LSTM Neural Networks for Transfer Learning in Online Moderation of Abuse Context

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Abstract: Recently, the impact of offensive language and derogatory speech to online discourse, motivated social media platforms to research effective moderation tools that safeguard internet access. However, automatically distilling and flagging inappropriate conversations for abuse remains a difficult and time consuming task. In this work, we propose an LSTM based neural model that transfers learning from a platform domain with a relatively large dataset to a domain much resource constraint, and improves the target performance of classifying toxic comments. Our model is pretrained on personal attack comments retrieved from a subset of discussions on Wikipedia, and tested to identify hate speech on annotated Twitter tweets. We achieved an F1 measure of 0.77, approaching performance of the in-domain model and outperforming out-domain baseline by about nine percentage points, without counseling the provided labels.

1 INTRODUCTION

The wider dissemination of the network and social media platforms have altered online discourse and allowed disrespectful behavior to transpire in forums. The public at large has since expressed increasing concerns that the content, tone, and intent of online interactions have undergone an evolution that becomes a liability. In a recently released large-scale survey, conducted by the Pew Research Center (Pew, 2017) and covering more than 1,500 technologists and academics, over 80% replied that they expect prevalence of online trolling to stay the course, while social platforms actively seeking best practices to balance security and privacy, freedom-of-speech, and user protections (Poland, 2016).

Abusive language is a very broad category that researchers struggle to define, and hence a reliable quantitative detection of hateful speech at scale is still an unresolved problem. Online conversations involve a wide range of audience sizes, from a single participant to an entire community, and the lack of a consistent abuse signal to a classifier is a key implication for the difficulty of the detection task. In an increasingly multicultural information society, ongoing work to automate identification and moderation of unacceptable discourse, adapted natural language processing (NLP) tools for building and annotating social media corpora. Diminishing the widespread presence of cyberbullying in online discussions turned to a world global goal that had spurred work mostly applied to English context (Waseem and Hovy, 2016; Wulczyn et al., 2017; Yenala et al., 2017) and seen constantly expanding to other languages (Ross et al., 2016; Prates De Pelle and Moreira, 2017; Pavlopoulos et al., 2017; Fišer et al., 2017).

Automated detection of abuse in online discourse is a relatively new discipline in NLP research. The work by Yin et al. (2009) is the earliest known to use a machine learning approach to identify harassment on the Web, by supplementing local TF-IDF (Baeza-Yates and Ribeiro-Neto, 1999; Salton et al., 1975) with sentiment and context features that are fed to a support vector machine (SVM) classifier. More recent work explored logistic regression (LR) and multilayer perceptrons (MLP) on either word or character level n-grams (Wulczyn et al., 2017). Davidson et al. (2017) showed that LR with L2 regularization performed markedly better than other baselines, however their model was biased toward classifying posts as less hateful or offensive compared to human judges.

Proving compelling performance when applied to a traditional NLP task as sentiment analysis (dos Santos and Gatti, 2014; Huang et al., 2016; Qian et al., 2017), deep learning models expressed in both their recurrent and convolutional variants of neural networks (Elman, 1990) has recently become a widespread foundation for sequential text classifica-

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tion (Kim, 2014; Lee and Dernoncourt, 2016; Yogatama et al., 2017). Text sequences fed to the network are often represented in a semantic vector space with either character or word embeddings (Pennington et al., 2014) that capture local context information via global co-occurrence counts.

To detect toxicity in comments, Chu et al. (2017b) explored separately long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) based recurrent neural network (RNN) and convolutional neural network (CNN) architectures. They observed that CNN performed better and prove more computationally efficient when paired with character than with word embeddings. Yenala et al. (2017) propose an architecture that synthesizes CNN and bidirectional LSTM to detect inadequate queries in Web search. Their model shown to significantly outperform pattern based and laborious hand-coded features. More recently, a CNN model fed by word vectors to classify hate-speech on Twitter (Gambäck and Sikdar, 2017), achieved an F1 score of 78.3% to improve performance over an LR baseline. Rather than toxicity, identifying constructiveness in news comments is studied in the work by Kolhatkar and Taboada (2017) that uses an LSTM based classifier with a highest test accuracy of 72.6%.

An impediment to algorithmic progress in detecting hateful speech is the scarcity of large publicly available datasets. Past work tends to use self curated datasets that rely on either manual and costly human annotations, or resort to searches of a limited set of keywords (Sood et al., 2012; Kwok and Wang, 2013). Saleem et al. (2017) found that widely used expletives and slurs are not necessarily indicative of abuse, and proposes self-identified hateful communities to label training examples and improve scalability.

To the extent of our knowledge, the current open datasets are limited to the Detecting Insults in Social Commentary released by Impermium for a Kaggle competition (Impermium, 2013; Krishnamoorthy et al., 2017), the Twitter Hate Speech annotations (Waseem and Hovy, 2016), and the English corpora of the Wikipedia Detox project (Wulczyn et al., 2017). The Impermium dataset contains over 8K comments annotated as either insulting or neutral, while the Twitter set comprises over 16K tweets, each labeled as one of racist, sexist, or neutral. Obtained from processing a large dump of Wikipedia discussion pages, the Wikipedia Detox annotations for personal attacks, aggression, and toxicity, each of over 100K comments, are by far the largest available and most well curated to reliably label insult in comments. In our work, we use both the Wikipedia and Twitter datasets.

In the field of machine learning, transfer learning aims to reuse previously acquired knowledge between task domains (Pan and Yang, 2010; Ruder and Plank, 2017; Joshi and Chowdhary, 2018). Often, the primary motivation for transfer learning is to improve performance of a task with limited training data by leveraging pretrained features, or hyperparameters, on a task with access to a large labeled resource. Knowledge transfer has been successfully applied to numerous domains in machine learning. Notably are visual recognition models trained on the large-scale ImageNet challenge (Russakovsky et al., 2015; Huh et al., 2016) and proven to be effective feature extractors in a variety of tasks including semantic image segmentation (Oquab et al., 2014), medical diagnostics (Esteva et al., 2017), and image captioning (Donahue et al., 2017). Shown to speed up training and outperform in-domain model performance, transfer learning benefited audio-related tasks such as speech recognition (Kunze et al., 2017) and music classification (Choi et al., 2017), and NLP specific tasks including neural machine translation (NMT) (Zoph et al., 2016), machine comprehension (Golub et al., 2017), semantic parsing (Fan et al., 2017), cross-lingual POS tagging (Kim et al., 2017), and text classification (Liu et al., 2017). Similarly, in our work, we pretrained a neural model on a large Wikipedia Detox dataset and reused learned weights and biases to bootstrap an abuse detection task on a small set of hateful speech annotations extracted from Twitter.

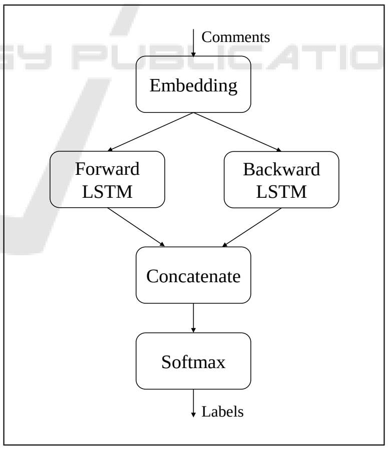
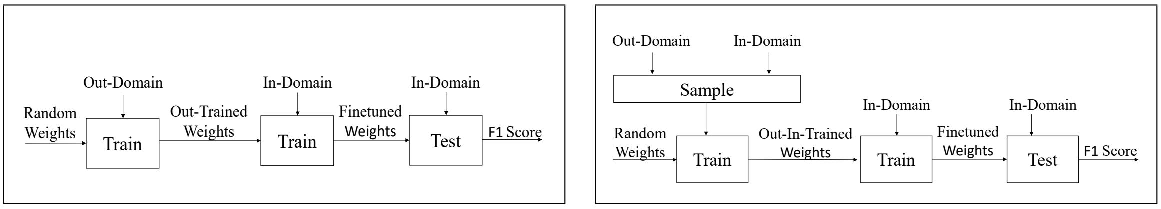


Figure 1: BiLSTM neural model architecture: word sequences are each mapped by the embedding layer into a series of dense vectors. Word embeddings are then fed into both forward and backward LSTMs, with their outputs concatenated and passed through a softmax activation function to produce probabilities for no-abuse and abuse labels.

The main contribution of this work is a novel transfer-learning model that facilitates state-of-the-art domain adaptation methods to benefit the performance of low-resource abuse detection in comments. Our study proposes to ameliorate the constraining



(a) Low-Resource Domain Adaptation

(b) Low-Resource Domain Matching

Figure 2: Transfer learning scenarios including (a) AD model adaptation to a low-resource domain and (b) generalizing an AD system to match a low to a high resource domain using oversampling.

scarcity of obtainable toxic-discourse corpora by motivating the creation of coarse-grained annotations, along with only a few large datasets to learn from. We show the effectiveness of our model by closely matching in-domain baseline performance. The rest of this paper is structured as follows. In Section 2, we overview the architecture of our LSTM-based neural model, and in Section 3, we proceed to highlight the base and compound methods we explored for transfer learning. Section 4 analyzes the semantical relation between the Wikipedia Detox and Twitter Hate Speech datasets, and details our training procedures. In Section 5, we present our evaluation methodology and report extensive quantitative results over a range of ablation studies. Summary and identified avenues for prospective work are provided in Section 6.

2 MODEL ARCHITECTURE

In this section, we formalize the task of abuse detection (AD). Our AD model takes as input a tokenized comment $c = \{c_1, c_2, \ldots, c_n\}$, where c_i are text words, and learns a function $f(c) \mapsto \{\text{no-abuse}, \text{abuse}\}$. Given a collection of l labeled comments $\{c\}_{i=1}^{l}$ from a distinct domain s, such as Wikipedia or Twitter, we can learn an AD model $f_s(c)$ to predict abuse in that domain. Moreover, we can adapt an AD model trained in one domain to classify abuse in another, and avoid prohibitively expensive and time consuming human labeling of new data. In this paper, we propose the task of knowledge transfer from an AD system $f_s(c)$ that is trained in a source domain to detect abuse over a target domain t with an unlabeled set $\{c\}_{i=1}^{k}$ of k comments, where $k \ll l$. We aim to improve rather than adversely impact target performance, and avoid negative transfer learning (Pan and Yang, 2010).

Our neural model (Figure 1) uses a bidirectional long short-term memory network (BiLSTM) (Hochreiter and Schmidhuber, 1997; Schuster and Paliwal, 1997) fed with distributed word representation. First, we transform each comment word $c_i \mapsto c_i^x$ into a continuous semantic vector-space through pretrained GloVe embeddings (Pennington et al., 2014). We then parametrize the word distribution of an input example $c^x = \{c_1^x, c_2^x, \ldots, c_n^x\}$ as an encoder-decoder gated RNN (Cho et al., 2014; Chung et al., 2014; Sutskever et al., 2014), and produce context-dependent word representations $h = \{h_1, h_2, \ldots, h_n\}$, as h_i consists of concatenations of $\overrightarrow{h_i}$ and $\overleftarrow{h_i}$, the forward and backward hidden states of the encoder, respectively. The encoder output of the last time step, h_n, is further weighted to enter a softmax activation function that renders the output probability distribution of comments, and produces no-abuse and abuse classification labels for each.

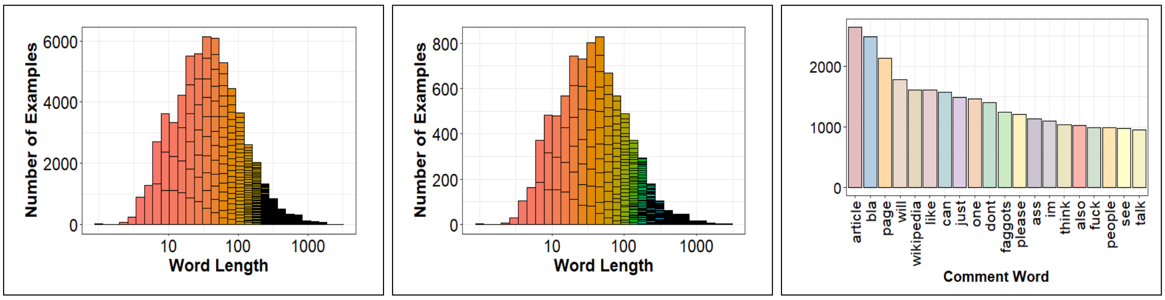
3 TRANSFER LEARNING

Knowledge transfer in a neural model encourages the sharing of statistical network regularities to help alleviate potential overfitting due to a large number of hyperparameters. In their recent work, Mou et al. (2016) have made the observation that whether a neural network is effectively transferable in NLP applications depends largely on how semantically close the source and target tasks are. We note that in our model, word embeddings pretrained on large external corpora are likely to be transferable even to semantically distant tasks. Additionally, they assert that the output layer of the underlying neural architecture is largely dataset specific and thus not transferable. Motivated by their results, this work explores two transfer learning scenarios, domain adaptation and domain matching, both perceived from a low-resource target domain. We hypothesize that these methods are plausible to achieve performance comparable to in-domain baselines.

In the first transfer scenario, we investigate the prospect of taking an existing AD model formerly trained on large amount of data from one domain, and finetune its network parameters on a small number of examples in another domain (Figure 2a). The latter scenario merges the rich data from the source domain with the scarce data from the target domain and concurrently trains samples in both domains (Figure

Table 1: Wikipedia Detox: comment distribution across train, development, and test sets.

	No-attack	Attack	Total	Min Length	Max Length	Mean Length
train	61,343	8,182	69,525	1	2,833	70.4
dev	20,429	2,731	23,160	1	2,376	69.7
test	20,501	2,677	23,178	1	2,500	71.5



(a) No-Attack Comments (b) Attack Comments (c) Vocabulary

Figure 3: Wikipedia Detox dataset: train set histograms of logarithmic-scaled word length across (a) no-attack annotated comments and (b) comments labeled attack, and (c) vocabulary distribution of top-20 frequent tokens.

2b). To ensure a statistically balanced comment presence of the source and target domains, required for the stochastic training process, we oversample the data of the low-resource domain (Chu et al., 2017a).

The transfer learning methods we chose differ primarily in the applied training protocol. In the domain adaptation pipeline, training progresses in two stages. Weights are randomly initialized first and trained next on the out-domain using the large source dataset. We then initialize the network with the weights learned previously and trained on the out-domain to finetune some of the weights using the sparse target dataset. Our in-domain abuse dataset is already annotated and hence we made the finetuning step an integral part of our framework. Domain matching, on the other hand, trains comment samples drawn from both the source and target datasets simultaneously. In a one-time preprocess, the low-resource in-domain is oversampled to match the dimensionality of the resource rich out-domain. We then alternate between the domains and randomly select a data sample from either domain to compute its gradient. The out-in trained weights we generate in this process follow finetuning and are used on the in-domain test set for abuse classification.

Combining domain adaptation and domain matching is a reasonable knowledge transfer proposition we further address in our evaluation analysis.

4 EXPERIMENTAL SETUP

In this section, we summarize the datasets we used in our experiments and quantify their semantic relationship. We review parameter settings for our model architecture, and provide training details for the various transfer learning methods we studied.

4.1 Wikipedia Detox

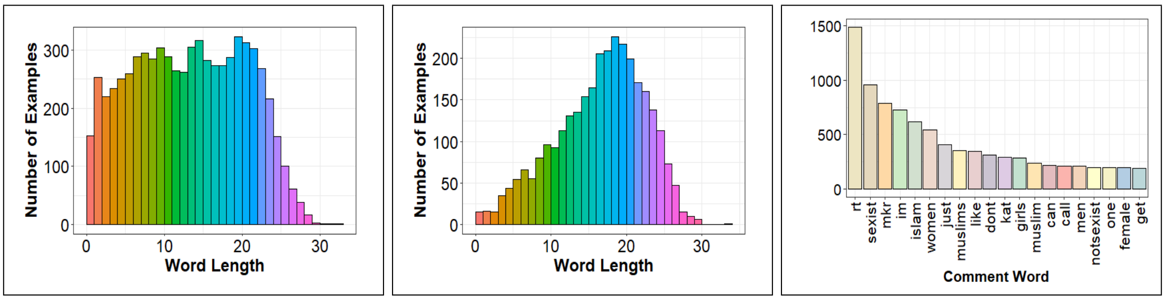
The Wikipedia Detox project [1] is part of Google's Jigsaw Conversation AI project [2], and provides a high-quality human-curated dataset of one million crowd-sourced annotations for disciplines including personal attacks, aggression, and toxicity. Annotated discourse were obtained from 100K English Wikipedia talk-pages with at least ten judgments per page (Wulczyn et al., 2017). The data was sampled from a corpus of 63 million comments processed from Wikipedia online discussions related to user pages and articles dated from 2001 to 2015. A classifier is then trained on the human-labeled dataset and machine annotates the entire corpus of comments. In our work, we chose the human-curated Wikipedia personal-attack corpus as the source for knowledge transfer that allows us to reference out-domain model behavior in existed research (Wulczyn et al., 2017; Chu et al., 2017b).

We randomly partitioned the English Wikipedia dataset into train, development, and test splits using a 3:1:1 ratio. The dataset consists of 115,863 comments, 69,525 of which are used for training, 23,160 for development, and 23,178 for the test set (Table 1). Each comment was labeled by at least ten different crowdsource annotators and categorized into one of four different attack groups namely quoting, recipient, third party, and other. A given comment might be flagged by the same annotator for multiple attack

[1] https://meta.wikimedia.org/wiki/Research:Detox
[2] https://jigsaw.google.com/projects/#conversation-ai

Table 2: Twitter Hate Speech: tweet distribution across train, development, and test sets.

	No-Hateful	Racism	Sexism	Total	Min Length	Max Length	Mean Length
train	6,894	1,176	1,882	9,952	1	34	14.7
dev	2,309	394	630	3,333	1	30	14.6
test	2,287	390	624	3,301	1	31	14.8



(a) No-Hateful Tweets (b) Hateful Tweets (c) Vocabulary

Figure 4: Twitter Hate Speech dataset: train set histograms of word length across (a) no-hateful annotated tweets and (b) hateful labeled tweets, and (c) vocabulary distribution of top-20 frequent tokens.

groups and is defined as a personal attack based on the majority of attack ratings among the top-10 selected judgments. On average, about 12 percentage points of comments from each of the data splits were labeled as attack (Table 1). In our work, we tag a comment as either no-attack or attack and consider identifying personal attacks in discourse as a two-class text classification task that we map onto a BiLSTM network.

The train set distribution of sequence lengths for no-attack and attack labeled comments are shown on a logarithmic scale in Figures 3a and 3b, respectively. Histogram patterns are fairly resembling for both benign and offensive type comments, with a comment size that averages about 70 words and tops at 2,833 tokens (Table 1). This data is useful to understand our model complexity for feeding sequential text into the BiLSTM network. Figure 3c provides vocabulary distribution of twenty most frequently occurring terms in the Wikipedia dataset, yet on their own, most are not qualified to assess insult in comments.

4.2 Twitter Hate Speech

The Twitter Hate Speech dataset (Waseem and Hovy, 2016) was sampled from 136,052 tweets collected from hundreds of users over a two-month period. Bootstrapped from a small sample of frequently occurring terms and slurs in hateful speech, the collection process used the public Twitter Search API to construct the entire corpus, while filtering for non-English tweets. The data was manually annotated for hateful speech using a succinct decision list of easily identified observations, and further reviewed objectively to alleviate annotator bias. In total, the dataset comprises 16,586 annotated tweets of which 1,960 are labeled as racist content, 3,136 as sexist, and 11,490 are neutral. To evaluate our model, we randomly divided each of the annotation classes into a 3-way data split for the train, development, and test sets, as shown in Table 2. We treat the problem of recognizing hateful speech in social media tweets as a binary classification task, by concatenating the racist and sexist short-text sequences into a single hateful speech category. We note that about 30% of the dataset tweets are tagged hateful.

The train set distribution of word lengths for both no-hateful and hateful flagged tweets are shown in Figures 4a and 4b, respectively. Despite the uniform average tweet size of 15 words across all the data splits, word lengths appear more evenly distributed for tweets of no-hateful speech compared to the ones tagged as hateful. The top-20 vocabulary terms occurring most frequently in tweets (Figure 4c), evidently require additional surrounding context to conclusively identify hateful speech in tweets. In our experiments, we used the Twitter dataset as the target for transfer learning, since it is at a much smaller data scale when contrasted with the Wikipedia domain.

4.3 Semantic Similarity

One of the prerequisites to a non-negative knowledge transfer in NLP tasks is to ensure semantic relatedness between the source and target domains (Mou et al., 2016). In this section, we discuss our generalized approach to quantitatively evaluate semantic closeness of a pair of textual datasets with arbitrary word counts. To this extent, we leveraged our word embed-

Table 3: Training stage dispatch across the source and target BiLSTMs, as a function of the underlying domain operator.

BiLSTM	Domain Operator			
	Adaptation	Matching	Adaptation-Matching	Matching-Adaptation
Source	Wikipedia	Wikipedia+Twitter	Wikipedia Wikipedia+Twitter	Wikipedia+Twitter Wikipedia
Target	Twitter	Twitter	Twitter	Twitter

dings representation and flattened both the source and target datasets to a linear set of word vectors we denote $a^{(s)} = \{c^x\}_{i=1}^{l}$ and $a^{(t)} = \{c^x\}_{i=1}^{k}$, respectively. We explored a concept that allows us to compute similarity more flexibly than with just a dot product, by expanding on the Chebychev distance between a pair of matrices with non-conformant dimensionality, defined by the formula

$$d(s,t) = \frac{1}{|a^{(s)}|} \sum_j \left\{ \max_i \left(\text{sim}(a_j^{(s)}, a_i^{(t)}) \right) \right\},$$

where $|a^{(s)}|$ is the dataset cardinality that amounts to the total number of distributed word vectors for representing the dataset, and $|a^{(s)}| \neq |a^{(t)}|$. Whereas sim() is a similarity function that operates on two word vectors and takes either a Euclidean or an angle form. We chose cosine similarity (Baeza-Yates and Ribeiro-Neto, 1999) that performs an inner product on a pair of normalized vectors u and v, $\frac{u \cdot v^T}{\|u\|_2 \|v\|_2}$, and returns a scalar value as a measure of proximity.

After flattening each of the Wikipedia and Twitter abuse datasets to a continuous set of word embeddings, we computed an inter-domain semantic distance of about 0.83. This appears a reasonably high similarity score in a $[0,1]$ range, despite the striking context difference between the abuse disciplines we used, namely personal attacks and harassment.

4.4 Training

In our experiments, we used distinct source and target BiLSTM networks that cooperate in conducting progressive training in either one, two, or three stages. Based on the knowledge transfer mode, we train the source BiLSTM model on either the Wikipedia train dataset or concurrently on the Wikipedia and Twitter train sets, with tweets of the latter oversampled to match the dimensionality of the Wikipedia dataset. The target BiLSTM is subsequently initialized with network weights learned on the source BiLSTM, and optionally follows finetuning of a subset of network settings on the Twitter train set. In practice, our implementation invokes a sequence of training stages over the source and target BiLSTMs that is prescribed by the various domain operators for transfer learning, and are illustrated in Table 3.

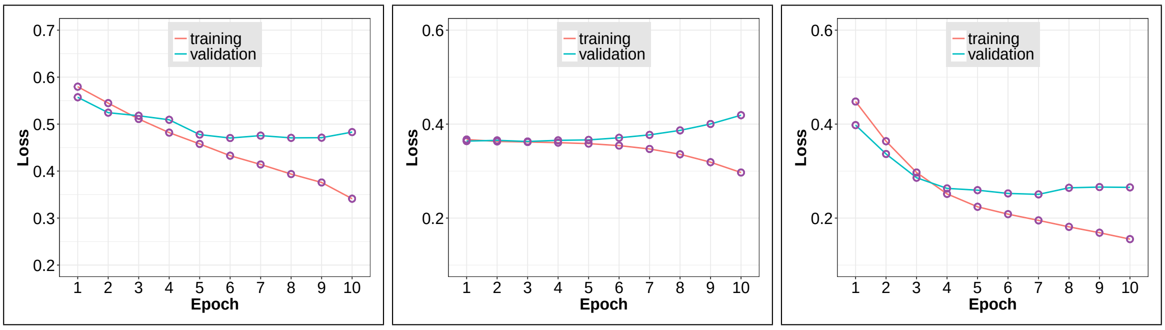
As a one-time preprocess, all comments from both the Wikipedia and Twitter datasets were tokenized and lowercased using R (R Core Team, 2013). Word embeddings were initialized with 200-dimensional GloVe vectors (Pennington et al., 2014) pretrained on large 6B token corpora including English Wikipedia dumps and GigaWord newswire text [3]. As the largest 300-sized vectors resulted in a diminishing performance return. Uniformly, all embeddings of unknown tokens are set to zero, and the combined source and target domains use a vocabulary size of 54,949 words.

We used BiLSTMs with 200 memory cells in the hidden layer for the source domain, and 100 memory cells for the low-resource target domain that is less memory intensive. We have trained both the AD source and target models with the Adam stochastic gradient optimizer (Kingma and Ba, 2014) using its provided default settings with a mini-batch size of 128 examples. In a batch, sequences of embeddings are expected of the same length, and are hence either clipped or padded to the mean and maximal length of Wikipedia comments (Table 1) and Twitter tweets (Table 2), respectively. Hyperparameters in the form of weight matrices and bias vectors were bootstrapped using Xavier initialization (Glorot and Bengio, 2010) and are further tuned in the validation phase. In total, our model has over two million parameters of which 161,202 are trainable.

To avoid overfitting, we regularized our networks by applying dropout (Srivastava et al., 2014) with a rate of 0.2 probability for randomly switching off connections between the input and hidden layers during training. Additionally, our model supports early termination of training by observing, after each epoch, the rate-of-change of both the loss and the quality of abuse detection on the participating development sets of either the source, target, or both domains, as outlined in the currently executed train stage (Table 3). Dropout and early stop of training were sufficient to reduce overfitting in our model, with a difference between training and development F1 scores of less than five percentage points before convergence.

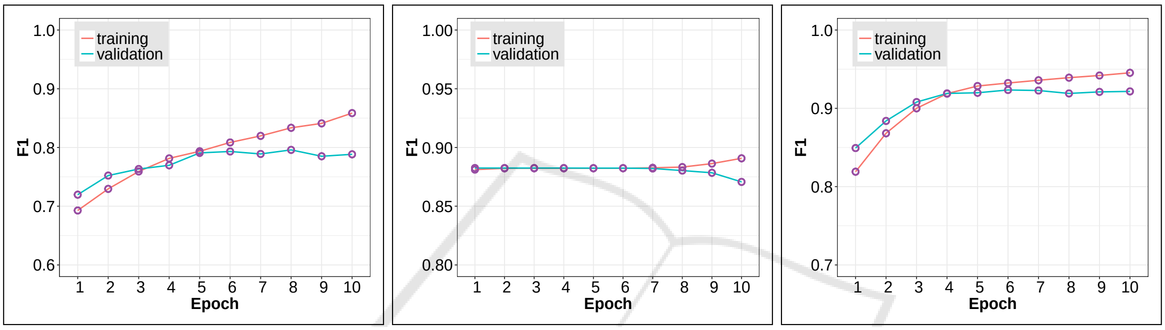
As part of the analysis we conducted, we monitored after each epoch both the cross-entropy error and performance as the stochastic training and vali-

[3] https://nlp.stanford.edu/projects/glove/



(a) No Transfer Learning (b) Domain Adaptation (c) Domain Matching

Figure 5: Contrasting training with validation loss behavior for transfer learning: showing loss as a function of epoch progression for (a) no knowledge transfer, (b) domain adaptation, and (c) domain matching scenarios.



(a) No Transfer Learning (b) Domain Adaptation (c) Domain Matching

Figure 6: Contrasting training with validation performance for transfer learning: showing F1 score as a function of epoch progression for (a) no knowledge transfer, (b) domain adaptation, and (c) domain matching scenarios.

dation processes progress iteratively. We show training and validation plots of our model loss and performance for the first ten epochs in Figure 5 and Figure 6, respectively. As corresponding split sets of the Twitter target, Wikipedia source, and combined source and oversampled target are used for (a) no knowledge transfer, (b) domain adaptation, and (c) domain matching scenarios, respectively. Apart from domain adaptation mode that shows almost identical training and validation performance for the first seven epochs, our performance plots mostly depict a desired behavior with validation scores slightly lower than the training scores. These results strongly support the network regularization steps we incorporated to alleviate potential data overfitting to the various training sets.

We chose to report F1 score for our metrics, consistent with the published non-transferable target baseline (Waseem and Hovy, 2016).

5 EXPERIMENTAL RESULTS

We analyzed our model performance for each of the basic transfer-learning schemes we laid out, namely domain adaptation and domain matching, and in addition we evaluated the performance impact of fusing the pair of basic methods in a two-stage training sequence. The fusion of the principal domain operators is inherently directional and thus has adaptation either precede or trail domain matching in the training cascade. Table 3 illustrates the order of train events that occur in fusing adaptation and matching. In adaptation-matching mode, we first train our model on the source Wikipedia dataset, and then resume training on both the Wikipedia and Twitter domains. As the matching-adaptation process, swaps the former train stages. In total, we explored four domain operators for experimenting with transfer learning, and for each we optionally invoked a final step of finetuning a subset of network parameters before evaluating the low-resource domain on the target test set.

In our work, we used Keras (Chollet et al., 2015), a high-level deep learning interface that runs on top of the TensorFlow [4] software library for executing high-performance numerical computation on a variety of platforms. Keras attractive quality of saving and loading the entire history of a pretrained neural-network

[4]https://www.tensorflow.org/

Table 4: In-domain baseline performance: F1 scores for a logistic regression classifier with word and character n-gram representations (Waseem and Hovy, 2016), and for our BiLSTM model without transfer learning.

Model	Baseline	F1
Feature Based	word n-gram features	0.65
	character n-gram features	0.74
BiLSTM	no transfer learning	**0.79**

model, played a pivotal role in our paradigm that dispatches multi-stage training, as illustrated in Table 3. Moreover, training can be set to resume at a user specified epoch and thus aid in boosting performance. In Keras early stopping, we set the threshold to quantify validation loss improvement or not to zero, and the patience parameter to two epochs with no observed improvement, after which training will be terminated.

We first provide in-domain baseline performance over the Twitter target dataset. In Table 4, we contrast a logistic regression classifier that uses both word and character n-gram representations (Waseem and Hovy, 2016) to our BiLSTM network stripped of knowledge transfer capacity. Our word embedding based neural-model achieved 0.79 F1 score and outperforms the manual feature-based system with F1 of 0.65 and 0.74 for word and character n-grams, respectively.

Next, we report our AD model performance of out-domain transfer learning for the basic and fused domain operators. In Table 5, we show both our raw and finetuned F1 scores, for each scenario. Our topmost scoring operator is domain matching with a raw F1 score of 0.77, only slightly under our in-domain baseline with an F1 rate of 0.79 (Table 4), and outperforming out-domain baseline performance of the LSTM model used in Chu et al. (2017b), by about nine percentage points. On the other hand, basic domain adaptation scores the lowest with a raw F1 score of 0.68. Evidenced by the scores of individual segments, the linking of basic domain operators appears to have little impact on our model performance, with observed F1 scores of 0.75 and 0.69 for adaptation-matching and matching-adaptation, respectively. We note that the non-leading domain operator of a fused pair, matching in adaptation-matching and adaptation in matching-adaptation, dominates the outcome rate of the model, and hence the obtained F1 scores are comparable to the respective basic operators. The optional training step of finetuning a subset of target network parameters has a larger performance impact on domain adaptation, yet it affects the matching operator end-result only mildly, as shown in Table 5. In all, finetuned F1 scores across domain operators are almost on par.

Conceptually, in transfer learning from a large-resource domain to a small domain data, we perceive training as a stochastic process applied to pairs of samples chosen alternately from the source and the target domains, with the latter conditioned by a given probability p. Hence in domain adaptation form we let $p = 0$ and all samples are drawn from the source domain. Whereas $p = 1$ for domain matching that uses balanced source and target data through in-domain oversampling, by generating an l-sized vector of random permutation of replicating indices $\in (1, k)$. Moreover, this warrants that all examples of both the source and target datasets are sampled. However, using fractional probabilities $p \in (0, 1)$ to compute the example gradient may not uphold robust sampling (Mou et al., 2016). Barring the finetuning step, we expected adaptation to perform lower due to absolute out-domain learning compared to the matching scenario that evens the distribution of in and out domain data. Thus our corresponding F1 scores of 0.68 and 0.77, appear entirely explicable.

Table 5: Wikipedia to Twitter transfer learning performance: F1 scores for our basic and fused domain operators configured with and without finetuning.

Domain Operator	Raw F1	Finetuned F1
adaptation	0.68	0.76
matching	**0.77**	**0.77**
adaptation-matching	0.75	0.73
matching-adaptation	0.69	0.75

Although the fused and basic domain operators performed practically identical, compound transfer learning incurs an appreciable runtime cost of training that is often overlooked. Since training time complexity is about linear with the number of examples in the dataset, by letting domain adaptation train in a normalized unit time, domain matching would hence train twice as slow, and each of the fused operators would triple the basic training time.

6 CONCLUSIONS

In this paper, we have explored transfer learning from a large corpus to a low-resource domain for the task of abuse detection in online discourse. We conducted our experiments under the interesting adaptation and matching scenarios over source and target datasets from orthogonal domains. We showed that the matching domain operator is most effective and performs just slightly lower than the in-domain baseline, as our neural network model is pretrained on the large source dataset mixed with an oversampled small target data. Fusing adaptation and matching methods, revealed however inconsequential performance gains over independent domain operators.

Despite the practical importance for the public at-large to benefit from curbing abusive language online, high cost linguistic annotation and resource creation are unlikely to be undertaken in the near future. Our contribution is intended to ameliorate the scarcity of large datasets that presently hinders advancement toward the ultimate automation of early intervention and moderation of offensive posts. To the extent of our knowledge, this paper is first to introduce transfer learning for the task of insult detection in comments. Our work motivates the curating of a multitude of low-resource abuse corpora that is substantially less time consuming, in conjunction with only a few, more elaborate large datasets.

A direct progression of our work is expanding our AD model to use an ensemble of low-resource target datasets for each abuse discipline, and improve robustness of knowledge transfer. This will also facilitate discipline centered multi-class classification towards a more fine-grained abuse moderation. Extending our model input representation to character embeddings and better address unedited and slang-filled toxic comments is one plausible approach to boost our classification performance. To mitigate the high sparsity of abuse data in foreign languages, we plan to incorporate an NMT model that translates in-domain data to English first. Efficient integration of the attention based sequence-to-sequence network, used for language translation, and our transfer learning model provides streamlined abuse detection in multi-lingual knowledge-transfer setting.

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