Improving Cultural Difference Detection System Using Confidence Value

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Abstract. The Cultural Difference Detection(CDD) concept was introduced to enhance machine translation(MT) utility by predicting possible misunderstanding. CDD compares images linked to a concept in two languages with the assumption that low image similarity may indicate possible cultural misunderstanding. This paper extends CDD by proposing a method to calculate *confidence value* that assess the accuracy of CDD. Confidence value can be used to decide whether to warn the user of a possible misunderstanding when a suspect word is used in a multilingual chat system.

Keywords: Intercultural collaboration · Cultural difference · Cultural misunderstanding.

1 Introduction

Despite MT's usefulness, it sometimes causes difficulties, for instance, conversation breakdown [2] and barriers to the establishment of mutual understanding [5]. The word '団子' (dan-go), which refers to Japanese sweet dumplings made of rice flour usually skewered onto a bamboo stick, is translated into 'dumpling' in English. Even though the translation is not wrong, the images of '団子' and 'dumpling' from image search are different meaning that people from different cultures tend to draw different mental images from each word. Based on this idea, we developed the Cultural Difference Detection(CDD) method to automatically detect words that were deemed likely to cause misunderstanding [3]. CDD is based on image databases and automated image comparison.

2 Cultural Difference Detection (CDD)

Images databases can be used to identify cultural differences when they are linked to or tagged with keywords in different languages. The process starts with selecting a synset (set of synonyms) from Japanese WordNet [1], a concept dictionary containing lexical data in Japanese and English. A synset contains various information but CDD uses only one or two word(s) in English and one or two word(s) in Japanese depending on availability. Each word is used as a keyword for searching several images. Then, each image is converted into feature

vectors and average feature vectors are calculated. After that, two average vectors are compared. The original paper used cosine similarity for this step. If the similarity is low or lower than a threshold, it is assumed that cultural differences exist. Conversely, if the similarity is higher than a threshold, it is assumed that the cultural difference is insignificant. The result from CDD can be used as a reference for cultural difference or applied to collaboration services, such as an MT-embedded chat system. An experiment assessed if it could warn MT users of potential cultural misunderstandings [4]. The aim was to create a system that warned its user when a word that could cause misunderstanding was used in an MT-embedded chat system.

3 Confidence Value

3.1 Motivation and Concept

To further develop the automated system as an intercultural support tool, we recreated the experiment conducted on the original CDD. We observed that during image collection, some set of images contained similar images while some sets contained different images. Fig. 1 displays images from Google image searches using the word 'Leftover' and the word 'Globe'. 'Leftover' contains images of different types of food which offer a close association with the keyword. However, when this set of images is used to generate the English language vector of 'Leftover', to permit comparison with image vectors from different languages, CDD accuracy fallls. 'globe', on the other hand, yields similar images, so CDD accuracy is acceptable. This suggests that there might be a correlation between the similarity of the images in the same set and the accuracy of CDD prediction.

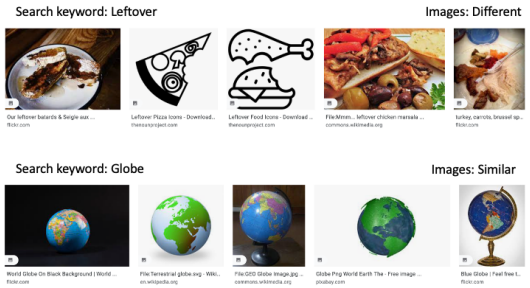

Fig. 1. Examples of keyword with different image search result (above) and keyword with similar image search results(below)

3.2 Confidence Value Calculation

The process displayed in Fig. 2 is used calculate the confidence value. For each word, the image set linked to that keyword, which is the same set of images for CDD calculation are loaded. The images are converted into feature vectors, and the feature vectors will be compared using the similarity calculated between all possible vector pairs. The similarity values are averaged which yields the confidence value.

To add confidence value to CDD, first, each keyword, or each word used in CDD determination can be associated with one confidence value. However, some synsets contain more than one keyword used in CDD determination. In that case, the confidence value between two keywords will be averaged. This averaged value could be used to indicate how reliable the calculated result is for each language in the same synset. In this paper, we focus on using confidence value to reflect the accuracy of the similarity between two languages, so the confidence value for each language is averaged once again to indicate how reliable each CDD result is.

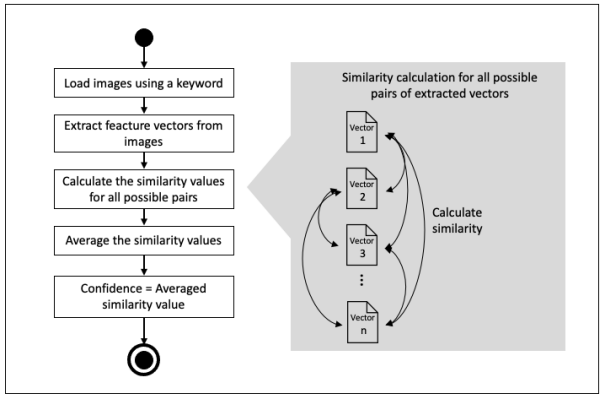

Fig. 2. Confidence value calculation process

4 Preliminary Experiment

We prepared 300 synsets and calculated the confidence value of each synset using the proposed concept. We asked 6 human evaluators, 3 native speakers of Japanese and 3 speakers of English, to evaluate the CDD result. Then, we calculated the percentage of correct predictions for each synset with a different confidence value range. The result shows that the synsets with high confidence value also offer accurate predictions. The correlation between accuracy for English and the confidence value is 0.843, while the correlation between accuracy

for Japanese and the confidence value is 0.927. From this result, we can infer that the proposed confidence value is strongly correlated to the accuracy of CDD prediction.

5 Discussion

For high confidence synsets, the confidence value can help to make fast decisions about what words will yield problematic translations; for the low confidence synsets, we suggest that it is necessary to apply some other methods to CDD, for example, dictionary-based prediction, which also a part of our future work.

6 Conclusion

The main contribution this paper is its proposal of a method to calculate confidence value for automated cultural different detection(CDD). This confidence value can be used to help to decide when the system should warn the user about potential cultural misunderstanding when a problematic word is typed into the chat window. In the future, we plan to conduct an experiment to evaluate the accuracy of the automated system by comparing CDD judgment to human evaluation. The preliminary experiment described herein shows that there is a high correlation between the proposed confidence value and the accuracy of CDD prediction.

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