Learning Scalar Adjective Intensity from Paraphrases

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Abstract

Adjectives like warm, hot, and scalding all describe temperature but differ in intensity. Understanding these differences between adjectives is a necessary part of reasoning about natural language. We propose a new paraphrase-based method to automatically learn the relative intensity relation that holds between a pair of scalar adjectives. Our approach analyzes over 36k adjectival pairs from the Paraphrase Database under the assumption that, for example, paraphrase pair (really hot ↔ scalding) suggests that hot < scalding. We show that combining this paraphrase evidence with existing, complementary pattern- and lexicon-based approaches improves the quality of systems for automatically ordering sets of scalar adjectives and inferring the polarity of indirect answers to yes/no questions.

1 Introduction

Semantically similar adjectives are not fully interchangeable in context. Although hot and scalding are related, the statement “the coffee was hot” does not imply the coffee was scalding. Hot and scalding are scalar adjectives that describe temperature, but they are not interchangeable because they vary in intensity. A native English speaker knows that their relative intensities are given by the ranking hot < scalding. Understanding this distinction is important for language understanding tasks such as sentiment analysis (Pang et al., 2008), question answering (de Marneffe et al., 2010), and textual inference (Dagan et al., 2006).

Existing lexical resources such as WordNet (Miller, 1995; Fellbaum, 1998) do not include the relative intensities of adjectives. As a result, there have been efforts to automate the process of learning intensity relations (e.g. Sheinman and Tokunaga (2009), de Melo and Bansal (2013), Wilkinson (2017), etc.). Many existing approaches rely on pattern-based or lexicon-based methods to predict the intensity ranking of adjectives. Pattern-based approaches search large corpora for lexical patterns that indicate an intensity relationship – for example, “not just X, but Y” implies X < Y. As with pattern-based approaches for other tasks (such as hypernym discovery (Hearst, 1992)), they are precise but have relatively sparse coverage of comparable adjectives, even when using web-scale corpora (de Melo and Bansal, 2013; Ruppenhofer et al., 2014). Lexicon-based approaches employ resources that map an adjective to a real-valued number that encodes both intensity and polarity (e.g. good might map to 1 and phenomenal to 5, while bad maps to -1 and awful to -3). They can also be precise, but may not cover all adjectives of interest.

We propose paraphrases as a new source of evidence for the relative intensity of scalar adjectives. A paraphrase is a pair of words or phrases with approximately similar meaning, such as (really great ↔ phenomenal). Adjectival paraphrases can be exploited to uncover intensity relationships. A paraphrase pair of the above form, where one phrase is composed of an intensifying adverb and an adjective (really great) and the other is a single-word adjective (phenomenal), provides evidence that (great < phenomenal). By drawing this evidence from large, automatically-generated
paraphrase resources like the Paraphrase Database (PPDB) \(^1\) (Ganitkevitch et al., 2013; Pavlick et al., 2015), it is possible to obtain high-coverage pairwise adjective intensity predictions at reasonably high accuracy.

We demonstrate the usefulness of paraphrase evidence for inferring relative adjective intensity in two tasks: ordering sets of adjectives along an intensity scale, and inferring the polarity of indirect answers to yes/no questions. In both cases, we find that combining the relatively noisy but high-coverage paraphrase evidence with more precise but low-coverage pattern- or lexicon-based evidence improves overall quality.

2 Related Work

Noting that adding adjective intensity relations to WordNet (Miller, 1995; Fellbaum, 1998) would be useful, Sheinman et al. (2013) propose a system for automatically extracting sets of same-attribute adjectives from WordNet ‘dumbbells’ – consisting of two direct antonyms at the poles and satellites of synonymous/related adjectives incident to each antonym (Gross and Miller, 1990) – and ordering them by intensity. The annotations, however, are not in WordNet as of its latest version (3.1).

Work on adjective intensity generally focuses on two related tasks: clustering adjectives by on the attributes they modify, and ranking same-attribute adjectives by intensity. With respect to the former, common approaches involve clustering adjectives by their contexts (Hatzivassiloglou and McKeown, 1993; Shivade et al., 2015). We do not focus on the clustering task in this paper, but concentrate on the second.

Approaches to the second task – ordering scalar adjectives by intensity – mostly fall under the paradigms of pattern-based or lexicon-based approaches. Pattern-based approaches work by extracting lexical (Sheinman and Tokunaga, 2009; de Melo and Bansal, 2013; Sheinman et al., 2013) or syntactic (Shivade et al., 2015) patterns indicative of an intensity relationship from large corpora. For example, the patterns “X, but not Y” and “not just X but Y” provide evidence that X is an adjective less intense than Y.

Lexicon-based approaches are derived from the premise that adjectives can provide information about the sentiment of a text (Hatzivassiloglou and McKeown, 1993). These methods draw upon a lexicon that maps adjectives to real-valued scores encoding both sentiment polarity and intensity. The lexicon might be compiled automatically – for example, from analyzing adjectives’ appearance in star-valued product or movie reviews (de Marneffe et al., 2010; Rill et al., 2012; Sharma et al., 2015; Ruppenhofer et al., 2014) – or manually. In our experiments we utilize the manually-compiled SO-CAL lexicon (Taboada et al., 2011).

Our paraphrase-based approach to inferring relative adjective intensity is based on paraphrases that combine adjectives with adverbial modifiers. A tangentially related approach is Collex (Ruppenhofer et al., 2014), which is motivated by the intuition that adjectives with extreme intensities are modified by different adverbs from adjectives with more moderate intensities: extreme adverbs like absolutely are more likely to modify extreme adjectives like brilliant than are moderate adverbs like very. Unlike Collex, which requires predetermined sets of ‘end-of-scale’ and ‘normal’ adverbial modifiers, our approach learns the identity and relative importance of intensifying adverbs.

Relative intensity is just one of several dimensions of gradable adjective semantics. In addition to intensity scales, a comprehensive model of scalar adjective semantics might also incorporate notions of intensity range (Morzycki, 2015), adjective class (Kamp and Partee, 1995), and scale membership. In this paper we take the position that relative intensity is worth studying on its own because it is an important component of adjective semantics, usable directly for some NLP tasks such as sentiment analysis (Pang et al., 2008), and as part of a more comprehensive model for other tasks like question answering (de Marneffe et al., 2010).

3 Paraphrase-based Intensity Evidence

Adjectival paraphrases provide evidence about the relative intensity of adjectives. A paraphrase of the form (\(RB\ JJ_u \leftrightarrow JJ_v\)) – where one phrase is comprised of an adjective modified by an intensifying adverb (\(RB\ JJ_u\)), and the other is a single-word adjective (\(JJ_v\)) – is evidence that the first adjective is less intense than the second (\(JJ_u < JJ_v\)). We propose a new method for encoding this evidence and using it to make pairwise adjective intensity predictions. First, a graph (JJGRAPH) is formed to represent over 36k adjectival paraphrases having the specified form. Next, data in the graph are

\(^1\)www.paraphrase.org
used to make pairwise adjective intensity predictions.

### 3.1 Identifying Intensifying Adverbs

In JJGRAPH, nodes are adjectives, and each directed edge \((J_{j_u} \rightarrow R B J_{j_v})\) corresponds to an adjectival paraphrase of the form \((RB J_{j_u} \leftrightarrow J_{j_v})\) – for example, \((\text{very tall} \leftrightarrow \text{large})\) – where one ‘phrase’ \((J_{j_v})\) is an adjective and the other \((RB J_{j_u})\) is an adjectival phrase containing an adverb and adjective (see Figure 1 for examples).

Adverbs in PPDB can be intensifying or de-intensifying. An intensifying adverb (e.g. very, totally) strengthens the adjectives it modifies. In contrast, a de-intensifying adverb (e.g. slightly, somewhat) weakens the adjectives it modifies. Since edges in JJGRAPH ideally point in the direction of increasing intensity, the first step in the process of creating JJGRAPH is to identify a set of adverbs that are likely intensifiers to be included as edges.

For this purpose, we generate a set \(R\) of likely intensifying adverbs within PPDB using a bootstrapping approach (Figure 2). The process starts with a small seed set of adjective pairs having a known intensity relationship. The seeds are pairs \((j_u, j_v)\) from PPDB-XXL\(^2\) such that \(j_u\) is a base-form adjective (e.g. hard), and \(j_v\) is its comparative or superlative form (e.g. harder or hardest). Using the seeds, we identify intensifying adverbs by finding adjectival paraphrases in PPDB of the form \((r_i j_u \leftrightarrow j_v)\); because \(j_u < j_v\), adverb \(r_i\) is inferred to be intensifying (Round 1). All such \(r_i\) are added to initial adverb set \(R_1\).

The process continues by extracting paraphrases \((r_i j_{u'} \leftrightarrow j_{v'})\) with \(r_i \in R_1\), indicating additional adjective pairs \((j_{u'}, j_{v'})\) with intensity direction inferred by \(r_i\) (Round 2). Finally, the adjectival pairs extracted in this second iteration are used to identify additional intensifying adverbs \(R_3\), which are added to final set \(R = R_1 \cup R_3\) (Round 3).

In all, this process generates a set of 610 adverbs. Examination of the set shows that the process does capture many intensifying adverbs like very and abundantly, and excludes many de-intensifying adverbs appearing in PPDB like far less and not as. However, due to the noise inherent in PPDB itself and in the bootstrapping process, there are also a few de-intensifying adverbs included in \(R\) (e.g. hardly, kind of) as well as adverbs that are neither intensifying nor de-intensifying (e.g. ecologically). It will be important to take this noise into consideration when using JJGRAPH to make pairwise intensity predictions.

### 3.2 Building JJGRAPH

JJGRAPH is built by extracting all 36,756 adjectival paraphrases in PPDB of the specified form, where the adverb belongs to \(R\). The resulting graph has 3,704 unique adjective nodes. JJGRAPH is a multigraph, as there are frequently multiple intensifying relationships between pairs of adjectives. For example, the paraphrases \((\text{pretty hard} \leftrightarrow \text{tricky})\) and \((\text{really hard} \leftrightarrow \text{tricky})\) are both present in PPDB. There can also be contradictory or cyclic edges in JJGRAPH, as in the example depicted in the JJGRAPH subgraph in Figure 3, where the adverb really connects tasty to lovely and vice versa. Self-edges are allowed (e.g. \((\text{really hard} \leftrightarrow \text{hard})\)).

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\(^2\)PPDB comes in six increasingly large sizes from S to XXXL; larger collections have wider coverage but lower precision. Our work uses XXL.
3.3 Pairwise Intensity Prediction

Examining the directed adverb edges between two adjectives $j_u$ and $j_v$ in JJGRAPH provides evidence about the relative intensity relationship between them. However, it has just been noted that JJGRAPH is noisy, containing both contradictory/cyclical edges and adverbs that are not uniformly intensifying. Rather than try to eliminate cycles, or manually annotate each adverb with a weight corresponding to its intensity and polarity (Ruppenhofer et al., 2015; Taboada et al., 2011), we aim to learn these weights automatically in the process of predicting pairwise intensity.

Given adjectives $(j_u, j_v)$, we build a classifier that outputs a score from 0 to 1 indicating the predicted likelihood that $j_u < j_v$. Its binary features correspond to adverb edges from $j_u$ to $j_v$ and from $j_v$ to $j_u$ in JJGRAPH. The feature space includes only adverbs from $R$ that appear at least 10 times in JJGRAPH, resulting in features for $m = 259$ unique adverbs in each direction (i.e. from $j_u$ to $j_v$ and vice versa) for $2m = 518$ binary features total. Note that while all adverb features correspond to predicted intensifiers from $R$, there are some features that are actually de-intensifying due to the noise inherent in the bootstrapping process (section 3.1).

We train the classifier on all 36.7k edges in JJGRAPH, based on a simplifying assumption that all adverbs in $R$ are indeed intensifiers. For each adjective pair $(j_u, j_v)$ with one or more direct edges from $j_u$ to $j_v$, a positive training instance for pair $(j_u, j_v)$ and a negative training instance for pair $(j_v, j_u)$ are added to the training set. A logistic regression classifier is trained on the data, using elastic net regularization and 10-fold cross validation to tune parameters.

The model parameters output by the training process are in a feature weights vector $w \in \mathbb{R}^{2m}$ (with no bias term) which can be used to generate a paraphrase-based score for each adjective pair:

$$score_{pp}(j_u, j_v) = \frac{1}{1 + \exp^{-wx_{uv}}} - 0.5 \quad (1)$$

where $x_{uv}$ is the binary feature vector for adjective pair $(j_u, j_v)$. The decision boundary 0.5 is subtracted from the sigmoid activation function so that pairs predicted to have the directed relation $j_u < j_v$ will have a positive score, and those predicted to have the opposite directional relation will have a negative score. Pairs with no connecting edges in JJGRAPH score 0.

4 Other Intensity Evidence

Our experiments compare the proposed paraphrase approach with existing pattern- and lexicon-based approaches.

4.1 Pattern-based Evidence

We experiment with the pattern-based approach of de Melo and Bansal (2013). Given a pair of adjectives to be ranked by their intensity, de Melo and Bansal (2013) cull intensity patterns from Google n-Grams (Brants and Franz, 2009) as evidence of their intensity order. Specifically, they identify 8 types of weak-strong patterns (e.g. “X, but not Y”) and 7 types of strong-weak patterns (e.g. “not X, but still Y”) that are used as evidence about the directionality of the intensity relationship between adjectives. Given an adjective pair $(j_u, j_v)$, an overall pattern-based weak-strong score is calculated:

$$score_{pat}(j_u, j_v) = \frac{(W_u - S_u) - (W_v - S_v)}{\text{count}(j_u) \cdot \text{count}(j_v)} \quad (2)$$

where $W_u$ and $S_u$ quantify the pattern evidence for the weak-strong and strong-weak intensity relations respectively for the pair $(j_u, j_v)$, and $W_v$ and $S_v$ quantify the pattern evidence for the pair $(j_v, j_u)$. $W_u$ and $S_u$ are calculated as:

$$W_u = \frac{1}{|P_1|} \sum_{p_1 \in P_{sw}} \text{count}(p_1(j_u, j_v))$$

$$S_u = \frac{1}{|P_2|} \sum_{p_2 \in P_{sw}} \text{count}(p_2(j_u, j_v)) \quad (3)$$

$W_v$ and $S_v$ are calculated similarly by swapping the places of $j_u$ and $j_v$. For example, given pair (good, great), $W_u$ might incorporate evidence from patterns “good, but not great” and “not only good but great”, while $S_v$ might incorporate evidence from the pattern “not great, just good”. $P_{sw}$ denotes the set of weak-strong patterns, $P_{sw}$ denotes the set of strong-weak patterns, and $P_1$ and $P_2$ give the total counts of all occurrences of any pattern in $P_{sw}$ and $P_{sw}$ respectively. The score is normalized by the frequencies of $j_u$ and $j_v$ in order to avoid bias due to high-frequency adjectives. As with the paraphrase-based scoring mechanism (Equation 1), scores output by this method can be positive or negative, with positive scores being indicative of a weak-strong relationship from $j_u$ to $j_v$. Note that $score(j_u, j_v) = -score(j_v, j_u)$.
4.2 Lexicon-based Evidence

We use the manually-compiled SO-CAL lexic as our third, lexicon-based method for inferring intensity. The SO-CAL lexicon assigns an integer weight in the range $[-5, 5]$ to 2,826 adjectives. The sign of the weight encodes sentiment polarity (positive or negative), and the value encodes intensity (e.g. *atrocious*, with a weight of -5, is more intense than *unlikable*, with a weight of -3). SO-CAL is used to derive a pairwise intensity prediction for adjectives $(j_u, j_v)$ as follows:

$$
\text{score}_{\text{socal}}(j_u, j_v) = |L(j_v)| - |L(j_u)|, \\
\text{iff } \text{sign}(j_u) = \text{sign}(j_v)
$$

where $L(j_v)$ gives the lexicon weight for $j_v$. Note that $\text{score}_{\text{socal}}$ is computed only for adjectives having the same polarity direction in the lexicon; otherwise the score is undefined. This is because adjectives belonging to different half scales, such as *freezing* and *steaming*, are frequently incomparable in terms of intensity (De Marneffe et al., 2010).

4.3 Combining Evidence

While the pattern-based and lexicon-based pairwise intensity scores are known to be precise but low-coverage (De Melo and Bansal, 2013; Ruppenhofer et al., 2015), we expect that the paraphrase-based score will produce higher coverage at lower accuracy. Thus we also experiment with scoring methods that combine two or three score types. When combining two metrics $x$ and $y$ to generate a score for a pair $(j_u, j_v)$, we simply use the first metric $x$ if it can be reliably calculated for the pair, and back off to metric $y$ otherwise. More formally, the combined score for metrics $x$ and $y$ is given by:

$$
\text{score}_{x+y}(j_u, j_v) = \alpha_x \cdot g_x(\text{score}_x(j_u, j_v)) + (1 - \alpha_x) \cdot g_y(\text{score}_y(j_u, j_v))
$$

where $\alpha_x \in \{0, 1\}$ is a binary indicator corresponding to the condition that $\text{score}_x$ can be reliably calculated for the adjective pair, and $g_x(\cdot)$ is a scaling function (see below). If $\alpha_x = 1$, then $\text{score}_x$ is used. Otherwise, if $\alpha_x = 0$, then we default to $\text{score}_y$. When combining three metrics $x$, $y$, and $z$, the combined score is given by:

$$
\text{score}_{x+y+z}(j_u, j_v) = \alpha_x \cdot g_x(\text{score}_x(j_u, j_v)) + (1 - \alpha_x) \cdot g_y(\text{score}_y(j_u, j_v)) + (1 - \alpha_y) \cdot g_z(\text{score}_z(j_u, j_v))
$$

The criteria for having $\alpha_x = 1$ varies depending on the metric type. For pattern-based evidence ($x=’pp’$), $\alpha_x = 1$ when adjectives $j_u$ and $j_v$ appear together in any of the intensity patterns culled from Google n-grams (e.g. “*j_u* but not *j_v*” exists). For lexicon-based evidence ($x=’socal’$), $\alpha_x = 1$ when both $j_u$ and $j_v$ are in the SO-CAL vocabulary, and have the same polarity (i.e. are both positive or both negative). For paraphrase-based evidence ($x=’pp’$), $\alpha_x = 1$ when $j_u$ and $j_v$ have one or more edges directly connecting them in JJ-GRAPH.

Since the metrics to be combined may have different ranges, we use a scaling function $g_x(\cdot)$ to make the scores output by each metric directly comparable:

$$
g_x(w) = \text{sign}(w) \cdot \left( \frac{\log(|w|) - \mu_x}{\sigma_x} + \gamma_x \right)
$$

where $\mu_x$ and $\sigma_x$ are the estimated population mean and standard deviation of $\log(\text{score}_x)$ (estimated over all adjective pairs in the dataset), and $\gamma_x$ is an offset equal to at least $5\sigma_x$.

5 Ranking Adjective Sets by Intensity

The first experimental application for the different paraphrase evidence is an existing model for predicting a global intensity ordering within a set of adjectives. Global ranking models are useful for inferring intensity comparisons between adjectives for which there is no explicit evidence. For example, in ranking three adjectives like *warm*, *hot*, and *scalding*, there may be direct evidence indicating *warm* $<$ *hot* and *hot* $<$ *scalding*, but no way of directly comparing *warm* to *scalding*. Global ranking models infer that *warm* $<$ *scalding* based on evidence from the other adjective pairs in the scale.

5.1 Global Ranking Model

We adopt the mixed-integer linear programming (MILP) approach of de Melo and Bansal (2013) for generating a global intensity ranking. This model takes a set of adjectives $A = \{a_1, \ldots, a_n\}$ and directed, pairwise adjective intensity scores $\text{score}(a_i, a_j)$ as input, and assigns each adjective
an ordering along a linear scale \( x_i \in [0, 1] \). The adjectives’ assigned values define the global ordering. If the predicted weights used as input are inconsistent, containing cycles, the model resolves these by choosing the globally optimal solution.

Recall that all pairwise scoring metrics produce a positive score for adjective pair \((j_u, j_v)\) when it is likely that \(j_u < j_v\), and a negative score otherwise. Consequently, the MILP approach should result in \(x_u < x_v\) when \(\text{score}(j_u, j_v)\) is positive, and \(x_u > x_v\) otherwise. This goal is achieved by maximizing the objective function:

\[
\sum_{u,v} \text{sign}(x_u - x_v) \cdot \text{score}(j_u, j_v)
\]  

De Melo and Bansal (2013) propose a MILP formulation for maximizing this objective, which we utilize in our experiments. Note that while De Melo and Bansal (2013) incorporate synonymy evidence from WordNet in their ranking method, we do not implement this part of the model.

### 5.2 Experiments

We experiment with using each of the paraphrase-, pattern-, and lexicon-based pairwise scores as input to the global ranking model in isolation. To examine how the scoring methods perform when used in combination, we also test all possible combinations of 2 and 3 scores.

Experiments are run over three distinct test sets (Table 1). Each dataset contains ordered sets of scalar adjectives belonging to the same scale. In general, scalar adjectives describing the same attribute can be ordered along a full scale (e.g. freezing to sweltering), or half scale (warm to sweltering); all three test sets group adjectives into half scales. The three datasets are described here, and their characteristics are given in Table 1.

**DeMeLO** (De Melo and Bansal, 2013)

87 adjective sets are extracted from WordNet ‘dumbbell’ structures (Gross and Miller, 1990), and partitioned into half-scale sets based on their pattern-based evidence in the Google N-Grams corpus (Brants and Franz, 2009). Sets are manually annotated for intensity relations (\(<, >,\) and \(=\)).

**Wilkinson** (Wilkinson and Oates, 2016). Twelve adjective sets are generated by presenting crowd workers with small seed sets (e.g. huge, small, microscopic), and eliciting similar adjectives. Sets are automatically cleaned for consistency, and then annotated for intensity by crowd workers. While the original dataset contains full scales, we manually sub-divide these into 21 half-scales for use in this study. Details on the modification from full- to half-scales are in the Supplemental Material.

**Crowd.** We also crowdsourced a new set of adjective scales with high coverage of the PPDB vocabulary. In a three-step process, we first asked crowd workers whether pairs of adjectives describe the same attribute (e.g. temperature) and therefore should belong along the same scale. Second, sets of same-scale adjectives were refined over multiple rounds. Finally, workers ranked the adjectives in each set by intensity. The final dataset includes 293 adjective pairs along 79 scales.

We measure the agreement between the gold standard ranking of adjectives along each scale and the predicted ranking using three commonly-used metrics:

**Pairwise accuracy.** For each pair of adjectives along the same scale, we compare the predicted ordering of the pair after global ranking (\(<, >,\) or \(=\)) to the gold-standard ordering of the pair, and report overall accuracy of the pairwise predictions.

**Kendall’s tau** (\(\tau_b\)). This metric computes the rank correlation between the predicted \((r_P(J))\) and gold-standard \((r_G(J))\) ranking permutations of each adjective scale \(J\), incorporating a correction for ties. Values for \(\tau_b\) range from \(-1\) to \(1\), with extreme values indicating a perfect negative or positive correlation, and a value of \(0\) indicating no correlation between predicted and gold rank-

| Dataset | # of Scales | Min/Max/Mean Scale Size | # of Unordered (unequal) Pairs | Example Scale |
|---------|-------------|-------------------------|-------------------------------|--------------|
| deMelo  | 87          | 3 / 8 / 3.90            | 524 (466)                     | \{clean\} < \{spotless, immaculate\} |
| Crowd   | 79          | 2 / 8 / 3.18            | 293 (250)                     | \{low\} < \{limited\} < \{scarce\} |
| Wilkinson | 21          | 2 / 5 / 2.81            | 61 (61)                       | \{dry\} < \{arid\} < \{parched\} |

Table 1: Characteristics of the scalar adjective datasets used for evaluation. The deMelo scale example shows an instance of an equally-intense pair (spotless, immaculate).
Table 2: Pairwise relation prediction and global ranking results for each score type in isolation, and for the best-scoring combinations of 2 and 3 score types on each dataset. For the global ranking accuracy and average \( \tau_b \) results, we denote with the \(*\) symbol scores for metrics incorporating paraphrase-based evidence that significantly out-perform both \( \text{score}_{\text{pat}} \) and \( \text{score}_{\text{socal}} \) under the paired Student’s t-test, using the Anderson-Darling test to confirm that scores conform to a normal distribution (Fisher, 1935; Anderson and Darling, 1954; Dror et al., 2018). Example output is also given, with correct rankings starred.

5.3 Experimental Results

The results of the global ordering experiment, reported in Table 2, are organized as follows: \( \text{Score Accuracy} \) pertains to performance of the scoring methods alone – prior to global ranking – while \( \text{Global Ranking Results} \) pertains to performance of each scoring method as used in the global ranking algorithm. Within \( \text{Score Accuracy} \) there are two metrics. \( \text{Coverage} \) gives the percent of unique same-scale adjective pairs from the test set that can be directly scored using the given method. For \( \text{score}_{\text{pat}} \), covered pairs are all those that appear together in any recognized pattern; for \( \text{score}_{\text{pp}} \), covered pairs are those directly connected in JJGRAPH by one or more direct edges; for \( \text{score}_{\text{socal}} \), covered pairs are all those for which both adjectives are in the SO-CAL lexicon and the metric is defined. \( \text{Pairwise Accuracy} \) gives the accuracy of the scoring method (before global ranking) on \( \text{just the covered pairs} \), meaning that the subset of pairs scored by each method varies. Within \( \text{Global Ranking Results} \), we report pairwise accuracy, weighted average \( \tau_b \), and \( \rho \) calculated over all pairs after ranking – including both pairs that are covered by the scoring method, and those whose pairwise intensity relationship has been inferred by the ranking algorithm.

The results indicate that the pairwise score accuracies (before ranking) for \( \text{score}_{\text{pat}} \) and \( \text{score}_{\text{socal}} \) are higher than those of \( \text{score}_{\text{pp}} \) for all datasets, but that their coverage is relatively limited. The one exception is the deMelo dataset, where \( \text{score}_{\text{pat}} \) has high coverage because the dataset was compiled specifically by finding adjective pairs that matched lexical patterns in the corpus. For all datasets, highest coverage was achieved using one of the combined metrics that incorporates paraphrase-based evidence.

The impact of these trends is visible on the Global Ranking Results. When using pairwise intensity scores to compute the global ranking,
higher coverage by a metric drives better results, as long as the metric’s accuracy is reasonably high. Thus the paraphrase-based scorepp, with its high coverage, gets better global ranking results than the other single-method scores for two of the three datasets. Further, we find that boosting coverage with a combined metric that incorporates paraphrase evidence produces the highest post-ranking pairwise accuracy scores overall for all three datasets, and the highest average $\tau_b$ and $\rho$ on the Crowd and Wilkinson datasets. We conclude that incorporating paraphrase evidence can improve the quality of this model for ordering adjectives along a scale because it gives high coverage with reasonably high quality.

The performance trends on the deMelo dataset differ from those on the Crowd and Wilkinson datasets. In particular, scorepp and scoresocal have substantially lower pre-ranking pairwise accuracy on the pairs they cover in the deMelo dataset than they do for Crowd and Wilkinson: scorepp has an accuracy of just 0.458 on covered pairs in the deMelo dataset, compared with 0.676 and 0.753 on the Crowd and Wilkinson datasets, and score differences for scoresocal are similar. The near-random prediction accuracies of scorepp and scoresocal on deMelo before ranking lead to near-zero correlation values on this dataset after global ranking. To explore possible reasons for these results, we assessed the level of human agreement with each dataset in terms of pairwise accuracy. For each test set, we asked five crowd workers to classify the intensity direction for each adjectival pair ($j_a$, $j_b$) in all scales as less than ($<$), greater than ($>$), or equal ($=$). We found that humans agreed with the ‘gold standard’ direction 65% of the time on the Bansal dataset, versus 70% of the time on the Crowd and Wilkinson datasets. It is possible that the more difficult nature of the Bansal dataset, coupled with its method of compilation (i.e., favoring adjective pairs that co-occur with pre-defined intensity patterns), lead to the lower coverage and lower accuracy of scorepp and scoresocal on this dataset.

6 Indirect Question Answering

The second task that we address is answering indirect yes or no questions. de Marneffe et al. (2010) observed that answers to polar (yes/no) questions frequently omit an explicit yes or no response. In some cases the implied answer depends on the relative intensity of adjective modifiers in the question and answer. For example, in the exchange:

Q: Was he a successful ruler?
A: Oh, a tremendous ruler.

the implied answer is yes, which is inferred because successful $\leq$ tremendous in terms of relative intensity. Conversely, in the exchange:

Q: Does it have a large impact?
A: It has a medium-sized impact.

the implied answer is no because large $>\ medium-sized$.

de Marneffe et al. (2010) compiled an evaluation set for this task by extracting 123 examples of such indirect question-answer pairs (IQAP) from dialogue corpora. In each exchange, the implied answer (annotated by crowd workers to be yes or no) depends on the relative intensity relationship between modifiers in the question and answer texts. In their original paper, the authors utilize an automatically-compiled lexicon to make a polarity prediction for each IQAP.

6.1 Predicting Answer Polarity

Our goal is to see whether paraphrase-based scores are useful for predicting the polarity of answers in the IQAP dataset. As before, we compare the quality of predictions made using the paraphrase-based evidence with predictions made using pattern-based, lexicon-based, and combined scoring metrics.

To use the pairwise scores for inference, we employ a decision procedure nearly identical to that of de Marneffe et al. (2010). If $j_q$ and $j_a$ are scorable (i.e., have a scorable intensity relationship along the same half-scale), then $j_q \leq j_a$ implies the answer is yes (first example above), and $j_q > j_a$ implies the answer is no (second example). If the pair of adjectives is not scorable, then the predicted answer is no, as the pair could be antonyms or completely unrelated. If either $j_q$ or $j_a$ is missing from the scoring vocabulary, the adjectives are impossible to compare and therefore the prediction is uncertain. The full decision procedure is given in Figure 4.

6.2 Experiments

The decision procedure in Figure 4 is carried out for the 123 IQAP instances in the dataset, varying the score type. We report the accuracy, and

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5The original dataset contains two additional examples where the answer is annotated as uncertain, but de Marneffe et al. (2010) exclude them from the results and so do we.
Given: A dialogue exchange consisting of a polar question and answer, where the answer depends on the relative intensities of distinct modifiers $j_q$ and $j_a$ in the question and answer respectively:

1. if $j_q$ or $j_a$ are missing from the score vocabulary, predict “UNCERTAIN”
2. else, if $\text{score}(JJ_q, JJ_a)$ is undefined, predict “NO”
3. else, if $\text{score}(JJ_q, JJ_a) \geq 0$, predict “YES”
4. else, predict “NO”
5. If the question or answer contains negation, map a “YES” answer to “NO” and a “NO” answer to “YES”

Figure 4: Decision procedure for using pairwise intensity scores for predicting polarity of an IQAP instance, based on de Marneffe et al. (2010).

Macro-averaged precision, recall, and F1-score of the 85 yes and 38 no instances, in Table 3 alongside the percent of instances with adjectives out of vocabulary. Only the combined scores for the two best-scoring combinations, $\text{score}_\text{soc}/\text{pat}+\text{pp}$ and $\text{score}_\text{soc}+\text{pp}$, are reported.

| Method                 | %OOV | Acc. | P    | R    | F    |
|-----------------------|------|------|------|------|------|
| all-“YES”             | .00  | .691 | .346 | .500 | .409 |
| deMarneffe (2010)     | .02  | .610 | .597 | .594 | .596 |
| $\text{score}_\text{soc}$          | .33  | .504 | .710 | .481 | .574 |
| $\text{score}_\text{pp}$            | .09  | .496 | .568 | .533 | .550 |
| $\text{score}_\text{pat}$            | .07  | .407 | .524 | .491 | .507 |
| $\text{score}_\text{soc}+\text{pp}$ | .09  | .634 | .690 | .663 | .676 |
| $\text{score}_\text{soc}/\text{pat}+\text{pp}$ | .06  | .642 | .684 | .683 | .684 |

Table 3: Accuracy and macro-averaged precision (P), recall (R), and F1-score (F) over yes and no responses on 123 question-answer pairs. The percent of pairs having one or both adjectives out of the score vocabulary is listed as %OOV.

The simplest baseline of predicting all answers to be “YES” gets highest accuracy in this imbalanced test set, but all score types perform better than the all-“YES” baseline in terms of precision and F1-score. Bouyed by its high precision, the $\text{score}_\text{soc}$ – which is derived from a manually-compiled lexicon – scored higher than $\text{score}_\text{pp}$ and $\text{score}_\text{pat}$. But it mis-predicted 33% of pairs as uncertain because of its limited overlap with the IQAP vocabulary. Meanwhile, $\text{score}_\text{pp}$ had relatively high coverage and a mid-level F-score, while $\text{score}_\text{pat}$ scored poorly on this dataset due to its sparsity; while all modifiers in the IQAP dataset are in the Google N-grams vocabulary, most do not have observed patterns and therefore return predictions of “NO” (item 2 in Figure 4). As in the global ranking experiments, the paraphrase-based evidence is complementary to the lexicon-based evidence, and thus the combined $\text{score}_\text{soc}/\text{pat}+\text{pp}$ and $\text{score}_\text{soc}+\text{pat}+\text{pp}$ produce significantly better accuracy than any score in isolation (McNemar’s test, $p < .01$), and also out-perform the original expected ranking method of de Marneffe et al. (2010) (although they do not beat the best-reported score on this dataset, F-score=0.706 (Kim and de Marneffe, 2013)).

7 Conclusion

We have presented adjectival paraphrases as a new source of evidence for predicting intensity relationships between scalar adjectives. While paraphrase-based intensity evidence produces pairwise predictions that are less precise than those produced by pattern- or lexicon-based evidence, the coverage is substantially higher. Thus paraphrases can be successfully used as a complementary source of information for reasoning about adjective intensity. We will publish the JJGRAPH resource, datasets, and code upon publication.

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