BRIGHTER: BRIdging the Gap in Human-Annotated Textual Emotion Recognition Datasets for 28 Languages

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Abstract

People worldwide use language in subtle and complex ways to express emotions. Although emotion recognition–an umbrella term for several NLP tasks–impacts various applications within NLP and beyond, most work in this area has focused on high-resource languages. This has led to significant disparities in research efforts and proposed solutions, particularly for under-resourced languages, which often lack high-quality annotated datasets. In this paper, we present BRIGHTER–a collection of multi-labeled, emotion-annotated datasets in 28 different languages and across several domains. BRIGHTER primarily covers low-resource languages from Africa, Asia, Eastern Europe, and Latin America, with instances labeled by fluent speakers. We highlight the challenges related to the data collection and annotation processes, and then report experimental results for monolingual and crosslingual multi-label emotion identification, as well as emotion intensity recognition. We analyse the variability in performance across languages and text domains, both with and without the use of LLMs, and show that the BRIGHTER datasets represent a meaningful step towards addressing the gap in text-based emotion recognition.

1 Introduction

While emotions are expressed and managed daily, they are complex, nuanced, and sometimes hard to articulate and interpret. That is, people use language in subtle and complex ways to express emotions across languages and cultures (Wiebe et al., 2005; Mohammad and Kiritchenko, 2018; Mohammad et al., 2018a) and perceive them subjectively, even within the same culture or social group. Emotion recognition is at the core of several NLP applications in healthcare, dialogue systems, computational social science, digital humanities, narrative analysis, and many others (Mohammad et al., 2018b; Saffar et al., 2023). It is an umbrella term for multiple NLP tasks, such as detecting the possible emotions of the speaker, identifying what

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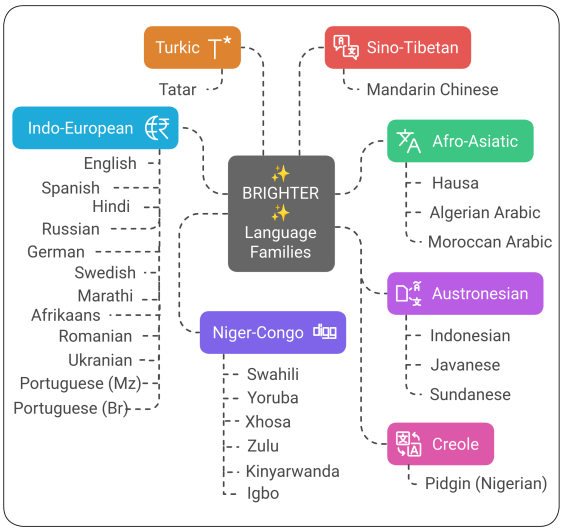


Figure 1: **Languages included in BRIGHTER** and their language families.

emotion a piece of text is conveying, and detecting the emotions evoked in a reader (Mohammad, 2022). In this paper, we use *emotion recognition* to refer to *perceived* emotions, i.e., what emotion most people think the speaker might have felt given a sentence or a short text snippet uttered by them.

Most work on emotion recognition has focused on high-resource languages such as English, Spanish, German, and Arabic (Strapparava and Mihalcea, 2007; Seyeditabari et al., 2018; Chatterjee et al., 2019; Kumar et al., 2022). This is partly due to the unavailability of datasets in under-served languages, which has led to a major research gap in the area, which is particularly noticeable in low-resource languages. That is, despite the linguistic diversity present in different parts of the world, such as Africa and Asia, which are home to more than 4,000 languages[1], few emotion recognition resources are available in these languages. To bridge this gap, we introduce BRIGHTER–a collection of manually annotated emotion datasets for 28 languages containing nearly 100,000 instances from diverse data sources: speeches, social media, news, literature, and reviews. The languages belong to 7 language families (see Figure 1) and are predominantly low-resource, mainly spoken in **Africa**, **Asia**, **Eastern Europe**, **Latin America**, along with mid- to high-resource languages such as English. Each instance in BRIGHTER is curated and annotated by fluent speakers based on six emotion classes: *joy, sadness, anger, fear, surprise, disgust,* and none for neutral. The instances are multi-labeled and include 4 levels of intensity that vary from 0 to 3 (examples in Figure 2). We describe the collection, annotation, and quality control steps used to construct BRIGHTER. We then test various baseline experiments and observe that LLMs still struggle with recognising perceived emotions in text. We further report on the observed discrepancies across languages such as the fact that, for low-resource languages, LLMs perform significantly better when prompted in English. We make our datasets public[2], which presents an important step towards work on emotion recognition and related tasks as we involve local communities in the collection and annotation. Our insights into language-specific characteristics of emotions in text, nuances, and challenges may enable the creation of more inclusive digital tools.

2 The BRIGHTER Dataset Collection

As our BRIGHTER collection includes datasets in 28 different languages, curated and annotated by fluent speakers, we use several data sources, collection, and annotation strategies depending on 1) the availability of the textual data potentially rich in emotions and 2) access to annotators. We detail the choices made when selecting and balancing sources, annotating the instances, and controlling for data quality in the following section.

2.1 Data Sources

Selecting appropriate data can be challenging when resources are scarce. Therefore, we typically combine multiple sources, as shown in Table 1. Below, we outline the main textual domain inputs used to construct BRIGHTER.

Social media posts We use social media data collected from various platforms, including Reddit (e.g., `eng`, `deu`), YouTube (e.g., `esp`, `ind`, `jav`, `sun`), Twitter (e.g., `hau`, `ukr`), and Weibo (e.g., `chn`). For some languages, we re-annotate existing sentiment datasets for emotions (e.g., the sentiment analysis benchmark AfriSenti (Muhammad et al., 2023a) for `ary`, `hau`, `kin`; the Twitter dataset by Bobrovnyk (2019) for `ukr`; the RED–v2 dataset (Ciobotaru et al., 2022) for `ron`).

[1] https://www.ethnologue.com/insights/how-many-languages

[2] The datasets are available at https://brighter-dataset.github.io. Note that they were used in SemEval-2025 Task 11, which attracted over 700 participants (Muhammad et al., 2025).

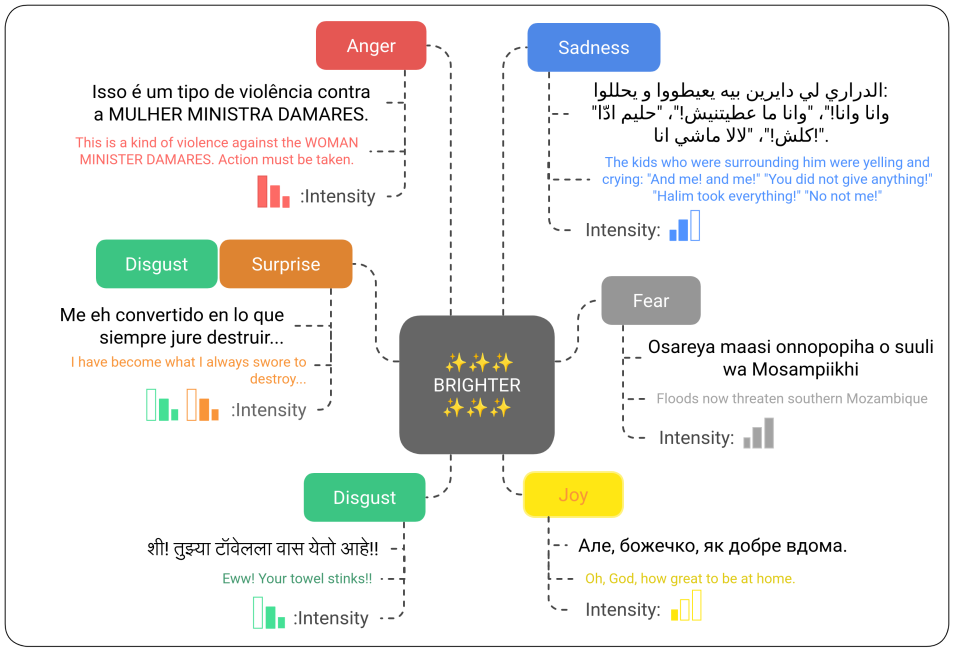


Figure 2: Examples from the BRIGHTER dataset collection in 6 different languages with their translations and intensity levels. Note that the instances can have one or more labels (e.g., disgust and surprise as shown in the figure).

Personal narratives, talks, and speeches Anonymised sentences from personal diary posts are ideal for extracting sentences where the speaker is centering their own emotions as opposed to the emotions of someone else. Hence, we use these in eng, deu, and ptbr, mainly from subreddits such as, e.g., IAmI.

Similarly, the afr dataset includes sentences from speeches and talks which constitute a good source for potentially emotive text.

Literary texts We manually translated the novel *"La Grande Maison"* (The Big House) by the Algerian author Mohammed Dib [3] from French to Algerian Arabic and further post-processed the translation to generate sentences to be annotated by native speakers. Note that the translator is bilingual and a native Algerian Arabic speaker. Such a source is typically rich in emotions as it includes interactions between various characters. Moreover, Algerian Arabic is mainly spoken due to the Arabic diglossia, which makes this resource valuable since it highly differs from social media datasets in arq.

News data Although we prefer emotionally rich social media data from different platforms, such data is not always available. Therefore, when data sources are limited, to collect a larger number of instances, we annotate news data and headlines in some African languages (e.g., yor, hau, and vmw).

Human-written and machine generated data We create a dataset from scratch for Hindi (hin) and Marathi (mar). We ask annotators to generate emotive sentences on a given topic (e.g., family). In addition, we automatically translate a small section of the Hindi dataset to Marathi, and native speakers manually fix the translation errors. Finally, we augment both datasets with a few hundred quality-approved instances generated by ChatGPT.

2.2 Pre-processing and Quality Control

Prior to annotation, we preprocess the data by removing duplicates, invisible characters, garbled encoding, and incorrectly rendered emoticons. We anonymise all texts and exclude content with excessive expletives or dehumanising language.

2.3 Annotating BRIGHTER

As a text snippet can elicit multiple emotions simultaneously, we ask the annotators to select all the emotions that apply to a given text rather than choosing a single dominant emotion class. The set of labels includes six categories of perceived emotions: *anger, sadness, fear, disgust, joy, surprise*, and is considered *neutral* if no emotion is picked.

[3] https://en.wikipedia.org/wiki/La_Grande_Maison

Language	Data source(s)	#Annotators (total)	#Ann. / sample	Train	Dev	Test	Total
Afrikaans (**afr**)	Speeches	3	3	1,325	115	1,247	2,687
Algerian Arabic (**arq**)	Literature	10	4 to 9	1,686	182	1,674	3,542
Moroccan Arabic (**ary**)	News, social media	3	3	1,813	300	931	3,044
Chinese (**chn**)	Social media	7	5	3,316	250	3,345	6,911
German (**deu**)	Social media	10	7	3,700	294	3,690	7,684
English (**eng**)	Social media	122	5 to 30	4,574	189	4,509	9,272
Latin American Spanish (**esp**)	Social media	12	5	2,835	256	2,340	5,431
Hausa (**hau**)	News, social media	5	5	2,656	440	1,352	4,448
Hindi (**hin**)	Created	5	4 to 5	2,841	108	1,070	4,019
Igbo (**ibo**)	News, social media	3	3	2,988	497	1,502	4,987
Indonesian (**ind**)	Social media	16	3	–	247	1,409	1,656
Javanese (**jav**)	Social media	13	3	–	250	1,395	1,645
Kinyarwanda (**kin**)	News, social media	3	3	5,350	426	1,298	4,299
Marathi (**mar**)	Created	4	4	2,590	108	1,103	3,864
Nigerian-Pidgin (**pcm**)	News, social media	3	3	1,553	888	2,691	8,929
Portuguese (Brazilian; **ptbr**)	Social media	5	5	2,318	228	2,580	5,398
Portuguese (Mozambican; **ptmz**)	News, social media	3	3	2,995	258	780	2,591
Romanian (**ron**)	Social media	8	3 to 8	1,352	123	1,893	4,536
Russian (**rus**)	Social media	10	3 to 10	3,443	225	1,127	4,347
Sundanese (**sun**)	Social media	16	3	1,495	292	1,351	2,995
Swahili (**swa**)	News, social media	3	3	1,000	573	1,727	5,743
Swedish (**swe**)	Social media	3	3	2,527	253	1,514	3,262
Tatar (**tat**)	Social media	3	2	1,558	200	1,000	2,200
Ukrainian (**ukr**)	Social media	106	5	3,133	255	2,278	5,060
Emakhuwa (**vmw**)	News, social media	3	3	1,558	259	781	2,598
isiXhosa (**xho**)	News, social media	3	3	–	745	1,744	2,489
Yoruba (**yor**)	News	3	3	3,133	520	1,572	5,225
isiZulu (**zul**)	News, social media	3	3	–	940	2,202	3,142

Table 1: **Data sources, number of annotators, and data split sizes for the BRIGHTER datasets**, sorted alphabetically by language code. Datasets without training splits (–) were used exclusively for testing (see Section 3).

The annotators further rate the selected emotion(s) on a four-point intensity scale: 0 (no emotion), 1 (low intensity), 2 (moderate intensity level), and 3 (high intensity). We provide the definitions of the categories and annotation guide in Appendix D.

We use Amazon Mechanical Turk to annotate the English dataset, and Toloka[4] to label the Russian, Ukrainian, and Tatar instances. However, as traditional crowdsourcing platforms do not have a large pool of annotators who speak various low-resource languages, we directly recruit fluent speakers to annotate the data and use the academic version of LabelStudio (Tkachenko et al., 2020-2025) and Potato (Pei et al., 2022) to set up our annotation platform.

2.4 Annotators' Reliability

While both inter-annotator agreement (IAA) and reliability scores evaluate annotation quality, they capture different aspects. IAA evaluates the extent to which annotators agree with one another, whereas reliability scores measure the consistency of aggregated labels across repeated annotation trials (Kiritchenko and Mohammad, 2016). Consequently, reliability scores tend to increase with a larger number of annotations, while IAA scores do not depend on the number of annotations per instance.

We report the annotation reliability using Split-Half Class Match Percentage (SHCMP; Mohammad, 2024). SHCMP extends the concept of Split-Half Reliability (SHR), traditionally applied to continuous scores (Kiritchenko and Mohammad, 2016), to discrete categories, such as our emotion intensity labels. SHCMP measures the extent to which n bins (i.e., random subsets) classify items consistently. The dataset is randomly split into n bins (corresponding to halves when $n = 2$) $1,000$ times, and the proportion of instances receiving the same class label across bins is averaged to return the final SHCMP score. A higher SHCMP indicates greater reliability, meaning that repeated annotations would likely result in similar class labels. Additional details are provided in Appendix D. Figure 3 shows a heatmap of SHCMP scores

[4] https://toloka.ai

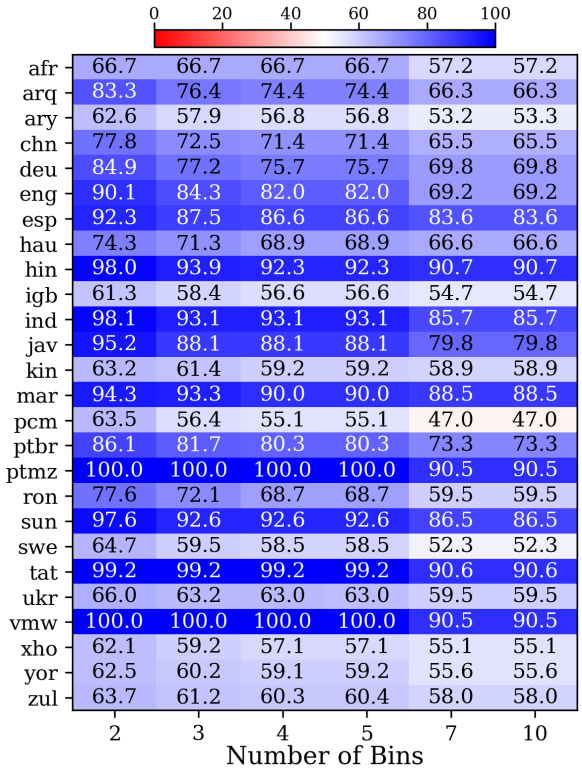


Figure 3: **Split-Half Class Match Percentage, SHCMP (%) values for the BRIGHTER datasets** across varying numbers of bins (2 to 10). Higher values indicate better reliability scores. Note that `ptmz` and `vwm` have the same score as `vwm` instances were translated from `ptmz` and the translation was verified.

for the BRIGHTER datasets. Overall, the SHCMP scores are high (greater than 60% for $n = 2$), indicating that our annotations are reliable.

2.5 Determining the Final Labels

We expected a level of disagreement as emotions are complex, subtle, and perceived differently even from people within the same culture. In addition, text-based communication is limited as it lacks cues such as tone, relevant context, and information about the speaker. Our approach for aggregating the per-annotator emotion and intensity labels is detailed below. We also publicly share the individual (non-aggregated) annotations, recognising that annotator disagreement can provide useful signals in itself (Plank, 2022).

Aggregating the emotion labels The final emotion labels are determined based on the emotions and associated intensity values selected by the annotators. That is, the given emotion is considered present if:

1. At least two annotators select a label with an intensity value of 1, 2, or 3 (low, medium, or high, respectively).
2. The average score exceeds a predefined threshold T. We set T to 0.5.

Aggregating the intensity labels Once the labels for perceived emotions are assigned, we determine the final intensity score for each instance by averaging the selected intensity scores and rounding them up to the nearest integer. We assign intensity scores only for datasets in which the majority of instances are annotated by ≥ 5 annotators, to ensure robustness. Therefore, BRIGHTER includes emotion labels for 28 languages and intensity labels for 10 languages.

2.6 Final Data Statistics

Figure 4 shows the distribution of the annotated emotions in the BRIGHTER datasets. The neutral class contains instances that do not belong to any of the six predefined categories (i.e., anger, disgust, fear, sadness, joy, and surprise). Although most languages include all six categories, the English dataset does not include disgust, and the Afrikaans one does not include surprise due to an insufficient class representation. Furthermore, class distributions show substantial variation as we chose various data sources as shown in Table 1.

3 Experiments

3.1 Setup

We report the data split sizes in Table 1. The test sets are relatively large, ranging from approximately $1,000$ to nearly $3,000$ instances. Datasets without training data are excluded from training and are used solely for testing in cross-lingual settings.

For our baseline experiments, we evaluate multi-label emotion classification and emotion intensity prediction using both Multilingual Language Models (MLMs) and Large Language Models (LLMs).

Multi-label emotion classification in few-shot settings We report emotion classification performance using five LLMs–`Qwen2.5-72B` (Yang et al., 2024), `Dolly-v2-12B` (Conover et al., 2023), `LlaMA-3.3-70B` (Touvron et al., 2023), `Mixtral-8x7B` (Jiang et al., 2024), and `DeepSeek-R1-70B` (DeepSeek-AI et al., 2025). We prompt the LLMs using Chain-of-Thought (CoT) reasoning to predict the presence of each emotion from the predefined set. We set the

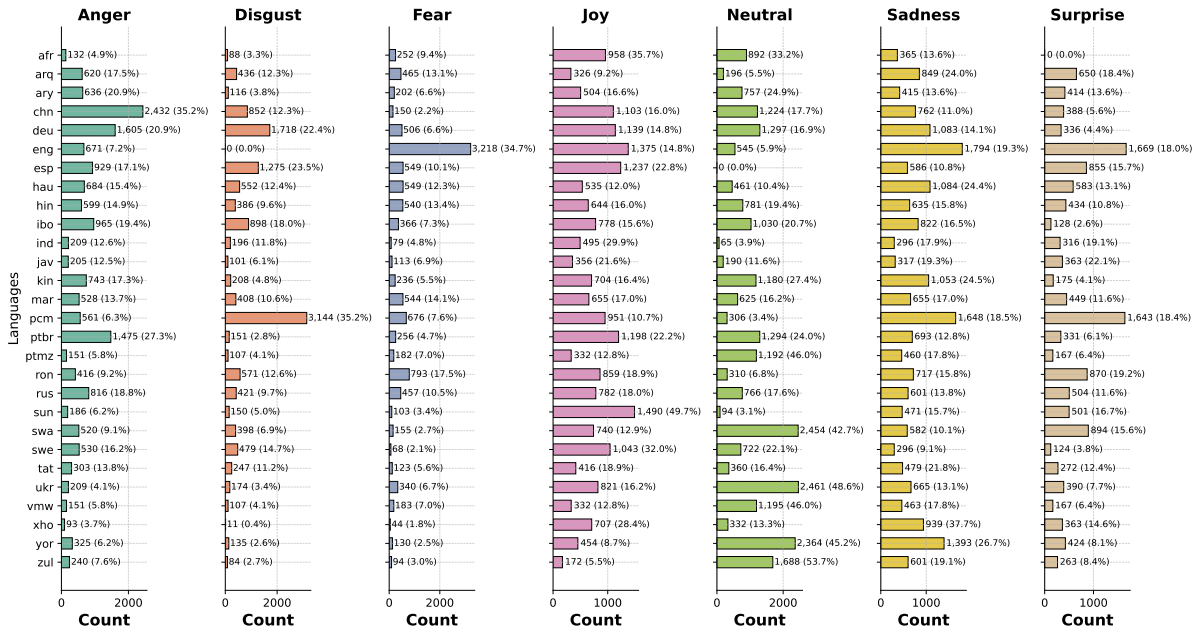


Figure 4: **Emotion label distribution across the BRIGHTER datasets**. Each bar represents the number of labeled instances per emotion (i.e., anger, disgust, fear, joy, sadness, surprise, and neutral) and its percentage.

number of few-shot examples to 8 and consider only the first generated answer (i.e., top-1). We report macro F1 scores across 28 languages. In Appendix D, we also provide monolingual classification results for the 24 languages with training data (see Table 5).

Multi-label emotion classification in crosslingual settings We report the macro F-score results for systems trained without using any data in the 28 target languages when testing on each. Hence, we train MLMs on all languages in one family (see Figure 1) except for one held-out target language, which we test on and report the results for each test set. For families with only one language (i.e., Sino-Tibetan, Creole, and Turkic), we train on Slavic languages (`rus` and `ukr`) and test on `tat`; two Niger-Congo languages (`swa` and `yor`) and test on `pcm`; and on `rus` and test on `chn`.

Emotion intensity prediction We report Pearson correlation scores for systems trained on the intensity-labeled training sets in 10 languages.

3.2 Experimental Results

Table 2 reports the results of few-shot and crosslingual experiments for multi-label emotion classification and Table 3 reports those for emotion intensity classification. Our results corroborate how challenging emotion classification is for LLMs, even for high-resource languages such as `eng` and `deu`. The performance is worse for low-resource languages, for which `Dolly-v2-12B` performs the worst, and `Qwen2.5-72B` performs the best on average.

We observe the largest performance for `yor` with a maximum of 27.44. `hin`, `mar`, and `tat` have the best performance among all languages, which is unsurprising since the `tat` dataset is single-labeled, and close to 70% and 80% of the test data for `mar` and `hin` respectively are single-labeled.

Multi-label emotion recognition results The crosslingual experiments demonstrate that model performance depends on both the languages used for transfer learning and those included in the pre-training of the models. For instance, in some cases, training on languages from the same family improves performance and even surpasses few-shot settings, e.g., `swe` benefits when RemBERT is fine-tuned on other Germanic languages. However, all Niger-Congo languages, particularly `vmw`, benefit the least from crosslingual transfer across all models, with RemBERT performing the worst. This is largely due to the severe under-resourcedness of these languages, even when data is combined. Notably, XLM-R performs exceptionally well on languages such as `deu`, `chn`, `hin`, and `ptbr`, but struggles significantly with others (e.g., `swe`, `ptmz`). In contrast, mDeBERTa yields the most consistent results across most languages, even though

	Few-Shot Multi-Label Classification					Crosslingual Multi-Label Classification				
Lang.	**Qwen2.5-72B**	**Dolly-v2-12B**	**Llama-3.3-70B**	**Mixtral-8x7B**	**DeepSeek-R1-70B**	**LaBSE**	**RemBERT**	**XLM-R**	**mBERT**	**mDeBERTa**
afr	60.18	23.58	**61.28**	53.69	43.66	35.12	35.04	**41.66**	16.95	33.25
arq	37.78	38.59	**55.75**	45.29	50.87	**35.93**	33.78	35.87	31.38	35.92
ary	**52.76**	24.27	44.96	35.07	47.21	**42.83**	35.46	33.88	24.83	36.28
chn	**55.23**	27.52	53.36	44.91	53.45	45.28	24.56	**53.84**	21.61	42.41
deu	**59.17**	26.86	56.99	51.20	54.26	42.45	46.84	**47.26**	28.60	42.61
eng	55.72	42.60	**65.58**	58.12	56.99	36.71	37.54	**37.60**	18.80	35.30
esp	72.33	36.41	61.27	65.72	**73.29**	54.56	**57.37**	44.52	30.09	37.09
hau	43.79	29.43	50.91	40.40	**51.91**	**38.46**	31.98	16.69	15.59	32.80
hin	**79.73**	27.59	60.59	62.19	76.91	69.78	13.75	**69.96**	36.94	57.74
ibo	**37.40**	24.31	33.18	31.90	32.85	**18.13**	7.49	10.42	9.94	9.52
ind	**57.29**	36.61	39.20	54.37	49.51	**47.50**	37.64	25.39	26.87	35.68
jav	**50.47**	36.18	41.88	48.37	43.05	46.24	**46.38**	20.39	26.16	35.34
kin	31.96	19.73	**34.36**	26.35	32.52	**30.35**	18.38	13.12	20.90	17.30
mar	74.58	25.69	67.40	50.36	**76.68**	74.65	**77.24**	76.21	42.32	54.05
pcm	38.66	34.41	**48.67**	45.61	45.00	**33.29**	1.01	21.08	22.55	25.39
ptbr	**51.60**	25.90	45.03	41.64	51.49	41.51	41.84	**43.09**	23.86	34.42
ptmz	**40.44**	16.70	34.06	36.52	39.58	**31.44**	29.67	7.30	13.54	24.46
ron	68.18	43.58	**71.28**	68.51	65.02	69.79	**76.23**	65.21	61.50	60.60
rus	73.08	29.72	62.61	61.72	**76.97**	61.32	**70.43**	21.14	37.15	29.70
sun	42.67	32.20	**46.33**	42.10	44.61	**34.79**	19.43	25.92	25.29	27.31
swa	27.36	17.63	29.47	26.51	**33.27**	21.66	**18.99**	16.94	18.61	14.94
swe	48.89	21.79	**50.26**	48.61	44.60	44.24	**51.18**	10.08	28.86	43.28
tat	51.58	25.12	49.84	39.44	**53.86**	**60.66**	44.54	39.58	35.81	47.72
ukr	**54.76**	17.16	42.34	40.15	51.19	44.37	**49.56**	34.06	25.69	35.12
vmw	**20.41**	16.03	18.96	19.00	19.09	9.65	5.22	**12.66**	12.11	11.74
xho	29.56	24.12	30.79	22.92	29.08	31.39	12.73	11.48	17.08	22.86
yor	24.99	16.00	23.70	19.67	**27.44**	**11.64**	5.33	6.64	9.62	10.03
zul	22.03	14.72	21.48	20.38	20.38	18.16	15.26	10.92	13.04	13.87
AVG	**49.71**	26.88	47.12	43.56	49.21	**40.50**	33.63	30.61	24.16	32.38

Table 2: **Average F1-Macro for multi-label emotion classification**. In the few-shot setting, we predict the emotion class on test set in 28 languages. In the crosslingual setting, we train on all languages within a language family except the target language, and evaluate on the test set of the target language. The best performance scores in few-shot and crosslingual settings are highlighted in blue and orange, respectively.

it shows low performance on ibo, vmw, and yor, which are not part of the CC-100 corpus (Conneau et al., 2020) used in its training. While mDeBERTa was also not trained on arq, the inclusion of Modern Standard Arabic (MSA) in its pretraining data might have positively influenced its performance.

Overall, our results indicate that multilingual models transfer more effectively to languages seen during pretraining, while often producing random or unreliable outputs for languages absent from their training data.

Emotion intensity prediction For intensity detection, a more challenging task, Dolly-v2-12B performs the worst, whereas DeepSeek-R1-70B shows promising results, outperforming other models in most languages. Llama-3.3-70B and Qwen2.5-72B achieve the highest scores in English. Interestingly, MLMs tend to perform better on high-resource languages–RemBERT, in particular, achieves strong results for deu, eng, esp, and rus, with chn being the only exception. In contrast, for primarily spoken, low-resource vernaculars (e.g., arq), LLMs demonstrate striking improvements – DeepSeek-R1-70B, for instance, achieves improvements exceeding 36 points.

4 Analysis

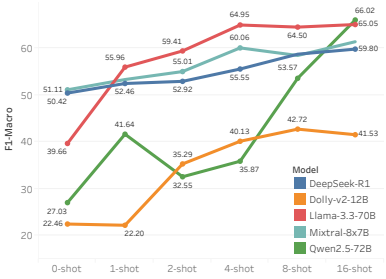
The results in Figure 5a suggest that LLM performance is highly dependent on the prompt wording when asking for the presence of emotion on the English test set using different paraphrases of the same text. Further, Figure 5b shows that, when testing the effect of n-shot settings on the English test set, we observe a significant improvement in performance with more shots, with Mixtral-8x7B and Llama-3.3-70B outperforming other models. However, the scores tend to reach a plateau at 4 shots for all LLMs except for Qwen2.5-72B, which suggests that 4 to 8 shots may be sufficient to obtain stable results. In addition, when testing how likely we can get the correct answer when prompting LLMs to generate tokens based on a selec-

	Multilingual Language Models (MLMs)					Large Language Models (LLMs)				
Lang.	**LaBSE**	**RemBERT**	**XLM-R**	**mBERT**	**mDeBERTa**	**Qwen2.5-72B**	**Dolly-v2-12B**	**Llama-3.3-70B**	**Mixtral-8x7B**	**DeepSeek-R1-70B**
arq	1.42	**1.64**	0.89	1.10	0.47	29.54	3.80	36.29	31.05	**36.37**
chn	23.37	**40.53**	36.92	21.96	23.25	46.17	8.11	**51.86**	46.52	48.57
deu	28.93	**56.21**	38.30	17.35	18.14	43.30	7.43	53.46	47.60	**54.78**
eng	35.34	**64.15**	37.36	25.74	8.85	**55.99**	13.35	44.14	55.26	48.08
esp	56.89	**72.59**	55.72	27.94	29.18	51.11	10.49	51.64	55.54	**60.74**
hau	26.13	**27.03**	24.68	2.79	0.00	27.00	6.43	**39.16**	25.84	38.85
ptbr	20.62	**29.74**	18.24	8.36	1.32	38.20	9.02	40.90	39.17	**46.72**
ron	35.57	**55.66**	37.77	21.99	4.63	55.48	12.62	45.87	57.07	**57.69**
rus	68.43	**87.66**	68.96	37.63	5.03	58.25	13.96	57.56	56.01	**62.28**
ukr	13.75	**39.94**	36.16	4.32	3.51	37.74	6.04	36.99	38.74	**43.54**
AVG	30.54	**46.61**	35.25	16.35	9.97	43.03	8.74	45.78	43.97	**48.88**

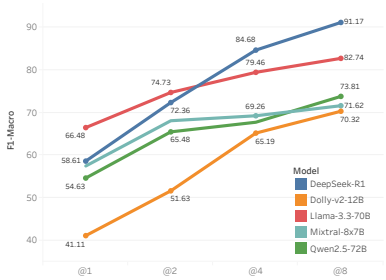
Table 3: **Pearson correlation scores for intensity classification** using MLMs and LLMs. The best performance scores are highlighted in blue and orange, respectively.

	Prompt v1	Prompt v2	Prompt v3
DeepSeek-R1	57.17	59.79	55.09
Dolly-v2-12B	36.53	42.26	44.51
Llama-3.3-70B	62.13	66.34	63.17
Mixtral-8x7B	61.15	59.35	64.64
Qwen2.5-72B	58.29	57.98	58.95

(a) **Performance of different LLMs** across three prompt paraphrases on the English test set. Different prompts impact model performance.



(b) **Few-shot performance of LLMs** on the English test set. Performance improves with more shots.



(c) **Pass@k performance of different LLMs** on the English test set. Higher k values increase the likelihood of retrieving the correct answer.

Figure 5: Ablation studies on the effect of prompt wording variation, few-shot examples, and pass@k predictions conducted on the English test set.

tion of k generations, the results shown in Figure 5c suggest that increasing the value of k results consistently in better performance, particularly when using `DeepSeekR1-70B`, which achieves an F-score > 90 when $k = 8$ whereas `Mixtral-8x7B` shows a smaller change in performance followed by `Llama-3.3-70B` and `Qwen2.5-72B`. The ranking of the models for $k = 8$ remains consistent with the one achieved for $k = 1$.

When comparing the performance of models prompted in English versus the target language, Figure 6 shows that LLMs generally perform better with English prompts except for `arq`, where `Qwen2.5-72B` achieves better results when prompted in Modern Standard Arabic (MSA). The improvement from using English prompts is particularly evident in low-resource languages (e.g., `hau`, `mar`, `vmw`), where models like `Dolly-v2-12B` and `Llama-3.3-70B` perform poorly with prompts in the target language.

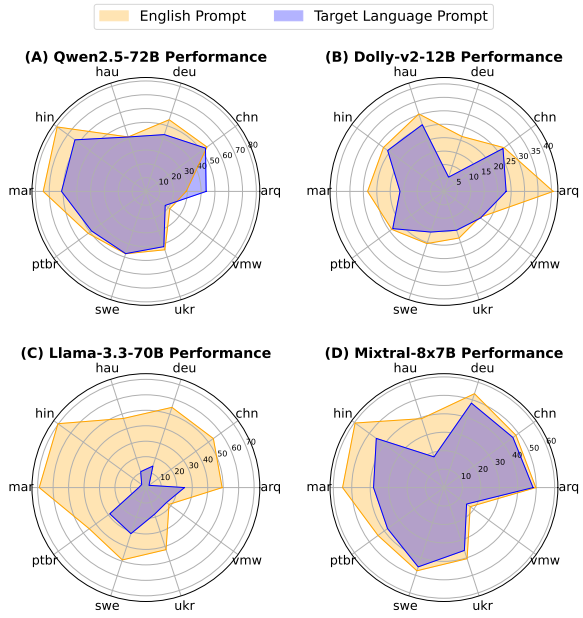


Figure 6: **Comparing models' performance across languages** when prompted in English (orange) vs. when prompted in the target language (blue). LLMs perform better when prompted in English.

5 Related Work

Appraisal theories of emotion propose that emotions arise from our evaluation of events based on personal experiences, leading to different emotional responses among individuals (Arnold, 1960; Frijda, 1986; Lazarus, 1991; Scherer, 2009; Ellsworth, 2013; Moors et al., 2013; Roseman, 2013; Ortony et al., 2022). The theory of constructed emotion claims that emotions are not hardwired or universal, but rather conceptual constructs formed by the brain (Barrett, 2016, 2017).

Early work in NLP primarily focused on sentiment analysis–identifying whether a text conveys positive, negative, or neutral valence (Mohammad, 2016; Muhammad et al., 2023b). More recent research has shifted toward a broader goal: detecting specific emotions in text, such as anger, fear, joy, and sadness. This shift aligns with discrete models of emotion, including Paul Ekman's six basic emotions (Ekman, 1992) and Plutchik's Wheel of Emotions (Plutchik, 1980), which includes anger, disgust, fear, happiness, sadness, surprise, anticipation, and trust.

Several initiatives have created emotion classification datasets for languages other than English such as Italian (Bianchi et al., 2021), Romanian (Ciobotaru et al., 2022), Indonesian (Saputri et al., 2018), and Bengali (Iqbal et al., 2022). However, the field remains predominantly Western-centric. Although multilingual datasets such as XED (Öhman et al., 2020) and XLM-EMO (Bianchi et al., 2022) exist, the latter's reliance on translated data for over ten languages may not adequately reflect cultural nuances in emotional expression. Emotions are culture-sensitive and highly contextual, shaped by different norms and values (Hershcovich et al., 2022; Havaldar et al., 2023; Mohamed et al., 2024; Plaza-del Arco et al., 2024).

Furthermore, although emotions can co-occur (Vishnubhotla et al., 2024), most existing datasets assume a single-label classification framework. While GoEmotions (Demszky et al., 2020) addresses multi-label emotion classification, to our knowledge, no multilingual resources capture simultaneous emotions and intensity across languages. This work aims to advance the field by introducing emotion-labeled data for 28 languages. Given the lack of consensus around what constitutes a low-resource language, approximately 15 to 17 among these could reasonably be considered as such.

6 Conclusion

We presented BRIGHTER, a collection of emotion recognition datasets in 28 languages spoken across various continents. The instances in BRIGHTER are multi-labeled, collected, and annotated by fluent speakers, with 10 datasets annotated for emotion intensity. When testing LLMs on our dataset collection, the results show that they still struggle with predicting perceived emotions and their intensity levels, especially for under-resourced languages. Further, our results show that LLM performance is highly dependent on the wording of the prompt, its language, and the number of shots in few-shot settings. We publicly release BRIGHTER, our annotation guidelines, and individual labels to the research community.

Limitations

Emotions are subjective, subtle, expressed, and perceived differently. We do not claim that BRIGHTER covers the true emotions of the speakers, is fully representative of the language use of the 28 languages, or covers all possible emotions. We discuss this extensively in the Ethics Section.

We are aware of the limited data sources in some low-resource languages. Therefore, our datasets cannot be used for tasks that require a large amount of data from a given language. However, they remain a good starting point for research in the area.

Ethical Considerations

Emotion perception and expression are inherently subjective and nuanced, as they are closely tied to a myriad of factors (e.g., cultural background, social group, personal experiences, and social context). As such, it is impossible to determine with absolute certainty how someone is feeling based solely on short text snippets. Therefore, we explicitly state that our datasets focus on *perceived* emotions–that is, the emotions most people believe the speaker may have felt. Accordingly, we do not claim to annotate the *true* emotion of the speaker, as this cannot be definitively inferred from short texts alone. We recognise the importance of this distinction, as perceived emotions may differ from actual emotions.

We also acknowledge potential biases in our data. Text-based communication inherently carries biases, and our data sources may reflect such tendencies. Similarly, annotators may come with

their own subtle, internalised biases. Moreover, although many of our datasets focus on low-resource languages, we do not claim they fully capture the usage of these languages. While we took care to exclude inappropriate content, some instances may have been inadvertently overlooked.

We strongly encourage careful ethical reflection before using our datasets. Use of the data for commercial purposes or by state actors in high-risk applications is strictly prohibited unless explicitly approved by the dataset creators. Systems developed using our datasets may not be reliable at the individual instance level and are sensitive to domain shifts. They should not be used to make critical decisions about individuals, such as in health-related applications, without appropriate expert oversight. See Mohammad (2022, 2023) for a comprehensive discussion on these issues.

Finally, all annotators involved in the study were compensated at rates exceeding the local minimum wage.

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A PLMs and LLMs Used

A.1 PLMs

1. https://huggingface.co/google-bert/bert-base-multilingual-cased
2. https://huggingface.co/FacebookAI/xlm-roberta-large
3. https://huggingface.co/microsoft/mdeberta-v3-base
4. https://huggingface.co/sentence-transformers/LaBSE
5. https://huggingface.co/microsoft/infoxlm-large
6. https://huggingface.co/google/rembert

A.2 LLMs

1. https://huggingface.co/databricks/dolly-v2-12b
2. https://huggingface.co/meta-llama/Meta-Llama-3.3-70B
3. https://huggingface.co/Qwen/Qwen2.5-72B-Instruct
4. https://huggingface.co/mistralai/Mixtral-8x7B-Instruct-v0.1
5. https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Llama-70B

B Data sources

- **afr**: Speeches from Barnard et al. (2014).
- **arq**: Manually translated novel (*La Grande Maison* by the Algerian author Mohammed Dib).
- **ary, hau, ibo, kin, pcm, swa, xho, zul**: **Afrisenti** Muhammad et al. (2023a) and BBC news headlines.
- **chn**: Weibo dataset https://github.com/aoguai/WeiboHotListDataSet?tab=readme-ov-file.
- **deu**: Anonymised Reddit data from nine German-language subreddits: *de, einfach_posten, FragReddit, beziehungen, schwanger, de_IAmA, germany, depression_de, Lagerfeuer*.
- **eng**: Personal narratives from the AskReddit subreddit collected by Ouyang and McKeown (2015) and instances from Zhuang et al. (2024).
- **esp**: YouTube comments from Latin American (i.e., Ecuadorian, Colombian, and Mexican) channels across three genres: *News/Politics, Entertainment, Education*.
- **hin, mar**: Newly created emotion dataset. Most instances were manually drafted, while some were generated using ChatGPT.
- **ind, jav, sun**: YouTube comments from Indonesian videos.
- **ron**: Data from the subreddit *r/Romania*, YouTube, and tweets from Ciobotaru et al. (2022).
- **rus**: Russian Twitter corpus https://study.mokoron.com.
- **swe**: Sentiment dataset from the Swedish data bank (Språkbanken Text, 2024).
- **tat**: Instances from Krylova et al. (2016).
- **vmw, ptmz**: News headlines from Ali et al. (2024).
- **yor**: News data from BBC Yorùbá and Alaroye. https://alaroye.org/.

C Annotation

C.1 Annotation Guidelines and Definitions

This is a guide for annotating text for emotion classification. The purpose of this study is to analyze the emotions expressed in a text. It is important to note that emotions can often be inferred even if they are not explicitly stated.

Task The task involves classifying text into predefined emotion categories. The annotated dataset will be used for training emotion classification models and studying how emotions are conveyed through language.

Emotion Categories We categorize emotions into the following seven classes:

Joy

- Definition: Expressions of happiness, pleasure, or contentment.

- Example: *"I just passed my exams!"*

Sadness

- Definition: Expressions of unhappiness, sorrow, or disappointment.
- Example: *"I miss my family so much. It's been a tough year."*

Anger

- Definition: Expressions of frustration, irritation, or rage.
- Example:*"Why is the internet so slow today?!"*

Fear

- Definition: Expressions of anxiety, apprehension, or dread.
- Example: *"There's a huge storm coming our way. I hope everyone stays safe."*

Surprise

- Definition: Expressions of astonishment or unexpected events.
- Example: *"I can't believe he just proposed to me!"*

Disgust

- Definition: A reaction to something offensive or unpleasant.
- Examples: *"That video was sickening to watch."*

Neutral

- Definition: Texts that do not express any of the above emotions.
- Example: *"The weather today is sunny with a chance of rain."*

Note: Factual statements can indicate an emotional state without explicitly stating it. For example:

- *"An earthquake today killed hundreds of people in my home town."*

Surprise differs from joy in that it represents an unexpected event, which may or may not be associated with happiness.

Emotion Description Categories The following list provides a broader categorization of emotions by including synonyms and related emotional states.

Anger

- Includes: *irritated, annoyed, aggravated, indignant, resentful, offended, exasperated, livid, irate*, etc.

Sadness

- Includes: *melancholic, despondent, gloomy, heartbroken, longing, mourning, dejected, downcast, disheartened, dismayed*, etc.

Fear

- Includes: *frightened, alarmed, apprehensive, intimidated, panicky, wary, dreadful, shaken*, etc.

Happiness

- Includes: *joyful, elated, content, cheerful, blissful, delighted, gleeful, satisfied, ecstatic, upbeat, pleased*, etc.

Surprise

- Includes: *taken aback, bewildered, astonished, amazed, startled, stunned, shocked, dumbstruck, confounded, stupefied*, etc.

Joy

- Includes: *happiness, delight, elation, pleasure, excitement, cheerfulness, bliss, euphoria, contentment, jubilation*.

C.1.1 Emotion Intensity

After selecting the emotion category, annotators were further asked to select the intensity label, which could be: 0: No Emotion, 1 - Slight Emotion, 2: Moderate Emotion and 3: High Emotion. The following examples illustrate different levels of emotion intensity.

Anger

- No Anger: *"I walked through the empty streets, the quiet hum of the city like a distant whisper."*
- Slight Anger: *"The buzz of voices around me blended into a monotonous drone, failing to distract from the pang of annoyance at the delay."*

- High Anger: *"When his friend's brother knocked on the door, he was greeted with a shotgun blast through the door, which left him dead at the doorstep."*

C.2 Pilot Annotation

We run a pilot annotation on different languages to further refine our guidelines. This has mainly led to clarifications related to the labeling process. For instance, the annotators were reminded that they should select all the labels that apply for a given text snippet, and that one label can encompass more than one specific emotion (e.g., in `arq`, we explained that a complex perceived emotion such as bitterness or jealousy might involve both anger and sadness).

C.3 Formula for Determining Final Labels

Aggregating emotion labels Aggregating emotion labels can be formally expressed as:

$$L_{\text{final}} = \begin{cases} 1, & \text{if Count}(1,2,3) \geq 2 \text{ and AvgScore} > T, \\ 0, & \text{otherwise.} \end{cases}$$
$$\text{Count}(1,2,3) = \sum_{i=1}^{N} \mathbb{1}(A_i \in \{1,2,3\}), \quad \text{AvgScore} = \frac{1}{N}\sum_{i=1}^{N} A_i$$

Where:

- A_i is the rating provided by annotator i.
- N is the total number of annotators.
- $\mathbb{1}(A_i \in \{1,2,3\})$ Membership function that returns 1 if $A_i \in \{1,2,3\}$, and 0 otherwise.
- T is the threshold for the average score, which we set as $T = 0.5$

Aggregating intensity Aggregating intensity can be formally expressed as:

$$\text{AvgScore} = \frac{\sum_{i=1}^{N} A_i}{N},$$

$$L_{\text{final}} = \begin{cases} 0, & \text{if } 0 \leq \text{AvgScore} < 1, \\ 1, & \text{if } 1 \leq \text{AvgScore} < 2, \\ 2, & \text{if } 2 \leq \text{AvgScore} < 3, \\ 3, & \text{if AvgScore} = 3. \end{cases}$$

Where:

- A_i is the intensity score provided by annotator i, where $A_i \in \{0,1,2,3\}$.
- N is the total number of annotators.

D SCHMP Calculation

The computation of SHCMP involves the following steps:

1. Random Splitting with Tie-Breaking The dataset of N annotated items is randomly divided into two equal subsets, A_1 and A_2. For datasets with an odd number of annotations, probabilistic tie-breaking is applied to ensure balanced splits.

2. Class Assignment For each item x_i ($i = 1, 2, \ldots, N$):

- Assign x_i a score based on its annotations in A_1 and A_2.
- Let $C_1(x_i)$ and $C_2(x_i)$ denote the class of x_i derived from A_1 and A_2, respectively.

3. Class Binning To manage continuous scores, divide the range of possible scores $[-3, 3]$ into equal-sized bins, where the bin size b is determined as:

$$b = \frac{6}{\#\text{Bins}}.$$

Scores from A_1 and A_2 are then assigned to their respective bins, denoted as c_1 and c_2.

4. Match Calculation Define a match indicator $M(x_i)$ to evaluate consistency for each item:

$$M(x_i) = \begin{cases} 1, & \text{if } |c_1 - c_2| < 1, \\ 0, & \text{otherwise.} \end{cases}$$

This ensures that items are considered consistent if their scores fall into the same bin or adjacent bins.

5. Proportion of Matches Compute the total number of matches, N_{match}, across all items:

$$N_{\text{match}} = \sum_{i=1}^{N} M(x_i).$$

6. SHCMP Computation The SHCMP score is calculated as the proportion of matches, expressed as a percentage:

$$\text{SHCMP (\%)} = \frac{N_{\text{match}}}{N} \times 100.$$

7. Averaging We repeat the process k times with different random splits and compute the average SHCMP score:

$$\text{SHCMP}_{\text{final}} = \frac{1}{k} \sum_{j=1}^{k} \text{SHCMP}_j,$$

where SHCMP_j is the SHCMP score from the j-th split.

E Experimental Settings

For LLMs, we used the default parameters from HuggingFace except for temperature which we set to 0 for deterministic output and top-k is set to 1. Only for the top-k ablations in which top-k > 1 in Figure 5c, we set temperature to 0.7. We ask all LLMs to perform CoT. We trained on the train set for 2 epochs with a learning rate of 1e-5 and and evaluated on test set. For MLMs experiments, we trained on the training set for 2 epochs with a learning rate of 1e-5 and evaluated on the test set.

Language	Train Set (%)			Development Set (%)			Test Set (%)		
	Single	Multi	Neutral	Single	Multi	Neutral	Single	Multi	Neutral
chn	54.00	23.74	22.26	53.60	23.58	22.82	53.90	24.30	21.80
sun	58.94	36.18	4.88	59.09	36.26	4.65	59.40	36.07	4.54
afr	47.79	6.69	45.52	56.14	7.86	36.01	37.39	10.35	52.26
swe	43.16	16.60	40.24	46.30	20.37	33.33	42.76	18.81	38.43
swa	41.67	3.33	55.00	45.78	3.56	50.66	46.26	3.81	49.93
esp	61.02	38.98	0.00	65.22	34.78	0.00	65.14	34.86	0.00
arq	28.53	50.05	9.42	28.57	50.00	10.71	27.95	44.76	8.35
ptbr	52.11	13.80	34.09	61.06	11.82	27.12	52.68	13.59	33.73
ptmz	52.00	0.44	47.56	50.92	0.37	48.71	53.03	0.51	46.45
ukr	44.77	2.24	52.99	47.24	2.36	50.39	45.23	1.79	52.98
mar	67.69	8.56	23.75	68.57	7.62	23.81	68.94	9.33	21.73
rus	64.63	11.08	24.29	66.35	12.23	21.42	66.91	12.89	20.20
ibo	72.44	3.63	23.93	61.12	10.91	27.97	73.61	3.97	22.42
amh	50.82	27.68	21.50	56.13	30.31	16.56	48.50	24.67	26.83
deu	41.78	34.05	24.17	41.84	35.19	22.97	41.23	32.10	26.66
vmw	52.80	0.45	46.75	53.49	0.39	46.12	53.46	0.52	46.32
pcm	55.00	40.46	4.54	50.00	36.63	4.37	51.57	38.08	4.35
eng	38.64	47.02	14.34	34.07	42.22	9.70	38.58	48.76	10.34
hin	66.35	10.80	22.85	60.40	7.92	31.68	77.31	5.66	13.92
tat	81.48	0.00	18.52	84.00	0.00	16.00	85.71	0.00	14.29

Table 4: Percentage distribution of *SingleLabel*, *MultiLabel*, and *NeutralLabel* for the Train, Development, and Test Sets.

	Monolingual Multi-Label Classification				
Lang.	LaBSE	RemBERT	XLM-R	mBERT	mDeBERTa
afr	30.76	**37.14**	10.82	25.87	16.66
arq	**45.46**	41.41	31.98	41.75	29.68
ary	45.81	**47.16**	40.66	36.87	38.00
chn	53.47	53.08	**58.48**	49.61	44.47
deu	55.02	**64.23**	55.37	46.78	44.09
eng	64.24	**70.83**	67.30	58.26	58.94
esp	72.88	**77.44**	29.85	54.41	60.17
hau	58.49	**59.55**	36.95	47.33	48.59
hin	75.25	**85.51**	33.71	54.11	54.34
ibo	45.90	**47.90**	18.36	37.23	31.92
ind	–	–	–	–	–
jav	–	–	–	–	–
kin	**50.64**	46.29	32.93	35.61	38.00
mar	80.76	**82.20**	78.95	60.01	66.01
pcm	51.30	**55.50**	52.03	48.42	46.21
ptbr	**42.60**	42.57	15.40	32.05	24.08
ptmz	36.95	**45.91**	30.72	14.81	21.89
ron	69.79	**76.23**	65.21	61.50	60.60
rus	75.62	**83.77**	78.76	61.81	54.79
sun	36.93	**37.31**	19.66	27.88	21.65
swa	**27.53**	22.65	22.71	22.99	22.84
swe	49.23	**51.98**	34.63	44.24	40.90
tat	**57.71**	53.94	26.48	43.49	35.02
ukr	50.07	**53.45**	17.77	31.74	28.55
vmw	**21.13**	12.14	9.92	10.28	11.13
xho	–	–	–	–	–
yor	**32.55**	9.22	11.94	21.03	17.88
zul	–	–	–	–	–

Table 5: **Average F1-Macro for monolingual multi-label emotion classification.** Each model is trained and evaluated within the same language. The best results are highlighted in blue.

Prompt Version	Prompt Text

Prompt v1	`Evaluate whether the following text conveys the emotion of {{EMOTION}}.`
	`Think step by step before you answer.`
	`Finish your response with 'Therefore, my answer is ' followed by 'yes' or 'no':`
	
	`{{INPUT}}`

Prompt v2	`Analyze the text below for the presence of {{EMOTION}}.`
	`Explain your reasoning briefly and conclude with 'Answer:' followed by either 'yes' or 'no'.`
	
	`{{INPUT}}`

Prompt v3	`Examine the following text to determine whether {{EMOTION}} is present.`
	`Provide a concise explanation for your assessment and end with 'Answer:' followed by either 'yes' or 'no'.`
	
	`{{INPUT}}`

Table 6: The prompt variants used in the monolingual emotion recognition ablation study.

Track A: Example Few-Shot Prompt

Task:
Analyze the text below for the presence of anger.
Explain your reasoning briefly and conclude with 'Answer:' followed by either 'yes' or 'no'.

Examples:
Example 1:
Input: "'When I answered the phone, my heart beat extremely fast... I was very nervous!"'
Answer: no

Example 2:
Input: "'I'll never forget how businesslike and calm the Israeli guy was."'
Answer: no

Example 3:
Input: "'I wake up, my eyes fluttering open to a shield of darkness."'
Answer: no

Example 4:
Input: "'I lay in a large bed, the sheets and quilt pulled up to my chin, and the curtains were drawn to keep out the light."'
Answer: no

Example 5:
Input: "'Either way that idiot is gone."'
Answer: yes

Example 6:
Input: "'Seriously... did I really just shut my finger in the car door."'
Answer: yes

Example 7:
Input: "'I was really uncomfortable because I was sitting behind my dad and there isn't enough room for my legs."'
Answer: yes

Example 8:
Input: "'He damn disturb plz, cover my head with a shirt that a customer which have body odour just tried on!!"'
Answer: yes

Your Turn:
Input: "'/ o So today I went in for a new exam with Dr. Polvi today, I had to file new paperwork for the automobile accident case which is being done differently than the scoliosis stuff. So he comes in and starts talking about insurance stuff and how this looks bad since I was getting treatment on my neck and stuff already blah blah."'

Figure 7: Example of the few-shot prompt template for assessing anger in Track A.

Track B: Example Few-Shot Prompt

Task:
In this task, you will assess the level of anger in a given text (0 = none, 1 = low, 2 = medium, 3 = high). Summarize your reasoning and conclude with 'Answer:' followed by the correct number.

Examples:
Example 1:
Input: "'I try extremely hard to keep my details hidden. It was nice to know that what I had given people to know was pleasant, but I couldn't deny the knot that was still in my stomach."'
Answer: 0

Example 2:
Input: "'I knew we were almost there when my midwife's voice got more excited and Joey leaned in real close and said into my ear, " Don't stop pushing! " ""
Answer: 0

Example 3:
Input: "'One ended up going to prison."'
Answer: 1

Example 4:
Input: "'Not to mention noisy."'
Answer: 1

Example 5:
Input: "'" but Urban Dictionary confirmed Spook is indeed a racial slur."'
Answer: 2

Example 6:
Input: "'And..at his funeral, they fired him!"'
Answer: 2

Example 7:
Input: "'I ended up metaphorically throwing my hands in the air in disgust and just cancelling my account altogether."'
Answer: 3

Example 8:
Input: "'He would manipulate me into it and I was extremely upset."'
Answer: 3

Your Turn:
Input: "'So today I went in for a new exam with Dr. Polvi today, I had to file new paperwork for the automobile accident case which is being done differently than the scoliosis stuff. So he comes in and starts talking about insurance stuff and how this looks bad since I was getting treatment on my neck and stuff already blah blah."'

Figure 8: Example of the few-shot prompt template for assessing anger in Track B.

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