MOTIVATION

TARGET GROUPS

Disadvantaged

People with reading and spelling difficulties and people with cognitive impairments benefit

Sources: Hirsh and Narion (1992), Krashen (1988), Louwerse et al. (2007), Paetzold and Specia (2016)

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Simpler texts enable the comprehension of more complex topics

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People with reading and spelling difficulties and people with cognitive impairments benefit

L2 Learners

Non-native speakers find it easier to understand and learn the new language

Students

Simpler texts enable the comprehension of more complex topics

Elderly

Older people often have a shorter attention span and thus find it easier to understand texts

Sources: Hirsh and Narion (1992), Krashen (1988), Louwerse et al. (2007), Paetzold and Specia (2016)

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01
Education
Material

Make complex topics more accesible; Learning a new language

02
Text
Summarization

03
Medical
Field

04
Government
Communication

05
News
Articles

Sources: van den Bercken et al. (2019), Petersen and Ostendorf (2007), Siddhartan (2014), Stajner (2021)

APPLICATIONS

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Make complex topics more accesible; Learning a new language

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Reduce complexity to make resulting summaries more accesible

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transparency,
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Improve transparency, especially for laws, regulations, etc.

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News

Articles

Educate a broader audience about what is going on in the world

Sources: van den Bercken et al. (2019), Petersen and Ostendorf (2007), Siddhartan (2014), Stajner (2021)

RELATED
WORK

TRANSFORMERS

- Introduced in 2017 by Vaswani et al.

- **Self-attention** mechanism: allows the network to weigh the importance of different input features

- Consists of an **encoder** & a **decoder**
  encoder: takes the input sequence and produces a sequence of hidden states
  decoder: takes output & generates a target sequence

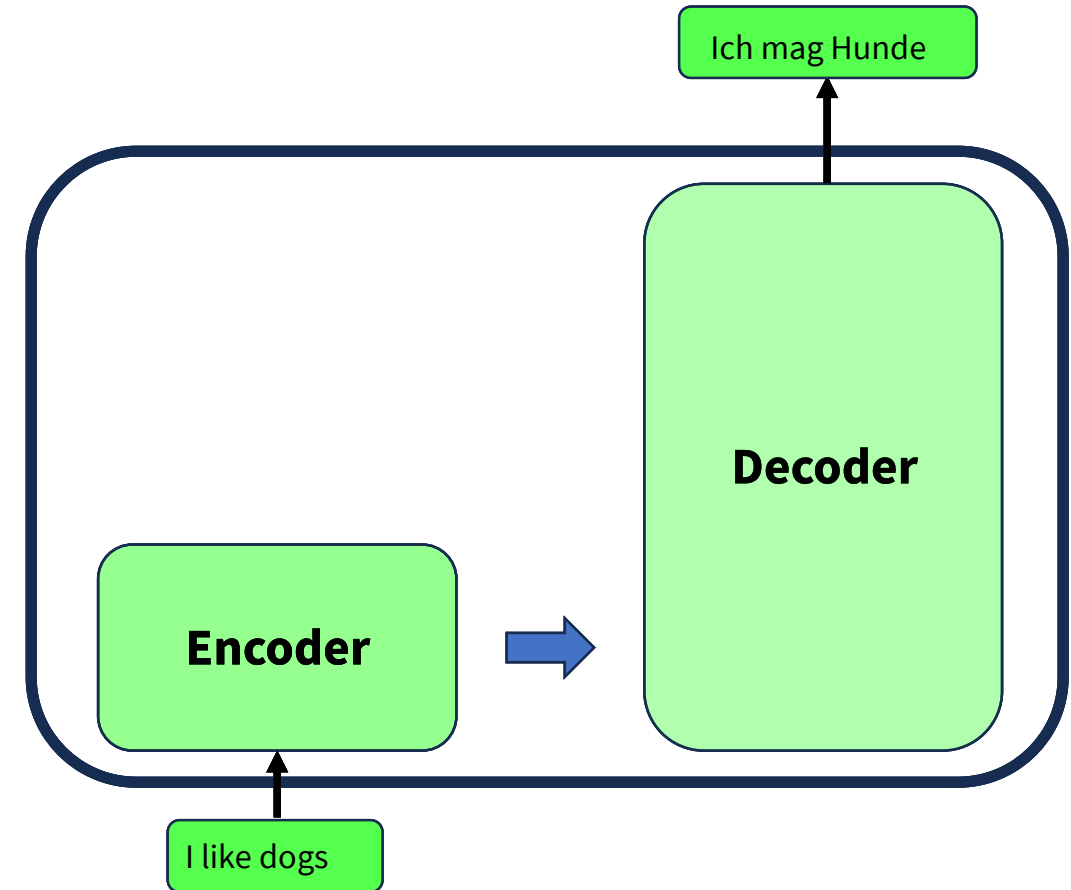- Approaches: Omelianchuk et al. (2021): Text Simplification by Tagging (TST); Truica et al. (2022): Simplex

Figure 1: simple representation of how transformers work; own illustration

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01

Lack of parallel

Ressources

Simplified content exists in many languages, but not in parallel

02

Different

Levels

There are different gradations concerning simplifications

03

Poor

Quality

The corpora that exist are qualitatively insufficient

04

Costly

Generation
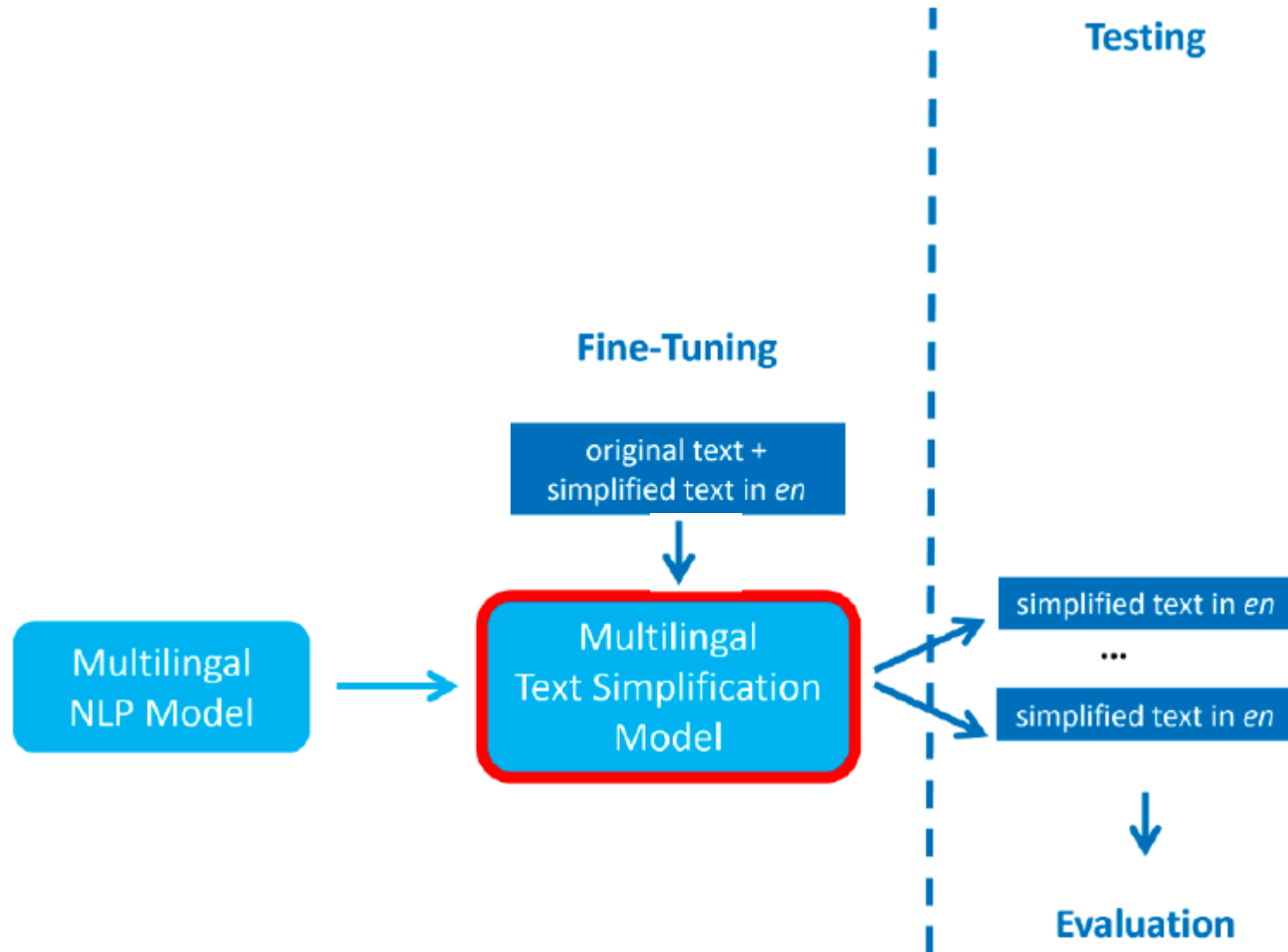
Generating parallel corpora manually takes time and ressources

05

Low-ressource

Scenarios

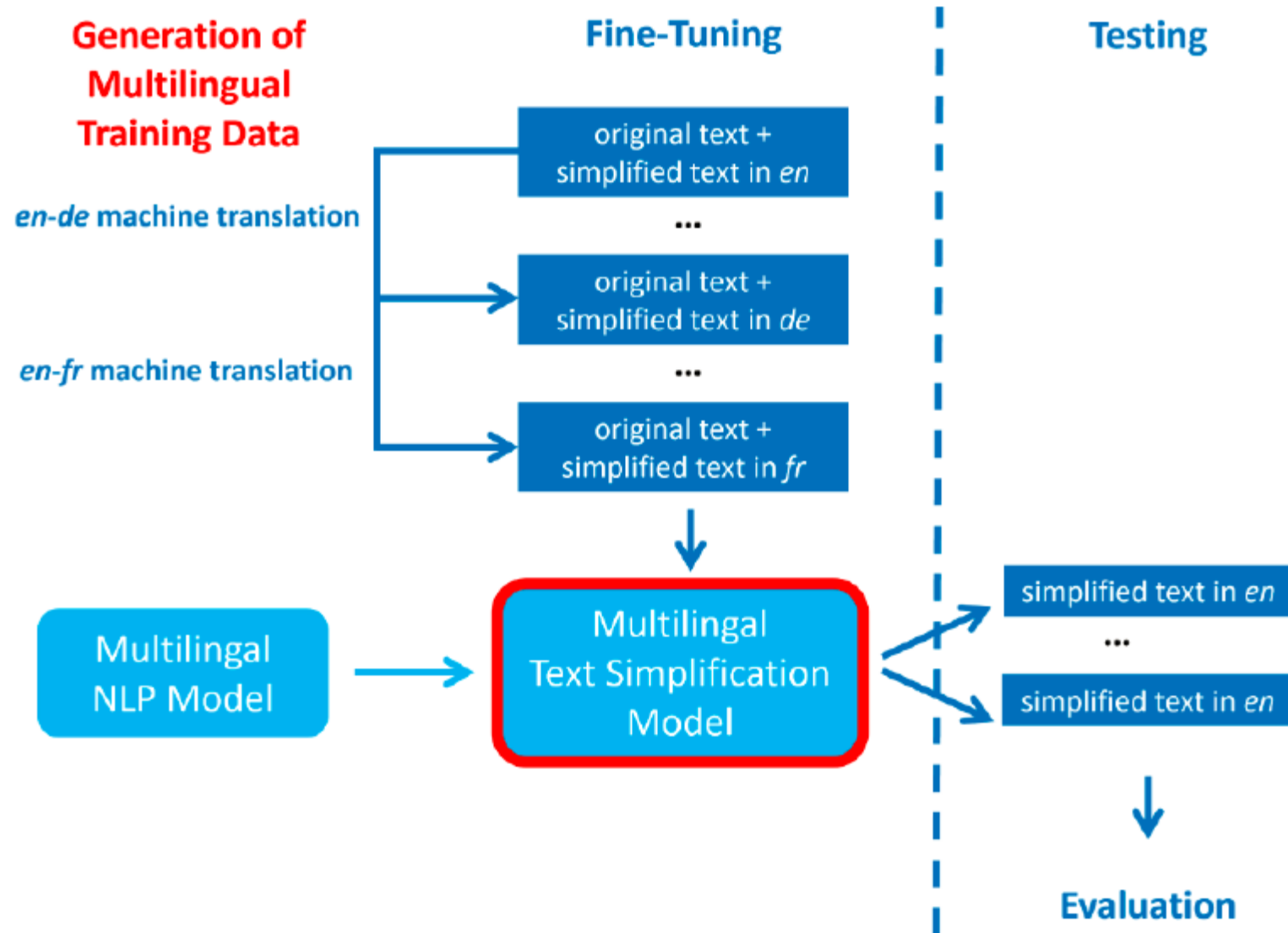Especially in low-ressource languages there is much less simplified content

Sources: Brunato et al. (2022), Kubota (2004), Qiang and Wu (2021), Xu et al. (2016)

MULTILINGUAL MODEL

TEXT SIMPLIFICATION

TEXT SIMPLIFICATION

SPECIFICATIONS OF MY EXPERIMENTAL SETUP

Model

Google's Flan-T5-Base

64 languages

8 epochs

3 tasks: Translate, Summarize, Paraphrase

Data

- ASSET corpus
- Training set: 1,000 sentences & its translations to enrich training data
- Test set: 500 sentences & its translations to evaluate our 5 languages
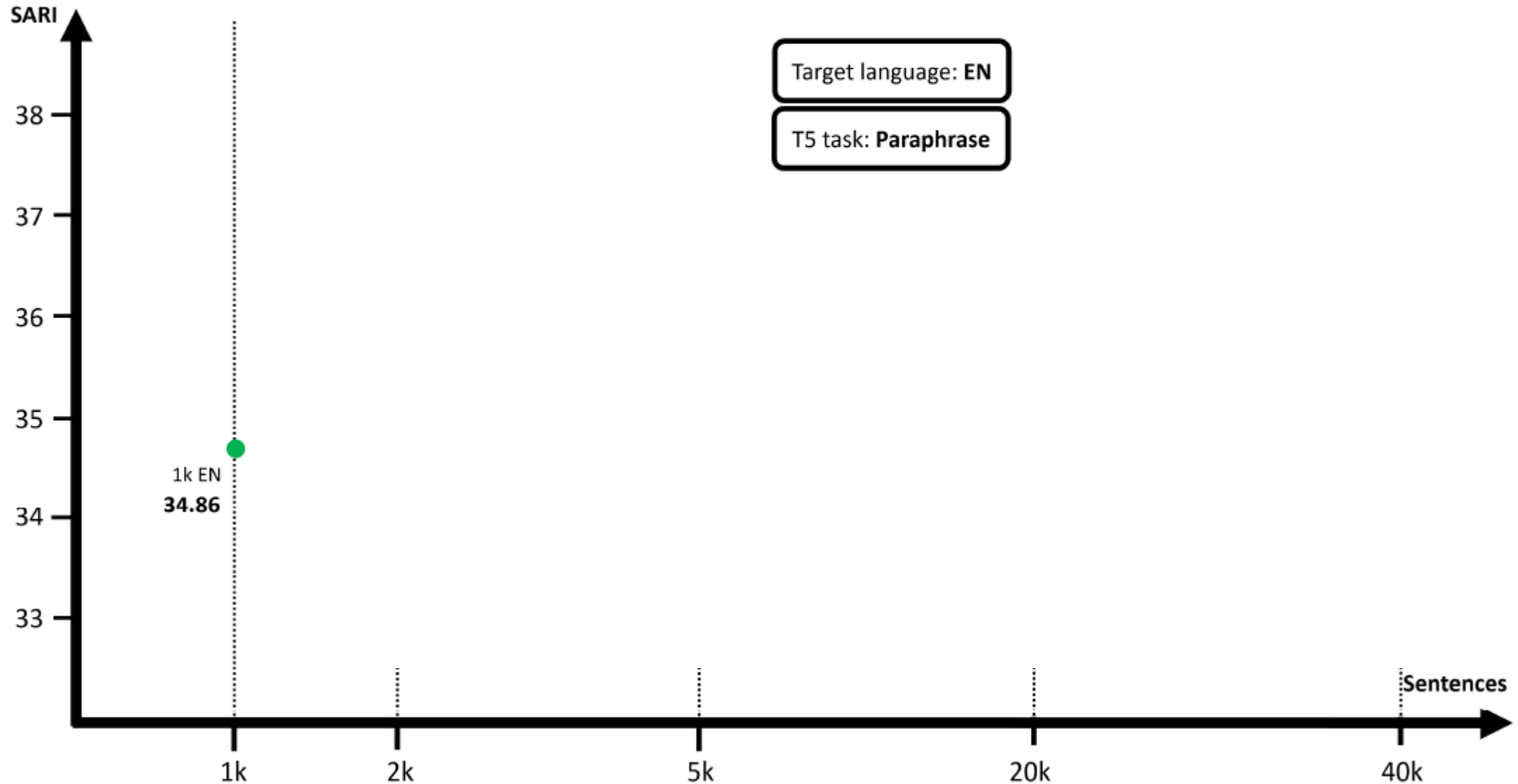- Validation set: 25% of training set

Languages

- Target: English, German, Portuguese, French, Spanish
- Translated with Google Translate API
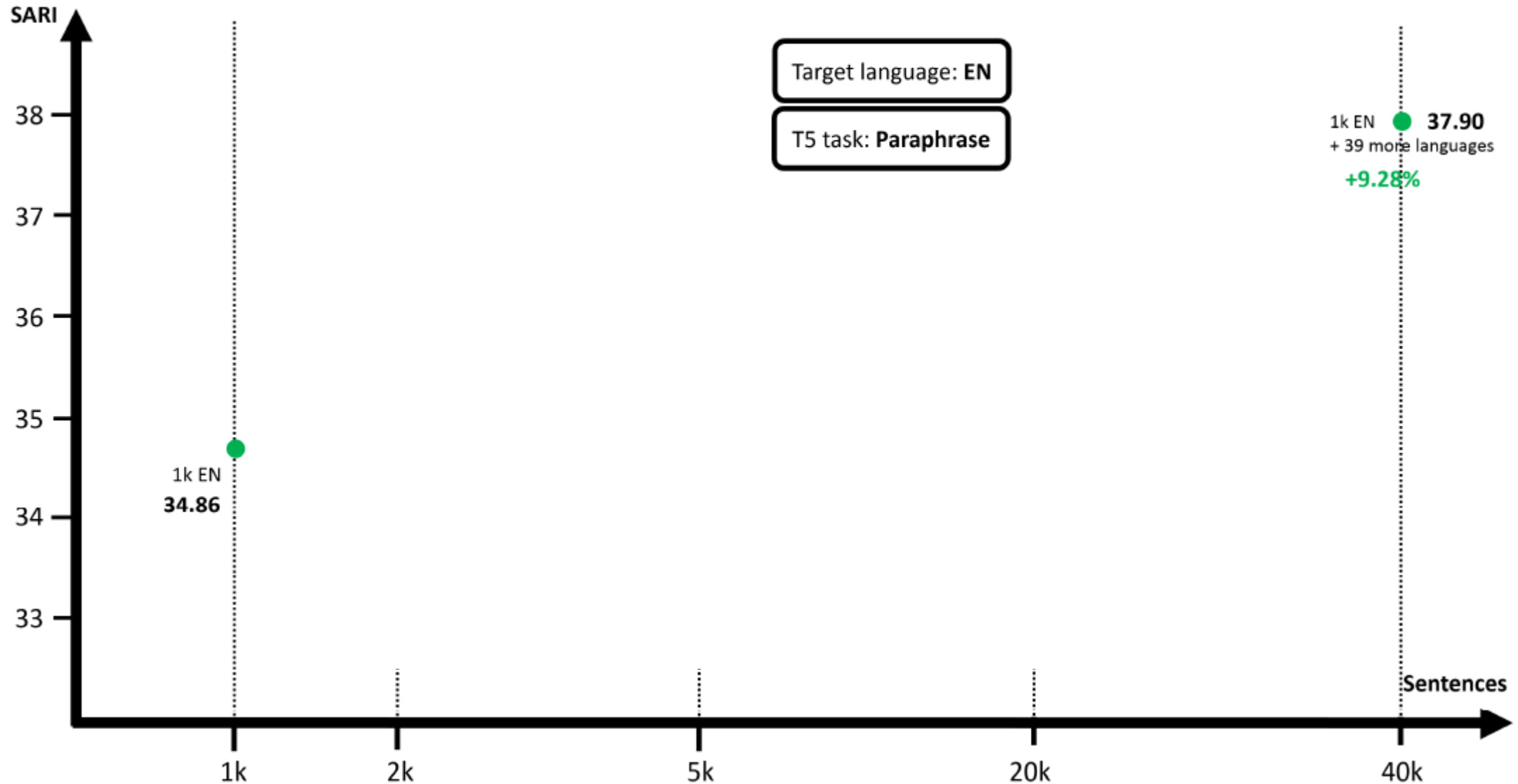- Trained with a total of 40 languages / 40,000 sentences

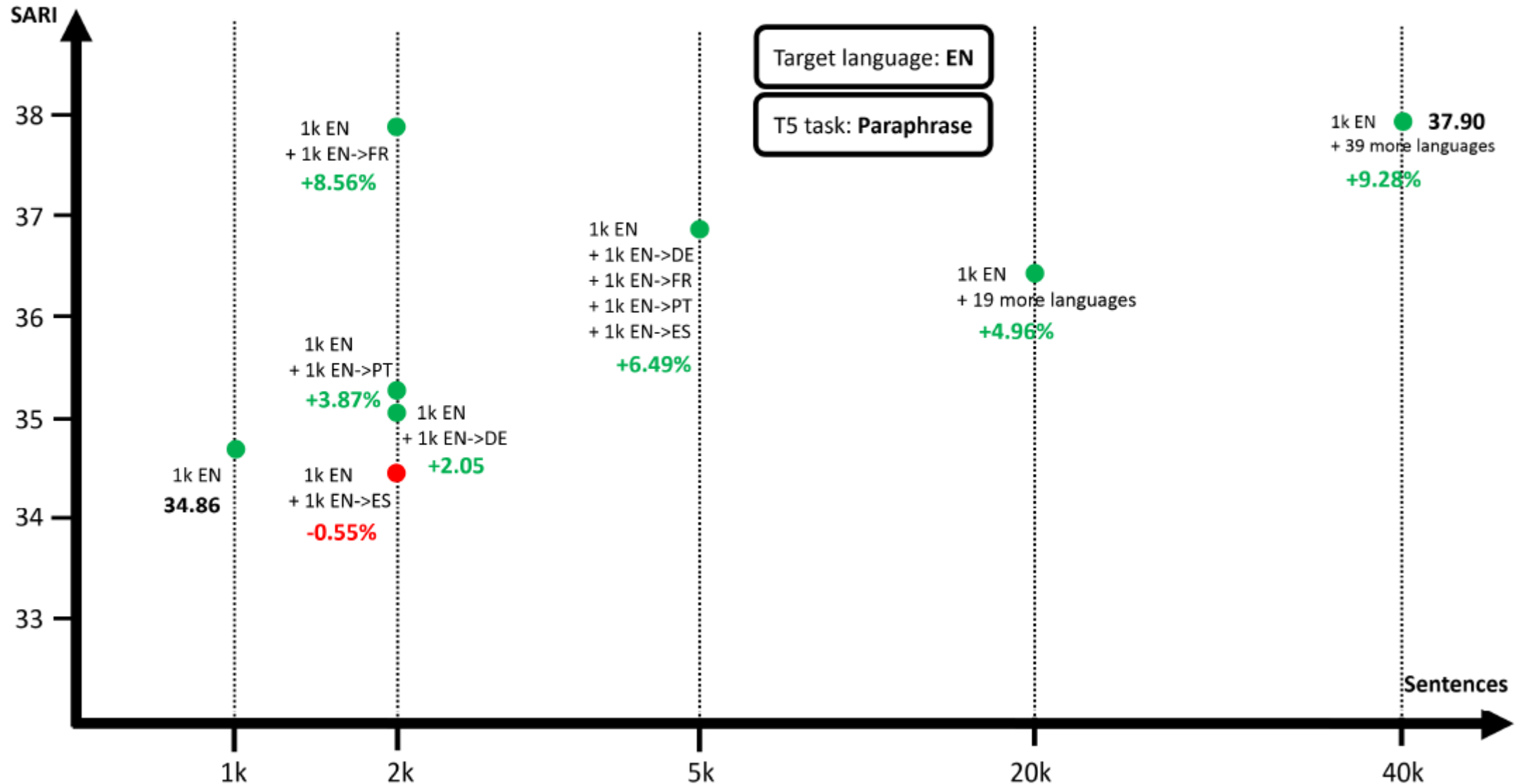Sources: Alva-Manchega et al. (2020), Chung et al. (2022)

04

EXPERIMENTS &
RESULTS

TEXT SIMPLIFICATION

Target language: **EN**

T5 task: **Paraphrase**

SARI

38

37

36

35

1k EN
34.86

34

33

Sentences

1k   2k   5k   20k   40k

TEXT SIMPLIFICATION

SARI

38 — 1k EN ● **37.90**
+ 39 more languages
+9.28%

37

Target language: **EN**

T5 task: **Paraphrase**

36

35 ●

1k EN
34.86

34

33

Sentences

1k   2k   5k   20k   40k

TEXT SIMPLIFICATION

Target language: **EN**

T5 task: **Paraphrase**

1k EN
+ 1k EN->FR
+8.56%

1k EN
+ 1k EN->PT
+3.87%

1k EN
+ 1k EN->DE
+2.05

1k EN
34.86

1k EN
+ 1k EN->ES
-0.55%

1k EN
+ 1k EN->DE
+ 1k EN->FR
+ 1k EN->PT
+ 1k EN->ES
+6.49%

1k EN
+ 19 more languages
+4.96%

1k EN
+ 39 more languages
37.90
+9.28%

ALL RESULTS

		SARI	
EN baselines	Translate$_{1kEN}$	33.35	
	Summarize$_{1kEN}$	33.53	
	Paraphrase$_{1kEN}$	34.68	
Best EN system	Paraphrase$_{1kEN+39k}$	37.90	
relative change to baseline		**9.28%**	
DE baselines	Translate$_{1kDE}$	28.13	
	Summarize$_{1kDE}$	27.69	
	Paraphrase$_{1kDE}$	27.63	
Best DE system	Paraphrase$_{1kDE+39k}$	29.60	
relative change to baseline		**5.23%**	
FR baselines	Translate$_{1kFR}$	22.70	
	Summarize$_{1kFR}$	22.70	
	Paraphrase$_{1kFR}$	22.79	
Best FR system	Paraphrase$_{1kFR+39k}$	23.31	
relative change to baseline		**2.28%**	
ES baselines	Translate$_{1kES}$	30.60	
	Summarize$_{1kES}$	31.16	
	Paraphrase$_{1kES}$	30.78	
Best ES system	Paraphrase$_{1kES+39k}$	32.79	
relative change to baseline		**5.23%**	
PT baselines	Translate$_{1kPT}$	31.32	
	Summarize$_{1kPT}$	31.44	
	Paraphrase$_{1kPT}$	31.94	
Best PT system	Paraphrase$_{1kPT+39k}$	33.60	
relative change to baseline		**5.23%**	

Table 1: Baseline systems vs. Best systems and relative change; source: Schlippe and Eichinger (2023)

HUMAN EVALUATION - SETUP

- 105 participants

- Compare my model to OpenAI's **ChatGPT**

- 5 English & German sentences from university scripts in social sciences

- 5 **criteria**:
    - Content
    - Fluency
    - Comprehensibility
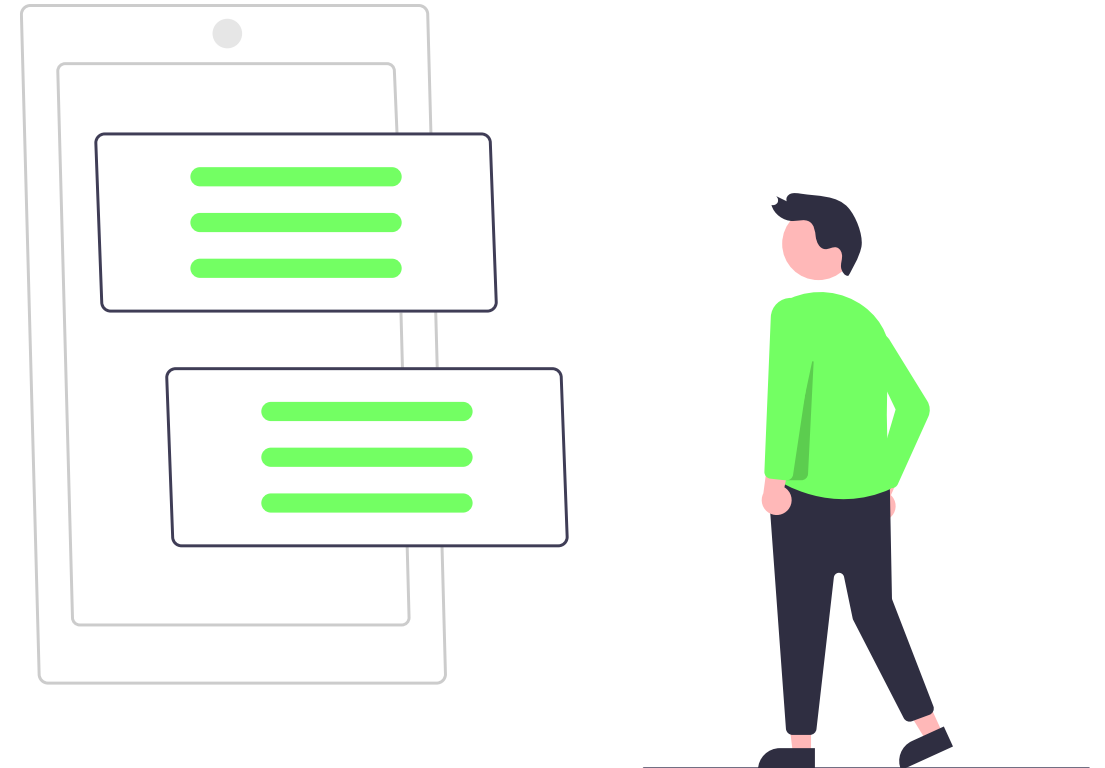   - Grammar
    - Simplification
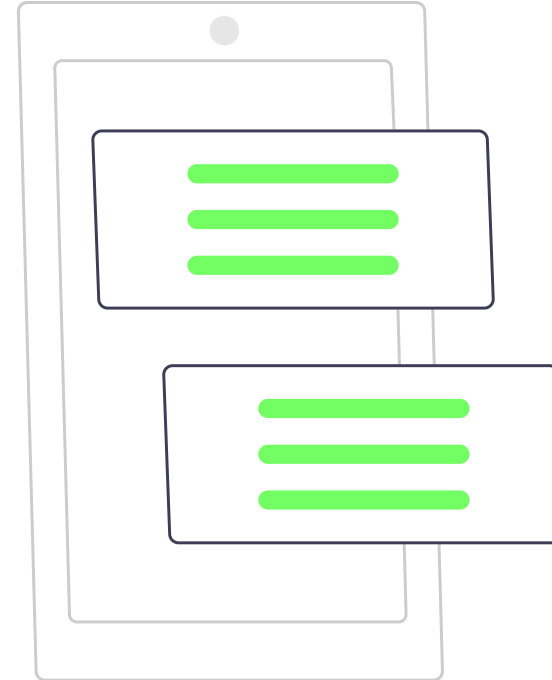
HUMAN EVALUATION – RESULTS

	My Model	ChatGPT	Relative change
content	4.13	**4.34**	-4.48%
fluency	**4.40**	4.29	+2.56%
comprehensibility	**4.41**	4.31	+2.32%
grammar	**4.47**	4.42	+1.13%
simplification	4.11	4.11	0.00%
average change			+0.24%

Table 2: Scores in each category for the English simplifications with the relative change; source: own results

	My Model	ChatGPT	Relative change
content	3.31	**4.09**	-19.07%
fluency	**4.39**	4.09	+7.33%
comprehensibility	**4.34**	4.03	+7.69%
grammar	**4.49**	4.29	+4.66%
simplification	**4.22**	3.39	+25.48%
average change			+5.02%

Table 3: Scores in each category for the German simplifications with the relative change; source: own results

Sources: Hirsh and Narion (1992), Krashen (1988), Louwerse et al. (2007), Paetzold and Specia (2016)
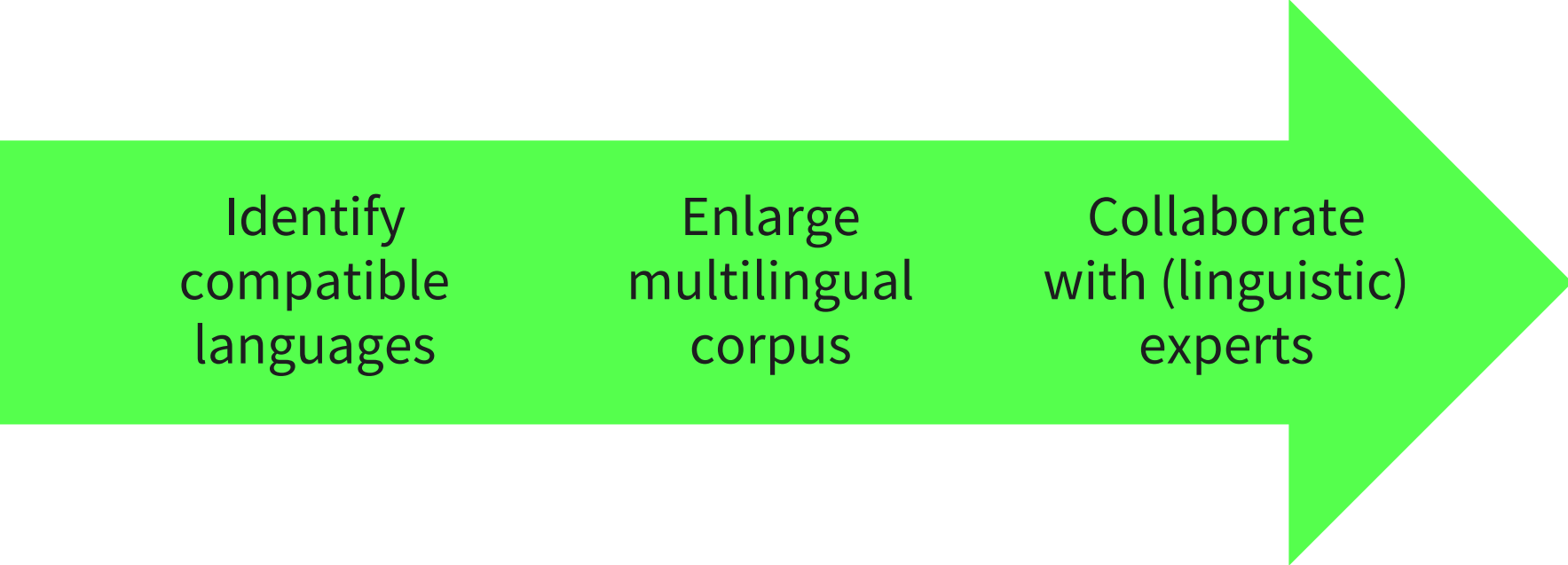
05

CONCLUSION

CONGLUSION

- Text simplification models can transform how people engage with complex texts

- **cross-lingual training** in text simplification models can improve performance, particularly in low-resource scenarios
  → with only 1,000 training sentences and a translator API I created a corpus consisting of 40,000 sentence pairs

- Effectiveness of cross-lingual training may vary based on the target language

- Our model outperformed OpenAI's ChatGPT during human evaluation

FUTURE WORK

Identify compatible languages

Enlarge multilingual corpus

Collaborate with (linguistic) experts

THANK YOU

Tim Schlippe

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SOURCES

Alva-Manchego, Fernando, Louis Martin, Antoine Bordes, Carolina Scarton, Benoît Sagot, and Lucia Specia. "ASSET: A Dataset for Tuning and Evaluation of Sentence Simplification Models with Multiple Rewriting Transformations." In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4668–79. Online: Association for Computational Linguistics, 2020. https://doi.org/10.18653/v1/2020.acl-main.424.

Alva-Manchego, Fernando, Carolina Scarton, and Lucia Specia. "The (Un)Suitability of Automatic Evaluation Metrics for Text Simplification." *Computational Linguistics* 47, no. 4 (December 2021): 861–89. https://doi.org/10.1162/coli_a_00418.

Bercken, Laurens van den, Robert-Jan Sips, and Christoph Lofi. "Evaluating Neural Text Simplification in the Medical Domain." In *The World Wide Web Conference*, 3286–92. WWW '19. New York, NY, USA: Association for Computing Machinery, 2019. https://doi.org/10.1145/3308558.3313630.

Brunato, Dominique, Felice Dell' Orletta, and Giulia Venturi. "Linguistically-Based Comparison of Different Approaches to Building Corpora for Text Simplification: A Case Study on Italian," Vol. 13, 2022. https://doi.org/10.3389/fpsyg.2022.707630.

Chung, Hyung Won, Le Hou, S. Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, et al. "Scaling Instruction-Finetuned Language Models." *ArXiv* abs/2210.11416 (2022). https://doi.org/10.48550/arXiv.2210.11416.

Hirsh, David, and Paul Nation. "What Vocabulary Size Is Needed to Read Unsimplified Texts for Pleasure?" *Reading in a Foreign Language*, 1992.

Krashen, Stephen D. *Second Language Acquisition and Second Language Learning*. Hoboken: Prentice-Hall International, 1988.

Kubota, Ryuko. "The Politics of Cultural Difference in Second Language Education." *Critical Inquiry in Language Studies* 1, no. 1 (2004): 21–39. https://doi.org/10.1207/s15427595cils0101_2.

Omelianchuk, Kostiantyn, Vipul Raheja, and Oleksandr Skurzhanskyi. "Text Simplification by Tagging." In *Proceedings of the 16th Workshop on Innovative Use of NLP for Building Educational Applications*, 11–25. Online: Association for Computational Linguistics, 2021. https://aclanthology.org/2021.bea-1.2.

Paetzold, Gustavo, and Lucia Specia. "Unsupervised Lexical Simplification for Non-Native Speakers." *Proceedings of the AAAI Conference on Artificial Intelligence* 30, no. 1 (March 2016). https://doi.org/10.1609/aaai.v30i1.9885.

Papineni, Kishore, Salim Roukos, Todd Ward, and Wei-Jing Zhu. "BLEU: A Method for Automatic Evaluation of Machine Translation." In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, 311–18. ACL '02. USA: Association for Computational Linguistics, 2002. https://doi.org/10.3115/1073083.1073135.

Petersen, Sarah E., and Mari Ostendorf. "Text Simplification for Language Learners: A Corpus Analysis." In *Slate*, 2007.

SOURCES

Post, Matt. "A Call for Clarity in Reporting BLEU Scores," 186–91, 2018. https://doi.org/10.18653/v1/W18-6319.

Qiang, Jipeng, and Xindong Wu. "Unsupervised Statistical Text Simplification." *IEEE Transactions on Knowledge and Data Engineering* 33, no. 4 (2021): 1802–6. https://doi.org/10.1109/TKDE.2019.2947679.

Schlippe, Tim, and Eichinger, Katharina. „Multilingual Text Simplification and its Performance on Social Sciences Coursebooks." In The 4th International Conference on Artificial Intelligence in Education Technology (AIET 2023), Berlin, Germany, 31 June-2 July 2023.

Schwarzer, Max, and David Kauchak. "Human Evaluation for Text Simplification: The Simplicity-Adequacy Tradeoff," 2018.

Siddharthan, Advaith. "A Survey of Research on Text Simplification." *ITL - International Journal of Applied Linguistics* 165 (December 2014): 259–98. https://doi.org/10.1075/itl.165.2.06sid.

Stajner, Sanja. "Automatic Text Simplification for Social Good: Progress and Challenges." In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, 2637–52. Online: Association for Computational Linguistics, 2021. https://doi.org/10.18653/v1/2021.findings-acl.233.

Sulem, Elior, Omri Abend, and Ari Rappoport. "BLEU Is Not Suitable for the Evaluation of Text Simplification." In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 738–44. Brussels, Belgium: Association for Computational Linguistics, 2018. https://doi.org/10.18653/v1/D18-1081.

Truică, Ciprian-Octavian, Andrei-Ionuţ Stan, and Elena-Simona Apostol. "SimpLex: A Lexical Text Simplification Architecture." *Neural Computing and Applications*, November 18, 2022. https://doi.org/10.1007/s00521-022-07905-y.

Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention Is All You Need." In *Advances in Neural Information Processing Systems,* edited by I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Vol. 30. Curran Associates, Inc., 2017. https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.

Xu, Wei, Courtney Napoles, Ellie Pavlick, Quanze Chen, and Chris Callison-Burch. "Optimizing Statistical Machine Translation for Text Simplification." *Transactions of the Association for Computational Linguistics* 4 (July 2016): 401–15. https://doi.org/10.1162/tacl_a_00107.