A Large Self-Annotated Corpus for Sarcasm

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Abstract
We introduce the Self-Annotated Reddit Corpus (SARC), a large corpus for sarcasm research and for training and evaluating systems for sarcasm detection. The corpus has 1.3 million sarcastic statements — 10 times more than any previous dataset — and many times more instances of non-sarcastic statements, allowing for learning in both balanced and unbalanced label regimes. Each statement is furthermore self-annotated — sarcasm is labeled by the author, not an independent annotator — and provided with user, topic, and conversation context. We evaluate the corpus for accuracy, construct benchmarks for sarcasm detection, and evaluate baseline methods.

Keywords: sarcasm, classification

1. Introduction
Sarcasm detection is an important component of many natural language processing (NLP) systems, directly relevant to natural language understanding, dialogue systems, and text mining. However, detecting sarcasm is difficult because it occurs infrequently and is difficult for even humans to discern (Wallace et al., 2014). Despite these properties, existing datasets either have balanced labels — data with roughly the same number of examples of each label (González-Ibáñez et al., 2011; Bamman and Smith, 2015; Joshi et al., 2015; Amir et al., 2016; Oraby et al., 2016) — or use humans to annotate sarcastic statements (Riloff et al., 2013; Swanson et al., 2014; Wallace et al., 2015). In this work, we make available the first corpus for sarcasm detection that has both unbalanced and self-annotated labels and does not consist of low-quality text snippets from Twitter. With more than a million examples of sarcastic statements, each provided with author, topic, and context information, the dataset exceeds all previous sarcasm corpora by an order of magnitude. This is possible due to the comment structure of the social media site Reddit as well its frequently-used and standardized annotation for sarcasm. Following a discussion of corpus construction and relevant statistics in Section 3.1, we discuss the quality of this dataset compared to alternative sources in Section 3.2, manually evaluating our corpus for noise. Then in Section 3.3, we use our dataset to construct suitable benchmarks for sarcasm detection systems and examine the performance of simple baseline methods and human evaluators on these subsets.

2. Related Work
Since our main contribution is a corpus and not a method for sarcasm detection, we point the reader to a recent survey by Joshi et al. (2016) that discusses many interesting efforts in this area. Note that many of the works the authors mention will be discussed by us in this section, with many papers using their own datasets; this illustrates the need for common baselines for evaluation.

Sarcasm datasets can largely be distinguished by the sources used to get sarcastic and non-sarcastic statements, the amount of human annotation, and whether the dataset is balanced or unbalanced. Reddit has been used before, notably by Wallace et al. (2015); while the authors allow unbalanced labeling, they do not exploit the possibility of using self-annotation and generate around 10,000 human-labeled sentences. Twitter is a frequent source due to the self-annotation provided by hashtags such as #sarcasm, #notsarcasm, and #irony (Reyes et al., 2013; Bamman and Smith, 2015). As discussed in Section 4.2, its low quality language and other properties make Twitter a less attractive source for annotated comments. However, it is by far the largest raw source of data for this purpose and has led to some large unbalanced corpora in previous efforts (Riloff et al., 2013; Přáček et al., 2014). A further source of comments is the Internet Argument Corpus (IAC) (Walker et al., 2012), a scraped corpus of Internet discussions that can be further annotated for sarcasm by humans or by machine learning; this is done by Lukin and Walker (2013) and Oraby et al. (2016), in both cases resulting in around 10,000 labeled statements.

3. Corpus Details
3.1. Reddit Structure and Annotation
Reddit is a social media site in which users communicate by commenting on submissions, which are titled posts consisting of embedded media, external links, and/or text, that are posted on topic-specific forums known as subreddits; examples of subreddits include funny, pics, and science. Users comment on submissions and on other comments, resulting in tree-like conversation structure such that each comment has a parent comment. We refer to elements as any nodes in the tree of a Reddit link (i.e., comments or submissions).

Reddit users have adopted a common method for sarcasm annotation consisting of adding the marker “/s” to the end of sarcastic statements; this originates from the HTML text delineation <sarcasm>...</sarcasm> As with Twitter hashtags, using these markers as indicators of sarcasm is noisy (Bamman and Smith, 2015), especially since many users do not make use of the marker, do not know about it,
Bankers celebrate dawn of the Trump era (politico.com)
submitted 4 months ago by Boartar
76 comments share save hide ... save report give gold REPLY
Welcome to /r/Politics! Please read the wiki before participating.

Figure 1: A Reddit submission and one of its comments. Note the conventional annotation “/s” indicating sarcasm.

or only use it where sarcastic intent is not otherwise obvious. We discuss the extent of this noise in Section 4.1.

3.2. Constructing SARC

Reddit comments from December 2005 have been made available due to web-scraping[^1] we construct our dataset as a subset of comments from January 2009-April 2017, comprising the vast majority of comments and excluding noisy data from earlier years. For each comment we provide a sarcasm label, author, the subreddit it appeared in, the comment score as voted on by users, the date of the comment, and identifiers linking back to the original dataset of all comments.

To reduce noise, we use several filters to remove noisy and uninformative comments. Many of these are standard preprocessing steps such as excluding URLs and limiting characters to be ASCII. To handle Reddit data, we also exclude comments that are descendants of sarcastic comments in the conversation tree, as annotation in such cases is extremely noisy, with authors agreeing or disagreeing with the previously expressed sarcasm with their own sarcasm but often with no marking.

Our raw corpus consists of three files:

1. An array in CSV format containing 533 million comments, of which around 1.3 million are sarcastic. This file only contains those comments whose authors know about the standard sarcasm annotation; this is determined by whether they have used the annotation in the same month as the comment was made or earlier. This limitation is added in order to reduce false negatives due to authors not annotating their sarcasm. Each row also contains the parent comment.

2. A hashtable in JSON format containing all comments and posts in the conversation thread of a sarcastic comment as well as all siblings of sarcastic comments.

3. An array in CSV format, with each row containing a sequence of comments leading up to a sarcastic comment, the (sarcastic and non-sarcastic) responses to the last element in that sequence, and the labels of those responses. Each element is given as a key to the previous file.

This raw corpus is very large and suitable for both large-scale machine learning and statistical analysis as well for deriving smaller benchmark tasks for evaluating sarcasm detection systems. These benchmarks, whether in the balanced or unbalanced regimes, require further subsampling of the corpus and an approach for dealing with noisy data in the face of sparse signals. We specify and evaluate an approach for doing so in Section 5.1 followed by the evaluation of learning algorithms on the output.

4. Corpus Evaluation

There are three major metrics of interest for evaluating our corpora: (1) size, (2) the proportion of sarcastic to non-sarcastic comments, and (3) the rate of false positives and false negatives. Of interest is also the quality of the text in the corpus and its applicability to other NLP tasks. Thus in this section we evaluate error in the raw corpus and provide comparison with other corpora used to construct sarcasm datasets.

4.1. Manual Evaluation

To investigate the noisiness of using Reddit as a source of self-annotated sarcasm we estimate the proportion of false positives and false negatives induced by our filtering. This is done by manually checking a random subset of 500 comments from SARC tagged as sarcastic and 500 tagged as non-sarcastic, with full access to the comment’s context. A comment was determined to be false positive if “/s” tag was not an annotation but part of the sentence and a false negative if the comment author was clearly being sarcastic to the human rater. This procedure yielded a false positive rate of 1.0% and a false negative rate of 2.0%. Although the false positive rate is reasonable, the false negative rate is significant compared to the sarcasm proportion (0.25%), indicating large variation in the working definition of sarcasm and the need for methods that can handle noisy data in the unbalanced setting. In the balanced setting this is still a fairly small amount of noise.

4.2. Comparison with other Sources

As noted before, Twitter has been the most common source for sarcasm in previous corpora; this is likely due to the explicit annotation provided by its hashtags. However, using Reddit as a source of sarcastic comments holds many research advantages. Unlike Reddit comments, which are not...
Figure 2: Sarcasm percentage for subreddits with more than a million comments in SARC. Well-moderated and special-interest forums such as science and asoiaf (referring to fantasy series A Song of Ice and Fire) have less sarcasm than controversial and less-moderated subreddits.

constrained by length and contain fewer hashtags, tweets are not written in true English. Hashtagged tokens are also frequently used as a part of the statement itself (e.g. “that was #sarcasm”), blurring the line between text and annotation; on Reddit “/s” is generally only used as something other than annotation when its use as an annotation is being referred to (e.g. “you forgot the /s”). The full conversation context is also much easier to provide on Reddit due to the shallow tree structure of an individual post and its comments.

Furthermore, from a subsample of Twitter and Reddit data from July 2014 we determined that a vastly smaller percentage (.002% vs. .927%) of Twitter authors make use of sarcasm annotation (#sarcasm, #sarcastic, or #sarcastictweet). We hypothesize that Reddit users require sarcastic annotation more frequently and in a more standardized form because they are largely anonymous and so cannot rely on a shared context to communicate sarcasm. Finally, Reddit also benefits from having subreddits, which enable featurization and data exploration based on an explicit topic assignment.

The Internet Argument Corpus (IAC) has also been used as a source of sarcastic comments (Walker et al., 2012). The corpus developers found 12% of examples in the IAC to be sarcastic, which is a much nicer class proportion for sarcasm detection than ours. As the Reddit data consists of arbitrary conversations, not just arguments, it is not surprising that our sarcasm percentage is much smaller, even when accounting for false negatives; this property also makes our dataset more realistic. Unlike Reddit and Twitter, the IAC also requires manual annotation of sarcasm.

5. Benchmarks for Sarcasm Detection

A direct application of our corpus is for training and evaluating sarcasm detection systems. Thus using the raw corpus described in Section 3, we construct several useful benchmarks for the task of classifying statements as sarcastic or non-sarcastic. All benchmarks provide the full conversation thread leading up to the target statements to the learning algorithm, along with comment metadata. Following their specification we consider a few context-free baseline methods depending only on linear classification over simple featurizations.

5.1. Evaluation Task

In the most general case, we use the provided raw files to construct datapoints for systems to learn the following task: given a post and a sequence of comments, determine which comments among the responses to the last comment in the sequence are sarcastic. Thus each datapoint consists of a conversation thread followed by a series of responses and sarcasm labels. Performance on this task is measured by precision and recall.

Before constructing this subcorpus we first remove from consideration all comments that are not complete sentences and not between 2 and 50 tokens long, allowing for cleaner comments in the evaluation. Although the responses are still largely non-sarcastic, the proportion of sarcastic comments is much greater here as each datapoint must correspond to a thread where at least one sarcastic annotation occurred. In total we construct 8.44 million sequences, with the average proportion of sarcastic responses being 28.1%.

5.1.1. Balanced Labels

We construct a balanced learning task by taking only one sarcastic and one non-sarcastic response from each set of responses to a comment sequence. The task the becomes one of picking which of two statements that share a context is sarcastic, with performance measured by accuracy. While having only posts with at least one sarcastic response is useful, it also increases the false negative rate as comments warranting a sarcastic response often draw other sarcastic statements that are similar in content to the labeled sarcastic responses but which themselves may not be labeled. Thus to reduce this issue when picking the non-sarcastic statement, we featurize all statements using the normalized sum of Common Crawl GloVe embeddings of the words and pick from only those non-sarcastic statements that have similarity \( \leq 0.95 \) with the sarcastic statement (Pennington et al., 2014).

5.1.2. Politics

The difficulty of detecting sarcasm rests not only on the need to understand the context of previous statements but also on understanding background information on the topic being discussed. Even humans will struggle with many sarcastic comments drawn from subreddits with which they
have little familiarity, such as those devoted to obscure hobbies or art forms. Thus we also test human and machine performance on comments drawn solely from the politics subreddit, a topic for which all evaluators had sufficient background information. This subsample contains 17 thousand sequences, with the average proportion of sarcastic responses being 23.2%.

5.2. Methods
For the case of balanced labels, a simple, no-context baseline method for the above task is to featurize the two responses and to train a logistic regression classifier to distinguish between the sarcastic and non-sarcastic response as separate classes. Then on the testing set pick the response with the highest probability of being labeled sarcastic as the sarcastic one. We split both datasets we test on 80%-20% between train-test subsets and report the results of the following three approaches in Table 2.

5.2.1. Bag-of-n-Grams
The Bag-of-n-Grams representation consists of using a document’s n-gram counts as features in a vector. We test two variants, the Bag-of-Words and the Bag-of-Bigrams. For the subsample containing all subreddits we use only those features that occur at least 5 times in the training comments.

5.2.2. Sentence Embeddings
Given a document, taking the elementwise sum of word embeddings of its words provides a simple low-dimensional document representation. We use 1600-dimensional GloVe representations trained on the Amazon product corpus, which is used instead of Common Crawl because of the semantic closeness between sentiment and sarcasm. (McAuley et al., 2015).

5.2.3. Human
Human performance on sarcasm detection was measured by giving 5 human evaluators 100 samples and asking them to perform the same task as the algorithm: determining which of two statements is sarcastic. The full context was provided, and the final human classifier was taken as the majority vote of all 5 evaluators.

5.3. Results
5.3.1. Baselines
The baselines in Table 2 perform reasonably well, but none of them match human performance on either dataset. There is clear scope for improvement for machine learning methods, starting with the use of context provided to make better decisions about sarcasm. As evident in Table 2 Bag-of-Word and Bag-of-Bigram representations perform better than sentence embeddings; however distributed representations may be necessary for incorporating context in future methods.

5.3.2. Human
As expected, human evaluators performed significantly better, both as a majority and on-average, than the baseline methods. There was significant but not perfect agreement among annotators: on the main dataset the Fleiss kappa score (Fleiss, 1971) was 0.5, indicating moderate agreement, while on the politics subsample it was 0.67, indicating substantial agreement. Interestingly, while individually human performance was worse on average on sequences drawn from all subreddits than on the politics subsample, taking the majority led to much better performance in the former case. This indicates that while individuals may not have enough context for all topics of discussion on Reddit, in aggregate there is enough information to do well, even more than for a well-known topic such as politics.

6. Conclusion
We introduce a large sarcasm dataset based on self-annotated Reddit comments. Both the raw data and evaluation subsamples are made freely available, with the former having over 1 million sarcastic sentences, larger than any existing dataset. We evaluate the baseline performance of simple machine learning methods and compare them with human performance. We hope that future users of this dataset will improve upon these benchmarks and find new ways of utilizing the large quantities of self-annotated information we provide.

7. Acknowledgements
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Table 3: Most positive and negative n-grams based on weights assigned by the Bag-of-Bigrams classifier. Positive (negative) weight for an n-gram implies it is a strong indicator for the comment being sarcastic (non-sarcastic). The weights indicate that positive n-grams are more important for linear classification of sarcasm.

| Positive n-Grams | Weights | Negative n-Grams | Weights |
|------------------|---------|------------------|---------|
| obviously        | 1.79    | :)               | -1.37   |
| clearly          | 1.66    | lmao             | -1.27   |
| so fun           | 1.49    | :(               | -1.17   |
| totally          | 1.39    | /                | -1.17   |
| good thing       | 1.35    | , but            | -1.10   |
| shocked          | 1.32    | lol              | -1.00   |
| shocking         | 1.23    | the original     | -0.98   |
| m sure           | 1.15    | wat              | -0.97   |
| omg              | 1.13    | why              | -0.96   |
| how dare         | 1.13    | oh god           | -0.95   |

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