Categorization of Comparative Sentences for Argument Mining

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Abstract
We present the first work on domain-independent comparative argument mining (CAM), which is the automatic extraction of direct comparisons from text. After motivating the need and identifying the widespread use of this so far under-researched topic, we present the first publicly available open-domain dataset for CAM. The dataset was collected using crowdsourcing and contains 7199 unique sentences for 217 distinct comparison target pairs selected over several domains, of which 27% contain a directed (better vs. worse) comparison. In classification experiments, we examine the impact of representations, features, and classifiers, and reach an F1-score of 88% with a gradient boosting model based on pre-trained sentence embeddings, especially reliably identifying non-comparative sentences. This paves the way for domain-independent comparison extraction from web-scale corpora for the use in result ranking and presentation for comparative queries.

1 Introduction
In modern society, individuals are faced with choice problems on a daily basis. The most prominent example is the choice between analogous products (e.g., what camera to buy), but more generally people decide between all kinds of things: cities to visit, universities to study at, or even programming languages to use. Every informed choice assumes a comparison and objective argumentation to favor one of the candidates. The ubiquity of such comparative information needs is emphasized by the fact that question answering (QA) platforms are packed with questions like "How does X compare to Y?". Furthermore, the web at large is full of pages about comparing various objects. Specialized online sites systematize results of typical comparisons (e.g., for cars, cameras, restaurants, or insurances) prepared by human experts. Other systems like WolframAlpha.com aim at providing comparative functionality across domains, but also usually suffer from coverage issues, since, similarly to domain-specific systems, they typically rely on structured databases as the only source of information, ignoring textual content from the web. Somewhat surprising, no system is currently able to satisfy comparative information needs for the general domain with sufficient coverage and explanations, i.e., no system exists for comparing a broad range of object types, arguing about their relative qualities and providing objective arguments about the best choice. Indeed, information retrieval systems like Google are able to directly answer many factoid questions, but do not treat comparative questions specially beyond returning default search results. Question answering systems, such as IBM’s Watson (Ferrucci, 2012), answer factoid questions, but cannot handle comparative questions. Therefore, despite the wealth of comparative information available in the web, there is still no widespread technology for its extraction. In this work, our attempt is to make the first step towards developing such a technology.

The contributions of this paper are three-fold. First, we define comparative argument mining and relate it to argument mining in general. Second, we release the first public dataset of comparative sentences for three domains. Third, we provide an evaluation for the classification of comparative sentences, identifying a well-performing combination of feature representation and machine learning algorithm.

We define comparative argument mining in Section 2. We review previous work on comparative systems both in academic and industrial settings in Section 3. In Section 4 we describe the selection and the collection of our dataset. Classification ex-
Experiments are described in Section 5 and evaluated in Section 6 before concluding in Section 7.

2 Comparative Argument Mining

Comparative Argument Mining (CAM) can be viewed as a sub-field of Argument Mining (Lippi and Torroni, 2016), which specifically extracts arguments along comparisons. The goal of CAM is to develop a system that is able to decide if a given sentence compares two known objects and, if it does, which object wins the comparison. For instance, for the sentence *Python is better than Java for data analysis as it has better support of deep learning libraries*, the system should answer that the sentence is comparative and that the sentence speaks in favor of *Python* in comparison to *Java*. Natural extensions of CAM are the identification of the comparison aspect (i.e. *data analysis*) and supporting statements, a.k.a. premises (i.e. *as it has better support of deep learning libraries*). In the claim-premise model, which is widely adopted in NLP for modeling arguments, the claim would be formed by the pair of objects, the aspect and the direction of comparison, which are all subject of CAM.

Such a system can be useful in several ways. First, it enables machines to understand the statements of such sentences. Second, this knowledge can be used in applications, like opinion mining or online comparison portals, which to-date rely on structured databases. Thus, CAM could directly support the information need of people to pick one item out of several potential options, based on their personal preferences, by providing statements of direct comparison, as opposed to single-item reviews. Comparison sentences are also a critical element in scientific publications, enabling authors to relate their new methodologies and findings to previous research.

3 Related Work

While comparative argument mining has been researched comparably little by computational linguists, there is a range of commercial web-based portals offering comparison capabilities. We will review a few previous attempts to mining comparisons from text, relevant works from the field of argumentation mining and shortly characterize current commercial solutions in this section.

Previous works on recognizing comparative sentences have mostly been conducted in the biomedical domain. Fiszman et al. (2007) collected sentences comparing elements of drug therapy and manually crafted patterns to recognize the subjects of comparison and the comparison direction. Relying on large amounts of domain knowledge and focussing on a lexically explicit comparison, they were able to reach very high precision at moderate recall. On a set of full-text articles on toxicology, Park and Blake (2012) succeeded in training a highly precise Bayesian Network for identifying comparative sentences, relying on lexical clues (comparatives and domain-specific vocabulary) and features derived from dependency parses, mostly regarding dependency paths between comparison targets. More recently, Gupta et al. (2017) described a system based on manually collected patterns on the basis of lexical matches and dependency parses in order to identify comparison targets and classify the type of comparison into the four classes given in (Jindal and Liu, 2006), distinguishing gradable vs. non-gradable and superlative comparisons.

In contrast to the use of dependency parses for finding and analysing comparative sentences in the biomedical domain, Aker et al. (2017) confirm the findings of Stab and Gurevych (2014) that these syntactic features do not help for finding the (general) argument structure in persuasive essays and Wikipedia articles, but are subsumed by simpler structural features such as punctuation. The role of discourse markers in the identification of claims and premises were discussed in (Eckle-Kohler et al., 2015), who conclude that such markers are moderately useful for identifying argumentative sentences. Likewise, after comparing the modeling of claims across different datasets, Daxenberger et al. (2017) note that claims share lexical clues. From their classification experiments, they conclude that data set sizes in argumentation mining might be too small to unleash the power of recent DNN-based classifiers and methods based on feature engineering still work best.

Conceiving a system for the general domain that works on user-generated content as found on the internet faces additional challenges, as described in (Šnajder, 2017) for mining arguments from social media. While authors emphasized that social media can hint at reasons for opinions, text is typically noisy, misses argument structures and contains poorly formulated claims. On the other hand, specialized jargon and idiosyncrasies of a platform
can be utilized, as e.g. hashtags for mining argumentative tweets, cf. (Dusmanu et al., 2017).

There are a number of online comparison portals such as GoCompare.com or Compare.com providing an access to structured databases where products of the same class can be ranked along with their aspects. More interestingly are systems that compare any pairs of objects on arbitrary properties, like Diffen.com and Versus.com. They reach high coverage through the integration of a large number of structured resources such as databases and semi-structured resources such as Wikipedia, but still list aspects side by side without providing further explanations, since none of the portals aim at extracting comparisons from text. A promising data source for comparative questions and answers are question answering portals like Quora.com or answers.yahoo.com.

An application area of CAM is opinion mining on comparative sentences, as described in (Ganapathibhotla and Liu, 2008). For e.g. adding a comparative argument machine to general search engines, comparative queries/questions would have to be identified, cf. (Nama et al., 2014).

### 4 Building a Dataset of Comparative Sentences from a Web-Scale Corpus

Since there is, to our knowledge, no existing publicly available cross-domain dataset for comparative argument mining, we describe our approach to creating such dataset from web sources. In order to address the main goals of CAM, the dataset is composed of sentences, annotated with BETTER/WORSE (the first object is better/worse than the second object) or NONE (the sentence does not contain a comparison of the target objects).

Since the dataset should not be biased towards domain-specific constructions in order to capture the nature of comparison and not the nature of the domain, we decided to control the specificity of domains by the selection of comparison targets. The domains were chosen in a way that a large set of people can decide whether a sentence contains a comparison or not. We hypothesized and could confirm in preliminary experiments that comparison targets usually have a common hypernym resp. are instances of the same class, which we utilized for pair selection.

The most specific domain is Computer Science, containing targets like programming languages, database products and technology standards such as Bluetooth and Ethernet. Many computer science concepts can be compared objectively, e.g. on transmission speed or suitability for certain applications. The objects for this domain were manually extracted from List of ... articles from Wikipedia; annotators were asked to only label this domain if they had some basic knowledge of computer science.

The second, broader domain is Brands. It contains objects of different types, e.g. cars, electronics, and food brands. As brands are present in everyday life of people, it is expected that anyone can label the majority of sentences containing well-known brands such as Coca-Cola or Mercedes. Again, targets for this domain were extracted from List of ... articles from Wikipedia.

The third domain is not restricted to any topic, i.e. Random. For each one of 24 randomly selected seed words

1. ten similar words were extracted using the distributional similarity API of JoBimText
2. duplicates or too broad terms were removed manually. The seed words were created using randomlists.com.

Especially for brands and computer science, resulting object lists were large (4493 brands and 1339 for computer science). All objects with a frequency of zero and ambiguous objects were removed from the list. For instance, the objects “RAID” (a hardware concept) and “Unity” (a game engine) were removed from the computer science list as they are also regularly used nouns. The remaining objects were combined to pairs. For each object type as given by the Wikipedia List page or the seed word, all possible combinations were created. We drew sentences from the publicly available CommonCrawl index of Panchenko et al. (2018), which has been filtered for duplicates and to include only English, containing over 3 billion distinct sentences.

The index was queried for entries containing both objects of each pair. For 90% of the queries, we added cue words to the query in order to bias the selection towards comparisons but at the same time. 

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1. seed words: book, car, carpenter, cellphone, Christmas, coffee, cork, Florida, hamster, hiking, Hoover, Metallica, NBC, Netflix, ninja, pencil, salad, soccer, Starbucks, sword, Tolkien, wine, wood, XBox, Yale

2. http://www.jobimtext.org

3. https://commoncrawl.org

4. cue words: better, easier, faster, nicer, wiser, cooler, decent, safer, superior, solid, terrific, worse, harder, slower, poorly, uglier, poorer, lousy, nastier, inferior, mediocre
time admit comparisons that do not contain any of the anticipated cues. This was necessary as a random sampling would have resulted in only a tiny fraction of comparisons. If a sentence contains a cue word like better, it does not mean that it expresses a comparison between comparison targets like dog and cat, e.g. as in “He’s the best pet that you can get, better than a dog or cat.”, and it is crucial to enable a classifier to learn not to rely on the existence of clue words too much. We keep pairs were the query yielded at least 100 sentences.

From all sentences of those pairs, 2500 for each category were randomly sampled as candidates for the crowdsourcing task that we conducted on CrowdFlower.com in several small batches. Each sentence was annotated by at least five trusted crowd workers. We ranked annotations by confidence, which is the CrowdFlower-internal measure of combining annotator trust and voting, and discarded annotations with a confidence below 50%. Of all annotated items, 71% received unanimous votes and for over 85%, at least four out of five crowd workers agreed, which renders our collection procedure successful.

Table 1 shows examples on uncertain sentences. The first two are comparative. Background knowledge is needed to label the first sentence correct. A decision for the second and fifth sentence is hard because context is missing. It is unclear if Groovy and Java are compared in the third sentence. On one hand, one can understand this sentence in a way Groovy is easier than Java. On the other hand, it can be understood in a way that Groovy supports Java programmers. The fourth sentence does not explicitly states that one is better than the other.

The final data set has 7199 sentences, each containing one of 271 distinct object pairs. Table 2 shows the class distribution, both per domain and overall. The majority of sentences (over 72%) are non-comparative despite biasing selection with cue words; for comparative sentences, the favored target is named first in 70% of cases.

5 Supervised Categorization of Comparative Sentences

The data collected from the crowdsourcing task as described in the previous section was split into a training set (5759 sentences; 4194 NONE, 1091 BETTER, and 474 WORSE) and a held-out set. During development, the experiments were evaluated on the training set using stratified $k$-fold cross-validation where $k$ equals five; the held-out set was only used for the final evaluation. If not stated otherwise, scikit-learn (Pedregosa et al., 2011) was used to perform feature processing, classification, and evaluation.

5.1 Preprocessing

Two preprocessing steps were used to generate the input for the feature calculation. The first preprocessing step decided if the full sentence or a part of it should be used. The first part contained all words from the beginning of the sentence to the first comparison target, while the last part contained all words from the second comparison target to the end of the sentence. The middle part contained all words between the first and the second target.

The second step was done to check the importance of the lexicalized targets for the classification. The objects either stayed untouched, were removed or replaced. Two different replacement strategies were tested. First, both comparison targets were replaced by the term OBJECT (replacement). Second, the first object was replaced by OBJECT A and the second by OBJECT B (distinct replacement). This resulted in sixteen versions of each of the features mentioned above (four parts $\times$ four target strategies).

5.2 Classification Models

To find the most suitable classification model, thirteen models (see Figure 1) were compared. Twelve are available via scikit-learn, for XGBoost we used the implementation of Chen and Guestrin (2016). Apart from XGBoost and Extra Trees Classifier, all algorithms have been used in at least one work on argumentation mining.

5.3 Sentence Representations

Because many machine learning algorithms work with numeric values as input, we encoded all features in numeric feature vectors.

Bag-of-Words and Bag-Of-Ngrams The bag-of-words (BOW) model is a simple vector representation for documents. All words in the corpus are collected into a vocabulary $V$. A document $j$ is represented by a vector $d_j$ of size $|V|$, where $d_{ij}$ is the frequency of word $V_i$ in the document $j$ (the term frequency $tf(i,j)$), cf. (Salton et al., 1975). We also try BOW models extended to n-grams of tokens and weighted by $tf-idf$ to dimin-
Table 1: Examples of uncertain sentences where annotators could not agree upon.

| Sentence                                                                 | BETTER | WORSE | NONE |
|-------------------------------------------------------------------------|--------|-------|------|
| 1 Goodnight NetBeans:[OBJECT_A], Hello Eclipse:[OBJECT_B]               | 2      | 2     | 1    |
| 2 stone:[OBJECT_A] is harder than metal:[OBJECT_B].                     | 1      | 2     | 2    |
| 3 The new version of the Groovy:[OBJECT_A] aims to make life easier for programmers who work with Java:[OBJECT_B] and SQL | 3      | 0     | 3    |
| 4 Even if this juice:[OBJECT_A] isn’t your typical cider:[OBJECT_B], it’s just as good if not better in our opinion! | 2      | 1     | 2    |
| 5 Only Nevada (14.4 percent), michigan:[OBJECT_A] (13 percent) and california:[OBJECT_B] (12.4 percent) were worse. | 2      | 1     | 2    |

Table 2: Class and domain distribution of final dataset.

| Domain   | BETTER | WORSE | NONE | total |
|----------|--------|-------|------|-------|
| CompSci  | 581    | 248   | 1596 | 2425  |
| Brands   | 404    | 167   | 1764 | 2335  |
| Random   | 379    | 188   | 1882 | 2439  |
| total    | 1364   | 593   | 5242 | 7199  |

Sentence Embeddings  Bags of words and mean word embeddings lose sequence information, which intuitively should help for comparison extraction. Sentence embeddings aim to learn embeddings for spans of text instead of single words, taking sequence information into account. Several methods have been proposed to create sentence embeddings, e.g. FastSent (Hill et al., 2016) and SkipTought (Kiros et al., 2015). In this work, we use InferSent as presented in (Conneau et al., 2017). InferSent learns sentence embedding in a similar way as word embeddings are learned: A neural network is trained on the Stanford Natural Language Inference (SNLI) data set (Bowman et al., 2015). SNLI contains 570,000 English sentence pairs. Each pair is labelled as entailment, contradiction or neutral. The authors assumed that the semantic nature of the task makes the data set suitable for learning universal sentence embeddings. In InferSent, two separate encoders are used to encode the text and the hypothesis. The embeddings $u$ and $v$ are combined into a feature vector, which contains the concatenation, the element-wise product and the element-wise difference of $u$ and $v$. This vector, containing information from both sentences, is then fed into a fully connected layer and a softmax layer that outputs the probabilities of each label. We used the pre-trained embeddings in our experiments.

Dependency-based Features  HypeNet, presented in (Shwartz et al., 2016), is a method to detect hypernym relations between words. It combines distributional and dependency path-based methods to create a vector representation for word pairs. LexNet, presented in (Shwartz and Dagan, 2016), is a generalization of HypeNet, which is
able to detect multiple semantic relationships between two words. Intuitively, this should capture dependency paths, which have been one of the major sources for comparison extraction (cf. Section 3). The dependency paths, encoded with an LSTM (Hochreiter and Schmidhuber, 1997), add information about joint occurrences of the two words.

Two features based on LexNet were created to encode dependency parsing information:

**LexNet (original)** The original code of LexNet was used to create the string representation of paths. An LSTM was used to create path embeddings out of the string paths. Because the paper does not mention any details about the LSTM encoder, different architectures and hyper-parameters were tested; we achieved the best results with one LSTM layer with 200 neurons, batch size of 128, RMSprop with learning rate 0.01 and 150 epochs, max pooling with a pool size of two. Keras’ embedding layer was used to create word embeddings of length 100 for the string path components.

Different setups for the string path creation were tested. In the original implementation, the paths were restricted to a length of four. The directionalities of edges was restricted as well: The first comparison target must be reachable from the lowest common head of the two targets by following left edges only, the second one by following right edges. In the following, this setup is called *original*. However, only 1519 sentences from the training set got a path with this restriction.

**LexNet (customized)** To overcome this problem, the restrictions were relaxed. The second LexNet setup (called *customised*) limits the paths to a size of sixteen and drops the directionalities restriction. With this setup, only 399 sentences in training do not get a path. All sentences without a generated path get the artificial path *NOPATH*.

### 6 Results: Categorization Experiments

#### 6.1 Performance Metrics

Precision, recall and F1 score are measures to check the classification performance. The measures are calculated per class and micro-averaged when reporting overall results.

#### 6.2 Trivial Baselines

The first baseline was created by assigning classes to the data at random, respecting the distribution of classes in the original data. This random stratified baseline achieves 0.57 F1 score, while the performance of the majority class baseline (predicting always *NONE*) is 0.61 F1 score for our dataset.

### 6.3 Impact of Classification Models

A sparse bag-of-words model computed on the whole sentence (see Section 5.3) was used for representation. The F1 score was used as the measure to compare the algorithms.

Tree-based methods and linear models worked well. Support Vector Machines with non-linear kernels assigned *NONE* to all sentences. As XGBoost and Logistic Regression achieved high F1-scores, no further investigations on the performance of other algorithms were done. A set of hyper-parameters for XGBoost was tested using exhaustive grid search and randomized search but without significant performance increases. For the remaining experiments, we selected XGBoost with 1000 estimators.

The main idea behind boosting is to fit weak learners (i.e. classifiers only performing slightly better than random guessing) sequentially on modified versions of the data, subsequently combining them to produce the final prediction. The XGBoost boosting method used here is *gradient boosting* (Friedman, 2001) with *decision trees* as learners. In gradient boosting, $G_{m+1}$ is fitted on the residuals of $G_{m}$. Thus, each tree tries to improve on the training examples on which the previous learner was weak on.

#### 6.4 Impact of Feature Representations

The classification results of the best-performing feature configurations in our three-class scenario are presented in Figure 2. Each feature was tested and evaluated using five stratified folds. The black bars show the standard deviation. All scores were calculated with scikit-learn’s metric module. All features except the *LexNet (original)* feature used the middle part of the sentence and left the objects untouched. In the LexNet features, the objects were replaced with *OBJECT_A* and *OBJECT_B*. *LexNet (original)* used the full sentence.

The best single feature (*InferSent* of the text in between objects) yielded a score 24 points above the baseline. The worst single feature (*LexNet (original)*)) was still eight points above the baseline. Bag-of-words (F1 score 0.848) and *InferSent* (F1 score 0.842) delivered almost identical results. The boolean *Contains JJR* feature yielded an F1
Figure 1: **Impact of classification model**: F1 scores on 5-fold cross validation of various classification algorithms based on a baseline binary bag-of-word representation. The black bars show the standard deviation.

Figure 2: **Impact of feature representation**: F1 scores of sentence classification model based on XGBoost. The black bars indicate the standard deviation in the 5-fold cross validation.

score of 14 points over the baseline as well. However, it did not cause any examples to be assigned to the **WORSE** class.

Despite the fact that only 1519 sentences got a path embedding for **LexNet (original)**, the feature is able to predict some sentences correctly. This indicates that this feature setup is reasonable and would work probably work well if more examples were present. An experiment with only the 1519 sentences confirms this, as the feature is able to achieve an F1 score of 0.75 on this subset.

To our surprise, combining feature representations did not help, i.e. we were not able to exceed over the score of the single best representation (**InferSent** on the middle part) in any setup, which is why we do not report results on combinations. Using the full sentence worked second best. Adding the first and/or last part of the sentence did not increase the F1 score at all, no matter if the same or another representation type than the one for the middle part is used. The first and second part alone never got an F1 score above the baseline. Replacing or removing the objects did not increase the score significantly. In most cases, the difference in the F1 score between no replacement/removal and the best replacement/removal strategy was only reflected in the third or fourth decimal place. Hence, the actual objects are not important at all for the classification, which hints at the domain-independence of the dataset. This is also supported by the fact that adding the word vectors of the objects as features did not increase the result for any feature.

An interesting observation is that the simple bag-of-words model performs equal to or better than most more complex models.

6.5 Error Analysis

**WORSE** was the hardest class to recognize. In total, 1311 sentences were incorrectly classified. We look at comparing the performance of **InferSent** and **LexNet (customized)** in more detail. Both fea-
Is Python better than Perl?
BETTER
0.6

Is Microsoft better because of Apple?
BETTER
1.0

Microsoft is the devil but Sony truly isn’t any better.
WORSE
1.0

Python is much better suited as a “glue” language, while Java is better characterized as a low-level implementation language.
BETTER
1.0

Its Azure PaaS/IaaS platform hasn’t overtaken Amazon yet in market share, but Microsoft has enjoyed nine straight quarters of growth at 10 percent or better.
NONE
WORSE
1.0

arrrgghh...Python is a terrible language - only Perl sucks worse.
WORSE
BETTER
1.0

Good to see again a Renault ahead of a Ferrari.
NONE
BETTER
1.0

Table 3: Example sentences for errors made by XGBoost in the three-class scenario with the InferSent feature and not the HypeNet feature. The objects of interest are printed bold. Confidence shows the confidence of the annotators and is calculated as judgments for majority class / total judgments.

1. Is Python better than Perl?
2. Is Microsoft better because of Apple?
3. Microsoft is the devil but Sony truly isn’t any better.
4. Python is much better suited as a "glue" language, while Java is better characterized as a low-level implementation language.
5. Its Azure PaaS/IaaS platform hasn’t overtaken Amazon yet in market share, but Microsoft has enjoyed nine straight quarters of growth at 10 percent or better.
6. arrrgghh...Python is a terrible language - only Perl sucks worse.
7. Good to see again a Renault ahead of a Ferrari.

The first two sentences look comparative, but they are questions. Despite annotation of questions as NONE as explicitly stated in the guidelines, InferSent frequently classified questions as comparative. Sentences three and four are comparative, but it has no clear winner of the comparison. The guidelines formulated that only sentences with clear winners should be labeled with BETTER or WORSE. InferSent was not able to learn this restriction. Sentence six has three negative words in it. Sentence seven is hard to classify, as it does not contain any cue word.

The LexNet feature made errors in fairly simple sentences like “Right now Apple is worse than Microsoft ever was”. While InferSent’s errors can be coarsely grouped, the errors made by LexNet seem more random. We assumed that the amount of training data for the neural network encoder is not large enough. However, the overall result of LexNet indicates that an encoder trained on more data would likely yield good results. The performance for LexNet path embeddings shows that this is a reasonable way to encode sentences. The original setup found only paths for 26% of the sentences, yet it yielded an F1 score eight points above the baseline. The customization made it even more powerful. While we expected that a combination of LexNet features and one of the other features like InferSent would be beneficial, as they encode different information (lexical and syntactical), this was not the case.

We explain relatively low performance of all models on the WORSE class by the fact that people tend to more often refer to use “BETTER constructions” than “WORSE constructions”, similarly to many opinion mining datasets, where the positive class is observed more often. Besides, the tested models do not use explicit representations of negations, which may lead to a confusion of the BETTER and WORSE classes.

7 Conclusion

This paper introduced the task of identification of comparative sentences, forming an important building block in domain-independent comparative systems, which extract information from texts. First, we presented a labeled dataset that contains a wide range of comparative sentences across several domains. Second, we tested a battery of state-of-the-art supervised machine learning approaches on this dataset, creating a system which is able to efficiently retrieve comparative sentences. Gradient boosted decision trees turned out to be the best classifier for this task. Various simple (like bag-of-words) and complex (like sentence embeddings) feature representations achieved F1 scores at least ten points over the baseline. It turned out that the words between the two compared objects are most important for detection of a comparison and its direction w.r.t. compared objects.

A first promising extension of this work is including context beyond single sentences. A second one is bootstrapping more examples in a semi-supervised way, e.g. with simpler classifiers, can help to gather more data, required to train more accurate but also more sparse syntax-based models.
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