XLM-T: A Multilingual Language Model Toolkit for Twitter

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Abstract

Language models are ubiquitous in current NLP, and their multilingual capacity has recently attracted considerable attention. However, current analyses have almost exclusively focused on (multilingual variants of) standard benchmarks, and have relied on clean pre-training and task-specific corpora as multilingual signals. In this paper, we introduce XLM-T, a framework for using and evaluating multilingual language models in Twitter. This framework features two main assets: (1) a strong multilingual baseline consisting of an XLM-R (Conneau et al., 2020) model pre-trained on millions of tweets in over thirty languages, alongside starter code to subsequently fine-tune on a target task; and (2) a set of unified sentiment analysis Twitter datasets in eight different languages. This is a modular framework that can easily be extended to additional tasks, as well as integrated with recent efforts also aimed at the homogenization of Twitter-specific datasets (Barbieri et al., 2020).

1 Introduction

Multilingual NLP is increasingly becoming popular. Despite the concerning disparity in terms of language resource availability (Joshi et al., 2020), the advent of Language Models (LMs) has indisputably enabled a myriad of multilingual architectures to flourish, ranging from LSTMs to the arguably more popular transformer-based models (Chronopoulou et al., 2019; Pires et al., 2019). Multilingual LMs integrate streams of multilingual textual data without being tied to one single task, learning general-purpose multilingual representations (Hu et al., 2020). As testimony of this landscape, we find multilingual variants stemming from well-known monolingual LMs, which have now become a standard among the NLP community. For instance, mBERT from BERT (Devlin et al., 2019), mT5 (Xue et al., 2020) from T5 (Raffel et al., 2020) or XLM-R (Conneau et al., 2020) from RoBERTa (Liu et al., 2019). Social media data, however, and specifically Twitter (the platform we focus on in this paper), seem to be so far surprisingly neglected from this trend of massive multilingual pretraining. This may be due to, in addition to its well-known uncurated nature (Derczynski et al., 2013), because of discursive and platform-specific factors such as out-of-distribution samples, misspellings, slang, vulgarisms, emoji and multimodality, among others (Barbieri et al., 2018; Camacho-Collados et al., 2020). This is an important consideration, as there is ample agreement that the quality of LM-based multilingual representations is strongly correlated with typological similarity (Hu et al., 2020), which is somewhat blurred out in the context of Twitter.

In this paper, we bridge this gap by introducing a toolkit for evaluating multilingual Twitter-specific language models. This framework, which we make available to the NLP community, is initially comprised of a large multilingual Twitter-specific LM based on XLM-R checkpoints (Sect. 2), from which we report an initial set of baseline results in different settings (including zero-shot). Moreover, we provide starting code for analyzing, fine-tuning and evaluating existing language models. To carry out a comprehensive multilingual evaluation, while also laying the foundations for future extensions, we devise a unified dataset in 8 languages for sentiment analysis (which we call Unified Multilingual Sentiment Analysis Benchmark, UMSAB henceforth), as this task is by far the most studied problem in NLP in Twitter (cf., e.g., Salameh et al. (2015); Zhou et al. (2016); Meng et al. (2012); Chen et al. (2018); Rasooli et al. (2018); Vilares et al. (2017); Barnes et al. (2019); Patwa et al. (2020); Barriere and Balahur (2020)). Finally, in order to have a solid point of comparison with respect to standard English Twitter tasks,
we also report results on the TweetEval framework (Barbieri et al., 2020). Our results suggest that when fine-tuning task-specific Twitter-based multilingual LMs, a domain-specific model proves more consistent than its general-domain counterpart, and that in some cases a smart selection of training data may be preferred than large-scale fine-tuning on many languages.

2 Language Models in Twitter

Our framework revolves around Twitter-specific language models. In particular, we train our own multilingual language-specific language model (Section 2.1), which we then fine-tune for various monolingual and multilingual applications, and for which we provide a suitable interface (Section 2.2). Additionally, we complement these basic functionalities with starter code for computing tweet embeddings, multilingual tweet retrieval and analysis based on the released language models.

2.1 Released Language Models

We used the Twitter API to retrieve 198M tweets\(^2\) posted between May’18 and March’20, which are our source data for LM pretraining. We only considered tweets with at least three tokens and with no URLs to avoid bot tweets and spam advertising. Additionally, we did not perform language filtering, aiming at capturing a general distribution. Figure 1 lists 30 most represented languages by frequency, showing a prevalence of widely spoken languages such as English, Portuguese and Spanish, with the first significant drop in frequency affecting Russian at the 11th position.

In terms of opting for pretraining a LM from scratch or building upon an existing one, we follow Gururangan et al. (2020) and Barbieri et al. (2020) and continue training an XLM-R language model from publicly available checkpoints\(^3\), which we selected due to the high results it has achieved in several multilingual NLP tasks (Hu et al., 2020). We use the same masked LM objective, and train until convergence in a validation set. The model converged after about 14 days on 8 NVIDIA V100 GPUs.\(^4\)

While this multilingual language model (referred to as \textit{XLM-Twitter} henceforth) is the main focus on this paper, our toolkit also integrates monolingual language models of any nature, including the English monolingual Twitter models released in Barbieri et al. (2020) and Nguyen et al. (2020).

2.2 Language Model Fine-tuning

In this section we explain the fine-tuning implementation of our framework. The main task evaluated in this paper is tweet classification, for which we provide unified datasets. One of the main differences with respect to standard fine-tuning is that we integrate the adapter technique (Houlsby et al., 2019), by means of which we freeze the LM and only fine-tune one additional classification layer. We follow the same adapter configuration proposed in Pfeiffer et al. (2020). This technique provides benefits in terms of memory and speed, which in practice facilitates the usage of multilingual lan-

\(^2\)1,724 million tokens (12G of uncompressed text).

\(^3\)https://huggingface.co/xlm-roberta-base.

\(^4\)The estimated cost for the language model pre-training is USD 5,000 on Google Cloud.
Starting code. In order to enable fast prototyping on our framework, in addition to datasets and pretrained models we also provide code base for feature extraction from Tweets (i.e., obtaining tweet embeddings) (Figure 2), tweet classification and model fine-tuning, which again, is based on the adapter technique (cf. Section 3.2).

3 Evaluation

We assess the reliability of our released multilingual Twitter-specific language model in two different ways: (1) we perform an evaluation on a wide range of English-specific datasets (Section 3.1); (2) we compose a large multilingual benchmark for sentiment analysis where we assess the multilingual capabilities of the language model (Section 3.2).

Experimental Setting. In each experiment we perform three runs with different seeds, and use early stopping on the validation loss. We only tune the learning rate (0.001 and 0.0001) and, unless noted otherwise, all results we report are the average of three runs of macro-average F1 scores.

In this paper we do not focus on evaluating the reliability of the adapter technique as this was tested in previous papers. Instead, we add this functionality as default for the code and all our experiments.

Table 1 shows the results of the language models and TweetEval baselines\(^7\) As can be observed, our proposed XLM-R-Twitter improves over strong baselines such as RoBERTa-base and XLM-R that do not make use of Twitter corpora, and RoBERTa-Twitter, which is trained on Twitter corpora only. This highlights the reliability of our multilingual model in language-specific settings. However, it underperforms when compared with monolingual Twitter-specific models, such as the RoBERTa model further pre-trained on English tweets proposed in Barbieri et al. (2020), as well as BERTweet (Nguyen et al., 2020), which was trained on a corpus that is an order of magnitude larger\(^8\). This is to be expected as goes in line with previous research that shows that monolingual models tend to underperform multilingual models in terms of models, we evaluate a standard pre-trained XLM-R and XLM-Twitter, our XLM-R model pretrained on a multilingual Twitter dataset starting from XLM-R checkpoints (see Sect. 2.1). For the monolingual experiments we also include a Fast-Text (FT) baseline (Joulin et al., 2017), which relies on monolingual FT embeddings trained on Common Crawl and Wikipedia (Grave et al., 2018) as initialization for each language lookup table.

3.1 Monolingual Evaluation (TweetEval)

In order to provide an additional point of comparison for our released multilingual language model, we perform an evaluation on standard Twitter-specific tasks in English, for which we can compare its performance with existing models. In particular, we evaluate XLM-Twitter on a suite of seven heterogeneous tweet classification tasks from the TweetEval benchmark (Barbieri et al., 2020). TweetEval is composed of seven tasks: emoji prediction (Barbieri et al., 2018), emotion recognition (Mohammad et al., 2018), hate speech detection (Basile et al., 2019), irony detection (Van Hee et al., 2018), offensive language identification (Zampieri et al., 2019), sentiment analysis (Rosenthal et al., 2019) and stance detection\(^6\) (Mohammad et al., 2016).

The stance detection dataset is in turn is divided in five subtopics.

\(^7\)Please refer to the original TweetEval paper (Barbieri et al., 2020) for details on the implementation of all the baselines.

\(^8\)While XLM-R-Twitter was fine-tuned on the same amount of English tweets (60M) than RoBERTa-Tw, BERTweet was trained on 850M English tweets.
Analysis (SA). We first flesh out the process followed in the evaluated models have completeness, in the appendix.

| Metric | Emoji | Emotion | Hate | Irony | Offensive | Sentiment | Stance | ALL |
|--------|-------|---------|------|-------|-----------|-----------|--------|-----|
| SVM    | 29.3  | 64.7    | 36.7 | 61.7  | 52.3      | 62.9      | 67.3   | 53.5 |
| FastText | 25.8  | 65.2    | 50.6 | 63.1  | 73.4      | 62.9      | 65.4   | 58.1 |
| BLSTM  | 24.7  | 66.0    | 52.6 | 62.8  | 71.7      | 58.3      | 59.4   | 56.5 |
| RoB-Bs | 30.9±0.2 (30.8) | 76.1±0.5 (76.6) | 46.6±2.5 (44.9) | 59.7±5.0 (55.2) | 79.5±0.7 (78.7) | 71.3±1.1 (72.0) | 68±0.8 (70.9) | 61.3 |
| RoB-RT | 31.4±0.4 (31.6) | 78.5±1.2 (79.8) | 52.3±2.0 (55.5) | 61.7±6.0 (62.5) | 80.5±1.4 (81.6) | 72.6±0.4 (72.9) | 69.3±1.1 (72.6) | 65.2 |
| RoB-Tw | 29.3±0.4 (29.5) | 72.0±2.9 (71.7) | 46.9±2.9 (45.1) | 65.4±3.1 (65.1) | 77.1±1.3 (78.6) | 69.1±2.2 (69.3) | 66.7±1.0 (67.9) | 61.0 |
| XLM-R  | 28.6±0.7 (27.7) | 72.3±3.6 (68.5) | 44.4±0.7 (43.9) | 57.4±1.7 (54.2) | 75.7±1.9 (73.6) | 68.6±1.2 (69.6) | 65.4±0.8 (66.0) | 57.6 |
| XLM-Tw | 30.9±0.5 (30.8) | 77.0±1.5 (78.3) | 50.8±6.0 (51.5) | 69.9±1.0 (70.0) | 79.9±0.8 (79.3) | 72.3±0.2 (72.3) | 67.1±1.4 (68.7) | 64.4 |
| SotA   | 33.4  | 79.3    | 56.4 | 82.1  | 79.5      | 73.4      | 71.2   | 67.9 |

Table 1: TweetEval test results. For neural models we report both the average result from three runs and its standard deviation, and the best result according to the validation set (parentheses). SotA results correspond to the best TweetEval reported system, i.e., Nguyen et al. (2020). 9

In the following section we evaluate XLM-Twitter on multilingual settings, including evaluation in monolingual and cross-lingual scenarios.

3.2 Multilingual Evaluation (Sentiment Analysis)

We focus our evaluation on multilingual Sentiment Analysis (SA). We first flesh out the process followed to compile and unify our cross-lingual SA benchmark (Sect. 3.2.1). Our experiments can then be grouped into two types: when no training in the target language is available, i.e., zero-shot (Sect. 3.2.2), and when the evaluated models have access to target language training data, either alone or as part of a larger fully multilingual setting (Sect. 3.2.3).

3.2.1 Unified Multilingual Sentiment Analysis Benchmark (UMSAB)

We aim at constructing a balanced multilingual SA dataset, i.e., where all languages are equally distributed in terms of frequency, and with representation of typologically distant languages. To this end, we compiled monolingual SA datasets for eight diverse languages, whose statistics we list in Table 2, as well as their spanning timeframes. Given that retaining the original distribution would skew the unified dataset towards the most frequent languages, we established a maximum number of tweets corresponding to the size of the smallest dataset, specifically the 3,033 for the Hindi portion, and prune all data splits for all languages with this threshold. This leaves 1,839 training tweets (with 15% of them allocated to a fixed validation set), and 870 for testing. The total size of the dataset is thus 24,262 tweets. Let us highlight two additional important design decisions: first, we enforced a balanced distribution across the three labels (positive, negative and neutral), and second, we kept the original training/test splits in each dataset. After this preprocessing, we obtain 8 datasets of 3,033 instances, respectively. Note that some languages in this dataset agglutinate or refer to specific variations. In particular, we use Hindi to refer to the grouping of Hindi, Bengali and Tamil, Portuguese for Brazilian Portuguese, and Spanish for Iberian, Peruvian and Costa Rican variations.

3.2.2 Zero-shot Cross-lingual Transfer

Table 3 shows zero-shot results of XLM-R and XLM-Twitter in our multilingual sentiment analysis benchmark. The performance of both models is competitive, especially considering the diversity of domains and that the source language was not seen during training. An interesting observation concerns those cases in which zero-shot models outperform their monolingual counterparts (e.g., English→Arabic or Italian→Hindi). Additionally, XLM-Twitter proves more robust, achieving the best overall results in six of the eight languages, with consistent improvements in general, and with remarkable improvements in e.g., Hindi, outperforming XLM-R by 7.9 absolute points. Finally,
Table 2: Sentiment analysis datasets for the eight languages used in our experiments.

| Language | Dataset | Time-Train | Time-Test |
|----------|---------|------------|-----------|
| Arabic   | SemEval-2017 (Rosenthal et al., 2017) | 09/2016 to 11/2016 | 12/2016 to 1/2017 |
| English  | SemEval-2017 (Rosenthal et al., 2017) | 01/2012 to 12/2015 | 12/2016 to 1/2017 |
| French   | Deft-2017 (Benamar et al., 2017) | 2014-2016 | Same |
| German   | SB-10K (Cieliebak et al., 2017) | 8/2013 to 10/2013 | Same |
| Hindi    | SAIL 2015 (Patra et al., 2015) | NA, 3 months | Same |
| Italian  | Sentipolc-2016 (Barbieri et al., 2016) | 2013-2016 | 2016 |
| Portuguese | SentiBR (Brum and Nunes, 2017) | 1/2017-7/2017 | Same |
| Spanish  | Intertass 2017 (Díaz Galíano et al., 2018) | 7/2016 to 01/2017 | Same |

Table 3: Zero-shot cross-lingual experiments. We use the best model in the language on the column and evaluate on the test set of the language of each row. For example, when we forward the best XLM-R trained on English text on the Arabic test set we obtain 64.1. In the columns All minus one (All-1) we train on all the languages excluding the one of each row. For example, we obtain a F1 of 59.2 on the Arabic test set when we train an XLM-R using all the languages excluding Arabic. On the diagonals, in gray, models are trained and evaluated on the same language.

| Language | XLM-R | | | | | XLM-Twitter | | | |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Ar       | 63.6  | 64.1  | 54.4  | 53.9  | 22.9  | 57.4  | 62.4  | 62.2  | 59.2  |
| En       | 64.2  | 68.2  | 61.6  | 63.5  | 23.7  | 68.1  | 65.9  | 67.8  | 68.2  |
| Fr       | 45.4  | 52.1  | 72.0  | 36.5  | 16.7  | 43.3  | 40.8  | 56.7  | 53.6  |
| De       | 43.5  | 64.4  | 55.2  | 73.6  | 21.5  | 60.8  | 60.1  | 62.0  | 63.6  |
| Hi       | 48.2  | 52.7  | 43.6  | 47.6  | 36.6  | 54.4  | 51.6  | 51.7  | 49.9  |
| It       | 48.8  | 65.7  | 63.9  | 66.9  | 22.1  | 71.5  | 63.1  | 58.9  | 65.7  |
| Pt       | 41.5  | 63.2  | 57.9  | 59.7  | 26.5  | 59.6  | 67.1  | 65.0  | 65.0  |
| Es       | 47.1  | 63.1  | 56.8  | 57.2  | 26.2  | 57.6  | 63.1  | 65.9  | 63.0  |

Table 4 shows macro-F1 results for the following three settings: (1) monolingual, where we train and test in one single language; (2) bilingual, where we use the best-performing cross-lingual zero-shot model, and continue fine-tuning on training data from the target language; and (3) an entirely multilingual setting where we train with data from all languages. One of the most notable conclusions in the light of these figures is that increasing the training data even in different languages is a useful strategy, and is particularly rewarding in the case of XLM-Twitter and in challenging datasets and languages (e.g., the Hindi results significantly increase from 40.29 to 56.39). Interestingly, a smart selection of languages based on validation accuracy achieves better results than if trained on all languages in half of the cases. This may be due to the (dis)similarity of the datasets (in terms of topic or typological proximity), although overall the main conclusion we can draw is that there is an obvious trade-off, as a single multilingual model is often more practical and versatile.

4 Qualitative Analysis

As an additional qualitative analysis, we plot in Figure 3 a sample of similarity scores (by cosine distance) between XLM-Twitter-based embeddings obtained from the English training set and the sentiment analysis test sets for the other 7 languages (see Section 3.2.1). In addition to the clearly low resemblance with Hindi, we find that the most similar languages in the embedding space are English
Table 4: Cross-lingual sentiment analysis F1 results on target languages using target language training data (Monolingual) only, combined with training data from another language (Bilingual) and with all languages at once (Multilingual). "All" is computed as the average of all individual results.

| Language | Monolingual | Bilingual | Multilingual |
|----------|-------------|-----------|--------------|
| Ar       | 45.98       | 63.56     | **67.67**    |
| En       | 50.85       | 68.18     | 66.89        |
| Fr       | 54.82       | 71.98     | 68.19        |
| De       | 59.56       | 73.61     | 76.13        |
| Hi       | 37.08       | 36.60     | 40.29        |
| It       | 54.65       | 71.47     | 70.91        |
| Pt       | 55.05       | 67.11     | 75.98        |
| Sp       | 50.06       | 65.87     | 68.52        |
| All      | 51.01       | 64.80     | 66.82        |

Figure 3: Cross-lingual similarity (by cosine distance) between the English training set and the test sets in the other 7 languages. The embeddings are obtained by averaging all the XLM-Twitter contextualized embeddings for each tweet.

are French, suggesting that not only typology, but also topic overlap, may play an important role in the quality of these multilingual representations. This becomes even more apparent in Arabic, which differs from English in typology and script, but has similar representations. The Arabic and English datasets were obtained using the same keywords.

5 Conclusions

We have presented a framework and an analysis on the cross-lingual capabilities of Twitter-based multilingual LMs. As main test bed for our multilingual experiments, we focused on sentiment analysis, for which we collected datasets in eight languages. After a unification and standardization of the evaluation benchmark, we compared the Twitter-based multilingual language model with a standard multilingual language model trained on general-domain corpora. This multilingual language model along with starting and evaluation code are released to facilitate research in Twitter at a multilingual scale (over thirty languages used for training data).

The results highlight the potential of the domain-specific language model, as more suited to handle social media and specifically multilingual SA. Finally, our analysis reveals trends and potential for this Twitter-based multilingual language model in zero-shot cross-lingual settings when language-specific training data is not available. For future work we are planning to extend this analysis to more languages and tasks, but also to deepen the cross-lingual zero and few shot analysis, particularly focusing on typologically similar languages. Finally, and due to the seasonal nature of Twitter, it would also be interesting to explore correlations between topic distribution and trends and performance in downstream applications.

Acknowledgments

We would like to thank Eugenio Martínez-Cámara for his involvement in the first stages of this project.

References

Francesco Barbieri, Valerio Basile, Danilo Croce, Malvina Nissim, Nicole Novielli, and Viviana Patti. 2016. Overview of the evalita 2016 sentiment polarity classification task. In Proceedings of third Italian conference on computational linguistics (CLiC-it 2016) & fifth evaluation campaign of natural lan-
Francesco Barbieri, Jose Camacho-Collados, Luis Espinosa Anke, and Leonardo Neves. 2020. **TweetEval**: Unified benchmark and comparative evaluation for tweet classification. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1644–1650, Online. Association for Computational Linguistics.

Francesco Barbieri, Jose Camacho-Collados, Francesco Ronzano, Luis Espinosa Anke, Miguel Ballesteros, Valerio Basile, Viviana Patti, and Horacio Saggion. 2018. Semeval 2018 task 2: Multilingual emoji prediction. In *Proceedings of The 12th International Workshop on Semantic Evaluation*, pages 24–33.

Jeremy Barnes, Lilja Òvrelid, and Erik Velldal. 2019. *Sentiment analysis is not solved! assessing and probing sentiment classification*. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 12–23, Florence, Italy. Association for Computational Linguistics.

Valentin Barriere and Alexandra Balahur. 2020. *Improving sentiment analysis over non-English tweets using multilingual transformers and automatic translation for data-augmentation*. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 266–271, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Valerio Basile, Cristina Bosco, Elisabetta Fersini, Debora Nozza, Viviana Patti, Francisco Manuel Rangel Pardo, Paolo Rosso, and Manuela Sanguinetti. 2019. *SemEval-2019 task 5: Multilingual detection of hate speech against immigrants and women in Twitter*. In *Proceedings of the 13th International Workshop on Semantic Evaluation*, pages 54–63, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Farah Benamara, Cyril Grouin, Jihen Karoui, Véronique Moriceau, and Isabelle Robba. 2017. Analyse d’opinion et langage figuratif dans des tweets: présentation et résultats du défi fouille de textes deft2017. In *Défi Fouille de Textes DEFT2017, Atelier TALN 2017*. Association pour le Traitement Automatique des Langues (ATALA).

Henrico Bertini Brum and Maria das Graças Volpe Nunes. 2017. Building a sentiment corpus of tweets in brazilian portuguese. *arXiv preprint arXiv:1712.08917*.

Jose Camacho-Collados, Yerai Doval, Eugenio Martínez-Cámara, Luis Espinosa-Anke, Francesco Barbieri, and Steven Schockaert. 2020. Learning cross-lingual word embeddings from twitter via distant supervision. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 14, pages 72–82.
Adapt language models to domains and tasks. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8342–8360, Online. Association for Computational Linguistics.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for nlp. In International Conference on Machine Learning, pages 2790–2799. PMLR.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalisation. In International Conference on Machine Learning, pages 4411–4421. PMLR.

Pratik Joshi, Sebastin Santy, Amar Budhiraja, Kalika Bali, and Monojit Choudhury. 2020. The state and fate of linguistic diversity and inclusion in the NLP world. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6282–6293, Online. Association for Computational Linguistics.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2017. Bag of tricks for efficient text classification. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 427–431, Valencia, Spain. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Xinfan Meng, Furu Wei, Xiaohua Liu, Ming Zhou, Ge Xu, and Houfeng Wang. 2012. Cross-lingual mixture model for sentiment classification. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 572–581. Association for Computational Linguistics.

Saif Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. Semeval-2018 task 1: Affect in tweets. In Proceedings of the 12th international workshop on semantic evaluation, pages 1–17.

Saif Mohammad, Svetlana Kiritchenko, Parinaz Sobhani, Xiaodan Zhu, and Colin Cherry. 2016. Semeval-2016 task 6: Detecting stance in tweets. In Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016), pages 31–41.

Dat Quoc Nguyen, Thanh Vu, and Anh Tuan Nguyen. 2020. BERTweet: A pre-trained language model for English tweets. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 9–14, Online. Association for Computational Linguistics.

Braj Gopal Patra, Dipankar Das, Amitava Das, and Rajendra Prasath. 2015. Shared task on sentiment analysis in indian languages (sail) tweets-an overview. In International Conference on Mining Intelligence and Knowledge Exploration, pages 650–655. Springer.

Parth Patwa, Gustavo Aguilar, Sudipta Kar, Suraj Pandey, Srinivas PYKL, Björn Gambäck, Tam moy Chakraborty, Thamar Solorio, and Amitava Das. 2020. SemEval-2020 task 9: Overview of sentiment analysis of code-mixed tweets. In Proceedings of the Fourteenth Workshop on Semantic Evaluation, pages 774–790, Barcelona (online). International Committee for Computational Linguistics.

Jonas Pfeiffer, Ashwarya Kamath, Andreas Rücklé, Kiyunghyun Cho, and Iryna Gurevych. 2020. Adapterfusion: Non-destructive task composition for transfer learning. arXiv preprint arXiv:2005.00247.

Telmo Pires, Eva Schlünger, and Dan Garrette. 2019. How multilingual is multilingual bert? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4996–5001.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. Journal of Machine Learning Research, 21:1–67.

Mohammad Sadegh Rasouli, Noura Farra, Axinia Radeva, Tao Yu, and Kathleen McKeown. 2018. Cross-lingual sentiment transfer with limited resources. Machine Translation, 32(1):143–165.

Sara Rosenthal, Noura Farra, and Preslav Nakov. 2017. Semeval-2017 task 4: Sentiment analysis in twitter. In Proceedings of the 11th international workshop on semantic evaluation (SemEval-2017), pages 502–518.

Sara Rosenthal, Noura Farra, and Preslav Nakov. 2019. Semeval-2017 task 4: Sentiment analysis in twitter. arXiv preprint arXiv:1912.00741.

Phillip Rust, Jonas Pfeiffer, Ivan Vulić, Sebastian Ruder, and Iryna Gurevych. 2020. How good is your tokenizer? on the monolingual performance of multilingual language models. arXiv preprint arXiv:2012.15613.

Mohammad Salameh, Saif Mohammad, and Svetlana Kiritchenko. 2015. Sentiment after translation of code-mixed tweets. In Proceedings of the Fourteenth Workshop on Semantic Evaluation (SemEval-2015), pages 4411–4421. PMLR.
Cynthia Van Hee, Els Lefever, and Véronique Hoste. 2018. SemEval-2018 task 3: Irony detection in English tweets. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 39–50.

David Vilares, Miguel A. Alonso, and Carlos Gómez-Rodríguez. 2017. Supervised sentiment analysis in multilingual environments. Information Processing & Management, 53(3):595 – 607.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2020. mt5: A massively multilingual pre-trained text-to-text transformer.

Marcos Zampieri, Shervin Malmasi, Preslav Nakov, Sara Rosenthal, Noura Farra, and Ritesh Kumar. 2019. SemEval-2019 task 6: Identifying and categorizing offensive language in social media (OffensEval). In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 75–86, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Xinjie Zhou, Xiaojun Wan, and Jianguo Xiao. 2016. Cross-lingual sentiment classification with bilingual document representation learning. In Proceedings of ACL, pages 1403–1412.