Multilingual Topic Classification in X: Dataset and Analysis

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Abstract

In the dynamic realm of social media, diverse topics are discussed daily, transcending linguistic boundaries. However, the complexities of understanding and categorising this content across various languages remain an important challenge with traditional techniques like topic modelling often struggling to accommodate this multilingual diversity. In this paper, we introduce X-Topic, a multilingual dataset featuring content in four distinct languages (English, Spanish, Japanese, and Greek), crafted for the purpose of tweet topic classification. Our dataset includes a wide range of topics, tailored for social media content, making it a valuable resource for scientists and professionals working on cross-linguistic analysis, the development of robust multilingual models, and computational scientists studying online dialogue. Finally, we leverage X-Topic to perform a comprehensive cross-linguistic and multilingual analysis, and compare the capabilities of current general- and domain-specific language models.

1 Introduction

Social platforms such as X (*Twitter*), Snapchat and Instagram provide an environment for content creation and information sharing among people and organisations. In particular, people use these platforms to express their sentiments, share their opinions on multiple topics, and discuss and influence each other (Barbieri et al., 2014; Hu et al., 2021; Ansari et al., 2020). In this scenario, these platforms are rich sources for informal short text, as they include content about recent events, shared by a heterogeneous group of users. The vast amount of content shared on social media, however, make it impossible to analyse and digest it without automatic tools.

Unsupervised approaches such as Latent Dirichlet Allocation (LDA) (Blei et al., 2003) and topic modelling variations (Steyvers and Griffiths, 2007), or more recently, BERTopic (Grootendorst, 2022), are common approaches to deal with this issue. However, these methods are usually built as an ad-hoc analysis, with the derived topics not being easily interpretable or comparable among different analyses. On the other hand, when looking at supervising approaches, existing resources mainly focus on the news articles domain, e.g., BBC News (Greene and Cunningham, 2006), Reuter (Lewis et al., 2004), 20News (Lang, 1995), and WMT News Crawl (Lazaridou et al., 2021) with few exceptions like scientific (arXiv) (Lazaridou et al., 2021) and medical (Ohsumed) (Hersh et al., 1994) domains.

Our paper focuses on expanding the resources available for multilingual tweet classification. We leverage an initial topic taxonomy of 19 topics, first proposed in Antypas et al. (2022), and introduce the new X-Topic dataset that includes tweets from four different languages: English, Spanish, Japanese and Greek. Our dataset is focused on *X* data and aims to address the lack of labelled multilingual social media data, as well as to encourage the creation of new methods for multilingual topic classification.

By leveraging X-Topic as a benchmark, we explore multiple model architectures and sizes for multilingual tweet topic classification: (1) zeroshot, (2) few-shot, (3) monolingual, (4) cross-lingual and (5) multilingual. Our analysis high-lights the challenging nature of the task and reveals interesting patterns in relation to the use of LLMs and supervised approaches for the topic classification task in social media, especially in relation to the type of data considered for training.

The X-Topic dataset, as well as the topic classification models built upon it, are made openly available. X-Topic is available at https://hu

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ggingface.co/datasets/cardiffnlp/t weet_topic_multilingual. Table 1 shows some sample instances of X-Topic for each language. Finally, the best multilingual models of *base* and *large* sizes are available at https:// huggingface.co/cardiffnlp/twitter-xlm -roberta-base-topic-multilingual and https://huggingface.co/cardiffnlp/twitte r-xlm-roberta-large-topic-multilingual, respectively.

2 Related Work

The task of classifying topics in social media content has garnered significant attention from the research community in recent years (Schlichtkrull et al., 2023; Zubiaga et al., 2018; Chua and Banerjee, 2016). Social media platforms like *X* have become hubs for the exchange of information, opinions, and sentiments, making the development of effective classification methods imperative.

Unsupervised Approaches. Due to the lack of labelled data and the dynamic nature of social media platforms, unsupervised methods have been widely used for topic modelling and classification on the content shared. Several variations of LDA have been introduced that try to address the challenges that arise when working with the often messy and unstructured world of social media. Such solutions, (Zhao et al., 2011; Rosen-Zvi et al., 2004; Steinskog et al., 2017) often try to combine author information with the text shared. Other approaches use unsupervised clustering algorithms, such as kmeans or hierarchical clustering, to group similar social media content based on their topic similarity (Wang et al., 2017). These methods are particularly useful when the underlying topics are not predefined and need to be inferred from the data. However, a drawback of these unsupervised approaches is that the derived topics may not always be easily interpretable or comparable across corpora.

Multilingual resources in social media. Supervised methods for topic classification in social media content involve training machine learning models on labelled data. While supervised approaches have demonstrated robust performance on social media tasks (Huang et al., 2013; Camacho-collados et al., 2022), there is a notable scarcity of labelled data for social media content, particularly in languages other than English (Selvaperumal and Suruliandi, 2014); while a lot of the available datasets

offer a limited taxonomy of topics (Vadivukarassi et al., 2019). Multilingual and cross-lingual topic classification in social media is therefore a limited explored area. It involves dealing with content in multiple languages, addressing language-specific nuances, and ensuring effective classification. Few resources and models are designed to handle multilingual topic classification. Existing datasets e.g. in Portuguese (Daouadi et al., 2021), Spanish (Imran et al., 2016), Urdu (Kausar et al., 2021) and others (Chowdhury et al., 2020), often suffer from weak labelling or a limited taxonomy of topics, or they are created to solve specific problems e.g. sentiment analysis (Muhammad et al., 2023) and hate speech (Ousidhoum et al., 2019). This presents a gap in the field as many social media platforms have a global user base. Our work addresses this gap by introducing the X-Topic dataset, which includes tweets in four different languages (English, Spanish, Japanese, and Greek), thereby expanding resources for multilingual topic classification in social media.

3 X-Topic, a Multilingual Tweet Topic Classification Benchmark

In this section, we describe our methodology to construct, a multilingual tweet topic classification benchmark. First, we describe the original Englishbased TweetTopic dataset, which we take as inspiration to construct a fully multilingual dataset.

TweetTopic (Antypas et al., 2022) is an English Twitter topic classification dataset consisting of a total of 11,267 English tweets assigned one or more classes from a predefined list of 19 topics such as "News & Social Concern", "Sports", and "Fashion & Style". The taxonomy of topics was decided by a team of social media experts and aims to cover the majority of content being shared in social media platforms. The tweets were distributed over time, from September 2019 to October 2021 and were extracted using keywords of trending topics in each week during the period. Each entry was labelled by five different annotators, and the topic was assigned if there was an agreement of at least two annotators.

In our work, we leverage the taxonomy originally presented in TweetTopic as a foundation for collecting a new set of recent tweets, leading to the introduction of X-Topic. X-Topic is mainly distinguished by its inclusion of entries in four diverse languages: Spanish, Greek, Japanese, and English.

| Tweet | Topics |
|---|--|
| en: I don't think I really want to go to Coachella unless Taylor Swift is headlining | Celebrity & Pop Culture, Music |
| es: quiero una date en un museo | Relationships, Arts & Culture, Diaries & Daily Life |
| translation: I want a date in a museum | Diaries & Daily Life |
| ja: 久々になーーんもしないでいい日が二日もあるのでゆっくり富平井絆果と | |
| 向き合うよ | |
| | Diaries & Daily Life, Gaming |
| translation: It's been a long time since I've had two days where I don't have to do anything, | |
| so I'm going to take my time and face Kizuna Fuhirai. | |
| gr: Μπα σε καλό σου μωρή Ανθουλα μας κοψοχολιασες πάλι ⁴ σασμός | |
| | Film, TV & Video |
| translation: Oh my goodness, Anthula, you've cracked us up again #sasmos | |

Table 1: Example of tweets present in each language subset of X-Topic.

3.1 Language Selection and Tweet Collection

The selection of languages was made by taking into account their popularity and practicality. X-Topic is a resource that helps to the analysis of frequently used languages in X (English, Spanish, Japanese) as well as a less frequently studied one (Greek). This linguistic diversity also provides a unique opportunity for comparative analysis between linguistically distant groups, such as Japanese and Greek. Moreover, our choice of the September 2021 to August 2022 timeframe continues the timeline of previous work and facilitates engaging in temporal analyses.

For the collection of the dataset, we follow a similar approach to that of the original TweetTopic. Initially, the Twitter API was utilised to collect 50 tweets every two hours for each language. However, in contrast to TweetTopic, we do not use any keyword filtering in our queries. In this way, we acquire a diverse set of tweets, approximately 220,000 tweets for each language, which is closer to the real distribution of content shared in X.

3.2 Preprocessing

Following the collection of the raw tweets we apply several preprocessing steps. First, we remove potentially remaining tweets in other languages by using a fastText-based language identifier (Bojanowski et al., 2017) on top of the Twitter predefined language identifier. Then, we remove tweets that are not in our target period, tweets containing incomplete sentences (too short or end in the middle of the sentence), or abusing words by applying some simple rule-based heuristics. We also apply a *near-duplication* filter to drop duplicated tweets. This process begins by normalising each tweet (i.e. remove irrelevant substrings and lemmatisation), and then retaining unique tweets only in terms of the normalised form. To ensure the quality of the tweets' content we remove entries that contain URLs, and those where multiple (more than four) emojis or mentions are present.¹ Finally, we sample 1,000 tweets from the remaining set of tweets after preprocessing for each language. The sampling is weighted based on the retweet count of each entry as well as the follower count of the user posting the tweet. This weighting is applied with the assumption that a higher quality content is usually more popular. As a final preprocessing step we mask all mentions of non-verified users with {USER} to ensure the privacy of users.

3.3 Annotation

The annotation process closely mirrored the procedure established in TweetTopic. Specifically, each entry of the dataset was annotated by five coders, where each coder had to select one or more labels from a selection of 19 topics in total. A topic was assigned to a tweet only if at least two annotators were in agreement about it. Following previous work on multi-label classification (Mohammad et al., 2018), we refrained from utilising a majority rule in order to create a more realistic and challenging dataset.

The coders who worked on this task were selected and filtered through the *Prolific.co* platform based on their fluency in the corresponding target language. The actual annotation was performed through an interface created with qualtrics^{XM}.² We did not utilise Amazon Mechanical Turk (AMT) due to both the lack of non-English annotators in AMT, as well as, due to the better quality of anno-

¹Detailed number of tweets dropped in each preprocessing step can be found in Table 6, Appendix B.1.

²The annotation guidelines for each language can be found in Appendix A.



Figure 1: Number of tweets per topic and language.

tators present in *Prolific.co*. Finally, we ensured the quality of the annotations as our research team includes native speakers in all the non-English languages, who monitored the whole annotation process for each language.

To assess the quality of our annotation process, we report the following three annotation agreement metrics: (1) Krippendorff's Alpha (*Alpha*) (Krippendorff, 2011), (2) Percent Agreement (*PA*), ratio of number of agreements to the total number of annotations, and (3) Agreement between each pair of coders on at least one label (*Overlap*). When comparing our results with those achieved in the TweetTopic annotation, as presented in Table 2, we can observe an overall smaller concordance among coders. The highest *Alpha* score observed was 0.26 in the Greek dataset, in contrast to TweetTopic's 0.34. Nevertheless, the agreement metrics remain

on par with similar multi-label annotation tasks such as the datasets *Affect in Tweets*, with a Fleiss' Kappa score of 0.26, (Mohammad et al., 2018) and *GoEmotions* (Demszky et al., 2020), with an *Alpha* score of 0.24, noting that a random annotation process would yield an *Alpha* score of 0.

| | Alpha | PA | Overlap | AVG Topics |
|------------|-------|------|---------|------------|
| English | 0.23 | 0.87 | 0.60 | 2.0 |
| Spanish | 0.23 | 0.89 | 0.63 | 1.8 |
| Japanese | 0.21 | 0.87 | 0.48 | 1.7 |
| Greek | 0.26 | 0.89 | 0.74 | 1.9 |
| TweetTopic | 0.34 | 0.90 | 0.70 | 1.6 |

Table 2: Annotator agreement in each language subset of X-Topic and TweetTopic, as well as the average number of topics (*AVG Topics*) assigned to each tweet.

3.4 Descriptive Analysis

X-Topic encompasses a total of 361 distinct topic combinations within its 4,000 tweets, showcasing its diversity in themes and coverage. In Table 1, we present illustrative entries from our dataset for each language, displaying various topics. Notably, each tweet, on average, is associated with 1.8 topics, with none of the entries assigned more than 5 topics.

Topic overlap. Upon examining the overlap between topics across all languages, as depicted in Figure 2, Appendix B.1, we observe interesting patterns. For instance, the *diaries_&_daily_life* (*diaries*) topic frequently co-occurs with other topics, such as family (79%) and relationships (76%). Furthermore, there is a substantial overlap between topics that we expected to be closely related in online discussions. For instance, *music* and *celebrities_&_pop_culture* exhibit a 45% overlap, while youth_&_student_life (youth) and learning_&_educational (learning) demonstrate a 25% overlap.

Topic distribution. As seen in Figure 1³, *diaries_&_daily_life* is the majority class across all four language subsets with 494, 592, 464, and 590 tweets present in English, Spanish, Japanese, and Greek respectively. When looking at less popular topics, differences between languages start becoming apparent with *news_&_social_concern* being the second most popular topic for English, Spanish, and Greek (221, 364, and 497 tweets respectively),

³A map of topic name abbreviations is provided in Appendix B.4.

and other_hobbies being the second most popular topic in Japanese (248 tweets). This is in contrast to the TweetTopic dataset which also exhibits an imbalanced distribution but to a lesser degree. This difference can be explained by the fact that in X-Topic we randomly extract tweets from X, aiming to replicate a realistic distribution, rather than utilising trending keywords. These variations in the topic distributions among the four languages, along with differences in the average post length (average number of characters: en: 149.02, es: 128.93, gr: 144.71, ja: 48.58) and the usage of emojis (average number of emojis: en: 0.43, es: 0.42, gr: 0.25, ja: 0.34), provide initial evidence of deeper differences between languages and cultures, present initial evidence into the challenges for developing cross-/multi-lingual models.

4 Experimental Setting

In this section, we introduce the models that we evaluate using X-Topic and outline the various settings employed for our analysis.

4.1 Data & Settings

To investigate the robustness of our models and the quality of the collected data, we perform a multi-purpose evaluation in a cross-validation setting. For each language subset of X-Topic, we implement a 5-fold cross-validation approach, with each fold encompassing 720/80/200 tweets for the train/validation/test sets. We ensure, whenever possible, that at least one instance of each topic is represented in each split. Then, we evaluate the following settings in the test splits of X-Topic.

Zero-shot (zero). No training data are provided. This setting aims to investigate the performance of zero-shot and unsupervised systems such as recent instruction tuning (Chung et al., 2022) and generative language models (Bubeck et al., 2023) in low-resource settings.

Few-shot (few). Five entries selected from the validation set of each fold are provided as examples. We aimed to maximise the coverage of topics present when selecting the entries. The goal of this setting is to assess the model's ability to generalise to new tasks or domains with limited training examples. For both the zero and few-shot settings the prompts utilised are similar to the ones used for the training of the BLOOMz and MT0 models in Muennighoff et al. (2022) (see Appendix B.3).

Cross-lingual (TweetTopic). In this setting, we

utilise the full English TweetTopic dataset (Antypas et al., 2022) as training set. The goal of the setting is to develop a cross-lingual classifier which will be evaluated on the language-specific test sets of X-Topic. This setting can serve as an indication of the performance in other languages not included in X-Topic for which training data is not available. In addition to the cross-lingual challenge, this setting will have the added temporal challenge, as training and test sets come from different time periods.

Monolingual (target). For each target language, we only make use of its respective training/validation splits in each fold to fine-tune classifiers, which are then evaluated on their respective test sets of the same language. The purpose of this configuration is to assess the capabilities of classifiers across languages as well as to learn from a limited amount of data.

Multilingual (all languages). In this scenario, we fine-tune a single model utilising all available training data in X-Topic in each fold, aiming to investigate the potential benefits of using a larger amount of training data and the model's capabilities in learning from labeled data in different languages.

For both the monolingual and multilingual settings above, we also explored the setting in which we add the original English TweetTopic as additional training data. The reason for this is to have a setting that includes all training data available, which is a common setting in many NLP tasks in which a larger amount of English data is available.

4.2 Comparison Models

We consider two types of models depending on whether they are fine-tuned, or used out of the box in zero- or few-shot settings via prompting.

4.2.1 Fine-tuning

We consider five different multilingual models, both general-purpose and specialised on social media and of different sizes, for the fine-tuning setting. **bernice** (DeLucia et al., 2022), a RoBERTa-based model trained on a large corpus of 2.5 billion tweets employing a customised tweet-focused tokenizer. Its training data includes 66 different languages with English, Spanish, and Japanese being the first, second, and fourth most frequent languages, making it an ideal candidate for the task at hand.

XLM-R (**xlmr**) (Conneau et al., 2019), a RoBERTa-like model trained on the Common-Crawls corpus (Wenzek et al., 2020) on 100 languages; and **XLM-T** (**xlmt**) (Barbieri et al., 2022), another XLM-R based model that utilises the last XLM-R checkpoint and further trains on a diverse dataset of over 1 billion tweets spanning over 30 languages.

For models based on XLM-R, we evaluate both the base and large versions. The inclusion of nonsocial media specific models (*xlmr*) is valuable as it offers insights into their performance in scenarios where the model is not specifically trained on social media content, shedding light on the inherent challenges of such settings. The implementation provided by Hugging Face (Wolf et al., 2020) is used for the fine-tuning of all the models. Hyper-parameter tuning, including batch size, epochs number, learning rate, and weight decay is conducted using Ray Tune (Liaw et al., 2018)⁴.

4.2.2 Zero and Few-shot

In order to assess the zero/few-shot capabilities of large language models in our task, we compare four models of different sizes and architectures.

BLOOMZ (bloomz) (Muennighoff et al., 2022), a decoder-only model based on the BLOOM models and trained with the xP3 dataset (Scao et al., 2022) with 7 billion parameters.

mt0 (Muennighoff et al., 2022), a multilingual variant of the multilingual Text-to-Text Transfer Transformer model (Xue et al., 2020). *Mt0*, similarly to *bloomz*, is further trained on the xP3 dataset using multitask prompted finetuning.

chat-gpt-3.5-turbo (**chat-gpt**) from OpenaAI, ⁵ an encoder/decoder model with approximately 175 billion parameters (Brown et al., 2020).

gpt-40 the latest and best performing model from OpenAI which significantly outperforms its predecessors.

4.3 Evaluation Metrics

Due to the nature of X-Topic, we use the macro-F1 score, which assigns equal weights to each label, as the evaluation metric. This metric is often used for multi-label classification tasks (Hazaa et al., 2023; Lipton et al., 2014; Mohammad et al., 2018). In order to better understand the performance of the models and due to the imbalanced nature, which can be a challenge for a model's performance evaluation (He and Garcia, 2009), micro-F1 is also reported.

5 Analysis of Results

The average macro and micro F1 scores for each model tested across various settings are presented in Table 3. Overall, the task presents a challenge for the tested models, with the top-performing classifier, *xlmt-large*, achieving an average performance of 57.6% macro-F1 when trained on all available data (TweetTopic and X-Topic). The majority of models demonstrate better micro-F1 scores, as they are not penalised as heavily for errors in less frequent topics.

5.1 Setting Comparison

Cross-lingual capabilities. We analyse the crosslingual capabilities by comparing the performance of models trained exclusively on TweetTopic with those trained solely on Target, taking only Spanish, Japanese and Greek into consideration. A distinct pattern emerges where cross-lingual models perform competitively (a macro-F1 score of 51.1 for the best model *xlmt_large* on average) consistently outperform their mono-lingual counterparts. For instance, the *xlmr* base model shows a performance drop of up to 31 points in macro-F1 when tested on Japanese. On average, mono-lingual models display a performance decline of approximately 15 points when compared to their cross-lingual variants. This result is encouraging as it means that cross-lingual models may be used in languages for which training data is currently not available. Even though the models' cross-lingual capabilities are remarkable, it is worth noting that the smaller size of training data available on Target (800 instances compared to the 11,267 instances in TweetTopic) has a positive effect on their performance.

Multilingual vs Monolingual. The experiments reveal a consistent increase in performance for multilingual models trained on the entire X-Topic compared to their monolingual counterparts. On average, multilingual models achieve a 17-point improvement in macro-F1. The most significant performance boost is observed in non-English languages, with an average macro-F1 increase of approximately 18 points for Spanish, Japanese, and Greek, compared to only 12 points for the English subset. In general, we observe that cross-lingual models tend to improve as more languages are added. Performance consistently increases with the inclusion of additional target language data or by incorporating more languages. The this trend can bee seen clearly when looking at the overall

⁴Details of the models used can be found in Appendix B. ⁵https://openai.com/chatgpt

| | | | | ŀ | Englis | h | | | s | panis | h | | | Ja | apane | se | | | | Greek | | |
|---------|-----------|------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | | TweetTopic | \checkmark | | | \checkmark | \checkmark | \checkmark | | _ | \checkmark | \checkmark | \checkmark | | _ | \checkmark | \checkmark | \checkmark | | | \checkmark | \checkmark |
| | | Target | | \checkmark | | \checkmark | |
| | | All | | | \checkmark | | \checkmark |
| | _ | bernice | 55.9 | 42.7 | 55.2 | 58.7 | 60.3 | 52.0 | 26.6 | 51.5 | 55.8 | 55.9 | 45.8 | 39.9 | 55.2 | 53.3 | 54.3 | 41.4 | 26.4 | 40.1 | 43.4 | 44.0 |
| | nec | xlmr_base | 47.0 | 25.1 | 45.9 | 58.0 | 57.6 | 42.4 | 11.6 | 35.1 | 48.4 | 49.1 | 34.4 | 2.7 | 39.9 | 50.1 | 52.5 | 29.5 | 12.3 | 34.2 | 40.0 | 39.7 |
| | finetuned | xlmr_large | 57.2 | 51.1 | 58.7 | 60.8 | <u>6</u> 3.3 | 51.8 | 32.6 | 49.4 | 53.0 | 57.2 | 49.1 | 38.5 | 55.9 | 56.6 | 56.7 | 44.0 | 26.7 | 45.6 | 45.5 | 46.2 |
| | fin | xlmt_base | 55.4 | 42.7 | 55.1 | 59.1 | 60.3 | 48.5 | 29.9 | 49.1 | 52.8 | 54.2 | 47.8 | 29.5 | 50.8 | 53.1 | 54.4 | 32.6 | 21.8 | 39.6 | 41.3 | 45.4 |
| _ | | xlmt_large | 60.2 | 52.0 | 59.9 | 62.1 | 61.7 | 52.9 | 45.4 | 54.4 | 56.6 | <u>6</u> 0.0 | 50.9 | 50.9 | 57.3 | 57.2 | <u>5</u> 8.5 | 40.6 | 30.1 | 49.3 | 48.6 | 50.3 |
| Ē | | bloomz | | | 23.4 | | | | | 15.5 | | | | | 15.2 | | | | | 1.5 | | |
| macro-F | zero | mt0 | | | 34.7 | | | | | 29.2 | | | | | 37.3 | | | | | 24.7 | | |
| ma | ž | chat-gpt | | | 44.9 | | | | | 37.2 | | | | | 35.6 | | | | | 33.2 | | |
| | | gpt-40 | | | 59.1 | | | | | 52.4 | | | | | 51.9 | | | | | 49.5 | | |
| | | bloomz | | | 21.0 | | | | | 17.3 | | | | | 14.0 | | | | | 5.2 | | |
| | few | mt0 | | | 35.7 | | | | | 29.1 | | | | | 39.0 | | | | | 25.1 | | |
| | Ę | chat-gpt | | | 54.1 | | | | | 43.6 | | | | | 43.9 | | | | | 39.5 | | |
| | | gpt-40 | | | 60.0 | | | | | 52.8 | | | | | 53.3 | | | | | 51.0 | | |
| | _ | bernice | 63.5 | 63.1 | 67.6 | 67.1 | 66.8 | 64.9 | 68.2 | 71.8 | 72.5 | 72.4 | 52.8 | 55.3 | 59.7 | 59.9 | 59.3 | 64.4 | 68.6 | 71.1 | 71.9 | 70.8 |
| | nec | xlmr_base | 57.3 | 51.9 | | 65.0 | 64.0 | 59.5 | | 68.5 | 69.4 | | 43.8 | 20.1 | 52.7 | 55.8 | 56.4 | 53.8 | 60.3 | 68.1 | 69.0 | 67.8 |
| | înetuned | xlmr_large | 64.4 | 66.2 | 67.5 | 67.2 | 68.8 | 65.4 | | | 71.7 | 72.4 | 52.3 | 52.5 | | 59.2 | | 64.4 | 68.7 | 72.6 | 72.1 | 71.2 |
| | fin | xlmt_base | 63.5 | 63.5 | 66.6 | 66.9 | 66.2 | 63.3 | 68.7 | 71.7 | 72.5 | 71.5 | 51.8 | 49.5 | 57.8 | 57.5 | 58.7 | 58.5 | 67.0 | 70.0 | 69.8 | 70.1 |
| _ | | xlmt_large | 66.3 | 66.3 | | 68.8 | 67.8 | 67.0 | 72.5 | | 73.9 | <u>7</u> 4.5 | 56.0 | 59.6 | - | 60.5 | 61.3 | 65.8 | 70.6 | - | 73.0 | 73.4 |
| Ē | | bloomz | | | 24.3 | | | | | 15.2 | | | | | 19.3 | | | | | 0.7 | | |
| micro-F | zero | mt0 | | | 38.7 | | | | | 24.7 | | | | | 42.7 | | | | | 43.2 | | |
| E. | ñ | chat-gpt | | | 48.6 | | | | | 49.8 | | | | | 39.2 | | | | | 46.6 | | |
| | | gpt-40 | | | 63.6 | | | | | 65.6 | | | | | 56.6 | | | | | 65.1 | | |
| | | bloomz | | | 23.5 | | | | | 14.6 | | | | | 17.4 | | | | | 4.4 | | |
| | few | mt0 | | | 38.8 | | | | | 25.2 | | | | | 41.8 | | | | | 45.5 | | |
| | đ | chat-gpt | | | 57.2 | | | | | 54.9 | | | | | 44.3 | | | | | 53.9 | | |
| | | gpt-40 | | | 63.2 | | | | | 62.3 | | | | | 57.8 | | | | | 68.6 | | |

Table 3: F1 scores (macro & micro average) for each setting tested in 5-fold cross validation. Fine-tuned models are evaluated on different settings depending on the used training data. *TweetTopic:* TweetTopic was used for training; *Target:* the respective language subset of X-Topic was used for training; *All:* all language subsets of X-Topic were used. The best result for each language is bolded, and underlined scores indicate statistically significant difference with respect to the second best score.

best-performing model *xlmt_large*, Figure 3, Appendix C.

Zero- and Few-Shot. In both zero- and few-shot settings, when considering macro-F1, bloomz, chatgpt, and gtp-40 perform better in English and display a noticeable decline in other languages. In general, gpt-40 consistently surprasses the smaller bloomz7b and mt0, and it's predecessor chat-gpt, across all language and metrics. It is interesting to note the differences in performance tha arise in the zero and few-shot benchmarks. The performance of most models, according to macro-F1, increase in the few-shot benchmark, bloomz being an exception and experiencing a drop of 2.4 points when tested in English. In contrast, gpt-40 displays a decrease in micro-F1 scores across all languages indicating a consistent difficulty in maintaining performance when handling imbalanced datasets with more frequent classes.

5.2 Model Comparison

Training Corpora. Overall, models trained on *X* data, consistently outperform the generic *XLMR* models. Notably, both *bernice* and *xlmt_base*

demonstrate superior performance compared to xlmr_base across all settings and languages, with an average increase in macro-F1 of 11.7 and 8.3 points, respectively. This trend also appears in the larger versions, where *xlmt_large* surpasses *xlmr_large* by an average of 3 macro-F1 points across settings. The performance gap between specific X models and generic XLMR models widens in settings with limited training data (trained only on Target). Specifically, the X-specific models outperform the generic ones by a significant margin, reaching up to a 37-point increase in macro-F1 (e.g., bernice trained on Japanese only) for the base versions and a 12-point increase for the larger versions (e.g., *xlmt_large* trained on Spanish only). These results highlight the benefit of training models on specific domain data.

Fine-tuned models vs few-shot LLMs. The experimental results of LLMs reveal that the task is challenging even for larger models. When compared to the finetuned models, the best performing LLM, *gpt-4o* in the *few-shot* setting, achieves comparable results with *xlmt_base* when fine-tuned on all avail-

| LN | xlmt_large | gpt-4o |
|----|--------------|-------------------|
| en | learning, 78 | other, 85 |
| | arts, 76 | learning, 73 |
| | other, 74 | youth, 69 |
| ja | news, 66 | business, 84 |
| | business, 64 | arts, 76 |
| | arts, 59 | relationships, 74 |
| es | other, 83 | other, 82 |
| | arts, 68 | youth, 80 |
| | travel, 67 | business, 75 |
| gr | other, 89 | other, 95 |
| | youth, 86 | youth, 87 |
| | arts, 76 | science, 71 |

Table 4: Topics with the highest occurrences of False Negatives errors (topic, error %). The results of *xlmt-large* when trained on *TweetTopic* and *All*, and of *gpt-4o* in the *few-shot* setting are displayed.

able datasets, with average macro-F1 of 54.3 and 53.6 for gpt-40 and xlmt_base respectively, however it achieves the best macro-F1 performance in Greek across all models. In order to better understand the behaviour of each type of model, Table 5 displays the average macro Recall and Precision scores achieved by four models of different architectures. Notably, chat-gpt seems to struggle more with identifying correctly the assigned labels, as it achieves relatively smaller Precision scores compared to other models. Instead, recall values of chat-gpt are similar or higher than other models, particularly for English and Spanish. On average, chat-gpt predicts 2, 2.5, 1.5, and 1.4 labels per tweet in English, Spanish, Japanese and Greek, respectively. In contrast, the best performing finetuned model, *xlmt_large*, predicts a more consistent average of 1.7, 1.7, 1.7, and 1.8 labels per tweet on the same languages.

5.3 Error Analysis

Using the best overall performing models, *xlmt-large* trained on *TweetTopic* and *All languages*, and *gpt-4o* in a *few-shot* setting, we attempt to identify patterns in the topics which it struggles the most. Generally, both models attain relatively low recall values (Table 5) compared to precision. We analyse this behaviour by examining the topics with the highest occurrences of errors by analysing the False Negative rates (Table 4). It is interesting to note the high occurrences of errors noted on the *xlmt_large* results across all languages within the relatively infrequent *Arts & Culture* topic, with

| | | Prec | ision | | Recall | | | | | | |
|--------------------|------|------|-------|------|--------|------|------|------|--|--|--|
| | | Es | | | | | | | | | |
| chat-gpt gpt-40 | 53.0 | 39.5 | 46.5 | 44.0 | 63.4 | 63.0 | 49.6 | 43.0 | | | |
| gpt-40 | 67.6 | 61.2 | 60.8 | 63.0 | 58.2 | 53.4 | 52.6 | 47.6 | | | |
| bernice xlm_t | 65.9 | 61.9 | 57.6 | 50.0 | 58.8 | 56.3 | 54.5 | 43.1 | | | |
| xlm_t | 69.2 | 67.7 | 62.1 | 61.1 | 58.1 | 57.9 | 58.4 | 48.2 | | | |

Table 5: Average macro Precision and Recall scores. Results from the few-shot setting are considered for *chat-gpt* and *gpt-4o*. For the *bernice* and *xlm_t* results we considered models trained on TweetTopic and X-Topic

error rates of 76%, 59%, 68%, and 76% for English, Japanese, Spanish, and Greek, respectively. In contrast, *gpt-40* appears to struggle more with the *Youth & Student Life* topic.

Investigating the models' performance in more detail (Tables 9 and 10, Appendix B), reveals a significant weaknesses for both *xlmt_large* and *gpt-40* in the *Other Hobbies* category. Both models exhibit low performance in all languages with *xlmt_large* and *gpt-40* achieving 28% and 25% average F1 respectively, highlighting the difficulty in classifying diverse and less defined subjects.

When looking at examples where the models tend to struggle more, there are clear errors like the tweet 'Being on the other side of the casting table today was so much fun. Saying "just have fun with it" and seeing actors literally just have fun with it was amazin' being classified by gpt-40 as "Family" but also there are entries such as "what are the best web3/crypto newsletters out there not many people know about?" which is labelled as "News & Social Concern", "Science & Technology" by xlmt_large instead of "News & Social Concern", "Business & Entrepreneurs", an arguably valid classification. This behaviour illustrates the difficulty of the task for both human annotators and language models.

6 Conclusions

The aim of this paper is to expand the resources available for the task of tweet classification, particularly in a multi-label setting and across multiple languages. We introduce the new X-Topic dataset, which includes tweets in English, Spanish, Japanese, and Greek, and is centred around a taxonomy of 19 social media topics. This dataset addresses the lack of labelled multilingual X data and encourages the development of new methods for multilingual topic classification.

We explore different model architectures and experimental settings, including zero-shot, monolingual, cross-lingual, and multilingual approaches, to tackle the challenge of multilingual topic classification in social media. Our findings indicate that the task is challenging, especially for less-resourced languages, and that models perform better when trained on a combination of data in various languages. Importantly, our analysis shows how recent LLMs underperform in few-shot settings in comparison to more efficient but fully-trained multilingual masked language models. Further research should focus on addressing these challenges and enhancing the performance of models in a cross-lingual and multilingual context, for which X-Topic can contribute to as a reliable benchmark.

7 Limitations

In this paper, we introduce a valuable new resource that is expected to benefit a wide range of researchers and industry professionals. It is important to acknowledge that there may be differing opinions regarding the methodology used for aggregating the data in X-Topic, specifically the requirement for two annotators' agreement. In any case, we plan to release all the collected annotations, along with the dataset version used in our experiments, to facilitate transparency and further research. The number of languages included in X-Topic selected is relatively small given budget constraints.

Finally, it is important to highlight that while our paper provides a comprehensive analysis of the cross-/multi-lingual capabilities of five different models, substantial research opportunities remain in exploring the potential of alternative classifiers. This includes investigating the performance and fine-tuning of larger models, considering diverse architectures, and optimising the prompts used for one-shot and few-shot learning.

8 Ethics Statement

We acknowledge the importance of the ACL Code of Ethics, and are committed to following the guidelines in the proposed task. Given that our task includes user generated content we are committed to respect the privacy of the users, by replacing each user mention in the texts with a placeholder.

We also make sure to fairly treat the annotators who labelled the dataset, by 1) fairly compensating them with an average of £8 per hour; and 2) do not share or store their personal information. Overall, the total time of annotation was approximately 180 hours with a median time of 25 minutes for each "batch" of 50 tweets and each batch requiring 5 coders.

Finally, we acknowledge the potential concerns around the analysis of individual behaviours using our dataset, but we designed the tasks to focus on aggregated social media content, by measuring systems performances on aggregated data rather than at individual user level. X-Topic will be shared under the CC BY-NC 4.0 Deed (Attribution-NonCommercial 4.0 International).

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A Annotation Guidelines

Below we provide the guidelines provided to the coders of each language.

A.0.1 English

Choose the appropriate topics expressed by the text. You can work on this task only once, multiple tasks from the same annotators will be rejected. Some simple sentences are designed to verify the quality of the annotations.. We will reject tasks where these simple test questions are not correct.

For privacy reasons and to make the annotation easier, all non-verified user mentions are represented as {{USER}} and all URL entries as {{URL}}.

1. Arts & Culture: Content about art forms, which evinces some degree of talent, training, or professionalism.

2. Business & Entrepreneurs: Content that relates to money, the economy, and wealth creation broadly. Including job tips, career advice, and day in the life.

3. Celebrity & Pop Culture: Stars and celebrities, their lives, funny moments, relationships, and fan communities.

4. Diaries & Daily Life: Slice of life, everyday content that illustrates personal opinions, feelings, occasions, and lifestyles.

5. Family: Family dynamics, in-jokes, and everyday moments.

6. Fashion & Style: Content about fashion, outfits, looks, shows, street style, collections, and designers. Both amateur and professional.

7. Film, TV & Video: Traditional media and entertainment, including film, and tv, as well as content about Netflix and other streaming shows.

8. Fitness & Health: Healthy living and the components thereof, including nutrition, exercise, progress, and wellness.

9. Food & Dining: Anything related to food and food culture. Cooking, restaurants, food, reviews, technique, and ASMR.

10. Learning & Educational: Instructive, informative, educational content that teaches a fact, skill or topic.

11. News & Social Concern: Awareness, activism, and discussion of societal issues and injustices contents that focus on coverage of newsworthy events, political and otherwise.

12. Relationships: Relationship dynamics, jokes, relatable moments, and the like between friend groups and romantic partners.

13. Science & Technology: Content related to technology, natural phenomena, as well as knowl-edge and theories about the future and the universe.

14. Youth & Student Life: Moments and memes of life at school and in the classroom, including teachers, events, and the like.

15. Music: Music performance, discussion, experiences and the like.

16. Gaming: Video games related content, gameplay, competition, culture and other games (e.g. board games).

17. Sports: All depictions of sports (e.g. football, baseball, cricket, tennis, etc.).

18. Travel & Adventure: Vacations, travel tips, lodgings, means of conveyance, and the experience of travel.

19. Other Hobbies: Hobbies and personal interests not included in the topics above.

Multiple topics are allowed, please check ALL the relevant topics to the text, when the topic is mixed. Make sure that you check at least one topic in each text.

Do you understand the instructions?

A.0.2 Spanish

Elija los temas apropiados expresados por el texto. Sólo puede trabajar en esta tarea una vez, se rechazarán varias tareas de los mismos anotadores. Algunas oraciones simples están diseñadas para verificar la calidad de las anotaciones. Rechazaremos las tareas en las que estas preguntas de prueba simples no sean correctas.

Por motivos de privacidad y para facilitar la anotación, todas las menciones de usuarios no verificados se representan como {{USUARIO}} y todas las entradas de URL como {{URL}}.

1. Arte y cultura: Contenido sobre formas de arte que demuestre algún grado de talento, capacitación o profesionalismo.

2. Negocios y emprendedores: Contenido relacionado con el dinero, la economía y la creación de riqueza en general. Incluyendo consejos de trabajo, de carrera u otros.

3. Celebridades y cultura pop: Estrellas y celebridades, sus vidas, momentos divertidos, relaciones y comunidades de admiradores.

4. Diarios y vida diaria: Contenido cotidiano y de vida diaria que ilustra opiniones personales, sentimientos, eventos y estilos de vida.

5. Familia: Dinámicas y referencias familiares, momentos cotidianos.

6. Moda y estilo: Contenido sobre moda, atuendos, looks, desfiles, estilo callejero, colecciones y diseñadores. Tanto amateur como profesional.

7. Cine, televisión y video: Medios tradicionales y de entretenimiento, incluidos cine y televisión, así como contenido sobre programas de streaming.

8. Estado físico y salud: Estilos de vida saludable y similar, incluida la nutrición, el ejercicio, el progreso y el bienestar.

9. Food & Dining: Todo lo relacionado con la comida y la cultura gastronómica. Cocina, restaurantes, comida, reseñas, recetas y otros.

10. Aprendizaje y educación: Contenido instructivo, informativo y educativo para enseñar hechos, habilidades o temáticas.

11. Noticias e interés social: Conciencia, activismo y debate sobre problemas sociales y contenidos de injusticias que se centran en la cobertura de eventos de interés periodístico, políticos y de otro tipo.

12. Relaciones: Dinámicas de relación, bromas, momentos identificables y similares entre grupos de amigos y parejas románticas.

13. Ciencia y Tecnología: Contenido de tecnología, fenómenos naturales, así como conocimientos y teorías sobre el futuro y el universo.

14. Juventud y Vida Estudiantil: Momentos y memes de la vida en la escuela y en clase, incluidos maestros, eventos y similares.

15. Música: Interpretación musical, discusión, experiencias y similares.

16. Juegos: Contenido relacionado con videojuegos, juegos de rol, competición y otros juegos (por ejemplo, juegos de mesa).

17. Deportes: Todo lo relacionado con el deporte (por ejemplo, fútbol, béisbol, atletismo, tenis, etc.).

18. Viajes y aventuras: Vacaciones, consejos de viaje, alojamiento, medios de transporte y experiencias de viaje.

19. Otros pasatiempos: Pasatiempos, hobbies e intereses personales no incluidos en los temas

anteriores.

Se permiten múltiples temas, marque TODOS los temas relevantes para el texto (puede ser más de uno cuando la temática es variada).

Asegúrese de marcar al menos un tema en cada texto.

¿Entiendes las instrucciones?

A.0.3 Japanese

インストラクション

ツイートの文章に対し、適切なトピックを リストから選んでください。このアノテー ションには一度しか参加することはできま せん。同じアノテーターから複数のアノテー ションがあった場合、それは受理されるこ とはありませんので注意してください。アノ テーションの品質保持のためアノテーション の中にはいくつか簡単な例題があり、それら を間違えた場合もアノテーションは受理され ません。

ツイートのプライバシー保護のため、nonverified user name 及びweb url はマスキングさ れています。

1. アート&カルチャー: アートや文化など 芸術性や専門性の高い物に関するツイート。

2. ビジネス: 経済やビジネス、金融などに 関わるツイート。キャリア形成や転職情報な ども含まれます。

3. 芸能: 芸能人やそれらが主催するイベントなどに関するツイート。

4. 日常: 日々の出来事などの日常的な事柄 に関するツイート。

5. 家族: 家族に関するツイート

6. ファッション: ストリートスナップやデ ザイン、ファッションに関するツイート。

7. 映画&ラジオ: TVやラジオ、映画などの エンタメ等に関するツイート。

8. フィットネス&健康: 栄養、フィットネスなどに関するツイート。

9. 料理: 料理やレストランなど食に関する ツイート

10. 教育関連: 教育に関するツイート。

11. 社会: 社会情勢やそれに通ずるニュー ス、政治などに関するツイート。

12. 人間関係: パートナーシップや恋人との関係性などに関するツイート。

13. サイエンス: IT含むサイエンスに関す るツイート。

14. 学校: 学校での出来事や行事に関する ツイート。

15. 音楽: 音楽フェスや音楽そのものに関 するツイート。 16. ゲーム: ゲーム(オンラインゲームや ビデオゲーム等)に関するツイート。

17. スポーツ: スポーツに関するツイート。 18. 旅行: 旅行に関するツイート。

19. その他: その他、趣味や個人の嗜好に 関するツイート。一つのツイートに対し複数 のラベルの付与が可能になってます。

少なくとも一つのトピックを選んでください。

インストラクションは理解できましたで しょうか?

A.0.4 Greek

Επιλέξτε τα κατάλληλα θέματα που εκφράζει το κείμενο.

Μπορείτε να εργαστείτε σε αυτήν την εργασία μόνο μία φορά, πολλές εργασίες από τους ίδιους σχολιαστές θα απορριφθούν. Ορισμένες απλές προτάσεις έχουν σχεδιαστεί για να επαληθεύουν την ποιότητα των σχολιασμών. Θα απορρίψουμε εργασίες όπου αυτές οι απλές ερωτήσεις δοχιμής δεν είναι σωστές. Για λόγους απορρήτου χαι για να γίνει ευχολότερος ο σχολιασμός, όλες οι μη επαληθευμένες αναφορές χρηστών αντιπροσωπεύονται ως {{USER}} χαι όλες οι URL ως {{URL}.

1. Τέχνες & Πολιτισμός: Περιεχόμενο για μορφές τέχνης, το οποίο δείχνει κάποιο βαθμό ταλέντου, κατάρτισης ή επαγγελματισμού.

2. Επιχειρήσεις & Επιχειρηματίες: Περιεχόμενο που σχετίζεται γενικά με τα χρήματα, την οικονομία και τη δημιουργία πλούτου. Συμπεριλαμβάνονται συμβουλές για δουλειά, συμβουλές σταδιοδρομίας, κτλ.

3. Διασημότητες & Ποπ χουλτούρα: Αστέρια και διασημότητες, η ζωή τους, αστείες στιγμές, σχέσεις και κοινότητες θαυμαστών.

4. Ημερολόγια & Καθημερινή ζωή: Στιγμές της ζωής, καθημερινό περιεχόμενο που απεικονίζει προσωπικές απόψεις, συναισθήματα, περιστάσεις και τρόπους ζωής.

5. Οικογένεια: Δυναμική της οικογένειας, αστεία και καθημερινές στιγμές.

6. Μόδα & Στυλ: Περιεχόμενο σχετικά με τη μόδα, τα ρούχα, τις εμφανίσεις, τις επιδείξεις, το στρεετ στψλε, τις συλλογές και τους σχεδιαστές. Ερασιτεχνική και επαγγελματική.

 Ταινίες, τηλεόραση & βίντεο: Παραδοσιακά μέσα και ψυχαγωγία, συμπεριλαμβανομένων ταινιών και τηλεόρασης, καθώς και περιεχόμενο για το Νετφλιξ και άλλες εκπομπές ροής. 8. Γυμναστική & Υγεία: Υγιεινή ζωή και τα συστατικά της, συμπεριλαμβανομένης της διατροφής, της άσκησης, της προόδου και της ευεξίας.

9. Φαγητό & Δείπνο: Οτιδήποτε σχετίζεται με το φαγητό και την κουλτούρα του φαγητού. Μαγειρική, εστιατόρια, φαγητό, κριτικές, τεχνική και ASMR.

10. Μάθηση & Εκπαίδευση: Εκπαιδευτικό, ενημερωτικό, εκπαιδευτικό περιεχόμενο που διδάσκει ένα γεγονός, μια δεξιότητα ή ένα θέμα.

11. Ειδήσεις & Κοινωνία: Ευαισθητοποίηση, ακτιβισμός και συζήτηση για κοινωνικά ζητήματα και αδικίες, περιεχόμενα που εστιάζουν στην κάλυψη γεγονότων άξιων ειδήσεων, πολιτικών και άλλων.

12. Σχέσεις: Δυναμική σχέσεων, αστεία, συγγενείς στιγμές και άλλα παρόμοια μεταξύ ομάδων φίλων και ρομαντικών συντρόφων.

13. Επιστήμη & Τεχνολογία: Περιεχόμενο αιχμής τεχνολογίας, φυσικά φαινόμενα, καθώς και γνώση και θεωρίες για το μέλλον και το σύμπαν.

14. Νεανική & Φοιτητική ζωή: Στιγμές και μεμες της ζωής στο σχολείο και στην τάξη, συμπεριλαμβανομένων δασκάλων, εκδηλώσεων και παρόμοια.

15. Μουσική: Μουσική παράσταση, συζήτηση, εμπειρίες και παρόμοια.

16. Παιχνίδια: περιεχόμενο σχετικό με βιντεοπαιχνίδια, παιχνίδι, ανταγωνισμό, πολιτισμό και άλλα παιχνίδια (π.χ. επιτραπέζια παιχνίδια).

17. Αθλητισμός: Όλες οι απεικονίσεις αθλημάτων (π.χ. ποδόσφαιρο, μπέιζμπολ, τένις).

18. Ταξίδια & Περιπέτεια: Διακοπές, ταξιδιωτικές συμβουλές, καταλύματα, μεταφορικά μέσα και η εμπειρία του ταξιδιού.

19. Άλλα χόμπι: Χόμπι και προσωπικά ενδιαφέροντα που δεν περιλαμβάνονται στα παραπάνω θέματα.

Επιτρέπονται πολλά θέματα, παραχαλούμε ελέγξτε ΟΛΑ τα σχετιχά θέματα στο χείμενο, όταν τα θέματα αναμιγνύονται. Βεβαιωθείτε ότι έχετε επιλέξει τουλάχιστον ένα θέμα σε χάθε χείμενο.

Καταλαβαίνετε τις οδηγίες.

B Models & Dataset

B.1 Dataset

Table 6 displays the number of remaining tweets in each preprocessing step for each language. The



Figure 2: Overlap between topics across all languages. Darker color indicates higher overlap

steps are: 1) language detection (ftext), 2) removal of incomplete/abusing tweets, 3) deduplication, 4) removal of tweets with high ammount of mentions and emojis, and 5) removal of tweets containing URLs.

Figure 2 displays the overlap between topics across all languages.

B.2 Models

In total we estimate 168 hours used for the training of *bernice*, *xlm_r*, and *xlm_t* models using a NVIDIA GeForce RTX 4090 GPU and 20 hours for *bloomz* and *mt0* models using an NVIDIA Quadro RTX 8000 GPU. Table 7 provides details for the models used in our experiments.

B.3 Prompts

Below we present the prompt used in the zero and few-shot settings of our experiments. The prompt used were similar to the ones used in Muennighoff et al. (2022).

Classify the text "{{ tweet }}" into the following topics: - {{ answer_choices | join('\n- ') }} Topics:

B.4 Topics Abbreviation

Below we provide the abbreviations of topics used in the paper:

Arts & Culture: arts Business & Entrepreneurs: business Celebrity & Pop Culture: celebrity Diaries & Daily Life: diaries Family: family Fashion & Style: fashion Film, TV & Video: film Fitness & Health: fitness Food & Dining: food Learning & Educational: learning News & Social Concern: news Relationships: relationships Science & Technology: science Youth & Student Life: youth Music: music Gaming: gaming Sports: sports Travel & Adventure: travel Other Hobbies: other

C Extended Results

Figure 3, displays the scores achieved by the overall best-performing model, *xlm_t-large*, in each language and setting.

Tables 9 and 10 display detail results for the two best performing models, *xlmt_large*, trained on *TweetTopic* and *All languages*, and *gpt-4o*, in the *few-shot* setting, respectively. The precision, recall, and f1 scores for each topic in every language are displayed.

Table 8 displays the macro and micro F1 scores achieved when using supervised SuperCTM (Card et al., 2017) with the default parameters as provided in the Contextualized Topic Models (CTM) (Bianchi et al., 2021) implementation. The model was trained using both TweetTopic and X-Topic. As seen by the results the model fails to perform well and only manages to achieve mediocre micro-F1 scores when tested on English and Spanish.

| | Total | ftext | incomplete/abusing | deduplication | mentions/emojis | URLS |
|----|---------|---------|--------------------|---------------|-----------------|---------|
| en | 225,400 | 217,491 | 208,442 | 193,560 | 178,841 | 81,929 |
| es | 225,350 | 218,163 | 197,617 | 186,266 | 178,060 | 110,669 |
| ja | 455,846 | 455,846 | 438,080 | 407,589 | 383,669 | 207,472 |
| gr | 225,300 | 218,461 | 214,031 | 206,147 | 203,947 | 30,858 |



Table 6: Number of remaining tweets for each preprocessing step for every language.

Figure 3: F1 scores (macro average) of the best overall performing model (*xlmt_large*) in each setting and language.

| Model | Parameters |
|----------------|--------------------|
| Bernice | 125M |
| XLM-R(T) base | 270M |
| XLM-R(T) large | 550M |
| bloomz | 7B |
| mt0 | 13B |
| chat-gpt | 175B (approximate) |

Table 7: Number of Parameters in different languagemodels used.

| Metric | en | es | ja | gr |
|--------|------|------|-----|-----|
| macro | 6.4 | 6.5 | 1.5 | 5.0 |
| micro | 30.4 | 44.0 | 8.3 | 7.4 |

Table 8: Macro and F1 scores for each language for the SuperCTM model.

| | | en | | | es | | | gr | | | ja | |
|--------------------------|----|-----|----|----|-----|----|----|-----|----|----|-----|----|
| topic | Pr | Rec | F1 |
| arts & culture | 26 | 20 | 23 | 60 | 34 | 40 | 48 | 42 | 44 | 32 | 19 | 24 |
| business & entrepreneurs | 79 | 65 | 70 | 55 | 34 | 41 | 51 | 36 | 41 | 64 | 45 | 52 |
| celebrity & pop culture | 54 | 49 | 51 | 60 | 57 | 57 | 48 | 42 | 43 | 60 | 70 | 64 |
| diaries & daily life | 80 | 71 | 75 | 77 | 85 | 81 | 70 | 81 | 75 | 80 | 83 | 81 |
| family | 85 | 60 | 69 | 60 | 58 | 59 | 66 | 78 | 71 | 57 | 50 | 53 |
| fashion & style | 70 | 70 | 69 | 80 | 65 | 68 | 56 | 50 | 52 | 40 | 30 | 33 |
| film tv & video | 73 | 74 | 73 | 46 | 51 | 47 | 61 | 65 | 62 | 67 | 66 | 66 |
| fitness & health | 69 | 54 | 57 | 74 | 52 | 60 | 79 | 65 | 72 | 62 | 62 | 62 |
| food & dining | 91 | 72 | 79 | 95 | 78 | 83 | 87 | 87 | 87 | 68 | 44 | 51 |
| gaming | 82 | 61 | 67 | 50 | 60 | 53 | 66 | 68 | 66 | 13 | 10 | 11 |
| learning & educational | 59 | 22 | 30 | 52 | 55 | 52 | 60 | 63 | 52 | 70 | 58 | 62 |
| music | 79 | 87 | 82 | 73 | 80 | 76 | 69 | 72 | 69 | 75 | 53 | 58 |
| news & social concern | 76 | 68 | 72 | 88 | 90 | 89 | 51 | 33 | 40 | 91 | 89 | 90 |
| other hobbies | 43 | 26 | 32 | 37 | 17 | 23 | 43 | 43 | 43 | 23 | 13 | 14 |
| relationships | 82 | 62 | 71 | 78 | 73 | 75 | 54 | 46 | 50 | 63 | 57 | 60 |
| science & technology | 66 | 68 | 67 | 90 | 65 | 71 | 38 | 33 | 34 | 63 | 33 | 39 |
| sports | 87 | 93 | 90 | 84 | 79 | 81 | 81 | 73 | 75 | 95 | 92 | 93 |
| travel & adventure | 68 | 50 | 57 | 63 | 32 | 39 | 65 | 56 | 60 | 27 | 29 | 25 |
| youth & student life | 46 | 31 | 37 | 64 | 37 | 44 | 87 | 76 | 78 | 31 | 12 | 17 |

Table 9: Precision (Pr), Recall (Rec), and F1 scores for each topic achieved by *xlmt_large* trained on *TweetTopic* and *All languages*.

| | | en | | | es | | | gr | | | ja | |
|--------------------------|----|-----|----|----|-----|----|----|-----|----|----|-----|----|
| topic | Pr | Rec | F1 |
| arts & culture | 52 | 28 | 36 | 65 | 34 | 39 | 55 | 40 | 44 | 61 | 28 | 38 |
| business & entrepreneurs | 72 | 50 | 58 | 79 | 27 | 39 | 88 | 34 | 44 | 47 | 13 | 20 |
| celebrity & pop culture | 50 | 65 | 56 | 50 | 58 | 53 | 70 | 55 | 61 | 51 | 47 | 46 |
| diaries & daily life | 86 | 40 | 55 | 91 | 38 | 54 | 93 | 50 | 65 | 76 | 60 | 67 |
| family | 82 | 67 | 73 | 49 | 63 | 52 | 45 | 56 | 50 | 58 | 62 | 59 |
| fashion & style | 55 | 93 | 68 | 39 | 70 | 46 | 47 | 50 | 47 | 41 | 55 | 46 |
| film tv & video | 86 | 69 | 76 | 57 | 39 | 46 | 95 | 49 | 64 | 63 | 63 | 62 |
| fitness & health | 57 | 65 | 60 | 62 | 37 | 45 | 58 | 47 | 49 | 82 | 53 | 64 |
| food & dining | 95 | 62 | 73 | 75 | 79 | 76 | 67 | 69 | 66 | 80 | 73 | 76 |
| gaming | 60 | 69 | 63 | 40 | 48 | 42 | 40 | 30 | 33 | 76 | 70 | 73 |
| learning & educational | 55 | 27 | 37 | 83 | 88 | 85 | 63 | 33 | 42 | 61 | 62 | 55 |
| music | 73 | 88 | 80 | 82 | 50 | 62 | 69 | 77 | 68 | 61 | 74 | 66 |
| news & social concern | 71 | 71 | 71 | 86 | 59 | 67 | 95 | 86 | 90 | 60 | 29 | 38 |
| other hobbies | 51 | 16 | 24 | 40 | 29 | 31 | 20 | 4 | 7 | 48 | 31 | 38 |
| relationships | 83 | 59 | 69 | 66 | 89 | 75 | 69 | 48 | 57 | 68 | 26 | 37 |
| science & technology | 69 | 62 | 65 | 30 | 60 | 40 | 60 | 29 | 36 | 20 | 35 | 25 |
| sports | 88 | 96 | 92 | 73 | 88 | 80 | 93 | 95 | 94 | 79 | 85 | 82 |
| travel & adventure | 59 | 52 | 54 | 50 | 42 | 45 | 37 | 42 | 35 | 66 | 67 | 63 |
| youth & student life | 47 | 34 | 39 | 22 | 15 | 17 | 35 | 12 | 18 | 52 | 49 | 49 |

Table 10: Precision (Pr), Recall (Rec), and F1 scores for each topic achieved by gpt-40 in the few-shot setting.