Title
Memory Representations of Source Information

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 23(23)

ISSN
1069-7977

Authors
Farivar, Reza
Silverbag, Noah
Kadlec, Helena

Publication Date
2001

Peer reviewed

Memory Representations of Source Information

Reza Farivar (reza@ego.psych.mcgill.ca)
Department of Psychology, McGill University
Montreal, QC, H3A 1B1, Canada

Noah Silverberg (noahs@uvic.ca)
Department of Psychology, University of Victoria
Victoria, BC, V8P 5C2, Canada

Helena Kadlec (hkadlec@uvic.ca)
Department of Psychology, University of Victoria
Victoria, BC, V8P 5C2, Canada

Abstract

Various characteristics can be encoded to define the source of particular information. How these characteristics interact to describe and define a source has so far been ignored. Our work focuses on the representation of source information in memory using the General Recognition Theory. The results are discussed in relation to current modelling efforts.

Introduction

How is a source defined? How do we represent context information about an event? How do we use this information in source monitoring? Source monitoring refers to the proper attribution of an item to its source (Lindsay and Johnson, 1991; Johnson, Hashtroudi, and Lindsay, 1993). Sources may be defined by a variety of characteristics, including but not limited to size, font, location, cognitive processes at encoding, affect, and so on. For written material, font, location, size, and possibly the syntax and structure used in a part of text may identify a part of text as a source. Memory for source is vulnerable, and source misattributions (SM) are common. Such errors may arise due to (1) failure of cognitive processes underlying the judgment, (2) adoption of a lax criterion which does not involve deliberate and conscious consideration of each judgment, and (3) similarity of the sources to such an extent that they are indistinguishable from one another. In other words, source monitoring involves normal memory processes and decisional processes, and a separation of the two can yield a better understanding of how sources are actually defined and how decisional processes can fail and cause SM errors.

Recently, a number of multinomial models of source monitoring have been proposed (Bayen, Murnane, and Erdfelder, 1996; Batchelder and Reifer, 1990; see Batchelder and Reifer, 1999 for a review). These statistical models assume a processing tree with a single root. Each branch of the tree represents one possible path in the stage of the process, and each fork in the branch represents a possible division of probabilities for a specific outcome. The branches end in response categories, from which all the fork parameters are estimated. This type of modelling allows an analysis of every possible contribution to each factor and thus enables one to model a cognitive process into discrete stages, collect categorical data, and then estimate the contributions made at each stage.

The advantages of such a model are easily visible. Interpretations are made effortless by the simple tree structure. Assumptions of independence between various fork parameters allow one to divide and separate various components of a process and to demonstrate independence between these components. However, such representation of source information is not modelled by this technique, and as such, these modelling efforts are limited in capturing the global features of source monitoring.

There are at least two major limitations to multinomial modelling. The first involves the degrees of freedom in the estimation procedure. Given that there are often more parameters than categories, some parameters must be assumed equal. This may sometimes be beneficial, since a model is reduced to its minimal, simplest components. Unfortunately, even with this parameter reduction, one may still have more parameters than categories, and the estimation procedure will thus result in a number of possible models rather than a single possible solution. From this pool of resulting models, using goodness of fit tests, one must determine which model actually represents the expected design or the data.

A consequence of this is that as findings in the field increase, such a model is more difficult to grow because of the increase in the free parameters. A multinomial model will therefore be limited to more general processes and will not be able to model details of a process, such as how source information is represented in memory. A lack of understanding about the details of a process can, in turn, result in a misunderstanding of the process as a whole as well as the relation of that process in the grand scheme of cognition.

The second limitation, already hinted at, is the requirement of assuming statistical independence between various fork parameters. What this means is that a process stage, modelled on a fork further down a tree, is thought to be independent of a process stage modelled further up the tree; no two processes can have dependence in such a model. As we will see below, this assumption presents a crucial limitation of multinomial models in capturing the representation of source information in memory.

How to test statistical independence

In a multidimensional setting of a source characteristics where various factors influence source memory and source judgments, how is one to assess independence while accounting for the influence of all memory and decision factors? Historically, for unidimensional stimuli, signal detection theory (SDT; Banks, 1970; see Swets, 1996) has been the method of choice for separating decisional and perceptual factors in perception and recognition. However, SDT does not allow for a test of independence and is also limited to the analysis of only unidimensional stimuli. Ideally, we would want a statistical technique similar to SDT that could also account for interactions of various dimensions on a recognition task while providing a test of independence and separation of decisional and perceptual factors. General Recognition Theory (GRT; Ashby and Townsend, 1986; Ashby, 1988), and the analytical method permitted by it (Multidimensional Signal Detection Analysis, or MSDA, Kadlec & Townsend, 1992a; Kadlec & Townsend, 1992b), meet our requirements.

GRT and MSDA

The GRT was developed by Ashby and Townsend (1986) in response to various issues that had been raised in perception research. These issues concerned the notion of independence and separability of the perception of stimulus dimensions as well as decisional factors. The GRT is a formal method of assessing independence and separability in terms of both stimulus dimensions and decisional processes. MSDA was then developed by Kadlec and Townsend (1992a) in order to facilitate the implementation of GRT in perception studies. This analytic method maps the traditional SDT parameters of sensitivity (d') and response bias onto a multidimensional scheme and permits us to analyse both interaction and independence between various stimulus dimensions.

Multidimensional signal detection analysis MSDA was originally developed to analyse the effects of manipulation on the perception of a stimulus, when the manipulations are varied on a number of dimensions (Kadlec, 1995). An example study would be one that looks at the dependence of the perception of eyebrow curvature on the perception of lip curvature. First, we would need a feature-complete factorial design, and we would create this by manipulating each of the two dimensions on two levels. We would thus manipulate each of the two dimensions on two levels. Thus the eyebrows will be varied on two levels (low and high curvature) and the same manipulation would be used for lip curvature. Table 1 demonstrates this matrix for all variations of stimulus A.

Table 1: Example of a feature-complete factorial design.

	Eyebrow Curve	
Lip Curve	Low $_{(a)}$	High $_{(b)}$
Low $_{(i)}$	A_{ai}	A_{bi}
High $_{(j)}$	A_{aj}	A_{bj}

The participant will see stimuli, which vary on two levels of two dimensions. It should be noted that the stimuli at each level vary only slightly from the stimuli at the other level. This is mainly due to the fact that the final analysis will be based on the amount of errors committed during the task, and simplifying the task and making the difference between the stimuli obvious may result in a near absence of errors.

In a typical experiment utilizing this design, participants are given a practice session in which they view the set of stimuli, one at a time, varied on the given dimensions, and make judgments about their location at the different levels of the dimensions. In other words, a participant who views stimulus Abj must try to categorize this stimulus on both dimensions. The correct response for this stimulus is high eyebrow curvature and high lip curvature. There are three types of errors that could be made in the categorization of each stimulus. These errors can be tabulated, resulting in proportions of each type of error, which then represents the volume under the distribution in one of 4 possible response regions. These response regions can be represented by normal distributions in multiple dimensions.

How could we, from these data and types of distributions, answer questions regarding independence of dimensions and decisional boundaries? In order to answer such questions, a slightly different view of the graphs must be utilized. Consider a plane passing horizontally through all the normal distributions in this multidimensional space at a given density level. Examining such a plane from above would yield a topography of the distributions, as can be seen in Figure 1.

The shape of these distributions corresponds to three types of independence (Ashby & Townsend, 1986). The first type is perceptual independence (PI), which is a statistical form of independence. PI is stated when for a stimulus Abj:

$$fbj(x,y) = gbj(x)*gbj(y)$$

In this equation g(x) refers to marginal densities, which are obtained by integrating (measuring the area under the curve) the two-dimensional density distribution across one dimension. Marginal densities can be thought of as the picture of a density distribution as would be taken from having a camera parallel to a dimensional axis.

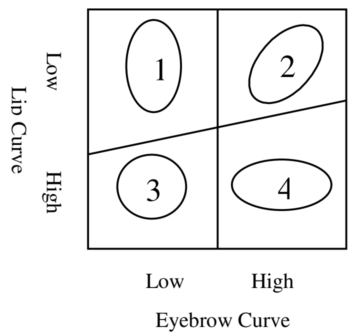

Figure 1: Topography of the distributions

PI is a strictly statistical form of independence and can be likened to coin toss probabilities, where the probability of obtaining two heads (assuming a fair coin; p(1H) = 0.5) is equal to the product of the probability of obtaining one head by the same probability:

$$p(2H) = p(1H) * p(1H) = 0.25$$

Thus PI asserts that the perception of one dimension within a stimulus is not dependent on the perception of the other dimension. From the topographical diagram, PI is represented by circular distributions and distributions which are elliptical but parallel to the axis of one dimension. From the diagram it may be observed that within stimuli 1, 3 and 4 the two dimensions are perceptually independent and the two-dimensional density distributions are equal to the product of the marginal densities of the stimulus on the individual dimensions.

Another form of independence, called perceptual separability (PS), is taken to exist when within one level of one dimension, the levels of the other dimension do not affect perception. In this case,

$$gi1(x) = gi2(x) \text{ and } gj1(x) = gj2(x)$$

where 1 and 2 refer to stimuli 1 and 2, i and j represent the two levels of eyebrow curvature, and g(x) refers to their marginal density distributions. If the two marginal distributions at the levels of one dimension (say high eyebrow curvature) are equal, then levels of the other dimension (lip curvature) do not influence the perception of the eyebrow curvature.

A third form of independence is decisional separability (DS). Recall that within the single dimension signal detection framework, a decisional boundary was set between the two distributions. Here too, within the multidimensional framework, some decisional boundary must be set. This decisional boundary is set by the participant and defines the area within which a stimulus will be identified by its specific characteristics. In our example, a decisional boundary must be set in order to differentiate between faces that vary differentially on eyebrow curvature and lip curvature. In other words, the decisional boundaries divide the multidimensional space into regions that define specific stimuli. Within this context, DS is observed when the decision about one dimension is not influenced by the decision made on the other dimensions. In our topography, DS holds when the decisional boundaries are parallel to the dimensional axis.

Methodology

From the above description of MSDA and its required experimental paradigm, it is more apparent how we would go about testing the independence of various source characteristics in a final source judgment. What we need is to create a feature-complete factorial design of at least two stimulus characteristics that can define a source, and then conduct our analysis on these dimensions.

Our study uses the characteristics of written text to assess this independence. The dimensions of written text tested are limited to size (large vs. small) and location (top vs. bottom). Within a multinomial framework, these two dimensions would have to be assumed independent of one another. In other words, independent of decisional biases, memory for an item being on top should have no effect on the memory of it being large. Such a model would represent a very basic and simple framework in which all sources are believed to be equal; if source characteristics do not interact and are independent, then any combination of the characteristics is remembered equally well.

Below we will present data to show that in this case, the assumption of independence is invalid, thus lying outside the structure of a multinomial model of source memory. Because the question of how various characteristics interact to define a source is central to the concept of source memory, we propose that multinomial models are limited in that they cannot capture this fundamental aspect of source memory.

Experiment 1

Participants

Eighteen undergraduate students enrolled in an introductory psychology course at the University of Victoria participated in the study for bonus marks. Responses from 3 participants were excluded because of incompleteness due to shortness of time. Responses from an additional participant were excluded due to apparatus failure. Overall, data from 14 participants were analysed. All data were kept confidential and no one was penalized for non-participation.

Material

A word-list was composed using 256 five-letter words randomly selected from the Francis-Kucera Frequency Norms. Of the 256 words, 160 were used at study and the remaining words were used as controls (novel words). Study items were factorially manipulated on size (large or small), font (Times or San Sarif), and location (top or bottom). An IBM-compatible computer with an Intel 486 processor was used for the experiment. All presentations were made on a 17" computer monitor and responses made on the computer keyboard.

Procedure

Participants were informed that they would view a list of words on the computer screen, varying in location, size, and font. They were instructed to try and remember all aspects of the words, as their memory for the words as well as these attributes would later be assessed. Following the instructions, the study list of 40 words was presented, each for 3 seconds, with 1second inter-stimulus-interval.

Immediately following the study phase, the test phase was conducted. Participants viewed the previously studied words in addition to 16 new words not previously seen. The words appeared in a small, neutral font (courier) at the centre of the screen. The first task was to make a remember/know/new judgement.

Following the instructions on remember/know/new judgements, participants were instructed on the identification task. Questions assessing the recognition for various item characteristics followed the remember/know/new judgements. The three questions asking for the recognition of levels of the three dimensions were randomised in presentation, so that for one item, font was asked first, followed by location and size, but for another, size was asked first followed by location and font, etc.; the sequence was randomised.

For both the remember/know/new judgements and the item judgements, participants made their response by selecting the first letter of the response on a computer keyboard (‘ r’ for ‘remember’, ‘t’ for times font when making font decision and top when making location decisions, and so on). The task was not timed, and participants were encouraged to consider each judgement carefully. Following the first study and test phase, three more study and test phases continued with the same instructions.

Results

Responses were collapsed across all subjects. To minimize variability due to practice (at the beginning of the session) as well as variability due to fatigue (at the end of the session), only responses from trials 2 and 3 were analysed; responses from these two trials were then combined, after no significant difference between them was observed on a chi-squared test. Due to space limitations, the results on remembering and knowing will not be discussed here, but we will only comment that near identical interactions were observed for remembered and known items; for the analysis, results associated with “remember” and “know” judgments (i.e. studied items judged as “old”) were combined.

The results are reported following Kadlec (1995). All tests of DS, PS, and PI are Z-tests with at least $p < 0.1$, unless otherwise noted. DS and PS held for all dimensions, whereas PI failed for all items.

To simplify the interpretation, the results were collapsed on to two dimensions, size and location. The resulting distribution topographies are represented in figure 2.

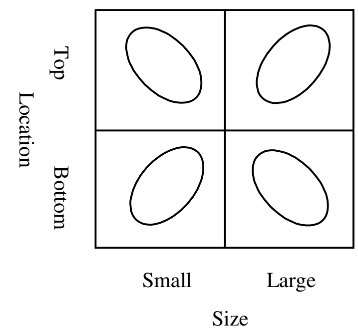

Figure 2: Schematic representation of results from experiment 1

The straight vertical and horizontal lines separating the distributions represent the decisional boundaries; they are parallel to the dimensional axese, because DS held for both dimensions. Furthermore, the distances between the distributions do not differ between the levels of each dimension, thus PS is also valid. However, PI has been violated in all instances, and in a consistent pattern: there is a strong positive tendency to remember large items as being on top and small items on the bottom, while there is a strong negative tendency to remember small items on top and large items on the bottom. Clearly, source definitions formed from these characteristics will result in a memory bias independent of decisional processes such as response biases. In other words, recolllected large words have a “topness” associated with them, and are dissociated from a “bottomness”, while the opposite is true for small words.

In order to further validate our results, we conducted a similar study, but we eliminated the presentation of a font dimension all together, as well as the remember/know judgments.

Experiment 2

Participants

Twenty-one undergraduate students enrolled in an introductory psychology course at the University of Victoria participated in the study for bonus marks.

Materials

One hundred sixty words with a frequency rating of 1 were obtained from the Francis-Kucera Word Pool and randomly divided into four lists of forty words. List presentation was fully counterbalanced. All the words were presented in random order in a study phase and were factorially manipulated on size (large and small) and location (top or bottom).

Procedure

Participants were informed that they would view a list of words on a computer screen, and that these words would vary on two dimensions, location on screen and font size. They were then instructed to do their best to 'remember' the words and how they were presented, as they would later be tested on these attributes. Firstly, in phase 1, a list of 40 words was presented for approximately 2 seconds each with an inter-stimuli interval of 1 second. Following this was a test phase in which subjects were asked 3 questions about 80 words (40 studied and 40 novel words): "Is this word old (o) or new (n)?", "Did it appear on the top (t) or bottom (b)?", and "Was it presented in a large (l) or small (s) size font?". The order of the questions was randomised. Subjects responded using a keyboard with the abbreviated letters corresponding to the responses to which they stand for (e.g. (o)=old). This task was not timed. Phase 2 followed and was a mere repetition of phase 1 but with different word lists. The whole session lasted 40 to 50 minutes.

Results

All tests of DS, PS, and PI are two-tailed Z-tests with at least $p<0.05$, unless otherwise noted. Analysis of the compiled old-correct matrix (where subjects responded "old" and were correct in doing so, whether in phase 1 or phase 2, or whether the new/old question preceded or followed the attribution questions) revealed an interaction of source characteristics, identical to that of experiment 1, represented in figure 2. Whereas DS and PS held for the two dimensions, PI failed in every case, such that there was both a positive dependency between "bottomness" and "smallness" and a positive dependency between "topness" and "largeness". Alternatively, it is also true that as words appear closer to the top of the screen, they are more likely to be remembered as having appeared in a larger size font. In analysis of unremembered items (where the item was presented, but judged as "new"), a bias was observed for words presented on top of the screen and in large size. This suggests that people have poor memory for such items; this and other result will be discussed below.

Discussion

How are source characteristics defined then? Using MSDA, we were able to separate decisional factors from memory factors. Our results are thus not based on a any decisional biases of the participant. In other words, it is not the case that participants recall an aspect of an item (e.g. having been presented in large size) and then infer from this information that the word must have been presented on top. If it were the case that participants recalled information on one dimension and inferred information on the other dimension, different criterion measures (C's) would have been observed at each level of any one dimension. However, measures of C were identical at every level of all dimensions, suggesting that decisional factors did not play a role at generating the observed patterns.

Perceptual separability also held for both dimensions, which suggest that memory for large items is no better than memory for smaller items, and that memory for items on top is no better than memory for items on the bottom. If this were not the case, d' measures for items presented on top or bottom would have differed when varied across the two sizes, and/or d' measures for items presented in large or small size fonts would have differed across the two different locations.

As both DS and PS held for both dimensions, we can infer that (1) decisional factors did not play a role in producing the observed pattern of results, and (2) that global features of the stimuli did not play such a role either. It can therefore be concluded that the interaction of the various source characteristics is a pure memory process.

This has implications for how source information is stored in memory. Our results suggest an information-compression taking place during encoding and/or storage of the source characteristics. In effect, error for the overall storage of such source information (size and location) is minimized by reducing error on the most frequently occurring instances of such a source. Source definitions composed of large items presented on the top of the screen are particularly common in all printed media such as newspapers, magazines, web pages, etc. Meanwhile, it occurs rarely that small print appears on the top part of a display, and the same is true for large items presented on the bottom of the screen. It may be the case that, in order to minimize errors on these frequently occurring source types, we are introducing biases into the process.

We believe that the compression (or consolidation) account is the most appropriate for our data; i.e. the way new information is stored is affected and directed by prior knowledge. This is analogous to perceptual illusions: perceptual illusions may exist as a consequence of a biased set of inputs which then results in a biased perception of illusory, but-otherwise-neutral items. It is likely that the same processes that cause perceptual illusions are responsible for the effects obtained here. In essence, our results may be demonstrative of a form of memory illusion, very distinct from prior studies of memory illusions with relation to eyewitness memory. In the case of eyewitness memory, some researchers (i.e. Loftus, Miller & Burns, 1978) suggest that presentation of secondary, post-event information impairs memory for an event by altering its contents. We suggest that *prior knowledge* impairs what new information can be learned in the first place, by limiting how the new information is represented.

What is the relation between our results and multinomial models of source monitoring? We suggest that multinomial models will be unable to incorporate our data in a meaningful way, because of inherent limitations in the estimation procedure for such models. Here, we are referring to the fact that multinomial models would have to assume independence between various source characteristics and, as our results show, such assumptions would be invalid. Therefore, such modelling techniques will not be able, in the long run, to present an accurate model of source memory.

Our results do not falsify any present uses of multinomial models. Multinomial modelling is insensitive to biases for sources, thus such modelling could capture the more general nature of our results. However, such a technique inherently does not allow for any type of representation of source memory and we believe that such a representation is crucial for an accurate model of source memory.

Recall from our results that studied items that were judged as "new" were more often items that had been presented on top of the screen and in large font. Although statistical analysis of this trend was not conducted for this paper, this may be a real effect worth considering, as it suggest that certain sources (or certain combinations of source characteristics) are easier to remember, such that this source combination may even affect item detection. Again, as statistical analysis of this was not conducted, we are only speculating on this point, but it is consistent with our findings, as they suggest a form of memory consolidation taking place.

Future work in the area can thus focus on assessing how sources are defined, as the tools now exist to answer such specific questions. Modelling efforts should also attempt to incorporate this representational information, as this will, without doubt, contribute to a more complete understanding of human memory.

Acknowledgements

This research was supported in part by a grant to the third author from the National Science and Engineering Research Council of Canada (NSERC). We thank Aidan Quigley for his help in collecting data.

References

Ashby, F. G. (1988). Estimating the parameters of multidimensional signal detection theory from simultaneous ratings on separate stimulus dimensions. *Perception & Psychophysics*, 44, 195-204.

Ashby, F. G. & Townsend, J. T. (1986). Varieties of perceptual independence. *Psychological Review*, 93, 154-179.

Bayen, U. J., Murnane, K., & Erdfelder, E. (1996). Source discrimination, item detection, and multinomial models of source monitoring. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 22, 197-215.

Batchelder W. H., & Riefer, D. M. (1999). Theoretical and empirical review of multinomial process tree modelling. *Psychonomic Bulletin & Review*, 6, 57-86.

Batchelder, W. H., & Riefer, D. M. (1990). Multinomial processing models of source monitoring. *Psychological Review*, 97, 548-564.

Johnson, M. K., Hashtroudi, S., and Lindsay, D. S. (1993). Source monitoring. *Psychological Bulletin*, 114, 3-28.

Kadlec, H. (1995). Multidimensional signal detection analyses (MSDA) for testing separability and independence: A Pascal program. *Behaviour Research Methods, Instruments, & Computers*, 27, 442-458.

Kadlec, H., & Townsend, J. T. (1992b). Signal detection analyses of dimensional interactions. In F. G. Ashby (Ed.), *Multidimensional models of perception and cognition*. Hillsdale, NJ: Erlbaum.

Kadlec, H., & Townsend, J. T. (1992a). Implications of marginal and conditional detection parameters for the separability and independence of perceptual dimensions. *Journal of Mathematical Psychology*, 36, 325-374

Lindsay, D. S., & Johnson, M. K. (1991). Recognition memory and source monitoring. *Bulletin of the Psychonomic Society*, 29, 203-205.

Loftus, E. F., Miller, D. G. & Burns, H. J. (1978). Semantic integration of verbal information into a visual memory. *Journal of Experimental Psychology: Human Learning and Memory,* 4, 19-31.

Swets, J. A. (1996). *Signal Detection Theory and ROC Analysis in Psychology and Diagnostics: Collected Papers*. Hillsdale, NJ: Lawrence Erlbaum Associates.