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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 40(0)

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Publication Date
2018

What's in an Association? The Relationship Between Similarity and Episodic Memory for Associations

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Abstract

When two events occur closely in time, an "association" exists between memories for those events. When a pair of associated events is semantically similar, it is easier to recognize the complete pair and easier to tell the complete pair apart from pairs of events that did not co-occur; there is also, however, a bias to report that similar events had co-occurred, even when they had not. A new experiment shows that these phenomena occur whenever two events share features, whether those features are perceptual or conceptual in nature and whether the events themselves are verbal or non-verbal. We present a dynamic model for storage and recognition of associations that shows how all these results can be explained by the principle that shared features lead to correlated processing of similar events, which in turn increases capacity to process associative information.

Keywords: Memory; associative recognition; similarity.

Introduction

When two events occur closely in time, it is often the case that an "association" is formed between the memories for those events. That is, not only is information about the events themselves stored in memory (often called "item" information), so is information about the fact that they co-occurred (often called "associative" information). The ability to store both kinds of information underlies numerous cognitive functions, such as the ability to associate a word with its referent, to discover analogies between similar scenarios, and to learn causal relationships between events. However, it remains unclear what the relationship is between memory for individual events (items) and for combinations of events (associations). In particular, it is not clear what the *content* of an association is—does it depend on properties of the associated items or is it independent? Based on a set of results regarding the relationship between similarity and associative memory, we present a model in which associative information is based upon alignment of item representations. Results from a new experiment lend support to this model.

Memory for associations can be studied using the *associative recognition* paradigm. In this task, participants study a set of pairs of items such as words or images. In a subsequent test phase, participants are asked to distinguish between pairs of items that were studied together ("intact" pairs) from those that were studied separately ("rearranged" pairs). Because the items in each test pair were always studied, this task selectively measures memory for the associations formed between items that were studied at the same time. Good associative memory is indicated by the ability to correctly recognize intact pairs (high hit rate and/or fast correct recognition) and to reject rearranged pairs (low false alarm rate and/or fast correct rejection). By manipulating the kinds of item pairs used in the study and test phases of this task, it is possible to assess what kinds of item information lead to better associative memory and, therefore, to learn about how the mnemonic content of individual events (items) is related to the content of associations formed between them.

Table 1: Examples of study and test pairs used by Dosher (1984) and Dosher and Rosedale (1991).

Partial study list	Test pair
PRESENT—GIFT	PRESENT—GIFT (S^+E^+)
CENTER—SUM TOTAL—MIDDLE	CENTER—SUM (S^-E^+)
DINNER—VOW PROMISE—SUPPER	DINNER—SUPPER (S^+E^-)
SUMMIT—PERSON CURTAIN—PATTERN	SUMMIT—PATTERN ($S^-E_u^-$)
MOVIE—FILM MOTIVE—REASON	MOVIE—REASON ($S^-E_r^-$)

Using this task, Dosher (1984) and Dosher and Rosedale (1991) investigated the relationship between semantic similarity and episodic memory for associations by using different kinds of study and test pairs (Table 1). S^+E^+ pairs are those that are both semantically related (S^+) and studied together (E^+); S^-E^+ pairs are those that are semantically unrelated (S^-) and studied together (E^+); S^+E^- pairs were not studied together (E^-) but are semantically related (S^+). There are two kinds of S^-E^- pairs, i.e., pairs that are neither semantically related nor had been studied together: $S^-E_u^-$ pairs are formed by rearranging pairs of items that had originally been studied with unrelated items; $S^-E_r^-$ pairs are formed by rearranging pairs of items that had been studied with semantically related items. They found three critical results:

1. Correct recognition of an episodic association is improved when pairs are semantically related ($S^+E^+ > S^-E^+$).
2. False recognition of a rearranged pair is reduced when its members were originally studied as part of semantically-related pairs ($S^-E_r^- < S^-E_u^-$).
3. Semantically related rearranged pairs (S^+E^-) tend to be falsely recognized as having been studied, but primarily when responding is rapid ($S^+E^- \approx S^+E^+$ early, $S^+E^- \approx S^-E_u^-$ late).

It is difficult for any single account to explain all these results: The first two results indicate that the presence of a semantic relationship between a pair of items leads to stronger encoding of their episodic relationship, since it not only improves correct recognition, but aids correct rejection as well. Results 1 and 3 might lead one to conclude that semantically related pairs are more familiar by virtue of co-occurring more often in general, but in fact such words do not tend to co-occur (synonyms or antonyms are used *in place of* one another, not *next to* one another), nor would this explain result 2. Result 2 might be attributed to an encoding-specificity effect (Tulving & Thompson, 1973), but this would not explain the other results nor why the effect is larger for pairs that were originally studied with a related word. Result 3 could indicate that associative recognition depends initially on an overall assessment of "relatedness", and a second source of purely episodic information "suppresses" this initial bias (e.g., a "recall-to-reject" mechanism). However, the suppression account does not explain why $S^+E^+ > S^-E^+$ even for slower responses (if semantic relatedness were suppressed, this should mitigate the advantage for S^+E^+ pairs) nor why it is easier to reject $S^-E_r^-$ pairs than $S^-E_u^-$ (unless studying a semantically related pair also made that pair easier to recall, which could allow S^+E^+ pairs to retain their advantage even for slow responses).

Recent work from our laboratory suggests these results may be a function of interactions between item memory and memory for associations. Cox and Shiffrin (2017) proposed a dynamic model for item and associative recognition in which associative recognition decisions were based on a set of features that emerged from the interrelation and/or elaboration of the features of the component items. Because associative features can only emerge after enough item features have been processed, this model implies a strong interaction between item and associative retrieval. Clear evidence for such an interaction was found by Cox and Criss (2017), however they also found that item and associative information were also separable, in that some decisions could be made on the basis of just one kind of information (cf. Buchler, Light, & Reder, 2008). This prior work focused on the mechanisms involved at *retrieval*, rather than what happens during *encoding*, leaving unspecified the precise nature of the interactions involved.

A Dynamic Model of Associative Encoding

While it would be possible to explain the set of results just reviewed in terms of multiple processes, we present a model that is based on a single set of encoding and retrieval mechanisms, based on the model for item and associative recognition described by Cox and Shiffrin (2017). Although we refer the reader to that source for additional detail, we lay out the essential components of the model below, and show how it helps explain the associative recognition results of Dosher (1984) and Dosher and Rosedale (1991). The core of our account is that encoding associative information depends on aligning item representations, and when items are similar they are processed in a correlated fashion that allows them to be aligned more easily and affords greater capacity to encode associative information. Four consequences follow directly from this account:

1. Shared features between items at study leads to greater storage of associative information.
2. Shared features between items at test allows extra capacity to cue memory with associative information.
3. Correlation between channels at test leads to a bias to give a positive response.
4. If shared features are used to encode an item at study but they are no longer available at test, the similarity between the test item and memory for the studied item is reduced.

It is apparent that many of these consequences map onto the partial explanations offered in the Introduction—the aim of our model is to show how they all flow from the single notion that shared features lead to correlated processing.

Representation and storage The event of encountering a pair of items at either study or test is represented in working memory as a set of binary (0 or 1) features. There are three types of feature, as depicted in the top row of Figure 1: *context* features, which represent the time and location of the study event; *item-specific* features, which represent the perceptual and conceptual aspects of each item; and *associative* features which represent the co-occurrence of the two items. There is a limited capacity to hold features in working memory. This capacity is determined by the number of *unique* features across the event, such that when items are similar less capacity is needed to represent them and more capacity is available to represent associative features. Each item feature has probability s of being shared between two semantically related words. The proportion of features devoted to encoding associative information is p_A for unrelated items and is $1-(1-p_A)(1-p_A s)$ for related items (in other words, either an associative feature is encoded normally with probability p_A or there is a shared feature with probability s *and* that capacity is used for an associative feature with probability p_A).

If the pair is presented for study, its working memory representation is stored as a trace in long-term memory[1]. Storage tends to be incomplete and error-prone. Because context features are persistent in the environment, we assume that all available context features are stored in the memory trace. However, due to limited time and attentional resources, not all item or associative features may be stored—we let u denote the probability that a non-context feature gets stored in the trace. If a feature is stored, it is stored correctly with probability c_S, otherwise a random value (either 0 or 1 with equal probability) is stored instead. There is also a potential cost that comes from encoding similar items with shared features in that the item features stored by relying on shared features may not match those stored without using these features, a type of encoding-specificity (Tulving & Thompson, 1973). Thus, while the effective *amount* of item features stored for pairs of similar items is no more or less than that for unrelated items, those features will not necessarily match the features that would have been stored for that item as part of a different pair. For example, the probability of feature overlap between "jam" as part of "traffic-jam" and "jam" as part of "strawberry-jam" would be $(1-s)+s^2$ (either it is unique with probability $(1-s)$ or is shared with *both* "traffic" and "strawberry" with probability s^2).

Following the paradigm of Dosher (1984) and Dosher and Rosedale (1991), we model storage of 21 memory traces, one

[1] Storage certainly occurs during test as well, but is not modeled here for simplicity.

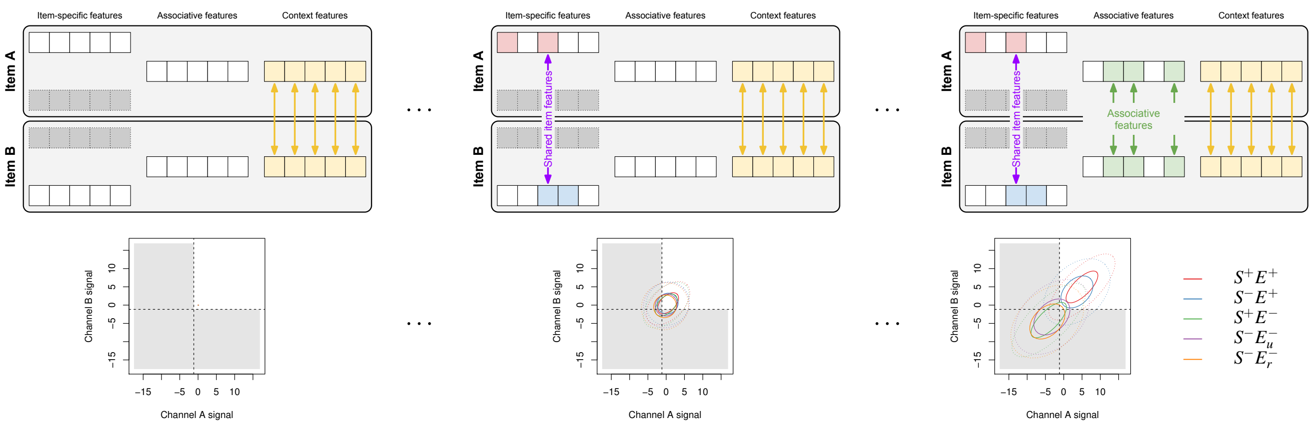

Figure 1: Illustration of how the two-channel memory probe evolves as different features become active (upper panels), changing the joint activation of the two channels (lower panels; gray area indicates where a "no" response will be made, white area where a "yes" response will be made). Each column corresponds to times denoted by the dotted vertical lines in Figure 2.

for each studied pair in the list, of which there were 7 related pairs and 14 pairs formed by recombining related word pairs. Note that this means some of the item features in a trace for an unrelated pair may be shared (with probability s) with some of the item features in a different memory trace.

Encoding dynamics Pairs are encoded in working memory according to the same dynamic process at either study or test, and it is this dynamic process that determines the shape of the speed-accuracy trade-off curves. At test, the working memory representation is compared to the traces stored in long-term memory to assess whether the pair is intact or rearranged. Initially, the two items are processed in separate channels. Each channel starts with just the features of the present context, which tend to match the stored context features of recent events, like those from the study list. These representations are compared, in parallel, to each of the traces in memory, resulting in an activation level $\lambda_i(t)$ for each trace i that is a function of the number of features that match ($N_i^M(t)$) or mismatch ($N_i^N(t)$) between the probe representation and the trace: $\lambda_i(t) = (1+c_S)^{N_i^M(t)}(1-c_S)^{N_i^N(t)}$. Because $\lambda_i(t)$ takes the form of a likelihood ratio (Shiffrin & Steyvers, 1997), it increases with the number of matching features and decreases with the number of mismatching features. As a result, a trace that has more features stored will be more strongly activated by a matching probe, but will also be more strongly *de*-activated by a mismatching probe.

The memory strength ("familiarity") for each probe is the logarithm of the average level of activation over those traces whose activation is greater than one, i.e., $\phi(t) = \log\langle\lambda_i(t)|\lambda_i(t) > 1\rangle$. Finally, recognition decisions are based on tracking how memory strength *changes* from its initial context-only level as the test pair is processed, such that the memory signal for a given probe is $x(t) = \phi(t) - \phi(t_0)$, where t_0 is the time at which the test pair begins being processed.

As the trial proceeds, features of each test item gradually arrive from perception (e.g., color or contour features) and knowledge (e.g., semantic features) and join the context features already in each probe, as illustrated in Figure 1. If the test items are related, they share features (again, with probability s), inducing a correlation between the signals from each channel (cf. Tulving, 1981)[2]. Encoding an associative feature depends on having a feature stored in the same "slot" for both items, a process we refer to as "alignment"; the intuition behind the need for an alignment process is that one cannot encode an association until one knows something about what is being associated. The effect of this is that associative features become active only after some item features have already been encoded. Associative features enter *both* channels, correlating their signals even more strongly. Once again, the proportion of the available encoding capacity that is devoted to associative features is p_A for unrelated items and $1-(1-p_A)(1-p_A s)$ for related items. The left two panels of Figure 2 illustrate how the relative proportion of item-specific and associative features in the probe yield different levels of correlation, which are reflected in the joint distribution of recognition signals between the two channels (bottom row, Figure 1).

Decision rule and related-pair bias In the signal-to-respond paradigm, participants withhold their response until a signal is given, at which point they make a response rapidly (typically within 300 ms) based on whatever features they were able to encode by the time of the signal. When the signal is given, a participant responds "yes" (the pair is intact) if *both* signals are above a criterion θ, otherwise they respond "no" (corresponding to the white "yes" and shaded "no" regions in the lower panels of Figure 1). This decision rule makes it clear why correlated signals due to shared features lead to a bias to give a positive response early on—by making it less likely for the signals to disagree (i.e., one above and one below the criterion), this makes negative responses less likely (see the lower middle panel of Figure 1). But the fact that shared features allow for more associative features to be encoded later on (once enough item features are encoded)

[2] Context features are also shared between channels, but because memory signals *subtract* the initial context-only level, they do not result in a cross-channel correlation.

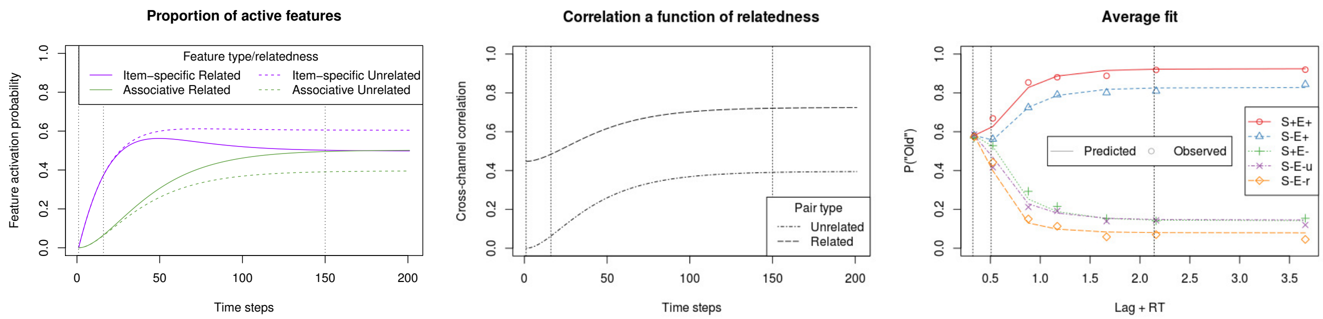

Figure 2: The proportion of feature types active in the memory probe over time (left panel) determines the level of correlation between the two channels (middle panel) which, in turn, determines the form of the bivariate distribution of signals in each channel which determine the response probabilities (right panel, showing data averaged from Dosher, 1984, Exp. 1 and Dosher & Rosedale, 1991, Exp. 1). Model parameters (see main text for definitions): $u = 0.51$, $c_S = 0.96$, $s = 0.45$, $p_A = 0.40$, $\theta = -1.2$, $t_0 = 0.100$, $\rho = 0.013$.

means that this early bias gets suppressed for S^+E^- pairs because it is easier to detect the *mis*-match between the associative features at test and those stored at study. Conversely, it is easier to detect the associative *match* for S^+E^+ pairs.

Model fit For simplicity, we assumed that the maximum number of either item, associative, or context features that could be held in either the probe or trace was 30. Model predictions were generated using a discrete-time approximation (Cox & Shiffrin, 2017, Appendix A), where each time step takes ρ seconds and processing begins at a time t_0 after the onset of the test pair. The complete model then has five more free parameters: u (feature storage probability), c_S (feature storage accuracy), s (probability of related items sharing features), p_A (proportion of capacity for associative features), and θ (response criterion). The right panel of Figure 2 shows that the model captures not only the qualitative features of the data, but the quantitative details as well (for average data, $R^2 = 0.98$; over individuals, R^2 ranged between 0.72 and 0.96, with median 0.91).

Experiment

Our dynamic account of associative encoding says that shared item features *of any kind* make it possible to encode more associative information in memory, leading to better recognition of intact pairs and better rejection of rearranged pairs, as well as an early bias to call related pairs "old" that gets overwhelmed by the fact that such pairs contain shared item features that allow for more associative features later on. However, our account was designed to explain results using verbal stimuli and semantic similarity only. Therefore, we conducted a new associative recognition experiment to assess whether our account remained plausible for non-verbal stimuli or non-semantic kinds of similarity.

Methods

Participants 79 Syracuse University undergraduate students participated in this study in exchange for course credit in accord with local Institutional Review Board policy.

Materials Stimuli were one of three kinds: pictures of common objects (drawn from Brady, Konkle, Alvarez, & Oliva, 2013), distorted versions of those objects, or words, as shown in Figure 3. The object stimuli consisted of 100 quartets, where each quartet comprise two pictures of two objects each, depicting each object in one of two states. There are three ways to draw two non-overlapping pairs from a quartet, such that there are three types of object pair: causally-related pairs (same object in two different states); categorically-related pairs (different objects but in the same state); and compound causal+category pairs (different objects in different states).

Distorted versions of each object quartet were created by vertically flipping each image and then translating its pixels according to a randomly generated Perlin fractal noise texture. Although different noise textures were used for each quartet, within a quartet, the same noise texture was used to distort each image. The effect was that each image in the same quartet was subjected to the same distortion, preserving the local pixel relationships while disrupting the global form of the images and making them unidentifiable as objects. By comparing normal to distorted objects, we can compare the extent to which low-level perceptual similarity or high-level conceptual relationships affect associative encoding.

Verbal stimuli were also designed to form quartets, where again any pair from the quartet embodies a particular relationship (or lack thereof) between the items in the pair. There were two kinds of verbal quartets: In one type, pair members either had no systematic relationship or could be combined to form compound words. In the other type of quartet, pair members were either synonyms, orthographic neighbors, or had no systematic relationship. The possible verbal relationships thus run the gamut from being unrelated, to being semantically similar (synonyms), perceptually similar (orthographic neighbors), or potentially unitized (compound words). In all, there were 48 of each type of verbal quartet.

Design and Procedure Each participant engaged in 16 study/test blocks, 4 using normal object stimuli, 4 using distorted object stimuli, and 8 using verbal stimuli. The order of blocks was randomized for each participant. Each study list consisted of 24 pairs of items—2 non-overlapping pairs from 12 quartets—presented for 3 seconds each in random order (with a 1 second inter-stimulus interval), under the constraint

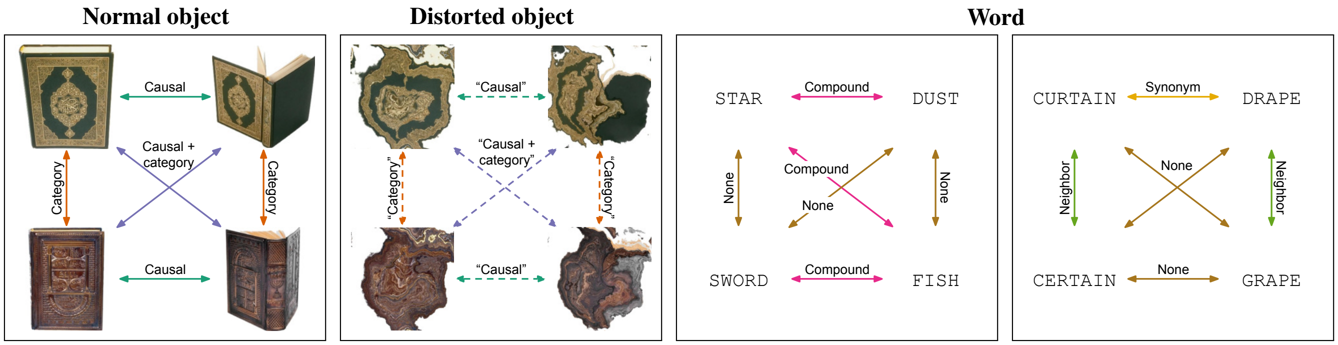

Figure 3: Examples of stimulus quartets used to generate study and test pairs.

that two pairs from the same quartet would not be presented one after the other. Which set of pairs was shown at study was counterbalanced across quartets, e.g., for object stimuli 4 quartets were causal pairs, 4 were category pairs, and 4 were causal+category pairs. Each verbal list was comprised of 6 sets of pairs from compound-word quartets and 6 sets of pairs from synonym/neighbor quartets (again, the set of pairs within a quartet that were studied was counterbalanced across quartets within each list). At test, half of the pairs were shown intact and half were rearranged, with assignment of intact/rearranged (and, for rearranged pairs, *how* they would be rearranged) being counterbalanced across quartets within a list. Any given item would only been seen by a participant in a single study/test block, and if a participant encountered an object quartet in distorted form, they would never encounter it in its original form, and vice versa.

During study, the items in each pair were presented next to one another in horizontal orientation, with left/right position determined randomly. Prior to each study list, participants were told to try to remember the items in the list as well as which items appeared together at the same time (i.e., as part of a pair). After presentation of the study list, test instructions were shown to participants for a minimum of 15 seconds, after which they could proceed. These instructed participants that they should give a positive response (using either the J or F key, randomly assigned per participant) when shown an intact pair and a negative response (using the other key) otherwise, and that they should try to make their responses as quickly and accurately as possible. The items in each test pair were presented on top of one another in vertical orientation, with top/bottom position determined randomly, to preclude any bias due to left/right item position at study. Each test trial began with a fixation cross in the center of the screen for 500 ms, followed by presentation of the test pair which remained on screen until the participant made their response. After responding, participants were told whether their response was correct or incorrect; if they made a response in less than 300 milliseconds, they were also shown a message to "Please take more time to respond" and if they responded in more than 4 seconds, they saw a message to "Please try to respond more quickly". Feedback was displayed for at least 1 second, and for an additional 3 seconds if the response was under 300 ms. A random interval between 1.25 and 1.75 seconds preceded the onset of the next test trial.

Results

The mean proportions of positive recognition responses as a function of both study and test relationship are shown in Figure 4[3]. For present purposes, we simply note a few crucial features of the data: Among normal object stimuli, causally-related pairs had slightly higher hit rates and were less likely to result in false alarms when rearranged, analogous to S^+E^+ and $S^-E_r^-$ pairs. When comparing normal to distorted objects, however, it is clear that at least some of the advantage for causally-related pairs is due to their shared low-level features rather than the conceptual relation—such pairs yield superior discriminability even when the objects are deprived of semantic content by distortion.

Among words, studying an unrelated pair leads to overall worse recognition (lower hit rates and generally higher false alarms), but there was no substantial difference between different kinds of foils in terms of false alarm rate, in accord with the finding above that any relatedness bias tends to occur when responses are rapid and not necessarily in free response. Although semantic relatedness lead to higher hit rates (and lower false alarms, at least for neighbor foils), pairs of orthographic neighbors (which are perceptually, not semantically, similar) or pairs that could form a compound word (which may not be similar to one another, but could be processed holistically) yielded even better correct recognition as well as lower false alarms, at least to unrelated foil pairs.

Discussion

Our experiment is consistent with our model in that shared features of any kind, whether perceptual (e.g., orthographic neighbors or similar distorted objects) or semantic (e.g., synonyms or identical undistorted objects) yield superior encoding of associative information, as evidenced in enhanced recognition of intact similar pairs and/or enhanced rejection of rearranged pairs that "break" similar pairs (like $S^-E_r^-$ pairs). Further, this holds not just for verbal stimuli, but for natural objects and abstract forms (the result of distorting the normal object images). Our results are thus congruent with

[3] Space constraints preclude plots of response time, however it is generally anti-correlated with accuracy, such that high-accuracy conditions also have faster responses on average.

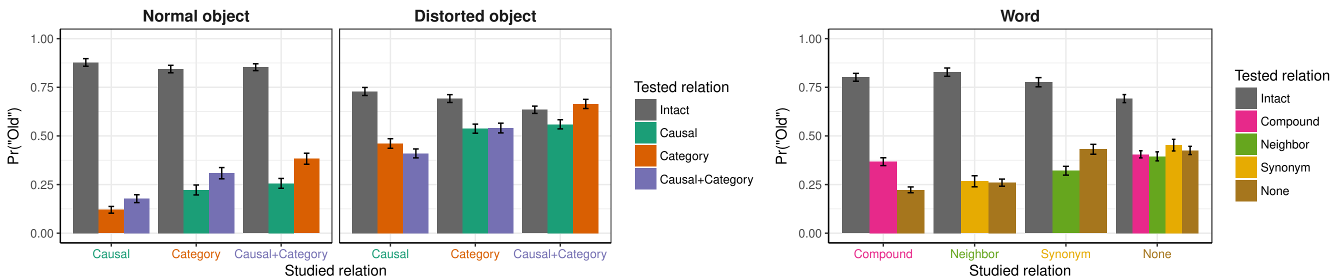

Figure 4: Mean proportion of positive recognition responses (error bars ±1 within-subject standard error about the mean).

results 1 and 2 from the Introduction. As for result 3, the lack of a similarity-based bias in our results is consistent with Dosher and Rosedale (1991) in finding that such biases are usually restricted to short response deadlines.

Discussion

We have shown how the presence of shared features between items—a single parameter (s)—leads to the three critical findings described in the Introduction: Shared item features leave extra capacity for storing associative features at study, meaning that an intact related pair will more strongly activate its corresponding study trace (result 1) but a test pair that *breaks* related pairs (i.e., $S^- E_r^-$) will more strongly *de*-activate those traces and is less likely to match the studied items (result 2). At test, shared item features induce a stronger correlation between the channels devoted to processing each item, leading to a bias to give a positive response to such pairs that is later suppressed as shared features allow more capacity for associative features (result 3). This model also builds on the account proposed by Cox and Shiffrin (2017) to illustrate how item and associative information interact during both encoding and retrieval (Cox & Criss, 2017).

Our experiment illustrates how *any* shared features, whether perceptual or conceptual, lead to these consequences. In addition, we can directly compare these results to pairs of words that form a compound, that is, a single unit, which elicited performance similar to that for pairs of orthographic neighbors (i.e., strong perceptual similarity). While it is true that the items in such a pair still form words in their own right, it is likely that compound word pairs are encoded with relatively few item-specific features and relatively more associative features. Within the context of the model, if only associative (and context) features are active at retrieval, the "two channels" are perfectly correlated—effectively forming a single-item unit, i.e., a compound.

That compound word pairs can be viewed as an extreme case of "feature sharing", even though their component items do not necessarily share any features, highlights how experience can alter the encoding of event memories and event associations. A feature that was once "associative", that is, that could only become available in the presence of combinations of other features, can become an "item" feature as those combinations are experienced repeatedly, a phenomenon often associated with the term "unitization" (LaBerge & Samuels, 1974; Goldstone, 2000). This suggests that the additional capacity for associative features that arises from shared item features is not solely the result of feature sharing being, itself, a type of associative feature. Instead, associative features may represent higher-order relationships between items. And while more work is needed to relate how associations are retrieved when all elements of the association are present (as in recognition) versus when they are only partially presented (as in cued recall), the strong correlation between associative recognition and cued recall—including how item properties affect performance in each task—suggests that similar mechanisms are involved (Cox, Hemmer, Aue, & Criss, 2018).

We do not pretend to have explored all possible models of associative representation and retrieval, and given the overwhelming number of as-yet-untested experimental manipulations of item and associative relationship, we suspect that any extant model—including the one we describe here—will eventually prove insufficient. What we have done is to illustrate how a diverse set of results that have been difficult to reconcile can be readily understood within a single dynamic framework for memory retrieval.

Acknowledgments

This work was supported by a grant from the National Science Foundation (BCS-0951612). We thank Bria Harris and Tommy Knoerl for assistance with data collection.

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