MASIVE: Open-Ended Affective State Identification in English and Spanish

Nicholas Deas, Elsbeth Turcan, Iván Pérez Mejía, Kathleen McKeown

Columbia University, Department of Computer Science

Correspondence: [ndeas,eturcan,iep2110,kathy]@cs.columbia.edu

Abstract

In the field of emotion analysis, much NLP research focuses on identifying a limited number of discrete emotion categories, often applied across languages. These basic sets, however, are rarely designed with textual data in mind, and culture, language, and dialect can influence how particular emotions are interpreted. In this work, we broaden our scope to a practically unbounded set of *affective states*, which includes any terms that humans use to describe their experiences of feeling. We collect and publish MASIVE, a dataset of Reddit posts in English and Spanish containing over 1,000 unique affective states each. We then define the new problem of *affective state identification* for language generation models framed as a masked span prediction task. On this task, we find that smaller fine-tuned multilingual models outperform much larger LLMs, even on region-specific Spanish affective states. Additionally, we show that pre-training on MASIVE improves model performance on existing emotion benchmarks. Finally, through machine translation experiments, we find that native speaker-written data is vital to good performance on this task.

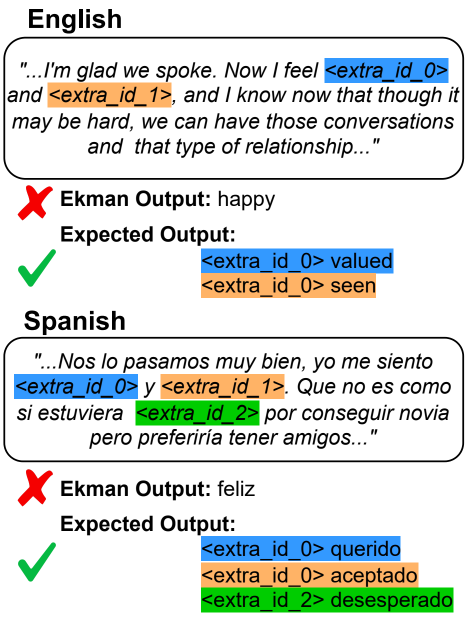

Figure 1: Paraphrased input and expected output examples from MASIVE in English and Spanish. Models are tasked with predicting *affective states* (highlighted), which reflect more nuanced feelings than label sets in prior work, such as the Ekman basic emotions.

1 Introduction

In the field of emotion analysis, much NLP research focuses on identifying a limited number of discrete emotion categories, typically using *basic emotion sets* from the field of psychology (Plaza-del Arco et al., 2024). These basic emotion sets are rarely designed with textual expression in mind (e.g., Ekman 1984, whose model defines basic emotions by the recognizability of facial expressions), and very little research examines the validity of adapting these sets to textual data.

Emotion analysis furthermore relies on largely the same emotion categories across languages, including, in some cases, translating resources such as lexicons, fine-tuning data, or evaluation data (Dhananjaya et al., 2024; Isbister et al., 2021; Kathunia et al., 2024). Previous research has also shown that existing multilingual models encode meaning in an Anglocentric way (Havaldar et al., 2023). As recent studies have found that culture and language influence the meaning of emotional terms like "love" (Jackson et al., 2019), models that fail to understand cultural context or rely on mainstream dialects may also fail to capture the nuances of an author's expression (Deas et al., 2023).

In this work, we argue for a descriptive approach to emotion analysis. We broaden our scope from a small set of basic emotions to a practically unbounded set of *affective states* (VandenBos, 2007), which includes any terms that humans use to describe their experiences of feeling, including emo-

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tions, moods, and figurative expressions of feelings (e.g. "blue" as an expression of sadness instead of the color). We then define the new problem of *affective state identification* (ASI), which is a targeted masked span prediction task: given a text description of an emotional experience, we train models to produce single-word affective states that correspond to the description. These affective states may include common emotion categories such as *happy* or *sad*, but they also allow us to incorporate nuance and intensity (e.g., *elated*, *calm*, *jealous*, *lonely*, etc.) as well as other classifications that are not typically considered emotions such as moods (e.g., longer-term feelings of being *motivated* or *stuck*).

We collect MASIVE: Multilingual Affective State Identification with Varied Expressions, a new benchmark dataset for ASI using Reddit data. We use a bootstrapping procedure to discover new affective state labels and collect posts containing natural emotional expressions in English and Spanish, yielding 1600 unique affective state labels in English and 1000 in Spanish. We evaluate our data collection methods with human annotation, finding that 88% and 72% of our automatically collected English and Spanish labels, respectively, reflect affective states, and document unique features of the data including negations and, in Spanish, grammatical gender. We then use this dataset to evaluate the performance of commonly-used generative models, finding that small fine-tuned models generally outperform LLMs. Beyond ASI, we experiment with using our corpora as pre-training data and show that MASIVE incorporates knowledge that generalizes to existing emotion detection benchmarks. Finally, we assess fine-tuning and evaluating models on machine-translated data and find that original texts written by native speakers are essential for performing ASI.

Our contributions in this work are as follows:

1. We introduce a novel benchmark for ASI with language generation models, including a significantly larger label set than prior related benchmarks[1];
2. We benchmark multilingual models and show that smaller, fine-tuned models outperform current LLMs on this dataset;
3. We analyze the behavior and performance of models on region-specific affective language, grammatical gender, and negations; and
4. We empirically argue that both fine-tuning and evaluating on texts authored by native speakers is vital for capturing nuances in multilingual affective writing

[1]We make our code and data available at `https://github.com/NickDeas/MASIVE`

2 Affective State Identification (ASI)

In contrast to traditional emotion detection, we propose a novel task, ASI. Our goal is to capture the broad set of ways in which humans describe their own feelings in text. We refer to these expressions as *affective states* (VandenBos, 2007); this is an umbrella term incorporating multiple kinds of feelings such as emotions and moods.

We highlight multiple implications of models that are capable of accurately inferring affective states. First, ASI enables the identification of more nuanced feelings derived from textual expressions of affect (e.g., distinguishing *despair* and *grief* which may be similarly described by basic emotions). Additionally, ASI-capable models can be adapted to multiple theories of emotion. Whereas a model specifically trained on one set of emotions (e.g., Ekman) must be fine-tuned for each label set (e.g., 27 emotions of Cowen and Keltner 2017), ASI models can be restricted to an arbitrary subset of affective state labels. Finally, ASI is grounded in expressions of feelings by the author in contrast to perceived emotion labels generated by annotators. These perceived emotion labels may train models to encode spurious factors affecting human emotion perception, such as cultural differences.

3 Data

3.1 MASIVE Corpus

We collect texts with expressions of affective states from Reddit[2] using a bootstrapping procedure (illustrated in Figure 2). We source data from Reddit due to the availability of large quantities of diverse texts, and because many submissions reflect casual narratives where authors are likely to express their feelings. Beginning with the adjective forms of the Ekman emotions (Step 1 in Figure 2), we search for texts containing forms of "*I feel <affect> and...*", "*I am feeling <affect> and...*", where *<affect>* is replaced with each emotion term (Step 2). Notably, we also search for "*I don't feel <affect> and...*" and "*I am not feeling <affect> and...*" to better capture the diversity of ways in which authors can express feelings. We extract affective state terms that follow the "*and*" from the retrieved posts (Step 3) to

[2]Using the PullPush API at `https://pullpush.io/`

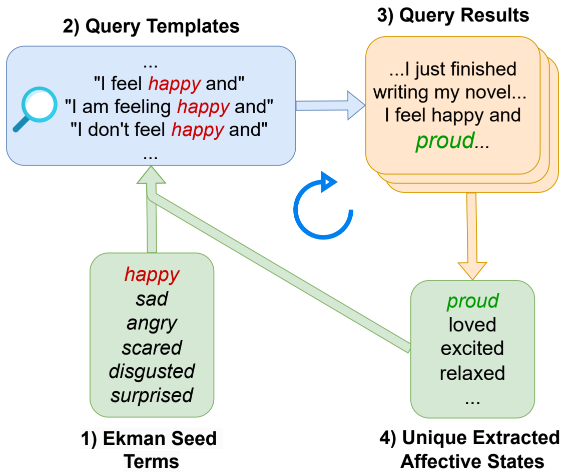

Figure 2: Illustration of the bootstrapping procedure used to collect texts and automatically extracted affective state labels in the MASIVE corpus.

form a new set of search phrases with these terms (Step 4). We repeat these steps, expanding the pool of query affective states in each round. Our primary assumption is that any adjective conjuncts of the query emotion term are also affective states, regardless of whether they are canonical emotion terms. For example, if "happy" was used to query the text "I feel happy and excited," the term "excited" is both an adjective and a conjunct; the same is true of "light" in "I feel happy and light". In contrast, in "I feel happy and want to smile", "want" is a verb and would not be considered an affective state. We evaluate this assumption in subsection 3.2.

In Spanish, we conduct the same procedure using forms of "*Estoy <affect> y...*", "*Me siento <affect> y...*", and "*Estoy sintiendo <affect> y...*". We also seed the process with the most common Spanish translations of the Ekman emotions on Reddit (see Appendix C). Additionally, as Spanish includes both masculine and feminine forms for some terms, we search for both forms where applicable. Finally, we also collect a challenge set including affective state labels associated with regional Spanish varieties, hand-selected by a native Spanish-speaker, to evaluate models' abilities to generalize to less-represented dialects (see Appendix C).

For both English and Spanish, we run 4 rounds of bootstrapping; for the regional Spanish terms, we run only a single round to avoid introducing non-regional terms. 15 affective states were randomly sampled from both datasets, and all posts containing those 15 affective states were reserved as part of each test set to evaluate models on unseen affective states. Summary statistics describing the English and Spanish splits as well as the regional Spanish challenge set are included in Table 1. We include examples of samples in MASIVE in Appendix B, and following Bender and Friedman (2018), we include a Data Statement in Appendix A.

Lang	Split	Size	Input Length	# AS/ Text	# Unique AS
En	Train	93,736	310.99	1.11	1,627
	Test	10,049	306.61	1.13	775
	Chal	4,720	299.00	1.15	320
Es	Train	30,958	240.99	1.06	1,002
	Test	4,274	247.90	1.08	618
	Chal	1,557	245.50	1.12	145
	Reg	559	233.95	1.07	59

Table 1: Summary statistics of English and Spanish MASIVE. Text lengths are measured in mT5 tokens. AS = Affective State; Chal = unseen challenge set

3.2 Data Validation Procedure

To validate the assumptions of our bootstrapping procedure and examine how affective states are used in our dataset, we collect human evaluations of the automatically identified affective states. Judgments are conducted by 2 native Spanish-speakers in Iberian Culture studies and 2 native English-speakers in Psychology for Spanish and English respectively. We randomly sample 200 texts from each language's test set for evaluation such that 50 texts are shared by each pair. Annotators are provided a full Reddit post with a single automatically-identified affective state highlighted.

We ask annotators to judge the term in context on 3 dimensions, beginning with whether the highlighted term reflects an affective state. If a term is judged to reflect an affective state, annotators are asked to judge whether the highlighted term better reflects an emotion or a mood[3] and whether the highlighted term is used figuratively (e.g., "blue") or literally (e.g., "sad"). All 3 dimensions are judged on 4-point Likert scales where higher values mean the term primarily reflects an affective state, an emotion, and a literal usage, respectively. According to Cohen's kappa, annotators achieved moderate agreement in English ($\kappa = .51$) and substantial agreement in Spanish ($\kappa = .69$). Additional details concerning human annotations are included in Appendix C.

[3] We distinguish emotions – shorter-term feelings triggered by identifiable events – from moods – longer-term feelings not necessarily triggered by an event.

Category	Example Affective States
Basic Emotions and Alternatives	**Ekman:** happy, sad, surprised, angry, afraid, disgusted **Plutchik:** remorseful, bored, ecstatic, etc. **Alternatives:** (*trust*) safe, comfortable, protected (*anticipation*) ready, excited, hopeful
Variation in Intensity	**happy**: giddy, euphoric, ecstatic, content, joyful **angry**: grumpy, enraged, resentful, irritated **afraid**: terrified, frightened, alarmed, fearful **surprised**: shocked, amazed, dazed, stunned
Context-Dependent	disconnected, uplifted, gullible, disrespected, underwhelmed
Metaphorical/Figurative Usage	weak, nauseous, empty, lost, spent

Table 2: Examples of different types of discovered English affective states manually categorized by the authors.

Lang	Human-Annotated			Automatic	
	Aff	Fig	Emo	Neg	Fem
En	88.4%	58.8%	34.2%	7.75%	
Es	71.5%	38.5%	18.5%	27.0%	28.0%

Table 3: Human and automatic analysis of how affective states in the English and Spanish datasets are used in context. *Aff*: Affective State; *Fig*: Figurative; *Emo*: Emotion; *Neg*: Negations; *Fem*: Feminine Form

Additionally, we analyze 2 aspects of our dataset that differentiate it from prior emotion detection benchmarks. First, because Spanish is a language with grammatical gender for adjectives, part of the affective state prediction problem in MASIVE includes choosing whether to use the masculine or feminine form in the context of the input. Second, authors in natural settings may also tend to express their feelings by stating how they do *not* feel (e.g., "I'm not happy, but...."), and we specifically include negations to test models' capability to contend with this construction in both English and Spanish.

3.3 Data Analysis

The results of the aforementioned data annotations as well as automatic statistics are included in Table 3. Human annotation results are reported as the percentage of affective states within the sample; for negations and grammatical gender, we report the percentage of texts in our datasets that include any target negations or any feminine adjectives.[4] Large majorities (88% and 72% in English and Spanish respectively) of terms were judged to reflect affective states, validating the contents of MASIVE. Additionally, annotators identified most affective states as longer-term moods without specific triggers (65.8% and 81.5% respectively). Finally, a significant portion of texts in both languages were determined to reflect figurative use rather than terms that are typically affective states (58.8% and 38.5% respectively), presenting a unique challenge to models compared to prior work.

We broadly categorize different types of affective states included in MASIVE that distinguish ASI from prior emotion detection work in Table 2. Beyond the seed Ekman emotions, MASIVE also contains many emotions from other models, such as the Plutchik emotion wheel or those listed in Wang et al. (2020). Emotions not included tend to lack clear adjective forms (e.g., *trust*), but MASIVE does include alternatives of similar meaning (e.g., *safe*, *comfortable*). Many emotions capture variations in intensity of basic emotions, such as *euphoric* or *content* which, in part, reflect different intensities of *happy*. In contrast to prior emotion detection work, our bootstrapping procedure captures many affective states that depend on a particular social context, such as *underwhelmed* which specifically implies unmet expectations.

3.4 Fixed-Label Set Data

We additionally evaluate the performance of MASIVE-fine-tuned models on two previously published datasets in both English and Spanish. A key distinction from MASIVE is that these datasets feature limited label sets; we describe our evaluation procedures in subsection 4.2. In English, we evaluate on GoEmotions (Demszky et al., 2020), a commonly-used emotion dataset consisting of Reddit comments; it is originally labeled with 27 distinct emotion categories, though the authors also relabel the data with the Ekman basic emotions. We additionally evaluate on EmoEvent (Plaza del Arco et al., 2020), a dataset with both English and Spanish subsets of Tweets (among other languages) also labeled with the Ekman set.

[4] Recall that a single datapoint may have multiple labels joined by *and*.

3.5 Machine-Translated Data

Finally, we conduct two cross-lingual experiments expanding on prior work investigating the use of machine translation for cross-lingual generalization (Isbister et al., 2021; Kathunia et al., 2024). In contrast to prior findings, however, we hypothesize that neither translating the training nor evaluation data will result in competitive performance with models trained on native data.

We evaluate both *translate-train* and *translate-test* approaches (Hu et al., 2020). First, translate-train involves translating the training data from a source language (e.g., English) into a target language (e.g., Spanish). A model is then subsequently fine-tuned on the generated training data in the target language (e.g., English translated into Spanish). Alternatively, translate-test leverages a model already trained in a source language (e.g., English). Test data texts in the target language (e.g., Spanish) are translated into the source language (e.g., Spanish translated into English) at inference time.

In both settings, we use bilingual Opus-MT models (Tiedemann and Thottingal, 2020) to independently translate the input documents and target affective state labels. We select Opus-MT models following Kathunia et al. (2024) and because they are accessible, open-source models, reflecting resources that may be used for large scale translation. Models fine-tuned on translated data or subset data are denoted $_{Tr}$ and $_{S}$ respectively, and translated test sets are also denoted $_{Tr}$.

4 Experimental Configuration

4.1 Models

We experiment with fine-tuning small language models on our original and machine-translated data. We also perform experiments with two Large Language Models (LLMs) in a zero-shot setting.

fine-tuned Generative Models. Most of our models are based on mT5-Large (Xue et al., 2021a). During fine-tuning and prediction on MASIVE, we mask affective state words wherever they appear and task models to fill them, mimicking mT5's pretraining. We additionally experiment with T5-large (Raffel et al., 2019) for English only[5]. In the results, models' superscripts denote that a model was fine-tuned on our English (T5^{En} and mT5^{En}) or Spanish (mT5^{Es}) corpus.

Large Language Models. We evaluate two modern, open-source LLMs–Llama-3[6] and Mixtral-Instruct (Jiang et al., 2024)–as these models have been specifically evaluated in multilingual settings. We instruct these models to perform the same masked token prediction task as mT5 (see Appendix D). Due to context window constraints and input lengths, LLMs are evaluated in a zero-shot setting. Further checkpoint and generation hyperparameter details are included in Appendix D.

4.2 Metrics

4.2.1 MASIVE Evaluation

We report **top-k accuracy** for our models with $k \in \{1, 3, 5\}$[7], along with two generative metrics: the **negative log-likelihood** (NLL) of the gold affective state and the model's **log perplexity**. In Spanish, if the gendered form of the prediction does not match that of the gold term (e.g. enojado vs. enojada), the prediction is considered incorrect, but the similarity of the prediction in these cases is captured by the **top-k similarity** metric, which we describe below.

Top-k Similarity. Because our label set is very large, we also report a measure of similarity between the model's top predictions and the gold. Here, we rely on contextual embeddings using multilingual, pre-trained BERT-base (Devlin et al., 2019). To ensure that the similarity model encodes affective senses of each term, we embed the predicted and gold emotion terms within 100-token contexts from the original post and calculate cosine similarity between them. We report the maximum similarity of these contextual embeddings when looking at the top 1, 3, and 5 most likely model predictions. Full details are available in Appendix E.

4.2.2 Fixed-Label Set Evaluation

To evaluate how well our dataset imbues models with general emotional knowledge, we evaluate two variants of mT5: first, mT5 fine-tuned only on existing emotion benchmarks, and second, mT5 fine-tuned on MASIVE followed by existing benchmarks (denoted with superscript ^{MAS}).

We frame affective state detection as a generative mask-filling task rather than a classification

[5]No comparable monolingual T5 checkpoint for Spanish has been made publicly available.

[6]https://llama.meta.com/llama3

[7]As some samples in the datasets have multiple labels, we calculate top-k accuracy at the sample level using beam search and report average sample-level scores.

Lang	Model	NLL↓	Log Perp↓	Acc@1↑	Acc@3↑	Acc@5↑	Sim@1↑	Sim@3↑	Sim@5↑
En	T5^{En}	6.87	6.85	20.05%	29.44%	34.64%	0.569	0.673	0.718
	mT5^{En}	10.93	10.90	**17.91%**	**26.81%**	**30.90%**	**0.564**	**0.670**	**0.711**
	Llama-3	60.79	44.84	1.29%	2.26%	2.92%	0.431	0.460	0.475
	Mixtral	1.52		7.83%	8.93%	10.55%	0.475	0.495	0.518
Es	mT5^{Es}	6.91	6.89	**24.51%**	**36.16%**	**41.23%**	**0.610**	**0.734**	**0.781**
	Llama-3	77.78	61.56	2.52%	4.69%	5.91%	0.445	0.480	0.498
	Mixtral	1.47		16.80%	19.47%	22.24%	0.525	0.553	0.583

Table 4: Comparison of T5, mT5, and two LLMs on our proposed Reddit dataset, aggregated scores only. Note that the Spanish test set and the English test set are not directly comparable as noted in subsection 4.2. **Bolded** scores highlight the best-performing multilingual model.

Dataset	Model	P	R	F1	Acc@1	Acc@3	Acc@5	Sim@1	Sim@3	Sim@5
GoEmotions (7)	mT5	**33.63**	19.28	16.25	**38.49%**	**70.73%**	**85.99%**	**0.736**	**0.884**	**0.946**
	mT5^{MAS}	33.06	**39.81**	**28.30**	17.49%	32.11%	39.25%	0.629	0.733	0.771
GoEmotions (27)	mT5	12.57	4.77	2.24	2.53%	**12.90%**	**23.51%**	**0.525**	**0.614**	**0.670**
	mT5^{MAS}	**27.08**	**18.76**	**11.92**	**7.54%**	12.22%	15.16%	0.508	0.602	0.639
EmoEvent (En)	mT5	30.06	14.36	2.84	10.50%	**71.70%**	**93.64%**	0.630	**0.880**	**0.974**
	mT5^{MAS}	**34.81**	**32.74**	**29.55**	**33.40%**	57.06%	69.38%	**0.712**	0.842	0.893
EmoEvent (Es)	mT5	26.13	14.52	6.41	24.29%	70.34%	**89.12%**	0.713	0.882	**0.955**
	mT5^{MAS}	**54.93**	**21.54**	**17.80**	**39.75%**	**82.62%**	86.11%	**0.750**	**0.918**	0.935

Table 5: Performance of mT5 fine-tuned on emotion classification datasets, with and without prior fine-tuning on MASIVE. **Bolded** scores highlight the best performing model on each dataset under each metric.

task. Therefore, to adapt the evaluation sets to our generative setting, we append "I feel <extra_id_0>" to the end of each input to match the format of our evaluation on MASIVE (see Figure 1), using adjective forms of the gold emotion labels. In this setting, we report **top-k accuracy** and **similarity** as we do for MASIVE. Additionally, to adapt models to a fixed-label set, we sort the fixed set of emotion labels by their likelihood according to the model and select the most probable emotion label as the prediction. For these experiments, we report macro **precision**, **recall**, and **F1 score**.

5 Results

5.1 MASIVE Evaluation

Table 4 presents the performance metrics for fine-tuned mT5, Llama-3, and Mixtral on our English and Spanish test sets, as well as fine-tuned T5 for the English test set only. Among multilingual models, **fine-tuned mT5 outperforms both LLMs on top-k accuracy and top-k similarity for both languages (Takeaway #1)**, despite having drastically fewer parameters.[8] Between the LLMs, Mixtral outperforms Llama-3. This performance difference may be explained by the difference in size between models, as well as the fact that multilingual data was upsampled in Mixtral's pre-training compared to prior models.

In English, the large variant of T5 has been shown to slightly outperform mT5 (Xue et al., 2021b). We find a similar difference, and in fact, monolingual T5 outperforms all other models in English. Because the remaining experiments include Spanish data, we focus on mT5. We note, however, that **dedicated monolingual models may offer significantly higher performance on ASI (Takeaway #2)** and leave further exploration of the differences between monolingual and multilingual models to future work.

While the differences in language and content of the English and Spanish datasets prevent us from making conclusions concerning their relative difficulty, Table 4 also shows that performance in Spanish tends to be higher than in English, despite the better representation of English in pre-training and larger size of the collected English data compared to Spanish. This trend could be due to the larger set of unique affective states in our English data than Spanish, with more nuanced affective states that may be difficult for models to predict accurately.

5.2 Fixed-Label Set Evaluation

To evaluate the generalized emotion detection capabilities afforded by fine-tuning on MASIVE, Ta-

[8]Llama-3 occasionally refuses to make a prediction if the content discussed is sensitive (e.g., drug use). Results taking invalid responses into account are included in Appendix F.

Lang	Model	Subset	Acc@1↑	Acc@3↑	Acc@5↑	Sim@1↑	Sim@3↑	Sim@5↑
En	T5^{En}	Seen	35.22%	50.31%	57.70%	0.640	0.756	0.805
		Unseen	2.92%	5.88%	8.61%	0.488	0.579	0.620
	mT5^{En}	Seen	32.85%	48.90%	56.13%	0.633	0.757	0.804
		Unseen	1.04%	1.88%	2.41%	0.487	0.571	0.607
Es	mT5^{Es}	Seen	37.89%	55.48%	62.63%	0.654	0.779	0.825
		Unseen	1.18%	2.44%	3.88%	0.532	0.655	0.704

Table 6: Comparison of mT5 performance between affective states included and held out from fine-tuning.

Model	Acc@1↑	Acc@3↑	Acc@5↑	Sim@1↑	Sim@3↑	Sim@5↑
mT5^{Es}	**14.07%**	**25.31%**	**31.37%**	**0.462**	**0.585**	**0.635**
Llama-3	0.00%	0.00%	0.00%	0.376	0.408	0.416
Mixtral	0.04%	0.16%	0.38%	0.342	0.358	0.372

Table 7: Evaluation of Spanish-fine-tuned mT5, Llama-3, and Mixtral on region-specific Spanish affective states. **Bolded** metrics highlight the best-performing model.

ble 5 shows the performance of mT5 fine-tuned on existing English and Spanish emotion benchmarks, both with and without prior fine-tuning on MASIVE. First, when used as a classifier, we find that mT5 fine-tuned on MASIVE first achieves a higher macro-F1 for all datasets. This suggests that **fine-tuning on our corpus gives models generalizable knowledge of emotions (Takeaway #3)**. Because our corpora contain many more affective state labels than the evaluation datasets, models fine-tuned on MASIVE will include more nuanced terms than basic emotions in the top-k predictions. So, as expected, models fine-tuned only on the emotion benchmarks typically achieve higher top-k accuracy and similarity, as they are more likely to predict terms within the smaller label sets. The top-k similarity scores for our models, however, remain high, suggesting that the generated affective states are similar to the ground truth basic emotion labels.

5.3 Unseen and Regional Set Evaluation

To analyze how well models generalize beyond affective states explicitly included in fine-tuning, we present performance metrics on seen and unseen affective states in both languages in Table 6. In both languages, all models perform considerably better on affective states included in the fine-tuning data than on unseen affective states. The monolingual T5^{En} model, however, maintains better performance on unseen affective states than mT5^{En}, suggesting that monolingual models may better generalize to unseen affective states.

In addition to unseen affective states, we present results on a subset of Spanish affective states which are region-specific in Table 7. Similarly to results on the full Spanish data, fine-tuned mT5^{Es} outperforms both LLMs in top-k accuracy and similarity. The performance of fine-tuned mT5^{Es} is lower on this regional subset than on the broader set of Spanish texts in MASIVE (Table 4) but is higher than performance on unseen affective states (Table 6). Llama-3 and Mixtral, which are not fine-tuned on our corpora, also perform significantly worse on the regional subset than they do on the Spanish data as a whole. Because top-k accuracy drops significantly on unseen and region-specific affective states (top-k similarity as well, though less so), **future work in this area should prioritize a generalized understanding of affective states, including regionalisms (Takeaway #4)**.

5.4 Grammatical Gender and Negations

We break down the top-k accuracy and top-k similarity results for each model by grammatical gender and negations in Figure 3. We see again that mT5 outperforms both LLMs across all subsets, and that mT5 often places the gold label among the top 3 or 5 predictions if not the top 1. In particular, mT5^{Es} performs better on feminine adjectives than masculine adjectives or those with only a single form, and T5^{En} and mT5^{En} perform better on negated targets than non-negated targets. Llama-3 and Mixtral achieve highest accuracy for masculine adjectives and highest similarity for single-form adjectives, while for negations, Llama-3 tends to perform better on non-negations and Mixtral tends to perform slightly better on negations. These results suggest that **explicit training on MASIVE may improve performance specifically on unique features of generative ASI (Takeaway #5)**.

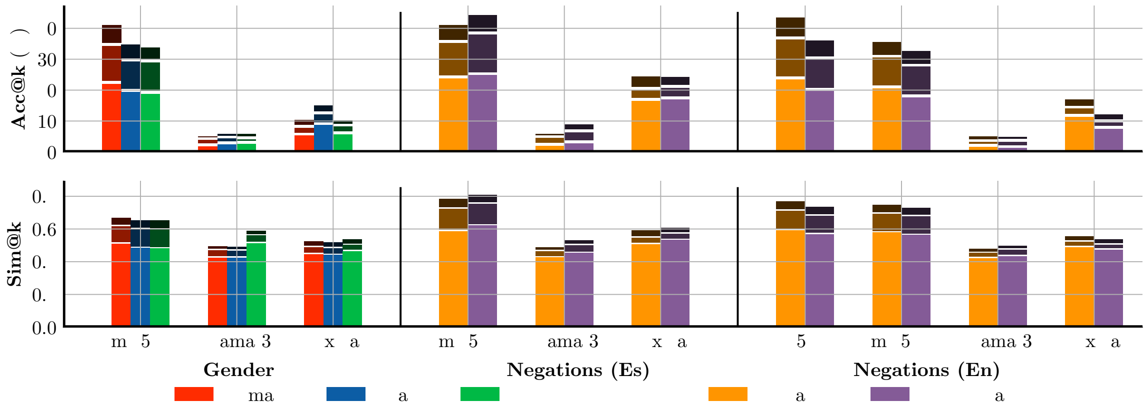

Figure 3: Top-k accuracy and similarity results on subsets reflecting different linguistic constructions in MASIVE: grammatical gender of affective states in Spanish (left) and negated expressions in Spanish (center) and English (right). Shades reflect different values of k separated by small gaps, where the lightest shade represents $k = 1$ and the darkest shade represents $k = 5$.

Test Set	Model	NLL↓	Log Perp↓	Acc@1↑	Acc@3↑	Acc@5↑	Sim@1↑	Sim@3↑	Sim@5↑
En	mT5_S^{En}	4.21	4.17	27.05%	41.37%	48.71%	0.598	0.719	0.769
	mT5_{Tr}^{En}	16.86	15.79	2.18%	4.45%	6.12%	0.418	0.532	0.579
Es_{Tr}	mT5^{Es}	59.37	59.23	2.35%	4.20%	5.46%	0.369	0.448	0.482
Es	mT5^{Es}	6.91	6.89	24.51%	36.16%	41.23%	0.610	0.734	0.781
	$\text{mT5}_{Tr,S}^{Es}$	15.80	15.54	2.37%	4.95%	6.58%	0.378	0.472	0.517
En_{Tr}	mT5_S^{En}	24.15	23.94	3.07%	6.60%	9.39%	0.443	0.532	0.573

Table 8: Comparison of mT5 fine-tuned on the original data reflecting native language use, fine-tuned on translated data (translate-train), and evaluated on translated data (translate-test) with MASIVE. Only aggregated scores are shown. All fine-tuning sets are randomly subset to the same size as the smallest set, the collected Spanish training set, and results are averaged across 5 different subsets (n = 30,958). Models with subsetted data are denoted with $_S$.

5.5 Machine-Translation vs. Natural Data

Finally, we evaluate *translate-train* and *translate-test* approaches to cross-lingual transfer (Hu et al., 2020) against models fine-tuned and evaluated on the original texts. First, we find an expected drop in performance when models are fine-tuned on machine-translated data for both English and Spanish. Interestingly, the average drop in similarity metrics in Spanish (36%) is notably larger than in English (27%). This could perhaps be explained by the translation model performing better in the Spanish to English direction than English to Spanish, as well as mT5's ability to better generalize in English than in Spanish.

As an alternative approach to fine-tuning on translated data, we also consider the case where data may be translated at inference time. In these cases (En_{Tr} and Es_{Tr} in Table 8), we find that performance falls. Artifacts of machine translation have been found to impact evaluation of translation models (Freitag et al., 2020), and similarly, errors and artifacts of unnatural translation may cause these changes in performance. In contrast to prior work suggesting that performance on the target data translated into English is comparable to fine-tuning on the target language for tasks such as sentiment detection, our results suggest that for our task, **machine-translating the evaluation data leads to poorer performance, and translating either at training or inference time result in similar performance (Takeaway #6)**.

6 Related Work

Emotion Taxonomies. Many different models of human emotion have been proposed, intending to capture the universal experience of different emotions across cultures. Some of the most notable categorical models in psychology and NLP research are the Ekman (1984, 2005) basic emotion set derived from facial expression and the Plutchik (1980) basic emotion set which assumes emotions occur in opposing pairs (e.g. joy and sadness), though other models exist (e.g., Ortony et al. 1988; Oatley and Johnson-laird 1987; Johnson-Laird and Oatley 1998; PS and Mahalakshmi 2017). Multiple different dimensional models have also been proposed, situating emotions in a space governed by features such as pleasantness and activation (Plutchik, 1980; Russell and Mehrabian, 1977; Russell, 1980; Bradley et al., 1992). Many such models of emotions have been frequently compared and evaluated in psychology and as they apply to emotion detection (see Rubin and Talarico 2009; PS and Mahalakshmi 2017; Lichtenstein et al. 2008).

Emotion and Language Generation. Numerous approaches to automated emotion detection in text have been proposed, including emotion lexicons (Strapparava and Valitutti, 2004; Staiano and Guerini, 2014; Araque et al., 2022; Mohammad and Turney, 2010) and classification models (see Acheampong et al. 2020 for a review of approaches). Most of this work focuses on small, finite emotion sets, usually Ekman or Plutchik, though larger sets have been employed, such as those listed in Wang et al. (2020) and used in other prior work (Sintsova et al., 2013; Liew et al., 2016; Subasic and Huettner, 2001; Mohammad and Kiritchenko, 2015). Other works have instead predicted affect dimensions for fine-grained emotion classification (Mohammad et al., 2018). In contrast, we consider discrete affective states derived from expressions in language and in this work, we evaluate models on predicting over 1,000 distinct affective states. More recently, language generation tasks have been proposed that call for models with greater emotional understanding, such as emotional dialogue generation (Ide and Kawahara, 2021; Song et al., 2019; Firdaus et al., 2020), controllable generation (Goswamy et al., 2020; Saha et al., 2022), and emotion trigger summarization (Sosea et al., 2023; Zhan et al., 2022). Given that language generation models have been employed to unify these and other tasks, endowing models with a greater understanding of human emotions would greatly benefit multiple applications.

Cross-cultural Emotion Perception. Many researchers have suggested that a basic set of emotions are universal, while others have argued that emotions are shaped by culture. Past work has built on Ekman's proposal and provided evidence that emotion categories are universal (Ekman, 1984; Hoemann et al., 2019), with Sauter (2018) finding little support for the argument that language plays a foundational role in perceiving emotions. Additionally, past work has in part supported differences in emotion perception across languages and cultures in humans (Chen et al., 2023; Mesquita et al., 2016; Jackson et al., 2019; Caldwell-Harris and Ayçiçeği-Dinn, 2009). Some work has demonstrated differences in model performance across languages and cultures (Havaldar et al., 2023; Hassan et al., 2022). Others have studied cross-lingual approaches both with and without machine translation on speech tasks (Yang and Hirschberg, 2019; Rizvi et al., 2023), text tasks (Patil et al., 2022; Dong et al., 2021), and specifically for sentiment and emotion tasks (Rasooli et al., 2018; Tafreshi et al., 2024; Zhang et al., 2024). Our work evaluates the use of machine translation, and we find that machine translation may not be sufficient for cross-lingual transfer on the ASI task.

7 Conclusion

In this work, we introduce the novel task of ASI, a language generation task prioritizing the authors' natural expressions of their feelings rather than using a prescribed set of emotion labels. For this task, we automatically collect and publish two datasets of Reddit posts in English and Spanish, both containing over 1,000 unique affective state labels.

We use this dataset to benchmark multilingual generative models, and find that **(Takeaway #1)** small fine-tuned T5 and mT5 models outperform zero-shot LLMs. Results specifically show that **(Takeaway #2)** T5 outperforms mT5 in English on ASI, suggesting that monolingual models may be more capable. Additionally, we show that **(Takeaway #3)** models fine-tuned on our corpora transfer knowledge that generalizes to existing emotion detection benchmarks. In analyzing model performance on unseen affective states and Spanish regionalisms, we argue that **(Takeaway #4)** generalization to a broader set of affective states, including those from underrepresented dialects, is an important avenue for future work. With respect to grammatical gender in Spanish and negations, **(Takeaway #5)** fine-tuning on MASIVE improves on specific linguistic constructions unique to generative ASI. Finally, we quantify the observed performance differences when using machine-translated data at fine-tuning or inference time, finding that in contrast to prior work, **(Takeaway #6)** machine translation leads to large performance drops. We hope these results spark future work into ASI to enable prediction of more nuanced feelings in a variety of languages and contexts, and ultimately, enable prediction of an unbounded set of labels.

Limitations

We limit ourselves in this work to investigating two high-resource languages, English and Spanish. We do this in part because, for this application, we find it important that members of the research team be able to speak the languages of study fluently. Additionally, we gather data from one source, Reddit, which limits the demographics of the people whose experiences are represented in our data. This choice of data source may particularly limit our Spanish data, which includes fewer texts and labels than English (Table 1). We choose not to control for attributes like topic or subreddit when collecting English and Spanish data separately because we wish to collect a natural variety of data, but this also means that we do not claim our two datasets to be parallel or equivalent.

Our data gathering framework collects only explicit expressions of affective states by searching for statements including an "I feel"-style template. While we can use models trained on this type of data to predict affective state labels for any input by simply appending an "I feel" statement to be filled (see subsubsection 4.2.2), our training targets do not include this type of data, and this paradigm impacts the types of affective states we are likely to collect.

We also acknowledge that our choices of specific resources limit our work in various ways. We use only Opus-MT models to perform our machine translation experiments because they exhibit good performance in both languages; however, it is possible that we would see different results with different translation models. Our similarity metric also uses pre-trained BERT embeddings because of the benefits of contextual embeddings and subword tokenization, but there are many other possible choices of embedding framework that may more accurately capture emotional nuances. Finally, we evaluate only open-source LLMs on our dataset.

Ethics Statement

We strictly collect publicly available user-authored texts on the pseudonymous social media website Reddit, but we acknowledge the privacy concerns of users when collecting data from social media. Accordingly, we will release the collected texts only with randomly assigned IDs and usernames stripped. We discourage others from attempting to identify authors of the texts in the collected dataset, and will remove data from the dataset upon request.

Because we rely entirely on open-source models, including open-source LLMs, and make our data available, our results are fully reproducible. In total, our fine-tuning and evaluation amounts to approximately 73 GPU hours using Nvidia A100 GPUs.

Our task allows models to predict a larger set of affective states, capturing more nuanced expressions of an authors' feelings than traditional emotion detection. At the same time, a larger label set could exacerbate the consequences of misclassification in sensitive contexts (e.g., mental health and crisis settings). In some applications of this task where this may be an important consideration, the label set can be artificially restricted, as we show in our external evaluation experiments.

Finally, the aim of predicting authors' expressions of their own feelings can require models to generate regional or dialectal texts. Prior work has identified dialectal biases in language models (e.g., African American Language; Deas et al. 2023; Groenwold et al. 2020) and we find that all evaluated models perform poorly on regional varieties of Spanish. We hope future work makes progress toward closing performance gaps among dialects and language varieties.

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A Data Statement

A.1 Curation Rationale

The aim of collecting the texts contained in MASIVE was to produce both a training dataset and benchmark for affective state identification. Affective state identification tasks models with predicting individual terms reflecting how a text's author feels, and in particular, predicting terms that would be used by the author. The dataset collection process was designed to automatically extract a large set of possible affective state labels from texts where an author explicitly describes how they feel. Both an English and Spanish version of the dataset were collected in the same fashion to enable research on cross-lingual work, as well as a small set of regional Spanish to enable work on linguistic variation. We intend to make the dataset publicly available

A.2 Language Variety

MASIVE contains texts both in English (en) and Spanish (es). Data collection was not restricted to a particular variety of English or Spanish, and distributions of these varieties likely reflects the overall demographics of English and Spanish-speaking users on Reddit. A small set of data was collected specifically to reflect Spanish specific to particular regions, including terms primarily associated with Spanish spoken in Mexico, Spain, Venezuela, and El Salvador among other regions and countries.

A.3 Annotator Demographics

Two sets of annotators were involved in validating the automatically extracted labels in MASIVE. For the English data, annotators were 2 native English-speakers and Psychology undergraduate students. Both English data annotators were American and female. For the Spanish data, annotators were 2 native Spanish-speakers and graduate students in the department of Latin American and Iberian Cultures. The Spanish data annotators were Colombian and Ecuadorian, and both were male.

A.4 Speech Situation

The collected texts in MASIVE were not restricted to a particular range of time, and may have been published anytime between the founding of Reddit (2005) and the time of data collection (April, 2024). Texts were also not restricted to a particular place, but likely reflect the countries of origin of English and Spanish-speaking Reddit users. All texts were originally written and published on Reddit, which may or may not have been edited before they were included in the dataset. As with most interactions through Reddit posts, the texts reflect asynchronous interactions and are likely intended for a general public audience in most cases.

A.5 Text Characteristics

The texts in MASIVE may discuss a wide variety of topics. All texts, however, contain explicit expressions of feelings or explicit mentions of terms that may reflect feelings. Thus, many texts may reflect personal narratives that provide context for an author's feelings. Thus, the dataset may also discuss sensitive topics and include the kinds of offensive or harmful content that can be found online.

B Data Examples

Examples of input texts and the identified affective state labels from MASIVE are included in Table 9.

C Data Collection and Annotation

C.1 Seed Emotions

The specific adjective forms of the Ekman emotions used to seed our bootstrapping procedure are shown in Table 10. These are also the terms used as the gold in our fixed-set label evaluation, with

En	Es
Four wait-lists to start my cycle... is this normal or a bad sign? Applied to all my schools in mid-late December. Over the past two weeks I've received my first decisions: wait-lists from Penn, Michigan, Cornell, and UT. I'm feeling discouraged at the moment because I definitely wasn't expecting to be waitlisted from all four of these schools. 7sage predictor gave me a 49%, 74%, 83%, and 93% chance at these schools, respectively. Getting waitlisted at a target, likely target, and two safeties to start my cycle has me fairly concerned. I had two strong LOR's (fantastic relationship with two of my college professors), and thought I did a great job on my P.S. I'm wondering if my lack of internship/work experience is going to hurt me this cycle, as I've been a server/front desk staff for two years since graduating college. Would appreciate anyone's thoughts on what might be going on/what to expect. I blanketed the T14 as well as applying to UCLA, BU, and Vandy. Thanks in advance for any guidance!! Wishing good luck to all of you!	Le platique a "un amigo" de una chava y la agrego a sus redes sociales Me causa inseguridad y molestia que haya hecho eso ¿con que intención lo hizo? El me había dicho que no la conocía ni ubicaba y ahora de la nada ya la tiene en redes. Ella y yo no tenemos nada serio, apenas estamos empezando a salir. Lo siento como una traición a mi confianza y falta de respeto, estoy pensando en confrontarlo y dejar de hablarle ya que eso no lo hace los amigos, y yo tengo que darme mi lugar y no permitir esas faltas de respeto. ¿Estoy exagerando? Necesito opiniones, no sé si este exagerando, mi desconfianza me este haciendo una jugada o lo estoy viendo como debería ser. No sé, no estoy seguro, pero internamente si me siento enojado y molesto.
Why I just started the SHEIN $100 game and I was .05 cents away and they said I reached the max assets. It said if I got people to join I'd receive 1 point for each and I only needed 5 and it started giving me .05 cents then said game over. I was at the $100 if it followed what it said but the game did not. What a rip!!! Not happy I feel cheated for sure! You make millions SHEIN, why do that to your customers?!	[Serio] me vaciaron la caja de ahorro Eso, hace una hora y media tenía 4k y ahora -4 pesos, lo único que hice fue sacar 500 pesos y después hace una compra con débito y en farmacity, no sé que hacer, estoy desesperada, no me atienden del número de banco nación, que puedo hacer? Ayuda por favor!! UPDATE: después de sufrir dos horas volvió todo mi saldo así como se fue, vacíe la cuenta y cambie de nuevo el pin de la tarjeta, ahora tengo un miedo de que me pase de vuelta, que puedo hacer para prevenir??

Table 9: Example texts and accompanying affective state labels from the English and Spanish subsets of MASIVE. Affective state labels are colored red.

the addition of '*nothing*' for the no-emotion class if it is used.

For fixed-label evaluation of GoEmotions (27), the following terms are used for the expanded label set: '*admiration*', '*amused*', '*angry*', '*annoyed*', '*approving*', '*caring*', '*confused*', '*curious*', '*desire*', '*disappointed*', '*disapproval*', '*disgusted*', '*embarrassed*', '*excited*', '*afraid*', '*grateful*', '*grief*', '*happy*', '*love*', '*nervous*', '*optimistic*', '*proud*', '*realized*', '*relieved*', '*remorseful*', '*sad*', '*surprised*', and '*nothing*'.

En		Es	
happy	surprised	feliz	sorprendido
sad	disgusted	triste	desagradado
angry	afraid	enojado	asustado

Table 10: Seed emotions (Ekman) for each language used in collecting MASIVE.

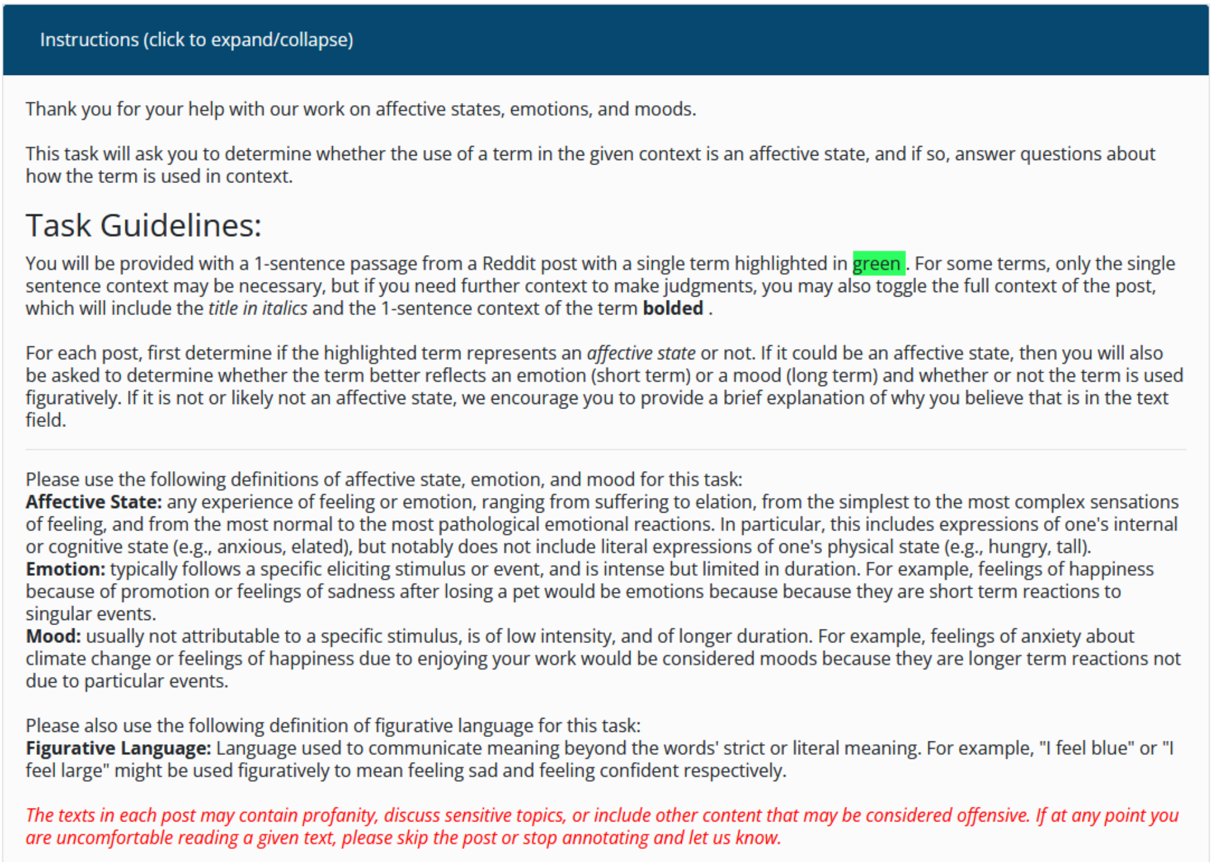
C.2 Regional Spanish Affective States

To collect affective state labels associated with one or more particular Spanish-speaking regions, we use the following set of terms: '*mamado/a*', '*patitieso/a*', '*emputado/a*', '*encandilado/a*', '*arrechado/a*', '*fastidiado/a*', '*encabronado/a*', '*hallado/a*', '*rayado/a*', '*achispado/a*', '*ahuevado/a*', '*enrabiado/a*', '*tusa*', '*chocho/a*', '*encachimbado/a*', '*bravo/a*', '*apantallado/a*', '*embromado/a*', '*engorilado/a*', '*alicaido/a*', '*flipando/a*', '*cagado/a*', '*aguitado/a*', '*engrinchado/a*', '*chato/a*', '*chipil*', '*picado/a*', '*bajoneado/a*', '*acojonado/a*', '*arrecho/a*'"

The terms are not exhaustive, but reflect varieties of Spanish spoken in Spain, Chile, Colombia, Venezuela, Mexico, Bolivia, Argentina, Uruguay, and Paraguay.

C.3 Data Annotation

The instructions and interface given to our human annotators are shown in Figure 4 and Figure 5, respectively. Annotators were paid $23/hour for their work in accordance with the standards of their university. Each annotator completed a pilot task of 30 examples before beginning to annotate the data in order to build familiarity with the platform and task.



Instructions (click to expand/collapse)

Thank you for your help with our work on affective states, emotions, and moods.

This task will ask you to determine whether the use of a term in the given context is an affective state, and if so, answer questions about how the term is used in context.

Task Guidelines:

You will be provided with a 1-sentence passage from a Reddit post with a single term highlighted in green. For some terms, only the single sentence context may be necessary, but if you need further context to make judgments, you may also toggle the full context of the post, which will include the *title in italics* and the 1-sentence context of the term **bolded** .

For each post, first determine if the highlighted term represents an *affective state* or not. If it could be an affective state, then you will also be asked to determine whether the term better reflects an emotion (short term) or a mood (long term) and whether or not the term is used figuratively. If it is not or likely not an affective state, we encourage you to provide a brief explanation of why you believe that is in the text field.

Please use the following definitions of affective state, emotion, and mood for this task:
Affective State: any experience of feeling or emotion, ranging from suffering to elation, from the simplest to the most complex sensations of feeling, and from the most normal to the most pathological emotional reactions. In particular, this includes expressions of one's internal or cognitive state (e.g., anxious, elated), but notably does not include literal expressions of one's physical state (e.g., hungry, tall).
Emotion: typically follows a specific eliciting stimulus or event, and is intense but limited in duration. For example, feelings of happiness because of promotion or feelings of sadness after losing a pet would be emotions because because they are short term reactions to singular events.
Mood: usually not attributable to a specific stimulus, is of low intensity, and of longer duration. For example, feelings of anxiety about climate change or feelings of happiness due to enjoying your work would be considered moods because they are longer term reactions not due to particular events.

Please also use the following definition of figurative language for this task:
Figurative Language: Language used to communicate meaning beyond the words' strict or literal meaning. For example, "I feel blue" or "I feel large" might be used figuratively to mean feeling sad and feeling confident respectively.

The texts in each post may contain profanity, discuss sensitive topics, or include other content that may be considered offensive. If at any point you are uncomfortable reading a given text, please skip the post or stop annotating and let us know.

Figure 4: Instructions provided to our human annotators, including definitions. Annotators may collapse or expand the instructions at will.

D Experimental Setup

D.1 Generation Configuration

Checkpoints. Throughout our experiments, we use the large variants of T5 (770 million parameters; *google-t5/t5-large*) and mT5 (1.2 billion parameters; *google/mt5-large*). For our two LLMs, we evaluate the instruct variants of Llama-3 (8 billion parameters; *meta-llama/Meta-Llama-3-8B-Instruct*) loaded in bfloat16 and Mixtral (7×22 billion parameters; *mistralai/Mixtral-8x22B-Instruct-v0.1*). Mixtral is accessed through the `fireworks.ai` API.

Beyond the evaluated models, we use two open-source, unidirectional translation models for our translation experiments. In particular, we employ the Helsinki-NLP English-to-Spanish (*Helsinki-NLP/opus-mt-en-es*) and Spanish-to-English (*Helsinki-NLP/opus-mt-es-en*) models. We also use a multilingual BERT checkpoint as part of the similarity metric (168 million parameters; *bert-base-multilingual-uncased*). Finally, we also rely on spacy (Honnibal et al., 2020) to identify parts of speech in English (*en_core_web_md*) and Spanish (*es_core_news_md*) during our data collection.

Generation. For T5, mT5, and Llama-3, we use beam search to generate the top-k most likely predictions, with 5 beams (as we need only the top-5 outputs). We use the default settings of Huggingface's `GenerationConfig`, including, e.g., no repetition penalty, etc.; though we expect a single-word output, we allow generations of up to 32 tokens.

The API used to run inference with Mixtral does not allow retrieving the top 5 most probable predictions as we do with the aforementioned models. Instead, Mixtral predictions are generated with a top-k of 5, and a temperature of 0.5. The top 5 candidate generations are then reranked by the log-probability according to Mixtral to be used in evaluating the ranked, top-5 predictions. Also due to accessing Mixtral through an API, we were not able to calculate the log perplexity of the ground truth labels.

Hyperparameters. T5 and mT5 models are finetuned with a batch size of 4 for 3 epochs each. Model parameters are optimized using Adafactor (Shazeer and Stern, 2018) as implemented by Hug-

Figure 5: Human annotation interface with a sample datapoint. Clicking the button to show more or less context toggles the display of the full Reddit post vs. the one-sentence context. As shown, the Emotion/Mood and Figurative Language questions only appear if the highlighted term is judged **like an affective state** or **completely an affective state**.

gingface's `transformers` with a learning rate of 1×10^{-4}, Huggingface's linear learning rate scheduler with default parameters, and a weight decay parameter (here, an L2 penalty) of 0.01. For each model, all data is tokenized using the correct pre-trained tokenizer corresponding to its pre-trained checkpoint. Any input that is longer than 512 tokens (including the end-of-sequence token) is trimmed to fit; in order to preserve the target affective state masks and the grammatical integrity of the text, this trimming removes full sentences (as parsed by `nltk`; Bird et al. 2009) from the end of the text if possible (i.e., if this will not remove a target mask), or the beginning otherwise, until the text fits within 512 tokens.

D.2 Prompts

Table 11 shows the prompts provided to Mixtral and Llama-3 throughout our experiments. In a minority of cases, models would reply in the form "Here is a list of terms to fill each <MASK>: ", in which case, only the terms following the colon were considered as the model's prediction.

D.3 Machine Translation Configuration

In the fine-tuning experiment, we subset the English data and translated English-to-Spanish data to keep the number of training steps constant across settings. For these two models, we repeat the experiment with 5 different random subsets and report the averages across the five trials.

Lang	Prompt
En	Determine the most likely term reflecting a feeling to replace each <MASK> in the following text: "*<MASKED_POST>*" Provide a single emotion term for each <MASK> token. Do not introduce the answer, respond ONLY with a comma-separated list of lowercase terms:
Es	Determine the most likely term reflecting a feeling to replace each <MASK> in the following text: "*<MASKED_POST>*" Provide a single emotion term for each <MASK> token. Do not introduce the answer, respond ONLY with a comma-separated list of lowercase terms in Spanish:

Table 11: Prompts provided to Llama-3 and Mixtral for evaluation. At inference time, *<POST>* is replaced with the input text containing masked affective states.

E Top-K Similarity

Let $P = [p_1, p_2, p_3, ...p_n]$, where $n \geq k$, be a list of predictions ordered according to descending likelihood, and let g be the gold (where p_i and g are strings). Additionally, let $E(x)$ be a function on a term x that incorporates 100 tokens of context, tokenizes and embeds the sequence with a pre-trained BERT tokenizer, and returns the contextual embedding corresponding to the first sub-word token in x. Then, we report top-k similarity specifically as

$$\text{sim}_k(P, g) = \max_{i \leq k} \left[\text{cosine\_sim}(E(p_i), E(g))\right]$$

F Extended Results

F.1 Limited Evaluation for Llama-3

For some inputs, Llama-3 would decline to make a prediction, particularly for inputs that discuss topics such as depression or drug use. While these are important topics for models to be able to accurately analyze as they are increasingly applied in mental health contexts, Llama-3's behavior may unfairly skew its evaluation results. Table 12 presents updated results for Llama-3 on the subset of texts for which the model's response followed the correct format. 60% of English, 70% of Spanish, and 76% of regional Spanish responses by Llama-3 were formatted correctly. Across datasets, scores improve only by up to ∼2.4% top-k accuracy and ∼.04 top-k similarity. Considering these results, no conclusions made are altered.

F.2 Full Fixed-Label Set Results

Extended results from the fixed-label evaluation are given in Table 13. Notably, we include results using T5 in English, where T5 represents a model fine-tuned only on the target dataset and T5^{MAS} represents a model fine-tuned on MASIVE and then fine-tuned on the target dataset. Precision, recall, and F1 are calculated by ranking the adjective forms of each emotion class (Appendix C) according to model likelihood and taking the most likely one as the predicted class, while top-k accuracy and similarity are calculated in a generative setting as in the remainder of the paper. T5 generally scores well on F1; pre-training on MASIVE does not usually improve T5's performance on GoEmotions, while it does for EmoEvent (En).

Lang	% Valid	Acc@1↑	Acc@3↑	Acc@5↑	Sim@1↑	Sim@3↑	Sim@5↑
En	59.69%	2.05%	3.63%	4.69%	0.433	0.479	0.502
Es	69.51%	3.53%	6.57%	8.27%	0.467	0.516	0.541
Es (Reg)	76.03%	0.00%	0.00%	0.00%	0.384	0.425	0.436

Table 12: Evaluation results of Llama-3 on each MASIVE dataset only considering samples with correctly formatted responses of the form "*prediction_1*, *prediction_2*, etc..."

Dataset	Model	P	R	F1	Acc@1	Acc@3	Acc@5	Sim@1	Sim@3	Sim@5
GoEmotions (7)	$T5^{En}$	**56.77**	24.67	21.09	**38.53%**	47.95%	55.74%	0.734	0.775	0.804
	$T5^{MAS}$	31.10	24.07	19.67	34.50%	47.26%	55.09%	0.708	0.774	0.803
	$mT5^{En}$	33.63	19.28	16.25	38.49%	**70.73%**	**85.99%**	**0.736**	**0.884**	**0.946**
	$mT5^{MAS}$	33.06	**39.81**	**28.30**	17.49%	32.11%	39.25%	0.629	0.733	0.771
GoEmotions (27)	$T5^{En}$	23.31	13.05	9.73	2.03%	3.27%	3.86%	0.197	0.461	0.492
	$T5^{MAS}$	11.09	5.19	1.26	2.64%	4.10%	5.14%	0.506	0.560	0.574
	$mT5^{En}$	12.57	4.77	2.24	2.53%	**12.90%**	**23.51%**	**0.525**	**0.614**	**0.670**
	$mT5^{MAS}$	**27.08**	**18.76**	**11.92**	**7.54%**	12.22%	15.16%	0.508	0.602	0.639
EmoEvent (En)	$T5^{En}$	51.06	26.63	25.05	27.44%	51.30%	56.38%	0.541	0.777	0.811
	$T5^{MAS}$	**35.46**	**33.65**	28.08	32.55%	59.56%	71.85%	0.671	0.837	0.892
	$mT5^{En}$	30.06	14.36	2.84	10.50%	**71.70%**	**93.64%**	0.630	**0.880**	**0.974**
	$mT5^{MAS}$	34.81	32.74	**29.55**	**33.40%**	57.06%	69.38%	**0.712**	0.842	0.893
EmoEvent (Es)	$mT5^{Es}$	26.13	14.52	6.41	24.29%	70.34%	**89.12%**	0.713	0.882	**0.955**
	$mT5^{MAS}$	**54.93**	**21.54**	**17.80**	**39.75%**	**82.62%**	86.11%	**0.750**	**0.918**	0.935

Table 13: Fixed-label evaluation of our models on prior emotion classification datasets. The best performance under each metric for each dataset is **bolded**.