Cross-lingual Zero- and Few-shot Hate Speech Detection utilising frozen Transformer Language Models and AXEL

Lukas Stappen*  
University of Augsburg, GER  
stappen@ieee.org

Fabian Brunn*  
TU Munich, GER  
fabian.brunn@tum.de

Björn Schuller  
Imperial College London, UK  
schuller@ieee.org

Abstract
Detecting hate speech, especially in low-resource languages, is a non-trivial challenge. To tackle this, we developed a tailored architecture based on frozen, pre-trained Transformers to examine cross-lingual zero-shot and few-shot learning, in addition to uni-lingual learning, on the HatEval challenge data set. With our novel attention-based classification block AXEL, we demonstrate highly competitive results on the English and Spanish subsets. We also re-sample the English subset, enabling additional, meaningful comparisons in the future.

1 Introduction
Hate speech, discriminatory communication intended to insult and intimidate specific groups or individuals due to their gender, race, sexual orientation or other characteristics has been a negative side effect of the growth of social media. Its effects are not confined to the virtual world; offline, it can result in criminal acts, including physical attacks (Müller and Schwarz, 2018; Goolsby et al., 2013). In an extreme example, it has been heavily implicated in inciting violence against Rohingya Muslims in Myanmar in 2017 (Stevenson, 2018; Subedar, 2018; Stecklow, 2018), which included the murder of thousands of civilians and created close to a million refugees (UN Human Rights Council, 2018).

With billions of text snippets posted daily on social media, detecting hate speech using human observers is unfeasible, motivating researchers to develop natural language processing (NLP) methods to automate the task. Attempts by industry have so far fallen short; according to Facebook, their detection algorithms failed in the lead-up to the Rohingya crisis due to a lack of training data in Burmese (Murphy, 2019).

Detection approaches that work effectively with small or non-existent training data sets in the target language, such as cross-lingual zero- and few-shot learning, have not been discussed in the recent hate speech literature. Goodfellow et al. (2016) defined zero-shot learning as an extreme form of transfer learning. Applying this concept to NLP, a model trained on one language or domain learns to predict samples from an unseen language using the latent structures of a pre-trained language model aligned across multiple languages. In cross-lingual few-shot learning, a percentage of samples from the target language is added to the training on the source language, thus, strengthening cross-lingual and task-specific alignment (Schuster et al., 2019).

Cross-lingual approaches are expected to bridge the deep learning performance gap between languages that have large corpora available and low-resource languages (Adams et al., 2017) and have been named as a hot topic for the next ten years by Zhou et al. (2018). One possible reason for the lack of application of these techniques to hate speech is a lack of appropriate, publicly available data sets. An additional problem is the varying definition of hate speech used in different data sets, preventing the combined use of any given high-resource language corpus with any given low-resource corpus. Here, we use the data set from the ACL 2019 Semantic Evaluation challenge (SemEval) Task 5 (Basile et al., 2019) that contains both English (EN) and Spanish (ES) hate speech tweets, identified according to the same definition of hate speech targeting women and immigrants, to develop monolingual and cross-lingual models.

As hate speech detection is already very challenging to model in an uni-language setting (MacAvaney et al., 2019; Zhang and Luo, 2019; Fortuna and Nunes, 2018), most existing work in this and related fields (Benballa et al., 2019; Aggarwal et al., 2019; Zhou et al., 2019; Pelicon et al.,...
focusing on enhancing NLP state-of-the-art deep learning architectures, namely variations of Transformer Language Models (TLM), such as bidirectional encoder representations from Transformers (BERT) (Devlin et al., 2019) or cross-lingual language model pre-training (XLM) (Lample and Conneau, 2019). The majority of SemEval submissions that successfully detected and classified offensive language on social media (Task 6) utilized BERT variations, fine-tuning them in an end-to-end fashion.

In this paper, we describe a novel approach for hate speech detection that uses frozen TLM architectures to extract features – the text representations – only from some of the TLM layers. By using TLMs purely as a feature extractor, we avoid the computation expensive, task-specific, fine-tuning training step, which adjusts up to 8.3 billion trainable parameters (Shoeybi et al., 2019). This strategy is briefly mentioned in the original BERT paper (Devlin et al., 2019), but only Peters et al. (2019) have carried out a broader evaluation. To the best of our knowledge, our approach is a novel idea both in the context of cross-lingual learning as well as for hate speech detection with small data sets.

Following the extraction of the representations, we feed them into 12 different classification blocks of varying complexity, which we install as trainable layers on top of the feature extraction network. Inspired by the results and intuition of state-of-the-art computer vision attention blocks, we also step-wise derived and crafted a novel representation classification block, Attention-Maximum-Average Pooling (AXEL), for this particular task.

During our investigations, we noticed that good recall performances often resulted in poor precision and an unstable F1 for EN. We attribute this to an out-of-domain sampling and propose reshuffled partitions of the English data (EN-S). All experiments were performed on both the original and proposed split. All associated code is openly available.

Our contributions are as follows. Firstly, we demonstrate that frozen TLMs can serve as pure deep feature extractors for hate speech detection that only need a fraction of trainable parameters compared to the normal fine-tuning approach. Secondly, we propose a novel classification block AXEL that enabled competitive results on unigram and cross-lingual hate speech detection. Thirdly, we demonstrated the efficiency of zero- and few-shot learning in this setting and, finally, we identify serious limitations in the generalisability of models trained with the EN HatEval data and propose a new sampling.

## 2 Network Architecture Components

The high-level structure of our architecture is depicted in Figure 1. Initially, the network receives the language tokens of the input text. This sequence is propagated forward through a frozen TLM architecture (either BERT or XLM), extracting the deep language features. In the next step, some or all of the extracted representations are selected or fused for further processing. For example, this can be the last representation of the output layer for a pure one dimensional classification block or the entire sequence for a sequential compression. Next, these representations are fed into a classification block where the target is predicted.

We also replaced the frozen TLM by common word embeddings, such as, fastText (Grave et al., 2018), GloVe (Pennington et al., 2014) or fastText aligned (Joulin et al., 2018) to encode the input text. fastText showed better results than GloVe on Twitter hate speech data (van Aken et al., 2018). fastText aligned has multi-language capabilities. The encoded representation was fed into a single or double recurrent neural network layer, e. g., a Long short-term Memory Network (Hochreiter and Schmidhuber, 1997) or its bidirectional version (BiLSTM), which have previously proved more effective than Convolutional Neural Networks for hate speech detection (Rizos et al., 2019; van Aken et al., 2018).

### 2.1 Extracting Transformer Language Model Features

We do not perform a fine-tuning step, instead we use the TLMs as a frozen language feature extractor. For a general description of the Transformer architecture we refer to Vaswani et al. (2017).

BERT was the first TLM to successfully train text representations bidirectionally (Devlin et al., 2019). Since a Spanish version of BERTLARGE was not available, we used the multilingual cased BERTBASE as one of our feature extractors. BERT is not explicitly cross-lingual pre-trained, whereas Lample and Conneau (2019) aligned the language representations in a two-step pre-training process.
Figure 1: Exemplified illustration of the architecture (e.g., BERTAvgPool). The frozen BERT model acts as a feature extractor (brown frame). Next, a module selections one or many output representations e.g., by pooling over the sequence (pink). The output of the selection is used as input for another representation enhancement module e.g., a dense feed-forward layers (green).

for XLM. In the first step, a masked language modeling is trained unsupervised using byte pair tokenised sub-words (Sennrich et al., 2015). In the second step, translation language modeling uses sentence pairs from different languages and feeds them in parallel into the model.

### 2.2 State-of-the-art Computer Vision Classification Blocks and Derived AXEL

Our novel classification block was designed to efficiently condense task-specific representations from a sequence of context-specific, general text representations from a general TLM. To do this, we analysed the structure of recent state-of-the-art attention modules, CAB (Zhang et al., 2018a), CBAM (Woo et al., 2018), CSAR (Hu et al., 2019), and RAM (Kim et al., 2018) that can simultaneously compress and enhance feature representations, e.g., in image super-resolution tasks. Most separate the attention block into spatial and channel attention layers. They extract information across the filter dimensions, then capture inter-dependencies in the feature channels utilising a three-step squeeze, excitation and scaling procedure (Kim et al., 2018). Since in our case the input data have one dimension less, specifically the RGB channels, we adapted the modules for text representation compression. For the spatial attention, we utilised a 1D convolution operation over the entire sequence length to combine all representations. For the channel attention, we used pooling over the feature vector dimension to distill information from each individual sequence representation.

We combine the most promising modules step-wise to create AXEL (cf. Figure 2). The context and two different channel attention modules enhance the underlying XLM features. Sharing the weights between the two different channel attention modules results in more robust representations, while the subsequent ReLU adds additional non-linearity. The two resulting representations are then fused with the output of a context attention module by stacking the three feature maps as synthetic filter channels. Next, a one-dimensional convolution (denoted 1x1) is used to deeply fuse the stacked filters. Finally, a feed-forward layer with softmax activation enabling hate speech prediction.

Figure 2: The XLM1L AXEL classification block compresses and enhances XLM features. Similar to a channel attention modules, a maximum and average pooling on the XLM output is used, followed by a feed-forward layer with shared weights and non-linear ReLU activation. This is fused with a context attention module with stacked feature maps as synthetic filter channels. The filters are fused by a one-dimensional convolution (denoted 1x1).
3 Data

3.1 HatEval Data Set

We evaluated the effectiveness of our proposed hate speech detection models on the HatEval data set released as part of the SemEval task 5 (Basile et al., 2019; May et al., 2019) and focused on the first sub-task only. The data set definition aims at women and immigrants hate speech. Hate speech directed at other groups, e.g., men was labelled as not hateful (cf. Figure 3).

The dataset comprises around 13,000 EN tweets and 6,600 ES tweets. We performed a simple descriptive statistical analysis to verify there were no obvious set or label-related patterns in the data. The data are slightly imbalanced; 42% were labelled as hate speech and 58% labelled as containing no hate speech. A detailed analysis of the hate speech text properties can be found in the appendix.

3.2 Proposing New Partitioning of the English HateEval

An analysis of the challenge baselines (Basile et al., 2019), submissions, and our own initial tests demonstrated a large discrepancy in performance between EN and ES. The challenge submissions and baselines produced average F1 scores of 44.84% and 68.21% with EN and ES respectively, with no explanation provided in the subsequent retrospective account of the challenge (Basile et al., 2019). Consequently, we investigated EN more closely and re-partitioned it before proceeding further.

3.2.1 Error Analysis of the English Sub-set: Out-of-Domain Sampling

To investigate the low performances obtained using EN, we trained a simple baseline model using fastText embeddings and a BiLSTM. As expected, the model, considerably trained and tuned well on the validation partition, achieved on testing a low precision of 43%, a high recall of 94%, and resulted in 1,564 false positives in 2,971 test samples.

| key phrases            | train-val | test |
|------------------------|-----------|------|
| build * wall           | 97%       | 35%  |
| MAGA                   | 88%       | 29%  |
| illegal aliens         | 89%       | 33%  |
| total anti-immigration  | 92%       | 34%  |
| total anti-women       | 79%       | 46%  |

Table 1: Occurrence of discriminate phrases, grouped as anti-immigration and anti-women (“bitch”), associated to hate speech on the training (train) and validation (val) partitions versus the test partition. The percentage is the hate speech ratio, the number of hate speech samples including a particular phrase divided by the total number of samples containing that phrase. “*” denotes that/the. MAGA = Make America great again.

When we made spot checks of false positive samples, certain repeatedly occurring signal words stood out. The phrases “bitch”, “build the [or that] wall”, “make America great again” and “illegal aliens” occurred at least once in 80% of false positives in the test set. In an example, Figure 4 shows a pair of tweets containing the word ‘bitch’; one is from the training/validation set (left) and the other is from from the test partition (right).

In summary, we believe that out-of-domain sampling of the EN test set hinders the development of sensible models that behave similar on all partitions and drawing of meaningful conclusions from qualitative analyses (e.g. model error analysis). We speculate that the test set was not collected nor partitioned with the rest of the data and that different criteria were applied, be they thematic or temporal, so that the domain of data distribution differs widely.

3.2.2 Proposed New English Partitions

Having identified a potential source of the deviations, we propose a simple approach to solve this issue. The goal of the new partitioning is an approximately equal distribution of data properties with the previously specified key phrases taking into account the binary label for hate speech. This results
Feminism is cancer. #TheRedPill is chemo. Burn those bitches away.

TweetID 4881

Women empowering other women – That shit is lit. Like yasss bitch, you are amazing, go you. We can all shine TOGETHER

TweetID 33195

Figure 4: Typical examples including the keyword “bitch” from training set (left) and test set (right).

in three categories: no key phrases, one or more anti-immigration key phrases and anti-women key phrases (“bitch”) – for hateful and not hateful data points, leading to a total of six classes for partition stratification. We merged all EN partitions, then equally re-distributed the tweets according to six categories. In the end, the hate speech ratio was balanced enabling a fair and comprehensible learning of automated hate speech detection models – comparable to that of the Spanish subset. In general, such heavy effects of sampling indicates that the amount of data is not enough to learn discriminative, fully generalisable features for any ambiguous context.

3.3 Preprocessing

We cleaned the tweets from the HatEval dataset to avoid biased training influences (Hassan et al., 2013), providing a description of our procedure in the appendix. The process markedly improved unique word coverage using fastText word embeddings, from 44.06% to 82.41% for EN and from 55.93% to 90.05% for ES words. In regard to the full text coverage, we achieved 97.43% for the EN and 98.08% for ES tweets, demonstrating the effectiveness of our comprehensive procedure.

4 Experiments

4.1 Experiment settings

The models were implemented in Python 3.6 using PyTorch. Without fine-tuning, we could use a moderate hardware (NVIDIA Tesla K80). All models use a cross-entropy loss function, Adam optimiser and early stopping. In addition, hyperparameters settings (P) of the abbreviation are provided in the appendix. We trained the models on training partitions measuring accuracy, precision, recall, and F1, but only report the latter for conciseness.

4.2 Baselines

The challenge organisers provided two baselines (Basile et al., 2019), a Most-Frequent-Classifier (MFC, EN: 36.7, ES: 45.1 in % F1) and a Support Vector Machine (SVM) using tf-idf vectorisation (SVM, EN: 45.1, ES: 70.1 in % F1). We have created additional baselines (Table 2), as our data pre-processing differs to Basile et al. (2019). Also, we require a benchmark for our newly crafted EN-S partition. Finally, no deep learning baseline was provided in the challenge and comparing the new context to the conventional word embeddings seems relevant.

| Model       | EN   | EN-S | ES    |
|-------------|------|------|-------|
| Base_SVM    | 59.78| 65.43| 64.90 |
| Base_GV     | 58.93| 63.44| 66.14 |
| Base_FT     | 60.18| 61.75| 67.49 |
| Base_FTA    | 58.08| 58.19| 63.63 |

On the EN-S data set, our Base_SVM achieved strong F1 scores with well balanced sub-metrics. We speculate that the performance of the word embeddings may be directly related to the amount of training data used in the embedding training. This behaviour is analogous to the results on the Spanish data set, where Base_FT achieved the best results. The F1 of the SVC baseline is above the average result of the challenge participants (Basile et al., 2019), and can, therefore, be considered a strong entry-level baseline. Overall, we have trained strong and robust baselines for both languages and evaluated various word embeddings. Based on these results, we choose Base_FT as our main deep learning baseline.
4.3 Results

4.3.1 Viability of Transformers as Deep Feature Extractors for Uni-Language Hate Speech Detection

BERT base  We started with naive approaches utilising classification blocks with no or few trainable parameters. Devlin et al. (2019) extracted the first token of the final BERT layer and fed them into a softmax layer (Bert1L_Dense). We also examined if the most informative token could be learnt by applying a global max-pooling layer (Bert1L_MaxPool) over the temporal sequence to limit the computational costs and memory footprint plus provides translation invariance. Bert1L_AvgPool with average pooling enabled us to evaluate if the average representation is informative. As evident in Table 3, all models perform worse than our baseline, with the pooling solutions performing better than the recommended first token approach.

We utilised the entire sequence of BERT by feeding it into a double stacked BiLSTM (Bert1L2LSTM) similar to Devlin et al. (2019), where the sequence outputs of the last four layers are extracted, concatenated across the layers, and fed into a two-layer BiLSTM (Bert4L2LSTM). The step-wise encoding of all the tokens by an LSTM increases the prediction performance considerably, on the EN-S data set by more than 7% (Bert1L2LSTM) and ES still marginally better than our benchmark. The previous experiments used the final BERT layers. Thus, an entire forward pass through the network was necessary. We evaluated the feasibility to extract only the first (Bert1F). For the EN-S data set, both achieved results above the benchmark and only slightly worse than propagated till the final layer.

XLM base  XLM is designed to train cross-lingual TLMs and is the foundation for our zero- and few-shot approaches. We transferred the block design one to one from BERT. Noticeable is the strong performance of XLM1L_Dense on all three subsets and the weak performance of XLM1L2LSTM (cf. Table 3). This also stands in contrast to the BERT model, where the sequential models were clearly superior to the non-sequential models. Given that sequential encoding does not add value to the use of XLM tokens, we also tried to learn a weighted representation through an attention layer XLM1L_Att. However, the model showed great performance on the EN set, but cannot beat XLM_Dense on the EN-S and ES.

| Model         | P EN | EN-S | ES |
|---------------|-----|------|----|
| Base_FT       | A   | 60.18| 61.75| 67.49 |
| Bert1L_Dense  | F  | 56.81| 61.31| 51.43 |
| Bert1L_MaxPool| G  | 59.86| 62.64| 56.62 |
| Bert1L_AvgPool| G  | 58.81| 58.54| 59.74 |
| Bert1L2LSTM   | D  | 60.55| 69.04| 65.23 |
| Bert4L2LSTM   | D  | 61.00| 68.98| 67.57 |
| Bert1F1LSTM   | F  | 59.37| 67.75| 64.85 |
| Bert1F2LSTM   | F  | 59.21| 67.28| 64.09 |
| XLM1L_Dense   | G  | 60.89| 67.73| 64.75 |
| XLM1L2LSTM    | H  | 60.20| 59.27| 62.37 |
| XLM1L_Att     | G  | 61.61| 67.56| 62.33 |

4.3.2 Analysis of Advanced Classification Block Designs: AXEL

For the development of the novel AXEL classification block, we got inspired by the latest attention developments in computer vision. Table 4 illustrates the performance of these blocks, whereby XLM_R CAB performs best on the EN and ES. Looking at the architectures in detail, it is the only one which does not utilise spatial attention. It can be deduced that, spatial attention is not ideal for our purpose, while the for text adjusted channel attention adds value to the representations. Furthermore, it is evident that the newly proposed AXEL classification block produced by far the best result, exceeding all other adapted blocks by at least 7% F1 on the EN-S and more than 2% for the ES. We provide an ablation study of all AXEL components in the appendix.

4.3.3 Cross-lingual learning

Zero-shot learning  To evaluate zero-shot capabilities, the models are tuned on the training set of one language and evaluated in another. Table 5
Table 4: Comparison of XLM classification blocks: RCAB (Zhang et al., 2018a), CBAM (Woo et al., 2018), CSAR (Hu et al., 2019), RAM (Kim et al., 2018), and our newly developed AXEL. All results are reported in F1 %.

| Model      | P | EN   | EN-S  | ES   |
|------------|---|------|-------|------|
| XLM_CBAB   | K | 62.36| 61.65 | 60.28|
| XLM_CBAM   | F | 60.90| 59.67 | 54.25|
| XLM_CSAR   | M | 61.45| 63.85 | 50.17|
| XLM_RAM    | M | 60.30| 60.67 | 55.21|
| XLM1L_AXEL | F | 62.03| 71.16 | 69.70|

illustrates that XLM1L_AXEL achieved the best results except on the EN data set, where XLM_Dense performed best but suffered one more time from high false positives. Overall, the models show general learnability, however, lack generalisability and the performance is much worse than in our monolingual experiments.

To probe if the causes of the performance loss are either on the data or the model side, we carried out additional experiments. To rule out that the different nature of the EN and ES training and test partitions is the reason, we automatically translated the test set into the language of the training set. The improved results in Table 5 indicate that the partition composition is probably not the cause, leaving only the extracted latent representations, which seems either not perfectly aligned for our task hate speech or across languages.

Table 5: Zero-shot performance comparison of XLM base XLM_Dense(G), XLM_Att(G), and XLM1L_AXEL (F) across languages and predictions on the translated test set in F1 in %. This shows that the latter outperforms other XLM based models as well as that the output latent structure for various languages differs. train ⇒ test; original → translation.

|        | Dense | Att | AXEL |
|--------|-------|-----|------|
| EN⇒ES  | 41.31 | 34.37 | **53.42** |
| ES⇒EN  | **60.83** | 48.47 | 52.48 |
| ES⇒EN-S| 49.38 | 39.10 | **53.24** |
| EN⇒(ES⇒EN)| 60.59 | 62.40 | **64.39** |
| ES⇒(EN⇒ES)| 56.89 | 49.17 | **58.31** |
| ES⇒(EN-S⇒ES)| 56.57 | 49.17 | **65.04** |

Furthermore, we tried to learn models in similar fashion using fastText aligned embeddings combined with various blocks. Most classifiers generalised badly, resulting in unstable losses (see appendix for experiments).

**Few-shot learning** The previous experiments have shown that zero-shot learning works, but performed much poorer than the monolingual models. Therefore, we determined whether the extracted latent structure can be stronger aligned or learnt by the classification block, when we inject a few percent of the samples of the predictive language into the training set.

Figure 5 shows that injecting only 1% of the data led to a boost in performance of almost 5% F1. Subsequently, the training continues mostly as expected, improving incrementally with more data. The final result for the EN-S exceeded even the monolingual experiments, which we attribute to data augmentation by the additional injected data. In order to verify this idea, we additionally experimented with augmentation techniques, such as, translation chains, but were unsuccessful in demonstrating an overarching and clearly positive effect. The original EN shows an atypical behaviour, and apparently barely improving over time due to the out-of-domain sampling issue (cf. section 3.2.1).

In order to verify that the network has actually learnt cross-lingually and not only from the few injected samples, the same experiments were carried out using exclusively the few-shot samples, thus, excluding the full training-language. These clearly show that the model makes use of cross-lingual
structures. For example, at 10% few-shot training samples, we obtained results of only 58.10% (EN), 59.06% (EN-S), and 58.66% (ES) F1, which are clearly lagging behind the few-shot results for EN-S and ES.

4.4 Discussion

One central motivation of our work was to access and improve cross-lingual learning, especially for low-resource languages. While the models using cross-lingual zero-shot learning produced mixed results, the benefits of few-shot learning based on extracted features are evident. Unfortunately, we were unable to use a genuinely low-resource language because of the limited availability of multilingual hate speech corpora using the same definition with one being of a rare language. However, using our artificially reduced high-resource data sets, a parallel training, even with very few data sets, resulted in a stronger alignment of XLM representations.

Reducing computation during task-specific fine-tuning was another important motivator in this work. When we compare the architectures presented here with the fine-tuning approach, the Bert4L_2LSTM classification block has less than 2M trainable parameters, while XLM AXEL has only around 1M. At the same time, we have to train 177M parameters for BERT, and 249M parameters for XLM to train these networks end-to-end. This insight is valuable for academia or industry where less resources are available. This is of less significance in terms of the inference time due to the highly efficient architecture of Transformers (Peters et al., 2018).

However, while far less parameters are used, we demonstrated that our novel AXEL classification block on frozen TLM could still easily beat our strong baselines. When ranked alongside the HatEval 2019 results, our approach ranked second on EN and is close to the third quartile (71.65% F1) on ES.

5 Related Work

In the original paper, Devlin et al. (2019) included little information about using extracted BERT features for named-entity recognition. More extensive research was carried out by Peters et al. (2019), evaluating both fine-tuned features as well as features from the general language model on a wider range of tasks. Predicting sentiment on movie reviews is the closest task to hate speech detection, showing that there is a slight trade-off between performance and computation cost for fine-tuning. Besides these works, there appears to be no other research conducted on small data sets or hate speech data utilising TLMs as pure feature extractors, making it an interesting area to investigate.

As interest in the research community in hate speech detection has grown; the number of publicly available data sets has also increased. Waseem (2016) created and extended (Waseem and Hovy, 2016) an English hate speech data set based on tweets. Davidson et al. (2017) also focused on offensive language on twitter, while de Gibert et al. (2019) crawled the white supremacist website Stormfront. There are multiple data sets available in languages other than English including Italian (Bosco et al., 2018), Portuguese (Fortuna et al., 2019), and Indonesian (Ibrohim and Budi, 2019). However, only (Basile et al., 2019) provides a corpus in two languages (English and Spanish) using the same definition of hate speech, enabling us to tackle this topic from a multilingual perspective.

Recent detailed comparisons of traditional and deep learning approaches (Kshirsagar et al., 2018; Robinson et al., 2018; van Aken et al., 2018; Lee et al., 2018; Zhang et al., 2018b) have demonstrated superior performances by the later in hate speech detection. Transformers became especially popular for deeply modelling language, resulting in the quick and wide adoption of networks such as BERT (Devlin et al., 2019) and XLM (Lample and Conneau, 2019). In Task 5 of SemEval-2019 for hate speech detection, the second-placed submission in the Spanish challenge (Gertner et al., 2019) used a fine-tuned BERT by adding additional tweets to the corpus. Also in the closely related Task 6, in which offensive language was detected (Zampieri et al., 2019), six out of the top ten top submissions used BERT. It is noteworthy that all the published participants in these two challenge tasks who used a TLM architecture fine-tuned their architectures (Zhang and Luo, 2018; Gertner et al., 2019; Benballa et al., 2019; Siddiqua et al., 2019; Aggarwal et al., 2019; Zhou et al., 2019; Zhu et al., 2019; Nikolov and Radivchev, 2019; Pelicon et al., 2019).

An extensive survey of cross-lingually word embeddings can be found in Ruder et al. (2017). Grave et al. (2018) and Conneau et al. (2017) cross-lingual pretrained embeddings are widely used, likely because they are freely available. Artetxe and
Schwenk (2018) suggested zero-shot, cross-lingual sentence embeddings, which showed a strong performance on some language combinations and partially competed with BERT. Wu and Dredze (2019) attempted to adjust the Transformer for BERT for cross-lingual tasks, but XLM performed superiorly.

6 Conclusion

The detection of hate speech on social media platforms is vital to prevent the incitement of violence. A particular challenge is the development of reliable, automatic detection systems, where there is a lack of task-specific, low-resource language data.

The aim of this work was to evaluate TLMs as deep feature extractors for this task. First, we built strong baselines and assessed various classification blocks for the detection of uni-language hate speech. The performance of the TLM-based models greatly surpasses that of those based on conventional word embeddings and demonstrated promising results compared to the submissions of challenge participants. On the EN, for example, they ranked second. Second, the poor generalization behaviour we observed on the EN partitions could be attributed to out-of-domain sampling and motivated our proposal of a newly stratified data split. We accompanied this with a first benchmark of EN-S partitions that we hope others will build upon, enabling sensible comparisons in the future. Finally, from our investigation of potential block designs, our results indicate two different strategies are required to successfully use BERT and XLM representations. While BERT efficiently utilised the entire sequence of representations, XLM worked better using only the first token. This motivated AXEL, which is, derived from state-of-the-art computer vision modules, designed to extract a wide range of stable features out of one compressed representation. We artificially simulated low language resources to demonstrate the cross-lingual capabilities of our AXEL module that outperformed our baselines by far and gave valuable insights for future research in this field.

Investigations of the representational differences from an architectural and training perspective (Why are XLM representations less effective for sequential blocks?) as well as general AXEL capabilities are interesting future research directions.

References

Oliver Adams, Adam Makarucha, Graham Neubig, Steven Bird, and Trevor Cohn. 2017. Cross-lingual word embeddings for low-resource language modeling. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 937–947, Valencia. ACL.

Piush Aggarwal, Tobias Horsmann, Michael Wojatزي, and Torsten Zesch. 2019. Ltl-ude at semeval-2019 task 6: Bert and two-vote classification for categorizing offensiveness. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 678–682, Minneapolis. ACL.

Betty van Aken, Julian Risch, Ralf Krestel, and Alexander Löser. 2018. Challenges for toxic comment classification: An in-depth error analysis. arXiv preprint arXiv:1809.07572.

Mikel Artetxe and Holger Schwenk. 2018. Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. arXiv preprint arXiv:1812.10464.

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. ACL.

Miriam Benballa, Sebastien Collet, and Romain Picot-Clemente. 2019. Saagie at Semeval-2019 Task 5: From Universal Text Embeddings and Classical Features to Domain-specific Text Classification. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 469–475, Minneapolis. ACL.

Cristina Bosco, Manuela Sanguinetti, Felice Dell’Orletta, Fabio Pololetto, and Maurizio Tesconi. 2018. Overview of the EVALITA 2018 Hate Speech Detection Task. In Proceedings of the Sixth Evaluation Campaign of Natural Language processing and Speech Tools for Italian, volume 2263, Turin. ACL.

Alexis Conneau, Guillaume Lample, Marc’Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2017. Word translation without parallel data. arXiv preprint arXiv:1710.04087.

Thomas Davidson, Dana Warmelsey, Michael Macy, and Ingrid Weber. 2017. Automated hate speech detection and the problem of offensive language. In Proceedings of the Eleventh International AAAI Conference on Web and Social Media (ICWSM 2017), pages 512–515.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of
deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis. ACL.

Paula Fortuna and Sérgio Nunes. 2018. A survey on automatic detection of hate speech in text. ACM Computing Surveys (CSUR), 51(4):85.

Paula Fortuna, João Rocha da Silva, Leo Wanner, Sérgio Nunes, et al. 2019. A hierarchically-labeled portuguese hate speech dataset. In Proceedings of the Third Workshop on Abusive Language Online, pages 94–104.

Abigail Gertner, John Henderson, Elizabeth Merkhofer, Amy Marsh, Ben Wellner, and Guido Zarrella. 2019. MITRE at SemEval-2019 Task 5: Transfer Learning for Multilingual Hate Speech Detection. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 453–459, Minneapolis. ACL.

Ona de Gibert, Naiara Perez, Aitor García-Pablos, and Montse Cuadros. 2019. Hate Speech Dataset from a White Supremacy Forum. In Proceedings of the Second Workshop on Abusive Language Online (ALW2), pages 11–20, Brussels. ACL.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. Deep Learning. MIT Press.

Rebecca Goolsby, Lea Shanley, and Aaron Lovell. 2013. On cybersecurity, crowdsourcing, and social cyber-attack. Technical report, Office of Naval Research, Arlington.

Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. 2018. Learning word vectors for 157 languages. In Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018).

Ammar Hassan, Ahmed Abbasi, and Daniel Zeng. 2013. Twitter Sentiment Analysis. In Proceedings - SocialCom 2013, pages 357–364. IEEE.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

Yanting Hu, Jie Li, Yuanfei Huang, and Xinbo Gao. 2019. Channel-wise and Spatial Feature Modulation Network for Single Image Super-resolution. IEEE Transactions on Circuits and Systems for Video Technology.

Muhammad Okky Ibrohim and Indra Budi. 2019. Multi-label hate speech and abusive language detection in indonesian twitter. In Proceedings of the Third Workshop on Abusive Language Online, pages 46–57.

Armand Joulin, Piotr Bojanowski, Tomas Mikolov, Hervé Jégou, and Edouard Grave. 2018. Loss in translation: Learning bilingual word mapping with a retrieval criterion. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2979–2984.

Jun-Hyuk Kim, Jun-Ho Choi, Manri Cheon, and Jong-Seok Lee. 2018. Ram: Residual attention module for single image super-resolution. arXiv preprint arXiv:1811.12043.

Rohan Kshirsagar, Tyus Cukuvac, Kathleen McKeown, and Susan McGregor. 2018. Predictive embeddings for hate speech detection on twitter. arXiv preprint arXiv:1809.10644.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. arXiv preprint arXiv:1901.07291.

Younghee Lee, Seunghyun Yoon, and Kyomin Jung. 2018. Comparative studies of detecting abusive language on twitter. arXiv preprint arXiv:1808.10245.

Ping Liu, Wen Li, and Liang Zou. 2019. Multi-label hate speech and abusive language detection in indonesian twitter. In Proceedings of the Third Workshop on Abusive Language Online, pages 46–57.

Ammar Hassan, Ahmed Abbasi, and Daniel Zeng. 2013. Twitter Sentiment Analysis. In Proceedings - SocialCom 2013, pages 357–364. IEEE.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

Yanting Hu, Jie Li, Yuanfei Huang, and Xinbo Gao. 2019. Channel-wise and Spatial Feature Modulation Network for Single Image Super-resolution. IEEE Transactions on Circuits and Systems for Video Technology.

Muhammad Okky Ibrohim and Indra Budi. 2019. Multi-label hate speech and abusive language detection in indonesian twitter. In Proceedings of the Third Workshop on Abusive Language Online, pages 46–57.

Armand Joulin, Piotr Bojanowski, Tomas Mikolov, Hervé Jégou, and Edouard Grave. 2018. Loss in translation: Learning bilingual word mapping with a retrieval criterion. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2979–2984.

Jun-Hyuk Kim, Jun-Ho Choi, Manri Cheon, and Jong-Seok Lee. 2018. Ram: Residual attention module for single image super-resolution. arXiv preprint arXiv:1811.12043.

Rohan Kshirsagar, Tyus Cukuvac, Kathleen McKeown, and Susan McGregor. 2018. Predictive embeddings for hate speech detection on twitter. arXiv preprint arXiv:1809.10644.
Andraž Pelicon, Matej Martinc, and Petra Kralj Novak. 2019. Embeddia at SemEval-2019 Task 6: Detecting Hate with Neural Network and Transfer Learning Approaches. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 604–610, Minneapolis. ACL.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing.

Matthew Peters, Sebastian Ruder, and Noah A. Smith. 2019. To tune or not to tune? adapting pretrained representations to diverse tasks. arXiv preprint arXiv:1903.05987.

Matthew E Peters, Mark Neumann, Luke Zettlemoyer, and Wen-tau Yih. 2018. Dissecting contextual word embeddings: Architecture and representation. arXiv preprint arXiv:1808.08949.

Georgios Rizos, Konstantin Hemker, and Björn Schuller. 2019. Augment to prevent: Short-text data augmentation in deep learning for hate-speech classification. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pages 991–1000. ACM.

David Robinson, Ziqi Zhang, and Jonathan Tepper. 2018. Hate speech detection on twitter: Feature engineering vs feature selection. In European Semantic Web Conference, pages 46–49. Springer.

Sebastian Ruder, Ivan Vulić, and Anders Søgaard. 2017. A survey of cross-lingual word embedding models. arXiv preprint arXiv:1706.04902.

Tal Schuster, Ori Ram, Regina Barzilay, and Amir Globerson. 2019. Cross-lingual alignment of contextual word embeddings, with applications to zero-shot dependency parsing. In Proceedings of the 2019 Conference of the NAACL: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1599–1613.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2015. Neural machine translation of rare words with subword units. arXiv preprint arXiv:1508.07909.

Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. 2019. Megatron-lm: Training multi-billion parameter language models using gpu model parallelism. arXiv preprint arXiv:1909.08053.

Umme Aymun Siddiqua, Abu Noorshed Chy, and Masaki Aono. 2019. KDEHatEval at SemEval-2019 Task 5: A Neural Network Model for Detecting Hate Speech in Twitter. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 365–370, Minneapolis. ACL.

Steve Stecklow. 2018. Why facebook is losing the war on hate speech in myanmar.
Appendices to accompany ”Cross-lingual Zero- and Few-shot Hate Speech Detection utilising frozen Transformer Language Models and AXEL”

A  Data set

A.1 Data Analysis of Hate Speech Language Properties.

In the Spanish corpus, we identified two overly long tweets (450 and 197 words) that contained obviously multiple, concatenated tweets. We removed these outliers. Also the tweets length seem to be quite homogeneous between the sets: labels and languages with around 22 words (±11) and approximately 140 chars (±70) in EN as well as roughly 21 words (±14) and almost 129 chars (±86) in ES. We also compared the usage of all caps words indicating emphasis or screaming and special characters (!, ?, #, ., @), both possible identifiers for hate speech. In the EN tweets, there is on average an almost 30% increase in the usage of block capital written words in a hate speech tweet (1.07 ± 2.56 vs 1.39 ± 3.29) while in Spanish this difference is insignificant (1.30 ± 4.19 vs 1.39 ± 4.68). In terms of the special characters, hateful EN tweets use exclamation marks nearly double as often than non-hateful tweets, also the usage of hashtags is slightly increased (0.92 vs 1.29 per tweet). Interestingly, this is contrary to the Spanish tweets, where the usage of hashtags is halved with 0.24 hashtags for non-hateful and 0.13 for hateful tweets, indicating cultural differences in the usage of hashtags. For all others properties we could not find clear differences.

A.2 Data Cleaning Procedure.

We eliminated all mentions (“@”) since we expect that the mentioned usernames could be associated more closely to one of the classes. Similar hyperlinks might be biased or, in the case of shortened ones have no predictive value at all, and, thus, are also excluded. Apostrophes, for example, “Trump’s wife” indicating genitives “’s” are completely removed, in singular form, this also included the latter.

The informal style of tweets makes it necessary to replace contractions by the full words (“you’re”→ “you are”). Besides a few simple transformations, for instance, standardising special characters (e.g., “–” (en-dash) or “—” (em-dash) → “-” (hyphen), and numbers (”2nd” → second) also more complex ones were necessary. To reduce neg-
ative effects of colloquial word usage, we, first, transformed specific, rare but decisive words and abbreviations, such as, “MAGA” → “make America great again” or “Obamacare” → “Obama health-care system”. Second, concatenated words and hash tags with capitalised letters (camel case) were separated to its unique words. Finally, we used the Python library emoji\(^3\) to replace smileys by text.

B Hyperparameter Abbreviation Table

Table 6 shows the non-static hyperparameters and values for each hyperparameter abbreviation (P).

Table 6: List of hyperparameter (P) combinations used.

| P  | learning rate | batch size | RNN feature size | RNN dropout |
|----|--------------|-----------|------------------|------------|
| A  | 0.001        | 32        | 128              | 0.0        |
| B  | 0.001        | 32        | 128              | 0.2        |
| C  | 0.0005       | 16        | 128              | 0.2        |
| D  | 0.00005      | 64        | 128              | 0.0        |
| E  | 0.00005      | 64        | –                | –          |
| F  | 0.0005       | 64        | –                | –          |
| G  | 0.00001      | 64        | –                | –          |
| H  | 0.0005       | 32        | 64               | 0.2        |
| I  | 0.0005       | 32        | 128              | 0.2        |
| J  | 0.0005       | 64        | 128              | 0.2        |
| K  | 0.00005      | 32        | –                | –          |
| L  | 0.00005      | 32        | 128              | 0.0        |

C Additional Results Including Accuracy, Precision, Recall, and F1

C.1 Baselines.

The performance of the baselines including all metrics are given in Table 7. It demonstrates the imbalanced metrics of accuracy, precision, and F1 to the recall results.

C.2 fastText aligned zero-shot learning.

Aligned fastText allows cross-lingual applications. As depict in Table 8, most of the classifier based on aligned fastText word embeddings failed completely in hate speech detection.

C.3 Few-shot learning.

Extensive results of our few-shot approach as described in section 4.3.3 are provided. We evaluated XLM1L AXEL for different percentages of injected few-shot samples in the training set (cf. Table 9)

\(^3\)https://github.com/carpedm20/emoji/ (accessed 6 October 2019)
Table 7: Performance comparison of our baselines with all metrics reported in accuracy (ACC), precision (PRC), recall (REC), and F1 in %. Base_SVM is based on the original baselines, with a slightly tuned C-value (3.5938). The other models utilise 300 dimensional word embeddings, namely, GloVe (GV), fastText (FT) and, fastText aligned (FTA) and a BiLSTM with a single feed-forward layer. The models are compared on the English (EN), English reshuffled (EN-S), and Spanish (ES) data set.

| Dataset | Model   | ACC  | PRC  | REC  | F1   |
|---------|---------|------|------|------|------|
| EN      | Base_SVM| 49.95| 45.19| 88.26| 59.78|
|         | Base_GV | 46.25| 43.61| 93.75| 58.93|
|         | Base_FT | **48.43**| **44.77**| **94.80**| **60.18**|
|         | Base_FTA| 46.38| 43.48| 90.42| 58.08|
| EN-S    | Base_SVM| 70.27| 64.11| 66.81| 65.43|
|         | Base_GV | 60.66| 52.23| **82.99**| **63.44**|
|         | Base_FT | 64.72| 56.17| 70.37| 61.75|
|         | Base_FTA| **65.42**| **59.11**| 59.09| 58.19|
| ES      | Base_SVM| 67.69| 58.79| 72.42| 64.90|
|         | Base_GV | 67.00| 57.15| **89.10**| **66.14**|
|         | Base_FT | 70.31| 61.02| 77.04| **67.49**|
|         | Base_FTA| **70.69**| **64.91**| 64.01| 63.63|

Table 8: Evaluation of the zero-shot performance of fastText aligned models. We trained a single LSTM layer FTA_LSTM(1), double LSTM layer FTA_2LSTM(1), and attention layer FTA_Att(1) version. Many version were not efficiently trainable, even with early stopping, resulting in failing models indicated in italic. The models are compared on the English (EN), English reshuffled (EN-S), and Spanish (ES) data set. Full results are reported in accuracy (ACC), precision (PRC), recall (REC), and F1 in %.

| Dataset | Model   | ACC  | PRC  | REC  | F1   |
|---------|---------|------|------|------|------|
| Train EN Test ES | FTA_LSTM | 39.62| 38.68| 79.34| 51.50|
|          | FTA_2LSTM| 39.37| **39.20**| **85.60**| **53.29**|
|          | FTA_Att  | **39.69**| 39.08| 82.69| 52.57|
| Train ES Test EN  | FTA_LSTM | **42.14**| **42.14**| 100.00| 58.73|
|          | FTA_2LSTM| 42.07| 42.10| 99.80| 58.65|
|          | FTA_Att  | 42.14| 42.14| 100.00| 58.73|
| Train ES Test EN-S | FTA_LSTM | **42.11**| **42.11**| 100.00| 58.79|
|          | FTA_2LSTM| 42.09| 42.10| 99.96| 58.77|
|          | FTA_Att  | **42.11**| **42.11**| 100.00| **58.79**|
Table 9: Results of XLM1LAXEL network over percentage of added few-shot samples. A certain percentage of the evaluation-language training set is added to the source-language training set. 0% added equals the zero-shot training. The models are compared on the English (EN), English reshuffled (EN-S), and Spanish (ES) data set. Full results are reported in accuracy (ACC), precision (PRC), recall (REC), and F1 in %.

| Dataset | % few-shot samples added | ACC  | PRC  | REC  | F1   |
|---------|-------------------------|------|------|------|------|
| Train ES Test EN | 0 | 58.80 | 51.06 | 53.99 | 52.48 |
|  | 1 | 58.20 | 50.27 | 75.24 | 60.27 |
|  | 5 | 58.33 | 50.37 | 75.72 | 60.50 |
|  | 10 | 54.90 | 47.97 | 83.07 | 60.82 |
|  | 25 | 52.61 | 46.77 | **90.34** | **61.63** |
| Train ES Test EN-S | 0 | 61.95 | 55.17 | 51.43 | 53.24 |
|  | 1 | 65.65 | 59.63 | 57.05 | 58.31 |
|  | 5 | 68.94 | 63.51 | 61.68 | 62.58 |
|  | 10 | 67.55 | 58.51 | **78.34** | **67.17** |
|  | 25 | **70.94** | **64.43** | 69.19 | 66.73 |
| Train EN Test ES | 0 | 49.00 | 42.86 | 70.91 | 53.42 |
|  | 1 | 57.50 | 48.96 | 71.52 | 58.13 |
|  | 5 | 55.56 | 47.93 | **89.24** | 62.36 |
|  | 10 | 67.56 | 59.78 | 65.30 | 62.42 |
|  | 25 | **69.31** | **60.10** | 76.21 | **67.20** |

Table 10: Experiment to validate the cross-lingual learning by training XLM1LAXEL(F) purely on few-shot samples. The results indicate that hate speech prediction cannot only be learnt with the few-shot samples, some models failed to train properly (italic). The models are compared on the English (EN), English reshuffled (EN-S), and Spanish (ES) data set. Full results are reported in accuracy (ACC), precision (PRC), recall (REC), and F1 in %.

| Dataset | % few-shot training samples | ACC  | PRC  | REC  | F1   |
|---------|-----------------------------|------|------|------|------|
| EN      | 1  | 42.48 | 42.20 | **98.80** | 59.14 |
|  | 5  | 46.95 | **43.99** | 94.65 | **60.06** |
|  | 10 | **47.56** | 43.80 | 86.26 | 58.10 |
| EN-S    | 1  | 45.27 | 43.22 | 95.49 | 59.51 |
|  | 5  | 43.09 | 42.52 | **99.83** | **59.63** |
|  | 10 | **68.37** | **64.91** | 54.18 | 59.06 |
| ES      | 1  | 41.25 | 41.25 | 100.00 | 58.41 |
|  | 5  | 41.25 | 41.25 | 100.00 | 58.41 |
|  | 10 | **48.56** | **43.88** | 88.48 | **58.66** |
Table 11: Comparing the performance of AXEL module by removing parts of it to determine the contributing factors: leaving out the max-pool module (XLM1L_AttAvgFC), leaving out the avg-pool module (XLM1L_AttMaxFC), not sharing weights (XLM1L_AttAvgFCMaxFC), aggregating the sub-modules instead of convolving (XLM1L_AttAvgFCMaxFCSum), using a tanh activation function instead of ReLU (XLM1L_AttAvgFCMaxFCTanh), adding an additional variance pooling submodule (XLM1L_AttAvgFCMaxFCVarFC), the pure attention XLM1L_Att, and XLM1L_AXEL. Performed on the English, reshuffled English, and Spanish data set. Adding more submodules to XLM1L_Att improves the performance, whereas the average pooling seems to have the strongest positive influence on the result.

| Model                  | EN  | EN-S | ES   |
|------------------------|-----|------|------|
|                        | ACC | PRC  | REC  | F1  |
| XLM1L_AXEL             | 51.53 | 46.30 | 93.93 | 62.03 |
| XLM1L_AttAvgFCMaxFCVarFC | 54.16 | 47.60 | 87.06 | 61.55 |
| XLM1L_AttAvgFCMaxFCTanh | 51.40 | 46.17 | 92.33 | 61.55 |
| XLM1L_AttAvgFCMaxFCSum | 53.55 | 47.24 | 87.62 | 61.39 |
| XLM1L_AttAvgFCMaxFC    | 48.37 | 44.79 | **96.73** | 61.22 |
| XLM1L_AttAvgFC         | 52.31 | 46.63 | 91.05 | 61.67 |
| XLM1L_AttMaxFC         | **54.90** | **48.06** | 87.06 | 61.93 |
| XLM1L_Att              | 52.84 | 46.89 | 89.78 | 61.61 |
| XLM1L_AXEL             | 71.27 | 61.65 | **84.14** | 71.16 |
| XLM1L_AttAvgFCMaxFCVarFC | 73.28 | 64.79 | 80.05 | **71.62** |
| XLM1L_AttAvgFCMaxFCTanh | 74.05 | 67.72 | 73.34 | 70.42 |
| XLM1L_AttAvgFCMaxFCSum | 73.00 | 64.38 | 80.29 | 71.46 |
| XLM1L_AttAvgFCMaxFC    | 74.02 | 68.19 | 71.81 | 69.96 |
| XLM1L_AttAvgFC         | **75.05** | **69.13** | 73.64 | 71.31 |
| XLM1L_AttMaxFC         | 73.79 | 67.28 | 73.52 | 70.26 |
| XLM1L_Att              | 70.76 | 63.40 | 72.30 | 67.56 |
| XLM1L_AXEL             | 68.81 | 58.16 | **86.97** | **69.70** |
| XLM1L_AttAvgFCMaxFCVarFC | 69.62 | 59.55 | 64.22 | 61.79 |
| XLM1L_AttAvgFCMaxFCTanh | 69.25 | 60.69 | 72.27 | 65.98 |
| XLM1L_AttAvgFCMaxFCSum | 64.63 | 54.63 | 84.09 | 66.23 |
| XLM1L_AttAvgFCMaxFC    | **73.01** | **65.07** | 68.15 | 67.62 |
| XLM1L_AttAvgFC         | 70.44 | 62.97 | 68.79 | 65.75 |
| XLM1L_AttMaxFC         | 69.81 | 64.39 | 60.00 | 62.12 |
| XLM1L_Att              | 68.12 | 60.81 | 63.94 | 62.33 |