Abstract

Ideological attitudes and stance are often expressed through subtle meanings of words and phrases. Understanding these connotations is critical to recognizing the cultural and emotional perspectives of the speaker. In this paper, we use distant labeling to create a new lexical resource representing connotation aspects for nouns and adjectives. Our analysis shows that it aligns well with human judgments. Additionally, we present a method for creating lexical representations that captures connotations within the embedding space and show that using the embeddings provides a statistically significant improvement on the task of stance detection when data is limited.

1 Introduction

Expressions of ideological attitudes are widespread in today’s online world, influencing how we perceive and react to events and people on a daily basis. These attitudes are often expressed through subtle expressions or associations (Somasundaran and Wiebe, 2010; Murakami and Putra, 2010). For example, the sentence “the people opposed gun control” conveys no information about the author’s opinion. However, by adding just one word, “the selfish people opposed gun control”, the author can convey their stance on both gun control (against) and the people who support it (not valuable and disliked). Discerning such linguistic subtleties is crucial for fully understanding and recognizing the hidden influences behind the barrage of content we encounter every day.

Recent studies in NLP have begun to examine these hidden influences through framing in social media and news (Asur and Huberman, 2010; Hartmann et al., 2019; Klenner, 2017) and style detection in hyperpartisan news (Potthast et al., 2018). Lexical connotations provide a method to study these influences, including stance, in more detail.

Connotations are implied cultural and emotional associations for words that augment their literal meanings (Carpuat, 2015; Feng et al., 2011). A connotation value is associated with a phrase (e.g., fear is associated with “cancer”) (Feng et al., 2011) and capture a wide range of nuances, such as whether a phrase is an insult or whether it implies value (see Figure 1).

In this paper, we define six new fine-grained connotation aspects for nouns and adjectives, filling a gap in the literature on connotation lexica which has focused on verbs (Sap et al., 2017; Rashkin et al., 2016; Rashkin et al., 2017) and coarse-grained polarity (Feng et al., 2011; Kang et al., 2014). We create a new distantly labeled lexicon that maps nouns and adjectives to our six aspects and show that it aligns well with human judgments.

We then learn a single connotation embedding space for words from all parts of speech, combining our lexicon with existing verb lexica and contributing to the literature on unifying lexica (Hoyle et al., 2019).
Intrinsic evaluation shows that our embeddings space captures clusters of connotatively-similar words. In addition, our embedding model can generate representations for new words without the numerous training examples required by standard word-embedding methods. Finally, we show that our connotation embeddings improve performance on stance detection, particularly in a low-resource setting.

Our contributions are as follows: (1) we create a new connotation lexicon and show that it aligns well with human judgments, (2) we train a connotation feature embedding for all parts of speech and show that it captures connotations within the embedding space, and (3) we show the connotation embeddings improve stance detection when data is limited. Our lexicon and embeddings will be made available.

2 Related Work

Studies of connotation build upon the literature examining subtle language nuances, including good and bad effects of verbs (Choi and Wiebe, 2014), evoked sentiments and emotions (Mohammad et al., 2013a; Mohammad and Turney, 2010; Mohammad, 2018b), multi-dimensional sentiment (Whissell, 2009; Mohammad, 2018a; Whissell, 1989), offensiveness (Klenner et al., 2018), and psycho-sociological properties of words (Stone and Hunt, 1963; Tausczik and Pennebaker, 2009). Work explicitly on connotations has focused primarily on detailed aspects for verbs (Rashkin et al., 2016; Rashkin et al., 2017; Sap et al., 2017; Klenner, 2017) or single polarities for many parts of speech (Feng et al., 2011; Feng et al., 2013; Kang et al., 2014). One exception is the work of Field et al. (2019), which extends limited detailed connotation dimensions from verbs to nouns within the context of certain verbs. Our work is unique in directly defining detailed aspects for nouns and adjectives.

Early work on stance detection applied topic-specific models to various genres, including online debate forums (Sridhar et al., 2015; Somasundaran and Wiebe, 2010; Murakami and Putra, 2010; Hasan and Ng, 2013; Hasan and Ng, 2014) and student essays (Paulkner, 2014). More recent studies have used a single model for many topics to predict stance in Tweets (Mohammad et al., 2016; Augenstein et al., 2016; Xu et al., 2018) and as part of the fact extraction and verification pipeline (Conforti et al., 2018; Ghanem et al., 2018; Riedel et al., 2017; Hanselowski et al., 2018). Klenner et al. (2017) explore the relationship between connotations and stance through verb frames. In contrast, our work studies stance using connotation representations from a learned joint embedding space for words from all parts of speech. Representation learning has been used for stance detection of online debates by Li et al. (2018), who develop a joint representation of the text and the authors. Our work, however, uses a representation of word connotations and does not use any author information (a strong feature in fully-supervised datasets but which may not be available in real-world settings).

3 Connotation Lexicon

We build a connotation lexicon for nouns and adjectives by defining six new aspects of connotation. We take inspiration from verb connotation frames and their extensions (Rashkin et al., 2016; Sap et al., 2017), which define aspects of connotation in terms of the agent and theme of transitive verbs. Rashkin et al. (2016) define six aspects of connotation for verbs (entities’, writer’s, and reader’s perspectives, effect, value, and mental state) in connotation frames (e.g., “suffer” ← negative effect on the agent) and Sap et al. (2017) extend these aspects to include power and agency.

We first define the six new aspects of connotation for nouns and adjectives in our work, then we describe our distant labeling procedure (§3.2) and human evaluation of the final lexicon (§3.3).

3.1 Definitions

We use $w$ to indicate a word and $w'$ to indicate the person, thing or attribute signified by $w$.

For each $w$, we define (1) **Social Value**: whether $w'$ is considered valuable by society, (2) **Politeness (Polite)**: whether $w$ is a socially polite term, (3) **Impact** whether $w'$ has an impact on society (or the thing modified by $w$ if $w$ is an adjective), (4) **Factuality (Fact)**: whether $w'$ is tangible, (5) **Sentiment (Sent)**: the sentiment polarity of $w'$, and (6) **Emotional association (Emo)**: the emotions associated with $w'$. We show examples in Table 1.

(1) **Social Value** includes both the value of objects or things and the social status and power of people
| Aspect       | Lexicon | Example Rules | Examples                  |
|--------------|---------|---------------|---------------------------|
| Social Value | GI      | Authoritative power $\rightarrow$ valuable | attorney $\sim$ valuable (+) |
|              |         | Related to failure $\rightarrow$ not valuable | aimless $\sim$ not valuable (-) |
| Politeness   | GI      | Gain of respect $\rightarrow$ polite | commendable $\sim$ polite (+) |
|              |         | Loss of affection $\rightarrow$ impolite | alienation $\sim$ impolite (-) |
| Impact       | GI      | Virtue $\rightarrow$ positive | adept $\sim$ positive impact (+) |
|              |         | Loss of well-being $\rightarrow$ negative | shock $\sim$ negative impact (-) |
| Factuality   | DAL     | Imagery$(w) > \theta_F \rightarrow$ factual | rocky $\sim$ factual (+) |
|              |         | Imagery$(w) < -\theta_F \rightarrow$ not factual | tradition $\sim$ not factual(-) |
| Sentiment    | CWN     | $v > \theta_S \rightarrow$ positive | song $\sim$ positive (+) |
|              |         | $v < -\theta_S \rightarrow$ negative | cancerous $\sim$ negative (-) |
| Emotional Association | NRC  | emotions $E \subseteq \{\text{anger, joy, fear, trust, anticipation, sadness, disgust, surprise}\}$ | snake $\sim$ disgusting, fear | effective $\sim$ trust |

Table 1: Example mappings from existing lexica to our connotation aspects. GI: Harvard General Inquirer, DAL: Dictionary of Affect in Language, CWN: Connotation WordNet, and NRC: NRC Emotion Lexicon. Scores for imagery, Imagery$(w)$, and sentiment, $v$, are real-valued.

or people-referring nouns (e.g., occupations). “Sociocultural pragmatic reasoning” (Colston and Katz, 2005) about such factors is crucial for understanding non-literal language such as connotations.

Initial work on connotation polarity lexica recognized the important role of Social Value in overall connotation by defining a ‘positive’ connotation for objects and concepts that people value (Feng et al., 2011). Later work made this idea more explicit by defining ‘Value’ for transitive verb arguments in connotation frames. More recently ‘power’ and ‘agency’, components of Social Value, have been defined for verbs in connotation frames and for nouns in context (Field et al., 2019) and have been used to analyze bias and framing in a variety of texts, illustrating the applications and importance of Social Value in connotations.

(2) Politeness follows the definition of Lakoff (1973) in noting words that make the addressee feel good but also includes notions of formality. These notions have been previously studied within the context of politeness as a set of behaviors and linguistic cues (Brown and Levinson, 1987; Danescu-Niculescu-Mizil et al., 2013; Aubakirova and Bansal, 2016). We focus on purely lexical distinctions because how one comprehends these distinctions affects one’s “attitude towards the speaker ... or some issue” as well as whether one feels insulted by the exchange (Colston and Katz, 2005). This aspect of perspective is a component of verb connotation frames and we extend it to nouns and adjectives in our lexicon through Politeness.

(3) Impact and effect have been studied in verb connotation frames and other verb lexica (Choi and Wiebe, 2014), capturing notions of implicit benefit or harm on the arguments of the verb. We extend this idea to nouns and adjectives by observing that while they do not directly have arguments, nouns (e.g. “democracy”) often impact society and adjectives (e.g. “sick”) impact the nouns they modify. Thus, we define Impact in this way.

(4) Factuality captures whether words correspond to real-world objects or attributes, following the sense of Saurí and Pustejovsky (2009). Klenner and Clematide (2016) argue that the factuality of events is crucial for understanding sentiment inferences. Building upon this, Klenner et al. (2017) use factuality as a key component of German verb connotations and of applying those connotations to analyze stance and sides in German Facebook posts. Imagery, as an “indicator of abstraction” (Whissell, 2009), also models a similar attribute to event factuality for all parts of speech. Given its importance, we include a notion of Factuality for nouns and adjectives as aspect of connotations.

(5) Sentiment polarity has been used to convey overall connotations since the early work on connotation lexica (Feng et al., 2011; Feng et al., 2013; Kang et al., 2014). As such, we deem it important to include this polarity in our lexicon.

(6) Emotional Associations for words can be strong, persisting long after they are formed and improving the recall of memories triggered by those words (Rubin, 2006). Emotions are also impacted
when people process non-literal meaning (Colston and Katz, 2005). To fully understand what a piece of text is trying to convey, it is important to understand what emotional associations exist in the text. For example, news headlines often aim to evoke strong emotions in their readers (Mohammad and Turney, 2013). To capture this, we include Emotional Association as an aspect of connotation.

3.2 Labeling Connotations

We use distant labeling to build our lexicon, since complete manual annotation of a lexical resource is a lengthy and costly process. Although crowdsourcing can lessen these burdens, the results are often unreliable with low inter-annotator agreement and, for this reason, many lexical resources are automatically created (Mohammad, 2012; Mohammad et al., 2013b; Kang et al., 2014). Following these researchers, we automatically generate our lexicon by combining several existing lexica.

To generate our lexicon, we map dimensions from existing lexica to connotation aspects (see Table 1). We use dimensions from the Harvard General Inquirer (Stone and Hunt, 1963) for Social Value, Politeness, and Impact. For Factuality we map the real-valued ‘Imagery’ dimension, Imagery($w$), from the revised Dictionary of Affect in Language (Whissell, 2009) into distinct classes. For Sentiment we directly use the polarity $v$ from Connotation WordNet (Kang et al., 2014) and for Emotional Association we use the eight Plutchik emotions (Plutchik, 2001) from the NRC Emotion Lexicon (Mohammad and Turney, 2013) (see appendix A for full rules).

The labels are word-sense-independent, following other automatically generated lexica, such as the Sentiment140 lexicon (Mohammad et al., 2013b), which do not treat word sense. In addition, sense-level annotations are not available for all lexica in our distant labeling method and therefore sense-level connotations would require both extensive manual annotation and automated word-sense disambiguation, introducing cost and additional noise. As a result, we use sense-level distinctions (e.g., in the Harvard General Inquirer) when available and combine the labels for an aspect across senses to generate the final connotation aspect label for a word.

Our resulting lexicon has 7,578 words fully-labeled for all aspects, with an additional ~93k words labeled only for some aspects (e.g., only Sentiment), resulting in 100,176 words total. For each non-emotion aspect, we have a label $l \in \{-1, 0, 1\}$. For Emotional Association, each of the eight emotions has label $l \in \{0, 1\}$.

We find that many aspects exhibit uneven class distributions (e.g., 10.5% of words are polite and only 1% are impolite) (see Table 2). For emotions, we calculate the class distribution using the number of fully-labeled words with at least one associated emotion (1,373 words or 18%). For these 1,373 words, the average number of associated emotions is ~2. Our distributions are similar to previous work on verb connotations, where distributions range from 1.4% to 20.2% for the smallest class (Rashkin et al., 2016).

3.3 Evaluation of the Lexical Resource

We evaluate the quality of the lexicon by creating a gold-labeled set and comparing the labels created with distant supervision against the human labels. We ask nine NLP researchers to annotate 350 words (175 nouns, 175 adjectives) for Social Value, Politeness, Impact and Factuality. We do not annotate Sentiment or Emotional Association, since these labels are taken directly from existing lexica.

Annotators are given a word $w$, along with its definitions (for all senses) and related words, and annotate connotation independent of word sense. This setup mimics the input to the representation learning models in §4. The average Fleiss’ $\kappa$ across nouns and adjectives is 0.60 (see Table 3), indicating substantial agreement. We select as the final annotator label the majority vote of three annotators.

We find that the distantly labeled lexicon agrees with human annotators the majority of the time (64.2% on average). If we consider non-conflicting value agreement (NC), the lexicon agreement with humans rises to 90%, where NC agreement is defined as: the pairs (+, neutral) and (−, neutral) agree but (+,−)

\begin{table}[h]
\centering
\begin{tabular}{lccc}
\hline
Aspect     & \% + & \% − \\
\hline
Social Value & 32.1 & 15.5 \\
Politeness  & 10.5 & 1.0  \\
Impact      & 14.8 & 13.3 \\
Factuality  & 19.0 & 67.2 \\
Sentiment   & 56.8 & 33.1 \\
\hline
\end{tabular}
\caption{Class distributions in the connotation lexicon for fully-labeled words.}
\end{table}

1 native English speakers recruited from Columbia University
does not. This shows that the lexicon and humans rarely select opposite values and instead disagree on the distinction of neutral vs. non-neutral.

Looking closer at disagreements between neutral and non-neutral, we see that the majority result from human annotators selecting a non-neutral label. That is, the lexicon makes fewer distinctions between neutral and non-neutral than humans; humans select a non-neutral value 68% of the time, compared to 56% in the lexicon. Despite this tendency towards neutral, the lexicon aligns with human judgments, agreeing the majority of the time and rarely providing a value opposite to humans.

### 4 Connotation Embedding

#### 4.1 Methods

Using our connotation lexicon, we train a dense connotation feature representation for words from all parts of speech. We combine three lexica (our lexicon and two verb lexica) into a single vector space, making connotations easier to use as model input and providing a single representation method for the connotations of any word.

We design a novel multi-task learning model that jointly predicts all of the connotation labels for a word $w$, from a learned representation $v_w$. Each task is to predict the label for one connotation aspect: one of the six aspects in §3.2 for nouns and adjectives and one of the 11 aspects in Connotation Frames+ (denoting connotation frames and their extension to power and agency) for verbs (Rashkin et al., 2016; Sap et al., 2017).

To learn a representation for $w$ we encode dictionary definitions of the word $w$ and words related to $w$ (e.g., synonyms) in a single vector, which we then use to predict connotation labels. We use definitions and related words since linguists have argued that definitions and related words convey a word’s meaning (Guralnik, 1958).

Let $w$ be a word with part of speech $t$. The input to the connotation encoding model is then: (1) a set of dictionary definitions $D_{wt}$ and (2) a set of words related to $w^t$, $R_{wt}$. We use multiple definitions to capture multiple senses of $w^t$. To emphasize more prevalent senses of $w^t$, we use similar repeated definitions for the same sense, collected from multiple sources. From $D_{wt}$ and $R_{wt}$, the encoder produces a connotation feature embedding $v_{wt} \in \mathbb{R}^d$ of dimension $d = 300$. Then we use $v_{wt}$ to predict the label $\ell_a$ for each connotation aspect $a$ (see Figure 2).

#### 4.1.1 Encoding Models

For a word $w^t$, the input to our encoder is $d_{wt} = [d_{wt}^1; d_{wt}^2; \ldots; d_{wt}^N] \in \mathbb{R}^{Nd_{in}}$, the sequence of fixed pre-trained token embeddings for concatenated definitions in $D_{wt}$. Then we take as our embedding the normalized final hidden state from a BiLSTM, a standard architecture for text encoding: $v_{wt} = \frac{h_{wt}}{||h_{wt}||}$, where $h_{wt} = \text{BiLSTM}(d_{wt})$ and $h_{wt} \in \mathbb{R}^{2H}$ is the concatenation of the last forward and backward hidden states (model CE).

As a variation of our model, we apply scaled dot-product attention (Vaswani et al., 2017) over the related words $R_{wt}$, using $h_{wt}$ as the attention query, to obtain $v_{wt}$. Then we add the result to $h_{wt}$ before normalizing in (model CE+R).

| Aspect   | Avg $\kappa$ | Avg % Agree | Lex % Agree | Lex % NC |
|----------|--------------|-------------|-------------|----------|
| Social   | .699         | 88.9        | 68.6        | 92.6     |
| Value    | .381         | 56.6        | 59.4        | 95.1     |
| Politeness | .630        | 87.6        | 73.7        | 94.6     |
| Impact   | .675         | 86.3        | 58.0        | 77.7     |
| Average  | .596         | 87.9        | 64.2        | 90.0     |

Table 3: Lexicon annotation results. Fleiss’ $\kappa$ and % agreement are averaged across nouns and adjectives. Lex % is agreement between annotators and the lexicon. NC indicates non-conflicting value agreement.
4.1.2 Label Classifier

For each connotation aspect, we train a separate linear layer plus softmax with the input \([v_{\text{wt}}; e_{\text{wt}}]\). For the non-emotion aspects, the layer has three target classes \([-1, 0, 1]\) for most aspects (four classes for the ‘power’ and ‘agency’ verb aspects) and we predict the label with highest output probability. For emotions, we do multi-label classification by thresholding the output probabilities for each emotion dimension with a fixed \(\theta \in \mathbb{R}\). We include \(e_{\text{wt}}\) in the predictor input to encourage \(v_{\text{wt}}\) to model connotation information that is complementary to the information already present in pre-trained word embeddings.

4.1.3 Learning

For each non-emotion connotation aspect \(a\) (e.g., Impact) we calculate the weighted cross-entropy loss \(L^a\). For the emotion aspect we calculate the one-versus-all cross-entropy loss on each of the eight emotions, \(L^\text{Emo}_i\) for \(1 \leq i \leq 8\), and sum them to obtain \(L^\text{Emo}\).

In our multi-task, joint learning framework we minimize the weighted sum of \(L^a\) across all connotation aspects (models \((J)\)). We also experiment with learning each connotation label classifier individually, training a separate encoding model for each connotation aspect \(a\) that minimizes \(L^a\) (models \((S)\)).

4.1.4 Baselines and Models

For each baseline, we implement one classifier per connotation aspect, or, for \(\text{Emo}\), one classifier for each emotion. Following Rashkin et al. (2016) we implement a Logistic Regression classifier trained on the 300-dimensional pre-trained word embedding for \(w\) using the standard L-BFGS optimization algorithm and sample re-weighting (LR). We also implement a majority class baseline (Maj).

We present three variations of our model: (i) our model trained jointly for all parts of speech on all connotation aspects without attention (CE \((J)\)), (ii) our model trained on each aspect individually with related word attention (CE+R \((S)\)), and (iii) our model trained jointly on all parts of speech and all connotation aspects with related word attention (CE+R \((J)\)).

4.2 Connotation Prediction

4.2.1 Data and Parameters

For nouns and adjectives, we train using the aspects described in §3 (6 aspects). For verbs, we train on 9 aspects \(^2\) from Rashkin et al. (2016) as well as ‘power’ and ‘agency’ from Sap et al. (2017) (11 aspects total). We split our connotation lexicon (§3) into train (60%), development (20%) and test (20%). For the verb Connotation Frames+, we preserve the originally published data splits where possible. We move words only to ensure that all parts of speech for a word are in the same split (e.g., ‘evil’ (noun) and ‘evil’ (adj) are both in the development set).

We collect dictionary definitions and related words from all seven dictionaries available on the Wordnik API\(^3\). These are extracted for each word and part-of-speech pair. We preprocess definitions by removing stopwords, punctuation, and the word itself. We train our models using pre-trained Concept-Net numberbatch embeddings, with \(d_{in} = 300\) (Speer et al., 2016).

|                | Maj | LR | CE+R (S) | CE (J) | CE+R (J) |
|----------------|-----|----|----------|--------|----------|
| N/Aj Avg       | .304| .594| .589     | .597   | .597     |
| Verb Avg       | .222| .553| .489     | .521   | .520     |
| All Avg        | .251| .568| .524     | .548   | .547     |

Table 4: Macro-averaged F1 results for connotation prediction on the test set, averaged across aspects. N/Aj indicates noun and adjective.

\(^2\) perspective of the writer on the agent/theme, perspective of the agent on the theme, effect on, and value and state of entities

\(^3\) https://www.wordnik.com/ American Heritage Dictionary, CMU Pronouncing Dictionary, Macmillan Dictionary, Wiktionary, Webster’s Dictionary, WordNet.
Second, we compare joint learning with \((CE+R(J))\) and without \((CE(J))\) related words to the strong LR baseline. We find that the model with related words \((CE+R(J))\) is statistically indistinguishable from the baseline\(^4\) (for \(p \leq 0.05\)). In contrast, our model without related words \((CE(J))\) is significantly worse than the LR baseline for one aspect (see Appendix B for aspect-level results). Thus we conclude that related words are beneficial for learning connotations.

Overall, our approach provides a single unified feature representation for the lexical connotations of all parts of speech, without any loss in label prediction performance. Specifically, our best representation learning model \((CE+R(J))\) has comparable label prediction performance to a strong baseline (LR), a baseline that does not learn any kind of representation. We use \((CE+R(J))\) to generate connotation embeddings that we use in all further evaluation.

**Observations** Our connotation representation learning model presents several advantages.

First, it can generate a representation for a word in a zero-shot manner from only a few dictionary definitions, rather than the thousands of examples of contextual use required by standard word-embedding methods. For example, we can generate representations for slang words (e.g., “gucci” meaning “really good”), where knowledge-base entries (e.g., in Concept-Net) do not capture the slang meaning. Specifically, in our connotation embedding space, the nearest neighbors of “gucci” include words related to the slang connotations (e.g., “beneficial” – positive impact, not factual), whereas neighbors in a pre-trained word embedding space are specific to the fashion meaning and connotations (e.g., “buy”, “italy”, “textile”). Along with slang, our model can also generate representations for new or rare words (e.g., “merchantile”) that don’t have a pre-trained word representation.

In addition, since dictionary definitions capture connotations across languages (see Table 5), we hypothesize that our model could be used to generate non-English connotation representations with no foreign language training data (using the English definitions available in foreign-language dictionaries).

We demonstrate further uses of our connotation representation \(v_w\) in intrinsic (§5.1) and extrinsic (§5.2) evaluation.

### 5 Experiments

#### 5.1 Intrinsic Evaluation

To evaluate the connotation embedding space, we look at the 50 nearest neighbors, by Euclidean distance, of every word in our training and development sets. We find that neighbors in the connotation embedding space are more closely related based on the connotation label than in the pre-trained embedding space.

Looking at example nearest neighbors (Table 6) we see that while nearest neighbors in the pre-trained embedding space include antonyms (e.g., “inability” is close to “ability”) and topically related words (e.g., “merry” is close to “wives”), the connotation embedding space includes more examples that have the same connotation label for some aspect but are topically or literally semantically unrelated. For example, “slug” (noun) is close to many impolite but otherwise unrelated words (e.g., “shove”, “murder”, “scum”) in the connotation embedding space while in the pre-trained space “slug” is close to topically related (e.g., “bug”) but polite words. Therefore, we can see that the connotation feature embeddings place words with similar connotations closer together, reshaping the pre-trained semantic space.

To quantify the semantic differences, we measure neighbor cluster connotation label purity. Specifically, for each connotation aspect \(a\) (e.g., Social Value) and each non-neutral label \(c\) (e.g., valuable (+)), we calculate \(r_{ac}(C)\): the average ratio of words with label \(c\) to label \(-c\) in the set of nearest neighbors of all words with label \(c\) for aspect \(a\). We compare it against the same ratio for the nearest neighbors.

\(^4\)We use an approximate randomization test.
selected using the same pre-trained word embeddings as in

We find that across connotation aspects, these ratios are higher for the learned connotation embeddings, compared to pre-trained word embeddings. For example, $r_{+}^{Social Val} = 21.27$, whereas $r_{+}^{Social Val} = 4.70$ (see Table 7). This shows the connotation embedding model clusters words based more on connotation labels than pre-trained word embeddings.

### 5.2 Extrinsic Evaluation

We further evaluate our connotation embedding using the stance detection task. Stance is often expressed through subtle language, and we hypothesize that connotations can improve stance detection. Given a text on a topic (e.g., “gun control”), the task is to predict the stance: whether the text supports the topic, is against the topic, or is neutral (see Figure 1).

#### 5.2.1 Methods and Experiments

**Models** As a baseline architecture, we implement the bidirectional conditional encoding model (Augenstein et al., 2016). This model encodes a text as $h_T$ with a BiLSTM, conditioned on a separate topic encoding $h_P$, and predicts stance from $h_T$ (BiC). We include connotation embeddings through scaled dot-product attention over the noun, adjective, and verb embeddings from the text, with $h_P$ as the query (see Figure 3). We experiment with three types of embeddings in the attention: pre-trained word embeddings ($BiC+W$), our connotation embeddings ($BiC+C$), and randomly initialized embeddings ($BiC+R$), as a baseline to measure the importance of attention. We also implement a Bag-of-Word-Vectors baseline ($BoWV$), encoding the text and topic as separate BoW vectors and passing their concatenation to a Logistic Regression classifier.

**Data and Parameters** We use the Internet Argument Corpus (Abbott et al., 2016), a collection of posts from online debate forums in our experiments (see Table 8). Since not every text will take a position on every topic, we augment the data with examples for the ‘neutral’ class where each example is assigned a new topic, different from the original, that we randomly sample from the original topic distribution. We split the data into train, development, and test such that no posts by one author are in multiple splits and preprocess the data by removing stopwords and punctuation and lowercasing.

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**Table 6**: Examples of nearest neighbors in the connotation embedding space (Conn Only), the pre-trained word embedding space (Word Only) and all the words in the nearest neighbors in both spaces (Both). NONE indicates no words in the top 50 are nearest neighbors in both spaces.

| Aspect     | Conn Only | Word Only |
|------------|-----------|-----------|
| Social Value | ability (+) | NONE      |
| Polite      | slug (-)   | NONE      |
| Impact      | merry (+)  | cheery, genial, joyful, fun, merriment, jolly, joy, delightful, cheerful |

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**Table 7**: Cluster connotation purity ratios. Emo is based on no emotions (0) or any number ($\geq 1$).

| Aspect  | $a$ | $c$ | $r_{+}^{a(C)}$ | $r_{+}^{a(P)}$ |
|---------|-----|-----|----------------|----------------|
| Social  | +   |     | 21.27          | 4.70           |
| Value   |     | -   | 5.88           | 2.38           |
| Polite  |     | +   | 2640.14        | 43.71          |
| -       |     | -   | 50.00          | 0.54           |
| Impact  |     | +   | 47.49          | 4.73           |
| -       |     | -   | 33.33          | 8.33           |
| Fact    |     | +   | 0.84           | 0.37           |
| Sent    |     | -   | 4.00           | 9.09           |
| Emo Avg |     |     | 0.28           | 0.27           |
|         | $\geq 1$ | 33.33 | 20.00           |

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**Figure 3**: Stance models $BiC+E$, with $E \in \{C, W, R\}$.
Stance is topic-dependent and as a result, models require numerous training examples for each individual topic. However, many examples are not always available for every topic. Since there are hundreds of thousands of potential topics, the vast majority of which will have very few examples, our goal is to build models that exhibit strong performance across all topics, regardless of size. Therefore, we experiment with three data scenarios: (i) training and evaluating using all the data (All Data), (ii) truncating each topic in training to $M$ size (at most $2k$ examples) and evaluating using all data (Trunc Train), and (iii) truncating each topic to $M$ size in training and in evaluation (Trunc All), so that topics have the same frequency for both training and evaluation.

### 5.2.2 Results

We find that when using all of the training data, the pre-trained embeddings and our connotation embeddings perform comparably (significance level $p = 0.3$). Note that both the connotation and pre-trained embeddings outperform the random embeddings in all scenarios, showing that the architecture difference is not the only reason for improvement when adding embeddings. We find that in both scenarios where data is limited per topic (Trunc Train and Trunc All), the connotation embeddings improve significantly over the pre-trained word embeddings. In fact, the same trend is visible across varying numbers of training examples (see Figure 4). Our results demonstrate that the connotation information is useful for detecting stance when data is limited.

We find further evidence that the connotation embeddings ($\text{BiC+C}$) make the model robust to loss of training data when we look at the results on the individual topic level. Namely, in setting Trunc Train, $\text{BiC+C}$ has a significant improvement (with $p < 0.05$) over $\text{BiC+W}$ on six topics, including four of the $M$ and truncated $L$ topics. In fact, for the four $M/L$ topics, the average per-topic decrease in F1 for $\text{BiC+C}$ is $1/4$ that of $\text{BiC+W}$. These per-topic results further highlight the robustness of $\text{BiC+C}$ when training data is restricted.

We conclude that connotation embeddings improve stance performance when training data is limited, suggesting they can be used in future work that generalizes stance models to topics with no training data (i.e. most topics).

### 6 Conclusion

We create a new lexicon with six new connotation aspects for nouns and adjectives that aligns well with human judgments. We use the lexicon to train a unified connotation representation for words from all parts of speech, yielding an embedding space that captures more connotative information than pre-trained word embeddings. Since the stance detection tasks encountered in real life concern a very large number of topics, zero-shot and low-resource stance detection are important extensions to the stance detection task. Our results show that models using our connotation representation may be better suited to such scenarios and have potential to generalize well to topics with little or no training data.

In future work we plan to explore the relationships between connotations, context, and word sense, as well as adapting our methods to learn multi-lingual connotation representations that accurately capture cultural and linguistic variations.
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A Connotation Labeling

We provide the complete distant labeling rules for each of the connotation aspects in Table 10 (see http://www.wjh.harvard.edu/~inquirer/homecat.htm for complete information on abbreviations). Within each connotation aspect, we determine the connotation polarity using the additional categories: Positiv, Negativ, Strong, Weak, Hostile, Submit, Active and Power.

| Aspect         | General Inquirer Categories                                                                 |
|----------------|---------------------------------------------------------------------------------------------|
| Social Value   | PowGain, PowLoss, PowEnds, PowCon, PowCoop, PowAuPt, PowPt, PowAuth, PowOth, RcEthic, RcRelig, RcGain, RcEnds, RcLoss, Virtue, Vice, WltPt WltTran, WltOth, Food, Object, Doctrin, Academ, Work, NatrObj, Vehicle, Econ@, Goal, EnlPt, EnlOth, EnlLoss, SklPt, SklAsth, SklOth, Exprsv, Legal, COLL, Means MeansLw, Fail, Solve, EndsLw, Try, WlbPhys, WlbGain, WlbPt, WlbLoss, WlbPsyc, Quality, SocRel |
| Politeness     | RspGain, RspLoss, RspOth, AffGain, AffLoss, AffOth, WlbPt, SklPt, EnlPt, Relig, WltPt, Polit, HU, Milit, Legal, Academ, Doctrin |
| Impact         | PosAff, Pleasur, Pain, NegAff, Anomie, NotLw, Vice, Virtue, RcGain, RcLoss, RspLoss, RcEthic, RspOth, WlbPsyc, RcEnds, EnlOth, WlbGain, RspGain, EnlGain, EnlEnds, EnlPt, WlbLoss, WlbPt, EnlLoss, SklOth, WlbPhys, Try, Goal, Work |
| Factuality     | \[ v = \begin{cases} -1 & \text{if } x \leq -0.25 \\
                                1 & \text{if } x \geq 0.25 \\
                                0 & \text{otherwise} \end{cases} \quad \text{where } x \text{ is the Imagery score normalized to } [-1, 1]. \]
| Sentiment      | \[ v = \begin{cases} -1 & \text{if } x \leq -0.25 \\
                                1 & \text{if } x \geq 0.25 \\
                                0 & \text{otherwise} \end{cases} \quad \text{where } x \text{ is the sentiment score normalized to } [-1, 1]. \]

Table 10: Categories from the Harvard General Inquirer used in distant labeling connotations.

B Connotation Modeling

Training All models are trained with hidden size \( H = 150 \), number of definition words \( N = 42 \), number of related words \(||R_w|| = 20\) and dropout of 0.5 to prevent overfitting. For emotion prediction we set \( \theta = 0.5 \). We use Concept-Net numberbatch embeddings (Speer et al., 2016) because we find empirically that these outperform other pre-trained embeddings (GloVe and dependency-based embeddings (Levy and Goldberg, 2014)) on the development set.

We optimize using Adam (Kingma and Ba, 2014) with learning rate 0.001 and minibatch-size of 64 for 80 epochs with early stopping. We optimize the parameters \( W^a, b^a \) for each noun and adjective aspect \( a \) separately from the parameters for each verb aspect \( a \), allowing both to update the parameters of the definition encoder, and attention layer. We tune the loss weights on the development set.

Detailed results We present aspect-level results for the task of connotation label prediction. For nouns and adjectives we evaluate on six aspects (see §3): Social Value, Politeness, Impact, Factivity, Sentiment, and Emotional Association. For verbs we evaluate on 11 aspects: perspective of the writer on the theme \( P(wt) \) and agent \( P(wa) \), perspective of the agent on the theme \( P(at) \), effect on the theme \( E(t) \) and agent \( E(a) \), value of the theme \( V(t) \) and agent \( V(a) \), and mental state of the theme \( S(t) \) and agent \( S(a) \).

C Extrinsic Stance Evaluation

Dataset Details We map the topic-stance annotations in the Internet Argument Corpus to individual topics and labels (e.g., ‘pro-life’ → topic ‘abortion’ with label ‘con’). We show dataset statistics in Table 12 where topics in the upper part are large sized, topics in the middle part are medium sized, and
Table 11: Macro-averaged F1 results for connotation prediction on the test set. The upper part shows noun/adjective aspect results, the bottom shows verb aspect results. Underline indicates the best performing model per row. **Bold** indicates the best performing joint learning model per row.

|         | Maj | LR | CE+R (S) | CE (J) | CE+R (J) |
|---------|-----|----|----------|--------|----------|
| Social Val | .228 | .664 | .651 | .632 | **.651** |
| Polite | .311 | .470 | .467 | **.518** | .464 |
| Impact | .278 | .669 | .681 | .687 | **.704** |
| Fact | .271 | .576 | .531 | .549 | **.560** |
| Sent | .247 | .585 | .606 | **.615** | **.615** |
| Emo | .487 | .604 | .599 | .578 | **.587** |
| **Avg** | **.304** | **.594** | **.589** | .597 | **.597** |
| P(wt) | .246 | .501 | .437 | **.481** | .439 |
| P(wa) | .213 | .564 | .487 | .544 | **.583** |
| P(at) | .204 | .649 | .553 | .623 | **.629** |
| E(t) | .156 | .721 | .673 | .655 | **.661** |
| E(a) | .226 | .573 | .420 | **.557** | .530 |
| V(t) | .109 | .369 | .365 | **.391** | .373 |
| V(a) | .320 | .449 | .428 | **.375** | .370 |
| S(t) | .286 | .640 | .548 | .586 | **.629** |
| S(a) | .203 | .551 | .481 | **.543** | .537 |
| power | .294 | .476 | .467 | .474 | **.480** |
| agency | .182 | .589 | .515 | **.505** | .490 |
| **Avg** | **.222** | **.553** | **.489** | .521 | **.520** |
| **Avg** | **.251** | **.568** | **.524** | .548 | **.547** |

Training Details: We split the data 60% train, 20% development, and 20% test. We train our models using pre-trained 100-dimensional word embeddings from GloVe (Pennington et al., 2014), as these are comparable to and more time-efficient than larger word embeddings. We use a hidden size of 60, dropout of 0.5, and train for 70 epochs with early stopping on the development set. We optimize Adam with learning rate 0.001 and minibatch-size of 64 on the cross-entropy loss. Our hyperparameters are set to be comparable to Augenstein et al., 2016.

When truncating to medium size in §5.2, we truncate train topics to at most 2000 examples (in Trunc Train and Trunc All) and truncate development and test topics to at most 600 examples (in Trunc All).

Topic Stance Analysis: We present a detailed analysis of the results of the models BiC+W and BiC+C on the stance detection on individual topics. First, we find that when the models are trained with all of the data (All Data), there are statistically significant differences on only two topics, one of which is very small (see Table 13a). This is further evidence that the models are comparable in this setting.

We then find that when trained with truncated training data (see §5.2 for details) (Trunc Train), BiC+C improves over BiC+W on six topics, including four of the medium or truncated large topics (see Table 13b). When trained and evaluated with truncated data (Trunc All), BiC+W and BiC+C have statistically significant improvements over each other on the same number of topics (two each) but BiC+C is significantly better overall (see Table 13c). These results further show that connotations help to learn stance when data is limited.
Table 12: Statistics for the stance detection dataset. C indicates ‘con’, P indicates ‘pro’, N indicates ’neutral’.

| Topic                                      | # Ex  | # C    | # P    | # N    |
|--------------------------------------------|-------|--------|--------|--------|
| abortion                                   | 12453 | 3962   | 5236   | 3255   |
| gay marriage                               | 11037 | 2907   | 5082   | 3048   |
| gun control                                | 10119 | 4610   | 2681   | 2828   |
| evolution                                  | 9896  | 2586   | 4480   | 2830   |
| existence of God                           | 7227  | 2588   | 2517   | 2122   |
| death penalty                              | 2834  | 995    | 951    | 888    |
| humans are responsible                     | 1608  | 560    | 538    | 510    |
| marijuana legalization                     | 1491  | 328    | 697    | 466    |
| communism is better than capitalism        | 1279  | 618    | 277    | 384    |
| illegal immigration                        | 291   | 108    | 87     | 96     |
| health care reform                         | 201   | 76     | 51     | 74     |
| legalize prostitution                       | 199   | 57     | 88     | 54     |
| Israel                                    | 100   | 29     | 38     | 33     |
| vegetarian diet is best                    | 79    | 29     | 29     | 21     |
| women in combat                            | 47    | 15     | 19     | 13     |
| minimum wage                               | 27    | 9      | 8      | 10     |
| Overall                                    | 58888 | 19477  | 22779  | 16632  |
| Topic                     | BiC +W | BiC +C | Topic                     | BiC +W | BiC +C | Topic                     | BiC +W | BiC +C |
|--------------------------|--------|--------|--------------------------|--------|--------|--------------------------|--------|--------|
| abortion                 | .49    | .49    | abortion                 | .46    | .47    | abortion                 | .49    | .48    |
| gay marriage             | .47    | .48    | gay marriage             | .48    | .46    | gay marriage             | .49*   | .46    |
| gun control              | .53    | .55    | gun control              | .50    | .55†   | gun control              | .51    | .50    |
| evolution                | .43    | .44    | evolution                | .41    | .43†   | evolution                | .43    | .43    |
| existence of God         | .52    | .52    | existence of God         | .48    | .51*   | existence of God         | .49    | .47    |
| death penalty            | .45    | .50†   | death penalty            | .48    | .50    | death penalty            | .48    | .46    |
| humans are responsible   | .49    | .54    | humans are responsible   | .45    | .53†   | humans are responsible   | .46    | .55†   |
| marijuana legalization    | .51    | .50    | marijuana legalization    | .51    | .50    | marijuana legalization    | .50    | .49    |
| communism is better than capitalism | .52    | .54    | communism is better than capitalism | .53    | .54    | communism is better than capitalism | .55    | .52    |
| illegal immigration      | .34    | .38    | illegal immigration      | .45†   | .36    | illegal immigration      | .44    | .44    |
| health care reform       | .64    | .91    | health care reform       | .62    | .64†   | health care reform       | .54    | .64†   |
| legalize prostitution     | .40    | .53    | legalize prostitution     | .49    | .50    | legalize prostitution     | .47    | .51    |
| Israel                   | .66    | .42    | Israel                   | .54    | .44    | Israel                   | .41    | .56    |
| vegetarian diet is best  | .52†   | .33    | vegetarian diet is best  | .10    | .11†   | vegetarian diet is best  | .52†   | .50    |
| women in combat          | .28    | .30    | women in combat          | .52    | .36    | women in combat          | .43    | .47    |
| minimum wage             | .30    | .22    | minimum wage             | .22    | .33    | minimum wage             | .33    | .35    |
| Overall                  | .57    | .57    | Overall                  | .54    | .56†   | Overall                  | .54    | .56†   |

Table 13: Macro F1 results on the test set for three different data scenarios. * indicates significance with \( p < 0.05 \), † indicates significance with \( p < 0.01 \).