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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 38(0)

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Publication Date
2016

Peer reviewed

Factors Influencing Categorization Strategy in Visual Category Learning

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Abstract

Studies in visual category learning show that participants use different category generalization strategies. Some studies report a preference for a rule-based strategy, while others report a preference for a similarity-based strategy. We conducted category learning experiments in which we varied three variables — family resemblance of a category, saliency of the defining rule and presentation of transfer stimulus after a delay. Our results show that these factors influence the choice of category generalization strategy. Our study offers a possible explanation for the divergent results in the literature.

Keywords: visual category learning; supervised learning; generalization; family resemblance; defining rule saliency

Introduction

Studies in visual category learning investigate how humans learn and generalize visual categories. Let us say that the items shown in Figure 1 are true instances of a category. The true instances have a common defining feature — the blue five pointed star. Now consider the transfer stimuli shown in Figure 2. Stimulus A has the defining feature (blue star). Stimulus B does not have the defining feature, but is more similar to the true instances shown in Figure 1. For the transfer stimuli in Figure 2, two generalization strategies are possible: defining rule-based strategy and similarity-based strategy.

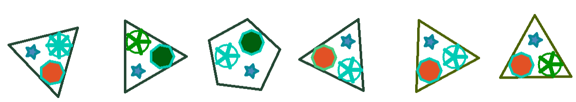

Figure 1: True instances of a target category. All the instances have a common defining feature (blue five pointed star).

In this article, we refer to categorization based on a defining feature as rule-based strategy. If a rule-based strategy is preferred, then participants will generalize stimulus A to the target category, but not stimulus B. On the other hand, if a similarity-based strategy is preferred, then stimulus B will be generalized to the target category, but not stimulus A.

Observational learning is a supervised learning paradigm where the participants are informed about the correct category of the training stimuli. Participants are then asked to categorize the transfer stimuli. No feedback is provided. Some studies in the observational learning literature report a preference for a rule-based strategy; while others report a preference for a similarity-based strategy. In our study, we try to identify the variables that influence the choice of categorization strategy.

Figure 2: Two transfer stimuli for the target category in Figure 1. Stimulus A has the defining feature, but stimulus B is more similar to the target category instances.

Studies on Supervised Learning

In the studies conducted by Xu and Tenenbaum (2007) and Schmidt (2009), observational learning paradigm was used. In each trial, participants were informed about the correct category of three stimuli. The participants were then asked to pick other items that might belong to the same category. Participants preferred a similarity-based generalization. Thomas and Karnick (2014) showed that participants preferred similarity-based generalization even when the target category had a defining feature.

Feldman (2000) showed that categories based on a simple rule (conjunction of boolean features) were learned more easily. Ashby, Maddox, and Bohil (2002) also showed that a rule-based category structure was easier to learn. In (Conaway & Kurtz, 2014; Rabi, Miles, & Minda, 2015; Deng & Sloutsky, 2015), a category could be generalized using either a rule-based strategy or a similarity-based strategy. The results showed that participants preferred a rule-based strategy over a similarity-based strategy.

The studies discussed above indicate that participants use different strategies for visual category generalization. In this study, we try to identify the variables that influence the choice of categorization strategy. Kloos and Sloutsky (2008) showed that participants were able to learn the defining rule when the family resemblance was low, but not when the family resemblance was high. So, family resemblance could be one factor that influences the choice of categorization strategy.

The study conducted by Yim, Castro, Wasserman, and Sloutsky (2014) showed that a category is easier to learn when the defining rule can be identified more easily. So, the ease with which the defining rule can be identified (rule saliency) might also affect the categorization strategy.

In the studies that report similarity-based generalization, the training and transfer stimuli are usually presented simultaneously (Xu & Tenenbaum, 2007; Schmidt, 2009; Thomas & Karnick, 2014). In (Feldman, 2000), training stimuli were presented simultaneously, but the transfer stimuli were presented in a separate testing block. In (Conaway & Kurtz, 2014; Rabi et al., 2015), the training stimuli were presented one by one, and the transfer stimuli were presented in a separate testing block. The results in (Feldman, 2000; Conaway & Kurtz, 2014; Rabi et al., 2015) show a preference for rule-based generalization, and in these studies the transfer stimuli were presented in a separate testing block. So, presenting the transfer stimuli separately could be another factor that might be influencing the choice of categorization strategy.

So the three variables that could be influencing the choice of categorization strategy are: family resemblance of a category, saliency of the defining feature (we will refer to this as rule saliency) and delayed presentation of transfer stimuli. If manipulating the above variables affects categorization strategy, then that would explain the divergent results in the visual category learning literature.

In Experiment 1, we trained a regression model using behavioral data to predict the rule saliency. In Experiment 2, we studied the effect of family resemblance and rule saliency on category generalization. In Experiment 3, we studied the effect of presenting the transfer stimulus after a delay. In the next section, we explain how we quantified the notion of family resemblance and rule saliency. Quantification allows us to study the effect of the independent variables as they change in a continuous manner.

Family Resemblance and Rule Saliency

In Figure 1, the family resemblance between the true instances is high. But, the defining rule (blue star) is not easy to spot. In other words, the rule saliency is low.

Figure 3 shows another set of target category instances. Here the family resemblance between the instances is low. But, the defining rule (red polygon) stands out from the other features; therefore, the rule saliency is high.

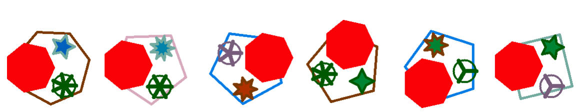

Figure 3: True instances of a target category. All the instances have a common defining feature (red polygon).

In our study, we use abstract figures having ten dimensions, where each dimension can take six distinct values. The stimuli dimensions are — number of outer boundary sides, outer boundary color, number of points in the star, star boundary color, star fill color, number of inner polygon sides, inner polygon boundary color, inner polygon fill color, number of spike-wheel points and spike-wheel color.

We use the concept of entropy to quantify family resemblance of a category. We estimate the entropy using the instances of a category. First, the entropy for each of the ten stimuli dimensions is calculated as follows:

$$dimEnt(j) = \sum_{k=1}^{6} -P(x_{jk}) \log_2 P(x_{jk}) \tag{1}$$

where $dimEnt(j)$ is the entropy of the j^{th} dimension, x_{jk} are the distinct values that the j^{th} dimension can take and $P(x_{jk})$ is the probability with which the value x_{jk} occurs among the instances of a category. The entropy of a category is found by averaging the entropy across all the dimensions as follows:

$$entropy(C) = \frac{1}{10} \sum_{j=1}^{10} dimEnt(j) \tag{2}$$

where $entropy(C)$ is the average entropy of the ten dimensions for category C. In our study, the value returned by Equation 2 is considered to be the category entropy. Category entropy will be low when there is less variability (high family resemblance) among the category instances. Category entropy will be maximum when the non-defining feature values are unique for every instance of the category. The maximum possible value of category entropy in our study is 2.07, because we have six distinct values for each dimension and there can be at most eight non-defining features.

We trained a regression model using behavioral data to quantify the notion of rule saliency. We explain this in more detail in the next section.

Experiment 1

In our experiments, the defining feature is the part of the figure that is common across all the instances of a category. Visual saliency is defined as the perceptual quality that makes a feature stand out from other features and grab our attention (Itti, 2007). In order to quantify visual saliency, we have followed the intuition that participants would take less time to detect the defining feature when it is more salient.

Participants were shown six stimuli like the ones depicted in Figures 1 and 3. Their task was to correctly identify the defining feature as quickly as possible. Participants could choose the defining feature from among the four options that appeared on the screen: boundary, star, polygon and spike-wheel.

In order to change the rule saliency, the area covered by the defining feature, and its color were randomly varied. The time taken by a participant to detect the defining feature was noted. This time was then used to quantify the visual saliency as follows:

$$saliency(i) = \frac{max_p - time_p(i)}{max_p - min_p} \tag{3}$$

where $saliency(i)$ is the saliency of the defining feature for the i^{th} trial, max_p is the maximum response time for the p^{th} participant, min_p is the minimum response time for the p^{th} participant, and $time_p(i)$ is the response time for the i^{th} trial by the p^{th} participant. In Equation 3, $saliency(i)$ will give a value of one for the trial in which a participant took minimum time to respond. Saliency would be zero for the trial in which a participant took maximum time. The saliency value given by Equation 3 will lie in the range $[0,1]$ for all trials.

Participants and Procedure

There were 22 adult participants (Males=16, Females=6, Mean age=24.27, S.D.=4.33). Participants were volunteers from the student community. Each participant had to respond to 35 trial questions. The first 15 questions were the practice trials, and the remaining 20 were the experimental trials. So the experiment gave us 440 (22 participants $\times$ 20 trials) data points to train our regression model.

In each trial, six abstract figures were shown. These figures were randomly generated. A part of the figure was randomly selected to be the defining feature, and was given a random size and color. Participants were expected to correctly identify the defining feature across the six abstract figures. The response times for only the correct responses were recorded. The maximum time permitted for the participants to identify the common defining feature was 20 seconds.

Modeling Rule Saliency

In this section, we describe the features that were used to train the linear regression model. First, the color value of the different parts of figures were converted from the RGB space to the Lab space. The advantage of Lab space is that the perceptual difference between two colors is proportional to the Euclidean distance between them.

The L value in Lab space corresponds to the lightness component of the color, and the a and b values correspond to the color information. We have used the following six properties of the different parts of the figure: L value, a value, b value, color-saliency, area and perimeter. The color-saliency is estimated using the technique mentioned in (Gelasca, Tomasic, & Ebrahimi, 2005).

For each of the above properties the difference (d_i) between the average defining feature values and the average non-defining feature values was found as follows:

$$d_i = \begin{cases} |v_i - w_i| & \text{if } i = 2 \text{ or } i = 3 \\ v_i - w_i & \text{otherwise} \end{cases} \tag{4}$$

where i ranges from 1 to 6 for each of the six properties mentioned above, v_i is the average value of the i^{th} property for the defining feature and w_i is the average value of the i^{th} property for the non-defining features. For each of the six property values Equation 4 indicates how different the defining feature is from the non-defining features.

In Equation 4, the absolute value of the difference is taken for properties 2 and 3. These two properties correspond to the a and b values in the Lab color space. If the a and b values of the defining feature are very different from the non-defining features, then it might make the defining feature more salient. Here the sign of the difference should not matter. But the sign of the difference matters for the remaining four properties.

For each trial the d_i value for each of the six properties is found. Then the maximum and minimum values for each d_i across all the trials is found. The features for training a linear regression model for saliency is calculated as follows:

$$f_i = e^{\frac{d_i - min(d_i)}{max(d_i) - min(d_i)}} - 1 \tag{5}$$

where i ranges from 1 to 6, and $min(d_i)$ and $max(d_i)$ are the minimum and maximum values of d_i respectively. The main function of Equation 5 is to scale the d_i values so that the corresponding features f_i lies in the range $[0, e-1]$. Features similar to those described in this section have been previously used to detect salient objects and regions of interest in images (Osberger & Rohaly, 2001; Tian, Wan, & Yue, 2010).

Results

The features obtained using Equation 5 were used to train a linear regression model for predicting the saliency values calculated using Equation 3. The linear regression model was trained using the gradient descent algorithm.

After training, the rule saliency values predicted by the saliency model for the category instances in Figures 1, 3 and 4 were .05, .98 and .41 respectively. A value close to zero means that rule saliency is low, and a value close to one means that the rule saliency is high. The stimuli in Figures 1, 3 and 4 were not part of the training or the test data. This shows that the values predicted by the regression model are reasonable.

Experiment 2

In this experiment, we studied the effect of rule saliency and category entropy on the generalization behavior. Figure 4 shows a sample screenshot. In each trial, six true and six false instances of a category, and a transfer stimulus were shown. Participants had to decide whether the transfer stimulus was a true instance of the category. A participant could respond by clicking Yes, No or Can't decide.

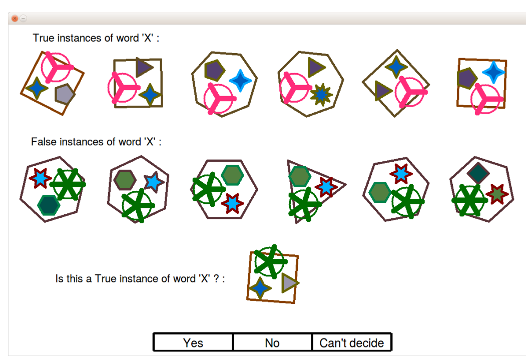

Figure 4: Sample screenshot for Experiment 2. The defining feature is the pink spike-wheel.

In each trial, the target and contrast category instances were generated randomly. A part of the stimuli (boundary, star, polygon or spike-wheel) was randomly selected to be the defining feature. A multinomial distribution was used to assign values to each of the non-defining dimensions. A

Table 1: The four types of transfer stimuli.

	Generated From	Defining Feature
Transfer type 1	Target Category	Present
Transfer type 2	Target Category	Absent
Transfer type 3	Contrast Category	Present
Transfer type 4	Contrast Category	Absent

multinomial distribution associates a probability with each of the six values that a dimension can take. An instance was generated by assigning to each dimension a value that was sampled from the multinomial distribution. In each trial, a random multinomial distribution was assigned for both target and contrast categories.

Category entropy was calculated based on the category instances that were generated in each trial. Category entropy captures the variability present in the instances that were shown in each trial. So, once the instances are generated, the multinomial distribution from which the instances were generated is not important. In each trial, the saliency of the defining feature was varied by changing its color and size.

Four types of transfer stimuli were used in our experiment. Transfer types 1 and 2 were generated using the target category multinomial distribution. Transfer types 3 and 4 were generated using the contrast category multinomial distribution. For the transfer types 2 and 3, the defining features were from the opposite category (i.e. the category from which they were not generated). Table 1 gives the details of the four types of transfer stimuli that were used in our experiments.

The transfer types 1 and 4 were the true and false instances of target category respectively. Transfer type 2 stimuli were similar to the true instances, but did not have the defining feature. Transfer type 3 stimuli had the defining feature, but were not similar to the true instances. If participants used a rule-based strategy, then transfer type 3 stimuli would be generalized to the target category, but not transfer type 2 stimuli. The opposite would happen if participants used a similarity-based strategy.

Participants and Procedure

The 40 adult participants (Males=26, Females=14, Mean age=22.00, S.D.=3.21) in Experiment 2 were volunteers from the student community. Each participant responded to 10 practice trials followed by 20 experimental trials. No feedback was given to the participants during the trials. 800 data points (40 participants $\times$ 20 trials) were obtained from the experiment. There were 640 datapoints corresponding to type 2 and type 3 transfer stimuli. Participants were made to respond to more type 2 and type 3 stimuli because these reveal more about participant generalization behavior. The maximum response time limit was 40 seconds. The generalization strategy of the participants was the dependent variable.

Results

Our results show that participants were able to correctly identify the type 1 stimuli as true instances, and type 4 stimuli as false instances of the target category. The overall percentage of correct, incorrect and can't decide responses for type 1 and type 4 stimuli were 78.75%, 11.25% and 10.0% respectively.

The 3D bars in Figure 5 show how the categorization strategy varied for transfer stimuli types 2 and 3. There were 640 datapoints. The median values of category entropy and rule saliency across Experiments 2 and 3 were used to divide the 640 datapoints into four sets. The four sets corresponded to the high and low values of rule saliency and category entropy. The percentages of similarity-based responses and rule-based responses for each set was found. Figure 5 shows that similarity-based responses (black bar) were preferred over rule-based responses (green bar).

The rule saliency values were obtained from the saliency model, and lie in the range $[0,1]$. Figure 6 shows the effect of rule saliency on rule-based responses (green line). We divided the 640 datapoints into five equal sized bins (each having 128 datapoints). In Figure 6, the numbers in brackets denote the datapoints in each bin. Figure 6 plots the percentage of rule-based responses for each of the five bins. In Figure 6, the x error bars denote the range of rule saliency in each bin.

Figure 6 also shows the effect of rule saliency on similarity-based responses (black line). The x error bars for similarity-based responses (black line) align with the x error bars for rule-based responses (green line) because they correspond to the same five bins. Figure 6 shows that similarity-based responses were preferred over the rule-based responses for different values of rule saliency.

In our study, rule saliency and category entropy are continuous variables. For each trial, rule-based response is a binary variable. Point-biserial correlation coefficient gives the correlation between a continuous variable and a binary variable. We use Pearson product moment correlation because it is equivalent to the point-biserial correlation. The Pearson correlation between rule saliency and rule-based responses was found to be not significant $(r(638) = .09, ns)$ [1].

Figure 7 shows the effect of category entropy on rule-based responses (green line), and similarity-based responses (black line). The figure shows that similarity-based responses are preferred over rule-based responses; except when entropy is very high. When entropy is very high, the non-defining feature values of category members are very different from each other. In this scenario, similarity will be mostly determined by the defining feature. Hence, for high values of category entropy there will be no difference between similarity-based categorization and rule-based categorization.

The Pearson correlation between category entropy and rule-based responses was found to be significant $(r(638) = .12, p < .01)$. The maximum value that the category entropy took in Experiment 2 was 1.85 (maximum possible value is 2.07).

[1] Here, $df = 638$ because there were 640 datapoints.

The results of Experiment 2 show that participants preferred similarity-based responses over rule-based responses. Category entropy had a significant effect on categorization strategy; but rule saliency did not.

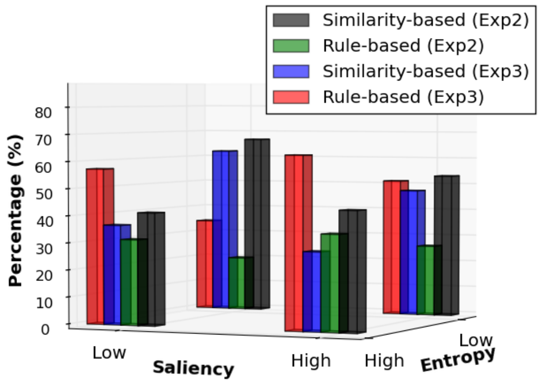

Figure 5: Rule-based and similarity-based responses for transfer stimuli types 2 and 3 in Experiments 2 and 3.

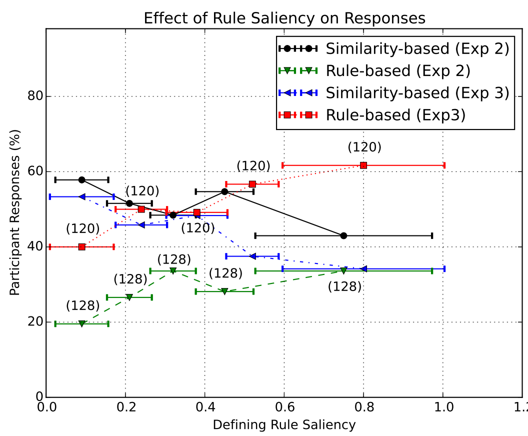

Figure 6: Effect of rule saliency on participant responses for transfer types 2 and 3.

Experiment 3

In Experiment 2, all stimuli were shown simultaneously. In Experiment 3, we wanted to study whether showing the transfer stimulus after a time delay will lead to a preference for rule-based responses.

In Experiment 3, participants were shown true and false instances of a category for a maximum duration of 40 seconds — just as in Experiment 2. When participants clicked the next button the screen would go blank for six seconds, and then the transfer stimulus would be presented. As before, a participant could select one of the three options — Yes, No or Can't decide. Apart from the delayed presentation of the transfer stimulus, every other detail remained the same as that in Experiment 2.

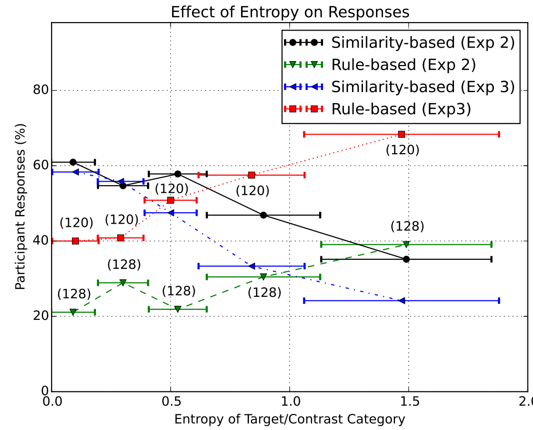

Figure 7: Effect of category entropy on participant responses for transfer types 2 and 3.

Participants and Procedure

We had a new set of 50 adult participants (Males=30, Females=20, Mean age=21.88, S.D.=3.73). The participants were volunteers from the student community. Each participant responded to 10 practice trials followed by 16 experimental trials. No feedback was given to the participants during the trials. We obtained 800 data points (50 participants × 16 trials) from the experiment. Out of 800 data points, 600 corresponded to type 2 and type 3 transfer stimuli.

Results

Our results show that participants were able to correctly categorize the type 1 stimuli as true instances, and type 4 stimuli as false instances of the target category. The overall percentage of correct, incorrect and can't decide responses for type 1 and type 4 stimuli were 87.5%, 10.0% and 2.5% respectively.

Figure 5 shows how the categorization strategy varied for transfer stimuli types 2 and 3. There were 600 datapoints. The median values of rule saliency and category entropy were used to divide the 600 datapoints into four sets, that corresponded to the high and low values of rule saliency and category entropy. Figure 5 shows that rule-based responses (red bar) were greater than similarity-based responses (blue bar) when either rule saliency or category entropy was high.

Figure 6 shows the effect of rule saliency on categorization strategy. The 600 datapoints were divided into 5 equal sized bins (each having 120 datapoints). Figure 6 shows that for higher values of saliency rule-based responses (red line) were preferred over the similarity-based response (blue line). The rule-based responses were found to be correlated with saliency $(r(598) = .15, p < .001)$ [2].

Figure 7 shows that rule-based responses (red line) were preferred over similarity-based responses (blue line) for high values of entropy. The rule-based responses were found to be correlated with entropy $(r(598) = .20, p < .0001)$.

[2]Here, $df = 598$ because there were 600 datapoints.

In Experiment 2, the number of rule-based and non-rule-based responses for type 2 and type 3 stimuli were 181 and 459 respectively (total 640 datapoints). In Experiment 3, the number of rule-based and non-rule-based responses for type 2 and type 3 stimuli were 309 and 291 respectively (total 600 datapoints). The difference between the observed frequencies of responses across the two experiments was found to be significant ($\chi^2(1, N = 1240) = 68.88, p < .0001$).

The results of Experiment 3 show that presenting the transfer stimulus after a delay caused a significant increase in rule-based responses.

Discussion and Conclusion

The aim of our study was to identify the variables that cause participants to prefer one categorization strategy over another. When the training and transfer stimuli were presented simultaneously, participants preferred similarity-based generalization. When transfer stimuli was presented after a six seconds delay, participants preferred rule-based responses for higher values of rule saliency and category entropy.

Our Experiment 2 results are consistent with the results in (Xu & Tenenbaum, 2007; Schmidt, 2009; Thomas & Karnick, 2014), that report a preference for similarity-based generalization. In (Kloos & Sloutsky, 2008), the transfer stimuli was presented in a separate testing block. Our Experiment 3 results show that participants prefer similarity-based generalization when category entropy is low, but rule-based generalization is preferred when entropy is high. This result is consistent with (Kloos & Sloutsky, 2008). In (Feldman, 2000; Conaway & Kurtz, 2014; Rabi et al., 2015), transfer stimuli was presented in a separate testing block, and participants preferred rule-based generalization. The Experiment 3 results can explain the above results as well.

When transfer stimulus is presented after a delay, participants use their short term memory to remember the training stimuli. Visual short term memory has a limited capacity (Todd & Marois, 2004). So, remembering all the features of the training stimuli would become difficult. This might be causing the participants to use a simple rule-based strategy, which puts less demand on the short term memory.

We have quantified family resemblance using category entropy, which does not take into account the saliency of different features. This allows us to independently vary category entropy and rule saliency. But, when defining rule saliency is increased it should lead to greater family resemblance. Category entropy does not take this effect into account.

Many studies in the literature make use of artificial categories. Artificial stimuli allow us to study the learning behavior in the absence of prior knowledge about the categories.

In this study, we have manipulated three variables: family resemblance, rule saliency and delayed presentation of transfer stimulus. Our results show that these variables influence the choice of categorization strategy. Our study offers possible explanations for the divergent results in the visual category learning literature.

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