NewsEdits: A Dataset of Revision Histories for News Articles  
(Technical Report: Data Processing)  

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Abstract  
News article revision histories have the potential to give us novel insights across varied fields of linguistics and social sciences. In this work, we present, to our knowledge, the first publicly available dataset of news article revision histories, or NewsEdits.  
Our dataset is multilingual; it contains 1,278,804 articles with 4,609,430 versions from over 22 English- and French-language newspaper sources based in three countries. Across version pairs, we count 10.9 million added sentences; 8.9 million changed sentences and 6.8 million removed sentences. Within the changed sentences, we derive 72 million atomic edits. NewsEdits is, to our knowledge, the largest corpus of revision histories of any domain.  

1 Introduction  
Revision histories gathered from various natural language domains like Wikipedia (Grundkiewicz and Junczys-Dowmunt, 2014), Wikihow (Faruqui et al., 2018) and student learner essays (Zhang and Litman, 2015) have been studied widely in NLP. These corpora have been used for as varied tasks as language modeling (Yin et al., 2018), sentence modification (Shah et al., 2020), argumentation design (Afrin et al., 2020), and even group collaboration dynamics (Murić et al., 2019).  
By utilizing a novel domain for revision histories, news article revision histories, we see the potential for strengthening methods for these aforementioned tasks, as well as the introduction of a novel set of tasks. Because news covers events (or worldstates) that are constantly updating, we hypothesize that many edits in news either (1) incorporate new information (2) update events or (3) broaden perspectives.  

1 Each of these categories of edits poses new questions that news edits are uniquely positioned to answer: What information is likely to change in the current state of a document? What must be incorporated? What perspectives need to be layered in, and when?  
We offer, to our knowledge, the first publicly available corpus of news article revision histories, called NewsEdits. We compile our corpus from various subcorpora collected by internet activists who track news article version changes. Each subcorpora is collected by monitoring article URLs, and downloading article text when a new version of the same news article is published.  
Our dataset consists of 1,278,804 articles and 4,609,430 versions from over 22 English-language newspaper outlets. These outlets are based in the U.S., Great Britain and Canada. As in Tamori et al. (2017), we compare article versions to each other on the sentence-level, and then, for matched sentences, the word level. We count 10,929,051 added sentences; 8,908,254 changed sentences and 6,807,624 removed sentences.  
Our contributions are the following:  
1. We introduce NewsEdits, the first publicly available academic corpus of news article version histories, as well as, to our knowledge, the largest version-history corpus.  
2. We process the dataset to identify various forms of structural edits, in order to facilitate a wide range of possible analyses. We provide simple, lightweight visualization tools to render article-comparisons in an intuitive format.  
In the remainder of the paper, we start by comparing this work to other edit corpora. We then discuss the dataset curation and processing. In upcoming work, we will present a schema for characterizing domains like Wikipedia (Yang et al., 2017), which tend to focus on counter vandalism and syntax edits.  

1This is in contrast with the distribution of edits in other
edits in news articles, developed with journalists and graduate students in the communications field.

2 Related Work

Previous work in natural language revision histories has primarily focused on two primary domains: student learner essays and Wikipedia. There is, additionally, emerging work in using WikiHow for similar ends as Wikipedia (Anthonio et al., 2020; Bhat et al., 2020).

2.1 Wikipedia Revisions

Wikipedia is a resource that is often used in text-revision research. Many tasks have benefited from studying Wikipedia revisions, such as text simplification (Yatskar et al., 2010), textual entailment (Zanzotto and Pennacchiotti, 2010) and discourse learning in edits (Daxenberger and Gurevych, 2012, 2013; Fong and Biuk-Aghai, 2010). Discourse learning for edits, as in other branches of discourse learning, focuses on developing schemas to elucidate the function or purpose of each edit, and then performing classification on these schema (Faigley and Witte, 1981). One such work, by Yang et al. (2017), developed a schema for Wikipedia edit intentions, included Wikipediaspecific edit categories, such as Counter-Vandalism and Wikification, as well as general categories like Elaboration and Refactoring. We take the general categories as a starting point for our own work.

The two largest-scale corpora to be processed and released, to our knowledge, are the WikEd Error Corpus, in English, which contains 12 million sentences and 14 million revisions (Grundkiewicz and Junczys-Dowmunt, 2014), and WikiAtomicEdits, which contains 43 million “atomic edits”. The WikEd Error Corpus has been used primarily for Grammar Error Correction (GEC), while WikiAtomicEdits has been used primarily for language modeling (Yin et al., 2018; Shah et al., 2020).

While our work has roughly the same number of changed sentences as the Wikipedia-based corpora (8.9 million), we have roughly twice as many atomic edits (72 million), and added/removed sentences, which neither Wikipedia corpus reports.

2.2 Student Learner Essays

Student Learner essays are another area of focus in revisions research. Such research focuses on editing revisions made during student essay-writing, particularly focusing on non-English speakers. Because of the difficulties in collecting data in this domain, most natural datasets tend to be small (Leacock et al., 2010). In recent work, researchers create an editing platform; they instruct students to write 3 drafts of an essay using their platform, and gather revisions made during the writing process (Zheng et al., 2017). They collect 60 essays with 180 versions, or 3 drafts per essay, and they focus on classifying the discursive purpose of each edit (i.e. what the edit introduces, like Evidence, or Claims).

In this vein, researchers have constructed Automated Writing Evaluation systems (AWE) and used these systems to evaluate writing when a student submits a draft (Wang et al., 2020; Zhang, 2020; Zhang and Litman, 2015). In one recent work by Afrin et al. (2020), researchers compile 143 essays with 286 versions, or 2 versions each. They develop an annotation scheme focused on improving the writing (ex: Evidence: Relevant or Irrelevant).

While such work is interesting because the generation process is fully controlled: i.e., students can be instructed to write about similar topics and be given similar feedback between rounds, the corpora collected are small by modern machine learning standards.

2.3 News

2.3.1 Academic Work

Despite the centrality of published news articles as sources to some of the most fundamental corpora in NLP (Marcus et al., 1993; Carlson et al., 2003; Pustejovsky et al., 2003; Walker, 2006), there is, to our knowledge, no revision-histories corpus based on news edits currently published in the academic literature. For research on linguistics, corpora from multiple domains can capture relevant mechanisms, but for research on language describing real-world events – such as event extraction or temporality – news is still the gold standard.

We are aware of just one academic work, and its followup, that focuses on news edits (Tamori et al., 2017; Hitomi et al., 2017). Authors analyzed news edits to predict quality of news articles, as well as to predict editing operations performed during text generation. A dataset of news revisions from

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4Authors are unclear about how many sentences this corresponds to, but in our work we found, on average, roughly 4 atomic edits per changed sentence.
a Japanese newspaper was used, but not released publicly.\(^5\)

In our work, in contrast, we publicly release a large dataset and outline several tasks that, in our opinion, are tasks for which news corpora are best suited. In previously studied revision-corpora, researchers typically assume, implicitly, that the writing focuses on a relatively static world-state – both Wikipedia and student learner essays tend to be focused on historical events or arguments (Yang et al., 2017). Thus in previous corpora, the nature of edits are primarily argumentative or corrective. However, news articles very often cover updating events. This difference has important implications for the kinds of edits we expect in our corpora.

We are not aware of any work using WikiNews\(^6\) as a source of revision histories, despite its proximity, as a domain, to other corpora that have been used in revision-history research, like Wikipedia and WikiHow. WikiNews corpora have been used for study in the communications literature (Thorsen, 2008; Roessing, 2019), as well as in subfields of NLP, including document summarization (Bravo-Marquez and Manriquez, 2012), timeline synthesis (Zhang and Wan, 2017; Minard et al., 2016) and word-identification tasks (Yimam et al., 2017). While we are aware of one work, on identifying entity-salience, that uses WikiNews editor-annnotations as part of their task (Wu et al., 2020), we are not aware of any other works that utilize

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\(^5\)Dataset could not be released due to copyright infringement, according to the authors in response to inquiry.
\(^6\)https://en.wikinews.org/wiki/Main_Page

| Corpus           | # Revisions                                                                 | Language   | Source     | Goal                                                   |
|------------------|-----------------------------------------------------------------------------|------------|------------|--------------------------------------------------------|
| WiKed Error Corpus | 12 million changed sentences                                                | English    | Wikipedia  | Grammatical Error Correction (GEC)                     |
| WikiAtomicEdits  | 43 million “atomic edits”\(^3\)                                             | 8 languages| Wikipedia  | Language Modeling                                      |
| WiCoPaCo         | 70,000 changed sentences                                                    | French     | Wikipedia  | GEC and Sentence paraphrasing                          |
| WikiHow-ToImprove | 2.7 million changed sentences                                               | English    | WikiHow    | Version prediction, article improvement                |
| NewsEdits        | 8.9 million changed sentences, 10.9 million added sentences, 6.7 million removed sentences, 72 million atomic edits. | English and French | 22 media outlets | Language modeling, event sequencing, computational journalism |

Table 1: A comparison of natural language revision history corpora.

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\(^3\)WiKed Error Corpus

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\(^7\)https://www.newssniffer.co.uk/
\(^8\)https://github.com/DocNow/diffengine
\(^9\)https://twitter.com/i/lists/821699483088076802
\(^10\)https://envirodatagov.org/

2.3.2 Nonacademic Work

Since at least 2006, internet activists have tracked changes made to major digital news articles (Herrmann, 2006). In 2012 NewsDiffs.org became one of the first websites to gain popular media attention for tracking changes to articles published in the New York Times, CNN, Politico, and others (Brisbane, 2012; Burke, 2016; Jones and Neubert, 2017; Fass and Main, 2014). Other similar trackers have since (or concurrently) emerged, such as NewsSniffer\(^7\) and DiffEngine.\(^8\) These tools collect article versions from RSS feeds and the Internet Archive. Using open-sourced technology, dozens of major newspapers are being analyzed,\(^9\) as well as thousands of government websites.\(^10\) Such diffs have been used by journalists, communications scholars and media critics to study instances of gender and
Table 2: A summary of the number of total number of articles and versions for different media outlets which comprise our dataset. Also shown is the original collection that they were derived from (DE for DiffEngine, and NS from NewsSniffer), and the date-ranges during which articles from each outlet were collected.

| Source  | # Articles  | # Versions  | Start   | End     | Ctry. | Lang. | Coll. |
|---------|-------------|-------------|---------|---------|-------|-------|-------|
| BBC     | 307,616     | 1,244,490   | 2006-08 | 2021-01 | U.K.  | En.   | NS    |
| Guardian| 231,252     | 852,324     | 2012-01 | 2021-01 | U.K.  | En.   | NS    |
| Nytimes | 87,556      | 395,643     | 2012-08 | 2020-12 | U.S.  | En.   | NS    |
| Telegraph| 78,619      | 124,128     | 2017-01 | 2018-09 | U.K.  | En.   | NS    |
| Fox     | 78,566      | 117,171     | 2017-01 | 2018-09 | U.S.  | En.   | DE    |
| CNN     | 58,569      | 117,202     | 2017-01 | 2018-09 | U.S.  | En.   | DE    |
| Independent| 55,009     | 158,881     | 2014-01 | 2018-05 | U.K.  | En.   | NS    |
| CBC     | 54,012      | 387,292     | 2017-08 | 2018-09 | Ca.   | En.   | DE    |
| DailyMail| 50,639      | 166,260     | 2017-01 | 2018-09 | U.K.  | En.   | DE    |
| La Presse | 42,797      | 99,082      | 2017-01 | 2018-09 | U.K.  | En.   | DE    |
| Heraldbc| 40,978      | 73,447      | 2017-08 | 2018-09 | Ca.   | Fr-Ca.| DE    |
| Reuters | 35,523      | 310,112     | 2017-08 | 2018-07 | Ca.   | En.   | DE    |
| AssociatedPress| 32,552 | 91,820     | 2017-08 | 2018-09 | Ca.   | En.   | DE    |
| National Post| 22,934 | 143,303    | 2017-08 | 2018-09 | U.K.  | En.   | DE    |
| Washington Post| 22,381 | 97,314     | 2017-08 | 2018-09 | U.S.  | En.   | DE    |
| GlobeMail| 19,184      | 68,612      | 2017-08 | 2018-09 | U.S.  | En.   | NS    |
| Toronto Sun| 19,121     | 46,353      | 2017-08 | 2018-09 | Ca.   | En.   | DE    |
| Calgary Herald| 7,728    | 33,427      | 2017-08 | 2018-09 | Ca.   | Fr-Ca.| DE    |
| The Rebel| 65          | 19,383      | 2017-08 | 2018-09 | Ca.   | En.   | DE    |
| Canada Land| 65          | 101         | 2017-12 | 2018-09 | Ca.   | En.   | DE    |

3 Dataset

We combine data from two primary sources: NewsSniffer (NS) and Twitter accounts powered by DiffEngine (DE). Currently, we have gathered data for 22 media outlets. The number of articles per outlet, as well as the time-frames for which we have collected data, is listed in Table 2. We are in the process of accumulating more data from La Nación, Clarín, Le Soir, and Le Monde from internet activists to broaden the number of languages we currently have access to.

3.1 Dataset Tables and Fields

Our dataset is released in a set of 5 SQLite tables. Three of them are primary data tables, and two are summary-statistic tables. Our primary data tables are: articles, sentence_diffs, word_diffs; the first two of which are shown in Tables 3a and 3b (word_diffs shares a similar structure with sentence_diffs). We compile two summary statistics tables to cache statistics from sentence_diffs and word_diffs; they calculate metrics such as NUM_SENTENCES_ADDED and NUM_SENTENCES_REMOVED per article.\(^\text{12}\)

The sentence_diffs data table’s schema is shown in Table 3 and some column-abbreviated sample rows are shown in Table 4. As can be seen, the diffs are calculated and organized on a sentence-level. Each row shows a comparison of sentences between two adjacent versions of the same article.\(^\text{13}\) Every row in sentence_diffs contains index columns: SOURCE, A_ID, VERSION_OLD, and VERSION_NEW. These columns can be used to uniquely map each row in sentence_diffs to two

\(^{11}\)http://www.newsdiffs.org/diff/192021/192137/
\(^{12}\)These summary statistic tables make it convenient to, say, filter sentence_diffs in order train a model on all articles that have one sentence added; or all articles that have no sentences removed.
\(^{13}\)So, for instance, article A, with versions 1, 2 where each version has sentences i, ii, iii would have 3 rows (assuming sentences were similar): A.1-2.i, A.1-2.ii, A.1-2.iii.
rows in article. \(^{14}\)

### 3.2 TAG columns in sentence_diffs

The columns TAG_OLD and TAG_NEW in sentence_diffs have specific meaning: how to transform from version to its adjacent version. In other words, TAG_OLD conveys where to find SENT_OLD in VERSION_NEW and whether to change it, whereas TAG_NEW does the same for SENT_NEW in VERSION_OLD.

More concretely, consider the examples in Table 4b, 4a and 4c. As can be seen, each tag is 3-part and has the following components. **Component 1** can be either M, A, or R. M means that the sentence in the current version was Matched with a sentence in the adjacent version. A means that a sentence was Added to the new version and R means the sentence was Removed from the old version. **Component 2** is only present for Matched sentences, and refers to the index or indices of the sentence(s) in the adjacent version. Additionally, **Component 3** is also only present if the sentence is Matched. It can be either C or U. C refers to whether the matched sentence was Changed and U to whether it was Unchanged.

Although not shown or described in detail, all M sentences have corresponding entry-matches in word_diffs table, which has a similar schema and tagging aim.

A user might use these tags in the following ways:

1. To compare only atomic edits, as in Faruqui et al. (2018), a user could filter sentence_diffs to sentences where M,C is in TAG_OLD (or equivalently, TAG_NEW). Then, they would join TAG_OLD.Component_2 with SENTENCE_ID. Finally, they would select SENT_OLD, SENT_NEW.\(^{17}\)
2. To view only refactorings, or when a sentence is moved from one location in the article to another, a user could filter sentence_diffs to only sentences containing M,U and follow a similar join process as in use-case 1.
3. To model which sentences might be added, i.e. \(p(\text{sentence}_i \in \text{article}_{t+1}| \text{sentence}_i \in \text{article}_t)\), a user would select all sentences in SENT_OLD, and all sentences in SENT_NEW where A is in TAG_NEW.
4. To model the inverse of use-case 3, i.e. which sentences would be removed, or \(p(\text{sentence}_i \notin \text{article}_{t+1}| \text{sentence}_i \in \text{article}_t)\), a user would select all sentences in SENT_NEW, and all sentences in SENT_OLD where R is in TAG_OLD.

### 3.3 Assigning sentence_diff Tag Columns

To assign the tags, we need to determine which sentences are Added, Removed and Matched. We seek to have our dataset reflect a general principle: sentences tagged as Added should contain novel information and sentences tagged as Removed should delete information that the journalist wishes to delete. Sentences tagged as Matched should be substantially similar except for syntactic changes, rephrasing, and updated information.

\(^{14}\)One mapping for sentence_diffs.VERSION_OLD = article.VERSION_ID and one mapping for sentence_diffs.VERSION_NEW = article.VERSION_ID.

\(^{15}\)i.e. an Added row is not present in the old version and a Removed row is not present in the new version. They have essentially the same meaning and we could have condensed notation, but we felt this was more intuitive.

\(^{16}\)i.e. in TAG_OLD, the index refers to the SENTENCE_ID of SENT_NEW

\(^{17}\)or simply look in the word_diffs table.
| Sent Idx | Old Tag | Old Version | New Version | New Tag |
|----------|---------|-------------|-------------|---------|
| 1        | M 1 C   | The Bundesbank would only refer to an interview Mr. Weidmann gave to Der Spiegel magazine last week, in which he said, “I can do my job best by staying in office.” | The Bundesbank would only refer to an interview published in Der Spiegel magazine last week, in which Mr. Weidmann said, “I can carry out my duty best if I remain in office.” | M 1 C   |

(a) Demo 1: Word-Level atomic edit corrections applied when a sentence-level match is found, using the difflib Python library.

| Sent Idx | Old Tag | Old Version | New Version | New Tag |
|----------|---------|-------------|-------------|---------|
| 1        | M 2 C   | DALLAS—Ebola patient Thomas Eric Duncan told his fiancee the day he was diagnosed last week that he regrets exposing her to the deadly virus and had he known he was carrying Ebola, he would have “preferred to stay in Liberia and died than bring this to you,” a family friend said. | DALLAS—Ebola patient Thomas Eric Duncan told his fiancee the day he was diagnosed last week that he regrets exposing her to the deadly virus. | M 1 C   |

(b) Demo 2: A sentence that is split results in the addition of a new sentence, but is matched with the previous dependent clause. Minimal word-level edits are applied.

| Sent Idx | Old Tag | Old Version | New Version | New Tag |
|----------|---------|-------------|-------------|---------|
| 1        | M 2 U   | “The mother, this was the first time seeing her son since he got to the States.” | “She has not seen him for 12 years, and the first time she saw him was through a monitor,” said Lloyd. | M 2 U   |
| 2        | M 1 U   | She has not seen him for 12 years, and the first time she saw him was through a monitor,” said Lloyd. | “The mother, this was the first time seeing her son since he got to the States.” | M 1 U   |
| 3        | A       | “She wept, and wept, and wept.” | | A       |

(c) Demo 3: Two features shown: (1) Refactoring, or order-swapping, makes sentences appear as though they have been deleted and then added. Swapped sentences are matched through their tags. (2) The last sentence is a newly added sentence and is not matched with any other sentence.

Table 4: Here we show demos of three tricky edge-cases and how our tagging scheme handles them. Old Tag annotates a Old Version relative to changes in the New Version (or “converts” the Old Version to the New Version). New Tag is the inverse. Tag components: Component 1: M, A, R. Whether the sentence is Matched, Added, or Removed. Component 2: Index. If Matched, what is the index of the sentence in version that it is matched to. Component 3: C, U. If Matched, is the sentence Changed or Unchanged.
3.3.1 Matching Algorithm

To do this, we develop an asymmetrical sentence-matching algorithm. The examples shown in Tables 4b, 4a and 4c illustrate our requirements. The first example, shown in Table 4b, occurs when a sentence is edited syntactically, but its meaning does not change.\footnote{Syntactic changes: synonyms are used, or phrasing is condensed, but substantially new information is not added.} So, we need our sentence-matching algorithm to use a sentence-similarity measure that considers semantic changes and does not consider surface-level changes. The second example, shown in Table 4a, occurs when a sentence is split (or inversely, two sentences are merged.) Thus, we need our sentence matching algorithm to consider many-to-one matchings for sentences. The third example, shown in Table 4c, occurs when sentence-order is rearranged, arbitrarily, throughout a piece. Finally, we need our sentence-matching algorithm to perform all pairwise comparisons of sentences.

Our algorithm is given in Algorithm 1. Given a list of sentences for pairwise versions, our algorithm computes the asymmetrical similarity between sentence-pairs in the Cartesian product of the sentences of adjacent article versions. It returns two mappings: (1) from sentences in the old version to the new, and (2) from sentences in the new to the old. This relies on an effective sentence-similarity score.

3.3.2 Sentence Matching

There is a wide body of research in sentence-matching (Quan et al., 2019; Abujar et al., 2019; Yao et al., 2018; Chen et al., 2018) including BERT-based approaches (Reimers and Gurevych, 2019), dependency-tree approaches (Le et al., 2018) and (Allan et al., 2003; Achananuparp et al., 2008). We desire a measure that considers semantics over syntactical changes, yet can appropriately match named entities (names, places or organizations) or other specific words not likely to be found in pre-trained models.

While we are still evaluating the effectiveness of several methods, our primary method so far is based on a matching algorithm similar to maximum alignment method, described by Kajiwara and Komachi (2016), shown below, where \( \phi(x_i, y_j) = \) similarity between word \( x_i \) and \( y_j \).

\[
\text{Sim}_{\text{asym}}(x, y) = \frac{1}{|x|} \sum_{i=1}^{|x|} \max_j \phi(x_i, y_j)
\]

This approach allows us to identify unidirectional matches, where sentence \( a \) might be a sub-sentence of sentence \( b \), as shown in Table 4a. We use this method because it is similar to one used in prior work on news article revision histories (Tamori et al., 2017).

We test several word-similarity functions, \( \phi \). The first uses a simple lexical overlap, where \( \phi(x, y) = 1 \) if \( \text{lemma}(x) = \text{lemma}(y) \) and 0 otherwise. This is based off of the hypothesis that proper nouns make up the majority of important components in our desired similarity measure, and these are poorly captured by large language models. The second uses contextual word-embeddings, where \( \phi(x, y) = \text{Emb}(x) \cdot \text{Emb}(y) \), and \( \text{Emb}(x) \) is the word-embeddings derived from a pretrained language model (Albert-XXLarge-Uncased,)\footnote{Syntactic changes: synonyms are used, or phrasing is condensed, but substantially new information is not added.}(Lan et al., 2020). We are still testing different similarity thresholds \( T \) in Algorithm 1 and still determining how well this embedding function captures proper nouns and entities.

4 Discussion and Possible Tasks

In this work, we have introduced, to our knowledge, the largest dataset of revision histories ever, and the first public dataset of news revision histories into the academic literature.
4.1 Tasks

We hope this resource will prove useful as a domain that is far more general in terms of standards and style than domains such as Wikipedia and WikiHow, for which revisions data already exists. Thus, tasks based off these existing corpora, such as edit language modeling (Yin et al., 2018) and fact-guided revisions (Shah et al., 2020), should stand to benefit.

However, as mentioned previously, news articles are, more often than Wikipedia or Student Learner articles, based on a world-state that is dynamically changing. Thus, we expect that edits in news articles are more likely to describe events that are changing and include primary-source material (in contrast to another source we considered, WikiNews). This has important implications for linguistic inquiries, such as:

1. Event-temporal relations, as edits update events that are changing through time (Ning et al., 2018)
2. Headline Generation (Shen et al., 2017)
3. Fact-guided updates (Shah et al., 2020)

This dataset is also interesting as it captures the lifecycles of news articles, which have standard arcs. Breaking news typically gets published first as a bare-bones paragraph containing a main event. Within the next few hours and days, additional quotes, contextual and explainer-paragraphs are added until the article comes to resemble a more standard news article. Thus, there are tasks this corpus sheds light on that have important implications for computational journalism:

1. News information gathering (Spangher et al., 2020)
2. Contextualization: discourse and article structure (Choubey et al., 2020; Spangher et al., 2021a)
3. How framing changes in response to an unfolding story (Spangher et al., 2021b)

Finally, the nature of our article updates – each version is captured upon publication, not drafting – also contain fewer grammatical and spelling errors than, say, student learner essays. Thus, edits made to change the syntax of a sentence rather than introduce or change information, are more likely to have stylistic purpose. This might lead to interesting subtasks in several fields of NLP, such as:

1. Style transfer (Fu et al., 2018)
2. Bias in news articles (Mehrabi et al., 2020)
3. Cross-cultural sensitivity (Tian et al., 2020)

In short, there are many tasks that we see emerging from such a dataset, and several tasks that are currently ongoing.

4.2 Future Work

To make this work more useful, we wish to develop a schema to describe the types of edits occurring, similar to the types of schemas exists in other work examining revisions corpora (Zhang et al., 2017; Yang et al., 2017; Afrin et al., 2020). We are inspired by the Wikipedia Intentions schema developed by Yang et al. (2017), and are working in collaboration with journalists to further clarify the differences. The development of a news edits schema would help to clarify the nature of these edits as well as focus further questions.

We are also interested in extending prior work (Spangher et al., 2020, 2021a) in this domain. We are pursuing collaborations (Spangher et al., 2021b). Please do not hesitate to reach the authors by email to discuss any possible collaborations or usages of the dataset.

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