The Impact of category structure and training methodology on the acquisition and generalizability of within-category information

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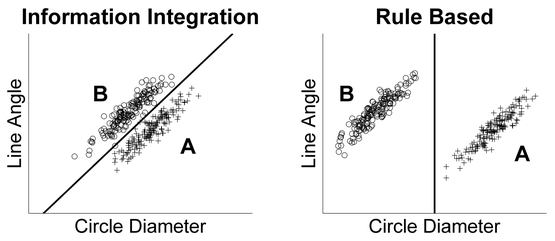
BACKGROUND

- Categorical representations can be broadly characterized as (Markman & Ross, 2003):
  - Within category – commonalities among category members
  - Between category – differences between category members and nonmembers
- Factors influencing the learning and generalizability of within-category information are not well characterized.
- We propose that category structure (Ashby & Ell, 2001; Ashby & Maddox, 2005) and training methodology (Markman & Ross, 2003; Casale & Ashby, 2008) are two critical factors.

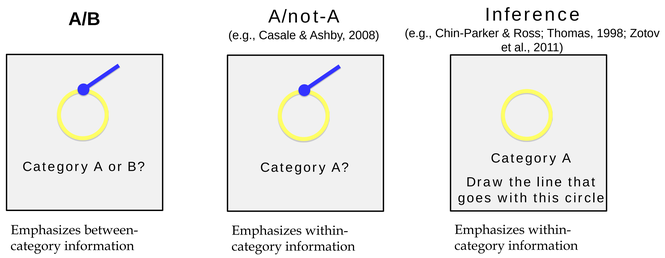
Category structure



- Recruits a procedural learning system that learns within-category information*
- Recruits a hypothesis-testing system that learns between-category information

*Knowledge of within-category correlation provides index of within-category information.

Training methodology



Emphasizes between-category information

Emphasizes within-category information

Emphasizes within-category information

The Current Study

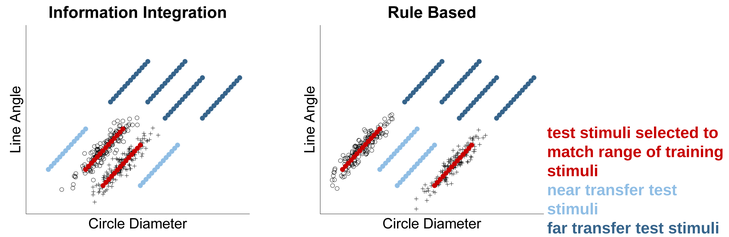
- *Prediction:* The ability to learn within-category information will depend upon both category structure and training methodology (Table 1).

Table 1	**Training Methodology**		
Category Structure	**A/B**	**A/not-A**	**Inference**
RB	No	Yes	Yes
II	Yes	Yes	Yes

- Once learned, can within-category information be generalized to both novel stimuli and novel tasks ?

EXPERIMENT 1: METHOD

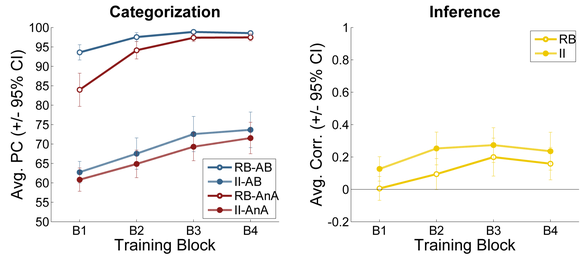
- 2 category structure (RB, II) x 3 training methodology (A/B, A/not-A, inference) , approximately 30 participants/condition
- Training
  - 4 blocks of 80 trials with trial-by-trial feedback
- Test
  - all participants tested on the inference task
  - 1 block of 112 trials without feedback



- Correlation between presented and inferred stimulus component provides index of within-category information

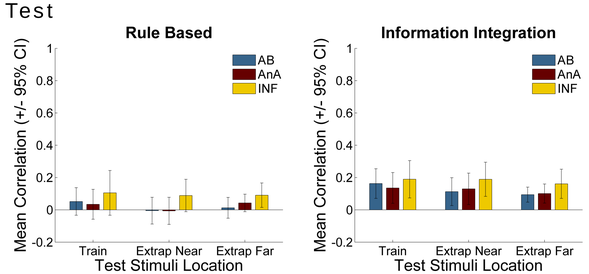
EXPERIMENT 1: RESULTS

Training



- *A/B and A/not-A*
  - Participants were able to learn the RB and II category structures
  - As expected, accuracy was much higher in the RB conditions
- *Inference*
  - Modest learning of the correlation between dimensions

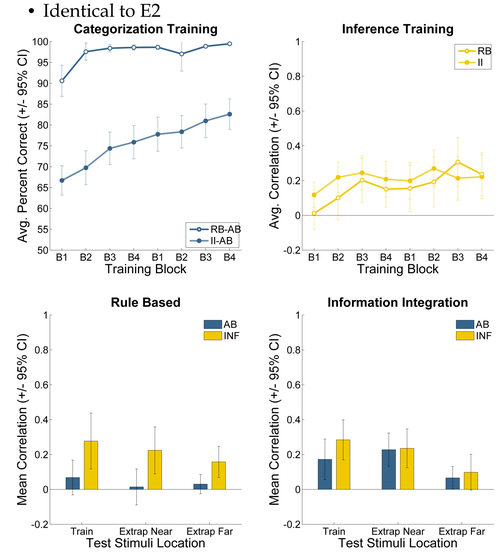
Test



- *Rule Based*
  - Limited generalizability of information across training conditions
- *Information Integration*
  - Evidence of within-category information that could be generalized to novel tasks and stimuli

EXPERIMENT 2: METHOD AND RESULTS

- Would extended training facilitate performance at test?
- Training
  - 8 blocks of 80 trials (across 2 days) with trial-by-trial feedback
  - Focused on A/B and inference training, approximately 30 participants/condition
- Test
  - Identical to E2



Training

- Evidence of learning in all conditions

Test

- *Rule Based*
  - Task-specific generalization of within-category information to novel stimuli
- *Information Integration*
  - Generalization of within-category information to novel tasks and stimuli
  - Generalization was less robust than in Experiment 1

SUMMARY

Learning

- Category structure and training methodology influence the learning of within-category information, but the influence of A/not-A training was not as robust as predicted (Table 2).

Table 2	**Training Methodology**		
Category Structure	**A/B**	**A/not-A**	**Inference**
RB	No	No	Yes
II	Yes	Yes	Yes

Generalization

- Category structure and training methodology influence the learning of within-category information

Rule Based

- Task-specific generalization to novel stimuli, but not novel tasks

Information Integration

- Consistent generalization to novel stimuli and tasks

- Results suggest that the training environment should be tailored to meet the goals for knowledge generalization.

Current and Future directions.

- Is knowledge generalization unidirectional?
  - For example, can within-category knowledge be generalized to (A/B) classification?
- Can these data be explained by computational models assuming within- and/or between-category knowledge?

REFERENCES

Ashby, F. G., & Ell, S. W. (2001). The neurobiology of human category learning. *Trends in Cognitive Science, 5, 204-210.*

Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology, 56, 149-178.*

Casale, M. B., & Ashby, F. G. (2008). A role for the perceptual representation memory system in category learning. *Perception & Psychophysics, 70, 983-999.*

Chin-Parker, S. & Ross, B. H. (2002). The effect of category learning on sensitivity to within-category correlations. *Memory & Cognition 30, 353-362 .*

Markman, A. B., & Ross, B. (2003). Category use and category learning. *Psychological Bulletin, 129, 529-613.*

Thomas, R. D. (1998). Learning correlations in categorization tasks using large, ill-defined categories. *Journal of Experimental Psychology: Learning, Memory, & Cognition 24, 119-143.*

Zotov, V., Jones, M. N. & Mewhort, D. J. (2011). Contrast and assimilation in categorization and exemplar production. *Attention Perception & Psychophysics 73, 621-639.*

ACKNOWLEDGEMENTS

This research was supported by NSF grants BCS-1349737 and BCS-1349677.

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