Personalized Normalization for a Multilingual Chat System

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Abstract
This paper describes the personalized normalization of a multilingual chat system that supports chatting in user defined short-forms or abbreviations. One of the major challenges for multilingual chat realized through machine translation technology is the normalization of non-standard, self-created short-forms in the chat message to standard words before translation. Due to the lack of training data and the variations of short-forms used among different social communities, it is hard to normalize and translate chat messages if user uses vocabularies outside the training data and create short-forms freely. We develop a personalized chat normalizer for English and integrate it with a multilingual chat system, allowing user to create and use personalized short-forms in multilingual chat.

1 Introduction
Processing user-generated textual content on social media and networking usually encounters challenges due to the language used by the online community. Though some jargons of the online language has made their way into the standard dictionary, a large portion of the abbreviations, slang and context specific terms are still uncommon and only understood within the user community. Consequently, content analysis or translation techniques developed for a more formal genre like news or even conversations cannot apply directly and effectively to the social media content. In recent years, there are many works (Aw et al., 2006; Cook et al., 2009; Han et al., 2011) on text normalization to preprocess user generated content such as tweets and short messages before further processing. The approaches include supervised or unsupervised methods based on morphological and phonetic variations. However, most of the multilingual chat systems on the Internet have not yet integrated this feature into their systems but requesting users to type in proper language so as to have good translation. This is because the current techniques are not robust enough to model the different characteristics featured in the social media content. Most of the techniques are developed based on observations and assumptions made on certain datasets. It is also difficult to unify the language uniqueness among different users into a single model.

We propose a practical and effective method, exploiting a personalized dictionary for each user, to support the use of user-defined short-forms in a multilingual chat system - AsiaSpik. The use of this personalized dictionary reduces the reliance on the availability and dependency of training data and empowers the users with the flexibility and interactivity to include and manage their own vocabularies during chat.

2 ASIASPIK System Overview
AsiaSpik is a web-based multilingual instant messaging system that enables online chats written in one language to be readable in other languages by other users. Figure 1 describes the system process. It describes the process flow between Chat Client, Chat Server, Translation Bot and Normalization Bot whenever Chat Client starts chat module.

When Chat Client starts chat module, the Chat Client checks if the normalization option for that language used by the user is active and activated. If
so, any message sent by the user will be routed to the Normalization Bot for normalization before reaching the Chat Server. The Chat Server then directs the message to the designated recipients. Chat Client at each recipient invokes a translation request to the Translation Bot to translate the message to the language set by the recipient. This allows the same source message to be received by different recipients in different target languages.

Figure 1. AsiaSpik Chat Process Flow

In this system, we use Openfire Chat Server by Ignite Realtime as our Chat Server. We custom build a web-based Chat Client to communicate with the Chat Server based on Jabber/XMPP to receive presence and messaging information. We also develop a user management plug-in to synchronize and authenticate user login. The translation and normalization function used by the Translation Bot and Normalization Bot are provided through Web Services.

The Translation Web Service uses in-house translation engines and supports the translation from Chinese, Malay and Indonesian to English and vice versa. Multilingual chat among these languages is achieved through pivot translation using English as the pivot language. The Normalization Web Service supports only English normalization. Both web services are running on Apache Tomcat web server with Apache Axis2.

3 Personalized Normalization

Personalized Normalization is the main distinction of AsiaSpik among other multilingual chat system. It gives the flexibility for user to personalize his/her short-forms for messages in English.

3.1 Related Work

The traditional text normalization strategy follows the noisy channel model (Shannon, 1948). Suppose the chat message is \( C \) and its corresponding standard form is \( S \), the approach aims to find \( \arg\max P(S \mid C) \) by computing \( \arg\max P(C \mid S) \) in which \( P(S) \) is usually a language model and \( P(C \mid S) \) is an error model.

The objective of using model in the chat message normalization context is to develop an appropriate error model for converting the non-standard and unconventional words found in chat messages into standard words.

\[
\hat{S} = \arg\max_S P(S \mid C) = \arg\max_S P(C \mid S) P(S)
\]

Recently, Aw et al. (2006) model text message normalization as translation from the texting language into the standard language. Choudhury et al. (2007) model the word-level text generation process for SMS messages, by considering graphemic/phonetic abbreviations and unintentional typos as hidden Markov model (HMM) state transitions and emissions, respectively. Cook and Stevenson (2009) expand the error model by introducing inference from different erroneous formation processes, according to the sample error distribution. Han and Baldwin (2011) use a classifier to detect ill-formed words, and generate correction candidates based on morphophonemic similarity. These models are effective on their experiments conducted, however, much works remain to be done to handle the diversity and dynamic of content and fast evolution of words used in social media and networking.

As we notice that unlike spelling errors which are made mostly unintentionally by the writers, abbreviations or slangs found in chat messages are introduced intentionally by the senders most of the time. This leads us to suggest that if facilities are given to users to define their abbreviations, the dynamic of the social content and the fast
evolution of words could be well captured and managed by the user. In this way, the normalization model could be evolved together with the social media language and chat message could also be personalized for each user dynamically and interactively.

3.2 Personalized Normalization Model

We employ a simple but effective approach for chat normalization. We express normalization using a probabilistic model as below:

\[
s_{\text{best}} = \arg \max_s P(s | c)
\]

and define the probability using a linear combination of features

\[
P(s | c) \propto \exp \sum_{k=1}^{m} \lambda_k h_k(s, c)
\]

where \(h_k(s, c)\) are two feature functions namely the log probability \(P(s_{i,j} | c_i)\) of a short-form, \(c_i\), being normalized to a standard form, \(s_{i,j}\); and the language model log probability. \(\lambda_k\) are weights of the feature functions.

We define \(P(s_{i,j} | c_i)\) as a uniform distribution computed through a set of dictionary collected from corpus, SMS messages and Internet sources. A total of 11,119 entries are collected and each entry is assigned with an initial probability, \(P(s_{i,j} | c_i) = \frac{1}{|c_i|}\), where \(|c_i|\) is the number of \(c_i\) entries defined in the dictionary. We adjust the probability manually for some entries that are very common and occur more than a certain threshold, \(t\), in the NUS SMS corpus (How and Kan, 2005) with a higher weight-age, \(w\). This model, together with the language model, forms our baseline system for chat normalization.

To enable personalized real-time management of user-defined abbreviations and short-forms, we define a personalized model \(P_{\text{user},j}(s_{i,j} | c_i)\) for each user based on his/her dictionary profile. Each personalized model is loaded into the memory once the user activates the normalization option. Whenever there is a change in the entry, the entry’s probability will be re-distributed and updated based on the following model. This characterizes the AsiaSpik system which supports personalized and dynamic chat normalization.

\[
P_{\text{user},j}(s_{i,j} | c_i) = \begin{cases} 
\frac{P(s_{i,j} | c_i) \times N}{N + M} & \text{if } c_i, s_{i,j} \in \text{SD} \\
\frac{1}{N + M} & \text{if } c_i \in \text{SD}, s_{i,j} \notin \text{SD} \\
\frac{1}{M} & \text{if } c_i \notin \text{SD}
\end{cases}
\]

where
- SD denotes default dictionary;
- \(N\) denotes the number of \(c_i\) entries in SD
- \(M\) denotes the number of \(c_i\) entries in user dictionary.

The feature weights in the normalization model are optimized by minimum error rate training (Och, 2003), which searches for weights maximizing the normalization accuracy using a small development set. We use standard state-of-the-art open source tools, Moses (Koehn, 2007), to develop the system and the SRI language modeling toolkit (Stolcke, 2003) to train a trigram language model on the English portion of the Europarl Corpus (Koehn, 2005).

3.3 Experiments

We conducted a small experiment using 134 chat messages sent by high school students. Out of these messages, 73 short-forms are uncommon and not found in our default dictionary. Most of these
short-forms are very irregular and hard to predict their standard forms using morphological and phonetic similarity. It is also hard to train a statistical model if training data is not available. We asked the students to define their personal abbreviations in the system and run through the system with and without the user dictionary. We asked them to give a score of 1 if the output is acceptable to them as proper English, otherwise a 0 will be given. We compared the results using both the baseline model and the model implemented using the same training data as in Aw et al. (2006).

Table 1 shows the number of accepted output between the two models. Both models show improvement with the use of user dictionary. It also shows that it is very critical to have similar training data for the targeted domain to have good normalization performance. A simple model helps if such training data is unavailable. Nevertheless, the use of a dictionary driven by the user is an alternative to improve the overall performance. One reason for the inability of both models to capture the variations fully is because many messages require some degree of rephrasing in addition to insertion and deletion to make it readable and acceptable. For example, the ideal output for “haiz, I wanna pontang school” is “Sigh, I do not feel like going to school”, which may not be just a normalization problem.

| Chat Message            | Chat Message normalized using the Default dictionary | Chat Message normalized with the supplement of user dictionary |
|-------------------------|-----------------------------------------------------|---------------------------------------------------------------|
| buy din 4 urself.       | Buy didn’t for yourself.                            | Buy dinner for yourself.                                       |
| dnr cook dun 4 me 2nite  | Don’t cook do not reply for me tonight              | Don’t cook dinner for me tonight                               |
| gtn bb ttyl tfn         | Got to go bb ttyl tfn                              | Got to go bye talk to you later bye bye                       |
| I dun feel lyk riting   | I don’t feel lyk riting                             | I don’t feel like writing                                      |
| im gng hme 2 mug        | I’m going hme two mug                               | I’m going home to study                                        |
| msg me wh u rch         | Message me wh you rch                               | Message me when you reach                                      |
| so sian I dun wanna do hw now | So sian I don’t want to do how now                  | So bored I don’t want to do homework now                      |

Table 2. Normalized chat messages

AsiaSpik Multilingual Chat

Figure 2 and Figure 3 show the personal lingo defined by two users. Note that expansions for “gtg” and “tgt” are defined differently and expanded differently for the two users. ‘Me’ in the message box indicates the message typed by the user while ‘Expansion’ is the message expanded by the system.

| Baseline Model | Baseline + User Dictionary | Aw et al. (2006) | Aw et al. (2006) + user Dictionary |
|----------------|-----------------------------|------------------|----------------------------------|
| 40             | 72                          | 17               | 42                               |

Table 1. Number of Correct Normalization Output

In the examples showed in Table 2, ‘din’ and ‘dnr’ are normalized to ‘didn’t’ and ‘do not reply’ based on the entries captured in the default dictionary. With the extension of normalization hypotheses in the user dictionary, the system produces the correct expansion to ‘dinner’.
4 Conclusions

AsiaSpik system provides an architecture for performing chat normalization for each user such that user can chat as usual and does not need to pay special attention to type in proper language when involving translation for multilingual chat. The system aims to overcome the limitations of normalizing social media content universally through a personalized normalization model. The proposed strategy makes user the active contributor in defining the chat language and enables the system to model the user chat language dynamically.

The normalization approach is a simple probabilistic model making use of the normalization probability defined for each short-form and the language model probability. The model can be further improved by fine-tuning the normalization probability and incorporate other feature functions. The baseline model can also be further improved with more sophisticated method without changing the architecture of the full system.

AsiaSpik is a demonstration system. We would like to expand the normalization model to include more features and support other languages such as Malay and Chinese. We would also like to further enhance the system to convert the translated English chat messages back to the social media language as defined by the user.

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