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碩士學位論文

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類別結構的亂度因素、刺激向度個數對分類學習行為的影響

Categorical entropy, number of stimulus dimensions, and category learning

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中文摘要

Sloutsky (2010; Kloos 與 Sloutsky, 2008) 操弄不同的類別結構亂度 (categorical entropy) 進行類別學習作業，藉此提出了雙系統理論，認為人們會啟動不同的系統，濃縮式系統 (compression-based system)或選擇式系統 (selection-based system)，以適應不同的類別結構組成之刺激材料。本研究回顧了 Sloutsky 的研究證據與過去類別學習領域的相關文獻，認為此雙系統理論可能只適用在向度數目較多的情境之下，因此設計了三個實驗，使用和 Kloos 與 Sloutsky (2008) 相同的實驗派典，欲說明刺激材料的向度個數確實會影響到人們的類別學習行為。實驗一發現，Sloutsky 所預測的類別結構與學習方式之交互作用只出現在向度個數較多的情境，向度個數少時則無此交互作用。實驗二得到與實驗一相同的結果，並排除了刺激材料本身特性（幾何圖形或類自然類別材料）此一混淆變項。實驗三採用特別設計的依變項，直接觀察受試者採用相似性(similarity)或規則(rule)的方式進行分類判斷，集群分析的結果顯示在向度數目少的情境時，不管何種類別結構受試者均傾向使用以規則為基礎的選擇式系統學習。因此，綜合以上發現，本研究認為 Sloutsky 的雙系統理論必須考慮到向度數目此一變項，才能更廣泛的應用於各種類別學習情境之中。

Abstract

The goal of this research is to point out that the dimensions of experimental materials can influence human category learning, which is neglected by traditional models of category learning. Three experiments in this research examined the effect of stimuli dimensionality by following the paradigms of Kloos and Sloutsky (2008). In Experiment 1, the prediction of Sloutsky's theory (2010) on the interaction effect between category structures and learning conditions succeeds only at high dimensionality of materials, but fails in the low dimensionality condition. Experiment 2 was conducted by the same experimental setting as Experiment 1, but the natural-like stimuli were replaced by well-defined artificial geometrics. The result of Experiment 2 is the same as Experiment 1, suggesting that the dimensionality of materials plays a critical role in category learning no matter what kind of stimuli are used. Experiment 3 found that various materials dimensionality had distinct effects on human category representations. Namely, when experimental stimuli are relatively complex, people would use the corresponding category learning system to represent stimuli to learn dense categories or sparse ones. In contrast, when the stimuli are relatively simple, participants would represent the stimuli in a rule-based manner both in dense and sparse category structures.

Literature Reviews

Categorization plays a crucial role in cognitive psychology, and numerous researches focus on how category learning performance is influenced by various category structures and learning conditions (Alfonso-Reese, Ashby, and Brainard, 2002; Ashby, Maddox, and Bohil, 2002; Ashby, Queller, and Berretty, 1999; Colreavy & Lewandowsky, 2008; Kruschke, 1993; Love, 2002; Shepard, Hovland, and Jenkins, 1961). Specifically, researchers focus on developing models to account for the type of mental representations and the process for categorization, which people use/generate in category learning (Ashby & Gott, 1988; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Erickson & Kruschke, 1998; Kruschke, 1992; Medin & Smith, 1981; Nosofsky, 1986). For instance, the generalized context model (GCM) is developed by the idea of storing every exemplar into mental memory space (Nosofsky, 1986), whereas the general recognition theory assumes that classification behaviors are determined by learning decision boundaries (Ashby & Gott, 1988). In contrast to single system theories, Sloutsky (2010) proposed a dual systems theory which posits that two systems, the selection-based system and the compression-based system are employed for learning categories of different “statistical density”. The index “statistical density” was developed in Sloutsky’s studies (Kloos & Sloutsky, 2008; Sloutsky, 2010) in order to represent the characteristics of category structure. A category structure composed of multi-dimensional exemplars can be simply described by the calculation of statistical density as simple figures ranging from 0 to 1. In addition, the statistical density indicates the regularity of category structure. Namely, a high level of density represents the category structure in high regularity. However, category structures maybe oversimplified by this index, for instance, some researchers suggest that the dimensionality of materials could influence participants' learning strategies and category perceptions (Livingstion, Andrews, and Harnad, 1998; Minda & Smith, 2001; Nosofsky, Stanton, and Zaki, 2005; Verguts, Ameel, and Storms, 2004). Therefore, the present study suggests that Sloutsky's dual systems theory should be re-organized with assessing the effects of materials dimensionality. This thesis is organized in the order of reviewing relevant categorization theories, re-examining Sloutsky's theory, showing the experiment results, and providing general discussions.

Past theories of categorization

The classic theory of Aristotle is known as the oldest theory of categorization. This theory assumes that an exemplar would belong to a specific category only if it has all features required by this category. For example, a square is defined as a closure figure which has four equal sides and four vertical angles. Therefore, a closure figure is a square if it has all features mentioned above (Smith & Medin, 1981). The closure figure with four equal sides and four vertical angles is definitely a square. This is so-called a "well-defined" stimulus where there is a condition of sufficient and necessary relation between item features and the concept of a category (Martin & Caramazza, 1980).

However, learning a category is more than learning the sufficient and necessary relations between the stimulus feature and the concept of category. Shepard, Hovland and Jenkins (1961) revealed that the human learning performance is influenced a lot by category structure. In their study, each stimulus could be defined by its size, shape, and color. For each dimension, there were two levels (e.g., the figure could be either triangle or square, either black or white, and either big or small). Therefore, there would be eight stimuli for all the combinations ($2^3 = 8$). Figure 1 displays one of the possible category structures. With the arrangements of stimuli, different category structures were created. Shepard and his colleagues (1961) carefully chose six out of seventy ($C_4^8 = 70$) types of category structures for testing, seen in Figure 2. They recorded the numbers of errors made by participants and found the difficulty of learning categories increased gradually from Type I to Type VI. According to the result, Shepard et al. (1961) concluded that the category structure of stimuli could affect the difficulty of category learning.

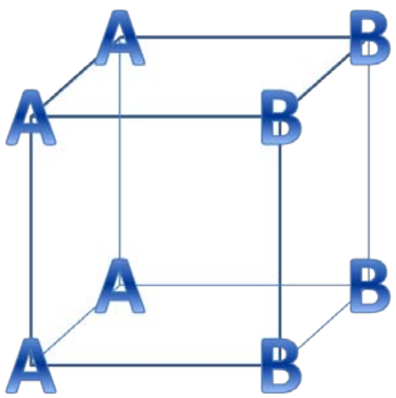

Figure 1. Example of category structure. Two categories are labeled as “A” and “B”.

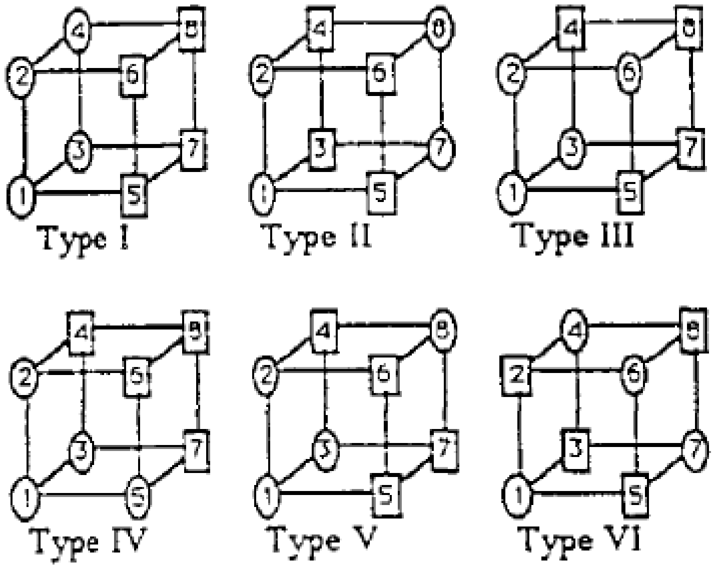

Figure 2. Category structures of stimuli used in the study of Shepard et al. (1961) (Nosofsky, Gluck, Palmeri, Mckinley, and Glauthier, 1994)

The result of Shepard et al. (1961) has been replicated by many experiments and become a classic, for which most contemporary models qualify themselves via showing the capability to account (Alfonso-Reese, et al., 2002; Ashby, Queller, Berretty, 1999; Kruschke, 1993; Kloos & Sloutsky, 2008; Love, 2002). In the past decades, a great deal of models were proposed and can be summarized to three major classes.

The similarity models posit that categorization is achieved by grouping similar objects together and by separating apart those dissimilar ones. Both the prototype and exemplar-based models are belonged to this class. Different from the classic theory of Aristotle, the main idea of prototype theory comes from the attempt to address categorization of natural objects instead of artificial items. It indicates that there are “natural prototypes” of concepts (Rosch, 1973). For example, when referring to a bird, the first idea comes to our mind may be a sparrow, but not a chicken nor a penguin. It suggests that a sparrow is more typical than a chicken when the concept of birds is mentioned. In this way, the relation between the features of exemplars and the concepts of a category is not sufficient and necessary. In other words, a bird may have some typical features like wings, feathers, being able to fly in the sky, and so on, but not every creature is categorized as a "bird" which has all features above. These kinds of stimuli are called 'ill-defined', which means the boundary of a concept cannot be clearly described (McCloskey & Glucksberg, 1978). There are idiosyncratic features in some exemplars (like penguin is a bird which cannot fly), while the core features of a concept are the mostly appeared (like every bird has feathers). Therefore, an exemplar with core features was the prototype of concept (Homa & Chambliss, 1975). In other words, the prototype is always the most typical exemplar of a category. This is unlike the classic theory, which assumes the representatives of each exemplar to a category concept are all the same.

The prototype model claims that people would compare a new stimulus to the most typical exemplars of a category, the prototype, when they need to do classification. The new stimulus would be classified as the same category if it is similar to the prototype, otherwise it would be classified as a different category.

Similar to the prototype model, the exemplar-based model posits that people would compare to a new stimulus to every exemplar, not the prototype only, in the categories and classify it as the category with a relatively high similarity (e.g., context model; Medin & Schaffer, 1978; GCM (generalized context model); Nosofsky, 1984, 1986, 1987).

Following the influential exemplar-based model, GCM, the similarity is derived from the negative exponential transformation of the distance between items in the psychological space. The probability of classifying Stimulus i to Category $\mathrm{C_J}$ can be illustrated by

$$\mathrm{P}\left(\mathrm{R_J}\middle|\mathrm{S_i}\right) = \frac{b_{\mathrm{J}} \sum_{\mathrm{j} \in \mathrm{C_J}} \eta_{\mathrm{ij}}}{\sum_{\mathrm{K}=1}^{\mathrm{m}} (b_{\mathrm{K}} \sum_{\mathrm{k} \in \mathrm{C_K}} \eta_{\mathrm{ik}})} \qquad \text{Equation 1-1}$$

where b_{J} represents the bias for making response $\mathrm{R_J}$ and the index "$\mathrm{j} \in \mathrm{C_J}$" means that similarity between $\mathrm{S_i}$ and each $\mathrm{S_j}$ belonging to $\mathrm{C_J}$ should be calculated. The η_{ij} which is adjusted by selective attention, *w*, representing the distance/similarity between Stimulus $\mathrm{S_i}$ and Stimulus $\mathrm{S_j}$:

$$\eta_{\mathrm{ij}} = \mathrm{f}(\mathrm{d_{ij}}), \text{ and} \qquad \text{Equation 1-2}$$

$$\mathrm{d_{ij}} = \mathrm{c}[\textstyle\sum_{\mathrm{k}=1}^{\mathrm{N}} w_{\mathrm{k}} \left|x_{\mathrm{ik}} - x_{\mathrm{jk}}\right|^{r}]^{1/r} \qquad \text{Equation 1-3}$$

where the parameter c represents the overall discriminability in the psychological space. Equation 1-3 shows that the less the psychological distance between two items, the more similar they are. Moreover, GCM assumes that the dimension would be attended more when it is more critical for correct categorization and less otherwise. That is, the psychological dimensions can be stretched or shrunk by multiplying the distance on dimension with an attention weight ($0 \leq w_{\mathrm{k}} \leq 1$) (Figure 3) and all attention weights are assumed to sum to 1.

ALCOVE (Attention Learning Covering Map) was proposed by Kruschke (1992), which is a 3-layered neural network model learning categories in an exemplar-based fashion. The nodes in the input layer correspond to the stimulus dimensions and the nodes in the hidden layer correspond to the exemplars, which would be activated to the extent of how similar they are to the current input stimulus. The nodes in the output layer correspond to the category labels. ALCOVE adopts an error-driven learning, in that the associative weights between the output and hidden nodes as well as the attention weights for all dimensions are adjusted for the aim to correctly assign exemplars to their corresponding categories. More than GCM as a static model, ALCOVE can trace the participants' learning performance trial by trial with the dynamic characteristic of neural network. Therefore, ALCOVE can account for those phenomena for which GCM can account, even including the learning difficulty gradient among category structures reported by Shepard, et al. (1961) (Nosofsky, Gluck, Palmeri, McKinley & Glauthier, 1994)

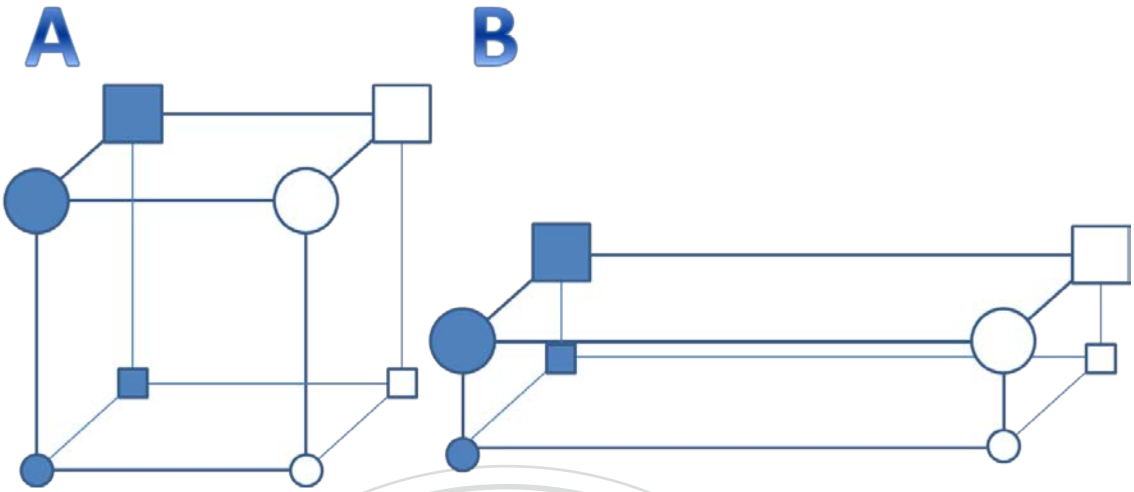

Figure 3. Mental representation structures transformed by different attentional weights on features. For example, there are total eight items defined by three dimensions, shape, size, and color. In this case, it is easier to differentiate two categories by color in structure of 3B than 3A.

The rule-based model, on the contrary, posits that to learn categories is to learn the rule for defining categories. For instance, in Taiwan, a student's studying performance can be regarded as two classes, pass and fail, depending on whether he/she gets a score larger than or equal to 60. Although broadly speaking, rule can be of any format, this thesis focuses on the models of the general recognition theory (GRT; Ashby & Gott, 1988) as the generic form of the rule-based models. According to the GRT, each item is a percept in the psychological space and different categories correspond to different regions in this space separated by a decision boundary, namely a rule, as in Figure 4. Thus, if an item's percept locates in the region corresponding to Category A, it will be classified to Category A. Accordingly, for the GRT, category learning is achieved when people form the decision bound(s) in the category learning task.

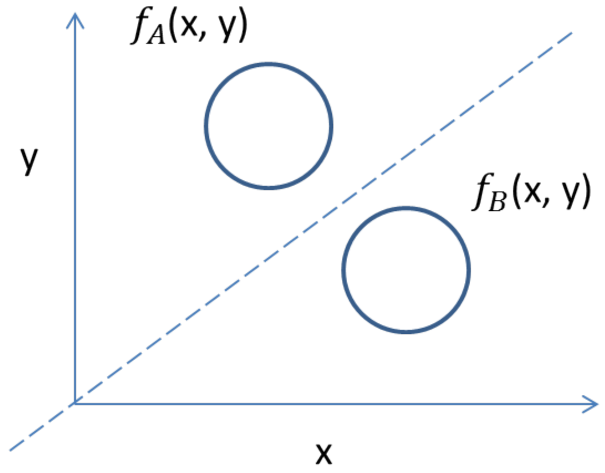

Figure 4. Mental category representation divided by a decision bound. (Ashby & Gott, 1988)

Although the rule-based and the similarity-based models are quite different, they both can predict human categorization behaviors very well (Maddox & Ashby, 1993, 1998; McKinley & Nosofsky, 1995, 1996). Thus, it is legitimate to posit that both types of representations people would use. This idea was supported empirically by Rouder and Ratcliff (2004). These authors revealed that the exemplar-based model outperformed the rule-based model when there were only few stimuli, whereas the rule-based model did when there were a lot of exemplars. This finding is explained as when there are only few stimuli, people can remember all the exemplars in the category, hence, it is reasonable to compare a new stimulus to every exemplar in the original category before giving a categorical label, whereas people would tend to learn categorical bounds when too many exemplars to remember.

Therefore, more and more models adopt the multiple representations view and these models are called multi-system model in this thesis. Besides, due to the rapidly progress in neural imaging techniques, some researchers suggests a multi-system theory not only in category learning (Ashby et al., 1998; Erikson & Kruschke, 1998; Nomura et al., 2007) but also other cognitive abilities or behaviors (Anderson & Lebiere, 1998; Sloman, 1996).

Erickson and Kruschke (1998) presented a connectionist model called ATRIUM. This hybrid model consists of both the rule- and exemplar-based representation. The authors claim that participants learn categories by a mechanism incorporating these two kinds of modules for achieving the best performance and displays that ATRIUM can account for empirical data of categorization better than a single system model. COVIS (The Competition between verbal and implicit systems) model is another famous multi-systems theory (Ashby et al, 1998). COVIS model suggests that there are two independent subsystems of category learning: the rule-based subsystem (explicit system) and the procedural learning-based subsystem (implicit system). The two subsystems would compete with each other and it has to be only one subsystem to function during category learning. It would not be addressed here, as the issue of this present study is far from the main concern of the COVIS model. Before introducing the Sloutsky's theory, which this study would address, two characteristics of category learning are discussed first.

Learning condition of categorization

The studies mentioned above, from the research of Shepard et al. (1961) to the debate between similarity-based theory and rule-based theory (Maddox & Ashby, 1993, 1998;

McKinley & Nosofsky, 1995, 1996; Nosofsky, Stanton, & Zaki, 2005; Stanton & Nosofsky, 2007), are mostly established by the evidences from supervised learning tasks. In a typical supervised learning task, participants would get a feedback or an instruction from each response. The feedback can be a visual message, like words of correct or wrong, or an auditory tone, like a high or low frequency beep**.** After receiving the feedbacks, participants can modify their learning strategies to approach the correct answers. Moreover, participants usually have little information at the beginning of task and learn the category rules through trial and error. Thus, it is reasonable that there are often many trials in a supervised learning task. Besides supervised learning, unsupervised learning is another kind of conditions in the experiments of category learning. In the unsupervised learning task, there is no any feedback from responses. Past studies showed that participants had different performances under different conditions of learning (Ashby, Queller, & Berretty, 1999; Colreavy & Lewandowsky; 2008; Love, 2002; Ashby, Maddox, & Bohil, 2002). Actually, the unsupervised learning is much more similar to the ways we learn categories in our daily life.

Category structures

As mentioned in the earlier paragraph, the category structure plays an important role on category learning (Shepard et al., 1961). Kruschke (1993) also found that “relevant dimensions” could influence participants’ performances. To explain further, assume there are two categories of the experiment materials (denoted as white and black circle in Figure 5), and each material could be represented by two dimensions of features, height and position, like Figure 5a and 5b. In the condition of Figure 5a, participants could differentiate materials in two categories by concentrating on only one dimension, either height (left) or position (right). This was named as "filtration task" because participants needed to filter out non-relevant dimensions and identify the relevant one for categorization. In the condition of Figure 5b, participants had to consider height and position dimensions simultaneously. Due to the fact that participants must condense multi-dimensions to one decision bound of category, this is called "condensation task".

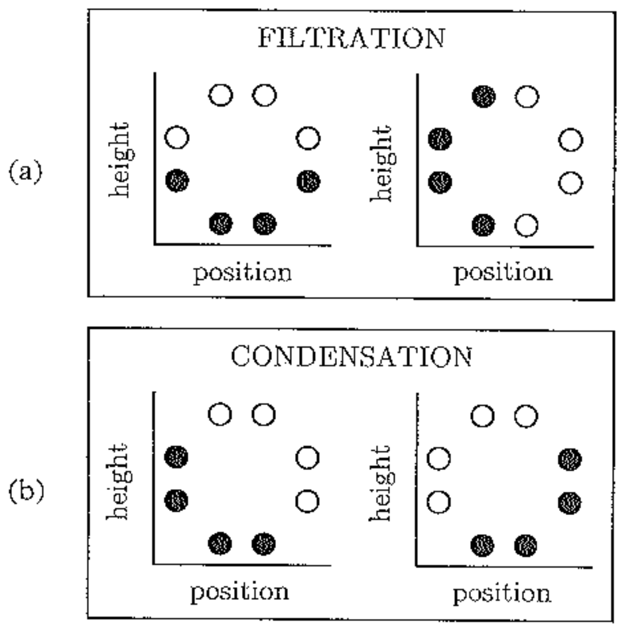

Figure 5. Category structures of stimuli used in Kruschke's study (1993).

The behavioral data showed that participants performed better on a filtration task than on a condensation task. Therefore, Kruschke (1993) concluded that the category learning task became harder when there were more relevant dimensions to be taken into account. The implications of Kruschke's results are twofold. First, the category structure is more complicated in a condensation task than a filtration task. That is, participants need to consider both dimensions at the same time and it results in worse performances. Second, since Kruschke's research was also based on the supervised learning, Kloos and Sloutsky (2008; see also in Sloutsky, 2010) argued that an immediate feedback could make an attentional shift more easily, which benefited the subjects' performances by enhancing the cognitive processing of locating and focusing on a specific relevant dimension. It, however, became an obstacle when subjects needed to spread their attention on all dimensions at the same time, e.g., in a condensation task.

To sum up, not only the learning paradigm but also the category structure can influence participants' performances. Furthermore, some researches of developmental psychology suggest that children have different ways from adults to learn categorization, which may be caused by the immaturity of brain area (Sowell, Thompson, Holmes, Batth, Jernigan, & Toga, 1999). Therefore, Sloutsky (2010) develops a dual systems theory of category learning, and tries to illustrate the relations among category structures, learning conditions, and categorical behaviors.

Sloutsky's dual systems theory

Sloutsky (2010) proposed a theory addressing the relationships among category representations, category structures, and learning conditions. This theory is one of the multi-system theories, as it assumes that the compression-based system and the selection-based system According to his theory, the manners people represent items are decided by category structures. In addition, these effects are detectable on the accuracy rates of various learning conditions.

Like COVIS model (Ashby et al., 1998), Sloutsky also tries to connect the explicit and implicit memory systems to category learning mechanisms. He assumes that there are two subsystems, compression-based systems and selection-based systems, corresponding to the similarity-based system and the rule-based system respectively. During learning categories, which one of the two systems will function depends on category structure as well as learning paradigm (e.g., supervised learning or unsupervised learning) (Sloutsky, 2010). In addition, Sloutsky's theory also has corresponding neural bases. The compression-based system is mainly related to the visual loop, which begins from the inferior temporal area through the tail of caudate in the striatum (Segar & Cincotta, 2002), with many cortex neurons merged into a never bundle of caudate nucleus (Bar-Gad, Morris, & Bergman, 2003). Since the visual loop is in charge of recording visual information by reducing or compressing the visual input, the compression-based system is assumed to learn categories by recording the often appeared features (see Figure 6). Thus, the common features of highly similar exemplars, after being repeatedly presented, would be recorded by the compression-based system with little or even no attention. On the other hand, the selection-based system is assumed to be relevant to the cognitive loop, which goes through the prefrontal lobe and the head of caudate, and is activated during category learning process in a rule-based manner (Segar, 2008). The cognitive loop is related to the dorsolateral prefrontal cortex and the anterior cingulated cortex. Past studies found that this brain area is related to selective attention, working memory, and executive function (Cohen et al., 1997; Cohen, Botvinick, & Carter, 2000; D'Esposito, Postle, Ballard, & Lease, 1999). The manner of the selection-based system to learn categories is to select and focus on particular dimension(s) while ignoring the others. Therefore, it is suitable for learning the stimuli which can be classified by considering feature dimensions (Figure 7).

The coordination between the compression-based system and the selection-based system follows "the winner takes all" rule, in that only one system would be executed in learning a category structure. The "default system" of these two systems is adjusted by the learning condition and the category structure in adults. In contrast, past researches showed that children do not develop the selection-based system until four or five year-old (Kloos & Sloutsky, 2008; Sloutsky, 2010). Therefore, the rule-based subsystem is apparently not the default learning system for children.

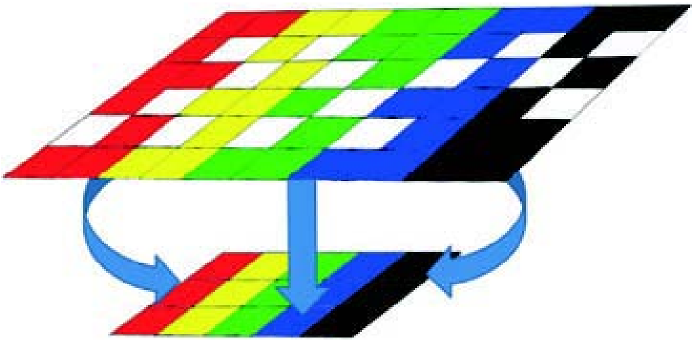

Figure 6. The learning progress of compression-based system (Sloutsky, 2010). This system records the most frequently occurring features.

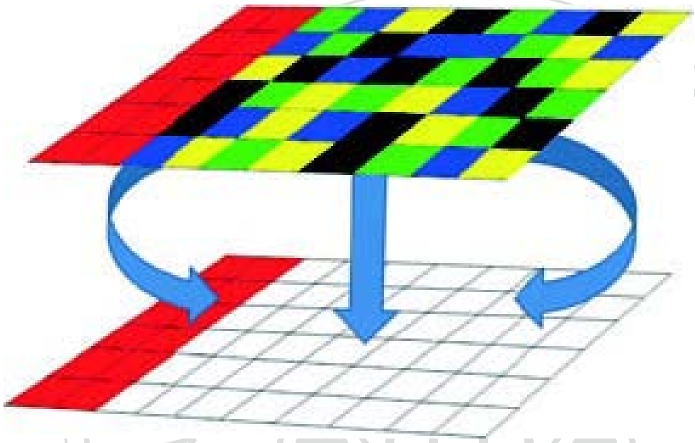

Figure 7. The learning progress of selection-based system (Sloutsky, 2010). This system is good at shift attention to focus on specific dimension(s) and ignore others.

Statistical density

Sloutsky's dual systems theory posits that people use different learning systems depending on "what materials look like", i.e., the category structure (Kloos & Sloustky, 2008; Sloutsky, 2010). That is, whether people would use the selection-based system or the compression-based system to learn the category task can be predicted by considering the composition of materials, specifically the category structure. In order to make different category structures comparable, Kloos and Sloutsky (2008) proposed an index named the statistical density. The calculation of statistical density is based on “entropy” in the information theory (Shannon, 1948). The entropy in Sloutsky’s dual system theory represents the extent of randomness, while the statistical density represents the regularity of stimuli. The relation between entropy and statistical density can be described as

$$\mathrm{D} = 1 - \frac{\mathrm{H_{within}}}{\mathrm{H_{between}}}, \qquad \text{Equation 2}$$

where D denotes the density and H denotes the entropy. When $\mathrm{H_{between}}$ remains constant, the larger the within-category entropy is, the lower the density becomes. On the other hand, if $\mathrm{H_{within}}$ stays constant, the larger the between-category entropy is, the higher the density becomes. According to Sloutsky, the compression-based system would be used when D is large, whereas the selection-based system would be activated when D is small. The within-category entropy, $\mathrm{H_{within}}$, is the variability of items within the target category, while the between-category entropy, $\mathrm{H_{between}}$, is acquired by considering the variability between the target category and the contrasting category. The within-category entropy is the sum of the dimensional and relational entropy within a category and the between-category entropy is the sum of the dimensional and relational entropy between categories, which are respectively computed as

$$\mathrm{H_{within}} = \mathrm{H_{within}^{dim}} + \mathrm{H_{within}^{rel}} \text{ and} \qquad \text{Equation 3-1}$$

$$\mathrm{H_{between}} = \mathrm{H_{between}^{dim}} + \mathrm{H_{between}^{rel}}. \qquad \text{Equation 3-2}$$

In addition, H_{within} would not be bigger than $H_{between}$ because the within-category variability is also considered in the calculation of $H_{between}$. Thus, the density is a number between 0 and 1.

The dimensional entropy within category and between categories are computed as

$$H^{dim}_{within} = -\sum_{i=1}^{M} w_i \left[\sum_{j=0,1\,within}(p_j \log_2 p_j)\right] \text{ and} \qquad \text{Equation 4-1}$$

$$H^{dim}_{between} = -\sum_{i=1}^{M} w_i \left[\sum_{j=0,1\,between}(p_j \log_2 p_j)\right] \qquad \text{Equation 4-2}$$

where, for the within-category case, p_j is the percentage of feature j on one dimension within a category, whereas, for the between-category case, p_j is the percentage of feature j on one dimension across categories. For instance, if the stimuli of the target category are all black and the contrasting category are all white, then $p_{j=1} = 1$ (j=1 for black and j=0 for white) on color dimension in the within-category case, whereas $p_{j=1} = 0.5$ in the between-category case. The dimensional entropy is the sum of the material variability on m dimensions, each of which is weighted by an attention weight, w.

Different from the dimensional entropy, the relational entropy concerns the extent of variability between every pair of dimensions, which is computed for the within-category case as well as the between-category cases as

$$H^{rel}_{within} = -\sum_{i=1}^{O} w_k \left[\sum_{\substack{m=0,1\\ n=0,1}} {}_{within}(p_{mn} \log_2 p_{mn})\right] \text{ and} \qquad \text{Equation 5-1}$$

$$H^{rel}_{between} = -\sum_{i=1}^{O} w_k \left[\sum_{\substack{m=0,1\\ n=0,1}} {}_{between}(p_{mn} \log_2 p_{mn})\right] \text{ with} \qquad \text{Equation 5-2}$$

$$O = C^M_2 = \frac{M!}{(M-2)! * 2!}. \qquad \text{Equation 6}$$

For M dimensions, there would be $O = C_2^M$ pairs. As the dimensions are dyadic, there would be four combinations of the feature values for each pair. Accordingly, p_{mn} is the probability of one of the combinations between "feature m" and "feature n". The variability information of different pair is differently weighted by the attention weight, w_k. For instance, if the target category members are all black squares while the contrasting category members are all white circles, the within-category variability of the color-shape pair for all four value combinations is 1, 0, 0, and 0 in the order of black-square, black-circle, white-square, and white-circle. However, the between-category variability is 0.5, 0, 0.5, and 0 in the order of black-square, black-circle, white-square, and white-circle.

Kloos and Sloutsky (2008) conducted a series of experiments and reviewed past literature to estimate the salience of varying dimensions. They led into a conclusion that the attentional weight of a particular dimension (w_i) was twice as large the dyadic relation between dimensions w_k, $w_k = \frac{1}{2} w_i$. In order to compute density in an easier way, the dimensional attention weight, w_i, is set as 1 and the relational weight, w_k, is set as 0.5 in the current study.

Statistical density is a convenient index to represent category structures. To illustrate this index in detail, two examples showing the calculation of density are included in the Appendix.

Incongruent evidence with Sloustky's dual systems theory

The main idea of Sloutsky's dual systems theory is to describe the relationship between category structures (in terms of density), conditions of learning, and category representations (Sloutsky, 2010). Because of the characteristics of the compression-based system and the selection-based system, Sloutsky predicts an interaction effect between learning conditions and category structures. Namely, the selection-based system would function during learning a low density category and improve the performance on the supervised learning condition, whereas the compression-based system would function during learning a high density category and improve the performance on the unsupervised learning condition. Kloos and Sloustky (2008) found that when learning categorization in the condition of dense category (high density, displayed in the upper part of Figure 8), participants performed better under the unsupervised learning condition than under the supervised learning condition. On the contrary, participants performed better under the supervised learning conditions than under the supervised learning in the condition of sparse category, when learning the low-density category structures (shown in the lower part of Figure 8). From now on, the high-density category structure is called the dense category and the low-density category structure is called the sparse category.

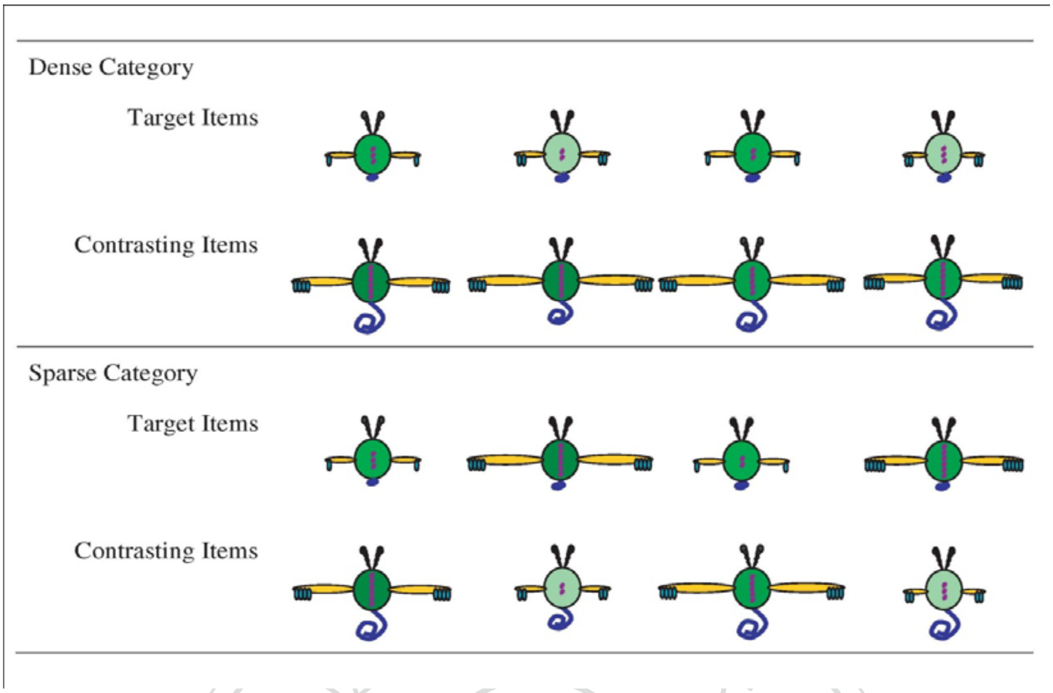

Figure 8. Examples of dense and sparse category (Kloos & Sloutsky, 2008). In this figure, the between-variability in dense and sparse category is the same. But both the target and contrasting items in the dense category share a similar within-group appearance, which represents a smaller within- variability. That is, the between entropy remains constantly, but the within-entropy is smaller in the dense category. As a consequence, the statistical density is larger in the dense category.

However, Sloutsky's dual systems theory has difficulty accounting for the learning difficulty gradient over category structure reported by Shepard et al. (1961). Figure 9 shows those category structures as well as their statistical densities. Shepard and his colleagues (1961) conducted their experiments in the condition of supervised learning. According to Sloutsky's (2010) opinion, the supervised learning condition would trigger the selection-based subsystem, which is suitable to learn the sparse categories rather than the dense ones. Therefore, type VI category structure (density = 0; sparse category) should be learned better in the supervised learning condition, while type I (density = 0.33; dense category) should be learned worse. However, Shepard et al. (1961), conversely, found that Type I was learned better than Type VI in the supervised learning condition.

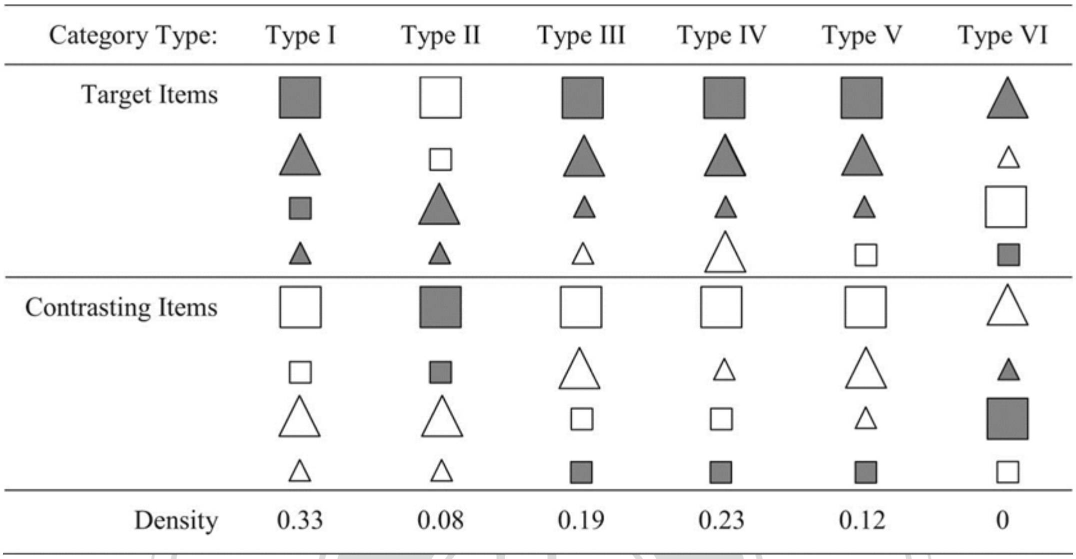

Figure 9. Density of category structure which Sheaprd et al. (1961) used (Kloos & Sloutsky, 2008).

Love (2002) examined the finding of Shepard et al. (1961) under both supervised and unsupervised learning conditions and found that participants performed better on Type I and worse on Type VI in no matter which learning condition, see in Table 1. This result challenges the Sloutsky's dual systems theory which predicts an interaction effect between the density and the learning condition.

Table 1. Results of Love's (2002) study

Category structure	Accuracy rate M	Accuracy rate SE	Reaction time (ms) M	Reaction time (ms) SE
Intentional unsupervised learning				
Type I	.85	.027	2,034	173
Type II	.64	.024	2,640	254
Type IV	.67	.018	2,641	160
Type VI	.54	.020	2,433	175
Supervised learning				
Type I	.89	.025	1,636	103
Type II	.73	.029	2,902	170
Type IV	.70	.021	2,649	163
Type VI	.61	.024	3,018	183

The discrepancy between Shepard, et al. (1961) and Love (2002) results and Sloutsky (2010) theory may come from the regimes of their experiments, specifically the stimulus type and the number of dimensions. First, Sloutsky often took bug-like materials as experimental stimuli, which were referred to as natural concepts (Kloos & Sloutsky, 2008), while the stimuli used in Shepard, et al.'s and Love's study were artificial geometrics. There are many studies showing the performance of participants could be influenced by the kinds of stimuli used (Love, 2003; Markman & Makin, 1998; Markman & Ross, 2003). Second, the stimuli in Kloos and Sloutsky's (2008) experiment had six, eight or ten dimensions (e.g. length of wings, color of body, number of fingers, etc.; as shown in Figure 8). In contrast, the materials had only three dimensions in Shepard's study, and four in Love's, which were substantially simpler in the respect of visual perception. The past research revealed that the learning strategy of participants could be influenced by the dimensionality of materials (Minda & Smith, 2001). In addition, Livingston, Andrews, and Harnad (1998) found that the dimensions of stimuli could mediate different effects in category perception. Namely, the distances between each member of the same category become closer after category training, the within-compression effects, were only observed when stimuli varied in two dimensions, but did not appear in one dimension. This result indicates that people perceive the category concepts differently when the number of stimulus dimensions is in different level.

As a consequence, the aim of this study is to illustrate the reasons making inconsistent results among Sloutsky's theory (2010; see also in Kloos & Sloutsky, 2008) and the past researches (Shepard et al, 1961; Love, 2002). Through the literature reviews and the direct comparison of the experimental settings of these researches, this study focuses on two possible factors, the overall dimensions of stimuli and the kinds of stimuli used. According to Sloutsky's theory, human learn categories by either selection-based system or compression-based system which depends on the statistical density, i.e., category structure. Thus, an interaction between category structure and representation is predicted. Besides, the characteristics of supervised and unsupervised learning condition make different effects during the learning of different subsystems, which indicates that an interaction between learning condition and category structure in terms of learning performance is also predicted.

However, if the predicted interactions are not displayed under the manipulations of different stimuli used or overall dimensions of stimuli, which means that the Sloutsky's dual systems theory needs to be modified under certain circumstances.

Methods

Experiment 1

According to Sloutsky's theory, the unsupervised learning condition would trigger the compression-based system, which suits the dense category structure, whereas the supervised learning condition would trigger the selection-based system, which suits the sparse category structure. Also, the dimensionality of material has nothing to do with the correspondence between category structure and learning condition. In order to examine this idea, two groups of participants were recruited, each for learning one type of category structure (dense or sparse). Each participant was asked to learn the assigned category structure with two types of dimensionality (eight vs. four dimensions) in two learning conditions (supervised learning vs. unsupervised learning). If there is no difference on the interaction effect (category structure x learning condition) with either material dimensionality, Sloutsky's theory is supported. Same as in the first and second experiment of Kloos and Sloutsky (2008), the artificial bug-like materials were used in this experiment (see Figure 10 and Figure 11).

Apparatus

The experiment was conducted in a quiet testing booth and the procedure and data collection were done by a Matlab program with the aid of Psychtoolbox version 2.5.4 (Brainard, 1997; Pelli, 1997) on an IBM compatible PC.

Participants

Ninety-eight undergraduate and graduate college students took part in the task voluntarily and were reimbursed with a small amount of money for their traffic expense. Participants were assigned equally to the conditions of dense or sparse categories. The age of these participants ranged from 18 to mid 30s. All participants' visions were reported normal or corrected to normal.

Stimulus

In the condition of low dimensionality, the stimuli were composed of four binary dimensions, the shading of antennas (dark or light colour), the number of fingers (many or few), the length of wings (long or short), and the shading of the body (dark or light colour) (Figure 10).

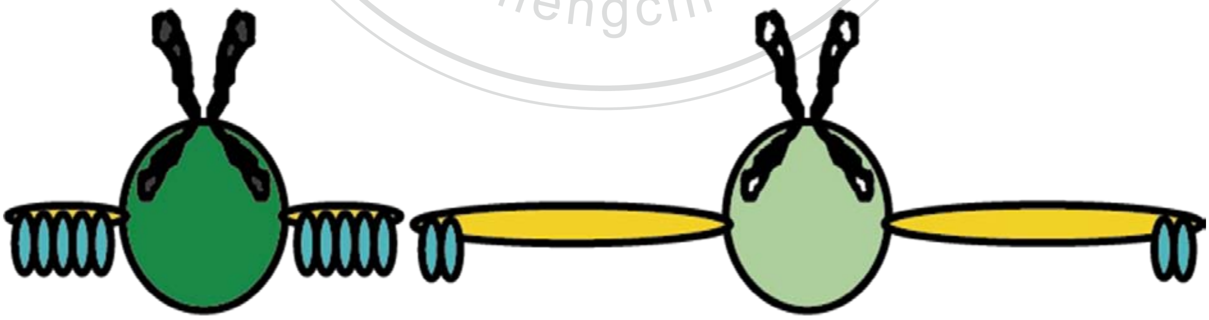

Figure 10. Examples of low dimensionality (4 dimensions) stimuli used in Experiment 1. The left figure has dark antennas, many fingers, dark body color, and short wings. The right one has light antennas, few fingers, light body, and long wings.

In the condition of high dimensionality, the stimuli varied along eight dimensions. In addition to the four dimensions used in the low dimensionality condition, the other four dimensions were: the length of fingers (long or short), the length of the tail (long or short), the number of buttons (many or few), and the shading of buttons (dark or light) (Figure 11). These eight dimensions were just same as Kloos and Sloutsky (2008) used in their fourth experiment.

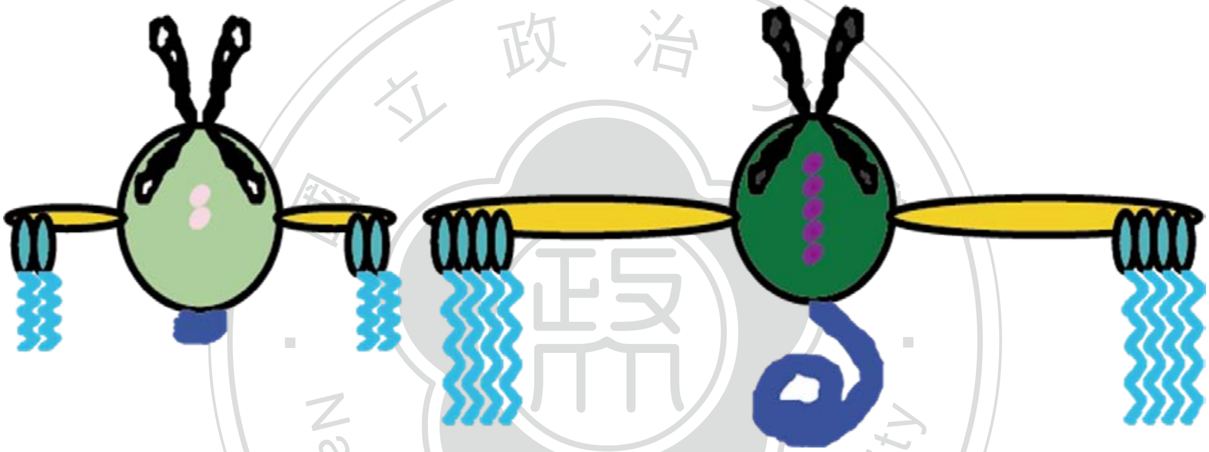

Figure 11. Examples of high dimensionality (8 dimensions) stimuli used in Experiment 1. The right figure has dark antennas, many and long fingers, dark body color, long tail, many and dark color buttons, and long wings. The left one has light antennas, few and short fingers, light body, few and light color buttons, and long wings.

Stimuli were generated as either in the statistically dense category or in the statistically sparse category. The statistical density of the dense category was 0.50 in the high dimensionality condition, and the sparse category was 0.13. In the condition of low dimensionality, the density of the dense category was 0.36, while the sparse category was 0.10. The dense category represented a category structure which had high similarity of target items, but looked quite different between target category and contrasting category (see Figure

8). Because the items could not be categorized by only few features, the better way to classify would be consider the overall appearance of stimuli. In contrast, in the sparse category structure, the members in the target category were less similar to each other. Thus, categorization became easier with only few specific features. These specific features were named as "arbitrary rules" in the sparse category condition, because the participants could decide to which category a stimulus belonged by these features only. Table 2 and 3 showed the category structure used in this experiment.

The target items of the dense category in the low dimensionality condition (i.e., four dimensions) were set to have short wings, light color of antennas, light color of body, and few fingers, while the contrasting items had long wings, dark color of antennas, dark color of body, and many fingers. On the other hand, in the high dimensionality condition, the target items of the dense category had short wings, light colour of antennas, light color of body, few fingers, short fingers, short tails, few buttons, and light colour of buttons, while the contrasting items had long wings, dark color of antennas, dark color of body, many fingers, long fingers, long tails, many buttons, and dark colour of buttons.

In addition, the four features, length of wings, shading of antennas, shading of body, and number of fingers were equally likely to be chosen as the arbitrary rule in sparse category, in order to prevent the feature specific effect on learning the rule.

Table 2. Category Structure of Stimuli Used in 4 dimensions in Experiment 1

Dimension	Dense category		Sparse category	
	Target item	Contrast item	Target item	Contrast item
length of wings	0	1	0	1
Shading of antennas	0	1	…	…
Shading of body	0	1	…	…
Number of fingers	0	1	…	…

Note. The numbers 0 and 1 refer to the values of each dimension (e.g., 0 is light color, while 1 is dark color). The "…" represents the varied randomly features.

Table 3. Category Structure of Stimuli Used in 8 dimensions in Experiment 1

Dimension	Dense category		Sparse category	
	Target item	Contrast item	Target item	Contrast item
Length of wings	0	1	0	1
Shading of antennas	0	1	…	…
Length of tails	0	1	…	…
Length of fingers	0	1	…	…
Number of buttons	0	1	…	…
Shading of buttons	0	1	…	…
Shading of body	0	1	…	…
Number of fingers	0	1	…	…

Note. The numbers 0 and 1 refer to the values of each dimension (e.g., 0 is light color, while 1 is dark color). The "…" represents the varied randomly features.

For the reason of testing the vigilance of participants, eight new items were added into the testing phase, which consisted of new features such as that they had a multi-colour body in a hexagonal shape, no finger, and no tail (Figure 12). Because these pictures had dissimilar appearances and different values of features, it was expected that the participants could reject those items accurately.

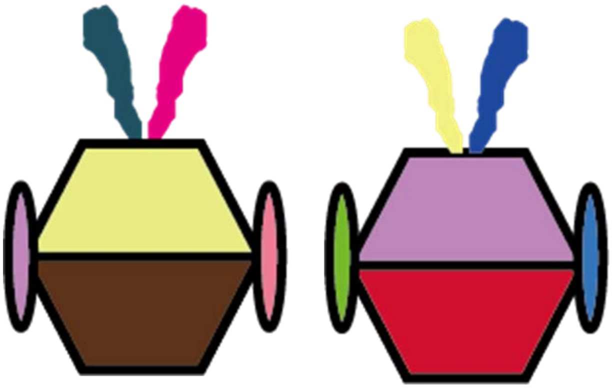

Figure 12. Examples of vigilance pictures used in Experiment 1. These pictures are supposed to be rejected in the testing phase.

Procedure

Each participant took in turn four sessions to learn stimuli of two complexities using two types of learning. The sequence of the four sessions was generated from a Latin square design. In each session, there were four blocks, each of which contained a training phase with and a testing phase.

In the training phase, participants were asked to learn the target category called "Ziblet" in a self-pace manner. The participants were given the information about the target item in verbal sentences (supervised learning) or in graphical figures (unsupervised learning). In the supervised learning condition, the verbal rules were listed on screen directly, while in the unsupervised learning condition, sixteen pictures of target items were displayed in a random sequence. Participants were told to remember the verbal rules and the pictures as possible as they could in the training phase. In addition, there was no any feedback in this section.

In order to make sure that the participants understood the name of every feature, the computer program would firstly show the feature and its corresponding name simultaneously in the beginning of every training phase. For instance, the picture of fingers and the name “finger” were both showed together on the screen.

In the testing phase, the participants were asked to answer whether or not the present pictures belonged to the target category. Sixteen pictures belonging to target category and sixteen pictures belonging to contrasting category were used in the testing phase. An additional eight vigilance pictures were added to examine whether the participants concentrated properly in the experiment. If more than three vigilance pictures were not rejected correctly in a block, the data of the participant would be excluded from further analyses. Therefore, a total of 40 pictures were used in the testing phase.

Results

Twenty subjects were excluded (10 out of 49 in the sparse category condition, and 10 out of 49 in the dense category condition) from data analyses, due to their failures to reject the pictures of vigilance testing (data was excluded if there was any condition that participant did not correctly reject at least 5 of 8 vigilance pictures). The accuracy rates of 32 items in the testing phases (without the eight vigilance pictures) of each participant were computed to examine the learning of the target category. A 2 (Density) × 2 (Dimensionality) × 2

(Learning Condition) mixed-design ANOVA revealed that the 3-way interaction was not significant ($F(1, 76) = 0.44$, $MSe = 0.09$, $p = .51$, $\eta^2 = 0.01$). The 2-way interaction was significant only between Learning condition × Density ($F(1, 76) = 6.61$, $MSe = 0.09$, $p < .05$, $\eta^2 = 0.08$), but not significant either between Learning condition × Dimensionality ($F(1, 76) = 1.57$, $MSe = 0.09$, $p = .22$, $\eta^2 = 0.02$) or Density × Dimensionality ($F(1, 76) = 0.01$, $MSe = 0.08$, $p = .91$, $\eta^2 = 0.00$). The main effects of Density ($F(1, 76) = 56.91$, $MSe = 0.18$, $p < .01$, $\eta^2 = 0.43$) and Dimensionality ($F(1, 76) = 5.08$, $MSe = 0.07$, $p < .05$, $\eta^2 = 0.06$) were significant, but Learning condition ($F(1, 76) = 0.01$, $MSe = 0.09$, $p = .92$, $\eta^2 = 0.00$) was not. Slousky's theory predicts an interaction between Density and Learning condition with no matter how complex the stimulus is. However, as discussed about Love's (2002) results in the previous section, the interaction effect between Density and Learning condition may disappear when the dimensionality of materials is low. Visual inspection on Figure 13 implies an interaction between Density and Learning condition only when the material is more complex (i.e., 8 dimensions). This observation was supported by the analysis for the interaction effects, that the interaction effect between Density and Learning condition was significant for high dimensionality materials ($F(1, 76) = 4.97$, $p < .05$, $MSe = 0.2$, $\eta^2 = 0.06$), but not significant for low dimensionality materials ($F(1, 76) = 2.00$, $MSe = 0.17$, $p = .16$, $\eta^2 = 0.02$).

Therefore, the result of this experiment reveals that dimensionality does influence category learning, which also means Sloutsky's theory should be modified by taking into consideration the dimensionality of materials.

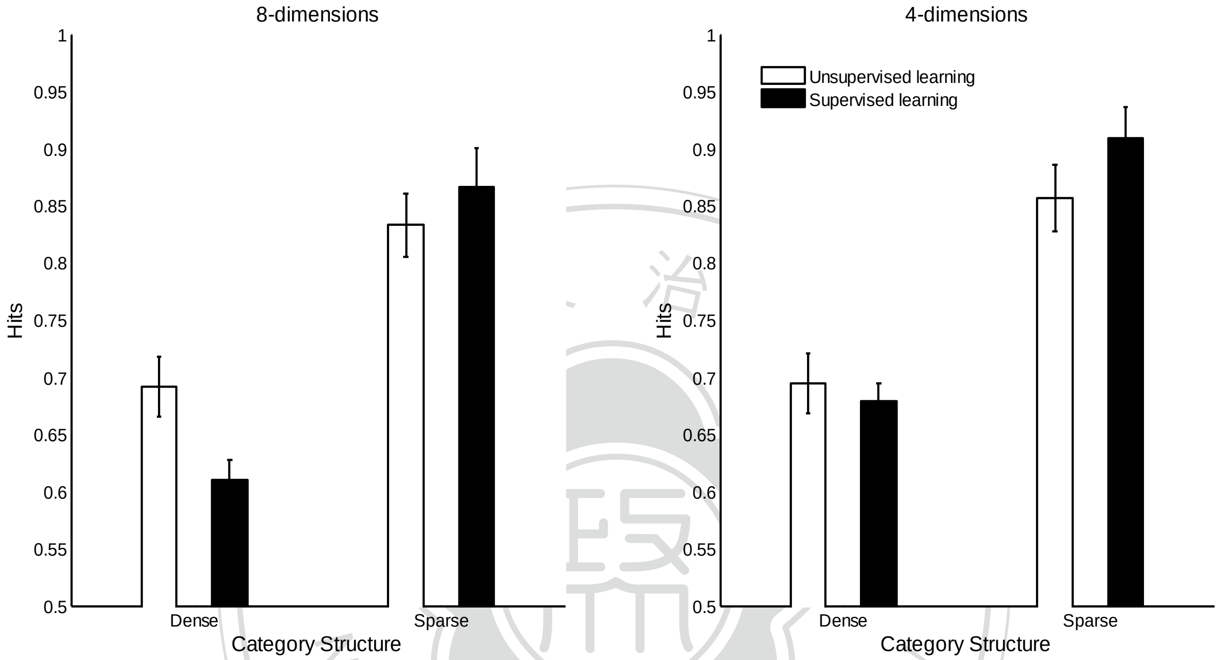

Figure 13. Mean accuracy scores by category type and learning condition in Experiment 1.

Experiment 2

The previous experiment reveals that the dimensionality of materials in terms of the number of dimensions would moderate the learning performance. In addition to the dimensionality of materials, the type of stimulus may also result in the different findings of Love (2002) and Shepard et al. (1961) from Sloutsky's. In Kloos and Sloutsky's study (2008), they mainly used natural-like stimuli which were composed of natural-like features such as wings, tails, antennas, etc. However, the stimuli used in the studies of Shepard et al. (1961) and Love (2002) were artificial geometrics, such as a dark large circle, etc. Therefore, Experiment 2 was designed to examine the effect by using artificial geometrics. For a parallel comparison with Experiment 1, Experiment 2 adopted the experimental design of Experiment 1, manipulating Density (between-subject variable), Dimensionality (within-subject variable), and Learning condition (within-subject variable), but using the artificial geometrics as stimuli.

Participants

Eighty-five college students were recruited with traffic reimbursement of one-hundred NT dollars per hour for their expense of time and money. For the density category condition, there were thirty-six participants and forty-nine for the sparse category condition. The age of these participants ranged from 18 to mid 30s. All participants reported that his/her vision was normal or corrected to normal.

Stimulus

The dense and sparse categories were defined by the same way used in Experiment 1. Also, same as in Experiment 1, the extent of material dimensionality was defined by the number of features (4 vs. 8). The low-dimensionality material consisted of four binary features: the shape of figure (square vs. rectangle), the color of figure (blue vs. purple), the color of frame (red vs. yellow), and whether there was a dot in the circle (Figure 14). The high-dimensionality material consisted of the four features of the low-dimensionality material and the other four features: the number of frame lines (1 vs. 2), the size of figure (big vs. small), whether the figure was open or closure, and whether there was a diagonal line or not (Figure 15).

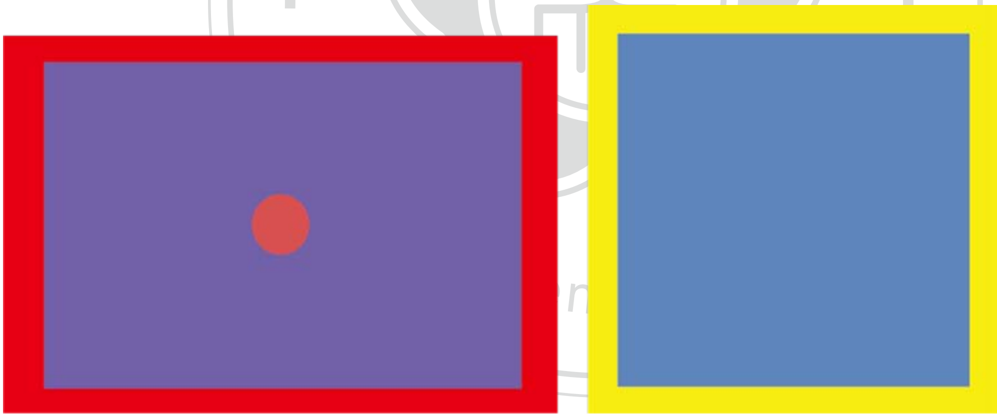

Figure 14. Examples of stimuli in low dimensionality used in Experiment 2. The left geometric is a rectangle with red frame line, purple body, and a dot in the middle, while the right one is a square with yellow frame line, blue body, and there is no dot in it.

The target items of the dense category in low dimensionality were purple squares with red frame line, while the contrasting items were blue rectangles with yellow frame line and a dot in the middle. The target items of the dense category in high dimensionality were small,

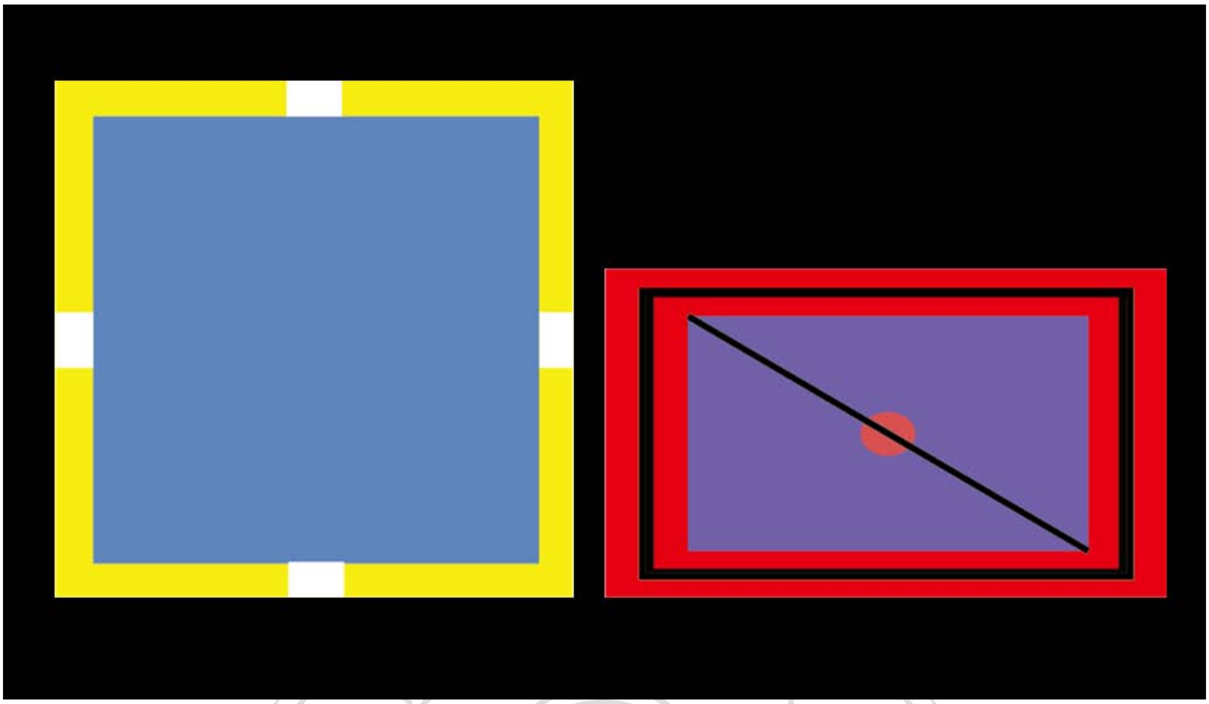

Figure 15. Examples of stimuli in high dimensionality used in Experiment 2. The left geometric is a big, open square with one yellow frame line, and there is no dot or diagonal line. The right figure is a small, closure rectangle with two red frame lines, a dot in the middle, and a diagonal line.

purple, and closure squares with one frame line in red color, while the contrasting items were big, blue, and open rectangles with two frame lines in yellow color, and there were a dot and a diagonal line inside the figure (Table 4 and Table 5).

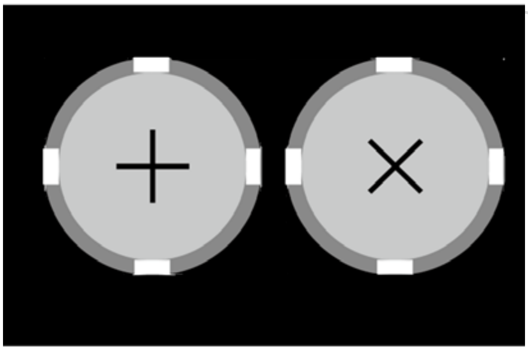

Figure 16. Examples of vigilance pictures used in Experiment 2. These pictures are supposed to be rejected.

Table 4. Category Structure of Stimuli Used in 4 dimensions in Experiment 2

Dimension	Dense category		Sparse category	
	Target item	Contrast item	Target item	Contrast item
Shape of figure	0	1	0	1
Color of frame line	0	1	…	…
Color of figure	0	1	…	…
A dot in the middle	0	1	…	…

Note. The numbers 0 and 1 refer to the values of each dimension. The "…" represents the varied randomly features.

Table 5. Category Structure of Stimuli Used in 8 dimensions in Experiment 2

Dimension	Dense category		Sparse category	
	Target item	Contrast item	Target item	Contrast item
Shape of figure	0	1	0	1
Color of frame line	0	1	…	…
Number of frame line	0	1	…	…
Color of figure	0	1	…	…
Size of figure	0	1	…	…
Open or Closure	0	1	…	…
A dot in the middle	0	1	…	…
Diagonal line	0	1	…	…

Note. The numbers 0 and 1 refer to the values of each dimension. The "…" represents the varied randomly features.

Same as in Experiment 1, the figure shape, the figure color, the color of frame line, and the presence of dot, had a same probability to make up the arbitrary rule in the sparse category. Also, there were eight vigilance pictures added in the testing phase (Figure 16). The statistical density of the dense category was as same as Experiment 1, 0.50 in the high dimensionality condition, and the sparse category was 0.13. In the condition of low dimensionality, the density of the dense category was 0.36, while the sparse category was 0.10.

Procedure

Except for the stimuli replaced by artificial geometrics, the experimental procedure was exactly as same as Experiment 1. Participants were asked to learn the “Ziblet” category in the training phase, and they needed to judge whether the each figure appearing in the testing phase belonged to the “Ziblet” category or not.

Results

Thirteen subjects were excluded from data analyses, due to their failure to reject the pictures for vigilance testing. A 2 (Density) × 2 (Dimensionality) × 2 (Learning condition) mixed-design ANOVA revealed that the 3-way interaction is not significant ($F(1, 70) = 3.02$, $MSe = 0.03$, $p = .09$, $\eta^2 = 0.04$). The 2-way interaction was found significant between Learning condition and Density ($F(1, 70) = 14.42$, $MSe = 0.04$, $p < .01$, $\eta^2 = 0.17$), but not significant either between Learning condition × Dimensionality ($F(1, 70) = 0.00$, $MSe = 0.03$, $p = .97$, $\eta^2 = 0.00$), or Denisty × Dimensionality ($F(1, 70) = 0.16$, $MSe = 0.04$, $p = .69$, $\eta^2 = 0.02$). Significant main effects of Density ($F(1, 70) = 29.49$, $MSe = 0.06$, $p < .01$, $\eta^2 = 0.30$), Learning condition ($F(1, 70) = 5.12$, $MSe = 0.04$, $p < .05$, $\eta^2 = 0.07$) and Dimensionality ($F(1, 70) = 5.52$, $MSe = 0.04$, $p < .05$, $\eta^2 = 0.07$) were found.

The interaction effect of Density × Learning condition was significant when the material dimensionality was high ($F(1, 70) = 19.16$, $MSe = 0.06$, $p < .01$, $\eta^2 = 0.22$), but not significant when the material dimensionality was low ($F(1, 70) = 2.66$, $MSe = 0.08$, $p = .11$) (See Figure 17).

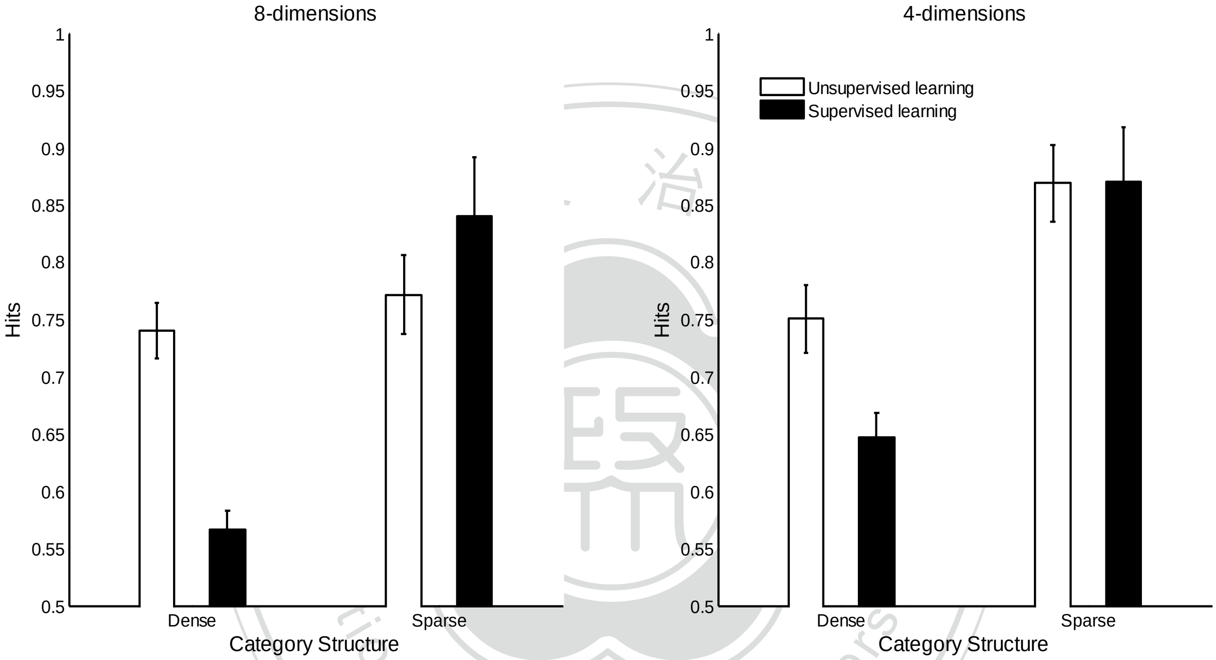

Figure 17. Mean accuracy scores by category type and learning condition in Experiment 2.

Same as found in Experiment 1, the interaction between Density and Learning condition appeared only when the material dimensionality was high. This result strengthens the challenge to Sloutsky's theory with a different type of stimuli. Also, the categories were ill defined in Kloos and Sloutsky (2008) as "Most Ziblets have long wings and dark antennas", whereas the categories in this experiment as well as in the studies of Shepard et al. (1961) and Love (2002) were well defined, as there was no exception to the definition of categories.

Therefore, this result shows that whether the categories were ill defined or well defined is not the cause for the discrepancy in the past research results. Considering the results of both Experiment 1 and Experiment 2, the dimensionality of material plays a crucial rule in category learning, which is not considered in Sloutsky's theory.

Experiment 3

Both Experiment 1 and Experiment 2 consistently indicate the dimensionality of materials can influence the category learning performance that is not predicted by Sloutsky's theory. That is, the expected interaction effect between the density of category structure and the learning manner only occurs for high dimensionality materials. Since the interaction effect is assumed to result from that the dense and sparse category structures respectively triggers the compression-based system and the selection-based system, it is worth examining the learning system on which the participants rely to learn different category structures, specifically when the stimulus materials are of different complexities.

Following the fourth experiment of Kloos and Sloutsky (2008), this experiment added diagnostic items in the test phase in order to examine which learning system was activated. The diagnostic items could be separated to two classes. One looked dissimilar to the target item but shared with the target item the arbitrary rule feature (i.e., the defining feature of the rule). The other looked similar to the target item but did not have the rule feature of the target item. If the dissimilar-appearance diagnostic item was classified to the target category, then it was indicated that the selection-based system was activated and. On the other hand, when the compression-based system was activated, participants should classify the similar-appearance diagnostic items to the target category.

Participants

Ninety-one participants were recruited in this experiment with traffic reimbursement of one-hundred NT dollars per hour for their expense of time and money. The participants were randomly assigned to one of four conditions (learning the dense vs. sparse category under low vs. high dimensionality). The age of these participants ranged from 18 to mid 30s. All participants reported that his/her vision was normal or corrected to normal.

Stimulus

The stimuli in this experiment were the same as in Experiment 1, except that two types of the diagnostic items were added. Each stimulus was composed of two types of features: the rule feature and the appearance feature. The rule feature was the one that could predict the target category 100% correct, whereas the appearance feature could not. The diagnostic item A_CR_T looked dissimilar to the target item (i.e., the appearance features had values of the contrasting category) but had the same value of the rule feature as the target item did. On the contrary, the diagnostic item A_TR_C looked similar to the target item (i.e., the appearance features had values of the target category) but had a different value of the rule feature as the target item did. The same naming principle could be applied to the other two types of items (A_CR_C and A_TR_T). For the low dimensionality materials, the feature of the number of fingers was set as the arbitrary rule. For the high dimensionality materials, the arbitrary rule was defined by the relation between the length of fingers and the shading of body. Table 6 and Table 7 all four types of items in the low and high dimensionality condition respectively.

Table 6. Examples of Stimuli Used in the Low Dimensionality Condition of Experiment 3 Presented in Abstract Notation

Feature	A_TR_T	A_TR_C	A_CR_T	A_CR_C
Appearance				
Length of wings	0	0	1	1
Shading of antennas	1	1	0	0
Shading of body	0	0	1	1
Rule				
Number of fingers	0	1	0	1

Note. The numbers 0 and 1 refer to the values of each dimension.

The statistical density of the dense category was 0.38 in the high dimensionality condition, and the sparse category was 0.01. In the condition of low dimensionality, the density of the dense category was 0.36, while the sparse category was 0.1.

Table 7. Examples of stimuli used in the high dimensionality condition of Experiment 1 presented in abstract notation.

	A_TR_T		A_TR_C		A_CR_T		A_CR_C	
Feature	Ex 1	Ex 2	Ex 1	Ex 2	Ex1	Ex 2	Ex 1	Ex 2
Appearance								
Length of tail	0	0	0	0	1	1	1	1
Length of wings	0	0	0	0	1	1	1	1
Shading of antennas	1	1	1	1	0	0	0	0
Number of fingers	0	0	0	0	1	1	1	1
Shading of buttons	0	0	0	0	1	1	1	1
Number of buttons	1	1	1	1	0	0	0	0
Rule								
Length of fingers	1	0	1	0	1	0	1	0
Shading of body	0	1	1	0	0	1	1	0

Note. There are two examples of each type of items (Ex1 and Ex2). The number 0 and 1 refer to the values of each dimension.

Procedure

In the beginning of the training phase, the experimenter firstly introduced all the features (the number of features depend on the experimental condition) to the participants. And then both verbal and graphic information of the target items were provided on the computer screen. The verbal rules were showed first, and then the graphs of the target stimuli were presented in a random sequence (eight pictures were also chosen randomly). Participants were told that they would receive the information of target category only in the training phase and instructed to learn both the verbal and graphical messages in a self-pace manner. After the training phase, the participants were given a recognition task incidentally. In this task, the participants were asked to recognize whether the present stimulus was seen in the training phase. Sixteen stimuli including eight A_TR_T pictures (which were showed in the training phase) and eight A_CR_C pictures were presented in a random sequence. The data of the participant who could answer correctly at least eleven out of sixteen trials in the recognition task were included in further data analyses.

In the testing phase, the participants were asked to judge for every single stimulus whether or not it belonged to the target category. The stimuli used in the testing phase were eight A_TR_C pictures and eight A_CR_T pictures presented in a random sequence.

Results

Twelve participants were excluded from data analyses due to failure to meet the criterion of the recognition task. The proportion of the diagnostic items classified to the target category is shown in Figure 18. Apparently, the participants rely on the selection-based system to make classification for the low dimensionality materials (the right panel), regardless of the density of category structure, as a large amount of the $A_C R_T$ items are classified to the target category and so are a small amount of the $A_T R_C$ items. However, for the high dimensionality materials, only when learning the sparse category structure, there are more $A_C R_T$ items than $A_T R_C$ ones classified to the target category (the left panel).

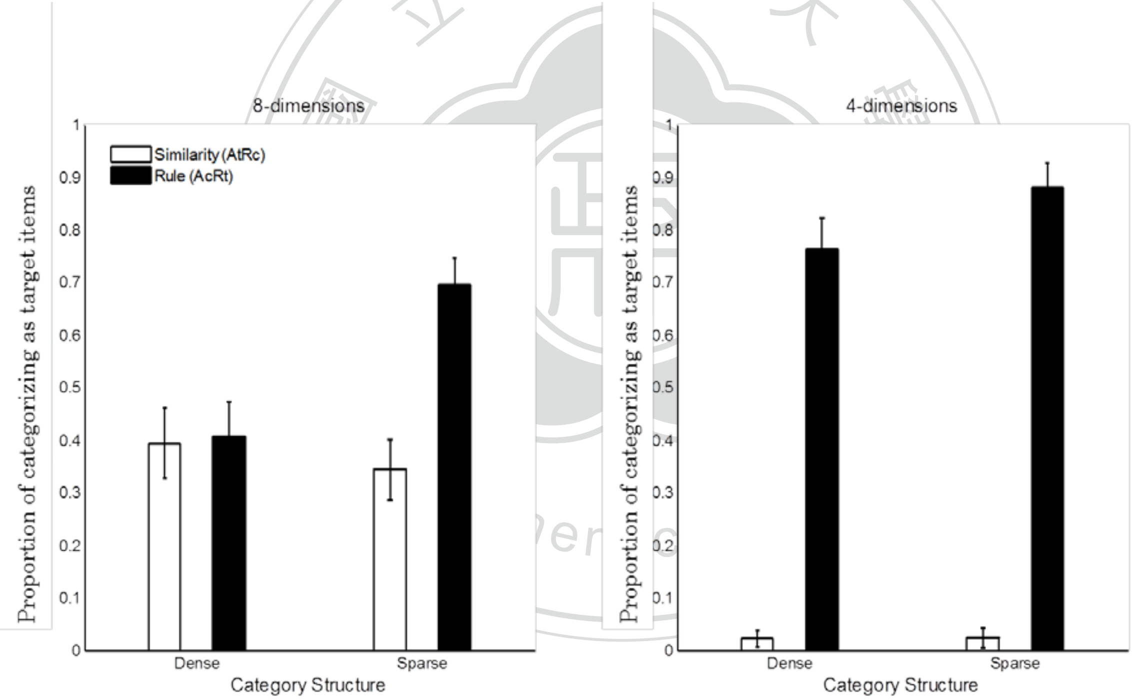

Figure 18. Mean accuracy scores by category type and learning condition in Experiment 3.

A 2 (Dimensionality) × 2 (Density) × 2 (Foil type: $A_T R_C$ and $A_C R_T$) mixed-design ANOVA was conducted. The 3-way interaction was not significant ($F(1, 75) = 1.75$, $MSe = 4.34$, $p = .19$, $\eta^2 = 0.02$). There were significant main effects on Density ($F(1, 75) = 10.54$, MSe = 2.20, $p < .01$, $\eta^2 = 0.12$) and Foil type ($F(1, 75) = 126.16$, MSe = 4.34, $p < .01$, $\eta^2 = 0.63$), but not on Dimensionality ($F(1, 75) = 1.60$, MSe = 2.20, $p = .21$, $\eta^2 = 0.02$). The interaction effects were significant for Foil type × Density ($F(1, 75) = 8.71$, MSe = 4.34, $p < .01$, $\eta^2 = 0.10$) and Foil type × Dimensionality ($F(1, 75) = 48.44$, MSe = 4.34, $p < .01$, $\eta^2 = 0.39$), but not significant between Density × Dimensionality ($F(1, 75) = 0.99$, MSe = 2.20, $p = .32$, $\eta^2 = 0.01$).

The interaction under different complexities was examined for understanding how the dimensionality of materials would influence which category learning system was activated. The interaction effects were significant for Foil type × Density in the high dimensionality condition ($F(1, 75) = 7.54$, MSe = 8.68, $p < .01$, $\eta^2 = 0.09$), but not significant in the low dimensionality condition ($F(1, 75) = 1.11$, MSe = 8.68, $p = .30$). However, the difference on the proportion of target category was not significant for A_CR_T and A_TR_C ($F(1, 75) = 0.02$, MSe = 2.20, $p = .88$). This result is not congruent with the fourth experiment of Kloos and Sloutstky (2008).

In order to understand whether this result is reliable at the individual level, a K-means cluster analysis was conducted to classify the participants to the similarity-based group (classifying the A_CR_T items as target category) or the rule-based group (classifying the A_TR_C items as target category), according to the distance of their testing response to each typical response of the groups.

Since there were eight A_TR_C and eight A_CR_T items presented in the testing phase, presumably the most typical rule-selection participant would classify all A_CR_T items and zero A_TR_C items as the target category, while the most typical compression-based participant would classify all A_TR_C items and zero A_CR_T items as the target category. Thus, the response in the testing phase could be recoded as a vector with the elements as the numbers of A_CR_T and A_TR_C items to be classified as the target category. The typical rule-based response was set as [8, 0] and the typical similarity-based response as [0, 8]. The distance between the participant's response vector and the typical response vector was the basis to classify participants in K-means cluster analysis. Table 8 shows the number of participants in each group and each dimensionality condition.

Table 8. Summary table of people using similarity or rule-based representations.

	Low dimensionality		High dimensionality	
Density	Similarity	Rule	Similarity	Rule
Dense	4	18	16	4
Sparse	1	20	6	10

Wickens (1989) proposed the concept of "conditional independence model" describing the relationship of a 3-way mixed design which is "two factors are conditionally unrelated at all levels of the third". To illustrate the relationship between the statistical density and the activating learning system when using different complexities of materials by this 3-way table, the conditional independence model was tested. If it was rejected, the density and the learning system are correlated at either one or all levels of the dimensionality of materials. According to Wickens (1989), the expected frequencies for this model is adjusted to

$$\mu_{\text{ijk}} = \frac{x_{\text{ij+}}\, x_{\text{+jk}}}{x_{\text{+j+}}} \qquad \text{Equation 7}$$

the degrees of freedom for it would be $(\mathrm{a}-1)\mathrm{b}(\mathrm{c}-1)$, where a, b, and c are the levels of each factor. The degrees of freedom are 2 in the present condition.

As a consequence, the hypothesis of conditional independence model was rejected ($X^2 = 8.64$, $\phi = 0.33$, $p<.05$), which indicated that the dimensionality is a moderator for the association between density and the activating learning system. To analyze further, the factors density and the system used by participants were found to be independent in the condition of low dimensionality ($X^2 = 1.88$, $p = .10$), but were not independent in the condition of high dimensionality ($X^2 = 6.76$, $\phi = 0.43$, $p <.01$). These findings demonstrate that people would use the corresponding learning system determined by the category structure when the materials are more complex, but only use the selection-based (rule-based) system to learn categories when the materials are simpler, namely, when the feature of stimuli has only four dimensions.

General Discussions

The main purpose of this study is to examine Sloutsky's theory, specifically focusing on examining the interaction between learning paradigm and density of category structure. According to Sloutsky's theory, the category structures of different densities induce different systems for learning categories. The compression-based system is assumed to process information in a compressed fashion like the way of the visual perception system. Thus, it is suitable to learn dense structures. In contrast, the selection-based system is assumed to learn categories in the way of focusing the specific features, which is suitable to learn sparse structures.

However, the Sloutsky's theory seems not able to account for well some past research results (e.g., Love, 2002; Shepard, et al., 1961). The possible reasons may include the dimensionality of materials and the type of stimulus (natural vs. artificial). Therefore, the aim of current study is to examine the effects of these two variables within Sloutsky's experimental regime.

Experiment 1 manipulated the dimensionality of materials (low vs. high) with the attempt to check whether the interaction effect between the learning paradigm and the density of category structure is moderated by the dimensionality of materials. Following Sloutsky's theory, the choice of learning systems should only depend on the density of category, regardless of the dimensionality of materials. However, the results show that the interaction effect between the learning paradigm and the density is significant only for the high dimensionality materials, which implies that the dimensionality of materials may moderate the correspondence between the learning system and the category structure. Experiment 2 used the artificial geometrics as stimuli with the same design of Experiment 1 and acquired the same results of Experiment 1. Obviously, the type of stimulus is not a factor to change the performance pattern. Experiment 3 further examined by which system the participants learned categories. The proportion of diagnostic items (A_CR_T and A_TR_C) to be classified to the target category suggests that for the low dimensionality materials, the selection-based system is used at all times whereas for the high dimensionality materials, only when learning the sparse categories the selection-based system is used. These three experiments converge on that the density is not the only factor to trigger the learning system.

Study Restrictions

Before further discussion, there are some restrictions in this study needed to mention here. First, when the complex stimuli are employed, although these experiments all report an interaction effect between the learning condition and the categorical density, the data patterns are not exactly consistent with the results of Kloos and Sloutsky (2008). According to Sloutsky's theory, the selection-based system should dominate the learning of the sparse categories, thus, the performance of supervised learning condition should be better than unsupervised learning. However, both Experiment 1 and 2 show that participants perform fairly well both in the supervised learning and the unsupervised learning condition for learning the sparse categories. This result indicates that the sparse categories do not favor the selection-based system comparing with the compression-based system. One possible explanation for this is that the task of learning sparse categories is too easy for the participants, indicating that the arbitrary feature can be easily found even in the condition of unsupervised learning. Another explanation is that the averaged data could not reveal the individual differences of the strategy use. For example, Figure 18 shows an unexpected data pattern that both A_CR_T and A_TR_C items have the same probability for being classified to the target category in the learning of complex stimuli (the leftmost panel of Figure 18), however, the result of K-means cluster analysis demonstrates that participants do use similarity representation to categorize under such condition (see the leftmost panel of Figure 19).

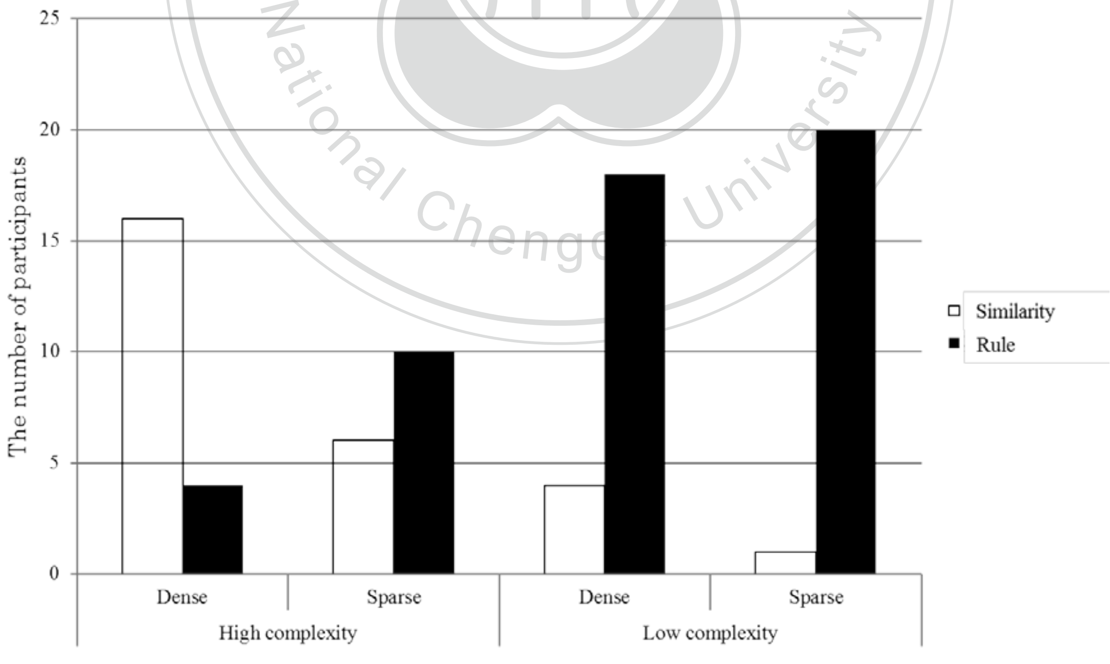

Figure 19. Bar chart of people using similarity or rule-based representations in Experiment 3.

Second, the supervised and unsupervised learning conditions used in the current study are not the only learning methods to examine Sloutsky's theory. Ashby, Maddox, and Bohil (2002) called a method as "observational training" in that the category label is presented before the stimulus and participants do not need to do any motor response, whereas another method as "feedback learning" in that the category label is presented as a feedback to participants after they make a response. They compared the observational training and the feedback training, concluding that the feedback training is more effective to learn a category structure requiring information integration for optimal responding. The supervised learning condition in the current study gave the explicit verbal rules without asking participants to do responses, which is similar to observational learning. Thus, the participants may perform better during learning dense categories in the supervised learning condition if the learning method is replaced by feedback learning paradigm. On the other hand, the unsupervised learning used in the current study is called intentional unsupervised learning (Love, 2002). That is, participants know that they would be tested after training. There is another way of unsupervised learning called incidental unsupervised learning that participants would not be noticed to do the category learning. For example, participants are told to judge the pleasantness of each figure but not learn the category of figures. According to Sloutsky's theory, the interaction between category structure (density) and learning conditions should exist no matter which kinds of learning paradigms (either observational learning or feedback learning and either intentional unsupervised learning or incidental unsupervised learning) are selected to use. For the intention to compare the results with Kloos and Sloutsky (2008), the current study used the exactly same learning conditions. However, it is worth the try to examine other kinds of learning conditions in the future for the purpose of generalizability.

Statistical Density

The statistical density represents a calculable index of category structure. It is convenient to use especially in the situation that stimuli have multiple dimensions. However, the statistical density still has some limitations. First, the concept of a dense category or a sparse category is not clearly differentiated. Kloos and Sloutsky (2008) designed the high density condition in different experiments by setting the statistical density level from 0.39 to 1.0, and the density of sparse condition was 0.17 to nearly 0. Because the definition of density (dense or sparse) is involved in the prediction of Sloutsky's theory, it is necessary to locate the exact point that can firmly differentiate a dense or a sparse category for further applications. For example, whether a category structure is a dense one or not while the statistical density of it is 0.25. Second, according to the results of the current study, the statistical density cannot represent all characteristics of materials. It seems that the density simplifies a category structure into a simple number, but the density considers the regularity only. All the three experiments show that the materials dimensionality is also a critical factor to affect human category learning. Third, there is a natural obstacle for the stimuli with few dimensions to apply this index in experiment. In this study, 0.1 is the best number we could require when the stimuli have only four dimensions, following the experimental setting of Kloos and Sloutsky (2008), and it would be larger if the number of dimensions is smaller. Therefore, if an experiment is conducted by using stimuli consisting of only one or two dimensions, it is hard to generate an appropriate condition of sparse categories. In other words, this is also the restriction of Sloutsky's theory.

Multiple Systems for Category Learning

The concept of multi-system model or multi-representation accounted for category learning has been widely discussed and accepted in recent years (Anderson & Betz, 2001; Ashby, et al., 1998; Erickson & Kruschke, 1998; Nosofsy, Clark, and Shin, 1989; Rouder & Ratcliff, 2004, 2006). There are many pieces of neural evidences supporting the point of view of the multi-system theory (Ashby et al., 1998; Cincotta & Seger, 2008; Kloos & Sloutsky, 2008; Nomura & Reber, 2008; Seger, 2008; Seger & Cincotta, 2002;).

Most of the multi-systems theories state that those systems work in a winner-takes-all manner to learn categories. For instance, the rule module (RULEX; Nosofsky, Palmeri, & McKinley, 1994) competes with the exemplar module (the exemplar-based random walk model; Nosofsky & Palmeri, 1997) in ACT-R (Anderson & Betz, 2001), and the explicit system competes with the implicit system in COVIS (Ashby, et al., 1998), and the compression-based system competes with the selection-based system in Sloutsky (2010) theory. The winner system is often assumed to be the one, which can best adapt to the category structure. For instance in the COVIS model, the explicit system is assumed to outperform the implicit system on learning the unidimensional structure (Ashby, et al. 1998). Also, in Slouthsky's (2010) theory, it is assumed that the sparse and the dense categories are learned respectively by the selection-based and the compression-based systems. However, the results of this study challenge Sloutsky's (2010) assumption. All three experiments do not show the full dissociation between the selection-based and the compression-based systems on learning the sparse and dense categories. Rather, when learning the simpler stimuli, the selection-based system is favored at all times. Accordingly, it suggests that the Sloutsky's (2010) argument about the dissociation between systems is insufficient. Further, across these three experiments, it is obviously to see that the selection-based system dominates in most of the cases, except when a dense category structure with complex stimuli is to learn. The condition of dense category structure with complex stimuli is relatively harder than other conditions to learn in terms of the number of stimulus dimension and the cognitive loading to compare similarity information. Therefore, although Sloutsky (2010) claimed that the default learning system is determined by category structure, i.e., the statistical density, the present results indicate that the default learning system should always be the rule-based system.

This assertion might as well have a neural-based support. For instance, Nomura et al. (2007) conducted an fMRI study and found that the medial temporal lobe was associated with the learning of unidimensional category structure, whereas the caudate was associated with the learning of two-dimensional structure. The prefrontal lobe, normally thought to be relevant to working memory (Cohen et al., 1997; Cohen, Botvinick, & Carter, 2000; D'Esposito et al., 1999) and the implementation of the explicit system in COVIS, is assumed to be in charge of the rule learning in a hypothesis-testing manner (see Ashby, et al., 1998).

Since many pieces of evidences show that the cortex matures later than the midbrain areas but takes a leading position in adults (Pfefferbaum et al., 1994; Sowell et al., 1999; Sloutsky, 2003), the COVIS model assumes, for adult participants, the explicit system is implemented first when learning categories. Following this idea, it is reasonable to assume a leading position for the selection-based system to take. Although Sloutsky's studies have mentioned this fact of the maturing speed of different brain areas (Kloos & Sloutsky, 2008; Sloutsky, 2010), he does not have a same conclusion with COVIS model as taking the rule-based subsystem as the default learning system.

Dimensionality of Materials

In spite of the dimensionality of materials has normally treated as a control factor in the past researches (e.g., Alfonso-Reese, et al., 2002; Smith, Murray, and Minda, 1997), there were still several researches indicating that the dimensionality of materials could influence human's learning strategies and category perception (Minda & Smith, 2001; Livingstion, et al., 1998; Nosofsky, et al., 2005). For instance, Minda and Smith (2001) indicated that the outperformance of the prototype model over the exemplar-based model became more significant when fitting to the data collected with high-dimensional categories. Also, Verguts, Ameel, and Storms (2004) proposed a modified ALCOVE model by adding the dimensional factor and found it could fit the data better. However, these studies did not mention the relationship between the dimensionality of stimulus and other factors in category learning.

The results of all these three experiments in the current study clearly reveal that various levels of the stimulus dimensionality would lead to different strategy (or representation) uses on category learning. Linking the current results and Sloutsky's (2010) theory as a foundation, it becomes more clear the idea that the stimulus dimensionality moderates the use of the learning strategy. However, the dimensions used in this study are psychologically separable. Past research indicated that the psychologically separable dimensions would induce attentional shift easily, while the psychologically integral dimensions are hard to use the selective attention (Nosofsky & Palmeri, 1998). Thus, the current results may not be extended to explain the tasks with the stimulus consisting of psychologically integral dimensions. To further examine the effect of stimulus dimensionality, it would be a great idea for the future studies to consider the characteristic of stimulus dimension (psychologically separable vs.

integral).

Base rate of categories

The number of target items and contrasting items is not manipulated in the current study. Although Medin and Edelson (1988) concluded that if the base rate information is conveyed that it is trivial, the consequences of categorization task would not be influenced by the base rate. Also, Spellman (1993) illustrated an inconsistent phenomenon for people to use base rate information. He claimed that the base rate information is perceived by participants accurately in the training phase, because it is an implicit learning process, but participants cannot apply the base rate in the testing phase appropriately because they need to access the information explicitly. These results indicate that the number of target or contrasting items may not be a critical factor influencing category learning behavior. However, the calculation of between-category entropy consists of both the target items and the contrasting items. If the entropy of contrasting items can affect the overall category structure, it is a reasonable doubt that the base rate of contrasting items can affect the categorization behavior as well. Also, the number of target items appearing in the training phase is not discussed both in the current study and the research of Kloos and Sloutsky (2008). It would be interesting to find out if the pattern of learning performances could be changed by manipulating the number of items in the training phase or the ratio of target items/ contrasting items in the testing phase.

Conclusion

This research reveals several facts about category learning. First, the dimensionality of materials can moderate the association between category structure and learning performances. Sloutsky's theory cannot describe the categorization behaviors when using low dimensionality stimuli. Second, people tend to use the rule-based system to learn categories when the dimensionality of materials is low, which is incongruent with Sloutsky's prediction and implicates that the rule-based system is the default learning system for categorization. These findings indicate that the role of stimulus dimensionality is important in category learning and category representation. However, there are still some restrictions and issues needed to be clarified, e.g. the various kinds of learning conditions, the characteristics of stimulus dimensions (psychologically separable or integral), and the base rate of categories, much more work on these topics in the future is clearly required.

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Appendix

Examples of calculating statistical density

To illustrate the procedure of calculating density more clearly, there is a simple example. Suppose that there are two dimensions of materials (e.g., shape and color), and two levels of each dimension (black and white, square and circle), therefore there are four possible combinations of shapes and colors. In this experiment, all the target items are squares in black, while all the contrasting items are circles in white. In addition, assume that the number of target items is same as contrasting items.

To calculate the density, the probability of each possible combination in within- and between-category is required. Within-category represents the target items only, which are all square in black in this example. Therefore, the probability of black-square is 1.0. Between-category represents both target and contrasting items, therefore, the probability of black-square is 0.5, as well as the probability of white-circle in between-category (see Table 10).

Table 9. Matrix of within-category and between-category probability in example 1

	Black Square	Black Circle	White Square	White Circle
Within-category	1.0	0	0	0
Between-category	0.5	0	0	0.5

After knowing the probability of each feature combination, now we continues to computing the H^{dim}, the dimensional entropy. Dimensional entropy has two parts, between-category and within-category (equation 4-1 and 4-2). To calculate, it is necessary to consider the probability matrices from the aspect of dimensions first. There is only one kind of stimuli in target category (black squares only), so the probability matrix of color in the within-category (p_{black} and p_{white}) would be $[1.0 \quad 0]$, and the probability matrix of shape in the within-category (p_{square} and p_{circle}) would also be $[1.0 \quad 0]$. And there is another possibility (white circle) when we consider the between-category probability, so the matrix will be $[.5 \quad .5]$ both in dimensions of color and shape (Table 11). Put these matrices into equation 4-1 (for within-category) and 4-2 (for between-category) respectively, then the $H^{\text{dim}}_{\text{within}}$ will be get as 0, and $H^{\text{dim}}_{\text{between}}$ will be 2 (have not considered the attention weight yet).

Table 10. Probability matrix of with- and between-category from the aspect of dimensions in example 1

	Color		Shape	
	Black	White	Square	Circle
Within-category	1.0	0	1.0	0
Between-category	0.5	0.5	0.5	0.5

Next is H^{rel}, the relational entropy. Before it is computed, the number of relations needs to be considered first. According to equation 5, there is only one relation between all two dimensions. To calculate the relational entropy, we use the matrix of feature combination which is displayed in Table 9. The matrix for within-category is $[1.0 \quad 0 \quad 0 \quad 0]$, and the matrix for between-category is $[0.5 \quad 0 \quad 0 \quad 0.5]$ in Table 10. Put these numbers of probability into equation 5-1 and 5-2 respectively. Then we can get the $H^{\text{rel}}_{\text{within}}$ as 0, while the $H^{\text{rel}}_{\text{between}}$ is 1 (have not considered the attention weight yet). Finally, we set w_i as 1, and w_k as 0.5, so $H_{\text{within}} = 1 * 0 + 0.5 * 0 = 0$，$H_{\text{between}} = 1 * 1 + 0.5 * 2 = 2$ And the density will be $1 - {}^{0}/_{2} = 1$.

Suppose that the feature combination is more complicated. Now the target items are composed of half black squares and half white circles, while the contrasting items are composed of black circles and white squares. The probability matrix of within- and between-category is shown in Table 12 and the probability matrix from the aspect of dimensions is shown as Table 13.

Table 11. Matrix of within-category and between-category probability in example 2

	Black Square	Black Circle	White Square	White Circle
Within-category	0.5	0	0	0.5
Between-category	0.25	0.25	0.25	0.25

Table 12. Probability matrix of with- and between-category from the aspect of dimensions in example 2

	Color		Shape	
	Black	White	Square	Circle
Within-category	0.5	0.5	0.5	0.5
Between-category	0.5	0.5	0.5	0.5

In this example, there are two kinds of stimuli in the target items (black squares and white circles). Assuming they are equal in number, then the probability matrix of colors in the within-category ($\mathrm{p_{black}}$ and $\mathrm{p_{white}}$) would be $[0.5 \quad 0.5]$, as well as shapes ($\mathrm{p_{square}}$ and $\mathrm{p_{circle}}$) when calculating the $\mathrm{H_{within}^{dim}}$ (see Table 13). Therefore, $\mathrm{H_{within}^{dim}}$ is 2 (have not considered the attention weight yet). On the other hand, there are four kinds of stimuli when considering between-category, mentioned as black squares, black circles, white squares and white circles, but the probability of matrix will as same as $[0.5 \quad 0.5]$ when considering each dimension (half stimuli are in black when considering the dimension of color, and half stimuli are squares when considering the dimension of shape) (see Table 13). Therefore, the $H_{\text{between}}^{\text{dim}}$ is also 2 (have not considered the attention weight yet). Compare to the calculation of dimensional entropy, it is more straightforward to compute the H^{rel}, just use the matrix $[.5 \quad 0 \quad 0 \quad .5]$ for the within-category and the matrix $[.25 \quad .25 \quad .25 \quad .25]$ for the between-category which are displayed in Table 12. Therefore, $H_{\text{within}}^{\text{rel}}$ is 1 and $H_{\text{between}}^{\text{rel}}$ is 2. Do not forget to consider the attention weight, then the $H_{\text{within}} = 1 * 2 + 0.5 * 1 = 2.5$, and the $H_{\text{between}} = 1 * 2 + 0.5 * 2 = 3$. So the density is $1 - {}^{2.5}/_{3} = 0.167$ in this example.

The fact which can be observed easily in the two examples above is that the density is markedly larger when there is less variability (all are black squares in example 1) in the target items (within-category), while the density become lower when the variability is larger in the target items (density as 0.167 in example 2). Therefore, the variability of target items is one of the dominant factors which can affect density. Still, the salience of features and the similarity of stimuli have some common ideas with density, but not the same (Sloutsky, 2010). The salience of each feature would affect density because the equations of density are composed of weighted entropy, but it simplifies the calculation of salience. It assumes that the saliences of features are all the same, and using a ratio to represent the relation between the attentional weight of dimensional and relational entropy instead of calculating attentional weights of all features. Also, the similarity is a part of concern in the concept of density, high similarity within target category may cause a high density. However, the equations of density include both dimensional entropy and relational entropy. It is said that high density could be generated by not only high similarity but less relational entropy.