Correcting Grammatical Verb Errors

Alla Rozovskaya — Columbia University
Dan Roth — University of Illinois
Vivek Srikumar — Stanford University

Overview of This Work

This work is a step in a long-term research program on grammatical correction of texts written by English as a Second Language writers. Earlier steps addressed both methodological and machine-learning/algorithmic issues and culminated in successful programs for this domain. **See Rozovskaya and Roth (NAACL'10), Rozovskaya and Roth (ACL'11), Rozovskaya and Roth (EMNLP'13), Rozovskaya et al. (CoNLL Shared Task 2013).**

Common Verb Errors Made by Non-Native English Writers

- **Subject-verb agreement**
  "We *discusses/discuss this very time."
- **Tense**
  "We *discuss/discussed this last week."
- **Form**
  "They left without *discuss/discussing this with me."

Special Challenges

- Most of the earlier work focused on article and preposition usage errors.
- Verb-related errors received very little attention in the error correction literature (though they are more common than article/preposition errors).
- The set of Verbs is not a closed class.
- Verb errors involve several grammatical phenomena.

Contributions

- We present a holistic, linguistically-motivated framework for correcting grammatical verb mistakes.
- We propose and evaluate:
  - methods of selecting verb candidates
  - an algorithm for determining verb finiteness
  - a finiteness-based verb error correction system
- We show that the specific challenges of verb error correction are better addressed by making use of the notion of verb finiteness in a linguistically-aware framework.
- We develop an annotation for a subset of the FCE dataset that specifies gold verb candidate information and verb finiteness.

Key Results

Model	Avg. Precision
Combined	81.39
Finiteness-based	**87.05**

Table 1: Verb finiteness contribution to error identification.

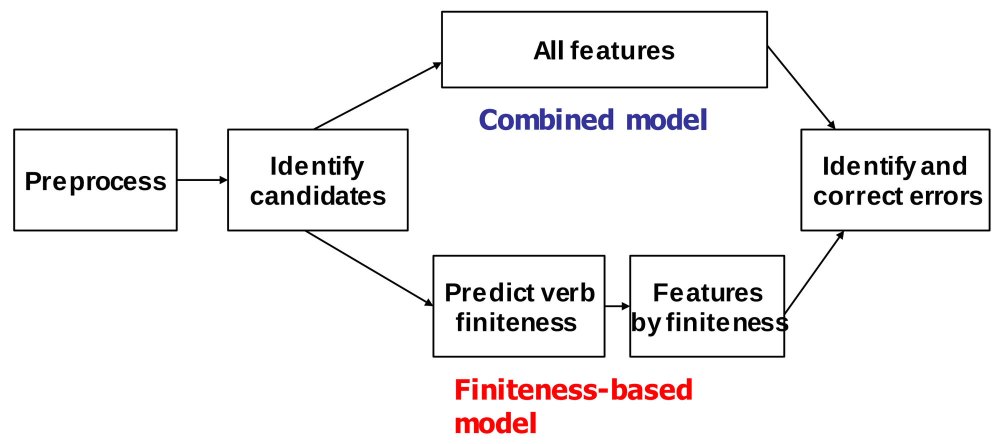
Error type	Correction			Identification		
	P	R	F1	P	R	F1
Agreement	90.62	9.70	17.52	90.62	9.70	17.52
Tense	60.51	7.47	13.31	86.62	10.70	19.05
Form	81.82	16.34	27.24	83.47	16.67	27.79
Total	**71.94**	**10.24**	**17.94**	**85.81**	**12.22**	**21.20**

Table 2: Performance of the complete model after the correction stage.

The Computational Model for Correcting Verb Errors

1. Candidate selection
2. Verb finiteness prediction
3. Feature generation – special features that depend on finiteness value and error type
4. Error identification
5. Error correction

The combined model is agnostic to the finiteness of the verb; **the finiteness-based model** uses the verb finiteness prediction made by the verb finiteness classifier.



Identifying Verbs in Noisy Learner Text: Candidate Selection Methods

Candidate selection is difficult for verbs:

- The class of verbs is open
- Learner text is noisy –> leads to many POS errors

Candidate selection methods	Recall on selecting erroneous verbs as candidates (%)	Avg. precision on error identification (%)
All VPs	83.00	79.49
+tokens POS tagged as verbs	91.96	86.48
+tokens that are valid verb lemmas	95.50	**87.05**
+tokens that are valid inflected verbs	**96.09**	86.81

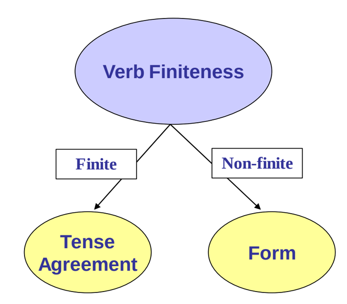
Table 3: Impact of candidate selection methods on error identification performance.

Verb Finiteness

Verb type	Example	Verb properties		
		Agreement	Tense	Form
Finite	He **discussed** this with me.	-	Past Simple	
	He **discusses** this with me.	3rd person, sing.	Present Simple	
Non-finite	He left without **discussing** it.			Gerund
	They let him **discuss** this.			Infinitive
	To discuss this now would be ill-advised.			To-Infinitive

Table 4: Examples of contexts that license finite and non-finite verbs.

Intuition:
Verb finiteness should benefit verb error correction, because properties associated with each type are mutually exclusive



Machine-Learning Components: Error Identification and Error Correction

Error identification – the goal is to identify errors and predict error type. We train a 4-class machine-learning classifier that operates in the label space {**Correct, Agreement, Tense, Form**}.
Error correction – three components -- one for each type of mistake -- applied to the output of the error identification model. Each component is a multiclass classifier and is run on the instances identified as errors of a particular error type.
We train all of the models with the SVM learning algorithm implemented in JLIS (Chang et al., 2010).

This material is based on research sponsored by DARPA under agreement number FA8750-13-2-0008 and by the Army Research Laboratory (ARL) under agreement W911NF-09-2-0053. Any opinions, findings, conclusions or recommendations are those of the authors and do not necessarily reflect the view of the agencies.