On the ability of monolingual models to learn language-agnostic representations

Leandro Rodrigues de Souza,1 Rodrigo Nogueira,1,2,3 Roberto Lotufo1,2

1 Faculty of Electrical and Computer Engineering, University of Campinas (UNICAMP)  
2 NeuralMind Inteligência Artificial  
3 David R. Cheriton School of Computer Science, University of Waterloo

Abstract

Pretrained multilingual models have become a de facto default approach for zero-shot cross-lingual transfer. Previous work has shown that these models are able to achieve cross-lingual representations when pretrained on two or more languages with shared parameters. In this work, we provide evidence that a model can achieve language-agnostic representations even when pretrained on a single language. That is, we find that monolingual models pretrained and finetuned on different languages achieve competitive performance compared to the ones that use the same target language. Surprisingly, the models show a similar performance on a same task regardless of the pretraining language. For example, models pretrained on distant languages such as German and Portuguese perform similarly on English tasks.

1 Introduction

Pretrained language models, such as BERT (Devlin et al., 2019) and T5 (Raffel et al., 2020), still rely on high quality labeled datasets for achieving good results in NLP tasks. Since creating such datasets can be challenging (Biswas et al., 2009; Sabou et al., 2012), many resource-lean languages suffer from the lack of data for training.

Multilingual pretraining has been developed to overcome this issue, giving rise to multilingual models like mBERT (Devlin et al., 2019), XLM (Conneau et al., 2018a, 2019) and mT5 (Xue et al., 2021). Differently from monolingual models, they are pretrained with mixed batches from a wide range of languages. The resulting model finetuned on a task in a high-resource language often performs well on the same task in a different language never seen during finetuning. Such models thus exhibit the so called zero-shot cross-lingual transfer ability.

This approach has become the de facto default language transfer paradigm, with multiple studies and benchmarks reporting high transfer performance (Pires et al., 2019; Hu et al., 2020). At first, it has been speculated that a shared vocabulary with common terms between languages would result in a shared input representation space, making it possible for the model to attain similar representations across languages (Pires et al., 2019). However, more recent work has shown that having a shared vocabulary is not critical for cross-lingual transfer (Artetxe et al., 2020; Conneau et al., 2020).

Conneau et al. (2020) have released a large study on bilingual models to identify the most important characteristics that enable cross-lingual transfer. The authors found that a shared vocabulary with anchor points (common terms in both languages) plays a minor role. Sharing the Transformers’ parameters when training on datasets from two languages seems to be critical. They also found an interesting property in monolingual models: they have similar representations in the first layers of the network that can be aligned with a simple orthogonal mapping function.

Similar findings have been presented by Artetxe et al. (2020). They developed a procedure to learn representations for a specific language (i.e., word embedding layer) aligned with pretrained English layers of a Transformer model. This enables the model to transfer knowledge between languages by only swapping its lexicon.

As it becomes clearer that models trained on different languages achieve similar representations and cross-lingual transfer can be reached with quite simple methods, we raise the following question: Would monolingual models be able to learn from labeled datasets in a foreign language (i.e., a different language from its pretraining) without any adjustments at all?

We ground our hypothesis on the fact that masked language modeling has demonstrated to achieve strong representations even in different domains (Lu et al., 2021; Zügner et al., 2021). To
the best of our knowledge, our work is the first to experiment on monolingual models learning from a dataset in a different language.

Based on these observations, we design an experiment to test if monolingual models can leverage concepts acquired during pretraining and learn a new language and a new task from finetuning only. We pretrain a model on a source language and fine-tune it on a different language. We also evaluate models without pretraining, as a control experiment, to discard the hypothesis that the model is learning patterns only from the finetuning dataset.

**Main contribution.** We demonstrate that monolingual models can learn a task in a foreign language. Our results show that, despite those models have inferior performance when compared to the standard approach (i.e., pretraining and finetuning a model on the same language), they can still learn representations for a downstream task and perform well when compared to models without pretraining. This raises the hypothesis that MLM pretraining provides the model some language-agnostic properties that can be leveraged regardless of the language of the task.

In contrast to the current literature, the monolingual models used in this work do not rely on shared parameters during pretraining with multilingual datasets. They are pretrained, instead, on a single language corpus and finetuned on a task in a different (foreign) language. The results raise questions about language-agnostic representations during MLM pretraining and contribute to future directions in cross-lingual knowledge transfer research.

## 2 Related Work

Multilingual pretraining has been widely adopted as a cross-lingual knowledge transfer paradigm (Devlin et al., 2019; Conneau and Lample, 2019; Conneau et al., 2019; Xue et al., 2021). Such models are pretrained on a multilingual corpus using masked language modeling objectives. The resulting models can be finetuned on high-resource languages and evaluated on a wide set of languages without additional training.

Pires et al. (2019) first speculated that the generalization ability across languages is due to the mapping of common word pieces to a shared space, such as numbers and web addresses.

This hypothesis was tested by Artetxe et al. (2020). The experiment consisted of pretraining an English BERT model’s lexicon in a target language dataset: only word embeddings are trainable. The authors, then, have transferred knowledge by taking a BERT model finetuned on English and swapping its lexicon to the desired language. They obtained results similar to those obtained by Pires et al. (2019). Therefore, they confirmed the hypothesis that the model can learn representations that are language-agnostic and that do not depend on a shared vocabulary nor joint pretraining.

Conneau et al. (2020) have also demonstrated that a shared vocabulary with anchor points contributes little to language transfer. In their experiments, the authors carried out an extensive analysis on the results of bilingual models to identify the factors that contribute most to language transfer. The results indicate that the main component is related to the sharing of model parameters, achieving good results even in the absence of parallel corpus or shared vocabulary. They also found that monolingual models pretrained on MLM have similar representations, that could be aligned with a simple orthogonal mapping.

Zhao et al. (2020) observed that having a cross-lingual training objective contributes to the model learning cross-lingual representations, while monolingual objectives resulted in language-specific subspaces. These results indicate that there is a negative correlation between the universality of a model and its ability to retain language-specific information, regardless of the architecture. Our experiments show that a single language pretraining still enables the model to achieve competitive performance in other languages via finetuning (on supervised data) only.

Libovický et al. (2019) found that mBERT word embeddings are more similar for languages of the same family, resulting in specific language spaces that cannot be directly used for zero-shot cross-lingual tasks. They also have shown that good cross-lingual representations can be achieved with a small parallel dataset. We show, however, that a monolingual model can achieve competitive performance in a different language, without parallel corpora, suggesting that it contains language-agnostic properties.

While multilingual models exhibit great performance across languages (Hu et al., 2020), monolingual models still perform better in their main language. For instance, Chi et al. (2020) distill a monolingual model into a multilingual one and
achieve good cross-lingual performance. We take
on a different approach by using the monolingual
model itself instead of extracting knowledge from
it.

Rust et al. (2020) compared multilingual and
monolingual models on monolingual tasks (i.e., the
tasks whose language is the same as the mono-
lingual model). They found that both the size of
pretraining data in the target language and vocabu-
lary have a positive correlation with monolingual
models’ performance. Based on our results, we
hypothesize that a model pretrained with MLM
using a large monolingual corpus develops both
language-specific and language-agnostic proper-
ties, being the latter predominant over the former.

3 Methodology

Our method consists of a pretrain-finetune ap-
proach that uses different languages for both. We
call source language as the language used for pre-
training our models. We refer to target language
as a second language, different from the one used
for pretraining our model. We apply the following
steps:

1. Pretrain a monolingual model on the source
language with masked language modeling
(MLM) objective using a large, unlabeled
dataset.

2. Finetune and evaluate the model on a down-
stream task with a labeled dataset in the target
language.

The novelty of our approach is to perform a
cross-lingual evaluation using monolingual models
instead of bi-lingual or multi-lingual ones. We aim
to assess if the model is able to rely on its masked
language pretraining to achieve good representa-
tions for a task even when finetuned on a different
language. If successful, this would suggest that
MLM pretraining provides the model with repre-
sentations for more abstract concepts rather than
learning a specific language.

Pretraining data. Our monolingual models are
pretrained on a large unlabeled corpus, using a
source language’s vocabulary. Some high-resource
languages, such as English, have a high presence
in many datasets from other languages, often cre-
ated from crawling web resources. This may influ-
ence the model’s transfer ability because it has seen
some examples from the foreign language during
pretraining. However, the corpora used to pretrain
our models have a very small amount of sentences
in other languages. For instance, Portuguese pre-
training corpus has only 14,928 sentences (0.01%) in
Vietnamese.

Control experiment. To discard the hypothesis
that the monolingual model can learn patterns from
the finetuning dataset, instead of relying on more
general concepts from both finetuning and pretrain-
ing, we perform a control experiment. We train
the models on the target language tasks without
any pretraining. If models with monolingual pre-
training have significantly better results, we may
conclude that it uses knowledge from its pretraining
instead of only learning patterns from finetuning
data.

Evaluation tasks. We follow a similar selection
as in Artetxe et al. (2020) and use two downstream
types of tasks for evaluation: natural language in-
ference (NLI) and question answering (QA). Even
though a classification task highlights the model’s
ability to understand the relationship between sen-
tences, it has been shown that the model may learn
some superficial cues to perform well (Gururangan
et al., 2018). Because of that, we also select ques-
tion answering, which requires natural language
understanding as well.

4 Experiments

In this section, we outline the models, datasets and
tasks we use in our experiments.

4.1 Models

We perform experiments with four base models,
highlighted in Table 1. The experiments run on the
Base versions of the BERT model (Devlin et al.,
2019), with 12 layers, 768 hidden dimensions and
12 attention heads. We use models initialized with
random weights. We also report the number of
parameters (in millions) and the pretraining dataset
sizes in Table 1.

4.2 Pretraining procedure

The selected models are pretrained from random
weights using a monolingual tokenizer, created
from data in their native language. We also select
models that have been pretrained using the Masked
Language Modeling (MLM) objective as described
by Devlin et al. (2019).
Table 1: Pretrained models used in this work.

| Model name                  | Initialization | Language          | # of params. | Data size |
|-----------------------------|----------------|-------------------|--------------|-----------|
| BERT-EN (Devlin et al., 2019) | Random         | English (en)      | 108 M        | 16 GB     |
| BERT-PT (ours)              | Random         | Portuguese (pt)   | 108 M        | 16 GB     |
| BERT-DE (Chan et al., 2020) | Random         | German (de)       | 109 M        | 12 GB     |
| BERT-VI (Nguyen and Nguyen, 2020) | Random       | Vietnamese (vi)   | 135 M        | 20 GB     |

4.3 Finetuning procedure

We use the AdamW optimizer (Loshchilov and Hutter, 2019) and finetune for 3 epochs, saving a checkpoint after every epoch. Results are reported using the best checkpoint based on validation metrics. The initial learning rate is $3e^{-5}$, followed by a linear decay with no warm-up steps.

For NLI, we use a maximum input length of 128 tokens and a batch size of 32. For QA, except for BERT-VI, our input sequence is restricted to 384 tokens with a document stride of 128 tokens and a batch size of 16. For BERT-VI, we use an input sequence of 256 tokens and a document stride of 85. This is due to the fact that BERT-VI was pretrained on sequences of 256 tokens, resulting in positional token embeddings limited to this size.

We have chosen this hyperparameter configuration based on preliminary experiments with English and Portuguese models trained on question answering and natural language inference tasks in their native languages. We do not perform any additional hyperparameter search.

For the control experiments, we finetune the models for 30 epochs using the same hyperparameters, with a patience of 5 epochs over the main validation metric. This longer training aims to discard the hypothesis that the pretrained models have an initial weight distribution that is favorable compared to a random initialization, which could be the main reason for better performance.

4.3.1 Finetuning tasks

**Question Answering.** We select the following tasks for finetuning: SQuAD v1.1\(^1\) for English (Rajpurkar et al., 2016); FaQuAD\(^2\) for Portuguese (Sayama et al., 2019); GermanQuAD\(^3\) for German (Chan et al., 2020); ViQuAD\(^4\) for Vietnamese

\(^1\)https://raw.githubusercontent.com/rajpurkar/SQuAD-explorer/master/dataset/
\(^2\)https://raw.githubusercontent.com/lliafacom/faquad/master/data/
\(^3\)https://www.deeppset.ai/datasets
\(^4\)https://sites.google.com/uit.edu.vn/uit-nlp/datasets-projects

**Natural Language Inference.** We use: MNLI\(^5\) for English (Williams et al., 2018); ASSIN2\(^6\) for Portuguese (Real et al., 2020); and XNLI\(^7\) for both Vietnamese and German (Conneau et al., 2018b).

5 Results

Table 2 reports the results for the question answering experiments and Table 3 for natural language inference. For every experiment, we provide a characterization of the pretraining (source) and finetune (target) languages we used. We also denote None as the models of our control experiment, which are not pretrained.

We use a color scheme for better visualization. Results highlighted in red are considered the upper bound, while blue is used for lower bound. Only cells of the same column are comparable since results belong to the same task.

(Nguyen et al., 2020).

5 Results

Table 2 reports the results for the question answering experiments and Table 3 for natural language inference. For every experiment, we provide a characterization of the pretraining (source) and finetune (target) languages we used. We also denote None as the models of our control experiment, which are not pretrained.

We use a color scheme for better visualization. Results highlighted in red are considered the upper bound (models pretrained and finetuned on the same language); orange is used for models finetuned on a different language from pretraining; blue is used for lower bound experiments (control experiments).

Models leverage pretraining, even when finetuned on different languages. For all selected languages, models can take advantage of its pretrain-

\(^5\)https://cims.nyu.edu/~sbowman/multinli/
\(^6\)https://sites.google.com/view/assin2/
\(^7\)https://github.com/facebookresearch/XNLI
Table 3: Results (accuracy) for Natural Language Inference in each language with different pretrainings. The last row highlights the number of classes for each task.

| Pretraining | Finetune and Evaluation |
|-------------|-------------------------|
|             | en  | de  | pt  | vi  |
| None        | 61.54 | 59.48 | 70.22 | 54.09 |
| en          | 83.85 | 67.71 | 82.56 | 64.20 |
| de          | 71.22 | 78.27 | 77.45 | 47.98 |
| pt          | 75.56 | 65.06 | 86.56 | 63.15 |
| vi          | 72.05 | 66.63 | 80.64 | 76.25 |

The most interesting finding in this work is that a monolingual model can learn a different language during a finetune procedure. Differently from the literature, we use a model pretrained on a single language and targeted to a task in a different language (English models learning Portuguese tasks and vice versa).

We see that those models achieve good results compared to models pretrained and finetuned on the same language and largely outperform models without pretraining. This finding suggests that MLM pretraining is not only about learning a language model, but also concepts that can be applied to many languages. This had been explored in more recent work that leverages language models in different modalities (Lu et al., 2021).

It is also noteworthy that those models could learn a different language with a finetune procedure even with small datasets (for instance, FaQuAD contains only 837 training examples; GermanQuAD has 11,518; and ViQuAD is comprised of 18,579). The English version of BERT could achieve a performance close to the upper bound for Portuguese on both NLI (82.56% of accuracy) and QA (45.22 F1 score) tasks with small datasets. This, together with the low performance of control models, shows that the model leverage most of its pretraining for a task.

6.2 Similar performance regardless of the pretraining language

Another finding is that similar results were achieved by models pretrained on a different language than the task’s. We can draw three different clusters from the results: the lower bound cluster, containing results for models without pretraining; the upper bound, with models pretrained on the same language as the task; and a third cluster, closer to the upper bound, with models pretrained on a different language.
Since the models are comparable in pretraining data size and number of parameters, we hypothesize that this observation is related to the language-agnostic concepts learned during pretraining versus language-specific concepts. The performance gap between the upper bound and third clusters may be explained by the language-specific properties not available to the latter group.

This conclusion can also be drawn from the experiments performed by Artetxe et al. (2020). The authors demonstrated that only swapping the lexicon enabled knowledge transfer between two languages. Since the embedding layer corresponds to a small portion of the total number of parameters of the model, it seems that language-specific properties represent a small portion of the whole model as well. Here, we go even further by showing that not even tokenizers and token embeddings need to be adapted to achieve cross-lingual transfer.

7 Conclusion

Recent work has shown that training a model with two or more languages and shared parameters is important, but also that representations from monolingual models pretrained with MLM can be aligned with simple mapping functions.

In this context, we perform experiments with monolingual models on foreign language tasks. Differently from previous work, we pretrain our models on a single language and evaluate their ability to learn representations for a task using a different language during finetuning, i.e., without using any cross-lingual transfer technique.

Our results suggest that models pretrained with MLM achieve language-agnostic representations that can be leveraged for target tasks. We argue that MLM pretraining contributes more to representations of abstract concepts than to a specific language itself.

The experiments conducted in this paper raise questions about the language-agnostic properties of language models and open directions for future work. Studying language-independent representations created from MLM pretraining may result in new ways to leverage this pretraining procedure for enabling models to perform in a wider range of tasks. More experiments on a wide range of languages and tasks are needed to strengthen our findings, which may lead to innovative language-agnostic methods for language models.

Acknowledgments

This research was funded by a grant from Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP) #2020/09753-5.

References

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020. On the cross-lingual transferability of monolingual representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4623–4637, Online. Association for Computational Linguistics.

Priyanka Biswas, Monojit Choudhury, and Kalika Bali. 2009. Complex Linguistic Annotation - No Easy Way Out! A Case from Bengali and Hindi POS Labeling Tasks. In Proceedings of the Third Linguistic Annotation Workshop, pages 10–18. Association for Computational Linguistics.

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

Zewen Chi, Li Dong, Furu Wei, Xianling Mao, and Heyan Huang. 2020. Can monolingual pretrained models help cross-lingual classification? In Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing, pages 12–17, Suzhou, China. Association for Computational Linguistics.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2018a. XNLI: Evaluating cross-lingual sentence representations. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018, pages 2475–2485.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel R. Bowman, Holger Schwenk, and Veselin Stoyanov. 2018a. XNLI: Evaluating Cross-lingual Sentence Representations. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018, pages 2475–2485.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel R. Bowman, Holger Schwenk, and Veselin Stoyanov. 2018b. XNLI: Evaluating cross-lingual sentence representations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018, pages 2475–2485.

Acknowledgments

This research was funded by a grant from Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP) #2020/09753-5.

References

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020. On the cross-lingual transferability of monolingual representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4623–4637, Online. Association for Computational Linguistics.

Priyanka Biswas, Monojit Choudhury, and Kalika Bali. 2009. Complex Linguistic Annotation - No Easy Way Out! A Case from Bengali and Hindi POS Labeling Tasks. In Proceedings of the Third Linguistic Annotation Workshop, pages 10–18. Association for Computational Linguistics.

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

Zewen Chi, Li Dong, Furu Wei, Xianling Mao, and Heyan Huang. 2020. Can monolingual pretrained models help cross-lingual classification? In Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing, pages 12–17, Suzhou, China. Association for Computational Linguistics.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2018a. XNLI: Evaluating cross-lingual sentence representations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018, pages 2475–2485.
in Natural Language Processing. Association for Computational Linguistics.

Alexis Conneau, Shahjib Wu, Haoran Li, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Emerging cross-lingual structure in pretrained language models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6022–6034, Online. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. 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. Association for Computational Linguistics.

Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel Bowman, and Noah A. Smith. 2018. Annotation artifacts in natural language inference data. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 107–112, New Orleans, Louisiana. Association for Computational Linguistics.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. XTREME: A Massively Multilingual Multi-task Benchmark for Evaluating Cross-lingual Generalisation. In International Conference on Machine Learning, pages 4411–4421. PMLR.

Jindřich Libovický, Rudolf Rosa, and Alexander Fraser. 2019. How language-neutral is multilingual bert? arXiv preprint arXiv:1911.03310.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization.

Kevin Lu, Aditya Grover, Pieter Abbeel, and Igor Mordatch. 2021. Pretrained transformers as universal computation engines.

Dat Quoc Nguyen and Anh Tuan Nguyen. 2020. PhoBERT: Pre-trained language models for Vietnamese. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1037–1042.

Kiet Nguyen, Vu Nguyen, Anh Nguyen, and Ngan Nguyen. 2020. A Vietnamese dataset for evaluating machine reading comprehension. In Proceedings of the 28th International Conference on Computational Linguistics, pages 2595–2605, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is Multilingual BERT? ACL 2019 - 57th Annual Meeting of the Association for Computational Linguistics. Proceedings of the Conference, pages 4996–5001.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21(140):1–67.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100, 000+ questions for machine comprehension of text. CoRR, abs/1606.05250.

Livy Real, Erick Fonseca, and Hugo Gonçalo Oliveira. 2020. The assin 2 shared task: A quick overview. In Computational Processing of the Portuguese Language, pages 406–412, Cham. Springer International Publishing.

Phillip Rust, Jonas Pfeiffer, Ivan Vulić, Sebastian Ruder, and Iryna Gurevych. 2020. How Good is Your Tokenizer? On the Monolingual Performance of Multilingual Language Models.

Marta Sabou, Kalina Bontcheva, and Arno Scharl. 2012. Crowdsourcing research opportunities: Lessons from natural language processing. In Proceedings of the 12th Conference on Knowledge Management and Knowledge Technologies, i-KNOW ’12, New York, NY, USA. Association for Computing Machinery.

H. F. Sayama, A. V. Araujo, and E. R. Fernandes. 2019. Faquad: Reading comprehension dataset in the domain of brazilian higher education. In 2019 8th Brazilian Conference on Intelligent Systems (BRACIS), pages 443–448.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122. Association for Computational Linguistics.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Baru, and Colin Raffel. 2021. mt5: A massively multilingual pre-trained text-to-text transformer.

Wei Zhao, Steffen Eger, Johannes Bjerva, and Isabelle Augenstein. 2020. Inducing language-agnostic multilingual representations. arXiv preprint arXiv:2008.09112.

Daniel Zügner, Tobias Kirschstein, Michele Catasta, Jure Leskovec, and Stephan Günnemann. 2021. Language-agnostic representation learning of source code from structure and context. In International Conference on Learning Representations.