Joint Emotion Label Space Modelling for Affect Lexica

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Emotion lexica are commonly used resources to combat data poverty in automatic emotion detection. However, methodological issues emerge when employing them: lexica are often not very extensive, and the way they are constructed can vary widely – from lab conditions to crowdsourced approaches and distant supervision. Furthermore, both categorical frameworks and dimensional frameworks coexist, in which theorists provide many different sets of categorical labels or dimensional axes. The heterogenous nature of the resulting emotion detection resources results in a need for a unified approach to utilising them.

This paper contributes to the field of emotion analysis in NLP by a) presenting the first study to unify existing emotion detection resources automatically and thus learn more about the relationships between them; b) exploring the use of existing lexica for the above-mentioned task; c) presenting an approach to automatically combining emotion lexica, namely by a multi-view variational auto-encoder (VAE), which facilitates the mapping of datasets into a joint emotion label space.

We test the utility of joint emotion lexica by using them as additional features in state-of-the-art emotion detection models. Our overall findings are that emotion lexica can offer complementary information to even extremely large pre-trained models such as BERT. The performance of our models is comparable to state-of-the-art models that are specifically engineered for certain datasets, and even outperform the state-of-the art on four datasets.

1. Introduction

Emotion detection has attracted growing interest in the field of natural language processing in the last few years (Mohammad et al. 2018; Chatterjee et al. 2019), spurring the creation of resources for the automatic modelling of emotions in different kinds of textual data, including datasets with fairy tales (Alm, Roth, and Sproat 2005), news headlines (Strapparava and Mihalcea 2007), blogs (Aman and Szpakowicz 2007) and tweets (Mohammad 2012a; Mohammad et al. 2015; Schuff et al. 2017).

Notwithstanding the long history of theoretical emotion research in psychology and its more recent surge in NLP, there is currently no consensus on a standard emotion framework. Categorical frameworks and dimensional frameworks coexist, in which theorists provide many different sets of categorical labels (Ekman 1992; Plutchik 1980)
or dimensional axes (Mehrabian and Russell 1974; Fontaine et al. 2007). This versatility is also reflected in the existing emotion datasets and lexica, which show a myriad of different categorical labels or numerical scales. The inconsistency in labels, together with the diversity of textual genres and domains, impedes the exchange of data and knowledge resources and hampers the comparison of different NLP models that handle emotions. This paper takes a holistic view of the emotion detection research landscape and presents a joint approach that can both unify emotion frameworks and automatically map between them, to bridge the gap between different streams of approaches.

Even though different emotion datasets exist, individually, they are still small, requiring methods that deal well with low amounts of resources. A commonly-used approach to combat this is distant supervision via external resources, here, emotion lexica. As emotion detection can be considered a more fine-grained variant of sentiment (polarity) analysis, methods for tackling the latter task recur when dealing with emotions. One such method is the use of affect lexica, in which words are annotated with sentiment or emotion scores and employed as a straight-forward way to automatically label texts or used as features in supervised machine learning approaches (Ma, Peng, and Cambria 2018). Even in state-of-the-art systems for emotion detection (e.g. the winning teams of the SemEval-2018 shared task on multi-label emotion classification), word embeddings in Bi-LSTM architectures are complemented with features from affect lexica (Baziotis et al. 2018; Meisheri and Dey 2018).

However, methodological issues emerge when employing lexica for emotion detection: lexica are often not very extensive, and the way they are constructed can vary widely — from lab conditions in the field of psychology (Bradley and Lang 1999), over crowdsourced approaches (Mohammad and Turney 2013) to distant supervision (Mohammad and Kiritchenko 2015). This asks for a unified, expanded emotion lexicon, a need that is even complicated by the miscellany of emotion frameworks. Questions arise such as to what extent the lexicon should match the domain and/or labels of the dataset at hand and how one should deal with different label schemes when combining lexica.

This paper aims to answer these questions by assembling eight existing English emotion lexica and evaluating each lexicon through an emotion classification (for categories) or regression (for dimensions) task on thirteen datasets. To evaluate combinations of lexica, we build on Hoyle et al. (2019), who introduce a multi-view variational auto-encoder (VAE) to combine six sentiment lexica with disparate label spaces, with each view corresponding to a different lexicon.

For each of the eight emotion lexica in our study, the VAE has multiple emission distributions and for each word in the merged vocabulary, the VAE considers a Dirichlet latent variable. These latent variables are situated in a shared space across the lexica, resulting in a joint emotion label space.

**Contributions:** This paper contributes to the field of emotion analysis in NLP by a) presenting the first study to unify existing emotion detection resources automatically and thus learn more about the relationships between them; b) exploring the use of existing lexica for the above-mentioned task; c) presenting an approach to automatically combine emotion lexica, which facilitates the mapping of datasets into a joint emotion label space.

Section 2 describes background on emotion frameworks and related studies that utilise lexica for emotion detection, or that combine lexica and datasets with disparate label spaces. In Section 3, we explain our methodology, with a description of the VAE model, the lexica and datasets, and the experiments. Section 4 reports the results, which we further discuss in Section 5. We end this paper with a conclusion in Section 6.
2. Related Work

Although being a relatively new research field, studies on the topic of emotion detection are manifold. Our aim is therefore not to provide an exhaustive overview of the research in the field. Instead, we will limit ourselves to briefly discussing the different frameworks in emotion theory (Section 2.1), illustrating the use of lexica for emotion detection (Section 2.2) and describing related studies dealing with different emotion frameworks in NLP (Section 2.3).

2.1 Exploring emotion frameworks

Two main approaches of emotion representation exist, namely categorical approaches and dimensional approaches.

In the categorical approach, emotions are represented as specific discrete categories, often with some emotions considered more basic than others. Ekman’s (1992) theory of six basic emotions (joy, sadness, anger, fear, disgust, and surprise) is the most well-known, but also Plutchik’s (1980) wheel of emotions — in which joy, sadness, anger, fear, disgust, surprise, trust, and anticipation are considered most basic — is a common framework in emotion studies. However, many other theorists provide basic emotion frameworks, which can count up to fourteen emotion categories (Izard 1971; Roseman 1984).

In dimensional models, on the other hand, emotions are represented as a point in a multidimensional space. According to Mehrabian and Russell (1974), every emotional state can be described by scores on the dimensions valence (unhappiness-happiness), arousal (calmness-excitement) and dominance (submission-dominance), known as the VAD-model. However, in later work Russell (1980) argued that the two dimensions valence and arousal suffice for describing emotional states, whereas Fontaine et al. (2007) suggest adding a fourth dimension: unpredictability.

Various resources have been created based on these different frameworks. Most lexica provide scores per word, either for the dimensions valence, arousal and dominance (Bradley and Lang 1999; Warriner, Kuperman, and Brysbaert 2013; Mohammad 2018a), or for basic emotions (Stevenson, Mikels, and James 2007; Mohammad and Kiritchenko 2015; Mohammad 2018b). Other lexica just annotate each word with one or more emotion categories (Strapparava and Valitutti 2004; Mohammad and Turney 2013), corresponding to binary annotation.

Looking at existing datasets, the categorical framework clearly dominates, mostly with label sets following Ekman’s six (Strapparava and Mihalcea 2007; Mohammad 2012a; Li et al. 2017), Plutchik’s eight (Mohammad et al. 2015; Schuff et al. 2017) or variations thereof (Alm, Roth, and Sproat 2005; Mohammad et al. 2018). Although Strapparava and Mihalcea (2007) approach the Ekman’s emotions in a dimensional way (by predicting intensities of emotion categories), the only datasets which truly employ the dimensional emotion model are the ones of Preoțiuc-Pietro et al. (2016) and Buechel and Hahn (2017a).

2.2 Using lexica for emotion detection

Lexica have been the main approach for tackling the task of sentiment analysis for a long time (Cambria et al. 2017). On their own, they can be used to score sentences in a straight-forward way (e.g. by summing scores of sentiment-bearing words in sentences and averaging them), which is the so-called key-word based approach (Ohana and
Moreover, they can serve as features in a supervised learning setting (Bravo-Marquez, Mendoza, and Poblete 2014).

In 2007, the first shared task on emotion detection was organised by Strapparava and Mihalcea (2007) as the Affective Text task in the SemEval series. The task was to identify Ekman’s emotion categories and valence in news headlines. UPAR (Chau-martin 2007) ended first in the subtask of identifying emotion categories and opted for a key-word based approach with the sentiment lexicon SentiWordNet (Esuli and Sebastiani 2006) and the Ekman emotion lexicon WordNet Affect (Strapparava and Valitutti 2004). The task organizers themselves experimented with two approaches: one based on the WordNet Affect lexicon and one corpus-based approach (Strapparava and Mihalcea 2008). Overall, the organizers’ lexicon-based approach gave the best performance.

Chaffar and Inkpen (2011) used WordNet Affect scores as features (together with bag of word and n-gram features) on the AFFECTIVE TEXT (Strapparava and Mihalcea 2007), TALES (Alm, Roth, and Sproat 2005) and BLOGS (Aman and Szpakowicz 2007) datasets with Decision Trees, Naive Bayes and SVM as classifiers. Also Kirange and Deshmukh (2012) performed experiments on the AFFECTIVE TEXT dataset and used WordNet Affect lexicon features with an SVM. Indeed, Mohammad (2012b) shows that using affect lexica performs better in sentence-level emotion classification than uni- or bigrams alone, using WordNet Affect and the NRC Emotion Lexicon on the AFFECTIVE TEXT and BLOGS datasets to support this.

Even in very recent studies, lexica are still used, for example as features in more sophisticated machine learning systems as deep neural networks. In SemEval-2018 Task 1: Affect in Tweets (Mohammad et al. 2018), one of the subtasks was a multi-label emotion classification task (with labels anger, anticipation, disgust, fear, joy, love, optimism, pessimism, sadness, surprise and trust). Apart from word embeddings, emotion and sentiment lexica were the most used features. Even the two best teams (Baziotis et al. 2018; Meisheri and Dey 2018) used a Bi-LSTM architecture, where word embedding features were complemented with features from affect lexica.

However, relying on lexica to tackle the task of emotion detection has its limitations. The biggest problem is coverage: lexica are often not very extensive. Several studies have tried to expand emotion lexica and used different approaches thereto. Giulianelli and de Kok (2018) for example used a label propagation method (Zhu and Ghahramani 2002) to expand existing emotion lexica. However, they only work with one original lexicon, namely the NRC Emotion Lexicon (Mohammad and Turney 2013). The choice of lexicon was based on the label set: they used the HASHTAG EMOTION CORPUS (Mohammad and Kiritchenko 2015) which is labeled with the Plutchik emotion categories, and chose their lexicon accordingly. They thus did not have to manage the combination of different label sets, which is another difficulty of using emotion lexica. In the next section, we will discuss some studies that do take into account different emotion frameworks.

2.3 Dealing with different frameworks

Due to the sometimes restricted nature of lexica, a unified, expanded emotion lexicon is desirable. This need, however, is complicated by the miscellany of emotion frameworks. To give an example, the word alien appears in seven emotion lexica and is thus labeled in seven different ways (see Table 1).

The problem of different emotion frameworks also emerges when dealing with datasets. Bostan and Klinger (2018) combine twelve different datasets by means of a
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| Lexicon          | Representations |
|------------------|-----------------|
| Affective Norms  | V A D            |
| (1-9 interval)   | 4.45 4.86 3.56  |
| ANEW             | V A D            |
| (1-9 interval)   | 5.6 5.45 4.64   |
| NRC VAD          | V A D            |
| (0-1 interval)   | 0.41 0.615 0.491|
| NRC Emotion      | Ang Ant Di F J Sa Su T |
| (binary)         | 0 0 1 1 0 0 0 0 0 |
| NRC Affect Intensity | Ang F J Sa | (0-1 interval)* |
|                  | 0 0.422 - -     |
| NRC Hashtag      | Ang Ant Di F J Sa Su T |
| (real-valued)*   | - 0.657 - 0.623 - 0.640 - - |
| Stevenson        | Ang Di F J Sa   |
| (1-5 interval)   | 1.47 1.69 2.42 1.29 1.28 |

Table 1: Representation of the word *alien* in different lexica. Abbreviations: A = Arousal, Ang = Anger, Ant = Anticipation, D = Dominance, Di = Disgust, F = Fear, J = Joy, Sa = Sadness, Su = Surprise, T = Trust, V = Valence.

* In some datasets, not all words get a score for each emotion category. In this example, this is indicated with -.

rule-based mapping between categorical label sets. This results in a final set of eleven emotion categories, in a multi-label approach with continuous values. However, dimensional representations (like the VAD model) are not taken into consideration.

Stevenson, Mikels, and James (2007) and Buechel and Hahn (2017b, 2018) investigated mapping methods to shift between categorical and dimensional word representations. This is not only beneficial for lexicon construction, but also for making annotated corpora and tools comparable. In the first study (Stevenson, Mikels, and James 2007), linear regression was used to predict dimensional (VAD) values with categorical data (affect intensity ratings for the discrete categories happiness, anger, sadness, fear and disgust), and vice versa. They found that no straightforward mapping was possible between emotional categories and dimensional information, but that each emotional category has a different impact on the separate dimensions.

Buechel and Hahn (2017b) trained a kNN model to learn a mapping. They used the intensity ratings of all categories (same as the ones from Stevenson, Mikels, and James (2007)) to predict one dimension value, or the information of all dimensions to predict the rating of one category. They obtained promising results, with an average Pearson correlation of 0.872 for mapping VAD to an emotion category and 0.844 for mapping categories to dimensions. In subsequent work, a multi-task feed-forward neural network was used to perform the same task and a Pearson correlation of 0.877 was obtained for mapping dimensions to categories and 0.853 for the other direction (Buechel and Hahn 2018).

The above-mentioned studies all try to map emotional dimensions to ratings for affect categories or the other way around. However, a simpler approach is to map
discrete categories in the VAD space, which corresponds to Mehrabian and Russell’s (1974) claim that all affective states can be represented by the VAD dimensions. Figure 1 shows the positions of Ekman’s basic emotions in the VAD space. Calvo and Mac Kim (2013) employ this idea by mapping emotion categories in the VAD space based on the ANEW rating for emotion words belonging to the categories. They calculate VAD scores for sentences using the ANEW lexicon and place them in the emotional space as well. By computing cosine similarity between the sentence and the previously mapped emotion categories, the emotional category of the sentence can be determined.

Mappings between VAD and categorical approaches are thus being used on the emotion classification level, but not yet on the level of emotion lexicon construction. However, combination techniques for disparate label spaces do exist for sentiment (polarity) lexica. Emerson and Declerck (2014) merged four German sentiment lexica by rescaling them linearly (multiplying all the scores by a constant factor per lexicon) and then combining the normalised scores by a Bayesian probabilistic model to calculate latent polarity values, which are assumed to be the ‘true’ values. The original lexica and the merged lexicon all had polarity values on the [-1, 1] interval. The Bayesian model thus just takes care of the noise coming from different sources.

Hoyle et al. (2019) go one step further and combine six lexica with disparate scales, ranging from binary annotations over two-dimensional ratings to 9-point scales. They use a multi-view variational autoencoder to merge the lexica in a latent space of three dimensions (potentially embodying the negative, neutral and positive dimension). They evaluate these latent scores on nine sentiment analysis datasets and find that they outperform both the individual lexica as well as a naive combination of the lexica. Because of the high flexibility this approach leverages, we adapt it to fit our emotion lexica combination task.
3. Method

We test the usability of eight common emotion lexica (see Table 2 for an overview) by evaluating them as features in a supervised machine learning classifier on thirteen of the most commonly used emotion datasets (see Table 3). As a baseline, we use a logistic/linear regression classifier with only the separate lexica as features. Against this, we compare two different methods for combining lexica: a) using a naive concatenation and b) obtaining latent scores from a variational autoencoder. Because a naive concatenation will most likely have conflicting information in it (see Table 1) and could hamper learning, we hypothesise that the VAE scores would work better.

Apart from this simple logistic/linear regression classifier, we also perform experiments with neural methods: Bi-LSTM with only lexica as features, Bi-LSTM with lexica and GloVe embeddings (Pennington, Socher, and Manning 2014) or embeddings from the state-of-the-art BERT language model (Devlin et al. 2019). In what follows, we explain the VAE approach, describe the lexica and datasets used, and document the performed experiments.

3.1 Joint Emotion Space Modelling using a Variational Autoencoder

For maximum vocabulary coverage, it is appropriate to combine multiple lexica when using lexicon information in an emotion detection task. However, seeing the variety of frameworks and perspectives by which lexica are annotated, this is not self-evident.

One could say that, when annotating words to create an emotion lexicon \(\mathcal{L}\), noise is added to the real emotion value \(\mathcal{L}(w)\) of a word \(w\), resulting in the observed emotion value \(x_w\). All emotion values that are observed in a lexicon, are thus distorted. However, the latent emotion values of each word can be inferred using a variational autoencoder (VAE). The noise added by annotation following different frameworks and perspectives, could be eliminated using this approach.

A traditional VAE consists of an encoder that takes observed values \(X\) as input and outputs parameters for the probability distribution \(P(Z|X)\) (which is approximated by a family of distributions \(Q_\lambda(Z|X)\)), from which we can sample to get a latent representation \(Z\). This latent representation is in its turn used as input for a decoder that outputs the parameters of the probability distribution of the data, in order to reconstruct the original input \(X\) (see Figure 2).

Following Hoyle et al. (2019), we extend the VAE to a multi-view model, in which each view corresponds to a different lexicon. This allows us to join lexica with disparate label spaces, mapping the different labels to a common latent space and resulting in a larger, unified emotion lexicon, which we will call the VAE latent emotion space.

Based on experiments on a development set (see Section 4), we determine the best hyperparameters, i.e. the dimension of the latent variable, the number of nodes in the fully-connected layer of the encoder and decoder network and the value of the diagonal in the covariance matrices of the emission distributions (see paragraph ‘Generative network’), being 8, 82 and 0.05 respectively.

**Inference network.** In the first step, the latent values of \(z^w\) are drawn from the prior distribution \(P(Z)\), parameterized by \(\alpha^w = (1, 1, 1, 1, 1, 1, 1, 1)\). The goal of the encoder network or inference network is to find parameters for the posterior distribution \(P(Z|X)\) given the prior \(P(Z)\) and \(P(X|Z)\), where:

\[
P(Z|X) = \frac{P(X|Z)P(Z)}{P(X)}.
\]
Because calculating $P(X)$ is intractable, we need to approximate the posterior distribution with a family of distributions $Q_{\lambda}(Z|X)$. Whereas the latent variables in regular VAE models are Gaussian, we use a Dirichlet latent variable like Hoyle et al. (2019). A fully-connected layer with 82 units is used to construct the Dirichlet parameters $\alpha^w$ for each of the latent dimensions. For more details about the implementation, we refer to Hoyle et al. (2019).

**Generative network.** In the decoder or generative network, $X$ is reconstructed by outputting the likelihood of $X$ given the latent representation $Z$. The joint probability distribution of the data and likelihood is defined as $P(X, Z) = P(X|Z)P(Z)$, where the distribution of the likelihood depends on the lexicon $d$. First, a latent vector is generated by sampling from the distribution described by the Dirichlet parameters (outputted by the inference network). For this sampling process, the generalized reparameterization trick of Ruiz, Titsias, and Blei (2016) is used. Then, the decoder network (again a 82-dimensional fully-connected layer) outputs parameters for the emission distribution $P(X|Z)$ of the data, from which $X$ is reconstructed. This distribution is lexicon-dependent.

Unlike the study of Hoyle et al. (2019), in which most lexica are unidimensional, the emotion lexica we are using are all multidimensional. The emission distributions of ANEW, Affective Norms and NRC VAD are three-dimensional Gaussians with means $\rho^w_d$ and diagonal covariance matrices equal to $0.05I$. NRC Affect Intensity, NRC Hashtag and Stevenson have a four, eight and five-dimensional Gaussian as emission distribution respectively, with means $\rho^y_d$ and diagonal covariance matrices equal to $0.05I$. WordNet Affect and NRC Emotion have respectively six and eight Bernoulli distributions parameterized collectively by $\rho^\beta_d$.

### 3.2 Emotion lexica used as features

**ANEW.** The Affective Norms for English Words (ANEW) by Bradley and Lang (1999) is the oldest set of normative emotional ratings for English words that is still influential in emotion (analysis) studies. 1,034 words have been rated for valence, arousal and dominance on a 9-point scale. The ratings were obtained under lab conditions and originate from the field of psychology.

**Stevenson.** Stevenson, Mikels, and James (2007) provide complementary ratings for the words in ANEW on the five discrete emotions anger, fear, sadness, joy and disgust, on a scale of 1 to 5. Just as ANEW, these ratings were obtained under lab conditions.
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| Name                        | Labels | Annotation | Size   | Reference                      |
|-----------------------------|--------|------------|--------|--------------------------------|
| Affective Norms             | VAD    | [1-9]^3    | 13,915 | Warriner, Kuperman, and Brysbaert (2013) |
| ANEW                        | VAD    | [1-9]^3    | 1,034  | Bradley and Lang (1999)        |
| NRC Emotion                 | Plutchik’s 8 | [0, 1]^8 | 14,182 | Mohammad and Turney (2013)     |
| NRC Affect Intensity        | Ang, F, S, J | [0-1]^4 | 4,192  | Mohammad (2018a)               |
| NRC VAD                     | VAD    | [0-1]^1    | 20,007 | Mohammad (2018a)               |
| NRC Hashtag Emotion         | Plutchik’s 8 | [0-∞]^8  | 16,862 | Mohammad and Kiritchenko (2015) |
| Stevenson                   | Ang, F, S, J, Di | [1-5]^6 | 1,034  | Stevenson, Mikels, and James (2007) |
| WordNet Affect              | Ekman’s 6  | [0, 1]^6   | 1,113  | Strapparava and Valitutti (2004) |

Table 2: Overview of the used emotion lexica. Abbreviations: A = Arousal, Ang = Anger, D = Dominance, Di = Disgust, F = Fear, J = Joy, S = Sadness, V = Valence.

**Affective Norms.** With as much as 13,915 lemmas rated for *valence*, *arousal* and *dominance*, the affective norms of Warriner, Kuperman, and Brysbaert (2013) form a substantial expansion of ANEW. Although originating from the psychology field, ratings were not obtained in the lab, but through crowdsourcing with Amazon Mechanical Turk.

**WordNet Affect.** This resource was created by NLP researchers. Strapparava and Valitutti (2004) developed an extension of WordNet (Miller 1995) by assigning affective labels to a subset of WordNet synsets, containing information about emotions, moods, attitudes, etc. The emotion label was extended with sublabels, referring to emotional categories. In the SemEval-2007 Affective Text task, Strapparava and Mihalcea (2007) extracted a list of words relevant to the Ekman emotions from WordNet Affect. This list contains 1,116 words with binary association scores (0 or 1) for the Ekman emotions.

**NRC Emotion.** These ratings were created by Mohammad and Turney (2013), specifically with the aim of using them in an NLP context. The ratings were obtained by calling in the crowd, which resulted in 14,182 words annotated with one or multiple of the Plutchik emotions (binary association scores).

**NRC VAD.** This lexicon is another crowdsourced resource for emotion analysis in NLP. Mohammad (2018a) obtained ratings for *valence*, *arousal* and *dominance* for 20,007 words, resulting in the largest emotion lexicon that is openly available.

**NRC Affect Intensity.** Mohammad (2018b) also provide a lexicon with ratings for (the intensity of) the emotions *anger*, *fear*, *sadness* and *joy*. The lexicon contains 4,192 unique words, where each word gets a rating between 0 and 1 for one or more of the emotion categories. This was again a result of a crowdsourcing effort.

**NRC Hashtag Emotion.** Unlike the previously discussed lexica, which were manually created, this lexicon was constructed automatically by computing the strength of association between a word and an emotion (based on the HASHTAG EMOTION CORPUS) (Mohammad and Kiritchenko 2015). The lexicon contains real-valued scores for the eight Plutchik emotions for 16,862 words.
3.3 Emotion datasets used for evaluation

**Blogs.** This is one of the oldest emotion datasets used in NLP. It was created by Aman and Szpakowicz (2007). They labeled 5,025 sentences (single-label) from blogs with the Ekman emotions, with additional labels mixed emotion and no emotion. Supplementary information like emotion intensity (low, medium, high) and emotion markers was given as well, but we will only use the single-label emotion information. Moreover, following other studies, we will only use the sentences with high agreement, resulting in a dataset with 4,090 sentences where the mixed emotion category is discarded.

**Emotion in Text.** This dataset was published by CrowdFlower (currently known as Figure Eight), an online data annotation platform. Crowdsourced annotations were collected for 40,000 tweets on the emotion categories anger, boredom, empty, enthusiasm, fun, happiness, hate, love, relief, sadness, surprise, worry and a neutral category (single-label).

**DailyDialog.** This fairly recent dataset was published by Li et al. (2017) and consists of 13,118 sentences from dialogs. The dataset is developed for the task of response retrieval and generation, but additionally, emotion information was annotated. The sentences are labeled following the Ekman emotions (with an additional no emotion label) in a single-label manner.

**ElectoralTweets.** Mohammad et al. (2015) collected 4,058 tweets in the political domain, more specifically with the aim to analyse how public sentiment is shaped when it comes to elections. 4,058 tweets were annotated via crowdsourcing for the categories acceptance, admiration, amazement, anger (including annoyance, hostility and fury), anticipation (including expectancy and interest), calmness (or serenity), disappointment, disgust, dislike, fear (including apprehension, panic and terror), hate, indifference, joy (including happiness and elation), like, sadness (including gloominess, grief and sorrow), surprise, trust, uncertainty (or indecision, confusion) and vigilance. The annotations are single-label.

**Emotion-Stimulus.** Originally, the purpose of this dataset was to identify emotion causes in texts. However, these data can also be used as an emotion detection dataset, as it contains emotion labels for 2,414 sentences. The annotations are done in a single-label manner with the Ekman categories and the additional category shame as labels.

**ISEAR.** In the International Survey on Emotion Antecedents and Reactions, Scherer and Wallbott (1994) asked people to report on emotional events for the seven emotions anger, disgust, fear, guilt, joy, sadness and shame. The sentences from these reports were extracted and linked to the emotion of interest, resulting in a dataset of 7,665 sentences with one out of seven labels.

**Tales.** Although being the oldest emotion dataset in the NLP field, this dataset from Alm, Roth, and Sproat (2005) is still a popular resource. The full dataset consists of 15,302 sentences from 185 fairy tales, annotated with the Ekman emotions, where the surprise category is broken up into positive surprise and negative surprise and a neutral label is added as well. The annotation happened in a single-label way. However, the ‘high-agreement’ version of this dataset, where anger and disgust are merged, no distinction is made between the kinds of surprise and neutral sentences are ignored, is used more frequently. We will therefore also rely on this reduced dataset, which comprises 1,207 sentences.
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| Type   | Name               | Labels                        | Size  | Reference                          |
|--------|--------------------|-------------------------------|-------|------------------------------------|
| SL     | BLOGS              | Ekman, no, mixed              | 5,025 | Aman and Sepkoskic (2007)          |
|        | EMOTION IN TEXT    | 13 categories                 | 40,000| CrowdFlower                        |
|        | DAILYDIALOG        | Ekman, no                     | 13,118| Li et al. (2017)                   |
|        | ELECTORALTWEETS    | 19 categories                 | 4,058 | Mohammad et al. (2015)             |
|        | EMOTION-STIMULUS   | Ekman + Sh                    | 2,414 | Ghazi, Inkpen, and Sepkoskic (2015) |
|        | ISEAR              | Ang, D, F, G, J, Sa, Sh       | 7,665 | Scherer and Wallbott (1994)        |
|        | TALES              | Ang, D, F, J, Sa, Su+, Su-, no| 15,302| Ais, Roth, and Sproul (2005)       |
|        | TEC                | Ekman                         | 21,051| Mohammad (2012a)                   |
| ML     | AFFECT IN TWEETS   | Plutchik + L, O, P            | 10,983| Mohammad et al. (2018)             |
|        | SSEC               | Plutchik                      | 4,868 | Schuff et al. (2017)               |
| Reg    | AFFECTIVE TEXT     | Ekman, V ([0-100])            | 1,250 | Strapparava and Mihalcea (2007)    |
|        | EMOBANK            | VAD ([0-100])                 | 10,548| Buechel and Hahn (2017a)           |
|        | FACEBOOK-VA        | V, A (9-point)                | 2,895 | Preojano-Peres et al. (2016)       |

Table 3: Overview of the used emotion datasets.
Abbreviations: A = Arousal, Ang = Anger, D = Disgust, F = Fear, J = Joy, G = Guilt, L = Love, ML = Multi-Label, no = no emotion, O = Optimism, P = Pessimism, Reg = Regression, Sa = Sadness, Sh = Shame, SL = Single-Label, Su = Surprise, Su+ = Positive Surprise, Su- = Negative Surprise, V = Valence.

TEC. The Twitter Emotion Corpus or TEC was automatically created by Mohammad (2012a) via distant supervision. Emotion word hashtags were used to collect tweets, and the hashtags were used for self-labeling. This resulted in a set of 21,051 tweets with (single-label) Ekman tags.

AFFECT IN TWEETS. In contrast to the previous datasets, the instances in the AFFECT IN TWEETS dataset can have multiple labels. The annotations were obtained via crowdsourcing for the Plutchik emotions and three additional labels love, optimism and pessimism. The dataset was used for one of the subtasks in SemEval-2018: Affect in Tweets (Mohammad et al. 2018).

SSEC. The Stance Sentiment Emotion Corpus is another multi-label dataset, published by Schuff et al. (2017). It is an extension of the stance and sentiment dataset from SemEval-2016 (Mohammad et al. 2016) and has annotations for the Plutchik emotions for 4,868 tweets.

AFFECTIVE TEXT. While the aforementioned datasets all contain discrete labels and are intended for emotion classification, the AFFECTIVE TEXT dataset from SemEval-2007 by Strapparava and Mihalcea (2007) can be used in regression tasks. 1,250 news headlines were scored for Ekman emotions on a 0 to 100 scale.

EMOBANK. This dataset by Buechel and Hahn (2017a) is also intended for emotion regression tasks. 10,548 sentences were annotated for the dimensions valence, arousal and dominance on a scale from 0 to 100. The sentences originate from various genres and domains, including the sentences from AFFECTIVE TEXT and subsets (blogs, essays, fiction, travel guides, ...) of the Manually Annotated Sub-Corpus of the American National Corpus (Ide et al. 2010).
FACEBOOK-VA. Preotiuc-Pietro et al. (2016) published a dataset consisting of 2,895 Facebook posts. The posts are annotated for the dimensions valence and arousal on a 9-point scale and thus are intended for regression tasks.

3.4 Experiments

We evaluate different lexicon approaches on eleven commonly used emotion datasets and two additional datasets also suited for emotion detection (DAILYDIALOG and EMOTION-STIMULUS). Eight of the thirteen datasets are annotated in a single-label categorical approach and are used for emotion classification. For these datasets, ordinary accuracy (percentage of correct predictions) is our evaluation metric of interest. Two datasets have a multi-label setup, for which we build separate binary classifiers for each of the categories and join the predictions afterwards. Here, we report Jaccard accuracy, a metric specifically used in multi-label tasks. Lastly, three datasets have dimensional annotations and are used in a regression task where we report Pearson correlations to measure the agreement between gold and predicted scores. If a train-test split is provided in the original dataset, we use this. Otherwise, we create an 80:20 train-test split. 10% from all data in the training set is reserved for development.

In a first set of experiments, we use the information from each lexicon separately as features in a simple machine learning model to predict labels/scores for each dataset. Each word in the utterance of interest is represented as its lexicon scores, and then these scores are averaged over the words to get lexicon scores for the complete data instance. In some lexica, not all words get scores for every label (see e.g. Anger, Joy and Sadness in NRC Affect Intensity in Table 1). In that case, we treat the label as 0. We use a logistic regression classifier for the categorical datasets and linear regression for the continuous datasets. The logistic regression classifier uses a liblinear solver with L2 regularization and C=1.0.

Using the same algorithms, we also compute performances for when the different lexica are combined. We explore three options: using a naive concatenation of all lexica (resulting in a combined feature vector of dimension 40), using the latent representations from the VAE, and using a naive combination where the VAE latent emotion space is concatenated as an additional lexicon (feature vector with dimension 40 + number of latent dimensions).

This threefold setting is also explored in a neural network approach. We use a bi-directional LSTM with three layers of size 900 and a dot attention layer. Our data is transformed to lexicon vectors (using the naively concatenated representation, the VAE dimensions and the naive concatenation plus VAE dimensions). Each data instance is thus represented as a feature vector where the words are represented by their lexicon scores. We train a network where we keep the input layer fixed, but we also train one where we further optimize our input representations.

We further test whether lexica can offer complementary gains to neural approaches, which typically rely solely on embeddings. We do this by adding lexicon features to the Bi-LSTM with GloVe word embeddings (Pennington, Socher, and Manning 2014) and the state-of-the-art BERT embeddings (Devlin et al. 2019) as input features. Because we are merely interested in comparing different approaches and not in finding the best model per se, we do not perform a large grid search over hyperparameters for our networks. For BERT, we simply use the pretrained BERT model and the PyTorch interface for BERT by Hugging Face (Wolf et al. 2019) and use the word vectors of the last layer in the BERT model as input word vectors. We investigate how our Bi-LSTM...
performs with only word embeddings as features and how the performance alters when lexicon features are added (again with the three scenarios discussed above).

We are interested in a) the strengths of individual lexica, for example regarding agreement of framework between lexicon and dataset or the effect of lexicon size and construction method; b) the effect of combining lexica compared to using individual lexica, more specifically when using latent representations from a VAE compared to a naive concatenation of lexica; c) the performance of different machine learning methods (although we limit ourselves to basic approaches and heavily tune those) and word representations; d) the performance of using lexica in combination with word embeddings compared to word embeddings or lexica on their own and e) the performance of using fixed lexicon scores compared to trainable inputs. Table 4 gives an overview of where these questions will be investigated in the following sections.

### 4. Results

First we perform some experiments to choose the dimension of the latent variable and to tune the number of nodes in the fully-connected layer and the value of the diagonal in the covariance matrices. We choose 82 nodes and a value of 0.05 for the covariance matrices.

We experiment with different sizes for the hidden variable, motivated by their correspondence to different theoretical emotion frameworks. As a three-dimensional model is the most dominant dimensional representation of emotions in psychological theories (Mehrabian and Russell 1974), we hypothesize that we can find a latent representation that will separate well alongside three axes (and possibly representing valence, arousal and dominance). However, we also try a 6-, 8- and 40-dimensional latent variables, respectively corresponding to the models of Ekman, Plutchik and the dimension of the naively concatenated lexicon feature vector. The latter allows us to assess whether just adding more features is more predictive than learning a valuable representation of the data. Based on the results shown in Table 5, we choose 8 as the final dimension for the latent representation in the VAE, which corresponds to the Plutchik framework, as this dimensionality leads to the highest results for most datasets.
Table 5: Results per dataset for the VAE dimensions with different dimensions (accuracy for single-label datasets, Jaccard accuracy for multi-label and Pearson’s \( r \) for regression). The best results per dataset are marked in bold.

| Dataset                  | Metric | 3-dim | 6-dim | 8-dim | 40-dim |
|--------------------------|--------|-------|-------|-------|--------|
| BLOGS                    | Acc.   | 0.695 | 0.709 | 0.707 | 0.708  |
| EMOTION IN TEXT          |        | 0.271 | 0.280 | 0.286 | 0.278  |
| DAILYDIALOG              |        | 0.817 | 0.819 | 0.820 | 0.819  |
| ELECTORAL TWEETS         |        | 0.250 | 0.253 | 0.264 | 0.247  |
| EMOTION-STIMULUS         |        | 0.536 | 0.646 | 0.644 | 0.633  |
| ISEAR                    |        | 0.271 | 0.378 | 0.374 | 0.353  |
| TALES                    |        | 0.467 | 0.554 | 0.574 | 0.500  |
| TEC                      |        | 0.417 | 0.451 | 0.454 | 0.437  |
| AFFECT IN TWEETS         | Jacc.  | 0.827 | 0.835 | 0.839 | 0.835  |
| SSEC                     |        | 0.664 | 0.668 | 0.669 | 0.665  |
| AFFECTIVE TEXT           |        | 0.308 | 0.336 | 0.323 | 0.294  |
| EMOBank                  |        | 0.262 | 0.282 | 0.298 | 0.343  |
| FACEBOOK-VA              |        | 0.382 | 0.384 | 0.385 | 0.392  |

4.1 Individual lexica

We train linear and logistic regression classifiers with lexicon scores as features. First, the individual lexica are used separately, and overall, the NRC Hashtag lexicon is the most predictive one. Table 6 reports the average accuracy, aggregated over the different single-label datasets, average Jaccard accuracy for the multi-label datasets and average Pearson correlation for the regression datasets. More specifically, NRC Hashtag was the best lexicon for nine out of thirteen datasets (EMOTION IN TEXT, DAILYDIALOG, ELECTORAL TWEETS, ISEAR, TALES, AFFECT IN TWEETS, SSEC, AFFECTIVE TEXT and FACEBOOK-VA). In three datasets, NRC Affect Intensity is the best lexicon overall. Stevenson gives the best performance on one dataset (TALES).

Affective Norms, NRC VAD, ANEW and WordNet Affect are most often the least predictive lexica. This indicates that lexica with a VAD-framework are less suited for emotion prediction than lexica annotated with (scores for) categories. Moreover, even for the datasets that are annotated with dimensions (valence and arousal in FACEBOOK-VA and valence, arousal and dominance in EMOBank), NRC Hashtag and NRC Affect Intensity are respectively the best lexica. Although one could suggest that VAD lexica perform better on dimensional datasets than on categorical datasets (with Affective Norms performing second best on FACEBOOK-VA and NRC VAD second best on EMOBank) there is no sign that VAD lexica are more suitable for datasets with dimensional annotations than categorical lexica.

Figure 3 visualizes the label overlap between the lexica and datasets (number of labels that overlap normalized by label set size in the dataset). We calculate Pearson correlation between label overlap and accuracy and find that only for some datasets label overlap has an influence, especially for EMOTIONS IN TEXT, DAILYDIALOG, EMOTION-STIMULUS, ISEAR and AFFECT IN TWEETS \( (r > 0.6) \). However, for the three regression datasets, there is no correlation between label overlap and performance \( (-0.2 < r < 0.001) \). Possibly, this task is harder because of its fine granularity, making lexica less valuable. We also find that the best performing lexica are the ones that use a categorical framework, on the condition that they use a continuous scale instead of a binary scale (NRC Hashtag Emotion, NRC Affect Intensity and Stevenson).
One factor that could influence the performance of the lexicon is the lexicon size. However, we find that this is not at all decisive. The second best performing lexicon is NRC Affect Intensity, but with its 4,192 unique words, this lexicon is rather small. Also Stevenson performs fairly well, although only containing 1,034 words. On the other hand, the largest lexicon is NRC VAD, but this lexicon performs rather badly (probably because it has VAD annotations instead of categorical annotations).

Lastly, it is compelling to link the origin of the lexica to their performance. Interestingly, the best performing lexicon has been constructed automatically. Lexica created under lab conditions do not necessarily perform well (ANEW performs badly and Affective Norms only average), while crowdsourced lexicon annotations can give fairly good results (as in the case of NRC Affect Intensity).

4.2 Combining lexica in linear classifiers

Again using linear and logistic regression classifiers, we test combinations of the different lexica for the emotion analysis tasks. The results are given in the second section of Table 6. The first approach is to use a naive concatenation of all lexica, resulting in a 40-dimensional feature vector. For all lexica, the naive concatenation gives better results than using any of the individual lexica. The second approach is to use the latent representations obtained by the VAE. For this, a latent dimensionality of 8 is used, based on the results in Table 5.

Compared to the naive concatenation, the VAE latent emotion space performs better for four datasets (ELECTORAL TWEETS, TALES, EMOBANK and FACEBOOK-VA). For the regression datasets, the VAE latent emotion space works best overall. However, adding the VAE dimensions to the naive concatenation (resulting in a 48-dimensional feature vector), resulted in the best accuracy score for ten out of the thirteen datasets. Table 6
|                         | Single-Label Accuracy (micro-F1) | Multi-Label Jaccard accuracy | Regression Pearson's $r$ |
|-------------------------|----------------------------------|------------------------------|-------------------------|
| △ NRC Hashtag           | 0.468                            | 0.361                        | 0.268                   |
| △ NRC Affect Intensity  | 0.459                            | 0.311                        | 0.265                   |
| △ WordNet Affect        | 0.450                            | 0.246                        | 0.122                   |
| △ Stevenson             | 0.444                            | 0.274                        | 0.176                   |
| △ NRC Emotion           | 0.441                            | 0.305                        | 0.207                   |
| ○ Affective Norms       | 0.420                            | 0.297                        | 0.244                   |
| ○ NRC VAD               | 0.414                            | 0.269                        | 0.245                   |
| ○ ANEW                  | 0.410                            | 0.246                        | 0.137                   |
| combi (-vae)            | 0.539                            | 0.415                        | 0.321                   |
| vae                     | 0.515                            | 0.413                        | 0.335                   |
| combi (+vae)            | 0.549                            | 0.426                        | 0.329                   |

Table 6: Results aggregated over datasets for separate lexica and combinations of lexica with logistic/linear regression.  
△ categorical lexicon  
○ dimensional lexicon  
  
Combinations of lexica: combi = naive concatenation, vae = combination with VAE latent emotion space; vae+combi = naive concatenation with vae latent emotion space included.  
  
Single-Label datasets = BLOGS, EMOTION IN TEXT, DAILYDIALOG, ELECTORAL TWEETS, EMOTION-STIMULUS, ISEAR, TALES, TEC.  
Multi-Label datasets = AFFECT IN TWEETS, SSEC.  
Regression datasets = AFFECTIVE TEXT, EMOBank, FACEBOOK-VA.  

shows that, on average, this combination approach works best for the single-label and multi-label datasets. This seems to suggest that the VAE space and the original lexica on their own capture complementary information, in the same way that unigram and bigram features can capture different aspects of useful information. Another possible reason for the VAE latent emotion space not performing better than the naive concatenation, is that the latent emotion representation contains relevant information that is lost during mapping the emotion to a specific emotion framework.  

4.3 Combining lexica in a Bi-LSTM  

We compare the same three scenarios as in the previous section (naive concatenation without VAE latent emotion space, the VAE latent emotion space on its own, and a naive concatenation with the VAE dimensions included). Table 7 shows the results for these experiments, aggregated over the single-label datasets, over the multi-label ones and the regression datasets. For brevity, we only report the results where the weights of the sentence vector were updated while training. We also test using the lexicon scores as input as such (fixed), but overall, this performs worse. This might be due to the domain discrepancy between datasets and lexica (even though we combined different lexica). Therefore, we hypothesise that training the VAE jointly with the classification network would perform better. This is something future research will need to confirm.  

In general, when only lexicon features are used, the linear/logistic regression classifier performs better than the Bi-LSTM, probably because the datasets are rather small and the classifier has (in this setup at least) few features to fit to, which makes it far from
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|                  | Single-Label Accuracy (micro-F1) | Multi-Label Jaccard accuracy | Regression Pearson’s r |
|------------------|----------------------------------|-------------------------------|------------------------|
| combi            | 0.427                            | 0.166                         | 0.107                  |
| vae              | 0.405                            | 0.181                         | 0.115                  |
| combi+vae        | 0.421                            | 0.272                         | -0.064                 |

Table 7: Results aggregated over datasets for combinations of lexica in Bi-LSTM. See Table 6 for datasets and abbreviations.

|                  | Single-Label Accuracy (micro-F1) | Multi-Label Jaccard accuracy | Regression Pearson’s r |
|------------------|----------------------------------|-------------------------------|------------------------|
| GloVe            | 0.580                            | 0.432                         | 0.259                  |
| GloVe+combi      | 0.604                            | 0.475                         | 0.110                  |
| GloVe+vae        | 0.588                            | 0.463                         | 0.274                  |
| GloVe+combi+vae  | 0.595                            | 0.442                         | 0.232                  |
| BERT             | 0.644                            | 0.512                         | 0.397                  |
| BERT+combi       | 0.637                            | 0.538                         | 0.275                  |
| BERT+vae         | 0.648                            | 0.507                         | 0.347                  |
| BERT+combi+vae   | 0.643                            | 0.499                         | 0.370                  |

Table 8: Results aggregated over datasets for GloVe/BERT embeddings and combinations of lexica in Bi-LSTM. See Table 6 for datasets and abbreviations.

optimal for neural network based approaches. We again see that the naive concatenation with VAE dimensions included works best for the multi-label datasets and the VAE latent emotion space on its own works best for the regression datasets. However, on average, the naive concatenation works best for the single-label datasets.

4.4 GloVe and BERT

Results aggregated over datasets are shown in Table 8. We find that, when using GloVe embeddings, adding lexicon information always boosts performance. In most cases (especially for the single-label and regression datasets), adding the naive lexicon concatenation works best, but in some adding the VAE latent emotion space performs better. Overall, the models with GloVe (strongly) outperform the models with only lexicon features, although models with only GloVe embeddings (without lexicon information) never perform better than when lexicon information is added.

For BERT, we see a different pattern. Here, adding lexicon information still performs better for the majority of datasets, but not for every single one. In four cases (EMOTION IN TEXT, DAILYDIALOG, ISEAR, AFFECTIVE TEXT), a model with only BERT embeddings as input performs best. For the other datasets, the best performing combination was often BERT combined with the VAE latent emotion space. Variants of the BERT model work best for all datasets except for EMOTION-STIMULUS and EMOBANK, where, respectively, trainable GloVe with the naive concatenation and the fixed naive concatenation in a Bi-LSTM work best. This pattern is in line with findings of related work: state-of-the-art models such as BERT lessen the need for lexicon-based features, but the latter still offer additional gains for the majority of datasets.
| Metric                     | Model            | Ours             | Score Reference |
|---------------------------|------------------|------------------|-----------------|
| Blogs*                    | Macro-F1         | BERT+combi+vae   | 0.616           |
| Emotion in Text*          | Acc.             | BERT             | 0.389           | Hosseini (2017) |
| DailyDialog               | Acc.             | BERT             | 0.854           | —               |
| Electoral Tweets*         | Acc.             | BERT+vae         | 0.328           | —               |
| Emotion-Stimulus*         | Acc.             | GloVe+combi      | 0.948           | —               |
| IsEar*                    | Acc.             | BERT             | 0.634           | Atmaja (2019)   |
| Tales*                    | Macro-F1         | BERT+combi+vae   | 0.700           | —               |
| TEC*                      | Macro-F1         | BERT             | 0.535           | —               |
| Affect in Tweets          | Jaccard acc.     | BERT+combi      | 0.530           | —               |
| Ssec                      | Micro-F1         | BERT+combi      | 0.691           | —               |
| Affective Text            | Pearson’s r      | BERT             | 0.376           | —               |
| EmoBank*                  | Pearson’s r      | combi           | 0.350           | —               |
| Facebook-VA*              | Pearson’s r      | BERT+vae         | 0.753           | —               |

Table 9: Comparison of our best models with state-of-the-art results.
* No train and test split in original dataset. We used an 80:20 train-test split. 10% from all data in the training set was set apart for validation. For Blogs, Electoral Tweets and Tales, the studies we compared our results with employed 10-fold cross validation for evaluation, while In TEC, 5-fold cross validation was used. For IsEar, the reported state-of-the-art metric was obtained in an 80:20 train-test split.
** Only 50% of data used, with a 3:1:1 train-dev-test ratio.
*** Only 40% of data used for training, 10% used for testing and 50% regarded as unlabeled data for semi-supervised learning.
△ Fixed instead of trainable embeddings gave a slightly better performance here.
– For DailyDialog and Emotion-Stimulus we have not found any benchmark results, as these datasets were originally not developed for the task of emotion detection, but for response retrieval/generation and detection of emotion stimuli respectively.

4.5 Comparison with state of the art

We compare the best results of our models with the reported state-of-the-art performance on the datasets of interest. Table 9 shows these scores in the metric as reported in the referred study. For two datasets – DailyDialog and Emotion-Stimulus – we have not found any benchmark results, as these datasets were originally not developed for the task of emotion detection, but for response retrieval/generation and detection of the causes of emotions respectively. We can beat the state-of-the-art on four datasets, namely IsEar, Tales, TEC and SSEC. For all of these four datasets, BERT was the best performing model, although not necessarily with the VAE latent emotion space. Note that we did not perform a large grid search over hyperparameters for our networks, so it is very likely that our results can be improved further by hyperparameter optimization and fine-tuning BERT representations.

5. Discussion

As lexica are still a widely used resource in solving sentiment and emotion analysis tasks, we explore eight existing emotion lexica and evaluate them on thirteen commonly
used emotion datasets. Moreover, we present an aggregated emotion lexicon with a large vocabulary coverage in a joint emotion label space.

We train linear and logistic regression classifiers with lexicon scores as features and Bi-LSTMs with GloVe or BERT embeddings and lexicon vectors as input representations. Overall, the BERT model performs best, mostly with some kind of lexicon information added. This means that emotion lexica can offer complimentary information to even extremely large pre-trained models.

Our models are comparable to state-of-the-art performances on emotion detection datasets. Different variants of our proposed models outperform the state of the art on four datasets, and introduce results for two further datasets, for which benchmark results were not available yet.

We performed different experiments that provide us with some insights on different factors, possibly influencing the performance of lexica used, namely lexicon size, label set and dimensionality, trainability of the input representation and lexicon combination strategy.

5.1 Effect of lexicon size

Different factors play a role in the performance of a lexicon. Vocabulary coverage is a crucial aspect, as lexicon features can only be useful when enough words in the text to be classified have lexicon annotations. Of course, lexicon size and vocabulary coverage are correlated, as the comparison of the individual lexica point out: although the three VAD lexica all perform rather poorly, ANEW is clearly worse than the other two lexica. With only 1,034 words, ANEW has only a limited size and a lot of words in the texts to be classified are not found in the lexicon. On the other hand, the best lexicon, NRC Hashtag, is fairly extended (16,862 words), supporting the hypothesis that large lexica perform better. However, the (regarding label set) rather similar datasets Stevenson and NRC Affect Intensity contain only 1,034 and 4,192 words respectively and also perform reasonably to very well.

The best scores are obtained when all lexica are combined, resulting in a naively combined lexicon of 30,351 unique words. These are by far the largest lexica used in our experiments and indeed, they perform significantly better than the individual lexica. However, the gain given by combining lexica is much more substantial than the gain of using the approximately 17,000 words in NRC Hashtag Emotion Lexicon compared to the smaller Stevenson or NRC Affect Intensity. This suggests that the benefit of combining lexica not only lies in expanding the vocabulary size, but also in combining the signals coming from various emotion frameworks to build a richer emotion representation for words.

5.2 Effect of label set and VAE dimensionality

We show that lexica with categorical annotations perform better than VAD lexica, on the condition that the categorical lexica have real-valued annotations instead of binary values. We figured label overlap could play a role in the performance (meaning that the more labels in the lexicon that overlap with the target labels of the dataset, the better the lexicon would perform on that dataset). For regression datasets, this assumption does not hold: VAD lexica are not better in predicting VAD scores in datasets than categorical lexica are. However, for half of the remaining datasets, there is a high correlation between label overlap and accuracy. This translates into the claim that the more labels are annotated in the lexicon, the better the lexicon performs.
We can link this intuition to the results of the preliminary, VAE dimensionality determining experiments. A dimension of three for the latent variable in the VAE turns out not to be the best option. One could imagine that these dimensions correspond to the dimensions \textit{valence}, \textit{arousal} and \textit{dominance}. We perform some correlation tests to determine Spearman’s $r$ between the scores of 500 random words of the VAE latent emotion space and ANEW, Affective Norms and NRC VAD respectively (see Table 4a). We find that there is high correlation ($r > 0.9$) between the first dimension of the VAE latent emotion space and \textit{valence} (though it also correlated rather highly ($0.5 < r < 0.8$) with \textit{dominance}) and a fair correlation between the third dimension and \textit{arousal} for the three VAD lexica ($0.1 < r < 0.4$). The second dimension, however, also correlates (weakly) with \textit{valence} for NRC VAD and \textit{valence} and \textit{arousal} for Affective Norms ($r \approx 0.1$), but does not correlate with any of the VAD dimensions in ANEW ($r < 0$). We can thus not irrefutably claim that the VAE dimensions correspond to \textit{valence}, \textit{arousal} and \textit{dominance}. Instead, we could hypothesise that these three dimensions are a) differently interpreted depending on the lexicon and b) interpreted differently depending on the annotator. Nonetheless, \textit{valence} and \textit{arousal} are indeed recognizable in the VAE latent emotion space. The word ‘relaxed’ for example, has scores 6.76, 1.96, 1.28 and ‘snake’ has 1.73, 1.27, 7.00 as scores. Indeed, the first and third dimension could be interpreted as \textit{valence} and \textit{arousal} respectively. Regardless of the dimensions corresponding to the VAD model or not, it is clear that a lexicon with only three dimensions is not the best choice.
The dimensionality that works best for the VAE latent emotion space is eight. This could be interpreted as Plutchik emotions. The word ‘snake’, which gets all zero values in the NRC Hashtag Emotion Lexicon except 0.49 for disgust and 0.67 for fear, has the following scores in the VAE(8) lexicon: 1.23, 1.22, 2.71, 1.29, 1.02, 4.99, 1.34, 1.20. There are two values standing out, possibly matching with disgust and fear. Indeed, correlation analysis for 500 random words between the VAE dimensions and the categories from NRC Hashtag shows that each of the VAE dimensions has a category which it (highly) correlates with (see Figure 4b). The first dimension can be linked to sadness ($r \approx 0.5$), the second to anger ($r \approx 0.6$), the third to disgust ($r \approx 0.6$), the fourth to trust ($r \approx 0.5$) and the fifth to joy ($r \approx 0.6$). The sixth dimension has the highest correlation with fear ($r \approx 0.5$), and anticipation can probably be linked to the seventh dimension, which it has the highest correlation with ($r \approx 0.2$). The eighth dimension can be linked to surprise ($r \approx 0.7$). This also corresponds to the ‘snake’ example, which suggested that the third and sixth dimension could be interpreted as disgust and fear. We can also observe that each of the dimensions encodes a mixture of emotions, where those with the highest correlation are also of a similar polarity, e.g. VAE-DIM3 is highly correlated with disgust and weakly correlated with joy and surprise.

We assume that the VAE learns some distinctive features in the latent representations and that the gain from going to an 8 instead of a 3-dimensional latent representation is not just due to adding more features, but also because this allows more space for expressing useful aspects in the features. When not combined with GloVe or BERT embeddings, the naive concatenation achieves better results than the VAE latent emotion space. However, the 40-dimensional VAE space does not perform as well as the 8-dimensional one, supporting the hypothesis that after eight dimensions no more useful distinctions are learned.

### 5.3 Effect of training embeddings

In the neural network approaches, the input representation of our data consists of word embeddings and/or lexicon vectors. The lexicon vectors can be seen as a pre-trained word embedding, which are concatenated or not with the pre-trained GloVe or BERT embeddings. We perform experiments with fixed pre-trained embeddings and investigate updating the learned weights of the words while training the model.

When lexicon vectors are used on their own, updating the word vectors increases performance in more than half of the datasets. When combined with GloVe or BERT embeddings, the trainable setting performs better in almost all cases. This means that tailoring the model to a specific dataset is valuable. Moreover, this also suggests that emotions (or the association of words with certain emotions) are not universal, but rather domain-specific. Further research where we get more insights on how emotion scores alter across domains is therefore desirable.

### 5.4 Effect of lexicon combination strategy

We consistently test the difference in performance of a naively concatenated lexicon, a learned joint lexicon obtained by a variational autoencoder, and a naively concatenated lexicon where the VAE latent emotion space is included.

In the logistic/linear regression approaches, the naive concatenation with the VAE latent emotion space included performs best on average. However, in the neural network approaches, the kind of lexicon information that performs best strongly varies over datasets. Combined with GloVe embeddings, it is often the naive concatenation
that works best, but combined with BERT, the VAE latent emotion space results in the best accuracy on several datasets.

While adding lexicon information almost always outperforms the GloVe-embedding-only approach (regardless of the lexicon combination strategy), this observation does not completely hold for BERT. In around half of the cases, the performance of BERT embeddings could not be improved by adding lexicon information, probably because large pre-trained models are already very strong. However, since lexicon information does improve performance in the other cases, we believe employing lexica still has value, especially when there is no access to large pre-trained models like in low-resource languages.

6. Conclusion

This paper addresses the task of emotion detection and presents an approach to unify existing emotion detection resources automatically to learn more about the relationships between them. We explore the role of existing emotion lexica, which have a high variety of construction approaches, label sets and vocabulary coverage. Using a multi-view variational auto-encoder, we unify different emotion lexica and map them in a joint emotion label space.

We assemble and discuss eight existing emotion lexica and evaluate them separately on thirteen emotion datasets by performing emotion classification and regression tasks, but also assess the performance of a naive concatenation of the lexica and of the unified lexicon produced by a variational autoencoder.

We find that lexica with categorical annotations perform better than VAD lexica, on the condition that the categorical lexica have real-valued annotations instead of binary values. Generally, it seems that the more labels are annotated in the lexicon, the better the classification performance on the dataset. In practice, this means that out of the existing emotion lexica, the Plutchik-annotated NRC Hashtag Emotion Lexicon is best. Also in the VAE latent emotion space, we find that a latent dimension of 8 works best, possibly corresponding to the Plutchik emotions.

We train linear and logistic regression classifiers with lexicon scores as features and Bi-LSTMs with GloVe or BERT embeddings and lexicon vectors as input representations. Overall, the BERT model with lexicon features performs best on average, with the best lexicon combination strategy varying over datasets. This means that emotion lexica can offer complimentary information to even extremely large pre-trained models. Models work best when they are tailored to the dataset at hand by updating the word and emotion vectors while training, suggesting that word-emotion associations are not universal, but rather domain-specific.

References

Agrawal, Ameeta, Aijun An, and Manos Papagelis. 2018. Learning emotion-enriched word representations. In Proceedings of the 27th International Conference on Computational Linguistics, pages 950–961, Association for Computational Linguistics, Santa Fe, New Mexico, USA.

Alm, Cecilia Ovesdotter, Dan Roth, and Richard Sproat. 2005. Emotions from text: Machine learning for text-based emotion prediction. In Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, pages 579–586, Association for Computational Linguistics, Vancouver, British Columbia, Canada.

Aman, Saima and Stan Szpakowicz. 2007. Identifying expressions of emotion in text. In Text, Speech and Dialogue, pages 196–205, Springer Berlin Heidelberg, Berlin, Heidelberg.
Atmaja, Bagus Tris. 2019. Deep learning-based categorical and dimensional emotion recognition for written and spoken text. Unpublished. INA-Rxiv. June 7. doi:10.31227/osf.io/fhu29.

Baziotis, Christos, Athanasiou Nikolaos, Alexandra Chronopoulou, Athanasia Kolovou, Georgios Paraskevopoulos, Nikolaos Ellinas, Shrikanth Narayanan, and Alexandros Potamianos. 2018. NTUA-SLP at SemEval-2018 task 1: Predicting affective content in tweets with deep attentive RNNs and transfer learning. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 245–255, Association for Computational Linguistics, New Orleans, Louisiana.

Bostan, Laura Ana Maria and Roman Klinger. 2018. An analysis of annotated corpora for emotion classification in text. In Proceedings of the 27th International Conference on Computational Linguistics, pages 2104–2119, Association for Computational Linguistics.

Bradley, Margaret M and Peter J Lang. 1999. Affective norms for english words (anew): Instruction manual and affective ratings. Technical report, University of Florida.

Bravo-Marquez, Felipe, Marcelo Mendoza, and Barbara Poblete. 2014. Meta-level sentiment models for big social data analysis. Knowledge-Based Systems, 69:86–99.

Buechel, Sven and Udo Hahn. 2016. Emotion analysis as a regression problem - dimensional models and their implications on emotion representation and metrical evaluation. In ECAI.

Buechel, Sven and Udo Hahn. 2017a. Emobank: Studying the impact of annotation perspective and representation format on dimensional emotion analysis. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 578–585.

Buechel, Sven and Udo Hahn. 2017b. A flexible mapping scheme for discrete and dimensional emotion representations. InCogSci 2017 Proceedings.

Buechel, Sven and Udo Hahn. 2018. Emotion representation mapping for automatic lexicon construction (mostly) performs on human level. In Proceedings of the 27th International Conference on Computational Linguistics, pages 2892–2904, Association for Computational Linguistics, Santa Fe, New Mexico, USA.

Calvo, Rafael A. and Sungwhan Mac Kim. 2013. Emotions in text: Dimensional and categorical models. Computational Intelligence, 29(3):527–543.

Cambria, Erik, Dipankar Das, Sivaji Bandyopadhyay, and Antonio Feraco. 2017. A practical guide to sentiment analysis. Springer.

Chaffar, Soumaya and Diana Inkpen. 2011. Using a heterogeneous dataset for emotion analysis in text. In Canadian conference on artificial intelligence, pages 62–67, Springer.

Chatterjee, Ankush, Kedhar Nath Narahari, Meghana Joshi, and Puneet Agrawal. 2019. SemEval-2019 task 3: EmoContext contextual emotion detection in text. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 39–48, Association for Computational Linguistics, Minneapolis, Minnesota, USA.

Chaumartin, François-Régis. 2007. UPAR7: A knowledge-based system for headline sentiment tagging. In Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007), pages 422–425, Association for Computational Linguistics, Prague, Czech Republic.

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

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

Emerson, Guy and Thierry Declerck. 2014. SentiMerge: Combining sentiment lexicons in a Bayesian framework. In Proceedings of Workshop on Lexical and Grammatical Resources for Language Processing, pages 30–38, Association for Computational Linguistics and Dublin City University, Dublin, Ireland.

Esuli, Andrea and Fabrizio Sebastiani. 2006. Sentiwordnet: A publicly available lexical resource for opinion mining. In LREC,
Computational Linguistics

volume 6, pages 417–422, Citeseer.
Fontaine, Johnny RJ, Klaus R Scherer, Etienne B Roesch, and Phoebe C Ellsworth. 2007. The world of emotions is not two-dimensional. Psychological Science, 18(12):1050–1057.

Ghazi, Diman, Diana Inkpen, and Stan Szpakowicz. 2015. Detecting emotion stimuli in emotion-bearing sentences. In Computational Linguistics and Intelligent Text Processing, pages 152–165, Springer International Publishing, Cham.

Giulianelli, Mario and Daniël de Kok. 2018. Semi-supervised emotion lexicon expansion with label propagation. Computational Linguistics in the Netherlands Journal, 8:99–121.

Hosseini, Akram Sadat. 2017. Sentence-level emotion mining based on combination of adaptive meta-level features and sentence syntactic features. Engineering Applications of Artificial Intelligence, 65:361–374.

Hoyle, Alexander Miserlis, Lawrence Wolf-Sonkin, Hanna Wallach, Ryan Cotterell, and Isabelle Augenstein. 2019. Combining Sentiment Lexica with a Multi-View Variational Autoencoder. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 635–640, Association for Computational Linguistics, Minneapolis, Minnesota.

Ide, Nancy, Collin Baker, Christiane Fellbaum, and Rebecca Passonneau. 2010. The manually annotated sub-corpus: A community resource for and by the people. In Proceedings of the ACL 2010 Conference Short Papers, pages 68–73, Association for Computational Linguistics, Uppsala, Sweden.

Izard, Carroll E. 1971. The Face of Emotion. Appleton-Century-Crofts.

Jabreel, Mohammed and Antonio Moreno. 2019. A deep learning-based approach for multi-label emotion classification in tweets. Applied Sciences, 9(6):1123.

Kirange, DK and RR Deshmukh. 2012. Emotion classification of news headlines using svm. Asian Journal of Computer Science and Information Technology, pages 104–106.

Li, Yang, Quan Pan, Suhang Wang, Tao Yang, and Erik Cambria. 2018. A generative model for category text generation. Information Sciences, 450:301–315.

Li, Yanran, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017. Dailydialog: A manually labelled multi-turn dialogue dataset. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 986–995, Asian Federation of Natural Language Processing, Taipei, Taiwan.

Ma, Yukun, Haiyun Peng, and Erik Cambria. 2018. Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive lstm. In AAAI Conference on Artificial Intelligence.

Mehrabian, Albert and James A Russell. 1974. An Approach to Environmental Psychology. MIT Press.

Meisheri, Hardik and Lipika Dey. 2018. TCS research at SemEval-2018 task 1: Learning robust representations using multi-attention architecture. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 291–299, Association for Computational Linguistics, New Orleans, Louisiana.

Miller, George A. 1995. Wordnet: a lexical database for english. Communications of the ACM, 38(11):39–41.

Mohammad, Saif. 2012a. #emotional tweets. In SEM 2012: The First Joint Conference on Lexical and Computational Semantics – Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation (SemEval 2012), pages 246–255, Association for Computational Linguistics, Montréal, Canada.

Mohammad, Saif. 2012b. Portable features for classifying emotional text. In Proceedings of the 2012 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 587–591, Association for Computational Linguistics, Montréal, Canada.

Mohammad, Saif, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. SemEval-2018 task 1: Affect in tweets. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 1–17, Association for Computational Linguistics, New Orleans, Louisiana.

Mohammad, Saif, Svetlana Kiritchenko, Parinaz Sobhani, Xiaodan Zhu, and Colin Cherry. 2016. SemEval-2016 task 6: Detecting stance in tweets. In Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016), pages 31–41, Association for Computational Linguistics, Minneapolis, Minnesota.
Joint Emotion Label Space Modelling for Affect Lexica

Mohammad, Saif, Xiaodan Zhu, Svetlana Kiritchenko, and Joel Martin. 2015. Sentiment, emotion, purpose, and style in electoral tweets. Information Processing & Management, 51(4):480 – 499.

Mohammad, Saif M. 2018a. Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words. In Proceedings of The Annual Conference of the Association for Computational Linguistics (ACL), Melbourne, Australia.

Mohammad, Saif M. 2018b. Word affect intensities. In Proceedings of the 11th Edition of the Language Resources and Evaluation Conference (LREC-2018), Miyazaki, Japan.

Mohammad, Saif M. and Svetlana Kiritchenko. 2015. Using hashtags to capture fine emotion categories from tweets. Computational Intelligence, 31(2):301–326.

Mohammad, Saif M. and Peter D. Turney. 2013. Crowdsourcing a word-emotion association lexicon. 29(3):436–465.

Ohana, Bruno and Brendan Tierney. 2009. Sentiment classification of reviews using sentiwordnet. In 9th. IT&T Conference, Dublin Institute of Technology.

Pennington, Jeffrey, Richard Socher, and Christopher D. Manning. 2014. Glove: Global vectors for word representation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543.

Plutchik, Robert. 1980. A general psychoevolutionary theory of emotion. In Robert Plutchik and Henry Kellerman, editors, Theories of Emotion. Academic Press, pages 3–33.

Preno˘ tuc-Pietro, Daniel, H Andrew Schwartz, Gregory Park, Johannes Eichstaedt, Margaret Kern, Lyle Ungar, and Elisabeth Shulman. 2016. Modelling valence and arousal in Facebook posts. In Proceedings of the 7th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 9–15.

Purpura, Alberto, Chiara Masiero, Gianmaria Silvello, and Gian Antonio Susto. 2019. Supervised lexicon extraction for emotion classification. In Companion Proceedings of The 2019 World Wide Web Conference, pages 1071–1078, ACM.

Roseman, Ira J. 1984. Cognitive determinants of emotion: A structural theory. Review of Personality & Social Psychology, 5:11–36.

Ruiz, Francisco J. R., Michalis K. Ttitsias, and David M. Blei. 2016. The generalized reparameterization gradient. In Advances in neural information processing systems, pages 460–468.

Russell, James A. 1980. A circumplex model of affect. Journal of Personality and Social Psychology, 39(6):1161–1178.

Scherer, Klaus R and Harald G Wallbott. 1994. Evidence for universality and cultural variation of differential emotion response patterning. Journal of personality and social psychology, 66(2):310.

Schuff, Hendrik, Jeremy Barnes, Julian Mohme, Sebastian Pado, and Roman Klinger. 2017. Annotation, modelling and analysis of fine-grained emotions on a stance and sentiment detection corpus. In Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 13–23, Association for Computational Linguistics, Copenhagen, Denmark.

Stevenson, Ryan A., Joseph A. Mikels, and Thomas W. James. 2007. Characterization of the affective norms for English words by discrete emotional categories. Behavior Research Methods, 39(4):1191–1207.

Warriner, Amy Beth, Victor Kuperman, and Marc Brysbaert. 2013. Norms of valence, arousal, and dominance for 13,915 English lemmas. Behavior Research Methods, 45(4):1191–1207.

Wolf, Thomas, Lyssandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierrick Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface’s transformers: State-of-the-art natural language processing. ArXiv, abs/1910.03771.

Wu, Chuhan, Fangzhao Wu, Sixin Wu, Zhigang Yuan, Junxin Liu, and Yongfeng Huang. 2019. Semi-supervised dimensional sentiment analysis with variational autoencoder. Knowledge-Based Systems, 165:30–39.