

MMTEB: MASSIVE MULTILINGUAL TEXT EMBEDDING BENCHMARK

Kenneth Enevoldsen^{1,†,‡}, Isaac Chung^{2,‡}, Imene Kerboua^{3,4,‡}, Márton Kardos^{1,‡},
Ashwin Mathur², David Stap⁵, Jay Gala⁶, Wissam Siblini², Dominik Krzemiński²,
Genta Indra Winata², Saba Sturua⁷, Saiteja Utpala⁸, Mathieu Ciancone⁹, Marion Schaeffer⁹,
Gabriel Sequeira², Diganta Misra^{56,57}, Shreeya Dhakal², Jonathan Rystrom¹¹, Roman Solomatin^{12,‡},
Ömer Çağatan¹³, Akash Kundu^{14,15}, Martin Bernstorff¹, Shitao Xiao¹⁶, Akshita Sukhlecha²,
Bhavish Pahwa⁸, Rafał Poświata¹⁷, Kranthi Kiran GV¹⁸, Shawon Ashraf¹⁹, Daniel Auras¹⁹,
Björn Plüster¹⁹, Jan Philipp Harries¹⁹, Loïc Magne², Isabelle Mohr⁷, Mariya Hendriksen⁵,
Dawei Zhu²⁰, Hippolyte Gisserot-Boukhlef^{21,22}, Tom Aarsen^{23,‡}, Jan Kostkan¹, Konrad Wojtasik²⁴,
Taemin Lee²⁵, Marek Šuppa^{27,28}, Crystina Zhang²⁹, Roberta Rocca¹, Mohammed Hamdy³⁰,
Andrianos Michail³¹, John Yang³², Manuel Faysse^{21,26}, Aleksei Vatolin³³, Nandan Thakur²⁹,
Manan Dey³⁴, Dipam Vasani², Pranjal Chitale³⁵, Simone Tedeschi³⁶, Nguyen Tai³⁷,
Artem Snegirev³⁸, Michael Günther⁷, Mengzhou Xia³⁹, Weijia Shi⁴⁰, Xing Han Lü¹⁰, Jordan Clive⁴¹,
Gayatri Krishnakumar⁴², Anna Maksimova³⁸, Silvan Wehrli⁴³, Maria Tikhonova^{38,44},
Henil Panchal⁴⁵, Aleksandr Abramov³⁸, Malte Ostendorff⁴⁶, Zheng Liu¹⁶, Simon Clematide³¹,
Lester James Miranda⁴⁷, Alena Fenogenova³⁸, Guangyu Song⁴⁸, Ruqiya Bin Safi⁴⁹, Wen-Ding Li⁵⁰,
Alessia Borghini³⁶, Federico Cassano⁵¹, Hongjin Su⁵², Jimmy Lin²⁹, Howard Yen³⁹, Lasse Hansen¹,
Sara Hooker³⁰, Chenghao Xiao^{53,‡}, Vaibhav Adlakha^{10,54,‡}, Orion Weller^{55,‡}, Siva Reddy^{10,54,‡},
Niklas Muennighoff^{32,47,58,‡}

¹Aarhus University, ²Individual Contributor, ³Esker, ⁴INSA Lyon, LIRIS,
⁵University of Amsterdam, ⁶MBZUAI, ⁷Jina AI, ⁸Microsoft Research,
⁹Wikiti, ¹⁰McGill University, ¹¹University of Oxford, ¹²ITMO University,
¹³Koç University, ¹⁴Heritage Institute of Technology, ¹⁵Apert Research, ¹⁶BAAI,
¹⁷National Information Processing Institute, ¹⁸New York University, ¹⁹Ellamind,
²⁰Peking University, ²¹CentraleSupélec, ²²Artefact Research Center, ²³Hugging Face,
²⁴Wrocław University ²⁵Korea University, ²⁶Illuin Technology,
²⁷Comenius University Bratislava, ²⁸Cisco Systems, ²⁹University of Waterloo,
³⁰Cohere For AI, ³¹University of Zurich, ³²Stanford University, ³³FRC CSC RAS,
³⁴Salesforce, ³⁵IIT Madras, ³⁶Sapienza University of Rome,
³⁷University of Pennsylvania, ³⁸SaluteDevices, ³⁹Princeton University,
⁴⁰University of Washington, ⁴¹Imperial College London, ⁴²R. V. College of Engineering,
⁴³Robert Koch Institute, ⁴⁴HSE University, ⁴⁵Nirma University, ⁴⁶Occiglot,
⁴⁷Allen Institute for AI, ⁴⁸Tano Labs, ⁴⁹The London Institute of Banking and Finance,
⁵⁰Cornell University, ⁵¹Northeastern University, ⁵²Hong Kong University
⁵³Durham University, ⁵⁴ServiceNow Research, ⁵⁵Johns Hopkins University,
⁵⁶ELLIS Institute Tübingen ⁵⁷MPI-IS Tübingen ⁵⁸Contextual AI

[‡] Managing Team

[†]Correspondence: kenneth.enevoldsen@cas.au.dkme

ABSTRACT

Text embeddings are typically evaluated on a limited set of tasks, which are constrained by language, domain, and task diversity. To address these limitations and provide a more comprehensive evaluation, we introduce the Massive Multilingual Text Embedding Benchmark (MMTEB) – a large-scale, community-driven expansion of MTEB, covering over 500 *quality-controlled* evaluation tasks across 250+ languages. MMTEB includes a diverse set of challenging, novel tasks such as instruction following, long-document retrieval, and code retrieval, representing the largest multilingual collection of evaluation tasks for embedding models to date. Using this collection, we develop several highly multilingual benchmarks, which we use to evaluate a representative set of models. We find that while large language models (LLMs) with billions of parameters can achieve state-of-the-art performance on certain language subsets and task categories, the best-performing publicly available model is multilingual-e5-large-instruct with only 560 million parameters. To facilitate accessibility and reduce computational cost, we introduce a novel downsampling method based on inter-task correlation, ensuring a diverse selection while preserving relative model rankings. Furthermore, we optimize tasks such as retrieval by sampling hard negatives, creating smaller but effective splits. These optimizations allow us to introduce benchmarks that drastically reduce computational demands. For instance, our newly introduced zero-shot English benchmark maintains a similar ranking order as the full-scale version but only requires 2% of the original documents vastly reducing the computational cost.¹

1 INTRODUCTION

Text embeddings are used in many applications, such as semantic search (Reimers & Gurevych, 2019; Muennighoff, 2022; Hendriksen et al., 2023; Winata et al., 2023a; 2024b) and classification tasks (Wang et al., 2018; 2019). Additionally, text embeddings play a crucial role in retrieval-augmented generation (RAG; Borgeaud et al. 2022; Lewis et al. 2021), and often provide significant gains in performance on low- to mid-resource languages, enabling the incorporation of previously inaccessible information. Despite the wide range of applications, there’s a lack of benchmarks that evaluate text embeddings across multiple domains, languages, and tasks. Existing benchmarks tend to focus on specific domains, demarcated by subject (e.g., medical, legal, fiction (Thorne et al., 2018b)), particular tasks (e.g., retrieval (Thakur et al., 2021)), literary type (e.g., fiction, and non-fiction) or form (e.g., spoken and written). Embeddings also tend to focus on a subset of languages (Nørregaard & Derczynski, 2021).

While recent efforts (Thakur et al., 2021; Muennighoff et al., 2023b; Zhang et al., 2022) have aimed to broaden the scope by encompassing more tasks, domains, or languages (Cohan et al., 2020a; Wrzalik & Krechel, 2021), a large gap in language coverage remains. This work bridges this gap by creating a benchmark that includes a much broader range of low- to mid-resource languages, along with broader coverage of domains and task categories. To create such an expansive benchmark, we initiated a large-scale, open collaboration. Contributors include native speakers from diverse linguistic backgrounds, NLP practitioners, academic and industry researchers, and enthusiasts. To ensure high-quality submissions, each dataset required systematic tests, detailed metadata, and a review.

The result of this extensive collaborative effort is MMTEB, the **Massive Multilingual Text Embedding Benchmark**, which comprises more than 500 distinct tasks across 10 task categories, covering over 250 languages, and spans a wide array of domains such as fiction, social media, medical texts, and technical programming documentation. It also integrates recent, high-quality benchmarks that test a model’s capabilities in following instructions (Winata et al., 2021; Weller et al., 2024), embedding long documents (Zhu et al., 2024), solving reasoning tasks (Xiao et al., 2024a; Su et al., 2024), and cross-lingual retrieval (Franco-Salvador et al., 2014). For an overview see Figure 1.

¹MMTEB comes with open-source code available at <https://github.com/embeddings-benchmark/mteb> and a public leaderboard available at <https://huggingface.co/spaces/mteb/leaderboard>.

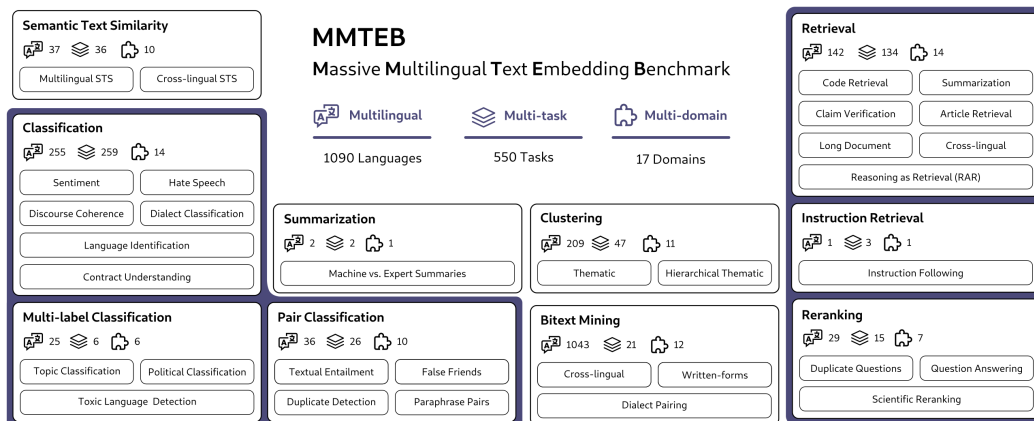


Figure 1: An overview of MMTEB. The boxes represent the overall task categories with a sample of task categories represented within each. Blue borders represent closely-related task categories.

Given the known co-occurrence of limited computational resources and low-resource languages, often referred to as the “low-resource double bind” (Ahia et al., 2021), we made it our goal to make the MMTEB benchmark accessible to low-resource communities. Evaluating models extensively is often resource-intensive. For example, evaluating a single 7B large language model (LLM) on the HELM benchmark consumes over 4,000 GPU hours (Liang et al., 2022). Similarly, the English MTEB (henceforth referred to as MTEB(eng, v1)) benchmark requires up to two days of processing on a single A100 GPU even for moderately sized LLMs (Muennighoff et al., 2023b; BehnamGhader et al., 2024). These high resource demands pose a challenge for low-resource language communities that often lack access to powerful computing resources. MMTEB addresses these challenges by expanding its coverage and optimizing the evaluation process. It significantly reduces computational cost (3.11 hours on an H100 GPU for a 7B model) by using only 2% of the original documents (6% of the original number of characters) while maintaining sensitivity as a benchmark to rank models accurately.

2 MMTEB CONSTRUCTION

2.1 OPEN SCIENCE EFFORT

To ensure the broad applicability of MMTEB across various domains, we recruited a diverse group of contributors. We actively encouraged participation from industry professionals, low-resource language communities, and academic researchers. To clarify authorship assignment and recognize desired contributions, we implemented a point-based system, similar to Lovenia et al. (2024). To facilitate transparency, coordination was managed through GitHub. A detailed breakdown of contributors and the point system can be found in Appendix A.

2.2 ENSURING TASK QUALITY

To guarantee the quality of the added tasks,² each task was reviewed by at least one of the main contributors. In addition, we required task submissions to include metadata fields. These fields included details such as annotation source, dataset source, license, dialects, and citation information. Appendix B.4 provides a comprehensive description of each field.

Furthermore, we ensured that the performance on submitted tasks fell within a reasonable range to avoid trivially low or unrealistically high performance. Therefore, we required two multilingual models to be run on the task; multilingual-e5-small (Wang et al., 2022) and MiniLM-L12 (Reimers & Gurevych, 2019). A task was examined further if the models obtained scores close to a random baseline (within a 2% margin), a near-perfect score, or if both models obtained roughly similar scores.

²A task includes a dataset and an implementation for model evaluation.

These tasks were examined for flawed implementation or poor data quality. Afterwards, a decision was made to either exclude or include the task. We consulted with contributors who are familiar with the target language whenever possible before the final decision. A task could be included despite failing these checks. For example, scores close to the random baseline might be due to the task’s inherent difficulty rather than poor data quality.

2.3 ACCESSIBILITY AND BENCHMARK OPTIMIZATION

As detailed in Section 1, extensive benchmark evaluations often require significant computational resources. This trend is also observed in MTEB(eng, v1) (Muennighoff et al., 2023b), where running moderately sized LLMs can take up to two days on a single A100 GPU. Accessibility for low-resource communities is particularly important for MMTEB, considering the common co-occurrence of computational constraints (Ahia et al., 2021).

Below, we discuss three main strategies implemented to make our benchmark more efficient. We additionally elaborate further code optimization in Appendix C.2.

2.3.1 DOWNSAMPLING AND CACHING EMBEDDINGS

The first strategy involves optimizing the evaluation process by downsampling datasets and caching embeddings. Encoding a large volume of documents for tasks such as retrieval and clustering can be a significant bottleneck in evaluation. Downsampling involves selecting a representative subset of the dataset and reducing the number of documents that require processing. Caching embeddings prevents redundant encoding by using already processed documents.

Clustering. In MTEB, clustering is evaluated by computing the v-measure score (Rosenberg & Hirschberg, 2007) on text embeddings clustered using k-means. This process is repeated over multiple distinct sets, inevitably resulting in a large number of documents being encoded. To reduce this encoding burden, we propose a bootstrapping approach that reuses encoded documents across sets. We first encode a 4% subsample of the corpus and sample 10 sets without replacement. Each set undergoes k-means clustering, and we record performance estimates. For certain tasks, this approach reduces the number of documents encoded by $100\times$. In Appendix B.2, we compare both approaches and find an average speedup of $16.11\times$ across tasks, while preserving the relative ranking of models (Average Spearman correlation: 0.96).

Retrieval. A key challenge in retrieval tasks is encoding large document collections, which can contain millions of entries Nguyen et al. (2024). To maintain performance comparable to the original datasets while reducing the collection size, we adopted the TREC pooling strategy (Buckley et al., 2007; Soboroff & Robertson, 2003), which aggregates scores from multiple models to select representative documents.³ For each dataset, we retained the top 250 ranked documents per query, a threshold determined through initial tests that showed negligible differences in absolute scores and no changes in relative rankings across representative models (see Appendix C.1.2 for details on downsampling effects). These documents are merged to form a smaller representative collection. For datasets exceeding 1,000 queries, we randomly sampled 1,000 queries, reducing the largest datasets from over 5 million documents to a maximum of 250,000. This approach accelerated evaluation while preserving ranking performance.

Bitext Mining. We apply similar optimization to bitext mining tasks. Some datasets, such as Flores (Costa-jussà et al., 2022) share the same sentences across several language pairs (e.g., English sentences are the same in the English-Hindi pair and the English-Bosnian pair). By caching the embeddings, we reduce the number of embedding computations, making it linear in the number of languages instead of quadratic. For the English documents within Flores this results in a reduction of documents needed to be embedded from 410,000 in MTEB(eng, v1) to just 1,012 in our benchmark.

³We utilized a range of models: BM25 for lexical hard negatives, e5-multilingual-large as a top-performing BERT-large multilingual model, and e5-Mistral-Instruct 7B, the largest model leveraging instruction-based data.

2.3.2 ENCOURAGING SMALLER DATASET SUBMISSIONS

The second strategy focused on encouraging contributors to downsample datasets before submission. To achieve this, we used a stratified split based on target categories. This helped us to ensure that the downsampled datasets could effectively differentiate between candidate models. To validate the process, we compared scores before and after downsampling. For details, we refer to Appendix C.1.

2.3.3 TASK SELECTION

To further reduce the computation overhead we seek to construct a task subset that can reliably predict task scores outside the subset.

For task selection, we followed an approach inspired by Xia et al. (2020). We seek to estimate the model $m_i \in M$ scores s_{t,m_i} on an unobserved task t based on scores on observed tasks $s_{j,m_k} \in S, j \neq t$. This allows us to consider the performance of tasks as features within a prediction problem. Thus we can treat task selection as feature reduction, a well-formulated task within machine learning. Note that this formulation allows us to keep the unobserved task arbitrary, representing generalization to unseen tasks (Chollet, 2019). We used a backward selection method, where one task is left out to be predicted, an estimator⁴ is fitted on the performance of all models except one, and the score of the held-out model is predicted. This process is repeated until predicted scores are generated for all models on all tasks. The most predictable task is then removed, leaving the estimators in the task subset group. Optionally, we can add additional criteria to ensure task diversity and language representation. Spearman’s rank correlation was chosen as the similarity score, as it best preserved the relative ranking when applied to the MTEB(eng, v1).

2.4 BENCHMARK CONSTRUCTION

From the extensive collection of tasks in MMTEB, we developed several representative benchmarks, including a highly multilingual benchmark, MTEB(Multilingual), as well as regional geopolitical benchmarks, MTEB(Europe) and MTEB(Indic). Additionally, we introduce a faster version of MTEB(eng, v1) (Muennighoff et al., 2023b), which we refer to as MTEB(eng, v2). MMTEB also integrates domain-specific benchmarks like CoIR for code retrieval (Li et al., 2024) and LongEmbed for long document retrieval (Zhu et al., 2024). MMTEB also introduces language-specific benchmarks, extending the existing suite that includes Scandinavian (Enevoldsen et al., 2024), Chinese (Xiao et al., 2024b), Polish (Poświata et al., 2024), and French (Ciancone et al., 2024). For an overview of the benchmarks, we refer to Appendix H.1.

In the following section, we detail a methodology that we designed to create more targeted and concise benchmarks. This methodology includes: 1) clearly defining the initial scope of the benchmark (**Initial Scope**), 2) reducing the number of tasks by iterative task selection tasks based on intertask correlation (**Refined Scope**), and 3) performing a thorough manual review (**Task Selection and Review**). We provide an overview in Table 1.

In addition to these benchmarks, we provide accompanying code to facilitate the creation of new benchmarks, to allow communities and companies to create tailored benchmarks. In the following, we present MTEB(Multilingual) and MTEB(eng, v2) as two example cases. For a comprehensive overview of benchmark construction and the tasks included in each benchmark, we refer to Appendix H.2.

MTEB(Multilingual): We select all available languages within MMTEB as the initial scope of the benchmark. This results in 550 tasks. We reduce this selection by removing machine-translated datasets, datasets with under-specified licenses, and highly domain-specific datasets such as code-retrieval datasets. This results in 343 tasks covering >250 languages. Following this selection, we evaluate this subset using a representative selection of models (See Section 3.1) and apply task selection to remove the most predictable tasks. To ensure language diversity and representation across task categories, we avoid removing a task that would eliminate a language from the respective task category. Additionally, we did not remove a task if the mean squared error between predicted

⁴We use the term “estimator” to differentiate between the evaluated embedding model. For our estimator, we use linear regression.

Benchmark	Initial Scope	Refined Scope	Task Selection and Review
MTEB(Multilingual)	>500	343	132
MTEB(Europe)	420	228	74
MTEB(Indic)	55	44	23
MTEB(eng, v2)	56	54	41

Table 1: Number of tasks in each benchmark after each filtering step. The initial scope includes tasks relevant to the benchmark goal, notably language of interest. The refined scope further reduced the scope, e.g. removing datasets with underspecified licenses.

and observed scores exceeded 0.5 standard deviations. This is to avoid inadvertently overindexing to easier tasks. The process of iterative task removal (Section 2.3.3) is repeated until the most predictable held-out task obtained a Spearman correlation of less than 0.8 between predicted and observed scores, or if no tasks were available for filtering. This results in a final selection of 131 diverse tasks. Finally, the selected tasks were reviewed, if possible, by contributors who spoke the target language. If needed, the selection criteria were updated, and some tasks were manually replaced with higher-quality alternatives.

MTEB(eng, v2): Unlike the multilingual benchmarks which target a language group, this benchmark is designed to match MTEB(eng, v1), incorporating computational efficiencies (see Section 2.3) and reducing the intertask correlation using task selection. To prevent overfitting, we intend it as a zero-shot benchmark, excluding tasks like MS MARCO (Nguyen et al., 2016) and Natural Questions (Kwiatkowski et al., 2019), which are frequently used in fine-tuning.

We start the construction by replacing each task with its optimized variant. This updated set obtains a Spearman correlation of 0.97, $p < .0001$ (Pearson 0.99, $p < .0001$) with MTEB(eng, v1) using mean aggregation for the selected models (see Subsection 3.1). The task selection process then proceeds similarly to MTEB(Multilingual), ensuring task diversity by retaining a task if its removal would eliminate a task category. Tasks, where the mean squared error between predicted and observed performance exceeds 0.2 standard deviations, are also retained. This process continues until the most predictable held-out task yields a Spearman correlation below 0.9 between predicted and observed scores. The final selection consists of 41 tasks. We compare this with MTEB(eng, v1) (Muennighoff et al., 2023b) in Section 4.

3 EXPERIMENTAL SETTINGS

3.1 MODELS

We select a representative set of models, focusing on multilingual models across various size categories. We benchmark the multilingual LaBSE (Feng et al., 2022), trained on paraphrase corpora, English and multilingual versions of MPNet (Song et al., 2020), and MiniLM (Wang et al., 2021b) model, trained on diverse datasets. We also evaluate the multilingual e5 series models (Wang et al., 2024; 2022) trained using a two-step approach utilizing weak supervision. Additionally, to understand the role of scale as well as instruction finetuning, we benchmark GritLM-7B (Muennighoff et al., 2024) and e5-multilingual-7b-instruct (Wang et al., 2023), which are both based on the Mistral 7B model (Jiang et al., 2023).

Revision IDs, model implementation, and prompts used are available in Appendix G. We ran the models on all the implemented tasks to encourage further analysis of the model results. Results, including multiple performance metrics, runtime, CO2 emissions, model metadata, etc., are publicly available in the versioned results repository.⁵

3.2 EVALUATION SCORES

For our performance metrics, we report average scores across all tasks, scores per task category, and weighted by task category. We compute model ranks using the Borda count method (Colombo et al.,

⁵<https://github.com/embeddings-benchmark/results>.

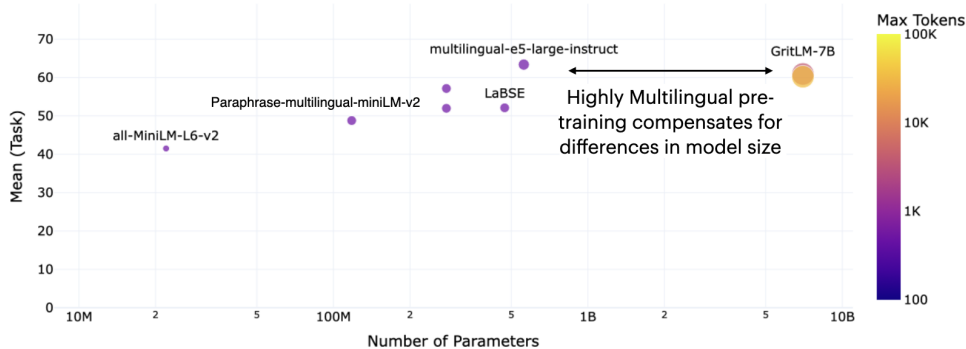


Figure 2: Mean performance across tasks on MTEB(Multilingual) according to the number of parameters. The circle size denotes the embedding size, while the color denotes the maximum sequence length of the model. To improve readability, only certain labels are shown. We refer to the public leaderboard for interactive visualization. We see that the notably smaller model obtains comparable performance to Mistral 7B and GritLM-7B, note that these overlap in the figure due to the similarity of the two models.

2022), derived from social choice theory. This method, which is also employed in election systems based on preference ranking, has been shown to be more robust for comparing NLP systems. To compute this score, we consider each task as a preference voter voting for each model, and scores are aggregated according to the Borda Count method. In the case of ties, we use the tournament Borda count method.

3.3 MULTILINGUAL PERFORMANCE

While MMTEB includes multiple benchmarks (see Appendix H.1), we select three multilingual benchmarks to showcase. These constitute a fully multilingual benchmark MTEB(Multilingual) and two targeting languages with varying levels of resources: MTEB(Europe) and MTEB(Indic). The performance of our selected models on these tasks can be seen in Table 2. For performance metrics per task, across domains, etc., we refer to Appendix E.

4 ANALYSIS AND DISCUSSION

Table 2 shows the performance across the three presented multilingual benchmarks. Two trends are clearly observable;

Models trained with instruction-tuning perform significantly better compared to those without it. This is especially clear when comparing the multilingual-e5-large to its instruction-tuned counterpart (multilingual-e5-large-instruct). Instruction tuning increases performance most drastically on bitext mining and clustering, though the effect remains pronounced across all task categories. Notably, this happens despite many tasks using generic prompts for the task category and no model-specific tuning of prompts per task. Surprisingly, multilingual-e5-large(-instruct) models, based on XLM-R Large (Conneau et al., 2019) generally outperform the considerably larger e5-mistral-7b-instruct and GritLM-7B, both of which are based on Mistral-7B (Jiang et al., 2023). This effect is notably pronounced for mid-to-low resource languages (<300M speaker; see Appendix E.1) and likely emerges due to differences in pre-training, with Mistral being predominantly pre-trained on English, while XLM-R targets 100 languages. All three models utilize similarly multilingual datasets for fine-tuning. However, GritLM still remains best in class for retrieval on MTEB(Multilingual), it has a higher maximum sequence length (see Figure 2) and outperforms the multilingual-e5-large-instruct on MTEB(Code) and MTEB(eng, v2).

Discrepancies in Multilingual benchmarks ranking seem to stem from discrepancies in pre-training. While the multilingual benchmarks obtain seemingly similar performance rankings, we see a few notable discrepancies. These discrepancies seem to mainly stem from a narrow multilingual focus (GritLM-7B, e5-mistral-7b-instruct, multilingual-mpnet-base) during training, resulting in disproportionately higher performance on the targeted languages (typically mid-high resource or Euro-

Model (↓)	Rank (↓)	Average Across		Average per Category								
	Borda Count	All	Category	Btxt	Pr Clf	Clf	STS	Rtrvl	M. Clf	Clust	Rrnk	
MTEB(Multilingual)												
Number of datasets (→)	(132)	(132)	(132)	(13)	(11)	(43)	(16)	(18)	(5)	(17)	(6)	
multilingual-e5-large-instruct	1 (1375)	63.2	62.1	80.1	80.9	64.9	76.8	57.1	22.9	51.5	62.6	
GritLM-7B	2 (1258)	60.9	60.1	70.5	79.9	61.8	73.3	58.3	22.8	50.5	63.8	
e5-mistral-7b-instruct	3 (1233)	60.3	59.9	70.6	81.1	60.3	74.0	55.8	22.2	51.4	63.8	
multilingual-e5-large	4 (1109)	58.6	58.2	71.7	79.0	59.9	73.5	54.1	21.3	42.9	62.8	
multilingual-e5-base	5 (944)	57.0	56.5	69.4	77.2	58.2	71.4	52.7	20.2	42.7	60.2	
multilingual-mpnet-base	6 (830)	52.0	51.1	52.1	81.2	55.1	69.7	39.8	16.4	41.1	53.4	
multilingual-e5-small	7 (784)	55.5	55.2	67.5	76.3	56.5	70.4	49.3	19.1	41.7	60.4	
LaBSE	8 (719)	52.1	51.9	76.4	76.0	54.6	65.3	33.2	20.1	39.2	50.2	
multilingual-MiniLM-L12	9 (603)	48.8	48.0	44.6	79.0	51.7	66.6	36.6	14.9	39.3	51.0	
all-mpnet-base	10 (526)	42.5	41.1	21.2	70.9	47.0	57.6	32.8	16.3	40.8	42.2	
all-MiniLM-L12	11 (490)	42.2	40.9	22.9	71.7	46.8	57.2	32.5	14.6	36.8	44.3	
all-MiniLM-L6	12 (418)	41.4	39.9	20.1	71.2	46.2	56.1	32.5	15.1	38.0	40.3	
MTEB(Europe)												
Number of datasets (→)	(74)	(74)	(74)	(7)	(6)	(21)	(9)	(15)	(2)	(6)	(3)	
GritLM-7B	1 (757)	63.0	62.7	90.4	89.9	64.7	76.1	57.1	17.6	45.3	60.3	
multilingual-e5-large-instruct	2 (732)	62.2	62.3	90.4	90.0	63.2	77.4	54.8	17.3	46.9	58.4	
e5-mistral-7b-instruct	3 (725)	61.7	61.9	89.6	91.2	62.9	76.5	53.6	15.5	46.5	59.8	
multilingual-e5-large	4 (586)	58.5	58.7	84.5	88.8	60.4	75.8	50.8	15.0	38.2	55.9	
multilingual-e5-base	5 (499)	57.2	57.5	84.1	87.4	57.9	73.7	50.2	14.9	38.2	53.9	
multilingual-mpnet-base	6 (463)	54.4	54.7	79.5	90.7	56.6	74.3	41.2	6.9	35.8	52.3	
multilingual-e5-small	7 (399)	55.0	55.7	80.9	86.4	56.1	71.6	46.1	14.0	36.5	54.1	
LaBSE	8 (358)	51.8	53.5	88.8	85.2	55.1	65.7	34.4	16.3	34.3	48.7	
multilingual-MiniLM-L12	9 (328)	51.7	52.4	77.0	88.9	52.7	72.5	37.6	5.7	34.4	50.2	
all-mpnet-base	10 (310)	44.7	44.7	29.8	80.5	49.2	63.9	37.3	10.9	36.2	49.6	
all-MiniLM-L12	11 (292)	44.4	44.1	32.1	81.5	49.2	64.2	36.2	7.6	32.5	49.2	
all-MiniLM-L6	12 (237)	43.4	43.2	27.2	80.2	47.8	62.7	37.3	8.8	33.6	47.7	
MTEB(Indic)												
Number of datasets (→)	(23)	(23)	(23)	(4)	(1)	(13)	(1)	(2)	(0)	(1)	(1)	
multilingual-e5-large-instruct	1 (209)	70.2	71.6	80.4	76.3	67.0	53.7	84.9		51.7	87.5	
multilingual-e5-large	2 (188)	66.4	65.1	77.7	75.1	64.7	43.9	82.6		25.6	86.0	
multilingual-e5-base	3 (173)	64.6	62.6	74.2	72.8	63.8	41.1	77.8		24.6	83.8	
multilingual-e5-small	4 (164)	64.7	63.2	73.7	73.8	63.8	40.8	76.8		29.1	84.4	
GritLM-7B	5 (151)	60.2	58.0	58.4	67.8	60.0	27.2	79.5		28.0	84.7	
e5-mistral-7b-instruct	6 (144)	60.0	58.4	59.1	73.0	59.6	23.0	77.3		32.7	84.4	
LaBSE	7 (139)	61.9	59.7	74.1	64.6	61.9	52.8	64.3		21.1	79.0	
multilingual-mpnet-base	8 (137)	58.5	55.2	44.2	82.0	61.9	34.1	57.9		32.1	74.3	
multilingual-MiniLM-L12	9 (98)	49.7	42.2	15.3	77.8	57.6	19.8	48.8		16.7	59.3	
all-mpnet-base	10 (68)	33.6	22.6	3.7	52.6	45.2	-2.5	12.9		4.0	42.6	
all-MiniLM-L12	11 (49)	33.1	23.2	3.5	55.0	43.9	-5.3	13.9		3.7	47.6	
all-MiniLM-L6	12 (40)	31.8	20.4	2.5	53.7	44.1	-6.3	6.2		3.1	39.2	

Table 2: The results for three multilingual benchmarks are ranked using Borda count. We provide averages across all tasks, per task category, and weighted by task category. The task categories are shortened as follows: Bitext Mining (Btxt), Pair Classification (Pr Clf), Classification (Clf), Semantic text similarity (STS), Retrieval (Rtrvl), Multilabel Classification (M. Clf), Clustering and Hierarchical Clustering (Clust) and Reranking (Rrnk). We highlight the best score in **bold**. Note that while Instruction retrieval (Weller et al., 2024) is included in MTEB(Europe) and MTEB(Multilingual), but is excluded from the average by task category due to limited model support. For a broader model evaluation, refer to the public leaderboard.

pean ones). These are typically outperformed by the multilingually pre trained XLM-Roberta-based multilingual-e5-large-instruct on lower-resource languages in MTEB(Europe) and all languages in

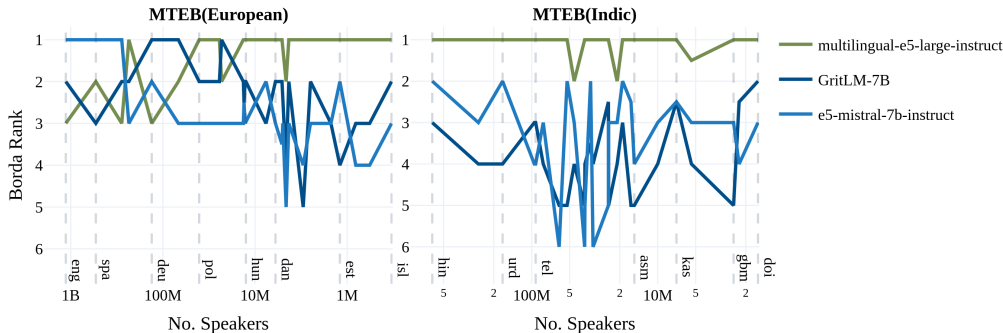


Figure 3: Performance rank of top 3 multilingual models on languages in MTEB(Europe) and MTEB(Indic) and by the number of native speakers. We see that Mistral-based models are outperformed by multilingual-e5-large-instruct on lower-resource languages, despite it having substantially fewer parameters.

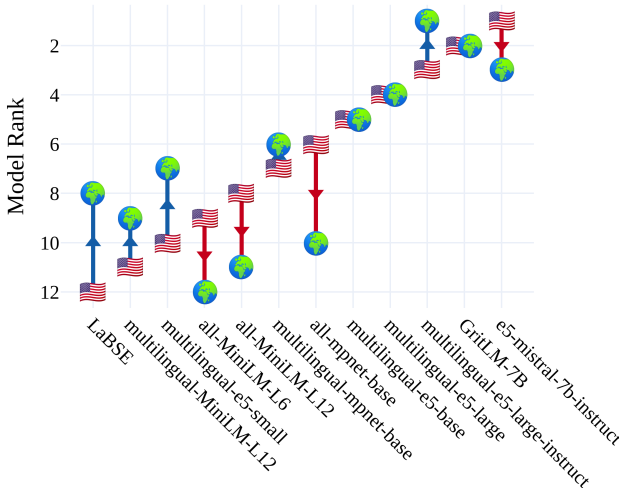


Figure 4: Performance difference on MTEB(eng, v1) (flag) and MTEB(Multilingual) (globe).

MTEB(Indic) (see Figure 3), despite being substantially smaller than Mistral models, the performance of which steadily decreases and becomes more volatile for languages with increasingly lower number of native speakers and this trade-off is well-known (Xue et al., 2020).

Besides these, we observe the expected detrimental performance of English models (all-MiniLM-L12, all-MiniLM-L6, all-mpnet-base) applied to non-English languages and a relatively high bitext performance of LaBSE (see Figure 4).

MTEB(eng, v1) vs. zero-shot MTEB(eng, v2) We compare the performance of MTEB(eng, v1) and MTEB(eng, v2) in Figure 5 obtaining a Spearman correlation of 0.90, $p < 0.0001$ (Pearson 0.96, $p < 0.0001$). For the precise scores, we refer to Subsection H.3. This includes a reduction from 56 to 40 tasks along with optimized task runtime speeding up the runtime on the benchmark (3.11 hours for GritLM-7B and 0.81 hours for all-MiniLM-L12 on an H100). We see that notably, the smaller English models (all-MiniLM-L12, all-MiniLM-L6, all-mpnet-base) perform worse on the new benchmark. This is likely because they were trained on MS MARCO and Natural questions, which were removed as part of the benchmark conversion to a zero-shot benchmark.

5 RELATED WORK

Text Embedding Benchmarks. BEIR (Thakur et al., 2021) pioneered the use of publicly available datasets from diverse information retrieval (IR) tasks and domains and evaluated 10 various retrieval

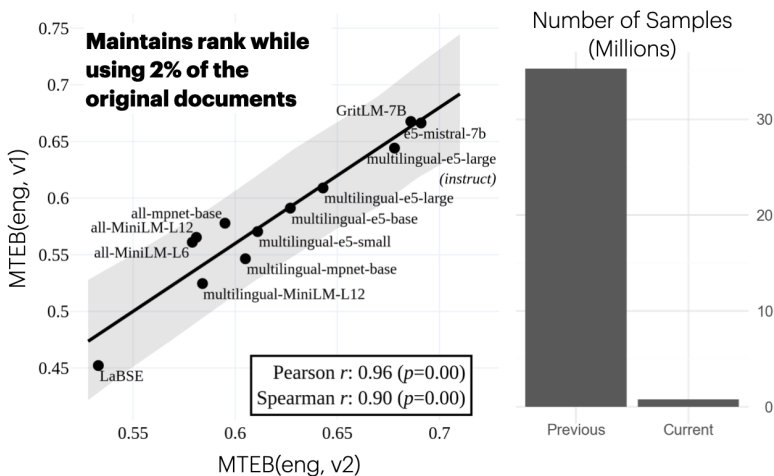


Figure 5: Performance on MTEB(eng, v1) and MTEB(eng, v2)

systems. MTEB (Muennighoff et al., 2023b) introduced a comprehensive text embedding benchmark that spans not only IR but also 8 other task categories, including clustering and re-ranking. MTEB covers a total of 58 tasks and 112 languages, though this multilinguality is mainly derived from machine-translated tasks or bitext mining. Its leaderboard has grown in popularity and evolved into the de facto embedding model benchmark that supports over 300 models. MIRACL (Zhang et al., 2022) supports 18 languages from different language families for monolingual retrieval. MINERS (Winata et al., 2024b) is designed to evaluate the ability of multilingual LMs in semantic retrieval tasks including classification and bitext mining tasks in more than 200 languages, including code-switching. Our work extends the number of languages to over 1000 (250 excluding bitext-mining tasks), particularly to cover more low-resource languages. We also expand the MTEB’s 8 embedding tasks to 10 and the 58 datasets to over 400, significantly broadening the scope of multilingual benchmarking.

Massive Collaborative Projects. Open research initiatives and participatory approaches to science have been shown to stimulate innovation (Park et al., 2023), reduce negative biases (Gudowsky, 2021; Gomez et al., 2022), and increase the diversity of data sources (Hanley et al., 2020; Singh et al., 2024b; Winata et al., 2024a). By involving diverse stakeholders, these practices enhance ethical, robust, and reproducible research (Hagerty & Rubinov, 2019). Recently, the field of natural language processing has seen a growing number of community-driven collaborative projects. These can be grouped into several categories. (a) *Model creation*, such as BLOOM (BigScience Workshop et al., 2023; Muennighoff et al., 2023c), StarCoder (Li et al., 2023a; Lozhkov et al., 2024), Aya model (Üstün et al., 2024), and Cendol (Cahyawijaya et al., 2024); (b) *Dataset creation*, such as NusaX (Winata et al., 2023b), OpenAssistant (Köpf et al., 2023), NusaWrites (Cahyawijaya et al., 2023c), and Aya dataset (Singh et al., 2024b); (c) *Benchmark creation*, such as BIG-Bench (Srivastava et al., 2023), NusaCrowd (Cahyawijaya et al., 2023a), WorldCuisines (Winata et al., 2024a), HLE (Phan et al., 2025), SEACrowd (Lovenia et al., 2024), and Eval-Harnesses (Gao et al., 2021; Ben Allal et al., 2022; Biderman et al., 2024); and (d) *Other artifacts*, such as NL-Augmenter (Dhole et al., 2021), the Data Provenance Initiative (Longpre et al., 2023; 2024a;b) or the Wikibench annotation tool (Kuo et al., 2024). MMTEB expands upon earlier work within the *Benchmark creation* category. Our effort significantly differs from prior collaborative benchmarks as we focus on text embeddings, use a custom point system to incentivize contributions, and handle all communication openly via GitHub.

6 CONCLUSION

This work introduced the Massive Multilingual Text Embedding Benchmark (MMTEB), a large-scale open collaboration resulting in a benchmark with more than 500 tasks covering more than 1000 languages. From these, we constructed three multilingual benchmarks: one fully multi-

REFERENCES

- David Ifeoluwa Adelani, Hannah Liu, Xiaoyu Shen, Nikita Vassilyev, Jesujoba O Alabi, Yanke Mao, Haonan Gao, and Annie En-Shiun Lee. Sib-200: A simple, inclusive, and big evaluation dataset for topic classification in 200+ languages and dialects. *arXiv preprint arXiv:2309.07445*, 2023a.
- David Ifeoluwa Adelani, Marek Masiak, Israel Abebe Azime, Jesujoba Alabi, Atnafu Lambebo Tonja, Christine Mwase, Odunayo Ogundepo, Bonaventure F. P. Dossou, Akintunde Oladipo, Doreen Nixdorf, Chris Chinenye Emezue, sana al azzawi, Blessing Sibanda, Davis David, Lolwethu Ndolela, Jonathan Mukiibi, Tunde Ajayi, Tatiana Moteu, Brian Odhiambo, Abraham Owodunni, Nnaemeka Obiefuna, Muhidin Mohamed, Shamsuddeen Hassan Muhammad, Teshome Mulugeta Ababu, Saheed Abdullahi Salahudeen, Mesay Gameda Yigezu, Tajuddeen Gwadabe, Idris Abdulmumin, Mahlet Taye, Oluwabusayo Awoyomi, Iyanuoluwa Shode, Tolulope Adelani, Habiba Abdulganiyu, Abdul-Hakeem Omotayo, Adetola Adeeko, Abeeb Afolabi, Anuoluwapo Aremu, Olanrewaju Samuel, Clemencia Siro, Wangari Kimotho, Onyekachi Ogbu, Chinedu Mbonu, Chiamaka Chukwuneke, Samuel Fanijo, Jessica Ojo, Oyinkansola Awosan, Tadesse Kebede, Toadoum Sari Sakayo, Pamela Nyatsine, Freedmore Sidume, Oreen Yousuf, Mardiyah Oduwole, Tshinu Tshinu, Ussen Kimanuka, Thina Diko, Siyanda Nxakama, Sinodos Nigusse, Abdulmejid Johar, Shafie Mohamed, Fuad Mire Hassan, Moges Ahmed Mehamed, Evrard Ngabire, Jules Jules, Ivan Ssenkungu, and Pontus Stenetorp. Masakhanews: News topic classification for african languages, 2023b.
- Eneko Agirre, Mona Diab, Daniel Cer, and Aitor Gonzalez-Agirre. Semeval-2012 task 6: a pilot on semantic textual similarity. In *Proceedings of the First Joint Conference on Lexical and Computational Semantics - Volume 1: Proceedings of the Main Conference and the Shared Task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation, SemEval '12*, pp. 385–393, USA, 2012. Association for Computational Linguistics.
- Eneko Agirre, Daniel Matthew Cer, Mona T. Diab, Aitor Gonzalez-Agirre, and Weiwei Guo. *sem 2013 shared task: Semantic textual similarity. In *International Workshop on Semantic Evaluation*, 2013. URL <https://api.semanticscholar.org/CorpusID:10241043>.
- Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Inigo Lopez-Gazpio, Montse Maritxalar, Rada Mihalcea, et al. Semeval-2015 task 2: Semantic textual similarity, english, spanish and pilot on interpretability. In *Proceedings of the 9th international workshop on semantic evaluation (SemEval 2015)*, pp. 252–263, 2015.
- Gustavo Aguilar, Sudipta Kar, and Thamar Solorio. Lince: A centralized benchmark for linguistic code-switching evaluation. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pp. 1803–1813, 2020.
- Orevaoghene Ahia, Julia Kreutzer, and Sara Hooker. The low-resource double bind: An empirical study of pruning for low-resource machine translation. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2021*, pp. 3316–3333, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-emnlp.282. URL <https://aclanthology.org/2021.findings-emnlp.282>.
- Vesa Akerman, David Baines, Damien Daspit, Ulf Hermjakob, Taeho Jang, Colin Leong, Michael Martin, Joel Mathew, Jonathan Robie, and Marcus Schwarting. The eible corpus: Data and model benchmarks for bible translation for low-resource languages. *arXiv preprint arXiv:2304.09919*, 2023.
- Dimosthenis Antypas, Asahi Ushio, Jose Camacho-Collados, Leonardo Neves, Vitor Silva, and Francesco Barbieri. Twitter Topic Classification. In *Proceedings of the 29th International Conference on Computational Linguistics*, Gyeongju, Republic of Korea, oct 2022. International Committee on Computational Linguistics.
- Gaurav Arora. iNLTK: Natural language toolkit for indic languages. In Eunjeong L. Park, Masato Hagiwara, Dmitrijs Milajevs, Nelson F. Liu, Geeticka Chauhan, and Liling Tan (eds.), *Proceedings of Second Workshop for NLP Open Source Software (NLP-OSS)*, pp. 66–71, Online, nov 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.nlposs-1.10. URL <https://aclanthology.org/2020.nlposs-1.10>.

- Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. On the cross-lingual transferability of monolingual representations. *CoRR*, abs/1910.11856, 2019.
- Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021.
- Soran Badawi, Arefeh Kazemi, and Vali Rezaie. Kurdisent: a corpus for kurdish sentiment analysis. *Language Resources and Evaluation*, pp. 1–20, 01 2024. doi: 10.1007/s10579-023-09716-6.
- Lucas Bandarkar, Davis Liang, Benjamin Muller, Mikel Artetxe, Satya Narayan Shukla, Donald Husa, Naman Goyal, Abhinandan Krishnan, Luke Zettlemoyer, and Madian Khabsa. The belebele benchmark: a parallel reading comprehension dataset in 122 language variants. *arXiv preprint arXiv:2308.16884*, 2023.
- Anil Bandhakavi, Nirmalie Wiratunga, Deepak P, and Stewart Massie. Generating a word-emotion lexicon from #emotional tweets. In Johan Bos, Anette Frank, and Roberto Navigli (eds.), *Proceedings of the Third Joint Conference on Lexical and Computational Semantics (*SEM 2014)*, pp. 12–21, Dublin, Ireland, aug 2014. Association for Computational Linguistics and Dublin City University. doi: 10.3115/v1/S14-1002. URL <https://aclanthology.org/S14-1002>.
- Francesco Barbieri, Luis Espinosa Anke, and Jose Camacho-Collados. XLM-T: Multilingual language models in Twitter for sentiment analysis and beyond. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pp. 258–266, Marseille, France, jun 2022. European Language Resources Association. URL <https://aclanthology.org/2022.lrec-1.27>.
- Parishad BehnamGhader, Vaibhav Adlakha, Marius Mosbach, Dzmitry Bahdanau, Nicolas Chapados, and Siva Reddy. Llm2vec: Large language models are secretly powerful text encoders. *arXiv preprint arXiv:2404.05961*, 2024.
- Loubna Ben Allal, Niklas Muennighoff, Logesh Kumar Umapathi, Ben Lipkin, and Leandro von Werra. A framework for the evaluation of code generation models, 2022. URL <https://github.com/bigcode-project/bigcode-evaluation-harness>.
- Chandra Bhagavatula, Ronan Le Bras, Chaitanya Malaviya, Keisuke Sakaguchi, Ari Holtzman, Hannah Rashkin, Doug Downey, Wen-tau Yih, and Yejin Choi. Abductive commonsense reasoning. In *International Conference on Learning Representations*, 2020.
- Paheli Bhattacharya, Kripabandhu Ghosh, Saptarshi Ghosh, Arindam Pal, Parth Mehta, Arnab Bhattacharya, and Prasenjit Majumder. Aila 2019 precedent & statute retrieval task, oct 2020. URL <https://doi.org/10.5281/zenodo.4063986>.
- Ergun Biçici. RTM-DCU: Predicting semantic similarity with referential translation machines. In Preslav Nakov, Torsten Zesch, Daniel Cer, and David Jurgens (eds.), *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pp. 56–63, Denver, Colorado, jun 2015. Association for Computational Linguistics. doi: 10.18653/v1/S15-2010. URL <https://aclanthology.org/S15-2010>.
- Stella Biderman, Hailey Schoelkopf, Lintang Sutawika, Leo Gao, Jonathan Tow, Baber Abbasi, Alham Fikri Aji, Pawan Sasanka Ammanamanchi, Sidney Black, Jordan Clive, et al. Lessons from the trenches on reproducible evaluation of language models. *arXiv preprint arXiv:2405.14782*, 2024.
- Teven Le Scao BigScience Workshop, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, Jonathan Tow, Alexander M. Rush, Stella Biderman, Albert Webson, Pawan Sasanka Ammanamanchi, Thomas Wang, Benoît Sagot, Niklas Muennighoff, et al. Bloom: A 176b-parameter open-access multilingual language model, 2023.
- Yonatan Bisk, Rowan Zellers, Jianfeng Gao, Yejin Choi, et al. Piqa: Reasoning about physical commonsense in natural language. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pp. 7432–7439, 2020.

- Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George van den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al. Improving language models by retrieving from trillions of tokens, 2022.
- Vera Boteva, Demian Gholipour, Artem Sokolov, and Stefan Riezler. A full-text learning to rank dataset for medical information retrieval. 2016. URL <http://www.cl.uni-heidelberg.de/~riezler/publications/papers/ECIR2016.pdf>.
- Chris Buckley, Darrin Dimmick, Ian Soboroff, and Ellen Voorhees. Bias and the limits of pooling for large collections. *Information retrieval*, 10:491–508, 2007.
- Samuel Cahyawijaya, Holy Lovenia, Alham Fikri Aji, Genta Winata, Bryan Wilie, Fajri Koto, Rahmad Mahendra, Christian Wibisono, Ade Romadhony, Karissa Vincentio, et al. Nusacrowd: Open source initiative for indonesian nlp resources. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 13745–13818, 2023a.
- Samuel Cahyawijaya, Holy Lovenia, Fajri Koto, Dea Adhista, Emmanuel Dave, Sarah Oktavianti, Salsabil Akbar, Jhonson Lee, Nuur Shadieq, Tjeng Wawan Cenggoro, Hanung Linuwih, Bryan Wilie, Galih Muridan, Genta Winata, David Moeljadi, Alham Fikri Aji, Ayu Purwarianti, and Pascale Fung. Nusawrites: Constructing high-quality corpora for underrepresented and extremely low-resource languages. In Jong C. Park, Yuki Arase, Baotian Hu, Wei Lu, Derry Wijaya, Ayu Purwarianti, and Adila Alfa Krisnadhi (eds.), *Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 921–945, Nusa Dua, Bali, nov 2023b. Association for Computational Linguistics. URL <https://aclanthology.org/2023.ijcnlp-main.60>.
- Samuel Cahyawijaya, Holy Lovenia, Fajri Koto, Dea Adhista, Emmanuel Dave, Sarah Oktavianti, Salsabil Akbar, Jhonson Lee, Nuur Shadieq, Tjeng Wawan Cenggoro, et al. Nusawrites: Constructing high-quality corpora for underrepresented and extremely low-resource languages. In *Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 921–945, 2023c.
- Samuel Cahyawijaya, Holy Lovenia, Fajri Koto, Rifki Afina Putri, Emmanuel Dave, Jhonson Lee, Nuur Shadieq, Wawan Cenggoro, Salsabil Maulana Akbar, Muhammad Ihza Mahendra, et al. Cendol: Open instruction-tuned generative large language models for indonesian languages. *arXiv preprint arXiv:2404.06138*, 2024.
- Iñigo Casanueva, Tadas Temcinas, Daniela Gerz, Matthew Henderson, and Ivan Vulić. Efficient intent detection with dual sentence encoders. In Tsung-Hsien Wen, Asli Celikyilmaz, Zhou Yu, Alexandros Papangelis, Mihail Eric, Anuj Kumar, Iñigo Casanueva, and Rushin Shah (eds.), *Proceedings of the 2nd Workshop on Natural Language Processing for Conversational AI*, pp. 38–45, Online, jul 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.nlp4convai-1.5. URL <https://aclanthology.org/2020.nlp4convai-1.5>.
- Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation. In Steven Bethard, Marine Carpuat, Marianna Apidianaki, Saif M. Mohammad, Daniel Cer, and David Jurgens (eds.), *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pp. 1–14, Vancouver, Canada, aug 2017. Association for Computational Linguistics. doi: 10.18653/v1/S17-2001. URL <https://aclanthology.org/S17-2001>.
- Ilias Chalkidis, Manos Fergadiotis, and Ion Androutsopoulos. Multieurlex – a multi-lingual and multi-label legal document classification dataset for zero-shot cross-lingual transfer. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2021. URL <https://arxiv.org/abs/2109.00904>.
- Amit Kumar Chaudhary, Kurt Micallef, and Claudia Borg. Topic classification and headline generation for Maltese using a public news corpus. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation*. Association for Computational Linguistics, may 2024.

- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, et al. Evaluating large language models trained on code, 2021.
- Xi Chen, Ali Zeynali, Chico Camargo, Fabian Fl"ock, Devin Gaffney, Przemyslaw Grabowicz, Scott Hale, David Jurgens, and Mattia Samory. SemEval-2022 task 8: Multilingual news article similarity. In Guy Emerson, Natalie Schluter, Gabriel Stanovsky, Ritesh Kumar, Alexis Palmer, Nathan Schneider, Siddharth Singh, and Shyam Ratan (eds.), *Proceedings of the 16th International Workshop on Semantic Evaluation (SemEval-2022)*, pp. 1094–1106, Seattle, United States, jul 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.semeval-1.155. URL <https://aclanthology.org/2022.semeval-1.155>.
- François Chollet. On the Measure of Intelligence. *arXiv:1911.01547 [cs]*, November 2019. URL <http://arxiv.org/abs/1911.01547>. arXiv: 1911.01547.
- Mathieu Ciancone, Imene Kerboua, Marion Schaeffer, and Wissam Sibli. Extending the massive text embedding benchmark to french, 2024.
- cjadams, Daniel Borkan, inversion, Jeffrey Sorensen, Lucas Dixon, Lucy Vasserman, and nithum. Jigsaw unintended bias in toxicity classification, 2019. URL <https://kaggle.com/competitions/jigsaw-unintended-bias-in-toxicity-classification>.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*, 2018.
- Benjamin Clavié. Jacolbert and hard negatives, towards better japanese-first embeddings for retrieval: Early technical report, 2023.
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems, 2021.
- Arman Cohan, Sergey Feldman, Iz Beltagy, Doug Downey, and Daniel S. Weld. Specter: Document-level representation learning using citation-informed transformers, 2020a.
- Arman Cohan, Sergey Feldman, Iz Beltagy, Doug Downey, and Daniel S. Weld. Specter: Document-level representation learning using citation-informed transformers. In *ACL*, 2020b.
- Pierre Colombo, Nathan Noiry, Ekhine Irurozki, and Stephan Cléménçon. What are the best systems? new perspectives on nlp benchmarking. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 26915–26932. Curran Associates, Inc., 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/file/ac4920f4085b5662133dd751493946a6-Paper-Conference.pdf.
- Tatoeba community. Tatoeba: Collection of sentences and translations, 2021.
- Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel R. Bowman, Holger Schwenk, and Veselin Stoyanov. Xnli: Evaluating cross-lingual sentence representations. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2018.
- 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. *arXiv preprint arXiv:1911.02116*, 2019.
- Marta R Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, et al. No language left behind: Scaling human-centered machine translation. *arXiv preprint arXiv:2207.04672*, 2022.
- Benoit Courty, Victor Schmidt, Goyal-Kamal, MarionCoutarel, Boris Feld, Jérémy Lecourt, LiamConnell, SabAmine, inimaz, supatomic, Mathilde Léval, Luis Blanche, Alexis Cruveiller, ouminasara, Franklin Zhao, Aditya Joshi, Alexis Bogroff, Amine Saboni, Hugues de Lavoreille, Niko Laskaris, Edoardo Abati, Douglas Blank, Ziyao Wang, Armin Catovic, alencon, Michał Stęchły, Christian Bauer, Lucas-Otavio, JPW, and MinervaBooks. mlco2/codecarbon: v2.4.1, May 2024. URL <https://doi.org/10.5281/zenodo.11171501>.

- Mathias Creutz. Open subtitles paraphrase corpus for six languages, 2018.
- Slawomir Dadas, Michał Perelkiewicz, and Rafał Poświata. Evaluation of sentence representations in Polish. In Nicoletta Calzolari, Fr'ed'eric B'echet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, H'el'ene Mazo, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pp. 1674–1680, Marseille, France, may 2020. European Language Resources Association. ISBN 979-10-95546-34-4. URL <https://aclanthology.org/2020.lrec-1.207>.
- Slawomir Dadas. Training effective neural sentence encoders from automatically mined paraphrases, 2022.
- David Davis. Swahili: News classification dataset (0.2). Zenodo, 2020. doi: 10.5281/zenodo.5514203. URL <https://doi.org/10.5281/zenodo.5514203>.
- Nisansa de Silva. Sinhala text classification: Observations from the perspective of a resource poor language. *Year of Publication*, 2015.
- Leon Derczynski and Alex Speed Kjeldsen. Bornholmsk natural language processing: Resources and tools. In *Proceedings of the Nordic Conference of Computational Linguistics (2019)*, pp. 338–344. Linköping University Electronic Press. URL https://pure.itu.dk/ws/files/84551091/W19_6138.pdf.
- Ameet Deshpande, Carlos E Jimenez, Howard Chen, Vishvak Murahari, Victoria Graf, Tanmay Rajpurohit, Ashwin Kalyan, Danqi Chen, and Karthik Narasimhan. Csts: Conditional semantic textual similarity. *arXiv preprint arXiv:2305.15093*, 2023.
- Swapnil Dhanwal, Hritwik Dutta, Hitesh Nankani, Nilay Shrivastava, Yaman Kumar, Junyi Jessy Li, Debanjan Mahata, Rakesh Gosangi, Haimin Zhang, Rajiv Ratn Shah, and Amanda Stent. An annotated dataset of discourse modes in Hindi stories. In *Proceedings of the 12th Language Resources and Evaluation Conference*, Marseille, France, may 2020. European Language Resources Association. ISBN 979-10-95546-34-4. URL <https://www.aclweb.org/anthology/2020.lrec-1.149>.
- Kaustubh D Dhole, Varun Gangal, Sebastian Gehrmann, Aadesh Gupta, Zhenhao Li, Saad Mahamood, Abinaya Mahendiran, Simon Mille, Ashish Shrivastava, Samson Tan, et al. NI-augmenter: A framework for task-sensitive natural language augmentation. *arXiv preprint arXiv:2112.02721*, 2021.
- Thomas Diggelmann, Jordan Boyd-Graber, Jannis Bulian, Massimiliano Ciaramita, and Markus Leippold. Climate-fever: A dataset for verification of real-world climate claims, 2021.
- Kenneth Enevoldsen, Márton Kardos, Niklas Muennighoff, and Kristoffer Laigaard Nielbo. The scandinavian embedding benchmarks: Comprehensive assessment of multilingual and monolingual text embedding. *arXiv preprint arXiv:2406.02396*, 2024.
- Alexander R Fabbri, Wojciech Kry'sci'nski, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. Summeval: Re-evaluating summarization evaluation. *arXiv preprint arXiv:2007.12626*, 2020.
- Christian Federmann, Tom Kocmi, and Ying Xin. NTREX-128 – news test references for MT evaluation of 128 languages. In *Proceedings of the First Workshop on Scaling Up Multilingual Evaluation*, pp. 21–24, Online, nov 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.sumeval-1.4>.
- Fangxiaoyu Feng, Yinfei Yang, Daniel Cer, Naveen Arivazhagan, and Wei Wang. Language-agnostic BERT sentence embedding. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 878–891, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.62. URL <https://aclanthology.org/2022.acl-long.62>.

- 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, Gokhan Tur, and Prem Natarajan. Massive: A 1m-example multilingual natural language understanding dataset with 51 typologically-diverse languages, 2022.
- Wikimedia Foundation. Wikimedia downloads. URL <https://dumps.wikimedia.org>.
- Marc Franco-Salvador, Paolo Rosso, and Roberto Navigli. A knowledge-based representation for cross-language document retrieval and categorization. In Shuly Wintner, Sharon Goldwater, and Stefan Riezler (eds.), *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 414–423, Gothenburg, Sweden, April 2014. Association for Computational Linguistics. doi: 10.3115/v1/E14-1044. URL <https://aclanthology.org/E14-1044>.
- Jay Gala, Pranjal A Chitale, A K Raghavan, Varun Gumma, Sumanth Doddapaneni, Aswanth Kumar M, Janki Atul Nawale, Anupama Sujatha, Ratish Puduppully, Vivek Raghavan, Pratyush Kumar, Mitesh M Khapra, Raj Dabre, and Anoop Kunchukuttan. Indictrans2: Towards high-quality and accessible machine translation models for all 22 scheduled indian languages. *Transactions on Machine Learning Research*, 2023. ISSN 2835-8856. URL <https://openreview.net/forum?id=vfT4YuzAYA>.
- Leo Gao, Jonathan Tow, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Kyle McDonell, Niklas Muennighoff, Jason Phang, Laria Reynolds, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, September 2021. URL <https://doi.org/10.5281/zenodo.5371628>.
- Gregor Geigle, Nils Reimers, Andreas Ruckl'e, and Iryna Gurevych. Tweac: Transformer with extendable qa agent classifiers. *arXiv preprint*, abs/2104.07081, 2021. URL <http://arxiv.org/abs/2104.07081>.
- Tsvetanka Georgieva-Trifonova, Milena Stefanova, and Stefan Kalchev. Dataset for “Customer Feedback Text Analysis for Online Stores Reviews in Bulgarian”, 2018. URL <https://doi.org/10.7910/DVN/TXIK9P>.
- Daniilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. The third PASCAL recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*, pp. 1–9, Prague, jun 2007. Association for Computational Linguistics. URL <https://aclanthology.org/W07-1401>.
- Hippolyte Gisserot-Boukhlef, Manuel Faysse, Emmanuel Malherbe, Céline Hudelot, and Pierre Colombo. Towards trustworthy reranking: A simple yet effective abstention mechanism. *arXiv preprint arXiv:2402.12997*, 2024.
- Dirk Goldhahn, Thomas Eckart, and Uwe Quasthoff. Building large monolingual dictionaries at the leipzig corpora collection: From 100 to 200 languages. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC'12)*, 2012.
- Charles J Gomez, Andrew C Herman, and Paolo Parigi. Leading countries in global science increasingly receive more citations than other countries doing similar research. *Nature Human Behaviour*, 6(7):919–929, 2022.
- Matilde González, Clara García, and Lucía Sánchez. Diabla: A corpus of bilingual spontaneous written dialogues for machine translation. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pp. 4192–4198, 2019.
- Naman Goyal, Cynthia Gao, Vishrav Chaudhary, Peng-Jen Chen, Guillaume Wenzek, Da Ju, Sanjana Krishnan, Marc Aurelio Ranzato, and Francisco Guzm'an. The flores-101 evaluation benchmark for low-resource and multilingual machine translation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 19–35, 2022.
- Niklas Gudowsky. Limits and benefits of participatory agenda setting for research and innovation. *European Journal of Futures Research*, 9(1):8, 2021.

- Neel Guha, Julian Nyarko, Daniel E. Ho, Christopher Ré, Adam Chilton, Aditya Narayana, Alex Chohlas-Wood, Austin Peters, Brandon Waldon, Daniel N. Rockmore, Diego Zambrano, Dmitry Talisman, Enam Hoque, Faiz Surani, Frank Fagan, Galit Sarfaty, Gregory M. Dickinson, Haggai Porat, Jason Hegland, Jessica Wu, Joe Nudell, Joel Niklaus, John Nay, Jonathan H. Choi, Kevin Tobia, Margaret Hagan, Megan Ma, Michael Livermore, Nikon Rasumov-Rahe, Nils Holzenberger, Noam Kolt, Peter Henderson, Sean Rehaag, Sharad Goel, Shang Gao, Spencer Williams, Sunny Gandhi, Tom Zur, Varun Iyer, and Zehua Li. Legalbench: A collaboratively built benchmark for measuring legal reasoning in large language models, 2023.
- Ren'e Haas and Leon Derczynski. Discriminating between similar Nordic languages. In Marcos Zampieri, Preslav Nakov, Nikola Ljubesic, Jörg Tiedemann, Yves Scherrer, and Tommi Jauhiainen (eds.), *Proceedings of the Eighth Workshop on NLP for Similar Languages, Varieties and Dialects*, pp. 67–75, Kiyv, Ukraine, apr 2021. Association for Computational Linguistics. URL <https://aclanthology.org/2021.vardial-1.8>.
- Ivan Habernal, Tom'as Pt'acek, and Josef Steinberger. Sentiment analysis in Czech social media using supervised machine learning. In Alexandra Balahur, Erik van der Goot, and Andres Montoyo (eds.), *Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pp. 65–74, Atlanta, Georgia, jun 2013. Association for Computational Linguistics. URL <https://aclanthology.org/W13-1609>.
- Alexa Hagerty and Igor Rubinov. Global ai ethics: A review of the social impacts and ethical implications of artificial intelligence, 2019.
- Margot Hanley, Apoorv Khandelwal, Hadar Averbuch-Elor, Noah Snaveley, and Helen Nissenbaum. An ethical highlighter for people-centric dataset creation. *arXiv preprint arXiv:2011.13583*, 2020.
- Mariya Hendriksen, Svitlana Vakulenko, Ernst Kuiper, and Maarten de Rijke. Scene-centric vs. object-centric image-text cross-modal retrieval: A reproducibility study. In *European Conference on Information Retrieval*, pp. 68–85. Springer, 2023.
- Dan Hendrycks, Steven Basart, Saurav Kadavath, Mantas Mazeika, Akul Arora, Ethan Guo, Collin Burns, Samir Puranik, Horace He, Dawn Song, and Jacob Steinhardt. Measuring coding challenge competence with apps. *NeurIPS*, 2021a.
- Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring mathematical problem solving with the math dataset. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021b.
- Søren Vejlgård Holm. Are gllms danoliterate? benchmarking generative nlp in danish. 2024.
- Doris Hoogeveen, Karin M. Verspoor, and Timothy Baldwin. Cqadupstack: A benchmark data set for community question-answering research. In *Proceedings of the 20th Australasian Document Computing Symposium (ADCS)*, ADCS '15, pp. 3:1–3:8, New York, NY, USA, 2015. ACM. ISBN 978-1-4503-4040-3. doi: 10.1145/2838931.2838934. URL <http://doi.acm.org/10.1145/2838931.2838934>.
- Christoph Hoppe, David Pelkmann, Nico Migenda, Daniel Hötte, and Wolfram Schenck. Towards intelligent legal advisors for document retrieval and question-answering in german legal documents. In *2021 IEEE Fourth International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)*, pp. 29–32, 2021. doi: 10.1109/AIKE52691.2021.00011.
- Junjie Huang, Duyu Tang, Linjun Shou, Ming Gong, Ke Xu, Daxin Jiang, Ming Zhou, and Nan Duan. Cosqa: 20,000+ web queries for code search and question answering, 2021. URL <https://arxiv.org/abs/2105.13239>.
- Hamel Husain, Ho-Hsiang Wu, Tiferet Gazit, Miltiadis Allamanis, and Marc Brockschmidt. CodeSearchNet challenge: Evaluating the state of semantic code search. *arXiv preprint arXiv:1909.09436*, 2019.
- Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118*, 2021.

- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L  lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth  e Lacroix, and William El Sayed. Mistral 7b, 2023.
- Dame Jovanoski, Veno Pachovski, and Preslav Nakov. Sentiment analysis in Twitter for Macedonian. In Ruslan Mitkov, Galia Angelova, and Kalina Bontcheva (eds.), *Proceedings of the International Conference Recent Advances in Natural Language Processing*, pp. 249–257, Hissar, Bulgaria, sep 2015. INCOMA Ltd. Shoumen, BULGARIA. URL <https://aclanthology.org/R15-1034>.
- Ehsan Kamalloo, Aref Jafari, Xinyu Zhang, Nandan Thakur, and Jimmy Lin. HAGRID: A human-llm collaborative dataset for generative information-seeking with attribution. *arXiv:2307.16883*, 2023.
- Jenna Kanerva, Filip Ginter, Li-Hsin Chang, Iiro Rastas, Valtteri Skantsi, Jemina Kilpel"ainen, Hanna-Mari Kupari, Jenna Saarni, Maija Sev'on, and Otto Tarkka. Finnish paraphrase corpus. In Simon Dobnik and Lilja  vrelid (eds.), *Proceedings of the 23rd Nordic Conference on Computational Linguistics (NoDaLiDa)*, pp. 288–298, Reykjavik, Iceland (Online), 2021. Link"oping University Electronic Press, Sweden. URL <https://aclanthology.org/2021.nodalida-main.29>.
- Jiwon Kim and Won Ik Cho. Kocasm: Korean automatic sarcasm detection. <https://github.com/SpellOnYou/korean-sarcasm>, 2019.
- Anoop Kunchukuttan, Divyanshu Kakwani, Satish Golla, Gokul N.C., Avik Bhattacharyya, Mitesh M. Khapra, and Pratyush Kumar. Ai4bharat-indicnlp corpus: Monolingual corpora and word embeddings for indic languages. *arXiv preprint arXiv:2005.00085*, 2020.
- Tzu-Sheng Kuo, Aaron Lee Halfaker, Zirui Cheng, Jiwoo Kim, Meng-Hsin Wu, Tongshuang Wu, Kenneth Holstein, and Haiyi Zhu. Wikibench: Community-driven data curation for ai evaluation on wikipedia. In *Proceedings of the CHI Conference on Human Factors in Computing Systems, CHI '24*, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400703300. doi: 10.1145/3613904.3642278. URL <https://doi.org/10.1145/3613904.3642278>.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. Natural questions: a benchmark for question answering research, 2019. URL <https://aclanthology.org/Q19-1026/>.
- Andreas K  pf, Yannic Kilcher, Dimitri von R  tte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Rich  rd Nagyfi, Shahul ES, Sameer Suri, David Glushkov, Arnav Dantuluri, Andrew Maguire, Christoph Schuhmann, Huu Nguyen, and Alexander Mattick. Openassistant conversations – democratizing large language model alignment, 2023.
- Wuwei Lan, Siyu Qiu, Hua He, and Wei Xu. A continuously growing dataset of sentential paraphrases. In Martha Palmer, Rebecca Hwa, and Sebastian Riedel (eds.), *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 1224–1234, Copenhagen, Denmark, sep 2017. Association for Computational Linguistics. doi: 10.18653/v1/D17-1126. URL <https://aclanthology.org/D17-1126>.
- Ken Lang. Newsweeder: Learning to filter netnews. In Armand Prieditis and Stuart Russell (eds.), *Machine Learning Proceedings 1995*, pp. 331–339. Morgan Kaufmann, San Francisco (CA), 1995. ISBN 978-1-55860-377-6. doi: <https://doi.org/10.1016/B978-1-55860-377-6.50048-7>. URL <https://www.sciencedirect.com/science/article/pii/B9781558603776500487>.
- 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, 2024.
- Jean Lee, Taejun Lim, Heejun Lee, Bogeun Jo, Yangsok Kim, Heegeun Yoon, and Soyeon Caren Han. K-MHaS: A multi-label hate speech detection dataset in Korean online news comment. In *Proceedings of the 29th International Conference on Computational Linguistics*, pp. 3530–3538, Gyeongju, Republic of Korea, oct 2022. International Committee on Computational Linguistics. URL <https://aclanthology.org/2022.coling-1.311>.

- Antoine Lefebvre-Brossard, Stephane Gazaille, and Michel C. Desmarais. Alloprof: a new french question-answer education dataset and its use in an information retrieval case study, 2023. URL <https://arxiv.org/abs/2302.07738>.
- Joao Augusto Leite, Diego F. Silva, Kalina Bontcheva, and Carolina Scarton. Toxic language detection in social media for brazilian portuguese: New dataset and multilingual analysis. *CoRR*, abs/2010.04543, 2020. URL <https://arxiv.org/abs/2010.04543>.
- Patrick Lewis, Barlas Oguz, Ruty Rinott, Sebastian Riedel, and Holger Schwenk. Mlqa: Evaluating cross-lingual extractive question answering. *arXiv preprint arXiv:1910.07475*, art. arXiv:1910.07475, 2019.
- Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. Retrieval-augmented generation for knowledge-intensive nlp tasks, 2021. URL <https://arxiv.org/abs/2005.11401>.
- Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, Joe Davison, Mario Sasko, Gunjan Chhablani, Bhavitvya Malik, Simon Brandeis, Teven Le Scao, Victor Sanh, Canwen Xu, Nicolas Patry, Angelina McMillan-Major, Philipp Schmid, Sylvain Gugger, Clement Delangue, Théo Matussière, Lysandre Debut, Stas Bekman, Pierric Cistac, Thibault Goehringer, Victor Mustar, François Lagunas, Alexander M. Rush, and Thomas Wolf. Datasets: A community library for natural language processing. *CoRR*, abs/2109.02846, 2021. URL <https://arxiv.org/abs/2109.02846>.
- 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, Jorg Tiedemann, and Reut Tsarfaty (eds.), *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pp. 2950–2962, Online, apr 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.257. URL <https://aclanthology.org/2021.eacl-main.257>.
- Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. Starcoder: may the source be with you!, 2023a.
- Xiangyang Li, Kuicai Dong, Yi Quan Lee, Wei Xia, Yichun Yin, Hao Zhang, Yong Liu, Yasheng Wang, and Ruiming Tang. Coir: A comprehensive benchmark for code information retrieval models, 2024. URL <https://arxiv.org/abs/2407.02883>.
- Yudong Li, Yuqing Zhang, Zhe Zhao, Linlin Shen, Weijie Liu, Weiquan Mao, and Hui Zhang. Csl: A large-scale chinese scientific literature dataset, 2022.
- Zehan Li, Xin Zhang, Yanzhao Zhang, Dingkun Long, Pengjun Xie, and Meishan Zhang. Towards general text embeddings with multi-stage contrastive learning, 2023b. URL <https://arxiv.org/abs/2308.03281>.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, et al. Holistic evaluation of language models. *arXiv preprint arXiv:2211.09110*, 2022.
- Daniele Licari, Praveen Bushipaka, Gabriele Marino, Giovanni Comand'e, and Tommaso Cucinotta. Legal holding extraction from italian case documents using italian-legal-bert text summarization. In *Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law, ICAIL '23*, pp. 148–156, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400701979. doi: 10.1145/3594536.3595177. URL <https://doi.org/10.1145/3594536.3595177>.
- Zi Lin, Zihan Wang, Yongqi Tong, Yangkun Wang, Yuxin Guo, Yujia Wang, and Jingbo Shang. Toxicchat: Unveiling hidden challenges of toxicity detection in real-world user-ai conversation, 2023.

- Shayne Longpre, Robert Mahari, Anthony Chen, Naana Obeng-Marnu, Damien Sileo, William Brannon, Niklas Muennighoff, Nathan Khazam, Jad Kabbara, Kartik Perisetla, Xinyi Wu, Enrico Shippole, Kurt Bollacker, Tongshuang Wu, Luis Villa, Sandy Pentland, Deb Roy, and Sara Hooker. The data provenance initiative: A large scale audit of dataset licensing & attribution in ai, 2023.
- Shayne Longpre, Robert Mahari, Ariel Lee, Campbell Lund, Hamidah Oderinwale, William Brannon, Nayan Saxena, Naana Obeng-Marnu, Tobin South, Cole Hunter, Kevin Klyman, Christopher Klamm, Hailey Schoelkopf, Nikhil Singh, Manuel Cherep, Ahmad Anis, An Dinh, Caroline Chitongo, Da Yin, Damien Sileo, Deividas Mataciunas, Diganta Misra, Emad Alghamdi, Enrico Shippole, Jianguo Zhang, Joanna Materzynska, Kun Qian, Kush Tiwary, Lester Miranda, Manan Dey, Minnie Liang, Mohammed Hamdy, Niklas Muennighoff, Seonghyeon Ye, Seungone Kim, Shrestha Mohanty, Vipul Gupta, Vivek Sharma, Vu Minh Chien, Xuhui Zhou, Yizhi Li, Caiming Xiong, Luis Villa, Stella Biderman, Hanlin Li, Daphne Ippolito, Sara Hooker, Jad Kabbara, and Sandy Pentland. Consent in crisis: The rapid decline of the ai data commons, 2024a. URL <https://arxiv.org/abs/2407.14933>.
- Shayne Longpre, Nikhil Singh, Manuel Cherep, Kushagra Tiwary, Joanna Materzynska, William Brannon, Robert Mahari, Manan Dey, Mohammed Hamdy, Nayan Saxena, Ahmad Mustafa Anis, Emad A. Alghamdi, Vu Minh Chien, Naana Obeng-Marnu, Da Yin, Kun Qian, Yizhi Li, Minnie Liang, An Dinh, Shrestha Mohanty, Deividas Mataciunas, Tobin South, Jianguo Zhang, Ariel N. Lee, Campbell S. Lund, Christopher Klamm, Damien Sileo, Diganta Misra, Enrico Shippole, Kevin Klyman, Lester JV Miranda, Niklas Muennighoff, Seonghyeon Ye, Seungone Kim, Vipul Gupta, Vivek Sharma, Xuhui Zhou, Caiming Xiong, Luis Villa, Stella Biderman, Alex Pentland, Sara Hooker, and Jad Kabbara. Bridging the data provenance gap across text, speech and video, 2024b. URL <https://arxiv.org/abs/2412.17847>.
- Holy Lovenia, Rahmad Mahendra, Salsabil Maulana Akbar, Lester James V Miranda, Jennifer Santoso, Elyanah Aco, Akhdan Fadhilah, Jonibek Mansurov, Joseph Marvin Imperial, Onno P Kampman, et al. Seacrowd: A multilingual multimodal data hub and benchmark suite for southeast asian languages. *arXiv preprint arXiv:2406.10118*, 2024.
- Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Nouamane Tazi, Ao Tang, Dmytro Pykhtar, Jiawei Liu, Yuxiang Wei, Tianyang Liu, Max Tian, Denis Kocetkov, Arthur Zucker, Younes Belkada, Zijian Wang, Qian Liu, Dmitry Abulkhanov, Indraneil Paul, Zhuang Li, Wen-Ding Li, Megan Risdal, Jia Li, Jian Zhu, Terry Yue Zhuo, Evgenii Zheltonozhskii, Nii Osae Osae Dade, Wenhao Yu, Lucas Krauß, Naman Jain, Yixuan Su, Xuanli He, Manan Dey, Edoardo Abati, Yekun Chai, Niklas Muennighoff, Xiangru Tang, Muhtasham Oblokulov, Christopher Akiki, Marc Marone, Chenghao Mou, Mayank Mishra, Alex Gu, Binyuan Hui, Tri Dao, Armel Zebaze, Olivier Dehaene, Nicolas Patry, Canwen Xu, Julian McAuley, Han Hu, Torsten Scholak, Sebastien Paquet, Jennifer Robinson, Carolyn Jane Anderson, Nicolas Chapados, Mostofa Patwary, Nima Tajbakhsh, Yacine Jernite, Carlos Muñoz Ferrandis, Lingming Zhang, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. Starcoder 2 and the stack v2: The next generation, 2024. URL <https://arxiv.org/abs/2402.19173>.
- Xing Han Lu, Siva Reddy, and Harm de Vries. The StatCan dialogue dataset: Retrieving data tables through conversations with genuine intents. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 2799–2829, Dubrovnik, Croatia, may 2023. Association for Computational Linguistics. URL <https://arxiv.org/abs/2304.01412>.
- Xing Han Lù, Zdeněk Kasner, and Siva Reddy. Weblinx: Real-world website navigation with multi-turn dialogue, 2024.
- 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 (eds.), *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pp. 142–150, Portland, Oregon, USA, jun 2011. Association for Computational Linguistics. URL <https://aclanthology.org/P11-1015>.
- Yash Madhani, Mitesh M. Khapra, and Anoop Kunchukuttan. Bhasa-abhijnaanam: Native-script and romanized language identification for 22 Indic languages. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association*

- for *Computational Linguistics (Volume 2: Short Papers)*, pp. 816–826, Toronto, Canada, jul 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-short.71. URL <https://aclanthology.org/2023.acl-short.71>.
- Andani Madodonga, Vukosi Marivate, and Matthew Adendorff. Izindaba-tindzaba: Machine learning news categorisation for long and short text for isizulu and siswati. 4, Jan. 2023. doi: 10.55492/dhasa.v4i01.4449. URL <https://upjournals.up.ac.za/index.php/dhasa/article/view/4449>.
- Wei Chen Maggie, Phil Culliton. Tweet sentiment extraction, 2020. URL <https://kaggle.com/competitions/tweet-sentiment-extraction>.
- Rahmad Mahendra, Alham Fikri Aji, Samuel Louvan, Fahrurrozi Rahman, and Clara Vania. IndoNLI: A natural language inference dataset for Indonesian. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 10511–10527, Online and Punta Cana, Dominican Republic, nov 2021. Association for Computational Linguistics. URL <https://aclanthology.org/2021.emnlp-main.821>.
- Arthur Malajyan, Karen Avetisyan, and Tsolak Ghukasyan. Arpa: Armenian paraphrase detection corpus and models, 2020.
- P. Malo, A. Sinha, P. Korhonen, J. Wallenius, and P. Takala. Good debt or bad debt: Detecting semantic orientations in economic texts. *Journal of the Association for Information Science and Technology*, 65, 2014.
- Marco Marelli, Stefano Menini, Marco Baroni, Luisa Bentivogli, Raffaella Bernardi, and Roberto Zamparelli. A SICK cure for the evaluation of compositional distributional semantic models. In Nicoletta Calzolari, Khalid Choukri, Thierry Declerck, Hrafn Loftsson, Bente Maegaard, Joseph Mariani, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, pp. 216–223, Reykjavik, Iceland, May 2014. European Language Resources Association (ELRA). URL http://www.lrec-conf.org/proceedings/lrec2014/pdf/363_Paper.pdf.
- Vukosi Marivate, Moseli Mots’Oehli, Valencia Wagner, Richard Lastrucci, and Isheanesu Dzingirai. Puoberta: Training and evaluation of a curated language model for setswana. In *SACAIR 2023 (To Appear)*, 2023.
- Philip May. Machine translated multilingual sts benchmark dataset. 2021. URL <https://github.com/PhilipMay/stsb-multi-mt>.
- Philip May, Brooke Fujita, and Tom Aarsen. stsb-multi-mt, 2021. URL <https://github.com/PhilipMay/stsb-multi-mt>. GitHub repository.
- Rui Meng, Ye Liu, Shafiq Rayhan Joty, Caiming Xiong, Yingbo Zhou, and Semih Yavuz. Sfr-embedding-mistral:enhance text retrieval with transfer learning. Salesforce AI Research Blog, 2024. URL <https://blog.salesforceairesearch.com/sfr-embedded-mistral/>.
- Yev Meyer, Marjan Emadi, Dhruv Nathawani, Lipika Ramaswamy, Kendrick Boyd, Maarten Van Segbroeck, Matthew Grossman, Piotr Mlocek, and Drew Newberry. Synthetic-Text-To-SQL: A synthetic dataset for training language models to generate sql queries from natural language prompts, April 2024. URL <https://huggingface.co/datasets/gretelai/synthetic-text-to-sql>.
- Roshanak Mirzaee, Hossein Rajaby Faghihi, Qiang Ning, and Parisa Kordjamshidi. Spartqa: A textual question answering benchmark for spatial reasoning. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 4582–4598, 2021.
- Julius Monsen and Arne Jonsson. A method for building non-english corpora for abstractive text summarization. In *Proceedings of CLARIN Annual Conference*, 2021.
- Niklas Muennighoff. Sgpt: Gpt sentence embeddings for semantic search, 2022.
- Niklas Muennighoff, Qian Liu, Armel Zebaze, Qinkai Zheng, Binyuan Hui, Terry Yue Zhuo, Swayam Singh, Xiangru Tang, Leandro von Werra, and Shayne Longpre. Octopack: Instruction tuning code large language models. *arXiv preprint arXiv:2308.07124*, 2023a.

- Niklas Muennighoff, Nouamane Tazi, Loic Magne, and Nils Reimers. MTEB: Massive text embedding benchmark. In Andreas Vlachos and Isabelle Augenstein (eds.), *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 2014–2037, Dubrovnik, Croatia, May 2023b. Association for Computational Linguistics. doi: 10.18653/v1/2023.eacl-main.148. URL <https://aclanthology.org/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, 2023c.
- Niklas Muennighoff, Hongjin Su, Liang Wang, Nan Yang, Furu Wei, Tao Yu, Amanpreet Singh, and Douwe Kiela. Generative representational instruction tuning, 2024.
- Shamsuddeen Hassan Muhammad, Idris Abdulmumin, Abinew Ali Ayele, Nedjma Ousidhoum, David Ifeoluwa Adelani, Seid Muhie Yimam, Ibrahim Sa'id Ahmad, Meriem Beloucif, Saif Mohammad, Sebastian Ruder, Oumaima Hourrane, Pavel Brazdil, Felermimo D'ario M'ario Ant'onio Ali, Davis Davis, Salomey Osei, Bello Shehu Bello, Falalu Ibrahim, Tajuddeen Gwadabe, Samuel Rutunda, Tadesse Belay, Wendimu Baye Messelle, Hailu Beshada Balcha, Sisay Adugna Chala, Hagos Tesfahun Gebremichael, Bernard Opoku, and Steven Arthur. Afrisenti:a twitter sentiment analysis benchmark for african languages. 2023.
- Timo Möller, Julian Risch, and Malte Pietsch. Germanquad and germandpr: Improving non-english question answering and passage retrieval, 2021.
- Jørgen Johnsen Navjord and Jon-Mikkel Ryen Korsvik. Beyond extractive: advancing abstractive automatic text summarization in norwegian with transformers. Master's thesis, Norwegian University of Life Sciences, Ås, 2023.
- Thong Nguyen, Mariya Hendriksen, Andrew Yates, and Maarten de Rijke. Multimodal learned sparse retrieval with probabilistic expansion control. In *European Conference on Information Retrieval*, pp. 448–464. Springer, 2024.
- Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. MS MARCO: A human generated machine reading comprehension dataset. *CoRR*, abs/1611.09268, 2016. URL <http://arxiv.org/abs/1611.09268>.
- Dan Nielsen. ScandEval: A benchmark for Scandinavian natural language processing. In Tanel Alum"ae and Mark Fishel (eds.), *Proceedings of the 24th Nordic Conference on Computational Linguistics (NoDaLiDa)*, pp. 185–201, T'orshavn, Faroe Islands, may 2023. University of Tartu Library. URL <https://aclanthology.org/2023.nodalida-1.20>.
- Joel Niklaus, Matthias Stürmer, and Ilias Chalkidis. An empirical study on cross-x transfer for legal judgment prediction, 2022.
- Joakim Nivre, Marie-Catherine De Marneffe, Filip Ginter, Yoav Goldberg, Jan Hajic, Christopher D. Manning, Ryan McDonald, Slav Petrov, Sampo Pyysalo, and Natalia Silveira. Universal dependencies v1: A multilingual treebank collection. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*, pp. 1659–1666, 2016.
- Jeppe Nørregaard and Leon Derczynski. DanFEVER: claim verification dataset for Danish. In Simon Dobnik and Lilja Øvrelid (eds.), *Proceedings of the 23rd Nordic Conference on Computational Linguistics (NoDaLiDa)*, pp. 422–428, Reykjavik, Iceland (Online), 2021. Link"oping University Electronic Press, Sweden. URL <https://aclanthology.org/2021.nodalida-main.47>.
- Maciej Ogrodniczuk and Mateusz Kope'c. The Polish summaries corpus. In Nicoletta Calzolari, Khalid Choukri, Thierry Declerck, Hrafn Loftsson, Bente Maegaard, Joseph Mariani, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, pp. 3712–3715, Reykjavik, Iceland, may 2014. European Language Resources Association (ELRA). URL http://www.lrec-conf.org/proceedings/lrec2014/pdf/1211_Paper.pdf.

- Maciej Ogrodniczuk and Łukasz Kobyliński (eds.). *Proceedings of the PolEval 2019 Workshop*, Warsaw, Poland, 2019. Institute of Computer Science, Polish Academy of Sciences. ISBN 978-83-63159-28-3. URL <http://2019.poleval.pl/files/poleval2019.pdf>.
- 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 (eds.), *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 7092–7108, Online and Punta Cana, Dominican Republic, nov 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.568. URL <https://aclanthology.org/2021.emnlp-main.568>.
- Nedjma Ousidhoum, Shamsuddeen Hassan Muhammad, Mohamed Abdalla, Idris Abdulmumin, Ibrahim Said Ahmad, Sanchit Ahuja, Alham Fikri Aji, Vladimir Araujo, Abinew Ali Ayele, Pavan Baswani, et al. Semrel2024: A collection of semantic textual relatedness datasets for 14 languages. *arXiv preprint arXiv:2402.08638*, 2024.
- Hille Pajupuu, Jaan Pajupuu, Rene Altrov, and Kairi Tamuri. Estonian Valence Corpus / Eesti valentsikorpus. 11 2023. doi: 10.6084/m9.figshare.24517054.v1. URL https://figshare.com/articles/dataset/Estonian_Valence_Corpus_Eesti_valentsikorpus/24517054.
- Christos Papaloukas, Ilias Chalkidis, Konstantinos Athinaios, Despina-Athanasia Pantazi, and Manolis Koubarakis. Multi-granular legal topic classification on greek legislation. In *Proceedings of the Natural Legal Language Processing Workshop 2021*, pp. 63–75, Punta Cana, Dominican Republic, 2021. Association for Computational Linguistics. doi: 10.48550/arXiv.2109.15298. URL <https://arxiv.org/abs/2109.15298>.
- Shantipriya Parida, Sambit Sekhar, Soumendra Kumar Sahoo, Swateek Jena, Abhijeet Parida, Satya Ranjan Dash, and Guneet Singh Kohli. Odiagenai: Generative ai and llm initiative for the odia language. <https://huggingface.co/OdiaGenAI>, 2023.
- Michael Park, Erin Leahey, and Russell J. Funk. Papers and patents are becoming less disruptive over time. *Nature*, 613:138–144, 2023. URL <https://api.semanticscholar.org/CorpusID:255466666>.
- Long Phan, Alice Gatti, Ziwen Han, Nathaniel Li, Josephina Hu, Hugh Zhang, Sean Shi, Michael Choi, Anish Agrawal, Arnav Chopra, Adam Khoja, Ryan Kim, Jason Hausenloy, Oliver Zhang, Mantas Mazeika, Daron Anderson, Tung Nguyen, Mobeen Mahmood, Fiona Feng, Steven Y. Feng, Haoran Zhao, Michael Yu, Varun Gangal, Chelsea Zou, Zihan Wang, Jessica P. Wang, Pawan Kumar, Oleksandr Pokutnyi, Robert Gerbicz, Serguei Popov, John-Clark Levin, Mstyslav Kazakov, Johannes Schmitt, Geoff Galgon, Alvaro Sanchez, Yongki Lee, Will Yeadon, Scott Sauer, Marc Roth, Chidozie Agu, Søren Riis, Fabian Giska, Saiteja Utpala, Zachary Giboney, Gashaw M. Goshu, Joan of Arc Xavier, Sarah-Jane Crowson, Mohinder Maheshbhai Naiya, Noah Burns, Lennart Finke, Zerui Cheng, Hyunwoo Park, Francesco Fournier-Facio, John Wydallis, Mark Nandor, Ankit Singh, Tim Gehringer, Jiaqi Cai, Ben McCarty, Darling Duclosel, Jungbae Nam, Jennifer Zampese, Ryan G. Hoerr, Aras Bacho, Gautier Abou Loume, Abdallah Galal, Hangrui Cao, Alexis C Garretson, Damien Sileo, Qiuyu Ren, Doru Cojoc, Pavel Arkhipov, Usman Qazi, Lianghui Li, Sumeet Motwani, Christian Schroeder de Witt, Edwin Taylor, Johannes Veith, Eric Singer, Taylor D. Hartman, Paolo Rissone, Jaehyeok Jin, Jack Wei Lun Shi, Chris G. Willcocks, Joshua Robinson, Aleksandar Mikov, Ameya Prabhu, Longke Tang, Xavier Alapont, Justine Leon Uro, Kevin Zhou, Emily de Oliveira Santos, Andrey Pupasov Maksimov, Edward Vendrow, Kengo Zenitani, Julien Guillod, Yuqi Li, Joshua Vendrow, Vladyslav Kuchkin, Ng Ze-An, Pierre Marion, Denis Efremov, Jayson Lynch, Kaiqu Liang, Andrew Gritsevskiy, Dakotah Martinez, Ben Pageler, Nick Crispino, Dimitri Zvonkine, Natanael Wildner Fraga, Saeed Soori, Ori Press, Henry Tang, Julian Salazar, Sean R. Green, Lina Brüssel, Moon Twayana, Aymeric Dieuleveut, T. Ryan Rogers, Wenjin Zhang, Bikun Li, Jinzhou Yang, Arun Rao, Gabriel Loiseau, Mikhail Kalinin, Marco Lukas, Ciprian Manolescu, Subrata Mishra, Ariel Ghislain Kmogne Kamdoun, Tobias Kreiman, Tad Hogg, Alvin Jin, Carlo Bosio, Gongbo Sun, Brian P Coppola, Tim Tarver, Haline Heidinger, Rafael Sayous, Stefan Ivanov, Joseph M Cavanagh, Jiawei Shen, Joseph Marvin Imperial, Philippe Schwaller, Shaipranesh Senthilkuma, Andres M Bran, Ali Dehghan, Andres Algaba, Brecht Verbeken, David Noever, Ragavendran P V, Lisa Schut, Ilia

Sucholutsky, Evgenii Zheltonozhskii, Derek Lim, Richard Stanley, Shankar Sivarajan, Tong Yang, John Maar, Julian Wykowski, Martí Oller, Jennifer Sandlin, Anmol Sahu, Yuzheng Hu, Sara Fish, Nasser Heydari, Archimedes Apronti, Kaivalya Rawal, Tobias Garcia Vilchis, Yuexuan Zu, Martin Lackner, James Koppel, Jeremy Nguyen, Daniil S. Antonenko, Steffi Chern, Bingchen Zhao, Pierrot Arsene, Alan Goldfarb, Sergey Ivanov, Rafał Poświata, Chenguang Wang, Daofeng Li, Donato Crisostomi, Andrea Achilleos, Benjamin Myklebust, Archan Sen, David Perrella, Nurdin Kaparov, Mark H Inlow, Allen Zang, Elliott Thornley, Daniil Orel, Vladislav Poritski, Shalev Ben-David, Zachary Berger, Parker Whitfill, Michael Foster, Daniel Munro, Linh Ho, Dan Bar Hava, Aleksey Kuchkin, Robert Lauff, David Holmes, Frank Sommerhage, Keith Schneider, Zakayo Kazibwe, Nate Stambaugh, Mukhwinder Singh, Ilias Magoulas, Don Clarke, Dae Hyun Kim, Felipe Meneguitti Dias, Veit Elser, Kanu Priya Agarwal, Victor Efren Guadarrama Vilchis, Immo Klose, Christoph Demian, Ujjwala Anantheswaran, Adam Zweiger, Guglielmo Albani, Jeffery Li, Nicolas Daans, Maksim Radionov, Václav Rozhoň, Ziqiao Ma, Christian Stump, Mohammed Berkani, Jacob Platnick, Volodymyr Nevirkovets, Luke Basler, Marco Piccardo, Ferenc Jeanplong, Niv Cohen, Josef Tkadlec, Paul Rosu, Piotr Padlewski, Stanislaw Barzowski, Kyle Montgomery, Aline Menezes, Arkil Patel, Zixuan Wang, Jamie Tucker-Foltz, Jack Stade, Tom Goertzen, Fereshteh Kazemi, Jeremiah Milbauer, John Arnold Ambay, Abhishek Shukla, Yan Carlos Leyva Labrador, Alan Givré, Hew Wolff, Vivien Roszbach, Muhammad FayeZ Aziz, Younesse Kaddar, Yanxu Chen, Robin Zhang, Jiayi Pan, Antonio Terpin, Niklas Muennighoff, Hailey Schoelkopf, Eric Zheng, Avishy Carmi, Adam Jones, Jainam Shah, Ethan D. L. Brown, Kelin Zhu, Max Bartolo, Richard Wheeler, Andrew Ho, Shaul Barkan, Jiaqi Wang, Martin Stehberger, Egor Kretov, Kaustubh Sridhar, Zienab EL-Wasif, Anji Zhang, Daniel Pyda, Joanna Tam, David M. Cunningham, Vladimir Goryachev, Demosthenes Patramanis, Michael Krause, Andrew Redenti, Daniel Bugas, David Aldous, Jesyin Lai, Shannon Coleman, Mohsen Bahaloo, Jiangnan Xu, Sangwon Lee, Sandy Zhao, Ning Tang, Michael K. Cohen, Micah Carroll, Orr Paradise, Jan Hendrik Kirchner, Stefan Steinerberger, Maksym Ovchynnikov, Jason O. Matos, Adithya Shenoy, Benedito Alves de Oliveira Junior, Michael Wang, Yuzhou Nie, Paolo Giordano, Philipp Petersen, Anna Szttyber-Betley, Priti Shukla, Jonathan Crozier, Antonella Pinto, Shreyas Verma, Prashant Joshi, Zheng-Xin Yong, Allison Tee, Jérémy Andréoletti, Orion Weller, Raghav Singhal, Gang Zhang, Alexander Ivanov, Seri Khoury, Hamid Mostaghimi, Kunvar Thaman, Qijia Chen, Tran Quoc Khánh, Jacob Loader, Stefano Cavalleri, Hannah Szlyk, Zachary Brown, Jonathan Roberts, William Alley, Kunyang Sun, Ryan Stendall, Max Lamparth, Anka Reuel, Ting Wang, Hanmeng Xu, Sreenivas Goud Raparathi, Pablo Hernández-Cámara, Freddie Martin, Dmitry Malishev, Thomas Preu, Tomek Korbak, Marcus Abramovitch, Dominic Williamson, Ziye Chen, Biró Bálint, M Saiful Bari, Peyman Kassani, Zihao Wang, Behzad Ansarinejad, Laxman Prasad Goswami, Yewen Sun, Hossam Elgnainy, Daniel Tordera, George Balabanian, Earth Anderson, Lynna Kvistad, Alejandro José Moyano, Rajat Maheshwari, Ahmad Sakor, Murat Eron, Isaac C. McAlister, Javier Gimenez, Innocent Enyekwe, Andrew Favre D. O., Shailesh Shah, Xiaoxiang Zhou, Firuz Kamalov, Ronald Clark, Sherwin Abdoli, Tim Santens, Khalida Meer, Harrison K Wang, Kalyan Ramakrishnan, Evan Chen, Alessandro Tomasiello, G. Bruno De Luca, Shi-Zhuo Looi, Vinh-Kha Le, Noam Kolt, Niels Münder, Avi Semler, Emma Rodman, Jacob Drori, Carl J Fossum, Milind Jagota, Ronak Pradeep, Honglu Fan, Tej Shah, Jonathan Eicher, Michael Chen, Kushal Thaman, William Merrill, Carter Harris, Jason Gross, Ilya Gusev, Asankhaya Sharma, Shashank Agnihotri, Pavel Zhelnov, Siranut Usawasutsakorn, Mohammadreza Mofayezi, Sergei Bogdanov, Alexander Piperski, Marc Carauleanu, David K. Zhang, Dylan Ler, Roman Leventov, Ignat Soroko, Thorben Jansen, Pascal Lauer, Joshua Duersch, Vage Taamazyan, Wiktor Morak, Wenjie Ma, William Held, Tran Đức Huy, Ruicheng Xian, Armel Randy Zebaze, Mohanad Mohamed, Julian Noah Leser, Michelle X Yuan, Laila Yacar, Johannes Lengler, Hossein Shahrtash, Edson Oliveira, Joseph W. Jackson, Daniel Espinosa Gonzalez, Andy Zou, Muthu Chidambaram, Timothy Manik, Hector Haffenden, Dashiell Stander, Ali Dasouqi, Alexander Shen, Emilien Duc, Bitá Golshani, David Stap, Mikalai Uzhou, Alina Borisovna Zhidkovskaya, Lukas Lewark, Mátyás Vincze, Dustin Wehr, Colin Tang, Zaki Hossain, Shaun Phillips, Jiang Muzhen, Fredrik Ekström, Angela Hammon, Oam Patel, Nicolas Remy, Faraz Farhidi, George Medley, Forough Mohammadzadeh, Madellene Peñaflo, Haile Kassahun, Alena Friedrich, Claire Sparrow, Taom Sakal, Omkar Dhamane, Ali Khajegili Mirabadi, Eric Hallman, Mike Battaglia, Mohammad Maghsoudimehrabani, Hieu Hoang, Alon Amit, Dave Hulbert, Roberto Pereira, Simon Weber, Stephen Mensah, Nathan Andre, Anton Peristyy, Chris Harjadi, Himanshu Gupta, Stephen Malina, Samuel Albanie, Will Cai, Mustafa Mehkary, Frank Reidegeld, Anna-Katharina Dick, Cary Friday, Jasdeep Sidhu, Wanyoung Kim, Mariana Costa, Hubeyb Gurdogan, Brian Weber,

- Harsh Kumar, Tong Jiang, Arunim Agarwal, Chiara Ceconello, Warren S. Vaz, Chao Zhuang, Haon Park, Andrew R. Tawfeek, Daattavya Aggarwal, Michael Kirchhof, Linjie Dai, Evan Kim, Johan Ferret, Yuzhou Wang, Minghao Yan, Krzysztof Burdzy, Lixin Zhang, Antonio Franca, Diana T. Pham, Kang Yong Loh, Joshua Robinson, Shreen Gul, Gunjan Chhablani, Zhehang Du, Adrian Cosma, Colin White, Robin Riblet, Prajvi Saxena, Jacob Votava, Vladimir Vinnikov, Ethan Delaney, Shiv Halasyamani, Syed M. Shahid, Jean-Christophe Mourrat, Lavr Vetoshkin, Renas Bacho, Vincent Ginis, Aleksandr Maksapetyan, Florencia de la Rosa, Xiuyu Li, Guillaume Malod, Leon Lang, Julien Laurendeau, Fatimah Adesanya, Julien Portier, Lawrence Hollom, Victor Souza, Yuchen Anna Zhou, Yiğit Yalın, Gbenga Daniel Obikoya, Luca Arnaboldi, Rai, Filippo Bigi, Kaniuar Bacho, Pierre Clavier, Gabriel Recchia, Mara Popescu, Nikita Shulga, Ngefor Mildred Tanwie, Thomas C. H. Lux, Ben Rank, Colin Ni, Alesia Yakimchyk, Huanxu, Liu, Olle Häggström, Emil Verkama, Himanshu Narayan, Hans Gundlach, Leonor Brito-Santana, Brian Amaro, Vivek Vajipey, Rynaa Grover, Yiyang Fan, Gabriel Poesia Reis e Silva, Linwei Xin, Yosi Kratish, Jakub Lucki, Wen-Ding Li, Justin Xu, Kevin Joseph Scaria, Freddie Vargus, Farzad Habibi, Long, Lian, Emanuele Rodolà, Jules Robins, Vincent Cheng, Declan Grabb, Ida Bosio, Tony Fruhauff, Ido Akov, Eve J. Y. Lo, Hao Qi, Xi Jiang, Ben Segev, Jingxuan Fan, Sarah Martinson, Erik Y. Wang, Kaylie Hausknecht, Michael P. Brenner, Mao Mao, Yibo Jiang, Xinyu Zhang, David Avagian, Eshawn Jessica Scipio, Muhammad Rehan Siddiqi, Alon Ragoler, Justin Tan, Deepakkumar Patil, Rebeka Plecnik, Aaron Kirtland, Roselynn Grace Montecillo, Stephane Durand, Omer Faruk Bodur, Zahra Adoul, Mohamed Zekry, Guillaume Douville, Ali Karakoc, Tania C. B. Santos, Samir Shamseldeen, Loukmane Karim, Anna Liakhovitskaia, Nate Resman, Nicholas Farina, Juan Carlos Gonzalez, Gabe Maayan, Sarah Hoback, Rodrigo De Oliveira Pena, Glen Sherman, Hodjat Mariji, Rasoul Pouriamanesh, Wentao Wu, Gözdenur Demir, Sandra Mendoza, Ismail Alarab, Joshua Cole, Danyelle Ferreira, Bryan Johnson, Hsiaoyun Milliron, Mohammad Safdari, Liangti Dai, Siriphan Arthornthurasuk, Alexey Pronin, Jing Fan, Angel Ramirez-Trinidad, Ashley Cartwright, Daphiny Pottmaier, Omid Taheri, David Outevsky, Stanley Stepanic, Samuel Perry, Luke Askew, Raúl Adrián Huerta Rodríguez, Abdelkader Dendane, Sam Ali, Ricardo Lorena, Krishnamurthy Iyer, Sk Md Salauddin, Murat Islam, Juan Gonzalez, Josh Ducey, Russell Campbell, Maja Somrak, Vasilios Mavroudis, Eric Vergo, Juehang Qin, Benjámín Borbás, Eric Chu, Jack Lindsey, Anil Radhakrishnan, Antoine Jallon, I. M. J. McInnis, Alex Hoover, Sören Möller, Song Bian, John Lai, Tejal Patwardhan, Summer Yue, Alexandr Wang, and Dan Hendrycks. *Humanity's last exam*, 2025. URL <https://arxiv.org/abs/2501.14249>.
- Lidia Pivovarova, Ekaterina Pronoza, Elena Yagunova, and Anton Pronoza. Paraphraser: Russian paraphrase corpus and shared task. In *Conference on artificial intelligence and natural language*, pp. 211–225. Springer, 2017.
- Rafał Poświata, Sławomir Dadas, and Michał Perełkiewicz. PL-MTEB: Polish Massive Text Embedding Benchmark. *arXiv preprint arXiv:2405.10138*, 2024.
- Gowtham Ramesh, Sumanth Doddapaneni, Aravinth Bheemaraj, Mayank Jobanputra, Raghavan AK, Ajitesh Sharma, Sujit Sahoo, Harshita Diddee, Mahalakshmi J, Divyanshu Kakwani, Navneet Kumar, Aswin Pradeep, Srihari Nagaraj, Kumar Deepak, Vivek Raghavan, Anoop Kunchukuttan, Pratyush Kumar, and Mitesh Shantadevi Khapra. Samanantar: The Largest Publicly Available Parallel Corpora Collection for 11 Indic Languages. *Transactions of the Association for Computational Linguistics*, 10:145–162, 02 2022. ISSN 2307-387X. doi: 10.1162/tacl_a_00452. URL https://doi.org/10.1162/tacl_a_00452.
- Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks, 2019.
- Nils Reimers, Philip Beyer, and Iryna Gurevych. Task-oriented intrinsic evaluation of semantic textual similarity. In Yuji Matsumoto and Rashmi Prasad (eds.), *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pp. 87–96, Osaka, Japan, December 2016. The COLING 2016 Organizing Committee. URL <https://aclanthology.org/C16-1009>.
- Neil Christian R. Riego, Danny Bell Villarba, Ariel Antwaun Rolando C. Sison, Fernandez C. Pineda, and Herminiño C. Lagunzad. Enhancement to low-resource text classification via sequential transfer learning. *United International Journal for Research and Technology*, 04:72–82, 2023.

- Kirk Roberts, Tasmee Alam, Steven Bedrick, Dina Demner-Fushman, Kyle Lo, Ian Soboroff, Ellen Voorhees, Lucy Lu Wang, and William R Hersh. Searching for scientific evidence in a pandemic: An overview of trec-covid, 2021.
- Anna Rogers, Olga Kovaleva, Matthew Downey, and Anna Rumshisky. Getting closer to ai complete question answering: A set of prerequisite real tasks. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pp. 8722–8731, 2020.
- Andrew Rosenberg and Julia Hirschberg. V-measure: A conditional entropy-based external cluster evaluation measure. In Jason Eisner (ed.), *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, pp. 410–420, Prague, Czech Republic, June 2007. Association for Computational Linguistics. URL <https://aclanthology.org/D07-1043>.
- Paul Rottger, Bertie Vidgen, Dong Nguyen, Zeerak Waseem, Helen Margetts, and Janet Pierrehumbert. HateCheck: Functional tests for hate speech detection models. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 41–58, Online, aug 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.4. URL <https://aclanthology.org/2021.acl-long.4>.
- Ivan Rybin, Vladislav Korablinov, Pavel Efimov, and Pavel Braslavski. Rubq 2.0: An innovated russian question answering dataset. In *ESWC*, pp. 532–547, 2021.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. Winogrande: An adversarial winograd schema challenge at scale. *Communications of the ACM*, 64(9):99–106, 2021.
- Maarten Sap, Hannah Rashkin, Derek Chen, Ronan Le Bras, and Yejin Choi. Social iqa: Commonsense reasoning about social interactions. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 4463–4473, 2019.
- Salim Sazzed. Cross-lingual sentiment classification in low-resource bengali language. In *Proceedings of the Sixth Workshop on Noisy User-generated Text (W-NUT 2020)*, pp. 50–60, 2020.
- Alexander Sboev, Aleksandr Naumov, and Roman Rybka. Data-driven model for emotion detection in russian texts. *Procedia Computer Science*, 190:637–642, 2021.
- Konstantinos Sechidis, Grigorios Tsoumakas, and Ioannis Vlahavas. On the stratification of multi-label data. In *Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2011, Athens, Greece, September 5-9, 2011, Proceedings, Part III* 22, pp. 145–158. Springer, 2011.
- Darsh Shah, Tao Lei, Alessandro Moschitti, Salvatore Romeo, and Preslav Nakov. Adversarial domain adaptation for duplicate question detection. In Ellen Riloff, David Chiang, Julia Hockenmaier, and Jun’ichi Tsujii (eds.), *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 1056–1063, Brussels, Belgium, 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1131. URL <https://aclanthology.org/D18-1131>.
- Zareen Sharf. Roman Urdu Data Set. UCI Machine Learning Repository, 2018. DOI: <https://doi.org/10.24432/C58325>.
- Eva Sharma, Chen Li, and Lu Wang. BIGPATENT: A large-scale dataset for abstractive and coherent summarization. *CoRR*, abs/1906.03741, 2019. URL <http://arxiv.org/abs/1906.03741>.
- Tatiana Shavrina, Alena Fenogenova, Anton Emelyanov, Denis Shevelev, Ekaterina Artemova, Valentin Malykh, Vladislav Mikhailov, Maria Tikhonova, Andrey Chertok, and Andrey Evlampiev. Russiansuperglue: A russian language understanding evaluation benchmark. *arXiv preprint arXiv:2010.15925*, 2020.
- Emily Sheng and David Uthus. Investigating societal biases in a poetry composition system, 2020.

- Iyanuoluwa Shode, David Ifeoluwa Adelani, Jing Peng, and Anna Feldman. Nollysenti: Leveraging transfer learning and machine translation for nigerian movie sentiment classification. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 986–998, 2023.
- Harman Singh, Nitish Gupta, Shikhar Bharadwaj, Dinesh Tewari, and Partha Talukdar. Indicgenbench: A multilingual benchmark to evaluate generation capabilities of llms on indic languages, 2024a.
- Shivalika Singh, Freddie Vargus, Daniel Dsouza, Börje F. Karlsson, Abinaya Mahendiran, Wei-Yin Ko, Herumb Shandilya, Jay Patel, Deividas Mataciunas, Laura OMahony, Mike Zhang, Ramith Hettiarachchi, Joseph Wilson, Marina Machado, Luisa Souza Moura, Dominik Krzemiński, Hakimeh Fadaei, Irem Ergün, Ifeoma Okoh, Aisha Alaagib, Oshan Mudannayake, Zaid Alyafeai, Vu Minh 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, 2024b.
- Artem Snegirev, Maria Tikhonova, Anna Maksimova, Alena Fenogenova, and Alexander Abramov. The russian-focused embedders’ exploration: rumteb benchmark and russian embedding model design, 2024. URL <https://arxiv.org/abs/2408.12503>.
- Vésteinn Snæbjarnarson, Annika Simonsen, Goran Glavaš, and Ivan Vulić. Transfer to a low-resource language via close relatives: The case study on faroese. In *Proceedings of the 24th Nordic Conference on Computational Linguistics (NoDaLiDa)*, Tórshavn, Faroe Islands, may 22–24 2023. Link"oping University Electronic Press, Sweden.
- Ian Soboroff and Stephen Robertson. Building a filtering test collection for trec 2002. In *Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval*, pp. 243–250, 2003.
- Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. Mpnet: Masked and permuted pre-training for language understanding. *Advances in neural information processing systems*, 33: 16857–16867, 2020.
- Gizem Soğancıoğlu, Hakime Öztürk, and Arzucan Özgür. BIOSSES: a semantic sentence similarity estimation system for the biomedical domain. *Bioinformatics*, 33(14):i49–i58, 07 2017. ISSN 1367-4803. doi: 10.1093/bioinformatics/btx238. URL <https://doi.org/10.1093/bioinformatics/btx238>.
- Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models, 2023.
- Michał Stefańnik, Marek Kadlc’ik, Piotr Gramacki, and Petr Sojka. Resources and few-shot learners for in-context learning in slavic languages. *arXiv preprint arXiv:2304.01922*, 2023.
- Hongjin Su, Howard Yen, Mengzhou Xia, Weijia Shi, Niklas Muennighoff, Han yu Wang, Haisu Liu, Quan Shi, Zachary S. Siegel, Michael Tang, Ruoxi Sun, Jinsung Yoon, Sercan O. Arik, Danqi Chen, and Tao Yu. Bright: A realistic and challenging benchmark for reasoning-intensive retrieval, 2024. URL <https://arxiv.org/abs/2407.12883>.
- Piotr Szymański and Tomasz Kajdanowicz. A network perspective on stratification of multi-label data. In Paula Branco Luís Torgo and Nuno Moniz (eds.), *Proceedings of the First International Workshop on Learning with Imbalanced Domains: Theory and Applications*, volume 74 of *Proceedings of Machine Learning Research*, pp. 22–35. PMLR, 22 Sep 2017. URL <https://proceedings.mlr.press/v74/szyma%C5%84ski17a.html>.
- Qingyu Tan, Hwee Tou Ng, and Lidong Bing. Towards benchmarking and improving the temporal reasoning capability of large language models. *arXiv preprint arXiv:2306.08952*, 2023.
- Nandan Thakur, Nils Reimers, Andreas R"uckl'e, Abhishek Srivastava, and Iryna Gurevych. BEIR: A heterogeneous benchmark for zero-shot evaluation of information retrieval models. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021. URL <https://openreview.net/forum?id=wCu6T5xFjeJ>.

- "Nandan Thakur, Luiz Bonifacio, Maik Fr"obe, Alexander Bondarenko, Ehsan Kamaloo, Martin Potthast, Matthias Hagen, and Jimmy Lin". "systematic evaluation of neural retrieval models on the Touch'e 2020 argument retrieval subset of BEIR". In *"Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval"*, 2024.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. FEVER: a large-scale dataset for fact extraction and VERification. In Marilyn Walker, Heng Ji, and Amanda Stent (eds.), *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 809–819, New Orleans, Louisiana, jun 2018a. Association for Computational Linguistics. doi: 10.18653/v1/N18-1074. URL <https://aclanthology.org/N18-1074>.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. Fever: a large-scale dataset for fact extraction and verification, 2018b.
- J"org Tiedemann and Santhosh Thottingal. Opus-*mt* — building open translation services for the world. In *Proceedings of the 22nd Annual Conference of the European Association for Machine Translation (EAMT)*, 2020.
- Herbert Ullrich, Jan Drchal, Martin R"ypar, Hana Vincourov'a, and V'aclav Moravec. Csfever and ctkfacts: acquiring czech data for fact verification. *Language Resources and Evaluation*, 57(4): 1571–1605, 2023.
- Elena Volodina, Yousuf Ali Mohammed, and Julia Klezl. Dalaj - a dataset for linguistic acceptability judgments for swedish: Format, baseline, sharing, 2021.
- Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Tal Linzen, Grzegorz Chrupała, and Afra Alishahi (eds.), *Proceedings of the 2018 EMNLP Workshop Black-boxNLP: Analyzing and Interpreting Neural Networks for NLP*, pp. 353–355, Brussels, Belgium, November 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-5446. URL <https://aclanthology.org/W18-5446>.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. *CoRR*, abs/1905.00537, 2019. URL <http://arxiv.org/abs/1905.00537>.
- Kexin Wang, Nils Reimers, and Iryna Gurevych. Tsdæ: Using transformer-based sequential denoising auto-encoder for unsupervised sentence embedding learning. *arXiv preprint arXiv:2104.06979*, 4 2021a. URL <https://arxiv.org/abs/2104.06979>.
- 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, 2022.
- Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Improving text embeddings with large language models. *arXiv preprint arXiv:2401.00368*, 2023.
- Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Multilingual e5 text embeddings: A technical report. *arXiv preprint arXiv:2402.05672*, 2024.
- Wenhui Wang, Hangbo Bao, Shaohan Huang, Li Dong, and Furu Wei. MiniLMv2: Multi-head self-attention relation distillation for compressing pretrained transformers. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pp. 2140–2151, Online, August 2021b. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.188. URL <https://aclanthology.org/2021.findings-acl.188>.
- Silvan Wehrli, Bert Arnrich, and Christopher Irrgang. German text embedding clustering benchmark, 2024. URL <https://arxiv.org/abs/2401.02709>.
- Orion Weller, Benjamin Chang, Sean MacAvaney, Kyle Lo, Arman Cohan, Benjamin Van Durme, Dawn Lawrie, and Luca Soldaini. Followir: Evaluating and teaching information retrieval models to follow instructions, 2024.

- Orion Weller, Benjamin Chang, Eugene Yang, Mahsa Yarmohammadi, Sam Barham, Sean MacAvaney, Arman Cohan, Luca Soldaini, Benjamin Van Durme, and Dawn Lawrie. mfollowir: a multilingual benchmark for instruction following in retrieval, 2025. URL <https://arxiv.org/abs/2501.19264>.
- Andika William and Yunita Sari. Click-id: A novel dataset for indonesian clickbait headlines. *Data in Brief*, 32:106231, 2020. ISSN 2352-3409. doi: <https://doi.org/10.1016/j.dib.2020.106231>. URL <http://www.sciencedirect.com/science/article/pii/S2352340920311252>.
- Genta Winata, Lingjue Xie, Karthik Radhakrishnan, Yifan Gao, and Daniel Preoŕiuc-Pietro. Efficient zero-shot cross-lingual inference via retrieval. In *Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 93–104, 2023a.
- Genta Indra Winata, Andrea Madotto, Zhaojiang Lin, Rosanne Liu, Jason Yosinski, and Pascale Fung. Language models are few-shot multilingual learners. In *Proceedings of the 1st Workshop on Multilingual Representation Learning*, pp. 1–15, 2021.
- Genta Indra Winata, Alham Fikri Aji, Samuel Cahyawijaya, Rahmad Mahendra, Fajri Koto, Ade Romadhony, Kemal Kurniawan, David Moeljadi, Radityo Eko Prasajo, Pascale Fung, Timothy Baldwin, Jey Han Lau, Rico Sennrich, and Sebastian Ruder. Nusax: Multilingual parallel sentiment dataset for 10 indonesian local languages, 2022.
- Genta Indra Winata, Alham Fikri Aji, Samuel Cahyawijaya, Rahmad Mahendra, Fajri Koto, Ade Romadhony, Kemal Kurniawan, David Moeljadi, Radityo Eko Prasajo, Pascale Fung, et al. Nusax: Multilingual parallel sentiment dataset for 10 indonesian local languages. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 815–834, 2023b.
- Genta Indra Winata, Frederikus Hudi, Patrick Amadeus Irawan, David Anugraha, Rifki Afina Putri, Yutong Wang, Adam Nohejl, Ubaidillah Ariq Prathama, Nedjma Ousidhoum, Afifa Amriani, et al. Worldcuisines: A massive-scale benchmark for multilingual and multicultural visual question answering on global cuisines. *arXiv preprint arXiv:2410.12705*, 2024a.
- Genta Indra Winata, Ruochen Zhang, and David Ifeoluwa Adelani. Miners: Multilingual language models as semantic retrievers. *arXiv preprint arXiv:2406.07424*, 2024b.
- Marco Wrzalik and Dirk Krechel. GerDaLIR: A German dataset for legal information retrieval. In *Proceedings of the Natural Legal Language Processing Workshop 2021*, pp. 123–128, Punta Cana, Dominican Republic, nov 2021. Association for Computational Linguistics. URL <https://aclanthology.org/2021.nllp-1.13>.
- Fangzhao Wu, Ying Qiao, Jiun-Hung Chen, Chuhan Wu, Tao Qi, Jianxun Lian, Danyang Liu, Xing Xie, Jianfeng Gao, Winnie Wu, and Ming Zhou. MIND: A large-scale dataset for news recommendation. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 3597–3606, Online, jul 2020a. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.331. URL <https://aclanthology.org/2020.acl-main.331>.
- Fangzhao Wu, Ying Qiao, Jiun-Hung Chen, Chuhan Wu, Tao Qi, Jianxun Lian, Danyang Liu, Xing Xie, Jianfeng Gao, Winnie Wu, et al. Mind: A large-scale dataset for news recommendation. In *Proceedings of the 58th annual meeting of the association for computational linguistics*, pp. 3597–3606, 2020b.
- Mengzhou Xia, Antonios Anastasopoulos, Ruochen Xu, Yiming Yang, and Graham Neubig. Predicting performance for natural language processing tasks. *CoRR*, abs/2005.00870, 2020. URL <https://arxiv.org/abs/2005.00870>.
- Chenghao Xiao, G Thomas Hudson, and Noura Al Moubayed. Rar-b: Reasoning as retrieval benchmark. *arXiv preprint arXiv:2404.06347*, 2024a.
- Shitao Xiao, Zheng Liu, Peitian Zhang, and Niklas Muennighoff. C-pack: Packaged resources to advance general chinese embedding, 2023.

- Shitao Xiao, Zheng Liu, Peitian Zhang, Niklas Muennighoff, Defu Lian, and Jian-Yun Nie. C-pack: Packed resources for general chinese embeddings. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 641–649, 2024b.
- 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, 2023.
- Wei Xu, Chris Callison-Burch, and Bill Dolan. SemEval-2015 task 1: Paraphrase and semantic similarity in Twitter (PIT). In Preslav Nakov, Torsten Zesch, Daniel Cer, and David Jurgens (eds.), *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pp. 1–11, Denver, Colorado, jun 2015. Association for Computational Linguistics. doi: 10.18653/v1/S15-2001. URL <https://aclanthology.org/S15-2001>.
- Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. mt5: A massively multilingual pre-trained text-to-text transformer. *arXiv preprint arXiv:2010.11934*, 2020.
- Weixiang Yan, Yuchen Tian, Yunzhe Li, Qian Chen, and Wen Wang. Codetransocean: A comprehensive multilingual benchmark for code translation, 2023. URL <https://arxiv.org/abs/2310.04951>.
- Hitomi Yanaka and Koji Mineshima. Compositional evaluation on japanese textual entailment and similarity. *Transactions of the Association for Computational Linguistics*, 10:1266–1284, 2022.
- Yinfei Yang, Yuan Zhang, Chris Tar, and Jason Baldridge. Paws-x: A cross-lingual adversarial dataset for paraphrase identification, 2019.
- Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William 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 (eds.), *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 2369–2380, Brussels, Belgium, 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1259. URL <https://aclanthology.org/D18-1259>.
- Longhui Yu, Weisen Jiang, Han Shi, Jincheng Yu, Zhengying Liu, Yu Zhang, James T Kwok, Zhenguo Li, Adrian Weller, and Weiyang Liu. Metamath: Bootstrap your own mathematical questions for large language models. *arXiv preprint arXiv:2309.12284*, 2023.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. Hellaswag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019.
- Xiang Zhang, Junbo Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc., 2015. URL https://proceedings.neurips.cc/paper_files/paper/2015/file/250cf8b51c773f3f8dc8b4be867a9a02-Paper.pdf.
- Xinyu Zhang, Nandan Thakur, Odunayo Ogundepo, Ehsan Kamaloo, David Alfonso-Hermelo, Xiaoguang Li, Qun Liu, Mehdi Rezagholizadeh, and Jimmy Lin. Making a miracl: Multilingual information retrieval across a continuum of languages, 2022.
- Xinyu Zhang, Nandan Thakur, Odunayo Ogundepo, Ehsan Kamaloo, David Alfonso-Hermelo, Xiaoguang Li, Qun Liu, Mehdi Rezagholizadeh, and Jimmy Lin. MIRACL: A Multilingual Retrieval Dataset Covering 18 Diverse Languages. *Transactions of the Association for Computational Linguistics*, 11:1114–1131, 09 2023. ISSN 2307-387X. doi: 10.1162/tacl_a_00595. URL https://doi.org/10.1162/tacl_a_00595.
- Tianyu Zheng, Ge Zhang, Tianhao Shen, Xueling Liu, Bill Yuchen Lin, Jie Fu, Wenhui Chen, and Xiang Yue. Opencodeinterpreter: Integrating code generation with execution and refinement. *arXiv preprint arXiv:2402.14658*, 2024.

- Dawei Zhu, Liang Wang, Nan Yang, Yifan Song, Wenhao Wu, Furu Wei, and Sujian Li. Longembed: Extending embedding models for long context retrieval. *arXiv preprint arXiv:2404.12096*, 2024.
- Elena Zotova, Rodrigo Agerri, Manuel Nuñez, and German Rigau. Multilingual stance detection in tweets: The Catalonia independence corpus. In Nicoletta Calzolari, Frédéric B´echet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, H´el`ene Mazo, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pp. 1368–1375. European Language Resources Association, may 2020. ISBN 979-10-95546-34-4.
- Pierre Zweigenbaum, Serge Sharoff, and Reinhard Rapp. Overview of the second BUCC shared task: Spotting parallel sentences in comparable corpora. In Serge Sharoff, Pierre Zweigenbaum, and Reinhard Rapp (eds.), *Proceedings of the 10th Workshop on Building and Using Comparable Corpora*, pp. 60–67, Vancouver, Canada, aug 2017. Association for Computational Linguistics. doi: 10.18653/v1/W17-2512. URL <https://aclanthology.org/W17-2512>.
- Ahmet Üstün, Viraat Aryabumi, Zheng-Xin Yong, Wei-Yin Ko, Daniel D’souza, Gbemileke Onilude, Neel Bhandari, Shivalika Singh, Hui-Lee Ooi, Amr Kayid, Freddie Vargus, Phil Blunsom, Shayne Longpre, Niklas Muennighoff, Marzieh Fadaee, Julia Kreutzer, and Sara Hooker. Aya model: An instruction finetuned open-access multilingual language model, 2024.
- Łukasz Augustyniak, Kamil Tagowski, Albert Sawczyn, Denis Janiak, Roman Bartusiak, Adrian Szymczak, Marcin Wątroba, Arkadiusz Janz, Piotr Szymański, Mikołaj Morzy, Tomasz Kajdanowicz, and Maciej Piasecki. This is the way: designing and compiling lepiszcze, a comprehensive nlp benchmark for polish, 2022. URL <https://arxiv.org/abs/2211.13112>.
- Michal Štefánik, Marek Kadlčík, Piotr Gramacki, and Petr Sojka. Resources and few-shot learners for in-context learning in slavic languages, 2023.

APPENDIX TABLE OF CONTENTS

A Contributions	33
B Overview and Construction of Tasks	35
B.1 Introduction to benchmark tasks	37
B.2 Task construction	38
B.3 Novel datasets	39
B.4 Task Metadata	40
B.4.1 Domains	40
C Benchmark Optimizations	42
C.1 Speeding Up Tasks	42
C.1.1 Clustering	42
C.1.2 Retrieval	44
C.2 Code Optimizations	45
D Task Overview	46
D.1 Tasks	46
D.2 Languages	46
D.3 Examples	48
E Full results	49
E.1 Performance per Number of Speakers	50
F New Metrics	50
F.1 Abstention for retrieval and reranking tasks	50
G Models	51
H Benchmark Construction and Overview	51
H.1 Benchmark creation	51
H.2 Benchmark task overview	52
H.3 Performance on MTEB(eng, v2)	53
H.4 Performance on MTEB(Code)	53

A CONTRIBUTIONS

We list the contributions of every author in Table 3. The possible types of contributions and their associated points are:

- **New dataset:** A new dataset includes creating a new implementation (subclass) of a task using a new dataset. 2 points were awarded for implementing the task and 4 points for each new language introduced by the task.

- **New task:** An implementation of a new task category such as multi-label classification or instruction retrieval. 2 points were given for a new task, as well as points following adding a new dataset.
- **Annotations:** Many existing datasets were not yet annotated with proper metadata. To encourage high-quality annotations we awarded 1 point for each full dataset annotation.
- **Fixes:** These included bug fixes, usability fixes, speed improvements and more. For these, we typically awarded 2-10 points depending on the size of the contribution.
- **Running Models:** This includes both running and implementing models for MMTEB. We typically awarded 1 point per model run on a full set of relevant tasks. Relevant tasks for a specific model are limited to those pertinent to its language. For instance, a Russian model does not need to be run on French tasks.
- **Review PR:** A large part of ensuring good dataset quality comes from the dataset review. We award 2 points for a review. If a PR had multiple reviewers, 2 points were awarded to each. Often reviewers finalized dataset additions, helped with data formatting, and resolving bugs. In many cases, adding 2 points for review was considered either too low (a perfect PR with little to no corrections) or too high (lengthy discussion examining dataset quality, debugging implementations and more), however on average we believe it was appropriate.
- **Writing:** At this point many of the authors writing the paper already qualified for co-authorship and thus had reasonable experience with the MMTEB point system. Thus, it was generally possible to discuss a reasonable amount of points based on the efforts made in earlier stages.
- **Coordination:** Included Coordination of contributors and initial ideation were given points at the end of the project based on relative effort. These points were given, similar to paper writing, based on relative effort.

A total of 10 points had to be obtained to be invited as a co-author. To see each contribution mapped to specific PRs, see <https://github.com/embeddings-benchmark/mteb/tree/main/docs/mteb/points>, where the name of JSON files corresponds to the PR id.

Table 3: Contributions by GitHub users. See Table 4 for the mapping between authors and GitHub handles

GitHub	Total	Bug fixes	Review PR	New dataset	Dataset annotations	Paper writing	Coordination	New task	Running Models
KennethEnevoldsen	597	87	326	68	35	0	81	0	0
isaac-chung	433	50	194	120	1	12	54	2	0
iminelydiaker	358	24	144	120	0	0	70	0	0
awinml	302	0	2	300	0	0	0	0	0
x-tabdeveloping	239	10	32	144	0	0	41	12	0
davidstap	176	0	0	176	0	0	0	0	0
jaygala24	149	0	0	149	0	0	0	0	0
wissam-sib	144	4	6	134	0	0	0	0	0
Muennighoff	142	0	48	0	0	0	70	0	24
orionw	125	20	20	0	0	0	75	10	0
dokato	112	12	6	94	0	0	0	0	0
gentaiscool	110	0	0	110	0	0	0	0	0
jupyterjazz	108	0	0	108	0	0	0	0	0
SaitejaUtpala	102	0	0	102	0	0	0	0	0
vaibhavad	93	8	4	6	0	0	75	0	0
MathieuCiancone	88	0	0	88	0	0	0	0	0
schmarion	88	0	0	88	0	0	0	0	0
GabrielSequeira	88	0	0	88	0	0	0	0	0
digantamisra98	71	0	0	71	0	0	0	0	0
shreeya-dhakal	62	0	8	54	0	0	0	0	0
Rysias	58	0	0	58	0	0	0	0	0
Samoed	51	22	2	18	0	0	0	0	9
gowithflow-1998	50	0	0	50	0	0	0	0	0
sivareddy	50	0	0	0	0	0	50	0	0
asparius	48	0	14	34	0	0	0	0	0
Akash190104	46	0	0	46	0	0	0	0	0
MartinBernstorff	43	13	8	2	0	0	20	0	0
staoxiao	40	0	0	40	0	0	0	0	0
akshita-sukhlecha	40	4	0	36	0	0	0	0	0
rafalposwiata	36	0	0	36	0	0	0	0	0
bp-high	36	0	0	36	0	0	0	0	0
KranthiGV	34	0	14	20	0	0	0	0	0
bjoempl	28	0	0	28	0	0	0	0	0

Continued on next page

Table 3: (Continued) Contributions by GitHub users. See Table 4 for the mapping between authors and GitHub handles

GitHub Handle	Total	Bug fixes	Review PR	New dataset	Dataset annotations	Paper writing	Coordination	New task	Running Models
rasdani	28	0	0	28	0	0	0	0	0
loicmagne	28	28	0	0	0	0	0	0	0
jphme	28	0	0	28	0	0	0	0	0
ShawonAshraf	28	0	0	28	0	0	0	0	0
violenil	26	0	0	26	0	0	0	0	0
mariyahendriksen	24	0	0	0	0	24	0	0	0
dwzhu-pku	24	0	0	24	0	0	0	0	0
hgissbkh	23	13	2	0	0	3	0	5	0
jankounchained	22	8	0	14	0	0	0	0	0
taeminlee	22	0	0	22	0	0	0	0	0
tomaarsen	22	0	2	0	0	0	20	0	0
kwojtasi	22	0	0	22	0	0	0	0	0
mrshu	21	0	4	16	1	0	0	0	0
crystina-z	21	0	0	21	0	0	0	0	0
ManuelFay	20	13	0	2	0	0	0	5	0
AlexeyVatolin	20	20	0	0	0	0	0	0	0
Andrian0s	20	2	4	14	0	0	0	0	0
rbroc	20	0	0	20	0	0	0	0	0
john-b-yang	20	0	0	0	0	20	0	0	0
mmhamdy	20	0	0	20	0	0	0	0	0
manandey	18	0	0	18	0	0	0	0	0
thakur-nandan	18	0	0	18	0	0	0	0	0
PranjaliChitale	16	0	0	16	0	0	0	0	0
Sakshamrzt	16	0	4	12	0	0	0	0	0
sted97	16	0	0	16	0	0	0	0	0
dipam7	16	0	2	14	0	0	0	0	0
artemsnegirev	14	0	0	12	2	0	0	0	0
taidnguyen	14	0	0	14	0	0	0	0	0
jordiclive	12	10	0	2	0	0	0	0	0
guenthermi	12	0	0	12	0	0	0	0	0
slvnwhrl	12	0	0	12	0	0	0	0	0
Art3mis07	12	0	0	12	0	0	0	0	0
xhluca	12	4	2	6	0	0	0	0	0
anpalmak2003	12	0	0	9	3	0	0	0	0
ab1992ao	11	0	0	8	3	0	0	0	0
MariyaTikhonova	11	0	0	7	4	0	0	0	0
henilp105	11	2	0	0	9	0	0	0	0
simon-clematide	10	0	0	10	0	0	0	0	0
jimmy-lin	10	0	0	0	0	0	10	0	0
sarahooker	10	0	0	0	0	10	0	0	0
swj0419	10	0	0	10	0	0	0	0	0
xiamengzhou	10	0	0	10	0	0	0	0	0
ABorghini	10	0	0	10	0	0	0	0	0
xu3kev	10	0	0	10	0	0	0	0	0
malteos	10	0	0	10	0	0	0	0	0
ljvmiranda921	10	0	0	10	0	0	0	0	0
howard-yen	10	0	0	10	0	0	0	0	0
hongjin-su	10	0	0	10	0	0	0	0	0
guangyusong	10	0	0	10	0	0	0	0	0
Alenush	10	0	0	6	4	0	0	0	0
cassanof	10	1	0	8	0	0	0	0	1
HLasse	10	5	0	0	5	0	0	0	0
ZhengLiu101	10	0	0	10	0	0	0	0	0
Ruqyai	10	0	8	2	0	0	0	0	0
izhx	6	0	0	6	0	0	0	0	0
marcobellagente93	6	0	0	6	0	0	0	0	0
monikernemo	2	0	0	2	0	0	0	0	0
NouamaneTazi	2	0	2	0	0	0	0	0	0
MexicanLemonade	2	0	0	2	0	0	0	0	0
bakriano	2	0	0	2	0	0	0	0	0
PhilipMay	2	0	2	0	0	0	0	0	0
achibb	2	0	0	2	0	0	0	0	0
antoniolanza1996	2	2	0	0	0	0	0	0	0
eslize	2	0	0	2	0	0	0	0	0
hanhainebula	2	0	0	2	0	0	0	0	0

B OVERVIEW AND CONSTRUCTION OF TASKS

In this appendix, we first provide an overview of existing tasks in MTEB benchmark and newly introduced tasks in our benchmark (Section B.1). We proceed by explaining how the tasks were constructed (Section B.2) from existing datasets. Lastly, we introduce newly constructed datasets specifically designed for MMTEB (Section B.3).

GitHub	First name	Last name	Affiliations
KennethEnevoldsen	Kenneth	Enevoldsen	Aarhus University
x-tabdeveloping	Márton	Kardos	Aarhus University
imenelydiaker	Imene	Kerboua	INSA Lyon, LIRIS
wissam-sib	Wissam	Sibli	Individual Contributor
GabrielSequeira	Gabriel	Sequeira	Individual Contributor
schmarion	Marion	Schaeffer	Wikit
MathieuCiancone	Mathieu	Ciancone	Wikit
MartinBernstorff	Martin	Bernstorff	Aarhus University
staoxiao	Shitao	Xiao	Beijing Academy of Artificial Intelligence
ZhengLiu101	Zheng	Liu	Beijing Academy of Artificial Intelligence
achibb	Aaron	Chibb	Individual Contributor
cassanof	Federico	Cassano	Northeastern University and Cursor AI
taidnguyen	Nguyen	Tai	University of Pennsylvania
xu3kev	Wen-Ding	Li	Cornell University
Rysias	Jonathan	Rystrøm	University of Oxford
taeminlee	Taemin	Lee	Korea University Human-Inspired AI Research
izhx	Xin	Zhang	Harbin Institute of Technology
orionw	Orion	Weller	Johns Hopkins University
slvnwhrl	Silvan	Wehrli	Robert Koch Institute
manandey	Manan	Dey	Salesforce
isaac-chung	Isaac	Chung	Individual Contributor
asparius	Ömer	Çağatan	Koç University, Turkey
rafalposwiata	Rafal	Poświata	National Information Processing Institute
rbroc	Roberta	Rocca	Aarhus University
awinml	Ashwin	Mathur	Individual Contributor
guangyusong	Guangyu	Song	Tano Labs
davidstap	David	Stap	University of Amsterdam
HLasse	Lasse	Hansen	Aarhus University
jaygala24	Jay	Gala	MBZUAI
digantamisra98	Diganta	Misra	Max Planck Institute for Intelligent Systems and ELLIS Institute Tübingen
PranjalChitale	Pranjal	Chitale	Indian Institute of Technology
Akash190104	Akash	Kundu	Heritage Institute of Technology and Apart Research
dwzhu-pku	Dawei	Zhu	Peking University
lvmiranda921	Lester James	Miranda	Allen Institute for AI
AndrianOs	Andrianos	Michail	University of Zurich
simon-clematide	Simon	Clematide	University of Zurich
SaitejaUtpala	Saiteja	Utpala	Microsoft Research
mmhamdy	Mohammed	Hamdy	Cohere For AI Community
jupyterjazz	Saba	Sturua	Jina AI
Ruqyai	Ruqya	Bin Safi	NaN
KranthiGV	Kranthi Kiran	GV	New York University
shreeya-dhakar	Shreeya	Dhakar	Individual Contributor
dipam7	Dipam	Vasani	Individual Contributor
Art3mis07	Gayatri	K	R. V. College of Engineering
jankounchained	Jan	Kostkan	Aarhus University
bp-high	Bhavish	Pahwa	Microsoft Research
rasdani	Daniel	Auras	ellamind, Germany
ShawonAshraf	Shawon	Ashraf	ellamind, Germany
bjoernpl	Björn	Plüster	ellamind, Germany
jphme	Jan Philipp	Harries	ellamind, Germany
malteos	Malte	Ostendorff	Occiglot
ManuelFay	Manuel	Faysse	CentraleSupélec and Illuin Technology
hgissbkh	Hippolyte	Gisserot-Boukhlef	CentraleSupélec and Artefact Research Center
sted97	Simone	Tedeschi	Sapienza University of Rome
gentaiscool	Genta Indra	Winata	Individual Contributor
henilp105	Henil	Panchal	Nirma University
ABorghini	Alessia	Borghini	Sapienza University of Rome
jordiclive	Jordan	Clive	Imperial College London
gowithetheflow-1998	Chenghao	Xiao	Durham University
maryiahendriksen	Mariya	Hendriksen	University of Amsterdam
dokato	Dominik	Krzemiński	Cohere For AI Community
Samood	Roman	Solomatin	AI Talent Hub and ITMO University
Alenush	Alena	Fenogenova	SaluteDevices
ab1992ao	Aleksandr	Abramov	SaluteDevices
artemsnegirev	Artem	Snegirev	SaluteDevices
anpalmak2003	Anna	Maksimova	SaluteDevices
MariyaTikhonova	Maria	Tikhonova	SaluteDevices and HSE University
vaibhavd	Vaibhav	Adlakha	Mila, McGill University and ServiceNow Research
sivareddy	Siva	Reddy	Mila, McGill University and ServiceNow Research
guenthermi	Michael	Günther	Jina AI
violeni	Isabelle	Mohr	Jina AI
akshita-sukhlecha	Akshita	Sukhlecha	Individual Contributor
Muennighoff	Niklas	Muennighoff	Stanford University and Contextual AI
AlexeyVatolin	Aleksei	Vatolin	FRC CSC RAS
xhluca	Xing Han	Lü	Mila, McGill University
crystina-z	Xinyu	Zhang	University of Waterloo
tomaarsen	Tom	Aarsen	Hugging Face
mrshu	Marek	Suppa	Comenius University Bratislava and Cisco Systems
swj0419	Weijia	Shi	University of Washington
xiamengzhou	Mengzhou	Xia	Princeton University
john-b-yang	John	Yang	Stanford University
thakur-nandan	Nandan	Thakur	University of Waterloo
loicmagne	Loic	Magne	Individual Contributor
sarahooker	Sara	Hooker	Cohere For AI
kwotasi	Konrad	Wojtasik	Wroclaw University of Science and Technology
jimmy-lin	Jimmy	Lin	University of Waterloo
hongjin-su	Hongjin	Su	University of Hong Kong
howard-yen	Howard	Yen	Princeton University

Table 4: Author overview, along with their affiliations and GitHub handles.

B.1 INTRODUCTION TO BENCHMARK TASKS

Classification First, a train set is constructed by sampling n (8-16) samples for each label. If only a test set is available, a section is split off as a training set. Both sets are then embedded and used to train a logistic regression using a maximum of 100 iterations. Afterwards, performance metrics are calculated. For robustness, this process is repeated 10 times.

Pair classification For two paired texts, the goal is to predict the label. Examples of such tasks include paraphrase detection or duplicate detection. The task is solved by embedding all documents and then computing the distance either using a model-specified metric, cosine, euclidean, dot product, or Manhattan. Using the best binary threshold, performance metrics are computed.

Bitext mining The dataset consists of matching pairs of sentences, and the goal is to find the match. All matching pairs of sentences are embedded, and the closest match is found using cosine similarity, and metrics are reported.

Clustering and hierarchical clustering Clustering starts with a set of documents and an associated set of labels. First we embed all documents, then take subsets of the data of size k for each of 10 consecutive experiments. All the documents are embedded, and a set of size k is sampled from the embedded documents. The embeddings are then clustered using K-means clustering, and performance metrics are calculated between the estimated clusters and labels. If the clustering problem is hierarchical, this procedure is repeated for each level of the hierarchy separately. Hierarchical tasks were formerly either split into multiple tasks, or later levels of the cluster hierarchy were ignored.

Note that this formulation differs from that of MTEB in that the sets are randomly sampled from the embedded documents instead of being specified a-priori. This drastically reduced runtime as one document can be used in multiple subsets without the need to embed it multiple times. The new formulation also allows us to gain a robust estimate of performance with a lower number of documents.

Retrieval Retrieval tasks consist of a corpus, queries, and mapping between the queries and their relevant documents. The goal is to retrieve these relevant documents. Both queries and documents are embedded using the model. We allow these to be embedded differently depending on the model. For each query, the corpus documents are ranked using a similarity score, and performance metrics are calculated based on the reference mapping.

Multi-label classification Classification tasks in MTEB were previously limited to utilizing only one label per document. As such, some, otherwise useful multi-label classification tasks had to be dropped or reformulated. We addressed this by introducing a multi-label classification task type. Similarly to our novel clustering task, we down sample training sets for 10 experiments. We limit the training sets to include 8 instances of each unique label, and train a K Nearest-Neighbours classifier. Every classifier is then evaluated on the same test set. We opted for Accuracy, F_1 and Label Ranking Average Precision (LRAP) as evaluation metrics.

Instruction retrieval Instruction retrieval builds on the traditional retrieval task by incorporating detailed instructions alongside the queries. Unlike standard retrieval, where queries are usually brief keywords, instruction retrieval pairs each query with a comprehensive instruction that outlines the criteria for document relevance. These instructions are specific to each query and not generic to the entire dataset. Therefore, the task involves using both the query and its associated instruction to retrieve relevant documents from the corpus. For the main metric, we use Robustness@10.

Reranking Similar to the retrieval task, reranking includes a corpus, query, and a list of relevant and irrelevant reference texts. The aim is to rank the results according to their relevance to the query. References and queries are embedded and references are compared to the query using cosine similarity. The resulting ranking is scored for each query and averaged across all queries, and performance metrics computed. For the main metric, we use MAP@1000.

Semantic text similarity Semantic text similarity (STS) tasks consist of sentence pairs, where the goal is to determine their similarity. Labels are continuous scores, with higher numbers indicating more similar sentences. All sentences are embedded using the model, and the similarity of the pair is computed using various distance metrics, allowing for model-specified similarity metrics. Distances

are benchmarked with ground truth similarities using Pearson and Spearman correlations. Spearman correlation based on highest similarity serves as the main metric (Reimers et al., 2016)

B.2 TASK CONSTRUCTION

This section outlines our approach to constructing tasks, primarily from pre-existing data. For details on the newly introduced dataset in MMTEB, we refer to Section B.3.

Task construction from existing datasets consisted of a number of steps to ensure that the task is compatible with formulations in the benchmark and matches our standards: 1. *Dataset preprocessing*: we start by applying minimal additional processing to ensure the data is in the required format. 2. *Dataset size reduction*: to maintain manageable evaluation times, we proceed by reducing dataset size whenever applicable. 3. *Relevance filtering*: To ensure the datasets are relevant for the types of tasks being evaluated, we apply relevance-based dataset filtering. 4. *Differentiation testing*: we assess the task’s ability to differentiate between the performance of two candidate models.

For further details on dataset transformations for specific tasks, we refer to the `dataset_transform` method implementation for each task.

Classification and pair classification For both classification tasks, we used existing datasets with minimal adjustments, primarily trimming them down to more manageable sizes. For performance evaluation, we rely on such metrics as F_1 score, accuracy, or average precision. Whenever feasible, we align our choice of the primary metric with those used in related publications. If no specific guidance exists, we default to accuracy for general classification tasks and average precision for pairwise classification. In scenarios with significant class imbalance, the F_1 score is prioritized.

Bitext mining Bitext mining tasks were constructed using established paired datasets. Similar to the classification tasks, the primary focus was on adjusting the dataset sizes to maintain the same model rank while reducing computational load. F_1 scores were chosen to be the primary metric, unless specified otherwise.

Clustering and hierarchical clustering Clustering tasks were derived from existing corpora, such as news articles or encyclopedic entries. The source datasets typically included categories or labels assigned by their original authors or publishers. In some cases, like the SNL and VG datasets (Navjord & Korsvik, 2023), which featured hierarchical labels, we reformulated the tasks from flat to hierarchical clustering.

Retrieval A variety of tasks were integrated as retrieval tasks, including existing retrieval, question-answer, and news datasets. For question-answer datasets, the questions were used as queries, and the answers formed the corpus, with correct answers identified as properly retrieved documents. In news datasets, headlines were treated as queries, and both the full articles were considered part of the corpus, with matched summaries and articles serving as relevant documents. For the primary metric, we use $nDCG@10$, unless otherwise specified by the dataset publication.

Multi-label classification For multi-label classification, we used existing datasets that required minimal adjustments. A critical aspect of these tasks was maintaining the balance of label distributions across the training and evaluation splits. To achieve this, we employed advanced stratification techniques (Szymański & Kajdanowicz, 2017; Sechidis et al., 2011) that consider higher-order relationships between labels, ensuring balanced samples and improved classification quality. For the main metric, we use accuracy.

Instruction Retrieval For instruction retrieval tasks, we incorporated datasets like FollowIR (Weller et al., 2024; 2025), which consist of comprehensive narratives created by professional assessors. These datasets were initially developed for TREC shared tasks and included rich, context-heavy queries to evaluate retrieval systems’ performance on more intricate retrieval problems.

Reranking For reranking tasks, we adapted datasets covering a range of topics and languages, including academic paper ranking, news articles (Wu et al., 2020b), QA pair relevance from online platforms, and passage ranking (Xie et al., 2023). For the primary metric, we use MAP unless otherwise specified by the dataset publication.

Semantic text similarity For STS tasks, we adapted well-known benchmarks like STSbenchmark (May et al., 2021) and cross-lingual STS datasets from SemEval (Agirre et al., 2015). We also adapted paraphrase datasets in various languages, such as the Russian ParaPhraser (Pivovarova et al., 2017) and the Finnish Paraphrase Corpus (Kanerva et al., 2021). As the main metric, we use Spearman correlation based on the highest similarity (Reimers et al., 2016).

B.3 NOVEL DATASETS

This section introduces task specifically created as a part of the MMTEB contributions. For information on how existing datasets were adapted to MTEB we refer to Appendix B.

PublicHealthQA: This retrieval task is built on top of a novel dataset containing question-and-answer pairs in Public Health, specifically related to the COVID-19 disease. They are sourced from Q&A pages and Frequently Asked Questions (FAQ) sections of the Centers for Disease Control and Prevention (CDC) and World Health Organization (WHO) websites. They were produced and collected between 2019-12 and 2020-04.

WebLINXReranking: This is a novel HTML reranking task derived from WebLINX, a benchmark for training and evaluating web agents with conversational capabilities (Lù et al., 2024). Whereas the original work introduces a retrieval task with the goal of retrieving HTML elements using a conversational context, we propose the first task with the goal of reranking HTML elements based on their relevance for actions executed in web environments, including clicks, hovers, and text insertions.

WikiClustering: is a multilingual clustering benchmark based on Wikipedia’s main topic classifications. The goal is to create a clustering benchmark that works for multiple languages.

To construct a WikiClustering dataset for a given language, we apply the following steps. First, download the wiki dump of the categories, the articles, and the category links. Second, we find the main topic classifications for all articles. The main topic classifications can be found by looking at the category page for the language⁶. We only use the first paragraph of each article to construct a paragraph-to-paragraph (P2P) task similar to other P2P tasks within MTEB. Third, we filter out articles with more than one main topic and remove any topic with only one article associated with it. This step avoids ambiguity in the clustering task. Finally, we sample 2048 articles with associated main topics.

While the WikiClustering benchmark can be extended to any language with main topic classifications, it is currently implemented for the following: Bosnian, Catalan, Czech, Danish, Basque, Manx, Ilokano, Kurdish, Latvian, Minangkabau, Maltese, Scots, Albanian, and Walloon. All code is available on GitHub.

WikipediaRetrievalMultilingual and **WikipediaRerankingMultilingual:** This is a multilingual retrieval and reranking dataset based on succinct queries generated by a strong multilingual LLM grounded in Wikipedia articles. The dataset was made to resemble SQuAD. Sampled Wikipedia articles of a target language were chunked and passed to GPT4-o using the following prompt:

"""

Your task is to anticipate possible search queries by users in the form of a question for a given document.

- The question must be written in {{ language }}
- The question should be formulated concretely and precisely and relate to the information from the given document
- The question must be coherent and should make sense without knowing the document
- The question must be answerable by the document
- The question should focus on one aspect and avoid using subclauses connected with 'and'
- The question should not be overly specific and should mimic a request of a user who is just starting to research the given topic
- Do not draw on your prior knowledge

⁶for details, we refer to https://en.wikipedia.org/wiki/Category:Main_topic_classificationsforEnglish

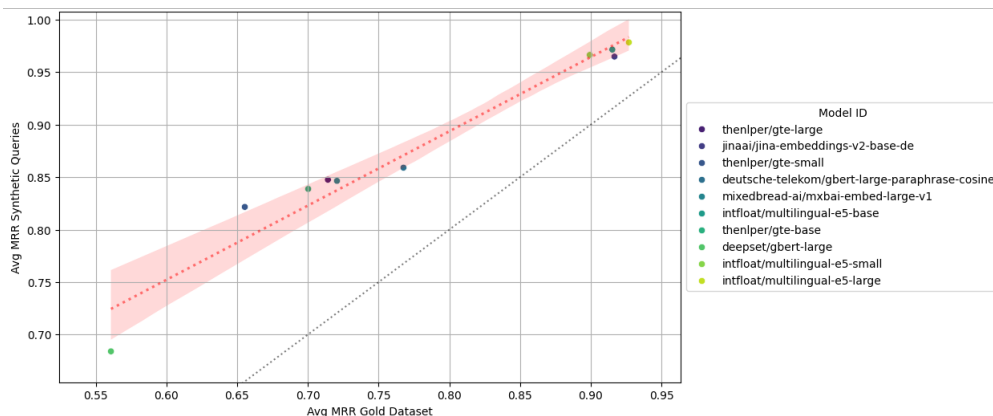


Figure 7: Comparison of MRR on synthetic retrieval and gold (GermanQuAD). The synthetic dataset was generated using GPT4-turbo.

Generate a question in `{{ language }}` for the following document:
`<document>`
`{{ document }}`
`</document>`

Search query:
`""`

We filtered articles with less than 9 paragraphs and sampled 1500 articles from the top 100k viewed articles. We then selected a random window of 9 consecutive paragraphs per article and chose the middle one to be the positive context and generated a query for it with gpt-4o. The surrounding 8 paragraphs act as hard negatives. The 9 paragraphs per article are used for the reranking task with one positive and 8 negatives. The one positive, 8 hard negatives, and the remaining corpus as negatives are used in the retrieval task.

These datasets were constructed from the following languages: "bul-Cyrl", "ben-Beng", "ces-Latn", "dan-Latn", "deu-Latn", "eng-Latn", "fas-Arab", "fin-Latn", "hin-Deva", "ita-Latn", "nld-Latn", "por-Latn", "ron-Latn", "srp-Cyrl", "dan-Latn", "nob-Latn", "swe-Latn".

To estimate the quality of these samples we compare it to the GermanQuAD (Möller et al., 2021) in Figure 7. We obtain a Spearman rank correlation of 0.93 with a 95% CI of [0.69; 1.].

B.4 TASK METADATA

Table 5 shows the required metadata to fill before adding a task to the benchmark. We provide a detailed description of each field, along with examples and possible values.

B.4.1 DOMAINS

For our domains, we include the following:

- **Academic:** Scholarly writing and research publications typically found in journals, theses, and dissertations.
- **Blog:** Informal or conversational posts often found on websites or personal pages, covering a wide range of topics.
- **Constructed:** Text or speech that is deliberately invented or constructed, often used for experimental purposes to target specific abilities.
- **Encyclopaedic:** Structured, reference-based texts that provide comprehensive and factual information on a wide range of subjects.

Field	Description
Name	A concise name for the task.
Description	A brief explanation of the task's goals and objectives..
Type	The primary task category (e.g., classification, summarization, retrieval).
Category	The general data structure or format of the task. This can be specified using a combination of single-letter codes (e.g., "s" for sentence, "p" for paragraph, "d" for document). For example, "s2s" indicates a sentence-to-sentence task, "s2p" indicates a sentence-to-paragraph task, and "p2p" indicates a paragraph-to-paragraph task.
Task Subtype	A more specific subcategory within the primary task type. This can be used to further refine the task and provide additional context. For example, "Summarization" might have subtypes like "Extractive Summarization" or "Abstractive Summarization".
Reference	A URL or citation to the original source material (e.g., paper, dataset repository).
Evaluation Splits	The specific subsets of the data used for training, validation, and testing.
Evaluation Languages	A list of ISO 639-3 language codes (e.g., "eng", "fra") followed by ISO 15924 script codes (e.g., "Latn", "Cyrl") for each language used in the evaluation. For example: [{"eng", "Latn"}, {"fra", "Latn"}]. If multiple scripts are used within a single language, we specify them as a list (e.g., [{"eng", ["Latn", "Grek"]}]).
Date	The time period when the data was gathered. Specified as a tuple of two dates.
Main score	The primary metric used to evaluate task performance.
Form	The format of the data (e.g., "spoken", "written")
License	The licensing terms for the dataset (e.g., CC BY-SA, MIT).
Domains	The subject areas or fields covered by the data (e.g., medical, legal, news). One dataset can belong to multiple domains.
Annotation Creators	The type of the annotators. Includes "expert-annotated" (annotated by experts), "human-annotated" (annotated e.g. by mturkers), "derived" (derived from structure in the data), "LM-generated" (generated using a language model) and "LM-generated and reviewed" (generated using a language model and reviewed by humans or experts).
Dialect	The specific dialect or regional variation of the language.
Text Creation	How the text was generated. Includes "found", "created", "human-translated and localized", "human-translated", "machine-translated", "machine-translated and verified", "machine-translated and localized", "LM-generated and verified".
Bibtex Citation	The BibTeX format citation for the dataset.
Number of samples	The total number of data points in the dataset.
Avg. Number of characters	The average character length of the samples in the dataset.

Table 5: Required metadata for adding a new task to MMTEB.

- **Fiction:** Narrative writing based on imaginative content, including novels, short stories, and other forms of storytelling.
- **Government:** Official documents, reports, and publications produced by governmental bodies.
- **Legal:** Documents and texts relating to laws, legal proceedings, contracts, and legal theory.
- **Medical:** Scientific and clinical literature related to healthcare, treatments, medical research, and patient care.
- **News:** Journalistic content that covers current events, politics, economy, and other topical issues.
- **Non-fiction:** Writing based on factual accounts and real-world subjects, such as biographies, essays, and documentaries.
- **Poetry:** Literary form focused on expressive language, often structured with meter, rhyme, or free verse.
- **Religious:** Texts related to religious teachings, doctrines, sacred scriptures, and spiritual discussions.
- **Reviews:** Critical evaluations of works such as books, movies, music, products, or services.
- **Social:** Written or spoken communication on social media platforms, forums, and other digital environments.
- **Spoken:** Oral communication, including speeches, dialogues, interviews, and recorded conversations.
- **Subtitles:** Textual transcriptions or translations of spoken language in films, videos, or multimedia presentations.
- **Web:** Text content found on websites, covering a wide range of subjects, often hyperlinked and multimedia-enriched.

- **Written:** General term for any form of text-based communication, whether printed or digital.
- **Programming:** Text written in programming languages to instruct computers, often for software development.

Our definition of domain aligns with that of the Universal Dependencies project (Nivre et al., 2016). We do not claim that our definition is neither precise nor comprehensive. However, we include subject fields such as "medical", "legal", and "news" and literary type such as "fiction", "non-fiction". They are not mutually exclusive.

C BENCHMARK OPTIMIZATIONS

C.1 SPEEDING UP TASKS

We aim to reduce the total amount of time needed to run the complete set of MTEB task. In particular, we investigate how to drastically reduce runtime on clustering and retrieval tasks while maintaining relative model rankings. This appendix provides full details of the approach described in Section 2.3.2.

C.1.1 CLUSTERING

Task	Spearman	Speedup
Biorxiv P2P	0.9505	31.50x
Biorxiv S2S	0.9890	14.31x
Medrxiv P2P	0.9615	21.48x
Medrxiv S2S	0.9560	8.39x
Reddit S2S	0.9670	11.72x
Reddit P2P	0.9670	22.77x
StackExchange S2S	0.9121	9.55x
StackExchange P2P	0.9670	20.20x
TwentyNewsgroups	1.0000	5.02x
Average	0.9634	16.11x

Table 6: Agreement on model rankings on a selection of English clustering tasks using Spearman’s correlation across the scores of 13 models of various sizes.

In the main paper, we present a down-sampled and bootstrapped version of the clustering task. We highlight the main results in Table 6 but refer to. We observe an average speedup across tasks of 16.11x while maintaining the relative ordering of models on the evaluated tasks. The largest average speed-up was seen for e5-large (16.93x), but we expect this effect to be even more pronounced among 7b or larger models.

9 single-level English clustering tasks are evaluated on 13 models across various sizes. A fraction of the documents are sampled and stratified by their target categories. At the same time, we wish to maintain robustness of the evaluation, i.e. the fast approach should be able to determine highly similar model ranking to that from the original approach. As such, we investigate the extent of agreement between the original clustering task and ours in each task on the model rankings.

The model ranking is determined from the mean of V-measure scores from evaluations, where a higher mean gives a higher model rank. Spearman’s rank correlation score is then calculated based on the ranks from ours and the original approach. We additionally calculate the significant model rank which is determined by computing the significance of the given model’s V-measure bootstrapped distribution based on its mean of V-measure scores using our approach against that of the original approach. Significant S is then calculated based on the significant ranks from our and the original approach.

To find a balance between speedup and the robustness of the approach, 4% of the dataset is chosen as the fraction to down-sample to, with the exception of RedditS2S and StackExchange where

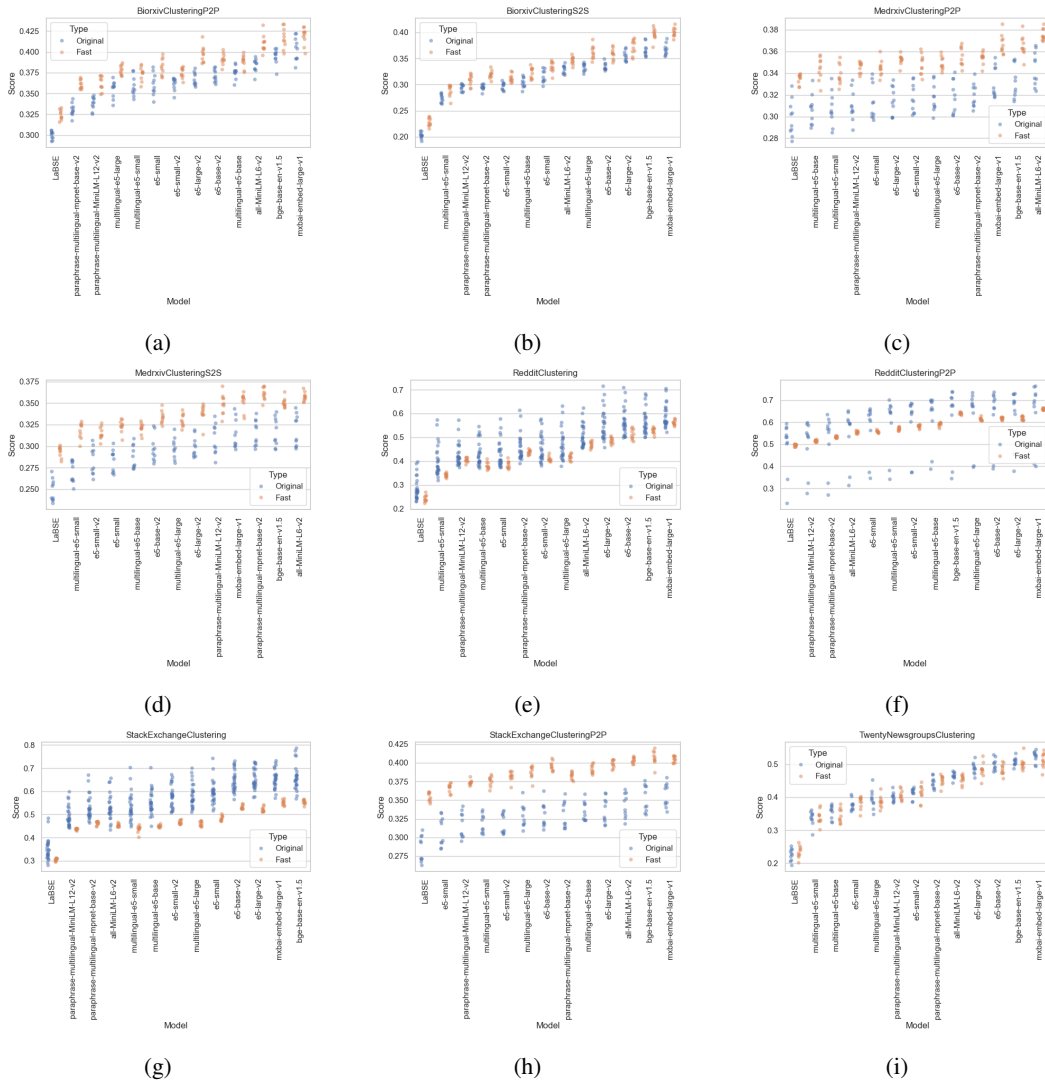


Figure 8: Distribution of scores per task across models.

Task	Sig. S
Biorxiv P2P	0.9390
Biorxiv S2S	0.9679
Medrxiv P2P	0.8200
Medrxiv S2S	0.9510
Reddit S2S	0.9790
Reddit P2P	0.7370
StackExchange S2S	0.9486
StackExchange P2P	0.9497
TwentyNewsgroups	0.9832
Average	0.9195

Table 7: Agreement on model rankings on English clustering tasks using significant Spearman’s rank correlation with selected models of various sizes.

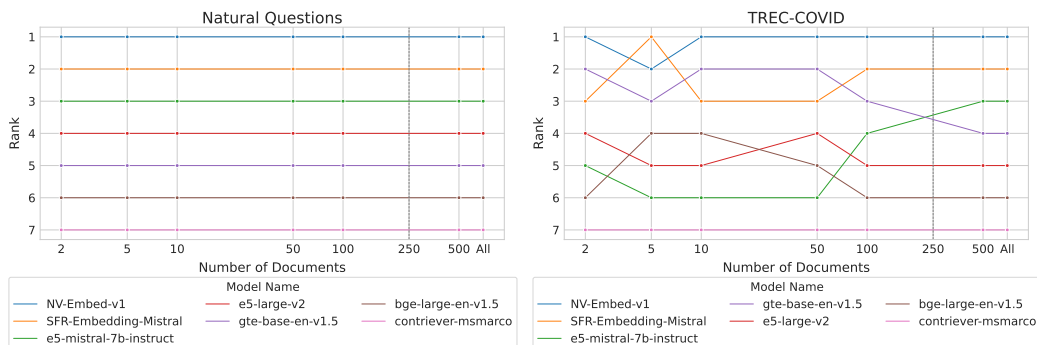


Figure 9: Ranking of different models on subsampled versions of the datasets using hard negatives. We see that NQ can be reduced to just two documents per query (relevant + 1 hard negative) while still maintaining the rank while TREC-COVID is less stable.

$n_samples = 32768$. Table 7 shows that all evaluated datasets have very high significant Spearman’s rank scores between our and the original approach. Figure 8 reports the distribution of V-measure scores obtained from evaluation per model in each dataset for the ClusteringFast and the original approach. There is generally strong agreement between the rankings from both approaches. We also observe that the ClusteringFast approach often (5 out of 9 datasets) produces a smaller spread (i.e. smaller variance) in its V-measure distributions. Reddit P2P has the lowest significant Spearman score among this set. It also has the lowest average character length for its documents.

C.1.2 RETRIEVAL

In this section we provide details about the method used to downsample retrieval datasets.

To ensure the downsampling kept the efficacy of the evaluation we aimed to examine several axes: (1) a wide range of models to be sure that the evaluation task could still properly rank the models - just as if it were not downsampled (2) that this method works for retrieval datasets that are sparsely judged *and* densely judged and (3) seeing if it was possible to use hard negatives from a smaller set of models due to the computational expense to gather these hard negatives on the full datasets.⁷

To meet these goals we chose NQ (for sparse relevance annotations, one per query) and TREC-COVID (for dense judgements, > 500 per query). To test using a small set of hard negatives, we gather the hard negatives with e5-large-v2 only. We evaluate a wide range of models for this analysis, including the current state-of-the-art and some of the previous state-of-the-art: NV-Embed-v1 (Lee

⁷We also tested whether ensuring that the ground truth relevant document is present in these hard negatives made a difference - we found that it did not, as most models ranked the ground truth in the top N, so manually including it was little help as it was already included.

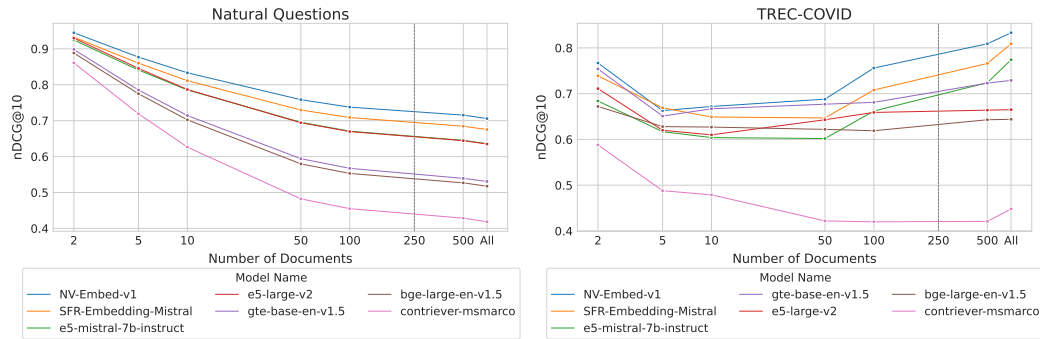


Figure 10: Absolute scores of different models on subsampled versions of the datasets using hard negatives. NQ has 1 relevant document per query while TREC-COVID has 500+ relevant documents per query which is why we see NQ scores gradually increasing whereas TREC-COVID scores vary.

et al., 2024), SFR-Embedding-Mistral (Meng et al., 2024), e5-mistral-7b-instruct (Wang et al., 2023), e5-large-v2 (Wang et al., 2022), gte-base-en-v1.5 (Li et al., 2023b), bge-large-en-v1.5 (Xiao et al., 2023), and contriever-msmarco (Izcard et al., 2021). We then evaluated the models on versions of the datasets with N hard negatives documents per query where $N \in \{2, 5, 10, 50, 100, 500, \text{all}\}$. We then compared the absolute scores and the relative rank positions to see what settings best retain the difficulty of the original task.

Ability to rank models correctly For a good evaluation, it must be able to rank models correctly and determine the best model. For this we examine how the ranking of the models change when we lower the number of hard negatives. For NQ the rank remains stable even with just one hard negatives (Figure 9). For TREC-COVID the ranking becomes unstable starting at 100 hard negatives, continuing to change as the number gets smaller.

Keeping the absolute score similar In an ideal case the scores for the task should remain similar and not trend towards perfect scores, remaining useful. We see that scores go very high when there are only a few hard negatives for NQ (Figure 10). For TREC-COVID it is more stable, but we see some wider swings with smaller documents. Overall, the scores are relatively similar at 100+ hard negatives.

Summary Overall, we see that staying above 100 hard negatives gives similar absolute scores while maintaining the ranking ability. Thus we opted for a conservative 250 documents per query to keep these characteristics.

C.2 CODE OPTIMIZATIONS

We here document the major code optimizations within MTEB not related to dataset scores, task reformulation

Dataset loading One important issue identified was about loading multilingual and cross-lingual datasets composed of numerous small files in their repositories. Even for total dataset sizes under 10MB, loading could take hours due to significant overhead from managing a high number of network requests and the improper opening and closing of gzipped files. In collaboration with the datasets team (Lhoest et al., 2021), we addressed these problems with two-side implementation improvements: the datasets library optimized the loading of a large number of requested files, and we restructured the datasets and our codebase to leverage the benefits of the newer implementation. This ultimately reduced loading times by almost a factor of 100, bringing the largely cross-lingual dataset bitext-mining loading to under a minute.

Deduplication Upon in-depth scrutiny of all datasets, cases with repeated samples were identified and deduplicated (e.g. MindSmallReranking). As this led to a change in scores, a second version

of the task was introduced to maintain compatible scores with existing benchmarks. To move the optimizations to existing MTEB tasks we implement a local cache to avoid encoding a sample twice.

D TASK OVERVIEW

D.1 TASKS

To get an overview of the all the tasks implemented in MMTEB we refer to the automatically updated tables in the documentation⁸, which include the available metadata for all of the task, including license, task category, domains, etc.

D.2 LANGUAGES

Additionally, the top 100 out of the total 1051 languages in ISO 639-3 language codes and their respective task counts are in Table 8.

ISO Code	Language	Family	BitextMining	Classification	Clustering	InstructionRetrieval	MultilabelClassification	PairClassification	Reranking	Retrieval	STS	Speed	Summarization	Sum
eng	English	Indo-European	16	143	16	3	1	8	8	92	13	2	1	303
deu	German	Indo-European	6	14	7	0	1	6	2	18	4	0	0	58
fra	French	Indo-European	7	13	8	0	1	5	3	15	4	0	1	57
rus	Russian	Indo-European	5	13	6	0	2	4	2	16	4	0	0	52
pol	Polish	Indo-European	4	11	4	0	1	4	0	18	4	0	0	46
cmn	Mandarin Chinese	Sino-Tibetan	4	10	4	0	0	3	4	10	9	0	0	44
spa	Spanish	Indo-European	4	13	4	0	1	2	2	13	4	0	0	43
hin	Hindi	Indo-European	9	12	2	0	0	1	2	10	2	0	0	38
code	unknown	Programming	0	0	0	0	0	0	0	37	0	0	0	37
jpn	Japanese	Japonic	5	8	3	0	0	1	3	13	2	0	0	35
kor	Korean	Koreanic	4	8	1	0	1	2	1	9	3	0	0	29
ara	Arabic	Afro-Asiatic	2	12	0	0	0	2	1	9	2	0	0	28
ben	Bengali	Indo-European	7	9	2	0	0	1	2	6	1	0	0	28
ita	Italian	Indo-European	5	9	1	0	1	2	1	5	3	0	0	27
por	Portuguese	Indo-European	4	9	1	0	2	2	1	5	3	0	0	27
tel	Telugu	Dravidian	7	7	2	0	0	0	1	5	2	0	0	24
dan	Danish	Indo-European	5	9	2	0	1	0	1	5	0	0	0	23
swe	Swedish	Indo-European	4	8	3	0	1	1	1	4	0	0	0	22
ind	Indonesian	Austronesian	6	7	1	0	0	1	1	4	1	0	0	21
tam	Tamil	Dravidian	7	7	2	0	0	1	0	3	1	0	0	21
tha	Thai	Tai-Kadai	4	8	1	0	0	1	1	6	0	0	0	21
mar	Marathi	Indo-European	7	6	2	0	0	1	0	2	2	0	0	20
zho	Chinese	Sino-Tibetan	2	2	1	0	0	1	1	13	0	0	0	20
fin	Finnish	Uralic	3	5	1	0	1	1	2	5	1	0	0	19
kan	Kannada	Dravidian	6	7	2	0	0	1	0	2	1	0	0	19
mal	Malayalam	Dravidian	7	7	2	0	0	0	0	2	1	0	0	19
nld	Dutch	Indo-European	6	6	1	0	1	0	1	2	2	0	0	19
nob	Norwegian Bokmål	Unclassified	4	7	5	0	0	0	0	3	0	0	0	19
tur	Turkish	Turkic	4	7	1	0	0	2	0	3	2	0	0	19
urd	Urdu	Indo-European	7	8	2	0	0	0	0	1	1	0	0	19

⁸For the latest version see <https://github.com/embeddings-benchmark/mteb/blob/main/docs/tasks.md>

guj	Gujarati	Indo-European	6	6	2	0	0	1	0	2	1	0	0	18
pan	Panjabi	Indo-European	6	6	2	0	0	1	0	2	1	0	0	18
ron	Romanian	Indo-European	5	6	1	0	1	0	1	3	1	0	0	18
vie	Vietnamese	Austroasiatic	5	6	1	0	0	1	0	5	0	0	0	18
fas	Persian	Indo-European	1	4	0	0	0	1	2	9	0	0	0	17
ces	Czech	Indo-European	4	5	2	0	1	1	1	2	0	0	0	16
ell	Modern Greek	Indo-European	3	6	1	0	1	2	0	3	0	0	0	16
yor	Yoruba	Atlantic-Congo	4	5	3	0	0	0	1	3	0	0	0	16
ory	Odia	Indo-European	5	4	2	0	0	1	0	2	1	0	0	15
swa	Swahili	Atlantic-Congo	1	7	2	0	0	1	1	3	0	0	0	15
amh	Amharic	Afro-Asiatic	3	6	3	0	0	0	0	1	1	0	0	14
asm	Assamese	Indo-European	5	3	2	0	0	1	0	2	1	0	0	14
hau	Hausa	Afro-Asiatic	4	5	3	0	0	0	0	1	1	0	0	14
bul	Bulgarian	Indo-European	3	4	1	0	1	1	1	2	0	0	0	13
jav	Javanese	Austronesian	4	7	1	0	0	0	0	1	0	0	0	13
hun	Hungarian	Uralic	5	3	1	0	1	0	0	2	0	0	0	12
ibo	Igbo	Atlantic-Congo	3	5	3	0	0	0	0	1	0	0	0	12
slk	Slovak	Indo-European	3	4	1	0	1	0	0	3	0	0	0	12
heb	Hebrew	Afro-Asiatic	4	5	1	0	0	0	0	1	0	0	0	11
afr	Afrikaans	Indo-European	3	4	1	0	0	0	0	1	1	0	0	10
hrv	Croatian	Indo-European	4	3	1	0	1	0	0	1	0	0	0	10
kat	Georgian	Kartvelian	4	3	1	0	0	0	0	2	0	0	0	10
san	Sanskrit	Indo-European	5	3	1	0	0	1	0	0	0	0	0	10
slv	Slovenian	Indo-European	3	4	1	0	1	0	0	1	0	0	0	10
xho	Xhosa	Atlantic-Congo	3	3	3	0	0	0	0	1	0	0	0	10
hye	Armenian	Indo-European	3	3	1	0	0	1	0	1	0	0	0	9
isl	Icelandic	Indo-European	3	4	1	0	0	0	0	1	0	0	0	9
min	Minangkabau	Austronesian	3	4	2	0	0	0	0	0	0	0	0	9
mlt	Maltese	Afro-Asiatic	2	2	2	0	2	0	0	1	0	0	0	9
mya	Burmese	Sino-Tibetan	3	4	1	0	0	0	0	1	0	0	0	9
som	Somali	Afro-Asiatic	3	2	3	0	0	0	0	1	0	0	0	9
srp	Serbian	Indo-European	4	1	1	0	0	0	1	2	0	0	0	9
sun	Sundanese	Austronesian	3	4	1	0	0	0	0	1	0	0	0	9
arb	Standard Arabic	Afro-Asiatic	3	1	1	0	0	0	0	2	1	0	0	8
cat	Catalan	Indo-European	3	2	2	0	0	0	0	1	0	0	0	8
cym	Welsh	Indo-European	3	4	1	0	0	0	0	0	0	0	0	8
est	Estonian	Uralic	2	2	1	0	1	0	0	2	0	0	0	8
eus	Basque	Unclassified	3	2	2	0	0	0	0	1	0	0	0	8
kaz	Kazakh	Turkic	3	3	1	0	0	0	0	1	0	0	0	8
khm	Khmer	Austroasiatic	3	3	1	0	0	0	0	1	0	0	0	8
kin	Kinyarwanda	Atlantic-Congo	2	3	1	0	0	0	0	1	1	0	0	8
lin	Lingala	Atlantic-Congo	2	2	3	0	0	0	0	1	0	0	0	8
lit	Lithuanian	Indo-European	4	1	1	0	1	0	0	1	0	0	0	8
lug	Ganda	Atlantic-Congo	2	2	3	0	0	0	0	1	0	0	0	8
nno	Norwegian Nynorsk	Unclassified	4	3	1	0	0	0	0	0	0	0	0	8
npi	Nepali	Indo-European	4	2	1	0	0	0	0	1	0	0	0	8
sna	Shona	Atlantic-Congo	2	2	3	0	0	0	0	1	0	0	0	8
snd	Sindhi	Indo-European	4	2	1	0	0	0	0	1	0	0	0	8
tgl	Tagalog	Austronesian	3	3	1	0	0	0	0	1	0	0	0	8
tir	Tigrinya	Afro-Asiatic	2	2	3	0	0	0	0	1	0	0	0	8
ukr	Ukrainian	Indo-European	4	2	1	0	0	0	0	1	0	0	0	8
ary	Moroccan Arabic	Afro-Asiatic	1	3	1	0	0	0	0	1	1	0	0	7
bug	Buginese	Austronesian	2	4	1	0	0	0	0	0	0	0	0	7
fao	Faroese	Indo-European	3	2	1	0	0	0	0	0	1	0	0	7
kir	Kirghiz	Turkic	2	3	1	0	0	0	0	1	0	0	0	7
mai	Maithili	Indo-European	4	2	1	0	0	0	0	0	0	0	0	7
mkd	Macedonian	Indo-European	3	2	1	0	0	0	0	1	0	0	0	7
mni	Manipuri	Sino-Tibetan	4	2	1	0	0	0	0	0	0	0	0	7
pcm	Nigerian Pidgin	Indo-European	1	4	2	0	0	0	0	0	0	0	0	7

sat	Santali	Austroasiatic	4	2	1	0	0	0	0	0	0	0	0	7
sin	Sinhala	Indo-European	2	3	1	0	0	0	0	1	0	0	0	7
ssw	Swati	Atlantic-Congo	2	3	1	0	0	0	0	1	0	0	0	7
tsn	Tswana	Atlantic-Congo	2	3	1	0	0	0	0	1	0	0	0	7
tso	Tsonga	Atlantic-Congo	1	4	1	0	0	0	0	1	0	0	0	7
uig	Uighur	Turkic	4	2	1	0	0	0	0	0	0	0	0	7
zul	Zulu	Atlantic-Congo	2	3	1	0	0	0	0	1	0	0	0	7
awa	Awadhi	Indo-European	3	2	1	0	0	0	0	0	0	0	0	6
bak	Bashkir	Turkic	2	3	1	0	0	0	0	0	0	0	0	6
bel	Belarusian	Indo-European	4	1	1	0	0	0	0	0	0	0	0	6
bho	Bhojpuri	Indo-European	2	2	1	0	0	1	0	0	0	0	0	6
bod	Tibetan	Sino-Tibetan	3	1	1	0	0	0	0	1	0	0	0	6
bos	Bosnian	Indo-European	3	1	2	0	0	0	0	0	0	0	0	6
ceb	Cebuano	Austronesian	3	1	1	0	0	0	0	1	0	0	0	6
ckb	Central Kurdish	Indo-European	3	1	1	0	0	0	0	1	0	0	0	6
ilo	Iloko	Austronesian	2	1	2	0	0	0	0	1	0	0	0	6

Table 8: The top 100 languages across all MMTEB tasks in ISO 639-3 language codes and their respective task counts.

D.3 EXAMPLES

Table 9 and Table 10 provide examples for each new task type introduced in MMTEB. For examples of bitext mining, classification, clustering, pair classification, reranking, retrieval, STS, and summarization datasets, we refer to the MTEB paper Muennighoff et al. (2023b).

Dataset	Query	OG Instructions	Short query	Relevant Document
Robust04	Who is involved in the Schengen agreement to eliminate border controls in Western Europe and what do they hope to accomplish?	Relevant documents will contain any information about the actions of signatories of the Schengen agreement such as: measures to eliminate border controls (removal of traffic obstacles, lifting of traffic restrictions); implementation of the information system data bank that contains unified visa issuance procedures; or strengthening of border controls at the external borders of the treaty area in exchange for free movement at the internal borders. Discussions of border crossovers for business purposes are not relevant.	Find documents that answer this question on Schengen agreement actions.	... Schengen Space Concerning the mission traditionally performed by PAF—overseeing border traffic—the new directorate must fit into a Europe of immigration. The interior minister is therefore asking DICILC to step up its control of crossborder traffic, "particularly at the future external borders of the Schengen space." Originally scheduled in February 1994 but constantly postponed, the implementation of the agreements signed in Schengen by nine European countries (the Twelve, minus Great Britain, Ireland, and Denmark), provides for the free circulation of nationals within the space common to the territories of their nine countries...

Table 9: Instruction Retrieval examples.

Dataset	Text	Label
Maltese News Categories	Hi kellha 82 sena Id-dinja muzikali fl-Italja tinsab f'luttu wara l-mewt tal-attriċi u kantanta popolari Milva, li fis-snin 70 kienet meqjusa "ikona" fost it-Taljani. Milva kienet kisbet suċċess kbir, fl-istess epoka ta' Mina u Ornella Vanoni. Milva ħarġet numru kbir ta' albums tul il-karriera tagħha u ħadet sehem f'Sanremo għal xejn anqas minn 15-il darba; iżda qatt ma rebħet il-festival. Hi kellha 82 sena, u telqet mix-xena tal-ispettaklu eżatt 10 snin ilu.	[culture(2), international(10)]

Table 10: Multilabel Classification examples.

```

import mteb
from mteb.task_selection import results_to_dataframe

tasks = mteb.get_tasks(
    task_types=["Retrieval"],
    languages=["eng", "fra"],
    domains=["legal"]
)

model_names = [
    "intfloat/multilingual-e5-small",
    "intfloat/multilingual-e5-base",
    "intfloat/multilingual-e5-large",
]

models = [mteb.get_model_meta(name) for name in model_names]

results = mteb.load_results(models=models, tasks=tasks)

df = results_to_dataframe(results)

```

Figure 11: Simple example of how to obtain all scores on English (eng) and French (fra) retrieval tasks within the Legal domain for a set of models.

E FULL RESULTS

During this work, multiple models were evaluated on more than >500 tasks, with multiple tasks containing multiple language subsets covering more than 1000 languages. This makes a comprehensive overview unreasonable. While we have supplied scores aggregated across task categories, we realize that readers might be interested in examining scores for their specific language, domain of interest, and task. To ensure that such aggregation is available and easily accessible, we make all results available on the public and versioned results repository⁹. These results include time of run, evaluation time, and a wide set of performance metrics pr. language subset, CO2 emission, version number, and more.

To make these detailed results subject to easy analysis, we have added functionality for loading and aggregating these results within the mteb package. It is, for instance, possible to retrieve the scores for specific models on all English (eng) and French (fra) retrieval tasks within the Legal domain using the code snippet in Figure 11

We refer to the documentation¹⁰ for the latest version of this code.

⁹<https://github.com/embeddings-benchmark/results> for the specific version of the repository used for this work see commit id 9a79f7e07542ad2f5cb47490fa1e5ac2ba57d7a8

¹⁰<https://github.com/embeddings-benchmark/mteb>

E.1 PERFORMANCE PER NUMBER OF SPEAKERS

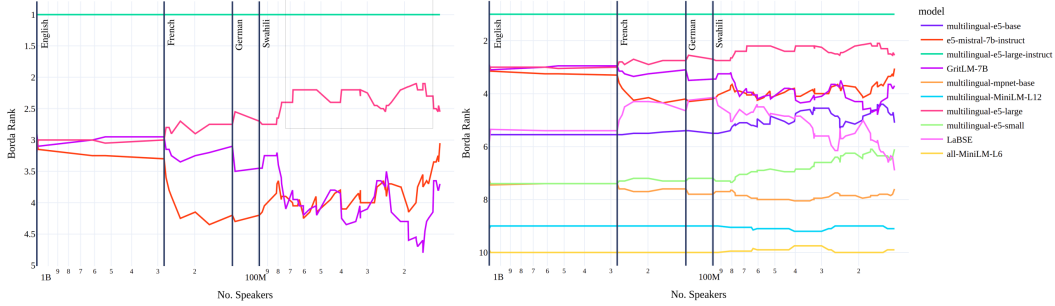


Figure 12: Models’ rank on the MTEB(Multilingual) by the total number of speakers of a language. Trendlines represent moving average with a window size of 10

F NEW METRICS

F.1 ABSTENTION FOR RETRIEVAL AND RERANKING TASKS

In addition to the existing ranking metrics used for Retrieval and Reranking tasks (Muennighoff et al., 2023b), we propose to assess score calibration through the evaluation of model abstention ability, using the implementation of Gisserot-Boukhlef et al. (2024).

Intuitively, a model abstains on a given instance (q, d_1, \dots, d_k) (one query and k candidate documents) if $c(q, d_1, \dots, d_k) < \tau$, where c is a confidence function¹¹ and τ is a threshold regulating abstention likelihood. Therefore, to evaluate abstention capacity on a given test set \mathcal{S} , an approach consists of making τ vary to achieve several abstention rates. In the case of effective abstention, the metric score increases with the abstention rate.

More formally, models’ ability to abstain is evaluated by computing the normalized area under the metric-abstention curve ($nAUC$). Given a confidence function c , a metric function m ¹² and a labeled test dataset \mathcal{S} , $nAUC$ is computed as follows:

1. **Multi-thresholding:** Given a model f and dataset \mathcal{D} , we define a set of abstention thresholds τ_1, \dots, τ_n , such that $\tau_1 < \dots < \tau_n$. For each threshold τ_i , we construct a corresponding sub-dataset $\mathcal{S}_i \subseteq \mathcal{D}$ by applying the abstention criterion. We then evaluate the model f on each sub-dataset \mathcal{S}_i using the metric function m . To quantify the model’s performance across these thresholds, we compute the area under the metric-abstention curve, denoted as AUC_{model} .
2. **Compute lower-bound:** Since AUC_{model} depends on the model’s raw performance without abstention, we compute the effective lower bound AUC^- . This corresponds to the area under the curve when the metric remains constant as abstention increases, representing the baseline where abstention does not improve the metric.
3. **Compute upper-bound:** To establish the upper bound, AUC^+ , we evaluate an oracle model that has access to the true labels. The oracle can selectively retain the best instances at each abstention rate, yielding the theoretical maximum area under the metric-abstention curve. This represents the optimal model performance under abstention.
4. **Compute normalized AUC:** Finally, we compute the normalized area under the curve, denoted $nAUC_{model}$, by scaling AUC_{model} between the lower and upper bounds:

$$nAUC_{model} = \frac{AUC_{model} - AUC^-}{AUC^+ - AUC^-}$$

¹¹In our implementation, we rely on three simple confidence functions all taking the instance’s query-document cosine similarity scores as input: the maximum score, the standard deviation of scores and the difference between the highest and second highest scores.

¹²We utilize the metrics initially implemented for the evaluation of Retrieval and Reranking MTEB tasks (Muennighoff et al., 2023b).

Name in Paper	HF Name	Revision ID
GritLM-7B	GritLM/GritLM-7B	13f00a0e36500c80ce12870ea513846a066004af
e5-mistral-7b-instruct	intfloat/e5-mistral-7b-instruct	07163b72af1488142a360786df853f237b1a3ca1
multilingual-e5-base	intfloat/multilingual-e5-base	d13f1b27baf31030b7fd040960d60d909913633f
multilingual-e5-large	intfloat/multilingual-e5-large	4dc6d853a804b9c8886ede6dda8a073b7dc08a81
multilingual-e5-large-instruct	intfloat/multilingual-e5-large-instruct	baa7be480a7de1539afce709c8f13f833a510e0a
multilingual-e5-small	intfloat/multilingual-e5-small	e4ce9877abf3edfe10b0d82785e83bdc973e22e
LaBSE	s-t/LaBSE	e34fab64a3011d2176c99545a93d5cbddc9a91b7
all-MiniLM-L12	s-t/all-MiniLM-L12-v2	a05860a77cef7b37e0048a7864658139bc18a854
all-MiniLM-L6	s-t/all-MiniLM-L6-v2	8b3219a92973c328a8e22fadcf821b5dc75636a
all-mpnet-base	s-t/all-mpnet-base-v2	84f2bcc00d77236f9e89c8a360a00fb1139bf47d
multilingual-MiniLM-L12	s-t/paraphrase-multilingual-MiniLM-L12-v2	bf3bf13ab40c3157080a7ab344c831b9ad18b5eb
multilingual-mpnet-base	s-t/paraphrase-multilingual-mpnet-base-v2	79f2382ceacceacf38563d7c5d16b9ff8d725d6

Table 11: Model name as it appears in the paper, its name on Huggingface Hub, and their associated revision IDs. Note: s-t stands for sentence-transformers.

G MODELS

Models used for task selection along with their revision IDs can be found in Table 11. Code for running the models, including prompts, is available within MTEB’s model registry available at <https://github.com/embeddings-benchmark/mteb/tree/main/mteb/models>. Unless otherwise specified within the model implementation, the prompt is available in the file <https://github.com/embeddings-benchmark/mteb/blob/main/mteb/models/instructions.py>. As some debugging happened during the running of the models, multiple versions of MTEB were used. Due to the computational cost of running these large models on the vast amount of datasets, it was deemed unfeasible to run all the models using the exact same version. However, for each task, all models were run on the same version of the specific task. Model results can be found in JSON format in the results repository; these include additional performance metrics, model metadata, CO₂ emission, time of run, and exact version of MTEB used: <https://github.com/embeddings-benchmark/results/tree/9a79f7e07542ad2f5cb47490fa1e5ac2ba57d7a8>.

H BENCHMARK CONSTRUCTION AND OVERVIEW

H.1 BENCHMARK CREATION

The following section introduces benchmarks created as a part of the MMTEB open contribution, which aren’t introduced within the main article. MTEB additionally includes a variety of benchmark including the language-specific, notably the original English MTEB, MTEB(eng, v2) (Muennighoff et al., 2023b), the Scandinavian embedding benchmark MTEB(Scandinavian) (Enevoldsen et al., 2024), the French benchmark MTEB(fra) (Ciancone et al., 2024), the German benchmark MTEB(deu) (Wehrli et al., 2024), the Korean benchmark MTEB(kor), the Chinese benchmark (Xiao et al., 2024b), the Polish benchmark MTEB(pol) (Poświata et al., 2024). Along with these MTEB also include an instruction based retrieval based benchmark MTEB(FollowIR) (Weller et al., 2024), a benchmark for law MTEB(Law), the bitext section of the MINER benchmark MINERSBitextMining target at low resource languages (Winata et al., 2024b), and the CoIR benchmark for code retrieval CoIR (Li et al., 2024). For this benchmark, we refer to their associated paper and pull requests.

For an up-to-date overview of maintained benchmarks please see the benchmark registry.¹³

MTEB(rus) (Snegirev et al., 2024): Although Russian has approximately 258 million speakers world-wide, it was almost completely absent from the original benchmark and represented only in few multilingual datasets (e.g., MassiveIntentClassification). To address this problem, we included a number of Russian datasets in the new multilingual benchmark. For this, we selected popular Russian time-tested and community-tested datasets representing the main MMTEB tasks. Additionally, we performed data cleaning and automatic filtering, where necessary, and formatted datasets in the

¹³<https://github.com/embeddings-benchmark/mteb/blob/main/mteb/benchmarks.py>

MMTEB format. The final Russian part includes 18 datasets covering 7 main tasks: Classification (7 datasets), Clustering (3 datasets), MultiLabelClassification (2 tasks), PairClassification (1 task), Reranking (1 task), Retrieval (2 tasks), and STS (2 tasks). This dataset was manually constructed.

RAR-b: The Reasoning as Retrieval Benchmark (RAR-b) (Xiao et al., 2024a) evaluates reasoning-level understanding abilities stored in embedding models, and assesses whether correct answers to reasoning questions can be retrieved as top similar to queries, under w/ and w/o instruction settings. The benchmark provides insights into whether representations of nuanced expressions are aligned and well-encoded by current embedding models, going beyond the established reliance on evaluating with STS or traditional topical-level IR tasks.

The benchmark puts together 17 tasks made from 15 datasets (with reasoning questions from 12 datasets and 3 extra datasets to enlarge the corpus), covering 1) commonsense reasoning: WinoGrande, PIQA, SIQA, α NLI, HellaSwag, ARC-Challenge, Quail, CSTS (Sakaguchi et al., 2021; Bisk et al., 2020; Sap et al., 2019; Bhagavatula et al., 2020; Zellers et al., 2019; Clark et al., 2018; Rogers et al., 2020; Deshpande et al., 2023), 2) temporal reasoning (Tan et al., 2023), 3) spatial reasoning: SpartQA (Mirzaee et al., 2021), 4) numerical reasoning: GSM8K, MATH (Hendrycks et al., 2021b; Cobbe et al., 2021; Yu et al., 2023), and 5) symbolic reasoning: HumanEvalPack and MBPP (Husain et al., 2019; Austin et al., 2021; Chen et al., 2021; Muennighoff et al., 2023a). The comprehensive assessment provides an early checkpoint for abilities envisioned to be necessary for next-generation embedding models (Xiao et al., 2024a).

MTEB(Europe): We begin by selecting 56 official languages of the European Union, along with languages recognized by Schengen-area countries, such as Norwegian Bokmål, Icelandic, Romani, and Basque. This initial selection results in 420 tasks. We then reduce this selection by filtering out machine-translated datasets, datasets with unclear licenses, and highly specialized datasets (e.g., code retrieval datasets). Additionally, we remove tasks such as AfriSentiClassification, which, while containing European languages, primarily target African or Indic languages. After these exclusions, 228 tasks remain. Next, we run a representative selection of models (see Section [3.1]) and iteratively filter out the most predictable tasks (see Section [2.3.3]). To preserve language diversity and ensure fair representation across task categories, we avoid removing any task if it would eliminate a language from a particular task category. Furthermore, we retain tasks where the mean squared error between predicted and observed performance exceeds 0.5 standard deviations. This process continues until the most predictable tasks yield a Spearman correlation of less than 0.8 between predicted and observed scores, or until no further tasks can be removed. Ultimately, this results in a final selection of 96 tasks. Finally, contributors proficient in the target languages review the selected tasks, replacing some manually with higher-quality alternatives if necessary.

MTEB(Indic): This benchmark is constructed similarly to the previous European benchmark but focuses on a set of Indic languages.¹⁴ Initially, we selected 55 tasks. After manual filtering, 44 tasks remain, and following task selection and review, the final benchmark contains 23 tasks.

H.2 BENCHMARK TASK OVERVIEW

The following tables give an overview of the tasks available within constructed benchmarks. For more information about the specific tasks, we refer to the task metadata available through the mteb package.¹⁵

- Table 12 and Table 13: Gives an overview of the ‘MTEB(Multilingual)’ benchmark
- Table 14: Gives an overview of the ‘MTEB(Europe)’ benchmark
- Table 15: Gives an overview of the ‘MTEB(Indic)’ benchmark
- Table 16: Gives an overview of the ‘MTEB(eng, v2)’ benchmark
- Table 17: Gives an overview of the ‘MTEB(Code)’ benchmark

¹⁴The following iso639-3 codes: asm, awa, ben, bgc, bho, doi, gbm, gom, guj, hin, hne, kan, kas, mai, mal, mar, mni, mup, mwr, nep, npi, ori, ory, pan, raj, san, snd, tam, tel, urd

¹⁵<https://github.com/embeddings-benchmark/mteb>

Type	Name	Languages	Domains	Sample creation	Annotations creators	Nb samples	
BiextMining	BUCV.v2 Zweigenbaum et al. (2017)	['cmm', 'deu', 'eng', ...]	['Written']	human-translated	human-annotated	35000	
	BibleNLPBiextMining Akerman et al. (2023)	['aai', 'aak', 'aau', ...]	['Religious', 'Written']	created	expert-annotated	417452	
	BornholmBiextMining Derczynski & Kjeldsen	['dan']	['Web', 'Social', 'Fiction', ...]	created	expert-annotated	500	
	DiaBlaBiextMining González et al. (2019)	['eng', 'fra']	['Social', 'Written']	created	human-annotated	11496	
	FloresBiextMining Goyal et al. (2022)	['ace', 'acm', 'acq', ...]	['Non-fiction', 'Encyclopaedic', 'Written']	created	human-annotated	41908944	
	IN22GenBiextMining Gala et al. (2023)	['asm', 'ben', 'brx', ...]	['Web', 'Legal', 'Government', ...]	created	expert-annotated	518144	
	IndicGenBenchFloresBiextMining Singh et al. (2024a)	['asm', 'awa', 'ben', ...]	['Web', 'News', 'Written']	human-translated and localized	expert-annotated	116522	
	NTRExBiextMining Federmann et al. (2022)	['af', 'amh', 'arb', ...]	['News', 'Written']	human-translated and localized	expert-annotated	3826252	
	NollySentiBiextMining Shode et al. (2023)	['eng', 'hau', 'ibo', ...]	['Social', 'Reviews', 'Written']	found	human-annotated	1640	
	NorwegianCoursBiextMining Tiedemann & Thottingal (2020)	['nno', 'nob']	['Legal', 'Written']	found	human-annotated	228	
	NusaTranslationBiextMining Cahyawijaya et al. (2023c)	['abs', 'bbc', 'bew', ...]	['Social', 'Written']	created	human-annotated	50200	
	NusaXBiextMining Winata et al. (2023b)	['ace', 'ban', 'bbc', ...]	['Reviews', 'Written']	created	human-annotated	5500	
	Tatoeba community (2021)	['af', 'amh', 'ang', ...]	['Written']	found	human-annotated	88877	
	Classification	AfriSentClassification Muhammad et al. (2023)	['amh', 'arq', 'ary', ...]	['Social', 'Written']	found	derived	18222
		AmazonCounterfactualClassification O'Neill et al. (2021)	['deu', 'eng', 'jpn']	['Reviews', 'Written']	found	human-annotated	5805
		BulgarianStoreReviewSentimentClassification Georgieva-Trifonova et al. (2018)	['bul']	['Reviews', 'Written']	found	human-annotated	182
		CSFDiskMovieReviewSentimentClassification Stefanik et al. (2023)	['slk']	['Reviews', 'Written']	found	derived	2048
		CataloniaTweetClassification Zotova et al. (2020)	['cat', 'spa']	['Social', 'Government', 'Written']	created	expert-annotated	8051
		CyrillicTurkicLangClassification Goldhahn et al. (2012)	['bak', 'chv', 'kaz', ...]	['Web', 'Written']	found	derived	2048
		CzechProductReviewSentimentClassification Habernal et al. (2013)	['ces']	['Reviews', 'Written']	found	derived	2048
		DBpediaClassification Zhang et al. (2015)	['eng']	['Encyclopaedic', 'Written']	found	derived	2048
		DalajClassification Volodina et al. (2021)	['sw']	['Non-fiction', 'Written']	created	expert-annotated	888
		EstonianValenceClassification Pajupuu et al. (2023)	['est']	['News', 'Written']	found	human-annotated	818
FilipinoShopeeReviewsClassification Riego et al. (2023)		['fil']	['Social', 'Written']	found	human-annotated	4096	
FinancialPhrasebankClassification Malo et al. (2014)		['eng']	['News', 'Written', 'Financial']	found	expert-annotated	2264	
GreekLegalCodeClassification Papaloukas et al. (2021)		['ell']	['Legal', 'Written']	found	human-annotated	4096	
GujaratiNewsClassification		['guj']	['News', 'Written']	found	derived	1318	
IndicLangClassification Madhani et al. (2023)		['asm', 'ben', 'brx', ...]	['Web', 'Non-fiction', 'Written']	created	expert-annotated	30418	
IndonesianIdClickbaitClassification William & Sari (2020)		['ind']	['News', 'Written']	found	expert-annotated	2048	
IsZuluNewsClassification Madodonga et al. (2023)		['zul']	['News', 'Written']	found	human-annotated	752	
ItaCaecholdClassification Licari et al. (2023)		['ita']	['Legal', 'Government', 'Written']	found	expert-annotated	221	
KorSarcsamClassification Kim & Cho (2019)		['kor']	['Social', 'Written']	found	expert-annotated	2048	
KurdishSentimentClassification Badawi et al. (2024)		['kur']	['Web', 'Written']	found	derived	1987	
MacedonianTweetSentimentClassification Jovanoski et al. (2015)		['mkd']	['Social', 'Written']	found	human-annotated	1139	
MasakhaNEWSClassification Adelani et al. (2023b)		['amh', 'eng', 'fra', ...]	['News', 'Written']	found	expert-annotated	6242	
MassiveIntentClassification FitzGerald et al. (2022)		['af', 'amh', 'ara', ...]	['Spoken']	human-translated and localized	human-annotated	255357	
MultiHateClassification R'otterger et al. (2021)		['ara', 'cmn', 'deu', ...]	['Constructed', 'Written']	created	expert-annotated	11000	
NepaliNewsClassification Arora (2020)		['nep']	['News', 'Written']	found	derived	2048	
NordicLangClassification Haas & Derczynski (2021)		['dan', 'fao', 'isl', ...]	['Encyclopaedic']	found	derived	3000	
NusaParaphraseEmotionClassification Cahyawijaya et al. (2023b)		['bbc', 'bew', 'bug', ...]	['Non-fiction', 'Fiction', 'Written']	found	human-annotated	5700	
NusaX-senti Winata et al. (2022)		['ace', 'ban', 'bbc', ...]	['Reviews', 'Web', 'Social', ...]	found	expert-annotated	4800	
OdiaNewClassification Kunchukuttan et al. (2020)		['ory']	['News', 'Written']	found	derived	2048	
PAC Lukasz Augustyniak et al. (2022)		['pol']	['Legal', 'Written']	found	derived	3453	
PoemSentimentClassification Sheng & Uthus (2020)		['eng']	['Reviews', 'Written']	found	human-annotated	209	
PolEmo2.0-OUT		['pol']	['Written', 'Social']	found	human-annotated	494	
PunjabiNewsClassification Kunchukuttan et al. (2020)		['pan']	['News', 'Written']	found	derived	157	
ScalaClassification Nielsen (2023)		['dan', 'nno', 'nob', ...]	['Fiction', 'News', 'Non-fiction', ...]	created	human-annotated	8192	
SentimentAnalysisHindi Parida et al. (2023)		['hin']	['Reviews', 'Written']	found	derived	2048	
SinhalaNewClassification de Silva (2015)		['sin']	['News', 'Written']	found	derived	2048	
SiswatiNewsClassification Madodonga et al. (2023)		['ssw']	['News', 'Written']	found	human-annotated	80	
SlovakMovieReviewSentimentClassification Stef'amik et al. (2023)		['svk']	['Reviews', 'Written']	found	derived	2048	
SwahiliNewsClassification Davis (2020)		['swa']	['News', 'Written']	found	derived	2048	
SwissJudgementClassification Niklaus et al. (2022)		['deu', 'fra', 'ita']	['Legal', 'Written']	found	expert-annotated	4908	
ToxicConversationsClassification cjdamas et al. (2019)		['eng']	['Social', 'Written']	found	human-annotated	2048	
TswanaNewClassification Marivate et al. (2023)		['tsn']	['News', 'Written']	found	derived	487	
TweetTopicSingleClassification Antypas et al. (2022)		['eng']	['Social', 'News', 'Written']	found	expert-annotated	1693	
Clustering		AlloProfClusteringS2S.v2 Letebvre-Brossard et al. (2023)	['fra']	['Encyclopaedic', 'Written']	found	human-annotated	2556
		ArXivHierarchicalClusteringP2P	['eng']	['Academic', 'Written']	found	derived	2048
		ArXivHierarchicalClusteringS2S	['eng']	['Academic', 'Written']	found	derived	2048
		BigPatentClustering.v2 Sharma et al. (2019)	['eng']	['Legal', 'Written']	found	derived	2048
	BiorxivClusteringP2P.v2	['eng']	['Academic', 'Written']	created	derived	53787	
	CLSClusteringP2P.v2 Li et al. (2022)	['cmn']	['Academic', 'Written']	found	derived	2048	
	HALClusteringS2S.v2 Cramone et al. (2024)	['fra']	['Academic', 'Written']	found	human-annotated	2048	
	MasakhaNEWClusteringS2S Adelani et al. (2023b)	['amh', 'eng', 'fra', ...]	None	created	derived	80	
	MedrxivClusteringP2P.v2	['eng']	['Academic', 'Medical', 'Written']	created	derived	37500	
	PiscClusteringP2P.v2	['pol']	['Academic', 'Written']	found	derived	2048	
	RomaniBibleClustering	['rom']	['Religious', 'Written']	human-translated and localized	derived	19788	
	SIB200ClusteringS2S Adelani et al. (2023a)	['ace', 'acm', 'acq', ...]	['News', 'Written']	human-translated and localized	expert-annotated	19788	
	SNLHierarchicalClusteringP2P Navjord & Korsvik (2023)	['nob']	['Encyclopaedic', 'Non-fiction', 'Written']	found	derived	1300	
	StackExchangeClustering.v2 Geigle et al. (2021)	['eng']	['Web', 'Written']	found	derived	2048	
	SwediaClusteringP2P Momen & Fonnson (2021)	['sw']	['News', 'Non-fiction', 'Written']	found	derived	68752	
	WikiCitesClustering Foundation	['eng']	['Encyclopaedic', 'Written']	found	derived	2048	
	WikiClusteringP2P.v2	['bos', 'cat', 'ces', ...]	['Encyclopaedic', 'Written']	created	derived	28672	

Table 12: The tasks included in MTEB(Multilingual) (part 1).

H.3 PERFORMANCE ON MTEB(eng, v2)

Table 18 show the performance of our representative set of model on MTEB(eng, v2).

H.4 PERFORMANCE ON MTEB(Code)

Table 19 show the performance of our representative set of model on MTEB(Code).

Type	Name	Languages	Domains	Sample creators	Annotations creators	Nb samples*	
InstructionReranking	Core17InstructionRetrieval Weller et al. (2024)	[eng]	['News', 'Written']	found	derived	19939	
	News2InstructionRetrieval Weller et al. (2024)	[eng]	['News', 'Written']	found	derived	30985	
	Robust04InstructionRetrieval Weller et al. (2024)	[eng]	['News', 'Written']	found	derived	47596	
MultilabelClassification	BrazilianToxicTweetsClassification Leite et al. (2020)	[por]	['Constructed', 'Written']	found	expert-annotated	2048	
	CDRClassification Sboev et al. (2021)	[rus]	['Web', 'Social', 'Blog', ...]	found	human-annotated	1882	
	KorHateSpeechMLClassification Lee et al. (2022)	[kor]	['Social', 'Written']	found	expert-annotated	2037	
	MalteseNewsClassification Chaudhary et al. (2024)	[mlt]	['Constructed', 'Written']	found	expert-annotated	2297	
	MultiEURLEXMultilabelClassification Chalkidis et al. (2021)	['bul', 'ces', 'dan', ...]	['Legal', 'Government', 'Written']	found	expert-annotated	115000	
PairClassification	ArmenianParaphrasePC Maljayan et al. (2020)	[hye]	['News', 'Written']	found	derived	1470	
	CTKFactNet11 Ullrich et al. (2023)	[ces]	['News', 'Written']	found	human-annotated	680	
	OpusparcusPC Creutz (2018)	['deu', 'eng', 'fin', ...]	['Spoken', 'Spoken']	created	human-annotated	18207	
	PawsXPairClassification Yang et al. (2019)	['cmn', 'deu', 'eng', ...]	['Web', 'Encyclopaedic', 'Written']	human-translated	human-annotated	28000	
	PpcPC Dadas (2022)	[pol]	['Fiction', 'Non-fiction', 'Web', ...]	found	derived	1000	
	RTE3 Giampiccolo et al. (2007)	['deu', 'eng', 'fra', ...]	['News', 'Web', 'Encyclopaedic', ...]	found	expert-annotated	1923	
	SprintDuplicateQuestions Shah et al. (2018)	[eng]	['Programming', 'Written']	found	derived	101000	
	TERRa Shavrina et al. (2020)	[rus]	['News', 'Web', 'Written']	found	human-annotated	307	
	TwitterURLCorpus Lan et al. (2017)	[eng]	['Social', 'Written']	found	derived	51534	
	XNLI Conneau et al. (2018)	['ara', 'bul', 'deu', ...]	['Non-fiction', 'Fiction', 'Government', ...]	created	expert-annotated	38220	
	indian1 Mahendran et al. (2021)	[ind]	['Encyclopaedic', 'Web', 'News', ...]	found	expert-annotated	2040	
	Reranking	AlloprofReranking Lefebvre-Brossard et al. (2023)	[fra]	['Web', 'Academic', 'Written']	found	expert-annotated	27355
		RuBQReranking Rybin et al. (2021)	[rus]	['Encyclopaedic', 'Written']	created	human-annotated	38998
		T2Reranking Xie et al. (2023)	[cmn]	None	found	derived	103330
VoyageMMarcoReranking Clavié (2023)		[jpn]	['Academic', 'Non-fiction', 'Written']	found	derived	55423	
WebLNXCandidatesReranking Lü et al. (2024)		[eng]	['Academic', 'Web', 'Written']	created	expert-annotated	5592142	
WikipediaRerankingMultilingual Foundation		['ben', 'bul', 'ces', ...]	['Encyclopaedic', 'Written']	LM-generated and verified	LM-generated and reviewed	240000	
Retrieval	ALLAStatues Bhattacharya et al. (2020)	[eng]	['Legal', 'Written']	found	derived	82 - 50	
	ArgoXano Boteva et al. (2016)	[eng]	['Medical', 'Written']	found	derived	8674 - 1406	
	BelebeleRetrieval Bandarkar et al. (2023)	['acm', 'afr', 'als', ...]	['Web', 'News', 'Written']	created	expert-annotated	183488 - 338378	
	CUREv1	[eng, 'fra', 'spa']	['Medical', 'Academic', 'Written']	created	expert-annotated	1541613 - 12000	
	CovidRetrieval	[cmn]	None	found	expert-annotated	100001 - 949	
	HazriatRetrieval Kamaloo et al. (2023)	[eng]	['Encyclopaedic', 'Written']	found	derived	496 - 406	
	LEMBPasskeyRetrieval Zhu et al. (2024)	[eng]	['Fiction', 'Written']	found	derived	800 - 400	
	LegalBenchCorporateLobbying Guba et al. (2023)	[eng]	['Legal', 'Written']	found	derived	319 - 340	
	MIRAACLRetrievalHardNegatives Zhang et al. (2023)	['ara', 'ben', 'deu', ...]	['Encyclopaedic', 'Written']	created	expert-annotated	2449382 - 11076	
	MLQARetrieval Lewis et al. (2019)	['ara', 'deu', 'eng', ...]	['Encyclopaedic', 'Written']	found	human-annotated	152379 - 173776	
	SCIDOCs Cohan et al. (2020b)	[eng]	['Academic', 'Written', 'Non-fiction']	found	derived	25657 - 1000	
	SpartQA Xiao et al. (2024a)	[eng]	['Encyclopaedic', 'Written']	found	derived	1592 - 3594	
	StackOverflowQA Li et al. (2024)	[eng]	['Programming', 'Written']	found	derived	19931 - 1994	
	StackOverflowQA Li et al. (2024)	[eng, 'fra']	['Government', 'Web', 'Written']	found	derived	23628 - 9436	
	TRECCOVID Roberts et al. (2021)	[eng]	['Medical', 'Academic', 'Written']	found	derived	171332 - 50	
	TempReasonL1 Xiao et al. (2024a)	[eng]	['Encyclopaedic', 'Written']	found	derived	12504 - 4000	
	TwitterHjemRetrieval Holm (2024)	[dan]	['Social', 'Written']	found	derived	262 - 78	
	WikipediaRetrievalMultilingual	['ben', 'bul', 'ces', ...]	['Encyclopaedic', 'Written']	LM-generated and verified	LM-generated and reviewed	216000 - 24000	
	WinoGrande Xiao et al. (2024a)	[eng]	['Encyclopaedic', 'Written']	found	derived	8095 - 1267	
	STS	FaroeseSTS Snebjornson et al. (2023)	[fao]	['News', 'Web', 'Written']	found	human-annotated	729
		FinParaSTS Kanerva et al. (2021)	[fin]	['News', 'Subtitles', 'Written']	found	expert-annotated	2000
		GermanSTS Benchmark May (2021)	[deu]	None	found	expert-annotated	2879
		IndicCrosslingualSTS Ramesh et al. (2022)	['asm', 'ben', 'eng', ...]	['News', 'Non-fiction', 'Web', ...]	created	expert-annotated	3072
		JSICK Yanaka & Minesshima (2022)	[jpn]	['Web', 'Written']	found	human-annotated	1986
		SICK-R Marelli et al. (2014)	[eng]	['Web', 'Written']	found	human-annotated	9927
		STS12 Agirre et al. (2012)	[eng]	['Encyclopaedic', 'News', 'Written']	created	human-annotated	3108
STS13 Agirre et al. (2013)		[eng]	['Web', 'News', 'Non-fiction', ...]	created	human-annotated	1500	
STS14 Bandhakavi et al. (2014)		[eng]	['Blog', 'Web', 'Spoken', ...]	created	derived	3750	
STS15 Biçici (2015)		[eng]	['Blog', 'News', 'Web', ...]	created	human-annotated	3000	
STS17 Cer et al. (2017)		['ara', 'deu', 'eng', ...]	['News', 'Web', 'Written']	created	human-annotated	5346	
STS22-v2 Chen et al. (2022)		['ara', 'cmn', 'deu', ...]	['News', 'Written']	found	human-annotated	3958	
STSB Xiao et al. (2024b)		[cmn]	None	found	human-annotated	2819	
STSBenchmark May (2021)		[eng]	['Blog', 'News', 'Written']	machine-translated and verified	human-annotated	1379	
STSES Agirre et al. (2015)		[spa]	['Written']	found	human-annotated	155	
SemRel24STS Oussidoum et al. (2024)		['afr', 'amh', 'arb', ...]	['Spoken', 'Written']	created	human-annotated	7498	

Table 13: The tasks included in MTEB(Multilingual) (part 2). *For the number of samples, are given the total number of samples all languages included, for Retrieval tasks are given the (number of queries - number of documents).

Type	Name	Languages	Domains	Sample creation	Annotation creators	Nb Samples*	
BitextMining	BornholmBitextMining Derczynski & Kjeldsen	[dan]	['Web', 'Social', 'Fiction', ...]	created	expert-annotated	500	
	BibleNLPIBitextMining Akerman et al. (2023)	['sai', 'aak', 'aau', ...]	['Religious', 'Written']	created	expert-annotated	417452	
	BUC v2 Zweigenbaum et al. (2017)	['cmn', 'deu', 'eng', ...]	['Written']	human-translated	human-annotated	35000	
	DialaBitextMining Gouzelok et al. (2019)	['eng', 'ara']	['Social', 'Written']	created	human-annotated	11496	
	FloresBitextMining Goyal et al. (2022)	['ace', 'acm', 'acq', ...]	['Non-fiction', 'Encyclopaedic', 'Written']	created	human-annotated	4190844	
	NorwegianCoursBitextMining Tiedemann & Thottingal (2020)	['nno', 'nob']	['Legal', 'Written']	found	human-annotated	228	
	NTRXBitextMining Federmann et al. (2022)	['afr', 'amh', 'arb', ...]	['News', 'Written']	human-translated and localized	expert-annotated	3826252	
	BulgarianBitextMining SentimentClassification Georgieva-Trifonova et al. (2018)	['bul']	['Reviews', 'Written']	found	human-annotated	182	
	CzechProductReviewSentimentClassification Habernal et al. (2013)	['ces']	['Reviews', 'Written']	found	derived	2048	
	GreekLegalCodeClassification Papaloukas et al. (2021)	['ell']	['Legal', 'Written']	found	human-annotated	4096	
Classification	DBpediaClassification Zhang et al. (2015)	['eng']	['Encyclopaedic', 'Written']	found	derived	2048	
	FinancialPhrasebankClassification Malo et al. (2014)	['eng']	['News', 'Written', 'Financial']	found	expert-annotated	2254	
	PoemSentimentClassification Sheng & Uthus (2020)	['eng']	['Reviews', 'Written']	found	human-annotated	209	
	ToxicChatClassification Lin et al. (2023)	['eng']	['Constructed', 'Written']	found	expert-annotated	1164	
	ToxicConversationsClassification cjadams et al. (2019)	['pol']	['Social', 'Written']	found	human-annotated	2048	
	EstonianValenceClassification Pajupou et al. (2023)	['est']	['News', 'Written']	found	human-annotated	818	
	ItaCaseloadClassification Licari et al. (2023)	['ita']	['Legal', 'Government', 'Written']	found	expert-annotated	221	
	AmazonCounterfactualClassification O'Neill et al. (2021)	['deu', 'eng', 'jpn']	['Reviews', 'Written']	found	human-annotated	5805	
	MassiveScenarioClassification FitzGerald et al. (2022)	['afr', 'amh', 'ara', ...]	['Spoken']	human-translated and localized	human-annotated	255357	
	MultiHateClassification R'otger et al. (2021)	['ara', 'cmn', 'deu', ...]	['Constructed', 'Written']	created	expert-annotated	11000	
	NordicLangClassification Haas & Derczynski (2021)	['dan', 'fao', 'isl', ...]	['Encyclopaedic']	found	derived	3000	
	ScalaClassification Nielsen (2023)	['dan', 'nno', 'nob', ...]	['Fiction', 'News', 'Non-fiction', ...]	created	human-annotated	8192	
	SwissJudgementClassification Niklaus et al. (2022)	['deu', 'fra', 'ita']	['Legal', 'Written']	found	expert-annotated	4908	
	TwesSentimentClassification Barberi et al. (2022)	['ara', 'deu', 'eng', ...]	['Social', 'Written']	found	human-annotated	2048	
	CBDOgrodniczak & Lakasz Kobylinski (2019)	['pol']	['Written', 'Social']	found	human-annotated	1000	
	PolEemo2.0-OUT	['pol']	['Written', 'Social']	found	derived	494	
	CSFDSKMovieReviewSentimentClassification Štefánik et al. (2023)	['slk']	['Reviews', 'Written']	found	derived	2048	
	DalaClassification Volodina et al. (2021)	['swe']	['Non-fiction', 'Written']	created	expert-annotated	888	
	Clustering	WikiELXClustering Foundation	['eng']	['Encyclopaedic', 'Written']	found	derived	1
		RomanBibleClustering	['rom']	['Religious', 'Written']	found	human-translated and localized	4
		BigPatentClustering v2 Sharma et al. (2019)	['eng']	['Legal', 'Written']	found	derived	2048
		BiorxivClusteringP2Pv2	['eng']	['Academic', 'Written']	created	derived	53787
		AlloProfClusteringS2S v2 Lefebvre-Brossard et al. (2023)	['fra']	['Encyclopaedic', 'Written']	found	human-annotated	2556
		HALClusteringS2S v2 Ciancone et al. (2024)	['fra']	['Academic', 'Written']	found	human-annotated	2048
		SIB200ClusteringS2S Adelmani et al. (2023a)	['ace', 'acm', 'acq', ...]	['News', 'Written']	human-translated and localized	expert-annotated	197788
WikiClusteringP2Pv2		['deu', 'eng', 'fra', ...]	['Encyclopaedic', 'Written']	created	derived	28672	
StackOverflowQA Li et al. (2024)		['eng']	['Programming', 'Written']	found	derived	19931 - 1994	
TwitterHjerneRetrieval Holm (2024)		[dan]	['Social', 'Written']	found	derived	262 - 78	
Retrieval	LegalQA D Hoppe et al. (2021)	['deu']	['Legal', 'Written']	found	derived	200 - 200	
	ArguAna Boteva et al. (2016)	['eng']	['Medical', 'Written']	found	derived	8674 - 1406	
	HagridRetrieval Kamaloo et al. (2023)	['eng']	['Encyclopaedic', 'Written']	found	expert-annotated	496 - 496	
	LegalBenchCOPoralLobbying Guba et al. (2023)	['eng']	['Legal', 'Written']	found	derived	319 - 340	
	LEMBPaskeyRetrieval Zhu et al. (2024)	['eng']	['Fiction', 'Written']	found	derived	800 - 400	
	SCIDOCs Cohan et al. (2020b)	['eng']	['Academic', 'Written', 'Non-fiction']	found	derived	25657 - 1000	
	SpartQA Xiao et al. (2024a)	['eng']	['Encyclopaedic', 'Written']	found	derived	1592 - 3594	
	TempReasoner Xiao et al. (2024a)	['eng']	['Encyclopaedic', 'Written']	found	derived	12504 - 4000	
	WinoGrande Xiao et al. (2024a)	['eng']	['Encyclopaedic', 'Written']	found	derived	5095 - 1267	
	AlloProfRetrieval Lefebvre-Brossard et al. (2023)	['fra']	['Encyclopaedic', 'Written']	found	human-annotated	2556 - 2316	
	BelebeRetrieval Bandarkar et al. (2023)	['acm', 'afr', 'als', ...]	['Web', 'News', 'Written']	created	expert-annotated	183488 - 338378	
	StacanDialogueDatasetRetrieval Lu et al. (2023)	['eng', 'fra']	['Government', 'Web', 'Written']	found	derived	23628 - 9436	
	WikipediaRetrievalMultilingual	['ben', 'bul', 'ces', ...]	['Encyclopaedic', 'Written']	LM-generated and verified	LM-generated and reviewed	216000 - 24000	
	InstructionRanking	Core1InstructionRetrieval Weller et al. (2024)	['eng']	['News', 'Written']	found	derived	19939
		New2InstructionRetrieval Weller et al. (2024)	['eng']	['News', 'Written']	found	derived	30985
		Robust4InstructionRetrieval Weller et al. (2024)	['eng']	['News', 'Written']	found	derived	47596
	MultilabelClassification	MalteseNewsClassification Chandhary et al. (2024)	['mlt']	['Constructed', 'Written']	found	expert-annotated	2297
		MultiELXMultilabelClassification Chalkidis et al. (2021)	['bul', 'ces', 'dan', ...]	['Legal', 'Government', 'Written']	found	expert-annotated	115000
	PairClassification	CTKFactNLI Ulfreh et al. (2023)	['ces']	['News', 'Written']	found	human-annotated	680
		SprintDuplicateQuestions Shah et al. (2018)	['eng']	['Programming', 'Written']	found	derived	101000
OpusparcusPC Creutz (2018)		['deu', 'eng', 'fin', ...]	['Spoken', 'Spoken']	created	human-annotated	18207	
RTE3 Giampiccolo et al. (2007)		['deu', 'eng', 'fra', ...]	['News', 'Web', 'Encyclopaedic', ...]	created	expert-annotated	1923	
NNL Conneau et al. (2018)		['ara', 'bul', 'deu', ...]	['Non-fiction', 'Fiction', 'Government', ...]	created	expert-annotated	38220	
PSC Ogrodniczak & Kopeć (2014)		['pol']	['News', 'Written']	found	derived	1078	
Ranking	WebLIxRankingRetrieval Li et al. (2023)	['eng']	['Encyclopaedic', 'Web', 'Written']	found	expert-annotated	559212	
	AlloProfRanking Lefebvre-Brossard et al. (2024)	['fra']	['Web', 'Academic', 'Written']	found	expert-annotated	27355	
STS	WikipediaRankingMultilingual Foundation	['ben', 'bul', 'ces', ...]	['Encyclopaedic', 'Written']	LM-generated and verified	LM-generated and reviewed	240000	
	SICK-R Mizzello et al. (2014)	['eng']	['Web', 'Written']	created	human-annotated	9927	
	STS12 Agirre et al. (2012)	['eng']	['Encyclopaedic', 'News', 'Written']	created	human-annotated	3108	
	STS14 Bandhakavi et al. (2014)	['eng']	['Blog', 'Web', 'Spoken']	created	derived	3750	
	STS15 Bgicj (2015)	['eng']	['Blog', 'News', 'Web', ...]	created	human-annotated	3000	
	STS8Benchmark May (2021)	['eng']	['News', 'News', 'Written']	found	machine-translated and verified	1379	
	FinParaSTS Kanerva et al. (2021)	['fin']	['News', 'Subtitles', 'Written']	found	expert-annotated	2000	
	STS17 Cer et al. (2017)	['ara', 'deu', 'eng', ...]	['News', 'Web', 'Written']	created	human-annotated	5346	
	SICK-R-PL Dadas et al. (2020)	['pol']	['Web', 'Written']	created	human-annotated	4906	
	STS8S Agirre et al. (2015)	['spa']	['Written']	found	human-translated and localized	155	

Table 14: The tasks included in MTEB(Europe). The language column shows all the languages of the task. When running the tasks we limit it to the languages specified in the benchmark. * For the number of samples, are given the total number of samples all languages included, for Retrieval tasks are given the (number of queries - number of documents).

Type	Name	Languages	Domains	Sample creation	Annotation creators	Nb samples*	
BitextMining	IN22ConvBitextMining Gala et al. (2023)	['asm', 'ben', 'bex', ...]	['Social', 'Spoken', 'Fiction', ...]	created	expert-annotated	760518	
	IN22GenBitextMining Gala et al. (2023)	['asm', 'ben', 'bex', ...]	['Web', 'Legal', 'Government', ...]	created	expert-annotated	518144	
	IndicGenBenchFloresBitextMining Singh et al. (2024a)	['asm', 'awa', 'ben', ...]	['Web', 'News', 'Written']	human-translated and localized	expert-annotated	116522	
Classification	LinceMTBitextMining Aguilar et al. (2020)	['eng', 'hin']	['Social', 'Written']	found	human-annotated	8059	
	BengaliSentimentAnalysis Sazzed (2020)	['ben']	['Reviews', 'Written']	found	human-annotated	2048	
	GujaratiNewsClassification	['guj']	['News', 'Written']	found	derived	1318	
	HindiDiscourseClassification Dhanwal et al. (2020)	['hin']	['Fiction', 'Social', 'Written']	found	expert-annotated	2048	
	IndicLangClassification Madhani et al. (2023)	['asm', 'ben', 'bex', ...]	['Web', 'Non-fiction', 'Written']	created	expert-annotated	30418	
	MTOPIntenClassification Li et al. (2021)	['deu', 'eng', 'fra', ...]	['Spoken', 'Spoken']	created	human-annotated	30517	
	MalayalamNewsClassification Kunchukuttan et al. (2020)	['mal']	['News', 'Written']	found	derived	12560	
	MultiHateClassification R'otger et al. (2021)	['ara', 'cmn', 'deu', ...]	['Constructed', 'Written']	created	expert-annotated	11000	
	NepaliNewsClassification Arora (2020)	['nep']	['News', 'Written']	found	derived	2048	
	PunjabiNewsClassification Kunchukuttan et al. (2020)	['pan']	['News', 'Written']	found	derived	157	
Clustering	SanskritShlokasClassification Arora (2020)	['san']	['Religious', 'Written']	found	derived	479	
	SentimentAnalysisHindi Parida et al. (2023)	['hin']	['Reviews', 'Written']	found	derived	2048	
	TwesSentimentClassification Barberi et al. (2022)	['ara', 'deu', 'eng', ...]	['Social', 'Written']	found	human-annotated	2048	
	UrduRomanSentimentClassification Sharf (2018)	['urd']	['Social', 'Written']	found	derived	2048	
	Retrieval	SIB200ClusteringS2S Adelmani et al. (2023a)	['ace', 'acm', 'acq', ...]	['News', 'Written']	human-translated and localized	expert-annotated	197788
		WikiELXRankingMultilingual Foundation	['ben', 'bul', 'ces', ...]	['Encyclopaedic', 'Fiction', 'Government', ...]	LM-generated and verified	LM-generated and reviewed	240000
	STS	XQuADRetrieval Artetxe et al. (2019)	['arb', 'deu', 'ell', ...]	['Web', 'Written']	created	expert-annotated	2880 - 14199
		IndicCrosslingualSTS Ramesh et al. (2022)	['asm', 'ben', 'eng', ...]	['News', 'Non-fiction', 'Web', ...]	created	expert-annotated	3072

Table 15: The tasks included in MTEB(Indic). The language column shows all the languages of the task. When running the tasks we limit it to the Indic languages specified in the benchmark. * For the number of samples, are given the total number of samples all languages included, for Retrieval tasks are given the (number of queries - number of documents).

Type	Name	Languages	Domains	Sample creation	Annotation creators	Nb samples*	
Classification	AmazonCounterfactualClassification O'Neill et al. (2021)	['deu', 'eng', 'jpn']	['Reviews', 'Written']	found	human-annotated	5805	
	Banking77Classification Casanueva et al. (2020)	['eng']	['Written']	found	human-annotated	3080	
	ImdbClassification Maas et al. (2011)	['eng']	['Reviews', 'Written']	found	derived	25000	
	MFOFDomainClassification Li et al. (2021)	['deu', 'eng', 'fra', ...]	['Spoken', 'Spoken']	created	human-annotated	30517	
	MassiveIntentClassification FitzGerald et al. (2022)	['afri', 'amh', 'ara', ...]	['Spoken']	human-translated and localized	human-annotated	255357	
	MassiveScenarioClassification FitzGerald et al. (2022)	['afri', 'amh', 'ara', ...]	['Spoken']	human-translated and localized	human-annotated	255357	
	ToxicConversationsClassification cjadams et al. (2019)	['eng']	['Social', 'Written']	found	human-annotated	2048	
	TweetSentimentExtractionClassification Maggie (2020)	['eng']	['Social', 'Written']	found	human-annotated	3534	
	Clustering	ArXivHierarchicalClusteringP2P	['eng']	['Academic', 'Written']	found	derived	2048
		ArXivHierarchicalClusteringS2S	['eng']	['Academic', 'Written']	found	derived	2048
BiorxivClusteringP2Pv2		['eng']	['Academic', 'Written']	created	derived	53787	
MedrxivClusteringP2Pv2		['eng']	['Academic', 'Medical', 'Written']	created	derived	37500	
MedrxivClusteringS2Sv2		['eng']	['Academic', 'Medical', 'Written']	created	derived	37500	
StackExchangeClusteringv2 Geigle et al. (2021)		['eng']	['Web', 'Written']	found	derived	2048	
StackExchangeClusteringP2Pv2 Geigle et al. (2021)		['eng']	['Web', 'Written']	found	derived	74914	
TwentyNewsgroupsClusteringv2 Lang (1995)		['eng']	['News', 'Written']	found	derived	59545	
PairClassification		SprintDuplicateQuestions Shah et al. (2018)	['eng']	['Programming', 'Written']	found	derived	101000
		TwitterSemEval2015 Xu et al. (2015)	['eng']	['Social', 'Written']	found	human-annotated	16777
Reranking	TwitterURLCorpus Lan et al. (2017)	['eng']	['Social', 'Written']	found	derived	51534	
	AskUbuntuDupQuestions Wang et al. (2021a)	['eng']	['Programming', 'Web']	found	human-annotated	7581	
Retrieval	MindSmallReranking Wu et al. (2020a)	['eng']	['News', 'Written']	found	expert-annotated	2367791	
	ArguAna Boteva et al. (2016)	['eng']	['Medical', 'Written']	found	derived	8674 - 1406	
	CQADupstackGamingRetrieval Hoozeven et al. (2015)	['eng']	['Web', 'Written']	found	derived	45301 - 1595	
	CQADupstackUnixRetrieval Hoozeven et al. (2015)	['eng']	['Written', 'Web', 'Programming']	found	derived	47382 - 1072	
	ClimateFEVERHardNegatives Diggelmann et al. (2021)	['eng']	['Encyclopaedic', 'Written']	found	human-annotated	47416 - 1000	
	FEVERHardNegatives Thorne et al. (2018a)	['eng']	None	None	human-annotated	163698 - 1000	
	FIQA2018 Thakur et al. (2021)	['eng']	['Written', 'Financial']	found	human-annotated	57638 - 648	
	HotpotQAHardNegatives Yang et al. (2018)	['eng']	['Web', 'Written']	found	human-annotated	225621 - 1000	
	SCIDOCs Cohan et al. (2020b)	['eng']	['Academic', 'Written', 'Non-fiction']	found	human-annotated	25657 - 1000	
	TRECCOVID Roberts et al. (2021)	['eng']	['Medical', 'Academic', 'Written']	found	human-annotated	171332 - 50	
	Touche2020Retrieval.v3 Thakur et al. (2024)	['eng']	['Academic']	found	human-annotated	303732 - 49	
	STS	BLOSSES Sogancioğlu et al. (2017)	['eng']	['Medical']	found	derived	100
		SKCK-R Marelli et al. (2014)	['eng']	['Web', 'Written']	found	human-annotated	9927
STS12 Agirre et al. (2012)		['eng']	['Encyclopaedic', 'News', 'Written']	created	human-annotated	3108	
STS13 Agirre et al. (2013)		['eng']	['Web', 'News', 'Non-fiction', ...]	created	human-annotated	1500	
STS14 Bandhakavi et al. (2014)		['eng']	['Blog', 'Web', 'Spoken']	created	derived	3750	
STS15 Biçici (2015)		['eng']	['Blog', 'News', 'Web', ...]	created	human-annotated	3000	
STS17 Cer et al. (2017)		['ara', 'deu', 'eng', ...]	['News', 'Web', 'Written']	created	human-annotated	5346	
STS22.v2 Chen et al. (2022)		['ara', 'cmn', 'deu', ...]	['News', 'Written']	found	human-annotated	3958	
STSBenchmark May (2021)		['eng']	['Blog', 'News', 'Written']	machine-translated and verified	human-annotated	1379	
Summarization		SummEvalSummarization.v2 Fabbri et al. (2020)	['eng']	['News', 'Written']	created	human-annotated	100

Table 16: The tasks included in MTEB(eng, v2). The language column shows all the languages of the task. When running the tasks we limit it to the languages specified in the benchmark. * For the number of samples, are given the total number of samples all languages included, for Retrieval tasks are given the (number of queries - number of documents).

Type	Name	Languages	Domains	Sample creation	Annotations creators	Nb Samples*
Retrieval	AppsRetrieval Hendrycks et al. (2021a)	['eng', 'python']	['Programming', 'Written']	found	derived	3765 - 8765
	COIRCodeSearchNetRetrieval Husain et al. (2019)	['go', 'java', 'javascript', 'php']	['Programming', 'Written']	found	derived	52561 - 1003765
	CodeEditSearchRetrieval Muenighoff et al. (2023a)	['c', 'c++', 'go', 'java']	['Programming', 'Written']	found	derived	13000 - 13000
	CodeFeedbackMT Zheng et al. (2024)	['eng']	['Programming', 'Written']	found	derived	13277 - 66383
	CodeFeedbackST Li et al. (2024)	['eng']	['Programming', 'Written']	found	derived	31306 - 156526
	CodeSearchNetCCRetrieval Li et al. (2024)	['go', 'java', 'javascript', 'php']	['Programming', 'Written']	found	derived	52561 - 1005474
	CodeSearchNetRetrieval Husain et al. (2019)	['go', 'java', 'javascript', 'php']	['Programming', 'Written']	found	derived	6000 - 6000
	CodeTransOceanContest Yan et al. (2023)	['c++', 'python']	['Programming', 'Written']	found	derived	221 - 1008
	CodeTransOceanDL Yan et al. (2023)	['python']	['Programming', 'Written']	found	derived	180 - 816
	CosQA Huang et al. (2021)	['eng', 'python']	['Programming', 'Written']	found	derived	500 - 20604
	StackOverflowQA Li et al. (2024)	['eng']	['Programming', 'Written']	found	derived	1994 - 19931
	SyntheticText2SQL Meyer et al. (2024)	['eng', 'sql']	['Programming', 'Written']	found	derived	5851 - 105851

Table 17: The tasks included in MTEB(Code). * For the number of samples, are given the total number of samples all languages included, for Retrieval tasks are given the (number of queries - number of documents).

model	Rank	Average Across		Average by Category					
		Borda Count	All	Category	Pair Clf.	Clf.	STS	Retrieval	Clustering
e5-mistral-7b-instruct	1 (393)	67.0	67.2	88.4	75.2	83.6	54.8	51.4	49.8
GritLM-7B	2 (384)	66.4	66.7	87.3	77.0	82.5	53.2	50.8	49.6
multilingual-e5-large-instruct	3 (357)	65.2	65.6	86.2	73.2	84.3	51.0	49.9	48.7
multilingual-e5-large	4 (270)	62.1	62.4	84.7	72.8	80.6	49.0	42.8	44.7
all-mpnet-base-v2	5 (211)	56.0	58.1	83.0	56.6	72.2	41.9	46.6	48.4
multilingual-e5-base	6 (211)	60.2	60.9	83.6	70.0	79.1	46.1	42.2	44.3
paraphrase-multilingual-mpnet-base-v2	7 (188)	57.3	58.8	81.7	68.6	79.8	34.1	43.5	45.2
all-MiniLM-L12-v2	8 (172)	54.7	57.0	82.5	55.8	70.7	40.7	44.6	47.5
all-MiniLM-L6-v2	9 (149)	54.4	56.7	82.4	55.4	70.4	39.8	44.9	47.1
multilingual-e5-small	10 (147)	58.4	59.3	82.7	67.7	77.6	43.7	40.8	43.2
paraphrase-multilingual-MiniLM-L12-v2	11 (109)	55.1	57.0	80.0	64.4	77.5	32.8	41.7	45.4
LaBSE	12 (49)	48.6	51.7	78.9	66.8	70.2	16.8	36.1	41.3

Table 18: Performance on MTEB(eng, v2) across task categories.

Model	Rank Borda Count	Average Across All	Average by Language						
			C++	Go	Java	JavaScript	PHP	Python	Ruby
GritLM-7B	1 (88)	73.6	73.1	83.8	84.9	81.7	77.8	86.4	83.8
e5-mistral-7b-instruct	2 (74)	69.2	68.3	83.0	80.9	79.4	75.6	83.6	81.1
multilingual-e5-large-instruct	3 (65)	65.0	56.4	74.7	74.7	71.7	71.6	79.1	74.9
multilingual-e5-large	4 (63)	61.7	46.8	73.4	72.2	66.6	69.1	75.7	73.4
multilingual-e5-base	5 (55)	57.5	48.9	73.2	71.0	66.1	67.8	75.2	72.7
multilingual-e5-small	6 (53)	58.4	48.4	70.6	67.9	65.2	66.6	73.6	68.1
all-mpnet-base-v2	7 (44)	56.4	46.3	67.4	62.2	63.1	61.7	69.0	65.7
all-MiniLM-L6-v2	8 (34)	52.7	48.1	64.4	57.4	62.2	60.4	68.1	66.6
all-MiniLM-L12-v2	9 (27)	50.2	46.8	68.1	57.3	63.6	62.7	68.7	67.8
LaBSE	10 (11)	28.8	27.6	40.6	36.6	42.3	34.8	43.9	42.2

Table 19: Performance on MTEB(Code) across task categories. Because all code-related tasks are for retrieval, metrics by category are omitted.