Inducing a Lexicon of Abusive Words – A Feature-Based Approach

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Abstract

We address the detection of abusive words. The task is to identify such words among a set of negative polar expressions. We propose novel features employing information from both corpora and lexical resources. These features are calibrated on a small manually annotated base lexicon which we use to produce a large lexicon. We show that the word-level information we learn cannot be equally derived from a large dataset of annotated microposts. We demonstrate the effectiveness of our (domain-independent) lexicon in the cross-domain detection of abusive microposts.

1 Introduction

Abusive or offensive language is commonly defined as hurtful, derogatory or obscene utterances made by one person to another person.[1] Examples are (1)-(3). In the literature, closely related terms include *hate speech* (Waseem and Hovy, 2016) or *cyber bullying* (Zhong et al., 2016). While there may be nuanced differences in meaning[2], they are all compatible with the general definition above for abusive language.[3]

(1) stop editing this, you **dumbass**.
(2) Just want to slap the **stupid** out of these **bimbos**!!!
(3) Go lick a pig you arab muslim piece of **scum**.

Due to the rise of user-generated web content, in particular on social media networks, the amount of abusive language is also steadily growing. NLP methods are required to focus human review efforts towards the most relevant microposts.

In this paper, we address the task of detecting abusive words (e.g. *dumbass*, *bimbo*, *scum*). Our main assumption is that abusive words form a subset of negative polar expressions. The classification task is to **filter the abusive words from a given set of negative polar expressions**. We proceed as follows. On a base lexicon that is a small subset of negative polar expressions where the abusive words among them have been marked via crowdsourcing (§3), we calibrate a supervised classifier by examining various novel features (§4). A classifier trained on that base lexicon, which contains 551 abusive words, is then applied to a very large list of unlabeled negative polar expressions (from Wiktionary) to extract an expanded lexicon of 2989 abusive words (§5).

We extrinsically evaluate our new lexicon in the novel task of **cross-domain classification** of abusive documents (§6) where we use it as a *high-level* feature. In this work, we consider microposts as documents. While for in-domain classification, supervised classifiers trained on generic features, such as bag of words or word embeddings, usually score very well, on cross-domain classification they perform poorly since they latch on to domain-specific information. In subjectivity, polarity and emotion classification, high-level features based on predictive domain-independent word lists have been proposed to bridge the domain mismatch (Dias et al., 2009; Mohammad, 2012; Wiegand et al., 2013).

New abusive words constantly enter natural language. For example, according to Wiktionary[4] the word *gimboid*, which refers to an incompetent person, was coined in the British television series *Red Dwarf*, possibly from the word *gimp* and the suffix *-oid*. According to Urban Dictionary[5], the word *twunt*, which is a portmanteau of the swearwords *twat* and *cunt*, has been invented

[1] http://thelawdictionary.org/
[2] For example, several research efforts just focus on utterances addressed towards minorities.
[3] The examples in this work are included to illustrate the severity of abusive language. They are taken from actual web data and in no way reflect the opinion of the authors.
[4] https://en.wiktionary.org
[5] www.urbandictionary.com

by humourist Chris Morris for the Channel 4 series 'Jam' in 2000. One of the most recent abusive words is *remoaner* which describes someone who complains about or rejects the outcome of the 2016 EU referendum on the UK's membership of the European Union. It is a blend of *moan* and *remainer*. Wiktionary states that this word has a pejorative connotation.

These examples show that the task of creating a lexicon of abusive words cannot be reduced to a one-time manual annotation effort. Recent web corpora and crowdsourced dictionaries (e.g. Wiktionary) should be ideal resources to find evidence of such words.

Our **contribution** is that we present the first work that systematically describes the *automatic* construction of a lexicon of abusive words. We examine novel features derived from various textual resources. We show that the information we learn cannot be equally derived from a large dataset with labeled microposts. The effectiveness of our expanded lexicon is demonstrated on cross-domain detection of abusive microposts. This is also the first work to address this task in general. The supplementary material to this paper[6] includes all resources newly created for our research.

We frame our task as a **binary classification problem**. Each given expression is to be classified as either abusive or not. We study this problem on English. However, many of our features should also be applicable to other languages.

2 Related Work

Lexical knowledge for the detection of abusive language has only received little attention in previous work. Most approaches consider it as one feature among many. Very often existing word lists from the web are employed (Xiang et al., 2012; Burnap and Williams, 2015; Nobata et al., 2016). Their limited effectiveness may be due to the fact that they were not built for the task of abusive language detection. Only the manually-compiled lexicon from Razavi et al. (2010) and the lexicon of *hate verbs* from Gitari et al. (2015) have been compiled for this specific task. Since the latter lexicon is not publicly available we can only consider the former in our evaluation. In both publications, very little is said on the creation of these resources.

Previous work focused on in-domain classification, a setting where generic features (e.g. bag of words) work well and word lists are less important. There have been investigations examining features on various datasets (Nobata et al., 2016; Samghabadi et al., 2017), however, these studies always trained and tested on the *same* domain. We show that a lexicon-based approach is effective in cross-domain classification.

For a more detailed overview on previous work on the detection of abusive language in general, we refer the reader to Schmidt and Wiegand (2017).

3 Data

Base Lexicon. Our base lexicon exclusively comprises negative polar expressions. It is a small set which we have **annotated via crowdsourcing**. We consider abusive words to be a proper subset of negative polar expressions. By just focusing on these types of words, we are more likely to obtain a significant amount of abusive words than just considering a sample of arbitrary words. This lexicon will be used as a gold standard for calibrating features of a classifier. That classifier will be run on a large set of unlabeled negative polar expressions to produce our expanded lexicon (§5).

We sampled 500 negative nouns, verbs and adjectives each from the Subjectivity Lexicon (Wilson et al., 2005). We chose that lexicon since we have extra information available for its entries that we want to examine, namely polar intensity (§4.1.1) and sentiment views (§4.1.2). However, since we noted that the Subjectivity Lexicon misses some prototypical abusive words (e.g. *nigger*, *slut*, *cunt*) we added another 10% (i.e. 150 words) which are abusive words frequently occurring in the word lists mentioned in Schmidt and Wiegand (2017).

Each of the negative polar expressions was judged by 5 annotators from the crowdsourcing platform *ProlificAcademic*.[7] Each annotator had to be a native speaker of English and possess a task approval rate of at least 90%. For our base lexicon (Table 1), we considered a binary word categorization: *abusive* or *non-abusive*. A word was only classified *abusive* if at least 4 out of the 5 raters judged the word to be abusive. This threshold should prevent many ambiguous words from being classified as abusive, a general problem of existing resources (Davidson et al., 2017).

Corpora. In our experiments we employ three

[6] https://github.com/miwieg/naacl2018

[7] The supplementary material contains more information regarding our annotation set-up (including guidelines).

	adj		noun		verb		all	
class	freq	%	freq	%	freq	%	freq	%
abusive	170	33.8	291	45.3	90	17.8	551	33.4
not abusive	332	66.2	352	54.7	415	82.2	1099	66.6

Table 1: The base lexicon: 1650 entries in total of which 551 are abusive.

		intensity (§4.1.1)		views (§4.1.2)	
class	**all**	weak	strong	actor	speaker
abusive	26.7	14.1	32.0	9.7	32.8
not abusive	73.3	85.9	68.0	90.3	67.2

all numbers only refer to the subset of the base lexicon (Table 1) taken from the Subjectivity Lexicon (i.e. 1500 entries)

Table 3: Percentage of abusive/not abusive instances among (binary) intensity and views.

unlabeled corpora (Table 2). The two larger corpora, the *Amazon Review Corpus – AMZ* (Jindal and Liu, 2008) and the *Web As Corpus – WAC* (Baroni et al., 2009), are used for inducing word embeddings (§4.2). AMZ and the smallest corpus, *rateitall.com – RIA*[8], are used for computing polar word intensity (§4.1.1) from star ratings.

4 Feature Calibration

In the following, we describe the two types of features of our feature-based approach: novel linguistic features and generic word embeddings. They will be examined against some baselines on our base lexicon. As a classifier we use an SVM as implemented in SVM^{light} (Joachims, 1999). We chose that classifier since it is most commonly used for the detection of abusive language (Schmidt and Wiegand, 2017). *For all classifiers in this paper, the supplementary material*[6] *contains information regarding (hyper)parameter settings.*

4.1 Linguistic Features

4.1.1 Polar Intensity (INT)

Intuitively, abusive language should coincide with high polar intensity. We inspect 3 different types.

Binary Intensity (INT$_{bin}$). Our first feature is a simple binary intensity feature we obtain from the Subjectivity Lexicon. In that resource, each entry is categorized as either a *weak* polar expression (e.g. *dirty*) or a *strong* polar expression (e.g. *filthy*). Table 3 (left half), which shows the distribution of intensity on the intersection of our base lexicon and the Subjectivity Lexicon, confirms that abusive words are rarely weak polar expressions and more frequently strong polar expressions.

Fine-grained Intensity (INT$_{fine}$). We also investigate a more fine-grained feature which assigns a real-valued intensity score to polar expressions. It is computed by leveraging the star-rating assigned to the reviews comprising the AMZ corpus (Table 2), a large publicly available review corpus. A review is awarded between 1 and 5 stars where 1 is the most negative score. We infer the polar intensity of a word by the distribution of star-ratings associated with the reviews in which it occurs. We assume negative polar expressions with a very high polar intensity to occur significantly more often in reviews assigned few stars (i.e. 1 or 2). Ruppenhofer et al. (2014) established that the most effective method to derive such polar intensity is by ranking words by their *weighted mean of star ratings* (Rill et al., 2012). All words of our base lexicon are ranked according to that score. As a feature we use the rank of a word.

Intensity Directed towards Persons (INT$_{person}$). Not all negative polar expressions with a high intensity are equally likely to be abusive. The high intensity expressions should also be words typically directed towards persons. Most polar statements in AMZ, however, are directed towards a movie, book or some electronic product. In order to extract negative polar intensity directed towards persons, we replace the AMZ corpus with the RIA corpus (Table 2). RIA contains reviews on arbitrary entities rather than just commercial products as in the case of AMZ. Each review has a category label (e.g. *computer*, *person*, *travel*) that very easily allows us to extract from RIA just those reviews that concern persons.

Table 4 compares a typical 1-star review from AMZ with one from RIA. We consider the RIA-review an abusive comment. It contains many words predictive of abusive language (e.g. *self-absorbed*, *loser*, *arrogant* or *loud-mouthed*).

4.1.2 Sentiment Views (VIEW)

Wiegand et al. (2016b) define sentiment views as the perspective of the opinion holder of polar expressions. They distinguish between expressions conveying the view of the implicit speaker of the utterance typically referred to as *speaker views* (e.g. *cheating* in (4); *ugly* and *stinks* in (5)), and expressions conveying the view of event participants typically referred to as *actor views* (e.g. *disappointed* and *horrified* in (6); *protested* in (7)).

[8]This is a crawl from the review website www.rateitall.com.

corpus	size	properties	purpose
RateItAll (**RIA**)	4.7M	review corpus focused on persons	computation of polar intensity (§4.1.1)
Amazon (**AMZ**)	1.2B	product review corpus	comp. of polar intensity (§4.1.1)/word embeddings (§4.2)
Web as Corpus (**WAC**)	2.3B	large general web corpus	computation of word embeddings (§4.2)

Table 2: Information about unlabeled corpora used (*by size we mean the number of tokens*).

AMZ	*on Halloween 5:* this movie is horrible with a bad plot a disappointment to the halloween series.
RIA	*on Bill Maher:* Self-absorbed loser who tries to pretend to be fair. He is rude, arrogant, loud-mouthed...

Table 4: 1-star reviews in different corpora.

WAC	liar (19), coward (7), name (6), idiot (6), hero (5), horse (5), saint (5), fool (5), snob (4), genius (4)
Twitter	bitch (1534), hoe (432), liar (317), cunt (274), whore (254), pussy (228), nigger (226), loser (217), faggot (217), slut (197)

Table 5: Comparison of the 10 most frequent pattern matches (*numbers in brackets indicate frequency*).

Wiegand et al. (2016b) provided sentiment-view annotations for the entries of the Subjectivity Lexicon.

(4) Peter is always **cheating**$_{speaker\ view}$. *(holder: speaker)*
(5) Mary is an **ugly**$_{speaker\ view}$ girl that **stinks**$_{speaker\ view}$. *(holder: speaker)*
(6) [Peter]$_{holder}$ was **disappointed**$_{actor\ view}$ and **horrified**$_{actor\ view}$ at the same time.
(7) [The public]$_{holder}$ **protested**$_{actor\ view}$ against that law.

Sentiment views have been used for improving the extraction of opinion holders and targets (Deng and Wiebe, 2016; Wiegand et al., 2016a). In this paper we show that they also have relevance for the detection of abusive words. Among actor-view words, there is a much lower proportion of abusive words than among speaker-view words (right half of Table 3). This can be explained by the fact that verbal abuse usually originates from the speaker of an utterance rather than some other discourse entity. We use sentiment-view information as a binary feature.

4.1.3 Emotion Categories (NRC)

We also examine whether knowledge of emotion categories associated with words is helpful. Potentially negative emotions, such as *disgust* or *anger*, should correlate with abusive words. We use the NRC lexicon (Mohammad and Turney, 2013) and employ the categories associated with the words contained in that resource as a feature.

4.1.4 Patterns (PAT)

Noun Pattern (PAT$_{noun}$). We found that the noun pattern (8) can be used to extract abusive nouns. Since this pattern is very sparse even on our largest corpus (i.e. WAC), we also run our pattern as a query on Twitter and extracted all matching tweets coming in a time period of 14 days. (We observed that by then we had reached a saturation point.)

(8) *pattern*: called {me|him|her} a(n) <noun>
(9) *pattern match example*: He called me a **bitch**.

Table 5 compares the most frequent matches for that pattern. Our pattern matches much more frequently on Twitter than on WAC. The quality of the matches on Twitter is also much better than on WAC, where we still find many false positives (e.g. *name* or *saint*). We assume that tweets, in general, are much more negative in tone than arbitrary web documents (as represented by WAC) which could explain the fewer false positives on Twitter. Note that the ranking from Twitter is not restricted to just prototypical abusive words (as Table 5 might suggest). The entire ranking also contains many less common words, such as *weaboo*, *dudebro* or *butterface*. The frequency ranks of the nouns extracted from Twitter are used as a feature.

Adjective Pattern (PAT$_{adj}$). Abusive adjectives often modify an abusive noun as in *brainless idiot*, *smarmy liar* or *gormless twat*. Therefore, we mined Twitter for adjectives modifying mentions of our extracted nouns (PAT$_{noun}$). (We were not able to find a construction identifying abusive verbs, so our output from PAT includes no verbs.)

4.1.5 WordNet (WN) and Wiktionary (WK)

We compare WordNet (Miller et al., 1990) and Wiktionary[4] as two general-purpose lexical resources. Unlike WordNet, Wiktionary is produced collaboratively by volunteers rather than linguistic experts. It contains more abusive words from our base lexicon, i.e. 97% (WK) vs. 87% (WN).

A common way to harness a general-purpose lexicon for induction tasks in sentiment analysis is by using its **glosses** (Choi and Wiebe, 2014; Kang et al., 2014). Assuming that the explanatory texts

of glosses are similar among abusive words, we treat glosses as a bag-of-words feature.

We also exploit information on **word usage**. Many abusive words are marked with tags such as *pejorative*, *derogatory* or *vulgar*. Both WordNet and Wiktionary contain such information. However, in Wiktionary more than 6 times as many of our entries include a tag compared to WordNet.

In order to incorporate a semantic representation more general than individual words, we employ **supersenses**. Supersenses are only contained in WordNet. They represent a set of 45 classes into which entries are categorized. They have been found effective for sentiment analysis (Flekova and Gurevych, 2016). Some categories correlate with abusive words. For example, 76% of the words of our base lexicon that belong to the supersense *person* (e.g. *loser*, *idiot*) are abusive words.

4.1.6 FrameNet (FN)

FrameNet (Baker et al., 1998) is a semantic resource which provides over 1200 semantic frames that comprise words with similar semantic behaviour. We use the frame-memberships of a word as features, expecting that abusive and non-abusive words occur in separate frames.

4.2 Generic Features: Word Embeddings

We induce word embeddings from the two largest corpora, i.e. AMZ and WAC (Table 2) using *Word2Vec* (Mikolov et al., 2013) in default configuration (i.e. 200 dimensions; cbow). The best performance was obtained by concatenating for each word the vectors induced from the two corpora.[9]

4.3 Baselines to Feature-based Approach

In addition to a majority-class classifier we consider the following baselines:

Weak Supervision (WSUP). With this baseline we want to build a lightweight classifier that does not require proper labeled training data. It is inspired by previous induction approaches for sentiment lexicons, such as Hatzivassiloglou and McKeown (1997) or Velikovich et al. (2010) which heuristically label some seed instances and then apply graph-based propagation to label the remaining words of a dataset. On the basis of word embeddings (§4.2), we build a word-similarity graph, where the nodes represent our negative polar expressions and each edge denotes the semantic similarity between two arbitrary words. We compute it by the cosine of their word-embedding vectors. The output of PAT from Twitter (§4.1.4) is considered as positive class seed instances. We chose PAT since it is an effective feature that does not depend on a lexical resource. As negative class seeds, we use the most frequent words in the WAC corpus (Table 2). Our rationale is that high-frequency words are unlikely to be abusive. We chose WAC instead of Twitter since the evidence of PAT (Table 5) suggested less abusive language in that corpus. This word-similarity graph is illustrated in Figure 1. In order to propagate the labels to the unlabeled words from the seeds, we use the Adsorption algorithm (Talukdar et al., 2008).

Using Labeled Microposts (MICR). With our last baseline we examine in how far we can detect abusive words by only using information from labeled microposts rather than labeled words. These experiments are driven by the fact that labeled microposts already exist. We consider two methods using the largest dataset comprising manually labeled microposts, *Wulczyn* (Table 8). The class labels of the microposts and our base lexicon (§3) are the same. Our aim is to produce a ranking of words where the high ranks represent words more likely to be abusive. Since we want to produce a strong baseline, we consider the best possible cut-off rank (*see supplementary material*[6]). Every word higher than this rank is considered abusive and all other words not abusive.

The first method **MICR:pmi** ranks the words of our base lexicon by their Pointwise Mutual Information with the class label *abusive* that is assigned to microposts. To be even more competitive, we introduce a second method **MICR:proj** that learns a projection of embeddings. MICR:proj has the advantage over MICR:pmi that it does not only rank words observed in the labeled microposts but all words represented by embeddings. Since our embeddings (§4.2) are induced on the combination of AMZ and WAC corpora, which together are about 360 times the size of the *Wulczyn* dataset, MICR:proj is likely to cover more abusive words. Let $\mathbf{M} = [\mathbf{w_1}, \ldots, \mathbf{w_n}]$ denote a labeled micropost of n words. Each column $\mathbf{w} \in \{0,1\}^v$ of $\mathbf{M}$ represents a word in a one-hot form. Our aim is learning a one-dimensional projection $\mathbf{S} \cdot \mathbf{E}$ where $\mathbf{E} \in \mathbb{R}^{e \times v}$ represents our unsupervised embeddings of dimensionality e over the vocabulary size v (§4.2) and $\mathbf{S} \in \mathbb{R}^{1 \times e}$ represents the learnt

[9] We also ran experiments with pretrained embeddings from *GoogleNews* but they did not improve classification.

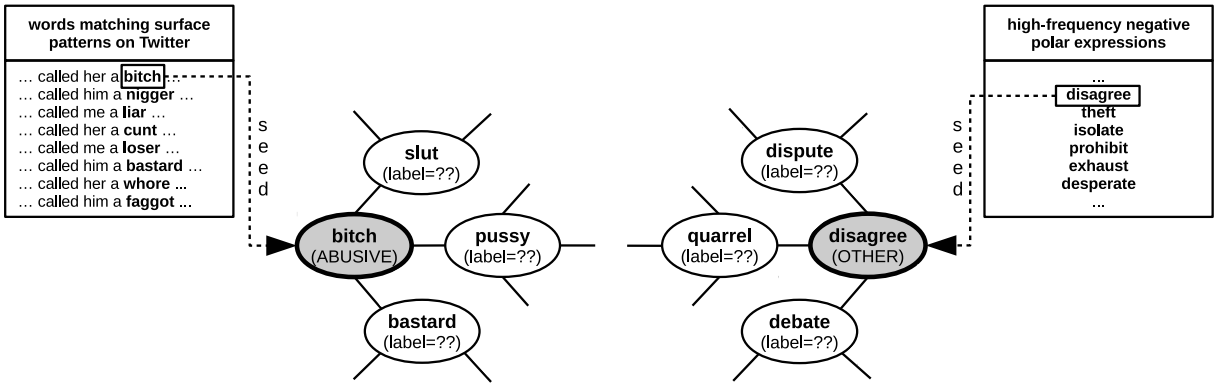

Figure 1: Illustration of word-similarity graph as used for weakly-supervised baseline (WSUP); seeds for abusive words (e.g. *bitch*) are obtained by the output of feature PAT (§4.1.4); seeds for non-abusive words (e.g. *disagree*) are high-frequency negative polar expressions.

classifier	Prec	Rec	F1
MAJORITY	33.3	50.0	40.0
MICR:pmi	65.3	59.5	62.2†
MICR:proj	67.1	64.6	65.8*†
WSUP	77.3	71.0	74.0*†
SVM:embeddings	77.6	73.9	75.7*
SVM:linguistic	81.6	73.8	77.5*
SVM:linguistic+WSUP	82.5	76.5	79.4*†
SVM:linguistic+embeddings	81.6	79.7	80.7*
SVM:linguistic+embed.+WSUP	**82.9**	**80.4**	**81.6**†

statistical significance testing (paired t-test at $p < 0.05$): *: better than previous line but 1; †: better than previous line

Table 6: Different classifiers on base lexicon (Table 1).

projection matrix. We compute a projected micropost $\mathbf{h} = \mathbf{S}\cdot\mathbf{E}\cdot\mathbf{M}$ which is an n-dimensional vector. Each component represents a word from the micropost. The value represents the predictability of the word towards being abusive. We then apply a bag-of-words assumption to use that projected micropost to predict the binary class label y: $p(y|\mathbf{M}) \propto exp(\mathbf{h}\cdot\mathbf{1})$ where $\mathbf{1} \in \{1\}^n$. This model is a feed-forward network trained using Stochastic Gradient Descent (Rumelhart et al., 1986). On the basis of the projected embeddings we rank our negative polar expressions.

4.4 Evaluation of Features on Base Lexicon

We conduct experiments on our base lexicon (Table 1) and report macro-average precision, recall and f-score. SVMs are evaluated on a 10-fold crossvalidation. Table 6 displays the performance of the different classifiers. The least effective information source are labeled microposts (MICR), though, as expected, the projected embeddings (MICR:proj) outperform PMI. The performance of weak supervision (WSUP) outperforms MICR.

Among the SVM configurations, embeddings are already effective. The linguistic features outperform all other methods. The best classifier is an SVM trained on embeddings, linguistic features and the output of WSUP as a further feature.[10]

Table 7 shows the performance of SVMs using different linguistic features (§4.1). Among the three intensity types, the most effective one is the person-based intensity (INT$_{person}$). However, it can be effectively combined with the remaining types. Among the lexical sentiment resources used (i.e. NRC, INT$_{bin}$ and VIEW), VIEW is most effective. Their combination also results in an improvement. The surface patterns (PAT) are surprisingly predictive. Of the general-purpose lexical resources (i.e. WN, WK and FN), WN and WK are both very effective resources. Glosses from WN are the strongest individual feature. Combining WK, WN and FN results in significant improvement. The best feature set combines all features.

Our results also suggest that for languages other than English, there are some very strong features, such as PAT, WK or embeddings, that could be easily adopted since they do not depend on a resource which is only available in English.

5 Expanding the Lexicon

We produce a large **feature-based lexicon** of abusive words by classifying all (unlabeled) negative polar expressions from Wiktionary. We chose Wiktionary since our previous experiments indicated a high coverage of abusive words on that resource (§4.1.5). The negative polar expressions

[10] We did not include MICR among the further features, as they are trained on the labeled microposts that we also use as test data in the extrinsic evaluation (§6).

features used in SVM	Prec	Rec	F1
MAJORITY	33.3	50.0	40.0
INT_{fine}	62.0	57.0	59.4†
INT_{bin}	61.7	60.4	61.0*
INT_{person}	70.8	55.4	62.1*
INT_{fine}+INT_{bin}+INT_{person}	70.8	60.7	65.3*†
NRC	60.2	60.1	60.2
VIEW	65.6	62.8	64.2†
INT_{bin}+NRC+VIEW	66.9	68.8	67.9*†
PAT_{noun}	79.9	58.4	67.4
PAT_{noun}+PAT_{adj}	76.4	63.2	69.1
WN_{usage}	82.6	52.6	64.3
FN	66.3	66.4	66.4
WK_{usage}	76.7	61.0	67.9*†
WK_{gloss}	74.8	64.9	69.5*†
WN_{super}	78.7	64.9	71.1*†
WN_{gloss}	75.9	67.4	71.4*
WN_{usage}+WN_{super}+WN_{gloss}	76.7	68.0	72.0*
WK_{usage}+WK_{gloss}	79.5	67.0	72.7*
all WN + *all* WK	80.0	68.7	73.9*
all WN + *all* WK + FN	80.3	69.5	74.5*
all from above	**81.6**	**73.8**	**77.5***†

statistical significance testing (paired t-test at $p < 0.05$): *: better than previous line but 1; †: better than previous line

Table 7: Performance of the different linguistic features on base lexicon (Table 1).

are identified by applying to the vocabulary of Wiktionary an SVM trained on the words from the Subjectivity Lexicon with their respective polarities. As features, we use word embeddings (§4.2). In order to produce the feature-based lexicon of abusive words another SVM is trained on our base lexicon (Table 1) using the best feature set from Table 6. With 2989 abusive words, our expanded lexicon is 5 times as large as the base lexicon.

In order to measure the impact of our proposed features on the quality of the resulting lexicon, we devised an alternative expansion which just employs word embeddings. For this, we used **SentProp**, the most effective induction method from the *SocialSent* package (Hamilton et al., 2016).[11]

6 Cross-domain Classification

6.1 Motivation and Set Up

We now apply our expanded lexicon (§5) to the classification of abusive microposts, i.e. we classify entire comments rather than words out of context. Table 8 shows the datasets of labeled microposts that we use. The difference between these datasets is the source from which they originate. Consequently, different topics are represented in the different datasets. Still, we find similar types

[11] Since SentProp produces a ranking rather than a classification, we consider 2989 as a cut-off value to separate the instances into 2 classes. This corresponds to the size of abusive words predicted by our feature-based lexicon (Table 9).

dataset	size†	abusive	source
(Warner and Hirschberg, 2012)	3438	14.3%	*diverse*
(Waseem and Hovy, 2016)	16165	35.3%	Twitter
(Razavi et al., 2010)	1525	31.9%	UseNet
(Wulczyn et al., 2017)	115643	11.6%	Wikipedia

†: total number of microposts in the dataset

Table 8: Datasets comprising labeled microposts.

of abusive language (e.g. *racism*, *sexism*). For example, both (10)-(11) from *Waseem* and (12) from *Wulczyn* are sexist comments[12] but (10)-(11) discuss the role of women in sports while (12) addresses women's hygiene in Slavic countries.

(10) *from Waseem dataset:* maybe that's where they should focus? Less **cunts** on *football*.

(11) *from Waseem dataset:* I would rather brush my teeth with sandpaper then watch *football* with a girl!!

(12) *from Wulczyn dataset:* slavic women don't like to wash ... Their **pussy** stinks.

Since our aim is to produce the best possible cross-domain classifier, **all classifiers are trained on one dataset and tested on another**. This is a real-life scenario. Often when a classifier for abusive microposts is needed, sufficient labeled data is only available for other text domains.

Having different topics in training and test data makes cross-domain classification difficult. For example, since a large proportion of sexist comments in *Waseem* relate to sports, traditional supervised classifiers (using bag of words or word embeddings) will learn correlations between words of that domain with the class labels. For instance, the domain-specific word *football* occurs frequently in *Waseem* (i.e. 90 occurrences) with a strong correlation towards abusive language (precision: 95%). Other words, such as *sports* and *commentator*, display a similar behaviour. A supervised classifier will assign a high weight to such words. While such domain-specific words may aid in-domain classification and enable a correct classification of microposts, such as (11), we will show that it has a detrimental effect on cross-domain classification. We claim that the predictive words that abusive comments share across different domains are abusive words, just of the sort that our expanded lexicon contains, e.g. *cunts* in (10) and *pussy* in (12).

Our **proposed classifier** for labeling *microposts* is an SVM trained on features derived from our expanded lexicon (§5). We do not use a binary feature encoding the presence of abusive words. Instead, we rank all abusive words of our lexicon

[12] (12) is also a racist comment.

baseline lexicons		newly created lexicons	
lexicon	**entries**	**lexicon**	**entries**
Hatebase	430	base (Table 1)	551
Derogatory	1609	expanded:SentProp (§5)	2989
Ottawa	1746	expanded:feature-based (§5)	2989

Table 9: Lexicons used in cross-domain classification of microposts (*figures denote the amount of unigrams*).

classifier	Razavi	Warner	Waseem	Wulczyn
expand.:feature-b. (SVM)	75.7	64.8	63.8	78.4
FastText	**83.4**	71.8	76.3	85.6
RNN	74.8	70.5	78.0	86.9
Yahoo (SVM)	82.4	**78.2**	**84.1**	**90.0**

Table 10: In-domain classification of microposts (*eval.: F1-score*).

according to the confidence score of the classifier it produced and use their ranks as features.

As **baseline classifiers** we consider publicly available word lists (Table 9). We include the resource from Razavi et al. (2010), henceforth referred to as ***Ottawa***, the entries of ***Hatebase***[13], which has been used in Nobata et al. (2016) and Davidson et al. (2017), and the derogatory words from Wiktionary (***Derogatory***)[14].[15] Finally, we also include our **base** lexicon (Table 1) in order to evaluate the expansion process of our two expanded lexicons (§5). For all lists, we train on a single feature indicating the frequency of abusive words in a micropost to be classified. *Ottawa* also contains weights assigned to abusive words. We weight the observed frequency with these weights.

We further evaluate 3 classifiers representing the state of the art of in-domain evaluations: ***FastText*** (Joulin et al., 2017), Gated Recurrent Units Recurrent Neural Networks ***RNN***, which have been reported to work best on English microposts (Pavlopoulos et al., 2017), and ***Yahoo***, an SVM trained on the sophisticated feature set proposed by Nobata et al. (2016). Next to character and token n-grams, *Yahoo* includes word and comment embeddings, syntactic features and some linguistic diagnostics.

[13] www.hatebase.org

[14] https://en.wiktionary.org/wiki/Category:English_derogatory_terms

[15] There are also similar but smaller lists in Wiktionary, e.g. *offensive terms*. They produced no better results.

		Yahoo		feature-b. lex.	
test	**train**	**all**	**explicit**	**all**	**explicit**
Warner	Razavi	55.4	65.2	65.0	80.6
	Waseem	58.1	55.9	64.6	79.0
	Wulczyn	60.2	72.8	63.4	80.7
	Average	57.9	64.6	64.3	80.1
Waseem	Warner	58.5	61.2	63.3	62.0
	Razavi	61.1	63.1	58.7	78.8
	Wulczyn	51.2	68.2	62.9	78.5
	Average	56.9	64.2	61.6	73.1

Table 12: Cross-domain classification of microposts: *all* test data vs. *explicit* subset (*eval.: F1-score*).

6.2 Results

In Table 10, we list the performance of the 3 state-of-the-art classifiers along with our proposed classifier using our expanded lexicon on in-domain 10-fold crossvalidation. Due to space limitations, we cannot list the other classifiers. We *only* provide this list to demonstrate the strength of the state-of-the-art classifiers on in-domain evaluation. On this setting, a lexicon-based approach is not competitive since domain-specific information is not included. However, as we show in Table 11, for cross-domain classification, it is exactly that property that ensures that our feature-based lexicon provides best performance. Compared to the in-domain setting, *FastText*, *RNN* and *Yahoo* display a huge drop in performance. They all suffer from overfitting to domain-specific knowledge.

Of all lexicons, our proposed feature-based lexicon performs best. We were surprised by the poor performance of *Hatebase* but attribute this to its small size and the high amount of ambiguous (and debatable) entries, such as *Charlie*, *pancake*, *Pepsi*. Although our feature-based lexicon is the largest of all tested (i.e. 2989 words), our experiments do not support the general rule that larger lexicons always outperform smaller ones. For instance, already our base lexicon with 551 abusive words is much better than the lexicons *Derogatory* or *Ottawa* which are about 3 times larger (Table 9). Each word in our base lexicon was only included if 4 out of 5 raters judged it to be abusive. This ensured a fairly reliable annotation. In contrast, *Derogatory* and *Ottawa* suffer from many ambiguous entries (e.g. *bag*, *Tim*, *yellow*). The high precision of our base lexicon is what ensures that our expanded lexicon does not include much noise.

Another shortcoming of most of the other existing lexicons is that they overwhelmingly focus on nouns. While nouns undoubtedly represent the most frequent abusive terms, there is, however, a substantial number of abusive words that belong to other parts of speech, particularly adjectives (e.g. *vile*, *sneaky*, *slimy*, *moronic*). In our base lexicon, more than 30% of the abusive words are of that part of speech. Our expanded lexicon,

					SVM						
datasets						**baseline lexicons**			**newly created lexicons**		
test	**training**	**majority**	**FastText**	**RNN**	**Yahoo**	**Hatebase**	**Derogat.**	**Ottawa**	**base**	**SentProp**	**feature-b.**
Razavi	Warner	40.50	50.59	53.76	53.40	40.50	40.50	60.95	61.08	64.20	**66.13**
	Waseem	40.50	51.64	53.39	51.66	44.29	51.35	63.13	69.69	63.12	**74.15**
	Wulczyn	40.50	71.74	71.59	**75.10**	40.50	40.50	40.50	40.50	68.50	74.83
	Average	40.50	57.99	59.58	60.05	41.76	44.12	54.86	57.09	66.27	**71.70**
Warner	Razavi	46.14	57.73	48.99	55.42	46.14	57.49	59.81	63.57	**67.57**	64.98
	Waseem	46.14	61.45	57.63	56.54	63.52	57.49	**64.67**	63.57	62.75	64.64
	Wulczyn	46.14	58.35	57.36	60.19	46.14	46.14	46.14	46.14	**65.34**	63.35
	Average	46.14	59.18	54.66	57.38	51.93	53.71	56.87	57.76	**65.22**	64.32
Waseem	Razavi	40.62	60.91	54.67	57.83	40.62	52.66	52.95	57.33	**64.56**	63.32
	Warner	40.62	58.28	58.85	**60.65**	40.62	40.62	40.62	54.93	51.98	58.66
	Wulczyn	40.62	56.33	54.13	51.76	40.62	40.62	40.62	40.62	50.27	**62.90**
	Average	40.62	58.51	55.88	56.75	40.62	44.63	44.73	50.96	55.60	**61.63**
Wulczyn	Razavi	46.88	64.65	64.43	70.70	46.88	50.97	57.70	69.56	67.69	**73.71**
	Warner	46.88	56.21	56.13	52.73	46.88	46.88	55.93	59.55	66.38	**70.06**
	Waseem	46.88	52.66	57.33	51.23	43.51	50.97	60.08	69.56	66.38	**72.39**
	Average	46.88	57.84	59.30	58.22	45.76	49.61	57.90	66.22	63.52	**72.05**

Table 11: Different classifiers on **cross-domain** classification of microposts; best result in **bold**; (*eval.: F1-score*).

which roughly preserves that ratio, includes about 800 adjectives in total. Since abusive adjectives often co-occur with abusive nouns (§4.1.4), they may compensate for abusive nouns that are missing from the lexicon. Such unknown nouns often occur when authors of microposts try to obfuscate their abusive language, e.g. *sneaky assh0le*, *slimy b*st*rd*. Interestingly, the modifying adjectives are not obfuscated, probably because they are considered slightly less offensive in tone.

Given that among the newly created lexicons our feature-based expanded lexicon performs best, we conclude that the expansion is effective (since we improve over the base lexicon), and the features are more effective than a generic induction approach (i.e. *SentProp*).

6.3 Explicitly vs. Implicitly Abusive Microposts

The results in Table 11 also show that the cross-domain performance of our proposed feature-based lexicon is lower on the two datasets *Warner* and *Waseem*. We observed that while on the other two datasets almost all abusive microposts can be considered *explicitly abusive* posts, i.e. they contain abusive words, a large proportion of microposts labeled abusive in *Warner* and *Waseem* are *implicitly abusive* (Waseem et al., 2017), i.e. the abuse is conveyed by other means, such as sarcasm or metaphorical language (11). We asked raters from Prolific Academic to identify explicitly abusive microposts by marking abusive words in those posts. The annotators were not given access to any lexicon of abusive words. We then conducted cross-domain classification on those subsets where the abusive instances were only those rated as explicit. The results are displayed in Table 12. The table shows that our feature-based lexicon is much better on this subset, while the most sophisticated supervised classifier (*Yahoo*) still performs worse. From that we conclude that only *explicitly* abusive microposts can be reliably detected in cross-domain classification.

7 Conclusion

We examined the task of inducing a lexicon of abusive words. We presented novel features including surface patterns, sentiment views, polar intensity and general purpose lexical resources, particularly Wiktionary. The information we thus acquire cannot be learnt all that effectively from labeled microposts, not even with a projection-based classifier. While a lexicon of abusive words can only aid the detection of explicit abuse, its effectiveness was demonstrated on the novel task of cross-domain detection of abusive microposts, where our domain-independent lexicon outperforms previous supervised classifiers which suffer from overfitting to domain-specific features.

Acknowledgements

The authors would like to thank Thomas Kleinbauer, Katja Markert and Ines Rehbein for feedback on earlier drafts of this paper. We are also grateful to William Warner and Diana Inkpen for granting us access to their data on abusive language detection. Special thanks go to Stefan Kazalski for crawling the *rateitall*-website. We also give thanks to John Pavlopoulos for helping us reconstructing the configurations of his RNN. The authors were partially supported by the German Research Foundation (DFG) under grants RU 1873/2-1 and WI 4204/2-1.

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