Towards Automated Document Revision: Grammatical Error Correction, Fluency Edits, and Beyond

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Abstract

Natural language processing (NLP) technology has rapidly improved automated grammatical error correction (GEC) tasks, and the GEC community has begun to explore *document-level* revision. However, there are two major obstacles to going beyond automated *sentence-level* GEC to NLP-based *document-level* revision support: (1) there are few public corpora with document-level revisions annotated by professional editors, and (2) it is infeasible to obtain all possible references and evaluate revision quality using such references because there are infinite revision possibilities. To address these challenges, this paper proposes a new document revision corpus, **T**ext **R**evision of **A**CL papers (TETRA), in which multiple professional editors have revised academic papers sampled from the ACL anthology. This corpus enables us to focus on document-level and paragraph-level edits, such as edits related to coherence and consistency. Additionally, as a case study using the TETRA corpus, we investigate reference-less and interpretable methods for meta-evaluation to detect quality improvements according to document revisions. We show the uniqueness of TETRA compared with existing document revision corpora and demonstrate that a fine-tuned pre-trained language model can discriminate the quality of documents after revision even when the difference is subtle.

1 Introduction

Document revision is a crucial step in the process of writing essays and argumentative texts. The writing process consists of two major parts: content organization and selection planning (henceforth, *planning part*) and realization of text improvement (henceforth, *realization part*), which are hierarchical and recursive. In addition, according to previous studies on argumentative writing (Flower and Hayes, 1981; Beason, 1993; Buchman et al., 2000; Seow, 2002; Allal et al., 2004), *realization part* in writing process typically comprises three main stages: *Revising*, *Editing*, and *Proofreading*. *Revising* is the initial editing step used to plan and structure the overall document at a high level, *Editing* focuses on making sentence-level or phrase-level expressions, and *Proofreading* is used to identify and correct errors such as spelling and grammar errors (see Figure 1, left). While the order of these steps is not set in stone, the writing process typically starts with a broad, high-level perspective, and gradually narrows down the scope of edits.

In contrast to the typical human writing process, GEC research in NLP field, which is primarily intended to support writing, initially focused on a fine-grained scope, e.g., spelling errors (Brill and Moore, 2000; Toutanova and Moore, 2002; Islam and Inkpen, 2009) and closed-class parts of speech (such as prepositions and determiners) (Han et al., 2006; Nagata et al., 2006; Felice and Pulman, 2008). The research community then expanded its focus to include edits at the phrase and sentence levels while also considering fluency (Sakaguchi et al., 2016; Napoles et al., 2017) (Figure 1, right). However, significantly less work has been done on *document-level* revisions due to two major challenges. First, document revisions encompass a broader range of concerns such as coherence and flow, compared to conventional GEC and fluency correction, which makes it difficult to find publicly available corpora that have been annotated by experts (professional editors). Second, evaluating the quality of revisions is challenging as it requires multiple reference points, as there are many ways to revise a single document. This suggests that *reference-less* evaluation metrics (Napoles et al., 2016; Choshen and Abend, 2018; Islam and Magnani, 2021) are hold significant importance in automated document revision models.

Considering these challenges associated with automated document revision, we propose a new high-quality corpus and explore possibilities for transpar-

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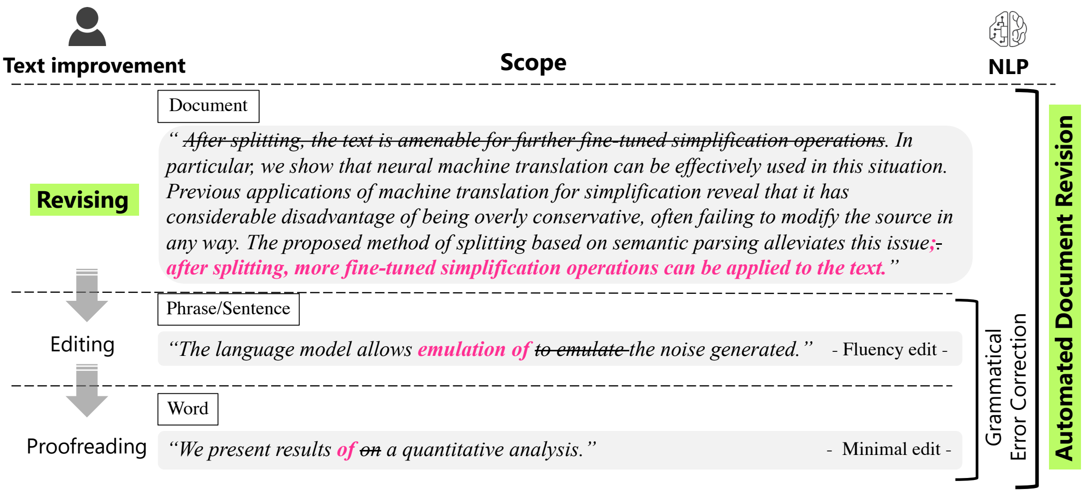
Text improvement
Scope
NLP
Document
" ~~After splitting, the text is amenable for further fine-tuned simplification operations~~. In particular, we show that neural machine translation can be effectively used in this situation. Previous applications of machine translation for simplification reveal that it has considerable disadvantage of being overly conservative, often failing to modify the source in any way. The proposed method of splitting based on semantic parsing alleviates this issue;~~.~~ after splitting, more fine-tuned simplification operations can be applied to the text."
Revising
Phrase/Sentence
"The language model allows emulation of ~~to emulate~~ the noise generated."
- Fluency edit -
Editing
Word
"We present results of ~~on~~ a quantitative analysis."
- Minimal edit -
Proofreading
Grammatical Error Correction
Automated Document Revision

Figure 1: Overview of the scope for automated document revision. Each example is taken from TETRA corpus. We focus on the document revision process which has been overlooked by GEC. Automated document revision extends the scope of GEC.

ent evaluation methods that are independent of gold standards or references. Our corpus, **T**ext **R**evision of **ACL** papers (TETRA), comprises academic papers from the ACL anthology with document-level revisions, revision types, and concrete feedback comments annotated by multiple professional editors. This corpus was designed based on a new XML-based annotation scheme that can handle edit types beyond sentences (e.g., argument flow) in addition to conventional word-level and phrase-level edits. TETRA has uniqueness in terms of the number of references, the expertise level of the editors, and topic diversity.

As a case study, we use TETRA to investigate whether it is possible to build an **i**nstance-wise **r**evision **c**lassification (IRC) method, in which a model can distinguish pre-edited or post-edited versions for a given single revision pair. In recent years, several studies have been conducted on the use of large language models (LLMs) as evaluators in language generation tasks. For example, GPT-4 (OpenAI, 2023) has demonstrated superior performance compared to existing automatic evaluation metrics in text summarization, dialogue generation, and machine translation (Liu et al., 2023; Kocmi and Federmann, 2023). In light of this current situation, we conduct experiments to evaluate how well pre-trained language models, such as BERT (Devlin et al., 2019) and LLMs such as GPT-4, can perform as a (meta-)evaluation method for each edit type, both with and without fine-tuning. The results demonstrate that the supervised method can accurately choose post-edited snippets with an accuracy of 0.85 to 0.96, indicating the feasible potential of automated evaluation in document revision.

We release TETRA to the public, and hope that it will encourage the community to work towards automated document-level revision.[1]

2 Background

The field of GEC, which has a multi-decade history, began with the goal of detecting and correcting targeted error types and providing feedback to English as a second language learners.[2] Early GEC systems primarily focused on a limited number of closed-class error types, such as articles (Han et al., 2006) and prepositions (Chodorow et al., 2007; Tetreault and Chodorow, 2008; Tetreault et al., 2010; Cahill et al., 2013; Nagata et al., 2014). The scope of GEC was later expanded to include all types of errors, including verb forms, subject-verb agreement, and word choice errors (Lee and Seneff, 2008; Tajiri et al., 2012; Rozovskaya and Roth, 2014). This line of research led to the establishment of shared benchmark tasks (Dale and Kilgarriff, 2011; Dale et al., 2012; Ng et al., 2013, 2014).

Motivated by the observation that error-coded local edits do not always sound natural to native speakers, the scope of GEC has been further expanded from word-level closed-class edits to phrase-level and sentence-level *fluency* ed-

[1] https://github.com/chemicaltree/tetra

[2] In this paper, we focus on GEC literature after the 2000s when statistical were widely adopted. For a comprehensive history of GEC in the 1980s and 1990s, including rule-based approaches, please refer to Leacock et al. (2014).

🟥 Grammaticality 🟪 Fluency 🟨 Clarity 🟩 Style 🟧 Readability 🟪 Redundancy 🟦 Consistency
This paper presents empirical studies and closely corresponding theoretical models of a chart parser's performance while~~the performance of a chart parser~~ exhaustively parsing the Penn Treebank with the Treebank's own context-free grammar (CFG)~~CFG grammar~~. We show how performance is dramatically affected by rule representation and tree transformations, but little by top-down vs. bottom-up strategies. We discuss grammatical saturation, provide an~~, including~~ analysis of the strongly connected components of the phrasal nonterminals in the Treebank, and model how, as sentence length increases, regions of the grammar are unlocked, increasing the effective grammar rule size ~~increases as regions of the grammar are unlocked,~~ and yielding super-cubic observed time behavior in some configurations.
We expect this approach to yield the following three improvements. Taking advantage of the representation learned by the English model will lead to shorter training times compared to training from scratch. Relatedly, the model trained using transfer learning will require ~~requires~~ less data for an equivalent score than a German-only model. Finally, the more layers we freeze the fewer layers we will need to back-propagate through during training; thus,~~. Thus~~ we expect to see a decrease in GPU memory usage since we do not have to maintain gradients for all layers.
We present the results of ~~on~~ a quantitative analysis of a number of publications in the NLP domain on the collection~~collecting~~, publishing, and availability of research data. We find that, although a wide range of publications rely on data crawled from the web, ~~but~~ few publications provide~~give~~ details of~~on~~ how potentially sensitive data was treated. In addition ~~Additionally, we find that~~, while links to repositories of data are given, they often do not work, even a short time after publication. We present~~put together~~ several suggestions on how to improve this situation based on publications from the NLP domain, as well as ~~but~~ also other research areas.

Table 1: Examples of revision. Each edit type is highlighted respectively.

its (Sakaguchi et al., 2016). With this expansion, the community has proposed new benchmark datasets (Daudaravicius et al., 2016; Napoles et al., 2017; Bryant et al., 2019; Napoles et al., 2019; Flachs et al., 2020; Zhang et al., 2023) and evaluation metrics (Dahlmeier and Ng, 2012; Felice and Briscoe, 2015; Napoles et al., 2015; Bryant et al., 2017; Napoles et al., 2019; Gotou et al., 2020; Gong et al., 2022; Ye et al., 2023) for sentence-to-sentence GEC. In addition, GEC models with deep neural network (DNN) techniques have been developed. Such models are robust against word-level and phrase-level local edits in a given sentence and exhibit human-parity performance on some benchmark datasets (Yuan and Briscoe, 2016; Ji et al., 2017; Chollampatt and Ng, 2018; Ge et al., 2018; Kiyono et al., 2019; Kaneko et al., 2020; Rothe et al., 2021; Li et al., 2023; Yang et al., 2023; Fang et al., 2023; Cao et al., 2023).

In contrast to the significant advancements in the area of grammar and fluency correction, relatively few studies have explored revisions for *document-level argumentative writing*, which require a greater investment of time and resources to create appropriate corpora or datasets. Lee and Webster (2012) made an initial attempt to construct a document revision corpus comprising 13,000 student writings with feedback comments from tutors in the Teaching English to Speakers of Other Languages (TESOL) program. Although the authors developed labels for paragraph-level revisions (e.g., coherence), only 3% of all revisions were annotated as paragraph-level revisions, 90% of the revisions were at the word-level, and 7% were at the sentence-level. This is because the corpus comprises writing from language learners, and the majority of errors were simple grammar and fluency errors. This lesson highlights the importance of using a corpus for document-level revision that has already been partially edited for grammar and fluency. However, due to copyright restrictions, this corpus may not be publicly available. The data source for a document-level corpus should be openly licensed to encourage community-based open research in the long term.

Another line of work (Zhang and Litman, 2014, 2015; Zhang et al., 2016, 2017; Kashefi et al., 2022) has created the ArgRewrite corpus, a collection of 86 argumentative essays that include three drafts, each with two cycles of revisions, and edit labels. The ArgRewrite corpus (both v1 and v2) contains roughly half of all edits as surface-level corrections (e.g., conventional GEC or fluency edits), and the other half of edits as content-level document revisions. While the ArgRewrite corpus has more document-level revisions than the corpus of Lee and Webster (2012), all of the essays in the ArgRewrite corpus were written on the same topic. The first version of the ArgRewrite corpus (Zhang et al., 2017) discusses the topic of *whether the proliferation of electronic enriches or hinders the development of interpersonal relationships*, and the second version (Kashefi et al., 2022) focuses on *whether to support or against self-driving cars*.

	Lee and Webster (2012)	Zhang et al. (2017)	Kashefi et al. (2022)	Du et al. (2022)	Ours (TETRA)
# docs	3,760	60	86	559	64
# sents (avg)	-	18.7	25.8	7.19	**26.92**
# references	1	1	1	1	**3**
Edit scope	Form?	Content&Form	Content&Form	Content&Form	**Form**
% beyondGECs	3.2	49.4	52.6	52.8	**56.9**
Drafted by	ESL	Native (*ESL)	Native (*ESL)	Native (*ESL)	**ESL/Native**
Revised by	Author (NonExp.)	Author (NonExp.)	Author (NonExp.)	Author (NonExp.)	**Exp.**
Edit-types by	NonExp.	NonExp.	NonExp.	NonExp.	**Exp.**
Feedback					✓
Topic diversity	✓			✓	✓
Public availability		✓	✓	✓	✓

Table 2: Characteristics of TETRA corpus compared to existing document revision corpora. The **uniqueness of TETRA** is highlighted. *Exp.* and *NonExp.* means expert and non-expert, respectively. *Edit scope* indicates whether it includes edits regarding content and/or form. *% beyondGECs* shows the ratio of edits that are not covered by GEC edit types. *Drafted by* indicates who wrote the (first) draft, *Revised by* shows who revised the draft, *Edit-types by* shows who annotates edit types. *Feedback* (✓) presents whether the corpus contains feedback comments or not. *Topic diversity* (✓) presents whether the corpus contains two or more topics, or a single topic only (no ✓). *Public availability* (✓) shows whether the corpus is publicly available to the community. Native (*ESL) indicates that most of the documents are drafted by native speakers, but some ESL is included.

This lack of topic diversity can lead to overfitting when developing and evaluating automated document revision models (Mita et al., 2019).

Recently, Du et al. (2022) released a corpus of iterative document revisions from Wikipedia, arXiv, and Wikinews, with edit intention labels annotated[3]. Although this work shares the same objective as ours, there are some differences such as the revision scope, the number of references, the expertise level of the editors, and the absence of feedback comments (Table 2). Furthermore, their annotations are done at a sentence level, whereas our dataset (TETRA) is annotated at a document (and sentence) level. Therefore, our dataset (TETRA) complements their corpus (and vice versa).

3 Automated Document Revision

Given a source document d that consists of paragraphs, a potentially automated editor f revises (R) d into d' ($f : d \mapsto d'$). Here, revision R is a set of edits e, and an edit e is defined as a tuple $e = (src, tgt, t, c)$, where *src* is the source phrase before the revision, *tgt* is the revised phrase, t is the edit type (e.g., grammar, word choice, or consistency), and c represents (optional) rational comments about the edit. When *src* is empty (Ø), this edit indicates *insertion*, and it indicates *deletion* when *tgt* is empty; otherwise, the edit is considered to be a *substitution*. Automated document revision includes various edit types (t), e.g., mechanics, word choice, conciseness, and coherence. This is discussed in further detail in §4.4. Note that t does not exclude the scope of conventional (sentential and subsentential) grammatical error and fluency correction. Rationale comments (c) are a useful resource in the study of feedback generation, which has become prominent in the GEC community (Nagata, 2019; Hanawa et al., 2021; Nagata et al., 2021). Thus, automated document revision is a natural extension of sentence-level error correction to document-level error correction with a wider context.

4 The TETRA Corpus

The validity of a dataset design is contingent upon the purpose and goals of the study. In line with §1 (and also Figure 1), the primary objective of this study is to introduce a novel task focused on enhancing document-level editing and its automated evaluation technologies, which is distinct from the existing GEC task. It is important to note that our aim is not to contribute to a broader understanding of "human revision" in general, which sets our study apart from the previous studies on revision (mentioned in §2).. Hence, it is crucial to create a dataset that minimizes the inclusion of minor grammatical errors and fluency-related edits, which are already emphasized as requirements in GEC. This is essential because proposing a new task entails the need to distinguish the technological aspects and linguistic phenomena targeted by the existing task and the proposed task.

[3] We are aware that other subsequent studies (Jiang et al., 2022; D'Arcy et al., 2023) and on text revision have appeared since the preprint of this study was published.

Aspects	Edit types (abr.)	Definition	Scope	%
Grammaticality	grammar, capitalization	edits that aimed to fix spelling/grammar mistakes	S	19.4
Fluency	word choice, word order	edits that aimed to increase sentence fluency	S	23.7
Clarity	clarity	edits that aimed to amplify meaning for clarity	S/D	19.4
Style	style, tone	edits that aimed to adapt the style	S/D	8.0
Readability	readability	edits that aimed to improve readability	S/D	16.8
Redundancy	redundancy, conciseness	edits that aimed to reduce redundancy	S/D	7.2
Consistency	consistency, flow	edits that aimed to increase paragraph fluency	D	5.5

Table 3: Definition of edit types. S and D (in the *scope* column) indicate the sentence and the document, respectively. We highlight edit types that rely on beyond sentence-level context to edit.

4.1 Data Source

To meet the aforementioned requirement, we utilized the ACL anthology [4] papers as our source data. These papers are generally well-written, peer-reviewed papers on NLP. This choice was made based on the hypothesis that addressing minor errors, such as grammatical errors, is necessary to observe global edits that improve coherence and consistency. Furthermore, (2) we chose the abstract and introduction sections since these sections tend to contain fewer embedded math and complex citations than other sections , and they are more likely to induce global editing specific to the document level due to their greater linguistic freedom.

We selected the source documents from the ACL anthology as follows. First, we created eight groups (=2^3) based on the possible combinations of three different attributes: (1) whether the paper was published at a conference or a workshop, (2) whether the paper is affiliated with a native vs. non-native English speaking country, and (3) whether the first author was a student (at the time the paper was published). We randomly sampled papers until we obtained eight unique papers for each group (i.e., 64 papers in total).

4.2 Annotation Scheme

The scope and granularity of edit types vary widely in previous studies, and there is no standard set of labels. Thus, we define categories of edit types (Table 3) based on previous literature on argumentative and discourse writing (Kneupper, 1978; Faigley and Witte, 1981; Burstein et al., 2003; Zhang et al., 2017). Table 1 provides concrete examples of each type of edit in TETRA.

To create the proposed TETRA, we selected an XML format for the following reasons. First, XML is easy to parse using standard libraries (e.g., Python ElementTree and the Java DOM parser)[5] compared to other formats that frequently require exclusive scripts. Such exclusive scripts incur higher maintenance costs to keep up with the updates of additional dependencies. Second, XML is more flexible than other formats in terms of embedding additional information, such as edit types, edit rationale, comments, and other meta information. For example, as shown in Table 1, document revisions include edit types based on various evaluation aspects, and can be further annotated for each edit with their rational comments using a flexible XML scheme (See Appendix C). Furthermore, edits beyond a single sentence, including sentence merging, splitting, and reordering, can be annotated in a flexible manner (See lines 5-7 in Table 7).

4.3 Annotators

We recruited three professional editors with years of experience editing and proofreading English academic writing, who are native English speakers, to independently revise all 64 documents on the Google Docs platform. They added an edit rationale whenever appropriate, and the revised documents were converted to XML format by the first two authors.[6] Information on how to recruit annotators and instructions for them can be found in the Appendix A and B, respectively.

4.4 Statistical Analysis

Table 2 summarizes the characteristics of TETRA corpus compared to existing document revision corpora. We can first emphasize the quality of the TETRA corpus since it is the only document

[4] https://aclanthology.org

[5] We made the nest of XML tags as shallow as possible for users to parse documents even more easily. In TETRA, the maximum depth of nested XML tags is two. We have established an annotation policy for cases of intersecting edit spans, but we did not encounter any such cases made by professional editors.

[6] During the conversion process, minor corrections and remapping of edit types were made only as necessary.

	Student		Non-student		Native		Non-native		Conf.		WS	
Aspects	#	%	#	%	#	%	#	%	#	%	#	%
Grammaticality	79	19.5	106	21.5	60	16.5	125	21.3	110	22.7	75	16.2
Fluency	115	25.2	110	22.4	74	20.4	151	25.8	99	20.4	126	27
Clarity	100	21.9	84	17.1	88	24.2	96	16.4	84	17.3	100	21.6
Style	39	8.5	37	7.5	29	8.0	47	8.0	46	9.5	30	6.5
Readability	74	16.2	85	17.3	75	20.7	84	14.3	92	19.0	67	14.4
Redundancy	32	7.0	36	7.3	22	6.1	46	7.8	25	5.2	43	9.3
Consistency	18	3.9	34	6.9	15	4.1	37	6.3	29	6.0	23	5.0

Table 4: Distributions of revision aspects by writer's attributes.

Levels	Avg	Min	Max
detection	0.32	0.27	0.35
correction	0.83	0.75	1.00

Table 5: Two levels of inter-annotator agreement: agreement on *detection* and *correction*.

revision corpus that is annotated with revisions by multiple experts, whereas most existing document revision corpora are based on revisions by authors themselves, leaving the quality of revisions in doubt. Existing corpora also have the limitation that the editor (*Revised by*) and the edit type annotator (*Edit-type by*) do not coincide, and thus cannot fully reflect the edit intent, but TETRA corpus overcomes this limitation since the edit type is provided by the person who made the revision. Furthermore, we find that the TETRA corpus contains more edits beyond the GEC (*% beyondGECs*) than the existing corpora, indicating that our hypothesis in source data selection (§4.1) is valid.

The right-most column in Table 3 shows the distribution of edit types found in 16 randomly sampled papers (i.e., 25% of the proposed TETRA corpus). We found that 56.9% of the edits were related to issues beyond the sentence-level context (e.g., redundancy), which is greater than other document revision corpora (Table 2). This is simply because TETRA's source documents are academic papers that have already been proofread to some degree compared to other existing document revision corpora where language learner essays are used as the source material. In terms of the differences among the three different attributes (§ 4.1), we did not find any clear trends, which indicates that the quality of papers in the ACL corpus is uniformly good across the venue and author attributes. The details are shown Table 4.

In document-level revision, it is not straightforward to compute inter-annotator agreement due to the diversity of potential revisions and the broad scope of applicable edits. Thus, we measured two levels of inter-annotator agreement, i.e., (1) agreement on *detection* and (2) agreement on *correction*. The first measurement computes how frequently edit spans overlap (i.e., agree) among annotators, and the second measurement computes how frequently edit type labels (e.g., clarity) match when two or more annotators detect the same (or overlapped) span. Table 5 shows the results.

The result demonstrates that the expert annotators agreed on the direction of editing when they decided an issue was in a certain span (the agreement rate on *correction* was approximately 0.8); however, the experts disagreed on where to consider an issue (the agreement rate on *detection* was approximately 0.3), which is a unique characteristic of automated document revision that differs from traditional GECs.

5 A Case Study: (Meta) evaluation

In addition to creating a corpus for automated document revision, it is essential to establish an evaluation that can measure a document's quality improvement (and possibly deterioration) relative to the applied revisions. As a case study, we use TETRA to investigate reference-less and interpretable methods for a (meta-)evaluation method to detect quality improvements according to document revisions.

5.1 How do we evaluate revisions?

Ultimately, the evaluation of document revision systems itself is a research challenge that could be as difficult as building high-quality automated essay scoring (AES) systems (Dikli, 2006). A typical scenario for evaluating text generation is to compute the textual similarity between the hypothesis and references, as in machine translation (BLEU (Papineni et al., 2002)) and summarization

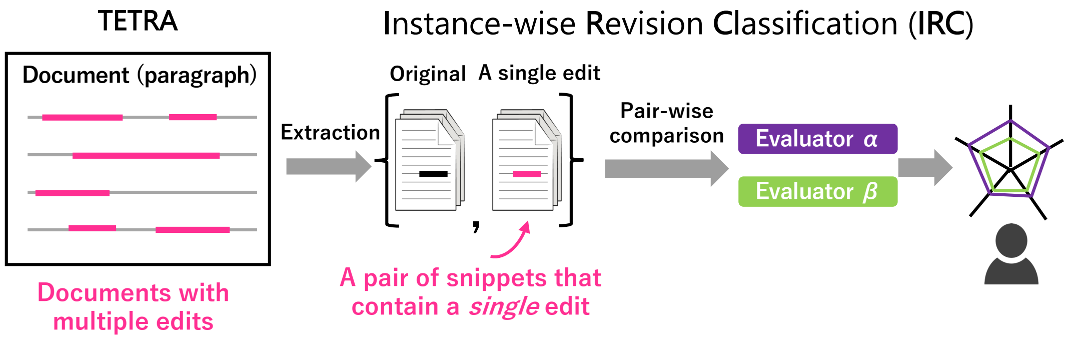
TETRA
Document (paragraph)
Documents with multiple edits
Extraction
Instance-wise Revision Classification (IRC)
Original
A single edit
A pair of snippets that contain a *single* edit
Pair-wise comparison
Evaluator α
Evaluator β

Figure 2: Overview of the IRC meta-evaluation with TETRA.

(ROUGE (Lin, 2004)). However, it is infeasible to elicit all possible gold references for document revision because there are infinite ways to edit a document. In fact, existing work using BLEU and ROUGE to evaluate document revisions shows that such reference-based metrics do not work due to the limited gold references (Du et al., 2022). In addition, given that the purpose of document revision is to support writing, simply presenting users (e.g., model developers and authors) with a single number (overall score) would be insufficient in terms of interpretability and transparency.

In light of the above, a good starting point for a first evaluation method for document revisions would be to develop an explanatory reference-free evaluation model for each evaluation perspective (e.g., clarity, readability, consistency) and then conduct a multidimensional evaluation using this model in an integrated manner.

5.2 Instance-wise revision classification

When using reference-free evaluation as described in §5.1, it is necessary to conduct a *meta-evaluation* of automatic evaluation models (evaluators) to see how well they correlate with human judgments and how reliable they are. Here, it is difficult to measure the quality of a revision automatically based on an *absolute* metric because a single document will contain a variety of edits based on many aspects of evaluation (Table 3). Thus, it is more straightforward to consider a *relative* metric, where a pair of documents is subject to a binary classification choosing the revised one. Such a pairwise comparison has been proven effective as a meta-evaluation method in cases where absolute evaluation is difficult (Guzmán et al., 2015; Christiano et al., 2017). Also, note that document revision contains multiple edits; thus, the binary prediction process cannot identify which edit(s) contributed to the improvement or the degree of improvement.

To address these concerns, we present **I**nstance-wise **r**evision **c**lassification (IRC) as a meta-evaluation methodology, where a pair of snippets that contain a *single* edit is given, and we compare the (reference-less) models according to the accuracy of the binary prediction (i.e., which of the snippets is a revision). By focusing on comparing 'single edit' differences, we can obtain transparent and interpretable measures for each type of edit (e.g., which edit type is more challenging to revise than other types). This is expected to enable us to investigate more effective evaluators (evaluation models) in the future. In fact, recent studies have demonstrated that such rubric-based interpretable evaluation correlates better with human judgments than single overall scoring techniques (Kasai et al., 2021a,b; Zhong et al., 2022). An overview of the proposed IRC is shown in Figure 2. The design philosophy of IRC is to provide users (e.g., model developers or writers) with analytical reports based on multidimensional evaluations to facilitate their understanding of the models, with the goal of moving away from chasing the highest overall number.

5.3 Experiment

In this subsection, we demonstrate how well existing large-scale pre-trained language models perform under the proposed IRC framework as (reference-less) models.

5.3.1 Data split

We divided TETRA into a training set (75%; 48 papers) and a test set (25%; 16 papers) to avoid paper overlap, and we converted the test data into pairs of snippets containing a single edit for IRC framework. Here, when multiple edit types were assigned, each edit type was extracted independently as a single edit snippet pair. When creating a pair of snippets,

	Grammaticality	**Fluency**	**Clarity**	**Style**	**Readability**	**Redudancy**	**Consistency**
BERT	**0.82**	**0.84**	**0.85**	**0.83**	**0.85**	0.79	**0.90**
GPT-4 zero-shot	0.42	0.57	0.55	0.59	0.46	0.47	0.58
+ explicit prompt	0.65	**0.79**	**0.67**	0.57	**0.71**	**0.92**	**0.62**
GPT-4 few-shot	0.47	0.48	0.56	0.51	0.44	0.45	0.40
+ explicit prompt	0.43	0.49	0.56	0.56	0.57	0.80	0.56

Table 6: Meta-evaluation result (Accuracy).

we extracted the entire paragraph as the context. In total, we extracted 1,368 snippet pairs for IRC meta-evaluation.

5.3.2 Evaluators

In this experiment, we compared BERT (Devlin et al., 2019) as fine-tuning and GPT-4 (OpenAI, 2023) as zero/few-shot settings to classify the original and single edit revision snippets.

BERT We converted the training set into a balanced positive/negative example by randomly swapping the order of snippet pairs in one-half of the training set. Specifically, we implemented this evaluator as a classification problem for the [CLS] tokens, using as input a sequence of tokens connecting the original and the single-edited revision documents with the [SEP] tokens. We used the PyTorch implementation for these Transformer models (Wolf et al., 2020). The hyperparameters used to train the model are shown in Appendix D

GPT-4 We build the model using the GPT-4 API (2024-02-15-preview) provided by OpenAI [7]. Two settings, zero-shot and few-shot (2-shot by following (Coyne et al., 2023)), were prepared to evaluate the performance with and without examples[8]. Furthermore, we created prompts focusing on text revision evaluation criteria (**explicit prompt**) to investigate the impact of prompts on evaluation performance, comparing them with the base prompt. Detailed information on each prompt is provided in Appendix E.

5.3.3 Results

As can be seen, the proposed IRC framework enabled us to evaluate the accuracy of each metric in terms of each aspect (i.e., edit type) while analyzing their strengths and weaknesses (Table 6). We also observe a significant disparity between fine-tuning and zero/few-shot results, highlighting the crucial role of fine-tuning in achieving automatic evaluation of text revision. Contrary to expectations, the LLM-based evaluator performed better in zero-shot compared to few-shot scenarios. One potential explanation is that presenting only a few cases might not only be insufficient but also noisy, especially in tasks involving diverse evaluation aspects and reasonable editing methods, such as text revision. On the other hand, compared to the base prompt, performance was significantly improved for many revision types when using explicit prompts. In particular, for redundancy, the GPT-4 evaluator with explicit prompt outperformed the finetuning model. This suggests the potential to realize an automatic evaluation model for high-performance text revision even for zero-shot by advancing prompt engineering in the future.

6 Analysis

The experimental results discussed in §5.3 demonstrated that the supervised metric can discriminate the original and revision snippets with reasonably high accuracy. However, the following question should be considered. *Is the high accuracy derived from actually detecting the quality improvement provided by the revision or annotation artifacts (spurious correlation) by commonly used words and phrases by expert annotators?*

To investigate this question, we evaluated the performance of *the same* supervised metric (BERT) used in §5.3 by applying corruption methods to TETRA in order to artificially degrade the quality of the source documents. If the same supervised metric is fine-tuned on the source and the (improved) revision can still select the original document over the degraded document, we can conclude that the metric actually distinguishes the *quality* of the document rather than spurious features.

6.1 Corruption Methods

Automatic Error Generation (AEG) Injecting grammatical errors as data augmentation has been studied actively to improve GEC. In this study, we

[7] https://github.com/openai/openai-python

[8] The example used for the few-shot was sampled from the train split.

used a back-translation model, which is the most commonly used model in GEC among AEG methods (Xie et al., 2018; Kiyono et al., 2019; Koyama et al., 2021), to deteriorate the original documents in terms of *grammaticality* and *fluency*. Here, a reverse model that generates an ungrammatical sentence from a given grammatical sentence was trained in the back-translation model. To construct the reverse model, we followed the general settings identified in previous studies (Kiyono et al., 2019; Koyama et al., 2021). The details of the experimental settings for the AEG model are described in Appendix F.

Sentence Shuffling As shown in Figure 1, the document revision process involves reordering sentences to improve the *flow* and *consistency* of argumentation. In this analytical experiment, after applying the AEG model, we further shuffled sentences with the same ratio as the *consistency* edit type (5% of the documents; refer to Table 3) to degrade the document relative to the sentence order.

6.2 Results

The binary classification accuracy obtained by BERT on the original vs. (degrading) corruption scenario was 0.96. We found that BERT can successfully select the original document over the degraded document. It should be noted that this is a simulation experiment with artificial errors and there are deviations from a realistic setting, but it suggests that the supervised baseline has the potential to learn to discriminate documents relative to quality rather than spurious features in the experts' annotations.

7 Conclusion

We have proposed the new document revision corpus and highlighted its uniqueness of it compared with existing corpora. As a case study using this corpus, we have explored reference-less and interpretable meta-evaluation methods and also demonstrated that a fine-tuned pre-trained language model can discriminate the quality of documents, which indicates the feasibility of automated document revision evaluation.

Limitations

The first limitation of this study is the scalability of the annotation. TETRA consists of *documents* revised by experts and is therefore expensive to scale up in its nature. This limitation could be mitigated by the choice of source data, i.e., there is room to replace experts with crowd workers by selecting source data that do not require expertise (e.g., general essays). We also reiterate that this work does not aim at proposing specific revision systems and evaluation models for automated document revision. Instead, we present a meta-evaluation scheme as a first step to develop such models and metrics with more transparency.

Ethics Statement

For developing a new document-level revision corpus, TETRA, we paid market rates to the professional editors for their annotations. With regard to the checklist items regarding the use and distribution of artifacts, none of the concerns apply to the dataset created in this study, as it was annotated based on the ACL Anthology materials. [9]

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[9] https://aclanthology.org/faq/copyright/

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A Recruitment procedure for annotators

We recruited professional editors who are native speakers of English and have domain expertise in academic writing, directly via Upwork (`https://www.upwork.com/`), a freelance marketplace, through interviews and screening tests to ensure the quality of the annotators. We paid market rates to them. Instead of using the services of an English proofreading company, which tends to be uncontrollable in terms of annotator quality, we directly hired annotators and provided them with feedback to control the annotation quality, which contributed to further improving the dataset's quality. We will extend the description of this annotation process in the camera ready.

B Instructions for annotators

The full text of the instructions to the annotators is reported below.

Summary You will be proofreading and editing the abstracts and the introduction sections of scientific papers published at NLP (Natural Language Processing) conferences and workshops. Please make edits to improve the quality of the papers, along with your comments mentioning what aspect of the paper the edit is intended to improve, without changing the meaning of the content (information contained in the paper).

About the papers

- These papers are randomly chosen from a pool of papers published at recent NLP conferences and workshops.
- These papers are written by a diverse set of authors, including native and non-native speakers of English at various stages of their careers (students, researchers, faculty members, etc.).
- These papers went through peer reviews and were accepted at conferences and workshops

Edits

- Make edits to the papers in order to improve their quality without changing the information contained in the papers. For each edit, mention what aspect of the paper the edit is intended to improve. These aspects include, but are not limited to: Mechanics, punctuation, grammar, spelling, word order, word usage, organization, development, cohesiveness, coherence, clarity, content, consistency, voice. Feel free to use your own tags/words to describe the purpose of your edit
- Refrain from making single edits that improve more than one aspect of the paper at the same time. Make two or more separate, overlapping edits in the same place if you need to improve multiple aspects.
- Feel free to be creative and make changes that span over multiple sentences or ones that rearrange sentences or even paragraphs if necessary. You are encouraged to rewrite the sentences and paragraphs if local edits aren't enough to improve the quality.
- Since these papers are already peer-reviewed, we expect fewer low-level edits related to punctuation, spelling, and grammar, although make sure to correct such errors if you do encounter them.
- Focus instead on types of edits that improve higher-level aspects of the paper (such as organization, development, cohesiveness, coherence, clarity, content, voice, etc.)

C Example of XML annotation

See Table 7.

D Hyper-parameters settings

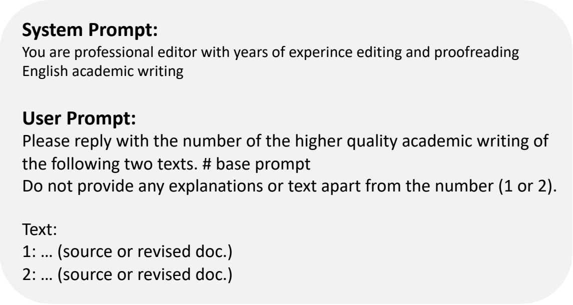
See Table 8.

E Prompts in the GPT-4 evaluators

The prompt used for GPT-4 evaluator is illustrated in Table 3. For prompts focused on evaluation criteria, the following sentence was replaced with base prompt.

```
<doc id="Pxx-xxxx" editor="A" format="Conference" position="Non-student" region="Native">
<abstract>
<text>In this paper, (...) extracted sense inventory. The</text>
<edit type="conciseness" crr="induction and disambiguation steps" comments="conciseness - just
    tightening it up a little bit.">induction step and the disambiguation step</edit>
<text>are based on the same principle: (...) topical dimensions</text>
<edit type="readability" crr=". In" comments="readability - this sentence is getting a bit long, so
    splitting it in two here.">; in</edit>
<text>a similar vein, ...</text>
...
</abstract>
<introduction>
<text>Word sense induction (...)</text>
<text>\n\n Word sense disambiguation (...)</text>
<edit type="punctuation" crr="" comments="punctuation - comma is not appropriate.">,</edit>
...
</introduction>
```

Table 7: Example of XML annotation. For brevity, we omitted a part of the text with "...".



System Prompt:
You are professional editor with years of experince editing and proofreading English academic writing

User Prompt:
Please reply with the number of the higher quality academic writing of the following two texts. # base prompt
Do not provide any explanations or text apart from the number (1 or 2).

Text:
1: ... (source or revised doc.)
2: ... (source or revised doc.)

Figure 3: Example of prompt.

Configurations	Values
Model Architecture	bert-base-uncased
Optimizer	Adam (Kingma and Ba, 2015)
Learning Rate	2e-5
Number of Epochs	10
Batch Size	32

Table 8: Hyper-parameters settings

- Grammaticality: "Please reply with a more grammatical text number."
- Fluency: "Please reply with a more fluent text number."
- Clarity: "Please reply with the number of the text whose meaning is clearer."
- Style: "Please reply with the number of the higher quality academic writing of the following two texts. Please focus your evaluation on the adaptation to an academic writing style in particular."
- Readability: "Please reply with a more readable text number."
- Redundancy: "Please reply with a text number that is less redundant."
- Consistency: "Please reply with more consistent text."

F Experimental settings for AEG

We adopted the "Transformer (big)" settings (Vaswani et al., 2017) using the implementation in the fairseq toolkit (Ott et al., 2019) as a GEC model. In addition, we used the BEA-2019 workshop official dataset (Bryant et al., 2019) as the training and validation data. For preprocessing, we tokenized the training data using the spaCy tokenizer[10]. Then, we removed sentence pairs where both sentences where identical or both longer than 80 tokens. Finally, we acquired subwords from the target sentence via the byte-pair-encoding (BPE) (Sennrich et al., 2016) algorithm. We used the subword-nmt implementation[11] and then applied BPE to split both source and target texts. The number of merge operations was set to 8,000.

[10] https://spacy.io/

[11] https://github.com/rsennrich/subword-nmt