Building a Large Annotated Corpus of Learner English: The NUS Corpus of Learner English

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Introduction

Motivation

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- Over one billion people in the world are studying English.

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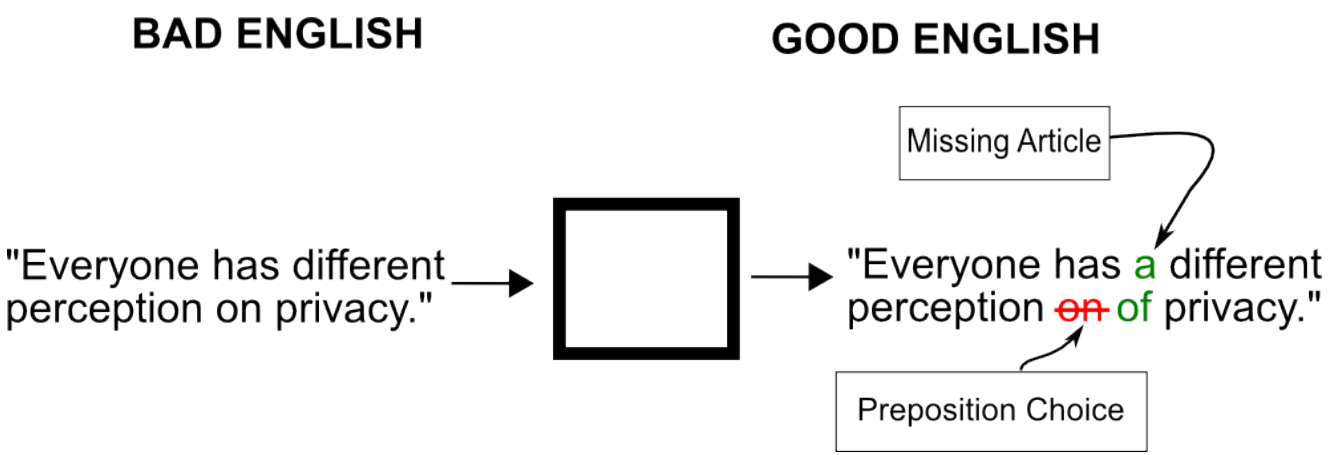
Vision

- Automatic, high-quality grammar correction through statistical NLP.

Statistical approach to grammatical error correction

Basic recipe for statistical grammatical error correction

1. Define the confusion set of possible corrections.
2. Engineer useful features that are predictive of the correct answer.
3. Train a classifier to predict correct word based on context features.
4. Test classifier on examples from learner text.



The problem: lack of data

Lack of large, annotated learner corpus

"...a reasonably sized public data set for evaluation and an accepted annotation standard are still sorely missing. Anyone developing such a resource and making it available to the research community would have a major impact on the field, ..." *[Leacock et al.2010]*

- Statistical approaches require data.
- No large annotated learner corpus for grammatical error correction.
- Existing annotated learner corpora either too small or proprietary.

Work around: train on non-learner text

"Fill in the blank" method

- Create training examples from grammatical non-learner text.
- Take the original word as the class label.
- Extract features from surrounding context.

It's free, no manual annotation required!

Example

Orig: I want to watch **a movie**.

- Class y = a
- Features $\mathbf{x}$ = [left_word=watch, right_word=movie, ...]

Work around: train on artificial learner text

Artificial learner text method

- Create artificial learner errors in non-learner text.
- Take the original word as the class label.
- Extract features from surrounding context and changed word.

Only requires statistics of learner errors.

Example

Orig : I want to watch **a movie**.
Changed : I want to watch **movie**.

- Class y = a
- Features $\mathbf{x}$ = [article=NULL, left_word=watch, right_word=movie, ...]

Advantages of real learner data

"Fill in the blank" method − −

- Cannot use the word used by the writer as a feature.
- Errors are not uniformly distributed, removing the word loses information.
- Errors are rare, the original word is often correct!

Artificial learner data −

- Artificial errors might not reflect real errors accurately.
- Generating errors just as hard as correcting them.

Real learner data +

- Learner text is a sample from the real error distribution.
- Allows for analyzing real errors and their distributions.
- Contains multiple, interacting errors.

Outline

In this talk...

1. We present the NUS Corpus of Learner English.
2. Explain the tag set and annotation process.
3. Show statistics of the collected learner data.
4. Report on an annotator agreement study for error correction.

NUCLE : NUS Corpus of Learner English

NUS Corpus of Learner English

- About 1,400 essays from university-level students with 1.2 million words.
- Completely annotated with error categories and corrections.
- Annotation performed by English instructors at NUS Centre for English Language Communication (CELC).
- Freely available for research.

Tag set

NUCLE tag set

- 27 error categories grouped into 13 broader categories.
- Developed at NUS Center for English Language Communication.
- Each error annotation contains
  1. start and end offset
  2. error category
  3. correction
  4. comment (optional)

Example

- ArtOrDet (Article or Determiner) *... the technology should not be used in* **[non-medical — a non-medical]** *situation.*
- Vform (Verb form) *Will the child blame the parents after he* **[growing — grows]** *up?*

Annotation process

Writing, Annotation, and Marking Platform (WAMP)

- **Select** arbitrary, contiguous text spans.
- **Classify** errors by choosing an error tag.
- **Correct** errors by typing the correction into a text box.
- **Comment** to give additional explanations (optional).

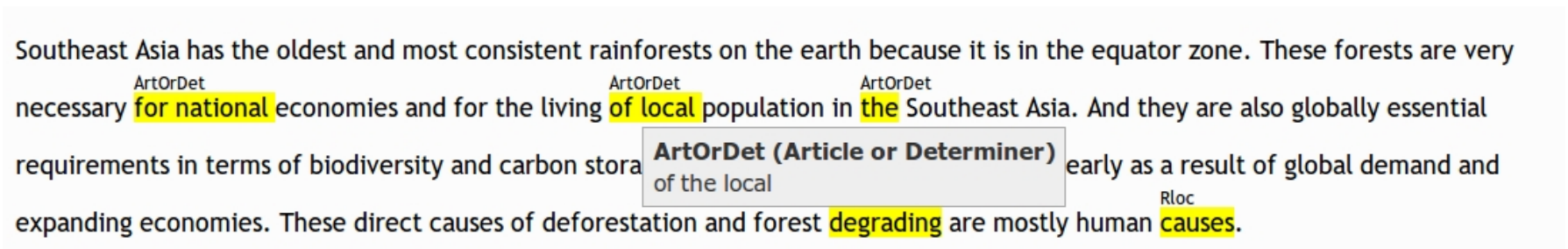


Figure: Example of NUCLE corpus.

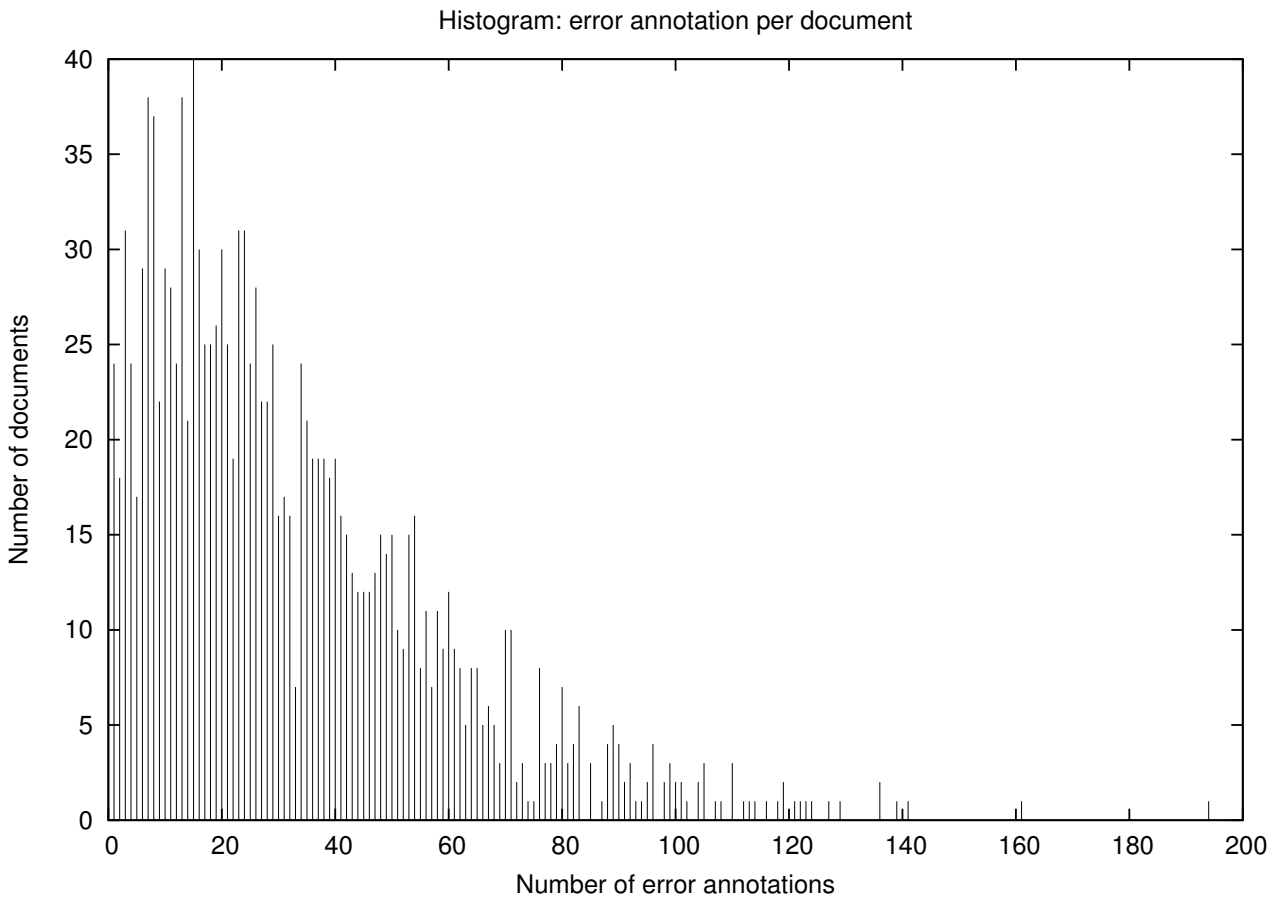
NUCLE corpus statistics

Documents	1,414
Sentences	59,871
Word tokens	1,220,257
Error annotations	**46,597**
# of error annotations per document	32.95
# of error annotations per 100 word tokens	3.82

NUCLE data collection & annotation

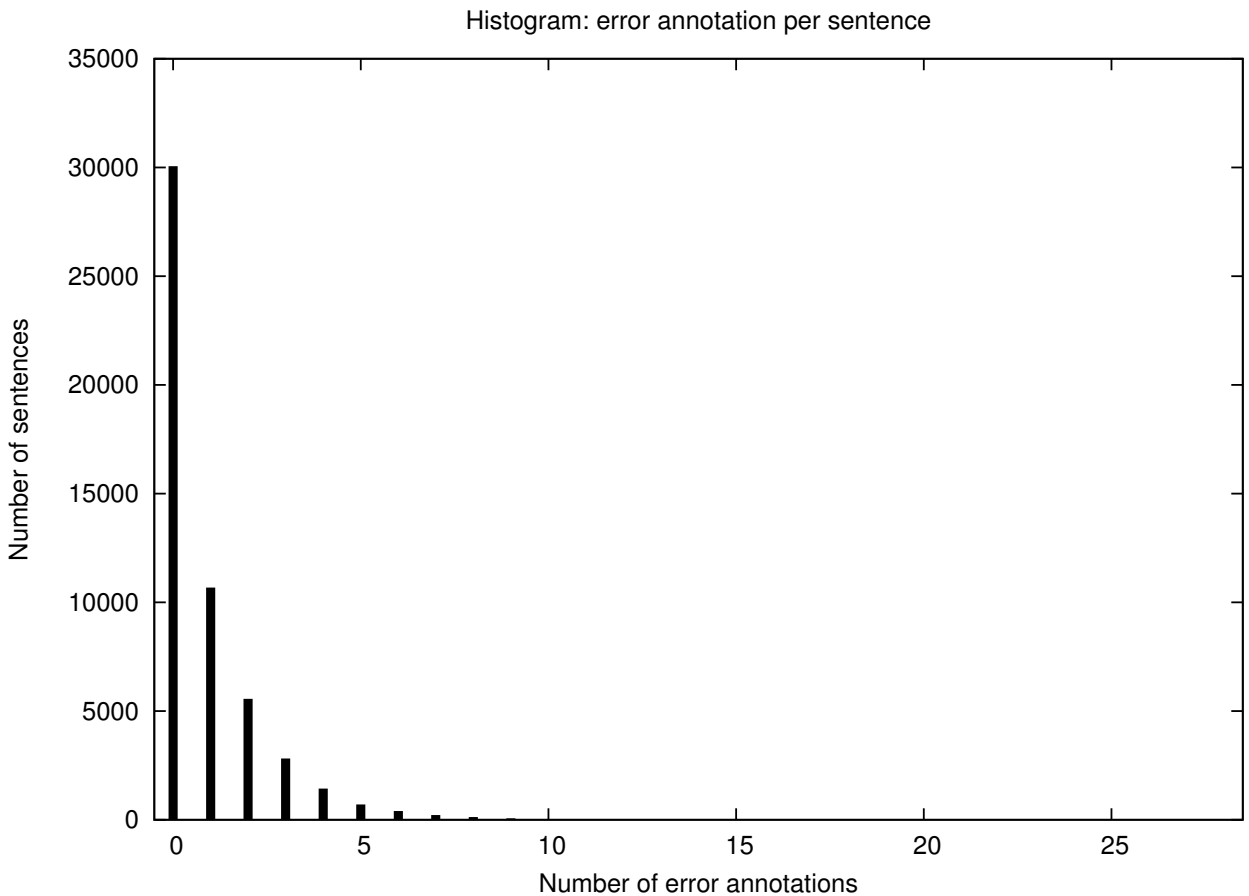
- Essays written by undergraduate students at NUS.
- Essays are take-home assignments for academic writing courses.
- 10 annotators from NUS CELC.

Histogram: errors per document



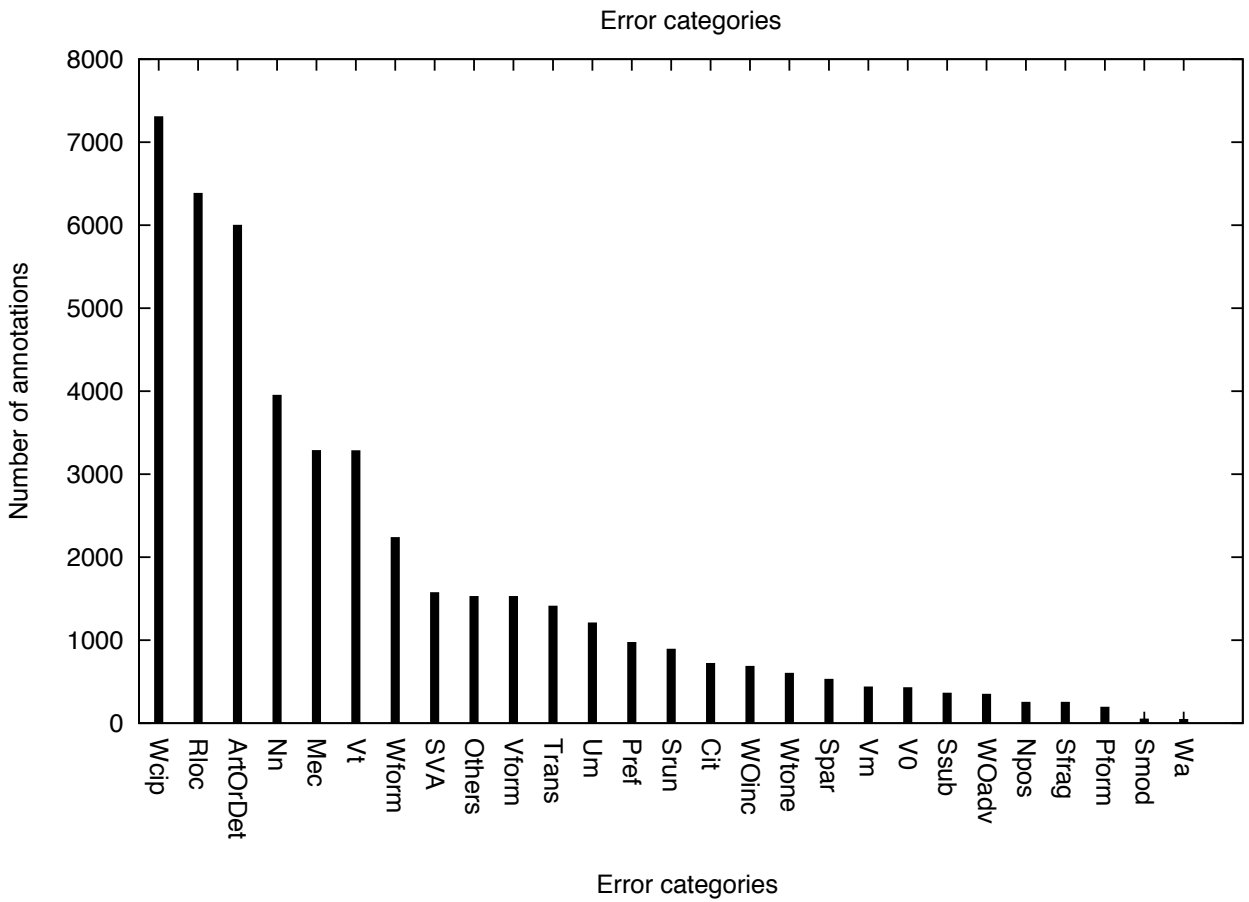
- Skewed distribution.
- Errors are rare in general, but some documents have many errors.

Histogram: errors per sentence



- Most sentences have no or few errors, but some sentences have many errors.

Histogram: error categories



- Some errors are very frequent, many errors are infrequent.
- Article and preposition errors are the most frequent error categories.

Annotator agreement study

Annotator agreement study

- Part of NUCLE pilot study prior to corpus creation.
- 3 annotators from NUS CELC.
- 96 documents.
- Two annotators per document.

Agreement criteria

- **Identification** Is something an error or not?
- **Classification** Agreement of error category, given identification.
- **Exact** Agreement of error category and correction, given identification.

Identification agreement

Source	:	This phenomenon opposes the real .
Annotator A	:	This phenomenon opposes the real .
Annotator B	:	This phenomenon opposes the real .

- Agree that *real* is an error.
- Disagree whether *the* is an error.
- Agree that all other tokens are correct.

Kappa agreement between two annotators

$$\kappa = \frac{Pr(a) - Pr(e)}{1 - Pr(e)}$$

$$\begin{aligned} Pr(a) &= \frac{\#\text{agreed tokens}}{\#\text{total tokens}} \\ Pr(e) &= Pr(A=1)Pr(B=1) + Pr(A=0)Pr(B=0) \\ Pr(A=1) &= \frac{\#\text{ annotated as error by annotator A}}{\#\text{ total tokens}} \end{aligned}$$

Classification and exact agreement

Source	:	This phenomenon opposes the real .
Annotator A	:	This phenomenon opposes the (real → reality (Wform)) .
Annotator B	:	This phenomenon opposes the (real → reality (Wform)) .

- Only consider tokens where annotators agree that they are errors.
- **Classification:** Agree that *real* is word form error.
- **Exact:** Agree that *real* is word form error and should be corrected as *reality*.

Results

Annotators	Kappa-iden	Kappa-class	Kappa-exact
A – B	0.4775	0.6206	0.5313
A – C	0.3627	0.5352	0.4956
B – C	0.3230	0.4894	0.4246
Average	0.3877	0.5484	0.4838

Results

- Fair agreement for identification.
- Moderate agreement for classification and exact agreement.
- Identifying errors seems to be harder than classifying or correcting them.
- Error correction is difficult, especially detecting errors.

Related work

Learner corpora for NLP

- ICLE - International Corpus of Learner English.
- Chinese Learner English Corpus.
  - Rozovskaya and Roth produced annotations for about 63,000 words from both corpora [Rozovskaya and Roth2010].
- CLC - Cambridge Learner Corpus [Yannakoudakis et al.2011].
- HOO 2011 and HOO 2012 shared task [Dale et al.2012].
- CoNLL 2013 shared task [Ng et al.2013].

Conclusion

Conclusion

- The NUS Corpus of Learner English is a one-million word learner corpus.
- Contains annotations of error categories and corrections.
- Error correction is a difficult problem, even for humans.

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