A Corpus of Sentence-level Revisions in Academic Writing: A Step towards Understanding Statement Strength in Communication

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Abstract

The strength with which a statement is made can have a significant impact on the audience. For example, international relations can be strained by how the media in one country describes an event in another; and papers can be rejected because they overstate or understate their findings. It is thus important to understand the effects of statement strength. A first step is to be able to distinguish between strong and weak statements. However, even this problem is understudied, partly due to a lack of data. Since strength is inherently relative, *revisions* of texts that make claims are a natural source of data on strength differences. In this paper, we introduce a corpus of sentence-level revisions from academic writing. We also describe insights gained from our annotation efforts for this task.

1 Introduction

It is important for authors and speakers to find the appropriate "pitch" to convey a desired message to the public. Indeed, sometimes heated debates can arise around the choice of statement strength. For instance, on March 1, 2014, an attack at Kunming's railway station left 29 people dead and more than 140 others injured.[1] In the aftermath, Chinese media accused Western media of "soft-pedaling the attack and failing to state clearly that it was an act of *terrorism*".[2] In particular, regarding the statement by the US embassy that referred to this incident as the "terrible and senseless act of violence in Kunming", a Weibo user posted "If you say that the Kunming attack is a 'terrible and senseless act of violence', then the 9/11 attack can be called a 'regrettable traffic incident'".[3]

This example is striking but not an isolated case, for settings in which one party is trying to convince another are pervasive; scenarios range from court trials to conference submissions. Since the strength and scope of an argument can be a crucial factor in its success, it is important to understand the effects of statement strength in communication.

A first step towards addressing this question is to be able to distinguish between strong and weak statements. As strength is inherently relative, it is natural to look at *revisions* that change statement strength, which we refer to as "*strength changes*". Though careful and repeated revisions are presumably ubiquitous in politics, legal systems, and journalism, it is not clear how to collect them; on the other hand, revisions to research papers may be more accessible, and many researchers spend significant time on editing to convey the right message regarding the strength of a project's contributions, novelty, and limitations. Indeed, statement strength in science communication matters to writers: understating contributions can affect whether people recognize the true importance of the work; at the same time, overclaiming can cause papers to be rejected.

With the increasing popularity of e-print services such as the arXiv[4], strength changes in scientific papers are becoming more readily available. Since the arXiv started in 1991, it has become "the standard repository for new papers in mathematics, physics, statistics, computer science, biology, and other disciplines" (Krantz, 2007). An intriguing observation is that many researchers submit multiple versions of the same paper on arXiv. For instance, among the 70K papers submitted in

[1] http://en.wikipedia.org/wiki/2014_Kunming_attack

[2] http://sinosphere.blogs.nytimes.com/2014/03/03/u-n-security-council-condemns-terrorist-attack-in-kunming/

[3] http://www.huffingtonpost.co.uk/2014/03/03/china-kunming-911_n_4888748.html

[4] http://arxiv.org/

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ID	Pairs
1	S1: The algorithm is *studied* in this paper . S2: The algorithm is *proposed* in this paper .
2	S1: ... circadian pattern and burstiness in *human communication activity* . S2: ... circadian pattern and burstiness in *mobile phone communication* .
3	S1: ... using minhash techniques , *at a significantly* lower *cost and with same privacy guarantees* . S2: ... using minhash techniques , *with* lower *costs* .
4	S1: the rows and columns of the covariate matrix *then* have *certain physical* meanings ... S2: the rows and columns of the covariate matrix *could* have *different* meanings ...
5	S1: they maximize the expected revenue of the seller but *induce efficiency loss* . S2: they maximize the expected revenue of the seller but *are inefficient* .

Table 1: Examples of potential strength differences.

2011, almost 40% (27.7K) have multiple versions. Many differences between these versions constitute a source of valid and motivated strength differences, as can be seen from the sentential revisions in Table 1. Pair 1 makes the contribution seem more impressive by replacing "studied" with "proposed". Pair 2 downgrades "human communication activity" to "mobile phone communication". Pair 3 removes "significantly" and the emphasis on "same privacy guarantees". Pair 4 shows an insertion of hedging, a relatively well-known type of strength reduction. Pair 5 is an interesting case that shows the complexity of this problem: on the one hand, S2 claims that something is "inefficient", which is an absolute statement, compared to "efficiency loss" in S1, where the possibility of efficiency still exists; on the other hand, S1 employs an active tone that emphasizes a causal relationship.

The main contribution of this work is to provide the first large-scale corpus of sentence-level revisions for studying a broad range of variations in statement strength. We collected labels for a subset of these revisions. Given the possibility of all kinds of disagreement, the fair level of agreement (Fleiss' Kappa) among our annotators was decent. But in some cases, the labels differed from our expectations, indicating that the general public can interpret the strength of scientific statements differently from researchers. The participants' comments may further shed light on science communication and point to better ways to define and understand strength differences.

2 Related Work and Data

Hedging, which can lead to strength differences, has received some attention in the study of science communication (Salager-Meyer, 2011; Lewin, 1998; Hyland, 1998; Myers, 1990). The CoNLL 2010 Shared Task was devoted to hedge detection (Farkas et al., 2010). Hedge detection was also used to understand scientific framing in debates over genetically-modified organisms in food (Choi et al., 2012).

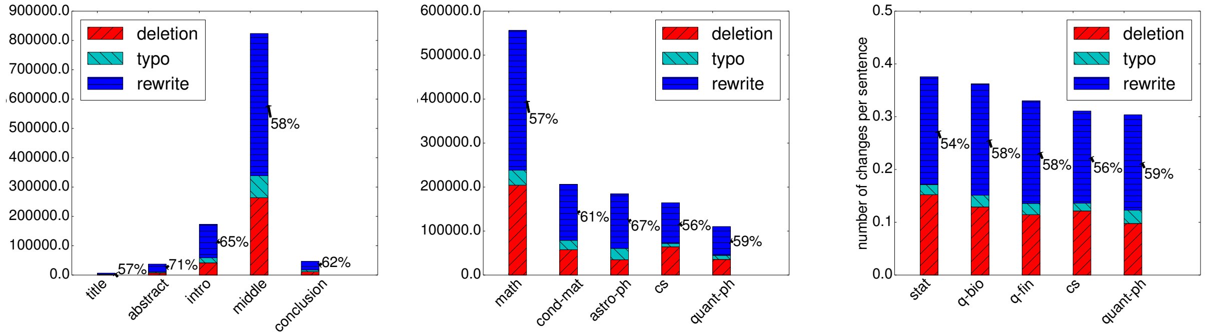
Revisions on Wikipedia have been shown useful for various applications, including spelling correction (Zesch, 2012), sentence compression (Yamangil and Nelken, 2008), text simplification (Yatskar et al., 2010), paraphrasing (Max and Wisniewski, 2010), and textual entailment (Zanzotto and Pennacchiotti, 2010). But none of the categories of Wikipedia revisions previously examined (Daxenberger and Gurevych, 2013; Bronner and Monz, 2012; Mola-Velasco, 2011; Potthast et al., 2008; Daxenberger and Gurevych, 2012) relate to statement strength. After all, the objective of editing on Wikipedia is to present neutral and objective articles.

Public datasets of science communication are available, such as the ACL Anthology,[5] collections of NIPS papers,[6] and so on. These datasets are useful for understanding the progress of disciplines or the evolution of topics. But the lack of edit histories or revisions makes them not immediately suitable for studying strength differences. Recently, there have been experiments with *open* peer review.[7] Records from open reviewing can provide additional insights into the revision process once enough data is collected.

[5] http://aclweb.org/anthology/

[6] http://nips.djvuzone.org/txt.html

[7] http://openreview.net



(a) Number of changes vs sections. "middle" refers to the sections between introduction and conclusion.

(b) Top 5 categories in number of changes.

(c) Top 5 categories in number of changes over the number of sentences.

Figure 1: In all figures, different colors indicate different types of changes.

3 Dataset Description

Our main dataset was constructed from all papers submitted in 2011 on the arXiv. We first extracted the textual content from papers that have multiple versions of tex source files. All mathematical environments were ignored. Section titles were not included in the final texts but are used in alignment.

In order to align the first version and the final version of the same paper, we first did macro alignment of paper sections based on section titles. Then, for micro alignment of sentences, we employed a dynamic programming algorithm similar to that of Barzilay and Elhadad (2003). Instead of cosine similarity, we used an idf-weighted longest-common-subsequence algorithm to define the similarity between two sentences, because changes in word ordering can also be interesting. Formally, the similarity score between sentence i and sentence j is defined as

$$Sim(i,j) = \frac{\text{Weighted-LCS}(S_i, S_j)}{max(\sum_{w \in S_i} idf(w), \sum_{w \in S_j} idf(w))},$$

where S_i and S_j refer to sentence i and sentence j. Since it is likely that a new version adds or deletes a large sequence of sentences, we did not impose a skip penalty. We set the mismatch penalty to 0.1.[8]

In the end, there are 23K papers where the first version was different from the last version.[9] We categorize sentential revisions into the following three types:

- Deletion: we cannot find a match in the final version.
- Typo: all sequences in a pair of matched sentences are typos, where a sequence-level typo is one where the edit distance between the matched sequences is less than three.
- Rewrite: matched sentences that are not typos. This type is the focus of this study.

What kinds of changes are being made? One might initially think that typo fixes represent a large proportion of revisions, but this is not correct, as shown in Figure 1a. Deletions represent a substantial fraction, especially in the middle section of a paper. But it is clear that the majority of changes are rewrites; thus revisions on the arXiv indeed provide a great source for potential strength differences.

Who makes changes? Figure 1b shows that the Math subarchive makes the largest number of changes. This is consistent with the mathematics community's custom of using the arXiv to get findings out early. In terms of changes per sentence (Figure 1c), statistics and quantitative studies are the top subareas.

Further, Figure 2 shows the effect of the number of authors. It is interesting that both in terms of sheer number and percentage, single-authored papers have the most changes. This could be because a single author enjoys greater freedom and has stronger motivation to make changes, or because multiple authors tend to submit a more polished initial version. This echoes the finding in Posner

[8] We did not allow cross matching (i.e., $i \to j-1, i-1 \to j$), since we thought matching this case as $(i-1, i) \to j$ or $i \to (j, j-1)$ can provide context for annotation purposes. But in the end, we focused on labeling very similar pairs. This decision had little effect.

[9] This differs from the number in Section 1 because articles may not have the tex source available, or the differences between versions may be in non-textual content.

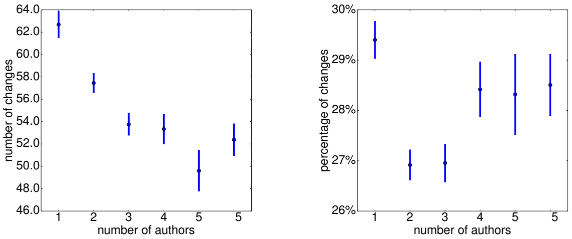
You should mark S2 as **Stronger** if

- (R1) S2 strengthens the degree of some aspect of S1, for example, S1 has the word ”better”, whereas S2 uses ”best”, or S2 removes the word ”possibly”
- (R2) S2 adds more evidence or justification (we *don’t* count adding details)
- (R3) S2 sounds more impressive in some other way: the authors’ work is more important/novel-/elegant/applicable/etc.

If instead S1 is stronger than S2 according to the reasons above, select **Weaker**. If the changes aren’t strengthenings or weakenings according to the reason above, select No Strength Change.

If there are both strengthenings and weakenings, or you find that it is really hard to tell whether the change is stronger or weaker, then select I can’t tell.

Table 2: Definition of labels in our labeling tasks.



(a) Number of changes vs number of authors.

(b) Percentage of changed sentences vs number of authors.

Figure 2: Error bars represent standard error. (a): up until 5 authors, a larger number of authors indicates a smaller number of changes. (b): percentage is measured over the number of sentences in the first version; there is an interior minimum where 2 or 3 authors make the smallest percentage of sentence changes on a paper.

and Baecker (1992) that the collaborative writing process differs considerably from individual writing. Also, more than 25% of the first versions are changed, which again shows that substantive edits are being made in these resubmissions.

4 Annotating Strength Differences

In order to study statement strength, reliable strength-difference labels are needed. In this section, we describe how we tried to define strength differences, compiled labeling instructions, and gathered labels using Amazon Mechanical Turk.

Label definition and collection procedure. We focused on matched sentences from abstracts and introductions to maximize the proportion of strength differences (as opposed to factual/no strength changes). We required pairs to have similarity score larger than 0.5 in our labeling task to make pairs more comparable. We also replaced all math environments with “[MATH]”.[10] We obtained 108K pairs that satisfy the above conditions, available at `http://chenhaot.com/pages/statement-strength.html`. To create the pool of pairs for labeling, we randomly sampled 1000 pairs and then removed pairs that we thought were processing errors.

We used Amazon Mechanical Turk. It may initially seem surprising to have annotations of technical statements not done by domain experts; we did this intentionally because it is common to communicate unfamiliar topics to the public in political and science communication (we comment on non-expert rationales later). We use the following set of labels: *Stronger, Weaker, No Strength Change, I can’t tell.* Table 2 gives our definitions. The instructions included 8 pairs as examples and 10 pairs to label as a training exercise. Participants were then asked to choose labels and write mandatory comments for 50 pairs. According to the comments written by participants, we believe that they did the labeling in good faith.

Quantitative overview. We collected 9 labels each for 500 pairs. Among the 500 pairs, Fleiss’ Kappa was 0.242, which indicates fair agreement (Landis and Koch, 1977). We took a conservative approach and only considered pairs with an absolute majority label, i.e., at least 5 of 9 labelers chose the same label. There are 386 pairs that satisfy this requirement (93 weaker, 194 stronger, 99 no change). On this subset of pairs, Fleiss’ Kappa is 0.322, and 74.4% of pairs were strength changes. Considering all the possible disagreement, this result was acceptable.

Qualitative observations. We were excited about the labels from these participants: despite

[10] These decisions were made based on the results and feedback that we got from graduate students in an initial labeling.

ID	Matched sentences and comments
1	S1: ... using data from numerics and experiments . S2: ... using data sets from numerics in the point particle limit and one experimental data set . (stronger) S2 is more specific in its description which seems stronger. (weaker) ”one experimental data set” weakens the sentence
2	S1: we also proved that if [MATH] is sufficiently homogeneous then ... S2: we also proved that if [MATH] is not totally disconnected and sufficiently homogeneous then ... (stronger) We have more detail/proof in S2 (stronger) the words ”not totally disconnected” made the sentence sound more impressive.
3	S1: we also show in general that vectors of products of jack vertex operators form a basis of symmetric functions . S2: we also show in general that the images of products of jack vertex operators form a basis of symmetric functions . (weaker) Vectors sounds more impressive than images (weaker) sentence one is more specific
4	S1: in the current paper we discover several variants of qd algorithms for quasiseparable matrices . S2: in the current paper we adapt several variants of qd algorithms to quasiseparable matrices . (stronger) in S2 Adapt is stronger than just the word discover. adapt implies more of a proactive measure. (stronger) s2 sounds as if they’re doing something with specifics already, rather than hunting for a way to do it

Table 3: Representative examples of surprising labels, together with selected labeler comments.

the apparent difficulty of the task, we found that many labels for the 386 pairs were reasonable. However, in some cases, the labels were counter-intuitive. Table 3 shows some representative examples.

First, participants tend to take details as evidence even when these details are not germane to the statement. For pair 1, while one turker pointed out the decline in number of experiments, most turkers simply labeled it as stronger because it was more specific. “Specific” turned out to be a common reason used in the comments, even though we said in the instructions that only additional justification and evidence matter. This echoes the finding in Bell and Loftus (1989) that even unrelated details influenced judgments of guilt.

Second, participants interpret constraints/conditions not in strictly logical ways, seeming to care little about scope at times. For instance, the majority labeled pair 2 as “stronger”. But in S2 for that pair, the result holds for strictly fewer possible worlds. But it should be said that there are cases that labelers interpreted logically, e.g., “compelling evidence” subsumes “compelling experimental evidence”.

Both of the above cases share the property that they seem to be correlated with a tendency to judge lengthier statements as stronger. Another interesting case that does not share this characteristic is that participants can have a different understanding of domain-specific terms. For pair 3, the majority thought that “vectors” sounds more impressive than “images”; for pair 4, the majority considered “adapt” stronger than “discover”. This issue is common when communicating new topics to the public not only in science communication but also in politics and other scenarios. It may partly explain miscommunications and misinterpretations of scientific studies in journalism.[11]

5 Looking ahead

Our observations regarding the annotation results raise questions regarding what is a generalizable way to define strength differences, how to use the labels that we collected, and how to collect labels in the future. We believe that this corpus of sentence-level revisions, together with the labels and comments from participants, can provide insights into better ways to approach this problem and help further understand strength of statements.

One interesting direction that this enables is a potentially new kind of learning problem. The comments indicate features that humans think salient. Is it possible to automatically learn new features from the comments?

The ultimate goal of our study is to understand the effects of statement strength on the public, which can lead to various applications in public communication.

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[11] http://www.phdcomics.com/comics/archive.php?comicid=1174

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