When Naming Means Forgetting: Verbal Classification Leads to Worse Memory

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Introduction

Associating categories with discrete, arbitrary labels (words) is a uniquely human trait. **What effect does labeling categories with their basic-level names have on representations of category members?**

With the exception of proper nouns, **words refer to categories of objects or actions**. Naming an item requires not merely retrieving a feature, but an active process of focusing on the properties relevant to the category and abstracting over those not relevant.

> "When we speak of 'table' we do not mean a special given table with all the accidental properties, but we mean "table" in general. The word is used as a representative of the category 'table;' as a symbol for the idea 'table.' We employ the word 'table' in this categorical sense when naming a particular table."
> (Goldstein, 1971/1936: 349).

The Questions

1. What effect does labeling pictures of familiar items have on mental representations of these items?
2. Does labeling have a different effect on typical vs. atypical (or ambiguous vs. unambiguous) category members?

Implementation

One way to study representations is through memory. If labeling an item results in some kind of representational change, one can compare memory for classified vs. non-classified items. In particular, **if classification skews representations, it may create a study-to-test mismatch, resulting in poorer recognition memory** (McClelland & Chappell, 1998; Shiffrin & Steyvers, 1997).

Predictions

If classifying an item with its category name results in a study-to-test mismatch, **participants should have worse recognition memory for the items they have classified** compared to those they did not.

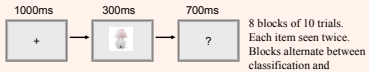
If classifying an item produces a more categorical representation (Lupyan, 2005), it should produce the **largest impairment for the typical items** (cf. Huttenlocher et al., 1991 shift-to-prototype account) since these items have features most strongly linked to the labeled category (Rosch, 1978).

A similar pattern should be observed when category ambiguity is used to predict memory after classification. **Participants should have poorest memory for items rated as being most unambiguously chairs or tables** (i.e., poorer memory for chairs with armrests and backs vs. stools).

Methods

Participants: 72 Carnegie Mellon undergraduates (18 per experiment)
Materials: 40 chairs and 40 lamps (Exps. 1,4), or chairs and tables (Exps. 2,3). Each study item has a matched lure, which was reserved for testing.
Procedure: **Study session:** Participants classify a random half of the items by responding with their category (chair, lamp, table) – *classification*, and make a non-category response (like / don't like) – *preference* – for the other half. They are also instructed to try to remember as much as possible about every item they see.
Test session: Participants see all the old items (40) and corresponding lures (40). Their task is to respond *old* or *new* depending on whether they remember seeing the exact item before.

Experiment 1

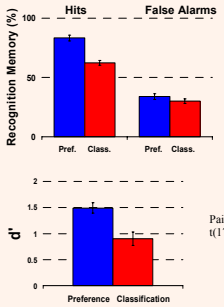


8 blocks of 10 trials. Each item seen twice. Blocks alternate between classification and preference trials

Block # 1 2 3 4 5 6 7 8
Response Type: Class Pref Class Pref Class Pref Class Pref
(Order counterbalanced)

Results

Memory was poorest for the classified items. Classified items were less likely to be correctly identified as old (*M*=.62) compared to non-classified items (*M*=.83). There was no difference in false alarms.



Bars are ±SE

Paired t-test:
Hits: t(17) = 6.13 p<.0005
FA: Not sig.

Paired t-test:
t(17) = 4.62 p<.0005

Analysis of item typicality:

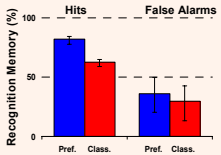
Typicality ratings were collected from an additional 10 participants who rated each study item on category typicality: 1 (most typical) to 5 (most atypical).

Overall, participants had better memory for the less typical items *r*(40)=.65, *p*<.0005. However, there was **a significantly greater relationship between typicality and hits for the classified items (r(40)=.67), compared to preference items (r(40)=.48): F(1,76)=7.82 p<.01.** There was no relationship between typicality and false alarms.

Experiment 2

Aim: Replicate the effect with more similar categories (chairs and tables). Does category *ambiguity* predict memory after classification?

Results



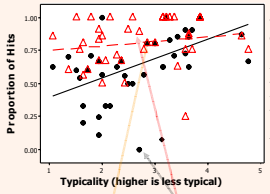
Paired t-test:
Hits: t(17) = 5.25 p<.0005
FA: Not sign.

d': t(17) = 2.54, *p*<.03

For further information
Please contact Gary Lupyan at *glupyan@cnbc.cmu.edu*.
A PDF copy of this poster is available at
www.cnbc.cmu.edu/~glupyan/lupyanCogSci2005.pdf

Typicality and ambiguity analyses

In addition to typicality ratings for the objects, ambiguity ratings were collected from a separate group of participants. **Memory was again poorest for the most typical items as well as the most unambiguous chairs and tables.** There was no relationship between typicality or ambiguity and false alarms.



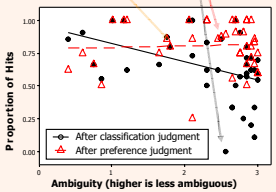
Typicality by hits correlations:

After preference: *r*(40) = .18 n.s.
After preference: *r*(40)=.54, *p*<.0005

F(1,76)=5.22 *p*<.03

Medium typicality and ambiguous: Classification has no effect

Medium typicality and unambiguous: Classification has a large effect



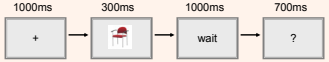
Ambiguity by hits correlations:

After preference: r(40) = .05 n.s.
After classification: r(40)=-.42 p<.01

Ambiguity is correlated with typicality (more typical items are less ambiguous *r*(40)=.49). However, ambiguity proves to be an independent predictor with typicality partialed out.

Experiment 3

Is the effect due to preference being a harder task?
Preference judgments are slower than classification judgments (e.g., Exp 2: *M*(classification) = 338ms; *M*(preference) = 413ms; *t*(17) = 8.19, *p*<.0005. Perhaps participants rush through classification, not paying enough attention to the stimuli. **Experiment 3 increased the response time, and instructed participants to consider their response during the delay period.**

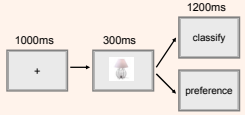


Results

Identical pattern as experiments 1 and 2.

Experiment 4

Is the poorer memory after classification actually due to the response or a difference in strategy? Perhaps participants pay attention to different details depending on the study block (classification or preference). **Experiment 4 randomizes responses so that participants don't know whether they will have to classify or indicate preference for a given item.**



Results

Identical pattern as experiments 1 and 2 (except participants now have higher false alarms as well as lower hits on the classified items).

Conclusions

Participants had poorer recognition memory for the items they classified with their basic level names (chairs, tables, lamps).

The detrimental effect of classifying was greatest for the most typical and the least ambiguous items. Both typicality and ambiguity predicted recognition memory after classification

Lower recognition accuracy (hits) for the classified items persists even when participants are given more time in which to consider their response (Exp. 3) and when participants cannot bias their visual processing on a desired response (Exp. 4).

Why does classification result in poorer item memory?

Basic-level words refer to entire categories. Classifying an item by its name alters the representation of the typical features of the item (the features most relevant to the category e.g., armrests for "chair", tabletop for "table"). **This results in a mismatch between the representation of the studied item and the original item re-presented at test.** Since the test item does not match the memory trace, it appears newer (McClelland & Chappell, 1998; Shiffrin & Steyvers, 1997), resulting in the observed difference in hits.

An alternate explanation based on depth of processing?

Depth of processing theories (e.g., Craik & Lockhart, 1976) **cannot account for the entire range of observed effects for the following reasons**:

1. They potentially predict the *opposite* effect: Classification requires semantic judgment; preference doesn't.
2. They potentially predict a difference in false alarms as well as Hits (not observed)
3. They would not predict greater correlations between typicality and memory for the classified stimuli.
4. The effect persists even when RTs are nearly equal between tasks (Exp 3), and persists when response type is not known ahead of time (Exp. 4).

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Acknowledgments

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