How Are Spelling Errors Generated and Corrected? A Study of Corrected and Uncorrected Spelling Errors Using Keystroke Logs

Yukino Baba
The University of Tokyo
yukino.baba@gmail.com

Hisami Suzuki
Microsoft Research
hisamis@microsoft.com

Abstract

This paper presents a comparative study of spelling errors that are corrected as you type, vs. those that remain uncorrected. First, we generate naturally occurring online error correction data by logging users’ keystrokes, and by automatically deriving pre- and post-correction strings from them. We then perform an analysis of this data against the errors that remain in the final text as well as across languages. Our analysis shows a clear distinction between the types of errors that are generated and those that remain uncorrected, as well as across languages.

1 Introduction

When we type text using a keyboard, we generate many spelling errors, both typographical (caused by the keyboard layout and hand/finger movement) and cognitive (caused by phonetic or orthographic similarity) (Kukich, 1992). When the errors are caught during typing, they are corrected on the fly, but unnoticed errors will persist in the final text. Previous research on spelling correction has focused on the latter type (which we call uncorrected errors), presumably because the errors that are corrected on the spot (referred to here as corrected errors) are not recoded in the form of a text. However, studying corrected errors is important for at least three reasons. First, such data encapsulates the spelling mistake and correction by the author, in contrast to the case of uncorrected errors in which the intended correction is typically assigned by a third person (an annotator), or by an automatic method (Whitelaw et al., 2009; Aramaki et al., 2010). Secondly, data on corrected errors will enable us to build a spelling correction application that targets correction on the fly, which directly reduces the number of keystrokes in typing. This is crucial for languages that use transliteration-based text input methods, such as Chinese and Japanese, where a spelling error in the input Roman keystroke sequence will prevent the correct candidate words from appearing in the list of candidates in their native scripts, thereby preventing them from being entered altogether. Finally, we can collect a large amount of spelling errors and their corrections by logging keystrokes and extracting the pre- and post-correction strings from them. By learning the characteristics of corrected and uncorrected errors, we can expect to use the data for improving the correction of the errors that persisted in the final text as well.

In this paper, we collect naturally occurring spelling error data that are corrected by the users online from keystroke logs, through the crowdsourcing infrastructure of Amazon’s Mechanical Turk (MTurk). As detailed in Section 3, we display images to the worker of MTurk, and collect the descriptions of these images, while logging their keystrokes including the usage of backspace keys, via a crowd-based text input service. We collected logs for two typologically different languages, English and Japanese. An example of a log along with the extracted pre- and post-correction strings is shown in Figure 1. We then performed two comparative analyses: corrected vs. uncorrected errors in English (Section 4.3), and English vs. Japanese corrected errors (Section 4.4). Finally, we remark on an additional cause of spelling errors observed in all the data we analyzed (Section 4.5).

2 Related Work

Studies on spelling error generation mechanisms are found in earlier work such as Cooper (1983). In particular, Grudin (1983) offers a detailed study of the errors generated in the transcription typing scenario, where the subjects are asked to transcribe a text without correcting the errors they make. In a more recent work, Aramaki et al. (2010) automatically extracted error-correction candidate pairs from Twitter data based on the assumption that these pairs...
fall within a small edit distance, and that the errors are not in the dictionary and substantially less frequent than the correctly spelled counterpart. They then studied the effect of five factors that cause errors by building a classifier that uses the features associated with these classes and running ablation experiments. They claim that finger movements cause the spelling errors to be generated, but the uncorrected errors are characterized by visual factors such as the visual similarity of confused letters. Their experiments however target only the persisted errors, and their claim is not based on the comparison of generated and persisted errors.

Outside of English, Zheng et al. (2011) analyzed the keystroke log of a commercial text input system for Simplified Chinese, and compared the error patterns in Chinese with those in English. Their use of the keystroke log is different from ours in that they did not directly log the input in pinyin (Romanized Chinese by which native characters are input), but the input pinyin sequences are recovered from the Chinese words in the native script (hanzi) after the character conversion has already applied.

3 Keystroke Data Collection

Amazon’s Mechanical Turk (MTurk) is a web service that enables crowdsourcing of tasks that are difficult for computers to solve, and has become an important infrastructure for gathering data and annotation for NLP research in recent years (Snow et al. 2008). To the extent of our knowledge, our work is the first to use this infrastructure to gather user keystroke data.

3.1 Task design

In order to collect naturally occurring keystrokes, we have designed two types of tasks, both of which consist of writing something about images. In one task type, we asked the workers to write a short description of images (image description task); in the other, the workers were presented with images of a person or an animal, and were asked to guess and type what she/he was saying (let-them-talk task). Using images as triggers for typing keeps the underlying motivation of keystroke collection hidden from the workers, simultaneously allowing language-independent data collection. For the image triggers, we used photos from the Flickr’s Your Best Shot 2009/2010 groups. Examples of the tasks and collected text are given in Figure 2.

3.2 Task interface

For logging the keystrokes including the use of backspaces, we designed an original interface for the text boxes in the MTurk task. In order to simplify the interpretation of the log, we disabled the cursor movements and text highlighting via a mouse or the arrow keys in the text box; the workers are therefore forced to use the backspace key to make corrections. In Japanese, many commercially available text input methods (IMEs) have an auto-complete feature which prevents us from collecting all keystrokes for inputting a word. We therefore used an in-house IME that has disabled this feature to collect logs. This IME is hosted as a web service, and keystroke logs are also collected through the service. For English, we used the service for log collection only.

4 Keystroke Log Analysis

4.1 Data

We used both keystroke-derived and previously available error data for our analysis.

Keystroke-derived error pairs for English and Japanese (en_keystroke, ja_keystroke): from the raw keystroke logs collected using the method described in Section 3, we extracted only those words that included a use of the backspace key. We then recovered the strings before and after correction by the following steps (Cf. Figure 1):

- To recover the post-correction string, we deleted the same number of characters preceding a sequence of backspace keys.
- To recover the pre-correction string, we compared the prefix of the backspace usage (misssp in Figure 1) with the substrings after error correction (miss, missp, ..., misspell), and considered that the prefix was spell-corrected into the substring which is the longest and with the smallest edit distance.

Figure 2: Examples of tasks and collected text (Translated text: “A flock of penguins are marching in the snow.” and “Mummy, my feet can’t touch the bottom.”)
We then lower-cased the pairs and extracted only those within the edit distance of 2. The resulting data which we used for our analysis consists of 44,104 pairs in English and 4,808 pairs in Japanese.

Common English errors (en_common): following previous work (Zheng et al., 2011), we obtained word pairs from Wikipedia and SpellGood. We lower-cased the entries from these sources, removed the duplicates and the pairs that included non-Roman alphabet characters, and extracted only those pairs within the edit distance of 2. This left us with 10,608 pairs.

4.2 Factors that affect errors

Spelling errors have traditionally been classified into four descriptive types: Deletion, Insertion, Substitution and Transposition (Damerau, 1964). For each of these types, we investigated the potential causes of error generation and correction, following previous work (Aramaki et al., 2010; Zheng et al., 2011).

Physical factors: (1) motor control of hands and fingers; (2) distance between the keys; Visual factors: (3) visual similarity of characters; (4) position in a word; (5) same character repetition; Phonological factors: (6) phonological similarity of characters/words.

In what follows, our discussion is based on the frequency ratio of particular error types, where the frequency ratio refers to the number of cases in spelling errors divided by the total number of cases in all data. For example, the frequency ratio of consonant deletion is calculated by dividing the number of missing consonants in errors by the total number of consonants.

4.3 Corrected vs. uncorrected errors in English

In this subsection, we compare corrected and uncorrected errors of English, trying to uncover what factors facilitate the error correction.

Error types (Figure 3) Errors in en_keystroke are dominated by Substitution, while Deletion errors are the most common in en_common, indicating that

Substitution mistakes are easy to catch, while Deletion mistakes tend to escape our attention. Zheng et al. (2011) reports that their pinyin correction errors are dominated by Deletion, which suggests that their log does in fact reflect the characteristics of corrected errors.

Position of error within a word (Figure 5) In en_keystroke, Deletion errors at the word-initial position are the most common, while Insertion and Substitution errors tend to occur both at the beginning and the end of a word. In contrast, in en_common, all error types are more prone to occur word-medially. This means that errors at word edges are corrected more often than the word-internal errors, which can be attributed to cognitive effect known as the bathtub effect (Aitchison, 1994), which states that we memorize words at the periphery most effectively in English.

Effect of character repetition (Figure 6) Deletion errors where characters are repeated, as in tomorrow→tomorrow, is observed significantly more frequently than in a non-repeating context in en_common, but no such difference is observed in en_keystroke, showing that visually conspicuous errors tend to be corrected.

Visual similarity in Substitution errors (Figure 4) We computed the visual similarity of characters by

\[ 2 \times \left( \frac{\text{the area of overlap between character A and B}}{\text{area of character A + area of character B}} \right) \]
When comparing the transposition errors by their Syllable-based transposition errors (Figure 7) are phonologically and orthographically motivated. Aramaki et al. (2010)’s experiments did not show that CV distinction affect the errors, while our data includes non-permutation look-ahead errors such as puclic→public and otigaga→otibaga.

4.5 Look-ahead and look-behind errors

In Substitution errors for all data we analyzed, substituting for the character that appeared before, or are to appear in the word was common (Figure 9). In particular, in en_keystroke and ja_keystroke, look-ahead errors are much more common than non-look-ahead errors. Grudin (1983) reports cases of permutation (e.g., gib→big) but our data includes non-permutation look-ahead errors such as puclic→public and otigaga→otibaga.

5 Conclusion

We have presented our collection methodology and analysis of error correction logs across error types (corrected vs. uncorrected) and languages (English and Japanese). Our next step is to utilize the collected data and analysis results to build online and offline spelling correction models.

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5We calculated the area using the Courier New font which we used in our task interface.
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