

Predicative Metaphors Are Understood as Two-Stage Categorization: Computational Evidence by Latent Semantic Analysis

Akira Utsumi (utsumi@se.uec.ac.jp)

Department of Systems Engineering
The University of Electro-Communications
1-5-1, Chofugaoka, Chofushi, Tokyo 182-8585, Japan

Maki Sakamoto (sakamoto@hc.uec.ac.jp)

Department of Human Communication
The University of Electro-Communications
1-5-1, Chofugaoka, Chofushi, Tokyo 182-8585, Japan

Abstract

In this paper, we address the problem of how people understand predicative metaphors such as “The rumor flew through the office”, and argue that two-stage categorization is the process via which predicative metaphors are understood. In the two-stage categorization process, the verb of a predicative metaphor (e.g., *fly*) evokes an intermediate category, which in turn evokes a metaphorical category of action or state to be attributed to the target noun (e.g., *rumor*), rather than directly creating a metaphorical category as argued by Glucksberg’s (2001) categorization theory. We test our argument by means of computer simulation experiment in which the meanings of predicative metaphors are computed from the representations of the verb and the noun in a multidimensional semantic space constructed by latent semantic analysis. In the simulation, three algorithms for predicative metaphor comprehension, i.e., two-stage categorization, categorization and comparison, are compared in terms of how well they mimic human interpretation of 30 predicative metaphors. The simulation result was that the two-stage categorization algorithm best mimicked human interpretation of predicative metaphors, but the comparison model yielded the best performance in the case of less apt metaphors. These findings suggest that predicative metaphors, in particular apt metaphors, are understood via a two-stage categorization process, but less apt metaphors may possibly be understood via a comparison process.

Keywords: Metaphor comprehension; Predicative metaphor; Two-stage categorization; Computational modeling; Latent semantic analysis

Introduction

How do people understand predicative metaphors (i.e., expressions that involve the metaphorical use of a verb) such as “The rumor flew through the office”? Although a considerable number of studies (e.g., Bowdle & Gentner, 2005; Gentner, Bowdle, Wolff, & Boronat, 2001; Glucksberg, 2001; Utsumi, in press) have been made on the cognitive mechanism of nominal metaphors (i.e., expressions that involve the metaphorical use of a noun) such as “*My job is a jail*”, very little attention has been paid to the comprehension mechanism of predicative metaphors. The cognitive linguistic research on metaphor (e.g., Kövecses, 2002; Lakoff & Johnson, 1980) has addressed predicative metaphors as manifestations of the conventionalized, conceptual metaphors. However, these studies do not explore how the conceptual metaphors are constructed, i.e., how a set of correspondences or mappings are made between the source domain and the target domain. On the other hand, Glucksberg (2001, 2003) argues that people comprehend predicative metaphors via a categorization process as they do for nominal metaphors. However, no clear empirical evidence has been provided for his argument. Although Torreano, Cacciari, and Glucksberg (2005)

demonstrated that the level of abstraction of a verb’s referent was related to the metaphoricality of a predicative metaphor, such finding does not necessarily mean that the verb directly evokes a metaphorical category in metaphor comprehension.

In this paper, therefore, we address the mechanism of predicative metaphor comprehension and argue that predicative metaphors are understood via a *two-stage categorization* process, which is an extended view of Glucksberg’s categorization theory. We test our argument by means of computer simulation of metaphor comprehension. For this purpose, we use a semantic space constructed by latent semantic analysis (LSA) (Landauer & Dumais, 1997) and provide a computational model of the two-stage categorization process, together with computational models of other possible processes for metaphor comprehension (Utsumi, 2006). In the computer simulation, we examine how well the two-stage categorization model mimics human interpretations of predicative metaphors as compared to the other comprehension models. The model that achieves the best simulation performance can be seen as embodying the most plausible comprehension mechanism of predicative metaphors. Note that our study differs from other LSA-based metaphor studies (e.g., Kintsch, 2000; Lemaire & Bianco, 2003) in that we use the LSA-based methodology to obtain novel findings on metaphor comprehension, while they only simulate the known findings.

Predicative Metaphor Comprehension

As we mentioned above, one candidate theory of predicative metaphor comprehension is Glucksberg’s (2001, 2003) categorization theory. The categorization theory addresses mainly nominal metaphors and argues that people understand nominal metaphors by seeing the target concept as belonging to the superordinate metaphorical category exemplified by the source concept. Glucksberg (2001) also argues that predicative metaphors function very much as do nominal metaphors; just as nominal metaphors use vehicles that epitomize certain categories of objects or situations, predicative metaphors use verbs that epitomize certain categories of actions. According to this theory, for example, a predicative metaphor “The rumor flew through the office” is comprehended so that the verb *fly through* evokes an ad hoc category of action such as “to move quickly” or “to spread rapidly and soon disappear” and such action is attributed to the target *rumor*, as illustrated in Figure 1.

Against the categorization theory of predicative metaphors, we propose a two-stage categorization theory. The intuitive idea behind two-stage categorization is that correspondences between the actions literally expressed by the verb and the

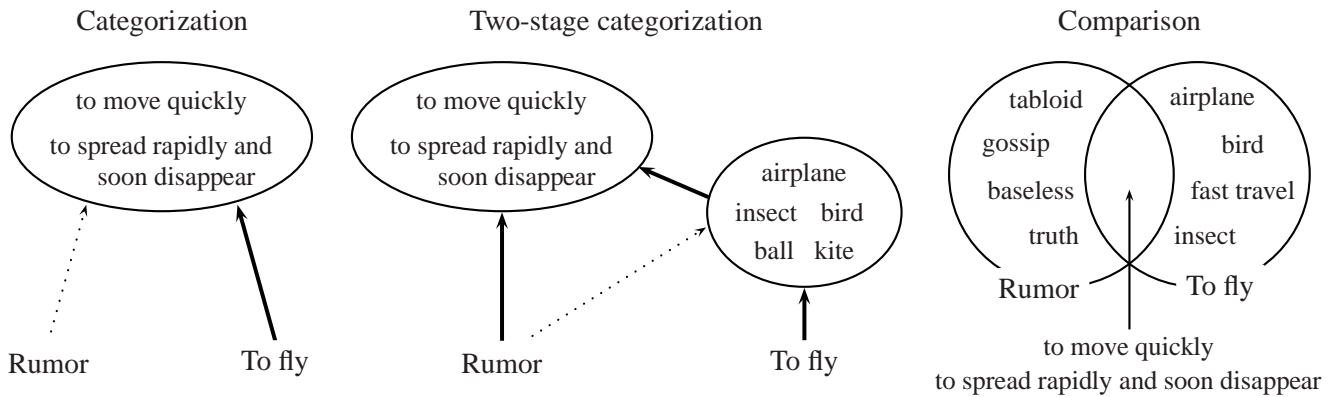


Figure 1: Three theories of predicative metaphor comprehension: The case of “The rumor flew through the office” metaphor

actions to be attributed to the target noun would be indirect, mediated by an intermediate category, rather than direct as predicted by the categorization theory. As Figure 1 illustrates, in the case of “fly” metaphor, the verb *fly* first evokes an intermediate category “things that fly”, which involves airplane, bird, insect, ball and kite. Some entities in the intermediate category that are relevant to the target *rumor* then evoke a final abstract category of “to move quickly”, to which the target *rumor*’s action being described belong.

The comparison theory of metaphor (Bowdle & Gentner, 2005; Gentner et al., 2001) would be the other candidate theory of predicative metaphor comprehension. This theory argues that metaphors are processed via a comparison process consisting of an initial alignment process between the source and the target concepts and a subsequent process of projection of aligned features into the target concept. According to the comparison theory, the “fly” metaphor is comprehended in such a way that two concepts *rumor* and *to fly* are aligned, some features such as ones about quick motion are found, and they are attributed to the target noun.

This paper examines which of these three theories best explains the mechanism of predicative metaphor comprehension by comparing these theories in terms of how accurately computational models embodying the theories simulate human behavior concerning metaphor comprehension. This paper also examines an effect of metaphor aptness on the comprehension of predicative metaphors. This is because the recent development of the categorization theory (Jones & Estes, 2006; Glucksberg, 2003; Glucksberg & Haught, 2006) has advocated that metaphor aptness influences the choice of comprehension strategy; apt metaphors are processed as categorizations, but less apt metaphors may be processed as comparisons after initially processed as categorizations because they are less easy to process as categorizations.

Computational Model

Vector Space Model

A vector space model is the most commonly used geometric model for the meanings of words. The basic idea of a vector space model is that words x are represented by high-dimensional vectors $v(x)$, i.e., *word vectors*, and the degree of semantic similarity $sim(x, y)$ between any two words x and y can be easily computed as a cosine $\cos(v(x), v(y))$ of the angle formed by their vectors.

Word vectors are constructed from the statistical analysis of huge corpus of written texts in the following way. First, all content words in a corpus are represented as m -dimensional feature vectors, and a matrix A is constructed using n feature vectors as rows. Then the dimension of M ’s rows is reduced from m to l . A number of methods have been proposed for computing feature vectors and for reducing dimensions (Widdows, 2004). In this paper, we used a LSA technique (Landauer & Dumais, 1997) for constructing word vectors. LSA uses the term frequency in a paragraph as an element of feature vectors, and singular value decomposition, a kind of linear algebra technique, as a method for dimensionality reduction. LSA was originally proposed as a document indexing technique for information retrieval, but several studies (e.g., Landauer et al., 2007) have shown that LSA successfully mimics many human behaviors associated with semantic processing. For example, using a semantic space derived from a corpus of Japanese newspaper used in this paper, similarity between *computer* (“*konpyuta*” in Japanese) and *Windows* (“*uindouzu*” in Japanese; Microsoft’s OS) is computed as .63, while similarity between *computer* and *window* (“*mado*” in Japanese; glass in the wall) is computed as $-.02$.

Metaphor Comprehension Algorithms

In the vector space model, a vector representation $v(s)$ of a piece of text s (e.g., phrase, clause, sentence) consisting of constituent words w_1, \dots, w_n can be defined as a function $f(v(w_1), \dots, v(w_n))$. Hence, predicative metaphor comprehension is modeled as computation of a vector $v(M) = f(v(w_T), v(w_V))$ which represents the meaning of a predicative metaphor M with the target noun w_T and the vehicle verb w_V . In the rest of this paper, we use the phrase “ n neighbors of a word (or a category) x ” to refer to words with n highest similarity to x , and denote a set of n neighbors of x by $N_n(x)$.

Categorization The algorithm of computing a metaphor vector $v(M)$ by the process of categorization is as follows.

1. Compute $N_{m_1}(w_V)$, i.e., m_1 neighbors of the verb w_V .
2. Selects k words with the highest similarity to the target noun w_T from $N_{m_1}(w_V)$.
3. Compute a vector $v(M)$ as the centroid of $v(w_T)$, $v(w_V)$ and k vectors of the words selected at Step 2.

This algorithm is identical to Kintsch’s (2000) predication algorithm and it is also used as a computational model of the categorization process in Utsumi’s (2006) simulation experiment. As Kintsch suggests, this algorithm embodies the categorization process in that a set of k words characterizes an abstract superordinate category exemplified by the vehicle.

Two-stage categorization We propose the algorithm of two-stage categorization as follows.

1. Compute $N_{m_1}(w_V)$, i.e., m_1 neighbors of the verb w_V .
2. Selects k words with the highest similarity to the target noun w_T from $N_{m_1}(w_V)$.
3. Compute a vector $v(C)$ of an intermediate category C as the centroid of $v(w_T)$, $v(w_V)$ and the vectors of k words selected at Step 2.
4. Compute $N_{m_2}(C)$, i.e., m_2 neighbors of the intermediate category C .
5. Compute a metaphor vector $v(M)$ as the centroid of $v(w_T)$, $v(w_V)$ and m_2 vectors of the words selected at Step 4.

The first three steps, which are identical to the original categorization algorithm, correspond to the process of generating an intermediate category. Steps 4 and 5 correspond to the second categorization process.

Comparison The algorithm of computing a metaphor vector $v(M)$ by the process of comparison is as follows.

1. Compute a set of k words (i.e., alignments between the target noun w_T and the verb w_V) by finding the smallest i that satisfies $|N_i(w_T) \cap N_i(w_V)| = k$.
2. Compute a metaphor vector $v(M)$ as the centroid of $v(w_T)$ and k vectors of the words selected at Step 1.

This algorithm is proposed by Utsumi (2006). Step 1 corresponds to the initial alignment process and Step 2 corresponds to the later projection process.

Method

Human experiment

As human interpretation of predicative metaphors, we used the result of the psychological experiment reported in Nakamura and Utsumi (2007). The materials were 30 Japanese predicative metaphors such as “Excitement gets cold” (“*Koufun ga sameru*” in Japanese) and “Share prices boil” (“*Kabuka ga futtou suru*”). They consisted of 15 verbs and each verb was paired with two nouns (or noun phrases).

Sixty Japanese undergraduate students of the University of Electro-Communications were assigned to 10 predicative metaphors so that each metaphor was seen by 20 participants. They were asked to consider the meaning of each metaphor, to list three or more features of the topic that were being described by the metaphorical use of the verb, and to rate how apt the metaphor was on a 7-point scale ranging from 1 (*not at all apt*) to 7 (*extremely apt*).

For the listed features of each metaphor, closely related words or phrases were accepted as the same feature if they met one of the criteria for feature identification (Utsumi,

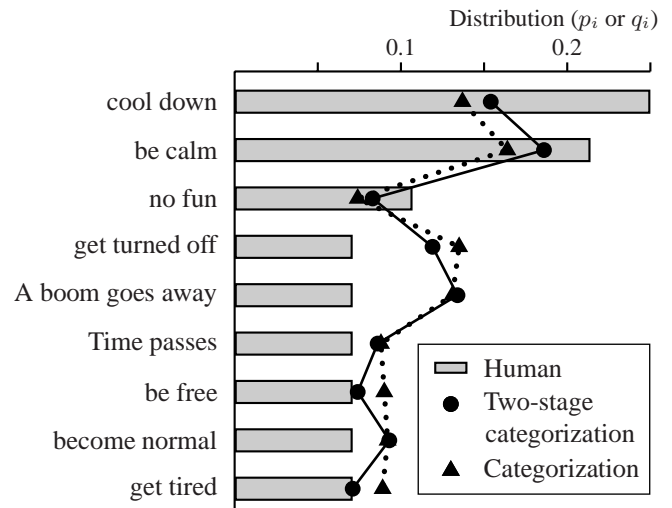


Figure 2: “Excitement gets cold” metaphor

2005), e.g., they belonged to the same deepest category of a Japanese thesaurus *Bunrui Goi Hyo*. The list of features was then amended by eliminating any feature that was mentioned by only one participant. For each feature w_i in the amended list for a predicative metaphor M , the degree of salience $sal(w_i, M)$ was then assessed as the number of participants who listed that feature, i.e., the number of tokens. These features were used as landmarks with respect to which computer’s interpretation and human interpretation were compared for evaluation. For example, as shown in the bar graph of Figure 2, nine features or meanings were listed for the metaphor “Excitement gets cold”, and the meaning *cool down* had the highest salience, i.e., the number of participants who listed it was largest.

Computer simulation

The semantic space used in the simulation was based on a Japanese corpus of 251,287 paragraphs containing 53,512 different words, which came from a CD-ROM of Mainichi newspaper articles (4 months) published in 1999. The dimension l of the semantic space was set to 300, and thus all words were represented as 300-dimensional vectors.

In the computer simulation, for each of the 30 predicative metaphors, three metaphor vectors were computed using the three comprehension algorithms presented in the preceding section, i.e., categorization, two-stage categorization and comparison algorithms. In computing the metaphor vectors, we varied the parameter m_1 in steps of 50 between 100 and 500, and the parameters k and m_2 from 1 to 10. After that, for all the features w_i, \dots, w_n listed for a predicative metaphor M in the human experiment, similarity to the metaphorical meaning $sim(w_i, M)$ was computed separately for three metaphor vectors. Features with higher similarity to the metaphorical meaning can be seen as more relevant to the interpretation of the metaphor. In Figure 2, for example, the feature *calm* had the highest similarity to both the metaphor vectors computed by the categorization algorithm and the two-stage categorization algorithm. The feature with the second highest similarity was *cool down*, which was the most salient feature, when the metaphor vector was computed

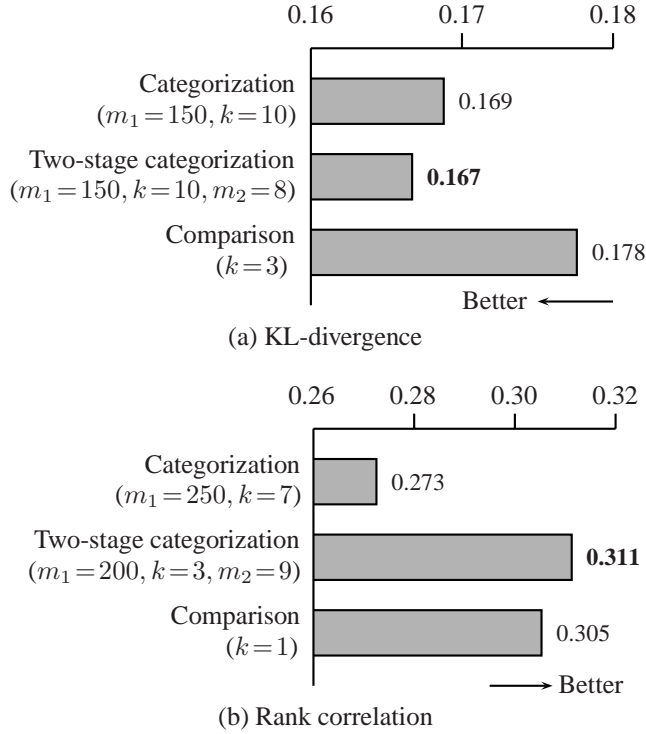


Figure 3: Simulation results: Comparison among the three comprehension algorithms for all metaphors

by the two-stage categorization algorithm, but *get turned off* when the metaphor vector was computed by the categorization algorithm.

Evaluation measures

To evaluate the ability of the algorithm to mimic human interpretations, we use the following measures, which were also used in Utsumi’s (2006) simulation experiment for nominal metaphors.

- *Kullback-Leibler divergence (KL-divergence)*:

$$D = \sum_{i=1}^n p_i \log \frac{p_i}{q_i} \quad (1)$$

$$p_i = \frac{sal(w_i, M)}{\sum_{j=1}^n sal(w_j, M)} \quad (2)$$

$$q_i = \frac{sim(w_i, M) - \min_x sim(x, M)}{\sum_{j=1}^n \{sim(w_j, M) - \min_x sim(x, M)\}} \quad (3)$$

The KL-divergence D defined by Eq. 1 measures how well a model simulates the salience distribution of features relevant to human interpretation, or in other words, the degree of dissimilarity between human interpretation and computer’s interpretation. Hence *lower divergence means that the algorithm achieves better performance*. In Figure 2, for example, the two-stage categorization algorithm ($m_1 = 150, k = 10$) shows lower divergence ($D = 0.091$) than the categorization algorithm ($D = 0.135, m_1 = 150, k = 10, m_2 = 8$). This result suggests that, in this case, the two-stage categorization algorithm better mimics human interpretation than the categorization algorithm.

- *Spearman’s rank correlation*:

$$r = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n^3 - n} \quad (4)$$

$$d_i = rank(sim(w_i, M)) - rank(sal(w_i, M)) \quad (5)$$

The rank correlation r defined by Eq 4 measures how strongly the computed similarity of relevant features is correlated with the degree of salience of those features. *A higher correlation means that the algorithm yields better performance*. In Figure 2 the two-stage categorization algorithm yields a higher correlation ($r = .604$) than the categorization algorithm ($r = .488$), which again indicates that the two-stage categorization algorithm is superior to the categorization algorithm.

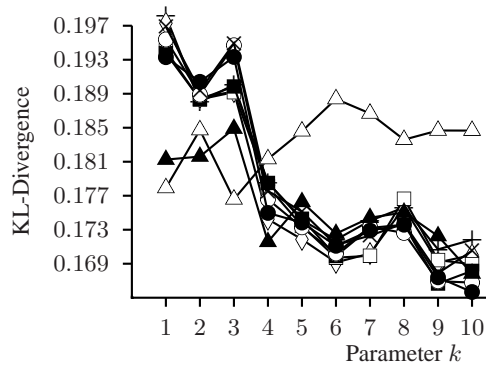
Result

For each of the 30 predicative metaphors, KL-divergences and rank correlations were computed using the three metaphor vectors. These values were averaged across metaphors.

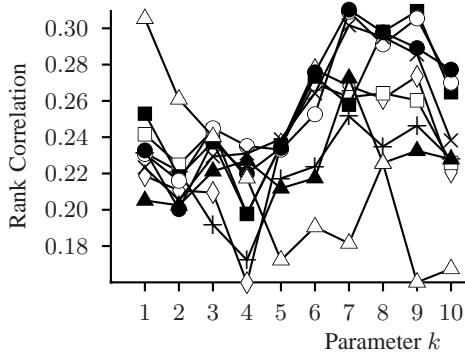
Concerning KL-divergence, the categorization algorithm achieved the best performance when $m_1 = 150$ and $k = 10$, the two-stage categorization algorithm did the best performance when $m_1 = 150, k = 10$ and $m_2 = 8$, and the comparison algorithm did the best performance when $k = 3$. Concerning rank correlation, the combination of $m_1 = 250$ and $k = 7$ was optimal for the categorization algorithm, while the combination of $m_1 = 200, k = 3$ and $m_2 = 9$ was optimal for the two-stage categorization algorithm. For the comparison algorithm, $k = 1$ was optimal.

Figure 3 shows mean divergences and correlations calculated using these optimal parameters. The two-stage categorization algorithm outperformed the other two algorithms on both measures, although the difference of KL-divergence between the categorization algorithm and the two-stage categorization algorithm was not so large. This result suggests that *the two-stage categorization theory may be the most plausible theory of predicative metaphor comprehension*. Furthermore, in order to demonstrate that this result in favor of the two-stage categorization theory is general, not specific to the particular values of parameters, we show the simulation results obtained with various values of the parameters in Figure 4. Figure 4(a) shows that, when they were compared at the same value of k , the two-stage categorization algorithm had lower divergence (i.e., better performance) than the categorization and the comparison algorithms at almost all the values of m_2 , although it had worse performance at lower values of k . Similarly, as shown in Figure 4(b), the two-stage categorization algorithm achieved a higher correlation (i.e., better performance) regardless of values of m_2 . These results indicate the plausibility of two-stage categorization as a cognitive model of predicative metaphor comprehension.

Furthermore, we examined an effect of aptness on the comprehension of predicative metaphors by dividing all the predicative metaphors into two groups, i.e., apt metaphors whose mean aptness rating was higher than the midpoint 4 and less apt metaphors whose aptness rating was 4 or lower, and by calculating mean KL-divergences and correlations for apt metaphors and less apt metaphors. Figure 5 shows the optimal divergences and correlations for apt and less apt metaphors.



(a) KL-divergence at $m_1 = 150$



(b) Rank correlations at $m_1 = 250$

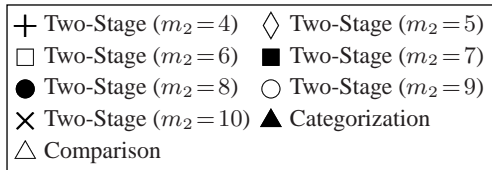


Figure 4: Simulation results of the three comprehension models obtained with various values of parameters k and m_2

As Figure 5 (a) shows, when only apt metaphors were considered, the two-stage categorization algorithm yielded the best performance on both measures, thus suggesting that apt predicative metaphors are likely to be understood via a two-stage categorization process, not via a categorization process. More interesting is that, as Figure 5 (b) shows, the comparison algorithm achieved the best performance on both measures in the case of less apt metaphors. This finding suggests that, when predicative metaphors are less apt, people may comprehend them via a comparison process, just as people may comprehend less apt nominal metaphors as comparisons (e.g., Glucksberg, 2003; Glucksberg & Haught, 2006).

Discussion

In this paper, we have shown that two-stage categorization is the process via which predicative metaphors (especially apt ones) are comprehended. One interesting question that arises here is whether the two-stage categorization theory can be generalized to other kinds of metaphors such as nominal metaphors and adjective metaphors. In order to answer this question, we conducted simulation experiments for nominal and adjective metaphors (Utsumi, 2006; Utsumi & Sakamoto,

Table 1: Simulation results (optimal divergences and correlations) for nominal and adjective metaphors

Metaphor type		Two	Cat	Com
Nominal	Div	0.262	0.260	0.270
	Cor	0.192	0.222	0.197
High-diversity	Div	0.187	0.185	0.219
	Cor	0.217	0.237	0.154
Low-diversity	Div	0.340	0.344	0.327
	Cor	0.186	0.206	0.244
Adjective	Div	0.369	0.378	0.376
	Cor	0.156	0.131	0.141

Note: Two = Two-stage categorization. Cat = Categorization. Com = Comparison. Div = KL-divergence. Cor = Rank correlation. Boldfaces indicate the best score for each row.

2007). The simulation method and evaluation measures used in the additional experiments were identical to those used in the experiment of this study. In the experiment for nominal metaphors, the metaphorical meanings of 40 metaphors such as “Life is a game” were computed by the two-stage categorization algorithm, and the results were compared with those of the categorization and the comparison algorithms obtained in our preceding study (Utsumi, 2006). In the experiment for adjective metaphors, the metaphorical meanings of 30 metaphors such as “red voice” were computed by the three comprehension algorithms (Utsumi & Sakamoto, 2007).

Table 1 shows the simulation results of these additional experiments. The two-stage categorization algorithm achieved the best performance of simulating adjective metaphor comprehension, thus suggesting that adjective metaphors are comprehended as two-stage categorization. On the other hand, in the case of nominal metaphors, the performance of the two-stage categorization algorithm was not better than that of the other algorithms. This result indicates that nominal metaphors are not understood via a two-stage categorization process; our interpretive diversity view (Utsumi, in press; Utsumi & Kuwabara, 2005) that interpretively diverse metaphors are comprehended as categorizations but less diverse metaphors are comprehended as comparisons is still the most plausible theory of nominal metaphor comprehension.

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References

- Bowdle, B., & Gentner, D. (2005). The career of metaphor. *Psychological Review*, *112*(1), 193–216.
- Gentner, D., Bowdle, B., Wolff, P., & Boronat, C. (2001). Metaphor is like analogy. In D. Gentner, K. Holyoak, & B. Kokinov (Eds.), *Analogical mind: Perspectives from cognitive science* (pp. 199–253). MIT Press.
- Glucksberg, S. (2001). *Understanding figurative language: From metaphors to idioms*. Oxford University Press.

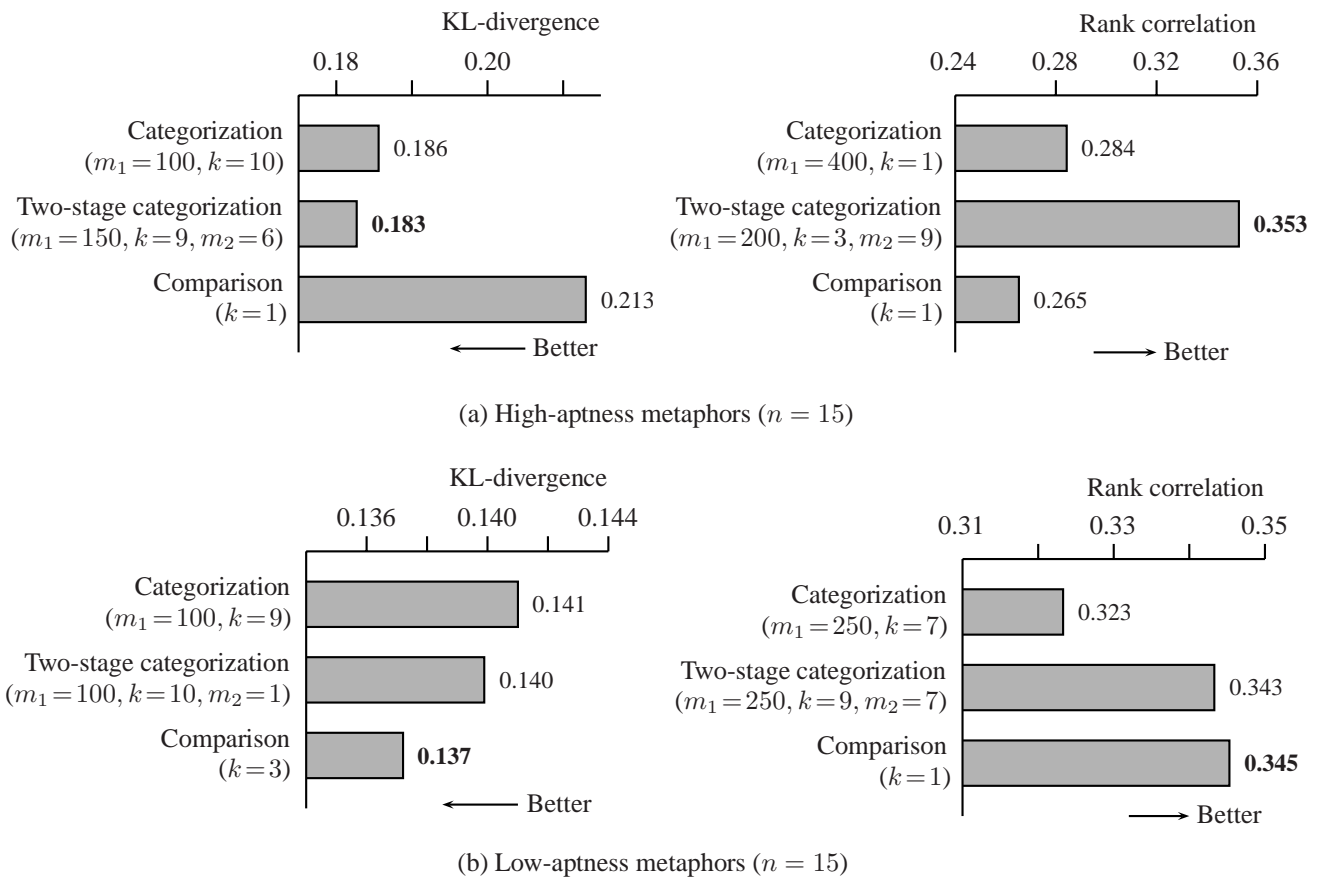


Figure 5: Simulation results: Comparison among the three comprehension algorithms for apt and less apt metaphors

- Glucksberg, S. (2003). The psycholinguistics of metaphor. *Trends in Cognitive Sciences*, 7(2), 92–96.
- Glucksberg, S., & Haught, C. (2006). On the relation between metaphor and simile: When comparison fails. *Mind & Language*, 21(3), 360–378.
- Jones, L., & Estes, Z. (2006). Roosters, robins, and alarm clocks: Aptness and conventionality in metaphor comprehension. *Journal of Memory and Language*, 55, 18–32.
- Kintsch, W. (2000). Metaphor comprehension: A computational theory. *Psychonomic Bulletin & Review*, 7(2), 257–266.
- Kövecses, Z. (2002). *Metaphor: A practical introduction*. Oxford University Press.
- Lakoff, G., & Johnson, M. (1980). *Metaphors we live by*. The University of Chicago Press.
- Landauer, T., McNamara, D., Dennis, S., & Kintsch, W. (2007). *Handbook of latent semantic analysis*. Lawrence Erlbaum Associates.
- Landauer, T. K., & Dumais, S. T. (1997). A solution to Plato's problem: The latent semantic analysis theory of the acquisition, induction, and representation of knowledge. *Psychological Review*, 104, 211–240.
- Lemaire, B., & Bianco, M. (2003). Contextual effects on metaphor comprehension: Experiment and simulation. In *Proceedings of the 5th International Conference on Cognitive Modeling (ICCM'2003)*.
- Nakamura, M., & Utsumi, A. (2007). An empirical investigation on the comprehension process of predicative metaphors. In *Proceedings of the 24th Annual Meeting of the Japanese Cognitive Science Society*. (in Japanese)
- Torreano, L., Cacciari, C., & Glucksberg, S. (2005). When dogs can fly: Level of abstraction as a cue to metaphorical use of verbs. *Metaphor and Symbol*, 20(4), 259–274.
- Utsumi, A. (2005). The role of feature emergence in metaphor appreciation. *Metaphor and Symbol*, 20(3), 151–172.
- Utsumi, A. (2006). Computational exploration of metaphor comprehension processes. In *Proceedings of the 28th Annual Meeting of the Cognitive Science Society* (pp. 2281–2286).
- Utsumi, A. (in press). Interpretive diversity explains metaphor-simile distinction. *Metaphor and Symbol*.
- Utsumi, A., & Kuwabara, Y. (2005). Interpretive diversity as a source of metaphor-simile distinction. In *Proceedings of the 27th Annual Meeting of the Cognitive Science Society* (pp. 2230–2235).
- Utsumi, A., & Sakamoto, M. (2007). Computational evidence for two-stage categorization as a process of adjective metaphor comprehension. In *Proceedings of the 2nd European Cognitive Science Conference (EuroCogSci2007)*.
- Widdows, D. (2004). *Geometry and meaning*. CSLI Publications.