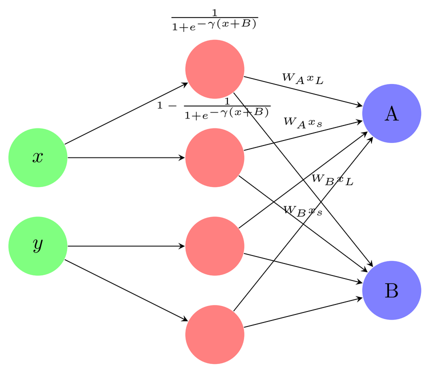

School of Rocks: Interaction of Learned Level and Category Structure in Learning Hierarchical Categories

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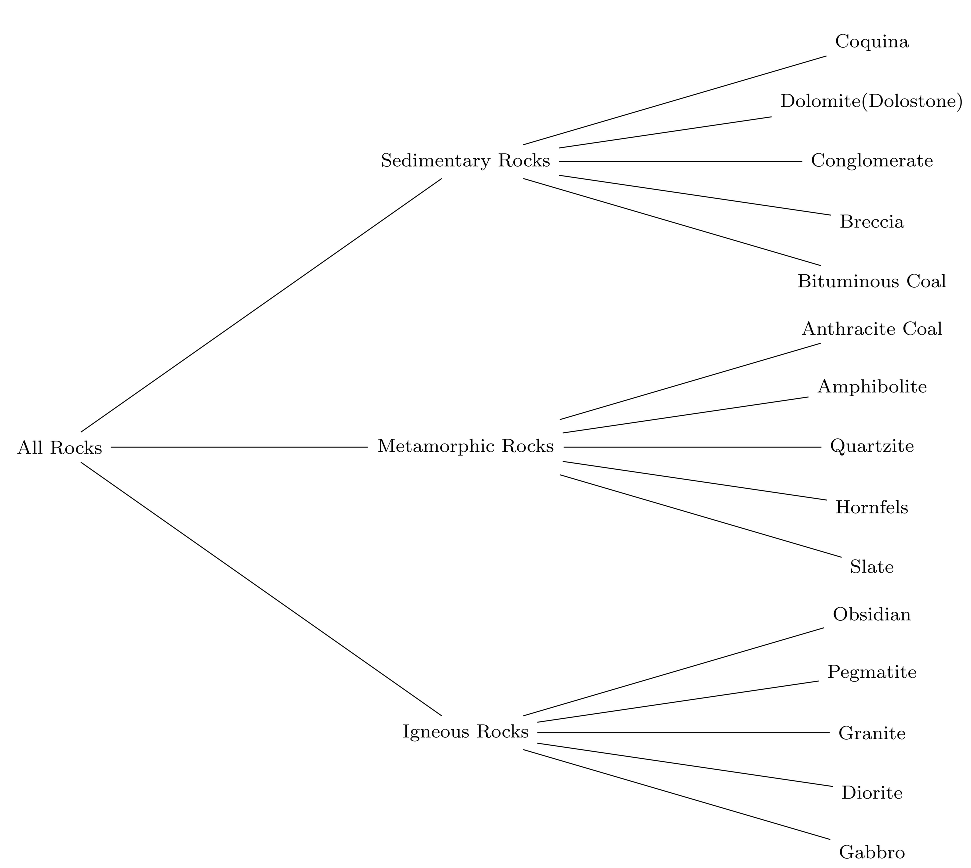
Introduction

Categories exist at varying levels of abstraction. In geology, rocks are categorized as Igneous, Sedimentary, or Metamorphic based on how they formed. These higher-level, superordinate, categories subdivide into a wide variety of sub-types based upon a heterogeneous range of considerations.



Question: Suppose we wish to learn to classify at the higher level, is it better to:

1. *directly* learn the superordinate categories
2. learn the superordinate categories *indirectly* at subtype level

Hypothesis: The answer may depend whether you are trying to learn a compact or a dispersed category set.

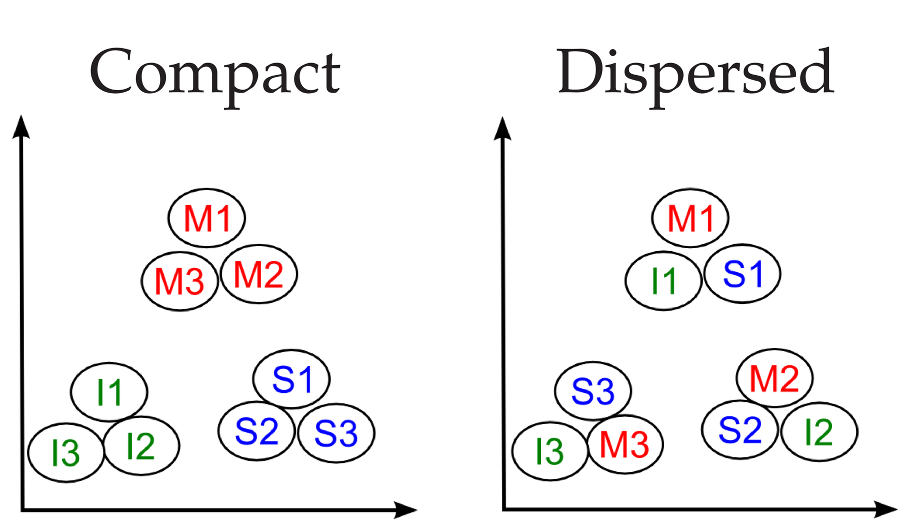


Figure 1: Illustration of two types of category structure. "M1" stands for Metamorphic Sub-type 1. Categories grouped closer together are percieved as more similar to one another then categories further away.

Methods

Design

Subjects were shown images of rocks and had to guess the rock's categorization. The following factors were manipulated:

Factor 1: Compact vs. Dispersed structure
Subjects recieved either a compact or a dispersed stimulus set. Each set consisted of 9 rock subtypes (3 ign., 3 sed, 3 meta.) with 6 tokens apiece. Structure of the sets is shown in Materials below.

Factor 2: High-level learning vs. Subtype-level learning
Subjects were assigned to either a high-level or a subtype-level learning condition.

- In the high-level condition S's classified rocks as Igneous, Sedimentary, or Metamorphic.
- In the subtype-level learning condition, S's classified rocks following the scheme *Igneous-1, Igneous-2, . . ., Sedimentary-9*

Factor 3: Training stimuli (old) vs. Transfer stimuli (new)
3 tokens of each subtype were randomly selected to be retained for the final block of the experiment. On the final block of the experiment all stimuli were shown, and percent correct measured separately for stimuli seen previously and stimuli appearing only on the final block.

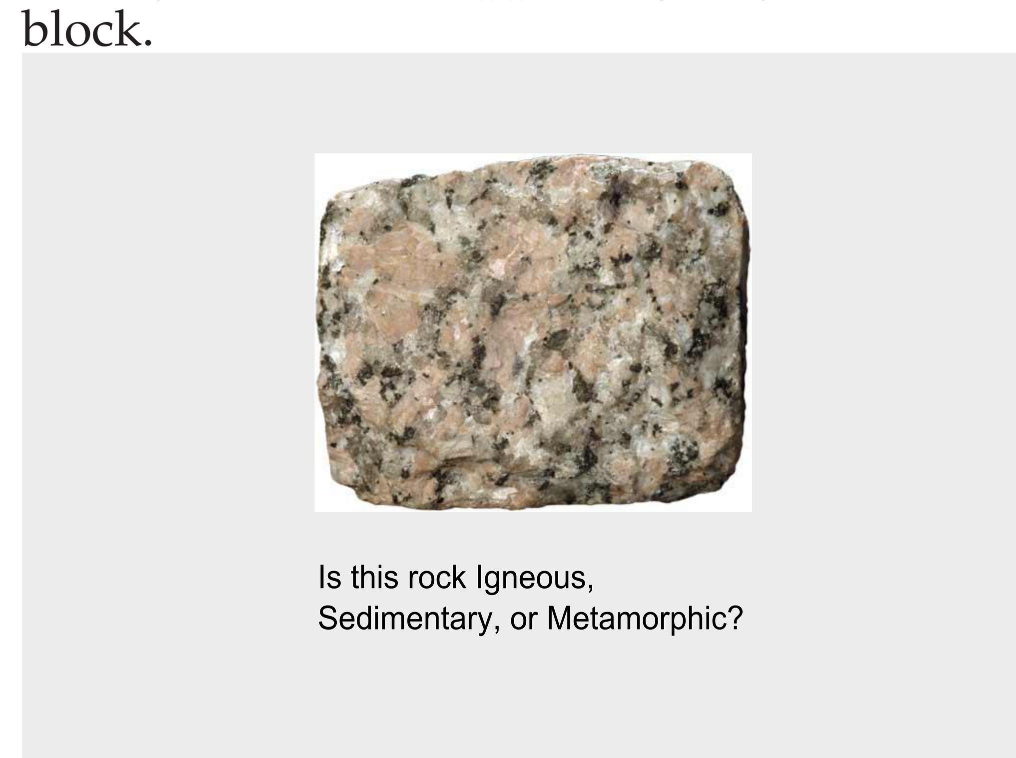


Figure 2: Example of a stimulus that would be shown in direct learning conditions.

Materials

In a separate experiment, similarity ratings were collected for the rocks used in the present experiment. In a process known as multidimensional scaling (MDS), these ratings were used to create the plots shown below.

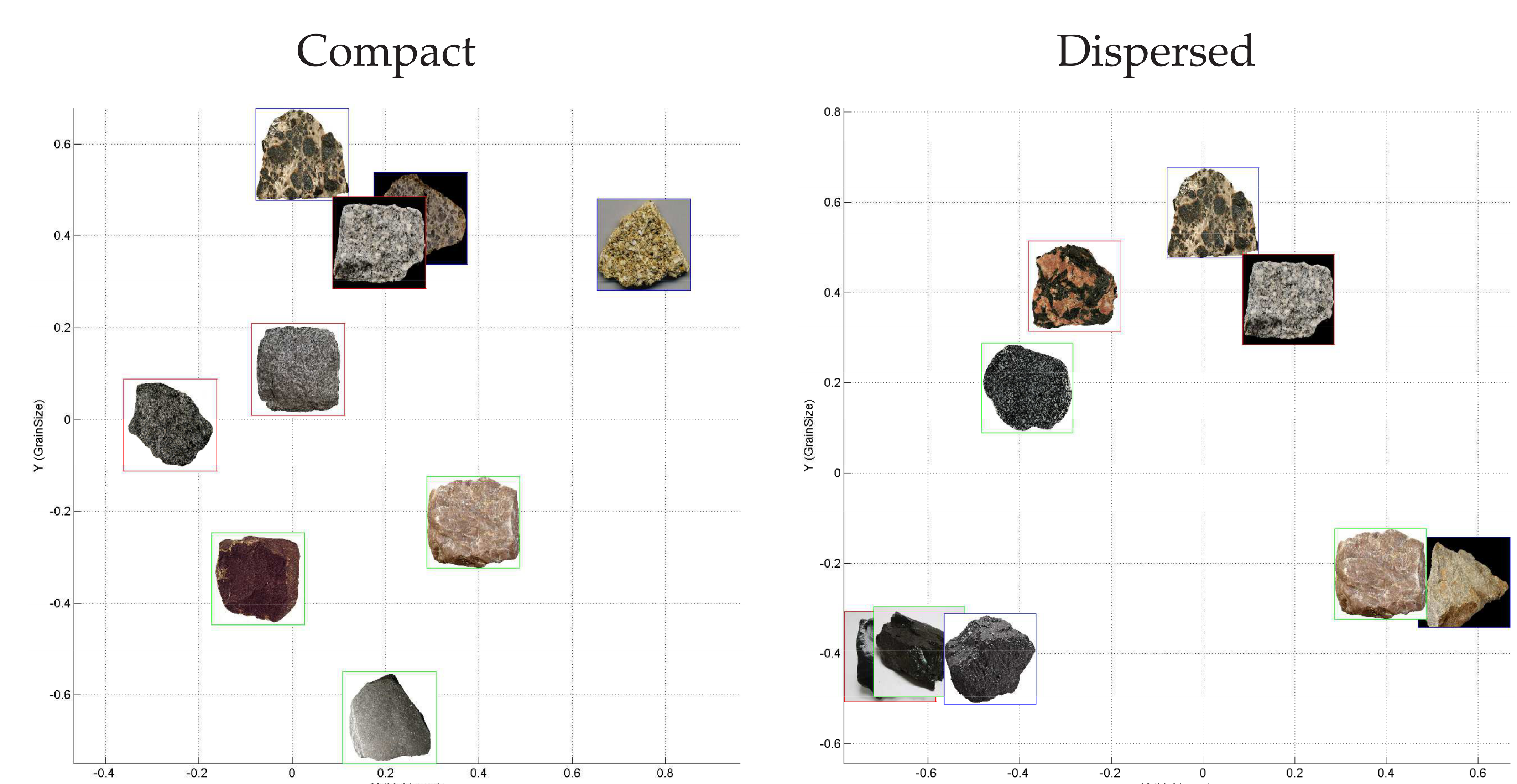
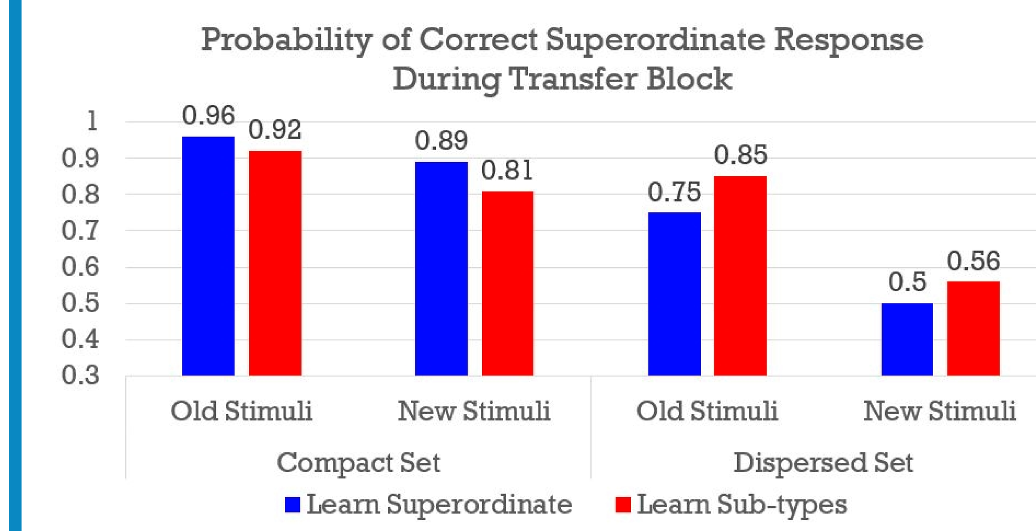


Figure 3: MDS representation of the categories used in each stimulus set. Rocks outlined in red are Igneous, green are Metamorphic, and blue are Sedimentary. Derived dimensions are Lightness and Average grain size.

Results



We observed main effects for stimulus novelty (F(1,120)=384, p<.001), with subjects performing better on stimuli seen during training; as well as for category structure (F(1,120)=182, p<.001), with participants who learned the compact set performing better than those who received the dispersed set. The main result however, is a **strong interaction between Category structure and Learned Level (F(1,120)=18.6, p<.001)**. Subjects learning the compact set performed better if they learned the categories directly. However if they learned the dispersed set the direction of the effect reverses: indirect subtype learning was better than direct high-level learning.

Discussion

The primary finding of note is that the hypothesized interaction between learned level and category structure did in fact take place. In light of the results, we conclude that if we're interested in teaching someone higher-level superordinate categories, then the best procedure depends upon the structure of the categories. Direct high-level learning is best if the categories are compact, but indirect subtype learning is best if the categories are dispersed.

Although not part of the present thesis, an exemplar storage model of categorization accounts for the complete set of results.