Feature Prioritization in Verification Classification of Novel Objects

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Summary

Object classification is essential to human learning as it helps us cope with various stimulus around the world. Regardless of multiple features within a single object, object classification seems to occur seamlessly within our cognitive process. In this experiment, we test how we prioritize each feature within an object and how these features are weighted when we categorize a certain object. Test subjects were given novel shapes that each featured either size, color, or orientation, and had to determine whether the shape belongs to a category of a given prototypical shape. The preliminary result showed that color was the single most determining feature when categorizing an object, showing 72.6% of incorporation in all trials, while orientation was the least with 60.7%, but the differences were not statistically significant. We further went on to use logistic regression to analyze the result, which showed thresholds for identifying a novel object to be in a certain category. However, these thresholds for each feature was not significantly different. The experiment suggests that categorization is more of an elaborate and holistic process that combines different features when categorizing a novel object.

Introduction

Object classification is an easily achieved ability for humans. After a few positive examples or one prototypical example, humans have the ability to accurately predict what other objects may fall in a certain category. Humans are constantly introduced to new objects that need to fit into the thousands of existing categories we've been presented with, which poses a great challenge when categorizing novel objects.[1] This leads us to question if there are certain features that humans may prioritize over others when categorizing novel objects. If there are certain features that are weighted more than other features, it could potentially simplify the thousands of calculations we make when determining new categories. Are there certain features that, if matching a prototypical example, are more likely to sway a person's inclination to categorize that object?

Methods

We began designing our experiment by devising five novel images to be the prototypical example of a category. These novel images consisted of putting simple shapes together to create slightly more complicated shapes. We did this in order to prevent experiment participants from easily determining the different feature we attempted to test. If the shape were too simple, say, a triangle, participants would be able to easily identity the differences in size, color, and orientation. If the novel images could not be identified as existing shapes, the differences in features would be less obvious.

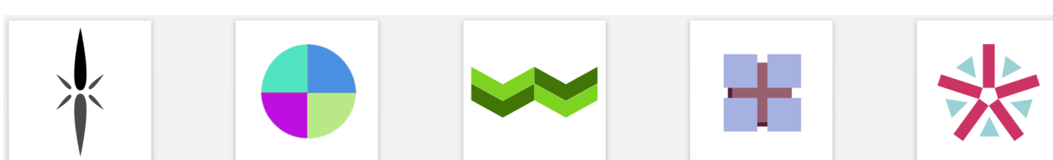


Figure 1: The five novel images created to stand as our prototypical examples for new categories. As noted before, these images are created out of simple shapes; however, cannot be classified into any

[1] Wu L., Luo S., Sun W. (2010) A Novel Object Categorization Model with Implicit Local Spatial Relationship. In: Zhang L., Lu BL., Kwok J. (eds) Advances in Neural Networks - ISNN 2010. ISNN 2010. Lecture Notes in Computer Science, vol 6064. Springer, Berlin, Heidelberg

already existing shape. Each category was presented to participants as “dax 1”, “dax 2” .. etc. accordingly.

After designing the prototypical example of five different categories, we designed five more novel images that look similar, but not exactly like the original daxes. Using these five new images, we varied the representation of certain features, specifically for the features of size, color, and orientation. By creating new objects that do not match the original daxes, we are able to distinguish between the weighting the features instead of creating an experiment based mostly on matching images to the original.

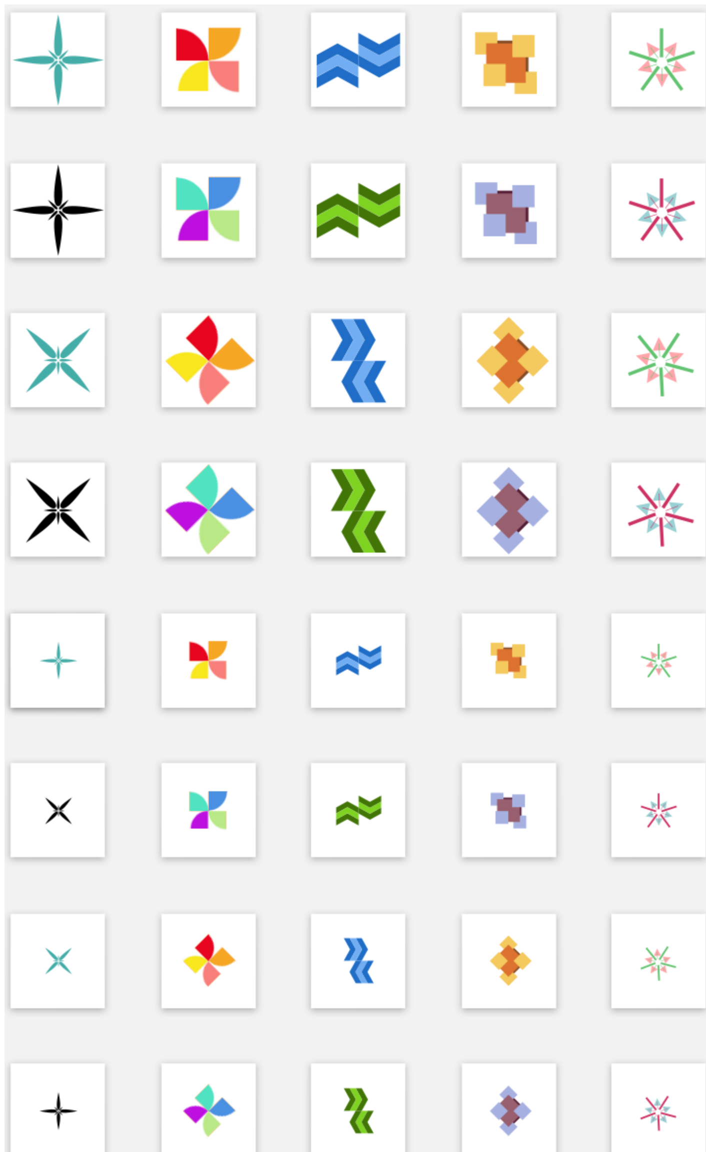


Figure 2: All the images created using the original daxes for reference. Each novel image is based on the original daxes from Figure 1 (column 1 correlates with dax 1, column 2 correlates with dax 2… etc.). Each row represents a different configuration of each of the features we are testing for. The configurations by row are as follows: Row 1: same size, different color, same orientation Row 2: same size, same color, same orientation Row 3: same size, different color, different orientation Row 4: same size, same color, different orientation Row 5: different size, different color, same orientation Row 6:

different size, same color, different orientation Row 7: different size, different color, different orientation Row 8: different size, same color, same orientation.

After the creation and design of our novel images, we surveyed and tested eight college students. When testing participants, they were shown the prototypical dax and the eight subsequent images with each configuration of features. Of the eight novel images, participants were asked to determine which they would consider to be a part of the dax category. Participants were allowed to choose as many images as they liked to be in the dax category. Participants were also allowed to state that none of the following novel images belonged in the dax category. The yes or no type response generated by these questions creates a binary representation of each of the images and the weights for each of the corresponding features. The question more specifically targets the categorization verification ability that is present in humans, aside from other categorization type questions such as identification and categorization detection.[2] The order in which the images were presented varied between each dax as to prevent users from finding a certain pattern in the novel images.

Figure 3: A sample of how each question was presented to participants. Participants were asked to list off or check off which images (range 3.1-3.8 in this particular example) would fall into the “dax 3” category.

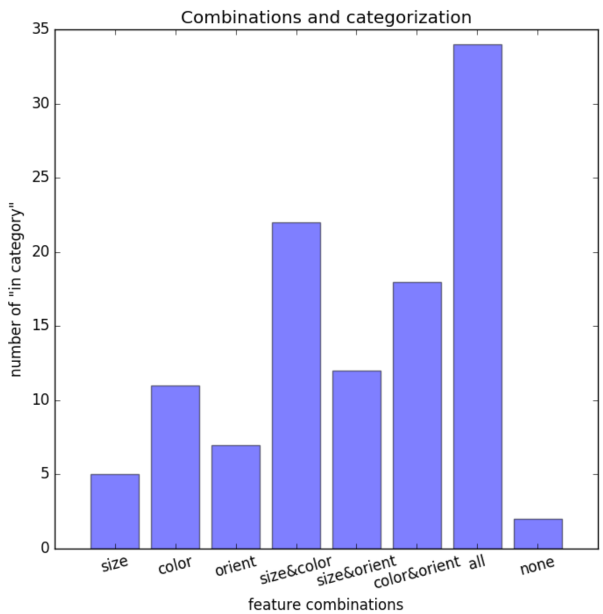
Results

After surveying participants, we converted participant responses into the previously mentioned binary representation. Depending on the images participants selected as belonging in the category, each image was weighted with a 3-digit representation. The digits correspond from the hundreds place of the ones place as: size, color, and orientation. A 1 represents a feature matching the original dax, a 0 corresponds to a feature differing from the original dax. For example, from Figure 3, if a participant chose 3.2 to be in the category, the numerical representation would be 111, meaning that 3.2 has matching size, color, and orientation to the original dax.

After converting our data into the 3-digit representation, we graphed the number of times each category and combinations of categories were selected. (Figure 4 and 5) Based on these graphs we can see, and confirm what we would already imagine, that the total combination of size, color, and orientation was confirmed as in the category in the most often. None of the other bars are significant in predicting if a participant would include the image in a certain category. Figure 5 removes the

[2] Fei-Fei, Li. "Object Categorization: Object Categorization: An Overview & Two Models." Stanford Vision Lab. Stanford, Palo Alto. 2007. Lecture.

dependencies and analyzes if any one particular feature was selected over others. While color is the most often picked feature, it does not show much significance over the other two features.



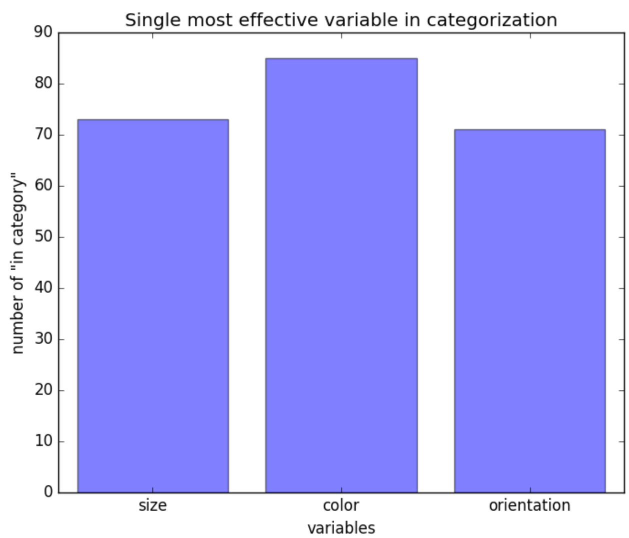


Figure 4 and 5: Figure 4 displays the number of times a certain configuration of features was selected to be in the category of a certain dax. The leftmost three columns represent the number of times a certain image was selected that only held one similar feature to the original dax. Figure 5 displays the number of times a certain feature matched the original dax. The combinations of other features involved were not taken into account.

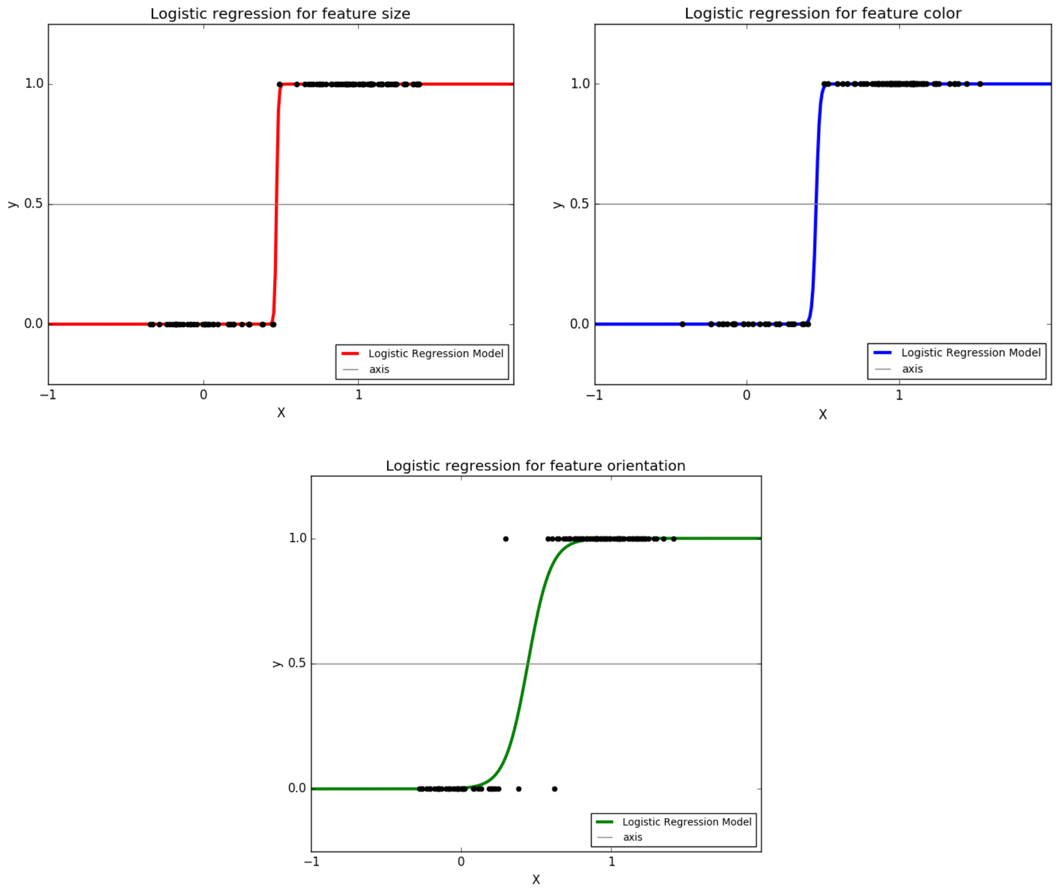


Figure 6: The graphs displaying the logistic regression for each of the features. Logistic regression was calculated from scikit's sklearn.linear_model.LogisticRegression package. We weighted our data from our previous research, applied a Gaussian distribution, and determined the x intercepts.

After simply calculating the number of times features of combinations of features were selected to be in the original category, we used our prior data to apply a logistic regression to determine the likelihood that a matching feature would be positively categorized. In order to calculate the logistic regression, we used the data we previously acquired, added noise from a Gaussian distribution and calculated the x intercepts when y = 0.5. Anything greater than the x intercept would imply that the model would categorize positively as in the category while anything less than the x intercept would be categorized negatively. The x intercept values are as follows in order of size, color, and orientation: 0.472, 0.454, 0.445. Because orientation has the smallest x intercept value, this means that it has the largest range in which a novel image would be categorized positively. However, the x intercept values are all very close together and all very close to 0.5, the probability of a coin flip. These values are ultimately nondeterministic.

Conclusion

Our experiment shows that there is no single most determining factor when we categorize a novel object. While we believed orientation to be the most important factor of the three primary features when categorizing, the difference in each feature shows no statistically significant results. Instead, the results suggest that categorization is rather a more elaborate process in which different features are equally weighted and prioritized when identifying novel objects. In order to further test this idea, we can devise future experiments to test more subjects with various categories.

References

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