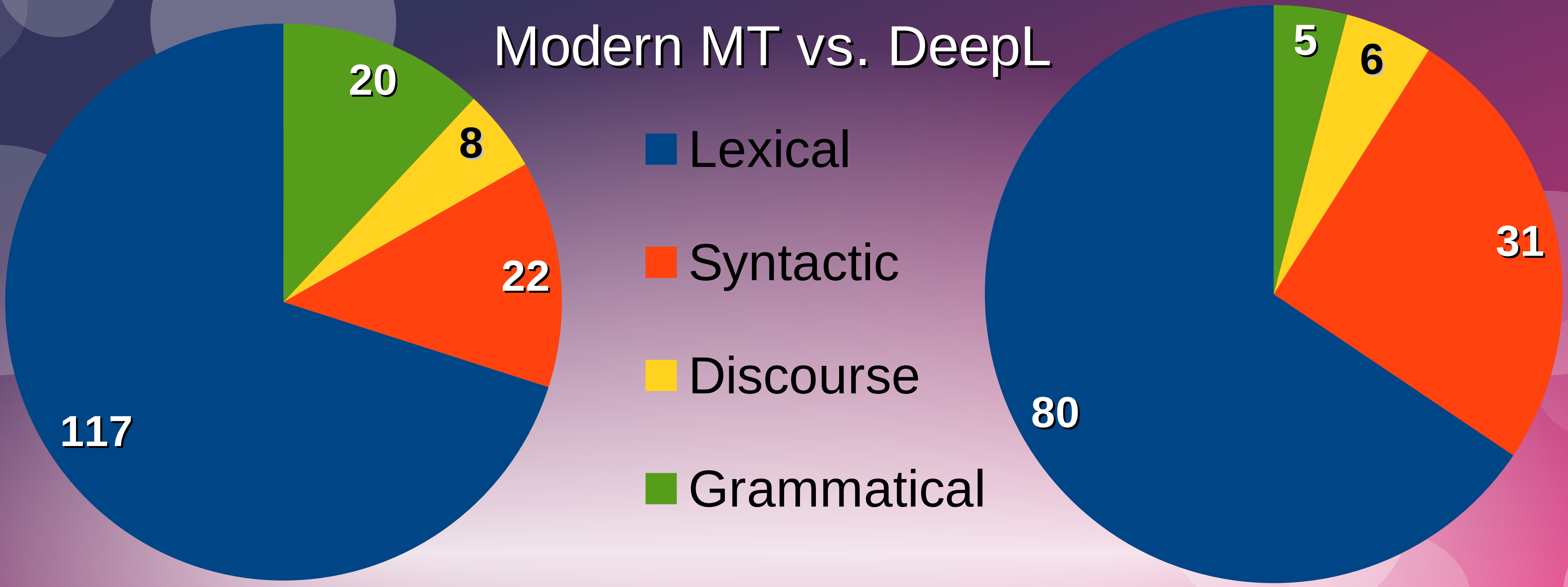
Limitations

- NMT is in the process of constant development and even some of the preliminary results might be already obsolete
- Numerous textual features that are difficult for NMT & impossibility to have all of them in the final program
- Limitations related to one language pair, domain and corpus size

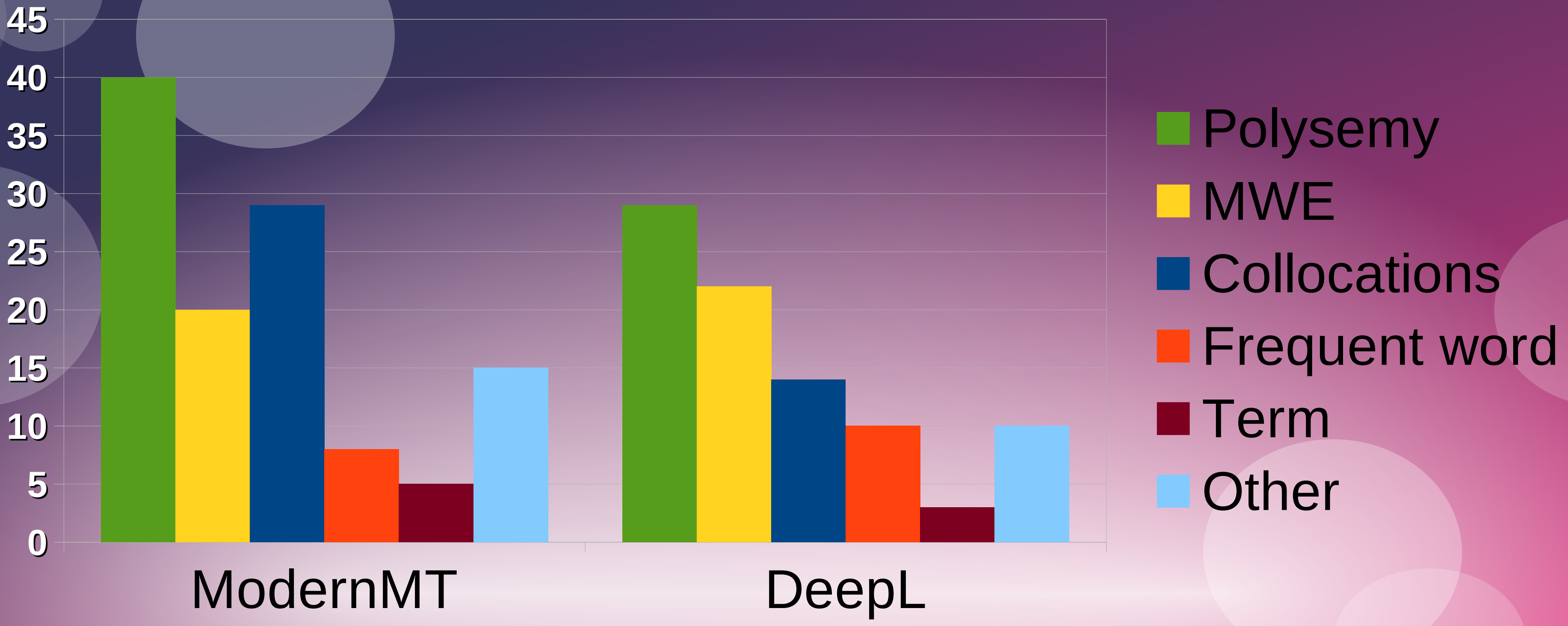
Preliminary results (I)

- 15 % of the texts analysed
- The author does not attempt to generalise these results to any extent and underlines that they apply only within the limits of the size and domain of the texts analysed

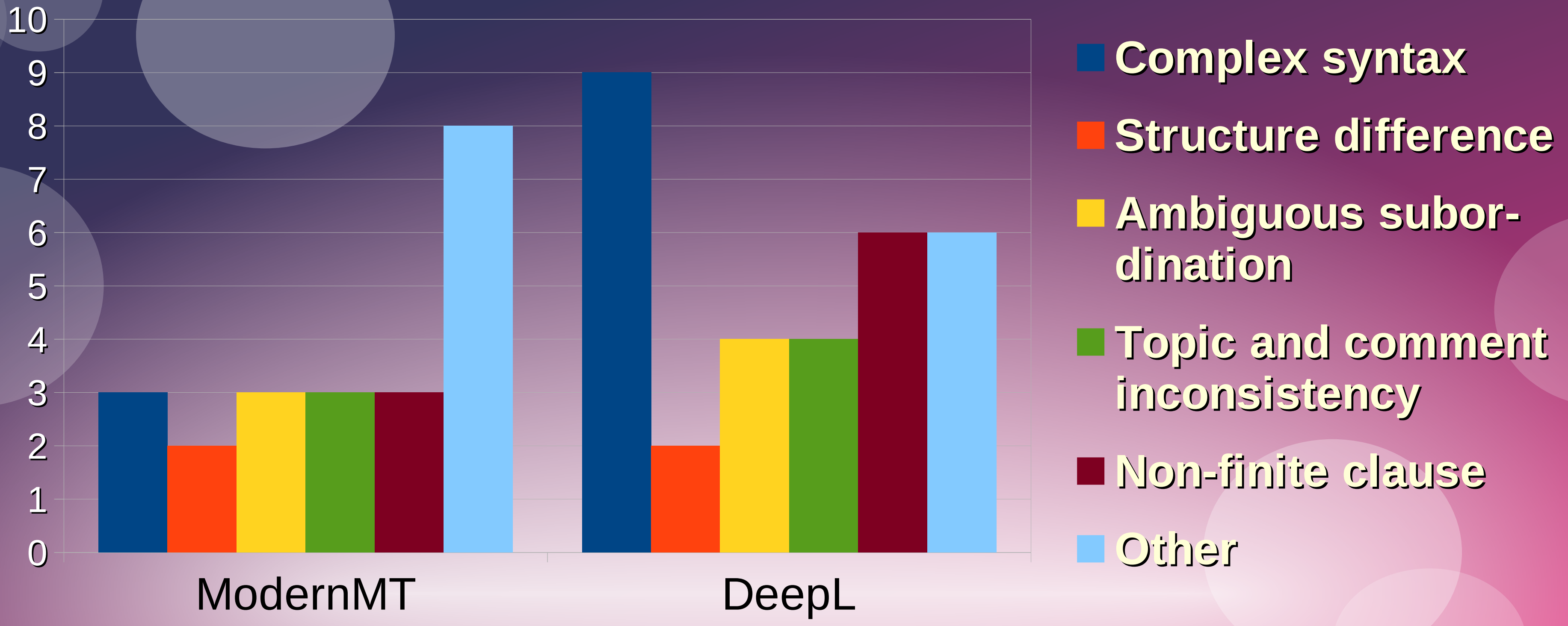
Preliminary results (II): sources of complexity



Preliminary results (III): lexical sources of complexity



Preliminary results (IV): syntactic sources of complexity



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