KaLM-Embedding: Superior Training Data Brings A Stronger Embedding Model

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https://huggingface.co/HIT-TMG/KaLM-embedding-multilingual-mini-instruct-v1.5



https://github.com/HITsz-TMG/KaLM-Embedding

Abstract

As retrieval-augmented generation prevails in large language models, embedding models are becoming increasingly crucial. Despite the growing number of general embedding models, prior work often overlooks the critical role of training data quality. In this work, we introduce KaLM-Embedding, a general multilingual embedding model that leverages a large quantity of cleaner, more diverse, and domain-specific training data. Our model has been trained with key techniques proven to enhance performance: (1) persona-based synthetic data to create diversified examples distilled from LLMs, (2) ranking consistency filtering to remove less informative samples, and (3) semi-homogeneous task batch sampling to improve training efficacy. Departing from traditional BERT-like architectures, we adopt Qwen2-0.5B as the pre-trained model, facilitating the adaptation of auto-regressive language models for general embedding tasks. Extensive evaluations of the MTEB benchmark across multiple languages show that our model outperforms others of comparable size, setting a new standard for multilingual embedding models with less than 1B parameters.

1 Introduction

In recent years, retrieval-augmented generation (RAG) has gained increasing popularity [Gao et al., 2023, Huang and Huang, 2024]. With the rapid advancement of large language models (LLMs), retrieval models have become the primary bottleneck for improvement within the RAG framework [Setty et al., 2024], leading to the emergence of numerous text embedding models [Huang et al., 2024, Lee et al., 2024, Li et al., 2023, Xiao et al., 2024a]. As the foundation for information acquisition in RAG systems, a general embedding model is required to demonstrate capabilities across multiple languages, domains, and tasks [Muennighoff et al., 2023a, Xiao et al., 2024a].

Although numerous general embedding models have been developed using extensive paired data, they frequently overlook the quality of the training data. Specifically, (1) the presence of false negative samples in the fine-tuning data, which are sometimes similar to the positive documents, can introduce noise into representation learning; and (2) the recent success of scaling LLMs demonstrates the promise of cleaner and diverse training data, these aspects remain underemphasized in the development of embedding models. Therefore, our objective is to develop a superior embedding model by optimizing the quality of the training data and distilling the Knowledge in large Language Models into Embedding Models (KaLM-Embedding).

In this work, we introduce the technical details of our general multilingual text embedding model, KaLM-Embedding. It is adapted from the auto-regressive language model Qwen2-0.5B [Yang et al.,

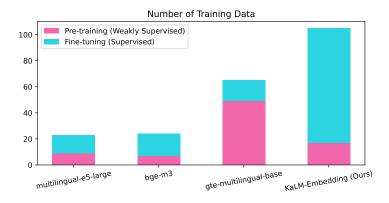


Figure 1: The size of our pre-training and fine-tuning dataset compared to prior work.

2024], with a carefully crafted training dataset for textual embeddings. We collect over 20 categories of data for pre-training and 70 categories of data for fine-tuning. The dataset is further augmented and cleaned with key techniques that we find particularly powerful: (1) Persona-based Synthetic Data [Wang et al., 2024a] to distill LLM knowledge into diverse data for embedding training, (2) Ranking Consistency Filtering [Dai et al., 2023, Wang et al., 2022] to improve data quality and reduce noise, and (3) semi-homogeneous task batching [Meng et al., 2024, Muennighoff et al., 2024], that combines the same task and random samples for in-batch negatives, to balance the hardness of negatives and the risk of false negatives. By combining these useful practices and scaling them into a larger and superior dataset, we demonstrate an even stronger capability for a compact decoder-only embedding model. Massive evaluation [Muennighoff et al., 2023a, Xiao et al., 2024a, Ciancone et al., 2024, Poswiata et al., 2024] represents that our models achieve state-of-the-art multilingual performance under 0.5B model size.

2 Training Methodology

2.1 Data Collection

Given our utilization of a pre-trained language model with robust performance capabilities, we adopt the conventional two-stage training approach to develop the embeddings. This process involves weakly-supervised contrastive pre-training followed by supervised fine-tuning.

Massive Open-source Dataset For the pre-training data, we utilized an extensive collection of title-body pairs from various documents, supplemented by a subset of large-scale supervised question-answering datasets. A detailed list of these datasets is presented in Table 8.

To ensure the model's generalization capability beyond merely fitting evaluation benchmarks, we employed fine-tuning data from a diverse array of sources. Specifically, during the fine-tuning phase, we incorporated over 70 different datasets, marking a significant departure from previous work in terms of training data selection strategy. These supervised datasets, characterized by high quality and diversity, typically feature relatively small data volumes, making them ideal for fine-tuning in the second phase. A comparison of the number of training datasets is shown in Figure 1, and a comprehensive list of the datasets used is provided in Table 9.

We included several classification and clustering datasets, treating each (sentence, category label) pair as a training instance. For datasets such as Arxiv, we mapped the label abbreviations back to their full label phrases to ensure that the labels convey better semantics. Additionally, we sampled hard negatives from the labels of all classification datasets, rather than mining them through the model. This approach helps mitigate the issue of having too few label categories in certain individual datasets, such as sentiment classification datasets with only two categories. For each specific dataset, we performed minor processing, such as filtering out samples with excessively short documents or excluding lower-quality parts based on the metadata provided with the dataset.



Figure 2: The framework of ranking consistency filtering.

To ensure data integrity and avoid contamination, we only utilized the training sets of all datasets, explicitly excluding any test sets. For some collected classification and clustering datasets without separated training and test sets, we first filtered out the test set samples included in the MTEB from the data, and then processed and sampled the remaining data. This approach guarantees that all examples present in the MTEB evaluations remain unseen during training.

Despite our fine-tuning data being primarily in Chinese and English, with only a small portion of multilingual data, the performance of our model in other languages remains satisfactory, showing that the multi-lingual advantage of pre-trained LLMs can carry over to embedding models.

Persona-based Synthetic Data Following previous work [Wang et al., 2024a], we generated 550k synthetic data using large language models, specifically QWen2-72B-Instruct, encompassing 6 types of tasks with 40k unique instructions. To enhance the diversity of the generated data, we incorporated randomly sampled personas from Persona Hub [Chan et al., 2024] as the system prompt for the large language model, effectively increasing the domain diversity of the generated data. Since 4 types of retrieval tasks require generating instructions before generating data, we introduced persona roles only during the instruction generation phase to avoid conflicts in persona roles between the two stages.

Ranking Consistency Filtering In addition to utilizing in-batch negatives, another approach for obtaining negative samples involves retrieving hard negatives from the dataset's corpus. However, in some datasets, a single query may correspond to multiple correct documents or answers, as exemplified on the right side of Figure 2. Furthermore, some queries may be overly broad, leading to their association with multiple documents despite low relevance between the query and the documents. Such scenarios can introduce false negatives, which can adversely affect model optimization, whether they are hard negatives (in the former case) or in-batch negatives (in the latter case).

To address this issue, we employ a ranking consistency filtering method, also known as top-k filtering [Dai et al., 2023, Wang et al., 2022], for fine-tuning data selection. This method involves ranking the similarity between the query and its original positive example data within the entire document corpus of the dataset, and filtering out samples where the positive example data pair does not rank within the top-k. It is important to note that this filtering method is conducted simultaneously with hard negative mining, as both processes require encoding all queries and the document corpus and calculating their relevance. Performing these tasks concurrently can effectively avoid redundant computations. The general process is illustrated on the left side of Figure 2.

2.2 Training Strategy

Semi-homogeneous Task Batching Previous studies have employed a method called homogeneous task batching [Meng et al., 2024, Muennighoff et al., 2024], where batches are formed exclusively from samples belonging to a single task. This approach effectively enhances training efficiency by increasing the hardness of in-batch negatives. Nevertheless, as mentioned earlier, utilizing a large homogeneous task batch carries the substantial drawback of potentially containing an excessive number of false negatives.

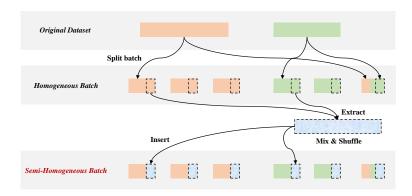


Figure 3: The process to construct the semi-homogeneous task batches.

In this study, we introduce the concept of semi-homogeneous task batching. This method involves creating a semi-batch that includes single-task samples, with the remaining portion of the batch consisting of randomly selected samples. As depicted in Figure 3, the semi-homogeneous task batching is constructed as follows: (1) Homogeneous task batch division: initially, a complete homogeneous task batch is constructed; (2) Semi-batch sampling and recombination: subsequently, a specified proportion of these homogeneous batches is sampled, mixed, and randomly reassigned back to their original batches. This approach aims to balance the difficulty of in-batch negatives with the risk of encountering false negatives.

However, this method was NOT utilized in our latest model; nonetheless, it offers a means of controlled analysis. Detailed analysis and conclusions can be found in the subsequent experimental sections.

Matryoshka Representation Learning Following many existing models and API services, in order to enhance the utility of embeddings, we have also incorporated Matryoshka Representation Learning (MRL) [Kusupati et al., 2022] training to achieve flexible dimension embedding. Specifically, we set the vector dimensions for MRL training to 896, 512, 256, 128, and 64, with corresponding training loss weights of 1.0, 0.3, 0.2, 0.1, and 0.1, respectively.

Task Instruction Instruction-finetuned language models are known for their strong generalization capabilities, yet this strategy remains underutilized in embedding models. We find that verbalized instructions can significantly enhance the performance of embedding models by reducing ambiguity in the embedding space. Concretely, in our training process, we prepended instruction prefixes to the queries of open-source data to differentiate between various tasks, employing a similar setup during testing. The instructions for different tasks are illustrated in Table 1. For synthetic data, we preserved the originally generated instructions, encompassing a variety of directives for retrieval tasks. Consequently, when deploying the model in practical applications, it is advisable to tailor task instructions to specific scenarios and requirements. Given that our model has been trained on a substantial volume of synthetic instructions, it demonstrates a robust capacity to comprehend and generalize instructions. The instructions used for the Classification and Clustering tasks in the MTEB evaluation are provided in Table 10.

	Task Type	Instruction	Example
	Retrieval, Reranking	General	Instruct: Given a query, retrieve documents that answer the query. \n Query: {query}
Asymmetric	Classification, Clustering	Specific	Instruct: Classifying the sentiment expressed in the given movie review text from the IMDB dataset \n Query: {query}
Symmetric	STS, PariClassification	None	-

Table 1: The task instruction of query for training and evaluation.

Model	Size		MTEB					
1.10401	5120	ZH	EN	FR	PL	avg		
Cohere-embed-multilingual-v3.0	-	-	64.01	56.02	-			
jina-embeddings-v3 (Multi-LoRA)	572M	-	65.51	62.29	63.97	-		
e5-mistral-7b-instruct	7111M	60.89	66.40	48.33	-	-		
paraphrase-multilingual-mpnet-base-v2	278M	44.59	54.64	55.21	48.67	50.78		
multilingual-e5-large [†]	560M	58.54	60.89	55.64	60.08	58.79		
bge-m3 (Dense) [†]	560M	61.07	59.57	58.79	60.35	59.95		
gte-multilingual-base (Dense) [†]	305M	62.72	61.40	59.79	58.22	60.53		
KaLM-embedding-mini-instruct	494M	64.13	64.94	63.08	57.05	62.3		

Table 2: Evaluation results on MTEB Chinese, English, French and Polish¹. Our model, **KaLM-embedding-mini-instruct**, achieves a new state-of-the-art among multilingual embedding models of <1B parameters, an economical choice for building applications such as retrieval-augmented systems.

3 Experiment

3.1 Experimental Setting

We utilize the InfoNCE loss function as our optimization objective, with the temperature parameter set to 0.01. Our base model is Qwen2-0.5B, employing mean pooling. The maximum input text length is capped at 512 tokens. The model is trained using mixed precision with bf16.

For pre-training, we exclusively use in-batch negatives to enhance efficiency. The pre-training process is conducted on 6 nodes, each equipped with 8 Ascend 910B NPUs having 65GB of memory. The model undergoes pre-training for 1 epoch, equivalent to approximately 19k steps, with a batch size of 512 and a learning rate of 1e-4.

During fine-tuning, we incorporate hard negatives after a filtering process. For hard negative mining within the fine-tuning dataset, we sample 7 negative examples from a range of 50 to 100. The top-k threshold for ranking consistency filtering is set to 50. Fine-tuning is performed on 3 nodes with NPUs. The model is fine-tuned for 1 epoch, approximately 4.5k steps, with a batch size of 48 and a learning rate of 1e-4. Matryoshka representation learning is applied during fine-tuning, utilizing dimensions of 896, 512, 256, 128, and 64 as previously specified.

3.2 Results

MTEB Evaluation: We employed the Massive Text Embedding Benchmark (MTEB) [Muennighoff et al., 2023a, Xiao et al., 2024a, Ciancone et al., 2024, Poswiata et al., 2024] as the primary dataset for evaluation and analysis due to its diverse task types and extensive datasets. While our primary optimization targets were Chinese (zh) and English (en), we also conducted evaluations in French (fr) and Polish (pl). A summary of the multilingual evaluation results is presented in Table 2, with detailed results for each language provided in the appendix. Our KaLM-embedding-mini-instruct model demonstrated significantly superior overall performance across multiple languages compared to other models. However, its performance in Polish was relatively weaker, likely due to the lower proportion of Polish in the training data, particularly within the language distribution of synthetic data [Conneau et al., 2020, Wang et al., 2024a].

Ablation Study: We conducted ablation studies on training strategies and data filtering, with the experimental results shown in Table 3. Since we assigned a smaller weight to the low-dimensional Matryoshka embedding during training, the Matryoshka Representation Learning had a minimal impact on the final results. An analysis of results across different dimensions is provided in subsequent sections. The impact of task instruction was particularly significant, especially given our use of a mixture of various types of training data. Ranking consistency filtering was particularly effective for our previous models, but its impact was relatively minor on this latest model, possibly due to the more comprehensive data coverage in this version. A similar ablation effect was observed with

¹The † symbol indicates results reused from Zhang et al. [2024]. Other evaluation results are sourced from the MTEB leaderboard (accessed on December 25, 2024).

Model	MTEB			
-	ZH	EN		
KaLM-embedding-mini-instruct	64.13	64.94		
w/o Matryoshka Representation Learning	64.07	65.00		
w/o Weakly-supervised Pre-training	64.06	64.07		
w/o Task Instructions	61.57	61.13		
w/o Ranking Consistency Filtering	64.25	64.19		

Table 3: Ablation of different training strategies.

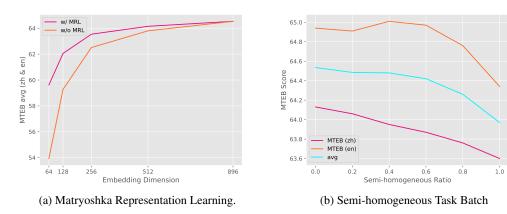


Figure 4: Impact of training strategy and parameters on MTEB in Chinese and English.

pre-training, which contrasts with the findings of many previous studies [Chen et al., 2024a, Zhang et al., 2024]. Additionally, data filtering had a more pronounced improvement effect on English than on Chinese, likely because the English evaluation included more out-of-domain data, making the enhancement in generalization through data filtering more evident in English.

3.3 Analysis

Matryoshka Embedding: We assessed the performance of embedding vectors truncated to various dimensions, as depicted in Figure 4a. The results clearly indicate that performance deteriorates with decreasing dimensionality. Nonetheless, models trained using Matryoshka Representation Learning demonstrate substantial improvements in the performance of low-dimensional embeddings. This enhancement is likely limited by our configuration of relatively small learning weights for low-dimensional embeddings, implying that there remains significant potential for further improvement in the performance of low-dimensional embeddings relative to their full-dimensional counterparts.

Semi-homogeneous Task Batch: In Figure 4b, we investigate the impact of varying ratios of Semi-homogeneous Task Batches on the final outcomes. Our analysis reveals that increasing the proportion of Semi-homogeneous Tasks negatively affects overall performance. As depicted in Figure 6 in the appendix, this detrimental effect is particularly evident in classification, clustering, and pair-classification tasks, whereas it positively influences retrieval and reranking tasks. This discrepancy primarily arises because the labels in the classification and clustering data within the training set are generally limited, leading to a significant number of false in-batch negatives when homogeneous task batches are used, especially when the batch size is large. Although this training strategy was not adopted in our final model, it remains a viable optimization method depending on specific optimization goals and the nature of the training data. This approach could be particularly useful in scenarios where classification/clustering training data is not utilized, or when there is a specific aim to optimize retrieval and reranking tasks.

Step and Batch Size: We conducted an analysis to examine the impact of training epochs (or training steps) and batch size (or the number of training nodes) on model performance, as illustrated

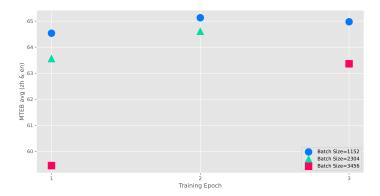


Figure 5: The impact of training epochs and batch size on MTEB in Chinese and English.

in Figure 5. The batch size was regulated by adjusting the number of training nodes, with a focus on the global batch size, excluding hard negatives. The experiments were performed using 3, 6, and 9 nodes. Given that training for one epoch with varying batch sizes results in different numbers of training steps for the same volume of training data, we also compared the outcomes across different epochs. Our findings indicate that an increased number of training steps positively influenced the overall performance of the model on the MTEB benchmark. However, when comparing scenarios with an equivalent number of steps (1 epoch with 3 nodes, 2 epochs with 6 nodes, and 3 epochs with 9 nodes), a larger batch size did not necessarily lead to better results. This phenomenon could be attributed to the higher probability of false negatives within the batch as the batch size increases, which also resulted in greater fluctuations in the observed loss during training. Ultimately, we selected the model trained with 1 epoch and 3 nodes as the final version, deeming it the most stable and reliable.

4 Conclusion

In this study, we introduce the KaLM-Embedding model, developed using a small-scale autoregressive language model. By leveraging a substantial volume of high-quality data and implementing effective training strategies, the KaLM-Embedding model achieves state-of-the-art performance in multilingual tasks at the 0.5B parameter scale. We have made our model open-source to facilitate access for researchers and practitioners interested in experimentation. We anticipate that our technical report will serve as a valuable resource for researchers in this field.

5 Discussion

Drawing from our experimental investigations and experience, we provide several discussions that may prove advantageous for future research endeavors:

Firstly, the embedding of long texts presents a promising area for further investigation. The Qwen model [Yang et al., 2024] we utilize employs Rotary Position Embedding (RoPE) [Su et al., 2024], which allows for the extension of context to longer sequences with relative ease. However, we have not yet adopted a single-vector approach for long text embedding due to the inherent complexity and diversity of information in long texts. Representing such texts with a single vector can lead to representation collapse or dilution [AI, 2024, Zhou et al., 2024]. Experimental results indicate that pure long text embedding (Dense) is less effective than BM25 (Sparse) [Chen et al., 2024a, Zhang et al., 2024, Zhao et al., 2024]. For single-vector representations, encoding minimal and clean information is preferable [Chen et al., 2024b], whereas the representation of long texts is better managed through the use of multiple vectors [Luo et al., 2024, Zhang et al., 2022].

Secondly, model merging as a multi-task learning approach warrants further exploration [Jin et al., 2023, Xiao et al., 2024b, Yu et al., 2024]. In this study, we attempted to train models separately on symmetric tasks (without instruction) and asymmetric tasks (with instruction), followed by weighted

averaging of the parameters. However, the separately trained models did not outperform their counterparts on their respective tasks. For example, the model trained on symmetric tasks underperformed on the STS task compared to the model trained with a mixture of all data. Additionally, the performance of the merged model deteriorated significantly, rendering it unusable. This may be attributed to a substantial gap or conflict between the two types of tasks, making direct parameter averaging infeasible [Yadav et al., 2023].

Lastly, the effects of different base models and pooling methods remain to be thoroughly explored. Current models employ various base models and pooling methods, yet there is a lack of rigorous comparison across different settings [Lee et al., 2024]. Our experiments revealed a consistent trend in the performance of different base models and pooling methods; however, the performance gap under the same training data and strategies was not significant. We posit that high-quality data is the fundamental driver for pushing the upper limits of model performance [Wang et al., 2024a, Zhang et al., 2024], while training strategies act as catalysts that facilitate models in reaching these limits. Furthermore, the potential for innovative model architecture designs remains an exciting avenue for future research.

References

- Jina AI. Still need chunking when long-context models can do it all?, 2024. URL https://jina.ai/news/still-need-chunking-when-long-context-models-can-do-it-all. Accessed: 2024-12-13.
- Luiz Henrique Bonifacio, Israel Campiotti, Roberto A. Lotufo, and Rodrigo Frassetto Nogueira. mmarco: A multilingual version of MS MARCO passage ranking dataset. *CoRR*, abs/2108.13897, 2021. URL https://arxiv.org/abs/2108.13897.
- Vera Boteva, Demian Gholipour Ghalandari, Artem Sokolov, and Stefan Riezler. A full-text learning to rank dataset for medical information retrieval. In Nicola Ferro, Fabio Crestani, Marie-Francine Moens, Josiane Mothe, Fabrizio Silvestri, Giorgio Maria Di Nunzio, Claudia Hauff, and Gianmaria Silvello, editors, *Advances in Information Retrieval 38th European Conference on IR Research, ECIR 2016, Padua, Italy, March 20-23, 2016. Proceedings*, volume 9626 of *Lecture Notes in Computer Science*, pages 716–722. Springer, 2016. doi: 10.1007/978-3-319-30671-1_58. URL https://doi.org/10.1007/978-3-319-30671-1_58.
- Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In Lluís Màrquez, Chris Callison-Burch, Jian Su, Daniele Pighin, and Yuval Marton, editors, *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pages 632–642. The Association for Computational Linguistics, 2015. doi: 10.18653/V1/D15-1075. URL https://doi.org/10.18653/v1/d15-1075.
- Iñigo Casanueva, Tadas Temcinas, Daniela Gerz, Matthew Henderson, and Ivan Vulic. Efficient intent detection with dual sentence encoders. CoRR, abs/2003.04807, 2020. URL https://arxiv. org/abs/2003.04807.
- Xin Chan, Xiaoyang Wang, Dian Yu, Haitao Mi, and Dong Yu. Scaling synthetic data creation with 1,000,000,000 personas. *CoRR*, abs/2406.20094, 2024. doi: 10.48550/ARXIV.2406.20094. URL https://doi.org/10.48550/arXiv.2406.20094.
- Jianlv Chen, Shitao Xiao, Peitian Zhang, Kun Luo, Defu Lian, and Zheng Liu. BGE m3-embedding: Multi-lingual, multi-functionality, multi-granularity text embeddings through self-knowledge distillation. CoRR, abs/2402.03216, 2024a. doi: 10.48550/ARXIV.2402.03216. URL https://doi.org/10.48550/arXiv.2402.03216.
- Jing Chen, Qingcai Chen, Xin Liu, Haijun Yang, Daohe Lu, and Buzhou Tang. The BQ corpus: A large-scale domain-specific chinese corpus for sentence semantic equivalence identification. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun'ichi Tsujii, editors, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 November 4, 2018*, pages 4946–4951. Association for Computational Linguistics, 2018. URL https://aclanthology.org/D18-1536/.

- Tong Chen, Hongwei Wang, Sihao Chen, Wenhao Yu, Kaixin Ma, Xinran Zhao, Hongming Zhang, and Dong Yu. Dense X retrieval: What retrieval granularity should we use? In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, EMNLP 2024, Miami, FL, USA, November 12-16, 2024*, pages 15159–15177. Association for Computational Linguistics, 2024b. URL https://aclanthology.org/2024.emnlp-main.845.
- Mathieu Ciancone, Imene Kerboua, Marion Schaeffer, and Wissam Siblini. Mteb-french: Resources for french sentence embedding evaluation and analysis. *arXiv* preprint arXiv:2405.20468, 2024.
- Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel R. Bowman, Holger Schwenk, and Veselin Stoyanov. XNLI: evaluating cross-lingual sentence representations. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun'ichi Tsujii, editors, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 November 4, 2018*, pages 2475–2485. Association for Computational Linguistics, 2018. doi: 10.18653/V1/D18-1269. URL https://doi.org/10.18653/v1/d18-1269.
- 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 Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel R. Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 8440–8451. Association for Computational Linguistics, 2020. doi: 10.18653/V1/2020.ACL-MAIN.747. URL https://doi.org/10.18653/v1/2020.acl-main.747.
- Marta R. Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, Anna Y. Sun, Skyler Wang, Guillaume Wenzek, Al Youngblood, Bapi Akula, Loïc Barrault, Gabriel Mejia Gonzalez, Prangthip Hansanti, John Hoffman, Semarley Jarrett, Kaushik Ram Sadagopan, Dirk Rowe, Shannon Spruit, Chau Tran, Pierre Andrews, Necip Fazil Ayan, Shruti Bhosale, Sergey Edunov, Angela Fan, Cynthia Gao, Vedanuj Goswami, Francisco Guzmán, Philipp Koehn, Alexandre Mourachko, Christophe Ropers, Safiyyah Saleem, Holger Schwenk, and Jeff Wang. No language left behind: Scaling humancentered machine translation. *CoRR*, abs/2207.04672, 2022. doi: 10.48550/ARXIV.2207.04672. URL https://doi.org/10.48550/arXiv.2207.04672.
- Yiming Cui, Ting Liu, Wanxiang Che, Li Xiao, Zhipeng Chen, Wentao Ma, Shijin Wang, and Guoping Hu. A span-extraction dataset for chinese machine reading comprehension. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 5882–5888. Association for Computational Linguistics, 2019. doi: 10.18653/V1/D19-1600. URL https://doi.org/10.18653/v1/D19-1600.
- Zhuyun Dai, Vincent Y. Zhao, Ji Ma, Yi Luan, Jianmo Ni, Jing Lu, Anton Bakalov, Kelvin Guu, Keith B. Hall, and Ming-Wei Chang. Promptagator: Few-shot dense retrieval from 8 examples. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=gmL46YMpu2J.
- DataCanary, hilfialkaff, Lili Jiang, Meg Risdal, Nikhil Dandekar, and tomtung. Quora question pairs, 2017. URL https://kaggle.com/competitions/quora-question-pairs.
- Matthew Dunn, Levent Sagun, Mike Higgins, V. Ugur Güney, Volkan Cirik, and Kyunghyun Cho. Searchqa: A new q&a dataset augmented with context from a search engine. *CoRR*, abs/1704.05179, 2017. URL http://arxiv.org/abs/1704.05179.
- Anthony Fader, Luke Zettlemoyer, and Oren Etzioni. Open question answering over curated and extracted knowledge bases. In Sofus A. Macskassy, Claudia Perlich, Jure Leskovec, Wei Wang, and Rayid Ghani, editors, *The 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '14, New York, NY, USA August 24 27, 2014*, pages 1156–1165. ACM, 2014. doi: 10.1145/2623330.2623677. URL https://doi.org/10.1145/2623330.2623677.

- Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. ELI5: long form question answering. In Anna Korhonen, David R. Traum, and Lluís Màrquez, editors, *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers*, pages 3558–3567. Association for Computational Linguistics, 2019. doi: 10.18653/V1/P19-1346. URL https://doi.org/10.18653/v1/p19-1346.
- Jack FitzGerald, Christopher Hench, Charith Peris, Scott Mackie, Kay Rottmann, Ana Sanchez, Aaron Nash, Liam Urbach, Vishesh Kakarala, Richa Singh, Swetha Ranganath, Laurie Crist, Misha Britan, Wouter Leeuwis, Gökhan Tür, and Prem Natarajan. MASSIVE: A 1m-example multilingual natural language understanding dataset with 51 typologically-diverse languages. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, ACL 2023, Toronto, Canada, July 9-14, 2023, pages 4277–4302. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.ACL-LONG.235. URL https://doi.org/10.18653/v1/2023.acl-long.235.
- Wikimedia Foundation. Wikimedia downloads, 2024. URL https://dumps.wikimedia.org. Accessed: 2024-05-01.
- Tianyu Gao, Xingcheng Yao, and Danqi Chen. Simcse: Simple contrastive learning of sentence embeddings. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih, editors, *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*, pages 6894–6910. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021. EMNLP-MAIN.552. URL https://doi.org/10.18653/v1/2021.emnlp-main.552.
- Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, Qianyu Guo, Meng Wang, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. *CoRR*, abs/2312.10997, 2023. doi: 10.48550/ARXIV.2312.10997. URL https://doi.org/10.48550/arXiv.2312.10997.
- Felix Hamborg, Norman Meuschke, Corinna Breitinger, and Bela Gipp. news-please A generic news crawler and extractor. In Maria Gäde, Violeta Trkulja, and Vivien Petras, editors, Everything Changes, Everything Stays the Same? Understanding Information Spaces. Proceedings of the 15th International Symposium of Information Science, ISI 2017, Berlin, Germany, March 13-15, 2017, volume 70 of Schriften zur Informationswissenschaft, pages 218–223. Verlag Werner Hülsbusch, 2017. doi: 10.18452/1447. URL https://doi.org/10.18452/1447.
- Tahmid Hasan, Abhik Bhattacharjee, Md. Saiful Islam, Kazi Samin Mubasshir, Yuan-Fang Li, Yong-Bin Kang, M. Sohel Rahman, and Rifat Shahriyar. Xl-sum: Large-scale multilingual abstractive summarization for 44 languages. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, *Findings of the Association for Computational Linguistics: ACL/IJCNLP 2021, Online Event, August 1-6, 2021*, volume ACL/IJCNLP 2021 of *Findings of ACL*, pages 4693–4703. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021.FINDINGS-ACL.413. URL https://doi.org/10.18653/v1/2021.findings-acl.413.
- Wei He, Kai Liu, Jing Liu, Yajuan Lyu, Shiqi Zhao, Xinyan Xiao, Yuan Liu, Yizhong Wang, Hua Wu, Qiaoqiao She, Xuan Liu, Tian Wu, and Haifeng Wang. Dureader: a chinese machine reading comprehension dataset from real-world applications. In Eunsol Choi, Minjoon Seo, Danqi Chen, Robin Jia, and Jonathan Berant, editors, *Proceedings of the Workshop on Machine Reading for Question Answering@ACL 2018, Melbourne, Australia, July 19, 2018*, pages 37–46. Association for Computational Linguistics, 2018. doi: 10.18653/V1/W18-2605. URL https://aclanthology.org/W18-2605/.
- Kevin Heffernan, Onur Çelebi, and Holger Schwenk. Bitext mining using distilled sentence representations for low-resource languages. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Findings of the Association for Computational Linguistics: EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022*, pages 2101–2112. Association for Computational Linguistics, 2022. doi: 10.18653/V1/2022.FINDINGS-EMNLP.154. URL https://doi.org/10.18653/v1/2022.findings-emnlp.154.

- Yupeng Hou, Jiacheng Li, Zhankui He, An Yan, Xiusi Chen, and Julian J. McAuley. Bridging language and items for retrieval and recommendation. *CoRR*, abs/2403.03952, 2024. doi: 10. 48550/ARXIV.2403.03952. URL https://doi.org/10.48550/arXiv.2403.03952.
- Baotian Hu, Qingcai Chen, and Fangze Zhu. LCSTS: A large scale chinese short text summarization dataset. In Lluís Màrquez, Chris Callison-Burch, Jian Su, Daniele Pighin, and Yuval Marton, editors, *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pages 1967–1972. The Association for Computational Linguistics, 2015. doi: 10.18653/V1/D15-1229. URL https://doi.org/10.18653/v1/d15-1229.
- Hai Hu, Kyle Richardson, Liang Xu, Lu Li, Sandra Kübler, and Lawrence S. Moss. OCNLI: original chinese natural language inference. In Trevor Cohn, Yulan He, and Yang Liu, editors, Findings of the Association for Computational Linguistics: EMNLP 2020, Online Event, 16-20 November 2020, volume EMNLP 2020 of Findings of ACL, pages 3512–3526. Association for Computational Linguistics, 2020. doi: 10.18653/V1/2020.FINDINGS-EMNLP.314. URL https://doi.org/10.18653/v1/2020.findings-emnlp.314.
- Xuming Hu, Zhijiang Guo, Guanyu Wu, Aiwei Liu, Lijie Wen, and Philip S. Yu. CHEF: A pilot chinese dataset for evidence-based fact-checking. In Marine Carpuat, Marie-Catherine de Marneffe, and Iván Vladimir Meza Ruíz, editors, *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL 2022, Seattle, WA, United States, July 10-15, 2022*, pages 3362–3376. Association for Computational Linguistics, 2022. doi: 10.18653/V1/2022.NAACL-MAIN.246. URL https://doi.org/10.18653/v1/2022.naacl-main.246.
- Junqin Huang, Zhongjie Hu, Zihao Jing, Mengya Gao, and Yichao Wu. Piccolo2: General text embedding with multi-task hybrid loss training. *CoRR*, abs/2405.06932, 2024. doi: 10.48550/ARXIV.2405.06932. URL https://doi.org/10.48550/arXiv.2405.06932.
- Yizheng Huang and Jimmy Huang. A survey on retrieval-augmented text generation for large language models. *CoRR*, abs/2404.10981, 2024. doi: 10.48550/ARXIV.2404.10981. URL https://doi.org/10.48550/arXiv.2404.10981.
- Hamel Husain, Ho-Hsiang Wu, Tiferet Gazit, Miltiadis Allamanis, and Marc Brockschmidt. Codesearchnet challenge: Evaluating the state of semantic code search. *CoRR*, abs/1909.09436, 2019. URL http://arxiv.org/abs/1909.09436.
- Qiao Jin, Bhuwan Dhingra, Zhengping Liu, William W. Cohen, and Xinghua Lu. Pubmedqa: A dataset for biomedical research question answering. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 2567–2577. Association for Computational Linguistics, 2019. doi: 10.18653/V1/D19-1259. URL https://doi.org/10.18653/v1/D19-1259.
- Xisen Jin, Xiang Ren, Daniel Preotiuc-Pietro, and Pengxiang Cheng. Dataless knowledge fusion by merging weights of language models. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=FCnohuR6AnM.
- Mandar Joshi, Eunsol Choi, Daniel S. Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In Regina Barzilay and Min-Yen Kan, editors, *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 August 4, Volume 1: Long Papers*, pages 1601–1611. Association for Computational Linguistics, 2017. doi: 10.18653/V1/P17-1147. URL https://doi.org/10.18653/v1/P17-1147.
- Daniel Khashabi, Amos Ng, Tushar Khot, Ashish Sabharwal, Hannaneh Hajishirzi, and Chris Callison-Burch. Gooaq: Open question answering with diverse answer types. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih, editors, Findings of the Association for Computational Linguistics: EMNLP 2021, Virtual Event / Punta Cana, Dominican

- Republic, 16-20 November, 2021, pages 421–433. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021.FINDINGS-EMNLP.38. URL https://doi.org/10.18653/v1/2021.findings-emnlp.38.
- Yuta Koreeda and Christopher D. Manning. Contractnli: A dataset for document-level natural language inference for contracts. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih, editors, *Findings of the Association for Computational Linguistics: EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 16-20 November, 2021*, pages 1907–1919. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021.FINDINGS-EMNLP.164. URL https://doi.org/10.18653/v1/2021.findings-emnlp.164.
- Aditya Kusupati, Gantavya Bhatt, Aniket Rege, Matthew Wallingford, Aditya Sinha, Vivek Ramanujan, William Howard-Snyder, Kaifeng Chen, Sham M. Kakade, Prateek Jain, and Ali Farhadi. Matryoshka representation learning. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh, editors, Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 December 9, 2022, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/c32319f4868da7613d78af9993100e42-Abstract-Conference.html.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: a benchmark for question answering research. *Trans. Assoc. Comput. Linguistics*, 7:452–466, 2019. doi: 10.1162/TACL_A_00276. URL https://doi.org/10.1162/tacl_a_00276.
- Chankyu Lee, Rajarshi Roy, Mengyao Xu, Jonathan Raiman, Mohammad Shoeybi, Bryan Catanzaro, and Wei Ping. Nv-embed: Improved techniques for training llms as generalist embedding models. *CoRR*, abs/2405.17428, 2024. doi: 10.48550/ARXIV.2405.17428. URL https://doi.org/10.48550/arXiv.2405.17428.
- Patrick S. H. Lewis, Yuxiang Wu, Linqing Liu, Pasquale Minervini, Heinrich Küttler, Aleksandra Piktus, Pontus Stenetorp, and Sebastian Riedel. PAQ: 65 million probably-asked questions and what you can do with them. *Trans. Assoc. Comput. Linguistics*, 9:1098–1115, 2021. doi: 10.1162/TACL_A_00415. URL https://doi.org/10.1162/tacl_a_00415.
- Haoran Li, Abhinav Arora, Shuohui Chen, Anchit Gupta, Sonal Gupta, and Yashar Mehdad. MTOP: A comprehensive multilingual task-oriented semantic parsing benchmark. In Paola Merlo, Jörg Tiedemann, and Reut Tsarfaty, editors, *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, EACL 2021, Online, April 19-23, 2021*, pages 2950–2962. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021.EACL-MAIN.257. URL https://doi.org/10.18653/v1/2021.eacl-main.257.
- Yudong Li, Yuqing Zhang, Zhe Zhao, Linlin Shen, Weijie Liu, Weiquan Mao, and Hui Zhang. CSL: A large-scale chinese scientific literature dataset. In Nicoletta Calzolari, Chu-Ren Huang, Hansaem Kim, James Pustejovsky, Leo Wanner, Key-Sun Choi, Pum-Mo Ryu, Hsin-Hsi Chen, Lucia Donatelli, Heng Ji, Sadao Kurohashi, Patrizia Paggio, Nianwen Xue, Seokhwan Kim, Younggyun Hahm, Zhong He, Tony Kyungil Lee, Enrico Santus, Francis Bond, and Seung-Hoon Na, editors, *Proceedings of the 29th International Conference on Computational Linguistics, COLING 2022, Gyeongju, Republic of Korea, October 12-17, 2022*, pages 3917–3923. International Committee on Computational Linguistics, 2022. URL https://aclanthology.org/2022.coling-1.344.
- Zehan Li, Xin Zhang, Yanzhao Zhang, Dingkun Long, Pengjun Xie, and Meishan Zhang. Towards general text embeddings with multi-stage contrastive learning. *CoRR*, abs/2308.03281, 2023. doi: 10.48550/ARXIV.2308.03281. URL https://doi.org/10.48550/arXiv.2308.03281.
- Hongcheng Liu, Yusheng Liao, Yutong Meng, and Yuhao Wang. Xiezhi: Chinese law large language model. https://github.com/LiuHC0428/LAW_GPT, 2023.
- Xin Liu, Qingcai Chen, Chong Deng, Huajun Zeng, Jing Chen, Dongfang Li, and Buzhou Tang. LCQMC: A large-scale chinese question matching corpus. In Emily M. Bender, Leon Derczynski, and Pierre Isabelle, editors, *Proceedings of the 27th International Conference on Computational*

- Linguistics, COLING 2018, Santa Fe, New Mexico, USA, August 20-26, 2018, pages 1952—1962. Association for Computational Linguistics, 2018. URL https://aclanthology.org/C18-1166/.
- Dingkun Long, Qiong Gao, Kuan Zou, Guangwei Xu, Pengjun Xie, Ruijie Guo, Jian Xu, Guanjun Jiang, Luxi Xing, and Ping Yang. Multi-cpr: A multi domain chinese dataset for passage retrieval. In Enrique Amigó, Pablo Castells, Julio Gonzalo, Ben Carterette, J. Shane Culpepper, and Gabriella Kazai, editors, SIGIR '22: The 45th International ACM SIGIR Conference on Research and Development in Information Retrieval, Madrid, Spain, July 11 15, 2022, pages 3046–3056. ACM, 2022. doi: 10.1145/3477495.3531736. URL https://doi.org/10.1145/3477495.3531736.
- Kun Luo, Zheng Liu, Shitao Xiao, Tong Zhou, Yubo Chen, Jun Zhao, and Kang Liu. Landmark embedding: A chunking-free embedding method for retrieval augmented long-context large language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, ACL 2024, Bangkok, Thailand, August 11-16, 2024, pages 3268–3281. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.ACL-LONG.180. URL https://doi.org/10.18653/v1/2024.acl-long.180.
- Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In Dekang Lin, Yuji Matsumoto, and Rada Mihalcea, editors, *The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, 19-24 June, 2011, Portland, Oregon, USA*, pages 142–150. The Association for Computer Linguistics, 2011. URL https://aclanthology.org/P11-1015/.
- Macedo Maia, Siegfried Handschuh, André Freitas, Brian Davis, Ross McDermott, Manel Zarrouk, and Alexandra Balahur. Www'18 open challenge: Financial opinion mining and question answering. In Pierre-Antoine Champin, Fabien Gandon, Mounia Lalmas, and Panagiotis G. Ipeirotis, editors, Companion of the The Web Conference 2018 on The Web Conference 2018, WWW 2018, Lyon, France, April 23-27, 2018, pages 1941–1942. ACM, 2018. doi: 10.1145/3184558.3192301. URL https://doi.org/10.1145/3184558.3192301.
- Chaitanya Malaviya, Subin Lee, Sihao Chen, Elizabeth Sieber, Mark Yatskar, and Dan Roth. Expertqa: Expert-curated questions and attributed answers. In Kevin Duh, Helena Gómez-Adorno, and Steven Bethard, editors, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), NAACL 2024, Mexico City, Mexico, June 16-21, 2024*, pages 3025–3045. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.NAACL-LONG.167. URL https://doi.org/10.18653/v1/2024.naacl-long.167.
- Julian J. McAuley and Jure Leskovec. Hidden factors and hidden topics: understanding rating dimensions with review text. In Qiang Yang, Irwin King, Qing Li, Pearl Pu, and George Karypis, editors, Seventh ACM Conference on Recommender Systems, RecSys '13, Hong Kong, China, October 12-16, 2013, pages 165–172. ACM, 2013. doi: 10.1145/2507157.2507163. URL https://doi.org/10.1145/2507157.2507163.
- Rui Meng, Ye Liu, Shafiq Rayhan Joty, Caiming Xiong, Yingbo Zhou, and Semih Yavuz. Sfrembedding-mistral:enhance text retrieval with transfer learning. Salesforce AI Research Blog, 2024. URL https://blog.salesforceairesearch.com/sfr-embedded-mistral/.
- Sepideh Mollanorozy, Marc Tanti, and Malvina Nissim. Cross-lingual transfer learning with persian. In *Proceedings of the 5th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*, pages 89–95, 2023.
- Niklas Muennighoff, Nouamane Tazi, Loïc Magne, and Nils Reimers. MTEB: massive text embedding benchmark. In Andreas Vlachos and Isabelle Augenstein, editors, *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2023, Dubrovnik, Croatia, May 2-6, 2023*, pages 2006–2029. Association for Computational Linguistics, 2023a. doi: 10.18653/V1/2023.EACL-MAIN.148. URL https://doi.org/10.18653/v1/2023.eacl-main.148.

- Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M. Saiful Bari, Sheng Shen, Zheng Xin Yong, Hailey Schoelkopf, Xiangru Tang, Dragomir Radev, Alham Fikri Aji, Khalid Almubarak, Samuel Albanie, Zaid Alyafeai, Albert Webson, Edward Raff, and Colin Raffel. Crosslingual generalization through multitask finetuning. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, *ACL 2023, Toronto, Canada, July 9-14, 2023*, pages 15991–16111. Association for Computational Linguistics, 2023b. doi: 10.18653/V1/2023.ACL-LONG.891. URL https://doi.org/10.18653/v1/2023.acl-long.891.
- Niklas Muennighoff, Hongjin Su, Liang Wang, Nan Yang, Furu Wei, Tao Yu, Amanpreet Singh, and Douwe Kiela. Generative representational instruction tuning. *CoRR*, abs/2402.09906, 2024. doi: 10.48550/ARXIV.2402.09906. URL https://doi.org/10.48550/arXiv.2402.09906.
- Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Awadallah. Orca: Progressive learning from complex explanation traces of GPT-4. *CoRR*, abs/2306.02707, 2023. doi: 10.48550/ARXIV.2306.02707. URL https://doi.org/10.48550/arXiv.2306.02707.
- Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, Xu Jiang, Karl Cobbe, Tyna Eloundou, Gretchen Krueger, Kevin Button, Matthew Knight, Benjamin Chess, and John Schulman. Webgpt: Browser-assisted question-answering with human feedback. *CoRR*, abs/2112.09332, 2021. URL https://arxiv.org/abs/2112.09332.
- Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. MS MARCO: A human generated machine reading comprehension dataset. In Tarek Richard Besold, Antoine Bordes, Artur S. d'Avila Garcez, and Greg Wayne, editors, Proceedings of the Workshop on Cognitive Computation: Integrating neural and symbolic approaches 2016 co-located with the 30th Annual Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain, December 9, 2016, volume 1773 of CEUR Workshop Proceedings. CEUR-WS.org, 2016. URL https://ceur-ws.org/Vol-1773/CoCoNIPS_2016_paper9.pdf.
- Jianmo Ni, Jiacheng Li, and Julian J. McAuley. Justifying recommendations using distantly-labeled reviews and fine-grained aspects. 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 2019, Hong Kong, China, November 3-7, 2019, pages 188–197. Association for Computational Linguistics, 2019. doi: 10.18653/V1/D19-1018. URL https://doi.org/10.18653/v1/D19-1018.
- James O'Neill, Polina Rozenshtein, Ryuichi Kiryo, Motoko Kubota, and Danushka Bollegala. I wish I would have loved this one, but I didn't A multilingual dataset for counterfactual detection in product review. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih, editors, *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*, pages 7092–7108. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021. EMNLP-MAIN.568. URL https://doi.org/10.18653/v1/2021.emnlp-main.568.
- Rafal Poswiata, Slawomir Dadas, and Michal Perelkiewicz. PL-MTEB: polish massive text embedding benchmark. *CoRR*, abs/2405.10138, 2024. doi: 10.48550/ARXIV.2405.10138. URL https://doi.org/10.48550/arXiv.2405.10138.
- Yujia Qin, Zihan Cai, Dian Jin, Lan Yan, Shihao Liang, Kunlun Zhu, Yankai Lin, Xu Han, Ning Ding, Huadong Wang, Ruobing Xie, Fanchao Qi, Zhiyuan Liu, Maosong Sun, and Jie Zhou. Webcpm: Interactive web search for chinese long-form question answering. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, *ACL 2023, Toronto, Canada, July 9-14, 2023*, pages 8968–8988. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.ACL-LONG.499. URL https://doi.org/10.18653/v1/2023.acl-long.499.

- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100, 000+ questions for machine comprehension of text. In Jian Su, Xavier Carreras, and Kevin Duh, editors, *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016*, pages 2383–2392. The Association for Computational Linguistics, 2016. doi: 10.18653/V1/D16-1264. URL https://doi.org/10.18653/v1/d16-1264.
- Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don't know: Unanswerable questions for squad. In Iryna Gurevych and Yusuke Miyao, editors, *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 2: Short Papers*, pages 784–789. Association for Computational Linguistics, 2018. doi: 10.18653/V1/P18-2124. URL https://aclanthology.org/P18-2124/.
- Chandan K. Reddy, Lluís Màrquez, Fran Valero, Nikhil Rao, Hugo Zaragoza, Sambaran Bandyopadhyay, Arnab Biswas, Anlu Xing, and Karthik Subbian. Shopping queries dataset: A large-scale ESCI benchmark for improving product search. *CoRR*, abs/2206.06588, 2022. doi: 10.48550/ARXIV.2206.06588. URL https://doi.org/10.48550/arXiv.2206.06588.
- Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 3980–3990. Association for Computational Linguistics, 2019. doi: 10.18653/V1/D19-1410. URL https://doi.org/10.18653/v1/D19-1410.
- Elvis Saravia, Hsien-Chi Toby Liu, Yen-Hao Huang, Junlin Wu, and Yi-Shin Chen. CARER: contextualized affect representations for emotion recognition. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun'ichi Tsujii, editors, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 November 4, 2018*, pages 3687–3697. Association for Computational Linguistics, 2018. doi: 10.18653/V1/D18-1404. URL https://doi.org/10.18653/v1/d18-1404.
- Holger Schwenk, Guillaume Wenzek, Sergey Edunov, Edouard Grave, Armand Joulin, and Angela Fan. Ccmatrix: Mining billions of high-quality parallel sentences on the web. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pages 6490–6500. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021. ACL-LONG.507. URL https://doi.org/10.18653/v1/2021.acl-long.507.
- Spurthi Setty, Katherine Jijo, Eden Chung, and Natan Vidra. Improving retrieval for RAG based question answering models on financial documents. *CoRR*, abs/2404.07221, 2024. doi: 10.48550/ARXIV.2404.07221. URL https://doi.org/10.48550/arXiv.2404.07221.
- Chih-Chieh Shao, Trois Liu, Yuting Lai, Yiying Tseng, and Sam Tsai. DRCD: a chinese machine reading comprehension dataset. *CoRR*, abs/1806.00920, 2018. URL http://arxiv.org/abs/1806.00920.
- Zhihong Shao, Minlie Huang, Jiangtao Wen, Wenfei Xu, and Xiaoyan Zhu. Long and diverse text generation with planning-based hierarchical variational model. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 3255–3266. Association for Computational Linguistics, 2019. doi: 10.18653/V1/D19-1321. URL https://doi.org/10.18653/v1/D19-1321.
- Shivalika Singh, Freddie Vargus, Daniel D'souza, Börje Karlsson, Abinaya Mahendiran, Wei-Yin Ko, Herumb Shandilya, Jay Patel, Deividas Mataciunas, Laura O'Mahony, Mike Zhang, Ramith Hettiarachchi, Joseph Wilson, Marina Machado, Luisa Souza Moura, Dominik Krzeminski, Hakimeh Fadaei, Irem Ergün, Ifeoma Okoh, Aisha Alaagib, Oshan Mudannayake, Zaid Alyafeai, Minh Vu Chien, Sebastian Ruder, Surya Guthikonda, Emad A. Alghamdi, Sebastian Gehrmann, Niklas Muennighoff, Max Bartolo, Julia Kreutzer, Ahmet Üstün, Marzieh Fadaee, and Sara Hooker. Aya dataset: An open-access collection for multilingual instruction tuning. In Lun-Wei Ku, Andre

- Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, ACL 2024, Bangkok, Thailand, August 11-16, 2024, pages 11521–11567. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.ACL-LONG.620. URL https://doi.org/10.18653/v1/2024.acl-long.620.
- Saba Sturua, Isabelle Mohr, Mohammad Kalim Akram, Michael Günther, Bo Wang, Markus Krimmel, Feng Wang, Georgios Mastrapas, Andreas Koukounas, Nan Wang, and Han Xiao. jina-embeddings-v3: Multilingual embeddings with task lora. *CoRR*, abs/2409.10173, 2024. doi: 10.48550/ARXIV. 2409.10173. URL https://doi.org/10.48550/arXiv.2409.10173.
- Hongjin Su, Weijia Shi, Jungo Kasai, Yizhong Wang, Yushi Hu, Mari Ostendorf, Wen-tau Yih, Noah A. Smith, Luke Zettlemoyer, and Tao Yu. One embedder, any task: Instruction-finetuned text embeddings. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, *Findings of the Association for Computational Linguistics: ACL 2023, Toronto, Canada, July 9-14, 2023*, pages 1102–1121. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023. FINDINGS-ACL.71. URL https://doi.org/10.18653/v1/2023.findings-acl.71.
- Jianlin Su, Murtadha H. M. Ahmed, Yu Lu, Shengfeng Pan, Wen Bo, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *Neurocomputing*, 568:127063, 2024. doi: 10.1016/J.NEUCOM.2023.127063. URL https://doi.org/10.1016/j.neucom.2023.127063.
- Maosong Sun, Jingyang Li, Zhipeng Guo, Yu Zhao, Yabin Zheng, Xiance Si, and Zhiyuan Liu. Thucto: An efficient chinese text classifier, 2016. URL http://thuctc.thunlp.org/. Accessed: 2024-05-01.
- Hongxuan Tang, Hongyu Li, Jing Liu, Yu Hong, Hua Wu, and Haifeng Wang. Dureader_robust: A chinese dataset towards evaluating robustness and generalization of machine reading comprehension in real-world applications. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 2: Short Papers), Virtual Event, August 1-6, 2021, pages 955–963. Association for Computational Linguistics, 2021. doi: 10.18653/V1/2021.ACL-SHORT.120. URL https://doi.org/10.18653/v1/2021.acl-short.120.*
- Shancheng Tang, Yunyue Bai, and Fuyu Ma. Chinese semantic text similarity training dataset, 2016. URL https://github.com/IAdmireu/ChineseSTS. Accessed: 2024-05-01.
- Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. BEIR: A heterogeneous benchmark for zero-shot evaluation of information retrieval models. In Joaquin Vanschoren and Sai-Kit Yeung, editors, *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual*, 2021. URL https://datasets-benchmarks-proceedings.neurips.cc/paper/2021/hash/65b9eea6e1cc6bb9f0cd2a47751a186f-Abstract-round2.html.
- Nandan Thakur, Jianmo Ni, Gustavo Hernández Ábrego, John Wieting, Jimmy Lin, and Daniel Cer. Leveraging llms for synthesizing training data across many languages in multilingual dense retrieval. In Kevin Duh, Helena Gómez-Adorno, and Steven Bethard, editors, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), NAACL 2024, Mexico City, Mexico, June 16-21, 2024*, pages 7699–7724. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.NAACL-LONG.426. URL https://doi.org/10.18653/v1/2024.naacl-long.426.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. FEVER: a large-scale dataset for fact extraction and verification. In Marilyn A. Walker, Heng Ji, and Amanda Stent, editors, *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pages 809–819. Association for Computational Linguistics, 2018. doi: 10.18653/V1/N18-1074. URL https://doi.org/10.18653/v1/n18-1074.

- Ustinian. Law question-answering dataset. https://www.heywhale.com/mw/dataset/5e953ca8e7ec38002d02fca7, 2020.
- Ellen M. Voorhees, Tasmeer Alam, Steven Bedrick, Dina Demner-Fushman, William R. Hersh, Kyle Lo, Kirk Roberts, Ian Soboroff, and Lucy Lu Wang. TREC-COVID: constructing a pandemic information retrieval test collection. *SIGIR Forum*, 54(1):1:1–1:12, 2020. doi: 10.1145/3451964. 3451965. URL https://doi.org/10.1145/3451964.3451965.
- David Wadden, Shanchuan Lin, Kyle Lo, Lucy Lu Wang, Madeleine van Zuylen, Arman Cohan, and Hannaneh Hajishirzi. Fact or fiction: Verifying scientific claims. In Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu, editors, *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 7534–7550. Association for Computational Linguistics, 2020. doi: 10.18653/V1/2020.EMNLP-MAIN.609. URL https://doi.org/10.18653/v1/2020.emnlp-main.609.
- Liang Wang, Nan Yang, Xiaolong Huang, Binxing Jiao, Linjun Yang, Daxin Jiang, Rangan Majumder, and Furu Wei. Text embeddings by weakly-supervised contrastive pre-training. CoRR, abs/2212.03533, 2022. doi: 10.48550/ARXIV.2212.03533. URL https://doi.org/10.48550/arXiv.2212.03533.
- Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Improving text embeddings with large language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics* (*Volume 1: Long Papers*), *ACL 2024*, *Bangkok, Thailand, August 11-16*, 2024, pages 11897–11916. Association for Computational Linguistics, 2024a. doi: 10.18653/V1/2024.ACL-LONG.642. URL https://doi.org/10.18653/v1/2024.acl-long.642.
- Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Multilingual E5 text embeddings: A technical report. *CoRR*, abs/2402.05672, 2024b. doi: 10.48550/ARXIV.2402.05672. URL https://doi.org/10.48550/arXiv.2402.05672.
- Lucy Lu Wang, Kyle Lo, Yoganand Chandrasekhar, Russell Reas, Jiangjiang Yang, Darrin Eide, Kathryn Funk, Rodney Kinney, Ziyang Liu, William Merrill, Paul Mooney, Dewey A. Murdick, Devvret Rishi, Jerry Sheehan, Zhihong Shen, Brandon Stilson, Alex D. Wade, Kuansan Wang, Chris Wilhelm, Boya Xie, Douglas Raymond, Daniel S. Weld, Oren Etzioni, and Sebastian Kohlmeier. CORD-19: the covid-19 open research dataset. *CoRR*, abs/2004.10706, 2020. URL https://arxiv.org/abs/2004.10706.
- Adina Williams, Nikita Nangia, and Samuel R. Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In Marilyn A. Walker, Heng Ji, and Amanda Stent, editors, *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pages 1112–1122. Association for Computational Linguistics, 2018. doi: 10.18653/V1/N18-1101. URL https://doi.org/10.18653/v1/n18-1101.
- Chaojun Xiao, Haoxi Zhong, Zhipeng Guo, Cunchao Tu, Zhiyuan Liu, Maosong Sun, Tianyang Zhang, Xianpei Han, Zhen Hu, Heng Wang, and Jianfeng Xu. CAIL2019-SCM: A dataset of similar case matching in legal domain. *CoRR*, abs/1911.08962, 2019. URL http://arxiv.org/abs/1911.08962.
- Shitao Xiao, Zheng Liu, Peitian Zhang, Niklas Muennighoff, Defu Lian, and Jian-Yun Nie. C-pack: Packed resources for general chinese embeddings. In Grace Hui Yang, Hongning Wang, Sam Han, Claudia Hauff, Guido Zuccon, and Yi Zhang, editors, *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2024, Washington DC, USA, July 14-18, 2024*, pages 641–649. ACM, 2024a. doi: 10.1145/3626772.3657878. URL https://doi.org/10.1145/3626772.3657878.
- Shitao Xiao, Zheng Liu, Peitian Zhang, and Xingrun Xing. Lm-cocktail: Resilient tuning of language models via model merging. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics, ACL 2024, Bangkok, Thailand and virtual meeting, August 11-16, 2024*, pages 2474–2488. Association for Computational Linguistics, 2024b.

- doi: 10.18653/V1/2024.FINDINGS-ACL.145. URL https://doi.org/10.18653/v1/2024.findings-acl.145.
- Xiaohui Xie, Qian Dong, Bingning Wang, Feiyang Lv, Ting Yao, Weinan Gan, Zhijing Wu, Xiangsheng Li, Haitao Li, Yiqun Liu, and Jin Ma. T2ranking: A large-scale chinese benchmark for passage ranking. In Hsin-Hsi Chen, Wei-Jou (Edward) Duh, Hen-Hsen Huang, Makoto P. Kato, Josiane Mothe, and Barbara Poblete, editors, *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2023, Taipei, Taiwan, July 23-27, 2023*, pages 2681–2690. ACM, 2023. doi: 10.1145/3539618.3591874. URL https://doi.org/10.1145/3539618.3591874.
- Liang Xu, Hai Hu, Xuanwei Zhang, Lu Li, Chenjie Cao, Yudong Li, Yechen Xu, Kai Sun, Dian Yu, Cong Yu, Yin Tian, Qianqian Dong, Weitang Liu, Bo Shi, Yiming Cui, Junyi Li, Jun Zeng, Rongzhao Wang, Weijian Xie, Yanting Li, Yina Patterson, Zuoyu Tian, Yiwen Zhang, He Zhou, Shaoweihua Liu, Zhe Zhao, Qipeng Zhao, Cong Yue, Xinrui Zhang, Zhengliang Yang, Kyle Richardson, and Zhenzhong Lan. CLUE: A chinese language understanding evaluation benchmark. In Donia Scott, Núria Bel, and Chengqing Zong, editors, *Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020*, pages 4762–4772. International Committee on Computational Linguistics, 2020. doi: 10.18653/V1/2020.COLING-MAIN.419. URL https://doi.org/10.18653/v1/2020.coling-main.419.
- Prateek Yadav, Derek Tam, Leshem Choshen, Colin A. Raffel, and Mohit Bansal. Tiesmerging: Resolving interference when merging models. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine, editors, Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 16, 2023, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/1644c9af28ab7916874f6fd6228a9bcf-Abstract-Conference.html.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. Qwen2 technical report. *CoRR*, abs/2407.10671, 2024. doi: 10.48550/ARXIV.2407.10671. URL https://doi.org/10.48550/arXiv.2407.10671.
- Dongjie Yang, Ruifeng Yuan, Yuantao Fan, Yifei Yang, Zili Wang, Shusen Wang, and Hai Zhao. Refgpt: Dialogue generation of gpt, by gpt, and for GPT. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Findings of the Association for Computational Linguistics: EMNLP 2023, Singapore, December 6-10, 2023*, pages 2511–2535. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.FINDINGS-EMNLP.165. URL https://doi.org/10.18653/V1/2023.findings-emnlp.165.
- Yinfei Yang, Yuan Zhang, Chris Tar, and Jason Baldridge. PAWS-X: A cross-lingual adversarial dataset for paraphrase identification. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 3685–3690. Association for Computational Linguistics, 2019. doi: 10.18653/V1/D19-1382. URL https://doi.org/10.18653/v1/D19-1382.
- Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W. Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun'ichi Tsujii, editors, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 November 4, 2018*, pages 2369–2380. Association for Computational Linguistics, 2018. doi: 10.18653/V1/D18-1259. URL https://doi.org/10.18653/v1/d18-1259.

- Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Language models are super mario: Absorbing abilities from homologous models as a free lunch. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=fq0NaiU8Ex.
- Sha Yuan, Hanyu Zhao, Zhengxiao Du, Ming Ding, Xiao Liu, Yukuo Cen, Xu Zou, Zhilin Yang, and Jie Tang. Wudaocorpora: A super large-scale chinese corpora for pre-training language models. *AI Open*, 2:65–68, 2021. doi: 10.1016/J.AIOPEN.2021.06.001. URL https://doi.org/10.1016/j.aiopen.2021.06.001.
- Sheng Zhang, Xin Zhang, Hui Wang, Lixiang Guo, and Shanshan Liu. Multi-scale attentive interaction networks for chinese medical question answer selection. *IEEE Access*, 6:74061–74071, 2018. doi: 10.1109/ACCESS.2018.2883637. URL https://doi.org/10.1109/ACCESS.2018.2883637.
- Shunyu Zhang, Yaobo Liang, Ming Gong, Daxin Jiang, and Nan Duan. Multi-view document representation learning for open-domain dense retrieval. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, *ACL 2022*, *Dublin, Ireland, May 22-27*, 2022, pages 5990–6000. Association for Computational Linguistics, 2022. doi: 10.18653/V1/2022. ACL-LONG.414. URL https://doi.org/10.18653/v1/2022.acl-long.414.
- Xin Zhang, Yanzhao Zhang, Dingkun Long, Wen Xie, Ziqi Dai, Jialong Tang, Huan Lin, Baosong Yang, Pengjun Xie, Fei Huang, Meishan Zhang, Wenjie Li, and Min Zhang. mgte: Generalized long-context text representation and reranking models for multilingual text retrieval. In Franck Dernoncourt, Daniel Preotiuc-Pietro, and Anastasia Shimorina, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing: EMNLP 2024 Industry Track, Miami, Florida, USA, November 12-16, 2024*, pages 1393–1412. Association for Computational Linguistics, 2024. URL https://aclanthology.org/2024.emnlp-industry.103.
- Xinyu Zhang, Xueguang Ma, Peng Shi, and Jimmy Lin. Mr. tydi: A multi-lingual benchmark for dense retrieval. *CoRR*, abs/2108.08787, 2021. URL https://arxiv.org/abs/2108.08787.
- Xinyu Zhang, Nandan Thakur, Odunayo Ogundepo, Ehsan Kamalloo, David Alfonso-Hermelo, Xiaoguang Li, Qun Liu, Mehdi Rezagholizadeh, and Jimmy Lin. MIRACL: A multilingual retrieval dataset covering 18 diverse languages. *Trans. Assoc. Comput. Linguistics*, 11:1114–1131, 2023. doi: 10.1162/TACL_A_00595. URL https://doi.org/10.1162/tacl_a_00595.
- Xinping Zhao, Yan Zhong, Zetian Sun, Xinshuo Hu, Zhenyu Liu, Dongfang Li, Baotian Hu, and Min Zhang. Funnelrag: A coarse-to-fine progressive retrieval paradigm for RAG. *CoRR*, abs/2410.10293, 2024. doi: 10.48550/ARXIV.2410.10293. URL https://doi.org/10.48550/arXiv.2410.10293.
- Zhen Zhao, Yuqiu Liu, Gang Zhang, Liang Tang, and Xiaolin Hu. The winning solution to the iflytek challenge 2021 cultivated land extraction from high-resolution remote sensing image. *CoRR*, abs/2202.10974, 2022. URL https://arxiv.org/abs/2202.10974.
- Tianyu Zheng, Ge Zhang, Tianhao Shen, Xueling Liu, Bill Yuchen Lin, Jie Fu, Wenhu Chen, and Xiang Yue. Opencodeinterpreter: Integrating code generation with execution and refinement. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics*, *ACL 2024*, *Bangkok*, *Thailand and virtual meeting*, *August 11-16*, 2024, pages 12834–12859. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024. FINDINGS-ACL.762. URL https://doi.org/10.18653/v1/2024.findings-acl.762.
- Chunting Zhou, Pengfei Liu, Puxin Xu, Srinivasan Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, Susan Zhang, Gargi Ghosh, Mike Lewis, Luke Zettlemoyer, and Omer Levy. LIMA: less is more for alignment. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine, editors, Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 16, 2023, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/ac662d74829e4407ce1d126477f4a03a-Abstract-Conference.html.

Yuqi Zhou, Sunhao Dai, Zhanshuo Cao, Xiao Zhang, and Jun Xu. Length-induced embedding collapse in transformer-based models. *CoRR*, abs/2410.24200, 2024. doi: 10.48550/ARXIV.2410.24200. URL https://doi.org/10.48550/arXiv.2410.24200.

Wei Zhu. Chatmed-dataset: An gpt generated medical query-response datasets for medical large language models. https://github.com/michael-wzhu/ChatMed, 2023.

A Appendix

We mainly compare the multilingual models paraphrase-multilingual-mpnet-base-v2 [Reimers and Gurevych, 2019], multilingual-e5-large [Wang et al., 2024b], bge-m3 [Chen et al., 2024a], and gte-multilingual-base [Zhang et al., 2024], along with some models that demonstrated multilingual results such as Cohere-embed-multilingual-v3.0, jina-embeddings-v3 [Sturua et al., 2024], and e5-mistral-7b-instruct [Wang et al., 2024a]. The detailed results on MTEB of different language is presented in Table 4, Table 5, Table 6 and Table 7.

Model	MTEB (zh)							
	avg	Class.	Clust.	PairCl.	Reran.	Retri.	STS	
e5-mistral-7b-instruct	60.89	70.47	52.30	72.19	61.86	61.75	50.22	
paraphrase-multilingual-mpnet-base-v2	44.59	62.7	39.67	80.90	44.91	22.92	39.11	
multilingual-e5-large	58.54	66.29	48.23	69.89	56.00	63.66	48.29	
bge-m3 (Dense)	60.80	66.95	45.75	73.98	62.88	65.43	52.43	
gte-multilingual-base (Dense)	62.72	64.27	47.48	78.34	68.17	71.95	52.73	
KaLM-embedding-mini-instruct	64.13	70.94	57.32	72.94	64.38	70.11	51.57	

Table 4: Embedding model performance on MTEB Chinese (C-MTEB).

Model				MTE	CB (en)			
	avg	Class.	Clust.	PairCl.	Reran.	Retri.	STS	Summ.
Cohere-embed-multilingual-v3.0	64.01	76.01	46.60	86.15	57.86	53.84	83.15	30.99
jina-embeddings-v3 (Multi-LoRA)	65.51	82.58	45.21	84.01	58.13	53.88	85.81	29.71
e5-mistral-7b-instruct	66.63	78.47	50.26	88.34	60.21	56.89	84.63	31.40
paraphrase-multilingual-mpnet-base-v2	54.64	67.46	38.50	80.81	53.80	35.34	80.77	31.57
multilingual-e5-large	60.89	71.77	41.23	84.75	55.96	51.40	81.62	29.64
bge-m3 (Dense)	59.84	74.08	37.27	84.50	55.28	48.82	81.37	31.55
gte-multilingual-base (Dense)	61.40	70.89	44.31	84.23	57.47	51.08	82.11	30.58
KaLM-embedding-mini-instruct	64.94	84.74	47.82	83.26	55.41	51.65	82.24	25.23

Table 5: Embedding model performance on MTEB English.

Model				MTE	EB (fr)			
	avg	Class.	Clust.	PairCl.	Reran.	Retri.	STS	Summ.
Cohere-embed-multilingual-v3.0	56.02	67.08	40.70	77.67	68.36	40.42	81.28	31.26
jina-embeddings-v3 (Multi-LoRA)	62.29	76.54	44.95	76.60	69.85	53.48	84.89	30.71
e5-mistral-7b-instruct	48.33	57.72	41.16	76.08	62.2	23.44	65.36	32.22
paraphrase-multilingual-mpnet-base-v2	55.21	64.73	41.79	75.80	74.09	38.13	78.18	29.47
multilingual-e5-large	55.64	66.54	38.70	76.19	72.14	42.17	79.36	30.92
bge-m3 (Dense)	58.79	71.57	36.54	79.78	77.36	51.13	80.78	31.05
gte-multilingual-base (Dense)	59.79	68.72	41.66	79.47	76.47	52.97	81.36	29.74
KaLM-embedding-mini-instruct	63.08	75.46	51.92	76.88	80.58	48.37	79.25	29.32

Table 6: Embedding model performance on MTEB French.

Model			MTF	EB (pl)		
	avg	Class.	Clust.	PairCl.	Retri.	STS
jina-embeddings-v3 (Multi-LoRA)	63.97	70.81	43.66	83.70	51.89	72.77
paraphrase-multilingual-mpnet-base-v2	48.67	54.08	25.62	86.23	29.17	65.19
multilingual-e5-large	60.08	63.82	33.88	85.5	48.98	66.91
bge-m3 (Dense)	60.35	65.15	25.21	86.46	48.51	69.44
gte-multilingual-base (Dense)	58.22	60.15	33.67	85.45	46.40	68.92
KaLM-embedding-mini-instruct	57.05	64.50	39.24	79.01	43.24	67.02

Table 7: Embedding model performance on MTEB Polish.

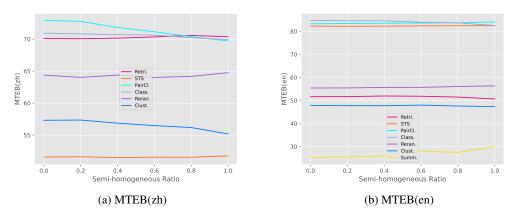


Figure 6: Impact of semi-homogeneous task batch on detailed tasks from MTEB in Chinese and English.

Source	Language	Pairs
Amazon-Reviews [Hou et al., 2024]	multilingual	23M
CC-News [Hamborg et al., 2017]	multilingual	100M
NLLB [Costa-jussà et al., 2022, Heffernan et al., 2022, Schwenk et al., 2021]	multilingual	2M
Wikipedia [Foundation, 2024]	multilingual	100M
xP3 [Muennighoff et al., 2023b]	multilingual	19M
XL-Sum [Hasan et al., 2021]	multilingual	1M
SWIM-IR (Monolingual) [Thakur et al., 2024]	multilingual	3M
SWIM-IR (Cross-lingual) [Thakur et al., 2024]	multilingual	15M
CSL [Li et al., 2022]	zh	0.4M
Wudao [Yuan et al., 2021]	zh	44M
THUCNews [Sun et al., 2016]	zh	0.8M
Zhihu-KOL	zh	0.8M
CodeSearchNet [Husain et al., 2019]	en	1M
PAQ [Lewis et al., 2021]	en	9M
Reddit	en	100M
StackExchange	en	14M
S2ORC S2ORC	en	41M

Table 8: Pre-training data list.

Source	Туре	Categ.	Language	Pairs	Pairs(filtered
CodeFeedback [Zheng et al., 2024]	Retrieval	s2p	en	50000	49090
ELI5 [Fan et al., 2019]	Retrieval	s2p	en	100000	76408
ExpertQA [Malaviya et al., 2024]	Retrieval	s2p	en	1261	1252
GooAQ [Khashabi et al., 2021]	Retrieval	s2p	en	50000	49833
MEDI2BGE [Muennighoff et al., 2024, Su et al., 2023]	Retrieval	s2p	en	100000	71790
OpenOrca [Mukherjee et al., 2023]	Retrieval	s2p	en	40000	38623
PAQ [Lewis et al., 2021]	Retrieval	s2p	en	50000	49849
PubMedQA [Jin et al., 2019]	Retrieval	s2p	en	80000	79954
earchQA [Dunn et al., 2017]	Retrieval	s2p	en	10000	9988
rxiv_qa	Retrieval	s2p	en	23397	17927
CC-News [Hamborg et al., 2017]	Retrieval	s2p	en	30000	28246
REC-COVID [Voorhees et al., 2020, Wang et al., 2020]	Retrieval		en	50000	48517
		s2p			
DBpedia-Entity [Thakur et al., 2021]	Retrieval	s2p	en	100000	96792
ESCI [Reddy et al., 2022]	Retrieval	s2p	en	30000	26043
EVER [Thorne et al., 2018]	Retrieval	s2p	en	87855	87216
iQA [Maia et al., 2018]	Retrieval	s2p	en	5490	4689
IotpotQA [Yang et al., 2018]	Retrieval	s2p	en	184057	150153
ILDR [Chen et al., 2024a]	Retrieval	s2p	en	41434	31097
ISMARCO [Nguyen et al., 2016]	Retrieval	s2p	en	175133	174190
ISMARCO-v2 [Nguyen et al., 2016]	Retrieval	s2p	en	277144	258617
FCorpus [Boteva et al., 2016]	Retrieval	s2p	en	10824	10471
ag-dataset-12000	Retrieval	s2p	en	9590	9272
ciFact [Wadden et al., 2020]	Retrieval	s2p	en	809	794
QuAD 2.0 [Rajpurkar et al., 2018, 2016]	Retrieval	s2p	en	130217	125816
riviaQA [Joshi et al., 2017]	Retrieval	s2p	en	52886	44442
VebGPT Comparisons [Nakano et al., 2021]	Retrieval	s2p	en	19242	18924
Vatural Questions [Kwiatkowski et al., 2019]	Retrieval	s2p	en	58622	56377
Vahoo Answers	Retrieval	s2p	en	30000	21724
ContractNLI [Koreeda and Manning, 2021]	STS	s2p s2s	en	3195	628
AultiNLI [Williams et al., 2018]	STS	s2s s2s	en	64674	63701
	STS	s2s s2s		36000	26504
VLLB [Costa-jussà et al., 2022, Heffernan et al., 2022]			en		
Quora [DataCanary et al., 2017]	STS	s2s	en	92674	89558
VikiAnswers [Fader et al., 2014]	STS	s2s	en	50000	47686
imCSE NLI [Gao et al., 2021]	STS	s2s	en	252397	217099
NLI [Bowman et al., 2015]	STS	s2s	en	24686	16480
rXiv	Classfication	s2s, p2s	en	15000	14529
Biorxiv	Classfication	s2s, p2s	en	6862	6787
Medrxiv	Classfication	s2s, p2s	en	2012	1999
AmazonPolarity [McAuley and Leskovec, 2013]	Classfication	s2s	en	10000	9007
MDB [Maas et al., 2011]	Classfication	s2s	en	10000	8575
anking77 [Casanueva et al., 2020]	Classfication	s2s	en	10000	9937
EmotionClassification [Saravia et al., 2018]	Classfication	s2s	en	10000	10000
weetSentimentExtraction	Classification	s2s	en	10000	10000
OxicConversations	Classification	s2s		7916	7800
			en		
AFQMC	STS	s2s	zh-en	4041	3876
AdvertiseGen [Shao et al., 2019]	Retrieval	s2p	zh-cn	20000	17526
CHEF [Hu et al., 2022]	Retrieval	s2p	zh-cn	4952	4824
ChatMed-Dataset [Zhu, 2023]	Retrieval	s2p	zh-cn	20000	18608
CMRC 2018 [Cui et al., 2019]	Retrieval	s2p	zh-cn	10000	9753
ORCD [Shao et al., 2018]	Retrieval	s2p	zh-cn	5000	4714
.CSTS [Hu et al., 2015]	Retrieval	s2p	zh-cn	20000	19535
IMA [Zhou et al., 2023]	Retrieval	s2p	zh-cn	2058	1991
Aulti-CPR [Long et al., 2022]	Retrieval	s2p	zh-cn	287881	234587
AWS-X (zh) [Yang et al., 2019]	Retrieval	s2p	zh-cn	1542	1542
tefGPT [Yang et al., 2023]	Retrieval	s2p	zh-cn	50000	49896
² Ranking [Xie et al., 2023]	Retrieval	s2p	zh-cn	199412	188606
HUCNews [Sun et al., 2016]	Retrieval	s2p	zh-cn	20000	19288
JMETRIP-QA	Retrieval	s2p	zh-cn	2647	2537
VebCPM [Qin et al., 2023]	Retrieval	s2p	zh-en	1605	1602
COVID-News	Retrieval		zh-en zh-en	5000	4727
		s2p			
MedQA-V2.0 [Zhang et al., 2018]	Retrieval	s2p	zh-en	223851	88109
CSL [Li et al., 2022]	Retrieval	s2p	zh-en	20000	19945
OuReader [He et al., 2018]	Retrieval	s2p	zh-en	80416	79229
OuReader _{checklist} [Tang et al., 2021]	Retrieval	s2p	zh-en	99992	97764
aw-gpt [Liu et al., 2023]	Retrieval	s2p	zh-cn	500	500
awzhidao [Ustinian, 2020]	Retrieval	s2p	zh-cn	8000	6784
nMARCO (zh) [Bonifacio et al., 2021]	Retrieval	s2p	zh-cn	400000	379870
etrieval_data_llm	Retrieval	s2p	zh-cn	32768	32551
vebqa	Retrieval	s2p	zh-cn	5000	4988
AIL2019-SCM [Xiao et al., 2019]	STS	s2s	zh-cn	5102	648
CINLID	STS	s2s	zh-cn	5000	2883
ChineseSTS [Tang et al., 2016]	STS	s2s	zh-en	2500	2497
MNLI [Xu et al., 2020]	STS	s2s	zh-en	125356	119029
li_zh [Chen et al., 2018, Liu et al., 2018, Yang et al., 2019]	STS	s2s s2s	zh-en	218887	185787
in_zii [Chen et al., 2018, Liu et al., 2018, Tang et al., 2019] CNLI [Hu et al., 2020]	STS	s2s s2s	zh-en	13464	11937
DEOTE [Hu et al., 2020]	STS			51620	47223
		s2s	zh-en	344038	290699
imCLUE	STS	s2s	zh-en		
[NLI (zh) [Conneau et al., 2018]	STS	s2s	zh-en	80000	74252
SL [Li et al., 2022]	Classfication	s2s, p2s	zh-en	15000	12249
HUCNews [Sun et al., 2016]	Classfication	s2s	zh-en	10000	9690
News	Classfication	s2s	zh-cn	10000	6762
DReview	Classfication	s2s	zh-cn	1232	1232
FlyTek [Zhao et al., 2022]	Classfication	s2s	zh-cn	10000	8221
OnlineShopping	Classfication	s2s	zh-cn	7852	7600
Vaimai	Classfication	s2s	zh-cn	7384	7376
aya Dataset [Singh et al., 2024]	Retrieval	s2p	multilingual	30000	26292
IIRACL [Zhang et al., 2023]	Retrieval	s2p	multilingual	40151	39946
Ar. TyDi [Zhang et al., 2021]	Retrieval		multilingual	48729	46997
		s2p			
AWS-X [Yang et al., 2019]	STS	s2s	multilingual	128435	128398
amazonReviews [Ni et al., 2019]	Classfication	s2s	multilingual	10000	7721
amazonCounterfactual [O'Neill et al., 2021]	Classfication	s2s	multilingual	10000	8323
AultilingualSentiment [Mollanorozy et al., 2023]	Classfication	s2s	multilingual	10000	9804
Amazon Massive Intent [FitzGerald et al., 2023]	Classfication	s2s	multilingual	10000	7832
	Classfication	s2s	multilingual	10000	7078
AmazonMassiveScenario [FitzGerald et al., 2023]	Ciassification				
	Classification	s2s	multilingual	10000	9610
mazonMassiveScenario [FitzGerald et al., 2023]			multilingual multilingual	10000 10000	9610 7952

AmazonPolarityClassification Instruct: Classify Banking77Classification Instruct: Given a EmotionClassification Instruct: Given a EmotionClassification Instruct: Classify joy, love, sadness ImdbClassification Instruct: Given a BassiveIntentClassification Instruct: Given a MassiveScenarioClassification Instruct: Given a MassiveScenarioClassification Instruct: Given a MTOPDomainClassification Instruct: Classify MTOPIntentClassification Instruct: Classify ToxicConversationsClassification Instruct: Classify ToxicConversationsClassification Instruct: Classify TweetSentimentExtractionClassification Instruct: Classify TNews Instruct: Given a MultilingualSentiment Instruct: Given a MultilingualSentiment Instruct: Classify DReview Instruct: Classify OnlineShopping Instruct: Classify Waimai Instruct: Classify MasakhaNEWSClassification Instruct: Classify PolEmo2.0-IN Instruct: Classify PolEmo2.0-OUT Instruct: Classify PolEmo2.0-OUT Instruct: Classify PAC Instruct: Classify PAC Instruct: Classify HeadlineClassification Instruct: Classify HeadlineClassification Instruct: Classify RuspropriatenessClassification Instruct: Classify RuspropriatenessClassification Instruct: Classify RuspropriatenessClassification Instruct: Classify RuspropriatenessClassification Instruct: Classify RuseviewClassification Instruct: Classify RusciBenchGRNTIClassification Instruct: Classify RusciBenchGEDClassification Instruct: Identify Policy Instruct: Identify Policy Instruct: Identify RedditClusteringP2P Instruct: Identify RedditClusteringP2P Instruct: Identify RedditClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify	Classification In Amazon review, judge whether it is counterfactual. \n Query: {query} ing Amazon reviews into positive or negative sentiment \n Query: {query} ing the given Amazon review into its appropriate rating category \n Query: {query} online banking query, find the corresponding intents \n Query: {query} ing the emotion expressed in the given Twitter message into one of the six emotions: anger, fee, and surprise \n Query: {query} ying the sentiment expressed in the given movie review text from the IMDB dataset \n Quer user utterance as query, find the user intents \n Query: {query} user utterance as query, find the user scenarios \n Query: {query} ing the intent domain of the given utterance in task-oriented conversation \n Query: {query} ing the intent of the given utterance in task-oriented conversation \n Query: {query} ing the given comments as either toxic or not toxic \n Query: {query} ing the sentiment of a given tweet as either positive, negative, or neutral \n Query: {query} izing the given news title \n Query: {query}
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MassiveIntentClassification Instruct: Given a MassiveScenarioClassification Instruct: Given a MTOPDomainClassification Instruct: Classify MTOPIntentClassification Instruct: Classify ToxicConversationsClassification Instruct: Classify TweetSentimentExtractionClassification Instruct: Classify TNews Instruct: Categor IFlyTek Instruct: Given an MultilingualSentiment Instruct: Classify JDReview Instruct: Classify OnlineShopping Instruct: Classify Waimai Instruct: Classify MasakhaNEWSClassification Instruct: Classify PolEmo2.0-IN Instruct: Classify PolEmo2.0-OUT Instruct: Classify PaC Instruct: Classify PAC Instruct: Classify PAC Instruct: Classify PAC Instruct: Classify RLAUZULA_A GeoreviewClassification Instruct: Classify ReadlineClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchGECDClassification Instruct: Classify CEDRClassification Instruct: Classify CEDRClassification Instruct: Classify RusciBenchOECDClassification Instruct: Classify ArxivClusteringP2P Instruct: Identify BiorxivClusteringP2P Instruct: Identify MedrxivClusteringP2P Instruct: Identify RedditClustering RedditClustering RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify ThuNewsClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify Ma	user utterance as query, find the user intents \n Query: {query} user utterance as query, find the user scenarios \n Query: {query} ing the intent domain of the given utterance in task-oriented conversation \n Query: {query} ing the intent of the given utterance in task-oriented conversation \n Query: {query} ing the given comments as either toxic or not toxic \n Query: {query} ing the sentiment of a given tweet as either positive, negative, or neutral \n Query: {query} izing the given news title \n Query: {query}
MassiveScenarioClassification Instruct: Given a MTOPDomainClassification Instruct: Classify MTOPIntentClassification Instruct: Classify ToxicConversationsClassification Instruct: Classify TweetSentimentExtractionClassification Instruct: Classify Thews Instruct: Categor IFlyTek Instruct: Given at MultilingualSentiment Instruct: Classify JDReview Instruct: Classify JDReview Instruct: Classify UnlineShopping Instruct: Classify Waimai Instruct: Classify Waimai Instruct: Classify Waimai Instruct: Classify MasakhaNEWSClassification Instruct: Classify PolEmo2.0-IN Instruct: Classify PolEmo2.0-OUT Instruct: Classify "KLAUZULA_A GeoreviewClassification Instruct: Classify "KLAUZULA_A GeoreviewClassification Instruct: Classify InappropriatenessClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchGECDClassification Instruct: Classify CEDRClassification Instruct: Classify CEDRClassification Instruct: Classify RuSciBenchGECDClassification Instruct: Classify SensitiveTopicsClassification Instruct: Classify CEDRClassification Instruct: Classify Policy Cedebra Instruct: Classify Rusive TopicsClassification Instruct: Classify CEDRClassification Instruct: Classify SensitiveTopicsClassification Instruct: Identify Policy Instruct: Identify Instruct: Identify MedrxivClustering P2P Instruct: Identify RedditClustering P2P Instruct: Identify Instruct: Iden	user utterance as query, find the user scenarios \n Query: {query} ing the intent domain of the given utterance in task-oriented conversation \n Query: {query} ing the intent of the given utterance in task-oriented conversation \n Query: {query} ing the given comments as either toxic or not toxic \n Query: {query} ing the sentiment of a given tweet as either positive, negative, or neutral \n Query: {query} izing the given news title \n Query: {query}
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"KLAUZULA_A GeoreviewClassification Instruct: Classify HeadlineClassification Instruct: Detectin KinopoiskClassification Instruct: Detectin KinopoiskClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Classify CEDRClassification Instruct: Detectin ArxivClusteringP2P Instruct: Identify ArxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClusteringP2P Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify	ing the sentiment of reviews from e-commerce marketplace Allegro \n Query: {query}
HeadlineClassification Instruct: Classify InappropriatenessClassification Instruct: Detectin KinopoiskClassification Instruct: Detectin KinopoiskClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Classify CEDRClassification Instruct: Detectin ArxivClusteringP2P Instruct: Identify ArxivClusteringP2P Instruct: Identify BiorxivClusteringP2P Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify	ing the sentence into one of the two types: "BEZPIECZNE_POSTANOWIENIE_UMOWNE" a BUZYWNA" \n Query: {query}
InappropriatenessClassification Instruct: Detectin KinopoiskClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Detectin Instruct: Detectin Instruct: Detectin Instruct: Detectin Instruct: Detectin Instruct: Detectin Instruct: Identify ArxivClusteringP2P Instruct: Identify Instruct: Identify BiorxivClusteringS2S Instruct: Identify Instruct: Identify MedrxivClusteringS2S Instruct: Identify Instruct: Identify RedditClustering Instruct: Identify Instruct: Identify RedditClustering Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify	ing the sentiment of Russian reviews. \n Query: {query}
KinopoiskClassification Instruct: Classify RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Detectin ArxivClusteringP2P Instruct: Identify ArxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	ing the topic of Russian headlines. \n Query: {query}
RuReviewsClassification Instruct: Classify RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Classify CEDRClassification Instruct: Detectin ArxivClusteringP2P Instruct: Identify ArxivClusteringS2S Instruct: Identify BiorxivClusteringB2P Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	g inappropriate messages on sensitive topics \n Query: {query}
RuSciBenchGRNTIClassification Instruct: Classify RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Classify CEDRClassification Instruct: Detectin ArxivClusteringP2P Instruct: Identify ArxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	ing the sentiment of Kinopoisk reviews. \n Query: {query}
RuSciBenchOECDClassification Instruct: Classify CEDRClassification Instruct: Detectin ArxivClusteringP2P Instruct: Identify ArxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	ing the sentiment of Russian product reviews. \n Query: {query}
CEDRClassification Instruct: Classification Instruct: Detecting SensitiveTopicsClassification Instruct: Detecting SensitiveTopicsClassification Instruct: Detecting SensitiveTopicsClassification Instruct: Detecting SensitiveTopicsClassification Instruct: Identify Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClustering Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify Instruct: Identif	ing the topic of Russian scientific papers. \n Query: {query}
SensitiveTopicsClassification ArxivClusteringP2P ArxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify Instruct: I	ing the topic of Russian scientific papers. \n Query: {query}
ArxivClusteringP2P Instruct: Identify ArxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringS2S Instruct: Identify BiorxivClusteringP2P Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	eation of sentences by emotions. \n Query: {query}
ArxivClusteringS2S Instruct: Identify BiorxivClusteringP2P Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	g inappropriate messages on sensitive topics. \n Query: {query}
ArxivClusteringS2S Instruct: Identify BiorxivClusteringP2P Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	Clustering
BiorxivClusteringP2P Instruct: Identify BiorxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main and secondary category of Arxiv papers based on the titles and abstracts \n Query: {quer
BiorxivClusteringS2S Instruct: Identify MedrxivClusteringP2P Instruct: Identify MedrxivClusteringS2S Instruct: Identify MedrxivClustering Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify The NewsClusteringP2P Instruct: Identify The NewsClusteringP2P Instruct: Identify The NewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main and secondary category of Arxiv papers based on the titles \n Query: {query}
MedrxivClusteringP2P Instruct: Identify MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of Biorxiv papers based on the titles and abstracts \n Query: {query}
MedrxivClusteringS2S Instruct: Identify RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify TWENTYNEWSGROUPSCLUSTERING INSTRUCT: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of Biorxiv papers based on the titles \n Query: {query}
RedditClustering Instruct: Identify RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify TWENTYNEWSGROUPSCLUSTERING INSTRUCT: Identify CLSClusteringS2S Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of Medrxiv papers based on the titles and abstracts \n Query: {query}
RedditClusteringP2P Instruct: Identify StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of Medrxiv papers based on the titles \n Query: {query}
StackExchangeClustering Instruct: Identify StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of Reddit posts based on the titles \n Query: {query}
StackExchangeClusteringP2P Instruct: Identify TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of Reddit posts based on the titles and posts \n Query: {query}
TwentyNewsgroupsClustering Instruct: Identify CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of StackExchange posts based on the titles \n Query: {query}
CLSClusteringS2S Instruct: Identify CLSClusteringP2P Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of StackExchange posts based on the given paragraphs \n Query: {query}
CLSClusteringP2P Instruct: Identify ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of the given news articles \n Query: {query}
ThuNewsClusteringS2S Instruct: Identify ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of scholar papers based on the titles \n Query: {query}
ThuNewsClusteringP2P Instruct: Identify AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of scholar papers based on the titles and abstracts \n Query: {query}
AlloProfClusteringP2P Instruct: Identify AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of the given news articles based on the titles \n Query: {query}
AlloProfClusteringS2S Instruct: Identify HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the topic or theme of the given news articles based on the titles and contents \n Query: {query}
HALClusteringS2S Instruct: Identify MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of Allo Prof document based on the titles and descriptions \n Query: {query
MasakhaNEWSClusteringP2P Instruct: Identify MasakhaNEWSClusteringS2S Instruct: Identify	the main category of Allo Prof document based on the titles and contents in Query: {query}
MasakhaNEWSClusteringS2S Instruct: Identify	the main category of academic passage based on the titles and contents \n Query: {query}
	the topic or theme of the given news articles based on the titles and contents \n Query! {query} the topic or theme of the given news articles based on the titles \n Query! {query}
mistracti Identity	the topic or theme of the given news articles based on the titles \n Query: {query} the topic or theme of the given articles based on the titles and contents \n Query: {query}
MLSUMClusteringS2S Instruct: Identify	the topic or theme of the given articles based on the titles and contents in Query: {query} the topic or theme of the given articles based on the titles \n Query: {query}
	of headlines from social media posts in Polish into 8 categories: film, history, food, medicing
	rk, sport and technology \n Query: {query}
	the topic or theme of the Russian reviews. \n Query: {query}
	the topic or theme of the Russian articles. \n Query: {query}
RuSciBenchOECDClusteringP2P Instruct: Identify	the topic or theme of the Russian articles. \n Query: {query}