# Generating Inflectional Errors for Grammatical Error Correction in Hindi

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## Abstract

Automated grammatical error correction has been explored as an important research problem within NLP, with the majority of the work being done on English and similar resource-rich languages. Grammar correction using neural networks is a data-heavy task, with the recent state of the art models requiring datasets with millions of annotated sentences for proper training. It is difficult to find such resources for Indic languages due to their relative lack of digitized content and complex morphology, compared to English. We address this problem by generating a large corpus of artificial inflectional errors for training GEC models. Moreover, to evaluate the performance of models trained on this dataset, we create a corpus of real Hindi errors extracted from Wikipedia edits. Analyzing this dataset with a modified version of the ERRANT error annotation toolkit, we find that inflectional errors are very common in this language. Finally, we produce the initial baseline results using state of the art methods developed for English.

## 1 Introduction

Grammatical Error Correction (GEC) involves automatically correcting errors in written text, whether relating to orthography, syntax or fluency. Today, most approaches for solving this problem highlight statistical and deep learning methods as opposed to rule-based methods. These methods treat GEC as a translation task, from an ungrammatical to a grammatically correct form of the same language (Brockett et al., 2006). This requires a considerable amount of supervised data in the form of 'edits', which are pairs of incorrect and correct sentences. Researchers have recently done remarkable work on English and a few other resource-rich languages and have released many datasets to evaluate state of the art methods. Comparatively less attention has been given to low resource languages, and Indic languages have been neglected in particular. Systems like UTTAM (Jain et al., 2018) and SCMIL (Etoori et al., 2018) have applied probabilistic approaches and deep learning, respectively, to the problem of spelling correction in Indic languages. Moreover, simple n-gram based models (Singh and Singh, 2019; Kanwar et al., 2017) have been used for "Real-Word" error correction, which is a very similar problem to GEC. However, to our knowledge, no such work exists for true GEC in this language. Thus, we sum up our contributions in the following manner:

1. We create a parallel corpus of synthetic errors by inserting errors into grammatically correct sentences using a rule-based process, focusing specifically on inflectional errors. Since this process is generic, it can easily be extended to other Indic languages.
2. We scrape Hindi edits from Wikipedia and filter them to provide another smaller corpus of errors. Since this corpus is extracted from a relatively natural source, it can be useful for evaluating GEC systems. We also analyze this corpus using an extended version of the ERRANT toolkit.
3. We evaluate a few well studied approaches for languages like English on these datasets, and thus produce the initial GEC results for the Hindi language. The code and data to reproduce our experiments are available at http://github.com/s-ankur/hindi_grammar_correction.

## 2 Related Work

The most common GEC datasets come from correction-annotated language learner essays. The English learner corpora include those from shared tasks such as Helping Our Own (Dale et al., 2012), CoNLL2014 (Ng et al., 2014) and recently, BEA2019 (Bryant et al., 2019). Similar learner corpora exist for the Russian (Rozovskaya and Roth, 2019) and the Czech (Náplava and Straka, 2019) languages. However, the problem with such manually annotated corpora is that they are not readily available for low resource languages, and their creation will be resource and time-intensive.

Another popular method has been the deliberate injection of errors into grammatically correct sentences, whether by a rule-based system or by strategies like round-trip translation (Lichtarge et al., 2019). The former approach has been essential for languages with limited training data. This was the case for English early on (Izumi et al., 2004; Foster and Andersen, 2009), and is still the case for low resource languages such as Indonesian (Irmawati et al., 2017). Provided that the artificial errors closely resemble real-world mistakes, this method can be applied to obtain large volumes of training data reliably.

A third approach involves mining edits from websites, such as language learner websites (Mizumoto et al., 2011) or from websites with public revision histories like Wikipedia[1] (Grundkiewicz and Junczys-Dowmunt, 2014; Faruqui et al., 2018; Boyd, 2018) or GitHub (Hagiwara and Mita, 2020). While this has the potential to yield natural datasets of considerable size, there are several issues with edits obtained by this method, as not all corrections made in the text are of a grammatical nature; and many simply add more information or are semantic improvements to the text. As the edits lack any human curation, this method results in a more noisy corpus.

## 3 Hindi Grammar

Hindi is a fusional language that expresses grammatical features like case, gender, number, tense, etc. via morphological changes. In particular, all verbs and some adjectives are inflected to agree with the number and gender of the associated noun (Shapiro, 2003). The same is the case for genitive pronouns, genitive post-positions, and ordinals. Additionally, the verb inflects for the person and the adjective declines for the case of the noun. With a few exceptions, these changes are indicated by vowel endings to the right of the lexical base, as shown with examples in Table 1. If the proper inflection is not specified, then the sentence becomes easily identifiable as ungrammatical due to the loss of agreement.

| Gender | Singular | Plural |
|---|---|---|
| Masculine | करता<br>karatā | करते<br>karate |
| Feminine | करती<br>karatī | करती<br>karatī |

Table 1: Paradigm for the verb करना (karanā, *"to do"*), showcasing the change in endings according to the gender and number.

## 4 Error Extraction from Hindi Wikipedia

The WikiEdits 2.0[2] (Grundkiewicz and Junczys-Dowmunt, 2014) software uses Wikipedia revision histories to extract a parallel corpus of errors. We modify this tool for Hindi and extract edits from a Wikipedia revision dump dated October 1, 2020 to create our dataset, which we term as HiWikEd. For filtering the edits, we constrain extracted sentence length to between 6 and 27 tokens and consider only substitution operations with a token-based Levenstein edit distance of less than 0.3. Additionally, we discard edits containing only a difference in punctuation or numbers and corrections involving extremely rare tokens or HTML markups. Edits relating to vandalism are also discarded.

## 5 Error Analysis

The ERRor ANotation Toolkit (ERRANT[3]) (Bryant et al., 2017; Felice et al., 2016) is a tool that uses morphological and dependency information to analyze, merge and categorize errors using a rule-based system. Initially created for English, it has since been extended to German (Boyd, 2018). We use a similar method to extend the toolkit to Hindi and use it to classify the errors in HiWikEd (See Table 2 for examples). Although the classification criteria consider many exceptional cases, the basic reasoning used by us is as follows:

1. POS tags and lemma for the tokens are obtained using the StanfordNLP tagger (Qi et al., 2018). By comparing POS tags for the edit, the error category is decided as follows.

[1] via http://dumps.wikimedia.org/

[2] http://github.com/snukky/wikiedits

[3] http://github.com/chrisjbryant/errant

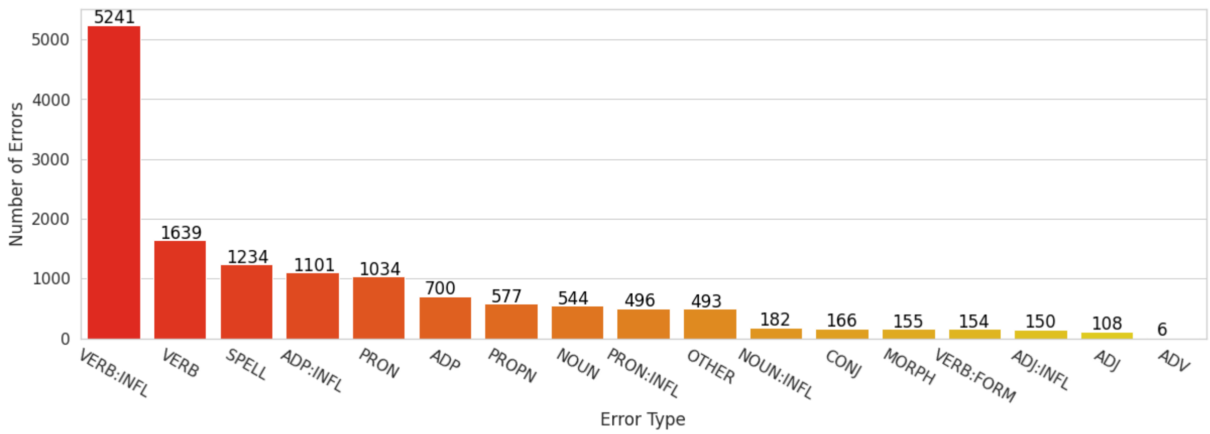


Figure 1: Frequencies of various error types in the HiWikEd dataset.

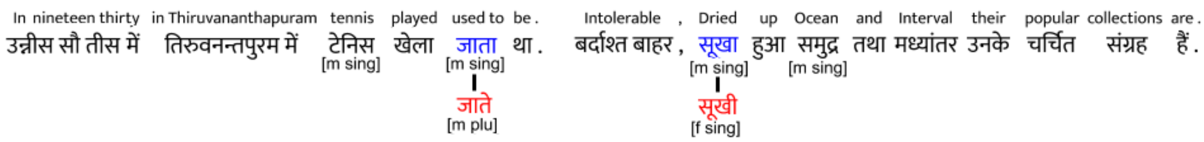


Figure 2: Example of error insertion. In the first sentence, the verb जाता (jātā, *"used to"*) agrees with the noun टेनिस (tenis, *"tennis"*) . We change the inflection of the verb and thus introduce disagreement into the sentence. The same is the case for the adjective सूखा (sūkhā, *"dry"*) in the next sentence.

2. Edits with the same lemma and POS are classified as <POS>:INFL errors and are grammatical in nature. For verbs, an additional category is introduced for tense termed as VERB:FORM.

3. Edits with different lemma but with the same POS are classified as <POS> errors. Most of these are simple semantic changes where one word is swapped for another (e.g. a synonym).

4. Edits having the same stem are classified as MORPH errors.

5. Edits with a low edit distance are classified as SPELL errors while the rest remain unclassified as OTHER.

## 6 Artificial Error Generation

Since inflectional errors form an easy to identify and common class of Hindi errors, we choose them to generate a synthetic dataset using the following process.

We first extract sentences from the Hindi Wikipedia revision dated June 1, 2020 (using WikiExtractor[4]), assuming that the recent versions are mostly grammatically correct. We tokenize these sentences and POS tag them using the Hindi POS Tagger (Reddy and Sharoff, 2011). We change the inflectional ending for all words of the VERB, ADP, ADV and PRON categories to a different random ending from the inflection table for that POS, taking care that exceptional cases are adequately handled (for examples, refer Table 3). For each of these changes, we create an edit containing a single incorrect word (See Figure 2). We randomly discard 40% of the sentence pairs thus generated. Keeping all sentences generated from a particular correct sentence in the same partition, we split the obtained dataset into train(80%) and valid(20%) partitions (refer Table 6).

## 7 Experiments and Evaluation

In our experiments, we first test the feasibility of the system using a basic transformer architecture (Vaswani et al., 2018) implemented using the Tensor2Tensor[5] library. For this we use the *transformer_base* setting as a baseline and train the model for 5K epochs. We then evaluate slightly modified versions of two state of the art models relating to English GEC. First, we train the multilayer convolutional encoder-decoder model (Chollampatt and Ng, 2018)[6] for 5 epochs using the de-

[4] http://github.com/attardi/wikiextractor

[5] http://github.com/tensorflow/tensor2tensor

[6] http://github.com/nusnlp/mlconvgec2018

| Error Type | Examples |
|---|---|
| VERB:FORM<br>Verb Tense | बन(ban) → बना(banā), मिलते(milte) → मिलने(milne)<br>make[pres → past], meet[past → inf] |
| VERB:INFL<br>Verb Inflection | हुआ(huā)→ हुई(huī), रहता(rahatā) → रहते(rahate)<br>happen[m.sing → f.sing], stay[m.sing → m.pl] |
| NOUN:INFL<br>Noun Inflection | सदस्य(sadasya) → सदस्यों(sadasyon), जिले(jile) → जिला(jilā)<br>member[nom → oblique], district[oblique → nom] |
| ADP:INFL<br>Postposition Inflection | का(kā) → की(kī), का(kā) → के(ke)<br>of[m.sing → f.sing], of[m.sing → pl] |
| PRON:INFL<br>Pronoun Inflection | उसका(usakā) → उसकी(usakī), आपने(āpane) → आपको(āpako)<br>his[m.sing → f.sing], you[erg → dat] |
| ADJ:INFL<br>Adjective Inflection | छोटा(chhotā) → छोटे(chhote), दूसरे(dūsare) → दूसरा(dūsarā)<br>small[m.sing → m.pl], other[m.sing.acc → m.sing] |
| VERB<br>Verb | रखने(rakhane) → करने(karane), मिला(milā) → दिया(diyā)<br>to keep → to do, found → gave |
| NOUN<br>Noun | सदी(sadī) → शताब्दी(shatabdī), विश्वास(wishwāsa) → शासन(shāsan)<br>century → centenary, trust → government |
| ADP<br>Postposition | में(men) → , को(ko), से(se) → का(kā)<br>in → to, from → of[m] |
| PRON<br>Pronoun | उसके(usake) → उनके(unake), ये(ye) → आप(āp)<br>his → their, these → you |
| ADJ<br>Adjective | सामान्य(sāmānya) → आम(ām), बड़ा(badā) → छोटा(chhotā)<br>common → ordinary, big → small |
| ADV<br>Adverb | साथ(sāth) → बाद(bād), बराबर(barābar) → लगातार(lagātār)<br>together → after, correctly → fast |
| CONJ<br>Conjunction | अगर(agar) → यदि(yadi), पर(par) → परंतु(parantu)<br>if → whether, but → however |
| MORPH<br>Morphological | बनना(banana) → बनाने(banāne)<br>become → make |
| SPELL<br>Spelling | कौवा(kauwā) → कौआ (kauā), गई(gaī) → गयी(gayī)<br>crow[spelling], went[spelling] |
| OTHER<br>Unclassified | और (aur) → के(ke), शहर(shahar) → भी(bhī)<br>and → of[pl], city → and also |

Table 2: Error categories of HiWikEd as classified using ERRANT and examples (original → edited).

| Error Type | Examples |
|---|---|
| ADP:INFL<br>Postposition Inflection | की(kī) → के(ke)<br>of[f.sing → pl] |
| PRON:INFL<br>Pronoun Inflection | मेरा(merā) → मेरी(merī), अपने(apane) → अपनी(apanī)<br>my[m.sing → f.sing], our[m.pl → f.sing] |
| ADJ:INFL<br>Adjective Inflection | लंबे(lambē) → लंबा(lambā), चौथा(chauthā) → चौथे(chauthē)<br>long[m.pl → m.sing], fourth[m.sing → m.pl] |
| VERB:INFL<br>Verb Inflection | करता(karatā) → करती(karatī), किये(kiyē) → की(kī)<br>do[m.sing → f.sing], do[pl.past → f.past] |

Table 3: List of word categories corrupted using our approach along with examples.

| System | ADP:INFL | | PRON:INFL | | ADJ:INFL | | VERB:INFL | | Full dataset | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $F_{0.5}$ | GLEU | $F_{0.5}$ | GLEU | $F_{0.5}$ | GLEU | $F_{0.5}$ | GLEU | $F_{0.5}$ | GLEU |
| Transf | 0.30 | 0.62 | 0.06 | 0.67 | 0.06 | 0.57 | 0.55 | 0.79 | 0.31 | 0.69 |
| MLConv | 0.66 | 0.81 | 0.26 | 0.86 | 0.36 | 0.83 | 0.65 | 0.83 | 0.35 | 0.73 |
| CopyAug | 0.70 | 0.84 | 0.29 | 0.71 | 0.39 | 0.69 | 0.70 | 0.87 | 0.49 | 0.80 |

Table 4: Results for the systems trained on the synthetic corpus and tested on the HiWikEd corpus including the $F_{0.5}$ and GLEU scores. We also specifically report the metrics for the four inflectional categories that we train on.

| | |
|---|---|
| Source | इस पर उनके पिता राजा नतमस्तक हो गया (gayā).<br>*"on this, his father, the king[m.pl], bowed[m.sing] down"* |
| Reference | इस पर उनके पिता राजा नतमस्तक हो गये (gaye).<br>*"on this, his father, the king[m.pl], bowed[m.pl] down"* |
| $\text{Output}_{Transf}$ | इस पर उनके पिता राजा नतमस्तक हो गया (gayā).<br>*"on this, his father, the king[m.pl], bowed[m.sing] down"* |
| $\text{Output}_{MLConv}$ | इस पर उनके पिता राजा नतमस्तक हो गये (gaye).<br>*"on this, his father, the king[m.pl], bowed[m.pl] down"* |
| $\text{Output}_{CopyAug}$ | इस पर उनके पिता राजा नतमस्तक हो गये (gaye).<br>*"on this, his father, the king[m.pl], bowed[m.pl] down"* |

Table 5: Example system outputs along with source and reference sentences from HiWikEd. The source sentence comes from the Etymology section of Wikipedia article for the Amer Fort.

| Dataset | #Sent | #Tok | %Err |
|---|---|---|---|
| Synthetic (Train) | 2.6M | 45.5M | 5.7 |
| Synthetic (Valid) | 0.5M | 9.1M | 5.7 |
| HiWikEd (Test) | 13K | 208K | 6.7 |

Table 6: Corpus statistics including error percentages, and number of sentences and tokens.

fault hyperparameters. Finally, for training the copy augmented transformer model (Zhao et al., 2019)[7], we skip the pretraining step with the denoising auto-encoder and train the system for 9 epochs.

For model evaluation, we use the GLEU metric (Napoles et al., 2015) as well as the $F_{0.5}$ metric calculated using the Max-Match($M^2$) scorer[8](Dahlmeier and Ng, 2012). The systems were trained on the synthetic dataset and then evaluated on the HiWikEd corpus, and the results are presented in Table 4 with an example output shown in Table 5. In addition to the metrics on the full HiWikEd dataset, we calculate the per error type metrics by categorizing the edits using ERRANT, for a more fine-grained analysis of the results.

[7] http://github.com/yuantiku/fairseq-gec
[8] http://github.com/nusnlp/m2scorer

## 8 Discussion and Future Work

Motivated by the lack of work in GEC for Indic languages, we present two novel error corpora in the Hindi language (as shown in Table 6) and also provide a method for generating a large quantity of artificial inflectional errors. Following error analysis of the HiWikEd corpus using the ERRANT toolkit, we observe that inflectional errors are a reasonably common category in Hindi, making up 49.92% of all errors (see Figure 1).

As seen from the example outputs in Table 5 as well as from the metrics presented in Table 4, the models are able to properly correct many inflectional errors. As expected, the simpler Transformer model is significantly outperformed by the other two models. However, all of the methods perform relatively poorly with regard to the whole dataset, which contains numerous spelling errors and semantic edits for which we do not train our models.

In addition, some grammatical errors in HiWikEd were not inflectional (such as ADJ:FORM) and thus not represented in the synthetic dataset. On manual observation of the dataset, we also find that some edits are identifiably incorrect or simply denote stylistic differences and are out of the scope of GEC. Thus, it may be fruitful to filter and annotate the dataset manually. Including other error types in the training dataset will undoubtedly improve the performance of the model.

Finally, while scraping edits from Wikipedia, we encountered numerous Hindi spelling errors, which we discarded as our focus was solely on grammatical errors. However, these edits may prove to be a valuable source of natural Hindi spelling errors, which can be used to circumvent the dataset problems faced by Etoori et al. (2018) and similar research. Since the approaches used by us for error generation and error categorization are not specific to Hindi, they can easily be extended to other Indic languages like Marathi and Bengali.

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