Error-repair Dependency Parsing for Ungrammatical Texts

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Abstract

We propose a new dependency parsing scheme which jointly parses a sentence and repairs grammatical errors by extending the non-directional transition-based formalism of Goldberg and Elhadad (2010) with three additional actions: SUBSTITUTE, DELETE, INSERT. Because these actions may cause an infinite loop in derivation, we also introduce simple constraints that ensure the parser termination. We evaluate our model with respect to dependency accuracy and grammaticality improvements for ungrammatical sentences, demonstrating the robustness and applicability of our scheme.

1 Introduction

Robustness has always been a desirable property for natural language parsers: humans generate a variety of noisy outputs, such as ungrammatical webpages, speech disfluencies, and the text in language learner’s essays. Such non-canonical text contains grammatical errors such as substitutions, insertions, and deletions. For example, a non-native speaker of English might write “*I look in forward hear from you”, where in is inserted, to is deleted, and hearing is substituted incorrectly.

We propose a novel dependency parsing scheme that jointly parses and repairs ungrammatical sentences with these sorts of errors. The parser is based on the non-directional easy-first (EF) parser introduced by Goldberg and Elhadad (2010) (GE herein), which iteratively adds the most probable arc until the parse tree is completed. These actions are called ATTACHLEFT and ATTACHRIGHT depending on the direction of the arc. We extend the EF parsing scheme to be robust for ungrammatical inputs by correcting grammatical errors with three new actions: SUBSTITUTE, INSERT, and DELETE. These new actions do not add an arc between tokens but instead they edit a single token. As a result, the parser is able to jointly parse and correct grammatical errors in the input sentence. We call this new scheme Error-Repair Non-Directional Easy-First parsing (EREF). Since the new actions may greatly increase the search space (e.g., infinite substitutions), we also introduce simple constraints to avoid such issues.

We first describe the technical details of EREF (§2) and then evaluate our EREF parser with respect to dependency accuracy (robustness) and grammaticality improvements (§3). Finally, we
position this effort at the intersection of noisy text parsing and grammatical error correction (§4).

2 Model

Non-directional Easy-first Parsing Let us begin with a brief review of a non-directional easy-first (EF) parsing scheme proposed by GE, which is the foundation of our proposed scheme described in the following sections.

The EF parser has a list of partial structures $p_1, ..., p_k$ (called pending) initialized with sentence tokens $w_1, ..., w_n$, and it keeps updating pending through derivations. Unlike left-to-right (e.g., shift-reduce) parsing algorithms (Yamada and Matsumoto, 2003; Nivre, 2004), EF iteratively selects the best pair of adjoining tokens and chooses the direction of attachment: ATTACHLEFT or ATTACHRIGHT. Once the action is committed, the corresponding dependency arc is added and the child token is removed from pending. The first two derivations in Figure 1 depict ATTACHRIGHT and ATTACHLEFT. Pseudocode is shown in Algorithm 1 (lines 1, 3-12).

The parser is trained using the structured perceptron (Collins, 2002) to choose actions to take given a set of features expanded from templates. The cost of actions is computed at every step by checking the validity: whether a new arc is included in the gold parse and whether the child already has all its children. See GE for further description of feature templates and structured perceptron training. Since it is possible that there are multiple valid sequence of actions and it is important to examine a large search space, the parser is allowed to explore (possibly incorrect) actions with a certain probability, termed learning with exploration by Goldberg and Nivre (2013).

Error-repair variant of EF Error-repair non-directional easy-first parsing scheme (EREF) is a variant of EF. We add three new actions: SUBSTITUTE, DELETE, INSERT as ActsER. We do not deal with a swapping action (Nivre, 2009) to deal with word reordering errors, since the errors are even less frequent than other error types (Leacock et al., 2014). SUBSTITUTE replaces a token to a grammatically more probable token, DELETE removes an unnecessary token, and INSERT inserts a new token at a designated index. These actions are shown in Figure 1 and Algorithm 1 (lines 13-25). Because the length of pending decreases as an attachment occurs, the parser also keeps the token indices in repaired (line 5), which holds all tokens in a sentence throughout the parsing process. Furthermore, the parser updates token indices in pending and repaired when INSERT or DELETE occurs. Technically, when a token at $i$ is deleted/inserted, the parser decrements/increments the indices that are $k >= i$ (before executing the action) in pending, repaired, and parents and children in a (partial) dependency tree (Arcs).

To find the best candidate for SUBSTITUTE and INSERT efficiently, we restrict candidates to the same part-of-speech or pre-defined candidate list. We select the best candidate by comparing each n-gram language model score with the same surrounding context.

Similar to EF, while training the parser, the cost

| Algorithm 1: Error-repair non-directional parsing |
|-----------------------------------------------|
| **Input:** ungrammatical sentence $= w_1 \ldots w_n$ |
| **Output:** a set of dependency arcs (Arcs), repaired sentence $(\hat{w}_1 \ldots \hat{w}_m)$ |
| 1. $Acts = \{ATTACHLEFT, ATTACHRIGHT\}$ |
| 2. $Acts_{ER} = \{DELETE, INSERT, SUBSTITUTE\}$ |
| 3. $Arcs = \{\}$ |
| 4. pending $= p_1 \ldots p_m \leftarrow w_1 \ldots w_n$ |
| 5. repaired $= \hat{w}_1 \ldots \hat{w}_m \leftarrow w_1 \ldots w_n$ |
| 6. while len (pending) > 1 do |
| 7. best $\leftarrow \arg\max_{act \in Acts \cap Acts_{ER}} \text{score (act (i))}$ s.t. $1 \leq i \leq \text{len(pending)} \cap \text{isLegal(act (i))}$ |
| 8. if best $\in Acts$ then |
| 9. (parent, child) $\leftarrow \text{edgeFor(best)}$ |
| 10. Arcs.add((parent, child)) |
| 11. pending.remove(child) |
| 12. else if best $\in SUBSTITUTE$ then |
| 13. $c = \text{bestCandidate(best, repaired)}$ |
| 14. pending.replace($p_i, c$) |
| 15. repaired.replace($\hat{w}_{p_i, idx}, c$) |
| 16. else if best $\in DELETE$ then |
| 17. pending.remove($p_i$) |
| 18. repaired.remove($\hat{w}_{p_i, idx}$) |
| 19. Arcs.updateIndex() |
| 20. else if best $\in INSERT$ then |
| 21. $c = \text{bestCandidate(best, repaired)}$ |
| 22. pending.insert($i, c$) |
| 23. repaired.insert($p_i, i, idx, c$) |
| 24. Arcs.updateIndex() |
| 25. end |
| 26. return Arcs, repaired |
Algorithm 2: Check validity during training
1 Function isValid(act, repaired, Gold)
2 \( d_{\text{before}} = \text{editDistance}(\text{repaired}, \text{Gold}) \)
3 \( \text{repaired}^+ = \text{repaired.apply(act)} \)
4 \( d_{\text{after}} = \text{editDistance}(\text{repaired}^+, \text{Gold}) \)
5 if \( d_{\text{before}} > d_{\text{after}} \), then return \( \text{true} \);
6 else return \( \text{false} \);
7 end

for \( \text{Act}_{\text{ER}} \) is based on validity. The validity of the new actions is computed by taking the edit distance \( (d) \) between the \( \text{Gold} \) tokens \((w_1^* \ldots w_m^*)\) and the sentence state that the parser stores in \( \text{repaired} \) \((\hat{w}_1 \ldots \hat{w}_m)\). When the edit distance after taking an action \( (d_{\text{after}}) \) is smaller than before \( (d_{\text{before}}) \), we regard the action as \textit{valid} (Algorithm 2).

One serious concern of EREF is that the new actions may cause an infinite loop during parsing (e.g., infinite \textit{SUBSTITUTE}, or an alternative \textit{DELETE} and \textit{INSERT} sequence). To avoid this, we introduce two constraints: (1) \textit{edit flag} and (2) \textit{edit limit}. \textit{Edit flag} is assigned for each token as a property, and a parser is not allowed to execute \( \text{Act}_{\text{ER}} \) on a token if its flag is on. The flag is turned on when a parser executes \( \text{Act}_{\text{ER}} \) on a token whose flag is off. In \textit{INSERT} action, the flag of the inserted token is activated, while the subsequent token (which gave rise to the \textit{INSERT}) is not. \textit{Edit limit} is set to be the number of tokens in a sentence, and the parser is not allowed to perform \( \text{Act}_{\text{ER}} \) when the total number of execution of \( \text{Act}_{\text{ER}} \) exceeds the limit. These two constraints prevent the parser from falling into an infinite loop as well as parsing in the same order of time complexity as GE. We also add the following constraints to avoid unreasonable derivations: (i) a word with a dependent cannot be deleted and (ii) any child words cannot be substituted. All the constraints are implemented in the \textit{isLegal()} function in Algorithm 1 (line 8). We note that these constraints not only prevent undesirable derivations but also leads to an efficiency in exploring the search space during training.

3 Experiment

Data and Evaluation We evaluate EREF with respect to dependency parsing accuracy (Exp1) and grammaticality improvement (Exp2).

In the first experiment, as in GE, we train and evaluate our parser on the English dataset from the Penn Treebank (Marcus et al., 1993) with the Penn2Malt conversion program (Sections 2-21 for training, 22 for tuning, and 23 for test). We use the PTB for the dependency experiment, since there are no ungrammatical text corpora that has dependency annotation on the \textit{corrected} texts by human.

We choose the following most frequent error types that are used in CoNLL 2013 shared task (Ng et al., 2013):

1. Determiner (substitution, deletion, insertion)
2. Preposition (substitution, deletion, insertion)
3. Noun number (singular vs. plural)
4. Verb form (tense and aspect)
5. Subject verb agreement

Regarding the candidate sets for \textit{INSERT} and \textit{SUBSTITUTE} actions, following Rozovskaya and Roth (2014), we focus on the most common candidates for each error type, setting the determiner candidates to be \( \{a, an, the, \phi \text{ (as deletion)}\} \), preposition candidates to be \( \{on, about, from, for, of, to, at, in, with, by, \phi\} \), and verb forms to be \( \{VB(P|Z|G|D|N)\} \). We build a 5-gram language model on English Gigaword with the KenLM Toolkit (Heafield, 2011) for EREF to select the best candidate.

We manually inject grammatical errors into PTB with certain error-rates similarly to the GenerRate toolkit by Foster and Andersen (2009), which is designed to create synthetic errors into sentences to improve grammatical error detection.

We train and tune EREF models with different token-level error injection rates from 5% (E05) to 20% (E20), because language learner corpora have generally around 5% to 15% of token level errors depending on learners’ proficiency (Leacock et al., 2014). Since the error injection is stochastic, we train each model with 10 runs and take an average of parser performance on the test set.

As a baseline, we use the original parser as described by GE, which is equivalent to EREF with training on an error-free corpus (E00). Since the EF baseline does not allow error correction during parsing, we pre-process the test data with a grammatical error correction system similar to Rozovskaya and Roth (2014), where a combination of classifiers for each error type corrects grammatical errors.

For evaluation, we jointly parse and correct grammatical errors in the test set with different
Table 2: Grammaticality scores by 1-4 scale regression model (Heilman et al., 2014). The first row shows the number of sentences that are made (at least one) change. Bold numbers show statistically significant improvements.

| (%) | Baseline | E05 | E10 | E15 | E20 |
|-----|----------|-----|-----|-----|-----|
| 0   | 91.43    | 91.12| 90.87| 90.61| 90.29|
| 5   | 89.99    | 90.00| 89.87| 89.72| 89.48|
| 10  | 87.84    | 87.99| 88.07| **88.14**| 88.04|
| 15  | 85.64    | 86.18| 86.54| 86.75| **86.82**|
| 20  | 84.12    | 84.78| 85.28| 85.50| **85.76**|
| ∇  | -0.37    | -0.32| -0.28| -0.26| **-0.23**|

Table 1: Unlabeled dependency accuracy results with the 5x5 models and test sets. ∇ shows the slope of deterioration in parser performance.

|                  | E05 | E10 | E15 | E20 |
|------------------|-----|-----|-----|-----|
| # edited sents (out of 5,124) | 175 | 391 | 583 | 861 |
| grammaticality (source)  | 2.92| 2.95| 2.95| 2.89 |
| grammaticality (this work) | 2.96| 2.99| **3.27**| **2.98** |

Results  Table 1 shows the result of unlabeled dependency accuracy (UAS). As previously presented (Foster, 2007; Cahill, 2015), our experiment also shows that parser performance deteriorated as the error rate in the test corpus increased. On the error-free test set (0%), the baseline (EF pipeline) outperforms other EREF models; the accuracy is lower when the parser is trained on noisier data. The difference among the models becomes small when the test set has 10% error injection rate. As the rate increases further, the trend of parser accuracy reverses. When the test set has 15% or higher noise, the E20 is the most accurate parser. This trend is presented by the slope of deterioration ∇ = \frac{\text{accuracy}_{\text{test}} - \text{accuracy}_{\text{0\%}}}{20} in Table 1; a parser trained on noisier training data shows smaller decline and more robustness. This indicates that the EREF is more robust than the vanilla EF on ungrammatical texts by jointly parsing and correcting errors.

Table 2 demonstrates the result of grammaticality improvement (1-4 scale) on the TLE corpus, and Table 3 shows successful and failure corrections by EREF. Minimally trained models (E05 and E10) show little improvement in grammaticality because the models are too conservative to make edits. The models with higher error-injection rates (E15 and E20) achieve 0.1 to 0.3 improvements that are statistically significant. There is still room to improve regarding the amount of corrections. This is probably because TLE contains a variety of errors (e.g., collocation, punctuation) in addition to the five error types we focus. To deal with other error types, we can extend EREF by adding more actions, although it increases the search space.

From a practical perspective, the level of ungrammaticality should be realized ahead of time. This is an issue to be addressed in future research.

SUCCESSFUL CASES

I’m looking forward to [−sec−] [+seeing+] you next summer
I’ve never [−approve−] {+approved+} his deal
There is not {+a+} possibility to travel

FAILURE CASES

I’ve [+assisted+] [+assisting+] your new musical show
I am writing to complain [−about−] {+with+} somethings
I hope you liked {+the+} everything I said

Table 3: Successful and failure examples by EREF. The edits are represented by [−deletion−] and [+insertion+]. Adjacent pairs of deletion and insertion are considered as substitution.
4 Related Work

Our work lies at the intersection of parsing non-canonical texts and grammatical error correction. Joint dependency parsing and disfluency detection has been pursued (Rasooli and Tetreault, 2013, 2014; Honnibal and Johnson, 2014; Wu et al., 2015; Yoshikawa et al., 2016), where a parser jointly parses and detects disfluency (e.g., reparandum and interregnum) for a given speech utterance. Our work could be considered an extension via adding SUBSTITUTE and INSERT actions, although we depend on easy-first non-directional parsing framework instead of a left-to-right strategy. Importantly, the DELETE action is easier to handle than the SUBSTITUTE and INSERT actions, because they bring us challenging issues about a process of candidate word generation and avoiding an infinite loop in derivation. We have addressed these issues as explained in §2.

In terms of the literature from grammatical error correction, this work is closely related to Dahlmeier and Ng (2012), where they show an error correction decoder with the easy-first strategy. The decoder iteratively corrects the most probable ungrammatical token by applying different classifiers for each error type. The EREF parser also depends on the easy-first strategy to find ungrammatical index to be deleted, inserted, or substituted, but it parses and corrects errors jointly whereas the decoder is designed as a grammatical error correction framework rather than a parser.

There is a line of work for parsing ungrammatical sentences (e.g., web forum) by adapting an existing parsing scheme on domain specific annotations (Petrov and McDonald, 2012; Cahill, 2015; Berzak et al., 2016; Nagata and Sakaguchi, 2016). Although we share an interest with respect to dealing with ungrammatical sentences, EREF focuses on the parsing scheme for repairing grammatical errors instead of adapting a parser with a domain specific annotation scheme.

More broadly, our work can also be regarded as one of the joint parsing and text normalization tasks such as joint spelling correction and POS tagging (Sakaguchi et al., 2012), word segmentation and POS tagging (Kaji and Kitsuregawa, 2014; Qian et al., 2015).

5 Conclusions

We have presented an error-repair variant of the non-directional easy-first dependency parser. We have introduced three new actions, SUBSTITUTE, INSERT, and DELETE into the parser so that it jointly parses and corrects grammatical errors in a sentence. To address the issue of parsing incompleteness due to the new actions, we have proposed simple constraints that keep track of editing history for each token and the total number of edits during derivation. The experimental result has demonstrated robustness of EREF parsers against EF and grammaticality improvement. Our work is positioned at the intersection of noisy text parsing and grammatical error correction. The EREF is a flexible formalism not only for grammatical error correction but other tasks with jointly editing and parsing a given sentence.

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