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Different Features of Real-World Objects Are Represented in a Dependent Manner in Long-Term Memory

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In the present study, we examined how real-world objects are represented in long-term memory. Two contrasting views exist with regard to this question: one argues that real-world objects are represented as a set of independent features, and the other argues that they form bound integrate representations. In 5 experiments, we tested the different predictions of each view, namely whether the different features of real-world items are remembered and forgotten independently from each other, in a feature-based manner, or conversely are stored and lost in an object-based manner, with all features depending upon each other. Across various stimuli, learning tasks (incidental or explicit), experimental setups (within- or between-subjects design), feature-dimensions, and encoding times, we consistently found that information is forgotten in an object-based manner. When an object ceases to be fully remembered, all of its features are lost, instead of only some of the object's features being lost whereas other features are still remembered. Furthermore, we found support for a strong form of dependency among the different features, namely a hierarchical structure. We conclude that visual long-term memory is object-based, challenging previous findings.

Keywords: visual long-term memory, object-based representations, feature dependency

Supplemental materials: http://dx.doi.org/10.1037/xge0000716.supp

When we see an object in the world, how do we later remember it? It is widely known that long-term memory (LTM) is capable of storing a vast amount of information (Brady, Konkle, Alvarez, & Oliva, 2008; Shepard, 1967; Standing, 1973; although see Cunningham, Yassa, & Egeth, 2015), and that LTM is vulnerable to forgetting (Ebbinghaus, 1885/1913), but many open issues remain regarding the nature of these processes. Specifically, an object can be remembered and forgotten in a feature-like manner, with the destiny of each feature being independent of the other features, or it can be remembered as an integrated representation, and, in turn, forgotten as a whole, such that all of the object's features depend upon each other. The general issue of dependent versus independent processing fostered an ongoing debate, not only with regards to memory, but at various levels of the visual system (e.g., Brady, Konkle, & Alvarez, 2011; Scholl, 2001).

Studies supporting the centrality of integrated objects provided evidence for a performance benefit for processing two features when they belong to one object, relative to when the same two features belong to different objects. For example, when subjects were asked to report both the orientation and the size of a line, accuracy was similar to a condition where subjects reported only the orientation. However, when they reported the orientation and the size of two different superimposed objects, accuracy declined (Duncan, 1984; for reviews of object-based attention see Chen, 2012; Scholl, 2001). Similar findings were reported in the change detection paradigm that taps into working memory ability: Several studies found that although adding more to-be-remembered objects dramatically reduced accuracy, adding more features to each object was cost-free, suggesting that integrated objects, and not individual features, are the basic building blocks of working memory (e.g., Luria & Vogel, 2011; Pratte, Park, Rademaker, & Tong, 2017; Vogel, Woodman, & Luck, 2001; see also Gajewski & Brockmole, 2006). In contrast, other studies did find a cost when additional features were added to objects encoded in working memory (Oberauer & Eichenberger, 2013; Olson & Jiang, 2002; Wheeler & Treisman, 2002). Importantly, even studies that did find some cost when features were added to an object still demonstrated a benefit when different features appeared as part of the same object, compared to when these features were distributed among several objects (e.g., Fougnie, Asplund, & Marois, 2010). Because both object-based and feature-based representations have been demonstrated in working memory, it is possible that working memory operates at multiple levels of representation (Brady et al., 2011; Vergauwe & Cowan, 2015).

In the context of LTM, it has been shown that when simple items such as colored shapes are retained in LTM, their features are better recalled when presented within the same item (Walker &

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Cuthbert, 1998; Wilton, 1989), suggesting an object-based representation in visual LTM. Similarly, it was demonstrated that when participants recall several features of the same object, all of these features are recalled together (Ceraso, Kourtzi, & Ray, 1998), indicating that objects are learned in an integrated manner. However, this evidence relied on simple stimuli, and thus it remained possible that the features of more complex visual stimuli, as the ones we normally encounter in our everyday lives, are represented independently in LTM. There have been claims that the features of real-world objects (e.g., faces) are retained somewhat independently in LTM. Support for this came from recognition ("old/new") tasks which tested participants on stimuli that were either presented during the study phase, completely new, or conjunction stimuli, which were comprised of parts of several different previously studied items, that is, these were "new" items whose parts were "old." The probability of recognizing an item as "old" was higher for conjunction stimuli than for completely new items (Albert, Reinitz, Beusmans, & Gopal, 1999; Reinitz, Lammers, & Cochran, 1992). This was taken to suggest that the different remembered features of an item were held separately in LTM, because participants' judgment of memory was based on whether a feature previously appeared, not only on its relation to the other features of the item to which it belonged. Yet, others have argued and demonstrated that these conjunction errors could be due to the greater familiarity of the compound stimuli, not to the fact an item's features are independently held in memory (Jones & Jacoby, 2001; Jones, Jacoby, & Gellis, 2001).

A related line of work showed that especially for recollection-based responses (but less so for familiarity-driven responses), across many stimuli and features, there is a "stochastic dependence" between the different source-dimensions of a given item (e.g., Meiser & Bröder, 2002). Namely, when items are learned in multidimensional contexts, the successful retrieval of one source dimension is correlated with the successful retrieval of the other. Although the phenomenon of stochastic dependence is well established, its basis is still debated (although see Horner & Burgess, 2013, 2014; for computational and neural analyses in the context of episodic memory), and it is unclear whether the different sources are actually bound together, or conversely whether the better performance is simply due to overall better memory to some items (for a review, see Hicks & Starns, 2015).

Recently, the issue of dependent (object-based) versus independent (feature-based) storage and forgetting of complex stimuli in LTM was examined by Brady and colleagues (Brady, Konkle, Alvarez, & Oliva, 2013), using pictures of everyday objects (in another recent paper, independence vs. dependence in LTM of real-world objects was tested using different paradigms by Utochkin & Brady, 2019; we return to this study in the General Discussion). They manipulated two object dimensions, by using different exemplars of the same object and presenting these similar objects in different states. Thus, each object-category included four pictures, created by factorially combining two possible exemplars in two possible states (see Figure 1a and 1b). The experiment began with an incidental study phase, in which participants viewed pictures of objects (one at a time) while performing a cover task. Then, participants were given a surprise memory test and were asked to select the object that was previously presented out of the four possibilities. Brady et al. (2013) calculated, for each participant, a dependence score, based on the memory benefit one feature gains from remembering the other feature (see Brady et al., 2013, for more details). To control for factors such as the overall accuracy of each dimension, they examined the change in this dependence score over time, by testing one group of subjects shortly after the study phase, and another group after 3 days. They found a high level of dependency between state and exemplar after a short delay, which could have been taken as evidence for integrated representations. However, in the long delay, Brady et al. (2013) found no significant dependency between the features. They concluded that the features were not integrated to begin with and were simply maintained separately at a high accuracy level, meaning that the actual memory storage and forgetting of the features was independent.

We argue that Brady et al.'s (2013) analysis is based on an implicit assumption of independence between the four possible responses. This is because at each step two of the response-categories are pooled together, while ignoring the other two response-categories (e.g., the conditional probability of state on exemplar is the correct-correct category divided by the sum of the correct-correct and correct-incorrect categories). Yet, the test phase includes all four pictures simultaneously, meaning that the possible response categories are very likely to affect each other. Indeed, using the same paradigm, we will provide evidence for a dependency of the response categories. We will also present logical arguments against this assumption in the General Discussion. Moreover, when applying Brady et al.'s (2013) original analysis to our results, for 73% of the subjects at least one of the obtained dependence scores, which should range between 0 and 1 because it is a probability score, was either larger than 1 or smaller than 0, which is difficult to interpret (see the online supplementary material for the results of this analysis; we return to compare the two approaches in the General Discussion). Although we hesitate to draw strong conclusions in this situation, it should be noted that even the dependency scores that were within the logical range were not in line with the original claims. Specifically, across five experiments we failed to replicate the decrease in dependency across time. In any case, because of these issues we propose a different analysis, which we used in five conceptual replications of Brady et al. (2013).

The Present Analysis

The first step of our analysis is to separate responses that reflect some memory from those reflecting complete guesses (Figure 1c). We start with the four response categories for each object: the correct exemplar in the correct state ("correct-correct"), the correct exemplar in the incorrect state ("correct-incorrect"), the incorrect exemplar in the correct state ("incorrect-correct"), and the incorrect exemplar in the incorrect state ("incorrect–incorrect"). Our assumption is that when subjects have no relevant memory, each of the four presented objects should be equally likely, which means that all four response categories logically contain roughly comparable numbers of guessed objects. Critically, we assume that the incorrect–incorrect category reflects only guessing, because this category does not include any correct information about the object's exemplar or state. Therefore, it should be chosen *only* when subjects encounter an object for which they have no available relevant memory, because if they had usable knowledge of the item's exemplar or state, they would have chosen the correct

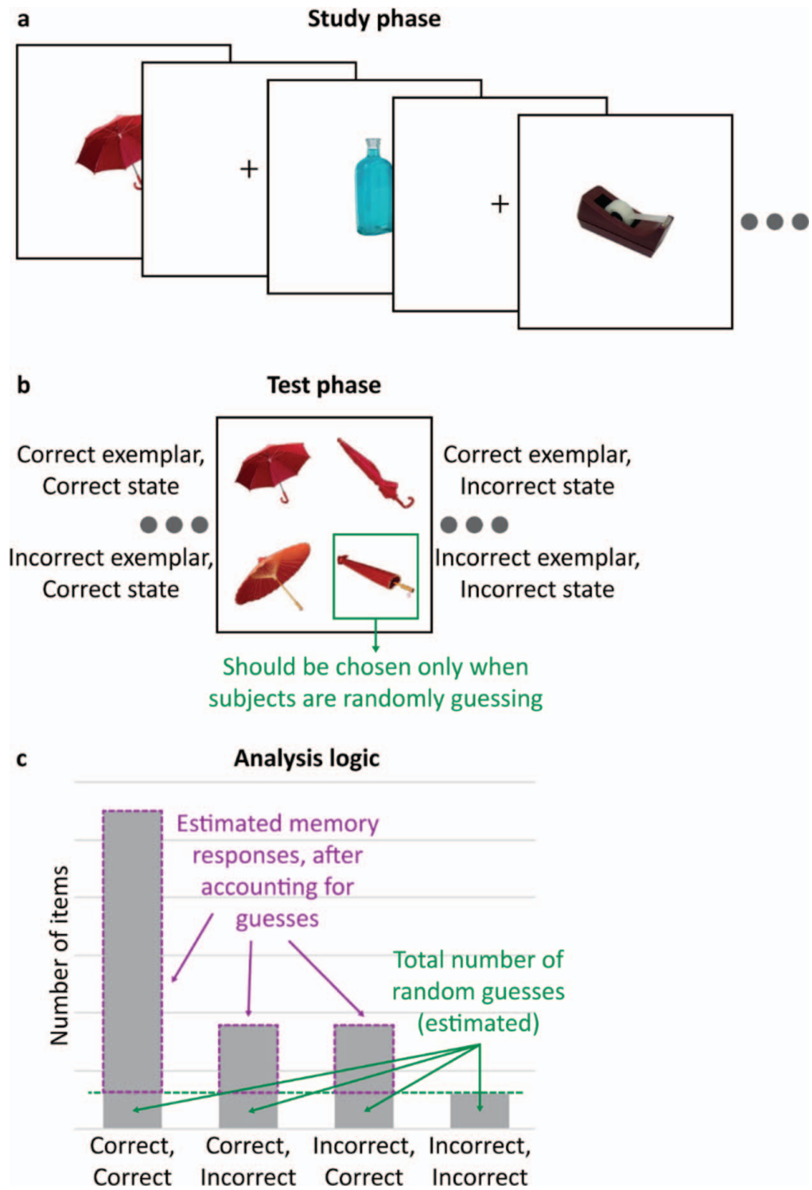

Figure 1. The paradigm used by Brady et al. (2013), Experiment 2, and our analysis of the present experiments. (a) The study phase, in which subjects view a single image on each trial, in a filler size-judgment task. The particular variant chosen for each object-category was randomly determined for each participant. (b) The surprise test phase (the colored frame is solely for illustrative purposed, and was not presented in the actual experiment), in which subjects were asked to choose the image they saw during the study phase, out of four possibilities: two exemplars in two states each. For different subjects or items, this phase took place either immediately after the study phase (in the short delay condition), or 3 days later (in the long delay condition). (c) The analysis we performed in all five experiments of the present study: subtracting the number of incorrect–incorrect responses from each of the other response categories, to control for random guesses. See the online article for the color version of this figure.

feature for at least one dimension (it is possible that they have other knowledge of the item, but that it doesn't help choosing among the four possibilities). Hence, we argue that the frequency of this responses category mainly reflects a guessing process (plus errors), and we can use it to estimate the "hidden" guesses in each of the other categories, which also contain memory responses (see Zhang & Luck, 2008, for similar assumptions).

To illustrate, if a subject chose the incorrect exemplar in the incorrect state (i.e., "incorrect–incorrect") on five trials, we assume that they actually guessed on approximately 20 trials, which were then evenly distributed across all four response categories (i.e., five guess-responses in each response category). This means that the number of responses in the other three categories is an overestimation of that subject's knowledge, because each category includes additional 5 responses that are due to random guesses. This is true regardless of the nature of LTM storage and forgetting: both the integrated and independent storage accounts predict guessing, simply because subjects' memory is not perfect. Thus, we could subtract, for each subject, the number of incorrect–incorrect responses from each of the other response categories, to exclude the approximate contribution of random guesses. The number of items in the other response-categories, corrected for guessing, as well as the overall number of estimated guesses were used as our main dependent measures.

Although both feature-based and object-based theories predict that the number of fully remembered objects should decrease as the delay is prolonged, because forgetting takes place, these theories differ regarding the nature of this forgetting (see Figure 2). According to the feature-based account, whether or not a given feature is remembered is unrelated to the fate of the other feature, because this model argues that features are stored independently. Hence, in this view, fully remembered objects are objects for which both features simply happened to be remembered. The prediction of the feature-based model is that over time, each feature would be forgotten independently, and hence in the long delay some of the objects that are no longer fully remembered are expected to be only partially remembered (only one feature instead of both), leading to an *increase* in the number of partially remembered objects as the delay is prolonged.

In contrast, according to the object-based account, if both features of an object are stored in LTM, they are bound together (e.g., Luck & Vogel, 1997). Therefore, when items are forgotten, they should be completely forgotten, rather than being partially remembered. Thus, over time, the decrease in the frequency of correct-correct responses should be mirrored only by an increase in the proportion of guessing (because when there is no available information, participants choose one random option), instead of more partially remembered objects.

Critically, the main prediction of the object-based account cannot be properly tested in a between-subjects design as the one used in the original study: the decrease over time in the number of fully remembered objects cannot be directly compared to the increase over time in the number of random guesses, because these measures are differences between the short and long delay conditions, and in a between-subjects design every subject participates in only one delay condition. Therefore, we tested these predictions in a *within-subjects* design replication of Brady et al. (2013), with an explicit study-phase (Experiment 1). We went on to perform four additional replications, manipulating different aspects of the study to establish the generality of our findings. Experiment 2 used a within-subjects design with an implicit study-phase, Experiment 3 included a between-subjects design with Brady et al.'s (2013) original stimuli, in Experiment 4 we used a novel stimulus-set we created, which manipulated different dimensions than in the original study, and Experiment 5 included a shorter presentation time. Across all five experiments, we found strong support for the object-based forgetting hypotheses, over the feature-based forgetting account.

Importantly, although there is only one type of feature-independence in forgetting (i.e., forgetting one feature of the object has no influence on the chance of remembering another feature), there are many ways in which the different features of an object can depend on each other in forgetting. For example, forgetting one feature can lead to either a lower (but still existing) chance of remembering another feature or to a zero chance of remembering that feature. Both of these situations point to a dependency, simply because one feature influences the fate of another feature. In addition, dependency can either be symmetrical, where all features

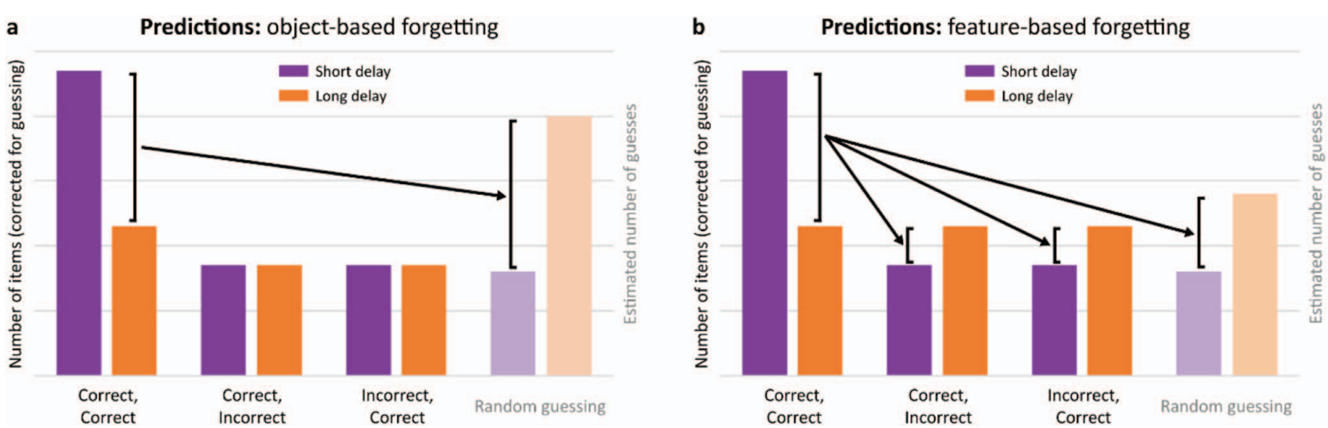

Figure 2. An illustration of the predictions made by the dependent (object-based) and the independent (feature-based) storage accounts. The hypothetical number of items in each response category are presented, as well as the estimated frequency of random guessing, separately for the short and long delay conditions. Both theories can explain high frequency of fully remembered items in the short delay, but as the delay gets longer, the predictions of the two theories diverge. (a) If forgetting of one feature is dependent on the other feature, the decrease in fully remembered items should be mirrored only by an increase in the number of random guessing, because if one feature is forgotten, all features of the objects should be forgotten. (b) If forgetting is independent for each feature, when moving from the short delay to the long delay, the items that are no longer fully remembered can either be fully forgotten (i.e., random guessing), or one of their features can be forgotten while the other feature is still remembered, leading to an increased in the number of partially remembered objects. See the online article for the color version of this figure.

affect each other's chances of being remembered to a similar extent, or it can be asymmetrical such that one feature has precedence over the others. In this hierarchical type of dependence, if one (privileged) feature is forgotten, the chance of remembering the other features diminishes, but not vice versa. Although every type of dependence found will contradict feature-independence, if indeed LTM operates in an object-based manner, it is interesting to examine the characteristics of this dependence. To formally compare the full continuum of dependency to independency, we introduce a formal multinomial model and present the results of applying this model to all five experiments. The results of the multinomial model agree with the results from our simplified analysis, revealing strong dependence between the features. Furthermore, both methods converged into a hierarchical view of memory dynamics, such that state, orientation, and color depend on exemplar, a point we elaborate on in the General Discussion.

Notably, our proposed analysis (much like the original analysis by Brady et al., 2013, and the multinomial model) treats memory as a high-threshold process. Aside from this, our approach involves as few assumptions as possible: We only assume that the incorrect–incorrect response category reflects random guesses that are evenly distributed across all four response-categories. Critically, we will show that this very simple guessing estimation is enough to support the predictions of a highly dependent storage, providing strong support for the possibility of object-based representations in LTM.

Experiment 1

Our goal was to examine whether the different features of an object are forgotten in a dependent or an independent manner from LTM. To allow statistically testing the main prediction of the dependent forgetting account, that the number of fully remembered objects forgotten from the short to the long delay would be mirrored only by an increase in guessing rate (instead of items being partially forgotten), we used a within-subjects design, such that for each participant half of the objects were tested immediately after the study phase, and the other half after 3 days. Because the long delay test could not be a surprise in this design (because all of the subjects were already tested after a short delay), we informed subjects before the study phase that they will be later tested, and thus the study phase was not incidental.

Each delay condition included a test of half the objects seen during the learning phase, meaning we needed more stimuli than in Brady et al.'s (2013) study. To that aim, we created a novel set of similar stimuli. Instead of using photographs of real-world items, we used a computer-aided design (CAD) software to create the objects. This stimulus-set is freely available at: http://people.socsci.tau.ac.il/mu/royluria/. Creating the stimuli in a CAD software allowed us much better control over the variation of each item. For example, when using photographs, two different exemplars of a given object-category in the stimulus-set usually differ in many dimensions (e.g., material, size, the presence of additional parts, etc.). In the CAD software stimulus-set, each exemplar differed only in its shape and not in other dimensions. In addition, we manipulated two other dimensions, namely the material the object is made of (e.g., plastic or metal for a water bottle), and its orientation (i.e., angle-of-view). Using computer-generated stimuli allowed us to change each manipulated dimension without affecting the other dimensions at all (e.g., two different exemplars could have the exact same material). To test whether our results are specific to any given dimension, we compared the LTM storage of material and orientation. All subjects saw the same stimuli during the study phase, but different subjects were tested on different dimension combinations in the test phase (see Figure 3). Half of the subjects were tested on the exemplar and material of the computer-generated objects (with orientation being held constant), and the other half were tested on the exemplar and orientation (with material being held constant). Importantly, in all experiments we found no differences between the two sets of stimuli or the different dimensions, suggesting that our conclusions can be generalized.

Materials and Methods

Data and code for all experiments is publicly available at the Open Science Framework: https://osf.io/3kjgv/.

Participants. Subjects were Tel Aviv University students who received payment or partial course credit for participation. All subjects had normal or corrected-to-normal visual acuity and nor-

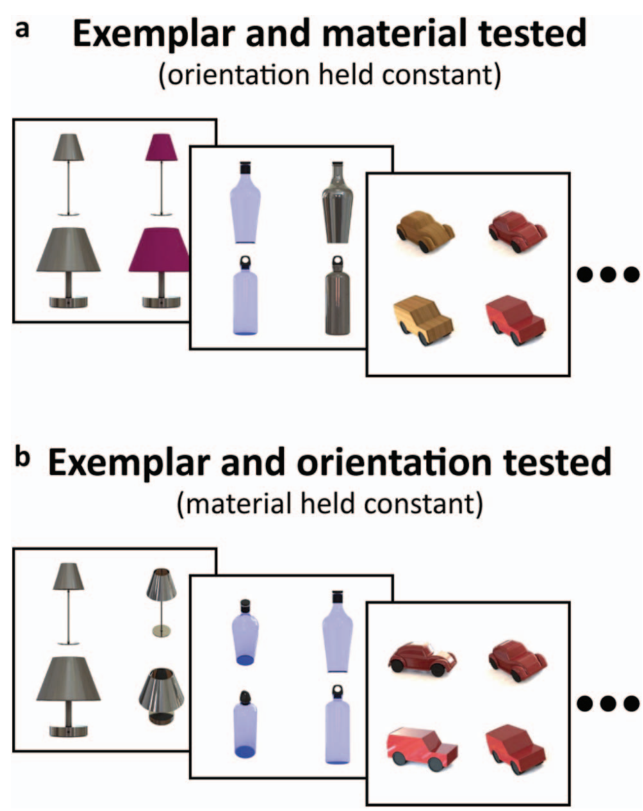

Figure 3. The test phase of the computer-generated stimuli blocks in Experiments 1 and 2, and of Experiments 3 and 4. (a) The material condition, in which subjects were asked to choose the image they saw out of the four combinations of exemplar and material. The orientation of all objects was the same as in the study phase. (b) The orientation condition, in which subjects were asked to choose the image they saw out of the four combinations of exemplar and orientation. The material of all objects was the same as in the study phase. See the online article for the color version of this figure.

mal color-vision (by self-report). All participants gave informed consent following the procedures of a protocol approved by the Ethics Committee at Tel Aviv University. The experiment included 32 participants (M_{age} = 22.4, 28 women). Sample size was determined based on Brady et al.'s (2013) Experiment 2 reported effect sizes (*M*: Cohen's $d = 0.8$), which necessitates approximately 30 participants for 85% power (32 participants were used to ensure an equal number in each combination of tested dimension and stimuli order, see below). Note that we replicated the basic findings in 5 experiments.

Stimuli. Stimuli were taken from two stimulus-sets. The first is Brady et al.'s (2013) published set of stimuli, including 100 categories of everyday objects. Each category included four colored pictures, created by the factorial combination of two exemplars and two states (i.e., different poses or part-configuration) each. The second is the novel set of stimuli, created using a CAD software (SolidWorks, Dassault Systèmes, Vélizy-Villacoublay, France). Models of two exemplars of 74 categories of everyday objects were found in free databases, and adjusted to eliminate accessory details, leaving the most basic model that could still be recognized as a specific object. We created four variations of each model (i.e., exemplar), by factorially manipulating the orientation (i.e., viewing angle) of the object and the material it is made of, for a total of eight variations for each category, and then produced high-resolution renderings on a neutral background. The set of stimuli is publicly available at our lab website: http://people.socsci.tau.ac.il/mu/royluria/.

Procedure. The experiment included a study phase and two test phases (see Figure 1a and 1b). Each trial of the study phase included the presentation of a single object (approximately 5.5° × 5.5° degrees of visual angle, from a viewing distance of 60 cm) at the center of the screen. Subjects had to indicate via button press whether the object depicted in the picture is larger or smaller than a reference box (an actual 3D plastic box) shown to them prior to the experiment. Following the picture presentation, subjects had 2,000 ms to respond; 400 ms after subjects' response, or 2,400 ms after picture offset if no response was emitted, the next picture appeared. Each picture was presented for a maximum of 800 ms (if participants responded faster than 800 ms, the picture disappeared, and the next picture appeared after a 400-ms delay). This was the same filler task used in the original study (aimed to encourage subjects to attend to the presented stimuli), but subjects were informed before starting this task that they will later be tested on the presented stimuli (although the exact nature of the test was not detailed). Each participant viewed a single picture from each category (randomly selected). The items from each stimulus-set were presented in separate blocks (order was counterbalanced across participants), and within each block the items were presented in a random order.

Immediately following this task, subjects were given a memory test on half of the items from each stimulus-set (i.e., the short delay condition). Three days after the first session (this delay was identical to the one used in Brady et al. (2013), to allow for ideal comparison with the original findings), subjects performed a second memory test, on the other half of the items (i.e., the long delay condition). In the test phase, subjects had to indicate which of four variations (see below) of an object they saw during the study phase. The four pictures were presented in an imaginary 2 × 2 grid (according to the manipulated feature-dimensions, see below), and subjects selected one of them using the mouse cursor, in an unspeeded manner. No feedback was given in any of the phases.

Three of the 100 object-categories from Brady et al.'s (2013) stimulus-set, and four of the 74 object-categories from the computer-generated novel stimulus-set were used as practice items. Hence, there were a total of 167 experimental trials in the study phase (one block of 97 trials and another block of 70 trials). The short delay memory test included two blocks, one with either 48 or 49 (randomly determined) object-categories from Brady et al.'s (2013), and the other with 35 object-categories from our computer-generated stimuli. The long delay memory test also included two blocks, each with the remaining stimuli of the corresponding stimulus-set.

At test, subjects were shown two exemplars of each object, each in two levels of another manipulated dimension. The location of the previously shown item was randomly chosen in each trial, and the other three items were located accordingly. For the stimuli from Brady et al.'s (2013) set, the other dimension was state (as in the original study). For the computer-generated stimulus-set, half of the subjects were tested on the items' material (holding orientation constant) and the other half were tested on their orientation (holding material constant). Responses at test were unspeeded.

Analysis. Our main dependent measure was the number of responses in each category, after accounting for random guessing. To achieve this, we used the number of incorrect–incorrect responses as an estimate for the amount of guessing and subtracted this number from the other three response-categories. We complemented the *p* values for our main results with Bayes factors (where BF_{10} indicates the degree of support for the alternative hypothesis, and BF_{01} indicates the degree of support for the null) calculated using the JASP software, with a wide (Cauchy scale of 1) prior. In addition, we report effect sizes (partial η^2 or Cohen's *d*) and 95% confidence intervals (CIs).

Results

Overall, subjects chose the correct image for an average of 49.7 items ($SE = 1.6$; 59% of the tested items) in the short delay, and 31.4 items ($SE = 0.8$; 38% of the tested items, which is still significantly above chance: $t(31) = 13.22$, $p < .001$, $d = 2.34$, 95% CI [0.36, 0.40]) in the long delay. The difference between delays was significant, $t(31) = 11.63$, $p < .001$, $d = 2.06$, difference 95% CI [0.18, 0.26], indicating that extending the delay was successful in inducing forgetting.

Our main goal was to test whether the objects' features were stored in a dependent manner in LTM, by examining performance across time (i.e., changes between the short and long delay conditions). The first step was to evaluate the overall guessing rate in each delay, using the frequency of the incorrect–incorrect responses. We assume that selecting a response that conveys none of the correct relevant information about the object is the result of a guessing process, and that guessing is random, leading to an equal distribution of guesses across all response categories. Thus, we subtracted the frequency of the incorrect–incorrect cell from the other response categories to account for random guessing. Note that the proportion of random guesses cannot distinguish between an object-based storage and a feature-based storage (both predict guessing), and therefore this analysis serves only to evaluate the overall guessing rate, and to account for guessing in the response categories that do include at least some information about the target. All subsequent analyses were based on the frequency of each response category after correcting for random guesses. The results are presented in Figure 4.

A longer delay led to a decrease in the number of fully remembered objects, with 24.0 fewer objects that were fully remembered, $t(31) = 10.92$, $p < .001$, $BF_{10} > 2{,}000{,}000{,}000$, $d = 1.93$, 95% CI [19.52, 28.48]. It is obviously not surprising that a longer delay produced forgetting, but each theory makes a different prediction regarding the nature of this forgetting process. According to the object-based account, all these objects should be completely lost, because the different features of the object should be forgotten together. Therefore, the decrease in the number of fully remembered objects should be mirrored only by an increase in the guessing rate. In contrast, the feature-based account predicts independent forgetting, meaning that at least some of the objects that were fully remembered will become partially remembered. In line with the object-based prediction, in the long delay, random guessing occurred for 23.1 more objects than in the short delay, which did not significantly differ from the 24-item decrease in fully remembered objects, $t(31) = 0.44$, $p = .66$, $BF_{01} = 6.64$, $d = 0.08$, 95% CI [−3.16, 4.91]. Furthermore, there was no support for the feature-based prediction of a significant increase in the number of partially remembered objects between the short and long delays, for both exemplar and the other probed feature, both $t < 1$, both ps $> .54$, both BF_{01}s > 6, both ds $<$ 0.12, exemplar-only 95% CI [−2.63, 3.20], other-only 95% CI [−1.56, 2.87]. These results provide strong support for the object-based account, because objects were completely lost and not partially remembered.

In line with this, in the short delay condition, there were more items for which subjects remembered both features (41.8 items, $SE = 2.2$) than items for which they remembered only the exemplar (8.4 items, $SE = 0.8$), $t(31) = 15.55$, $p < .001$, $BF_{10} > 2 \times 10^{13}$, $d = 2.75$, 95% CI [29.08, 37.86], or only the other feature (state, orientation, or material; 2.0 items, $SE = 0.7$), $t(31) = 17.27$, $p < .001$, $BF_{10} > 3 \times 10^{14}$, $d = 3.05$, 95% CI [35.14, 44.55]. According to the object-based view, this is support for an integrated representation. However, according to the feature-based view, this should be taken to indicate good independent memory: If both features are remembered accurately, there will be many items for which both features are indeed remembered. If this is the case, after forgetting takes place, more items are expected to be only partially remembered, simply because memory becomes worse as the delay is prolonged. Importantly, in the long delay there were also more fully remembered objects (17.8 items, $SE =$ 1.3) than partially remembered objects: only exemplar (8.7 items, $SE = 1.3$): $t(31) = 8.28$, $p < .001$, $BF_{10} > 5{,}000{,}000$, $d = 1.46$, 95% CI [6.93, 11.45]; only the other feature (2.7 items, $SE = 0.8$): $t(31) = 11.34$, $p < .001$, $BF_{10} > 6{,}000{,}000{,}000$, $d = 2.00$, 95% CI [12.45, 17.92].

This trend cannot be attributed to subjects simply having overall excellent memory for both features and remembering them independently, because the results strongly indicate that memory for the various features is actually asymmetrical: the feature other than exemplar (state, material, or orientation) was very poorly remembered when exemplar was forgotten. There were more objects for which only the exemplar was correctly chosen, than objects for which only the other feature (state, material, or orientation) was correctly chosen, both after a short delay, $t(31) = 5.98$, $p < .001$, $BF_{10} = 14{,}677$, $d = 1.06$, 95% CI [4.20, 8.55], and after a long delay, $t(31) = 4.79$, $p < .001$, $BF_{10} = 581$, $d = 0.85$, 95% CI [3.44, 8.56]. Thus, subjects were much more likely to remember the exemplar of an item and not remember its other features, than to remember only the state, material or orientation of an item whose exemplar is forgotten. Note that the low number of objects in this category cannot be attributed to the other features being simply too difficult, because there were more objects for which both exemplar and the other feature were remembered than objects for which only exemplar was remembered (see above). Thus, state,

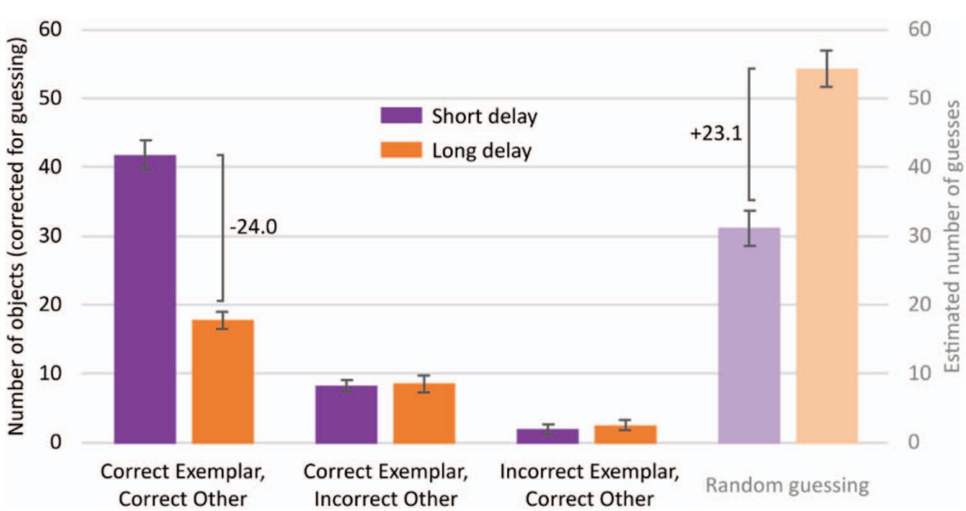

Figure 4. The results of Experiment 1: The number of objects chosen (after accounting for random guesses, by subtracting the number of objects for which neither feature was remembered) in each response-category and the overall estimated number of guesses, by delay length. Error bars depict standard error of the mean. The numbers on the figure indicate the decrease in the number of fully remembered items, and the increase in the number of random guesses. See the online article for the color version of this figure.

material, or orientation could be remembered quite well, as long as the object's exemplar was also remembered. This suggests a strong form of dependency between the features in memory, namely a hierarchy: only if an object's exemplar is remembered, can its other features be remembered as well. We return to this point in the General Discussion.

Finally, it is important to make sure that the dependent forgetting findings are not limited to certain stimuli or dimensions. First, every subject was tested on both pictures and computer-generated objects, but an analysis of variance (ANOVA) with delay and stimuli type as factors on the number of remembered items as a dependent variable revealed no effect of type, $F(1, 31) = 2.01$, $p = .17$, $\eta^2 = 0.06$, and no interaction of type and delay ($F < 1$, $p = .55$, $\eta^2 = 0.01$). Second, for the computer-generated items, half of the subjects were tested on the objects' orientation, and half on their material (the second dimension was always exemplar), but an ANOVA with tested dimension and delay as factors on the number of remembered items revealed no effect of dimension, $F(1, 30) = 2.12$, $p = .16$, $\eta^2 = 0.07$, and no interaction of dimension and delay, $F(1, 30) = 2.42$, $p = .13$, $\eta^2 = 0.07$. We conclude that the two types of stimuli (pictures vs. computer-generated images) and the three dimensions (state, orientation, and material) were retained similarly in memory.

Experiment 2

The results of Experiment 1 suggested that the different features of objects were lost from LTM in a dependent manner. This contrasts with the results of Brady et al. (2013), which supported an independent-forgetting account. One key difference between the current setup and the original one, however, is that our task included an explicit memory test instead of an implicit one. Our goal in Experiment 2 was to examine whether using an incidental learning phase, without subjects knowing that they will be later tested on the items, will lead to an independent forgetting of each feature. The experiment was the same as in Experiment 1, except for the instructions given to subjects, which now did not mention that they will be later tested.

Materials and Methods

Participants. We used 32 fresh participants ($M_{age} = 23.9$, 26 women).

Stimuli. Stimuli were the same as in Experiment 1.

Procedure. The procedure was identical to Experiment 1, except that only after they completed the cover task were subjects told that they would be tested on the items presented in the (incidental) learning phase. Because this was a within-subjects design, this means that the short delay test was a surprise test, but the long delay test was not.

Results

Overall, subjects chose the correct image for an average of 48.6 items ($SE = 1.8$, 58% of the tested items) in the short delay, and an average of 29.3 items ($SE = 1.2$, 35% of items) in the long delay, which was still above chance: $t(31) = 7.21$, $p < .001$, $d = 1.28$, 95% CI [0.32, 0.38]. The decrease in accuracy over time was significant, $t(31) = 11.87$, $p < .001$, $d = 2.10$, difference 95% CI [0.19, 0.27], showing forgetting. The results, after correcting for random guesses, are presented in Figure 5. They replicated the findings of Experiment 1.

A longer delay led to a decrease in the number of fully remembered objects, with 26.1 fewer objects that were fully remembered, $t(31) = 12.18$, $p < .001$, $BF_{10} > 40{,}000{,}000{,}000$, $d = 2.15$, 95% CI [21.73, 30.46]. The prediction of the object-based account is that these items will be fully forgotten, meaning that in the long delay they will be completely guessed, instead of being only partially forgotten (with one of their features still remembered). In contrast, the prediction of the feature-based account is that at least some of the fully remembered objects will become partially remembered, which should translate to an increase in the number of

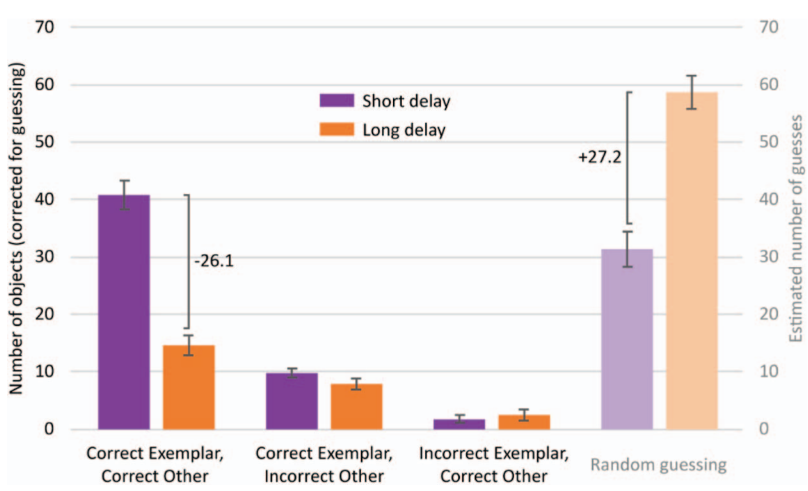

Figure 5. The results of Experiment 2: The number of objects chosen (after accounting for random guesses, by subtracting the number of objects for which neither feature was remembered) in each response-category and the overall estimated number of guesses, by delay length. Error bars depict standard error of the mean. The numbers on the figure indicate the decrease in the number of fully remembered items, and the increase in the number of random guesses. See the online article for the color version of this figure.

partially remembered items in the long delay. Critically, as in Experiment 1, the decrease in the number of fully remembered items was matched by the increase in the number of guesses, which was 27.2, $t(31) = 0.62$, $p = .54$, $BF_{01} = 6.06$, $d = 0.11$, 95% CI [−2.65, 4.96], without a significant change in the number of partially remembered objects, for both exemplar, $t(31) = 1.46$, $p = .15$, $BF_{01} = 2.67$, $d = 0.26$, 95% CI [−0.77, 4.64] and the other probed feature, $t(31) = 0.64$, $p = .52$, $BF_{01} = 5.96$, $d = 0.11$, 95% CI [−1.55, 2.99].

Again, after a short delay, there were more fully remembered items (40.7 items, $SE = 2.5$) than partially remembered items, for both the exemplar (9.7 items, $SE = 0.8$), $t(31) = 12.66$, $p < .001$, $BF_{10} > 10^{11}$, $d = 2.24$, 95% CI [26.01, 35.99], and the other feature (1.7, $SE = 0.7$), $t(31) = 15.62$, $p < .001$, $BF_{10} > 2 \times 10^{13}$, $d = 2.76$, 95% CI [33.91, 44.09]. Importantly, this was true also when the delay was prolonged, with more items for which both features were remembered (14.6, $SE = 1.7$) than items for which only the exemplar was remembered (7.8, $SE = 1.0$), $t(31) = 3.79$, $p < .001$, $BF_{10} = 43.3$, $d = 0.67$, 95% CI [3.16, 10.52], or only the other feature was remembered (2.44, $SE = 1.0$), $t(31) = 8.37$, $p < .001$, $BF_{10} > 7{,}000{,}000$, $d = 1.48$, 95% CI [9.22, 15.16]. This shows that even after forgetting took place, subjects' responses were not randomly distributed among all response categories, but focused on fully remembered objects, in line with the dependent storage account.

As in Experiment 1, the results cannot be explained by both features (exemplar and the other feature) simply having excellent and independent memory, because accuracy for one feature strongly depended on the other feature. Specifically, there were more objects for which only exemplar was remembered than objects for which only the other feature was remembered, both after a short delay, $t(31) = 7.79$, $p < .001$, $BF_{10} > 1{,}000{,}000$, $d = 1.38$, 95% CI [5.91, 10.09] and after a long delay, $t(31) = 4.74$, $p < .001$, $BF_{10} = 516$, $d = 0.84$, 95% CI [3.05, 7.64]. Again, this also cannot be explained by overall poor memory for the other feature, because it was very well remembered when exemplar was remembered, as can be seen from the larger number of fully remembered objects than objects for which only exemplar was remembered. Thus, state, material or orientation were remembered only if exemplar was remembered, suggesting a hierarchy (i.e., a form of dependency) of the features in memory.

Supporting the generality of the findings, as in Experiment 1, within the computer-generated stimuli, there was also no significant effect of tested dimension ($F < 1$, $p = .9$, $\eta^2 = 0.0005$), and no significant interaction of dimension and delay ($F < 1$, $p = .79$, $\eta^2 = 0.002$). Although the interaction of stimuli type (pictures vs. computer-generated items) was marginally significant ($F = 3.73$, $p = .06$, $\eta^2 = 0.11$), there was no significant effect of stimuli type on the number of remembered items ($F = 1.06$, $p = .31$, $\eta^2 = 0.03$).

Thus, using an incidental learning paradigm led to very similar results as using explicit learning instructions, namely dependent forgetting dynamics. In both Experiment 1 and Experiment 2, we found that as objects were forgotten from LTM, their different features were not lost independently, but rather all their features were lost as one unit.

Experiment 3

The results of Experiments 1 and 2 supported a dependent forgetting account of LTM dynamics, unlike the conclusion of Brady et al. (2013). Contrary to the originally study, however, we used a within-subjects design. This allowed us to directly compare the decrease in the number of fully remembered items with the increase in guessing, which, as predicted by the dependent forgetting account, indeed closely matched each other. Perhaps the fact that we probed subjects' memory twice (although on different items) somehow contributed to the observed dynamics of features being lost dependently from LTM. In Experiment 3, we conducted a closer replication of Brady et al.'s (2013) Experiment 2, using only the original stimuli, and a between-subjects design, such that we randomly assigned the subjects to either the short delay or the long delay conditions. This design will only allow us to statistically test the prediction of the feature-based account, but not the main prediction of object-based account (because there is no individual-subject measure of the changes between the short and long delay). However, the predicted pattern of the object-based view is still clear: If items are forgotten in an object-based manner, the decrease in the number of fully remembered items should only be mirrored by an increase in guessing, and the number of partially remembered items should not increase. Although we will not be able to statistically test one of the predictions, it is important to note that in the feature-based account, there is no reason to expect such a specific pattern of results.

Materials and Methods

Participants. We used 20 fresh participants ($M_{age} = 23.8$, 12 women).

Stimuli. We used only the real-world pictures of Experiments 1 and 2.

Procedure. The procedure was the same as in Experiment 2, except that half of subjects were given the surprise memory test on all of the items immediately after the study phase (the short delay condition), and the other half were tested 3 days after the study phase (the long delay condition). In the long delay condition, subjects knew that they will continue the experiment in a second session 3 days after the first one but were not told (even after the study phase) what was the purpose of this session.

Results

Overall, subjects chose the correct image for an average of 56.5 items ($SE = 4.1$, 58% of the tested items) in the short delay, and an average of 36.6 items ($SE = 2.2$, 38% of items) in the long delay, which was still above chance: $t(9) = 5.60$, $p < .001$, $d = 1.77$, 95% CI [0.33, 0.43]. The decrease in accuracy over time was significant, $t(18) = 4.27$, $p < .001$, $d = 1.91$, difference 95% CI [0.10, 0.31], indicating forgetting. The results after accounting for random guesses are presented in Figure 6.

In the long delay condition, there were 27.8 fewer objects that were fully remembered than in the short delay, $t(18) = 4.31$, $p < .001$, $BF_{10} = 70.89$, $d = 1.93$, 95% CI [14.23, 41.37]. Importantly, if this forgetting indicated the loss of an integrated object, all off these objects are expected to be fully forgotten, that is, mirrored by an increase in guessing without a change in the number of partially

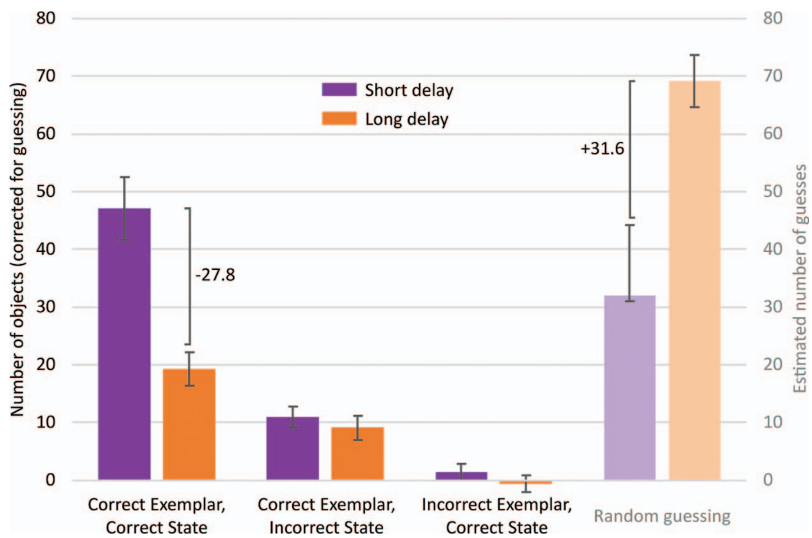

Figure 6. The results of Experiment 3: The number of objects chosen (after accounting for random guesses, by subtracting the number of objects for which neither feature was remembered) in each response-category and the overall estimated number of guesses, by delay length. Error bars depict standard error of the mean. The numbers on the figure indicate the decrease in the number of fully remembered items, and the increase in the number of random guesses. See the online article for the color version of this figure.

remembered items. Conversely, if objects were forgotten in a feature-based manner, the number of partially remembered items should increase. In line with the object-based view, as in Experiments 1 and 2, there was no significant difference in the number of partially remembered items, for both exemplar, $t(18) = 0.62$, $p = .54$, $BF_{01} = 2.77$, $d = 0.28$, 95% CI [−4.30, 7.90] and state, $t(18) = 0.95$, $p = .35$, $BF_{01} = 2.25$, $d = 0.43$, 95% CI [−2.41, 6.41]. Although we cannot statistically compare the decrease in the number of fully remembered items with the increase in the number of guesses (because the between-subjects design means there is no measure of the changes between the delays for each individual subject), we note that numerically they are quite similar, with 31.6 more guess responses in the long delay (i.e., even slightly more items in the long delay). Of course, this cannot be used as strong support for the dependent forgetting account, but along with the pattern of partial responses, the results of Experiment 3 are in line with those of the previous two experiments.

In addition, after a short delay, there were more fully remembered items (47.1 items, $SE = 5.4$) than items for which only the exemplar (10.9 items, $SE = 1.8$), $t(9) = 6.26$, $p < .001$, $BF_{10} = 246$, $d = 1.98$, 95% CI [23.11, 49.29], or only the state (1.4 items, $SE = 1.4$), $t(9) = 8.70$, $p < .001$, $BF_{10} = 2{,}405$, $d = 2.57$, 95% CI [33.81, 57.59], were remembered. Importantly, the same was true also for the long delay, with more fully remembered (19.3 items, $SE = 2.9$) than partially remembered objects, for both features—only exemplar (9.1 items, $SE = 2.1$): $t(9) = 2.87$, $p = .019$, $BF_{10} = 3.62$, $d = 0.91$, 95% CI [2.15, 18.25]; only state (−0.6 items, $SE = 1.4$): $t(9) = 7.00$, $p < .001$, $BF_{10} = 525$, $d = 2.21$, 95% CI [13.47, 26.33]. Thus, even after forgetting took place, subjects' responses were focused on the correct-correct category, instead of being randomly distributed among all response categories, in line with a dependency of the different features of each object.

As in previous experiments, this pattern of results cannot be explained by excellent memory for both features independently, because the level of memory for one feature depended on the other: there were more objects for which only exemplar was remembered than objects for which only state was remembered, both after a short delay, $t(9) = 4.41$, $p = .0017$, $BF_{10} = 28.70$, $d = 1.39$, 95% CI [4.62, 14.38] and after a long delay, $t(9) = 3.99$, $p = .0032$, $BF_{10} = 16.73$, $d = 1.26$, 95% CI [4.2, 15.2]. As mentioned before, this pattern cannot be explained by poor state memory, because state was very well remembered given that exemplar was remembered, producing a larger number of fully remembered objects than objects for which only exemplar was remembered. Thus, state could be very well remembered, but only given that the object's exemplar was remembered, otherwise memory was quite poor. We elaborate on the hierarchy of features arising from this in the General Discussion.

Experiment 4

In Experiment 3, we closely followed the methods of Brady et al.'s (2013) study, but obtained support for a high level of dependency between the different features of objects that are forgotten from LTM, and no support for the feature-based view. Our goal in Experiment 4 was to further generalize these findings, by replicating them using our computer-generated stimuli, which are more controlled, and involve dimensions other than state (namely orientation and material).

Materials and Methods

Participants. We used 40 fresh participants ($M_{age} = 22.9$, 33 women).

Stimuli. We used only the computer-generated stimuli of Experiments 1 and 2.

Procedure. The procedure was the same as in Experiment 3, except that half of the subjects were tested on orientation and half on material (all of the subjects were tested on exemplar), as in Experiments 1 and 2.

Results

Overall, subjects chose the correct image for an average of 39.4 items out of 70 (SE = 1.5; 56% of the tested items) in the short delay, and 27.6 items (SE = 1.1; 39% of items) in the long delay, which was significantly above chance, $t(19) = 9.05$, $p < .001$, d = 2.02, 95% CI [0.36, 0.43]. The difference between delays was significant, $t(38) = 6.38$, $p < .001$, $d = 2.02$, difference 95% CI [0.12, 0.22], indicating forgetting. The frequencies of each response category, after accounting for random guessing, presented in Figure 7, is a replication of the previous experiments.

As expected, after a longer delay the number of fully remembered objects decreased (by 16.7 objects), $t(38) = 6.72$, $p < .001$, $BF_{10} > 200{,}000$, $d = 2.13$, 95% CI [11.63, 21.67]. Although the feature-based view predicts an increase in the number of partially remembered objects, the object-based view predicts no increase, because items should be completely lost (and hence only the guessing rate should increase). As in the previous experiments, we found no increase in the number of partially remembered objects, which did not statistically differ between the delays—exemplar: $t(38) = 1.37$, $p = .18$, $BF_{01} = 1.90$, $d = 0.43$, 95% CI [−1.14, 5.94] (note that there were *fewer* partially remembered items in the long delay); material or orientation—$t(38) = 0.09$, $p = .93$, $BF_{01} = 4.29$, $d = 0.03$, 95% CI = [−3.07, 3.37]—meaning there was no support for the feature-based view's prediction. Furthermore, although we cannot statistically compare the two numbers, we note that the increase in the number of random guesses, 19.2 objects, was of similar magnitude to the decrease in the number of fully remembered items. This is in line with the dependent forgetting hypothesis, according to which the objects that were no longer fully remembered were not partially forgotten but rather fully forgotten.

Also in line with the object-based view, in the short delay, there were more fully remembered objects (34.3 items, SE = 1.9) than partially remembered objects—only exemplar (11.9 items, SE = 1.3): $t(19) = 9.31$, $p < .001$, $BF_{10} > 1{,}000{,}000$, $d = 2.08$, 95% CI [17.29, 27.31]; only material or orientation (3.2 items, SE = 0.8): $t(19) = 16.79$, $p < .001$, $BF_{10} > 10^{10}$, $d = 3.76$, 95% CI [27.18, 34.92]. As in the previous experiments, these results cannot be explained by assuming that both features happened to be remembered, because there were more fully remembered objects also in the long delay condition (17.6 items, SE = 1.5), compared with only exemplar (9.6 items, SE = 1.2): $t(19) = 4.44$, $p < .001$, $BF_{10} = 112$, $d = 0.99$, 95% CI [4.25, 11.85]; and compared with only the material or orientation (3.1 items, SE = 1.3): $t(19) = 9.15$, $p < .001$, $BF_{10} > 700{,}000$, $d = 2.05$, 95% CI [11.22, 17.88]. Thus, more objects were fully remembered even after substantial forgetting took place, in line with a dependent storage account.

As before, the results cannot be explained by both features being independently excellently remembered, because we found strong evidence for a dependency of one feature on the other, in an asymmetric way. There were more objects for which only exemplar was remembered than objects for which only the other feature was remembered, both after a short delay, $t(19) = 10.46$, $p < .001$, $BF_{10} > 5{,}000{,}000$, $d = 2.34$, 95% CI [7, 10.5], and after a long delay, $t(19) = 4.82$, $p < .001$, $BF_{10} = 249$, $d = 1.08$, 95% CI [3.68, 9.32]. Furthermore, this cannot be explained by poor memory for the other feature, because there were more objects for which both it and exemplar were remembered than objects for which only exemplar was remembered, meaning that memory for the other feature was very good when exemplar was remembered. This suggests that the memory of the other feature (material or orientation) depends on the memory of exemplar, a point we return to in the General Discussion.

The effect of probed dimension (orientation or material) on the number of remembered items was marginally significant, $F(1, 36)$ = 3.59, $p = .07$, $\eta^2 = 0.09$, but the interaction of dimension and delay was not significant ($F < 1$, $p = .93$, $\eta^2 = 0.0002$), suggesting that forgetting was similar between the probed dimensions.

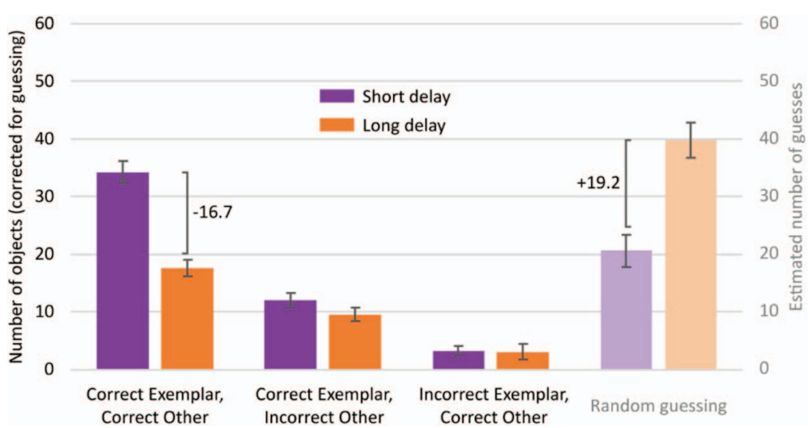

Figure 7. The results of Experiment 4: The number of objects chosen (after accounting for random guesses, by subtracting the number of objects for which neither feature was remembered) in each response-category and the overall estimated number of guesses, by delay length. Error bars depict standard error of the mean. The "other" feature was material for half of the subjects, and orientation for the other half; the results are collapsed across these two dimensions. The numbers on the figure indicate the decrease in the number of fully remembered items, and the increase in the number of random guesses. See the online article for the color version of this figure.

Experiment 5

In the previous four experiments, we found no evidence for a separate forgetting of the different features. Note that during the study phase, we presented the items for 800 ms, and there is evidence that the integration of different features develops over time, at least in working memory (e.g., Balaban & Luria, 2016; Luria & Vogel, 2011; Woodman & Vogel, 2008). In Experiment 5, we shortened the presentation time to only 200 ms. If the binding process takes time to complete, the prediction is that shortening object presentation might increase the level of independence between the different features, because they will not have enough time to be integrated.

Materials and Methods

Participants. We used 40 fresh participants. The data from three participants (one in the short delay and two in the long delay) was lost due to experimenter error. The final set of subjects thus included 37 participants (M_{age} = 23.2, 21 women).

Stimuli. Stimuli were the same as in Experiment 4.

Procedure. The procedure was the same as in Experiment 4, except that during the study phase, each picture was presented for 200 ms instead of 800.

Results

Overall, subjects chose the correct image for an average of 38.2 items (SE = 2.2; 55% of the tested items) in the short delay, and 25.6 items in the long delay (SE = 1.1; 37% of items), which was significantly above chance: $t(17) = 6.97$, $p < .001$, $d = 1.64$, 95% CI [0.33, 0.40]. The difference between delays was significant, $t(35) = 4.94$, $p < .001$, $d = 1.63$, difference 95% CI [0.11, 0.26], indicating forgetting. The frequencies of each response category, after accounting for random guessing, appear in Figure 8, and they suggest that shortening the presentation duration of the objects did not change the overall pattern of results.

The long delay resulted in 18.1 fewer fully remembered objects, $t(35) = 5.00$, $p < .001$, BF_{10} = 1,233, $d = 1.64$, 95% CI [10.75, 25.44], indicating forgetting. As in the previous experiments, there was no significant difference in the number of partially remembered objects—exemplar: $t(35) = 0.96$, $p = .34$, $BF_{01} = 2.78$, $d = 0.32$, 95% CI [−1.66, 4.67]; material or orientation: $t(35) = 1.85$, $p = .07$, $BF_{01} = 0.98$, $d = 0.61$, 95% CI [−0.2, 4.5] (indicating there were slightly *fewer* partially remembered items in the long delay). Thus, there was no support for the feature-based prediction of an increase in the number of partially remembered items, and support for the object-based prediction of no change. Furthermore, although we cannot statistically compare the decrease in the number of fully remembered items to the increase in guessing, we note that they once again closely match, with 21.7 more randomly guessed items in the long delay relative to the short delay (here, as in the previous experiments, the increase was even slightly larger than the decrease). Overall, this is in line with a dependent forgetting account, in which items moved from being fully remembered to fully forgotten.

As in the previous experiments, in the short delay, there were more fully remembered objects (31.4 items, SE = 3.0) than partially remembered objects—only exemplar (8.9 items, SE = 1.0): $t(18) = 7.47$, $p < .001$, BF_{10} = 32,008, $d = 1.71$, 95% CI [16.11, 28.73]; only material or orientation (2.3 items, SE = 0.7) $t(18) = 9.69$, $p < .001$, BF_{10} > 1,000,000, $d = 2.22$, 95% CI [22.75, 35.35]. As in the previous four experiments, even in the long delay, there were more fully remembered objects (13.3 items, SE = 1.7) than partially remembered objects—only exemplar (7.4 items, SE = 1.2): $t(17) = 3.29$, $p = .004$, $BF_{10} = 9.87$, $d = 0.77$, 95% CI = [2.09, 9.58]; only the other feature (0.2 items, SE = 0.9): $t(17) = 9.01$, $p < .001$, BF_{10} > 250,000, $d = 2.12$, 95% CI [10.04, 16.18]—suggesting that after forgetting occurred, items were still largely fully remembered, in line with the dependent storage account.

As before, the results cannot be explained by both features being excellently remembered independently, because memory for the

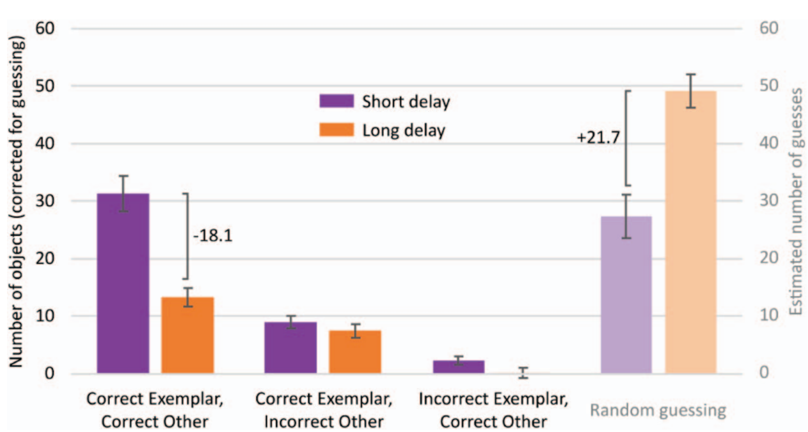

Figure 8. The results of Experiment 5: The number of objects chosen (after accounting for random guesses, by subtracting the number of objects for which neither feature was remembered) in each response-category and the overall estimated number of guesses, by delay length. Error bars depict standard error of the mean. The "other" feature was material for half of the subjects, and orientation for the other half; the results are collapsed across these two dimensions. The numbers on the figure indicate the decrease in the number of fully remembered items, and the increase in the number of random guesses. See the online article for the color version of this figure.

different features was highly dependent. Specifically, there were more objects for which only exemplar was remembered than objects for which only the other feature (material or orientation) was remembered, both after a short delay, $t(18) = 5.42$, $p < .001$, $BF_{10} = 727$, $d = 1.24$, 95% CI [4.06, 9.20], and after a long delay, $t(17) = 6.87$, $p < .001$, $BF_{10} = 8{,}457$, $d = 1.62$, 95% CI [5.04, 9.51]. Again, this also cannot be explained by overall poor memory for the other feature, because it could be very well remembered, but only when exemplar was remembered: there were more objects for which both features were remembered than objects for which only exemplar was remembered, suggesting a hierarchy of the features in memory.

Similar to the previous experiments, there was no effect of probed dimension or an interaction of dimension and delay on the number of remembered items (both Fs < 1, both ps $> .7$, both η^2s < 0.005), suggesting similar patterns across the different dimensions.

A Multinomial Process Model of Feature Dependency

The results of all five experiments supported the notion of an object-based memory, regardless of the dimensions, stimuli, learning tasks, experimental setups, or encoding times used. These findings were based on the analytical approach we described, of estimating the number of random guesses in a simplified manner, by using the number of incorrect–incorrect responses. Although this approach has the benefits of being quite straightforward and relying on a small number of assumptions (that memory is a high-threshold process, and that guesses are uniformly distributed), it is important to examine the data also in a manner that would make all of the assumptions explicit and formally estimate the level of dependency.

Hence, we next describe a formal generative model for the memory of the different features of an object, namely a multinomial process model (for a review, see Batchelder & Riefer, 1999). For a given object, participants will remember its exemplar with probability E. If the exemplar is remembered, the other feature will be remembered with probability F_1, and if the exemplar is not remembered, the other feature will be remembered with probability F_0. We assume a 50% probability of guessing for each feature that is not remembered, because there are two options (correct/incorrect) from which participants should choose randomly when guessing. This model can be translated to the different response categories in our task (CC = correct exemplar and correct other-feature; CI = correct exemplar and incorrect other-feature; IC = incorrect exemplar and correct other-feature; II = incorrect exemplar and incorrect feature), as shown in Figure 9.

The probabilities of each response category are given by the following equations:

$$p(CC) = E \times F_1 + E \times (1 - F_1) \times 0.5 + (1 - E) \times F_0 \times 0.5 + (1 - E) \times (1 - F_0) \times 0.25$$

$$p(CI) = E \times (1 - F_1) \times 0.5 + (1 - E) \times (1 - F_0) \times 0.25$$

$$p(IC) = (1 - E) \times F_0 \times 0.5 + (1 - E) \times (1 - F_0) \times 0.25$$

$$p(II) = (1 - E) \times (1 - F_0) \times 0.25$$

From the above equation, we can isolate the following observed combinations of the three model parameters:

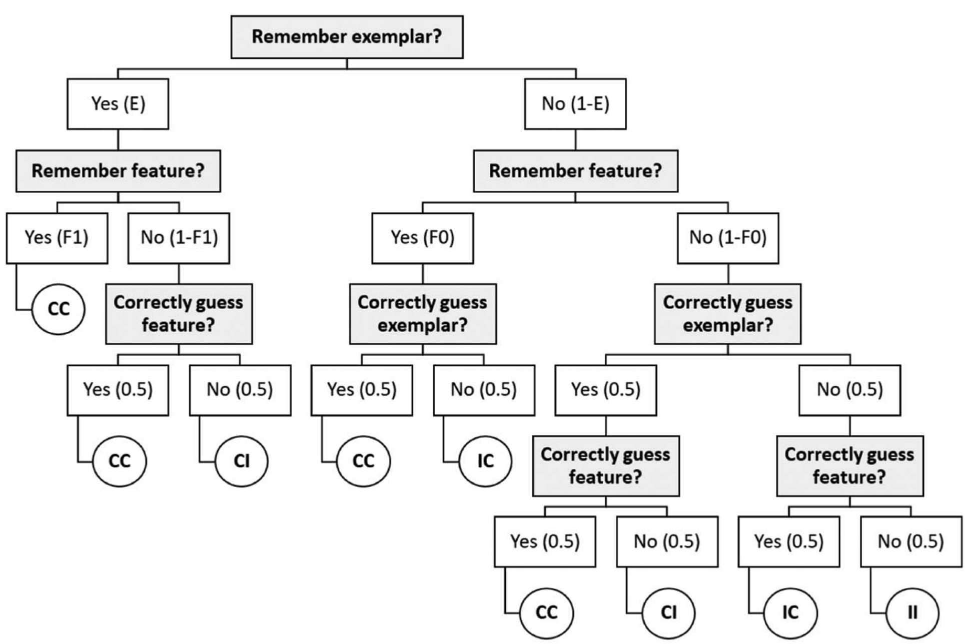

Figure 9. A multinomial process tree model. The probabilities of each step are indicated in parentheses (E = remembering exemplar; F_1 = remembering the other feature given that exemplar was remembered; F_0 = remembering the other feature given that exemplar was not remembered). Final response categories are presented in circles (CC = correct exemplar and correct other-feature; CI = correct exemplar and incorrect other-feature; IC = incorrect exemplar and correct other-feature; II = incorrect exemplar and incorrect other-feature).

$$E \times F_1 = p(CC) - p(CI) - p(IC) + p(II)$$
$$E \times (1 - F_1) = 2 \times (p(CI) - p(II))$$
$$(1 - E) \times F_0 = 2 \times (p(IC) - p(II))$$

As can be seen, we have three parameters and three independent equations, meaning the parameters can be extracted for each participant (in Experiments 1 and 2, separately for each delay condition), with the probabilities of the response category being the empirical probabilities observed in the experiment. If a calculated combination ($E \times F_1$, $E \times (1 - F_1)$, or $(1 - E) \times F_0$, see above) was negative, it was set to 0.

For example, F_1 is calculated as follows:

$$\frac{F_1}{1 - F_1} = \frac{p(CC) - p(CI) - p(IC) + p(II)}{2 \times (p(CI) - p(II))}$$

Two main theoretical models can be postulated regarding the dependency of the other feature on exemplar, namely independency versus dependency. The predictions of these theoretical models focus on the F_0 parameter of the multinomial model (see, e.g., Meiser & Bröder, 2002). In an independent model, the probability of remembering the other feature is, by definition, independent from the fate of the exemplar: $F_0 = F_1$. Any significant deviation from this pattern points to a dependence of the two tested features, and specifically any dependent model predicts there is a larger probability of remembering the other feature if the exemplar was remembered than if it was not: $F_0 < F_1$ (for a similar approach, see, e.g., Meiser, 2014). As mentioned in the introduction, dependence can take on a range of different forms, and in the extreme case, if the exemplar is not remembered, the other feature is never remembered: $F_0 = 0$. However, note that the model's parameters cannot be negative for any participant, effectively creating a skewed distribution of potential F_0 values, meaning that it is not likely to find support for this type of dependence at the group level. To get a better indication of the level of dependence, we therefore examined also how many participants' F_0 values are within a small range (1 *SD*) from 0.

The results of applying the tree model to all of our five experiments are presented in Table 1 (one participant in Experiment 1 was excluded from the analysis because the model failed to produce numerical results for them, probably due to low overall accuracy). The trend in all experiments, for both the short and long delays, was for a larger F_1 than F_0, a result that was significant in all but Experiment 4. This provides strong evidence that the different features in our experiments were not independent from each other.

Furthermore, we found that F_0 was either 0 or close to 0 for many of the participants. Across experiments and delays, we found that 50–80% of participants had a very low value of F_0. This suggests that not only do exemplar and the other feature depend on each other in LTM, in many cases there is complete hierarchy, such that the other feature cannot be remembered if exemplar is forgotten.

Thus, the results of the formal model analysis converged with our simplified analysis. Both approaches clearly contradict the notion that the different features of an object are independent from each other in memory. Instead, memory seems to be object-based, such that there is a dependency between the different features of the same object. The multinomial model also corroborated our finding that the dependency is very strong, with the other feature almost never remembered if the exemplar is not remembered (i.e., F_0 was close to 0). This suggests a hierarchical structure of memory, with other features depending on exemplar, a point we return to in the General Discussion.

General Discussion

The present study examined whether different features of the same object are remembered and forgotten independently or dependently in LTM. Across five experiments, participants viewed pictures or computer-generated renderings of real objects in a learning task (explicit or incidental), and in the test phase, asked to indicate which of several versions of the object they saw, choosing among four alternatives that orthogonally varied in two dimen-

Table 1
Results of the Multinomial Tree Model by Experiment and Delay

Experiment and delay	F_1	F_0	F_1 vs. F_0	% $F_0 = 0$	% $F_0 < 0 + SD$	E
Experiment 1						
Short	.64 (.04)	.07 (.02)	$p < .001$, $d = 2.33$	39%	55%	.57 (.03)
Long	.31 (.05)	.07 (.01)	$p < .001$, $d = 0.77$	35%	71%	.31 (.04)
Experiment 2						
Short	.59 (.03)	.1 (.02)	$p < .001$, $d = 2.27$	38%	66%	.58 (.03)
Long	.35 (.06)	.07 (.01)	$p < .001$, $d = 0.72$	38%	56%	.27 (.03)
Experiment 3						
Short	.59 (.07)	.15 (.05)	$p < .002$, $d = 1.49$	40%	50%	.58 (.06)
Long	.42 (.1)	.05 (.03)	$p < .02$, $d = 0.95$	60%	80%	.31 (.03)
Experiment 4						
Short	.44 (.05)	.31 (.07)	$p = .23$, $d = .28$	25%	60%	.61 (.02)
Long	.26 (.06)	.19 (.04)	$p = .49$, $d = .16$	30%	55%	.37 (.02)
Experiment 5						
Short	.5 (.05)	.24 (.06)	$p < .002$, $d = 0.87$	37%	58%	.54 (.05)
Long	.39 (.07)	.07 (.03)	$p < .002$, $d = 0.87$	72%	72%	.31 (.03)

Note. We present the average estimated parameters F_1 and F_0 (*SE* in parentheses), the *p* value and Cohen's *d* of the comparison between F_1 and F_0, the percentage of participants for which $F_0 = 0$, the percentage of participants for which F_0 was within 1 *SD* from 0, and average estimated *E* parameter (*SE* in parentheses). If features are independent, F_1 should be equal to F_0, and if features are dependent, F_1 should be larger than F_0.

sions: exemplar and state, exemplar and material, or exemplar and orientation. Probing subjects' memory either immediately after the study phase or 3 days later allowed us to test the dynamics of memory performance as forgetting takes place. Our experiments followed the protocol of Experiment 2 from Brady et al. (2013), but we analyzed the results using a novel approach that examines the frequency of different responses (i.e., both features remembered correctly, only exemplar remembered correctly, or only the other feature—state, material, or orientation—remembered correctly) after accounting for random guesses.

Dependent Forgetting in LTM

All experiments provided strong evidence for dependent (i.e., object-based) forgetting in LTM. First, in all five experiments, we found more fully remembered objects (i.e., items for which both features were remembered) than partially remembered objects (i.e., items for which only one feature was remembered) in the long delay. This suggests that even after substantial forgetting occurred, responses were not randomly distributed with regards to each item's different features, in line with the object-based forgetting account, and in contrast to the feature-based forgetting account. This cannot be explained by good memory for both features independently, because when the exemplar was not remembered, the other feature was almost never remembered (see further discussion below).

When the test was delayed, the number of fully remembered objects decreased, which is expected due to forgetting. If this forgetting is independent for each feature, some of these objects should be partially remembered in the long delay. Conversely, if forgetting is dependent, objects that are no longer fully remembered should be completely forgotten. In all five experiments, we found that the decrease in fully remembered objects was mirrored only by an increase in the frequency of random guesses that occur when no relevant memory is available, while the frequency of partial responses was similar across delays. This provides a second support for the object-based forgetting view, and goes against the feature-based forgetting view, because when an object is lost from LTM, all of its features are lost together. These results echo many findings of object-based dynamics at earlier stages of visual processing, that is, attention and working memory (e.g., Scholl, 2001; Vogel et al., 2001), which suggests that objects are the basic building blocks on which much of visual processing operates.

Notably, in all five experiments, some of the objects were only partially remembered in the long delay, and it could be argued that this shows independent forgetting, such that these items were fully remembered after a short delay but then one of their features were forgotten. However, it is important to note that some of the items were partially remembered already after a short delay. Therefore, it is reasonable to assume that the partially remembered items in the long delay mainly reflect items for which the other feature was not encoded in the first place. We return to the issue of partial responses in a later section, where we explain why their presence isn't in itself an indication of feature-independence.

Another line of support for a dependency between the different features came from the multinomial process tree model. This formal mathematical analysis allowed us to compare the probability of remembering the other feature given that the object's exemplar is remembered, to the probability of remembering this feature when the exemplar is forgotten. If the two probed features are independently forgotten, the two probabilities should be the same. The model converged with our simplified analysis, such that the probability of remembering the other features of objects whose exemplar was forgotten was lower than the probability of remembering the other features of objects whose exemplar was remembered. In fact, for most participants across our experiments, the probability of remembering the other features of objects whose exemplar was forgotten was close to zero.

Finally, we note that our findings were consistent across all five experiments, which varied in the types of stimuli (real-world pictures vs. computer-generated items), learning tasks (explicit or incidental), setups (within- or between-subjects designs), probed feature-dimensions (state, material, and orientation), and presentation durations (800 or 200 ms). This stability supports the generality of the present findings. One factor we did not vary was the length of the long delay, which was fixed at three days across all experiments. The reason for this was to keep the setup as similar as possible to the original study of Brady et al. (2013), to make the comparison maximally straightforward. It might be that a shorter delay would allow more partial responses to arise, so an interesting direction for future studies would be to more systematically vary the delay length, probing some objects after an intermediate delay (e.g., a few hours).

Dependent Storage in LTM

Our main findings suggest that when information is lost from LTM, this happens largely in a dependent manner for the different features of an object. A related but different question regards the nature of LTM *storage*. Notably, the way in which items are forgotten does not necessarily demonstrate how these items were maintained before being forgotten (see below). Forgetting implies a failure of the memory system, while remembering indicates a stable and successful memory process. Notably, Brady et al.'s (2013) original findings regard only the issue of dependent versus independent *forgetting*, and not storage. Looking at our data, we can ask whether remembering, rather than forgetting, is object-based or feature-based.

Across all experiments, most responses (78–91%) reflected an all-or-none storage, with objects either being fully remembered or completely forgotten. Examining the remaining 9–22% of objects, which were only partially remembered, can shed light on the format of memory storage. The clearly asymmetrical pattern of these responses supports a strong form of dependency between the features, namely a hierarchy, with the fate of the object's state, material or orientation depending on the memory for the object's exemplar. In all five experiments, we found more objects for which only exemplar was remembered than objects for which only another feature (state, material, or orientation) was remembered while exemplar was forgotten. In fact, the frequency of partial-responses for the other features was close to 0. Note that this cannot be explained by the difficulty level of these features, because in all five experiments we found more fully remembered objects (i.e., objects for which both exemplar and the other feature were remembered) than objects for which only exemplar was remembered. This is especially telling when considering that in different experiments we tested three different dimensions alongside exemplar, namely state, material, and orientation, but the results were stable across all dimensions.

Thus, our results strongly indicate that different features are not only lost in a dependent manner, but also retained in a dependent manner in LTM. Specifically, the fact that more exemplar-only items than other-only items were found suggests a hierarchical structure of LTM storage, at least for the dimensions we tested. Only if an object's exemplar is remembered, can its other features (e.g., state) also be remembered. In other words, it is possible to remember, for example, a state-free exemplar, but not to remember an exemplar-free state. This points to a dependency of features within LTM.

Note that our results suggest that even if an exemplar is remembered, not all the other features are mandatorily remembered, a point we return to later. However, our main analysis showed that in most cases, items are either fully remembered or completely forgotten, and critically, that fully remembered objects do not become partially remembered but fully forgotten, meaning that objects are forgotten in an all-or-none manner. The findings described in the above section simply suggest that even for objects that were not perfectly encoded, memory is still not independent but hierarchical, with the other feature depending on exemplar. However, it is important to keep in mind that in the present results, the form of dependency was in almost all cases "all-or-none."

Finding a hierarchy in LTM dynamics raises several questions, which we hope future studies can help answer. First, at what stage does this hierarchy emerge? It might occur during storage in LTM, during the retrieval of information for response purposes, or already be present during the items' encoding into LTM. Because the frequency of partial responses was similar in the short and long delays, our results suggest that at least some level of hierarchy was present early on, presumably at the encoding of the items, but this should be tested directly. It is of course entirely possible that hierarchy emerges at multiple stages, or at different stages for different items or dimensions.

Another issue concerns the generality of the hierarchy. Is the asymmetrical pattern between exemplar and other features (state, color, and orientation) specific to LTM, or might it be a more general property of our cognitive system? The present results can only speak of LTM, and this issue has not been systematically studied in related areas such as working memory. Interestingly, a hint for the possible generality of the hierarchy can be found in cognitive development, where it was shown that infants can use shape and size information to individuate objects earlier than other features such as color (Wilcox, 1999; Woods & Wilcox, 2006). Thus, exemplar, as defined by shape, might be a fundamental feature by which we categorize items in everyday life, a hypothesis which future studies might examine.

Finally, another open question remains regarding the dependency between the features other than exemplar. For example, future studies could examine whether an object's material and orientation are also maintained in a dependent manner in LTM. These different features might not have an obvious hierarchy between them, and hence it would be interesting to test whether they posit the same type of dependency as observed here (i.e., hierarchy), or are represented in a more symmetrical way.

Different Analytical Approaches to the Study of LTM Dynamics

Over the years, the issue of feature-based versus object-based representations was studied by employing different approaches, each with its own advantages and limitations. Some studies examined object-based benefits with techniques similar to those used in attention and working memory research, by comparing memory for features when they belong to the same object and when they belong to different objects (Walker & Cuthbert, 1998; Wilton, 1989), but this relied on very simple stimuli. Other studies used more complex, real-world stimuli such as faces or scenes and tested for conjunction errors that were interpreted as reflecting an independence storage of features (Albert et al., 1999; Reinitz et al., 1992), but there have been claims that this reflects familiarity rather than the format of storage (Jones et al., 2001; Jones & Jacoby, 2001). Still others examined the dependence between the different source dimensions that make up the context of an item, however whether the stochastic dependence observed reflects actual binding remains debated (for a review, see Hicks & Starns, 2015).

Recently, Brady et al. (2013) suggested a new analysis method based on an estimation of the dependency of features, calculating the ratio of the observed dependency (the difference between conditional accuracy when the second feature was correct and when it was incorrect) and the dependency predicted from a fully dependent model that takes into account the feature's rate of remembering. However, this treats the different response-options (i.e., being correct in two features, and being correct in only one) as independent, because the calculation examines the responses in one dimension while pooling across the other dimension. Since at test the different variants of the object were presented together, this approach suggests participants can ignore exemplar and respond only to state, for example. However, we presented evidence that the different features are likely to affect each other.

We suggested an alternative approach, which compares the different response-options, after correcting for random guesses in a simple manner. We argue that this further supports the dependent representation account: using coarse simplified assumptions was enough to reveal strong evidence for object-based organization of memory. Notably, a formal mathematical model of memory and guesses approves the conclusions from our analysis. Note that our analysis assumes a difference between the processes involved in no-memory responses (i.e., guessing) and those involved in responses that include at least some memory. Conversely, Brady et al.'s (2013) original analysis assumes that even when subjects have some memory, they can respond in an independent manner for the different features, which is circular when the question at hand regards the independency of features. Because our findings, based on this new analytical method, differ from the original ones, it is important to compare the two approaches.

Brady et al.'s (2013) method has the benefit of relying on a well-defined computational model, which potentially can produce a good estimate of feature dependency. However, when attempting to apply the original method to our results, despite the fact that the dependence score is a proportion (of the observed dependency out of the predicted perfect dependency) and should thus range between 0 and 1, for many of our subjects the results far exceeded this range (for 73% of the subjects at least one of the obtained dependence scores exceeded the theoretically possible range; see the online supplementary material). This might be due to the smaller number of trials (per delay period) in our study, or to lower overall accuracy, pointing to potential limitations of Brady et al.'s method, which might work well only for data with high accuracy rates. It is important to note that the differences between the original study and ours were not dramatic, and yet Brady et al.'s method did not fit many cases in our data-set. Furthermore, even the estimates that were within the logical range (less than 60% of the data) failed to replicate the original claims of a decrease in dependency across time, suggesting that the original method might not be stable enough. In addition, as mentioned above, the model's assumption of response-independency is problematic in a paradigm that simultaneously presents multiple variants of an object.

The major drawback of our approach is that it is based on a rough estimate of random guesses. However, this might also be an advantage, because our method includes relatively few assumptions as for the nature of responses or forgetting. This could mean that our approach is suitable in relatively noisy situations (e.g., few trials, or low accuracy). Notably, with relatively low overall accuracy, as found here, one could have expected that almost no fully remembered objects are found. Instead, we systematically observed a larger number of fully remembered than partially remembered objects, supporting the dependent storage account.

Importantly, we accept that Brady et al.'s approach is valid in some situations, and simply argue that our proposal is an equally valid alternative. Because the conclusions drawn from the two approaches did not converge, we posit that more research is needed before a clear-cut conclusion regarding dependent or independent forgetting could be reached.

Recently, Utochkin and Brady (2019) tested the integration of the different features of real-world objects in LTM in two novel ways. In the first task, after viewing objects from different categories, participants were presented with four images for each category: two exemplars, each in two states. They were asked to select the correct state for each exemplar. When each exemplar was associated with a different state (as compared with both having the same state), participants were at chance in selecting the correct state for each exemplar. This was taken to contradict a holistic storage of exemplar and state, which the authors argued should predict no interference because the features of each item are separately stored (although note that interference could instead arise at the test phase, see Awh, Barton, & Vogel, 2007). In the second task, the study phase included a single exemplar from each category, and in the test phase participants were shown two exemplars and asked to choose the old one. Performance was unaffected by irrelevant changes in the test items' states, suggesting participants could generalize across states.

Although the results from these two paradigms were interpreted as supporting independent storage of features, they are actually in line with the hierarchical *dependent* storage that we found. This is because Utochkin and Brady (2019) showed that an object's exemplar could presumably be maintained without state information being available, but there was no indication that state can be remembered without exemplar information (this direction was simply not tested). Indeed, when two features that should not have this hierarchical structure, namely luminance and hue, were used, the generalization was abolished, suggesting the two features were held together in LTM.

The Format of Storage Versus the Nature of Forgetting

As mentioned above, we systematically found a small but reliable number of partial responses, that is, objects for which only exemplar, but not the other probed feature, was remembered. This suggests that even if an object's exemplar is remembered, its other features might not be remembered. Does this pose a problem for the dependent structure of LTM? We maintain that it does not and argue that three distinct issues should be addressed when considering the nature of LTM-storage.

The first is whether all of an item's features are *mandatorily* remembered, for which the answer seems to be a simple "no." For example, imagine you remember a person's name, but not their date of birth. In fact, there is recent evidence that in working memory tasks, subjects are completely unable to report a salient feature of a target when completing a task on another feature, even for the feature used to identify the target (H. Chen & Wyble, 2015). For example, when subjects repeatedly reported only the location of a letter among digits, and then were surprisingly asked to report the target's identity, which is the very attribute used to choose the letter in all preceding trials, they were unable to do so. This strongly suggests that not all of an object's features are automatically encoded. Similarly, it should be perfectly reasonable to encode an object's exemplar but not its state. Therefore, we argue that finding some items for which only some of the features were remembered does not contradict a dependent structure of LTM, because those features that were encoded could still be stored in a unitized manner. This goes against some of the past models and investigations of feature- versus object-based memory, which treated "object-based" as implying an all-or-none rule in storage (i.e., that all of the object's feature, regardless of task-relevance, difficulty, etc., must be encoded). Instead, we maintain that whenever the independency of features is violated, this suggests that the object is a meaningful unit of representation.

The second question regards the nature of forgetting for the features that *were* remembered to begin with. This is the main issue addressed by Brady et al.'s original study. They found support for an independent loss of features, however using very similar stimuli and manipulation, we could not replicate their results. Instead, across five experiments, both our analysis and the formal mathematical model supported a dependency of features. Future studies might help clarify whether in other conditions forgetting can occur in an independent manner, but our results strongly suggest that forgetting the different features of real-world objects happens in a dependent manner.

Moreover, we claim that the way in which information is lost from LTM does not inevitably reveal the way in which the information was stored prior to forgetting. Even if forgetting occurs independently for each feature, it does not necessarily entail that *storage* is independent. It is plausible that different features of an object are stored in LTM as one "node," but when forgetting takes place, the integration breaks down and some of this information is gradually lost (while some information is still available), perhaps even in an independent way for each feature.

Thus, the third, and arguably most interesting, question, is the dependency of features while they are maintained in LTM, and specifically, whether all the *remembered* features of an object are stored together. In other words, if you remember an object's exemplar *and* its state (or a person's name and their date of birth), are these two pieces of information independent of each other (for a similar approach, see Ceraso et al., 1998)? Some past evidence supported an independent storage (Albert et al., 1999; Reinitz et al., 1992), whereas others supported a dependent storage (Walker & Cuthbert, 1998; Wilton, 1989), and each of the previously used methods had its limitations. Generally, it is much more difficult to probe the nature of LTM-storage, since retrieving information might change it, making interpretation problematic. Interestingly, the present results did include indirect evidence for the structure of LTM-storage, by pointing to a hierarchy of features, with exemplar having a special status. This suggests that different features depend on one another not only in forgetting but also during their maintenance in LTM.

Conclusion

Across five experiments varying in dimensions, stimuli, learning tasks, experimental setups, and encoding times, we found that items are lost from LTM in an object-based manner. People tend to remember objects fully and not partially, and critically, this is not due to good independent memory for both features. Furthermore, when objects are lost from memory, forgetting is complete and not independently for each feature. Finally, LTM appears to have a hierarchical structure, such that an exemplar can be remembered without all of the features associated with the item (state, orientation, or material), but a feature cannot be remembered without the exemplar that carried it. Overall, the results suggest that forgetting from LTM occurs in a dependent manner for all of an object's features, and that likely the storage of these features is also dependent.

Context

Object-based representations have been demonstrated at different levels of visual processing, using various paradigms and analytical methods. Recent work by Brady et al. (2013) challenged this view, by demonstrating that real-world objects are represented as independent features in LTM. We tried to recognize the possible reasons for this discrepancy, but our attempt to use Brady et al.'s (2013) analytical method on our results failed. Instead, we propose a novel analytical approach, based on only one main assumption, which produced very strong support for object-based representations in LTM. In five experiments, we generalized these results to a range of stimuli, experimental setups, learning tasks, feature dimensions, and encoding times. This suggests the robustness of our conclusion that real-world are represented in an object-based integrated manner, also in LTM.

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