A Broad-Coverage Normalization System for Social Media Language

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Abstract

Social media language contains huge amount and wide variety of nonstandard tokens, created both intentionally and unintentionally by the users. It is of crucial importance to normalize the noisy nonstandard tokens before applying other NLP techniques. A major challenge facing this task is the system coverage, i.e., for any user-created nonstandard term, the system should be able to restore the correct word within its top $n$ output candidates. In this paper, we propose a cognitively-driven normalization system that integrates different human perspectives in normalizing the nonstandard tokens, including the enhanced letter transformation, visual priming, and string/phonetic similarity. The system was evaluated on both word- and message-level using four SMS and Twitter data sets. Results show that our system achieves over 90% word-coverage across all data sets (a 10% absolute increase compared to state-of-the-art); the broad word-coverage can also successfully translate into message-level performance gain, yielding 6% absolute increase compared to the best prior approach.

1 Introduction

The amount of user generated content has increased drastically in the past few years, driven by the prosperous development of the social media websites such as Twitter, Facebook, and Google+. As of June 2011, Twitter has attracted over 300 million users and produces more than 2 billion tweets per week (Twitter, 2011). In a broader sense, Twitter messages, SMS messages, Facebook updates, chat logs, Emails, etc. can all be considered as “social text”, which is significantly different from the traditional news text due to the informal writing style and the conversational nature. The social text serves as a very valuable information source for many NLP applications, such as the information extraction (Ritter et al., 2011), retrieval (Subramaniam et al., 2009), summarization (Liu et al., 2011a), sentiment analysis (Celikyilmaz et al., 2010), etc. Yet existing systems often perform poorly in this domain due to the extensive use of the nonstandard tokens, emoticons, incomplete and ungrammatical sentences, etc. It is reported that the Stanford named entity recognizer (NER) experienced a performance drop from 90.8% to 45.8% on tweets (Liu et al., 2011c); the part-of-speech (POS) tagger and dependency parser degraded 12.2% and 20.65% respectively on tweets (Foster et al., 2011). It is therefore of great importance to normalize the social text before applying the standard NLP techniques. Text normalization is also crucial for building robust text-to-speech (TTS) systems, which need to determine the pronunciations for nonstandard words in the social text.

The goal of this work is to automatically convert the noisy nonstandard tokens observed in the social text into standard English words. We aim for a robust text normalization system with “broad coverage”, i.e., for any user-created nonstandard token, the system should be able to restore the correct word within its top $n$ candidates ($n = 1, 3, 10...$). This is a very challenging task due to two facts: first, there exists huge amount and a wide variety of nonstandard tokens. (Liu et al., 2011b) found more than 4 million distinct out-of-vocabulary tokens in the Edinburgh Twitter corpus (Petrovic et al., 2010); second, the nonstandard tokens consist
Table 1: Nonstandard tokens and their frequencies in the Edinburgh Twitter corpus. The corresponding standard words are “together” and “you”, respectively.

| Frequency | Nonstandard Token |
|-----------|-------------------|
| 2gether 6326 | togetha (919) |
| 2gther 1206 | together (207) |
| 2gether (178) | together (94) |
| 2getter 10 | togeter (49) |

The rapid growth of SMS and social media content, text normalization system has drawn increasing attention in the recent decade, where the focus is on converting the noisy nonstandard tokens in the informal text into standard dictionary words. (Choudhury et al., 2007) modeled each standard English word as a hidden Markov model (HMM) and calculated the probability of observing the noisy token under each of the HMM models; (Cook and Stevenson, 2009) calculated the sum of the probabilities of a noisy token being generated by a specific word and a word formation process; (Beaufort et al., 2010) employed the weighted finite-state machines (FSMs) and rewriting rules for normalizing French SMS; (Pennell and Liu, 2010) focused on tweets created by handsets and developed a CRF tagger for deletion-based abbreviation. The text normalization problem was also tackled under the machine transla-
tion (MT) or speech recognition (ASR) framework. (Aw et al., 2006) adapted a phrase-based MT model for normalizing SMS and achieved satisfying performance. (Kobus et al., 2008) showed that using a statistical MT system in combination with an analogy of the ASR system improved performance in French SMS normalization. (Pennell and Liu, 2011) proposed a two-phase character-level MT system for expanding the abbreviations into standard text.

Recent work also focuses on normalizing the Twitter messages, which is generally considered a more challenging task. (Han and Baldwin, 2011) developed classifiers for detecting the ill-formed words and generated corrections based on the morphophonemic similarity. (Liu et al., 2011b) proposed to normalize the nonstandard tokens without explicitly categorizing them. (Xue et al., 2011) adopted the noisy-channel framework and incorporated orthographic, phonetic, contextual, and acronym expansion factors in calculating the likelihood probabilities. (Gouws et al., 2011) revealed that different populations exhibit different shortening styles.

Most of the above systems limit their processing scope to certain categories (e.g., deletion-based abbreviations, misspellings) or require large-scale human annotated corpus for training, which greatly hinders the scalability of the system. In this paper, we propose a novel cognitively-driven text normalization system that robustly tackle both the unintentional misspellings and the intentionally-created noisy tokens. We propose a global context-based approach to purify the automatically collected training data and learn the letter transformation patterns without human supervision. We also propose a cognitively-grounded “visual priming” approach that leverages the “priming” effect to suggest the candidate words. By integrating different perspectives, our system can successfully mimic the human rationales and yield broad word-coverage on both SMS and Twitter messages. To the best of our knowledge, we are the first to integrate these human perspectives in the text normalization system.

3 Broad-Coverage Normalization System

In this section, we describe our broad-coverage normalization system, which consists of four key components. For a standard/nonstandard token, three subnormalizers each suggest their most confident candidates from a different perspective\(^3\): “Enhanced Letter Transformation” automatically learns a set of letter transformation patterns and is most effective in normalizing the intentionally created nonstandard tokens through letter insertion, repetition, deletion, and substitution (Section 3.1); “Visual Priming” proposes candidates based on the visual cues and a primed perspective (Section 3.2); “Spell Checker” corrects the misspellings (Section 3.3). The fourth component, “Candidate Combination” introduces various strategies to combine the candidates with or without the local context (Section 3.4).

Note that it is crucial to integrate different human perspectives so that the system is flexible in processing both unintentional misspellings and various intentionally-created noisy tokens.

3.1 Enhanced Letter Transformation

Given a noisy token \( t_i \) seen in the text, the letter transformation subnormalizer produces a list of correction candidates \( s_i \) under the noisy channel model:

\[
\hat{s} = \arg \max_{s_i} p(s_i|t_i) = \arg \max_{s_i} p(t_i|s_i)p(s_i)
\]

where we assume each nonstandard token \( t_i \) is dependent on only one English word \( s_i \), that is, we are not considering acronyms (e.g., “bbl” for “be back later”) in this study. \( p(s_i) \) can be calculated as the unigram count from a background corpus. We formulate the process of generating a nonstandard token \( t_i \) from the dictionary word \( s_i \) using a letter transformation model, and use the model confidence as the probability \( p(t_i|s_i) \). Figure 1 shows several example (word, token) pairs.

To form a nonstandard token, each letter in the dictionary word can be labeled with: (a) one of the 0-9 digits; (b) one of the 26 characters including itself; (c) the null character “"”; (d) a letter combination\(^4\). This transformation process from dictio-

\(^3\)For the dictionary word, we allow the subnormalizers to either return the word itself or candidates that are the possibly intended words in the given context (e.g., with, “wit”).

\(^4\)The set of letter combinations used in this work are \{ah, ai, aw, ay, ck, ea, ey, ie, ou, te, wh\}
nary words to nonstandard tokens will be learned by a character-level sequence labeling system using the automatically collected (word, token) pairs. Next, we create a large lookup table by applying the character-level labeling system to the standard dictionary words and generate multiple variations for each word using the n-best labeling output, the labeling confidence is used as \( p(t_i|s_i) \). During testing, we search this lookup table to find the best candidate words for the nonstandard tokens. For tokens with letter repetition, we first generate a set of variants \( \{ \text{"pleas", "pleaas", "pleeaas", "pleeeaas"} \} \) for \( t_i = \{ \text{"pleeaaas"} \} \), then select the maximum posterior probability among all the variants:

\[
p(t_i|s_i) = \max_{t_i \in C_i} p(t_i|s_i)
\]

Different from the work in (Liu et al., 2011b), we enhanced the letter transformation process with two novel aspects: first, we devise a set of phoneme-, syllable-, morpheme- and word-boundary based features that effectively characterize the formation process of the nonstandard tokens; second, we propose a global context-aware approach to purify the automatically collected training (word, token) pairs, resulting system yielded similar performance but with only one ninth of the original data. We name this subnormalizer “Enhanced Letter Transformation”.

### 3.1.1 Context-Aware Training Pair Selection

Manual annotation of the noisy nonstandard tokens takes a lot of time and effort. (Liu et al., 2011b) proposed to use Google search engine to automatically collect large amount of training pairs. Yet the resulting (work, token) pairs are often noisy, containing pairs such as (events, “ents”), (downtown, “downto”), etc. The ideal training data should consist of the most frequent nonstandard tokens paired with the corresponding corrections, so that the system can learn from the most representative letter transformation patterns.

Motivated by research on word sense disambiguation (WSD) (Mihalcea, 2007), we hypothesize the nonstandard token and the standard word share a lot of common terms in their global context. For example, “luv” and “love” share “i”, “you”, “u”, “it”, etc. among their top context words. Based on this finding, we propose to filter out the low-quality training pairs by evaluating the global contextual similarity between the word and token. To the best of our knowledge, we are the first to explore this global contextual similarity for the text normalization task.

Given a noisy (word, token) pair, we construct two context vectors \( v_i \) and \( v_j \) by collecting the most frequent terms appearing before or after the work/token. We consider two terms on each side of the word/token as context and restrict the vector length to the top 100 terms. The frequency information were calculated using a large background corpus; stopwords were not excluded from the context vector. The contextual similarity of the (word, token) pair is defined as the cosine similarity between the context vectors \( v_i \) and \( v_j \):

\[
\text{ContextSim}(v_i, v_j) = \frac{\sum_{k=1}^{n} w_{i,k} \times w_{j,k}}{\sqrt{\sum_{k=1}^{n} w_{i,k}^2} \times \sqrt{\sum_{k=1}^{n} w_{j,k}^2}}
\]

where \( w_{i,k} \) is the weight of term \( t_k \) within the context of term \( t_i \). The term weights are defined using a normalized TF-IDF method:

\[
w_{i,k} = \frac{TF_{i,k}}{TF_i} \times \log\left(\frac{N}{DF_{t_k}}\right)
\]

where \( TF_{i,k} \) is the count of term \( t_k \) appearing within the context of term \( t_i \); \( TF_i \) is the total count of \( t_i \) in the corpus. \( \frac{TF_{i,k}}{TF_i} \) is therefore the relative frequency of \( t_k \) appearing in the context of \( t_i \); \( \log\left(\frac{N}{DF_{t_k}}\right) \) denotes the inverse document frequency of \( t_k \), calculated as the logarithm of total tweets \( (N) \) divided by the number of tweets containing \( t_k \).

To select the most representative (word, token) pairs for training, we rank the automatically collected 46,288 pairs by the token frequency, filter out pairs whose contextual similarity lower than a threshold \( \theta \) (set empirically at 0.0003), and retain only the top portion (5,000 pairs) for experiments.

### 3.1.2 Character-level Sequence Labeling

For a dictionary word \( s_i \), we use the conditional random fields (CRF) model to perform character-level labeling to generate its variant \( t_i \). In the training stage, we align the collected (word, token) pairs at the character level (Liu et al., 2011b), then construct a feature vector for each letter of the dictionary word, using its mapped character as the reference label. This aligned data set is used to train a CRF model (Lafferty et al., 2001; Kudo, 2005)
with L-BFGS optimization. We use the character/phoneme n-gram and binary vowel features as in (Liu et al., 2011b), but develop a set of boundary features to effectively characterize the letter transformation process.

We notice that in creating the nonstandard tokens, humans tend to drop certain letter units from the word or replace them with other letters. For example, in abbreviating “advertisements” to “ads”, humans may first break the word into smaller units “ad-ver-tise-ment-s”, then drop the middle parts. This also conforms with the word construction theory where a word is composed of smaller units and construction rules. Based on this assumption, we decompose the dictionary words on the phoneme-, syllable-, morpheme-, and word-level, labeled with the “BILOU” encoding scheme.

Table 2: Example boundary tags for word “advertisements” on the phoneme-, syllable-, morpheme-, and word-level, labeled with the “BILOU” encoding scheme.

| Character | advertisements |
|-----------|-----------------|
| Phoneme   | AE D V E R E R T A Y Z M AH N T S |
| Syllable boundary | O O O B1 L1 O O O O O O O |
| Morpheme boundary | B L B I I I I I I B I I I L U |
| Word boundary | B I I I I I I I I |

3.2 Visual Priming Approach

A second key component of the broad-coverage normalization system is a novel “Visual Priming” subnormalizer. It is built on a cognitively-driven “priming” effect, which has not been explored by other studies yet was shown to be effective across all our data sets.

“Priming” is an implicit memory effect caused by spreading neural networks (Tulving and Stark, 1982). As an example, in the word-stem completion task, participants are given a list of study words, and then asked to complete word “stems” consisting of first 3 letters. A priming effect is observed when participants complete stems with words on the study list more often than with the novel words. The study list activates parts of the human brain right before the stem completion task, later when a word stem is seen, less additional activation is needed for one to choose a word from the study list.

We argue that the “priming” effect may play an important role in human comprehension of the noisy tokens. A person familiarized with the “social talk” is highly primed with the most commonly used words; later when a nonstandard token shows only minor visual cues or visual stimulus, it can still be quickly recognized by the person. In this process, the first letter or first few letters of the word serve as a very important visual stimulus. Based on this assumption, we introduce the “priming” subnormalizer based only on the word frequency and the minor visual stimulus. Concretely, this approach proposes candidate words based on the following equation:

$$VisualPrim(s_i|t_i) = \frac{\text{len}(LCS(s_i|t_i))}{\text{len}(t_i)} \times \log(TF(s_i))$$

Where $TF(s_i)$ is the term frequency of $s_i$ as in the background social text corpus; $\log(TF(s_i))$ primes the system with the most common words in the social text; $LCS(\cdot)$ means the longest common character subsequence; $\text{len}(\cdot)$ denotes the length of the
character sequence. Together \( \frac{\text{len}(\text{LCS}(t_i, s_i))}{\text{len}(t_i)} \) provides the minor visual stimulus from \( t_i \). Note that the first character has been shown to be a crucial visual cue for the brain to understand jumbled words (Davis, 2007), we therefore consider as candidates only those words \( s_i \) that start with the same character as \( t_i \). In the case that the nonstandard token \( t_i \) starts with a digit (e.g., “2moro”), we use the mostly likely corresponding letter to search the candidates (those starting with letter “t”). This setting also effectively reduces the candidate search space.

The “visual priming” subnormalizer promotes the candidate words that are frequently used in the social talk and also bear visual similarity with the given noisy token. It slightly deviates from the traditional “priming” notion in that the frequency information were acquired from the global corpus rather than from the prior context. This approach also inherently follows the noisy channel framework, with \( p(t_i|s_i) \) represents the visual stimulus and \( p(s_i) \) being the logarithm of frequency. The candidate words are ranked by \( \hat{s} = \arg \max_s \text{VisualPrim}(s_i|t_i) \). We show that the “priming” subnormalizer is robust across data sets abide its simplistic representation.

### 3.3 Spell Checker

The third subnormalizer is the spell checker, which combines the string and phonetic similarity algorithms and is most effective in normalizing the misspellings. We use the Jazzy spell checker (Idzelis, 2005) that integrates the DoubleMetaphone phonetic matching algorithm and the Levenshtein distance using the near-miss strategy, which enables the interchange of two adjacent letters, and the replacing/deleting/adding of letters.

### 3.4 Candidate Combination

Each of the three subnormalizers is a stand-alone system and can suggest corrections for the nonstandard tokens. Yet we show that each subnormalizer mimics a different perspective that humans use to decode the nonstandard tokens, as a result, our broad-coverage normalization system is built by integrating candidates from the three subnormalizers using various strategies.

For a noisy token seen in the informal text, the most convenient way of system combination is to harvest up to \( n \) candidates from each of the subnormalizers, and use the pool of candidates (up to \( 3n \)) as the system output. This sets an upper bound for other candidate combination strategies, and we name this approach “Oracle”.

A second combination strategy is to give higher priority to candidates from high-precision subsystems. Both “Letter Transformation” and “Spell Checker” have been shown to have high precision in suggesting corrections (Liu et al., 2011b), while “Visual Priming” may not yield high precision due to its definition. We therefore take the top-3 candidates from each of the “Letter Tran.” and “Spell Checker” subsystems, but put candidates from “Letter Tran.” ahead of “Spell Checker” if the confidence of the best candidate is greater than a threshold \( \lambda \) and vice versa. The list of candidates is then compensated using the “Visual Priming” output until the total number reaches \( n \). We name this approach “Word-level” combination since no message-level context information is involved.

Based on the “Word-level” combination output, we can further rerank all the candidates using a message-level Viterbi decoding process (Pennell and Liu, 2011) where the local context information is used to select the best candidate. This approach is named “Message-level” combination.

### 4 Experiments

#### 4.1 Experimental Setup

We use four SMS and Twitter data sets to evaluate the system effectiveness. Statistics of these data sets are summarized in Table 3. Data set (1) to (3) are used for word-level evaluation; data set (4) for both word- and message-level evaluation. In Table 3, we also present the number of distinct nonstandard tokens found in each data set, and notice that only a small portion of the nonstandard tokens correspond to multiple standard words. We calculate the dictionary coverage of the manually annotated words since this sets an upper bound for any normalization system. We use the Edinburgh Twitter corpus (Petrovic et al., 2010) as the background corpus for frequency calculation, and a dictionary containing 82,324 words.\(^8\) The nonstandard tokens may consist of both numbers/characters and apostrophe.

\(^8\)The dictionary is created by combining the CMU (CMU, 2007) and Aspell (Atkinson, 2006) dictionaries and dropping words with frequency < 20 in the background corpus. “rt” and all single characters except “a” and “i” are excluded.
The goal of word-level normalization is to convert the list of distinct nonstandard tokens into standard words. For each nonstandard token, the system is considered correct if any of the corresponding standard words is among the n-best output from the system. We adopt this word-level n-best accuracy to make our results comparable to other state-of-the-art systems. On message-level, we evaluate the 1-best system output using precision, recall, and f-score, calculated respective to the nonstandard tokens.

4.2 Word-level Results

The word-level results are presented in Table 4, 5, and 6, evaluated on data set (1), (2), (3) respectively. We present the n-best accuracy \((n = 1, 3, 10, 20)\) of the system as well as the “Oracle” results generated by pooling the top-20 candidates from each of the three subnormalizers. The best prior results on the data sets are also included in the tables.

We notice that the broad-coverage system outperforms all other systems on the reported data sets. It achieves about 90% word-level accuracy on data set (1) and (2) with the top-10 candidates (an average 10% performance gain compared to (Liu et al., 2011)). This is of crucial importance to a normalization system, since the high accuracy and limited number of candidates will enable more sophisticated reranking or supervised learning techniques to select the best candidate. We also observe the “Oracle” system has averagely only 5% gap to the dictionary coverage. A detailed analysis shows that the human annotators perform many semantic/grammar corrections as well as inconsistent annotations, e.g., (sleepy, “zzz”), (disliked, “unliked”). These are out of the capabilities of the current text normalization system and partly explains the remaining 5% gap.

Regarding the subnormalizer performance, the spell checker yields only 50% to 60% accuracy on all data sets, indicating that the vast amount of the intentionally created nonstandard tokens can hardly be tackled by a system relies solely on the lexical/phonetic similarity. The “Visual Priming” sub-normalizer performs surprisingly well and shows robust performance across all data sets. A minor side-effect is that the candidates were restricted to have the same first letter with the noisy token, this sets the upper bound of the approach to 89.77%, 92.45%, and 93.51%, respectively on data set (1), (2), and (3). Compared to other subnormalizers, the “Enhanced Letter Tran.” is effective at normalizing intentionally created tokens and has better precision regarding its top candidate \((n = 1)\). We demonstrate the context-aware training pair selection results in Figure 2, by plotting the learning curve using different amounts of training data, ranging from 1,000 (word, token) pairs to the total 46,288 pairs. We notice that the system can effectively learn the letter transformation patterns from a small number of high quality training pairs. The final system was trained using the top 5,000 pairs and the lookup table was created by generating 50 variations for each dictionary word.

4.3 Message-level Results

The goal of message-level normalization is to replace each occurrence of the nonstandard token with the candidate word that best fits the local context.

| Index | Domain          | Time Period             | #Msgs | #Uniq Nonstan. Tokens | %Nonstan. Tkns w/ Multi-cands | %Dict cov. ReferenceTokens w/ Multi-cands | Reference         |
|-------|------------------|-------------------------|-------|-----------------------|-------------------------------|------------------------------------------|-------------------|
| (1)   | SMS              | Around 2007             | n/a   | 303                   | 1.32%                         | 100%                                     | (Choudhury et al., 2007) |
| (2)   | Twitter          | Nov 2009 – Feb 2010     | 6150  | 3802                  | 3.87%                         | 99.34%                                   | (Liu et al., 2011)  |
| (3)   | SMS/Twitter      | Aug 2009                | 4660  | 2040                  | 2.41%                         | 96.84%                                   | (Pennell and Liu, 2011) |
| (4)   | Twitter          | Aug 2010 – Oct 2010     | 549   | 558                   | 2.87%                         | 99.10%                                   | (Han and Baldwin, 2011) |

Table 3: Statistics of different SMS and Twitter data sets.

| SMS Dataset (303 pairs) | Word Level Accuracy (%) |
|-------------------------|-------------------------|
|                         | 1-best | 3-best | 10-best | 20-best | Oracle |
| Jazzy Spell Checker     | 43.89  | 55.45  | 56.77   | 56.77   | n/a    |
| Visual Priming          | 54.13  | 74.92  | 84.82   | 87.13   | n/a    |
| Enhanced Letter Tran.   | 61.06  | 74.92  | 80.86   | 82.51   | n/a    |
| Broad-Cov. System       | 64.36  | 80.20  | 89.77   | 91.75   | 94.06  |

Table 4: Word-level results on data set (1). * denotes system requires human annotations for training.

| Twitter Dataset (3802 pairs) | Word Level Accuracy (%) |
|-----------------------------|-------------------------|
|                            | 1-best | 3-best | 10-best | 20-best | Oracle |
| Jazzy Spell Checker         | 47.19  | 56.92  | 59.13   | 59.18   | n/a    |
| Visual Priming              | 54.34  | 70.59  | 80.83   | 84.74   | n/a    |
| Enhanced Letter Tran.       | 61.05  | 70.07  | 74.04   | 74.75   | n/a    |
| Broad-Cov. System           | 69.81  | 82.51  | 92.24   | 93.79   | 95.71  |

Table 5: Word-level results on data set (2).
Table 6: Word-level results on data set (3). * denotes system requires human annotations for training.

| SMS/Twitter Dataset                  | Word Level Accuracy (%) |
|--------------------------------------|-------------------------|
| 2404 pairs                           |                         |
|                                      | 1-best 3-best 10-best 20-best Oracle |
| Jazzy Spell Checker                  | 39.89 46.51 48.54 48.67 n/a |
| Visual Priming                      | 54.12 68.59 78.83 83.11 n/a |
| Enhanced Letter Tran.               | 57.65 67.18 71.01 71.88 n/a |
| Broad-Cov. System                   | 64.39 78.29 86.56 88.69 91.60 |
| (Pennell et al., 2011)*             | 57.40 n/a n/a 72.38 n/a |

Table 7: Message-level results on data set (4). * denotes system requires human annotations for training.

| Twitter Dataset (549 Tweets)        | Message-level P/R/F |
|-------------------------------------|---------------------|
|                                      | Precision (%) Recall (%) F-score (%) |
| Word-level w/o Context              | 75.69 66.81 70.97 |
| w/ Context                          | 79.12 77.11 78.10 |
| Web LM                              | 84.13 78.38 81.15 |
| Twitter LM                          | (Han and Baldwin, 2011)* 75.30 75.30 75.30 |

5 Conclusion

In this paper, we propose a broad-coverage normalization system for the social media language without using the human annotations. It integrates three key components: the enhanced letter transformation, visual priming, and string/phonetic similarity. The system was evaluated on both word- and message-level using four SMS and Twitter data sets. We show that our system achieves over 90% word-coverage across all data sets and the broad word-coverage can be successfully translated into message-level performance gain. We observe that the social media is an emotion-rich language, therefore future normalization system will need to address various sentiment-related expressions, such as emoticons (“:d”, “X-8”), interjections (“bwahaha”, “brrrr”), acronyms (“lol”, “lmao”), etc., whether and how these expressions should be normalized is an unaddressed issue and worths future investigation.

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