

# Efficient Zero-Shot Cross-lingual Inference via Retrieval

Genta Indra Winata, Lingjue Xie, Karthik Radhakrishnan,  
Yifan Gao, Daniel Preotiuc-Pietro

Bloomberg  
gwinata@bloomberg.net

## Abstract

Resources for building NLP applications, such as data and models, are usually only created and curated for a limited set of high resource languages. Thus, the ability to transfer knowledge to a new language is a key way in which to enable access to NLP technology for a wider population. This paper presents a framework to perform zero-shot inference in a target language by using cross-lingual retrieval from another language where limited annotated data for a comparable domain is available. Results on two large-scale multilingual datasets show that, in this setup, this framework improves over fine-tuning multilingual models or translating annotated data, and achieves results relatively close to fine-tuning the model on the target language directly. These results show that models can be transferred efficiently across languages for a given task and domain, even for languages not covered by multilingual model training approaches.

## 1 Introduction

Multilingual pre-trained language models (LMs) allow for sharing and transfer of knowledge across languages (Conneau and Lample, 2019; Pires et al., 2019; Wu and Dredze, 2019; Goyal et al., 2021; Lin et al., 2022; Muennighoff et al., 2023; Scao et al., 2022; Shliazhko et al., 2022). This limits the need of gathering annotated data for a specific task and/or domain and language pair to obtain good performance by bootstrapping the model using higher resource source language(s) (Siddhant et al., 2020). This is beneficial to enabling access to NLP technology across the globe, and especially in low-resource or regional languages and dialects, because collecting new datasets is costly and requires effort in finding or training annotators for a given language and task (Adelani et al., 2022a,b; Mahendra et al., 2021; Aji et al., 2022; Ebrahimi et al., 2022; Winata et al., 2023). Recent research has shown that few-shot learning abilities are able

to carry over to some extent even to languages unseen in the pre-training data of the multilingual model (Scao et al., 2022; Srivastava et al., 2023; Winata et al., 2022; Yong et al., 2023).

A common approach to zero-shot cross-lingual inference involves fine-tuning a model on the source language, then applying it to the target language (Artetxe and Schwenk, 2019; Liu et al., 2019; Lauscher et al., 2020; Phang et al., 2020; Nooralahzadeh et al., 2020; Bari et al., 2021; Kanakagiri and Radhakrishnan, 2021; Nozza, 2021), with the assumption that the underlying learned representations are aligned and will transfer to the task in another language. This approach also requires a full fine-tuning for each language and domain which makes scaling across multiple languages cumbersome.

Separately, multilingual sentence representations are trained to obtain a joint representation of utterances across multiple languages and can be directly used as inputs to train classifiers that can be applied across languages (?). Further, fine-tuning encoder models for sentence representations, for example using the natural language inference task, shows an ability to generalize for both monolingual (Yin et al., 2019) and multilingual classification tasks (Winata et al., 2021). However, these approaches are less robust and do not perform as well as full fine-tuning on downstream tasks (Ma et al., 2021).

In this paper, we present a simple, yet effective framework for zero-shot inference in a target language via cross-lingual retrieval. Effectively, for each utterance in the target language, we use a multilingual sentence representation model to retrieve similar examples from a pool of labeled data in the source language and project their labels onto the target by combining label distributions and averaging across multiple samples. This framework is efficient for zero-shot cross-lingual inference, as it does not require any training or parameter updates,

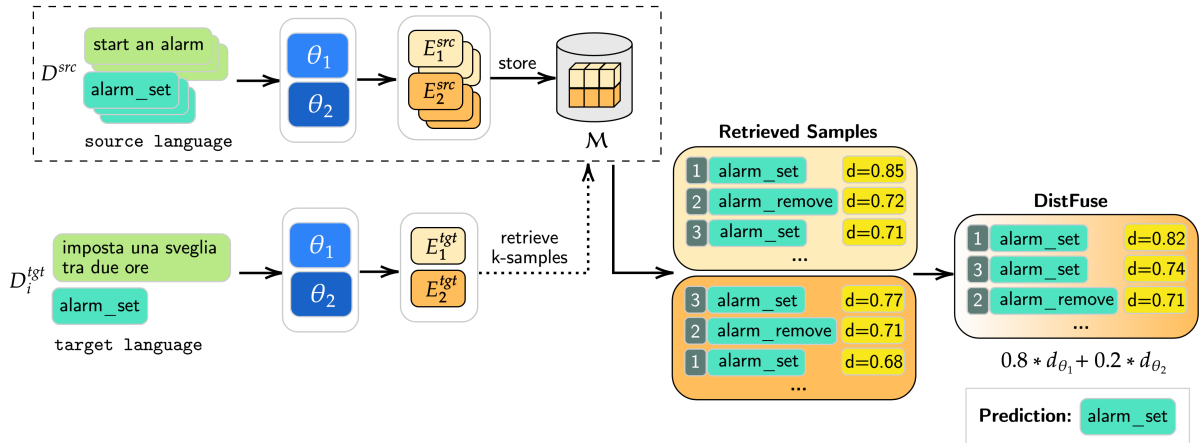


Figure 1: Inference using our proposed zero-shot framework. In this example, we use two different models  $\theta_1$  and  $\theta_2$ , and the model weights are  $w_1 = 0.8$  and  $w_2 = 0.2$ .

allowing it to scale effectively to multiple target languages. It is also lightweight, as it only requires the availability of a multilingual sentence representation model. Different from Bari et al. (2021), this framework does not require any few-shot samples or prior adaptation using a source language.

We evaluate this method for classification across two large-scale multilingual datasets, NusaX (Winata et al., 2023) and MAS-SIVE (FitzGerald et al., 2023), where annotated data in multiple languages from the same domain is available. Results show that this method outperforms cross-lingual fine-tuning on the source language and fine-tuning on the translated training data. Further, based on the findings in Winata et al. (2022), we evaluate the ability of this framework when the target language is not seen in pre-training of the LMs or training of the sentence representations. Results on these unseen languages show that our framework is more robust and obtains a greater relative improvement over the fine-tuning on source language data approach, albeit with a wider gap to the upper bound performance of fine-tuning with data from the target language.

Our contributions are as follows:

- We propose a lightweight and efficient inference framework for cross-lingual zero-shot text classification without any gradient updates.
- We benchmark cross-lingual zero-shot learning approaches on two large-scale multilingual datasets, and study the robustness of our framework on languages that are unseen in the training on the LMs.
- We show the effectiveness of merging output

distribution from multiple models, showing the ability to capture complementary information.

## 2 Methods

### 2.1 Problem Definition

Our goal is zero-shot cross-lingual text classification, where no labeled data from the target language is seen in training, and labeled data for the same task and domain is available in a different source language.

### 2.2 Proposed Framework

Our framework for zero-shot inference is based on the intuition that similar documents across languages should have the same label. We use multilingual sentence representation models to find similar samples to the target language utterance. Figure 1 presents an illustration of the framework. We formalize this as follows:

**Models** We define  $\theta_j$  as multilingual pre-trained encoder LM to which we can pass samples from the source and target languages to generate embeddings  $E_j^{src}$  and  $E_j^{tgt}$ .

**Data**  $D^{src}$  is the labeled dataset from the source language and  $D_i^{tgt}$  is the labeled dataset from the target language  $i$ , where each dataset has input-label pairs.

**Memory** We store embeddings  $E_j^{src}$  and the corresponding labels to a memory  $\mathcal{M}$  that will be used as a source for retrieval.

**Sample Retrieval** We pass the test sample to the models  $\theta_j$  to get test sample embeddings  $E_j^{tgt}$ . We then retrieve the  $k$  most similar embeddings from  $\mathcal{M}$  from each model by calculating their cosine similarity  $d_{\theta_j} = sim(E_j^{src}, E_j^{tgt})$ .

Model	seen			unseen								avg.
	ind	jav	sun	ace	ban	bbc	bjn	bug	mad	min	nij	
<b>Baselines</b>												
Random	33.33	33.33	33.33	33.33	33.33	33.33	33.33	33.33	33.33	33.33	33.33	33.33
Majority	38.25	38.25	38.25	38.25	38.25	38.25	38.25	38.25	38.25	38.25	38.25	38.25
Zero-shot XLM-R <sub>XNLI</sub>	59.28	55.11	53.50	44.74	44.20	37.67	53.97	40.43	51.24	53.36	47.52	49.18
Fine-tune (src lang)	87.16	71.66	52.25	40.62	51.90	29.99	63.84	28.55	46.30	57.31	43.25	52.08
Fine-tune (translate train)	85.18	77.11	46.48	-	-	-	-	-	-	-	-	-
Fine-tune (translate test)	79.10	62.35	44.42	-	-	-	-	-	-	-	-	-
<b>Our Zero-Shot Framework</b>												
XLM-R <sub>BASE</sub>	71.29	56.32	52.64	33.52	41.59	31.71	54.91	35.24	34.30	48.94	37.86	45.30
CMLM	73.60	72.21	74.29	64.92	68.41	55.09	72.31	51.56	63.32	69.47	61.49	66.06
LaBSE	74.10	74.50	76.08	65.52	66.76	64.38	70.99	58.55	64.11	71.80	67.09	68.54
DistFuse	78.75	78.50	78.75	65.50	70.50	65.25	75.25	58.00	67.25	73.50	70.25	<b>71.05</b>
<b>Target Language Data (Upper Bounds)</b>												
Fine-tune (tgt lang) <sup>†</sup>	88.40	78.90	80.10	73.90	72.80	62.30	76.60	66.60	69.70	79.10	75.00	74.85
Fine-tune (src + tgt lang)	90.50	82.60	81.33	76.90	81.41	72.47	81.41	70.19	74.62	80.54	74.77	78.79

Table 1: Results on the NusaX dataset in the zero-shot cross-lingual setting. <sup>†</sup>The results are taken from Winata et al. (2023), showing the upper bound model performance when the training data on the target language is available.

**DistFuse** If there is more than one model, we take the distance of the label distributions from the models  $\theta$  and merge them using a linear combination:  $d_{\text{FUSE}} = \sum_{j=1}^M w_j d_{\theta_j}$ , where  $w_j$  is the weight for model  $\theta_j$ .

**Aggregate** We aggregate the nearest  $k$  samples by taking the majority label.

Note that this framework does not involve any model training or parameter updates.

### 3 Experimental Setup

#### 3.1 Datasets

We use two multilingual datasets. NusaX (Winata et al., 2023) is a multilingual sentiment analysis dataset comprising 12 languages, including 10 Indonesian regional languages. MASSIVE (FitzGerald et al., 2023) is a multilingual natural language understanding dataset with 51 languages for which we use the intent detection data.

In all our experiments, we use English as the source language for cross-lingual transfer to maintain the uniformity and tractability of experiments. Identifying the best language to transfer from is an orthogonal direction of exploration (Lin et al., 2019; Eronen et al., 2023) we consider beyond our scope and thus leave it for future work.

#### 3.2 Models

Our framework uses XLM-R<sub>BASE</sub> (Conneau et al., 2020) as the base LM, and LaBSE (Feng et al., 2022) and CMLM (Yang et al., 2021) as the multilingual sentence representation models. The param-

eter count for the models are: XLM-R<sub>BASE</sub> – 270M parameters, LaBSE and CMLM – 471M parameters, and M2M100 – 1.2B parameters. We define *seen* languages those included in pre-training or training of the models; otherwise, we classify languages as *unseen*. For the translation methods, we use the M2M100 1.2B model (Fan et al., 2021) to obtain the translated text. We pick this over commercial systems as it is a high performing system that is both open-source and transparent, which makes our results easily reproducible and can help isolate the effects of training data and languages covered by this model.

#### 3.3 Baselines

We use the following models as baselines for comparison:

- **Random:** Assigns each sample with a random label uniformly chosen from possible labels.
- **Majority:** Assigns each sample with the majority label from the training set.
- **Zero-shot:** Zero-shot prediction using an existing cross-lingual fine-tuned model on XNLI data (Conneau et al., 2018).<sup>1</sup>
- **Fine-tune (src lang):** The base LM fine-tuned on data from the source language only.
- **Fine-tune (translate train):** The base LM fine-tuned on the training set translated from the source language to the target language.
- **Fine-tune (translate test):** The base LM fine-tuned with the training set and evaluated with the

<sup>1</sup>The model can be accessed at <https://huggingface.co/joeddav/xlm-roberta-large-xnli>.

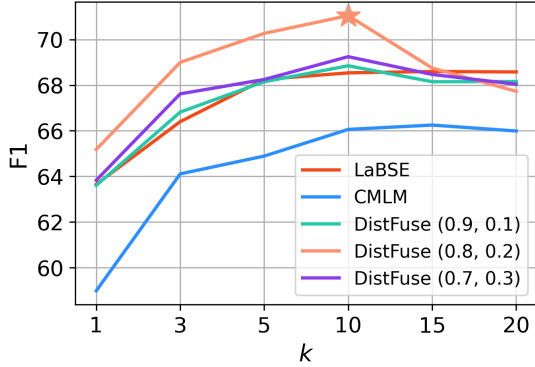


Figure 2: Performance with different  $k$  and DistFuse weights on NusaX dataset. The star marker  $\star$  shows the optimal performance.

test data translated from the target to the source language.

In addition, for comparison purposes, we include the two following methods which use data from the target language and that should be considered an upper bound for classification performance, as these are trained :

- **Fine-tune (tgt):** The base LM fine-tuned with the target language data.
- **Fine-tune (src + tgt):** The base LM fine-tuned with data from both the source and target languages.

### 3.4 Hyper-parameters

We run the fine-tuning baselines with five seeds and report the average F1 scores for NusaX and average Accuracy scores for MASSIVE. We train for a maximum of 20 epochs with a batch size of 32 on a V100 32GB GPU. We do early stopping after three consecutive epochs without performance improvement, and use a learning rate of  $1e-5$  for NusaX and  $5e-5$  for MASSIVE. We explore different retrieval samples size  $k \in \{1, 3, 5, 10, 15, 20\}$  and DistFuse weights  $(0.9, 0.1), (0.8, 0.2), (0.7, 0.3), (0.6, 0.4), (0.5, 0.5)$ . We report results with the best parameters  $k = 10$  and DistFuse weights of  $w_1 = 0.8$  (LaBSE) and  $w_2 = 0.2$  (CMLM).

## 4 Results and Discussion

Tables 1 and 2 show results on the NusaX and MASSIVE datasets, respectively. We observe that the proposed zero-shot framework (DistFuse) significantly outperforms the Fine-tune (src lang) by  $\sim 19\%$  F1 on NusaX. Our proposed model achieves similar performance as Fine-tune (src lang) on MASSIVE with a minor improvement. Moreover,

the XLM-R<sub>XNLI</sub> results are also lagging behind the sentence transformers models, LaBSE and CMLM, as the model does not use any labeled data from the same domain. We also see that LaBSE obtains better results than CMLM on both datasets. We hypothesise this is because LaBSE is optimized for bitext mining.

We also calculate the average performance of each model from Table 1 on seen and unseen languages on the NusaX dataset and summarize the results in Table 7. The breakdown performance analysis again suggests our proposed methods are effective on both seen and unseen languages, and often surpass the baselines by a large margin.

Fine-grained results for each language on the MASSIVE dataset are available in Table 5 and Table 6.

### 4.1 Generalization to Unseen Languages

As shown in Table 1, DistFuse is able to handle unseen languages significantly better than Fine-tune (src lang) baseline on the NusaX dataset ( $\sim 21\%$  F1 on the average of nine languages), showing the strong generalization ability on languages that are not supported by the encoder LMs. This is feasible because the unseen languages share subword tokens with the LM vocabulary (Winata et al., 2022).

### 4.2 Retrieved Samples

Figure 2 shows the zero-shot cross-lingual performance when varying  $k$ . LaBSE’s performance increases with larger  $k$  but tapers off after  $k = 10$ , while CMLM’s performance drops after  $k = 15$ . Thus, we fix  $k = 10$  in all our experiments for optimal results.

### 4.3 DistFuse Weights

The optimal fusion is obtained when  $k = 10$  with the weight proportion  $w_1 = 0.8$  (LaBSE) and  $w_2 = 0.2$  (CMLM), showing the need to give a higher weight on a more robust model LaBSE when combining the two distributions. In general, combining LaBSE and CMLM by fusing distributions is shown to boost performance (+2.51 on NusaX, +0.58 on MASSIVE), showing the two methods can capture complementary information. An analysis of performance on the validation set for different DistFuse weights is presented in Table 8.

### 4.4 Qualitative Analysis

Table 3 shows the top 10 retrieved sentences with the LaBSE (top) and XLM-R (bottom) models. We

Model	low	mid	high	avg. all langs
<b>Baselines</b>				
Random	1.67	1.67	1.67	1.67
Majority	7.03	7.03	7.03	7.03
Zero-shot XLM-R <sub>XNLI</sub>	29.26	33.74	34.98	32.53
Fine-tune (src lang)	63.31	75.95	69.43	70.96
Fine-tune (translate train) <sup>#</sup>	39.49	62.59	53.09	57.22
Fine-tune (translate test) <sup>#</sup>	51.72	73.81	59.87	68.73
<b>Our Zero-Shot Framework</b>				
XLM-R <sub>BASE</sub>	25.10	13.25	27.27	23.62
CMLM	66.83	70.81	71.05	69.60
LaBSE	68.73	71.84	72.01	70.89
DistFuse	69.31	72.46	72.48	<b>71.47</b>
<b>Target Language Data (Upper Bounds)</b>				
Fine-tune (tgt lang)	76.09	81.85	71.88	78.48
Fine-tune (src + tgt lang)	75.03	80.91	69.20	77.23

Table 2: Results on the MASSIVE dataset in the zero-shot cross-lingual setting. The languages are grouped into three vitality classes based on Joshi et al. (2020): 1-2→low, 3-4→mid, 5→high. The full mapping is in Table 4 from the Appendix. <sup>#</sup>The M2M100 model does not support te-IN and zh-TW.

can observe that 8 out of 10 sentences retrieved using LaBSE have the correct label for the input. Moreover, this sentence transformer model can retrieve English sentences even though the input is in Javanese. It also captures the semantics of the entities in Javanese (e.g., television agencies *trans.tv* and *net.tv*) and identifies similar keywords in English, such as *kancaku*, which is the literal translation of *my friend*. The model also retrieves the sentence with an entity *Transmart*, which is an organization that is associated with *trans tv*. This presents the ability of the LaBSE model to not only search for the same keywords during retrieval but also semantically related keywords in another language. However, the XLM-R model performs much worse compared to LaBSE. The retrieved sentences do not have overlapping entities; they generally have different semantic contexts. It shows that the XLM-R representations are not suitable for bitext mining without any additional fine-tuning for cross-lingual alignment. Nevertheless, by taking the majority voting over the 10 sentences, we are still able to predict the correct label.

## 5 Conclusion

We introduce a simple but effective framework to utilize sentence representation models for text classification without requiring parameter updates. We experiment on two large-scale multilingual datasets and show that our framework outperforms zero-shot cross-lingual fine-tuning. This shows the fea-

Input: Aku nembe ngerti ketemu <b>kancaku</b> sek makarya nang <b>trans tv</b>	Label: neutral	
Translation: I just found out that I met <b>my friend</b> while working at <b>trans tv</b>		
Retrieved sentence (LaBSE)	Score	Label
My dad is an employee in <b>net.tv</b>	0.5346	neutral
Now I know I've hated that foreign online shop too much	0.4282	negative
<b>My friend</b> works at Gojek	0.4222	neutral
I heard they'll build a <b>Transmart</b> there, next to that building	0.4062	neutral
I've been dreaming of travelling abroad for a long time	0.3903	neutral
<b>My friend</b> applies for a position in Tokopedia	0.3762	neutral
Lots of <b>my friends</b> also work in Bukalapak	0.3748	neutral
Lots of my family have worked as civil servants.	0.3441	neutral
Last week there was some 4G network in my village for a while.	0.3417	neutral
So bored. I've watched all the films and now I'm drawing a blank	0.3253	negative
<b>Prediction:</b> neutral ( $k=1$ ); neutral ( $k=10$ )		
Retrieved sentence (XLM-R)	Score	Label
Poor Ungu personnels, can't find a gig after Pasha left	0.9957	negative
Win cool prizes by entering the "Baik untuk Men" photo contest in Alfamart	0.9956	neutral
Pos Indonesia's services are so pathetic nowadays.	0.9953	negative
The PIK Waterboom Jakarta tickets are rising in price.	0.9951	negative
Rode on the Jayabaya train from Malang to Jakarta, stopped in Gubeng, the ticket costed 35 thousand plus 6k insurance via Traveloka.	0.9949	neutral
How much is the minimal if I may ask, I wanna buy Tiket Kami for Senen - Yogyakarta using the May promo	0.9949	neutral
The PIK Waterboom Jakarta tickets are rising in price.	0.9948	neutral
The employees at Graha Indosat is so rude	0.9946	negative
The denizens found 2.910 KTP-el cards in the bushes.	0.9946	neutral
I wanna help by giving the info connections, but my internet quota is limited	0.9945	neutral
<b>Prediction:</b> negative ( $k=1$ ); neutral ( $k=10$ )		

Table 3: Retrieved English sentences from the NusaX example with LaBSE (top) and XLM-R (bottom). The input is a Javanese sample from the test set.

sibility of utilizing encoder LMs as zero-shot cross-lingual learners without additional gradient updates. The framework can also be dynamically scaled by updating the memory and combining the output distribution of multiple sentence representation models. Our framework can be further applied to unseen languages that have subword token overlaps with the LM vocabulary.

## 6 Limitations

This paper only studies text classification tasks with two multilingual datasets; we expect no unseen labels on the test sets. We only experiment using two multilingual sentence transformer models and one variant of the XLM-R model. We only use English as the source language, and we expect better results using the closest language as the source language. We leave the exploration of other models and experiment settings as future work.

## 7 Ethics Statement

In our experiments, we use publicly available datasets with permissive licenses for research experiments. We do not release new data or annotations as part of this work. There are no potential risks.

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Language	Language Code	Taxonomy (1-5) <sup>‡</sup>	Vitality*	Seen on Encoders	Seen on M2M100
Afrikaans	af-ZA	3	mid	✓	✓
Albanian	sq-AL	1	low	✓	✓
Amharic	am-ET	2	low	✓	✓
Arabic	ar-SA	5	high	✓	✓
Armenian	hy-AM	1	low	✓	✓
Azerbaijani	az-AZ	1	low	✓	✓
Bengali	bn-BD	3	mid	✓	✓
Burmese	my-MM	1	low	✓	✓
Danish	da-DK	3	mid	✓	✓
Dutch	nl-NL	4	mid	✓	✓
English	en-US	5	high	✓	✓
Finnish	fi-FI	4	mid	✓	✓
French	fr-FR	5	high	✓	✓
Georgian	ka-GE	3	mid	✓	✓
German	de-DE	5	high	✓	✓
Greek	el-GR	3	mid	✓	✓
Hebrew	he-IL	3	mid	✓	✓
Hindi	hi-IN	4	mid	✓	✓
Hungarian	hu-HU	4	mid	✓	✓
Icelandic	is-IS	2	low	✓	✓
Indonesian	id-ID	3	mid	✓	✓
Italian	it-IT	4	mid	✓	✓
Japanese	ja-JP	5	high	✓	✓
Javanese	jv-ID	1	low	✓	✓
Kannada	kn-IN	1	low	✓	✓
Khmer	km-KH	1	low	✓	✓
Korean	ko-KR	4	mid	✓	✓
Latvian	lv-LV	3	mid	✓	✓
Malay	ms-MY	3	mid	✓	✓
Malayalam	ml-IN	1	low	✓	✓
Mandarin (simp)	zh-CN	5	high	✓	✓
Mandarin (trad) <sup>‡</sup>	zh-TW	5	high	✓	×
Mongolian	mn-MN	1	low	✓	✓
Norwegian	nb-NO	1	low	✓	✓
Persian	fa-IR	4	mid	✓	✓
Polish	pl-PL	4	mid	✓	✓
Portuguese	pt-PT	4	mid	✓	✓
Romanian	ro-RO	3	mid	✓	✓
Russian	ru-RU	4	mid	✓	✓
Slovenian	sl-SI	3	mid	✓	✓
Spanish	es-ES	5	high	✓	✓
Swahili	sw-KE	2	low	✓	✓
Swedish	sv-SE	4	mid	✓	✓
Tagalog	tl-PH	3	mid	✓	✓
Tamil	ta-IN	3	mid	✓	✓
Telugu	te-IN	1	low	✓	×
Thai	th-TH	3	mid	✓	✓
Turkish	tr-TR	4	mid	✓	✓
Urdu	ur-PK	3	low	✓	✓
Vietnamese	vi-VN	4	mid	✓	✓
Welsh	cy-GB	1	low	✓	✓

Table 4: Language category mapping on MASSIVE. \* It maps the language taxonomy class to three vitality classes: 1-2→low, 3-4→mid, 5→high. † Mandarin (trad) is considered as Mandarin. ‡ The language taxonomy is taken from Joshi et al. (2020).

Language	Language Code	Zero-shot NLI	Fine-tune			
			src lang	tgt lang	translate-test	translate-train
Afrikaans	az-AZ	70.9 ± 1.6	86.2 ± 1.2	31.04	44.69	45.29
Albanian	sq-AL	67.6 ± 1.7	86.4 ± 1.2	31.2	64.51	71.5
Amharic	am-ET	51.9 ± 1.8	81.7 ± 1.4	24.92	50.75	20.66
Arabic	ar-SA	62.8 ± 1.7	80.7 ± 1.4	30.13	62.13	45.8
Arfrikaans	af-ZA	71.7 ± 1.6	85.6 ± 1.3	30.87	80.51	57.3
Armenian	hy-AM	71.6 ± 1.6	84.4 ± 1.3	29.99	62.06	37.66
Bengali	bn-BD	66 ± 1.7	84.1 ± 1.3	32.65	50.07	68.41
Burmese	my-MM	67.6 ± 1.7	83.6 ± 1.3	29.52	47.43	30.74
Danish	da-DK	83.1 ± 1.3	86.9 ± 1.2	34.26	84.4	78.02
Dutch	nl-NL	82.1 ± 1.4	86.8 ± 1.2	35.07	82.64	80.85
English	en-US	88.3 ± 1.2	88.3 ± 1.2	36.65	N/A	N/A
Finnish	fi-FI	80.2 ± 1.4	85.5 ± 1.3	36.35	82.39	50.03
French	fr-FR	80.8 ± 1.4	86.3 ± 1.2	35.74	68.44	79.49
Georgian	ka-GE	61.2 ± 1.8	80.3 ± 1.4	26.8	58.63	36.86
German	de-DE	77.6 ± 1.5	85.7 ± 1.3	33.86	66.26	76.35
Greek	el-GR	74 ± 1.6	86.2 ± 1.2	33.62	64.46	58.85
Hebrew	he-IL	73.2 ± 1.6	85.9 ± 1.3	32.92	77.41	54.87
Hindi	hi-IN	74.8 ± 1.6	85.8 ± 1.3	32.62	66.12	59.8
Hungarian	hu-HU	77.1 ± 1.5	86.2 ± 1.2	32.65	82.38	72.6
Icelandic	is-IS	66.7 ± 1.7	85.3 ± 1.3	29.62	48.68	63.11
Indonesian	id-ID	83.1 ± 1.3	87.1 ± 1.2	37.53	82.09	67.41
Italian	it-IT	76.4 ± 1.5	86.6 ± 1.2	33.25	83.8	75.55
Japanese	ja-JP	44.8 ± 1.8	83.9 ± 1.3	37.09	81.73	73.47
Javanese	ja-ID	46.5 ± 1.8	82.9 ± 1.4	25.02	47.83	40.24
Kannada	kn-IN	63.5 ± 1.7	84 ± 1.3	29.93	31.99	5.62
Khmer	km-KH	61.3 ± 1.8	77.2 ± 1.5	26.63	46.52	32.48
Korean	ko-KR	77 ± 1.5	86.5 ± 1.2	35.27	57.17	60.67
Latvian	lv-LV	69.2 ± 1.7	86.1 ± 1.2	34.26	78.51	64.11
Malay	ms-MY	76.7 ± 1.5	86.1 ± 1.2	33.25	63.69	73.82
Malayalam	ml-IN	70.1 ± 1.6	85.1 ± 1.3	33.32	71.46	39.59
Mandarin (simp)	zh-CN	61.9 ± 1.7	84.9 ± 1.3	36.82	68.43	71.59
Mandarin (trad)	zh-TW	60.4 ± 1.8	83 ± 1.3	35.07	63.99	N/A
Mongolian	mn-MN	64.4 ± 1.7	84.3 ± 1.3	31.98	50.93	31.22
Norwegian	nb-NO	83.6 ± 1.3	87.3 ± 1.2	35.84	85.15	80.03
Persian	fa-IR	81.1 ± 1.4	87 ± 1.2	34.77	66.72	67.83
Polish	pl-PL	80.7 ± 1.4	85.8 ± 1.3	35.91	83.44	61.76
Portuguese	pt-PT	79.5 ± 1.5	86.7 ± 1.2	34.73	83.02	79.09
Romanian	ro-RO	80.8 ± 1.4	86.9 ± 1.2	32.08	83.31	76.64
Russian	ru-RU	81.3 ± 1.4	87.2 ± 1.2	34.7	83.51	62.08
Slovenian	sl-SI	69.5 ± 1.7	86.3 ± 1.2	31.44	74.5	60.11
Spanish	es-ES	78.8 ± 1.5	86.9 ± 1.2	34.5	67.96	78.02
Swahili	sw-KE	46.6 ± 1.8	83.1 ± 1.3	22.6	63.99	41.39
Swedish	sv-SE	85.2 ± 1.3	87.9 ± 1.2	34.57	84.15	65.6
Tagalog	tl-PH	63.7 ± 1.7	84.6 ± 1.3	32.08	64.73	45.37
Tamil	ta-IN	68.1 ± 1.7	83.5 ± 1.3	31.91	65.31	24.88
Telugu	te-IN	68.2 ± 1.7	84.5 ± 1.3	31.1	N/A	N/A
Thai	th-TH	77.4 ± 1.5	84.7 ± 1.3	35.61	49.54	66.06
Turkish	tr-TR	78.4 ± 1.5	86.3 ± 1.2	35.54	80.59	70.46
Urdu	ur-PK	65.6 ± 1.7	83.2 ± 1.3	30.77	71.64	57.54
Vietnamese	vi-VN	79.2 ± 1.5	86.3 ± 1.2	36.15	79.74	50.84
Welsh	cy-GB	46.9 ± 1.8	82.6 ± 1.4	24.75	39.85	34.8

Table 5: Fine-grained baseline results on MASSIVE. We label “N/A” for English and languages that are not supported by the M2M100 machine translation model.

Language	Language Code	XLM-R	CMLM	LaBSE	DistFuse
Afrikaans	az-AZ	19.22	67.79	68.76	69.29
Albanian	sq-AL	18.2	71.3	71.87	72.5
Amharic	am-ET	6.22	64.5	67.78	68.28
Arabic	ar-SA	15.52	57.96	60.21	60.34
Arfrikaans	af-ZA	27.33	71.29	72.78	73.48
Armenian	hy-AM	17.68	68.94	69.48	69.38
Bengali	bn-BD	13.36	70.98	71.82	72.05
Burmese	my-MM	6.68	66.38	66.87	67.59
Danish	da-DK	33.37	71.49	73.12	73.72
Dutch	nl-NL	39.67	73.64	73.77	74.06
English	en-US	60.14	76.7	78.07	78.53
Finnish	fi-FI	32.04	70.65	73.1	72.79
French	fr-FR	34.77	73.82	74.49	74.36
Georgian	ka-GE	14.29	61.45	62.9	63.39
German	de-DE	30.62	69.3	70.35	71.23
Greek	el-GR	24.33	68.48	71.42	72.07
Hebrew	he-IL	20.55	70.9	70.61	71.28
Hindi	hi-IN	20.83	73.51	73.98	74.02
Hungarian	hu-HU	29.96	70.61	72.47	72.91
Icelandic	is-IS	14.1	67.77	68.82	69.21
Indonesian	id-ID	33.69	73.07	74.11	74.26
Italian	it-IT	30.38	70.54	72.95	74.14
Japanese	ja-JP	25.41	74.57	73.79	74.45
Javanese	jv-ID	9.59	63.42	64.39	66.05
Kannada	kn-IN	10.26	71.24	72.1	73.32
Khmer	km-KH	10.82	58.88	61.36	60.01
Korean	ko-KR	24.98	71.32	71.92	73.01
Latvian	lv-LV	19.1	70.66	71.5	71.36
Malay	ms-MY	28.03	69.23	72.04	72.37
Malayalam	ml-IN	13.16	70.89	72.86	73.47
Mandarin (simp)	zh-CN	26.65	72.54	73.2	73.89
Mandarin (trad)	zh-TW	27.83	71.01	71.12	71.5
Mongolian	mn-MN	13.22	68.19	70.58	70.73
Norwegian	nb-NO	30.22	71.11	72.24	74.15
Persian	fa-IR	29.09	72.63	73.65	73.71
Polish	pl-PL	34.42	73.77	72.92	74.42
Portuguese	pt-PT	35.82	73.23	75.45	74.94
Romanian	ro-RO	35.78	71.33	73.14	73.88
Russian	ru-RU	35.56	70.47	71.27	72.38
Slovenian	sl-SI	27.23	73.3	71.85	74.1
Spanish	es-ES	35.34	72.49	74.86	75.51
Swahili	sw-KE	10.35	63.4	65.18	66.06
Swedish	sv-SE	34.18	72.58	73.19	74.66
Tagalog	tl-PH	22.21	68.92	70.63	70.65
Tamil	ta-IN	13.69	69.25	68.85	69.16
Telugu	te-IN	10.16	70	72.77	73.75
Thai	th-TH	22.25	68.46	69.84	69.32
Turkish	tr-TR	23.06	69.98	71.79	72.87
Urdu	ur-PK	14.42	68.4	70.85	71.21
Vietnamese	vi-VN	31.03	70.22	68.67	71.38
Welsh	cy-GB	7.72	57	63.85	64.03

Table 6: Fine-grained zero-shot results on MASSIVE.

<b>Model</b>	<b>seen</b>	<b>unseen</b>
<b>Baselines</b>		
Random	33.33	33.33
Majority	38.25	38.25
Zero-shot XLM-R <sub>XNLI</sub>	55.96	46.64
Fine-tune (src lang)	70.36	45.22
Fine-tune (translate train)	69.59	-
Fine-tune (translate test)	61.96	-
<b>Our Zero-Shot Framework</b>		
XLM-R <sub>BASE</sub>	60.75	40.03
CMLM	73.36	63.32
LaBSE	74.89	66.15
DistFuse	<b>78.66</b>	<b>68.19</b>
<b>Target Language Data (Upper Bounds)</b>		
Fine-tune (tgt lang) <sup>†</sup>	82.47	72.00
Fine-tune (src + tgt lang)	84.81	76.54

Table 7: Average performance on the seen and unseen languages from the NusaX dataset.

<b>Language</b>	<b>Ratio (LabSE and CMLM)</b>				
	[0.9,0.1]	[0.8,0.2]	[0.7,0.3]	[0.6,0.4]	[0.5,0.5]
acehnese	67.05	61.26	61.42	64.43	66.96
balinese	66.05	65.38	64.35	62.72	64.93
banjarese	62.84	60.54	59.78	65.17	67.33
buginese	58.33	59.68	57.76	57.45	58.41
english	80.24	77.24	79.62	77.36	75.55
indonesian	76.40	77.71	76.44	75.98	77.48
javanese	75.38	76.32	71.86	72.75	72.75
madurese	58.15	59.20	60.12	58.90	59.88
minangkabau	65.67	66.86	69.70	68.83	67.2
ngaju	60.35	61.38	63.15	64.12	63.95
sundanese	76.88	76.02	79.16	77.52	78.56
toba_batak	58.8	59.78	57.05	59.65	59.73
avg.	67.18	66.78	66.70	67.07	67.73

Table 8: Average performance on the validation set from the NusaX dataset.