Automated Evaluation of Scientific Writing:
AESW Shared Task Proposal

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Abstract

The goal of the Automated Evaluation of Scientific Writing (AESW) Shared Task is to analyze the linguistic characteristics of scientific writing to promote the development of automated writing evaluation tools that can assist authors in writing scientific papers. The proposed task is to predict whether a given sentence requires editing to ensure its "fit" with the scientific writing genre. We describe the proposed task, training, development, and test data sets, and evaluation metrics.

Quality means doing it right when no one is looking.
– Henry Ford

1 Introduction

De facto, English is the main language for writing and publishing scientific papers. In reality, the mother-tongue of many scientists is not English. Writing a scientific paper is likely to require more effort for researchers who are nonnative English speakers compared to native speakers. The lack of authoring support tools available to nonnative speakers for writing scientific papers in English is a formidable barrier nonnative English-speaking authors who are trying to publish, and this is becoming visible in academic community. Many papers, after acceptance to journals, require improvement in overall writing quality which may be addressed by publishers. However, this is not the case with most conference proceedings.

The vast number of scientific papers being authored by nonnative English speakers creates a large demand for effective computer-based writing tools to help writers compose scientific articles. Several shared tasks have been organized (Dale and Kilgarriff, 2011; Dale et al., 2012; Ng et al., 2013; Ng et al., 2014) which constituted a major step toward evaluating the feasibility of building novel grammar error correction technologies. English language learner (ELL) corpora were made available for research purposes (Dahlmeier et al., 2013; Yannakoudakis et al., 2011). An extensive overview of the feasibility of automated grammatical error detection for language learners was conducted by Leacock et al. (2010). While these achievements are critical for language learners, we also need to develop tools that support genre-specific writing features. The shared task proposed here focuses on the genre of scientific writing.

Above and beyond correct use of English conventions, the genre of scientific writing is characterized by features, including, but not limited to declarative voice, and appropriate academic and discipline-specific terminology. There are many issues for writers that are not necessarily related to grammar issues such as, vocabulary usage, and correct word and phrase order among other issues. In addition, many ELL writers have a different way of thinking and reasoning in their native language which may be reflected in their writing. For instance, it is likely that ELLs and native English (EN) writers would write the same text in different ways:

1. ELL "Completely different role of elastic interaction occurs due to local variations in the strain field...

EN "Elastic interaction takes on a completely
The difference in the readability and the fluency of texts due to grammatical errors is apparent.

The task of automated writing evaluation applied to scientific writing is critical, but it is not well studied because no data for research have been available until recently when the dataset of language edits of scientific texts was published (Daudaravicius, 2014).

On the other hand, some scientists propose to use Scientific Globish versus scientific English (Tyчинин and Камнев, 2013). The term ‘Globish’ denotes the international auxiliary language proposed by Jean-Paul Nerrière, which relies on a vocabulary of 1500 English words and a subset of standard English grammar\(^1\). The proposed adoption of ‘scientific Globish’ as a simplified language standard may appeal to authors who have difficulty with English proficiency. However, Globish might lead to further deterioration of the quality of English-language scientific writing, and, in general, it cannot be a reasonable direction. Therefore, we propose the automated evaluation of scientific writing shared task.

## 2 Language Quality in Scientific Discourse

In this section, we define the concept of language quality and provide examples of previous work that has evaluated scientific writing.

### 2.1 Definition

While writers may have proficiency in English, they may still struggle to be effective writers in the genre of scientific writing. The concept of ‘quality’ in scientific discourse is ill-defined. For instance, a student in a seventh-grade science classroom asked a question ‘Maestro, what is quality?’ during an experiment engaging students to address two questions: “What is the quality of air in my community?” and “What is the quality of water in our river?”

\(^1\)See: http://en.wikipedia.org/wiki/Globish_(Nerriere)

(Moje et al., 2001). The student was asking, “What do you mean when you talk about quality?” As a result of this question, Maestro Tomas spent a class period working on what it meant to refer to quality, especially in science, and how scientists determined quality. In the most explicit discussion, Maestro Tomas told the students that quality differs depending on one’s purpose, one’s background, and one’s position (e.g., as a scientist, an activist, an industrialist, a community member).

We find that the concept of academic language and the concept of the language of academic writing are different at a conceptual level. Krashen and Brown (2007) discuss the concept of academic language proficiency. They argue that academic language proficiency consists of the knowledge of academic language and specialized subject matter. The academic language concept can be described as a proper use of discipline-specific and academic vocabulary to express topic and discourse structure.

### 2.2 Previous work: Scientific Writing Evaluation

Natural language software requirements are the communication medium between users and software developers. Ormandjieva et al. (2007) addressed a problem of writing evaluation of natural language software requirements, and applied a text classification technique for automatic detection of ambiguities in natural language requirements. Sentences were classified as “ambiguous” or “unambiguous”, in terms of surface understanding. Fabbrini et al. (2001) present a tool called QuARS (Quality Analyzer of Requirements Specification) for the analysis of textual software requirements. The Quality Model aims at providing a quantitative, corrective and repeatable evaluation of software requirement documents. Berrocal Rojas and Sliesarieva (2010) examine the automated detection of language issues affecting accuracy, ambiguity and verifiability in natural language software requirements. Lexical analysis, syntactic analysis, WordNet (Miller et al., 1993) and VerbNet (Schuler, 2005) were used for the automated quality evaluation. Burchardt et al. (2015) provided practical guidelines for the use of the Multidimensional Quality Metrics (MQM) framework for assessing translation quality in scientific research projects. MQM provide detailed
The boundary problem for \( V(t, x) \) is of the form

\[
(\partial_t + L - r)V(t, x) = 0, \quad x > h, \ t < T; \tag{1}
\]
\[
V(t, x) = 0, \quad x \leq h, \ t \leq T; \tag{2}
\]
\[
V(T, x) = G(x), \quad x > h. \tag{3}
\]

Boyarchenko and Levendorski ˇi (BLbook; BLAAP02) derived the generalization of the Black–Scholes equation 1 under a weak regularity condition: the process \((t, X_t)\) in 2D satisfies the (ACP) condition (for the definition, see e.g. (Sa)). Note that the (ACP) condition is satisfied if the process \(X\) has a transition density. Equation 1 is understood in the sense of the theory of generalized functions: for any infinitely smooth function \(u\) with compact support \(\text{supp } u \subset (-\infty, T) \times (h, +\infty)\),

\[
(V, (-\partial_t + \tilde{L} - r)u)_{L^2} = 0,
\]

where \(\tilde{L}\) is the infinitesimal generator of the dual process.

Figure 1: A short example of common academic text writing (from (Kudryavtsev and Levendorski, 2009)).

3 The Language of Scientific Texts

Some elements of scientific writing that are distinct from other genres of writing, include, but are not limited to the following:

- Formal notations, e.g. \( f(x) = \cos(x) \).
- Extensive mathematical expressions which can be independent sentences or a continuation of a preceding sentence, see example in Fig 1.
- Discipline-specific terminology.
- Citations.
- Section headers.
- References to other elements of a paper, which are of logical relation only. The scientific writing is highly multidimensional compared to linear daily language.
- Lists and enumerations.
- Bibliography elements.

A wide range of translation quality evaluation aspects show that the field is growing, and more efforts needed to solve many issues of translation quality evaluation.
Table 1: Main characteristics of the training dataset.

| Domain               | The Number of Paragraphs | The Number of Edits |
|----------------------|--------------------------|---------------------|
| Physics              | 41,188                   | 164,813             |
| Mathematics          | 32,981                   | 79,019              |
| Engineering          | 14,968                   | 43,551              |
| Statistics           | 12,115                   | 35,988              |
| Computer Science     | 7,028                    | 16,013              |
| Astrophysics         | 4,278                    | 15,594              |
| Business and Management | 3,454         | 8,262               |
| Psychology           | 2,604                    | 6,189               |
| Finance              | 2,241                    | 6,016               |
| Economics            | 185                      | 314                 |
| **Total**            | **121,042**              | **375,759**         |

– Figures are also used as the continuation of sentences, though not so frequently.

– Hypertext references.

4 The Task Objectives and Definition

The objectives of the AESW Shared Task are to promote the use of NLP tools to help ELL writers the quality of their scientific writing.

In the scope of the task, the main goals are:

– to identify sentence-level features that are unique to scientific writing;

– to provide a common ground for development and comparison of sentence-level automated writing evaluation systems for scientific writing;

– to establish the state-of-the-art performance in the field.

Some interesting uses of sentence-level quality evaluations are the following:

– automated writing evaluation of submitted scientific articles;

– authoring tools in writing English scientific texts;

– filtering out sentences that need quality improvement.

The task will examine automated evaluation of scientific writing at the sentence-level by using the output of the professionally edited scientific texts, which are text extracts before and after editing (by native English speakers).

**The goal of the task is to predict** whether a given sentence needs for any kind of editing to improve it. The task is a binary classification task. Two cases of decisions are examined: binary decision (False or True) and probabilistic estimation (between 0 and 1).

5 Data

5.1 The Editing Process

This section describes the role of the professional language editors who completed the data editing described in Section 5.3. **Language editors are defined as individuals who perform proofreading** (see Smith (2003)). There are no standards that define language quality. The language editors use best practices, for instance (see Society for Editors and Proofreaders (2015)).

Language editors edited selected papers as part of publishing service. Each edited paper has two versions: text before and after editing. Language editors do their best to improve writing quality within the limited time span. In this data set, however, there was no double-annotation for quality control. We estimate that approximately 20% of the data may still contain errors, and also that there may be errors in the editors edits.

5.2 Tex2TXT

We use the open-source tool tex2txt\textsuperscript{2} for the conversion from \LaTeX{} to text, which was developed

\textsuperscript{2}See: http://textmining.lt:8080/tex2txt.htm
Let us ultimately insist on the fact that the expression in the right hand side \( \text{MATH} \) is a function of \( \text{MATH} \) due to the action of the shift and is therefore a different function than \( \text{MATH} \). Let us finally insist on the fact that the expression in the right hand side \( \text{MATH} \) is a function of \( \text{MATH} \) due to the action of the shift and is therefore a different function than \( \text{MATH} \).

Only the expectations of both expressions of Eq. (\REF) are equal.

Figure 3: Training data example of the paragraph annotation with data before language editing, after language editing, and the difference.

Figure 4: A sample from the test data.

specifically for this task. The tool is stand-alone and does not require any other \LaTeX{} processing tools or packages. The primary goal was to extract the correct textual information.

5.3 The Data Set

The data set is the collection of text extracts from more than 4,000 published journal articles (mainly from physics and mathematics) \textit{before} and \textit{after} language editing. The data were edited by professional editors (per above) who were native English speakers\footnote{\LaTeX{} provides \LaTeX{}-based publishing solutions and data services to the scientific community and science publishers. Publishers often request language editing services for papers accepted for publication. The data of our proposed shared task are based on selected papers published in 2006–2009 by Springer publishing company and edited at \LaTeX{} by professional language editors.}. Editing includes grammar error corrections, text cleaning, rephrasing, spelling correction, stylistics, and sentence structure corrections. Each extract is a paragraph which contains at least one edit done by language editor. All paragraphs in the dataset were randomly ordered for the source text anonymization purpose. The distribution of paragraphs and edits are presented in Table 1.

Sentences were tokenized automatically, and then both versions – texts \textit{before} and \textit{after} editing – automatically aligned with a modified \texttt{diff} algorithm. Each sentence is annotated as either ‘original’, or ‘edited’, or ‘nonedited’. Non-edited sentences contained no errors. The \textit{original text} – the text before language editing – can be restored simply by deleting sentences that are annotated as ‘edited’. Also, the \textit{edited text} can be restored simply by deleting sentences that are annotated as ‘original’.

The \textit{training data}: The training data will be at least 121,000 paragraphs with 375,000 edits. The number of edited sentences will be at least 235,000, and the number of original sentences will be at least 234,000. There will be 335,000 sentences that were non-edited. These numbers show that 41\% of all sentences were edited. See
Figure 3 for an example of annotated training data.

The training data will include annotations to show differences between the ‘original’ and ‘edited’ texts. The ‘edits’ data are used for a quick reference to what the changes are.

**The development data:** An additional 5,000 paragraphs similar to test data will be provided. The development data set will be comprised of a set of articles that are independent from articles used for compiling the training and test sets. The development data will be distributionally similar to training data and test data with regard to edited and non-edited sentences, and domain.

**The test data:** An additional 5,000 paragraphs will be provided for testing the registered systems of the AESW Shared Task. The test data set will be comprised of a set of articles that are independent from articles used for compiling the training and development sets. Test paragraphs will retain ‘original’ and ‘nonedited’ versions only. The ‘edited’ sentence version will be removed. The test data annotation will be similar to training and development data. However, no data about edits and sentence class will be provided until submission of system results. See an example in Figure 4.

Shared Task participating teams will be allowed to use external data that are publicly available. Teams will not be able to use proprietary data. Use of external data should be specified in the final system report.

6 **The Task and Evaluation**

The task is to predict the class of a test sentence: ‘original’ or ‘edited’. In Section 2, we saw that both Boolean and probabilistic prediction are used for various tasks. Therefore, there will be two tracks of the task:

**Boolean Decision:** The prediction of whether a test sentence is edited (TRUE), or before editing and corrections are needed (FALSE).

**Probabilistic Estimation:** The probability estimation of whether a test sentence is edited ($P = 0$), or before editing and corrections are needed ($P = 1$).

Participating teams will be allowed to submit up to two system results for each track. In total, a maximum of four system results will be accepted. All participating teams are encouraged to participate in both tracks.

The primary goal of the task is to predict ‘original’ sentences with poor writing quality. Each registered system will be evaluated with a Detection score, which is described below.

6.1 **Detection score**

The score will be an F-score of ‘original’ class prediction. The score will be computed for both tracks individually. For the Boolean decision track, a gold standard sentence $G_i$ is considered detected if there is an alignment in the set that contains $G_i$. We calculate Precision ($P$) as the proportion of the sentences that were ‘original’ in the gold standard:

$$P_{\text{bool}} = \frac{\# \text{Sentence}_{\text{detected}}}{\# \text{Sentence}_{\text{spurious}} + \# \text{Sentence}_{\text{detected}}}.$$  

Similarly, Recall ($R$) will be calculated as:

$$R_{\text{bool}} = \frac{\# \text{Sentence}_{\text{detected}}}{\# \text{Sentence}_{\text{gold}}}.$$  

The detection score is the harmonic mean (F-score):

$$\text{DetectionScore}_{\text{bool}} = 2 \cdot \frac{P_{\text{bool}} \cdot R_{\text{bool}}}{P_{\text{bool}} + R_{\text{bool}}}.$$  

For the probabilistic estimation track, the Mean squared error (MSE) will be used. A gold standard sentence $G_i$ is assigned to 1 if it is ‘original’, and to 0 if it is ‘nonedited’. A gold standard sentence $G_i$ is considered detected if there is correlation in the set that contains $G_i$. We calculate Precision as the MSE of the sentences $E_i$ that were estimated as ‘original’, i.e., their estimated probability is above 0.5:

$$P_{\text{prob}} = 1 - \frac{1}{n} \sum_{i=1}^{n} (E_i > 0.5 - G_i)^2.$$  

The higher the $P_{\text{prob}}$ the better the system is. Similarly, we calculate Recall as the MSE of the sentences $G_i$ that were ‘original’ in the gold standard:

$$R_{\text{prob}} = 1 - \frac{1}{n} \sum_{i=1}^{n} (E_i - G_{i,\text{original}})^2.$$  

61
| ID | Type    | G_{pool} | G_{prob} | Boolean Decision Track | TEAM1 | TEAM2 | TEAM3 | Probabilistic Estimation Track | TEAM1 | TEAM2 | TEAM3 |
|----|---------|----------|----------|------------------------|-------|-------|-------|--------------------------------|-------|-------|-------|
| 1  | original | F        | 1        | F                      | T     | F     | 0.7   | 0     | 1     |
| 2  | original | F        | 1        | F                      | T     | F     | 0.8   | 0     | 1     |
| 3  | nonedited| T        | 0        | T                      | T     | F     | 0.1   | 0     | 1     |
| 4  | nonedited| T        | 0        | F                      | T     | F     | 0.6   | 0     | 1     |
| 5  | nonedited| T        | 0        | T                      | T     | F     | 0.2   | 0     | 1     |
| 6  | nonedited| T        | 0        | T                      | F     | 0.7   | 0     | 1     |
| 7  | original | F        | 1        | F                      | T     | F     | 0.9   | 0     | 1     |
| 8  | nonedited| T        | 0        | T                      | T     | F     | 0.1   | 0     | 1     |
| 9  | nonedited| T        | 0        | T                      | T     | F     | 0.4   | 0     | 1     |

$P$

$R$

\[ DetectionScore \]

Table 2: DetectionScore calculation example.

The harmonic mean $DetectionScore_{prob}$ is calculated similarly as $DetectionScore_{bool}$. The higher the $DetectionScore_{prob}$ the better the system is. An example of score calculation is shown in Table 2.

7 Report submission

The authors of participant systems are expected to submit a shared task paper describing their system. The task papers should be 4-8 pages long and contain a detailed description of the system and any further insights.

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