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# Augmenting semantic lexicons using word embeddings and transfer learning

Thayer Alshaabi,  $^{1,\,2,\,*}$ Colin Van Oort,  $^{1,\,2}$  Mikaela Fudolig,  $^1$  Michael V.

Arnold,<sup>1</sup> Christopher M. Danforth,<sup>1,3,2</sup> and Peter Sheridan Dodds<sup>1,2,3</sup>

<sup>1</sup>Vermont Complex Systems Center, University of Vermont, Burlington, VT 05405.

<sup>2</sup>Department of Computer Science, University of Vermont, Burlington, VT 05405.

<sup>3</sup>Department of Mathematics & Statistics, University of Vermont, Burlington, VT 05405.

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Sentiment-aware intelligent systems are essential to a wide array of applications including marketing, political campaigns, recommender systems, behavioral economics, social psychology, and national security. These sentiment-aware intelligent systems are driven by language models which broadly fall into two paradigms: 1. Lexicon-based and 2. Contextual. Although recent contextual models are increasingly dominant, we still see demand for lexicon-based models because of their interpretability and ease of use. For example, lexicon-based models allow researchers to readily determine which words and phrases contribute most to a change in measured sentiment. A challenge for any lexicon-based approach is that the lexicon needs to be routinely expanded with new words and expressions. Crowdsourcing annotations for semantic dictionaries may be an expensive and time-consuming task. Here, we propose two models for predicting sentiment scores to augment semantic lexicons at a relatively low cost using word embeddings and transfer learning. Our first model establishes a baseline employing a simple and shallow neural network initialized with pre-trained word embeddings using a non-contextual approach. Our second model improves upon our baseline, featuring a deep Transformer-based network that brings to bear word definitions to estimate their lexical polarity. Our evaluation shows that both models are able to score new words with a similar accuracy to reviewers from Amazon Mechanical Turk, but at a fraction of the cost.

Keywords: Sentiment analysis; Semantic lexicons; Transformers; BERT; FastText; Word embedding; labMT

### I. INTRODUCTION

In computational linguistics and natural language processing (NLP), sentiment analysis involves extracting emotion and opinion from text data. There is an increasing demand for sentiment-aware intelligent systems. Indeed, the growth of sentiment-aware frameworks in online services can be seen across a vast, multidisciplinary set of applications [1–3].

With the modern volume of text data—which has long rendered human annotation infeasible—automated sentiment analysis is used, for example, by businesses in evaluating customer feedback to make informed decisions regarding product development and risk management [4, 5]. Combined with recommender systems, sentiment analysis has also been used with the intent to improve consumer experience through aggregated and curated feedback from other consumers, particularly in retail [6–8], e-commerce [9, 10], and entertainment [11, 12].

Beyond applications in industry, sentiment analysis has been widely applied in academic research, particularly in the social and political sciences [13]. Public opinion, e.g., support for or opposition to policies, can be potentially gauged from online political discourse, giving policymakers an important window into public awareness and attitude [14, 15]. Sentiment analysis tools have shown mixed results in forecasting elections [16] and monitoring inflammatory discourse on social media, with vital relevance to national security [17]. Sentiment analysis has also been used in the public health domain [18–20], with recent studies analyzing social media discourse surrounding mental health [21, 22], disaster response and emergency management [23].

The growing number of applications of sentimentaware systems has led the NLP community in the past decade to develop end-to-end models to examine shortand medium-length text documents [24, 25], particularly for social media [26–28].

Some researchers have considered the many social and political implications of using AI for sentiment detection across media [29, 30]. Recent studies highlight some of the implicit hazards of crowdsourcing text data [31], especially in light of the latest advances in NLP and emerging ethical concerns [32, 33]. Identifying potential racial and gender disparity in NLP models is essential to develop better models [34].

Sentiment analysis tools can be classified into two broad groups depending on their definition of sentiment and their model for its estimation. The probability of belonging to a discrete class (e.g., positive, negative) is a common way of defining sentiment for a given piece of text. When edge cases are frequent, adding a neutral class has been reported to improve overall performance [35]. However, sometimes a cardinal measure is desired, requiring a spectrum of sentiment scores rather than a sentiment class [36]. This more nuanced sentiment scoring paradigm has been widely adopted for ecommerce, movies, and restaurant reviews [37].

Sentiment analysis models largely derive from two

<sup>\*</sup> thayer.alshaabi@uvm.edu

major paradigms: 1. Lexicon-based models and 2. Contextual models. Lexicon-based models compute sentiment scores based on sentiment dictionaries typically constructed by human annotators [38–40]. Contextual models, on the other hand, extrapolate semantics by converting words to vectors in an embedding space, and learning from large-scale annotated datasets to predict sentiment based on co-occurrence relationships between words [24–27, 41]. Contextual models have the advantage in differentiating multiple meanings, as in the case of "The dog is *lying* on the beach" vs. "I never said that—you are lying", while lexicon-based models usually have a single score for each word, regardless of usage. Despite the flexibility of contextual models, they suffer from reduced interpretability, as the high-dimensional latent space in which they are embedded renders explanation difficult. The ease of use and transparent comprehension of lexicon-based models help explain their continued popularity [17, 38, 39]. For example, while the linguistic mechanisms leading to change in sentiment may be hard to explain with word embeddings, one can straightforwardly use lexicon scores to reveal the words contributing to shifted sentiment [42-44].

A major challenge for the simpler and more interpretable lexicon-based models is the time and financial investment associated with maintaining them. Lexicon dictionaries must be updated regularly to mitigate the out-of-vocabulary (OOV) problem—words and phrases that were either not considered or did not exist when the dictionaries were originally constructed [45]. While researchers show general sentiment trends are observable unless the lexicon dictionary does not have enough words, having a versatile dictionary with specialized and rarely used words improves the signal [43, 46]. Notably, language is an evolving sociotechnical phenomenon. New words and phrases are created constantly, especially on social media [47]. Words occasionally substitute others or drift in meaning over time. For example, the word 'covid' grew to be the most narratively trending n-gram in reference to the global Coronavirus outbreak during Feburary and March 2020 [48].

In this work, we propose an automated framework extending sentiment for semantic lexicons to OOV words. reducing the need for crowdsourcing scores from human annotators, a process that can be time-consuming and expensive. Although our framework can be used in a more general sense, we focus on predicting happiness scores based on the labMT dataset [39]. This dataset was constructed from human ratings of the "happiness" of words on a continuous scale, averaging scores from multiple annotators for more than 10,000 words. We discuss this dataset in detail in Sec. III A. In Sec. II, we discuss recent developments using deep learning in NLP, and how they relate to our work. We introduce two models, demonstrating accuracy on par with human performance (see Sec. III for technical details). We first introduce a baseline model—a neural network initialized with pre-trained word embeddings—to gauge happiness scores. Second, we present a deep Transformer-based model that uses word definitions to estimate their lexical polarity. We will refer to our models as the 'Token' and 'Dictionary' models, respectively. We present our results and model evaluation in Sec. IV, highlighting how the models perform compared with reviewers from Amazon's Mechanical Turk. Finally, we highlight key limitations of our approach, and outline some potential future developments in concluding remarks.

### **II. RELATED WORK**

Word embeddings are abstract numerical representations of the relationships between words, derived from statistics on individual corpora, and encoding language patterns so that concepts with similar semantics have similar representations [49]. Researchers have shown that efficient representations of words can both express meanings and preserve context [50–53]. While there are many ways to construct word embedding models (e.g., matrix factorization), we often use the term to refer to a specific class of word embeddings that are learnable via neural networks.

Word2Vec is one of the key breakthroughs in NLP, introducing an efficient way for learning word embeddings from a given text corpus [54, 55]. At its core, it builds off of a simple idea borrowed from linguistics and formally known as the 'distributional hypothesis' words that are semantically similar are also used in similar ways, and likely to appear with similar context words [56].

Starting from a fixed vocabulary, we can learn a vector representation for each word via a shallow network with a single hidden layer trained in one of two fashions [54, 55]. Both approaches formalize the task as a unsupervised prediction problem, whereby an embedding is learned jointly with a network that is trained to either predict an anchor word given the words around it (i.e., continuous bag-of-words (CBOW)), or by predicting context words for an anchor word (i.e., skip-gram (SG)) [54]. Both approaches, however, are limited to local context bounded by the size of the context window. Global Vectors (GloVe) addresses that problem by capturing corpus global statistics with a word co-occurrence probability matrix [57].

While Word2Vec and GloVe offer substantial improvements over previous methods, they both fail to encode unfamiliar words—tokens that were not processed in the training corpora. FastText refines word embeddings by supplementing the learned embedding matrix with subwords to overcome the challenge of OOV tokens [58, 59]. This is achieved by training the network with characterlevel *n*-grams ( $n \in \{3, 4, 5, 6\}$ ), then taking the sum of all subwords to construct a vector representation for any given word. Although the idea behind FastText is rather simple, it presents an elegant solution to account for rare words, allowing the model to learn more general word representations.

A major shortcoming of the earlier models is their inability to capture contextual descriptions of words as they all produce a fixed vector representation for each word. In building context-aware models, researchers often use fundamental building blocks such as recurrent neural networks (RNN) [60]—particularly long shortterm memory (LSTM) [61]—that are designed to process sequential data. Many methods have provided incremental improvements over time [62–64]. ELMo is one of the key milestones towards efficient contextualized models, using deep bi-directional LSTM language representations [65].

In late 2017, the advent of Transformers [66] rapidly changed the landscape in the NLP community. The encoder-decoder framework, powered by attention blocks, enables faster processing of the input sequence while also preserving context [66]. Recent adaptations of the building blocks of Transformers continue to break records, improving the state-of-the-art across all NLP benchmarks with recent applications to computer vision and pattern recognition [67].

Exploiting the versatile nature of Transformers, we observe the emergence of a new family of language models widely known as "self-supervised" including as bidirectional encoders (e.g., BERT) [68], and left-to-right decoders (e.g., GPT) [69]. Self-supervised language models are pre-trained by masking random tokens in the unlabeled input data and training the model to predict these tokens. Researchers leverage recent subword tokenization techniques, such as WordPiece [70], SentencePiece [71], and Byte Pair Encoding (BPE) [72], to overcome the challenge of rare and OOV words. Subtle contextualized representations of words can be learned by predicting whether sentence B follows sentence A [68]. Pretrained language models can then be fine-tuned using labeled data for downstream NLP tasks, such as NER, question answering, text summarization, and sentiment analysis [68, 69].

Recent advances in NLP continue to improve the language facility of Transformer-based models. The introduction of XLNet [73] is another remarkable breakthrough that combines the bidirectionality of BERT [68] and the autoregressive pre-training scheme from Transformer-XL [74]. While the current trend of making ever-larger and deeper language models shows an impressive track record, it is arguably unfruitful to maintain unreasonably large models that only giant corporations can afford to use due to hardware limitations [75]. Vitally, less expensive language models need to be both computationally efficient and exhibit performance on par with larger models. Addressing that challenge, researchers proposed clever techniques of leveraging knowledge distillation [76] to train smaller and faster models (e.g, DistilBERT [77]). Similarly, efficient parameterization strategies via sharing weights across layers can also reduce the size of the model while maintaining state-of-the-art results (e.g., ALBERT [78]). Building on the recent models discussed above, we develop a framework for augmenting semantic dictionaries using word embeddings and transfer learning. Our tool reduces the need for crowdsourcing scores from human annotators while still providing similar, and often better, results compared with random reviewers from Amazon Mechanical Turk at a fraction of the cost.

### **III. DATA AND METHODS**

We propose two models for predicting happiness scores for the labMT lexicon [39]—a general-purpose sentiment dictionary used to measure happiness in text corpora (see Sec. III A for more details).

Our first model is a neural network initialized with pre-trained FastText word embeddings. The model uses fixed word representations to gauge the happiness score for a given expression, enabling us to augment the labMT dataset at a low cost. For simplicity, we will refer to this model as the Token model.

Bridging the link between lexicon-based and contextualized models, we also propose a deep Transformer-based model that uses word definitions to estimate their happiness scores—namely, the Dictionary model. The contextualized nature of the input data allows our model to accurately estimate the expressed happiness score for a given word based on its lexical meaning.

We implement our models using Tensorflow [79] and Transformers [80]. See Sec. III B and Sec. III C for further technical details of our Token and Dictionary models, respectively. Our source code, along with pre-trained models, are publicly available via our GitLab repository (https://gitlab.com/compstorylab/sentiment-analysis).

### A. Data

In this study, we use the labMT dataset as an example semantic dictionary to test and evaluate our models [39]. The labMT lexicon contains roughly ten thousand unique words—combining the five thousand most frequently used words from New York Times articles. Google Books, Twitter messages, and music lyrics [39]. It is a lexicon designed to gauge changes in the happiness (i.e., valence or hedonic tone) of text corpora. Happiness is defined on a continuous scale  $h \in \{1 \rightarrow 9\}$ , where 1 bounds the most negative (sad) side of the spectrum, and 9 is the most positive (happy). Ratings for each word are crowdsourced via Amazon Mechanical Turk (AMT), taking the average score  $h_{avg}$  from 50 reviewers to set a happiness score for any given word. For example, the words 'suicide', 'terrorist', and 'coronavirus' have the lowest happiness scores, while the words 'laughter', 'happiness', and 'love' have the highest scores. Function and stop words along with numbers and names tend to have neutral scores  $(h_{avg} \approx 5)$ , such as 'the', 'fourth', 'where', and 'per'.

The labMT dataset also powers the Hedonometer, an instrument quantifying daily happiness on Twitter [42]. Over the past few years, the labMT dictionary was updated to include new words that were not found in the original survey (e.g, terms related to the COVID19 pandemic [48]).

We are particularly interested in this dataset because it also provides the standard deviation of human ratings for each word, which we use to evaluate our models. In this work, we propose two models to estimate  $h_{avg}$  using word embeddings, and thus provide an automated tool to augment the labMT dataset both reliably and efficiently.

In Fig. 1, we display a 2D histogram of the human rated happiness scores in the labMT dataset. The figure highlights the degree of uncertainty in human ratings of the emotional valence of words. For example, the word 'the' has an average happiness score of  $h_{avg} = 4.98$ , with standard deviation of  $\sigma = 0.91$ , while the word 'hahaha' has a happier score with  $h_{avg} = 7.94$  and  $\sigma = 1.56$ . Some words also have a relatively large standard deviation such as 'church' ( $h_{avg} = 5.48, \sigma = 1.85$ ), and 'cigarettes' ( $h_{avg} = 3.31, \sigma = 2.6$ ).

While the majority of words are neutral, with a score between 4 and 6, we still observe a human positivity bias in the English language [39, 81]. On average, the standard deviation of human ratings is 1.38. In our evaluation (Sec. IV), we show how our models perform relative to the uncertainty observed in human ratings.

### B. Token Model

Our first model uses a neural network that learns to map words from the labMT lexicon to their corresponding sentiment scores. While still being able to learn a non-linear mapping between the words and their happiness scores, the model only considers the individual words as input—enriching its internal utility function with subword representations to estimate the happiness score.

The input word is first processed into a token embedding—sequentially breaking each word into its equivalent character-level *n*-grams whereby  $n \in \{3, 4, 5\}$ (see Fig. 2 for an illustration). English words have an average length of 5 characters [82, 83], which would yield 5 unique character-level *n*-grams given our tokenization scheme. While we did try shorter and longer sequences, we fix the length of the input sequence to a size of 50 and pad shorter sequences to ensure a universal input size. We choose a longer sequence length to allow us to encode longer *n*-grams and rare words.

We then pass the token embeddings to a 300dimensional embedding layer. We initialize the embedding layer with weights trained with subword information on Common Crawl and Wikipedia using FastText [59]. In particular, we use weights from a pre-trained model using CBOW with character-level *n*-grams of length 5 and a window size of 5 and 10 (https://fasttext.cc/docs/ en/english-vectors.html).

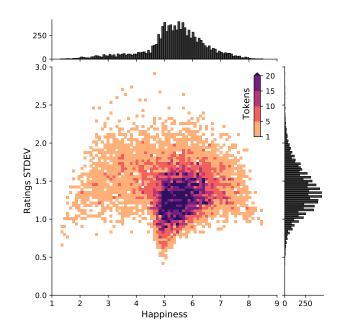


FIG. 1. Emotional valence of words and uncertainty in human ratings of lexical polarity. A 2D histogram of happiness  $h_{avg}$  and standard deviation of human ratings for each word in the labMT dataset. Happiness is defined on a continuous scale from 1 to 9, where 1 is the least happy and 9 is the most. Words with a score between 4 and 6 are considered neutral. While the vast majority of words are neutral, there is a positive bias in human language [39]. The average standard deviation of human ratings for estimating the emotional valence of words in the labMT dataset is 1.38.

The output of the embedding layer is pooled down and passed to a sequence of three dense layers of decreasing sizes: 128, 64, and 32, respectively. We use a rectified linear activation function (ReLU) for all dense layers. We also add a dropout layer after each dense layer, with a 50% dropout rate to encode stochasticity into the model as a simple estimate of uncertainty and standard deviation of the network's predictions [84].

We experimented with a few different layout configurations, finding that making the network either wider or deeper has minimal effect on the network performance. Therefore, we choose to keep our model rather simple with roughly 10 million trainable parameters. The output of the last dense layer is finally passed over to a single output layer with a linear activation function to regress a sentiment score between 1 and 9. See Fig. 3 for a simple diagram of the model architecture.

### C. Dictionary Model

Historically, lexicon-based models have only considered simple statistical methods to estimate the emotional valance of words. Here, we try to bridge the connection between the conventional techniques among the commu-

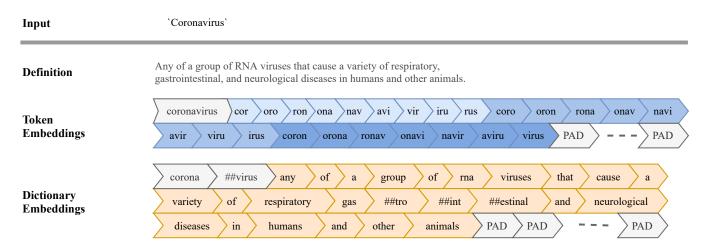


FIG. 2. Input sequence embeddings. We use two encoding schemes to prepare input sequences for our models: token embeddings (blue) and dictionary embeddings (orange) for our Token and Dictionary models, respectively. Given an input word (e.g., 'coronavirus'), we first break the input token into character-level *n*-grams ( $n \in \{3, 4, 5\}$ ). The resulting sequence of *n*-grams along with the original word at the beginning of the embeddings are used in our Token model. Sequences shorter than a specified length are appended with PAD, a padding token ensuring a universal input size. For our Dictionary model, we first look up a dictionary definition for the given input. We then process the input word along with its definition into subwords using WordPiece [70]. Uncommon and novel words are broken into subwords, with double hashtags indicating that the given token is not a full word.

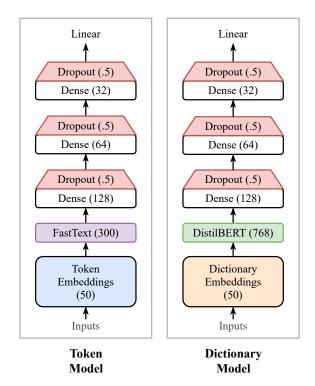


FIG. 3. **Model architectures.** Our first model is a neural network initialized with pre-trained word embeddings to estimate happiness scores. Our second model, is a deep Transformer-based model that uses word definitions to estimate their sentiment scores. See Sec. III B and Sec. III C for further technical details of each model, respectively. Note the Token model is considerably smaller with roughly 10 million trainable parameters compared with the Dictionary model that has a little over 66 million parameters.

nity and recent advances in NLP.

For our second model, we use a contextualized Transformer-based language model to estimate the sentiment score for a given word based on its dictionary definition. While still predicting scores for individual words, we now do so by augmenting each word with its expressed meaning(s) from a general dictionary. Given an input word, we look up its definition via a free online dictionary API available at https://dictionaryapi.dev.

The average length of definitions for the words found in labMT is roughly 38 words. We choose a maximum definition length of 50 words—which covers the 75th percentile of that distribution—to ensure that words with multiple definitions are adequately represented. While increasing the sequence length beyond 50 did not improve our accuracy, it increases the model complexity slowing our training and inference time substantially. Therefore, we fix the length of word definitions to a maximum of 50 words. We pad shorter sequences, and truncate words 51 and beyond to ensure a fixed input size.

We estimate the sentiment of each labMT word as follows. The word, along with its definition, is processed into dictionary embeddings by breaking each word into subwords based on their frequency of usage using Word-Piece [70]. This is a widely adopted tokenization technique that breaks uncommon and novel words into subwords, which reduces the vocabulary size of language models and enables them to handle OOV tokens. Other tokenization models will give similar results [71]. We only use the word as input to our model for terms without definitions.

In principle, the dictionary embeddings can be passed to a vanilla Transformer model (e.g., BERT [68],

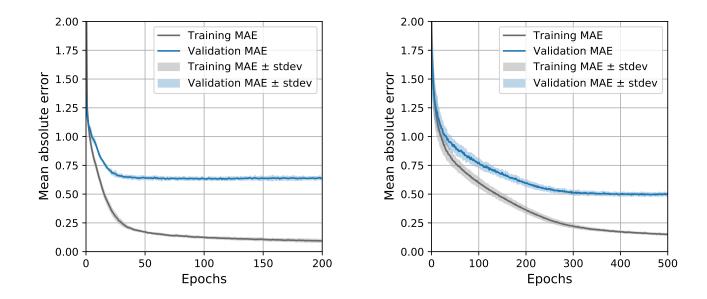


FIG. 4. Learning curves for the Token model (left), and Dictionary model (right). We train our models using 5-fold cross-validation, with a maximum of 500 epochs per fold. The left panel shows the learning curves for the Token model (see Sec. III B), while the right panel shows the Dictionary model (see Sec. III C). We display our average mean absolute error (MAE) as well as standard deviation across all folds for training (grey) and validation (blue).

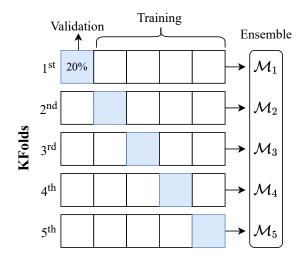


FIG. 5. Ensemble learning and k-fold cross-validation. Using an 80/20 split for training/validation, we train our models for a maximum of 500 epochs per fold for a total of 5 folds. We use the model trained from each fold to build an ensemble because the average performance of an ensemble is less biased and better than the individual models.

XLNet [73]). However, we prefer more manageable models (i.e., smaller and faster) due to their efficiency while maintaining state-of-the-art results. We tried both ALBERT [78] and DistilBERT [77]. Both models have equivalent performance on our task. The output of the model's pooling layer is passed to a sequence of three dense layers of decreasing sizes with dropout applied after each layer—similar to our approach in the Token model. Finally, the output of the last dense layer is projected down to a single output value that servers as the sentiment score prediction.

The Token model is considerably lighter in terms of memory usage, and faster in terms of training and inference time than the Dictionary model. Our current configuration of the Token model results in roughly 10 million trainable parameters compared with the Dictionary model that has over 66 million parameters.

# IV. RESULTS AND DISCUSSION

### A. Ensemble learning and k-fold cross-validation

Given that our dataset is relatively small, we use k-fold cross-validation rather than a fixed testing subset to set an upper limit on our margin of error and mitigate any risk of overfitting [85, 86]. Using 80/20 split for training/validation, we train models for a maximum of 500 epochs per fold for a total of 5 folds. While there are many gradient descent optimization algorithms, we use Adam [87] as a popular and well-established optimizer, keeping its default configuration and setting our initial learning rate to 0.001. In Fig. 4, we display learning curves, showing that both models have converged successfully.

Ensemble learning is a widely known and adopted family of methods in which the average performance of an ensemble is shown to be both less biased and better than

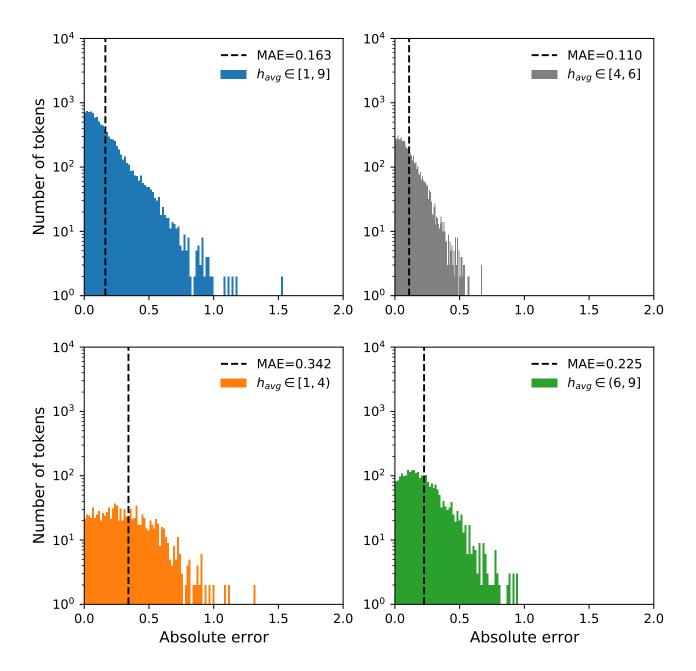


FIG. 6. Error distributions for the Token model. We display mean absolute errors for predictions using the Token model on all words in labMT. We arrange the happiness scores into three groups: negative  $(h_{avg} \in [1, 4), \text{ orange})$ , neutral  $(h_{avg} \in [4, 6], \text{ grey})$ , and positive  $(h_{avg} \in (6, 9], \text{ green})$ . Most words have an MAE less than 1 with the exception of a few outliers. We see a relatively higher MAE for negative and positive terms compared to neutral expressions.

the individual models [85, 88]. Capitalizing on our 5-fold cross-validation strategy, we use the model trained from each fold to build an ensemble (see Fig. 5). To get a happiness score for a given word, we aggregate over 100 predictions per model and report the average and standard deviation of predictions from all models as our final prediction for a given ensemble.

## B. Comparing predictions to human ratings

While both strategies tested here perform well namely using character-level *n*-grams and word definitions— the Dictionary model outperforms the Token model. Our evaluation shows the Token model has an average cross-validation MAE of  $0.64 \pm 0.01$ , trailing behind the Dictionary model which has an

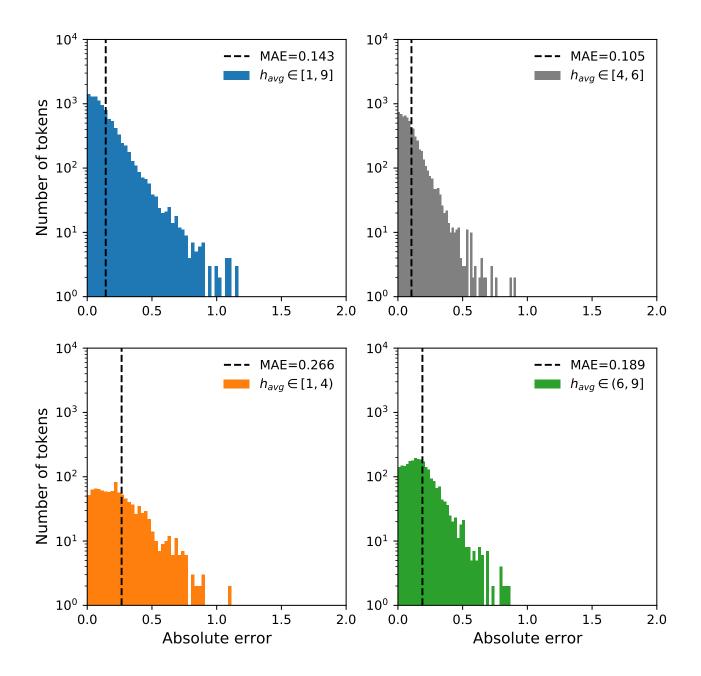


FIG. 7. Error distributions for the Dictionary model. We display mean absolute errors for predictions using the Dictionary model on all words in labMT. Again, we categorize the happiness scores into three groups: negative  $(h_{avg} \in [1, 4),$  orange), neutral  $(h_{avg} \in [4, 6], \text{grey})$ , and positive  $(h_{avg} \in (6, 9], \text{green})$ . Similar to the Token model, most words have an MAE less than 1 with the exception of a few outliers. While the Dictionary model outperforms the Token model, we still observe a higher MAE for negative and positive terms compared to neutral expressions.

average cross-validation MAE of  $0.50 \pm 0.01$ .

As discussed, the cross-validation defines an upper limit on margin of error for predicting happiness scores in the labMT dictionary. We further examine the error distributions to investigate if the models have a bias towards high or low happiness scores. labMT dataset. In Figs. 6 and 7, we display a breakdown of our MAE distributions for the Token and Dictionary models, respectively. We categorize the happiness scores into three groups: negative  $(h_{avg} \in [1, 4))$ , neutral  $(h_{avg} \in [4, 6])$ , and positive  $(h_{avg} \in (6, 9])$ . While the distributions show our models operate well on all words, particularly neutral expressions, we note a relatively high-

We rerun our models on all words recorded in the

Human ratings

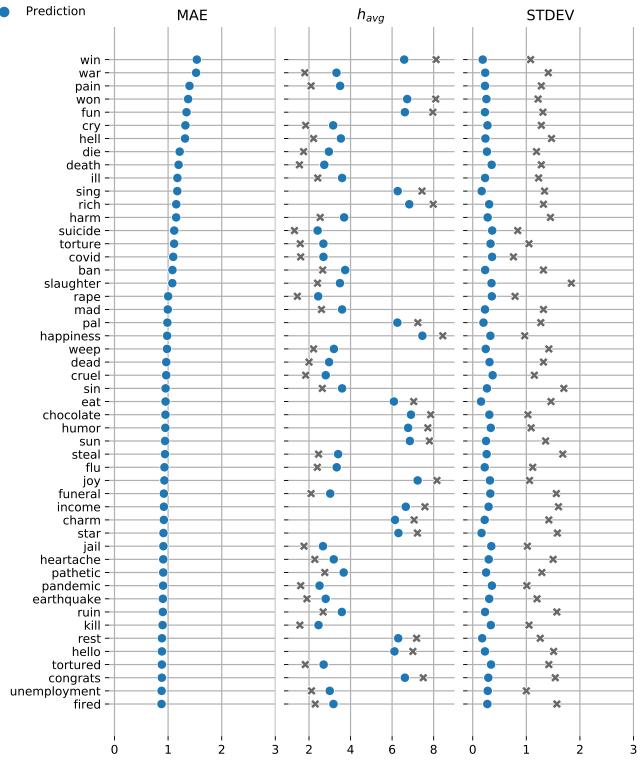


FIG. 8. Token model: Top-50 words with the highest mean absolute error. Model predictions are shown in blue and the crowdsourced annotations are displayed in grey. While still maintaining relatively low MAE, most of our predictions are conservative—marginally underestimating words with extremely high happiness scores, and overestimating words with low happiness scores.

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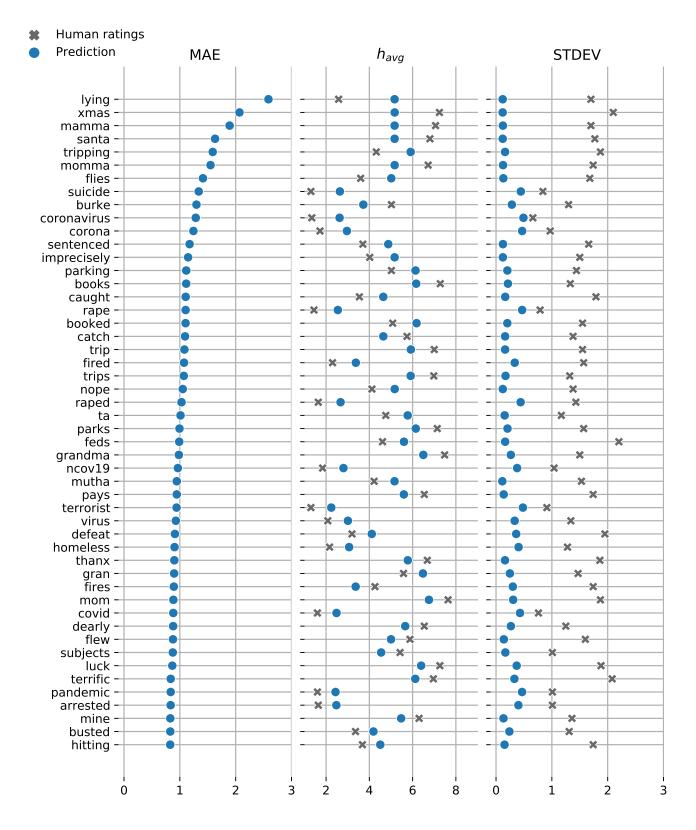


FIG. 9. Dictionary model: Top-50 words with the highest mean absolute error. Model predictions are shown in blue and the crowdsourced annotations are displayed in grey. Note, the vast majority of words with relatively high MAE also have high standard deviations of AMT ratings. Words that have multiple definitions will have a neutral score (e.g., lying). A neutral happiness score is also often predicted for words because we are unable to obtain good definitions for them to use as input. Although we have definitions for most words in our dataset, we still have a little over 1500 words with missing definitions. Most of these words are names (e.g., 'Burke'), and slang (e.g., 'xmas', and 'ta').

er MAE for negative words, whereby our predictions to these terms are more positive than the annotations.

We further compare our predictions to the groundtruth ratings, examining the degree to which the models either overshoot or undershoot the happiness scores crowdsourced via AMT. Words in the labMT lexicon were scored by taking the average happiness score of distinct evaluations from 50 different individuals (see Table S2 [39]). Since the variance of human ratings and our model MAEs are on the same scale, we can use the observed average variance of the ratings (1.17) as a baseline to assess rater confidence in the reported scores. Comparing our models to that baseline, we note that all models offer consistent predictions with similar expectations to a random and reliable reviewer from AMT. See Table I for further statistical details.

In Figs. 8 and 9, we display the top-50 words with the highest mean absolute error for the Token and Dictionary models, respectively. While the models always predict the right emotional attitude outlining each word based on its lexical polarity, they bias toward neutral by undershooting scores for happy words, and overshooting scores for sad expressions.

One possible explanation of this systematic behavior is the lack of words with extreme happiness scores in the labMT lexicon. It is possible to train models with a smaller but balanced subset of the dataset to overcome that challenge. Doing so, however, would reduce the size of training/validation samples substantially. Still, our margin of error is relatively low compared to human ratings. Future investigations may test and improve the models by examining larger sentiment lexicons.

Another key factor that plays a big role in our prediction error is obtaining good word definitions, or the lack thereof, to use as input for our Dictionary model. Surprisingly, outsourcing definitions from online dictionaries for a large set of words is rather challenging, especially if you opt-out of reliable but paid services. In our work, we choose not to use an urban dictionary or any services with paid APIs. We use a free online dictionary API that is available at https://dictionaryapi.dev.

While we do have definitions for most words in our dataset, a total of 1518 words have missing definitions. Most of these words are names, abbreviations, and slang terms (e.g., 'xams', 'foto', 'nvm', and 'lmao'). Words with multiple definitions can also cancel each other's score (e.g., 'lying').

Notably, the vast majority of words with high MAE also have high AMT standard deviations. To further investigate prediction accuracy, we examine the overlap between the predictions and human ratings. In particular, we compute the intersection over union (IOU) between the predicted happiness score  $h'_{avg} \pm \sigma'$ , and the corresponding value from the annotated ratings  $h_{avg} \pm \sigma$ .

The Token model underestimates the happiness score for 'win'—the only word with a prediction that falls outside the range of human annotated happiness scores. The remaining predicted happiness scores fall well within the range of scores crowdsourced via AMT. Similarly, the Dictionary model slightly underestimates the happiness scores for 'mamma' while overestimating the scores for 'lying', and 'coronavirus'.

### V. CONCLUDING REMARKS

As the growing demand for sentiment-aware intelligent systems increases, we will continue to see improvements to both lexicon-based models and contextual language models. While contextualized models are suitable for a wide set of applications, lexicon-based models are used by computational linguistics, journalists, and data scientists who are interested in studying how individual words contribute to sentiment trends.

Lexicon based sentiment dictionaries, however, have to be updated periodically to support new words and expressions that were not considered when the dictionaries were assembled. In this paper, we proposed two models for predicting sentiment scores to augment semantic dictionaries using word embeddings and transfer learning. Our first model establishes a baseline using a neural network initialized with pre-trained word embeddings, while our second model features a deep Transformerbased network that brings into play word definitions to estimate their lexical polarity. Our results and evaluation of both models demonstrate human-level performance on a state-of-the-art human annotated list of words.

Although both models can predict scores for novel words, we acknowledge a few shortcomings. Our Token model relies on subword information to estimate a happiness score for any given word. For example, using subwords for 'coronavirus' yields a good estimate given that it contains 'virus'. By contrast, parsing character-level *n*-grams for other words (e.g., 'covid') may not reveal any further information. We can overcome that hurdle by using the word definition as input to our Dictionary model to gauge its happiness score. Words, however, often have different meanings based on context. Finding good definitions may be challenging, especially for slang, informal expressions, and abbreviations. We recommend using the Dictionary model whenever it is possible to outsource a good definition of the word.

A natural next step would be to develop similar models for other languages, for example by building a model for each language, or a multilingual model. Fortunately, FastText [59] provides pre-trained word embeddings for over 100 languages. Therefore, it is easy to upgrade the Token model to support other languages. Updating the Dictionary model is also a straightforward task by simply adopting a multilingual Transformer-based model pre-trained with several languages (e.g., Multilingual BERT [68]).

Another vast space of improvements would be to adopt our proposed strategies to develop prediction models for other semantic dictionaries. Researchers can further finetune these models to predict other sentiment scores. For

12

	All words		$Out\-of\-sample$		All words	
	STDEV	Variance	MAE	MAE	MAE	MAE
	Human Ratings	Human Ratings	Token Model	Dictionary Model	Token Model	Dictionary Model
Average	1.38	1.17	0.64	0.50	0.16	0.14
$25^{th}$ Percentile	1.18	1.09	0.63	0.49	0.05	0.05
$50^{th}$ Percentile	1.36	1.17	0.64	0.50	0.12	0.10
$75^{th}$ Percentile	1.56	1.25	0.65	0.51	0.22	0.19
$85^{th}$ Percentile	1.69	1.30	0.65	0.51	0.30	0.25
$95^{th}$ Percentile	1.90	1.38	0.66	0.52	0.48	0.40

TABLE I. We report summary statistics comparing our models to the annotated ratings reported in labMT. Each word in the labMT lexicon is scored by 50 distinct individuals and the final happiness score is derived by taking the average score of these evaluations [39]. We report the standard deviation and variance of the ratings as a baseline to assess the human's confidence in the reported scores. Comparing our predictions with the annotations crowdsourced via AMT, our MAEs are on par with the variance observe in the human annotated labMT scores.

example, the happiness scores in the labMT [39] dataset are closely aligned with the valence scores in the NRC-VAD lexicon [89]. We envision future work developing similar models to predict other semantic differentials such as arousal and dominance [89], EPA [90], and SocialSent [91].

More importantly, researchers would need to fine-tune the models using annotated scores for words and expressions in other languages. We caution against translating words and using the same English scores because most words do not have a one-to-one mapping into other languages, and are often used to express different meanings by the native speakers of any given language [39]. Our primary goal is to provide an easy and robust method to augment semantic dictionaries to empower researchers to

- T. Nasukawa and J. Yi. Sentiment analysis: Capturing favorability using natural language processing. In Proceedings of the 2nd International Conference on Knowledge Capture, pages 70–77, 2003.
- [2] W. Medhat, A. Hassan, and H. Korashy. Sentiment analysis algorithms and applications: A survey. Ain Shams Engineering Journal, 5(4):1093–1113, 2014.
- [3] R. K. Bakshi, N. Kaur, R. Kaur, and G. Kaur. Opinion mining and sentiment analysis. In 2016 3rd international Conference on Computing for Sustainable Global Development (INDIACom), pages 452–455. IEEE, 2016.
- [4] L. Cabral and A. Hortacsu. The dynamics of seller reputation: Evidence from eBay. *The Journal of Industrial Economics*, 58(1):54–78, 2010.
- [5] P. D. Turney. Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. In Proceedings of the 40th Annual Meeting on Association for Computational Linguistics, ACL '02, page 417–424, USA, 2002. Association for Computational Linguistics.
- [6] A. Kumar and C. M. Lee. Retail investor sentiment and return comovements. *The Journal of Finance*,

maintain and expand them at a relatively low cost using today's state-of-the-art NLP methods.

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61(5):2451-2486, 2006.

- [7] H. Tang, S. Tan, and X. Cheng. A survey on sentiment detection of reviews. *Expert Systems with Applications*, 36(7):10760–10773, 2009.
- [8] Y. Yu, W. Duan, and Q. Cao. The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems*, 55(4):919– 926, 2013.
- [9] A. Bhatt, A. Patel, H. Chheda, and K. Gawande. Amazon review classification and sentiment analysis. *International Journal of Computer Science and Information Technologies*, 6(6):5107–5110, 2015.
- [10] T. U. Haque, N. N. Saber, and F. M. Shah. Sentiment analysis on large scale Amazon product reviews. In 2018 IEEE international conference on innovative research and development (ICIRD), pages 1–6. IEEE, 2018.
- [11] L. Terveen, W. Hill, B. Amento, D. McDonald, and J. Creter. PHOAKS: A system for sharing recommendations. *Communications of the ACM*, 40(3):59–62, 1997.
- [12] B. Pang, L. Lee, and S. Vaithyanathan. Thumbs up? Sentiment classification using machine learning tech-

- [13] H. Chen, C. Yang, X. Zhang, Z. Liu, M. Sun, and J. Jin. From symbols to embeddings: A tale of two representations in computational social science, 2021. Available online at https://arxiv.org/abs/2106.14198.
- [14] M. Laver, K. Benoit, and J. Garry. Extracting policy positions from political texts using words as data. *American Political Science Review*, pages 311–331, 2003.
- [15] M. Thomas, B. Pang, and L. Lee. Get out the vote: Determining support or opposition from congressional floor-debate transcripts. In *Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing*, pages 327–335, Sydney, Australia, July 2006. Association for Computational Linguistics.
- [16] A. Tumasjan, T. Sprenger, P. Sandner, and I. Welpe. Predicting elections with Twitter: What 140 characters reveal about political sentiment. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 4, 2010.
- [17] B. Pang and L. Lee. Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval, 2(1-2):1–135, 2008.
- [18] G. Coppersmith, M. Dredze, and C. Harman. Quantifying mental health signals in Twitter. In *In Proceedings of* the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, pages 51–60, Baltimore, Maryland, USA, 2014.
- [19] A. Yadollahi, A. G. Shahraki, and O. R. Zaiane. Current state of text sentiment analysis from opinion to emotion mining. ACM Computing Surveys (CSUR), 50(2):1–33, 2017.
- [20] S. Gohil, S. Vuik, and A. Darzi. Sentiment analysis of health care tweets: Review of the methods used. JMIR Public Health and Surveillance, 4(2):e43, 2018.
- [21] K. C. Bathina, M. Ten Thij, L. Lorenzo-Luaces, L. A. Rutter, and J. Bollen. Individuals with depression express more distorted thinking on social media. *Nature Human Behaviour*, 5(4):458–466, 2021.
- [22] A. M. Stupinski, T. Alshaabi, M. V. Arnold, J. L. Adams, J. R. Minot, M. Price, P. S. Dodds, and C. M. Danforth. Quantifying language changes surrounding mental health on Twitter, 2021. Available online at https://arxiv.org/abs/2106.01481.
- [23] G. Beigi, X. Hu, R. Maciejewski, and H. Liu. An overview of sentiment analysis in social media and its applications in disaster relief. *Sentiment analysis and ontology engineering*, pages 313–340, 2016.
- [24] T. Wilson, J. Wiebe, and P. Hoffmann. Recognizing contextual polarity in phrase-level sentiment analysis. In Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing, HLT '05, pages 347–354, USA, 2005. Association for Computational Linguistics.
- [25] R. Feldman. Techniques and applications for sentiment analysis. Communications of the ACM, 56(4):82–89, 2013.
- [26] A. Pak and P. Paroubek. Twitter as a corpus for sentiment analysis and opinion mining. In Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10), Valletta, Malta, 2010. European Language Resources Association (ELRA).

- [27] A. Agarwal, B. Xie, I. Vovsha, O. Rambow, and R. Passonneau. Sentiment analysis of Twitter data. In Proceedings of the Workshop on Language in Social Media (LSM 2011), pages 30–38, Portland, Oregon, 2011. Association for Computational Linguistics.
- [28] I. Korkontzelos, A. Nikfarjam, M. Shardlow, A. Sarker, S. Ananiadou, and G. H. Gonzalez. Analysis of the effect of sentiment analysis on extracting adverse drug reactions from tweets and forum posts. *Journal of Biomedical Informatics*, 62:148–158, 2016.
- [29] K. Crawford and T. Paglen. Excavating ai: The politics of images in machine learning training sets. AI & SOCIETY, pages 1–12, 2021.
- [30] K. Crawford. Halt the use of facial-recognition technology until it is regulated. *Nature*, 572(7771):565–566, 2019.
- [31] B. Shmueli, J. Fell, S. Ray, and L.-W. Ku. Beyond fair pay: Ethical implications of NLP crowdsourcing. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3758–3769, Online, June 2021. Association for Computational Linguistics.
- [32] D. Hovy and S. L. Spruit. The social impact of natural language processing. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 591–598, 2016.
- [33] M. Conway and D. O'Connor. Social media, big data, and mental health: Current advances and ethical implications. *Current Opinion in Psychology*, 9:77–82, 2016.
- [34] R. Tatman. Gender and dialect bias in YouTube's automatic captions. In Proceedings of the First ACL Workshop on Ethics in Natural Language Processing, pages 53–59, Valencia, Spain, Apr. 2017. Association for Computational Linguistics.
- [35] F. N. Ribeiro, M. Araújo, P. Gonçalves, M. A. Gonçalves, and F. Benevenuto. SentiBench - a benchmark comparison of state-of-the-practice sentiment analysis methods. *EPJ Data Science*, 5(1):1–29, 2016.
- [36] M. Thelwall, K. Buckley, G. Paltoglou, D. Cai, and A. Kappas. Sentiment strength detection in short informal text. Journal of the American Society for Information Science and Technology, 61(12):2544–2558, 2010.
- [37] B. Snyder and R. Barzilay. Multiple aspect ranking using the good grief algorithm. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Proceedings of the Main Conference, pages 300–307, Rochester, New York, 2007. Association for Computational Linguistics.
- [38] M. Taboada, J. Brooke, M. Tofiloski, K. Voll, and M. Stede. Lexicon-Based Methods for Sentiment Analysis. *Computational Linguistics*, 37(2):267–307, 2011.
- [39] P. S. Dodds, E. M. Clark, S. Desu, M. R. Frank, A. J. Reagan, J. R. Williams, L. Mitchell, K. D. Harris, I. M. Kloumann, J. P. Bagrow, K. Megerdoomian, M. T. McMahon, B. F. Tivnan, and C. M. Danforth. Human language reveals a universal positivity bias. *Proceedings* of the National Academy of Sciences, 112(8):2389–2394, 2015.
- [40] L. Augustyniak, P. Szymański, T. Kajdanowicz, and W. Tuligłowicz. Comprehensive study on lexicon-based ensemble classification sentiment analysis. *Entropy*, 18(1):4, 2016.

- [41] R. Socher, A. Perelygin, J. Wu, J. Chuang, C. D. Manning, A. Ng, and C. Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods* in Natural Language Processing, pages 1631–1642, Seattle, Washington, USA, Oct. 2013. Association for Computational Linguistics.
- [42] P. S. Dodds, K. D. Harris, I. M. Kloumann, C. A. Bliss, and C. M. Danforth. Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter. *Plos One*, 6(12):e26752, 2011.
- [43] A. J. Reagan, C. M. Danforth, B. Tivnan, J. R. Williams, and P. S. Dodds. Sentiment analysis methods for understanding large-scale texts: A case for using continuumscored words and word shift graphs. *EPJ Data Science*, 6:1–21, 2017.
- [44] R. J. Gallagher, M. R. Frank, L. Mitchell, A. J. Schwartz, A. J. Reagan, C. M. Danforth, and P. S. Dodds. Generalized word shift graphs: A method for visualizing and explaining pairwise comparisons between texts. *EPJ Data Science*, 10(1):4, 2021.
- [45] E. Riloff. An empirical study of automated dictionary construction for information extraction in three domains. *Artificial Intelligence*, 85(1-2):101–134, 1996.
- [46] P. S. Dodds and C. M. Danforth. Measuring the happiness of large-scale written expression: Songs, blogs, and presidents. *Journal of Happiness Studies*, 11(4):441–456, 2010.
- [47] T. Alshaabi, J. L. Adams, M. V. Arnold, J. R. Minot, D. R. Dewhurst, A. J. Reagan, C. M. Danforth, and P. S. Dodds. Storywrangler: A massive exploratorium for sociolinguistic, cultural, socioeconomic, and political timelines using Twitter. *Science Advances*, 2021. In press.
- [48] T. Alshaabi, M. V. Arnold, J. R. Minot, J. L. Adams, D. R. Dewhurst, A. J. Reagan, R. Muhamad, C. M. Danforth, and P. S. Dodds. How the world's collective attention is being paid to a pandemic: COVID-19 related n-gram time series for 24 languages on Twitter. *Plos One*, 16(1):e0244476, 2021.
- [49] Y. Bengio, R. Ducharme, P. Vincent, and C. Janvin. A neural probabilistic language model. *Journal of Machine Learning Research*, 3:1137–1155, 2003.
- [50] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 142–150, Portland, Oregon, USA, 2011. Association for Computational Linguistics.
- [51] G. Hollis and C. Westbury. The principals of meaning: Extracting semantic dimensions from co-occurrence models of semantics. *Psychonomic Bulletin & Review*, 23(6):1744–1756, 2016.
- [52] G. Hollis, C. Westbury, and L. Lefsrud. Extrapolating human judgments from skip-gram vector representations of word meaning. *Quarterly Journal of Experimental Psychology*, 70(8):1603–1619, 2017.
- [53] M. Li, Q. Lu, Y. Long, and L. Gui. Inferring affective meanings of words from word embedding. *IEEE Transactions on Affective Computing*, 8(4):443–456, 2017.
- [54] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. In Y. Bengio and Y. LeCun, editors, 1st International Con-

ference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings, 2013.

- [55] T. Mikolov, I. Sutskever, K. Chen, G. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In *Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'13, pages 3111–3119, Red Hook, NY, USA, 2013. Curran Associates Inc.
- [56] Z. S. Harris. Distributional structure. Word, 10(2-3):146– 162, 1954.
- [57] J. Pennington, R. Socher, and C. Manning. GloVe: Global vectors for word representation. In *Proceedings* of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, Doha, Qatar, Oct. 2014. Association for Computational Linguistics.
- [58] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov. Bag of tricks for efficient text classification. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 427–431, Valencia, Spain, Apr. 2017. Association for Computational Linguistics.
- [59] P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146, 2017.
- [60] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Learning Internal Representations by Error Propagation*, pages 318–362. MIT Press, Cambridge, MA, USA, 1986.
- [61] S. Hochreiter and J. Schmidhuber. Long short-term memory. Neural Computation, 9(8):1735–1780, 1997.
- [62] M. Peters, W. Ammar, C. Bhagavatula, and R. Power. Semi-supervised sequence tagging with bidirectional language models. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics* (Volume 1: Long Papers), pages 1756–1765, Vancouver, Canada, 2017. Association for Computational Linguistics.
- [63] K. Lee, L. He, M. Lewis, and L. Zettlemoyer. End-to-end neural coreference resolution. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 188–197, Copenhagen, Denmark, 2017. Association for Computational Linguistics.
- [64] Q. Chen, X. Zhu, Z.-H. Ling, S. Wei, H. Jiang, and D. Inkpen. Enhanced LSTM for natural language inference. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1657–1668, Vancouver, Canada, 2017. Association for Computational Linguistics.
- [65] M. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana, June 2018. Association for Computational Linguistics.
- [66] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, and I. Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, Advances in Neural Information Processing Systems, volume 30. Curran Associates,

Inc., 2017.

- [67] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *Proceedings of the International Conference on Learning Representations*, ICRL'21, 2021.
- [68] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota, 2019. Association for Computational Linguistics.
- [69] A. Radford, K. Narasimhan, T. Salimans, and I. Sutskever. Improving language understanding by generative pretraining. 2018.
- [70] Y. Wu, M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey, J. Klingner, A. Shah, M. Johnson, X. Liu, L. Kaiser, S. Gouws, Y. Kato, T. Kudo, H. Kazawa, K. Stevens, G. Kurian, N. Patil, W. Wang, C. Young, J. Smith, J. Riesa, A. Rudnick, O. Vinyals, G. Corrado, M. Hughes, and J. Dean. Google's neural machine translation system: Bridging the gap between human and machine translation, 2016. Available online at https://arxiv.org/abs/1609.08144.
- [71] T. Kudo and J. Richardson. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 66–71, Brussels, Belgium, 2018. Association for Computational Linguistics.
- [72] R. Sennrich, B. Haddow, and A. Birch. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany, 2016. Association for Computational Linguistics.
- [73] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc., 2019.
- [74] Z. Dai, Z. Yang, Y. Yang, J. Carbonell, Q. Le, and R. Salakhutdinov. Transformer-XL: Attentive language models beyond a fixed-length context. In *Proceedings* of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2978–2988, Florence, Italy, 2019. Association for Computational Linguistics.
- [75] N. C. Thompson, K. Greenewald, K. Lee, and G. F. Manso. The computational limits of deep learning, 2020. Available online at https://arxiv.org/abs/2007.05558.
- [76] G. Hinton, O. Vinyals, and J. Dean. Distilling the knowledge in a neural network. In NIPS Deep Learning and Representation Learning Workshop, 2015.
- [77] V. Sanh, L. Debut, J. Chaumond, and T. Wolf. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. In *Proceedings of the 7th International Conference on Neural Information Processing Systems*, 5th Workshop on Energy Efficient Machine Learning and Cognitive Computing. MIT Press, 2019.

- [78] Z. Lan, M. Chen, S. Goodman, K. Gimpel, P. Sharma, and R. Soricut. ALBERT: A lite BERT for selfsupervised learning of language representations. In *Pro*ceedings of the International Conference on Learning Representations, 2020.
- [79] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga, S. Moore, D. G. Murray, B. Steiner, P. Tucker, V. Vasudevan, P. Warden, M. Wicke, Y. Yu, and X. Zheng. Tensorflow: A system for large-scale machine learning. In *Proceedings of the 12th* USENIX Conference on Operating Systems Design and Implementation, OSDI'16, pages 265–283, USA, 2016. USENIX Association.
- [80] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz, J. Davison, S. Shleifer, P. von Platen, C. Ma, Y. Jernite, J. Plu, C. Xu, T. Le Scao, S. Gugger, M. Drame, Q. Lhoest, and A. Rush. Transformers: State-of-theart natural language processing. In *Proceedings of the* 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online, 2020. Association for Computational Linguistics.
- [81] M. A. Mahabhaleshwara and C. Tan. On positivity bias in negative reviews. In In Proceedings of the Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (ACL-IJCNLP 2021). Association for Computational Linguistics, 2021.
- [82] G. A. Miller, E. B. Newman, and E. A. Friedman. Length-frequency statistics for written English. *Infor*mation and Control, 1(4):370–389, 1958.
- [83] M. S. Mayzner and M. E. Tresselt. Tables of single-letter and digram frequency counts for various word-length and letter-position combinations. *Psychonomic Monograph Supplements*, 1965.
- [84] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15(1):1929–1958, 2014.
- [85] A. Krogh and J. Vedelsby. Neural network ensembles, cross validation and active learning. In *Proceedings of the 7th International Conference on Neural Information Processing Systems*, NIPS'94, pages 231–238, Cambridge, MA, USA, 1994. MIT Press.
- [86] Y. Bengio and Y. Grandvalet. No unbiased estimator of the variance of k-fold cross-validation. *Journal of Machine Learning Research*, 5:1089–1105, 2004.
- [87] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. In Y. Bengio and Y. LeCun, editors, 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.
- [88] L. K. Hansen and P. Salamon. Neural network ensembles. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(10):993–1001, 1990.
- [89] S. Mohammad. Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 174–184, Melbourne, Australia, 2018. Association for Computational Linguistics.

- [90] C. E. Osgood. Studies on the generality of affective meaning systems. American Psychologist, 17(1):10, 1962.
- [91] W. L. Hamilton, K. Clark, J. Leskovec, and D. Jurafsky. Inducing domain-specific sentiment lexicons from unlabeled corpora. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 595–605, Austin, Texas, 2016. Association for Computational Linguistics.