Do Multilingual Language Models Capture Differing Moral Norms?

Katharina Hämmerl¹, Björn Deiseroth²,³, Patrick Schramowski³, Jindřich Libovický⁵,¹, Alexander Fraser¹, and Kristian Kersting³,⁴

¹Center for Information and Language Processing, LMU Munich, Germany
²Aleph Alpha GmbH, Heidelberg, Germany
³Artificial Intelligence and Machine Learning Lab, TU Darmstadt, Germany
³Hessian Center for Artificial Intelligence (hessian.AI), Darmstadt, Germany
⁵Institute of Formal and Applied Linguistics, Charles University, Czech Republic

Abstract

Massively multilingual sentence representations are trained on large corpora of uncurated data, with a very imbalanced proportion of languages included in the training. This may cause the models to grasp cultural values including moral judgments from the high-resource languages and impose them on the low-resource languages. The lack of data in certain languages can also lead to developing random and thus potentially harmful beliefs. Both these issues can negatively influence zero-shot cross-lingual model transfer and potentially lead to harmful outcomes. Therefore, we aim to (1) detect and quantify these issues by comparing different models in different languages, (2) develop methods for improving undesirable properties of the models. Our initial experiments using the multilingual model XLM-R show that indeed multilingual LMs capture moral norms, even with potentially higher human-agreement than monolingual ones. However, it is not yet clear to what extent these moral norms differ between languages.

Recent work demonstrated large pre-trained language models (PLM) obtain symbolic, relational [12] but also commonsense knowledge [5]. Further, West et al. [17] showed that one is able to extract the commonsense knowledge from the large, general language model GPT-3 [2] via symbolic knowledge distillation. This encoded “knowledge” includes information of our society reflecting ethical
and social norms [9, 14]. Hereby the knowledge of a PLM is acquired during the self-supervised pre-training phase, which in case of most current state-of-the-art models uses scraped data from the web.

Therefore, approaches investigating the agreement of the model’s norms and human values [14] and benchmark datasets [7] aiming to align human and machine values with human labelled data arose. The work of Jiang et al. [10] showed promise in terms of obtaining such alignment, i.e., teaching these kinds of models commonsense moral reasoning.

However, social norms are constantly evolving and differ between cultures. Whereas “general” alignment is an open question, teaching AI systems moral norms includes the representation of (moral) values from different societies, e.g., cultures. Can one model differentiate between cultural differences or can we observe differences in moral norms in models trained on different cultural data in the first place? The results of [15] show promise for at least the latter question.

**Can multilingual language models capture moral norms?** Multilingual language models are trained on large corpora of uncurated data, with a very imbalanced proportion of languages included in the training. While basic semantic properties are often accessible across languages, there is an inherent problem in achieving perfect language neutrality [11], meaning that two sentences in differing languages with the same semantics receive very similar embeddings. There are techniques for improving the alignment, for instance, we have worked on an approach combining the strengths of static and contextualised embeddings [8]. But a very interesting and unexplored area of research is to consider whether multilingual language models capture differing moral norms, e.g., that the moral norms corresponding to the Chinese space in a multilingual language model may systematically differ from those in the Portuguese space.

**Research Questions.** With this study, we build upon these recent findings and aim to investigate the following:

- The extraction of commonsense knowledge on moral norms from pre-trained language models.
- Does a multilingual model encode differing information compared to monolingual models?
- Whether a multilingual language model can capture differing moral norms from several language sources.

From initial experiments, a version of XLM-R tuned with the S-BERT framework [13] shows good correlation with the global user study conducted by [14] when used with their MORALDIRECTION (MD) framework (see Table I). Simply mean-pooling representations from XLM-R [4], mBERT [6], or monolingual

---

1The best correlations were achieved by sentence-transformers/xlm-r-100langs-bert-base-nli-mean-tokens
| Model                          | en  | ar  | cs  | de  | zh  |
|-------------------------------|-----|-----|-----|-----|-----|
| mBERT (mean-pooled)           | 0.65| -0.11| -0.11| -0.21| 0.61 |
| XLM-R (mean-pooled)           | -0.15| -0.03| 0.01| -0.17| -0.01|
| monolingual (mean-pooled)     | -0.15| 0.43| 0.01| 0.15| 0.69|
| monolingual BERT (S-BERT)     | 0.79|     |     |    |     |
| XLM-R (best S-BERT)           | 0.85| 0.82| 0.84| 0.82| 0.80|

Table 1: Initial experiments with different multilingual and monolingual transformer models in the *MoralDirection* framework. The multilingual XLM-R model achieves a higher correlation with human moral norms than the monolingual BERT.

| language | en  | ar  | cs  | de  | zh  |
|----------|-----|-----|-----|-----|-----|
| en       | 1.0 |     |     |     |     |
| ar       | 0.92| 1.0 |     |     |     |
| cs       | 0.93| 0.96| 1.0 |     |     |
| de       | 0.94| 0.96| 0.98| 1.0 |     |
| zh       | 0.92| 0.96| 0.95| 0.96| 1.0 |

Table 2: Correlation of XLM-R languages, cf. Table 1.

Transformer models \[6, 1, 16, 3\] generally does not achieve a correlation, highlighting the need for semantic sentence representations for this goal. There are some exceptions to this rule which may be due to details in how the different models are trained and how much training data is available for each language in the multilingual models. Since this specific version of XLM-R was tuned with some parallel data, and these numbers were obtained from a single user study with a relatively small set of moral statements, it is difficult to say how much this reflects shared moral norms between the respective cultures, and to what extent it reflects the internal alignment of the model.

In Table 2 we can observe very high alignment between languages within the XLM-R model, which may not be surprising. Recall that the model is trained so that two sentences in different languages with the same semantics receive very similar embeddings. Also note that the tested statements provided by \[14\] do not aim to grasp cultural differences. An interesting question raised by these initial results is whether language alignment is in fact desirable when considering moral norms, which can differ in differing cultures.

Summarised, these observations already confirm the results of \[14\] in a larger multilingual setting and indicate that multilingual LMs indeed capture moral norms. To what extent they differ, however, is still unclear. Therefore, we further aim to clarify this by experimenting on monolingual as well as multilingual transformer models.
References

[1] Wissam Antoun, Fady Baly, and Hazem Hajj. Arabert: Transformer-based model for arabic language understanding. In LREC 2020 Workshop Language Resources and Evaluation Conference, may 2020.

[2] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, (NeurIPS), 2020.

[3] Branden Chan, Stefan Schweter, and Timo Möller. German’s next language model. In Proceedings of the 28th International Conference on Computational Linguistics, pages 6788–6796, Barcelona, Spain (Online), December 2020. International Committee on Computational Linguistics.

[4] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440–8451, Online, July 2020. Association for Computational Linguistics.

[5] Joe Davison, Joshua Feldman, and Alexander M. Rush. Commonsense knowledge mining from pretrained models. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors, Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, (EMNLP-IJCNLP). Association for Computational Linguistics, 2019.

[6] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.

[7] Dan Hendrycks, Collin Burns, Steven Basart, Andrew Critch, Jerry Li, Dawn Song, and Jacob Steinhardt. Aligning AI with shared human values. In Proceedings of the International Conference on Learning Representations (ICLR). OpenReview.net, 2021.
[8] Katharina Hämmerl, Jindřich Libovický, and Alexander Fraser. Combining static and contextualised multilingual embeddings. In *Findings of ACL*, 2022.

[9] Sophie Jentzsch, Patrick Schramowski, Constantin A. Rothkopf, and Kristian Kersting. Semantics derived automatically from language corpora contain human-like moral choices. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (AIES)*, pages 37–44, 2019.

[10] Liwei Jiang, Jena D. Hwang, Chandra Bhagavatula, Ronan Le Bras, Maxwell Forbes, Jon Borchardt, Jenny Liang, Oren Etzioni, Maarten Sap, and Yejin Choi. Delphi: Towards machine ethics and norms. *CoRR*, abs/2110.07574, 2021.

[11] Jindřich Libovický, Rudolf Rosa, and Alexander Fraser. On the language neutrality of pre-trained multilingual representations. In *Findings of EMNLP*, November 2020.

[12] Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick S. H. Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander H. Miller. Language models as knowledge bases? In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Association for Computational Linguistics, 2019.

[13] Nils Reimers and Iryna Gurevych. Making monolingual sentence embeddings multilingual using knowledge distillation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4512–4525, Online, November 2020. Association for Computational Linguistics.

[14] Patrick Schramowski, Cigdem Turan, Nico Andersen, Constantin A. Rothkopf, and Kristian Kersting. Large pre-trained language models contain human-like biases of what is right and wrong to do. *Nature Machine Intelligence*, 2022.

[15] Patrick Schramowski, Cigdem Turan, Sophie Jentzsch, Constantin A. Rothkopf, and Kristian Kersting. The moral choice machine. *Frontiers Artif. Intell.*, 3:36, 2020.

[16] Milan Straka, Jakub Náplava, Jana Straková, and David Samuel. Robeczech: Czech roberta, a monolingual contextualized language representation model. In Kamil Ekštein, František Pártl, and Miloslav Konopík, editors, *Text, Speech, and Dialogue*, pages 197–209, Cham, 2021. Springer International Publishing.

[17] Peter West, Chandra Bhagavatula, Jack Hessel, Jena D. Hwang, Liwei Jiang, Ronan Le Bras, Ximing Lu, Sean Welleck, and Yejin Choi. Symbolic knowledge distillation: from general language models to commonsense models. *CoRR*, abs/2110.07178, 2021.