

ALEE: Any-Language Evaluation of Embeddings via English-Centric Minimal Pairs

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Abstract

Text embeddings are standard for semantic similarity tasks, yet their evaluation remains an open challenge. Current benchmarks are static, cover only a limited set of languages, are often domain-specific, susceptible to overfitting, and poorly representative of low-resource languages. To address these limitations, we introduce ALEE, a framework that extends *Sentence Smith* (Li et al., 2025) to the cross-lingual and paragraph level. ALEE uses Abstract Meaning Representations (AMR) to generate English minimal pairs with controlled, fine-grained semantic shifts, which are paired with translations in target languages. This approach enables targeted diagnostics for models in any language with English parallel data. We conduct a large-scale empirical study across a diverse set of embedding models and 275+ languages spanning three parallel datasets. On ALEE, performance varies substantially across languages, text lengths, and linguistic phenomena, exposing persistent gaps in cross-lingual semantic representation that track language prevalence in training resources and subword tokenization. We release ALEE at <https://github.com/Andrian0s/any-lang-embed-eval>.

1 Introduction

Semantic text embeddings are central to modern information retrieval, clustering, and cross-lingual alignment (Reimers and Gurevych, 2019; Gao et al., 2021). However, their evaluation is largely based on static benchmarks with coarse-grained similarity judgments (Muennighoff et al., 2023). These datasets have three major limitations: they are biased toward high-resource languages, they are vulnerable to data leakage and overfitting because they are fixed, and they are too coarse-grained to distinguish semantic equivalence from lexical overlap.

To address these limitations, we propose a dynamic minimal-pair evaluation setting leverag-

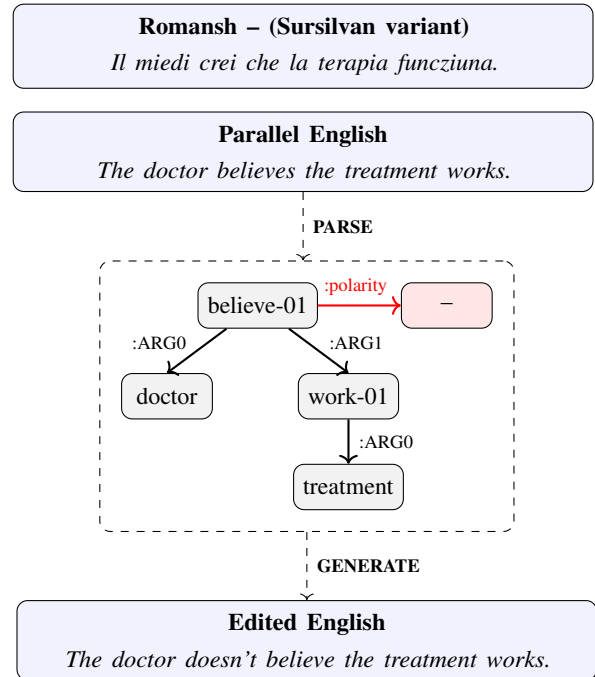


Figure 1: Controlled cross-lingual polarity flip in ALEE.

ing Abstract Meaning Representation (AMR, Banarescu et al., 2013). AMR is a formal semantic representation of a text’s meaning, explicating semantic phenomena such as *entities* and their *roles*, *negation*, *cause*, and more—making it suitable for controlled representation and generation tasks (Wein and Opitz, 2024; Sadeddine et al., 2024). Instead of relying on fixed sentence pairs as in previous embedding evaluations, we use AMR to generate challenging sentence examples that are lexically and syntactically close to a source sentence but differ by one controlled semantic operation.

Figure 1 illustrates the minimal pair generation with a sentence in Sursilvan, a Romansh variety spoken in the Swiss canton of Graubünden (Moseley, 2010). The English parallel sentence, “The doctor believes the treatment works” is parsed into an AMR graph, and a *:polarity -* edge is added to the predicate *believe-01*. This yields the sentence

“The doctor doesn’t believe the treatment works,” while the Sursilvan sentence remains unchanged: “Il miedi crei che la terapia funcziuna”. Henceforth, we denote such a generation also by *foil* or *confounder*, as this indicates its functional purpose within our embedding evaluation framework.

This construction allows us to test whether a model assigns higher similarity to the original English sentence than to its minimally perturbed foil, in relation to the same target-language sentence.

Because the English sentences differ only in one controlled semantic feature, a model’s preference for the original over the foil provides a targeted diagnostic of its cross-lingual embedding behavior. This way, we can test whether target-language representations are aligned closely enough with English to preserve distinctions such as polarity, argument structure, or lexical-semantic contrast.

In this paper, we introduce ALEE (Any-Language Evaluation of Embeddings), a framework that combines English-side semantic control with broad language coverage. By generating English minimal pairs and pairing them with target-language data, we create a diagnostic testbed for any language with English parallel data. We show the value of ALEE by evaluating a diverse set of embedding models across 275+ languages, including very low-resource varieties, and report consistent patterns.

Our contributions and findings:

1. We introduce ALEE, a dynamic cross-lingual benchmark construction framework based on English AMR-derived minimal pairs and target-language parallel data.
2. Even strong embedding models fail to resolve all minimal pairs, with structural and lexical shifts such as role reversals, antonymy, and abstraction-level changes proving harder than polarity negation; notably, larger decoder-based models do not outperform smaller encoders. Furthermore, longer, multi-sentence texts are substantially harder than shorter ones.
3. ALEE performance correlates with language prevalence in training corpora: both pretraining and fine-tuning language distributions correlate with per-language performance, with fine-tuning more strongly associated.
4. Greater subtoken fragmentation correlates strongly with lower downstream performance.
5. In a Romansh case study, performance declines across varieties in roughly the order of speaker population, mirroring written prevalence and tokenizer coverage down to the dialect level.

2 Related Work

Cross-Lingual Embedding Evaluation. Common evaluation tasks are cross-lingual information retrieval (CLIR; Lawrie et al., 2025), semantic text similarity (X-STs; Cer et al., 2017), and bitext mining (Zweigenbaum et al., 2017). These evaluations provide a useful overall view of model quality, but they offer limited insight into which semantic distinctions a model captures across languages. Strong results may arise from broad lexical or topical overlap, underweighting sensitivity to finer meaning contrasts (Fodor et al., 2025). Further, the staticness of datasets risks overfitting effects, and the concentration on higher-resource languages makes them less-suitable for fine-grained diagnosis in low-resource settings, and unsuitable for languages not covered, such as the Romansh varieties that we cover in our work here.

Embedding evaluation also ties closely to embedding interpretability (Opitz et al., 2025, 2026). A recurring challenge is to move beyond holistic similarity scores and identify which semantic properties account for textual differences. Our work aligns with this goal by using controlled semantic edits for targeted probes of cross-lingual spaces.

Minimal Pairs aim to isolate specific linguistic contrasts, but their datasets require costly manual effort and are static (e.g., BLiMP and Multi-BLiMP; Warstadt et al., 2020; Jumelet et al., 2026). By contrast, *Sentence Smith* (Li et al., 2025) generates English minimal pairs through rule-based edits to AMR graphs as an intermediate representation—in a dynamic fashion that allows ad-hoc generation of novel pairs. ALEE extends this idea cross-lingually by applying English-side perturbations to parallel corpora. Unlike other work relying on black-box LLM verification or costly human data creation (Nastase et al., 2024; Michail et al., 2025), we use explicit semantic representation and can scale to any language with English parallel data.

3 ALEE

We use ALEE to denote both the dataset construction pipeline and the resulting evaluation datasets.

3.1 Controlled Foil Generation via AMR

To generate semantically controlled minimal pairs, we build on *Sentence Smith* (Li et al., 2025). Its pipeline consists of three stages: (1) parsing an English source sentence into an AMR graph, (2)

Transformation	Linguistic Target	Relation Induced	Description
PN	Truth-functional Logic	Contradictory / Contrary	Negates via <i>:polarity -</i> . Distinguishes Syntactic and morphological opposition.
RS	Argument Structure	Reversal of Thematic Roles	Swaps <i>:ARG0</i> (Agent) and <i>:ARG1</i> (Patient). Tests sensitivity to semantic structure.
AR	Lexical Semantics	Polar Opposition	Replaces node with WordNet antonym. Targets conceptual opposites.
HS	Taxonomic Hierarchy	Hyponymy / Entailment	Replaces concept with superordinate. Breaks bidirectional entailment.

Table 1: Mapping AMR Transformations to Linguistic Targets and Semantic Relations.

applying a rule-based semantic edit to the graph, and (3) generating text from the modified graph.

ALEE extends this process to a cross-lingual setting by applying the edit to the English side of a parallel corpus. This yields triplets of the form $(en_{orig}, en_{foil}, target_{orig})$. We then evaluate whether a model assigns higher similarity to the original cross-lingual pair $(en_{orig}, target_{orig})$ than to the foil pair $(en_{foil}, target_{orig})$.

3.2 Semantic Manipulation Types

Following Li et al. (2025), we apply four AMR-based perturbation types to English pivot texts. Each targets a different type of semantic distinction, as summarized in Table 1.

- **Polarity Negation (PN):** This manipulation reverses the truth value of a predicate by adding the *:polarity -* attribute. It covers cases of **syntactic negation** (e.g., *approve* $\rightarrow$ *not approve*), which functions as a logical **contradictory** (absence of a property), and in some cases **morphological negation** (e.g., *just* $\rightarrow$ *unjust*), although the latter is not always strictly equivalent to simple negation.
- **Role Swap (RS):** This manipulation perturbs **predicate-argument structure** by exchanging thematic roles such as Agent and Patient. By swapping the *:ARG0* and *:ARG1* nodes, it changes *who did what to whom* while preserving most lexical material, thereby testing sensitivity to structure rather than surface overlap.
- **Antonym Replacement (AR):** This manipulation substitutes a concept with a WordNet-derived **antonym**, e.g., *good* $\rightarrow$ *bad*. Unlike polarity negation, it relies on lexical substitution rather than a negation marker, thereby probing sensitivity to lexical-semantic opposition.
- **Hypernym Substitution (HS):** This manipulation replaces a concept with its taxonomic

superordinate (e.g., *penguin* $\rightarrow$ *bird*). Because the resulting sentence is semantically less specific, this perturbation tests whether embeddings preserve distinctions involving lexical entailment relations and level of abstraction.

3.3 Validation of Generated Foils

Not every graph manipulation might yield a correct foil: in some cases, the generated sentence could remain too close in meaning to the source or the semantic change could be neutralized during generation, e.g., by the AMR generator failing to express our change. We therefore apply a bidirectional entailment filter using the robustified NLI model of Steen et al. (2023), adding an additional verification step that is efficient and fully automated.

For each source-foil pair, we run the NLI model in both directions: source $\rightarrow$ foil and foil $\rightarrow$ source. To reduce false positives, we reject a candidate if (i) both directions are predicted as entailment, or (ii) $P(\text{entail})$ in either direction exceeds 0.8. The latter may be seen as standing in some conflict with the desired HS-relation, but practical experiments with the specific NLI module indicated (i) and (ii) as a suitable setup for minimizing false positives.

3.4 Iterative Paragraph Manipulation

AMR-based generation works best at the sentence level. To handle the paragraph-length texts in datasets such as WMT24++, we propose an iterative first-success procedure:

1. **Decomposition:** The paragraph is segmented into individual sentences using NLTK’s `sent_tokenize(v3.9)`.
2. **Surgical Edit:** We attempt an AMR manipulation on the i -th sentence (start with $i=0$).
3. **Sentence Validation:** The modified sentence is checked through an NLI check against the original sentence as described in Section 3.3.

4. **Construction & Validation:** The edited sentence is integrated in the paragraph. An NLI check is also run against the original paragraph.
5. **Recursion:** If the NLI model fails to confirm a semantic shift at either stage (i.e., the paragraphs remain bi-directionally entailed), we revert the change, increment i , return to step 2.

Discussion. These four perturbation types allow us to evaluate models along distinct semantic dimensions for any language paired with English parallel data. In the cross-lingual setting, the model must determine which of two closely related English sentences better matches a target-language sentence. In the next section, we describe the parallel datasets used to instantiate this framework.

3.5 Multilingual Corpora

We instantiate ALEE on three parallel datasets to provide broad linguistic and structural coverage.

FLORES-200 is a widely used Machine Translation test set with professionally translated sentences in **200 languages** (Team, 2022). We refer to this dataset instance as **ALEE-F200**.

WMT24++ is an expanded parallel corpus containing 998 texts in 55 languages (Deutsch et al., 2025); a later extension adds six Romansh varieties, yielding **61 languages** in total (Vamvas et al., 2025). Because WMT24++ includes both sentence-level and paragraph-level material, it also utilizes the iterative editing pipeline described above. We refer to this dataset instance as **ALEE-MT61**.

BOUQuET is a multi-way parallel, multi-register benchmark whose source texts were handcrafted by linguists in 8 diverse languages and translated into English and 266 additional language varieties, yielding **275 languages** in total (Andrews et al., 2025; Team, 2026). Because BOUQuET, like WMT24++, provides both sentence-level and paragraph-level material, it also utilizes the iterative editing pipeline. We refer to this dataset instance as **ALEE-BQ275**.

ALEE-F200 Statistics. We apply all four transformations to 1,012 English source sentences from FLORES-200. Table 2 reports the number of validated foils per transformation. The median source length is 24 tokens (IQR: 19–29), and the median foil length is 20 tokens (IQR: 15–26).

	ALEE F200	ALEE MT61	ALEE BQ275
English sources	1,012	818	1,052
Polarity negation	558	668	669
Role swap	334	377	333
Antonym replacement	484	609	597
Hypernym substitution	216	354	341

Table 2: Count of sources and NLI-validated foils.

ALEE-MT61 Statistics. We exclude 180 (out of 998) flagged as low quality by the corpus providers, leaving 818 texts for foil generation. Success rates are higher than in **ALEE-F200** (Table 2), likely because paragraph-level texts offer multiple opportunities to obtain at least one valid edit. The median source length is 38 tokens (IQR: 17–73), and the median foil length is 44 tokens (IQR: 19–76).

ALEE-BQ275 Statistics. We apply all four transformations to 854 sentences and 198 paragraphs from BOUQuET; Table 2 reports the amount of yielded foils. Median source length is 15 tokens (IQR: 10–16); median foil length 14 (IQR: 9–14).

3.6 Quality Assessment

We manually inspect 200 English source–foil pairs sampled from each dataset. In **ALEE-F200**, all 200 pairs are judged to be valid minimal pairs, and 98% are judged grammatical. Most grammaticality errors arise from local syntactic artifacts that resemble poorly integrated template insertions. For the 200 sampled pairs from **ALEE-MT61**, we obtain similarly high quality. We judge 99% of the minimal pairs to be valid and 96% to be grammatical. The remaining errors are mainly due to formatting artifacts, such as HTML tags, or punctuation errors. For **ALEE-BQ275** all sampled minimal pairs are considered valid, while 98% are grammatical. Overall, this manual assessment is consistent with the high data quality reported by Li et al. (2025).

Note that role-swapped constructions occasionally do not adhere to selectional preferences, i.e., the semantic constraints that predicates impose on their arguments (Wilks, 1975; Dowty, 1991). E.g.:
orig: *The effect the team was looking for would be caused by tidal forces between the galaxy’s dark matter and the Milky Way’s dark matter.*

foil: *The effects that the tide looks at are caused by the team forcing the dark matter of the galaxy to darken.*

Yet, we emphasize that even in those cases, the

main aim of the operation has been achieved. The **foil** in this case may appear nonsensical or odd, but it is a valid test case.

4 General Setup

Evaluation Metric. We follow Li et al. (2025) and use Triplet Accuracy (*TACC*), defined as the proportion of triplets in which a model assigns higher similarity to the original cross-lingual pair than to the foil pair. When aggregating over perturbation types, we report **Macro-TACC**, which averages **TACC** across the four augmentations. Higher values are better; random performance is 0.5.

Examined Embedding Models. We evaluate a set of widely used embedding models with fewer than 600M parameters: the bitext-mining model sentence_transformers_LaBSE (Feng et al., 2022), the paraphrase-aligned paraphrase_multil_mpnet_base (Reimers and Gurevych, 2019, 2020), Google’s google_embeddinggemma_300m (Vera et al., 2025), nomic_embed_text_v2_moe (Nussbaum and Duderstadt, 2025), Alibaba_NLP_gte_multilingual_base (Zhang et al., 2024), BAAI_bge_m3 in dense mode (Chen et al., 2024), the jina_embeddings_v3 and jina_embeddings_v5_text_small/nano models (Sturua et al., 2025; Akram et al., 2026), ibm_granite_embed_107/278m_multil (Awasthy et al., 2025), and the Multilingual E5 family—multilingual_e5_base/large/instruct (Wang et al., 2024). Detailed configurations are provided in Appendix Table 4.

5 Research Findings

5.1 Fine-Grained Linguistic Evaluation

Research Question. We first ask how embedding models perform on ALEE overall and how their performance varies across the four semantic perturbation types.

Setup. For each model and each transformation, we compute TACC averaged over languages, separately for each ALEE dataset.

Findings. Figure 2 summarizes the results. We observe three main patterns: (1) Multilingual E5-instruct and LaBSE rank at or near the top on all three datasets. Multilingual E5-instruct leads on **ALEE-F200** and **ALEE-BQ275**, while LaBSE—a model trained for bitext mining with hard negatives—edges ahead on **ALEE-MT61**. At the same time, no model reaches perfect accuracy,

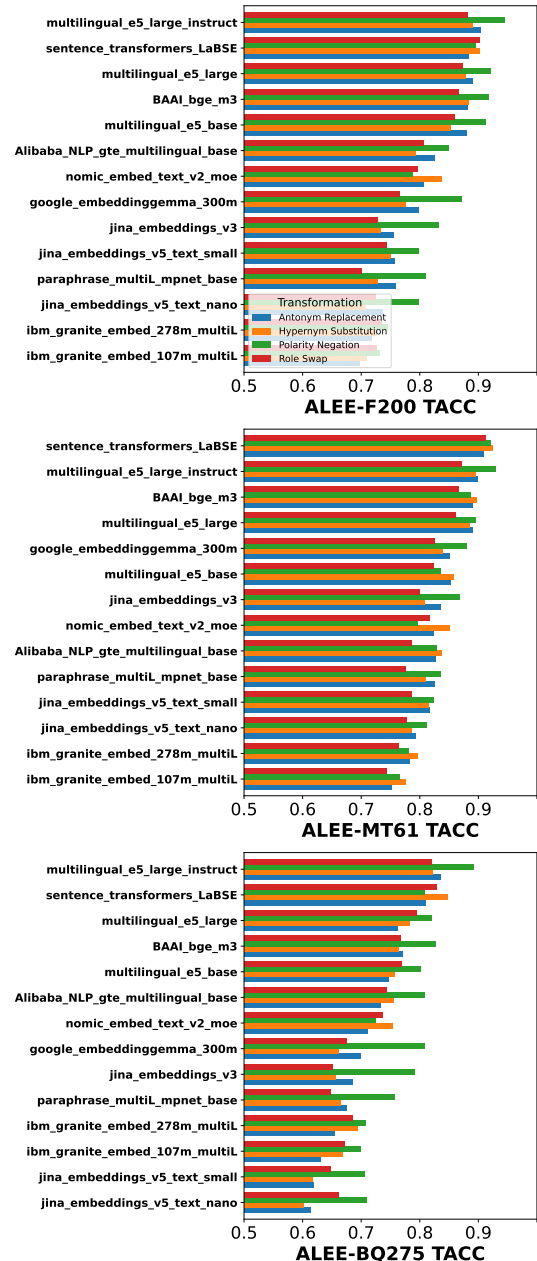


Figure 2: Mean TACC per model broken down by semantic edit type, on ALEE-F200 (top), ALEE-MT61 (middle) and ALEE-BQ275 (bottom). Models are sorted by averages across minimal pair types.

indicating that all models fail on a non-trivial subset of minimal pairs. (2) Across all three datasets, polarity negation is consistently the easiest perturbation, whereas role swap, antonym replacement, and hypernym substitution are closely clustered and show no stable ordering across datasets. This suggests that models detect explicit polarity reversals more reliably than the other contrasts, which they handle at broadly similar levels. (3) In aggregate, performance is highest on **ALEE-MT61**, followed by **ALEE-F200** and **ALEE-BQ275** (Table 5). We

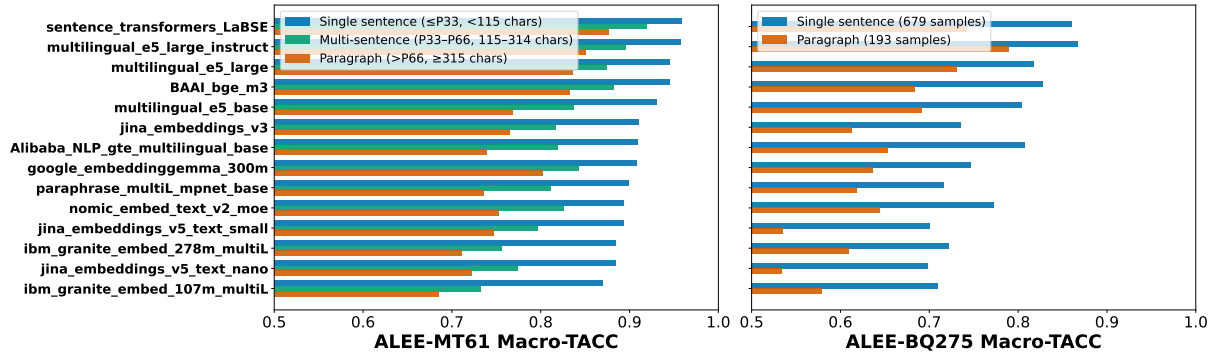


Figure 3: ALEE-MT61, ALEE-BQ275 Macro-TACC across different text lengths.

attribute this ordering to language coverage rather than text difficulty: ALEE-F200 and ALEE-BQ275 include more low-resource languages, which lowers their averaged scores. Restricting the comparison to languages shared across all three datasets removes this effect. Full per-language results are in Appendix B, where a language can be located by searching (Ctrl+F) for its three-letter code followed by an underscore (e.g., “deu_” for German).

5.2 Effects of Text Length

Research Question. A key extension of *Sentence Smith* in ALEE is the ability to manipulate longer, multi-sentence texts through the iterative sentence processing pipeline described in Section 3.4. We therefore examine how model performance varies with text length, averaged across all languages.

Setup. In ALEE-MT61, we divide texts into three bins based on character-length percentiles (below P33, between P33 and P66, and above P66) and compute the average Macro-TACC for each model in each bin. In ALEE-BQ275, we use the provided sentence or paragraph level flag and compute the average Macro-TACC for each model in each bin.

Findings. Figure 3 shows a consistent decline in performance as text length increases, even though each foil modifies only a single sentence. In ALEE-MT61, the average drop across models is 9.4% from single- to multi-sentence texts and 15.4% from single-sentence to paragraph. Within ALEE-BQ275, performance drops similarly by 16.0% from sentence to paragraph level. This suggests that semantic discrimination becomes more difficult as the amount of surrounding context grows.

5.3 Training Language Distribution Effects

Research Question. We now investigate which language-level factors are associated with perfor-

mance differences across languages. To this aim, we first investigate the language distribution of a widely used pretraining corpus, and finally aim to disentangle the contributions of pretraining and fine-tuning data for an exemplar model.

5.3.1 Pretraining Data Distribution

Setup. To move beyond coarse resource membership, we examine the relationship between pretraining data size and downstream performance. Because 5 of the 14 encoder models use XLM-RoBERTa (Conneau et al., 2020) as a backbone and 3 others reuse its tokenizer, we use CC-100 language proportions as an approximate proxy for pretraining exposure. For each language reported in CC-100, we compare log-scaled data size with Macro-TACC averaged across models, separately for ALEE-F200 and ALEE-BQ275.

Findings. Figure 4 shows a strong positive correlation between CC-100 data size and performance on both datasets (Spearman $\rho=0.766$ on ALEE-F200; $\rho=0.733$ on ALEE-BQ275). This trend is consistent with the broader pattern: languages with greater representation in pretraining resources tend to achieve better embedding performance.

Note that this finding is tied to the models with the same backbone. To further corroborate this finding from a broader perspective, we assess performance of all embedding models on different subsets of languages, adopting the assumption that a low-resource language is a language that occurs less frequently on the internet. The result in Figure 5 clearly corroborates the strong relationship between embedding performance and language representation in online texts.

5.3.2 MLM vs. Contrastive Training

Setup. To distinguish the contributions of pretraining and fine-tuning, we examine GTE Multi-

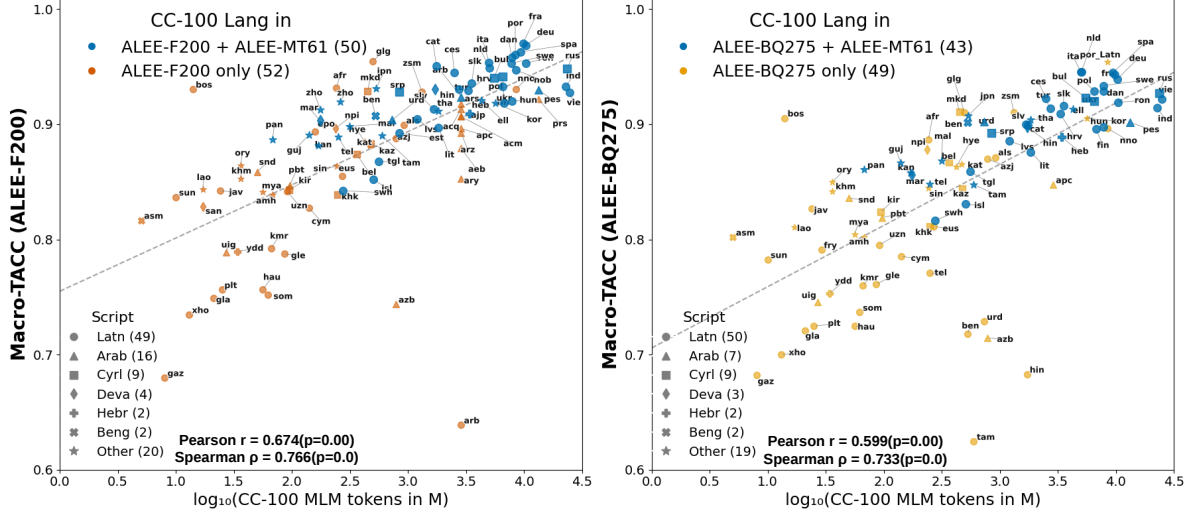


Figure 4: Per-language Macro-TACC vs. CC-100 pretraining data size (log-scaled), averaged across all models, for **ALEE-F200** (left) and **ALEE-BQ275** (right). Each point is a language, colored by whether it also appears in **ALEE-MT61**. Marker shapes indicate writing script.

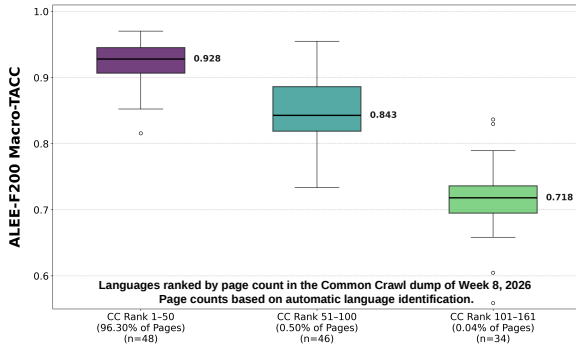


Figure 5: **ALEE-F200** Macro-TACC distribution by Common Crawl language prevalence. **ALEE-MT61** and **ALEE-BQ275** show similar patterns (Figs. 11 and 12).

lingual Base, which openly reports its MLM pre-training and contrastive fine-tuning data distributions per language. For each language, we plot its Macro-TACC against the log-scaled data volumes, separately for each ALEE dataset.

Findings. Figure 6 shows that both training stages correlate positively with performance across all three datasets, with contrastive fine-tuning data more strongly associated with performance than MLM pretraining data. This gap varies by dataset: it is largest on **ALEE-MT61** ($\rho=0.638$ vs $\rho=0.340$), and smaller on **ALEE-F200** ($\rho=0.681$ vs $\rho=0.554$) and **ALEE-BQ275** ($\rho=0.619$ vs $\rho=0.548$). This may be because **ALEE-MT61** contains longer texts and thus provides a stronger out-of-distribution test than **ALEE-F200** and **ALEE-BQ275**.

Across all three correlation analyses, perfor-

mance is consistently associated with language representation in the training pipeline, including broad corpus coverage and training volumes.

5.4 Subword Tokenization Effects

Setup. As a corpus-independent proxy for language coverage, we compute the median number of XLM-R subtokens per language and correlate it with the average TACC over all models. A higher number of subtokens may reflect not only limited vocabulary coverage, but also morphological complexity or script-related properties.

Findings. Figure 7 shows the results for **ALEE-MT61**; Results **ALEE-F200** and **ALEE-BQ275** are reported in the Appendix Figures 9 and 10.

Languages whose texts are split into more subtokens tend to show lower performance ($\rho=-0.516$ on **ALEE-MT61**; $\rho=-0.786$ on **ALEE-F200**, $\rho=-0.708$ on **ALEE-BQ275**). The Romansh idioms illustrate this pattern perfectly: they require the largest number of subtokens and show the lowest performance, with an almost perfectly negative correlation across the six idioms ($\rho=-0.986$).

Overall, greater subword fragmentation is associated with lower embedding performance, whether it arises from limited vocabulary coverage or language-specific structural properties.

5.5 Case Study: Romansh

Research Question. We finally examine an extreme low-resource case: how do multilingual

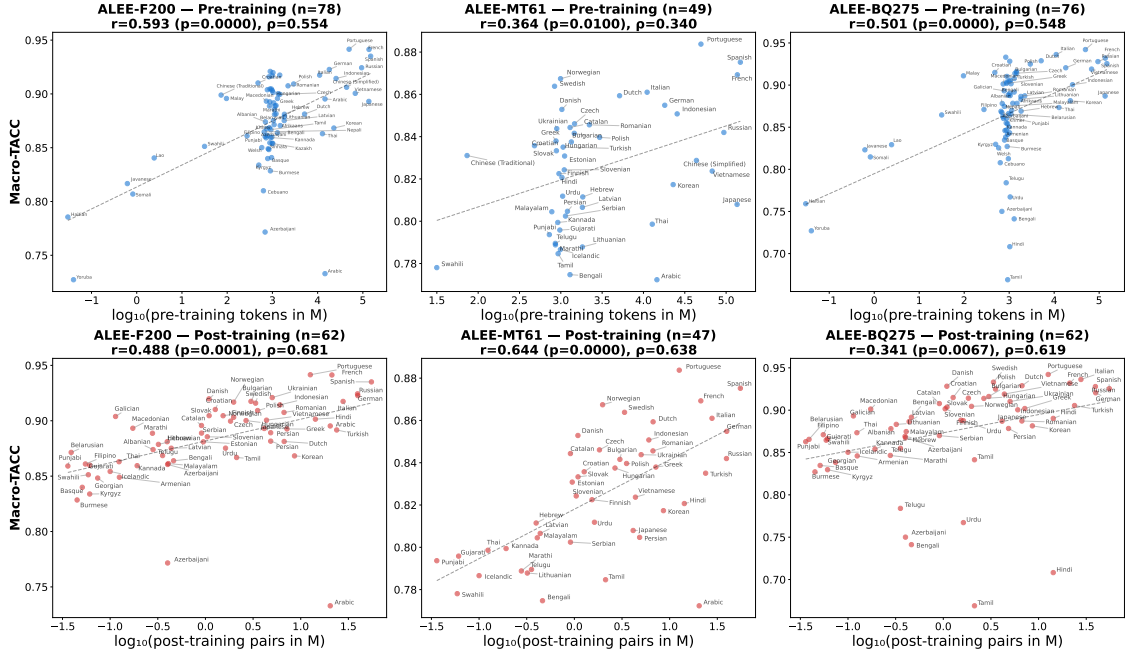


Figure 6: multilingual-gte-base. Per-language TACC vs. training data size for pretraining tokens (top) and post-training pairs (bottom). r/ρ Pearson’s/Spearman’s coefficient.

	Rank	ALEE F200	ALEE MT61	ALEE BQ275	Avg
LaBSE	2	0.896	0.917	0.823	0.879
Qwen3-Emb-8B	6	0.842	0.839	0.723	0.801
gte-multilingual-base	7	0.818	0.819	0.760	0.799
Qwen3-Emb-4B	11	0.777	0.799	0.680	0.752
granite_embed107_multiL	16	0.716	0.759	0.667	0.714
Qwen3-Emb-0.6B	17	0.696	0.735	0.644	0.691

Table 3: Overall and per-dataset Macro-TACC for the Qwen decoder-based models and selected comparison models. Rank is over all evaluated models on the three-dataset average.

embedding models perform across the six written Romansh varieties? Romansh is a Rhaeto-Romance language and the fourth national language of Switzerland, with roughly 60,000 speakers in total. It comprises five traditional written varieties, or “idioms”: *Sursilvan*, *Sutsilvan*, *Surmiran*, *Puter*, and *Vallader*, which differ substantially in orthography and phonology (Gross, 2004). *Rumantsch Grischun* (Schmid, 1982) is a standardized written form designed for inter-variety communication and official use (Gross, 2004; Ayres-Bennett and Carruthers, 2018; Vamvas et al., 2025). Evaluating these varieties allows us to test model behavior in a fine-grained and low-resource setting.

Setup. We calculate, for all embedding models and all six Romansh varieties, the average Macro-TACC over all four minimal pair types.

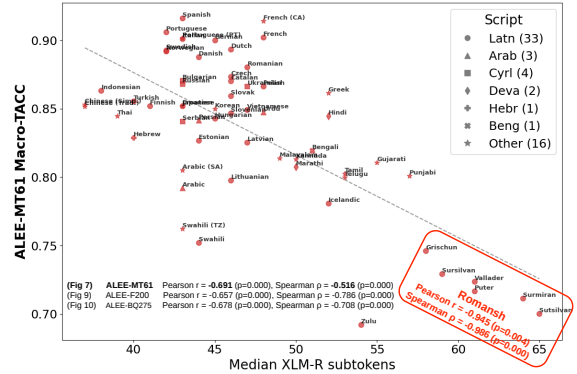


Figure 7: Per-language Macro-TACC vs. median XLM-R subtoken count on ALEE-MT61, averaged across all models. Marker shapes indicate writing script. Figures 9 & 10 in the Appendix show ALEE-F200/BQ275 results.

Findings. Figure 8 shows that performance is highest for Rumantsch Grischun and then generally declines across the spoken varieties in roughly the order of speaker population. This pattern is also accompanied by increasing subtoken fragmentation. The result is consistent with earlier analyses suggesting that written prevalence and tokenizer coverage are associated with better performance. Relative to each model’s overall average across languages, performance on Romansh is typically 10–20% lower. There are also some notable ranking shifts: for example, mGTE rises to fifth place, and mE5-instruct surpasses LaBSE on ALEE-

	Grischun	Vallader	Sursilvan	Puter	Surmiran	Sutsilvan	
multilingual_e5_large_instruct	0.814	0.804	0.807	0.795	0.778	0.781	Macro-TACC
sentence_transformers_LaBSE	0.823	0.809	0.798	0.778	0.788	0.768	
multilingual_e5_large	0.780	0.776	0.773	0.767	0.750	0.745	
BAAI_bge_m3	0.781	0.778	0.764	0.753	0.738	0.745	
Alibaba_NLP_gte_multilingual_base	0.773	0.746	0.746	0.748	0.725	0.723	
multilingual_e5_base	0.747	0.742	0.737	0.729	0.719	0.706	
google_embeddinggemma_300m	0.736	0.724	0.719	0.717	0.715	0.719	
ibm_granite_embed_107m_multiL	0.733	0.724	0.715	0.716	0.713	0.684	
ibm_granite_embed_278m_multiL	0.740	0.715	0.725	0.710	0.705	0.689	
nomic_embed_text_v2_moe	0.731	0.718	0.691	0.682	0.709	0.679	
jina_embeddings_v3	0.707	0.681	0.673	0.676	0.669	0.654	
paraphrase_multiL_mpnet_base	0.695	0.667	0.674	0.662	0.671	0.655	
jina_embeddings_v5_text_small	0.702	0.667	0.660	0.657	0.640	0.634	
jina_embeddings_v5_text_nano	0.686	0.660	0.649	0.642	0.641	0.621	
Number of Speakers	Gov. Docs only	6,500	18,000	5,500	3,000	1,000	
XLNet-R Subtokens (median)	58	61	59	58	64	65	

Figure 8: ALEE MT61 Macro-TACC for Romansh variants. Speaker count according to Gross (2004); year 2000.

MT61 for this subset, suggesting that model rankings can change substantially in very low-resource settings. Overall, this suggests that ALEE could help inform the selection of an embedding model for a low-resource language or dialect of interest, since the performance of embedding models on different languages is not directly indicative of their performance on a specific low-resource language.

5.6 Decoder-Based Embedding Models

Research Question. We ask whether recent decoder-based LLM embeddings can improve cross-lingual discrimination on ALEE.

Setup. We evaluate the Qwen3-Embedding family (0.6B, 4B, 8B) (Zhang et al., 2025) under the same TACC protocol, comparing against some of the sub-600M encoder models (Table 3).

Findings. Scale helps within the family: Qwen3-Embedding rises from 0.691 (0.6B) to 0.752 (4B) to 0.801 (8B). But it does not close the gap to encoders. The largest decoder (8B) ranks sixth overall, below LaBSE (0.879) despite roughly an order of magnitude more parameters, and is matched or beaten by smaller encoder models (Table 3). Parameter count is thus not the primary driver here: the tested decoder-based models do not appear to capture the fine-grained cross-lingual contrasts in

ALEE as reliably as smaller encoders, which remain more effective despite their size. The pattern holds across all three datasets (per-augmentation breakdowns are reported in Appendix Table 5).

6 Conclusions

We present ALEE, a dynamic cross-lingual evaluation framework that generates fine-grained semantic stress tests for embedding models in any language with English parallel data. Across 275+ languages—many previously lacking embedding evaluation resources—we find (1) persistent gaps in cross-lingual semantic representation; (2) that explicit semantic reversals such as negation are easier to detect than structural shifts like role swaps or abstraction-level changes; (3) and that paragraph-level texts are more challenging than single sentences. Further, (4) performance is strongly tied to language prevalence in training data and tokenizer coverage, a pattern that holds down to the dialect level, as shown in our Romansh case study. Model rankings also shift across languages, meaning aggregate scores can obscure important per-language differences. Beyond these findings, ALEE provides dynamic evaluation for numerous languages, including many low-resource varieties not previously covered by embedding benchmarks.

Acknowledgments

This research is conducted under the project *Impresso – Media Monitoring of the Past II. Beyond Borders: Connecting Historical Newspapers and Radio*. Impresso is a research project funded by the Swiss National Science Foundation (SNSF 213585) and the Luxembourg National Research Fund (17498891). MW acknowledges funding by the Swiss National Science Foundation (project InvestigaDiff; no. 10000503).

Limitations

Our framework applies semantic perturbations on the English side of parallel data, enabling precise and controllable edits through AMR. As a result, it evaluates cross-lingual alignment to semantic contrasts expressed in English, rather than performing edits directly within the target language. While this introduces an English-centric perspective, it provides a consistent and scalable evaluation setup; extending controlled perturbations to additional languages is a promising direction for future work.

The dynamically generated benchmark’s quality depends on the AMR parser, generation model, and NLI-based filtering. While manual inspection suggests high validity, some noise may remain. In addition, certain perturbations (e.g., role swaps) can produce less natural sentences, which can also be interpreted as testing robustness to atypical or adversarial inputs. Advances in generation and validation could further improve naturalness and control.

Our evaluation uses a pairwise ranking metric (Triplet Accuracy), which provides a clear signal of relative preferences but does not assess absolute similarity calibration. Complementary evaluation metrics could provide a more complete picture.

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A Appendix

Model Short Name	Hugging Face ID	Instructions / Prompt / Prefix / Adapter
sentence_transformers_LaBSE	sentence-transformers/LaBSE	—
BAAI_bge_m3	BAAI/bge-m3	—
multilingual_e5_large_instruct	intfloat/multilingual-e5-large-instruct	{Prefix;} Instruct: Represent every detail of this text to avoid matching to hard negatives.\nQuery:
Qwen3-Embedding-0.6B	Qwen/Qwen3-Embedding-0.6B	{Prefix;} Instruct: Represent every detail of this text to avoid matching to hard negatives.\nQuery:
Qwen3-Embedding-4B	Qwen/Qwen3-Embedding-4B	{Prefix;} Instruct: Represent every detail of this text to avoid matching to hard negatives.\nQuery:
Qwen3-Embedding-8B	Qwen/Qwen3-Embedding-8B	{Prefix;} Instruct: Represent every detail of this text to avoid matching to hard negatives.\nQuery:
multilingual_e5_large	intfloat/multilingual-e5-large	{Prefix;} query:
multilingual_e5_base	intfloat/multilingual-e5-base	{Prefix;} query:
jina_embeddings_v3	jinaai/jina-embeddings-v3	{Adapter;} text-matching
google_embeddinggemma_300m	google/embeddinggemma-300m	Prefix: task: sentence similarity query:
nomic_embed_text_v2_moe	nomic-ai/nomic-embed-text-v2-moe	{Prefix;} search_query:
jina_embeddings_v5_text_small	jinaai/jina-embeddings-v5-text-small	{Adapter;} text-matching
paraphrase_multiL_mpnet_base	sentence-transformers/paraphrase-multilingual-mpnet-base-v2	—
jina_embeddings_v5_text_nano	jinaai/jina-embeddings-v5-text-nano	{Adapter;} text-matching
gte-multilingual-base	Alibaba-NLP/gte-multilingual-base	—
ibm_granite_embed_107m_multiL	ibm-granite/granite-embedding-107m-multilingual	—
ibm_granite_embed_278m_multiL	ibm-granite/granite-embedding-278m-multilingual	—

Table 4: Embedding model configurations used in the evaluation.

Model	ALEE-F200					ALEE-MT61					ALEE-BQ275				
	PN	RS	AR	HS	Avg	PN	RS	AR	HS	Avg	PN	RS	AR	HS	Avg
multilingual_e5_large_instruct	0.945	0.882	0.904	0.889	0.905	0.929	0.872	0.899	0.895	0.899	0.892	0.821	0.835	0.821	0.842
sentence_transformers_LaBSE	0.896	0.903	0.884	0.903	0.896	0.920	0.913	0.910	0.925	0.917	0.807	0.828	0.810	0.847	0.823
multilingual_e5_large	0.920	0.873	0.889	0.878	0.890	0.895	0.860	0.891	0.885	0.883	0.821	0.795	0.761	0.783	0.790
BAAI_bge_m3	0.917	0.867	0.881	0.884	0.887	0.888	0.866	0.890	0.896	0.885	0.828	0.767	0.771	0.764	0.782
multilingual_e5_base	0.912	0.860	0.880	0.852	0.876	0.835	0.824	0.852	0.858	0.842	0.801	0.769	0.747	0.756	0.768
Qwen3 Embedding 8B	0.880	0.821	0.836	0.833	0.842	0.872	0.810	0.847	0.826	0.839	0.778	0.707	0.710	0.697	0.723
Alibaba_NLP_gte_multilingual_base	0.849	0.806	0.825	0.793	0.818	0.828	0.785	0.827	0.837	0.819	0.808	0.743	0.733	0.755	0.760
google_embeddinggemma_300m	0.871	0.765	0.798	0.775	0.802	0.881	0.826	0.852	0.838	0.849	0.807	0.675	0.699	0.661	0.711
nomic_embed_text_v2_moe	0.788	0.797	0.807	0.837	0.807	0.796	0.818	0.824	0.850	0.822	0.725	0.737	0.710	0.754	0.732
jina_embeddings_v3	0.832	0.729	0.756	0.732	0.762	0.869	0.799	0.835	0.808	0.828	0.791	0.651	0.685	0.656	0.696
Qwen3 Embedding 4B	0.825	0.754	0.766	0.762	0.777	0.828	0.773	0.795	0.801	0.799	0.755	0.645	0.667	0.656	0.680
paraphrase_multiL_mpnet_base	0.811	0.700	0.759	0.728	0.750	0.835	0.776	0.826	0.810	0.812	0.756	0.647	0.675	0.664	0.686
jina_embeddings_v5_text_small	0.797	0.744	0.757	0.751	0.762	0.824	0.786	0.816	0.816	0.810	0.706	0.648	0.619	0.617	0.648
ibm_granite_embed_278m_multiL	0.744	0.735	0.718	0.726	0.731	0.781	0.765	0.782	0.797	0.781	0.708	0.685	0.654	0.695	0.685
jina_embeddings_v5_text_nano	0.797	0.724	0.736	0.708	0.741	0.811	0.777	0.792	0.786	0.791	0.709	0.661	0.613	0.602	0.646
ibm_granite_embed_107m_multiL	0.732	0.726	0.697	0.709	0.716	0.765	0.743	0.753	0.775	0.759	0.699	0.672	0.631	0.668	0.667
Qwen3 Embedding 0.6B	0.715	0.682	0.682	0.704	0.696	0.737	0.725	0.735	0.742	0.735	0.666	0.631	0.630	0.648	0.644

Table 5: Per-category Macro-TACC results across all three ALEE datasets.

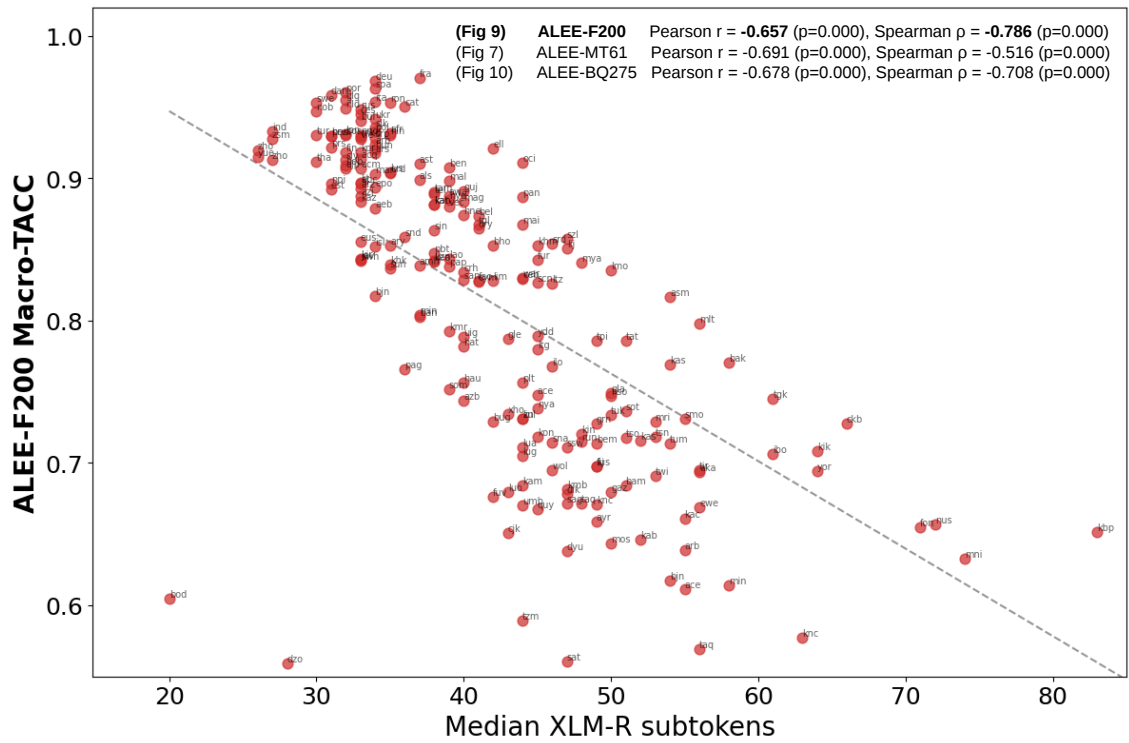


Figure 9: Per-language Macro-TACC vs. median XLM-R subtoken count on **ALEE-F200**, averaged across all models. Marker shapes indicate writing script.

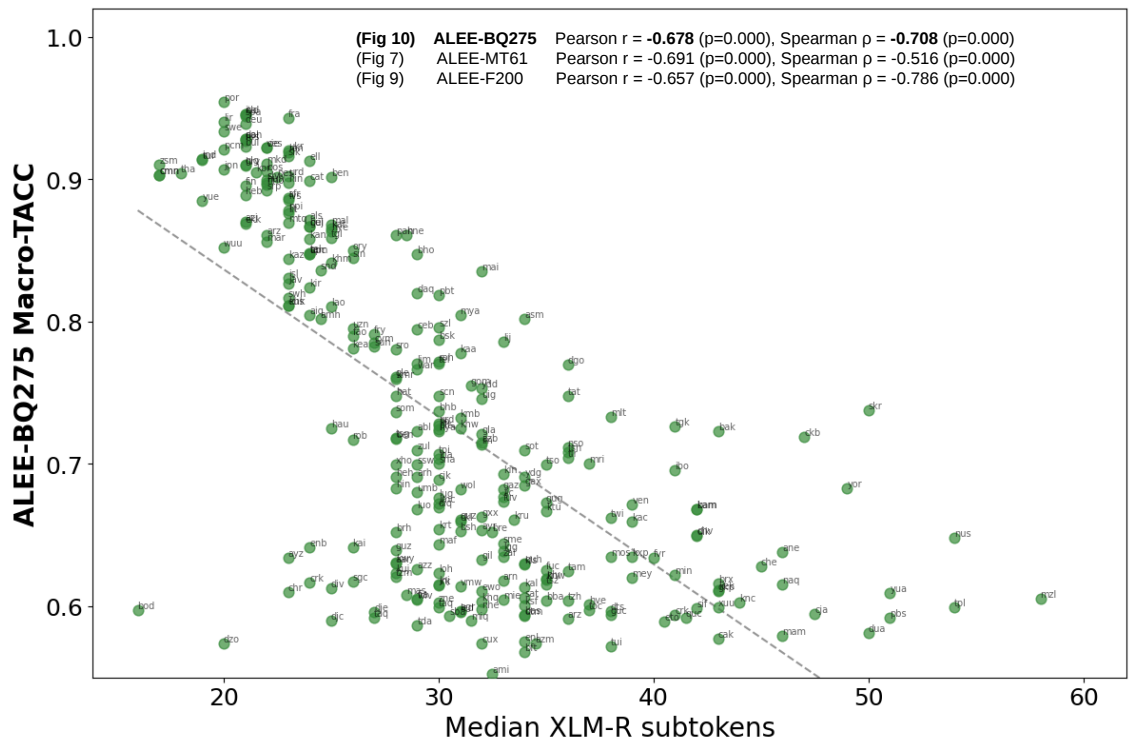


Figure 10: Per-language Macro-TACC vs. median XLM-R subtoken count on **ALEE-BQ275**, averaged across all models. Marker shapes indicate writing script.

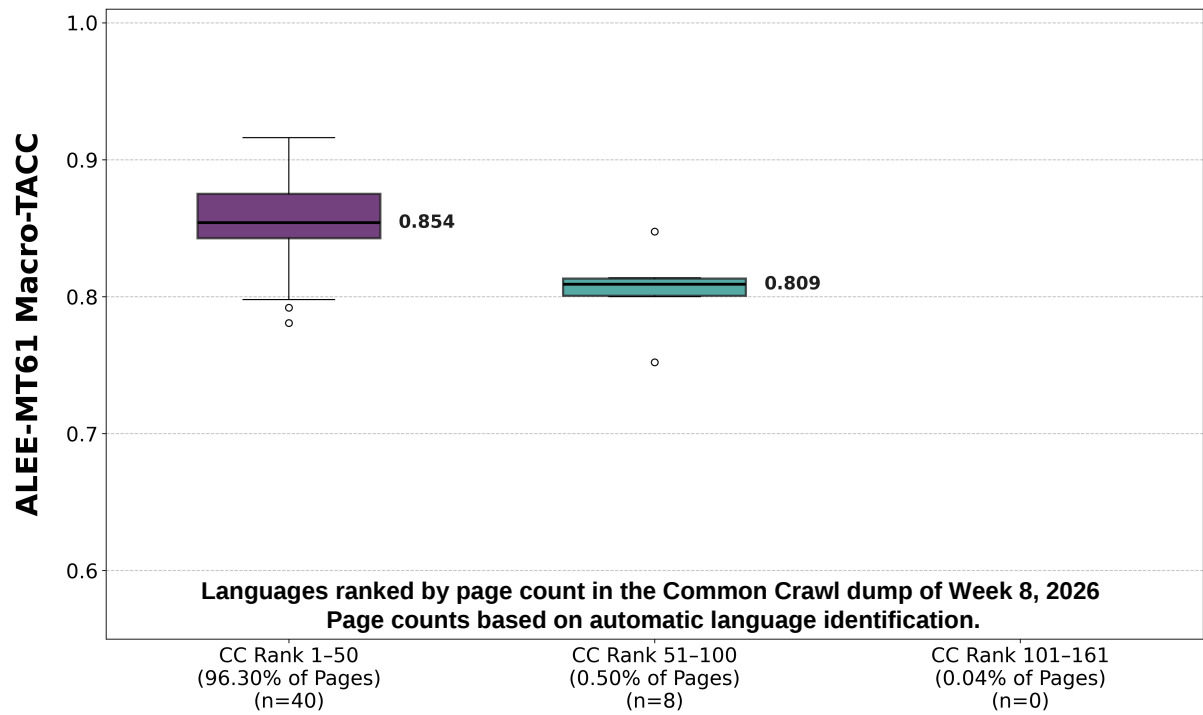


Figure 11: ALEE-MT61 Macro-TACC distribution by Common Crawl language prevalence. Analogous to Figure 5.

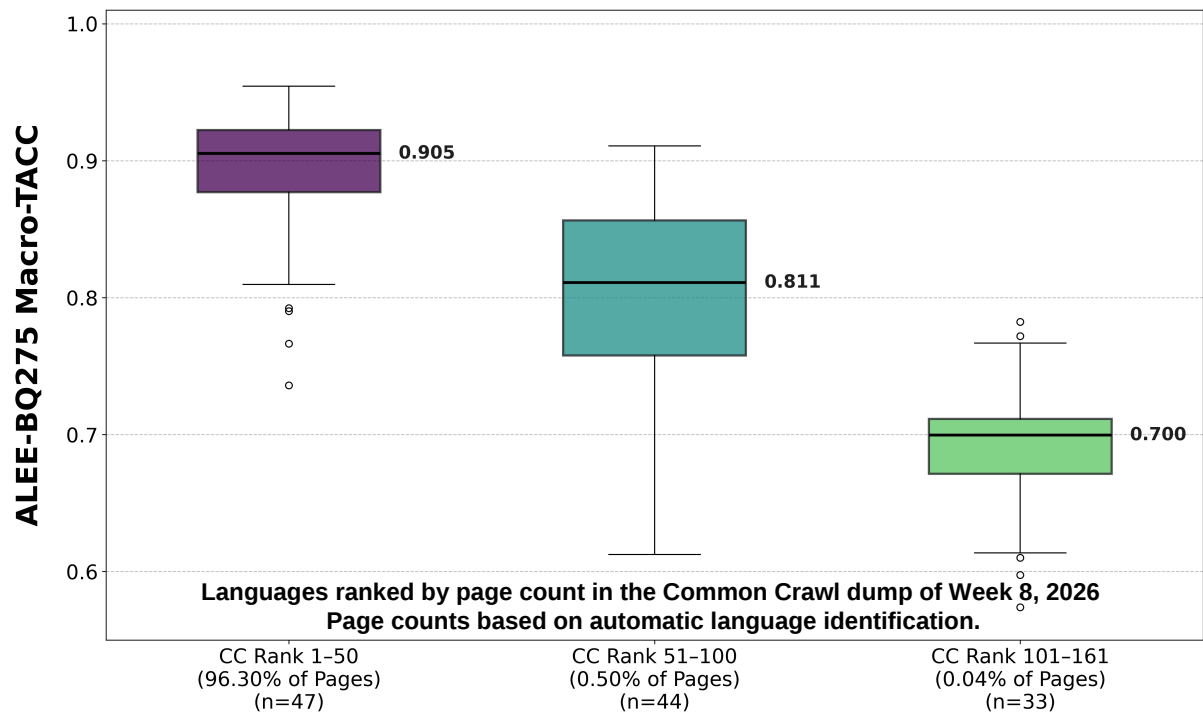


Figure 12: ALEE-BQ275 Macro-TACC distribution by Common Crawl language prevalence. Analogous to Figure 5.

B Appendix: Per Language Results

ALEX-F200MT61BQ275 TACC										ber_Beng										bul_Cyrl										cat_Latn										ces_Latn										
F200		MT61		BQ275		F200		MT61		BQ275		F200		MT61		BQ275		F200		MT61		BQ275		F200		MT61		BQ275		F200		MT61		BQ275																
Alibaba_NLP_gpt_multilingual_base	0.866	0.852	0.900	0.838	0.784	0.889	0.780	0.727	0.891	0.891	0.907	0.877	0.919	0.912	0.937	0.901	0.851	0.845	0.861	0.888	0.928	0.917	0.936	0.899	0.931	0.861	0.928	0.880	0.866	0.848	0.849	0.814	0.898	0.924	0.918	0.892	0.899	0.889	0.889	0.934	0.877	0.840	0.880	0.837	0.928	0.930	0.928	0.871		
BAAI_gpt_ac3	0.899	0.968	0.968	0.928	0.901	0.898	0.877	0.846	0.951	0.951	0.951	0.901	0.869	0.967	0.987	0.987	0.951	0.921	0.924	0.941	0.978	0.971	0.981	0.931	0.933	0.902	0.887	0.956	0.938	0.980	0.919	0.937	0.981	0.980	0.967	0.931	0.924	0.984	0.981	0.980	0.965	0.975	0.984	0.981	0.980	0.965	0.975	0.984		
Qwen3_Embedding_0.6B	0.764	0.847	0.794	0.769	0.736	0.714	0.724	0.623	0.822	0.826	0.825	0.763	0.813	0.844	0.866	0.853	0.749	0.796	0.784	0.837	0.868	0.868	0.870	0.832	0.870	0.871	0.894	0.868	0.844	0.787	0.791	0.873	0.811	0.845	0.843	0.837	0.823	0.761	0.734	0.841	0.846	0.862	0.838	0.814	0.841	0.846	0.838	0.814		
Qwen3_Embedding_4B	0.887	0.889	0.923	0.838	0.767	0.784	0.803	0.765	0.901	0.900	0.921	0.844	0.951	0.944	0.951	0.956	0.916	0.855	0.880	0.977	0.827	0.837	0.881	0.981	0.986	0.980	0.931	0.833	0.880	0.887	0.819	0.884	0.965	0.925	0.952	0.944	0.940	0.937	0.961	0.930	0.922	0.916	0.934	0.940	0.937	0.961	0.934	0.940	0.937	0.961
Qwen3_Embedding_8B	0.938	0.931	0.951	0.801	0.847	0.885	0.881	0.963	0.981	0.981	0.981	0.965	0.968	0.971	0.955	0.958	0.948	0.984	0.984	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955		
google_embeddinggerman_300m	0.855	0.849	0.964	0.913	0.873	0.869	0.914	0.854	0.972	0.947	0.966	0.904	0.915	0.926	0.961	0.981	0.981	0.983	0.975	0.882	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956		
ibm_granite_embedding_107m_multitask	0.828	0.856	0.849	0.796	0.779	0.729	0.697	0.791	0.815	0.813	0.796	0.860	0.870	0.887	0.865	0.877	0.793	0.762	0.789	0.836	0.874	0.854	0.832	0.901	0.944	0.914	0.931	0.754	0.813	0.777	0.801	0.811	0.827	0.828	0.799	0.809	0.826	0.807	0.880	0.846	0.877	0.880	0.846	0.794	0.784	0.863	0.868	0.877	0.820	
ibm_granite_embedding_270m_multitask	0.815	0.846	0.834	0.829	0.766	0.710	0.747	0.695	0.854	0.856	0.889	0.829	0.887	0.884	0.901	0.913	0.789	0.813	0.840	0.884	0.901	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	0.913	
ibm_granite_embedding_v5_test_xano	0.911	0.949	0.941	0.886	0.822	0.879	0.840	0.886	0.935	0.939	0.940	0.961	0.968	0.966	0.971	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983		
ibm_granite_embedding_v5_test_xano	0.909	0.926	0.927	0.862	0.830	0.823	0.819	0.876	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920	0.920			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956			
ibm_granite_embedding_v5_test_xano	0.908	0.958	0.973	0.910	0.870	0.851	0.880	0.919	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.956	0.9										

ALEE-F200/MT61 TACC	arb_Arab								est_Latn								kor_Hang								nob_Latn								por_Latn							
	F200				MT61				F200				MT61				F200				MT61				F200				MT61											
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS				
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS				
Alibaba_NLP_gte_multilingual_base	0.888	0.903	0.916	0.874	0.784	0.787	0.780	0.738	0.893	0.847	0.907	0.877	0.858	0.854	0.835	0.776	0.888	0.861	0.903	0.820	0.817	0.837	0.829	0.786	0.921	0.894	0.930	0.922	0.860	0.872	0.884	0.854	0.948	0.940	0.950	0.928	0.888	0.895	0.901	0.851
BAAI_bge_m3	0.957	0.958	0.968	0.934	0.842	0.848	0.829	0.781	0.963	0.981	0.980	0.970	0.909	0.927	0.922	0.881	0.952	0.949	0.955	0.952	0.899	0.886	0.893	0.846	0.973	0.986	0.987	0.979	0.932	0.959	0.948	0.946	0.977	0.972	0.982	0.973	0.922	0.927	0.918	0.908
Qwen3_Embedding_0.6B	0.870	0.912	0.855	0.844	0.710	0.752	0.700	0.686	0.661	0.708	0.720	0.710	0.653	0.662	0.646	0.654	0.845	0.898	0.817	0.820	0.782	0.796	0.765	0.738	0.874	0.870	0.849	0.868	0.789	0.799	0.802	0.797	0.915	0.917	0.930	0.910	0.863	0.854	0.820	0.865
Qwen3_Embedding_4B	0.909	0.884	0.934	0.886	0.779	0.755	0.814	0.727	0.868	0.847	0.907	0.841	0.741	0.776	0.787	0.757	0.895	0.894	0.910	0.907	0.833	0.843	0.857	0.770	0.934	0.935	0.959	0.913	0.833	0.851	0.864	0.832	0.959	0.963	0.971	0.949	0.886	0.889	0.910	0.865
Qwen3_Embedding_8B	0.963	0.968	0.971	0.940	0.852	0.793	0.863	0.814	0.938	0.935	0.955	0.907	0.820	0.805	0.851	0.773	0.942	0.940	0.948	0.937	0.881	0.843	0.899	0.863	0.950	0.949	0.975	0.946	0.901	0.866	0.927	0.881	0.963	0.972	0.986	0.967	0.921	0.886	0.930	0.900
google_embeddinggemma_300m	0.965	0.949	0.975	0.967	0.865	0.854	0.899	0.846	0.843	0.810	0.894	0.829	0.761	0.735	0.800	0.757	0.950	0.944	0.977	0.937	0.944	0.930	0.936	0.900	0.950	0.931	0.961	0.925	0.881	0.913	0.924	0.878	0.990	0.972	0.989	0.970	0.939	0.953	0.974	0.932
ibm_granite_embed_107m_multil.	0.860	0.856	0.853	0.847	0.708	0.717	0.750	0.697	0.736	0.773	0.792	0.769	0.680	0.720	0.761	0.716	0.878	0.866	0.878	0.868	0.799	0.787	0.828	0.759	0.903	0.912	0.885	0.877	0.797	0.834	0.799	0.795	0.967	0.968	0.971	0.964	0.898	0.901	0.878	0.873
ibm_granite_embed_278m_multil.	0.866	0.856	0.866	0.814	0.723	0.755	0.741	0.659	0.777	0.782	0.841	0.787	0.746	0.755	0.790	0.743	0.888	0.861	0.871	0.856	0.809	0.787	0.828	0.759	0.903	0.912	0.885	0.877	0.797	0.834	0.799	0.795	0.967	0.968	0.971	0.964	0.898	0.901	0.878	0.873
jina_embeddings_v3	0.938	0.926	0.961	0.922	0.809	0.810	0.829	0.757	0.934	0.949	0.961	0.928	0.858	0.840	0.878	0.838	0.909	0.935	0.943	0.871	0.848	0.770	0.837	0.776	0.952	0.972	0.977	0.946	0.896	0.878	0.931	0.905	0.971	0.963	0.977	0.961	0.909	0.886	0.918	0.870
jina_embeddings_v5_text_nano	0.948	0.951	0.957	0.925	0.787	0.793	0.817	0.724	0.831	0.792	0.846	0.796	0.686	0.700	0.706	0.741	0.952	0.951	0.944	0.928	0.893	0.886	0.875	0.888	0.946	0.940	0.957	0.943	0.875	0.872	0.907	0.870	0.971	0.958	0.982	0.955	0.924	0.904	0.919	0.876
jina_embeddings_v5_text_small	0.946	0.907	0.957	0.907	0.782	0.784	0.809	0.754	0.829	0.792	0.851	0.784	0.705	0.723	0.748	0.692	0.934	0.940	0.950	0.904	0.880	0.878	0.860	0.781	0.961	0.940	0.966	0.934	0.884	0.869	0.896	0.849	0.973	0.940	0.977	0.961	0.913	0.889	0.924	0.895
multilingual_e5_base	0.926	0.898	0.946	0.898	0.782	0.819	0.755	0.732	0.940	0.921	0.950	0.931	0.856	0.872	0.848	0.846	0.919	0.907	0.923	0.907	0.842	0.834	0.840	0.776	0.957	0.968	0.982	0.961	0.893	0.936	0.910	0.884	0.911	0.907	0.907	0.883	0.893	0.930	0.864	0.881
multilingual_e5_large	0.940	0.935	0.966	0.916	0.835	0.819	0.811	0.778	0.959	0.958	0.978	0.949	0.919	0.918	0.918	0.895	0.946	0.963	0.962	0.919	0.913	0.904	0.895	0.846	0.975	0.991	0.952	0.946	0.901	0.907	0.861	0.865	0.963	0.986	0.939	0.957	0.891	0.892	0.845	0.884
multilingual_e5_large_instruct	0.971	0.963	0.973	0.967	0.868	0.875	0.887	0.838	0.959	0.949	0.980	0.955	0.908	0.927	0.959	0.865	0.938	0.944	0.966	0.949	0.911	0.901	0.925	0.881	0.981	0.986	0.993	0.973	0.929	0.945	0.966	0.905	0.988	0.986	0.993	0.976	0.949	0.936	0.959	0.914
nomic_embed_text_v2_moe	0.913	0.912	0.906	0.889	0.805	0.819	0.724	0.751	0.917	0.921	0.880	0.886	0.850	0.846	0.808	0.835	0.884	0.921	0.880	0.868	0.825	0.851	0.805	0.789	0.959	0.991	0.952	0.946	0.901	0.907	0.861	0.865	0.963	0.986	0.939	0.957	0.891	0.892	0.845	0.884
paraphrase_multil_mnpnet_base	0.930	0.903	0.930	0.874	0.749	0.770	0.726	0.700	0.955	0.935	0.937	0.910	0.888	0.866	0.881	0.822	0.919	0.903	0.919	0.862	0.828	0.843	0.849	0.773	0.975	0.958	0.970	0.952	0.904	0.918	0.933	0.900	0.975	0.954	0.966	0.957	0.909	0.904	0.883	0.854
sentence_transformers_LaBSE	0.969	0.968	0.973	0.979	0.837	0.857	0.886	0.822	0.963	0.968	0.968	0.952	0.926	0.936	0.936	0.949	0.955	0.963	0.964	0.955	0.916	0.933	0.916	0.873	0.969	0.986	0.971	0.955	0.937	0.971	0.960	0.973	0.971	0.986	0.982	0.961	0.950	0.945	0.944	0.946

ALEE-F200/MT61 TACC	zho_Hans								zho_Hant							
	F200				MT61				F200				MT61			
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS
Alibaba_NLP_gte_multilingual_base	0.909	0.880	0.950	0.886	0.840	0.840	0.860	0.776	0.903	0.884	0.928	0.880	0.850	0.854	0.845	0.776
BAAI_bge_m3	0.944	0.921	0.957	0.919	0.888	0.883	0.881	0.862	0.957	0.931	0.966	0.907	0.899	0.910	0.886	0.849
Qwen3_Embedding_0.6B	0.924	0.931	0.905	0.925	0.845	0.857	0.817	0.841	0.893	0.931	0.882	0.916	0.827	0.845	0.826	0.841
Qwen3_Embedding_4B	0.952	0.949	0.955	0.934	0.893	0.889	0.895	0.838	0.950	0.935	0.959	0.940	0.855	0.878	0.883	0.819
Qwen3_Embedding_8B	0.967	0.963	0.975	0.967	0.917	0.886	0.930	0.873	0.967	0.958	0.975	0.964	0.881	0.872	0.901	0.835
google_embeddinggemma_300m	0.967	0.958	0.982	0.946	0.941	0.933	0.953	0.924	0.967	0.940	0.970	0.925	0.926	0.930	0.936	0.897
ibm_granite_embed_107m_multil	0.866	0.889	0.876	0.871	0.792	0.834	0.773	0.781	0.855	0.852	0.828	0.847	0.790	0.813	0.765	0.792
ibm_granite_embed_278m_multil	0.893	0.884	0.887	0.889	0.807	0.819	0.776	0.781	0.880	0.861	0.855	0.826	0.804	0.825	0.782	0.751
jina_embeddings_v3	0.857	0.852	0.891	0.841	0.776	0.755	0.816	0.738	0.897	0.898	0.903	0.850	0.804	0.799	0.834	0.786
jina_embeddings_v5_text_nano	0.957	0.907	0.950	0.934	0.888	0.878	0.872	0.830	0.948	0.940	0.932	0.928	0.873	0.875	0.846	0.851
jina_embeddings_v5_text_small	0.950	0.949	0.953	0.931	0.896	0.898	0.880	0.838	0.936	0.935	0.932	0.913	0.883	0.895	0.875	0.859
multilingual_e5_base	0.903	0.912	0.914	0.910	0.848	0.866	0.797	0.827	0.915	0.898	0.941	0.889	0.845	0.854	0.790	0.803
multilingual_e5_large	0.938	0.949	0.966	0.913	0.904	0.880	0.881	0.908	0.952	0.949	0.982	0.925	0.870	0.875	0.875	0.859
multilingual_e5_large_instruct	0.957	0.935	0.973	0.937	0.908	0.918	0.936	0.900	0.948	0.926	0.966	0.943	0.899	0.901	0.924	0.873
nomic_embed_text_v2_moe	0.893	0.907	0.864	0.868	0.830	0.878	0.779	0.822	0.886	0.917	0.866	0.862	0.843	0.872	0.784	0.797
paraphrase_multil_mnpnet_base	0.942	0.917	0.928	0.898	0.835	0.834	0.852	0.814	0.934	0.889	0.916	0.862	0.870	0.848	0.860	0.811
sentence_transformers_LaBSE	0.940	0.944	0.962	0.964	0.891	0.901	0.869	0.889	0.944	0.949	0.943	0.943	0.894	0.924	0.886	0.884

[illegible][illegible]

ALIEE-F200/BQ275 TACC	hne_Devo										hyc_Artem										ilo_Latn										jav_Latn									
	F200					BQ275					F200					BQ275					F200					BQ275					F200					BQ275				
	AR	HS	PN	RS	HN	AR	HS	PN	RS	HN	AR	HS	PN	RS	HN	AR	HS	PN	RS	HN	AR	HS	PN	RS	HN	AR	HS	PN	RS	HN	AR	HS	PN	RS	HN					
Alibaba_NLP_gpt_multilingual_base	0.847	0.819	0.884	0.799	0.873	0.889	0.904	0.832	0.874	0.801	0.898	0.823	0.843	0.865	0.868	0.808	0.800	0.755	0.821	0.799	0.772	0.812	0.839	0.769	0.750	0.759	0.704	0.743	0.732	0.777	0.806	0.769	0.820	0.796	0.848	0.802	0.811	0.845	0.851	0.787
BAAI_bge_m3	0.922	0.940	0.946	0.934	0.936	0.930	0.916	0.883	0.955	0.935	0.970	0.919	0.915	0.925	0.915	0.913	0.885	0.819	0.916	0.835	0.760	0.780	0.819	0.836	0.833	0.866	0.821	0.838	0.750	0.765	0.877	0.769	0.820	0.821	0.977	0.925	0.896	0.930	0.977	0.895
ByteDance-LLM-Embedding_0.6B	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874	0.833	0.894	0.811	0.843	0.836	0.840	0.790	0.564	0.597	0.658	0.633	0.572	0.727	0.686	0.738	0.728	0.638	0.779	0.631	0.804	0.838	0.755	0.803	0.809	0.843	0.858	0.748	0.804	0.858	0.748	
Qwen2_Embedding_985	0.866	0.851	0.892	0.793	0.846	0.881	0.888	0.786	0.874</																															

AEE-P200/BQ275 TACC	kaz_Latn										kaz_Latn										kaz_Gee										kaz_Cyrl										kaz_Latn									
	F200					BQ275					F200					BQ275					F200					BQ275					F200					BQ275					F200					BQ275				
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS						
Albans_NLP_emb_multilingual_base	0.729	0.600	0.765	0.710	0.700	0.739	0.590	0.754	0.674	0.742	0.676	0.812	0.684	0.746	0.674	0.810	0.739	0.851	0.838	0.875	0.828	0.826	0.877	0.873	0.778	0.870	0.833	0.874	0.841	0.816	0.871	0.870	0.817	0.835	0.796	0.844	0.688	0.772	0.821	0.824	0.762	0.814	0.769	0.804	0.796	0.804	0.796	0.804		
Albans_NLP_emb_multilingual_base_0.976	0.729	0.600	0.765	0.710	0.700	0.739	0.590	0.754	0.674	0.742	0.676	0.812	0.684	0.746	0.674	0.810	0.739	0.851	0.838	0.875	0.828	0.826	0.877	0.873	0.778	0.870	0.833	0.874	0.841	0.816	0.871	0.870	0.817	0.835	0.796	0.844	0.688	0.772	0.821	0.824	0.762	0.814	0.769	0.804	0.796	0.804	0.796	0.804		
Albans_Emb_400	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.667	0.759	0.740	0.685	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688	0.660	0.742	0.688		
Albans_Emb_400_0.976	0.581	0.537	0.619	0.596	0.561	0.601	0.602	0.619	0.594	0.605	0.624	0.596	0.534	0.590	0.620	0.605	0.628	0.638	0.669	0.688	0.628	0.648	0.775	0.745	0.768	0.665	0.713	0.706	0.622	0.																				

[illegible]

ALIE-F200/BQ275 TACC	kmr_Lat						knc_Arabo						lao_Lao						Hj_Lat						Hm_Lat															
	F200			BQ275			F200			BQ275			F200			BQ275			F200			BQ275			F200			BQ275												
	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN	AR	HS	PN										
Alibaba_NLP_gpt_multilingual_base	0.781	0.741	0.826	0.811	0.747	0.760	0.827	0.760	0.676	0.667	0.726	0.659	0.651	0.622	0.764	0.652	0.853	0.796	0.080	0.822	0.836	0.823	0.865	0.793	0.833	0.824	0.858	0.817	0.799	0.824	0.862	0.787	0.812	0.773	0.823	0.784	0.781	0.859	0.834	0.742
BAAI_bge_m3	0.938	0.903	0.901	0.899	0.891	0.904	0.838	0.614	0.579	0.602	0.590	0.573	0.371	0.644	0.634	0.952	0.954	0.968	0.902	0.921	0.933	0.933	0.948	0.901	0.944	0.952	0.904	0.829	0.833	0.903	0.878	0.895	0.880	0.925	0.874	0.814	0.833	0.897	0.763	
BAAI_bge_m3_embedding_0.6B	0.967	0.944	0.940	0.940	0.939	0.940	0.889	0.589	0.562	0.589	0.562	0.549	0.359	0.649	0.640	0.980	0.980	0.980	0.979	0.979	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	
OpenAI_Embedding_4b	0.665	0.708	0.675	0.698	0.598	0.601	0.722	0.595	0.631	0.518	0.491	0.443	0.667	0.617	0.514	0.881	0.778	0.857	0.766	0.757	0.771	0.819	0.688	0.814	0.861	0.871	0.808	0.771	0.736	0.854	0.676	0.820	0.822	0.880	0.814	0.755	0.745	0.839	0.649	
Qwen2_Embedding_8b	0.806	0.792	0.716	0.769	0.673	0.672	0.792	0.642	0.576	0.588	0.622	0.596	0.499	0.589	0.514	0.901	0.884	0.918	0.868	0.859	0.877	0.883	0.888	0.894	0.921	0.871	0.817	0.833	0.873	0.766	0.807	0.935	0.877	0.822	0.815	0.867	0.782	0.785		
Qwen2.5-72B-Instruct	0.663	0.644	0.681	0.684	0.586	0.589	0.562	0.589	0.562	0.570	0.549	0.529	0.359	0.649	0.640	0.980	0.980	0.980	0.979	0.979	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	0.980	
bm_granite_embedding_107m_multitask	0.634	0.681	0.683	0.683	0.591	0.677	0.713	0.682	0.642	0.644	0.514	0.515	0.516	0.607	0.583	0.589	0.769	0.633	0.763	0.771	0.840	0.779	0.766	0.738	0.852	0.765	0.775	0.685	0.762	0.786	0.735	0.745	0.688	0.769	0.668	0.717	0.668	0.712	0.668	0.712
bm_granite_embedding_107m_multitask_v2	0.634	0.681	0.683	0.683	0.591	0.677	0.713	0.682	0.642	0.644	0.514	0.515	0.516	0.607	0.583	0.589	0.769	0.633	0.763	0.771	0.840	0.779	0.766	0.738	0.852	0.765	0.775	0.685	0.762	0.786	0.735	0.745	0.688	0.769	0.668	0.717	0.668	0.712	0.668	0.712
jina_embeddings_v3	0.831	0.773	0.878	0.877	0.754	0.871	0.842	0.715	0.543	0.417	0.638	0.548	0.546	0.543	0.625	0.886	0.843	0.903	0.829	0.823	0.821	0.891	0.817	0.775	0.881	0.775	0.881	0.775	0.881	0.775	0.881	0.775	0.881	0.775	0.881	0.775	0.881	0.775	0.881	
jina_embeddings_v3_text_small	0.593	0.620	0.652	0.617	0.646	0.592	0.650	0.644	0.674	0.588	0.590	0.541	0.457	0.611	0.574	0.707	0.657	0.814	0.701	0.648	0.604	0.756	0.625	0.800	0.866	0.819	0.801	0.690	0.736	0.771	0.676	0.785	0.792	0.823	0.790	0.697	0.716	0.700	0.716	
jina_multilingual_es_base	0.886	0.832	0.923	0.853	0.841	0.892	0.848	0.898	0.790	0.599	0.574	0.671	0.556	0.616	0.562	0.667	0.697	0.881	0.848	0.871	0.834	0.812	0.897	0.799	0.884	0.861	0.904	0.892	0.841	0.806	0.814	0.886	0.889	0.899	0.904	0.872	0.824	0.837	0.763	
jina_multilingual_es_base_instruct	0.875	0.825	0.910	0.840	0.828	0.876	0.832	0.887	0.780	0.590	0.565	0.666	0.551	0.611	0.557	0.660	0.690	0.870	0.833	0.856	0.819	0.837	0.896	0.799	0.884	0.861	0.904	0.892	0.841	0.806	0.814	0.886	0.889	0.899	0.904	0.872	0.824	0.837	0.763	
jina_multilingual_es_large_instruct	0.880	0.884	0.941	0.901	0.884	0.886	0.919	0.901	0.871	0.620	0.794	0.641	0.714	0.692	0.697	0.924	0.924	0.986	0.946	0.902	0.908	0.934	0.933	0.934	0.954	0.954	0.940	0.896	0.906	0.948	0.877	0.880	0.907	0.961	0.880	0.881	0.865	0.825	0.827	
paraphrase-multilingual-mistral	0.791	0.792	0.814	0.796	0.735	0.762	0.804	0.724	0.510	0.472	0.616	0.482	0.504	0.478	0.628	0.508	0.800	0.861	0.864	0.826	0.816	0.801	0.865	0.775	0.748	0.759	0.796	0.731	0.628	0.683	0.777	0.672	0.779	0.736	0.739	0.760	0.650	0.683		
sentence_transformers_LaBSE	0.955	0.972	0.964	0.967	0.936	0.959	0.952	0.940	0.940	0.694	0.572	0.662	0.704	0.789	0.641	0.913	0.957	0.955	0.955	0.955	0.931	0.938	0.927	0.925	0.895	0.949	0.952	0.946	0.858	0.899	0.897	0.874	0.926	0.934	0.904	0.838	0.891	0.813		

[illegible][illegible]

	F200				BQ27				F200				BQ275				F200				BQ275				F200				BQ275												
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS									
Albaa_nlp_gae_multilingual_base	0.899	0.884	0.919	0.808	0.908	0.906	0.931	0.883	0.886	0.829	0.900	0.844	0.869	0.853	0.888	0.805	0.793	0.759	0.814	0.817	0.779	0.780	0.843	0.811	0.738	0.699	0.789	0.754	0.675	0.606	0.762	0.754	0.684	0.618	0.764	0.839	0.779	0.777	0.812	0.861	0.784
Albaa_nlp_gae_multilingual_v3	0.901	0.885	0.915	0.808	0.912	0.905	0.931	0.883	0.886	0.829	0.900	0.844	0.869	0.853	0.888	0.805	0.793	0.759	0.814	0.817	0.779	0.780	0.843	0.811	0.738	0.699	0.789	0.754	0.675	0.606	0.762	0.754	0.684	0.618	0.764	0.839	0.779	0.777	0.812	0.861	0.784
Albaa_nlp_gae_multilingual_0.6B	0.917	0.909	0.939	0.808	0.912	0.905	0.931	0.883	0.886	0.829	0.900	0.844	0.869	0.853	0.888	0.805	0.793	0.759	0.814	0.817	0.779	0.780	0.843	0.811	0.738	0.699	0.789	0.754	0.675	0.606	0.762	0.754	0.684	0.618	0.764	0.839	0.779	0.777	0.812	0.861	0.784
Qwen1_Embedding_4b	0.917	0.935	0.921	0.817	0.930	0.909	0.926	0.860	0.850	0.901	0.802	0.807	0.789	0.886	0.912	0.618	0.593	0.722	0.617	0.533	0.513	0.677	0.580	0.576	0.523	0.710	0.540	0.513	0.499	0.668	0.541	0.622	0.580	0.615	0.617	0.533	0.633	0.688	0.535		
Qwen1_Embedding_8b	0.950	0.940	0.962	0.934	0.951	0.900	0.942	0.886	0.921	0.911	0.944	0.886	0.986	0.853	0.915	0.793	0.751	0.581	0.569	0.695	0.622	0.655	0.621	0.622	0.655	0.621	0.622	0.655	0.621	0.622	0.655	0.621	0.622	0.655	0.621	0.622	0.655	0.621	0.622	0.655	
Qwen1.5_Embedding_72B-300m	0.930	0.847	0.878	0.835	0.809	0.824	0.828	0.751	0.843	0.873	0.876	0.835	0.879	0.871	0.802	0.550	0.556	0.661	0.549	0.623	0.607	0.628	0.541	0.532	0.677	0.578	0.548	0.581	0.622	0.529	0.546	0.604	0.617	0.553	0.599	0.638	0.640	0.637			
nlp_granite_embedding_107m_multilingual	0.783	0.819	0.832	0.817	0.740	0.792	0.794	0.784	0.804	0.792	0.851	0.769	0.812	0.815	0.877	0.760	0.759	0.569	0.623	0.584	0.566	0.605	0.588	0.537	0.629	0.597	0.584	0.536	0.679	0.610	0.590	0.546	0.590	0.626	0.519	0.595	0.649	0.637			
nlp_granite_embedding_278m_multilingual	0.830	0.847	0.878	0.835	0.809	0.824	0.828	0.751	0.843	0.873	0.876	0.835	0.879	0.871	0.802	0.550	0.556	0.661	0.549	0.623	0.607	0.628	0.541	0.532	0.677	0.578	0.548	0.581	0.622	0.529	0.546	0.604	0.617	0.553	0.599	0.638	0.640	0.637			
jina_embeddings_v3_text_nano	0.944	0.940	0.961	0.935	0.896	0.868	0.931	0.877	0.912	0.943	0.847	0.879	0.839	0.838	0.814	0.576	0.514	0.720	0.545	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	0.528	0.544	
jina_embeddings_v3_text_small	0.936	0.931	0.957	0.934	0.894	0.891	0.912	0.859	0.864	0.838	0.910	0.814	0.799	0.818	0.790	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_base	0.945	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579	0.518	0.483	0.452	0.564	0.566	0.549	0.597	0.567	0.617	0.534	0.583	0.637	0.535				
multilingual_v3_instruct	0.946	0.931	0.957	0.934	0.892	0.891	0.912	0.859	0.861	0.838	0.911	0.813	0.799	0.818	0.789	0.616	0.610	0.766	0.640	0.629	0.577	0.556	0.532	0.579																	

[illegible]

ALEE-MT61 TACC	arb_SA_Arab				fra_CA_Latin				por_PT_Latin				roh_ruter				roh_rungger				roh_surnairan				roh_sutisly				roh_sursilv				roh_vallader				svk_TZ_Latin			
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS				
Alibaba_NLP_gte_multilingual_base	0.774	0.802	0.809	0.695	0.888	0.904	0.896	0.857	0.889	0.886	0.893	0.846	0.751	0.776	0.756	0.711	0.772	0.784	0.770	0.768	0.788	0.778	0.721	0.695	0.705	0.761	0.709	0.678	0.756	0.752	0.770	0.705	0.756	0.778	0.741	0.711	0.782	0.778	0.809	0.768
BAAI_bge_m3	0.848	0.848	0.784	0.825	0.784	0.927	0.808	0.875	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	0.887	
Qwen3_Embedding_0.6B	0.713	0.741	0.713	0.700	0.861	0.869	0.869	0.887	0.860	0.843	0.871	0.830	0.655	0.644	0.662	0.627	0.660	0.624	0.680	0.654	0.637	0.630	0.669	0.623	0.625	0.609	0.648	0.605	0.630	0.618	0.677	0.649	0.652	0.606	0.666	0.641	0.673	0.680	0.616	
Qwen3_Embedding_4B	0.765	0.741	0.765	0.741	0.880	0.865	0.865	0.887	0.865	0.848	0.871	0.830	0.655	0.644	0.662	0.627	0.660	0.624	0.680	0.654	0.637	0.630	0.669	0.623	0.625	0.609	0.648	0.605	0.630	0.618	0.677	0.649	0.652	0.606	0.666	0.641	0.673	0.680	0.616	
Qwen3_Embedding_72B	0.828	0.810	0.827	0.810	0.926	0.915	0.915	0.937	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.938		
google_embedding_multilingual_300m	0.880	0.878	0.915	0.846	0.934	0.939	0.976	0.938	0.938	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939	0.939		
ibn_genic_embod_107m_multil.	0.703	0.735	0.764	0.708	0.896	0.886	0.875	0.876	0.886	0.889	0.880	0.870	0.670	0.717	0.715	0.727	0.716	0.772	0.716	0.773	0.715	0.768	0.698	0.729	0.684	0.657	0.700	0.744	0.635	0.742	0.693	0.726	0.715	0.727	0.677	0.676	0.710	0.677		
ibn_genic_embod_278m_multil.	0.752	0.758	0.752	0.758	0.913	0.892	0.881	0.882	0.888	0.889	0.890	0.873	0.700	0.729	0.715	0.697	0.711	0.776	0.718	0.754	0.685	0.717	0.723	0.697	0.663	0.682	0.727	0.684	0.685	0.730	0.724	0.732	0.715	0.755	0.756	0.774	0.698	0.712		
ibn_genic_embod_278m_multil_v3	0.820	0.877	0.841	0.714	0.916	0.883	0.944	0.895	0.913	0.878	0.925	0.876	0.655	0.638	0.675	0.627	0.696	0.682	0.717	0.673	0.670	0.621	0.714	0.619	0.686	0.636	0.719	0.595	0.673	0.638	0.777	0.635	0.650	0.641	0.744	0.654	0.734	0.682		
jina_embeddings_v5_text_nano	0.797	0.810	0.810	0.797	0.911	0.886	0.921	0.892	0.908	0.886	0.907	0.910	0.617	0.627	0.662	0.662	0.668	0.676	0.703	0.641	0.621	0.671	0.589	0.617	0.647	0.619	0.629	0.642	0.643	0.654	0.647	0.684	0.676	0.653	0.643	0.654	0.677	0.681		
jina_embeddings_v5_text_small	0.815	0.796	0.840	0.746	0.921	0.927	0.925	0.916	0.911	0.892	0.901	0.895	0.667	0.665	0.667	0.665	0.627	0.703	0.714	0.700	0.689	0.662	0.661	0.649	0.669	0.630	0.621	0.627	0.675	0.609	0.646	0.646	0.699	0.647	0.634	0.662	0.637			
jina_embeddings_v5_text_medium	0.794	0.822	0.817	0.797	0.903	0.915	0.890	0.891	0.895	0.849	0.849	0.726	0.575	0.716	0.719	0.719	0.719	0.761	0.757	0.696	0.732	0.712	0.685	0.714	0.730	0.695	0.731	0.746	0.764	0.727	0.715	0.743	0.724	0.749	0.740	0.814				
jina_embeddings_v5_text_large	0.835	0.837	0.825	0.786	0.939	0.930	0.936	0.916	0.944	0.921	0.919	0.914	0.756	0.783	0.754	0.772	0.782	0.768	0.774	0.782	0.768	0.774	0.735	0.790	0.806	0.771	0.773	0.790	0.855	0.779	0.855	0.872	0.883	0.846	0.846	0.846				
multilingual_e5_base	0.866	0.880	0.890	0.838	0.949	0.948	0.954	0.941	0.942	0.945	0.927	0.767	0.700	0.866	0.776	0.790	0.884	0.776	0.864	0.764	0.764	0.861	0.732	0.764	0.767	0.860	0.735	0.771	0.805	0.867	0.773	0.770	0.871	0.875	0.773	0.843	0.837			
multilingual_e5_large	0.812	0.816	0.752	0.759	0.880	0.920	0.864	0.884	0.898	0.910	0.920	0.870	0.675	0.711	0.654	0.689	0.711	0.692	0.746	0.679	0.767	0.668	0.724	0.655	0.729	0.662	0.670	0.683	0.755	0.684	0.749	0.677	0.738	0.646	0.705	0.711	0.716			
multilingual_e5_large_instruct	0.792	0.802	0.794	0.719	0.906	0.901	0.916	0.841	0.894	0.872	0.881	0.835	0.644	0.633	0.621	0.651	0.708	0.673	0.752	0.649	0.682	0.638	0.747	0.616	0.653	0.638	0.721	0.605	0.691	0.627	0.724	0.624	0.674	0.654	0.670	0.566	0.684			
multilingual_e5_large_instruct_nano	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_medium	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_small	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_tiny	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_xl	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_xxl	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_xxxl	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_xxxxl	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_xxxxxl	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830			
multilingual_e5_large_instruct_xxxxxx	0.871	0.880	0.904	0.839	0.954	0.963	0.959	0.946	0.950	0.938	0.952	0.747	0.787	0.801	0.771	0.805	0.807	0.816	0.838	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830				

	khw_Latn				khw_Arab				kls_Arab				knw_Latn				kor_Kore				krt_Latn				kru_Deva				ksf_Latn				ktn_Latn				kuj_Latn			
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS				
Alibaba_NLP_gte_multilingual_base	0.605	0.619	0.683	0.637	0.730	0.733	0.834	0.670	0.623	0.589	0.768	0.670	0.593	0.630	0.665	0.670	0.898	0.880	0.898	0.850	0.648	0.707	0.762	0.691	0.657	0.718	0.720	0.679	0.571	0.616	0.698	0.637	0.660	0.698	0.786	0.688	0.618	0.663	0.712	0.679
BAAI_bge_m3	0.605	0.610	0.637	0.673	0.752	0.736	0.848	0.661	0.653	0.566	0.785	0.616	0.613	0.607	0.643	0.655	0.934	0.947	0.956	0.589	0.670	0.704	0.777	0.660	0.660	0.692	0.665	0.693	0.596	0.589	0.710	0.655	0.724	0.727	0.822	0.742	0.638	0.601	0.730	0.670
Qwen3_Embedding_0.6B	0.508	0.531	0.572	0.574	0.650	0.584	0.701	0.565	0.541	0.540	0.571	0.541	0.556	0.548	0.619	0.598	0.894	0.874	0.845	0.772	0.556	0.575	0.637	0.586	0.576	0.601	0.628	0.589	0.511	0.572	0.556	0.599	0.538	0.540	0.605	0.595	0.533	0.580	0.592	
Qwen3_Embedding_4B	0.497	0.519	0.530	0.535	0.680	0.657	0.791	0.571	0.533	0.499	0.659	0.514	0.526	0.513	0.646	0.514	0.510	0.412	0.913	0.853	0.561	0.563	0.703	0.550	0.623	0.639	0.732	0.571	0.508	0.481	0.632	0.532	0.544	0.525	0.601	0.535	0.511	0.472	0.635	0.533
Qwen3_Embedding_8B	0.524	0.519	0.564	0.577	0.717	0.695	0.806	0.640	0.581	0.525	0.692	0.553	0.526	0.525	0.608	0.568	0.930	0.927	0.936	0.580	0.572	0.637	0.592	0.675	0.695	0.744	0.637	0.536	0.525	0.634	0.583	0.551	0.513	0.665	0.562	0.561	0.560	0.632	0.601	
google_embeddinggemma_300m	0.570	0.513	0.707	0.565	0.704	0.716	0.849	0.658	0.590	0.566	0.776	0.601	0.623	0.487	0.746	0.520	0.963	0.953	0.975	0.916	0.621	0.595	0.792	0.598	0.705	0.699	0.797	0.685	0.596	0.597	0.714	0.562	0.610	0.540	0.767	0.589	0.618	0.525	0.741	0.589
ibm_granite_embed_107m_multit	0.573	0.575	0.610	0.634	0.653	0.668	0.689	0.616	0.582	0.559	0.657	0.586	0.571	0.589	0.626	0.637	0.849	0.848	0.868	0.805	0.581	0.581	0.679	0.619	0.533	0.651	0.572	0.607	0.508	0.581	0.602	0.601	0.549	0.578	0.650	0.580	0.516	0.522	0.567	0.613
ibm_granite_embed_278m_multit	0.539	0.598	0.574	0.619	0.625	0.695	0.697	0.640	0.561	0.537	0.620	0.588	0.581	0.622	0.626	0.628	0.843	0.862	0.874	0.817	0.595	0.607	0.680	0.640	0.591	0.683	0.608	0.616	0.509	0.595	0.590	0.585	0.554	0.581	0.653	0.586	0.614	0.537	0.583	0.610
jina_embeddings_v3	0.571	0.534	0.697	0.550	0.678	0.680	0.828	0.547	0.568	0.522	0.764	0.541	0.625	0.551	0.722	0.538	0.894	0.877	0.921	0.838	0.596	0.543	0.768	0.541	0.657	0.645	0.719	0.592	0.553	0.510	0.738	0.514	0.566	0.525	0.735	0.526	0.536	0.548	0.667	0.541
jina_embeddings_v5_text_nano	0.441	0.472	0.525	0.544	0.702	0.628	0.798	0.619	0.499	0.440	0.586	0.556	0.482	0.478	0.616	0.583	0.921	0.897	0.918	0.859	0.511	0.481	0.674	0.604	0.596	0.610	0.634	0.640	0.449	0.478	0.574	0.501	0.645	0.671	0.571	0.509	0.472	0.659	0.592	
jina_embeddings_v5_text_small	0.395	0.475	0.444	0.523	0.632	0.622	0.789	0.604	0.529	0.452	0.688	0.514	0.454	0.452	0.540	0.593	0.918	0.928	0.947	0.534	0.490	0.670	0.544	0.580	0.610	0.614	0.610	0.420	0.434	0.534	0.556	0.501	0.431	0.602	0.571	0.514	0.446	0.658	0.550	
jina_embeddings_v5_text_medium	0.541	0.578	0.602	0.679	0.729	0.736	0.846	0.667	0.588	0.554	0.728	0.617	0.568	0.613	0.601	0.661	0.905	0.909	0.934	0.871	0.621	0.639	0.723	0.709	0.652	0.669	0.647	0.661	0.544	0.575	0.632	0.622	0.759	0.707	0.843	0.781	0.605	0.613	0.679	0.709
jina_embeddings_v5_text_large	0.590	0.516	0.647	0.694	0.760	0.798	0.876	0.766	0.588	0.575	0.732	0.694	0.531	0.631	0.604	0.646	0.935	0.939	0.955	0.928	0.660	0.709	0.721	0.648	0.686	0.646	0.712	0.538	0.613	0.662	0.661	0.734	0.809	0.879	0.814	0.591	0.633	0.686	0.721	
jina_embeddings_v5_text_xlarge	0.698	0.710	0.794	0.733	0.809	0.839	0.897	0.745	0.714	0.674	0.839	0.709	0.698	0.695	0.786	0.706	0.970	0.971	0.964	0.962	0.742	0.718	0.845	0.736	0.754	0.754	0.825	0.727	0.702	0.765	0.819	0.818	0.817	0.811	0.693	0.689	0.801	0.718		
nomie_embed_text_v2_moe	0.588	0.692	0.599	0.667	0.725	0.774	0.770	0.667	0.645	0.619	0.700	0.657	0.668	0.724	0.658	0.688	0.898	0.903	0.895	0.845	0.847	0.680	0.650	0.658	0.640	0.701	0.668	0.619	0.580	0.607	0.587	0.631	0.615	0.636	0.650	0.649	0.583	0.622	0.598	0.661
paraphrase_multit_mnpnet_base	0.534	0.591	0.611	0.550	0.683	0.752	0.610	0.686	0.540	0.726	0.562	0.635	0.551	0.702	0.556	0.931	0.909	0.903	0.844	0.595	0.589	0.722	0.583	0.615	0.595	0.648	0.565	0.599	0.557	0.674	0.520	0.571	0.581	0.695	0.514	0.546	0.531	0.650	0.550	
sentence_transformers_LaBSE	0.692	0.768	0.587	0.574	0.831	0.839	0.883	0.766	0.744	0.701	0.800	0.786	0.704	0.724	0.672	0.628	0.926	0.944	0.937	0.883	0.712	0.777	0.668	0.727	0.687	0.801	0.809	0.754	0.700	0.745	0.665	0.697	0.720	0.760	0.667	0.730	0.727	0.751	0.768	0.784

	kwy_Latn				ksp_Arab				led_Latn				lgl_Latn				lir_Latn				loa_Latn				loh_Latn				maf_Latn				mam_Latn				mas_Latn				
	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS	AR	HS	PN	RS					
Alibaba_NLP_gte_multilingual_base	0.575	0.619	0.692	0.643	0.658	0.657	0.710	0.604	0.606	0.669	0.683	0.619	0.613	0.704	0.744	0.667	0.930	0.918	0.934	0.901	0.697	0.768	0.780	0.709	0.628	0.628	0.764	0.673	0.621	0.672	0.686	0.709	0.593	0.625	0.637	0.613	0.595	0.651	0.716	0.622	
BAAI_bge_m3	0.685	0.636	0.803	0.691	0.620	0.680	0.664	0.622	0.665	0.660	0.673	0.655	0.642	0.648	0.71	0.70	0.946	0.944	0.945	0.946	0.704	0.701	0.870	0.736	0.655	0.619	0.708	0.649	0.640	0.714	0.676	0.558	0.572	0.596	0.643	0.635	0.625	0.737	0.643		
Qwen3_Embedding_0.6B	0.529	0.516	0.590	0.562	0.533	0.592	0.564	0.526	0.529	0.545	0.567	0.523	0.549	0.581	0.629	0.541	0.535	0.599	0.540	0.591	0.620	0.657	0.644	0.601	0.543	0.528	0.577	0.562	0.561	0.557	0.601	0.574	0.521	0.551	0.536	0.577	0.643	0.569	0.562	0.683	
Qwen3_Embedding_4B	0.523	0.501	0.658	0.538	0.596	0.589	0.698	0.583	0.529	0.534	0.637	0.511	0.536	0.563	0.673	0.535	0.940	0.942	0.922	0.925	0.653	0.678	0.728	0.586	0.504	0.645	0.622	0.517	0.526	0.544	0.600	0.574	0.570	0.575	0.577	0.526	0.487	0.652	0.511		
Qwen3_Embedding_8B	0.546	0.564	0.660	0.601	0.678	0.685	0.825	0.595	0.587	0.607	0.580	0.580	0.575	0.605	0.595	0.541	0.561	0.957	0.965	0.961	0.957	0.685	0.670	0.561	0.586	0.586	0.640	0.586	0.586	0.640	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.586	
google_embeddinggemma_300m	0.593	0.522	0.726	0.562	0.658	0.598	0.768	0.589	0.577	0.557	0.706	0.562	0.588	0.545	0.640	0.968	0.953	0.975	0.976	0.610	0.730	0.692	0.818	0.694	0.559	0.469	0.473	0.574	0.616	0.588	0.671	0.586	0.539	0.547	0.503	0.540	0.477	0.616	0.541		
ibm_granite_embed_107m_multit	0.521	0.551	0.633	0.634	0.578	0.619	0.596	0.631	0.531	0.607	0.568	0.571	0.544	0.598	0.613	0.622	0.948	0.939	0.946	0.931	0.591	0.663	0.653	0.646	0.511	0.563	0.611	0.628	0.539	0.549	0.549	0.539	0.565	0.539	0.535	0.575	0.572	0.616	0.616		
ibm_granite_embed_278m_multit	0.541	0.578	0.609	0.619	0.558	0.633	0.581	0.607	0.549	0.639	0.578	0.568	0.570	0.584	0.616	0.631	0.935	0.945	0.946	0.933	0.677	0.670	0.723	0.709	0.652	0.669	0.647	0.661	0.544	0.575	0.632	0.622	0.661	0.541	0.563	0.547	0.568	0.558	0.551	0.599	0.599
jina_embeddings_v3	0.568	0.519	0.713	0.526	0.598	0.598	0.704	0.568	0.534	0.560	0.640	0.511	0.549	0.545	0.729	0.547	0.956	0.924	0.964	0.907	0.663	0.645	0.795	0.586	0.585	0.531	0.759	0.529	0.583	0.554	0.765	0.562	0.563	0.481	0.709	0.526	0.551	0.525	0.670	0.553	
google_embeddinggemma_300m	0.591	0.525	0.740	0.514	0.598	0.581	0.707	0.601	0.520	0.569	0.616	0.541	0.549	0.586	0.616	0.622	0.948	0.939	0.946	0.931	0.591	0.663	0.653	0.646	0.511	0.563	0.611	0.628	0.539	0.549	0.549	0.539	0.565	0.539	0.535	0.575	0.572	0.616	0.616		
jina_embeddings_v3_text_small	0.514	0.434	0.655	0.514	0.546	0.607	0.602	0.568	0.602	0.538	0.466	0.44	0.538	0.466	0.44	0.538	0.466	0.527	0.568	0.523	0.390	0.495	0.883	0.568	0.601	0.446	0.616	0.516	0.455	0.631	0.547	0.494	0.507	0.619	0.580	0.427	0.443	0.532	0.299	0.481	0.443
multilingual_e5_base	0.667	0.677	0.758	0.694	0.603	0.619	0.616	0.616	0.617	0.636	0.593	0.646	0.603	0.648	0.688	0.688	0.961	0.959	0.966	0.916	0.682	0.757	0.750	0.733	0.693	0.613	0.685	0.682	0.593	0.633	0.638	0.733	0.519	0.538	0.622	0.573	0.601	0.629	0.606		
multilingual_e5_large_instruct	0.631	0.676	0.741	0.676	0.603	0.619	0.616	0.616	0.617	0.636	0.593	0.646	0.603	0.648	0.688	0.688	0.961	0.959	0.966	0.916	0.682	0.757	0.750	0.733	0.693	0.613	0.685	0.682	0.593	0.633	0.638	0.733	0.519	0.538	0.622	0.573	0.601	0.629	0.606		
multilingual_e5_large_instruction	0.739	0.737	0.833	0.772	0.769	0.768	0.769	0.768	0.769	0.768	0.769	0.768	0.769	0.768	0.769	0.768	0.962	0.961	0.968	0.965	0.922	0.782	0.785	0.788	0.778	0.727	0.695	0.828	0.730	0.727	0.716	0.825	0.745	0.658	0.633	0.753	0.629	0.709	0.689	0.821	
nonic_embedding_text_v2_moe	0.583	0.601	0.640	0.625	0.648	0.647	0.701	0.599	0.643	0.573	0.639	0.505	0.643	0.586	0.686	0.665	0.961	0.951	0.953	0.934	0.925	0.816	0.763	0.691	0.661	0.611	0.628	0.628	0.676	0.601	0.692	0.652	0.682	0.599	0.609	0.564	0.646	0.596	0.622	0.599	
openai_gpt4o_multilingual	0.547	0.574	0.658	0.574	0.591	0.578	0.604	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.576	0.959	0.953	0.953	0.950	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	0.616	
sentence_transformers_LaBSE	0.653	0.713	0.663	0.730	0.647	0.760	0.754	0.700	0.700	0.768	0.607	0.706	0.722	0.815	0.815	0.796	0.958	0.958	0.964	0.964	0.964	0.777	0.830	0.758	0.763	0.730	0.727	0.695	0.766	0.755	0.783	0.731	0.799	0.648	0.674	0.604	0.697	0.677	0.710	0.623	0.672