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## Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 39(0)

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## Publication Date
2017

Peer reviewed

# Decisions based on verbal probabilities: Decision bias or decision by belief sampling?

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**Abstract**

We examined decisions based on verbal probability phrases, such as "small chance," "likely," or "doubtful" (we call these phrases *verbal probabilities*). Verbal probabilities have communicative functions called *directionality* and can be categorized into positive (e.g., "likely" or "probable") or negative (e.g., "unlikely," "doubtful") phrases in terms of their directionality. Previous studies have shown that the directionality of phrases affects decisions. Although such decisions seem biased, we argue that they are not. We hypothesize that since a speaker has the option to choose the directionality used during communication, the selected directionality becomes relevant information to a decision maker, and is taken into account in making decisions. We modeled these processes using the *Decision by Belief Sampling* (DbBS) model. We found that the observed data could be well explained by our hypothesis, and that the DbBS model could be one of the best potential models for decisions based on verbal probability information.

**Keywords:** Verbal probabilities; decisions based on verbal probabilities; directionality; decision by belief sampling.

## Introduction

In the research on judgment and decision making, topics pertaining to probabilities, such as probability judgment and decisions based on probability information, have been some of the most studied. In the present study, we shall discuss decision making based on different kinds of probability information.

Probability information can be expressed in various forms. The most basic of these expressions is numerical probability, such as “20%.” Probability information is also expressed with verbal phrases such as "it is likely," "it is doubtful," or "it is certain."[1] In the present study, we examined decisions based on verbal probabilities and analyzed how the difference in expressions affected cognitive processes.

Particularly, we focus on the communicative functions of verbal probabilities. Teigen and Brun (1995) showed that verbal probabilities have communicative functions, called *directionality*, which change the listeners' focus. Verbal probabilities can be categorized into positive or negative phrases in terms of their directionality. Positive phrases (e.g., "small chance," "likely," "certain") make listeners focus on the occurrence of uncertain events. In contrast, negative phrases (e.g., "unlikely," "doubtful," "uncertain") make listeners focus on the non-occurrence of uncertain events. Previous studies have shown that the directionality affected decision making. Here, we introduce one of the most intriguing studies, the "*Marianne study*" (Study 1) in Teigen and Brun (1999). This experiment involved a task describing the probable effectiveness of a treatment with either a positive phrase ("there is some possibility that the treatment will be helpful in her case") or a negative phrase ("it is quite uncertain that the treatment will be helpful in her case"). Participants rated how likely they would recommend this treatment to a patient (Marianne) based on these phrasings, using a 4-point scale (1: absolutely yes, 4: absolutely not). Numerical translations for positive and negative phrases answered by different participants were 31.7% and 31.3%. Based on these results, the two phrases should have conveyed highly similar degrees of certainty for the effectiveness of treatment. However, the participants gave highly different decision ratings depending on the probability expressions. Mean ratings for positive and negative phrases were, 1.78 and 2.78, respectively (when scores of 1 or 2 were jointly regarded as "Yes" decisions, the proportions of "Yes" decisions for the two phrases were 90.6% and 32.4%, respectively).

Ostensibly, the results in Teigen and Brun (1999) may have suggested a decision bias produced by the difference in probability expression, perhaps another form of the framing effect (Teigen & Brun, 2003). In the following sections, we shall claim that the effect of different probability expressions on decisions is not a decision bias, and that such decisions derive from a decision maker's inferences regarding background information based on speaker’s choice of directionality. Furthermore, we model this decision processes using a *Decision by Belief Sampling* model.

[1] Hereafter, we call verbal probability phrases *verbal probabilities*.

## Speaker's choice of directionality and listener's inferences in communication

In communication, speakers will select an expression according to situational factors. McKenzie and Nelson (2003) and Sher and McKenzie (2006, 2008) argued that a speaker's reference point affects her/his choice of expression when conveying quantitative information, such as the amount of water in a glass (e.g., "half full" or "half empty"). In a task examining this phenomenon, it was found when the glass (a 500ml capacity) had 250ml of water, participants used the description of "half full" when the glass had previously 0ml of water more often than when the glass had previously 500ml of water. It was also found that a listener could infer the speaker's original reference point (e.g., the amount of water originally in the glass before more was added or removed) based on the selected expression. Honda and Yamagishi (2017) found analogous tendencies in communication using verbal probabilities. Imagine trying to convey that an uncertain event had a 50% chance of occurrence using verbal probabilities. Honda and Yamagishi (2017) showed that when a speaker's prior expectation of the event occurrence was lower (higher) than 50%, they tended to prefer positive (negative) phrases. Honda and Yamagishi (2017) also found that listeners could infer the speaker's expectation based on the phrases used. When a positive phrase was presented, listeners tended to infer that speaker's prior expectation of the probability was lower than when a negative phrase was presented.

These findings indicate that the selected phrase implicitly conveys important information for decision making. For example, given that a speaker follows the above regularity, 50% conveyed by a positive (negative) phrase implies "good (bad)" situation relative to the speaker's expectation. Thus, the findings of Teigen and Brun (1999) (i.e., participants tended to recommend a treatment conveyed by a positive phrase more than one conveyed by a negative phrase) suggest that in making decisions, participants took into account the relevant information (i.e., relatively "good" or "bad" situations) implied by the directionality chosen.

## Model of decision making based on verbal probabilities: Decision by Belief Sampling

As described above, previous findings suggest that different phrases implicitly convey information about the relative status of the decision situation, and people utilize this information in making decisions. In the present study, we model such decision processes based on the *Decision by Sampling* model (*DbS*, Stewart, 2009; Stewart, Chater, & Brown, 2006). In the DbS model, subjective attribute values are constructed by a series of binary, ordinal comparisons to a sample of attribute values that reflect the immediate decision context and real-world distribution. The subjective value for a target is calculated as follows:

$$\mathrm{r} = \frac{R-1}{N-1} \qquad (1)$$

where r ($0 \leq r \leq 1$) denotes the subjective value for a target, and R denotes the rank of the target within the decision sample of N items. In this model, if the decision sample differs, r varies in the relationship between R and the decision sample. Imagine the subjective value for 40%. When decision samples are 10%, 20%, 30%, 30%, and 50%, the subjective value is r = (5-1)/(6-1) = 0.8. In contrast, in decision samples of 20%, 30%, 70%, 80%, and 90%, the subjective value is r = (3-1)/(6-1) = 0.4. That is, even when the target has the same attribute value, the subjective value varies depending on decision samples. Previous studies have shown that decision samples affect an evaluation of the target value and the evaluation for the same target varies depending on the samples (e.g., Stewart, Chater, Stott & Reimers, 2003; Stewart, Reimers, & Harris, 2014).

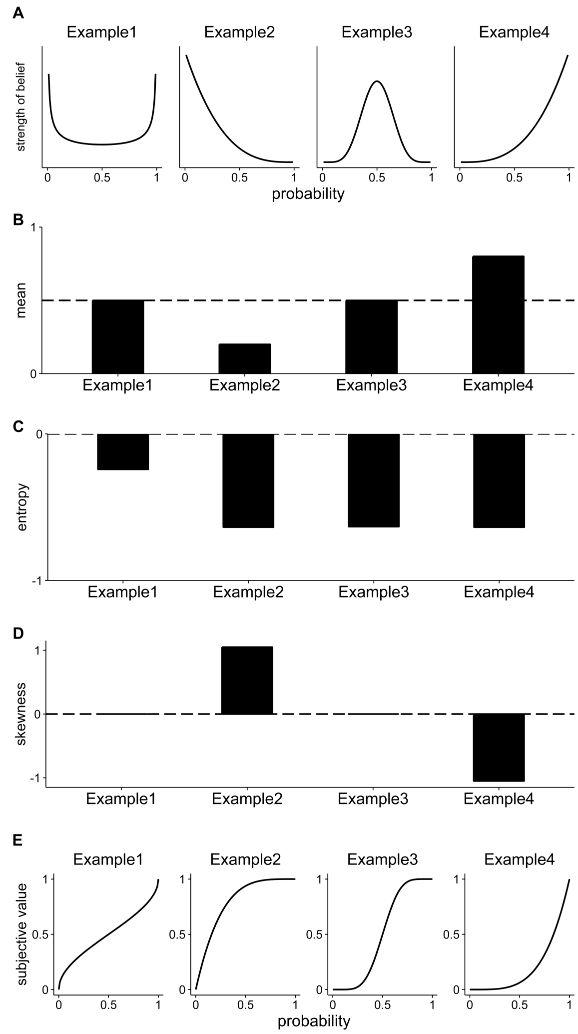


Figure 1. Summaries of DbBS. (A) Probabilistic belief regarding an uncertain event. This is represented by the density function of the beta distribution. (B) Mean of belief. (C) Entropy of belief. (D) Skewness of belief. (E) Subjective value in DbBS. This is represented with the cumulative distribution function of the beta distribution.

In the present study, we propose a decision model, *Decision by Belief Sampling (DbBS)*, based on the DbS model. Figure 1 summarizes DbBS. Here, we introduce basic two assumptions: Firstly, the decision maker (DM) refers to memory samples in making decisions, and these samples represent the DM's probabilistic belief of event occurrence. For example, imagine the probable success rates of medical procedures for both a serious disease and appendicitis, respectively. Generally, people believe that the probability of success in treating a serious disease is low compared to the probable success of treating appendicitis (Honda & Matsuka, 2014). We assume that the DM refers to memory samples according to her/his probabilistic belief. We represent these beliefs using beta distributions. Figure 1 (A) shows four examples of a DM's subjective beliefs regarding uncertain events. We can discuss the features of probabilistic belief based on its statistical characteristics such as mean, entropy (i.e., uncertainties about successes or failures), and skewness of beta distributions (see Figure 1 (B), (C), and (D)). Example 1 represents the belief such that an event will occur or not with high uncertainty and without skewness. Likewise, in Examples 2 and 4, the DM has the belief such that the event will happen with low or high probability with relatively low uncertainty and positive or negative skewness. Example 3 represents the belief that an event has around 50% of occurrence with low uncertainty and without skewness. Thus, beta distributions can represent extensive kinds of beliefs about uncertain events. Secondly, we assume that a subjective value for a target is constructed by the comparison between the target value and memory samples. Figure 1 (E) shows subjective values calculated by the DbBS model (i.e., equation (1)). Given that beta distributions represent beliefs about uncertain events, subjective values correspond to values in the cumulative distribution functions (CDF) of beta distributions. As is apparent, depending on the beliefs, the subjective values differ even for the same target probability. One of the most notable features in the DbS (or DbBS) model is that subjective values are highly affected by the skewness of distributions in decision (or memory) samples (Brown & Matthews, 2011). Therefore, subjective values highly differ between beliefs with high probability and those with low probability (see Examples 2 and 4 in Figure 1).

We believe that the DbBS model can clarify the following points regarding decisions based on verbal probabilities. First, the DbBS model can clarify the implicit assumptions (i.e., beliefs about uncertain events) people have in making decisions. Although Honda and Yamagishi (2017) showed that listeners have different assumptions depending on the directionality of verbal probabilities, it remains an empirical question whether people have such assumptions in making decisions. Using the DbBS model, we can examine this question. Second, the DbBS model will provide a new perspective on phenomena regarding decisions based on verbal probabilities. For example, we can discuss whether the influence of directionality on decisions reflects decision bias.

According to previous findings (Honda & Yamagishi, 2017) and the assumptions of the DbBS model, our hypothesis is as follows: DMs refer to different memory samples depending on the directionality of verbal probabilities because the selected directionality become relevant information to DMs. In particular, DMs refer to memory samples with lower probability when presented with positive phrases than when presented with negative phrases. As a result, decision patterns differ between positive and negative phrases. For example, even when DMs think that a probability of an uncertain event is 30% when presented with a verbal probability, the subjective value for the probability will be higher when presented with a positive phrase than a negative phrase, because DMs have lower memory samples (see Examples 2 and 4 in Figure 1 (A) and (E)).

## Behavioral experiment

In order to examine the above hypothesis, we conducted behavioral experiments about decisions based on verbal probabilities.

### Method

**Participants** Japanese undergraduates (N = 60) participated as part of their course work.

**Tasks, materials, and procedure** We conducted two tasks: a decision task and a task measuring the membership function for verbal probabilities. The decision task was based on the Marianne study (Study 1) in Teigen and Brun (1999). The cover story was as follows:

Your friend has periodically been suffering

Table 1. Verbal probabilities used in the experiment.

| Verbal probabilities | $M_{peak}$ | $SD_{peak}$ |
|---|---|---|
| **positive phrases** | | |
| It is almost certain that * | 0.957 | 0.037 |
| There is a good chance that * | 0.779 | 0.126 |
| It is possible that * | 0.418 | 0.167 |
| It is likely that * | 0.540 | 0.164 |
| There is a small possibility that * | 0.346 | 0.129 |
| There is some possibility that * | 0.232 | 0.116 |
| There is a slight hope that * | 0.121 | 0.115 |
| There is a tiny hope that * | 0.074 | 0.097 |
| **negative phrases** | | |
| There are minor concerns that * | 0.602 | 0.167 |
| It is quite doubtful that * | 0.494 | 0.188 |
| It is not certain that * | 0.532 | 0.165 |
| It is uncertain whether * | 0.466 | 0.178 |
| It is quite unlikely that * | 0.433 | 0.141 |
| There is little hope that * | 0.177 | 0.088 |
| It is unlikely that * | 0.137 | 0.103 |
| It is almost impossible that * | 0.027 | 0.038 |

*(the treatment will be helpful in that case.)

from migraine headaches, and is now considering a new method of treatment based on acupuncture. The treatment is rather costly and long-lasting. The friend asks if you think the friend should give it a try. Fortunately, you happen to know a physician with good knowledge of migraine treatment, whom you can ask for advice.

Participants were presented with a verbal probability by the physician (e.g., "It is likely that the treatment will be helpful in that case."). Considering this information, participants were asked to rate how much they would recommend that their friend try this treatment, using a scale that was labeled "do not recommend at all" on the far left and "recommend very much" on the far right. This rating scale contained 101 points (0 - 100)[2].

We also measured membership function of verbal probabilities based on Budescu, Karelitz, and Wallsten (2003). Participants were presented with a single verbal probability and 11 probability values (1%, 10%, 20%, ..., 90%, and 99%) simultaneously and asked to rate the degree (i.e., membership value) to which the verbal probability describes each probability, using a scale that was labeled "not at all" on the far left and "absolutely" on the far right. Therefore, this task measures the degree of certainty attributed to a verbal probability. This rating was recorded with 101 points (0-100).

For these two tasks, we used eight positive and eight negative phrases based on Honda and Yamagishi (2017). Table 1 shows the sixteen phrases used in the experiment.

We conducted the two tasks individually using a computer. In both tasks, a single phrase was randomly presented and participants answered the question. In the decision task, participants answered the question for each phrase once. When measuring membership function, participants answered the question for each phrase twice.

## Results and discussion

**Numerical representation of verbal probabilities** According to Wallsten, Budescu, Rapoport, Zwick, and Forsyth (1986), we assumed that the degree of certainty attributed to a verbal probability could be represented with a membership function. Peak (the probability with the highest membership value) is one of the most discriminative features of membership functions (Budescu et al., 2003). Accordingly, we assumed that the peak of the membership function represented the degree of certainty for a verbal probability felt by a participant. Since participants rated membership values twice for each phrase, the mean of the membership values was regarded as the membership value for the phrase. Table 1 shows means and SDs of peaks for 16 phrases.

**Decision ratings for aggregated data** First, we examined the aggregated data. Figure 2 shows the relationship between the mean degrees of certainty for phrases (peaks of the membership function) and decision ratings for 8 positive and 8 negative phrases. As is apparent, even though positive and negative phrases were perceived to be analogous in the degree of certainty, decision ratings differed such that participants tended to answer with higher ratings for positive phrases. Therefore, the findings of Teigen and Brun (1999) were essentially replicated in the present study.

**Model-based analyses for individual data** Next, we analyzed the individual data using the DbBS model. In our DbBS model, we assumed that subjective value of certainty conveyed by a phrase corresponds to the CDF in the beta distribution. Therefore, we estimated two parameters ($\alpha$ and $\beta$) of the beta distribution whose CDF best explains the decision ratings. The two parameters were estimated by a grid search in the range of 0.1 and 10, with increments of 0.1. That is, we estimated the parameter using 10000 sets. The parameter set with which the model showed the highest $r^2$ between model predictions and decision data was regarded as the best model. We searched the best parameter sets for positive and negative phrases, respectively, for each participant.

We found that the DbBS model generally explained the observed decisions well. The medians of $r^2$s between model predictions and observed data for 60 participants were 0.77 and 0.66 for positive and negative phrases, respectively. In the following analyses, when the model fittings in both positive and negative phrases for a participant showed more than 0.3 in $r^2$, we used her/his data. With this criterion, we used data from 45 out of 60 participants (75.0%). Figure 3 shows five examples of decision ratings and model fittings for positive and negative phrases.

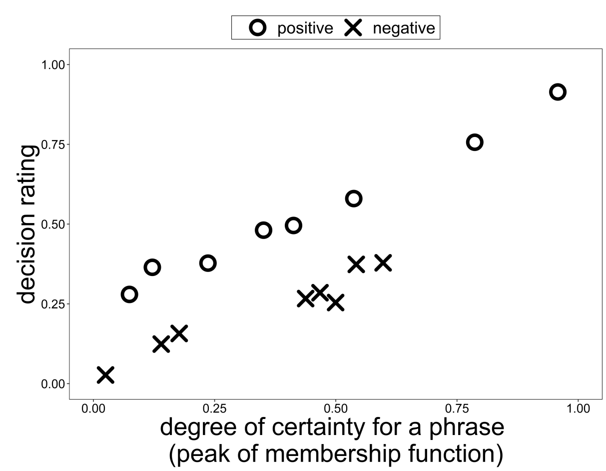


Figure 2. Relationship between subjective degree of certainty for phrases (peak of the membership function) and decision rating.

[2] In the following analyses, the ratings were mapped onto 0-1 scale.

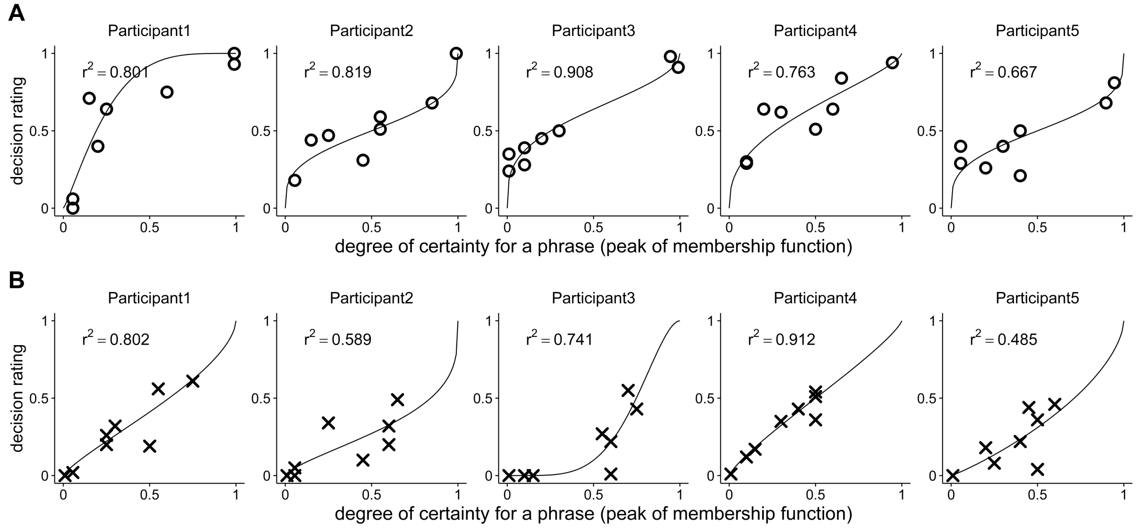


Figure 3. Examples of observed decision rating (points) and model fitting (line) for five participants. (A) shows data for positive phrases. (B) shows data for negative phrases.

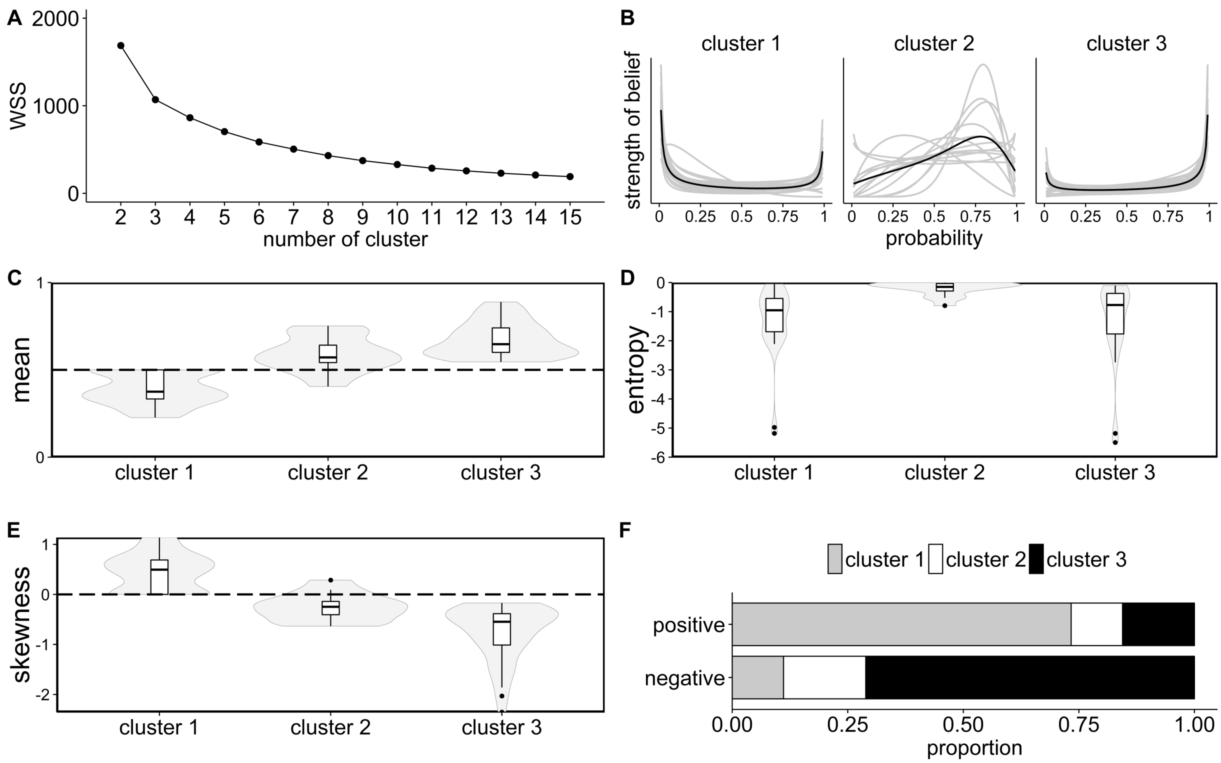


Figure 4. Summaries of model-based analyses. (A) Scree plot for within-cluster sum of squares (WSS) in K-Means clustering. (B) Three clusters on decision sample. The black line denotes mean of cluster. The grey line denotes individual data. (C), (D), and (E) show distributions of statistics (mean, entropy, and skewness) in each cluster. (F) Proportions of data in positive and negative phrases that were categorized into each cluster.

Next, we examined participants' memory samples in detail with the following procedures. First, we clustered shapes of beta distributions using probability densities. In particular, patterns of probability densities[3] for 45 (number of participants) * 2 (positive and negative phrases) = 90 data sets were clustered using the K-Means method. We used scree plots for the within-cluster sum of squares (WSS) for each cluster in order to determine the number of clusters (see Figure 4(A)). We adopted three clusters for the following two reasons. Firstly, the reduction of WSS was relatively sharp with up to three clusters. Secondly, since

[3] In this analysis, we used density values for 99 probabilities (1%, 2%, 3%, …, 97%, 98%, and 99%).

there were at least 13 data for every cluster, we can assume that each cluster does not necessarily represent rare memory samples.

Figure 4 (B) shows three clusters of memory samples. The black line denotes mean of cluster, and the grey line denotes individual data. Using individual data, we calculated the mean, entropy, and skewness. Figure 5 (C), (D), and (E) show distributions of these statistics in each cluster. Figure 4 (F) shows the proportions of data that were categorized into one of the three clusters by positive or negative phrase. The decision patterns were explained with the different assumption between positive and negative phrases. When presented with positive phrases, decision patterns were well explained with the assumption that participants referred to memory samples with low probability (see cluster 1 in Figure 4). In contrast, for the negative phrases, decision patterns were explained under the assumption that participants referred to samples with high probability (see clusters 2 and 3 in Figure 4).

Taken together, we found that the DbBS model generally explained decisions based on verbal probabilities. It was also found that decision patterns were well explained under the different assumptions between positive and negative phrases. For positive (negative) phrases, decision patterns were well explained under the assumption that participants referred to memory samples with low (high) probability. Therefore, our hypothesis was corroborated.

## General discussion

In the present study, we examined decisions based on verbal probabilities. Particularly, we examined whether the DbBS model explained the decision processes. We found that the DbBS model explained the decision patterns well.

Observed differences in memory samples were essentially in accord with our hypotheses based on previous findings about the speaker's choice of directionality in communication (Honda & Yamagishi, 2017). As previously noted, decisions affected by directionality seem like evidence of decision bias because people make different decisions even when positive and negative phrases convey analogous probabilities. Our present findings answer the question, "Why are people affected by directionality when making decisions?" Our answer is: people take into account the information conveyed by the selected directionality, and as a result refer to different memory samples. Therefore, decisions affected by directionality are not examples of decision bias, but decisions according to different memory samples.

## Acknowledgments

This research was supported by Grants-in-Aid for Scientific Research (A, 16H01725; B, 25280049; B, 16H02835), Innovative Areas (26118002; 16H06569), and Young Scientists (B, 16K16070).

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