Learning Word Ratings for Empathy and Distress from Document-Level User Responses

João Sedoc*,1, Sven Buechel*,2, Yehonathan Nachmany3, Anneke Buffone4, and Lyle Ungar1
1Johns Hopkins University, 2Friedrich-Schiller-Universität Jena, 3University of Pennsylvania, 4Facebook
jsedoc@jhu.edu, sven.buechel@uni-jena.de, yoninachmany@gmail.com, anneke@fb.com, ungar@cis.upenn.edu

Abstract
Despite the excellent performance of black box approaches to modeling sentiment and emotion, lexica (sets of informative words and associated weights) that characterize different emotions are indispensable to the NLP community because they allow for interpretable and robust predictions. Emotion analysis of text is increasing in popularity in NLP; however, manually creating lexica for psychological constructs such as empathy has proven difficult. This paper automatically creates empathy word ratings from document-level ratings. The underlying problem of learning word ratings from higher-level supervision has to date only been addressed in an ad hoc fashion and is missing deep learning methods. We systematically compare a number of approaches to learning word ratings from higher-level supervision against a Mixed-Level Feed Forward Network (MLFFN), which we find performs best, and use the MLFFN to create the first-ever empathy lexicon. We then use Signed Spectral Clustering to gain insights into the resulting words.

Keywords: lexicon creation, empathy, distress

1. Introduction
Deep learning, applied to ever larger datasets, has led to large improvements in performance in sentiment and emotion analysis. In light of this development, lexica, lists of words and associated weights for a particular affective variable, which used to be a key component for feature extraction (Mohammad and Bravo-Marquez, 2017b), may seem obsolete. However, this is far from the truth. Lexica can be used as features to improve performance for sentence-level emotion prediction even in advanced neural architectures (Mohammad and Bravo-Marquez, 2017a). De Bruyne et al. (2019). Word ratings are also often used to refine pre-trained embedding models for specific tasks (Yu et al., 2017). Khosla et al. (2018). But much more importantly, word ratings are relatively cheap to acquire and have been found to be robust across domains and even languages, regarding their translational equivalents (Leveau et al., 2012). Warriner et al. (2013). This gives lexica a pivotal role for processing under-resourced languages. Perhaps most importantly, using lexica allows for interpretable models since the resulting document-level predictions can be easily broken down to the words within it. This gives lexica an important role for building justifiable AI and addressing related ethical challenges (Clos et al., 2017). Interpretability is also crucial for NLP use in other academic disciplines such as psychology, social science, discourse linguistics, and the digital humanities, where understanding the nature of “constructs” (as psychologists call them) such as emotions is far more important than making accurate predictions (Schwartz et al., 2013). Eichstaedt et al., 2015. Pennebaker (2011). Liu et al. (2016).

While lexica for many kinds of emotion already exist (see Section 2.1), there is no such resource for empathy despite its growing popularity in the NLP community (Khanpour et al., 2017). Buechel et al. (2018). In fact, psychologists have tried to gather word ratings for empathy, but this task has proven difficult. Hand-curated lexica for empathy are difficult to create in part because there is no clear set of words that can accurately distinguish empathy from self-focused distress. The gold standard for discriminating these is an emotion rating scale by Batson et al. (1987). This scale is a collection of emotion words (e.g., compassionate, tender, warm) that could serve as a rudimentary lexicon, but it contains many words that are rarely used (e.g., “perturbed”), and many words that can take on meanings that are far from empathy (e.g., “warm”, “tender”). These word-based scales have shown good reliability for self-report of these emotional states, but would make poor guides for a proper lexicon of empathy. In this paper, we construct the first empathy lexicon. Specifically, we learn ratings for two kinds of empathy—empathic concern (feeling for someone) and personal distress (suffering with someone)—for words given existing document-level ratings from the recently published Empathic Reactions dataset (Buechel et al., 2018). We first train a model to predict document-level empathy in a regular supervised set-up and then “invert” the resulting model to derive word ratings. We conclude with an in-depth analysis of the resulting resource.

2. Related Work

2.1. Lexica for Psychological Quantities
The notion of describing (part of) a word’s meaning, such as the emotion typically associated with it, in terms of numerical ratings has a long tradition in psychology, dating back at least to Osgood et al. (1957). Today, many sets of word ratings exist, covering numerous constructs and languages, particularly relating to sentiment and emotion. Early work in NLP was mostly focused on positive-vs.-negative resources such as SentiWordNet and VADER (Baccianella et al., 2010). Hutto and Gilbert, 2014. In

* These authors contributed equally to this work.

1The empathy lexicon will be made publicly available upon acceptance of this paper.
contrast, resources from psychologists tend to focus on valence and arousal (or other representations of affective states (Ekman, 1992)). In particular, this includes the Affective Norms for English Words (ANEW; (Bradley and Lang, 1999)) which have been adopted to many languages (Redondo et al., 2007) [Montefinese et al., 2014], and their extension by Warnier et al. (2013). Such lexica have recently become popular in NLP (Wang et al., 2016; Sedoc et al., 2017b) [Mohammad, 2018]. Lexica also exist for many other constructs, including concrete/abstractness, familiarity, imageability and humor (Brysbaert et al., 2014) [Yee, 2017; Englert and Hills, 2017]. Yet, noticeably, an empathy lexicon is missing.

Psychologists use such lexica either for content analysis, most noticeably using the Linguistic Inquiry and Word Count (LIWC) lexica (Tausczik and Pennebaker, 2010), or as controlled stimuli for experiments, e.g., on language processing and memory (Hofmann et al., 2009) [Monnier and Syssau, 2008]. Applications of lexica in NLP has been discussed in Section 1.

Whereas most lexica are created manually, there is an extensive body of work on learning such ratings automatically (see (Kulkarni et al., 2019) for a survey). Early work focused on deriving scores through linguistic patterns or statistical association with a small set of seed words (Hatzivasiloglou and McKeown, 1997) [Turney and Littman, 2003]. More recent approaches almost always rely on word embeddings (Hamilton et al., 2016) [Li et al., 2017; Buechel and Hahn, 2018]. This line of work is predominantly based on word-level supervision. In contrast, we learn word ratings from document-level ratings.

2.2. Empathy and Distress in Psychology

Empathy, the “reactions of one individual to the observed experiences of another” (Davis, 1983), often in response to their need or suffering, is complex and controversial, with luminary scientists both arguing for the benefits of empathy (De Waal, 2009) and “against empathy” (Bloom, 2014). Empathy has been linked to a multitude of positive outcomes, from volunteering (Baison et al., 1997), to charitable giving (Pavey et al., 2012), and even longevity (Poulin et al., 2015), but it can also cause the empathizing person increased stress (Buffone et al., 2017) and emotional pain (Chikovani and Surguladze, 2015). In this paper, we build lexica of state (momentary) empathy and distress based on the subscales of Interpersonal Reactivity Index (IRI) questionnaire (Davis, 1980). The scale creator defines these as follows: Empathic Concern assesses “other-oriented” feelings of sympathy and concern for unfortunate others and Personal Distress measures “self-oriented” feelings of personal anxiety and unease in tense interpersonal settings.

2.3. Empathy and Distress in AI

Most previous work in language-centered AI for empathy has been conducted with a focus on speech and especially spoken dialogue. Conversational agents, psychological interventions, and call center applications has been addressed particularly often (McQuiggan and Lester, 2007) [Fung et al., 2016; Perez-Rosas et al., 2017] [Alam et al., 2017]. In contrast, studies addressing empathy in written language are surprisingly rare. Abdul-Mageed et al. (2017), in contrast, focus on trait empathy, a temporally more stable personal attribute. In particular, they studied the detection of “pathogenic empathy”, marked by self-focused distress, a potentially detrimental form of empathy associated with health risks, in social media language using a wide array of features, including n-grams and demographic information.

Khanpour et al. (2017) present a corpus of messages from online health communities which has binary empathy annotations on the sentence-level. They report an .78 F-Score using a CNN-LSTM. The corpus, however, is not publicly available. In contrast, Buechel et al. (2018) recently presented the first publicly available gold standard dataset supported by proper psychological theories. The dataset consists of responses to news articles and scales for empathy and distress between 1 and 7. They collected empathy and distress ratings from the writer of an informal message using a sophisticated annotation methodology borrowed from psychology. In this contribution, we build upon their work by using their document-level ratings to predict word labels.

2.4. Lexicon Learning from Document Labels

Few studies address learning word ratings based on document-level supervision. However, those studies (described in detail below) focus on their particular application rather than addressing the underlying, abstract learning problem (formalized in Section 3). As a result, previously proposed methods have not been quantitatively compared. In an early study, Mihalcea and Liu (2006) computed the happiness factor of a word type as the ratio of documents labeled “happy” to all blog posts it occurs in. Labels were given by the blog users. The resulting lexicon was used to estimate user happiness over the course of an average 24-hour day as well as a seven-day week. Rill et al. (2012) independently came up with a very similar approach for identifying the evaluative meaning of adjectives and adjective phrases (absolutely fantastic vs. just awful) based on a corpus of online product reviews. Since the individual reviews come with a one-to-five star rating, the evaluative meaning of an adjective or phrase was computed as the average rating of all reviews it occurs in (Mean Star Rating, see Section 3). This approach was later adopted by Ruppenhofer et al. (2014) who found that it works quite well for classifying quality and intelligence adjectives into intensity classes (excellent vs. mediocre and brilliant vs. dim, respectively). Another related approach was proposed by Mohammad (2012), who used hashtags in Twitter posts as distant supervision labels of emotion categories, e.g., #sadness. Word ratings were then computed based on pointwise mutual information between word types and emotion labels.

The above methods all derive word labels directly using relatively simple statistical operations. From this group, we selected the Mean Star Rating approach for experimental comparison (Section 4), as it expects numerical document labels, in line with the later employed empathy gold standard (Section 5).
Figure 1: Schematic illustration of the MLFFN: Step 1 Train a model to predict a document rating from the embedding of the document text; Step 2 “Invert” the trained model to compute a word rating for each word embedding.

Note that these contributions are distinct from pattern-based approaches, e.g., presented by Hatzivassiloglou and McKeown (1997), who distinguish positive and negative words based on their usage pattern with particular conjunctions: “A and B” implies that A and B have the same polarity whereas “A but B” implies opposing polarity. Such approaches are not considered here because they base lexicon learning on linguistic usage patterns instead of document-level supervision and hence rely on large quantities of raw text.

In another line of work, (Sap et al., 2014) address the task of modeling user age and gender in social media. They showed that by training a linear model with Bag-of-Words (BoW) unigram features, the resulting feature weights can effectively be interpreted as word-level ratings. In a later study, Preot¸iuc-Pietro et al. (2016) employed the same method to create a valence and arousal lexicon based on annotated Facebook posts. This is the second baseline method we used in our evaluation; Technical details are given in Section 5 (Regression Weights).

In a recent study, Wang and Xia (2017) present a three-step approach to infer word polarity. Based on a Twitter corpus with hashtag-derived polarity labels, they (1) apply the method of Mohammad (2012) to generate a first set of word labels (see above). Those ratings are used (2) to train sentiment-aware word embeddings. The embeddings are then used (3) as input to a classifier which is trained on a set of seed words to predict the final word ratings. In essence, this is a semi-supervised approach because the last step requires word-level gold data and does not address the problem at hand.

3. Methods

This section formalizes the learning problem we address, describes the two baseline methods we compare against and the Mixed-Level Feed Forward Network, and concludes with a brief discussion. Section 5 then describes signed spectral clustering, which we use for qualitative interpretation of our new empathy lexicon.

Problem Statement. We address the problem of learning word ratings for an arbitrary lexical characteristic based on gold labels of the same characteristic but for a higher linguistic level (see Figure 1). For example, how can one learn word-level polarity ratings based on document-level polarity gold labels? More formally, let \( W = \{w_1, w_2, \ldots, w_n\} \) denote a set of words with corresponding gold labels \( Y^w = (y_1^w, y_2^w, \ldots, y_n^w) \). Let \( D = \{d_1, d_2, \ldots, d_m\} \) be a set of higher level linguistic units with corresponding gold labels \( Y^d = (y_1^d, y_2^d, \ldots, y_m^d) \). Those linguistic units can be anything from phrases over paragraphs to whole books, yet for conciseness we will refer to those units as documents. Our problem is to predict \( Y^w \) given \( W \), \( D \), and \( Y^d \). To the best of our knowledge, this is the first contribution ever formulating this as an abstract learning problem (rather than looking at concrete applications in isolation) and studying it in a systematic manner—the baseline methods have so far not been compared against each other. We now proceed by introducing methods for solving this problem.

Mean Star Rating. Following Rill et al. (2012), we predict \( y_i^w \) by averaging the gold labels of documents \( d_j \) in which the word \( w_i \) occurs. We denote the set of documents containing \( w_i \) as \( D(w_i) \). Hence this baseline method can be described as follows:

\[
\hat{y}_i^w = \frac{1}{|D(w_i)|} \sum_{d_j \in D(w_i)} y_j^d,
\]

Mean Binary Rating. As previously mentioned, Mihalcea and Liu (2006) created lexica for happiness and sadness from binary labels. To apply this method to numerical document labels (as present in the empathic reactions dataset; see Section 5) we first apply a median split (documents labels below (above) the median are recorded as 0 (1)). Subsequently, we calculate Mean Binary Rating using the same equation as for Mean Star Rating (Equation 1) thus showing the resemblances between Mihalcea and Liu (2006) and Rill et al. (2012).

Regression Weights. Following Sap et al. (2014), this baseline method learns word ratings by fitting a linear regression model with Bag-of-Words (BoW) features. First, consider a multivariate linear regression model for the predicting document ratings \( Y^d \). In general, such a model is given by

\[
\hat{y}_i^d = a_0 + \sum_{j \in \text{features}} a_j \cdot x_j,
\]

where \( a_0 \) denotes the intercept and \( a_j \) and \( x_j \) represent weight and value for feature \( j \), respectively.

Using a BoW approach, relative frequency of a word in a document is often used as features. Except for the intercepts, the linear model can conversely be interpreted as computing the weighted average of all weight terms \( a_j \), the relative term frequency then being the weighting factor. With this interpretation in mind, a linear BoW model aligns perfectly with a lexicon-based approach to achieve document-level prediction, with feature weights corresponding to word ratings (see Sap et al. (2014) for a more detailed explanation). Hence the above equation can be rewritten as

\[
\hat{y}_i^d = a_0 + \sum_{j \in \text{features}} a_j \cdot x_j,
\]
\[
\hat{y}^d_i = a_0 + \sum_{w_j \in W} \hat{y}^w_j \cdot rf(w_j, d_i),
\]

where \( rf(w_j, d_i) \) denotes the relative frequency of word \( w_j \) in document \( d_i \). Thus, by fitting the model to predict document ratings, we learn word ratings, simultaneously. In practice, ridge regression is used for fitting the model parameters (word ratings) thus introducing \( \ell_2 \) penalization to avoid overfitting.

**Mixed-Level Feed Forward Network.** We learn a Feed Forward Network (FFN; illustrated in Figure 1) on the document-level using a neural BoW approach with an external, pre-trained embedding model. By training the FFN on this task, it implicitly learns to map points of the embedding space to gold labels, which we then exploit for predicting word level ratings.

In general, a Feed Forward Network consists of an input layer \( a^{(0)} \in \mathbb{R}^{d_{in}} \) followed by multiple hidden layers with activation,

\[
a^{(l+1)} = \sigma(W^{(l+1)}a^{(l)} + b^{(l+1)}),
\]

where \( W^{(l+1)} \) and \( b^{(l+1)} \) denote weights and biases of layer \( l + 1 \), respectively, and \( \sigma \) is a nonlinear function. Since we predict numerical values (document-level ratings), the activation on the output layer \( a^{(out)} \), where \( out \) is the number of non-input layers, is given by the affine transformation

\[
\hat{y}^d = a^{(out)} = W^{(out)}a^{(out-1)} + b^{(out)}.
\]

For fitting the model parameters, consider a pre-trained embedding model such that \( vec(\omega) \in \mathbb{R}^{dim} \) denotes the vector representation of a word \( \omega \). This would be either the learned representation of \( \omega \) or a zero vector of length \( dim \) if \( \omega \) is not in the embedding model. We can now train the model to predict the document gold ratings \( Y^d \) using a gradient descent-based method. For a document \( d_i \), the embedding centroid of tokens present in \( d_i \) is used as input \( a^{(0)}(d_i) \).

That is,

\[
a^{(0)}(d_i) = \frac{1}{\text{len}(d_i)} \sum_{\omega \in d_i} vec(\omega),
\]

where \( \text{len}(d_i) \) is the number of tokens in \( d_i \). Embeddings are not updated during training.

Until this point, the described model is quite similar to deep averaging networks (DAN) proposed by [Lyver et al., 2015] in that it is a Feed Forward Network that predicts document labels from embedding centroid features. What differs is that we used the model to predict word labels, once it is fit to predict the document labels \( Y^d \). Conceptually, by fitting the model parameters, the FFN learns to map points of the (pre-trained) embedding space to points in the label space of \( Y^d \). But using the same embedding model, we can also represent words \( w_j \in W \), the ones we want to predict labels for, within the same feature space. Moreover, note that per our problem definition, word and document labels populate the same label space. Hence, we can predict \( \hat{y}^w_j \) by feeding \( vec(w_j) \) into the FFN without any further adjustments. Since the FFN can predict both word and document labels, we call this model Mixed-Level Feed Forward Network (MLFFN). For the MLFFN, Shapley Additive exPlanations (SHAP) ([Lundberg and Lee, 2017]) is mathematically equivalent to our method of using individual words to derive ratings.

**Discussion of Model Properties.** Mean Star Rating, Binary Star Rating, and Regression Weights learn exclusively from the available document-level gold data. In contrast, one of the major advantages of the MLFFN is that it builds on pre-trained word embeddings, thus implicitly leveraging vast amounts of unlabeled text data. For our experiments we use publicly available embeddings which are trained on hundreds of billions of tokens. MLFFN is also more flexible than Regression Weights, since it can learn nonlinear dependencies between relative word frequencies of a document and its gold label.

Another major advantage of the MLFFN model relates to the set of words that gold labels can be predicted for. Whereas Mean Star Rating, Mean Binary Rating, and Regression Weights are conceptually limited to words which occur in the gold data, MLFFN can predict ratings for any word for which embeddings are known. In practice, this implies that with our approach empathy ratings for millions of word types can be induced.

**Hyperparameters and Implementation.** The implementation of Mean Star Rating and Mean Binary Rating is straightforward and requires no further details. For Regression Weights we used the same setup as [Sap et al., 2014], as implemented in the Differential Language Analysis Toolkit (DLATK, [Schwartz et al., 2017]). For MLFFN, we follow the hyperparameter choices [Buechel et al., 2018] used for the Empathic Reactions dataset. Thus, MLFFN has two hidden layers (256 and 128 units, respectively) with ReLU activation. The model was trained using the Adam optimizer ([Kingma and Ba, 2015]) with a learning rate of \( 10^{-3} \) and a batch size of 32. We trained for a maximum of 200 epochs, and applied early stopping if the performance on the validation set did not improve for 20 consecutive epochs. We applied dropout with probabilities .2 and .5 on input and dense layers, respectively. Moreover \( \ell^2 \) regularization of .001 was applied to the weights of dense layers. Keras ([Chollet and others, 2015]) was used for implementation.

**4. Experiments.** We next conduct a systematic comparison of the above approaches. The best evaluation strategy would require having both document-level and word-level ratings for empathy. One could then train the models on the former and test the performance in predicting the later, possibly using resampling to get a distribution of scores. However, this option is not available, since the difficulty of acquiring empathy word ratings is exactly the point of this paper. Furthermore, cross-validation results to predict document-level ratings from derived word-level lexica using the empathic reactions dataset lack statistical power to distinguish between methods due to an insufficient number of examples, thus we require an alternative approach.

We adopt two alternative approaches: First, in place of empathy, we rely on other affective variables, namely, valence,
arousal, and dominance (VAD), for which both document and word ratings are available. The assumption here is that performance results for VAD are transferable to empathy. Second, we use the Empathic Reaction dataset to create one lexicon for each method under consideration. We then use it to predict trait-level empathy ratings, thus testing the generalizability of the resulting lexica to other domains as well as from state to trait empathy (see Section 2).

4.1. Intrinsic Evaluation with Emotion Data

We use the following gold standards for evaluation: Document-level supervision is provided by We use the following gold standards for evaluation: Document-level supervision is provided by EmoBank (Buechel and Hahn, 2017)\footnote{https://github.com/JULIELab/EmoBank}, a large-scale corpus manually annotated with emotion according to the psychological Valence-Arousal-Dominance scheme. EmoBank contains ten thousand sentences with multiple genres and has annotations from both writer and reader emotion. Word-level supervision to test against comes from the well-known affective norms (psychological valence, arousal, and dominance) dataset collected by Warriner et al. (2013) containing 13,915 English word types.

We fit all four models on EmoBank and evaluate against the word ratings by Warriner et al. (2013) using 10-fold cross-validation. For word embeddings we used off-the-shelf Fasttext subword embeddings \footnote{https://github.com/facebookresearch/fasttext\footnote{https://dl.fbaipublicfiles.com/fasttext/vectors-english/crawl-300d-2M-subword.zip}}\footnote{https://github.com/facebookresearch/fasttext\footnote{https://dl.fbaipublicfiles.com/fasttext/vectors-english/crawl-300d-2M-subword.zip}}. The embeddings are trained with subword information on Common Crawl (600B tokens). Performance will be measured in terms of correlation between predicted and gold labels.

Table 1: Evaluation of lexicon learning methods in Pearson correlation. Left column group: intrinsic evaluation on emotion corpus and lexicon (VAD = Valence-Arousal-Dominance); Right column group: Extrinsic evaluation on Twitter corpus annotated with person-level empathy.

| Method            | V     | A     | D     |
|-------------------|-------|-------|-------|
| Mean Binary Rating | .31   | .18   | .11   |
| Regression Weights| .36   | .22   | .13   |
| Mean Star Rating  | .39   | .22   | .14   |
| MLFNN             | \textbf{.64} | \textbf{.45} | \textbf{.50} |

Table 1: Evaluation of lexicon learning methods in Pearson correlation. Left column group: intrinsic evaluation on emotion corpus and lexicon (VAD = Valence-Arousal-Dominance); Right column group: Extrinsic evaluation on Twitter corpus annotated with person-level empathy.

Nevertheless, this is consistent with intrinsic results. The MLFFN widely outperforms the other approaches (having about twice as high performance figures), the latter being roughly similar in performance.

5. The Empathy Dictionary

The final empathy dictionary consists of the predictions of the MLFFN from the last experiment, which we then adjusted using a log min-max rescaling into the interval \([1,7]\) for consistency with Buechel et al. (2018). We restricted ourselves to words which appear in the Empathic Reaction dataset and did not make use of the ability of the MLFFN to predict ratings for all word of the embedding model (left for future work). This was done to ensure interpretability of word ratings relative to their usage in the corpus (achieved via clustering analysis in Section 5.2).

Table 2: Illustrative examples from final lexicon: highest/lowest ranking words for empathy and distress.

| Method | Empathy | Distress |
|--------|---------|----------|
| High Empathy | lukemia | 6.90 | 5.09 |
|         | lakota  | 6.70 | 4.88 |
|         | healing | 6.60 | 4.90 |
| Low Empathy | joke  | 1.10 | 1.52 |
|         | worrying | 1.10 | 3.93 |
|         | wacky  | 1.10 | 1.49 |
| High Distress | inhumane | 4.07 | 6.55 |
|         | dehumanizes | 5.46 | 6.40 |
|         | mistreating | 4.85 | 6.31 |
| Low Distress | somewhere | 1.82 | 1.05 |
|         | dunno  | 1.31 | 1.05 |
|         | guessing | 1.38 | 1.06 |

\footnote{While 0.18 may seem low, our results are similar to those from Abdul-Mageed et al. (2017) who use a regression model with LDA topics trained on Facebook posts.}
High Empathy
- grieve, grieving, loss, prayers, grief, heartbroken, losses, depression, condolences, widowed
- wounds, wounded, scars, heal, blisters, trauma, wound, heals, bleeding, fasciitis
- duckworth, salama, mansour, santiago, gilbert, fernandez, braves, vaughn, colonialism, crowe
- minneapolis, neighborhoods, detroit, chicago, charlotte, cincinnati, brisbane, angeles, atlanta, drescher

Low Empathy
- fool, clueless, dumbass, idiotic, lazy, stupidity, morons, idiot, idiots, dumb
- bother, slightest, anything, else, nobody, anybody, any, nothing, anyone, himself
- loser, bs, moron, dingus, maniac, buffoon, ffs, loon, crap, psycho
- wacky, bizarre, odd, creepy, weird, unnerving, masochistic, freaks, unusual, strange

High Distress
- homicide, killings, murdered, massacre, murdering, homicides, genocide, murder, murderers, killed
- brutalized, assaulted, raped, bullied, tormented, harassed, detained, molested, reprimanded, beaten
- horrific, witnessed, retched, wretched, atrocious, awful, horrid, foul, shoddy, unpleasant
- horrifying, terrifying, harrowing, overdoses, suicides, deaths, suicide, gruesome, devastating, tragedy

Low Distress
- dunno, guessing, guess, gues, probably, assuming, maybe, clue, bet, assume
- wont, knowlegde, alot, doesnt, isnt, wasnt, ahve, dont, didnt, exempt
- sort, lot, bunch, sorts, type, whatever, plenty, depending, types, range
- intact, stays, remember, keeping, keeps, always, kept, vague, rember, stay

Table 3: Signed Spectral Clustering results for qualitative analysis.

Figure 2: Label distribution in our Empathy Dictionary.

5.1. Dataset Description
Our final lexicon consists of 9,356 word types (lower-cased, non-lemmatized, including named entities and spelling errors) each with associated empathy and distress ratings. For illustration Table 2 lists the highest and lowest ranking words for each construct (empathy and distress). An extended list is given in the appendix. High-empathy words contain many named entities that experience or cause suffering making a reader feel empathetic (lukemia, lakota). This is likely because the Empathic Reactions corpus used news stories to evoke empathy in subjects who then referred to those named entities for expressing their feeling. Low-empathy words, on the other hand, are often ones used for ridiculing, hence expressing a lack of empathy (joke, wacky). High-Distress words contain predominantly adjectives, nouns, and participles which can be used to characterize abusive behaviour (inhumane, mistreating) thus causing personal distress in readers when taking the perspective of the affected entity. Interestingly, low-distress words do not seem to display any clear pattern, making us suspect that personal distress should be addressed in terms of a unipolar rather than a bipolar scale.

5.2. Qualitative Clustering Analysis
To assess the face validity of the lexica, we partition the lexica into groups (clusters) of words that are semantically similar and simultaneously have similar ratings. Straightforward clustering does not take the ratings into account, and is less interpretable. We use the Signed Spectral Clustering (SSC) algorithm to cluster words that are similar semantically and in their ratings (Sedoc et al., 2017b). Weighted edges are added between words such that words of similar empathy have positive connections and those of differing empathy are negative (see appendix and Sedoc et al. (2017a) for precise mathematical formulation). SSC minimizes the cumulative edge weights cut within clusters versus between clusters, while simultaneously minimizing the negative edge weights within the clusters, thus pulling words of similar empathy or distress into the same clusters and pushing those that differ away. We follow the method used by Sedoc et al. (2017b).

As seen in Table 3, the clusters of words for high and low empathy and for high distress are strikingly well illustrated. There are many clusters of topics around situations where people feel empathy. Furthermore, there are lists of different negative emotions. The lists that are all places and people names are less useful obviously for psychological analysis. However, these lists are places where bad things happen, and people to whom bad things happen, which is useful for predictive models. Usable lexica must be inter-
pretatable, SSC allows us not only to give words and ratings, but also, groups of high magnitudes. These allow domain experts then to analyze and possibly modify the lexica.

6. Conclusion

The Mixed-Level Feed-Forward Net (MLFFN) successfully learns word ratings from document-level ratings by backprop word ratings from a trained neural net, performing substantially better than methods that others have used for lexicon creation. The empathy and personal distress lexica we learn using the MLFFN look sensible; we look forward to further validating them by using them in predictive models and psychological experiments, and to exploring the extent to which using the SHAP (SHapley Additive exPlanations) [Lundberg and Lee, 2017] calculations of feature importance for CNNs or RNNs improve lexicon quality over the simple neural nets which we used.

7. Bibliographical References

Abdul-Mageed, M., Buffone, A., Peng, H., Eichstaedt, J. C., and Ungar, L. H. (2017). Recognizing pathogenic empathy in social media. In ICWSM, pages 448–451, Montreal, Canada, May 15–18, 2017.

Alam, F., Danieli, M., and Riccardi, G. (2017). Annotating and modeling empathy in spoken conversations. Computer Speech & Language, pages 40–61.

Baccianella, S., Esuli, A., and Sebastiani, F. (2010). SentìWordNet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. In LREC, pages 2200–2204. European Language Resources Association (ELRA).

Batson, C. D., Fultz, J., and Schoenrade, P. A. (1987). Distress and empathy: Two qualitatively distinct vicarious emotions with different motivational consequences. Journal of personality, 55(1):19–39.

Batson, C. D., Polycarpou, M. P., Harmon-Jones, E., Imhoff, H. J., Mitchener, E. C., Bednar, L. L., Klein, T. R., and Highberger, L. (1997). Empathy and attitudes: Can feeling for a member of a stigmatized group improve feelings toward the group? Journal of personality and social psychology, 72(1):105.

Bloom, P. (2014). Against Empathy.

Bradley, M. M. and Lang, P. J. (1999). Affective Norms for English Words (ANEW): Stimuli, instruction manual and affective ratings. Technical Report C-1, The Center for Research in Psychophysiology, University of Florida, Gainesville, Florida, USA.

Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. Behavior Research Methods, 46(3):904–911, September.

Buechel, S., and Hahn, U. (2017). Emobank: Studying the impact of perspective and representation format on dimensional emotion analysis. In EACL, volume 2, pages 578–585.

Buechel, S., and Hahn, U. (2018). Word emotion induction for multiple languages as a deep multi-task learning problem. In NAACL, volume 1, long papers, pages 1907–1918, New Orleans, Louisiana, USA, June 1–6, 2018.

Buechel, S., Buffone, A., Slaff, B., Ungar, L., and Sedoc, J. (2018). Modeling empathy and distress in reaction to news stories. In EMNLP, pages 4758–4765.

Buffone, A. E., Poulin, M., DeLury, S., Ministero, L., Morrison, C., and Scaleo, M. (2017). Don’t walk in her shoes! different forms of perspective taking affect stress physiology. Journal of Experimental Social Psychology, 72:161 – 168.

Chikovani, G., B. L. I. N. G. T. and Surguladze, S. (2015). Empathy costs: Negative emotional bias in high empathisers. Psychiatry Research, 229(1-2):340–346.

Chollet, F. et al. (2015). Keras, https://keras.io.

Clos, J., Wiratunga, N., and Massie, S. (2017). Towards explainable text classification by jointly learning lexicon and modifier terms. In IJCAI-17 Workshop on Explainable AI (XAI), page 19.

Davis, M. H. (1980). A multidimensional approach to individual differences in empathy. JSAS Catalog of Selected Documents in Psychology, 10:85.

Davis, M. H. (1983). Measuring individual differences in empathy: Evidence for a multidimensional approach. Journal of Personality and Social Psychology, 44:113–126.

De Bruyne, L., Atanasova, P., and Augenstein, I. (2019). Joint Emotion Label Space Modelling for Affect Lexica. arXiv:1911.08782.

De Waal, F. (2009). The age of empathy.

Eichstaedt, J. C., Schwartz, H. A., Kern, M. L., Park, G., Labarthe, D. R., Merchant, R. M., Jha, S., Agrawal, M., Dziurzynski, L. A., Sap, M., et al. (2015). Psychological language on twitter predicts county-level heart disease mortality. Psychological science, 26(2):159–169.

Ekman, P. (1992). An argument for basic emotions. Cognition & Emotion, 6(3-4):169–200.

Engelthaler, T. and Hills, T. T. (2017). Humor norms for 4,997 English words. Behavior Research Methods, July.

Fung, P., Dey, A., Siddique, F. B., Lin, R., Yang, Y., Wan, Y., and Chan, H. Y. R. (2016). Zara the supergirl: An empathetic personality recognition system. In NAACL, volume 3, demonstrations, pages 87–91, San Diego, California, USA, June 12–17, 2016.

Hamilton, W. L., Clark, K., Leskovec, J., and Jurafsky, D. (2016). Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. In EMNLP, pages 595–605, Austin, Texas. Association for Computational Linguistics.

Hatzivassiloglou, V. and McKeown, K. R. (1997). Predicting the semantic orientation of adjectives. In EACL.

Hofmann, M. J., Kuchinke, L., Tamm, S., Vö, M. L. H., and Jacobs, A. M. (2009). Affective processing within 1/10th of a second: High arousal is necessary for early facilitative processing of negative but not positive words. Cognitive, Affective, & Behavioral Neuroscience, 9(4):389–397, December.

Hutto, C. J. and Gilbert, E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In Eighth international AAAI conference on weblogs and social media.

Iyyer, M., Manjunatha, V., Boyd-Graber, J., and Daumé III,
Kingma, D. and Ba, J. (2015). A method for stochastic optimization. In *ICLR*, pages 1–15, San Diego, California, USA, May 7–9, 2015.

Kulkarni, P. V., Nagori, M. B., and Kshirsagar, V. P. (2019). An in-depth survey of techniques employed in construction of emotional lexicon. In *Information and Communication Technology for Intelligent Systems*, pages 609–620. Springer.

Leveau, N., Jhean-Larose, S., Denhière, G., and Nguyen, B.-L. (2012). Validating an interlingual metanorm for emotional analysis of texts. *Behavior Research Methods*, 44(4):1007–1014.

Li, M., Lu, Q., Long, Y., and Gui, L. (2017). Inferring Affective Meanings of Words from Word Embedding. *IEEE Transactions on Affective Computing*, PP(99):1–1.

Liu, L., Preotuc-Pietro, D., Samani, Z. R., Moghaddam, M. E., and Ungar, L. (2016). Analyzing personality through social media profile picture choice. In *Tenth International AAAI conference on web and social media*.

Lundberg, S. M. and Lee, S.-I. (2017). A unified approach to interpreting model predictions. In I. Guyon, et al., editors, *NIPS*, pages 4765–4774. Curran Associates, Inc.

McQuiggan, S. W. and Lester, J. C. (2007). Modeling and evaluating empathy in embodied companion agents. *International Journal of Human-Computer Studies*, 65(4):348–360.

Mihalcea, R. and Liu, H. (2006). A corpus-based approach to finding happiness. In *AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs*, pages 139–144.

Mikolov, T., Grave, E., Bojanowksi, P., Puhrsch, C., and Joulin, A. (2018). Advances in pre-training distributed word representations. In *LREC*.

Mohammad, S. and Bravo-Marquez, F. (2017a). WASSA-2017 shared task on emotion intensity. In *WASSA*, pages 34–49, Copenhagen, Denmark, September 8, 2017.

Mohammad, S. M. and Bravo-Marquez, F. (2017b). Emotion intensities in tweets. In *SEM 2017 — Proceedings of the 6th Joint Conference on Lexical and Computational Semantics*, pages 65–77, Vancouver, British Columbia, Canada, August 3–4, 2017.

Mohammad, S. M. (2012). #Emotional Tweet. In *SEM 2012 — First Joint Conference on Lexical and Computational Semantics*, pages 246–255, Montreal, Canada, June 7–8, 2012.

Mohammad, S. (2018). Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words. In *ACL*, pages 174–184, Melbourne, Australia. Association for Computational Linguistics.

Monnier, C. and Syssau, A. (2008). Semantic contribution to verbal short-term memory: Are pleasant words easier to remember than neutral words in serial recall and serial recognition? *Memory & Cognition*, 36(1):35–42, January.

Montefinese, M., Ambrosini, E., Fairfield, B., and Mammarella, N. (2014). The adaptation of the Affective Norms for English Words (ANEW) for Italian. *Behavior Research Methods*, 46(3):887–903.

Osgood, C., Suci, G. J., and Tannenbaum, P. (1957). *The Measurement of Meaning*. University of Illinois, Urbana, IL.

Pavée, L., Greitemeyer, T., and Sparks, P. (2012). “i help because i want to, not because you tell me to”: Empathy increases autonomously motivated helping. *Personality and Social Psychology Bulletin*, 38(5):681–689. PMID: 22326945.

Pennebaker, J. (2011). *The Secret Life of Pronouns: What Our Words Say About Us*.

Pérez-Rosas, V., Mihalcea, R., Resnicow, K., Singh, S., and An, L. (2017). Understanding and predicting empathic behavior in counseling therapy. In *ACL*, volume 1, long papers, pages 1426–1435, Vancouver, British Columbia, Canada, July 30 – August 4, 2017.

Poulin, M. J., Brown, S. L., Dillard, A. J., and Smith, D. M. (2013). Giving to others and the association between stress and mortality. *American Journal of Public Health*, 103(9):1649–1655. PMID: 23327269.

Preotuc-Pietro, D., Schwartz, H. A., Park, G., Eichstaedt, J., Kern, M., Ungar, L., and Shulman, E. (2016). Modelling valence and arousal in FACEBOOK posts. In *WASSA*, pages 9–15, San Diego, California, USA, June 16, 2016.

Redondo, J., Fraga, I., Padrón, I., and Comesaña, M. (2007). The Spanish adaptation of ANEW (Affective Norms for English Words). *Behavior Research Methods*, 39(3):600–605.

Rill, S., Drescher, J., Reinel, D., Scheidt, J., Schuetz, O., Wogenstein, F., and Simon, D. (2012). A generic approach to generate opinion lists of phrases for opinion mining applications. In *Proceedings of the KDD-WISDOM*.

Ruppenhofer, J., Wiegand, M., and Brandes, J. (2014). Comparing methods for deriving intensity scores for adjectives. In *EACL*, pages 117–122.

Sap, M., Park, G., Eichstaedt, J., Kern, M., Stillwell, D., Kosinski, M., Ungar, L., and Schwartz, H. A. (2014). Developing age and gender predictive lexica over social media. In *EMNLP*, pages 1146–1151.

Schwartz, H. A., Eichstaedt, J. C., Dziurzynski, L., Kern, M. L., Blanco, E., Kosinski, M., Stillwell, D., Seligman, M. E., and Ungar, L. H. (2013). Toward personality insights from language exploration in social media. In *2013 AAAI Spring Symposium Series*.

Schwartz, H. A., Giorgi, S., Sap, M., Crutchley, P., Ungar, L., and Eichstaedt, J. (2017). Dlatk: Differential lan-
guage analysis toolkit. In EMNLP: System Demonstrations, pages 55–60.
Sedoc, J., Gallier, J., Foster, D., and Ungar, L. (2017a). Semantic word clusters using signed spectral clustering. In ACL, pages 939–949.
Sedoc, J., PreoT ¸ iuc-Pietro, D., and Ungar, L. (2017b). Predicting emotional word ratings using distributional representations and signed clustering. In EACL, pages 564–571.
Tausczik, Y. R. and Pennebaker, J. W. (2010). The psychological meaning of words: Liwc and computerized text analysis methods. *Journal of language and social psychology*, 29(1):24–54.
Turney, P. D. and Littman, M. L. (2003). Measuring praise and criticism: Inference of semantic orientation from association. *ACM Transactions on Information Systems*, 21(4):315–346.
Wang, L. and Xia, R. (2017). Sentiment lexicon construction with representation learning based on hierarchical sentiment supervision. In EMNLP, pages 502–510, Copenhagen, Denmark, September 7–11, 2017.
Wang, J., Yu, L.-C., Lai, K. R., and Zhang, X. (2016). Dimensional sentiment analysis using a regional CNN-LSTM model. In ACL, volume 2, short papers, pages 225–230, Berlin, Germany, August 7–12, 2016.
Warriner, A. B., Kuperman, V., and Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods*, 45(4):1191–1207.
Yee, L. T. S. (2017). Valence, arousal, familiarity, concreteness, and imageability ratings for 292 two-character Chinese nouns in Cantonese speakers in Hong Kong. *PLOS ONE*, 12(3):1–16.
Yu, L.-C., Wang, J., Lai, K. R., and Zhang, X. (2017). Refining word embeddings for sentiment analysis. In EMNLP, pages 534–539.