A Computational System of Metaphor Generation with Evaluation Mechanism*

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Abstract. This study regards metaphor generation as a process where an expression consisting of a target (A) is modified by certain features to become a metaphorical expression of the form "target (A) like vehicle (B)". A computational system consisting of a metaphor generation process and a metaphor evaluation process is developed. In the metaphor generation process, a metaphor generation model [1] outputs candidate nouns for vehicles from input expressions. In the metaphor evaluation process, the candidate nouns are evaluated based on the similarities between the meanings of metaphors including the candidate nouns and the meaning of the input expression.

1 Introduction

The purpose of this study is to construct a computational system that generates metaphors of the form "A (target) like B (vehicle)" from the features of the target based on statistical language analysis and that incorporates an evaluation mechanism. Some computational models of metaphor generation using a corpus have been developed [2][3][1]. For instance, Kitada and Hagiwara[2] constructed a figurative composition support system including a model of metaphor generation based on an electronic dictionary. In contrast, Abe, Sakamoto and Nakagawa's model[3] is based on the results of statistical language analysis, which is more objective than existing dictionaries that must be compiled through the considerable efforts of language professionals. Moreover, Terai and Nakagawa [1] constructed a model that incorporates the dynamic interaction among features using the statistical language analysis.

The earlier models based on a corpus can output candidate nouns from the inputs for the target and its features that are represented by adjectives or verbs. However, the models do not have a mechanism of evaluating the candidate nouns. Abe, et al.'s model and Terai and Nakagawa's model do not evaluate their outputs. Kitada and Hagiwara's model[2] is a support system for metaphorical composition. The system outputs candidate nouns for the vehicle and features that are represented by the metaphor including the candidate noun for the vehicle.

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Users are responsible for the evaluation and selection of the candidate nouns by referring to the presented features.

Sako, Nakamura and Yoshida[4] constructed a computational model of metaphor generation based on a psychological experiment. The model does not represent the dynamic interaction among features and is not able to technically cover all general metaphors because the model is based on a psychological experiment. However, the model has an advantage over the previous models based on corpus[2][3][1]. The advantage lies in the fact that it has an evaluation mechanism. The model technically consists of a metaphor generation process and a metaphor evaluation process. In the metaphor generation process, the model outputs candidate nouns for the vehicle. In the subsequent metaphor evaluation process, first, each similarity between the target and each candidate noun is computed. Next, the candidate nouns are evaluated based on these similarities. From a cognitive point of view, it is important to evaluate the candidates for the vehicle, in order to generate metaphorical expressions that evoke a common view between speakers and listeners. However, in the metaphor evaluation process, their model does not evaluate the meaning represented by the generated metaphorical expression, but rather it evaluates the figurativeness of the generated metaphorical expression.

The present study implements an evaluation mechanism within the model proposed by Terai and Nakagawa[1], which represents the dynamic interaction among features based on statistical language analysis. Thus, the newly proposed system has two processes: a metaphor generation process and a metaphor evaluation process. In the metaphor generation process, the metaphor generation model[1] outputs candidate nouns for the vehicles from the inputs for the target and its features that are represented by adjectives or verbs. In the metaphor evaluation process, first, the meaning of the metaphor including the candidate noun as the vehicle and the meaning of the expression consisting of the inputs for the target and its features are computed. Next, the similarities between the meaning of the metaphor and the meaning of the input expression are computed and the candidate nouns are evaluated based on these similarities. Thus, the metaphor that is most similar to the input expression is output as the most adequate metaphor.

2 A Computational System of Metaphor Generation

2.1 Knowledge Structure Based on Statistical Language Analysis

The metaphor generation system is constructed using a knowledge structure based on a statistical language analysis[5], which was also used in previous studies[3][1]. The statistical language analysis[5] estimates latent classes among nouns and adjectives (or verbs) as a knowledge structure using four kinds of frequency data extracted for adjective-noun modifications (Adj) and three kinds of verb-noun modifications: noun(subject)-verb (S-V), verb-noun(modification) (V-M), and verb-noun(object) (V-O). These frequency data are extracted from the Japanese newspaper for the period 1993-2002. The statistical method assumes that $P(n_i^r, a_j^r)$ (r refers to the kind of data set) can be computed using the following formula(1):

$$P(n_i^r, a_j^r) = \sum_k P(n_i^r|c_k^r)P(a_j^r|c_k^r)P(c_k^r), \tag{1}$$

where c_k^r indicates the kth latent class assumed within this method for the r type of modification data. The parameters ($P(n_i^r|c_k^r)$, $P(a_j^r|c_k^r)$, and $P(c_k^r)$) are estimated using the EM algorithm. The statistical language analysis is applied to each set of co-occurrence data fixing the number of latent classes at 200. The conditional probabilities, $P(c_k^r|n_i^r)$ and $P(c_k^r|a_j^r)$, are computed using Bayes' theory. The 18,142 noun types (n_h^*) that are common to all four types of modification data and the features are represented as vectors using the following formula,

$$V_p(n_h^*) = P(c_k^r|n_h^*), \tag{2}$$

$$V_p(a_j^r) = \begin{cases} P(c_k^r|a_j^r) & \\ 0 & \text{else,} \end{cases} \tag{3}$$

where $V_p(n_h^*)$ indicates the pth component of the vector that corresponds to the noun n_h^*. p refers to the successive number of latent classes extracted from the four data sets. When $1 \leq p \leq 200$, r indicates the "Adj" modification and $k = p$, when $201 \leq p \leq 400$, r indicates the "S-V" modification and $k = p - 200$, when $401 \leq p \leq 600$, r indicates the "V-M" modification and $k = p - 400$, and when $600 \leq p \leq 800$, r indicates the "V-O" modification and $k = p - 600$.

2.2 The Metaphor Generation Process

The metaphor generation process is realized using the metaphor generation model[1]. The model outputs candidate nouns for the vehicles from inputs consisting of the target and its features that are represented by adjectives or verbs. The model consists of three layers: an input layer, a hidden layer, and an output layer. The input layer consists of feature nodes, which each indicating either an adjective or a verb. Each feature node relating to the target has mutual and symmetric connections with the other feature nodes relating to the target. The mutual connections represent the dynamic interaction among features. The hidden layer consists of nodes which indicate the latent classes estimated using the statistical language analysis. The output layer consists of noun nodes. Sets of input expressions, such as "$a_{j_1}^{r_1}$ - n_h^*","$a_{j_2}^{r_2}$ - n_h^*", are input into the model. The model outputs each noun's adequacy for the vehicle, which represents a set of input expressions, such as "n_h^* (target) like B (vehicle)".

2.3 The Metaphor Evaluation Process

In the metaphor evaluation process, the meanings of the generated metaphorical expressions and the meaning of the expression consist of the inputs for the target and its features are computed, and the candidate nouns are evaluated based on the similarities between the meaning of the metaphor and the meaning of the input expression. These are estimated based on Kintsch's predication algorithm[6]. This algorithm can be used to estimate the meaning vectors of a metaphorical expression and a literal expression using different parameter values. Thus, in this process, the meaning vector of a metaphor including candidate noun and the meaning vector of a set of input literal expressions are computed. Then, the metaphor including the candidate nouns are evaluated based on the similarities between these vectors.

Estimating the Meaning of the Metaphor Expression. The meaning of the metaphor consisting of the target and the candidate vehicle is estimated using the meaning vectors. This algorithm represents the class inclusion theory which explains metaphor understanding in terms of class-inclusion statements, where a target is regarded as a member of an ad hoc category of which the vehicle is a prototypical member[7]. For example, in comprehending the metaphor "Hope like glim", the target "hope" can be regarded as belonging to a "transient" category that could be typically represented by a vehicle such as "glim". First, the semantic neighborhood ($N(n_h)$) of a vehicle of size Sn^m is computed on the basis of the similarity to the vehicle, which is represented by the cosine of the angles between the meaning vectors. Next, S^m nouns are selected from the semantic neighborhood ($N(n_h)$) of the vehicle on the basis of their similarity to the target. Finally, a vector ($V(M)$) is computed as the centroid of the meaning vectors for the target, the vehicle and the selected S^m nouns. The computed vector ($V(M)$) indicates the assigned meaning of the target as a member of the ad-hoc category of the vehicle in the metaphor M. The category consisting of the vehicle and the selected S^m nouns is regarded as an ad hoc category of which the vehicle is a prototypical member according to class inclusion theory[7].

Estimating the Meaning of the Input Expression. The meaning of the expression consisting of the inputs for the target and its features, which is called as the input expression, is also estimated. First, the semantic neighborhood ($N(a_{j_u}^{r_u})$) of a feature of size Sn^l is computed on the basis of the similarity to the feature, which is represented by the cosine of the angles between feature vectors. Next, S^l features are selected from the semantic neighborhood ($N(a_{j_u}^{r_u})$) of the feature on the basis of their similarity to the target. Finally, a vector ($V(L)$) is computed as the centroid of the meaning vectors for the target, the vehicle and the selected S^l features. The computed vector ($V(L)$) indicates the meaning of the target, which is modified using the input features as the lateral expression L.

2.4 Result of the Simulation

In this study[1], the evaluation model simulates using the parameters $Sn^m = 50$, $S^m = 3$, $Sn^l = 10$, $S^l = 3$. It is arranged that the value of Sn^m is higher than

[1] The metaphor generation model[1] simulates using the parameters $\alpha = ln(10)$, $\beta = 0.1$, $\gamma = 10$.

Table 1. The results of the metaphor evaluation process for the results of the metaphor generation model with interaction and for the model without interaction (similarity:ranking in the generation process)

	"transient hope", "hope disappear"	
	the model with an interaction	the model without an interaction
1	pin money (0.6549:10)	delight (0.5417:8)
2	light bulb (0.6344:9)	conviction (0.5123:5)
3	glim (0.5963:4)	interest (0.6552:2)
4	neon (0.5914:6)	question (0.4889:4)
5	illuminations (0.5833:5)	motivation (0.4781:6)
6	lamp (0.5627:3)	requirement (0.4455:9)
7	celebratory drink (0.5378:2)	disposition (0.5645:10)
8	candle (0.5144:8)	request (0.6538:3)
9	afterglow (0.3934:7)	afterglow (0.5928:7)
10	red light (0.3532:1)	red light (0.5646:1)

that of Sn^l, because it was been reported that the simulation of metaphorical expressions requires a larger semantic neighborhood than literal expressions[6]. The similarity between the metaphorical and input expressions is represented by the cosine of the angles between the vectors of the metaphorical expression ($V(M)$) and of the input expression ($V(L)$). Each similarity between the input target and each candidate noun is computed. The higher the similarity of the candidate noun is, the more adequate the candidate noun is for the vehicle. The results are shown in Table1.

A psychological experiment was conducted in order to verify these results. In the psychological experiment, 14 graduate students were presented with the input set of "transient hope" and "hope disappear". They were asked to answer the vehicle in the metaphor "hope like B" using a noun. The three nouns responded as the vehicle by more than two people were "candle" (by 4 people), "glim" (by 3 people) and "bubble" (by 3 people). The metaphor generation model with interaction estimates "candle" and "glim" among the top 10 candidate nouns but the model without interaction does not. "Glim" is the fourth candidate noun for the metaphor generation process is emphasized as the third candidate noun in the metaphor evaluation process. It can be considered that "red light" is not so transient and so is less adequate for the vehicle than the other candidate nouns. However, it is estimated as the most adequate candidate in the metaphor generation process. In the metaphor evaluation process, it is estimated as the tenth candidate. This result indicates the necessity of the metaphor evaluation process. Furthermore, the similarities of the candidates from the model without interaction are less than those from the model with interaction. The results of the evaluation process indicate that the metaphor generation model with interaction performs better simulations than the model without interaction.

3 Discussion

In this study, a computational system of metaphor generation incorporating an evaluation mechanism was constructed based on data obtained through a statistical language analysis[5] using a previous model[1]. Although a noun, which does not represent the image of the input feature, can be estimated as the most adequate candidate within the metaphor generation process, the noun may be estimated as a less than adequate candidate within the evaluation process. In addition, the results of the psychological experiment support the result of the system using the metaphor generation model with interaction[1]. However, the psychological experiment was conducted with only one input expression. In order to examine the more general validity of the system, an experiment should be conducted with a wider range of expression sets. And, it needs to examine an effect of the parameter values on results. In addition, although the participants did not respond with “pin money” for the vehicle, the system output the original metaphor “hope like pin money” as the most adequate metaphor for “transient hope” and “hope disappears”. That suggests that the system has the potential to generate more original metaphors than humans.

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