Abstract

Automatically generated emotion arcs—that capture how an individual or a population feels over time—are widely used in industry and research. However, there is little work on evaluating the generated arcs. This is in part due to the difficulty of establishing the true (gold) emotion arc. Our work, for the first time, systematically and quantitatively evaluates automatically generated emotion arcs. We also compare two common ways of generating emotion arcs: Machine-Learning (ML) models and Lexicon-Only (LexO) methods. Using a number of diverse datasets, we systematically study the relationship between the quality of an emotion lexicon and the quality of the emotion arc that can be generated with it. We also study the relationship between the quality of an instance-level emotion detection system (say from an ML model) and the quality of emotion arcs that can be generated with it. We show that despite being markedly poor at instance level, LexO methods are highly accurate at generating emotion arcs by aggregating information from hundreds of instances. This has wide-spread implications for commercial development, as well as research in psychology, public health, digital humanities, etc. that values simple interpretable methods and disprefers the need for domain-specific training data, programming expertise, and high-carbon-footprint models.

1 Introduction

Commercial applications as well as research projects often benefit from accurately tracking the emotions associated with an entity over time (Park and Kwak, 2020; Singh et al., 2020; Chong and Gottipati, 2020; Seidl, 2020; Somasundaran et al., 2020; Kim et al., 2017). Here, the goal is not to determine some absolute value of emotion associated with the entity, but rather whether the degree of that emotion has remained steady, increased, or decreased from one time step to the next. For example, how has the anger towards the state of public infrastructure in a city changed from one month to another over the last ten years. In this example, the time steps of consideration are months, but other time steps commonly used are days, weeks, and years. This series of time step–emotion value pairs, which can be represented as a time-series graph, is often referred to as an emotion arc (Mohammad, 2011; Reagan et al., 2016).

When the amount of data involved is large enough that human annotations of emotions are prohibitive, then one can employ automatic methods to estimate emotion arcs. Automatic methods will be less accurate than human assessments, but can be applied at scale and easily adjusted to changes in needs (e.g., tracking new, different, or additional entities of interest).

The input to these systems are usually:

- The text of interest where the individual sentences (or instances) are temporally ordered; possibly through available timestamps indicating when the instances were posted/uttered: e.g., all the tweets relevant to (or mentioning) a government policy along with their meta-data that includes the date and time of posting.
- The emotion dimension/category of interest: e.g., anxiety, anger, valence, arousal, etc.
- The time step granularity of interest (e.g., days, weeks, months etc.)

The automatic methods usually employ the steps listed below to determine the time step–emotion value pairs (the emotion arc):

- Suitable pre-processing of the text (e.g., converting text to lowercase, removing urls and numbers, tokenizing text, etc.).
- Apply emotion labels to units of text. Two common approaches for labeling units of text are: (1) The Lexicon-Only (LexO) Method: to label words using emotion lexicons and (2) The Machine-Learning (ML) Method: to label
whole sentences using supervised ML models (with or without using emotion lexicons).

- Aggregate the information to compute time step–emotion value scores; e.g., if using the lexicon approach: for each time step, compute the percentage of angry words or average valence of the words in the target text pertaining to each time step, and if using the ML approach: for each time step, compute the percentage of angry sentences or average valence of the sentences for each time step.

The time steps used can be non-overlapping, e.g., months of a year, but they can also be overlapping, e.g., ten-day time steps starting at every day of a year. Here, every adjacent time step has nine overlapping days. Overlapping steps produce smoother emotion arcs, and thus are preferred in some applications. The number of textual instances (usually sentences or tweets) pertaining to a time step are referred to as the size of the time step or bin size. In case the data does not come with associated time stamps, but simply a temporal order from beginning to end (such as the text in a novel), then often a time step is determined by a pre-chosen fixed amount of textual units (e.g., 200 words, 100 sentences, or one chapter). Thus, here all bins have the same size.

Despite their wide-spread use in industry and research, there is little work on evaluating the generated emotion arcs. This is in part due to the difficulty of establishing the true (gold) emotion arc. We also know little about how best to aggregate information when using emotion lexicons; e.g., is it better to use coarse or fine-grained lexicons, should we ignore slightly emotional words, and how to handle out of vocabulary (OOV) terms (terms not in the emotion lexicon). Our work, for the first time, systematically and quantitatively evaluates automatically generated emotion arcs. We also compare the ML and LexO methods for generating arcs. We conduct experiments to study the relationship between the quality of an emotion lexicon and the quality of emotion arcs that can be generated with it, by varying various parameters involved. We also study the relationship between the quality of an instance-level emotion detection system (say, from an ML model) and the quality of emotion arcs that can be generated with it. Specifically, we explore these research questions:

1. How accurate are the ML and LexO methods for emotion arc generation?
2. Are the gains obtained using an ML model enough to offset its accessibility, interpretability, financial, and environmental costs?
3. How to best use an emotion lexicon to generate emotion arcs?
4. How does the quality of the generated emotion arcs change with the level of aggregation (number of instances binned together to form a time step)? These results will help one judge how to balance emotion arc quality and the level of detail/granularity at which emotion arcs should be generated.
5. How good are existing emotion lexicons in terms of generating corresponding emotion arcs? Is it harder to generate accurate arcs for some emotions compared to others? These results will shed light on the nature of different emotions.
6. How does the granularity of the association scores available in an emotion lexicon impact the quality of emotion arcs? Does the use of fine-grained lexicons containing real-valued emotion association scores lead to substantially better emotion arcs than with the use of coarse grained lexicons that only indicate whether a word is associated with an emotion or not associated. These results will help one judge whether to invest in the costlier fine-grained lexicons for a language.
7. For a given emotion dimension or category, should we use the full set of associated words or only those words that have an association greater than some threshold? Does this threshold vary widely across emotions or is it roughly within a narrow band of association scores?
8. How best to handle out of vocabulary terms (words not in an emotion lexicon)?
9. Is it viable to use automatic translations of emotion lexicons to generate emotion arcs in a low-resource language?

We conduct these experiments on a diverse set of datasets, including: tweets, SMS messages, personal diary posts, and movie reviews. We make the data and code freely available. Notably, the code allows users to easily generate high-quality emotion arcs for their text of interest.¹

¹https://github.com/dteodore/EmotionArcs
2 Related Work

Several systems for generating emotion arcs have been previously proposed in various works, most commonly for creating emotion arcs for characters in story dialogues. Mohammad (2011) analyzed the flow of emotions across various novels and books using emotion lexicons. Kim et al. (2017) built on this work by creating emotion arcs to determine emotion information for various genres using the NRC Emotion Lexicon. Somasundaran et al. (2020) generated emotion arcs to analyze, and assess the quality of narratives written by students using an event polarity lexicon (Ding and Riloff, 2018) and a connotation lexicon (Feng et al., 2013) for extracted events. Hipson and Mohammad (2021) recently analyzed emotion arcs for characters in movie dialogues using emotion lexicons. Bhyravajjula et al. (2022) create a pipeline for plotting a character’s arc using ML methods such as a fine-tuned RoBERTa (Liu et al., 2020) model. Brahman and Chaturvedi (2020) model emotion arcs for protagonists in generated stories using supervised and reinforcement learning methods. Further, other work has approached constructing emotion arcs using reinforcement learning, as Brahman and Chaturvedi (2020) do for protagonists in stories. Lastly emotion arcs have been employed to assist writers with creating stories which match an emotion arc that readers are expecting and desire (Ashida et al., 2021). However, there is surprisingly little work on arc evaluation. A key reason for this is that it is hard to determine the true emotion arc of a story from data annotation. It is hard for people to read a large amount of text, say from a novel, and produce an emotion arc for it.

Emotion arcs commonly employed in commerce and social media research are fundamentally different from the arcs in novels. There, one is often interested in the arcs associated with posts that mention a pre-chosen product, such as a certain brand of cellphone (Park and Kwak, 2020), government policy (Singh et al., 2020), a person (Chong and Gottipati, 2020), or entity such as Uber (Seidl, 2020). For example, an emotion arc of tweets that mention the latest iPhone. Here, the different instances are not part of a coherent narrative. Thus, while it would be difficult to find a literary theorist who would agree that the true emotion arc of a novel is simply the average of the emotions of the constituent sentences, it is arguably more persuasive to consider the gold emotion arcs to be simply the average of the emotion scores of all the tweets pertaining to the time steps. For example, the average human-annotated emotion scores of the iPhone tweets posted every day.

3 Experimental Setup to Evaluate Automatically Generated Emotion Arcs

We construct gold emotion arcs from existing datasets where individual instances are manually annotated for emotion labels. Here, an instance could be a tweet, a sentence from a customer review, a sentence from a personal blog, etc. Depending on the dataset, manual annotations for an instance may represent the emotion of a speaker, or sentiment towards a product or entity. For a pre-chosen bin size say 100 instances per bin, we compute the gold emotion score by taking the average of the human-labeled emotion scores of the instances in that bin (in-line with the commerce and social media use cases discussed earlier). We move the window forward by one instance, compute the average in that bin, and so on.\(^2\)

We standardized all of the emotion arcs (aka z-score normalization) so that the gold emotion arcs are comparable to automatically generated arcs.\(^3\) Finally, we evaluate an automatically generated emotion arc by computing the linear correlation between the system-predicted emotion arc and the gold arc using Spearman correlation (Spearman, 1987). High correlation implies greater fidelity: no matter what the overall shape of the gold emotion arc, when it goes up (or down), the predicted emotion arc also goes up (or down).\(^4\)

Table 1 shows details of the instance-labeled English (Eng) test data used in our experiments. Observe that the datasets are of two kinds: those with categorical labels such as the SemEval 2014, which has -1 (negative), 0 (neutral), and 1 (positive), as well as those with continuous labels such as SemEval 2018 (EI-Reg), which has real-valued emotion intensity scores (for four emotions) between 0 (lowest/no intensity) and 1 (highest intensity).

We use the above evaluation setup to study:

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\(^2\)Using larger window sizes does not impact conclusions.

\(^3\)Subtract the mean from the score and divide by the standard deviation (arcs then have zero mean and unit variance).

\(^4\)Shape of the emotion arc: Different emotion arc shapes can be generated by ordering the data differently. Whether using the shapes using the time-stamps associated with the instances or any other method, we found the same Spearman correlations (and conclusions) as described in the paper ahead.
Table 1: Dataset descriptive statistics. The No. of instances includes the train, dev, and test sets for the Sem-Eval 2014 Task 9 and the Sem-Eval 2018 Task 1 (EI-OC, EI-Reg, V-OC and V-Reg). Multiple*: The SemEval 2014 dataset has collections of LiveJournal posts (1141), SMS messages (2082), regular tweets (15302), and sarcastic tweets (86) for a total of 18611 instances. The Movie Reviews Categorical dataset is often also referred to as SST-2.

Table 2: Lexicons used this study. The subset of emotions explored in our experiments are marked in bold.

1. The relationship between the quality of word-level emotion labeling (the usual lexicon approach) on the generated emotion arcs (§4).
2. The relationship between the quality of instance-level emotion labeling (the usual ML approach) on the generated emotion arcs (§5).

Table 2 shows the lexicons we used to generate emotion arcs studied in §4. These lexicons are widely used to support sentiment analysis and have both categorical and real-valued versions, which is useful to study whether using fine-grained lexicons leads to markedly better emotion arcs than when using coarse categorical lexicons (keeping the vocabulary of the lexicon constant). We simulate performance of ML models with varying accuracies using an Oracle system described in §5.

Finally, to determine whether using automatic translations of English lexicons into relatively less-resource languages is a viable option, we experimented with the Arabic (Ar) and Spanish (Es) emotion-labeled tweet data from SemEval 2018 Task 1 (Mohammad et al., 2018). Similarly to the English dataset, these contain original tweets in the language (not translated) with emotion labels by native speakers, on categorical and continuous scales. Details of these datasets are in Tables 4 and 5 in the Appendix.

In all, we conducted experiments on 36 emotion-labeled datasets from three languages, with labels that are categorical and continuous for five affect categories. This helps determine whether the inferences we draw are limited to individual datasets or more general. While the core experiments are presented in the main paper, other result tables are available in the Appendix. The results on individual datasets also establish key benchmarks; useful to practitioners for estimating the quality of the arcs under various settings.

4 LexO Arcs: Emotion Arcs Generated from Counting Emotion Words

As discussed in the Introduction, the quality of an emotion lexicon is expected to impact the quality of the automatically generated emotion arcs. We now describe experiments where we systematically vary various parameters associated with using an emotion lexicon to generate emotion arcs.

We begin by generating arcs of valence (or sentiment) using lexicons of different score granularities (categorical labels and continuous labels), two different methods of handling out of vocabulary (OOV) terms, and using various levels of aggregation or bin sizes (groupings of instances used to generate the emotion scores for an arc) which we describe in Section 4.1. For our experiments we explored bin sizes of 1, 10, 50, 100, 200, and 300. The two OOV handling methods explored were: 1. Assign label NA (no score available) and disregard these words, and 2. Assign 0 score (neutral or not associated with emotion category), thereby, leading
to a lower average score for the instance than if the word was disregarded completely.

We then evaluate how closely the arcs correspond to the gold valence arcs. The same experiment is then repeated for various other emotion categories, to see if we find consistent patterns (Section 4.2). For each emotion category or dimension, we generate the predicted emotion arcs using the corresponding existing emotion lexicons listed in Table 2. In Section 4.3, we show the impact of using emotion lexicons more selectively. Specifically, by only using entries that have an emotion association greater than some pre-determined threshold.

4.1 Valence: Impact of Bin Size, Lexicon Granularity, OOV Handling

Figure 1 shows the correlations between valence arcs generated using information from the lexicons and the gold valence arcs created from the categorically labeled test data. Figure 4 shows the results for the same experiments but for gold arcs from continuously labeled valence test data.

**Bin Size:** Overall, across datasets and regardless of the type of lexicon used and how OOV words are handled, increasing the bin size dramatically improves correlation with the gold arcs. In fact, with bin sizes as small as 50, many of the generated arcs have correlations above 0.9. With bin size 100 correlations are around 0.95, and approach high 0.90’s to 0.99 with bin sizes of 200 and 300.

**Discussion:** For many social media applications, one has access to tens of thousands, if not millions of tweets. There, it is not uncommon to have time-steps (bins) that include thousands of tweets. Thus it is remarkable that even with relatively small bin sizes of a few hundred tweets, the simple lexicon approach is able to obtain very high correlations. Of course, the point is not that the lexicon approach is somehow special, but rather that aggregation of information can very quickly generate high quality arcs, even if the constituent individual emotion signals are somewhat weak.

**Translated Lexicons:** Using Arabic and Spanish translations of the English emotion lexicons also resulted in high correlation scores for larger bin sizes (just as in the case of the English datasets).

**Discussion:** Thus, one key outcome of these experiments is that for low-resource languages, where labeled training data and emotion lexicons are scarce, using translations of English lexicons to generate emotion arcs is particularly attractive. This approach can thus unlock the potential for affect-related psychology, health science, and digital humanities research for a vast number of languages.

**Categorical vs. Real-Valued Lexicons:** Using a real-valued lexicon obtains higher correlations across bin sizes, methods for processing OOV terms, and datasets. The difference is marked for very small bin sizes (such as 1 and 10) but progressively smaller for higher bin sizes.

**Discussion:** Entries from real-valued lexicons carry more fine-grained emotion information, and it is likely that this extra information is especially helpful when emotion scores are determined from very little text (as in the case of small bins), but less useful for larger bin sizes where even coarse information from the additional text is sufficient to obtain high correlations.

**Processing OOV Terms:** Each of the two methods for processing OOV words performed slightly better than the other method, roughly an equal number of times. Overall, for larger bin sizes such as 200 and 300 both methods obtained similar (very high) correlations.

**Discussion:** Results for OOV handling are somewhat mixed, and might merit further enquiry in sparse data scenarios, but the issue is not of practical relevance for bin sizes of 100 and above, where either approach leads to similar results.

4.2 Anger, Fear, Joy, Sadness: Impact of Bin Size, Lexicon Granularity, OOV Handling

Figure 2 shows the correlations between emotion arcs generated using information from the lexicons and the gold emotion arcs created from the categorically labeled emotion test data (for anger, fear, joy, and sadness). We observed similar results on arcs generated from the continuously labeled emotion test data as observed on the gold arcs created from categorical data. We include those results in the Appendix (Figure 5).

**Bin Size:** We observe the same trend for anger, fear, joy, and sadness, as we did for valence earlier: with increased bin sizes correlations with arcs generated from humans annotations increases substantially. However, we note that overall the correlations for these emotion categories are lower than for valence, with values ranging from 0.10 and 0.20 for Ar, mid 0.20’s for Eng, and 0.30 for Es at bin size 1 to mid 0.80–high 0.90’s for bin sizes 200 and 300.
Figure 1: Valence: Spearman correlations between arcs generated using lexicons and gold arcs created from categorically labeled test data.

Discussion: Past work has shown that emotion detection at the instance level is less accurate for emotions such as anger and sadness compared to valence (Mohammad et al., 2018). Work in psychology has also shown valence to be the prime dimension of connotative meaning (Osgood et al., 1957; Russell, 2003; Russell and Mehrabian, 1977). Thus, the lower correlations we observe for categorical emotions (especially for Ar and Eng) compared to valence aligns with those findings; suggesting that there are more overt, easier to discern, clues for valence.

Categorical vs. Real-Valued Lexicons: We observe the same trend for the anger, fear, joy and sadness, as we did for valence: Generally, the real-valued lexicons obtain higher correlations than the categorical lexicons (this is especially prominent for Eng sadness and Es fear). (A notable exception is anger Ar for bin size 1, 50, 100 and fear Eng for bin size 100 and above, and lastly sadness Es for bin size 50 and above based on the lexicon scores type.) Also, unlike as in the case of valence and for noted exceptions, real-valued lexicons are markedly better for higher bin sizes as well.
**Discussion:** Greater benefit from the real-valued lexicons in case of anger, sadness, etc., as compared to valence, is probably because they are relatively harder to identify; and so the extra information from real-valued lexicons is especially beneficial. **Processing OOV Terms:** Figure 2 shows that depending on the emotion, a certain method for handling OOV words produces higher correlation scores. For example, the assigned neutral score obtains higher correlations for Eng anger with bin sizes 10 and up, whereas assigning NA to OOV words and disregarding them generally produces higher scores for Eng joy and fear. **Discussion:** Just as for valence, the method of handling OOVs becomes practically relevant only for smaller bin sizes, as for larger bin sizes the methods produce similar results overall.

### 4.3 Impact of Selectively Using the Lexicon

The continuously labeled emotion lexicons include words that may be very mildly associated with an emotion category or dimension. It is possible that the very low emotion association entries may in fact mislead the system, resulting in poor emotion arcs. We therefore investigate the quality of emotion arcs by generating them only from terms with an emotion association score greater than a pre-chosen threshold; thereby using the lexicon entries more selectively. We systematically vary the threshold to study what patterns of threshold lead to better arcs across the emotion test datasets.\(^5\)

Overall, we observed that valence benefits from including all terms, even lowly associated emotion words, as the optimal threshold across continuous and categorically datasets is 0 with a few notable exceptions (SemEval 2014 LiveJournal, SemEval 2014 tweets, and V-OC); Whereas anger, fear, joy and sadness, benefit from some degree of thresholding. For example, the optimal threshold for each is approximately: anger 0.75, fear 0.25, joy 0.66, and sadness 0.66–0.75.

Generally, including only terms with emotion scores above 0.33 to 0.5 improves the quality of emotion arcs, with anger and sadness preferring higher thresholds. (Figures 6 through 9 in the Appendix show the full sets of correlations for reference) for valence and other emotion datasets.

### 5 ML Arcs: Emotion Arcs Generated from Counting ML-Labeled Sentences

Even though the primary focus of this paper is to study how effective lexicon-based word-level emotion labeling methods are at generating emotion arcs, we devote this section to study how the accuracy of instance-level (sentence- or tweet-level)
emotion labeling impacts the quality of the generated emotion arcs.

We approached this by creating an ‘oracle’ system, which has access to the gold instance emotion labels. There are several metrics for evaluating sentiment analysis at the instance level such as accuracy, correlation, or F-score. However we focus on accuracy as it is a simple intuitive metric. Inputs to the Oracle system are a dataset of text (for emotion labelling) and a level of accuracy such as 90% accuracy (to perform instance-level emotion labelling at). Then, the system goes through each instance and predicts the correct emotion label with a probability corresponding to the pre-chosen accuracy. In the case where the system decides to assign an incorrect label, it chooses one of the possible incorrect labels at random. We use the oracle to generate emotion labels pertaining to various levels of accuracy, for the same dataset. We then generate emotion arcs just as described in the previous section (by taking the average of the scores for each instance in a bin), and evaluate the generated arcs just as before (by determining correlation with the gold arc). This Oracle Systems allows us to see how accurate an instance level emotion labelling approaches needs to be to obtain various levels of quality when generating emotion arcs.

Figure 3 shows the correlations of the valence arcs generated using the Oracle System with the gold valence arcs created from the SemEval 2018 V-OC test set (that has 7 possible labels: -3 to 3). We observe that, as expected the Oracle Systems with instance-level accuracy greater than approximately the random baseline (14.3% for this dataset) obtain positive correlations; whereas those with less than 14% accuracy obtain negative correlations. As seen with the results of the previous section, correlations increase markedly with increase in bin size. Even with an instance-level accuracy of 60%, correlation approaches 1 at larger bin sizes. Overall, we again observe high quality emotion arcs with bin sizes of just a few hundred instances.

Table 3 shows the correlations obtained on the same dataset when using various deep neural network and transformer-based systems. Observe that the recent systems obtain nearly perfect correlation at bin sizes 200 and 300. That said, for applications where simple, interpretable, low-cost, and low-carbon-footprint systems are desired, the lexicon based systems described in the previous section, are perhaps more suitable.

6 Conclusions

This work, systematically and quantitatively, evaluated two broad approaches to automatically generating emotion arcs. We showed that the arcs generated using lexicons, and with bin sizes of just a few hundred instances, obtain very high correlations with the gold arcs. The patterns remain consistent across a variety of datasets and a number of emotion dimensions. We also showed that

Table 3: Valence: Spearman correlations between arcs generated using various neural models for instance-level sentiment classification and gold arcs created from the SemEval 2018 V-OC dataset.

| Source          | Model   | Instance-Level Accuracy | Bin Size |
|-----------------|---------|-------------------------|----------|
|                 |         |                         | 1        | 10    | 50   | 100  | 200  | 300  |
| Socher et al. (2013) | RNTN    | 85.4%                   | 0.829    | 0.972 | 0.980 | 0.983 | 0.986 | 0.992 |
| Devlin et al. (2019) | BERT-base | 93.5%                   | 0.921    | 0.981 | 0.984 | 0.988 | 0.993 | 0.996 |
| Devlin et al. (2019) | BERT-large | 94.9%                   | 0.932    | 0.986 | 0.984 | 0.988 | 0.993 | 0.996 |
| Yang et al. (2019)  | XLNet   | 97.0%                   | 0.959    | 0.990 | 0.985 | 0.988 | 0.993 | 0.996 |
| Liu et al. (2020)   | RoBERTa | 96.4%                   | 0.958    | 0.989 | 0.986 | 0.989 | 0.994 | 0.997 |
the best neural ML models generate arcs that are close to perfect with bin sizes of just a few hundred instances. However, the lexicon approach is competitive with those approaches, and likely a better choice in applications that need high interpretability, low cost, low carbon footprint, and no need for domain-specific training. This also allows a vast number of researchers, from fields such as Psychology and Digital Humanities, who may not have the resources or necessary programming experience to deploy deep neural models, to still develop high-quality emotion arcs for their work.

7 Limitations
This work has only explored estimating aggregate level emotion arcs by simply averaging the emotion scores of instances (in relevant bins / time steps). However, emotion arcs in coherent narratives, such as stories, are more complex, and may not be captured by this method. Understanding emotion arcs of narratives remains an open challenge.

8 Ethics Considerations
Our research interest is to study emotions at an aggregate/group level. This has applications in determining public policy (e.g., pandemic-response initiatives) and commerce (understanding attitudes towards products). However, emotions are complex, private, and central to an individual’s experience. Additionally, each individual expresses emotion differently through language, which results in large amounts of variation. Therefore, several ethical considerations should be accounted for when performing any textual analysis of emotions (Mohammad, 2022, 2020). The ones we would particularly like to highlight are listed below:

- Our work on studying emotion word usage should not be construed as detecting how people feel; rather, we draw inferences on the emotions that are conveyed by users via the language that they use.
- The language used in an utterance may convey information about the emotional state (or perceived emotional state) of the speaker, listener, or someone mentioned in the utterance. However, it is not sufficient for accurately determining any of their momentary emotional states. Deciphering true momentary emotional state of an individual requires extra-linguistic context and world knowledge. Even then, one can be easily mistaken.
- The inferences we draw in this paper are based on aggregate trends across large populations. We do not draw conclusions about specific individuals or momentary emotional states.

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APPENDIX

To determine the generality of the claims made in the paper, we conducted experiments on 36 emotion labeled datasets from three languages with labels that are categorical and continuous for five affect categories. While the core representative experiments are presented in the main paper, remaining results tables are available in the Appendix below. The results on individual datasets also establish key benchmarks that be useful for researchers.
and developers to assess the expected quality of the emotion arcs under various settings. Readers can examine individual tables of interest to them.

Appendix A presents additional dataset summary statistics. The next four appendices present correlation scores between the gold arcs and the generated arcs: first with the full lexicons and the continuous datasets (Appendix B and C); and then with the thresholded lexicons and both the categorical and continuous datasets (Appendix D and E). Results using the full lexicon and the categorical datasets are in the main paper.

A Data Descriptive Statistics

Tables 4 and 5 show key summarizing information about the Arabic and Spanish datasets, respectively. Table 6 shows the average number of words per instance in each of the Arabic, English, and Spanish datasets.

B Gold–Auto Correlations for Valence and Continuously Labeled Test Data

Figure 4 shows the Spearman correlations between automatically generated emotion arcs and arcs created from human annotations for valence from continuously labeled test data. It shows similar patterns as those discussed in the paper for categorical data overall.

C Gold–Auto Correlations for Anger, Fear, Joy, Sadness and Continuously Labeled Test Data

Figure 5 shows the Spearman correlations between automatically generated emotion arcs and arcs created from human annotations for anger, fear, joy and sadness arcs from continuously labeled test data. It shows similar patterns as those discussed in the paper for categorical data overall.

D Gold–Auto Correlations for Valence and Thresholded Lexicons

Figure 6 shows the correlations between generated emotion arcs and arcs created using human annotations when only considering terms which have an emotion score in the lexicon above a given threshold. We first look at the datasets for valence which have categorical and then continuous labels.

The optimal threshold for the highest correlation results across all categorically labeled datasets is close to 0 with a few notable exceptions (SemEval 2014 LiveJournal, SemEval 2014 tweets, and V-OC). This means that when generating emotion arcs for valence, it is beneficial to consider mostly all terms regardless of their emotion scores as this information builds higher quality emotion arcs.

Likewise, a similar pattern holds for valence with continuous labels as shown in Figure 7. The optimal thresholds for these datasets is 0 to 0.33-0.50.

E Gold–Auto Correlations for Anger, Fear, Joy, Sadness and Thresholded Lexicons

Figure 8 shows the correlations between generated emotion arcs and those created using human annotations when only considering terms which have an emotion score in the lexicon above a given threshold for anger, fear, joy and sadness in categorical labeled datasets.

The optimal threshold producing the highest correlations differs based on emotion. For anger it is 0.75, for fear 0.25, for joy 0.66, and lastly for sadness 0.75. These results contrast those found with valence, where the optimal threshold was close to 0. When generating emotion arcs for anger, fear, joy, and sadness they benefit from including only more highly associated emotion terms.

In Figure 9 we show the results for anger, fear, joy and sadness with continuously labeled datasets. Overall, these optimal thresholds are similar to those for categorical labeled dataset.

F Impact of the Quality of Instance-Level Emotion Labeling on Emotion Arcs

Figures 10 and 11 show the results for the Oracle System on the categorically labeled SemEval 2014 and SemEval 2018 datasets. We observe similar patterns as discussed in the paper for the Movie Reviews dataset. (Note that the instance-level random-guess baseline is dependent on the number of class labels; thus, the minimum Oracle System Accuracy at which positive correlations with gold arcs appear is different across the datasets.)
| Dataset Source Domain | Dimension | Label Type | # Instances |
|-----------------------|-----------|------------|-------------|
| Mohammad et al. (2018) | tweets | anger, fear, joy, sadness | 1400 |
| Mohammad et al. (2018) | tweets | anger, fear joy, sadness | 1400 |
| Mohammad et al. (2018) | tweets | valence | 1800 |
| Mohammad et al. (2018) | tweets | valence | 1800 |

Table 4: Dataset descriptive statistics for datasets in Arabic. The No. of instances includes the train, development, and test sets for the Sem-Eval 2018 Task 1 (EI-OC, EI-Reg, V-OC and V-Reg).

| Dataset Source Domain | Dimension | Label Type | # Instances |
|-----------------------|-----------|------------|-------------|
| Mohammad et al. (2018) | tweets | anger, fear, joy, sadness | 1986, 1986 |
| Mohammad et al. (2018) | tweets | anger, fear joy, sadness | 1990, 1991 |
| Mohammad et al. (2018) | tweets | valence | 2443 |
| Mohammad et al. (2018) | tweets | valence | 2443 |

Table 5: Dataset descriptive statistics for datasets in Spanish. The No. of instances includes the train, development, and test sets for the Sem-Eval 2018 Task 1 (EI-OC, EI-Reg, V-OC and V-Reg).

| Dataset Source Domain | Dimension | Label Type | # Instances |
|-----------------------|-----------|------------|-------------|
| Mohammad et al. (2013) | movie | | 16.38 |
| Rosenthal et al. (2014) | Multiple* | | 16.07 |
| Mohammad et al. (2018) | tweets | 13.29 |
| Mohammad et al. (2018) | tweets | 13.05 |
| Mohammad et al. (2018) | tweets | 13.29 |
| Mohammad et al. (2018) | tweets | 13.05 |
| Mohammad et al. (2018) | tweets | 13.29 |
| Mohammad et al. (2018) | tweets | 13.05 |

Table 6: The average number of words per instance includes the train, development, and test sets for the Sem-Eval 2014 Task 9 and the Sem-Eval 2018 Task 1 (EI-OC, EI-Reg, V-OC and V-Reg), and considers the data after tokenizing and only words composed of alphabet letters. Multiple*: The SemEval 2014 dataset has collections of LiveJournal posts (1141), SMS messages (2082), regular tweets (15302), and sarcastic tweets (86) for a total of 18611 instances. The Movie Reviews Categorical dataset is often also referred to as SST-2.

Figure 4: Valence: Spearman correlations between arcs generated using lexicons and gold arcs created from continuously labeled test data.
| Test Data Language | Test Data  | Emotion | OOV   | Lexicon Scores | Bin Size |
|--------------------|-----------|---------|-------|----------------|----------|
|                    | 2018 (El-Reg) | anger   | assigned NA | categorical real-valued | 0.094 0.289 0.427 0.526 0.739 0.876 | 0.081 0.297 0.495 0.566 0.730 0.861 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.095 0.300 0.341 0.350 0.390 0.452 | 0.079 0.285 0.333 0.385 0.512 0.652 |
|                    |           | fear    | assigned NA | categorical real-valued | 0.151 0.367 0.643 0.754 0.889 0.967 | 0.214 0.544 0.796 0.851 0.900 0.910 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.156 0.464 0.739 0.866 0.940 0.982 | 0.207 0.563 0.819 0.918 0.969 0.990 |
|                    |           | joy     | assigned NA | categorical real-valued | 0.157 0.399 0.626 0.716 0.772 0.772 | 0.181 0.500 0.758 0.868 0.955 0.977 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.125 0.330 0.528 0.624 0.727 0.786 | 0.141 0.403 0.616 0.763 0.891 0.911 |
|                    |           | sadness | assigned NA | categorical real-valued | 0.191 0.410 0.657 0.699 0.819 0.877 | 0.199 0.470 0.748 0.819 0.871 0.914 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.173 0.382 0.612 0.645 0.715 0.708 | 0.182 0.446 0.703 0.802 0.940 0.961 |
|                    | Eng       | anger   | assigned NA | categorical real-valued | 0.106 0.252 0.448 0.575 0.677 0.773 | 0.118 0.291 0.484 0.627 0.770 0.862 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.105 0.347 0.561 0.700 0.783 0.846 | 0.115 0.376 0.610 0.751 0.841 0.905 |
|                    |           | fear    | assigned NA | categorical real-valued | 0.231 0.514 0.789 0.880 0.942 0.956 | 0.245 0.556 0.816 0.901 0.947 0.969 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.237 0.576 0.808 0.876 0.948 0.965 | 0.250 0.606 0.829 0.889 0.951 0.972 |
|                    |           | joy     | assigned NA | categorical real-valued | 0.232 0.595 0.867 0.912 0.947 0.954 | 0.248 0.633 0.893 0.936 0.961 0.965 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.209 0.575 0.848 0.906 0.941 0.952 | 0.222 0.617 0.869 0.922 0.956 0.973 |
|                    |           | sadness | assigned NA | categorical real-valued | 0.138 0.391 0.658 0.750 0.843 0.898 | 0.179 0.575 0.798 0.886 0.929 0.953 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.135 0.428 0.693 0.803 0.909 0.941 | 0.174 0.604 0.824 0.901 0.951 0.965 |
|                    | Es        | anger   | assigned NA | categorical real-valued | 0.144 0.389 0.585 0.637 0.648 0.597 | 0.163 0.400 0.660 0.719 0.719 0.691 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.136 0.361 0.610 0.703 0.692 0.654 | 0.159 0.440 0.692 0.767 0.761 0.752 |
|                    |           | fear    | assigned NA | categorical real-valued | 0.149 0.342 0.585 0.688 0.805 0.830 | 0.205 0.527 0.767 0.820 0.900 0.965 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.172 0.476 0.721 0.789 0.816 0.826 | 0.219 0.582 0.800 0.831 0.879 0.897 |
|                    |           | joy     | assigned NA | categorical real-valued | 0.246 0.607 0.888 0.944 0.974 0.983 | 0.287 0.696 0.905 0.953 0.975 0.991 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.201 0.538 0.859 0.939 0.954 0.970 | 0.244 0.637 0.844 0.916 0.944 0.955 |
|                    |           | sadness | assigned NA | categorical real-valued | 0.280 0.576 0.828 0.889 0.943 0.987 | 0.316 0.626 0.893 0.949 0.978 0.991 |
|                    |           |         | assigned neutral score | categorical real-valued | 0.303 0.652 0.875 0.935 0.962 0.980 | 0.332 0.671 0.892 0.951 0.988 0.993 |

Figure 5: Anger, fear, joy and sadness: Spearman correlations between arcs generated using lexicons and gold arcs created from continuously labeled test data.
| Test Data       | Test Data Language | Emotion Scores | Threshold | 1     | 10    | 50    | 100   | 200   | 300   |
|----------------|--------------------|----------------|-----------|-------|-------|-------|-------|-------|-------|
| Movie Reviews  | Eng                | valence        | categorical 0 | 0.296 | 0.701 | 0.852 | 0.861 | 0.860 | 0.862 |
| Categorical    |                    | real-valued    | 0          | 0.335 | 0.750 | 0.859 | 0.863 | 0.863 | 0.864 |
|                |                    |                | 0.1        | 0.335 | 0.749 | 0.859 | 0.863 | 0.863 | 0.864 |
|                |                    |                | 0.25       | 0.335 | 0.750 | 0.859 | 0.863 | 0.863 | 0.863 |
|                |                    |                | 0.5        | 0.317 | 0.739 | 0.858 | 0.862 | 0.864 | 0.862 |
|                |                    |                | 0.75       | 0.266 | 0.685 | 0.856 | 0.863 | 0.865 | 0.861 |
|                |                    |                | 0.9        | 0.133 | 0.414 | 0.723 | 0.819 | 0.860 | 0.862 |
| SemEval 2014   | Eng                | valence        | categorical 0 | 0.317 | 0.725 | 0.878 | 0.924 | 0.963 | 0.987 |
| (LiveJournal)  |                    | real-valued    | 0          | 0.378 | 0.811 | 0.923 | 0.939 | 0.965 | 0.988 |
|                |                    |                | 0.1        | 0.377 | 0.809 | 0.921 | 0.939 | 0.964 | 0.988 |
|                |                    |                | 0.25       | 0.382 | 0.807 | 0.920 | 0.940 | 0.964 | 0.990 |
|                |                    |                | 0.5        | 0.402 | 0.829 | 0.930 | 0.941 | 0.959 | 0.985 |
|                |                    |                | 0.75       | 0.441 | 0.837 | 0.930 | 0.948 | 0.961 | 0.991 |
|                |                    |                | 0.9        | 0.280 | 0.751 | 0.901 | 0.917 | 0.946 | 0.975 |
| SemEval 2014   | Eng                | valence        | categorical 0 | 0.274 | 0.656 | 0.864 | 0.882 | 0.902 | 0.907 |
| (SMS)          |                    | real-valued    | 0          | 0.337 | 0.738 | 0.885 | 0.894 | 0.914 | 0.916 |
|                |                    |                | 0.1        | 0.335 | 0.736 | 0.884 | 0.893 | 0.914 | 0.916 |
|                |                    |                | 0.25       | 0.328 | 0.734 | 0.886 | 0.894 | 0.911 | 0.915 |
|                |                    |                | 0.5        | 0.319 | 0.734 | 0.881 | 0.891 | 0.894 | 0.896 |
|                |                    |                | 0.75       | 0.388 | 0.768 | 0.887 | 0.884 | 0.863 | 0.878 |
|                |                    |                | 0.9        | 0.330 | 0.720 | 0.851 | 0.865 | 0.874 | 0.885 |
| SemEval 2014   | Eng                | valence        | categorical 0 | 0.206 | 0.587 | 0.873 |       |       |       |
| (tweets        |                    | real-valued    | 0          | 0.270 | 0.722 | 0.935 |       |       |       |
| sarcasm)       |                    |                | 0.1        | 0.261 | 0.715 | 0.934 |       |       |       |
|                |                    |                | 0.25       | 0.238 | 0.740 | 0.931 |       |       |       |
|                |                    |                | 0.75       | 0.046 | 0.392 | 0.783 |       |       |       |
|                |                    |                | 0.9        | -0.107 | -0.229 | -0.606 |       |       |       |
| SemEval 2014   | Eng                | valence        | categorical 0 | 0.244 | 0.609 | 0.851 | 0.897 | 0.911 | 0.913 |
| (tweets)       |                    | real-valued    | 0          | 0.322 | 0.728 | 0.898 | 0.912 | 0.915 | 0.915 |
|                |                    |                | 0.1        | 0.322 | 0.728 | 0.899 | 0.912 | 0.915 | 0.915 |
|                |                    |                | 0.25       | 0.320 | 0.729 | 0.900 | 0.912 | 0.914 | 0.915 |
|                |                    |                | 0.5        | 0.340 | 0.759 | 0.908 | 0.913 | 0.915 | 0.916 |
|                |                    |                | 0.75       | 0.381 | 0.809 | 0.914 | 0.915 | 0.916 | 0.920 |
|                |                    |                | 0.9        | 0.293 | 0.713 | 0.866 | 0.906 | 0.914 | 0.918 |
| SemEval 2018   | Eng                | valence        | categorical 0 | 0.427 | 0.850 | 0.964 | 0.976 | 0.979 | 0.980 |
| (V-OC)         |                    | real-valued    | 0          | 0.476 | 0.880 | 0.970 | 0.979 | 0.981 | 0.984 |
|                |                    |                | 0.1        | 0.476 | 0.880 | 0.970 | 0.979 | 0.981 | 0.984 |
|                |                    |                | 0.25       | 0.479 | 0.882 | 0.971 | 0.979 | 0.980 | 0.983 |
|                |                    |                | 0.5        | 0.502 | 0.887 | 0.972 | 0.981 | 0.982 | 0.986 |
|                |                    |                | 0.75       | 0.470 | 0.866 | 0.972 | 0.980 | 0.983 | 0.987 |
|                |                    |                | 0.9        | 0.371 | 0.784 | 0.950 | 0.973 | 0.983 | 0.988 |

Figure 6: Valence: Spearman correlations between arcs generated using lexicons only containing terms with an emotion score above the given threshold and gold arcs created from categorically labeled test data.
Figure 7: Valence: Spearman correlations between arcs generated using lexicons only containing terms with an emotion score above the given threshold and gold arcs created from continuously labeled test data.

| Test Data      | Test Data Language | Emotion Scores | Threshold | 1    | 10   | 50   | 100  | 200  | 300  |
|----------------|--------------------|----------------|-----------|------|------|------|------|------|------|
| Movie Reviews  | Eng                | valence        | categorical | 0.344| 0.763| 0.921| 0.951| 0.972| 0.978|
|                |                    |                | real-valued | 0.386| 0.805| 0.942| 0.965| 0.981| 0.985|
|                |                    |                | 0.1        | 0.385| 0.805| 0.942| 0.965| 0.980| 0.985|
|                |                    |                | 0.25       | 0.385| 0.804| 0.940| 0.964| 0.980| 0.984|
|                |                    |                | 0.33       | 0.381| 0.800| 0.937| 0.960| 0.977| 0.981|
|                |                    |                | 0.5        | 0.369| 0.796| 0.938| 0.961| 0.977| 0.982|
|                |                    |                | 0.66       | 0.357| 0.782| 0.938| 0.963| 0.981| 0.986|
|                |                    |                | 0.75       | 0.310| 0.732| 0.919| 0.951| 0.971| 0.978|
|                |                    |                | 0.9        | 0.154| 0.466| 0.770| 0.860| 0.917| 0.935|
| SemEval 2018   | Eng                | valence        | categorical | 0.438| 0.845| 0.959| 0.978| 0.991| 0.997|
| (V-Reg)        |                    |                | real-valued | 0.488| 0.874| 0.964| 0.979| 0.990| 0.997|
|                |                    |                | 0.1        | 0.488| 0.874| 0.965| 0.979| 0.991| 0.997|
|                |                    |                | 0.25       | 0.491| 0.874| 0.965| 0.979| 0.991| 0.997|
|                |                    |                | 0.33       | 0.498| 0.878| 0.966| 0.981| 0.992| 0.997|
|                |                    |                | 0.5        | 0.513| 0.882| 0.967| 0.980| 0.991| 0.998|
|                |                    |                | 0.66       | 0.499| 0.877| 0.965| 0.980| 0.990| 0.997|
|                |                    |                | 0.75       | 0.479| 0.868| 0.963| 0.978| 0.987| 0.996|
|                |                    |                | 0.9        | 0.379| 0.796| 0.942| 0.956| 0.979| 0.987|

Correlation: 0.000 to 1.000
| Test Data Language | Emotion Scores | Threshold | 1  | 10  | 50  | 100 | 200 | 300 |
|-------------------|---------------|-----------|----|-----|-----|-----|-----|-----|
| **SemEval 2018**  | **Eng**       | **anger** | **categorical** | 0 | 0.105 | 0.329 | 0.644 | 0.765 | 0.824 | 0.846 |
|                   |               |           | **real-valued** | 0 | 0.116 | 0.365 | 0.691 | 0.797 | 0.847 | 0.875 |
|                   |               |           | 0.1          |   | 0.115 | 0.364 | 0.690 | 0.796 | 0.846 | 0.875 |
|                   |               |           | 0.25         |   | 0.117 | 0.367 | 0.691 | 0.795 | 0.846 | 0.875 |
|                   |               |           | 0.33         |   | 0.119 | 0.370 | 0.695 | 0.801 | 0.851 | 0.879 |
|                   |               |           | 0.5          |   | 0.120 | 0.375 | 0.714 | 0.816 | 0.860 | 0.883 |
|                   |               |           | 0.66         |   | 0.140 | 0.396 | 0.722 | 0.825 | 0.877 | 0.908 |
|                   |               |           | 0.75         |   | 0.149 | 0.421 | 0.766 | 0.863 | 0.899 | 0.932 |
|                   |               |           | 0.9          |   | 0.031 | 0.086 | 0.191 | 0.281 | 0.323 | 0.362 |
|                   |              | **fear**  | **categorical** | 0 | 0.199 | 0.495 | 0.744 | 0.802 | 0.803 | 0.789 |
|                   |               |           | **real-valued** | 0 | 0.209 | 0.522 | 0.751 | 0.788 | 0.782 | 0.773 |
|                   |               |           | 0.1          |   | 0.209 | 0.523 | 0.752 | 0.787 | 0.781 | 0.772 |
|                   |               |           | 0.25         |   | 0.213 | 0.523 | 0.752 | 0.789 | 0.783 | 0.774 |
|                   |               |           | 0.33         |   | 0.211 | 0.519 | 0.747 | 0.783 | 0.779 | 0.772 |
|                   |               |           | 0.5          |   | 0.180 | 0.467 | 0.716 | 0.757 | 0.756 | 0.759 |
|                   |               |           | 0.66         |   | 0.158 | 0.424 | 0.656 | 0.732 | 0.737 | 0.744 |
|                   |               |           | 0.75         |   | 0.183 | 0.462 | 0.704 | 0.766 | 0.769 | 0.772 |
|                   |               |           | 0.9          |   | 0.102 | 0.314 | 0.549 | 0.607 | 0.663 | 0.738 |
|                   |              | **joy**   | **categorical** | 0 | 0.196 | 0.560 | 0.786 | 0.843 | 0.863 | 0.875 |
|                   |               |           | **real-valued** | 0 | 0.208 | 0.607 | 0.820 | 0.857 | 0.874 | 0.883 |
|                   |               |           | 0.1          |   | 0.207 | 0.606 | 0.820 | 0.857 | 0.874 | 0.882 |
|                   |               |           | 0.25         |   | 0.210 | 0.608 | 0.821 | 0.857 | 0.874 | 0.883 |
|                   |               |           | 0.33         |   | 0.215 | 0.616 | 0.828 | 0.861 | 0.876 | 0.886 |
|                   |               |           | 0.5          |   | 0.224 | 0.622 | 0.831 | 0.864 | 0.878 | 0.887 |
|                   |               |           | 0.66         |   | 0.235 | 0.630 | 0.845 | 0.878 | 0.885 | 0.898 |
|                   |               |           | 0.75         |   | 0.220 | 0.577 | 0.822 | 0.869 | 0.881 | 0.888 |
|                   |               |           | 0.9          |   | 0.039 | 0.150 | 0.355 | 0.470 | 0.540 | 0.553 |
|                   |              | **sadness** | **categorical** | 0 | 0.144 | 0.430 | 0.706 | 0.761 | 0.819 | 0.855 |
|                   |               |           | **real-valued** | 0 | 0.181 | 0.582 | 0.841 | 0.881 | 0.895 | 0.910 |
|                   |               |           | 0.1          |   | 0.184 | 0.582 | 0.842 | 0.881 | 0.895 | 0.910 |
|                   |               |           | 0.25         |   | 0.178 | 0.577 | 0.837 | 0.879 | 0.893 | 0.906 |
|                   |               |           | 0.33         |   | 0.202 | 0.605 | 0.857 | 0.890 | 0.900 | 0.916 |
|                   |               |           | 0.5          |   | 0.235 | 0.667 | 0.886 | 0.904 | 0.915 | 0.930 |
|                   |               |           | 0.66         |   | 0.261 | 0.693 | 0.897 | 0.924 | 0.940 | 0.953 |
|                   |               |           | 0.75         |   | 0.266 | 0.688 | 0.904 | 0.929 | 0.944 | 0.959 |
|                   |               |           | 0.9          |   | 0.197 | 0.536 | 0.769 | 0.856 | 0.902 | 0.911 |

Correlation 0.000 | 1.000

Figure 8: Anger, fear, joy and sadness: Spearman correlations between arcs generated using lexicons only containing terms with an emotion score above the given threshold and gold arcs created from categorically labeled test data.
| Test Data | Language | Emotion | Lexicon Scores | Threshold | 1    | 10   | 50   | 100  | 200  | 300  |
|-----------|----------|---------|----------------|-----------|------|------|------|------|------|------|
| SemEval   | Eng      | anger   | categorical    | 0         | 0.105| 0.347| 0.561| 0.700| 0.783| 0.846|
| 2018      |          |         | real-valued    | 0         | 0.115| 0.376| 0.610| 0.751| 0.841| 0.905|
| (EI-Reg)  |          |         |                | 0.1       | 0.112| 0.375| 0.610| 0.750| 0.840| 0.904|
|           |          |         |                | 0.25      | 0.113| 0.374| 0.609| 0.751| 0.843| 0.907|
|           |          |         |                | 0.33      | 0.115| 0.375| 0.615| 0.759| 0.851| 0.913|
|           |          |         |                | 0.5       | 0.116| 0.375| 0.620| 0.767| 0.863| 0.929|
|           |          |         |                | 0.66      | 0.137| 0.405| 0.672| 0.792| 0.876| 0.932|
|           |          |         |                | 0.75      | 0.147| 0.429| 0.720| 0.841| 0.933| 0.962|
|           |          |         |                | 0.9       | 0.233| 0.801| 0.177| 0.240| 0.211| 0.162|
| fear      | categorical | 0      | 0.237| 0.576| 0.808| 0.876| 0.948| 0.965|
|           | real-valued | 0      | 0.250| 0.606| 0.829| 0.889| 0.951| 0.972|
|           |            | 0.1    | 0.252| 0.607| 0.829| 0.888| 0.950| 0.972|
|           |            | 0.25   | 0.255| 0.611| 0.832| 0.892| 0.952| 0.974|
|           |            | 0.33   | 0.251| 0.604| 0.826| 0.887| 0.951| 0.974|
|           |            | 0.5    | 0.217| 0.551| 0.803| 0.868| 0.932| 0.967|
|           |            | 0.66   | 0.184| 0.484| 0.764| 0.854| 0.922| 0.957|
|           |            | 0.75   | 0.199| 0.507| 0.770| 0.845| 0.918| 0.960|
|           |            | 0.9    | 0.125| 0.373| 0.673| 0.804| 0.870| 0.884|
| joy       | categorical | 0      | 0.209| 0.575| 0.848| 0.906| 0.941| 0.952|
|           | real-valued | 0      | 0.222| 0.617| 0.868| 0.922| 0.956| 0.973|
|           |            | 0.1    | 0.221| 0.617| 0.868| 0.922| 0.956| 0.974|
|           |            | 0.25   | 0.223| 0.619| 0.870| 0.923| 0.958| 0.976|
|           |            | 0.33   | 0.230| 0.624| 0.873| 0.927| 0.962| 0.979|
|           |            | 0.5    | 0.237| 0.629| 0.869| 0.922| 0.963| 0.981|
|           |            | 0.66   | 0.244| 0.616| 0.872| 0.918| 0.964| 0.982|
|           |            | 0.75   | 0.229| 0.568| 0.833| 0.899| 0.962| 0.979|
|           |            | 0.9    | 0.043| 0.146| 0.358| 0.504| 0.595| 0.646|
| sadness   | categorical | 0      | 0.135| 0.428| 0.693| 0.803| 0.909| 0.941|
|           | real-valued | 0      | 0.174| 0.604| 0.824| 0.901| 0.951| 0.965|
|           |            | 0.1    | 0.177| 0.605| 0.824| 0.901| 0.952| 0.965|
|           |            | 0.25   | 0.172| 0.598| 0.819| 0.896| 0.950| 0.962|
|           |            | 0.33   | 0.200| 0.632| 0.836| 0.910| 0.953| 0.966|
|           |            | 0.5    | 0.234| 0.688| 0.874| 0.923| 0.953| 0.966|
|           |            | 0.66   | 0.260| 0.697| 0.880| 0.920| 0.955| 0.975|
|           |            | 0.75   | 0.264| 0.694| 0.887| 0.920| 0.945| 0.959|
|           |            | 0.9    | 0.197| 0.552| 0.800| 0.821| 0.831| 0.848|

Figure 9: Anger, fear, joy and sadness: Spearman correlations between arcs generated using lexicons only containing terms with an emotion score above the given threshold and gold arcs created from continuously labeled test data.
| Test data        | Emotion | Instance OS: Accuracy | Bin Size |
|------------------|---------|-----------------------|----------|
|                  |         |                       | 1   | 10 | 50 | 100 | 200 | 300 |
| SemEval 2014 (LiveJournal) | valence | 0                     | -0.474 | -0.853 | -0.935 | -0.959 | -0.974 | -0.994 |
|                  |         | 20                    | -0.154 | -0.451 | -0.750 | -0.850 | -0.943 | -0.978 |
|                  |         | 40                    | 0.113  | 0.348  | 0.649  | 0.780  | 0.824  | 0.864  |
|                  |         | 60                    | 0.378  | 0.839  | 0.947  | 0.958  | 0.981  | 0.995  |
|                  |         | 80                    | 0.683  | 0.993  | 0.947  | 0.964  | 0.985  | 0.997  |
|                  |         | 100                   | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |
| SemEval 2014 (SMS) | valence | 0                     | -0.361 | -0.777 | -0.863 | -0.850 | -0.829 | -0.798 |
|                  |         | 20                    | -0.126 | -0.387 | -0.655 | -0.735 | -0.774 | -0.806 |
|                  |         | 40                    | 0.080  | 0.229  | 0.478  | 0.621  | 0.691  | 0.761  |
|                  |         | 60                    | 0.358  | 0.756  | 0.866  | 0.877  | 0.886  | 0.903  |
|                  |         | 80                    | 0.654  | 0.880  | 0.894  | 0.901  | 0.916  | 0.932  |
|                  |         | 100                   | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |
| SemEval 2014 (tweets sarcasm) | valence | 0                     | -0.562 | -0.797 | -0.995 |
|                  |         | 20                    | -0.160 | -0.652 | -0.887 |
|                  |         | 40                    | 0.180  | 0.707  | 0.958  |
|                  |         | 60                    | 0.502  | 0.904  | 0.995  |
|                  |         | 80                    | 0.754  | 0.921  | 0.999  |
|                  |         | 100                   | 1.000  | 1.000  | 1.000  |
| SemEval 2014 (tweets) | valence | 0                     | -0.403 | -0.823 | -0.917 | -0.919 | -0.921 | -0.923 |
|                  |         | 20                    | -0.170 | -0.480 | -0.780 | -0.870 | -0.908 | -0.911 |
|                  |         | 40                    | 0.092  | 0.281  | 0.553  | 0.694  | 0.824  | 0.882  |
|                  |         | 60                    | 0.367  | 0.783  | 0.913  | 0.916  | 0.917  | 0.918  |
|                  |         | 80                    | 0.663  | 0.914  | 0.918  | 0.918  | 0.920  | 0.922  |
|                  |         | 100                   | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |

Figure 10: Valence: Spearman correlations of the arcs generated using the Oracle System with the gold arcs created from the categorically labeled Sem-Eval 2014 test data. Note: ‘OS (Accuracy)’ refers to the accuracy of the Oracle System on instance-level sentiment classification.
Figure 11: Emotions: Spearman correlations of the arcs generated using the Oracle System with the gold arcs created from the *categorically* labeled Sem-Eval 2018 test data. Note: ‘OS (Accuracy)’ refers to the accuracy of the Oracle System on instance-level sentiment classification.

| Test data | Emotion | Instance OS: Accuracy | 1     | 10    | 50    | 100   | 200   | 300   |
|-----------|---------|-----------------------|-------|-------|-------|-------|-------|-------|
| SemEval 2018 (EI-OC) | anger 0 | -0.347                | -0.759 | -0.917 | -0.947 | -0.962 | -0.975 |
|           |         | 20                   | -0.093 | -0.275 | -0.575 | -0.731 | -0.854 | -0.914 |
|           |         | 40                   | 0.198  | 0.530  | 0.845  | 0.913  | 0.941  | 0.952  |
|           |         | 60                   | 0.488  | 0.880  | 0.961  | 0.963  | 0.966  | 0.974  |
|           |         | 80                   | 0.744  | 0.953  | 0.963  | 0.967  | 0.975  | 0.981  |
|           |         | 100                  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |
|           | fear 0  | -0.292                | -0.635 | -0.804 | -0.847 | -0.860 | -0.868 |
|           |         | 20                   | -0.066 | -0.199 | -0.409 | -0.499 | -0.637 | -0.736 |
|           |         | 40                   | 0.177  | 0.475  | 0.741  | 0.778  | 0.786  | 0.813  |
|           |         | 60                   | 0.426  | 0.758  | 0.843  | 0.852  | 0.860  | 0.868  |
|           |         | 80                   | 0.679  | 0.833  | 0.849  | 0.853  | 0.859  | 0.864  |
|           |         | 100                  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |
|           | joy 0   | -0.329                | -0.754 | -0.933 | -0.965 | -0.974 | -0.980 |
|           |         | 20                   | -0.084 | -0.269 | -0.631 | -0.779 | -0.884 | -0.921 |
|           |         | 40                   | 0.177  | 0.509  | 0.802  | 0.882  | 0.916  | 0.933  |
|           |         | 60                   | 0.447  | 0.861  | 0.957  | 0.963  | 0.972  | 0.983  |
|           |         | 80                   | 0.740  | 0.958  | 0.971  | 0.975  | 0.980  | 0.988  |
|           |         | 100                  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |
|           | sadness 0 | -0.345              | -0.769 | -0.927 | -0.949 | -0.962 | -0.969 |
|           |         | 20                   | -0.091 | -0.294 | -0.574 | -0.688 | -0.839 | -0.891 |
|           |         | 40                   | 0.201  | 0.528  | 0.822  | 0.890  | 0.922  | 0.938  |
|           |         | 60                   | 0.490  | 0.880  | 0.952  | 0.956  | 0.970  | 0.977  |
|           |         | 80                   | 0.725  | 0.947  | 0.957  | 0.959  | 0.963  | 0.965  |
|           |         | 100                  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |
|           | SemEval 2018 (V-OC) | valence 0 | -0.125 | -0.390 | -0.703 | -0.801 | -0.872 | -0.893 |
|           |         | 20                   | 0.092  | 0.262  | 0.489  | 0.607  | 0.783  | 0.846  |
|           |         | 40                   | 0.320  | 0.715  | 0.927  | 0.959  | 0.979  | 0.985  |
|           |         | 60                   | 0.505  | 0.861  | 0.965  | 0.977  | 0.986  | 0.992  |
|           |         | 80                   | 0.730  | 0.963  | 0.982  | 0.984  | 0.988  | 0.995  |
|           |         | 100                  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  | 1.000  |