Conservatism and Over-conservatism in Grammatical Error Correction

Abstract

Grammatical Error Correction systems (henceforth, *correctors*) aim to correct ungrammatical text, while changing it as little as possible. However, while such conservatism is a virtue for correctors, we find that state-of-the-art systems make substantially less changes to the source sentences than needed. Analyzing the distribution of possible corrections for a given sentence, we show that this over-conservatism likely stems from the inability of a handful of references to account for the full variation of valid corrections for a given sentence, which results in unduly penalization of valid corrections, thus dincentivizing correctors to make changes. Moreover, we show that simply increasing the number of references is unlikely to resolve this gap, and conclude by presenting an alternative reference-less approach based on semantic similarity.

1 Introduction

Grammatical Error Correction (GEC) is receiving considerable interest recently, notably through the GEC-HOO (Dale and Kilgarriff, 2011; Dale et al., 2012) and CoNLL shared tasks (Kao et al., 2013; Ng et al., 2014). Within GEC, considerable effort has been placed on system evaluation (Tetreault and Chodorow, 2008; Madnani et al., 2011; Dahlmeier and Ng, 2012; Felice and Briscoe, 2015; Napoles et al., 2015), a notoriously difficult challenge, in part due to the many valid corrections each source sentence may have (Chodorow et al., 2012).

An important criterion in the evaluation of correctors is their ability to generate corrections that are faithful to meaning of the source. In fact, many would prefer a somewhat cumbersome or even an occasionally ungrammatical correction over a correction that alters the meaning of the source (Brockett et al., 2006). As a result, often when compiling gold standard corrections for the task, annotators are instructed to be conservative in their corrections (e.g., in the Treebank of Learner English (Nicholls, 2003)). There were different attempts to formally capture this precision/recall asymmetry such as the standardized use of $F_{0.5}$ over F_1, where Precision is emphasized over Recall (Dahlmeier and Ng, 2012) and the choices of weights in I-measure(Felice and Briscoe, 2015).

However, penalizing over-correction more harshly than under-correction may lead to reluctance of correctors to make any changes (henceforth, *over-conservatism*). Using one or two reference corrections, which is a common practice in GEC, compounds this problem, as correctors are not only harshly penalized for making incorrect changes, but are often penalized for making correct changes not found in the reference.

Indeed, we show that current state of the art systems suffer from over-conservatism. Evaluating the output of 12 recent correctors, we find that all of them substantially under-predict corrections relative to the gold standard (§2).

We first assess whether the undue penalization of valid corrections can be resolved by increasing the number of references, which we denote with M (§3). We start by estimating the number and frequency distribution of the valid corrections per sentence, arriving at an estimate of over 1000 corrections for sentences of no more than 15 tokens. We then consider two representative reference-based

measures (henceforth, ***RBMs***) for assessing the validity of a proposed correction relative to a set of references and characterize the distribution of their scores as a function of M. Our results show that both measures substantially under-estimate the true performance of the correctors. Moreover, they show that increasing M only partially addresses the incurred bias, as both RBMs approach saturation with M values of 10–20, indicating that a prohibitively large value for M may be required for reliable estimation.

Our findings echo the results of Bryant and Ng (2015), who study the effect of M on the F-score measure, the most commonly used RBM for GEC. Their work focused on obtaining a more reliable estimate of correctors' performance, and proposed to do so by normalizing corrector's estimated performance with the performance of a human corrector using the same measure. However, while such normalization may yield more realistic performance estimates, it does not have any effect on the training and tuning of correctors.

We conclude by proposing an alternative reference-less semantic evaluation approach which assesses the extent to which a correction faithfully represents the semantics of the source, by measuring the similarity of their semantic structures (§4). This approach can be combined with a measure of grammaticality, based on automatic error detection, as proposed by Napoles et al. (2016). Our experiments support the feasibility of the proposed approach, by showing that (1) semantic structural annotation can be consistently applied to learner's language (LL), and (2) that the proposed measure is less prone to unduly penalize valid corrections.

2 Over-Conservativism in GEC Systems

We demonstrate that current correctors suffer from over-conservatism: they tend to make too few changes to the source.

2.1 Notation

We assume each source sentence x has a set of valid corrections $Correct_x$, and a discrete distribution $\mathcal{D}_x$ over them, where $P_{\mathcal{D}_x}(y)$ for $y \in Correct_s$ is the probability a human annotator would correct x as y.

Let X be the evaluated set of source LL sentences where X consists of the sentences $x_1 \dots x_N$, each independently sampled from some distribution $\mathcal{L}$ over LL sentences and denote $\mathcal{D}_{x_i} \coloneqq \mathcal{D}_i$. . Each x_i is paired with M corrections $Y = \{y_i^1, \dots, y_i^M\}$, which are independently sampled from $\mathcal{D}_i$.[1] We define the *coverage* of M references for a sentence x_i to be $P(y \in Y | y \in Correct_i)$ for Y of size M, and y sampled according to $\mathcal{D}_y$.

A corrector C is a function from LL sentences to proposed corrections (strings). A corrector's output is a set of proposed corrections $\{C(x_1), ..., C(x_N)\}$. An assessment measure is a function from X, Y and C to a real number. We use the term "true measure" to refer to the measure's output where the references include all possible corrections, i.e., $y_i = Correct_i$ for every i.

Experimental Setup. Our experiments are on the NUCLE dataset, a parallel corpus of LL essays and their corrected versions, which is the de facto standard in GEC. The corpus contains 1,414 essays in LL, each of about 500 words.

We evaluate all participating systems in the CoNLL 2014 shared task, in addition to the best performing system on this dataset (Rozovskaya and Roth, 2014). The particiapting systems and their abbreviations are: Adam Mickiewicz University (AMU), University of Cambridge (CAMB), Columbia University and the University of Illinois at Urbana-Champaign (CUUI), Indian Institute of Technology, Bombay (IITB), Instituto Politecnico Nacional (IPN), National Tsing Hua University (NTHU), Peking University (PKU), Pohang University of Science and Technology (POST), Research Institute for Artificial Intelligence, Romanian Academy (RAC), Shanghai Jiao Tong University (SJTU), University of Franche-Comte (UFC), University of Macau (UMC), and the best performing system by Rozovskaya and Roth (2016, RoRo). All are trained and tested on the NUCLE corpus.

We compare the prevalence of changes made to the source by the correctors, relative to their prevalence in the NUCLE reference. In order to focus on the more substantial changes, we exclude from our evaluation all non-alphanumeric characters, both

[1] Our analysis assumes M is fixed across source sentences. Generalizing the analysis to sentence-dependent M values is straightforward.

within tokens or as token of their own.

Measures of Conservatism. We consider three types of divergences between the source and the reference. First, we measure to what extent *words* were changed: altered, deleted or added. To do so, we compute word alignment between the source and the reference, casting it as a weighted bipartite matching problem, between the source's words and the correction's. Edge weights are assigned to be the edit distance between the tokens. We note that aligning words in GEC is much simpler than in machine translation, as most of the words are kept unchanged, deleted fully, added, or changed slightly. Following word alignment, we define the WORDCHANGE measure as the number of unaligned words and aligned words that were changed in any way.

Second, we quantify word *order* differences by computing Spearman's ρ between the order of the words in the source sentence, and the order of their corresponding words in the correction according to the word alignment. $\rho = 0$ where the word order is uncorrelated, and $\rho = 1$ where the orders exactly match. We report the average ρ over all source sentences pairs.

Third, we report how many source sentences were split and how many concatenated by the references and by each of the correctors.

Results. Figure 1 presents the outcome of the three measures. Results show that the reference corrections make changes to considerably more source sentences than any of the correctors, and within each changed sentence changes more words and makes more word order changes, often an order of magnitude more. For example, in the reference corrections there are 44 sentences which have 5 words corrections, where the most sentences with 5 word corrections by any corrector is 11.

For completeness, we also measured the prevalence of changes in another corpus, the TreeBank of Learner English (Yannakoudakis et al., 2011), and obtain similar results to those obtained on NUCLE.

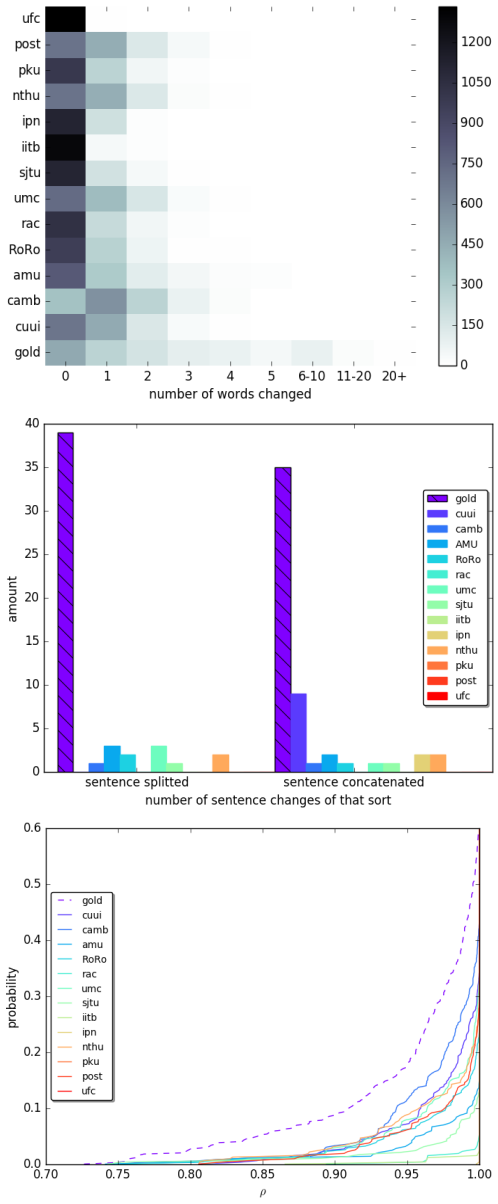

Figure 1: The prevalence of changes of different types in corrector's output and in the NUCLE references. The top figure presents the number of sentence pairs (heat) for each number of word changes (x-axis; measured by WORDCHANGE) for each of the different systems and the references (y-axis). The middle figure presents the percentage of sentence pairs (y-axis) where the Spearman ρ values do not exceed a certain threshold (x-axis). The bottom figure presents the number of source sentences (y-axis) split (right bars) or concatenated (left bars) in the references (striped column) and in the corrector's output (colored columns). See §2.1 for a legend of the correctors. The three figures show that under all measures, the gold standard references make substantially more changes to the source sentences than any of the correctors, in some cases an order of magnitude more.

3 Multi-Reference Measures

In this section we argue that the observed over-conservatism of correctors likely stems from them being developed to optimize RBMs that suffer from

low coverage. We begin with a motivating analysis of the relation between low-coverage and over-conservatism (§3.1), and continue with an empirical assessment of the distribution of corrections for a given sentence (§**??**), and the effect of M on commonly used RBMs (§**??**). We discuss the implication of our results in §**??**, concluding that reference-based evaluation may only partially address over-conservatism.

3.1 Motivating Analysis

The relation between coverage and over-conservatism requires some explanation. We abstract away from the details of the training procedure, and assume that correctors attempt to maximize the evaluation measure, over some training or development data.

Assume the corrector is faced with a phrase which it predicts to be ungrammatical. Assume p_{detect} is the probability that this prediction is correct. Assume $p_{correct}$ is the probability that the model is able to predict a valid correction for this phrase (given that it correctly identified it as erroneous). Finally, assume that the corrector is evaluated against M references, and that $p_{coverage}$ is the coverage of the phrase by M references, namely the probability that a valid correction for it will be found among M randomly sampled references.[2]

We will now assume that the corrector may either choose not to correct the phrase, or choose to correct it with the correction it finds the most likely.[3] If it selected not to correct the sentence, its probability of being rewarded (i.e., producing an output in the reference set Y) is $(1 - p_{correct})$. Otherwise, its probability of being rewarded is $p_{detect} \cdot p_{correct} \cdot p_{coverage}$. In cases where

$$p_{detect} \cdot p_{correct} \cdot p_{coverage} \cdot R - (1 - p_{correct}) \cdot P < 0, \quad (1)$$

a corrector is dincentivized from predicting a correction. We expect Condition 1 to frequently hold in cases that require non-trivial changes, which are characterized both by low $p_{coverage}$ (as non-trivial changes can often be made in numerous ways), and by lower expected performance by the corrector.

Moreover, when using asymmetric measures, that penalize invalidly correcting a sentence more harshly than not correcting an ungrammatical sentence (i.e., $P > R$), condition 1 is even more likely to hold. An example of such measure is the commonly used $F_{0.5}$.

3.2 Data

Our analysis assumes that we have a reliable estimate for the distribution of corrections $\mathcal{D}_x$ for the source sentences we evaluate. Our experiments in the following section are run on a random sample of 52 sentences with a maximum length of 15 from the NUCLE test data. The length restriction was introduced to avoid introducing too many independent errors that may drastically increase the number of annotations variants (as every combination of corrections to these errors are possible), thus resulting in an unreliable estimation for $\mathcal{D}_x$. Sentences with less than 6 words were discarded, as they were mostly a result of sentence segmentation errors.

Crowdsourcing has proven effective in GEC evaluation (Madnani et al., 2011; Napoles et al., 2015) and in related tasks such as machine translation (Zaidan and Callison-Burch, 2011; Post et al., 2012). We thus use crowdsourcing for obtaining a sample from $\mathcal{D}_x$. Specifically, for each of the 52 source sentences, we elicited 50 corrections by Amazon Mechanical Turk workers. To correct grammaticality and not fluency we told the workers that there is no need to rephrase for styling, and that when unnecessary the sentence or parts of it should be left like the original. 4 sentences did not need require any correction according to a large part of the workers and were hence discarded.

3.3 Estimating The Distribution of Corrections

We begin by estimating $\mathcal{D}_x$ for each sentence, using the crowdsourced corrections. We use UNSEEN-EST (Zou et al., 2015), a non-parametric algorithm that estimates a multinomial distribution, in which the individual values do not matter, only the distribution of probabilities across values.UNSEENEST was originally developed for assessing how many variants a gene might have, including undiscovered ones, which is a similar estimation problem to the one tackled here. Our Manual tests of unseenEst with small artificially created frequencies showed

[2] LC: we define it twice, should we delete it from the notations?

[3] LC: not sure I understand, what other options are there? or could less likely be more probable to be covered?

satisfactory results.[4]

By the estimates from UNSEENEST, most source sentences have a large number of corrections with low probability accounting for the bulk of the probability mass and a rather small number of frequent corrections. The estimated distributions tend to have steps, with many corrections with the same (low) frequency. Table 1 presents the mean numbers of different corrections with frequency at least γ (for different values of γ), and their total probability mass. For instance, 8.72 corrections account for 58% of the total probability mass of the corrections, each occurring with a probability of 0.01 or higher.

	Frequency Threshold (γ)			
	0	0.001	0.01	0.1
Variants	1351.24	74.34	8.72	1.35
Mass	1	0.75	0.58	0.37

Table 1: Estimating the distribution of corrections $\mathcal{D}_x$. The table presents the mean number of corrections with a probability of more than γ (top row), as well as their total probability mass (bottom row).

3.4 Under-estimation as a function of M

In the previous section we presented empirical assessment of the distribution of corrections to a sentence. We now turn to estimating the resulting bias, namely the under-estimation of reference-based similarity measures, for different values of M.

We discuss two similarity measures. One is the sentence-level accuracy (also called "Exact Match") and the other is the GEC F-score.

Sentence-level Accuracy. Sentence-level accuracy is the number of sentences whose corrections exactly match one of the references (also called "Exact Match"). Accuracy is a basic, interpretable measure, used in GEC by, e.g., (Rozovskaya and Roth, 2010). It is also closely related to the 0-1 loss function commonly used for training statistical correctors (Chodorow et al., 2012; Rozovskaya and Roth, 2013).

Formally, given test sentences $X = \{x_1, \ldots, x_N\}$, their references $Y_1, \ldots, Y_N$, and proposed corrections $\{C(x_1), ..., C(x_N)\}$, we define C's accuracy to be

$$Acc\,(C; X, Y) = \frac{1}{N} \sum_{i=1}^{n} \mathbb{1}_{C(x_i) \in Y_i}. \quad (2)$$

Note that C's accuracy is in fact an estimate of C's probability to produce a valid correction for a sentence, or C's *true accuracy*. Formally:

$$TrueAcc\,(C) = P_{x \sim L}\,(C\,(x) \in Correct_x)\,. \quad (3)$$

The bias of $Acc\,(C; X, Y)$ for a sample of N sentences, each paired with M references is then

$$TrueAcc\,(C) - \mathbb{E}_{X,Y}\,[Acc\,(C; X, Y)] = \quad (4)$$
$$TrueAcc\,(C) - P\,(C\,(x) \in Y) = \quad (5)$$
$$Pr\,(C\,(x) \in Correct_x) \cdot \quad (6)$$
$$(1 - Pr\,(C\,(x) \in Y | C\,(x) \in Correct_x)) \quad (7)$$

It is easy to see that the bias is not affected by N, only by M. As M grows, Y becomes a better approximation of $Correct_x$, and b_M tends to 0.

In order to gain insight about the evaluation measure and the GEC task (and not the idiosyncrasies of specific systems), we consider an idealized learner, which, when correct, produces a valid correction with the same distribution as a human annotator (i.e., according to $\mathcal{D}_x$). Formally, we assume that, if $C(x) \in Correct_x$ then $C(x) \sim \mathcal{D}_x$. Hence the bias (Equation 7) can be re-written as

$$P(C(x) \in Correct_x) \cdot (1 - P_{\mathcal{D}_x}(y \in Y)). \quad (8)$$

We will from now on assume that C is perfect (i.e., its true accuracy $Pr(C(x) \in Correct_x$ is 1), and denote its bias with b_M. It is easy to see that assuming any other value for C's true accuracy would simply scale the bias by that accuracy. Similarly, assuming only a percentage p of the sentences require correction will scale the bias by p.

We estimate b_M empirically using its empirical mean on our experimental corpus:

$$\hat{b}_M = 1 - \frac{1}{N} \sum_{i=1}^{N} P_{Y \sim \mathcal{D}_i^M, y \sim \mathcal{D}_i}\,(y \in Y)\,. \quad (9)$$

Using the UNSEENEST estimations of $\mathcal{D}_i$, we can compute $\hat{b}_M$ for any size of Y_i (value of M). However, as this computation is highly computationally demanding, we estimate it using sampling.

[4] All data we collected, along with the estimated distributions can be found in <to be disclosed upon publication>

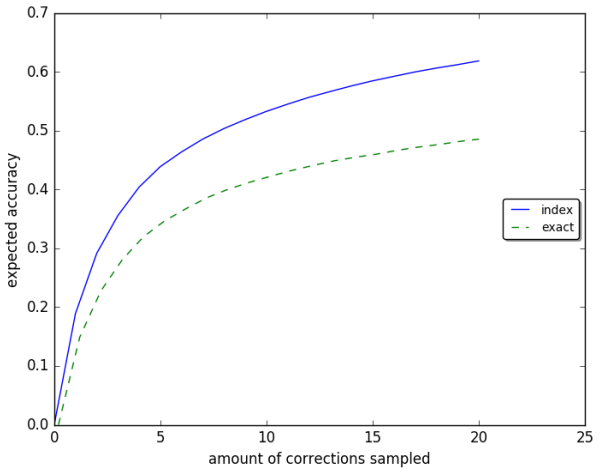

Figure 2: Accuracy and Exact Index Match values for a perfect corrector (y-axis) as a function of the number of references M (x-axis).

Specifically, for every $M = 1, ..., 20$ and x_i, we sample Y_i 1000 times (with replacement), and estimate $P(y \in Y_i)$ as the covered probability mass $P_{\mathcal{D}_i}\{y : y \in Y_i\}$.

We repeated all our experiments where Y_i is sampled without replacement, in order to simulate a case where reference corrections are collected by a single annotator, and are thus not repeated. We find similar trends with faster increase in accuracy reaching above 0.7 with $M = 20$.

Figure 2 presents the expected accuracy values for our perfect corrector (i.e., 1-$\hat{b}_M$) for different values of M. Results show that even for values of M which are much larger than those considered in the GEC literature (e.g., $M = 20$), the expected accuracy is only of about 0.5. As M increases the contribution of each additional corrections gets smaller to the point it contributes little to the accuracy (the slope is about ... around $M = 20$)[5].

We also experiment with a more relaxed measure, *Exact Index Match*, which is only sensitive to the identity of the changed words and not to what they were changed to. Formally, two proposed corrections c and c' over a source sentence x match if their word alignments with the source (computed as above) $a : \{1, ..., |x|\} \rightarrow \{1, ..., |c|, Null\}$ and $a' : \{1, ..., |x|\} \rightarrow \{1, ..., |c'|, Null\}$, it holds that $c_{a(i)} \neq x_i$ iff $c'_{a'(i)} \neq x_i$ (y_{NULL} and y'_{NULL} are empty strings).

Figure 2 also presents the expected accuracy in this case for different values of M, which indicate that while scores of a perfect corrector are somewhat higher, still with $M = 5$ it is no less than 0.5. As Exact Index Match can be interpreted as an accuracy measure for error detection (rather than correction), our results indicate that grammar detection systems may suffer from similar difficulties.

The analytic tools ws have developed support the computation of the entire distribution of the accuracy, and not only it's expected values. From Equation 2 we see that Accuracy has a Poisson Binominal distribution (i.e., it is a sum of independent Bernoulli variables with different success probabilities), whose success probabilities are $P_{y,Y\sim\mathcal{D}_i}(y \in Y)$, which can be computed, as before, using UNSEENEST's estimate for $\mathcal{D}_i$. Estimating the density function allows for the straightforward creations of significance tests for the measure, and can be performed efficiently (Hong, 2013).[6]

F-Score. While accuracy is commonly used as a loss function for training GEC systems, the F_α score is standard when reporting system performance (and consequently in hyper-paramter tuning).

Computing F-score for GEC is not at all straightforward. The score is computed in terms of *edit* matches between the correction and the reference, where edits are sub-strings of the source that are replaced in the correction/reference. Since correctors do not normally produce edits, F-score is defined optimistically, maximizing over all possible ways to annotate the source with edits, so as to end up with the correction.[7] The resulting optimization problem is NP-hard, but designated scorers have been developed to estimate it, notably the M^2 scorer (Dahlmeier and Ng, 2012).

The complexity of the measure prohibits an analytic analysis, and we instead use a bootstrapping approach to estimate the bias incurred by not being able to exhaustively enumerate the set of valid corrections. As with accuracy, in order to avoid confounding our results with system-specific biases, we

[5] OA: fill in

[6] An implementation of this method and the estimated density functions will be released upon publication.

[7] Since our crowdsourced corrections do not include an explicit annotation of edits, we produce edits heuristically.

assume the evaluated corrector is perfect and samples its corrections from from the human distribution of corrections $\mathcal{D}_x$. Our experiment is very similar to that of Bryant and Ng (2015), who also compared the F-score of a human correction against an increasing number of references.

Concretely, given a value for M and for N, we uniformly sample from our experimental corpus source sentences $x_1, ..., x_N$, and M corrections for each $Y_1, ..., Y_N$ (with replacement). Setting a realistic value for N in our experiments is important for obtaining comparable results to those obtained on the NUCLE corpus (see below), as the expected value of F-score may depend on N (unlike Accuracy, it is not additive). In accordance with the NUCLE's test set, we set $N = 1312$ and assume that 136 of the sentences require no correction. The latter reduce the overall bias by their frequency in the corpus, and are thus important to include for obtaining comparable results.

The bootstrapping procedure is carried out by the accelerated bootstrap procedure (Efron, 1987), with 1000 iterations. We also report confidence intervals ($p = .95$), computed using the same procedure.[8]

Figure 3 presents the results of this procedure, which further indicate the insufficiency of commonly used M values for training and development (1 or 2) for obtaining a reliable estimation of a corrector's performance. For instance, the $F_{0.5}$ score for our perfect corrector, whose true F-score is 1, is only 0.42 with $M = 2$. Moreover, the saturation effect observed in accuracy is even more pronounced with our experiments on F-score. Similar results were obtained by Bryant and Ng (2015).

3.5 Significance of Real-World Correctors

The bootstrapping method for computing the significance of the F-score can also be useful for assessing the significance of the differences in corrector's performance reported in the literature. We report results with the bootstrapping protocol (§3.4) to compute the confidence interval of different correctors with the current NUCLE test data ($M = 2$).

Figure 4 shows our results, which present a mixed picture: some of the differences between previously

[8]We use the standard Python scikits.bootstrap implementation of this method.

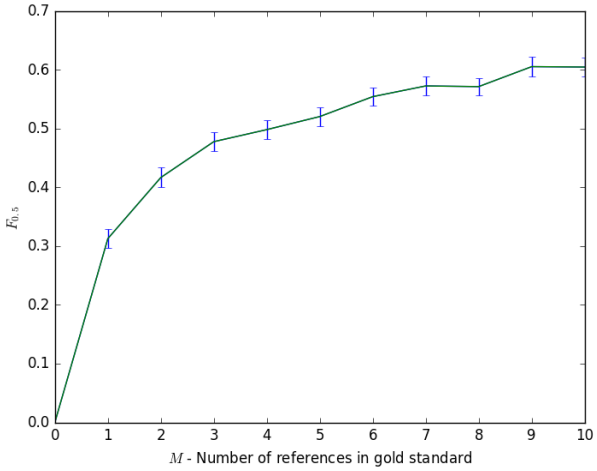

Figure 3: $F_{0.5}$ values for a perfect corrector (y-axis) as a function of the number of references M (x-axis). Each data point is paired with a confidence interval ($p = .95$).

reported F-scores are indeed significant and some are not. For example, the best performing corrector is significantly better than the second, but the latter is not significantly better than the third and fourth.

3.6 Discussion

Our empirical results show that the number of corrections needed for a reliable reference-based estimation may be prohibitively large in practice. Results suggest that there are hundreds of valid corrections with low probability, whose total probability mass is substantial. RBMs such as accuracy and F-score thus show diminishing returns from increasing the value of M over values of 10 so.

Returning to condition **??**, we find that the coverage (which is equal to the accuracy depicted in Figure 2) is lower than 0.5 for $M = 2$ on average (for short sentences). For cases of non-trivial changes, we expect it might be even lower, suggesting that condition **??** often holds in practice, incentivizing over-conservatism.

Considering the F-score of the best performing systems in Figure 4, and comparing them to the F-score of a perfect corrector with $M = 2$, we find that their scores are comparable, where RoRo in fact surpass a perfect corrector's F-score. While it is possible that such systems outperform the perfect corrector by learning how to correct a sentence in the same way as one of the NUCLE annotators did, we view this possibility as unlikely as our results (§2)

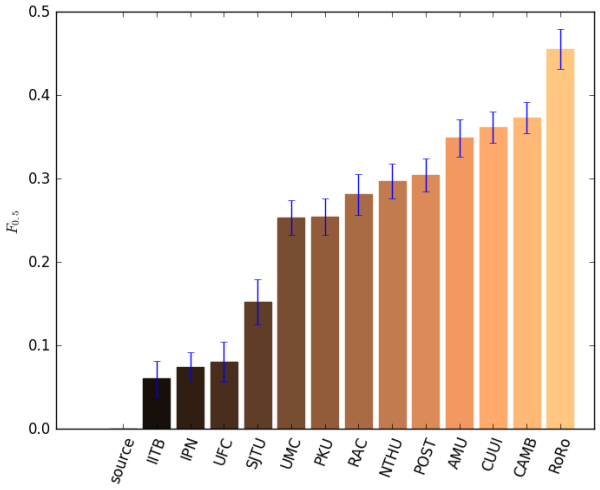

Figure 4: $F_{0.5}$ values for different correctors, including confidence interval ($p = .95$). The left-most column ("source") presents the F-score of a corrector that doesn't make any changes to the source sentences. See §2.1 for a legend of the correctors.

show that the output of these systems considerably diverges from NUCLE's references. A more likely possibility is that these systems high performance relative to a perfect corrector's is due to these correctors having learned to predict when not to correct.

Finally, we note that the proposal of (Bryant and Ng, 2015) to address under-estimation by comparing to the score of a human correction (in our terms, a perfect corrector) with the same M does not address under-conservatism, as it only scales the original measure. Moreover, as we have seen above, the score obtained for a human correction is not necessarily an upper bound, as an over-conservative corrector may surpass a perfect corrector in performance.

4 Semantic Faithfulness Measure

In this section we propose a reference-less semantic measure that eschews the use of reference corrections, instead measuring the semantic faithfulness of the proposed correction to the source. Concretely, we propose to measure the semantic similarity of the source and the proposed correction, through the graph similarity of their semantic representations. Such a measure has to be complemented with an error detection procedure, as it only captures the faithfulness dimension, namely the extent to which the meaning of the source is preserved in the correction, and not the correction's grammaticality. See (Napoles et al., 2016) for a proposal of a complementary grammaticality measure based on automatic error detection.

As a test case, we use the UCCA scheme to define semantic structures (Abend and Rappoport, 2013), motivated by its recent use in semantic machine translation evaluation (Birch et al., 2016).

We conduct two experiments that support the feasibility of our approach. First, we show that semantic annotation can be consistently applied to LL, through inter-annotator agreement (IAA) experiments. Second, we show that a perfect corrector scores high on this measure.

4.1 Structural Representation in LL

While linguistic theories propose that each learner makes consistent use of syntax (Huebner, 1985; Tarone, 1983), this use may not conform the syntax of the learned language, or of any other known language. This entails difficulties in defining syntactic annotation for LL, as, on the face of it, the language of each learner has to be annotated in its own terms.

LL resources differ as to how they annotate syntactic errors. Berzak et al. (2016) and Ragheb and Dickinson (2012) annotate syntactic structures according to the syntax used by the learner, even if this use is not grammatical. Such annotation may be unreliable as a source of semantic information, as semantically similar sentences, formulated by different learners, may have considerably different structures. Nagata and Sakaguchi (2016) take an opposite approach, and attempt to be faithful to the syntax intended by the learner. However, such an approach faces difficulties due to the multitude of different syntactic structures that can be used to express a similar meaning.

In this section, we use semantic annotation to structurally represent LL text. Semantic structures are faithful to the intended meaning of the sentence, and not its formal realization, and thus face less conflicts where the syntactic structure used diverges from the one intended. We are not aware of any previous attempts to semantically annotate LL text.

UCCA. UCCA is a a semantic annotation scheme that builds on typological and cognitive linguistic

theories. The scheme's aims are to provide a coarse-grained, cross-linguistically applicable representation. Importantly, UCCA's categories directly reflect semantic, rather than distributional distinctions. For instance, UCCA is not sensitive to POS distinctions: a Scene's main relation can be a verb but also an adjective ("He is **thin**") or a noun ("John's **decision**"). Indeed, Sulem et al. (2015) has found that UCCA structures are preserved remarkably well across English-French translations.

UCCA structures are directed acyclic graphs, where the words in the text correspond to (a subset of) their leaves. The nodes of the graphs, called *units*, are either terminals or several elements jointly viewed as a single entity according to some semantic or cognitive consideration. The edges bear one or more categories, indicating the role of the sub-unit in the relation that the parent represents.

UCCA views the text as a collection of *Scenes* and relations between them. A Scene, the most basic notion of this layer, describes a movement, an action or a state which is persistent in time. Every Scene contains one main relation, zero or more *Participants*, which are interpreted in a broad sense, and include locations, destinations and complement clauses, and *Adverbials*, such as manner or temporal descriptions.

4.2 Experimental Setup

We employ two annotators, trained by annotating both LL and standard English passages, until a high enough agreement was reached (6 hours of training in total). Training passages were excluded from the evaluation. We use UCCA's standard annotation guidelines,[9] without introducing any adaptations.

We experiment on 7 essays and their corrections from NUCLE, each of about 500 tokens. In order to measure IAA, we assigned 4 of these essays to both annotators and compute their agreement. In order to measure the faithfulness score for a perfect corrector, we annotate both the source and the corrected version for 6 essays, some of which were annotated by both annotators.

[9] http://www.cs.huji.ac.il/~oabend/ucca/guidelines.pdf

4.3 Semantic Similarity Measures

IAA Measure. We define a similarity measure over UCCA annotations G_1 and G_2 over the same set of leaves (tokens) W. For a node v in either graph, define its yield $yield(v) \subseteq W$ as its set of leaf descendants. Define a pair of edges $(v_1, u_1) \in G_1$ and $(v_2, u_2) \in G_2$ to be matching if $yield(u_1) = yield(u_2)$ and they have the same label. Labeled precision and recall are defined by dividing the number of matching edges in G_1 and G_2 by $|E_1|$ and $|E_2|$, respectively, and the *DAG F-score* is their harmonic mean. We note that the measure collapses to the common parsing F-score if G_1 and G_2 are trees.

Semantic Faithfulness Measure. Computing a faithfulness measure is slightly more involved, as the source sentence graph G_s and its correction G_c do not share the same set of leaves.[10]

We assume a (possibly partial, possibly many-to-1) alignment between G_s and G_c, $A \subset V_s \times V_c$. An edge $(v_1, v_2) \in E_c$ is said to match an edge $(u_1, u_2) \in E_s$ if they have the same label and $(v_2, u_2) \in A$. Recall (Precision) is defined as the ratio of edges in E_s (E_c) that have a match in E_c (E_s) respectively, and F-score is their harmonic mean. We note that this measure indeed collapses to the DAG F-score discussed above where A includes all pairs of nodes in E_s and E_c that have the same yield.

In order to define the alignment between V_s and V_c, we begin by aligning the leaves (tokens) in V_s and V_c using the same method detailed in §2. Denote the results leaf alignment with $A_l \subset Leaves_s \times Leaves_c$. We now extend A_l to define the node alignment A, aligning each non-leaf $v \in V_s$ with the node $u \in V_c$ that maximizes

$$w(v,u) = \frac{|A_l \cap (yield(u) \times yield(v))|}{|yield(u)|}. \quad (10)$$

We exclude from A pairs v, u such that $w(v,u) = 0$. The resulting F-score measure, using the resulting A is called UCCA Similarity (UCCASIM). As the resulting alignment may differ when aligning nodes from V_c to V_s and the other way around, we report the resulting F-score in both directions.

Note that UCCASIM is somewhat more relaxed than DAG F-score defined above, as it also aligns

[10] The use of graph kernels as a similarity measure between UCCA structures is unsuitable here due to the small size of UCCA DAGs (Kashima et al., 2003).

nodes whose yields are not in perfect alignment with one another, unlike DAG F-score which requires a perfect match. While this relaxation is necessary, given that corrections often add or removes nodes, thus eliminating the possibility of a perfect alignment, in order to obtain comparable IAA scores, we report IAA using UCCASIM as well.

For completeness, we also replicate the protocol used by Sulem et al. (2015) for comparing the UCCA annotations of English-French translations, which we call Distributional Similarity (DISTSIM). For a given UCCA label l, denote $c_i(l)$ the number of l-labled UCCA nodes in the i-th source sentence, and $d_i(l)$ the number of l-labled UCCA nodes in its corresponding correction. We define DISTSIM(l) between these sentences to be $\frac{1}{N}\sum_{i=1}^{N}|c_i(l) - d_i(l)|$, where N is the total number of sentence pairs.

4.4 The Faithfulness of a Perfect Corrector

We obtain an IAA DAG F-score of 0.845 (Precision 0.834, Recall 0.857), which is comparable to the IAA reported for English Wikipedia texts by (Abend and Rappoport, 2013). As another point of comparison, we doubly annotate 3 corrected NUCLE passages, obtaining a similar IAA.

These results suggest that annotating LL with UCCA does not lead to any degradation of IAA, and can be applied as consistently to LL text as to standard English text.

Table 2 (left side) presents the UCCASIM scores obtained by comparing the NUCLE references and the source sentences, or equivalently the UCCASIM score of a perfect corrector. In order to control for differences between the annotators, we explore both a setting where both sides were annotated by the same annotator, and a setting where they were annotated by different ones. As an upper bound on the score of a perfect corrector (using different annotators), we also report the IAA on source sentences, computed using UCCASIM.

Our results indicate that a perfect corrector obtains a score comparable to the IAA, which indicates that UCCASIM is indeed insensitive to the surface divergence between a source sentence and its valid correction. However, more work is required to establish whether the converse holds, namely that the measure is sensitive enough to unfaithfulness of a proposed correction. This, of course, depends on the scope of distinctions covered by the semantic annotation. In UCCA's case, it is predicate-argument structures, the inter-relations between them, as well as the semantic heads of complex arguments.

Our attempts to conduct experiments to determine UCCASIM's sensitivity to correction errors introduced by the correctors described in §2 were unsuccessful, as these systems make only very few structural (rather than word-level) corrections (see Figure 1). We expect that once the over-conservatism of existing correctors is resolved, such evaluation will be more informative.

Finally, the right-hand side of Table 2 presents DISTSIM between the source and reference sentences. Our results are similar to the ones obtained by Sulem et al. (2015), who compared standard English sentences and their French translations.

	UCCASIM			DISTSIM	
	s→r	r→s	Avg	A+D	Scene
Different	0.85	0.83	0.84	0.96	0.93
Same	0.92	0.91	0.92	0.97	0.96
IAA	0.85	0.81	0.83	-	-
SAR15	-	-	-	0.95	0.96

Table 2: The faithfulness of a perfect corrector. The left-hand side presents results with UCCASIM where the alignment is computed from the source to the reference (s→r), the opposite direction (r→s), and their average (Avg). The right-hand side presents DISTSIM for the UCCA categories Participants and Adverbials, considered together (A+D), and for Scene units (Scene), as reported by Sulem et al. (2015). The rows show values when the source and reference are annotated by the same annotator or by different ones. As a point of reference, we report IAA computed using UCCASIM (IAA row). Results show that the faithfulness of a perfect corrector is comparable with the IAA. The bottom row presents the results reported by Sulem et al. (SAR15) on English-French translations, which are comparable to ours.

5 Previous Work

A number of evaluation measures have been proposed for GEC. An earlier version of F-score was used in the HOO shared task, which required that the proposed corrections include edits (markings of phrases that were changed in the source) explicitly.

The M^2 measure, used for the CoNLL shared tasks and the standard measure since, automatically produces edits on the corrections, thus relieving correctors from the need to do so.

Felice and Briscoe (2015) proposed the I-MEASURE, which introduces some novel features to GEC evaluation, such as distinguishing different quality levels of ungrammatical corrections (e.g., some improve the quality of the source, while others degrade it), and restricting edits to only consist of single words, rather than phrases. Napoles et al. (2015) compares the system ranking of different correctors inspired by M^2 and I-measure, relative crowdsourced human rankings. They find a low correlation between these rankings, and propose the GLEU measure (an adaptation of BLEU), which is shown to correlate much better with human rankings. Sakaguchi et al. (2016) argue for emphasizing fluency over conservatism in compiling reference annotations.

We expect that our findings, that RBMs substantially under-estimate the performance of correctors, to generalize to these RBMs, as they all apply string similarity measures relative to a small number of references. These measures thus address orthogonal gaps in GEC evavaluation from the ones presented here.

Napoles et al. (2016) address the insufficiency of RBMs and propose to combine RBMs for assessing faithfulness and grammatical error detection systems for measuring grammaticality. We complement their efforts by proposing a faithfulness measure based on semantic similarity.

6 Conclusion

This paper addresses the shortcomings of existing reference-based evaluation protocols in GEC. We present evidence that state of the art GEC systems suffer from over-conservatism and argue that this over-conservatism results from the use of measures that not only more harshly penalize over-correction over under-correction, but also often penalize correctors for proposing perfectly valid corrections. In fact, our results indicate that systems are often more likely to be penalized for a valid correction than to receive credit for it, due to the small number of references taken into account.

Estimating the number and distribution of valid corrections for a sentence, we find that increasing the number of references is beneficial only up to a point, after which the heavy tail of the corrections distribution entails only minor improvement to the coverage with every increase of the value of M. We propose a semantic measure for measuring the semantic faithfulness of the correction to the source. thereby avoiding the pitfalls of reference-based evaluation. We argue that using reference-less measures in conjunction with reference-based measures in the training and development of GEC systems will better address the challenge of over-conservatism.

Future work will assess the relative importance, ascribed by users of GEC systems, to different evaluation criteria of the output. We believe that in terms of conservatism, end users will be tolerant to (possibly necessary) changes in the sentence structure, i.e., violation of conservatism, but much less tolerant to changes in the sentence's meaning, i.e., violation of faithfulness. A better understanding of how these factors interact may lead to improved protocols of semantic evaluation, that will alleviate the requirement for a high number of references.

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