GEC into the future:
Where are we going and how do we get there?

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Abstract

The field of grammatical error correction (GEC) has made tremendous bounds in the last ten years, but new questions and obstacles are revealing themselves. In this position paper, we discuss the issues that need to be addressed and provide recommendations for the field to continue to make progress, and propose a new shared task. We invite suggestions and critiques from the audience to make the new shared task a community-driven venture.

1 Introduction

In the field of grammatical error correction (GEC), the Helping Our Own shared tasks in 2011 (Dale and Kilgarriff, 2011) and 2012 (Dale et al., 2012), and then the CoNLL shared tasks of 2013 (Ng et al., 2013) and 2014 (Ng et al., 2014) marked a sea change. For the first time there were public datasets, most notably the NUS Corpus of Learner English (NUCLE; Dahlmeier et al., 2013), and evaluation metrics, of which the most commonly used to date is M^2 (Dahlmeier and Ng, 2012). This has allowed researchers from other fields, such as machine translation, to enter GEC more easily. It has also enabled new developments, with many papers published on metrics, new algorithms (most recently neural methods), and occasionally new datasets.

Even with the accelerated progress in GEC, problems yet remain in the field. The use of specific datasets may be GEC's worst enemy, as system and even evaluation metric development rely too heavily on the NUCLE test set. While probably one of the most important contributions to the field's development to date, the lack of publicly available alternatives has caused some over-optimization. Other issues have also gone undiscussed. For example, nearly all work that has been published in the NLP community has focused on standalone systems, and very few investigate their impact on downstream users, except, e.g., Nagata and Nakatani (2010); Chodorow et al. (2010).

In this short paper, we take stock of the current state of GEC (§2) and its limitations (§3), and outline where we believe the field should be five years from now (§4). We finish with a recommendation for a new *community-driven* shared task that will help the field progress even further (§5). We look forward to discussing this proposal with the community and to refine a shared task for 2018.

2 GEC: A Quick Retrospective

A complete retrospective is outside the scope of this paper and thus we focus on two key aspects of the field: For a more detailed review of the field, we refer the reader to Leacock et al. (2014).

2.1 Datasets

There are several error-annotated corpora, and for the purposes of this paper, we only focus on the most recent public datasets. The size and characteristics of each corpus is summarized in Table 1. The most frequently used corpus for GEC is NUCLE, which was the official dataset of the 2013 and 2014 shared tasks. It is a collection of essays written by students at the National University of Singapore (Dahlmeier et al., 2013). The test set and system results from the most recent shared task were released to the community (Ng et al., 2014), and have been the focus of recent work on automatic metrics (see §2.2). Additionally, this test set has been augmented with eight additional annotations from Bryant and Ng (2015) and eight from Sakaguchi et al. (2016).

The Cambridge Learner Corpus (CLC) contains a broader representation of native languages than the NUCLE, however only the First Certificate in

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Corpus	Num. refs.	Num. sent.	Sents. changed	Err. type labeled	Fluency edits	Err. span >1 sent.	Diverse proficiency	Diverse topic	Diverse L1	Native speakers
NUCLE	59k	2	38%	✓	(✗)	✓	✗	✗	✗	✗
FCE	34k	1	62%	✓	✗	✓	✓	✓	✓	✗
Lang-8	2.5M	≥1	42%	✗	✓	✓	✓	✓	✓	✗
AESW	1.2M	1	39%	✗	✗	✓	✗	✗	✓	✓+✗
JFLEG	1.5k	4	86%	✗	✓	✗	✓	✓	✓	✗

Table 1: GEC corpora available for free (for research purposes) and desired properties, identified in §3.1. ✓ and ✗ indicate whether the corpus exhibits each property. Fluency edits for the NUCLE test set were added by Sakaguchi et al. (2016).

English (FCE) portion is publicly available (Yannakoudakis et al., 2011). The FCE is approximately the same size as NUCLE and was used for the 2012 shared task. However it has not been used to the same extent as NUCLE, presumably because it lacks multiple annotations and the 2012 shared task system outputs were not released.

All of the corpora described above have been annotated with spans of text containing an error and assigned an error code. Unlike these, the Lang-8 Learner Corpora Corpus of Learner English (Tajiri et al., 2012) is a parallel set of original and corrected sentences from `lang-8.com`, an online community of language learners who post text that is corrected by other users. It is also the largest public GEC corpora, with more than 2 million English sentences.[1] Another large corpus currently available was released for the first Automatic Evaluation of Scientific Writing shared task (AESW; Daudaravicius et al., 2016). Unlike the other corpora, it contains scientific writing by native and non-native English speakers, corrected by professional editors. Because the writers are highly proficient, there is a lower diversity of errors than the other corpora. More than half of the errors are related to punctuation (Flickinger et al., 2016), which compose less than 7% of NUCLE errors.

Finally, the JHU FLuency-Extended GUG corpus (JFLEG) is a small dataset for tuning and evaluating GEC systems. 1.5k sentences are taken from the GUG corpus (Heilman et al., 2014), which labels sentences with an ordinal grammaticality score. In JFLEG, each sentence is corrected four times for grammaticality and *fluency* (Sakaguchi et al., 2016).

2.2 Evaluation

Precision, recall, and F-score have been used to evaluate GEC systems that correct targeted error types. Three additional evaluation metrics have been proposed for GEC: MaxMatch (M^2; Dahlmeier and Ng, 2012), I-measure (Felice and Briscoe, 2015), and GLEU (Napoles et al., 2015). The first two metrics compare the changes made in the output to error-coded spans of the reference corrections. M^2 was the metric used for the 2013 and 2014 CoNLL GEC shared tasks (Ng et al., 2013, 2014). It captures word- and phrase-level edits by building an edit lattice and calculating an F-score over the lattice. I-measure (IM) is based on token-level alignment-based accuracy among the source, hypothesis, and gold-standard. IM considers the distinction between "do-nothing (already grammatical) baseline" and systems that only propose wrong corrections (i.e., make the source sentence worse). Unlike these two approaches, GLEU does not need error-coded references (Napoles et al., 2015). Based on BLEU (Papineni et al., 2002), it computes n-gram precision of the system output against reference sentences, and additionally penalizes n-grams in the hypothesis that should have been corrected but failed.

3 Limitations

3.1 Problems with Datasets

As we saw in the previous section, the majority of the commonly used datasets are limited to students, specifically college-level ESL writers. To date, the overwhelmingly majority of publications benchmark on NUCLE, save for a few exceptions such as Cahill et al. (2013) and Rei and Yannakoudakis (2016) which means that research efforts are becoming over-optimized for one set. This lack of diversity means that it is not clear how systems perform on other genres under different training conditions. We should look to the parsing community as a warning sign. For well over a decade, the field was heavily focused on improving parsing accuracy on the Penn Treebank (Marcus et al., 1993), but robustness was greatly improved with the advent of Ontonotes (Hovy et al., 2006) and the Google Web Treebank (Petrov and

[1]Because of noise and implementation differences in sentence extraction, the size varies from 2–2.5 million sentences.

System	GLEU [0,100]	IM [-100, 100]	M^2 [0, 100] P	R	$F_{0.5}$
“a”	0.2	0.0	28.4	31.3	28.9
“a a”	0.6	0.0	28.7	31.8	29.3
“a a a”	1.6	0.0	28.7	32.0	29.4
Source	57.4	0.0	100.0	0.0	0.0
CAMB14	64.3	-5.3	39.7	30.1	37.3
CUUI14	64.6	-2.2	41.8	24.9	36.8
AMU14	64.6	-2.5	41.6	21.4	35.0
Src>Game	✓	✗	✓	✗	✗
Src<Sys	✓	✗	✗	✓	✓

Table 2: Metric scores of three artificially contrived systems (Game), input source sentences (Src), and top 3 system outputs (Sys) on CoNLL14 data. The bottom two rows show whether each metric scores the systems better than Game or worse than Source. Humans judge all systems be better than over Source.

McDonald, 2012).

Another issue is training data size. The sister field of machine translation (MT) usually has datasets in the orders of millions or even tens of millions of sentence pairs. The largest GEC datasets barely approach that figure, with 2.5 million sentences at a maximum, a number which includes sentences that were not corrected.

Table 1 summarizes the strengths and weaknesses of the most commonly used GEC corpora across different properties ranging from size to diversity in native language (L1). The most notable weakness across corpora is the lack of multiple reference corrections. NUCLE contains two corrections per sentence and JFLEG 4. M^2 and GLEU scores increase with more references but at a diminishing rate (Bryant and Ng, 2015; Sakaguchi et al., 2016). Further investigation is warranted to determine what an ideal number of references is, given the trade off between cost and reliability. Some corpora contain little diversity in proficiency, topic, and/or native language of the writers (namely NUCLE and AESW), however AESW is the only corpus to contain sentences by native English speakers.

3.2 Problems with Evaluation

The 2014 CoNLL shared task has enabled, for the first time, the development of evaluation metrics. These metrics are evaluated by comparing their ranking of the shared task systems with the ranking done by human annotators. Sakaguchi et al. (2016) showed that GLEU could rank systems closer to a human ranking than M^2 and IM, and a higher correlation could be found when combining GLEU with a reference-less fluency metric (Napoles et al., 2017). However, it is important to take these results with a grain of salt—all benchmarking of the metrics was done with the CoNLL 2014 systems and data, and it remains to be seen if this ranking would hold on other, larger datasets.

Another issue with the metrics is the number of references available for comparison. As in machine translation, the more references (human-generated gold-standard corrections) one has, the better one can evaluate a system. The CoNLL 2014 test set has 18 references annotated, but one can find examples where a system produces a correction which is not reflected in the references. This gets more complicated when human raters feel it is necessary to rewrite a sentence.

A third issue is that no metric directly measures meaning preservation. This means that a system could produce a more fluent version of the original but accidentally change one word, and that could change the meaning of the whole sentence. For example, if a system accidentally corrected *documentary* to *document* in “The documentary gave a nice summary of global warming.” By current metrics, that error would have the same penalty as a minor spelling mistake.

Finally, the most commonly used GEC metric, M^2, has a serious weakness, which has been noted in earlier papers (Felice and Briscoe, 2015; Sakaguchi et al., 2016; Bryant et al., 2017). The phrasal alignments under-penalize a sequence of incorrect tokens, and to illustrate how troubling this is, we tested a series of dummy systems, where each system produces the same sentence regardless of input (the sentences produced by each system are *a*, *a a*, and *a a a*). Table 2 shows their scores on the CoNLL 2014 test set evaluated on the official NUCLE references (without alternatives), compared to the top 3 systems in the shared task, CAMB14 (Felice et al., 2014), CUUI14 (Rozovskaya et al., 2014), and AMU14 (Junczys-Dowmunt and Grundkiewicz, 2014). The reader will notice that GLEU and IM score these sentences at or near zero, however according to M^2, the dummy system that only returns the string “a a” scores higher than 7/13 systems participating in the 2014 Shared Task. The IM score is also problematic in that the gamed sentences have the same score as the source.

System	Sentence	Metric score (rank) GLEU [0,100]	IM [-100,100]	M^2 [0,100]
Source	In both advertisements is said that these tooth pastes will make your teeth briliant and brighter .	15.7 (4)	0.0 (4)	0.0 (5)
Reference	□ Both advertisements □ say that the toothpaste will make your teeth brilliant and brighter .	50.7 (1)	17.4 (3)	65.2 (3)
AMU16 & NUS16	In both advertisements is said that these tooth pastes will make your teeth briliant and brighter .	15.7 (4)	0.0 (4)	0.0 (5)
CAMB14	In both advertisements is said that these tooth pastes will make your teeth brilliant and brighter .	35.5 (3)	100.0 (1)	83.3 (1)
CAMB16	In both advertisements it is said that these tooth problems will make your teeth brilliant and brighter .	39.5 (2)	56.1 (2)	71.4 (2)
Dummy	a a a .	2.9 (5)	-47.7 (5)	52.6 (4)

Table 3: An original source sentence and candidate corrections, along with the score of each sentence from different metrics. Changed or inserted spans are underlined and □ indicates deletions.

4 Looking into the Future

In this section we outline our recommendations for how the field should develop.

4.1 Data

As the world's communication is not limited to college-level essays, it is important that we have datasets which better represent as much breadth as possible. Ideally, datasets should span different genres (such as emails, blog posts, and official documents) and include content from both native and non-native speakers, as well as from different proficiency levels. All of these changes will enable the field to better assess how we are helping *more* of the world's writers under different conditions, and also enable one to test adaptation between domains.

4.2 Evaluation

We envision evaluation metrics which check that corrections are not only grammatically valid, but also check that the corrections are native-sounding and preserve the original meaning or intent of the writer. Future metrics should be easy to compute and be interpretable. For instance, a range between -1 and 1 may be preferred (like IM uses), since it is possible a suggested set of corrections could produce a sentence which is *worse* than the original. If multiple references are used, metrics should assign credit to corrections which match different references in different places, assuming the outcome is overall coherent. In addition, most (if not all) evaluation schemes to date have focused on the sentence as the minimal unit. It would be good to take the entire document into account and allow for more global rewrites, such as consistent tense.

Ultimately, a metric should say whether or not a system has attained the same level of performance as a human judge. One way of doing this is through a GEC Turing Test, where system outputs are blindly judged alongside human corrections of the same sentences. If human adjudicators think the system outputs are indistinguishable in quality from the human corrections (for example, given a set of criteria such as being good corrections, meaning preserving and native-sounding) then that is a very strong signal that GEC has attained human-level performance.

To illustrate the shortcomings of current metrics, Table 3 contains a JFLEG sentence corrected by current leading systems (AMU16 (Junczys-Dowmunt and Grundkiewicz, 2016); NUS16 (Chollampatt et al., 2016); CAMB16 (Yuan and Briscoe, 2016)) and the automatic metric scores.[2] Notice that the CAMB16 sentence, which changes *tooth pastes* → *tooth problems*, is ranked the highest system output by GLEU and the second highest by IM and M^2. All metrics score it higher than the unchanged Source sentence. Another issues evidenced in the table is that IM and M^2 score the imperfect correction (CAMB14) as better than Reference; and according to M^2, the Dummy output is better than Source.

We believe that the GEC field should take

[2] All metrics run with default settings. Reference is evaluated against the other 3 references; other sentences are evaluated against all 4 references.

notes from the Workshop on Machine Translation (WMT) (Bojar et al., 2016). There the participants in the evaluation shared tasks are also responsible for contributing system ranking judgments. This makes the whole effort more community-driven and takes the pressure off one group from having to supply all annotations.

4.3 Consensus on Goals and Applications

As a corollary to data and metrics, the end-goal of GEC also needs to be refined within the community. Initial approaches to GEC seemed to focus on providing feedback to English language learners where specific error types would be targeted and feedback would be given in terms of detection or possible corrections. The work was also motivated by concurrent work in using NLP for automatic essay scoring (for example, Attali and Burstein (2006)). Chodorow et al. (2012) noted several other applications for GEC: improving overall writing quality for both native and non-native writers, assistive language learning, and applications within NLP (such as post-editing in MT). More recently the field has drifted to "whole sentence GEC" using statistical or neural MT approaches. In this situation, the writer simply gets a complete rewrite of their sentence, which may be useful as an instructional tool in some circumstances, but not all.

There is no consensus on what the focus application(s) should be. Which application determines which methods and which evaluation metrics one uses. For example, if one wants to provide feedback to language learners, then a high-precision, interpretable method is preferred. Conversely, if the application is simply to automatically clean up one's writing without any feedback, then a whole sentence approach may be preferred. Very few papers delve into error detection and correction for goals other than whole-sentence error correction or targeted feedback for ESL writers. Datasets and metrics should be created with a specific goal in mind. Thus, the field should reassess what are the goals and how we evaluate with respect to these goals.

5 Proposal for a New Shared Task

We believe it is time for another shared task in the field, this one designed with consideration the field should be several years from now. The CoNLL shared tasks were instrumental in unifying the field with a common benchmark corpus and metric, and the AESW shared task provided data from a new domain to evaluate on. We recommend the following:

- **Data**: A new corpus for training and evaluation that spans different genres. We have already begun collecting conversational data from native and non-native writers and from genres other than essays, such as emails. Our aim is to construct a corpus larger than the NUCLE to support the development of data-hungry methods such as neural MT.
- **Annotation**: The data is corrected for fluency with crowdsourcing as in Sakaguchi et al. (2016) which is a cheap and efficient way of collecting annotations of reasonable quality. Error types can be automatically tagged using a method such as that described in Bryant et al. (2017)
- **Metric Evaluation**: Borrowing from the WMT community, the shared task should also be a venue to improve automatic GEC evaluation. Participants will provide judgments on system rankings.

We invite discussion from the community and seek others to help contribute data, annotations and other resources to make this a community-driven event. Our goal is to host a shared task in 2018. We believe that this type of collaboration has made the WMT evaluations a success, and will similarly benefit GEC. We have set up a public mailing list where others can post their comments and suggestions: `https://groups.google.com/forum/#!forum/gec-sharedtask`.

6 Conclusions

The goal of this paper is to laud the progress that the GEC field has made, but also highlight the limitations that must be addressed for the field to grow further. The reliance on a few narrow datasets is problematic as it has a major impact on system development and metric development, as well as robustness when applying these approaches in the real world. Our concern is that unless data and metrics are improved, it will be hard to assess the value of new algorithms optimized for a small set of datasets and metrics. We list a recommendation for a new shared task to fuel discussion offline as well as at the BEA12 Workshop in Copenhagen.[3]

[3] `https://www.cs.rochester.edu/~tetreaul/emnlp-bea12.html`

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